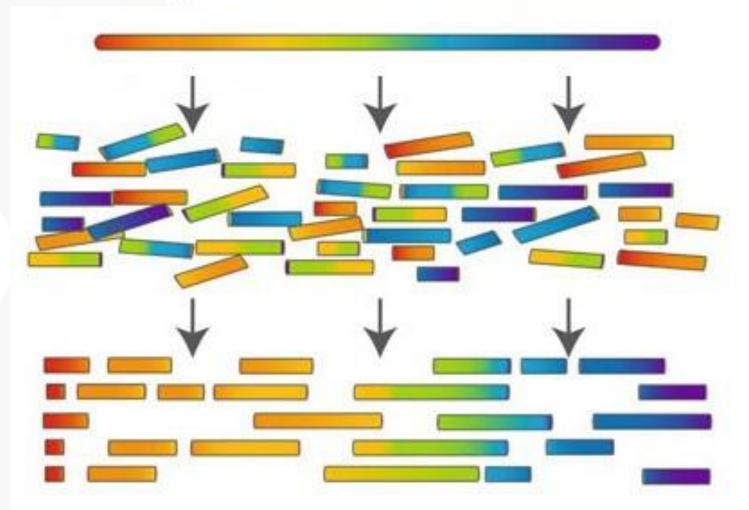
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# Genome Assembly Team 3: Background and Strategy

Maddala Aparna Yang Ruize Kundnani Deepali Xiao Yiqiong Singu Swetha Gowri

# What is genome assembly?



#### genome sequence

#### reads (output of sequencing)

alignment

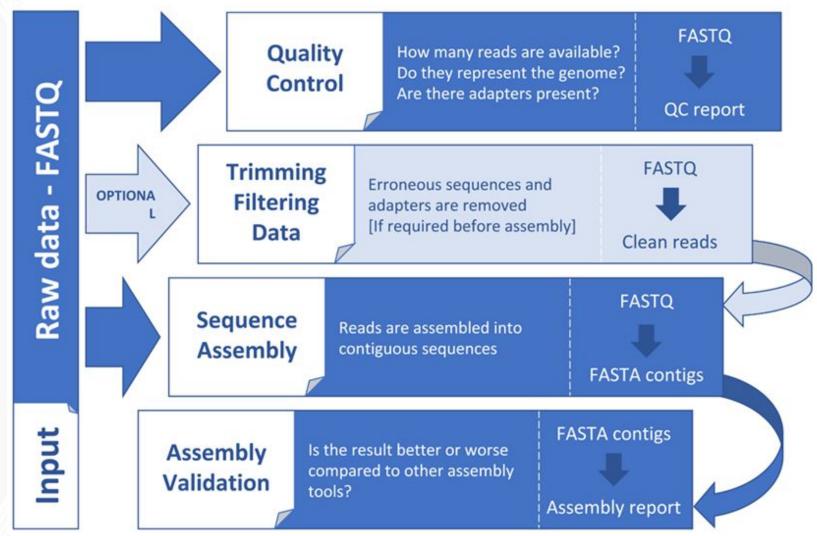
#### 

Adapted from: Commins, Jennifer et al. "Computational biology methods and their application to the comparative genomics of endocellular symbiotic bacteria of insects." Biological Procedures vol. 11 52-78. 11 Mar. 2009.

contigs



## **Steps of Genome Assembly**



Dominguez Del Angel V, Hjerde E, Sterck L et al. Ten steps to get started in Genome Assembly and Annotation [version 1]. F1000Research 2018, 7:148 (doi: 10.12688/f1000research.13598.1)

# **Quality Control for Raw Reads**

• Tools:

- FastQC & Trimmomatic
  - FastQC quality control on raw sequence reads
  - Trimmomatic flexible trimming tool designed for Illumina NGS data
- fastp
  - A tool designed to provide fast all-in-one preprocessing for FastQ files
  - integrates trimming and QC into a single tool
  - Quality control features specifically designed for paired-end data
- MultiQC
  - consolidates multiple quality control reports generated by FastQC or fastp

