

Comparison of microbial eukaryotic single cell genome assembly tools

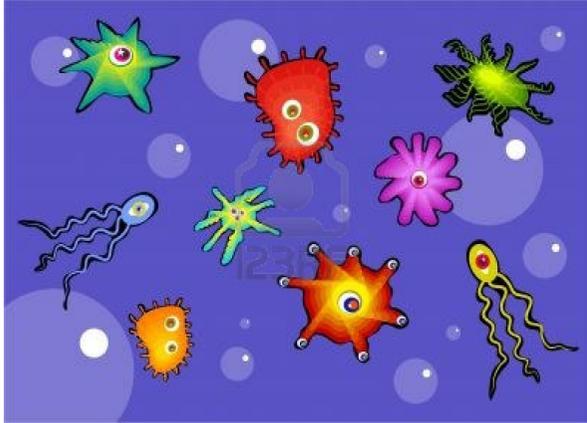
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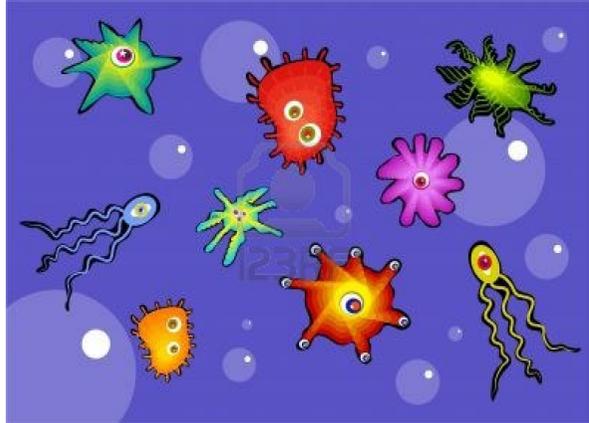
²BioMaPS Institute for Quantitative Biology, Rutgers University, Piscataway, NJ 08854, USA.

³Department of Ecology, Evolution and Natural Resources, Rutgers University, New Brunswick, NJ 08901, USA.

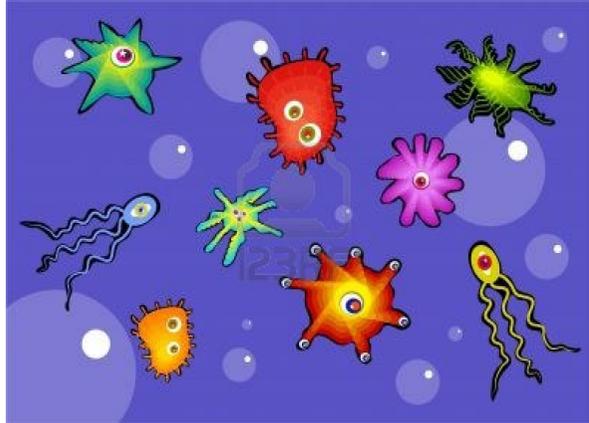
Why single cell *de novo* genome assembly?



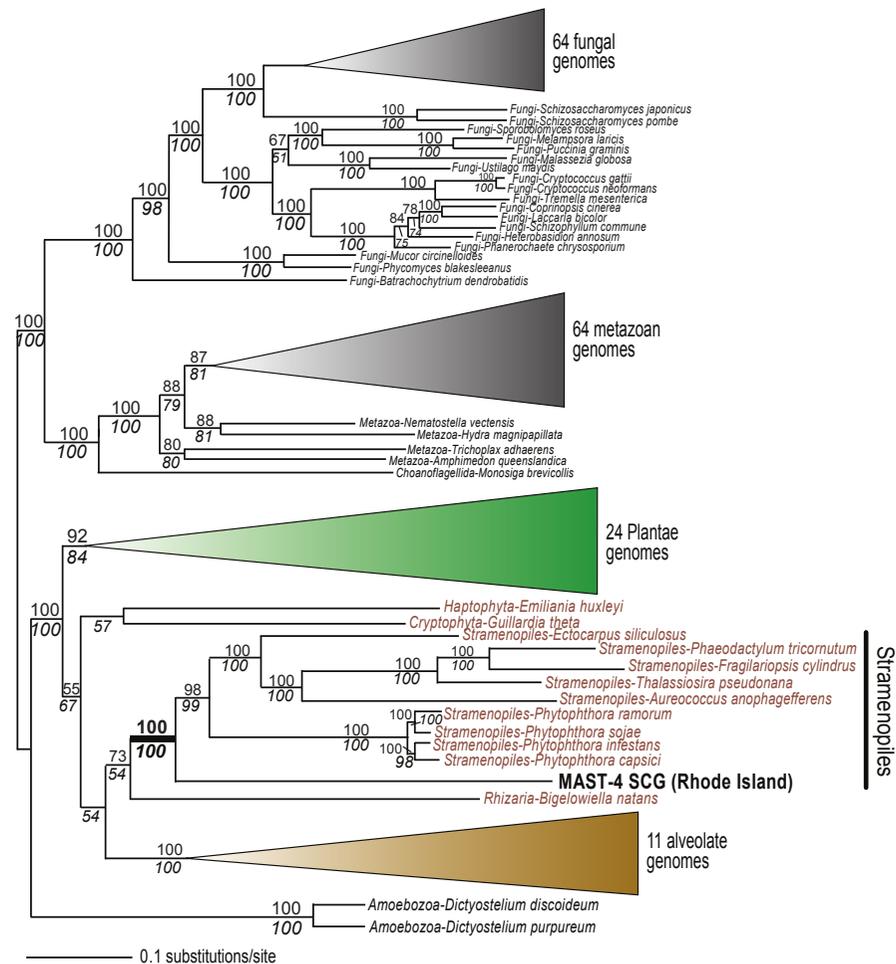
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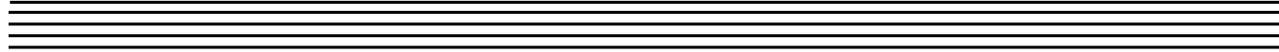
Evolutionary analysis of a wild-caught stramenopile



