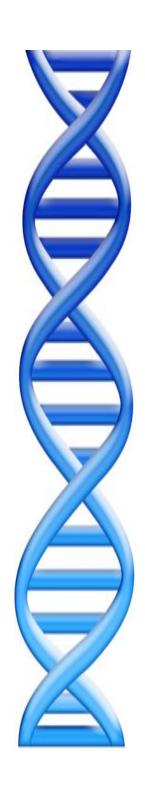
Cloud Computing and the DNA Data Race Michael Schatz

March 28, 2011 Columbia University





Outline

- I. Milestones in DNA Sequencing
- 2. Hadoop & Cloud Computing

- 3. Sequence Analysis in the Clouds
 - I. Sequence Alignment
 - 2. Mapping & Genotyping
 - 3. Genome Assembly

1970 1980 1990 2000 2010

Articles

Nucleotide sequence of bacteriophage
Φ X174 DNA

F. Sanger, G. M. Air', B. G. Barrell, N. L. Brown', A. R. Coulson, J. C. Fiddes, C. A. Hutchison III', P. M. Slocombe³ & M. Smith'

MRC Laboratory of Molecular Biology, Hills Road, Cambridge CB2 2QH, UK

A DNA sequence for the genome of bacteriophage ΦX174 of approximately 5,375 melloutiles has been determined using the rapid and simple 'plus and risins' method. The sequence identifies many of the features responsible for the production of the proteins of the mine known genes of the organism, including industries and semination sites for the proteins and RNAs. Two pairs of genes are coded by the same region of DNA using different reading frames.

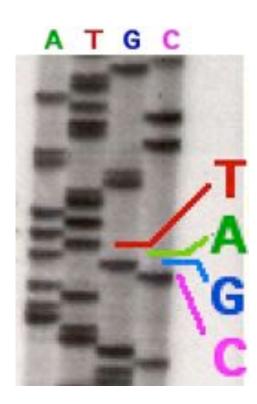
This genome of bacteriophage 4X174 is a single-stranded, circular DNA of approximately 5,600 nucleotists coding for nine known proteins. The order of these grees, as determined by genetic techniques 1-1, in 4-8-C-D-E-J-F-G-H. Genes F, G and H code for structural proteins of the virus capid, and gene Idan defined by sensuring work; codes for a small basic more designed.

strand DNA of ΦX has the same sequence as the mRNA and, in certain conditions, with hind stheoroms so that a protected fragment can be notated and sequenced. Only one respect site was found, By comparison with the armon acid sequence data fit was found, By comparison with the armon acid sequence dedle fit was found that this relevance brinding site sequence ceded for the initiation of the gene G protein¹⁰ (position $X_2 M - X_1 M - X_2 M - X_1 M - X_2 M - X_2 M - X_3 M - X_$

At this stage isquencing techniques using primed synthesis with DNA polymerase were being dividuped²¹ and Schotti' synthesised a decanscloride with a sequence complementary to part of the rishosene binding sist. This was used to prime into the intercistronic region between the F and G gence, using DNA polymerase and ²¹⁸-labelled riphosphaters'. The ribo-substitution techniques' facilitated the sequence determination of the labelled DNA produced. This decanscloride-primed system was also used to develop the plus and reistes method. Statistic synthesis persons are however, difficult to prepare and as

1977

Sanger et al. Ist Complete Organism Bacteriophage ϕ X174 5375 bp



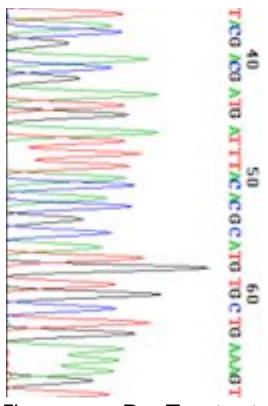
Radioactive Chain Termination 5000bp / week / person

http://en.wikipedia.org/wiki/File:Sequencing.jpg http://www.answers.com/topic/automated-sequencer

1970 1980 1990 2000 2010



I 987
Applied Biosystems markets the ABI 370 as the first automated sequencing machine



Fluorescent Dye Termination 350bp / lane x 16 lanes = 5600bp / day / machine

1970 1980 1990 2000 2010



I 995
Fleischmann et al.
Ist Free Living Organism
TIGR Assembler. I.8Mbp



2000 Myers et al. Ist Large WGS Assembly. Celera Assembler. I 16 Mbp



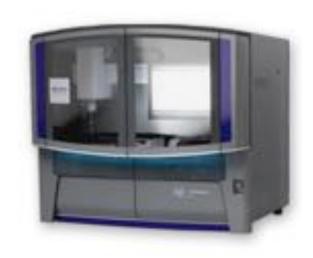
Venter et al., Human Genome Celera Assembler. 2.9 Gbp

