Accelerating Genome Analysis A Primer on an Ongoing Journey

Onur Mutlu

omutlu@gmail.com

https://people.inf.ethz.ch/omutlu

6 September 2022

Barcelona Supercomputing Center





Carnegie Mellon

Overview

- System design for bioinformatics is a critical problem
 - It has large scientific, medical, societal, personal implications
- This talk is about accelerating a key step in bioinformatics: genome sequence analysis
 - In particular, read mapping
- Many bottlenecks exist in accessing and manipulating huge amounts of genomic data during analysis
- We will cover various recent ideas to accelerate read mapping
 - My personal journey since September 2006

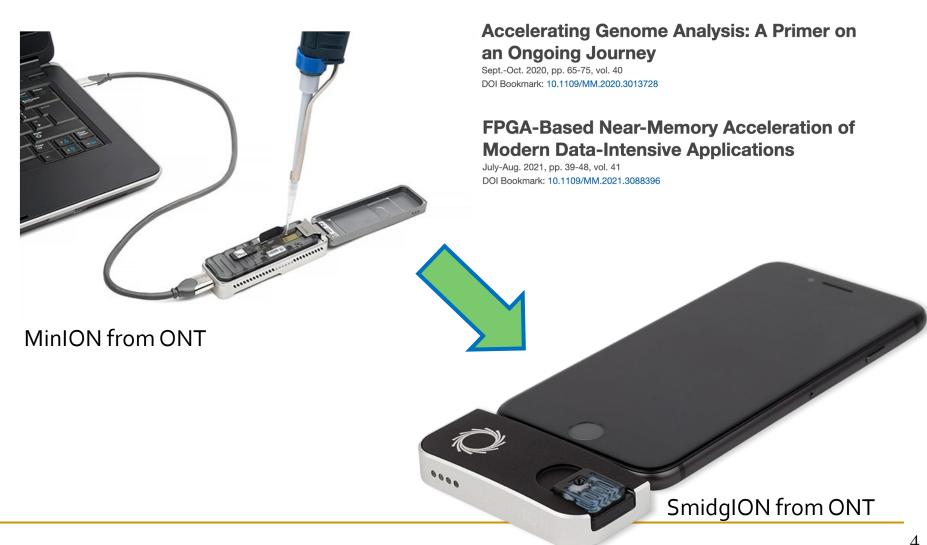
Our Dream (circa 2007)

- An embedded device that can perform comprehensive genome analysis in real time (within a minute)
 - Which of these DNAs does this DNA segment match with?
 - What is the likely genetic disposition of this patient to this drug?
 - What disease/condition might this particular DNA/RNA piece associated with?

u . . .

A Bright Future for Intelligent Genome Analysis

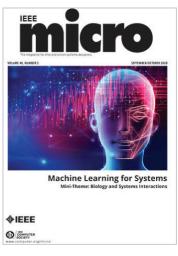
Mohammed Alser, Zülal Bingöl, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, Onur Mutlu "Accelerating Genome Analysis: A Primer on an Ongoing Journey" IEEE Micro, August 2020.



A Few Overview Readings (I)

Mohammed Alser, Zülal Bingöl, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, Onur Mutlu

"Accelerating Genome Analysis: A Primer on an Ongoing Journey" IEEE Micro, August 2020.





Home / Magazines / IEEE Micro / 2020.05

IEEE Micro

Accelerating Genome Analysis: A Primer on an Ongoing Journey

Sept.-Oct. 2020, pp. 65-75, vol. 40 DOI Bookmark: 10.1109/MM.2020.3013728

Authors

Mohammed Alser, ETH Zürich
Zulal Bingol, Bilkent University
Damla Senol Cali, Carnegie Mellon University
Jeremie Kim, ETH Zurich and Carnegie Mellon University
Saugata Ghose, University of Illinois at Urbana–Champaign and Carnegie Mellon University
Can Alkan, Bilkent University
Onur Mutlu, ETH Zurich, Carnegie Mellon University, and Bilkent University

A Few Overview Readings (II)

Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios Diamantopoulos, Juan Gomez-Luna, Henk Corporaal, Onur Mutlu,

"FPGA-Based Near-Memory Acceleration of Modern Data-Intensive

Applications"

IEEE Micro, 2021.

[Source Code]





Home / Magazines / IEEE Micro / 2021.04

IEEE Micro

FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications

July-Aug. 2021, pp. 39-48, vol. 41

DOI Bookmark: 10.1109/MM.2021.3088396

Authors

Gagandeep Singh, ETH Zürich, Zürich, Switzerland
Mohammed Alser, ETH Zürich, Zürich, Switzerland
Damla Senol Cali, Carnegie Mellon University, Pittsburgh, PA, USA
Dionysios Diamantopoulos, Zürich Lab, IBM Research Europe, Rüschlikon, Switzerland
Juan Gomez-Luna, ETH Zürich, Zürich, Switzerland
Henk Corporaal, Eindhoven University of Technology, Eindhoven, The Netherlands
Onur Mutlu, ETH Zürich, Zürich, Switzerland

A Few Overview Readings (III)

Mohammed Alser, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu
"From Molecules to Genomic Variations: Intelligent Algorithms and Architectures for Intelligent Genome Analysis"

Computational and Structural Biotechnology Journal, 2022

[Source code]







journal homepage: www.elsevier.com/locate/csbj

Review

From molecules to genomic variations: Accelerating genome analysis via intelligent algorithms and architectures



Mohammed Alser*, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu*

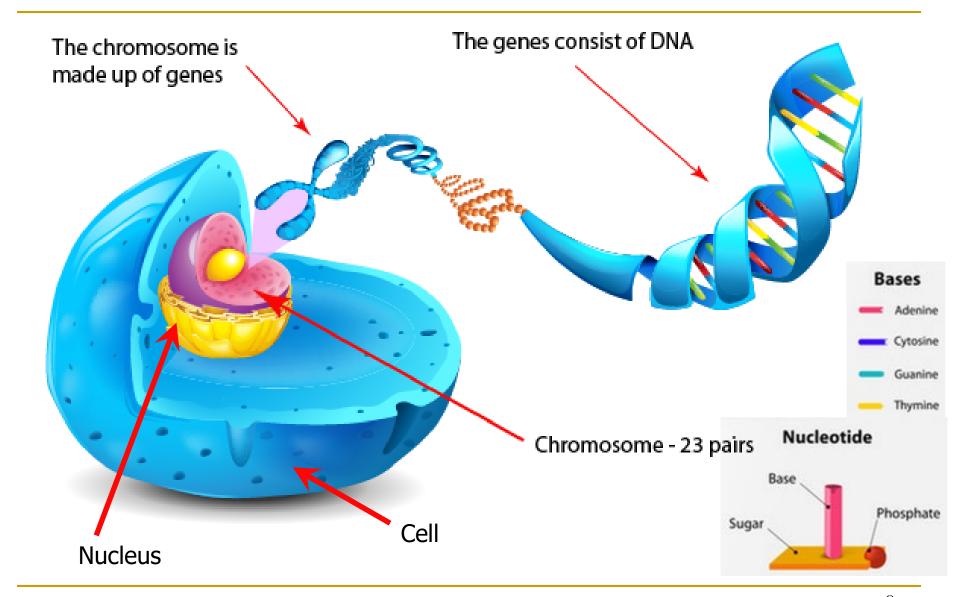
ETH Zurich, Gloriastrasse 35, 8092 Zürich, Switzerland

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

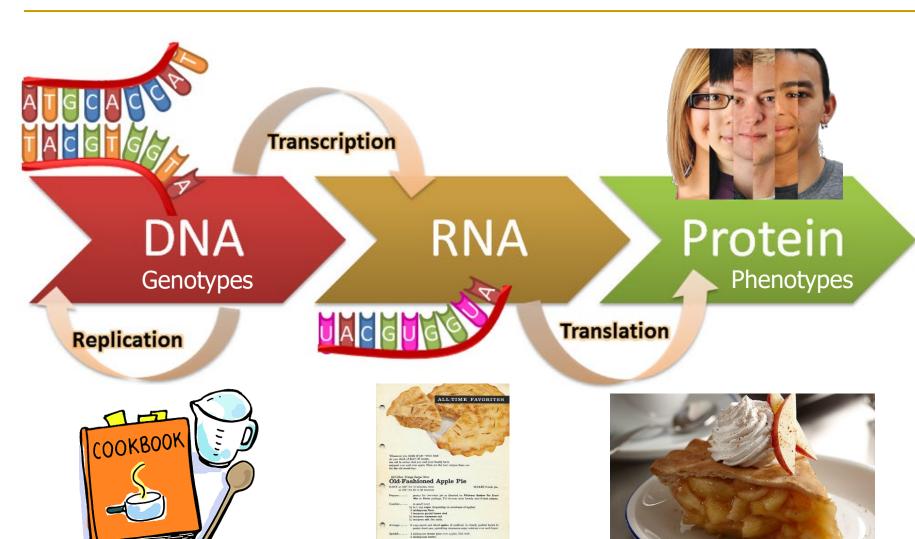


What Is a Genome Made Of?





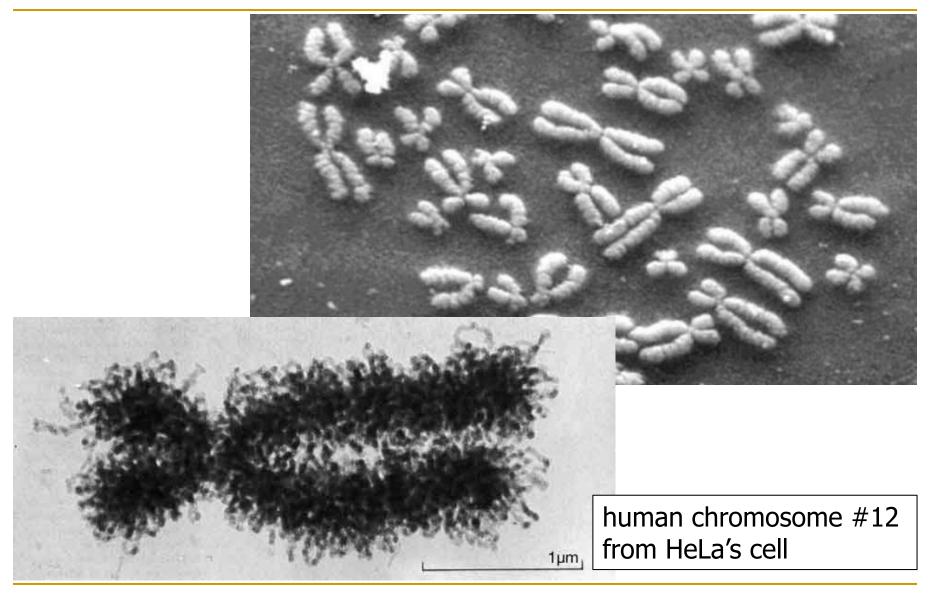
The Central Dogma of Molecular Biology







DNA Under Electron Microscope



CCTCCTCAGTGCCACCCAGCCCACTGGCAGCTCCCAAACA GGCTCTTATTAAAACACCCTGTTCCCTGCCCCTTTGGAGTG AGAAAAGAAAAGAATTTAAAATTTAAGTAATTCTTTGAA AAAAACTAATTTCTAAGCTTCTTCATGTCAAGGACCTAATG TGCTAAACAGCACTTTTTTGACCATTATTTTGGATCTGAAA GAAATCAAGAATAAATGAAGGACTTGATACATTGGAAGA AAGAAAAGAAAAGAATTTAAAATTTAAGTAATTCTTTGA AAAAAACTAATTTCTAAGCTTCTTCATGTCAAGGACCTAAT GTCTGTGTTGCAGGTCTTCTTGCATTTCCCTGTCAAAAGA AAAAGAATTTAAAATTTAAGTAATTCTTTGAAAAAAACTA ATTTCTAAGCTTCTTCATGTCAAGGACCTAATGTCAGGCC GGCTCTTATTAAAACACCCTGTTCCCTGCCCCTTGGAGTG

How Large is a Genome?



DNA Sequencing

Goal:

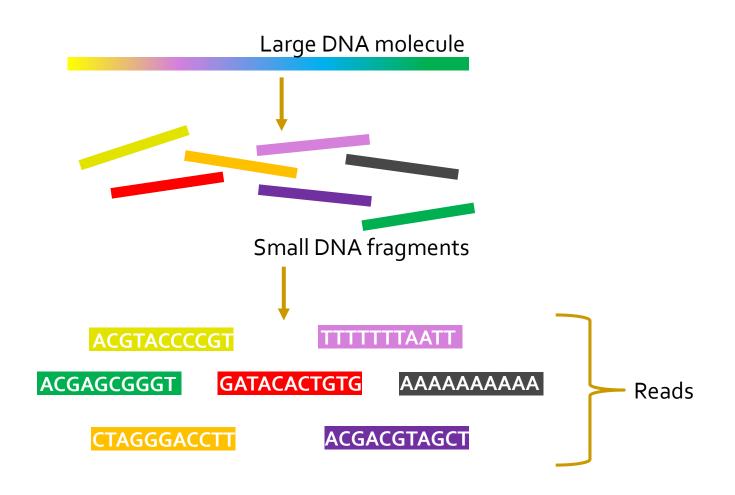
Find the complete sequence of A, C, G, T's in an organism's DNA

Challenge:

- There is no machine that takes long DNA as an input, and gives the complete sequence as output
- All sequencing machines chop DNA into pieces and identify relatively small pieces (but not how they fit together)

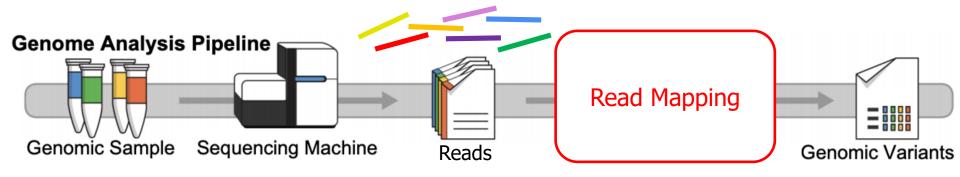


Genome Sequencing





Genome Sequencing and Analysis



Current sequencing machines provide small randomized fragments of the original DNA sequence

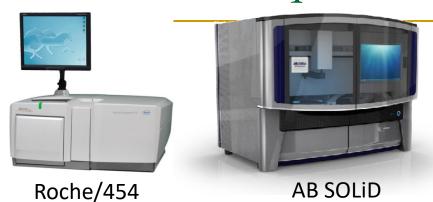
Alser+, "Technology dictates algorithms: Recent developments in read alignment", Genome Biology, 2021



Untangling Yarn Balls & DNA Sequencing



Genome Sequencers



Illumina HiSeq2000



AB SOLID



Pacific Biosciences RS



Ion Torrent PGM **Ion Torrent Proton**



Illumina MiSeq



Complete Genomics





Oxford Nanopore GridION



... and more! All produce data with different properties.

High-Throughput Sequencers



Illumina MiSeq



Illumina NovaSeq 6000



Pacific Biosciences Sequel II

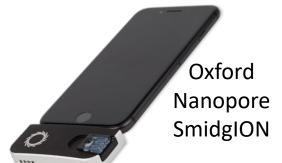


Pacific Biosciences RS II





Oxford Nanopore MinION



... and more! All produce data with different properties.



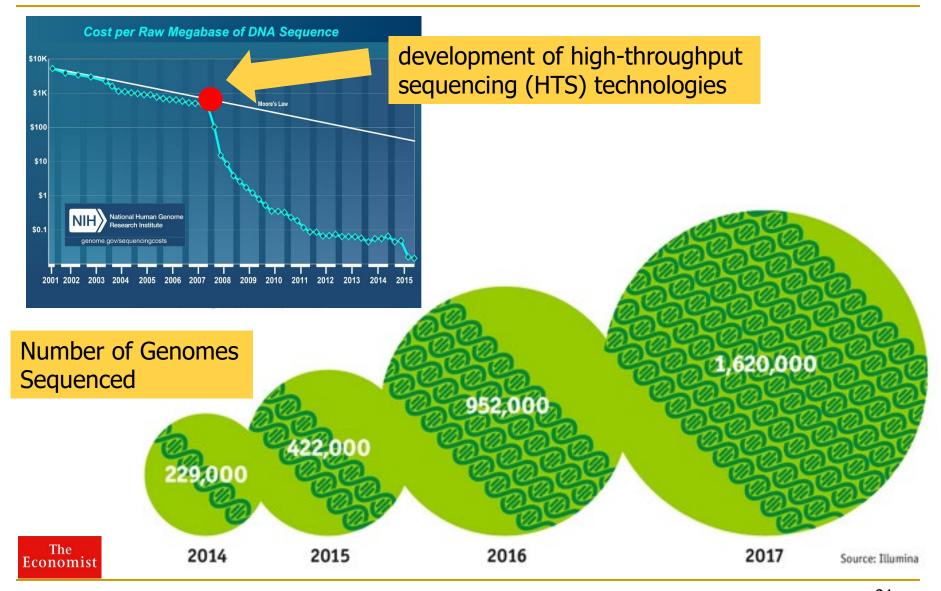
The Genomic Era

1990-2003: The Human Genome Project (HGP) provides a complete and accurate sequence of all **DNA base pairs** that make up the human genome and finds 20,000 to 25,000 human genes.





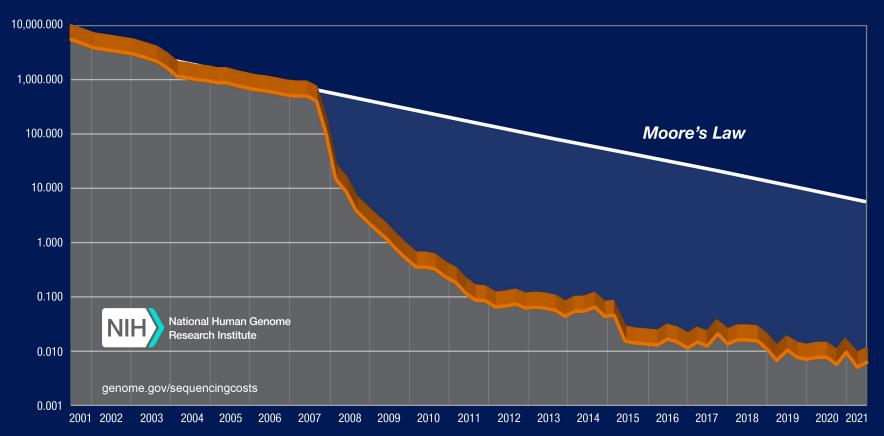
The Genomic Era (continued)





Genome Sequencing Cost Is Reducing

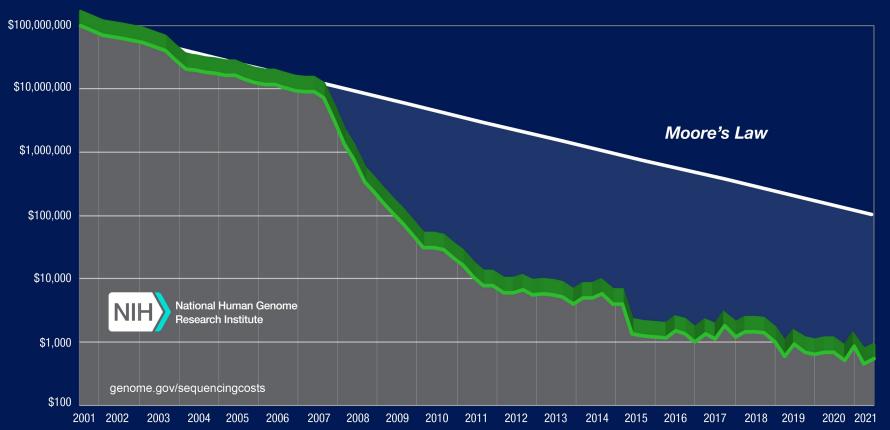
Cost per Raw Megabase of DNA Sequence



*From NIH (https://www.genome.gov/about-genomics/fact-sheets/DNA-Sequencing-Costs-Data)

Genome Sequencing Cost Is Reducing



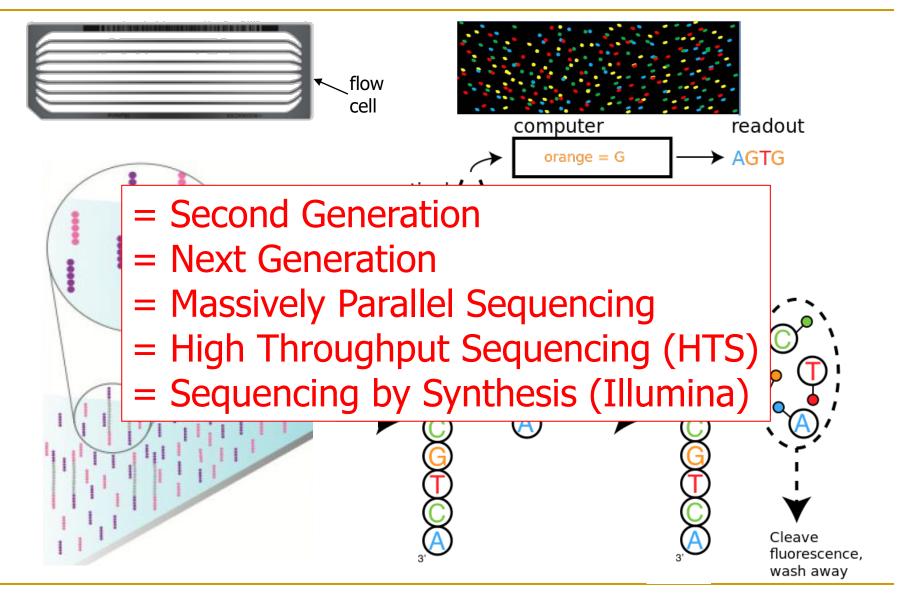


*From NIH (https://www.genome.gov/about-genomics/fact-sheets/DNA-Sequencing-Costs-Data)



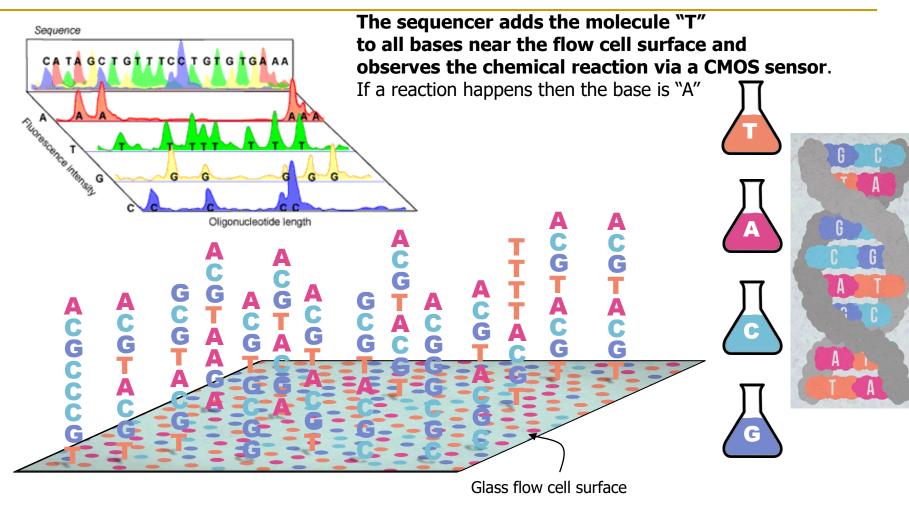


High-Throughput Sequencing (HTS)





High-Throughput Sequencing (HTS)



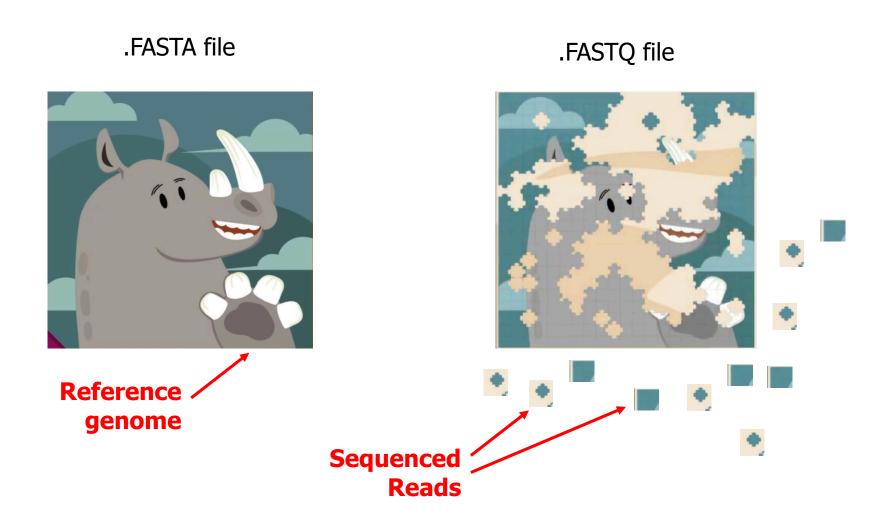
As a workaround, HTS technologies sequence random short DNA fragments (75-300 basepairs long) of copies of the original molecule.

High-Throughput Sequencing

- Massively parallel sequencing technology
 - Illumina, Roche 454, Ion Torrent, SOLID...
- Small DNA fragments are first amplified and then sequenced in parallel, leading to
 - High throughput
 - High speed
 - Low cost
 - Short reads
- Sequencing is done by either reading optical signals as each base is added, or by detecting hydrogen ions instead of light, leading to:
 - Low error rates (relatively)
 - Reads lack information about their order and which part of genome they are originated from



Solving the Puzzle



https://www.pacb.com/smrt-science/smrt-sequencing/hifi-reads-for-highly-accurate-long-read-sequencing/



Newer Genome Sequencing Technologies

Nanopore sequencing technology and tools for genome assembly: computational analysis of the current state, bottlenecks and future directions

Damla Senol Cali ™, Jeremie S Kim, Saugata Ghose, Can Alkan, Onur Mutlu

Briefings in Bioinformatics, bby017, https://doi.org/10.1093/bib/bby017

Published: 02 April 2018 Article history ▼



Oxford Nanopore MinION

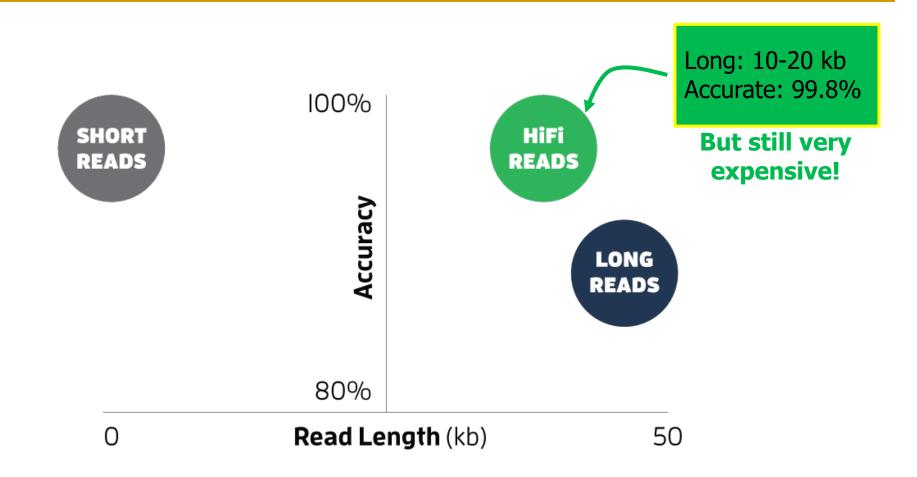
Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome

Assembly: Computational Analysis of the Current State, Bottlenecks
and Future Directions," Briefings in Bioinformatics, 2018.

[Open arxiv.org version] [Slides (pptx) (pdf)] [Talk Video at AACBB 2019]



Types of Genomic Reads



Wenger+, "Accurate circular consensus long-read sequencing improves variant detection and assembly of a human genome", Nature Biotechnology, 2019



Sequencing

Genome Analysis Reference Genome Read Mapping 2

Read

Alignmer

Short Read

reference: TTTATCGCTTCCATGACGCAG

read1: ATCGCATCC read2: TATCGCATC

read3: CATCCATGA

read4: CGCTTCCAT

read5: CCATGACGC

read6: **TTCCATGAC**



Scientific Discovery 4

Read Mapping Techniques in 111 Pages

In-depth analysis of 107 read mappers (1988-2020)

Mohammed Alser, Jeremy Rotman, Dhrithi Deshpande, Kodi Taraszka, Huwenbo Shi, Pelin Icer Baykal, Harry Taegyun Yang, Victor Xue, Sergey Knyazev, Benjamin D. Singer, Brunilda Balliu, David Koslicki, Pavel Skums, Alex Zelikovsky, Can Alkan, Onur Mutlu, Serghei Mangul

"<u>Technology dictates algorithms: Recent developments in read alignment</u>" Genome Biology, 2021

[Source code]

Alser et al. Genome Biology (2021) 22:249 https://doi.org/10.1186/s13059-021-02443-7

Genome Biology

REVIEW Open Access

Technology dictates algorithms: recent developments in read alignment



Mohammed Alser^{1,2,3†}, Jeremy Rotman^{4†}, Dhrithi Deshpande⁵, Kodi Taraszka⁴, Huwenbo Shi^{6,7}, Pelin Icer Baykal⁸, Harry Taegyun Yang^{4,9}, Victor Xue⁴, Sergey Knyazev⁸, 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*†}

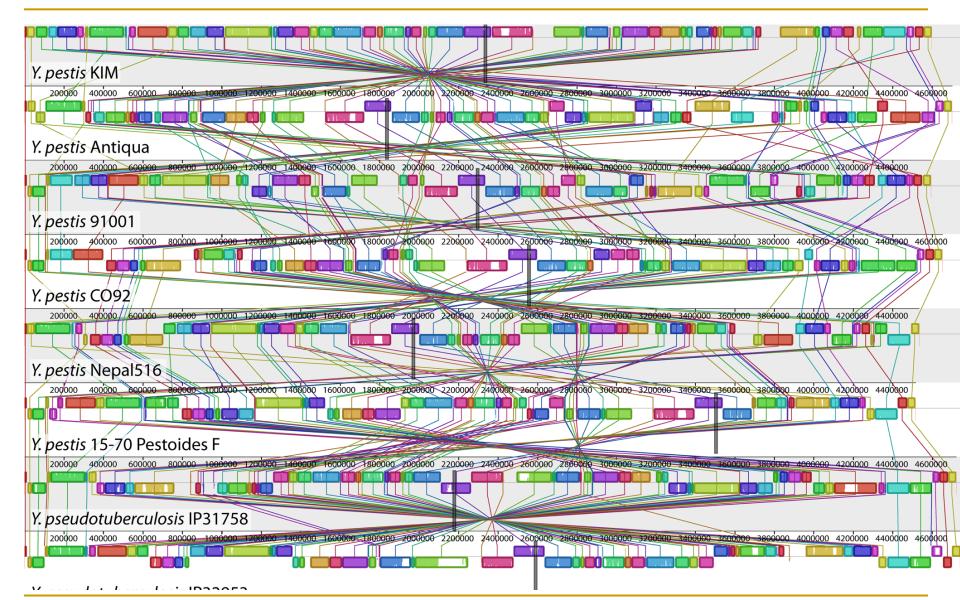
Why Do We Care?

Multiple sequence alignment

```
PHDHtm.
                                                                    MMMMMMMMMMMMMMM-
16082665
            T acid
                          ----MASDRKSEGFOSGAGLIRYFEEEEIKGPALDPKLVVYMGIAVAIIVEIAKIFWPF
                                                                                                     (55)
                          ---- MASDKKSEGFOSGAGLIRYFERENIKGPALDPKLVVYIGIAVAIMVELAKIFWPP-
13541150
            T volc
                                                                                                     (55)
                          -MTSMAKDNONENFQSGAGLIRYFNDEDIKGPAIDPKLIIYIGIAMGVIVELAKVFWP
RFAC01077
            F acid
                                                                                                     (58)
                          ---- MSSGONSGGLMSSAGLVRYFDSEDSNALOIDPRSVVAVGAFFGLVVLLAOFFA
15791336
            H NRC1
                                                                                                     (53)
                         MAKAPKGKAKTPPLMSSAGIMRYFED-DKTOIN
RAG22196
            A fula
                                                                                                     (68)
                          -----MAKEKTTLPPTGAGLMRFFDE-DTRAIKITPKGAVALTLILIIFEIILHVVGPRIFG
RP001000
                                                                                                     (56)
            P abys
                            ---makekttlpptgag<mark>lmrff</mark>de-dtra<mark>ikitpkgaialvliliifeillhvv</mark>gpr<mark>i</mark>fg
RPH01741
                                                                                                     (56)
            P hori
                            --makkdkktlppsgag<mark>lvryf</mark>ee<mark>-d</mark>tkg<mark>fkl</mark>tpe<mark>qvvvm</mark>siilavfclvlr<mark>fs</mark>g
AE000914
            M ther
                                                                                                     (52)
                          -----MSKRESTGLATSAG<mark>LIR</mark>YMDB-TFSK<mark>IRV</mark>KPEHVIGVTVAFVIIEAILTYGRF
RMJ09857
            M jann
                                                                                                     (53)
                         -MPSSKKKKETUPLASMAGLIRYYED-PNEKIMISPKLLIIISIIMVAGVIVASILIP
                                                                                                     (58)
15920503
            S toko
AE006662
            S solf
                          -MPSSKKKKETVPVMSMAGLIRYYED-DNEKVWISPKIVIGASLALTIIVIVITKLF
                                                                                                     (55)
                          --MARRKYEGINPFVAAGLIKFSEEGELEKIKLTPRAAVVISLAIIGLLIAINLLLPPL--
RPK02491
                                                                                                     (58)
            P aero
RAP00437
                          -MSVRRRERRATPVTAAGLLSFYEE-YEGKIKISPTIVVGAAILVSAVVAAAHIFLPAVP-
                                                                                                     (59)
            A pern
                              ------SAGTGGMWRFYTR-DSPGLWVGRVPVLVMSLLFIASVFMLHIWGKYTRS
5803165
                                                                                                     (96)
            H sapi
13324684
            M musc
                                    -SAGTGGMWRFYTR-DSPGLWVGPVPVLVMSLLFIAAVFML IWGKYTRS
                                                                                                     (96)
                              -----GAGTGGMWRFYTD-DSPGINVGPVPVLVMSLLFIASVFMLHIWGKYNRS
6002114
            D mela
                                                                                                   (100)
                                                      -DSTG<mark>lkigPvPvLvmslvFiasvFvl</mark>tiwgk<mark>FT</mark>RS
14574310
            C eleg
                                                                                                     (81)
                                  ----GGSSSTMLKLYTD-ESQGLK
            Y lipo
10697176
                                                               DPVVVMVLSLGFIFSVVALEILAKVSTK
                                                                                                     (91)
                                 -----GGSSSSILKLYTD-PANGFRVDSLVVLFLSVGFIFSVIALHLLTKFTHI
6320857
                                                                                                     (88)
6320932
            S cere
                                    -tnsnns<mark>ilkiy</mark>sd-eatgl<mark>rv</mark>d<mark>pl</mark>vvlflavgfifsvval<mark>e</mark>visk<mark>va</mark>gk
                                                                                                     (82)
```

Example Question: If I give you a bunch of sequences, tell me where they are the same and where they are different.

Genome Sequence Alignment: Example



The Genetic Similarity Between Species



Human ~ Human 99.9%





Human ~ Chimpanzee 96%



Human ~ Cat 90%



Human ~ Cow 80%



Human ~ Banana 50-60%



Finding Variations Associated with Traits

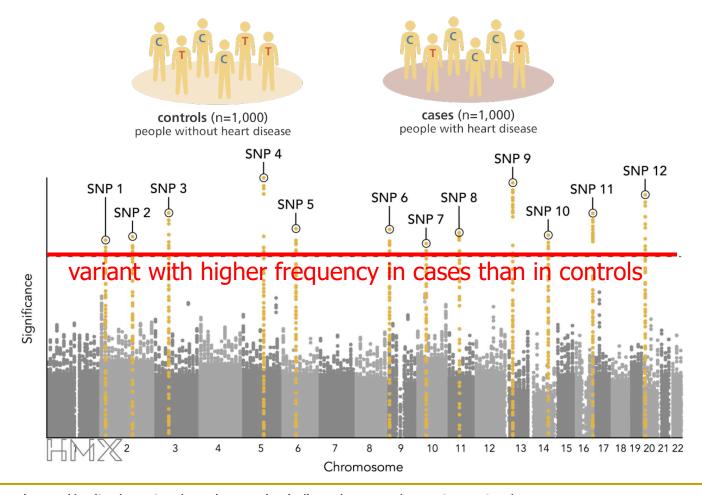
	SNP1	SNP2	Blood Pressure
Individual #1	ACATGCCGACATTTC	CATAGGCC	180
Individual #2	ACATGCCGACATTTC	CATAAGCC	175
Individual #3	ACATGCCGACATTTC	CATAGGCC	170
Individual #4	ACATGCCGACATTTC	CATAAGCC	165
Individual #5	ACATGCCGACATTTC	CATAGGCC	160
Individual #6	ACATGCCGACATTTC	CATAGGCC	145
Individual #7	ACATGCCGACATTTC	CATAAGCC	140
Individual #8	ACATGCCGACATTTC	CATAAGCC	130
Individual #9	ACATGTCGACATTTC	ATAGGCC	120
Individual #10	ACATGTCGACATTTC	ATAAGCC	120
Individual #11	ACATGTCGACATTTC	ATAGGCC	115
Individual #12	ACATGTCGACATTTC	ATAAGCC	110
Individual #13	ACATGTCGACATTTC	ATAGGCC	110
Individual #14	ACATGTCGACATTTC	ATAAGCC	110
Individual #15	ACATGTCGACATTTC	ATAGGCC	105
Individual #16	ACATGTCGACATTTC	ATAAGCC	100

SNP: single nucleotide polymorphism

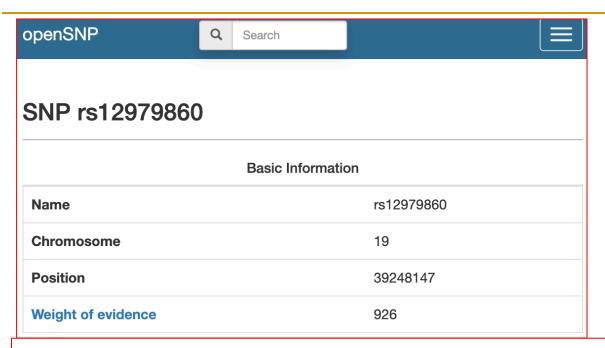


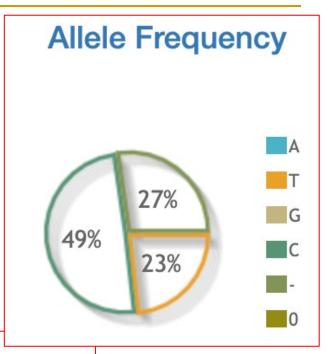
Genome-Wide Association Studies (GWAS)

 Enables detection of genetic variants associated with phenotypes using two groups of people.



SNPs and Personalized Medicine





Links to SNPedia

Title	Summary
rs12979860 T/T	~20-25% of such hepatitis c patients respond to treatment
rs12979860 C/C	~80% of such hepatitis c patients respond to treatment
rs12979860 C/T	~20-40% of such hepatitis c patients respond to treatment

Much Larger Structural Variations



AUTISM

Weiss, *N Eng J Med* 2008 Deletion of 593 kb



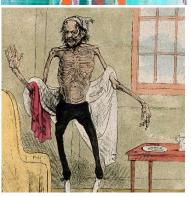
SCHIZOPHRENIA

McCarthy, *Nat Genet* 2009 Duplication of 593 kb



OBESITY

Walters, *Nature* 2010 Deletion of 593 kb



UNDERWEIGHT

Jacquemont, *Nature* 2011 Duplication of 593 kb



Deletion in the short arm of chromosome 16 (16p11.2)



Duplication in the short arm of chromosome 16 (16p11.2)





Personalized Medicine for Critically Ill Infants

- rWGS can be performed in 2-day (costly) or 5-day time to interpretation.
- Diagnostic rWGS for infants
 - Avoids morbidity
 - Reduces hospital stay length by 6%-69%
 - Reduces inpatient cost by \$800,000-\$2,000,000.

