Spark-like and query-like analysis systems and tools

(what works, what doesn't work, what's needed, and what we're building to fill that need)

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“Analysis system” is a data access optimization scenario

The following are often true about end-user data analysis:

- Only need a small fraction of the event and particle attributes, like a few dozen.
  (A handful of trigger flags, details on two or three particle types, maybe a veto on another’s kinematics, but nowhere close to the thousands of available attributes.)
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Consider this request: “Please submit a GRID job to plot the muon p_T spectrum. Then we’ll think about what we want to look at next.” Is that unreasonable?

An example of what I have in mind: Google BigQuery

Google BigQuery

COMPOSE QUERY

Query History

Job History

Filter by ID or label

HEPQuery

No datasets found in this project.

Please create a dataset or select a new project from the menu above.

Public Datasets

- bigquery-public-data:hacker_news
- bigquery-public-data:noaa_gsod
- bigquery-public-data:samples
- bigquery-public-data:usa_names
- gdelt-bq:hathitrustbooks
- gdelt-bq:internetarchivebooks
- lookerdata:cdc
- nyc-tlc:green
- nyc-tlc:yellow

New Query

Query Editor | UDF Editor

```sql
SELECT timestamp, country_code, file.filename, file.version, file.type, url, details.distro.name, details.distro.version, details.system.name, details.system.release, details.cpu
FROM TABLE_DATE_RANGE(
  [the-psf:pypi.downloads],
  TIMESTAMP("2017-01-20"),
  CURRENT_TIMESTAMP()
)
WHERE file.project="uproot" and details.installer.name == "pip" and details.distro.name == "Raspbian GNU/Linux"
```

Ctrl + Enter: run query, Tab or Ctrl + Space: autocomplete.

RUN QUERY | Save Query | Save View | Format Query | Show Options

Query complete (30.2s elapsed, 1.82 TB processed)

Results | Details

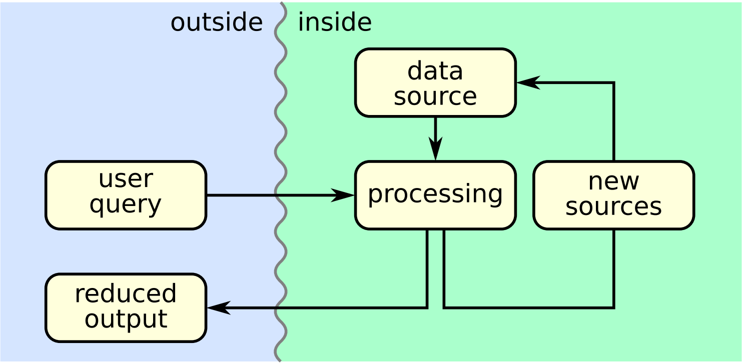
Download as CSV | Download as JSON | Save as Table | Save to Google Sheets

