

Assembly of Large Genomes using Cloud Computing

Michael Schatz

July 23, 2010

Illumina Sequencing Panel



How to compute with 1000s of cores

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Parallel Architectures

- Why Parallel?
 - CPU manufactures up against fundamental limitations
 - Need it done faster, problem is too big for a single machine
- Multi-core (2-10s of cores)
 - Familiar programming environment
 - Limited scaling
- GPU & FPGA (10s – 1000 of cores)
 - Very high performance for some applications
 - Limited/Slow memory, complicated development environment
- Cluster / Distributed Programming (10s – 1000s of machines)
 - Well suited for very large data problems
 - Scheduling, Fault tolerance & Network communication

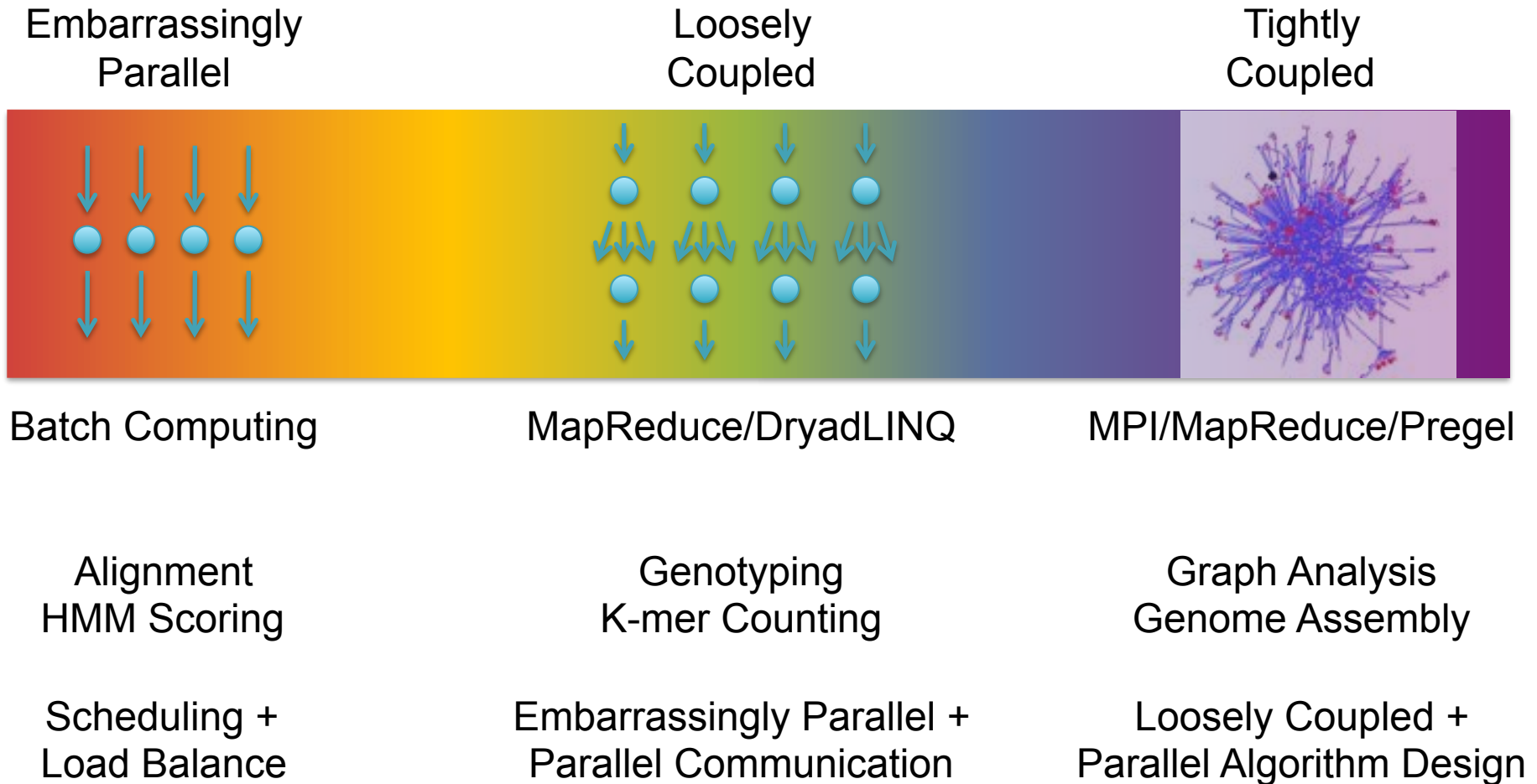
Amazon Web Services

<http://aws.amazon.com>

- “All you need is a credit card to use one of the largest datacenters in the world”
 - Best for large infrequent computations
- Elastic Compute Cloud (EC2)
 - On demand computing power
 - Support for Windows, Linux, & OpenSolaris
 - Starting at 8.5¢ / core / hour
- Simple Storage Service (S3)
 - Scalable data storage
 - 10¢ / GB upload fee, 15¢ / GB monthly fee

