

High Performance Histograms as Objects

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A histogram is best described as an object.









Current Status Quo

np.histogram
 plt.hist
 ↓
Unbinned data → bins, edge arrays

1D, 2D, ND have different functions/APIs

Hard to plot results of np.histogram

Generalized histograms: scipy.stats.binned_static

And how about binning/manipulating histograms afterwards?

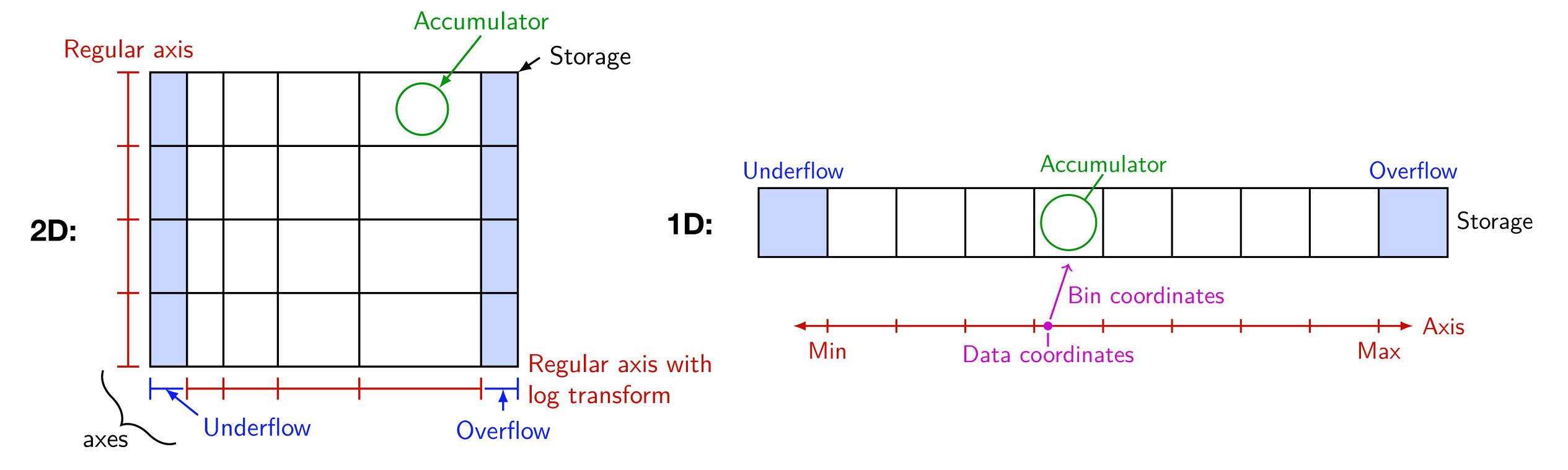








What would a "Histogram" look like?



