

Reviews in Quantitative Biology

Applications of kmer analysis in quantitative biology

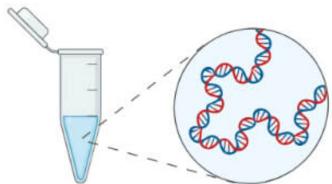
Sina Majidian

November 18th, 2022

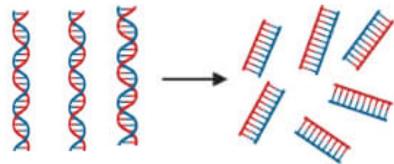
Outline

- **Introduction**
 - DNA sequencing
 - Kmer definition
 - Minimizer definition
- **Applications**
 - Metagenomics
 - Genome assembly
 - Kmer counting
- **Discussion**

DNA Sequencing



DNA extraction



Amplification



Sequencing

GGCGTCTATATCTGGCTCTAGGCCCTCATTTTTT

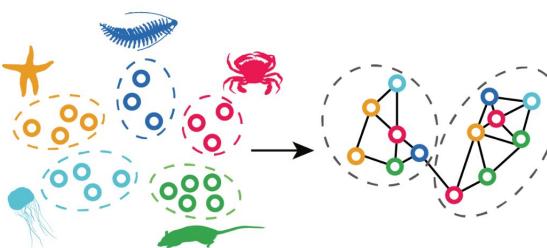
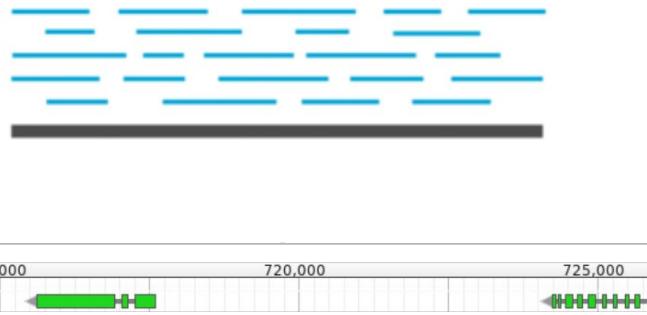
GGCGTCTATATCTGGCTCTAGGCCCTCATTTTTT

GGCGTCTATATCTGGCTCTAGGCCCTCATTTTTT

GGCGTCTATATCTGGCTCTAGGCCCTCATTTTTT

GGCGTCTA TATCTCGG CTCTAGGCCCTC ATTTTTT
GGC GTCTATAT CTCGGCTCTAGGCCCTCA TTTTTT
GGCGTC TATATCT CGGCTCTAGGCCCT CATTTTTT
GGCGTCTAT ATCTCGGCTCTAG GCCCTCA TTTTTT

Genomics pipelines



- 1) De novo genome assembly
- 2) Gene annotation
- 3) Orthology inference

CATCGA**CCGAGCGCGATGCTAGCTAGGTGATCGT**
TGCCGC**CATCGACCGAGCGCGATGCTAGCTAGGTGATCGT**
GCATGCCGC**CATCGACCGAGCGCGATGCTAGCTAGGTGATCGT**
GTGCATGCCGC**CATCGACCGAGCGCGATGCTAGCTAGGTGATCGT**
.AGGTGCATGCCGC**CATCGACCGAGCGCGATGCTAGCTAGGTGATCGT**

- 4) Read alignment
- 5) Variant calling & genotyping
- 6) Metagenomics

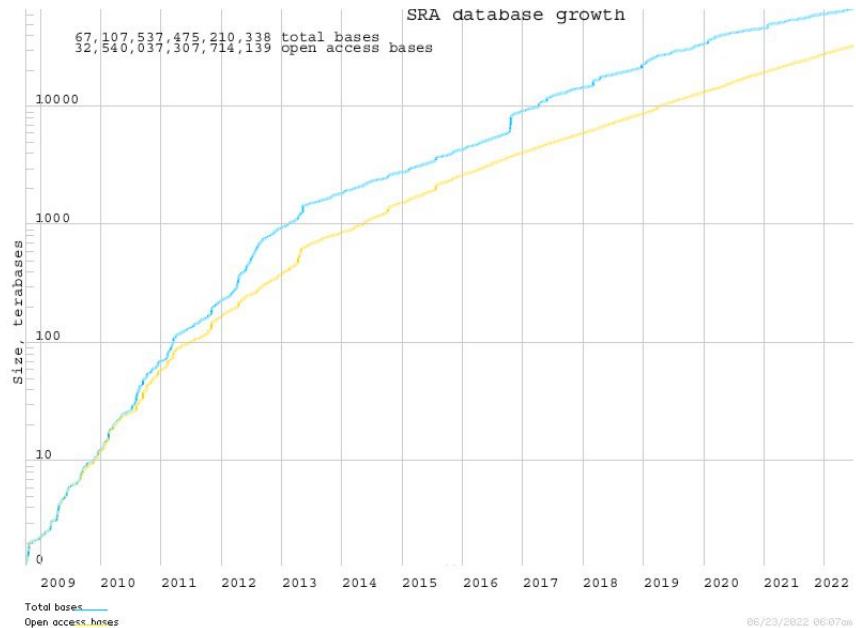
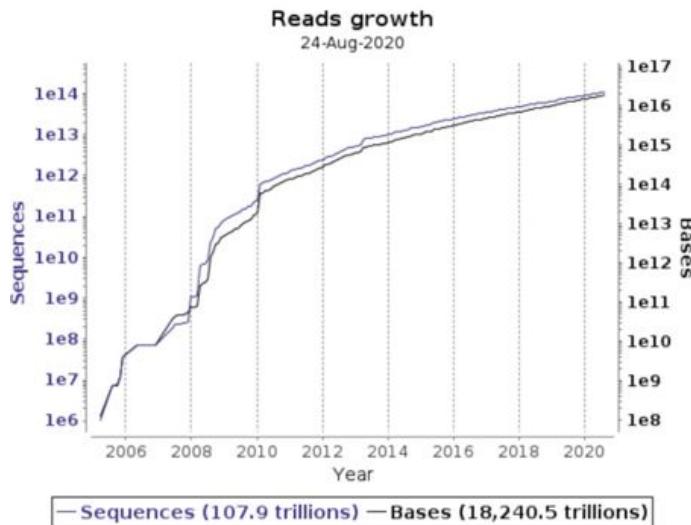


Genome assembly: importance of scalable methods

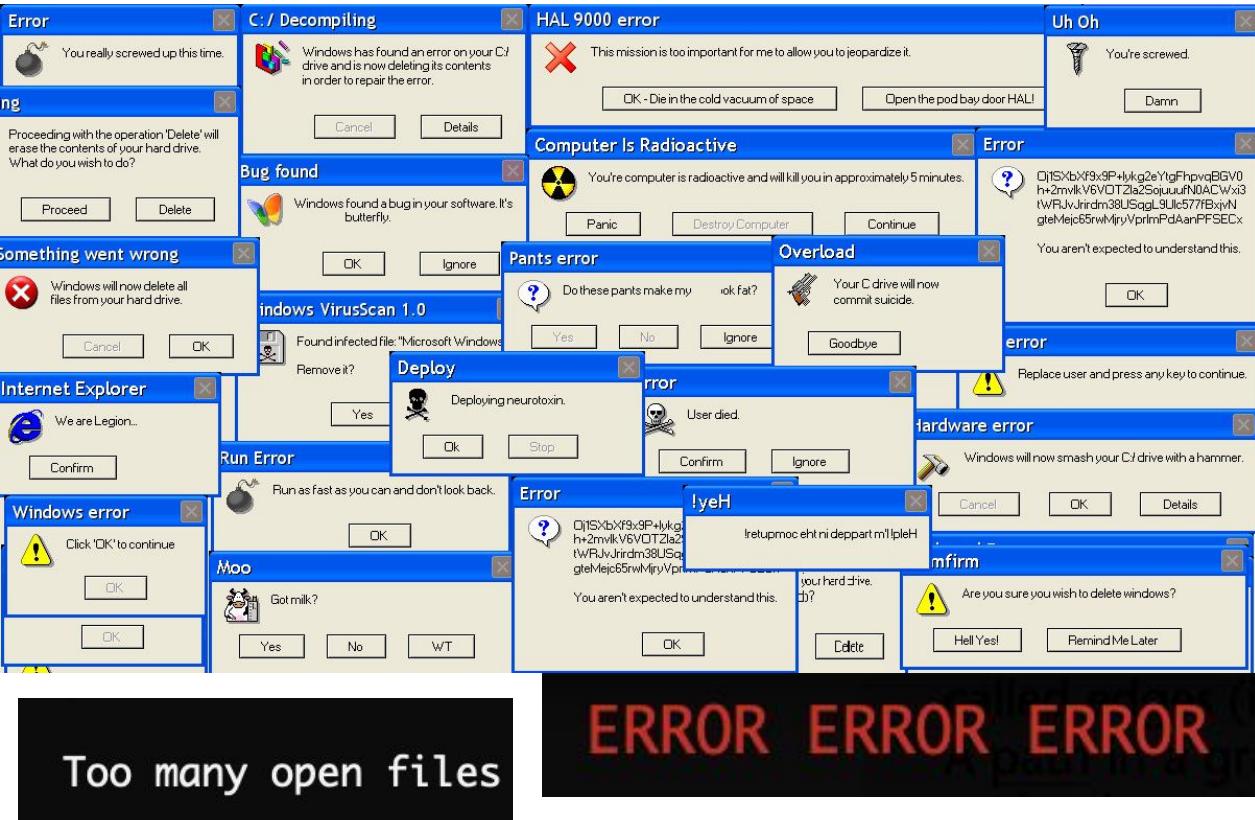
Tool	<i>D. mel</i> 100× real HiFi reads				Human real HiFi reads			
	Peregrine	HiCanu	Hifiasm	Rust-mdbg	Peregrine	Hifiasm	Rust-mdbg	
Time	40 min 11s	7 h 43min	5 h 17min	1 min 9 s	14 h 8 min	58 h 41min	10 min 23 s	
Memory	12 GB	12 GB	21 GB	1.5 GB	188 GB	195 GB	10 GB	

We need efficient methods in terms of **memory, speed and storage**.

