# Searching massive amounts of sequencing data using K-mers and graphs

Finlay Maguire February 15, 2023

FCS, Dalhousie

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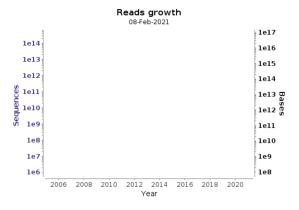
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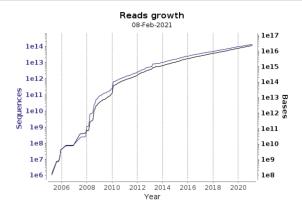
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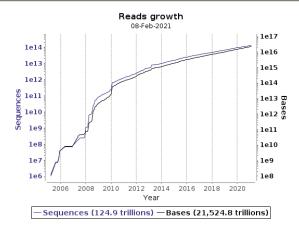
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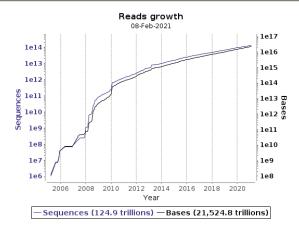
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- Describe the core algorithm used by BlastFrost (colour aggregative) and BIGSI (k-mer aggregative)

# Massive datasets?



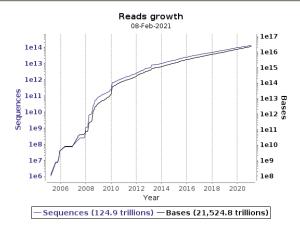






European Nucleotide Archive: Read Data

• Uncompressed at 2-bits per base:



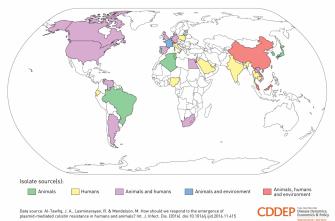
- Uncompressed at 2-bits per base:
- 5,381.2 TB (without any metadata or accession information)

Countries reporting plasmid-mediated colistin resistance encoded by mcr-1

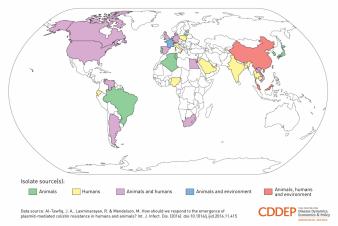
Data source: Al-Tawliq, J. A., Laxminarayan, R. & Mendelson, M. How should we respond to the emergence of plasmid-mediated colistin resistance in humans and animals? Int. J. Infect. Dis. (2016). doi:10.1016/j.ijid.2016.11.415



	Countries reporting plasmid-mediated colistin resistance encoded by mcr-1				
	Animals	Humans	Animals and humans	Animals and environment	Animals, humans and environment
Data source: Al-Tawliq, J. A., Laxminarayan, R. & Mendelson, M. How should we respond to the emergence of plasmid-mediated colistin resistance in humans and animals? Int. J. Infect. Dis. (2016). doi:10.1016/j.jid.2016.11.415					CDDEP Disease Dynamics, Economics & Policy



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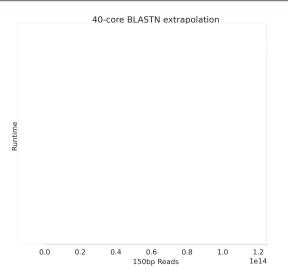
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• Which genome and metagenome read sets from all over the world contain MCR-1?

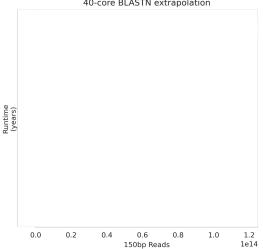
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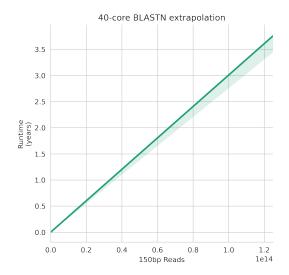
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- S is a query sequence of arbitrary length (including > *len(read*))
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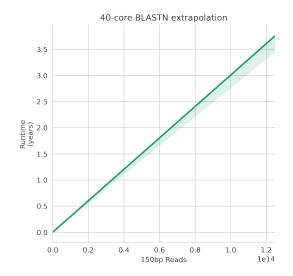
#### Just use BLAST?



