



Session 2.3 - Ensamblado

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Assembly

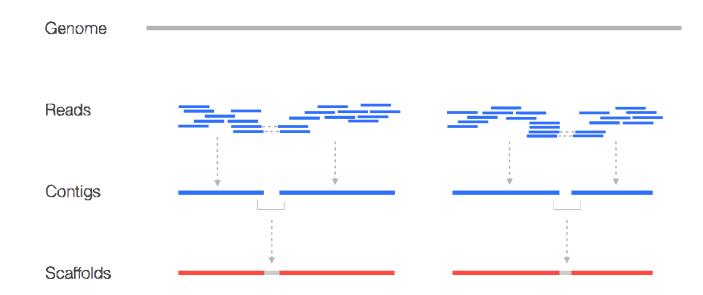
Reconstruct the sequence of the original DNA from shorter DNA sequences or small fragments known as reads

- **De novo:** with no previous knowledge of the genome to be assembled. It overlap the end of the end of each read in order to create a longer sequence.
- Assembly with reference: A similar but not identical genome guides the assembly process. Map reads over supplied genome.



Assembly: contig y scaffold

- Contig: continuous sequence made up of overlaping shorter sequences
- Scaffold: two or more contigs located and rearranged according to spatial information (pair-end, mate pair, reference)

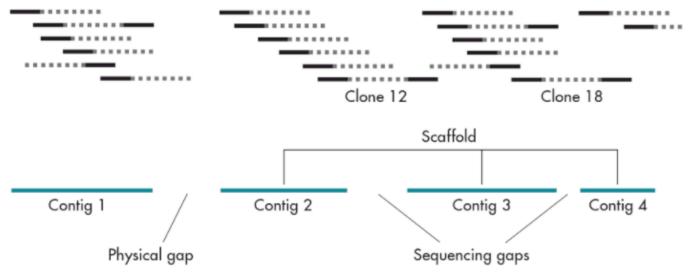


https://www.biostars.org/p/253222/



Assembly: gaps

- Sequencing gaps: Position and orientation known by spatial information
- Physical gaps: No information about adjacent contigs



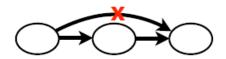
Gene Cloning, Lodge et al.

Assembly: Algorithms

- Overlap, Layout, Consensus (OLC overlap graph):
 - O first overlaps among all the reads are found
 - L then it carries out a layout of all the reads and overlaps information on a graph
 - Removes redundant and low quality overlaps
 - C and finally the consensus sequence is inferred

Ex. Newbler, Mira, Celera Assembler, CAP3, PCAP, Phrap, Phusion.









Assembly: Algorithms

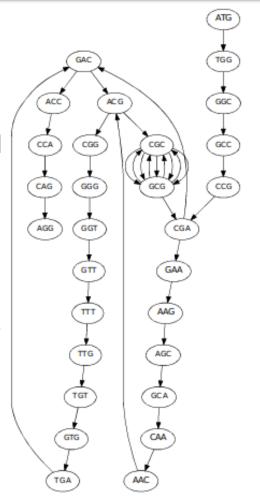
• De Brujin Graph (DBG: k-mer graph)

Chopping reads into much shorter k-mers (fixed length fragments) and then using all the k-mers to form a DBG and infer the contigs.

- Nodes in the graph are k-mers
- Edges represent consecutive k-mers (which overlap by k-n symbols)

Ex. SPAdes, ABySS, Velvet, AllPaths, Soap....

https://medium.com/@han_chen



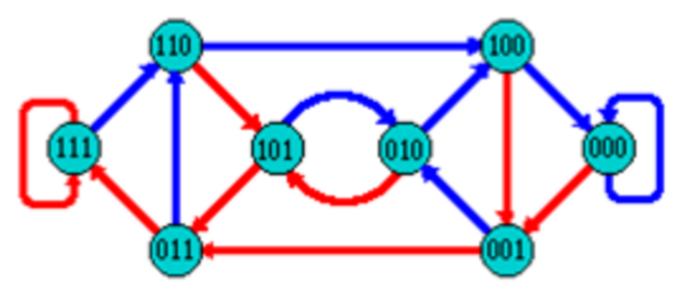




de Bruijn Graphs

- A directed graph of sequences of symbols
- Nodes in the graph are k-mers
- Edges represent consecutive k-mers (which overlap by k-1 symbols)

Consider the 2 symbol alphabet (0 & 1) de Bruijn Graph for k = 3

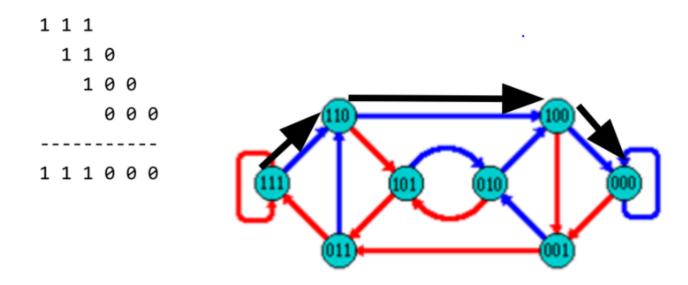






Producing sequences

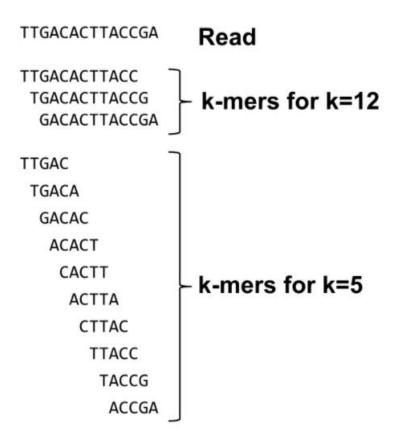
Sequences of symbols are produced by moving through the graph







What are K-mers?