Evolutionary analysis of single cell genome data from a wild-caught marine stramenopile. Rajat S. Roy, Dana C. Price, Alexander Schliep, Guohong Cai, Anton Korobeynikov, Hwan Su Yoon, Eun Chan Yang, and D Bhattacharya. (In preparation), 2013.

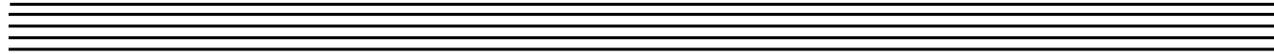
Genome Assembly

Multiple copies of the target genome

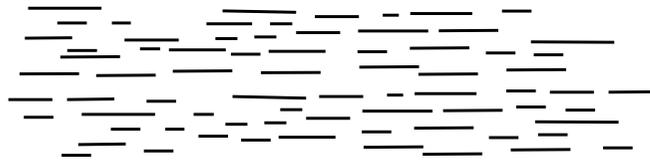


Genome Assembly

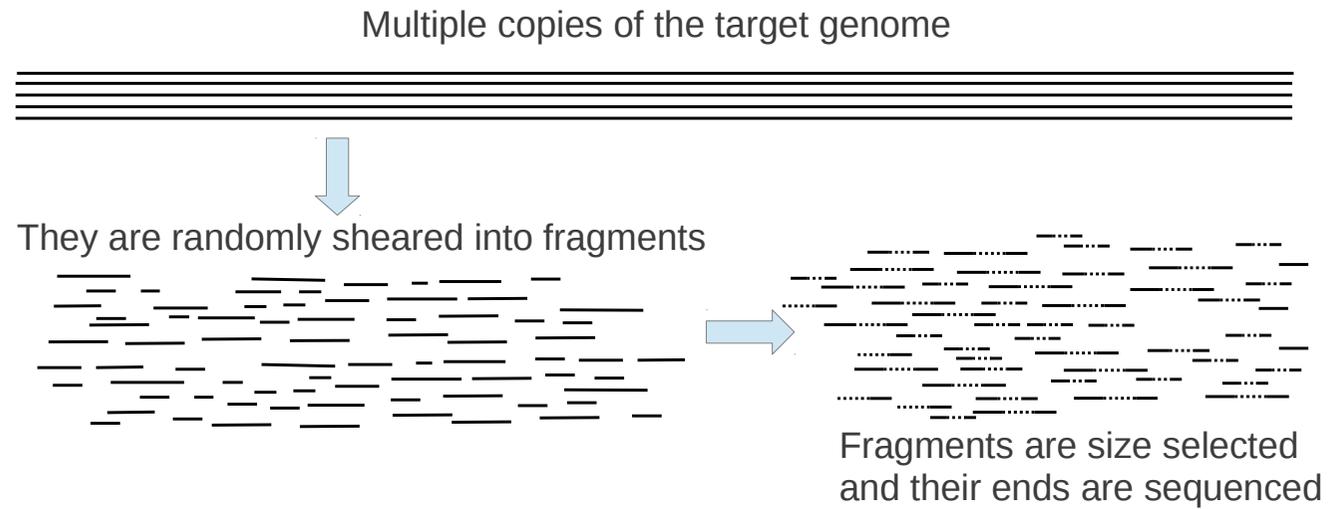
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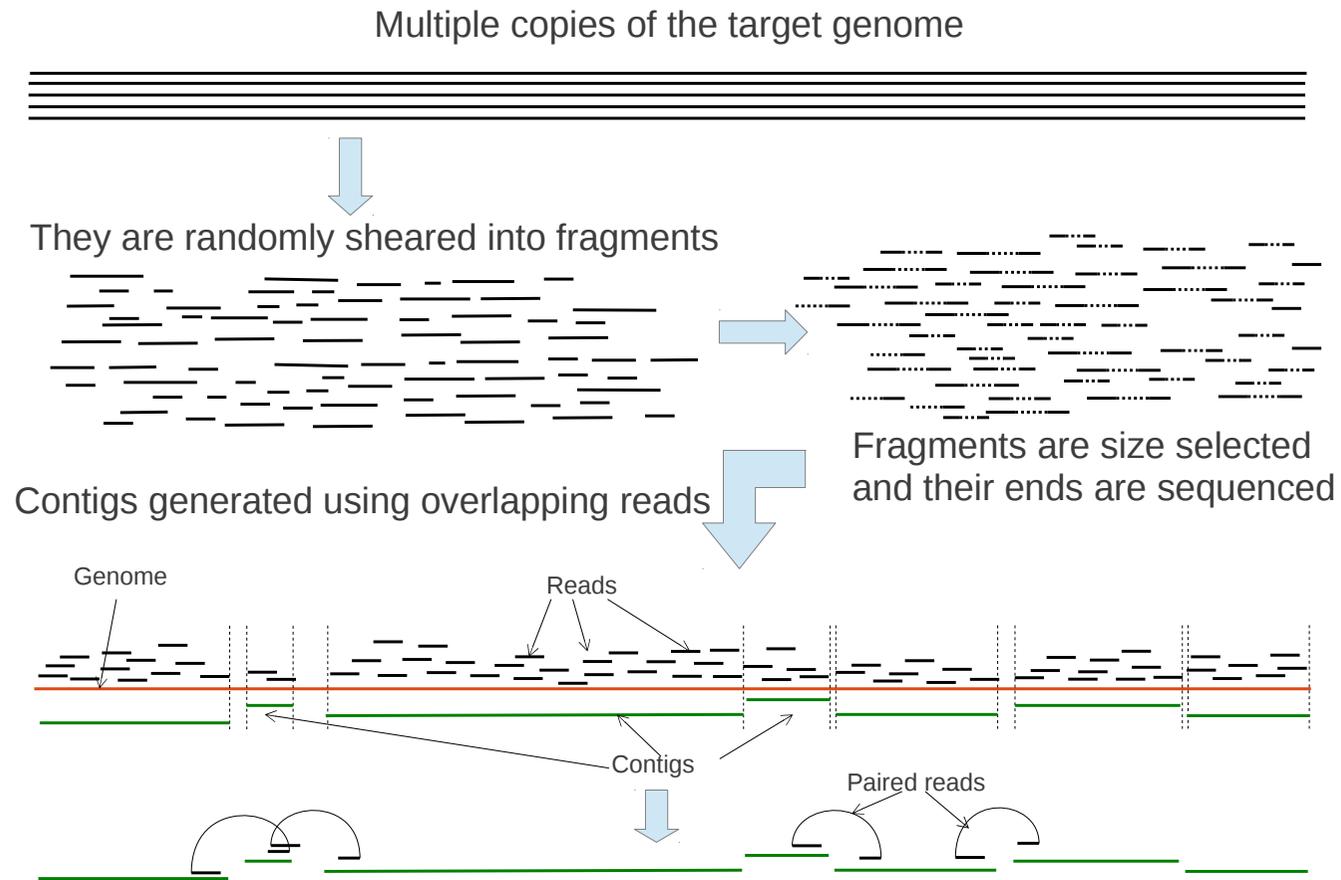
They are randomly sheared into fragments