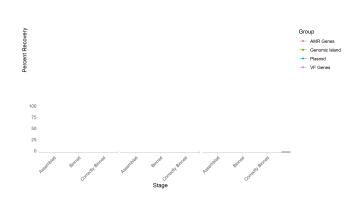
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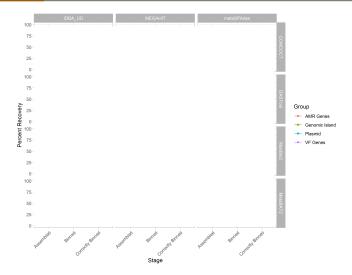


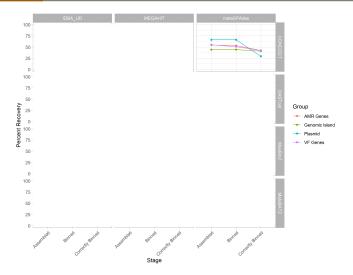
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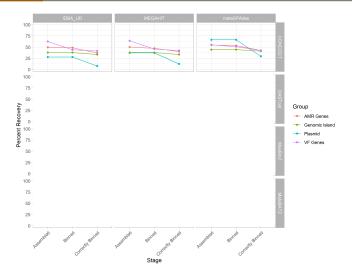


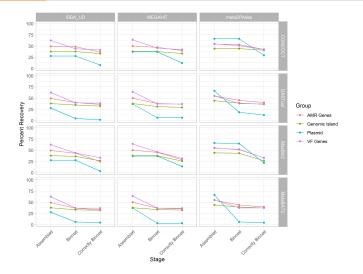
 $\cdot$  By the end, there will be  $\sim$  3x more data than at the start.

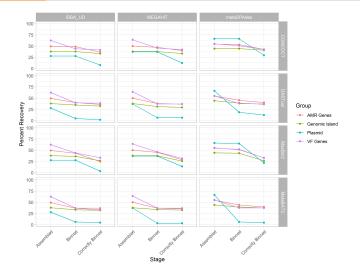












• No matter the method, assembly causes loss of information.

Let's complicate but actually simplify this problem

Sequence Sets

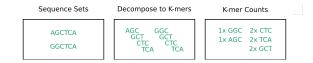
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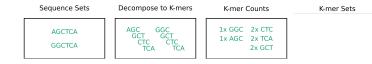
GGCTCA





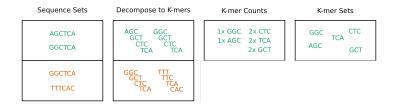


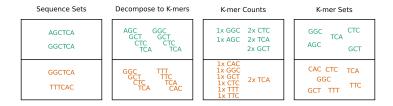












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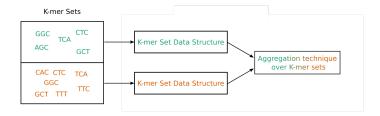
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- Bonus: also applicable to anything you can decompose into k-mers e.g., assembled sequences and long-reads

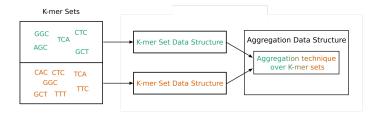
# Algorithms to query a set of k-mer sets

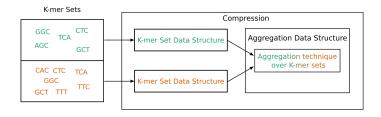












# Indexing a single set of k-mers

sequence

ATGGAAGTCGCGGAATC

sequence ATGGAAGTCGCGGAATC

7mers

sequence ATGGAAGTCGCGGAATC

ATGGAAG

7mers

sequence

ATGGAAGTCGCGGAATC

7mers



sequence

7mers



ATGGAAGTCGCGGAATC

A

sequence

7mers





de Bruijn graph

sequence

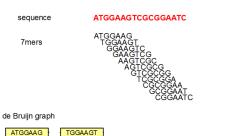
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de Bruijn graph





