

# Structures de données pour les grands ensembles de $k$ -mer

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Séminaire MIAT  
28 janvier 2022

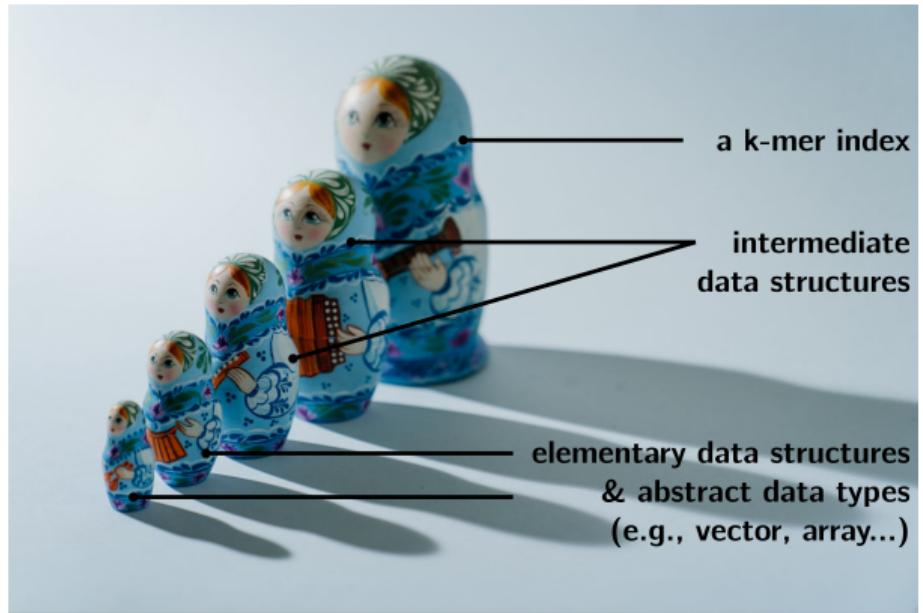
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 @CamilleMrcht



# Introduction - Data structures

- Russian dolls
  - Legos or "building blocks"
  - *Abstract data types*: set, multi-set, list...
- Existence (or not) of an implementation



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# Introduction - Data structures

Data structures are purposeless without **operations**

- Test for emptiness
- Add/delete elements
- Check membership of an element
- Go over all elements

Operations go hand in hand with notions of cost and complexity

- Computation time
- Size in memory

# Introduction - When it comes to $k$ -mers

	human		<i>Pinus taeda</i>		<i>Ambystoma mexicanum</i>		<i>Paris japonica</i>		metagenomics
# 31-mers	3.2G		10.5G		18.5G		~150G		...

In practice :

- $k$  sizes : 11-15 (long reads), 21-51 (short reads)
- Billions (of distinct  $k$ -mers) easily reached in experiments
- The notion of cost becomes central

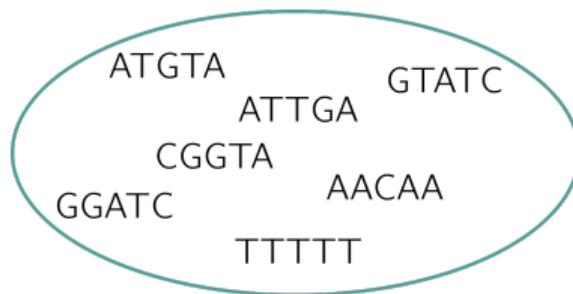
# Introduction - $k$ -mer data structures

These data structures are foundations of many applications:

- alignment methods
- alignment-free methods (pseudo-alignment, quantification, taxonomic assignation, ecological distances...)
- quality analysis, read correction
- representation and usage of graphs (assembly, variant calling, ...)

# Data structures for $k$ -mers sets

Representation of  $k$ -mer sets



**k-mer sets** - Burrows Wheeler transform?<sup>1</sup>

```

text      row_row_row_your_boat
          row_row_row_your_boat
          row_row_row_your_boat$  

          ↓  

Burrows Wheeler transform (BWT)    trrrwwwwwwooo_bbbyyyrrrrrrrrruuutt$aaa  

          ↓  

Compression through run length encoding  

(t,1)(r,3)(w,9)(o,3)...( ,3)

```

<sup>1</sup>Adapted from Ben Langmead's course

## **k-mer sets** - Right contexts of w's

**very similar right lexicographic contexts for all w's**

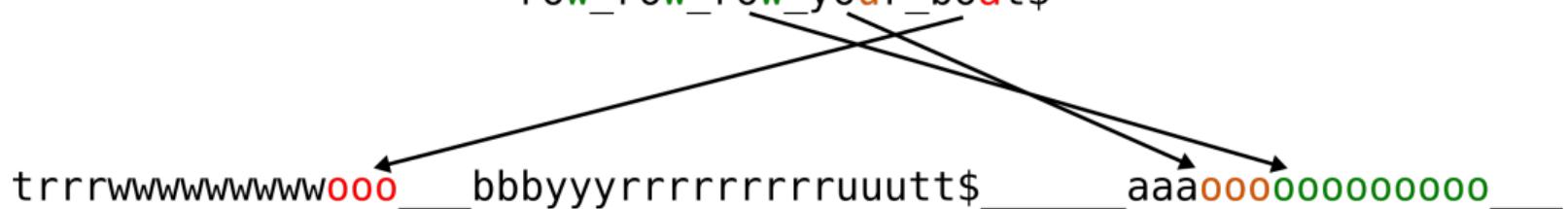
row\_row\_row\_your\_boat  
row\_row\_row\_your\_boat  
row\_row\_row\_your\_boat\$

trrrwwwwooo bbyyyrrrrrrrruuutt\$ aaaooooooo0000000000

## $k$ -mer sets - Right contexts of o's

right lexicographic contexts for o's

row\_row\_row\_your\_boat  
row\_row\_row\_your\_boat  
row\_row\_row\_your\_boat\$



