

---

# **pyhf Documentation**

***Release 0.6.2.dev48***

**Lukas Heinrich, Matthew Feickert, Giordon Stark**

**May 21, 2021**



# CONTENTS

<b>1</b>	<b>HistFactory</b>	<b>3</b>
<b>2</b>	<b>Declarative Formats</b>	<b>7</b>
<b>3</b>	<b>Additional Material</b>	<b>9</b>
3.1	Footnotes . . . . .	9
3.2	Bibliography . . . . .	9
<b>4</b>	<b>Likelihood Specification</b>	<b>11</b>
4.1	Workspace . . . . .	11
4.2	Channel . . . . .	12
4.3	Sample . . . . .	12
4.4	Modifiers . . . . .	13
4.5	Data . . . . .	15
4.6	Measurements . . . . .	15
4.7	Observations . . . . .	16
4.8	Toy Example . . . . .	16
4.9	Additional Material . . . . .	17
<b>5</b>	<b>Fundamentals</b>	<b>19</b>
5.1	Piecewise Linear Interpolation . . . . .	19
5.2	Tensorizing Interpolators . . . . .	25
5.3	Empirical Test Statistics . . . . .	43
5.4	Using Calculators . . . . .	48
<b>6</b>	<b>Examples</b>	<b>53</b>
6.1	ShapeFactor . . . . .	53
6.2	XML Import/Export . . . . .	56
6.3	Visualization with Altair . . . . .	62
6.4	Hello World, pyhf style . . . . .	64
6.5	Multi-bin Poisson . . . . .	65
6.6	Multibin Coupled HistoSys . . . . .	70
6.7	Running Monte Carlo simulations (toys) . . . . .	74
6.8	Binned HEP Statistical Analysis in Python . . . . .	79
<b>7</b>	<b>Outreach</b>	<b>85</b>
7.1	Abstract . . . . .	85
7.2	Presentations . . . . .	85
7.3	Tutorials . . . . .	87
7.4	Posters . . . . .	87
7.5	In the Media . . . . .	87

<b>8</b>	<b>Installation</b>	<b>89</b>
8.1	Install latest stable release from PyPI...	89
8.2	Install latest development version from GitHub...	90
8.3	Updating pyhf	91
<b>9</b>	<b>Developing</b>	<b>93</b>
9.1	Testing	93
9.2	Publishing	94
9.3	Context Files and Archive Metadata	94
<b>10</b>	<b>FAQ</b>	<b>95</b>
10.1	Questions	95
10.2	Troubleshooting	96
<b>11</b>	<b>Translations</b>	<b>97</b>
11.1	HistFitter	97
11.2	TRExFitter	98
<b>12</b>	<b>Command Line API</b>	<b>101</b>
12.1	pyhf	101
<b>13</b>	<b>Python API</b>	<b>113</b>
13.1	Top-Level	113
13.2	Probability Distribution Functions (PDFs)	119
13.3	Making Models from PDFs	123
13.4	Backends	138
13.5	Optimizers	170
13.6	Modifiers	174
13.7	Interpolators	177
13.8	Inference	179
13.9	Exceptions	204
13.10	Utilities	207
13.11	Contrib	208
<b>14</b>	<b>Use and Citations</b>	<b>215</b>
14.1	Citation	215
14.2	Use in Publications	215
14.3	Published Likelihoods	217
<b>15</b>	<b>Roadmap (2019-2020)</b>	<b>219</b>
15.1	Overview and Goals	219
15.2	Time scale	220
15.3	Roadmap	220
15.4	Presentations During Roadmap Timeline	222
<b>16</b>	<b>Release Notes</b>	<b>223</b>
16.1	v0.6.1	223
16.2	v0.6.0	223
16.3	v0.5.4	226
16.4	v0.5.3	227
<b>17</b>	<b>Contributors</b>	<b>229</b>
<b>18</b>	<b>pure-python fitting/limit-setting/interval estimation HistFactory-style</b>	<b>231</b>
18.1	Hello World	231
18.2	What does it support	233

18.3	Todo . . . . .	233
18.4	A one bin example . . . . .	233
18.5	A two bin example . . . . .	235
18.6	Installation . . . . .	237
18.7	Questions . . . . .	237
18.8	Citation . . . . .	237
18.9	Authors . . . . .	238
18.10	Milestones . . . . .	238
18.11	Acknowledgements . . . . .	238
<b>19</b>	<b>Indices and tables</b>	<b>239</b>
	<b>Bibliography</b>	<b>241</b>
	<b>Python Module Index</b>	<b>243</b>
	<b>Index</b>	<b>245</b>



Measurements in High Energy Physics (HEP) rely on determining the compatibility of observed collision events with theoretical predictions. The relationship between them is often formalised in a statistical *model*  $f(x|)$  describing the probability of data  $x$  given model parameters . Given observed data, the *likelihood*  $\mathcal{L}()$  then serves as the basis to test hypotheses on the parameters . For measurements based on binned data (*histograms*), the family of statistical models has been widely used in both Standard Model measurements [\[intro-4\]](#) as well as searches for new physics [\[intro-5\]](#). In this package, a declarative, plain-text format for describing -based likelihoods is presented that is targeted for reinterpretation and long-term preservation in analysis data repositories such as HEPData [\[intro-3\]](#).





## HISTFACTORY

Statistical models described using [intro-2] center around the simultaneous measurement of disjoint binned distributions (*channels*) observed as event counts. For each channel, the overall expected event rate<sup>1</sup> is the sum over a number of physics processes (*samples*). The sample rates may be subject to parametrised variations, both to express the effect of *free parameters*<sup>2</sup> and to account for systematic uncertainties as a function of *constrained parameters*. The degree to which the latter can cause a deviation of the expected event rates from the nominal rates is limited by *constraint terms*. In a frequentist framework these constraint terms can be viewed as *auxiliary measurements* with additional global observable data, which paired with the channel data completes the observation  $x = (, )$ . In addition to the partition of the full parameter set into free and constrained parameters  $= (, )$ , a separate partition  $= (, )$  will be useful in the context of hypothesis testing, where a subset of the parameters are declared *parameters of interest* and the remaining ones as *nuisance parameters*.

$$f(x) = f(x | \underbrace{\text{free}}_{\text{constrained}}, \underbrace{\text{parameters of interest}}_{\text{nuisance parameters}}) \quad (1.1)$$

Thus, the overall structure of a probability model is a product of the analysis-specific model term describing the measurements of the channels and the analysis-independent set of constraint terms:

$$f(, |, ) = \underbrace{\prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb} | \nu_{cb}(, ))}_{\text{Simultaneous measurement of multiple channels}} \underbrace{\prod_{a \in \text{auxiliary measurements}} c(a | )}_{\text{constraint terms}}, \quad (1.2)$$

where within a certain integrated luminosity we observe  $n_{cb}$  events given the expected rate of events  $\nu_{cb}(, )$  as a function of unconstrained parameters and constrained parameters. The latter has corresponding one-dimensional constraint terms  $c(a | )$  with auxiliary data  $a$  constraining the parameter. The event rates  $\nu_{cb}$  are defined as

$$\nu_{cb}(, ) = \sum_{s \in \text{samples}} \nu_{scb}(, ) = \sum_{s \in \text{samples}} \left( \underbrace{\prod_{\kappa \in \kappa} \kappa_{scb}(, )}_{\text{multiplicative modifiers}} \right) \left( \underbrace{\nu_{scb}^0(, ) + \sum_{\Delta \in \Delta} \Delta_{scb}(, )}_{\text{additive modifiers}} \right). \quad (1.3)$$

The total rates are the sum over sample rates  $\nu_{scb}$ , each determined from a *nominal rate*  $\nu_{scb}^0$  and a set of multiplicative and additive denoted *rate modifiers*  $\kappa()$  and  $\Delta()$ . These modifiers are functions of (usually a single) model parameters. Starting from constant nominal rates, one can derive the per-bin event rate modification by iterating over all sample rate modifications as shown in (1.3).

As summarised in *Modifiers and Constraints*, rate modifications are defined in for bin  $b$ , sample  $s$ , channel  $c$ . Each modifier is represented by a parameter  $\phi \in \{\gamma, \alpha, \lambda, \mu\}$ . By convention bin-wise parameters are denoted with  $\gamma$  and

<sup>1</sup> Here rate refers to the number of events expected to be observed within a given data-taking interval defined through its integrated luminosity. It often appears as the input parameter to the Poisson distribution, hence the name “rate”.

<sup>2</sup> These *free parameters* frequently include the of a given process, i.e. its cross-section normalised to a particular reference cross-section such as that expected from the Standard Model or a given BSM scenario.

interpolation parameters with  $\alpha$ . The luminosity  $\lambda$  and scale factors  $\mu$  affect all bins equally. For constrained modifiers, the implied constraint term is given as well as the necessary input data required to construct it.  $\sigma_b$  corresponds to the relative uncertainty of the event rate, whereas  $\delta_b$  is the event rate uncertainty of the sample relative to the total event rate  $\nu_b = \sum_s \nu_{sb}^0$ .

Modifiers implementing uncertainties are paired with a corresponding default constraint term on the parameter limiting the rate modification. The available modifiers may affect only the total number of expected events of a sample within a given channel, i.e. only change its normalisation, while holding the distribution of events across the bins of a channel, i.e. its “shape”, invariant. Alternatively, modifiers may change the sample shapes. Here supports correlated an uncorrelated bin-by-bin shape modifications. In the former, a single nuisance parameter affects the expected sample rates within the bins of a given channel, while the latter introduces one nuisance parameter for each bin, each with their own constraint term. For the correlated shape and normalisation uncertainties, makes use of interpolating functions,  $f_p$  and  $g_p$ , constructed from a small number of evaluations of the expected rate at fixed values of the parameter  $\alpha$ <sup>3</sup>. For the remaining modifiers, the parameter directly affects the rate.

Table 1: Modifiers and Constraints

Description	Modification	Constraint Term $c$	Input
Uncorrelated Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Pois}(r_b = \sigma_b^{-2}   \rho_b = \sigma_b^{-2} \gamma_b)$	$\sigma_b$
Correlated Shape	$\Delta_{scb}(\alpha) = f_p(\alpha   \Delta_{scb, \alpha=-1}, \Delta_{scb, \alpha=1})$	$\text{Gaus}(a = 0   \alpha, \sigma = 1)$	$\Delta_{scb, \alpha=\pm 1}$
Normalisation Unc.	$\kappa_{scb}(\alpha) = g_p(\alpha   \kappa_{scb, \alpha=-1}, \kappa_{scb, \alpha=1})$	$\text{Gaus}(a = 0   \alpha, \sigma = 1)$	$\kappa_{scb, \alpha=\pm 1}$
MC Stat. Uncertainty	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Gaus}(a_{\gamma_b} = 1   \gamma_b, \delta_b)$	$\delta_b^2 = \sum_s \delta_{sb}^2$
Luminosity	$\kappa_{scb}(\lambda) = \lambda$	$\text{Gaus}(l = \lambda_0   \lambda, \sigma_\lambda)$	$\lambda_0, \sigma_\lambda$
Normalisation	$\kappa_{scb}(\mu_b) = \mu_b$		
Data-driven Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$		

Given the likelihood  $\mathcal{L}()$ , constructed from observed data in all channels and the implied auxiliary data, *measurements* in the form of point and interval estimates can be defined. The majority of the parameters are *nuisance parameters* — parameters that are not the main target of the measurement but are necessary to correctly model the data. A small subset of the unconstrained parameters may be declared as *parameters of interest* for which measurements hypothesis tests are performed, e.g. profile likelihood methods [intro-1]. The *Symbol Notation* table provides a summary of all the notation introduced in this documentation.

<sup>3</sup> This is usually constructed from the nominal rate and measurements of the event rate at  $\alpha = \pm 1$ , where the value of the modifier at  $\alpha = \pm 1$  must be provided and the value at  $\alpha = 0$  corresponds to the corresponding identity operation of the modifier, i.e.  $f_p(\alpha = 0) = 0$  and  $g_p(\alpha = 0) = 1$  for additive and multiplicative modifiers respectively. See Section 4.1 in [intro-2].

Table 2: Symbol Notation

Symbol	Name
$f(x )$	model
$\mathcal{L}()$	likelihood
$x = \{, \}$	full dataset (including auxiliary data)
	channel data (or event counts)
	auxiliary data
$\nu()$	calculated event rates
$= \{, \} = \{, \}$	all parameters
	free parameters
	constrained parameters
	parameters of interest
	nuisance parameters
$\kappa()$	multiplicative rate modifier
$\Delta()$	additive rate modifier
$c(a )$	constraint term for constrained parameter
$\sigma$	relative uncertainty in the constrained parameter



## DECLARATIVE FORMATS

While flexible enough to describe a wide range of LHC measurements, the design of the `specification` is sufficiently simple to admit a *declarative format* that fully encodes the statistical model of the analysis. This format defines the channels, all associated samples, their parameterised rate modifiers and implied constraint terms as well as the measurements. Additionally, the format represents the mathematical model, leaving the implementation of the likelihood minimisation to be analysis-dependent and/or language-dependent. Originally XML was chosen as a specification language to define the structure of the model while introducing a dependence on `yaml` to encode the nominal rates and required input data of the constraint terms [intro-2]. Using this specification, a model can be constructed and evaluated within the `pyhf` framework.

This package introduces an updated form of the specification based on the ubiquitous plain-text JSON format and its schema-language *JSON Schema*. Described in more detail in *Likelihood Specification*, this schema fully specifies both structure and necessary constrained data in a single document and thus is implementation independent.



## ADDITIONAL MATERIAL

### 3.1 Footnotes

### 3.2 Bibliography





## LIKELIHOOD SPECIFICATION

The structure of the JSON specification of models follows closely the original XML-based specification [likelihood-2].

### 4.1 Workspace

```
{
  "$schema": "http://json-schema.org/draft-06/schema#",
  "$id": "https://scikit-hep.org/pyhf/schemas/1.0.0/workspace.json",
  "$ref": "defs.json#/definitions/workspace"
}
```

The overall document in the above code snippet describes a *workspace*, which includes

- **channels:** The channels in the model, which include a description of the samples within each channel and their possible parametrised modifiers.
- **measurements:** A set of measurements, which define among others the parameters of interest for a given statistical analysis objective.
- **observations:** The observed data, with which a likelihood can be constructed from the model.

A workspace consists of the channels, one set of observed data, but can include multiple measurements. If provided a JSON file, one can quickly check that it conforms to the provided workspace specification as follows:

```
import json, requests, jsonschema

workspace = json.load(open("/path/to/analysis_workspace.json"))
# if no exception is raised, it found and parsed the schema
schema = requests.get("https://scikit-hep.org/pyhf/schemas/1.0.0/workspace.json").json()
# If no exception is raised by validate(), the instance is valid.
jsonschema.validate(instance=workspace, schema=schema)
```

## 4.2 Channel

A channel is defined by a channel name and a list of samples [likelihood-1].

```
{
  "channel": {
    "type": "object",
    "properties": {
      "name": { "type": "string" },
      "samples": { "type": "array", "items": { "$ref": "#/definitions/sample" },
↪ "minItems": 1 }
    },
    "required": ["name", "samples"],
    "additionalProperties": false
  },
}
```

The Channel specification consists of a list of channel descriptions. Each channel, an analysis region encompassing one or more measurement bins, consists of a `name` field and a `samples` field (see *Channel*), which holds a list of sample definitions (see *Sample*). Each sample definition in turn has a `name` field, a `data` field for the nominal event rates for all bins in the channel, and a `modifiers` field of the list of modifiers for the sample.

## 4.3 Sample

A sample is defined by a sample name, the sample event rate, and a list of modifiers [likelihood-1].

```
{
  "sample": {
    "type": "object",
    "properties": {
      "name": { "type": "string" },
      "data": { "type": "array", "items": { "type": "number" }, "minItems": 1 },
      "modifiers": {
        "type": "array",
        "items": {
          "anyOf": [
            { "$ref": "#/definitions/modifier/histosys" },
            { "$ref": "#/definitions/modifier/lumi" },
            { "$ref": "#/definitions/modifier/normfactor" },
            { "$ref": "#/definitions/modifier/normsys" },
            { "$ref": "#/definitions/modifier/shapefactor" },
            { "$ref": "#/definitions/modifier/shapesys" },
            { "$ref": "#/definitions/modifier/staterror" }
          ]
        }
      }
    },
    "required": ["name", "data", "modifiers"],
    "additionalProperties": false
  },
}
```

## 4.4 Modifiers

The modifiers that are applicable for a given sample are encoded as a list of JSON objects with three fields. A name field, a type field denoting the class of the modifier, and a data field which provides the necessary input data as denoted in *Modifiers and Constraints*.

Based on the declared modifiers, the set of parameters and their constraint terms are derived implicitly as each type of modifier unambiguously defines the constraint terms it requires. Correlated shape modifiers and normalisation uncertainties have compatible constraint terms and thus modifiers can be declared that *share* parameters by re-using a name<sup>1</sup> for multiple modifiers. That is, a variation of a single parameter causes a shift within sample rates due to both shape and normalisation variations.

We review the structure of each modifier type below.

### 4.4.1 Uncorrelated Shape (shapesys)

To construct the constraint term, the relative uncertainties  $\sigma_b$  are necessary for each bin. Therefore, we record the absolute uncertainty as an array of floats, which combined with the nominal sample data yield the desired  $\sigma_b$ . An example is shown below:

```
{ "name": "mod_name", "type": "shapesys", "data": [1.0, 1.5, 2.0] }
```

An example of an uncorrelated shape modifier with three absolute uncertainty terms for a 3-bin channel.

**Warning:** Nuisance parameters will not be allocated for any bins where either

- the samples nominal expected rate is zero, or
- the absolute uncertainty is zero.

These values are, in the context of uncorrelated shape uncertainties, unphysical. If this situation occurs, one needs to go back and understand the inputs as this is undefined behavior in HistFactory.

The previous example will allocate three nuisance parameters for `mod_name`. The following example will allocate only two nuisance parameters for a 3-bin channel:

```
{ "name": "mod_name", "type": "shapesys", "data": [1.0, 0.0, 2.0] }
```

### 4.4.2 Correlated Shape (histosys)

This modifier represents the same source of uncertainty which has a different effect on the various sample shapes, hence a correlated shape. To implement an interpolation between sample distribution shapes, the distributions with a “downward variation” (“lo”) associated with  $\alpha = -1$  and an “upward variation” (“hi”) associated with  $\alpha = +1$  are provided as arrays of floats. An example is shown below:

```
{ "name": "mod_name", "type": "histosys", "data": { "hi_data": [20,15], "lo_data": [10,10] } }
```

An example of a correlated shape modifier with absolute shape variations for a 2-bin channel.

<sup>1</sup> The name of a modifier specifies the parameter set it is controlled by. Modifiers with the same name share parameter sets.

### 4.4.3 Normalisation Uncertainty (normsys)

The normalisation uncertainty modifies the sample rate by a overall factor  $\kappa(\alpha)$  constructed as the interpolation between downward (“lo”) and upward (“hi”) as well as the nominal setting, i.e.  $\kappa(-1) = \kappa_{\alpha=-1}$ ,  $\kappa(0) = 1$  and  $\kappa(+1) = \kappa_{\alpha=+1}$ . In the modifier definition we record  $\kappa_{\alpha=+1}$  and  $\kappa_{\alpha=-1}$  as floats. An example is shown below:

```
{ "name": "mod_name", "type": "normsys", "data": {"hi": 1.1, "lo": 0.9} }
```

An example of a normalisation uncertainty modifier with scale factors recorded for the up/down variations of an  $n$ -bin channel.

### 4.4.4 MC Statistical Uncertainty (statererror)

As the sample counts are often derived from Monte Carlo (MC) datasets, they necessarily carry an uncertainty due to the finite sample size of the datasets. As explained in detail in [likelihood-2], adding uncertainties for each sample would yield a very large number of nuisance parameters with limited utility. Therefore a set of bin-wise scale factors  $\gamma_b$  is introduced to model the overall uncertainty in the bin due to MC statistics. The constrained term is constructed as a set of Gaussian constraints with a central value equal to unity for each bin in the channel. The scales  $\sigma_b$  of the constraint are computed from the individual uncertainties of samples defined within the channel relative to the total event rate of all samples:  $\delta_{csb} = \sigma_{csb} / \sum_s \nu_{scb}^0$ . As not all samples within a channel are estimated from MC simulations, only the samples with a declared statistical uncertainty modifier enter the sum. An example is shown below:

```
{ "name": "mod_name", "type": "statererror", "data": [0.1] }
```

An example of a statistical uncertainty modifier.

### 4.4.5 Luminosity (lumi)

Sample rates derived from theory calculations, as opposed to data-driven estimates, are scaled to the integrated luminosity corresponding to the observed data. As the luminosity measurement is itself subject to an uncertainty, it must be reflected in the rate estimates of such samples. As this modifier is of global nature, no additional per-sample information is required and thus the data field is nulled. This uncertainty is relevant, in particular, when the parameter of interest is a signal cross-section. The luminosity uncertainty  $\sigma_\lambda$  is provided as part of the parameter configuration included in the measurement specification discussed in *Measurements*. An example is shown below:

```
{ "name": "mod_name", "type": "lumi", "data": null }
```

An example of a luminosity modifier.

### 4.4.6 Unconstrained Normalisation (normfactor)

The unconstrained normalisation modifier scales the event rates of a sample by a free parameter  $\mu$ . Common use cases are the signal rate of a possible BSM signal or simultaneous in-situ measurements of background samples. Such parameters are frequently the parameters of interest of a given measurement. No additional per-sample data is required. An example is shown below:

```
{ "name": "mod_name", "type": "normfactor", "data": null }
```

An example of a normalisation modifier.

### 4.4.7 Data-driven Shape (shapefactor)

In order to support data-driven estimation of sample rates (e.g. for multijet backgrounds), the data-driven shape modifier adds free, bin-wise multiplicative parameters. Similarly to the normalisation factors, no additional data is required as no constraint is defined. An example is shown below:

```
{ "name": "mod_name", "type": "shapefactor", "data": null }
```

An example of an uncorrelated shape modifier.

## 4.5 Data

The data provided by the analysis are the observed data for each channel (or region). This data is provided as a mapping from channel name to an array of floats, which provide the observed rates in each bin of the channel. The auxiliary data is not included as it is an input to the likelihood that does not need to be archived and can be determined automatically from the specification. An example is shown below:

```
{ "chan_name_one": [10, 20], "chan_name_two": [4, 0] }
```

An example of channel data.

## 4.6 Measurements

Given the data and the model definitions, a measurement can be defined. In the current schema, the measurements defines the name of the parameter of interest as well as parameter set configurations.<sup>2</sup> Here, the remaining information not covered through the channel definition is provided, e.g. for the luminosity parameter. For all modifiers, the default settings can be overridden where possible:

- **inits**: Initial value of the parameter.
- **bounds**: Interval bounds of the parameter.
- **auxdata**: Auxiliary data for the associated constraint term.
- **sigmas**: Associated uncertainty of the parameter.

An example is shown below:

```
{
  "name": "MyMeasurement",
  "config": {
    "poi": "SignalCrossSection", "parameters": [
      { "name": "lumi", "auxdata": [1.0], "sigmas": [0.017], "bounds": [[0.915, 1.085]],
      ↪ "inits": [1.0] },
      { "name": "mu_ttbar", "bounds": [[0, 5]] },
      { "name": "rw_1CR", "fixed": true }
    ]
  }
}
```

<sup>2</sup> In this context a parameter set corresponds to a named lower-dimensional subspace of the full parameters. In many cases these are one-dimensional subspaces, e.g. a specific interpolation parameter  $\alpha$  or the luminosity parameter  $\lambda$ . For multi-bin channels, however, e.g. all bin-wise nuisance parameters of the uncorrelated shape modifiers are grouped under a single name. Therefore in general a parameter set definition provides arrays of initial values, bounds, etc.

An example of a measurement. This measurement, which scans over the parameter of interest `SignalCrossSection`, is setting configurations for the luminosity modifier, changing the default bounds for the normfactor modifier named `mu_ttbar`, and specifying that the modifier `rw_1CR` is held constant (fixed).

## 4.7 Observations

This is what we evaluate the hypothesis testing against, to determine the compatibility of signal+background hypothesis to the background-only hypothesis. This is specified as a list of objects, with each object structured as

- **name**: the channel for which the observations are recorded
- **data**: the bin-by-bin observations for the named channel

An example is shown below:

```
{
  "name": "channel1",
  "data": [110.0, 120.0]
}
```

An example of an observation. This observation recorded for a 2-bin channel `channel1`, has values `110.0` and `120.0`.

## 4.8 Toy Example

```
{
  "channels": [
    { "name": "singlechannel",
      "samples": [
        { "name": "signal",
          "data": [5.0, 10.0],
          "modifiers": [ { "name": "mu", "type": "normfactor", "data": null } ]
        },
        { "name": "background",
          "data": [50.0, 60.0],
          "modifiers": [ { "name": "uncorr_bkguncrt", "type": "shapesys", "data": [5.
↪0, 12.0]} ]
        }
      ]
    }
  ],
  "observations": [
    { "name": "singlechannel", "data": [50.0, 60.0] }
  ],
  "measurements": [
    { "name": "Measurement", "config": { "poi": "mu", "parameters": [] } }
  ],
  "version": "1.0.0"
}
```

In the above example, we demonstrate a simple measurement of a single two-bin channel with two samples: a signal sample and a background sample. The signal sample has an unconstrained normalisation factor  $\mu$ , while the background

sample carries an uncorrelated shape systematic controlled by parameters  $\gamma_1$  and  $\gamma_2$ . The background uncertainty for the bins is 10% and 20% respectively.

## 4.9 Additional Material

### 4.9.1 Footnotes

### 4.9.2 Bibliography





## FUNDAMENTALS

Notebooks:

```
[1]: %pylab inline
from ipywidgets import interact
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

Populating the interactive namespace from numpy and matplotlib
```

### 5.1 Piecewise Linear Interpolation

References: <https://cds.cern.ch/record/1456844/files/CERN-OPEN-2012-016.pdf>

We wish to understand interpolation using the piecewise linear function. This is `intercode=0` in the above reference. This function is defined as (nb: vector denotes bold)

$$\eta_s(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) + \underbrace{\sum_{p \in \text{Syst}} I_{\text{lin.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-)}_{\text{deltas to calculate}}$$

with

$$I_{\text{lin.}}(\alpha; I^0, I^+, I^-) = \begin{cases} \alpha(I^+ - I^0) & \alpha \geq 0 \\ \alpha(I^0 - I^-) & \alpha < 0 \end{cases}$$

In this notebook, we'll demonstrate the technical implementation of these interpolations starting from simple dimensionality and increasing the dimensions as we go along. In all situations, we'll consider a single systematic that we wish to interpolate, such as Jet Energy Scale (JES).

Let's define the interpolate function. This function will produce the deltas we would like to calculate and sum with the nominal measurement to determine the interpolated measurements value.

```
[2]: def interpolate_deltas(down, nom, up, alpha):
    delta_up = up - nom
    delta_down = nom - down
    if alpha > 0:
        return delta_up * alpha
    else:
        return delta_down * alpha
```

Why are we calculating deltas? This is some additional foresight that you, the reader, may not have yet. Multiple interpolation schemes exist but they all rely on calculating the change with respect to the nominal measurement (the delta).

### 5.1.1 Case 1: The Single-binned Histogram

Let's first start with considering evaluating the total number of events after applying JES corrections. This is the single-bin case. Code that runs through event selection will vary the JES parameter and provide three histograms, each with a single bin. These three histograms represent the nominal-, up-, and down- variations of the JES nuisance parameter.

When processing, we find that there are 10 events nominally, and when we vary the JES parameter downwards, we only measure 8 events. When varying upwards, we measure 15 events.

```
[3]: down_1 = np.array([8])
     nom_1 = np.array([10])
     up_1 = np.array([15])
```

We would like to generate a function  $f(\alpha_{\text{JES}})$  that linearly interpolates the number of events for us so we can scan the phase-space for calculating PDFs. The `interpolate_deltas()` function defined above does this for us.

```
[4]: alphas = np.linspace(-1.0, 1.0)
     deltas = [interpolate_deltas(down_1, nom_1, up_1, alpha) for alpha in alphas]
     deltas[5]
```

```
[4]: [array([-2.]),
     array([-1.91836735]),
     array([-1.83673469]),
     array([-1.75510204]),
     array([-1.67346939])]
```

So now that we've generated the deltas from the nominal measurement, we can plot this to see how the linear interpolation works in the single-bin case, where we plot the measured values in black, and the interpolation in dashed, blue.

```
[5]: plt.plot(alphas, [nom_1 + delta for delta in deltas], linestyle='--')
     plt.scatter((-1, 0, 1), (down_1, nom_1, up_1), color='k')
     plt.xlabel(r'$\alpha_{\mathrm{JES}}$')
     plt.ylabel(r'Events')
```

```
[5]: Text(0,0.5,'Events')
```



Here, we can imagine building a 1-dimensional tensor (column-vector) of measurements as a function of  $\alpha_{\text{JES}}$  with each row in the column vector corresponding to a given  $\alpha_{\text{JES}}$  value.

### 5.1.2 Case 2: The Multi-binned Histogram

Now, let's increase the computational difficulty a little by increasing the dimensionality. Assume instead of a single-bin measurement, we have more measurements! We are good physicists after all. Imagine continuing on the previous example, where we add more bins, perhaps because we got more data. Imagine that this was binned by collection year, where we observed 10 events in the first year, 10.5 the next year, and so on...

```
[6]: down_hist = np.linspace(8, 10, 11)
nom_hist = np.linspace(10, 13, 11)
up_hist = np.linspace(15, 20, 11)
```

Now, we still need to interpolate. Just like before, we have varied JES upwards and downwards to determine the corresponding histograms of variations. In order to interpolate, we need to interpolate by bin for each bin in the three histograms we have here (or three measurements if you prefer).

Let's go ahead and plot these histograms as a function of the bin index with black as the nominal measurements, red and blue as the down and up variations respectively. The black points are the measurements we have, and for each bin, we would like to interpolate to get an interpolated histogram that represents the measurement as a function of  $\alpha_{\text{JES}}$ .

```
[7]: def plot_measurements(down_hist, nom_hist, up_hist):
    bincenters = np.arange(len(nom_hist))
    for i, h in enumerate(zip(up_hist, nom_hist, down_hist)):
        plt.scatter([i] * len(h), h, color='k', alpha=0.5)

    for c, h in zip(['r', 'k', 'b'], [down_hist, nom_hist, up_hist]):
        plt.plot(bincenters, h, color=c, linestyle='-', alpha=0.5)

    plt.xlabel('Bin index in histogram')
    plt.ylabel('Events')

plot_measurements(down_hist, nom_hist, up_hist)
```



What does this look like if we evaluate at a single  $\alpha_{\text{JES}} = 0.5$ ? We'll write a function that interpolates and then plots the interpolated values as a function of bin index, in green, dashed.

```
[8]: def plot_interpolated_histogram(alpha, down_hist, nom_hist, up_hist):
    bincenters = np.arange(len(nom_hist))
    interpolated_vals = [
        nominal + interpolate_deltas(down, nominal, up, alpha)
        for down, nominal, up in zip(down_hist, nom_hist, up_hist)
    ]

    plot_measurements(down_hist, nom_hist, up_hist)
    plt.plot(bincenters, interpolated_vals, color='g', linestyle='--')
```

```
plot_interpolated_histogram(0.5, down_hist, nom_hist, up_hist)
```



We can go one step further in visualization and see what it looks like for different  $\alpha_{\text{JES}}$  using iPyWidget's interactivity. Change the slider to get an idea of how the interpolation works.

```
[9]: x = interact(
    lambda alpha: plot_interpolated_histogram(alpha, down_hist, nom_hist, up_hist),
    alpha=(-1, 1, 0.1),
)
```

aW50ZXJhY3RpdmoUoY2hpbGRyZW49KEZsb2F0U2xpZGVyKHZhbHVlPTAuMCwgZGVzY3JpcHRpb249dSdhbHB0YScsIG1heD0xLjAsIG1

The magic in `plot_interpolated_histogram()` happens to be that for a given  $\alpha_{\text{JES}}$ , we iterate over all measurements bin-by-bin to calculate the interpolated value

```
[nominal + interpolate_deltas(down, nominal, up, alpha) for down, nominal, up in zip(...
↪ hist...)]
```

So you can imagine that we're building up a 2-dimensional tensor with each row corresponding to a different  $\alpha_{\text{JES}}$  and each column corresponding to the bin index of the histograms (or measurements). Let's go ahead and build a 3-dimensional representation of our understanding so far!

```
[10]: def interpolate_alpha_range(alphas, down_hist, nom_hist, up_hist):
    at_alphas = []
    for alpha in alphas:
```

(continues on next page)

(continued from previous page)

```

    interpolated_hist_at_alpha = [
        nominal + interpolate_deltas(down, nominal, up, alpha)
        for down, nominal, up in zip(down_hist, nom_hist, up_hist)
    ]
    at_alphas.append(interpolated_hist_at_alpha)
return np.array(at_alphas)

```

And then with this, we are interpolating over all histograms bin-by-bin and producing a 2-dimensional tensor with each row corresponding to a specific value of  $\alpha_{JES}$ .

```

[11]: alphas = np.linspace(-1, 1, 11)

interpolated_vals_at_alphas = interpolate_alpha_range(
    alphas, down_hist, nom_hist, up_hist
)

print(interpolated_vals_at_alphas[alphas == -1])
print(interpolated_vals_at_alphas[alphas == 0])
print(interpolated_vals_at_alphas[alphas == 1])

[[ 8.   8.2  8.4  8.6  8.8  9.   9.2  9.4  9.6  9.8 10. ]]
[[10.   10.3 10.6 10.9 11.2 11.5 11.8 12.1 12.4 12.7 13. ]]
[[15.   15.5 16.   16.5 17.   17.5 18.   18.5 19.   19.5 20. ]]

```

We have a way to generate the 2-dimensional tensor. Let's go ahead and add in all dimensions. Additionally, we'll add in some extra code to show the projection of the 2-d plots that we made earlier to help understand the 3-d plot a bit better. Like before, let's plot specifically colored lines for  $\alpha_{JES} = 0.5$  as well as provide an interactive session.

```

[13]: def plot_wire(alpha):
    alphas = np.linspace(-1, 1, 51)
    at_alphas = interpolate_alpha_range(alphas, down_hist, nom_hist, up_hist)
    bincenters = np.arange(len(nom_hist))
    x, y = np.meshgrid(bincenters, alphas)
    z = np.asarray(at_alphas)
    bottom = np.zeros_like(x)
    fig = plt.figure(figsize=(10, 10))
    ax1 = fig.add_subplot(111, projection='3d')
    ax1.plot_wireframe(x, y, z, alpha=0.3)

    x, y = np.meshgrid(bincenters, [alpha])
    z = interpolate_alpha_range([alpha], down_hist, nom_hist, up_hist)

    ax1.plot_wireframe(x, y, z, edgecolor='g', linestyle='--')
    ax1.set_xlim(0, 10)
    ax1.set_ylim(-1.0, 1.5)
    ax1.set_zlim(0, 25)
    ax1.view_init(azim=-125)
    ax1.set_xlabel('Bin Index')
    ax1.set_ylabel(r'$\alpha_{\mathrm{JES}}$')
    ax1.set_zlabel('Events')

    # add in 2D plot goodness

```

(continues on next page)

(continued from previous page)

```

for c, h, zs in zip(
    ['r', 'k', 'b'], [down_hist, nom_hist, up_hist], [-1.0, 0.0, 1.0]
):
    ax1.plot(bincenters, h, color=c, linestyle='-', alpha=0.5, zdir='y', zs=zs)
    ax1.plot(bincenters, h, color=c, linestyle='-', alpha=0.25, zdir='y', zs=1.5)

    ax1.plot(bincenters, z.T, color='g', linestyle='--', zdir='y', zs=alpha)
    ax1.plot(bincenters, z.T, color='g', linestyle='--', alpha=0.5, zdir='y', zs=1.5)

plt.show()

plot_wire(0.5)

interact(plot_wire, alpha=(-1, 1, 0.1))

```



```
aW50ZXJhY3RpdmUoY2hpbGRyZW49KEZsb2F0U2xpZGVyKHZhbHV1PTAuMCwgZGVzY3JpcHRpb249dSdhbHB0YScsIG1heD0xLjAsIG1
```

```
[13]: <function __main__.plot_wire>
```

## 5.2 Tensorizing Interpolators

This notebook will introduce some tensor algebra concepts about being able to convert from calculations inside for-loops into a single calculation over the entire tensor. It is assumed that you have some familiarity with what interpolation functions are used for in pyhf.

To get started, we'll load up some functions we wrote whose job is to generate sets of histograms and alphas that we will compute interpolations for. This allows us to generate random, structured input data that we can use to test the tensorized form of the interpolation function against the original one we wrote. For now, we will consider only the numpy backend for simplicity, but can replace `np` to `pyhf.tensorlib` to achieve identical functionality.

The function `random_histosets_alphasets_pair` will produce a pair (`histogramsets`, `alphasets`) of histograms and alphas for those histograms that represents the type of input we wish to interpolate on.

```
[1]: import numpy as np

def random_histosets_alphasets_pair(
    nsysts=150, nhistos_per_syst_upto=300, nalphas=1, nbins_upto=1
):
    def generate_shapes(histogramssets, alphasets):
        h_shape = [len(histogramssets), 0, 0, 0]
        a_shape = (len(alphasets), max(map(len, alphasets)))
        for hs in histogramssets:
            h_shape[1] = max(h_shape[1], len(hs))
            for h in hs:
                h_shape[2] = max(h_shape[2], len(h))
                for sh in h:
                    h_shape[3] = max(h_shape[3], len(sh))
        return tuple(h_shape), a_shape

    def filled_shapes(histogramssets, alphasets):
        # pad our shapes with NaNs
        histos, alphas = generate_shapes(histogramssets, alphasets)
        histos, alphas = np.ones(histos) * np.nan, np.ones(alphas) * np.nan
        for i, syst in enumerate(histogramssets):
            for j, sample in enumerate(syst):
                for k, variation in enumerate(sample):
                    histos[i, j, k, : len(variation)] = variation
        for i, alphasets in enumerate(alphasets):
            alphas[i, : len(alphasets)] = alphasets
        return histos, alphas

    nsyst_histos = np.random.randint(1, 1 + nhistos_per_syst_upto, size=nsysts)
    nhistograms = [np.random.randint(1, nbins_upto + 1, size=n) for n in nsyst_histos]
    random_alphas = [np.random.uniform(-1, 1, size=nalphas) for n in nsyst_histos]
```

(continues on next page)

(continued from previous page)

```

random_histogramssets = [
    [ # all histos affected by systematic $nh
      [ # sample $i, systematic $nh
        np.random.uniform(10 * i + j, 10 * i + j + 1, size=nbin).tolist()
        for j in range(3)
      ]
      for i, nbin in enumerate(nh)
    ]
    for nh in nhistograms
  ]
h, a = filled_shapes(random_histogramssets, random_alphas)
return h, a

```

### 5.2.1 The (slow) interpolations

In all cases, the way we do interpolations is as follows:

1. Loop over both the histogramssets and alphasets simultaneously (e.g. using python's zip())
2. Loop over all histograms set in the set of histograms sets that correspond to the histograms affected by a given systematic
3. Loop over all of the alphas in the set of alphas
4. Loop over all the bins in the histogram sets simultaneously (e.g. using python's zip())
5. Apply the interpolation across the same bin index

This is already exhausting to think about, so let's put this in code form. Depending on the kind of interpolation being done, we'll pass in `func` as an argument to the top-level interpolation loop to switch between linear (`interpcode=0`) and non-linear (`interpcode=1`).

```

[2]: def interpolation_looper(histogramssets, alphasets, func):
    all_results = []
    for histoset, alpha in zip(histogramssets, alphasets):
        all_results.append([])
        set_result = all_results[-1]
        for histo in histoset:
            set_result.append([])
            histo_result = set_result[-1]
            for alpha in alphasets:
                alpha_result = []
                for down, nom, up in zip(histo[0], histo[1], histo[2]):
                    v = func(down, nom, up, alpha)
                    alpha_result.append(v)
                histo_result.append(alpha_result)
    return all_results

```

And we can also define our linear and non-linear interpolations we'll consider in this notebook that we wish to tensorize.

```

[3]: def interpolation_linear(histogramssets, alphasets):
    def summand(down, nom, up, alpha):
        delta_up = up - nom
        delta_down = nom - down

```

(continues on next page)



(continued from previous page)

```

    if alpha > 0:
        delta = delta_up * alpha
    else:
        delta = delta_down * alpha
    return nom + delta

return interpolation_looper(histogramssets, alphasets, summand)

def interpolation_nonlinear(histogramssets, alphasets):
    def product(down, nom, up, alpha):
        delta_up = up / nom
        delta_down = down / nom
        if alpha > 0:
            delta = delta_up ** alpha
        else:
            delta = delta_down ** (-alpha)
        return nom * delta

    return interpolation_looper(histogramssets, alphasets, product)

```

We will also define a helper function that allows us to pass in two functions we wish to compare the outputs for:

```

[4]: def compare_fns(func1, func2):
    h, a = random_histosets_alphasets_pair()

    def _func_runner(func, histsets, alphasets):
        return np.asarray(func(histsets, alphasets))

    old = _func_runner(func1, h, a)
    new = _func_runner(func2, h, a)

    return (np.all(old[~np.isnan(old)] == new[~np.isnan(new)]), (h, a))

```

For the rest of the notebook, we will detail in explicit form how the linear interpolator gets tensorized, step-by-step. The same sequence of steps will be shown for the non-linear interpolator – but it is left up to the reader to understand the steps.

## 5.2.2 Tensorizing the Linear Interpolator

### Step 0

Step 0 requires converting the innermost conditional check on `alpha > 0` into something tensorizable. This also means the calculation itself is going to become tensorized. So we will convert from

```

if alpha > 0:
    delta = delta_up*alpha
else:
    delta = delta_down*alpha

```

to

```
delta = np.where(alpha > 0, delta_up*alpha, delta_down*alpha)
```

Let's make that change now, and let's check to make sure we still do the calculation correctly.

```
[5]: # get the internal calculation to use tensorflow backend
def new_interpolation_linear_step0(histogramssets, alphaset):
    all_results = []
    for histoset, alphaset in zip(histogramssets, alphaset):
        all_results.append([])
        set_result = all_results[-1]
        for histo in histoset:
            set_result.append([])
            histo_result = set_result[-1]
            for alpha in alphaset:
                alpha_result = []
                for down, nom, up in zip(histo[0], histo[1], histo[2]):
                    delta_up = up - nom
                    delta_down = nom - down
                    delta = np.where(alpha > 0, delta_up * alpha, delta_down * alpha)
                    v = nom + delta
                    alpha_result.append(v)
                histo_result.append(alpha_result)
            return all_results
```

And does the calculation still match?

```
[6]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step0)
print(result)
```

```
True
```

```
[7]: %%timeit
interpolation_linear(h, a)
```

```
189 ms ± 6.14 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[8]: %%timeit
new_interpolation_linear_step0(h, a)
```

```
255 ms ± 11.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Great! We're a little bit slower right now, but that's expected. We're just getting started.

## Step 1

In this step, we would like to remove the innermost `zip()` call over the histogram bins by calculating the interpolation between the histograms in one fell swoop. This means, instead of writing something like

```
for down,nom,up in zip(histo[0],histo[1],histo[2]):
    delta_up = up - nom
    ...
```

one can instead write

```
delta_up = histo[2] - histo[1]
...
```

taking advantage of the automatic broadcasting of operations on input tensors. This sort of feature of the tensor backends allows us to speed up code, such as interpolation.

```
[9]: # update the delta variations to remove the zip() call and remove most-nested loop
def new_interpolation_linear_step1(histogramssets, alphaset):
    all_results = []
    for histoset, alphaset in zip(histogramssets, alphaset):
        all_results.append([])
        set_result = all_results[-1]
        for histo in histoset:
            set_result.append([])
            histo_result = set_result[-1]
            for alpha in alphaset:
                alpha_result = []
                deltas_up = histo[2] - histo[1]
                deltas_dn = histo[1] - histo[0]
                calc_deltas = np.where(alpha > 0, deltas_up * alpha, deltas_dn * alpha)
                v = histo[1] + calc_deltas
                alpha_result.append(v)
                histo_result.append(alpha_result)
        return all_results
```

And does the calculation still match?

```
[10]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step1)
print(result)

True
```

```
[11]: %%timeit
interpolation_linear(h, a)

188 ms ± 7.14 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[12]: %%timeit
new_interpolation_linear_step1(h, a)

492 ms ± 42.8 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Great!

## Step 2

In this step, we would like to move the giant array of the deltas calculated to the beginning – outside of all loops – and then only take a subset of it for the calculation itself. This allows us to figure out the entire structure of the input for the rest of the calculations as we slowly move towards including `einsum()` calls (einstein summation). This means we would like to go from

```
for histo in histoset:
    delta_up = histo[2] - histo[1]
...
```

to

```
all_deltas = ...
for nh, histo in enumerate(histoset):
    deltas = all_deltas[nh]
    ...
```

Again, we are taking advantage of the automatic broadcasting of operations on input tensors to calculate all the deltas in a single action.

```
[13]: # figure out the giant array of all deltas at the beginning and only take subsets of it,
      ↪ for the calculation
def new_interpolation_linear_step2(histogramssets, alphaset):
    all_results = []

    allset_all_histo_deltas_up = histogramssets[:, :, 2] - histogramssets[:, :, 1]
    allset_all_histo_deltas_dn = histogramssets[:, :, 1] - histogramssets[:, :, 0]

    for nset, (histoset, alphaset) in enumerate(zip(histogramssets, alphaset)):
        set_result = []

        all_histo_deltas_up = allset_all_histo_deltas_up[nset]
        all_histo_deltas_dn = allset_all_histo_deltas_dn[nset]

        for nh, histo in enumerate(histoset):
            alpha_deltas = []
            for alpha in alphaset:
                alpha_result = []
                deltas_up = all_histo_deltas_up[nh]
                deltas_dn = all_histo_deltas_dn[nh]
                calc_deltas = np.where(alpha > 0, deltas_up * alpha, deltas_dn * alpha)
                alpha_deltas.append(calc_deltas)
            set_result.append([histo[1] + d for d in alpha_deltas])
        all_results.append(set_result)
    return all_results
```

And does the calculation still match?

```
[14]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step2)
      print(result)
```

```
True
```

```
[15]: %%timeit
      interpolation_linear(h, a)
```

```
179 ms ± 12.4 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[16]: %%timeit
      new_interpolation_linear_step2(h, a)
```

```
409 ms ± 20.8 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Great!

### Step 3

In this step, we get to introduce einstein summation to generalize the calculations we perform across many dimensions in a more concise, straightforward way. See [this blog post](#) for some more details on einstein summation notation. In short, it allows us to write

$$c_j = \sum_i \sum_k A_{ik} B_{kj} \quad \rightarrow \quad \text{einsum}("ij, jk \rightarrow i", A, B)$$

in a much more elegant way to express many kinds of common tensor operations such as dot products, transposes, outer products, and so on. This step is generally the hardest as one needs to figure out the corresponding einsum that keeps the calculation preserved (and matching). To some extent it requires a lot of trial and error until you get a feel for how einstein summation notation works.

As a concrete example of a conversion, we wish to go from something like

```
for nh, histo in enumerate(histoset):
    for alpha in alphasets:
        deltas_up = all_histo_deltas_up[nh]
        deltas_dn = all_histo_deltas_dn[nh]
        calc_deltas = np.where(alpha > 0, deltas_up*alpha, deltas_dn*alpha)
    ...
```

to get rid of the loop over alpha

```
for nh, histo in enumerate(histoset):
    alphas_times_deltas_up = np.einsum('i, j->ij', alphasets, all_histo_deltas_up[nh])
    alphas_times_deltas_dn = np.einsum('i, j->ij', alphasets, all_histo_deltas_dn[nh])
    masks = np.einsum('i, j->ij', alphasets > 0, np.ones_like(all_histo_deltas_dn[nh]))

    alpha_deltas = np.where(masks, alphas_times_deltas_up, alphas_times_deltas_dn)
    ...
```

In this particular case, we need an outer product that multiplies across the alphasets to the corresponding histoset for the up/down variations. Then we just need to select from either the up variation calculation or the down variation calculation based on the sign of alpha. Try to convince yourself that the einstein summation does what the for-loop does, but a little bit more concisely, and perhaps more clearly! How does the function look now?

