Managing data with columnar granularity

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November 16, 2017

Nature of this talk

This talk isn't about how we manage data in HEP, but how we *might.*

- Therefore, it isn't a "how-to" talk but a "what-if" talk.
- If you have experience in this, I want to hear from you!

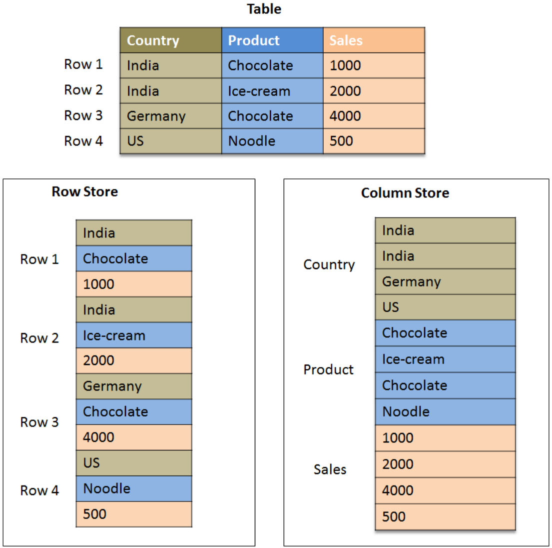
Columnar data

Serializing data in columns is an old idea in HEP:

- 1989: Column-Wise-N-tuples (CWN) in PAW
- 1996: “split” (columnar) C++ objects in ROOT

. . .

- 2002: MonetDB
- 2005: C-Store (Vertica)
- 2010: Google Dremel paper
- 2013: Apache Parquet
- 2016: Apache Arrow



Table

	Country	Product	Sales
Row 1	India	Chocolate	1000
Row 2	India	Ice-cream	2000
Row 3	Germany	Chocolate	4000
Row 4	US	Noodle	500

Row Store

Row 1	India Chocolate 1000
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Column Store

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Hierarchically nested columnar data

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  - Dremel/Parquet: "repetition level"; packed small integers, but no $\mathcal{O}(1)$ lookup.

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Whether it's ROOT or Parquet, the file structure glues a set of columns together to be downloaded, replicated, versioned, or migrated to colder storage *as a unit.*

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- “Heavy flavor study” needs jets, electrons, and muons with isolation and B-tagging variables.
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Columnar data lets us read relevant attributes from disk one at a time (or with XRootD, over the network), but data management systems are unaware of how to open up a ROOT file and operate on individual columns.

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What could we do if data management were column-aware?

Case 1: serve the most desirable attributes from RAM or SSD and less desirable attributes of the same dataset from disk or tape.

Currently, we make 2 or 3 levels of “slimmed” copies (AOD/MiniAOD/NanoAOD) to serve with different latencies. Three sizes does not fit all, so individual analysis groups make their own subsets (and have to find their own storage).

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Case 2: define datasets with overlapping sets of physical columns.

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Case 4: speed up filtering with database-style indexing.

Case 1: lower latency for popular columns

Same object-array mapping example:

logical data	`[[`	`(a,1),`	`(b,2),`	`(c,3),`	`(d,4)],`	`[],`	`[(e,5),`	`(f,6)]],`	`[],`	`[[(g,7)]`	`]`
outer stops	`[`							`3,`	`3,`		`4]`
inner stops	`[`				`4,`	`4,`		`6,`		`7`	`]`
1st attribute	`[`	`a,`	`b,`	`c,`	`d,`		`e,`	`f,`		`g`	`]`
2nd attribute	`[`	`1,`	`2,`	`3,`	`4,`		`5,`	`6,`		`7`	`]`

If the 2nd attribute is more popular than the 1st attribute, raise the 2nd attribute into warmer cache (on the server).

To the degree that analysts' interests overlap (e.g. the all-popular kinematic variables), one copy in hot cache may be shared by all. This is impossible for private skims.