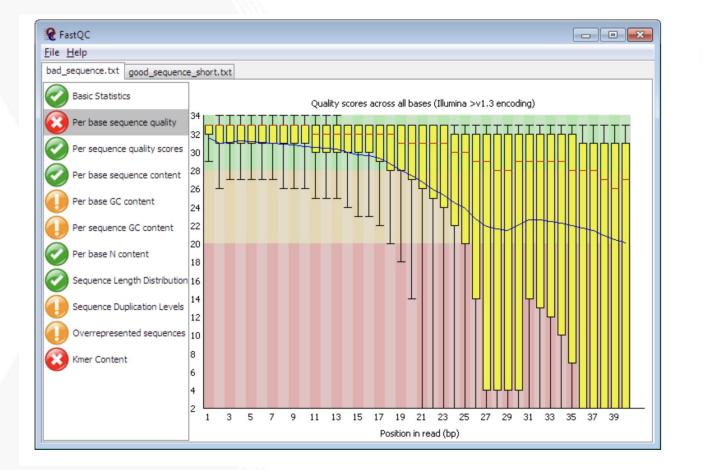




	fastp	FastQC, Trimmomatic
Reliability	more recent	cited often, industry standard
Suitability	paired-end base correction	treats paired reads separately
Speed	faster than FastQC	runs fairly quickly
Information provided	interactive plots allow us to zoom in on regions of interest	generates per-base sequence quality scores with boxplots



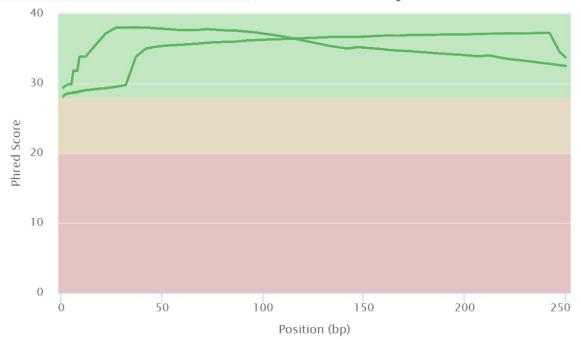
# FastQC vs. fastp



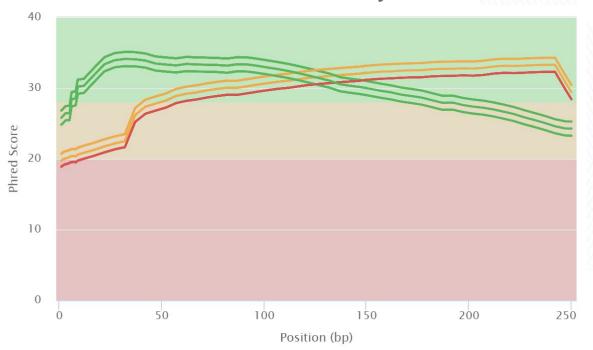
#### Before filtering: read1: quality Value of each position will be shown on mouse over. 🙆 🔍 🕂 🖪 🗖 🖾 🖄 🖄 👘 🚍 🚺 35.4158 35.363 A 35.3313 G 35.3131 mean 35 35.2769 A mean 34 quality 33 32 30 5 10 15 16 20 25 position