Example #1:

HAPPI PINE INESS APPIN







Example #1:

HAPPI PINE INESS APPIN

All 4-mers:

HAPP PINE INES APPI

APPI NESS PPIN

Unique 4-mers:

HAPP APPI PINE PPIN INES NESS







Example #1:

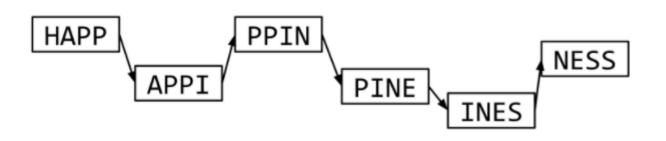
HAPPI PINE INESS APPIN

k = 4 k-mers:

HAPP APPI

PINE PPIN

INES NESS









Example #1:

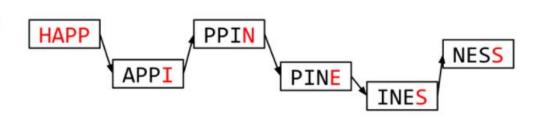
HAPPI PINE INESS APPIN

k = 4 k-mers:

HAPP APPI

PINE PPIN

INES NESS



HAPPINESS

Easy!







Example #2:
MISSIS SSISSI SSIPPI







```
Example #2:
```

MISSIS SSISSI SSIPPI

All 4-mers (9):

MISS SSIS SSIP

ISSI SISS SIPP

SSIS ISSI IPPI

Unique 4-mers (7):

MISS SSIS SSIP ISSI SISS SIPP IPPI



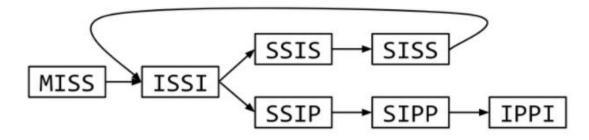


Example #2:

MISSIS SSISSI SSIPPI

All 4-mers:

MISS ISSI SSIS SISS SSIP SIPP IPPI







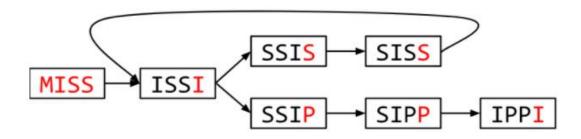


Example #2:

MISSIS SSISSI SSIPPI

All 4-mers:

MISS ISSI SSIS SISS SSIP SIPP IPPI



MISSISSIPPI or MISSISSISSIPPI or ...





Example #2a:

MISSIS SSISSI SSIPPI





Example #2a:

MISSIS SSISSI SSIPPI

All 5-mers (6):

MISSI SSISS SSIPP

ISSIS SISSI SIPPI

Unique 5-mers (6, no duplicates):
MISSI ISSIS SSISS SISSI SSIPP SIPPI



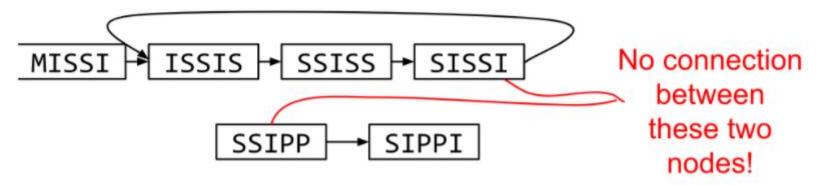


Example #2a:

MISSIS SSISSI SSIPPI

This time k = 5 k-mers:

MISSI ISSIS SSISS SISSI SSIPP SIPPI





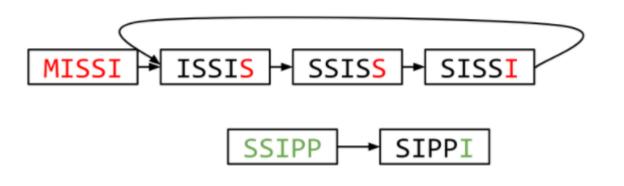


Example #2a:

MISSIS SSISSI SSIPPI

This time k = 5 k-mers:

MISSI ISSIS SSISS SISSI SSIPP SIPPI



MISSISSIS

SSIPPI





Choose k wisely

- Lower k
 - More connections
 - Less chance of resolving small repeats
 - Higher k-mer coverage
- Higher k
 - Less connections
 - More chance of resolving small repeats
 - Lower k-mer coverage

Optimum value for k will balance these effects.

23



Read errors

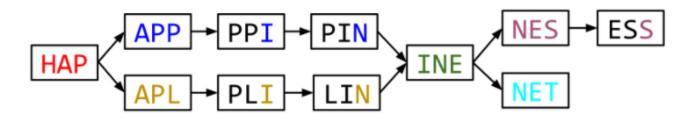


Example #3:

HAPPI INESS APLIN PINET

k = 3 k-mers:

HAP APP PPI INE NES ESS APL PLI LIN PIN NET



6 contigs: HAP APPIN APLIN INE NESS NET





More coverage

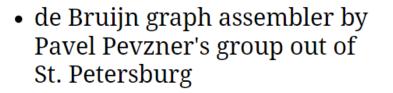


- Errors won't be duplicated in every read
- Most reads will be error free
- We can count the frequency of each k-mer
- Annotate the graph with the frequencies
- Use the frequency data to clean the de Bruijn graph

More coverage depth will help overcome errors!