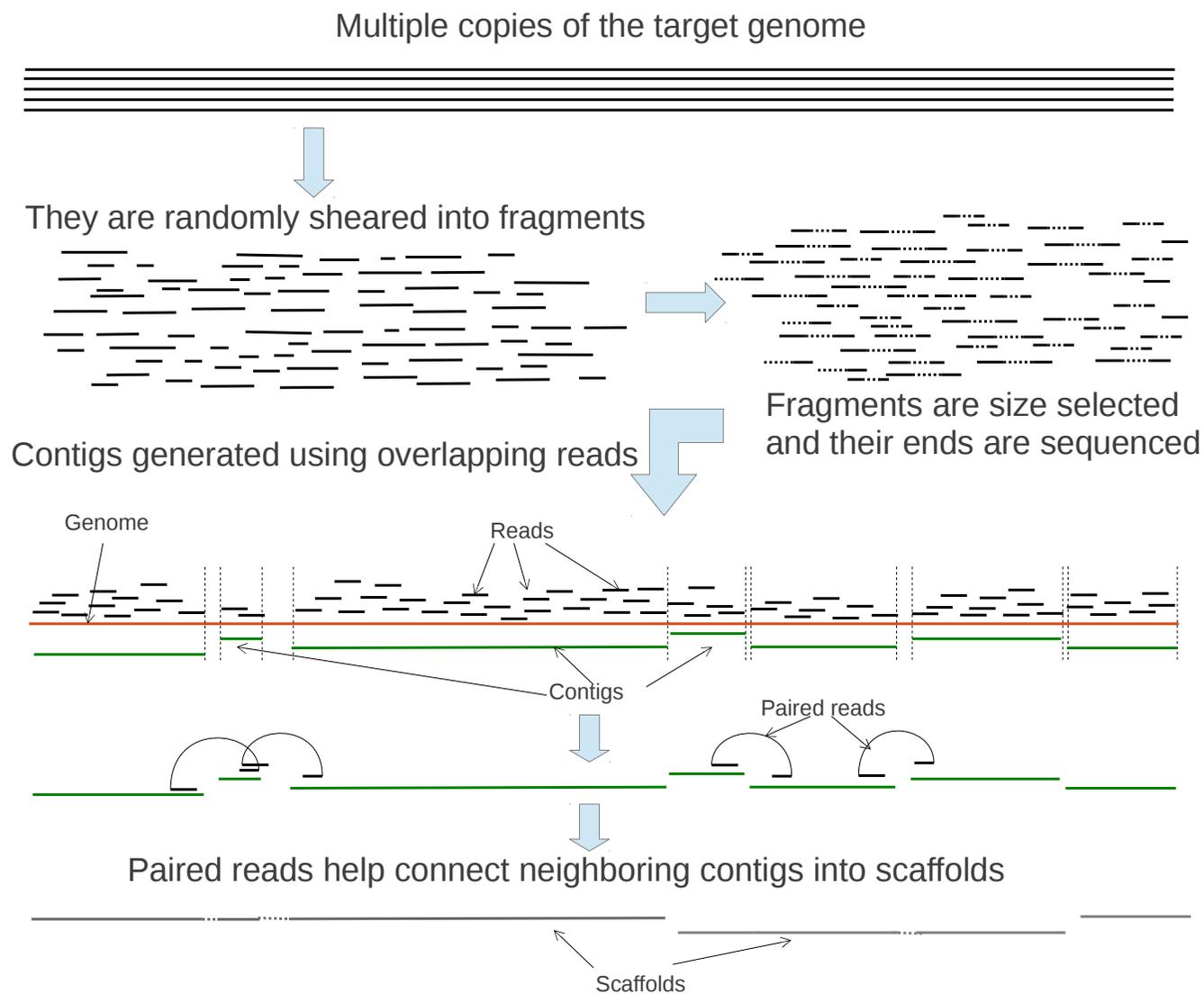
Genome Assembly



Genome Assembly



Genome Assembly



Single Cell Genomics

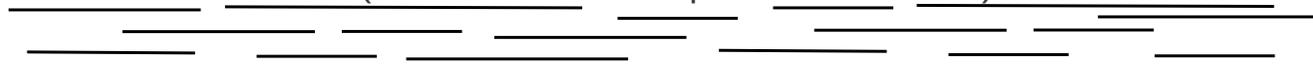