# **Approach to Trimming**

Read 1: Mean Quality Scores



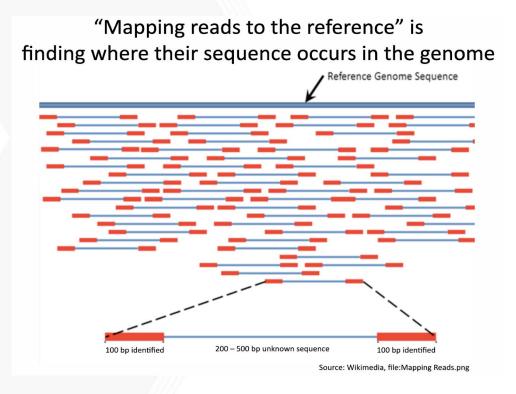
Read 2: Mean Quality Scores





# Assembly

## **Reference based assembly**



### De novo assembly

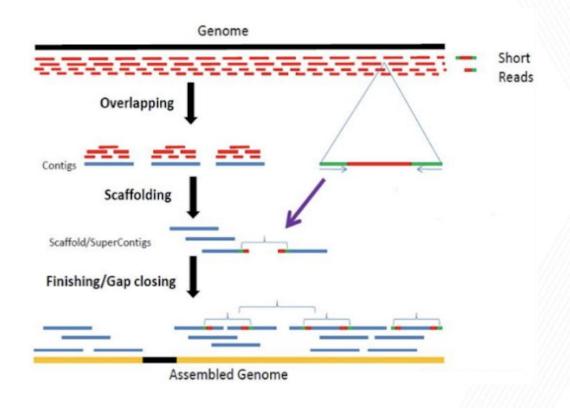


Image from: https://www.arraygen.com/De-novo-Assembly.php

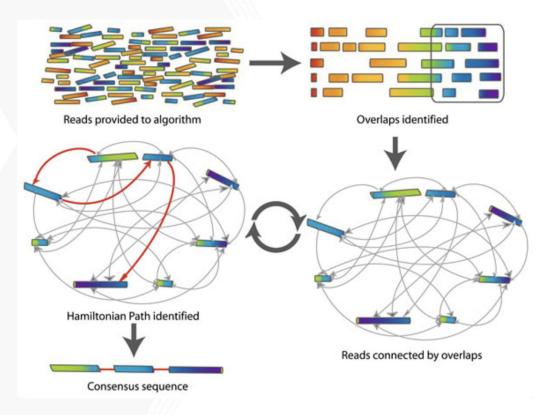


#### Image from :

https://www.mn.uio.no/ifi/studier/masteroppgaver/bmi/benchmarking-system.html

# **Algorithms**

### **OLC** Graph



#### De Bruijn Graph



Reads are now 2-node graphs
Nodes are prefix/suffix

Edge is the actual read

Genome path

TAA AAT ATG TGC GCC CCA CAT ATG TGG GGG GGA GAT ATG TGT GTT TA + AA + AT + TG + GC + CC + CA + AT + TG + GG + GG + GA + AT + TG + GT + TT

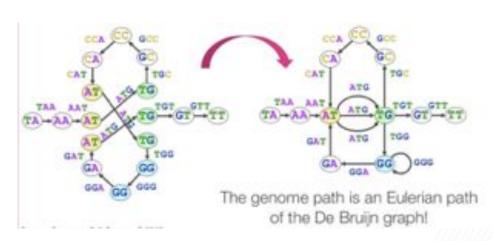


Image from : https://www.slideshare.net/JosHctorGlvez/basics-of-genome-assembly

Image from: https://www.researchgate.net/figure/Overlap-layout-consensus-genome -assembly-algorithm-Reads-are-provided-to-the-algorithm\_fig2\_26266221 Georgia Tech

9

## How to select a De novo tool?

Why not a single tool?

The GAGE-B - Genome Assembly Gold-standard Evaluation for Bacterial study [2] shows that assembly software that performs well on one organism often performs poorly on other organisms.

Test several approaches and also with different parameter settings



## **Parameters considered when selecting tool:**

- Known: Genome size, Ploidy, paired end, short reads.
- Coverage
- Which algorithm to use
- Low Computational resource consumption
- Strongest performance **common heuristics** for selecting the best assembly when the true genome sequence is unknown:
  - higher N50 contig size
  - higher sequence coverage
  - low assembly error rates



# **Tool Comparison table**

Study : A Comprehensive Study of De Novo Genome Assemblers: Current Challenges and Future Prospective