Row	timestamp	country_code	file_filename	file_version	file_type	url	details_distro_name	details_distro_version	det
1	2017-11-24 23:26:53.000 UTC	null	uproot-2.0.2.tar.gz	2.0.2	sdist	/packages/f4/06/91b0cc7d9b5ef9cb071e72b8ce77195baa22a6c99c431680a144ab858026/uproot-2.0.2.tar.gz	Raspbian GNU/Linux	9	Linu
2	2017-11-24 23:02:03.000 UTC	null	uproot-2.0.2.tar.gz	2.0.2	sdist	/packages/f4/06/91b0cc7d9b5ef9cb071e72b8ce77195baa22a6c99c431680a144ab858026/uproot-2.0.2.tar.gz	Raspbian GNU/Linux	9	Linu
3	2017-12-11 21:51:53.000 UTC	null	uproot-2.5.9.tar.gz	2.5.9	sdist	/packages/7d/b0/ecf6134c205e2678ca28fa7493303576313221638 49c017b2fd635822291/uproot-2.5.9.tar.gz	Raspbian GNU/Linux	8	Linu
4	2017-11-30 14:15:25.000 UTC	null	uproot-2.1.5.tar.gz	2.1.5	sdist	/packages/96/1c/f246d9beae81fbad3fc1d0bd675a0516b4286c23b9afefe92f3099bf5f6d/uproot-2.1.5.tar.gz	Raspbian GNU/Linux	8	Linu
5	2017-11-30 13:35:34.000 UTC	null	uproot-2.3.3.tar.gz	2.3.3	sdist	/packages/5d/8b/dc6486334876c81c23034e60dd836fe9b2bf7eb4e5b39df1a83e1e8aaa23/uproot-2.3.3.tar.gz	Raspbian GNU/Linux	8	Linu
6	2018-01-03 23:50:16.000 UTC	null	uproot-2.5.15.tar.gz	2.5.15	sdist	/packages/7a/1f/c4fcb3b32809f45c03c3d7adfb1051176b6ad35c104040fc9fa38f47b44c/uproot-2.5.15.tar.gz	Raspbian GNU/Linux	8	Linu
7	2018-01-03 16:47:34.000 UTC	null	uproot-2.5.14.tar.gz	2.5.14	sdist	/packages/e8/65/858fd40c433c9a1034fa3062897ff3aa19a58c2d80d596fdbbf6df573c2f/uproot-2.5.14.tar.gz	Raspbian GNU/Linux	8	Linu
8	2017-11-04 02:11:29.000 UTC	null	uproot-1.0.1.tar.gz	1.0.1	sdist	/packages/d3/50/4af1773d449a454ee31e20278ec114bceba1bc473b636a11685d40b6552f/uproot-1.0.1.tar.gz	Raspbian GNU/Linux	8	Linu
9	2017-11-04 02:11:54.000 UTC	null	uproot-1.4.2.tar.gz	1.4.2	sdist	/packages/e1/9b/6ae6cc054af7e61fecc7cfb45b7a18c0f3c06dcfd1a596ca2cb844f84a93/uproot-1.4.2.tar.gz	Raspbian GNU/Linux	8	Linu
10	2017-11-04 02:12:01.000 UTC	null	uproot-1.6.0.tar.gz	1.6.0	sdist	/packages/98/0c/7a7f934b1e7a9a302e8ef16edc030ba17e5759141ed9e86aaefbb0464734/uproot-1.6.0.tar.gz	Raspbian GNU/Linux	8	Linu
11	2017-11-04 02:11:55.000 UTC	null	uproot-1.5.3.tar.gz	1.5.3	sdist	/packages/60/14/bfa043c970b66b6f73fe0765ffdeec5964338c2a29301cc2a1c7740be209/uproot-1.5.3.tar.gz	Raspbian GNU/Linux	8	Linu
12	2017-11-04 02:11:55.000 UTC	null	uproot-1.5.0.tar.gz	1.5.0	sdist	/packages/b7/12/3fd299b2fd9c2076d491933ac7a1177ade4a0d715fbc56beb8e14c91cf66/uproot-1.5.0.tar.gz	Raspbian GNU/Linux	8	Linu
13	2017-11-04 02:11:27.000 UTC	null	uproot-1.0.0.tar.gz	1.0.0	sdist	/packages/5c/0a/7ca1f587d460cb8fe70306a94308822b2cce5bf176cd4f0879246950c73f/uproot-1.0.0.tar.gz	Raspbian GNU/Linux	8	Linu
14	2017-11-04 02:11:29.000 UTC	null	uproot-1.2.0.tar.gz	1.2.0	sdist	/packages/c0/e1/c249b359c0dfce204968f6fefff84813199b77b66a43b36727c4d2ed60f4/uproot-1.2.0.tar.gz	Raspbian GNU/Linux	8	Linu
15	2017-11-04 02:11:39.000 UTC	null	uproot-1.3.0.tar.gz	1.3.0	sdist	/packages/7e/6d/f070aff4821b78a8bf7d133922ad93540c82a01924473e1d77149d6fb9be/uproot-1.3.0.tar.gz	Raspbian GNU/Linux	8	Linu
16	2017-11-04 02:12:05.000 UTC	null	uproot-1.6.1.tar.gz	1.6.1	sdist	/packages/d7/39/8eadf6a705cd6b6b778fc2b067d920b0776bb1b3b11e3359f55d786640cb/uproot-1.6.1.tar.gz	Raspbian GNU/Linux	8	Linu
17	2017-11-04 02:11:40.000 UTC	null	uproot-1.3.1.tar.gz	1.3.1	sdist	/packages/1b/b2/c59d1916ca1aa631f2264114cbc4ac16a226ac705821a2ab48e6bb16a352/uproot-1.3.1.tar.gz	Raspbian GNU/Linux	8	Linu