Single copy of the target genome (haploid/ diploid)

Single Cell Genomics

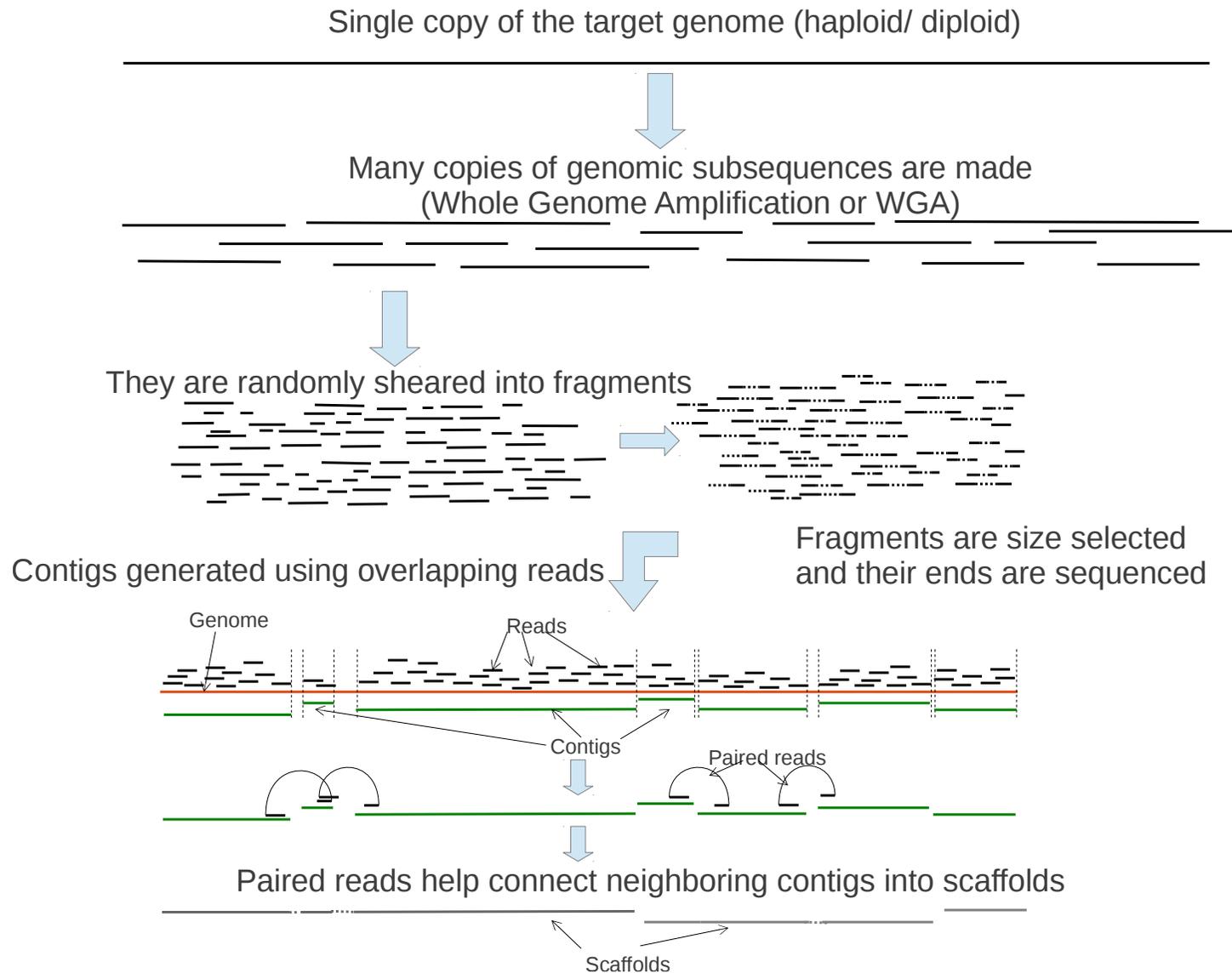
Single copy of the target genome (haploid/ diploid)



