Analysis of physics analysis

Jim Pivarski and Henry Schreiner

Princeton University – IRIS-HEP

May 9, 2023

Dark computing

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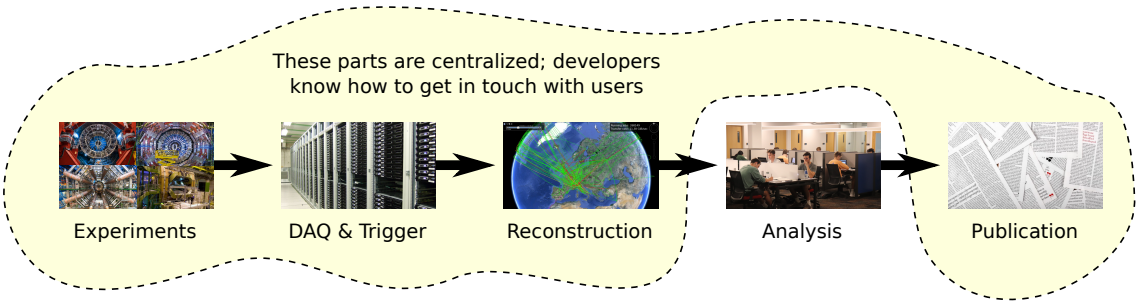

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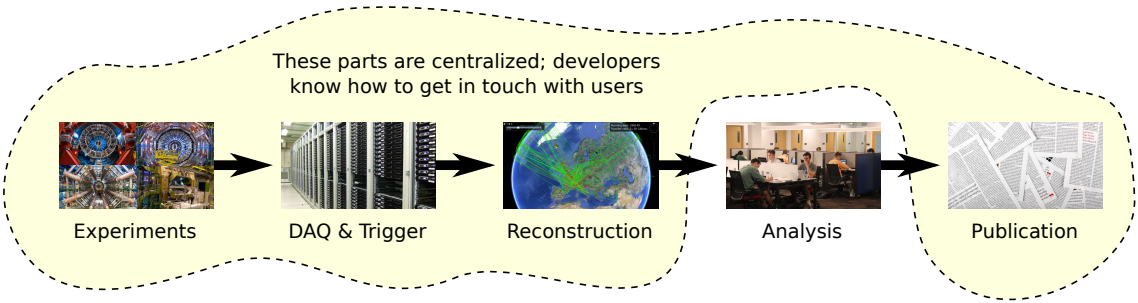

- The "analysis" step is the only one in the pipeline for which we don't even know *who* all the users are.

We don't do this

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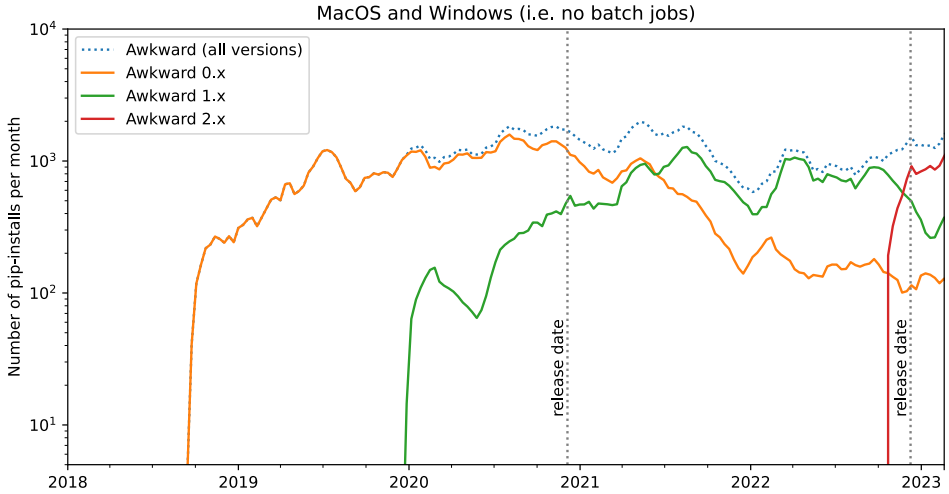
What download stats are good for (one slide)

Relative rates, such as new version adoption.



