SKA Imaging Software Designing with domain specific languages

Braam Research, LLC

me

1983 - 2000 Academia

- Maths & Computer Science

Entrepreneur with startups

- 4 startups
- Lustre emerged
- Held executive jobs with acquirers

2014 – Independent research

- Primarily work with SKA SDP @ Cambridge
- Work on Imaging HPC software and storage
- Help others

What is the project about?

- Imaging software for radio telescopes has proven to be complex
- Can we leverage state of the art programming language techniques to make it much simpler?
- Key requirements remain:
  - Separate layers for application software and low level compute kernels
  - Easy modifiability
  - Automatic optimization
  - Data flow approach
  - Plan to integrate work from others
  - Use state of the art compute cluster & cloud ideas

Content of talk

- Very quick sketch of the imaging problem
- Data flow programming
- Automatic optimization
- Radio Cortex (RC) and Declarative Numerical Analysis (DNA)
- Next steps

Background Material

- The Radio Cortex / DNA project will produce quarterly reports
  - What was the focus
  - Results from study
  - Results from prototyping
  - References

- Gradually more information will appear on GitHub to allow others to experiment

- Report 1: http://goo.gl/0n75aa
- Report 2: expected Dec 15

Material used and amended from public SDP slidedeck

Imaging software description

Input is data from baselines

There are ~1000 antenna's
Hence 500,000 baselines

Each baseline measures 256K frequency channels

Correlator gives a measurement ~2x / sec
Each measurement is 3 complex numbers and 3 coordinates (~30 bytes)

30b x 256K x 500K x 2/sec ~= 7.5 TB /sec

Baselines are not regularly laid out on a grid

Imaging pipeline

Operations are simple:

- Put baselines on grid ("gridding")
- Project one grid onto another
- Fourier transform
- Subtract known grid values
- De-grid

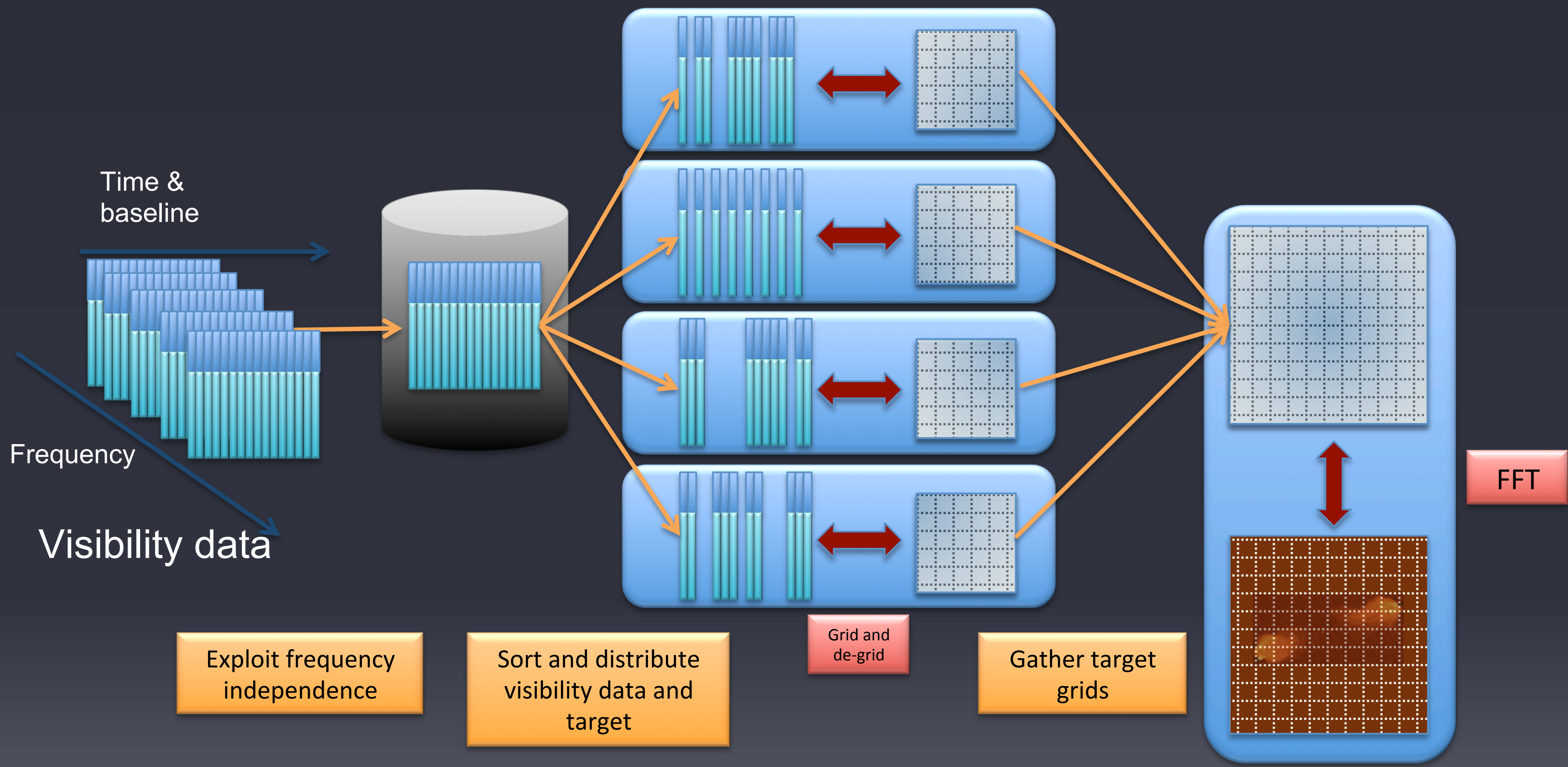
Several steps are repeated, some 10 times

