Jagged, ragged, awkward arrays!

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Institute for Research and Innovation in Software for High Energy Physics (IRIS-HEP)

Computational and data science research to enable discoveries in fundamental physics

IRIS-HEP is a software institute funded by the National Science Foundation. It aims to develop the state-of-the-art software cyberinfrastructure required for the challenges of data intensive scientific research at the High Luminosity Large Hadron Collider (HL-LHC) at CERN, and other planned HEP experiments of the 2020's. These facilities are discovery machines which aim to understand the fundamental building

Upcoming Events:

Sep 10–11, 2019 — *Fermilab*

Blueprint: Accelerated Machine Learning and Inference

Sep 12–13, 2019 — *Fermilab*

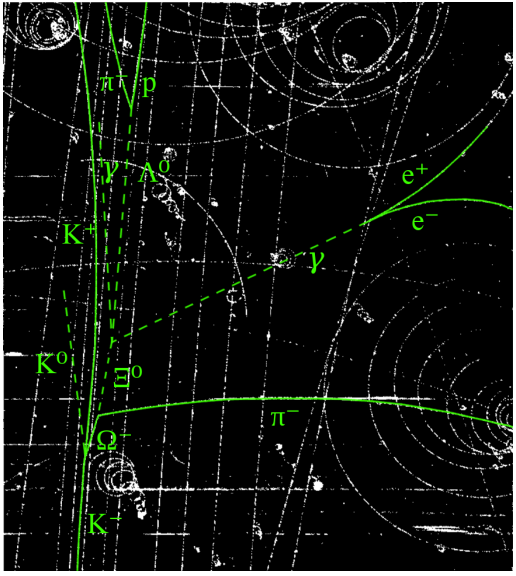
Motivation: particle physics analysis

This is a photo of subatomic particles leaving tracks in a detector.

In 1964, a group at Berkeley scanned 100,000 photos to find this one: the discovery of the Ω baryon.

Do you see it?

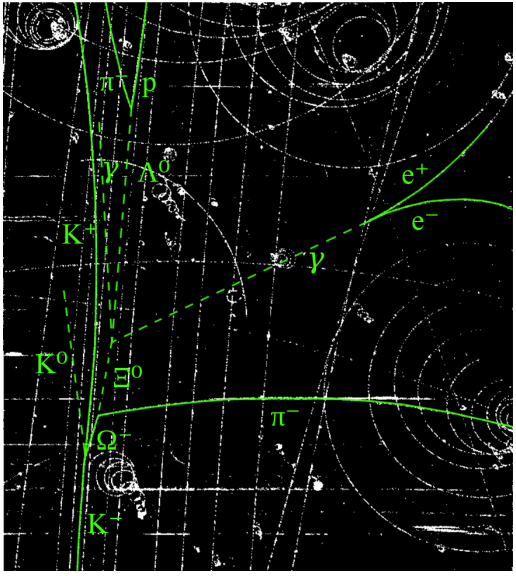
Motivation: particle physics analysis



How about now?

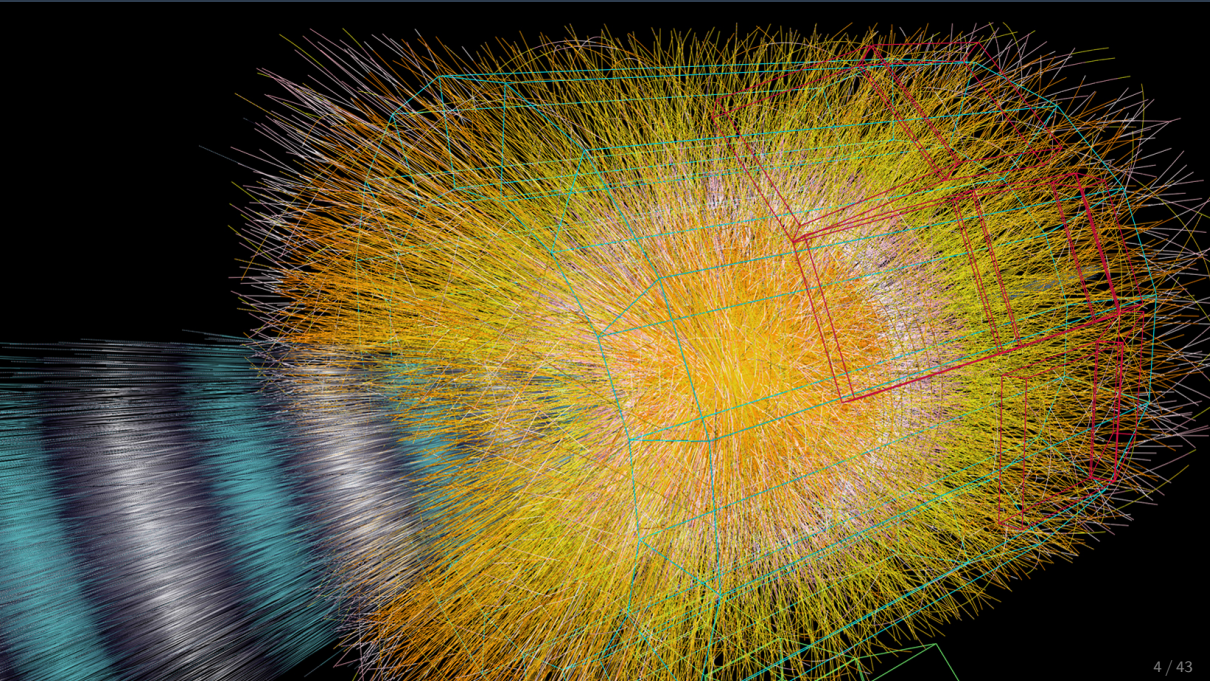
$$K^- + p \to \Omega^- + K^+ + K^0$$
$$\Omega^- \to \Xi^0 + \pi^-$$
$$\Xi^0 \to \Lambda^0 + \pi^0$$
$$\Lambda^0 \to \pi^- + p$$
$$\pi^0 \to \gamma_1 + \gamma_2$$
$$\gamma_1 \to e^+ + e^-$$
$$\gamma_2 \to e^+ + e^-$$

Motivation: particle physics analysis

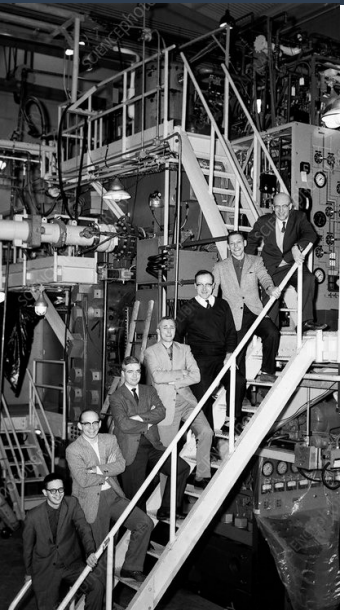


This is what particle physicists do: collide particles, produce new ones and take pictures of the decays.

