Analysis 2.0:
New approaches to high-level particle physics analysis

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A post-doc at:
University of BRISTOL
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A fellow of:
Software Sustainability Institute

A founder of:
FAST HEP

A convener of:
PyHEP

Goals

1. **Showcase recent developments** for analysis of last couple of years
2. **Highlight where the UK** is already playing a significant role

Outline

1. **Challenges facing our field**
2. **Python as a solution**
3. **Columnar Analysis**
4. **FAST-HEP**

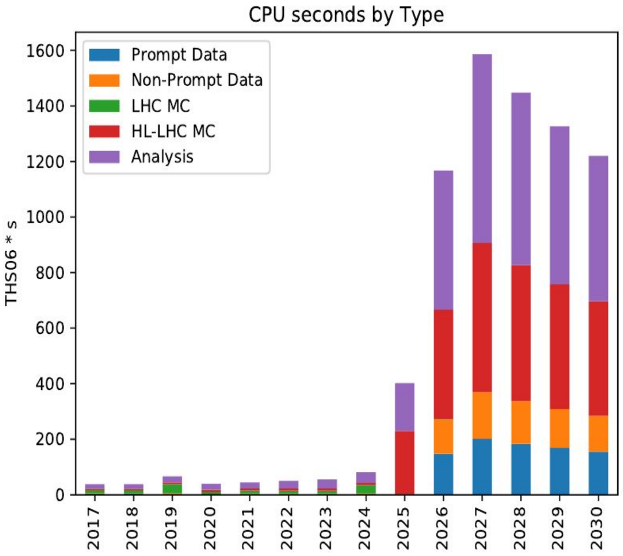
- High-level analysis = very final stages of processing
- This is a very broad topic: need a whole conference
- Some personal opinions: I welcome any counter-opinions!

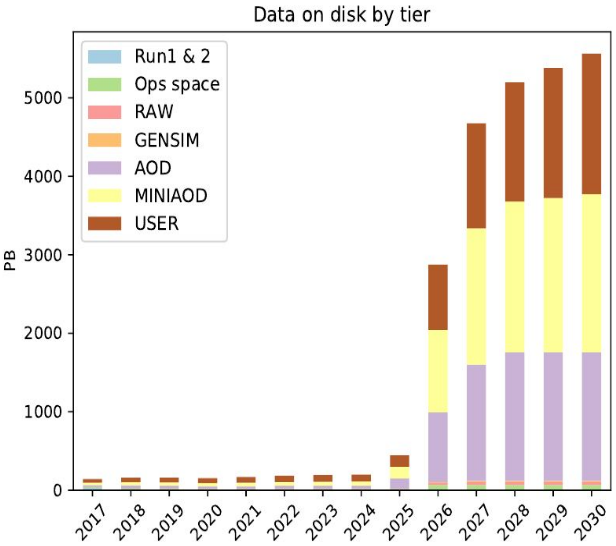
Three challenges facing our field

Future data volumes: HL-LHC

HSF Roadmap: [DOI: 10.1007/s41781-018-0018-8](https://doi.org/10.1007/s41781-018-0018-8)

From CMS: “User data” 30% of disk space, “Analysis” 40% of CPU



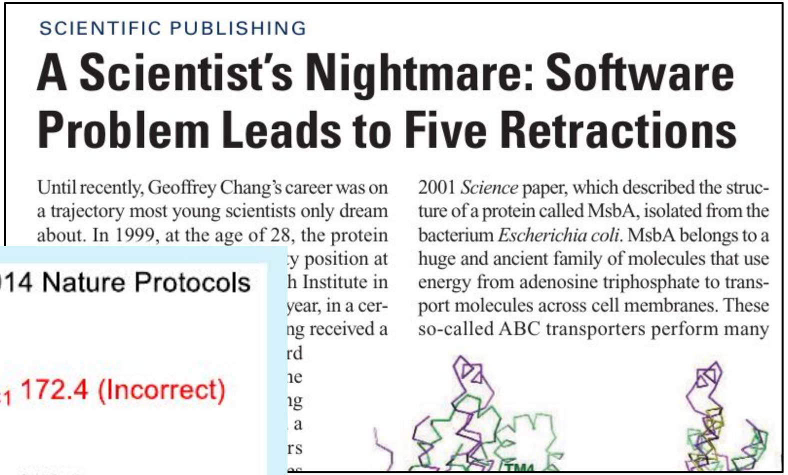


A hypothesis:

Time to **learn** $\propto$ Time to **code** $\propto$ Time to **insight**

Bugs and reproducibility

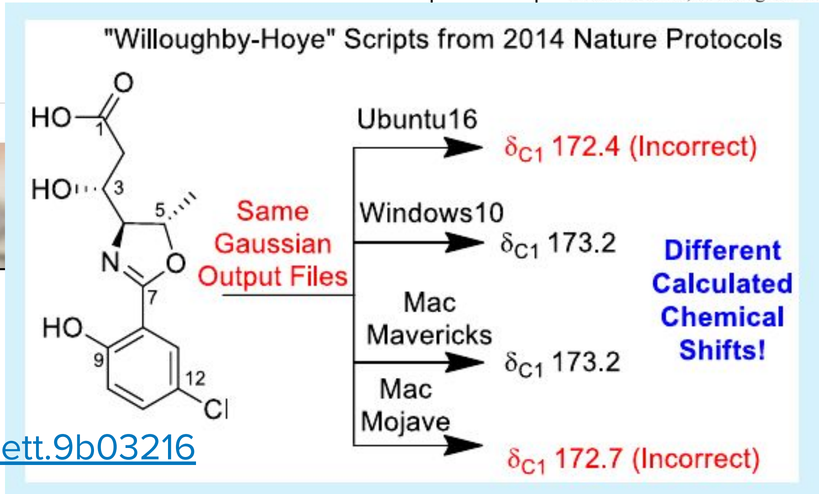
Dec. 2006 [DOI: 10.1126/science.314.5807.1856](https://doi.org/10.1126/science.314.5807.1856)


SCIENTIFIC PUBLISHING

A Scientist's Nightmare: Software Problem Leads to Five Retractions

Until recently, Geoffrey Chang's career was on a trajectory most young scientists only dream about. In 1999, at the age of 28, the protein ... y position at ... h Institute in ... year, in a cer- ... ng received a ... rd ... ne ... ng ... a ... rs

2001 *Science* paper, which described the structure of a protein called MsbA, isolated from the bacterium *Escherichia coli*. MsbA belongs to a huge and ancient family of molecules that use energy from adenosine triphosphate to transport molecules across cell membranes. These so-called ABC transporters perform many



Oct. 2019
[DOI:10.1021/acs.orglett.9b03216](https://doi.org/10.1021/acs.orglett.9b03216)

Challenge #1

Our data will grow massively unlike our resources

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Challenge #2

Physicists first, developers second: code is slow to write & run and often error-prone

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Challenge #3

A paper is not enough to describe a HEP analysis in a reproducible way

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Challenge #2

Challenge #3

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way

Rethink our approach

Solution #1

Too much data:

What does “Big data” do?
Use resources more intelligently

Solution #2

Good code is tough:

Adopt easier languages and open source practices

Solution #3

Irreproducibility:

Reduce gap between paper and actual analysis code

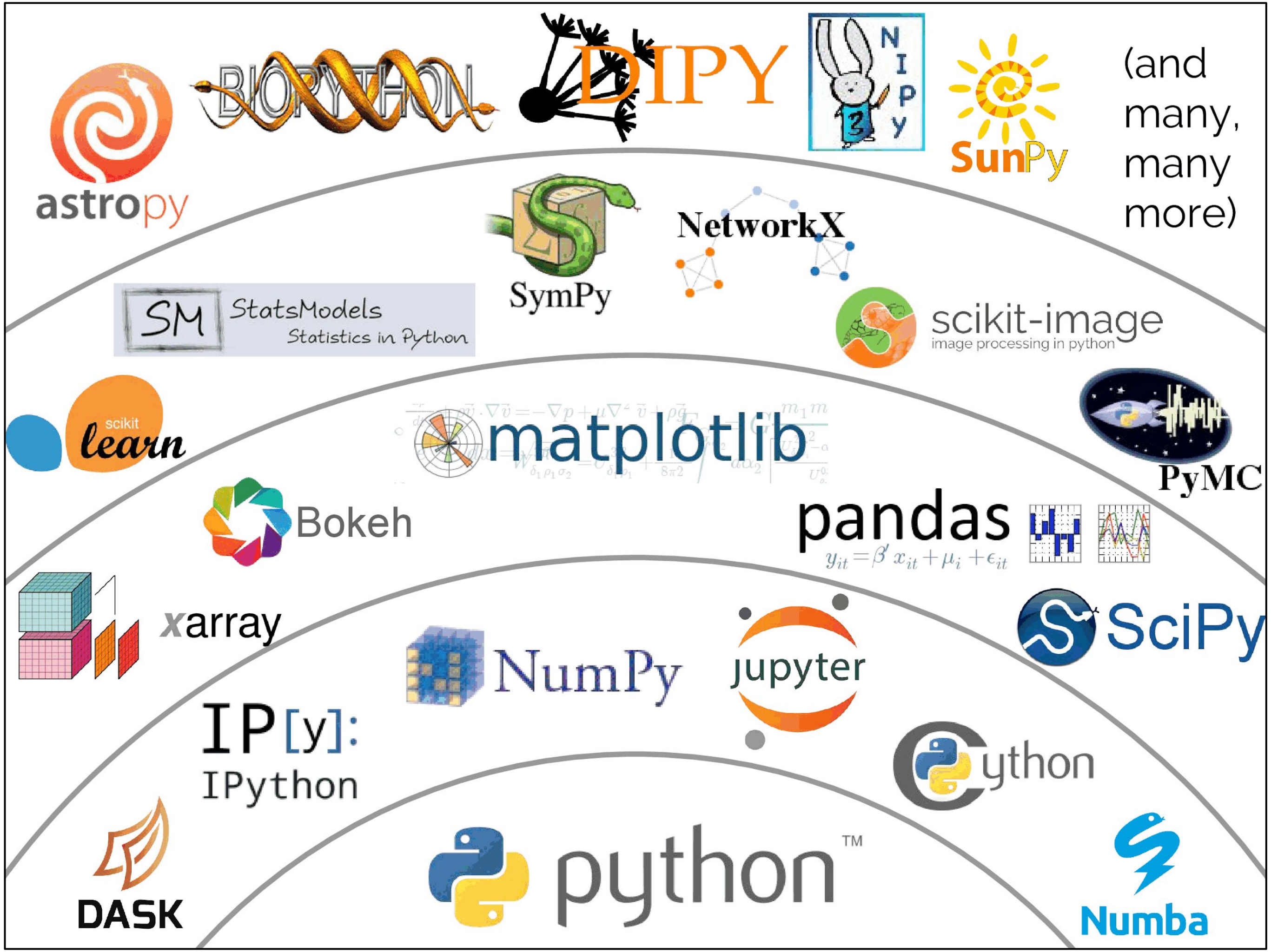
Python for Particle Physics

Why Python for scientific research?

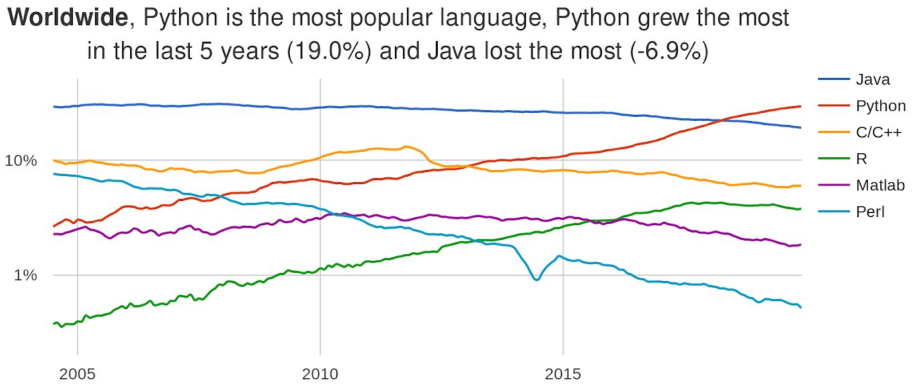
Adapted from Jake Vander Plas' The unexpected effectiveness of Python in Scientific Research

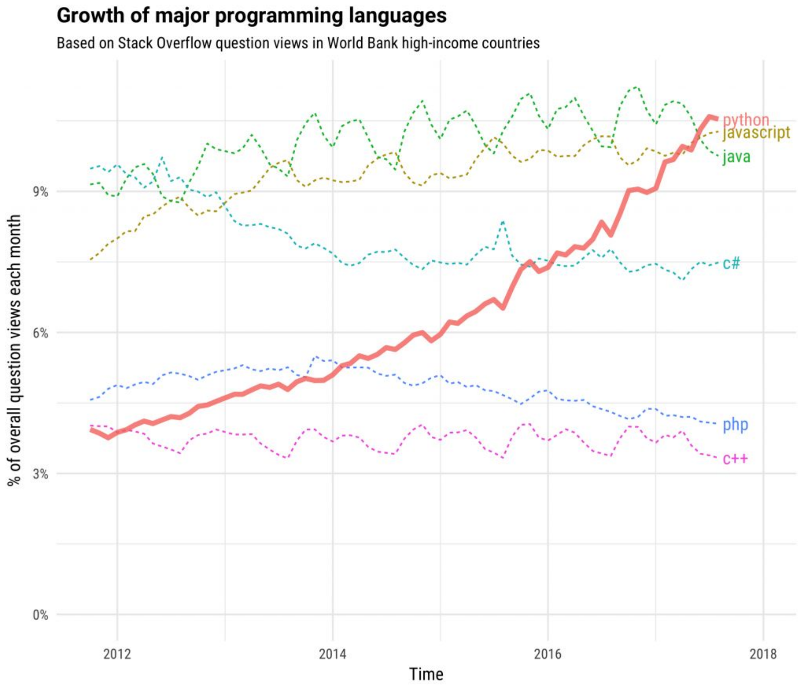
- Interoperability with other languages
  - Bindings to C++, fortran, etc
  - We can continue using existing tools (if wanted)
- Perfect for exploratory work
  - No compiling
  - Little boilerplate code
  - E.g. Jupyter notebooks (though this is no longer python-only)
- Package ecosystem
  - "Batteries included" so standard library provides many functions: argparse, globbing, regular expressions, URL requests, math
  - Package manager gives access to huge community-driven ecosystem
  - "Open-source" by default

[Jake VanderPlas: PyCon 2017]



As a result: Python world’s most popular language





PYPL index, Dec. 2019: based on web searches for tutorials on a given language

Stack Overflow queries: Since 2017 Python has been most popular

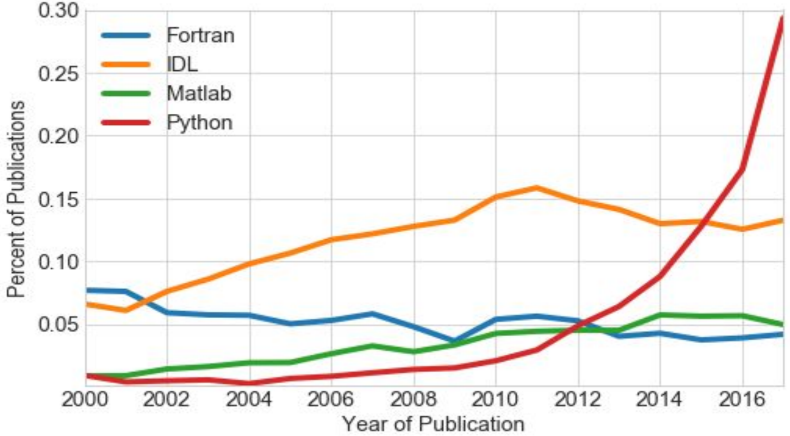
Why Python for high-level particle physics analysis?

