Particle Physics, 10 000 times faster

Jim Pivarski

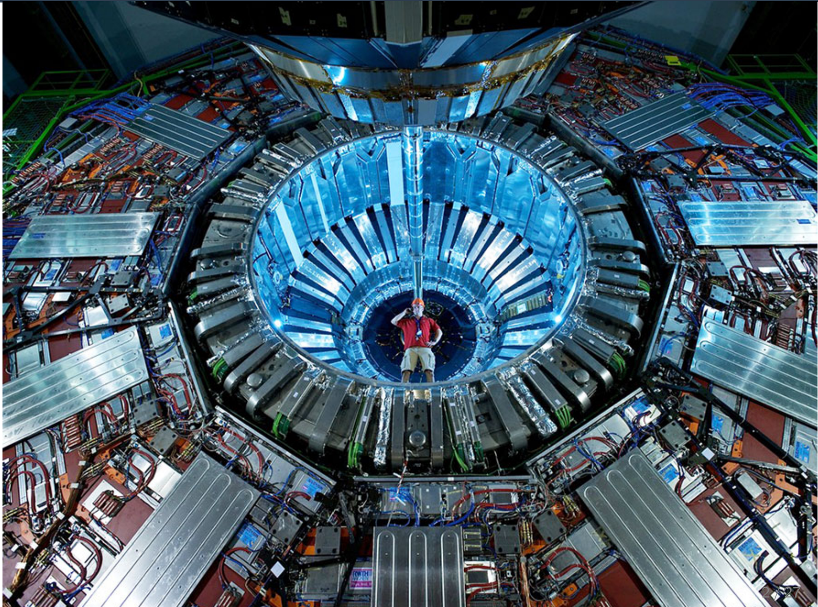
Princeton University – DIANA

September 30, 2017

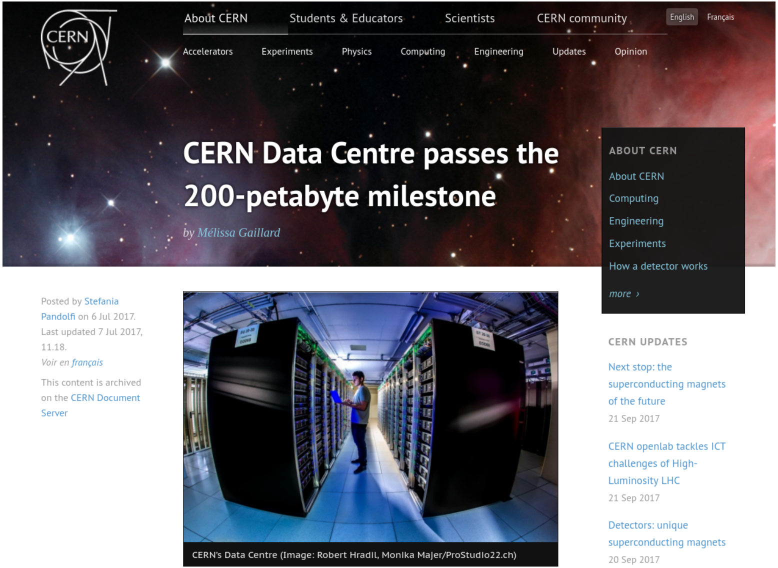
Particle physics: the most industrial field of academia

The goals are academic: to explore strange new phenomena; to seek out new particles and new interactions. . .

The scale is industrial: billion dollar hardware, planning on decadal time-scales, millions of lines of code. . .



It's big data...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CERN Data Centre passes the 200-petabyte milestone

by Mélissa Gaillard

Posted by Stefania Pandolfi on 6 Jul 2017. Last updated 7 Jul 2017, 11.18.

Voir en français

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CERN's Data Centre (Image: Robert Hradil, Monika Majer/ProStudio22.ch)

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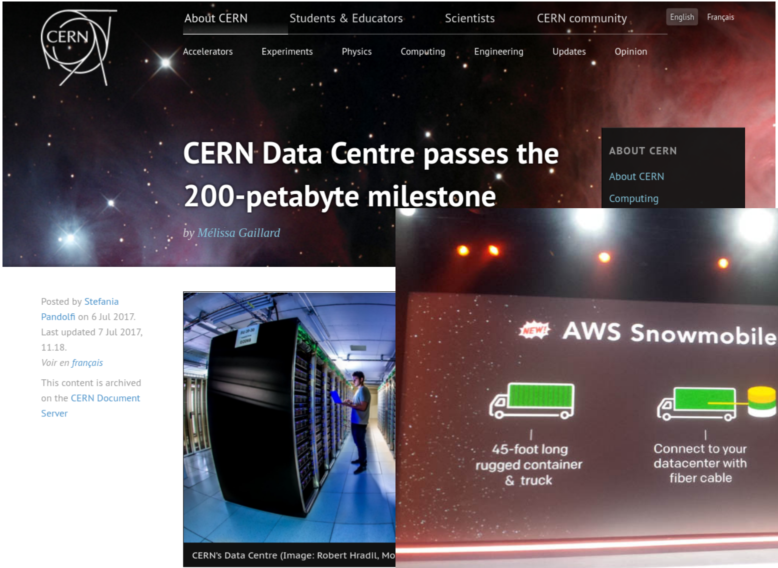
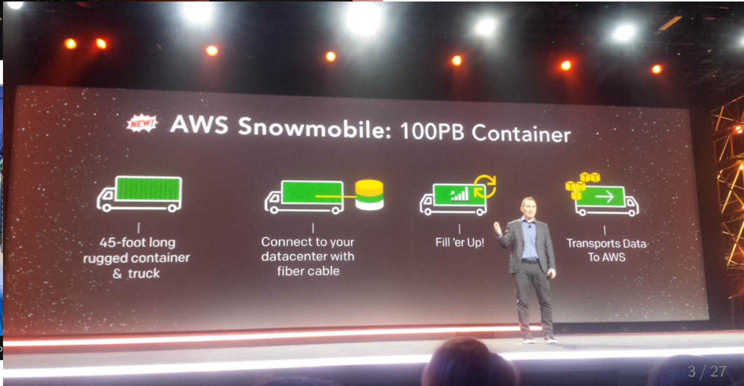
21 Sep 2017

CERN openlab tackles ICT challenges of High-Luminosity LHC
21 Sep 2017

Detectors: unique superconducting magnets
20 Sep 2017

It's big data... but not *really* big





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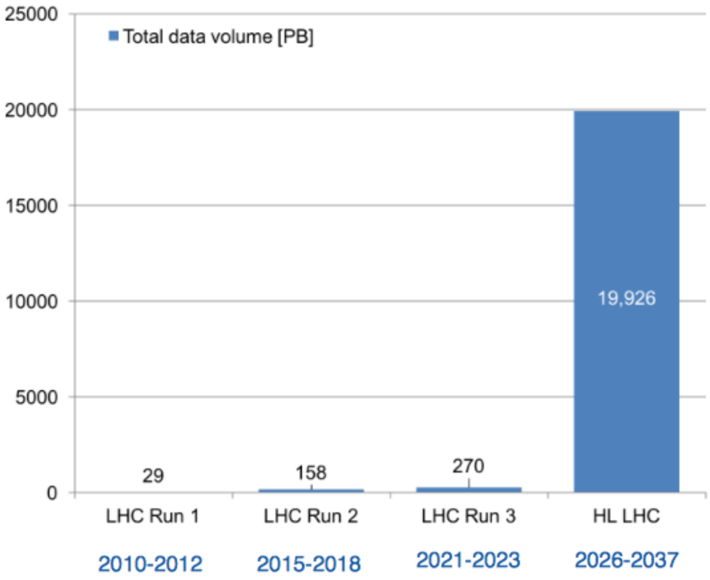