De novo Tools	Assembler type	Good for read length	Programmi ng language	Citations	Advantages	Disadvantages
AbySS	DBG	Single and paired end	C++	3078	High N50, high genome fraction, Time efficient and High scalability	More memory and high cpu usage
Velvet	DBG	Single and paired end	С	8667	Time efficient, High genome fraction	High cpu usage, Low N50
Edena	OLC	Single and paired end	C++	675	Lowest Memory usage and low CPU usage	Average accuracy (mean genome fraction)
SGA	String graph	Paired end	C++	-	Memory efficient	Only paired end, High cpu usage and Average accuracy (mean genome fraction)
RAY	Hybrid	Single and paired end	C++	475	High genome fraction	Highest time [500 mins]
SSAKE	Greedy	Single and paired end	Perl	600	time and CPU usage efficient	Worst genome fraction
Perga	Greedy	Single and paired end	С	11	Good N50 contig length	High memory usage, Average accuracy (mean genome fraction)

12

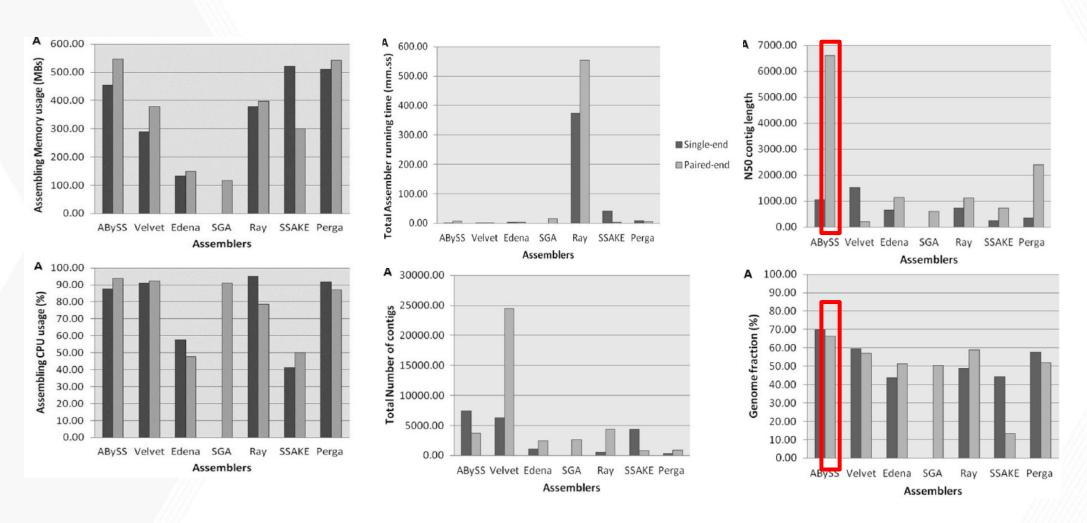
Geora

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Efficiency evaluation, Accuracy evaluation and Statistical analysis is done

# **Tool comparison plots**

Study : A Comprehensive Study of De Novo Genome Assemblers: Current Challenges and Future Prospective



Graph plots from the study "Abdul Rafay Khan et.al [2018] - "A Comprehensive Study of De Novo Genome Assemblers: Current Challenges and Future Prospective"

## **Tool comparison**

Study : GAGE-B: an evaluation of genome assemblers for bacterial organisms

Assembler	Species assembled								
	HiSe	q (100 bp) rea	ds	MiSeq (250 bp) reads					
	R.sphaeroides	M.abscessus	V.cholerae	B.cereus	R.sphaeroides	M.abscessus	V.cholerae		
ABySS	13.0	115.7	93.0	130.6	21.4	68.5	60.3		
CABOG	11.2	78.2	48.8	150.5	30.5	8.3	32.5		
MIRA	17.7	129.2	87.1	100.0	15.4	75.0	108.7		
MaSuRCA	176.8	194.0	236.4	246.7	130.7	36.2	71.6		
SGA	12.1	27.9	23.4	25.5	9.1	12.8	27.3		
SOAPdenovo	10.5	147.2	106.5	246.3	33.5	113.3	65.5		
SPAdes	83.5	147.9	77.1	103.7	118.1	215.4	246.6		
Velvet	13.1	60.3	39.5	24.5	24.2	41.5	67.1		