Table | JSON

First < Prev Rows 1 - 17 of 37 Next > Last

Basic block diagram



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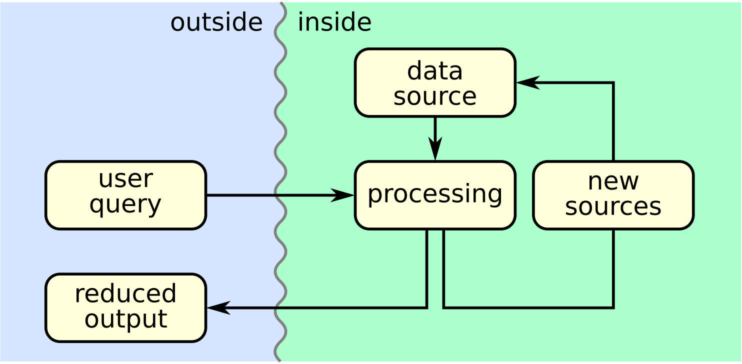

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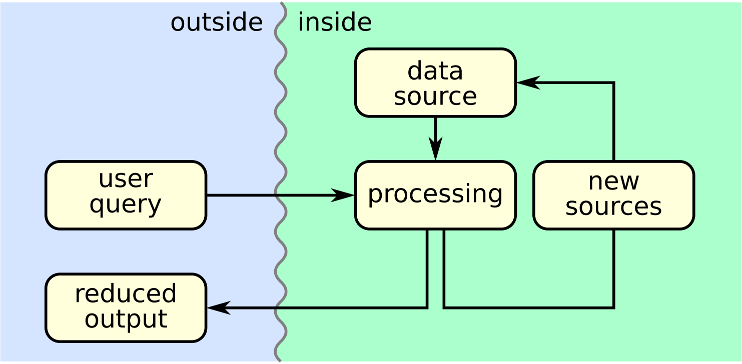

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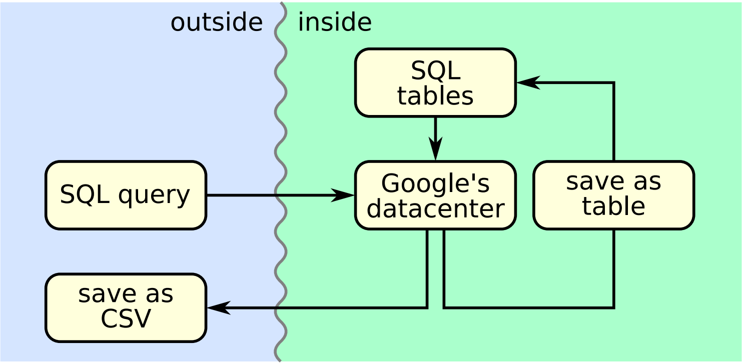

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- Reason #2: Data model. The BigQuery paper ("Dremel"), Parquet & Drill (open source versions of the same), Apache Arrow, and SparkSQL all describe rich, nested data models sufficient to describe HEP events.

  However, *for every one of these,* you quickly encounter "not implemented yet" messages when you try to use them for HEP events.