SPAdes





- Uses multiple k-mers to build the graph
 - Graph has connectivity and specificity
 - Usually use a low, medium and high k-mer size together.
- Performs error correction on the reads first
- Maps reads back to the contigs and scaffolds as a check
- Under active development
- Much slower than Velvet
- Should be used in preference to Velvet now.

Assembly: Scaffolding

From draft:

```
Order contigs (Nucmer, if there is reference it can be used to align and guide)

Fill the GAPs (GapFiller, fill sequencing gap (not physical gap)

Solve repeated sequence ambiguities (Expander)

Resequence with different library:
```

- Longer fragments and/or distance
- Tools for assembly improvement

SSPACE (Scaffolding) REAPR (evaluate scaffolding, breaking incorrect scaffolds)

Assembly visualyzing

Artemis, ACT (compare two or more sequences), Icarus (Quast)





A move back to OLC

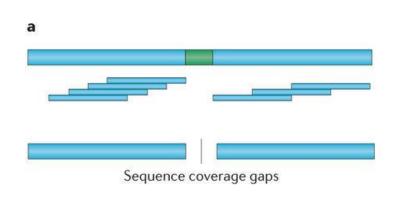
- New long read technologies
 - PacBio and MinIon
- Assemblers: HGap, CANU
 - Use overlap, layout consensus approach
- CANU can perform hybrid assemblies with long and short reads

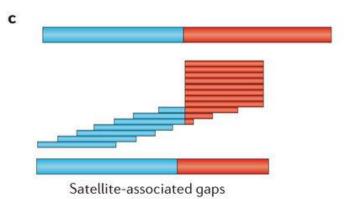


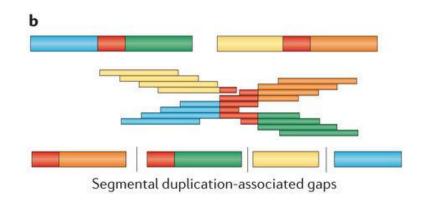


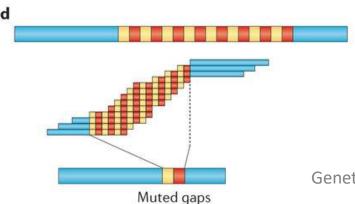


Ensamblado: Errores









- A. Gaps región del genoma sin secuenciar
- B. Duplicaciones de gran tamaño
 - Quimeras
- Regiones repetidas colapsadas
 - C. Terminales
 - D. Intersticiales

Genetic variation and the de novo assembly of human genomes

Chaisson et al. 2015

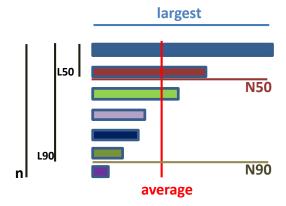
Nature Reviews | Genetics



Assembly: Metrics

- sum = total bases number
- n = contigs number
- average = average contig length
- largest = largest contig
- N50 = length of the shortest contig where 50% of sum is held
- L50 = number of contigs which have 50% of the genome
- N90 = length of the shortest contig where 90% of sum is held.
- L90 = number of contigs which have 90% of the genome





Assembly: Evaluation

- Software that evaluate differets algorithms & parameters iMetAMOS, Koren et al., BMCBioinformatics 2014, 15:126
 GAGE-B, Magoc et al., Bioinformatics 2013,29(14):1718-25
- **Graph evaluation:** Bandage, Wick R.R., Schultz M.B., Zobel J. & Holt K.E. (2015)
- Assembly evaluation: Quast, Gurevich et al., Bioinformatics 2013, 29:8
- Metrics for a good assembly:

```
Large N50
Sum closest to expected
Low n
Low L50
```



Assembly: Evaluation - Quast

• Assembly evaluation: Quast, Gurevich et al., Bioinformatics 2013, 29:8

Worst Median Best Show heatmap											
Genome statistics	RA_L2073_paired_assembly	RA_L2391_paired_assembly	RA_L2677_paired_assembly	RA_L2978_paired_assembly	RA_L2281_paired_assembly	RA_L2450_paired_assembly	RA_L2701_paired_assembly				
Genome fraction (%)	81.079	88.828	84.92	90.172	85.733	88.172	92.463				
Duplication ratio	1	1	1.001	1.001	1.001	1	1				
# genomic features	1736 + 824 part	2113 + 600 part	1881 + 768 part	2157 + 611 part	1992 + 637 part	2073 + 643 part	2368 + 412 part				
Largest alignment	16612	33 033	21 336	25 068	29 638	30 305	40 471				
Total aligned length	2 405 510	2 635 297	2519300	2 675 166	2 543 440	2 615 874	2743 222				
NGA50	3176	6162	4234	5948	5104	5358	9519				
LGA50	267	151	219	153	166	166	96				
Misassemblies											
# misassemblies	23	1	14	2	17	12	4				
Misassembled contigs length	84193	9611	45 868	6390	111 490	72 879	37 962				
Mismatches											
# mismatches per 100 kbp	17	18.78	15	16.71	341.39	15.75	13.49				
# indels per 100 kbp	1.21	1.25	1.87	1.94	7.27	1.45	0.87				
# N's per 100 kbp	0	0	0	0	0	0	0				
Statistics without reference											
# contigs	748	546	684	569	569	584	392				
Largest contig	16612	33 033	21 336	25 068	30915	30 305	40 471				
Total length	2 440 656	2 676 227	2 562 578	2714287	2 629 607	2 618 624	2787129				
Total length (>= 1000 bp)	2 439 127	2 676 227	2 559 569	2714287	2 628 029	2 615 105	2 785 415				
Total length (>= 10000 bp)	257 236	739 181	320 638	811 392	700516	658319	1 419 641				
Total length (>= 50000 bp)	0	0	0	0	0	0	0				