# **Tools interested**

ABySS

- Assembly by Short Sequences
- DBG, Parallel, paired-end assembler designed for short reads
- Pros: high genome fraction, high N50, time efficient
- Cons: more memory and cpu usage than velvet

MaSuRCA

- Maryland Super-Read Celera Assembler
- Combination of OLC + De bruijn graph
- selects optimal k-mer [k-mer length comparison not necessary]
- Pros: usually larger assembly, high N50
- Cons: mis-assemblies



# **SPAdes**

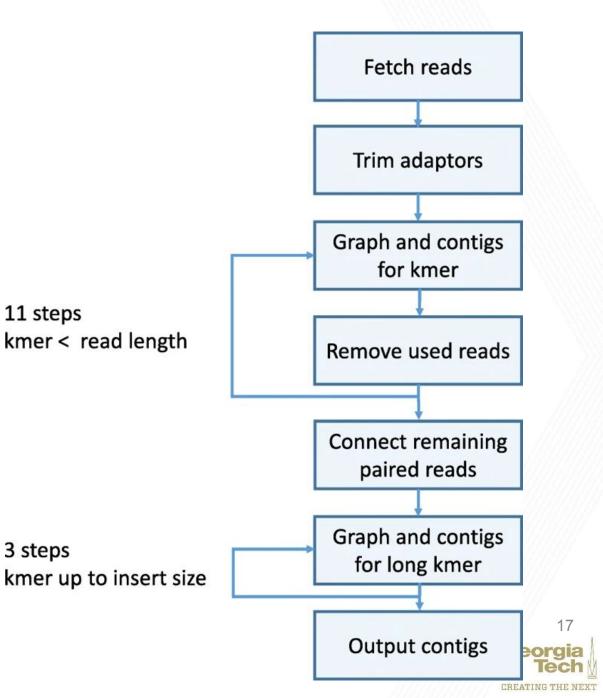
- DBG assembler for small genomes
- Designed to address issues in single-cell sequencing
- Multisized de Bruijn graph: build graph from small to large k-mer sizes, each based on previous one. Allows SPAdes to get the advantages of both small k-mer assemblies (a more connected graph) and large k-mer assemblies (ability to resolve repeats).
- **Resolve repeats: paired-end information**. Since two reads in a pair are close to each other in the original DNA, SPAdes can use this to trace paths in the graph to form larger contigs
- **Pros:** High N50, Genome fraction, No. of complete genes.
- **Cons:** Time-consuming



