Executing code on columnar data

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February 8, 2017

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

Collaborating with Jin Chang and Igor Mandrichenko on the server.

Why I'm interested in columnar data

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.)

Why I'm interested in columnar data

The essential feature of Femtocode is that it can compile 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()
""")
```

compiles to

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

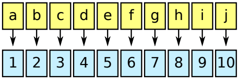
rather than

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.

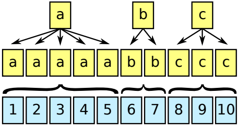
Scope of computability

Three types of data transformations:

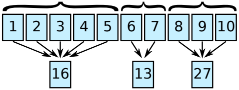
Flat: apply N-argument function to each element of N aligned arrays, ignoring boundaries.



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



Reduce: emulate counters, sum, mean, max, etc. by combining elements of an array so that it becomes aligned with an outer level of structure.



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` vectorizes if possible (depends on `flat_operation`).
- Easiest form for CPU to prefetch memory and/or pipeline operations.
- Also ideal for GPU calculations.
- There is a standard for functions of this form: 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

```
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.)

Explode operation

Depends critically on the way we represent structure. For the "recursive counter" method I described in the last talk,

```
Given:             [ [ a b c ] [ d e f g ] ] [ [ h ] [ i j ] ]
Data array:            a b c     d e f g           h     i j
Recursive counter: 2 3         4             2 1     2
```

Calculating arbitrary explosions is solved in two cases:

- explode scalar to fit a list's counter (35 lines of C)
- explode list to fit another list's counter (470 lines, recursive).

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Illustration of the first:

xs $\rightarrow$ [1, 2, 3, 4], [], [5, 6, 7] and y $\rightarrow$ 100, 200, 300

Computing

```
xs.map(x => x + y)
```

yields

```
[101, 102, 103, 104], [], [305, 306, 307]
```

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Illustration of the second:

xss → [[100, 200], [300, 400], [500, 600]] and ys → [1, 2, 3, 4]

Computing

```
xss.map(xs => xs.map(x => ys.map(y => x + y)))
```

yields

```
[[[101, 102, 103, 104], [201, 202, 203, 204]],
 [[301, 302, 303, 304], [401, 402, 403, 404]],
 [[501, 502, 503, 504], [601, 602, 603, 604]]]
```

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[[[101, 201], [102, 202], [103, 203], [104, 204]],
 [[301, 401], [302, 402], [303, 403], [304, 404]],
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```

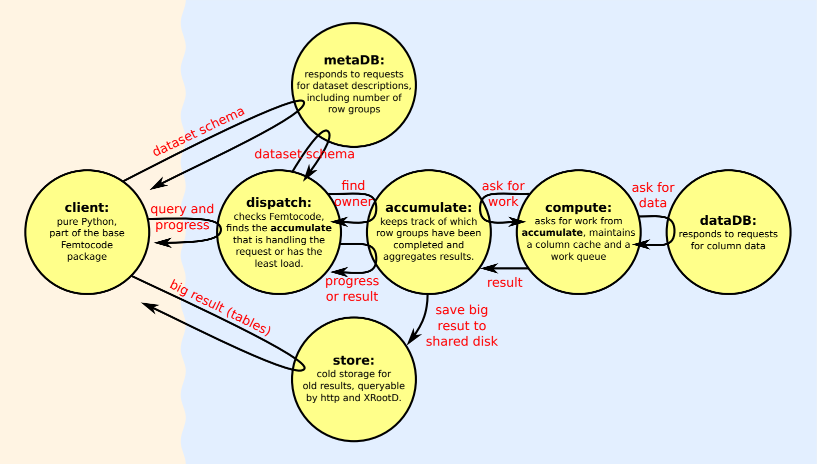
Reduce operations

Haven't been implemented, but they're pretty straightforward.

Query server

Before finishing the language, we want to understand how it will fit into the server.

Preliminary design:



Query server

If this is going to replace private skims, it has to respond to aggregations over whole datasets in seconds.

Purpose of early studies: determine what performance is *possible.*

Reading from a CMS MiniAOD file

File-reading rates in events/ms per process (kHz per process), with the goal of extracting only p_T.

particle	#/event	# branches	CMSSW	`TTree::Draw()`	fast reader
photon	2.9	205	1.14	435	769
electron	2.5	231	1.02	417	833
muon	2.7	192	1.02	16.5	770
tau	6.3	88	1.55	244	417
jet	16.7	95	1.15	123	182
AK8 jet	1.8	95	2.10	556	1000

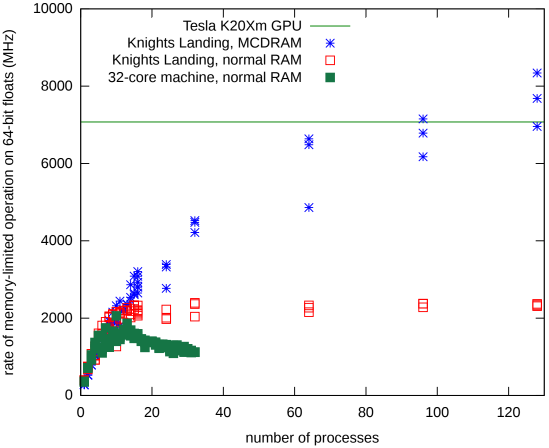
- CMSSW loads all branches to reconstruct particles as a C++ objects. Loading all branches just to cut on p_T is wasteful.
- `TTree::Draw()` is more streamlined, only loads required branches. (Low muon rate not understood.)
- "fast reader" is based on a code snippet Philippe prepared for me, using some of the same techniques as `TTree::Draw()`.

Repeated queries on that file

We plan to maintain an in-memory cache of recently used *columns*, on the supposition that the column-popularity distribution is steep enough to cause frequent cache-hits.

Rate for simple, flat functions on cached columns is limited only by memory bandwidth.

Could reach a peak of 7 GHz on KNL or GPU.



Conclusions

- I'm developing Femtocode to translate object semantics into vectorized operations as part of a project to create a fast query server.
- The "recursive counter" representation of nested structure can be exploded and reduced.
  - This representation is identical to ROOT's for depth-1 lists.
  - Any interest in extending to arbitrary split depth?
- Flat functions are
  - quick to compute,
  - extensible using Numpy's "ufunc" standard.
- For a cached query server,
  - $\sim$1 MHz column entries is attainable for cache-misses,
  - $\sim$1 GHz column entries is attainable for cache-hits.