- Data analysis outside of particle physics not in C++ these days:
  - It's primarily in Python
  - ⇒ guidance and tutorials already online
  - ⇒ more useful for students after a PhD
  - ⇒ use industry-standard tools with little extra work ⇒ free personpower

- For example: machine learning
  - https://github.com/josephmisiti/awesome-machine-learning
  - 291 libraries in Python
  - 59 tools in C++

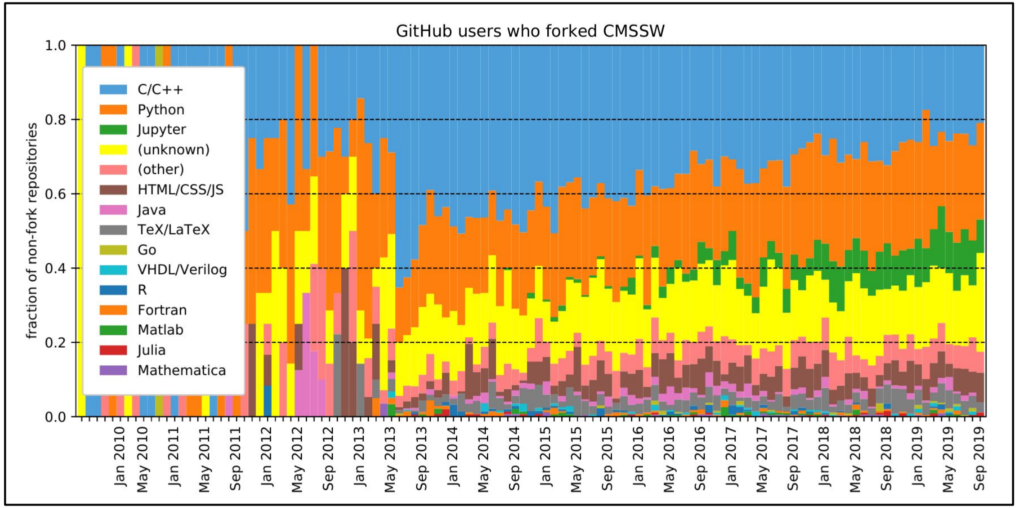
This is not a new message

Easily the dominant language in Astrophysics



https://gist.github.com/jakevdp/f75c09e43320290ffbedbca43f9fd917

On CMS: most users' code outside of CMSSW is now Python

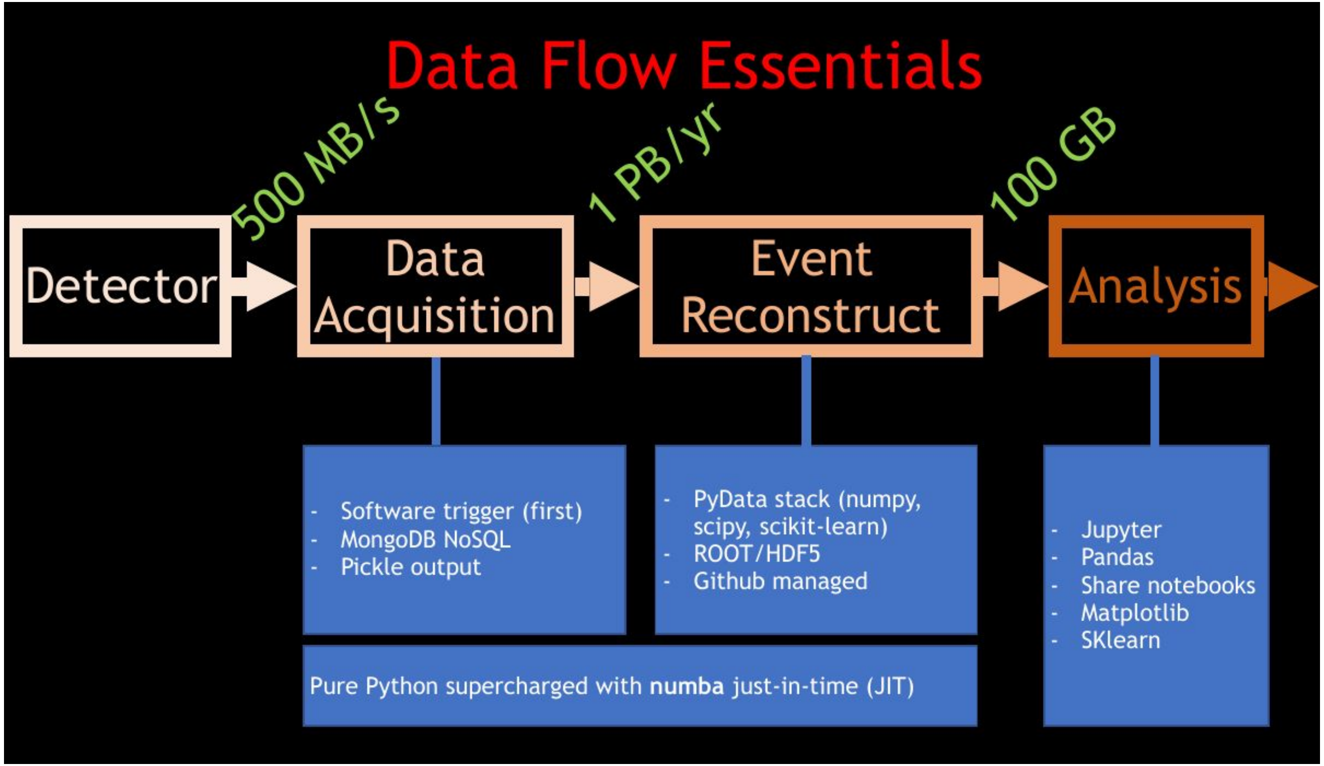


Analysis by Jim Pivarski

Full experiment stack: Xenon1T

DAQ, trigger, reco and analysis code all in python

Chris Tunnel for Xenon1T, PyHEP2018 https://zenodo.org/record/1418513



Point 1:

Python as a 1st class analysis language: many examples in HEP & lots to be gained

But: “isn’t Python slow?”

Sort of:

- Interpreted not compiled
- Global Interpreter Lock: standard interpreted not multi-threaded
- Dynamically typed: attribute look-up more involved
- Primitive types use relatively large

Although:

- Python can now be Just in time compiled (e.g. Numba)
- Other interpreters maturing (e.g. PyPy)

And, crucially, there are other ways of doing things….

Columnar Analysis

How do I say:

“He’s as cool as a cucumber”

in french ?

"Il a froid comme un concombre"

“Il est d'un calme olympien”

“He is calmly Olympian”

✓

which is a long way to say:
to get good results when going from C++ to Python **change how you think, not just the words**

Numpy

Manipulate arrays of data in one go using high-level interface

```python
import numpy

px = numpy.random.normal(0, 100, size=1_000_000)
py = numpy.random.normal(0, 100, size=1_000_000)
```

Pure python loop over px and py pairs:

```python
pt = []
for i in range(len(px)):
    pt.append(numpy.sqrt(px[i]**2 + py[i]**2))
```

O(N) python instructions

*Summary shamelessly ripped from Chris Burr, CERN

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```

O(1) python instructions

O(N) heavily optimised instructions

Numpy operations are: Single Instruction Multiple Data (SIMD)

```
selected = mass[(pt > 1000) & (2 < eta) & (eta < 5)]
```


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Numpy (2)

A high-level interface to low-level routines:

- Uses vectorized programming in CPU for efficiency
- Supports multi-dimensional arrays

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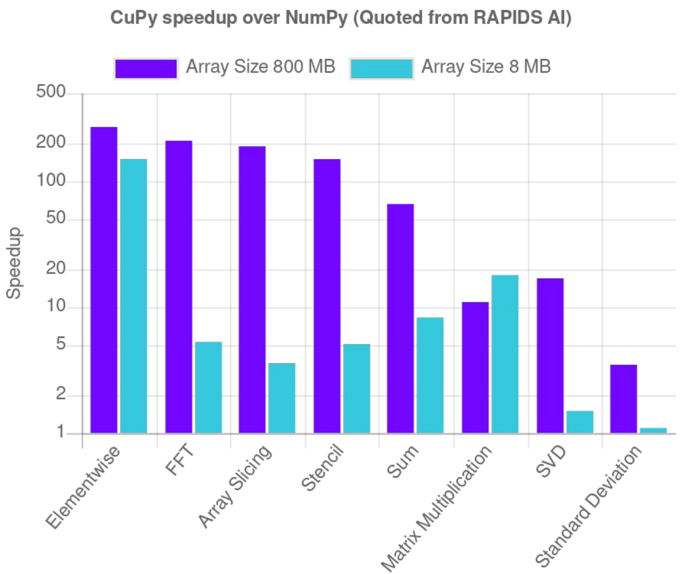
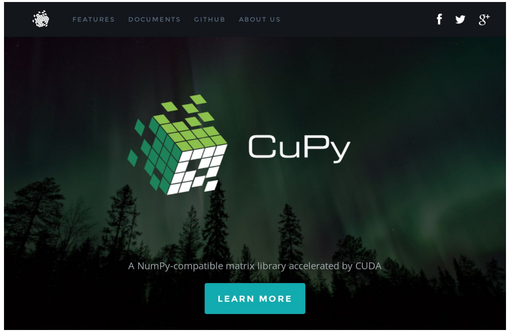
But this is python:

- Dynamic nature of language
- Package ecosystem
- ⇒ Cupy: Same user code can run on GPUs
- See also PyHEADTAIL





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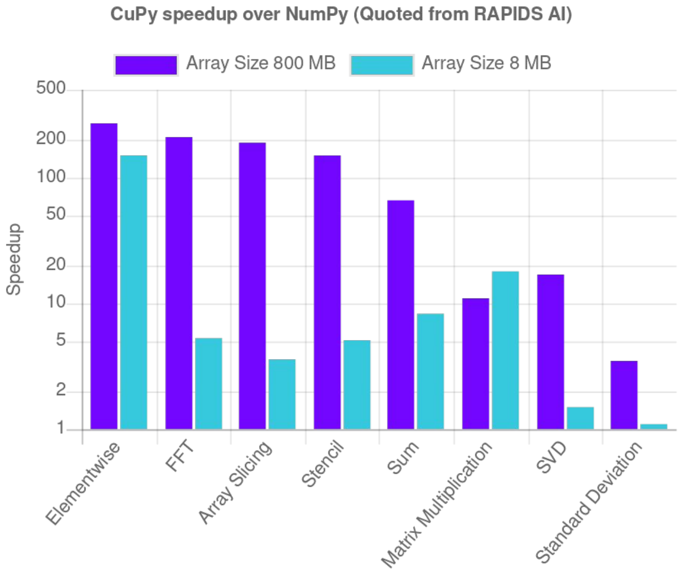
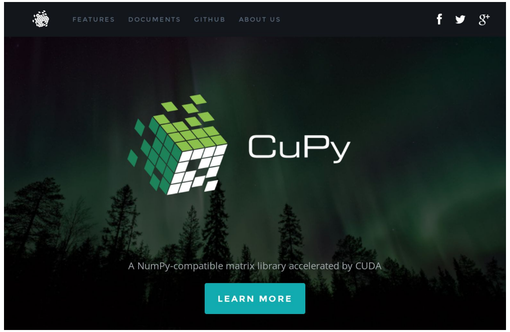
Difficulties for HEP:

- Getting data from ROOT files into such arrays without a for-loop
- Our data is often more structured than simple arrays





Filling a ROOT Tree in ROOT w. event loop

Pseudo-code (not python or c++)

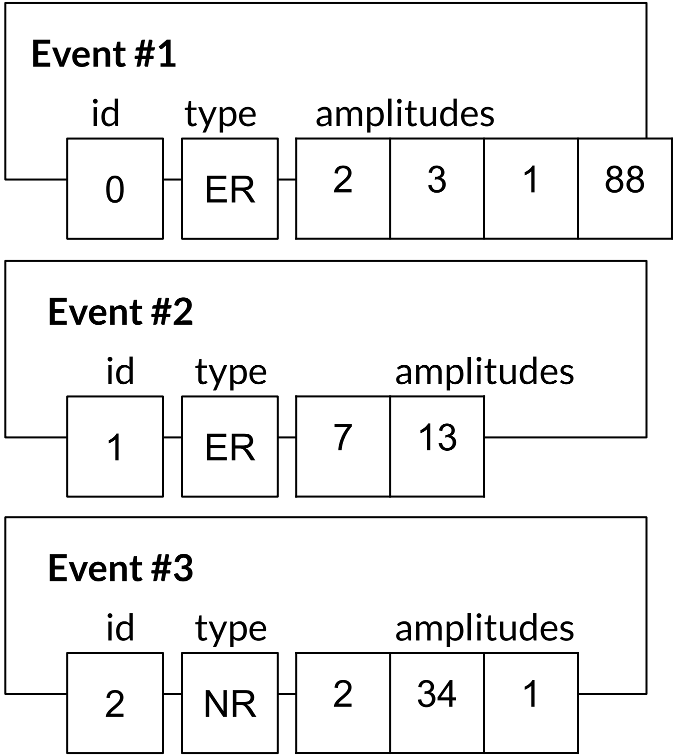
```
Class Event:
        Int id
        Enum type
        Vector<Float> pulse_amplitudes

Function WriteTree():
        TFile file(“outfile”)
        TTree tree(...)
        Event an_event
        tree.Branch(“event”, &an_event)

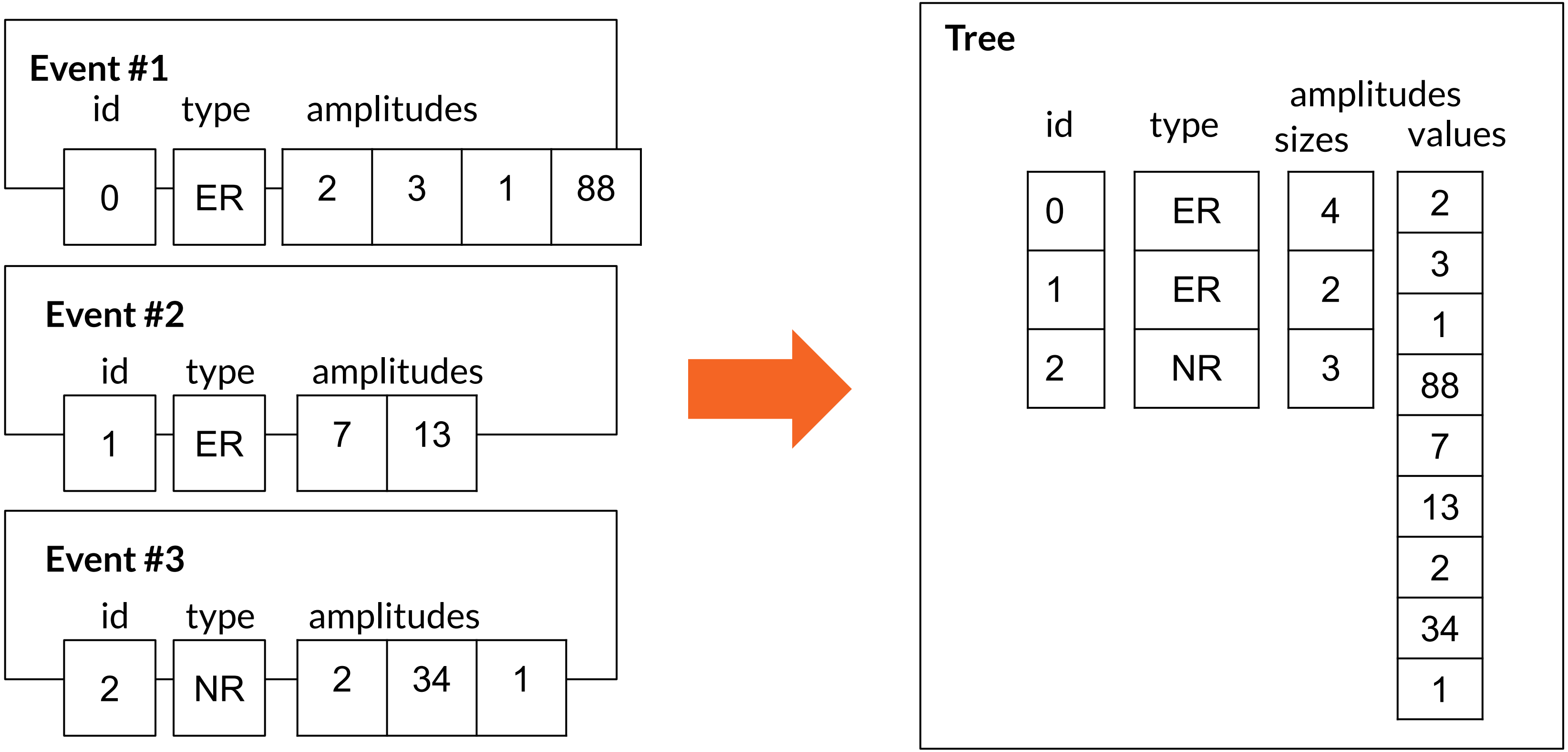
        For each event:
                an_event.id = event number
                an_event.type = some event type
                For each pulse:
                        an_event.pulse_amplitudes.append(some value)

                tree.Fill()
        tree.Write()
```