Optimizations

- Data locality
- Data movement
- Fast computation

The optimizations require a data centric approach as much as choosing good algorithms

Another perspective



- Further data parallelism in locality in UVW-space
- Use to balance memory bandwidth per node
- Some overlap regions on target grids needed
- UV data buffered either on a locally shared object store of locally on each node

Architectural principles

DSL
- **Domain Specific Languages & Data Flow**
- Express algorithms use of kernels concisely

Strategy
- Determine what to compute where
- Address parallelization & locality

Compile
- Compile optimized kernels
- Schedule on cluster

Execute
- Run the program
- Adapt to failures

Data Flow Programming

Basic Principles

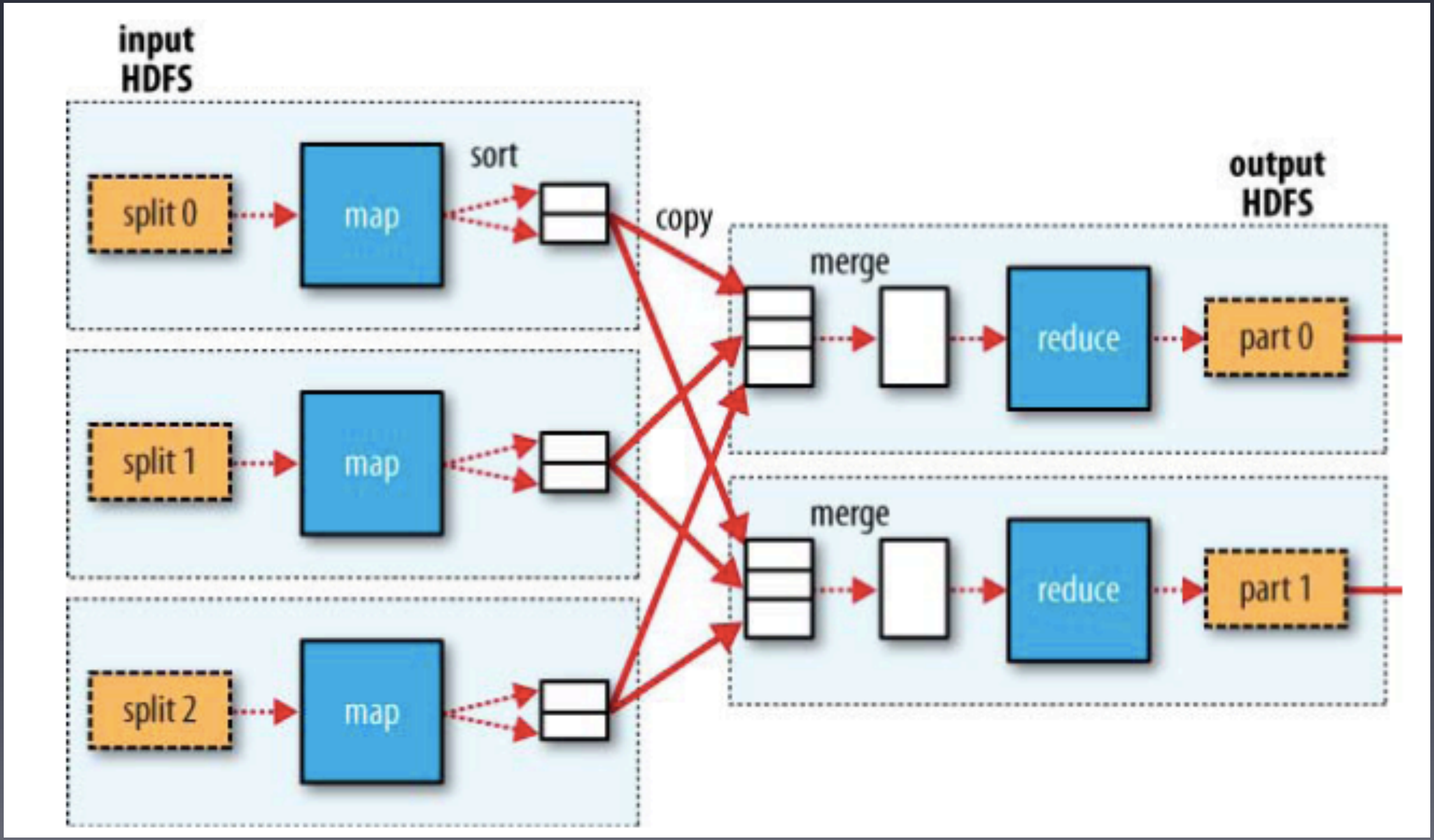
Express a computation using actors connected with data channels where:

- the actors fire when all required data on their input channels is available
- data is exclusively owned by an actor or a channel

Contrast with multithreaded programming:

- avoid state accessed by all threads as part of progress of the computation (concurrency control).
- All actors and channels do compute concurrently.

Map reduce as dataflow



Variations

Variations

How is the graph encoded

Actors can spawn dynamically

One or more input channels

Channels perform *matching*

Are channels ordered?

Are actors stateless / state full

Select expected messages from channels

Unexpected msg stay in the channel or may crash an actor

channels reliable / unreliable

Examples

Hardware design languages

 clocks

Actor model

 no fixed graph

 deep theory

Reactive programming

 more stream oriented

Event driven programming

 origins in GUI

Cell driven programming

 like spreadsheets

Lofty claims and lots of confusion

Actor model wikipedia: This section may be confusing or unclear to readers. In particular, links between paragraphs are unclear. Seeming non sequitur, or confusing language in second paragraph. (September 2014)

According to Carl Hewitt, unlike previous models of computation, the Actor model was inspired by physics including general relativity and quantum mechanics.

I now realize that Robin [Milner]’s work [on Calculus of Communicating Systems (CCS) and pi-Calculus] should really have been included in the previous chapter, but I just wasn’t aware of it when I wrote my book.

