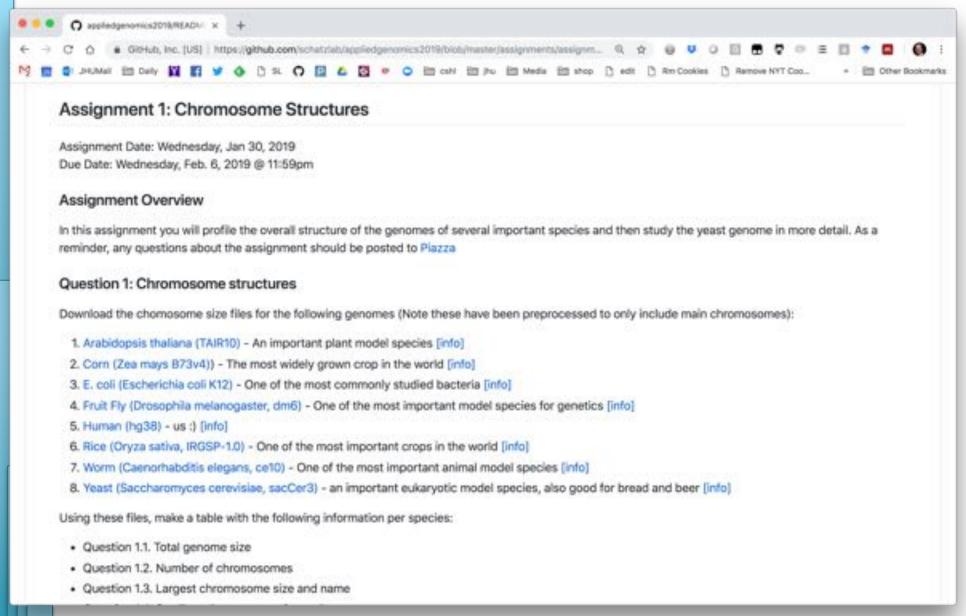
Assembly & Whole Genome Alignment

Michael Schatz

Feb 4, 2019 Lecture 4: Applied Comparative Genomics



Assignment I: Chromosome Structures Due Feb 6 @ 11:59pm







Outline

I. Assembly theory

Assembly by analogy

2. Practical Issues

Coverage, read length, errors, and repeats

3. Next-next-gen Assembly

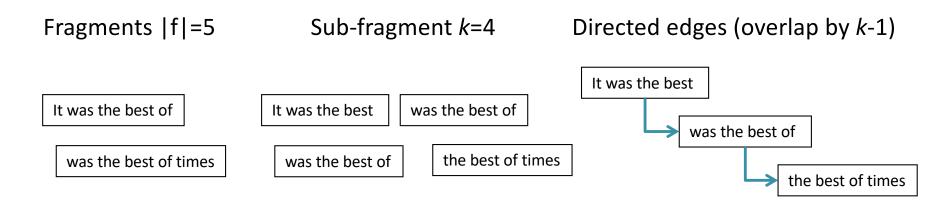
Canu: recommended for PacBio/ONT project