Builds events that look like:



… which on disk ROOT's split mode makes



ROOT file splitting

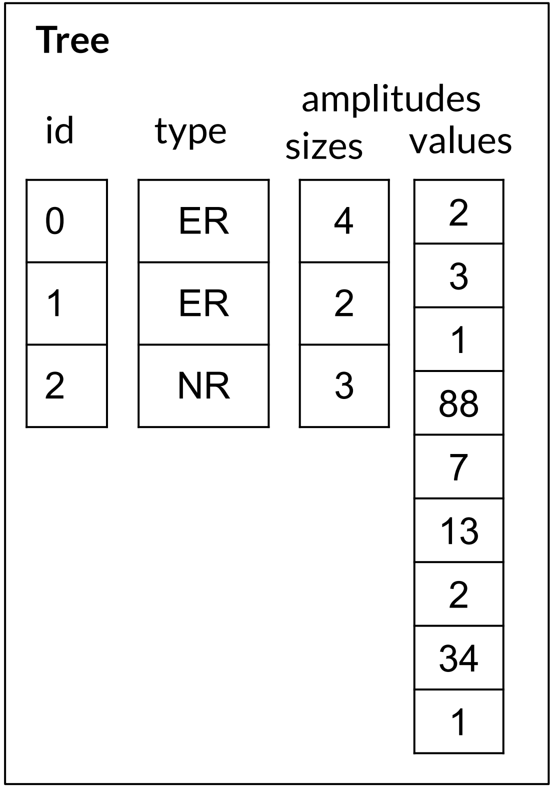
Fails for complex objects e.g. vectors of vectors of floats in each event

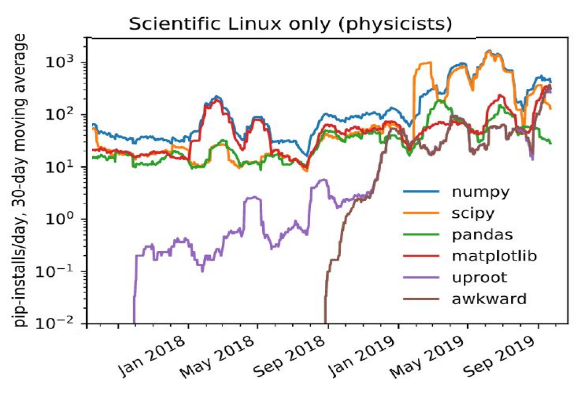
Improves compression on disk

Is why SetBranchStatus speeds up reading back data: only read the branches you want

The on disk layout of split branches is a set of contiguous arrays

- Read all data for a branch directly into a numpy array





- Uproot = micro pythonic ROOT
  - Does one thing: Read (and now write) ROOT files in python
  - Efficient TTree handling: baskets of data on disk copied into numpy array directly
  - About 2 years old -- one of the most important packages for particle physics with python
- Uproot can now write trees as well as read them
  - Currently limited to writing single values per event
  - Vectors of values per event expected soon
- After this: uproot will be maintenance only, no other major developments planned

But how to make “numpy arrays” for variables with different lengths in each event?

Jagged Arrays

Jagged Array internals

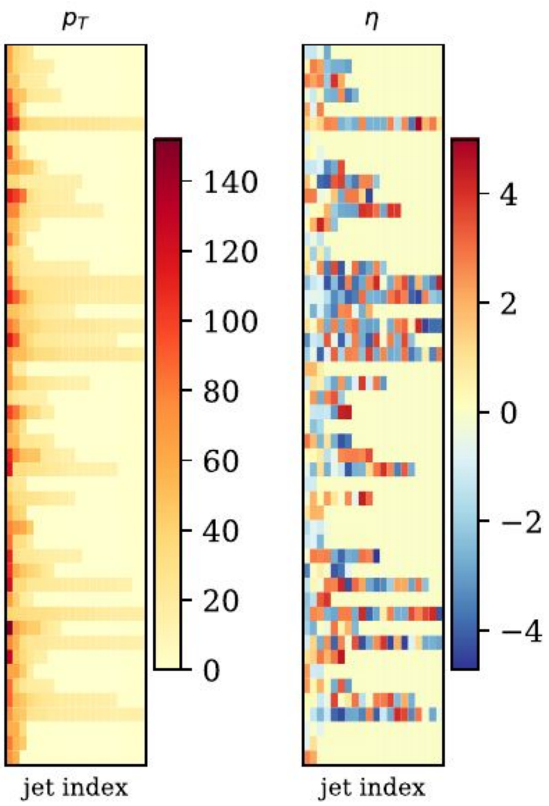
starts	stops	values
0	4	2
4	6	3
6	9	1
		88
		7
		13
		2
		34
		1

Jagged Array as a user sees it

#1	2	3	1	88
#2	7	13		
#3	2	34	1	

Something like a 2D numpy array

E.g. `array.max()` gives the largest value in each event



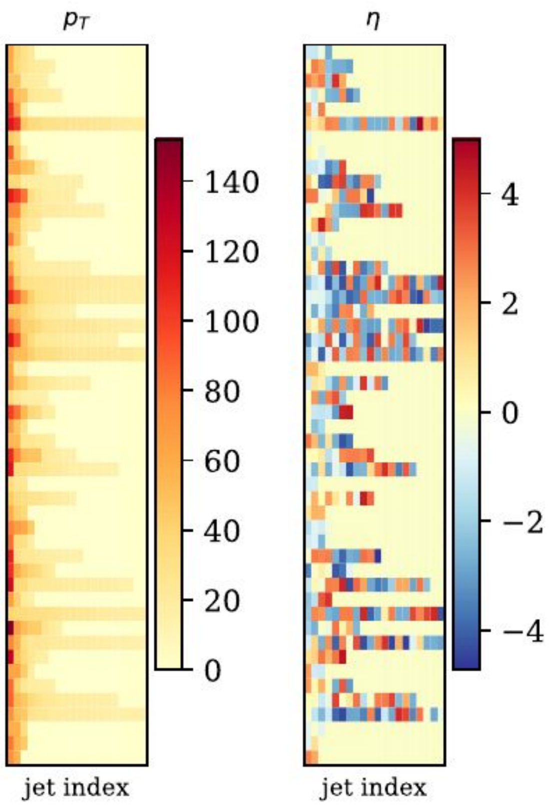
Jagged Arrays

For example, find the momentum of the most forward-going jet in each event:

```
pt = Jet_pt[numpy.abs(Jet_eta).argmax()]
```

Break it down:

- `numpy.abs(Jet_eta)`= absolute eta of every jet in every event
- `numpy.abs(Jet_eta).argmax()`= index of jet with largest absolute eta for each event. Number between 0 and Njet
- `Jet_pt[numpy.abs(Jet_eta).argmax()]`= pt of the jet with the largest absolute eta for each event, now a simple 1D array



Awkward Array

- Implements the concept of jagged arrays
  - Broadcasting, masking, reducing
- Methods to manipulate these without a python for loop: very quick operations
  - Internally using numpy
- Version 1.0 should be released soon:
  - Rewrite the internals
  - Tidy up the interface
  - Let other packages interpret awkward arrays easily (numba, numexpr)

Coffea - Column Object Framework for Effective Analysis

Fermilab project to build an analysis framework on top of awkward array and uproot

Separation of “user code” and “executors”

- User writes a Processor to do the analysis
- Executor runs this on different distributed job systems, e.g.:
  - Local multiprocessing, Parsl or Dask (batch systems), Spark cluster

Coffea ***achieved 1 to 3 MHz*** event processing rates

- Using Spark cluster on same site as data at Fermilab

Point 2:

Interfacing to “big data” tools can bring MHz event processing

PyHEP: Building a community for Python in HEP

PyHEP 2019 workshop

Building a community of Python users and developers within particle physics

55 people for 2.5 days at Cosener's House in Abingdon

Second in series, first at CHEP '18 (Sofia, Bulgaria)

Indico page: https://indico.cern.ch/e/PyHEP2019

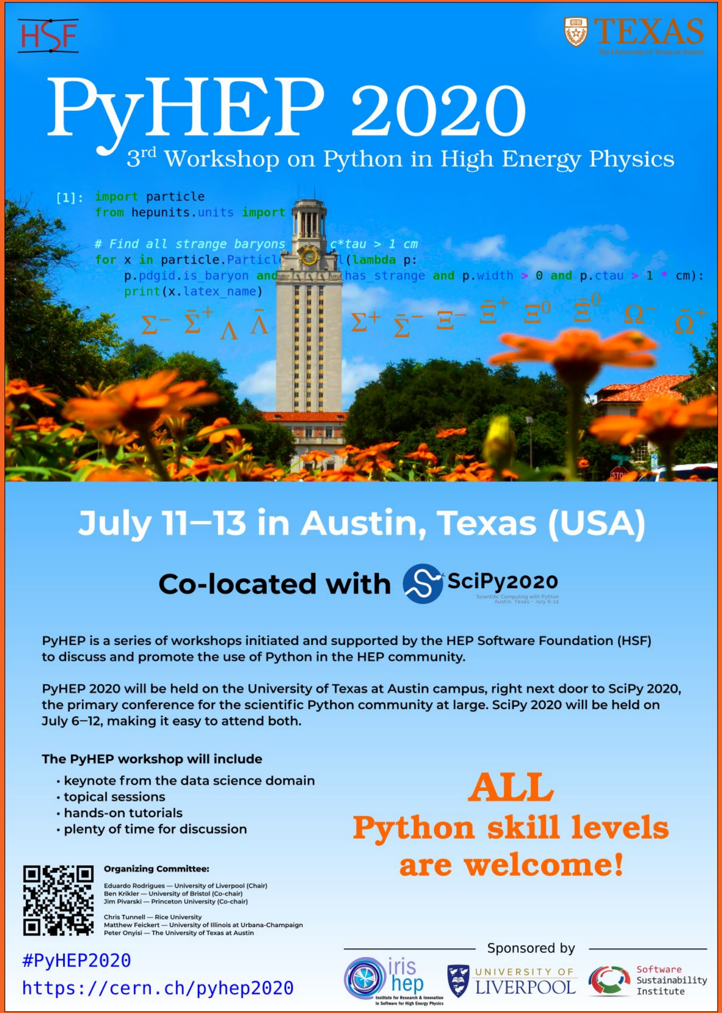
3rd edition: July 2020 in Austin, Texas alongside [SciPy2020]()

PyHEP2020

indico.cern.ch/e/PyHEP2020

11 to 13th July in Austin, Texas

Co-located with SciPy (6 - 12th)



scikit-hep

http://scikit-hep.org/
https://github.com/scikit-hep/

The success of Python for astronomy is partly due to the Astropy project

Uproot and Awkward-array exist within scikit-hep project

Many other packages on there:

- Particle: Python interface to PDG

```python
from particle import PDGID
```

```python
pid = PDGID(211)
pid
```

```
<PDGID: 211>
```

```python
PDGID(99999999)
```

```
<PDGID: 99999999 (is_valid=
```

```python
print(pid.info())
```

```
A               None
C               None
J               0.0
L               0
P               -1
S               0
Z               None
abspid          211
charge          1.0
```

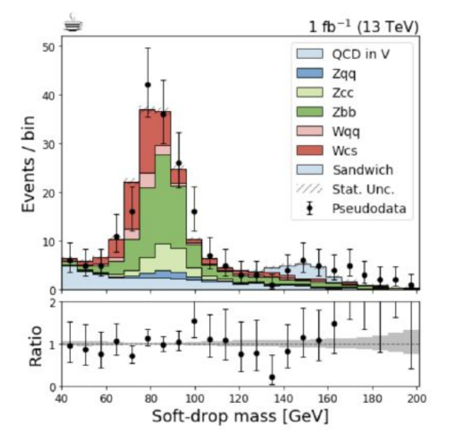
From a PDG ID

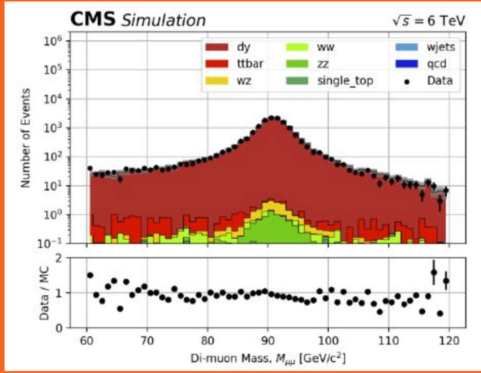
```python
Particle.from_pdgid(211)
```

π^+

- Validation, Particle Decays, Statistics

mpl-hep





Particle Physics loves histograms!