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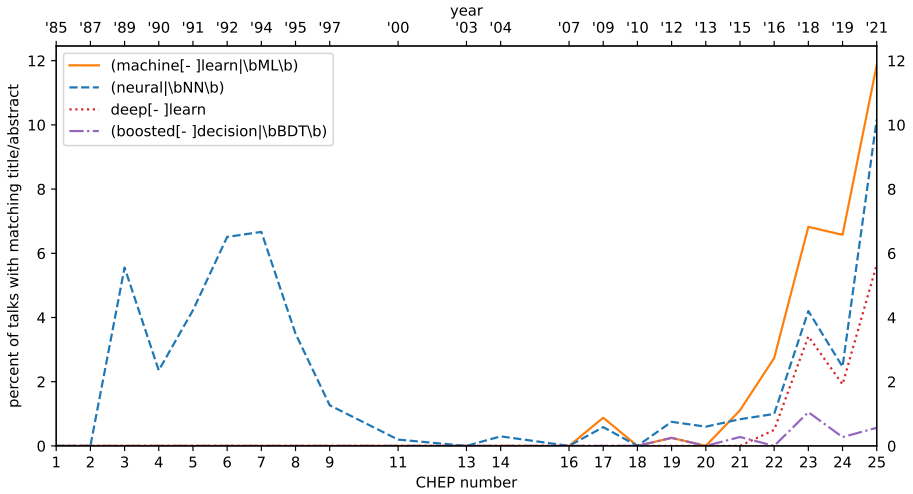
What textual analysis of CHEP/ACAT is good for (one slide)

Discovering trends and changing interests.



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Analysis of source code online	Fine-grained, quantitative, average over many users.	Only public repos, have to identify demographics with some seed: how to define "particle physicists"?

Analysis of source code online (the rest of this talk)

A few years ago (2019), Jim stumbled upon a good technique:

- CMSSW has been on GitHub since 2013.
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So the technique is: select GitHub users who forked CMSSW ("CMS physicists") and look at all of their non-fork repos. 3 697 people, 22 961 repos over 10 years.

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But what about experiments other than CMS?

A complementary dataset

- GitHub Archive (**https://www.gharchive.org/**) has been collecting all fork, PR, issue, wiki, watch, and comment events since 2017. We can get a list of GitHub users who have had any interaction at all with a specified repo.
- **https://github.com/root-project/root** seems like a logical choice to define "particle physicists."
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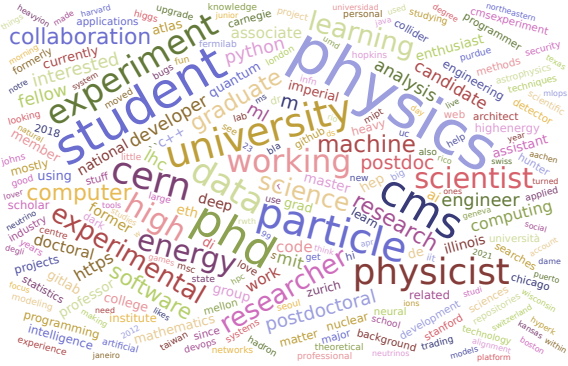
Interestingly, only 143 are in both (3.9% of CMSSW and 5.1% of ROOT).

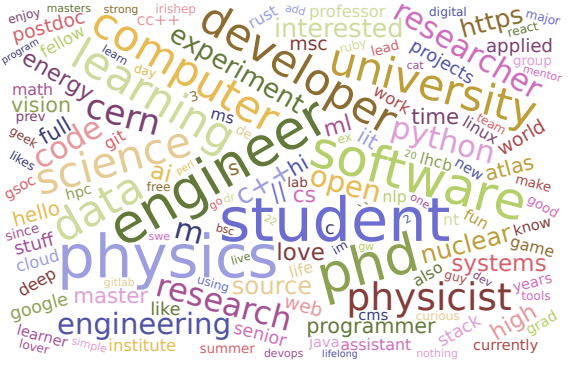
What they said in their profile bios

Selected by CMSSW fork



A lot of “physics,” “student,” “particle,” “physicist,” “PhD,” “CERN,” and “CMS.”

Selected by ROOT interaction



A little more “software,” “engineer,” but still lots of “physics,” “student,” and “PhD.”

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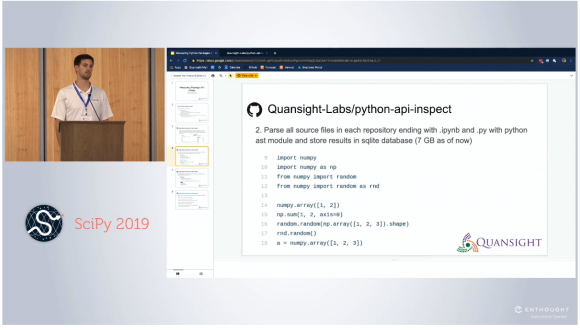
Prior art: see Chris Ostrouchov's Measuring API Usage (2019).