Article | Open Access | Published: 04 April 2018

Rapid whole-genome sequencing decreases infant morbidity and cost of hospitalization

Lauge Farnaes, Amber Hildreth, Nathaly M. Sweeney, Michelle M. Clark, S. Chowdhury, Shareef Nahas, Julie A. Cakici, Wendy Benson, Robert H. Kal Richard Kronick, Matthew N. Bainbridge, Jennifer Friedman, Jeffrey J. Go Ding, Narayanan Veeraraghavan, David Dimmock & Stephen F. Kingsmore

npj Genomic Medicine 3, Article number: 10 (2018) | Cite this article

Article | Open Access | Published: 05 May 2020

Clinical utility of 24-h rapid trio-exome sequencing for critically ill infants

Huijun Wang, Yanyan Qian, Yulan Lu, Qian Qin, Guoping Lu, Guoqiang Cheng, Ping Zhang, Lin Yang, Bingbing Wu \boxtimes & Wenhao Zhou \boxtimes

npj Genomic Medicine 5, Article number: 20 (2020) | Cite this article



Recommended Reading

nature reviews genetics

Explore our content > Journal information >

nature > nature reviews genetics > review articles > article

Review Article | Published: 15 November 2019

Structural variation in the sequencing era

Steve S. Ho, Alexander E. Urban & Ryan E. Mills ⊠

Nature Reviews Genetics 21, 171–189(2020) | Cite this article

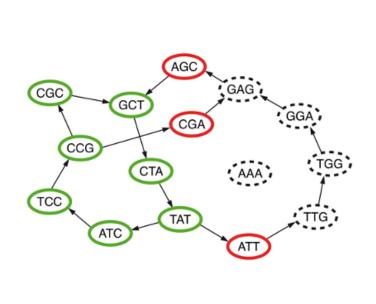
15k Accesses | 16 Citations | 309 Altmetric | Metrics

Ho+, "Structural variation in the sequencing era", Nature Reviews Genetics, 2020



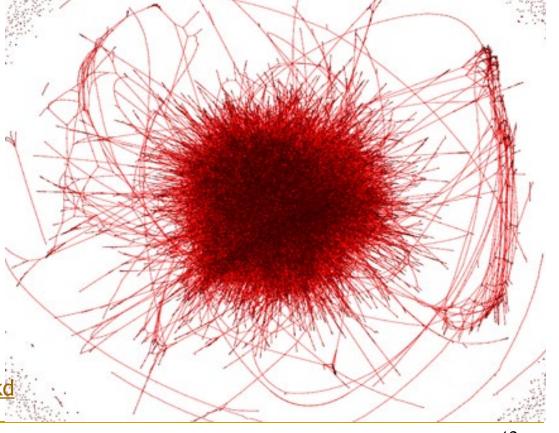
Metagenomics, genome assembly, de novo sequencing

Question 2: Given a bunch of short sequences, Can you identify the approximate species cluster for genomically unknown organisms (bacteria)?



uncleaned de Bruijn graph

http://math.oregonstate.edu/~koslickd

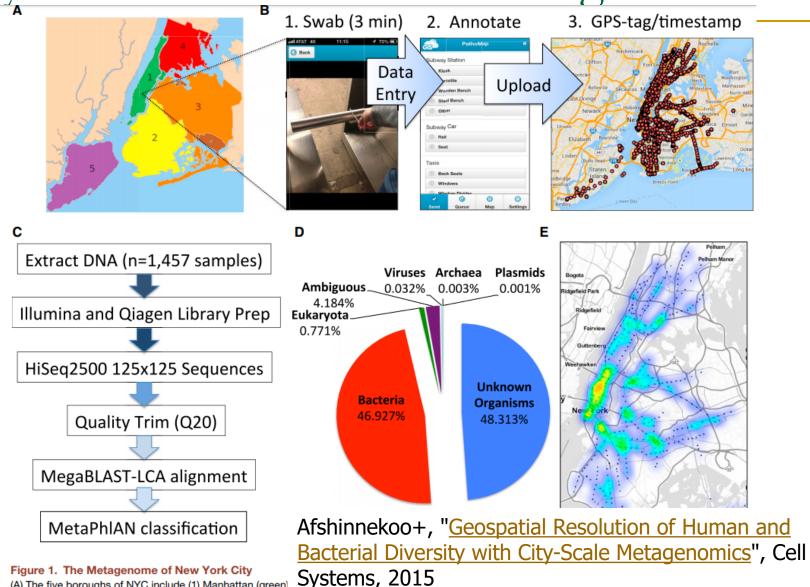


Population-Scale Microbiome Profiling





City-Scale Microbiome Profiling

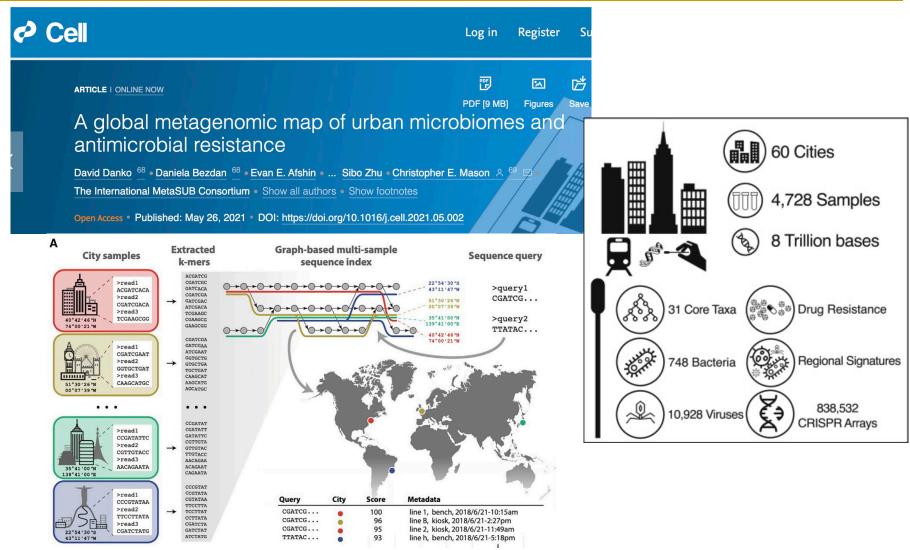


(A) The five boroughs of NYC include (1) Manhattan (green)

(B) The collection from the 466 subway stations of NYC across the 24 subway lines involved three main steps: (1) collection with Copan Elution swabs, (2) data entry into the database, and (3) uploading of the data. An image is shown of the current collection database, taken from http://pathomap.giscloud.com. (C) Workflow for sample DNA extraction, library preparation, sequencing, quality trimming of the FASTQ files, and alignment with MegaBLAST and MetaPhlAn to discern taxa present



Global-Scale Microbiome Profiling



Danko+, "A global metagenomic map of urban microbiomes and antimicrobial resistance", Cell, 2021



A Tsunami of Sequencing Data

A Tera-scale increase in sequencing production in the past 25 years									
Genes & Operons	1990	Kilo = 1,000							
Bacterial genomes	1995	Mega = 1,000,000							
Human genome	2000	Giga = 1,000,000,000							
Human microbiome	2005	Tera = 1,000,000,000,000							
50K Microbiomes	2015	Peta = 1,000,000,000,000,000							
what is expected for the next 15 years ? (a Giga?)									
200K Microbiomes	2020	Exa = 1,000,000,000,000,000,000							
1M Microbiomes	2025	Zetta = 1,000,000,000,000,000,000,000							
Earth Microbiome	2030	Yotta = 1,000,000,000,000,000,000,000,000							

Source: <a>@kyrpides

Another Question: Example from 2020-...

200 Oxford Nanopore sequencers have left UK for China, to support rapid, near-sample coronavirus sequencing for outbreak surveillance

Fri 31st January 2020

Following extensive support of, and collaboration with, public health professionals in China, Oxford Nanopore has shipped an additional 200 MinION sequencers and related consumables to China. These will be used to support the ongoing surveillance of the current coronavirus outbreak, adding to a large number of the devices already installed in the country.



Each MinION sequencer is approximately the size of a stapler, and can provide rapid sequence information about the coronavirus.





700Kg of Oxford Nanopore sequencers and consumables are on their way for use by Chinese scientists in understanding the current coronavirus outbreak.

Example: Scalable SARS-CoV-2 Testing







HOME | ABOU

Search

Comments (I)

Swab-Seq: A high-throughput platform for massively scaled up SARS-CoV-2 testing

Doshua S. Bloom, Eric M. Jones, De Molly Gasperini, De Nathan B. Lubock, Laila Sathe, Chetan Munugala, De A. Sina Booeshaghi, De Oliver F. Brandenberg, De Longhua Guo, De James Boocock, De Scott W. Simpkins, Isabella Lin, Nathan LaPierre, Duke Hong, Yi Zhang, Gabriel Oland, Bianca Judy Choe, Sukantha Chandrasekaran, Evann E. Hilt, De Manish J. Butte, De Robert Damoiseaux, De Aaron R. Cooper, De Yi Yin, De Lior Pachter, De Omai B. Garner, De Jonathan Flint, De Eleazar Eskin, De Chongyuan Luo, De Sriram Kosuri, De Leonid Kruglyak, De Valerie A. Arboleda

doi: https://doi.org/10.1101/2020.08.04.20167874

Bloom+, "Swab-Seq: A high-throughput platform for massively scaled up SARS-CoV-2 testing", medRxiv, 2020

Example: Rapid Surveillance of Ebola Outbreak

Figure 1: Deployment of the portable genome surveillance system in Guinea.









Quick+, "Real-time, portable genome sequencing for Ebola surveillance", Nature, 2016



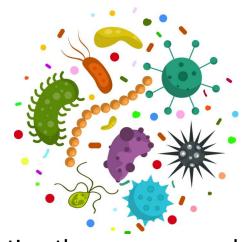
We Need Faster & Scalable Genome Analysis



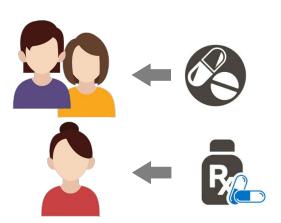
Understanding genetic variations, species, evolution, ...



Rapid surveillance of disease outbreaks



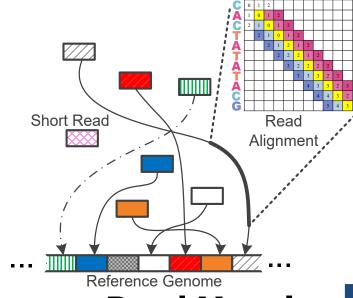
Predicting the presence and relative abundance of **microbes** in a sample



Developing personalized medicine

One Problem

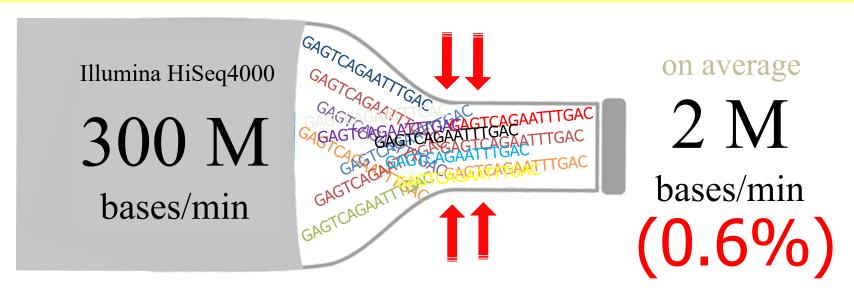




Read Mapping

1 Sequencing

We Are Bottlenecked in Read Mapping

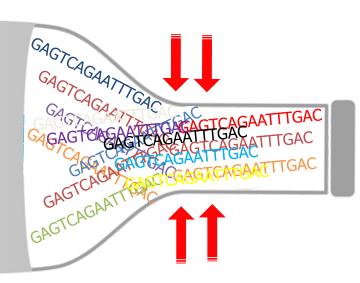




The Read Mapping Bottleneck

300 Million bases/minute

Read Sequencing **



→ Million bases/minute

Read Mapping*

150x slower

^{*} BWA-MEM





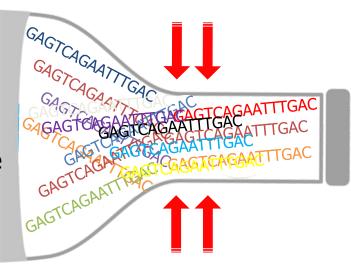
The Read Mapping Bottleneck

48 Human whole genomes

at 30× coverage

in about 2 days

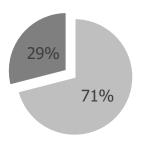
Illumina NovaSeq 6000



1 Human genome

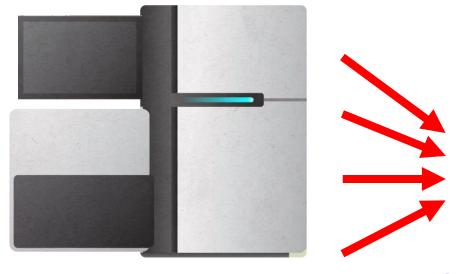
32 CPU hours

on a 48-core processor

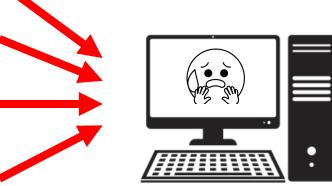


■ Read Mapping ■ Others

Problem with (Genome) Analysis Today



Special-Purpose Machine for Data Generation



General-Purpose Machine for Data Analysis

FAST

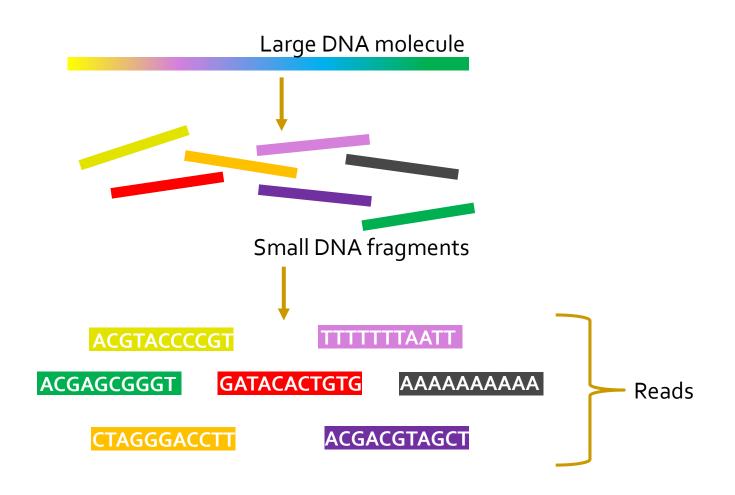
SLOW

Slow and inefficient processing capability

Need to construct the entire genome from many sequenced reads



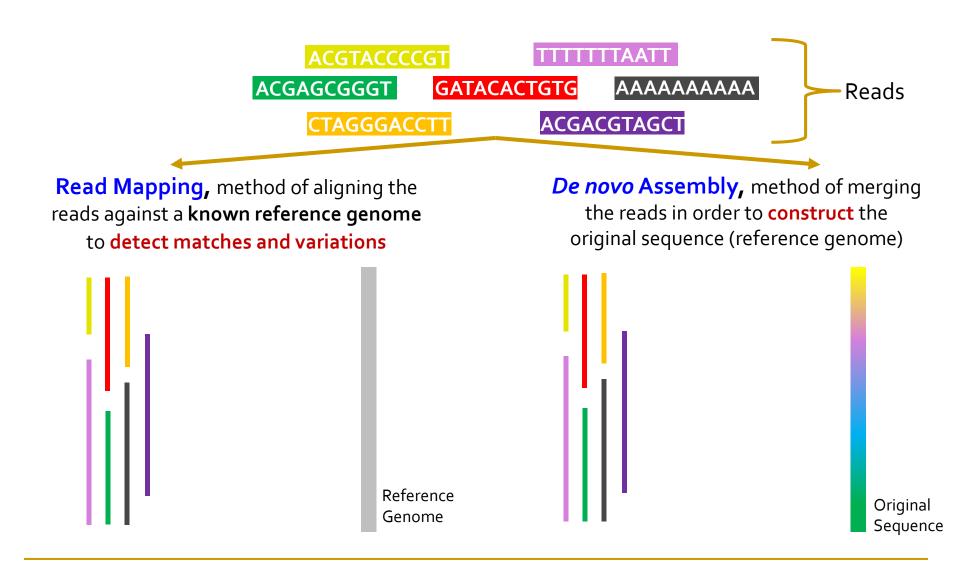
Genome Sequencing







Genome Sequence Analysis

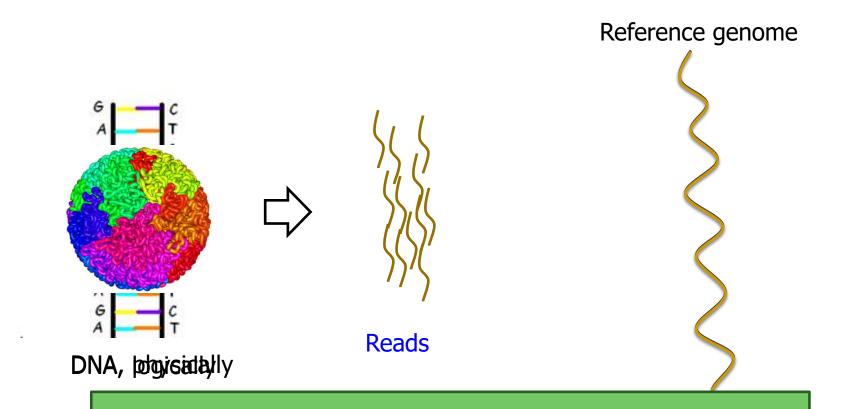






Read Mapping

 Map many short DNA fragments (reads) to a known reference genome with some differences allowed



Mapping short reads to reference genome is challenging (billions of 50-300 base pair reads)

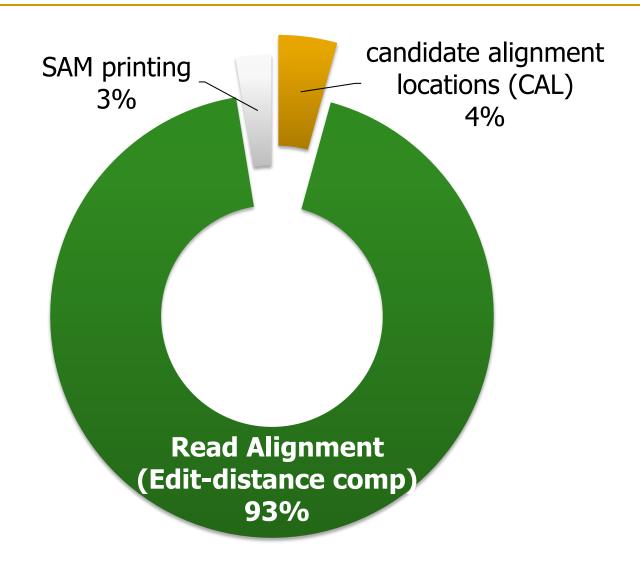


Read Mapping for Metagenomic Analysis

Reads from different unknown donors at sequencing time are mapped to many known reference genomes Genetic material recovered directly from environmental Reads in Reference samples "text format" Database



Read Mapping Execution Time (Old Times)



Matching Each Read to Reference Genome

Reference Genome .FASTA file:

Sequenced Reads .FASTQ file:

```
@HWI-EAS209_0006_FC706VJ:5:58:5894:21141#ATCACG/1

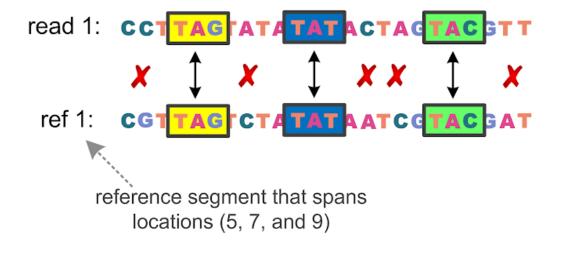
T' AATAAATCT TTAGATN NNNNNNNNTAG

+HWI-EAS209_0006_FC706VJ:5:58:5894:21141#ATCACG/1

efcfffffcfeefffcfffffddf`feed]`]_Ba_^_[YBBBBBBBBBBTT
```



Base-by-Base Comparison





Read Alignment/Verification

Edit distance is defined as the minimum number of edits
 (i.e. insertions, deletions, or substitutions) needed to make
 the read exactly match the reference segment.

NETHERLANDS x SWITZERLAND



match
deletion
insertion
mismatch



Challenges in Read Mapping

- Need to find many mappings of each read
 - A short read may map to many locations, especially with High-Throughput DNA Sequencing technologies
 - How can we find all mappings efficiently?
- Need to tolerate small variances/errors in each read
 - Each individual is different: Subject's DNA may slightly differ from the reference (Mismatches, insertions, deletions)
 - How can we efficiently map each read with up to e errors present?
- Need to map each read very fast (i.e., performance is important)
 - □ Human DNA is 3.2 billion base pairs long → Millions to billions of reads (State-of-the-art mappers take weeks to map a human's DNA)
 - How can we design a much higher performance read mapper?

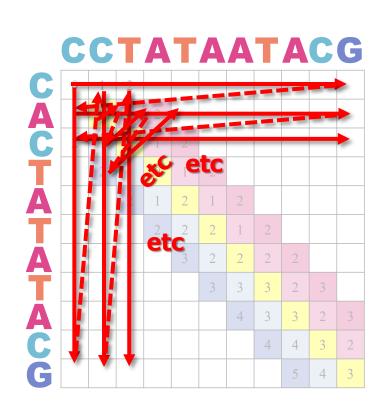


Why Is Read Alignment Slow?

Quadratic-time dynamicprogramming algorithm(s)

 Data dependencies limit the computation parallelism

 Entire matrix computed even though strings may be dissimilar



Read Alignment



Example: Dynamic Programming Table

NETHERLANDS x SWITZERLAND

immediate left, upper left, upper entries of its own

		N	Е	Т	Н	Ε	R	L	Α	N	D	S
			2	3	4	5	6	7	8	9	10	11
S		1										
W	2			K	lack							
Ι	3			+	7							
Т	4											
Z	5											
Е	6											
R	7											
L	8											
Α	9											
N	10											
D	11											



Example: Dynamic Programming Table

NETHERLANDS x SWITZERLAND

		N	Е	Т	Н	Ε	R	L	Α	N	D	S
	0	1	2	3	4	5	6	7	8	9	10	11
S	1	1	2	3	4	5	6	7	8	9	10	10
W	2	2	2	3	4	5	6	7	8	9	10	11
Ι	3	3	3	3	4	5	6	7	8	9	10	11
Т	4	4	4	3	4	5	6	7	8	9	10	11
Z	5	5	5	4	4	5	6	7	8	9	10	11
Е	6	6	5	5	5	4	5	6	7	8	9	10
R	7	7	6	6	6	5	4	5	6	7	8	9
L	8	8	7	7	7	6	5	4	5	6	7	8
Α	9	9	8	8	8	7	6	5	4	5	6	7
N	10	9	9	9	9	8	7	6	5	4	5	6
D	11	10	10	10	10	9	8	7	6	5	4	5

- Matrix-filling is O(mn) time and space.
- Backtrace is O(m + n) time.





Example: Dynamic Programming

Quadratic-time dynamicprogramming algorithm WHY?!

Enumerate all possible prefixes

NETHERLANDS x SWITZERLAND

- NETHERLANDS x S
- NETHERLANDS x SW
 - **C** NETHERLANDS x SWI

NETERLANDS x SWIT

NETHERLANDS x SWITZ

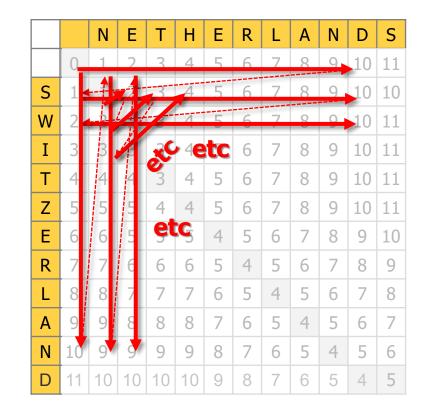
NETHERLANDS x SWITZE

NETHERLANDS x SWITZER

NETHERLANDS x SWITZERL

- NETHERLANDS x SWITZERLA
 - c NETHERLANDS x SWITZERLAN

NETHERLANDS x SWITZERLAND



Computational Cost is Mathematically Proven

arXiv.org > cs > arXiv:1412.0348

Search...

Help | Advanced

Computer Science > Computational Complexity

[Submitted on 1 Dec 2014 (v1), last revised 15 Aug 2017 (this version, v4)]

Edit Distance Cannot Be Computed in Strongly Subquadratic Time (unless SETH is false)

Arturs Backurs, Piotr Indyk

The edit distance (a.k.a. the Levenshtein distance) between two strings is defined as the minimum number of insertions, deletions or substitutions of symbols needed to transform one string into another. The problem of computing the edit distance between two strings is a classical computational task, with a well-known algorithm based on dynamic programming. Unfortunately, all known algorithms for this problem run in nearly quadratic time. In this paper we provide evidence that the near-quadratic running time bounds known for the problem of computing edit distance might be tight. Specifically, we show that, if the edit distance can be computed in time $O(n^{2-\delta})$ for some constant $\delta > 0$, then the satisfiability of conjunctive normal form formulas with N variables and M clauses can be solved in time $M^{O(1)}2^{(1-\epsilon)N}$ for a constant $\epsilon>0$. The latter result would violate the Strong Exponential Time Hypothesis, which postulates that such algorithms do not exist.

Read Mapping Techniques in 111 Pages

In-depth analysis of 107 read mappers (1988-2020)

Mohammed Alser, Jeremy Rotman, Dhrithi Deshpande, Kodi Taraszka, Huwenbo Shi, Pelin Icer Baykal, Harry Taegyun Yang, Victor Xue, Sergey Knyazev, Benjamin D. Singer, Brunilda Balliu, David Koslicki, Pavel Skums, Alex Zelikovsky, Can Alkan, Onur Mutlu, Serghei Mangul

"<u>Technology dictates algorithms: Recent developments in read alignment</u>" Genome Biology, 2021

Source code

Alser et al. Genome Biology (2021) 22:249 https://doi.org/10.1186/s13059-021-02443-7

Genome Biology

REVIEW Open Access

Technology dictates algorithms: recent developments in read alignment

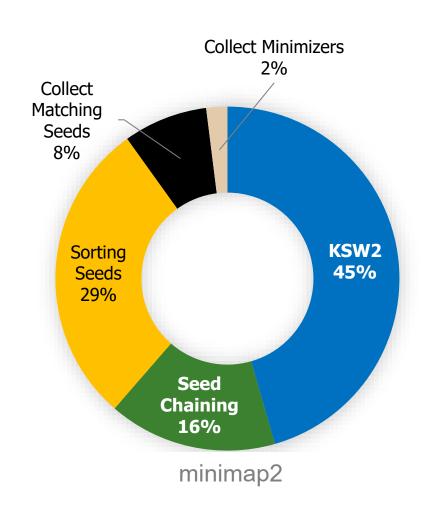


Mohammed Alser^{1,2,3†}, Jeremy Rotman^{4†}, Dhrithi Deshpande⁵, Kodi Taraszka⁴, Huwenbo Shi^{6,7}, Pelin Icer Baykal⁸, Harry Taegyun Yang^{4,9}, Victor Xue⁴, Sergey Knyazev⁸, Benjamin D. Singer^{10,11,12}, Brunilda Balliu¹³, David Koslicki^{14,15,16}, Pavel Skums⁸, Alex Zelikovsky^{8,17}, Can Alkan^{2,18}, Onur Mutlu^{1,2,3†} and Serghei Mangul^{5*†}

Read Mapping Execution Time (Modern)

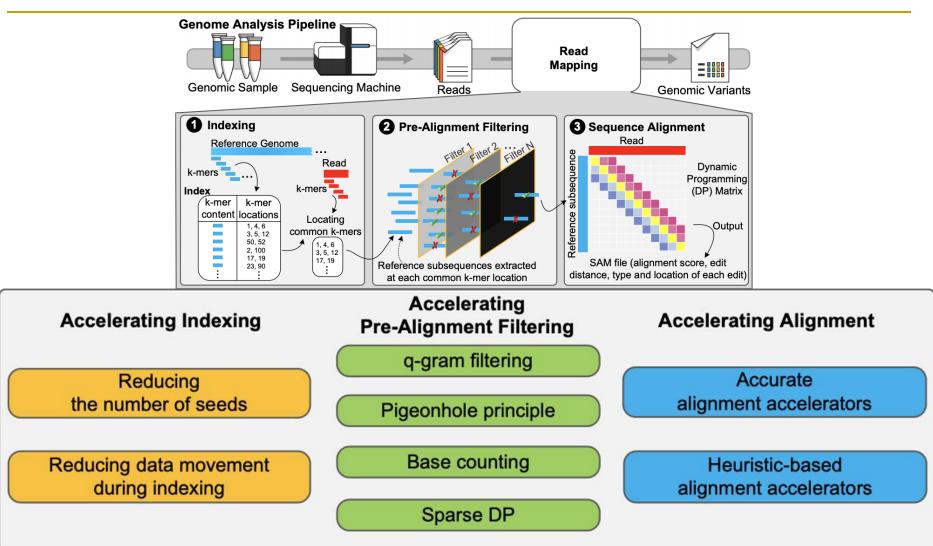
>60%

of the read mapper's execution time is spent in sequence alignment



ONT FASTQ size: 103MB (151 reads), Mean length: 356,403 bp, std: 173,168 bp, longest length: 817,917 bp

Accelerating Read Mapping

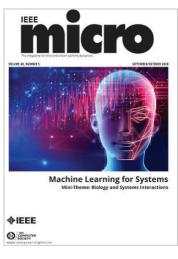


Alser+, "Accelerating Genome Analysis: A Primer on an Ongoing Journey", IEEE Micro, 2020.

Detailed Analysis of Tackling the Bottleneck

Mohammed Alser, Zülal Bingöl, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, Onur Mutlu

"Accelerating Genome Analysis: A Primer on an Ongoing Journey" IEEE Micro, August 2020.





Home / Magazines / IEEE Micro / 2020.05

IEEE Micro

Accelerating Genome Analysis: A Primer on an Ongoing Journey

Sept.-Oct. 2020, pp. 65-75, vol. 40

DOI Bookmark: 10.1109/MM.2020.3013728

Authors

Mohammed Alser, ETH Zürich

Zulal Bingol, Bilkent University

Damla Senol Cali, Carnegie Mellon University

Jeremie Kim, ETH Zurich and Carnegie Mellon University

Saugata Ghose, University of Illinois at Urbana-Champaign and Carnegie Mellon University

Can Alkan, Bilkent University

Onur Mutlu, ETH Zurich, Carnegie Mellon University, and Bilkent University

74

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Read Mapping Algorithms: Two Styles

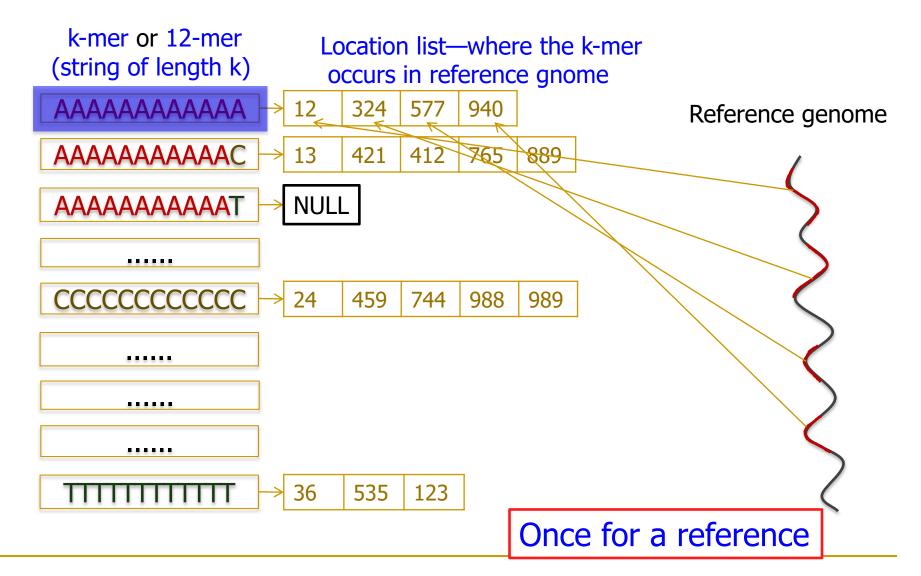
- Hash based seed-and-extend (hash table, suffix array, suffix tree)
 - Index the "k-mers" in the genome into a hash table (pre-processing)
 - When searching a read, find the location of a k-mer in the read; then extend through alignment
 - More sensitive (can find all mapping locations), but slow
 - Requires large memory; this can be reduced with cost to run time
- Burrows-Wheeler Transform & Ferragina-Manzini Index based aligners
 - BWT is a compression method used to compress the genome index
 - Perfect matches can be found very quickly, memory lookup costs increase for imperfect matches
 - Reduced sensitivity

Hash Table Based Read Mappers

- Key Idea
 - Preprocess the reference into a Hash Table
 - Use Hash Table to map reads



Hash Table-Based Mappers [Alkan+ Nature Gen'09]

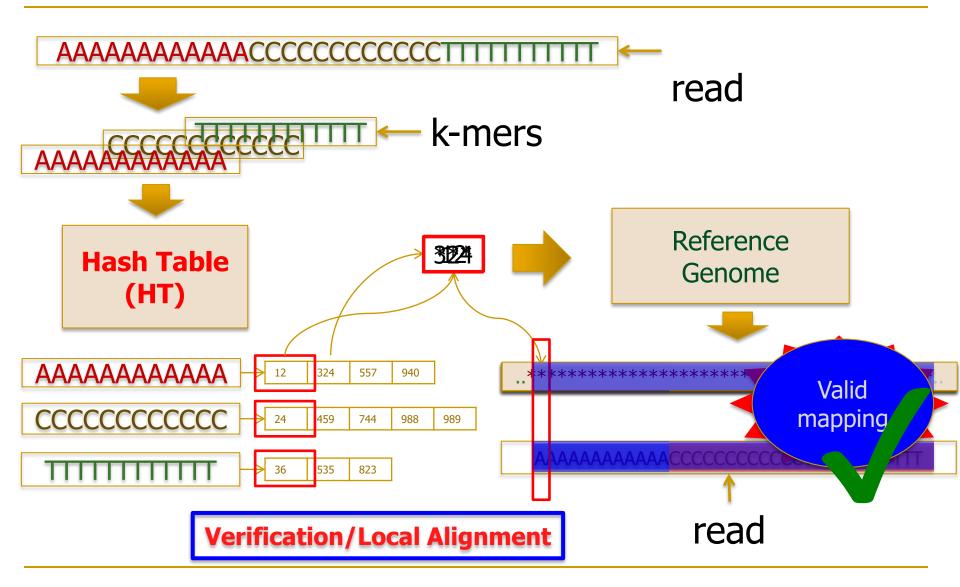


Hash Table Based Read Mappers

- Key Idea
 - Preprocess the reference into a Hash Table
 - Use Hash Table to map reads



Hash Table-Based Mappers [Alkan+ Nature Gen'09]





Our First Step: Comprehensive Mapping

- + Guaranteed to find all mappings → sensitive
- + Can tolerate up to e errors



http://mrfast.sourceforge.net/

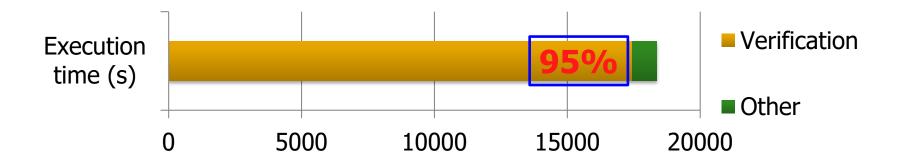
Personalized copy number and segmental duplication maps using next-generation sequencing

Can Alkan^{1,2}, Jeffrey M Kidd¹, Tomas Marques-Bonet^{1,3}, Gozde Aksay¹, Francesca Antonacci¹, Fereydoun Hormozdiari⁴, Jacob O Kitzman¹, Carl Baker¹, Maika Malig¹, Onur Mutlu⁵, S Cenk Sahinalp⁴, Richard A Gibbs⁶ & Evan E Eichler^{1,2}



Problem and Goal

- Poor performance of existing read mappers: Very slow
 - Verification/alignment takes too long to execute
 - Verification requires a memory access for reference genome + many base-pair-wise comparisons between the reference and the read (edit distance computation)



Goal: Speed up the mapper by reducing the cost of verification

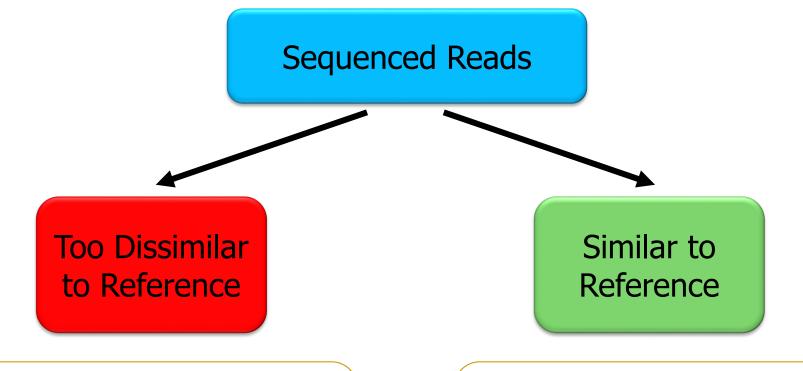
Overarching Key Idea

Filter fast before you align

Minimize costly edit distance computations

("approximate string comparisons")

Overarching Key Idea



Quickly find these and filter them out w/o costly computation

Focus processing power on these (e.g., edit distance comp.)

Accelerating Genome Analysis: Overview

 Mohammed Alser, Zulal Bingol, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, and Onur Mutlu,

"Accelerating Genome Analysis: A Primer on an Ongoing Journey"

IEEE Micro (IEEE MICRO), Vol. 40, No. 5, pages 65-75, September/October 2020.