ABI 3700: 500 bp reads \times 768 samples / day = 384,000 bp / day. "The machine was so revolutionary that it could decode in a single day the same amount of genetic material that most DNA labs could produce in a year." J. Craig Venter

1970 1980 1990 2010







2004 454/Roche Pyrosequencing Titanium: IM 400bp reads / run = IGbp / day

2007
Illumina
Sequencing by Synthesis
HiSeq 2000:
2.5B 100bp reads / run =
25Gbp / day

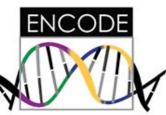
2008
ABI / Life Technologies
SOLiD Sequencing
5500xl:
5B 75bp reads / run =
30Gbp / day

Second Generation Sequencing Applications

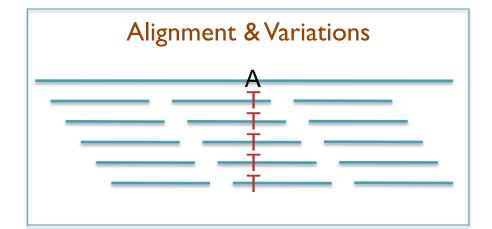


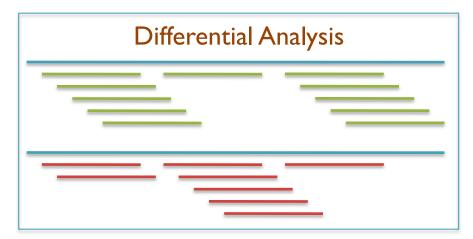




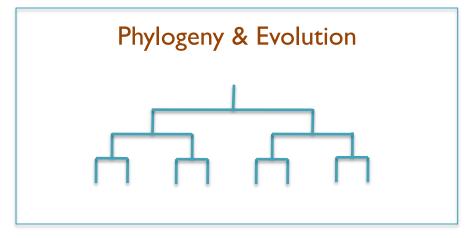






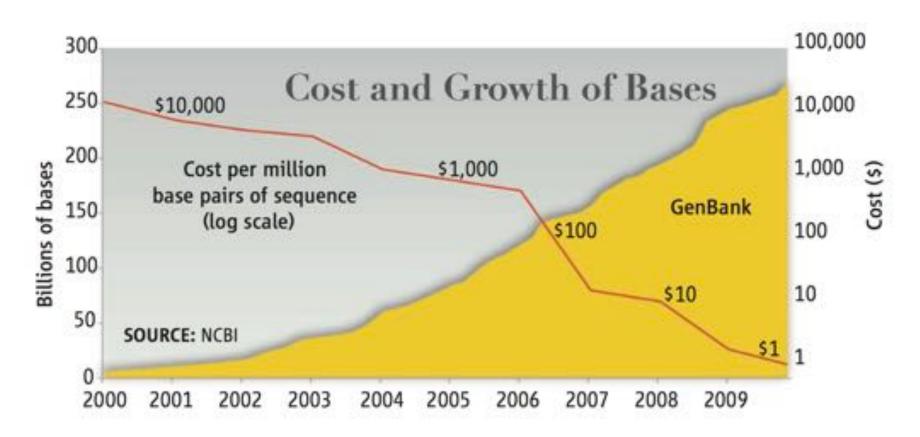






The DNA Data Tsunami

Current world-wide sequencing capacity exceeds 10Tbp/day (3.6Pbp/year) and is growing at 5x per year!



"Will Computers Crash Genomics?"

Elizabeth Pennisi (2011) Science. 331(6018): 666-668.

Hadoop MapReduce

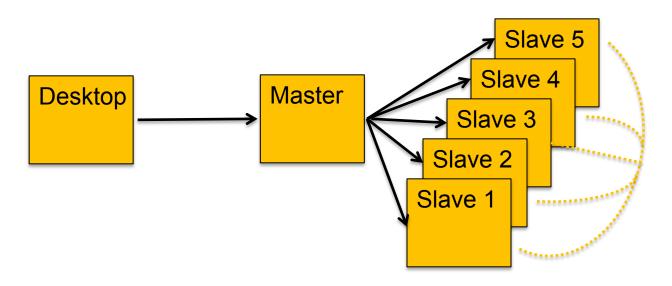
http://hadoop.apache.org

- MapReduce is Google's framework for large data computations
 - Data and computations are spread over thousands of computers
 - Indexing the Internet, PageRank, Machine Learning, etc... (Dean and Ghemawat, 2004)
 - 946,460 TB processed in May 2010 (Jeff Dean at Stanford, 11.10.2010)
 - Hadoop is the leading open source implementation
 - Developed and used by Yahoo, Facebook, Twitter, Amazon, etc
 - · GATK is an alternative implementation specifically for NGS
- Benefits
 - Scalable, Efficient, Reliable
 - Easy to Program
 - Runs on commodity computers
- Challenges
 - Redesigning / Retooling applications
 - Not Condor, Not MPI
 - Everything in MapReduce