```
[17]: # remove the loop over alphas, starts using einsum to help generalize to more dimensions
def new_interpolation_linear_step3(histogramssets, alphasets):
    all_results = []

    allset_all_histo_deltas_up = histogramssets[:, :, 2] - histogramssets[:, :, 1]
    allset_all_histo_deltas_dn = histogramssets[:, :, 1] - histogramssets[:, :, 0]

    for nset, (histoset, alphasets) in enumerate(zip(histogramssets, alphasets)):
        set_result = []

        all_histo_deltas_up = allset_all_histo_deltas_up[nset]
        all_histo_deltas_dn = allset_all_histo_deltas_dn[nset]

        for nh, histo in enumerate(histoset):
            alphas_times_deltas_up = np.einsum(
                'i, j->ij', alphasets, all_histo_deltas_up[nh]
            )
```

(continues on next page)

(continued from previous page)

```

    alphas_times_deltas_dn = np.einsum(
        'i,j->ij', alphasets, all_histo_deltas_dn[nh]
    )
    masks = np.einsum(
        'i,j->ij', alphasets > 0, np.ones_like(all_histo_deltas_dn[nh])
    )

    alpha_deltas = np.where(
        masks, alphas_times_deltas_up, alphas_times_deltas_dn
    )
    set_result.append([histo[1] + d for d in alpha_deltas])

    all_results.append(set_result)
    return all_results

```

And does the calculation still match?

```
[18]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step3)
      print(result)
```

```
True
```

```
[19]: %%timeit
      interpolation_linear(h, a)
```

```
166 ms ± 11.6 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[20]: %%timeit
      new_interpolation_linear_step3(h, a)
```

```
921 ms ± 133 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Great! Note that we've been getting a little bit slower during these steps. It will all pay off in the end when we're fully tensorized! A lot of the internal steps are overkill with the heavy einstein summation and broadcasting at the moment, especially for how many loops in we are.

## Step 4

Now in this step, we will move the einstein summations to the outer loop, so that we're calculating it once! This is the big step, but a little bit easier because all we're doing is adding extra dimensions into the calculation. The underlying calculation won't have changed. At this point, we'll also rename from `i` and `j` to `a` and `b` for `alpha` and `bin` (as in the `bin` in the histogram). To continue the notation as well, here's a summary of the dimensions involved:

- `s` will be for the set under consideration (e.g. the modifier)
- `a` will be for the alpha variation
- `h` will be for the histogram affected by the modifier
- `b` will be for the bin of the histogram

So we wish to move the `einsum` code from

```
for nset, (histoset, alphasets) in enumerate(zip(histogramssets, alphasets)):
    ...
```

(continues on next page)

(continued from previous page)

```

for nh,histo in enumerate(histoset):
    alphas_times_deltas_up = np.einsum('i,j->ij',alphaset,all_histo_deltas_up[nh])
    ...

```

to

```

all_alphas_times_deltas_up = np.einsum('...',alphaset,all_histo_deltas_up)
for nset,(histoset, alphaset) in enumerate(zip(histogramssets,alphasets)):
    ...

    for nh,histo in enumerate(histoset):
        ...

```

So how does this new function look?

```

[21]: # move the einsums to outer loops to get ready to get rid of all loops
def new_interpolation_linear_step4(histogramssets, alphasets):
    allset_all_histo_deltas_up = histogramssets[:, :, 2] - histogramssets[:, :, 1]
    allset_all_histo_deltas_dn = histogramssets[:, :, 1] - histogramssets[:, :, 0]
    allset_all_histo_nom = histogramssets[:, :, 1]

    allsets_all_histos_alphas_times_deltas_up = np.einsum(
        'sa,shb->shab', alphasets, allset_all_histo_deltas_up
    )
    allsets_all_histos_alphas_times_deltas_dn = np.einsum(
        'sa,shb->shab', alphasets, allset_all_histo_deltas_dn
    )
    allsets_all_histos_masks = np.einsum(
        'sa,s...u->s...au', alphasets > 0, np.ones_like(allset_all_histo_deltas_dn)
    )

    allsets_all_histos_deltas = np.where(
        allsets_all_histos_masks,
        allsets_all_histos_alphas_times_deltas_up,
        allsets_all_histos_alphas_times_deltas_dn,
    )

    all_results = []
    for nset, histoset in enumerate(histogramssets):
        all_histos_deltas = allsets_all_histos_deltas[nset]
        set_result = []
        for nh, histo in enumerate(histoset):
            set_result.append([d + histoset[nh, 1] for d in all_histos_deltas[nh]])
        all_results.append(set_result)
    return all_results

```

And does the calculation still match?

```

[22]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step4)
print(result)

```

True

```
[23]: %%timeit
interpolation_linear(h, a)

160 ms ± 5 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[24]: %%timeit
new_interpolation_linear_step4(h, a)

119 ms ± 3.19 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

Great! And look at that huge speed up in time already, just from moving the multiple, heavy einstein summation calculations up through the loops. We still have some more optimizing to do as we still have explicit loops in our code. Let's keep at it, we're almost there!

## Step 5

The hard part is mostly over. We have to now think about the nominal variations. Recall that we were trying to add the nominals to the deltas in order to compute the new value. In practice, we'll return the delta variation only, but we'll show you how to get rid of this last loop. In this case, we want to figure out how to change code like

```
all_results = []
for nset, histoset in enumerate(histogramssets):
    all_histos_deltas = allsets_all_histos_deltas[nset]
    set_result = []
    for nh, histo in enumerate(histoset):
        set_result.append([d + histoset[nh,1] for d in all_histos_deltas[nh]])
    all_results.append(set_result)
```

to get rid of that most-nested loop

```
all_results = []
for nset, histoset in enumerate(histogramssets):
    # look ma, no more loops inside!
```

So how does this look?

```
[25]: # slowly getting rid of our loops to build the right output tensor -- gotta think about_
      ↪ nominals
def new_interpolation_linear_step5(histogramssets, alphasets):
    allset_all_histo_deltas_up = histogramssets[:, :, 2] - histogramssets[:, :, 1]
    allset_all_histo_deltas_dn = histogramssets[:, :, 1] - histogramssets[:, :, 0]
    allset_all_histo_nom = histogramssets[:, :, 1]

    allsets_all_histos_alphas_times_deltas_up = np.einsum(
        'sa,shb->shab', alphasets, allset_all_histo_deltas_up
    )
    allsets_all_histos_alphas_times_deltas_dn = np.einsum(
        'sa,shb->shab', alphasets, allset_all_histo_deltas_dn
    )
    allsets_all_histos_masks = np.einsum(
        'sa,s...u->s...au', alphasets > 0, np.ones_like(allset_all_histo_deltas_dn)
    )
```

(continues on next page)



(continued from previous page)

```

allsets_all_histos_deltas = np.where(
    allsets_all_histos_masks,
    allsets_all_histos_alphas_times_deltas_up,
    allsets_all_histos_alphas_times_deltas_dn,
)

all_results = []

for nset, (_, alphasets) in enumerate(zip(histogramssets, alphasets)):
    all_histos_deltas = allsets_all_histos_deltas[nset]
    noms = histogramssets[nset, :, 1]

    all_histos_noms_repeated = np.einsum('a,hn->han', np.ones_like(alphasets), noms)

    set_result = all_histos_deltas + all_histos_noms_repeated
    all_results.append(set_result)
return all_results

```

And does the calculation still match?

```
[26]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step5)
print(result)
```

```
True
```

```
[27]: %%timeit
interpolation_linear(h, a)
```

```
160 ms ± 8.28 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[28]: %%timeit
new_interpolation_linear_step5(h, a)
```

```
1.57 ms ± 75.2 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

Fantastic! And look at the speed up. We're already faster than the for-loop and we're not even done yet.

## Step 6

The final frontier. Also probably the best Star Wars episode. In any case, we have one more for-loop that needs to die in a slab of carbonite. This should be much easier now that you're more comfortable with tensor broadcasting and einstein summations.

What does the function look like now?

```
[29]: def new_interpolation_linear_step6(histogramssets, alphasets):
    allset_allhisto_deltas_up = histogramssets[:, :, 2] - histogramssets[:, :, 1]
    allset_allhisto_deltas_dn = histogramssets[:, :, 1] - histogramssets[:, :, 0]
    allset_allhisto_nom = histogramssets[:, :, 1]

    # x is dummy index

    allsets_allhistos_alphas_times_deltas_up = np.einsum(

```

(continues on next page)

(continued from previous page)

```

    'sa,shb->shab', alphasets, allset_allhisto_deltas_up
)
allsets_allhistos_alphas_times_deltas_dn = np.einsum(
    'sa,shb->shab', alphasets, allset_allhisto_deltas_dn
)
allsets_allhistos_masks = np.einsum(
    'sa,sxu->sxau',
    np.where(alphasets > 0, np.ones(alphasets.shape), np.zeros(alphasets.shape)),
    np.ones(allset_allhisto_deltas_dn.shape),
)

allsets_allhistos_deltas = np.where(
    allsets_allhistos_masks,
    allsets_allhistos_alphas_times_deltas_up,
    allsets_allhistos_alphas_times_deltas_dn,
)
allsets_allhistos_noms_repeated = np.einsum(
    'sa,shb->shab', np.ones(alphasets.shape), allset_allhisto_nom
)
set_results = allsets_allhistos_deltas + allsets_allhistos_noms_repeated
return set_results

```

And does the calculation still match?

```

[30]: result, (h, a) = compare_fns(interpolation_linear, new_interpolation_linear_step6)
print(result)

True

```

```

[31]: %%timeit
interpolation_linear(h, a)

156 ms ± 6.29 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

```

```

[32]: %%timeit
new_interpolation_linear_step6(h, a)

468 µs ± 37.1 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

```

And we're done tensorizing it. There are some more improvements that could be made to make this interpolation calculation even more robust – but for now we're done.

### 5.2.3 Tensorizing the Non-Linear Interpolator

This is very, very similar to what we've done for the case of the linear interpolator. As such, we will provide the resulting functions for each step, and you can see how things perform all the way at the bottom. Enjoy and learn at your own pace!

```

[33]: def interpolation_nonlinear(histogramssets, alphasets):
    all_results = []
    for histoset, alphaset in zip(histogramssets, alphasets):
        all_results.append([])

```

(continues on next page)

(continued from previous page)

```

    set_result = all_results[-1]
    for histo in histoset:
        set_result.append([])
        histo_result = set_result[-1]
        for alpha in alphasets:
            alpha_result = []
            for down, nom, up in zip(histo[0], histo[1], histo[2]):
                delta_up = up / nom
                delta_down = down / nom
                if alpha > 0:
                    delta = delta_up ** alpha
                else:
                    delta = delta_down ** (-alpha)
                v = nom * delta
                alpha_result.append(v)
            histo_result.append(alpha_result)
    return all_results

def new_interpolation_nonlinear_step0(histogramssets, alphasets):
    all_results = []
    for histoset, alphasets in zip(histogramssets, alphasets):
        all_results.append([])
        set_result = all_results[-1]
        for histo in histoset:
            set_result.append([])
            histo_result = set_result[-1]
            for alpha in alphasets:
                alpha_result = []
                for down, nom, up in zip(histo[0], histo[1], histo[2]):
                    delta_up = up / nom
                    delta_down = down / nom
                    delta = np.where(
                        alpha > 0,
                        np.power(delta_up, alpha),
                        np.power(delta_down, np.abs(alpha)),
                    )
                    v = nom * delta
                    alpha_result.append(v)
                histo_result.append(alpha_result)
    return all_results

def new_interpolation_nonlinear_step1(histogramssets, alphasets):
    all_results = []
    for histoset, alphasets in zip(histogramssets, alphasets):
        all_results.append([])
        set_result = all_results[-1]
        for histo in histoset:
            set_result.append([])
            histo_result = set_result[-1]
            for alpha in alphasets:

```

(continues on next page)

(continued from previous page)

```

        alpha_result = []
        deltas_up = np.divide(histo[2], histo[1])
        deltas_down = np.divide(histo[0], histo[1])
        bases = np.where(alpha > 0, deltas_up, deltas_down)
        exponents = np.abs(alpha)
        calc_deltas = np.power(bases, exponents)
        v = histo[1] * calc_deltas
        alpha_result.append(v)
        histo_result.append(alpha_result)
    return all_results

def new_interpolation_nonlinear_step2(histogramssets, alphasets):
    all_results = []

    allset_all_histo_deltas_up = np.divide(
        histogramssets[:, :, 2], histogramssets[:, :, 1]
    )
    allset_all_histo_deltas_dn = np.divide(
        histogramssets[:, :, 0], histogramssets[:, :, 1]
    )

    for nset, (histoset, alphaset) in enumerate(zip(histogramssets, alphasets)):
        set_result = []

        all_histo_deltas_up = allset_all_histo_deltas_up[nset]
        all_histo_deltas_dn = allset_all_histo_deltas_dn[nset]

        for nh, histo in enumerate(histoset):
            alpha_deltas = []
            for alpha in alphaset:
                alpha_result = []
                deltas_up = all_histo_deltas_up[nh]
                deltas_down = all_histo_deltas_dn[nh]
                bases = np.where(alpha > 0, deltas_up, deltas_down)
                exponents = np.abs(alpha)
                calc_deltas = np.power(bases, exponents)
                alpha_deltas.append(calc_deltas)
            set_result.append([histo[1] * d for d in alpha_deltas])
        all_results.append(set_result)
    return all_results

def new_interpolation_nonlinear_step3(histogramssets, alphasets):
    all_results = []

    allset_all_histo_deltas_up = np.divide(
        histogramssets[:, :, 2], histogramssets[:, :, 1]
    )
    allset_all_histo_deltas_dn = np.divide(
        histogramssets[:, :, 0], histogramssets[:, :, 1]
    )

```

(continues on next page)

(continued from previous page)

```

for nset, (histoset, alphasets) in enumerate(zip(histogramssets, alphasets)):
    set_result = []

    all_histo_deltas_up = allset_all_histo_deltas_up[nset]
    all_histo_deltas_dn = allset_all_histo_deltas_dn[nset]

    for nh, histo in enumerate(histoset):
        # bases and exponents need to have an outer product, to essentially tile or
        ↪repeat over rows/cols
        bases_up = np.einsum(
            'a,b->ab', np.ones(alphasets.shape), all_histo_deltas_up[nh]
        )
        bases_dn = np.einsum(
            'a,b->ab', np.ones(alphasets.shape), all_histo_deltas_dn[nh]
        )
        exponents = np.einsum(
            'a,b->ab', np.abs(alphasets), np.ones(all_histo_deltas_up[nh].shape)
        )

        masks = np.einsum(
            'a,b->ab', alphasets > 0, np.ones(all_histo_deltas_dn[nh].shape)
        )
        bases = np.where(masks, bases_up, bases_dn)
        alpha_deltas = np.power(bases, exponents)
        set_result.append([histo[1] * d for d in alpha_deltas])

    all_results.append(set_result)
return all_results

def new_interpolation_nonlinear_step4(histogramssets, alphasets):
    all_results = []

    allset_all_histo_nom = histogramssets[:, :, 1]
    allset_all_histo_deltas_up = np.divide(
        histogramssets[:, :, 2], allset_all_histo_nom
    )
    allset_all_histo_deltas_dn = np.divide(
        histogramssets[:, :, 0], allset_all_histo_nom
    )

    bases_up = np.einsum(
        'sa,shb->shab', np.ones(alphasets.shape), allset_all_histo_deltas_up
    )
    bases_dn = np.einsum(
        'sa,shb->shab', np.ones(alphasets.shape), allset_all_histo_deltas_dn
    )
    exponents = np.einsum(
        'sa,shb->shab', np.abs(alphasets), np.ones(allset_all_histo_deltas_up.shape)
    )

```

(continues on next page)

(continued from previous page)

```

    masks = np.einsum(
        'sa,shb->shab', alphasets > 0, np.ones(allset_all_histo_deltas_up.shape)
    )
    bases = np.where(masks, bases_up, bases_dn)

    allsets_all_histos_deltas = np.power(bases, exponents)

    all_results = []
    for nset, histoset in enumerate(histogramssets):
        all_histos_deltas = allsets_all_histos_deltas[nset]
        set_result = []
        for nh, histo in enumerate(histoset):
            set_result.append([histoset[nh, 1] * d for d in all_histos_deltas[nh]])
        all_results.append(set_result)
    return all_results

def new_interpolation_nonlinear_step5(histogramssets, alphasets):
    all_results = []

    allset_all_histo_nom = histogramssets[:, :, 1]
    allset_all_histo_deltas_up = np.divide(
        histogramssets[:, :, 2], allset_all_histo_nom
    )
    allset_all_histo_deltas_dn = np.divide(
        histogramssets[:, :, 0], allset_all_histo_nom
    )

    bases_up = np.einsum(
        'sa,shb->shab', np.ones(alphasets.shape), allset_all_histo_deltas_up
    )
    bases_dn = np.einsum(
        'sa,shb->shab', np.ones(alphasets.shape), allset_all_histo_deltas_dn
    )
    exponents = np.einsum(
        'sa,shb->shab', np.abs(alphasets), np.ones(allset_all_histo_deltas_up.shape)
    )

    masks = np.einsum(
        'sa,shb->shab', alphasets > 0, np.ones(allset_all_histo_deltas_up.shape)
    )
    bases = np.where(masks, bases_up, bases_dn)

    allsets_all_histos_deltas = np.power(bases, exponents)

    all_results = []
    for nset, (_, alphaset) in enumerate(zip(histogramssets, alphasets)):
        all_histos_deltas = allsets_all_histos_deltas[nset]
        noms = allset_all_histo_nom[nset]
        all_histos_noms_repeated = np.einsum('a,hn->han', np.ones_like(alphaset), noms)
        set_result = all_histos_deltas * all_histos_noms_repeated
        all_results.append(set_result)

```

(continues on next page)

(continued from previous page)

```

    return all_results

def new_interpolation_nonlinear_step6(histogramssets, alphaset):
    all_results = []

    allset_all_histo_nom = histogramssets[:, :, 1]
    allset_all_histo_deltas_up = np.divide(
        histogramssets[:, :, 2], allset_all_histo_nom
    )
    allset_all_histo_deltas_dn = np.divide(
        histogramssets[:, :, 0], allset_all_histo_nom
    )

    bases_up = np.einsum(
        'sa,shb->shab', np.ones(alphaset.shape), allset_all_histo_deltas_up
    )
    bases_dn = np.einsum(
        'sa,shb->shab', np.ones(alphaset.shape), allset_all_histo_deltas_dn
    )
    exponents = np.einsum(
        'sa,shb->shab', np.abs(alphaset), np.ones(allset_all_histo_deltas_up.shape)
    )

    masks = np.einsum(
        'sa,shb->shab', alphaset > 0, np.ones(allset_all_histo_deltas_up.shape)
    )
    bases = np.where(masks, bases_up, bases_dn)

    allsets_all_histos_deltas = np.power(bases, exponents)
    allsets_allhistos_noms_repeated = np.einsum(
        'sa,shb->shab', np.ones(alphaset.shape), allset_all_histo_nom
    )
    set_results = allsets_all_histos_deltas * allsets_allhistos_noms_repeated
    return set_results

```

```
[34]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step0)
print(result)
```

```
True
```

```
[35]: %%timeit
interpolation_nonlinear(h, a)
```

```
149 ms ± 9.45 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[36]: %%timeit
new_interpolation_nonlinear_step0(h, a)
```

```
527 ms ± 29.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[37]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step1)
print(result)
```

True

```
[38]: %%timeit
interpolation_nonlinear(h, a)

150 ms ± 5.21 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[39]: %%timeit
new_interpolation_nonlinear_step1(h, a)

456 ms ± 17.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[40]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step2)
print(result)

True
```

```
[41]: %%timeit
interpolation_nonlinear(h, a)

154 ms ± 4.49 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[42]: %%timeit
new_interpolation_nonlinear_step2(h, a)

412 ms ± 31 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[43]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step3)
print(result)

True
```

```
[44]: %%timeit
interpolation_nonlinear(h, a)

145 ms ± 5.15 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[45]: %%timeit
new_interpolation_nonlinear_step3(h, a)

1.28 s ± 74.4 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

```
[46]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step4)
print(result)

True
```

```
[47]: %%timeit
interpolation_nonlinear(h, a)

147 ms ± 8.4 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[48]: %%timeit
new_interpolation_nonlinear_step4(h, a)
```



```
120 ms ± 3.06 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[49]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step5)
      print(result)
```

```
True
```

```
[50]: %%timeit
      interpolation_nonlinear(h, a)
```

```
151 ms ± 5.29 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[51]: %%timeit
      new_interpolation_nonlinear_step5(h, a)
```

```
2.65 ms ± 57.6 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

```
[52]: result, (h, a) = compare_fns(interpolation_nonlinear, new_interpolation_nonlinear_step6)
      print(result)
```

```
True
```

```
[53]: %%timeit
      interpolation_nonlinear(h, a)
```

```
156 ms ± 3.35 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

```
[54]: %%timeit
      new_interpolation_nonlinear_step6(h, a)
```

```
1.49 ms ± 16 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

## 5.3 Empirical Test Statistics

In this notebook we will compute test statistics empirically from pseudo-experiment and establish that they behave as assumed in the asymptotic approximation.

```
[1]: import numpy as np
      import matplotlib.pyplot as plt
      import pyhf

      np.random.seed(0)
      plt.rcParams.update({"font.size": 14})
```

First, we define the statistical model we will study.

- the signal expected event rate is 10 events
- the background expected event rate is 100 events
- a 10% uncertainty is assigned to the background

The expected event rates are chosen to lie comfortably in the asymptotic regime.

```
[2]: model = pyhf.simplemodels.uncorrelated_background(
    signal=[10.0], bkg=[100.0], bkg_uncertainty=[10.0]
)
```

The test statistics based on the profile likelihood described in [arXiv:1007.1727](#) cover scenarios for both

- POI allowed to float to negative values (unbounded;  $\mu \in [-10, 10]$ )
- POI constrained to non-negative values (bounded;  $\mu \in [0, 10]$ )

For consistency, test statistics  $(t_\mu, q_\mu)$  associated with bounded POIs are usually denoted with a tilde ( $\tilde{t}_\mu, \tilde{q}_\mu$ ).

We set up the bounds for the fit as follows

```
[3]: unbounded_bounds = model.config.suggested_bounds()
    unbounded_bounds[model.config.poi_index] = (-10, 10)

    bounded_bounds = model.config.suggested_bounds()
```

Next we draw some synthetic datasets (also referred to as “toys” or pseudo-experiments). We will “throw” 300 toys:

```
[4]: true_poi = 1.0
    n_toys = 300
    toys = model.make_pdf(pyhf.tensorlib.astensor([true_poi, 1.0])).sample((n_toys,))
```

In the asymptotic treatment the test statistics are described as a function of the data’s best-fit POI value  $\hat{\mu}$ .

So let’s run some fits so we can plot the empirical test statistics against  $\hat{\mu}$  to observe the emergence of the asymptotic behavior.

```
[5]: pars = np.asarray(
    [pyhf.infer.mle.fit(toy, model, par_bounds=unbounded_bounds) for toy in toys]
)
fixed_params = model.config.suggested_fixed()
```

We can now calculate all four test statistics described in [arXiv:1007.1727](#)

```
[6]: test_poi = 1.0
    tmu = np.asarray(
    [
        pyhf.infer.test_statistics.tmu(
            test_poi,
            toy,
            model,
            init_pars=model.config.suggested_init(),
            par_bounds=unbounded_bounds,
            fixed_params=fixed_params,
        )
        for toy in toys
    ]
)
```

```
[7]: tmu_tilde = np.asarray(
    [
        pyhf.infer.test_statistics.tmu_tilde(
            test_poi,
```

(continues on next page)

(continued from previous page)

```

        toy,
        model,
        init_pars=model.config.suggested_init(),
        par_bounds=bounded_bounds,
        fixed_params=fixed_params,
    )
    for toy in toys
]
)

```

```

[8]: qmu = np.asarray(
    [
        pyhf.infer.test_statistics.qmu(
            test_poi,
            toy,
            model,
            init_pars=model.config.suggested_init(),
            par_bounds=unbounded_bounds,
            fixed_params=fixed_params,
        )
        for toy in toys
    ]
)

```

```

[9]: qmu_tilde = np.asarray(
    [
        pyhf.infer.test_statistics.qmu_tilde(
            test_poi,
            toy,
            model,
            init_pars=model.config.suggested_init(),
            par_bounds=bounded_bounds,
            fixed_params=fixed_params,
        )
        for toy in toys
    ]
)

```

Let's plot all the test statistics we have computed

```

[10]: muhat = pars[:, model.config.poi_index]
      muhat_sigma = np.std(muhat)

```

We can check the asymptotic assumption that  $\hat{\mu}$  is distributed normally around it's true value  $\mu' = 1$

```

[11]: fig, ax = plt.subplots()
      fig.set_size_inches(7, 5)

      ax.set_xlabel(r"$\hat{\mu}$")
      ax.set_ylabel("Density")
      ax.set_ylim(top=0.5)

```

(continues on next page)

(continued from previous page)

```
ax.hist(muhat, bins=np.linspace(-4, 5, 31), density=True)
ax.axvline(true_poi, label="true poi", color="black", linestyle="dashed")
ax.axvline(np.mean(muhat), label="empirical mean", color="red", linestyle="dashed")
ax.legend();
```



Here we define the asymptotic profile likelihood test statistics:

$$t_{\mu} = \frac{(\mu - \hat{\mu})^2}{\sigma^2}$$

$$\tilde{t}_{\mu} = \begin{cases} t_{\mu}, & \hat{\mu} > 0 \\ t_{\mu} - t_0, & \text{else} \end{cases}$$

$$q_{\mu} = \begin{cases} t_{\mu}, & \hat{\mu} < \mu \\ 0, & \text{else} \end{cases}$$

$$\tilde{q}_{\mu} = \begin{cases} \tilde{t}_{\mu}, & \hat{\mu} < \mu \\ 0, & \text{else} \end{cases}$$

```
[12]: def tmu_asymp(mutest, muhat, sigma):
    return (mutest - muhat) ** 2 / sigma ** 2

def tmu_tilde_asymp(mutest, muhat, sigma):
    a = tmu_asymp(mutest, muhat, sigma)
    b = tmu_asymp(mutest, muhat, sigma) - tmu_asymp(0.0, muhat, sigma)
    return np.where(muhat > 0, a, b)

def qmu_asymp(mutest, muhat, sigma):
```

(continues on next page)

(continued from previous page)

```

    return np.where(
        muhat < mutest, tmu_asymp(mutest, muhat, sigma), np.zeros_like(muhat)
    )

def qmu_tilde_asymp(mutest, muhat, sigma):
    return np.where(
        muhat < mutest, tmu_tilde_asymp(mutest, muhat, sigma), np.zeros_like(muhat)
    )

```

And now we can compare them to the empirical values:

```

[13]: muhat_asymp = np.linspace(-3, 5)
fig, axarr = plt.subplots(2, 2)
fig.set_size_inches(14, 10)

labels = [r"$t_{\mu}$", "$\\tilde{t}_{\mu}$", r"$q_{\mu}$", "$\\tilde{q}_{\mu}$"]
data = [
    (tmu, tmu_asymp),
    (tmu_tilde, tmu_tilde_asymp),
    (qmu, qmu_asymp),
    (qmu_tilde, qmu_tilde_asymp),
]

for ax, (label, d) in zip(axarr.ravel(), zip(labels, data)):
    empirical, asymp_func = d
    ax.scatter(muhat, empirical, alpha=0.2, label=label)
    ax.plot(
        muhat_asymp,
        asymp_func(1.0, muhat_asymp, muhat_sigma),
        label=f"{label} asymptotic",
        c="r",
    )
    ax.set_xlabel(r"$\hat{\mu}$")
    ax.set_ylabel(f"{label}")
    ax.legend(loc="best")

```



## 5.4 Using Calculators

One low-level functionality of pyhf when it comes to statistical fits is the idea of a calculator to evaluate with asymptotics or toybased hypothesis testing.

This notebook will introduce very quickly what these calculators are meant to do and how they are used internally in the code. We'll set up a simple model for demonstration and then show how the calculators come into play.

```
[1]: import numpy as np
import pyhf
```

```
np.random.seed(0)
```

```
[2]: model = pyhf.simplemodels.uncorrelated_background([6], [9], [3])
data = [9] + model.config.auxdata
```

### 5.4.1 The high-level API

If the only thing you are interested in is the hypothesis test result you can just run the high-level API to get it:

```
[3]: CLs_obs, CLs_exp = pyhf.infer.hypotest(1.0, data, model, return_expected_set=True)
print(f'CLs_obs = {CLs_obs}')
print(f'CLs_exp = {CLs_exp}')

CLs_obs = 0.1677886052335611
CLs_exp = [array(0.0159689), array(0.05465771), array(0.16778861), array(0.41863467),
↪array(0.74964133)]
```

### 5.4.2 The low-level API

Under the hood, the hypothesis test computes *test statistics* (such as  $q_\mu, \tilde{q}_\mu$ ) and uses *calculators* in order to assess how likely the computed test statistic value is under various hypotheses. The goal is to provide a consistent API that understands how you wish to perform your hypothesis test.

Let's look at the asymptotics calculator and then do the same thing for the toybased.

#### Asymptotics

First, let's create the calculator for asymptotics using the  $\tilde{q}_\mu$  test statistic.

```
[4]: asymp_calc = pyhf.infer.calculators.AsymptoticCalculator(
    data, model, test_stat='qtilde'
)
```

Now from this, we want to perform the fit and compute the value of the test statistic from which we can get our  $p$ -values:

```
[5]: teststat = asymp_calc.teststatistic(poi_test=1.0)
print(f'qtilde = {teststat}')

qtilde = 0.0
```

In addition to this, we can ask the calculator for the distributions of the test statistic for the background-only and signal+background hypotheses:

```
[6]: sb_dist, b_dist = asymp_calc.distributions(poi_test=1.0)
```

From these distributions, we can ask for the  $p$ -value of the test statistic and use this to calculate the  $CL_s$  — a “modified”  $p$ -value.

```
[7]: p_sb = sb_dist.pvalue(teststat)
p_b = b_dist.pvalue(teststat)
p_s = p_sb / p_b

print(f'CL_sb = {p_sb}')
print(f'CL_b = {p_b}')
print(f'CL_s = CL_sb / CL_b = {p_s}')

CL_sb = 0.08389430261678055
CL_b = 0.5
CL_s = CL_sb / CL_b = 0.1677886052335611
```

In a similar procedure, we can do the same thing for the expected  $CL_s$  values as well. We need to get the expected value of the test statistic at each  $\pm\sigma$  and then ask for the expected  $p$ -value associated with each value of the test statistic.

```
[8]: teststat_expected = [b_dist.expected_value(i) for i in [2, 1, 0, -1, -2]]
p_expected = [sb_dist.pvalue(t) / b_dist.pvalue(t) for t in teststat_expected]
p_expected

[8]: [0.01596890401598493,
      0.05465770873260968,
      0.1677886052335611,
      0.4186346709326618,
      0.7496413276864433]
```

However, these sorts of steps are somewhat time-consuming and lengthy, and depending on the calculator chosen, may differ a little bit. The calculator API also serves to harmonize the extraction of the observed  $p$ -values:

```
[9]: p_sb, p_b, p_s = asymp_calc.pvalues(teststat, sb_dist, b_dist)

print(f'CL_sb = {p_sb}')
print(f'CL_b = {p_b}')
print(f'CL_s = CL_sb / CL_b = {p_s}')

CL_sb = 0.08389430261678055
CL_b = 0.5
CL_s = CL_sb / CL_b = 0.1677886052335611
```

and the expected  $p$ -values:

```
[10]: p_exp_sb, p_exp_b, p_exp_s = asymp_calc.expected_pvalues(sb_dist, b_dist)

print(f'exp. CL_sb = {p_exp_sb}')
print(f'exp. CL_b = {p_exp_b}')
print(f'exp. CL_s = CL_sb / CL_b = {p_exp_s}')

exp. CL_sb = [array(0.00036329), array(0.00867173), array(0.0838943), array(0.35221608),
↪array(0.73258689)]
exp. CL_b = [array(0.02275013), array(0.15865525), array(0.5), array(0.84134475),
↪array(0.97724987)]
exp. CL_s = CL_sb / CL_b = [array(0.0159689), array(0.05465771), array(0.16778861),
↪array(0.41863467), array(0.74964133)]
```

## Toy-Based

The calculator API abstracts away a lot of the differences between various strategies, such that it returns what you want, regardless of whether you choose to perform asymptotics or toy-based testing. It hopefully delivers a simple but powerful API for you!

Let's create a toy-based calculator and "throw" 500 toys.

```
[11]: toy_calc = pyhf.infer.calculators.ToyCalculator(
      data, model, test_stat='qtilde', ntoys=500
    )
```

Like before, we'll ask for the test statistic. Unlike the asymptotics case, where we compute the Asimov dataset and perform a series of fits, here we are just evaluating the test statistic for the observed data.



```
[12]: teststat = toy_calc.teststatistic(poi_test=1.0)
print(f'qtilde = {teststat}')

qtilde = 1.902590865638981
```

```
[13]: inits = model.config.suggested_init()
bounds = model.config.suggested_bounds()
fixeds = model.config.suggested_fixed()
pyhf.infer.test_statistics.qmu_tilde(1.0, data, model, inits, bounds, fixeds)

[13]: array(1.90259087)
```

So now the next thing to do is get our distributions. This is where, in the case of toys, we fit each and every single toy that we've randomly sampled from our model.

Note, again, that the API for the calculator is the same as in the asymptotics case.

```
[14]: sb_dist, b_dist = toy_calc.distributions(poi_test=1.0)
```

From these distributions, we can ask for the  $p$ -value of the test statistic and use this to calculate the  $CL_s$ .

```
[15]: p_sb, p_b, p_s = toy_calc.pvalues(teststat, sb_dist, b_dist)

print(f'CL_sb = {p_sb}')
print(f'CL_b = {p_b}')
print(f'CL_s = CL_sb / CL_b = {p_s}')

CL_sb = 0.084
CL_b = 0.52
CL_s = CL_sb / CL_b = 0.16153846153846155
```

In a similar procedure, we can do the same thing for the expected  $CL_s$  values as well. We need to get the expected value of the test statistic at each  $\pm\sigma$  and then ask for the expected  $p$ -value associated with each value of the test statistic.

```
[16]: p_exp_sb, p_exp_b, p_exp_s = toy_calc.expected_pvalues(sb_dist, b_dist)

print(f'exp. CL_sb = {p_exp_sb}')
print(f'exp. CL_b = {p_exp_b}')
print(f'exp. CL_s = CL_sb / CL_b = {p_exp_s}')

exp. CL_sb = [array(0.), array(0.008), array(0.084), array(0.318), array(1.)]
exp. CL_b = [array(0.02540926), array(0.17), array(0.52), array(0.846), array(1.)]
exp. CL_s = CL_sb / CL_b = [array(0.), array(0.04594333), array(0.16153846), array(0.
↪ 37939698), array(1.)]
```



## EXAMPLES

Try out in Binder!

Notebooks:

## 6.1 ShapeFactor

```
[1]: import logging
import json
import numpy as np
import matplotlib.pyplot as plt

import pyhf
from pyhf.contrib.viz import brazil

logging.basicConfig(level=logging.INFO)
```

```
[2]: def prep_data(sourcedata):
    spec = {
        'channels': [
            {
                'name': 'signal',
                'samples': [
                    {
                        'name': 'signal',
                        'data': sourcedata['signal']['bindata']['sig'],
                        'modifiers': [
                            {'name': 'mu', 'type': 'normfactor', 'data': None}
                        ],
                    },
                ],
            },
            {
                'name': 'bkg1',
                'data': sourcedata['signal']['bindata']['bkg1'],
                'modifiers': [
                    {
                        'name': 'coupled_shapefactor',
                        'type': 'shapefactor',
                        'data': None,
                    },
                ],
            },
        ],
    }
```

(continues on next page)

(continued from previous page)

```

        },
    ],
},
{
    'name': 'control',
    'samples': [
        {
            'name': 'background',
            'data': sourcedata['control']['bindata']['bkg1'],
            'modifiers': [
                {
                    'name': 'coupled_shapefactor',
                    'type': 'shapefactor',
                    'data': None,
                }
            ],
        }
    ],
},
],
},
]
}
pdf = pyhf.Model(spec)
data = []
for channel in pdf.config.channels:
    data += sourcedata[channel]['bindata']['data']
data = data + pdf.config.auxdata
return data, pdf

```

```

[3]: source = {
    "channels": {
        "signal": {
            "binning": [2, -0.5, 1.5],
            "bindata": {
                "data": [220.0, 230.0],
                "bkg1": [100.0, 70.0],
                "sig": [20.0, 20.0],
            },
        },
        "control": {
            "binning": [2, -0.5, 1.5],
            "bindata": {"data": [200.0, 300.0], "bkg1": [100.0, 100.0]},
        },
    },
}

data, pdf = prep_data(source['channels'])
print(f'data: {data}')

init_pars = pdf.config.suggested_init()
print(f'expected data: {pdf.expected_data(init_pars)}')

par_bounds = pdf.config.suggested_bounds()

```

```
INFO:pyhf.pdf:Validating spec against schema: model.json
INFO:pyhf.pdf:adding modifier mu (1 new nuisance parameters)
INFO:pyhf.pdf:adding modifier coupled_shapefactor (2 new nuisance parameters)

data: [200.0, 300.0, 220.0, 230.0]
expected data: [100. 100. 120.  90.]
```

```
[4]: print(f'initialization parameters: {pdf.config.suggested_init()}')
```

```
unconpars = pyhf.infer.mle.fit(data, pdf)
print(f'parameters post unconstrained fit: {unconpars}')
```

```
initialization parameters: [1.0, 1.0, 1.0]
parameters post unconstrained fit: [1.000004623 1.99998941 3.000000438]
```

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/pyhf/tensor/numpy_backend.py:334:
↳RuntimeWarning: divide by zero encountered in log
    return n * np.log(lam) - lam - gammaln(n + 1.0)
```

```
[5]: obs_limit, exp_limits, (poi_tests, tests) = pyhf.infer.intervals.upperlimit(
    data, pdf, np.linspace(0, 5, 61), level=0.05, return_results=True
)
```

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/pyhf/infer/calculators.py:352:
↳RuntimeWarning: invalid value encountered in double_scalars
    teststat = (qmu - qmu_A) / (2 * self.sqrtqmuA_v)
```

```
[6]: fig, ax = plt.subplots(figsize=(10, 7))
    artists = brazil.plot_results(poi_tests, tests, test_size=0.05, ax=ax)
    print(f'expected upper limits: {exp_limits}')
    print(f'observed upper limit : {obs_limit}')
```

```
expected upper limits: [array(0.74138115), array(0.994935), array(1.38451391), array(1.
↳92899382), array(2.59407668)]
observed upper limit : 2.1945969322493744
```



## 6.2 XML Import/Export

```
[1]: # NB: python -m pip install pyhf[xml]
import pyhf
```

```
[2]: !ls -lavh ../../../../validation/xmlimport_input
```

```
total 1752
drwxr-xr-x  7 kratsg  staff   238B Oct 16 22:20 .
drwxr-xr-x 21 kratsg  staff   714B Apr  4 14:26 ..
drwxr-xr-x  6 kratsg  staff   204B Feb 27 17:13 config
drwxr-xr-x  7 kratsg  staff   238B Feb 27 23:41 data
-rw-r--r--  1 kratsg  staff  850K Oct 16 22:20 log
drwxr-xr-x 17 kratsg  staff   578B Nov 15 12:24 results
-rw-r--r--  1 kratsg  staff   21K Oct 16 22:20 scan.pdf
```

### 6.2.1 Importing

In order to convert HistFactory XML+ROOT to the pyhf JSON spec for likelihoods, you need to point the command-line interface `pyhf xml2json` at the top-level XML file. Additionally, as the HistFactory XML specification often uses relative paths, you might need to specify the base directory `--basedir` from which all other files are located, as specified in the top-level XML. The command will be of the format

```
pyhf xml2json {top-level XML} --basedir {base directory}
```

This will print the JSON representation of the XML+ROOT specified. If you wish to store this as a JSON file, you simply need to redirect it

```
pyhf xml2json {top-level XML} --basedir {base directory} > spec.json
```

```
[3]: !pyhf xml2json --hide-progress ../../../../validation/xmlimport_input/config/example.xml --
↳ basedir ../../../../validation/xmlimport_input | tee xml_importexport.json
```

```
{
  "channels": [
    {
      "name": "channel1",
      "samples": [
        {
          "data": [
            20.0,
            10.0
          ],
          "modifiers": [
            {
              "data": {
                "hi": 1.05,
                "lo": 0.95
              },
              "name": "syst1",
              "type": "normsys"
            },
            {
              "data": null,
              "name": "SigXsecOverSM",
              "type": "normfactor"
            }
          ],
          "name": "signal"
        },
        {
          "data": [
            100.0,
            0.0
          ],
          "modifiers": [
            {
              "data": null,
              "name": "lumi",
              "type": "lumi"
            }
          ]
        }
      ]
    }
  ]
}
```

(continues on next page)

(continued from previous page)

```

        },
        {
            "data": [
                5.0000000074505806,
                0.0
            ],
            "name": "staterror_channel1",
            "type": "staterror"
        },
        {
            "data": {
                "hi": 1.05,
                "lo": 0.95
            },
            "name": "syst2",
            "type": "normsys"
        }
    ],
    "name": "background1"
},
{
    "data": [
        0.0,
        100.0
    ],
    "modifiers": [
        {
            "data": null,
            "name": "lumi",
            "type": "lumi"
        },
        {
            "data": [
                0.0,
                10.0
            ],
            "name": "staterror_channel1",
            "type": "staterror"
        },
        {
            "data": {
                "hi": 1.05,
                "lo": 0.95
            },
            "name": "syst3",
            "type": "normsys"
        }
    ],
    "name": "background2"
}
]
}

```

(continues on next page)



(continued from previous page)

```

],
"data": {
  "channel1": [
    122.0,
    112.0
  ]
},
"toplvl": {
  "measurements": [
    {
      "config": {
        "parameters": [
          {
            "auxdata": [
              1.0
            ],
            "bounds": [
              [
                0.5,
                1.5
              ]
            ],
            "fixed": true,
            "inits": [
              1.0
            ],
            "name": "lumi",
            "sigmas": [
              0.1
            ]
          },
          {
            "fixed": true,
            "name": "alpha_syst1"
          }
        ],
        "poi": "SigXsecOverSM"
      },
      "name": "GaussExample"
    },
    {
      "config": {
        "parameters": [
          {
            "auxdata": [
              1.0
            ],
            "bounds": [
              [
                0.5,
                1.5
              ]
            ]
          }
        ]
      }
    }
  ]
}

```

(continues on next page)

(continued from previous page)

```

        ],
        "fixed": true,
        "inits": [
            1.0
        ],
        "name": "lumi",
        "sigmas": [
            0.1
        ]
    },
    {
        "fixed": true,
        "name": "alpha_syst1"
    }
],
"poi": "SigXsecOverSM"
},
"name": "GammaExample"
},
{
    "config": {
        "parameters": [
            {
                "auxdata": [
                    1.0
                ],
                "bounds": [
                    [
                        0.5,
                        1.5
                    ]
                ],
                "fixed": true,
                "inits": [
                    1.0
                ],
                "name": "lumi",
                "sigmas": [
                    0.1
                ]
            },
            {
                "fixed": true,
                "name": "alpha_syst1"
            }
        ],
        "poi": "SigXsecOverSM"
    },
    "name": "LogNormExample"
},
{
    "config": {

```

(continues on next page)

(continued from previous page)

```

        "parameters": [
            {
                "auxdata": [
                    1.0
                ],
                "bounds": [
                    [
                        0.5,
                        1.5
                    ]
                ],
                "fixed": true,
                "inits": [
                    1.0
                ],
                "name": "lumi",
                "sigmas": [
                    0.1
                ]
            },
            {
                "fixed": true,
                "name": "alpha_syst1"
            }
        ],
        "poi": "SigXsecOverSM"
    },
    "name": "ConstExample"
},
"resultprefix": "./results/example"
}

```

## 6.2.2 Exporting

In order to convert the pyhf JSON to the HistFactory XML+ROOT spec for likelihoods, you need to point the command-line interface `pyhf json2xml` at the JSON file you want to convert. As everything is specified in a single file, there is no need to deal with base directories or looking up additional files. This will produce output XML+ROOT in the `--output-dir=./` directory (your current working directory), storing XML configs under `--specroot=config` and the data file under `--dataroot=data`. The XML configs are prefixed with `--resultprefix=FitConfig` by default, so that the top-level XML file will be located at `{output_dir}/{prefix}.xml`. The command will be of the format

```
pyhf json2xml {JSON spec}
```

Note that the output directory must already exist.

```
[4]: !mkdir -p output
      !pyhf json2xml xml_importexport.json --output-dir output
      !ls -lavh output/*
```

```
/Users/jovyan/pyhf/src/pyhf/writexml.py:120: RuntimeWarning: invalid value encountered_
↪ in true_divide
  attrs['HistoName'], np.divide(modifierspec['data'], sampledata).tolist()
-rw-r--r--  1 kratsg  staff   822B Apr  9 09:36 output/FitConfig.xml

output/config:
total 8
drwxr-xr-x  3 kratsg  staff   102B Apr  9 09:36 .
drwxr-xr-x  5 kratsg  staff   170B Apr  9 09:36 ..
-rw-r--r--  1 kratsg  staff   1.0K Apr  9 09:36 FitConfig_channel1.xml

output/data:
total 96
drwxr-xr-x  3 kratsg  staff   102B Apr  9 09:36 .
drwxr-xr-x  5 kratsg  staff   170B Apr  9 09:36 ..
-rw-r--r--  1 kratsg  staff    46K Apr  9 09:36 data.root
```

```
[5]: !rm xml_importexport.json
     !rm -rf output/
```

```
[1]: import pyhf
     import pandas
     import numpy as np
     import altair as alt
```

## 6.3 Visualization with Altair

Altair is a python API for generating Vega visuazliation specifications. We demonstracte how to use this to build an interactive chart of pyhf results.