However, these pictures come to us unlabeled: lots of interactions overlap the "interesting" ones.



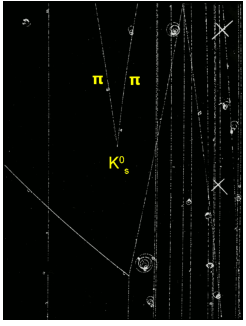
Modern particle physics scales this up

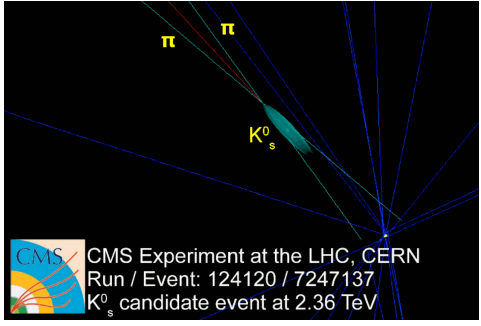


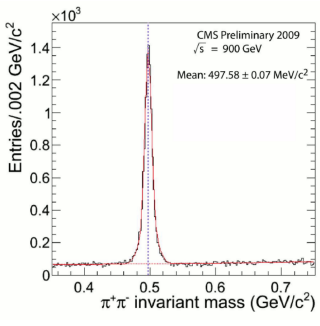
photographs	digitized signals
100,000 events	∼trillion events
manual/semi-automated scans	algorithmic searches and machine learning
30 authors	3,000 authors

Automatically identifying a particle decay

1. Loop over all pairs of particle tracks, tentatively labeling them π^+ and π^-.
2. Calculate $\mathrm{m} = \sqrt{(E_{\pi^+} + E_{\pi^-})^2 - |\vec{p}_{\pi^+} + \vec{p}_{\pi^-}|^2}$ for each pair.
3. The ones with $m \sim \mathrm{mass}(K_s^0) = 0.5\ \mathrm{GeV}/c^2$ are good candidates.

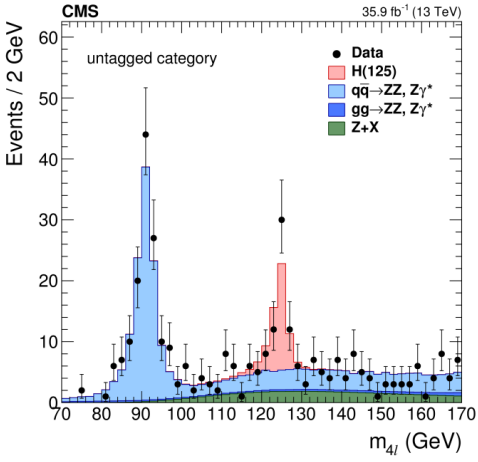


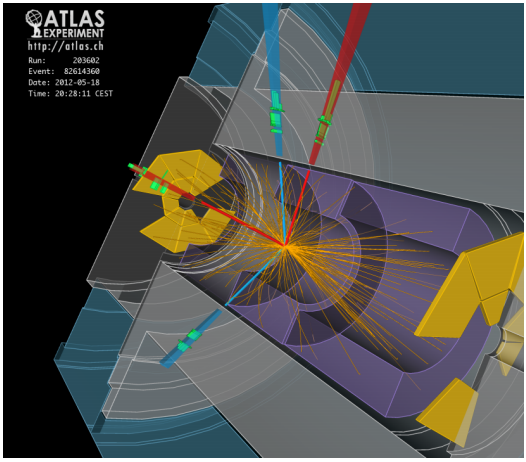




Apply this technique successively down the decay chain

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





From a computational point of view...

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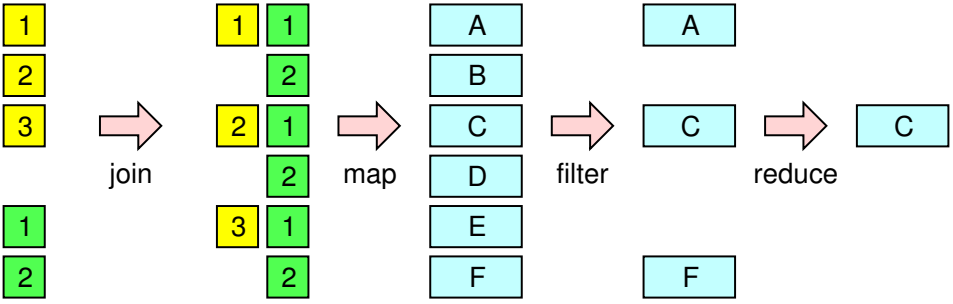
- Decay candidates may be thought of as a **`SELF JOIN`** (single collection) or a **`CROSS JOIN`** (different collections) but always **`ON`** `t1.eventId == t2.eventId`.
- Good candidates are identified by *filtering* (throw away the bad) and/or *reduction* (pick the best of what remains.)

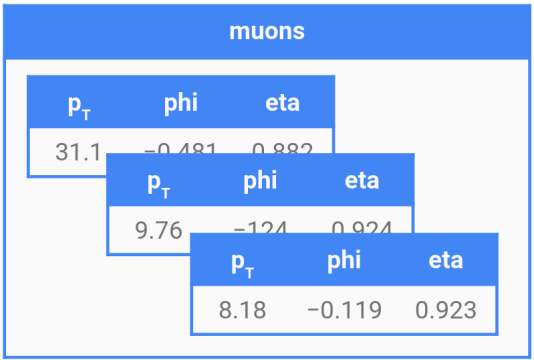
From a computational point of view. . .



. . . independently for each event.

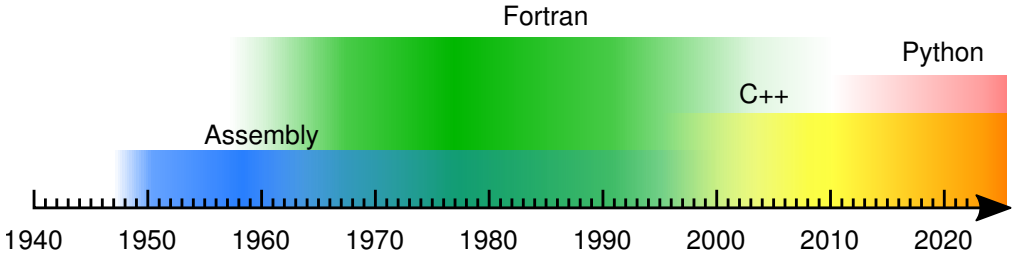
From a computational point of view. . .