Extended report

Assembly: Evaluation - Quast

 Assembly evaluation: Quast, Gurevich et al., Bioinformatics 2013, 29:8





Assembly: Assemblers

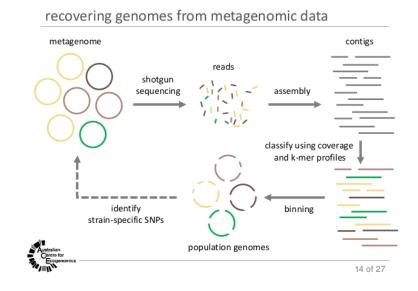
Name	Туре	Technologies	Author	Presented /Last updated	Licence*	Homepage
<u>DNASTAR</u> Lasergene Genomics Suite	(large) genomes, exomes, transcriptomes, metagenomes, ESTs	Illumina, ABI SOLID, Roche 454, Ion Torrent, Solexa, Sanger	DNASTAR	2007 / 2016	С	link
Newbler	genomes, ESTs	454, Sanger	454/Roche	2004/2012	С	link
Canu	Small and large, haploid/diploid genomes	PacBio/Oxford Nanopore reads	Koren et al. ^[8]	2001 / 2018	os	link
SPAdes	(small) genomes, single- cell	Illumina, Solexa, Sanger, 454, Ion Torrent, PacBio, Oxford Nanopore	Bankevich, A et al.	2012 / 2017	os	link
Velvet	(small) genomes	Sanger, 454, Solexa, SOLiD	Zerbino, D. et al.	2007 / 2011	OS	link

^{*}Licences: OS = Open Source; C = Commercial; C / NC-A = Commercial but free for non-commercial and academics



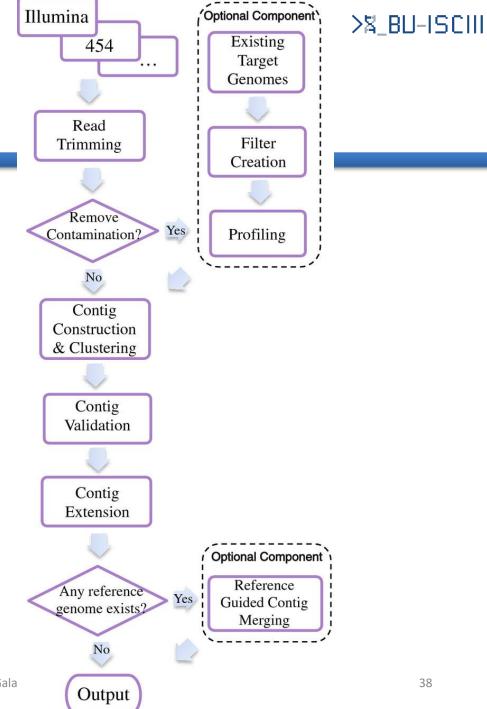
Assembly: Specials assemblers

- Diploid genomes
- Metagenomics
- Plasmids
- Transcriptome
- Virus
 - VICUNA: population consensus genome assembly
 - IVA: assembler for RNA viruses



VICUNA & IVA

 VICUNA is a de novo assembly program targeting populations with high mutation rates





Rnaviral Spades: CoronaSpades

https://github.com/ablab/spades#sec1.2

Coronavirus assembly mode for SPAdes assembler (also known as coronaSPAdes).

It allows to assemble full-length coronaviridae genomes from the transcriptomic and metatranscriptomic data. Algorithmically, coronaSPAdes is an rnaviralSPAdes that uses the set of HMMs from Pfam SARS-CoV-2 2.0 set as well as additional HMMs

HMM-guided mode: amino acid profile HMMs are aligned to the edges of assembly graph

Bioinformatics 2021 Dec 22;38(1):1-8. doi: 10.1093/bioinformatics/btab597



METAVIRALSPADES: assembly of viruses from metagenomic data

Bioinformatics, 36(14), 2020, 4126-4129 doi: 10.1093/bioinformatics/btaa490

METAVIRALSPADES tool for identifying viral genomes in metagenomic assembly graphs that is based on analyzing variations in the coverage depth between viruses and bacterial chromosomes

METAVIRALSPADES includes VIRALASSEMBLY, VIRALVERIFY and VIRALCOMPLETE modules

https://github.com/ablab/spades/tree/metaviral_publication,

https://github.com/ablab/viralVerify/ https://github.com/ablab/viralComplete/.

viralVerify classifies contigs (output of metaviralSPAdes or other assemblers) as viral, non-viral or uncertain, based on gene content. Also for non-viral contigs it can optionally provide plasmid/non-plasmid classification. viralVerify predicts genes in the contig using Prodigal in the metagenomic mode, runs hmmsearch on the predicted proteins and classifies the contig as vrial or non-viral by applying the Naive Bayes classifier (NBC). For the set of predicted HMMs, viralVerify uses trained NBC to classify this set to be viral or chromosomal.

viralComplete is intended for completeness verification of novel viral contigs. It heavily relies on following assumptions:
1.Virus genome size is consistent across the viral family.