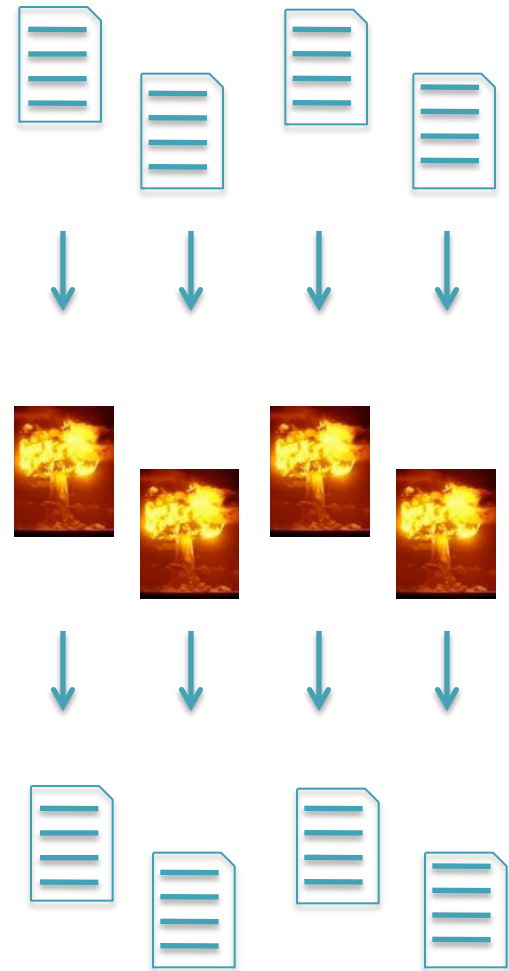


Parallel Algorithms Spectrum



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

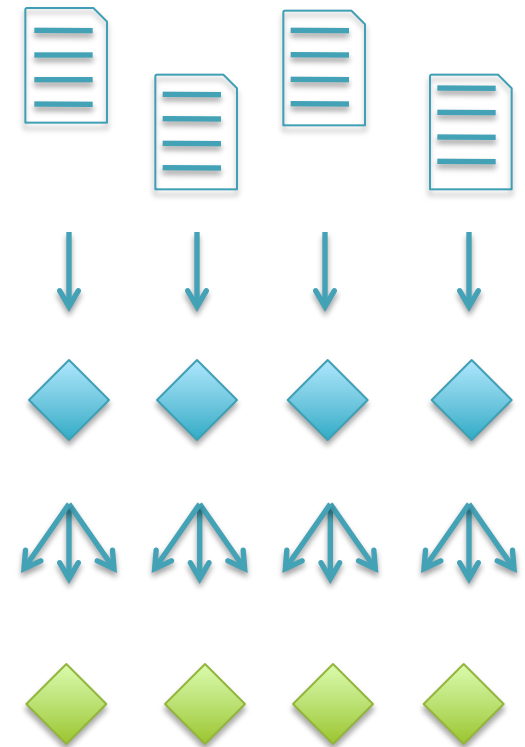


Elementary School Dance



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



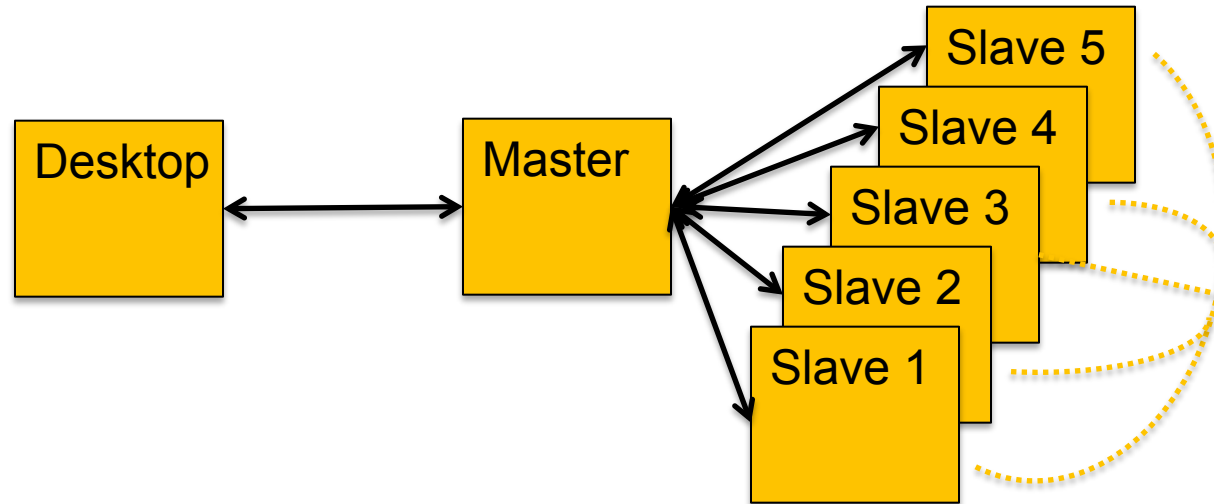
Hadoop MapReduce

<http://hadoop.apache.org>

- MapReduce is the parallel distributed framework invented by Google for large data computations.
 - Data and computations are spread over thousands of computers, processing petabytes of data each day (Dean and Ghemawat, 2004)
 - Indexing the Internet, PageRank, Machine Learning, etc...
 - Hadoop is the leading open source implementation
 - 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

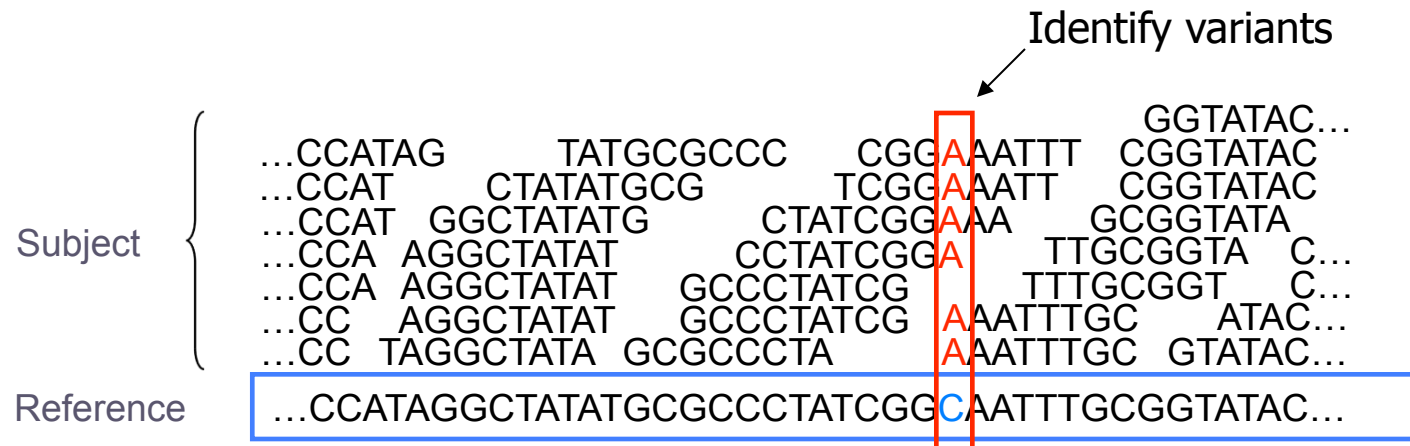


Hadoop Architecture



- 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

Short Read Mapping



- Given a reference and many subject reads, report one or more “good” end-to-end 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

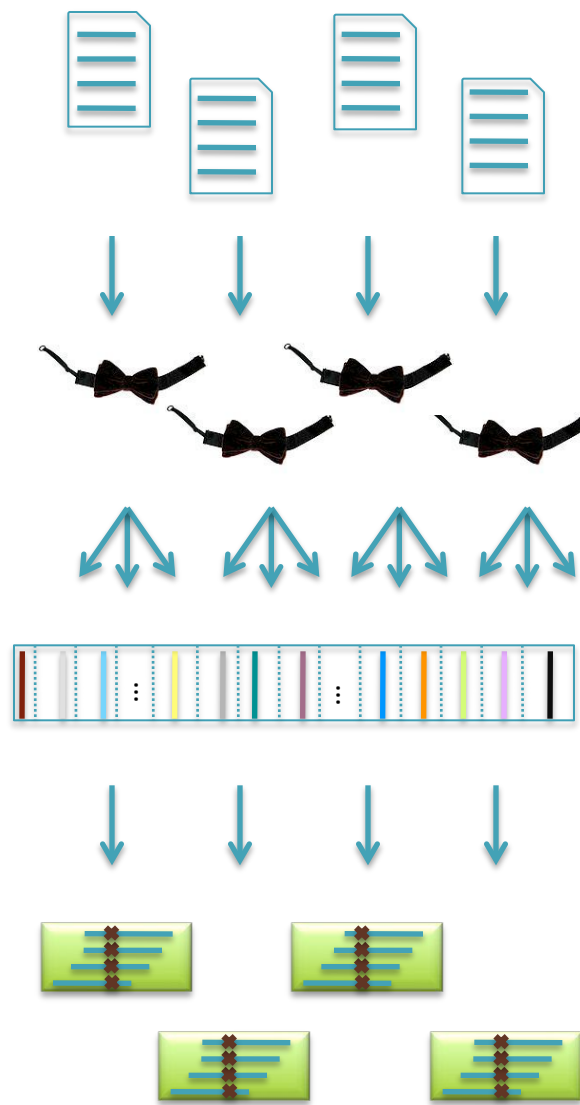
- Desperate need for scalable solutions
 - Single human requires ~1,000 CPU hours / genome



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	1h :15m	40 cores	\$3.40
Setup	0h : 15m	320 cores	\$13.94
Alignment	1h : 30m	320 cores	\$41.82
Variant Calling	1h : 00m	320 cores	\$27.88
End-to-end	4h : 00m		\$97.69