- Large number of events, processed in parallel.
- Each event has an *arbitrary number* of record-like structures.
- Not reducible to a flat table without padding and/or loss.



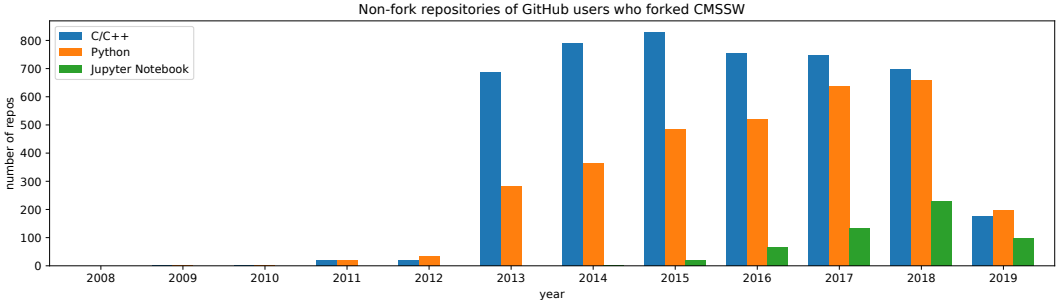
mu1 p_T	mu1 phi	mu1 eta	mu2 p_T	mu2 phi	mu2 eta
31.1	−0.481	0.882	9.76	−0.124	0.924
5.27	1.246	−0.991	n/a	n/a	n/a
4.72	−0.207	0.953	n/a	n/a	n/a
8.59	−1.754	−0.264	8.714	0.185	0.629

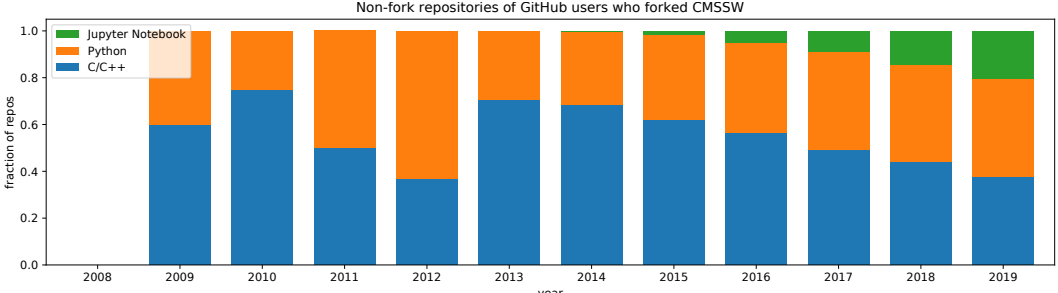
Programming languages used in particle physics



- First programmable computers were used for particle physics simulations.
- Fortran was used to analyze events soon after the language was invented; physicists wrote packages (BOS, HYDRA, ZBOOK) to add data structures.
- Major transition from Fortran to C++ in the late 1990's/early 2000's.
- Very recent adoption of Python (alongside C++).

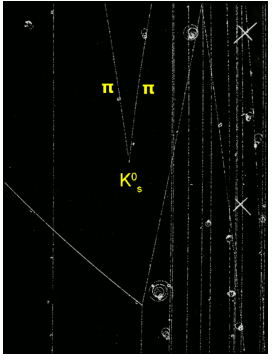
The Python transition is happening *right now*





In our field, “conventional” analysis means C++

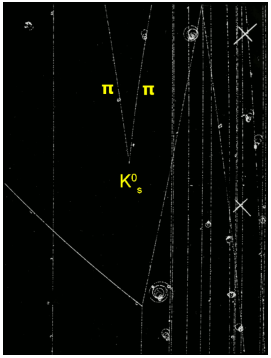
```
std::vector<Kaon*> getKaons(Event event) {
  std::vector<Track*> tracks = event.getTracks();
  std::vector<Kaon*> kaons;
  for (auto t1 = tracks.begin(); t1 != tracks.end(); ++t1) {
    for (auto t2 = t1 + 1; t2 != tracks.end(); ++t2) {
      if (t1->charge != t2->charge) {
        double m = mass(t1, t2);
        if (fabs(m - 0.5) < 0.01) {
          kaons.push_back(new Kaon(t1, t2));
        }
      }
    }
  }
  return kaons;
}
```

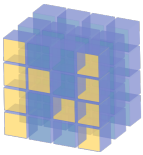


But direct translation to Python would be a performance disaster

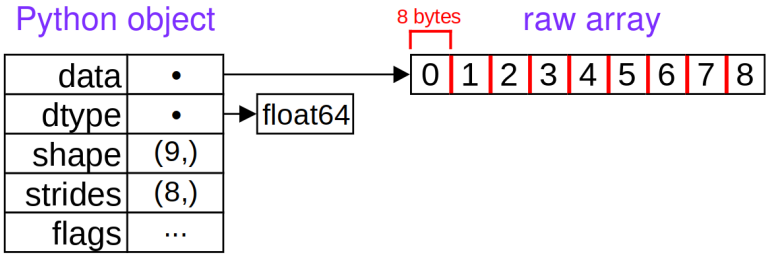
```
def getKaons(event):
  tracks = event.getTracks()
  kaons = []
  for i, t1 in enumerate(tracks):
    for t2 in tracks[i + 1:]:
      if t1.charge != t2.charge:
        m = mass(t1, t2)
        if abs(m - 0.5) < 0.01:
          kaons.append(Kaon(t1, t2))

  return kaons
```





NumPy


Python object
8 bytes
raw array
data
dtype
shape
strides
flags
(9,)
(8,)
···
float64
0
1
2
3
4
5
6
7
8

High-performance processing in Python? Numpy!