Fast growing genomics data



No Space Left on Device



Segmentation fault

Segmentation fault

Core dumped

Basics on K-mer & Minimizers

K-mer definition

- a contiguous substring of length k.
- alphabet= {A,C,G,T}
- string (sequence)= GATTACA
- Example: k=2, 2mers
- GA, AT, TT, TA, AC, CA
- Number of 2-mers = 6

GATTACA

GATTACA

GATTACA

GATTACA

GATTACA

GATTACAC

K-mer stats

For the same sequence GATTACA ($L=7$)

$k=3$: GAT, ATT, TTA, TAC, ACA (5 kmers)

$k=4$: GATT, ATTA, TTAC, TACA (4 kmers)

GATTACA

GATTACA

GATTACA

GATTACA

GATTACA

- How many 3-mers do exist for a sequence of length $L=100$?
 - Number of 3-mers = $100-3+1 = 98$ ($L-k+1$)
- How many different 3-mers do exist?
 - $4^3=64$ (4^k)



Sequence comparison

Two similar sequences **with one base error**:

s1=	ACTGATGATAGTAGAA	s2=	ACTGATGA C AGTAGAA
	ACTG		ACTG
	CTGA		CTGA
	TGAT		TGAT
	GATG		GATG
	ATGA		ATGA
	TGAT		TGA C
	GATG		GAC G
	ATGT		ACGT
	TGTA		CGTA
	GTAG		GTAG
	TAGA		TAGA
	AGAA		AGAA

- Many shared 4-mers (green)
- Neighbors of C/T are not shared.
- Repeated kmers

Impact of k on specificity

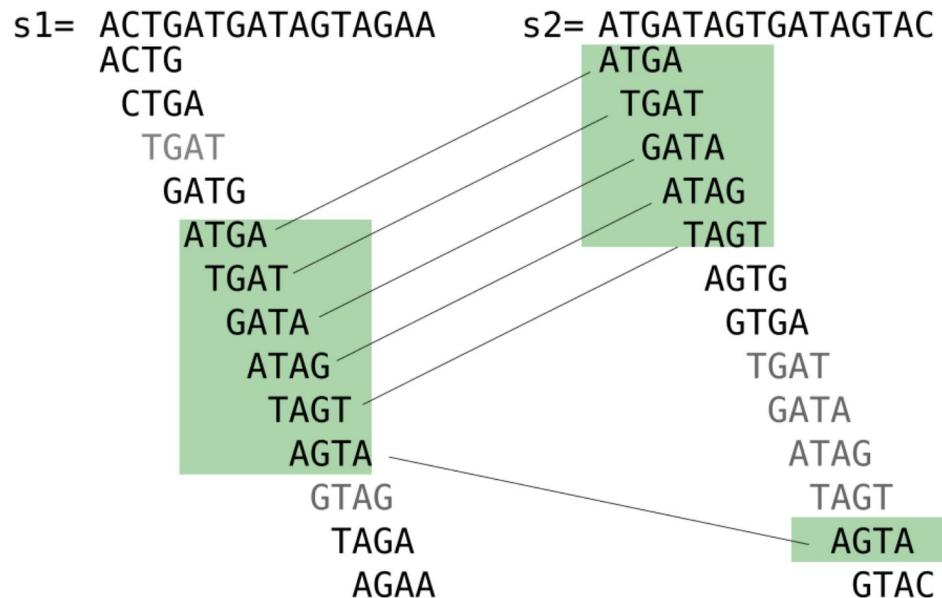
By increasing k, we can keep the differences.

s1= ACTGATGATAGTAGAA
ACTGAT
CTGATG
TGATGA
GATGAT
ATGATG
TGATGT
GATGTA
ATGTAG
TGTAGA
GTAGAA

s2= ACTGATGA**C**AGTAGAA
ACTGAT
CTGATG
TGATGA
GATGAC
ATGAC**G**
TGACGT
GACGTA
ACGTAG
CGTAGA
GTAGAA

Impact of k on specificity

- Two not so similar sequences:
- Still a lot of shared 4-mers
- Number 5-mers= $4^5=1024$
- Every 1k, one shared kmer by chance. (if distributed uniformly)



K-mer stats

- Billions (10^9) of k-mers exist in a metagenomic datasets,
- resulting in computational challenges

Dataset	k	Total	Distinct
Cow rumen	28	7.39×10^9	5.09×10^9
	55	4.69×10^9	3.73×10^9
Marine	28	7.26×10^9	3.73×10^9
	55	4.57×10^9	3.04×10^9

- Each k-mer contains little information compared to the nearest one.
- Idea: sampling (also referred to as “sketching”)

GAT TACA

GATT ACA

GA TT ACA

GAT TACA

GATT ACA

Minimizer

- The smallest kmer in a window.
- Alphabetical order: AA < AT
- Window of size 5, 3-mers.

1st window GATTA : ATT

2nd window ATTAC : ATT

3rd window TTACA : ACA

Minimizers for GATTACA are ATT, ACA.

(2 fingerprints instead of 5 kmers)

Similar sequences ~ shared minimizers.

GATTA

GATTA

GATTA

ATTAC

ATTAC

ATTAC

TTACA

TTACA

TTACA

GATTACA

GATTACA

1st window

GATTACA

2nd window

GATTACA

3rd window

Different ordering

1. Alphabetical order: AA < TT

2. Defining a function on a string

A=1, C=2, G=3, T=4

TAAT = 4114

CTTT = 2444

TAAT > CTTT

3. Hash function

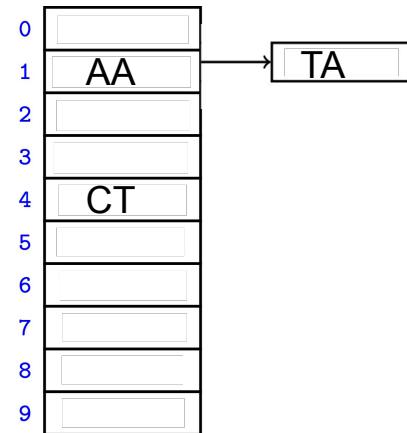
$$h(x) = x \bmod 11$$

“remainder of a division by 10”

$$\text{AA} = 11 \rightarrow \{\text{AA}:1\}$$

$$\text{CT} = 24 = 2 * 10 + 4$$

$$\text{TA} = 41 = 4 * 10 + 1$$

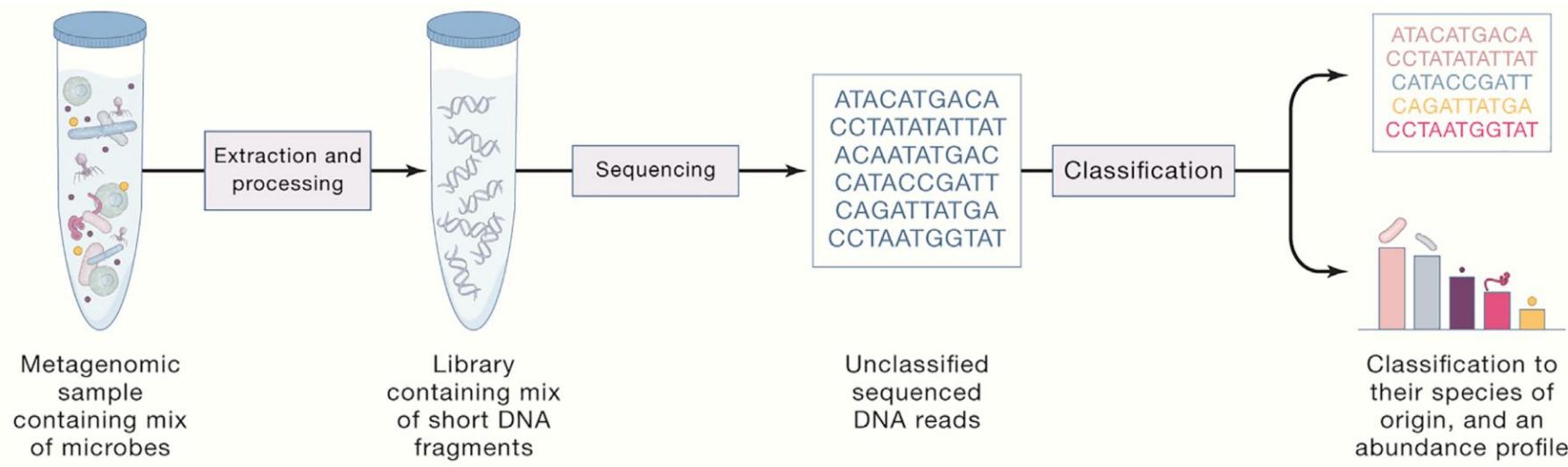


Applications

1- Metagenomics

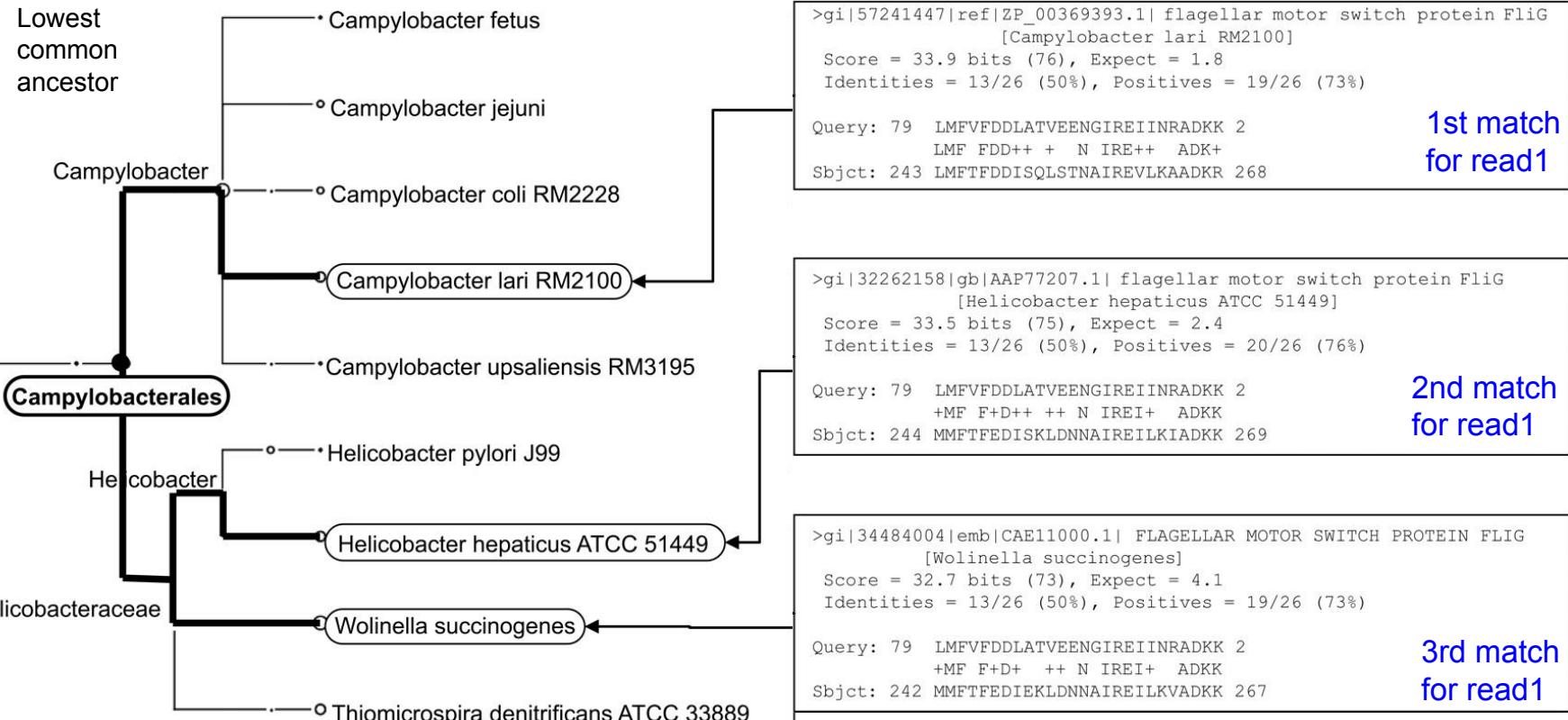
Metagenomics

Metagenomics: the study of genomic sequences obtained directly from an environment (gut microbiome, wastewater surveillance, ...)