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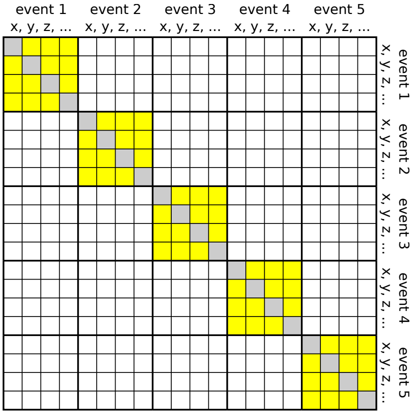
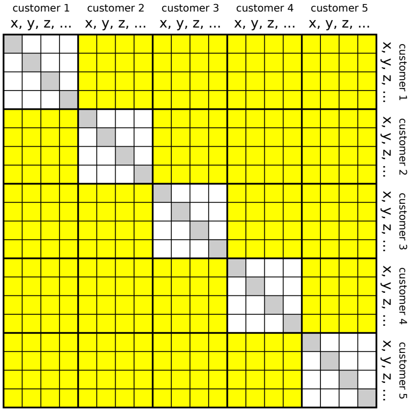
- Reason #3: User interface. The web form is fun, but we need queries embedded in an interactive, programmable environment with plotting and statistics libraries: ROOT or Python or both (probably both).

HEP analysis is simpler

HEP functions never have to cross events.



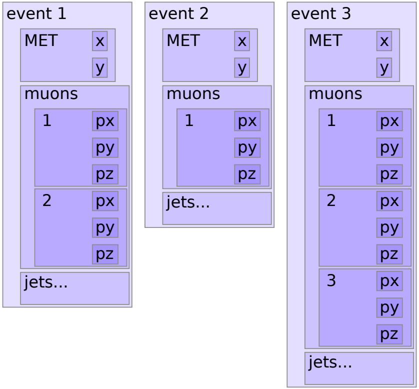
Common elsewhere: e.g. market basket analysis.



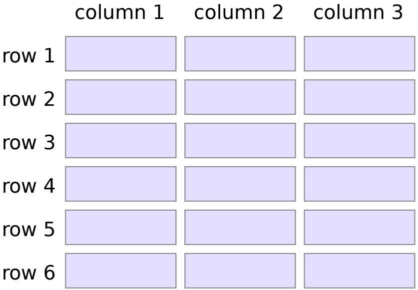
HEP is both simpler and more complex than relational analytics

HEP analysis is more complex

HEP data are variable-length, nested data structures, and we typically need to loop over combinations of particles.



In many fields, data are not considered ready for analysis until they're in a tabular form. (Earlier steps are called "tidying.")



HEP is both simpler and more complex than relational analytics

	independent events	all-to-all shuffle
tabular data	basic spreadsheets	relational analytics
variable-length, nested data	HEP analysis	graph analytics

What should our data source be?

Identically typed, variable-length, nested data can be split into columns:

- All attribute values at a given level of hierarchy are stored together and may be retrieved independently of the rest.
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- **Avoid touching disk:** sorted partitions do not need to be fully read if a cut is being applied to the sorted variable (most likely p_T).

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- √ Array fetching is through an arbitrary dict-like object: may defer to disk, network, or per-column cache.
- √ OAMap has enough indirection that different particle types can be *independently sorted* by their own p_Ts. Thus, a filter like "muon $p_T > X$ and jet $p_T > Y$" may touch disk for only half the muon data and half the jet data.

OAMap example

```
>>> import uproot
>>> import oamap.source.root

>>> url = "http://scikit-hep.org/uproot/examples/HZZ.root"
>>> events = uproot.open(url)["events"].oamap()
>>> events.schema.content["muons"].show()
List(
  starts = 'NMuon',      # schema maps object attributes to array names
  stops = 'NMuon',
  content = Record(      # at all levels of nesting
    fields = {
      'px': Primitive(dtype('float32'), data='Muon_Px'),
      'py': Primitive(dtype('float32'), data='Muon_Py'),
      'pz': Primitive(dtype('float32'), data='Muon_Pz'),
      'energy': Primitive(dtype('float32'), data='Muon_E'),
      'charge': Primitive(dtype('int32'), data='Muon_Charge'),
      'isolation': Primitive(dtype('float32'), data='Muon_Iso')
    }))
```

OAMap example

The dataset looks like a nested Python list.

```
>>> events
[<Event at index 0>, <Event at index 1>, <Event at index 2>, ...,
 <Event at index 2418>, <Event at index 2419>, <Event at index 2420>]

>>> events[0].muons
[<Muon at index 0>, <Muon at index 1>]

>>> [x.px for x in events[0].muons]
[-52.899456, 37.73778]
```