2.If a newly constructed viral contig is complete and belongs to a known family of viruses then its gene content should be similar to the gene content of a known virus.

We thus compute the "similarity" of a given contig (based on the Naive Bayesian Classifier) to each known virus from the RefSeq database, and check whether the most similar known virus have length similar to the contig length.



Haploflow: strain-resolved de novo assembly of viral

Fritz et al. Genome Biology (2021) 22:212 https://doi.org/10.1186/s13059-021-02426-8

A deBruijn graph-based assembler for de novo genome assembly of viral strains from mixed sequence samples using a novel flow algorithm.

Haploflow reconstructs viral strain genomes from patient HCMV samples and SARS-CoV-2 wastewater samples identical to clinical isolates

genomes



Haploflow: strain-resolved de novo assembly of viral genomes Fritz et al. Genome Biology (2021

Fritz et al. Genome Biology (2021) 22:212 https://doi.org/10.1186/s13059-021-02426-8

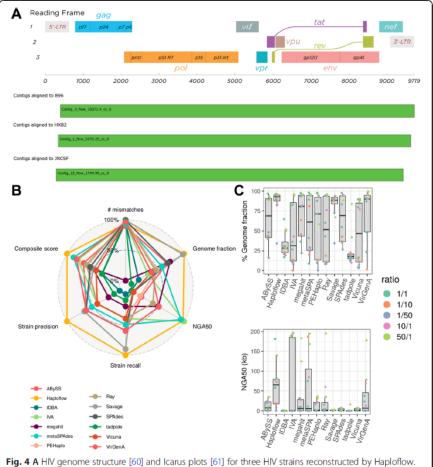


Fig. 4 A HIV genome structure [60] and Icarus plots [61] for three HIV strains reconstructed by Haploflow. For each of the three reference genomes, there is one contig spanning almost the complete genome. B Radar plot of relative performance with commonly used and strain-resolved genome assembly metrics for Haploflow and 12 other methods on the HCMV benchmark data (best values are at 100%, see the "Performance evaluation" section). Haploflow, in orange, ranks first in genome fraction, strain recall, strain precision, and composite score. C Boxplots with median and interquartile range of genome fraction and NGA50 values across samples for different methods



Choice of assembly software has a critical impact on virome characterisation Sutton et al. Microbiome (2019)

Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

Metagenomic assemblers typically use de Bruijn graph (DBG)

CHALLENGES:

- Uneven sequencing coverage of organisms within the metagenome.
- The presence of conserved regions across different species.
- Repeat regions within genomes.
- The introduction of false k-mers by both closely related genomes at differing abundances and sequencing errors at high read coverage.
- Virome data is characterised by:
 - high proportions of repeat regions
 - hypervariable genomic regions associated with host interaction
 - high mutation rates which lead to increased metagenomic complexity and strain variation



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

DATASETS

- Simulated viromes dataset (572 genomes)
- Mock viral communities
- Human gut viromes spiked with a known exogenous bacteriophage
- Human virome data

AIMS

- Assembly efficacy and accuracy comparison
- Runtime and RAM usage
- Impact of sequencing coverage
- Genomic repeats



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

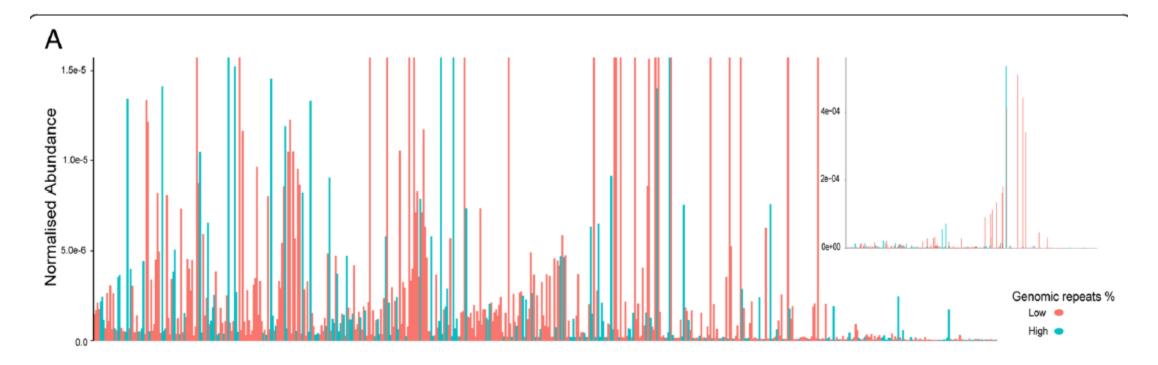
Table 1 A list of assemblers used in this study

	Link	Version used	Reference
ABySS	http://www.bcgsc.ca/downloads/abyss/	v2.0.2	[50]
CLC	https://www.qiagenbioinformatics.com/products/clc-assembly-cell/	v5.0.5	https://www.qiagenbioinformatics.com/
Geneious	https://www.geneious.com/features/assembly-mapping/	v11.0.3	[22]
IDBA UD	https://i.cs.hku.hk/~alse/hkubrg/projects/idba_ud	v1.1.1	[43]
MEGAHIT	https://github.com/voutcn/megahit	v1.1.1-2	[25]
MetaVelvet	https://metavelvet.dna.bio.keio.ac.jp/	v1.2.02	[38]
MIRA	http://www.chevreux.org/mira_downloads.html	v4.0.2	[14]
Ray Meta	http://denovoassembler.sourceforge.net/	v2.3.0	[5]
SOAPdenovo2	http://soap.genomics.org.cn/soapdenovo.html	v2.04	[29]
SPAdes	http://cab.spbu.ru/software/spades/	v3.10.0	[4]
SPAdes meta	http://cab.spbu.ru/software/spades/ (variation of SPAdes applied with flag)	v3.10.0	[40]
Velvet	https://www.ebi.ac.uk/~zerbino/velvet/	v1.2.10	[58]
VICUNA	https://github.com/broadinstitute/mvicuna	v1.3	[53]