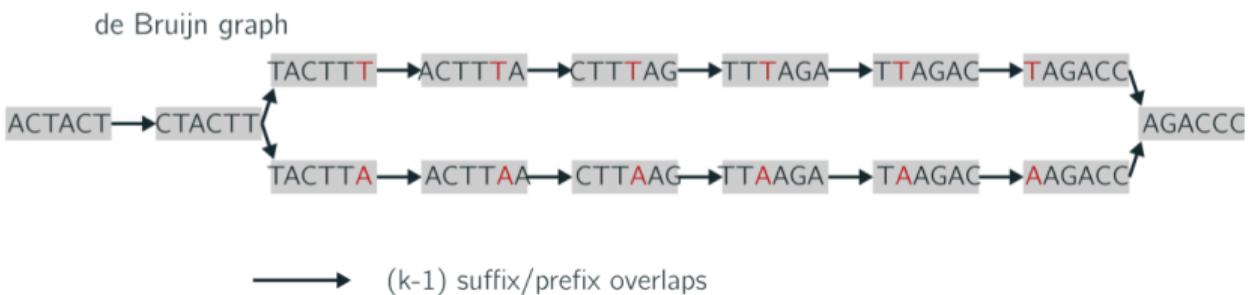
## ***k-mer sets*** - BWT for *k-mer sets*?

- BWTs can be queried with strings of arbitrary length: answer to *k-mer membership*
- *k-mer sets* are not texts (while genomes are): BWTs will index read sets or genomes
- Which other structure can we choose?

## **k-mer sets** - Representation using a de Bruijn graph<sup>2</sup>

k-mer set

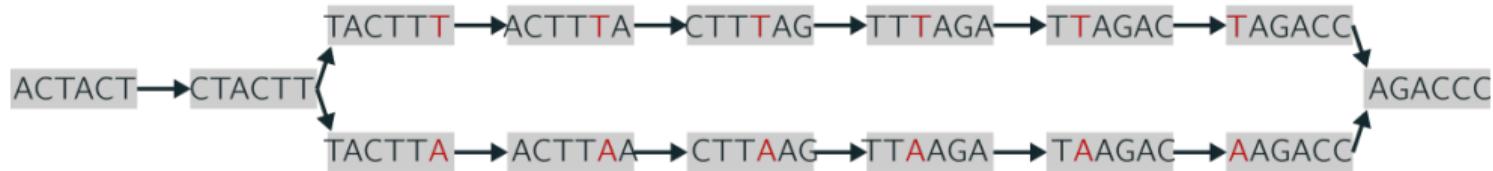
ACTACT TACTTA  
CTACTT ACTTAA  
TACCTT CTTAAG  
ACTTTA TTAAGA  
CTTTAG TAAGAC  
TTTAGA AAGACC  
TTAGAC TAGACC  
AGACCC



<sup>2</sup>I use the *node-centric* definition of a DBG

## **k-mer sets** - Representation using unitigs

de Bruijn graph



unitig graph



- Compacted de Bruijn graph

## **k-mer sets** - Representation using unitigs

k-mer set

ACTACT  
CTACTT  
TACTTA  
ACTTAC  
CTTACA  
TTACAG

unitig set

?

## **k-mer sets** - Representation using unitigs

k-mer set

ACTACT  
CTACTT  
TACCTA  
ACTTAC  
CTTACA  
TTACAG

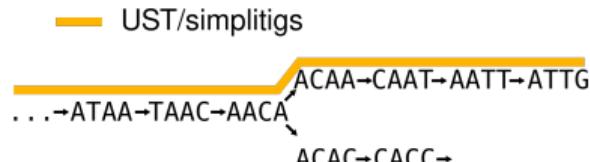
unitig set

ACTACTTACAG

$$6 \times 6 = 36 \text{ bases} \quad 6 + 5 = 11 \text{ bases}$$

## ***k*-mer sets** - Spectrum preserving string sets

- Other sequences extracted from the DBG are now used
- Spectrum preserving string sets (SPSS)<sup>3</sup>



{ATAACAATTG, ACACC} 15 nucleotides  
(other possibility: {ATAACACC, ACAATTG} 15 nucleotides)

- [Rahman et al. 2020, Brinda et al. 2020] Greedy algorithm, nearly optimal
- Applications: de Bruijn graph implementation, alignment
- Open question: constraints on SPSS

<sup>3</sup>A brief description of several SPSS: <https://kamimrcht.github.io/webpage/tigs.html>