But matplotlib is a little tricky with pre-binned data

Survey on plotting needs:

- Stacked histograms
- Good error bars
- Ratios of 1D plots
- Simple “COLZ” option
- Consistent plot styling

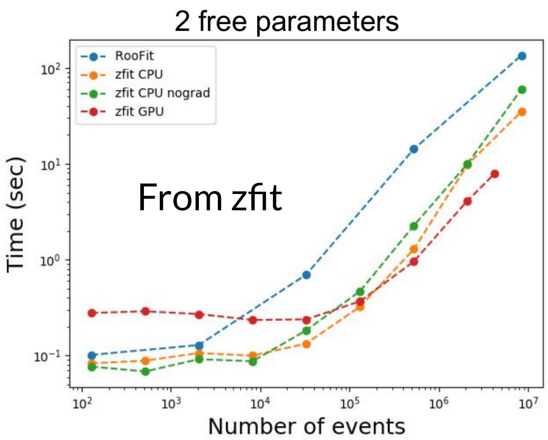
Mpl-hep package should become associated with matplotlib (spoken with matplotlib devs)

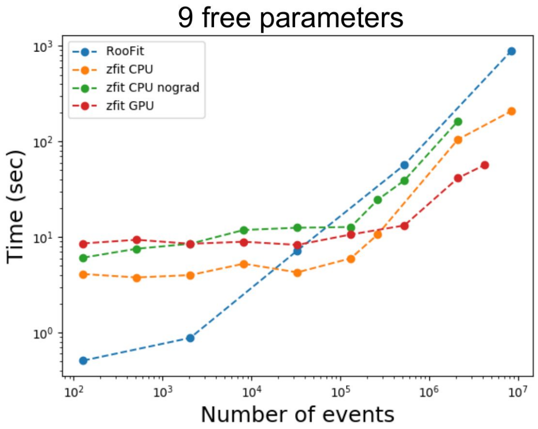
Fitting

Many presentations on fitting and statistics

Using TensorFlow as a backend:

- Zfit -- focussed on unbinned fits, adapting deep learning techniques for model fitting
- PyHF -- store the entire likelihood on HEPData





Point 3:
We’re growing a community of Python HEP users

(and 2 of 3 convenors in the UK)

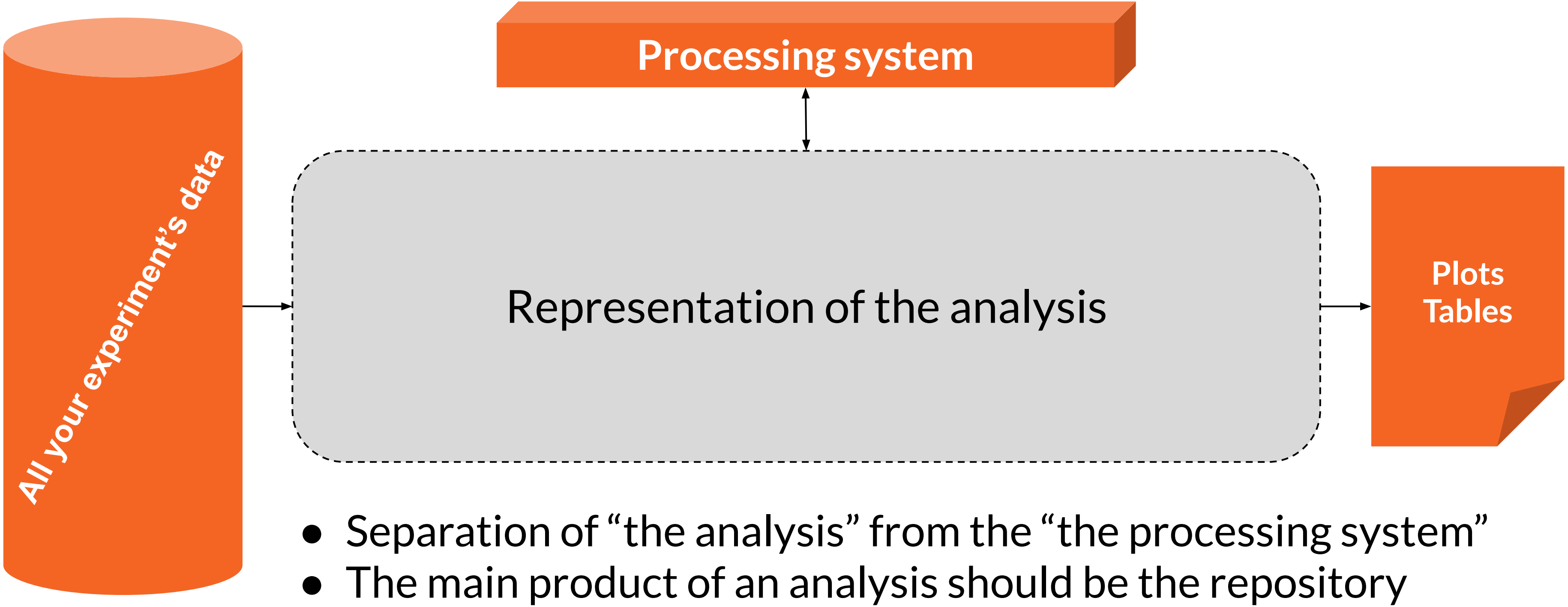
But: Is Python “high-level” enough?

User decides flow control

Writing full jagged array manipulations can be tough (e.g. object matching)

Analysis description languages

Analysis *versus* analysis tools



- Separation of “the analysis” from the “the processing system”
- The main product of an analysis should be the repository

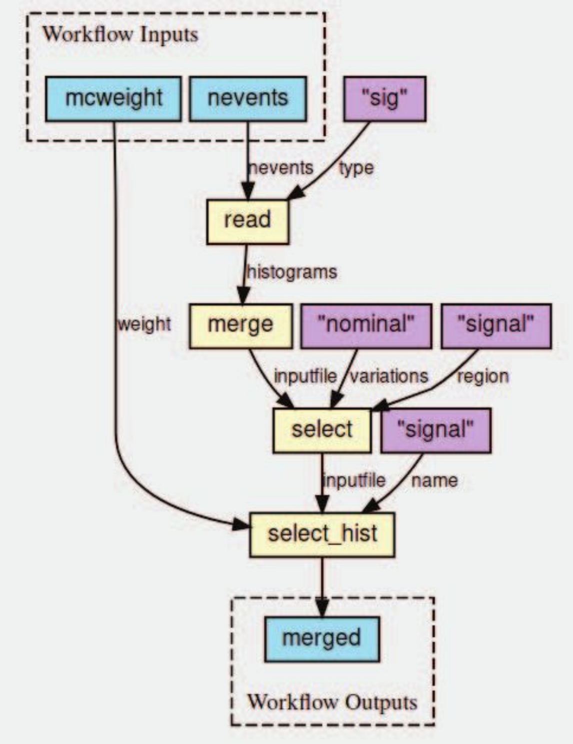
Declarative programming

- Declarative languages the **user says WHAT**, the **interpretation decides HOW**
- User gives up flow control:
    - Cannot do: “Loop over each event, add this to that if something is true, etc”
- Allows:
    - More concise description
    - Fewer bugs
    - Easier to reproduce and share
    - Optimisation behind the scenes

From the description to a workflow

Description → Directed Acyclic Graph (DAG) = the “how”

- Common to Spark, Dask, Parsl, Airflow, etc
- Allows for caching at each node
- Can optimise the DAG: “elide” (remove) nodes if result is never used



Analysis description languages

A large fraction of LHC analyses involve only a few steps

Can we encapsulate these into a “Domain Specific Language”?

Several different attempts to build an ADL:

- LINQ (Gordon Watts et al)
- NAIL (Andrew Rizzi)
- FAST-HEP (this talk)
- Dedicated workshop at Fermilab last May: https://indico.cern.ch/event/769263/

The FAST HEP toolkit

F.A.S.T = Faster Analysis Software Taskforce

- UK-based particle physicists
- Started around May 2017
- Explore ways to accelerate and improve our analysis code
- Use of 1 to 3-day “hack-shops” to test new ideas

How we have worked

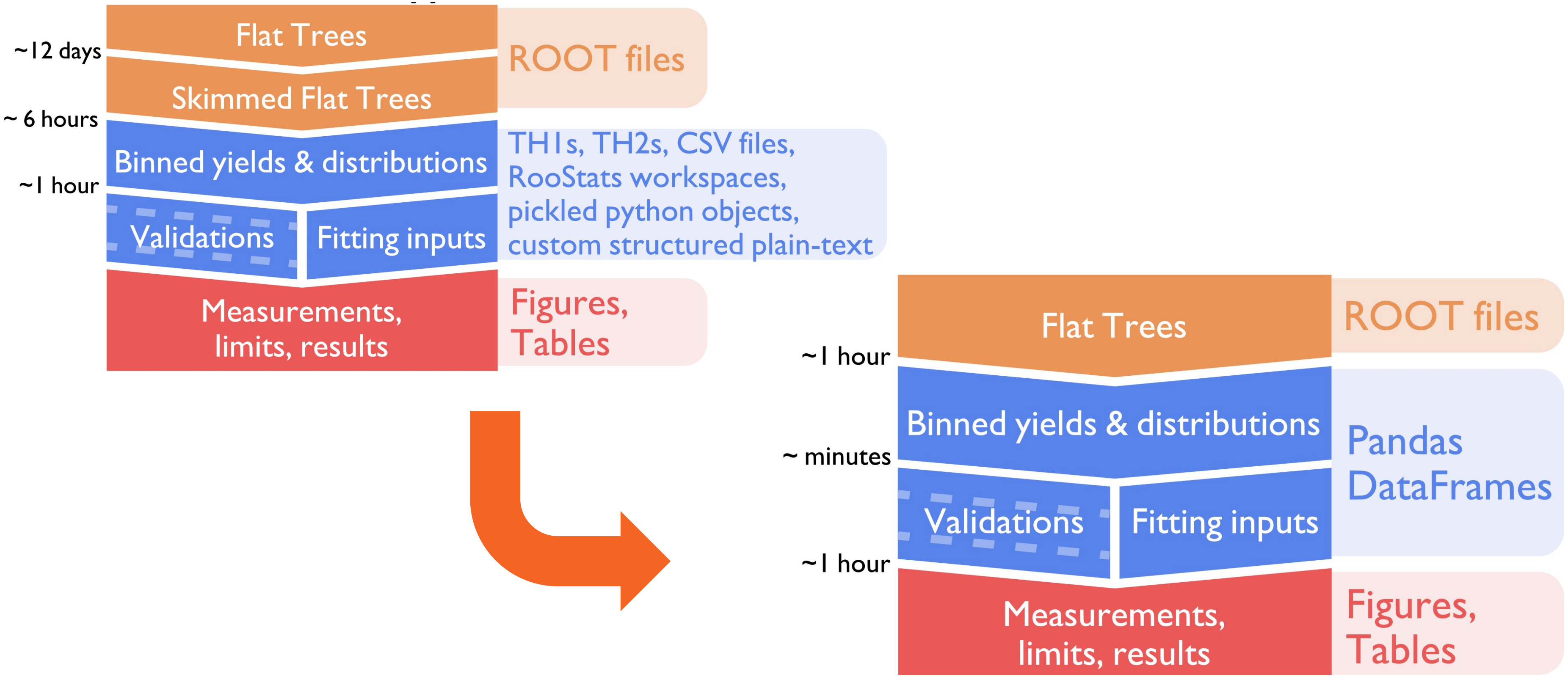
Design principles:

- Write as little code as possible: act as glue
- Contribute first to other projects
- Value modularity

Goals:

a. Reproducibility
b. Simplicity
c. Speed
d. Documentation
e. Automation

Streamlining analysis



The FAST toolkit

For internals:
use Python

NumPy

uproot

Awkward Array

NumExpr

at ()

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For data:
use Pandas
Demoed at CHEP 2018

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

What is Pandas?

- Programmatic tables, built on numpy
- A staple of data science
- https://pandas.pydata.org/

```
A = ['foo', 'bar', 'foo', 'bar']
B = ['one', 'one', 'two', 'three']
C = np.random.randn(4)
D = np.random.randn(4)

df = pd.DataFrame({"A": A, "B": B,
                   "C": C, "D": D})
```

```
df
```

	A	B	C	D
0	foo	one	-0.678386	0.072926
1	bar	one	-0.338564	-1.038362
2	foo	two	0.527912	-0.478806
3	bar	three	-0.237991	-1.296666

```
df.set_index(["A", "B"])
```

		C	D
A	**B**		
foo	**one**	-0.678386	0.072926
bar	**one**	-0.338564	-1.038362
foo	**two**	0.527912	-0.478806
bar	**three**	-0.237991	-1.296666

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For descriptions:
use YAML...

Describing analysis with YAML

- A superset of JSON
  - Easier to read
- Naturally declarative:
  - No "control flow" (e.g. no for loops)
- Widely used to describe pipeline configuration:
  - gitlab-CI, travis-CI, Azure CI/CD, Ansible, Kubernetes, etc
  - HEPData: YAML for reproducible Data

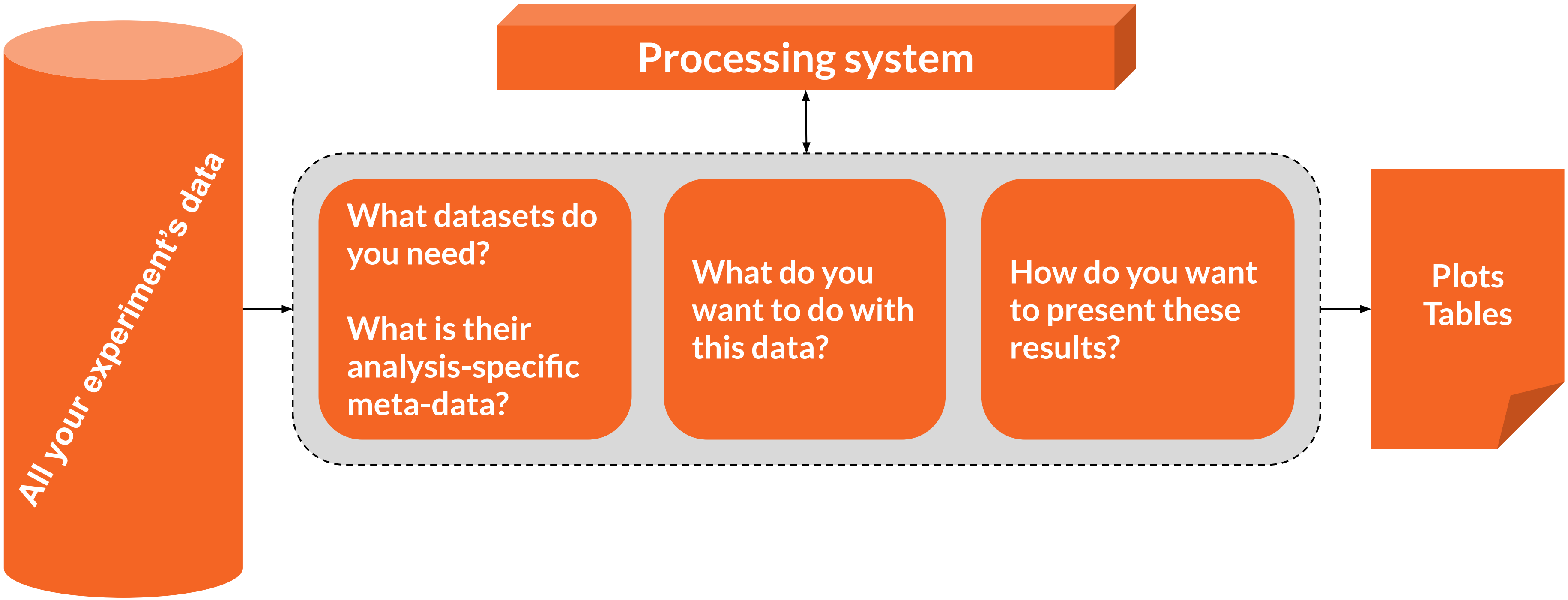
JSON

```
[{"martin":{"name": "Martin Devloper",
    "job": "Developer",`
    "Skills": ["python", "perl", "pascal"]}
,{"tabitha":{"name": "Tabitha Bitumen", "job":
"Developer", "Skills": ["lisp", "fortran",
"erlang"]}}]
```

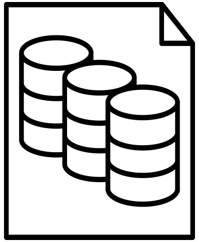
YAML

```
-  martin:
    name: Martin Devloper
    job: Developer
    skills:
      - python
      - perl
      - pascal
-  tabitha:
    name: Tabitha Bitumen
    job: Developer
    skills:
      - lisp
      - fortran
      - erlang
```

Analysis *versus* analysis tools

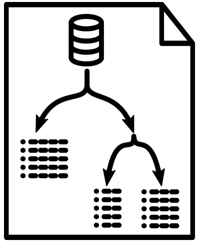


Step 1:
`fast_curator`



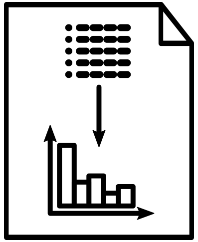
Dataset description

Step 2:
`fast_carpenter`
`(using fast-flow)`



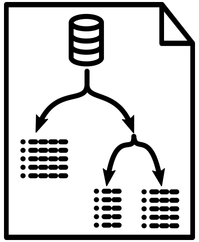
Analysis description

Step 3:
`fast_plotter`
`fast_datacard`



Plotting and postprocessing

Step 2:
`fast_carpenter`



Analysis description

Take your trees and make them into tables

- Just like a carpenter

Table = Pandas DataFrame

Two main types of table for now:

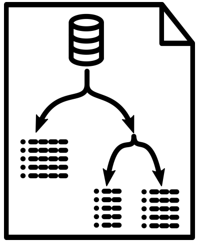
- Histogram
- Cutflow

Cover most typical particle physics analyses

- BUT: very easy to extend

Command-line switch between different work-flow managers / batch systems

Step 2:
fast_carpenter



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- BU

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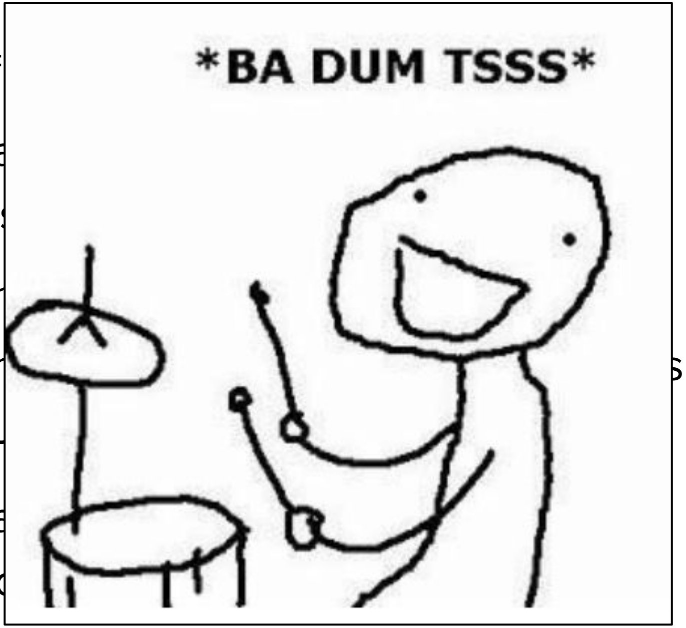

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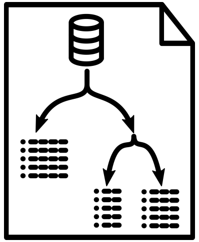

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Command-line switch between different work-flow managers / batch systems

Describe what to do with the data

What type of action to take at each step:

- Stage1 = A built-in stage of fast-carpenter
- Stage2 = A stage imported from a python module
- IMPORT = Import a list of stages and their descriptions from another YAML file

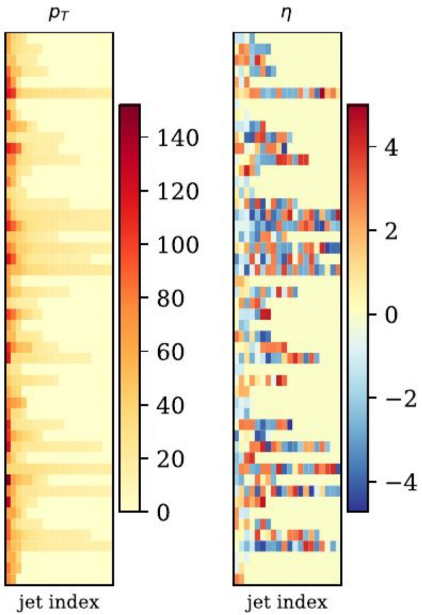
Configure each named stage above

```yaml
stages:
  - Stage1: StageFromBackend
  - Stage2: module.that.provides.some.Stage
  - IMPORT: "{this_dir}/another_description.yaml"

Stage1:
  keyword: value
  another_keyword: [a, list, of, values]

Stage2:
  arg1:
      takes: ["a", "dict"]
      with: 3
      different: keys
```

Define Stage:
fast_carpenter.Define

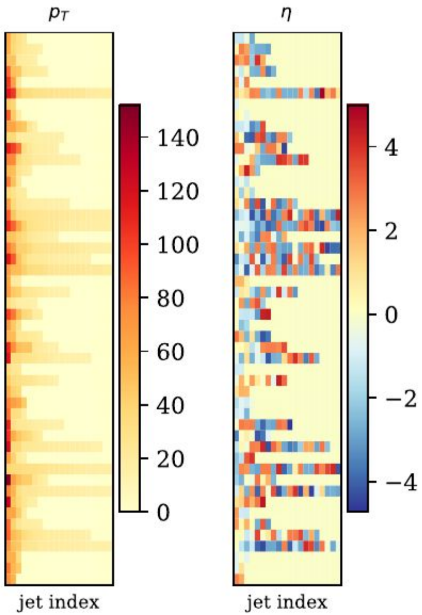


From Joosep Pata's talk at PyHEP19

```yaml
- Muon_Pt: "sqrt(Muon_Px ** 2 + Muon_Py ** 2)"
- IsoMuon_Idx: (Muon_Iso / Muon_Pt) < 0.10
- HasTwoMuons: NIsoMuon >= 2
```

- Simple operations
- Preserve the "jaggedness"

Define Stage:
fast_carpenter.Define



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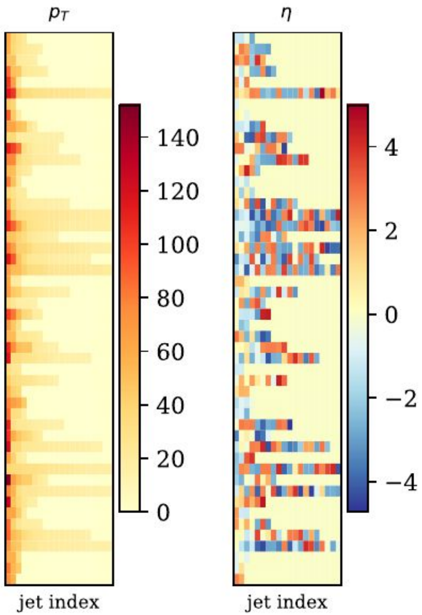
- HasTwoMuons: NIsoMuon >= 2
```

- Simple operations
- Preserve the "jaggedness"

Take the Nth object
(on the deepest dimension)

```yaml
- Muon_lead_Pt: {reduce: 0, formula: Muon_Pt}
- Muon_sublead_Pt: {reduce: 1, formula: Muon_Pt}
```

Define Stage:
fast_carpenter.Define



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- Preserve the "jaggedness"

Take the Nth object
(on the deepest dimension)

```
- Muon_lead_Pt: {reduce: 0, formula: Muon_Pt}
- Muon_sublead_Pt: {reduce: 1, formula: Muon_Pt}
```

```
- NIsoMuon:
    formula: IsoMuon_Idx
    reduce: count_nonzero

- IsoMuPtSum:
    formula: Muon_Pt
    reduce: sum
    mask: IsoMuon_Idx
```

- Reduce dimensionality with a function
- Mask out objects in the event

Select events
fast_carpenter.CutFlow

```yaml
DiMu_controlRegion:
    weights: {nominal: weight}
    selection:
        All:
          - {reduce: 0, formula: Muon_pt > 30}
          - leadJet_pt > 100
          - DiMuon_mass > 60
          - DiMuon_mass < 120
          - Any:
            - nCleanedJet == 1
            - DiJet_mass < 500
            - DiJet_deta < 2
```

Remove events from subsequent stages

Produces a cut-flow summary table

- Weighted / raw counts

Selection is specified as nested dictionaries of **`All`**, **`Any`** and a list of expressions

Individual cuts use same scheme as variable definition

Fill a histogram

fast_carpenter.BinnedDataFrame
fast_carpenter.BuildAghast

```
NumberMuons:
  binning:
      - {in: NMuon}
      - {in: NIsoMuon}
  weights: [EventWeight, EventWeight_NLO_up]

DiMuonMass:
  binning:
      - in: DiMuon_Mass
        bins: {low: 60, high: 120, nbins: 60}
  weights: {weighted: EventWeight}
```

- Binning scheme:
  - Assume variable already discrete (eg. NumberHits)
  - Equal-width bins over a range (eg. DiMuonMass)
  - List of bin edges
- Event weights
  - Multiple weight schemes add columns
- Output written to disk:
  - Pandas to produce a dataframe in any format
  - Also (experimentally) to a Ghast

Output of BinnedDataframe stage

```
>>> import pandas as pd
>>> df = pd.read_csv('tbl_dataset.dimu_mass--weighted.csv')
>>> print(df.groupby('dataset').nth([0, 1, 2]).set_index('dimu_mass', append=True))
                               n  weighted:sumw  weighted:sumw2
dataset    dimu_mass
data       (-inf, 60.0]    993.0            NaN             NaN
           (60.0, 61.0]     38.0            NaN             NaN
           (61.0, 62.0]     25.0            NaN             NaN
dy         (-inf, 60.0]    821.0     655.570801     1017.549133
           (60.0, 61.0]     56.0      23.963226       12.091142
           (61.0, 62.0]     56.0      25.572840       13.094129
qcd        (-inf, 60.0]      0.0       0.000000        0.000000
           (60.0, 61.0]      0.0       0.000000        0.000000
           (61.0, 62.0]      0.0       0.000000        0.000000
single_top (-inf, 60.0]     32.0       1.741041        0.100682
           (60.0, 61.0]      1.0       0.065288        0.004263
           (61.0, 62.0]      1.0       0.005831        0.000034
ttbar      (-inf, 60.0]     49.0      11.392980        3.072051
           (60.0, 61.0]      3.0       0.840432        0.236490
           (61.0, 62.0]      2.0       0.319709        0.075986
wjets      (-inf, 60.0]      1.0       0.311917        0.097292
           (60.0, 61.0]      0.0       0.000000        0.000000
           (61.0, 62.0]      0.0       0.000000        0.000000
ww         (-inf, 60.0]     61.0       3.600221        0.221474
           (60.0, 61.0]      1.0       0.063284        0.004005
           (61.0, 62.0]      2.0       0.102053        0.005617
wz         (-inf, 60.0]     15.0       0.320914        0.007842
           (60.0, 61.0]      2.0       0.053328        0.001424
           (61.0, 62.0]      0.0       0.000000        0.000000
zz         (-inf, 60.0]     47.0       0.360053        0.002981
           (60.0, 61.0]      0.0       0.000000        0.000000
           (61.0, 62.0]      0.0       0.000000        0.000000
```

Showing only first three rows for each dataset (using groupby operation)

User-defined stages

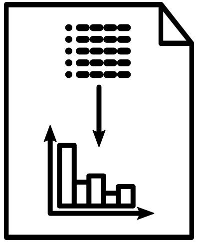
```yaml
stages:
  - BasicVars: fast_carpenter.Define
  - DiMuons: cms_hep_tutorial.DiObjectMass
  - Histogram: BinnedDataframe

...

DiMuons:
    mask: IsoMuon_Idx
```

- Carpenter should provide most commonly needed stages
- But if it doesn't: can define your own
  - Break out of declarative YAML to full, imperative python
- Any importable python class with the correct interface
- Keep separation of analysis decision from data-flow

User-defined stages

```python
def event(self, chunk):
    # Get the data as a pandas dataframe
    px, py, pz, energy = chunk.tree.arrays(self.branches, outputtype=tuple)

    # Rename the branches so they're easier to work with here
    if self.mask:
        mask = chunk.tree.array(self.mask)
        px = px[mask]
        py = py[mask]
        pz = pz[mask]
        energy = energy[mask]

    # Find the second object in the event (which are sorted by Pt)
    has_two_obj = px.counts > 1

    # Calculate the invariant mass
    p4_0 = TLorentzVectorArray(px[has_two_obj, 0], py[has_two_obj, 0],
                               pz[has_two_obj, 0], energy[has_two_obj, 0])
    p4_1 = TLorentzVectorArray(px[has_two_obj, 1], py[has_two_obj, 1],
                               pz[has_two_obj, 1], energy[has_two_obj, 1])
    di_object = p4_0 + p4_1

    # insert nans for events that have fewer than 2 objects
    masses = np.full(len(chunk.tree), np.nan)
    masses[has_two_obj] = di_object.mass