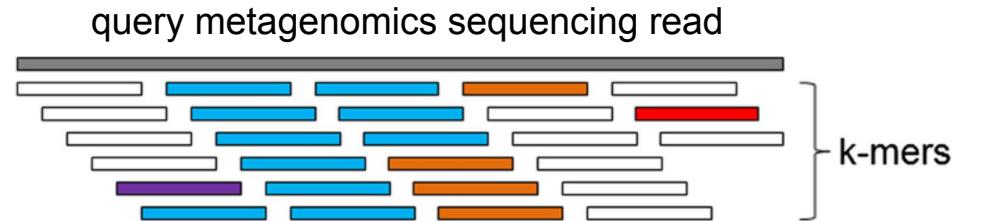
MEGAN: exploring taxonomical content

BLASTX read1 against NCBI-NR

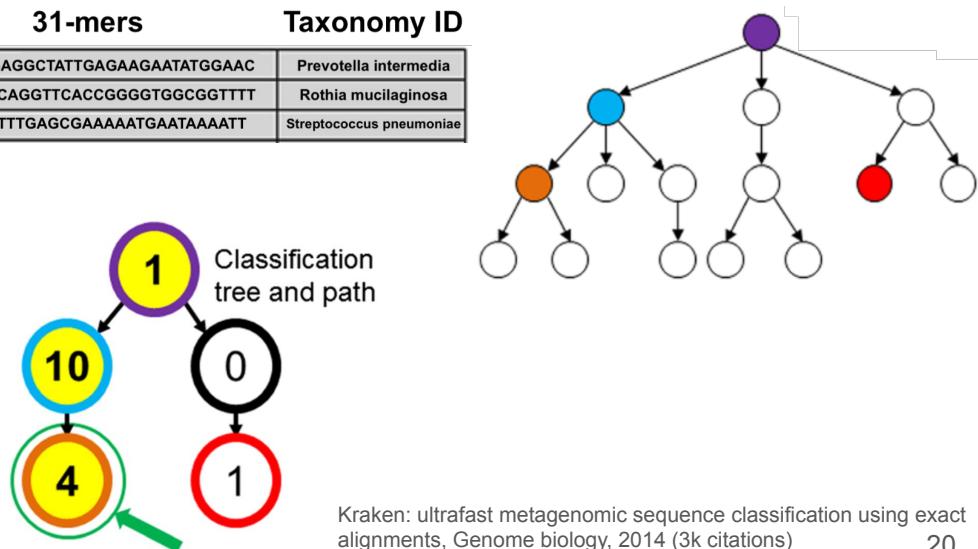


Kraken: assigning taxonomic labels

1. Extract k-mers from the input sequencing read (query)
2. Use precomputed database, extract the taxonomic ID of 31-mers
3. Count # kmers assigned to each taxonomic level
4. Find the path with maximum sum
5. Report the leaf as the taxonomic label



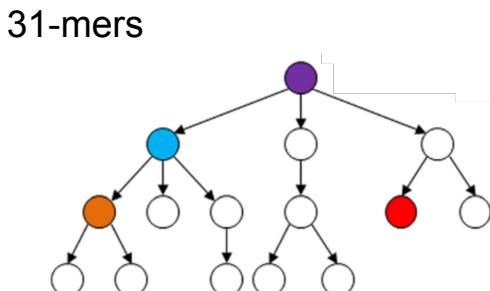
31-mers	Taxonomy ID
GACAAGGGAGGCTATTGAGAAGAAATATGGAAC	Prevotella intermedia
TAGCAGGCAGGTTCACCGGGGTGGCGGTTT	Rothia mucilaginosa
ATATGATTTGAGCGAAAAATGAATAAAATT	Streptococcus pneumoniae



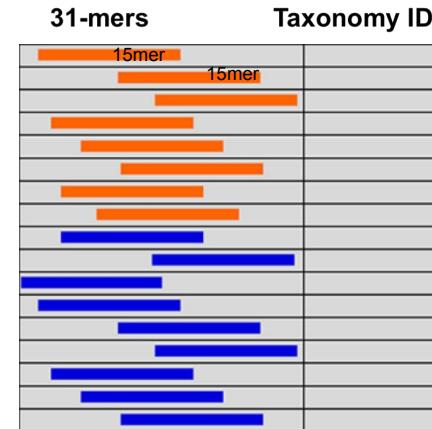
Kraken: kmer-LCA table

- Pre-computing the kmer-LCA database
- Extract all 31-mers from microbial genome in NCBI RefSeq

31-mers	Taxonomy ID
GACAAGGGAGGCTATTGAGAAGAAATGGAAC	Prevotella intermedia
TAGCAGGCAGGTTCACCGGGGTGGCGGTTT	Rothia mucilaginosa
ATATGATTGAGCGAAAAATGAATAAAATT	Streptococcus pneumoniae



- To speed up kmer search in the table
- Use 15mer minimizer for grouping similar 31mer

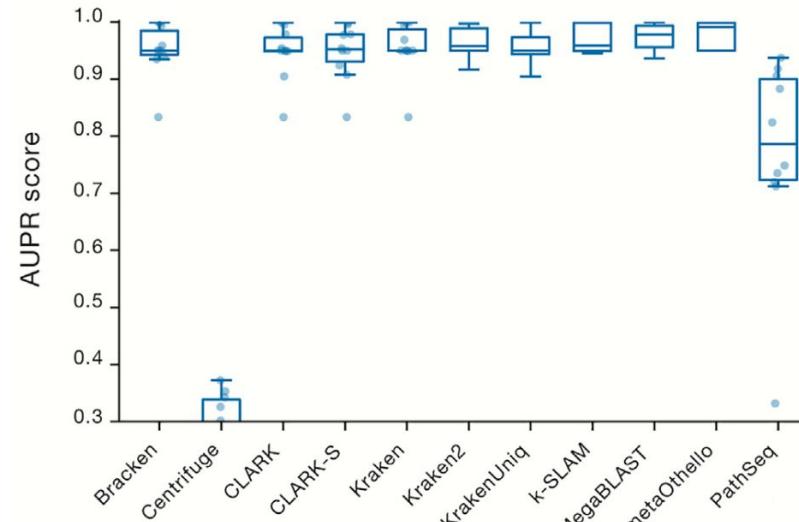


- Fill the table with 31-mers of shared minimizer near each other
- For a 31-mer query, start searching within its minimizer

Kraken2 results

Classification accuracy and speed comparison on a simulated dataset

Classifier	Memory Required	Time Required
Bracken	<1 Gb	<1 min
Centrifuge	20 Gb	7 min
CLARK	80 Gb	2 min
CLARK-S	170 Gb	40 min
Kraken	190 Gb	1 min
Kraken2	36 Gb	1 min
KrakenUniq	200 Gb	1 min
k-SLAM	130 Gb	2 h
MegaBLAST	61 Gb	4 h
metaOthello	30 Gb	1 min
PathSeq	140 Gb	5 min



Article | Open Access | Published: 11 July 2019

Strain-level metagenomic assignment and compositional estimation for long reads with MetaMaps

Alexander T. Dilthey  Chirag Jain, Sergey Koren & Adam M. Phillippy

Nature Communications 10, Article number: 3066 (2019) | [Cite this article](#)

15k Accesses | 49 Citations | 68 Altmetric | [Metrics](#)

Short Report | Open Access | Published: 28 November 2019

Improved metagenomic analysis with Kraken 2

Derrick E. Wood, Jennifer Lu & Ben Langmead 

Genome Biology 20, Article number: 257 (2019) | [Cite this article](#)

52k Accesses | 1081 Citations | 91 Altmetric | [Metrics](#)

Journals & Magazines > IEEE/ACM Transactions on Comp... > Volume: 19 Issue: 1 

K2Mem: Discovering Discriminative K-mers From Sequencing Data for Metagenomic Reads Classification

Publisher: IEEE

[Cite This](#)

 [PDF](#)

Improved kraken2

Davide Storato ; Matteo Comin  [All Authors](#)

Research | Open Access | Published: 31 October 2022

Sketching and sampling approaches for fast and accurate long read classification

Arun Das  & Michael C. Schatz

BMC Bioinformatics 23, Article number: 452 (2022) | [Cite this article](#)

19 Accesses | 3 Altmetric | [Metrics](#) Comparing minimizer with MinHash & ..



◀ BIOINFORMATICS AND GENOMICS

Deconvolute individual genomes from metagenome sequences through short read clustering

[Research article](#) Bioinformatics Microbiology Data Science

Kexue Li*^{1,2}, Yakang Lu*^{1,2}, Li Deng^{✉ 1,2,3}, Lili Wang^{1,2}, Lizhen Shi⁴, Zhong Wang^{✉ 3,5,6}

Published April 8, 2020

Metagenome assembly

MetaProb 2: Metagenomic Reads Binning Based on Assembly Using Minimizers and K-Mers Statistics

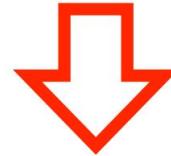
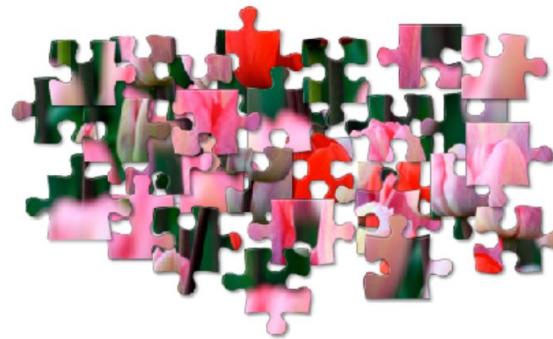
FRANCESCO ANDREACE, CINZIA PIZZI, and MATTEO COMINⁱ

Metagenome assembly

Applications

2- Genome assembly

De novo genome assembly



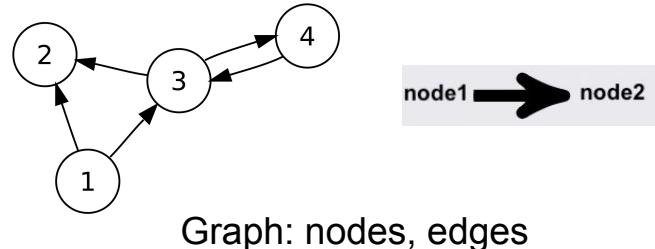
Sequencing reads

CTAGGCCCTCAATT
GGCGTCTATATCT
CTCTAGGCCCTCAATT
TCTATATCTGGCTCTAGG
GGCTCTAGGCCCTCATT
CTCGGCTCTAGCCCCTCATT
TATCTCGACTCTAGGCCCTCA
GGCGTCGATATCT
TATCTCGACTCTAGGCC
GGCGTCTATATCTCG

CTAGGCCCTCAATTTT
CTCTAGGCCCTCAATTTT
GGCTCTAGGCCCTCATTTTT
CTCGGCTCTAGCCCCTCATT
TATCTCGACTCTAGGCCCTCA
TATCTCGACTCTAGGCC
TCTATATCTGGCTCTAGG
GGCGTCTATATCTCG
GGCGTCGATATCT
GGCGTCTATATCT
GGCGTCTATATCTGGCTCTAGGCCCTCATT

- de Bruijn graphs
 - assemble the genome.
 - finding overlaps between kmers of reads

de Bruijn graphs



- Nodes: kmers
- Edge: link between k-mers that overlap by k-1 bases.
- Example:
 - 3mers for the sequence ACTG
 - 3mers: ACT, CTG
- Merging two nodes result in a K+1 mer (=a part of the sequence).