Many copies of genomic subsequences are made
(Whole Genome Amplification or WGA)

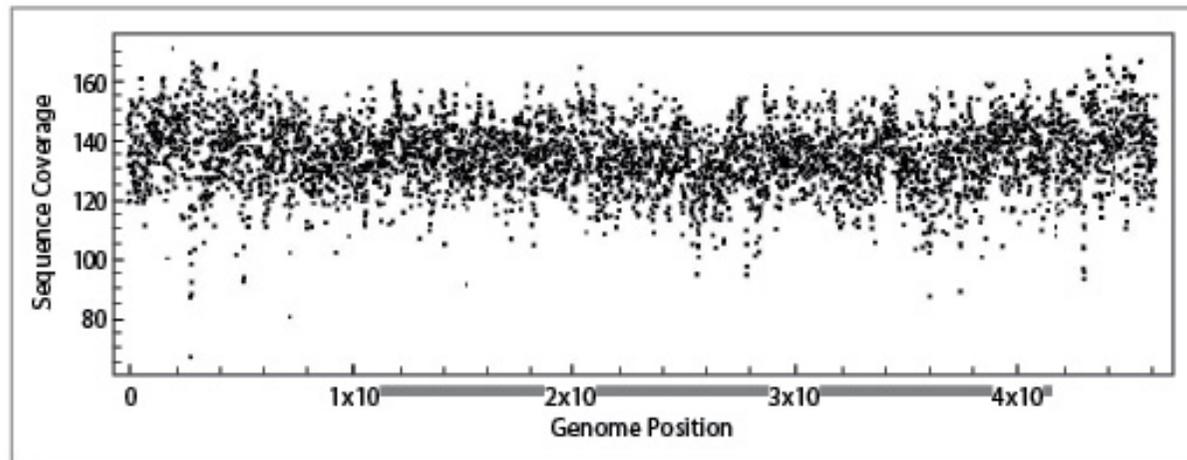


Single Cell Genomics



Cultured vs. amplified library coverage

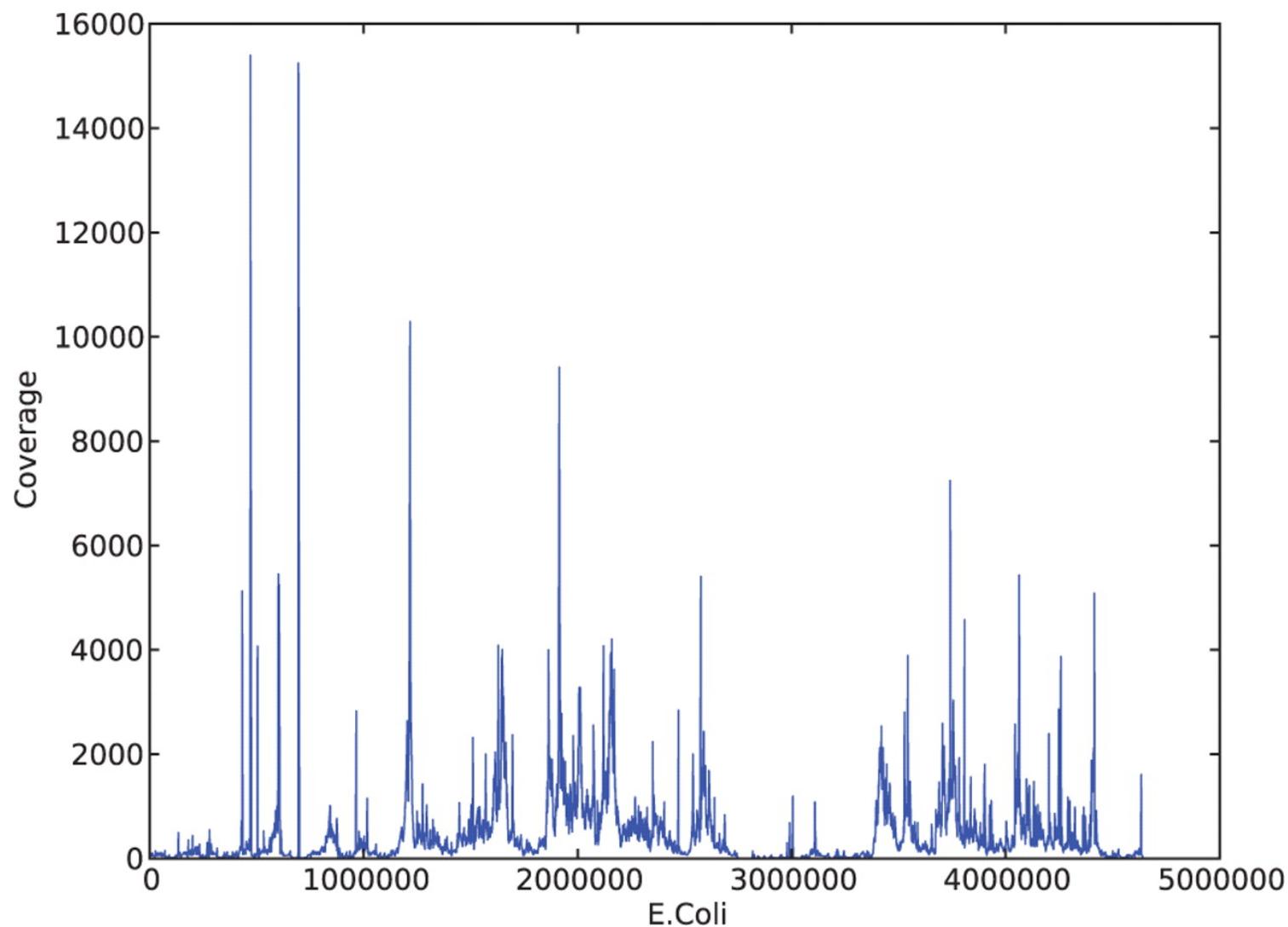
Sequencing libraries from culture show an almost uniform coverage.



Source: http://www.neb.uk.com/whats_new/documents/NEBNext_Sample_Prep_Reagents.asp

Cultured vs. amplified library coverage

Single cell libraries show a very uneven coverage[2].

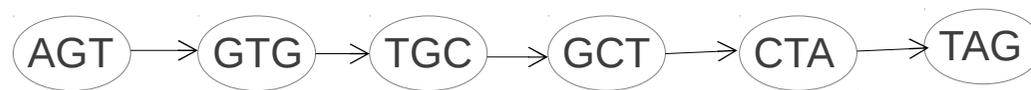


de novo Assembly with *de Bruijn* graphs

Genomic sequence: AGTGCTAG

Reads: AGTGCT, GTGCT, TGCTAG

3-mers: AGT, GTG, TGC, GCT, CTA, TAG



A walk from AGT to TAG spells out the genome AGTGCTAG

Assembling low coverage regions

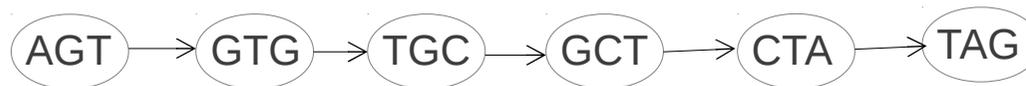
Genomic sequence: AGTGCTAG

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4-mers: AGTG, GTGC, GCTA, CTAG