Axes: Regular, Variable, Category, **Accumulators:**

Int, Double, WeightedSum Mean,













Basics of boost-histogram







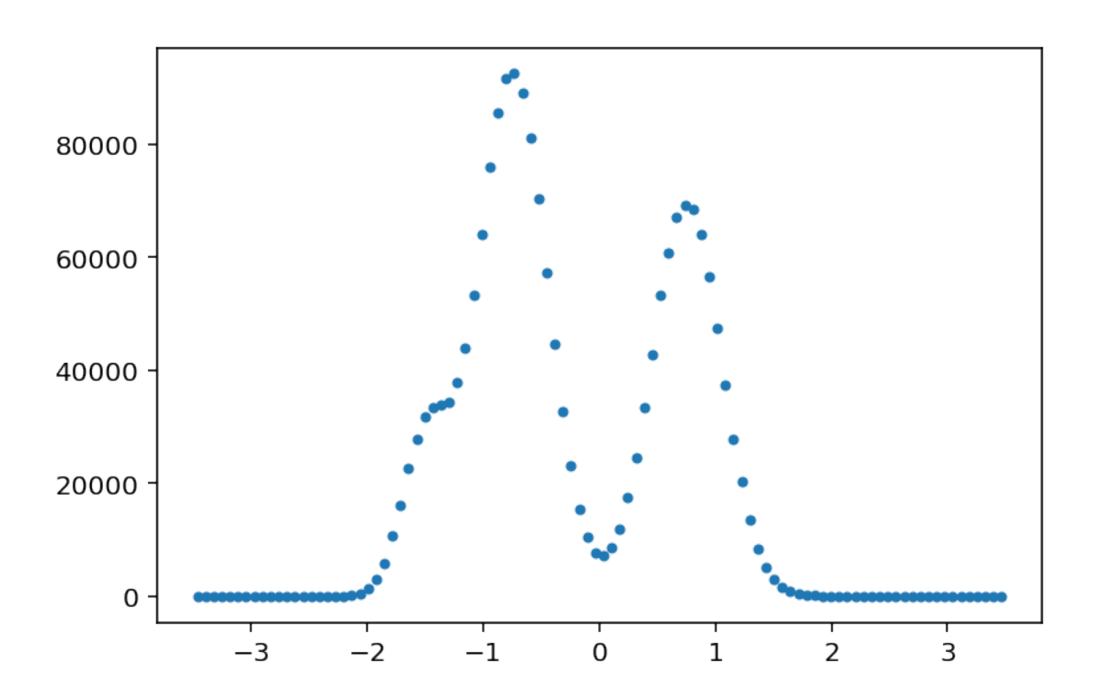


A taste of manipulation

Assume we have a hist "h":

Plot a histogram: (simple)

plt.plot(*h.axes.centers, h, ".")



NumPy comparison:

```
bins, edges = h.to_numpy()
centers = (bins[1:] + bins[:-1]) / 2
plt.plot(centers, bins, ".")
```

Compute the density:

```
V = np.prod(h.axes.widths, axis=0)
density = h.view() / h.sum() / V
```









A taste of manipulation

Assume we have a hist "h":

Manual threaded fill:

```
def fun(d):
    return h.copy().reset().fill(d)

chunks = np.array_split(data, threads)

with ThreadPoolExecutor(threads) as pool:
    results = pool.map(fun, chunks)

for res in results:
    h += res
```

Or just use this:

```
h.fill(data, threads=threads)
```

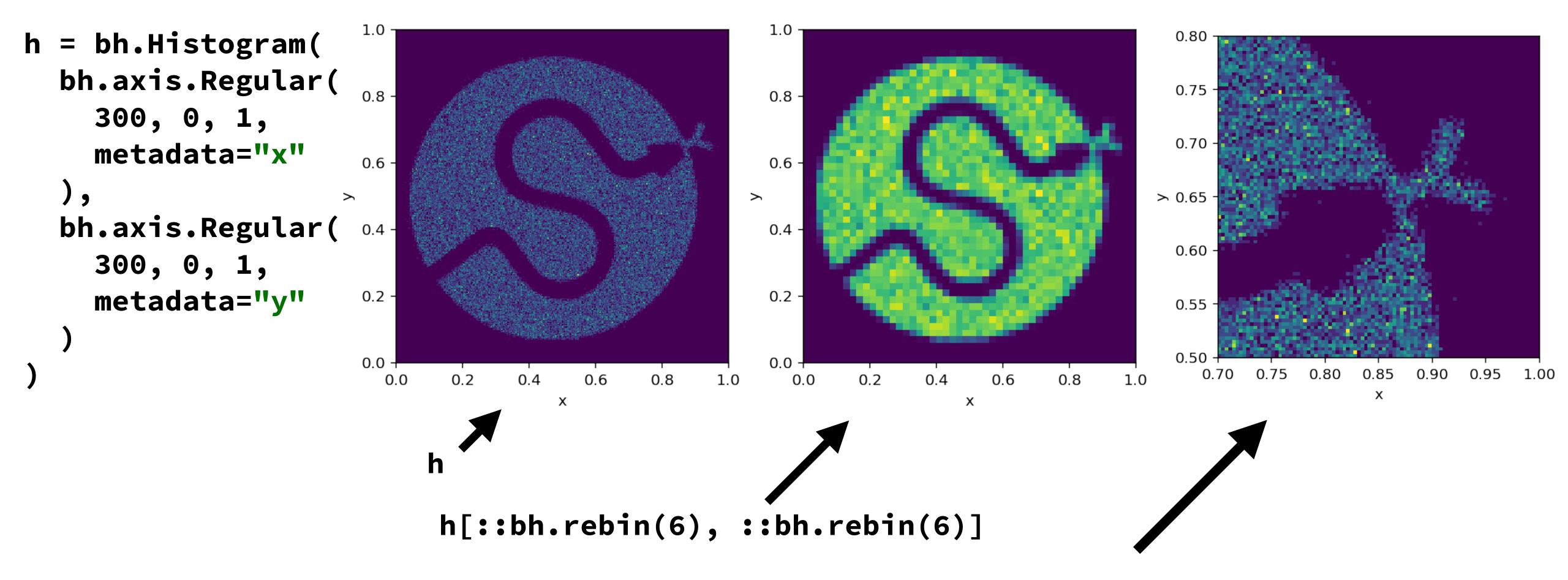








A taste of manipulation (2)



h[bh.loc(.7):, bh.loc(.5):bh.loc(.8)]