ACT → CTG

dBG for few reads

ACTG

CTGC

TGCC

ACT → CTG → TGC → GCC

ACTG

ACTG

CTGC

CTGC

CTGC

TGCC

TGCC

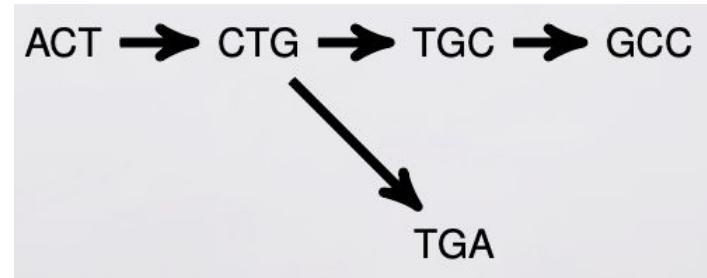
A sequencing error on de Bruijn graph

ACTG

CTGC

TGCC

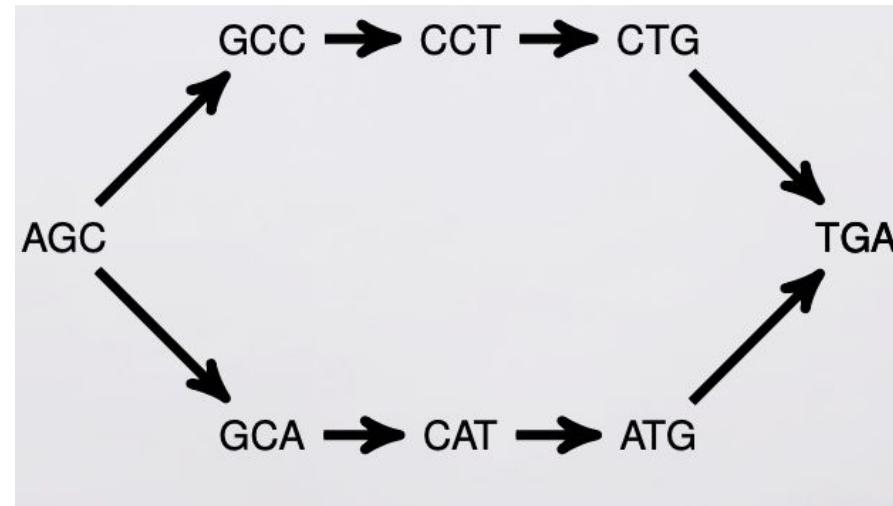
CTGA^A



SNPs in the graph

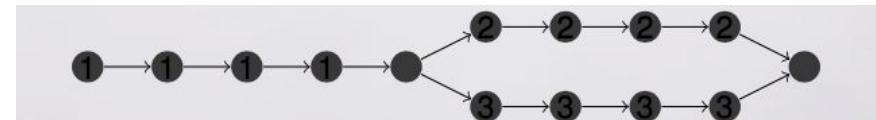
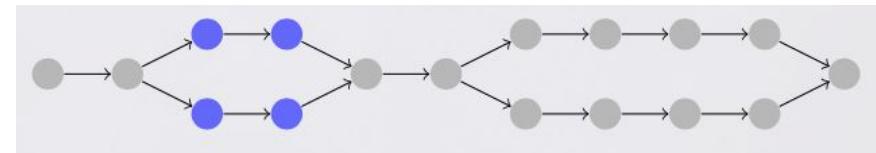
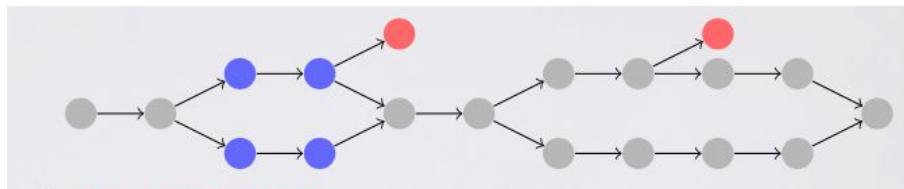
AGC**C**TGA

AGC**A**TGA



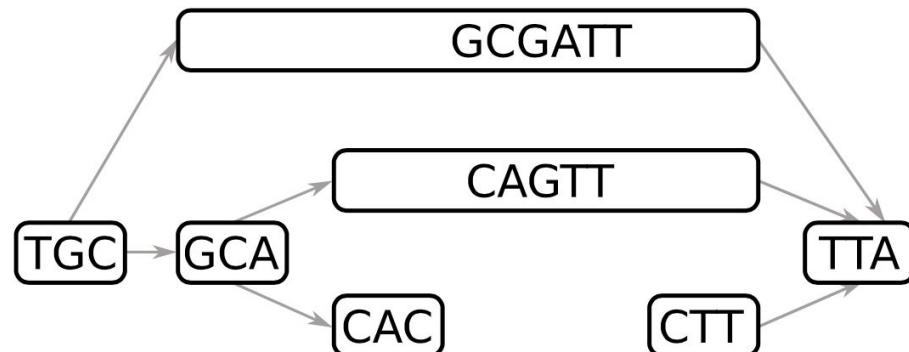
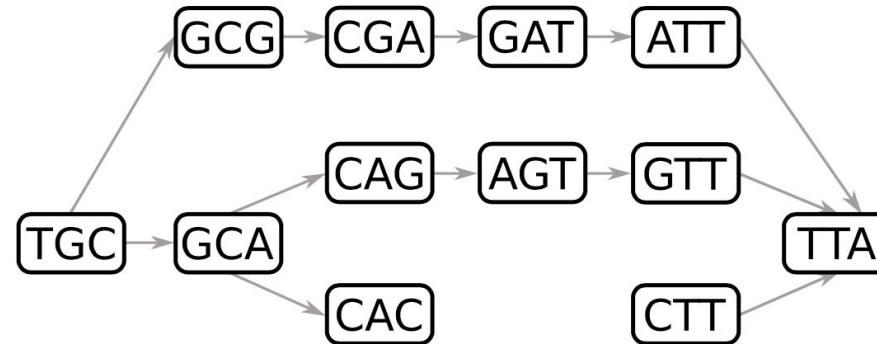
Short read assemblers

- Construct de Bruijn graph
- Remove likely sequencing errors
- Remove variations
- Return simple paths (contigs)
 - Combining all kmers in the path
- Extra steps: repeat-resolving, scaffolding



Compacting the de Bruijn graph

1 TB seq data
700 GB kmers

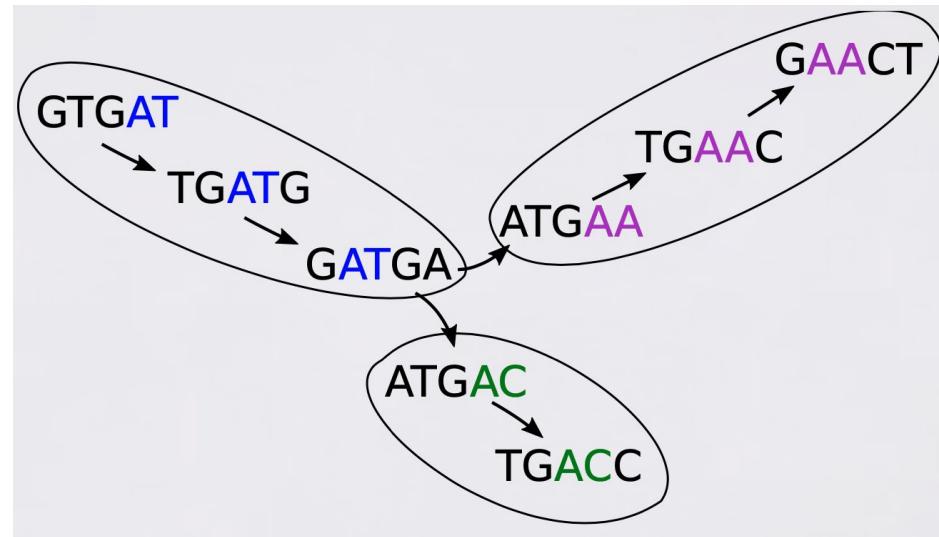


Compacting in parallel

GTG^{AT}GA

ATG^{AC}C

ATG^{AA}CT



Grouping kmers based on their minimizer to work it parallel.

BCALM2 is a tool for compacting the de Bruijn graph.

Sequence analysis
MBG: Minimizer-based sparse de Bruijn Graph construction

Compacting de Bruijn graphs from sequencing data quickly and in low memory

Bioinformatics, 32, 2016, i201–i208
doi: 10.1093/bioinformatics/btw279
ISMB 2016



Bioinformatics, 37(16), 2021, 2476–2478
doi: 10.1093/bioinformatics/btab004
Advance Access Publication Date: 21 January 2021
Applications Note



Holley and Melsted *Genome Biology* (2020) 21:249
<https://doi.org/10.1186/s13059-020-02135-8>

Genome Biology

SOFTWARE

Open Access

Bifrost: highly parallel construction and indexing of colored and compacted de Bruijn graphs



Research Articles

JOURNAL OF COMPUTATIONAL BIOLOGY
Volume 22, Number 5, 2015
© Mary Ann Liebert, Inc.
Pp. 336–352
DOI: 10.1089/cmb.2014.0160

On the Representation of De Bruijn Graphs

Too much math

A Preprocessor for Shotgun Assembly of Large Genomes

Ye et al. *BMC Bioinformatics* 2012, **13**(Suppl 6):S1
<http://www.biomedcentral.com/1471-2105/13/S6/S1>



PROCEEDINGS

Open Access

Exploiting sparseness in *de novo* genome assembly

Bioinformatics, 36(12), 2020, 3885–3887
doi: 10.1093/bioinformatics/btaa253
Advance Access Publication Date: 20 April 2020
Applications Note



Genome analysis

ntJoin: Fast and lightweight assembly-guided scaffolding using minimizer graphs

ARTICLES

<https://doi.org/10.1038/s41587-020-00747-w>



Check for updates

OPEN

Efficient hybrid *de novo* assembly of human genomes with WENGAN



Cell Systems

Article

Minimizer-space de Bruijn graphs: Whole-genome assembly of long reads in minutes on a personal computer

LJA: Assembling Long and Accurate Reads Using Multiplex de Bruijn Graphs

Anton Bankevich, Andrey Bzikadze, Mikhail Kolmogorov, Dmitry Antipov, Pavel A. Pevzner
doi: <https://doi.org/10.1101/2020.12.10.420448>

ARTICLES

<https://doi.org/10.1038/s41587-022-01220-6>

Check for updates

Multiplex de Bruijn graphs enable genome assembly from long, high-fidelity reads

Applications

3- Kmer counting

K-mer counting

- Given a string, counting the number of occurrences of every kmer.
- Many applications
- A naive approach:
 - `count_dict={}; count_dict['ATA']=1; count_dict['ATC']=2.`
 - k-mers as keys and their counts as values.
- Efficient in terms of speed, space and memory
- Parallelization: locking memory

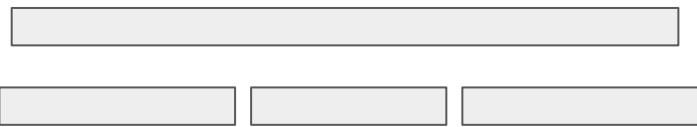
JellyFish: based on Hash table

- k-mers are stored as keys and their counts are stored as values.
- Lock-free hash table allowing parallel insertion of k-mers and frequency updates.