[Slides (pptx)(pdf)]

Talk Video (1 hour 2 minutes)

Accelerating Genome Analysis: A Primer on an Ongoing Journey

Mohammed Alser

ETH Zürich

Zülal Bingöl

Bilkent University

Damla Senol Cali

Carnegie Mellon University

Jeremie Kim

ETH Zurich and Carnegie Mellon University

Saugata Ghose

University of Illinois at Urbana–Champaign and Carnegie Mellon University

Can Alkan

Bilkent University

Onur Mutlu

ETH Zurich, Carnegie Mellon University, and Bilkent University

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Our First Filter: Pure Software Approach

- Download the source code and try for yourself
 - Download link to FastHASH

Xin et al. BMC Genomics 2013, **14**(Suppl 1):S13 http://www.biomedcentral.com/1471-2164/14/S1/S13



PROCEEDINGS

Open Access

Accelerating read mapping with FastHASH

Hongyi Xin¹, Donghyuk Lee¹, Farhad Hormozdiari², Samihan Yedkar¹, Onur Mutlu^{1*}, Can Alkan^{3*}

From The Eleventh Asia Pacific Bioinformatics Conference (APBC 2013) Vancouver, Canada. 21-24 January 2013



Reducing the Cost of Verification

- Most verification (edit distance computation) calculations are unnecessary
 - 1 out of 1000 potential locations passes the verification process

- We can get rid of unnecessary verification calculations by
 - Detecting and rejecting early invalid mappings (filtering)
 - Reducing the number of potential mappings to examine



Key Observations [Xin+, BMC Genomics 2013]

Observation 1

- Adjacent k-mers in the read should also be adjacent in the reference genome
- Read mapper can quickly reject mappings that do **not** satisfy this property

Observation 2

- Some k-mers are cheaper to verify than others because they have shorter location lists (they occur less frequently in the reference genome)
 - Mapper needs to examine only e+1 k-mers' locations to tolerate e errors
- Read mapper can choose the cheapest e+1 k-mers and verify their locations



FastHASH Mechanisms [Xin+, BMC Genomics 2013]

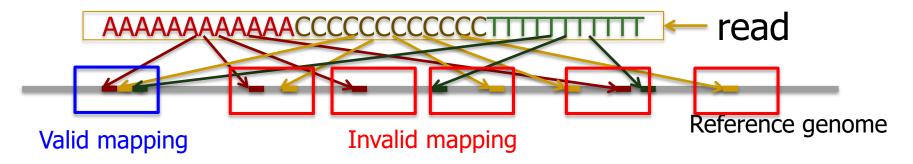
 Adjacency Filtering (AF): Rejects obviously invalid mapping locations at early stage to avoid unnecessary verifications

Cheap K-mer Selection (CKS): Reduces the absolute number of potential mapping locations to verify



Adjacency Filtering (AF)

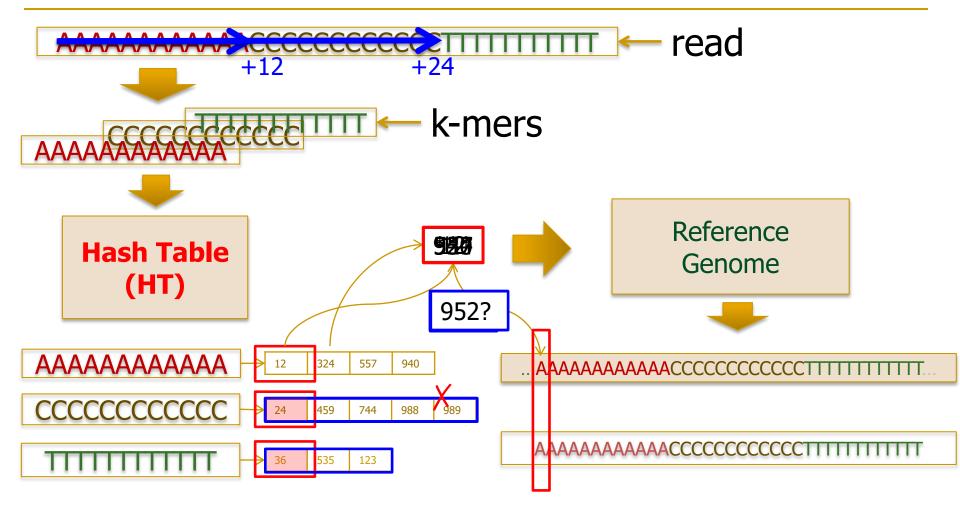
- Goal: detect and filter out invalid mappings at early stage
- Key Insight: For a valid mapping, adjacent k-mers in the read are also adjacent in the reference genome



- Key Idea: search for adjacent locations in the k-mers' location lists (in the index)
 - If more than e k-mers fail → there must be more than e errors → invalid mapping



Adjacency Filtering (AF)





FastHASH Mechanisms [Xin+, BMC Genomics 2013]

 Adjacency Filtering (AF): Rejects obviously invalid mapping locations at early stage to avoid unnecessary verifications

Cheap K-mer Selection (CKS): Reduces the absolute number of potential mapping locations to verify



Cheap K-mer Selection (CKS)

Goal: Reduce the number of potential mappings to examine

Key insight:

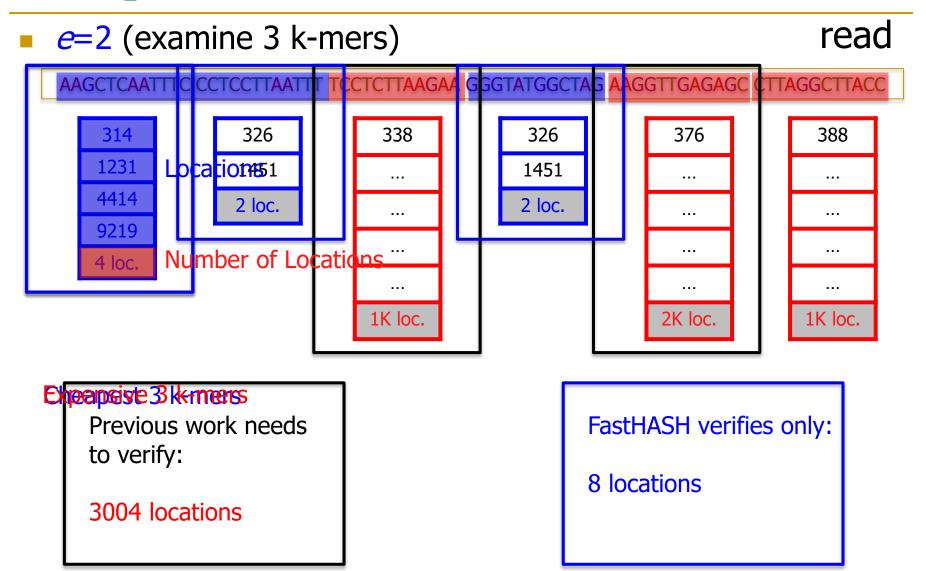
 K-mers have different cost to examine: Some k-mers are cheaper as they have fewer locations than others (occur less frequently in reference genome)

Key idea:

- Sort the k-mers based on their number of locations
- Select the k-mers with the fewest number locations to verify



Cheap K-mer Selection



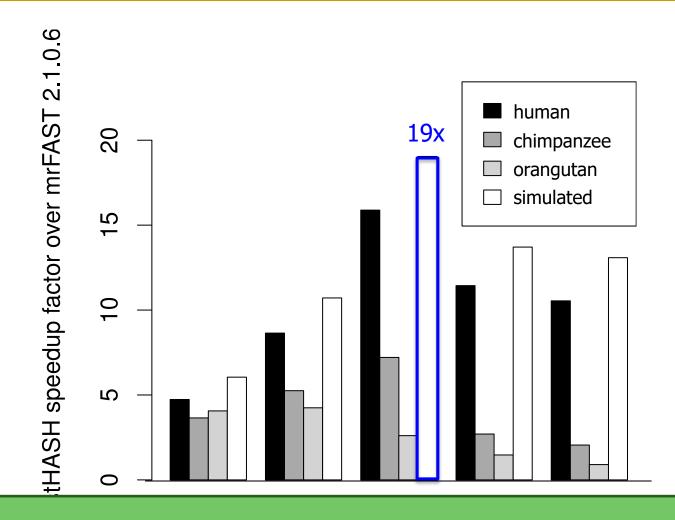


Methodology

- Implemented FastHASH on top of state-of-the-art mapper: mrFAST
 - New version mrFAST-2.5.0.0 over mrFAST-2.1.0.6
- Tested with real read sets generated from Illumina platform
 - 1M reads of a human (160 base pairs)
 - 500K reads of a chimpanzee (101 base pairs)
 - 500K reads of a orangutan (70 base pairs)
- Tested with simulated reads generated from reference genome
 - 1M simulated reads of human (180 base pairs)
- Evaluation system
 - Intel Core i7 Sandy Bridge machine
 - 16 GB of main memory



FastHASH Speedup: Entire Read Mapper

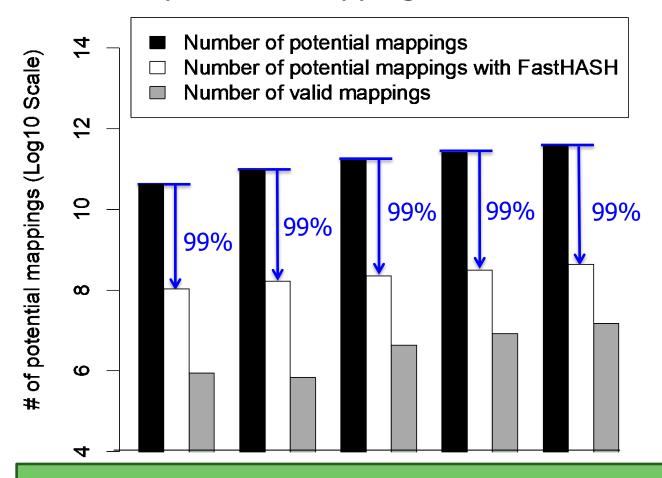


With FastHASH, new mrFAST obtains up to 19x speedup over previous version, without losing valid mappings



Analysis

Reduction of potential mappings with FastHASH



FastHASH filters out over 99% of the potential mappings without sacrificing any valid mappings



FastHASH Summary & Conclusion

- Problem: Existing read mappers perform poorly, especially in the presence of errors
- Observation: Most of the verification (edit distance) calculations are unnecessary → filter them out
- Key Idea: Exploit the structure of the genome to
 - Reject invalid mappings early (Adjacency Filtering)
 - Reduce the number of possible mappings to examine (Cheap K-mer Selection)
- Key Result: FastHASH obtains up to 19x speedup over the state-of-the-art mapper without losing valid mappings

More on FastHASH

- Download source code and try for yourself
 - Download link to FastHASH

Xin et al. BMC Genomics 2013, **14**(Suppl 1):S13 http://www.biomedcentral.com/1471-2164/14/S1/S13



PROCEEDINGS

Open Access

Accelerating read mapping with FastHASH

Hongyi Xin¹, Donghyuk Lee¹, Farhad Hormozdiari², Samihan Yedkar¹, Onur Mutlu^{1*}, Can Alkan^{3*}

From The Eleventh Asia Pacific Bioinformatics Conference (APBC 2013) Vancouver, Canada. 21-24 January 2013

Xin+, "Accelerating Read Mapping with FastHASH", BMC Genomics 2013. 100

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Shifted Hamming Distance: SIMD Acceleration

https://github.com/CMU-SAFARI/Shifted-Hamming-Distance

Bioinformatics, 31(10), 2015, 1553-1560

doi: 10.1093/bioinformatics/btu856

Advance Access Publication Date: 10 January 2015

Original Paper



Sequence analysis

Shifted Hamming distance: a fast and accurate SIMD-friendly filter to accelerate alignment verification in read mapping

Hongyi Xin^{1,*}, John Greth², John Emmons², Gennady Pekhimenko¹, Carl Kingsford³, Can Alkan^{4,*} and Onur Mutlu^{2,*}

Xin+, "Shifted Hamming Distance: A Fast and Accurate SIMD-friendly Filter to Accelerate Alignment Verification in Read Mapping", Bioinformatics 2015.



Shifted Hamming Distance

Key observation:

- If two strings differ by E edits, then every bp match can be aligned in at most 2E shifts (of one of the strings).
 - Insight: Shifting a string by one "corrects" for one "error"

Key idea:

- Compute "Shifted Hamming Distance": AND of 2E Hamming Distances of two strings, to filter out invalid mappings
 - Uses bit-parallel operations that nicely map to SIMD instructions

Key result:

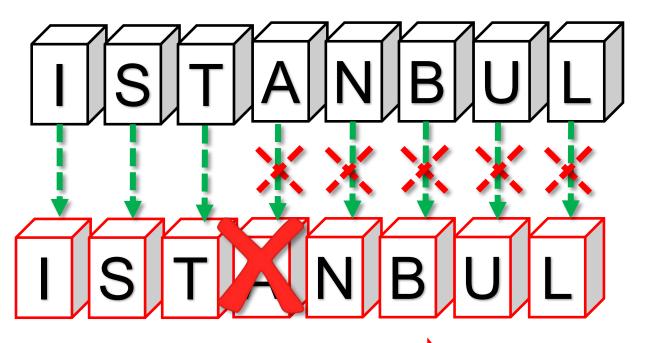
- SHD is 3x faster than SeqAn (the best implementation of Gene Myers' bit-vector algorithm), with only a 7% false positive rate
- The fastest CPU-based filtering (pre-alignment) mechanism



Hamming Distance ($\Sigma \oplus$)

3 matches 5 mismatches

<u>Edit = 1 Deletion</u>



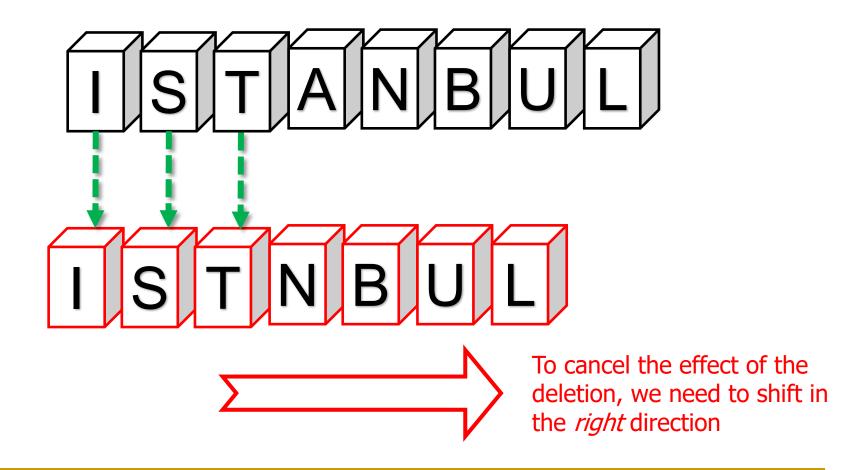


To cancel the effect of a deletion, we need to shift in the *right* direction



Insight: Shifting a String Helps Similarity Search

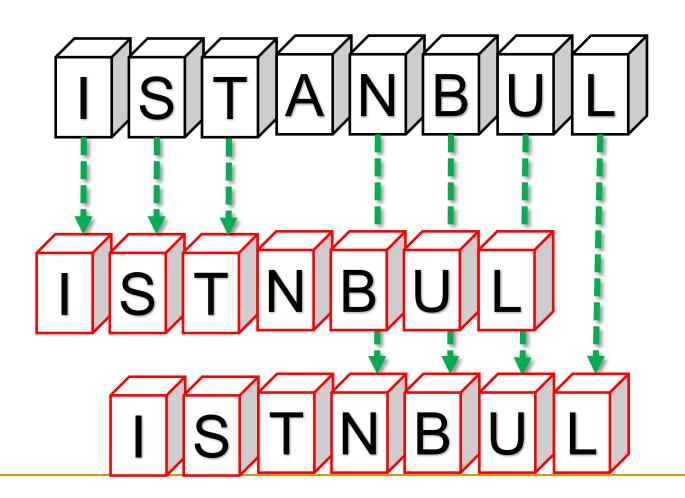
3 matches 5 mismatches



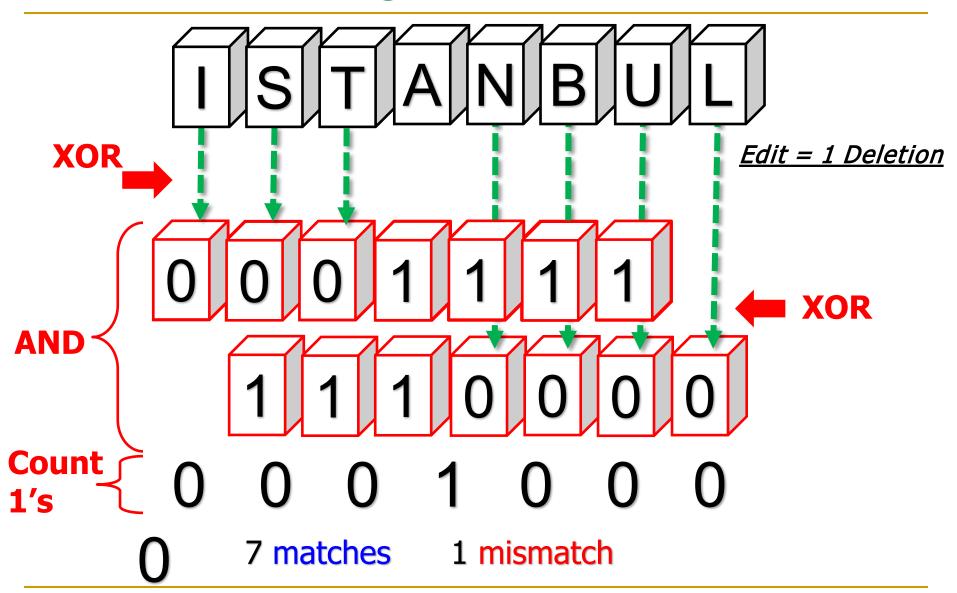


Insight: Shifting a String Helps Similarity Search

7 matches 1 mismatch



Shifted Hamming Distance

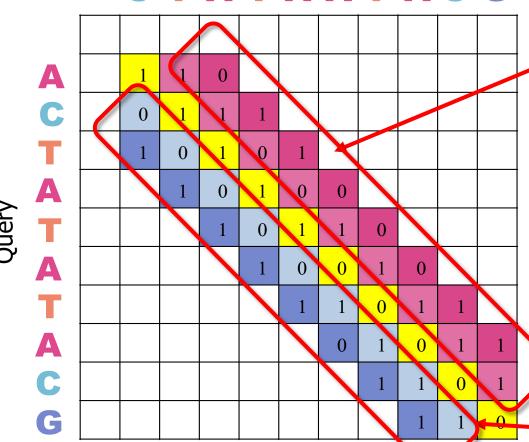




Highly Parallel Matrix Computation







2 Deletion Hamming masks

We need to compute 2E+1 vectors, E=edit distance threshold

No data dependencies!

2 Insertion Hamming masks



Key Idea of SHD Filtering

Generate 2E+1 masks

Needleman-Wunsch

Alignment

Amend random zeros: $101 \rightarrow 111 \& 1001 \rightarrow 1111$

AND all masks, ACCEPT iff number of `1' ≤ Threshold

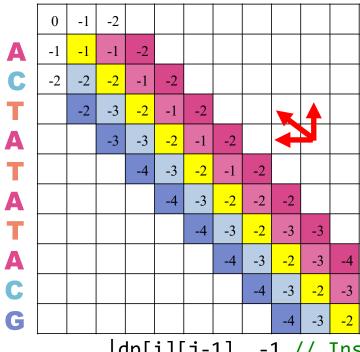
:GAGAGAGATATTTAGTGTTGCAGCACTACAACACAAAAGAGGGCCAACTTACGTGTCTAAAAAGGGGGAACATTGTTGGGCCGGA Reference GAGAGAGATAGTTAGTGTTGCAGCCACTACAACACAAAAGAGGACCAACTTACGTGTCTAAAAGGGGAGACATTGTTGGGCCGG 01 11101110111110 --- Masks after amendment ---



Alignment vs. Pre-alignment (Filtering)



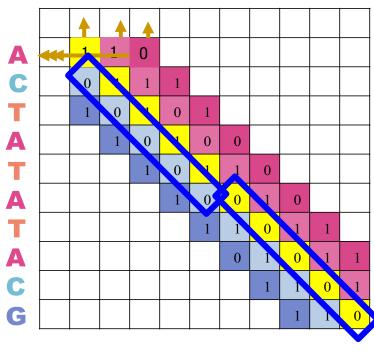
CTATAATACG



|dp[i][j-1] -1 // Inser.

Neighborhood Map





dp[i][i]=|0 if X[i]=Y[i]

Our goal is to track the diagonally consecutive matches in the neighborhood map

pre-computed cells!

<u>No data dependencies!</u>

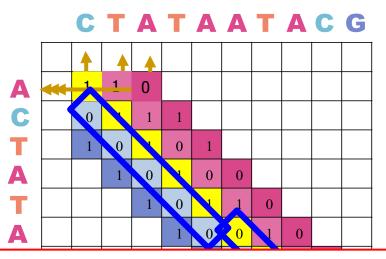


Alignment Matrix vs. Neighborhood Map

Needleman-Wunsch

Neighborhood Map

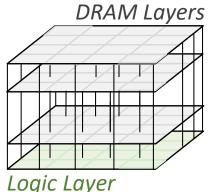




Independent vectors can be processed in parallel using hardware technologies







New Bottleneck: Filtering (Pre-Alignment)

Sequencing generates many reads, each of which potentially mapping to many locations

 \rightarrow

Filtering (Pre-alignment) eliminates the need to verify/align read to invalid mapping locations

 \rightarrow

Alignment/verification (costly edit distance computation) is performed **only** on reads that pass the filter

 New bottleneck in read mapping becomes the "filtering (pre-alignment)" step

More on Shifted Hamming Distance

https://github.com/CMU-SAFARI/Shifted-Hamming-Distance

Bioinformatics, 31(10), 2015, 1553-1560

doi: 10.1093/bioinformatics/btu856

Advance Access Publication Date: 10 January 2015

Original Paper



Sequence analysis

Shifted Hamming distance: a fast and accurate SIMD-friendly filter to accelerate alignment verification in read mapping

Hongyi Xin^{1,*}, John Greth², John Emmons², Gennady Pekhimenko¹, Carl Kingsford³, Can Alkan^{4,*} and Onur Mutlu^{2,*}

Xin+, "Shifted Hamming Distance: A Fast and Accurate SIMD-friendly Filter to Accelerate Alignment Verification in Read Mapping", Bioinformatics 2015.

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications



Location Filtering (Pre-alignment)

- Alignment is expensive
 - We need to align millions to billions of reads

- Modern read mappers reduce the time spent on alignment for increased performance. Can be done in two ways:
 - 1. Optimize the algorithm for alignment
 - Reduce the number of alignments necessary by filtering out mismatches quickly

Both methods are used by mappers today, but filtering has replaced alignment as the bottleneck [Xin+, BMC Genomics 2013]



Location Filtering (Pre-alignment)

- Alignment is expensive
 - We need to align millions to billions of reads

Our goal is to accelerate read mapping by improving the filtering step

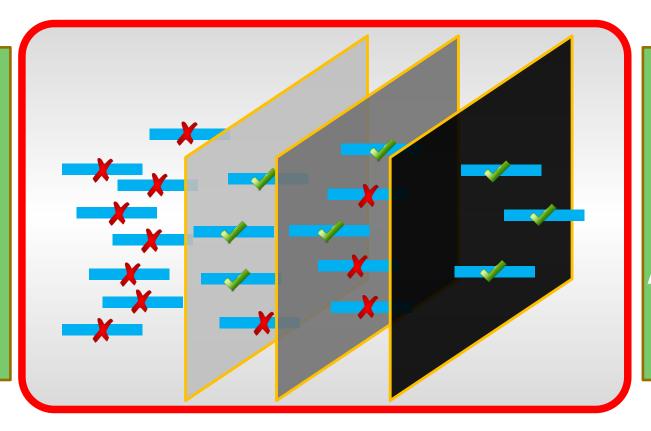
out moments quickly

Both methods are used by mappers today, but filtering has replaced alignment as the bottleneck [Xin+, BMC Genomics 2013]



Ideal Location Filtering Algorithm

Step 2
Query
the
Index



Step 3 Read Alignment

- 1. Filters out most of the incorrect mappings
- 2. Preserves all correct mappings
- 3. Does this quickly



Location Filtering Example

Read Sequence (100 bp)

AMgbihg...

Mlismistgh. False Accept

Hash Table

37 140 894 1203 1564 **Reference Genome**

Filter







Alignment vs. Pre-alignment (Filtering)

Needleman-Wunsch

CTATAATACG

SHD

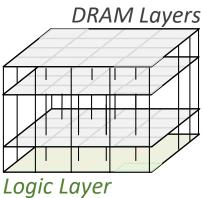
CTATAATACG

A	1	1	0						
A	0	1	1	1					
T	1	0	1	0	1				
A		1	0	1	0	0			
T			1	0	1	1	0		
A				1	0	0	1	0	

Independent vectors can be processed in parallel using hardware technologies

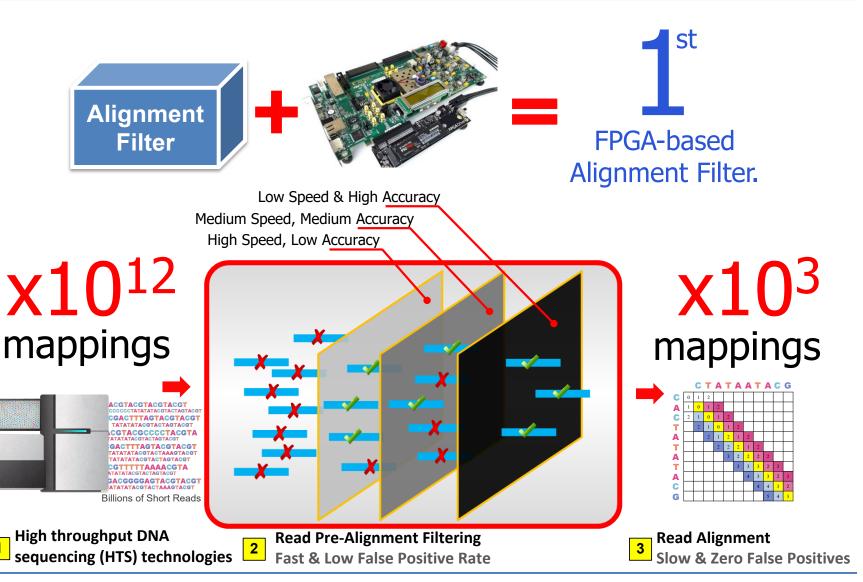








GateKeeper: FPGA-Based Alignment Filtering



GateKeeper: FPGA-Based Alignment Filtering

 Mohammed Alser, Hasan Hassan, Hongyi Xin, Oguz Ergin, Onur Mutlu, and Can Alkan

"GateKeeper: A New Hardware Architecture for Accelerating Pre-Alignment in DNA Short Read Mapping" Bioinformatics, [published online, May 31], 2017.

[Source Code]

[Online link at Bioinformatics Journal]

GateKeeper: a new hardware architecture for accelerating pre-alignment in DNA short read mapping

Mohammed Alser ™, Hasan Hassan, Hongyi Xin, Oğuz Ergin, Onur Mutlu ™, Can Alkan ™

Bioinformatics, Volume 33, Issue 21, 1 November 2017, Pages 3355–3363,

https://doi.org/10.1093/bioinformatics/btx342

Published: 31 May 2017 Article history ▼

SAFARI



GateKeeper Walkthrough

Generate 2E+1 masks

Alignment

Amend random zeros: $101 \rightarrow 111 \& 1001 \rightarrow 1111$

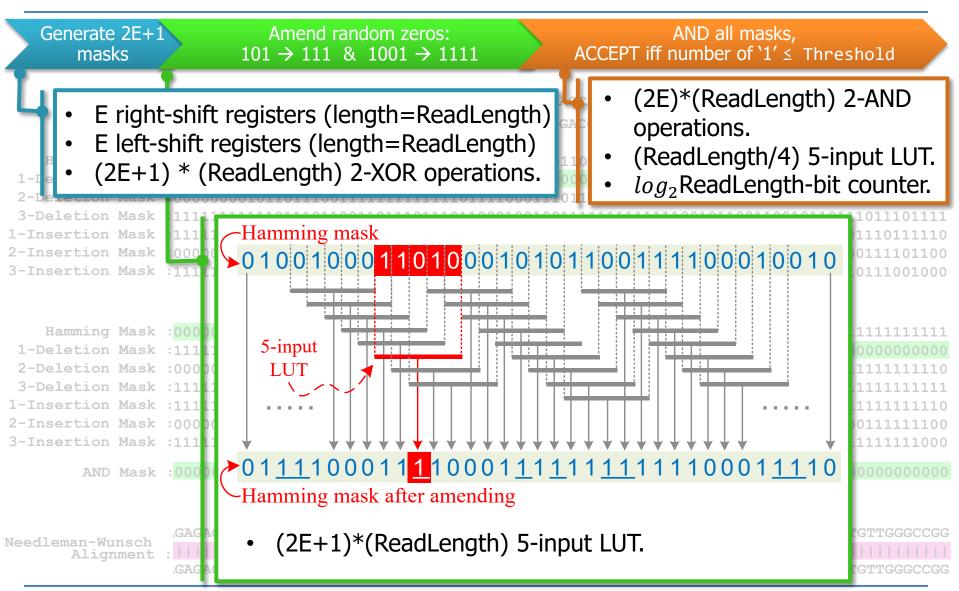
AND all masks,
ACCEPT iff number of `1' ≤ Threshold

:GAGAGAGATATTTAGTGTTGCAGCACTACAACACAAAAGAGGACCAACTTACGTGTCTAAAAAGGGGGAACATTGTTGGGCCGGA Reference :GAGAGAGATAGTTAGTGTTGCAGCCACTACAACACAAAAGAGGACCAACTTACGTGTCTAAAAGGGGAGACATTGTTGGGCCGG --- Masks after amendment ---.GAGAGAGATATTTAGTGTTGCAG-CACTACAACACAAAAGAGGACCAACTTACGTGTCTAAAAGGGGGAACATTGTTGGGCCGG Needleman-Wunsch

GAGAGAGATAGTTAGTGTTGCAGCCACTACAACACAAAAGAGGACCAACTTACGTGTCTAAAAAGGGGAGACATTGTTGGGCCGG.



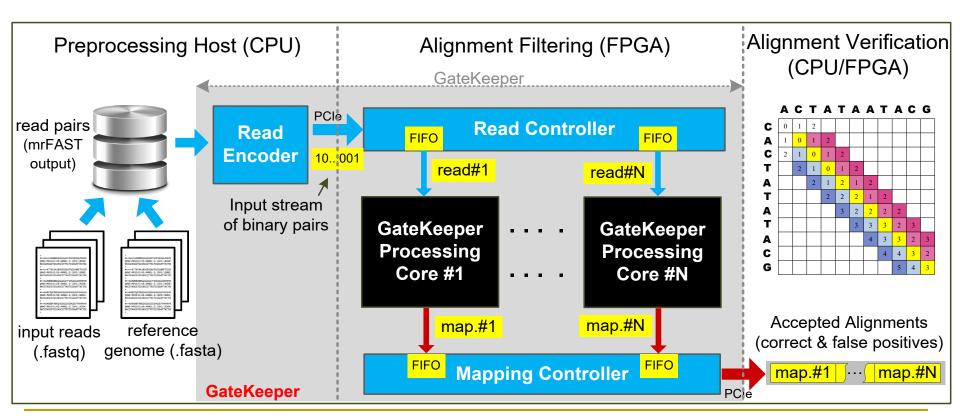
GateKeeper Walkthrough (cont'd)





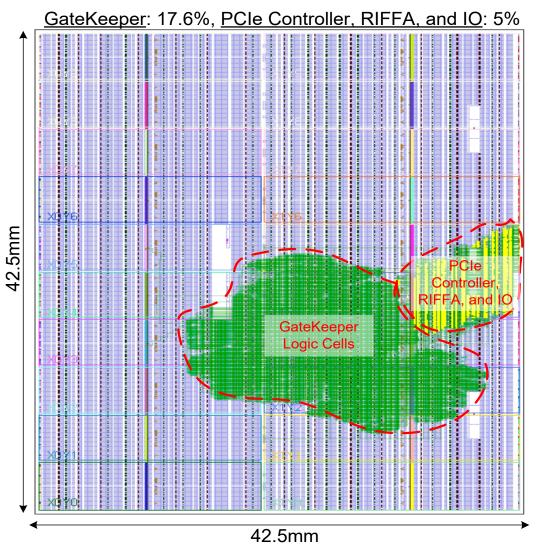
GateKeeper Accelerator Architecture

- Maximum data throughput $= \sim 13.3$ billion bases/sec
- Can examine 8 (300 bp) or 16 (100 bp) mappings concurrently at 250 MHz
- Occupies 50% (100 bp) to 91% (300 bp) of the FPGA slice LUTs and registers





FPGA Chip Layout



Read length:

300 bp

Error threshold:

E=15

GateKeeper vs. SHD

GateKeeper

- FPGA (Xilinx VC709)
- Multi-core (parallel)
- Examines a single mapping @ 125 MHz
- Limited to PCIe Gen3(4x)
 transfer rate (128 bits @ 250MHz)
- Amending requires:
 - (2E+1) 5-input LUT.

SHD

- Intel SIMD
- Single-core (sequential)
- Examines a single mapping @ ~2MHz
- Limited to a read length of 128 bp (SSE register size)
- Amending requires:
 - \bullet 4(2E+1) bitwise OR.
 - 4(2E+1) packed shuffle.
 - 3(2E+1) shift.

GateKeeper: Speed & Accuracy Results

90x-130x faster filter

than SHD (Xin et al., 2015) and the Adjacency Filter (Xin et al., 2013)

4x lower false accept rate

than the Adjacency Filter (Xin et al., 2013)

10x speedup in read mapping

with the addition of GateKeeper to the mrFAST mapper (Alkan et al., 2009)

Freely available online

github.com/BilkentCompGen/GateKeeper

GateKeeper Conclusions

- FPGA-based pre-alignment greatly speeds up read mapping
 - 10x speedup of a state-of-the-art mapper (mrFAST)

- FPGA-based pre-alignment can be integrated with the sequencer
 - It can help to hide the complexity and details of the FPGA
 - Enables real-time filtering while sequencing
 - Paves the way to on-device genome analysis

More on GateKeeper

 Mohammed Alser, Hasan Hassan, Hongyi Xin, Oguz Ergin, Onur Mutlu, and Can Alkan

"GateKeeper: A New Hardware Architecture for Accelerating Pre-Alignment in DNA Short Read Mapping" Bioinformatics, [published online, May 31], 2017.

Source Code

[Online link at Bioinformatics Journal]

GateKeeper: a new hardware architecture for accelerating pre-alignment in DNA short read mapping

Mohammed Alser ™, Hasan Hassan, Hongyi Xin, Oğuz Ergin, Onur Mutlu ™, Can Alkan ™

Bioinformatics, Volume 33, Issue 21, 1 November 2017, Pages 3355–3363,

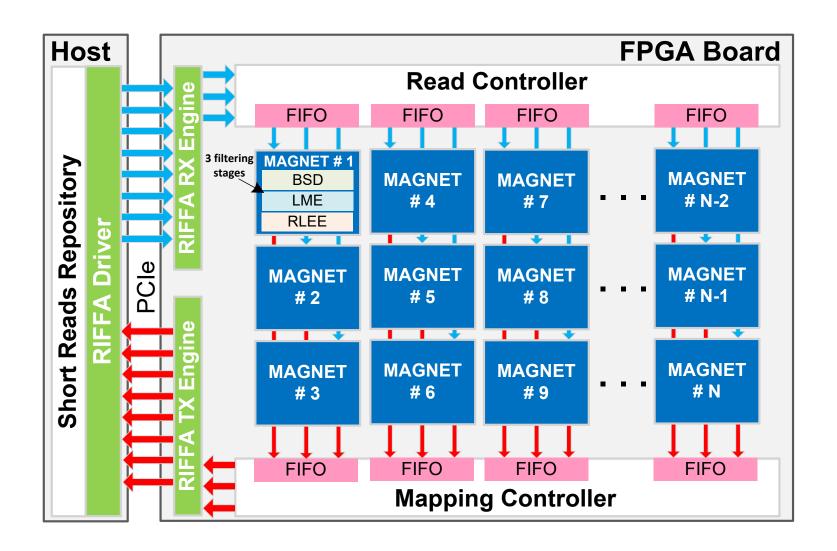
https://doi.org/10.1093/bioinformatics/btx342

Published: 31 May 2017 Article history ▼

SAFARI



MAGNET Accelerator [Alser+, TIR 2017]

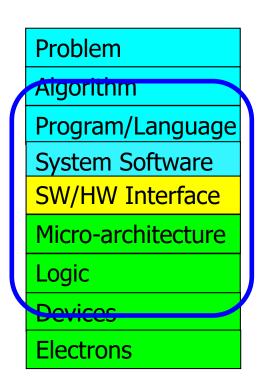




Faster, More Accurate, More Scalable Pre-Alignment Filtering

Algorithm-Arch-Device Co-Design is Critical

Computer Architecture (expanded view)



Shouji (障子) [Alser+, Bioinformatics 2019]

Mohammed Alser, Hasan Hassan, Akash Kumar, Onur Mutlu, and Can Alkan, "Shouji: A Fast and Efficient Pre-Alignment Filter for Sequence Alignment" Bioinformatics, [published online, March 28], 2019.

Source Code

Online link at Bioinformatics Journal

Bioinformatics, 2019, 1–9 doi: 10.1093/bioinformatics/btz234 Advance Access Publication Date: 28 March 2019 Original Paper



Sequence alignment

Shouji: a fast and efficient pre-alignment filter for sequence alignment

Mohammed Alser^{1,2,3,*}, Hasan Hassan¹, Akash Kumar², Onur Mutlu^{1,3,*} and Can Alkan^{3,*}

¹Computer Science Department, ETH Zürich, Zürich 8092, Switzerland, ²Chair for Processor Design, Center For Advancing Electronics Dresden, Institute of Computer Engineering, Technische Universität Dresden, 01062 Dresden, Germany and ³Computer Engineering Department, Bilkent University, 06800 Ankara, Turkey

*To whom correspondence should be addressed.

Associate Editor: Inanc Birol

SAFARI

Shouji

Key observation:

- Correct alignment always includes long identical subsequences
- Processing the entire sequence at once is ineffective for hardware design

Key idea:

 Use an overlapping sliding window approach to quickly and accurately find all long identical subsequences (consecutive zeros)

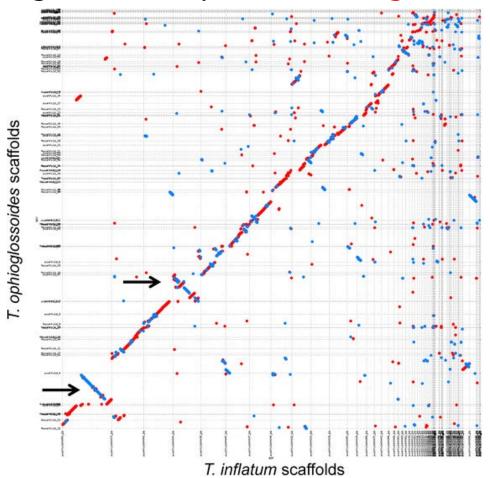
Key result:

- Shouji accelerates the best-performing CPU read aligner Edlib (Bioinformatics 2017) by up to 18.8x using 16 filtering units that work in parallel
- Shouji on FPGA is up to 10,000x faster than on CPU
- Shouji is 2.4x to 467x more accurate than GateKeeper (Bioinformatics 2017) and SHD (Bioinformatics 2015)

Shouji

Key observation:

Correct alignment always includes long identical subsequences

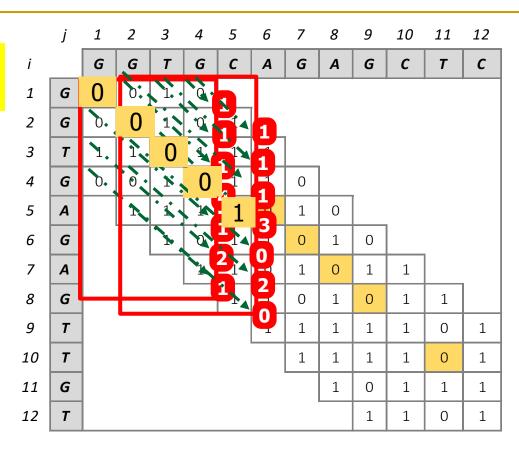


Dot plot, dot matrix (Lipman and Pearson, 1985)

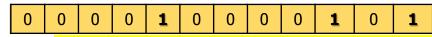
Shouji Walkthrough

Build the Neighborhood Map

Find all common subsequences (diagonal segments of consecutive zeros) shared between two given sequences



Store longest subsequence in Shouji Bit-vector

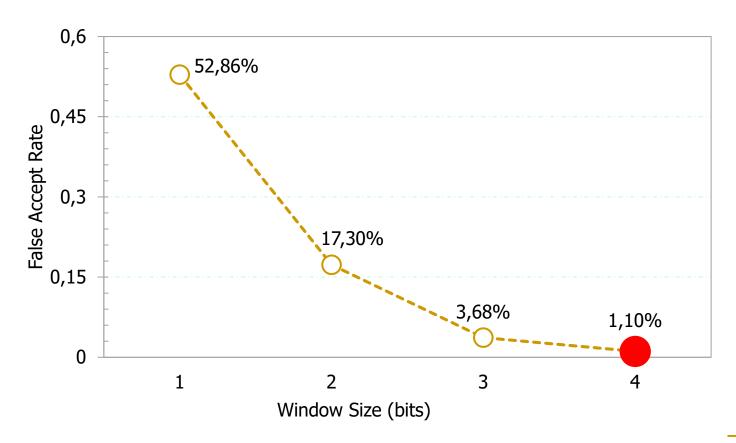


ACCEPT iff number of '1's ≤ Threshold

Shouji: a fast and efficient pre-alignment filter for sequence alignment, *Bioinformatics* 2019, https://doi.org/10.1093/bioinformatics/btz234

Effect of Sliding Window Size

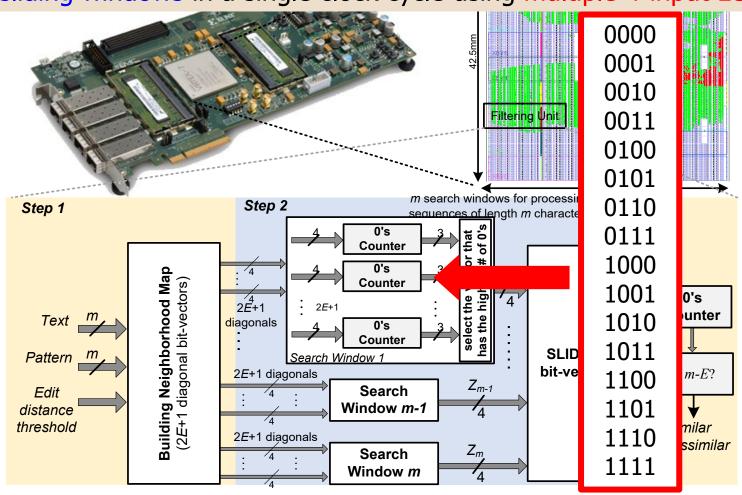
- Large enough window to accurately capture longer streaks of matches → lower false positives
- Small enough window to perform fast computation





Hardware Implementation

Counting is performed concurrently for all bit-vectors and all sliding windows in a single clock cycle using multiple 4-input LUTs



More on Shouji (障子) [Alser+, Bioinformatics 2019]

Mohammed Alser, Hasan Hassan, Akash Kumar, Onur Mutlu, and Can Alkan, "Shouji: A Fast and Efficient Pre-Alignment Filter for Sequence Alignment" Bioinformatics, [published online, March 28], 2019.

Source Code

Online link at Bioinformatics Journal

Bioinformatics, 2019, 1–9 doi: 10.1093/bioinformatics/btz234 Advance Access Publication Date: 28 March 2019 Original Paper



Sequence alignment

Shouji: a fast and efficient pre-alignment filter for sequence alignment

Mohammed Alser^{1,2,3,*}, Hasan Hassan¹, Akash Kumar², Onur Mutlu^{1,3,*} and Can Alkan^{3,*}

¹Computer Science Department, ETH Zürich, Zürich 8092, Switzerland, ²Chair for Processor Design, Center For Advancing Electronics Dresden, Institute of Computer Engineering, Technische Universität Dresden, 01062 Dresden, Germany and ³Computer Engineering Department, Bilkent University, 06800 Ankara, Turkey

Associate Editor: Inanc Birol

SAFARI

^{*}To whom correspondence should be addressed.

SneakySnake [Alser+, Bioinformatics 2020]

Mohammed Alser, Taha Shahroodi, Juan-Gomez Luna, Can Alkan, and Onur Mutlu, "SneakySnake: A Fast and Accurate Universal Genome Pre-Alignment Filter for CPUs, GPUs, and FPGAs"

Bioinformatics, to appear in 2020.