### 6.3.1 Preparing the data

Altair reads the data as a pandas dataframe, so we create one.

```
[2]: model = pyhf.simplemodels.uncorrelated_background([7], [20], [5])
     data = [25] + model.config.auxdata
```

```
[3]: muscan = np.linspace(0, 5, 31)
     results = [
         pyhf.infer.hypotest(mu, data, model, return_expected_set=True) for mu in muscan
     ]
```

```
[4]: data = np.concatenate(
     [
         muscan.reshape(-1, 1),
         np.asarray([r[0] for r in results]).reshape(-1, 1),
         np.asarray([r[1] for r in results]).reshape(-1, 5),
     ],
     axis=1,
```

(continues on next page)

(continued from previous page)

```
)
df = pandas.DataFrame(data, columns=["mu", "obs"] + [f"exp_{i}" for i in range(5)])
df.head()
```

```
[4]:
```

	mu	obs	exp_0	exp_1	exp_2	exp_3	exp_4
0	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
1	0.166667	0.885208	0.670809	0.771258	0.870322	0.949235	0.989385
2	0.333333	0.795986	0.438838	0.581516	0.743696	0.890881	0.975022
3	0.500000	0.726450	0.279981	0.428500	0.623443	0.825621	0.956105
4	0.666667	0.672216	0.174235	0.308524	0.512383	0.754629	0.931866

### 6.3.2 Defining the Chart

We need to filled areas for the 1,2 sigma bands and two lines for the expected and observed CLs value. For interactivity we add a hovering label of the observed result

```
[5]: band1 = (
    alt.Chart(df)
    .mark_area(opacity=0.5, color="green")
    .encode(x="mu", y="exp_1", y2="exp_3")
)

band2 = (
    alt.Chart(df)
    .mark_area(opacity=0.5, color="yellow")
    .encode(x="mu", y="exp_0", y2="exp_4")
)

line1 = alt.Chart(df).mark_line(color="black").encode(x="mu", y="obs")

line2 = (
    alt.Chart(df).mark_line(color="black", strokeDash=[5, 5]).encode(x="mu", y="exp_2")
)

nearest = alt.selection_single(
    nearest=True, on="mouseover", fields=["mu"], empty="none"
)

point = (
    alt.Chart(df)
    .mark_point(color="black")
    .encode(x="mu", y="obs", opacity=alt.condition(nearest, alt.value(1), alt.value(0)))
    .add_selection(nearest)
)

text = line1.mark_text(aligned="left", dx=5, dy=-5).encode(
    text=alt.condition(nearest, "obs", alt.value(" "))
)

band2 + band1 + line1 + line2 + point + text
```

```
[5]: alt.LayerChart(...)
```

## 6.4 Hello World, pyhf style

Two bin counting experiment with a background uncertainty

```
[1]: import pyhf
```

Returning the observed and expected  $CL_s$

```
[2]: model = pyhf.simplemodels.uncorrelated_background(
    signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
)
data = [51, 48] + model.config.auxdata
test_mu = 1.0
CLs_obs, CLs_exp = pyhf.infer.hypotest(
    test_mu, data, model, test_stat="qtilde", return_expected=True
)
print(f"Observed: {CLs_obs}, Expected: {CLs_exp}")
```

```
Observed: 0.052515541856109765, Expected: 0.06445521290832805
```

Returning the observed  $CL_s$ ,  $CL_{s+b}$ , and  $CL_b$

```
[3]: CLs_obs, p_values = pyhf.infer.hypotest(
    test_mu, data, model, test_stat="qtilde", return_tail_probs=True
)
print(f"Observed CL_s: {CLs_obs}, CL_sb: {p_values[0]}, CL_b: {p_values[1]}")
```

```
Observed CL_s: 0.052515541856109765, CL_sb: 0.023324961200974572, CL_b: 0.
↪ 44415349012077077
```

A reminder that

$$CL_s = \frac{CL_{s+b}}{CL_b} = \frac{p_{s+b}}{1 - p_b}$$

```
[4]: assert CLs_obs == p_values[0] / p_values[1]
```

Returning the expected  $CL_s$  band values

```
[5]: import numpy as np
```

```
[6]: CLs_obs, CLs_exp_band = pyhf.infer.hypotest(
    test_mu, data, model, test_stat="qtilde", return_expected_set=True
)
print(f"Observed CL_s: {CLs_obs}\n")
for p_value, n_sigma in enumerate(np.arange(-2, 3)):
    print(
        "Expected CL_s{}: {}".format(
            " " * 10 if n_sigma == 0 else f"({n_sigma} )",

```

(continues on next page)

(continued from previous page)

```

        CLs_exp_band[p_value],
    )
)

```

```
Observed CL_s: 0.052515541856109765
```

```
Expected CL_s(-2 ): 0.0026064088679947964
```

```
Expected CL_s(-1 ): 0.013820657528619273
```

```
Expected CL_s      : 0.06445521290832805
```

```
Expected CL_s(1 ): 0.23526103626937836
```

```
Expected CL_s(2 ): 0.5730418174887743
```

## 6.5 Multi-bin Poisson

```

[1]: import logging
import json
import math
import numpy as np
import matplotlib.pyplot as plt

import pyhf
from pyhf import Model, optimizer
from pyhf.simplermodels import uncorrelated_background
from pyhf.contrib.viz import brazil

from scipy.interpolate import griddata
import scrapbook as sb

```

```

[2]: def plot_histo(ax, binning, data):
    bin_width = (binning[2] - binning[1]) / binning[0]
    bin_leftedges = np.linspace(binning[1], binning[2], binning[0] + 1)[: -1]
    bin_centers = [le + bin_width / 2.0 for le in bin_leftedges]
    ax.bar(bin_centers, data, 1, alpha=0.5)

def plot_data(ax, binning, data):
    errors = [math.sqrt(d) for d in data]
    bin_width = (binning[2] - binning[1]) / binning[0]
    bin_leftedges = np.linspace(binning[1], binning[2], binning[0] + 1)[: -1]
    bin_centers = [le + bin_width / 2.0 for le in bin_leftedges]
    ax.bar(
        bin_centers,
        data,
        0,
        yerr=errors,
        linewidth=0,
        error_kw=dict(ecolor='k', elinewidth=1),
    )
    ax.scatter(bin_centers, data, c='k')

```

```
[3]: validation_datadir = '../validation/data'
```

```
[4]: source = json.load(open(validation_datadir + '/1bin_example1.json'))
model = uncorrelated_background(
    source['bindata']['sig'], source['bindata']['bkg'], source['bindata']['bkgerr']
)
data = source['bindata']['data'] + model.config.auxdata

init_pars = model.config.suggested_init()
par_bounds = model.config.suggested_bounds()

obs_limit, exp_limits, (poi_tests, tests) = pyhf.infer.intervals.upperlimit(
    data, model, np.linspace(0, 5, 61), level=0.05, return_results=True
)

/srv/conda/envs/notebook/lib/python3.7/site-packages/pyhf/infer/calculators.py:352:
↳ RuntimeWarning: invalid value encountered in double_scalars
    teststat = (qmu - qmu_A) / (2 * self.sqrtqmuA_v)
```

```
[5]: fig, ax = plt.subplots(figsize=(10, 7))
artists = brazil.plot_results(poi_tests, tests, test_size=0.05, ax=ax)
print(f'expected upper limits: {exp_limits}')
print(f'observed upper limit : {obs_limit}')

expected upper limits: [array(1.07644221), array(1.44922838), array(2.01932904), array(2.
↳ 83213651), array(3.84750318)]
observed upper limit : 2.381026330918668
```





```
[6]: source = {
    "binning": [2, -0.5, 1.5],
    "bindata": {
        "data": [120.0, 145.0],
        "bkg": [100.0, 150.0],
        "bkgerr": [15.0, 20.0],
        "sig": [30.0, 45.0],
    },
}

my_observed_counts = source['bindata']['data']

model = uncorrelated_background(
    source['bindata']['sig'], source['bindata']['bkg'], source['bindata']['bkgerr']
)
data = my_observed_counts + model.config.auxdata

binning = source['binning']

nompars = model.config.suggested_init()
```

(continues on next page)

(continued from previous page)

```

bonly_pars = [x for x in nompars]
bonly_pars[model.config.poi_index] = 0.0
nom_bonly = model.expected_data(bonly_pars, include_auxdata=False)

nom_sb = model.expected_data(nompars, include_auxdata=False)

init_pars = model.config.suggested_init()
par_bounds = model.config.suggested_bounds()

print(init_pars)

bestfit_pars = pyhf.infer.mle.fit(data, model, init_pars, par_bounds)
bestfit_cts = model.expected_data(bestfit_pars, include_auxdata=False)

[1.0, 1.0, 1.0]

```

```

[7]: f, axarr = plt.subplots(1, 3, sharey=True)
f.set_size_inches(12, 4)

plot_histo(axarr[0], binning, nom_bonly)
plot_data(axarr[0], binning, my_observed_counts)
axarr[0].set_xlim(binning[1:])

plot_histo(axarr[1], binning, nom_sb)
plot_data(axarr[1], binning, my_observed_counts)
axarr[1].set_xlim(binning[1:])

plot_histo(axarr[2], binning, bestfit_cts)
plot_data(axarr[2], binning, my_observed_counts)
axarr[2].set_xlim(binning[1:])

plt.ylim(0, 300);

```



```

[8]: ## DUMMY 2D thing

```

```

def signal(m1, m2):
    massscale = 150.0

```

(continues on next page)

(continued from previous page)

```

minmass = 100.0
countscale = 2000

effective_mass = np.sqrt(m1 ** 2 + m2 ** 2)
return [countscale * np.exp(-(effective_mass - minmass) / massscale), 0]

def CLs(m1, m2):
    signal_counts = signal(m1, m2)
    pdf = uncorrelated_background(
        signal_counts, source['bindata']['bkg'], source['bindata']['bkger']
    )
    try:
        cls_obs, cls_exp_set = pyhf.infer.hypotest(
            1.0, data, pdf, init_pars, par_bounds, return_expected_set=True
        )
        return cls_obs, cls_exp_set, True
    except AssertionError:
        print(f'fit failed for mass points ({m1}, {m2})')
        return None, None, False

```

```

[9]: nx, ny = 15, 15
grid = grid_x, grid_y = np.mgrid[
    100 : 1000 : complex(0, nx), 100 : 1000 : complex(0, ny)
]
X = grid.T.reshape(nx * ny, 2)
results = [CLs(m1, m2) for m1, m2 in X]

```

```

[10]: X = np.array([x for x, (_, _, success) in zip(X, results) if success])
yobs = np.array([obs for obs, exp, success in results if success]).flatten()
yexp = [
    np.array([exp[i] for obs, exp, success in results if success]).flatten()
    for i in range(5)
]

```

```

[11]: int_obs = griddata(X, yobs, (grid_x, grid_y), method='linear')

int_exp = [griddata(X, yexp[i], (grid_x, grid_y), method='linear') for i in range(5)]

plt.contourf(grid_x, grid_y, int_obs, levels=np.linspace(0, 1))
plt.colorbar()

plt.contour(grid_x, grid_y, int_obs, levels=[0.05], colors='w')
for level in int_exp:
    plt.contour(grid_x, grid_y, level, levels=[0.05], colors='w', linestyle='dashed')

plt.scatter(X[:, 0], X[:, 1], c=yobs, vmin=0, vmax=1);

```



```
[12]: sb.glue("number_2d_successpoints", len(X))
```

Data type cannot be displayed: application/scrapbook.scrap.json+json

## 6.6 Multibin Coupled HistoSys

```
[1]: %pylab inline
```

Populating the interactive namespace from numpy and matplotlib

```
[2]: import logging
import json

import pyhf
from pyhf import Model
```

```
logging.basicConfig(level=logging.INFO)
```

```
[3]: def prep_data(sourcedata):
    spec = {
        "channels": [
            {
                "name": "signal",
                "samples": [
                    {
                        "name": "signal",
                        "data": sourcedata["signal"]["bindata"]["sig"],
                        "modifiers": [
                            {"name": "mu", "type": "normfactor", "data": None}
                        ],
                    },
                ],
            },
        ],
    }
```

(continues on next page)

(continued from previous page)

```

        "name": "bkg1",
        "data": sourcedata["signal"]["bindata"]["bkg1"],
        "modifiers": [
            {
                "name": "coupled_histosys",
                "type": "histosys",
                "data": {
                    "lo_data": sourcedata["signal"]["bindata"][
                        "bkg1_dn"
                    ],
                    "hi_data": sourcedata["signal"]["bindata"][
                        "bkg1_up"
                    ],
                },
            },
        ],
    },
    {
        "name": "bkg2",
        "data": sourcedata["signal"]["bindata"]["bkg2"],
        "modifiers": [
            {
                "name": "coupled_histosys",
                "type": "histosys",
                "data": {
                    "lo_data": sourcedata["signal"]["bindata"][
                        "bkg2_dn"
                    ],
                    "hi_data": sourcedata["signal"]["bindata"][
                        "bkg2_up"
                    ],
                },
            },
        ],
    },
],
},
{
    "name": "control",
    "samples": [
        {
            "name": "background",
            "data": sourcedata["control"]["bindata"]["bkg1"],
            "modifiers": [
                {
                    "name": "coupled_histosys",
                    "type": "histosys",
                    "data": {
                        "lo_data": sourcedata["control"]["bindata"][
                            "bkg1_dn"
                        ],
                        "hi_data": sourcedata["control"]["bindata"][

```

(continues on next page)

(continued from previous page)

```
        ],  
    },  
],  
},  
],  
},  
],  
}  
pdf = Model(spec)  
data = []  
for c in pdf.spec["channels"]:  
    data += sourcedata[c["name"]]["bindata"]["data"]  
data = data + pdf.config.auxdata  
return data, pdf
```

```
[4]: validation_datadir = "../..validation/data"
```

```
[5]: source = json.load(open(validation_datadir + "/2bin_2channel_coupledhisto.json"))
```

```
data, pdf = prep_data(source["channels"])

print(data)

init_pars = pdf.config.suggested_init()
par_bounds = pdf.config.suggested_bounds()

unconpars = pyhf.infer.mle.fit(data, pdf, init_pars, par_bounds)
print(f"parameters post unconstrained fit: {unconpars}")

conpars = pyhf.infer.mle.fixed_poi_fit(0.0, data, pdf, init_pars, par_bounds)
print(f"parameters post constrained fit: {conpars}")

pdf.expected_data(conpars)

[170.0, 220.0, 110.0, 105.0, 0.0]
parameters post unconstrained fit: [1.53170588e-12 2.21657891e+00]
parameters post constrained fit: [0.          2.21655133]
```

```
[5]: array([116.08275666, 133.24826999, 183.24826999, 98.08967672,
        2.21655133])
```

```
[6]: def plot_results(test_mus, cls_obs, cls_exp, poi_tests, test_size=0.05):
    plt.plot(poi_tests, cls_obs, c="k")
    for i, c in zip(range(5), ["grey", "grey", "grey", "grey", "grey"]):
        plt.plot(poi_tests, cls_exp[i], c=c)
    plt.plot(poi_tests, [test_size] * len(test_mus), c="r")
    plt.ylim(0, 1)
```

```
[7]: def invert_interval(test_mus, cls_obs, cls_exp, test_size=0.05):  
      crossing_test_stats = {"exp": [], "obs": None}
```

(continues on next page)

(continued from previous page)

```

for cls_exp_sigma in cls_exp:
    crossing_test_stats["exp"].append(
        np.interp(
            test_size, list(reversed(cls_exp_sigma)), list(reversed(test_mus))
        )
    )
crossing_test_stats["obs"] = np.interp(
    test_size, list(reversed(cls_obs)), list(reversed(test_mus))
)
return crossing_test_stats

```

```

[8]: poi_tests = np.linspace(0, 5, 61)
tests = [
    pyhf.infer.hypotest(
        poi_test, data, pdf, init_pars, par_bounds, return_expected_set=True
    )
    for poi_test in poi_tests
]
cls_obs = np.array([test[0] for test in tests]).flatten()
cls_exp = [np.array([test[1][i] for test in tests]).flatten() for i in range(5)]

```

```

[9]: print("\n")
plot_results(poi_tests, cls_obs, cls_exp, poi_tests)
invert_interval(poi_tests, cls_obs, cls_exp)

```

```

[9]: {'exp': [0.3654675198094938,
0.4882076670368835,
0.683262284467055,
0.9650584704888153,
1.3142329292131938],
'obs': 0.3932476110375604}

```



```
[1]: import numpy as np
import matplotlib.pyplot as plt
import pyhf

[2]: np.random.seed(0)
plt.rcParams.update({"font.size": 14})
```

## 6.7 Running Monte Carlo simulations (toys)

Finding the (expected) significance can involve costly Monte Carlo calculations (“toys”). The asymptotic approximation described in the paper by Cowan, Cranmer, Gross, Vitells: *Asymptotic formulae for likelihood-based tests of new physics* [arXiv:1007.1727] provides an alternative to these computationally expensive toy calculations.

This notebook demonstrates a reproduction of one of the key plots in the paper using pyhf.



Figure 5: (a) The pdfs  $f(q_1|1)$  and  $f(q_1|0)$  for the counting experiment. The solid curves show the formulae from the text, and the histograms are from Monte Carlo using  $s = 6$ ,  $b = 9$ ,  $\tau = 1$ . (b) The same set of histograms with the alternative statistic  $\tilde{q}_1$ . The oscillatory structure evident in the histograms is a consequence of the discreteness of the data. The vertical line indicates the Asimov value of the test statistic corresponding to  $\mu' = 0$ .

### 6.7.1 Counting Experiment

Consider a counting experiment where one observes  $n$  events, following a Poisson distribution with expectation value

$$E[n] = \mu s + b$$

with  $s$  expected signal events and  $b$  expected background events, and signal strength parameter  $\mu$ . Follow up in the paper to understand more of the math behind this as the notation is being introduced here. What we will show is the distribution of the (alternative) test statistic  $q_1$  ( $\tilde{q}_1$ ) calculated under the assumption of the nominal signal model ( $\mu = 1$ ) for data corresponding to the strength parameter of the background-only ( $\mu' = 0$ ) and signal+background ( $\mu' = 1$ ) model hypotheses. For the rest of this notebook, we’ll refer to the background-like model  $\mu' = 0$  and the signal-like model  $\mu' = 1$ .



The first thing we will do is set up the pyhf model with  $s = 6$  signal events and  $b = 9$  background events (adding a Poisson uncertainty on the background).

```
[3]: signal = 6
background = 9
background_uncertainty = 3
model = pyhf.simplemodels.uncorrelated_background(
    [signal], [background], [background_uncertainty]
)
print(f"Channels: {model.config.channels}")
print(f"Samples: {model.config.samples}")
print(f"Parameters: {model.config.parameters}")
```

```
Channels: ['singlechannel']
Samples: ['background', 'signal']
Parameters: ['mu', 'uncorr_bkguncrt']
```

This is a single channel with two samples: signal and background.  $\mu$  here is the signal strength. Next, we need to define the background-like and signal-like p.d.f.s.

```
[4]: # mu' = 0: background-like
pars_bkg = model.config.suggested_init()
pars_bkg[model.config.poi_index] = 0.0
print(f"Background parameters: {list(zip(model.config.parameters, pars_bkg))}")

# mu' = 1: signal-like
pars_sig = model.config.suggested_init()
pars_sig[model.config.poi_index] = 1.0
print(f"Signal parameters: {list(zip(model.config.parameters, pars_sig))}")

# make the pdfs
pdf_bkg = model.make_pdf(pyhf.tensorlib.astensor(pars_bkg))
pdf_sig = model.make_pdf(pyhf.tensorlib.astensor(pars_sig))

Background parameters: [('mu', 0.0), ('uncorr_bkguncrt', 1.0)]
Signal parameters: [('mu', 1.0), ('uncorr_bkguncrt', 1.0)]
```

Notice that the parameter of interest,  $\mu'$  is set to zero for background-like models and to one for signal-like models.

## Running Toys by Hand

Now that we've built our pdfs, we can go ahead and randomly (Monte Carlo) sample them. In this case, we want to “run 10,000 pseudo-experiments” (or “throw toys” as particle physicists would say). This means to draw  $n = 10000$  samples from the models:

```
[5]: # note: pdf.sample takes in a "shape" N=(10000,) given the number of samples
n_samples = 10000

# mu' = 0
mc_bkg = pdf_bkg.sample((n_samples,))
# mu' = 1
mc_sig = pdf_sig.sample((n_samples,))

print(mc_bkg.shape)
print(mc_sig.shape)
```

```
(10000, 2)
(10000, 2)
```

You'll notice that the shape for `mc_bkg` and `mc_sig` is not the input shape we passed in `(10000,)` but rather `(10000, 2)`! Why is that? The `HistFactory` model is a product of many separate pdfs: Poissons representing the main model, and Gaussians representing the auxiliary measurements. In `pyhf`, this is represented under the hood as a `Simultaneous` [pdf of the main model and the auxiliary model](https://scikit-hep.org/pyhf/_generated/pyhf.probability.Simultaneous.html) — hence the second dimension.

We can now calculate the test statistic distributions for  $\tilde{q}_1$  given the background-like and signal-like models. This inference step (running the toys) will take some time:

```
[6]: init_pars = model.config.suggested_init()
    par_bounds = model.config.suggested_bounds()
    fixed_params = model.config.suggested_fixed()

    qtilde_bkg = pyhf.tensorlib.astensor(
        [
            pyhf.infer.test_statistics.qmu_tilde(
                1.0, mc, model, init_pars, par_bounds, fixed_params
            )
            for mc in mc_bkg
        ]
    )
    qtilde_sig = pyhf.tensorlib.astensor(
        [
            pyhf.infer.test_statistics.qmu_tilde(
                1.0, mc, model, init_pars, par_bounds, fixed_params
            )
            for mc in mc_sig
        ]
    )
```

## Running Toys using Calculators

However, as you can see, a lot of this is somewhat cumbersome as you need to carry around two pieces of information: one for background-like and one for signal-like. Instead, `pyhf` provides a statistics calculator API that both simplifies and harmonizes some of this work for you.

This calculator API allows you to:

- compute a test statistic for the observed data
- provide distributions of that test statistic under various hypotheses

These provided distributions additionally have extra functionality to compute a *p*-value for the observed test statistic.

We will create a toy-based calculator and evaluate the model ( $\mu = 1$ ) for data simulated under background-like hypothesis ( $\mu' = 0$ ) and under the signal-like hypothesis ( $\mu' = 1$ ). This will compute  $\tilde{q}_1$  for both values of  $\mu'$ .

```
[7]: toy_calculator_qtilde = pyhf.infer.utils.create_calculator(
    "toybased",
    model.expected_data(pars_sig),
    model,
    ntoys=n_samples,
```

(continues on next page)

(continued from previous page)

```

    test_stat="qtilde",
)
qtilde_sig, qtilde_bkg = toy_calculator_qtilde.distributions(1.0)

```

To compute  $q_1$ , we just need to alleviate the bounds to allow for  $\mu$  (the parameter of interest) to go below zero. Right now, it is set to the default for `normfactor` which is  $[0, 10]$  — a very sensible default most of the time. But if the  $\hat{\mu}$  (the maximum likelihood estimator for  $\mu$ ) for our model is truly negative, then we should allow the fit to scan negative  $\mu$  values as well.

```

[8]: qmu_bounds = model.config.suggested_bounds()
print(f"Old bounds: {qmu_bounds}")
qmu_bounds[model.config.poi_index] = (-10, 10)
print(f"New bounds: {qmu_bounds}")

```

```

Old bounds: [(0, 10), (1e-10, 10.0)]
New bounds: [(-10, 10), (1e-10, 10.0)]

```

And then run the toys

```

[9]: toy_calculator_qmu = pyhf.infer.utils.create_calculator(
    "toybased",
    model.expected_data(model.config.suggested_init()),
    model,
    par_bounds=qmu_bounds,
    ntoys=n_samples,
    test_stat="q",
)
qmu_sig, qmu_bkg = toy_calculator_qmu.distributions(1.0)

```

```

Signal-like:  0%|          | 0/10000 [00:00<?, ?toy/s]/Users/jovyan/pyhf/src/pyhf/
↳ tensor/numpy_backend.py:253: RuntimeWarning: invalid value encountered in log
    return n * np.log(lam) - lam - gammaln(n + 1.0)

```

Now that we've ran the toys, we can make the key plots .

```

[10]: fig, axes = plt.subplots(nrows=1, ncols=2)
for ax in axes:
    ax.set_xticks(np.arange(0, 10))
ax0, ax1 = axes.flatten()

bins = np.linspace(0, 10, 26)

ax0.hist(
    qmu_sig.samples,
    bins=bins,
    histtype="step",
    density=True,
    label="$f(q_1|1)$ signal-like",
    linewidth=2,
)
ax0.hist(

```

(continues on next page)

(continued from previous page)

```

    qmu_bkg.samples,
    bins=bins,
    histtype="step",
    density=True,
    label="$f(q_1|0)$ background-like",
    linewidth=2,
)
ax0.set_xlabel(r"(a)  $q_1$ ", fontsize=18)
ax0.set_ylabel(r"$f(\cdot, q_1|\mu')$", fontsize=18)
ax0.set_title(r"Test statistic  $q_1$  distributions")
ax0.legend()

ax1.hist(
    qtilde_sig.samples,
    bins=bins,
    histtype="step",
    density=True,
    label=r"$f(\tilde{q}_1|1)$ signal-like",
    linewidth=2,
)
ax1.hist(
    qtilde_bkg.samples,
    bins=bins,
    histtype="step",
    density=True,
    label=r"$f(\tilde{q}_1|0)$ background-like",
    linewidth=2,
)
ax1.set_xlabel(r"(b)  $\tilde{q}_1$ ", fontsize=18)
ax1.set_ylabel(r"$f(\cdot, \tilde{q}_1|\mu')$", fontsize=18)
ax1.set_title(r"Alternative test statistic  $\tilde{q}_1$  distributions")
ax1.legend()

plt.setp(axes, xlim=(0, 9), ylim=(1e-3, 2), yscale="log")
fig.set_size_inches(14, 6)
fig.tight_layout(pad=2.0)

```



```
[1]: from pathlib import Path

import numpy as np
import matplotlib.pyplot as plt

import pyhf
import pyhf.readxml
from pyhf.contrib.viz import brazil

import base64
from IPython.core.display import display, HTML
from ipywidgets import interact, fixed
```

## 6.8 Binned HEP Statistical Analysis in Python

### 6.8.1 HistFactory

HistFactory is a popular framework to analyze binned event data and commonly used in High Energy Physics. At its core it is a template for building a statistical model from individual binned distribution (‘Histograms’) and variations on them (‘Systematics’) that represent auxiliary measurements (for example an energy scale of the detector which affects the shape of a distribution)

### 6.8.2 pyhf

pyhf is a work-in-progress standalone implementation of the HistFactory p.d.f. template and an implementation of the test statistics and asymptotic formulae described in the paper by Cowan, Cranmer, Gross, Vitells: *Asymptotic formulae for likelihood-based tests of new physics* [arXiv:1007.1727].

Models can be defined using JSON specification, but existing models based on the XML + ROOT file scheme are readable as well.

### 6.8.3 The Demo

The input data for the statistical analysis was built generated using the containerized workflow engine [yadage](#) (see demo from KubeCon 2018 [\[youtube\]](#)). Similarly to Binder this utilizes modern container technology for reproducible science. Below you see the execution graph leading up to the model input data at the bottom.

```
[2]: anim = base64.b64encode(open('workflow.gif', 'rb').read()).decode('ascii')
HTML(f'')
[2]: <IPython.core.display.HTML object>
```

### 6.8.4 Read in the Model from XML and ROOT

The ROOT files are read using scikit-hep's [uproot](#) module.

```
[3]: spec = pyhf.readxml.parse('meas.xml', Path.cwd())
workspace = pyhf.Workspace(spec)
```

From the `meas.xml` spec, we construct a probability density function (p.d.f). As the model includes systematics, it will be a simultaneous joint p.d.f. of the main model (poisson) and constraint model. The latter is defined by the implied “auxiliary measurements”.

```
[4]: pdf = workspace.model(measurement_name='meas')
data = workspace.data(pdf)
# what is the measurement?
workspace.get_measurement(measurement_name='meas')
[4]: {'name': 'meas',
      'config': {'poi': 'SigXsecOverSM',
                  'parameters': [{'name': 'lumi',
                                   'auxdata': [1.0],
                                   'bounds': [[0.5, 1.5]],
                                   'inits': [1.0],
                                   'sigmas': [0.1]},
                                {'name': 'SigXsecOverSM',
                                   'bounds': [[0.0, 3.0]],
                                   'inits': [1.0],
                                   'fixed': False}]}}
```

The p.d.f is build from one data-driven “qcd” (or multijet) estimate and two Monte Carlo-based background samples and is parametrized by five parameters: One parameter of interest `SigXsecOverSM` and four *nuisance parameters* that affect the shape of the two Monte Carlo background estimates (both weight-only and shape systematics)

```
[5]: print(f'Samples:\n {workspace.samples}')
print(f'Parameters:\n {workspace.parameters}')
Samples:
['mc1', 'mc2', 'qcd', 'signal']
Parameters:
['SigXsecOverSM', 'lumi', 'mc1_shape_conv', 'mc1_weight_var1', 'mc2_shape_conv', 'mc2_
↪weight_var1']
[6]: par_name_dict = {k: v["slice"].start for k, v in pdf.config.par_map.items()}
all_par_settings = {
```

(continues on next page)

(continued from previous page)

```

n[0]: tuple(m)
for n, m in zip(
    sorted(reversed(list(par_name_dict.items()))), key=lambda x: x[1]),
    pdf.config.suggested_bounds(),
)
}
default_par_settings = {n[0]: sum(tuple(m)) / 2.0 for n, m in all_par_settings.items()}

```

```

[7]: def get_mc_counts(pars):
    deltas, factors = pdf._modifications(pars)
    allsum = pyhf.tensorlib.concatenate(
        deltas + [pyhf.tensorlib.astensor(pdf.nominal_rates)]
    )
    nom_plus_delta = pyhf.tensorlib.sum(allsum, axis=0)
    nom_plus_delta = pyhf.tensorlib.reshape(
        nom_plus_delta, (1,) + pyhf.tensorlib.shape(nom_plus_delta)
    )
    allfac = pyhf.tensorlib.concatenate(factors + [nom_plus_delta])
    return pyhf.tensorlib.product(allfac, axis=0)

animate_plot_pieces = None

def init_plot(fig, ax, par_settings):
    global animate_plot_pieces

    nbins = sum(list(pdf.config.channel_nbins.values()))
    x = np.arange(nbins)
    data = np.zeros(nbins)
    items = []
    for i in [3, 2, 1, 0]:
        items.append(ax.bar(x, data, 1, alpha=1.0))
    animate_plot_pieces = (
        items,
        ax.scatter(x, workspace.data(pdf, with_aux=False), c="k", alpha=1.0, zorder=99),
    )

def animate(ax=None, fig=None, **par_settings):
    global animate_plot_pieces
    items, obs = animate_plot_pieces
    pars = pyhf.tensorlib.astensor(pdf.config.suggested_init())
    for k, v in par_settings.items():
        pars[par_name_dict[k]] = v

    mc_counts = get_mc_counts(pars)
    rectangle_collection = zip(*map(lambda x: x.patches, items))

    for rectangles, binvalues in zip(rectangle_collection, mc_counts[:, 0].T):
        offset = 0
        for sample_index in [3, 2, 1, 0]:

```

(continues on next page)

(continued from previous page)

```

        rect = rectangles[sample_index]
        binvalue = binvalues[sample_index]
        rect.set_y(offset)
        rect.set_height(binvalue)
        offset += rect.get_height()

fig.canvas.draw()

def plot(ax=None, order=[3, 2, 1, 0], **par_settings):
    pars = pyhf.tensorlib.astensor(pdf.config.suggested_init())
    for k, v in par_settings.items():
        pars[par_name_dict[k]] = v

    mc_counts = get_mc_counts(pars)
    bottom = None
    # nb: bar_data[0] because evaluating only one parset
    for i, sample_index in enumerate(order):
        data = mc_counts[sample_index][0]
        x = np.arange(len(data))
        ax.bar(x, data, 1, bottom=bottom, alpha=1.0)
        bottom = data if i == 0 else bottom + data
    ax.scatter(x, workspace.data(pdf, with_aux=False), c="k", alpha=1.0, zorder=99)

```

## 6.8.5 Interactive Exploration of a HistFactory Model

One advantage of a pure-python implementation of Histfactory is the ability to explore the pdf interactively within the setting of a notebook. Try moving the sliders and observe the effect on the samples. For example changing the parameter of interest SigXsecOverSM (or  $\mu$ ) controls the overall normalization of the (BSM) signal sample ( $\mu=0$  for background-only and  $\mu=1$  for the nominal signal-plus-background hypothesis)

```

[8]: %matplotlib notebook
fig, ax = plt.subplots(1, 1)
fig.set_size_inches(10, 5)
ax.set_ylim(0, 1.5 * np.max(workspace.data(pdf, with_aux=False)))

init_plot(fig, ax, default_par_settings)
interact(animate, fig=fixed(fig), ax=fixed(ax), **all_par_settings);

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

interactive(children=(FloatSlider(value=1.0, description='lumi', max=1.5, min=0.5),
↵FloatSlider(value=1.5, des...

```

```

[9]: nominal = pdf.config.suggested_init()
background_only = pdf.config.suggested_init()
background_only[pdf.config.poi_index] = 0.0
best_fit = pyhf.infer.mle.fit(data, pdf)

```



```
/srv/conda/envs/notebook/lib/python3.7/site-packages/pyhf/tensor/numpy_backend.py:334:
↳RuntimeWarning: invalid value encountered in log
    return n * np.log(lam) - lam - gammaln(n + 1.0)
```

### 6.8.6 Fitting

We can now fit the statistical model to the observed data. The best fit of the signal strength is close to the background-only hypothesis.

```
[10]: fig, (ax1, ax2, ax3) = plt.subplots(1, 3, sharey=True, sharex=True)
fig.set_size_inches(18, 4)
ax1.set_ylim(0, 1.5 * np.max(workspace.data(pdf, with_aux=False)))
ax1.set_title('nominal signal + background  $\mu = 1$ ')
plot(ax=ax1, **{k: nominal[v] for k, v in par_name_dict.items()})

ax2.set_title('nominal background-only  $\mu = 0$ ')
plot(ax=ax2, **{k: background_only[v] for k, v in par_name_dict.items()})

ax3.set_title(f'best fit  $\mu = \{best\_fit[pdf.config.poi\_index]:.3g\}$ ')
plot(ax=ax3, **{k: best_fit[v] for k, v in par_name_dict.items()});

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>
```

### 6.8.7 Interval Estimation (Computing Upper Limits on $\mu$ )

A common task in the statistical evaluation of High Energy Physics data analyses is the estimation of confidence intervals of parameters of interest. The general strategy is to perform a series of hypothesis tests and then *invert* the tests in order to obtain an interval with the correct coverage properties.

A common figure of merit is a modified p-value, CLs. Here we compute an upper limit based on a series of CLs tests.

```
[11]: mu_tests = np.linspace(0, 1, 16)
obs_limit, exp_limits, (poi_tests, tests) = pyhf.infer.intervals.upperlimit(
    data, pdf, mu_tests, level=0.05, return_results=True
)
```

```
[12]: fig, ax = plt.subplots()
fig.set_size_inches(7, 5)

ax.set_title("Hypothesis Tests")
artists = brazil.plot_results(mu_tests, tests, test_size=0.05, ax=ax)

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>
```

```
[13]: print(f"Observed upper limit: {obs_limit:.3f}\n")
for i, n_sigma in enumerate(np.arange(-2, 3)):
    print(
        "Expected Limit{}: {:.3f}".format(
```

(continues on next page)

(continued from previous page)

```
        """ if n_sigma == 0 else f"({n_sigma} )", exp_limits[i]
    )
)
```

Observed upper limit: 0.630

Expected Limit(-2 ): 0.297

Expected Limit(-1 ): 0.393

Expected Limit: 0.546

Expected Limit(1 ): 0.762

Expected Limit(2 ): 1.000

## OUTREACH

We are always interested in talking about `pyhf`. See the abstract and a list of previously given presentations and feel free to invite us to your next conference/workshop/meeting!

### 7.1 Abstract

The HistFactory p.d.f. template [CERN-OPEN-2012-016] is per-se independent of its implementation in ROOT and it is useful to be able to run statistical analysis outside of the ROOT, RooFit, RooStats framework. `pyhf` is a pure-python implementation of that statistical model for multi-bin histogram-based analysis and its interval estimation is based on the asymptotic formulas of “Asymptotic formulae for likelihood-based tests of new physics” [1007.1727]. `pyhf` supports modern computational graph libraries such as TensorFlow and PyTorch in order to make use of features such as auto-differentiation and GPU acceleration.

The HistFactory p.d.f. template [\href{https://cds.cern.ch/record/1456844}](https://cds.cern.ch/record/1456844)[CERN-OPEN-2012-016] is per-se independent of its implementation in ROOT and it is useful to be able to run statistical analysis outside of the ROOT, RooFit, RooStats framework. `pyhf` is a pure-python implementation of that statistical model for multi-bin histogram-based analysis and its interval estimation is based on the asymptotic formulas of "Asymptotic formulae for likelihood-based tests of new physics" [\href{https://arxiv.org/abs/1007.1727}](https://arxiv.org/abs/1007.1727)[arXiv:1007.1727]. `pyhf` supports modern computational graph libraries such as TensorFlow and PyTorch in order to make use of features such as autodifferentiation and GPU acceleration.

### 7.2 Presentations

This list will be updated with talks given on `pyhf`:

- Matthew Feickert. Likelihood preservation and statistical reproduction of searches for new physics. CHEP 2019, Nov 2019. URL: <https://indico.cern.ch/event/773049/contributions/3476143/>.
- Matthew Feickert. `pyhf`: pure-Python implementation of HistFactory. PyHEP 2019 Workshop, Oct 2019. URL: <https://indico.cern.ch/event/833895/contributions/3577824/>.

- Matthew Feickert. pyhf: a pure Python statistical fitting library with tensors and autograd. 19th Python in Science Conference (SciPy 2020), July 2020. URL: <http://conference.scipy.org/proceedings/scipy2020/slides.html>, doi:10.25080/Majora-342d178e-023.
- Matthew Feickert. pyhf: pure-Python implementation of HistFactory with tensors and automatic differentiation. Tools for High Energy Physics and Cosmology 2020 Workshop, Nov 2020. URL: <https://indico.cern.ch/event/955391/contributions/4075505/>, doi:10.5281/zenodo.4246056.
- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: a pure Python implementation of HistFactory with tensors and autograd. DIANA Meeting - pyhf, October 2018. URL: <https://indico.cern.ch/event/759480/>.
- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: pure-Python implementation of HistFactory models with autograd. 2018 US LHC Users Association Meeting, October 2018. URL: <https://indico.fnal.gov/event/17566/session/0/contribution/99>.
- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: pure-Python implementation of HistFactory models with autograd. (Internal) 3rd ATLAS Machine Learning Workshop, October 2018. URL: <https://indico.cern.ch/event/735932/contributions/3136879/>.
- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: pure-Python implementation of HistFactory models with autograd. (Internal) Joint Machine Learning & Statistics Fora Meeting, September 2018. URL: <https://indico.cern.ch/event/757657/contributions/3141134/>.
- Lukas Heinrich. Gaussian Process Shape Estimation and Systematics. (Internal) Joint Machine Learning & Statistics Fora Meeting, Dec 2018. URL: <https://indico.cern.ch/event/777561/contributions/3234669/>.
- Lukas Heinrich. HEP in the Cloud Computing and Open Science Era. EP-IT Data science seminar, Oct 2019. URL: <https://indico.cern.ch/event/840837/>.
- Lukas Heinrich. Likelihoods associated with statistical fits used in searches for new physics on HEPData and use of RECAST. (Internal) ATLAS Weekly Meeting, Nov 2019. URL: <https://indico.cern.ch/event/864395/contributions/3642165/>.
- Lukas Heinrich. Traditional inference with machine learning tools. 1st Pan-European Advanced School on Statistics in High Energy Physics, Oct 2019. URL: <https://indico.desy.de/indico/event/22731/session/4/contribution/19>.
- Lukas Heinrich. pyhf: Full Run-2 ATLAS likelihoods. (Internal) Joint Machine Learning & Statistics Fora Meeting, May 2019. URL: <https://indico.cern.ch/event/817483/contributions/3412907/>.
- Lukas Heinrich, Matthew Feickert, Giordon Stark, and Kyle Cranmer. pyhf: A standalone HistFactory Implementation. (Re)interpreting the results of new physics searches at the LHC Workshop, May 2018. URL: <https://indico.cern.ch/event/702612/contributions/2958658/>.
- Giordon Stark. Likelihood Preservation and Reproduction. West Coast LHC Jamboree 2019, Oct 2019. URL: <https://indico.cern.ch/event/848030/contributions/3616614/>.
- Giordon Stark. New techniques for use of public likelihoods for reinterpretation of search results. 27th International Conference on Supersymmetry and Unification of Fundamental Interactions (SUSY2019), May 2019. URL: <https://indico.cern.ch/event/746178/contributions/3396797/>.

## 7.3 Tutorials

This list will be updated with tutorials and schools given on pyhf:

- Matthew Feickert. pyhf: Accelerating analyses and preserving likelihoods. PyHEP 2020 Workshop (pyhf v0.4.4), Jul 2020. URL: <https://indico.cern.ch/event/882824/contributions/3931292/>.
- Lukas Heinrich. Introduction to pyhf. (Internal) ATLAS Induction Day + Software Tutorial (pyhf v0.1.2), Oct 2019. URL: <https://indico.cern.ch/event/831761/contributions/3484275/>.
- Lukas Heinrich. pyhf tutorial. (Internal) ATLAS Induction Day + Software Tutorial (pyhf v0.4.4), Jul 2020. URL: <https://indico.cern.ch/event/892952/contributions/3853306/>.
- Giordon Stark. ATLAS Exotics + SUSY Workshop 2020 pyhf Tutorial. ATLAS Exotics + SUSY Workshop 2020, September 2020. URL: <https://pyhf.github.io/tutorial-ATLAS-SUSY-Exotics-2020/introduction.html>.

## 7.4 Posters

This list will be updated with posters presented on pyhf:

- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: a pure Python statistical fitting library for High Energy Physics with tensors and autograd. July 2019. 18th Scientific Computing with Python Conference (SciPy 2019). URL: <http://conference.scipy.org/proceedings/scipy2019/slides.html>, doi:10.25080/Majora-7ddc1dd1-019.
- Matthew Feickert, Lukas Heinrich, Giordon Stark, and Kyle Cranmer. pyhf: pure Python implementation of HistFactory. November 2019. 24th International Conference on computing in High Energy & Nuclear Physics (CHEP 2019). URL: <https://indico.cern.ch/event/773049/contributions/3476180/>.
- Lukas Heinrich, Matthew Feickert, Giordon Stark, and Kyle Cranmer. pyhf: auto-differentiable binned statistical models. 19th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2019), March 2019. URL: <https://indico.cern.ch/event/708041/contributions/3272095/>.

## 7.5 In the Media

This list will be updated with media publications featuring pyhf:

- Katarina Anthony. New open release streamlines interactions with theoretical physicists. *ATLAS News*, December 2019. URL: <https://atlas.cern/updates/atlas-news/new-open-likelihoods>.
- Katarina Anthony. New open release allows theorists to explore LHC data in a new way. *CERN News*, January 2020. URL: <https://home.cern/news/news/knowledge-sharing/new-open-release-allows-theorists-explore-lhc-data-new-way>.
- Sabine Kraml. LHC reinterpreters think long-term. *CERN Courier Volume 61, Number 3, May/June 2021*, April 2021. <https://cds.cern.ch/record/2765233>. URL: <https://cerncourier.com/a/lhc-reinterpreters-think-long-term/>.
- Stephanie Melchor. ATLAS releases 'full orchestra' of analysis instruments. *Symmetry Magazine*, January 2021. URL: <https://www.symmetrymagazine.org/article/atlas-releases-full-orchestra-of-analysis-instruments>.