CAG	62
GGA	33

Gerbil: with minimizer



Evaluation

Data

- Illumina reads
- H. sapiens
- 292 GByte

System

- memory: 64GB
- Hard disk 1TB
- CPUs 16
- Intel CPU E5–2698 2.30GHz

Minimizer -> not equal bins

	Time (s)	RAM (GB)	Disk (GB)
Jellyfish (2.2.6)	>15 hours (system hang)		
DSK (2.2.0)	7,722	12	133
DSK (2.2.0; gzip)	9,240	11	134
KAnalyze (2.0.0)	Failed: "IO error writing segment file: no space left on device"		
KAnalyze (2.0.0; gzip)	Failed: "IO error writing segment file: no space left on device"		
KMC3	3,725*	10	78
KMC3 (gzip)	1,964	11	79
Gerbil (1.0)	4,078	6*	66*
Gerbil (1.0; gzip)	2,849	6	66
KCMBT (1.0)	>23 hours		
MSPKmerCounter (0.1)	>15 hours (phase 2 failed: "OutOfMemoryError")		
aTurtle (0.3)	Aborted (core dumped)		



Sequence analysis

KMC 2: fast and resource-frugal k -mer counting

Sebastian Deorowicz^{1,*}, Marek Kokot¹, Szymon Grabowski² and
Agnieszka Debudaj-Grabysz¹

Bioinformatics Advances, 2022, 1–8
<https://doi.org/10.1093/bioadv/vbac029>
Advance Access Publication Date: 29 April 2022
Original Paper



Sequence Analysis

kmtricks: efficient and flexible construction of Bloom filters for large sequencing data collections

Téo Leman¹, Paul Medvedev^{2,3,4}, Rayan Chikhi⁵ and Pierre Peterlongo^{1,*}

Data Set-Adaptive Minimizer Order Reduces Memory Usage in k -Mer Counting

DAN FLOMIN, DAVID PELLOW, and RON SHAMIR

Bioinformatics, 37(17), 2021, 2563–2569
doi: 10.1093/bioinformatics/btab156
Advance Access Publication Date: 8 March 2021
Original Paper



Sequence analysis

Compact and evenly distributed k -mer binning for genomic sequences

Johan Nyström-Persson^{1,2,*}, Gabriel Keeble-Gagnère³ and Niamat Zawad²

RESEARCH

Open Access

Space-efficient representation of genomic k -mer count tables

Yoshihiro Shibuya¹, Djamal Belazzougui² and Gregory Kucherov^{1,3*}

Erbert et al. Algorithms Mol Biol (2017) 12:9
DOI 10.1186/s13015-017-0097-9



RESEARCH

Open Access

Gerbil: a fast and memory-efficient k -mer counter with GPU-support

Marius Erbert, Steffen Rechner^{*} and Matthias Müller-Hannemann



Interdisciplinary Sciences: Computational Life Sciences (2020) 12:99–108
<https://doi.org/10.1007/s12539-019-00348-5>

ORIGINAL RESEARCH ARTICLE

Review paper

Counting Kmers for Biological Sequences at Large Scale

Jianqiu Ge¹ · Jintao Meng¹ · Ning Guo¹ · Yanjie Wei¹ · Pavan Balaji² · Shengzhong Feng¹



doi: 10.1093/gigascience/giy125
Advance Access Publication Date: 22 October 2018
Review

Review paper

REVIEW

A benchmark study of k -mer counting methods for high-throughput sequencing

Thank you!

QA?



ETHAN HAWKE UMA THURMAN

GATTACA

HOW DO YOU HIDE WHEN YOU'RE RUNNING FROM YOURSELF?

COLUMBIA PICTURES PRESENTS A JERSEY FILMS PRODUCTION A FILM BY ANDREW NICCOL STARRING ETHAN HAWKE, UMA THURMAN "GATTACA" ALAN ARKIN, JUDE LAW, LOREN DIAZ, ERNEST BORGnine
ASCAP MEMBER MICHAEL NYMAN MUSIC COLLECTOR'S EDITION IN USA ZERO CHARGE DIRECTOR OF PHOTOGRAPHY: JAI ROELFS EDITOR: SEABOURNE DODD PRODUCED BY BARRY DEUTCH, MICHAEL SHAMBURG, STACEY SHER
www.gattaca.com © 1997 COLUMBIA TRISTAR FILM CORPORATION A Division of Sony Pictures Releasing International

Available reviews papers

Rowe *Genome Biology* (2019) 20:199
<https://doi.org/10.1186/s13059-019-1809-x>

Genome Biology

REVIEW **Open Access**

When the levee breaks: a practical guide to sketching algorithms for processing the flood of genomic data

Will P. M. Rowe^{1,2} 

Tutorial + basics 

Annual Review of Biomedical Data Science

Sketching and Sublinear Data Structures in Genomics

Guillaume Marçais,^{1,*} Brad Solomon,^{2,*} Rob Patro,³ and Carl Kingsford¹

Two pages on Minimizer

Time order O(n) ACM Computing Surveys, Vol. 54, No. 1, Article 17. Publication date: March 2021.

Data Structures to Represent a Set of k -long DNA Sequences

RAYAN CHIKHI, Center of Bioinformatics and Biostatistics and Integrative Biology
JAN HOLUB, Department of Theoretical Computer Science, Czech Technical University in Prague
PAUL MEDVEDEV, Center for Computational Biology and Bioinformatics

Review

Data structures based on k -mers for querying large collections of sequencing data sets

Camille Marchet,¹ Christina Boucher,² Simon J. Puglisi,³ Paul Medvedev,^{4,5,6}
Mikaël Salson,¹ and Rayan Chikhi⁷



Useful, we can write similarly describing Biological applications.
Good supplementary describing basics

A survey of mapping algorithms in the long-reads era

Intro on seeding, anchor, kmer

4- Sequence compression

Bioinformatics, 35(12), 2019, 2066–2074
doi: 10.1093/bioinformatics/bty936
Advance Access Publication Date: 8 November 2018
Original Paper

OXFORD

SCIENTIFIC
REPORTS

nature research

Corrected: Author Correction

FQSqueezer: k -mer-based compression of sequencing data

Sebastian Deorowicz¹

JOURNAL OF COMPUTATIONAL BIOLOGY
Volume 25, Number 7, 2018
© Mary Ann Liebert, Inc.
Pp. 825–836
DOI: 10.1089/cmb.2018.0068

Dynamic Alignment-Free and Reference-Free
Read Compression

PLOS COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

Hamming-shifting graph of genomic short reads: Efficient construction and its application for compression

Yuansheng Liu¹, Jinyan Li^{1,*}

Data Science Institute, University of Technology Sydney, Sydney, Australia

Sequence analysis

Index suffix–prefix overlaps by (w, k) -minimizer to generate long contigs for reads compression

Bioinformatics, 31(9), 2015, 1389–1395
doi: 10.1093/bioinformatics/btu844
Advance Access Publication Date: 22 December 2014
Original Paper

OXFORD

Sequence analysis

Disk-based compression of data from genome sequencing

Szymon Grabowski¹, Sebastian Deorowicz^{2,*} and Łukasz Roguski^{3,4}

Bioinformatics, 34(16), 2018, 2748–2756
doi: 10.1093/bioinformatics/bty205
Advance Access Publication Date: 29 March 2018
Original Paper

OXFORD

Sequence analysis

FaStore: a space-saving solution for raw sequencing data

Łukasz Roguski^{1,2}, Idoia Ochoa³, Mikel Hernaez⁴ and
Sebastian Deorowicz^{5,*}

5- Sequence error correction

LaPierre et al. BMC Bioinformatics (2019) 20:552
<https://doi.org/10.1186/s12859-019-3103-z>

BMC Bioinformatics

SOFTWARE

Open Access

De novo Nanopore read quality improvement using deep learning



nature communications



Article

<https://doi.org/10.1038/s41467-022-34381-8>

VeChat: correcting errors in long reads using variation graphs

Simultaneous compression of multiple error-corrected short-read sets for faster data transmission and better de novo assemblies



ARTICLE

<https://doi.org/10.1038/s41467-020-20340-8>

OPEN

Error correction enables use of Oxford Nanopore technology for reference-free transcriptome analysis

Kristoffer Sahlin ¹ & Paul Medvedev^{2,3,4}

Bioinformatics. 37(11), 2021, 1604–1606
doi: 10.1093/bioinformatics/btaa915
Advance Access Publication Date: 28 October 2020
Applications Note

OXFORD

Sequence analysis
Minirmd: accurate and fast duplicate removal tool for short reads via multiple minimizers

Yuansheng Liu ¹, Xiaocai Zhang², Quan Zou ³ and Xiangxiang Zeng^{1,*}

Not a priority

6- Variant calling & MSA

Dysgu: efficient structural variant calling using short or long reads

Kez Cleal * and Duncan M. Baird *

State-of-the-art structural variant calling:
What went conceptually wrong and how
to fix it?

Markus Schmidt¹ and Arne Kutzner^{1,}*

Mapping-free variant calling using haplotype reconstruction from k-mer frequencies

Peter A. Audano*, Shashidhar Ravishankar and Fredrik O. Vannberg*

FAME: fast and memory efficient multiple sequences alignment tool through compatible chain of roots

Etminan Naznooshsadat¹, Parvinnia Elham^{1,*} and Sharifi-Zarchi Ali²

7- Read alignment (good reviews exist)

Bioinformatics, 36, 2020, i11–i118
doi: 10.1093/bioinformatics/btaa435
ISMB 2020



Weighted minimizer sampling improves long read mapping

Chirag Jain^{1,*}, Arang Rhee¹, Haowen Zhang², Claudia Chu², Brian P. Walenz¹, Sergey Koren¹ and Adam M. Phillippy¹

nature methods

ARTICLES

<https://doi.org/10.1038/s41592-022-01457-8>

Long-read mapping to repetitive reference sequences using Winnowmap2

Chirag Jain^{1,2*}, Arang Rhee^{1,2}, Nancy F. Hansen³, Sergey Koren² and Adam M. Phillippy²

Rautainen and Marschall *Genome Biology* (2020) 21:253
<https://doi.org/10.1186/s13059-020-02157-2>

Genome Biology

SOFTWARE Open Access

GraphAligner: rapid and versatile sequence-to-graph alignment

Mikko Rautainen^{1,2,3*} and Tobias Marschall^{4*}



REVIEW

Open Access

Technology dictates algorithms: recent developments in read alignment

Mohammed Aiser^{1,2,3†}, Jeremy Rotman^{4†}, Dhriti Deshpande⁵, Kodi Tarascka⁶, Huwenbo Shi^{6,7}, Pelin Icer Baykal⁸, Harry Taegyun Yang^{6,9}, Victor Xue⁶, Sergey Knyazev⁶, Benjamin D. Singer^{10,11,12}, Brunilda Balliu¹³, David Koslicki^{14,15,16}, Pavel Skums⁸, Alex Zelikovsky^{8,17}, Can Alkan^{2,18}, Onur Mutlu^{1,2,3†} and Serghei Mangul^{5*†}



A survey of mapping algorithms in the long-reads era

Kristoffer Sahlin

Department of Mathematics, Science for Life Laboratory, Stockholm University, 106 91, Stockholm, Sweden.

Focused on minimizer

Bioinformatics, 34(18), 2018, 3094–3100
doi: 10.1093/bioinformatics/bty191
Advance Access Publication Date: 10 May 2018
Original Paper



Sequence analysis

Minimap2: pairwise alignment for nucleotide sequences

Heng Li*

Department of Medical Population Genetics Program, Broad Institute, Cambridge, MA 02142, USA

Bioinformatics, 32(14), 2016, 2103–2110
doi: 10.1093/bioinformatics/btw152
Advance Access Publication Date: 19 March 2016
Original Paper



Sequence analysis

Minimap and miniasm: fast mapping and de novo assembly for noisy long sequences

Heng Li

Alternative data structures (math+computer sci.)