    # Add this variable to the tree
    chunk.tree.new_variable(self.out_var, masses)
    return True
```

Step 3:
`fast_plotter`
`fast_datacard`



Plotting and postprocessing

fast-plotter:

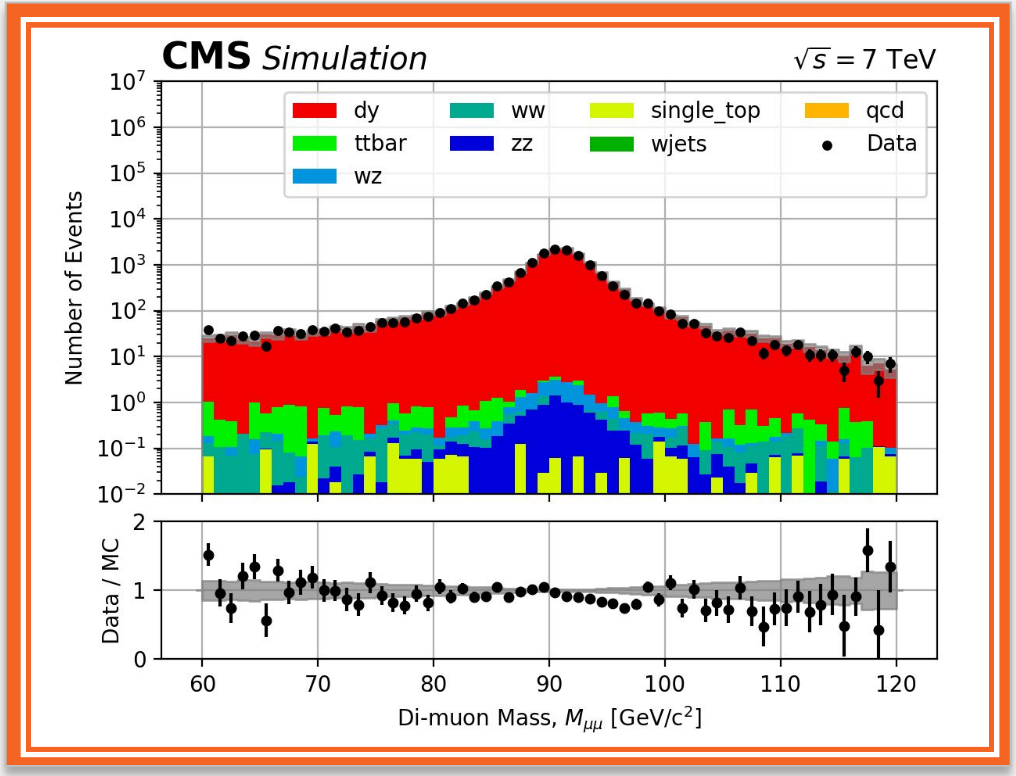
- Easy to produce basic plots, tools to support final publication-quality
- Command-line tool with reasonable defaults and simple configuration

fast-datacard:

- Bring resulting DataFrames into CMS' Combine fitting procedures

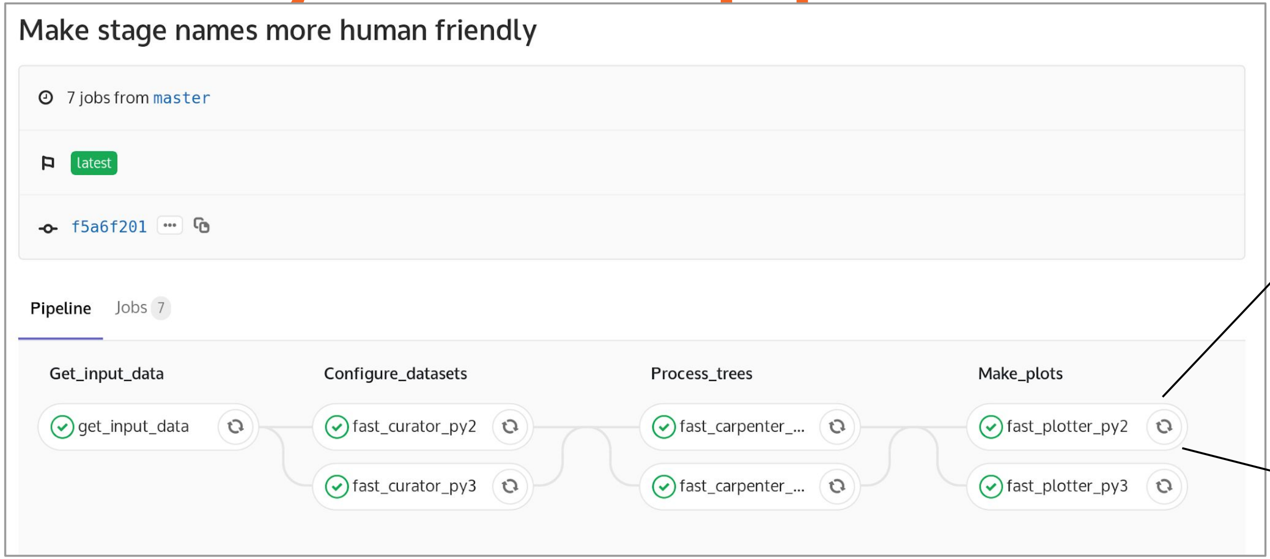
BinnedDataframes into plots

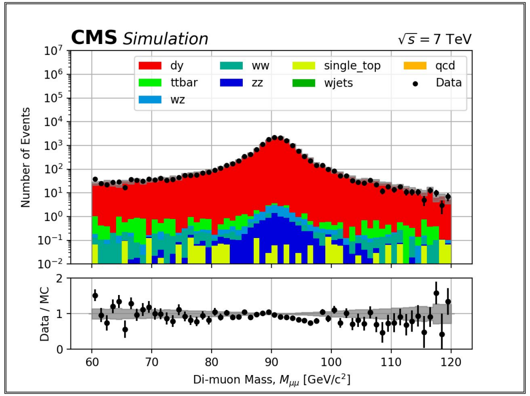
- Plot on the right with:
```
fast_plotter -y log \
-c plot_config.yml \
-o tbl_*.csv
```
- YAML config:
  - Colour scheme, axis labels
  - Dataset definition
  - Annotations
  - Legend

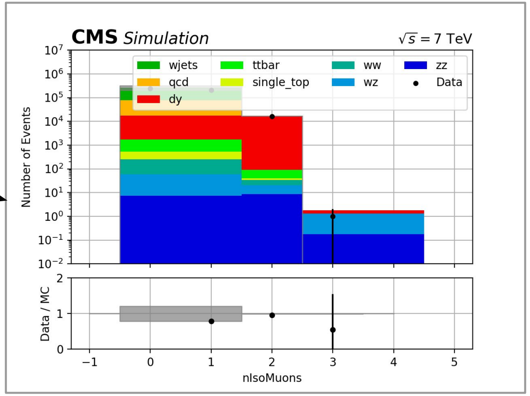


Plot of DiMuonMass using binned dataframe from fast-carpenter stage

“Analysis in a CI pipeline”







- To run this:
  - Demo analysis in a pipeline
  - The gitlab-ci config
  - Script tying the commands together
- Feasibility for huge datasets unclear, but can happily manage subsets of data for testing

Just how “fast” is this?

On a laptop: as quick as a C++ equivalent

For example, the demo repo:

- fast-carpenter: 6 seconds
- C++ example: 4 seconds

More benchmarks and examples on their way

Many optimisations possible

- caching, DAG optimisation, etc
- started working with Coffea to use them under the hood

Current FAST-HEP codebase

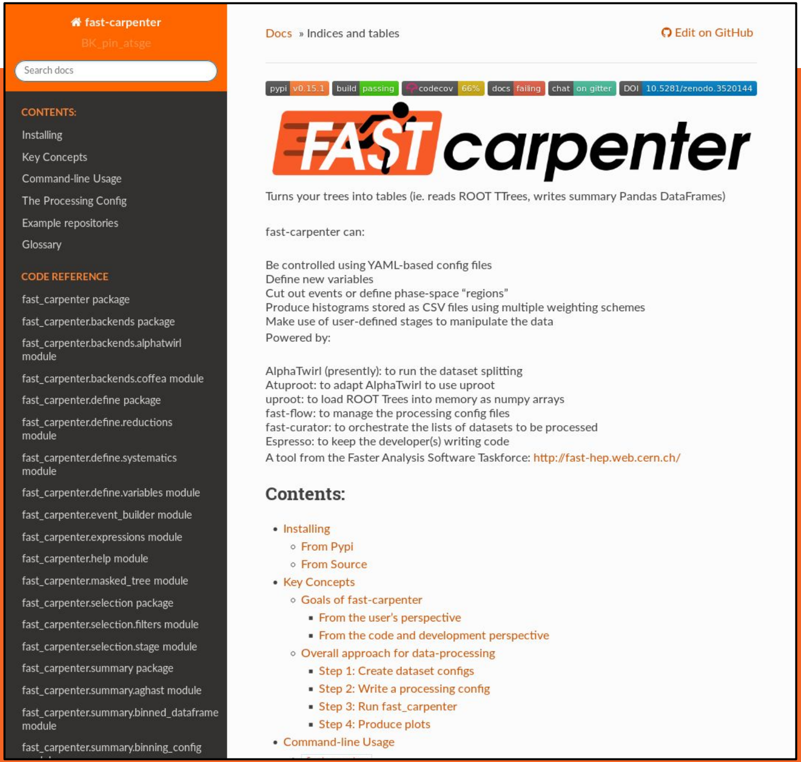
Being used for **2 CMS analyses**, **LUX-ZEPLIN** and **ATLAS** investigated, used for design studies of **DUNE,** and **FCC** experiments

New features being fed back to core packages from analysis-specific repositories

- Direct use in Jupyter notebooks
- Writing skimmed / slimmed outputs
- Persistency outside of CSV formats
- Docker container for running at NERSC, etc

Where to find the code

- All public on github:
  - github.com/fast-hep/
  - Main package: github.com/fast-hep/fast-carpenter
- On PyPI, e.g. fast-carpenter
- Docker image with all tools: fasthep/fast-hep-docker
- Docs: fast-carpenter.readthedocs.io/
- Clonable demo analysis repository:
  - gitlab.cern.ch/fast-hep/public/fast_cms_public_tutorial
- Chat: gitter.im/FAST-HEP



fast-carpenter

Search docs

CONTENTS:

Installing
Key Concepts
Command-line Usage
The Processing Config
Example repositories
Glossary

CODE REFERENCE

fast_carpenter package
fast_carpenter.backends package
fast_carpenter.backends.alphatwirl module
fast_carpenter.backends.coffea module
fast_carpenter.define package
fast_carpenter.define.reductions module
fast_carpenter.define.systematics module
fast_carpenter.define.variables module
fast_carpenter.event_builder module
fast_carpenter.expressions module
fast_carpenter.help module
fast_carpenter.masked_tree module
fast_carpenter.selection package
fast_carpenter.selection.filters module
fast_carpenter.selection.stage module
fast_carpenter.summary package
fast_carpenter.summary.aghast module
fast_carpenter.summary.binned_dataframe module
fast_carpenter.summary.binning_config

Docs » Indices and tables

Edit on GitHub

pypi v0.15.1 | build passing | codecov 66% | docs failing | chat on gitter | DOI 10.5281/zenodo.3520144

FAST carpenter

Turns your trees into tables (ie. reads ROOT TTrees, writes summary Pandas DataFrames)

fast-carpenter can:

Be controlled using YAML-based config files
Define new variables
Cut out events or define phase-space "regions"
Produce histograms stored as CSV files using multiple weighting schemes
Make use of user-defined stages to manipulate the data
Powered by:

AlphaTwirl (presently): to run the dataset splitting
Atuproot: to adapt AlphaTwirl to use uproot
uproot: to load ROOT Trees into memory as numpy arrays
fast-flow: to manage the processing config files
fast-curator: to orchestrate the lists of datasets to be processed
Espresso: to keep the developer(s) writing code
A tool from the Faster Analysis Software Taskforce: http://fast-hep.web.cern.ch/

Contents:

- Installing
  - From Pypi
  - From Source
- Key Concepts
  - Goals of fast-carpenter
    - From the user's perspective
    - From the code and development perspective
  - Overall approach for data-processing
    - Step 1: Create dataset configs
    - Step 2: Write a processing config
    - Step 3: Run fast_carpenter
    - Step 4: Produce plots
- Command-line Usage

Point 4:

FAST-HEP has been exploring new ideas for about 2.5 years: where should we go next?

Wrapping up

Summary

Particle physics faces major computing challenges

- Lots of data
- Fewer relative resources

Python is a first class analysis language

- E.g. industry, astrophysics
- We seem to be at a tipping point within HEP?

Many new approaches to integrate HEP analyses with other tools

- PyHEP and scikit-hep projects
- Columnar Data Analysis

FAST-HEP has been exploring new approaches within the UK

- Resulting tools seeing use on several experiments

How can we best capitalise on these existing UK-led endeavours ?

Links to talks that inspired this

Andrea Rizzi: CHEP 2019

https://indico.cern.ch/event/773049/contributions/3581369/attachments/1940586/3217540/Rizzi_CHEP.pdf

Jim Pivarski: CHEP 2018 plenary:

https://indico.cern.ch/event/587955/contributions/3012337/attachments/1683637/2706186/pivarski-chep-analysistools.pdf

Jim Pivarski: CHEP 2018 parallel:

https://indico.cern.ch/event/587955/contributions/2937525/attachments/1678398/2695563/pivarski-chep-columnardata.pdf

Jake VanderPlas: PyCon 2017

https://speakerdeck.com/jakevdp/the-unexpected-effectiveness-of-python-in-science

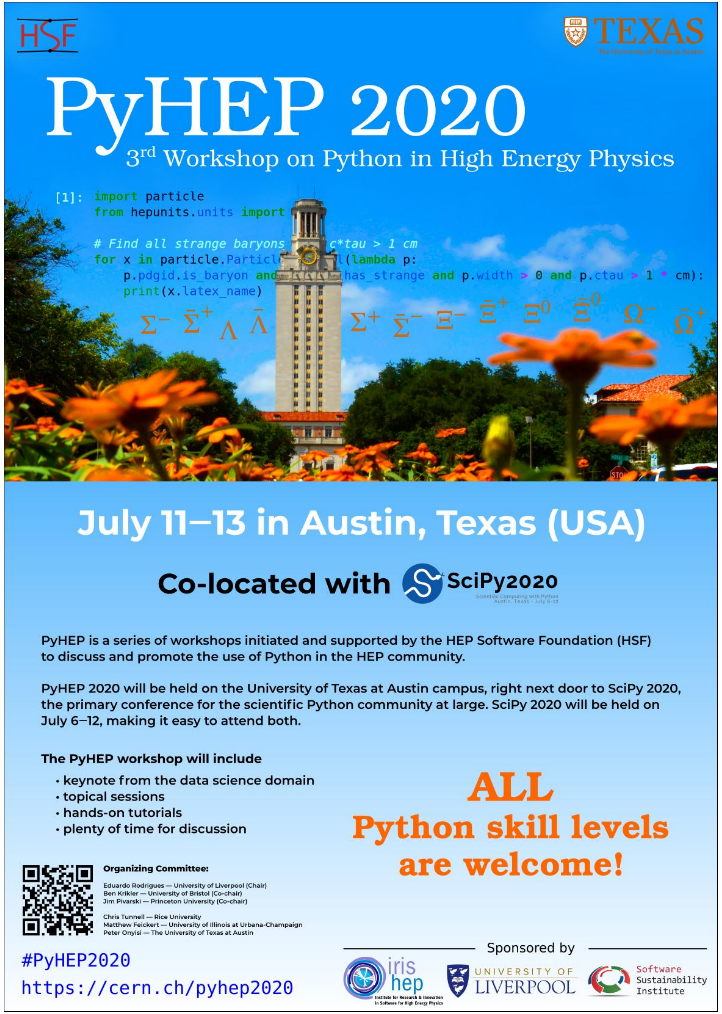
Jake VanderPlas: PyCon 2018

https://speakerdeck.com/jakevdp/seven-strategies-for-optimizing-numerical-code

Thank You

b.krikler@cern.ch

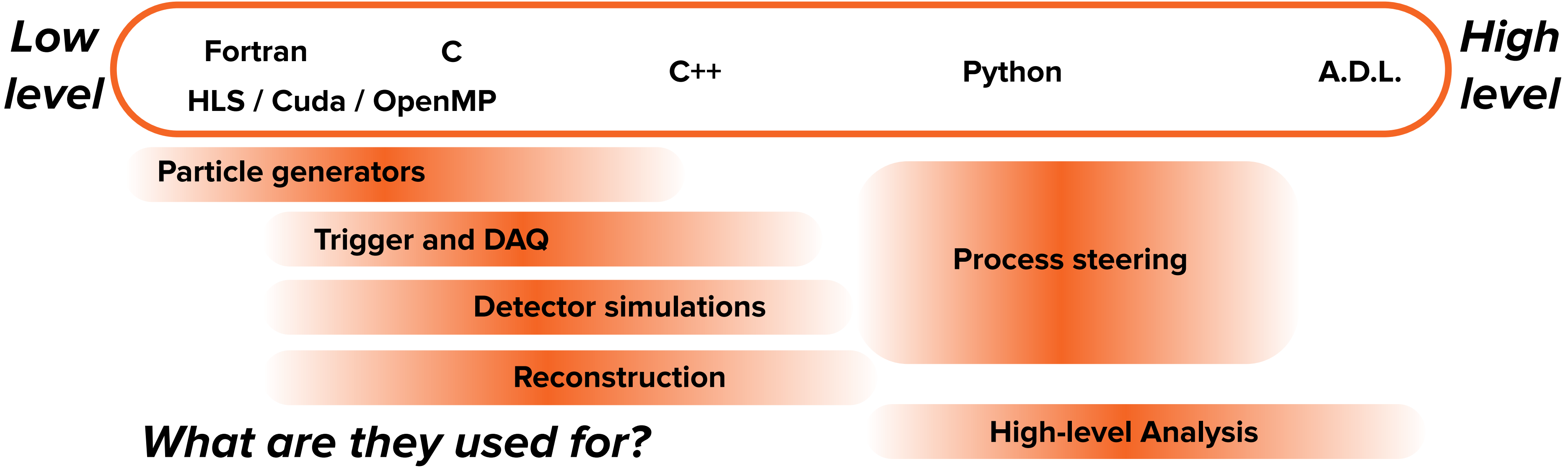
@benkrikler



The future HEP code landscape (?)

Low level	Fortran	C	C++	Python	A.D.L.	*High level*
	HLS / Cuda / OpenMP					

The future HEP code landscape (?)



The future HEP code landscape (?)

Who needs to know them?

1st year HEP PhD student

Finishing HEP PhD student

Applied / detector PhD student

Analysis teams

Sims / reconstruction experts

Low level

Fortran **C**

HLS / Cuda / OpenMP

C++

Python

A.D.L.

High level

Particle generators

Trigger and DAQ

Process steering

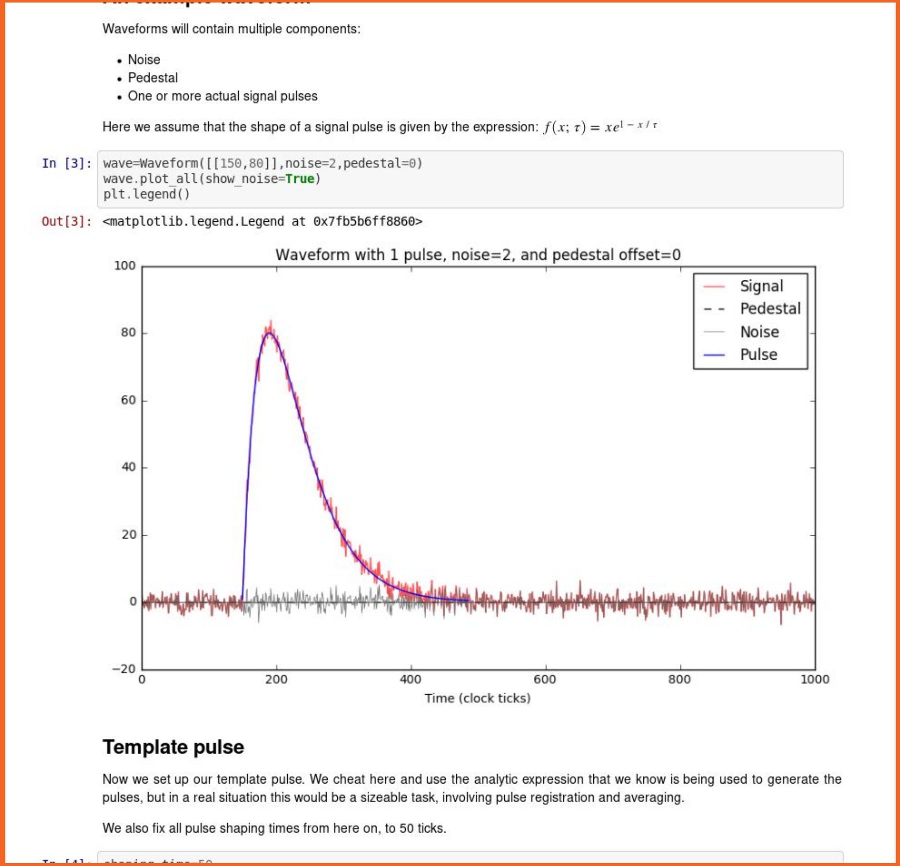
Detector simulations

Reconstruction

High-level Analysis

What are they used for?

Jupyter Notebook?



- Great:
  - Mixing code, documentation, and results
- Bad:
  - Code can still be dense
  - Scaling to full analysis?
  - Connecting to batch system tricky
  - Version control
- Carpenter can be used via Python API: provide python dicts instead of YAML
  - Addresses some of bad points above

DecayLanguage

Programmatic interface to:

- Parametrise
- Visualise
- And generate from

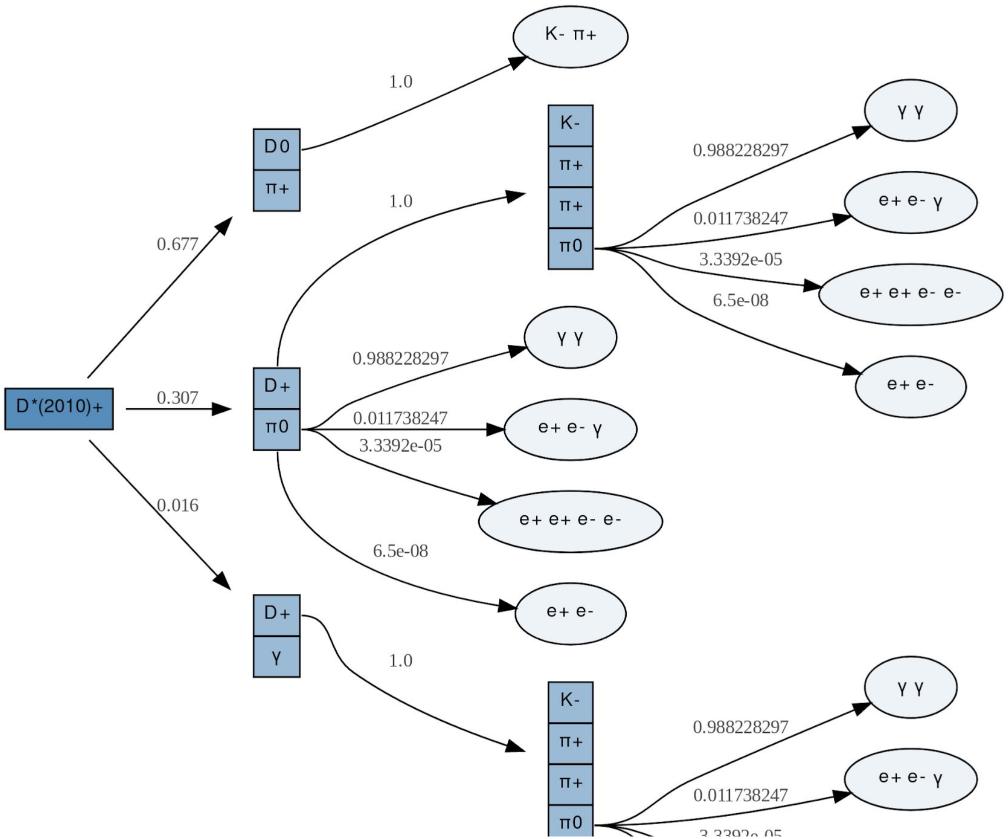
Particle decay chains

Mainly used on LHCb so far

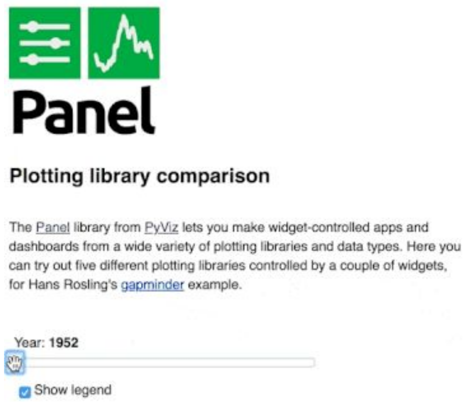
Helpful for our background tables?

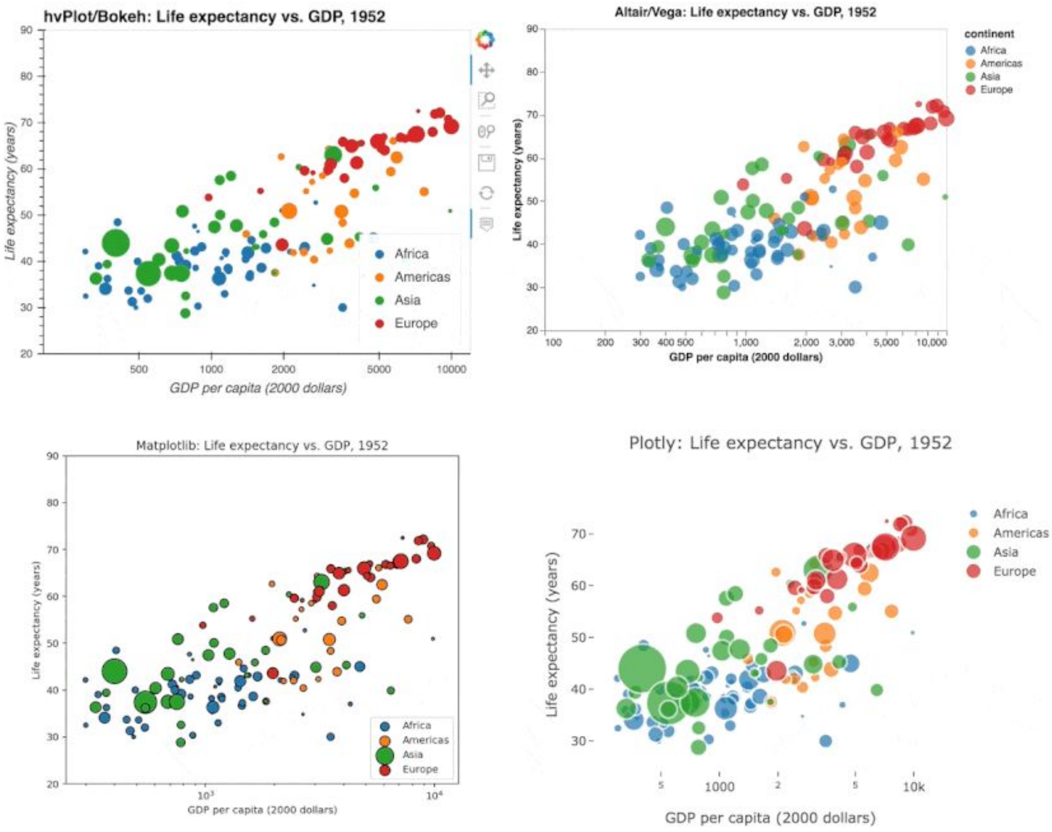
- Can extend particle data with isot