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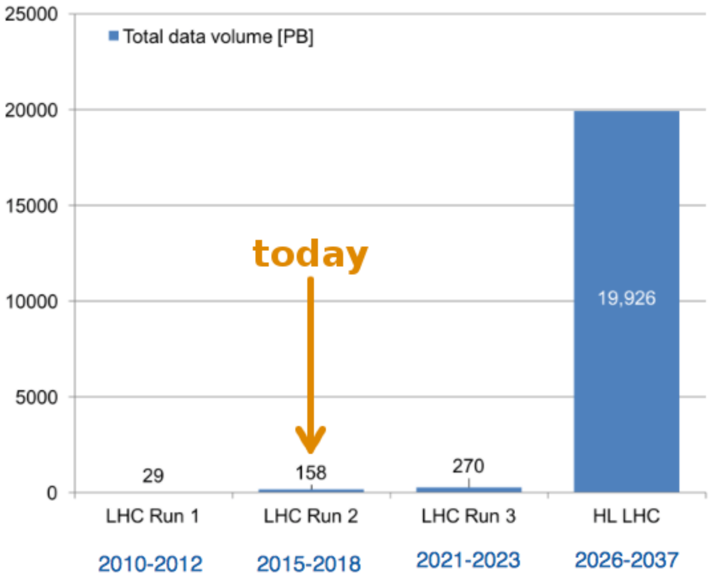
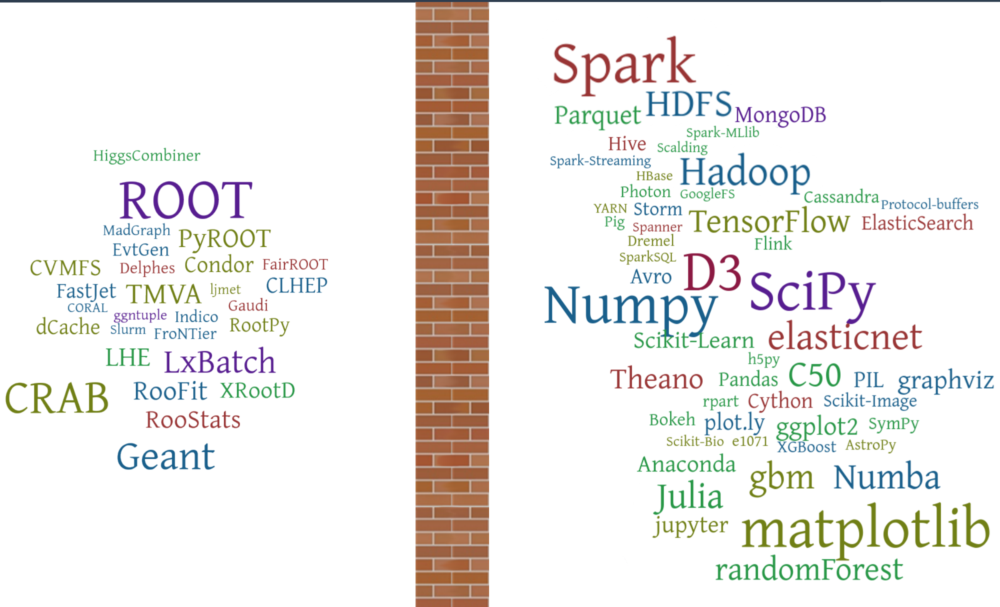


Our software developed outside the big data ecosystem

dianahep



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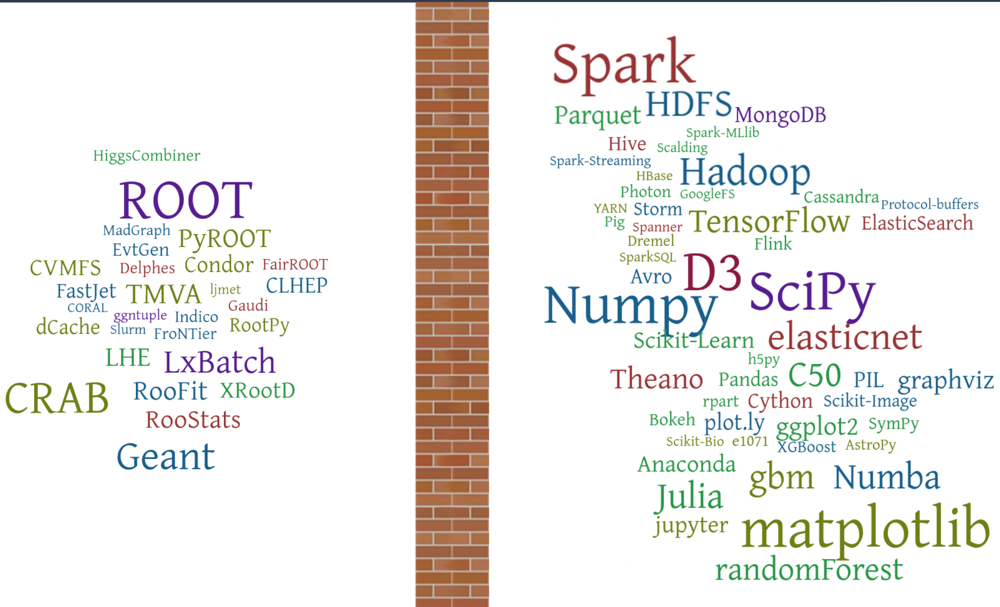

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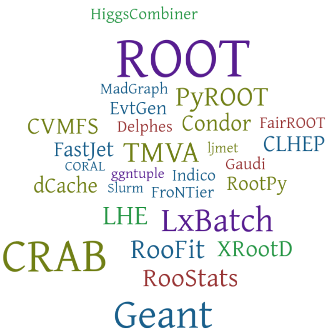
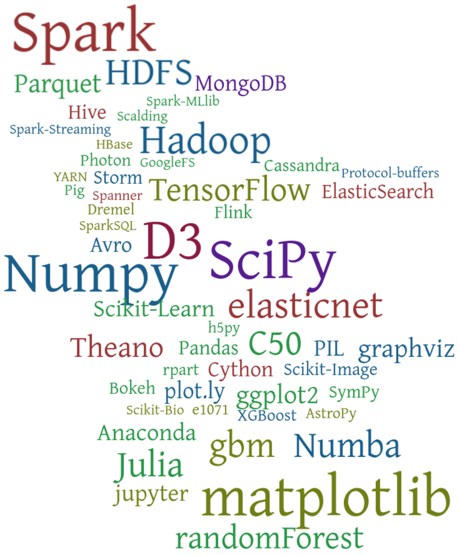
It's my job to try to find ways to bridge the divide.