Source Code

Online link at Bioinformatics Journal

Bioinformatics

doi.10.1093/bioinformatics/xxxxxx

Advance Access Publication Date: Day Month Year

Manuscript Category



Subject Section

SneakySnake: A Fast and Accurate Universal Genome Pre-Alignment Filter for CPUs, GPUs, and FPGAs

Mohammed Alser ^{1,2,*}, Taha Shahroodi ¹, Juan Gómez-Luna ^{1,2}, Can Alkan ^{4,*}, and Onur Mutlu ^{1,2,3,4,*}

¹Department of Computer Science, ETH Zurich, Zurich 8006, Switzerland

²Department of Information Technology and Electrical Engineering, ETH Zurich, Zurich 8006, Switzerland

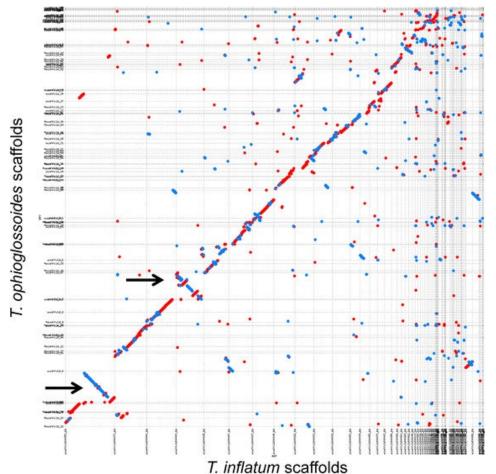
³Department of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh 15213, PA, USA

⁴Department of Computer Engineering, Bilkent University, Ankara 06800, Turkey

SneakySnake

Key observation:

Correct alignment is a sequence of non-overlapping long matches



Dot plot, dot matrix (Lipman and Pearson, 1985)

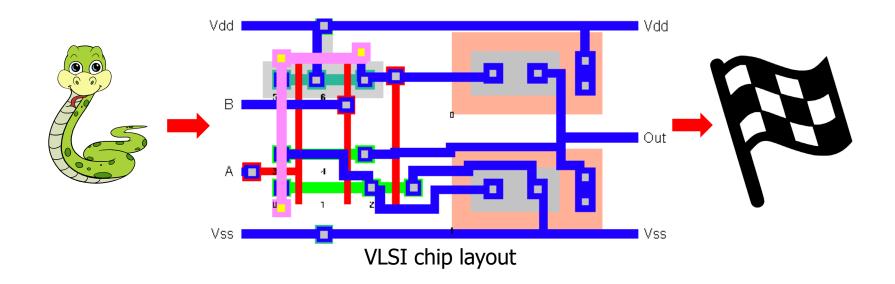
SneakySnake

Key observation:

Correct alignment is a sequence of non-overlapping long matches

Key idea:

 Reduce the approximate string matching problem to the Single Net Routing problem in VLSI chip layout



SneakySnake

Key observation:

Correct alignment is a sequence of non-overlapping long matches

Key idea:

 Reduce the approximate string matching problem to the Single Net Routing problem in VLSI chip layout

Key result:

- SneakySnake is up to four orders of magnitude more accurate than Shouji (Bioinformatics'19) and GateKeeper (Bioinformatics'17)
- SneakySnake greatly accelerates state-of-the-art CPU sequence aligners, Edlib (Bioinformatics'17) and Parasail (BMC Bioinformatics'16)
 - \Box by up to 37.7× and 43.9× (>12× on average), on CPUs
 - □ by up to $413 \times$ and $689 \times$ (>400× on average) with FPGAs/GPUs

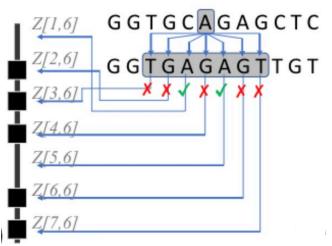


SneakySnake Walkthrough

Building Neighborhood Map

Finding the Optimal Routing Path

Examining the Snake Survival





column	1	2	3	4	5	6	7	8	9	10	11	12
3 rd Upper Diagonal	1	1	1	0	1	1	0	0	0	1	1	1
2 nd Upper Diagonal	1	1	1	0	1	1	1	1	1	1	0	1
1 st Upper Diagonal	1	0	1	1	1	0	0	0	0	1	0	1
Main Diagonal	0	0	0	0	1	1	1	1	1	1	1	1
1 st Lower Diagonal	0	1	1	1	1	0	0	1	1	1	0	1
2 nd Lower Diagonal	1	0	1	0	1	1	1	1	0	1	1	1
3 rd Lower Diagonal	0	1	1	1	1	1	1	1	1	1	1	1





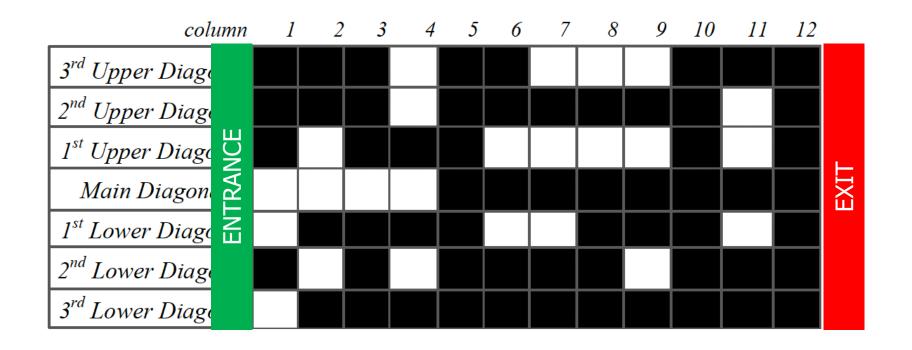
SneakySnake Walkthrough

Building Neighborhood Map

Finding the Optimal Routing Path

Examining the Snake Survival

$$E = 3$$





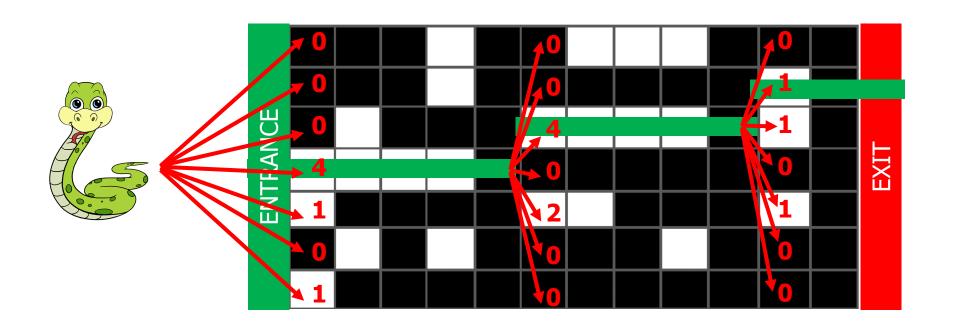
SneakySnake Walkthrough

Building Neighborhood Map

Finding the Optimal Routing Path

Examining the Snake Survival









SneakySnake Walkthrough

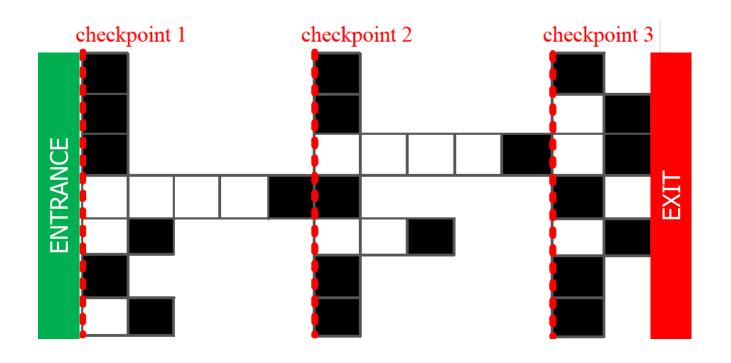
Building Neighborhood Map

Finding the Routing Travel Path

Examining the Snake Survival

This is what you actually need to build and it can be done on-the-fly!







FPGA Resource Analysis

 FPGA resource usage for a single filtering unit of GateKeeper, Shouji, and Snake-on-Chip for a sequence length of 100 and under different edit distance thresholds (E).

	<i>E</i> (bp)	Slice LUT	Slice Register	No. of Filtering Units
GateKeeper	2	0.39%	0.01%	16
	5	0.71%	0.01%	16
Shouji	2	0.69%	0.08%	16
	5	1.72%	0.16%	16
Snake-on-Chip	2	0.68%	0.16%	16
	5	1.42%	0.34%	16

Key Results of SneakySnake

 SneakySnake is up to four orders of magnitude more accurate than Shouji (Bioinformatics'19) and GateKeeper (Bioinformatics'17)

Short reads:

- SneakySnake accelerates Edlib (Bioinformatics'17) and Parasail (BMC Bioinformatics'16) by
- up to $37.7 \times$ and $43.9 \times$ (>12 \times on average), on CPUs
- up to 413× and 689× (>400× on average) using FPGAs/GPUs

Long reads:

 SneakySnake accelerates Parasail and KSW2 by 140.1× and 17.1× on average, respectively, on CPUs

Long Read Mapping (SneakySnake vs Parasail)

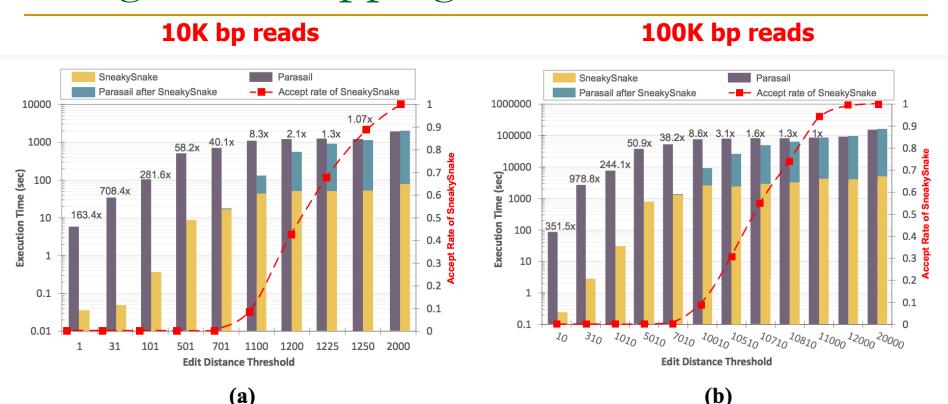


Fig. 10: The execution time of SneakySnake, Parasail, and SneakySnake integrated with Parasail using long sequences, (a) 10Kbp and (b) 100Kbp, and 40 CPU threads. The left y-axes of (a) and (b) are on a logarithmic scale. For each edit distance threshold value, we provide in the right y-axes of (a) and (b) the rate of accepted pairs (out of 100,000 pairs for 10Kbp and out of 74,687 pairs for 100Kbp) by SneakySnake that are passed to Parasail. We present the end-to-end speedup values obtained by integrating SneakySnake with Parasail.

Long Read Mapping (SneakySnake vs KSW2)



Fig. 11: The execution time of SneakySnake, KSW2, and SneakySnake integrated with KSW2 using long sequences, (a) 10Kbp and (b) 100Kbp, and a single CPU thread. The left y-axes of (a) and (b) are on a logarithmic scale. For each edit distance threshold value, we provide in the right y-axes of (a) and (b) the rate of accepted pairs (out of 100,000 pairs for 10Kbp and out of 74,687 pairs for 100Kbp) by SneakySnake that are passed to KSW2. We present the end-to-end speedup values obtained by integrating SneakySnake with KSW2.

More on SneakySnake [Alser+, Bioinformatics 2020]

Mohammed Alser, Taha Shahroodi, Juan-Gomez Luna, Can Alkan, and Onur Mutlu, "SneakySnake: A Fast and Accurate Universal Genome Pre-Alignment Filter for CPUs, GPUs, and FPGAs"

Bioinformatics, to appear in 2020.

Source Code

[Online link at Bioinformatics Journal]

Bioinformatics

doi.10.1093/bioinformatics/xxxxxx

Advance Access Publication Date: Day Month Year

Manuscript Category



Subject Section

SneakySnake: A Fast and Accurate Universal Genome Pre-Alignment Filter for CPUs, GPUs, and FPGAs

Mohammed Alser ^{1,2,*}, Taha Shahroodi ¹, Juan Gómez-Luna ^{1,2}, Can Alkan ^{4,*}, and Onur Mutlu ^{1,2,3,4,*}

¹Department of Computer Science, ETH Zurich, Zurich 8006, Switzerland

²Department of Information Technology and Electrical Engineering, ETH Zurich, Zurich 8006, Switzerland

³Department of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh 15213, PA, USA

⁴Department of Computer Engineering, Bilkent University, Ankara 06800, Turkey

GenASM Framework [MICRO 2020]

Damla Senol Cali, Gurpreet S. Kalsi, Zulal Bingol, Can Firtina, Lavanya Subramanian, Jeremie S. Kim, Rachata Ausavarungnirun, Mohammed Alser, Juan Gomez-Luna, Amirali Boroumand, Anant Nori, Allison Scibisz, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu, "GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis"
Proceedings of the 53rd International Symposium on Microarchitecture (MICRO), Virtual, October 2020.

[<u>Lighting Talk Video</u> (1.5 minutes)]
[<u>Lightning Talk Slides (pptx) (pdf)</u>]
[<u>Talk Video</u> (18 minutes)]
[<u>Slides (pptx) (pdf)</u>]

GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis

Damla Senol Cali^{†™} Gurpreet S. Kalsi[™] Zülal Bingöl[▽] Can Firtina[⋄] Lavanya Subramanian[‡] Jeremie S. Kim^{⋄†} Rachata Ausavarungnirun[⊙] Mohammed Alser[⋄] Juan Gomez-Luna[⋄] Amirali Boroumand[†] Anant Nori[™] Allison Scibisz[†] Sreenivas Subramoney[™] Can Alkan[▽] Saugata Ghose^{*†} Onur Mutlu^{⋄†▽}

† Carnegie Mellon University [™] Processor Architecture Research Lab, Intel Labs [▽] Bilkent University [⋄] ETH Zürich

‡ Facebook [⊙] King Mongkut's University of Technology North Bangkok ^{*} University of Illinois at Urbana–Champaign

153



Problem & Our Goal

- ☐ Multiple steps of read mapping require *approximate string matching*
 - ASM enables read mapping to account for sequencing errors and genetic variations in the reads
- □ ASM makes up a significant portion of read mapping (more than 70%)
- One of the major bottlenecks of genome sequence analysis

Our Goal:

Accelerate approximate string matching by designing a fast and flexible framework, which can be used to accelerate *multiple steps* of the genome sequence analysis pipeline



GenASM: ASM Framework for GSA

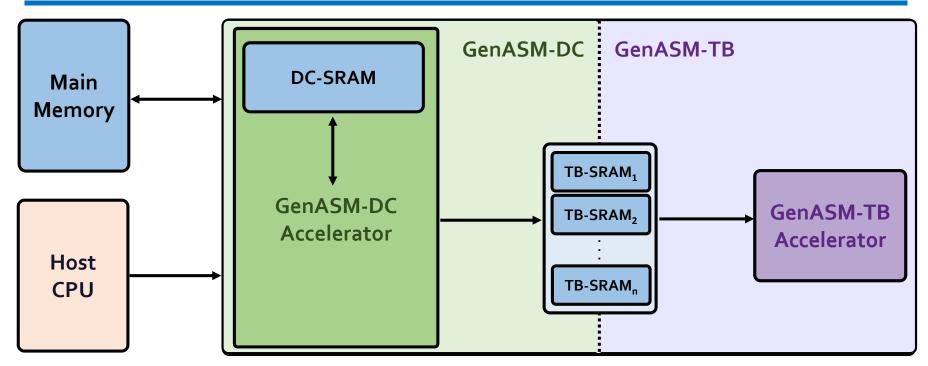
Our Goal:

Accelerate approximate string matching by designing a fast and flexible framework, which can accelerate *multiple steps* of genome sequence analysis

- GenASM: First ASM acceleration framework for GSA
 - Based on the Bitαp algorithm
 - Uses fast and simple bitwise operations to perform ASM
 - Modified and extended ASM algorithm
 - Highly-parallel Bitap with long read support
 - Bitvector-based novel algorithm to perform traceback
 - Co-design of our modified scalable and memory-efficient algorithms with low-power and area-efficient hardware accelerators



GenASM: Hardware Design



GenASM-DC:

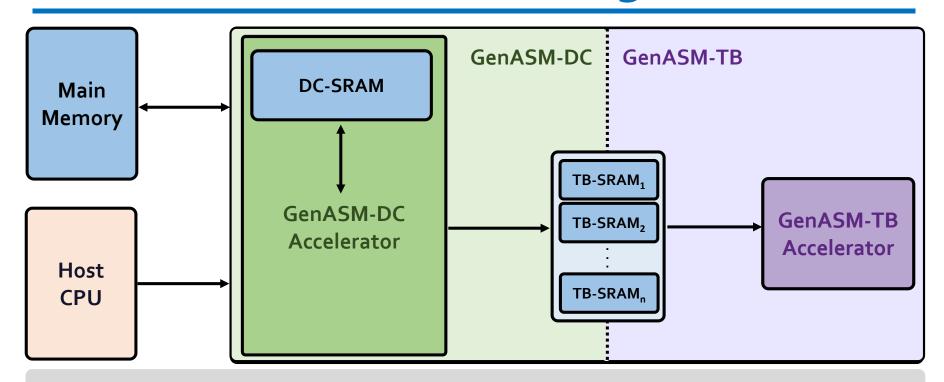
generates bitvectors and performs edit Distance Calculation

GenASM-TB:

performs TraceBack and assembles the optimal alignment



GenASM: Hardware Design



Our specialized compute units and on-chip SRAMs help us to:

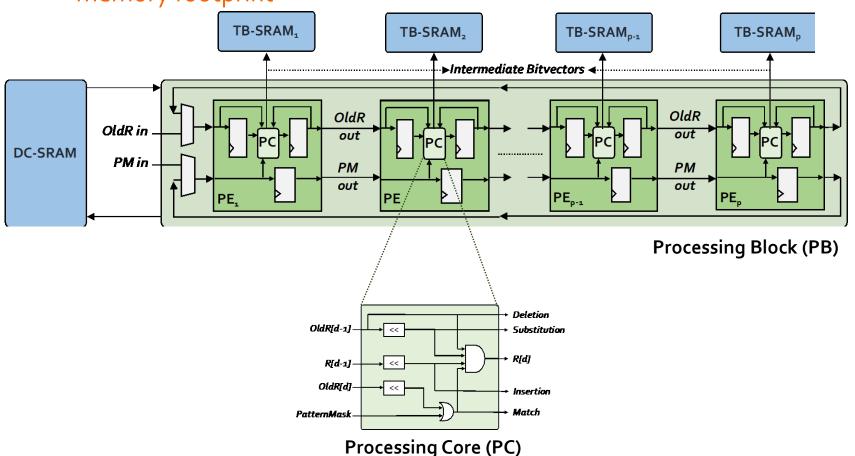
- → Match the rate of computation with memory capacity and bandwidth
 - → Achieve high performance and power efficiency
 - → Scale linearly in performance with

the number of parallel compute units that we add to the system



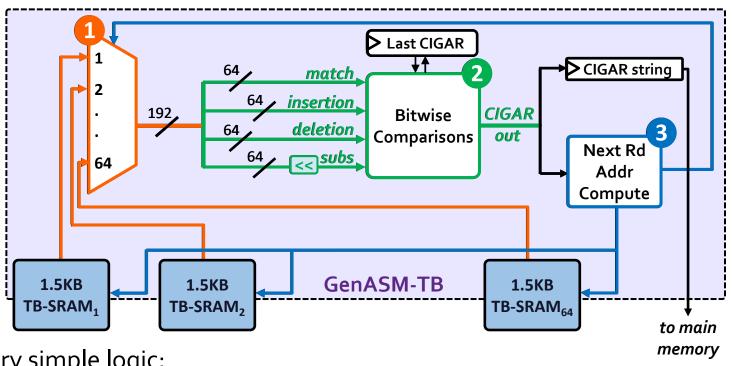
GenASM-DC: Hardware Design

- Linear cyclic systolic array based accelerator
 - Designed to maximize parallelism and minimize memory bandwidth and memory footprint





GenASM-TB: Hardware Design



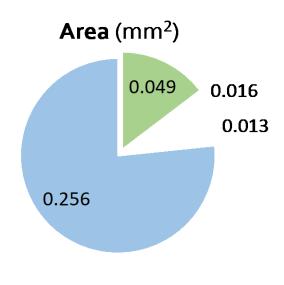
- Very simple logic:
 - 1 Reads the bitvectors from one of the TB-SRAMs using the computed address
 - 2 Performs the required bitwise comparisons to find the traceback output for the current position
 - 3 Computes the next TB-SRAM address to read the new set of bitvectors



Key Results – Area and Power

- Based on our **synthesis** of **GenASM-DC** and **GenASM-TB** accelerator datapaths using the Synopsys Design Compiler with a **28nm** LP process:
 - Both GenASM-DC and GenASM-TB operate @ 1GHz







Total (1 vault): 0.334 mm²

Total (32 vaults): 10.69 mm²

% of a Xeon CPU core: 1%

0.101 W

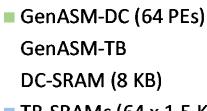
3.23 W

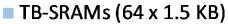
1%

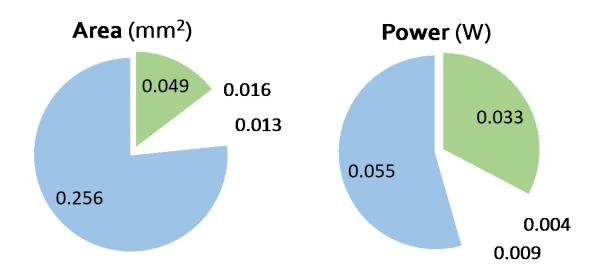


Key Results – Area and Power

- Based on our **synthesis** of **GenASM-DC** and **GenASM-TB** accelerator datapaths using the Synopsys Design Compiler with a **28nm** LP process:
 - Both GenASM-DC and GenASM-TB operate @ 1GHz



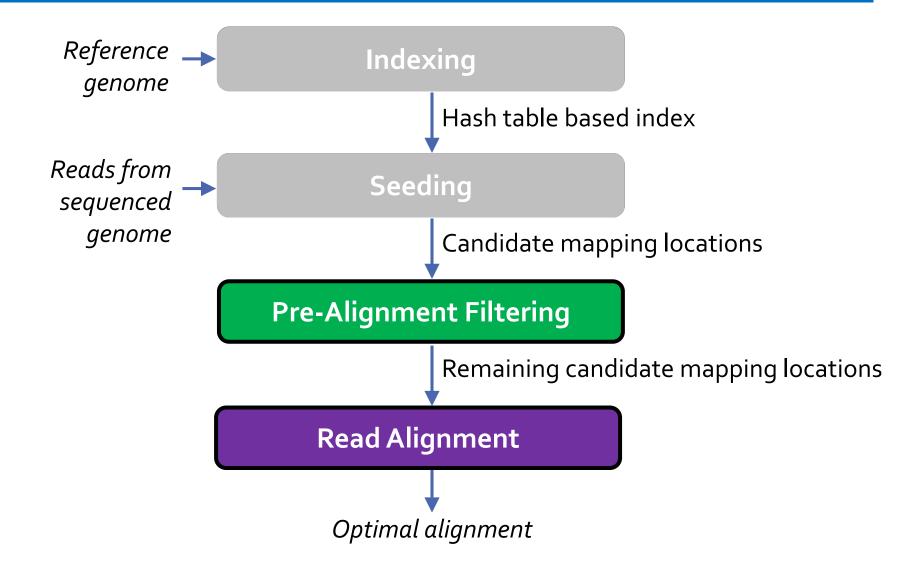




GenASM has low area and power overheads



Use Cases of GenASM





Use Cases of GenASM (cont'd.)

(1) Read Alignment Step of Read Mapping

 Find the optimal alignment of how reads map to candidate reference regions

(2) Pre-Alignment Filtering for Short Reads

 Quickly identify and filter out the unlikely candidate reference regions for each read

(3) Edit Distance Calculation

- Measure the similarity or distance between two sequences
- We also discuss other possible use cases of GenASM in our paper:
 - Read-to-read overlap finding, hash-table based indexing, whole genome alignment, generic text search



Key Results

(1) Read Alignment

- 116× speedup, 37× less power than Minimap2 (state-of-the-art SW)
- 111× speedup, 33× less power than BWA-MEM (state-of-the-art SW)
- 3.9× better throughput, 2.7× less power than Darwin (state-of-the-art HW)
- 1.9× better throughput, 82% less logic power than GenAx (state-of-the-art HW)

(2) Pre-Alignment Filtering

■ 3.7× speedup, 1.7× less power than Shouji (state-of-the-art HW)

(3) Edit Distance Calculation

- 22-12501× speedup, 548-582× less power than Edlib (state-of-the-art SW)
- 9.3–400× speedup, 67× less power than ASAP (state-of-the-art HW)

More on GenASM Framework [MICRO 2020]

Damla Senol Cali, Gurpreet S. Kalsi, Zulal Bingol, Can Firtina, Lavanya Subramanian, Jeremie S. Kim, Rachata Ausavarungnirun, Mohammed Alser, Juan Gomez-Luna, Amirali Boroumand, Anant Nori, Allison Scibisz, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu, "GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis"
Proceedings of the 53rd International Symposium on Microarchitecture (MICRO), Virtual, October 2020.

[<u>Lighting Talk Video</u> (1.5 minutes)]
[<u>Lightning Talk Slides (pptx) (pdf)</u>]
[<u>Talk Video</u> (18 minutes)]
[<u>Slides (pptx) (pdf)</u>]

GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis

Damla Senol Cali^{†™} Gurpreet S. Kalsi[™] Zülal Bingöl[▽] Can Firtina[⋄] Lavanya Subramanian[‡] Jeremie S. Kim^{⋄†} Rachata Ausavarungnirun[⊙] Mohammed Alser[⋄] Juan Gomez-Luna[⋄] Amirali Boroumand[†] Anant Nori[™] Allison Scibisz[†] Sreenivas Subramoney[™] Can Alkan[▽] Saugata Ghose^{*†} Onur Mutlu^{⋄†▽}

† Carnegie Mellon University [™] Processor Architecture Research Lab, Intel Labs [▽] Bilkent University [⋄] ETH Zürich

‡ Facebook [⊙] King Mongkut's University of Technology North Bangkok ^{*} University of Illinois at Urbana–Champaign

165

Accelerating Sequence-to-Graph Mapping

Damla Senol Cali, Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie Kim, Nika MansouriGhiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu, "SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping"

Proceedings of the <u>49th International Symposium on Computer Architecture</u> (ISCA), New York, June 2022.

arXiv version

SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali¹ Konstantinos Kanellopoulos² Joël Lindegger² Zülal Bingöl³ Gurpreet S. Kalsi⁴ Ziyi Zuo⁵ Can Firtina² Meryem Banu Cavlak² Jeremie Kim² Nika Mansouri Ghiasi² Gagandeep Singh² Juan Gómez-Luna² Nour Almadhoun Alserr² Mohammed Alser² Sreenivas Subramoney⁴ Can Alkan³ Saugata Ghose⁶ Onur Mutlu²

¹Bionano Genomics ²ETH Zürich ³Bilkent University ⁴Intel Labs ⁵Carnegie Mellon University ⁶University of Illinois Urbana-Champaign



SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali, Ph.D.

<u>damlasenolcali@gmail.com</u> <u>https://damlasenolcali.github.io/</u>

Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie S. Kim, Nika Mansouri Ghiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, Onur Mutlu















Genome Sequence Analysis

Mapping the reads to a reference genome (i.e., read mapping) is a critical step in genome sequence analysis

Linear Reference: ACGTACGT

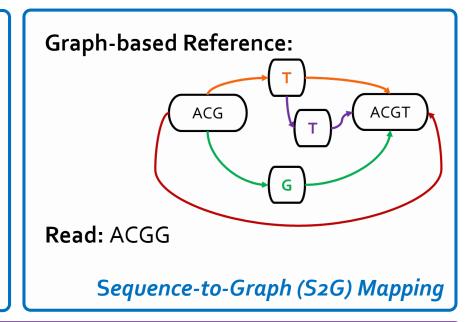
Read: ACGG

Alternative Sequence: ACGGACGT

Alternative Sequence: ACGTTACGT

Alternative Sequence: ACG-ACGT

Sequence-to-Sequence (S2S) Mapping



Sequence-to-graph mapping results in notable quality improvements.

However, it is a more difficult computational problem,

with no prior hardware design.



SeGraM: First Graph Mapping Accelerator

Our Goal:

Specialized, high-performance, scalable, and low-cost algorithm/hardware co-design that alleviates bottlenecks in multiple steps of sequence-to-graph mapping

SeGraM: First universal algorithm/hardware co-designed genomic mapping accelerator that can effectively and efficiently support:

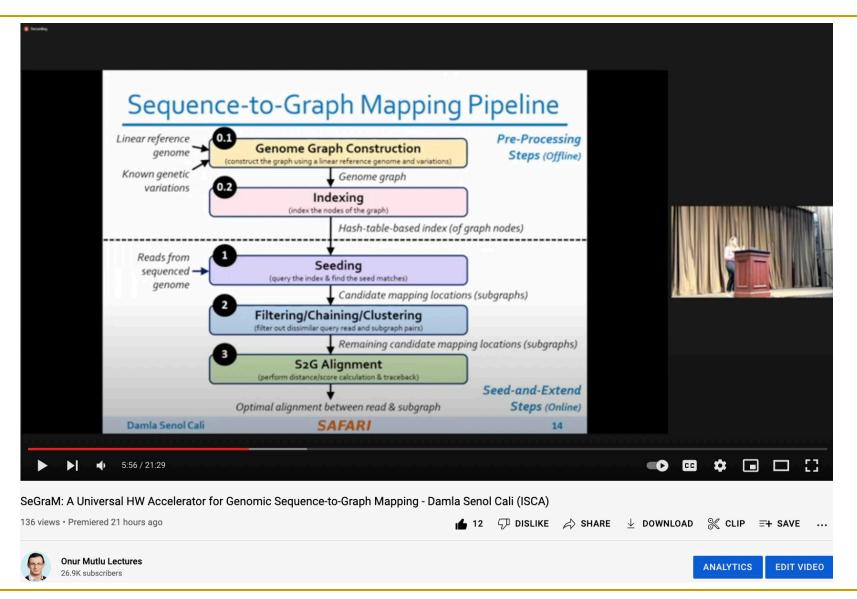
- Sequence-to-graph mapping
- Sequence-to-sequence mapping
- Both short and long reads



Use Cases & Key Results

- (1) Sequence-to-Graph (S2G) Mapping
- 5.9×/106× speedup, 4.1×/3.0× less power than **GraphAligner** for long and short reads, respectively (state-of-the-art SW)
- 3.9×/742× speedup, 4.4×/3.2× less power than vg for long and short reads, respectively (state-of-the-art SW)
- (2) Sequence-to-Graph (S2G) Alignment
- 41×-539× speedup over PaSGAL with AVX-512 support (state-of-the-art SW)
- (3) Sequence-to-Sequence (S2S) Alignment
- 1.2×/4.8× higher throughput than **GenASM** and **GACT of Darwin** for long reads (state-of-the-art **HW**)
- 1.3×/2.4× higher throughput than GenASM and SillaX of GenAX for short reads (state-of-the-art HW)

SeGraM Talk Video



Accelerating Sequence-to-Graph Mapping

Damla Senol Cali, Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie Kim, Nika MansouriGhiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu,
 "SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping"

Proceedings of the <u>49th International Symposium on Computer Architecture</u> (ISCA), New York, June 2022.

arXiv version

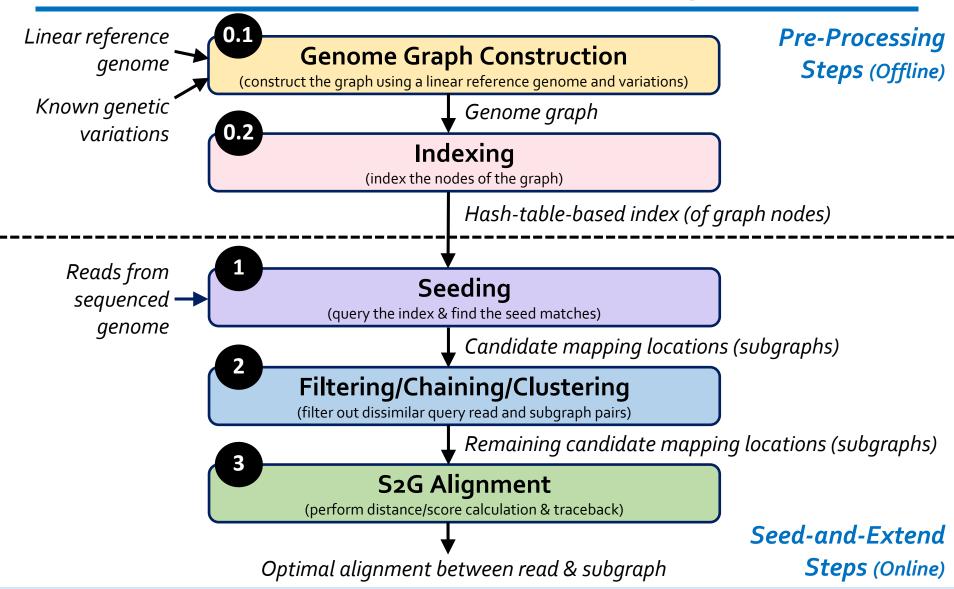
SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali¹ Konstantinos Kanellopoulos² Joël Lindegger² Zülal Bingöl³ Gurpreet S. Kalsi⁴ Ziyi Zuo⁵ Can Firtina² Meryem Banu Cavlak² Jeremie Kim² Nika Mansouri Ghiasi² Gagandeep Singh² Juan Gómez-Luna² Nour Almadhoun Alserr² Mohammed Alser² Sreenivas Subramoney⁴ Can Alkan³ Saugata Ghose⁶ Onur Mutlu²

¹Bionano Genomics ²ETH Zürich ³Bilkent University ⁴Intel Labs ⁵Carnegie Mellon University ⁶University of Illinois Urbana-Champaign



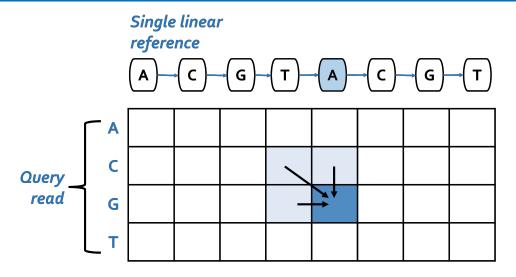
Sequence-to-Graph Mapping Pipeline



Damla Senol Cali SAFARI 173



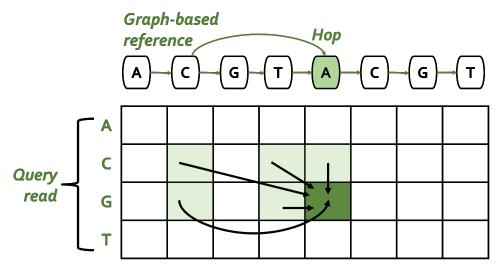
S2S vs. S2G Alignment



Sequence-to-Sequence (S2S) Alignment



S2S vs. S2G Alignment



Sequence-to-Graph (S2G) Alignment

In contrast to S2S alignment,

S2G alignment must incorporate non-neighboring characters as well whenever there is an edge (i.e., hop) from the non-neighboring character to the current character



Analysis of State-of-the-Art Tools

Based on our analysis with **GraphAligner** and **vg**:

SW

Observation 1: Alignment step is the bottleneck

Observation 2: Alignment suffers from high cache miss rates

Observation 3: Seeding suffers from the DRAM latency bottleneck

Observation 4: Baseline tools scale sublinearly

Observation 5: Existing S2S mapping accelerators are unsuitable for the S2G mapping problem

HW

Observation 6: Existing graph accelerators are unable to handle S2G alignment



SeGraM: Universal Genomic Mapping Accelerator

- □ First universal genomic mapping accelerator that can support both sequence-to-graph mapping and sequence-to-sequence mapping, for both short and long reads
- □ *First algorithm/hardware co-design* for accelerating sequence-to-graph mapping
- ☐ We base SeGraM upon a minimizer-based seeding algorithm
- We propose a novel bitvector-based alignment algorithm to perform approximate string matching between a read and a graph-based reference genome

SW

■ We co-design both algorithms with high-performance, scalable, and efficient hardware accelerators

HW



SeGraM Hardware Design

Main Memory (graph-based reference & index) Input Scratchpad **Minimizer** Seed Scratchpad Scratchpad Generate **Hop Queues** Bitvectors Filter Find **Find Minimizers** Candidate **Minimizers** by Frequency **Seed Regions Bitvector Scratchpad** Read **Perform** Traceback Scratchpad MinSeed (MS) BitAlign (BA) SeGraM Accelerator

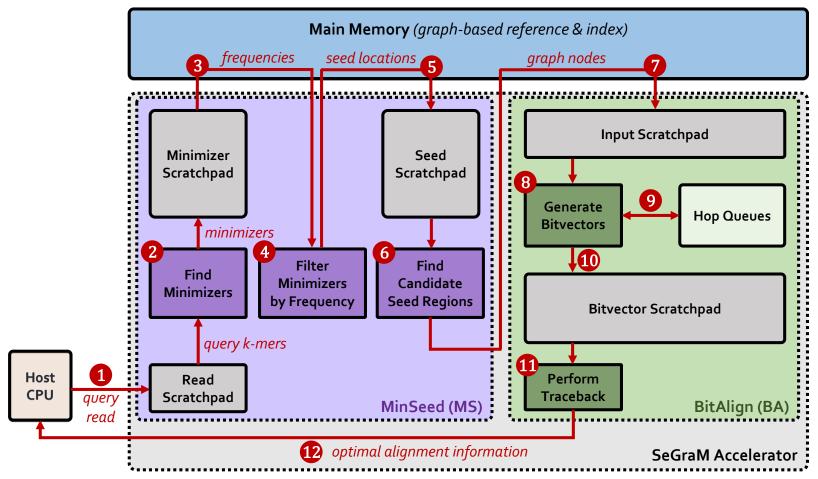
Host CPU

MinSeed: first hardware accelerator for Minimizer-based Seeding

BitAlign: first hardware accelerator for (Bitvectorbased) sequence-to-graph Alignment



SeGraM Hardware Design



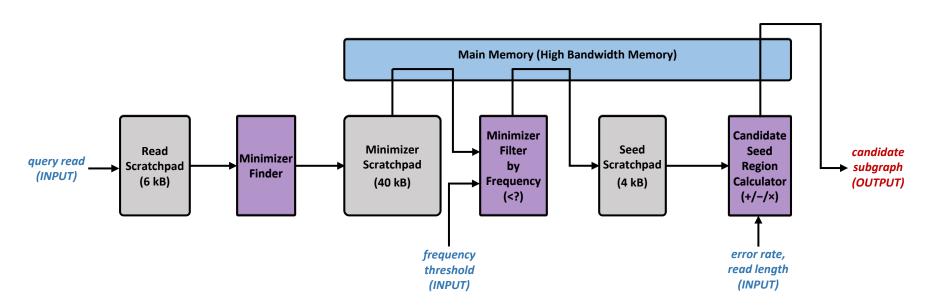
MinSeed: first hardware accelerator for Minimizer-based Seeding

BitAlign: first hardware accelerator for (Bitvectorbased) sequence-to-graph Alignment



MinSeed HW

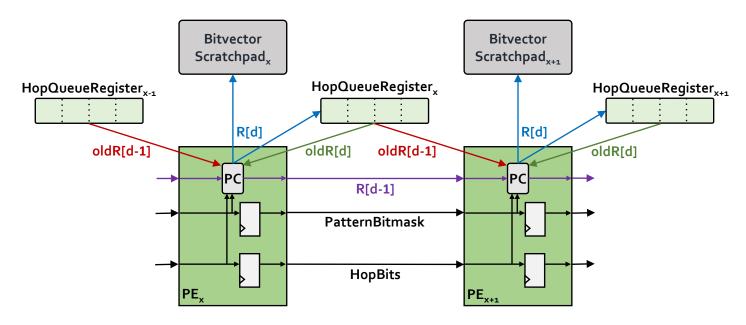
- ☐ MinSeed = 3 computation modules + 3 scratchpads + memory interface
 - Computation modules: Implemented with simple logic
 - Scratchpads: 50kB in total; employ double buffering technique to hide the latency of MinSeed
 - High-Bandwidth Memory (HBM): Enables low-latency and highly-parallel memory access





BitAlign HW

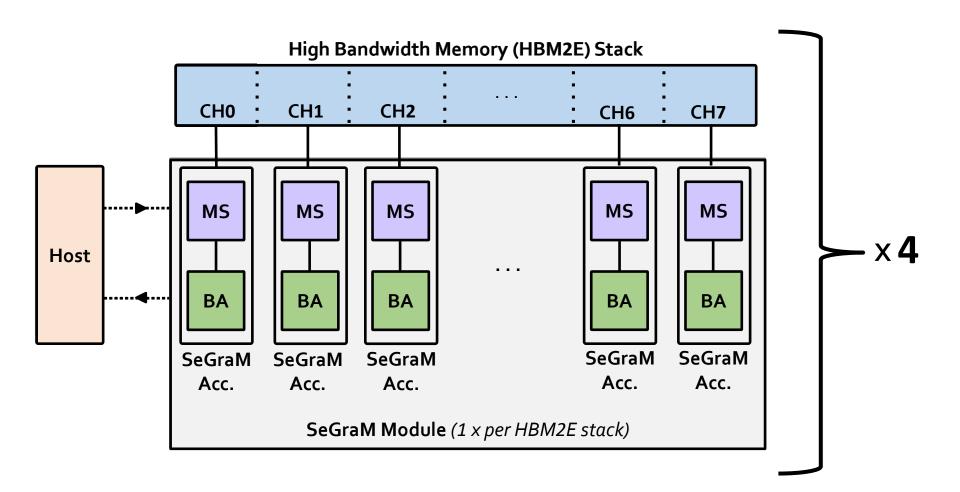
- ☐ Linear cyclic systolic array-based accelerator
- Based on the GenASM hardware design*
- Incorporates hop queue registers to feed the bitvectors of non-neighboring characters/nodes (i.e., hops)



