

Pythonic Data Analysis

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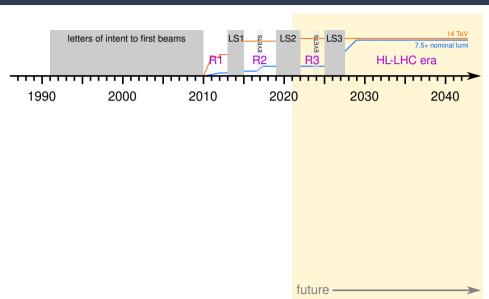
May the 4^{th} be with you



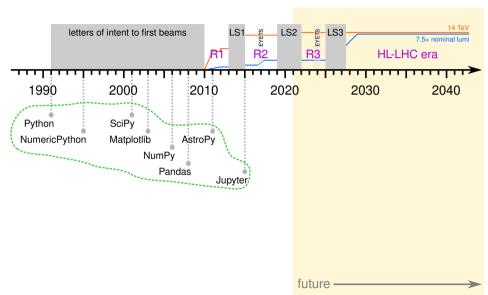
Part 1: Trends in data analysis software

Part 2: Status of Pythonic HEP software

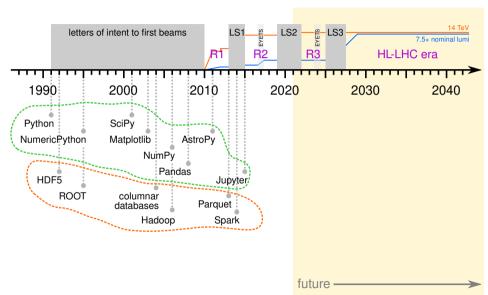




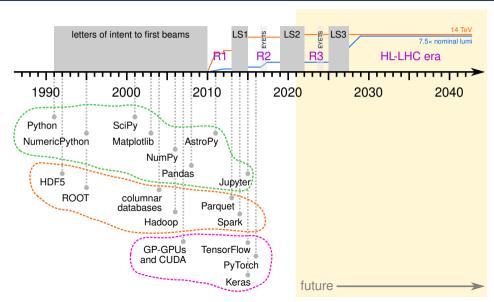




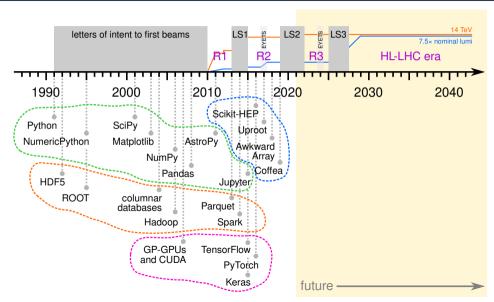




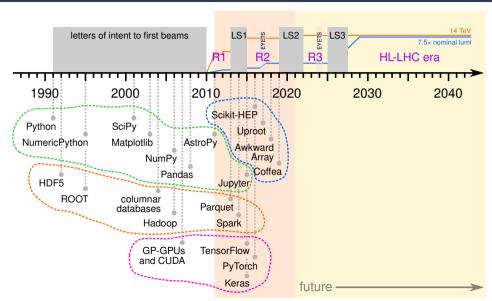








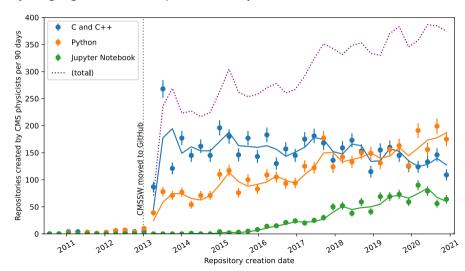




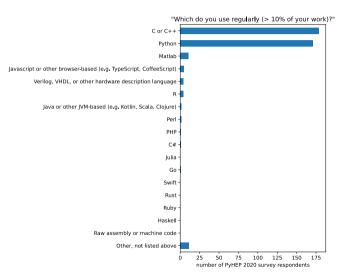
What were the physicists doing in this decade?



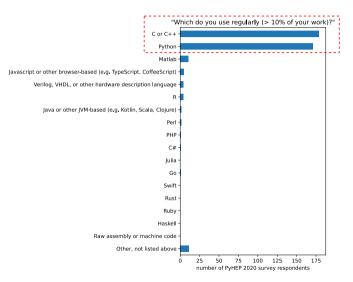
Primary language of GitHub repos created by users who forked CMSSW:



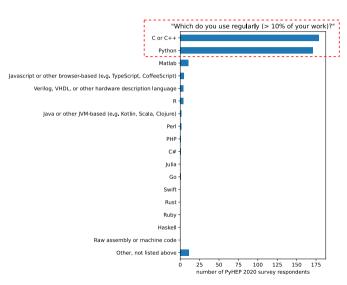




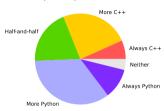




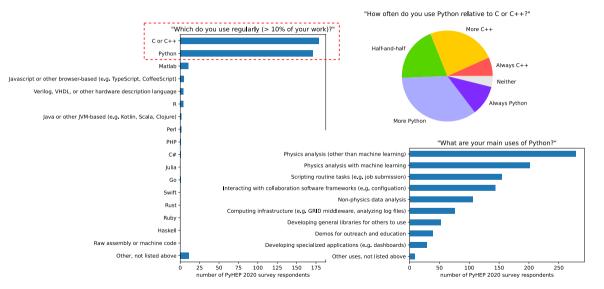




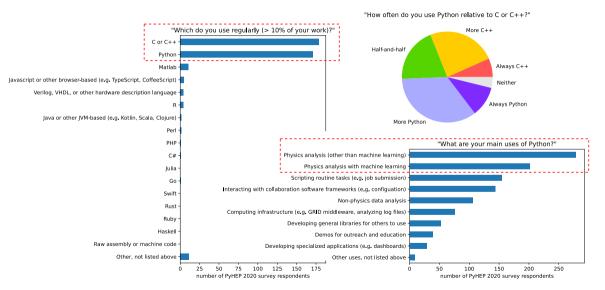
"How often do you use Python relative to C or C++?"