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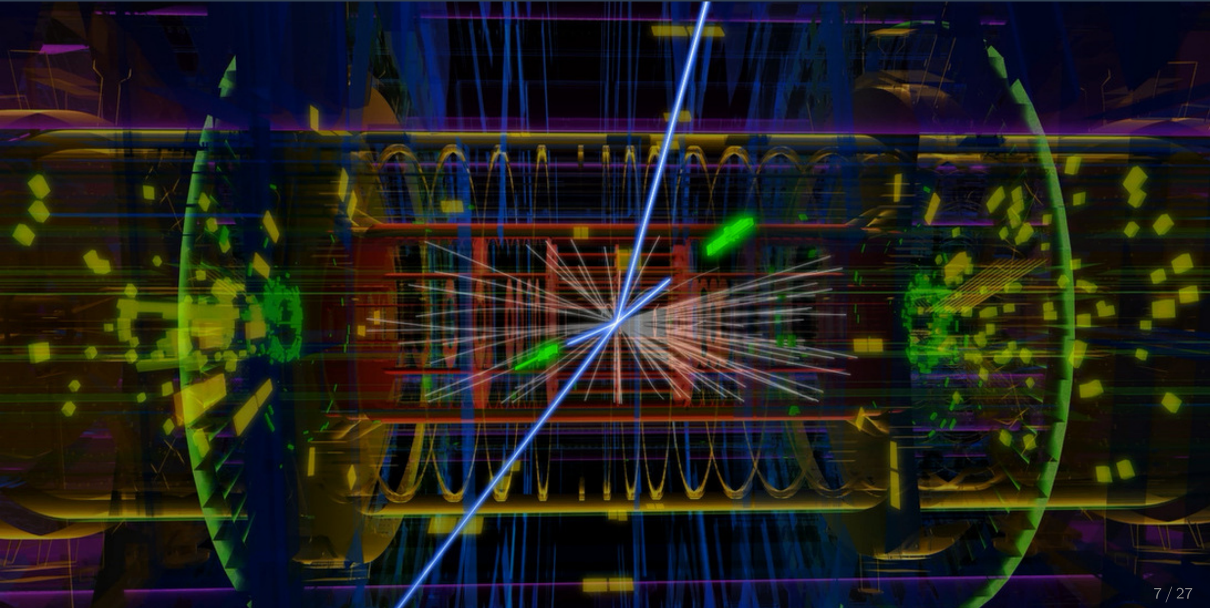
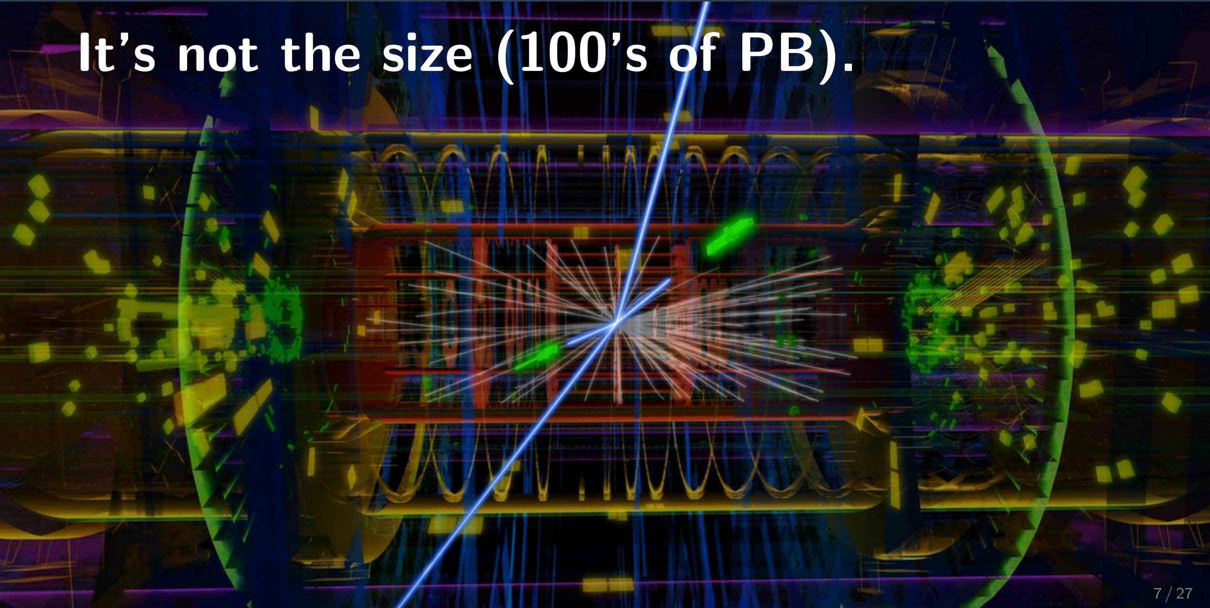
This represents an opportunity on both sides: alien civilizations that evolved on different planets can learn a lot from each other!

So, what is unique about particle physics data?



It’s not the size (100’s of PB).



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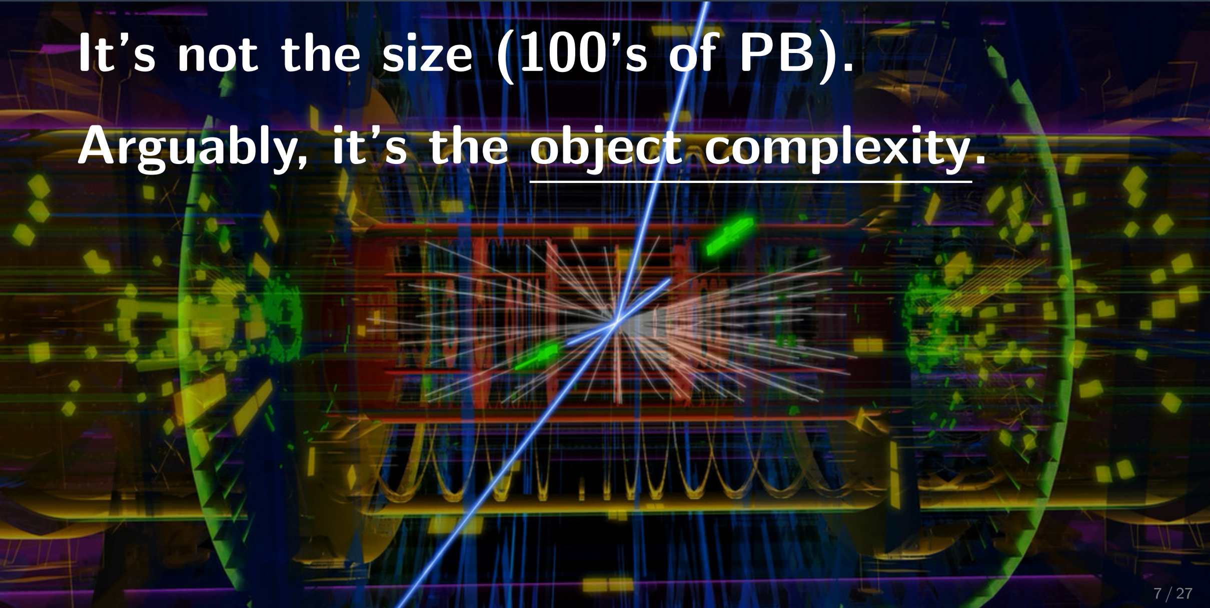