[*] D. Senol Cali *et al.* "GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis" (MICRO'20)



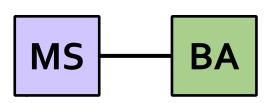
Overall System Design of SeGraM



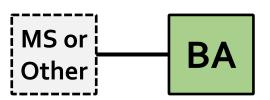


Use Cases of SeGraM

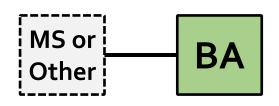
(1) Sequence-to-Graph Mapping



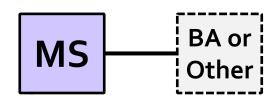
(2) Sequence-to-Graph Alignment



(3) Sequence-to-Sequence Alignment



(4) Seeding





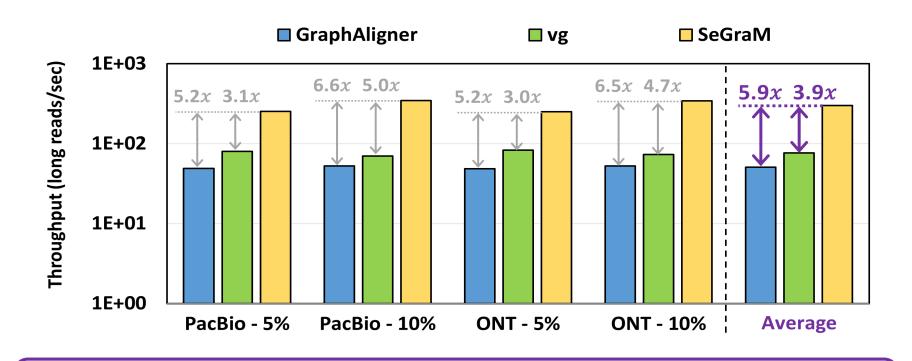
Key Results – Area & Power

■ Based on our **synthesis** of **MinSeed** and **BitAlign** accelerator datapaths using the Synopsys Design Compiler with a **28nm** process (**a 1GHz**):

Component	Area (mm²)	Power (mW)
MinSeed – Logic	0.017	10.8
Read Scratchpad (6 kB)	0.012	7.9
Minimizer Scratchpad (40 kB)	0.055	22.7
Seed Scratchpad (4 kB)	0.008	6.4
BitAlign – Edit Distance Calculation Logic with Hop Queue Registers (64 PEs)	0.393	378.0
BitAlign – Traceback Logic	0.020	2.7
Input Scratchpad (24 kB)	0.033	13.3
Bitvector Scratchpads (128 kB)	0.329	316.2
Total – 1 SeGraM Accelerator	0.867	758.0 (0.8 W)
Total – 4 SeGraM Modules (32 SeGraM Accelerators)	27.744	24.3 W
HBM2E (4 stacks)		3.8 W



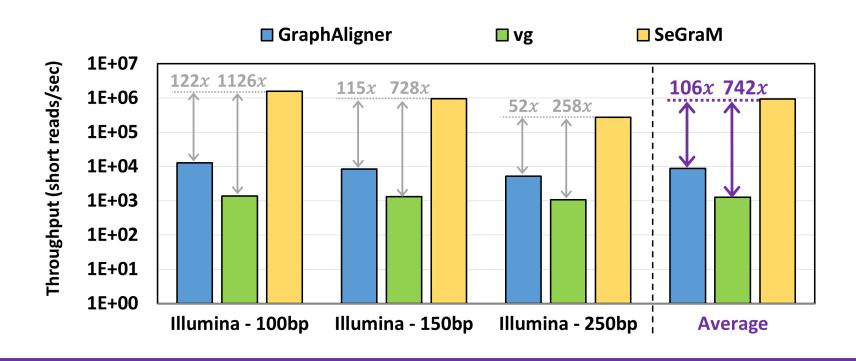
Key Results – SeGraM with Long Reads



SeGraM provides **5.9**× and **3.9**× throughput improvement over GraphAligner and vg, while reducing the power consumption by **4.1**× and **4.4**×



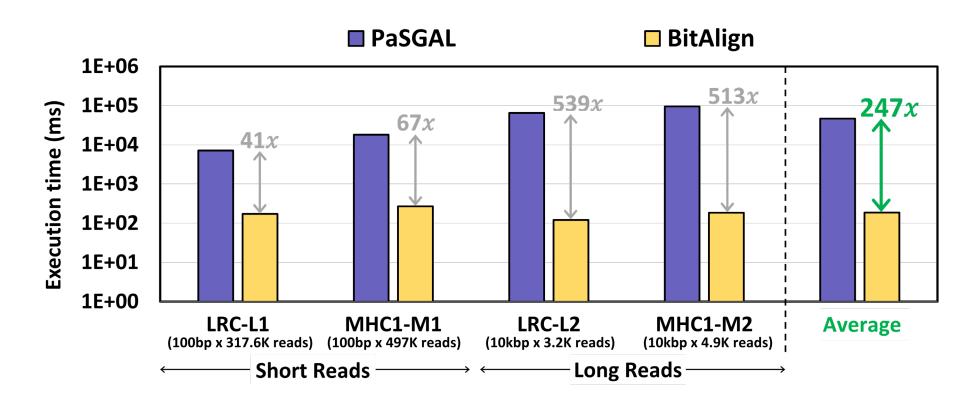
Key Results – SeGraM with Short Reads



SeGraM provides 106× and 742× throughput improvement over GraphAligner and vg, while reducing the power consumption by 3.0× and 3.2×



Key Results – BitAlign (S2G Alignment)



BitAlign provides 41×-539× speedup over PaSGAL



Conclusion

- □ **SeGraM**: First universal algorithm/hardware co-designed genomic mapping accelerator that supports:
 - Sequence-to-graph (S2G) & sequence-to-sequence (S2S) mapping
 - Short & long reads
 - MinSeed: First minimizer-based seeding accelerator
 - BitAlign: First (bitvector-based) S2G alignment accelerator
- SeGraM supports multiple use cases:
 - End-to-end S2G mapping
 - S2G alignment
 - S2S alignment
 - Seeding
- ☐ SeGraM outperforms state-of-the-art software & hardware solutions

Accelerating Sequence-to-Graph Mapping

Damla Senol Cali, Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie Kim, Nika MansouriGhiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu,
 "SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping"

Proceedings of the <u>49th International Symposium on Computer Architecture</u> (ISCA), New York, June 2022.

arXiv version

SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali¹ Konstantinos Kanellopoulos² Joël Lindegger² Zülal Bingöl³ Gurpreet S. Kalsi⁴ Ziyi Zuo⁵ Can Firtina² Meryem Banu Cavlak² Jeremie Kim² Nika Mansouri Ghiasi² Gagandeep Singh² Juan Gómez-Luna² Nour Almadhoun Alserr² Mohammed Alser² Sreenivas Subramoney⁴ Can Alkan³ Saugata Ghose⁶ Onur Mutlu²

¹Bionano Genomics ²ETH Zürich ³Bilkent University ⁴Intel Labs ⁵Carnegie Mellon University ⁶University of Illinois Urbana-Champaign

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Read Mapping & Filtering

- Problem: Heavily bottlenecked by Data Movement
- GateKeeper, Shouji, SneakySnake performance limited by DRAM bandwidth [Alser+, Bioinformatics 2017,2019,2020]
- Ditto for SHD [Xin+, Bioinformatics 2015]
- Solution: Processing-in-memory can alleviate the bottleneck
- We need to design mapping & filtering algorithms to fit processing-in-memory

Read Mapping & Filtering in Memory

We need to design mapping & filtering algorithms that fit processing-in-memory

Near-Memory Pre-Alignment Filtering

Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios Diamantopoulos, Juan Gomez-Luna, Henk Corporaal, Onur Mutlu,

"FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications"

IEEE Micro, 2021.

Source Code





Home / Magazines / IEEE Micro / 2021.04

IEEE Micro

FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications

July-Aug. 2021, pp. 39-48, vol. 41

DOI Bookmark: 10.1109/MM.2021.3088396

Authors

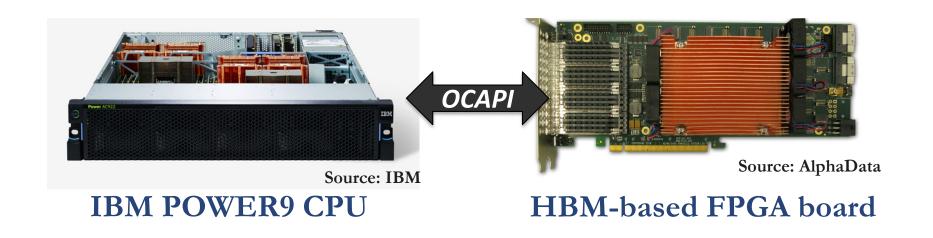
Gagandeep Singh, ETH Zürich, Zürich, Switzerland
Mohammed Alser, ETH Zürich, Zürich, Switzerland
Damla Senol Cali, Carnegie Mellon University, Pittsburgh, PA, USA
Dionysios Diamantopoulos, Zürich Lab, IBM Research Europe, Rüschlikon, Switzerland
Juan Gomez-Luna, ETH Zürich, Zürich, Switzerland
Henk Corporaal, Eindhoven University of Technology, Eindhoven, The Netherlands
Onur Mutlu, ETH Zürich, Zürich, Switzerland

Near-Memory SneakySnake

- Problem: Read mapping is heavily bottlenecked by data movement from main memory
- Solution: Perform read mapping near where data resides using specialized logic
- We carefully redesign the accelerator logic of SneakySnake to exploit near-memory computation capability on real FPGA boards that use HBM (high-bandwidth memory)
- Near-memory SneakySnake improves performance and energy efficiency by 27.4× and 133×, respectively, over a 16-core (64-thread) IBM POWER9 CPU



Near-Memory Acceleration using FPGAs



Near-HBM FPGA-based accelerator

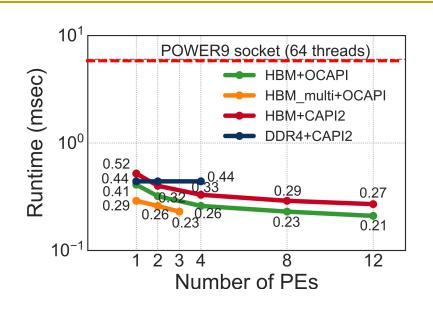
Two communication technologies: CAPI2 and OCAPI

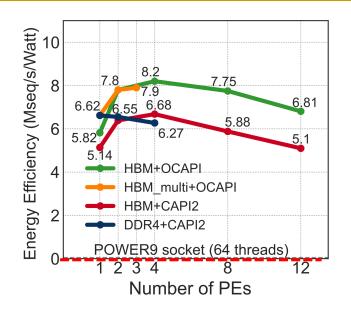
Two memory technologies: DDR4 and HBM

Two workloads: Weather Modeling and Genome Analysis



Performance & Energy Greatly Improve





5-27× performance vs. a 16-core (64-thread) IBM POWER9 CPU

12-133× energy efficiency vs. a 16-core (64-thread) IBM POWER9 CPU

HBM alleviates memory bandwidth contention vs. DDR4

More On Near-Memory SneakySnake

Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios Diamantopoulos, Juan Gomez-Luna, Henk Corporaal, Onur Mutlu,

"FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications"

IEEE Micro, 2021.

Source Code





Home / Magazines / IEEE Micro / 2021.04

IEEE Micro

FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications

July-Aug. 2021, pp. 39-48, vol. 41

DOI Bookmark: 10.1109/MM.2021.3088396

Authors

Gagandeep Singh, ETH Zürich, Zürich, Switzerland
Mohammed Alser, ETH Zürich, Zürich, Switzerland
Damla Senol Cali, Carnegie Mellon University, Pittsburgh, PA, USA
Dionysios Diamantopoulos, Zürich Lab, IBM Research Europe, Rüschlikon, Switzerland
Juan Gomez-Luna, ETH Zürich, Zürich, Switzerland
Henk Corporaal, Eindhoven University of Technology, Eindhoven, The Netherlands
Onur Mutlu, ETH Zürich, Zürich, Switzerland

Location Filtering in 3D-Stacked PIM

 Jeremie S. Kim, Damla Senol Cali, Hongyi Xin, Donghyuk Lee, Saugata Ghose, Mohammed Alser, Hasan Hassan, Oguz Ergin, Can Alkan, and Onur Mutlu,

"GRIM-Filter: Fast Seed Location Filtering in DNA Read Mapping Using Processing-in-Memory Technologies"

BMC Genomics, 2018.

Proceedings of the <u>16th Asia Pacific Bioinformatics Conference</u> (APBC), Yokohama, Japan, January 2018.

[Slides (pptx) (pdf)]

[Source Code]

[arxiv.org Version (pdf)]

Talk Video at AACBB 2019

Research | Open Access | Published: 09 May 2018

GRIM-Filter: Fast seed location filtering in DNA read mapping using processing-in-memory technologies

<u>Jeremie S. Kim</u> ⊆, <u>Damla Senol Cali</u>, <u>Hongyi Xin</u>, <u>Donghyuk Lee</u>, <u>Saugata Ghose</u>, <u>Mohammed Alser</u>, <u>Hasan Hassan</u>, <u>Oguz Ergin</u>, <u>Can Alkan</u> ⊆ & <u>Onur Mutlu</u> ⊆

BMC Genomics 19, Article number: 89 (2018) | Cite this article

4340 Accesses | 39 Citations | 9 Altmetric | Metrics

GRIM-Filter

- Key observation: FPGA and GPU accelerators are heavily bottlenecked by data movement
- Key idea: exploit the high memory bandwidth and the logic layer of 3Dstacked memory to perform highly-parallel filtering in the DRAM chip itself
- GRIM-Filter, an algorithm-hardware co-designed PIM system for pre-alignment filtering
- Key results:
 - GRIM-Filter is 1.8x-3.7x (2.1x on average) faster than the FastHASH filter (BMC Genomics'13) across real data sets
 - GRIM-Filter has 5.6x-6.4x (6.0x on average) lower false accept rate than the FastHASH filter (BMC Genomics'13) across real data sets

Our Proposal: GRIM-Filter

- 1. Data Structures: Bins & Bitvectors
- Checking a Bin
- 3. Integrating GRIM-Filter into a Mapper



GRIM-Filter: Bins

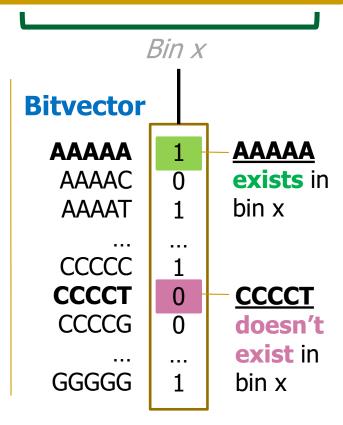
We partition the genome into large sequences (bins).

Bin x - 3

Bin x - 1

Bin x - 2

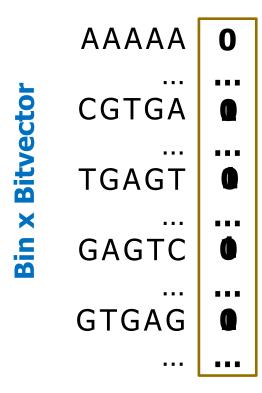
- Represent each bin with a bitvector that holds the occurrence of all permutations of a small string (token) in the bin
- To account for matches that straddle bins, we employ overlapping bins
 - A read will now always completely fall within a single bin



GRIM-Filter: Bitvectors



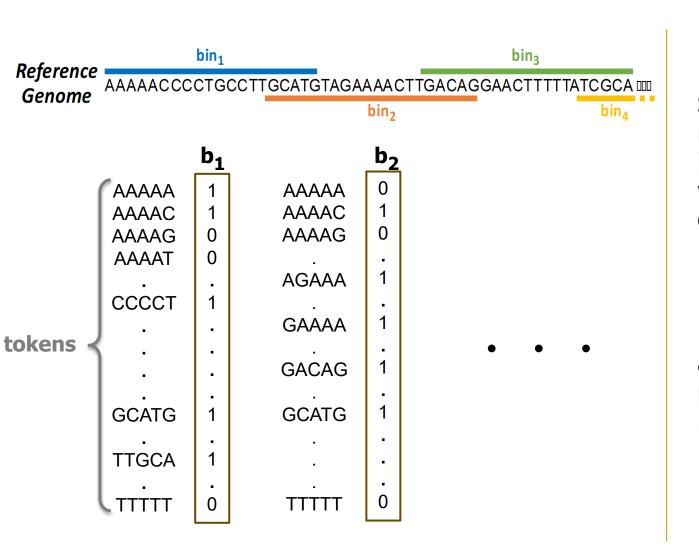
Bin x







GRIM-Filter: Bitvectors



Storing all bitvectors requires $4^n * t$ bits in memory, where t = number of bins.

For **bin size** ~200, and **n** = 5, **memory footprint** ~3.8 GB



Our Proposal: GRIM-Filter

1. Data Structures: Bins & Bitvectors

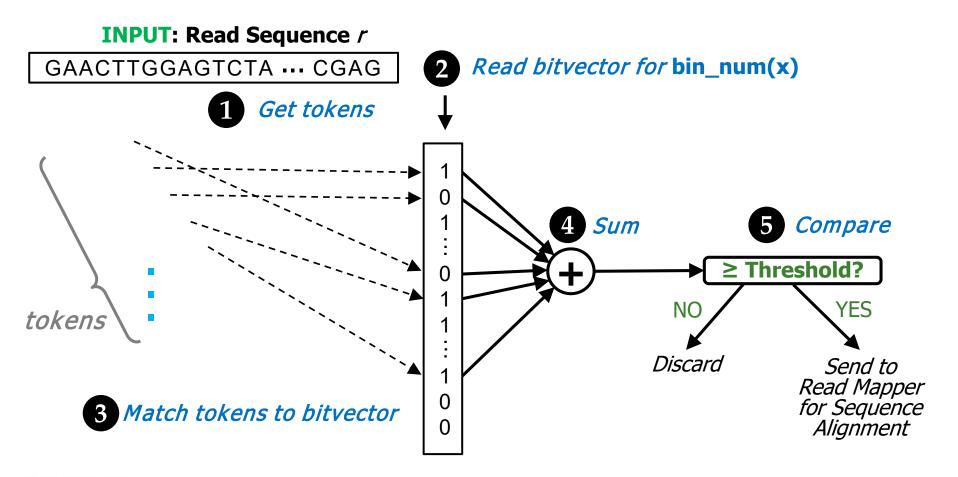
2. Checking a Bin

3. Integrating GRIM-Filter into a Mapper



GRIM-Filter: Checking a Bin

How GRIM-Filter determines whether to **discard** potential match locations in a given bin **prior** to alignment

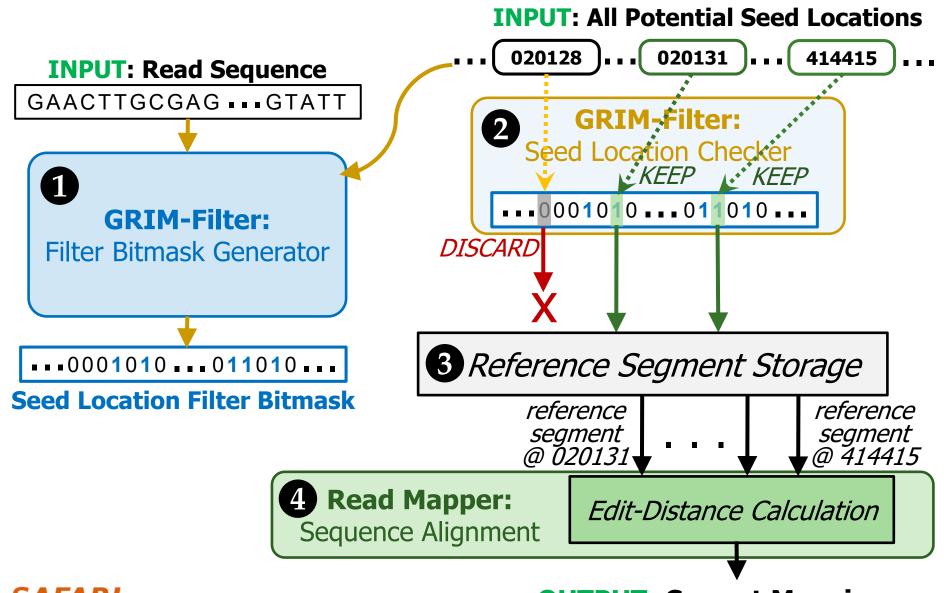




Our Proposal: GRIM-Filter

- 1. Data Structures: Bins & Bitvectors
- Checking a Bin
- 3. Integrating GRIM-Filter into a Mapper

Integrating GRIM-Filter into a Read Mapper



SAFARI

OUTPUT: Correct Mappings



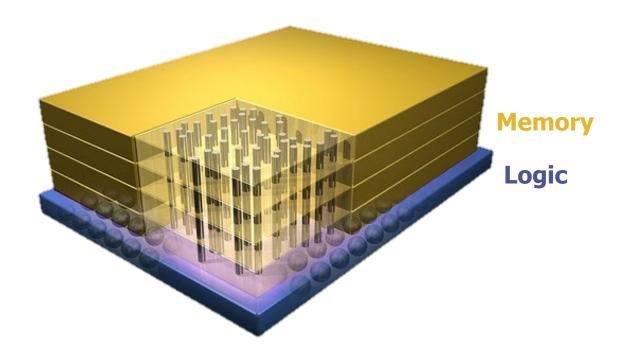
Key Properties of GRIM-Filter

1. Simple Operations:

- To check a given bin, find the sum of all bits corresponding to each token in the read
- Compare against threshold to determine whether to align
- 2. Highly Parallel: Each bin is operated on independently and there are many many bins
- 3. Memory Bound: Given the frequent accesses to the large bitvectors, we find that GRIM-Filter is memory bound

These properties together make GRIM-Filter a good algorithm to be run in 3D-Stacked DRAM

Opportunity: 3D-Stacked Logic+Memory



Other "True 3D" technologies under development

DRAM Landscape (circa 2015)

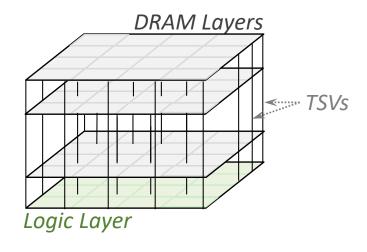
Segment	DRAM Standards & Architectures
Commodity	DDR3 (2007) [14]; DDR4 (2012) [18]
Low-Power	LPDDR3 (2012) [17]; LPDDR4 (2014) [20]
Graphics	GDDR5 (2009) [15]
Performance	eDRAM [28], [32]; RLDRAM3 (2011) [29]
3D-Stacked	WIO (2011) [16]; WIO2 (2014) [21]; MCDRAM (2015) [13]; HBM (2013) [19]; HMC1.0 (2013) [10]; HMC1.1 (2014) [11]
Academic	SBA/SSA (2010) [38]; Staged Reads (2012) [8]; RAIDR (2012) [27]; SALP (2012) [24]; TL-DRAM (2013) [26]; RowClone (2013) [37]; Half-DRAM (2014) [39]; Row-Buffer Decoupling (2014) [33]; SARP (2014) [6]; AL-DRAM (2015) [25]

Table 1. Landscape of DRAM-based memory

Kim+, "Ramulator: A Flexible and Extensible DRAM Simulator", IEEE CAL 2015.



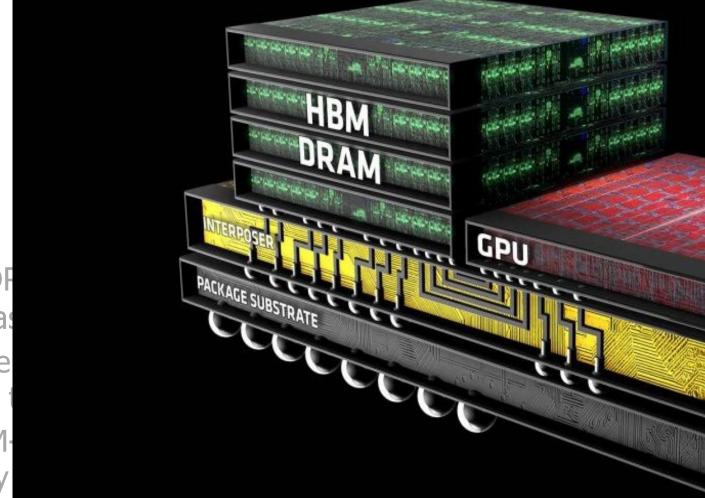
3D-Stacked Memory



- 3D-Stacked DRAM architecture has extremely high bandwidth as well as a stacked customizable logic layer
 - Logic Layer enables Processing-in-Memory, via highbandwidth low-latency access to DRAM layers
 - Embed GRIM-Filter operations into DRAM logic layer and appropriately distribute bitvectors throughout memory



3D-Stacked Memory



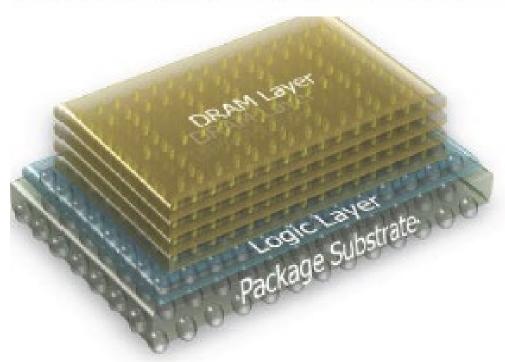
- 3D-Stacked DF bandwidth as
 - Logic Layer e computation t
 - Embed GRIMappropriately



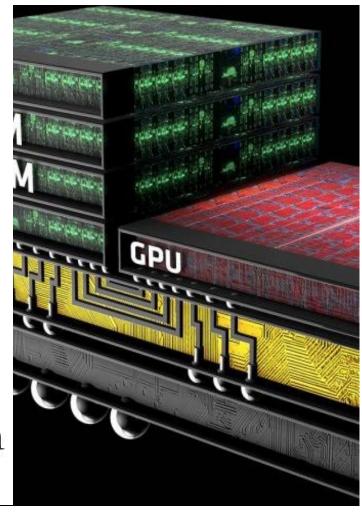


3D-Stacked Memory

Micron's HMC



Micron has working demonstration components

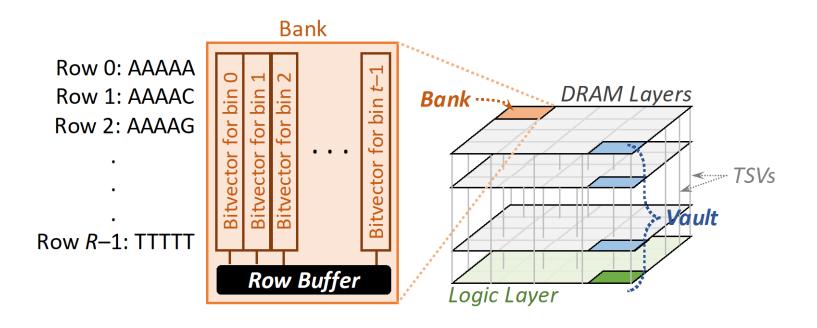


http://images.anandtech.com/doci/9266/HBMCar_678x452.jpg





GRIM-Filter in 3D-Stacked DRAM

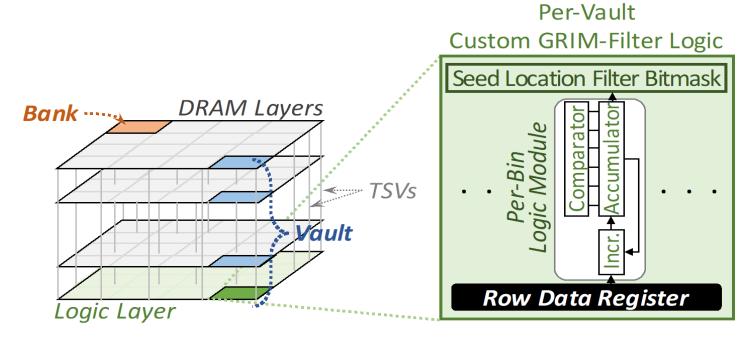


- Each DRAM layer is organized as an array of banks
 - □ A bank is an array of cells with a row buffer to transfer data
- The layout of bitvectors in a bank enables filtering many bins in parallel





GRIM-Filter in 3D-Stacked DRAM



- Customized logic for accumulation and comparison per genome segment
 - Low area overhead, simple implementation
 - For HBM2, we use 4096 incrementer LUTs, 7-bit counters, and comparators in logic layer



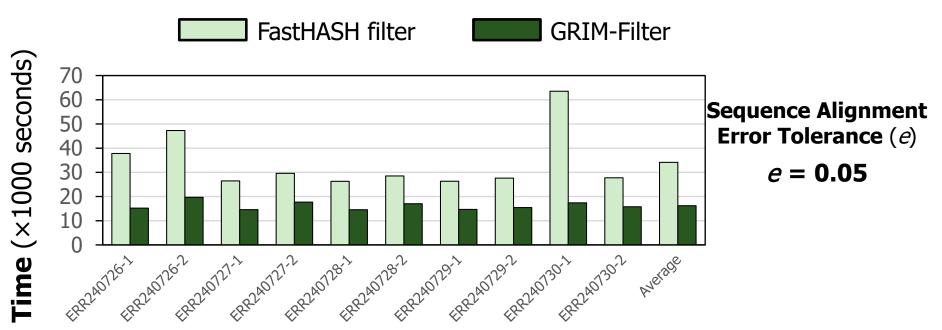
Methodology

- Performance simulated using an in-house 3D-Stacked DRAM simulator
- Evaluate 10 real read data sets (From the 1000 Genomes Project)
 - Each data set consists of 4 million reads of length 100
- Evaluate two key metrics
 - Performance
 - False negative rate
 - The fraction of locations that pass the filter but result in a mismatch
- Compare against a state-of-the-art filter, FastHASH [xin+, BMC Genomics 2013] when using mrFAST, but GRIM-Filter can be used with ANY read mapper



GRIM-Filter Performance

Benchmarks and their Execution Times



1.8x-3.7x performance benefit across real data sets
2.1x average performance benefit

GRIM-Filter gets performance due to its hardware-software co-design

GRIM-Filter False Negative Rate





5.6x-6.4x False Negative reduction across real data sets 6.0x average reduction in False Negative Rate

GRIM-Filter utilizes more information available in the read to filter

More on GRIM-Filter

 Jeremie S. Kim, Damla Senol Cali, Hongyi Xin, Donghyuk Lee, Saugata Ghose, Mohammed Alser, Hasan Hassan, Oguz Ergin, Can Alkan, and <u>Onur Mutlu</u>,

"GRIM-Filter: Fast Seed Location Filtering in DNA Read Mapping Using Processing-in-Memory Technologies"

BMC Genomics, 2018.

Proceedings of the <u>16th Asia Pacific Bioinformatics Conference</u> (APBC), Yokohama, Japan, January 2018.

[Slides (pptx) (pdf)]

[Source Code]

[arxiv.org Version (pdf)]

Talk Video at AACBB 2019

Research | Open Access | Published: 09 May 2018

GRIM-Filter: Fast seed location filtering in DNA read mapping using processing-in-memory technologies

<u>Jeremie S. Kim</u> ⊆, <u>Damla Senol Cali</u>, <u>Hongyi Xin</u>, <u>Donghyuk Lee</u>, <u>Saugata Ghose</u>, <u>Mohammed Alser</u>, <u>Hasan Hassan</u>, <u>Oguz Ergin</u>, <u>Can Alkan</u> ⊆ & <u>Onur Mutlu</u> ⊆

BMC Genomics 19, Article number: 89 (2018) | Cite this article

4340 Accesses | 39 Citations | 9 Altmetric | Metrics

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

In-Storage Genome Filtering [ASPLOS 2022]

Nika Mansouri Ghiasi, Jisung Park, Harun Mustafa, Jeremie Kim, Ataberk Olgun, Arvid Gollwitzer, Damla Senol Cali, Can Firtina, Haiyu Mao, Nour Almadhoun Alserr, Rachata Ausavarungnirun, Nandita Vijaykumar, Mohammed Alser, and Onur Mutlu, "GenStore: A High-Performance and Energy-Efficient In-Storage Computing System for Genome Sequence Analysis"

Proceedings of the <u>27th International Conference on Architectural Support for</u>
<u>Programming Languages and Operating Systems</u> (ASPLOS), Virtual, February-March 2022.

[<u>Lightning Talk Slides (pptx) (pdf)</u>]
[<u>Lightning Talk Video</u> (90 seconds)]

GenStore: A High-Performance In-Storage Processing System for Genome Sequence Analysis

Nika Mansouri Ghiasi¹ Jisung Park¹ Harun Mustafa¹ Jeremie Kim¹ Ataberk Olgun¹ Arvid Gollwitzer¹ Damla Senol Cali² Can Firtina¹ Haiyu Mao¹ Nour Almadhoun Alserr¹ Rachata Ausavarungnirun³ Nandita Vijaykumar⁴ Mohammed Alser¹ Onur Mutlu¹

¹ETH Zürich ²Bionano Genomics ³KMUTNB ⁴University of Toronto

Genome Sequence Analysis

Data Movement from Storage

Storage System Main Memory Cache

Computation
Unit
(CPU or
Accelerator)

Alignment



Computation overhead



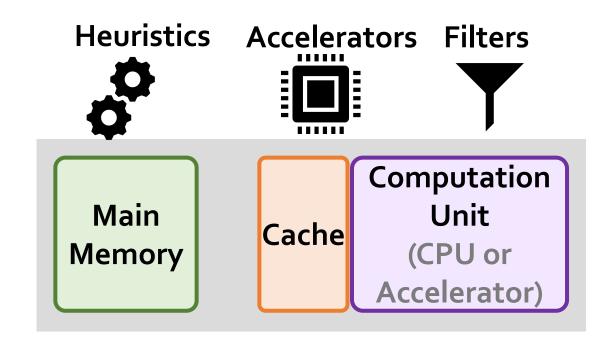
Data movement overhead





Accelerating Genome Sequence Analysis

Storage System





Computation overhead



Data movement overhead



Key Idea

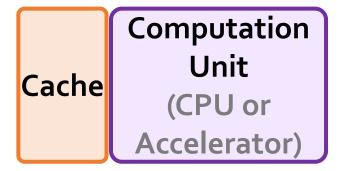


Filter reads that do not require alignment inside the storage system



Filtered Reads





Exactly-matching reads

Do not need expensive approximate string matching during alignment

Non-matching reads

Do not have potential matching locations and can skip alignment



Filtering Opportunities

- Sequencing machines produce one of two kinds of reads
 - Short reads: highly accurate and short
 - Long reads: less accurate and long

Reads that do not require the expensive alignment step:

Exactly-matching reads

Do not need expensive approximate string matching during alignment

- Low sequencing error rates (short reads) combined with
- Low genetic variation

Non-matching reads

Do not have potential matching locations, so they skip alignment

- High sequencing error rates (long reads) or
- High genetic variation (short or long reads)



Challenges



Filter reads that do not require alignment inside the storage system

Storage System

Filtered Reads

Main Memory Cache

Computation
Unit
(CPU or
Accelerator)

Read mapping workloads can exhibit different behavior

There are limited hardware resources in the storage system



GenStore



Filter reads that do not require alignment inside the storage system

GenStore-Enabled Storage System

Main Memory Cache

Computation
Unit
(CPU or
Accelerator)



Computation overhead



Data movement overhead

GenStore provides significant speedup (1.4x - 33.6x) and energy reduction (3.9x - 29.2x) at low cost

In-Storage Genome Filtering [ASPLOS 2022]

Nika Mansouri Ghiasi, Jisung Park, Harun Mustafa, Jeremie Kim, Ataberk Olgun, Arvid Gollwitzer, Damla Senol Cali, Can Firtina, Haiyu Mao, Nour Almadhoun Alserr, Rachata Ausavarungnirun, Nandita Vijaykumar, Mohammed Alser, and Onur Mutlu, "GenStore: A High-Performance and Energy-Efficient In-Storage Computing System for Genome Sequence Analysis"

Proceedings of the <u>27th International Conference on Architectural Support for</u>
<u>Programming Languages and Operating Systems</u> (ASPLOS), Virtual, February-March 2022.

[<u>Lightning Talk Slides (pptx) (pdf)</u>]
[<u>Lightning Talk Video</u> (90 seconds)]

GenStore: A High-Performance In-Storage Processing System for Genome Sequence Analysis

Nika Mansouri Ghiasi¹ Jisung Park¹ Harun Mustafa¹ Jeremie Kim¹ Ataberk Olgun¹ Arvid Gollwitzer¹ Damla Senol Cali² Can Firtina¹ Haiyu Mao¹ Nour Almadhoun Alserr¹ Rachata Ausavarungnirun³ Nandita Vijaykumar⁴ Mohammed Alser¹ Onur Mutlu¹

¹ETH Zürich ²Bionano Genomics ³KMUTNB ⁴University of Toronto

PIM Review and Open Problems

A Modern Primer on Processing in Memory

Onur Mutlu^{a,b}, Saugata Ghose^{b,c}, Juan Gómez-Luna^a, Rachata Ausavarungnirun^d

SAFARI Research Group

^aETH Zürich

^bCarnegie Mellon University

^cUniversity of Illinois at Urbana-Champaign

^dKing Mongkut's University of Technology North Bangkok

Onur Mutlu, Saugata Ghose, Juan Gomez-Luna, and Rachata Ausavarungnirun,

"A Modern Primer on Processing in Memory"

Invited Book Chapter in <u>Emerging Computing: From Devices to Systems - Looking Beyond Moore and Von Neumann</u>, Springer, to be published in 2021.

PIM Review and Open Problems (II)

A Workload and Programming Ease Driven Perspective of Processing-in-Memory

Saugata Ghose[†] Amirali Boroumand[†] Jeremie S. Kim[†]§ Juan Gómez-Luna[§] Onur Mutlu^{§†}

†Carnegie Mellon University §ETH Zürich

Saugata Ghose, Amirali Boroumand, Jeremie S. Kim, Juan Gomez-Luna, and Onur Mutlu, "Processing-in-Memory: A Workload-Driven Perspective"

Invited Article in <u>IBM Journal of Research & Development</u>, Special Issue on Hardware for Artificial Intelligence, to appear in November 2019.

[Preliminary arXiv version]

More on Processing-in-Memory

Onur Mutlu,

"Memory-Centric Computing Systems"

Invited Tutorial at <u>66th International Electron Devices</u>

Meeting (IEDM), Virtual, 12 December 2020.