Masked Minimizers: Unifying sequence sketching methods

A randomized parallel algorithm for efficiently finding near-optimal universal hitting sets

Sequence-specific minimizers via polar sets

Hongyu Zheng, Carl Kingsford and Guillaume Marçais*

Improved design and analysis of practical minimizers

Hongyu Zheng, Carl Kingsford and Guillaume Marçais*

BLight: efficient exact associative structure for k-mers

Camille Marchet *, Mael Kerbiriou and Antoine Limasset *



Syncmers are more sensitive than minimizers for selecting conserved k -mers in biological sequences

Robert Edgar
None, Corte Madera, CA, USA

Effective sequence similarity detection with strobemers

Kristoffer Sahlin

A performant bridge between fixed-size and variable-size seeding

Arne Kutzner¹, Pok-Son Kim² and Markus Schmidt^{1*}

The minimizer Jaccard estimator is biased and inconsistent*

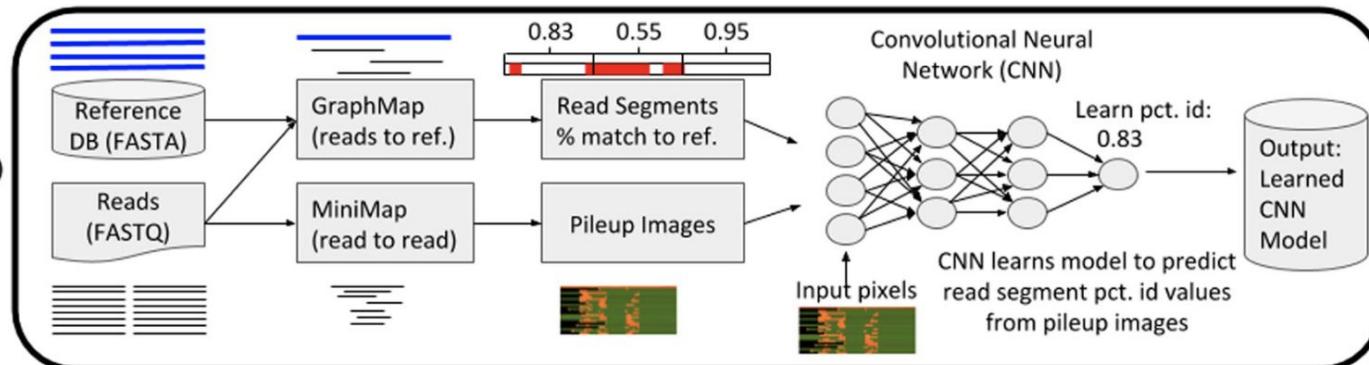
Paper outline “**Applications of Minimizer in genomics**”

1. intro (importance, why now(biogenome project), definition)
2. metagenomics (7)
3. de Bruijn graph (4)
4. genome assembly (7)
5. kmer counting (5)
6. sequence compression (6)
7. sequence error correction (3)
8. variant calling (3)
9. Discussion and conclusion

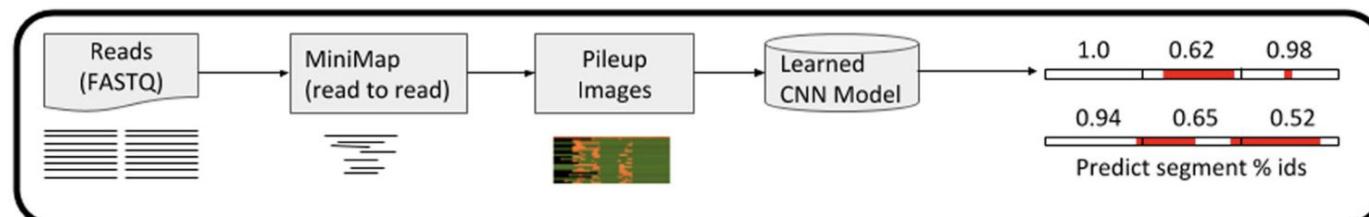
Tables, figure.

a. Model Training (pre-computed)

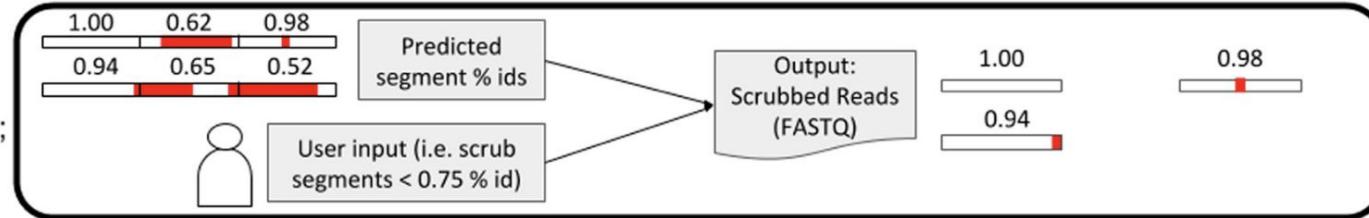
■ = ref.
■ = read
■ = errors



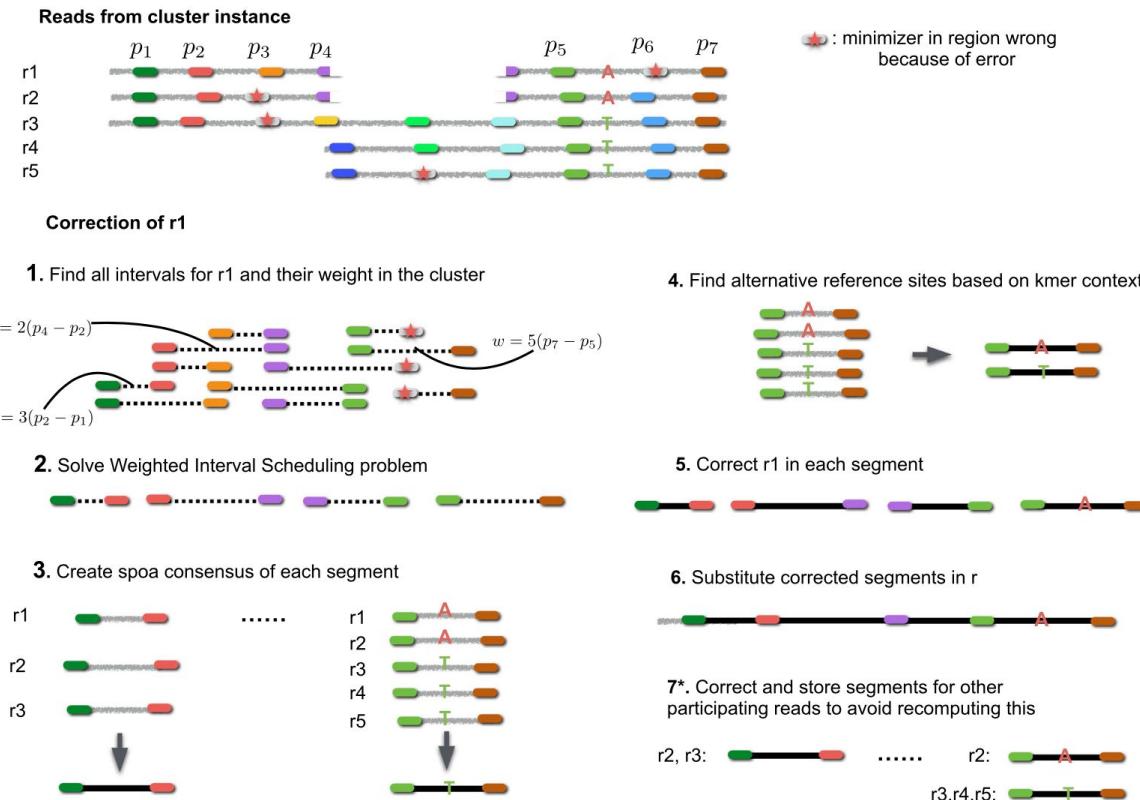
b. Predict read segment pct. ids (*de novo*)



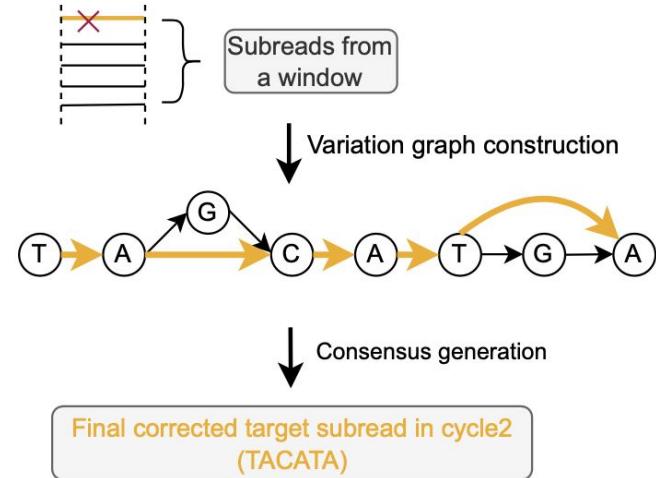
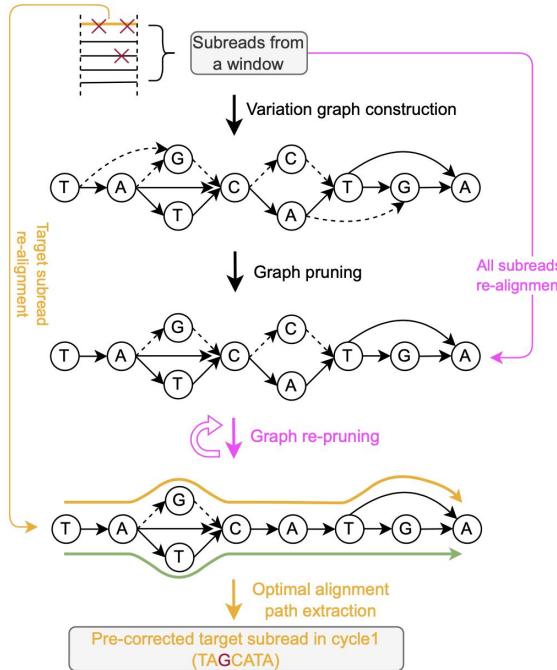
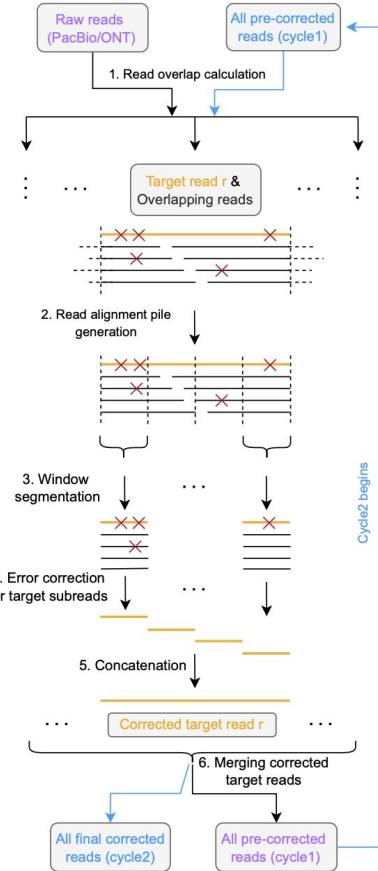
c. Read scrubbing (user side; *de novo*)



isONcorrect method

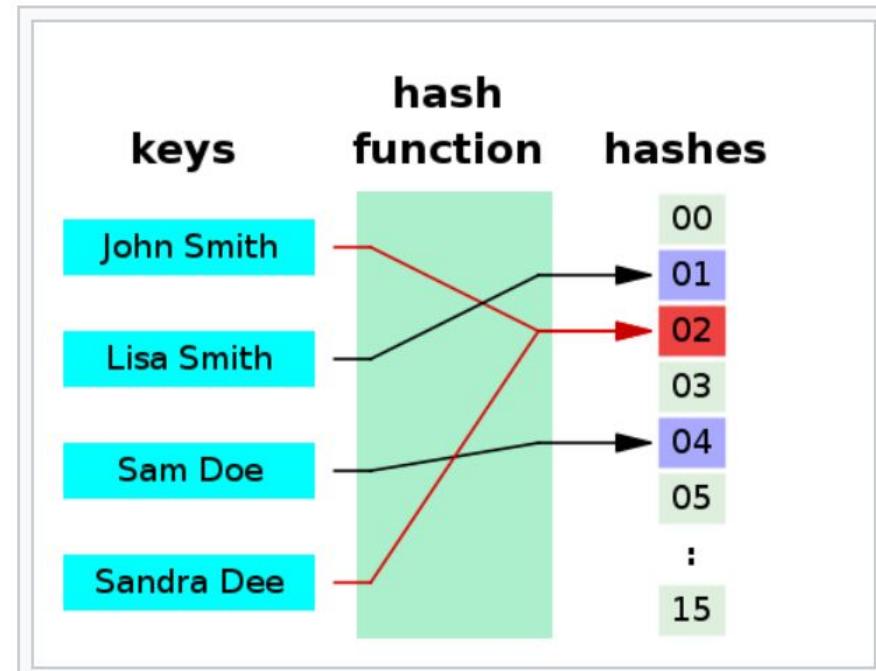


Error correction enables use of Oxford Nanopore technology for reference-free transcriptome analysis, Nature communication, 2021.