Numpy has a suite of operations that each apply to whole arrays (compiled, maybe vectorized loop):

```
def calculate(pt, eta):
    pz = pt * numpy.sinh(eta)

calculate(pt_scalar, eta_scalar)
calculate(pt_array,  eta_array)
```

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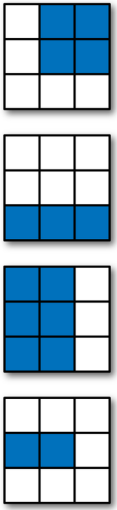
    pz = pt * numpy.sinh(eta)

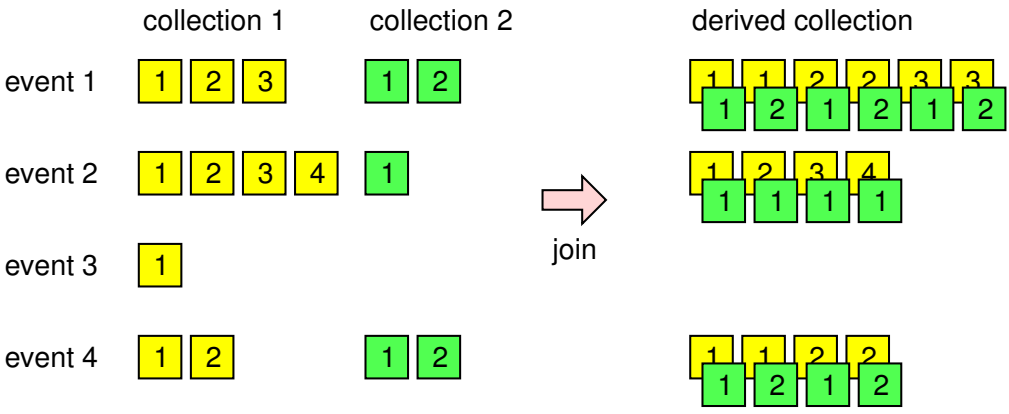
calculate(pt_scalar, eta_scalar)
calculate(pt_array,  eta_array)
```

By manipulating the `shape` and `strides`, slices are $\mathcal{O}(1)$ and zero-copy.



Expression	Shape
`arr[:2, 1:]`	(2, 2)
`arr[2]`	(3,)
`arr[2, :]`	(3,)
`arr[2:, :]`	(1, 3)
`arr[:, :2]`	(3, 2)
`arr[1, :2]`	(2,)
`arr[1:2, :2]`	(1, 2)

But Numpy doesn't have anything for unequal-length lists



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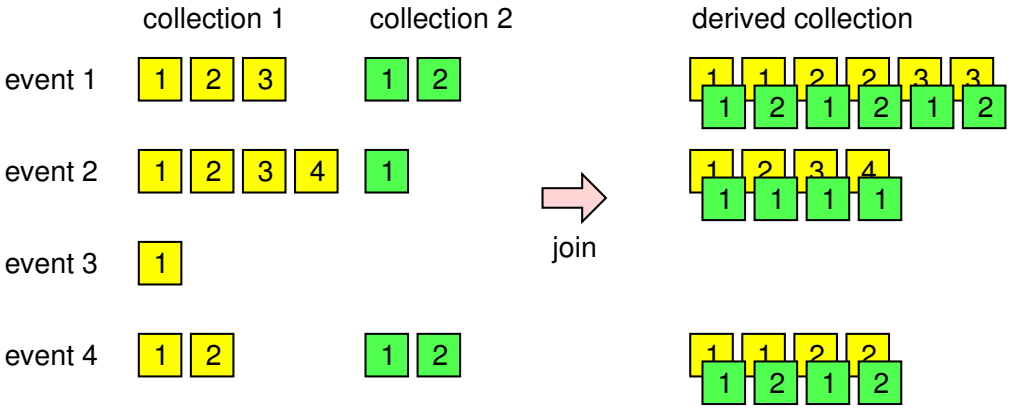

Some libraries* can represent arrays of unequal-length arrays, known as "jagged" or "ragged" arrays.

*Apache Arrow, XND, TensorFlow, Zarr (genetics), and ROOT (particle physics)

Jagged/nested data can be contiguous by field ("columnar")

```
[[Muon(31.1, -0.481, 0.882),
      Muon(9.76, -0.124, 0.924),
      Muon(8.18, -0.119, 0.923)],
 [Muon(5.27, 1.246, -0.991)],
 [Muon(4.72, -0.207, 0.953)],
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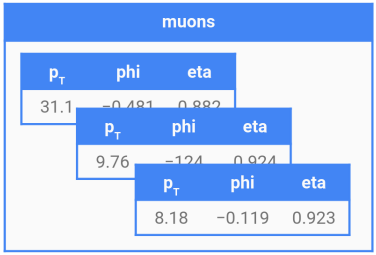
      Muon(8.714, 0.185, 0.629)]
]
```



The trick: represent structure with counts or offsets or starts/stops or parents.

counts	3,			1,	1,	2	
p_T	31.1,	9.76,	8.18,	5.27,	4.72,	8.59,	8.714
phi	-0.481,	-0.123,	-0.119,	1.246,	-0.207,	-1.754,	0.185
eta	0.882,	0.924,	0.923,	-0.991,	0.953,	-0.264,	0.629

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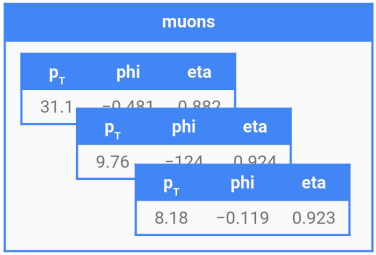

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offsets `0, 3, 4, 5, 7`

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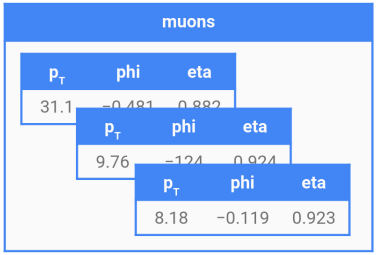

The trick: represent structure with counts or offsets or starts/stops or parents.

starts	0,			3,	4,	5	
stops	3,			4,	5,	7	
p_T	31.1,	9.76,	8.18,	5.27,	4.72,	8.59,	8.714
phi	-0.481,	-0.123,	-0.119,	1.246,	-0.207,	-1.754,	0.185
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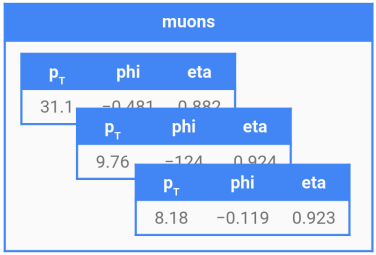

The trick: represent structure with counts or offsets or starts/stops or parents.

parents	0,	0,	0,	1,	2,	3,	3
p_T	31.1,	9.76,	8.18,	5.27,	4.72,	8.59,	8.714
phi	-0.481,	-0.123,	-0.119,	1.246,	-0.207,	-1.754,	0.185
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But we can go beyond *representing* columnar jagged arrays and *manipulate* them in this form

Example of a jagged operation: manipulating jagged arrays

"Remove the first muon from each event."