[Slides (pptx) (pdf)]

[Executive Summary Slides (pptx) (pdf)]

[Tutorial Video (1 hour 51 minutes)]

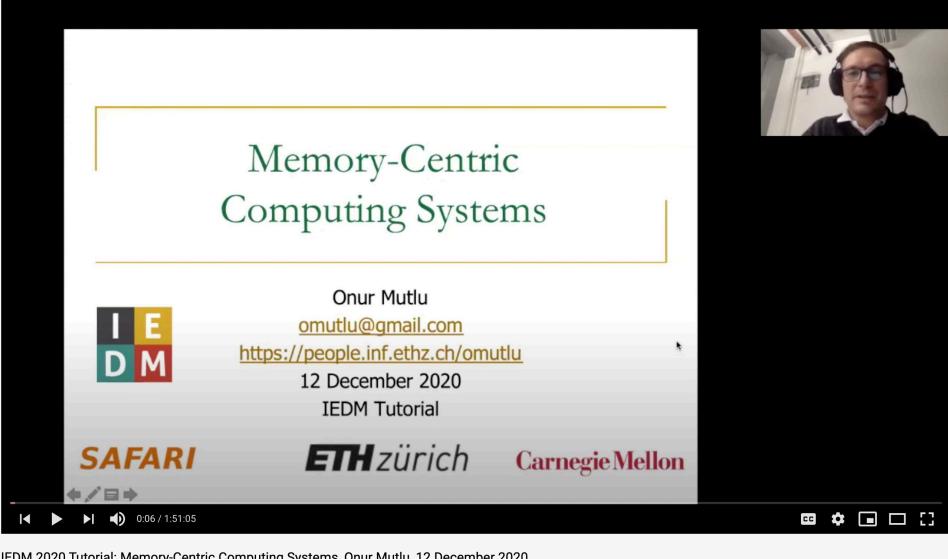
[Executive Summary Video (2 minutes)]

[Abstract and Bio]

[Related Keynote Paper from VLSI-DAT 2020]

[Related Review Paper on Processing in Memory]

https://www.youtube.com/watch?v=H3sEaINPBOE

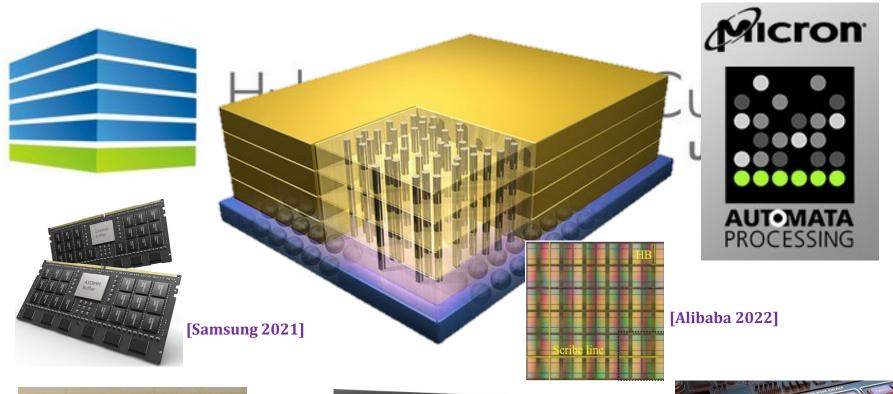


IEDM 2020 Tutorial: Memory-Centric Computing Systems, Onur Mutlu, 12 December 2020

1,641 views • Dec 23, 2020 SHARE



Processing-in-Memory Landscape Today









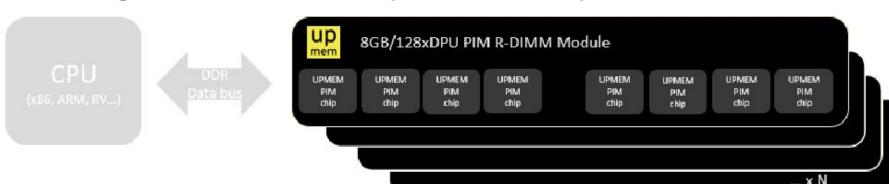
[Samsung 2021]



[UPMEM 2019]

UPMEM Processing-in-DRAM Engine (2019)

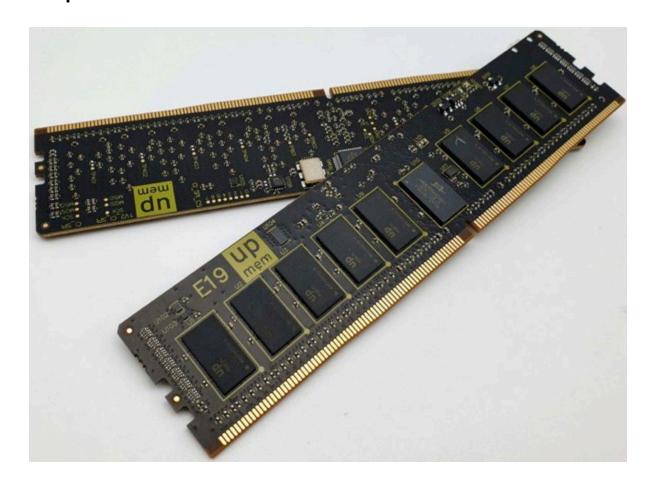
- Processing in DRAM Engine
- Includes standard DIMM modules, with a large number of DPU processors combined with DRAM chips.
- Replaces standard DIMMs
 - DDR4 R-DIMM modules
 - 8GB+128 DPUs (16 PIM chips)
 - Standard 2x-nm DRAM process
 - Large amounts of compute & memory bandwidth





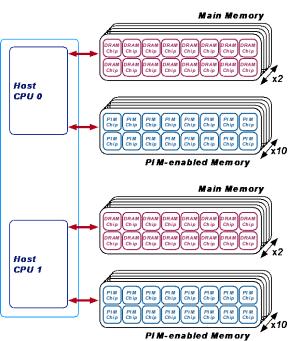
UPMEM Memory Modules

- E19: 8 chips DIMM (1 rank). DPUs @ 267 MHz
- P21: 16 chips DIMM (2 ranks). DPUs @ 350 MHz





2,560-DPU Processing-in-Memory System



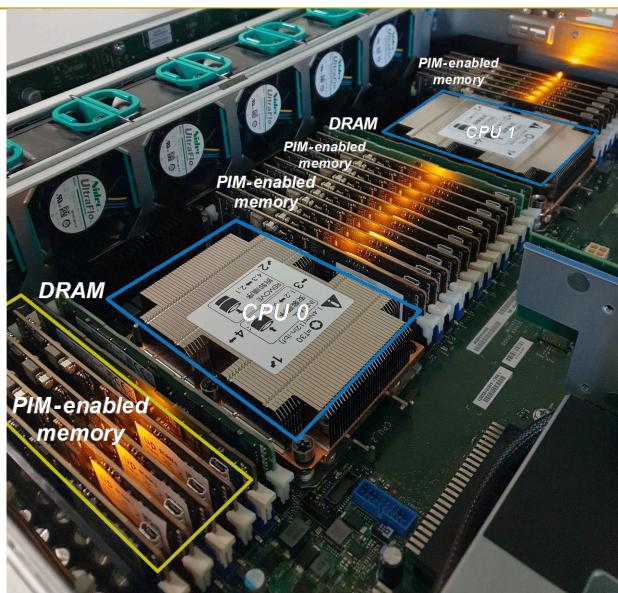
Benchmarking a New Paradigm: An Experimental Analysis of a Real Processing-in-Memory Architecture

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland
IZZAT EL HAJJ, American University of Beirut, Lebanon
IVAN FERNANDEZ, ETH Zürich, Switzerland and University of Malaga, Spain
CHRISTINA GIANNOULA, ETH Zürich, Switzerland and NTUA, Greece
GERALDO F. OLIVEIRA, ETH Zürich, Switzerland
ONUR MUTLU, ETH Zürich, Switzerland

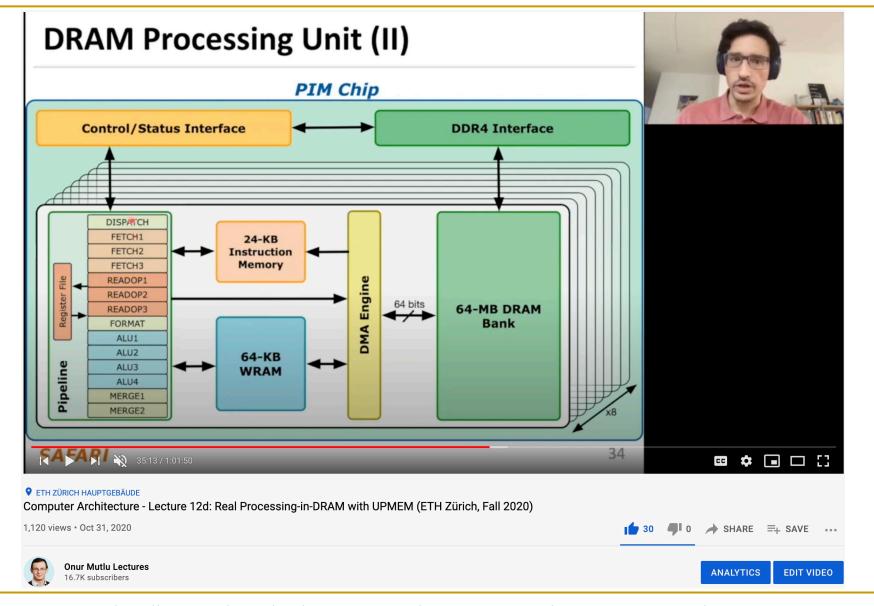
Many modern workloads, such as neural networks, databases, and graph processing, are fundamentally memory-bound. For such workloads, the data movement between main memory and CPU cores imposes a significant overhead in terms of both latency and energy. A major reason is that this communication happens through a narrow bus with high latency and limited bandwidth, and the low data reuse in memory-bound workloads is insufficient to amortize the cost of main memory access. Fundamentally addressing this data movement bottleneck requires a paradigm where the memory system assumes an active role in computing by integrating processing capabilities. This paradigm is known as processing—in-memory (PM).

Recent research explores different forms of PIM architectures, motivated by the emergence of new 3Dstacked memory technologies that integrate memory with a logic layer where processing elements can be easily placed. Past works evaluate these architectures in simulation or, at best, with simplified hardware prototypes. In contrast, the UPMEM Company has designed and manufactured the first publicly-available real-world PIM architecture. The UPMEM PIM architecture combines traditional DRAM memory arrays with general-purpose in-order cores, called DRAM Processing Units (DPUS), integrated in the same chip.

This paper provides the first comprehensive analysis of the first publicly-available real-world PIM architecture. We make two key contributions. First, we conduct an experimental characterization of the UPMEM-based PIM system using microbenchmarks to assess various architecture limits such as compute throughput and memory bandwidth, yielding new insights. Second, we present PIM (Processing,-in-length potential) as a benchmark suite of 16 workloads from different application domains (e.g., dense/sparse linear algebra, databases, data analytics, graph processing, which we identify as memory-bound. We evaluate the performance and scaling characteristics of PIM benchmarks on the UPMEM PIM architecture, and compare their performance and energy consumption to their state-of-the-art CPU and CPU counterparts. Our extensive evaluation conducted on two real UPMEM-based PIM systems with 460 and 25.50 DPUs provides new insights about suitability of different workloads to the PIM systems in the day of the programming recommendations for software designers, and suggestions and hints for hardware and architecture designers of thruse PIM systems.



More on the UPMEM PIM System



Experimental Analysis of the UPMEM PIM Engine

Benchmarking a New Paradigm: An Experimental Analysis of a Real Processing-in-Memory Architecture

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland IZZAT EL HAJJ, American University of Beirut, Lebanon IVAN FERNANDEZ, ETH Zürich, Switzerland and University of Malaga, Spain CHRISTINA GIANNOULA, ETH Zürich, Switzerland and NTUA, Greece GERALDO F. OLIVEIRA, ETH Zürich, Switzerland ONUR MUTLU, ETH Zürich, Switzerland

Many modern workloads, such as neural networks, databases, and graph processing, are fundamentally memory-bound. For such workloads, the data movement between main memory and CPU cores imposes a significant overhead in terms of both latency and energy. A major reason is that this communication happens through a narrow bus with high latency and limited bandwidth, and the low data reuse in memory-bound workloads is insufficient to amortize the cost of main memory access. Fundamentally addressing this *data movement bottleneck* requires a paradigm where the memory system assumes an active role in computing by integrating processing capabilities. This paradigm is known as *processing-in-memory (PIM)*.

Recent research explores different forms of PIM architectures, motivated by the emergence of new 3D-stacked memory technologies that integrate memory with a logic layer where processing elements can be easily placed. Past works evaluate these architectures in simulation or, at best, with simplified hardware prototypes. In contrast, the UPMEM company has designed and manufactured the first publicly-available real-world PIM architecture. The UPMEM PIM architecture combines traditional DRAM memory arrays with general-purpose in-order cores, called *DRAM Processing Units* (*DPUs*), integrated in the same chip.

This paper provides the first comprehensive analysis of the first publicly-available real-world PIM architecture. We make two key contributions. First, we conduct an experimental characterization of the UPMEM-based PIM system using microbenchmarks to assess various architecture limits such as compute throughput and memory bandwidth, yielding new insights. Second, we present *PrIM* (*Processing-In-Memory benchmarks*), a benchmark suite of 16 workloads from different application domains (e.g., dense/sparse linear algebra, databases, data analytics, graph processing, neural networks, bioinformatics, image processing), which we identify as memory-bound. We evaluate the performance and scaling characteristics of PrIM benchmarks on the UPMEM PIM architecture, and compare their performance and energy consumption to their state-of-the-art CPU and GPU counterparts. Our extensive evaluation conducted on two real UPMEM-based PIM systems with 640 and 2,556 DPUs provides new insights about suitability of different workloads to the PIM system, programming recommendations for software designers, and suggestions and hints for hardware and architecture designers of future PIM systems.

https://arxiv.org/pdf/2105.03814.pdf

Upcoming TECHCON Presentation

- Dr. Juan Gomez-Luna
 - Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-in-Memory Hardware
 - Based on two major works
 - https://arxiv.org/pdf/2105.03814.pdf
 - https://arxiv.org/pdf/2207.07886.pdf

Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-In-

Memory Hardware

Year: 2021, Pages: 1-7

DOI Bookmark: 10.1109/IGSC54211.2021.9651614

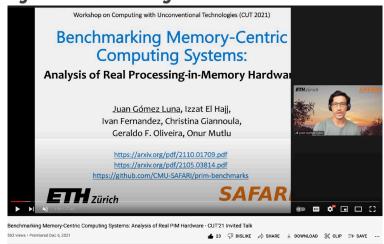
Authors

Juan Gómez-Luna, ETH Zürich
Izzat El Hajj, American University of Beirut
Ivan Fernandez, University of Malaga
Christina Giannoula, National Technical University

Christina Giannoula, National Technical University of Athens

Geraldo F. Oliveira, ETH Zürich

Onur Mutlu, ETH Zürich





UPMEM PIM System Summary & Analysis

Juan Gomez-Luna, Izzat El Hajj, Ivan Fernandez, Christina Giannoula, Geraldo F. Oliveira, and Onur Mutlu,

"Benchmarking Memory-Centric Computing Systems: Analysis of Real **Processing-in-Memory Hardware**"

Invited Paper at Workshop on Computing with Unconventional

Technologies (CUT), Virtual, October 2021.

[arXiv version]

[PrIM Benchmarks Source Code]

[Slides (pptx) (pdf)]

[Talk Video (37 minutes)]

[<u>Lightning Talk Video</u> (3 minutes)]

Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-in-Memory Hardware

Juan Gómez-Luna ETH Zürich

Izzat El Haji American University of Beirut

University of Malaga

National Technical University of Athens

Ivan Fernandez Christina Giannoula Geraldo F. Oliveira Onur Mutlu ETH Zürich

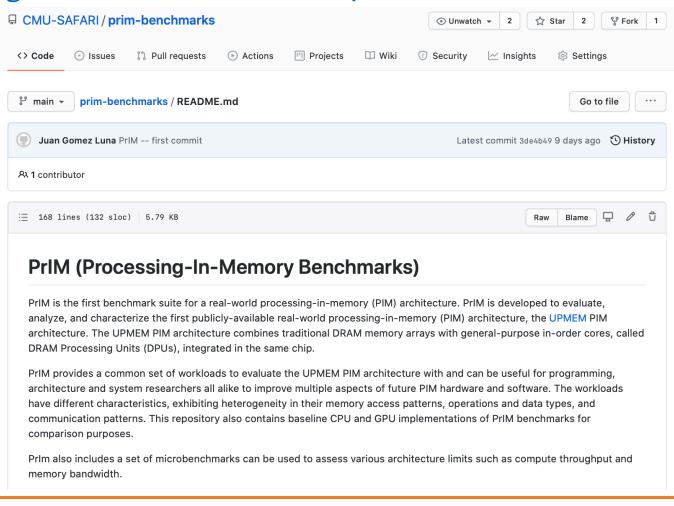
ETH Zürich

PrIM Benchmarks: Application Domains

Domain	Benchmark	Short name
Dense linear algebra	Vector Addition	VA
	Matrix-Vector Multiply	GEMV
Sparse linear algebra	Sparse Matrix-Vector Multiply	SpMV
Databases	Select	SEL
	Unique	UNI
Data analytics	Binary Search	BS
	Time Series Analysis	TS
Graph processing	Breadth-First Search	BFS
Neural networks	Multilayer Perceptron	MLP
Bioinformatics	Needleman-Wunsch	NW
Image processing	Image histogram (short)	HST-S
	Image histogram (large)	HST-L
Parallel primitives	Reduction	RED
	Prefix sum (scan-scan-add)	SCAN-SSA
	Prefix sum (reduce-scan-scan)	SCAN-RSS
	Matrix transposition	TRNS

PrIM Benchmarks are Open Source

- All microbenchmarks, benchmarks, and scripts
- https://github.com/CMU-SAFARI/prim-benchmarks



Understanding a Modern PIM Architecture

Benchmarking a New Paradigm: Experimental Analysis and Characterization of a Real Processing-in-Memory System

JUAN GÓMEZ-LUNA¹, IZZAT EL HAJJ², IVAN FERNANDEZ^{1,3}, CHRISTINA GIANNOULA^{1,4}, GERALDO F. OLIVEIRA¹, AND ONUR MUTLU¹

Corresponding author: Juan Gómez-Luna (e-mail: juang@ethz.ch).

https://arxiv.org/pdf/2105.03814.pdf
https://github.com/CMU-SAFARI/prim-benchmarks

¹ETH Zürich

²American University of Beirut

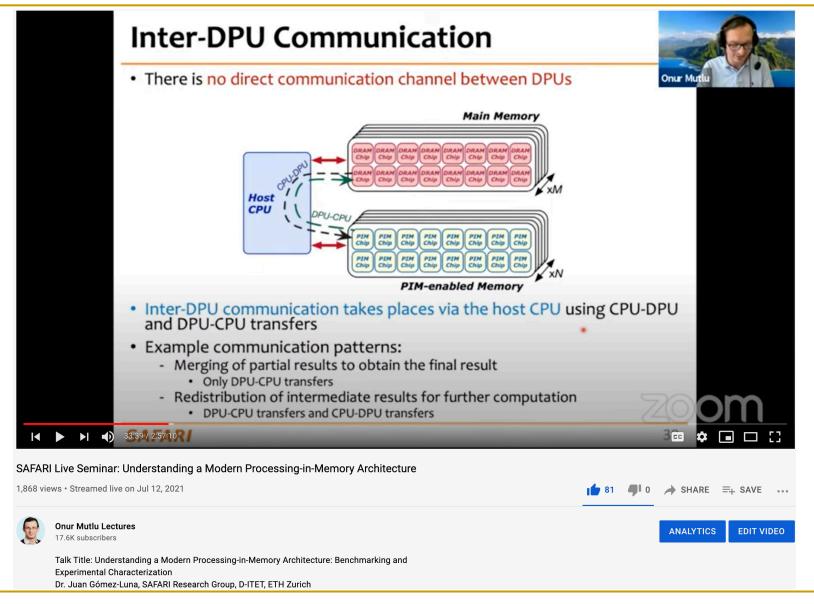
³University of Malaga

⁴National Technical University of Athens

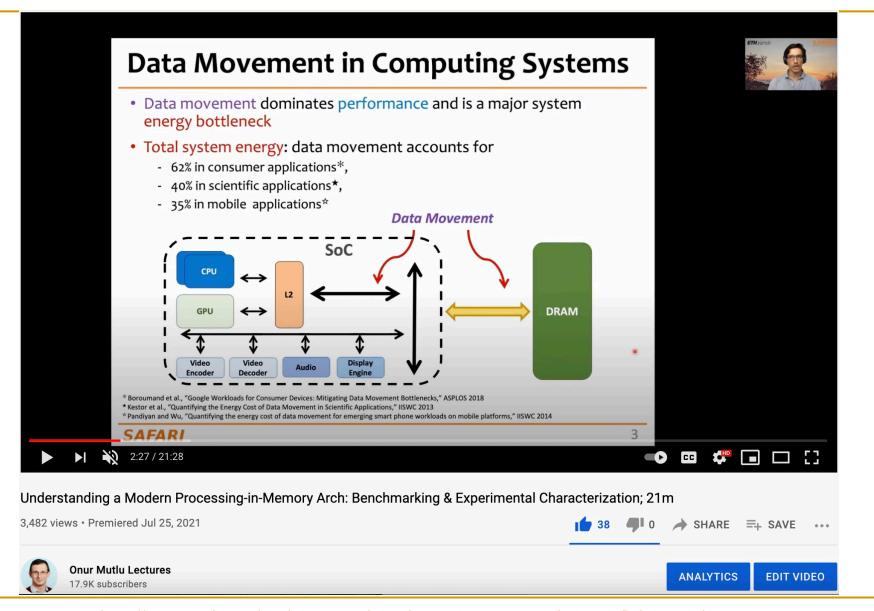
Understanding a Modern PIM Architecture



More on Analysis of the UPMEM PIM Engine



More on Analysis of the UPMEM PIM Engine



More on PRIM Benchmarks

Juan Gomez-Luna, Izzat El Hajj, Ivan Fernandez, Christina Giannoula, Geraldo F. Oliveira, and Onur Mutlu, "Benchmarking a New Paradigm: An Experimental **Analysis of a Real Processing-in-Memory Architecture**" Preprint in <u>arXiv</u>, 9 May 2021. [arXiv preprint] [PrIM Benchmarks Source Code] [Slides (pptx) (pdf)] [Long Talk Slides (pptx) (pdf)] [Short Talk Slides (pptx) (pdf)] [SAFARI Live Seminar Slides (pptx) (pdf)] [SAFARI Live Seminar Video (2 hrs 57 mins)] [Lightning Talk Video (3 minutes)]

UPMEM PIM System Summary & Analysis

Juan Gomez-Luna, Izzat El Hajj, Ivan Fernandez, Christina Giannoula, Geraldo F. Oliveira, and Onur Mutlu,

"Benchmarking Memory-Centric Computing Systems: Analysis of Real **Processing-in-Memory Hardware**"

Invited Paper at Workshop on Computing with Unconventional

Technologies (CUT), Virtual, October 2021.

[arXiv version]

[PrIM Benchmarks Source Code]

[Slides (pptx) (pdf)]

[Talk Video (37 minutes)]

[<u>Lightning Talk Video</u> (3 minutes)]

Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-in-Memory Hardware

Juan Gómez-Luna ETH Zürich

Izzat El Haji American University of Beirut

University of Malaga

National Technical University of Athens

Ivan Fernandez Christina Giannoula Geraldo F. Oliveira Onur Mutlu ETH Zürich

ETH Zürich

ML Training on a Real PIM System

Machine Learning Training on a Real Processing-in-Memory System

Juan Gómez-Luna¹ Yuxin Guo¹ Sylvan Brocard² Julien Legriel² Remy Cimadomo² Geraldo F. Oliveira¹ Gagandeep Singh¹ Onur Mutlu¹

¹ETH Zürich ²UPMEM

An Experimental Evaluation of Machine Learning Training on a Real Processing-in-Memory System

Juan Gómez-Luna¹ Yuxin Guo¹ Sylvan Brocard² Julien Legriel² Remy Cimadomo² Geraldo F. Oliveira¹ Gagandeep Singh¹ Onur Mutlu¹

¹ETH Zürich ²UPMEM

Short version: https://arxiv.org/pdf/2206.06022.pdf

Long version: https://arxiv.org/pdf/2207.07886.pdf

https://www.youtube.com/watch?v=qeukNs5XI3g&t=11226s

AIM (PIM Sequence Alignment Framework)

Safaa Diab, Amir Nassereldine, Mohammed Alser, Juan Gómez-Luna, Onur Mutlu, Izzat El Hajj

"A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems"

arXiv, 2022

Source code

A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems

Safaa Diab¹, Amir Nassereldine¹, Mohammed Alser², Juan Gómez Luna², Onur Mutlu², Izzat El Hajj¹

 1 American University of Beirut, Lebanon 2 ETH Zürich, Switzerland

Connecting Basecalling and Read Mapping in PIM

 Haiyu Mao, Mohammed Alser, Mohammad Sadrosadati, Can Firtina, Akanksha Baranwal, Damla Senol Cali, Aditya Manglik, Nour Almadhoun Alserr, and Onur Mutlu,

"GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping"

Proceedings of the <u>55th International Symposium on Microarchitecture</u> (MICRO), Chicago, Illinois, October 2022.

GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping

Haiyu Mao¹ Mohammed Alser¹ Mohammad Sadrosadati¹ Can Firtina¹ Akanksha Baranwal¹ Damla Senol Cali² Aditya Manglik¹ Nour Almadhoun Alserr¹ Onur Mutlu¹

IETH Zürich* ** **Pionano Genomics***

Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Newer Genome Sequencing Technologies

Nanopore sequencing technology and tools for genome assembly: computational analysis of the current state, bottlenecks and future directions

Damla Senol Cali ™, Jeremie S Kim, Saugata Ghose, Can Alkan, Onur Mutlu

Briefings in Bioinformatics, bby017, https://doi.org/10.1093/bib/bby017

Published: 02 April 2018 Article history ▼



Oxford Nanopore MinION

Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome

Assembly: Computational Analysis of the Current State, Bottlenecks

and Future Directions," Briefings in Bioinformatics, 2018.

[Open arxiv.org version] [Slides (pptx) (pdf)] [Talk Video at AACBB 2019]

New Applications: Graph Genomes

Damla Senol Cali, Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie Kim, Nika MansouriGhiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu,
 "SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping"

Proceedings of the <u>49th International Symposium on Computer Architecture</u> (ISCA), New York, June 2022.

arXiv version

SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali¹ Konstantinos Kanellopoulos² Joël Lindegger² Zülal Bingöl³ Gurpreet S. Kalsi⁴ Ziyi Zuo⁵ Can Firtina² Meryem Banu Cavlak² Jeremie Kim² Nika Mansouri Ghiasi² Gagandeep Singh² Juan Gómez-Luna² Nour Almadhoun Alserr² Mohammed Alser² Sreenivas Subramoney⁴ Can Alkan³ Saugata Ghose⁶ Onur Mutlu²

¹Bionano Genomics ²ETH Zürich ³Bilkent University ⁴Intel Labs ⁵Carnegie Mellon University ⁶University of Illinois Urbana-Champaign

New Applications: Ref Genome Updates

RESEARCH

AirLift: A Fast and Comprehensive Technique for Remapping Alignments between Reference Genomes

Jeremie S. Kim¹, Can Firtina¹, Meryem Banu Cavlak², Damla Senol Cali³, Nastaran Hajinazar^{1,4}, Mohammed Alser¹, Can Alkan² and Onur Mutlu^{1,2,3*}

https://people.inf.ethz.ch/omutlu/pub/AirLift genome-remapper arxiv21.pdf

Remapping Reads Between References

 Jeremie S. Kim, Can Firtina, Meryem Banu Cavlak, Damla Senol Cali, Nastaran Hajinazar, Mohammed Alser, Can Alkan, and Onur Mutlu,
 "AirLift: A Fast and Comprehensive Technique for Remapping

Preprint in arXiv and bioRxiv, 2021.

Alignments between Reference Genomes"

[bioRxiv preprint]

arXiv preprint

[AirLift Source Code and Data]

METHOD

AirLift: A Fast and Comprehensive Technique for Remapping Alignments between Reference Genomes

Jeremie S. $Kim^{1\dagger}$, Can Firtina^{1†}, Meryem Banu Cavlak², Damla Senol Cali³, Nastaran Hajinazar^{1,4}, Mohammed Alser¹, Can Alkan² and Onur Mutlu^{1,2,3*}

256

Mapping Constant Regions Between References

Jeremie S. Kim, Can Firtina, Meryem Banu Cavlak, Damla Senol Cali, Can Alkan, and Onur Mutlu,

"FastRemap: A Tool for Quickly Remapping Reads between Genome **Assemblies**"

Bioinformatics, btac554.

[FastRemap Source Code]

FastRemap: A Tool for Quickly Remapping Reads between Genome Assemblies

Jeremie S. Kim¹

Can Firtina¹ Meryem Banu Cavlak¹

Damla Senol Cali^{2,3}

Can Alkan⁴ Onur Mutlu^{1,2,4}

¹ETH Zürich

²Carnegie Mellon University ³Bionano Genomics

⁴Bilkent University

Newer Genome Sequencing Technologies

Nanopore sequencing technology and tools for genome assembly: computational analysis of the current state, bottlenecks and future directions

Damla Senol Cali ™, Jeremie S Kim, Saugata Ghose, Can Alkan, Onur Mutlu

Briefings in Bioinformatics, bby017, https://doi.org/10.1093/bib/bby017

Published: 02 April 2018 Article history ▼



Oxford Nanopore MinION

Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly: Computational Analysis of the Current State, Bottlenecks and Future Directions," Briefings in Bioinformatics, 2018.

[Open arxiv.org version] [Slides (pptx) (pdf)] [Talk Video at AACBB 2019]

Recall: High-Throughput Sequencing

- Massively parallel sequencing technology
 - Illumina, Roche 454, Ion Torrent, SOLID...
- Small DNA fragments are first amplified and then sequenced in parallel, leading to
 - High throughput
 - High speed
 - Low cost
 - Short reads
 - Amplification step limits the read length since too short or too long fragments are not amplified well.
- Sequencing is done by either reading optical signals as each base is added, or by detecting hydrogen ions instead of light, leading to:
 - Low error rates (relatively)
 - Reads lack information about their order and which part of genome they are originated from



Nanopore Sequencing Technology

 Nanopore sequencing is an emerging and a promising single-molecule DNA sequencing technology

- First nanopore sequencing device, MinION, made commercially available by Oxford Nanopore
 Technologies (ONT) in May 2014.
 - Inexpensive
 - Long read length (> 882K bp)
 - Portable: Pocket-sized
 - Produces data in real-time



Nanopore Sequencing Technology



an emerging and a promising ncing technology

read length → Longer read length

- First nanopore sequencing device, MinION, made commercially available by Oxford Nanopore Technologies (ONT) in May 2014.
 - Inexpensive
 - Long read length (> 882K bp)
 - Portable: Pocket-sized
 - Produces data in real-time



Oxford Nanopore Sequencers NANOPOR











MinION Mk1B

MinION Mk1C

GridION Mk1

PromethION 24/48

	MinION Mk1B	MinION Mk1C	GridION Mk1 PromethION 24		PromethION 48	
Read length	> 2Mb	> 2Mb	> 2Mb	> 2Mb	> 2Mb	
Yield per flow cell	50 Gb	50 Gb	50 Gb	6b 220 Gb 220 Gb		
Number of flow cells per device	1	1	5	24	48	
Yield per device	<50 Gb	<50 Gb	<250 Gb	<5.2 Tb	<10.5 Tb	
Starting price	\$1,000	\$4,990	\$49,995	\$195,455	\$327,455	

Illumina Sequencers



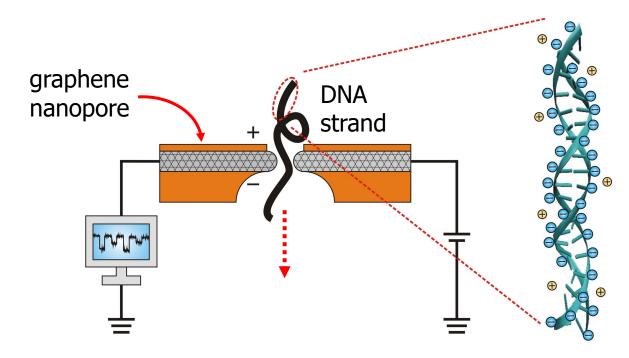


Run time	9.5–19 hrs	4–24 hrs	4–55 hrs	12–30 hrs	24-48 hrs	13-44 hrs
Max. reads per run	4 million	25 million	25 million	400 million	1 billion	20 billion
Max. read length	2 × 150 bp	2 × 150 bp	2 × 300 bp	2 × 150 bp	2 × 150 bp	2 x 250
Max. output	1.2 Gb	7.5 Gb	15 Gb	120 Gb	300 Gb	6000 Gb
Estimated price	\$19,900	\$49,500	\$128,000	\$275,000	\$335,000	\$985,000

<u>.mı</u>

263

How Does Nanopore Sequencing Work?



- Nanopore is a nano-scale hole (<20nm).</p>
- In nanopore sequencers, an ionic current passes through the nanopores
- When the DNA strand passes through the nanopore, the sequencer measures the the change in current
- This change is used to identify the bases in the strand with the help of different electrochemical structures of the different bases

Advantages of Nanopore Sequencing

Nanopores:

- Do not require any labeling of the DNA or nucleotide for detection during sequencing
- Rely on the electronic or chemical structure of the different nucleotides for identification
- Allow sequencing very long reads, and
- Provide portability, low cost, and high throughput.

Challenges of Nanopore Sequencing

- One major drawback: high error rates
- Nanopore sequence analysis tools have a critical role to:
 - overcome high error rates
 - take better advantage of the technology
- Faster tools are critically needed to:
 - Take better advantage of the real-time data production capability of nanopore sequencing
 - Enable fast, real-time data analysis

Nanopore Genome Assembly Pipeline

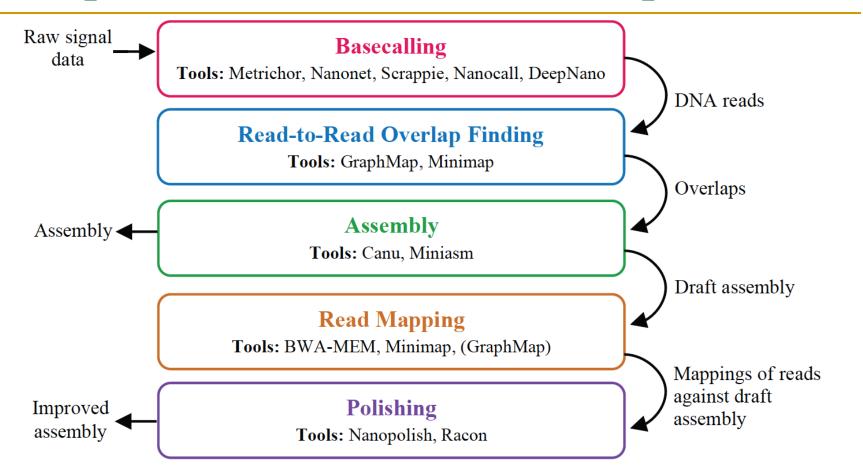


Figure 1. The analyzed genome assembly pipeline using nanopore sequence data, with its five steps and the associated tools for each

step.

Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly" Briefings in Bioinformatics, 2018.

Nanopore Genome Assembly Tools (I)

Table 12. Accuracy analysis results for the full pipeline with a focus on the last two steps.

									Number of	Number of	Identity	Coverage	Number of	Number of
									Bases	Contigs	(%)	(%)	Mismatches	Indels
1	Metrichor	+	_	+	Canu +	BWA-MEM	+	Nanopolish	4,683,072	1	99.48	99.93	8,198	15,581
2	Metrichor	+	Minimap	+	Miniasm+	BWA-MEM	+	Nanopolish	4,540,352	1	92.33	96.31	162,884	182,965
3	Metrichor	+	GraphMaj	p +	Miniasm+	BWA-MEM	+	Nanopolish	4,637,916	2	92.38	95.80	159,206	180,603
4	Metrichor	+	_	+	Canu +	BWA-MEM	+	Racon	4,650,502	1	98.46	100.00	18,036	51,842
5	Metrichor	+	_	+	Canu +	Minimap	+	Racon	4,648,710	1	98.45	100.00	17,906	52,168
6	Metrichor	+	Minimap	+	Miniasm+	BWA-MEM	+	Racon	4,598,267	1	97.70	99.91	24,014	82,906
7	Metrichor	+	Minimap	+	Miniasm+	Minimap	+	Racon	4,600,109	1	97.78	100.00	23,339	79,721
8	Nanonet	+	_	+	Canu +	BWA-MEM	+	Racon	4,622,285	1	98.48	100.00	16,872	52,509
9	Nanonet	+	_	+	Canu +	Minimap	+	Racon	4,620,597	1	98.49	100.00	16,874	52,232
10	Nanonet	+	Minimap	+	Miniasm+	BWA-MEM	+	Racon	4,593,402	1	98.01	99.97	20,322	72,284
11	Nanonet	+	Minimap	+	Miniasm+	Minimap	+	Racon	4,592,907	1	98.04	100.00	20,170	70,705
12	Scrappie	+	_	+	Canu +	BWA-MEM	+	Racon	4,673,871	1	98.40	99.98	13,583	60,612
13	Scrappie	+	_	+	Canu +	Minimap	+	Racon	4,673,606	1	98.40	99.98	13,798	60,423
14	Scrappie	+	Minimap	+	Miniasm+	BWA-MEM	+	Racon	5,157,041	8	97.87	99.80	18,085	78,492
15	Scrappie	+	Minimap	+	Miniasm+	Minimap	+	Racon	5,156,375	8	97.87	99.94	17,922	77,807
16	Nanocall	+	_	+	Canu +	BWA-MEM	+	Racon	1,383,851	86	93.49	28.82	19,057	65,244
17	Nanocall	+	_	+	Canu +	Minimap	+	Racon	1,367,834	86	94.43	28.74	15,610	55,275
18	Nanocall	+	Minimap	+	Miniasm+	BWA-MEM	+	Racon	4,707,961	5	90.75	97.11	91,502	347,005
19	Nanocall	+	Minimap	+	Miniasm+	Minimap	+	Racon	4,673,069	5	92.23	97.10	72,646	291,918
20	DeepNano	+	_	+	Canu +	BWA-MEM	+	Racon	7,429,290	106	96.46	99.24	27,811	102,682
21	DeepNano	+	_	+	Canu +	Minimap	+	Racon	7,404,454	106	96.03	99.21	34,023	110,640
22	DeepNano	+	Minimap	+	Miniasm+	BWA-MEM	+	Racon	4,566,253	1	96.76	99.86	25,791	125,386
23	DeepNano	+	Minimap	+	Miniasm+	Minimap	+	Racon	4,571,810	1	96.90	99.97	24,994	119,519

Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly" Briefings in Bioinformatics, 2018.

Nanopore Genome Assembly Tools (II)

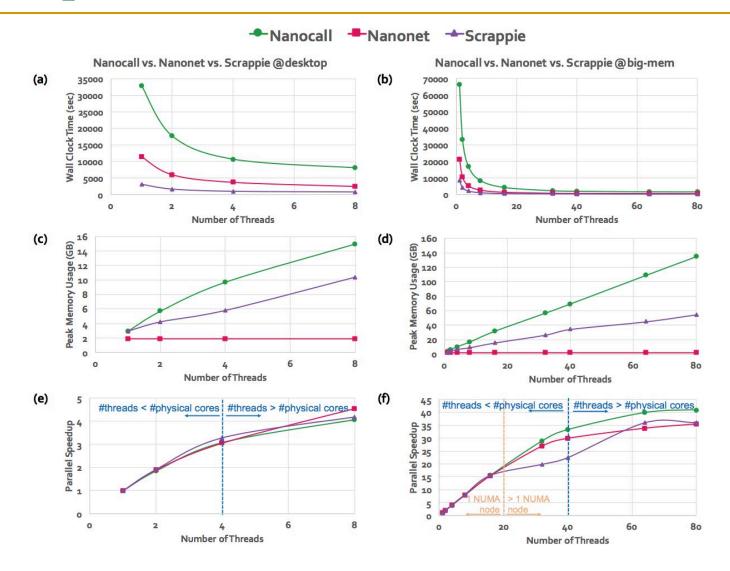
Table 13. Performance analysis results for the full pipeline with a focus on the last two steps.

-									Step 4: Read Mapper			Step 5: Polisher			
									Wall Clock Time (h:m:s)	CPU Time (h:m:s)	Memory Usage (GB)	Wall Clock Time (h:m:s)	CPU Time (h:m:s)	Memory Usage (GB)	
1	Metrichor	+	_	+	Canu +	BWA-MEM	+	Nanopolish	24:43	15:47:21	5.26	5:51:00	191:18:52	13.38	
2	Metrichor	+	Minimap	+	Miniasm +	BWA-MEM	+	Nanopolish	12:33	7:50:54	3.75	122:52:00	4458:36:10	31.36	
3	Metrichor	+	GraphMap	+	Miniasm +	BWA-MEM	+	Nanopolish	12:47	7:57:58	3.60	129:46:00	4799:03:51	31.31	
4	Metrichor	+	_	+	Canu +	BWA-MEM	+	Racon	24:20	15:43:40	6.60	14:44	9:09:22	8.11	
5	Metrichor	+	_	+	Canu +	Minimap	+	Racon	3	1:35	0.26	15:12	9:45:33	14.55	
6	Metrichor	+	Minimap	+	Miniasm +	BWA-MEM	+	Racon	12:10	7:48:10	5.19	15:43	9:33:39	9.98	
7	Metrichor	+	Minimap	+	Miniasm +	Minimap	+	Racon	3	1:24	0.26	20:28	8:57:40	18.24	
8	Nanonet	+	_	+	Canu +	BWA-MEM	+	Racon	9:08	5:53:18	4.84	6:33	4:02:10	4.47	
9	Nanonet	+	_	+	Canu +	Minimap	+	Racon	2	54	0.26	6:45	4:17:26	7.93	
10	Nanonet	+	Minimap	+	Miniasm +	BWA-MEM	+	Racon	4:40	2:58:02	3.88	7:08	4:19:30	5.35	
11	Nanonet	+	Minimap	+	Miniasm +	Minimap	+	Racon	2	46	0.26	7:01	4:18:48	9.53	
12	Scrappie	+	_	+	Canu +	BWA-MEM	+	Racon	33:41	21:11:06	8.66	13:32	8:24:44	7.58	
13	Scrappie	+	_	+	Canu +	Minimap	+	Racon	3	1:39	0.27	18:45	7:43:17	13.20	
14	Scrappie	+	Minimap	+	Miniasm +	BWA-MEM	+	Racon	22:41	14:31:00	6.08	14:37	8:53:59	9.50	
15	Scrappie	+	Minimap	+	Miniasm +	Minimap	+	Racon	3	1:27	0.27	15:10	9:02:45	12.72	
16	Nanocall	+	_	+	Canu +	BWA-MEM	+	Racon	4:52	3:01:15	3.80	11:07	3:26:52	5.63	
17	Nanocall	+	_	+	Canu +	Minimap	+	Racon	3	1:16	0.22	7:28	2:50:35	3.62	
18	Nanocall	+	Minimap	+	Miniasm +	BWA-MEM	+	Racon	16:06	10:27:20	5.06	18:56	11:32:45	11.47	
19	Nanocall	+	Minimap	+	Miniasm +	Minimap	+	Racon	4	1:18	0.26	11:49	7:08:59	10.98	
20	DeepNano	+	_	+	Canu +	BWA-MEM	+	Racon	17:36	11:30:20	4.43	12:48	7:13:04	8.88	
21	DeepNano	+	_	+	Canu +	Minimap	+	Racon	3	1:24	0.28	11:39	6:55:01	3.73	
22	DeepNano	+	Minimap	+	Miniasm +	BWA-MEM	+	Racon	8:15	5:22:29	4.11	14:16	8:34:32	10.30	
23	DeepNano	+	Minimap	+	Miniasm +	Minimap	+	Racon	3	1:10	0.26	12:29	7:55:32	17.11	

Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly" Briefings in Bioinformatics, 2018.