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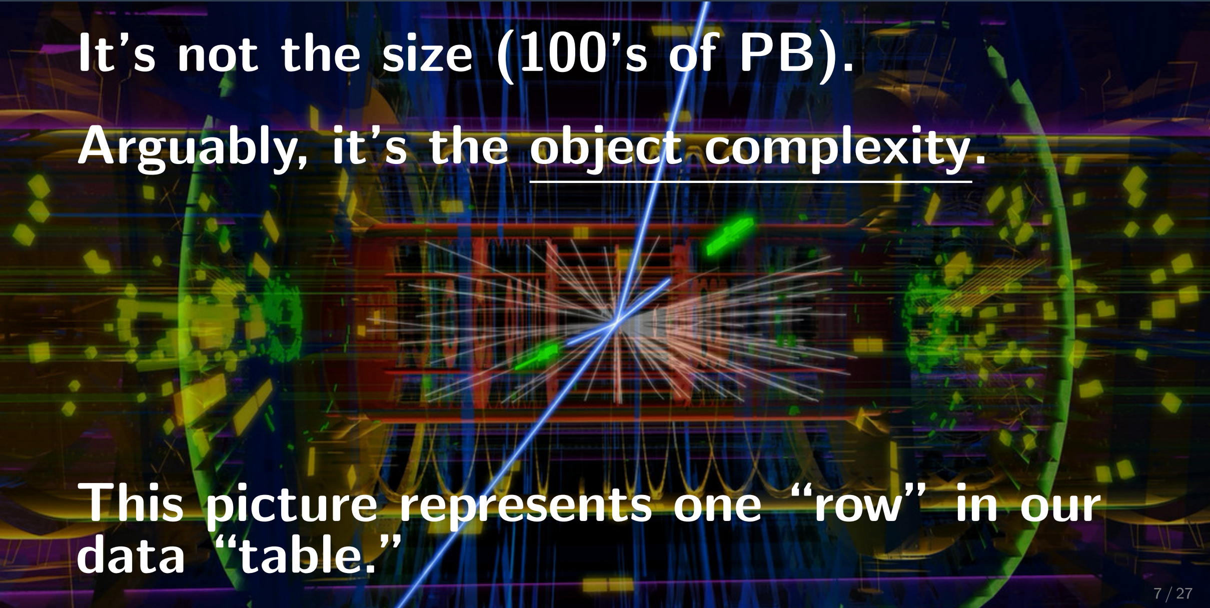

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This picture represents one "row" in our data "table."

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Why?

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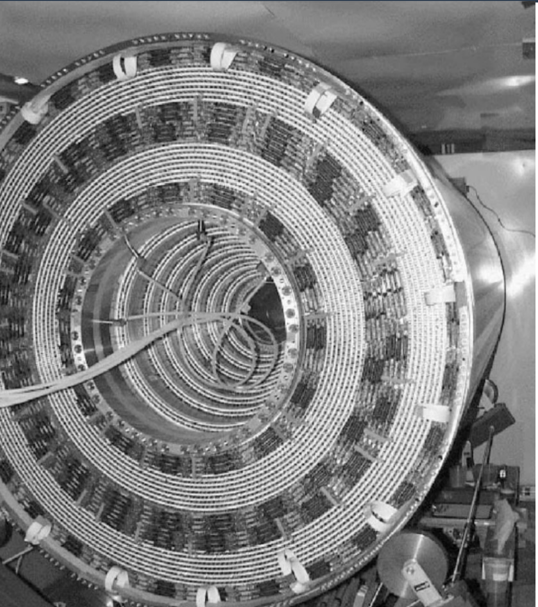
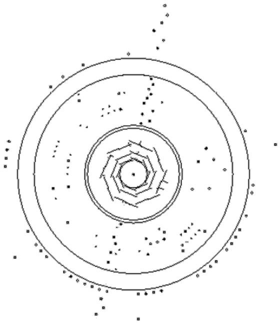
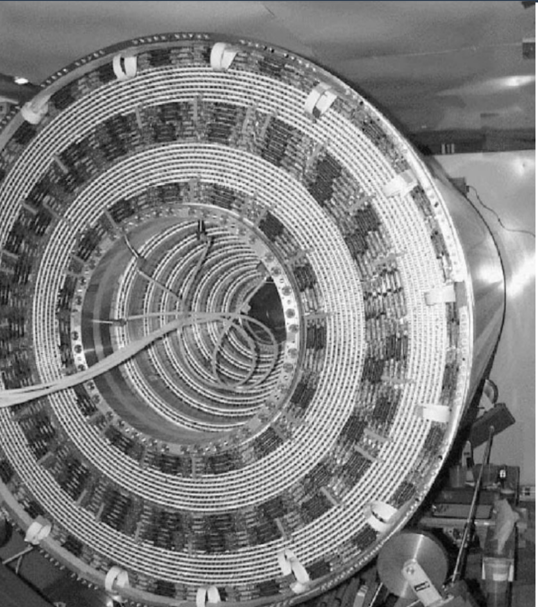
To give a sense of the problem, I'll walk through the steps of an analysis.



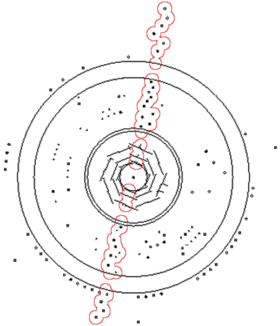
Can you see the particle tracks?



From raw signals to tracks



How about now?



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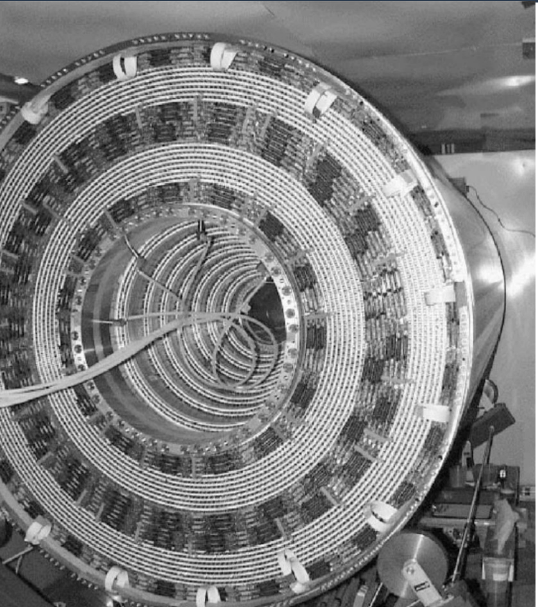

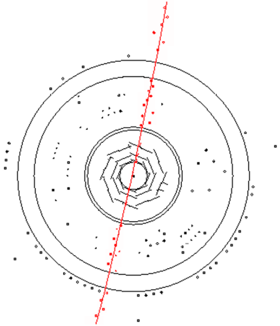

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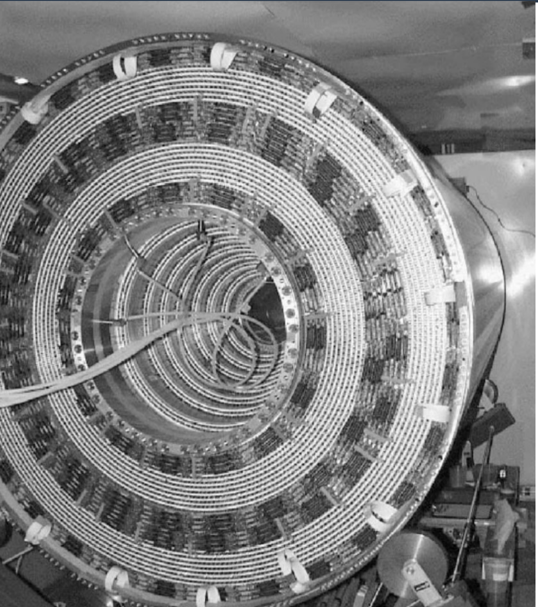