3-mers: AGT, GTG, TGC, GCT, CTA, TAG

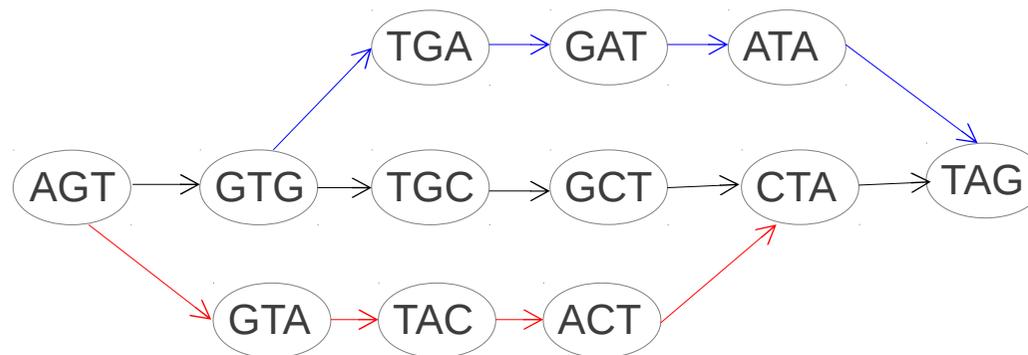


de Bruijn graph with erroneous k-mers

Genomic sequence: AGTGCTAG

Reads: AGTGCT, GT^ACT, TG^BTAG

3-mers: AGT, GTG, TGC, GCT, GTA, TAC, ACT, TGA, GAT, ATA, TAG



A walk from AGT to TAG spells out the genome AGTGCTAG

Common strategies for handling uneven coverage

- ① Assembling low coverage regions using iterative assembly.
- ② Correct reads from high coverage regions.

Single cell assembly on bacterial dataset

Assembly performance comparison of some Single Cell Assemblers. The dataset was a single cell MDA amplified read library with the following statistics: 6.3 Gbp in total, 29M reads, 2x100bp, insert size \approx 270bp. The reference genome is 4.64 Mbp in size.

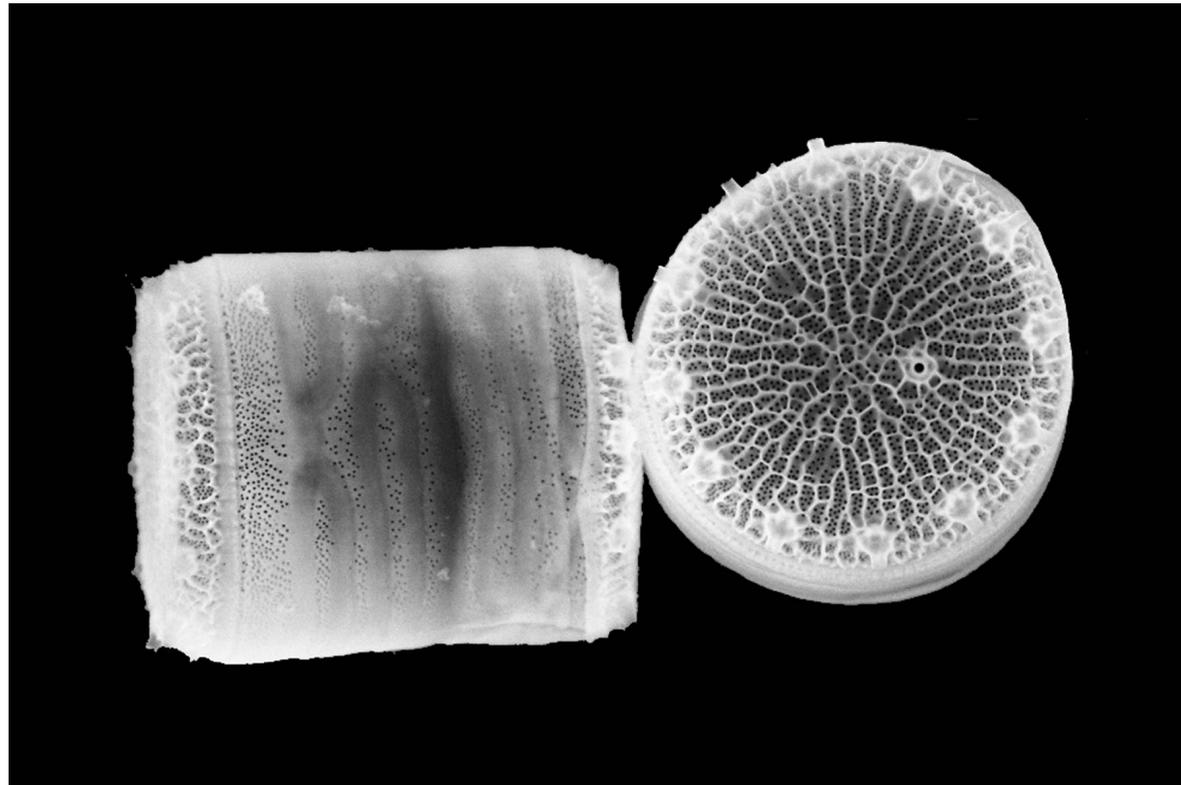
Tool	Assembly size (Mbp)	No of contigs	N50	Max Scaffold length	Genome coverage (%)
ABYSS	4.35	179	68534	178720	88.25
IDBA1.1	4.81	244	98306	284464	94.89
SPAdes2.4	4.88	277	110539	269177	95.62

source: <http://bioinf.spbau.ru/spades>

How do they perform with eukaryotic genomes?

Our model single cell eukaryote

Thalassiosira pseudonana: Marine diatom.



Reference assembly available at <http://genome.jgi-psf.org/Thaps3/Thaps3.home.html>

source:http://www.awi.de/fileadmin/user_upload/News/Press_Releases/2004/3._Quarter/Tpseudonana-2_p.jpg

Test datasets.