Nanopore Genome Assembly Tools (III)



Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly" to appear in Briefings in Bioinformatics, 2018.

More on Nanopore Sequencing & Tools

Nanopore sequencing technology and tools for genome assembly: computational analysis of the current state, bottlenecks and future directions

Damla Senol Cali ™, Jeremie S Kim, Saugata Ghose, Can Alkan, Onur Mutlu

Briefings in Bioinformatics, bby017, https://doi.org/10.1093/bib/bby017

Published: 02 April 2018 Article history ▼



Senol Cali+, "Nanopore Sequencing Technology and Tools for Genome Assembly: Computational Analysis of the Current State, Bottlenecks and Future Directions," Briefings in Bioinformatics, 2018.

[Preliminary arxiv.org version]

Why Do We Care? An Example from 2020

200 Oxford Nanopore sequencers have left UK for China, to support rapid, near-sample coronavirus sequencing for outbreak surveillance

Fri 31st January 2020

Following extensive support of, and collaboration with, public health professionals in China, Oxford Nanopore has shipped an additional 200 MinION sequencers and related consumables to China. These will be used to support the ongoing surveillance of the current coronavirus outbreak, adding to a large number of the devices already installed in the country.



Each MinION sequencer is approximately the size of a stapler, and can provide rapid sequence information about the coronavirus.



700Kg of Oxford Nanopore sequencers and consumables are on their way for use by Chinese scientists in understanding the current coronavirus outbreak.



Sequencing of COVID-19

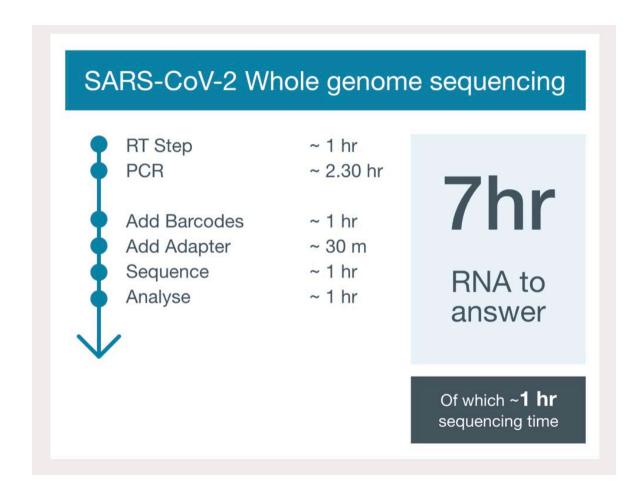
Whole genome sequencing (WGS) and sequence data analysis are important

- To detect the virus from a human sample such as saliva,
 Bronchoalveolar fluid etc.
- To understand the sources and modes of transmission of the virus
- □ To discover the genomic characteristics of the virus, and compare with better-known viruses (e.g., 02-03 SARS epidemic)
- To design and evaluate the diagnostic tests and deep-dive studies

Two key areas of COVID-19 genomic research

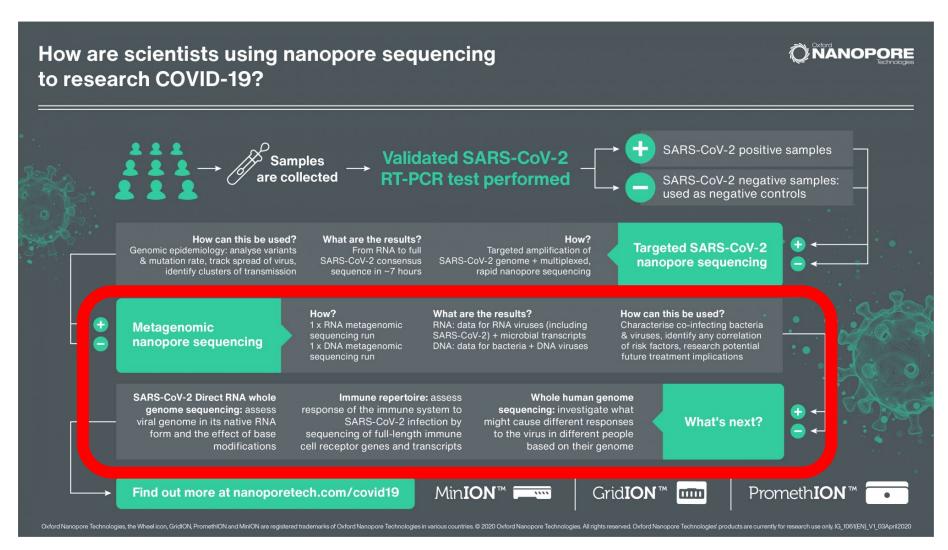
- To sequence the genome of the virus itself, COVID-19, in order to track the mutations in the virus.
- To explore the genes of infected patients. This analysis can be used to understand why some people get more severe symptoms than others, as well as, help with the development of new treatments in the future.

COVID-19 Nanopore Sequencing (I)



From ONT (https://nanoporetech.com/covid-19/overview)

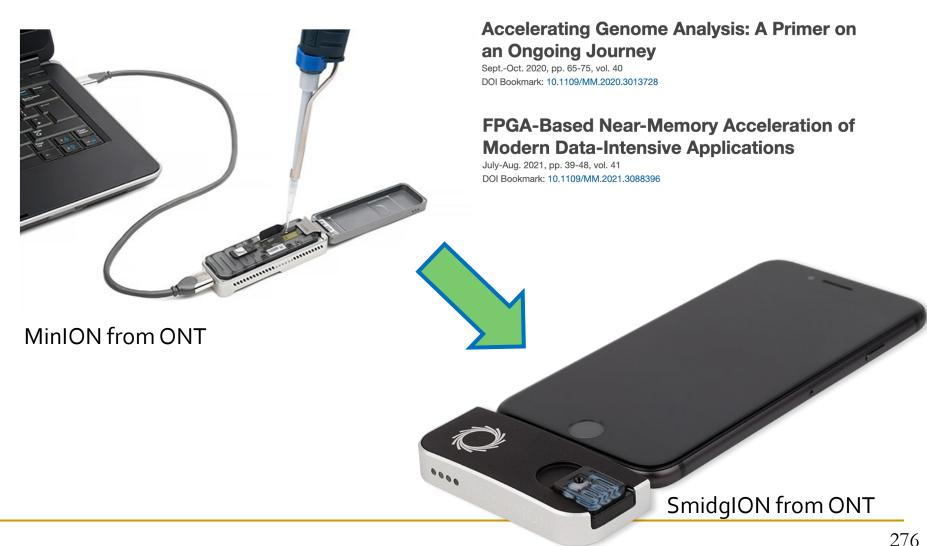
COVID-19 Nanopore Sequencing (II)



From ONT (https://nanoporetech.com/covid-19/overview)

A Bright Future for Intelligent Genome Analysis

Mohammed Alser, Zülal Bingöl, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, Onur Mutlu "Accelerating Genome Analysis: A Primer on an Ongoing Journey" IEEE Micro, August 2020.



Agenda

- The Problem: DNA Read Mapping
 - State-of-the-art Read Mapper Design
- Algorithmic Acceleration
 - Exploiting Structure of the Genome
 - Exploiting SIMD Instructions
- Hardware Acceleration
 - Specialized Architectures
 - Processing in Memory & Storage
- Future Opportunities: New Technologies & Applications

Conclusion

Things Are Happening In Industry

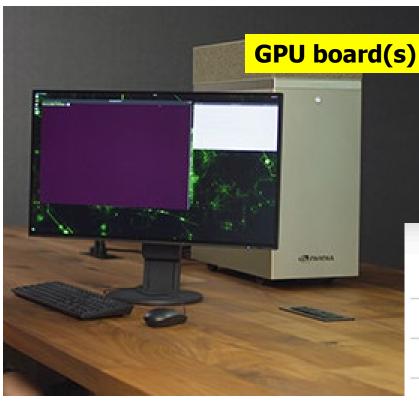
Illumina DRAGEN Bio-IT Platform (2018)

 Processes whole genome at 30x coverage in ~25 minutes with hardware support for data compression

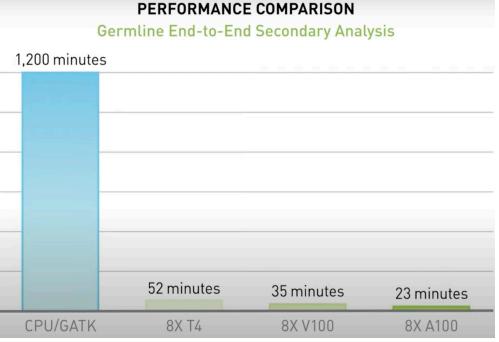


<u>emea.illumina.com/products/by-type/informatics-products/dragen-bio-it-platform.html</u> <u>emea.illumina.com/company/news-center/press-releases/2018/2349147.html</u>

NVIDIA Clara Parabricks (2020)



A University of Michigan startup in 2018 joined NVIDIA in 2020

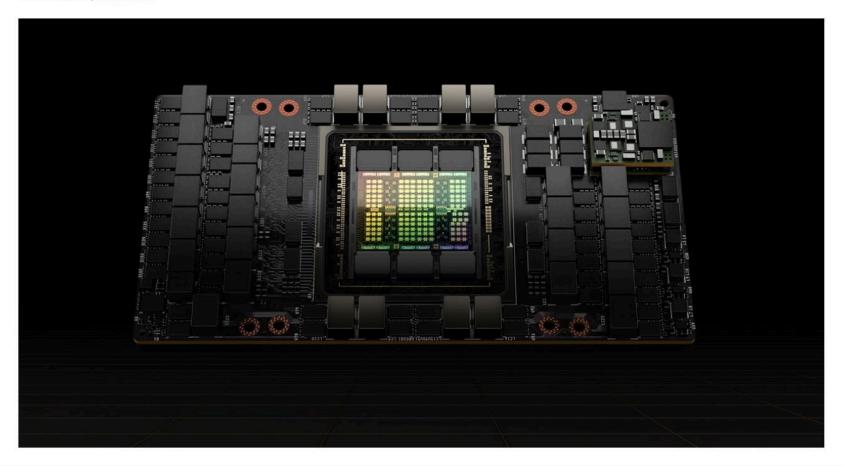


NVIDIA Hopper DPX Instructions (2022)

NVIDIA Hopper GPU Architecture Accelerates Dynamic Programming Up to 40x Using New DPX Instructions

Dynamic programming algorithms are used in healthcare, robotics, quantum computing, data science and more.

March 22, 2022 by DION HARRIS



Recall Our Dream (from 2007)

- An embedded device that can perform comprehensive genome analysis in real time (within a minute)
- Still a long ways to go
 - Energy efficiency
 - Performance (latency)
 - Security & privacy
 - Huge memory bottleneck

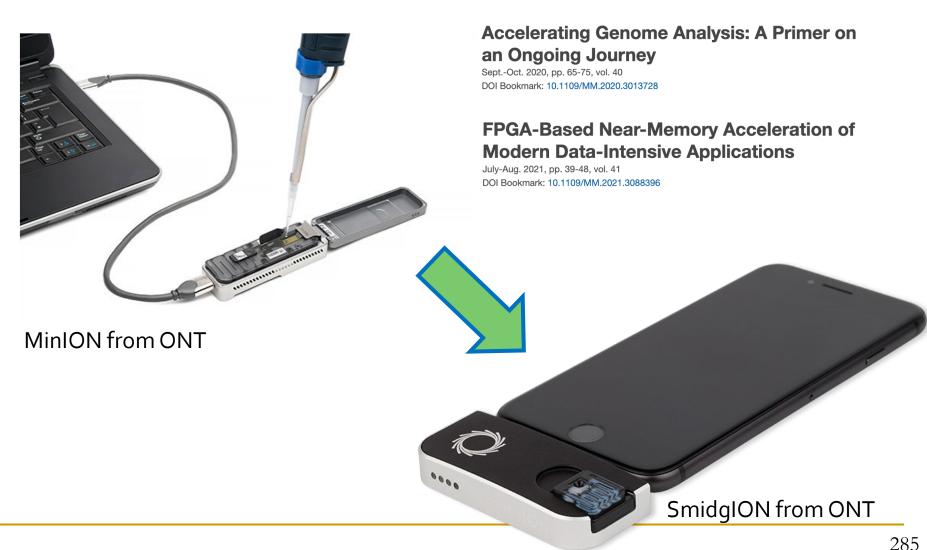
Conclusion

- System design for bioinformatics is a critical problem
 - It has large scientific, medical, societal, personal implications
- This talk is about accelerating a key step in bioinformatics: genome sequence analysis
 - In particular, read mapping
- We covered various recent ideas to accelerate read mapping
 - My personal journey since September 2006
- Many future opportunities exist
 - Especially with new sequencing technologies
 - Especially with new applications and use cases

284

A Bright Future for Intelligent Genome Analysis

Mohammed Alser, Zülal Bingöl, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, Onur Mutlu "Accelerating Genome Analysis: A Primer on an Ongoing Journey" IEEE Micro, August 2020.



Resources & Acknowledgments

Accelerating Genome Analysis: Overview

 Mohammed Alser, Zulal Bingol, Damla Senol Cali, Jeremie Kim, Saugata Ghose, Can Alkan, and Onur Mutlu,

"Accelerating Genome Analysis: A Primer on an Ongoing Journey"

<u>IEEE Micro</u> (IEEE MICRO), Vol. 40, No. 5, pages 65-75, September/October 2020.

[Slides (pptx)(pdf)]

Talk Video (1 hour 2 minutes)

Accelerating Genome Analysis: A Primer on an Ongoing Journey

Mohammed Alser

ETH Zürich

Zülal Bingöl

Bilkent University

Damla Senol Cali

Carnegie Mellon University

Jeremie Kim

ETH Zurich and Carnegie Mellon University

Saugata Ghose

University of Illinois at Urbana–Champaign and Carnegie Mellon University

Can Alkan

Bilkent University

Onur Mutlu

ETH Zurich, Carnegie Mellon University, and Bilkent University

PIM Review and Open Problems

A Modern Primer on Processing in Memory

Onur Mutlu^{a,b}, Saugata Ghose^{b,c}, Juan Gómez-Luna^a, Rachata Ausavarungnirun^d

SAFARI Research Group

^aETH Zürich

^bCarnegie Mellon University

^cUniversity of Illinois at Urbana-Champaign

^dKing Mongkut's University of Technology North Bangkok

Onur Mutlu, Saugata Ghose, Juan Gomez-Luna, and Rachata Ausavarungnirun,

"A Modern Primer on Processing in Memory"

Invited Book Chapter in Emerging Computing: From Devices to Systems
Looking Beyond Moore and Von Neumann, Springer, to be published in 2021.

PIM Review and Open Problems (II)

A Workload and Programming Ease Driven Perspective of Processing-in-Memory

Saugata Ghose[†] Amirali Boroumand[†] Jeremie S. Kim[†]§ Juan Gómez-Luna[§] Onur Mutlu^{§†}

†Carnegie Mellon University §ETH Zürich

Saugata Ghose, Amirali Boroumand, Jeremie S. Kim, Juan Gomez-Luna, and Onur Mutlu, "Processing-in-Memory: A Workload-Driven Perspective"

Invited Article in <u>IBM Journal of Research & Development</u>, Special Issue on Hardware for Artificial Intelligence, to appear in November 2019.

[Preliminary arXiv version]

More on Memory-Centric System Design

Onur Mutlu,

```
"Memory-Centric Computing Systems"
```

Invited Tutorial at <u>66th International Electron Devices</u>

Meeting (IEDM), Virtual, 12 December 2020.

[Slides (pptx) (pdf)]

[Executive Summary Slides (pptx) (pdf)]

[Tutorial Video (1 hour 51 minutes)]

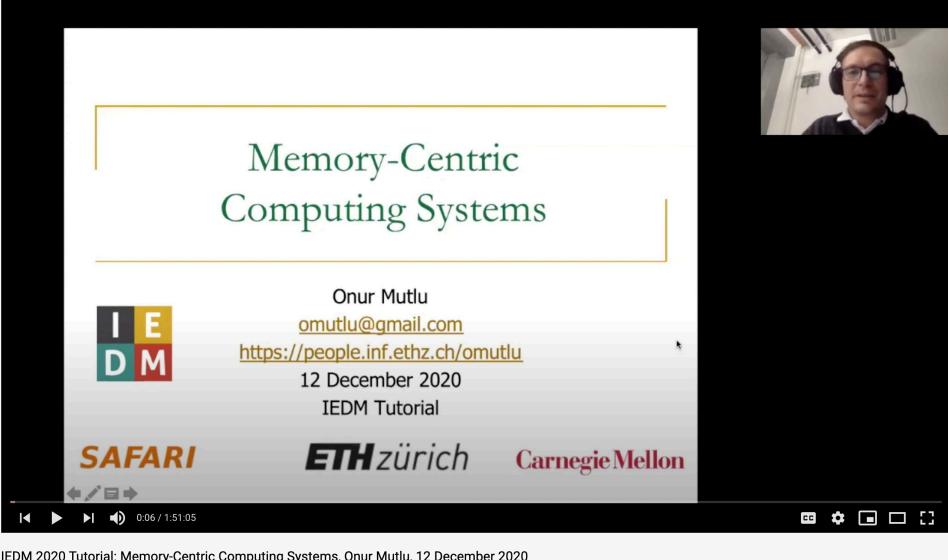
[Executive Summary Video (2 minutes)]

[Abstract and Bio]

[Related Keynote Paper from VLSI-DAT 2020]

[Related Review Paper on Processing in Memory]

https://www.youtube.com/watch?v=H3sEaINPBOE



IEDM 2020 Tutorial: Memory-Centric Computing Systems, Onur Mutlu, 12 December 2020

1,641 views • Dec 23, 2020 SHARE



Special Research Sessions & Courses

Special Session at ISVLSI 2022: 9 cutting-edge talks



Overview Readings (II)

Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios Diamantopoulos, Juan Gomez-Luna, Henk Corporaal, Onur Mutlu,

"FPGA-Based Near-Memory Acceleration of Modern Data-Intensive

Applications"

IEEE Micro, 2021.

[Source Code]



Previous Next

☐ Table of Contents
☐ Past Issues

Home / Magazines / IEEE Micro / 2021.04

IEEE Micro

FPGA-Based Near-Memory Acceleration of Modern Data-Intensive Applications

July-Aug. 2021, pp. 39-48, vol. 41

DOI Bookmark: 10.1109/MM.2021.3088396

Authors

Gagandeep Singh, ETH Zürich, Zürich, Switzerland

Mohammed Alser, ETH Zürich, Zürich, Switzerland

Damla Senol Cali, Carnegie Mellon University, Pittsburgh, PA, USA

Dionysios Diamantopoulos, Zürich Lab, IBM Research Europe, Rüschlikon, Switzerland

Juan Gomez-Luna, ETH Zürich, Zürich, Switzerland

Henk Corporaal, Eindhoven University of Technology, Eindhoven, The Netherlands

Onur Mutlu, ETH Zürich, Zürich, Switzerland

293

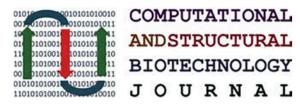
Overview Readings (III)

Mohammed Alser, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu
"From Molecules to Genomic Variations: Intelligent Algorithms and Architectures for Intelligent Genome Analysis"

Computational and Structural Biotechnology Journal, 2022

[Source code]







journal homepage: www.elsevier.com/locate/csbj

Review

From molecules to genomic variations: Accelerating genome analysis via intelligent algorithms and architectures



Mohammed Alser*, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu*

ETH Zurich, Gloriastrasse 35, 8092 Zürich, Switzerland

Detailed Lectures on Genome Analysis

- Computer Architecture, Fall 2020, Lecture 3a
 - Introduction to Genome Sequence Analysis (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=CrRb32v7SJc&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=5
- Computer Architecture, Fall 2020, Lecture 8
 - Intelligent Genome Analysis (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=ygmQpdDTL7o&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=14
- Computer Architecture, Fall 2020, Lecture 9a
 - GenASM: Approx. String Matching Accelerator (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=XoLpzmN Pas&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=15
- Accelerating Genomics Project Course, Fall 2020, Lecture 1
 - Accelerating Genomics (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=rgjl8ZyLsAg&list=PL5Q2soXY2Zi9E2bBVAgCqL gwiDRQDTyId

Genomics (Spring 2022)

Spring 2022 Edition:

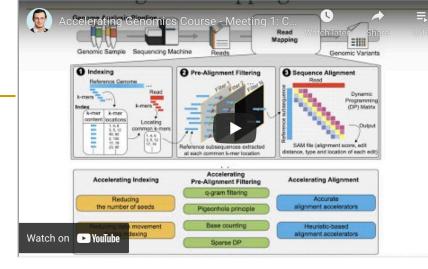
https://safari.ethz.ch/projects and semi nars/spring2022/doku.php?id=bioinforma tics

Youtube Livestream:

https://www.youtube.com/watch?v=DEL 5A Y3TI&list=PL5Q2soXY2Zi8NrPDgOR 1yRU Cxxjw-u18

Project course

- Taken by Bachelor's/Master's students
- Genomics lectures
- Hands-on research exploration
- Many research readings



Spring 2022 Meetings/Schedule

Week	Date	Livestream	Meeting	Learning Materials	Assignment
W1	11.3 Fri.	You Live	M1: P&S Accelerating Genomics Course Introduction & Project Proposals (PDF) (PPT)	Required Materials Recommended Materials	
W2	18.3 Fri.	You Tube Live	M2: Introduction to Sequencing (PDF) (PPT)		
W3	25.3 Fri.	You Tube Premiere	M3: Read Mapping (PDF) (PPT)		
W4	01.04 Fri.	You Tube Premiere	M4: GateKeeper (PDF) (PPT)		
W5	08.04 Fri.	You Tube Premiere	M5: MAGNET & Shouji (PDF) (PPT)		
W6	15.4 Fri.	You Tube Premiere	M6: SneakySnake (PDF) (PPT)		
W7	29.4 Fri.	You Tube Premiere	M7: GenStore (PDF) (PPT)		
W8	06.05 Fri.	You Tube Premiere	M8: GRIM-Filter (PDF) (PPT)		
W9	13.05 Fri.	You Tube Premiere	M9: Genome Assembly (PDF) (PPT)		
W10	20.05 Fri.	You Tube Live	M10: Genomic Data Sharing Under Differential Privacy (PDF) (PPT)		
W11	10.06 Fri.	You Tube Premiere	M11: Accelerating Genome Sequence Analysis		



Genomics (Fall 2021)

Fall 2021 Edition:

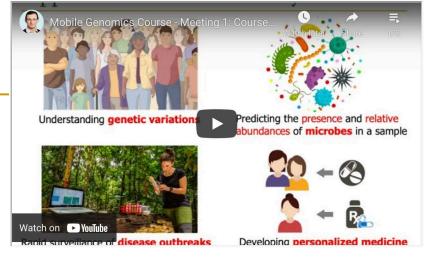
 https://safari.ethz.ch/projects_and_semi nars/fall2021/doku.php?id=bioinformatic s

Youtube Livestream:

https://www.youtube.com/watch?v=Mno gTeMjY8k&list=PL5Q2soXY2Zi8sngH-TrNZnDhDkPq55J9J

Project course

- Taken by Bachelor's/Master's students
- Genomics lectures
- Hands-on research exploration
- Many research readings



Fall 2021 Meetings/Schedule

Week	Date	Livestream	Meeting	Learning Materials	Assignments
W1	5.10 Tue.	You Tube Live	M1: P&S Accelerating Genomics Course Introduction & Project Proposals (PDF) (PPT) You to Video	Required Materials Recommended Materials	
W2	20.10 Wed.	You Live	M2: Introduction to Sequencing (PDF) (PPT)		
W3	27.10 Wed.	You Tube Live	M3: Read Mapping (PDF) (PDF)		
W4	3.11 Wed.	You Tube Live	M4: GateKeeper (PDF) (PPT)		
W5	10.11 Wed.	You Tube Live	M5: MAGNET & Shouji		
W6	17.11 Wed.		M6.1: SneakySnake (PDF) (PDF) (PDF) Video		
			M6.2: GRIM-Filter (PDF) (PDF) (PPT) You (Video		
W7	24.11 Wed.		M7: GenASM (PDF) (ma) (PPT) You (PDF) Video		
W8	01.12 Wed.	You Tube Live	M8: Genome Assembly		
W9	13.12 Mon.	You Tube Live	M9: GRIM-Filter (PDF) (PPT)		
W10	15.12 Wed.	You Tube Live	M10: Genomic Data Sharing Under Differential Privacy (PDF) (PPT)		

Fall 2021 Edition:

https://safari.ethz.ch/architecture/fall2021/doku. php?id=schedule

Fall 2020 Edition:

https://safari.ethz.ch/architecture/fall2020/doku. php?id=schedule

Youtube Livestream (2021):

https://www.youtube.com/watch?v=4yfkM 5EFq o&list=PL5Q2soXY2Zi-Mnk1PxjEIG32HAGILkTOF

Youtube Livestream (2020):

https://www.youtube.com/watch?v=c3mPdZA-Fmc&list=PL5Q2soXY2Zi9xidyIqBxUz7xRPS-wisBN

Master's level course

- Taken by Bachelor's/Masters/PhD students
- Cutting-edge research topics + fundamentals in Computer Architecture
- 5 Simulator-based Lab Assignments
- Potential research exploration
- Many research readings

Computer Architecture - Fall 2021

race: · readings · start · schedule

- Lectures/Schedule
- Lecture Buzzwords
- Readings
- Related Courses

- Computer Architecture FS20
- Computer Architecture FS20
- Digitaltechnik SS21: Course
- Digitaltechnik SS21: Lecture
- Mondle Mondle
- M HotCRE
- Verilog Practice Website (HDLBits)

Lecture Video Playlist on YouTube

S Livestream Lecture Playlist



Recorded Lecture Playlist



Fall 2021 Lectures & Schedule

Week	Date	Livestream	Lecture	Readings	Lab	HW
W1	30.09 Thu.	You tive	L1: Introduction and Basics	Required Mentioned	Lab 1 Out	HW 0
	01.10 Fri.	You Tube Live	L2: Trends, Tradeoffs and Design Fundamentals (PDF) (PPT)	Required Mentioned		
W2	07.10 Thu.	You Tubb Live	L3a: Memory Systems: Challenges and Opportunities (PDF) in (PPT)	Described Suggested		HW 1 Out
			L3b: Course Info & Logistics			
			L3c: Memory Performance Attacks	Described Suggested		
	08.10 Fri.			Described Suggested	Lab 2 Out	
			L4b: Data Retention and Memory Refresh (PDF) (PPT)	Described Suggested		
			L4c: RowHammer	Described Suggested		

DDCA (Spring 2022)

Spring 2022 Edition:

 https://safari.ethz.ch/digitaltechnik/spring2022/do ku.php?id=schedule

Spring 2021 Edition:

 https://safari.ethz.ch/digitaltechnik/spring2021/do ku.php?id=schedule

Youtube Livestream (Spring 2022):

https://www.youtube.com/watch?v=cpXdE3HwvK 0&list=PL5Q2soXY2Zi97Ya5DEUpMpQ2bbAoaG7c6

Youtube Livestream (Spring 2021):

https://www.youtube.com/watch?v=LbC0EZY8yw 4&list=PL5Q2soXY2Zi_uej3aY39YB5pfW4SJ7LIN

Bachelor's course

- 2nd semester at ETH Zurich
- Rigorous introduction into "How Computers Work"
- Digital Design/Logic
- Computer Architecture
- 10 FPGA Lab Assignments



Trace: • schedule

Home

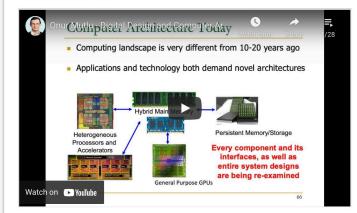
Announcements

Materials

- Lectures/Schedule
- Lecture Buzzwords
- Readings
- Optional HWs
- LabsExtra Assignments
- Exams
 Technical Docs
- Posouroos
- Computer Architecture (CMU)
- SS15: Lecture Videos
- Scomputer Architecture (CMU) SS15: Course Website
- Spigitaltechnik SS18: Lecture Videos
- Digitaltechnik SS18: Course Website
- Digitaltechnik SS19: Lecture Videos
 Digitaltechnik SS19: Course
- Spigitaltechnik SS20: Lecture
- Videos

 Digitaltechnik SS20: Course
- Website
- Moodle

Lecture Video Playlist on YouTube



Recent Changes Media Manager Siter

Recorded Lecture Playlist



Spring 2021 Lectures/Schedule

Week	Date	Livestream	Lecture	Readings	Lab	HW
W1	25.02 Thu.	You Tube Live	L1: Introduction and Basics	Required Suggested Mentioned		
	26.02 Fri.	You Tube Live	L2a: Tradeoffs, Metrics, Mindset	Required		
			L2b: Mysteries in Computer Architecture (PDF)	Required Mentioned		
W2	04.03 Thu.	You Tube Live	L3a: Mysteries in Computer Architecture II	Required Suggested		

Shate R/www.youtube.com/onurmutlulectures

Seminar in Comp Arch (Spring & Fall)

Spring 2022 Edition:

https://safari.ethz.ch/architecture_seminar/spring20
 22/doku.php?id=schedule

Fall 2021 Edition:

 https://safari.ethz.ch/architecture_seminar/fall2021 /doku.php?id=schedule

Youtube Livestream (Spring 2022):

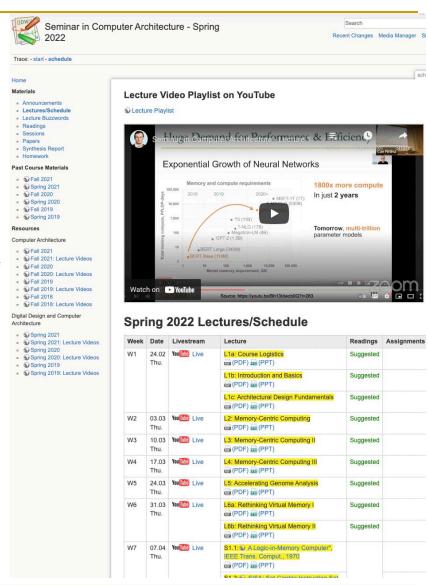
https://www.youtube.com/watch?v=rS9UPk509AQ& list=PL5Q2soXY2Zi hxizriwKmFHgcoe2Q8-m0

Youtube Livestream (Fall 2021):

https://www.youtube.com/watch?v=4TcP297mdsI& list=PL5Q2soXY2Zi 7UBNmC9B8Yr5JSwTG9yH4

Critical analysis course

- Taken by Bachelor's/Masters/PhD students
- Cutting-edge research topics + fundamentals in Computer Architecture
- 20+ research papers, presentations, analyses



PIM Course (Spring 2022)

Spring 2022 Edition:

 https://safari.ethz.ch/projects and semi nars/spring2022/doku.php?id=processing in memory

Youtube Livestream:

 https://www.youtube.com/watch?v=9e4
 Chnwdovo&list=PL5Q2soXY2Zi-841fUYYUK9EsXKhQKRPyX

Project course

- Taken by Bachelor's/Master's students
- Processing-in-Memory lectures
- Hands-on research exploration
- Many research readings



Spring 2022 Meetings/Schedule

Week	Date	Livestream	Meeting	Learning Materials	Assignments
W1	10.03 Thu.	YouTube Live	M1: P&S PIM Course Presentation (PDF) (PPT)	Required Materials Recommended Materials	HW 0 Out
W2	15.03 Tue.		Hands-on Project Proposals		
	17.03 Thu.	You Tube Premiere	M2: Real-world PIM: UPMEM PIM		
W3	24.03 Thu.	You Tube Live	M3: Real-world PIM: Microbenchmarking of UPMEM PIM @ (PDF) m (PPT)		
W4	31.03 Thu.	You Tube Live	M4: Real-world PIM: Samsung HBM-PIM (PDF) (PDF) (PPT)		
W5	07.04 Thu.	You Tobe Live	M5: How to Evaluate Data Movement Bottlenecks (PDF) (PPT)		
W6	14.04 Thu.	You Tube Live	M6: Real-world PIM: SK Hynix AiM (PDF) (PPT)		
W7	21.04 Thu.	YouTube Premiere	M7: Programming PIM Architectures (PDF) (PPT)		
W8	28.04 Thu.	YouTube Premiere	M8: Benchmarking and Workload Suitability on PIM (PDF) (PPT)		
W9	05.05 Thu.	You Tobe Premiere	M9: Real-world PIM: Samsung AXDIMM (PDF) (PPT)		
W10	12.05 Thu.	You to Premiere	M10: Real-world PIM: Alibaba HB-PNM		
W11	19.05 Thu.	You tobe Live	M11: SpMV on a Real PIM Architecture (PDF) (PPT)		
W12	26.05 Thu.	You Live	M12: End-to-End Framework for Processing-using-Memory (PDF) (PPT)		
W13	02.06 Thu.	You Live	M13: Bit-Serial SIMD Processing using DRAM (PDF) (PPT)		
W14	09.06 Thu.	You to Live	M14: Analyzing and Mitigating ML Inference Bottlenecks		
W15	15.06 Thu.	You Live	M15: In-Memory HTAP Databases with HW/SW Co-design (PDF) (PPT)		
W16	23.06 Thu.	You Live	M16: In-Storage Processing for Genome Analysis (In-Storage Processing for Genome Analysis (IPDF) (IPDF) (IPDF)		
W17	18.07 Mon.	You Tibe Premiere	M17: How to Enable the Adoption of PIM?		
W18	09.08 Tue.	You to Premiere	SS1: ISVLSI 2022 Special Session on PIM (PDF & PPT)		



Hetero. Systems (Spring'22)

Spring 2022 Edition:

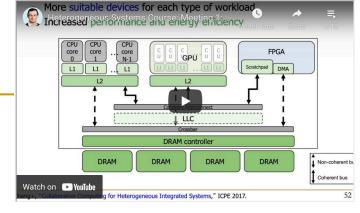
 https://safari.ethz.ch/projects_and_semi nars/spring2022/doku.php?id=heterogen eous_systems

Youtube Livestream:

https://www.youtube.com/watch?v=oFO 5fTrgFIY&list=PL5Q2soXY2Zi9XrgXR38IM FTjmY6h7Gzm

Project course

- Taken by Bachelor's/Master's students
- GPU and Parallelism lectures
- Hands-on research exploration
- Many research readings



Spring 2022 Meetings/Schedule

Week	Date	Livestream	Meeting	Learning Materials	Assignments
W1	15.03 Tue.	You Tube Premiere	M1: P&S Course Presentation (PDF) (PPT)	Required Materials Recommended Materials	HW 0 Out
W2	22.03 Tue.	You Tube Premiere	M2: SIMD Processing and GPUs (PDF) (PPT)		
W3	29.03 Tue.	You Tube Premiere	M3: GPU Software Hierarchy (PDF) (PPT)		
W4	05.04 Tue.	You Tube Premiere	M4: GPU Memory Hierarchy (PDF) (PPT)		
W5	12.04 Tue.	You Tube Premiere	M5: GPU Performance Considerations (PDF) (PPT)		
W6	19.04 Tue.	You Tube Premiere	M6: Parallel Patterns: Reduction (PDF) (PPT)		
W7	26.04 Tue.	You Tube Premiere	M7: Parallel Patterns: Histogram (PDF) (PPT)		
W8	03.05 Tue.	You Tube Premiere	M8: Parallel Patterns: Convolution (PDF) (PPT)		
W9	10.05 Tue.	You Tube Premiere	M9: Parallel Patterns: Prefix Sum (Scan) (PDF) (PPT)		
W10	17.05 Tue.	You Tube Premiere	M10: Parallel Patterns: Sparse Matrices (PDF) (PPT)		
W11	24.05 Tue.	You Tube Premiere	M11: Parallel Patterns: Graph Search (PDF) (PPT)		
W12	01.06 Wed.	You Tube Premiere	M12: Parallel Patterns: Merge Sort (PDF) (PPT)		
W13	07.06 Tue.	You Tube Premiere	M13: Dynamic Parallelism (PDF) (PPT)		
W14	15.06 Wed.	You Tube Premiere	M14: Collaborative Computing (PDF) (PPT)		
W15	24.06 Fri.	You Tube Premiere	M15: GPU Acceleration of Genome Sequence Alignment (PDF) (PPT)		
W16	14.07 Thu.	You Tube Premiere	M16: Accelerating Agent-based Simulations (PDF) (ODP)		

HW/SW Co-Design (Spring 2022)

Spring 2022 Edition:

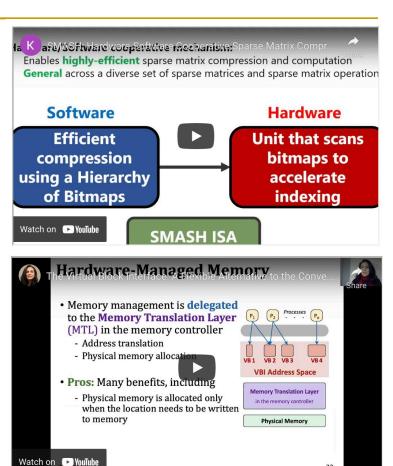
https://safari.ethz.ch/projects_and_semi_ nars/spring2022/doku.php?id=hw_sw_co_ design_

Youtube Livestream:

https://youtube.com/playlist?list=PL5Q2s oXY2Zi8nH7un3ghD2nutKWWDk-NK

Project course

- Taken by Bachelor's/Master's students
- HW/SW co-design lectures
- Hands-on research exploration
- Many research readings



2022 Meetings/Schedule (Tentative)

Week	Date	Livestream	Meeting	Materials	Assignments
W0	16.03	You Tube Live	Intro to HW/SW Co-Design (PPTX) (PDF)	Required	HW 0 Out
W1	23.03		Project selection	Required	
W2	30.03	YouTube Live	Virtual Memory (I) (PPTX) (PDF)		
W3	13.04	You Tube Live	Virtual Memory (II) (PPTX) (PDF)		

SSD Course (Spring 2022)

Spring 2022 Edition:

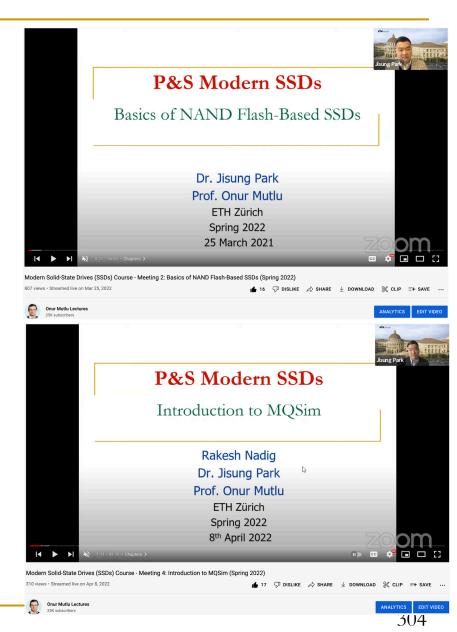
 https://safari.ethz.ch/projects and semi nars/spring2022/doku.php?id=modern s sds

Youtube Livestream:

https://www.youtube.com/watch?v=_q4r m71DsY4&list=PL5Q2soXY2Zi8vabcse1kL 22DEcqMl2RAq

Project course

- Taken by Bachelor's/Master's students
- SSD Basics and Advanced Topics
- Hands-on research exploration
- Many research readings



Funding Acknowledgments

- Alibaba, AMD, ASML, Google, Facebook, Hi-Silicon, HP Labs, Huawei, IBM, Intel, Microsoft, Nvidia, Oracle, Qualcomm, Rambus, Samsung, Seagate, VMware, Xilinx
- NSF
- NIH
- GSRC
- SRC
- CyLab
- EFCL

Acknowledgments



Think BIG, Aim HIGH!

https://safari.ethz.ch

Onur Mutlu's SAFARI Research Group

Computer architecture, HW/SW, systems, bioinformatics, security, memory

https://safari.ethz.ch/safari-newsletter-january-2021/



Think BIG, Aim HIGH!

SAFARI

https://safari.ethz.ch

SAFARI Newsletter April 2020 Edition

https://safari.ethz.ch/safari-newsletter-april-2020/





View in your browser

Think Big, Aim High



Dear SAFARI friends,

SAFARI Newsletter January 2021 Edition

https://safari.ethz.ch/safari-newsletter-january-2021/





Newsletter January 2021

Think Big, Aim High, and Have a Wonderful 2021!



Dear SAFARI friends,

SAFARI Newsletter December 2021 Edition

https://safari.ethz.ch/safari-newsletter-december-2021/



Think Big, Aim High





View in your browser December 2021



Referenced Papers, Talks, Artifacts

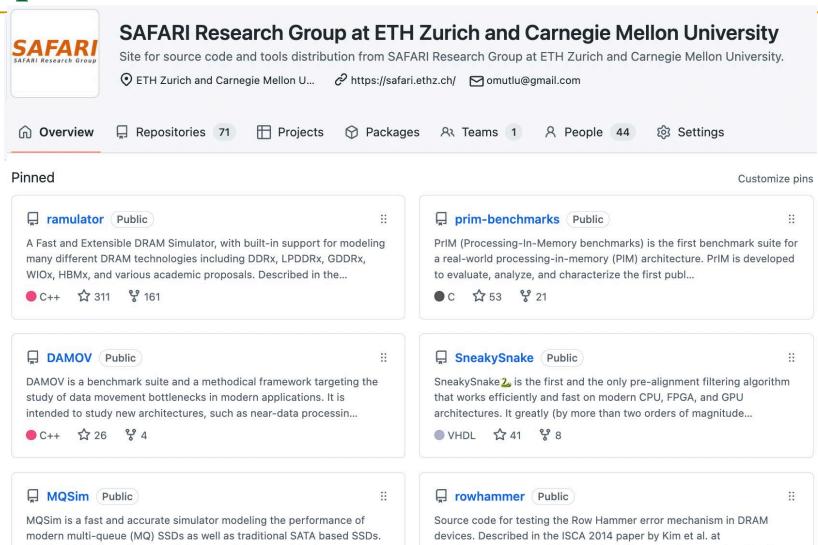
All are available at

https://people.inf.ethz.ch/omutlu/projects.htm

https://www.youtube.com/onurmutlulectures

https://github.com/CMU-SAFARI/

Open Source Tools: SAFARI GitHub



http://users.ece.cmu.edu/~omutlu/pub/dram-row-hammer_isca14.pdf.