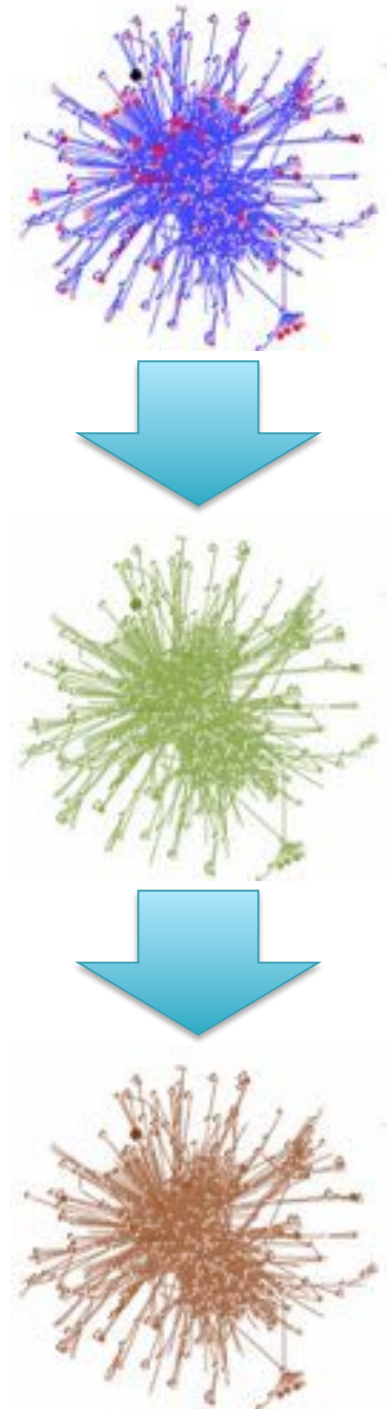
Analyze an entire human genome for ~\$100 in an afternoon.
Accuracy validated at >99%

Searching for SNPs with Cloud Computing.

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

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

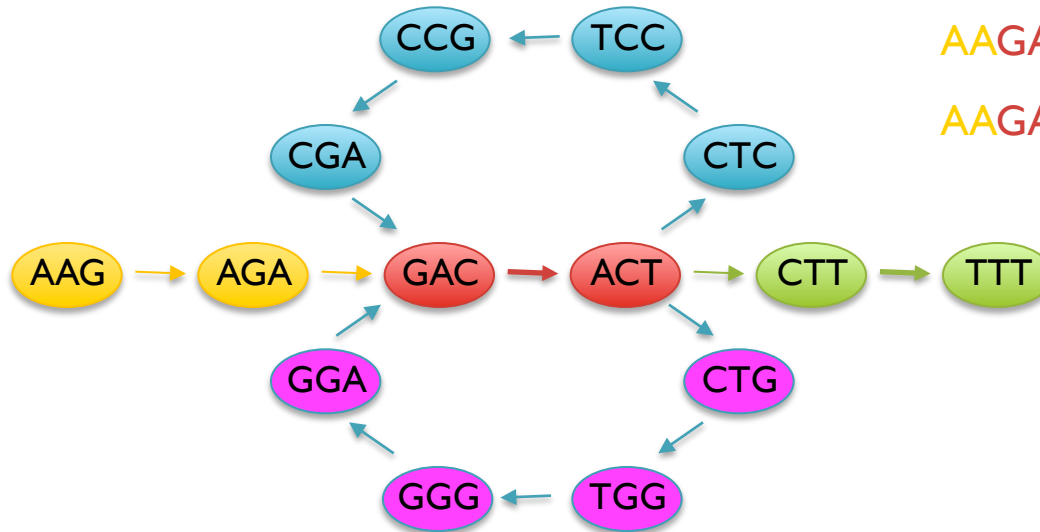


Short Read Assembly

Reads

AAGA
ACTT
ACTC
ACTG
AGAG
CCGA
CGAC
CTCC
CTGG
CTTT
...

de Bruijn Graph



Potential Genomes

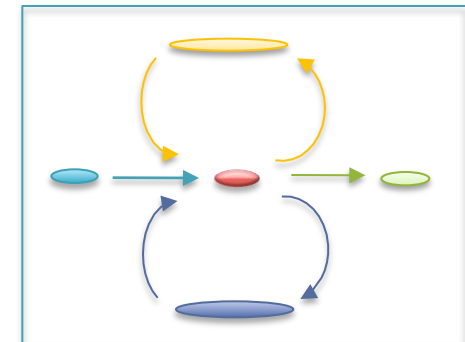
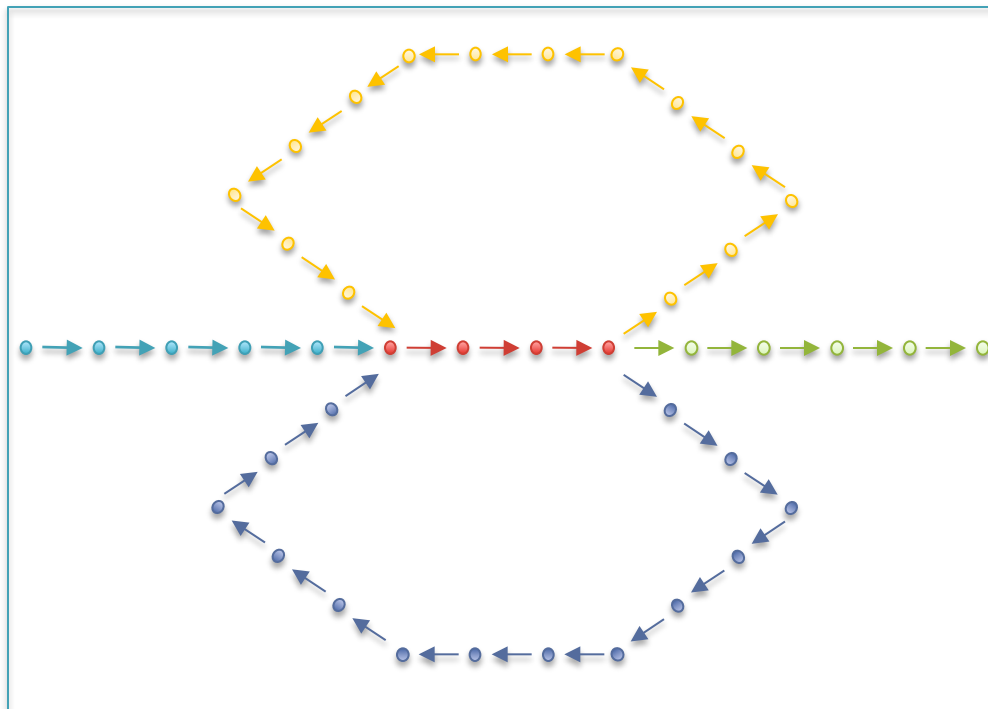
AAGACTCCGACTGGGACTTT

AAGACTGGGACTCCGACTTT

- 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 x weeks
 - 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

- Graph construction straightforward in MapReduce
 - Straightforward extension to k-mer counting
- 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 July 23?
 - You can only compare to one person at a time