System Architecture



- Hadoop Distributed File System (HDFS)
 - Data files partitioned into large chunks (64MB), replicated on multiple nodes
 - Computation moves to the data, rack-aware scheduling
- Hadoop MapReduce system won the 2009 GreySort Challenge
 - Sorted 100 TB in 173 min (578 GB/min) using 3452 nodes and 4x3452 disks

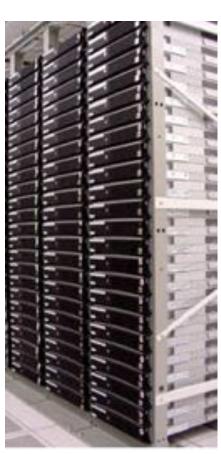
Amazon Web Services

http://aws.amazon.com

 All you need is a credit card, and you can immediately start using one of the largest datacenters in the world



- Elastic Compute Cloud (EC2)
 - On demand computing power
- Simple Storage Service (S3)
 - Scalable data storage
- Plus many, many more



EC2 Architecture

- Very large cluster of machines
 - Effectively infinite resources
 - High-end servers with many cores and many GB RAM
- Machines run in a virtualized environment
 - Amazon can subdivide large nodes into smaller instances
 - You are 100% protected from other users on the machine
 - You get to pick the operating system, all installed software

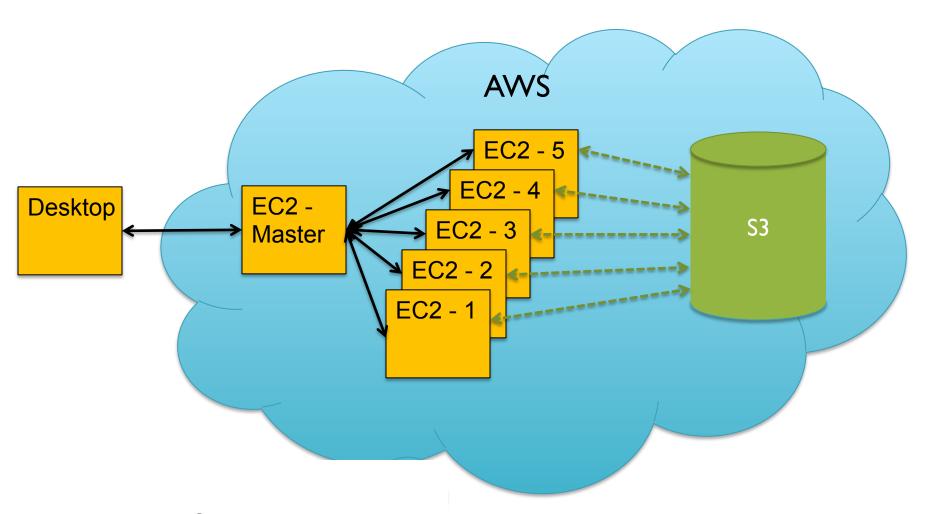


Amazon S3

- S3 provides persistent storage for large volumes of data
 - Very high speed connection from S3 to EC2 compute nodes
 - Public data sets include s3://1000genomes
- Tiered pricing by volume
 - Pricing starts at I5¢ / GB / month
 - 5.5¢ / GB / month for over 5 PB
 - Pay for transfer in and out of Amazon
- Import/Export service for large volumes
 - FedEx your drives to Amazon