## INSTALLATION

To install, we suggest first setting up a [virtual environment](#)

```
# Python3  
python3 -m venv pyhf
```

and activating it

```
source pyhf/bin/activate
```

### 8.1 Install latest stable release from PyPI...

#### 8.1.1 ... with NumPy backend

```
python -m pip install pyhf
```

#### 8.1.2 ... with TensorFlow backend

```
python -m pip install pyhf[tensorflow]
```

#### 8.1.3 ... with PyTorch backend

```
python -m pip install pyhf[torch]
```

#### 8.1.4 ... with JAX backend

```
python -m pip install pyhf[jax]
```

### 8.1.5 ... with all backends

```
python -m pip install pyhf[backends]
```

### 8.1.6 ... with xml import/export functionality

```
python -m pip install pyhf[xmlio]
```

## 8.2 Install latest development version from GitHub...

### 8.2.1 ... with NumPy backend

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git#egg=pyhf"
```

### 8.2.2 ... with TensorFlow backend

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git  
↪#egg=pyhf[tensorflow]"
```

### 8.2.3 ... with PyTorch backend

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git  
↪#egg=pyhf[torch]"
```

### 8.2.4 ... with JAX backend

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git#egg=pyhf[jax]  
↪"
```

### 8.2.5 ... with all backends

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git  
↪#egg=pyhf[backends]"
```



### 8.2.6 ... with xml import/export functionality

```
python -m pip install --upgrade "git+https://github.com/scikit-hep/pyhf.git  
↪#egg=pyhf[xmlio]"
```

## 8.3 Updating pyhf

Rerun the installation command. As the upgrade flag (-U, --upgrade) is used then the libraries will be updated.



## DEVELOPING

To develop, we suggest using [virtual environments](#) together with `pip` or using `pipenv`. Once the environment is activated, clone the repo from GitHub

```
git clone https://github.com/scikit-hep/pyhf.git
```

and install all necessary packages for development

```
python -m pip install --upgrade --editable .[complete]
```

Then setup the Git pre-commit hook for [Black](#) by running

```
pre-commit install
```

as the `rev` gets updated through time to track changes of different hooks, simply run

```
pre-commit autoupdate
```

to have pre-commit install the new version.

## 9.1 Testing

### 9.1.1 Data Files

A function-scoped fixture called `datadir` exists for a given test module which will automatically copy files from the associated test modules data directory into a temporary directory for the given test execution. That is, for example, if a test was defined in `test_schema.py`, then data files located in `test_schema/` will be copied to a temporary directory whose path is made available by the `datadir` fixture. Therefore, one can do:

```
def test_patchset(datadir):  
    data_file = open(datadir.join("test.txt"))  
    ...
```

which will load the copy of `test.txt` in the temporary directory. This also works for parameterizations as this will effectively sandbox the file modifications made.

### 9.1.2 TestPyPI

pyhf tests packaging and distributing by publishing each commit to `master` to [TestPyPI](#). In addition, installation of the latest test release from TestPyPI can be tested by first installing pyhf normally, to ensure all dependencies are installed from PyPI, and then upgrading pyhf to a dev release from TestPyPI

```
python -m pip install pyhf
python -m pip install --upgrade --extra-index-url https://test.pypi.org/simple/ --pre_
↪pyhf
```

---

**Note:** This adds TestPyPI as an additional package index to search when installing. PyPI will still be the default package index pip will attempt to install from for all dependencies, but if a package has a release on TestPyPI that is a more recent release then the package will be installed from TestPyPI instead. Note that dev releases are considered pre-releases, so `0.1.2` is a “newer” release than `0.1.2.dev3`.

---

## 9.2 Publishing

Publishing to PyPI and TestPyPI is automated through the PyPA’s [PyPI publish GitHub Action](#) and the [pyhf Tag Creator GitHub Actions workflow](#). A release can be created from any PR created by a core developer by adding a `bumpversion` tag to it that corresponds to the release type: `major`, `minor`, `patch`. Once the PR is tagged with the label, the GitHub Actions bot will post a comment with information on the actions it will take once the PR is merged. When the PR has been reviewed, approved, and merged, the Tag Creator workflow will automatically create a new release with `bump2version` and then deploy the release to PyPI.

## 9.3 Context Files and Archive Metadata

The `.zenodo.json` and `codemeta.json` files have the version number automatically updated through `bump2version`, though their additional metadata should be checked periodically by the dev team (probably every release). The `codemeta.json` file can be generated automatically **from a PyPI install** of pyhf using `codemetapy`

```
codemetapy --no-extras pyhf > codemeta.json
```

though the author metadata will still need to be checked and revised by hand. The `.zenodo.json` is currently generated by hand, so it is worth using `codemeta.json` as a guide to edit it.

Frequently Asked Questions about pyhf and its use.

## 10.1 Questions

### 10.1.1 Where can I ask questions about pyhf use?

If you have a question about the use of pyhf not covered in the [documentation](#), please ask a question on the [GitHub Discussions](#).

If you believe you have found a bug in pyhf, please report it in the [GitHub Issues](#).

### 10.1.2 How can I get updates on pyhf?

If you're interested in getting updates from the pyhf dev team and release announcements you can join the [pyhf-announcements mailing list](#).

### 10.1.3 Is it possible to set the backend from the CLI?

Yes. Use the `--backend` option for `pyhf cls` to specify a tensor backend. The default backend is NumPy. For more information see `pyhf cls --help`.

### 10.1.4 Does pyhf support Python 2?

No. Like the rest of the Python community, as of January 2020 the latest releases of pyhf no longer support Python 2. The last release of pyhf that was compatible with Python 2.7 is [v0.3.4](#), which can be installed with

```
python -m pip install pyhf~=0.3
```

### 10.1.5 I only have access to Python 2. How can I use pyhf?

It is recommended that pyhf is used as a standalone step in any analysis, and its environment need not be the same as the rest of the analysis. As Python 2 is not supported it is suggested that you setup a Python 3 runtime on whatever machine you're using. If you're using a cluster, talk with your system administrators to get their help in doing so. If you are unable to get a Python 3 runtime, versioned Docker images of pyhf are distributed through [Docker Hub](#).

Once you have Python 3 installed, see the [Installation](#) page to get started.

### 10.1.6 I validated my workspace by comparing pyhf and HistFactory, and while the expected CLs matches, the observed CLs is different. Why is this?

Make sure you're using the right test statistic ( $q$  or  $\tilde{q}$ ) in both situations. In HistFactory, the asymptotics calculator, for example, will do something more involved for the observed CLs if you choose a different test statistic.

### 10.1.7 I ran validation to compare HistFitter and pyhf, but they don't match exactly. Why not?

pyhf is validated against HistFactory. HistFitter makes some particular implementation choices that pyhf doesn't reproduce. Instead of trying to compare pyhf and HistFitter you should try to validate them both against HistFactory.

### 10.1.8 How is pyhf typeset?

As you may have guessed from this page, pyhf is typeset in all lowercase. This is largely historical, as the core developers had just always typed it that way and it seemed a bit too short of a library name to write as PyHF. When typesetting in LaTeX the developers recommend introducing the command

```
\newcommand{\pyhf}{\texttt{pyhf}}
```

If the journal you are publishing in requires you to use `textsc` for software names it is okay to instead use

```
\newcommand{\pyhf}{\textsc{pyhf}}
```

## 10.2 Troubleshooting

- `import torch` or `import pyhf` causes a Segmentation fault (core dumped)

This is may be the result of a conflict with the NVIDIA drivers that you have installed on your machine. Try uninstalling and completely removing all of them from your machine

```
# On Ubuntu/Debian
sudo apt-get purge nvidia*
```

and then installing the latest versions.

## TRANSLATIONS

One key goal of `pyhf` is to provide seamless translations between other statistical frameworks and `pyhf`. This page details the various ways to translate from a tool you might already be using as part of an existing analysis to `pyhf`. Many of these solutions involve extracting out the `HistFactory` workspace and then running `pyhf xml2json` which provides a single JSON workspace that can be loaded directly into `pyhf`.

### 11.1 HistFitter

In order to go from `HistFitter` to `pyhf`, the first step is to extract out the `HistFactory` workspaces. Assuming you have an existing configuration file, `config.py`, you likely run an exclusion fit like so:

```
HistFitter.py -f -D "before,after,corrMatrix" -F excl config.py
```

The name of output workspace files depends on four parameters you define in your `config.py`:

- `analysisName` is from `configMgr.analysisName`
- `prefix` is defined in `configMgr.addFitConfig({prefix})`
- `measurementName` is the first measurement you define via `fitConfig.addMeasurement(name={measurementName},...)`
- `channelName` are the names of channels you define via `fitConfig.addChannel("cuts", [{channelName}], ...)`
- `cachePath` is where `HistFitter` stores the cached histograms, defined by `configMgr.histCacheFile` which defaults to `data/{analysisName}.root`

To dump the `HistFactory` workspace, you will modify the above to skip the fit `-f` and plotting `-D` so you end up with

```
HistFitter.py -wx -F excl config.py
```

The `-w` flag tells `HistFitter` to (re)create the `HistFactory` workspace stored in `results/{analysisName}/{prefix}_combined_{measurementName}.root`. The `-x` flag tells `HistFitter` to dump the XML files into `config/{analysisName}/`, with the top-level file being `{prefix}.xml` and all other files being `{prefix}_{channelName}_cuts.xml`.

Typically, `prefix = 'FitConfig'` and `measurementName = 'NormalMeasurement'`. For example, if the following exists in your `config.py`

```
from configManager import configMgr

# ...
configMgr.analysisName = "3b_tag21.2.27-1_RW_ExpSyst_36100_multibin_bkg"
```

(continues on next page)

(continued from previous page)

```

configMgr.histCacheFile = f"cache/{configMgr.analysisName:s}.root"
# ...
fitConfig = configMgr.addFitConfig("Excl")
# ...
channel = fitConfig.addChannel("cuts", ["SR_0L"], 1, 0.5, 1.5)
# ...
meas1 = fitConfig.addMeasurement(name="DefaultMeasurement", lumi=1.0, lumiErr=0.029)
meas1.addPOI("mu_SIG1")
# ...
meas2 = fitConfig.addMeasurement(name="DefaultMeasurement", lumi=1.0, lumiErr=0.029)
meas2.addPOI("mu_SIG2")

```

Then, you expect the following files to be made:

- config/3b\_tag21.2.27-1\_RW\_ExpSyst\_36100\_multibin\_bkg/Excl.xml
- config/3b\_tag21.2.27-1\_RW\_ExpSyst\_36100\_multibin\_bkg/Excl\_SR\_0L\_cuts.xml
- cache/3b\_tag21.2.27-1\_RW\_ExpSyst\_36100\_multibin\_bkg.root
- results/3b\_tag21.2.27-1\_RW\_ExpSyst\_36100\_multibin\_bkg/Excl\_combined\_DefaultMeasurement.root

These are all the files you need in order to use `pyhf xml2json`. At this point, you could run

```
pyhf xml2json config/3b_tag21.2.27-1_RW_ExpSyst_36100_multibin_bkg/Excl.xml
```

which will read all of the XML files and load the histogram data from the histogram cache.

The HistFactory workspace in `results/` contains all of the information necessary to rebuild the XML files again. For debugging purposes, the pyhf developers will often ask for your workspace file, which means `results/3b_tag21.2.27-1_RW_ExpSyst_36100_multibin_bkg/Excl_combined_DefaultMeasurement.root`. If you want to generate the XML, you can open this file in ROOT and run `DefaultMeasurement->PrintXML()` which puts all of the XML files into the current directory you are in.

## 11.2 TRexFitter

---

**Note:** For more details on this section, please refer to the ATLAS-internal [TRexFitter documentation](#).

---

In order to go from TRexFitter to pyhf, the good news is that the RooWorkspace files (XML and ROOT) are already made for you. For a given configuration which looks like

```

Job: "pyhf_example"
Label: "...

```

You can expect some files to be made after the `n/h` and `w` steps:

- pyhf\_example/RooStats/pyhf\_example.xml
- pyhf\_example/RooStats/pyhf\_example\_Signal\_region.xml
- pyhf\_example/Histograms/pyhf\_example\_Signal\_region\_histos.root

These are all the files you need in order to use `pyhf xml2json`. At this point, you could run



```
pyhf xml2json pyhf_example/RooStats/pyhf_example.xml
```

which will read all of the XML files and load the histogram data from the histogram cache.

**Warning:** There are a few caveats one needs to be aware of with this conversion:

- Uncorrelated shape systematics cannot be pruned, see Issue [#662](#).
- Custom expressions for normalization factors cannot be used, see Issue [#850](#).



## COMMAND LINE API

### 12.1 pyhf

Top-level CLI entrypoint.

```
pyhf [OPTIONS] COMMAND [ARGS]...
```

#### Options

**--version**

Show the version and exit.

**--cite, --citation**

Print the bibtex citation for this software

#### 12.1.1 cls

Compute CLs value(s) for a given pyhf workspace.

Example:

```
$ curl -sL https://git.io/JJYDE | pyhf cls
```

```
{
  "CLs_exp": [
    0.07807427911686156,
    0.17472571775474618,
    0.35998495263681285,
    0.6343568235898907,
    0.8809947004472013
  ],
  "CLs_obs": 0.3599845631401915
}
```

```
pyhf cls [OPTIONS] [WORKSPACE]
```

## Options

**--output-file** <output\_file>  
The location of the output json file. If not specified, prints to screen.

**--measurement** <measurement>

**-p, --patch** <patch>

**--test-poi** <test\_poi>

**--test-stat** <test\_stat>

**Options** q | qtilde

**--calctype** <calctype>

**Options** asymptotics | toybased

**--backend** <backend>  
The tensor backend used for the calculation.

**Options** numpy | pytorch | tensorflow | jax | np | torch | tf

**--optimizer** <optimizer>  
The optimizer used for the calculation.

**Options** scipy | minuit

**--optconf** <optconf>

## Arguments

**WORKSPACE**  
Optional argument

### 12.1.2 combine

Combine two workspaces into a single workspace.

See [\*pyhf.workspace.Workspace.combine\(\)\*](#) for more information.

```
pyhf combine [OPTIONS] [WORKSPACE_ONE] [WORKSPACE_TWO]
```

## Options

**-j, --join** <join>  
The join operation to apply when combining the two workspaces.

**Options** none | outer | left outer | right outer

**--output-file** <output\_file>  
The location of the output json file. If not specified, prints to screen.

**--merge-channels, --no-merge-channels**  
Whether or not to deeply merge channels. Can only be done with left/right outer joins.

## Arguments

**WORKSPACE\_ONE**

Optional argument

**WORKSPACE\_TWO**

Optional argument

### 12.1.3 completions

Generate shell completion code.

```
pyhf completions [OPTIONS] SHELL
```

## Arguments

**SHELL**

Required argument

### 12.1.4 contrib

Contrib experimental operations.

**Note:** Requires installation of the `contrib` extra.

```
$ python -m pip install pyhf[contrib]
```

```
pyhf contrib [OPTIONS] COMMAND [ARGS]...
```

## download

Download the patchset archive from the remote URL and extract it in a directory at the path given.

Example:

```
$ pyhf contrib download --verbose https://doi.org/10.17182/hepdata.90607.v3/r3 1Lbb-  
↳likeliheids
```

```
1Lbb-likeliheids/patchset.json  
1Lbb-likeliheids/README.md  
1Lbb-likeliheids/BkgOnly.json
```

**Raises:** `InvalidArchiveHost`: if the provided archive host name is not known to be valid

```
pyhf contrib download [OPTIONS] ARCHIVE_URL OUTPUT_DIRECTORY
```

## Options

- v, --verbose**  
Enables verbose mode
- f, --force**  
Force download from non-approved host
- c, --compress**  
Keep the archive in a compressed tar.gz form

## Arguments

- ARCHIVE\_URL**  
Required argument
- OUTPUT\_DIRECTORY**  
Required argument

### 12.1.5 digest

Use hashing algorithm to calculate the workspace digest.

**Returns:** digests (`dict`): A mapping of the hashing algorithms used to the computed digest for the workspace.

Example:

```
$ curl -sL https://raw.githubusercontent.com/scikit-hep/pyhf/master/docs/examples/json/2-  
bin_1-channel.json | pyhf digest  
sha256:dad8822af55205d60152cbe4303929042dbd9d4839012e055e7c6b6459d68d73
```

```
pyhf digest [OPTIONS] [WORKSPACE]
```

## Options

- a, --algorithm <algorithm>**  
The hashing algorithm used to compute the workspace digest.
- j, --json, -p, --plaintext**  
Output the hash values as a JSON dictionary or plaintext strings

## Arguments

- WORKSPACE**  
Optional argument

### 12.1.6 fit

Perform a maximum likelihood fit for a given pyhf workspace.

Example:

```
$ curl -sL https://git.io/JJYDE | pyhf fit --value
```

```
{
  "mle_parameters": {
    "mu": [
      0.00017298628839781602
    ],
    "uncorr_bkguncrt": [
      1.0000015671710816,
      0.9999665895859197
    ]
  },
  "twice_nll": 23.19636590468879
}
```

```
pyhf fit [OPTIONS] [WORKSPACE]
```

#### Options

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

**--measurement** <measurement>

**-p, --patch** <patch>

**--value**

Flag for returning the fitted value of the objective function.

**--backend** <backend>

The tensor backend used for the calculation.

**Options** numpy | pytorch | tensorflow | jax | np | torch | tf

**--optimizer** <optimizer>

The optimizer used for the calculation.

**Options** scipy | minuit

**--optconf** <optconf>

## Arguments

### WORKSPACE

Optional argument

## 12.1.7 inspect

Inspect a pyhf JSON document.

Example:

```
$ curl -sL https://raw.githubusercontent.com/scikit-hep/pyhf/master/docs/examples/json/2-  
bin_1-channel.json | pyhf inspect
```

Summary		
-----		
channels	1	
samples	2	
parameters	2	
modifiers	2	
channels	nbins	
-----		
singlechannel	2	
-----		
samples		
-----		
background		
signal		
-----		
parameters	constraint	modifiers
-----		
mu	unconstrained	normfactor
uncorr_bkguncrt	constrained_by_poisson	shapesys
-----		
measurement	poi	parameters
-----		
(*) Measurement	mu	(none)

```
pyhf inspect [OPTIONS] [WORKSPACE]
```

## Options

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

**--measurement** <measurement>



## Arguments

### WORKSPACE

Optional argument

## 12.1.8 json2xml

Convert pyhf JSON back to XML + ROOT files.

```
pyhf json2xml [OPTIONS] [WORKSPACE]
```

## Options

**--output-dir** <output\_dir>

**--specroot** <specroot>

**--dataroot** <dataroot>

**--resultprefix** <resultprefix>

**-p, --patch** <patch>

## Arguments

### WORKSPACE

Optional argument

## 12.1.9 patchset

Operations involving patchsets.

```
pyhf patchset [OPTIONS] COMMAND [ARGS]...
```

## apply

Apply a patch from patchset to the background-only workspace specification.

**Raises:** *InvalidPatchLookup*: if the provided patch name is not in the patchset *PatchSetVerificationError*: if the patchset cannot be verified against the workspace specification

**Returns:** workspace (*Workspace*): The patched background-only workspace.

```
pyhf patchset apply [OPTIONS] [BACKGROUND_ONLY] [PATCHSET]
```

## Options

- name** <name>  
The name of the patch to extract.
- output-file** <output\_file>  
The location of the output json file. If not specified, prints to screen.

## Arguments

- BACKGROUND\_ONLY**  
Optional argument
- PATCHSET**  
Optional argument

## extract

Extract a patch from a patchset.

**Raises:** *InvalidPatchLookup*: if the provided patch name is not in the patchset

**Returns:** jsonpatch (*list*): A list of jsonpatch operations to apply to a workspace.

```
pyhf patchset extract [OPTIONS] [PATCHSET]
```

## Options

- name** <name>  
The name of the patch to extract.
- output-file** <output\_file>  
The location of the output json file. If not specified, prints to screen.
- with-metadata, --without-metadata**  
Include patchset metadata in output.

## Arguments

- PATCHSET**  
Optional argument

## inspect

Inspect the PatchSet (e.g. list individual patches).

**Returns:** None

```
pyhf patchset inspect [OPTIONS] [PATCHSET]
```

## Arguments

### PATCHSET

Optional argument

## verify

Verify the patchset digests against a background-only workspace specification. Verified if no exception was raised.

**Raises:** *PatchSetVerificationError*: if the patchset cannot be verified against the workspace specification

**Returns:** None

```
pyhf patchset verify [OPTIONS] [BACKGROUND_ONLY] [PATCHSET]
```

## Arguments

### BACKGROUND\_ONLY

Optional argument

### PATCHSET

Optional argument

## 12.1.10 prune

Prune components from the workspace.

See *pyhf.workspace.Workspace.prune()* for more information.

```
pyhf prune [OPTIONS] [WORKSPACE]
```

## Options

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

**-c, --channel** <CHANNEL>...>

**-s, --sample** <SAMPLE>...>

**-m, --modifier** <MODIFIER>...>

**-t, --modifier-type** <modifier\_type>

**Options** histosys | lumi | normfactor | normsys | shapefactor | shapesys | staterror

**--measurement** <MEASUREMENT>...>

## Arguments

### WORKSPACE

Optional argument

### 12.1.11 rename

Rename components of the workspace.

See [`pyhf.workspace.Workspace.rename\(\)`](#) for more information.

```
pyhf rename [OPTIONS] [WORKSPACE]
```

## Options

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

**-c**, **--channel** <PATTERN> <REPLACE>...>

**-s**, **--sample** <PATTERN> <REPLACE>...>

**-m**, **--modifier** <PATTERN> <REPLACE>...>

**--measurement** <PATTERN> <REPLACE>...>

## Arguments

### WORKSPACE

Optional argument

### 12.1.12 sort

Sort the workspace.

See [`pyhf.workspace.Workspace.sorted\(\)`](#) for more information.

Example:

```
$ curl -sL https://raw.githubusercontent.com/scikit-hep/pyhf/master/docs/examples/json/2-  
↪bin_1-channel.json | pyhf sort | jq '.' | md5  
8be5186ec249d2704e14dd29ef05ffb0
```

```
$ curl -sL https://raw.githubusercontent.com/scikit-hep/pyhf/master/docs/examples/json/2-  
↪bin_1-channel.json | jq -S '.channels|=sort_by(.name)|.channels[].samples|=sort_by(  
↪name)|.channels[].samples[].modifiers|=sort_by(.name,.type)|.observations|=sort_by(  
↪name)' | md5  
8be5186ec249d2704e14dd29ef05ffb0
```

```
pyhf sort [OPTIONS] [WORKSPACE]
```

## Options

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

## Arguments

**WORKSPACE**

Optional argument

### 12.1.13 xml2json

Entrypoint XML: The top-level XML file for the PDF definition.

<code>pyhf xml2json [OPTIONS] ENTRYPOINT_XML</code>
---

## Options

**--basedir** <basedir>

The base directory for the XML files to point relative to.

**--output-file** <output\_file>

The location of the output json file. If not specified, prints to screen.

**--track-progress, --hide-progress**

## Arguments

**ENTRYPOINT\_XML**

Required argument



## 13.1 Top-Level

<i>default_backend</i>	NumPy backend for pyhf
<i>default_optimizer</i>	Optimizer that uses <code>scipy.optimize.minimize()</code> .
<i>tensorlib</i>	NumPy backend for pyhf
<i>optimizer</i>	Optimizer that uses <code>scipy.optimize.minimize()</code> .
<i>get_backend</i>	Get the current backend and the associated optimizer
<i>set_backend</i>	Set the backend and the associated optimizer
<i>readxml</i>	
<i>writexml</i>	
<i>compat</i>	Compatibility functions for translating between ROOT and pyhf

### 13.1.1 `pyhf.default_backend`

`pyhf.default_backend = <pyhf.tensor.numpy_backend.numpy_backend object>`  
NumPy backend for pyhf

### 13.1.2 `pyhf.default_optimizer`

`pyhf.default_optimizer = <pyhf.optimize.scipy_optimizer object>`  
Optimizer that uses `scipy.optimize.minimize()`.

### 13.1.3 `pyhf.tensorlib`

`pyhf.tensorlib = <pyhf.tensor.numpy_backend.numpy_backend object>`  
NumPy backend for pyhf

### 13.1.4 pyhf.optimizer

`pyhf.optimizer = <pyhf.optimize.scipy_optimizer object>`  
Optimizer that uses `scipy.optimize.minimize()`.

### 13.1.5 pyhf.get\_backend

`pyhf.get_backend()`  
Get the current backend and the associated optimizer

#### Example

```
>>> import pyhf
>>> backend, optimizer = pyhf.get_backend()
>>> backend
<pyhf.tensor.numpy_backend.numpy_backend object at 0x...>
>>> optimizer
<pyhf.optimize.scipy_optimizer object at 0x...>
```

**Returns** backend, optimizer

### 13.1.6 pyhf.set\_backend

`pyhf.set_backend(backend, custom_optimizer=None, precision=None)`  
Set the backend and the associated optimizer

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> pyhf.tensorlib.name
'tensorflow'
>>> pyhf.tensorlib.precision
'64b'
>>> pyhf.set_backend(b"pytorch", precision="32b")
>>> pyhf.tensorlib.name
'pytorch'
>>> pyhf.tensorlib.precision
'32b'
>>> pyhf.set_backend(pyhf.tensor.numpy_backend())
>>> pyhf.tensorlib.name
'numpy'
>>> pyhf.tensorlib.precision
'64b'
```

#### Parameters

- **backend** (`str` or `pyhf.tensor` backend) – One of the supported pyhf backends: NumPy, TensorFlow, PyTorch, and JAX



- **custom\_optimizer** (*pyhf.optimize* optimizer) – Optional custom optimizer defined by the user
- **precision** (*str*) – Floating point precision to use in the backend: 64b or 32b. Default is backend dependent.

**Returns** None

### 13.1.7 pyhf.readxml

#### Description

#### Functions

<code>clear_filecache()</code>	
<code>dedupe_parameters(parameters)</code>	
<code>extract_error(hist)</code>	Determine the bin uncertainties for a histogram.
<code>import_root_histogram(rootdir, filename, ...)</code>	
<code>parse(configfile, rootdir[, track_progress])</code>	
<code>process_channel(channelxml, rootdir[, ...])</code>	
<code>process_data(sample, rootdir, inputfile, ...)</code>	
<code>process_measurements(toplvl[, ...])</code>	For a given XML structure, provide a parsed dictionary adhering to defs.json/#definitions/measurement.
<code>process_sample(sample, rootdir, inputfile, ...)</code>	

#### pyhf.readxml.clear\_filecache

`pyhf.readxml.clear_filecache()`

#### pyhf.readxml.dedupe\_parameters

`pyhf.readxml.dedupe_parameters(parameters)`

#### pyhf.readxml.extract\_error

`pyhf.readxml.extract_error(hist)`

Determine the bin uncertainties for a histogram.

If *fSumw2* is not filled, then the histogram must have been filled with no weights and *.Sumw2()* was never called. The bin uncertainties are then Poisson, and so the *sqrt(entries)*.

**Parameters** *hist* (`uproot.behaviors.TH1.TH1`) – The histogram

**Returns** The uncertainty for each bin in the histogram

**Return type** `list`

#### **pyhf.readxml.import\_root\_histogram**

`pyhf.readxml.import_root_histogram(rootdir, filename, path, name, filecache=None)`

#### **pyhf.readxml.parse**

`pyhf.readxml.parse(configfile, rootdir, track_progress=False)`

#### **pyhf.readxml.process\_channel**

`pyhf.readxml.process_channel(channelxml, rootdir, track_progress=False)`

#### **pyhf.readxml.process\_data**

`pyhf.readxml.process_data(sample, rootdir, inputfile, histopath)`

#### **pyhf.readxml.process\_measurements**

`pyhf.readxml.process_measurements(toplvl, other_parameter_configs=None)`

For a given XML structure, provide a parsed dictionary adhering to `defs.json/#definitions/measurement`.

##### **Parameters**

- **toplvl** (`xml.etree.ElementTree`) – The top-level XML document to parse.
- **other\_parameter\_configs** (`list`) – A list of other parameter configurations from other non-top-level XML documents to incorporate into the resulting measurement object.

**Returns** A measurement object.

**Return type** `dict`

#### **pyhf.readxml.process\_sample**

`pyhf.readxml.process_sample(sample, rootdir, inputfile, histopath, channelname, track_progress=False)`

### **13.1.8 pyhf.writexml**

#### **Description**

#### **Functions**

---

`build_channel(spec, channelspec, obsspec)`

---

`build_data(obsspec, channelname)`

---

continues on next page

Table 3 – continued from previous page

<code>build_measurement</code> ( <i>measurementspec</i> , <i>modifier-</i> types)	Build the XML measurement specifica- tion for a given measurement adhering to defs.json/#definitions/measurement.
<code>build_modifier</code> ( <i>spec</i> , <i>modifierspec</i> , ...)	
<code>build_sample</code> ( <i>spec</i> , <i>samplespec</i> , <i>channelname</i> )	
<code>indent</code> ( <i>elem</i> [, <i>level</i> ])	

**pyhf.writexml.build\_channel**

`pyhf.writexml.build_channel`(*spec*, *channelspec*, *obsspec*)

**pyhf.writexml.build\_data**

`pyhf.writexml.build_data`(*obsspec*, *channelname*)

**pyhf.writexml.build\_measurement**

`pyhf.writexml.build_measurement`(*measurementspec*, *modifiertypes*)

Build the XML measurement specification for a given measurement adhering to  
defs.json/#definitions/measurement.

**Parameters**

- **measurementspec** (*dict*) – The measurements specification from a [Workspace](#).
- **modifiertypes** (*dict*) – A mapping from modifier name (*str*) to modifier type (*str*).

**Returns** The XML measurement specification.

**Return type** `xml.etree.cElementTree.Element`

**pyhf.writexml.build\_modifier**

`pyhf.writexml.build_modifier`(*spec*, *modifierspec*, *channelname*, *samplename*, *sampledata*)

**pyhf.writexml.build\_sample**

`pyhf.writexml.build_sample`(*spec*, *samplespec*, *channelname*)

## pyhf.writexml.indent

pyhf.writexml.indent(*elem*, *level=0*)

## 13.1.9 pyhf.compat

### Description

Compatibility functions for translating between ROOT and pyhf

### Functions

<code>interpret_rootname</code> (rootname)	Interprets a ROOT-generated name as best as possible.
<code>paramset_to_rootnames</code> (paramset)	Generates parameter names for parameters in the set as ROOT would do.

### pyhf.compat.interpret\_rootname

pyhf.compat.interpret\_rootname(*rootname*)

Interprets a ROOT-generated name as best as possible.

Possible properties of a ROOT parameter are:

- "constrained": `bool` representing if parameter is a member of a constrained paramset.
- "is\_scalar": `bool` representing if parameter is a member of a scalar paramset.
- "name": The name of the param set.
- "element": The index in a non-scalar param set.

It is possible that some of the parameter names might not be determinable and will then hold the string value "n/a".

**Parameters** `rootname` (`str`) – The ROOT-generated name of the parameter.

**Returns** The interpreted key-value pairs.

**Return type** `dict`

### Example

```
>>> import pyhf
>>> interpreted_name = pyhf.compat.interpret_rootname("gamma_foo_0")
>>> pyhf.compat.interpret_rootname("gamma_foo_0")
{'constrained': 'n/a', 'is_scalar': False, 'name': 'foo', 'element': 0}
>>> pyhf.compat.interpret_rootname("alpha_foo")
{'constrained': True, 'is_scalar': True, 'name': 'foo', 'element': 'n/a'}
>>> pyhf.compat.interpret_rootname("Lumi")
{'constrained': False, 'is_scalar': True, 'name': 'lumi', 'element': 'n/a'}
```

## pyhf.compat.paramset\_to\_rootnames

`pyhf.compat.paramset_to_rootnames(paramset)`

Generates parameter names for parameters in the set as ROOT would do.

**Parameters** `paramset` (`pyhf.paramsets.paramset`) – The parameter set.

**Returns** The generated parameter names (for the non-scalar/scalar case) respectively.

**Return type** `List[str]` or `str`

### Example

pyhf parameter names and then the converted names for ROOT:

- "lumi" -> "Lumi"
- unconstrained scalar parameter "foo" -> "foo"
- constrained scalar parameter "foo" -> "alpha\_foo"
- non-scalar parameters "foo" -> "gamma\_foo\_i"

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.parameters
['mu', 'uncorr_bkguncrt']
>>> pyhf.compat.paramset_to_rootnames(model.config.param_set("mu"))
'mu'
>>> pyhf.compat.paramset_to_rootnames(model.config.param_set("uncorr_bkguncrt"))
['gamma_uncorr_bkguncrt_0', 'gamma_uncorr_bkguncrt_1']
```

## 13.2 Probability Distribution Functions (PDFs)

<i>Normal</i>	The Normal distribution with mean <code>loc</code> and standard deviation <code>scale</code> .
<i>Poisson</i>	The Poisson distribution with rate parameter <code>rate</code> .
<i>Independent</i>	A probability density corresponding to the joint distribution of a batch of identically distributed random variables.
<i>Simultaneous</i>	A probability density corresponding to the joint distribution of multiple non-identical component distributions

### 13.2.1 Normal

**class** pyhf.probability.**Normal**(*loc, scale*)

Bases: pyhf.probability.\_SimpleDistributionMixin

The Normal distribution with mean *loc* and standard deviation *scale*.

#### Example

```
>>> import pyhf
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> pyhf.probability.Normal(means, stds)
<pyhf.probability.Normal object at 0x...>
```

**\_\_init\_\_**(*loc, scale*)

#### Parameters

- **loc** (tensor or `float`) – The mean of the Normal distribution
- **scale** (tensor or `float`) – The standard deviation of the Normal distribution

#### Methods

**expected\_data**()

The expectation value of the Normal distribution.

#### Example

```
>>> import pyhf
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> normals = pyhf.probability.Normal(means, stds)
>>> normals.expected_data()
array([5., 8.])
```

**Returns** The mean of the Normal distribution (which is the *loc*)

**Return type** Tensor

### 13.2.2 Poisson

**class** pyhf.probability.**Poisson**(*rate*)

Bases: pyhf.probability.\_SimpleDistributionMixin

The Poisson distribution with rate parameter *rate*.

### Example

```
>>> import pyhf
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> pyhf.probability.Poisson(rates)
<pyhf.probability.Poisson object at 0x...>
```

**\_\_init\_\_**(*rate*)

**Parameters** **rate** (tensor or `float`) – The mean of the Poisson distribution (the expected number of events)

### Methods

**expected\_data**()

The expectation value of the Poisson distribution.

### Example

```
>>> import pyhf
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> poissons = pyhf.probability.Poisson(rates)
>>> poissons.expected_data()
array([5., 8.])
```

**Returns** The mean of the Poisson distribution (which is the rate)

**Return type** Tensor

## 13.2.3 Independent

**class** `pyhf.probability.Independent`(*batched\_pdf*, *batch\_size=None*)

Bases: `pyhf.probability._SimpleDistributionMixin`

A probability density corresponding to the joint distribution of a batch of identically distributed random variables.

### Example

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> rates = pyhf.tensorlib.astensor([10.0, 10.0])
>>> poissons = pyhf.probability.Poisson(rates)
>>> independent = pyhf.probability.Independent(poissons)
>>> independent.sample()
array([10, 11])
```

**\_\_init\_\_**(*batched\_pdf*, *batch\_size=None*)

### Parameters

- **batched\_pdf** (pyhf.probability distribution) – The batch of pdfs of the same type (e.g. Poisson)
- **batch\_size** (int) – The size of the batch

### Methods

#### **log\_prob**(value)

The log of the probability density function at the given value. As the distribution is a joint distribution of the same type, this is the sum of the log probabilities of each of the distributions the compose the joint.

#### Example

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> rates = pyhf.tensorlib.astensor([10.0, 10.0])
>>> poissons = pyhf.probability.Poisson(rates)
>>> independent = pyhf.probability.Independent(poissons)
>>> values = pyhf.tensorlib.astensor([8.0, 9.0])
>>> independent.log_prob(values)
-4.262483801927939
>>> broadcast_value = pyhf.tensorlib.astensor([11.0])
>>> independent.log_prob(broadcast_value)
-4.347743645878765
```

**Parameters** **value** (tensor or float) – The value at which to evaluate the distribution

**Returns** The value of  $\log(f(x|\theta))$  for  $x = \text{value}$

**Return type** Tensor

## 13.2.4 Simultaneous

**class** pyhf.probability.**Simultaneous**(pdfobjs, tensorview, batch\_size=None)

Bases: object

A probability density corresponding to the joint distribution of multiple non-identical component distributions

#### Example

```
>>> import pyhf
>>> import numpy.random as random
>>> from pyhf.tensor.common import _TensorViewer
>>> random.seed(0)
>>> poissons = pyhf.probability.Poisson(pyhf.tensorlib.astensor([1., 100.]))
>>> normals = pyhf.probability.Normal(pyhf.tensorlib.astensor([1., 100.]), pyhf.
↪ tensorlib.astensor([1., 2.]))
>>> tv = _TensorViewer([[0, 2], [1, 3]])
```

(continues on next page)



(continued from previous page)

```
>>> sim = pyhf.probability.Simultaneous([poissons, normals], tv)
>>> sim.sample((4,))
array([[ 2.          ,  1.3130677 , 101.          ,  98.29180852],
       [ 1.          , -1.55298982,  97.          , 101.30723719],
       [ 1.          ,  1.8644362 , 118.          ,  98.51566996],
       [ 0.          ,  3.26975462,  99.          ,  97.09126865]])
```

**\_\_init\_\_**(pdfobjs, tensorview, batch\_size=None)

Construct a simultaneous pdf.

#### Parameters

- **pdfobjs** (Distribution) – The constituent pdf objects
- **tensorview** (\_TensorViewer) – The \_TensorViewer defining the data composition
- **batch\_size** (int) – The size of the batch

#### Methods

**static \_joint\_logpdf**(terms, batch\_size=None)

**expected\_data**()

The expectation value of the probability density function.

**Returns** The expectation value of the distribution  $E[f(\theta)]$

**Return type** Tensor

**log\_prob**(value)

The log of the probability density function at the given value.

**Parameters** **value** (tensor) – The observed value

**Returns** The value of  $\log(f(x|\theta))$  for  $x = \text{value}$

**Return type** Tensor

**sample**(sample\_shape=())

The collection of values sampled from the probability density function.

**Parameters** **sample\_shape** (tuple) – The shape of the sample to be returned

**Returns** The values  $x \sim f(\theta)$  where  $x$  has shape **sample\_shape**

**Return type** Tensor

## 13.3 Making Models from PDFs

<i>Model</i>	The main pyhf model class.
<i>_ModelConfig</i>	Configuration for the <i>Model</i> .
<i>Workspace</i>	A JSON-serializable object that is built from an object that follows the <code>workspace.json</code> schema.
<i>PatchSet</i>	A way to store a collection of patches ( <i>Patch</i> ).
<i>Patch</i>	A way to store a patch definition as part of a patchset ( <i>PatchSet</i> ).

continues on next page

Table 6 – continued from previous page

<code>simplemodels.uncorrelated_background</code>	Construct a simple single channel <i>Model</i> with a <i>shapesys</i> modifier representing an uncorrelated background uncertainty.
<code>simplemodels.correlated_background</code>	Construct a simple single channel <i>Model</i> with a <i>histosys</i> modifier representing a background with a fully correlated bin-by-bin uncertainty.
<code>simplemodels.hepdata_like</code>	
<hr/>	
<b>Note:</b> Deprecating <code>API:</code> Use <code>uncorrelated_background()</code>	
<hr/>	

### 13.3.1 Model

**class** `pyhf.pdf.Model(spec, batch_size=None, **config_kwargs)`

Bases: `object`

The main pyhf model class.

**\_\_init\_\_**(*spec*, *batch\_size*=None, *\*\*config\_kwargs*)

Construct a HistFactory Model.

#### Parameters

- **spec** (`jsonable`) – The HistFactory JSON specification
- **batch\_size** (`None` or `int`) – Number of simultaneous (batched) Models to compute.
- **config\_kwargs** – Possible keyword arguments for the model configuration

**Returns** The Model instance.

**Return type** model (*Model*)

#### Attributes

**nominal\_rates**

Nominal value of bin rates of the main model.

#### Methods

**\_modifications**(*pars*)

**constraint\_logpdf**(*auxdata*, *pars*)

Compute the log value of the constraint pdf.

#### Parameters

- **auxdata** (`tensor`) – The auxiliary measurement data
- **pars** (`tensor`) – The parameter values

**Returns** The log density value

**Return type** Tensor

**expected\_actualdata(*pars*)**

Compute the expected value of the main model.

**Parameters** **pars** (tensor) – The parameter values

**Returns** The expected data of the main model (no auxiliary data)

**Return type** Tensor

**expected\_auxdata(*pars*)**

Compute the expected value of the auxiliary measurements.

**Parameters** **pars** (tensor) – The parameter values

**Returns** The expected data of the auxiliary pdf

**Return type** Tensor

**expected\_data(*pars*, *include\_auxdata=True*)**

Compute the expected value of the main model

**Parameters** **pars** (tensor) – The parameter values

**Returns** The expected data of the main and auxiliary model

**Return type** Tensor

**logpdf(*pars*, *data*)**

Compute the log value of the full density.

**Parameters**

- **pars** (tensor) – The parameter values
- **data** (tensor) – The measurement data

**Returns** The log density value

**Return type** Tensor

**mainlogpdf(*maindata*, *pars*)**

Compute the log value of the main term.

**Parameters**

- **maindata** (tensor) – The main measurement data
- **pars** (tensor) – The parameter values

**Returns** The log density value

**Return type** Tensor

**make\_pdf(*pars*)**

Construct a pdf object for a given set of parameter values.

**Parameters** **pars** (tensor) – The model parameters

**Returns** A distribution object implementing the main measurement pdf of HistFactory

**Return type** pdf

**pdf(*pars*, *data*)**

Compute the density at a given observed point in data space of the full model.

**Parameters**

- **pars** (tensor) – The parameter values

- **data** (tensor) – The measurement data

**Returns** The density value

**Return type** Tensor

### 13.3.2 `_ModelConfig`

**class** `pyhf.pdf._ModelConfig(spec, **config_kwargs)`

Bases: `pyhf.mixins._ChannelSummaryMixin`

Configuration for the *Model*.

---

**Note:** `_ModelConfig` should not be called directly. It should instead be accessed through the `config` attribute of *Model*.

---

`__init__`(spec, \*\*config\_kwargs)

**Parameters** `spec` (jsonable) – The HistFactory JSON specification.

#### Methods

`_create_and_register_paramsets(required_paramsets)`

`par_slice(name)`

The slice of the model parameter tensor corresponding to the model parameter name.

**Returns** Slice of the model parameter tensor.

**Return type** `slice`

#### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.par_slice("uncorr_bkguncrt")
slice(1, 3, None)
```

`param_set(name)`

The paramset for the model parameter name.

**Returns** Corresponding paramset.

**Return type** paramsets

### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> param_set = model.config.param_set("uncorr_bkguncrt")
>>> param_set.pdf_type
'poisson'
```

### `set_poi(name)`

Set the model parameter of interest to be model parameter name.

### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.set_poi("mu")
>>> model.config.poi_name
'mu'
```

### `suggested_bounds()`

Return suggested parameter bounds for the model.

**Returns** Suggested bounds on model parameters.

**Return type** `list`

### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.suggested_bounds()
[(0, 10), (1e-10, 10.0), (1e-10, 10.0)]
```

### `suggested_fixed()`

Identify the fixed parameters in the model.

**Returns** A list of booleans, True for fixed and False for not fixed.

**Return type** `list`

### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.suggested_fixed()
[False, False, False]
```

Something like the following to build `fixed_vals` appropriately:

```
fixed_pars = model.config.suggested_fixed()
inits = model.config.suggested_init()
fixed_vals = [
    (index, init)
    for index, (init, is_fixed) in enumerate(zip(inits, fixed_pars))
    if is_fixed
]
```

### `suggested_init()`

Return suggested initial parameter values for the model.

**Returns** Suggested initial model parameters.

**Return type** `list`

### Example

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.config.suggested_init()
[1.0, 1.0, 1.0]
```

## 13.3.3 Workspace

**class** `pyhf.workspace.Workspace`(*spec*, *\*\*config\_kwargs*)

Bases: `pyhf.mixins._ChannelSummaryMixin`, `dict`

A JSON-serializable object that is built from an object that follows the `workspace.json` [schema](#).

**\_\_init\_\_**(*spec*, *\*\*config\_kwargs*)

Workspaces hold the model, data and measurements.

## Attributes

`valid_joins = ['none', 'outer', 'left outer', 'right outer']`

## Methods

`_prune_and_rename`(*prune\_modifiers=None, prune\_modifier\_types=None, prune\_samples=None, prune\_channels=None, prune\_measurements=None, rename\_modifiers=None, rename\_samples=None, rename\_channels=None, rename\_measurements=None*)

Return a new, pruned, renamed workspace specification. This will not modify the original workspace.

Pruning removes pieces of the workspace whose name or type matches the user-provided lists. The pruned, renamed workspace must also be a valid workspace.

A workspace is composed of many named components, such as channels and samples, as well as types of systematics (e.g. *histosys*). Components can be removed (pruned away) filtering on name or be renamed according to the provided `dict` mapping. Additionally, modifiers of specific types can be removed (pruned away).

This function also handles specific peculiarities, such as renaming/removing a channel which needs to rename/remove the corresponding *observation*.

### Parameters

- **prune\_modifiers** – A `str` or a `list` of modifiers to prune.
- **prune\_modifier\_types** – A `str` or a `list` of modifier types to prune.
- **prune\_samples** – A `str` or a `list` of samples to prune.
- **prune\_channels** – A `str` or a `list` of channels to prune.
- **prune\_measurements** – A `str` or a `list` of measurements to prune.
- **rename\_modifiers** – A `dict` mapping old modifier name to new modifier name.
- **rename\_samples** – A `dict` mapping old sample name to new sample name.
- **rename\_channels** – A `dict` mapping old channel name to new channel name.
- **rename\_measurements** – A `dict` mapping old measurement name to new measurement name.

**Returns** A new workspace object with the specified components removed or renamed

**Return type** *Workspace*

**Raises** *InvalidWorkspaceOperation* – An item name to prune or rename does not exist in the workspace.

**classmethod** `build(model, data, name='measurement')`

Build a workspace from model and data.

### Parameters

- **model** (*Model*) – A model to store into a workspace
- **data** (*tensor*) – A array holding observations to store into a workspace
- **name** (*str*) – The name of the workspace measurement

**Returns** A new workspace object

**Return type** *Workspace*

**classmethod** `combine(left, right, join='none', merge_channels=False)`

Return a new workspace specification that is the combination of the two workspaces.

The new workspace must also be a valid workspace. A combination of workspaces is done by combining the set of:

- channels,
- observations, and
- measurements

between the two workspaces. If the two workspaces have modifiers that follow the same naming convention, then correlations across the two workspaces may be possible. In particular, the *lumi* modifier will be fully-correlated.

If the two workspaces have the same measurement (with the same POI), those measurements will get merged.

**Raises** `InvalidWorkspaceOperation` – The workspaces have common channel names, incompatible measurements, or incompatible schema versions.

**Parameters**

- **left** (`Workspace`) – A workspace
- **right** (`Workspace`) – Another workspace
- **join** (`str`) – How to join the two workspaces. Pick from “none”, “outer”, “left outer”, or “right outer”.
- **merge\_channels** (`bool`) – Whether or not to merge channels when performing the combine. This is only done with “outer”, “left outer”, and “right outer” options.

**Returns** A new combined workspace object

**Return type** `Workspace`

**data**(*model*, *with\_aux=True*)

Return the data for the supplied model with or without auxiliary data from the model.

The model is needed as the order of the data depends on the order of the channels in the model.

**Raises** `KeyError` – Invalid or missing channel

**Parameters**

- **model** (`Model`) – A model object adhering to the schema model.json
- **with\_aux** (`bool`) – Whether to include auxiliary data from the model or not

**Returns** data

**Return type** `list`

**get\_measurement**(*poi\_name=None*, *measurement\_name=None*, *measurement\_index=None*)

Get (or create) a measurement object.

The following logic is used:

1. if the poi name is given, create a measurement object for that poi
2. if the measurement name is given, find the measurement for the given name
3. if the measurement index is given, return the measurement at that index
4. if there are measurements but none of the above have been specified, return the 0th measurement



Raises *InvalidMeasurement* – If the measurement was not found

#### Parameters

- **poi\_name** (*str*) – The name of the parameter of interest to create a new measurement from
- **measurement\_name** (*str*) – The name of the measurement to use
- **measurement\_index** (*int*) – The index of the measurement to use

**Returns** A measurement object adhering to the schema `defs.json#/definitions/measurement`

**Return type** *dict*

**model**(\*\**config\_kwargs*)

Create a model object with/without patches applied.

See `pyhf.workspace.Workspace.get_measurement()` and `pyhf.pdf.Model` for possible keyword arguments.

#### Parameters

- **patches** – A list of JSON patches to apply to the model specification
- **config\_kwargs** – Possible keyword arguments for the measurement and model configuration

**Returns** A model object adhering to the schema `model.json`

**Return type** *Model*

**prune**(*modifiers=None, modifier\_types=None, samples=None, channels=None, measurements=None*)

Return a new, pruned workspace specification. This will not modify the original workspace.

The pruned workspace must also be a valid workspace.

#### Parameters

- **modifiers** – A *str* or a *list* of modifiers to prune.
- **modifier\_types** – A *str* or a *list* of modifier types to prune.
- **samples** – A *str* or a *list* of samples to prune.
- **channels** – A *str* or a *list* of channels to prune.
- **measurements** – A *str* or a *list* of measurements to prune.

**Returns** A new workspace object with the specified components removed

**Return type** *Workspace*

Raises *InvalidWorkspaceOperation* – An item name to prune does not exist in the workspace.

**rename**(*modifiers=None, samples=None, channels=None, measurements=None*)

Return a new workspace specification with certain elements renamed.

This will not modify the original workspace. The renamed workspace must also be a valid workspace.

#### Parameters

- **modifiers** – A *dict* mapping old modifier name to new modifier name.
- **samples** – A *dict* mapping old sample name to new sample name.
- **channels** – A *dict* mapping old channel name to new channel name.
- **measurements** – A *dict* mapping old measurement name to new measurement name.

**Returns** A new workspace object with the specified components renamed

**Return type** *Workspace*

**Raises** *InvalidWorkspaceOperation* – An item name to rename does not exist in the workspace.

**classmethod** `sorted(workspace)`

Return a new workspace specification that is sorted.

**Parameters** `workspace` (*Workspace*) – A workspace to sort

**Returns** A new sorted workspace object

**Return type** *Workspace*

### 13.3.4 PatchSet

**class** `pyhf.patchset.PatchSet(spec, **config_kwargs)`

Bases: *object*

A way to store a collection of patches (*Patch*).

It contains *metadata* about the PatchSet itself:

- a high-level *description* of what the patches represent or the analysis it is for
- a list of *references* where the patchset is sourced from (e.g. hepdata)
- a list of *digests* corresponding to the background-only workspace the patchset was made for
- the *labels* of the dimensions of the phase-space for what the patches cover

In addition to the above metadata, the PatchSet object behaves like a:

- smart list allowing you to iterate over all the patches defined
- smart dictionary allowing you to access a patch by the patch name or the patch values

The below example shows various ways one can interact with a *PatchSet* object.

#### Example

```
>>> import pyhf
>>> patchset = pyhf.PatchSet({
...     "metadata": {
...         "references": { "hepdata": "ins1234567" },
...         "description": "example patchset",
...         "digests": { "md5": "098f6bcd4621d373cade4e832627b4f6" },
...         "labels": ["x", "y"]
...     },
...     "patches": [
...         {
...             "metadata": {
...                 "name": "patch_name_for_2100x_800y",
...                 "values": [2100, 800]
...             },
...             "patch": [
...                 {
```

(continues on next page)

(continued from previous page)

```

...         "op": "add",
...         "path": "/foo/0/bar",
...         "value": {
...             "foo": [1.0]
...         }
...     ]
... }
... ],
... "version": "1.0.0"
... })
...
>>> patchset.version
'1.0.0'
>>> patchset.references
{'hepdata': 'ins1234567'}
>>> patchset.description
'example patchset'
>>> patchset.digests
{'md5': '098f6bcd4621d373cade4e832627b4f6'}
>>> patchset.labels
['x', 'y']
>>> patchset.patches
[<pyhf.patchset.Patch object 'patch_name_for_2100x_800y(2100, 800)' at 0x...>]
>>> patchset['patch_name_for_2100x_800y']
<pyhf.patchset.Patch object 'patch_name_for_2100x_800y(2100, 800)' at 0x...>
>>> patchset[(2100,800)]
<pyhf.patchset.Patch object 'patch_name_for_2100x_800y(2100, 800)' at 0x...>
>>> patchset[[2100,800]]
<pyhf.patchset.Patch object 'patch_name_for_2100x_800y(2100, 800)' at 0x...>
>>> patchset[2100,800]
<pyhf.patchset.Patch object 'patch_name_for_2100x_800y(2100, 800)' at 0x...>
>>> for patch in patchset:
...     print(patch.name)
...
patch_name_for_2100x_800y
>>> len(patchset)
1

```

**\_\_init\_\_**(*spec*, *\*\*config\_kwargs*)

Construct a PatchSet.

#### Parameters

- **spec** (jsonable) – The patchset JSON specification
- **config\_kwargs** – Possible keyword arguments for the patchset validation

**Returns** The PatchSet instance.

**Return type** patchset (*PatchSet*)

## Attributes

### description

The description in the PatchSet metadata

### digests

The digests in the PatchSet metadata

### labels

The labels in the PatchSet metadata

### metadata

The metadata of the PatchSet

### patches

The patches in the PatchSet

### references

The references in the PatchSet metadata

### version

The version of the PatchSet

## Methods

### apply(*spec*, *key*)

Apply the patch associated with the key to the background-only workspace specification.

#### Parameters

- **spec** (*Workspace*) – The workspace specification to verify the patchset against.
- **key** (*str* or *tuple* of *int/float*) – The key to look up the associated patch - either a name or a set of values.

#### Raises

- *InvalidPatchLookup* – if the provided patch name is not in the patchset
- *PatchSetVerificationError* – if the patchset cannot be verified against the workspace specification

**Returns** The background-only workspace with the patch applied.

**Return type** workspace (*Workspace*)

### verify(*spec*)

Verify the patchset digests against a background-only workspace specification. Verified if no exception was raised.

**Parameters** **spec** (*Workspace*) – The workspace specification to verify the patchset against.

**Raises** *PatchSetVerificationError* – if the patchset cannot be verified against the workspace specification

**Returns** None

### 13.3.5 Patch

**class** pyhf.patchset.Patch(*spec*)

Bases: jsonpatch.JsonPatch

A way to store a patch definition as part of a patchset (*PatchSet*).

It contains *metadata* about the Patch itself:

- a descriptive *name*
- a list of the *values* for each dimension in the phase-space the associated *PatchSet* is defined for, see *labels*

In addition to the above metadata, the Patch object behaves like the underlying jsonpatch.JsonPatch.

**\_\_init\_\_**(*spec*)

Construct a Patch.

**Parameters** *spec* (jsonable) – The patch JSON specification

**Returns** The Patch instance.

**Return type** patch (*Patch*)

#### Attributes

**metadata**

The metadata of the patch

**name**

The name of the patch

**operations** = mappingproxy({'remove': <class 'jsonpatch.RemoveOperation'>, 'add': <class 'jsonpatch.AddOperation'>, 'replace': <class 'jsonpatch.ReplaceOperation'>, 'move': <class 'jsonpatch.MoveOperation'>, 'test': <class 'jsonpatch.TestOperation'>, 'copy': <class 'jsonpatch.CopyOperation'>})

A JSON Patch is a list of Patch Operations.