Find winner among 16 teams in just 4 rounds

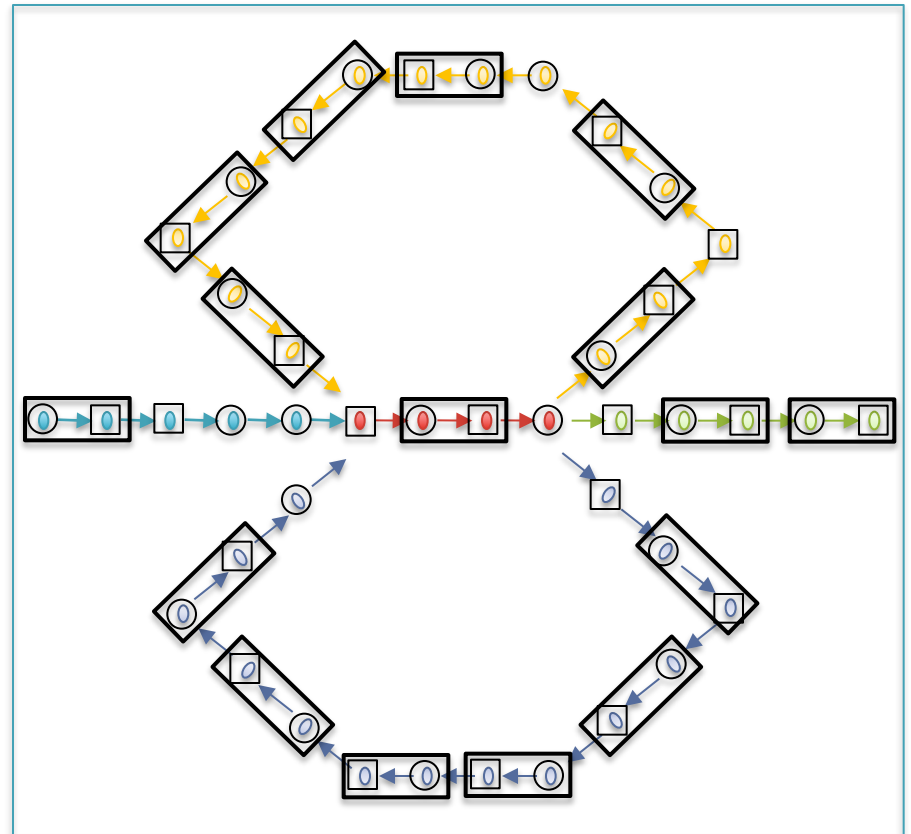
Fast Path Compression

Challenges

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

Randomized List Ranking

- Randomly assign \textcircled{H} / $\square T$ to each compressible node
- Compress $\textcircled{H} \rightarrow \square T$ links



Initial Graph: 42 nodes

Randomized Speed-ups in Parallel Computation.

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

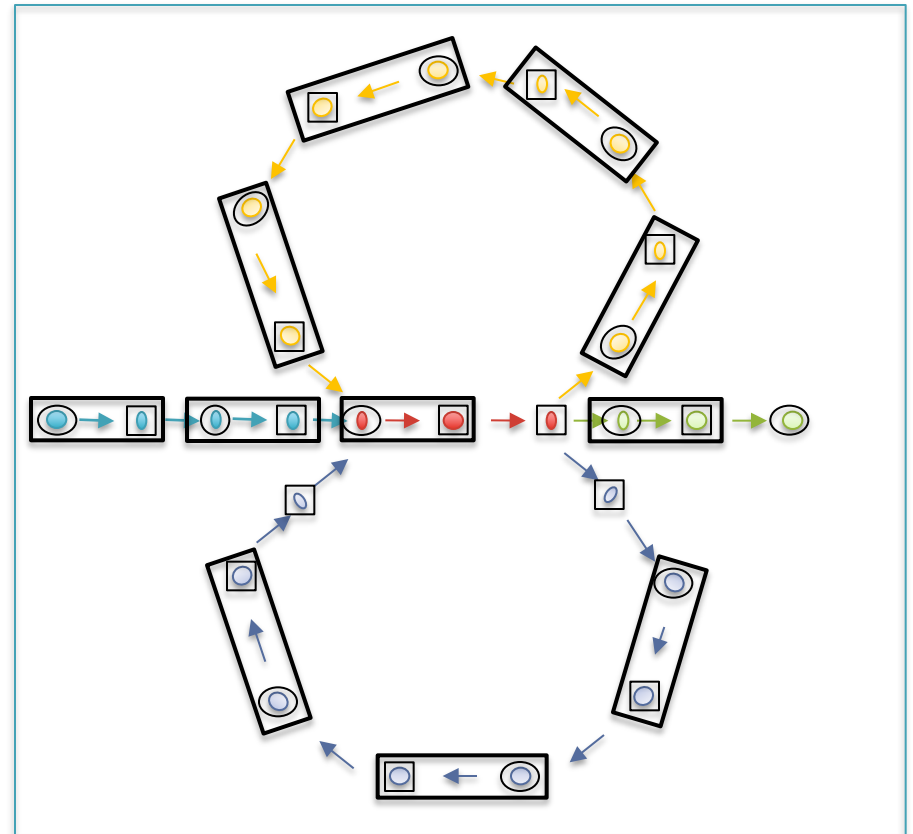
Fast Path Compression

Challenges

- Nodes stored on different computers
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Randomized List Ranking

- Randomly assign $\textcircled{\text{H}}$ / $\square{\text{T}}$ to each compressible node
- Compress $\textcircled{\text{H}} \rightarrow \square{\text{T}}$ links



Round 1: 26 nodes (38% savings)

Randomized Speed-ups in Parallel Computation.

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

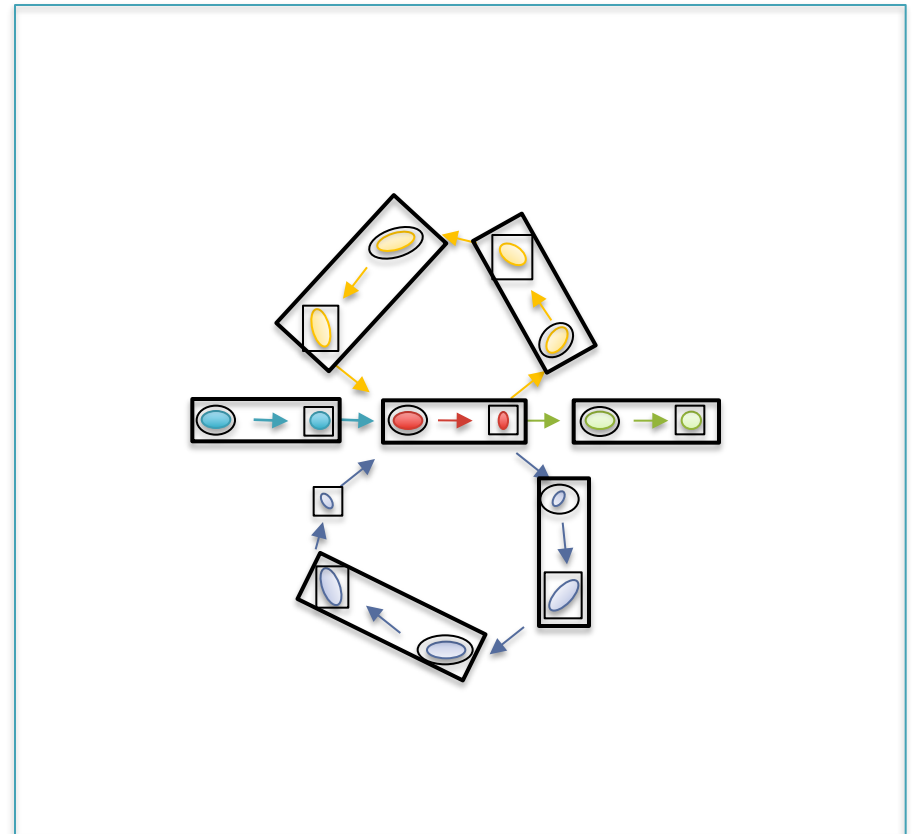
Fast Path Compression

Challenges

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

Randomized List Ranking

- Randomly assign $\textcircled{\text{H}}$ / $\boxed{\text{T}}$ to each compressible node
- Compress $\textcircled{\text{H}} \rightarrow \boxed{\text{T}}$ links



Round 2: 15 nodes (64% savings)

Randomized Speed-ups in Parallel Computation.