And boost-histogram is fast

Tests on 2.4 GHz 8-Core Intel Core i9

1D, 100 bins, 10,000,000 data points

bh.numpy.histogram(data, bins, ranges)

np.histogram(data, bins, ranges)

43.1 ms

74.5 ms

(41.6 ms in object mode)

Threaded

13.8 ms

(13.3 ms in object mode)

2D, 100x100 bins, 10,000,000x2 data points

bh.numpy.histogram2d(data, bins, ranges)

np.histogram2d(data, bins, ranges)

84.7 ms

874 ms

(77.6 ms in object mode)

Threaded

29.6 ms

(28.7 ms in object mode)









A firm foundation



Seamless operability between C++11 and Python, used by SciPy, 1,934 GitHub repos



...one of the most highly regarded and expertly designed C++ library projects in the world.

— Herb Sutter and Andrei Alexandrescu, C++ Coding Standards



Designed by Hans Dembinski, accepted into Boost 1.70, improved every version since.

Boost.Histogram features

- Static / Dynamic storage (can avoid allocator!)
- Static fill becomes 57 lines of vectorized assembly
- Adding, scaling, slicing, rebinning, projections, more
- High performance filling and bin iteration

Customizable:

- Storage
- Allocators
- Accumulators
- Axes
- Axis metadata
- Axis transforms

Boost.Histogram author closely involved in boost-histogram!



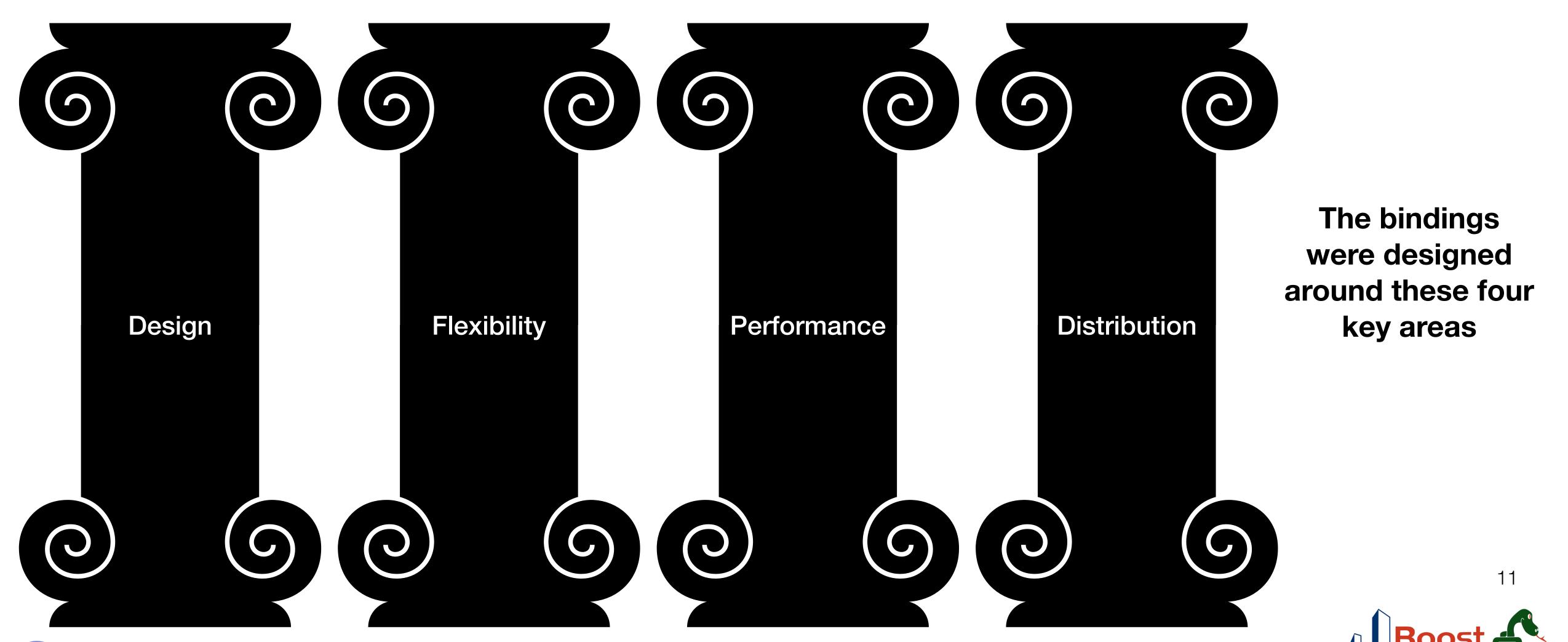
Henry Schreiner Hans Dembinski 🗍 Jim Pivarski 🕏 Shuo Liu 👀