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But first, reproducing the previous studies

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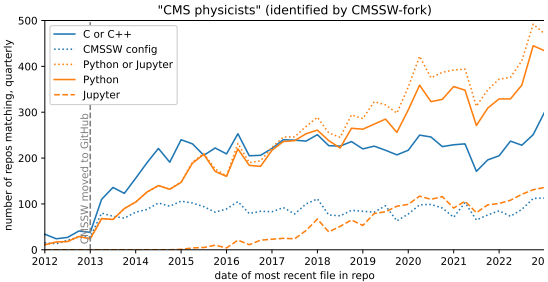

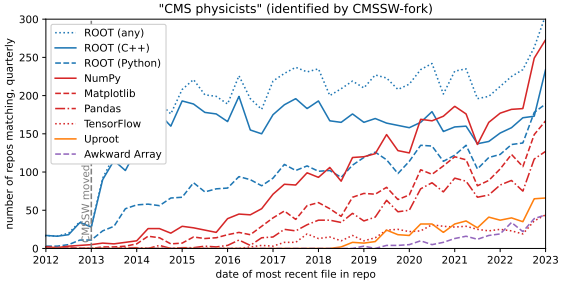

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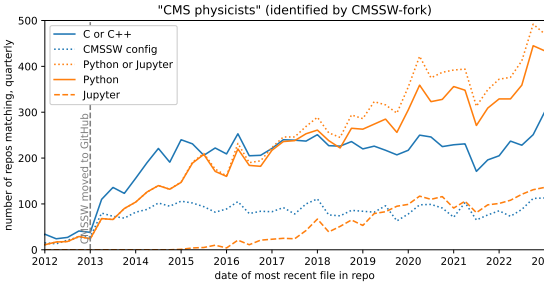

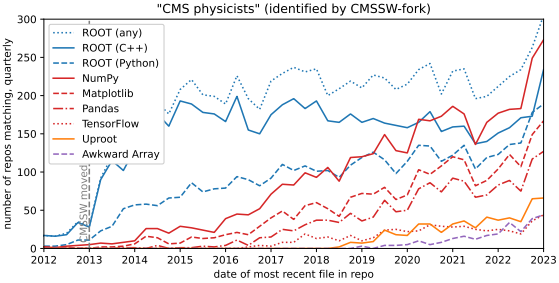

Conclusion is the same: C++ and CMSSW config (Python with `import FWCore`) are flat, while Python and Jupyter (Python) increase.

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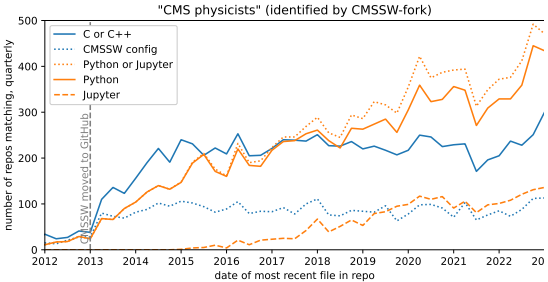

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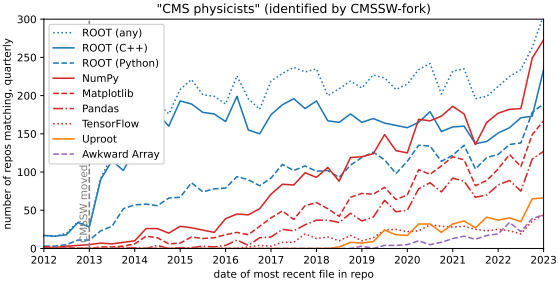

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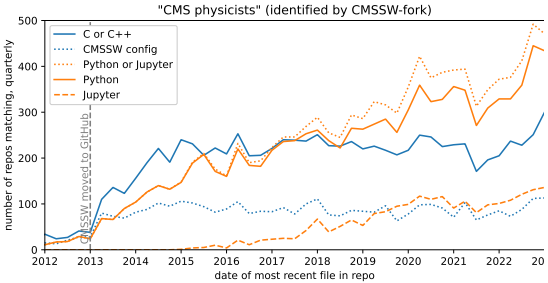

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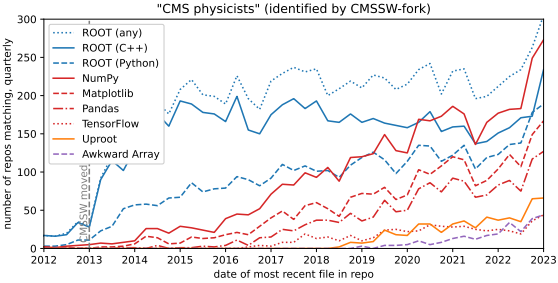