4. Whole Genome Alignment

MUMmer recommended

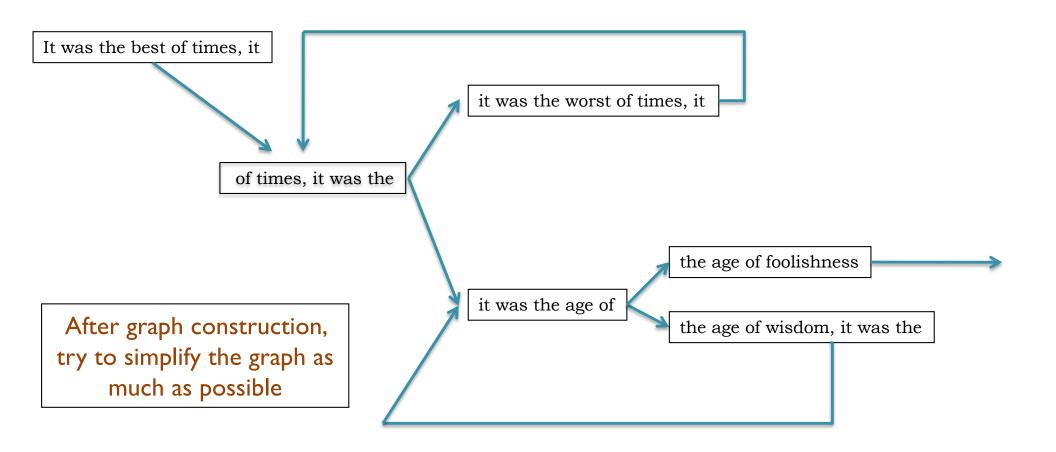
de Bruijn Graph Construction

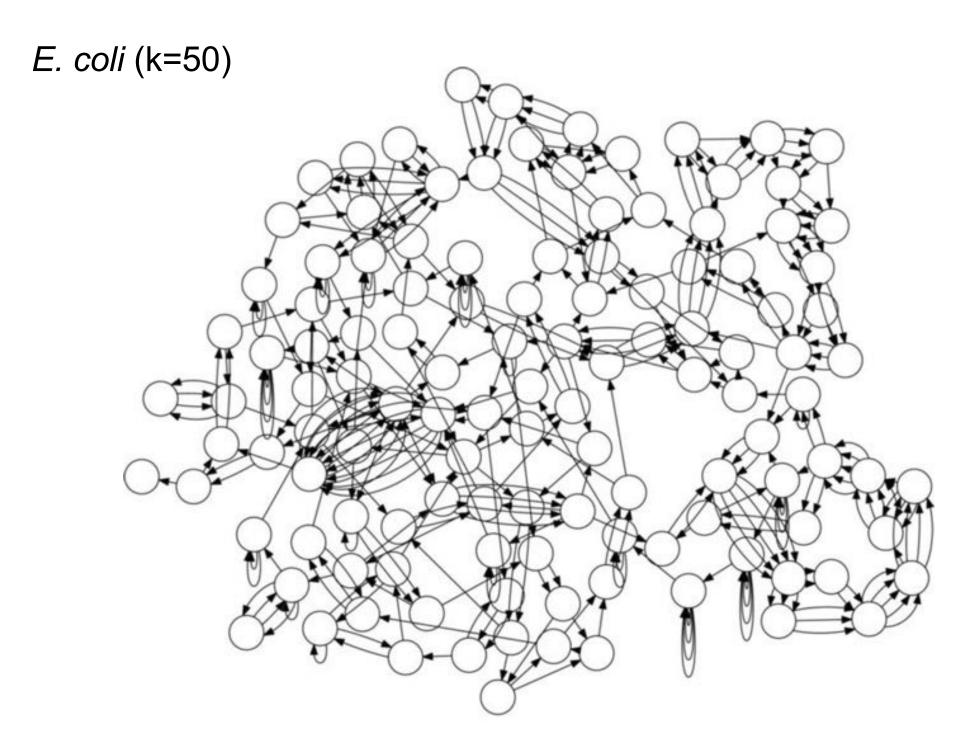
- $G_k = (V,E)$
 - V = Length-k sub-fragments
 - E = Directed edges between consecutive sub-fragments
 - Sub-fragments overlap by k-I words