```
dc = dfp_Dst.build_decay_chains('D*+')
DecayChainViewer(dc)
```



Panel and PyViz

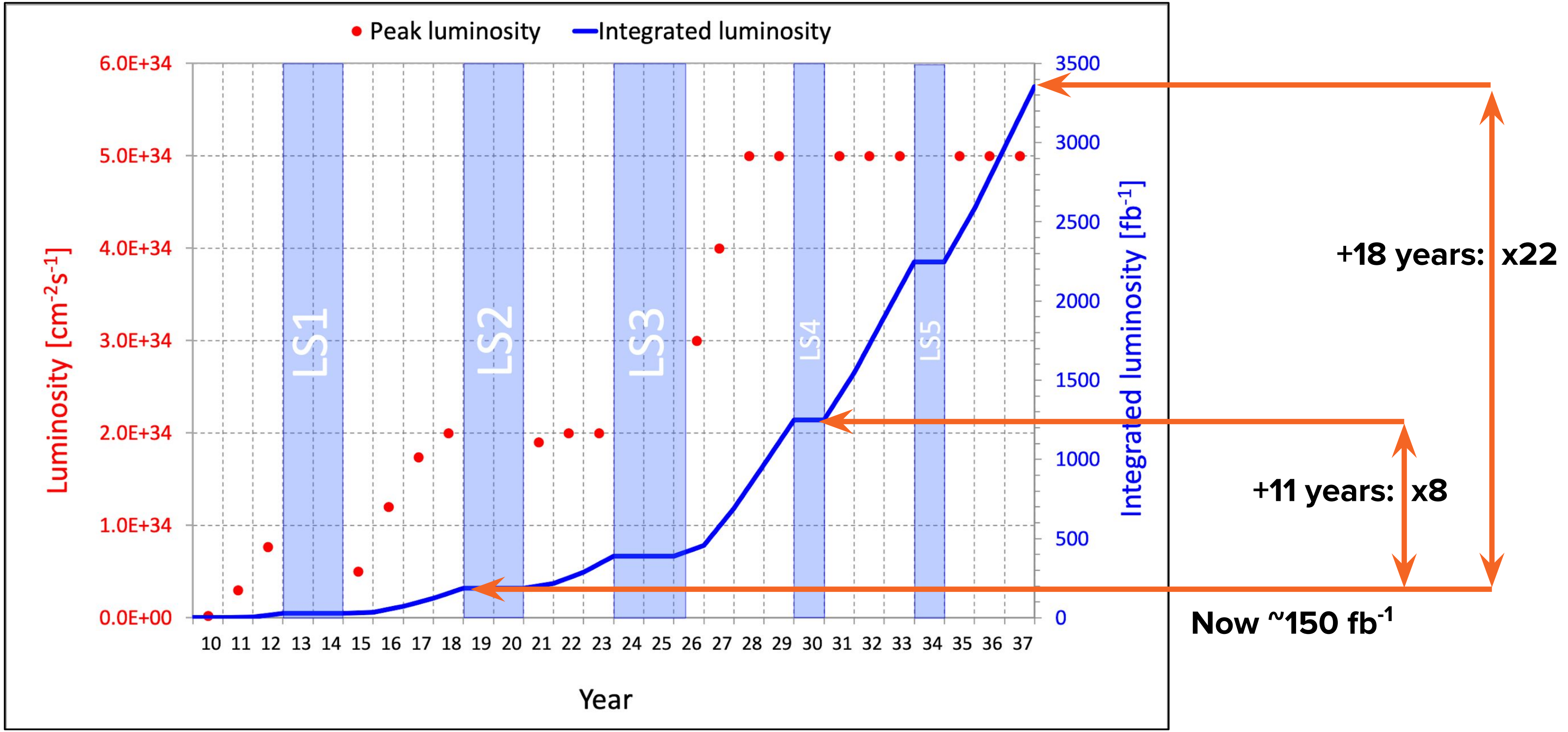




Keynote on interactive data exploration using Panel

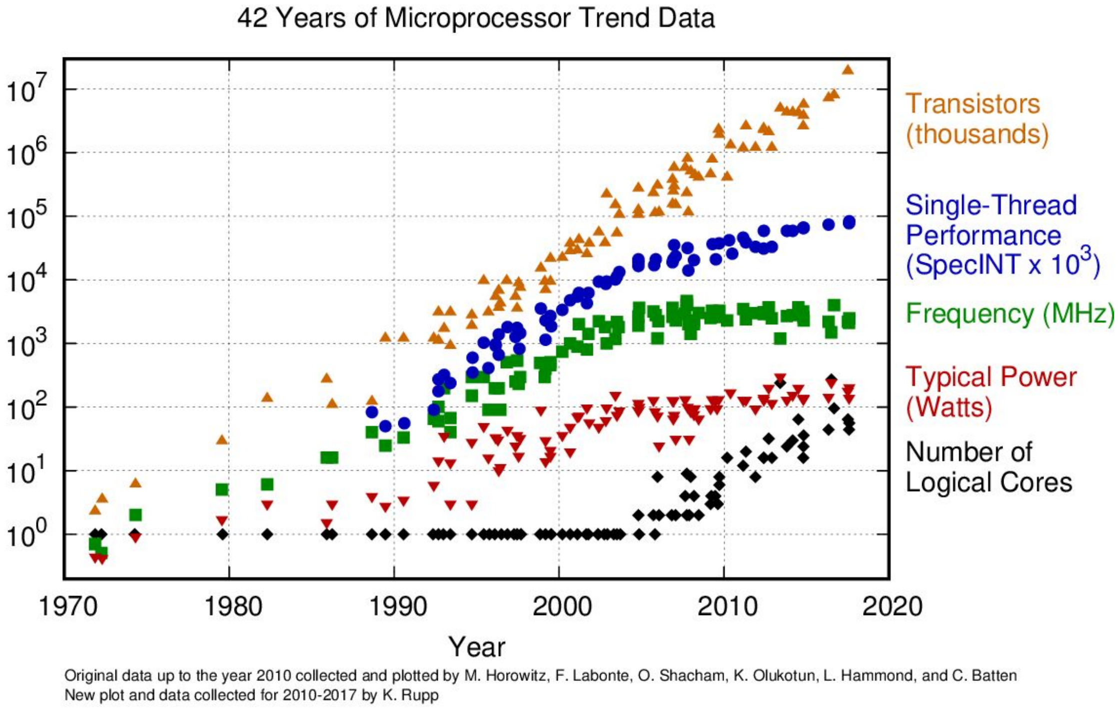
- https://medium.com/@philipp.jfr/panel-announcement-2107c2b15f52

Future data volumes: HL-LHC



https://lhc-commissioning.web.cern.ch/lhc-commissioning/schedule/images/optimistic-nominal-19.png

Processing trends



Moore's law faltering: predictions for early 2020s

Manufacturers abandoning "transistors per chip" metric already

Operating frequency fixed ("Dennard Scaling" has stopped)

Seeing more cores per chip: need more parallelisation

https://www.karlrupp.net/2018/02/42-years-of-microprocessor-trend-data/

Minh Huynh, CHEP 2019
[The Square Kilometre Array Computing]

Square Kilometer Array

SDP headline design numbers*

CSIRO

Input
- ~800 GByte/s INGEST (in total), from Central Signal Processor

Temporarily store
- Data set up to 15 PBytes
- 100PBytes total distributed buffer

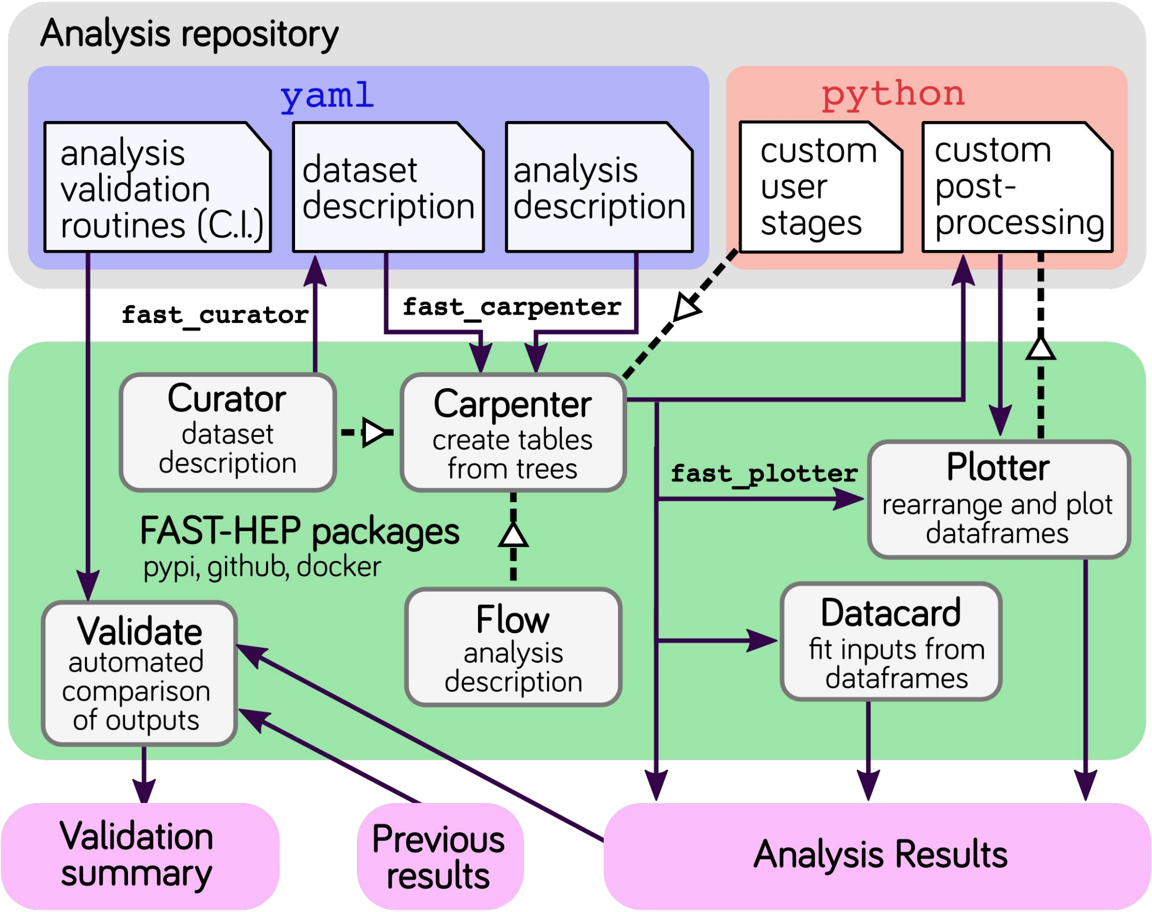
Process
- 250 PFLOPS total peak
    - 10% efficiency assumed

Preserve and ship
- (up to) 2 PetaByte per day of Science Data Products

*all numbers subject to change (Totals for both SKA-Low and SKA-Mid SDP)

> 600 PB per year for around 50 years
⇒ 30 Exabytes of data
⇒ “Exascale computing”

Interplay in a typical user's analysis repo



Scikit-validate

- Luke’s package grown out of FAST hack-shops
- Predominantly used on LZ so far
- Interested from various people in the room to use it

Hack-shop=

½ ***hack***athon **+** ½ work***shop***

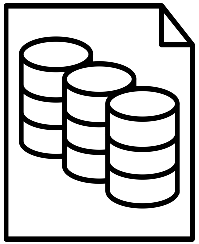
- Talks to set the scene, get everyone up to speed, layout goals
  - Given newcomers: Today will also be walkthrough / tutorial
- Focussed hacking: people “in a room” for a couple of days
  - e.g. “play” with setting up an analysis using these tools
- Feel free to ask questions at any time
  - Collaborative not competitive like traditional hackathon
  - Slack or Zoom

Output of CutFlow stage