But it is generated on demand from arrays.

```
"NMuon":   array([2, 1, 2, ..., 1, 1, 1], dtype=int32)
"Muon_Px": array([-52.899456,  37.73778,  -0.81645936, ...,
                  -29.756786, 1.1418698,  23.913206  ], dtype=float32)
```

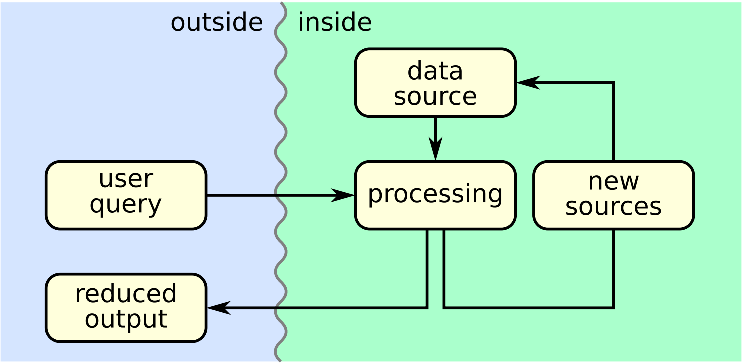
OAMap example

It can also be included in compiled code with no change in syntax.

```
>>> import numpy
>>> import numba
>>> import oamap.compiler
>>> @numba.njit                        # declares the following function to be compiled
... def compute(events, out):
...     i = 0
...     for event in events:           # "event" and "event.muons" are a compiler fiction
...         if len(event.muons) == 2:
...             mu1, mu2 = event.muons[0], event.muons[1]
...             px = mu1.px + mu2.px
...             py = mu1.py + mu2.py
...             pz = mu1.pz + mu2.pz
...             energy = mu1.energy + mu2.energy
...             out[i] = sqrt(energy**2 - px**2 - py**2 - pz**2)
...             i += 1

>>> out = numpy.empty(1371)
>>> compute(events, out)               # compilation and array-fetching happen on first call
>>> out
array([90.22780609, 74.74654388, 89.75765991, ..., 92.06494904,
       85.44384003, 75.96061707])
```

Current thinking. . .



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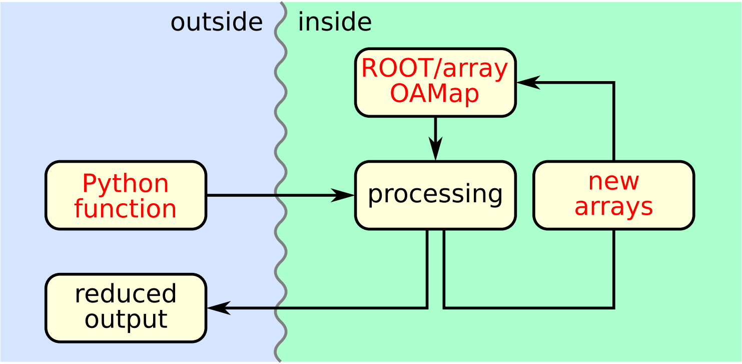

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- Pandas has more in common with *histograms* than it does with *event sources*.

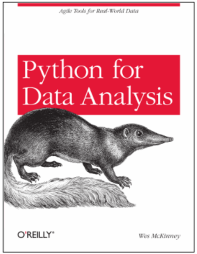
Just an example. . .

I'll illustrate these operations through a series of examples. Consider a small DataFrame with string arrays as row and column indexes:

```
In [94]: data = DataFrame(np.arange(6).reshape((2, 3)),
   ....:                  index=pd.Index(['Ohio', 'Colorado'], name='state'),
   ....:                  columns=pd.Index(['one', 'two', 'three'], name='number'))

In [95]: data
Out[95]:
number    one  two  three
state
Ohio        0    1      2
Colorado    3    4      5
```

Using the `stack` method on this data pivots the columns into the rows, producing a Series:

```
In [96]: result = data.stack()

In [97]: result
Out[97]:
state     number
Ohio      one       0
          two       1
          three     2
Colorado  one       3
          two       4
          three     5
```