```
>>> patch = JsonPatch([
...     {'op': 'add', 'path': '/foo', 'value': 'bar'},
...     {'op': 'add', 'path': '/baz', 'value': [1, 2, 3]},
...     {'op': 'remove', 'path': '/baz/1'},
...     {'op': 'test', 'path': '/baz', 'value': [1, 3]},
...     {'op': 'replace', 'path': '/baz/0', 'value': 42},
...     {'op': 'remove', 'path': '/baz/1'},
... ])
>>> doc = {}
>>> result = patch.apply(doc)
>>> expected = {'foo': 'bar', 'baz': [42]}
>>> result == expected
True
```

JsonPatch object is iterable, so you can easily access each patch statement in a loop:

```
>>> lpatch = list(patch)
>>> expected = {'op': 'add', 'path': '/foo', 'value': 'bar'}
>>> lpatch[0] == expected
```

(continues on next page)

(continued from previous page)

```
True
>>> lpatch == patch.patch
True
```

Also JsonPatch could be converted directly to `bool` if it contains any operation statements:

```
>>> bool(patch)
True
>>> bool(JsonPatch([]))
False
```

This behavior is very handy with `make_patch()` to write more readable code:

```
>>> old = {'foo': 'bar', 'numbers': [1, 3, 4, 8]}
>>> new = {'baz': 'qux', 'numbers': [1, 4, 7]}
>>> patch = make_patch(old, new)
>>> if patch:
...     # document have changed, do something useful
...     patch.apply(old)
{...}
```

#### values

The values of the associated labels for the patch

#### Methods

### 13.3.6 pyhf.simplemodels.uncorrelated\_background

`pyhf.simplemodels.uncorrelated_background(signal, bkg, bkg_uncertainty, batch_size=None)`

Construct a simple single channel *Model* with a *shapesys* modifier representing an uncorrelated background uncertainty.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> model.schema
'model.json'
>>> model.config.channels
['singlechannel']
>>> model.config.samples
['background', 'signal']
>>> model.config.parameters
['mu', 'uncorr_bkguncrt']
>>> model.expected_data(model.config.suggested_init())
array([ 62.          ,  63.          , 277.77777778,  55.18367347])
```

#### Parameters

- **signal** (*list*) – The data in the signal sample
- **bkg** (*list*) – The data in the background sample
- **bkg\_uncertainty** (*list*) – The statistical uncertainty on the background sample counts
- **batch\_size** (*None* or *int*) – Number of simultaneous (batched) Models to compute

**Returns** The statistical model adhering to the `model.json` schema

**Return type** *Model*

### 13.3.7 pyhf.simplemodels.correlated\_background

`pyhf.simplemodels.correlated_background(signal, bkg, bkg_up, bkg_down, batch_size=None)`

Construct a simple single channel *Model* with a *histosys* modifier representing a background with a fully correlated bin-by-bin uncertainty.

#### Parameters

- **signal** (*list*) – The data in the signal sample.
- **bkg** (*list*) – The data in the background sample.
- **bkg\_up** (*list*) – The background sample under an upward variation corresponding to  $\alpha = +1$ .
- **bkg\_down** (*list*) – The background sample under a downward variation corresponding to  $\alpha = -1$ .
- **batch\_size** (*None* or *int*) – Number of simultaneous (batched) Models to compute.

**Returns** The statistical model adhering to the `model.json` schema.

**Return type** *Model*

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.correlated_background(
...     signal=[12.0, 11.0],
...     bkg=[50.0, 52.0],
...     bkg_up=[45.0, 57.0],
...     bkg_down=[55.0, 47.0],
... )
>>> model.schema
'model.json'
>>> model.config.channels
['single_channel']
>>> model.config.samples
['background', 'signal']
>>> model.config.parameters
['correlated_bkg_uncertainty', 'mu']
>>> model.expected_data(model.config.suggested_init())
array([62., 63.,  0.]
```

### 13.3.8 pyhf.simplemodels.hepdata\_like

`pyhf.simplemodels.hepdata_like(signal_data, bkg_data, bkg_uncerts, batch_size=None)`

---

**Note:** Deprecated API: Use `uncorrelated_background()` instead.

---

**Warning:** `hepdata_like()` will be removed in pyhf v0.7.0.

## 13.4 Backends

The computational backends that pyhf provides interfacing for the vector-based calculations.

<code>numpy_backend.numpy_backend</code>	NumPy backend for pyhf
<code>pytorch_backend.pytorch_backend</code>	PyTorch backend for pyhf
<code>tensorflow_backend.tensorflow_backend</code>	TensorFlow backend for pyhf
<code>jax_backend.jax_backend</code>	JAX backend for pyhf

### 13.4.1 numpy\_backend

`class pyhf.tensor.numpy_backend.numpy_backend(**kwargs)`

Bases: `object`

NumPy backend for pyhf

`__init__`(\*\*kwargs)

Initialize self. See `help(type(self))` for accurate signature.

#### Attributes

`default_do_grad`

`dtypesmap`

`name`

`precision`

#### Methods

`_setup()`

Run any global setups for the numpy lib.

`abs(tensor)`

`astensor(tensor_in, dtype='float')`

Convert to a NumPy array.



### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> type(tensor)
<class 'numpy.ndarray'>
```

**Parameters** **tensor\_in** (*Number or Tensor*) – Tensor object

**Returns** A multi-dimensional, fixed-size homogenous array.

**Return type** *numpy.ndarray*

**boolean\_mask**(*tensor, mask*)

**clip**(*tensor\_in, min\_value, max\_value*)

Clips (limits) the tensor values to be within a specified min and max.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> a = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> pyhf.tensorlib.clip(a, -1, 1)
array([-1., -1., 0., 1., 1.])
```

#### Parameters

- **tensor\_in** (tensor) – The input tensor object
- **min\_value** (scalar or tensor or *None*) – The minimum value to be clipped to
- **max\_value** (scalar or tensor or *None*) – The maximum value to be clipped to

**Returns** A clipped *tensor*

**Return type** NumPy ndarray

**concatenate**(*sequence, axis=0*)

Join a sequence of arrays along an existing axis.

#### Parameters

- **sequence** – sequence of tensors
- **axis** – dimension along which to concatenate

**Returns** the concatenated tensor

**Return type** output

**conditional**(*predicate, true\_callable, false\_callable*)

Runs a callable conditional on the boolean value of the evaluation of a predicate

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> tensorlib = pyhf.tensorlib
>>> a = tensorlib.astensor([4])
>>> b = tensorlib.astensor([5])
>>> tensorlib.conditional((a < b)[0], lambda: a + b, lambda: a - b)
array([9.])
```

#### Parameters

- **predicate** (scalar) – The logical condition that determines which callable to evaluate
- **true\_callable** (callable) – The callable that is evaluated when the predicate evaluates to true
- **false\_callable** (callable) – The callable that is evaluated when the predicate evaluates to false

**Returns** The output of the callable that was evaluated

**Return type** NumPy ndarray

**divide**(*tensor\_in\_1*, *tensor\_in\_2*)

**einsum**(*subscripts*, *\*operands*)

Evaluates the Einstein summation convention on the operands.

Using the Einstein summation convention, many common multi-dimensional array operations can be represented in a simple fashion. This function provides a way to compute such summations. The best way to understand this function is to try the examples below, which show how many common NumPy functions can be implemented as calls to einsum.

#### Parameters

- **subscripts** – str, specifies the subscripts for summation
- **operands** – list of array\_like, these are the tensors for the operation

**Returns** the calculation based on the Einstein summation convention

**Return type** tensor

**erf**(*tensor\_in*)

The error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erf(a)
array([-0.99532227, -0.84270079,  0.          ,  0.84270079,  0.99532227])
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the error function at the given points.

**Return type** NumPy ndarray

**erfinv**(*tensor\_in*)

The inverse of the error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erfinv(pyhf.tensorlib.erf(a))
array([-2., -1., 0., 1., 2.]
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the inverse of the error function at the given points.

**Return type** NumPy ndarray

**exp**(*tensor\_in*)

**gather**(*tensor, indices*)

**isfinite**(*tensor*)

**log**(*tensor\_in*)

**normal**(*x, mu, sigma*)

The probability density function of the Normal distribution evaluated at *x* given parameters of mean of *mu* and standard deviation of *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> pyhf.tensorlib.normal(0.5, 0., 1.)
0.3520653267642995
>>> values = pyhf.tensorlib.astensor([0.5, 2.0])
>>> means = pyhf.tensorlib.astensor([0., 2.3])
>>> sigmas = pyhf.tensorlib.astensor([1., 0.8])
>>> pyhf.tensorlib.normal(values, means, sigmas)
array([0.35206533, 0.46481887])
```

#### Parameters

- **x** (tensor or float) – The value at which to evaluate the Normal distribution p.d.f.
- **mu** (tensor or float) – The mean of the Normal distribution
- **sigma** (tensor or float) – The standard deviation of the Normal distribution

**Returns** Value of Normal(*x*|*mu*, *sigma*)

**Return type** NumPy float

**normal\_cdf**(*x, mu=0, sigma=1*)

The cumulative distribution function for the Normal distribution

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> pyhf.tensorlib.normal_cdf(0.8)
0.7881446014166034
>>> values = pyhf.tensorlib.astensor([0.8, 2.0])
>>> pyhf.tensorlib.normal_cdf(values)
array([0.7881446 , 0.97724987])
```

#### Parameters

- **x** (tensor or `float`) – The observed value of the random variable to evaluate the CDF for
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The CDF

**Return type** NumPy float

**normal\_dist**(*mu*, *sigma*)

The Normal distribution with mean *mu* and standard deviation *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> normals = pyhf.tensorlib.normal_dist(means, stds)
>>> normals.log_prob(values)
array([-1.41893853, -2.22579135])
```

#### Parameters

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The Normal distribution class

**Return type** Normal distribution

**normal\_logpdf**(*x*, *mu*, *sigma*)

**ones**(*shape*, *dtype*='float')

**outer**(*tensor\_in\_1*, *tensor\_in\_2*)

**poisson**(*n*, *lam*)

The continuous approximation, using  $n! = \Gamma(n + 1)$ , to the probability mass function of the Poisson distribution evaluated at *n* given the parameter *lam*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> pyhf.tensorlib.poisson(5., 6.)
0.16062314104797995
>>> values = pyhf.tensorlib.astensor([5., 9.])
>>> rates = pyhf.tensorlib.astensor([6., 8.])
>>> pyhf.tensorlib.poisson(values, rates)
array([0.16062314, 0.12407692])
```

#### Parameters

- **n** (tensor or `float`) – The value at which to evaluate the approximation to the Poisson distribution p.m.f. (the observed number of events)
- **lam** (tensor or `float`) – The mean of the Poisson distribution p.m.f. (the expected number of events)

**Returns** Value of the continuous approximation to  $\text{Poisson}(n|\text{lam})$

**Return type** NumPy float

#### `poisson_dist(rate)`

The Poisson distribution with rate parameter `rate`.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> poissons = pyhf.tensorlib.poisson_dist(rates)
>>> poissons.log_prob(values)
array([-1.74030218, -2.0868536 ])
```

**Parameters** **rate** (tensor or `float`) – The mean of the Poisson distribution (the expected number of events)

**Returns** The Poisson distribution class

**Return type** Poisson distribution

#### `poisson_logpdf(n, lam)`

#### `power(tensor_in_1, tensor_in_2)`

#### `product(tensor_in, axis=None)`

#### `ravel(tensor)`

Return a flattened view of the tensor, not a copy.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> pyhf.tensorlib.ravel(tensor)
array([1., 2., 3., 4., 5., 6.])
```

**Parameters** **tensor** (*Tensor*) – Tensor object

**Returns** A flattened array.

**Return type** *numpy.ndarray*

**reshape**(*tensor, newshape*)

**shape**(*tensor*)

**simple\_broadcast**(\**args*)

Broadcast a sequence of 1 dimensional arrays.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> pyhf.tensorlib.simple_broadcast(
...     pyhf.tensorlib.astensor([1]),
...     pyhf.tensorlib.astensor([2, 3, 4]),
...     pyhf.tensorlib.astensor([5, 6, 7]))
[array([1., 1., 1.]), array([2., 3., 4.]), array([5., 6., 7.])]
```

**Parameters** **args** (*Array of Tensors*) – Sequence of arrays

**Returns** The sequence broadcast together.

**Return type** list of Tensors

**sqrt**(*tensor\_in*)

**stack**(*sequence, axis=0*)

**sum**(*tensor\_in, axis=None*)

**tile**(*tensor\_in, repeats*)

Repeat tensor data along a specific dimension

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> a = pyhf.tensorlib.astensor([[1.0], [2.0]])
>>> pyhf.tensorlib.tile(a, (1, 2))
array([[1., 1.],
       [2., 2.]])
```

#### Parameters

- **tensor\_in** (tensor) – The tensor to be repeated
- **repeats** (tensor) – The tuple of multipliers for each dimension

**Returns** The tensor with repeated axes

**Return type** NumPy ndarray

#### **to\_numpy**(*tensor\_in*)

Return the input tensor as it already is a `numpy.ndarray`. This API exists only for `pyhf.tensorlib` compatibility.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> numpy_ndarray = pyhf.tensorlib.to_numpy(tensor)
>>> numpy_ndarray
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> type(numpy_ndarray)
<class 'numpy.ndarray'>
```

**Parameters** **tensor\_in** (tensor) – The input tensor object.

**Returns** The tensor converted to a NumPy ndarray.

**Return type** `numpy.ndarray`

#### **tolist**(*tensor\_in*)

#### **where**(*mask, tensor\_in\_1, tensor\_in\_2*)

#### **zeros**(*shape, dtype='float'*)

### 13.4.2 pytorch\_backend

**class** pyhf.tensor.pytorch\_backend.pytorch\_backend(\*\*kwargs)

Bases: `object`

PyTorch backend for pyhf

**\_\_init\_\_**(\*\*kwargs)

Initialize self. See help(type(self)) for accurate signature.

#### Attributes

**default\_do\_grad**

**dtypesmap**

**name**

**precision**

#### Methods

**\_setup**()

Run any global setups for the pytorch lib.

**abs**(tensor)

**astensor**(tensor\_in, dtype='float')

Convert to a PyTorch Tensor.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
tensor([[1., 2., 3.],
        [4., 5., 6.]])
>>> type(tensor)
<class 'torch.Tensor'>
```

**Parameters** **tensor\_in** (*Number or Tensor*) – Tensor object

**Returns** A multi-dimensional matrix containing elements of a single data type.

**Return type** torch.Tensor

**boolean\_mask**(tensor, mask)

**clip**(tensor\_in, min\_value, max\_value)

Clips (limits) the tensor values to be within a specified min and max.



### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> a = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> pyhf.tensorlib.clip(a, -1, 1)
tensor([-1., -1., 0., 1., 1.])
```

#### Parameters

- **tensor\_in** (tensor) – The input tensor object
- **min\_value** (scalar or tensor or `None`) – The minimum value to be clipped to
- **max\_value** (scalar or tensor or `None`) – The maximum value to be clipped to

**Returns** A clipped *tensor*

**Return type** PyTorch tensor

**concatenate**(*sequence*, *axis=0*)

Join a sequence of arrays along an existing axis.

#### Parameters

- **sequence** – sequence of tensors
- **axis** – dimension along which to concatenate

**Returns** the concatenated tensor

**Return type** output

**conditional**(*predicate*, *true\_callable*, *false\_callable*)

Runs a callable conditional on the boolean value of the evaluation of a predicate

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> tensorlib = pyhf.tensorlib
>>> a = tensorlib.astensor([4])
>>> b = tensorlib.astensor([5])
>>> tensorlib.conditional((a < b)[0], lambda: a + b, lambda: a - b)
tensor([9.])
```

#### Parameters

- **predicate** (scalar) – The logical condition that determines which callable to evaluate
- **true\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `true`
- **false\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `false`

**Returns** The output of the callable that was evaluated

**Return type** PyTorch Tensor

**divide**(*tensor\_in\_1*, *tensor\_in\_2*)

**einsum**(*subscripts*, *\*operands*)

This function provides a way of computing multilinear expressions (i.e. sums of products) using the Einstein summation convention.

**Parameters**

- **subscripts** – str, specifies the subscripts for summation
- **operands** – list of array\_like, these are the tensors for the operation

**Returns** the calculation based on the Einstein summation convention

**Return type** tensor

**erf**(*tensor\_in*)

The error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erf(a)
tensor([-0.9953, -0.8427,  0.0000,  0.8427,  0.9953])
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the error function at the given points.

**Return type** PyTorch Tensor

**erfinv**(*tensor\_in*)

The inverse of the error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erfinv(pyhf.tensorlib.erf(a))
tensor([-2.0000, -1.0000,  0.0000,  1.0000,  2.0000])
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the inverse of the error function at the given points.

**Return type** PyTorch Tensor

**exp**(*tensor\_in*)

**gather**(*tensor*, *indices*)

**isfinite**(*tensor*)

**log**(*tensor\_in*)

**normal**(*x*, *mu*, *sigma*)

The probability density function of the Normal distribution evaluated at *x* given parameters of mean of *mu* and standard deviation of *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> pyhf.tensorlib.normal(0.5, 0., 1.)
tensor(0.3521)
>>> values = pyhf.tensorlib.astensor([0.5, 2.0])
>>> means = pyhf.tensorlib.astensor([0., 2.3])
>>> sigmas = pyhf.tensorlib.astensor([1., 0.8])
>>> pyhf.tensorlib.normal(values, means, sigmas)
tensor([0.3521, 0.4648])
```

### Parameters

- **x** (tensor or `float`) – The value at which to evaluate the Normal distribution p.d.f.
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** Value of Normal(*x*|*mu*, *sigma*)

**Return type** PyTorch FloatTensor

**normal\_cdf**(*x*, *mu*=0.0, *sigma*=1.0)

The cumulative distribution function for the Normal distribution

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> pyhf.tensorlib.normal_cdf(0.8)
tensor(0.7881)
>>> values = pyhf.tensorlib.astensor([0.8, 2.0])
>>> pyhf.tensorlib.normal_cdf(values)
tensor([0.7881, 0.9772])
```

### Parameters

- **x** (tensor or `float`) – The observed value of the random variable to evaluate the CDF for
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The CDF

**Return type** PyTorch FloatTensor

**normal\_dist**(*mu*, *sigma*)

The Normal distribution with mean *mu* and standard deviation *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> normals = pyhf.tensorlib.normal_dist(means, stds)
>>> normals.log_prob(values)
tensor([-1.4189, -2.2258])
```

#### Parameters

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The Normal distribution class

**Return type** PyTorch Normal distribution

**normal\_logpdf**(*x*, *mu*, *sigma*)

**ones**(*shape*, *dtype*='float')

**outer**(*tensor\_in\_1*, *tensor\_in\_2*)

Outer product of the input tensors.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> a = pyhf.tensorlib.astensor([1.0, 2.0, 3.0])
>>> b = pyhf.tensorlib.astensor([1.0, 2.0, 3.0, 4.0])
>>> pyhf.tensorlib.outer(a, b)
tensor([[ 1.,  2.,  3.,  4.],
        [ 2.,  4.,  6.,  8.],
        [ 3.,  6.,  9., 12.]])
```

#### Parameters

- **tensor\_in\_1** (tensor) – 1-D input tensor.
- **tensor\_in\_2** (tensor) – 1-D input tensor.

**Returns** The outer product.

**Return type** PyTorch tensor

**poisson**(*n*, *lam*)

The continuous approximation, using  $n! = \Gamma(n + 1)$ , to the probability mass function of the Poisson distribution evaluated at *n* given the parameter *lam*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> pyhf.tensorlib.poisson(5., 6.)
tensor(0.1606)
>>> values = pyhf.tensorlib.astensor([5., 9.])
>>> rates = pyhf.tensorlib.astensor([6., 8.])
>>> pyhf.tensorlib.poisson(values, rates)
tensor([0.1606, 0.1241])
```

#### Parameters

- **n** (tensor or `float`) – The value at which to evaluate the approximation to the Poisson distribution p.m.f. (the observed number of events)
- **lam** (tensor or `float`) – The mean of the Poisson distribution p.m.f. (the expected number of events)

**Returns** Value of the continuous approximation to  $\text{Poisson}(n|lam)$

**Return type** PyTorch FloatTensor

**poisson\_dist**(*rate*)

The Poisson distribution with rate parameter *rate*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> poissons = pyhf.tensorlib.poisson_dist(rates)
>>> poissons.log_prob(values)
tensor([-1.7403, -2.0869])
```

**Parameters** **rate** (tensor or `float`) – The mean of the Poisson distribution (the expected number of events)

**Returns** The Poisson distribution class

**Return type** PyTorch Poisson distribution

**poisson\_logpdf**(*n*, *lam*)

**power**(*tensor\_in\_1*, *tensor\_in\_2*)

**product**(*tensor\_in*, *axis=None*)

**ravel**(*tensor*)

Return a flattened view of the tensor, not a copy.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> pyhf.tensorlib.ravel(tensor)
tensor([1., 2., 3., 4., 5., 6.]
```

**Parameters** **tensor** (*Tensor*) – Tensor object

**Returns** A flattened array.

**Return type** *torch.Tensor*

**reshape**(*tensor, newshape*)

**shape**(*tensor*)

**simple\_broadcast**(\**args*)

Broadcast a sequence of 1 dimensional arrays.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> pyhf.tensorlib.simple_broadcast(
...     pyhf.tensorlib.astensor([1]),
...     pyhf.tensorlib.astensor([2, 3, 4]),
...     pyhf.tensorlib.astensor([5, 6, 7]))
[tensor([1., 1., 1.]), tensor([2., 3., 4.]), tensor([5., 6., 7.])]
```

**Parameters** **args** (*Array of Tensors*) – Sequence of arrays

**Returns** The sequence broadcast together.

**Return type** list of Tensors

**sqrt**(*tensor\_in*)

**stack**(*sequence, axis=0*)

**sum**(*tensor\_in, axis=None*)

**tile**(*tensor\_in, repeats*)

Repeat tensor data along a specific dimension

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> a = pyhf.tensorlib.astensor([[1.0], [2.0]])
>>> pyhf.tensorlib.tile(a, (1, 2))
tensor([[1., 1.],
        [2., 2.]])
```

#### Parameters

- **tensor\_in** (tensor) – The tensor to be repeated
- **repeats** (tensor) – The tuple of multipliers for each dimension

**Returns** The tensor with repeated axes

**Return type** PyTorch tensor

**to\_numpy**(*tensor\_in*)

Convert the PyTorch tensor to a `numpy.ndarray`.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("pytorch")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
tensor([[1., 2., 3.],
        [4., 5., 6.]])
>>> numpy_ndarray = pyhf.tensorlib.to_numpy(tensor)
>>> numpy_ndarray
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> type(numpy_ndarray)
<class 'numpy.ndarray'>
```

**Parameters** **tensor\_in** (tensor) – The input tensor object.

**Returns** The tensor converted to a NumPy ndarray.

**Return type** `numpy.ndarray`

**tolist**(*tensor\_in*)

**where**(*mask*, *tensor\_in\_1*, *tensor\_in\_2*)

**zeros**(*shape*, *dtype*='float')

### 13.4.3 tensorflow\_backend

**class** pyhf.tensor.tensorflow\_backend.tensorflow\_backend(\*\*kwargs)

Bases: `object`

TensorFlow backend for pyhf

**\_\_init\_\_**(\*\*kwargs)

Initialize self. See help(type(self)) for accurate signature.

#### Attributes

**default\_do\_grad**

**dtypesmap**

**name**

**precision**

#### Methods

**\_setup**()

Run any global setups for the tensorflow lib.

**abs**(*tensor*)

**astensor**(*tensor\_in*, *dtype*='float')

Convert to a TensorFlow Tensor.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
<tf.Tensor: shape=(2, 3), dtype=float64, numpy=
array([[1., 2., 3.],
       [4., 5., 6.]])>
>>> type(tensor)
<class 'tensorflow.python.framework.ops.EagerTensor'>
```

**Parameters** **tensor\_in** (*Number or Tensor*) – Tensor object

**Returns** A symbolic handle to one of the outputs of a *tf.Operation*.

**Return type** *tf.Tensor*

**boolean\_mask**(*tensor*, *mask*)

**clip**(*tensor\_in*, *min\_value*, *max\_value*)

Clips (limits) the tensor values to be within a specified min and max.



### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> a = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> t = pyhf.tensorlib.clip(a, -1, 1)
>>> print(t)
tf.Tensor([-1. -1.  0.  1.  1.], shape=(5,), dtype=float64)
```

#### Parameters

- **tensor\_in** (tensor) – The input tensor object
- **min\_value** (scalar or tensor or `None`) – The minimum value to be clipped to
- **max\_value** (scalar or tensor or `None`) – The maximum value to be clipped to

**Returns** A clipped *tensor*

**Return type** TensorFlow Tensor

**concatenate**(*sequence, axis=0*)

Join a sequence of arrays along an existing axis.

#### Parameters

- **sequence** – sequence of tensors
- **axis** – dimension along which to concatenate

**Returns** the concatenated tensor

**Return type** output

**conditional**(*predicate, true\_callable, false\_callable*)

Runs a callable conditional on the boolean value of the evaluation of a predicate

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> tensorlib = pyhf.tensorlib
>>> a = tensorlib.astensor([4])
>>> b = tensorlib.astensor([5])
>>> t = tensorlib.conditional((a < b)[0], lambda: a + b, lambda: a - b)
>>> print(t)
tf.Tensor([9.], shape=(1,), dtype=float64)
```

#### Parameters

- **predicate** (scalar) – The logical condition that determines which callable to evaluate
- **true\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `true`
- **false\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `false`

**Returns** The output of the callable that was evaluated

**Return type** TensorFlow Tensor

**divide**(*tensor\_in\_1*, *tensor\_in\_2*)

**einsum**(*subscripts*, *\*operands*)

A generalized contraction between tensors of arbitrary dimension.

This function returns a tensor whose elements are defined by equation, which is written in a shorthand form inspired by the Einstein summation convention.

**Parameters**

- **subscripts** – str, specifies the subscripts for summation
- **operands** – list of array\_like, these are the tensors for the operation

**Returns** the calculation based on the Einstein summation convention

**Return type** TensorFlow Tensor

**erf**(*tensor\_in*)

The error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> t = pyhf.tensorlib.erf(a)
>>> print(t)
tf.Tensor([-0.99532227 -0.84270079  0.          0.84270079  0.99532227],
          shape=(5,), dtype=float64)
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the error function at the given points.

**Return type** TensorFlow Tensor

**erfinv**(*tensor\_in*)

The inverse of the error function of complex argument.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> t = pyhf.tensorlib.erfinv(pyhf.tensorlib.erf(a))
>>> print(t)
tf.Tensor([-2. -1.  0.  1.  2.], shape=(5,), dtype=float64)
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the inverse of the error function at the given points.

**Return type** TensorFlow Tensor

**exp**(*tensor\_in*)**gather**(*tensor*, *indices*)**isfinite**(*tensor*)**log**(*tensor\_in*)**normal**(*x*, *mu*, *sigma*)

The probability density function of the Normal distribution evaluated at *x* given parameters of mean of *mu* and standard deviation of *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.normal(0.5, 0., 1.)
>>> print(t)
tf.Tensor(0.3520653267642995, shape=(), dtype=float64)
>>> values = pyhf.tensorlib.astensor([0.5, 2.0])
>>> means = pyhf.tensorlib.astensor([0., 2.3])
>>> sigmas = pyhf.tensorlib.astensor([1., 0.8])
>>> t = pyhf.tensorlib.normal(values, means, sigmas)
>>> print(t)
tf.Tensor([0.35206533 0.46481887], shape=(2,), dtype=float64)
```

### Parameters

- **x** (tensor or `float`) – The value at which to evaluate the Normal distribution p.d.f.
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** Value of Normal(*x*|*mu*, *sigma*)

**Return type** TensorFlow Tensor

**normal\_cdf**(*x*, *mu*=0.0, *sigma*=1)

Compute the value of cumulative distribution function for the Normal distribution at *x*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.normal_cdf(0.8)
>>> print(t)
tf.Tensor(0.7881446014166034, shape=(), dtype=float64)
>>> values = pyhf.tensorlib.astensor([0.8, 2.0])
>>> t = pyhf.tensorlib.normal_cdf(values)
>>> print(t)
tf.Tensor([0.7881446 0.97724987], shape=(2,), dtype=float64)
```

### Parameters

- **x** (tensor or `float`) – The observed value of the random variable to evaluate the CDF for

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The CDF

**Return type** TensorFlow Tensor

**normal\_dist**(*mu*, *sigma*)

Construct a Normal distribution with mean *mu* and standard deviation *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> normals = pyhf.tensorlib.normal_dist(means, stds)
>>> t = normals.log_prob(values)
>>> print(t)
tf.Tensor([-1.41893853 -2.22579135], shape=(2,), dtype=float64)
```

### Parameters

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The Normal distribution class

**Return type** TensorFlow Probability Normal distribution

**normal\_logpdf**(*x*, *mu*, *sigma*)

The log of the probability density function of the Normal distribution evaluated at *x* given parameters of mean of *mu* and standard deviation of *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.normal_logpdf(0.5, 0., 1.)
>>> print(t)
tf.Tensor(-1.0439385332046727, shape=(), dtype=float64)
>>> values = pyhf.tensorlib.astensor([0.5, 2.0])
>>> means = pyhf.tensorlib.astensor([0., 2.3])
>>> sigmas = pyhf.tensorlib.astensor([1., 0.8])
>>> t = pyhf.tensorlib.normal_logpdf(values, means, sigmas)
>>> print(t)
tf.Tensor([-1.04393853 -0.76610747], shape=(2,), dtype=float64)
```

### Parameters

- **x** (tensor or `float`) – The value at which to evaluate the Normal distribution p.d.f.

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** Value of  $\log(\text{Normal}(x|\mu, \sigma))$

**Return type** TensorFlow Tensor

**ones**(*shape*, *dtype*='float')

**outer**(*tensor\_in\_1*, *tensor\_in\_2*)

**poisson**(*n*, *lam*)

The continuous approximation, using  $n! = \Gamma(n + 1)$ , to the probability mass function of the Poisson distribution evaluated at *n* given the parameter *lam*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.poisson(5., 6.)
>>> print(t)
tf.Tensor(0.1606231410479..., shape=(), dtype=float64)
>>> values = pyhf.tensorlib.astensor([5., 9.])
>>> rates = pyhf.tensorlib.astensor([6., 8.])
>>> t = pyhf.tensorlib.poisson(values, rates)
>>> print(t)
tf.Tensor([0.16062314 0.12407692], shape=(2,), dtype=float64)
```

### Parameters

- **n** (tensor or `float`) – The value at which to evaluate the approximation to the Poisson distribution p.m.f. (the observed number of events)
- **lam** (tensor or `float`) – The mean of the Poisson distribution p.m.f. (the expected number of events)

**Returns** Value of the continuous approximation to  $\text{Poisson}(n|lam)$

**Return type** TensorFlow Tensor

**poisson\_dist**(*rate*)

Construct a Poisson distribution with rate parameter *rate*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> poissons = pyhf.tensorlib.poisson_dist(rates)
>>> t = poissons.log_prob(values)
>>> print(t)
tf.Tensor([-1.74030218 -2.0868536 ], shape=(2,), dtype=float64)
```

**Parameters** **rate** (tensor or `float`) – The mean of the Poisson distribution (the expected number of events)

**Returns** The Poisson distribution class

**Return type** TensorFlow Probability Poisson distribution

**poisson\_logpdf**(*n*, *lam*)

The log of the continuous approximation, using  $n! = \Gamma(n + 1)$ , to the probability mass function of the Poisson distribution evaluated at *n* given the parameter *lam*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.poisson_logpdf(5., 6.)
>>> print(t)
tf.Tensor(-1.8286943966417..., shape=(), dtype=float64)
>>> values = pyhf.tensorlib.astensor([5., 9.])
>>> rates = pyhf.tensorlib.astensor([6., 8.])
>>> t = pyhf.tensorlib.poisson_logpdf(values, rates)
>>> print(t)
tf.Tensor([-1.8286944 -2.0868536], shape=(2,), dtype=float64)
```

### Parameters

- **n** (tensor or `float`) – The value at which to evaluate the approximation to the Poisson distribution p.m.f. (the observed number of events)
- **lam** (tensor or `float`) – The mean of the Poisson distribution p.m.f. (the expected number of events)

**Returns** Value of the continuous approximation to  $\log(\text{Poisson}(n|\text{lam}))$

**Return type** TensorFlow Tensor

**power**(*tensor\_in\_1*, *tensor\_in\_2*)

**product**(*tensor\_in*, *axis=None*)

**ravel**(*tensor*)

Return a flattened view of the tensor, not a copy.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> t_ravel = pyhf.tensorlib.ravel(tensor)
>>> print(t_ravel)
tf.Tensor([1. 2. 3. 4. 5. 6.], shape=(6,), dtype=float64)
```

**Parameters** **tensor** (*Tensor*) – Tensor object

**Returns** A flattened array.

**Return type** *tf.Tensor*

**reshape**(*tensor*, *newshape*)

**shape**(*tensor*)

**simple\_broadcast**(\**args*)

Broadcast a sequence of 1 dimensional arrays.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> b = pyhf.tensorlib.simple_broadcast(
...     pyhf.tensorlib.astensor([1]),
...     pyhf.tensorlib.astensor([2, 3, 4]),
...     pyhf.tensorlib.astensor([5, 6, 7]))
>>> print([str(t) for t in b])
['tf.Tensor([1. 1. 1.], shape=(3,), dtype=float64)',
 'tf.Tensor([2. 3. 4.], shape=(3,), dtype=float64)',
 'tf.Tensor([5. 6. 7.], shape=(3,), dtype=float64)']
```

**Parameters** *args* (*Array of Tensors*) – Sequence of arrays

**Returns** The sequence broadcast together.

**Return type** list of Tensors

**sqrt**(*tensor\_in*)

**stack**(*sequence*, *axis*=0)

**sum**(*tensor\_in*, *axis*=None)

**tile**(*tensor\_in*, *repeats*)

Repeat tensor data along a specific dimension

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> a = pyhf.tensorlib.astensor([[1.0], [2.0]])
>>> t = pyhf.tensorlib.tile(a, (1, 2))
>>> print(t)
tf.Tensor(
[[1. 1.]
 [2. 2.]], shape=(2, 2), dtype=float64)
```

**Parameters**

- **tensor\_in** (tensor) – The tensor to be repeated
- **repeats** (tensor) – The tuple of multipliers for each dimension

**Returns** The tensor with repeated axes

**Return type** TensorFlow Tensor

**to\_numpy**(*tensor\_in*)

Convert the TensorFlow tensor to a `numpy.ndarray`.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> print(tensor)
tf.Tensor(
[[1. 2. 3.]
 [4. 5. 6.]], shape=(2, 3), dtype=float64)
>>> numpy_ndarray = pyhf.tensorlib.to_numpy(tensor)
>>> numpy_ndarray
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> type(numpy_ndarray)
<class 'numpy.ndarray'>
```

**Parameters** **tensor\_in** (*tensor*) – The input tensor object.

**Returns** The tensor converted to a NumPy ndarray.

**Return type** `numpy.ndarray`

**tolist**(*tensor\_in*)

**where**(*mask*, *tensor\_in\_1*, *tensor\_in\_2*)

Apply a boolean selection mask to the elements of the input tensors.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("tensorflow")
>>> t = pyhf.tensorlib.where(
...     pyhf.tensorlib.astensor([1, 0, 1], dtype='bool'),
...     pyhf.tensorlib.astensor([1, 1, 1]),
...     pyhf.tensorlib.astensor([2, 2, 2]),
... )
>>> print(t)
tf.Tensor([1. 2. 1.], shape=(3,), dtype=float64)
```

#### Parameters

- **mask** (*bool*) – Boolean mask (boolean or tensor object of booleans)
- **tensor\_in\_1** (*Tensor*) – Tensor object
- **tensor\_in\_2** (*Tensor*) – Tensor object

**Returns** The result of the mask being applied to the tensors.

**Return type** TensorFlow Tensor



`zeros(shape, dtype='float')`

### 13.4.4 jax\_backend

`class pyhf.tensor.jax_backend.jax_backend(**kwargs)`

Bases: `object`

JAX backend for pyhf

`__init__`(\*\*kwargs)

Initialize self. See help(type(self)) for accurate signature.

#### Attributes

`default_do_grad`

`dtypesmap`

`name`

`precision`

#### Methods

`_setup()`

Run any global setups for the jax lib.

`abs(tensor)`

`astensor(tensor_in, dtype='float')`

Convert to a JAX ndarray.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
DeviceArray([[1., 2., 3.],
              [4., 5., 6.]], dtype=float64)
>>> type(tensor)
<class '...DeviceArray'>
```

**Parameters** `tensor_in` (*Number or Tensor*) – Tensor object

**Returns** A multi-dimensional, fixed-size homogenous array.

**Return type** `jaxlib.xla_extension.DeviceArray`

`boolean_mask(tensor, mask)`

`clip(tensor_in, min_value, max_value)`

Clips (limits) the tensor values to be within a specified min and max.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> a = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> pyhf.tensorlib.clip(a, -1, 1)
DeviceArray([-1., -1., 0., 1., 1.], dtype=float64)
```

#### Parameters

- **tensor\_in** (tensor) – The input tensor object
- **min\_value** (scalar or tensor or `None`) – The minimum value to be clipped to
- **max\_value** (scalar or tensor or `None`) – The maximum value to be clipped to

**Returns** A clipped *tensor*

**Return type** JAX ndarray

**concatenate**(*sequence, axis=0*)

Join a sequence of arrays along an existing axis.

#### Parameters

- **sequence** – sequence of tensors
- **axis** – dimension along which to concatenate

**Returns** the concatenated tensor

**Return type** output

**conditional**(*predicate, true\_callable, false\_callable*)

Runs a callable conditional on the boolean value of the evaluation of a predicate

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> tensorlib = pyhf.tensorlib
>>> a = tensorlib.astensor([4])
>>> b = tensorlib.astensor([5])
>>> tensorlib.conditional((a < b)[0], lambda: a + b, lambda: a - b)
DeviceArray([9.], dtype=float64)
```

#### Parameters

- **predicate** (scalar) – The logical condition that determines which callable to evaluate
- **true\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `true`
- **false\_callable** (callable) – The callable that is evaluated when the predicate evaluates to `false`

**Returns** The output of the callable that was evaluated

**Return type** JAX ndarray

**divide**(*tensor\_in\_1*, *tensor\_in\_2*)

**einsum**(*subscripts*, *\*operands*)

Evaluates the Einstein summation convention on the operands.

Using the Einstein summation convention, many common multi-dimensional array operations can be represented in a simple fashion. This function provides a way to compute such summations. The best way to understand this function is to try the examples below, which show how many common NumPy functions can be implemented as calls to einsum.

#### Parameters

- **subscripts** – str, specifies the subscripts for summation
- **operands** – list of array\_like, these are the tensors for the operation

**Returns** the calculation based on the Einstein summation convention

**Return type** tensor

**erf**(*tensor\_in*)

The error function of complex argument.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erf(a)
DeviceArray([-0.99532227, -0.84270079, 0.          , 0.84270079,
              0.99532227], dtype=float64)
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the error function at the given points.

**Return type** JAX ndarray

**erfinv**(*tensor\_in*)

The inverse of the error function of complex argument.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> a = pyhf.tensorlib.astensor([-2., -1., 0., 1., 2.])
>>> pyhf.tensorlib.erfinv(pyhf.tensorlib.erf(a))
DeviceArray([-2., -1., 0., 1., 2.], dtype=float64)
```

**Parameters** **tensor\_in** (tensor) – The input tensor object

**Returns** The values of the inverse of the error function at the given points.

**Return type** JAX ndarray

**exp**(*tensor\_in*)

**gather**(*tensor*, *indices*)

**isfinite**(*tensor*)

**log**(*tensor\_in*)

**normal**(*x*, *mu*, *sigma*)

The probability density function of the Normal distribution evaluated at *x* given parameters of mean of *mu* and standard deviation of *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> pyhf.tensorlib.normal(0.5, 0., 1.)
DeviceArray(0.35206533, dtype=float64)
>>> values = pyhf.tensorlib.astensor([0.5, 2.0])
>>> means = pyhf.tensorlib.astensor([0., 2.3])
>>> sigmas = pyhf.tensorlib.astensor([1., 0.8])
>>> pyhf.tensorlib.normal(values, means, sigmas)
DeviceArray([0.35206533, 0.46481887], dtype=float64)
```

#### Parameters

- **x** (tensor or `float`) – The value at which to evaluate the Normal distribution p.d.f.
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** Value of Normal(*x*|*mu*, *sigma*)

**Return type** JAX ndarray

**normal\_cdf**(*x*, *mu=0*, *sigma=1*)

The cumulative distribution function for the Normal distribution

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> pyhf.tensorlib.normal_cdf(0.8)
DeviceArray(0.7881446, dtype=float64)
>>> values = pyhf.tensorlib.astensor([0.8, 2.0])
>>> pyhf.tensorlib.normal_cdf(values)
DeviceArray([0.7881446 , 0.97724987], dtype=float64)
```

#### Parameters

- **x** (tensor or `float`) – The observed value of the random variable to evaluate the CDF for
- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The CDF

**Return type** JAX ndarray

**normal\_dist**(*mu*, *sigma*)

The Normal distribution with mean *mu* and standard deviation *sigma*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> means = pyhf.tensorlib.astensor([5, 8])
>>> stds = pyhf.tensorlib.astensor([1, 0.5])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> normals = pyhf.tensorlib.normal_dist(means, stds)
>>> normals.log_prob(values)
DeviceArray([-1.41893853, -2.22579135], dtype=float64)
```

### Parameters

- **mu** (tensor or `float`) – The mean of the Normal distribution
- **sigma** (tensor or `float`) – The standard deviation of the Normal distribution

**Returns** The Normal distribution class

**Return type** Normal distribution

**normal\_logpdf**(*x*, *mu*, *sigma*)

**ones**(*shape*, *dtype*='float')

**outer**(*tensor\_in\_1*, *tensor\_in\_2*)

**poisson**(*n*, *lam*)

The continuous approximation, using  $n! = \Gamma(n+1)$ , to the probability mass function of the Poisson distribution evaluated at *n* given the parameter *lam*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> pyhf.tensorlib.poisson(5., 6.)
DeviceArray(0.16062314, dtype=float64)
>>> values = pyhf.tensorlib.astensor([5., 9.])
>>> rates = pyhf.tensorlib.astensor([6., 8.])
>>> pyhf.tensorlib.poisson(values, rates)
DeviceArray([0.16062314, 0.12407692], dtype=float64)
```

### Parameters

- **n** (tensor or `float`) – The value at which to evaluate the approximation to the Poisson distribution p.m.f. (the observed number of events)
- **lam** (tensor or `float`) – The mean of the Poisson distribution p.m.f. (the expected number of events)

**Returns** Value of the continuous approximation to  $\text{Poisson}(n|lam)$

**Return type** JAX ndarray

**poisson\_dist**(*rate*)

The Poisson distribution with rate parameter *rate*.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> rates = pyhf.tensorlib.astensor([5, 8])
>>> values = pyhf.tensorlib.astensor([4, 9])
>>> poissons = pyhf.tensorlib.poisson_dist(rates)
>>> poissons.log_prob(values)
DeviceArray([-1.74030218, -2.0868536 ], dtype=float64)
```

**Parameters** **rate** (tensor or `float`) – The mean of the Poisson distribution (the expected number of events)

**Returns** The Poisson distribution class

**Return type** Poisson distribution

**poisson\_logpdf**(*n*, *lam*)

**power**(*tensor\_in\_1*, *tensor\_in\_2*)

**product**(*tensor\_in*, *axis=None*)

**ravel**(*tensor*)

Return a flattened view of the tensor, not a copy.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> pyhf.tensorlib.ravel(tensor)
DeviceArray([1., 2., 3., 4., 5., 6.], dtype=float64)
```

**Parameters** **tensor** (*Tensor*) – Tensor object

**Returns** A flattened array.

**Return type** *jaxlib.xla\_extension.DeviceArray*

**reshape**(*tensor*, *newshape*)

**shape**(*tensor*)

**simple\_broadcast**(\**args*)

Broadcast a sequence of 1 dimensional arrays.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> pyhf.tensorlib.simple_broadcast(
...     pyhf.tensorlib.astensor([1]),
...     pyhf.tensorlib.astensor([2, 3, 4]),
...     pyhf.tensorlib.astensor([5, 6, 7]))
[DeviceArray([1., 1., 1.], dtype=float64), DeviceArray([2., 3., 4.],
dtype=float64), DeviceArray([5., 6., 7.], dtype=float64)]
```

**Parameters** **args** (*Array of Tensors*) – Sequence of arrays

**Returns** The sequence broadcast together.

**Return type** list of Tensors

**sqrt**(*tensor\_in*)

**stack**(*sequence*, *axis=0*)

**sum**(*tensor\_in*, *axis=None*)

**tile**(*tensor\_in*, *repeats*)

Repeat tensor data along a specific dimension

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> a = pyhf.tensorlib.astensor([[1.0], [2.0]])
>>> pyhf.tensorlib.tile(a, (1, 2))
DeviceArray([[1., 1.],
             [2., 2.]], dtype=float64)
```

#### Parameters

- **tensor\_in** (tensor) – The tensor to be repeated
- **repeats** (tensor) – The tuple of multipliers for each dimension

**Returns** The tensor with repeated axes

**Return type** JAX ndarray

**to\_numpy**(*tensor\_in*)

Convert the TensorFlow tensor to a `numpy.ndarray`.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("jax")
>>> tensor = pyhf.tensorlib.astensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
>>> tensor
DeviceArray([[1., 2., 3.],
              [4., 5., 6.]], dtype=float64)
>>> numpy_ndarray = pyhf.tensorlib.to_numpy(tensor)
>>> numpy_ndarray
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> type(numpy_ndarray)
<class 'numpy.ndarray'>
```

**Parameters** `tensor_in` (tensor) – The input tensor object.

**Returns** The tensor converted to a NumPy ndarray.

**Return type** `numpy.ndarray`

**tolist**(*tensor\_in*)

**where**(*mask*, *tensor\_in\_1*, *tensor\_in\_2*)

**zeros**(*shape*, *dtype*='float')

## 13.5 Optimizers

<code>mixins.OptimizerMixin</code>	Mixin Class to build optimizers.
<code>opt_scipy.scipy_optimizer</code>	Optimizer that uses <code>scipy.optimize.minimize()</code> .
<code>opt_minuit.minuit_optimizer</code>	Optimizer that minimizes via <code>iminuit.Minuit.migrad()</code> .

### 13.5.1 OptimizerMixin

**class** `pyhf.optimize.mixins.OptimizerMixin`(\*\**kwards*)

Bases: `object`

Mixin Class to build optimizers.

**\_\_init\_\_**(\*\**kwards*)

Create an optimizer.