History

- Goes back to the 60's (IBM)
- Is absolutely vast
- Includes some of the finest computer science literature, such as Robin Milner's work on the pi-Calculus
- Many dozens of deep theoretical models
- Many 100's of languages
- It's a darling of many areas, including super computing

Examples

- Key primitives: *send* data items and *wait* for them
- "Ebay" – the channels build up complex state and do "joins"

```
expect Buyer itemTypeA, Seller itemTypeA -> arrange sale
```

- Simple to deadlock

```
actor A = do
      b <- waitfor: from B
      send a
  actor B = do
      a <- waitfor: from A
      send b
```

- Different to debug – history vs stack
- Easy to get very complicated things

Automatic Optimization

General structure

- I do not know the full history, there are dozens of automatic optimizers
- Famous example is FFTW
  - DFT’s can be factored. Locality of data is key.
  - FFTW automatically generates numerous strategies and returns optimal one
  - Core algorithm is (monadic) functional program, output is C (or lower)
- How does it work?

```
fftw_complex *in, *out;
fftw_plan p;
in = (fftw_complex*) fftw_malloc(sizeof(fftw_complex) * N);
out = (fftw_complex*) fftw_malloc(sizeof(fftw_complex) * N);
p = fftw_plan_dft_1d(N, in, out, FFTW_FORWARD, FFTW_ESTIMATE);
fftw_execute(p);
```

Optimization using Halide

Halide is a language for image processing – used for cameras.

Algorithm:

what is computed?

Schedule

Question 1: In what order should it compute the output

Question 2: In what order should it compute its inputs

Separation of Algorithm and Schedule is much better:

tinkering with optimizations can't break the algorithm

Halides' optimizations

- parallelism: threads, SIMD vectors
- locality: tiling, fusion (including re-computation, duplicating data)
- unfortunately not yet "binning" our 500K baselines

Example - blurring

```
Var x,y
Function blurx, blury
blurx(x,y) = (inp(x-1,y) + inp(x,y) + inp(x+1,y))/3
blury(x,y) = (blurx(x,y-1) + blurx(x,y) + blur(x,y+1))/3
```

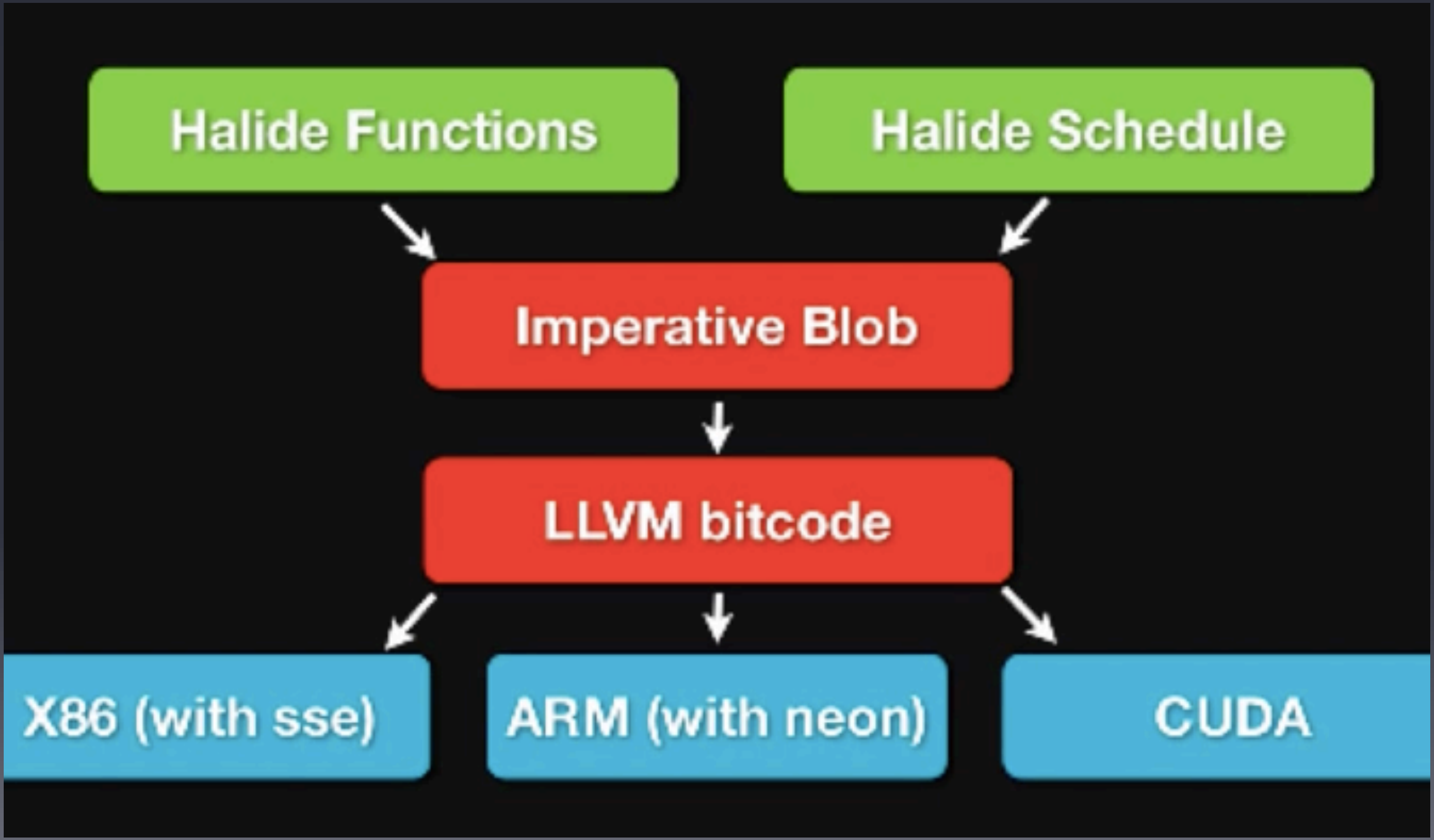
Multiple scheduling strategies will be shown in a movie