```
>>> import pandas as pd
>>> pd.read_csv("cuts_EventSelection-weighted.csv", header=[0, 1], index_col=[0, 1, 2])
                                                                 passed_incl               passed_excl                totals_excl
                                                                  unweighted   EventWeight  unweighted   EventWeight   unweighted   EventWeight
dataset    depth cut
data       0     All                                                 15995.0  15995.000000     15995.0  15995.000000    469384.0  469384.000000
           1     NIsoMuon >= 2                                       16208.0  16208.000000     16208.0  16208.000000    469384.0  469384.000000
                 triggerIsoMu24 == 1                                469384.0 469384.000000     16208.0  16208.000000     16208.0   16208.000000
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}           229710.0 229710.000000     15995.0  15995.000000     16208.0   16208.000000
dy         0     All                                                 37263.0  16628.843750     37263.0  16628.843750     77729.0   34115.511719
           1     NIsoMuon >= 2                                       37559.0  16829.451172     37559.0  16829.451172     77729.0   34115.511719
                 triggerIsoMu24 == 1                                 77729.0  34115.511719     37559.0  16829.451172     37559.0   16829.451172
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}            73374.0  32168.121094     37263.0  16628.843750     37559.0   16829.451172
qcd        0     All                                                     0.0      0.000000         0.0      0.000000       142.0   79160.507812
           1     NIsoMuon >= 2                                           0.0      0.000000         0.0      0.000000       142.0   79160.507812
                 triggerIsoMu24 == 1                                   142.0  79160.507812         0.0      0.000000         0.0       0.000000
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}               16.0   6014.819336         0.0      0.000000         0.0       0.000000
single_top 0     All                                                   110.0      5.676235       110.0      5.676235      5684.0     311.622986
           1     NIsoMuon >= 2                                         111.0      5.748312       111.0      5.748312      5684.0     311.622986
                 triggerIsoMu24 == 1                                  5684.0    311.622986       111.0      5.748312       111.0       5.748312
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}             5278.0    290.494965       110.0      5.676235       111.0       5.748312
ttbar      0     All                                                   206.0     47.293686       206.0     47.293686     36941.0    7929.475586
           1     NIsoMuon >= 2                                         226.0     51.629749       226.0     51.629749     36941.0    7929.475586
                 triggerIsoMu24 == 1                                  4515.0   1001.804932       206.0     47.293686       226.0      51.629749
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}             5067.0   1109.433960       206.0     47.293686       206.0      47.293686
wjets      0     All                                                     1.0      0.311917         1.0      0.311917    109737.0  209603.531250
           1     NIsoMuon >= 2                                           1.0      0.311917         1.0      0.311917    109737.0  209603.531250
                 triggerIsoMu24 == 1                                109737.0 209603.531250         1.0      0.311917         1.0       0.311917
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}            99016.0 191354.781250         1.0      0.311917         1.0       0.311917
ww         0     All                                                   243.0     12.577849       243.0     12.577849      4580.0     229.949570
           1     NIsoMuon >= 2                                         244.0     12.639496       244.0     12.639496      4580.0     229.949570
                 triggerIsoMu24 == 1                                  4580.0    229.949570       244.0     12.639496       244.0      12.639496
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}             4214.0    212.997131       243.0     12.577849       244.0      12.639496
wz         0     All                                                   623.0     13.157759       623.0     13.157759      3367.0      69.927917
           1     NIsoMuon >= 2                                         623.0     13.157759       623.0     13.157759      3367.0      69.927917
                 triggerIsoMu24 == 1                                  3367.0     69.927917       623.0     13.157759       623.0      13.157759
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}             3125.0     65.436157       623.0     13.157759       623.0      13.157759
zz         0     All                                                  1232.0      8.985804      1232.0      8.985804      2421.0      16.922522
           1     NIsoMuon >= 2                                        1235.0      8.998816      1235.0      8.998816      2421.0      16.922522
                 triggerIsoMu24 == 1                                  2421.0     16.922522      1235.0      8.998816      1235.0       8.998816
                 {'formula': 'Muon_Pt > 25', 'reduce': 0}             2325.0     16.362473      1232.0      8.985804      1235.0       8.998816
```

Resulting cut-flow outputs from EventSelection config on earlier slide

Step 1:
`fast_curator`



Dataset description

Curator: what files do you want to work on?

Dataset descriptions don’t change often

- Track descriptions in repo, easy to review

Command line tool to help write YAML

- Wild-card on the command line
- Hooks ready for experiment-specific catalogues, e.g. CMS DAS
- Integrate with Rucio (?)

Dataset description

```yaml
datasets:
  - eventtype: data
    Files: [input_files/HEPTutorial/files/data.root]
    name: data
    nevents: 469384
  - files:
     - input_files/HEPTutorial/files/dy.root
     - input_files/HEPTutorial/files/dy_2.root
    name: dy
    nevents: 77729
    nfiles: 2

defaults:
  eventtype: mc
  nfiles: 1
  tree: events

import:
  - "{this_dir}/WW.yml"
  - "{this_dir}/WZ.yml"
```

- Each dataset has a list of files
- A unique dataset name

- Default metadata

- Can Import other dataset files
- Build complex nested dataset descriptions

An example set of stages

```yaml
stages:
  # Just defines new variables
  - BasicVars: Define
  # A custom class to form the invariant mass of a
  # two-object system
  - DiMuons: cms_hep_tutorial.DiObjectMass
  # Filled a binned dataframe
  - NumberMuons: fast_carpenter.BinnedDataframe
  # Select events by applying cuts
  - EventSelection: CutFlow
  # Fill another binned dataframe
  - DiMuonMass: BinnedDataframe
```

Depreciation of Python 2

➤ Python 2.7 support will be withdrawn on 1st January 2020 (it was released 3rd July 2010)

➤ Key packages have dropped support:

IPython, Jupyter, matplotlib, numpy, pandas, scikit-learn, XGboost, dask, …

For LHCb: Ganga

Guido van Rossum - Python Language - PyCon 2016

34 days!

https://python3statement.org/

Other reasons to use Python 3

- Dictionaries are ordered (CPython 3.6+, Python 3.7+)
- * and ** behave sensibly `test(**dict_1, **dict_2)`
- In my experience, it's been faster!
- print is actually function with kwargs like `sep`, `end` and `flush`
- Separate str/bytes types
- Exception chaining
- Keyword only arguments
- Many little standard library improvements:
  - Recursive globbing, LRU cache, secrets module, Enum

Overall: It's not any one feature, it's just makes everything **quicker, easier and less buggy!**

f-strings

- My number one feature is f-strings (Python 3.6+)

```
mass_low = 1890
mass_high = 2050
cut = f'({mass_low} < D_Mass) & (D_Mass < {mass_high})'
```

- Why are they better?
  - Compact and easy to read
  - Bugs are generally easier to see
  - Plays nicely with linters

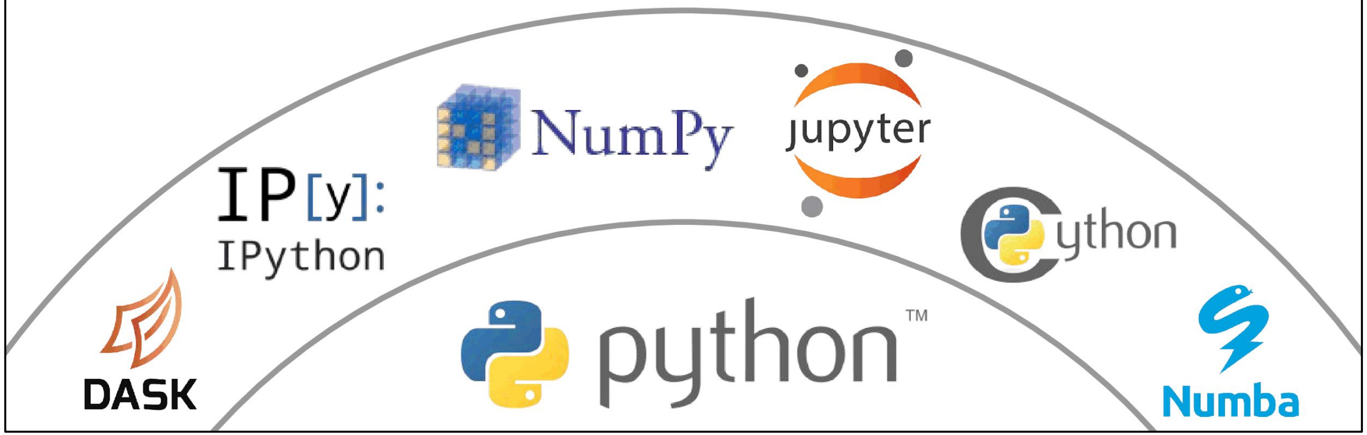
```
cut = '(%f < D_Mass) & (D_Mass < %f)' % mass_low, mass_high

cut = '({0} < D_Mass) & (D_Mass < {1})'.format(mass_low, mass_high)

cut = '({mass_low} < D_Mass) & (D_Mass < {mass_high})'.format(mass_low, m
```

Python 2 will still work so why care?

- You'll be stuck using old versions of libraries
  - No bug fixes
  - No new features
  - No support: some libraries not automatically close issues that mention Python 2
- You can't use new libraries
  - No new shiny machine learning tools
- Wastes the time of library developers who support both
  - Time can be better spent on support, bugfixes or new features
- If you're ever forced to move, it will only get harder
  - Minor incompatible changes to libraries add up over time
  - It's easier to do many minor updates instead of a few massive ones

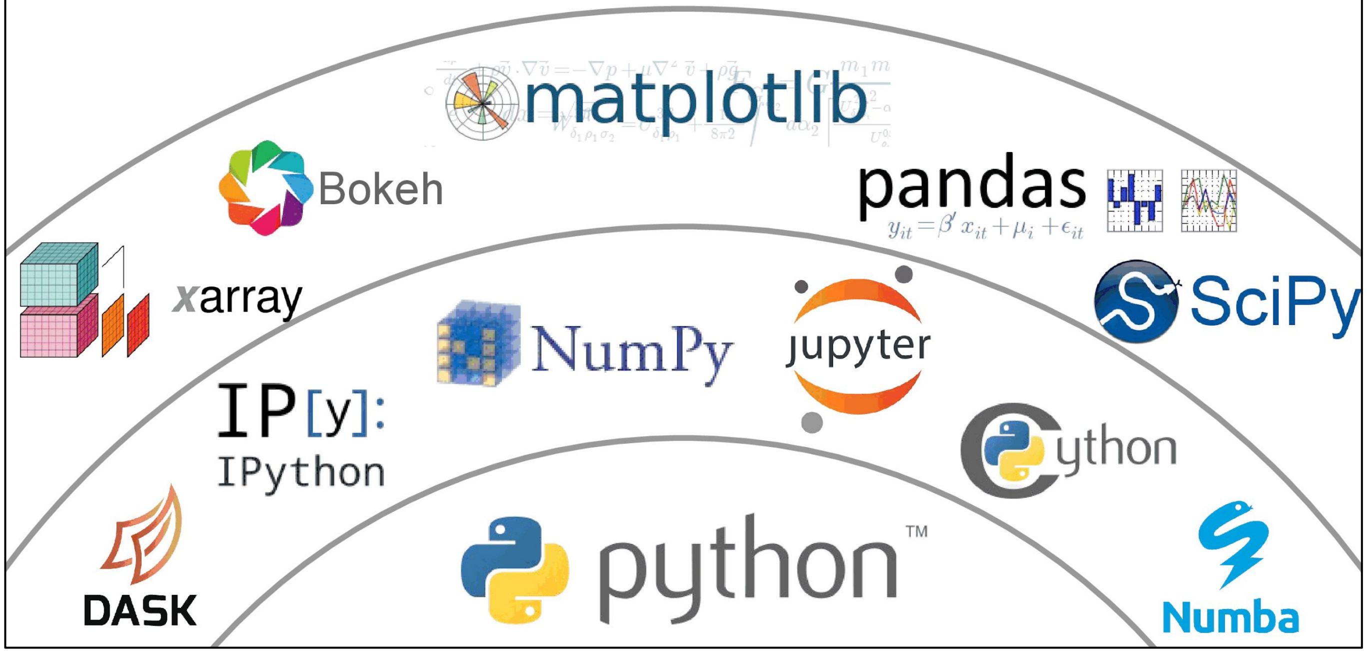
[Jake VanderPlas: PyCon 2017]

Python's Scientific Stack



[Jake VanderPlas: PyCon 2017]

Python's Scientific Stack



[Jake VanderPlas: PyCon 2017]

Python's Scientific Stack