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New bindings: boost-histogram









Design

Pickle

Directly supports pickling (v>0) **Optimized for performance** Cloudpickle supported too

Copy

Supports h.copy(), copy(h), and deepcopy(h)

Operators

h1 + h2h * 2.0

Python 2 Statement

1.0 LTS w/ Python 2 support Python 3 should not suffer

UFuncts

NumPy 1.13 overloads being adopted for accumulator storages

Axes access

Axes return an enhanced tuple h.axes.centers h.axes.widths h.axes.edges h.index(value) h.value(index)

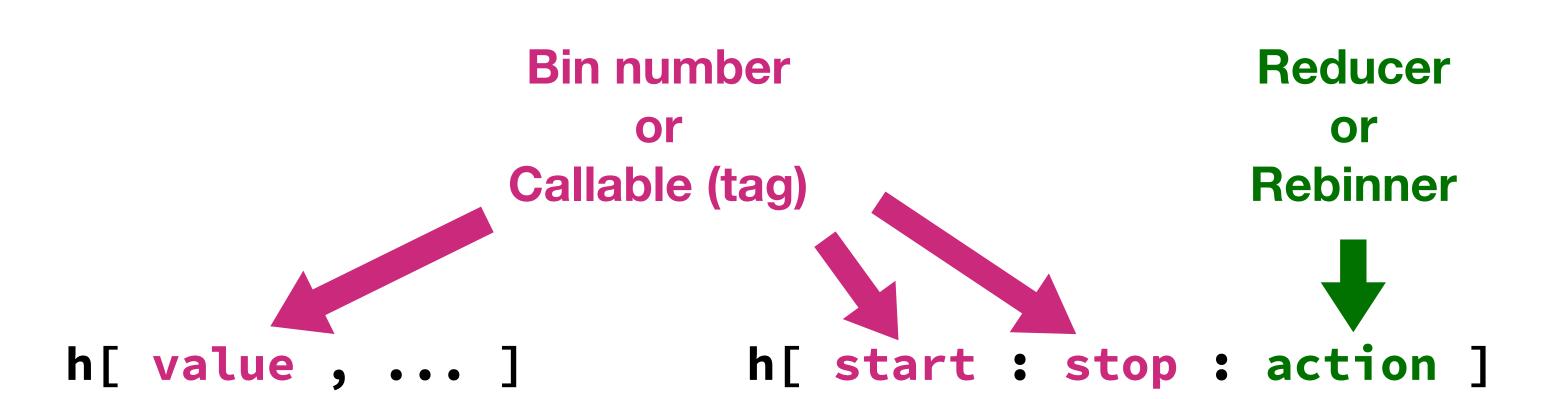






2020

Design: Unified Histogram Indexing



Anything that would go in a normal indexer

Axis number

h[{ 0: slice() }]