**Parameters**

- **maxiter** (`int`) – maximum number of iterations. Default is 100000.
- **verbose** (`int`) – verbose output level during minimization. Default is off (0).



## Attributes

**maxiter**

**verbose**

## Methods

**\_internal\_minimize**(*func, x0, do\_grad=False, bounds=None, fixed\_vals=None, options={}*)

**\_internal\_postprocess**(*fitresult, stitch\_pars, return\_uncertainties=False*)

Post-process the fit result.

**Returns** A modified version of the fit result.

**Return type** fitresult (`scipy.optimize.OptimizeResult`)

**minimize**(*objective, data, pdf, init\_pars, par\_bounds, fixed\_vals=None, return\_fitted\_val=False, return\_result\_obj=False, return\_uncertainties=False, return\_correlations=False, do\_grad=None, do\_stitch=False, \*\*kwargs*)

Find parameters that minimize the objective.

### Parameters

- **objective** (*func*) – objective function
- **data** (*list*) – observed data
- **pdf** (*Model*) – The statistical model adhering to the schema model.json
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_vals** (*list of list/tuple*) – The pairs of index and constant value for a constant model parameter during minimization. Set to None to allow all parameters to float.
- **return\_fitted\_val** (*bool*) – Return bestfit value of the objective. Default is off (False).
- **return\_result\_obj** (*bool*) – Return `scipy.optimize.OptimizeResult`. Default is off (False).
- **return\_uncertainties** (*bool*) – Return uncertainties on the fitted parameters. Default is off (False).
- **return\_correlations** (*bool*) – Return correlations of the fitted parameters. Default is off (False).
- **do\_grad** (*bool*) – enable autodifferentiation mode. Default depends on backend (`pyhf.tensorlib.default_do_grad`).
- **do\_stitch** (*bool*) – enable splicing/stitching fixed parameter.
- **kwargs** – other options to pass through to underlying minimizer

### Returns

- **parameters** (*tensor*): fitted parameters
- **minimum** (*float*): if `return_fitted_val` flagged, return minimized objective value
- **result** (`scipy.optimize.OptimizeResult`): if `return_result_obj` flagged

**Return type** Fitted parameters or tuple of results

## 13.5.2 scipy\_optimizer

**class** `pyhf.optimize.opt_scipy.scipy_optimizer(*args, **kwargs)`

Bases: `pyhf.optimize.mixins.OptimizerMixin`

Optimizer that uses `scipy.optimize.minimize()`.

**\_\_init\_\_**(\*args, \*\*kwargs)

Initialize the scipy\_optimizer.

See `pyhf.optimize.mixins.OptimizerMixin` for other configuration options.

### Parameters

- **tolerance** (`float`) – Tolerance for termination. See specific optimizer for detailed meaning. Default is `None`.
- **solver\_options** (`dict`) – additional solver options. See `scipy.optimize.show_options()` for additional options of optimization solvers.

### Attributes

`maxiter`

`name`

`solver_options`

`tolerance`

`verbose`

### Methods

**\_get\_minimizer**(*objective\_and\_grad, init\_pars, init\_bounds, fixed\_vals=None, do\_grad=False*)

**\_minimize**(*minimizer, func, x0, do\_grad=False, bounds=None, fixed\_vals=None, options={}*)

Same signature as `scipy.optimize.minimize()`.

### Minimizer Options:

- `maxiter` (`int`): Maximum number of iterations. Default is `100000`.
- `verbose` (`bool`): Print verbose output during minimization. Default is `False`.
- `method` (`str`): Minimization routine. Default is `'SLSQP'`.
- `tolerance` (`float`): Tolerance for termination. See specific optimizer for detailed meaning. Default is `None`.
- `solver_options` (`dict`): additional solver options. See `scipy.optimize.show_options()` for additional options of optimization solvers.

**Returns** the fit result

**Return type** `fitresult` (`scipy.optimize.OptimizeResult`)

### 13.5.3 minuit\_optimizer

**class** `pyhf.optimize.opt_minuit.minuit_optimizer(*args, **kwargs)`

Bases: `pyhf.optimize.mixins.OptimizerMixin`

Optimizer that minimizes via `iminuit.Minuit.migrad()`.

**\_\_init\_\_**(\*args, \*\*kwargs)

Create `iminuit.Minuit` optimizer.

---

**Note:** `errordef` should be 1.0 for a least-squares cost function and 0.5 for negative log-likelihood function. See page 37 of <http://hep.fi.infn.it/minuit.pdf>. This parameter is sometimes called UP in the MINUIT docs.

---

#### Parameters

- **errordef** (`float`) – See minuit docs. Default is 1.0.
- **steps** (`int`) – Number of steps for the bounds. Default is 1000.
- **strategy** (`int`) – See `iminuit.Minuit.strategy`. Default is None.
- **tolerance** (`float`) – Tolerance for termination. See specific optimizer for detailed meaning. Default is 0.1.

#### Attributes

`errordef`

`maxiter`

`name`

`steps`

`strategy`

`tolerance`

`verbose`

#### Methods

**\_get\_minimizer**(*objective\_and\_grad*, *init\_pars*, *init\_bounds*, *fixed\_vals=None*, *do\_grad=False*)

**\_minimize**(*minimizer*, *func*, *x0*, *do\_grad=False*, *bounds=None*, *fixed\_vals=None*, *options={}*)

Same signature as `scipy.optimize.minimize()`.

Note: an additional *minuit* is injected into the fitresult to get the underlying minimizer.

#### Minimizer Options:

- **maxiter** (`int`): Maximum number of iterations. Default is 100000.
- **strategy** (`int`): See `iminuit.Minuit.strategy`. Default is to configure in response to `do_grad`.
- **tolerance** (`float`): Tolerance for termination. See specific optimizer for detailed meaning. Default is 0.1.

**Returns** the fit result

**Return type** fitresult (`scipy.optimize.OptimizeResult`)

## 13.6 Modifiers

---

*histosys*

---

*normfactor*

---

*normsys*

---

*shapefactor*

---

*shapesys*

---

*statererror*

---

### 13.6.1 histosys

**class** `pyhf.modifiers.histosys`

Bases: `object`

`__init__()`

Initialize self. See `help(type(self))` for accurate signature.

#### Attributes

`is_constrained = True`

`op_code = 'addition'`

`pdf_type = 'normal'`

#### Methods

**classmethod** `required_parset(sample_data, modifier_data)`

### 13.6.2 normfactor

**class** `pyhf.modifiers.normfactor`

Bases: `object`

`__init__()`

Initialize self. See `help(type(self))` for accurate signature.

#### Attributes

```
is_constrained = False
op_code = 'multiplication'
pdf_type = None
```

#### Methods

```
classmethod required_parset(sample_data, modifier_data)
```

### 13.6.3 normsys

```
class pyhf.modifiers.normsys
```

```
    Bases: object
```

```
    __init__()
```

```
        Initialize self. See help(type(self)) for accurate signature.
```

#### Attributes

```
is_constrained = True
op_code = 'multiplication'
pdf_type = 'normal'
```

#### Methods

```
classmethod required_parset(sample_data, modifier_data)
```

### 13.6.4 shapefactor

```
class pyhf.modifiers.shapefactor
```

```
    Bases: object
```

```
    __init__()
```

```
        Initialize self. See help(type(self)) for accurate signature.
```

#### Attributes

```
is_constrained = False
op_code = 'multiplication'
pdf_type = None
```

### Methods

`classmethod required_parset(sample_data, modifier_data)`

## 13.6.5 shapesys

`class pyhf.modifiers.shapesys`

Bases: `object`

`__init__()`

Initialize self. See help(type(self)) for accurate signature.

### Attributes

`is_constrained = True`

`op_code = 'multiplication'`

`pdf_type = 'poisson'`

### Methods

`classmethod required_parset(sample_data, modifier_data)`

## 13.6.6 staterror

`class pyhf.modifiers.staterror`

Bases: `object`

`__init__()`

Initialize self. See help(type(self)) for accurate signature.

### Attributes

`is_constrained = True`

`op_code = 'multiplication'`

`pdf_type = 'normal'`

### Methods

`classmethod required_parset(sample_data, modifier_data)`

## 13.7 Interpolators

<code>code0</code>	The piecewise-linear interpolation strategy.
<code>code1</code>	The piecewise-exponential interpolation strategy.
<code>code2</code>	The quadratic interpolation and linear extrapolation strategy.
<code>code4</code>	The polynomial interpolation and exponential extrapolation strategy.
<code>code4p</code>	The piecewise-linear interpolation strategy, with polynomial at $ a  < 1$ .

### 13.7.1 code0

**class** pyhf.interpolators.**code0**(*histogramssets*, *subscribe=True*)

Bases: `object`

The piecewise-linear interpolation strategy.

$$\sigma_{sb}(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) + \underbrace{\sum_{p \in \text{Syst}} I_{\text{lin.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-)}_{\text{deltas to calculate}}$$

with

$$I_{\text{lin.}}(\alpha; I^0, I^+, I^-) = \begin{cases} \alpha(I^+ - I^0) & \alpha \geq 0 \\ \alpha(I^0 - I^-) & \alpha < 0 \end{cases}$$

**\_\_init\_\_**(*histogramssets*, *subscribe=True*)

Piecewise-linear Interpolation.

#### Methods

**\_precompute**()

**\_precompute\_alphasets**(*alphasets\_shape*)

### 13.7.2 code1

**class** pyhf.interpolators.**code1**(*histogramssets*, *subscribe=True*)

Bases: `object`

The piecewise-exponential interpolation strategy.

$$\sigma_{sb}(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) \underbrace{\prod_{p \in \text{Syst}} I_{\text{exp.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-)}_{\text{factors to calculate}}$$

with

$$I_{\text{exp.}}(\alpha; I^0, I^+, I^-) = \begin{cases} \left(\frac{I^+}{I^0}\right)^\alpha & \alpha \geq 0 \\ \left(\frac{I^-}{I^0}\right)^{-\alpha} & \alpha < 0 \end{cases}$$

```
__init__(histogramssets, subscribe=True)
```

Piecewise-Exponential Interpolation.

### Methods

```
_precompute()
```

```
_precompute_alphasets(alphasets_shape)
```

## 13.7.3 code2

```
class pyhf.interpolators.code2(histogramssets, subscribe=True)
```

Bases: `object`

The quadratic interpolation and linear extrapolation strategy.

$$\sigma_{sb}(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) + \underbrace{\sum_{p \in \text{Syst}} I_{\text{quad.lin.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-)}_{\text{deltas to calculate}}$$

with

$$I_{\text{quad.lin.}}(\alpha; I^0, I^+, I^-) = \begin{cases} (b + 2a)(\alpha - 1) & \alpha \geq 1 \\ a\alpha^2 + b\alpha & |\alpha| < 1 \\ (b - 2a)(\alpha + 1) & \alpha < -1 \end{cases}$$

and

$$a = \frac{1}{2}(I^+ + I^-) - I^0 \quad \text{and} \quad b = \frac{1}{2}(I^+ - I^-)$$

```
__init__(histogramssets, subscribe=True)
```

Quadratic Interpolation.

### Methods

```
_precompute()
```

```
_precompute_alphasets(alphasets_shape)
```

## 13.7.4 code4

```
class pyhf.interpolators.code4(histogramssets, subscribe=True, alpha0=1)
```

Bases: `object`

The polynomial interpolation and exponential extrapolation strategy.

$$\sigma_{sb}(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) \underbrace{\prod_{p \in \text{Syst}} I_{\text{poly|exp.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-, \alpha_0)}_{\text{factors to calculate}}$$



with

$$I_{\text{poly|exp.}}(\alpha; I^0, I^+, I^-, \alpha_0) = \begin{cases} \left(\frac{I^+}{I^0}\right)^\alpha & \alpha \geq \alpha_0 \\ 1 + \sum_{i=1}^6 a_i \alpha^i & |\alpha| < \alpha_0 \\ \left(\frac{I^-}{I^0}\right)^{-\alpha} & \alpha < -\alpha_0 \end{cases}$$

and the  $a_i$  are fixed by the boundary conditions

$$\sigma_{sb}(\alpha = \pm\alpha_0), \left. \frac{d\sigma_{sb}}{d\alpha} \right|_{\alpha=\pm\alpha_0}, \text{ and } \left. \frac{d^2\sigma_{sb}}{d\alpha^2} \right|_{\alpha=\pm\alpha_0}.$$

Namely that  $\sigma_{sb}(\vec{\alpha})$  is continuous, and its first- and second-order derivatives are continuous as well.

**\_\_init\_\_**(*histogramssets*, *subscribe=True*, *alpha0=1*)  
Polynomial Interpolation.

### Methods

**\_precompute**()  
**\_precompute\_alphasets**(*alphasets\_shape*)

## 13.7.5 code4p

**class** `pyhf.interpolators.code4p`(*histogramssets*, *subscribe=True*)  
Bases: `object`

The piecewise-linear interpolation strategy, with polynomial at  $|a| < 1$ .

$$\sigma_{sb}(\vec{\alpha}) = \sigma_{sb}^0(\vec{\alpha}) + \underbrace{\sum_{p \in \text{Syst}} I_{\text{lin.}}(\alpha_p; \sigma_{sb}^0, \sigma_{psb}^+, \sigma_{psb}^-)}_{\text{deltas to calculate}}$$

**\_\_init\_\_**(*histogramssets*, *subscribe=True*)  
Piecewise-Linear + Polynomial Interpolation.

### Methods

**\_precompute**()  
**\_precompute\_alphasets**(*alphasets\_shape*)

## 13.8 Inference

### 13.8.1 Test Statistics

---

*test\_statistics.q0*

The test statistic,  $q_0$ , for discovery of a positive signal as defined in Equation (12) in [1007.1727], for  $\mu = 0$ .

continues on next page

---

Table 11 – continued from previous page

<code>test_statistics.qmu</code>	The test statistic, $q_\mu$ , for establishing an upper limit on the strength parameter, $\mu$ , as defined in Equation (14) in [1007.1727]
<code>test_statistics.qmu_tilde</code>	The “alternative” test statistic, $\tilde{q}_\mu$ , for establishing an upper limit on the strength parameter, $\mu$ , for models with bounded POI, as defined in Equation (16) in [1007.1727]
<code>test_statistics.tmu</code>	The test statistic, $t_\mu$ , for establishing a two-sided interval on the strength parameter, $\mu$ , as defined in Equation (8) in [1007.1727]
<code>test_statistics.tmu_tilde</code>	The test statistic, $\tilde{t}_\mu$ , for establishing a two-sided interval on the strength parameter, $\mu$ , for models with bounded POI, as defined in Equation (11) in [1007.1727]
<code>utils.get_test_stat</code>	Get the test statistic function by name.

### pyhf.infer.test\_statistics.q0

`pyhf.infer.test_statistics.q0(mu, data, pdf, init_pars, par_bounds, fixed_params)`

The test statistic,  $q_0$ , for discovery of a positive signal as defined in Equation (12) in [1007.1727], for  $\mu = 0$ .

$$q_0 = \begin{cases} -2 \ln \lambda(0), & \hat{\mu} \geq 0, \\ 0, & \hat{\mu} < 0, \end{cases} \quad (13.1)$$

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [60, 65]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_mu = 0.0
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> fixed_params = model.config.suggested_fixed()
>>> pyhf.infer.test_statistics.q0(test_mu, data, model, init_pars, par_bounds,
→fixed_params)
array(2.98339447)
```

#### Parameters

- **mu** (*Number or Tensor*) – The signal strength parameter (must be set to zero)
- **data** (*Tensor*) – The data to be considered
- **pdf** (*Model*) – The HistFactory statistical model used in the likelihood ratio calculation
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (*list of bool*) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The calculated test statistic,  $q_0$

**Return type** Float

### pyhf.infer.test\_statistics.qmu

`pyhf.infer.test_statistics.qmu(mu, data, pdf, init_pars, par_bounds, fixed_params)`

The test statistic,  $q_\mu$ , for establishing an upper limit on the strength parameter,  $\mu$ , as defined in Equation (14) in [1007.1727]

$$q_\mu = \begin{cases} -2 \ln \lambda(\mu), & \hat{\mu} < \mu, \\ 0, & \hat{\mu} > \mu \end{cases} \quad (13.2)$$

where  $\lambda(\mu)$  is the profile likelihood ratio as defined in Equation (7)

$$\lambda(\mu) = \frac{L(\mu, \hat{\hat{\theta}})}{L(\hat{\mu}, \hat{\theta})}.$$

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_mu = 1.0
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> par_bounds[model.config.poi_index] = [-10.0, 10.0]
>>> fixed_params = model.config.suggested_fixed()
>>> pyhf.infer.test_statistics.qmu(test_mu, data, model, init_pars, par_bounds,
↳ fixed_params)
array(3.9549891)
```

### Parameters

- **mu** (*Number or Tensor*) – The signal strength parameter
- **data** (*Tensor*) – The data to be considered
- **pdf** (*Model*) – The HistFactory statistical model used in the likelihood ratio calculation
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (*list of bool*) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The calculated test statistic,  $q_\mu$

**Return type** Float

**pyhf.infer.test\_statistics.qmu\_tilde**

`pyhf.infer.test_statistics.qmu_tilde(mu, data, pdf, init_pars, par_bounds, fixed_params)`

The “alternative” test statistic,  $\tilde{q}_\mu$ , for establishing an upper limit on the strength parameter,  $\mu$ , for models with bounded POI, as defined in Equation (16) in [1007.1727]

$$\tilde{q}_\mu = \begin{cases} -2 \ln \tilde{\lambda}(\mu), & \hat{\mu} < \mu, \\ 0, & \hat{\mu} > \mu \end{cases} \quad (13.3)$$

where  $\tilde{\lambda}(\mu)$  is the constrained profile likelihood ratio as defined in Equation (10)

$$\tilde{\lambda}(\mu) = \begin{cases} \frac{L(\mu, \hat{\boldsymbol{\theta}}(\mu))}{L(\hat{\mu}, \hat{\boldsymbol{\theta}}(0))}, & \hat{\mu} < 0, \\ \frac{L(\mu, \hat{\boldsymbol{\theta}}(\mu))}{L(\hat{\mu}, \hat{\boldsymbol{\theta}})}, & \hat{\mu} \geq 0. \end{cases} \quad (13.4)$$

**Example**

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_mu = 1.0
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> fixed_params = model.config.suggested_fixed()
>>> pyhf.infer.test_statistics.qmu_tilde(test_mu, data, model, init_pars, par_
↳ bounds, fixed_params)
array(3.93824492)
```

**Parameters**

- **mu** (*Number or Tensor*) – The signal strength parameter
- **data** (*tensor*) – The data to be considered
- **pdf** (*Model*) – The statistical model adhering to the schema model.json
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (*list of bool*) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The calculated test statistic,  $\tilde{q}_\mu$

**Return type** Float

**pyhf.infer.test\_statistics.tmu**

`pyhf.infer.test_statistics.tmu(mu, data, pdf, init_pars, par_bounds, fixed_params)`

The test statistic,  $t_\mu$ , for establishing a two-sided interval on the strength parameter,  $\mu$ , as defined in Equation (8) in [1007.1727]

$$t_\mu = -2 \ln \lambda(\mu)$$

where  $\lambda(\mu)$  is the profile likelihood ratio as defined in Equation (7)

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}.$$

**Example**

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_mu = 1.0
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> par_bounds[model.config.poi_index] = [-10.0, 10.0]
>>> fixed_params = model.config.suggested_fixed()
>>> pyhf.infer.test_statistics.tmu(test_mu, data, model, init_pars, par_bounds,
↳ fixed_params)
array(3.9549891)
```

**Parameters**

- **mu** (*Number or Tensor*) – The signal strength parameter
- **data** (*Tensor*) – The data to be considered
- **pdf** (*Model*) – The statistical model adhering to the schema model.json
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (*list of bool*) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The calculated test statistic,  $t_\mu$

**Return type** Float

**pyhf.infer.test\_statistics.tmu\_tilde**

`pyhf.infer.test_statistics.tmu_tilde(mu, data, pdf, init_pars, par_bounds, fixed_params)`

The test statistic,  $\tilde{t}_\mu$ , for establishing a two-sided interval on the strength parameter,  $\mu$ , for models with bounded POI, as defined in Equation (11) in [1007.1727]

$$\tilde{t}_\mu = -2 \ln \tilde{\lambda}(\mu)$$

where  $\tilde{\lambda}(\mu)$  is the constrained profile likelihood ratio as defined in Equation (10)

$$\tilde{\lambda}(\mu) = \begin{cases} \frac{L(\mu, \hat{\hat{\theta}}(\mu))}{L(\hat{\mu}, \hat{\hat{\theta}}(0))}, & \hat{\mu} < 0, \\ \frac{L(\mu, \hat{\hat{\theta}}(\mu))}{L(\hat{\mu}, \hat{\theta})}, & \hat{\mu} \geq 0. \end{cases} \quad (13.5)$$

**Example**

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_mu = 1.0
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> fixed_params = model.config.suggested_fixed()
>>> pyhf.infer.test_statistics.tmu_tilde(test_mu, data, model, init_pars, par_
↳ bounds, fixed_params)
array(3.93824492)
```

**Parameters**

- **mu** (*Number or Tensor*) – The signal strength parameter
- **data** (*tensor*) – The data to be considered
- **pdf** (*Model*) – The statistical model adhering to the schema model.json
- **init\_pars** (*list of float*) – The starting values of the model parameters for minimization.
- **par\_bounds** (*list of list/tuple*) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (*list of bool*) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The calculated test statistic,  $\tilde{t}_\mu$

**Return type** Float

## pyhf.infer.utils.get\_test\_stat

`pyhf.infer.utils.get_test_stat(name)`

Get the test statistic function by name. The following test statistics are supported:

- `q0()`
- `qmu()`
- `qmu_tilde()`

### Example

```
>>> from pyhf.infer import utils, test_statistics
>>> utils.get_test_stat("q0")
<function q0 at 0x...>
>>> utils.get_test_stat("q0") == test_statistics.q0
True
>>> utils.get_test_stat("q")
<function qmu at 0x...>
>>> utils.get_test_stat("q") == test_statistics.qmu
True
>>> utils.get_test_stat("qtilda")
<function qmu_tilde at 0x...>
>>> utils.get_test_stat("qtilda") == test_statistics.qmu_tilde
True
```

**Parameters** `name` (`str`) – The name of the test statistic to retrieve

**Returns** The test statistic function

**Return type** callable

## 13.8.2 Calculators

<code>calculators.generate_asimov_data</code>	Compute Asimov Dataset (expected yields at best-fit values) for a given POI value.
<code>calculators.AsymptoticTestStatDistribution</code>	The distribution the test statistic in the asymptotic case.
<code>calculators.EmpiricalDistribution</code>	The empirical distribution of the test statistic.
<code>calculators.AsymptoticCalculator</code>	The Asymptotic Calculator.
<code>calculators.ToyCalculator</code>	The Toy-based Calculator.
<code>utils.create_calculator</code>	Creates a calculator object of the specified <i>calctype</i> .

### pyhf.infer.calculators.generate\_asimov\_data

`pyhf.infer.calculators.generate_asimov_data(asimov_mu, data, pdf, init_pars, par_bounds, fixed_params)`

Compute Asimov Dataset (expected yields at best-fit values) for a given POI value.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> pyhf.infer.calculators.generate_asimov_data(mu_test, data, model, None, None,
↪None)
array([ 60.61229858,  56.52802479, 270.06832542,  48.31545488])
```

#### Parameters

- **asimov\_mu** (`float`) – The value for the parameter of interest to be used.
- **data** (`tensor`) – The observed data.
- **pdf** (`Model`) – The statistical model adhering to the schema `model.json`.
- **init\_pars** (`tensor of float`) – The starting values of the model parameters for minimization.
- **par\_bounds** (`tensor`) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be `(n, 2)` for `n` model parameters.
- **fixed\_params** (`tensor of bool`) – The flag to set a parameter constant to its starting value during minimization.

**Returns** The Asimov dataset.

**Return type** `Tensor`

### AsymptoticTestStatDistribution

`class pyhf.infer.calculators.AsymptoticTestStatDistribution(shift, cutoff=- inf)`

Bases: `object`

The distribution the test statistic in the asymptotic case.

Note: These distributions are in  $-\hat{\mu}/\sigma$  space. In the ROOT implementation the same sigma is assumed for both hypotheses and  $p$ -values etc are computed in that space. This assumption is necessarily valid, but we keep this for compatibility reasons.

In the  $-\hat{\mu}/\sigma$  space, the test statistic (i.e.  $\hat{\mu}/\sigma$ ) is normally distributed with unit variance and its mean at the  $-\mu'$ , where  $\mu'$  is the true poi value of the hypothesis.

`__init__(shift, cutoff=- inf)`

Asymptotic test statistic distribution.



**Parameters** `shift` (`float`) – The displacement of the test statistic distribution.

**Returns** The asymptotic distribution of test statistic.

**Return type** *AsymptoticTestStatDistribution*

## Methods

**cdf**(*value*)

Compute the value of the cumulative distribution function for a given value of the test statistic.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> bkg_dist = pyhf.infer.calculators.AsymptoticTestStatDistribution(0.0)
>>> bkg_dist.cdf(0.0)
0.5
```

**Parameters** `value` (`float`) – The test statistic value.

**Returns** The integrated probability to observe a test statistic less than or equal to the observed value.

**Return type** `Float`

**expected\_value**(*nsigma*)

Return the expected value of the test statistic.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> bkg_dist = pyhf.infer.calculators.AsymptoticTestStatDistribution(0.0)
>>> n_sigma = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> bkg_dist.expected_value(n_sigma)
array([-2., -1., 0., 1., 2.])
```

**Parameters** `nsigma` (`int` or `tensor`) – The number of standard deviations.

**Returns** The expected value of the test statistic.

**Return type** `Float`

**pvalue**(*value*)

The  $p$ -value for a given value of the test statistic corresponding to signal strength  $\mu$  and Asimov strength  $\mu'$  as defined in Equations (59) and (57) of [1007.1727]

$$p_{\mu} = 1 - F(q_{\mu}|\mu') = 1 - \Phi\left(\sqrt{q_{\mu}} - \frac{(\mu - \mu')}{\sigma}\right)$$

with Equation (29)

$$\frac{(\mu - \mu')}{\sigma} = \sqrt{\Lambda} = \sqrt{q_{\mu,A}}$$

given the observed test statistics  $q_\mu$  and  $q_{\mu,A}$ .

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> bkg_dist = pyhf.infer.calculators.AsymptoticTestStatDistribution(0.0)
>>> bkg_dist.pvalue(0.0)
array(0.5)
```

**Parameters** **value** (`float`) – The test statistic value.

**Returns** The integrated probability to observe a value at least as large as the observed one.

**Return type** `Tensor`

## EmpiricalDistribution

`class pyhf.infer.calculators.EmpiricalDistribution(samples)`

Bases: `object`

The empirical distribution of the test statistic.

Unlike *AsymptoticTestStatDistribution* where the distribution for the test statistic is normally distributed, the *p*-values etc are computed from the sampled distribution.

`__init__(samples)`

Empirical distribution.

**Parameters** **samples** (`tensor`) – The test statistics sampled from the distribution.

**Returns** The empirical distribution of the test statistic.

**Return type** *EmpiricalDistribution*

## Methods

`expected_value(nsigma)`

Return the expected value of the test statistic.

## Examples

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> mean = pyhf.tensorlib.astensor([5])
>>> std = pyhf.tensorlib.astensor([1])
>>> normal = pyhf.probability.Normal(mean, std)
>>> samples = normal.sample((100,))
>>> dist = pyhf.infer.calculators.EmpiricalDistribution(samples)
>>> dist.expected_value(nsigma=1)
6.15094381209505
```

```

>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> fixed_params = model.config.suggested_fixed()
>>> mu_test = 1.0
>>> pdf = model.make_pdf(pyhf.tensorlib.astensor(init_pars))
>>> samples = pdf.sample((100,))
>>> dist = pyhf.infer.calculators.EmpiricalDistribution(
...     pyhf.tensorlib.astensor(
...         [
...             pyhf.infer.test_statistics.qmu_tilde(
...                 mu_test, sample, model, init_pars, par_bounds, fixed_params
...             )
...             for sample in samples
...         ]
...     )
... )
>>> n_sigma = pyhf.tensorlib.astensor([-2, -1, 0, 1, 2])
>>> dist.expected_value(n_sigma)
array([0.00000000e+00, 0.00000000e+00, 5.53671231e-04, 8.29987137e-01,
       2.99592664e+00])

```

**Parameters** *nsigma* (*int* or *tensor*) – The number of standard deviations.

**Returns** The expected value of the test statistic.

**Return type** *Float*

**pvalue**(*value*)

Compute the *p*-value for a given value of the test statistic.

### Examples

```

>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> mean = pyhf.tensorlib.astensor([5])
>>> std = pyhf.tensorlib.astensor([1])
>>> normal = pyhf.probability.Normal(mean, std)
>>> samples = normal.sample((100,))
>>> dist = pyhf.infer.calculators.EmpiricalDistribution(samples)
>>> dist.pvalue(7)
array(0.02)

```

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> init_pars = model.config.suggested_init()
>>> par_bounds = model.config.suggested_bounds()
>>> fixed_params = model.config.suggested_fixed()
>>> mu_test = 1.0
>>> pdf = model.make_pdf(pyhf.tensorlib.astensor(init_pars))
>>> samples = pdf.sample((100,))
>>> test_stat_dist = pyhf.infer.calculators.EmpiricalDistribution(
...     pyhf.tensorlib.astensor(
...         [pyhf.infer.test_statistics.qmu_tilde(mu_test, sample, model, init_
... pars, par_bounds, fixed_params) for sample in samples]
...     )
... )
>>> test_stat_dist.pvalue(test_stat_dist.samples[9])
array(0.3)
```

**Parameters** *value* (`float`) – The test statistic value.

**Returns** The integrated probability to observe a value at least as large as the observed one.

**Return type** Tensor

## AsymptoticCalculator

```
class pyhf.infer.calculators.AsymptoticCalculator(data, pdf, init_pars=None, par_bounds=None,
                                                  fixed_params=None, test_stat='qtilde',
                                                  calc_base_dist='normal')
```

Bases: `object`

The Asymptotic Calculator.

```
__init__(data, pdf, init_pars=None, par_bounds=None, fixed_params=None, test_stat='qtilde',
         calc_base_dist='normal')
```

Asymptotic Calculator.

### Parameters

- **data** (tensor) – The observed data.
- **pdf** (`Model`) – The statistical model adhering to the schema `model.json`.
- **init\_pars** (tensor of `float`) – The starting values of the model parameters for minimization.
- **par\_bounds** (tensor) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be `(n, 2)` for `n` model parameters.
- **fixed\_params** (tensor of `bool`) – The flag to set a parameter constant to its starting value during minimization.
- **test\_stat** (`str`) – The test statistic to use as a numerical summary of the data: `'qtilde'`, `'q'`, or `'q0'`.

- 'qtilde': (default) performs the calculation using the alternative test statistic,  $\tilde{q}_\mu$ , as defined under the Wald approximation in Equation (62) of [1007.1727] (*qmu\_tilde()*).
- 'q': performs the calculation using the test statistic  $q_\mu$  (*qmu()*).
- 'q0': performs the calculation using the discovery test statistic  $q_0$  (*q0()*).
- **calc\_base\_dist** (*str*) – The statistical distribution, 'normal' or 'clipped\_normal', to use for calculating the  $p$ -values.
  - 'normal': (default) use the full Normal distribution in  $\hat{\mu}/\sigma$  space. Note that expected limits may correspond to unphysical test statistics from scenarios with the expected  $\hat{\mu} > \mu$ .
  - 'clipped\_normal': use a clipped Normal distribution in  $\hat{\mu}/\sigma$  space to avoid expected limits that correspond to scenarios with the expected  $\hat{\mu} > \mu$ . This will properly cap the test statistic at 0, as noted in Equation (14) and Equation (16) in [1007.1727].

The choice of `calc_base_dist` only affects the  $p$ -values for expected limits, and the default value will be changed in a future release.

**Returns** The calculator for asymptotic quantities.

**Return type** *AsymptoticCalculator*

## Methods

### `distributions(poi_test)`

Probability distributions of the test statistic, as defined in § 3 of [1007.1727] under the Wald approximation, under the signal + background and background-only hypotheses.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> asymptotic_calculator = pyhf.infer.calculators.AsymptoticCalculator(data,
↳ model, test_stat="qtilde")
>>> _ = asymptotic_calculator.teststatistic(mu_test)
>>> sig_plus_bkg_dist, bkg_dist = asymptotic_calculator.distributions(mu_test)
>>> sig_plus_bkg_dist.pvalue(mu_test), bkg_dist.pvalue(mu_test)
(array(0.00219262), array(0.15865525))
```

**Parameters** `poi_test` (*float* or *tensor*) – The value for the parameter of interest.

**Returns** The distributions under the hypotheses.

**Return type** *Tuple (AsymptoticTestStatDistribution)*

### `expected_pvalues(sig_plus_bkg_distribution, bkg_only_distribution)`

Calculate the  $CL_s$  values corresponding to the median significance of variations of the signal strength from the background only hypothesis ( $\mu = 0$ ) at  $(-2, -1, 0, 1, 2)\sigma$ .

### Example

```

>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> asymptotic_calculator = pyhf.infer.calculators.AsymptoticCalculator(
...     data, model, test_stat="qtilde"
... )
>>> _ = asymptotic_calculator.teststatistic(mu_test)
>>> sig_plus_bkg_dist, bkg_dist = asymptotic_calculator.distributions(mu_test)
>>> CLsb_exp_band, CLb_exp_band, CLs_exp_band = asymptotic_calculator.expected_
↳ pvalues(sig_plus_bkg_dist, bkg_dist)
>>> CLs_exp_band
[array(0.00260626), array(0.01382005), array(0.06445321), array(0.23525644),
↳ array(0.57303621)]

```

#### Parameters

- **sig\_plus\_bkg\_distribution** (*AsymptoticTestStatDistribution*) – The distribution for the signal + background hypothesis.
- **bkg\_only\_distribution** (*AsymptoticTestStatDistribution*) – The distribution for the background-only hypothesis.

**Returns** The  $p$ -values for the test statistic corresponding to the  $CL_{s+b}$ ,  $CL_b$ , and  $CL_s$ .

**Return type** Tuple (tensor)

**pvalues**(*teststat, sig\_plus\_bkg\_distribution, bkg\_only\_distribution*)

Calculate the  $p$ -values for the observed test statistic under the signal + background and background-only model hypotheses.

### Example

```

>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> asymptotic_calculator = pyhf.infer.calculators.AsymptoticCalculator(
...     data, model, test_stat="qtilde"
... )
>>> q_tilde = asymptotic_calculator.teststatistic(mu_test)
>>> sig_plus_bkg_dist, bkg_dist = asymptotic_calculator.distributions(mu_test)
>>> CLsb, CLb, CLs = asymptotic_calculator.pvalues(q_tilde, sig_plus_bkg_dist,
↳ bkg_dist)

```

(continues on next page)

(continued from previous page)

```
>>> CLsb, CLb, CLs
(array(0.02332502), array(0.4441594), array(0.05251497))
```

**Parameters**

- **teststat** (tensor) – The test statistic.
- **sig\_plus\_bkg\_distribution** (*AsymptoticTestStatDistribution*) – The distribution for the signal + background hypothesis.
- **bkg\_only\_distribution** (*AsymptoticTestStatDistribution*) – The distribution for the background-only hypothesis.

**Returns** The  $p$ -values for the test statistic corresponding to the  $CL_{s+b}$ ,  $CL_b$ , and  $CL_s$ .

**Return type** Tuple (tensor)

**teststatistic**(*poi\_test*)

Compute the test statistic for the observed data under the studied model.

**Example**

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> asymptotic_calculator = pyhf.infer.calculators.AsymptoticCalculator(data,
... model, test_stat="qtilde")
>>> asymptotic_calculator.teststatistic(mu_test)
array(0.14043184)
```

**Parameters** **poi\_test** (float or tensor) – The value for the parameter of interest.

**Returns** The value of the test statistic.

**Return type** Tensor

**ToyCalculator**

```
class pyhf.infer.calculators.ToyCalculator(data, pdf, init_pars=None, par_bounds=None,
fixed_params=None, test_stat='qtilde', ntoys=2000,
track_progress=True)
```

Bases: *object*

The Toy-based Calculator.

```
__init__(data, pdf, init_pars=None, par_bounds=None, fixed_params=None, test_stat='qtilde', ntoys=2000,
track_progress=True)
```

Toy-based Calculator.

**Parameters**

- **data** (tensor) – The observed data.
- **pdf** (Model) – The statistical model adhering to the schema `model.json`.
- **init\_pars** (tensor of float) – The starting values of the model parameters for minimization.
- **par\_bounds** (tensor) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be  $(n, 2)$  for  $n$  model parameters.
- **fixed\_params** (tensor of bool) – The flag to set a parameter constant to its starting value during minimization.
- **test\_stat** (str) – The test statistic to use as a numerical summary of the data: 'qtilde', 'q', or 'q0'. 'qtilde' (default) performs the calculation using the alternative test statistic,  $\tilde{q}_\mu$ , as defined under the Wald approximation in Equation (62) of [1007.1727] (`qmu_tilde()`), 'q' performs the calculation using the test statistic  $q_\mu$  (`qmu()`), and 'q0' performs the calculation using the discovery test statistic  $q_0$  (`q0()`).
- **ntoys** (int) – Number of toys to use (how many times to sample the underlying distributions).
- **track\_progress** (bool) – Whether to display the *tqdm* progress bar or not (outputs to *stderr*).

**Returns** The calculator for toy-based quantities.

**Return type** *ToyCalculator*

## Methods

**distributions**(*poi\_test*, *track\_progress=None*)

Probability Distributions of the test statistic value under the signal + background and background-only hypothesis.

## Example

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> toy_calculator = pyhf.infer.calculators.ToyCalculator(
...     data, model, ntoys=100, track_progress=False
... )
>>> sig_plus_bkg_dist, bkg_dist = toy_calculator.distributions(mu_test)
>>> sig_plus_bkg_dist.pvalue(mu_test), bkg_dist.pvalue(mu_test)
(array(0.14), array(0.76))
```

## Parameters

- **poi\_test** (float or tensor) – The value for the parameter of interest.



- **track\_progress** (*bool*) – Whether to display the *tqdm* progress bar or not (outputs to *stderr*)

**Returns** The distributions under the hypotheses.

**Return type** Tuple (*EmpiricalDistribution*)

**expected\_pvalues**(*sig\_plus\_bkg\_distribution, bkg\_only\_distribution*)

Calculate the  $CL_s$  values corresponding to the median significance of variations of the signal strength from the background only hypothesis ( $\mu = 0$ ) at  $(-2, -1, 0, 1, 2)\sigma$ .

### Example

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> toy_calculator = pyhf.infer.calculators.ToyCalculator(
...     data, model, ntoys=100, track_progress=False
... )
>>> sig_plus_bkg_dist, bkg_dist = toy_calculator.distributions(mu_test)
>>> CLsb_exp_band, CLb_exp_band, CLs_exp_band = toy_calculator.expected_
pvalues(sig_plus_bkg_dist, bkg_dist)
>>> CLs_exp_band
[array(0.), array(0.), array(0.06186224), array(0.28450033), array(1.)]
```

### Parameters

- **sig\_plus\_bkg\_distribution** (*EmpiricalDistribution*) – The distribution for the signal + background hypothesis.
- **bkg\_only\_distribution** (*EmpiricalDistribution*) – The distribution for the background-only hypothesis.

**Returns** The  $p$ -values for the test statistic corresponding to the  $CL_{s+b}$ ,  $CL_b$ , and  $CL_s$ .

**Return type** Tuple (tensor)

**pvalues**(*teststat, sig\_plus\_bkg\_distribution, bkg\_only\_distribution*)

Calculate the  $p$ -values for the observed test statistic under the signal + background and background-only model hypotheses.

### Example

```

>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> toy_calculator = pyhf.infer.calculators.ToyCalculator(
...     data, model, ntoys=100, track_progress=False
... )
>>> q_tilde = toy_calculator.teststatistic(mu_test)
>>> sig_plus_bkg_dist, bkg_dist = toy_calculator.distributions(mu_test)
>>> CLsb, CLb, CLs = toy_calculator.pvalues(q_tilde, sig_plus_bkg_dist, bkg_
dist)
>>> CLsb, CLb, CLs
(array(0.01), array(0.41), array(0.02439024))

```

#### Parameters

- **teststat** (tensor) – The test statistic.
- **sig\_plus\_bkg\_distribution** ([EmpiricalDistribution](#)) – The distribution for the signal + background hypothesis.
- **bkg\_only\_distribution** ([EmpiricalDistribution](#)) – The distribution for the background-only hypothesis.

**Returns** The  $p$ -values for the test statistic corresponding to the  $CL_{s+b}$ ,  $CL_b$ , and  $CL_s$ .

**Return type** Tuple (tensor)

#### **teststatistic**(*poi\_test*)

Compute the test statistic for the observed data under the studied model.

### Example

```

>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> toy_calculator = pyhf.infer.calculators.ToyCalculator(
...     data, model, ntoys=100, track_progress=False
... )

```

(continues on next page)

(continued from previous page)

```
>>> toy_calculator.teststatistic(mu_test)
array(3.93824492)
```

**Parameters** `poi_test` (`float` or `tensor`) – The value for the parameter of interest.

**Returns** The value of the test statistic.

**Return type** `Tensor`

### pyhf.infer.utils.create\_calculator

`pyhf.infer.utils.create_calculator(calctype, *args, **kwargs)`

Creates a calculator object of the specified *calctype*.

See *AsymptoticCalculator* and *ToyCalculator* on additional arguments to be specified.

### Example

```
>>> import pyhf
>>> import numpy.random as random
>>> random.seed(0)
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0],
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> mu_test = 1.0
>>> toy_calculator = pyhf.infer.utils.create_calculator(
...     "toybased", data, model, ntoys=100, test_stat="qtilde", track_progress=False
... )
>>> qmu_sig, qmu_bkg = toy_calculator.distributions(mu_test)
>>> qmu_sig.pvalue(mu_test), qmu_bkg.pvalue(mu_test)
(array(0.14), array(0.76))
```

### Parameters

- `calctype` (`str`) – The calculator to create. Choose either
- or `'toybased'`. (`'asymptotics'`) –

**Returns** A calculator.

**Return type** `calculator(object)`

### 13.8.3 Fits and Tests

<code>mle.twice_nll</code>	Two times the negative log-likelihood of the model parameters, $(\mu, \theta)$ , given the observed data.
<code>mle.fit</code>	Run a maximum likelihood fit.
<code>mle.fixed_poi_fit</code>	Run a maximum likelihood fit with the POI value fixed.
<code>hypotest</code>	Compute $p$ -values and test statistics for a single value of the parameter of interest.
<code>intervals.upperlimit</code>	Calculate an upper limit interval $(0, \text{poi\_up})$ for a single Parameter of Interest (POI) using a fixed scan through POI-space.
<code>utils.all_pois_floating</code>	Check whether all POI(s) are floating (i.e.

#### pyhf.infer.mle.twice\_nll

`pyhf.infer.mle.twice_nll(pars, data, pdf)`

Two times the negative log-likelihood of the model parameters,  $(\mu, \theta)$ , given the observed data. It is used in the calculation of the test statistic,  $t_\mu$ , as defined in Equation (8) in [1007.1727]

$$t_\mu = -2 \ln \lambda(\mu)$$

where  $\lambda(\mu)$  is the profile likelihood ratio as defined in Equation (7)

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}.$$

It serves as the objective function to minimize in `fit()` and `fixed_poi_fit()`.

#### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> parameters = model.config.suggested_init() # nominal parameters
>>> twice_nll = pyhf.infer.mle.twice_nll(parameters, data, model)
>>> twice_nll
array([30.77525435])
>>> -2 * model.logpdf(parameters, data) == twice_nll
array([ True])
```

#### Parameters

- **pars** (tensor) – The parameters of the HistFactory model
- **data** (tensor) – The data to be considered
- **pdf** (Model) – The statistical model adhering to the schema model.json

**Returns** Two times the negative log-likelihood,  $-2 \ln L(\mu, \theta)$

**Return type** Tensor

### pyhf.infer.mle.fit

`pyhf.infer.mle.fit(data, pdf, init_pars=None, par_bounds=None, fixed_params=None, **kwargs)`

Run a maximum likelihood fit. This is done by minimizing the objective function `twice_nll()` of the model parameters given the observed data. This is used to produce the maximal likelihood  $L(\hat{\mu}, \hat{\theta})$  in the profile likelihood ratio in Equation (7) in [1007.1727]

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$$

**Note:** `twice_nll()` is the objective function given to the optimizer and is returned evaluated at the best fit model parameters when the optional kwarg `return_fitted_val` is `True`.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> bestfit_pars, twice_nll = pyhf.infer.mle.fit(data, model, return_fitted_
↪ val=True)
>>> bestfit_pars
array([0.          , 1.0030512 , 0.96266961])
>>> twice_nll
array(24.98393521)
>>> -2 * model.logpdf(bestfit_pars, data) == twice_nll
array([ True])
```

### Parameters

- **data** (tensor) – The data
- **pdf** (Model) – The statistical model adhering to the schema model.json
- **init\_pars** (list of float) – The starting values of the model parameters for minimization.
- **par\_bounds** (list of list/tuple) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be (n, 2) for n model parameters.
- **fixed\_params** (list of bool) – The flag to set a parameter constant to its starting value during minimization.
- **kwargs** – Keyword arguments passed through to the optimizer API

**Returns** See optimizer API

### pyhf.infer.mle.fixed\_poi\_fit

`pyhf.infer.mle.fixed_poi_fit(poi_val, data, pdf, init_pars=None, par_bounds=None, fixed_params=None, **kwargs)`

Run a maximum likelihood fit with the POI value fixed. This is done by minimizing the objective function of `twice_nll()` of the model parameters given the observed data, for a given fixed value of  $\mu$ . This is used to produce the constrained maximal likelihood for the given  $\mu$ ,  $L(\mu, \hat{\theta})$ , in the profile likelihood ratio in Equation (7) in [1007.1727]

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$$

---

**Note:** `twice_nll()` is the objective function given to the optimizer and is returned evaluated at the best fit model parameters when the optional kwarg `return_fitted_val` is `True`.

---

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> test_poi = 1.0
>>> bestfit_pars, twice_nll = pyhf.infer.mle.fixed_poi_fit(
...     test_poi, data, model, return_fitted_val=True
... )
>>> bestfit_pars
array([1.         , 0.97224597, 0.87553894])
>>> twice_nll
array(28.92218013)
>>> -2 * model.logpdf(bestfit_pars, data) == twice_nll
array([ True])
```

#### Parameters

- **data** – The data
- **pdf** (`Model`) – The statistical model adhering to the schema `model.json`
- **init\_pars** (`list` of `float`) – The starting values of the model parameters for minimization.
- **par\_bounds** (`list` of `list/tuple`) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be `(n, 2)` for `n` model parameters.
- **fixed\_params** (`list` of `bool`) – The flag to set a parameter constant to its starting value during minimization.
- **kwargs** – Keyword arguments passed through to the optimizer API

**Returns** See optimizer API

## pyhf.infer.hypotest

```
pyhf.infer.hypotest(poi_test, data, pdf, init_pars=None, par_bounds=None, fixed_params=None,
                    calctype='asymptotics', return_tail_probs=False, return_expected=False,
                    return_expected_set=False, **kwargs)
```

Compute  $p$ -values and test statistics for a single value of the parameter of interest.

See [AsymptoticCalculator](#) and [ToyCalculator](#) on additional keyword arguments to be specified.