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

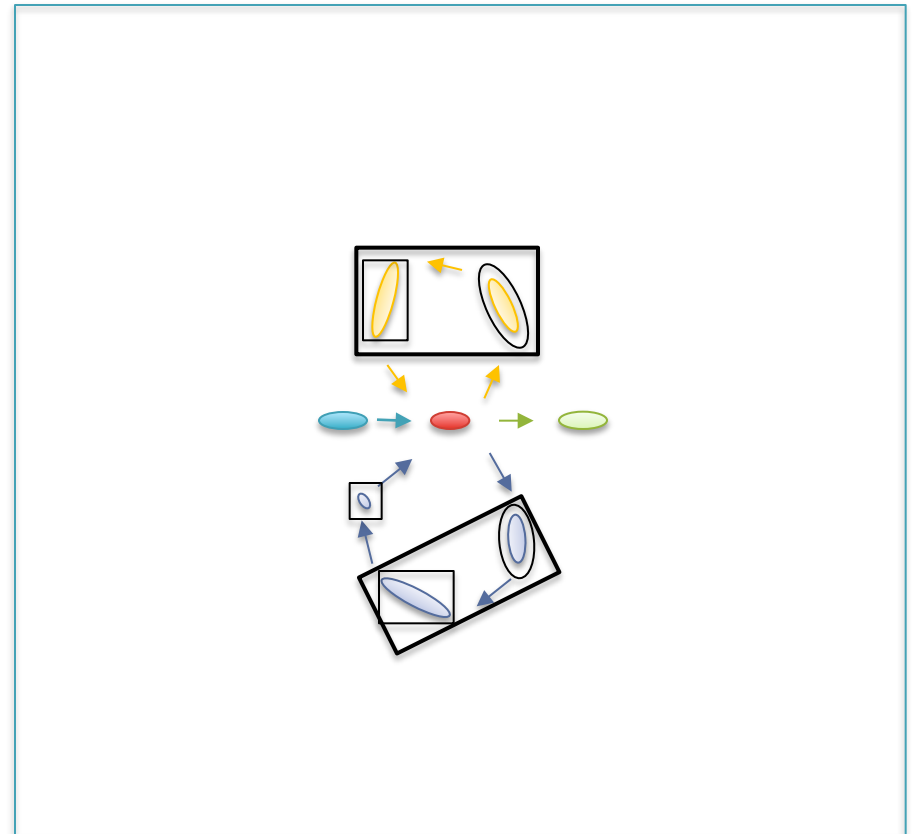
Fast Path Compression

Challenges

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

Randomized List Ranking

- Randomly assign $\textcircled{\text{H}}$ / $\boxed{\text{T}}$ to each compressible node
- Compress $\textcircled{\text{H}} \rightarrow \boxed{\text{T}}$ links



Round 2: 8 nodes (81% savings)

Randomized Speed-ups in Parallel Computation.

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

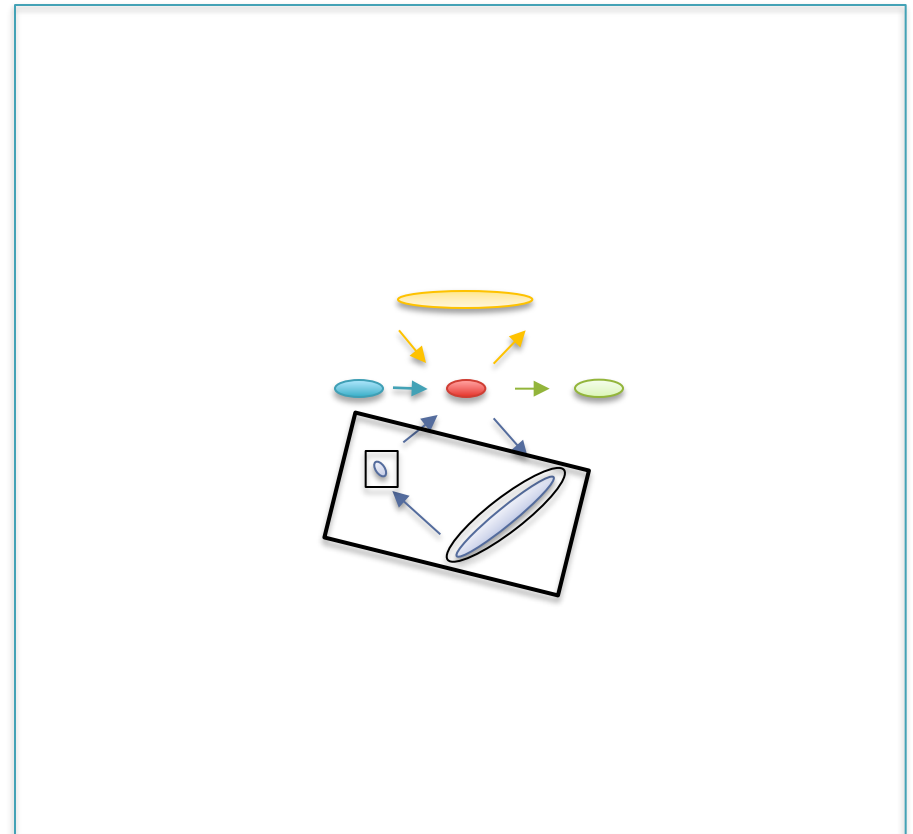
Fast Path Compression

Challenges

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

Randomized List Ranking

- Randomly assign $\textcircled{\text{H}}$ / $\boxed{\text{T}}$ to each compressible node
- Compress $\textcircled{\text{H}} \rightarrow \boxed{\text{T}}$ links



Round 3: 6 nodes (86% savings)

Randomized Speed-ups in Parallel Computation.

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

Fast Path Compression

Challenges

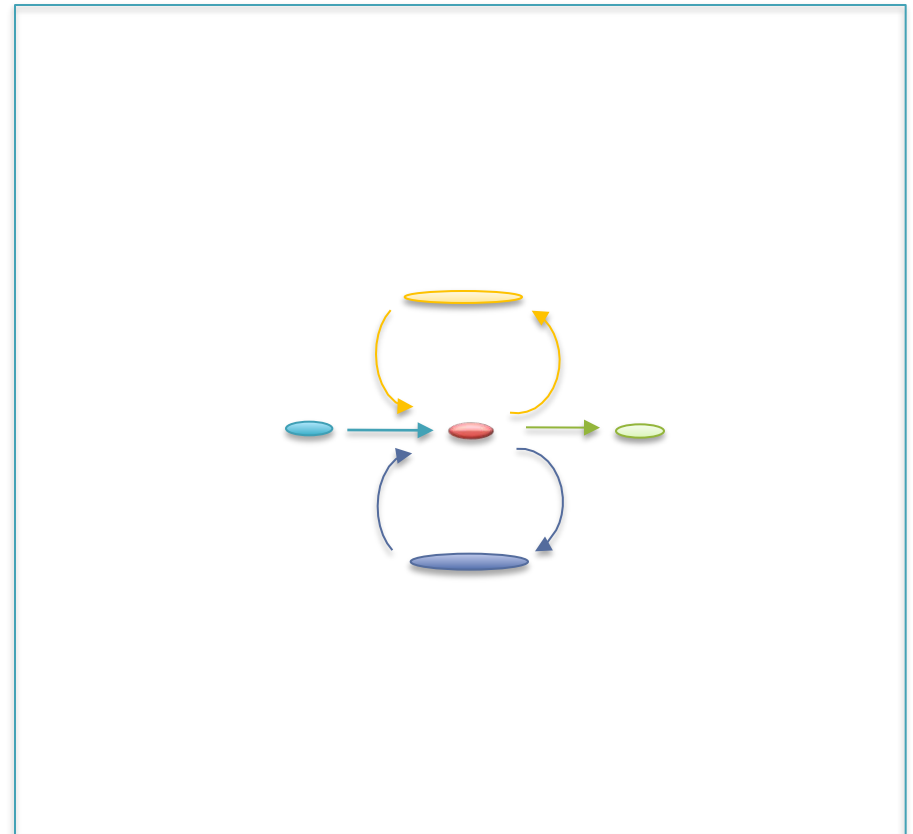
- Nodes stored on different computers
- Nodes can only access direct neighbors