Pandas generalizes what we do with histograms

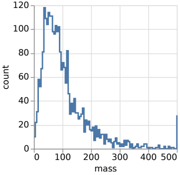
```python
import pandhist
# define bins in many dimensions; we'll think about how to plot later
muonhist = (pandhist
              .bin(100, 0, 500, "mass")
              .cut("q1*q2 < 0")
              .irrbin([0.2, 0.5], "mt1")
              .irrbin([0.2, 0.5], "mt2")
              .fillable())       # creates a fillable Pandas DataFrame

for muons, charge, mt2activity in uproot.iterate(
  "RA2Analysis/*.root", "TreeMaker2/PreSelection",
  ["Muons", "Muons_charge", "Muons_MT2Activity"], outputtype=tuple):
    for i in range(len(muons)):
        if len(charge[i]) == 2:
            mu1, mu2 = muons[i]
            q1,  q2  = charge[i]
            mt1, mt2 = mt2activity[i]
            # fill method has an argument for each variable
            muonhist.fill((mu1 + mu2).mass, q1, q2, mt1, mt2)
```

Pandas generalizes what we do with histograms

```
>>> muonhist
                                                        count   # in this example, count is
mass            q1*q2 < 0 mt1           mt2                     # the only column; the rest
[-inf, 0.0)     fail      [-inf, 0.2)   [-inf, 0.2)       0.0   # is a hierarchical index
                                        [0.2, 0.5)        0.0   # (mass, q1*q2 < 0, mt1, mt2)
                                        [0.5, inf)        0.0
                          [0.2, 0.5)    [-inf, 0.2)       0.0
                                        [0.2, 0.5)        0.0   # if we asked for weights,
                                        [0.5, inf)        0.0   # sumw and sumw2 would be
                          [0.5, inf)    [-inf, 0.2)       0.0   # separate columns
                                        [0.2, 0.5)        0.0
                                        [0.5, inf)        0.0
                pass      [-inf, 0.2)   [-inf, 0.2)       0.0   # if we asked for a profile,
                                        [0.2, 0.5)        0.0   # we'd get sum(y) and sum2(y)
                                        [0.5, inf)        0.0
                          [0.2, 0.5)    [-inf, 0.2)       0.0
                                        [0.2, 0.5)        0.0   # but most of the work is done
                                        [0.5, inf)        0.0   # by the hierarchical index
                          [0.5, inf)    [-inf, 0.2)       0.0
                                        [0.2, 0.5)        0.0
                                        [0.5, inf)        0.0
...                                                       ...
[1836 rows x 1 columns]
```

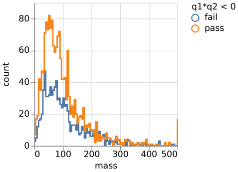
Pandas generalizes what we do with histograms

```
>>> pandhist.steps("mass").data(muonhist)
```



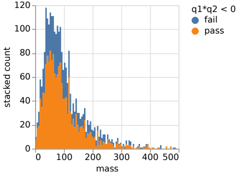
Pandas generalizes what we do with histograms

```
>>> pandhist.steps("mass").overlay("q1*q2 < 0").data(muonhist)
```



Pandas generalizes what we do with histograms

```
>>> pandhist.area("mass").stack("q1*q2 < 0").data(muonhist)
```



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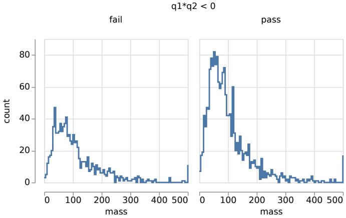
```
>>> pandhist.steps("mass").column("q1*q2 < 0").data(muonhist)
```