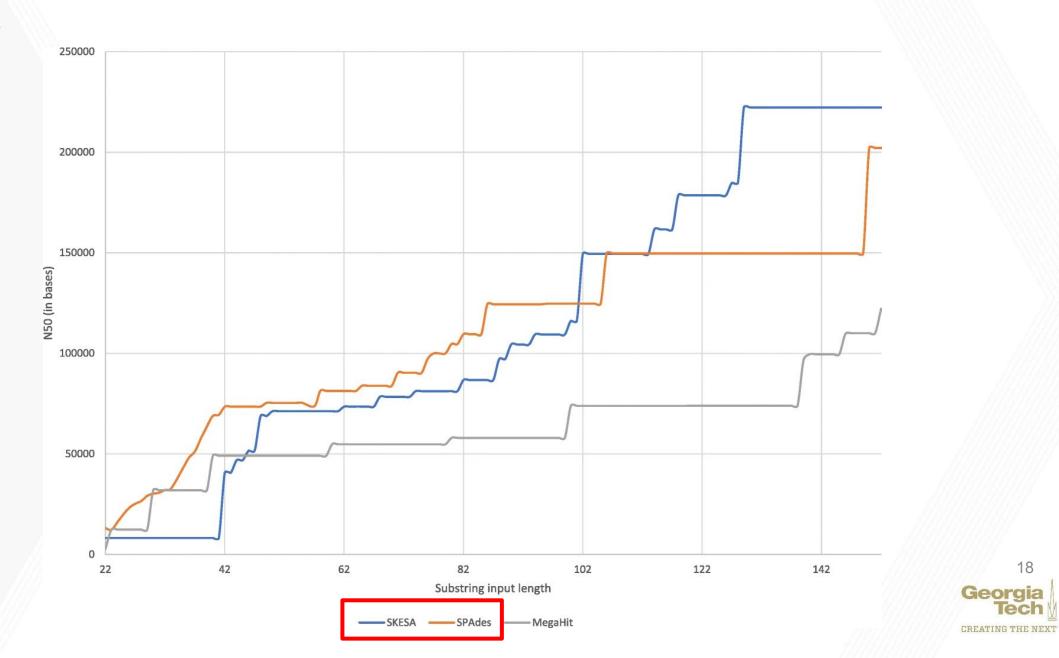
## **SKESA**

- DBG assembler for microbial genomes sequenced using Illumina
- Using different k-mer sizes:

  - Increases upto to insert size, in 3 iterations
- Assemble repeats shorter than insert size but longer than the mate length
- Pros: fast and reproducible
- Cons: no built-in scaffolding tool



- SKESA
- N50:





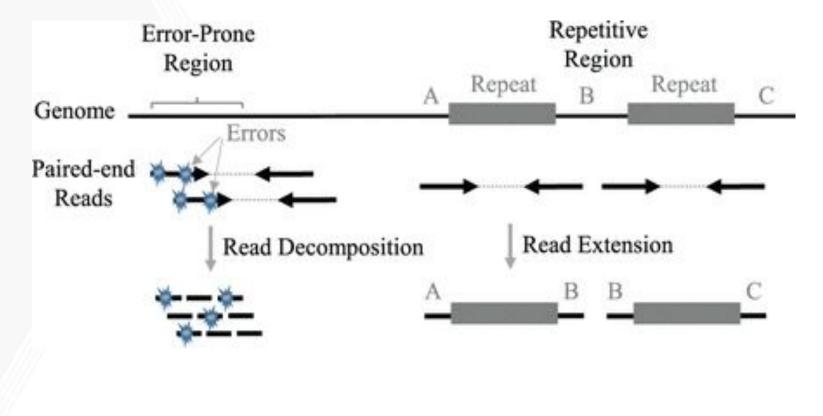
### • Misassemblies:

Benchmark set			
Measure	SKESA	SPAdes	MegaHit
Median	0.08	2.76	1.89
Maximum	7.78	41.60	31.94
Average	0.40	3.21	2.79
Assembly counts in benchmark set			
Mismatches range	SKESA	SPAdes	MegaHit
0	105	1	1
0.01–1	247	40	80
1.01–2	9	76	121
2.01–3	9	89	58
3.01-4	1	71	45
> 4	10	104	76
1////	10.		11/1/11/11/11/11/1





- Combination of string and de Bruijn graphs.
- Reads in error-prone region are decomposed into overlapping subreads.
- The paired-end reads are extended into long reads using an FM-index, to resolve **repeats longer than read length**.



## **StriDe**

• N50:

						_	
ABySS	CABOG	MaSuRCa	SOAPdenovo	SGA	SPAdes	Velvet	StriDe
237.7	278.4	838.5	243.9	67.1	237.6	184.4	827.8
41.6	61.1	75.2	57.9	20.5	78.6	38.9	90.6
116.3	94.2	99.7	116.1	45.0	127.4	125.2	151.5
128.5	78.2	147.4	147.2	28.7	278.4	60.3	298.0
115.8	11.2	36.4	10.5	4.8	173.3	13.1	175.1
99.2	102.8	228.9	146.3	39.9	148.1	122.5	222.2
172.6	48.8	167.9	106.5	23.8	344.0	39.5	356.0
74.1	105.8	115.7	74.2	48.9	117.2	83.0	113.0