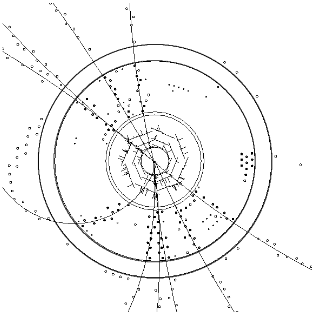

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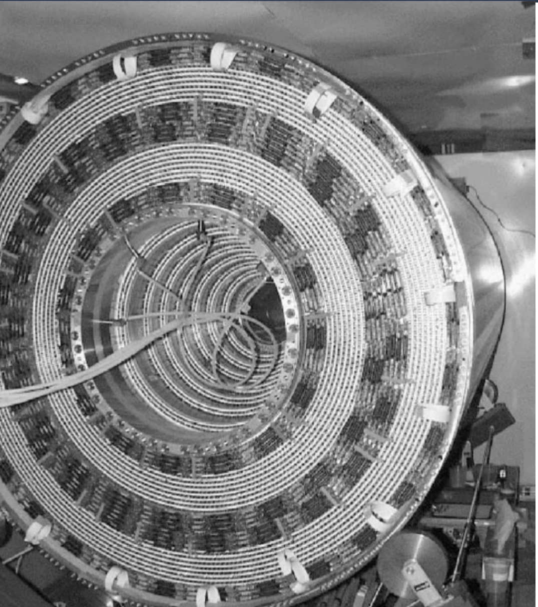
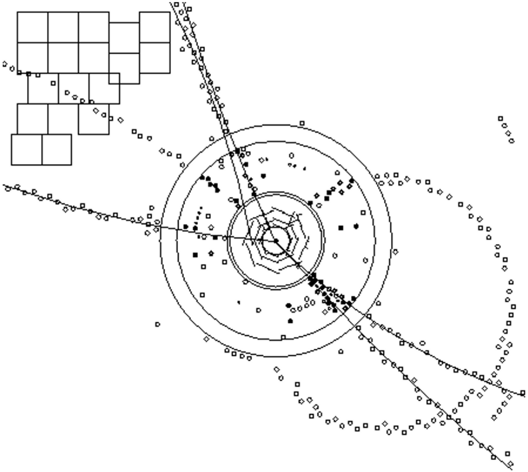
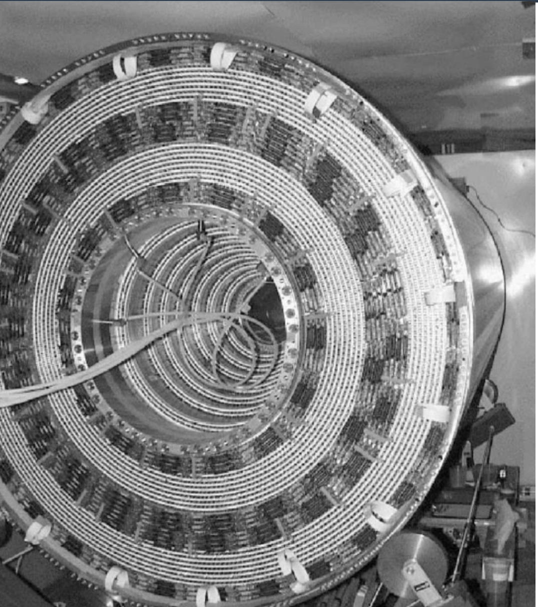
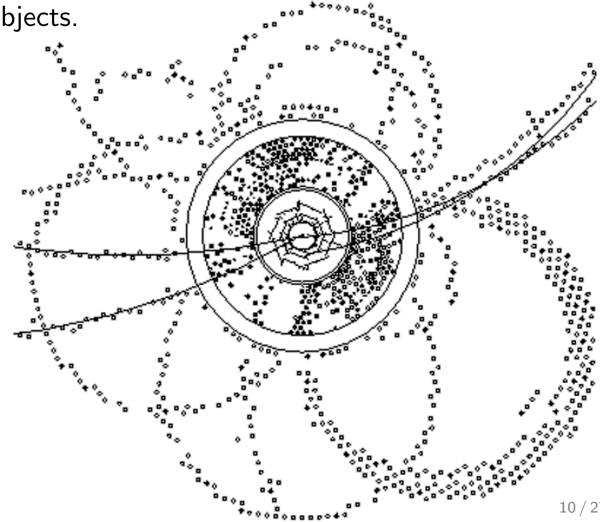




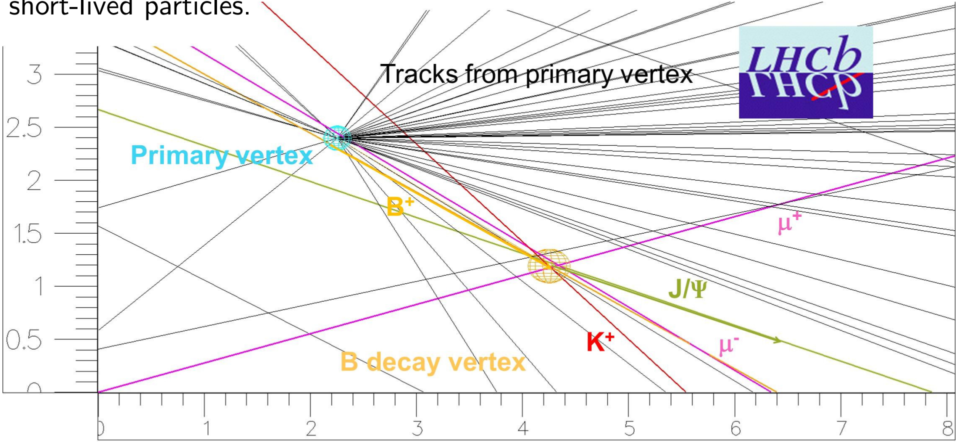


Raw data could have been a (sparsely filled) table, but tracks are an arbitrary-length list of objects.



From tracks to particles

Tracks are long-lived particles (on the nanosecond scale) that came from the decay of very short-lived particles.