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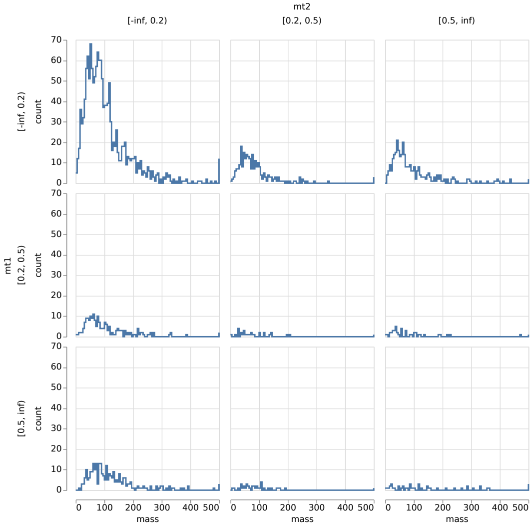
```
>>> pandhist.steps("mass").row("mt1").column("mt2").data(muonhist)
```



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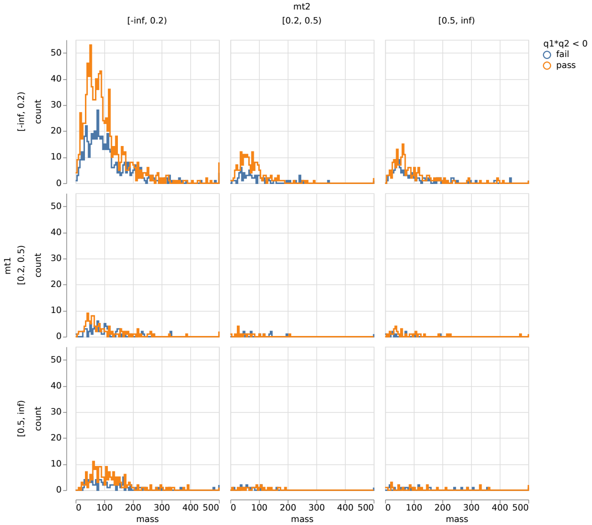
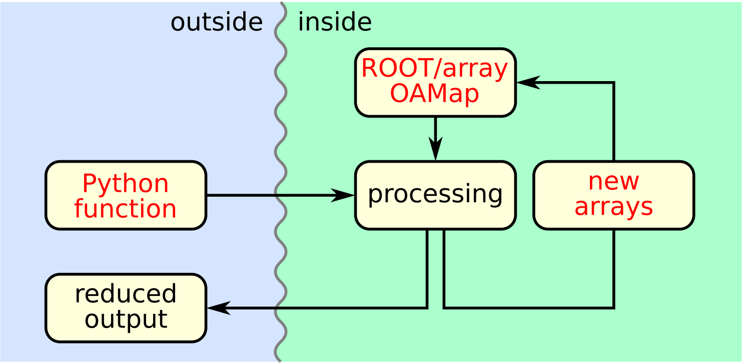


Current thinking. . .



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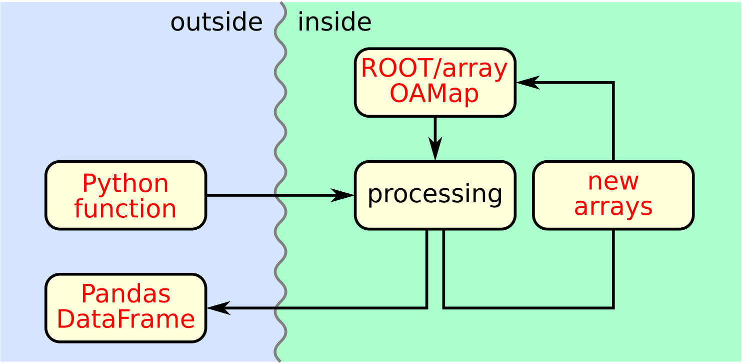

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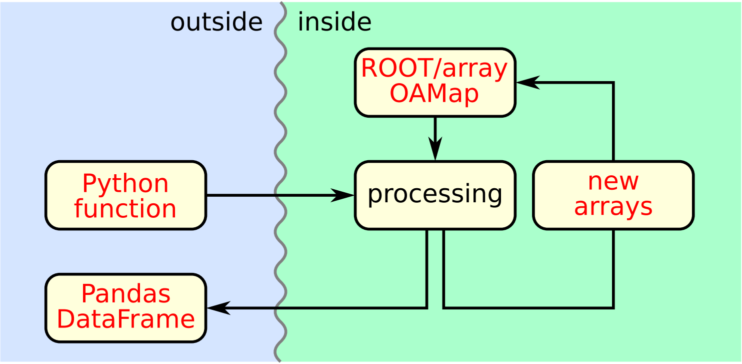
- Thanat Jatuphattharachat (summer student) investigated raw Zookeeper coordination, but this is getting close to DIY.
- Dask looks like a good choice: it's in the C++/Python world, general enough to piece together what we need out of basic parts.