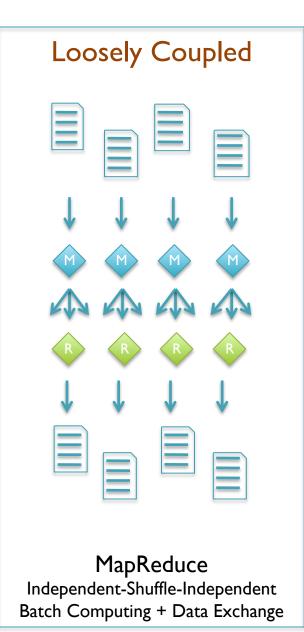
Hadoop on AWS

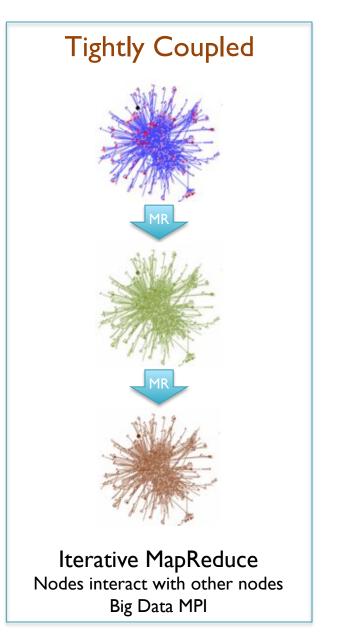


- If you don't have 1000s of machines, rent them from Amazon
 - After machines spool up, ssh to master as if it was a local machine.
 - Use S3 for persistent data storage, with very fast interconnect to EC2.

Programming Models

Embarrassingly Parallel Map-only Each item is Independent Traditional Batch Computing





I. Embarrassingly Parallel

Batch computing

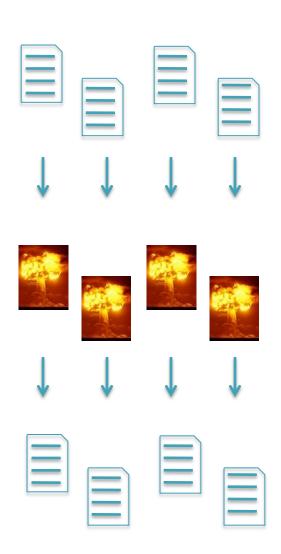
- Each item is independent
- Split input into many chunks
- Process each chunk separately on a different computer

Challenges

 Distributing work, load balancing, monitoring & restart

Technologies

- Condor, Sun Grid Engine
- Amazon Simple Queue

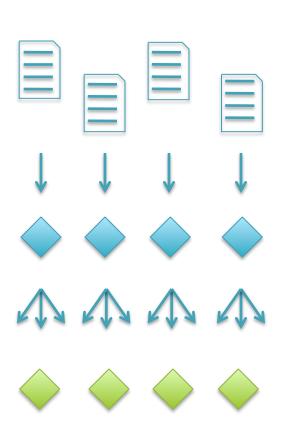


Elementary School Dance



2. Loosely Coupled

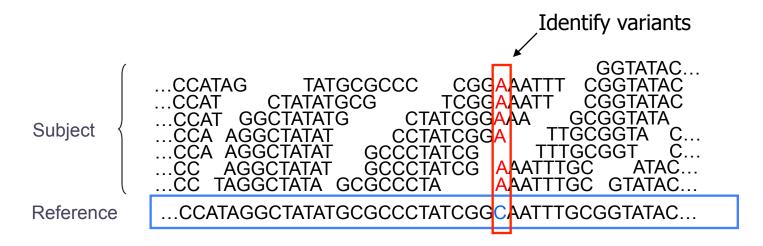
- Divide and conquer
 - Independently process many items
 - Group partial results
 - Scan partial results into final answer
- Challenges
 - Batch computing challenges
 - + Shuffling of huge datasets
- Technologies
 - Hadoop, Elastic MapReduce, Dryad
 - Parallel Databases



Junior High Dance



Short Read Mapping



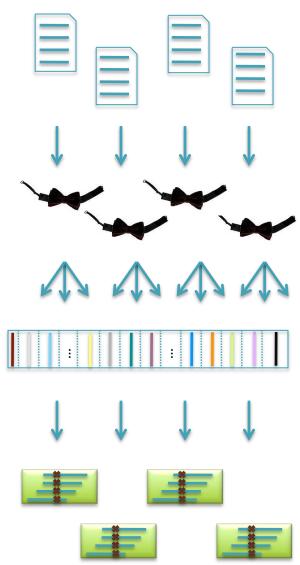
- Given a reference and many subject reads, report one or more "good" end-toend alignments per alignable read
 - Find where the read most likely originated
 - Fundamental computation for many assays
 - Genotyping RNA-Seq Methyl-Seq
 Structural Variations Chip-Seq Hi-C-Seq
- Desperate need for scalable solutions
 - Single human requires > 1,000 CPU hours / genome



Crossbow

http://bowtie-bio.sourceforge.net/crossbow

- Align billions of reads and find SNPs
 - Reuse software components: Hadoop Streaming
- Map: Bowtie (Langmead et al., 2009)
 - Find best alignment for each read
 - Emit (chromosome region, alignment)
- Shuffle: Hadoop
 - Group and sort alignments by region
- Reduce: SOAPsnp (Li et al., 2009)
 - Scan alignments for divergent columns
 - Accounts for sequencing error, known SNPs