## ***k*-mer sets** - Two paradigms

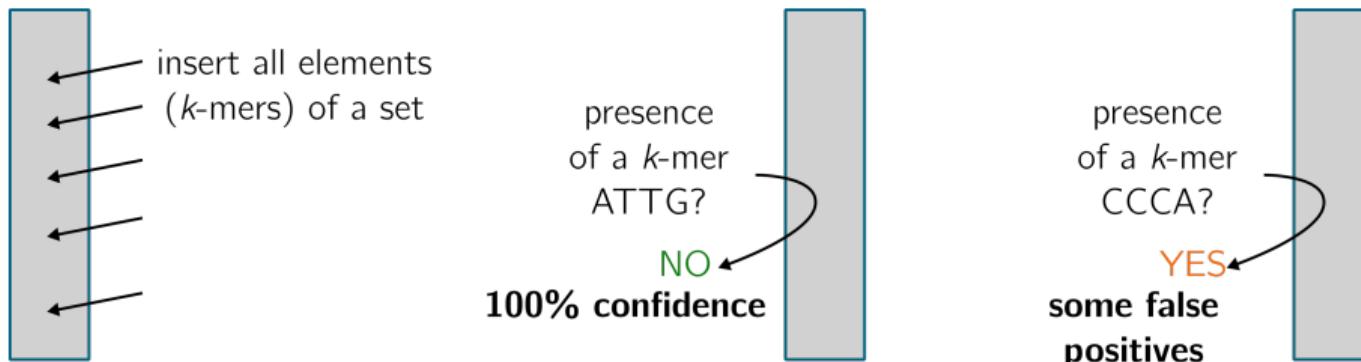
- Full-text methods (BWT) rely on the **lexicographic context** of nucleotides to provide a compressed representation
  - Needs a text such as a genome as an input
- SPSS-based methods rely on the **genomic context** ("assemblability") of nucleotides to provide a compacted representation
  - Will structure a *k*-mer set according to the underlying genome

de Bruijn graphs:

- Can be seen as objects to:
  1. assemble sequences
  2. represent a *k*-mer set and to structure the redundancy of datasets in some way
- Interesting feature: facilitate error correction/filtering → impact on performances

## ***k*-mers sets** - A third way: probabilistic representation

### Bloom filters [Bloom 1970]



- Extreme simplicity in terms of implementation: a bit array + hash functions

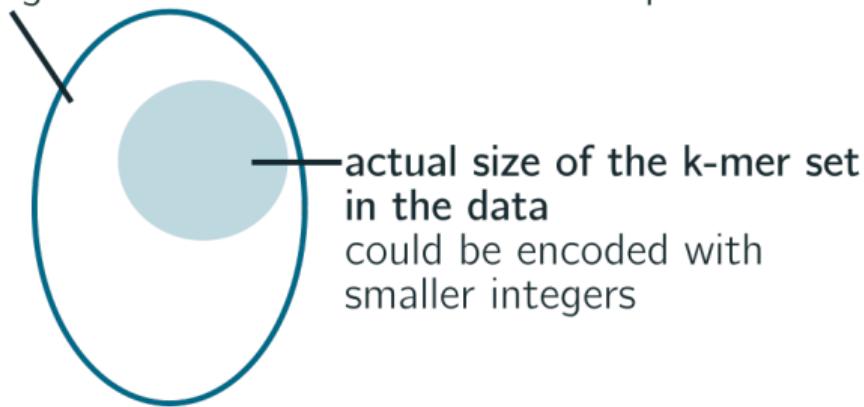
## ***k*-mers sets** - A third way: probabilistic representation

base encoding	<i>k</i> -mers, <i>k</i> =2	binary representation
A 00	AC	0001
C 01	AA	0000
G 10	TG	1110
T 11	...	4 bits for 2 bases

in practice, 64 bits integers for *k*-mers of size up to 32

## **k-mers sets** - A third way: probabilistic representation

universe of k-mers of size n:  $4^n$  possibilities  
needs integers of size  $2n$  bits to encode all possibilities

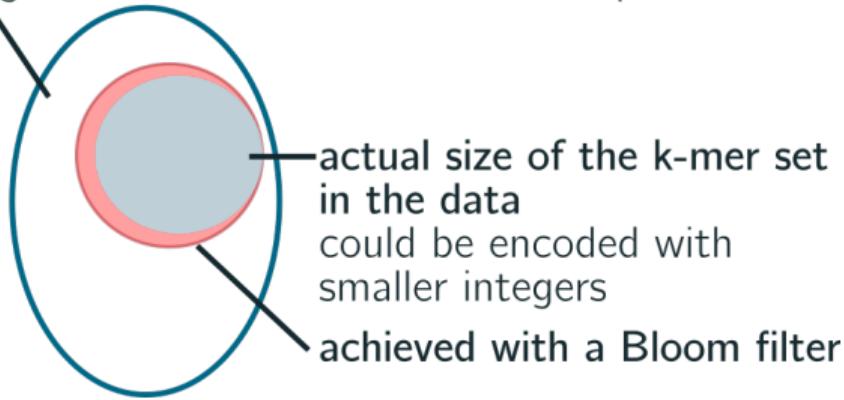


- Example:  $\sim 3.10^9$  31-mers in the human genome vs  $\sim 4.10^{18}$  possible 31-mers

## ***k*-mers sets** - A third way: probabilistic representation

universe of *k*-mers of size  $n$ :  $4^n$  possibilities

needs integers of size  $2n$  bits to encode all possibilities



- Example:  $\sim n = 3.10^9$  human 31-mers, BF size of  $10n$  bits
- $\sim 30.10^9$  bits or  $\sim 4\text{GB}$  and a false positive rate of  $\sim \frac{1}{10^f}$
- Applications: assembly (Minia, Abyss, Hifi-asm), *k*-mer counting (Jellyfish), alignment (Minimap)