  (More about this in the concurrency session.)

Current thinking...



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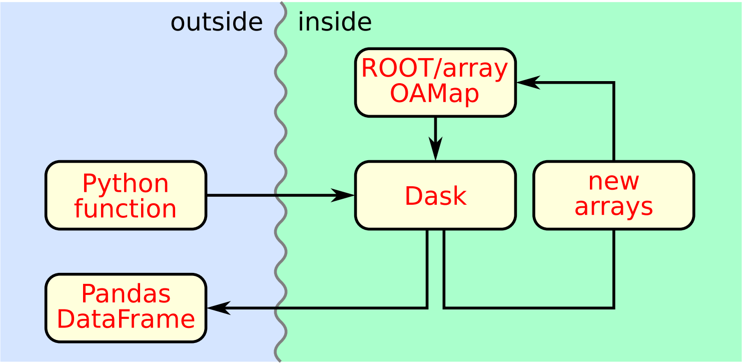

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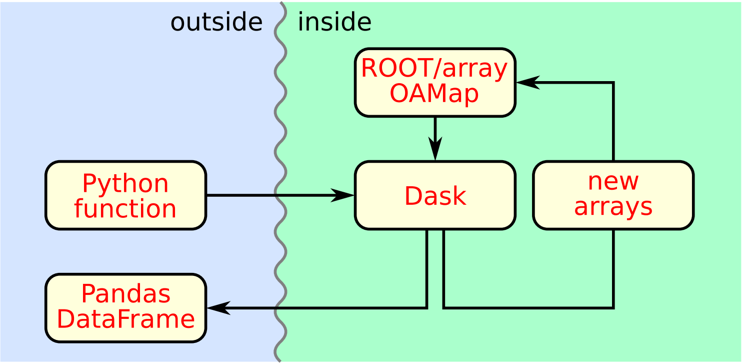
- Ceph is both an object store and a filesystem, and it minimizes metadata overhead by coordinating data placement through a static function, rather than a dynamic service.
  - Lets us experiment both ways.
  - We could use the static function to place executable tasks, improving data locality. . .

Current thinking. . .



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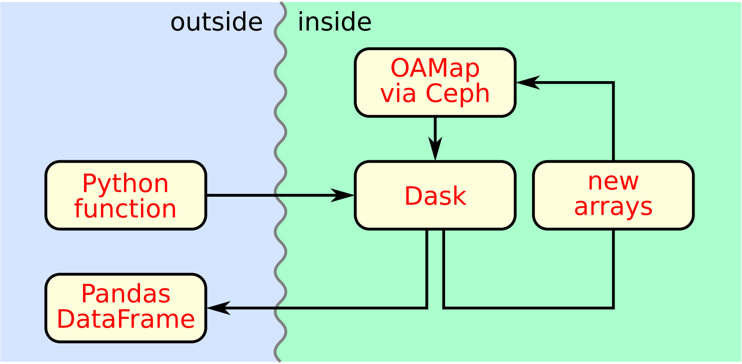

Conclusions

Though an analysis service should use as many open source parts as possible, some functionality is missing and we need to build our own.

Software products developed along the way:

uproot	Quickly access ROOT branches as arrays.	mature, in use
oamap	Translate between object-oriented Python and low-level array operations.	ready for testing
pandhist	Reinterpretation of Pandas DataFrames as super-histograms. (Plotting in Vega-Lite.)	experimental
vegascope	Browser-based TCanvas for Vega/Vega-Lite, so that you don't have to use Jupyter if you don't want to.	done (simple)
?	OAMap as a collection in Dask.	
?	Column manager (for sharing data among datasets).	
?	All-in-one environment for query-based analysis.	