kmtricks: creating bloom filters for indexing large sequencing data collections

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6th july 2022













K. Katz et al., 2022

- Tara Ocean Project: 250 billions metaG reads
- 100,000 Genome Project: 20 PB
- SRA: 🚀

Indexing motivations

Ocean Gene Atlas



https://tara-oceans.mio.osupytheas.fr/ocean-gene-atlas/

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 $^{^{1}}$ B. Solomon and C. Kingsford. Fast search of thousands of short-read sequencing experiments. Nature Biotechnology, 2016.

 $^{^{2}}$ Y. Yu, et al. Seqothello: querying rna-seq experiments at scale. Genome Biology, 2018.

 $^{^3}$ N .Luhmann, et al. Blastfrost: Fast querying of 100,000 s of bacterial genomes in bifrost graphs. Genome Biology, 2021.

⁴R. Wittler. Alignment-and reference-free phylogenomics with colored de Bruijn graphs. Algorithms for Molecular Biology, 2020. + 🛬 + 🛬 + 🛬 - 🤌 🔍

Indexing motivations

Ocean Gene Atlas



https://tara-oceans.mio.osupytheas.fr/ocean-gene-atlas/

And others:

- RNA-Seq
 - Expressed isoform according to tissues¹
 - Gene fusion²
- Microbial genomics
 - Antimicrobial resistance³
- Genome dynamics
 - Phylogeny⁴
- ...

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Given an experiments set, and a sequence of interest, which sample contains this sequence ?

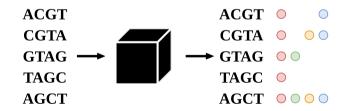
Given an experiments set, and a sequence of interest, which sample contains this sequence ? In terms of k-mers:

• A query Q matches a sample S if at least a fraction θ of Q's k-mers are present in S.

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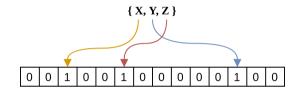
k-mer indexing & Bloom filters

- BFT (Holley et al., 2016)
- Sequence Bloom Tree
 - SBT (Solomon & Kingsford, 2016)
 - AllSomeSBT (Sun et al., 2017)
 - SSBT (Solomon & Kingsford, 2018)
 - HowDeSBT (Harris & Medvedev, 2019)
- Mantis (Pandey et al., 2018)
- SeqOthello (Yu et al., 2018)
- BIGSI (Bradley *et al.*, 2019)
- COBS (Bingmann et al., 2019)
- REINDEER (Marchet et al., 2020)
- Metagraph (Karasikov et al., 2021)

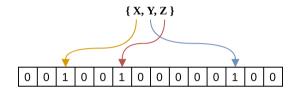
Review of *k*-mer indexing:

Data structure based on k-mers for querying large collections of sequencing datasets (Marchet *et al.*, 2019)

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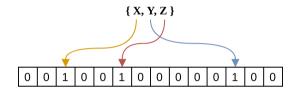


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Construction

- Count k-mers
- For each k-mer: compute hashes and set corresponding bits



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Issues

- k-mer counting is a huge bottleneck
- Bad data locality

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kmtricks: Bloom filters matrix construction

| S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | Sn |
|----|----|----|----|----|----|----|----|----|--------|
| 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 |
| 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 |
| 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |

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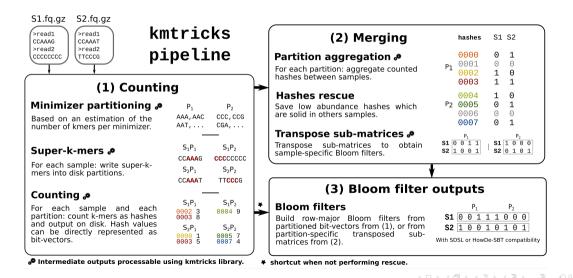
kmtricks: Bloom filters matrix construction

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | Sn |
|-----|----|----|----|----|----|----|----|----|----|--------|
| | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| Ρ1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 |
| PI | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | 0 |
| | | | | | | | | | | |
| | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| P2 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| 12 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| | | | | | | | | | | 1 |
| | | | | | | | | | | |
| | | | | | | | | | | |
| | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| Pn | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 |
| FII | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| | 1 | | | | | | | | | |

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kmtricks: Bloom filters matrix construction



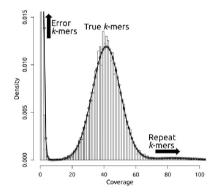
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kmtricks

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k-mer filtering

Hard abundance threshold vs kmtricks rescue strategy



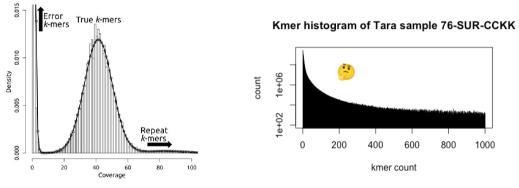


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k-mer filtering

Hard abundance threshold vs kmtricks rescue strategy



D. Laehnemann et al., 2015

The holistic view of k-mers abundances across samples allows custom errors screening

| | | | | | Post filtration result | | | | | |
|-------------------------|----------|----------------|----------|----------|------------------------|----|----|----|----|----|
| | | D1 D2 D3 D4 D5 | | | | D1 | D2 | D3 | D4 | D5 |
| ab. threshold | 3 | 2 | 2 | 3 | 2 | | | | | |
| k1 | 2 | θ | 2 | <u>5</u> | 2 | 1 | 0 | 1 | 1 | 1 |
| k2 | <u>4</u> | 0 1 | <u>6</u> | 2 | θ | 1 | 0 | 1 | 0 | 0 |
| hard-min=1. share-min=3 | | | | | | | | | | |