Overlaps between fragments are implicitly computed

de Bruijn Graph Assembly

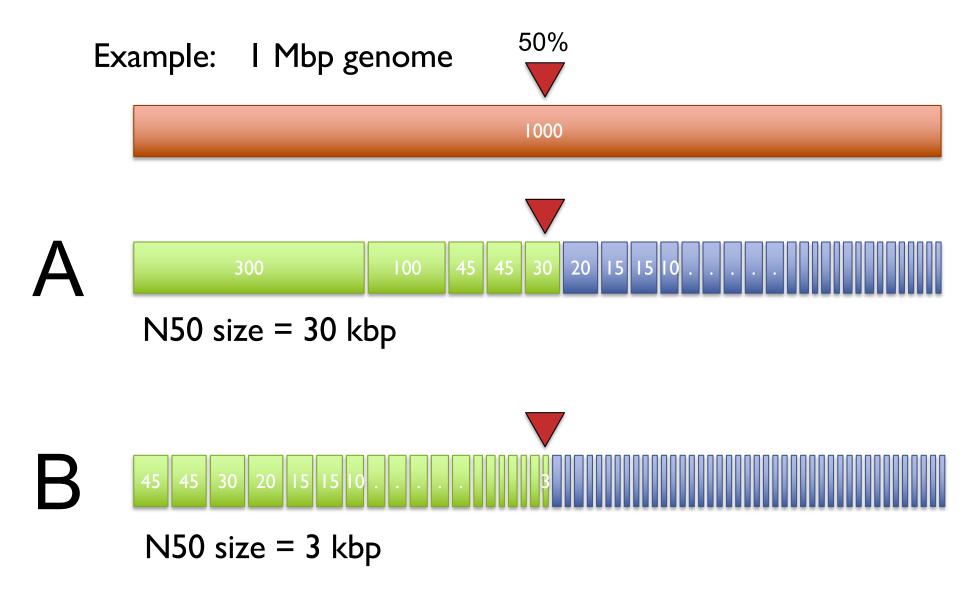




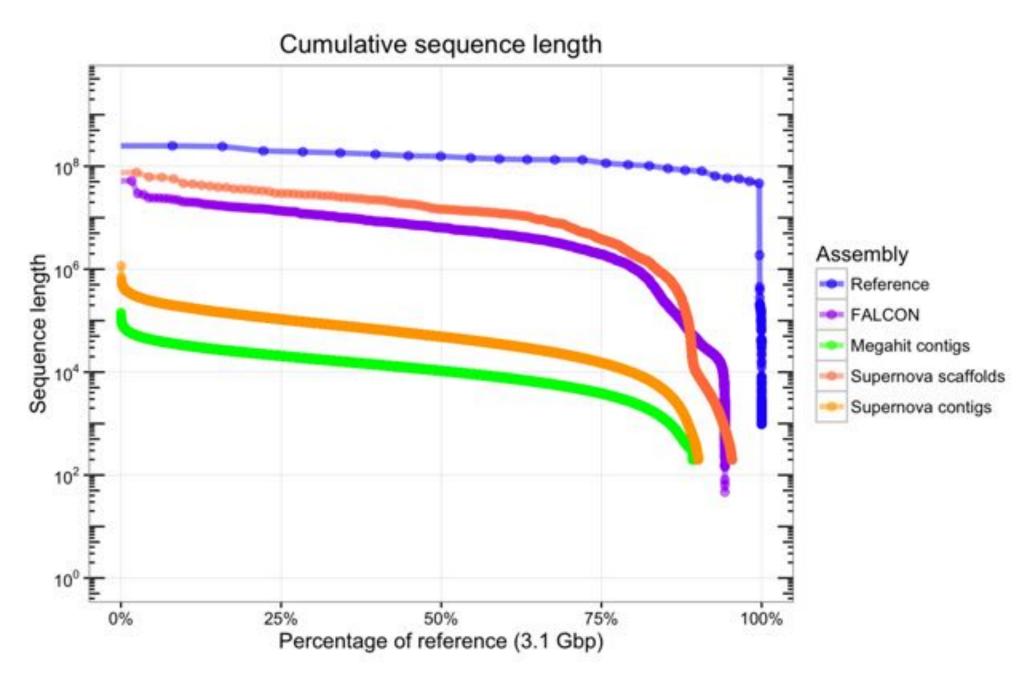
Reducing assembly complexity of microbial genomes with single-molecule sequencing Koren et al (2013) Genome Biology. **14**:R101 https://doi.org/10.1186/gb-2013-14-9-r101

Contig N50

Def: 50% of the genome is in contigs as large as the N50 value



Contig Nchart





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Whole Genome Alignment with MUMmer

Slides Courtesy of Adam M. Phillippy NHGRI

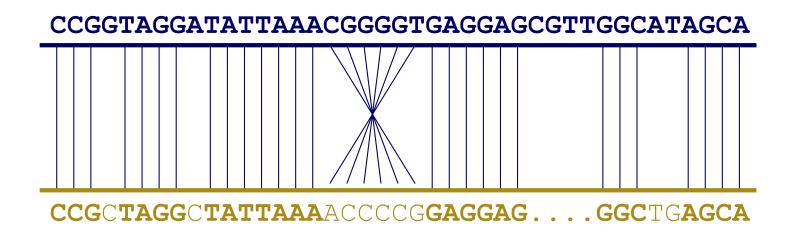
Goal of WGA

 For two genomes, A and B, find a mapping from each position in A to its corresponding position in B



Not so fast...

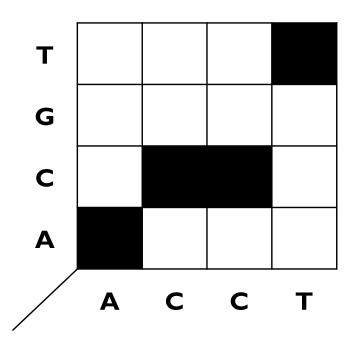
• Genome A may have insertions, deletions, translocations, inversions, duplications or SNPs with respect to B (sometimes all of the above)