# Data structures for $k$ -mers sets

## Associative indexes for $k$ -mer sets

ATGTA : 6
GTATC : 127
ATTGA : 2
CGGTA : 53
AACAA : 55
TTTTT : 272

## ***k*-mers sets index** - full-text methods

Full-text methods based on the BTW, with the same limitations as previously stated:

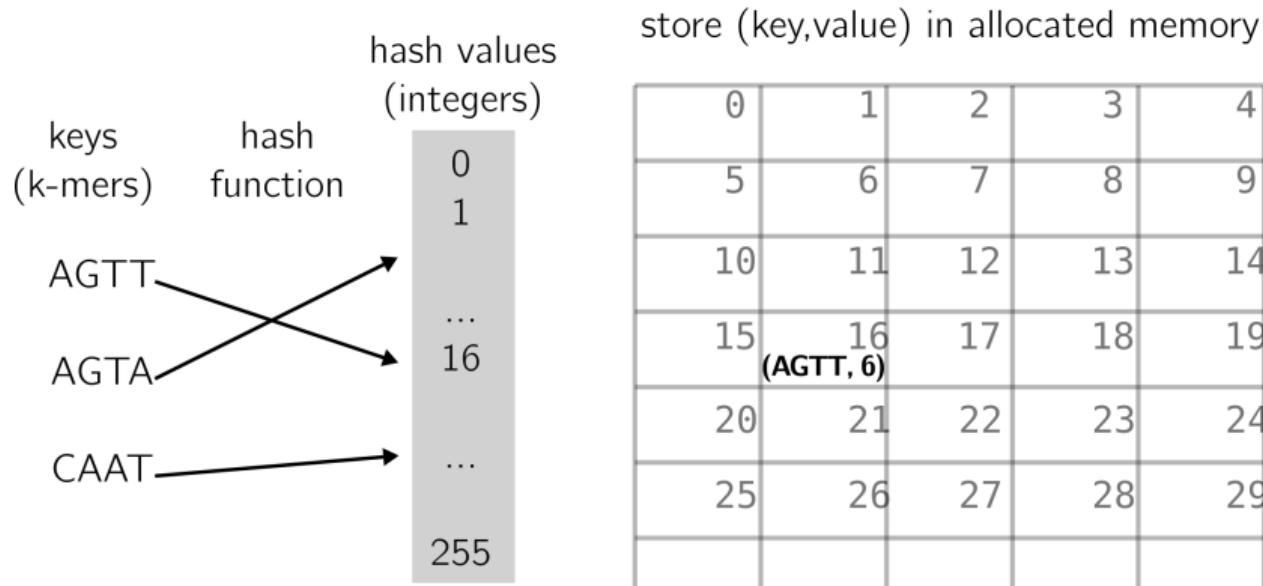
- FM-index [Ferragina & Manzini 2004], r-index [Gagie et al. 2017] (improves on space complexity)

Use the paths of the de Bruijn graph as a text, then index the *k*-mers:

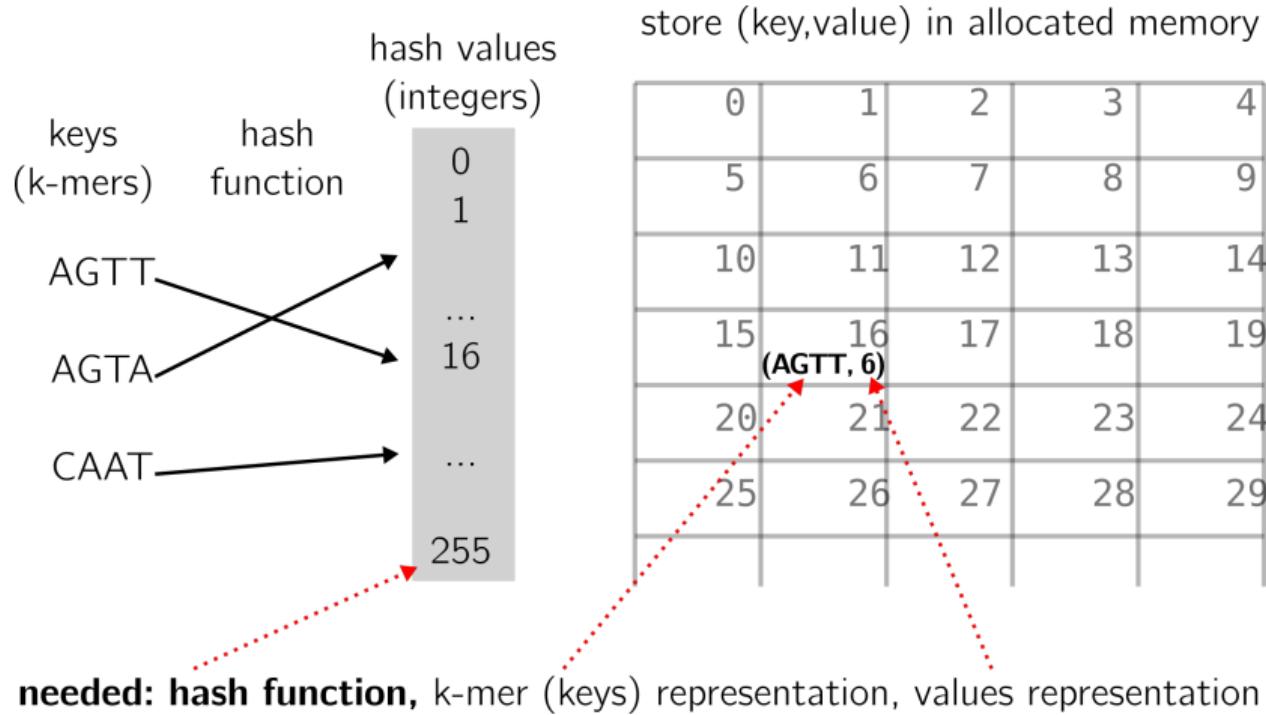
- BOSS [Bowe et al. 2012]: a FM-index specialized for *k*-mers
- Applications: indexing large collections of bacterial datasets [Muggli et al. 2017, 2019], implementing de Bruijn graphs [Boucher et al. 2015; Karasikov et al. 2021]
- Main downsides:
  - Hypothesis on the paths lengths
  - Slower query in comparison to other approaches

