

## CS33001: DATA-INTENSIVE COMPUTING SYSTEMS SEMINAR

### Today

- Presto discussion
- Data-intensive computing archetypes
- Data Parallel Data-intensive computing
  - Page Rank <http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf>
  - Map Reduce <http://research.google.com/archive/mapreduce.html>
- Example Data-intensive computing projects
- Systems (and RCC access)

### Monday: Andrew Baptist, Cleversafe

- Julie Bellanca Cleversafe slides (Basics of AONT Security architecture)
- Jim Plank FAST05 tutorial "Erasure Codes and Storage"
  - What more you'd like to know/understand
- Short writeups on Data-intensive computing infrastructure

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## PRESTO/BLOCKUS

**Summary** – multicore+distributed parallelism to scale-up. Distributed, partitioned arrays as basis for parallelism. Focus was matrix operations, including graph problems formulated. Do it out of core. Scale to out of core.

### 3 Good

- Fills need for large data sets in R (seems that all high level environments tend to not support scale well)
- Did get speedup; scaleup. And able to do dynamic load balance – but simple at this point.
- Use of shared memory good for space efficiency

### 3 Bad

- Took a long time to figure out the natural load balance.
- Ongoing overhead (lots of kinds). Garbage collection.
- Lots of other systems have introduced parallelism in this fashion
- Still dependence on the master node for scheduling (failures, scaling)

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## DATA-INTENSIVE COMPUTING ARCHETYPES (PART I)

### “Data Parallel”

- Large data set over which intensive computation happens
  - Similar to HPC, but Input data driven (not model driven), large input, small output
  - Examples: Netflix, Page rank, Walmart buying trends, etc.

### “Tile, Sample, Sensor Integration”

- Large collection of smaller data samples, each of which requires processing and construction of a integrated view as a precursor to “data parallel”
  - Often partitionable into many tasks, executed over distributed data sets and resources, even samples over time. Image, spatial data processing.
  - Examples: Montage/EOSDIS, Google StreetView, Microsoft Streetside, Realtor websites, Traffic Maps

+ generated problems

+compositions of these

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## COMPUTING ARCHETYPES (PART II - TEMPORAL)

Data Parallel

Tile, Sample, Sensor integration

+ incremental update

+ real-time update

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## **COMPUTING ARCHETYPES (PART III - CAPACITY)**

**Data Parallel**

**Tile, Sample, Sensor integration**

**+ incremental**

**+ real-time update**

**+ data set doesn't fit into memory**

- Scaleout and Streaming versions
- Partition w/ database, in-database computation systems

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## **DATA-INTENSIVE COMPUTING ARCHETYPES (PART IV)**

**Data Parallel**

**Tile, Sample, Sensor integration**

**+ incremental**

**+ real-time update**

**+ data set doesn't fit into memory**

**Scaleout and Streaming versions**

**Partition w/ database, in-database computation systems**

**+ naturally distributed, constrained to be distributed**

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## TODAY'S READINGS

**Page Rank** <http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf>

**Map Reduce**

<http://research.google.com/archive/mapreduce.html>

- programming model for distributed computing
- Map + reduce (design pattern), strict adherence
- => very large data size scaling, simple transparent fault tolerance, load balance.
- System pays for them, not the programmer

**Classification? Data parallel + out of core**

**Summary?**

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## 3 GOOD

**Pagerank**

- First major graph structure based ranking => required large-scale computation across the web graph
- Produced more robust results; elegance reduces to simple, well understood linear algebra problems

**Mapreduce**

- Transparent scaling, fault-tolerance, load imbalance
- Works well for embarrassingly parallel. But everything
- Tasks are idempotent (each phase is side-effect free)
- Centralized scheduler – good for scheduling, completion time, focuses where to invest for FT

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## 3 BAD

### Pagerank

- Unclear how they crawl? (sensitivity about completeness and “edges” – open graph)
- Unclear how to prevent manipulation (but better than keyword stuff)
- Popularity in links  $\leftrightarrow$  Rank (and that's not good)... Understand content, and search intent

### Mapreduce

- Parallel elements can't communicate, awkward and inefficient in some cases
- Phase splitting makes complex data structures and algorithms very difficult to use
- Prevents any locality (streaming model to/from disk, a lot of work in every phase of the computation); can't easily carry forward partial results from phase to phase in a computation
- Centralized master – bad for scaling, bad for fault tolerance

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## DISCUSSION

### Data-intensive computing projects

- Netflix: Zach and Tanakorn
  - Recommenders - 2M reviews/day, 1-5 score, movie metadata
  - Matrix: subscribers x Movies, can derive new information about movies, but not users
  - Real-time update desirable; data small (10's of GB)
  - Computation is large  $N^3$ . Does additional data continue to help?
- EOSDIS: Aiman
  - 1TB/day, inherently distributed, search view based on indexing. Primary image data, metadata
  - Produce data products for further analysis; smooth fields
  - Global vs. Urban focus
- Graph Formulations of Tiling: Max
  - Tiling  $\leftrightarrow$  graph algorithms, don't have locality properties
  - Grow exponentially; not a huge variance in node degree
- Massively distributed data distribution: Yuan
  - Avalanche – bittorrent improvement; coding is symmetric
  - Is computational effort to encode the critical bottleneck?
- Tbd: Matt

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## **DICSYSTEMS PROJECT INFRASTRUCTURE**

**What might you need?**

**What do you have access to?**

**Cleversafe**

**LSSG cluster (100 cores)**

**RCC cluster (2000 cores)**

**Amazon EC2**

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## **SUMMARY**

**Data Intensive computing archetypes**

**Data-parallel – mapreduce and pagerank**

**Data-intensive computing projects**

**Next time: Erasure codes, Andrew Baptist. Come with interesting questions!**

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## PROJECT ASSIGNMENT (MONDAY 4/15)

### Download, install, and run a data-intensive computing infrastructure

- A widely used one? (MongoDB, Hbase/H\*, Graphlab, Cassandra)
- Or get started with Presto/Blockus or Cleversafe
- What is it capable of?
- What types of problems is it particularly well suited to? Intended workload?
- Does it scales? (in data? In speed/capability?) does it scale down?
- Robustness/Resilience of the system – hw/sw, operating point/usage, does it degrade or collapse?
- Recovery and Diagnosis – what can you recover in a failure? And what can you deduce about the cause of the failure?
- What kind of hardware was designed for? (clusters, HPC) – communication, reliability, system balance issues. Distribution?
- Is it efficient? (cost, energy, algorithmically, human effort)

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## CANDIDATES

HBASE/H\*, VoltDB

PIG/H\*

HadoopDB/H\*

Cassandra

SciDB

BLOOM/MR Online/?

MongoDB

Graphlab/Graphchi

Swift

?

**Preference: something new**

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## ASSIGNMENT TURN-IN FORMAT (4/15)

Output: 4 slide  
summary

- Which & why
- What you did
- Answer to Q's

**1-page writeup describing system and its capabilities**

**5-minute presentation in class using 4 slides – summarize capabilities and your experience with it (what you did)**

- For each, we'll have a discussion on what its being used for
- What its good at
- What are its shortcomings
- What kinds of projects it might be suitable for

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