```
[[Muon(31.1, -0.481, 0.882), Muon(9.76, -0.124, 0.924), Muon(8.18, -0.119, 0.923)],
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Example of a jagged operation: manipulating jagged arrays

"Remove the first muon from each event." ⟶ **rewrite all inner lists.**

```
[[                                  Muon(9.76, -0.124, 0.924), Muon(8.18, -0.119, 0.923)],
 [                                ],
 [                                ],
 [                                   Muon(8.714, 0.185, 0.629)],
 ...
```

"Remove the first muon from each event." ⟶ **increase all starts by 1.**

starts	1,			4,	5,	6	
stops	3,			4,	5,	7	
p_T	31.1,	9.76,	8.18,	5.27,	4.72,	8.59,	8.714
phi	-0.481,	-0.123,	-0.119,	1.246,	-0.207,	-1.754,	0.185
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 [                              ],
 [                              ],
 [                                 Muon(8.714, 0.185, 0.629)],
 ...
```

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starts	1,			4,	5,	6	
stops	3,			4,	5,	7	
p_T	31.1,	9.76,	8.18,	5.27,	4.72,	8.59,	8.714
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eta	0.882,	0.924,	0.923,	-0.991,	0.953,	-0.264,	0.629

We didn't need to touch any contents (i.e. read from disk/decompress them).

Can be very useful if only ∼10% of the fields are of interest!

Properties of columnar data

- Columnar data structures are *fully composable:* a jagged array's content can be another jagged array, some fields of a record structure can be jagged, others not.

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Properties of columnar data

- Columnar data structures are *fully composable:* a jagged array's content can be another jagged array, some fields of a record structure can be jagged, others not.
- Other non-trivial data types may be encoded this way: heterogeneous lists, nullable types, pointers...
- Most operations (beyond just slicing) can modify the structure (`counts`/`offsets`/`starts`,`stops`/`parents`) without touching the nested content.

Awkward Array: columnar data with a Numpy-like interface

```
>>> import awkward
>>> array = awkward.fromiter(
...     [[1.1, 2.2, None, 3.3, None],
...      [4.4, [5.5]],
...      [{"x": 6, "y": {"z": 7}}, None, {"x": 8, "y": {"z": 9}}]])
```

Awkward Array

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>>> print(array)              # an array of columnar data
[[1.1 2.2 None 3.3 None] [4.4 [5.5]] [<Row 0> None <Row 1>]]
```

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>>> print(array)              # an array of columnar data
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>>> print(array[:, -2:])      # get whole outer list, last two of inner
[[3.3 None] [4.4 [5.5]] [None <Row 1>]]
```

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>>> print(array[:, -2:])      # get whole outer list, last two of inner
[[3.3 None] [4.4 [5.5]] [None <Row 1>]]

>>> (array + 100).tolist()    # element-wise function applied to arrays
                              # i.e. a Numpy ufunc (all ufuncs work)
[[101.1, 102.2, None, 103.3, None],
 [104.4, [105.5]],
 [{'x': 106, 'y': {'z': 107}}, None, {'x': 108, 'y': {'z': 109}}]]
```

Internally, it's a bunch or Numpy arrays *interpreted* as nested data

```
>>> array.layout
 layout
[            ()] JaggedArray(starts=layout[0], stops=layout[1], content=layout[2])
[             0]   ndarray(shape=3, dtype=dtype('int64'))
[             1]   ndarray(shape=3, dtype=dtype('int64'))
[             2]   IndexedMaskedArray(mask=layout[2, 0], content=layout[2, 1], maskedwhen=-1)
[          2, 0]     ndarray(shape=10, dtype=dtype('int64'))
[          2, 1]     UnionArray(tags=layout[2, 1, 0], index=layout[2, 1, 1],
                                contents=[layout[2, 1, 2], layout[2, 1, 3], layout[2, 1, 4]])
[       2, 1, 0]       ndarray(shape=7, dtype=dtype('uint8'))
[       2, 1, 1]       ndarray(shape=7, dtype=dtype('int64'))
[       2, 1, 2]       ndarray(shape=4, dtype=dtype('float64'))
[       2, 1, 3]       JaggedArray(starts=layout[2, 1, 3, 0], stops=layout[2, 1, 3, 1],
                                   content=layout[2, 1, 3, 2])
[    2, 1, 3, 0]         ndarray(shape=1, dtype=dtype('int64'))
[    2, 1, 3, 1]         ndarray(shape=1, dtype=dtype('int64'))
[    2, 1, 3, 2]         ndarray(shape=1, dtype=dtype('float64'))
[       2, 1, 4]       Table(x=layout[2, 1, 4, 0], y=layout[2, 1, 4, 1])
[    2, 1, 4, 0]         ndarray(shape=2, dtype=dtype('int64'))
[    2, 1, 4, 1]         Table(z=layout[2, 1, 4, 1, 0])
[2, 1, 4, 1, 0]           ndarray(shape=2, dtype=dtype('int64'))
```

Array indexing is a function; arrays have functional type

```
>>> # array type formatted to look like a curried function's type
>>> print(array.type)
[0, 3) -> [0, inf) -> ?((float64                |
                        [0, inf) -> float64 |
                        'x' -> int64
                        'y' -> 'z' -> int64 ))
```

How to read the above:

- First square bracket in `array[x]` takes a non-negative integer less than 3.
- Second takes a non-negative integer (unknown upper limit because it's jagged).
- What that returns is nullable (might be `None`).
- And it could be a `float`, a jagged array of floats, or a record taking `'x'` or `'y'`.
- `'x'` returns an integer; `'y'` returns another record taking `'z'` to integers.

Aside: arrays are functions; integer indexing is composition

Consider any two $\mathbb{Z}^{\geq 0} \to \mathbb{Z}^{\geq 0}$ functions,

```
def f(x):
    return x**2 - 5*x + 10
def g(y):
    return max(0, 2*y - 10) + 3
```

sample them as arrays, including the composition $f \circ g$,

```
F   = numpy.array([f(i) for i in range(10)])      # F is f at 10 elements
G   = numpy.array([g(i) for i in range(100)])     # G is g at 100 elements (to cover max(F))
GoF = numpy.array([g(f(i)) for i in range(10)])   # GoF is gof at 10 elements
```

and indexing `G` by `F` is the same as the sampled composition `GoF`:

```
print("G\u2218F =", G[F])    # integer indexing (numpy.take)
print("g\u2218f =", GoF)     # array of the composed functions returns the same thing
```

```
GoF = [13  5  3  3  5 13 25 41 61 85]
gof = [13  5  3  3  5 13 25 41 61 85]
```

The associativity of function composition $(f(g(x)) == (f \circ g)(x))$ lets us delay operations on nested arrays. (I'd love to find any literature references on this, if anyone knows where to look...)