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

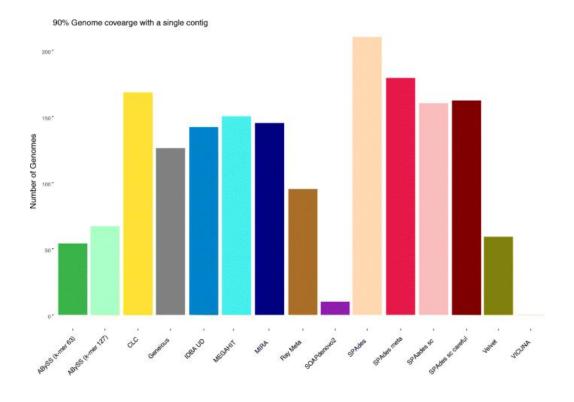
Simulated viromes dataset (572 genomes)





Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

Simulated viromes dataset (572 genomes)



Number of contigs each assembler recovered to a minimum genome fraction of 90% in a single contig



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

Simulated viromes dataset (572 genomes)

Table 2 The number of false positive and false negative contigs generated by each assembler for the simulated community, together with the sensitivity rates

	False positives	False negative	True positives	No. of contigs returned ^a	Sensitivity
ABSS (k-mer 63)	0	111	461	7957	80.59
ABySS (k-mer 127)	1	123	449	7732	78.50
CLC	34	5	567	9152	99.13
Geneious	9	190	382	958	66.78
IDBA UD	25	9	563	8999	98.43
MEGAHIT	21	8	564	10,083	98.60
MetaVelvet	N/A	N/A	N/A	N/A	N/A
MIRA	4	13	559	27,600	97.73
Ray Meta	0	213	359	4224	62.76
SOAPdenovo2	536	116	456	11,548	79.72
SPAdes	29	3	569	8230	99.48
SPAdes meta	5	14	558	7419	97.55
SPAdes sc	38	7	565	9506	98.78
SPAdes sc careful	40	6	566	9724	98.95
Velvet	1	65	507	6343	88.64
VICUNA	0	558	14	4	2.45

false positive: no alignment to reference genomes

false negative: recovered genome fraction of 0%

Sensitivity: true positive / (false
positive + false negative)

^a572 in community



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

 Mock community dataset - were used to investigate the impact of high and low abundance ssDNA viruses on assembly performance

<u>Mock A</u> (Table 3a) contained 12 viral genomes, 10 of which were at equal abundance (9.82% of the total community) and 2 ssDNA genomes (NC_001330 and NC_001422) at low abundance (0.92%).

Table 3 The number of false positive and false negative contigs generated by each assembler for (a) mock community A and (b) mock community B along with the sensitivity rates for each

	False positives	False negative	True positive	No. of contigs returned ^a	Sensitivity
ABySS (k-mer 63)	52	4	8	61	66.67
ABySS (k-mer 127)	50	6	6	56	50.00
CLC	1143	0	12	1299	100.00
Geneious	53	0	12	65	100.00
IDBA UD	0	0	12	12	100.00
MEGAHIT	0	0	12	13	100.00
MetaVelvet	0	3	9	26	75.00
MIRA	0	0	12	89	100.00
Ray Meta	0	0	12	12	100.00
SOAPdenovo2	2	0	12	23	100.00
SPAdes	0	0	12	14	100.00
SPAdes meta	0	0	12	14	100.00
SPAdes sc	1513	0	12	1527	100.00
SPAdes sc careful	0	0	12	15	100.00
Velvet	0	3	9	26	75.00
VICUNA	4969	0	12	5385	100.00

Mock B (Table 3b) contained 12 viral genomes, 10 of which were at equal abundance (9.82% of the total community) and 2 ssDNA genomes (NC_001330 and NC_001422) at higher abundance (32.47%).

1					
ABySS (k-mer 63)	60	4	8	69	
ABySS (k-mer 127)	132	6	6	139	
CLC	450	0	12	505	
Geneious	14	0	12	30	
IDBA UD	0	0	12	12	•
MEGAHIT	0	0	12	14	1
MetaVelvet	0	1	11	24	ġ
MIRA	94	1	11	157	Ġ
Ray Meta	0	0	12	13	
SOAPdenovo2	2	2	10	27	8
SPAdes	0	0	12	13	1
SPAdes meta	0	0	12	14	1
SPAdes sc	593	0	12	607	
SPAdes sc careful	0	0	12	14	
Velvet	0	1	11	24	
VICUNA	0	0	12	15	



Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

Human gut viromes spiked with a known exogenous bacteriophage

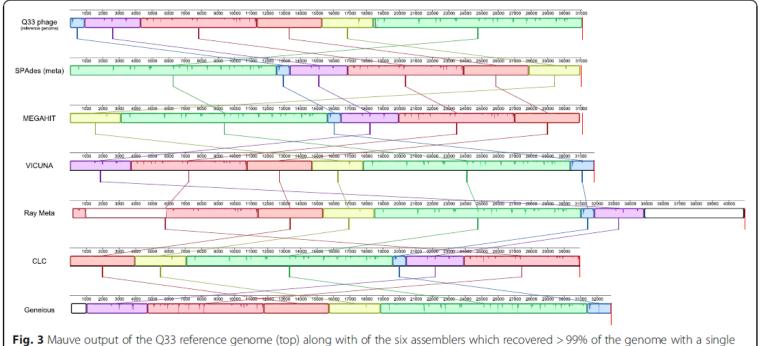


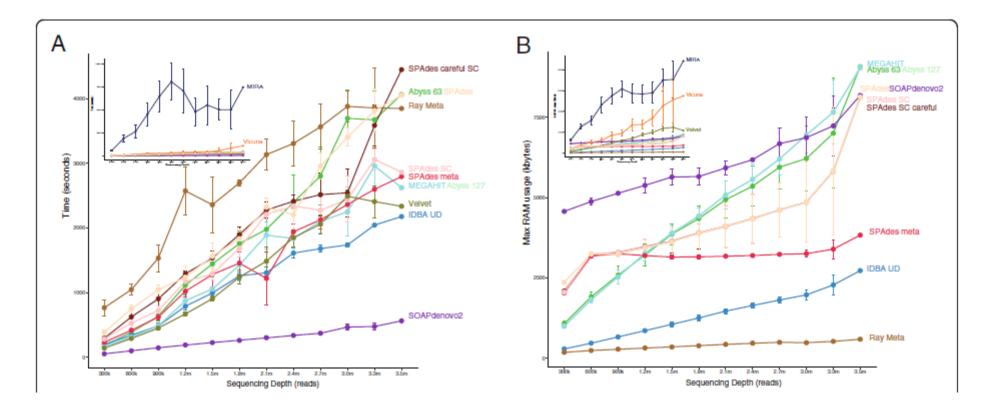
Fig. 3 Mauve output of the Q33 reference genome (top) along with of the six assemblers which recovered > 99% of the genome with a single contig. Assembly regions outside of locally collinear blocks which do not share homology to the reference genome are highlighted by a black outline. Reverse complement of assemblies in the opposite orientation to the reference were plotted for visualisation purposes (VICUNA, CLC, Geneious)



Choice of assembly software has a critical impact on virome characterisation Sutton et al. Sutton e

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healthy human gut viromes and various sequencing depths





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healthy human gut viromes and various sequencing depths

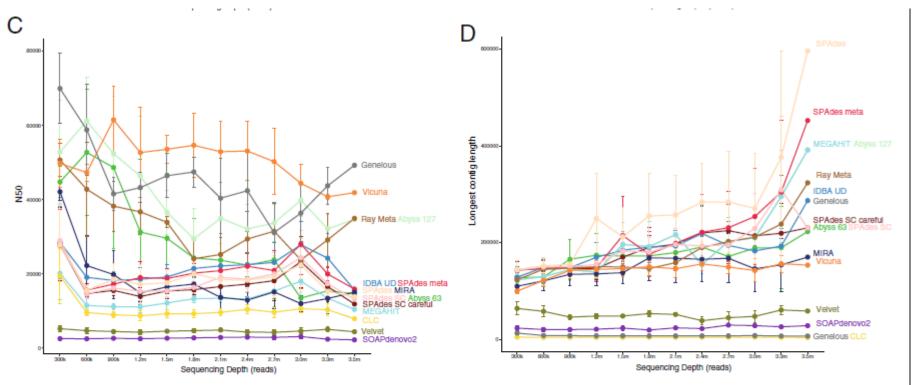


Fig. 4 a Time, measured in seconds, for each assembly to reach completion successfully for each read subset. **b** The maximum RAM, measured in MB, used for each assembly for each read subset. **c** Mean N50 length and **d** mean contig length for four samples for each assembly across the read subsets after filtering contigs less than 1000 bases. Points represent the mean time for the four samples while error bars are the standard error



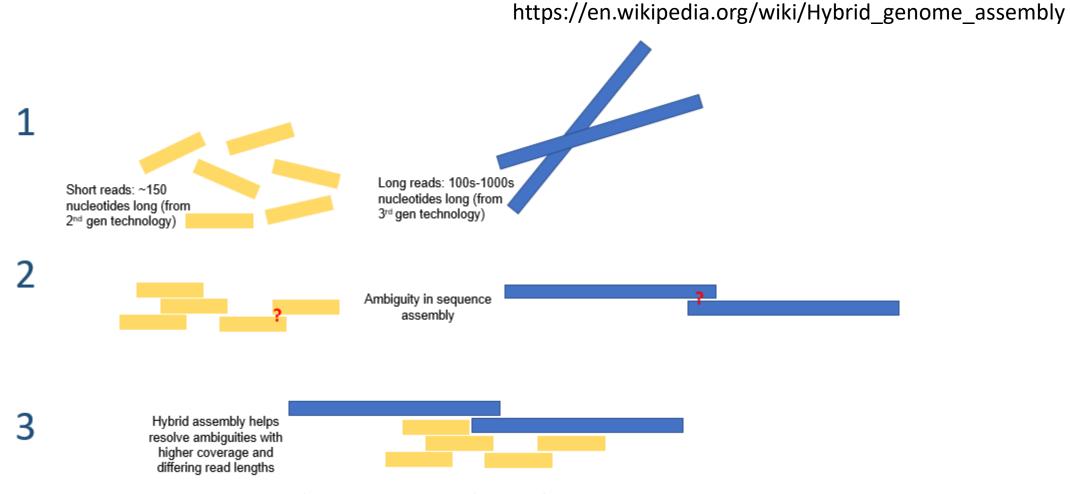
Sutton et al. Microbiome (2019) 7:12 https://doi.org/10.1186/s40168-019-0626-5