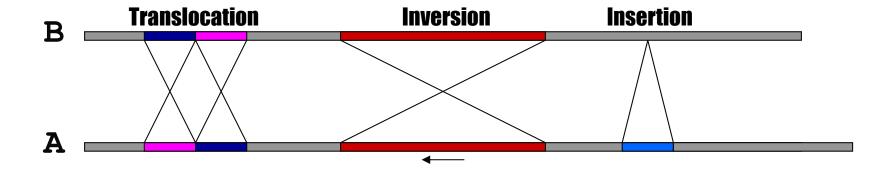
WGA visualization

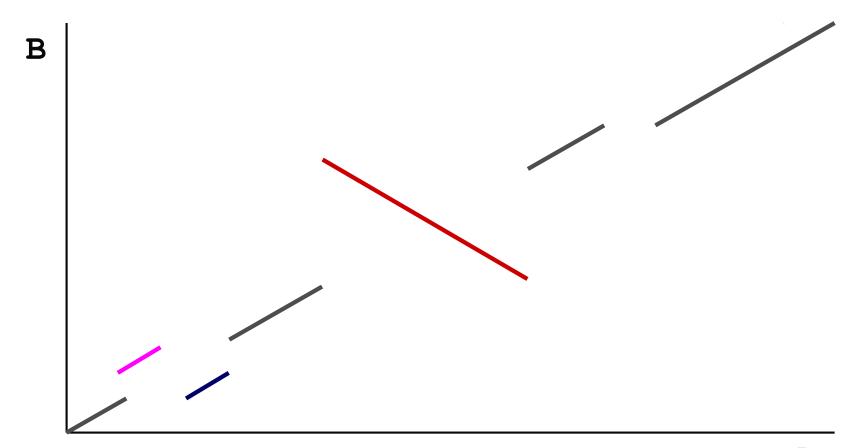
How can we visualize whole genome alignments?

- With an alignment dot plot
 - $-N \times M$ matrix
 - Let i = position in genome A
 - Let j = position in genome B
 - Fill cell (i,j) if A_i shows similarity to B_i