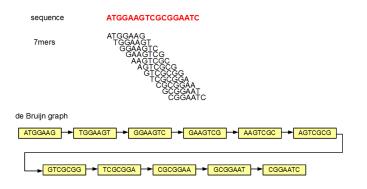


ATGGAAG TGGAAGT



de Bruijn graph

ATGGAAG TGGAAGT ► GGAAGTC



homolog.us/Tutorials/book4/p2.1.html

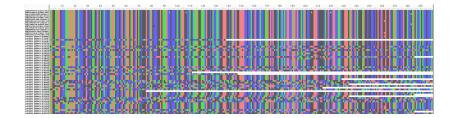
19 28 29 49 59 60 71 60 19 100 111 12 10 114 19 10 114 19 10 110 119 20 211 20 216 240 20 241 20 74 20



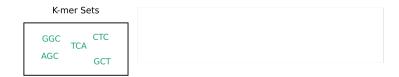








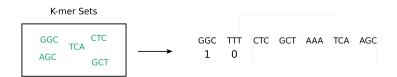
## de Bruijn graph collapses diversity: NDM

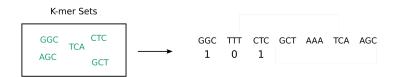




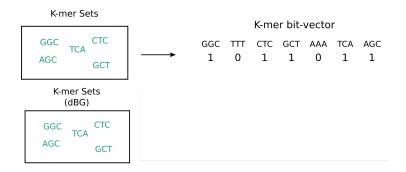


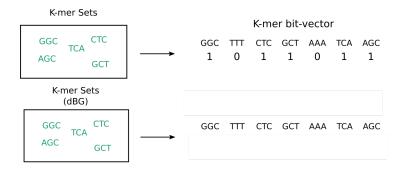


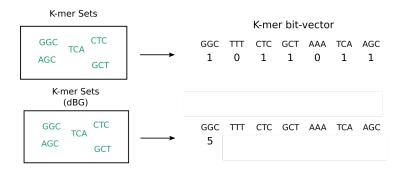


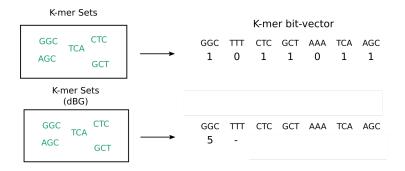


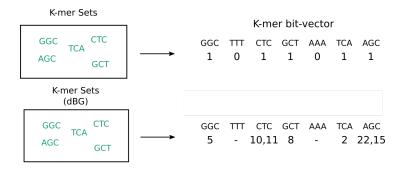


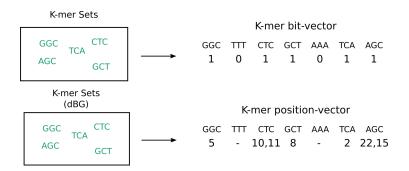




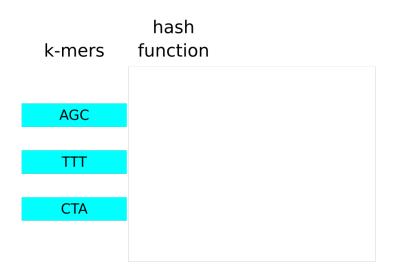


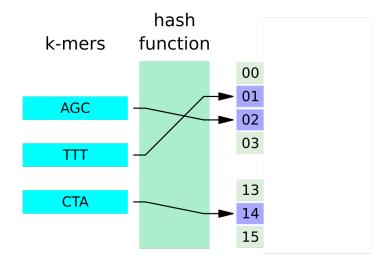


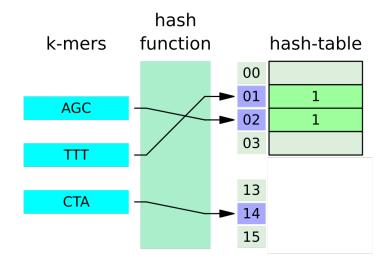


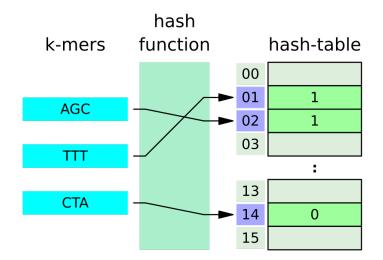


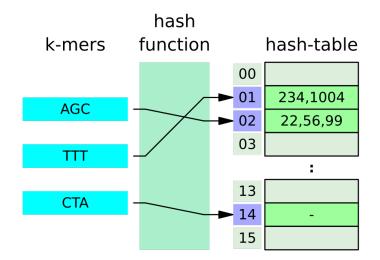


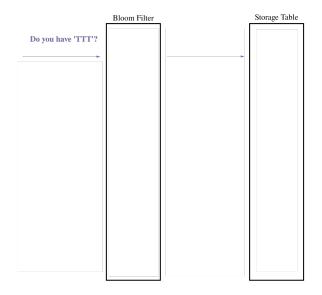


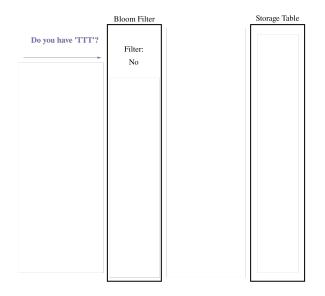