Randomized List Ranking

- Randomly assign $\textcircled{\text{H}}$ / $\boxed{\text{T}}$ to each compressible node
- Compress $\textcircled{\text{H}} \rightarrow \boxed{\text{T}}$ links

Performance

- Compress all chains in $\log(S)$ rounds

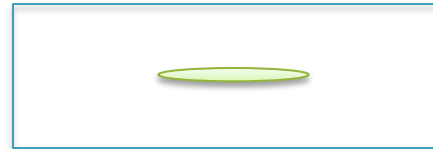


Round 4: 5 nodes (88% savings)

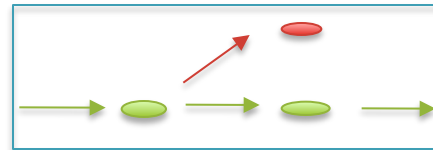
Randomized Speed-ups in Parallel Computation.

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

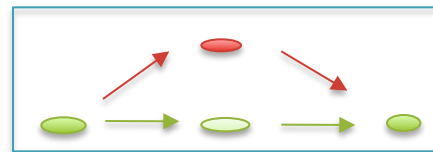
Node Types



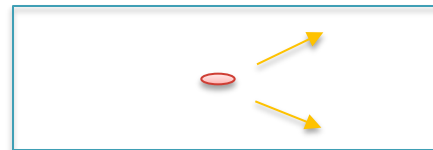
Isolated nodes (10%)



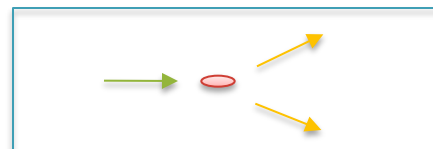
Tips (46%)



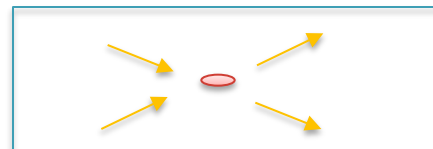
Bubbles/Non-branch (9%)



Dead Ends (.2%)



Half Branch (25%)



Full Branch (10%)

(Chaisson, 2009)

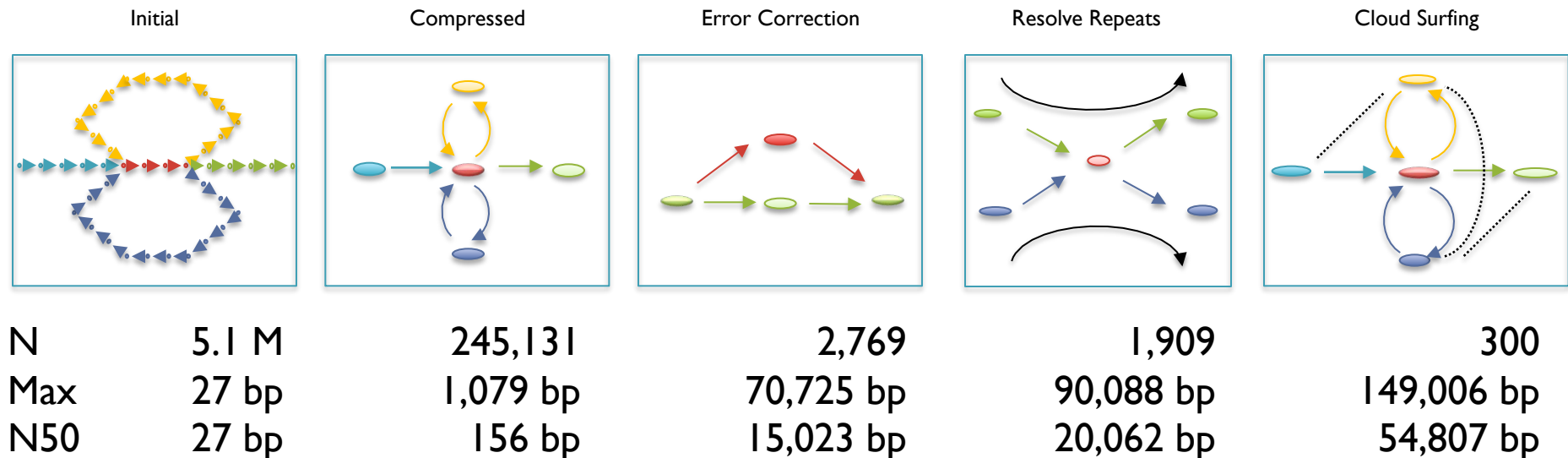
Contrail

<http://contrail-bio.sourceforge.net>



De novo bacterial assembly

- *Genome: E. coli* K12 MGI655, 4.6Mbp
- *Input: 20.8M 36bp reads, 200bp insert (~150x coverage)*
- *Preprocessor: Quality-Aware Error Correction*



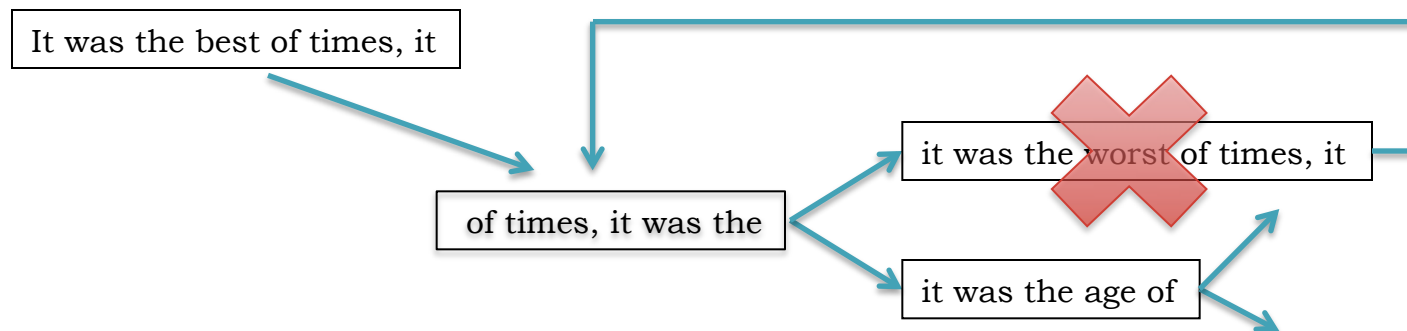
Assembly of Large Genomes with Cloud Computing.

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

E. coli Assembly Quality

Incorrect contigs: Align at < 95% identity or < 95% of their length

Assembler	Contigs \geq 100bp	N50 (bp)	Incorrect contigs
Contrail PE	300	54,807	4
Contrail SE	529	20,062	0
SOAPdenovo PE	182	89,000	5
ABYSS PE	233	45,362	13
Velvet PE	286	54,459	9
EULER-SR PE	216	57,497	26
SSAKE SE	931	11,450	38
Edena SE	680	16,430	6



A person is standing on a stage to the left of a large projection screen. The screen displays the text "One more thing..." in white on a blue background. A vertical purple light beam is visible on the left side of the stage.

One more thing...