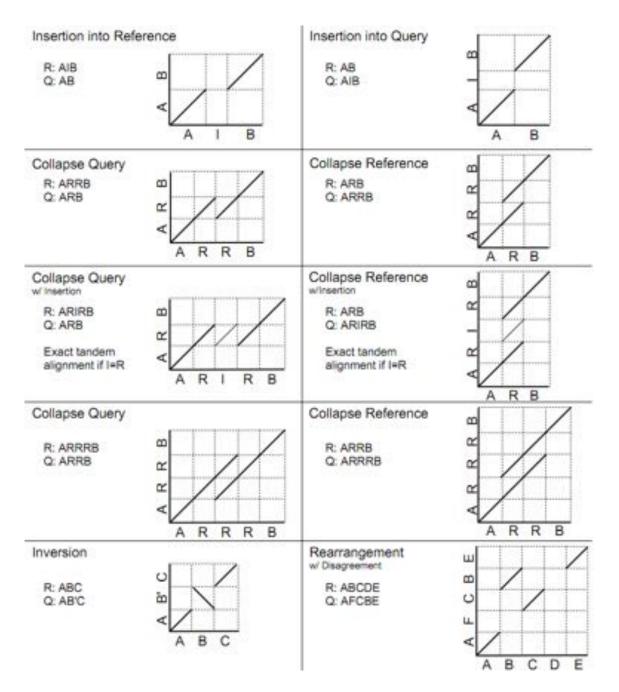


 A perfect alignment between A and B would completely fill the positive diagonal



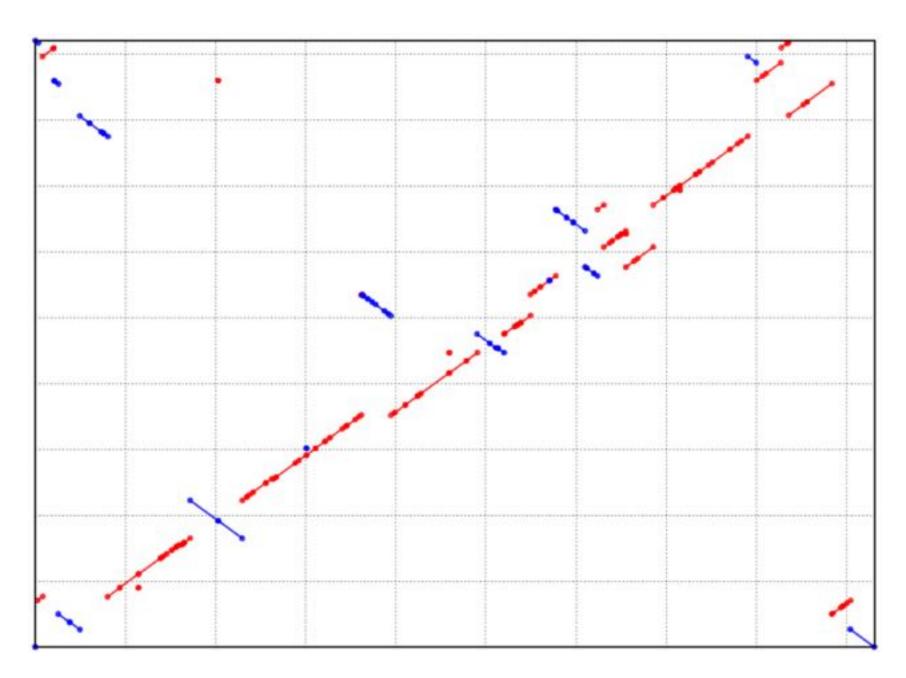


SV Types



- Different structural variation types / misassemblies will be apparent by their pattern of breakpoints
- Most breakpoints will be at or near repeats
- Things quickly get complicated in real genomes

http://mummer.sf.net/manual/ AlignmentTypes.pdf

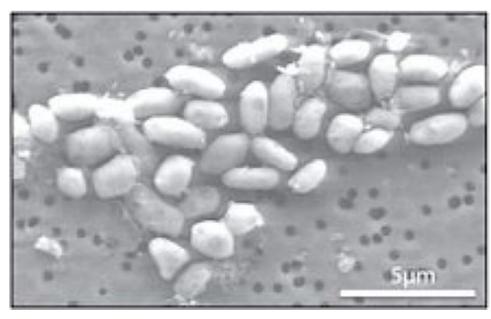


Alignment of 2 strains of Y. pestis

http://mummer.sourceforge.net/manual/

Halomonas sp. GFAJ-I





Library 1: Fragment

Avg Read length: 100bp

Insert length: 180bp

Library 2: Short jump

Avg Read length: 50bp

Insert length: 2000bp

A Bacterium That Can Grow by Using Arsenic Instead of Phosphorus Wolfe-Simon et al (2010) Science. 332(6034) 1 163-1 166.

Digital Information Storage

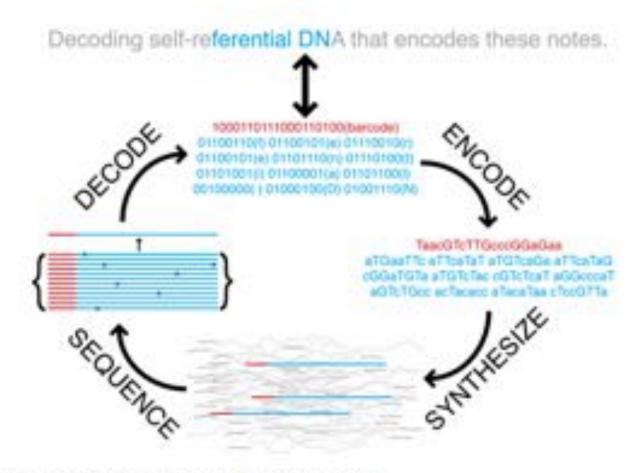


Fig. S1. Schematic of DNA information storage.

Encoding/decoding algorithm implemented in dna-encode.pl from David Dooling.

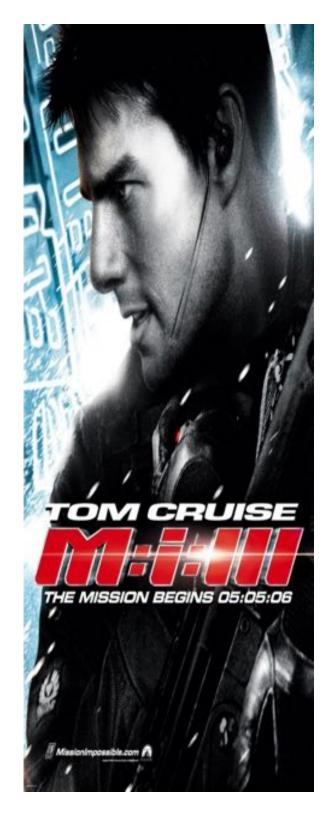
Next-generation Digital Information Storage in DNA

Church et al (2010) Science. 337(6102)1628

Assignment 2: Genome Assembly Due Wednesday Feb 13 @ 11:59pm

- 1. Setup Docker/VirtualBox/Ubuntu
- 2. Initialize Tools
- 3. Download Reference Genome & Reads
- 4. Decode the secret message
 - 1. Estimate coverage, check read quality
 - 2. Check kmer distribution
 - 3. Assemble the reads with spades
 - 4. Align to reference with MUMmer
 - 5. Extract foreign sequence
 - 6. dna-encode.pl -d

https://github.com/schatzlab/appliedgenomics2019/blob/master/assignments/assignment2/README.md