Getting back to the main point: let's look at real data

NASA exoplanets dataset: stars may have more than one planet

```
>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))

>>> stars
<Table [<Row 0> <Row 1> <Row 2> ... <Row 2933> <Row 2934>]>
```

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```
>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))

>>> stars[8:10].tolist()
[{'name': '24 Sex', 'ra': 155.86821, 'dec': -0.902244, 'dist': 72.21,
  'mass': 1.54, 'radius': 4.9, 'planets': [
      {'name': 'b', 'orbit': 1.333, 'eccen': 0.09, 'period': 452.8,
       'mass': 1.99, 'radius': None},
      {'name': 'c', 'orbit': 2.08, 'eccen': 0.29, 'period': 883.0,
       'mass': 0.86, 'radius': None}]},
 {'name': '2MASS J01225093-2439505', 'ra': 20.712243, 'dec': -24.664049,
  'dist': 36.0, 'mass': 0.4, 'radius': None, 'planets': [
      {'name': 'b', 'orbit': 52.0, 'eccen': None, 'period': None,
       'mass': 24.5, 'radius': None}]}
]
```

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```
>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))
>>> print(stars.type)
[0, 2935) -> 'name'    -> <class 'str'>
             'ra'      -> float64
             'dec'     -> float64
             'dist'    -> ?(float64)
             'mass'    -> ?(float64)
             'radius'  -> ?(float64)
             'planets' -> [0, inf) -> 'name'   -> <class 'str'>
                                      'orbit'  -> ?(float64)
                                      'eccen'  -> ?(float64)
                                      'period' -> ?(float64)
                                      'mass'   -> ?(float64)
                                      'radius' -> ?(float64)
```

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>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))

>>> stars["mass"]
<MaskedArray [2.7 2.78 2.2 ... 2.3 1.3 2.2]>

>>> stars["planets"]["mass"]
<JaggedArray [[19.4] [14.74] [4.8] ... [20.6] [0.6876 1.981 4.132] [2.8]]>
```

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>>> import urllib.request
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>>> stars["planets"]["mass"]
<JaggedArray [[19.4] [14.74] [4.8] ... [20.6] [0.6876 1.981 4.132] [2.8]]>

>>> print(stars["mass"].type)              # just selecting a column
[0, 2935) -> ?(float64)
>>> print(stars["planets"]["mass"].type)   # projecting through a column
[0, 2935) -> [0, inf) -> ?(float64)
```

This "projection" selects a column that slices through rows, but in a "jagged" way.

NASA exoplanets dataset: stars may have more than one planet

```
>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))

>>> stars[8]["planets"][1]["mass"]          # projecting through columns:
0.86                                        # int and str indexes commute!
>>> stars[8]["planets"]["mass"][1]
0.86
>>> stars["planets"][8][1]["mass"]
0.86
>>> stars["planets"][8]["mass"][1]
0.86
>>> stars["planets"]["mass"][8][1]
0.86
>>> stars["planets"]["mass"][8, 1]
0.86
```

NASA exoplanets dataset: stars may have more than one planet

```
>>> import urllib.request
>>> stars = awkward.fromiter(
...     json.load(
...         urllib.request.urlopen(
...             "http://scikit-hep.org/uproot/examples/exoplanets.json")))
>>> awkward.topandas(stars, flatten=True)  # put jaggedness in the index
```

		name	ra	dec	dist	mass	radius	planets					
								name	orbit	eccen	period	mass	radius
0	0	11 Com	185.179276	17.792868	93.37	2.70	19.00	b	1.290000	0.2310	326.03000	19.4000	NaN
1	0	11 UMi	229.274536	71.823898	125.72	2.78	29.79	b	1.530000	0.0800	516.21997	14.7400	NaN
2	0	14 And	352.822571	39.236198	75.59	2.20	11.00	b	0.830000	0.0000	185.84000	4.8000	NaN
3	0	14 Her	242.601303	43.817646	17.94	0.90	0.93	b	2.930000	0.3700	1773.40002	4.6600	NaN
4	0	16 Cyg B	295.466553	50.517525	21.41	1.08	1.13	b	1.660000	0.6800	798.50000	1.7800	NaN
5	0	18 Del	314.608063	10.839286	76.38	2.30	8.50	b	2.600000	0.0800	993.30000	10.3000	NaN
6	0	1RXS J16	242.376268	-21.083036	145.00	0.85	0.00	b	330.000000	NaN	NaN	8.0000	NaN
7	0	24 Boo	217.157547	49.844852	96.25	0.99	10.64	b	0.190000	0.0420	30.35060	0.9100	NaN
8	0	24 Sex	155.868210	-0.902244	72.21	1.54	4.90	b	1.333000	0.0900	452.80000	1.9900	NaN
	1	24 Sex	155.868210	-0.902244	72.21	1.54	4.90	c	2.080000	0.2900	883.00000	0.8600	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2932	0	tau Gem	107.784882	30.245163	112.64	2.30	26.80	b	1.170000	0.0310	305.50000	20.6000	NaN
2933	0	ups And	24.199345	41.405460	13.41	1.30	1.56	b	0.059222	0.0215	4.61703	0.6876	NaN
	1	ups And	24.199345	41.405460	13.41	1.30	1.56	c	0.827774	0.2596	241.25800	1.9810	NaN
	2	ups And	24.199345	41.405460	13.41	1.30	1.56	d	2.513290	0.2987	1276.46000	4.1320	NaN
2934	0	xi Aql	298.562012	8.461452	56.27	2.20	12.00	b	0.680000	0.0000	136.75000	2.8000	NaN

[3933 rows x 12 columns]

Relationship to Pandas

Jaggedness → MultiIndex rows

```
>>> awkward.topandas(
...   awkward.fromiter(
...     [[[1.1, 2.2], [], [3.3]],
...      [],
...      [[4.4], [5.5, 6.6]],
...      [[7.7]],
...      [[8.8]]]
...   ), flatten=True)
```

0	0	0	1.1
		1	2.2
	2	0	3.3
2	0	0	4.4
	1	0	5.5
		1	6.6
3	0	0	7.7
4	0	0	8.8

Nested records → MultiIndex columns

```
>>> awkward.topandas(
...   awkward.fromiter([
...     {"I":
...        {"a": _, "b": {"i": _}},
...      "II":
...        {"x": {"y": {"z": _}}}}
...     for _ in range(0, 50, 10)]
...   ), flatten=True)
```