### Example

```
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> mu_test = 1.0
>>> CLs_obs, CLs_exp_band = pyhf.infer.hypotest(
...     mu_test, data, model, return_expected_set=True, test_stat="qtilde"
... )
>>> CLs_obs
array(0.05251497)
>>> CLs_exp_band
[array(0.00260626), array(0.01382005), array(0.06445321), array(0.23525644),
↪ array(0.57303621)]
```

### Parameters

- **poi\_test** (*Number or Tensor*) – The value of the parameter of interest (POI)
- **data** (*Number or Tensor*) – The data considered
- **pdf** ([Model](#)) – The statistical model adhering to the schema `model.json`
- **init\_pars** (tensor of [float](#)) – The starting values of the model parameters for minimization.
- **par\_bounds** (tensor) – The extrema of values the model parameters are allowed to reach in the fit. The shape should be  $(n, 2)$  for  $n$  model parameters.
- **fixed\_params** (tensor of [bool](#)) – The flag to set a parameter constant to its starting value during minimization.
- **calctype** ([str](#)) – The calculator to create. Choose either ‘asymptotics’ (default) or ‘toy-based’.
- **return\_tail\_probs** ([bool](#)) – Bool for returning  $CL_{s+b}$  and  $CL_b$
- **return\_expected** ([bool](#)) – Bool for returning  $CL_{exp}$
- **return\_expected\_set** ([bool](#)) – Bool for returning the  $(-2, -1, 0, 1, 2)\sigma$   $CL_{exp}$  — the “Brazil band”

### Returns

- $CL_s$ : The modified  $p$ -value compared to the given threshold  $\alpha$ , typically taken to be 0.05, defined in [1007.1727] as

$$\text{CL}_s = \frac{\text{CL}_{s+b}}{\text{CL}_b} = \frac{p_{s+b}}{1 - p_b}$$

to protect against excluding signal models in which there is little sensitivity. In the case that  $\text{CL}_s \leq \alpha$  the given signal model is excluded.

- $[\text{CL}_{s+b}, \text{CL}_b]$ : The signal + background model hypothesis  $p$ -value

$$\text{CL}_{s+b} = p_{s+b} = p(q \geq q_{\text{obs}} | s + b) = \int_{q_{\text{obs}}}^{\infty} f(q | s + b) dq = 1 - F(q_{\text{obs}}(\mu) | \mu')$$

and 1 minus the background only model hypothesis  $p$ -value

$$\text{CL}_b = 1 - p_b = p(q \geq q_{\text{obs}} | b) = 1 - \int_{-\infty}^{q_{\text{obs}}} f(q | b) dq = 1 - F(q_{\text{obs}}(\mu) | 0)$$

for signal strength  $\mu$  and model hypothesis signal strength  $\mu'$ , where the cumulative density functions  $F(q(\mu) | \mu')$  are given by Equations (57) and (65) of [1007.1727] for upper-limit-like test statistic  $q \in \{q_\mu, \tilde{q}_\mu\}$ . Only returned when `return_tail_probs` is `True`.

---

**Note:** The definitions of the  $\text{CL}_{s+b}$  and  $\text{CL}_b$  used are based on profile likelihood ratio test statistics. This procedure is common in the LHC-era, but differs from procedures used in the LEP and Tevatron eras, as briefly discussed in § 3.8 of [1007.1727].

---

- $\text{CL}_{s,\text{exp}}$ : The expected  $\text{CL}_s$  value corresponding to the test statistic under the background only hypothesis ( $\mu = 0$ ). Only returned when `return_expected` is `True`.
- $\text{CL}_{s,\text{exp}}$  band: The set of expected  $\text{CL}_s$  values corresponding to the median significance of variations of the signal strength from the background only hypothesis ( $\mu = 0$ ) at  $(-2, -1, 0, 1, 2)\sigma$ . That is, the  $p$ -values that satisfy Equation (89) of [1007.1727]

$$\text{band}_{N\sigma} = \mu' + \sigma \Phi^{-1}(1 - \alpha) \pm N\sigma$$

for  $\mu' = 0$  and  $N \in \{-2, -1, 0, 1, 2\}$ . These values define the boundaries of an uncertainty band sometimes referred to as the “Brazil band”. Only returned when `return_expected_set` is `True`.

**Return type** Tuple of Floats and lists of Floats

## pyhf.infer.intervals.upperlimit

`pyhf.infer.intervals.upperlimit(data, model, scan, level=0.05, return_results=False)`

Calculate an upper limit interval (`0`, `poi_up`) for a single Parameter of Interest (POI) using a fixed scan through POI-space.



### Example

```

>>> import numpy as np
>>> import pyhf
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = pyhf.tensorlib.astensor(observations + model.config.auxdata)
>>> scan = np.linspace(0, 5, 21)
>>> obs_limit, exp_limits, (scan, results) = pyhf.infer.intervals.upperlimit(
...     data, model, scan, return_results=True
... )
>>> obs_limit
array(1.01764089)
>>> exp_limits
[array(0.59576921), array(0.76169166), array(1.08504773), array(1.50170482),
↪ array(2.06654952)]

```

#### Parameters

- **data** (tensor) – The observed data.
- **model** (`Model`) – The statistical model adhering to the schema `model.json`.
- **scan** (iterable) – Iterable of POI values.
- **level** (float) – The threshold value to evaluate the interpolated results at.
- **return\_results** (bool) – Whether to return the per-point results.

#### Returns

- Tensor: The observed upper limit on the POI.
- Tensor: The expected upper limits on the POI.
- Tuple of Tensors: The given scan along with the *hypotest* results at each test POI. Only returned when `return_results` is True.

**Return type** Tuple of Tensors

### pyhf.infer.utils.all\_pois\_floating

`pyhf.infer.utils.all_pois_floating(pdf, fixed_params)`  
 Check whether all POI(s) are floating (i.e. not within the fixed set).

#### Parameters

- **pdf** (`Model`) – The statistical model adhering to the schema `model.json`.
- **fixed\_params** (list or tensor of bool) – Array of bool indicating if model parameters are fixed.

**Returns** The result whether all POIs are floating.

**Return type** bool

## 13.9 Exceptions

Various exceptions, apart from standard python exceptions, that are raised from using the pyhf API.

<i>InvalidMeasurement</i>	InvalidMeasurement is raised when a specified measurement is invalid given the specification.
<i>InvalidNameReuse</i>	
<i>InvalidSpecification</i>	InvalidSpecification is raised when a specification does not validate against the given schema.
<i>InvalidPatchSet</i>	InvalidPatchSet is raised when a given patchset object does not have the right configuration, even though it validates correctly against the schema.
<i>InvalidPatchLookup</i>	InvalidPatchLookup is raised when the patch lookup from a patchset object has failed
<i>PatchSetVerificationError</i>	PatchSetVerificationError is raised when the workspace digest does not match the patchset digests as part of the verification procedure
<i>InvalidWorkspaceOperation</i>	InvalidWorkspaceOperation is raised when an operation on a workspace fails.
<i>InvalidModel</i>	InvalidModel is raised when a given model does not have the right configuration, even though it validates correctly against the schema.
<i>InvalidModifier</i>	InvalidModifier is raised when an invalid modifier is requested.
<i>InvalidInterpCode</i>	InvalidInterpCode is raised when an invalid/unimplemented interpolation code is requested.
<i>ImportBackendError</i>	MissingLibraries is raised when something is imported by sustained an import error due to missing additional, non-default libraries.
<i>InvalidBackend</i>	InvalidBackend is raised when trying to set a backend that does not exist.
<i>InvalidOptimizer</i>	InvalidOptimizer is raised when trying to set an optimizer that does not exist.
<i>InvalidPdfParameters</i>	InvalidPdfParameters is raised when trying to evaluate a pdf with invalid parameters.
<i>InvalidPdfData</i>	InvalidPdfData is raised when trying to evaluate a pdf with invalid data.

### 13.9.1 pyhf.exceptions.InvalidMeasurement

**exception** pyhf.exceptions.InvalidMeasurement

InvalidMeasurement is raised when a specified measurement is invalid given the specification.

### 13.9.2 `pyhf.exceptions.InvalidNameReuse`

**exception** `pyhf.exceptions.InvalidNameReuse`

### 13.9.3 `pyhf.exceptions.InvalidSpecification`

**exception** `pyhf.exceptions.InvalidSpecification(ValidationError, schema=None)`

`InvalidSpecification` is raised when a specification does not validate against the given schema.

### 13.9.4 `pyhf.exceptions.InvalidPatchSet`

**exception** `pyhf.exceptions.InvalidPatchSet`

`InvalidPatchSet` is raised when a given patchset object does not have the right configuration, even though it validates correctly against the schema.

### 13.9.5 `pyhf.exceptions.InvalidPatchLookup`

**exception** `pyhf.exceptions.InvalidPatchLookup`

`InvalidPatchLookup` is raised when the patch lookup from a patchset object has failed

### 13.9.6 `pyhf.exceptions.PatchSetVerificationError`

**exception** `pyhf.exceptions.PatchSetVerificationError`

`PatchSetVerificationError` is raised when the workspace digest does not match the patchset digests as part of the verification procedure

### 13.9.7 `pyhf.exceptions.InvalidWorkspaceOperation`

**exception** `pyhf.exceptions.InvalidWorkspaceOperation`

`InvalidWorkspaceOperation` is raised when an operation on a workspace fails.

### 13.9.8 `pyhf.exceptions.InvalidModel`

**exception** `pyhf.exceptions.InvalidModel`

`InvalidModel` is raised when a given model does not have the right configuration, even though it validates correctly against the schema.

This can occur, for example, when the provided parameter of interest to fit against does not get declared in the specification provided.

### 13.9.9 pyhf.exceptions.InvalidModifier

**exception** `pyhf.exceptions.InvalidModifier`

`InvalidModifier` is raised when an invalid modifier is requested. This includes:

- creating a custom modifier with the wrong structure
- initializing a modifier that does not exist, or has not been loaded

### 13.9.10 pyhf.exceptions.InvalidInterpCode

**exception** `pyhf.exceptions.InvalidInterpCode`

`InvalidInterpCode` is raised when an invalid/unimplemented interpolation code is requested.

### 13.9.11 pyhf.exceptions.ImportBackendError

**exception** `pyhf.exceptions.ImportBackendError`

`MissingLibraries` is raised when something is imported by sustained an import error due to missing additional, non-default libraries.

### 13.9.12 pyhf.exceptions.InvalidBackend

**exception** `pyhf.exceptions.InvalidBackend`

`InvalidBackend` is raised when trying to set a backend that does not exist.

### 13.9.13 pyhf.exceptions.InvalidOptimizer

**exception** `pyhf.exceptions.InvalidOptimizer`

`InvalidOptimizer` is raised when trying to set an optimizer that does not exist.

### 13.9.14 pyhf.exceptions.InvalidPdfParameters

**exception** `pyhf.exceptions.InvalidPdfParameters`

`InvalidPdfParameters` is raised when trying to evaluate a pdf with invalid parameters.

### 13.9.15 pyhf.exceptions.InvalidPdfData

**exception** `pyhf.exceptions.InvalidPdfData`

`InvalidPdfData` is raised when trying to evaluate a pdf with invalid data.

## 13.10 Utilities

---

*load\_schema*

---

*validate*

---

*options\_from\_eqdelimstring*

---

*digest*

Get the digest for the provided object.

*citation*

Get the bibtex citation for pyhf

---

### 13.10.1 pyhf.utils.load\_schema

`pyhf.utils.load_schema(schema_id, version=None)`

### 13.10.2 pyhf.utils.validate

`pyhf.utils.validate(spec, schema_name, version=None)`

### 13.10.3 pyhf.utils.options\_from\_eqdelimstring

`pyhf.utils.options_from_eqdelimstring(opts)`

### 13.10.4 pyhf.utils.digest

`pyhf.utils.digest(obj, algorithm='sha256')`

Get the digest for the provided object. Note: object must be JSON-serializable.

The hashing algorithms supported are in `hashlib`, part of Python's Standard Libraries.

#### Example

```
>>> import pyhf
>>> obj = {'a': 2.0, 'b': 3.0, 'c': 1.0}
>>> pyhf.utils.digest(obj)
'a38f6093800189b79bc22ef677baf90c75705af2cfc7ff594159eca54eaa7928'
>>> pyhf.utils.digest(obj, algorithm='md5')
'2c0633f242928eb55c3672fed5ba8612'
>>> pyhf.utils.digest(obj, algorithm='sha1')
'49a27f499e763766c9545b294880df277be6f545'
```

**Raises** `ValueError` – If the object is not JSON-serializable or if the algorithm is not supported.

#### Parameters

- **obj** (jsonable) – A JSON-serializable object to compute the digest of. Usually a `Workspace` object.
- **algorithm** (str) – The hashing algorithm to use.

**Returns** The digest for the JSON-serialized object provided and hash algorithm specified.

**Return type** digest (`str`)

### 13.10.5 pyhf.utils.citation

`pyhf.utils.citation(online=False)`

Get the bibtex citation for pyhf

#### Example

```
>>> import pyhf
>>> pyhf.utils.citation(online=True)
'@software{pyhf, author = {Lukas Heinrich and Matthew Feickert and Giordon Stark},
↪ title = "{pyhf: v0.6.1}", version = {0.6.1}, doi = {10.5281/zenodo.1169739},
↪ url = {https://doi.org/10.5281/zenodo.1169739}, note = {https://github.com/
↪ scikit-hep/pyhf/releases/tag/v0.6.1}}@article{pyhf_joss, doi = {10.21105/joss.
↪ 02823}, url = {https://doi.org/10.21105/joss.02823}, year = {2021}, publisher_
↪ = {The Open Journal}, volume = {6}, number = {58}, pages = {2823}, author =
↪ {Lukas Heinrich and Matthew Feickert and Giordon Stark and Kyle Cranmer}, title_
↪ = {pyhf: pure-Python implementation of HistFactory statistical models}, journal_
↪ = {Journal of Open Source Software}}'
```

**Keyword Arguments** `online` (`bool`) – Whether to provide citation with new lines (default) or as a one-liner.

**Returns** The citation for this software

**Return type** citation (`str`)

## 13.11 Contrib

<code>viz.brazil</code>	Brazil Band Plots.
<code>utils.download</code>	Download the patchset archive from the remote URL and extract it in a directory at the path given.

### 13.11.1 pyhf.contrib.viz.brazil

#### Description

Brazil Band Plots.

## Classes

---

<code>BrazilBandCollection(cls_obs, cls_exp, ...)</code>	<code>collections.namedtuple</code> containing the <code>matplotlib.artist.Artist</code> objects of the “Brazil Band” and the observed $CL_{s+b}$ and $CL_b$ — the components of the $CL_s$ ratio.
--	--

---

### BrazilBandCollection

**class** `pyhf.contrib.viz.brazil.BrazilBandCollection`(*cls\_obs, cls\_exp, one\_sigma\_band, two\_sigma\_band, test\_size, clsb, clb, axes*)

Bases: `pyhf.contrib.viz.brazil.BrazilBandCollection`

`collections.namedtuple` containing the `matplotlib.artist.Artist` objects of the “Brazil Band” and the observed  $CL_{s+b}$  and  $CL_b$  — the components of the  $CL_s$  ratio. Returned by `plot_results()`.

#### Parameters

- **cls\_obs** – The `matplotlib.lines.Line2D` of the  $CL_{s,obs}$  line.
- **cls\_exp** – The list of `matplotlib.lines.Line2D` of the  $CL_{s,exp}$  lines.
- **one\_sigma\_band** – The `matplotlib.collections.PolyCollection` of the  $CL_{s,exp} \pm 1\sigma$  band.
- **two\_sigma\_band** – The `matplotlib.collections.PolyCollection` of the  $CL_{s,exp} \pm 2\sigma$  band.
- **test\_size** – The `matplotlib.lines.Line2D` of the test size line.
- **clsb** – The `matplotlib.lines.Line2D` of the observed  $CL_{s+b}$  line.
- **clb** – The `matplotlib.lines.Line2D` of the observed  $CL_b$  line.
- **axes** – The `matplotlib.axes.Axes` the artists are plotted on.

**`__init__()`**

Initialize self. See `help(type(self))` for accurate signature.

#### Attributes

**axes**

Alias for field number 7

**clb**

Alias for field number 6

**cls\_exp**

Alias for field number 1

**cls\_obs**

Alias for field number 0

**clsb**

Alias for field number 5

**one\_sigma\_band**

Alias for field number 2

**test\_size**

Alias for field number 4

**two\_sigma\_band**

Alias for field number 3

**Methods****Functions**

<code>plot_brazil_band(test_pois, cls_obs, ...)</code>	Plot the values of $CL_{s,obs}$ and the $CL_{s,exp}$ band (the “Brazil band”) for a series of hypothesis tests for various POI values.
<code>plot_cls_components(test_pois, tail_probs, ...)</code>	Plot the values of $CL_{s+b}$ and $CL_b$ — the components of the $CL_s$ ratio — for a series of hypothesis tests for various POI values.
<code>plot_results(test_pois, tests[, test_size, ax])</code>	Plot a series of hypothesis tests for various POI values.

**pyhf.contrib.viz.brazil.plot\_brazil\_band**`pyhf.contrib.viz.brazil.plot_brazil_band(test_pois, cls_obs, cls_exp, test_size, ax, **kwargs)`Plot the values of  $CL_{s,obs}$  and the  $CL_{s,exp}$  band (the “Brazil band”) for a series of hypothesis tests for various POI values.**Example**`plot_brazil_band()` is generally meant to be used inside `plot_results()` but can be used by itself.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> import pyhf
>>> import pyhf.contrib.viz.brazil
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> test_pois = np.linspace(0, 5, 41)
>>> results = [
...     pyhf.infer.hypotest(test_poi, data, model, return_expected_set=True)
...     for test_poi in test_pois
... ]
>>> cls_obs = np.array([test[0] for test in results]).flatten()
>>> cls_exp = [
...     np.array([test[1][sigma_idx] for test in results]).flatten()
...     for sigma_idx in range(5)
... ]
>>> test_size = 0.05
>>> fig, ax = plt.subplots()
>>> artists = pyhf.contrib.viz.brazil.plot_brazil_band(
```

(continues on next page)



(continued from previous page)

```
... test_pois, cls_obs, cls_exp, test_size, ax
... )
```

**Parameters**

- **test\_pois** (`list` or `array`) – The values of the POI where the hypothesis tests were performed.
- **cls\_obs** (`list` or `array`) – The values of  $CL_{s,obs}$  for the POIs tested in `test_pois`.
- **cls\_exp** (`list` or `array`) – The values of the  $CL_{s,exp}$  band for the POIs tested in `test_pois`.
- **test\_size** (`float`) – The size,  $\alpha$ , of the test.
- **ax** (`matplotlib.axes.Axes`) – The matplotlib axis object to plot on.

**Returns** The matplotlib artist objects drawn.

**Return type** `tuple`

**pyhf.contrib.viz.brazil.plot\_cls\_components**

`pyhf.contrib.viz.brazil.plot_cls_components(test_pois, tail_probs, ax, **kwargs)`

Plot the values of  $CL_{s+b}$  and  $CL_b$  — the components of the  $CL_s$  ratio — for a series of hypothesis tests for various POI values.

**Example**

`plot_cls_components()` is generally meant to be used inside `plot_results()` but can be used by itself.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> import pyhf
>>> import pyhf.contrib.viz.brazil
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> test_pois = np.linspace(0, 5, 41)
>>> results = [
...     pyhf.infer.hypotest(
...         test_poi, data, model, return_expected_set=True, return_tail_probs=True
...     )
...     for test_poi in test_pois
... ]
>>> tail_probs = np.array([test[1] for test in results])
>>> fig, ax = plt.subplots()
>>> artists = pyhf.contrib.viz.brazil.plot_cls_components(test_pois, tail_probs, ax)
```

**Parameters**

- **test\_pois** (*list* or *array*) – The values of the POI where the hypothesis tests were performed.
- **tail\_probs** (*list* or *array*) – The values of  $CL_{s+b}$  and  $CL_b$  for the POIs tested in `test_pois`.
- **ax** (`matplotlib.axes.Axes`) – The matplotlib axis object to plot on.
- **Keywords** –
  - `no_clb` (*bool*): Bool for not plotting the  $CL_b$  component.
  - `no_cls_b` (*bool*): Bool for not plotting the  $CL_{s+b}$  component.

**Returns** The `matplotlib.lines.Line2D` artists drawn.

**Return type** `tuple`

### `pyhf.contrib.viz.brazil.plot_results`

`pyhf.contrib.viz.brazil.plot_results(test_pois, tests, test_size=0.05, ax=None, **kwargs)`

Plot a series of hypothesis tests for various POI values. For more detail on use of keywords see `plot_brazil_band()` and `plot_cls_components()`.

#### Example

A Brazil band plot.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> import pyhf
>>> import pyhf.contrib.viz.brazil
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> test_pois = np.linspace(0, 5, 41)
>>> results = [
...     pyhf.infer.hypotest(test_poi, data, model, return_expected_set=True)
...     for test_poi in test_pois
... ]
>>> fig, ax = plt.subplots()
>>> artists = pyhf.contrib.viz.brazil.plot_results(test_pois, results, ax=ax)
```

A Brazil band plot with the components of the  $CL_s$  ratio drawn on top.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> import pyhf
>>> import pyhf.contrib.viz.brazil
>>> pyhf.set_backend("numpy")
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
```

(continues on next page)

(continued from previous page)

```

>>> observations = [51, 48]
>>> data = observations + model.config.auxdata
>>> test_pois = np.linspace(0, 5, 41)
>>> results = [
...     pyhf.infer.hypotest(
...         test_poi, data, model, return_expected_set=True, return_tail_probs=True
...     )
...     for test_poi in test_pois
... ]
>>> fig, ax = plt.subplots()
>>> artists = pyhf.contrib.viz.brazil.plot_results(
...     test_pois, results, ax=ax, components=True
... )

```

#### Parameters

- **test\_pois** (*list* or *array*) – The values of the POI where the hypothesis tests were performed.
- **tests** (*list* or *array*) – The collection of  $p$ -value-like values ( $CL_s$  values or tail probabilities) from the hypothesis tests. If the `components` keyword argument is `True`, `tests` is required to have the same structure as `pyhf.infer.hypotest()`'s return when using `return_expected_set=True` and `return_tail_probs=True`: a tuple of  $CL_s$ ,  $[CL_{s+b}, CL_b]$ ,  $CL_{s,\text{exp}}$  band.
- **test\_size** (*float*) – The size,  $\alpha$ , of the test.
- **ax** (`matplotlib.axes.Axes`) – The matplotlib axis object to plot on.

**Returns** Artist containing the `matplotlib.artist` objects drawn.

**Return type** *BrazilBandCollection*

### 13.11.2 pyhf.contrib.utils.download

`pyhf.contrib.utils.download(archive_url, output_directory, force=False, compress=False)`

Download the patchset archive from the remote URL and extract it in a directory at the path given.

#### Example

```

>>> from pyhf.contrib.utils import download
>>> download("https://doi.org/10.17182/hepdata.90607.v3/r3", "1Lbb-likelihoods")
>>> import os
>>> sorted(os.listdir("1Lbb-likelihoods"))
['BkgOnly.json', 'README.md', 'patchset.json']
>>> download("https://doi.org/10.17182/hepdata.90607.v3/r3", "1Lbb-likelihoods.tar.
↪ gz", compress=True)
>>> import glob
>>> glob.glob("1Lbb-likelihoods.tar.gz")
['1Lbb-likelihoods.tar.gz']

```

#### Parameters

- **archive\_url** (`str`) – The URL of the *PatchSet* archive to download.
- **output\_directory** (`str`) – Name of the directory to unpack the archive into.
- **force** (`bool`) – Force download from non-approved host. Default is `False`.
- **compress** (`bool`) – Keep the archive in a compressed `tar.gz` form. Default is `False`.

**Raises** `InvalidArchiveHost` – if the provided archive host name is not known to be valid

## USE AND CITATIONS

### 14.1 Citation

The preferred BibTeX entry for citation of pyhf includes both the [Zenodo](#) archive and the [JOSS](#) paper:

```
@software{pyhf,  
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark},  
  title = "{pyhf: v0.6.1}",  
  version = {0.6.1},  
  doi = {10.5281/zenodo.1169739},  
  url = {https://doi.org/10.5281/zenodo.1169739},  
  note = {https://github.com/scikit-hep/pyhf/releases/tag/v0.6.1}  
}  
  
@article{pyhf_joss,  
  doi = {10.21105/joss.02823},  
  url = {https://doi.org/10.21105/joss.02823},  
  year = {2021},  
  publisher = {The Open Journal},  
  volume = {6},  
  number = {58},  
  pages = {2823},  
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark and Kyle Cranmer},  
  title = {pyhf: pure-Python implementation of HistFactory statistical models},  
  journal = {Journal of Open Source Software}  
}
```

### 14.2 Use in Publications

Updating list of citations and use cases of pyhf:

- Waleed Abdallah and others. Reinterpretation of LHC Results for New Physics: Status and Recommendations after Run 2. 2020. [arXiv:2003.07868](#).
- Gaël Alguero, Jan Heisig, Charanjit K. Khosa, Sabine Kraml, Suchita Kulkarni, Andre Lessa, Philipp Neuhuber, Humberto Reyes-González, Wolfgang Waltenberger, and Alicia Wongel. New developments in SModelS. In *Tools for High Energy Physics and Cosmology*. 12 2020. [arXiv:2012.08192](#).

- Gaël Alguero, Sabine Kraml, and Wolfgang Waltenberger. A SModelS interface for pyhf likelihoods. Sep 2020. [arXiv:2009.01809](#).
- J. Alison and others. Higgs Boson Pair Production at Colliders: Status and Perspectives. In B. Di Micco, M. Gouzevitch, J. Mazzitelli, and C. Vernieri, editors, *Double Higgs Production at Colliders*. 9 2019. [arXiv:1910.00012](#).
- B.C. Allanach, Tyler Corbett, and Maeve Madigan. Sensitivity of Future Hadron Colliders to Leptoquark Pair Production in the Di-Muon Di-Jets Channel. *Eur. Phys. J. C*, 80(2):170, 2020. [arXiv:1911.04455](#), [doi:10.1140/epjc/s10052-020-7722-3](#).
- Simone Amoroso, Deepak Kar, and Matthias Schott. How to discover QCD Instantons at the LHC. In *Topological Effects in the Standard Model: Instantons, Sphalerons and Beyond at LHC*. 12 2020. [arXiv:2012.09120](#).
- Andrei Angelescu, Damir Bečirević, Darius A. Faroughy, Florentin Jaffredo, and Olcyr Sumensari. On the single leptoquark solutions to the  $B\bar{B}$ -physics anomalies. 3 2021. [arXiv:2103.12504](#).
- Andrei Angelescu, Darius A. Faroughy, and Olcyr Sumensari. Lepton Flavor Violation and Dilepton Tails at the LHC. *Eur. Phys. J. C*, 80(7):641, 2020. [arXiv:2002.05684](#), [doi:10.1140/epjc/s10052-020-8210-5](#).
- Jack Y. Araz and others. Proceedings of the second MadAnalysis 5 workshop on LHC recasting in Korea. *Mod. Phys. Lett. A*, 36(01):2102001, 2021. [arXiv:2101.02245](#), [doi:10.1142/S0217732321020016](#).
- Johann Brehmer, Felix Kling, Irina Espejo, and Kyle Cranmer. MadMiner: Machine learning-based inference for particle physics. *Comput. Softw. Big Sci.*, 4(1):3, 2020. [arXiv:1907.10621](#), [doi:10.1007/s41781-020-0035-2](#).
- G. Brooijmans and others. Les Houches 2019 Physics at TeV Colliders: New Physics Working Group Report. In 2020. [arXiv:2002.12220](#).
- Rodolfo Capdevilla, Federico Meloni, Rosa Simoniello, and Jose Zurita. Hunting wino and higgsino dark matter at the muon collider with disappearing tracks. 2 2021. [arXiv:2102.11292](#).
- Vincenzo Cirigliano, Kaori Fuyuto, Christopher Lee, Emanuele Mereghetti, and Bin Yan. Charged Lepton Flavor Violation at the EIC. 2 2021. [arXiv:2102.06176](#).
- Belle II Collaboration. Search for  $B^+ \rightarrow K^+ \nu \bar{\nu}$  decays using an inclusive tagging method at Belle II. 4 2021. [arXiv:2104.12624](#).
- Matthew Feickert, Lukas Heinrich, and Giordon Stark. Likelihood preservation and statistical reproduction of searches for new physics. *EPJ Web Conf.*, 2020. [doi:10.1051/epjconf/202024506017](#).
- Lukas Heinrich, Holger Schulz, Jessica Turner, and Ye-Ling Zhou. Constraining  $A_4$  Leptonic Flavour Model Parameters at Colliders and Beyond. 2018. [arXiv:1810.05648](#).
- Charanjit K. Khosa, Sabine Kraml, Andre Lessa, Philipp Neuhuber, and Wolfgang Waltenberger. SModelS database update v1.2.3. *LHEP*, 158:2020, 5 2020. [arXiv:2005.00555](#), [doi:10.31526/lhep.2020.158](#).
- Jeffrey Krupa and others. GPU coprocessors as a service for deep learning inference in high energy physics. 7 2020. [arXiv:2007.10359](#).
- Wolfgang Waltenberger, André Lessa, and Sabine Kraml. Artificial Proto-Modelling: Building Precursors of a Next Standard Model from Simplified Model Results. 12 2020. [arXiv:2012.12246](#).
- ATLAS Collaboration. Reproducing searches for new physics with the ATLAS experiment through publication of full statistical likelihoods. Geneva, Aug 2019. URL: <https://cds.cern.ch/record/2684863>.
- ATLAS Collaboration. Search for new phenomena in events with two opposite-charge leptons, jets and missing transverse momentum in  $\sqrt{s}$  collisions at  $\sqrt{s} = 13$  TeV with the ATLAS detector. 2 2021. [arXiv:2102.01444](#).

## 14.3 Published Likelihoods

Updating list of HEPData entries for publications using HistFactory JSON likelihoods:

- Search for bottom-squark pair production with the ATLAS detector in final states containing Higgs bosons,  $b\bar{b}$ -jets and missing transverse momentum. 2019. URL: <https://doi.org/10.17182/hepdata.89408>, doi:10.17182/hepdata.89408.
- Search for chargino-neutralino production with mass splittings near the electroweak scale in three-lepton final states in  $\sqrt{s} = 13$  TeV  $pp$  collisions with the ATLAS detector. 2019. URL: <https://doi.org/10.17182/hepdata.91127>, doi:10.17182/hepdata.91127.
- Search for direct stau production in events with two hadronic -leptons in  $\sqrt{s} = 13$  TeV  $pp$  collisions with the ATLAS detector. 2019. URL: <https://doi.org/10.17182/hepdata.92006>, doi:10.17182/hepdata.92006.
- Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two  $b\bar{b}$ -jets in (pp) collisions at  $\sqrt{s}=13$  TeV with the ATLAS detector. 2020. URL: <https://doi.org/10.17182/hepdata.90607.v2>, doi:10.17182/hepdata.90607.v2.
- Search for displaced leptons in  $\sqrt{s} = 13$  TeV  $pp$  collisions with the ATLAS detector. 2020. URL: <https://doi.org/10.17182/hepdata.98796>, doi:10.17182/hepdata.98796.
- Search for squarks and gluinos in final states with same-sign leptons and jets using 139 fb $^{-1}$  of data collected with the ATLAS detector. 2020. URL: <https://doi.org/10.17182/hepdata.91214.v3>, doi:10.17182/hepdata.91214.v3.
- Search for trilepton resonances from chargino and neutralino pair production in  $\sqrt{s} = 13$  TeV  $pp$  collisions with the ATLAS detector. 2020. URL: <https://doi.org/10.17182/hepdata.99806>, doi:10.17182/hepdata.99806.





## ROADMAP (2019-2020)

This is the pyhf 2019 into 2020 Roadmap (Issue #561).

### 15.1 Overview and Goals

We will follow loosely Seibert's Hierarchy of Needs



(Stan Seibert, SciPy 2019)

As a general overview that will include:

- Improvements to docs

- Add lots of examples
- Add at least 5 well documented case studies
- Issue cleanup
- Adding core feature support
- “pyhf evolution”: integration with columnar data analysis systems
- GPU support and testing
- Publications
  - Submit pyhf to JOSS
  - Submit pyhf to pyOpenSci
  - Start pyhf paper in 2020
- Align with IRIS-HEP Analysis Systems NSF milestones

## 15.2 Time scale

The roadmap will be executed over mostly Quarter 3 of 2019 through Quarter 1 of 2020, with some projects continuing into Quarter 2 of 2020

- 2019-Q3
- 2019-Q4
- 2020-Q1
- (2020-Q2)

## 15.3 Roadmap

### 1. Documentation and Deployment

- Add docstrings to all functions and classes (Issues #38, #349) [2019-Q3]
- [Greatly revise and expand examples](#) (Issues #168, #202, #212, #325, #342, #349, #367) [2019-Q3 → 2019-Q4]
  - Add small case studies with published sbottom likelihood from HEPData
- Move to [scikit-hep](#) GitHub organization [2019-Q3]
- Develop a release schedule/criteria [2019-Q4]
- Automate deployment with [STRIKEOUT:Azure pipeline (talk with Henry Schreiner) (Issue #517)] GitHub Actions (Issue #508) [2019-Q3]
- Finalize logo and add it to website (Issue #453) [2019-Q3 → 2019-Q4]
- Write submission to [JOSS](#) (Issue #502) and write submission to [pyOpenSci](#) [2019-Q4 → 2020-Q2]
- Contribute to [IRIS-HEP Analysis Systems Milestones](#) “Initial roadmap for ecosystem coherency” and “Initial roadmap for high-level cyberinfrastructure components of analysis system” [2019-Q4 → 2020-Q2]

### 2. Revision and Maintenance

- Add tests using HEPData published sbottom likelihoods (Issue #518) [2019-Q3]

- Add CI with GitHub Actions and Azure Pipelines (PR #527, Issue #517) [2019-Q3]
- Investigate rewrite of pytest fixtures to use modern pytest (Issue #370) [2019-Q3 → 2019-Q4]
- Factorize out the statistical fitting portion into `pyhf.infer` (PR #531) [2019-Q3 → 2019-Q4]
- Bug squashing at large [2019-Q3 → 2020-Q2]
  - Unexpected use cases (Issues #324, #325, #529)
  - Computational edge cases (Issues #332, #445)
- Make sure that all backends reproduce sbottom results [2019-Q4 → 2020-Q2]

### 3. Development

- Batch support (PR #503) [2019-Q3]
- Add ParamViewer support (PR #519) [2019-Q3]
- Add setting of NPs constant/fixed (PR #653) [2019-Q3]
- Implement pdf as subclass of distributions (PR #551) [2019-Q3]
- Add sampling with toys (PR #558) [2019-Q3]
- Make general modeling choices (e.g., Issue #293) [2019-Q4 → 2020-Q1]
- Add “discovery” test stats ( $p_0$ ) (PR #520) [2019-Q4 → 2020-Q1]
- Add better Model creation [2019-Q4 → 2020-Q1]
- Add background model support (Issues #514, #946) [2019-Q4 → 2020-Q1]
- Develop interface for the optimizers similar to tensor/backend (Issue #754, PR #951) [2019-Q4 → 2020-Q1]
- Migrate to TensorFlow v2.0 (PR #541) [2019-Q4]
- Drop Python 2.7 support at end of 2019 (Issue #469) [2019-Q4 (last week of December 2019)]
- Finalize public API [2020-Q1]
- Integrate pyfitcore/Statistactory API [2020-Q1]

### 4. Research

- Add pyfitcore/Statistactory integrations (Issue #344, [zfit Issue 120](#)) [2019-Q4]
- Hardware acceleration scaling studies (Issues #93, #301) [2019-Q4 → 2020-Q1]
- Speedup through Numba (Issue #364) [2019-Q3 → 2019-Q4]
- Dask backend (Issue #259) [2019-Q3 → 2020-Q1]
- Attempt to use pyhf as fitting tool for full Analysis Systems pipeline test in early 2020 [2019-Q4 → 2020-Q1]
- pyhf should satisfy [IRIS-HEP Analysis Systems Milestone “GPU/accelerator-based implementation of statistical and other appropriate components”](#) [2020-Q1 → 2020-Q2] and contributes to [“Benchmarking and assessment of prototype analysis system components”](#) [2020-Q3 → 2020-Q4]

## 15.3.1 Roadmap as Gantt Chart



## 15.4 Presentations During Roadmap Timeline

- Talk at IRIS-HEP Institute Retreat (September 12-13th, 2019)
- Talk at PyHEP 2019 (October 16-18th, 2019)
- Talk at CHEP 2019 (November 4-8th, 2019)
- Poster at CHEP 2019 (November 4-8th, 2019)

## RELEASE NOTES

### 16.1 v0.6.1

This is a patch release from v0.6.0 → v0.6.1.

#### 16.1.1 Important Notes

- As a result of changes to the default behavior of `torch.distributions` in PyTorch v1.8.0, accommodating changes have been made in the underlying implementations for `pyhf.tensor.pytorch_backend.pytorch_backend()`. These changes require a new lower bound of torch v1.8.0 for use of the PyTorch backend.

#### 16.1.2 Fixes

- In the PyTorch backend the `validate_args` kwarg is used with `torch.distributions` to ensure a continuous approximation of the Poisson distribution in torch v1.8.0+.

#### 16.1.3 Features

##### Python API

- The `solver_options` kwarg can be passed to the `pyhf.optimize.opt_scipy.scipy_optimizer()` optimizer for additional configuration of the minimization. See `scipy.optimize.show_options()` for additional options of optimization solvers.
- The `torch` API is now used to provide the implementations of the `ravel`, `tile`, and `outer` tensorlib methods for the PyTorch backend.

### 16.2 v0.6.0

This is a minor release from v0.5.4 → v0.6.0.

### 16.2.1 Important Notes

- Please note this release has **API breaking changes** and carefully read these notes while updating your code to the `v0.6.0` API. Perhaps most relevant is the changes to the `pyhf.infer.hypotest()` API, which now uses a `calctype` argument to differentiate between using an asymptotic calculator or a toy calculator, and a `test_stat` kwarg to specify which test statistic the calculator should use, with `'qtilde'`, corresponding to `pyhf.infer.test_statistics.qmu_tilde()`, now the default option. It also relies more heavily on using kwargs to pass options through to the optimizer.
- Following the recommendations of [NEP 29 — Recommend Python and NumPy version support as a community policy standard](#) pyhf `v0.6.0` drops support for Python 3.6. [PEP 494 – Python 3.6 Release Schedule](#) also notes that Python 3.6 will be end of life in December 2021, so pyhf is moving forward with a minimum required runtime of Python 3.7.
- Support for the discovery test statistic,  $q_0$ , has now been added through the `pyhf.infer.test_statistics.q0()` API.
- Support for pseudoexperiments (toys) has been added through the `pyhf.infer.calculators.ToyCalculator()` API. Please see the corresponding [example notebook](#) for more detailed exploration of the API.
- The minuit extra, `python -m pip install pyhf[minuit]`, now uses and requires the `iminuit v2.X` release series and API. Note that `iminuit v2.X` can result in slight differences in minimization results from `iminuit v1.X`.
- The documentation will now be versioned with releases on ReadTheDocs. Please use [pyhf.readthedocs.io](https://pyhf.readthedocs.io) to access the documentation for the latest stable release of pyhf.
- pyhf is transitioning away from Stack Overflow to [GitHub Discussions](#) for resolving user questions not covered in the documentation. Please check the [GitHub Discussions](#) page to search for discussions addressing your questions and to open up a new discussion if your question is not covered.
- pyhf has published a paper in the Journal of Open Source Software. Please make sure to include the paper reference in all citations of pyhf, as documented in the [Use and Citations](#) section of the documentation.

### 16.2.2 Fixes

- Fix bug where all extras triggered warning for installation of the `contrib` extra.
- float-like values are used in division for `pyhf.writexml()`.
- `Model.spec` now supports building new models from existing models.
- $p$ -values are now reported based on their quantiles, instead of interpolating test statistics and converting to  $p$ -values.
- Namespace collisions between `uproot3` and `uproot/uproot4` have been fixed for the `xmlio` extra.
- The `normsys` modifier now uses the `pyhf.interpolators.code4` interpolation method by default.
- The `histosys` modifier now uses the `pyhf.interpolators.code4p` interpolation method by default.

## 16.2.3 Features

### Python API

- The `tensorlib` API now supports a `tensorlib.to_numpy` and `tensorlib.ravel` API.
- The `pyhf.infer.calculators.ToyCalculator()` API has been added to support pseudoexperiments (toys).
- The empirical test statistic distribution API has been added to help support the `ToyCalculator` API.
- Add a `tolerance` kwarg to the optimizer API to set a `float` value as a tolerance for termination of the fit.
- The `pyhf.optimize.opt_minuit.minuit_optimizer()` optimizer now can return correlations of the fitted parameters through use of the `return_correlation` Boolean kwarg.
- Add the `pyhf.utils.citation` API to get a `str` of the preferred BibTeX entry for citation of the version of `pyhf` installed. See the example for the CLI API for more information.
- The `pyhf.infer.hypotest()` API now uses a `calctype` argument to differentiate between using an asymptotic calculator or a toy calculator, and a `test_stat` kwarg to specify which test statistic to use. It also relies more heavily on using kwargs to pass options through to the optimizer.
- The default `test_stat` kwarg for `pyhf.infer.hypotest()` and the calculator APIs is `'qtilde'`, which corresponds to the alternative test statistic `pyhf.infer.test_statistics.qmu_tilde()`.
- The return type of  $p$ -value like functions is now a 0-dimensional tensor (with shape `()`) instead of a `float`. This is required to support end-to-end automatic differentiation in future releases.

### CLI API

- The CLI API now supports a `--citation` or `--cite` option to print the preferred BibTeX entry for citation of the version of `pyhf` installed.

```
$ pyhf --citation
@software{pyhf,
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark},
  title = "{pyhf: v0.6.0}",
  version = {0.6.0},
  doi = {10.5281/zenodo.1169739},
  url = {https://doi.org/10.5281/zenodo.1169739},
  note = {https://github.com/scikit-hep/pyhf/releases/tag/v0.6.0}
}

@article{pyhf_joss,
  doi = {10.21105/joss.02823},
  url = {https://doi.org/10.21105/joss.02823},
  year = {2021},
  publisher = {The Open Journal},
  volume = {6},
  number = {58},
  pages = {2823},
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark and Kyle Cranmer},
  title = {pyhf: pure-Python implementation of HistFactory statistical models},
  journal = {Journal of Open Source Software}
}
```

## 16.2.4 Contributors

v0.6.0 benefited from contributions from:

- Alexander Held
- Marco Gorelli
- Pradyumna Rahul K
- Eric Schanet
- Henry Schreiner

## 16.3 v0.5.4

This is a patch release from v0.5.3 → v0.5.4.

### 16.3.1 Fixes

- Require uproot3 instead of uproot v3.X releases to avoid conflicts when uproot4 is installed in an environment with uproot v3.X installed and namespace conflicts with uproot-methods. Adoption of uproot3 in v0.5.4 will ensure v0.5.4 works far into the future if XML and ROOT I/O through uproot is required.

#### Example:

Without the v0.5.4 patch release there is a regression in using uproot v3.X and uproot4 in the same environment (which was swiftly identified and patched by the fantastic uproot team)

```
$ python -m pip install "pyhf[xmlio]<0.5.4"
$ python -m pip list | grep "pyhf\|uproot"
pyhf              0.5.3
uproot            3.13.1
uproot-methods    0.8.0
$ python -m pip install uproot4
$ python -m pip list | grep "pyhf\|uproot"
pyhf              0.5.3
uproot            4.0.0
uproot-methods    0.8.0
uproot4           4.0.0
```

this is resolved in v0.5.4 with the requirement of uproot3

```
$ python -m pip install "pyhf[xmlio]>=0.5.4"
$ python -m pip list | grep "pyhf\|uproot"
pyhf              0.5.4
uproot3           3.14.1
uproot3-methods   0.10.0
$ python -m pip install uproot4 # or uproot
$ python -m pip list | grep "pyhf\|uproot"
pyhf              0.5.4
uproot            4.0.0
uproot3           3.14.1
uproot3-methods   0.10.0
uproot4           4.0.0
```



## 16.4 v0.5.3

This is a patch release from v0.5.2 → v0.5.3.

### 16.4.1 Fixes

- Workspaces are now immutable
- ShapeFactor support added to XML reading and writing
- An error is raised if a fit initialization parameter is outside of its bounds (preventing hypotest with POI outside of bounds)

### 16.4.2 Features

#### Python API

- Inverting hypothesis tests to get upper limits now has an API with `pyhf.infer.intervals.upperlimit`
- Building workspaces from a model and data added with `pyhf.workspace.build`

#### CLI API

- Added CLI API for `pyhf.infer.fit`: `pyhf fit`
- `pyhf combine` now allows for merging channels: `pyhf combine --merge-channels --join <join option>`
- Added utility to download archived pyhf pallets (workspaces + patchsets) to contrib module: `pyhf contrib download`

### 16.4.3 Contributors

v0.5.3 benefited from contributions from:

- Karthikeyan Singaravelan



## CONTRIBUTORS

`pyhf` is openly developed and benefits from the contributions and feedback from its users. The `pyhf` dev team would like to thank all contributors to the project for their support and help. Thank you!

Contributors include:

- Jessica Forde
- Ruggero Turra
- Tadej Novak
- Frank Sauerburger
- Lars Nielsen
- Kanishk Kalra
- Nikolai Hartmann
- Alexander Held
- Karthikeyan Singaravelan
- Marco Gorelli
- Pradyumna Rahul K
- Eric Schanet
- Henry Schreiner





## PURE-PYTHON FITTING/LIMIT-SETTING/INTERVAL ESTIMATION HISTFACTORY-STYLE

The HistFactory p.d.f. template [CERN-OPEN-2012-016] is per-se independent of its implementation in ROOT and sometimes, it's useful to be able to run statistical analysis outside of ROOT, RooFit, RooStats framework.

This repo is a pure-python implementation of that statistical model for multi-bin histogram-based analysis and its interval estimation is based on the asymptotic formulas of “Asymptotic formulae for likelihood-based tests of new physics” [arXiv:1007.1727]. The aim is also to support modern computational graph libraries such as PyTorch and TensorFlow in order to make use of features such as autodifferentiation and GPU acceleration.

### 18.1 Hello World

This is how you use the pyhf Python API to build a statistical model and run basic inference:

```
>>> import pyhf
>>> model = pyhf.simplemodels.uncorrelated_background(
...     signal=[12.0, 11.0], bkg=[50.0, 52.0], bkg_uncertainty=[3.0, 7.0]
... )
>>> data = [51, 48] + model.config.auxdata
>>> test_mu = 1.0
>>> CLs_obs, CLs_exp = pyhf.infer.hypotest(
...     test_mu, data, model, test_stat="qtilde", return_expected=True
... )
>>> print(f"Observed: {CLs_obs}, Expected: {CLs_exp}")
Observed: 0.05251497423736956, Expected: 0.06445320535890459
```

Alternatively the statistical model and observational data can be read from its serialized JSON representation (see next section).

```
>>> import pyhf
>>> import requests
>>> wspace = pyhf.Workspace(requests.get("https://git.io/JJYDE").json())
>>> model = wspace.model()
>>> data = wspace.data(model)
```

(continues on next page)

(continued from previous page)

```
>>> test_mu = 1.0
>>> CLs_obs, CLs_exp = pyhf.infer.hypotest(
...     test_mu, data, model, test_stat="qtilde", return_expected=True
... )
>>> print(f"Observed: {CLs_obs}, Expected: {CLs_exp}")
Observed: 0.3599840922126626, Expected: 0.3599840922126626
```

Finally, you can also use the command line interface that pyhf provides

```
$ cat << EOF | tee likelihood.json | pyhf cls
{
  "channels": [
    { "name": "singlechannel",
      "samples": [
        { "name": "signal",
          "data": [12.0, 11.0],
          "modifiers": [ { "name": "mu", "type": "normfactor", "data": null} ]
        },
        { "name": "background",
          "data": [50.0, 52.0],
          "modifiers": [ { "name": "uncorr_bkguncrt", "type": "shapesys", "data": [3.
→0, 7.0]} ]
        }
      ]
    }
  ],
  "observations": [
    { "name": "singlechannel", "data": [51.0, 48.0] }
  ],
  "measurements": [
    { "name": "Measurement", "config": { "poi": "mu", "parameters": [] } }
  ],
  "version": "1.0.0"
}
EOF
```

which should produce the following JSON output:

```
{
  "CLs_exp": [
    0.0026062609501074576,
    0.01382005356161206,
    0.06445320535890459,
    0.23525643861460702,
    0.573036205919389
  ],
  "CLs_obs": 0.05251497423736956
}
```

## 18.2 What does it support

### Implemented variations:

- HistoSys
- OverallSys
- ShapeSys
- NormFactor
- Multiple Channels
- Import from XML + ROOT via [uproot](#)
- ShapeFactor
- StatError
- Lumi Uncertainty
- Non-asymptotic calculators

### Computational Backends:

- NumPy
- PyTorch
- TensorFlow
- JAX

### Optimizers:

- SciPy (`scipy.optimize`)
- MINUIT (`iminuit`)

All backends can be used in combination with all optimizers. Custom user backends and optimizers can be used as well.