Find and decode

```
nucmer -maxmatch ref.fasta \
  default/ASSEMBLIES/test/final.contigs.fasta
              Find maximal exact matches (MEMs) without repeat filtering
  -maxmatch
  -p refctq
              Set the output prefix for delta file
mummerplot --layout --png out.delta
  --layout Sort the alignments along the diagonal
  --png Create a png of the results
show-coords -rclo out.delta
              Sort alignments by reference position
  -r
              Show percent coverage
  -C
  -1
              Show sequence lengths
              Annotate each alignment with BEGIN/END/CONTAINS
  -\circ
samtools faidx default/ASSEMBLIES/test/final.contigs.fasta
  Index the fasta file
samtools faidx default/ASSEMBLIES/test/final.contigs.fasta \
   contig_XXX:YYY-ZZZ | ./dna-encode -d
```



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Assembly Applications

Novel genomes



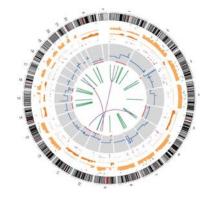


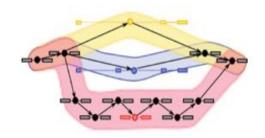
Metagenomes





- Sequencing assays
 - Structural variations
 - Transcript assembly





– ...

Why are genomes hard to assemble?

I. Biological:

- (Very) High ploidy, heterozygosity, repeat content

2. Sequencing:

(Very) large genomes, imperfect sequencing

3. Computational:

(Very) Large genomes, complex structure

4. Accuracy:

(Very) Hard to assess correctness



Assembling a Genome

I. Shear & Sequence DNA

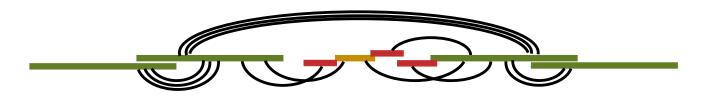


2. Construct assembly graph from reads (de Bruijn / overlap graph)

3. Simplify assembly graph



4. Detangle graph with long reads, mates, and other links



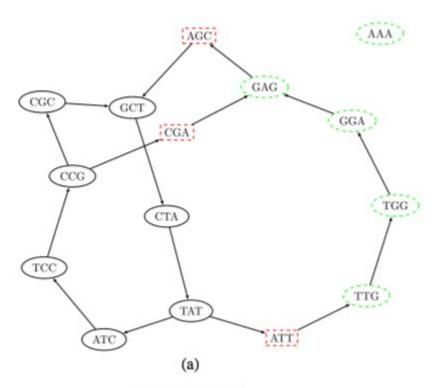
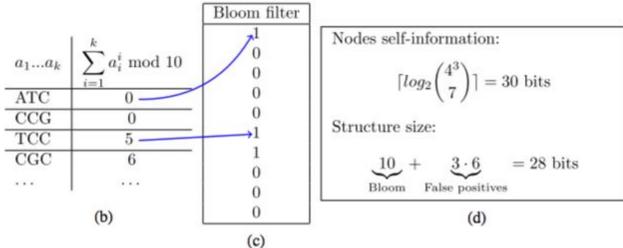


Table 2 de novo human genome (NA18507) assemblies

Method	Minia	C. & B.	ABySS	SOAPdenovo
Value of k chosen	27	27	27	25
Number of contigs (M)	3.49	7.69	4.35	-
Longest contig (kbp)	18.6	22.0	15.9	(2)
Contig N50 (bp)	1156	250	870	886
Sum (Gbp)	2.09	1.72	2.10	2.08
Nb of nodes/cores	1/1	1/8	21/168	1/16
Time (wall-clock, h)	23	50	15	33
Memory (sum of nodes, GB)	5.7	32	336	140

de novo human genome (NA18507) assemblies reported by our assembler (Minia), Conway and Bromage assembler [9], ABySS [8], and SOAPdenovo [7]. Contigs shorter than 100 bp were discarded. Assemblies were made without any pairing information.