Performance in Amazon EC2

http://bowtie-bio.sourceforge.net/crossbow

	Asian Individual Genome		
Data Loading	3.3 B reads	106.5 GB	\$10.65
Data Transfer	Ih:15m	40 cores	\$3.40
Setup	0h : 15m	320 cores	\$13.94
Alignment	Ih:30m	320 cores	\$41.82
Variant Calling	Ih:00m	320 cores	\$27.88
End-to-end	4h:00m		\$97.69

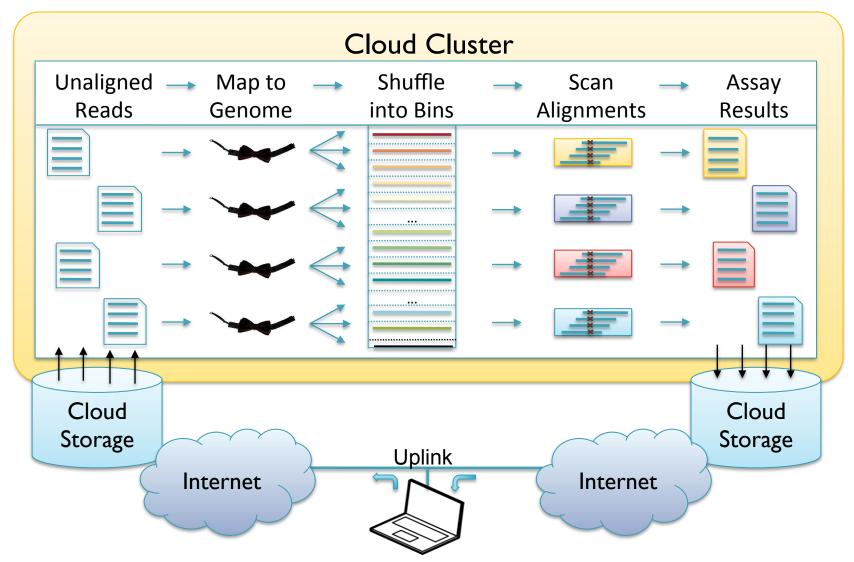
Discovered 3.7M SNPs in one human genome for ~\$100 in an afternoon.

Accuracy validated at >99%

Searching for SNPs with Cloud Computing.

Langmead B, Schatz MC, Lin J, Pop M, Salzberg SL (2009) Genome Biology. 10:R134

Map-Shuffle-Scan for Genomics

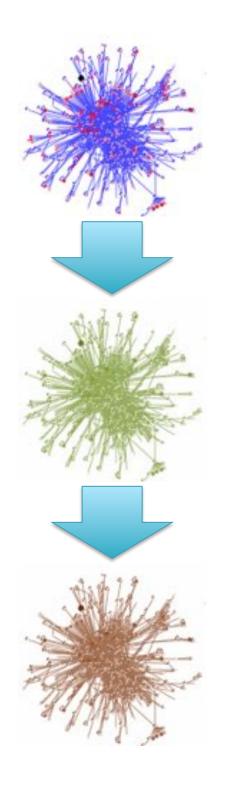


Cloud Computing and the DNA Data Race.

Schatz, MC, Langmead B, Salzberg SL (2010) Nature Biotechnology. 28:691-693

3. Tightly Coupled

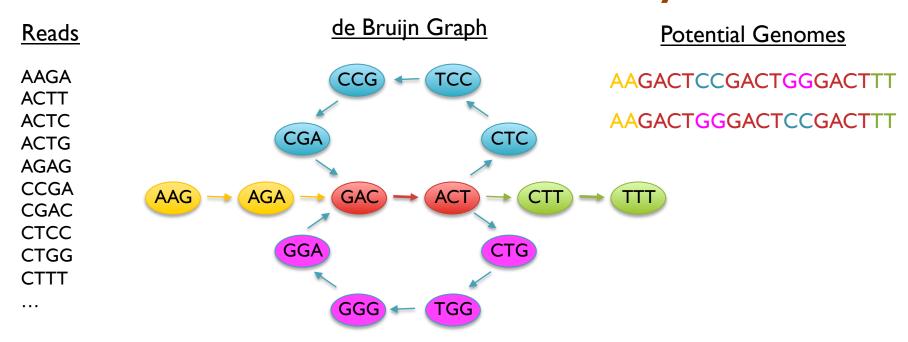
- Computation that cannot be partitioned
 - Graph Analysis
 - Molecular Dynamics
 - Population simulations
- Challenges
 - Loosely coupled challenges
 - + Parallel algorithms design
- Technologies
 - MPI
 - MapReduce, Dryad, Pregel