CONCLUSIONS

- ❖ Assemblers were assessed using four independent virome datasets, namely, simulated reads, two mock communities, viromes spiked with a known phage and human gut viromes.
- ❖ Assembly performance varied significantly across all test datasets, with SPAdes (meta) performing consistently well.
- ❖ It was also found that while some assemblers addressed the challenges of virome data better than others, all assemblers had limitations
- ❖ Low read coverage and genomic repeats resulted in assemblies with poor genome recovery, high degrees of fragmentation and low-accuracy contigs across all assemblers.



Hybrid genome assembly - short and long reads



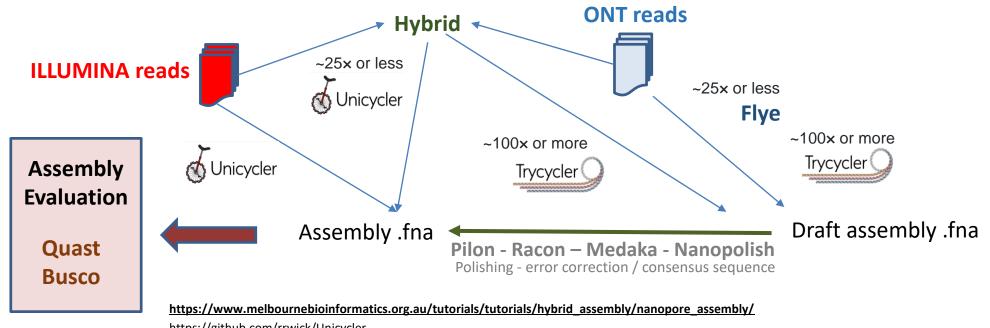
Hybrid genome assembly - nanopore and illumina

Short reads (ILLUMINA) + Long reads (ONT) \rightarrow deNovo assembly (De novo assembly is the process of assembling a genome from scratch using only the sequenced reads as input - no reference genome is used.) \rightarrow high-quality assembly

ONT: >40.000b, higher error rate – **genome structure**

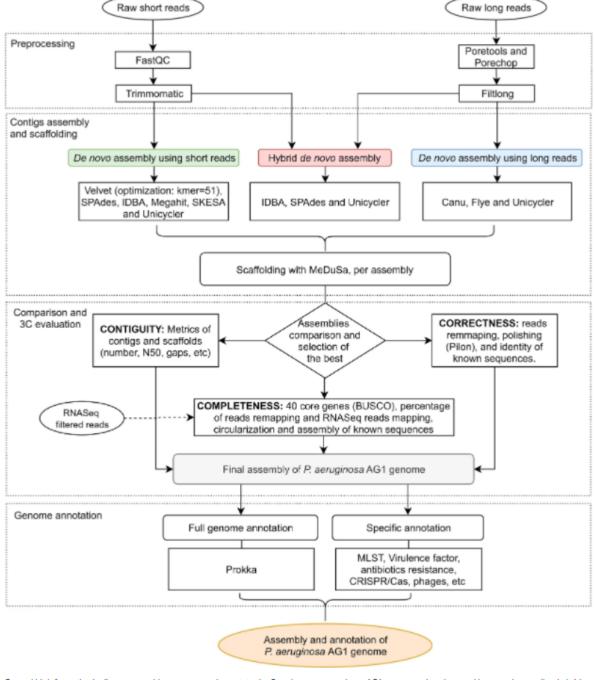
ILLUMINA: 300b, lower error rate – high base-level accuracy

Higher COST





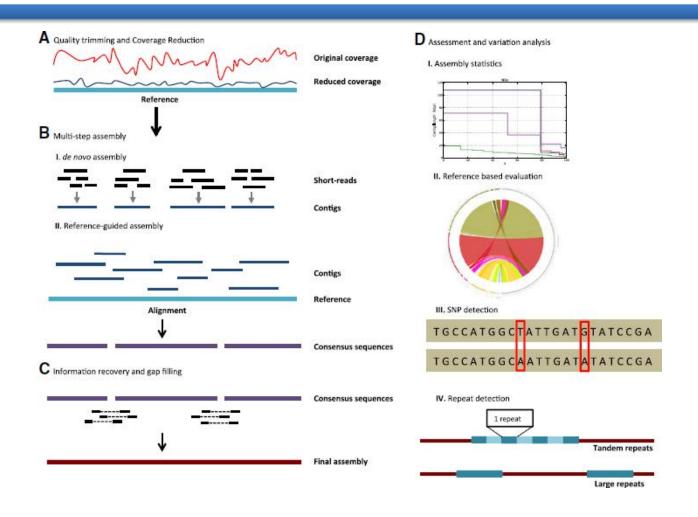




Molina-Mora et al., Scientific Reports 2020



VirAmp: a galaxy-based viral genome assembly pipeline



Gigascience, Volume 4, Issue 1, December 2015, s13742-015-0060-y, https://doi.org/10.1186/s13742-015-0060-y

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Thanks for your attention!

Questions?