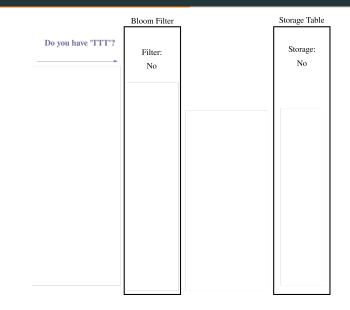


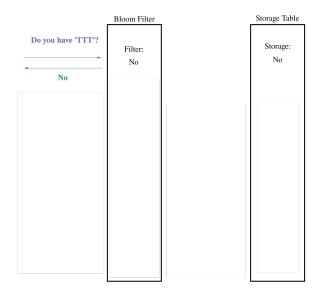


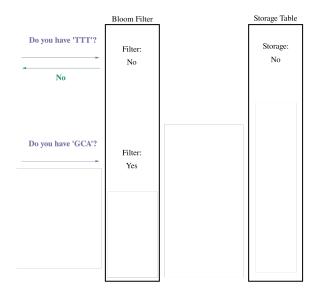


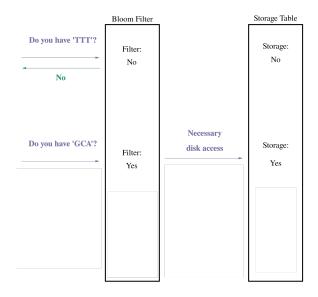


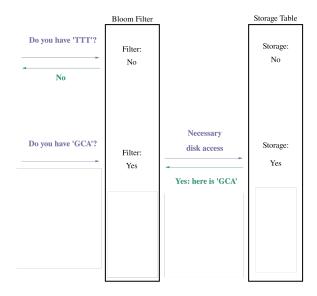


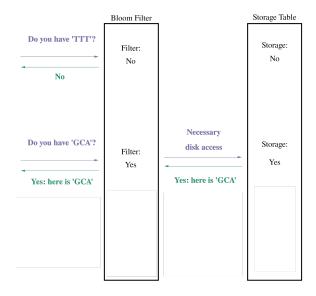


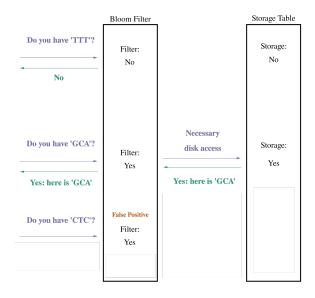


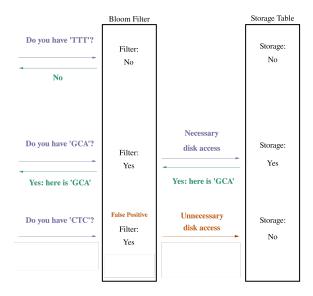


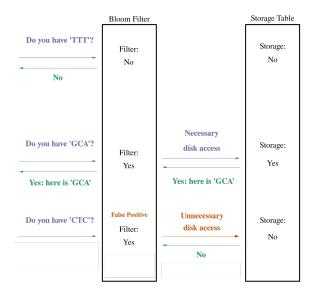


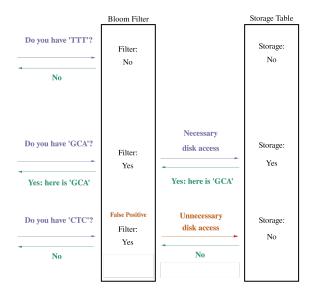






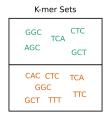




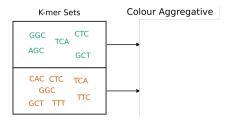


# How do we index across sets of k-mers?

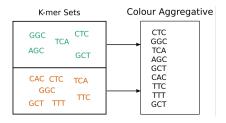
## Two possible approaches: colour or k-mer aggregative

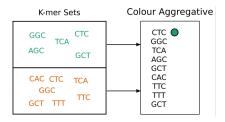


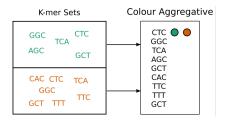
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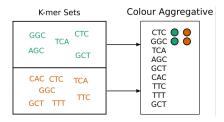


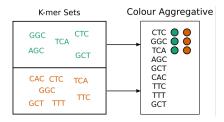
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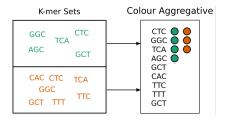


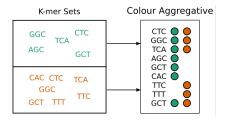


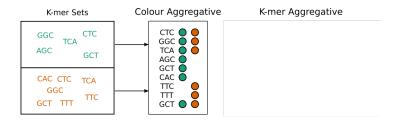