Play 2 short segments from Halide movie:

14:25 – 17:28

19:17 – 21:31

Halide Compiler



Gridding with Halide

```
result(u, v, pol, x)  = (T)0.0;
result(u, v, pol, 0) +=
     weightr(bl, intU(bl, timest), intV(bl, timest),u,v)
           * visibilityr(bl, timest, pol);
```

- Didn’t work so well ….
  - += obtains much concurrency (which a different scheme can avoid)
  - Concurrency is expensive
  - Halide does like “indexing” arrays with the values of others, e.g. by using the baseline coordinates (Halide is built for “whole” regular camera images”)
  - Yet, Halide demonstrates extremely well how to organize the code
  - And searches automatically for optimized algorithms.

Radio Cortex – RC &
Declarative Numerical Analysis - DNA

Radio Cortex & DNA

Target is to produce a compelling design & prototype (2 years)

Milestone 1:

- Problem: dot product of a computed vector and vector in a file
- Used Lustre shared storage and cloud-per node storage model
- Ran it with Slurm
- Implemented data flow program with cloud Haskell
- Ran it up to 1200 cores on Wilkes
- Had high availability operational in version 1
- Did careful profiling
- Integrated it with C-code

We learned things needed to become a lot simpler!

Milestone 2: gridding

Basic Gridders – turned out to be basic and not so basic

Compare with Romein's gridding

Much simpler DSL

Much easier debug & profile log management

More precise profiling

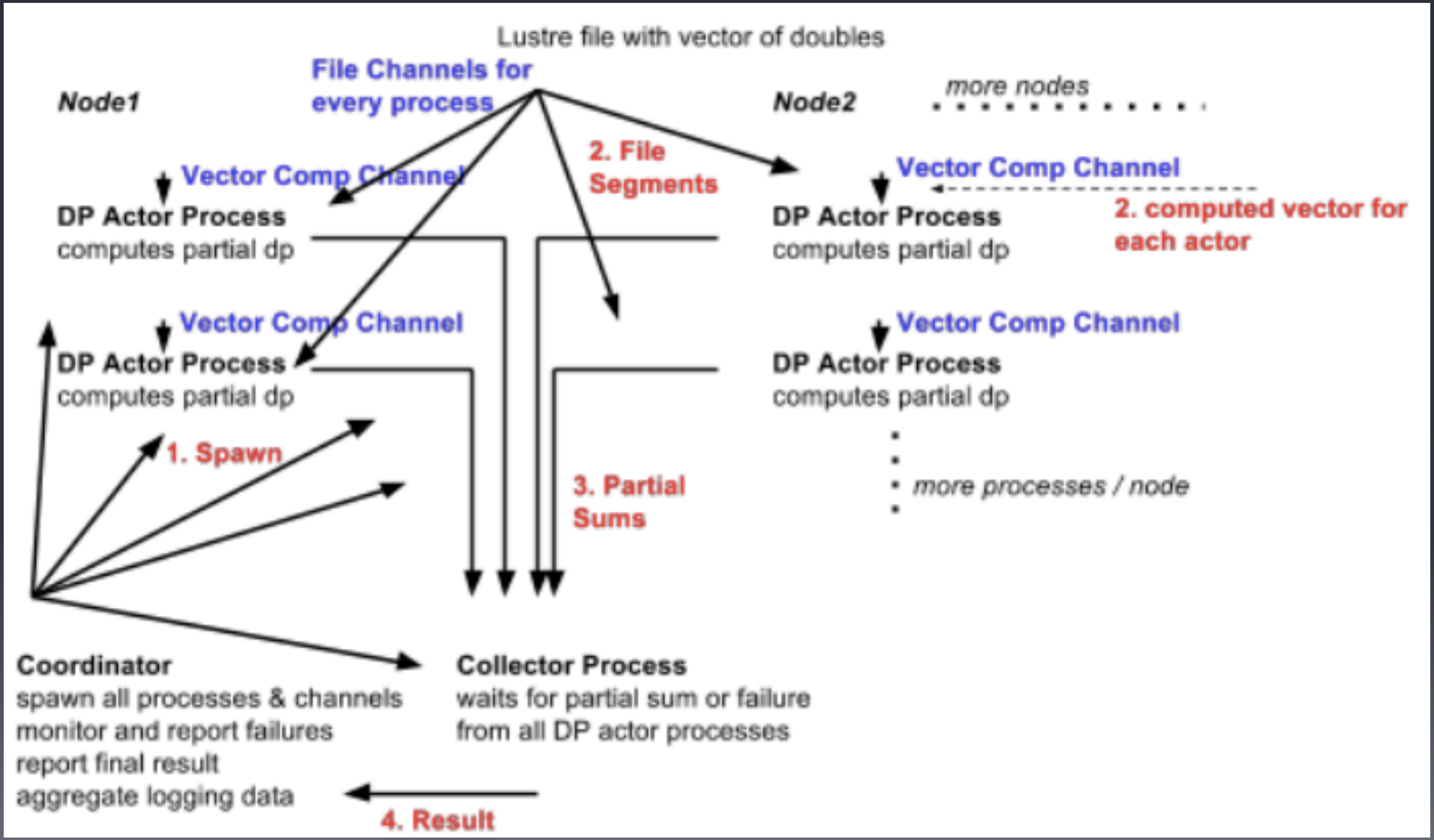
Use GPU's and CPU's

Run again at scale

Keep high availability

Tighter integration with Slurm

Data Flow diagram



Simpler DSL – map reduce

```
master_actor (CAD, M, R)
     mapProcs = schedule(M, CAD)
     reduceProcs = schedule(R, CAD)
     fork(nodes:mapProcs, process:map_actor, output:reduceProcs,
crash:restart, input: File )
     fork(nodes:reduceProcs, process:reduce_actor, input:mapProcs,
crash:fail, output: File)
     result = wait(reduceProcs)
     start


map_actor
    map computations ….
    join(zip(map_outputs, reduceProcs))  -- sends the map output to the
reduceProcs and exits

reduce_actor
    wait(input, mapProcs)
    reduce computations ….
    join(result, parent)
```

What’s next with RC / DNA?

Possible next steps

- By end of 2015 fully working prototype for imaging
- Collaboration with Intel and nVidia to explore integration of fast kernels
- Collect domain specific knowledge into systematic design documents
- Plan for success!

Thank you! Questions?