High School Dance



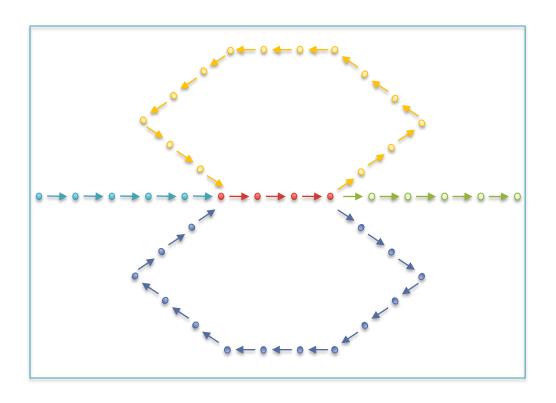
Short Read Assembly

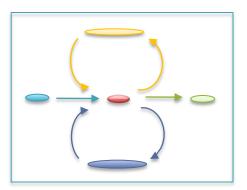


- Genome assembly as finding an Eulerian tour of the de Bruijn graph
 - Human genome: >3B nodes, >10B edges
- The new short read assemblers require tremendous computation
 - Velvet (Zerbino & Birney, 2008) serial: > 2TB of RAM
 - ABySS (Simpson et al., 2009) MPI: 168 cores x ~96 hours
 - SOAPdenovo (Li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





Warmup Exercise

- Who here was born closest to March 28?
 - You can only compare to I other person at a time



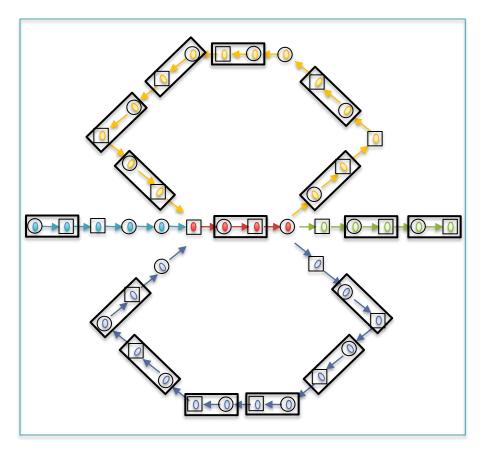
Find winner among 64 teams in just 6 rounds

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)→T links



Initial Graph: 42 nodes

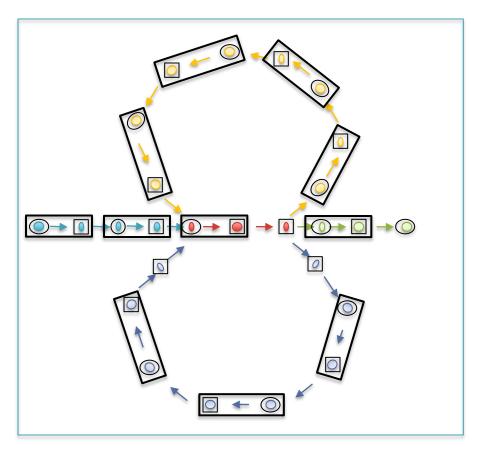
Randomized Speed-ups in Parallel Computation.

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)→T links



Round 1: 26 nodes (38% savings)

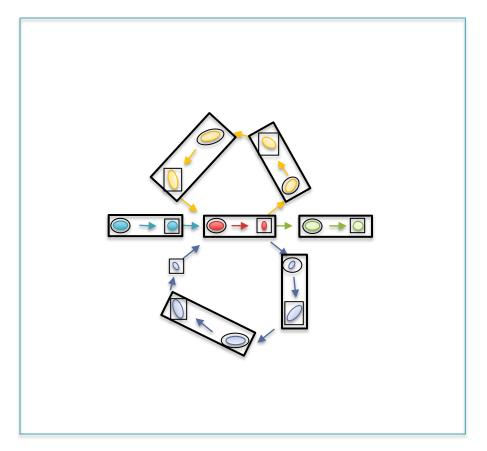
Randomized Speed-ups in Parallel Computation.

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)→T links



Round 2: 15 nodes (64% savings)

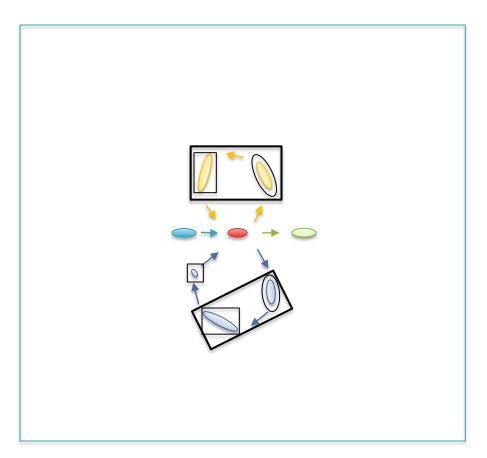
Randomized Speed-ups in Parallel Computation.