Hash function

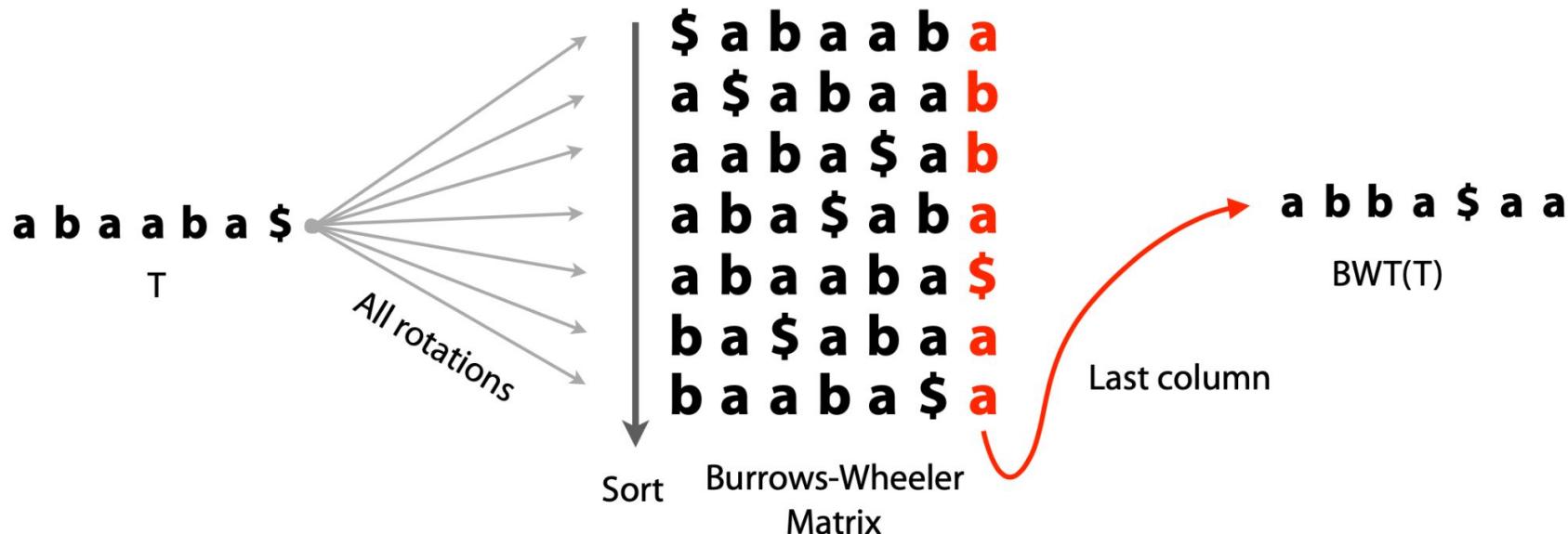
A hash function is any function that can be used to map data of arbitrary size to fixed-size values.



A hash function that maps names to integers from 0 to 15. There is a **collision** between keys "John Smith" and "Sandra Dee".

wikipedia

Burrows–Wheeler transform



Suffix array

\$ a b a a b a
a \$ a b a a b
a a b a \$ a b
a b a \$ a b a
a b a a b a \$
b a \$ a b a a
b a a b a \$ a

6	\$
5	a \$
2	a a b a \$
3	a b a \$
0	a b a a b a \$
4	b a \$
1	b a a b a \$

BWT

FM index

Using the BWT matrix

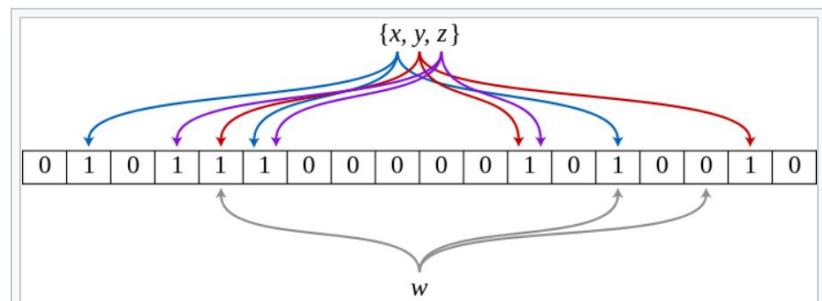
a last-to-first column mapping $LF(i)$ from an index i to ϵ
 $L[i]$

F	L
\$	a b a a b
a	\$ a b a a
a	a b a \$ a
a	b a \$ a b
a	b a a b a
b	a \$ a b a
b	a a b a \$

Not stored in index

Bloom filter

- a space-efficient probabilistic data structure
- test whether an element is a member of a set
- False positive matches are possible, but false negatives are not
- An empty Bloom filter is a bit array of m bits, all set to 0.
- Using k different hash functions
- each function maps (hashes) an element to one of the m array positions.



An example of a Bloom filter, representing the set $\{x, y, z\}$. The colored arrows show the positions in the bit array that each set element is mapped to. The element w is not in the set $\{x, y, z\}$, because it hashes to one bit-array position containing 0. For this figure, $m = 18$ and $k = 3$.

Bloom filters

indexable

[
hashfn \emptyset
hashfn1
hashfn2
hashfn3

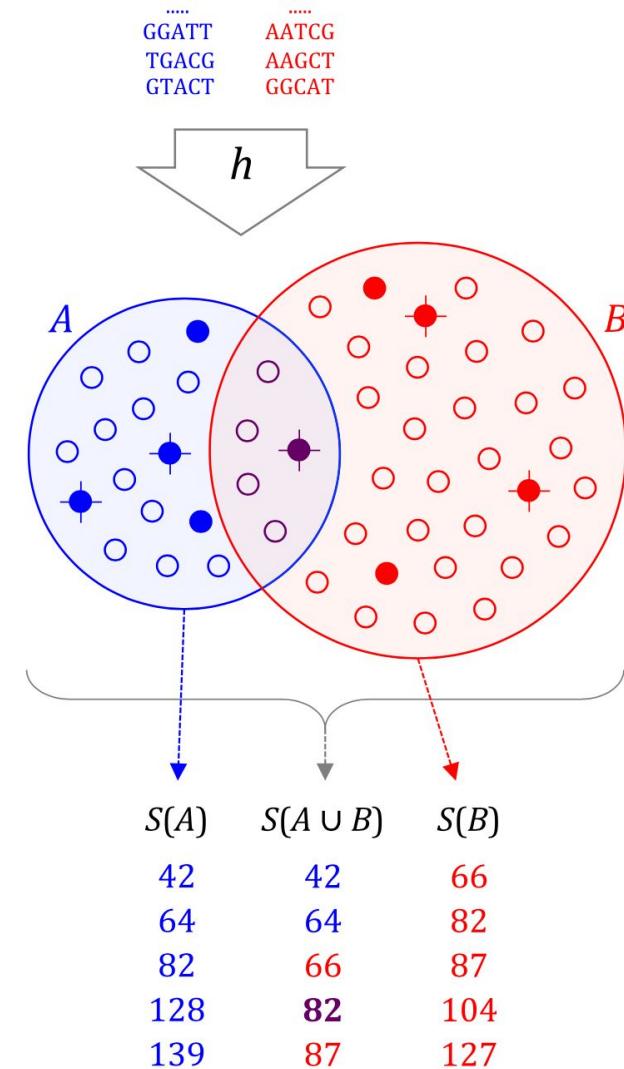
	\emptyset	1	2	3	
kmer 1	5	12	7	3	
kmer 2	18	9	11	5	
kmer 1	5	12	7	3	TP ✓
kmer 3	15	10	21	16	TN X
kmer 4	11	5	3	18	FP ✓



MinHASH

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \approx \frac{|S(A \cup B) \cap S(A) \cap S(B)|}{|S(A \cup B)|}$$

Fig. 1 Overview of the MinHash bottom sketch strategy for estimating the Jaccard index. First, the sequences of two datasets are decomposed into their constituent k-mers (top, blue and red) and each k-mer is passed through a hash function h to obtain a 32- or 64-bit hash, depending on the input k-mer size. The resulting hash sets, A and B , contain $|A|$ and $|B|$ distinct hashes each (small circles). The Jaccard index is simply the fraction of shared hashes (purple) out of all distinct hashes in A and B . This can be approximated by considering a much smaller random sample from the union of A and B . MinHash sketches $S(A)$ and $S(B)$ of size $s = 5$ are shown for A and B , comprising the five smallest hash values for each (filled circles). Merging $S(A)$ and $S(B)$ to recover the five smallest hash values overall for $A \cup B$ (crossed circles) yields $S(A \cup B)$. Because $S(A \cup B)$ is a random sample of $A \cup B$, the fraction of elements in $S(A \cup B)$ that are shared by both $S(A)$ and $S(B)$ is an unbiased estimate of $J(A, B)$.



StrobeMer

$k=3$, $w=5$, $n=4$

window
position of the strobe in the window

strobemer 1:

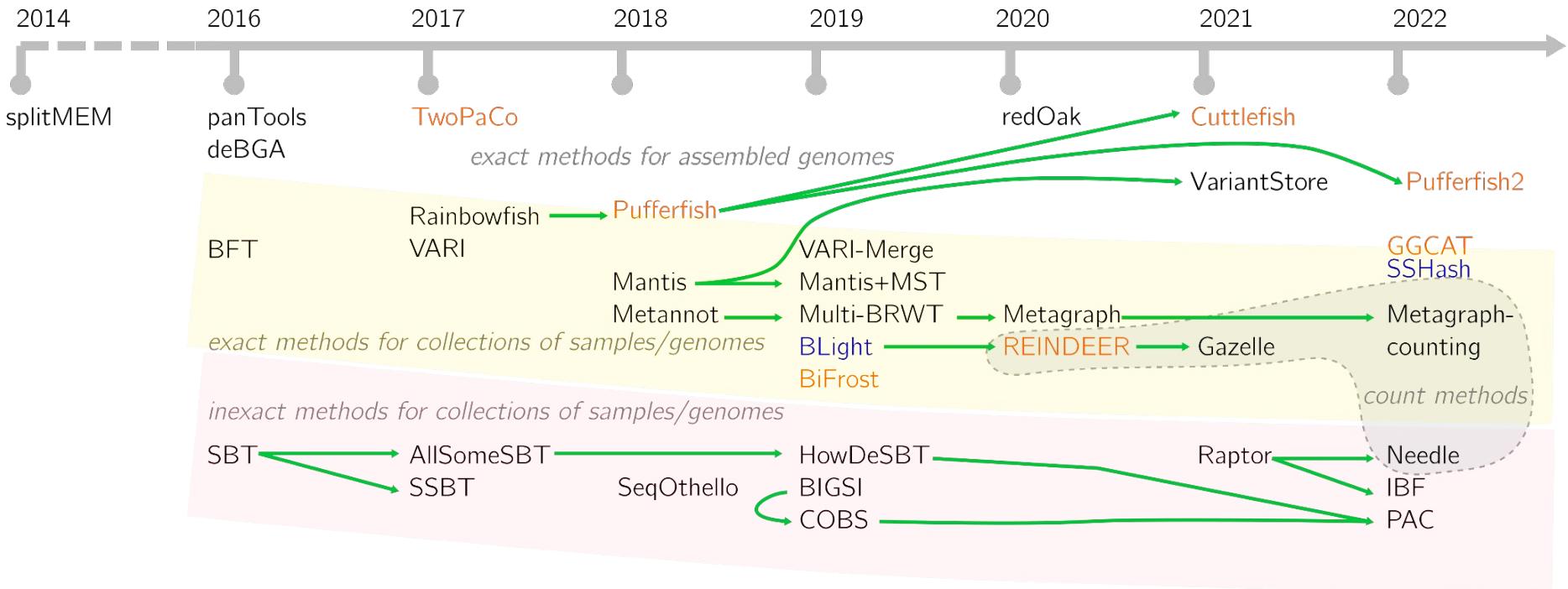
k_1 
ACTCTAACACATTGGCGTCT...