Statistics of three (A, B, C) MDA-derived *T.pseudonana* cultured samples we used as test datasets. The reference genome length is 32.61Mbp. Bowtie 2 [1] was used for read mapping.

Sample	Read Library size (Gbp)	Mean read length	Std of read length	Mean insert length	Std of insert length	Mapped (%)
A	1.30	144.22	18.81	356.41	4189.19	92.34
B	0.98	144.28	19.26	394.33	4812.72	88.27
C	1.18	141.86	22.37	360.24	4902.67	90.16

Comparing contigs

Comparison of contig assembly for sample A, B, C. The reference assembly is 32.61Mbp.

Dataset	Assembler	Total (Gbp)	Contig statistics			Time (hr:min)	Memory (GB)
			Count	N50	Max (Kbp)		
A	ABySS	38.20	10147	11913	104	05:54	3.8
	IDBA1.1	36.22	36604	2571	47	36:48	9.0
	SPAdes2.4	35.47	12164	39813	294	14:35	19.8
B	ABySS	45.17	9108	17960	112	08:50	4.2
	IDBA1.1	38.83	39218	3137	87	39:50	10.9
	SPAdes2.4	41.43	18846	26519	179	20:32	23.6
C	ABySS	50.99	9118	22406	105	11:14	4.1
	IDBA1.1	40.70	39480	3778	87	44:12	11.6
	SPAdes2.4	43.08	16853	28664	163	28:55	22.9

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Comparing contigs

Comparison of contig assembly for sample A, B, C considering only good contigs (those with $\geq 90\%$ alignment to reference). Reference contigs were produced by mapping reads to the reference genome and declaring contiguous regions with a coverage of at least 3 to be contigs.

Dataset	Assembler	Contig statistics			
		Total (Gbp)	Count	N50	Max (Kbp)
A	ABySS	20.15	6276	3005	57
	IDBA1.1	30.36	27539	2214	46
	SPAdes2.4	8.34	1240	0	121
	<i>Reference</i>	<i>31.77</i>	<i>4535</i>	<i>27981</i>	<i>251</i>
B	ABySS	26.33	5211	8913	79
	IDBA1.1	31.28	27947	2709	87
	SPAdes2.4	19.55	4784	3140	195
	<i>Reference</i>	<i>32.20</i>	<i>1565</i>	<i>122162</i>	<i>441</i>
C	ABySS	30.85	5307	13106	104
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	SPAdes2.4	19.33	4520	3054	155
	<i>Reference</i>	<i>32.25</i>	<i>1018</i>	<i>250158</i>	<i>994</i>

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Observations

- SPAdes produces long but often incorrectly assembled sequences.
- IDBA-UD produces the largest amount of correctly assembled (but more fragmented) sequences.
- ABySS produces the best sequences in terms of average length.
- ABySS is the most time and space efficient assembler.

Characterizing un-culturable single-cell organisms

Protein predictions and their annotations may help to:

- Perform phylogenetic analysis.
- Metabolic pathway analysis.

No transcriptome data is available.

Measuring assembly quality via protein prediction

Comparison of protein predictions for sample A, B, C. The reference protein library has 11849 proteins. CEGMA presents 458 core eukaryotic proteins.

Dataset	Assembler	Predicted proteins				
		KOGs		Total	Correct	
		(count)	(%)	(Augustus)	(> 70% alignment)	(%)
A	ABySS	380	82.96	12178	9170	77.39
	IDBA1.1	340	74.23	12266	8532	72.00
	SPAdes2.4	388	84.71	10659	7450	62.87
B	ABySS	392	85.59	14039	10469	88.35
	IDBA1.1	365	79.69	13748	8671	73.18
	SPAdes2.4	385	84.06	13403	8502	71.75
C	ABySS	402	87.77	16786	11636	98.20
	IDBA1.1	370	80.78	14099	8751	73.85
	SPAdes2.4	395	86.24	15366	9314	78.60

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	SPAdes2.4	395	86.24	15366	9314	78.60

Major conclusion

Average sequence length seems to be more important than N50 for protein prediction.

Improving single cell assembly

- We observed¹ that contig scaffolding can become much simpler and accurate when the contigs are correct.
- Perform read correction (using a combination of Multiple sequence alignment and k -mer spectrum based approaches) and coverage normalization as a preprocessing step.
- Design a scaffolder that attempts to maximize average sequence length while maintaining accuracy and genome coverage.

1. Rajat S. Roy, Kevin C. Chen, Anirvan M. Sengupta, and Alexander Schliep. SLIQ: simple linear inequalities for efficient contig scaffolding. *Journal of Computational Biology*, Oct 2012.

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- 
- Ben Langmead and Steven L Salzberg.
Fast gapped-read alignment with bowtie 2.
Nat Methods, 9(4):357–359, Apr 2012.
- 
- Paul Medvedev, Eric Scott, Boyko Kakaradov, and Pavel Pevzner.
Error correction of high-throughput sequencing datasets with
non-uniform coverage.
Bioinformatics, 27(13):i137–i141, Jul 2011.