## 18.3 Todo

- StatConfig

results obtained from this package are validated against output computed from HistFactory workspaces

## 18.4 A one bin example

```
import pyhf
import numpy as np
import matplotlib.pyplot as plt
from pyhf.contrib.viz import brazil

pyhf.set_backend("numpy")
model = pyhf.simplemodels.uncorrelated_background(
    signal=[10.0], bkg=[50.0], bkg_uncertainty=[7.0]
```

(continues on next page)

(continued from previous page)

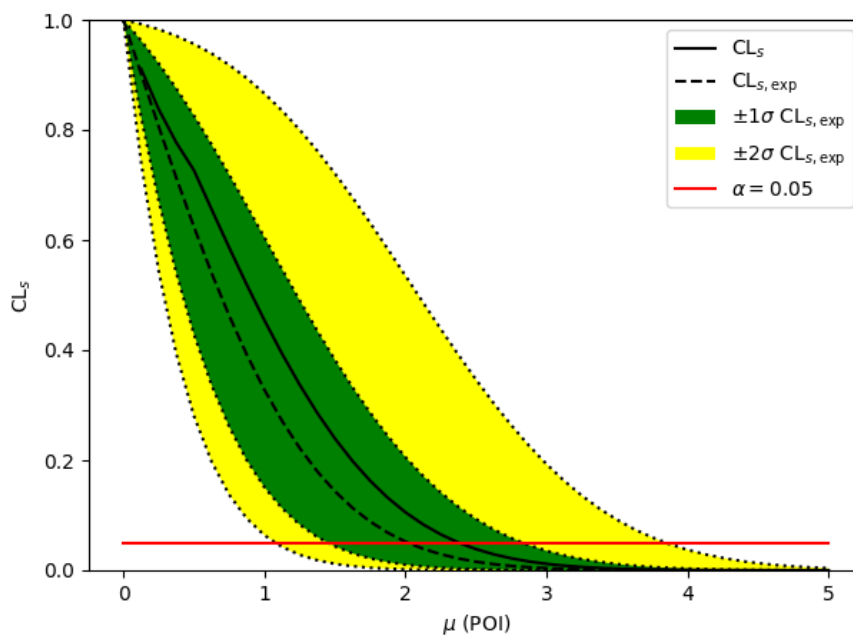
```

)
data = [55.0] + model.config.auxdata

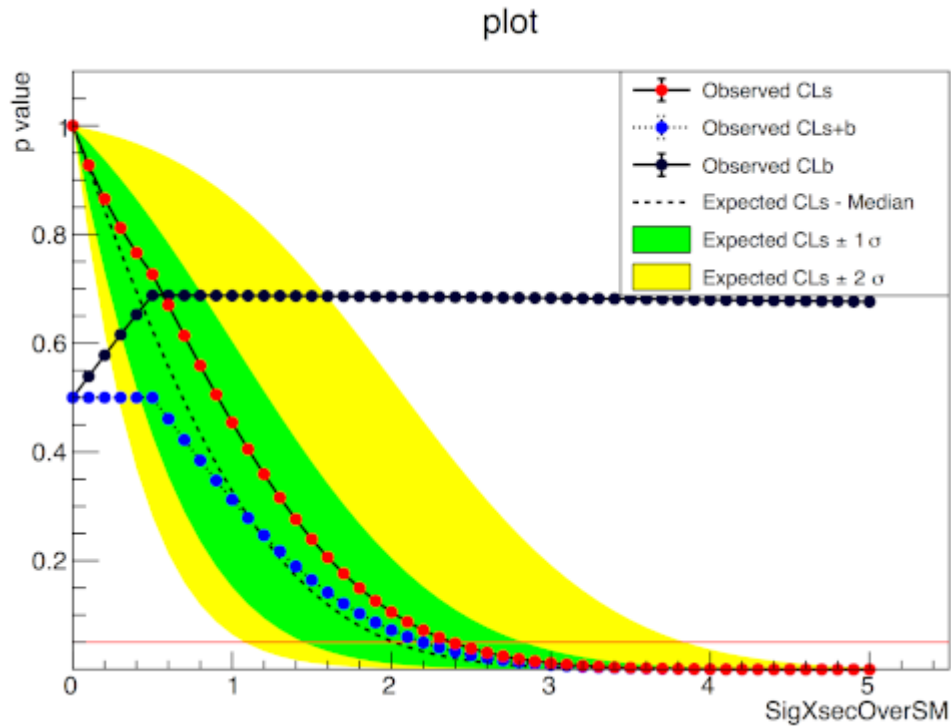
poi_vals = np.linspace(0, 5, 41)
results = [
    pyhf.infer.hypotest(
        test_poi, data, model, test_stat="qtilde", return_expected_set=True
    )
    for test_poi in poi_vals
]

fig, ax = plt.subplots()
fig.set_size_inches(7, 5)
brazil.plot_results(poi_vals, results, ax=ax)
fig.show()

```

**pyhf****ROOT**





## 18.5 A two bin example

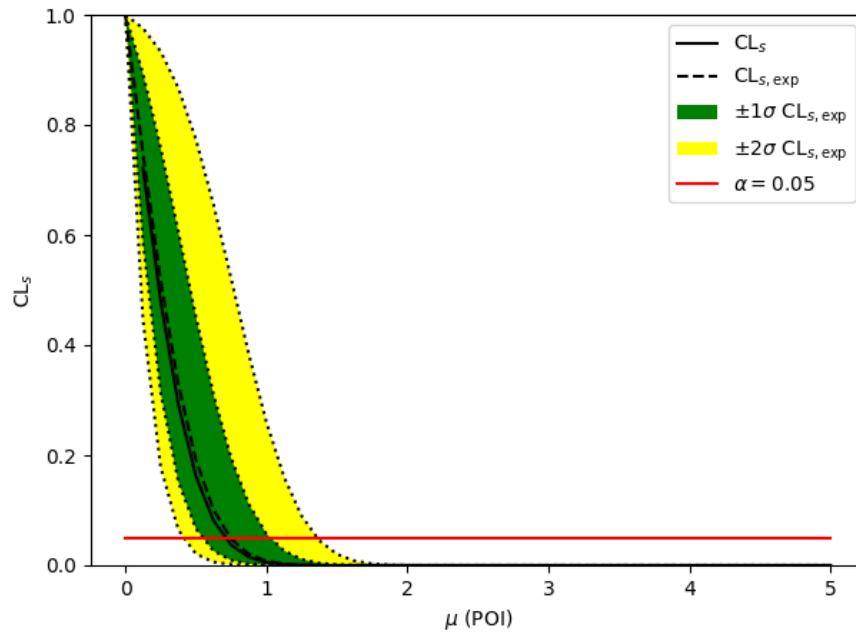
```
import pyhf
import numpy as np
import matplotlib.pyplot as plt
from pyhf.contrib.viz import brazil

pyhf.set_backend("numpy")
model = pyhf.simplemodels.uncorrelated_background(
    signal=[30.0, 45.0], bkg=[100.0, 150.0], bkg_uncertainty=[15.0, 20.0]
)
data = [100.0, 145.0] + model.config.auxdata

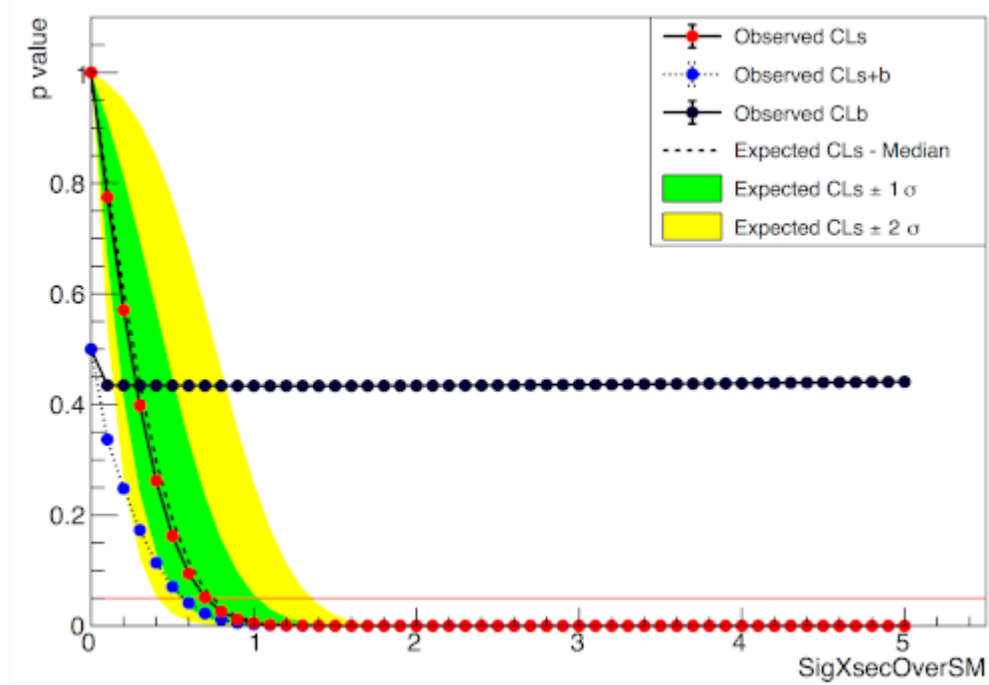
poi_vals = np.linspace(0, 5, 41)
results = [
    pyhf.infer.hypotest(
        test_poi, data, model, test_stat="qtilde", return_expected_set=True
    )
    for test_poi in poi_vals
]

fig, ax = plt.subplots()
fig.set_size_inches(7, 5)
brazil.plot_results(poi_vals, results, ax=ax)
fig.show()
```

pyhf



## ROOT



## 18.6 Installation

To install pyhf from PyPI with the NumPy backend run

```
python -m pip install pyhf
```

and to install pyhf with all additional backends run

```
python -m pip install pyhf[backends]
```

or a subset of the options.

To uninstall run

```
python -m pip uninstall pyhf
```

## 18.7 Questions

If you have a question about the use of pyhf not covered in [the documentation](#), please ask a question on the [GitHub Discussions](#).

If you believe you have found a bug in pyhf, please report it in the [GitHub Issues](#). If you're interested in getting updates from the pyhf dev team and release announcements you can join the [pyhf-announcements mailing list](#).

## 18.8 Citation

As noted in [Use and Citations](#), the preferred BibTeX entry for citation of pyhf includes both the [Zenodo](#) archive and the [JOSS](#) paper:

```
@software{pyhf,
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark},
  title = "{pyhf: v0.6.1}",
  version = {0.6.1},
  doi = {10.5281/zenodo.1169739},
  url = {https://doi.org/10.5281/zenodo.1169739},
  note = {https://github.com/scikit-hep/pyhf/releases/tag/v0.6.1}
}

@article{pyhf_joss,
  doi = {10.21105/joss.02823},
  url = {https://doi.org/10.21105/joss.02823},
  year = {2021},
  publisher = {The Open Journal},
  volume = {6},
  number = {58},
  pages = {2823},
  author = {Lukas Heinrich and Matthew Feickert and Giordon Stark and Kyle Cranmer},
  title = {pyhf: pure-Python implementation of HistFactory statistical models},
  journal = {Journal of Open Source Software}
}
```

## 18.9 Authors

pyhf is openly developed by Lukas Heinrich, Matthew Feickert, and Giordon Stark.

Please check the [contribution statistics](#) for a [list of contributors](#).

## 18.10 Milestones

- 2020-07-28: 1000 GitHub issues and pull requests. (See PR [#1000](#))

## 18.11 Acknowledgements

Matthew Feickert has received support to work on pyhf provided by NSF cooperative agreement [OAC-1836650](#) (IRIS-HEP) and grant [OAC-1450377](#) (DIANA/HEP).

## INDICES AND TABLES

- `genindex`
- `modindex`
- `search`



## BIBLIOGRAPHY

- [intro-1] Glen Cowan, Kyle Cranmer, Eilam Gross, and Ofer Vitells. Asymptotic formulae for likelihood-based tests of new physics. *Eur. Phys. J. C*, 71:1554, 2011. [arXiv:1007.1727](#), doi:10.1140/epjc/s10052-011-1554-0.
- [intro-2] Kyle Cranmer, George Lewis, Lorenzo Moneta, Akira Shibata, and Wouter Verkerke. HistFactory: A tool for creating statistical models for use with RooFit and RooStats. Technical Report CERN-OPEN-2012-016, New York U., New York, Jan 2012. URL: <https://cds.cern.ch/record/1456844>.
- [intro-3] Eamonn Maguire, Lukas Heinrich, and Graeme Watt. HEPData: a repository for high energy physics data. *J. Phys. Conf. Ser.*, 898(10):102006, 2017. [arXiv:1704.05473](#), doi:10.1088/1742-6596/898/10/102006.
- [intro-4] ATLAS Collaboration. Measurements of Higgs boson production and couplings in diboson final states with the ATLAS detector at the LHC. *Phys. Lett. B*, 726:88, 2013. [arXiv:1307.1427](#), doi:10.1016/j.physletb.2014.05.011.
- [intro-5] ATLAS Collaboration. Search for supersymmetry in final states with missing transverse momentum and multiple  $(b)$ -jets in proton–proton collisions at  $\sqrt{s} = 13$  TeV with the ATLAS detector. ATLAS-CONF-2018-041, 2018. URL: <https://cds.cern.ch/record/2632347>.
- [likelihood-1] Histfactory definitions schema. Accessed: 2019-06-20. URL: <https://scikit-hep.org/pyhf/schemas/1.0.0/defs.json>.
- [likelihood-2] Kyle Cranmer, George Lewis, Lorenzo Moneta, Akira Shibata, and Wouter Verkerke. HistFactory: A tool for creating statistical models for use with RooFit and RooStats. Technical Report CERN-OPEN-2012-016, New York U., New York, Jan 2012. URL: <https://cds.cern.ch/record/1456844>.





## PYTHON MODULE INDEX

### p

`pyhf.compat`, [118](#)  
`pyhf.contrib.viz.brazil`, [208](#)  
`pyhf.readxml`, [115](#)  
`pyhf.writexml`, [116](#)



## Symbols

- `__ModelConfig` (class in `pyhf.pdf`), 126
- `__init__()` (`pyhf.contrib.viz.brazil.BrazilBandCollection` method), 209
- `__init__()` (`pyhf.infer.calculators.AsymptoticCalculator` method), 190
- `__init__()` (`pyhf.infer.calculators.AsymptoticTestStatDistribution` method), 186
- `__init__()` (`pyhf.infer.calculators.EmpiricalDistribution` method), 188
- `__init__()` (`pyhf.infer.calculators.ToyCalculator` method), 193
- `__init__()` (`pyhf.interpolators.code0` method), 177
- `__init__()` (`pyhf.interpolators.code1` method), 177
- `__init__()` (`pyhf.interpolators.code2` method), 178
- `__init__()` (`pyhf.interpolators.code4` method), 179
- `__init__()` (`pyhf.interpolators.code4p` method), 179
- `__init__()` (`pyhf.modifiers.histosys` method), 174
- `__init__()` (`pyhf.modifiers.normfactor` method), 174
- `__init__()` (`pyhf.modifiers.normsys` method), 175
- `__init__()` (`pyhf.modifiers.shapefactor` method), 175
- `__init__()` (`pyhf.modifiers.shapesys` method), 176
- `__init__()` (`pyhf.modifiers.staterror` method), 176
- `__init__()` (`pyhf.optimize.mixins.OptimizerMixin` method), 170
- `__init__()` (`pyhf.optimize.opt_minuit.minuit_optimizer` method), 173
- `__init__()` (`pyhf.optimize.opt_scipy.scipy_optimizer` method), 172
- `__init__()` (`pyhf.patchset.Patch` method), 135
- `__init__()` (`pyhf.patchset.PatchSet` method), 133
- `__init__()` (`pyhf.pdf.Model` method), 124
- `__init__()` (`pyhf.pdf._ModelConfig` method), 126
- `__init__()` (`pyhf.probability.Independent` method), 121
- `__init__()` (`pyhf.probability.Normal` method), 120
- `__init__()` (`pyhf.probability.Poisson` method), 121
- `__init__()` (`pyhf.probability.Simultaneous` method), 123
- `__init__()` (`pyhf.tensor.jax_backend.jax_backend` method), 163
- `__init__()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 138
- `__init__()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 146
- `__init__()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 154
- `__init__()` (`pyhf.workspace.Workspace` method), 128
- `_create_and_register_paramsets()` (`pyhf.pdf._ModelConfig` method), 126
- `_get_minimizer()` (`pyhf.optimize.opt_minuit.minuit_optimizer` method), 173
- `_get_minimizer()` (`pyhf.optimize.opt_scipy.scipy_optimizer` method), 172
- `_internal_minimize()` (`pyhf.optimize.mixins.OptimizerMixin` method), 171
- `_internal_postprocess()` (`pyhf.optimize.mixins.OptimizerMixin` method), 171
- `_joint_logpdf()` (`pyhf.probability.Simultaneous` static method), 123
- `_minimize()` (`pyhf.optimize.opt_minuit.minuit_optimizer` method), 173
- `_minimize()` (`pyhf.optimize.opt_scipy.scipy_optimizer` method), 172
- `_modifications()` (`pyhf.pdf.Model` method), 124
- `_precompute()` (`pyhf.interpolators.code0` method), 177
- `_precompute()` (`pyhf.interpolators.code1` method), 178
- `_precompute()` (`pyhf.interpolators.code2` method), 178
- `_precompute()` (`pyhf.interpolators.code4` method), 179
- `_precompute()` (`pyhf.interpolators.code4p` method), 179
- `_precompute_alphasets()` (`pyhf.interpolators.code0` method), 177
- `_precompute_alphasets()` (`pyhf.interpolators.code1` method), 178
- `_precompute_alphasets()` (`pyhf.interpolators.code2` method), 178
- `_precompute_alphasets()` (`pyhf.interpolators.code4` method), 179
- `_precompute_alphasets()` (`pyhf.interpolators.code4p` method), 179
- `_prune_and_rename()` (`pyhf.workspace.Workspace` method), 129

`_setup()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 163

`_setup()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 138

`_setup()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 146

`_setup()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 154

`--algorithm <algorithm>`  
pyhf-digest command line option, 104

`--backend <backend>`  
pyhf-cls command line option, 102  
pyhf-fit command line option, 105

`--basedir <basedir>`  
pyhf-xml2json command line option, 111

`--calctype <calctype>`  
pyhf-cls command line option, 102

`--channel <CHANNEL>...>`  
pyhf-prune command line option, 109

`--channel <PATTERN> <REPLACE>...>`  
pyhf-rename command line option, 110

`--citation`  
pyhf command line option, 101

`--cite`  
pyhf command line option, 101

`--compress`  
pyhf-contrib-download command line option, 104

`--dataroot <dataroot>`  
pyhf-json2xml command line option, 107

`--force`  
pyhf-contrib-download command line option, 104

`--hide-progress`  
pyhf-xml2json command line option, 111

`--join <join>`  
pyhf-combine command line option, 102

`--json`  
pyhf-digest command line option, 104

`--measurement <MEASUREMENT>...>`  
pyhf-prune command line option, 109

`--measurement <PATTERN> <REPLACE>...>`  
pyhf-rename command line option, 110

`--measurement <measurement>`  
pyhf-cls command line option, 102  
pyhf-fit command line option, 105  
pyhf-inspect command line option, 106

`--merge-channels`  
pyhf-combine command line option, 102

`--modifier <MODIFIER>...>`  
pyhf-prune command line option, 109

`--modifier <PATTERN> <REPLACE>...>`  
pyhf-rename command line option, 110

`--modifier-type <modifier_type>`  
pyhf-prune command line option, 109

`--name <name>`  
pyhf-patchset-apply command line option, 108

`pyhf-patchset-extract` command line option, 108

`--do-merge-channels`  
pyhf-combine command line option, 102

`--optconf <optconf>`  
pyhf-cls command line option, 102  
pyhf-fit command line option, 105

`--optimizer <optimizer>`  
pyhf-cls command line option, 102  
pyhf-fit command line option, 105

`--output-dir <output_dir>`  
pyhf-json2xml command line option, 107

`--output-file <output_file>`  
pyhf-cls command line option, 102  
pyhf-combine command line option, 102  
pyhf-fit command line option, 105  
pyhf-inspect command line option, 106  
pyhf-patchset-apply command line option, 108

`pyhf-patchset-extract` command line option, 108

`pyhf-prune` command line option, 109

`pyhf-rename` command line option, 110

`pyhf-sort` command line option, 111

`pyhf-xml2json` command line option, 111

`--patch <patch>`  
pyhf-cls command line option, 102  
pyhf-fit command line option, 105  
pyhf-json2xml command line option, 107

`--plaintext`  
pyhf-digest command line option, 104

`--resultprefix <resultprefix>`  
pyhf-json2xml command line option, 107

`--sample <PATTERN> <REPLACE>...>`  
pyhf-rename command line option, 110

`--sample <SAMPLE>...>`  
pyhf-prune command line option, 109

`--specroot <specroot>`  
pyhf-json2xml command line option, 107

`--test-poi <test_poi>`  
pyhf-cls command line option, 102

`--test-stat <test_stat>`  
pyhf-cls command line option, 102

`--track-progress`  
pyhf-xml2json command line option, 111

`--value`  
pyhf-fit command line option, 105

`--verbose`  
pyhf-contrib-download command line option, 104

--version  
     pyhf command line option, 101

--with-metadata  
     pyhf-patchset-extract command line option, 108

--without-metadata  
     pyhf-patchset-extract command line option, 108

-a  
     pyhf-digest command line option, 104

-c  
     pyhf-contrib-download command line option, 104  
     pyhf-prune command line option, 109  
     pyhf-rename command line option, 110

-f  
     pyhf-contrib-download command line option, 104

-j  
     pyhf-combine command line option, 102  
     pyhf-digest command line option, 104

-m  
     pyhf-prune command line option, 109  
     pyhf-rename command line option, 110

-p  
     pyhf-cls command line option, 102  
     pyhf-digest command line option, 104  
     pyhf-fit command line option, 105  
     pyhf-json2xml command line option, 107

-s  
     pyhf-prune command line option, 109  
     pyhf-rename command line option, 110

-t  
     pyhf-prune command line option, 109

-v  
     pyhf-contrib-download command line option, 104

## A

abs() (pyhf.tensor.jax\_backend.jax\_backend method), 163

abs() (pyhf.tensor.numpy\_backend.numpy\_backend method), 138

abs() (pyhf.tensor.pytorch\_backend.pytorch\_backend method), 146

abs() (pyhf.tensor.tensorflow\_backend.tensorflow\_backend method), 154

all\_pois\_floating() (in module pyhf.infer.utils), 203

apply() (pyhf.patchset.PatchSet method), 134

ARCHIVE\_URL  
     pyhf-contrib-download command line option, 104

astensor() (pyhf.tensor.jax\_backend.jax\_backend method), 163

astensor() (pyhf.tensor.numpy\_backend.numpy\_backend method), 138

astensor() (pyhf.tensor.pytorch\_backend.pytorch\_backend method), 146

astensor() (pyhf.tensor.tensorflow\_backend.tensorflow\_backend method), 154

AsymptoticCalculator (class in pyhf.infer.calculators), 190

AsymptoticTestStatDistribution (class in pyhf.infer.calculators), 186

axes (pyhf.contrib.viz.brazil.BrazilBandCollection attribute), 209

## B

### BACKGROUND\_ONLY

    pyhf-patchset-apply command line option, 108

    pyhf-patchset-verify command line option, 109

boolean\_mask() (pyhf.tensor.jax\_backend.jax\_backend method), 163

boolean\_mask() (pyhf.tensor.numpy\_backend.numpy\_backend method), 139

boolean\_mask() (pyhf.tensor.pytorch\_backend.pytorch\_backend method), 146

boolean\_mask() (pyhf.tensor.tensorflow\_backend.tensorflow\_backend method), 154

BrazilBandCollection (class in pyhf.contrib.viz.brazil), 209

build() (pyhf.workspace.Workspace class method), 129

build\_channel() (in module pyhf.writexml), 117

build\_data() (in module pyhf.writexml), 117

build\_measurement() (in module pyhf.writexml), 117

build\_modifier() (in module pyhf.writexml), 117

build\_sample() (in module pyhf.writexml), 117

## C

cdf() (pyhf.infer.calculators.AsymptoticTestStatDistribution method), 187

citation() (in module pyhf.utils), 208

clb (pyhf.contrib.viz.brazil.BrazilBandCollection attribute), 209

clear\_filecache() (in module pyhf.readxml), 115

clip() (pyhf.tensor.jax\_backend.jax\_backend method), 163

clip() (pyhf.tensor.numpy\_backend.numpy\_backend method), 139

clip() (pyhf.tensor.pytorch\_backend.pytorch\_backend method), 146

clip() (pyhf.tensor.tensorflow\_backend.tensorflow\_backend method), 154

cls\_exp (pyhf.contrib.viz.brazil.BrazilBandCollection attribute), 209

- `cls_obs` (`pyhf.contrib.viz.brazil.BrazilBandCollection` attribute), 209
- `clsb` (`pyhf.contrib.viz.brazil.BrazilBandCollection` attribute), 209
- `code0` (class in `pyhf.interpolators`), 177
- `code1` (class in `pyhf.interpolators`), 177
- `code2` (class in `pyhf.interpolators`), 178
- `code4` (class in `pyhf.interpolators`), 178
- `code4p` (class in `pyhf.interpolators`), 179
- `combine()` (`pyhf.workspace.Workspace` class method), 129
- `concatenate()` (`pyhf.tensor.jax_backend.jax_backend` method), 164
- `concatenate()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 139
- `concatenate()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 147
- `concatenate()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 155
- `conditional()` (`pyhf.tensor.jax_backend.jax_backend` method), 164
- `conditional()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 139
- `conditional()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 147
- `conditional()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 155
- `constraint_logpdf()` (`pyhf.pdf.Model` method), 124
- `correlated_background()` (in module `pyhf.simplemodels`), 137
- `create_calculator()` (in module `pyhf.infer.utils`), 197
- D**
- `data()` (`pyhf.workspace.Workspace` method), 130
- `dedupe_parameters()` (in module `pyhf.readxml`), 115
- `default_backend` (in module `pyhf`), 113
- `default_do_grad` (`pyhf.tensor.jax_backend.jax_backend` attribute), 163
- `default_do_grad` (`pyhf.tensor.numpy_backend.numpy_backend` attribute), 138
- `default_do_grad` (`pyhf.tensor.pytorch_backend.pytorch_backend` attribute), 146
- `default_do_grad` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` attribute), 154
- `default_optimizer` (in module `pyhf`), 113
- `description` (`pyhf.patchset.PatchSet` attribute), 134
- `digest()` (in module `pyhf.utils`), 207
- `digests` (`pyhf.patchset.PatchSet` attribute), 134
- `distributions()` (`pyhf.infer.calculators.AsymptoticCalculator` method), 191
- `distributions()` (`pyhf.infer.calculators.ToyCalculator` method), 194
- `divide()` (`pyhf.tensor.jax_backend.jax_backend` method), 164
- `divide()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 140
- `divide()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 147
- `divide()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 156
- `download()` (in module `pyhf.contrib.utils`), 213
- `dtypesmap` (`pyhf.tensor.jax_backend.jax_backend` attribute), 163
- `dtypesmap` (`pyhf.tensor.numpy_backend.numpy_backend` attribute), 138
- `dtypesmap` (`pyhf.tensor.pytorch_backend.pytorch_backend` attribute), 146
- `dtypesmap` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` attribute), 154
- E**
- `einsum()` (`pyhf.tensor.jax_backend.jax_backend` method), 165
- `einsum()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 140
- `einsum()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 148
- `einsum()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 156
- `EmpiricalDistribution` (class in `pyhf.infer.calculators`), 188
- `ENTRYPOINT_XML`
- `pyhf-xml2json` command line option, 111
- `erf()` (`pyhf.tensor.jax_backend.jax_backend` method), 165
- `erf()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 140
- `erf()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 148
- `erf()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 156
- `erfinv()` (`pyhf.tensor.jax_backend.jax_backend` method), 165
- `erfinv()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 141
- `erfinv()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 148
- `erfinv()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 156
- `errordef` (`pyhf.optimize.opt_minuit.minuit_optimizer` attribute), 173
- `exp()` (`pyhf.tensor.jax_backend.jax_backend` method), 165
- `exp()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 141
- `exp()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 148

- `exp()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 156
- `expected_actualdata()` (*pyhf.pdf.Model* method), 124
- `expected_auxdata()` (*pyhf.pdf.Model* method), 125
- `expected_data()` (*pyhf.pdf.Model* method), 125
- `expected_data()` (*pyhf.probability.Normal* method), 120
- `expected_data()` (*pyhf.probability.Poisson* method), 121
- `expected_data()` (*pyhf.probability.Simultaneous* method), 123
- `expected_pvalues()` (*pyhf.infer.calculators.AsymptoticCalculator* method), 191
- `expected_pvalues()` (*pyhf.infer.calculators.ToyCalculator* method), 195
- `expected_value()` (*pyhf.infer.calculators.AsymptoticTestStatDistribution* method), 187
- `expected_value()` (*pyhf.infer.calculators.EmpiricalDistribution* method), 188
- `extract_error()` (in module *pyhf.readxml*), 115
- ## F
- `fit()` (in module *pyhf.infer.mle*), 199
- `fixed_poi_fit()` (in module *pyhf.infer.mle*), 200
- ## G
- `gather()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 165
- `gather()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 141
- `gather()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 148
- `gather()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 157
- `generate_asimov_data()` (in module *pyhf.infer.calculators*), 186
- `get_backend()` (in module *pyhf*), 114
- `get_measurement()` (*pyhf.workspace.Workspace* method), 130
- `get_test_stat()` (in module *pyhf.infer.utils*), 185
- ## H
- `hepdata_like()` (in module *pyhf.simplemodels*), 138
- `histosys` (class in *pyhf.modifiers*), 174
- `hypotest()` (in module *pyhf.infer*), 201
- ## I
- `import_root_histogram()` (in module *pyhf.readxml*), 116
- `ImportBackendError`, 206
- `indent()` (in module *pyhf.writexml*), 118
- `Independent` (class in *pyhf.probability*), 121
- `interpret_rootname()` (in module *pyhf.compat*), 118
- `InvalidBackend`, 206
- `InvalidInterpCode`, 206
- `InvalidMeasurement`, 204
- `InvalidModel`, 205
- `InvalidModifier`, 206
- `InvalidNameReuse`, 205
- `InvalidOptimizer`, 206
- `InvalidPatchLookup`, 205
- `InvalidPatchSet`, 205
- `InvalidPdfData`, 206
- `InvalidPdfParameters`, 206
- `InvalidSpecification`, 205
- `InvalidWorkspaceOperation`, 205
- `is_constrained` (*pyhf.modifiers.histosys* attribute), 174
- `is_constrained` (*pyhf.modifiers.normfactor* attribute), 175
- `is_constrained` (*pyhf.modifiers.normsys* attribute), 175
- `is_constrained` (*pyhf.modifiers.shapefactor* attribute), 175
- `is_constrained` (*pyhf.modifiers.shapesys* attribute), 176
- `is_constrained` (*pyhf.modifiers.staterror* attribute), 176
- `isfinite()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 166
- `isfinite()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 141
- `isfinite()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 148
- `isfinite()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 157
- ## J
- `jax_backend` (class in *pyhf.tensor.jax\_backend*), 163
- ## L
- `labels` (*pyhf.patchset.PatchSet* attribute), 134
- `load_schema()` (in module *pyhf.utils*), 207
- `log()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 166
- `log()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 141
- `log()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 148
- `log()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 157
- `log_prob()` (*pyhf.probability.Independent* method), 122
- `log_prob()` (*pyhf.probability.Simultaneous* method), 123
- `logpdf()` (*pyhf.pdf.Model* method), 125
- ## M
- `mainlogpdf()` (*pyhf.pdf.Model* method), 125



`make_pdf()` (*pyhf.pdf.Model* method), 125  
`maxiter` (*pyhf.optimize.mixins.OptimizerMixin* attribute), 171  
`maxiter` (*pyhf.optimize.opt\_minuit.minuit\_optimizer* attribute), 173  
`maxiter` (*pyhf.optimize.opt\_scipy.scipy\_optimizer* attribute), 172  
`metadata` (*pyhf.patchset.Patch* attribute), 135  
`metadata` (*pyhf.patchset.PatchSet* attribute), 134  
`minimize()` (*pyhf.optimize.mixins.OptimizerMixin* method), 171  
`minuit_optimizer` (class in *pyhf.optimize.opt\_minuit*), 173  
`Model` (class in *pyhf.pdf*), 124  
`model()` (*pyhf.workspace.Workspace* method), 131  
`module`  
    *pyhf.compat*, 118  
    *pyhf.contrib.viz.brazil*, 208  
    *pyhf.readxml*, 115  
    *pyhf.writexml*, 116

## N

`name` (*pyhf.optimize.opt\_minuit.minuit\_optimizer* attribute), 173  
`name` (*pyhf.optimize.opt\_scipy.scipy\_optimizer* attribute), 172  
`name` (*pyhf.patchset.Patch* attribute), 135  
`name` (*pyhf.tensor.jax\_backend.jax\_backend* attribute), 163  
`name` (*pyhf.tensor.numpy\_backend.numpy\_backend* attribute), 138  
`name` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* attribute), 146  
`name` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* attribute), 154  
`nominal_rates` (*pyhf.pdf.Model* attribute), 124  
`Normal` (class in *pyhf.probability*), 120  
`normal()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 166  
`normal()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 141  
`normal()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 148  
`normal()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 157  
`normal_cdf()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 166  
`normal_cdf()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 141  
`normal_cdf()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 149  
`normal_cdf()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 157

`normal_dist()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 167  
`normal_dist()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 142  
`normal_dist()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 149  
`normal_dist()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 158  
`normal_logpdf()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 167  
`normal_logpdf()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 142  
`normal_logpdf()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 150  
`normal_logpdf()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 158  
`normfactor` (class in *pyhf.modifiers*), 174  
`normsys` (class in *pyhf.modifiers*), 175  
`numpy_backend` (class in *pyhf.tensor.numpy\_backend*), 138

## O

`one_sigma_band` (*pyhf.contrib.viz.brazil.BrazilBandCollection* attribute), 209  
`ones()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 167  
`ones()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 142  
`ones()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 150  
`ones()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 159  
`op_code` (*pyhf.modifiers.histosys* attribute), 174  
`op_code` (*pyhf.modifiers.normfactor* attribute), 175  
`op_code` (*pyhf.modifiers.normsys* attribute), 175  
`op_code` (*pyhf.modifiers.shapefactor* attribute), 175  
`op_code` (*pyhf.modifiers.shapesys* attribute), 176  
`op_code` (*pyhf.modifiers.staterror* attribute), 176  
`operations` (*pyhf.patchset.Patch* attribute), 135  
`optimizer` (in module *pyhf*), 114  
`OptimizerMixin` (class in *pyhf.optimize.mixins*), 170  
`options_from_eqdelimstring()` (in module *pyhf.utils*), 207  
`outer()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 167  
`outer()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 142  
`outer()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 150  
`outer()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 159

## OUTPUT DIRECTORY

`pyhf-contrib-download` command line option, 104



## P

- `par_slice()` (*pyhf.pdf.\_ModelConfig* method), 126
- `param_set()` (*pyhf.pdf.\_ModelConfig* method), 126
- `paramset_to_rootnames()` (in module *pyhf.compat*), 119
- `parse()` (in module *pyhf.readxml*), 116
- `Patch` (class in *pyhf.patchset*), 135
- `patches` (*pyhf.patchset.PatchSet* attribute), 134
- PATCHSET**
  - `pyhf-patchset-apply` command line option, 108
  - `pyhf-patchset-extract` command line option, 108
  - `pyhf-patchset-inspect` command line option, 109
  - `pyhf-patchset-verify` command line option, 109
- `PatchSet` (class in *pyhf.patchset*), 132
- `PatchSetVerificationError`, 205
- `pdf()` (*pyhf.pdf.Model* method), 125
- `pdf_type` (*pyhf.modifiers.histosys* attribute), 174
- `pdf_type` (*pyhf.modifiers.normfactor* attribute), 175
- `pdf_type` (*pyhf.modifiers.normsys* attribute), 175
- `pdf_type` (*pyhf.modifiers.shapefactor* attribute), 175
- `pdf_type` (*pyhf.modifiers.shapesys* attribute), 176
- `pdf_type` (*pyhf.modifiers.staterror* attribute), 176
- `plot_brazil_band()` (in module *pyhf.contrib.viz.brazil*), 210
- `plot_cls_components()` (in module *pyhf.contrib.viz.brazil*), 211
- `plot_results()` (in module *pyhf.contrib.viz.brazil*), 212
- `Poisson` (class in *pyhf.probability*), 120
- `poisson()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 167
- `poisson()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 142
- `poisson()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 150
- `poisson()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 159
- `poisson_dist()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 168
- `poisson_dist()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 143
- `poisson_dist()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 151
- `poisson_dist()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 159
- `poisson_logpdf()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 168
- `poisson_logpdf()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 143
- `poisson_logpdf()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 151
- `poisson_logpdf()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 160
- `precision` (*pyhf.tensor.jax\_backend.jax\_backend* attribute), 163
- `precision` (*pyhf.tensor.numpy\_backend.numpy\_backend* attribute), 138
- `precision` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* attribute), 146
- `precision` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* attribute), 154
- `process_channel()` (in module *pyhf.readxml*), 116
- `process_data()` (in module *pyhf.readxml*), 116
- `process_measurements()` (in module *pyhf.readxml*), 116
- `process_sample()` (in module *pyhf.readxml*), 116
- `product()` (*pyhf.tensor.jax\_backend.jax\_backend* method), 168
- `product()` (*pyhf.tensor.numpy\_backend.numpy\_backend* method), 143
- `product()` (*pyhf.tensor.pytorch\_backend.pytorch\_backend* method), 151
- `product()` (*pyhf.tensor.tensorflow\_backend.tensorflow\_backend* method), 160
- `prune()` (*pyhf.workspace.Workspace* method), 131
- `pvalue()` (*pyhf.infer.calculators.AsymptoticTestStatDistribution* method), 187
- `pvalue()` (*pyhf.infer.calculators.EmpiricalDistribution* method), 189
- `pvalues()` (*pyhf.infer.calculators.AsymptoticCalculator* method), 192
- `pvalues()` (*pyhf.infer.calculators.ToyCalculator* method), 195
- pyhf** command line option
  - `--citation`, 101
  - `--cite`, 101
  - `--version`, 101
- pyhf** compat module, 118
- pyhf** contrib.viz.brazil module, 208
- pyhf** readxml module, 115
- pyhf** writexml module, 116
- pyhf-cls** command line option
  - `--backend <backend>`, 102

```
--calctype <calctype>, 102
--measurement <measurement>, 102
--optconf <optconf>, 102
--optimizer <optimizer>, 102
--output-file <output_file>, 102
--patch <patch>, 102
--test-poi <test_poi>, 102
--test-stat <test_stat>, 102
-p, 102
WORKSPACE, 102
pyhf-combine command line option
--join <join>, 102
--merge-channels, 102
--no-merge-channels, 102
--output-file <output_file>, 102
-j, 102
WORKSPACE_ONE, 103
WORKSPACE_TWO, 103
pyhf-completions command line option
SHELL, 103
pyhf-contrib-download command line option
--compress, 104
--force, 104
--verbose, 104
-c, 104
-f, 104
-v, 104
ARCHIVE_URL, 104
OUTPUT_DIRECTORY, 104
pyhf-digest command line option
--algorithm <algorithm>, 104
--json, 104
--plaintext, 104
-a, 104
-j, 104
-p, 104
WORKSPACE, 104
pyhf-fit command line option
--backend <backend>, 105
--measurement <measurement>, 105
--optconf <optconf>, 105
--optimizer <optimizer>, 105
--output-file <output_file>, 105
--patch <patch>, 105
--value, 105
-p, 105
WORKSPACE, 106
pyhf-inspect command line option
--measurement <measurement>, 106
--output-file <output_file>, 106
WORKSPACE, 107
pyhf-json2xml command line option
--dataroot <dataroot>, 107
--output-dir <output_dir>, 107
--patch <patch>, 107
--resultprefix <resultprefix>, 107
--specroot <specroot>, 107
-p, 107
WORKSPACE, 107
pyhf-patchset-apply command line option
--name <name>, 108
--output-file <output_file>, 108
BACKGROUND_ONLY, 108
PATCHSET, 108
pyhf-patchset-extract command line option
--name <name>, 108
--output-file <output_file>, 108
--with-metadata, 108
--without-metadata, 108
PATCHSET, 108
pyhf-patchset-inspect command line option
PATCHSET, 109
pyhf-patchset-verify command line option
BACKGROUND_ONLY, 109
PATCHSET, 109
pyhf-prune command line option
--channel <CHANNEL>..., 109
--measurement <MEASUREMENT>..., 109
--modifier <MODIFIER>..., 109
--modifier-type <modifier_type>, 109
--output-file <output_file>, 109
--sample <SAMPLE>..., 109
-c, 109
-m, 109
-s, 109
-t, 109
WORKSPACE, 110
pyhf-rename command line option
--channel <PATTERN> <REPLACE>..., 110
--measurement <PATTERN> <REPLACE>..., 110
--modifier <PATTERN> <REPLACE>..., 110
--output-file <output_file>, 110
--sample <PATTERN> <REPLACE>..., 110
-c, 110
-m, 110
-s, 110
WORKSPACE, 110
pyhf-sort command line option
--output-file <output_file>, 111
WORKSPACE, 111
pyhf-xml2json command line option
--basedir <basedir>, 111
--hide-progress, 111
--output-file <output_file>, 111
--track-progress, 111
ENTRYPOINT_XML, 111
```

`pytorch_backend` (class in `pyhf.tensor.pytorch_backend`), 146

## Q

`q0()` (in module `pyhf.infer.test_statistics`), 180

`qmu()` (in module `pyhf.infer.test_statistics`), 181

`qmu_tilde()` (in module `pyhf.infer.test_statistics`), 182

## R

`ravel()` (`pyhf.tensor.jax_backend.jax_backend` method), 168

`ravel()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 143

`ravel()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 151

`ravel()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 160

`references` (`pyhf.patchset.PatchSet` attribute), 134

`rename()` (`pyhf.workspace.Workspace` method), 131

`required_parset()` (`pyhf.modifiers.histosys` class method), 174

`required_parset()` (`pyhf.modifiers.normfactor` class method), 175

`required_parset()` (`pyhf.modifiers.normsys` class method), 175

`required_parset()` (`pyhf.modifiers.shapefactor` class method), 176

`required_parset()` (`pyhf.modifiers.shapesys` class method), 176

`required_parset()` (`pyhf.modifiers.staterror` class method), 176

`reshape()` (`pyhf.tensor.jax_backend.jax_backend` method), 168

`reshape()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`reshape()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`reshape()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

## S

`sample()` (`pyhf.probability.Simultaneous` method), 123

`scipy_optimizer` (class in `pyhf.optimize.opt_scipy`), 172

`set_backend()` (in module `pyhf`), 114

`set_poi()` (`pyhf.pdf._ModelConfig` method), 127

`shape()` (`pyhf.tensor.jax_backend.jax_backend` method), 168

`shape()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`shape()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`shape()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

in `shapefactor` (class in `pyhf.modifiers`), 175

`shapesys` (class in `pyhf.modifiers`), 176

SHELL

`pyhf-completions` command line option, 103

`simple_broadcast()` (`pyhf.tensor.jax_backend.jax_backend` method), 168

`simple_broadcast()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`simple_broadcast()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`simple_broadcast()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

`Simultaneous` (class in `pyhf.probability`), 122

`solver_options` (`pyhf.optimize.opt_scipy.scipy_optimizer` attribute), 172

`sorted()` (`pyhf.workspace.Workspace` class method), 132

`sqrtd()` (`pyhf.tensor.jax_backend.jax_backend` method), 169

`sqrtd()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`sqrtd()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`sqrtd()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

`stack()` (`pyhf.tensor.jax_backend.jax_backend` method), 169

`stack()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`stack()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`stack()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

`staterror` (class in `pyhf.modifiers`), 176

`steps` (`pyhf.optimize.opt_minuit.minuit_optimizer` attribute), 173

`strategy` (`pyhf.optimize.opt_minuit.minuit_optimizer` attribute), 173

`suggested_bounds()` (`pyhf.pdf._ModelConfig` method), 127

`suggested_fixed()` (`pyhf.pdf._ModelConfig` method), 127

`suggested_init()` (`pyhf.pdf._ModelConfig` method), 128

`sum()` (`pyhf.tensor.jax_backend.jax_backend` method), 169

`sum()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`sum()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`sum()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

## T

`tensorflow_backend` (class in `pyhf.tensor.tensorflow_backend`), 154

`tensorlib` (in module `pyhf`), 113

`test_size` (`pyhf.contrib.viz.brazil.BrazilBandCollection` attribute), 209

`teststatistic()` (`pyhf.infer.calculators.AsymptoticCalculator` method), 193

`teststatistic()` (`pyhf.infer.calculators.ToyCalculator` method), 196

`tile()` (`pyhf.tensor.jax_backend.jax_backend` method), 169

`tile()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 144

`tile()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 152

`tile()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 161

`tmu()` (in module `pyhf.infer.test_statistics`), 183

`tmu_tilde()` (in module `pyhf.infer.test_statistics`), 184

`to_numpy()` (`pyhf.tensor.jax_backend.jax_backend` method), 169

`to_numpy()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 145

`to_numpy()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 153

`to_numpy()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 162

`tolerance` (`pyhf.optimize.opt_minuit.minuit_optimizer` attribute), 173

`tolerance` (`pyhf.optimize.opt_scipy.scipy_optimizer` attribute), 172

`tolist()` (`pyhf.tensor.jax_backend.jax_backend` method), 170

`tolist()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 145

`tolist()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 153

`tolist()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 162

`ToyCalculator` (class in `pyhf.infer.calculators`), 193

`twice_nll()` (in module `pyhf.infer.mle`), 198

`two_sigma_band` (`pyhf.contrib.viz.brazil.BrazilBandCollection` attribute), 210

## U

`uncorrelated_background()` (in module `pyhf.simplemodels`), 136

`upperlimit()` (in module `pyhf.infer.intervals`), 202

## V

`valid_joins` (`pyhf.workspace.Workspace` attribute), 129

`validate()` (in module `pyhf.utils`), 207

`values` (`pyhf.patchset.Patch` attribute), 136

`verbose` (`pyhf.optimize.mixins.OptimizerMixin` attribute), 171

`verbose` (`pyhf.optimize.opt_minuit.minuit_optimizer` attribute), 173

`verbose` (`pyhf.optimize.opt_scipy.scipy_optimizer` attribute), 172

`verify()` (`pyhf.patchset.PatchSet` method), 134

`version` (`pyhf.patchset.PatchSet` attribute), 134

## W

`where()` (`pyhf.tensor.jax_backend.jax_backend` method), 170

`where()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 145

`where()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 153

`where()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 162

### WORKSPACE

`pyhf-cls` command line option, 102

`pyhf-digest` command line option, 104

`pyhf-fit` command line option, 106

`pyhf-inspect` command line option, 107

`pyhf-json2xml` command line option, 107

`pyhf-prune` command line option, 110

`pyhf-rename` command line option, 110

`pyhf-sort` command line option, 111

`Workspace` (class in `pyhf.workspace`), 128

`WORKSPACE_ONE`

`pyhf-combine` command line option, 103

`WORKSPACE_TWO`

`pyhf-combine` command line option, 103

## Z

`zeros()` (`pyhf.tensor.jax_backend.jax_backend` method), 170

`zeros()` (`pyhf.tensor.numpy_backend.numpy_backend` method), 145

`zeros()` (`pyhf.tensor.pytorch_backend.pytorch_backend` method), 153

`zeros()` (`pyhf.tensor.tensorflow_backend.tensorflow_backend` method), 163