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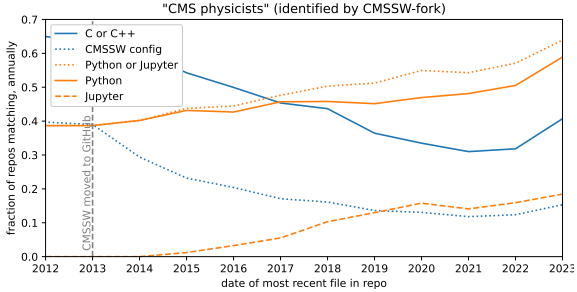

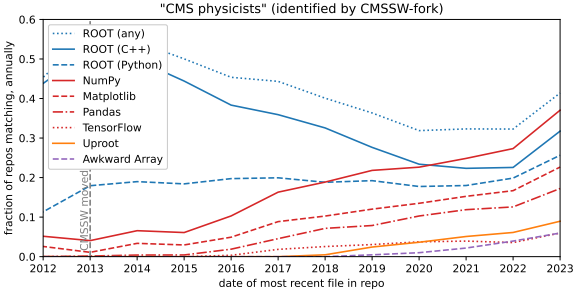

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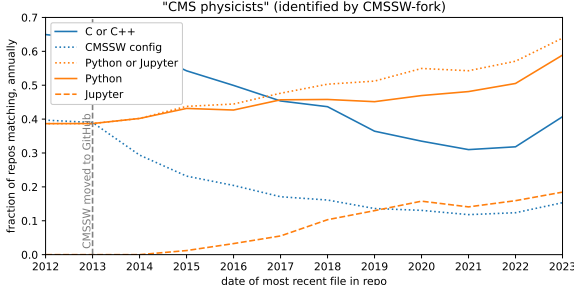

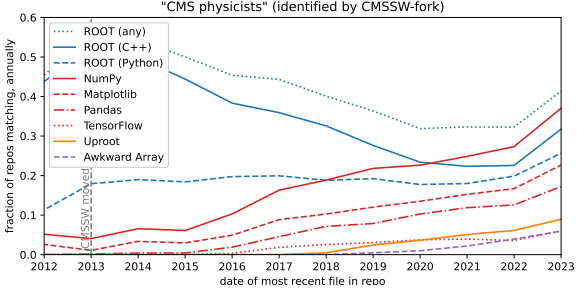

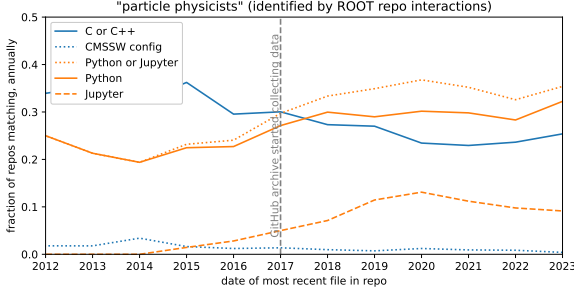

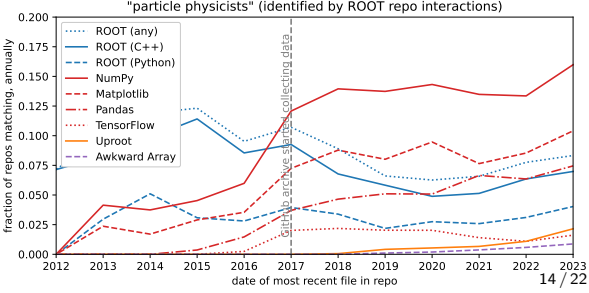

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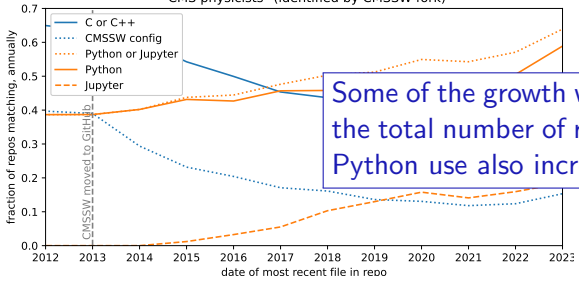
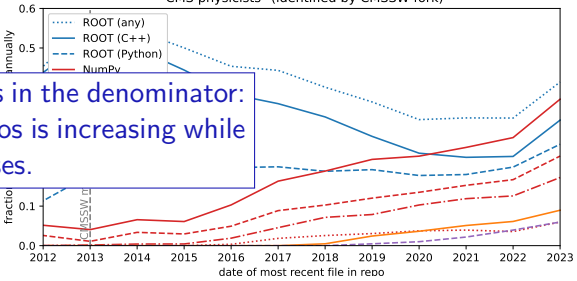
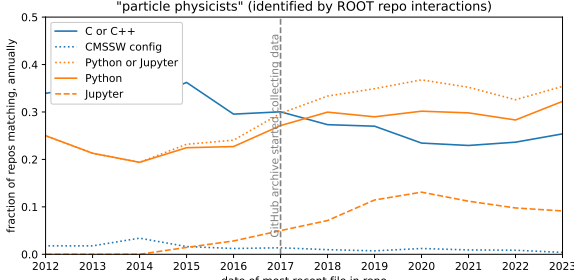
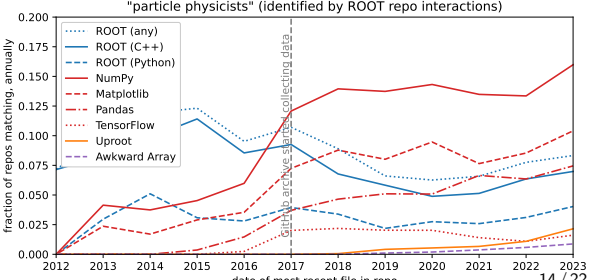