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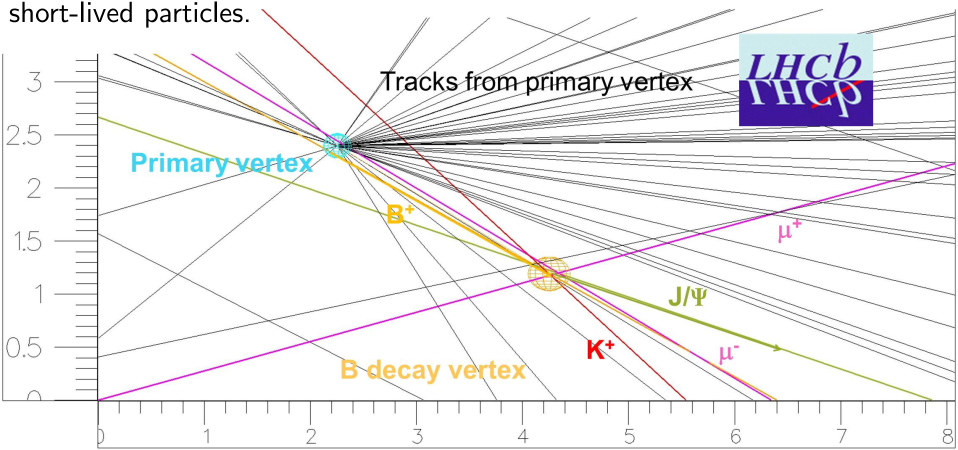
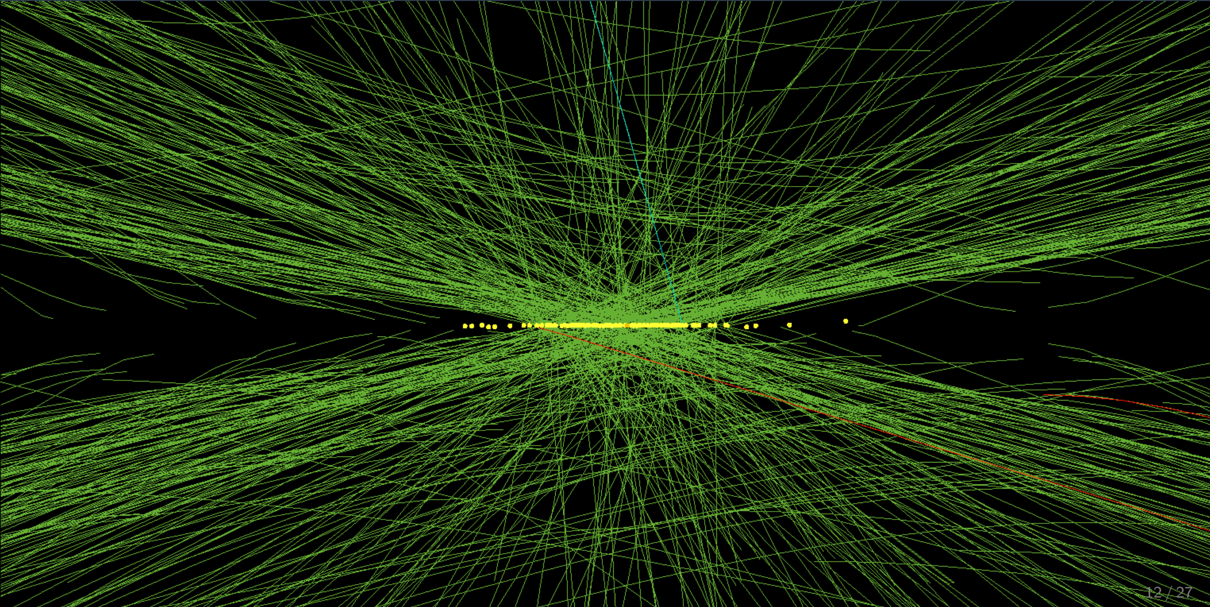


Tracks have structured associations with one another, and those associations are not certain: flexibility has to be carried through to the final analysis.

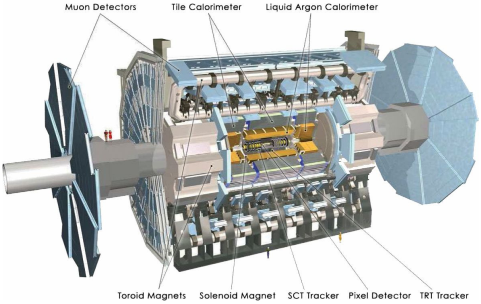
And there are a lot of combinations to consider. . .

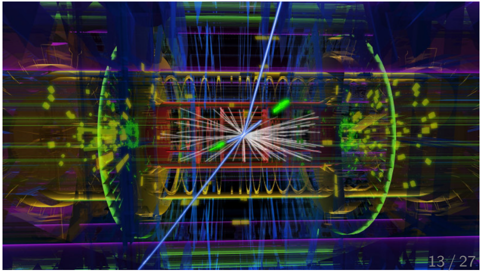


From particles to discovery

Suppose there's a particle called "Higgs" that would decay into two "Z bosons," each of which decays into two electrons or two muons.

$$H \to ZZ \to e^+e^-\mu^+\mu^-$$





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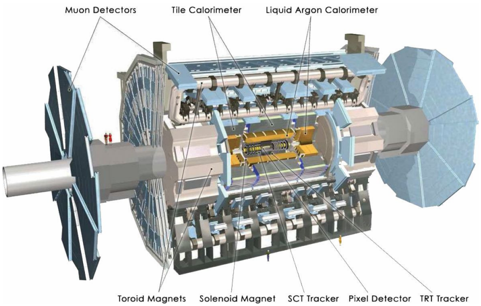

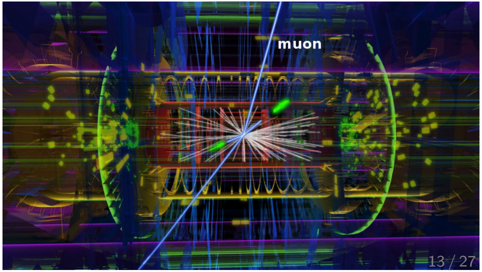

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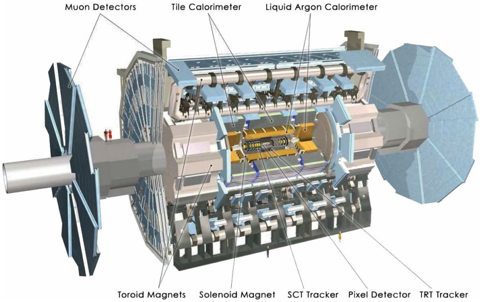

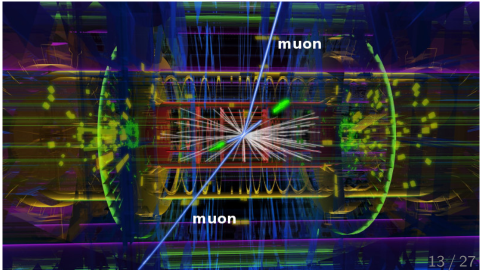

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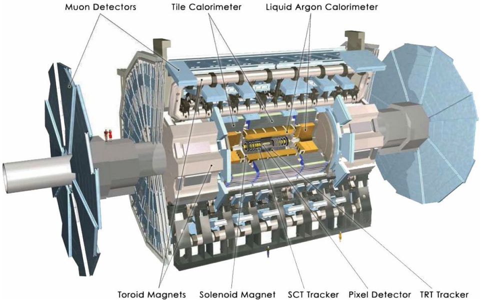

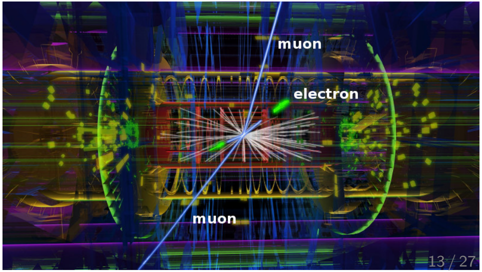

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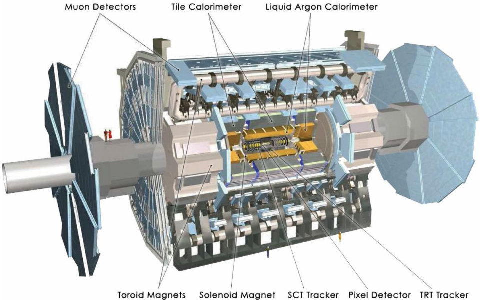

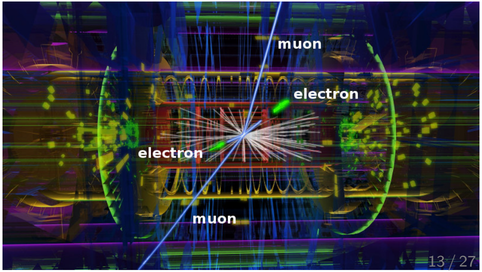

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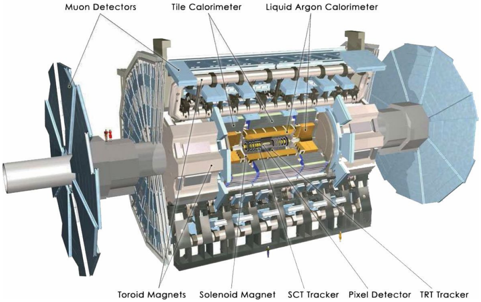