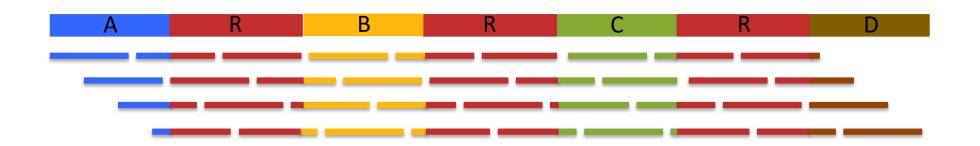


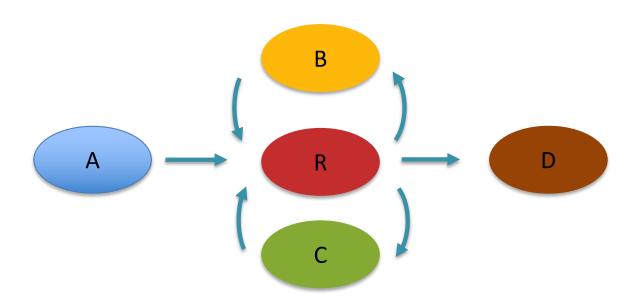
Space-efficient and exact de Bruijn graph representation based on a Bloom filter Chikhi and Rizk (2013) Algorithms for Molecular Biology. 8:22