Some of the growth was in the denominator: the total number of repos is increasing while Python use also increases.





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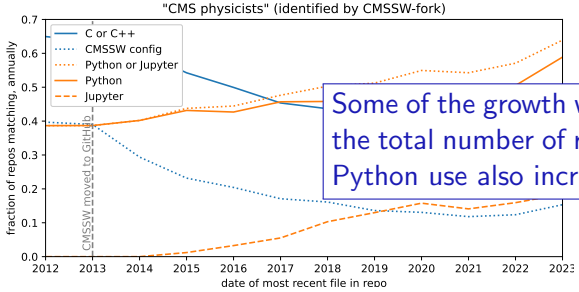

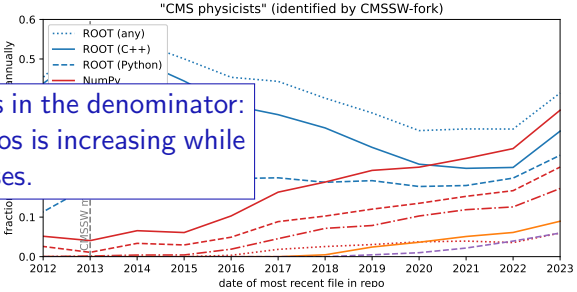

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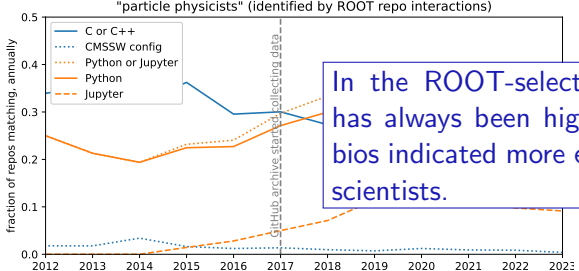
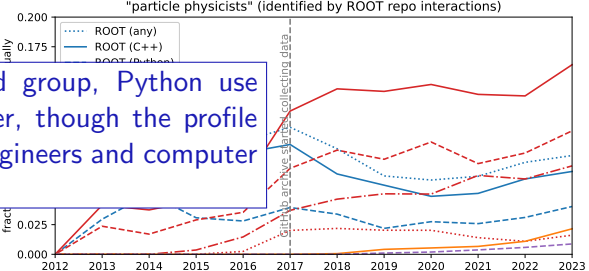
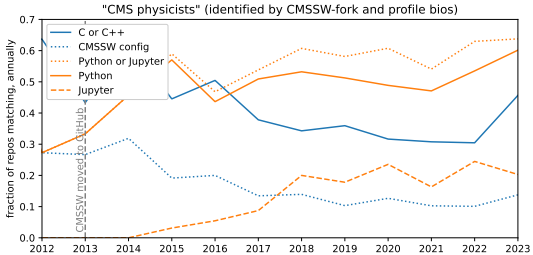


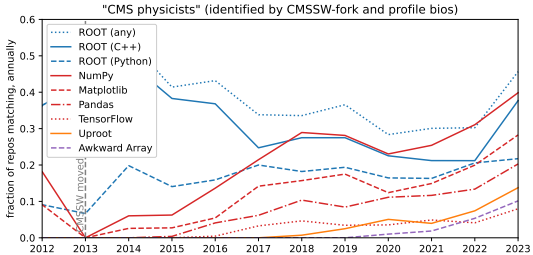


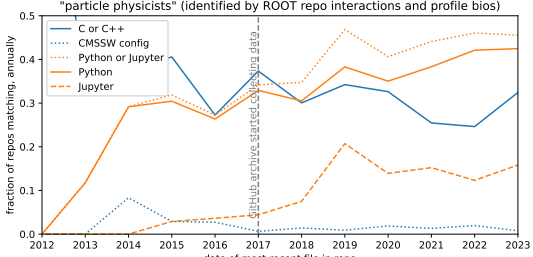
In the ROOT-selected group, Python use has always been higher, though the profile bios indicated more engineers and computer scientists.