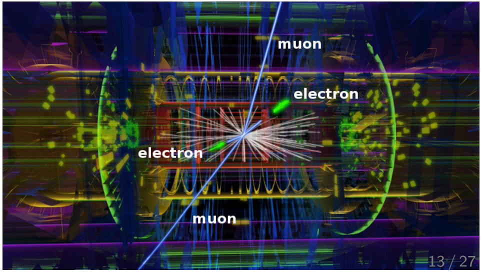

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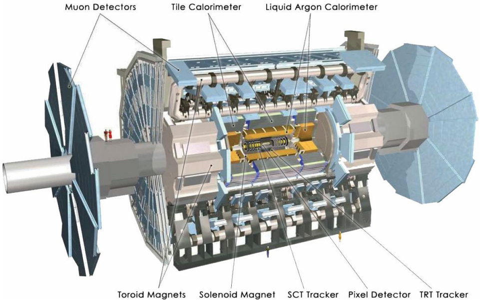

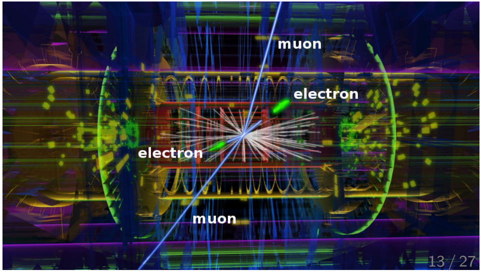

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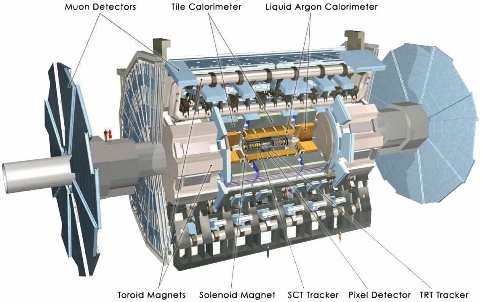

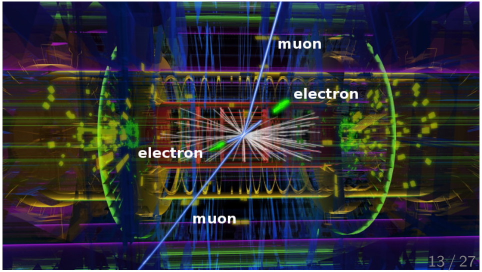

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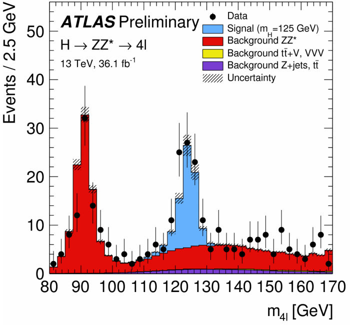
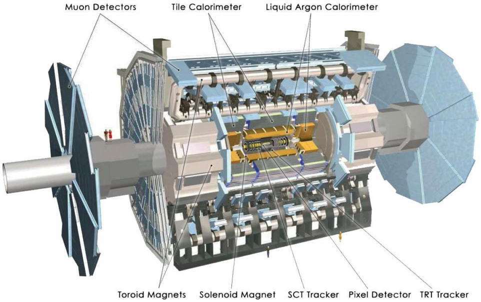
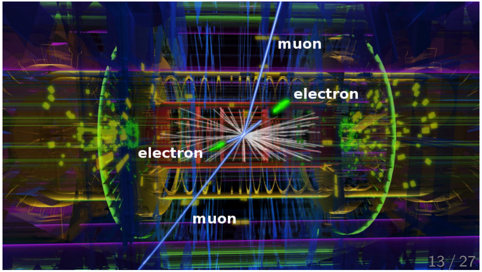
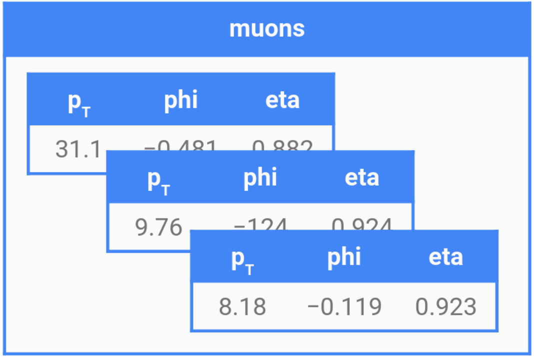






Objects versus flat tables



mu1 p_T	mu1 phi	mu1 eta	mu2 p_T	mu2 phi	mu2 eta
31.1	−0.481	0.882	9.76	−0.124	0.924
5.27	1.246	−0.991	n/a	n/a	n/a
4.72	−0.207	0.953	n/a	n/a	n/a
8.59	−1.754	−0.264	8.714	0.185	0.629

To try different associations between particles, between data from different detectors, in many different combinations. . .

. . . it's easier to write these as *algorithms over objects!*

Modern SQL can *represent* that

```sql
CREATE TYPE PARTICLE FROM
  STRUCT<pt: FLOAT,
         eta: FLOAT,
         phi: FLOAT
         charge: INT>;

CREATE TABLE events (
  eventid   INT,
  electrons ARRAY<PARTICLE>,
  muons     ARRAY<PARTICLE>,
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);
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But to do the Higgs search, you'd have to

1. explode the `electrons` array into a table,
2. explode the `muons` array into a table,
3. do an outer join of the `electrons` table on itself, subject to the constraints that they have the same `eventid` and opposite `charge`,
4. filter for those close to the Z mass,
5. do the same for the `muons` table,
6. do a join of *those* two tables to compute H masses,
7. group-by to make a histogram.

Modern SQL can *represent* that

```
CREATE TYPE PARTICLE FROM
  STRUCT<pt: FLOAT,
         eta: FLOAT,
         phi: FLOAT,
         charge: INT>;

CREATE TABLE events (
  eventid   INT,
  electrons ARRAY<PARTICLE>,
  muons     ARRAY<PARTICLE>,
  UNIQUE KEY eventid
);
```

But to do the Higgs search, you'd have to

1. explode the `electrons` array into a table,
2. explode the `muons` array into a table,
3. do an outer join of the `electrons` table on itself, subject to the constraints that they have the same `eventid` and opposite `charge`,
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This is in no way easier than writing a nested for loop!

We can get the best of both worlds by adding first-class functions to SQL.

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```
dataset.histogram(90, 80, 170, flatten({event =>
    electrons = event.tracks.filter(
        e => 0.9 < e.calorimeterEnergy / e.trackMomentum < 1.1)
    muons = event.tracks.filter(m => m.outerHits > 4)

    def goodz(p1, p2):
        p1.charge * p2.charge < 0 and 60 < mass(p1, p2) < 120

    ez = electrons.distinctpairs.filter(goodz)
    mz =     muons.distinctpairs.filter(goodz)

    table(ez, mz).map((e1, e2), (m1, m2) => mass(e1, e2, m1, m2))
}))
```

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We can apply the new data representation on its own, without introducing a new language.