## • Misassemblies:

ABySS	CABOG	MaSuRCa	SGA	SOAPdenovo	SPAdes	Velvet	StriDe
1 (140.14)	0 (281.24)	3 (235.23)	0 (97.50)	1 (127.95)	1 (115.88)	0 (108.65)	1 (115.44)
3 (0.98)	7 (5.81)	7 (3.58)	1 (0.43)	9 (0.67)	5 (0.48)	4 (0.74)	5 (0.43)
9 (5.37)	4 (1.55)	5 (2.13)	1 (0.30)	2 (1.94)	2 (1.19)	2 (0.31)	3 (0.70)
3 (3.98)	20 (6.84)	16 (6.00)	3 (2.60)	21 (3.67)	7 (3.03)	5 (3.37)	3 (2.85)
					2876 (6)	57. 37.	1000

# **Assembly Quality - Broad Overview**

- Using Assembly information
  - N50 family metrics (quast)
  - remapping reads to assembled contigs (AMOSValidate, REAPR, FRCbam, Pilon, VALET)
  - computing probability of reads given the assembly (ALE, CGAL, LAP)
- Using External information
  - map to near reference genome (quast, dnAQET or Assemblytics)
  - counting number of conserved genes in assembly (BUSCO)

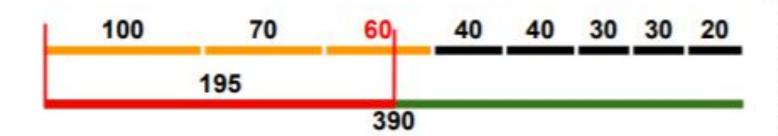


# **Assembly Quality - N50 family metrics**

Length of largest contig

number of contigs

• N50 and L50



• N75 and L75



## **Assembly Quality - Quast Example output**

Assembly	<pre>pit_fna</pre>	cef_fna	car_fna
<pre># contigs (&gt;= 0 bp)</pre>	100	91	94
# contigs (>= 1000 bp)	62	58	61
Total length (>= 0 bp)	6480635	6481216	6480271
Total length (>= 1000 bp)	6466917	6468946	6467103
# contigs	71	66	70
Largest contig	848753	848766	662053
Total length	6473173	6474698	6473810
GC (%)	66.33	66.33	66.33
N50	270269	289027	254671
N75	136321	136321	146521
L50	7	7	8
L75	15	15	16
# N's per 100 kbp	0.00	0.00	0.00

# **Assembly Quality with Quast**

N50 family metrics

### Conserved genes using BUSCO

--conserved-genes-finding (or -b)

Enables search for Universal Single-Copy Orthologs using BUSCO (only on Linux, only with Python 2.7 or Python 3). Disabled by default.