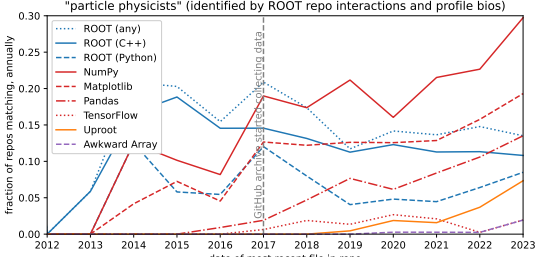
Narrow in on physicists, selecting by their profile bios

Regex `(phys|analy|hep|particle|cern|cms|atlas|alice|lhc)` selects 7.6% of users.









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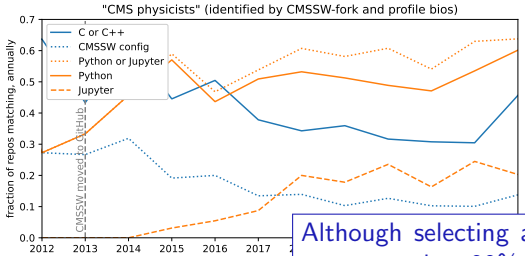
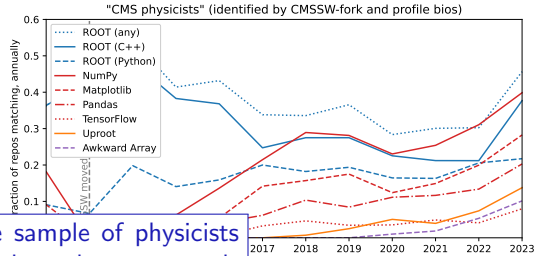
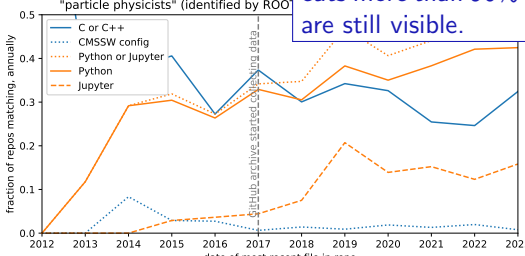
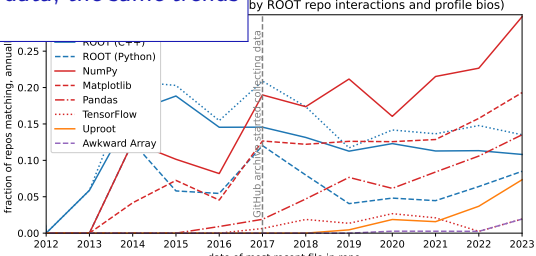


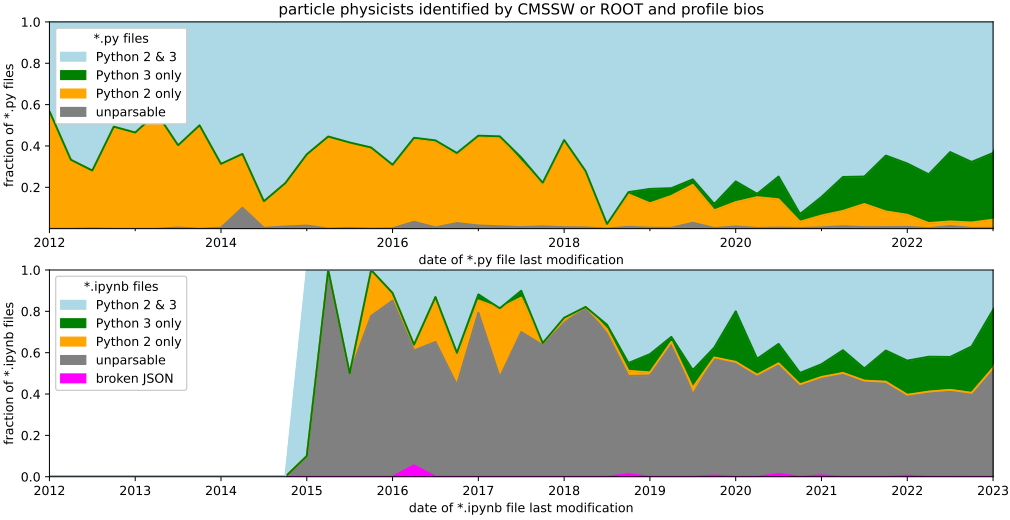


Although selecting a pure sample of physicists cuts more than 90% of the data, the same trends are still visible.