Genomics Arsenal in the year 2019

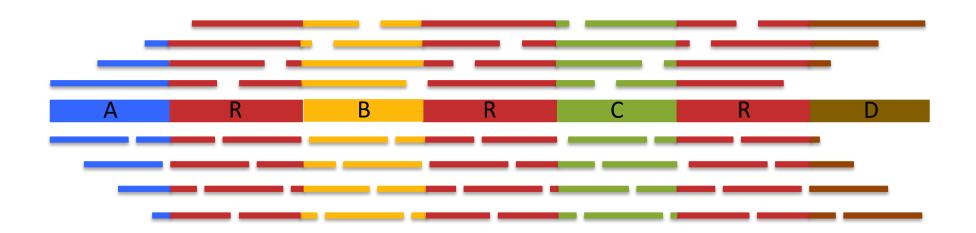


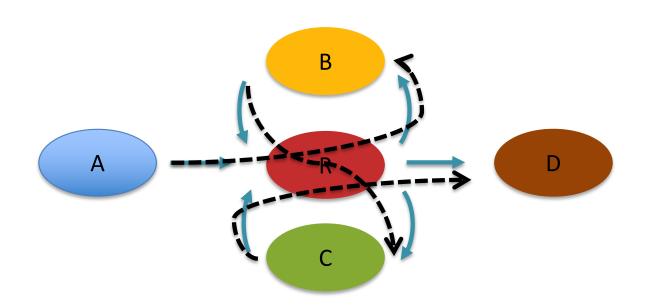
Assembly Complexity



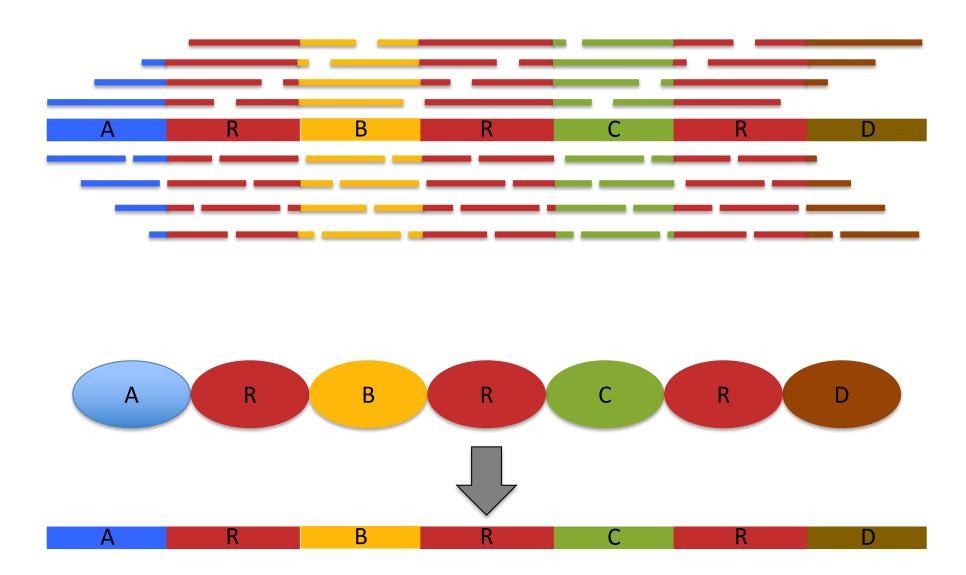


Assembly Complexity





Assembly Complexity

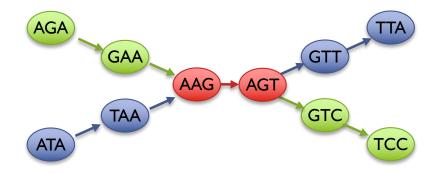


The advantages of SMRT sequencing

Roberts, RJ, Carneiro, MO, Schatz, MC (2013) Genome Biology. 14:405

Two Paradigms for Assembly

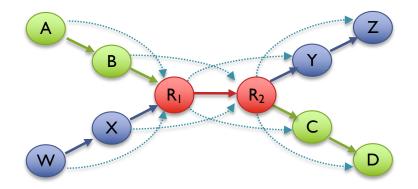
de Bruijn Graph



Short read assemblers

- Repeats depends on word length
- Read coherency, placements lost
- Robust to high coverage

Overlap Graph



Long read assemblers

- Repeats depends on read length
- Read coherency, placements kept
- Tangled by high coverage

Assembly of Large Genomes using Second Generation Sequencing Schatz MC, Delcher AL, Salzberg SL (2010) *Genome Research*. 20:1165-1173.

Overlap between two sequences

overlap (19 bases) overhang (6 bases)

...AGCCTAGACCTACAGGATGCGCGGACACGTAGCCAGGAC

CAGTACTTGGATGCGCTGACACGTAGCTTATCCGGT...

overhang % identity = 18/19 % = 94.7%

overlap - region of similarity between regions

overhang - un-aligned ends of the sequences

The assembler screens merges based on:

- length of overlap
- % identity in overlap region
- maximum overhang size.

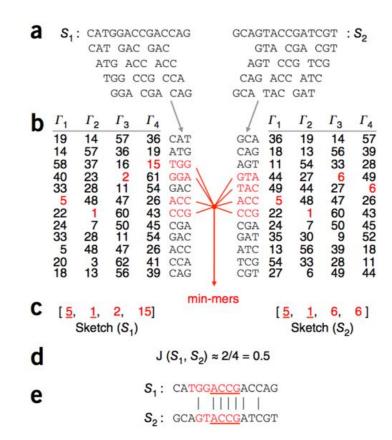
[How do we compute the overlap?]

[Do we really want to do all-vs-all?]

Very fast approximate overlapping

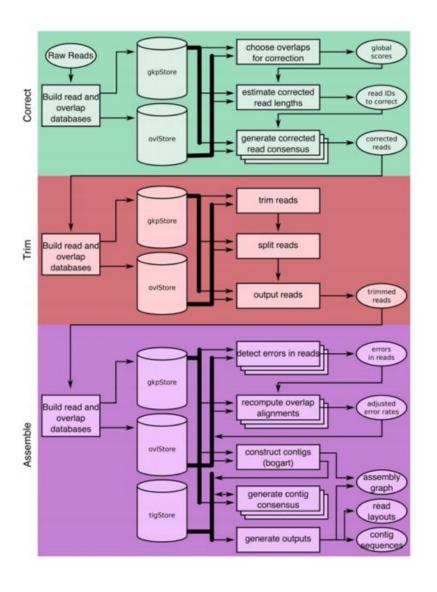
Maybe we don't need to compute the exact identity of the overlap region, just approximate it

- If two reads overlap, they should share many of the same kmers: Their Jaccard coefficient should be high: |intersection| / |union|
- But tracking all of the kmers for a read is a lot of overhead
- Instead, compare the "sketch" of the reads: a small fraction of kmers carefully chosen
- LSH: Find the sketch by applying N hash functions to the kmers, and keeping the minimum hash values reported from each (N=4 in example)
- This forms a nice "random" sample of the reads, and the Jaccard coefficient is a good approximation of the sequence similarity



Assembling large genomes with single-molecule sequencing and locality-sensitive hashing Berlin et al (2015) *Nature Biotechnology*

Canu Workflow



Three rounds of analysis:

- Error Correction: Use MHAP to overlap the reads, then compute a mini assembly centered around each read of good overlaps to error correct
- 2. **Trim:** Use MHAP to recompute overlaps to find regions that are not well supported and discard
- 3. Unitigging: Use Dynamic Programming to carefully overlap the error corrected reads, construct overlap graph, and then "unitig" those overlaps to build the contigs

Canu: scalable and accurate long-read assembly via adaptive k-mer weighting and repeat separation Koren et al (2017) *Genome Research*

Next Steps

- I. Reflect on the magic and power of DNA ©
- 2. Check out the course webpage
- 3. Register on Piazza
- 4. Work on Assignment I
 - I. Set up Linux, set up Virtual Machine
 - 2. Set up Dropbox for yourself!
 - 3. Get comfortable on the command line