***k*-mers sets index** - associate (key,value) pairs with a hash table

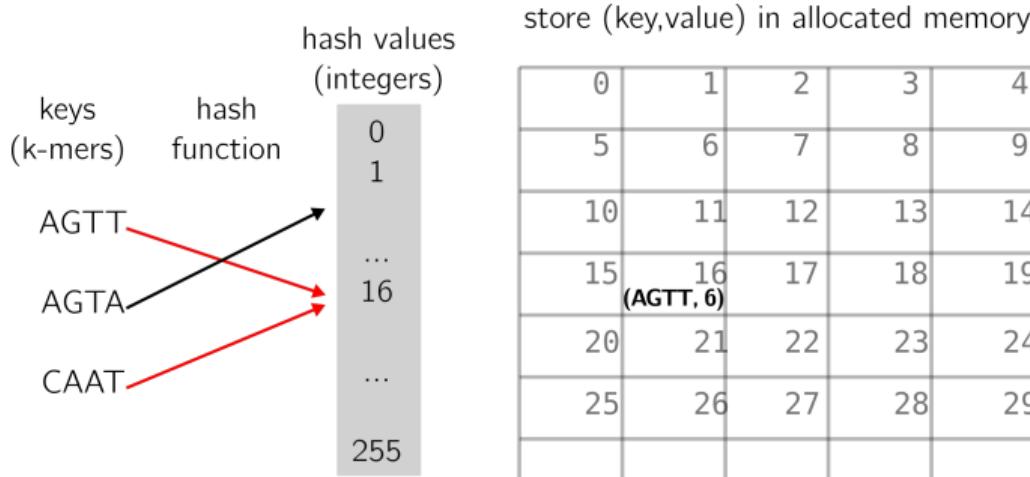
associate ***k*-mers to their abundances**  
**AGTT:6, AGTA:100, CAAT:4**



## $k$ -mers sets index - hash table



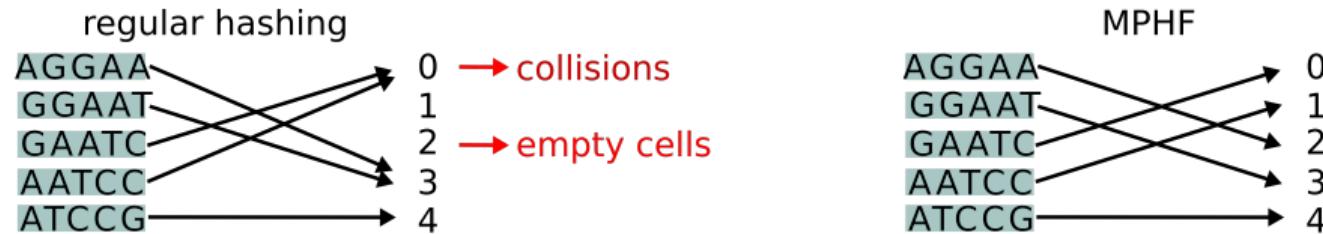
## ***k*-mers sets index - collisions: a big issue**



Solutions:

- Pointers: decrease space performances
- Open addressing: decreases time performances (loss of locality)
- A third way...

## ***k*-mer sets index - Minimal perfect hash functions (MPHF)**



Implementations used in bioinformatics:

- BBHASH [Limasset et al. 2014]
- PTHash [Pibiri et al. 2021]
  
- $\Delta$  MPHFs are static
- $\Delta$  MPHFs are **only hash functions**, in order to build a hash table they need a representation of the keys to deal with alien keys

## ***k*-mer sets index** - Specialized hash tables

Efficient *k*-mer hash tables:

- Pufferfish: MPHF+unitigs [Almodaresi et al. 2018]
- BLight: MPHF+partitioning+SPSS [Marchet et al. 2019]<sup>4</sup>
- Counting quotient filters [Pandey et al. 2017]: another hashing strategy

Applications:

- Example of achievement:  
index the 31-mers of the human genome in RAM in <8GB (BLight)
- Counting *k*-mers [Pandey et al. 2018]
- Large scale quantification [Marchet et al. 2020]
- Read alignment [Almodaresi et al. 2021]

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<sup>4</sup>and a promising recent preprint by Pibiri in 2022