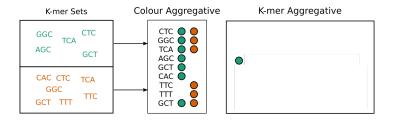


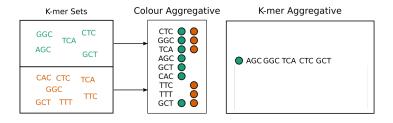


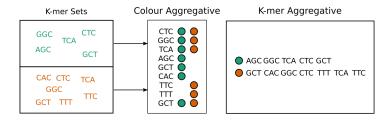


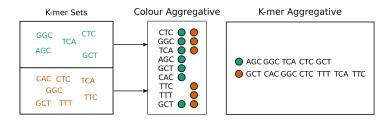




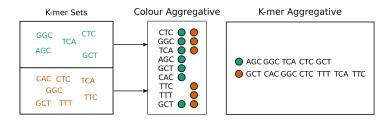






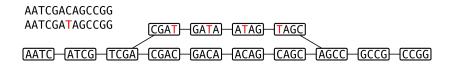


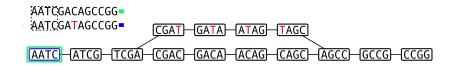
Colour aggregative: k-mer -> sample(s)

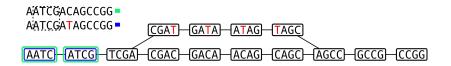


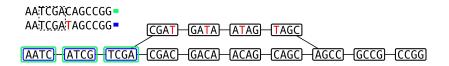
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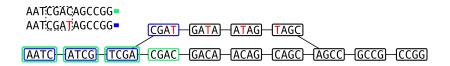
Colour aggregative methods

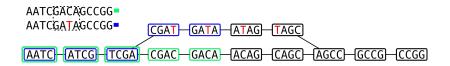


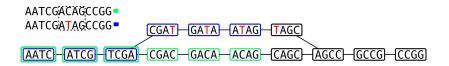


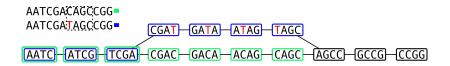


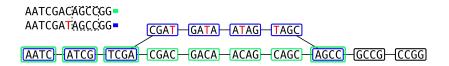


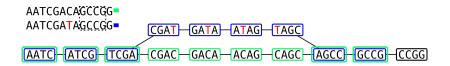


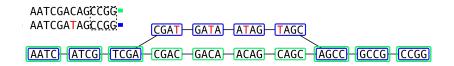




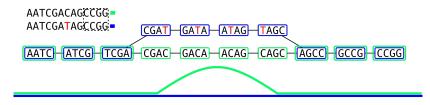


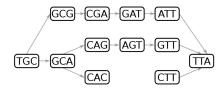


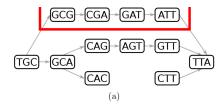




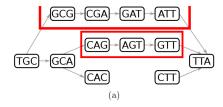
#### Coloured de Bruijn graph



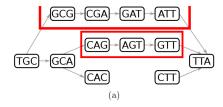




(b)