	I		II
	a	b	x
		i	y
			z
0	0	0	0
1	10	10	10
2	20	20	20
3	30	30	30
4	40	40	40

Limitation of Pandas's MultiIndex

Since jaggedness is represented by the DataFrame's index, a single DataFrame can't contain two differently jagged collections.

```
>>> array = awkward.fromiter([{"a": [1, 2, 3], "b": [1.1, 2.2]},
                              {"a":         [], "b":       [3.3]},
                              {"a":    [4, 5], "b": [4.4, 5.5]}])

                                                          #       index values
>>> awkward.topandas(array["a"], flatten=True)            # -->    0  0      1
                                                          #            1      2
                                                          #            2      3
                                                          #         2  0      4
                                                          #            1      5

>>> awkward.topandas(array["b"], flatten=True)            # -->    0  0    1.1
                                                          #            1    2.2
                                                          #         1  0    3.3
                                                          #         2  0    4.4
                                                          #            1    5.5

>>> awkward.topandas(array, flatten=True)
ValueError: this array has more than one jagged array structure
```

Relationship to other packages

- Apache Arrow: columnar representation of nested data, memory management, shared memory, streaming, and I/O.
- XND: columnar representation of nested, cross-referenced data, generalizing Numpy ufuncs, math kernels, and GPUs.
- TensorFlow: maching learning, but it includes a `RaggedTensor` type.
- Zarr: array I/O and delivery, including a `VLenArray` (ragged array) because it's useful for genetics.
- ROOT: particle physics data analysis; I/O is columnar for better compression, but in-memory data are C++ class instances.

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Awkward Array's focus is *not* I/O or numerical math, it's the structure manipulation that physicists regularly need to analyze particle decays.

Examples of Awkward Array's focus:

how it solves various physics problems

Problem 1: mass of $A \to X + Y$ and $B \to X + X$ candidates

Traditional for loop:

```
for event in dataset:
    event.A = []
    for x in event.X:
        for y in event.Y:
            event.A.append(mass(x, y))
    event.B = []
    for i in range(len(event.X)):
        for j in range(i + 1, len(event.X)):
            event.B.append(mass(event.X[i], event.X[j]))
```

Array manipulation:

```
dataset["A"] = dataset["X"].cross(dataset["Y"])       # cross-join
dataset["B"] = dataset["X"].choose(2)                 # self-join
```

How are `cross` and `choose` implemented? Numpy tricks!

```
def cross(self, other):
    offsets = counts2offsets(self.counts * other.counts)
    parents = offsets2parents(offsets)
    indexes = numpy.arange(offsets[-1], dtype=int)

    ocp = other.counts[parents]              # no for loops
    iop = indexes - offsets[parents]         # fully vectorizable
    iop_ocp = iop // ocp

    left = self.content[self.starts[parents] + iop_ocp]
    right = other.content[other.starts[parents] + iop - ocp * iop_ocp]

    return JaggedArray.fromoffsets(offsets, Table(left, right))

def choose(self, n):
    # vectorized as well
    # (in fact, it's n <= 5 because there's no solution to the quintic!)
    ...
```

Problem 2: filtering $A \to X + Y$ candidates

Traditional for loop:

```
dataset.byevent = []
for event in dataset:
    event.bycandidate = []
    for a in event.A:
        if quality(a) > cut:
            event.bycandidate.append(a)
    biggest = None
    for a in event.A:
        if biggest is None or quality(a) > quality(biggest):
            biggest = a
    if biggest is not None and biggest > cut:
        dataset.byevent.append(biggest)
```

Array manipulation:

```
dataset["bycandidate"] = events["A"][events["A"] > cut]
dataset["byevent"]     = events["A"][events["A"].max() > cut]
```

Masking by an array (i.e. `numpy.compress`) → jagged masking

```
>>> x
<JaggedArray [[ 1.1,   2.2,  3.3], [  4.4,   5.5], [ 6.6,  7.7,  8.8]]>

>>> mask
array(       [        True,             False,             True      ])

>>> jaggedmask
<JaggedArray [[True, False, True], [False, False], [True, True, True]]>
```

Flat array of booleans does what Numpy does; jagged booleans selects within each inner list.

```
>>> x[mask]
<JaggedArray [[1.1 2.2 3.3] [6.6 7.7 8.8]]>

>>> x[jaggedmask]
<JaggedArray [[1.1 3.3] [] [6.6 7.7 8.8]]>
```

Problem 3: Select the best $A \to X + Y$ candidate

Traditional for loop:

```
for event in dataset:
    event.best = []                  # using an empty collection as None
    for a in event.A:
        if len(event.best) == 0 or quality(a) > quality(event.best[0]):
            event.best = [a]
```

Array manipulation:

```
argbest = quality(events["A"]).argmax()    # jagged array of integers

dataset["best"] = events["A"][argbest]
```

Problem 3: Select the best $A \to X + Y$ candidate

Traditional for loop:

```
for event in dataset:
    event.best = []                  # using an empty collection as None
    for a in event.A:
        if len(event.best) == 0 or quality(a) > quality(event.best[0]):
            event.best = [a]
```

Array manipulation:

```
argbest = quality(events["A"]).argmax()    # jagged array of integers

dataset["best"] = events["A"][argbest]


# remove empty lists and concatenate singletons by dropping offsets
only_the_best = dataset["best"].flatten()
```

Indexing by an array (i.e. `numpy.take`) → jagged indexing

```
>>> x
<JaggedArray [[ 1.1, 2.2, 3.3, 4.4], [5.5, 6.6], [7.7, 8.8, 9.9]]>

>>> index
array([-1, 0, 0])

>>> jaggedindex
<JaggedArray [[0, 0, -1], [0, 0, -1], [0, 0, -1]]>
```

Flat array of integers does what Numpy does; jagged indexes takes from each inner list.

```
>>> x[index]
<JaggedArray [[7.7 8.8 9.9] [1.1 2.2 3.3 4.4] [1.1 2.2 3.3 4.4]]>

>>> x[jaggedindex]
<JaggedArray [[1.1 1.1 4.4] [5.5 5.5 6.6] [7.7 7.7 9.9]]>
```

Maybe a domain-specific language is in order. . .

Problem statement (from a physicist):

"For events with at least three leptons (electrons or muons) and a same-flavor opposite-sign lepton pair, find the same-flavor opposite-sign lepton pair with the mass closest to 91.2 GeV and make a histogram of the pT of the leading other lepton."