Iteration over single attribute in many objects

Such as (single-threaded):

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for (i = 0;  i < numEvents;  i++)
    for (j = 0;  j < events[i].numTracks;  j++)
        fill_histogram(events[i].tracks[j].trackMomentum);
```

Four orders of magnitude between how we currently access data
and how we <u>could</u> access data!

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dianahep

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5. `GOTO #1`.

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For the new style of analysis workflow to compete,

- responses must be rapid enough for end-user analysis (seconds per plot)
- the interface must allow for algorithms on nested objects.

Key idea: <u>leave</u> the data in columns!

Leave the data in columns!

We've always *stored* the data as exploded columns (similar to Apache Parquet), but we also shouldn't spend time materializing them as objects.

Suppose that `[[a, b, c, d], [], [e, f]], [], [[g]]` is stored as

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for outer in lists:
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we should instead execute

```
for (i = 0; i < 3; i++)
    for (j = outer[i]; j < outer[i+1]; j++)
        for (k = inner[j]; k < inner[j+1]; k++)
            print(data[k]);
```

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The data representation is Apache Arrow; the code transformation can be automated.

Measurements in a real system

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# objects in Python code
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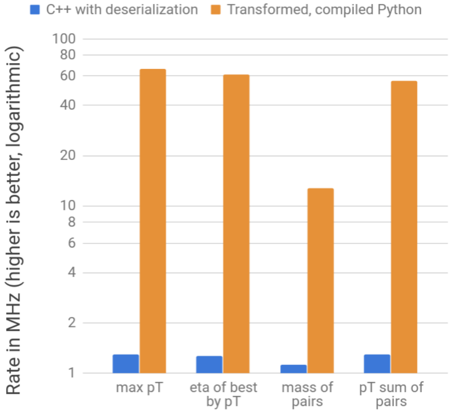

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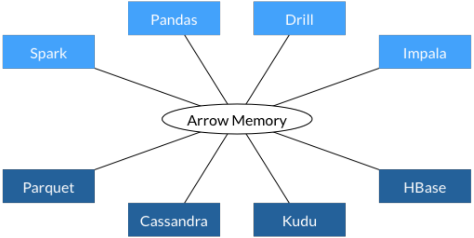
https://github.com/diana-hep/plur

Relationship to Apache Arrow

The way that Primitives, Lists, (sparse) Unions, and Records are represented are a subset of the Apache Arrow specification, so in principle this ought to make Python— with arbitrarily nested loops— fast on Arrow dataframes.



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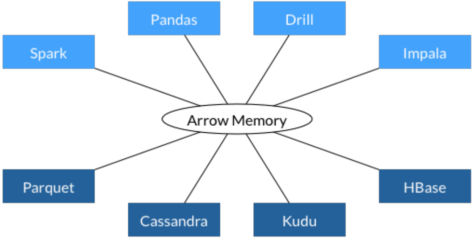

Is anyone else interested in that?

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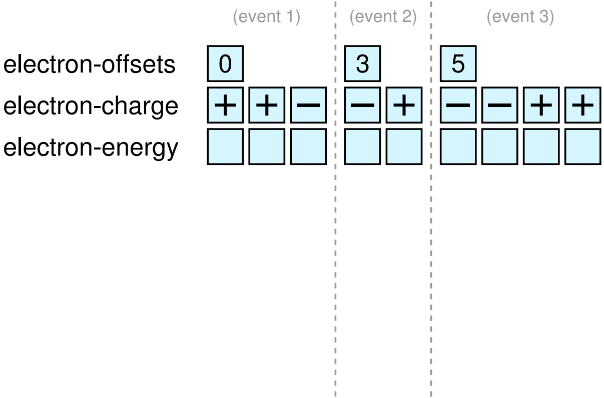
One reason users copy data is to enrich it with derived features:



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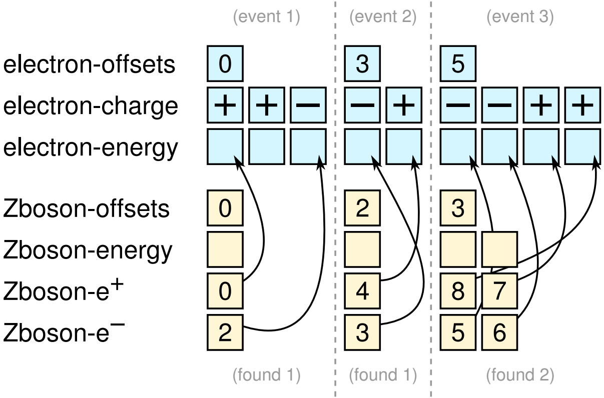

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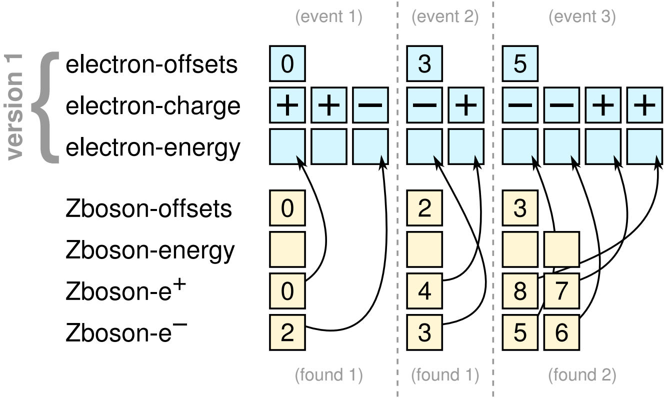

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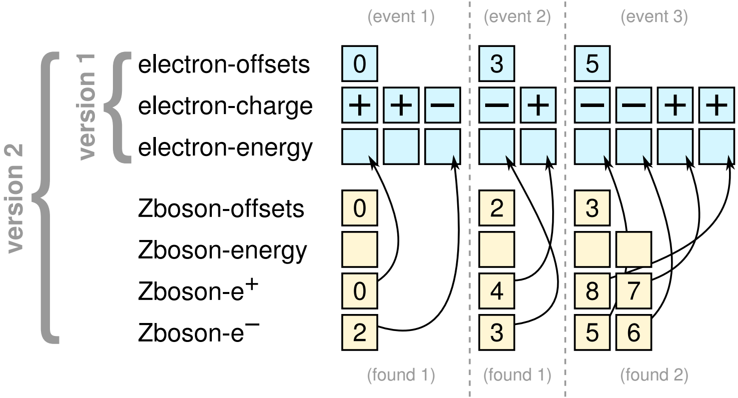

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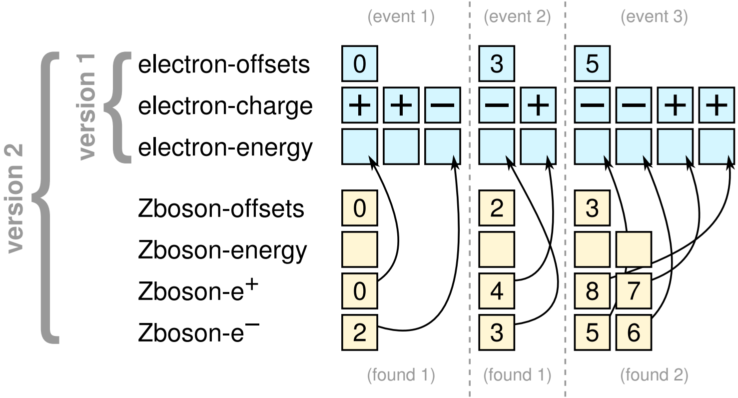

If the data are addressed as individual columns, rather than files, users can change the structure of the data by adding new columns, *without copying.*

I hope it was interesting to learn about data issues in particle physics.

But I'm really interested in hearing back from you: do you have suggestions or do you think these tools could be useful in your work?

If it would help but needs to be more mature, are you interested in collaborating?

`pivarski@fnal.gov`