strokes: $k_1=ACT$
 $k_2=AAA$
 $k_3=ATT$
 $k_4=CGT$

strobemer 2:

k_1 
ACTCTAACACATTGGCGTCT...

strokes: $k_1=CTC$
 $k_2=AAA$
 $k_3=ATT$
 $k_4=CGT$



acgt: compacted colored de Bruijn graphs
 acgt: general purpose k -mer hash tables with possible color/feature coding

→ some level of relatedness, either from shared data-structures or inherited ideas,

https://kamimrcht.github.io/webpage/sets_kmer_sets.html

Time and space

count information with each k -mer. Rather than present how this is done, we have a separate section (Section 7.4) dedicated to data structures that supports it, we have a separate section (Section 7.4) dedicated to data structures that support count information.

3 BASIC APPROACHES

Perhaps the most basic static representation that is used in practice is a list of k -mers. The construction time is $O(nk)$ using any linear time algorithm, the space needed to store the list is $\Theta(nk)$. A membership query is expensive in time $O(k \log n)$. This representation is both space- and time-inefficient. There are other approaches we will discuss (e.g., unitig-based approaches or BOSS). But this approach is simple and can be understood by someone with very limited computer science background, making it still relevant.

Sorted lists can be partitioned to speed up queries. In this approach, [2014], the k -mers are partitioned according to a minimizer function. The minimizer of a k -mer x is the smallest (according to some given p-

Swap and compare kmer counting

Example:

workers W1 & W2.

W1: read count
of AAT (0) W1: increment
AAT 0->1

W2: read count
of ATT (0) W2: increment
ATT 0->1

AAT	1
ATT	1

W1:
W2: read count
AAT (1)

W1: read count
AAT (1)
W2: increment
AAT 1->2

AAT	2
ATT	1

W1: increment
AAT 1->2
W2:

AAT	2
ATT	1

W1, No, I won't increment
AAT as 1->2 does not hold

to ensure low random access memory (RAM) usage, as has been argued by Li et al. (2013).

In this study, we introduce a new approach for adapting the minimizer order to the target sequence data. The method, called Adaptive Order (AdaOrder), iteratively updates the minimizer order based on an estimate of the minimizer loads in the data to reduce the maximum load. We demonstrated its ability to lower the maximum load compared with all predefined orders, except the frequency-based order.

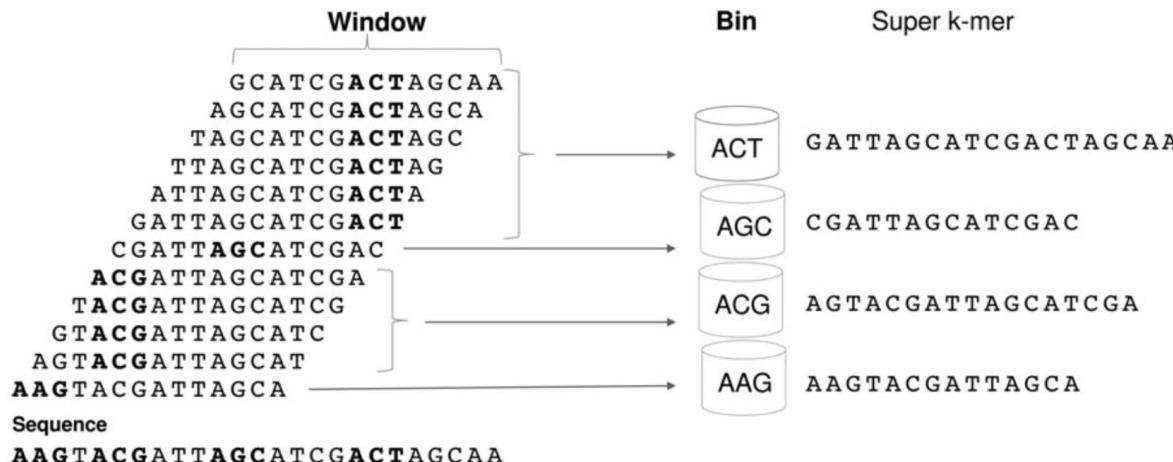


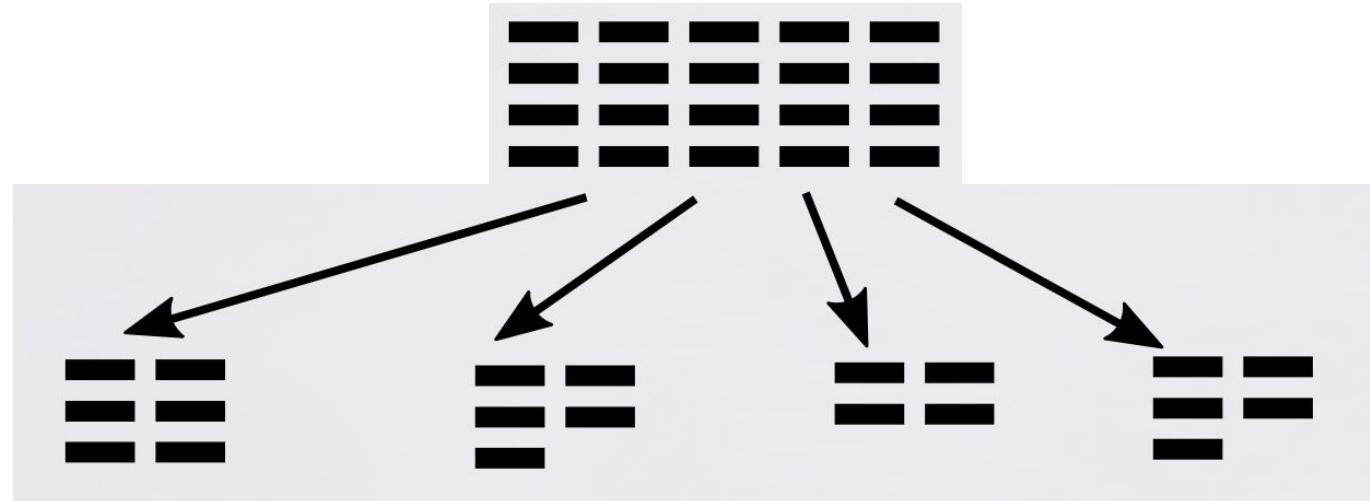
FIG. 1. Illustration of a minimizer scheme and binning. Here $k=12$ and $m=3$. The input sequence is broken into windows of length k , and in each window the m -long minimizer according to the lexicographic order (shown in bold) is selected. The k -mer is assigned to the partition whose label is the minimizer. Consecutive windows tend to select the same minimizer, and the concatenation of the consecutive windows forms the super- k -mer that is stored in the bin.

Sequence comparison with minimizer

- Number of minimizer at most = $L-w+1$ but
- Similar sequences have high probability of having the same minimizers.
- Sequence of minimizers is also called a sketch of the original seq.
- With non-overlapping windows $\rightarrow L/w$ minimizers for sequence of length L .
- For a random order (w not too large), a factor of $2/(w + 1)$.

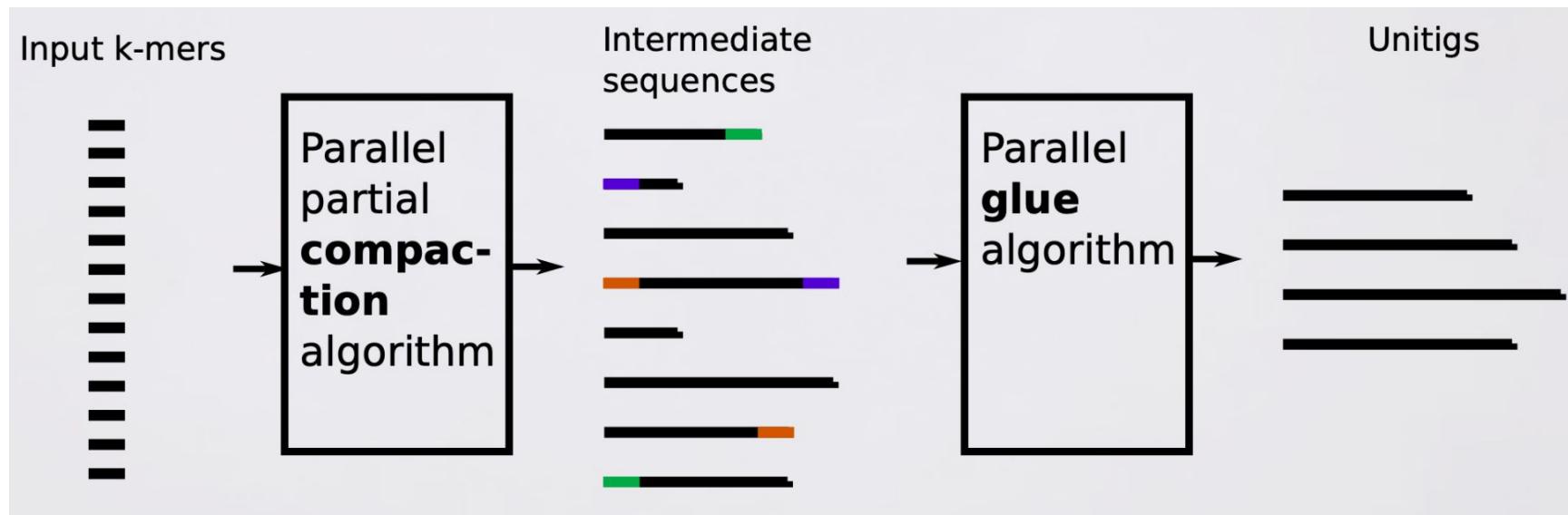
Memory and speed; minimizer

- partitioning input k-mers on disk
- based on minimizers

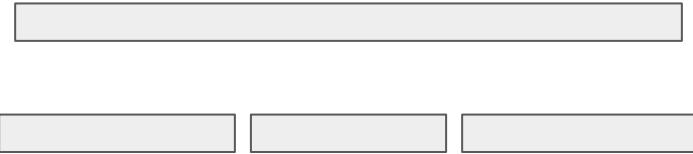


BCALM 2

A tool for compacting the de Bruijn graph



Parallel counting: splitting the sequence



Issues: missing kmers, combining stats of each part.

Gerbil: with minimizer

- 4-mers
- 3-mer minimizer (bold)
- Finding (overlapping) part of sequence with the same minimizer on temp files



CAAGAACAGTG	
CAAG	1. CAAGA
AAGA	
AGAA	2. AGAA
GAAC	3. GAACA
AACA	
ACAG	4. ACAG
CAGT	
AGTG	5. CAGTG