## Summary on indexing $k$ -mer sets

- Full-text (BWT-based) or hashing+SPSS appear to be the two major ways for indexing  $k$ -mers
  - Tradeoff: BWT-based has more expressivity (order preserving) but lower performances in practice (notably query)
- Indexing de Bruijn graphs (+navigational operations, dynamicity) is a field on its own<sup>5</sup>

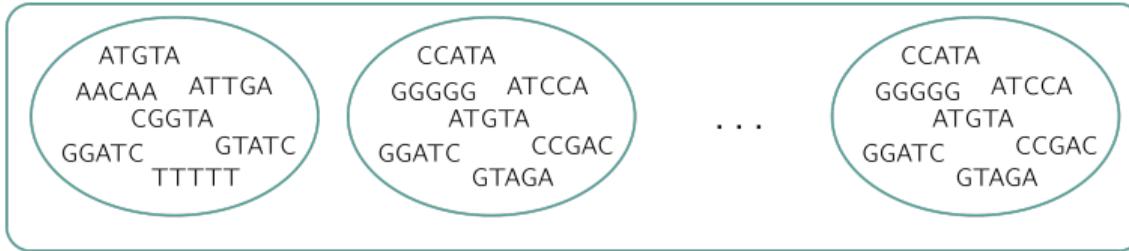
A survey about all these data structures: Chikhi R, Holub J, Medvedev P. 2019. Data structures to represent a set of  $k$ -long DNA sequences. *ACM Computing Surveys*

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<sup>5</sup>see for instance <http://rayan.chikhi.name/pdf/2021-july-9-cie.pdf>

# Data structures for $k$ -mers sets

## Collections of $k$ -mer sets



# Collections of $k$ -mer sets

a set of datasets  $\{d_1, d_2, \dots, d_n\}$   
(reads multisets)

query sequence  
...ATTACGTAGTA...

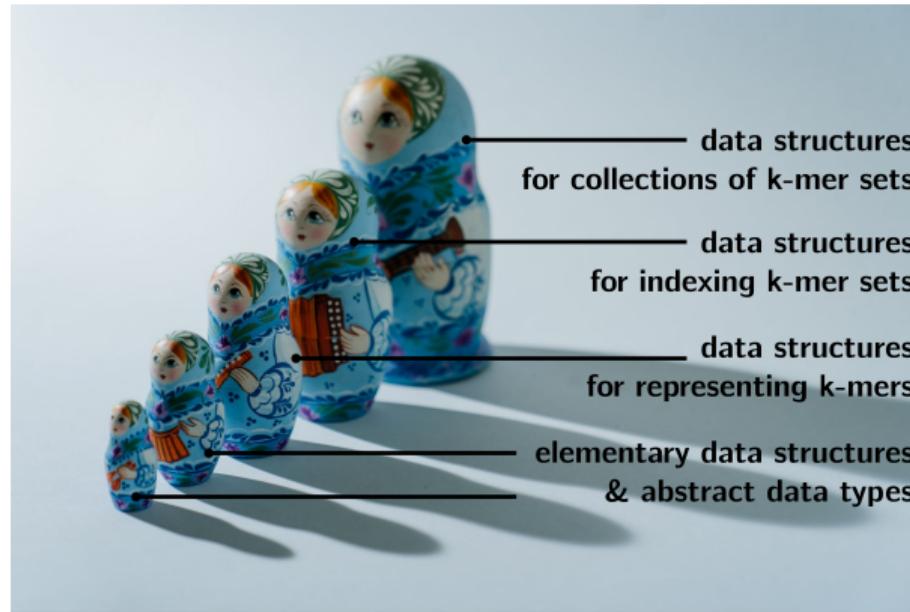


return all  $d_i$ 's where the query occurs

- Each dataset (and the query) are seen as sets of  $k$ -mers
- The query is "present" in a dataset if *enough* of its  $k$ -mers are found

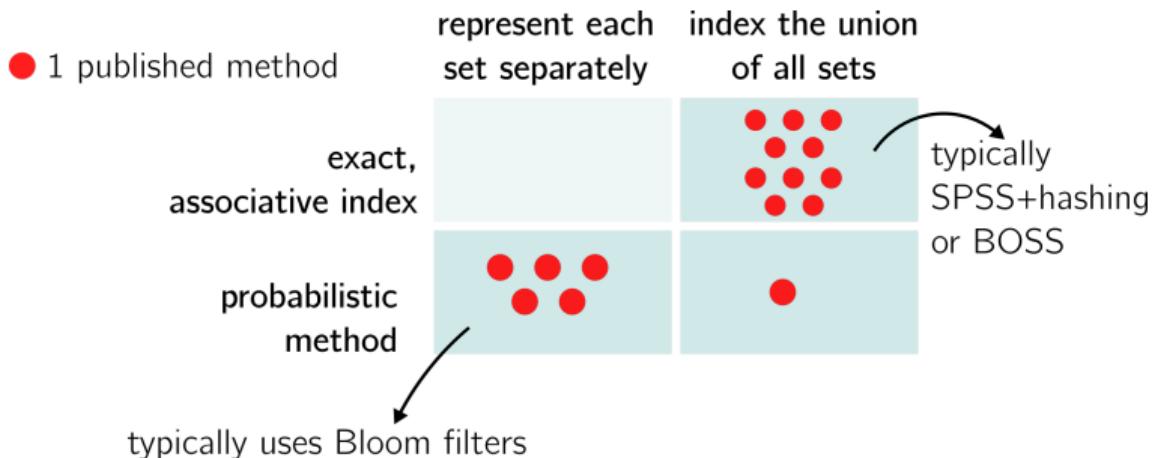
# Collections of $k$ -mer sets

We need to handle **multiple** sets of  $k$ -mers and query the presence/absence of a sequence