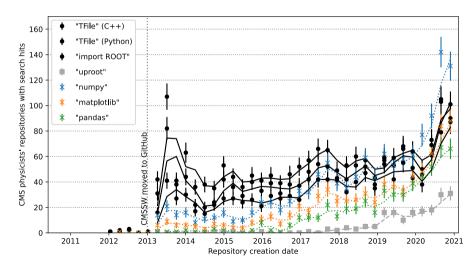




Pythonic analysis is mainstream, and the trend preceded Uproot

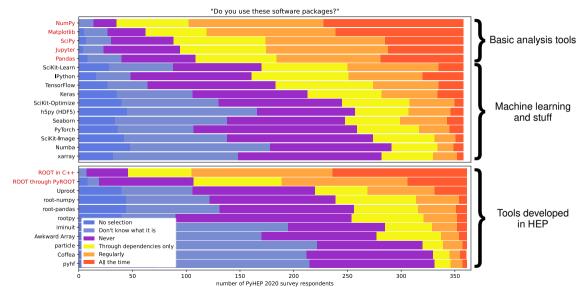


GitHub repos matching search strings: Pythonic analysis is as common as "TFile".



This is also consistent with self-reported usage







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Not a single group, but mostly shared vision

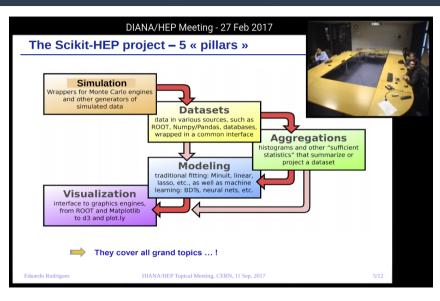


Most of the developers of Pythonic HEP software

- ▶ aim for small package granularity, providing tools that address a well-defined class of problems at one level of abstraction,
- aim for interoperability with each other and the larger Pythonic ecosystem,
- avoid overlapping functionality, by communicating through HSF and IRIS-HEP channels,
- focus on domain-specific problems that won't be addressed by non-HEP software <u>or</u> focus on connecting HEP-specific tools to the larger ecosystem.

Scikit-HEP: a clearinghouse for Pythonic HEP software





Originally conceived as a core package with "affiliates" like AstroPy; now it's "just affiliates."

A common brand for packages that work together and with the Python ecosystem.

Scikit-HEP's 5 pillars today:



Simulation: other than numpythia and pyhepmc, this is mostly left to non-Python packages (which fill files that can be read with Python).

Datasets: root-numpy, uproot, pylhe, awkward, as well as numpy and pandas. Some use HDF5/h5py because of its recognition by ML tools.

Aggregations: boost-histogram/hist, coffea, fast-carpenter.

Modeling/fitting: by far, the most covered: pyhf (dozens of publications), iminuit, zfit, hepstats, goofit, SModelS, direct use of Pandas, ML...

Visualization: most modeling tools output to matplotlib, mplhep is widely used as a dependency. coffea, hist, histoprint.

Should also add Distributed computing: some pyspark, but more dask, often through coffea (future coffea-casa/ServiceX).

Should also add Acceleration/JIT-compilation: numba, jax, ROOT.RDataFrame.

Should also add HEP domain-specific: corrections in coffea, Lorentz vectors in vector, PDG in particle, jet clustering in pyjet...



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HEP domain-specific: coffea covers each use-case before it gets its own library.

Breakdown by strategy



Domain-specific stuff we do

- (super)histograms as fillable objects
- ► HEP-style plots (pulls, Brazil, efficiency...)
- ansatz fitting, limit setting, discovery significance
- applying corrections, clustering, Lorentz vector manipulation

Connections to externals

- ▶ ROOT, LHE files ↔ arrays, Pandas, ML
- using ML packages to
 do HEP fits:
 pyhf/combinetf
- extending Numba for jagged arrays, Lorentz vectors, histogramming
- ► events → histograms workflow in distributed computing frameworks
- building Query Systems out of standard parts

External libraries we use

- machine learning
- distributed computing
- JIT-compilation
- autodifferentiation
- interactive notebooks

Conclusions



The question is not quite, "Will the whole ecosystem be ready for the HL-LHC?"

Many pieces are in-use <u>now</u>, and they're growing to fill real analysis needs <u>now</u>.

- ▶ I personally know of \sim 10 analyses using Python almost exclusively (CMS $H \to \gamma \gamma$, $\to \mu \mu$, $\to c\bar{c}$, di-Higgs, top EFT, Dazsle analyses...).
- ► There is a wave of such analyses gradually approaching publication.

From current trends, it looks like Pythonic analysis will either predominate in Run 3 or stay evenly mixed with C++, it is today.