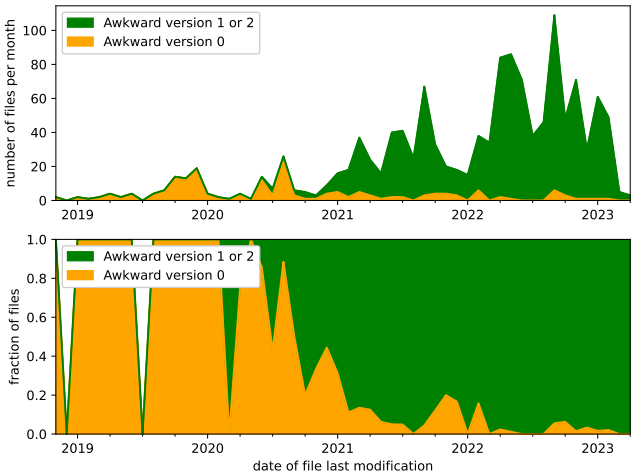




Now actually parse the repos: Python 3 adoption among physicists



Ask specific questions: Awkward 1 adoption by function name




```
def is_awkward0(obj):
    return obj.function.name.startswith(
        "ak.JaggedArray"
    ) or obj.function.name.startswith(
        "ak.array.jagged.JaggedArray"
    ) or obj.function.name in (
            "ak.IndexedArray",
            "ak.Table",
            "ak.fromarrow",
            "ak.fromiter",
            "ak.hdf5",
            "ak.load",
            "ak.save",
            "ak.toarrow",
            "ak.topandas",
            "ak.util.concatenate",
        )
```

Most common function calls/argument patterns

	Awkward Array		Uproot
2832	`ak.flatten(?)`	2150	`uproot.open(?)`
2498	`ak.num(?)`	889	`uproot.open('str')`
2193	`ak.to_numpy(?)`	198	`uproot.recreate(?)`
874	`ak.sum(?, axis=1)`	179	`uproot.tree.TBranchMethods.array(?)`
865	`ak.flatten(?, axis=None)`	74	`uproot.lazy(?)`
564	`ak.sum(?)`	58	`uproot.newtree(?)`
455	`ak.ones_like(?)`	57	`uproot.pandas.iterate(?, 'str', ['stri`
406	`ak.Array(?)`	44	`uproot.open(?, xrootdsource=?)`
283	`ak.concatenate(?)`	23	`uproot.lazy(?, filter_name=?)`
265	`ak.singletons(?)`	22	`uproot.recreate('str')`
248	`ak.num(?, axis=1)`	18	`uproot.create(?)`
246	`ak.concatenate(?, axis=1)`	15	`uproot.recreate(?, compression=?)`
235	`ak.any(?, axis=1)`	13	`uproot.newbranch(?, size='str')`
234	`ak.zip(?, with_name='str')`	11	`uproot.numentries(?, ?)`
233	`ak.to_pandas(?)`	11	`uproot.ArrayCache('str')`
226	`ak.unzip(?)`	10	`uproot.numentries(?, ?, total=False)`
221	`ak.firsts(?)`	10	`uproot.numentries(?, ?, executor=?, to`

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Uproot relies more on object methods. We'd have to statically analyze *object types*, not functions on global modules, which is hard in a dynamically typed language.

Most common function calls/argument patterns

Awkward Array

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Compare to web traffic on awkward-array.org...

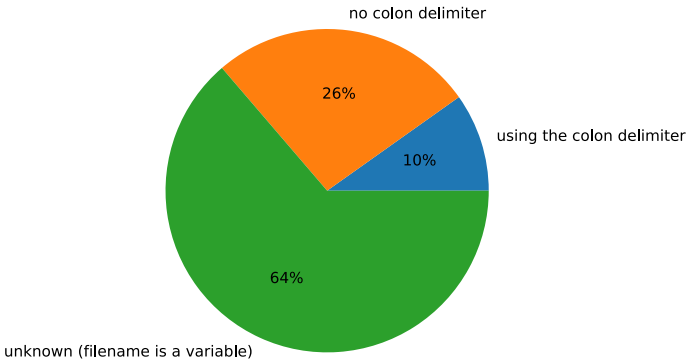
function	#unique visitors	#views	avg. time
ak.Array	785	1100	3m33s
ak.concatenate	223	293	4m35s
ak.count	210	265	4m20s
ak.flatten	203	242	4m23s
ak.where	202	262	3m54s
ak.num	184	235	3m07s
ak.to_numpy	181	218	3m25s
ak.mask	178	231	3m52s
ak.zip	163	221	5m02s
ak.fill_none	162	214	3m11s
ak.broadcast_arrays	156	210	4m20s
ak.combinations	136	171	3m58s
ak.sum	136	165	4m42s
ak.behavior	125	152	6m25s
ak.ArrayBuilder	124	161	3m02s
ak.cartesian	121	159	3m09s
ak.pad_none	114	146	3m00s