bin_number
bh.loc(value)
bh.loc(value) + shift
bh.underflow
bh.overflow
len

bh.rebin(N)
sum

When setting with an array, you can include flow bins if start or stop is None

Any callable works, takes the axes and returns bin number, from -1 to len(ax)+1

Currently only these implemented, UHI spec includes arbitrary actions

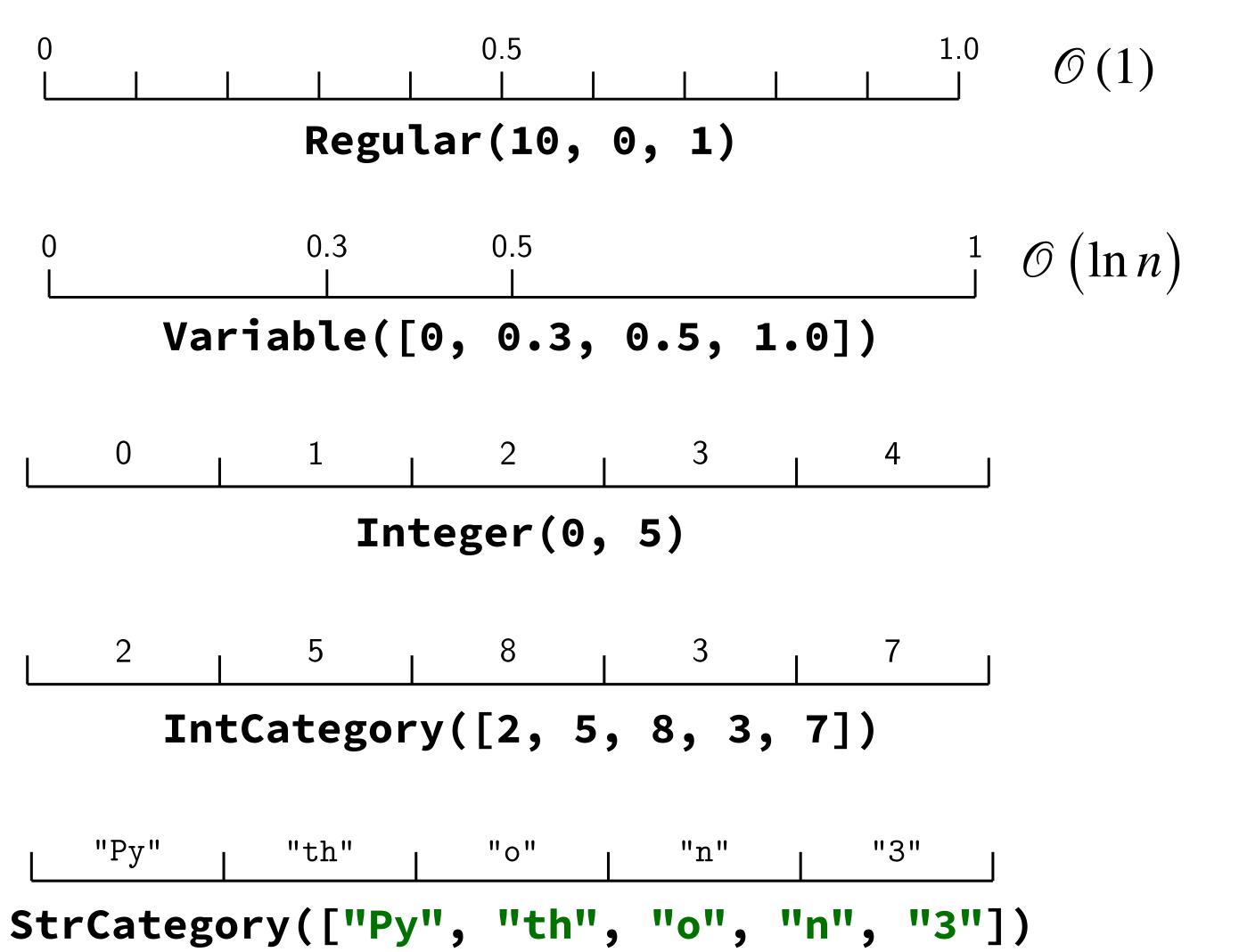


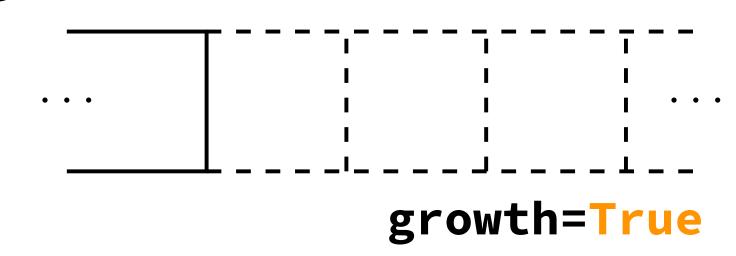


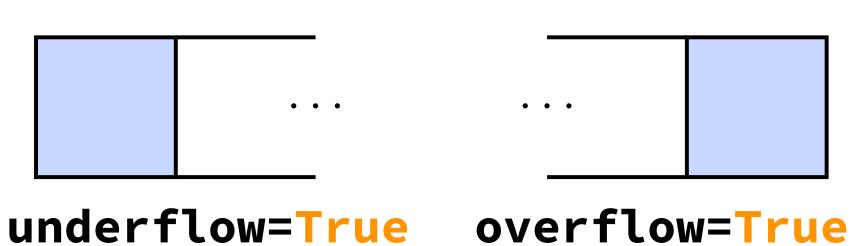


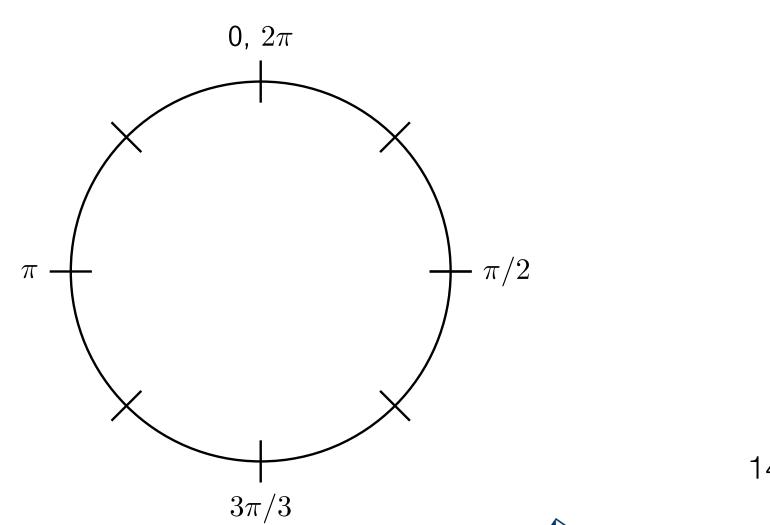


Flexibility: Axes Types

























Flexibility: Transforms

Regular axes scale better than variable, no sorted lookup. If the irregularity is functional, you can avoid the lookup!









Flexibility: Transforms

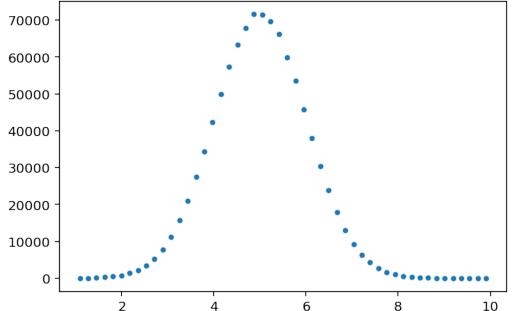
Regular axes scale better than variable, no sorted lookup. pl If the irregularity is functional, you can avoid the lookup!
You are not just limited to precompiled transforms (sqrt, log, Pow)!
import numba

```
@numba.cfunc(numba.float64(numba.float64))
def exp(x):
    return math.exp(x)