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Application on Tara Ocean bacterial metagenome - Index

241 sampling stations

- 712 short read samples, +6TB of compressed data
- 266 billions of distinct k-mers





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Benchmark environment

- 128 threads
- 970 MB/s and 216 MB/s sequential read/write

| | Time (min) | Memory (GB) | Disk (TB) | | | | |
|---|--------------------|-------------------|-------------------|--|--|--|--|
| kmtricks | 1433 | 83.4 | 1.5 | | | | |
| $Jellyfish^a + \mathtt{makebf}$ | $\approx 8071^{b}$ | 80.6 ^b | $\approx 0.8^{b}$ | | | | |
| KMC3 ^a + makebf | $\approx 5310^{b}$ | 100 ^b | $\approx 0.8^{b}$ | | | | |
| ^a Stopped after 72h computation. ^b Extrapolated estimation. | | | | | | | |

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Application on Tara Ocean bacterial metagenome - Filtering

Hard abundance threshold vs kmtricks rescue strategy

 For each sample, we know the error rate of the sequencer used thanks to the Genoscope benchmarks.

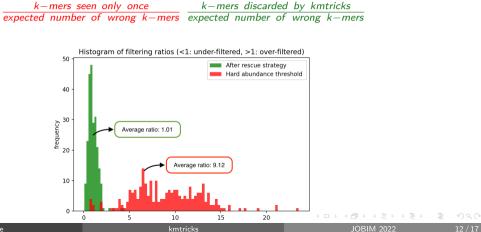
<u>k-mers seen only once</u> <u>expected number of wrong k-mers</u> <u>k-mers discarded by kmtricks</u> <u>expected number of wrong k-mers</u>

Application on Tara Ocean bacterial metagenome - Filtering

Hard abundance threshold vs kmtricks rescue strategy

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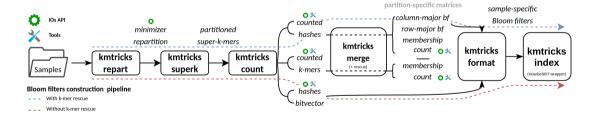
kmtricks: a k-mer matrix toolbox

CLI

- **pipeline**: end-to-end matrix construction
- modules: step-by-step matrix construction
- tools: work with kmtricks outputs

C++ API and plugin support

- I/O
- Matrix streaming
- Extend features, e.g. matrix filtering



O https://github.com/tlemane/kmtricks

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Example of application: Differential k-mer analysis

kmdiff: large-scale and user-friendly differential kmer analyses

| | C | ontr | ol | | 9 | |
|----|---|------|----|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| k0 | 2 | 1 | 3 | 2 | 3 | 1 |
| k1 | 3 | 8 | 9 | 1 | 0 | 2 |
| k2 | 7 | 5 | 8 | 0 | 0 | 0 |
| k3 | 4 | 4 | 6 | 3 | 7 | 5 |
| k4 | 2 | 0 | 6 | 8 | 9 | 9 |
| | | | | | | |
| kn | 6 | 4 | 8 | 2 | 2 | 3 |

 Uses kmtricks streaming features along with a state-of-the-art statistical model¹ to find differentially represented k-mers between two cohorts

¹A. Rahman et al., "Association mapping from sequencing reads using k-mers", 2018

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| k4 | 2 | 0 | 6 | 8 | 9 | 9 |
| | | | | | | |
| kn | 6 | 4 | 8 | 2 | 2 | 3 |

- Uses kmtricks streaming features along with a state-of-the-art statistical model¹ to find differentially represented k-mers between two cohorts
- 40vs40 human Illumina WGS (+3TB gz)
 9h, 11GB ram (vs 138h, 85GB ram)¹
- Applications
 - GWAS on non-model species

O https://github.com/tlemane/kmdiff

¹A. Rahman et al., "Association mapping from sequencing reads using k-mers", 2018

Conclusion

- Efficient and flexible Bloom/k-mer matrix toolbox
- Supports medium/large datasets like Tara Ocean
- Comes with a set of utilities/API/plugins for downstream analysis
- Obviously, still very insufficient to hope to scale up on very large databases like SRA

Future work:

- Characterization of rare rescued k-mers
- Take advantage of the partitioned structure of Bloom filters for a more efficient construction/query of the HowDeSBT tree

Now available in Bioinformatics Advances: T. Lemane, P. Medvedev, R. Chikhi, P. Peterlongo, "kmtricks: Efficient and flexible construction of Bloom filters for large sequencing data collections", Bioinformatics Advances, 2022