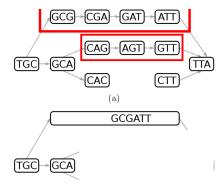


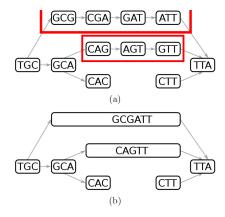
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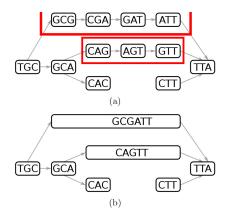




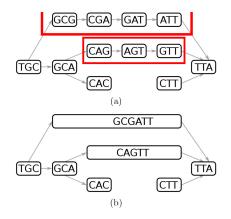
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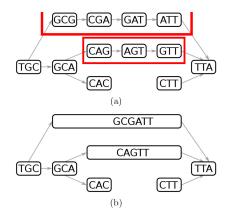




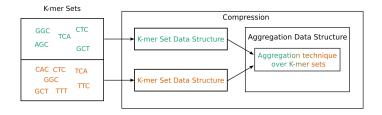
 Compact maximal non-branching paths into untigs

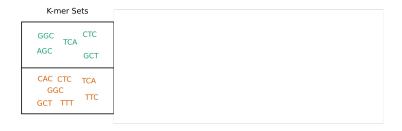


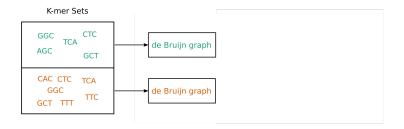
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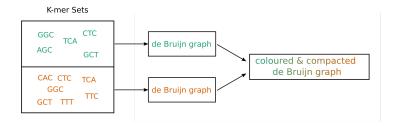


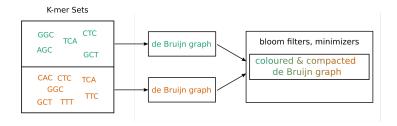
- Compact maximal non-branching paths into untigs
- Use probabilistic data structures e.g. bloomfilters, minhash sketches, minimisers
- AKA make things more approximate but smaller!

