Computational Architecture of Cloud Environments Michael Schatz

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Nebulous question:

Cloud computing = Utility computing + Enabling Computational Technologies Goal: Many computers working together to analyze huge datasets Challenge: 100x processors rarely means 100x faster

Why Parallel?

- Moore's Law is valid in 2010
 - But CPU speed is flat
 - Vendors switching to multicore solutions instead
- Why parallel
 - Need it done faster
 - Doesn't fit on one machine



The Free Lunch Is Over: A Fundamental Turn Toward Concurrency in Software Herb Sutter, http://www.gotw.ca/publications/concurrency-ddj.htm

Parallel Computing Spectrum



Batch Computing Many Good Solutions

MapReduce Enabling Technologies Emerging MPI & PRAM Open Research Area

BLAST HMM Scoring Parameter Sweep Align-Shuffle-Scan Genotyping K-mer Counting Graph Analysis Genome Assembly MD Simulations

Embarrassingly Parallel

- Batch computing
 - Each item is independent
 - Split input into many chunks
 - Process each chunk separately on a different computer
- Challenges
 - Distributing work, load balancing, monitoring & restart
- Technologies
 - Condor, Sun Grid Engine
 - Amazon Simple Queue





Elementary School Dance



Regularly Parallel

- Align-Shuffle-Scan in MapReduce
 - Align a large set of reads
 - Shuffle to group and sort by chromosome
 - Scan alignments for SNPs
- Challenges
 - Batch computing challenges
 - + Shuffling of huge datasets
- Technologies
 - Hadoop, Elastic MapReduce, Dryad
 - Parallel Databases



Junior High Dance



Crossbow Scaling



• Even with this relatively simple parallel application, we do not achieve perfect efficiency.

- Interesting tradeoffs in time vs. money

Deeply Parallel

- Computation that cannot be partitioned
 - Graph Analysis
 - Molecular Dynamics
 - Population simulations
- Challenges
 - Regular parallel challenges
 - + Parallel algorithms design
- Technologies
 - MPI
 - MapReduce, Dryad



High School Dance



Short Read Assembly



- Genome assembly as finding an Eulerian tour of the de Bruijn graph
 - Human genome: >3B nodes, >10B edges
- The new short read assemblers require tremendous computation
 - Velvet (Zerbino & Birney, 2008) serial: > 2TB of RAM
 - ABySS (Simpson et al., 2009) MPI: 168 cores x ~96 hours
 - SOAPdenovo (Li et al., 2010) pthreads: 40 cores x 40 hours, >140 GB RAM

Graph Compression

- After construction, many edges are unambiguous
 - Merge together compressible nodes
 - Graph physically distributed over hundreds of computers





Fast Path Compression

Challenges

- Nodes stored on different computers
- Nodes can only access direct neighbors

Randomized List Ranking

- Randomly assign (H)/T to each compressible node
- Compress $(H) \rightarrow T$ links

Performance

- Compress all chains in log(S) rounds

Randomized Speed-ups in Parallel Computation.

Vishkin U. (1984) ACM Symposium on Theory of Computation. 230-239.



Scalable Genome Assembly with MapReduce

- Genome: African male NAI8507 (Bentley et al., 2008)
- Input: 3.5B 36bp reads, 210bp insert (SRA000271)
- Preprocessor: Quality-Aware Error Correction

Assembly of Large Genomes with Cloud Computing.

Schatz MC, Sommer D, Kelley D, Pop M, et al. In Preparation.





Contrail

http://contrail-bio.sourceforge.net



Summary

- Surviving the data deluge means computing in parallel
 - Good solutions for "easy" parallel problems, but gets fundamentally more difficult as dependencies get deeper

Parallel systems require connecting many components

- We can get started by agreeing on common input and output formats, open source software
- Move the computation to the data
- Emerging technologies are a great start, but we need continued research integrating computational biology with research in HPC
 - A word of caution: new technologies are new

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