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)→T links



Round 2: 8 nodes (81% savings)

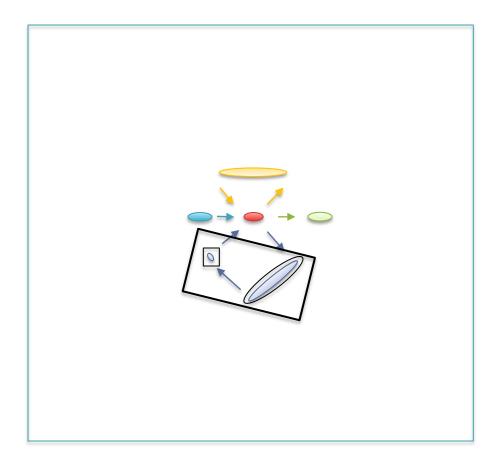
Randomized Speed-ups in Parallel Computation.

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)→T links



Round 3: 6 nodes (86% savings)

Randomized Speed-ups in Parallel Computation.

Challenges

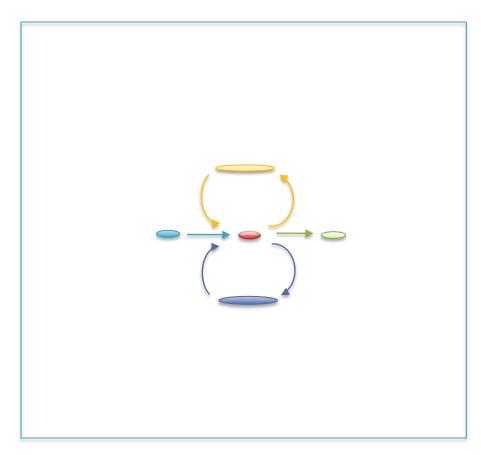
- Nodes stored on different computers
- Nodes can only access direct neighbors

Randomized List Ranking

- Randomly assign (H)/ T to each compressible node
- Compress (H)→T links

Performance

Compress all chains in log(S) rounds

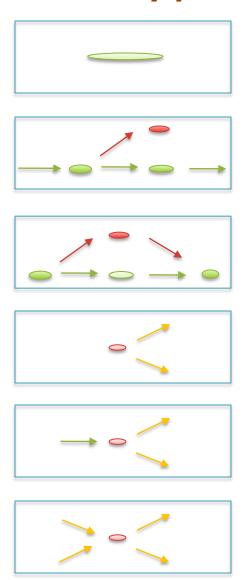


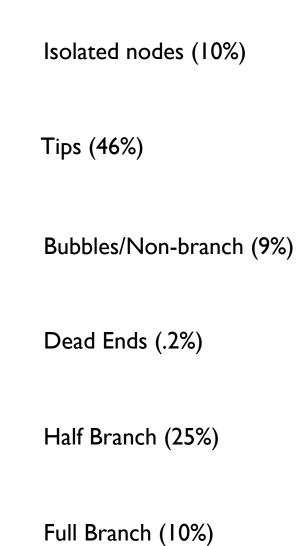
Round 4: 5 nodes (88% savings)

Randomized Speed-ups in Parallel Computation.

Node Types







(Chaisson, 2009)

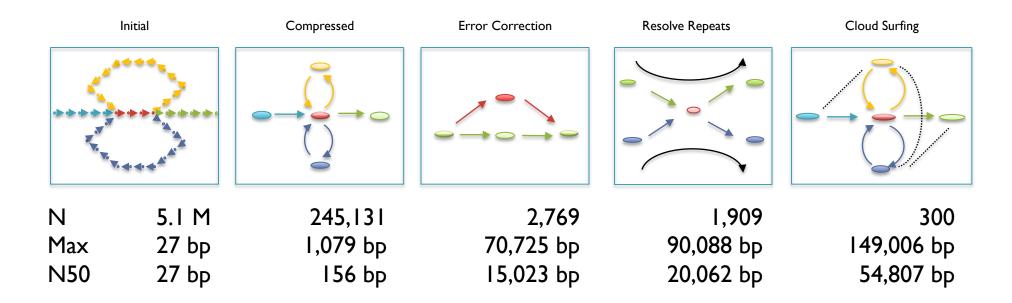
Contrail

http://contrail-bio.sourceforge.net



De novo bacterial assembly

- Genome: E. coli K12 MG1655, 4.6Mbp
- Input: 20.8M 36bp reads, 200bp insert (~150x coverage)
- Preprocessor: Quake Error Correction



Assembly of Large Genomes with Cloud Computing.