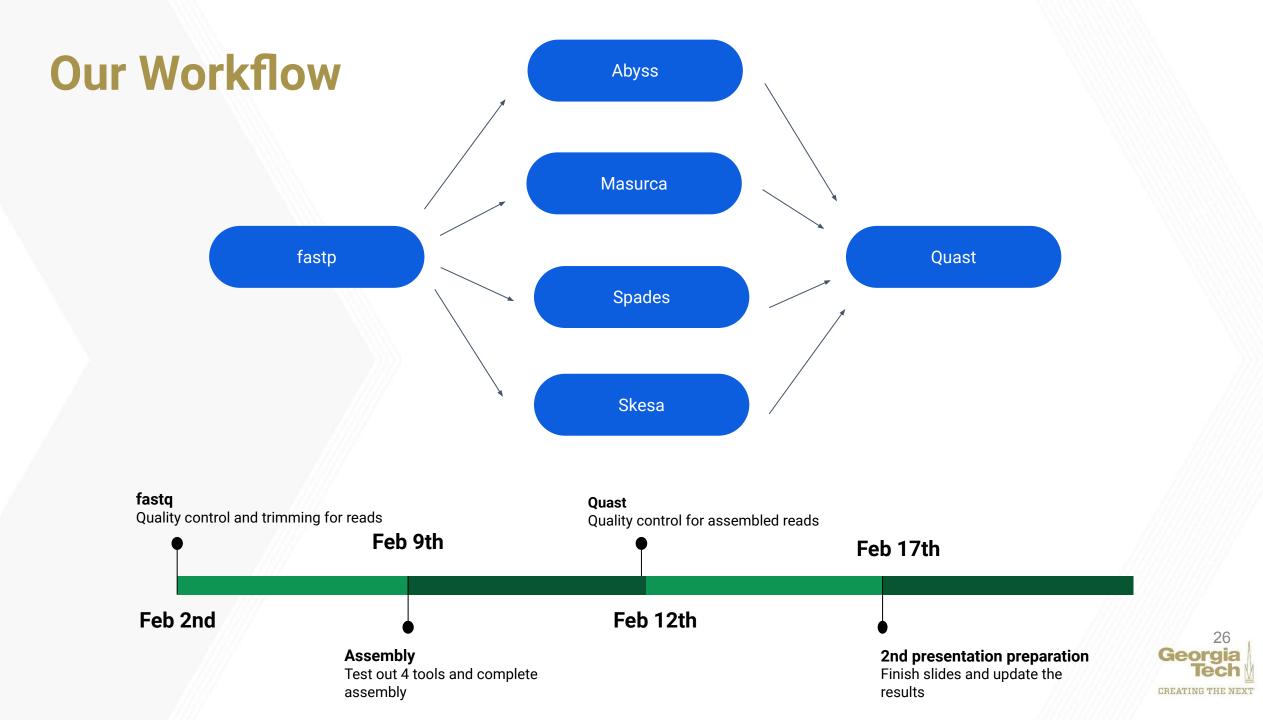
By default, we assume that the genome is prokaryotic, and BUSCO uses the bacterial database of orthologs. If the genome is eukaryotic (fungal), use <u>--eukaryote</u> (<u>--fungus</u>) option to force BUSCO to work with the eukaryotic (fungal) database.

## NG stats based on estimated reference size?

--est-ref-size <int>

Estimated reference genome size (in bp) for computing NGx statistics. This value will be used only if a reference genome file is not specified (see -r option).







- Commins, J., Toft, C., & Fares, M. A. (2009). Computational biology methods and their application to the comparative genomics of endocellular symbiotic bacteria of insects. Biological Procedures Online, 11, 52–78. doi:<u>10.1007/s12575-009-9004-1</u>
- 2. Dominguez Del Angel V, Hjerde E, Sterck L et al. Ten steps to get started in Genome Assembly and Annotation [version 1; peer review: 2 approved]. F1000Research 2018, 7(ELIXIR):148
- Abdul Rafay Khan et.al [2018] "A Comprehensive Study of De Novo Genome Assemblers: Current Challenges and Future Prospective" -PMID: <u>29511353</u>, doi: <u>10.1177/1176934318758650</u>
- 4. Tanja Magoc et.al [2013] "GAGE-B: an evaluation of genome assemblers for bacterial organisms" PMID: <u>23665771</u>, doi: <u>10.1093/bioinformatics/btt273</u>
- 5. Alla Mikheenko, Andrey Prjibelski, Vladislav Saveliev, Dmitry Antipov, Alexey Gurevich, Versatile genome assembly evaluation with QUAST-LG, Bioinformatics (2018) 34 (13): i142-i150. doi: 10.1093/bioinformatics/bty266
- 6. Bankevich, A.; Nurk, S. et al. (2012). SPAdes: A New Genome Assembly Algorithm and Its Applications to Single-Cell Sequencing. Journal of Computational Biology, 19(5), 455–477. doi: 10.1089/cmb.2012.0021
- Huang, Y.-T., & Liao, C.-F. (2016). Integration of string and de Bruijn graphs for genome assembly. Bioinformatics, 32(9), 1301–1307. doi: 10.1093/bioinformatics/btw011
- 8. Souvorov, A., Agarwala, R., & Lipman, D. J. (2018). SKESA: strategic k-mer extension for scrupulous assemblies. Genome Biology, 19(1). doi: 10.1186/s13059-018-1540-z

