Executing code on columnar data: the translation problem and formats that help

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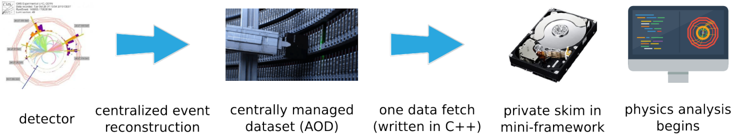
Why I'm interested in columnar data

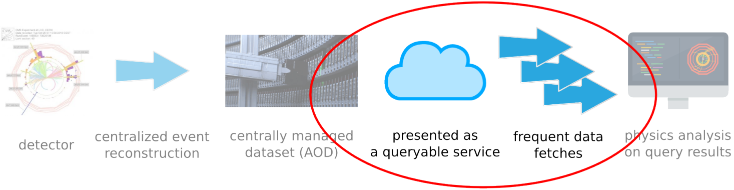
I'm working on a query language and database server to aggregate large samples of HEP data on the fly.

Purpose: to eliminate the need for private skims in most situations.

to replace



with



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The query language, Femtocode, plays a similar role as TTreeFormula:

- a high-level language for the physicist
- usually for filling a histogram (so query responses are small)
- but generally useful for transforming one dataset into another.

However, it's a full-fledged language with assignments and user-defined functions, so that it can encompass a larger part of the analysis.

(I've examined SQL, LINQ, and others, and they are not sufficient. I would use a standard if I could.)

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The essential feature of Femtocode is that it can transform complex structure-manipulations, which would ordinarily have to be performed in object-oriented code, into a series of vectorized kernels.

It operates on columns.

Data reduction without objects

Example:

```
hist = dataset..bin(100, 0, 50, """
    muons.map(m => sqrt(m.px**2 + m.py**2)).max()
""")
```

transforms to

1. Pass over all muons, computing $\sqrt{{p_x}^2 + {p_y}^2}$ on all muons, ignoring event boundaries.
2. Find the maximum such value for each event.
3. Bin those events and fill the histogram.

rather than

1. Loop over events:
   - 1.1 Loop over muons:
     - 1.1.1 Compute $\sqrt{{p_x}^2 + {p_y}^2}$ for each.
   - 1.2 Fill a histogram with the maximum.

Scope of computability

Three types of data transformations:

Flat: apply N-argument function to each element of N aligned arrays.

Known in the Numpy community as a "ufunc."

Explode: emulate (nested) for loops by replicating data in one array so that it becomes aligned with another array.

Reduce: emulate reducer functions (sum, mean, max...) by combining elements of an array so that it becomes aligned with an outer level of structure.

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What's missing?

"Repeat until convergence." Whatever determines "convergence" may be different for each element of the array: they'd all wait for the last one, anyway.

Flat transformations

The majority of steps in a typical calculation are flat:

```
double in[ZILLION];
double out[ZILLION];

for (int i = 0;  i < ZILLION;  i++)
  out[i] = flat_operation(in[i]);
```

- Compilation with `-O3` does auto-vectorization if possible (depends on `flat_operation`).
- Easiest form for CPU to prefetch memory and/or pipeline operations.
- This form is also ideal for GPU calculations.
- There is a standard for functions like this: Numpy's ufunc is widely used among scientific libraries.
  - Easy way for a user to add functions to the language!

ROOT functions can be ufuncs, too

```python
import ctypes, numpy, numba

libMathCore = ctypes.cdll.LoadLibrary("libMathCore.so")
chi2_ctypes = libMathCore._ZN5TMath17ChisquareQuantileEdd # c++filt!
chi2_ctypes.argtypes = (ctypes.c_double, ctypes.c_double)
chi2_ctypes.restype = ctypes.c_double

# compile to pure-C ufunc
@numba.vectorize(["f8(f8, f8)"], nopython=True)
def chi2_ufunc(p, ndf):
    return chi2_ctypes(p, ndf)

p = numpy.random.uniform(0, 1, int(1e6)) # million random numbers
result = chi2_ufunc(p, 100)              # call ufunc on all of them
# 3.22 seconds

import ROOT
result = [ROOT.TMath.ChisquareQuantile(pi, 100) for pi in p]
# 9.32 seconds
```

(Performance comparison is just to show that the ufunc computes `ChisquareQuantile` in C, not in Python. Simpler functions show a more dramatic difference.)