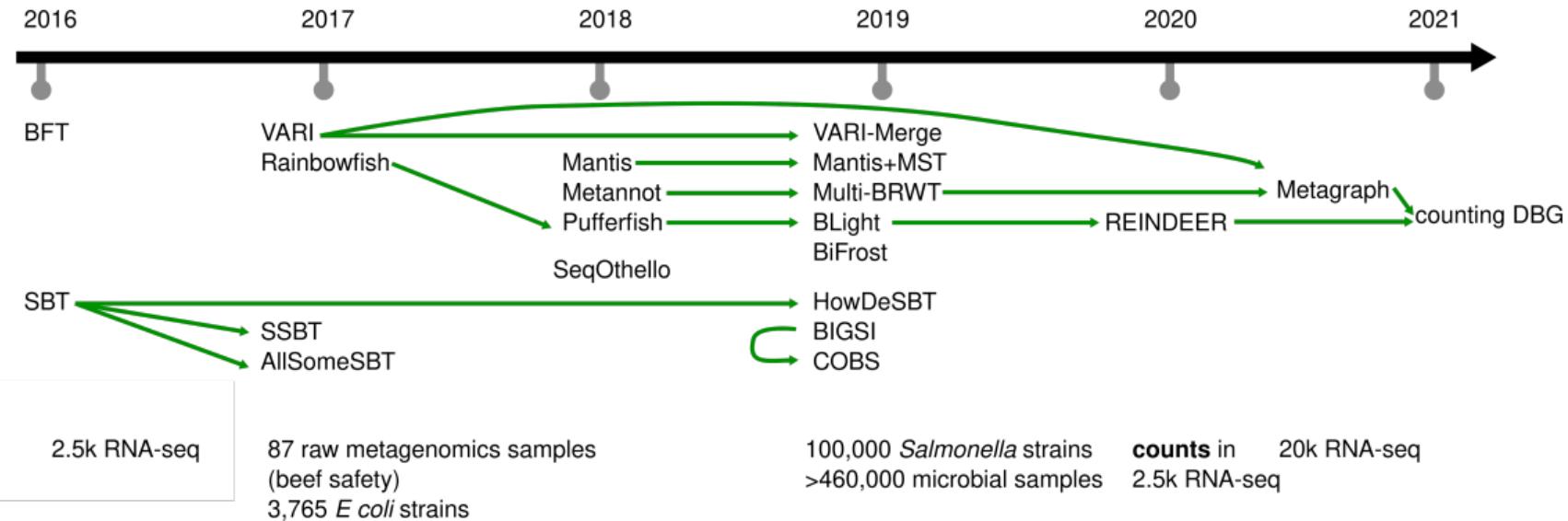
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# Collections of $k$ -mer sets - State of the art



- Exact methods: for precise, short queries or when colored de Bruijn graphs are needed
- Probabilistic methods: better scalability if false positives are acceptable

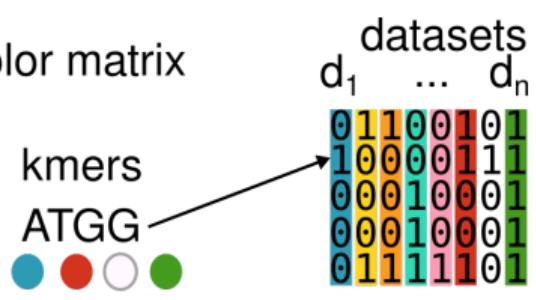
# Collections of $k$ -mer sets - State of the art



- Different optimizations/features: construction time, space, query speed, dynamicity
- Examples of queries: search of a mutation, alternative splicing, ...

## Collections of $k$ -mer sets - Exact methods

Associate  $k$ -mers to color matrix:



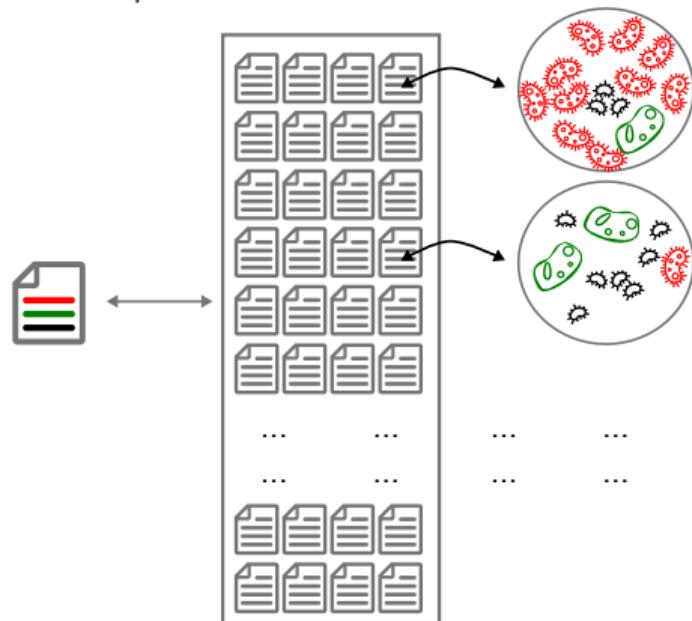
color matrix	datasets									
	0	1	2	3	4	5	6	7	8	9
	1	0	0	0	0	1	1			
	0	0	0	1	0	0	0	1		
	0	0	0	1	0	0	0	1		
	0	1	1	1	1	1	0	1		
kmers	ATGG									
	●	●	○	●						