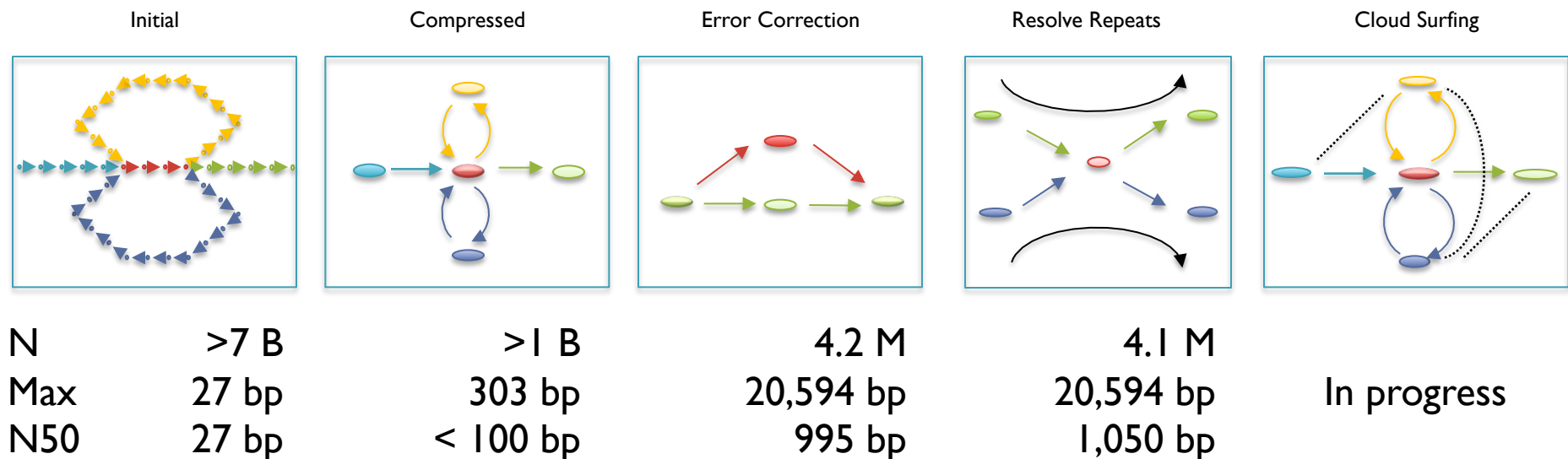
Contrail

<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.*


Scalable Solutions for DNA Sequence Analysis

Step 1: Align
To whole genome using Bowtie.
Parallel across reads.




Bin by genomic bin, sort along forward reference strand

Step 2: Overlap
With gene annotations.
Parallel across genomic bins.




Bin by technical replicate, sort by gene count

Step 3: Normalise
From gene count distribution, choose normalisation factor.
Parallel across technical replicates.



Bin by technical replicate, sort by gene count

Step 4: Statistics
Calculate p-value from expression matrix.
Parallel across genes.



Sort by p-value, Postprocess

Myrna

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

Cloud-scale differential gene expression from RNA-seq

Ben Langmead,
Kasper Hansen, Jeff Leek



Quake

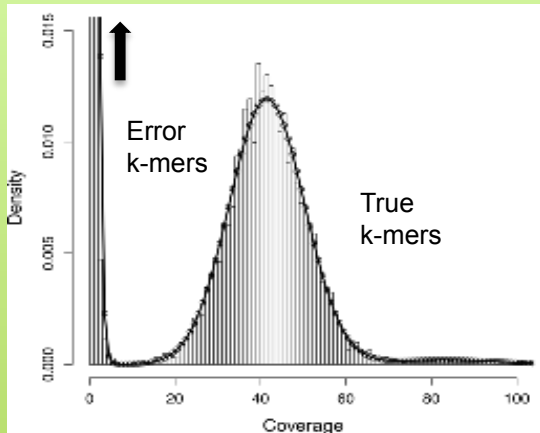
<http://www.cbc.umd.edu/software/quake>

Quality-aware error correction of sequencing reads

David Kelley,
Michael Schatz, Steven Salzberg

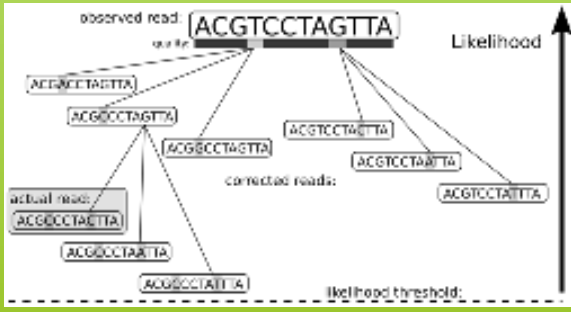
Step 1: Compute Q-mer Distribution

Compute in parallel across reads, merging together results across files



Step 2: Correct reads

Untrusted k-mers are evaluated in order of decreasing likelihood.





Summary

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

Acknowledgements



Steven Salzberg



Mihai Pop



Jimmy Lin



Ben Langmead



Dan Sommer



David Kelley



Thank You!

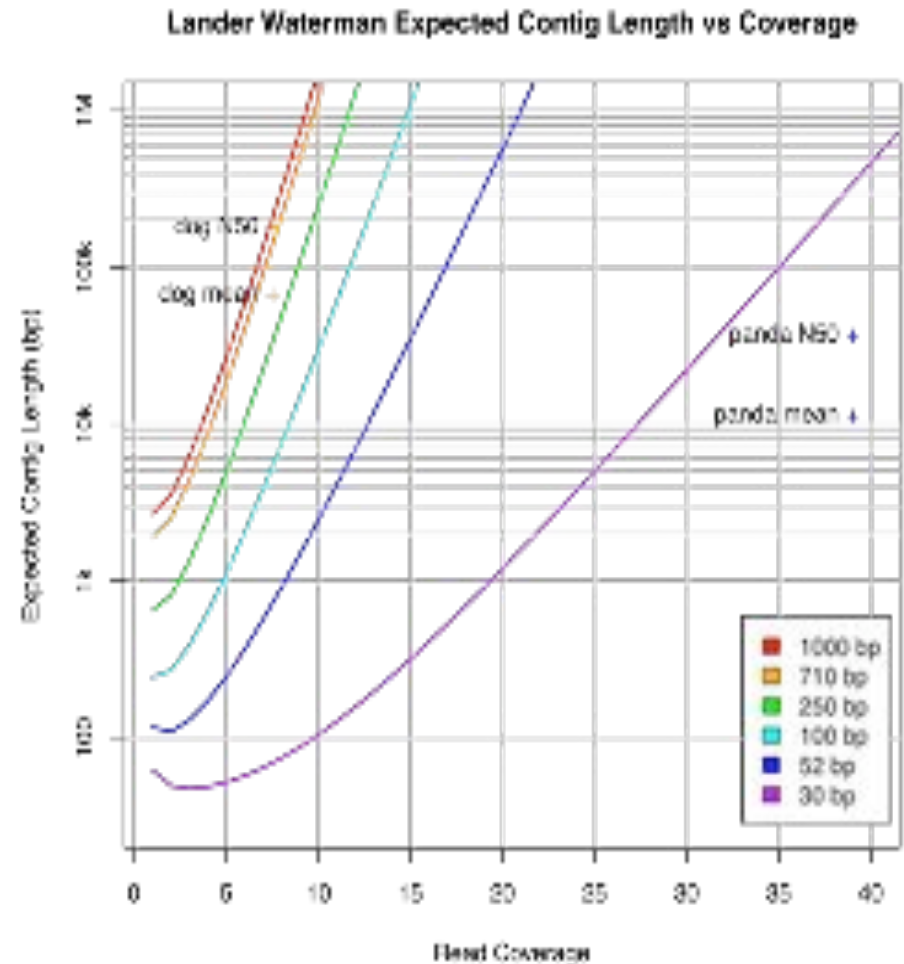
<http://www.cbcu.umd.edu/~mschatz>

@mike_schatz

Genome Coverage

Idealized assembly

- Uniform probability of a read starting at a given position
 - $p = G/N$
- Poisson distribution in coverage along genome
 - Contigs end when there is no overlapping read
- Contig length is a function of coverage and read length
 - Short reads require much higher coverage