```

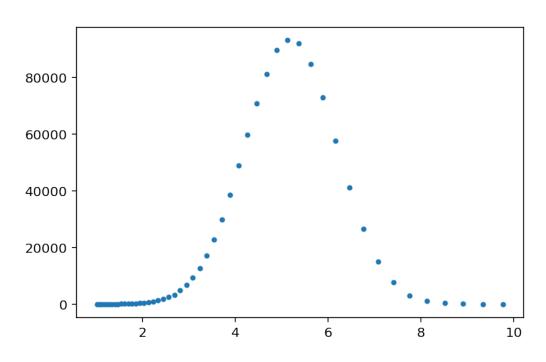
```
@numba.cfunc(numba.float64(numba.float64))
def log(x):
    return math.log(x)
```

```
bh.axis.Regular(10, 1, 4,
```

plt.plot(*ho.axes.centers, ho, '.')



plt.plot(*hl.axes.centers, ho, '.')



You can use any ctypes function pointer, or pure Python (slower)





transform=bh.axis.transform.Function(log, exp))





Flexibility: Storages

Boost-histogram ships with 7 storages:

Double() (default)
Fast, flexible, simple

Int64()
Fast, strict, simple

AtomicInt64()
Threadsafe fills

Unlimited()
No overflow guarantee,

Resizes to optimize small ints

Accumulator storages



Weight()
Stores value and variance

Mean()
High accuracy

WeightedMean()
Mean and weight

Views into accumulators are "smart":

- NumPy record structure
- Property access to real and computed values
- NEP 13 (NumPy 1.13+) UFunc support
- Accessing an element returns an accumulator

```
h.view().value
h.view().variance
np.sum(h.view())
```

The accumulators (including Sum()) act like 0D histograms, and can be filled!