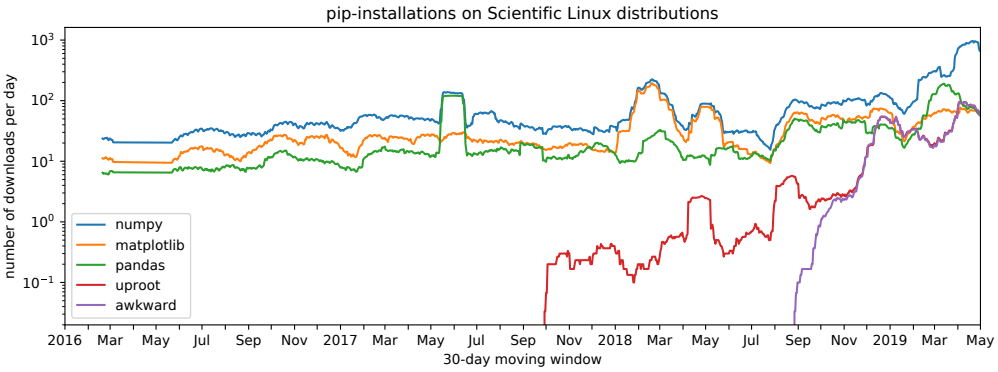
```
leptons = electrons union muons

cut count(leptons) >= 3 named "three_leptons" {
    Z = electrons as (lep1, lep2) union muons as (lep1, lep2)
            where lep1.charge != lep2.charge
            min by abs(mass(lep1, lep2) - 91.2)

    third = leptons except [Z.lep1, Z.lep2] max by pt

    hist third.pt by regular(100, 0, 250) named "third_pt"
                          titled "Leading other lepton pT"
}
```

Awkward Array project status



- Made a dependency of uproot (I/O library for particle physics) last September.
  ROOT file → Numpy or Awkward arrays, depending on structure (most are jagged).
- Several user-contributed methods, a dozen more inspired by user needs.

Current suite of nestable array types

`JaggedArray`	array containing unequal-length subarrays
`Table`	struct of arrays, presented as an array of structs
`ObjectArray`	creates Python objects on demand, such as `TLorentzVector`
`Methods`	vectorized methods, like `muons.delta_phi(muons.jet)`
`StringArray`	strings (jagged array of characters)
`IndexedArray`	"pointers" into another array (via integer indexes)
`SparseArray`	inverse of `IndexedArray`: zero everywhere except specified indexes
`MaskedArray`	marks elements as `None` with a byte array
`BitMaskedArray`	marks elements as `None` with a bit array
`IndexedMaskedArray`	indexes and masks in one array to avoid placeholders in the data array
`UnionArray`	contains multiple (enumerated) types
`ChunkedArray`	view discontiguous memory buffers as one array
`AppendableArray`	efficiently grow an array in chunks
`VirtualArray`	load data on demand

used to read ROOT files, used to read/write Arrow, used for both

lazy arrays are `ChunkedArrays` containing `VirtualArrays`

Rewrite/redesign in C and C++

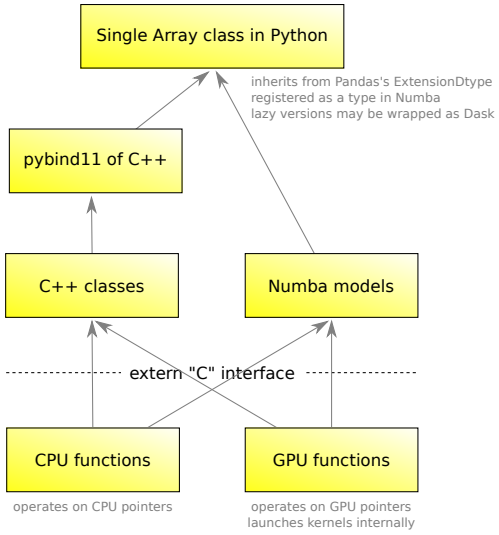
- We want versions in C++ (for interfaces) and Numba (to allow procedural programming), but keeping three versions in sync is beyond our resources.

Rewrite/redesign in C and C++

- We want versions in C++ (for interfaces) and Numba (to allow procedural programming), but keeping three versions in sync is beyond our resources.
- We also want to fix interface design flaws:
  - `A.cross(B)` versus `awkward.cross(A, B)`
  - should hide `JaggedArray`/`Table`/`MaskedArray`/etc. structure in a single `Array` class.

Rewrite/redesign in C and C++

- We want versions in C++ (for interfaces) and Numba (to allow procedural programming), but keeping three versions in sync is beyond our resources.
- We also want to fix interface design flaws:
  - `A.cross(B)` versus `awkward.cross(A, B)`
  - should hide `JaggedArray`/`Table`/`MaskedArray`/etc. structure in a single `Array` class.
- So we're rewriting it in layers $\longrightarrow \longrightarrow \longrightarrow$



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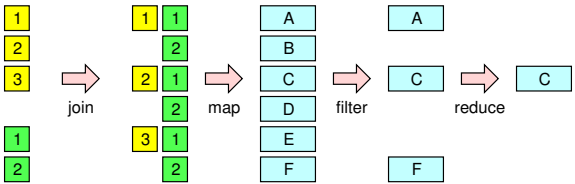

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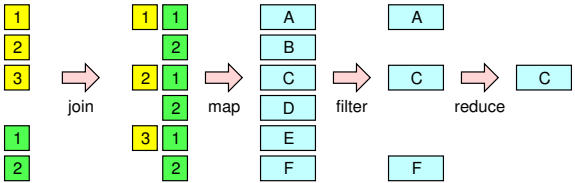

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`awkward.fromiter` could be used with `simdjson` to convert huge JSON datasets into Awkward Arrays. Do you have big JSON datasets to analyze?

Thanks!

Many people have been enormously helpful in this work:

- Jaydeep Nandi (GSoC): clever algorithms for `cross`, `pairs`, and jagged reduce
- Charles Escott (GSoC): investigation into pybind11 and C++
- The Coffea Team (Fermilab): extensive feedback from use in CMS physics
- Nick Smith (Fermilab): clever algorithms for `choose`, `argmax`, `argsort`
- Jonas Rembser (LLR-École Polytechnique): clever algorithms for `concatenate`
- Mason Proffitt (U. Washington): stress tests, bug reports, and fixes
- Henry Schreiner (Princeton): tests and feedback on HDF5 persistence
- Joosep Pata (Caltech): exploring Awkward Array on GPUs
- Alistair Miles and Gavin Band (Oxford): conversations about Zarr and genetics
- The XND Team: conversations about scope and direction of XND
- Wes McKinney and Julien Le Dem: conversations about Apache Arrow
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