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

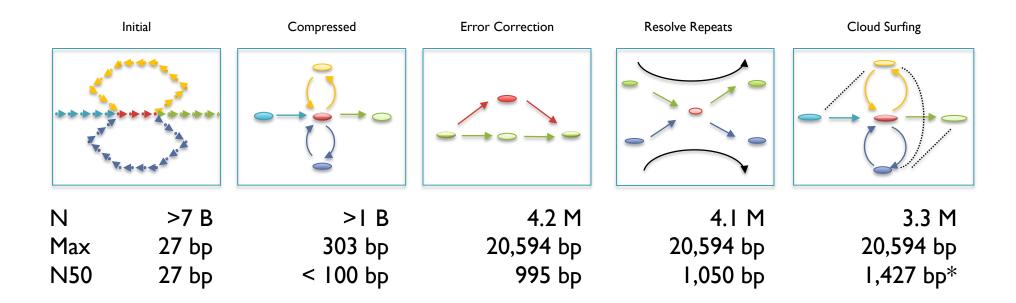
Contrail

http://contrail-bio.sourceforge.net



De novo Assembly of the Human Genome

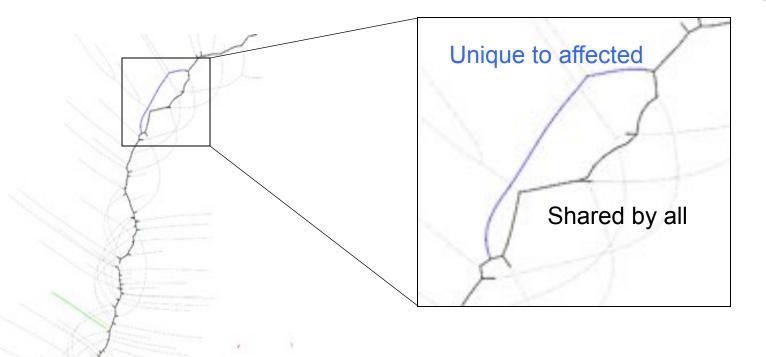
- Genome: African male NA18507 (SRA000271, Bentley et al., 2008)
- Input: 3.5B 36bp reads, 210bp insert (~40x coverage)



Assembly of Large Genomes with Cloud Computing.

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

De novo mutations and de Bruijn Graphs

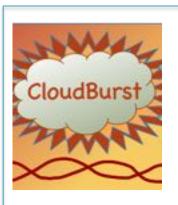


Searching for de novo mutations in the families of 3000 autistic children.

- Assemble together reads from mom, dad, affected & unaffected children
- Look for sequence paths unique to affected child

MRCILI

Hadoop for NGS Analysis



CloudBurst

Highly Sensitive Short Read Mapping with MapReduce

100x speedup mapping on 96 cores @ Amazon

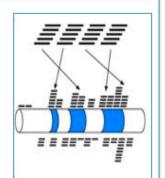
http://cloudburst-bio.sf.net

(Schatz, 2009)

Myrna

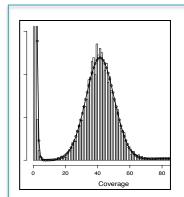
Cloud-scale differential gene expression for RNA-seq

Expression of 1.1 billion RNA-Seq reads in ~2 hours for ~\$66



(Langmead, Hansen, Leek, 2010)

http://bowtie-bio.sf.net/myrna/



Quake

Quality-aware error correction of short reads

Correct 97.9% of errors with 99.9% accuracy

http://www.cbcb.umd.edu/software/quake/

(Kelley, Schatz, Salzberg, 2010)

Genome Indexing

Rapid Parallel Construction of Genome Index

Construct the BWT of the human genome in 9 minutes

\$GATTACA A\$GATTACA\$G ACA\$GATTACA\$G CA\$GATTACA£ GATTACA£ TACA\$GATTACA£

(Menom, Bhat, Schatz, 2011*)

http://code.google.com/p/ genome-indexing/



Summary

- Staying afloat in the data deluge means computing in parallel
 - Hadoop + Cloud computing is an attractive platform for large scale sequence analysis and computation
- Significant obstacles ahead
 - Price
 - Transfer time
 - Privacy / security requirements
 - Time and expertise required for development
- Emerging technologies are a great start, but we need continued research
 - Need integration across disciplines
 - A word of caution: new technologies are new

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<u>JHU</u>

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Jeff Leek

Univ. of Maryland

Steven Salzberg

Mihai Pop

Art Delcher

Jimmy Lin

Adam Phillippy

David Kelley

Dan Sommer



Thank You!

http://schatzlab.cshl.edu @mike_schatz