- $k$ -mers in SPSS or BWT
- Hash-table or FM-index (BOSS)
- Compression of colored matrix
- Some methods support de Bruijn graph operations

- Examples of exact methods: VARI [Muggli et al. 2017], Mantis [Pandey et al. 2018], BiFrost [Holley & Melsted 2019]

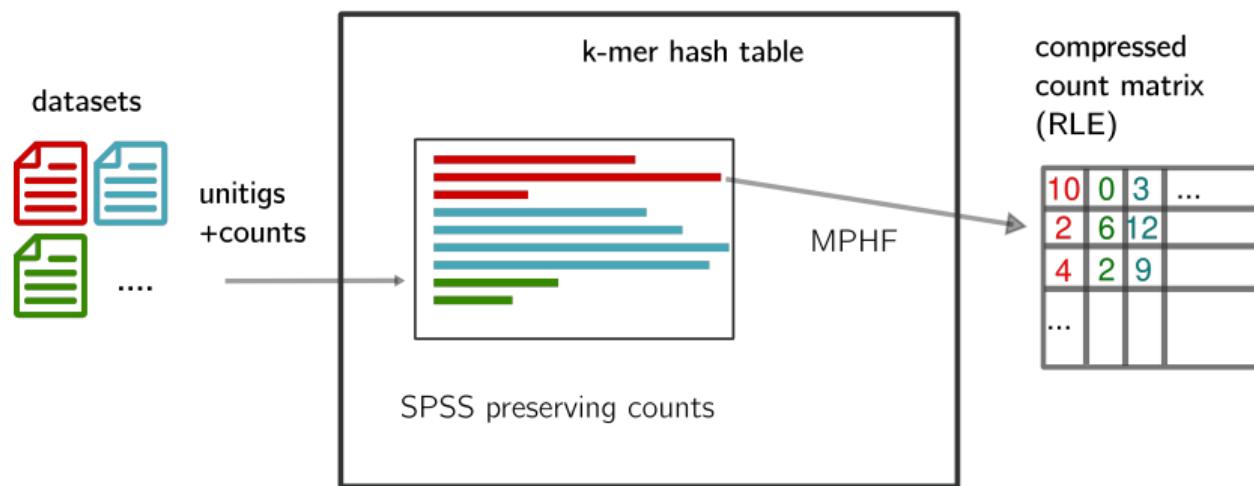
# Collections of $k$ -mer sets - Quantification

Associate  $k$ -mers with presence/absence abundances in datasets



# Collections of $k$ -mer sets - large scale abundance index

REINDEER [Marchet et al. 2020]<sup>6</sup>



<sup>6</sup>and very recently, counting de Bruijn graphs [Karasikov et al. 2021]

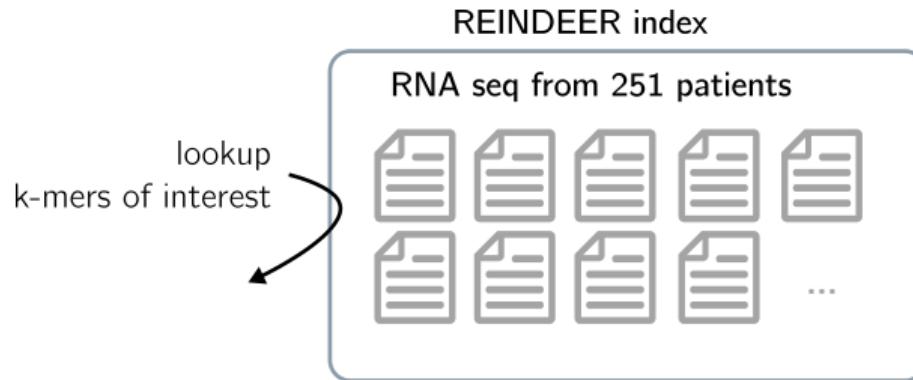
# Collections of $k$ -mer sets - large scale abundance index

~ 2500 human RNA-seq datasets (~ 4 billions 31-mers)

	Tool	Counts	Time (h)	Peak RAM (GB)	Index Size (GB)
<i>k</i> -mer aggregative	SBT	No	55	25	200
	HowDeSBT	No	10	N/A	15
	BIGSI	No	N/A	N/A	145
color aggregative	Mantis	No	20	N/A	30
	SeqOthello	No	2	15	20
REINDEER - presence/absence		No	40	27	36
REINDEER - counts		Yes	45	56	52

# Collections of $k$ -mer sets - example of application

- Stéphane Pyronnet's team @CRCT Toulouse
- Acute myeloid leukemia (AML)
- An (anonymized) WHO gene is a good prognosis indicator for survival.  
But why?



# Conclusion - large scale $k$ -mer data structures

- Alignment-free, large scale discovery/search of biological markers
- A survey on set collections data structures: [Marchet C, et al 2019. Data structures based on k-mers for querying large collections of sequencing data sets.](#)

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