Performance

Tests on 2.4 GHz 8-Core Intel Core i9

1D, 100 bins, 10,000,000 data points 2D, 100x100 bins, 10,000,000x2 data points

Setup	Single threaded	X	Multithreaded	X
NumPy 1D	74.5 ± 2.4 ms	1		
BH 1D	41.6 ± 0.7 ms	1.8	13.3 ± 0.2 ms	5.5
BHNP 1D	43.1 ± 0.8 ms	1.7	13.8 ± 0.2 ms	5.4
NumPy 2D	874 ± 22 ms	1		
BH 2D	77.6 ± 0.6 ms	11	28.7 ± 0.7 ms	30
BHNP 2D	85 ± 3 ms	10	29.6 ± 0.5 ms	29









Performance: Single Histogram loop

```
value_ax = bh.axis.Regular(100, -5, 5)
valid_ax = bh.axis.Integer(0, 2,
                           underflow=False,
                           overflow=False)
label_ax = bh.axis.StrCategory([], growth=True)
hist = bh.Histogram(value_ax, valid_ax, label_ax)
hist.fill([-2, 2, 4, 3],
          [True, False, True, True], Loops over the data just once!
          ["a", "b", "a", "b"])
# Just valid data, combine all labels
all_valid = hist[:, bh.loc(True), ::sum]
# 2D histogram of just the "a" label
a_only = hist[..., bh.loc("a")]
```







Distribution

Making a distribution:

- Needs to work everywhere
- + Header-only Boost + PyBind11
- C++14

Wheels

Python	2.7	3.5	3.6	3.7	3.8
Manylinux1*	V	V	V	V	V
Manylinux2010	V	V	V	V	V
macOS 10.9+	V	V	V	V	V
Windows	*	V	V	V	V

Conda-Forge

Python	2.7	3.5	3.6	3.7	3.8
Linux 64	*	V	V	V	
Linux ppc64le		V	V	V	V
Linux aarch64		V	V	V	V
macOS 10.9+	*	V	V	V	
Windows		V	V	V	

Solutions:

- git submodules for Boost + Pybind11
- Fully setuptools-based build, optional CMake build
- Custom wheel build system
 - Custom image with GCC 9 (manylinux1)
 - Manylinux2014 arch wheels under investigation
 - Replaced by cibuildwheel recently
 - 4-5 other Scikit-HEP packages now provide wheels
- SDist builds on a modern system
 - PEP 518; C++14 support required

https://iscinumpy.gitlab.io/categories/azure-devops/

https://scikit-hep.org/developer









Distribution: checks

Pre-commit & GHA:

- Black
- Pre-commit-hooks
- Flake8 with bugbear
- MyPy (basic)
- Check Manifest
- Clang Format (C++)

Test suite:

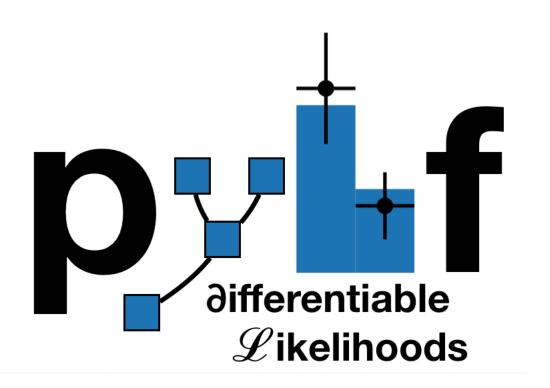
- PyTest
- PyTest-Benchmark
- Weekly dependency check

Releases:

- Automated by GHA
- setuptools scm for versioning

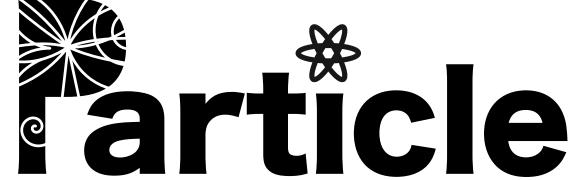


Several other packages in Scikit-HEP are now adopting recommendations and build tools!

























The Scikit-HEP ecosystem

Focused packages working together.



NumPy, Physt, and HEP-specific formats



Fill and manipulate histograms

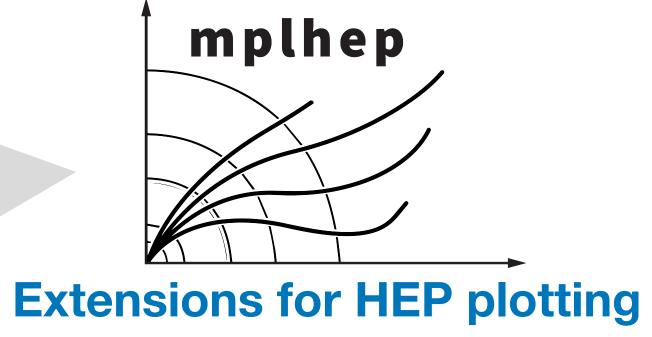
Core library



Hist:

Friendly histograms for analysis

GSoC project just started



Histograms and more

histoprint:

Display histograms on the command line

- Newest member of Scikit-HEP
- Can plot up to 5 at a time

Scikit-HEP Tutorials: Packages working together

Powerered by JupyterBook Beta

















Hist

Python 3.6+ library for users

Testing useful shortcuts (some may be upstreamed if popular)

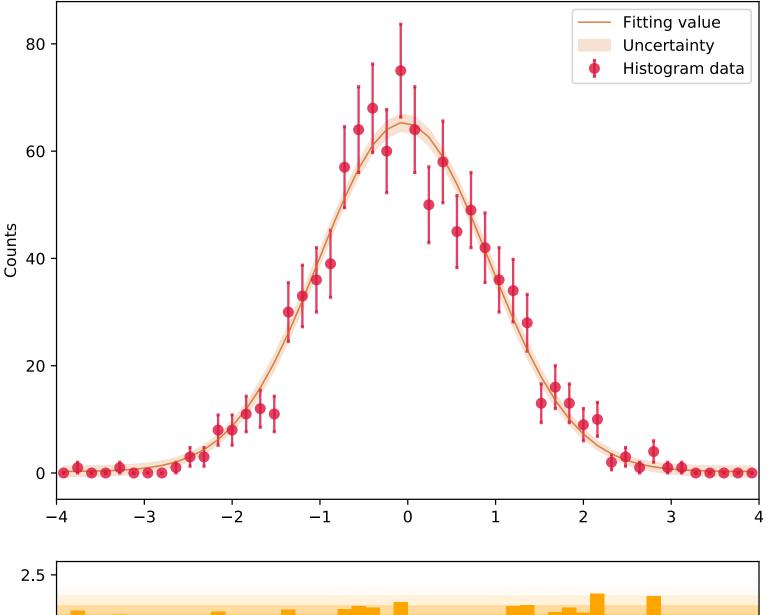
h[bh.loc(.7):, bh.loc(.5):bh.loc(.8)+1]
$$\rightarrow$$
 h[.7j, .5j:.8j+1] h[bh.loc("hi")] \rightarrow h["hi"]

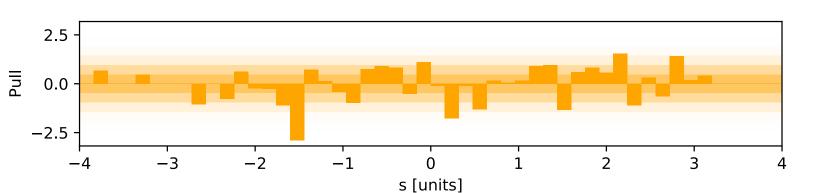
Assign meaning to metadata name, title, units, etc.

Fill and access by name instead of position \ \frac{1}{2} \ \ \dagger{1}{2} (NamedHist enforces name access)

> **Direct access to plots** 1D, 2D, pull plots, and more

Allowed to have dependencies such as matplotlib





Early example of pull plot

















Summary

Design

Built on a firm foundation

Can handle complex situations with ease

Flexibility

Dozens of axes types x 7 storages

Can be extended in the future

Performance

Fast, efficient filling loops, with threads Can reduce the number of histograms used

Distribution

Easy to build on a modern system
Wheels for every platform
Conda-forge support as well

Easy to install:

pip install boost-histogram
Or
conda install boost-histogram -c conda-forge

Easy to convert from NumPy:

np.histogram* → bh.numpy.histogram*
Add histogram=bh.Histogram to return object
Use .to_numpy() to get NumPy tuple back

And more exciting developments coming this Summer, like Hist!









A histogram is best described as an object.

Hopefully you now agree with me.

And boost-histogram is a great example of one!









Acknowledgments

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https://boost-histogram.readthedocs.io

https://github.com/scikit-hep/boost-histogram









Reference links

https://root.cern

https://scipy.org

https://numpy.org

https://iris-hep.org

https://scikit-hep.org

https://www.boost.org

https://numba.pydata.org

https://pandas.pydata.org

https://github.com/scikit-hep/hist

https://github.com/pybind/pybind11

https://github.com/joerick/cibuildwheel

https://github.com/scikit-hep/histoprint

https://github.com/scikit-hep/awkward-1.0