Case 2: overlapping dataset definitions

logical data	`[[(a,1), (b,2), (c,3), (d,4)], [], [(e,5), (f,6)]], [], [[(g,7)]]`
outer stops	`[ 3, 3, 4]`
inner stops	`[ 4, 4, 6, 7 ]`
1st attribute	`[ a, b, c, d, e, f, g ]`
2nd attribute (v1)	`[ 1, 2, 3, 4, 5, 6, 7 ]`
2nd attribute (v2)	`[ 9, 9, 9, 9, 9, 9, 9 ]`

Dataset version 1 schema:

```
List(stops = "outer stops",
  List(stops = "inner stops",
    Pair(first = "1st attribute",
         second = "2nd attribute (v1)"
    )))
```

Dataset version 2 schema:

```
List(stops = "outer stops",
  List(stops = "inner stops",
    Pair(first = "1st attribute",
         second = "2nd attribute (v2)"
    )))
```

(Not all arrays can be combined into datasets; validity determined by provenance.)

Case 3: zero-copy views of selections

logical data	[[(a,1), (b,2), (c,3), (d,4)], [], [(e,5), (f,6)]], [], [[(g,7)]]
outer offsets	[0, 3, 3, 4]
inner offsets	[0, 4, 4, 6, 7]
1^{st} attribute	[a, b, c, d, e, f, g]
2^{nd} attribute	[1, 2, 3, 4, 5, 6, 7]
inner starts (v2)	[0, 4]
inner stops (v2)	[1, 5]
outer starts (v2)	[0, 2]
outer stops (v2)	[2, 2]
logical data (v2)	[[(a,1)], [(e,5)]], []

- inner starts/stops (v2) keeps only the first pair of each sublist: particle selection.
- outer starts/stops (v2) keeps only the first two sublists: event selection.

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inner starts (v2)	[0, 4]
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- inner starts/stops (v2) keeps only the first pair of each sublist: particle selection.
- outer starts/stops (v2) keeps only the first two sublists: event selection.
- If a new 2^{nd} attribute is created, we can immediately update the selected data.

Case 4: database-style indexing (only a sorting example)

logical data	`[[(a,1), (b,2), (c,3), (d,4)], [], [(e,5), (f,6)]], [], [[(g,7)]]`
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inner starts	`[0, 4, 4, 6]`
inner stops	`[4, 4, 6, 7]`
1st attribute	`[a, b, c, d, e, f, g]`
2nd attribute	`[1, 2, 3, 4, 5, 6, 7]`
1st attribute (v2)	`[g, e, f, a, b, c, d]`
2nd attribute (v2)	`[7, 5, 6, 1, 2, 3, 4]`
inner starts (v2)	`[3, 1, 1, 0]`
inner stops (v2)	`[7, 1, 3, 1]`
logical data (v2)	unchanged!

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      inner starts  [0,                            4,  4,                    6       ]
       inner stops  [4,                            4,  6,                    7       ]
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- Different sublists can be sorted differently, e.g. muon attributes by max muon p_T per event and jet attributes by max jet p_T per event.

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1st attribute (v2)  [  g,           e,     f,            a,     b,     c,     d     ]
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- Different sublists can be sorted differently, e.g. muon attributes by max muon p_T per event and jet attributes by max jet p_T per event.
- Request for ${p_T}^{\text{muon}} > X$ AND ${p_T}^{\text{jet}} > Y$ only touches one end of all the arrays.

How might it be implemented?

This is not an Object-Relational Mapping (ORM): the order of the arrays is important and they should be served in contiguous blocks.

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Option 2: use ROOT's OAM and interpretive layer, but replace its file-backed storage with the object store.

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Option 2: use ROOT's OAM and interpretive layer, but replace its file-backed storage with the object store.

Option 2 is more limited (no start/stop arrays), but less needs to be invented and old analysis scripts would function in the new system.

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- No artificial boundaries in the dataset: only segmented into baskets, which are hidden from users.
- Need to develop new interfaces to share basket data among versioned datasets and track provenance.

Questions for HEP: any use-case concerns? Missing features?

Questions for others: does this look familiar? Do you have experience with systems like this? If so, what worked/didn't work?