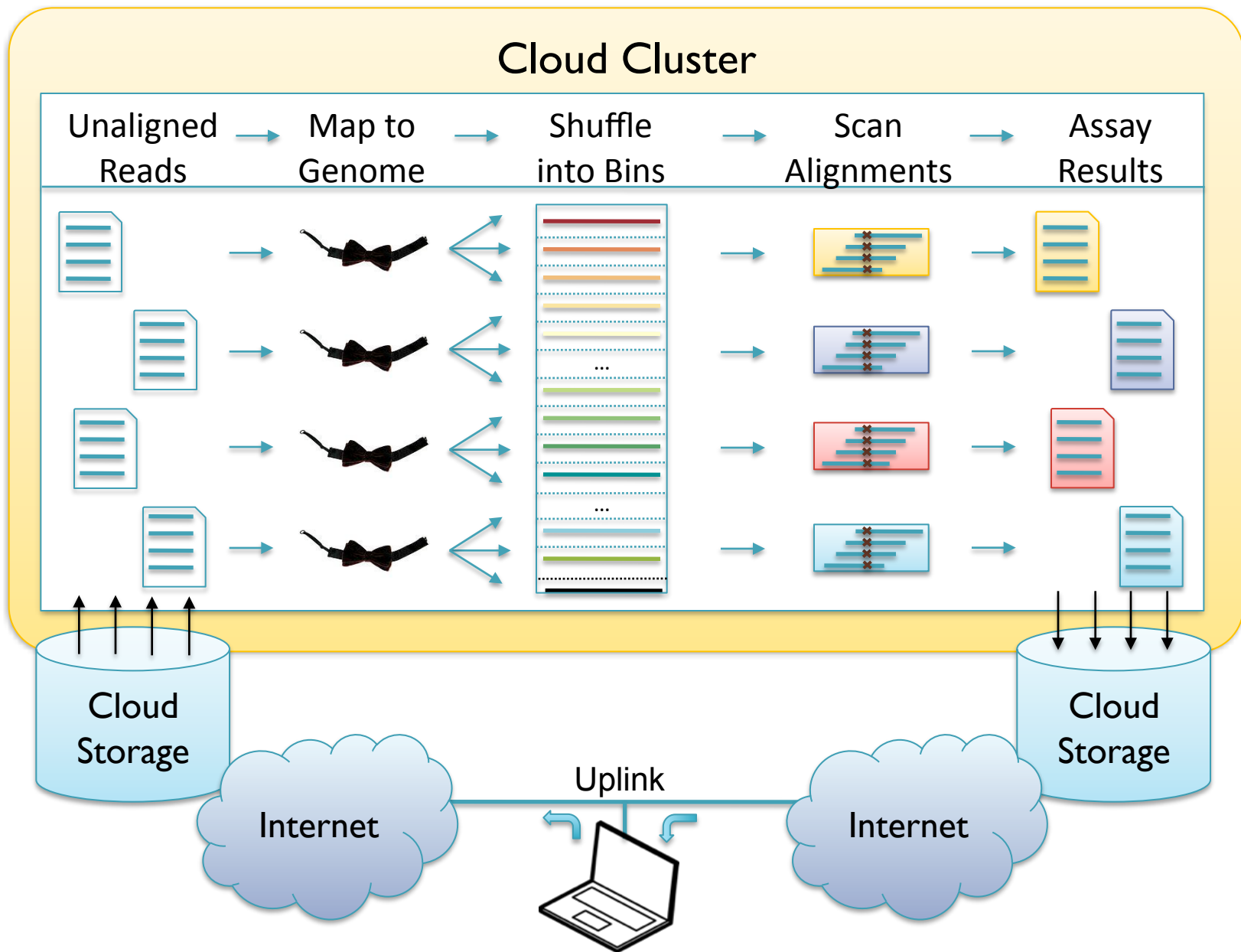
Assembly of Large Genomes using Second Generation Sequencing

Schatz MC, Delcher AL, Salzberg SL (2010) *Genome Research*.

Recent Large Assemblies

Table 1. De novo assembly of second generation sequencing projects.

Organism/ Genome Size	Assembly Status	Input Sequenced						Assemblies								
		Type	Paired Ends	Avg Reads/Pair	# Reads	Read Len	Paired Len	Contigs				Scaffolds				
								#	Size	Avg	Total	#	Size	Avg	Total	
Human 4 x 10 ⁹ 1.8Gb	AGFA Feb 2009	SA	100M	31.4b	3.3b	40x	12M	1,700	1,000	18,800	1,000	50	50	50	50	
Drosophila 1 x 10 ⁸ 100Mb	HG/SL Feb 2007	Large	2.5M	17b	1,000	6.5x	4.2x	68,821	18,000	2,000	20,000	2,000	1,000	1,000	10,000	+
		Large	400	50	100	0.10x	0.1x									
		Large	1,000	50	400	0.10x	0.1x									
		SA	100	100	1,000	4.2x	-									
Drosophila 1 x 10 ⁸ 100Mb	HG/SL Feb 2009	Large	2.5M	17b	1,000	6.5x	4.2x	61,821	18,000	50	20,000	41,807	1,000	50	20,000	+
		Large	400	50	100	0.10x	0.1x									
		Large	100M	50	50,000	0.10x	0.1x									
		SA	200	50	20,000	0.10x	0.1x									
		SA	100M	50	10,000	0.10x	0.1x									
Human 4 x 10 ⁹ 1.8Gb	HG/SL Feb 2009	SA	100	50	1,000	14.7x	41.5x	200,000	20,000	50,000	1,000	50,000	1,000	50,000	2,000	+
		SA	100	50	10,000	14.7x	41.5x									
		SA	200	70	20,000	14.7x	41.5x									
		SA	500	100	50,000	8.0x	12.0x									
		SA	1000	100	100,000	4.2x	6.5x									
Drosophila 1 x 10 ⁸ 100Mb	HG/SL & HG/SL Assembled	SA	100	100	1,000	1.0x	-	68,821	18,000	20,000	20,000	2,000	1,000	1,000	10,000	+
		SA	100	100	10,000	1.0x	-									
		SA	1,000	100	1,000	1.0x	6.5x									
		SA	1000	100	1,000	1.7x	6.5x									
		SA	100	10	100	1.0x	-									
		SA	200	10	1,000	0.10x	6.5x									
Human 4 x 10 ⁹ 1.8Gb	HG/SL Assembled	SA	100	100	100	10	50	100,000	10,000	1000	10,000	50,000	1,000	1000	50	+
		SA	200	100	200	0.2x	100									
		SA	1000	100	1000	0.1x	100									
		SA	1000	10	1000	0.1x	100									
		SA	100	10	100	0.1x	-									



Cloud Computing and the DNA Data Race.

Schatz, MC, Langmead, B, Salzberg SL (2010) *Nature Biotechnology*.

Human Assembly Quality

Assembler	Contigs \geq 100bp	N50 (bp)	Total Length (Gbp)
Contrail SE	4,285,080	1,050	2.13
SOAPdenovo PE	NA	4,611	2.63
SOAPdenovo SE	NA	886	2.10
ABYSS PE	2,762,173	1,499	2.18
ABYSS SE	4,348,132	870	2.10