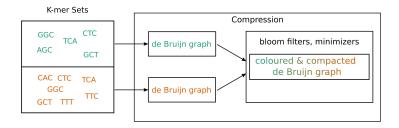


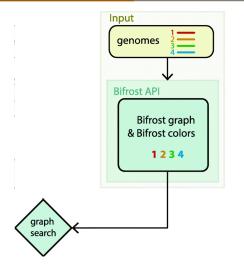


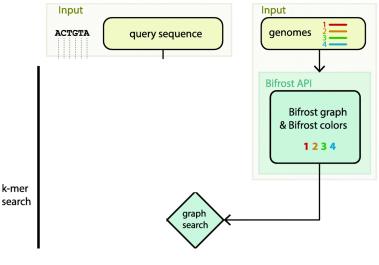


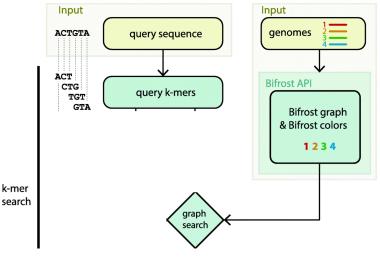


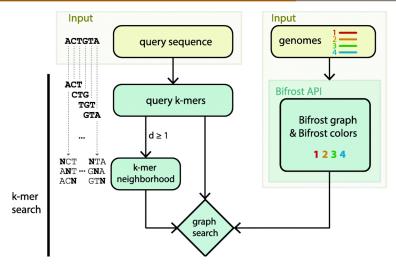




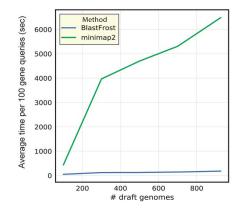




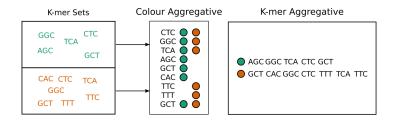


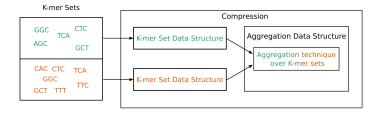


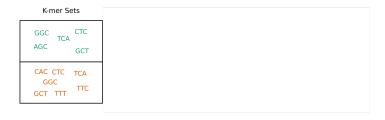
#### BlastFrost scaling

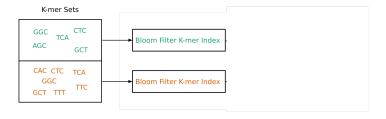


K-mer aggregative methods

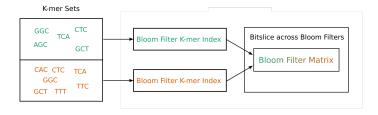


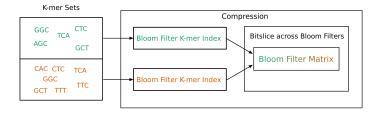












Searching a snapshot of publically available bacterial WGS datasets from the ENA/SRA (N=455,632) Dec 2016.

This is a proof-of-concept demonstration of the BIGSI search index for microbial genomes. We have indexed the complete bacterial and viral whole-genome sequence content of the European Nucleotide Archive as of December 2016. See our paper.

Thanks to CLIMB for hosting

You can use this to search for samples with a given gene, plasmid, or SNP. Queries must be at least 61bp in length. Species metadata provided by analysis by Bracken + Kraken.

More info at https://bigsi.readme.io/ and http://github.com/phelimb/bigsi.

ATGAAAAACACACAATACATATCAACTTCGCTATTTTTTTAATAATTGCAAATATTATCTACAGCAGCGCCAGTGCATCAACAC Properties of query k-mens threshold: 100

e.g. MCR-1,OXA-1

6446 results

Ottov of quary I-mm Sundi in ERR-14940 (Charlmaila cui: 90/9% Shight fatami: 1299%)
OttoV of quary I-mm Sundi in ERR-1420 (Charlmaila cui: 90/9% Shight fatami: 131%)
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- Indexing all bacterial, viral and parasitic reads in ENA (500,000 sets, 170TB of data)
- 1.5TB index that be queried near instantaneously

# Which method?

method name	aggregation technique	k-mer set data structure	aggregation data structure
BiFrost	color aggregative methods	hash table	1 or several color matrices
BIGSI	k-mer aggregative methods ACA, ATC, CAT ATA, CAT, GCA	Bloom filter	Bloom filter matrix /matrices

[Marchet et al., 2021]

method name	aggregation technique	k-mer set data structure	aggregation data structure
SeqOthello		hashing techique	
BiFrost			
Metannot	color aggregative methods	hash table	
Multi-BRWT			
Pufferfish			1 or several
BLight	ACA • ATA •		color matrices
VARI(-Merge), Rainbowfish	ATC • CAT • GCA •	BWT	
Mantis(+MST)		Counting Quotient Filter	
BFT		Bloom filter trie	
SBT, SSBT, AllSomeSBT HowDeSBT	k-mer aggregative methods • ACA, ATC, CAT • ATA, CAT, GCA	Bloom filter	search tree/forest
BIGSI, COBS, RAMBO			Bloom filter matrix /matrices

[Marchet et al., 2021]

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[Marchet et al., 2021]

- It depends: complexity, sequence length, query length
- What features you need e.g., inserting new sets, space vs time trade-offs

Summary

• Vast amount of sequence data and it is growing rapidly

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- Assembly just a path through graph NOT all possible paths

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  - BIGSI creates a big matrix of bloom filters where each column is a sample
- Active field and choosing best method is very data and task specific

# **Questions?**

#### References i

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Luhmann, N., Holley, G., and Achtman, M. (2020). Blastfrost: Fast querying of 100,000 s of bacterial genomes in bifrost graphs. *BioRxiv*.



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