Use feature adoption to make decisions about deprecation

The colon in `uproot.open("file.root:dir/tree")` causes many problems:

- **Test a URL with an HTTP port number** scikit-hep/uproot5#47
- **uproot4 unable to open ROOT file with colons in the name that uproot3 can** scikit-hep/uproot5#79
- **Simplify file path/object splitter** scikit-hep/uproot5#80
- **Removed the colon-parsing and replaced it with dicts.** scikit-hep/uproot5#81
- **Reading in multiple root files into pandas/dask DataFrame** scikit-hep/uproot5#129
- **Reading an object with colon in its name** scikit-hep/uproot5#365
- **Not possible to escape colon in filenames / avoid object-in-file path syntax (?)** scikit-hep/uproot5#541
- **Aliases and cuts when reading ROOT file** scikit-hep/uproot5#543
- **Accessing ROOT files with colons and double slashes in the path** scikit-hep/uproot5#669
- **pathlib.Path drops '//' (naturally), but it's sometimes used for URLs** scikit-hep/uproot5#670
- **fix: Ignore semicolon in EOS token when separating file name and object name** scikit-hep/uproot5#875

Use feature adoption to make decisions about deprecation

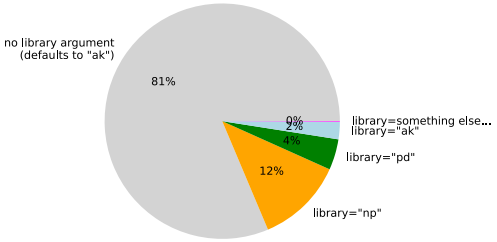


But removing it would upset at least 10% of workflows.

The deprecation period has to be *long*, if it is to be removed at all.

Focus on Uproot's array-fetching functions

How do people use the `library="??"` argument?



When it's used, it's much more often used for NumPy than for Pandas.

```
if isinstance(tree, ast.Call):
    name = ast.unparse(tree.func)
    if (   # select Uproot functions only
        (name.endswith(".array") and name not in (
            "np.array", "np.ma.array", "numpy.array",
            "NUMPY_LIB.array", "array.array",
            "self.NUMPY_LIB.array", "cupy.array",
        ))
        or name.endswith(".arrays")
        or name.endswith(".iterate")
        or (name.endswith(".concatenate") and name not
            "np.concatenate", "ak.concatenate",
            "awk.concatenate", "awkward.concatenate",
            "awkward.JaggedArray.concatenate",
            "JaggedArray.concatenate",
            "tf.concatenate",
        ))
        or name.endswith(".dask")
    ):
        matches.append(tree)
```

What libraries are Awkward and Uproot used *with*?

Awkward Array

numpy	90.5%	torch	4.2%
uproot	56.9%	seaborn	3.7%
matplotlib	49.8%	yahist	3.6%
coffea	35.6%	xgboost	3.2%
pandas	31.2%	sklearn	2.9%
mplhep	20.4%	h5py	2.9%
ROOT	11.9%	memory_profiler	2.6%
numba	11.8%	pympler	2.3%
hist	8.8%	psutil	2.1%
uproot_methods	8.4%	correctionlib	1.9%
yaml	8.2%	sortedcontainers	1.8%
utils	7.4%	cycler	1.7%
tqdm	6.7%	networkx	1.7%
boost_histogram	5.8%	pylab	1.5%
tensorflow	5.0%	PIL	1.5%
scipy	4.8%	helpers	1.4%
vector	4.3%	tabulate	1.4%

Uproot

numpy	88.5%	seaborn	3.9%
matplotlib	59.4%	hist	3.9%
pandas	46.5%	boost_histogram	3.9%
awkward	31.7%	keras	3.5%
ROOT	23.6%	CMS_lumi	3.5%
coffea	14.0%	histo_utilities	3.1%
mplhep	13.8%	analysis_utilities	3.1%
tqdm	11.0%	torch	2.9%
tensorflow	9.4%	h5py	2.8%
scipy	8.2%	progressBar	2.8%
sklearn	7.0%	cebefo_style	2.3%
uproot_methods	6.2%	lumi_utilities	2.1%
xgboost	6.0%	yahist	1.9%
yaml	5.8%	common	1.8%
numba	5.8%	config	1.8%
utils	5.1%	root_pandas	1.8%
root_numpy	4.5%	psutil	1.6%

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How to get the analysis code (source data are in public S3 buckets):

https://github.com/jpivarski-talks/2023-05-09-chep23-analysis-of-physicists