گ 41

C \$\frac{1}{2} 189

MQSim faithfully models new high-bandwidth protocol implement...

● C++ ☆ 146

Accelerating Genome Analysis A Primer on an Ongoing Journey

Onur Mutlu

omutlu@gmail.com

https://people.inf.ethz.ch/omutlu

6 September 2022

Barcelona Supercomputing Center





Carnegie Mellon

Some Recent Papers

Connecting Basecalling and Read Mapping in PIM

 Haiyu Mao, Mohammed Alser, Mohammad Sadrosadati, Can Firtina, Akanksha Baranwal, Damla Senol Cali, Aditya Manglik, Nour Almadhoun Alserr, and Onur Mutlu,

"GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping"

Proceedings of the <u>55th International Symposium on Microarchitecture</u> (MICRO), Chicago, Illinois, October 2022.

GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping

Haiyu Mao¹ Mohammed Alser¹ Mohammad Sadrosadati¹ Can Firtina¹ Akanksha Baranwal¹ Damla Senol Cali² Aditya Manglik¹ Nour Almadhoun Alserr¹ Onur Mutlu¹

IETH Zürich* ** **Pionano Genomics***

Finding Approximate Seed Matches

 Can Firtina, Jisung Park, Mohammed Alser, Jeremie S. Kim, Damla Senol Cali, Taha Shahroodi, Nika Mansouri-Ghiasi, Gagandeep Singh, Konstantinos Kanellopoulos, Can Alkan, and Onur Mutlu,

"BLEND: A Fast, Memory-Efficient, and Accurate Mechanism to Find Fuzzy Seed Matches"

Preprint in <u>arXiv</u>, 2021.

arXiv preprint

[BLEND Source Code and Data]

BLEND: A Fast, Memory-Efficient, and Accurate Mechanism to Find Fuzzy Seed Matches

Can Firtina¹ Jisung Park¹ Mohammed Alser¹ Jeremie S. Kim¹ Damla Senol Cali²
Taha Shahroodi³ Nika Mansouri-Ghiasi¹ Gagandeep Singh¹ Konstantinos Kanellopoulos¹
Can Alkan⁴ Onur Mutlu¹

¹ETH Zurich ²Bionano Genomics ³TU Delft ⁴Bilkent University

Hardware Acceleration for pHMMs

Can Firtina, Kamlesh Pillai, Gurpreet S. Kalsi, Bharathwaj Suresh, Damla Senol Cali, Jeremie S. Kim, Taha Shahroodi, Meryem Banu Cavlak, Joel Lindegger, Mohammed Alser, Juan Gómez-Luna, Sreenivas Subramoney, and Onur Mutlu, "ApHMM: A Profile Hidden Markov Model Acceleration Framework for Genome Analysis"

Preprint in <u>arXiv</u>, 2022.

Source Code

ApHMM: A Profile Hidden Markov Model Acceleration Framework for Genome Analysis

Can Firtina¹ Kamlesh Pillai² Gurpreet S. Kalsi² Bharathwaj Suresh² Damla Senol Cali³ Jeremie S. Kim¹ Taha Shahroodi⁴ Meryem Banu Cavlak¹ Joel Lindegger¹ Mohammed Alser¹ Juan Gómez Luna¹ Sreenivas Subramoney² Onur Mutlu¹

1ETH Zurich ²Intel Labs ³Bionano Genomics ⁴TU Delft

Remapping Reads Between References

 Jeremie S. Kim, Can Firtina, Meryem Banu Cavlak, Damla Senol Cali, Nastaran Hajinazar, Mohammed Alser, Can Alkan, and Onur Mutlu,

"AirLift: A Fast and Comprehensive Technique for Remapping Alignments between Reference Genomes"

Preprint in <u>arXiv</u> and <u>bioRxiv</u>, 2021.

bioRxiv preprint

[arXiv preprint]

[AirLift Source Code and Data]

METHOD

AirLift: A Fast and Comprehensive Technique for Remapping Alignments between Reference Genomes

Jeremie S. $Kim^{1\dagger}$, Can Firtina^{1†}, Meryem Banu Cavlak², Damla Senol Cali³, Nastaran Hajinazar^{1,4}, Mohammed Alser¹, Can Alkan² and Onur Mutlu^{1,2,3*}

318

Mapping Constant Regions Between References

Jeremie S. Kim, Can Firtina, Meryem Banu Cavlak, Damla Senol Cali, Can Alkan, and Onur Mutlu,

"FastRemap: A Tool for Quickly Remapping Reads between Genome Assemblies"

Bioinformatics, btac554.

[FastRemap Source Code]

FastRemap: A Tool for Quickly Remapping Reads between Genome Assemblies

Jeremie S. Kim¹

Can Firtina¹ Meryem Banu Cavlak¹

Damla Senol Cali^{2,3}

Can Alkan⁴ Onur Mutlu^{1,2,4}

¹ETH Zürich

²Carnegie Mellon University ³Bionano Genomics

⁴Bilkent University

COVIDHunter

Mohammed Alser, Jeremie S. Kim, Nour Almadhoun Alserr, Stefan W. Tell, Onur Mutlu

"COVIDHunter: COVID-19 Pandemic Wave Prediction and Mitigation via Seasonality

Aware Modeling"

Frontiers in Public Health 2022

[Source Code]



Frontiers | Frontiers in Public Health

ORIGINAL RESEARCH

published: 17 June 2022 doi: 10.3389/fpubh.2022.877621

COVIDHunter: COVID-19 Pandemic Wave Prediction and Mitigation via Seasonality Aware Modeling

Mohammed Alser*, Jeremie S. Kim, Nour Almadhoun Alserr, Stefan W. Tell and Onur Mutlu

Department of Information Technology and Electrical Engineering (D-ITET), ETH Zurich, Zurich, Switzerland

Packaging Omics Methods

Mohammed Alser, Sharon Waymost, Ram Ayyala, Brendan Lawlor, Richard J. Abdill, Neha Rajkumar, Nathan LaPierre, Jaqueline Brito, Andre M. Ribeiro-dos-Santos, Can Firtina, Nour Almadhoun, Varuni Sarwal, Eleazar Eskin, Qiyang Hu, Derek Strong, Byoung-Do (BD)Kim, Malak S. Abedalthagafi, Onur Mutlu, Serghei Mangul "Packaging, containerization, and virtualization of computational omics methods: Advances, challenges, and opportunities" arrXiv 2022

Packaging, containerization, and virtualization of computational omics methods: Advances, challenges, and opportunities

Mohammed Alser¹, Sharon Waymost², Ram Ayyala^{3,4}, Brendan Lawlor⁵, Richard J. Abdill⁶, Neha Rajkumar⁷, Nathan LaPierre², Jaqueline Brito⁴, André M. Ribeiro-dos-Santos⁸, Can Firtina¹, Nour Almadhoun¹, Varuni Sarwal², Eleazar Eskin^{2,9,10}, Qiyang Hu¹¹, Derek Strong¹², Byoung-Do (BD) Kim¹², Malak S. Abedalthagafi^{13,14,15*}, Onur Mutlu^{1,*}, Serghei Mangul^{4,*}

Demeter (HD Food Microbiome Profiling)

Taha Shahroodi, Mahdi Zahedi, Can Firtina, Mohammed Alser, Stephan Wong, Onur Mutlu, Said Hamdioui

"<u>Demeter: A Fast and Energy-Efficient Food Profiler using Hyperdimensional Computing in Memory"</u>

IEEE Access, 2022





Demeter: A Fast and Energy-Efficient Food Profiler Using Hyperdimensional Computing in Memory

TAHA SHAHROODI^{®1}, MAHDI ZAHEDI^{®1}, CAN FIRTINA², MOHAMMED ALSER^{®2}, STEPHAN WONG¹, (Senior Member, IEEE), ONUR MUTLU^{®2}, (Fellow, IEEE), AND SAID HAMDIOUI^{®1}, (Senior Member, IEEE)

¹Q&CE Department, EEMCS Faculty, Delft University of Technology (TU Delft), 2628 CD Delft, The Netherlands ²SAFARI Research Group, D-ITET, ETH Zürich, 8092 Zürich, Switzerland



AIM (PIM Sequence Alignment Framework)

Safaa Diab, Amir Nassereldine, Mohammed Alser, Juan Gómez-Luna, Onur Mutlu, Izzat El Hajj

"A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems" arXiv, 2022

[Source code]

A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems

Safaa Diab¹, Amir Nassereldine¹, Mohammed Alser², Juan Gómez Luna², Onur Mutlu², Izzat El Hajj¹

 1 American University of Beirut, Lebanon 2 ETH Zürich, Switzerland

Scrooge

Joël Lindegger, Damla Senol Cali, Mohammed Alser, Juan Gómez-Luna, Nika Mansouri Ghiasi, Onur Mutlu

"Scrooge: A Fast and Memory-Frugal Genomic Sequence Aligner for CPUs, GPUs, and

ASICs"

arXiv, 2022

[Source code]

Bioinformatics
doi.10.1093/bioinformatics/xxxxxx
Advance Access Publication Date: Day Month Year
Original paper



Genome analysis

Scrooge: A Fast and Memory-Frugal Genomic Sequence Aligner for CPUs, GPUs, and ASICs

Joël Lindegger ^{1,*}, Damla Senol Cali ², Mohammed Alser ¹, Juan Gómez-Luna ¹, Nika Mansouri Ghiasi ¹ and Onur Mutlu ^{1,*}

²Bionano Genomics, San Diego, CA 92121, USA.



¹Department of Information Technology and Electrical Engineering, ETH Zurich, Zurich 8006, Switzerland and

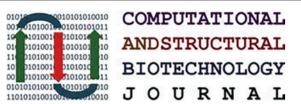
Intelligent Genome Analysis

Mohammed Alser, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu

"From Molecules to Genomic Variations: Intelligent Algorithms and Architectures for Intelligent Genome Analysis"

Computational and Structural Biotechnology Journal, 2022 [Source code]







journal homepage: www.elsevier.com/locate/csbj

Review

From molecules to genomic variations: Accelerating genome analysis via intelligent algorithms and architectures



Mohammed Alser*, Joel Lindegger, Can Firtina, Nour Almadhoun, Haiyu Mao, Gagandeep Singh, Juan Gomez-Luna, Onur Mutlu*

ETH Zurich, Gloriastrasse 35, 8092 Zürich, Switzerland



Pairwise Sequence Alignment using PIM

 Safaa Diab, Amir Nassereldine, Mohammed Alser, Juan Gómez Luna, Onur Mutlu, and Izzat El Hajj,

"High-throughput Pairwise Alignment with the Wavefront Algorithm using Processing-in-Memory"

Preprint in <u>arXiv</u>, 2022.

High-throughput Pairwise Alignment with the Wavefront Algorithm using Processing-in-Memory

Safaa Diab¹, Amir Nassereldine¹, Mohammed Alser², Juan Gómez Luna², Onur Mutlu², Izzat El Hajj¹

¹American University of Beirut, Lebanon ²ETH Zürich, Switzerland

Backup Slides for Further Info

Detailed Lectures on PIM (I)

- Computer Architecture, Fall 2020, Lecture 6
 - Computation in Memory (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=oGcZAGwfEUE&list=PL5Q2soXY2Zi9xidyIgBxUz 7xRPS-wisBN&index=12
- Computer Architecture, Fall 2020, Lecture 7
 - Near-Data Processing (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=j2GIigqn1Qw&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=13
- Computer Architecture, Fall 2020, Lecture 11a
 - Memory Controllers (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=TeG773OgiMQ&list=PL5Q2soXY2Zi9xidyIgBxUz 7xRPS-wisBN&index=20
- Computer Architecture, Fall 2020, Lecture 12d
 - Real Processing-in-DRAM with UPMEM (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=Sscy1Wrr22A&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=25

Detailed Lectures on PIM (II)

- Computer Architecture, Fall 2020, Lecture 15
 - Emerging Memory Technologies (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=AlE1rD9G_YU&list=PL5Q2soXY2Zi9xidyIgBxUz 7xRPS-wisBN&index=28
- Computer Architecture, Fall 2020, Lecture 16a
 - Opportunities & Challenges of Emerging Memory Technologies
 (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=pmLszWGmMGQ&list=PL5Q2soXY2Zi9xidyIgBx Uz7xRPS-wisBN&index=29
- Computer Architecture, Fall 2020, Guest Lecture
 - In-Memory Computing: Memory Devices & Applications (ETH Zürich, Fall 2020)
 - https://www.youtube.com/watch?v=wNmqQHiEZNk&list=PL5Q2soXY2Zi9xidyIgBxUz7xRPS-wisBN&index=41



Genome Analysis



nachine can read the entire content of a genome





Genome Analysis



No machine can read the *entire* content of a genome



>CCTO GACC CATGT GAAG ACTA AAGT GAAA

TTGT(

Why?

AAAAAAAAAAAAAGAAAAGAAAAAGAAATTTAAAATTTAAGTAATTCTTTGAAAAAAACTAATTTCTAAGCTT**T**TTCATGTCAAGGACC TAATGTAGCTATACTGAACGTTATCTAGGGGAAAGATTGAAGGGGGAGCTCTAAGGTCAACACACCACCACTTCCCAGAAAGCTTCTTCA......

SAFARI

CAAG

TCTT

CATTG

AAAA

ATTT

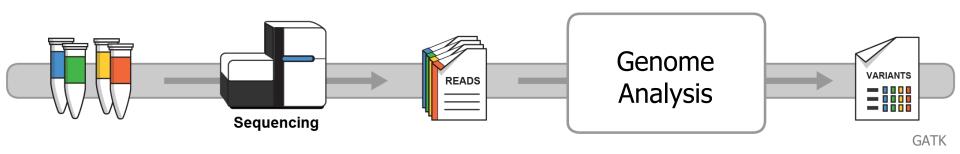
AAAA

ATGG

GAAA



Genome Sequencer is a Chopper



CCCCCTATATATACGTACTAGTACGT

ACGACTTTAGTACGTACGT
TATATATACGTACTAGTACGT

ACGTACG CCCCTACGTA
TATATATACGTACTACGTACGT

ACGACTTTAGTACGTACGT TATATATACGTACTAAAGTACGT TATATATACGTACTAGTACGT

ACG TTTTTAAAACGTA
TATATATACGTACTACGT

ACGAC GGGGAGTACGT



1x10¹² bases*



44 hours*



<1000 \$

* NovaSeq 6000

Oxford Nanopore Sequencers NANOPORE











MinION Mk1B

MinION Mk1C

GridION Mk1

PromethION 24/48

	MinION Mk1B	MinION Mk1C	GridION Mk1	PromethION 24	PromethION 48
Read length	> 2Mb	> 2Mb	> 2Mb	> 2Mb	> 2Mb
Yield per flow cell	50 Gb	50 Gb	50 Gb 220 Gb		220 Gb
Number of flow cells per device	1	1	5	24	48
Yield per device	<50 Gb	<50 Gb	<250 Gb	<5.2 Tb	<10.5 Tb
Starting price	\$1,000	\$4,990	\$49,995	\$195,455	\$327,455

Illumina Sequencers



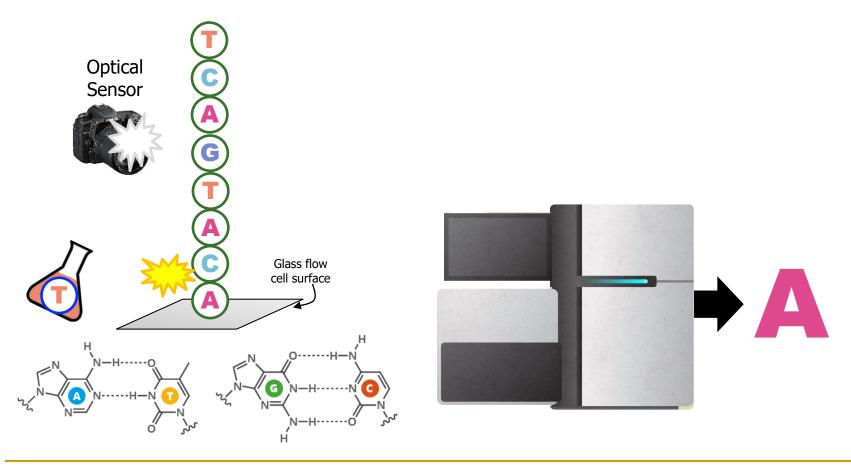


Run time	9.5–19 hrs	4–24 hrs	4–55 hrs	12–30 hrs	24-48 hrs	13-44 hrs
Max. reads per run	4 million	25 million	25 million	400 million	1 billion	20 billion
Max. read length	2 × 150 bp	2 × 150 bp	2 × 300 bp	2 × 150 bp	2 × 150 bp	2 x 250
Max. output	1.2 Gb	7.5 Gb	15 Gb	120 Gb	300 Gb	6000 Gb
Estimated price	\$19,900	\$49,500	\$128,000	\$275,000	\$335,000	\$985,000

SAFARI https://www.illumina.com/systems/sequencing-platforms.html



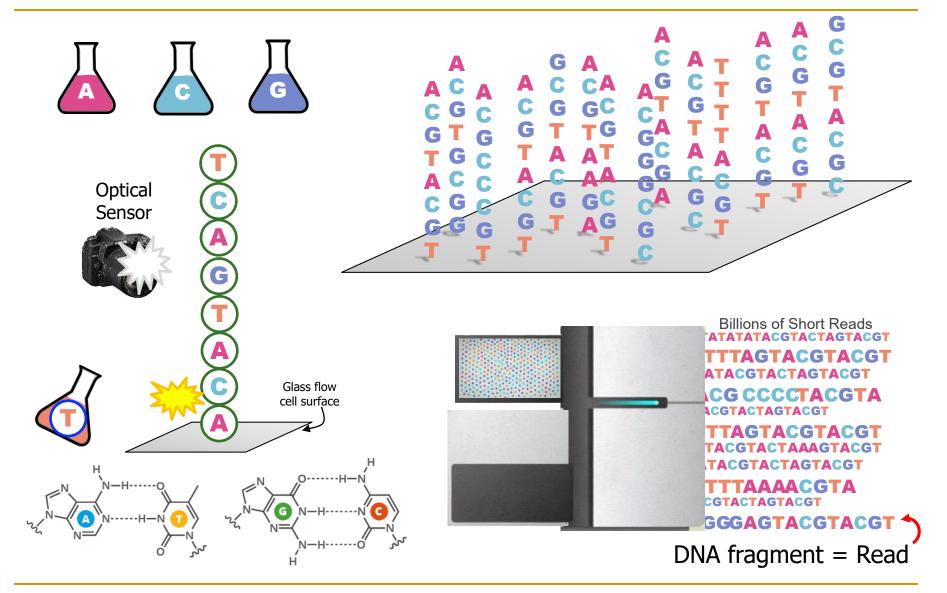
How Does Illumina Machine Work?







How Does Illumina Machine Work?





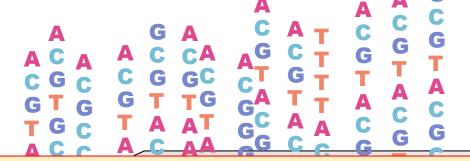
How Does Illumina Machine Work?





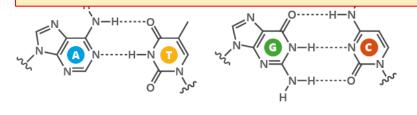






Check Illumina virtual tour:

https://emea.illumina.com/systems/sequencing-platforms/iseq/tour.html

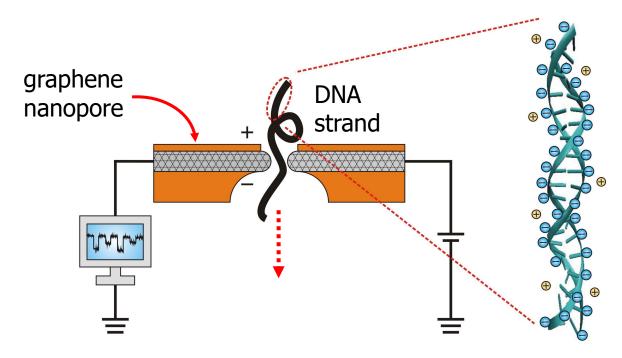


TTTAAAACGTA GGTACTAGTACGT GGGAGTACGTACGT

DNA fragment = Read



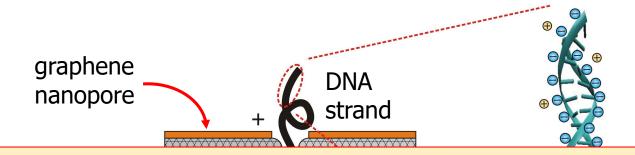
How Does Nanopore Machine Work?



- Nanopore is a nano-scale hole (<20nm).</p>
- In nanopore sequencers, an ionic current passes through the nanopores
- When the DNA strand passes through the nanopore, the sequencer measures the the change in current
- This change is used to identify the bases in the strand with the help of different electrochemical structures of the different bases

338

How Does Nanopore Machine Work?



Check Nanopore virtual tour:

https://nanoporetech.com/resource-centre/minion-video

measures the the change in current

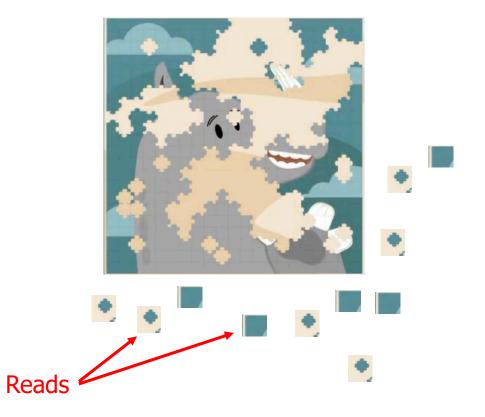
 This change is used to identify the bases in the strand with the help of different electrochemical structures of the different bases





Solving the Puzzle





https://www.pacb.com/smrt-science/smrt-sequencing/hifi-reads-for-highly-accurate-long-read-sequencing/

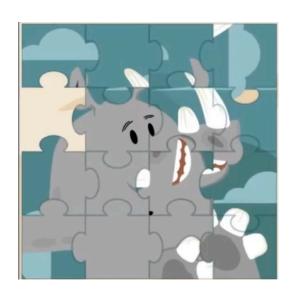


HTS Sequencing Output

Small pieces of a puzzle short reads (Illumina)



Large pieces of a puzzle long reads (ONT & PacBio)



Which sequencing technology is the best?

- □ 100-300 bp
- \square low error rate (\sim 0.1%)

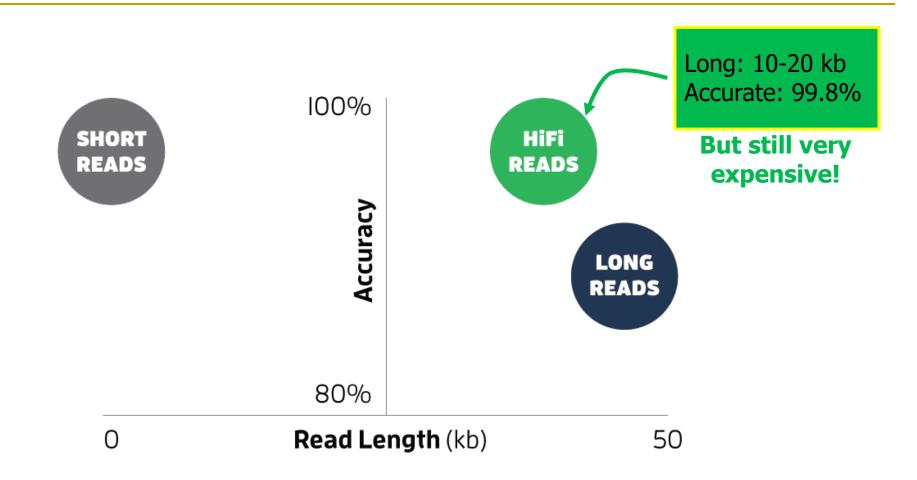
- □ 500-2M bp
- □ high error rate (~15%)

https://www.pacb.com/smrt-science/smrt-sequencing/hifi-reads-for-highly-accurate-long-read-sequencing/





HiFi Reads (PacBio)



Wenger+, "<u>Accurate circular consensus long-read sequencing improves variant</u> detection and assembly of a human genome", *Nature Biotechnology*, 2019

How Long is DNA?





Cracking the 1st Human Genome Sequence

 1990-2003: The Human Genome Project (HGP) provides a complete and accurate sequence of all DNA base pairs that make up the human genome and finds 20,000 to 25,000 human genes.



Obtaining the Human Reference Genome

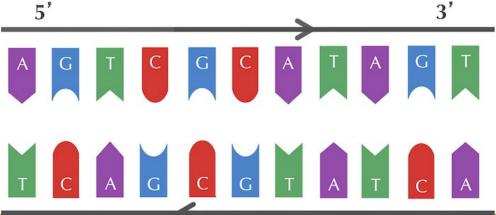
GRCh38.p13

- Description: Genome Reference Consortium Human Build 38 patch release 13 (GRCh38.p13)
- Organism name: <u>Homo sapiens (human)</u>
- Date: 2019/02/28
- 3,099,706,404 bases
- Compressed .fna file (964.9 MB)
- https://www.ncbi.nlm.nih.gov/assembly/GCF_000001405.39



Challenges in Read Mapping

- Need to find many mappings of each read
- Need to tolerate variances/sequencing errors in each read
- Need to map each read very fast (i.e., performance is important, life critical in some cases)
- Need to map reads to both forward and reverse strands





Revisiting the Puzzle



http://www.pacb.com/smrt-science/smrt-sequencing/hifi-reads-for-highly-accurate-long-read-sequencing/



Reference Genome Bias

nature genetics

Letter | Open Access | Published: 19 November 2018

Assembly of a pan-genome from deep sequencing of 910 humans of African descent

Rachel M. Sherman ⊠, Juliet Forman, [...] Steven L. Salzberg ⊠

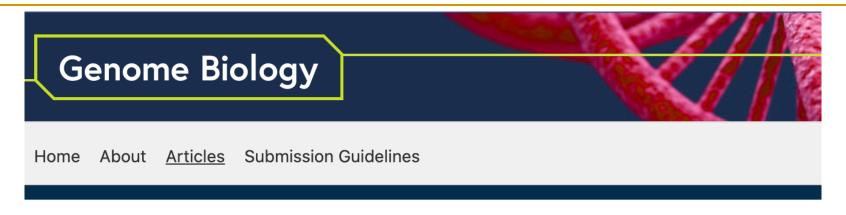
Nature Genetics **51**, 30–35(2019) Cite this article

"African pan-genome contains ~10% more DNA bases than the current human reference genome"





Time to Change the Reference Genome



Opinion | Open Access | Published: 09 August 2019

Is it time to change the reference genome?

Sara Ballouz, Alexander Dobin & Jesse A. Gillis ≥

Genome Biology 20, Article number: 159 (2019) Cite this article

12k Accesses | 11 Citations | 45 Altmetric | Metrics

"Switching to a consensus reference would offer important advantages over the continued use of the current reference with few disadvantages"



MAGNET (AACBB 2018, TIR 2017)

- Key observation: the use of AND operation to check if a zero (match) exists in a column introduces filtering inaccuracy.
- <u>Key Idea:</u> count the **consecutive zeros** in each mask and select the longest in a divide-and-conquer approach.
- MAGNET is 17x to 105x more accurate than GateKeeper and SHD.



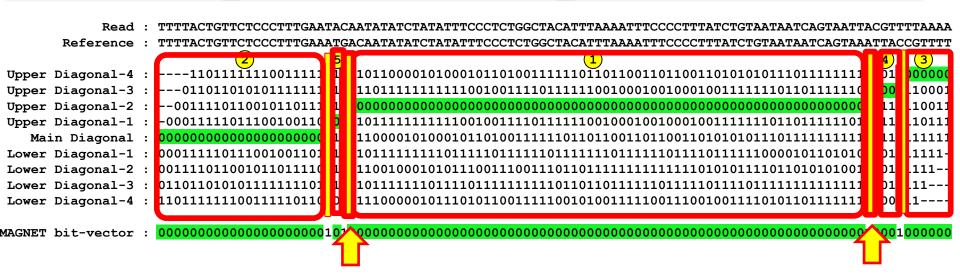


MAGNET Walkthrough

Build Neighborhood Map

Track the Diagonally Consecutive Matches

ACCEPT iff number of '1' ≤ Threshold



Find the longest segment of consecutive zeros

Exclude the errors from the search space

Divide the problem into two subproblems and repeat



What if we got a new version of the reference genome?

AirLift

- Key observation: Reference genomes are updated frequently.
 Repeating read mapping is a computationally expensive workload.
- Key idea: Update the mapping results of only affected reads depending on how a region in the old reference relates to another region in the new reference.

Key results:

- reduces number of reads that needs to be re-mapped to new reference by up to 99%
- reduces overall runtime to re-map reads by 6.94x, 208x, and 16.4x for large (human), medium (C. elegans), and small (yeast) reference genomes

Clustering the Reference Genome Regions

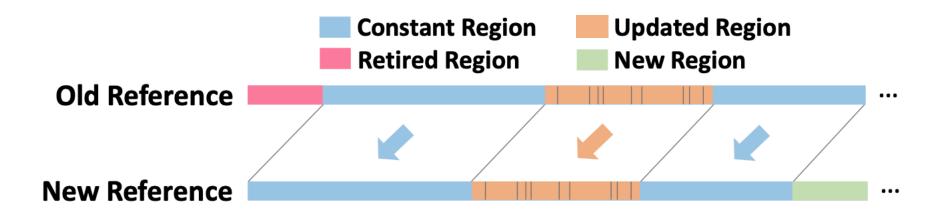


Fig. 2. Reference Genome Regions.

More Details on AirLift

arXiv.org > q-bio > arXiv:1912.08735

Search... Help | Advanc

Quantitative Biology > Genomics

[Submitted on 18 Dec 2019]

AirLift: A Fast and Comprehensive Technique for Translating Alignments between Reference Genomes

Jeremie S. Kim, Can Firtina, Damla Senol Cali, Mohammed Alser, Nastaran Hajinazar, Can Alkan, Onur Mutlu

GitHub: https://github.com/CMU-SAFARI/AirLift

Kim+, "AirLift: A Fast and Comprehensive Technique for Translating Alignments between Reference Genomes", arXiv, 2020

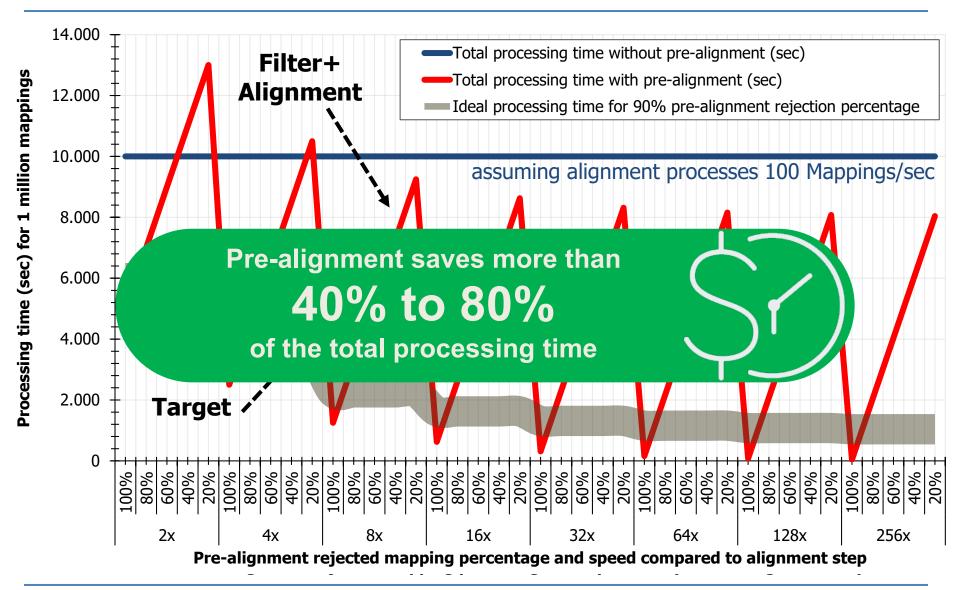
Nanopore Sequencing



- Nanopore is a nano-scale hole
- In nanopore sequencers, an ionic current passes through the nanopores
- When the DNA strand passes through the nanopore, the sequencer measures the the change in current
- This change is used to identify the bases in the strand with the help of different electrochemical structures of the different bases



The Effect of Pre-Alignment (Theoretically)



Aside: In-Memory Graph Processing

Large graphs are everywhere (circa 2015)



36 Million Wikipedia Pages



1.4 Billion Facebook Users

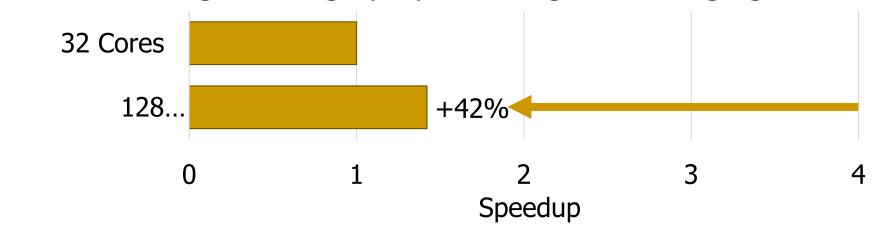


300 Million Twitter Users



30 Billion Instagram Photos

Scalable large-scale graph processing is challenging

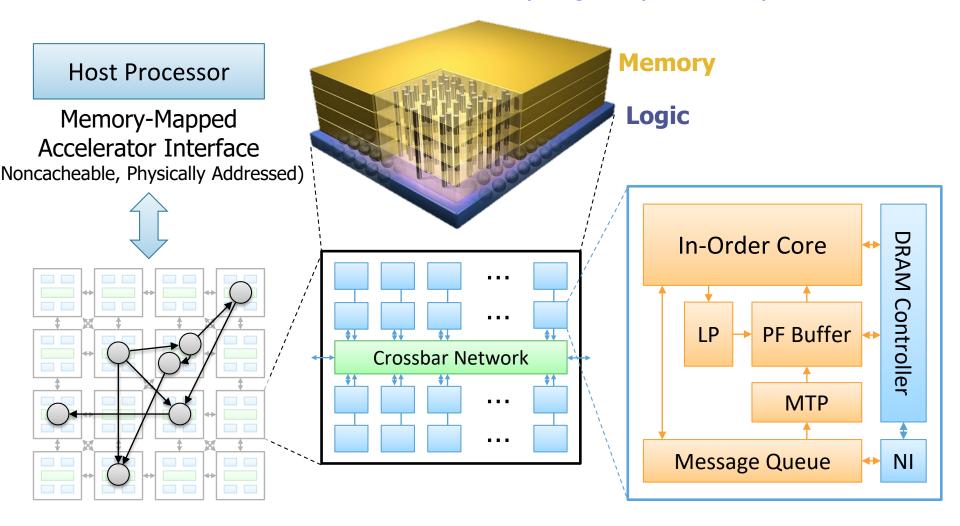


Key Bottlenecks in Graph Processing

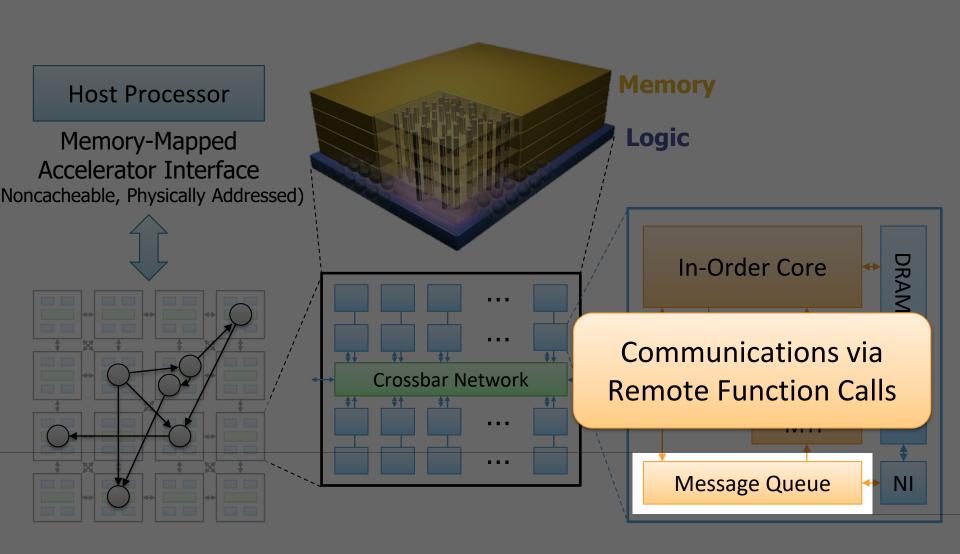
```
for (v: graph.vertices) {
     for (w: v.successors) {
       w.next rank += weight * v.rank;
                       1. Frequent random memory accesses
                                   &w
            V
 w.rank
w.next rank
                              weight * v.rank
 w.edges
            W
                              2. Little amount of computation
```

Tesseract System for Graph Processing

Interconnected set of 3D-stacked memory+logic chips with simple cores

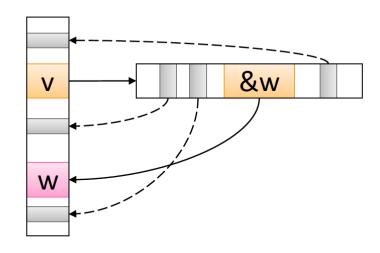


Tesseract System for Graph Processing



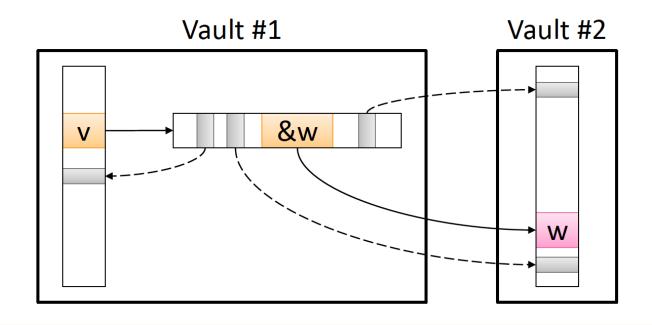
Communications In Tesseract (I)

```
for (v: graph.vertices) {
   for (w: v.successors) {
      w.next_rank += weight * v.rank;
   }
}
```



Communications In Tesseract (II)

```
for (v: graph.vertices) {
   for (w: v.successors) {
      w.next_rank += weight * v.rank;
   }
}
```



Communications In Tesseract (III)

```
for (v: graph.vertices) {
                              Non-blocking Remote Function Call
  for (w: v.successors) {
    put(w.id, function() { w.next_rank += weight * v.rank; });
                                 Can be delayed
                                 until the nearest barrier
barrier();
                  Vault #1
                                               Vault #2
                                         put
                           &w
         V
                put
                                         put
                                                  W
                                         put
```

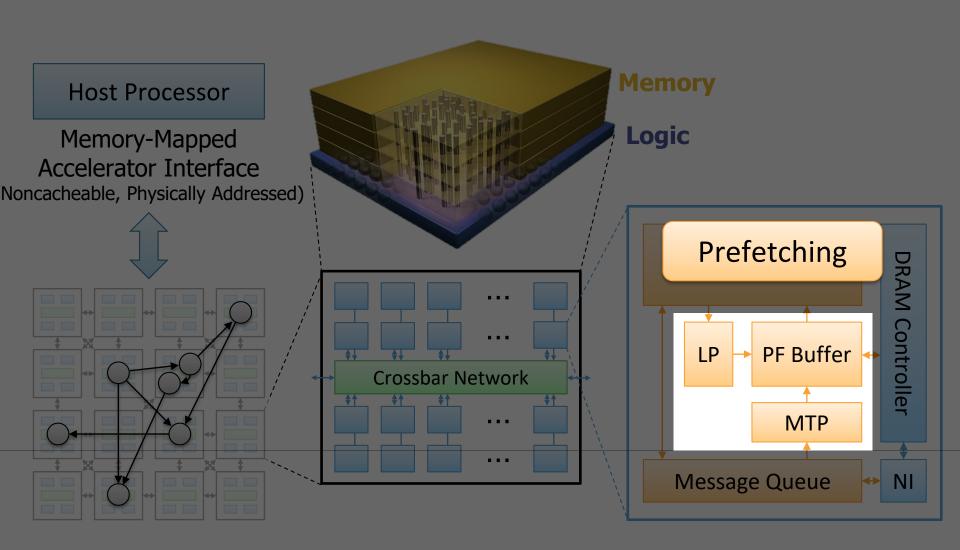
Remote Function Call (Non-Blocking)

- 1. Send function address & args to the remote core
- 2. Store the incoming message to the message queue
- Flush the message queue when it is full or a synchronization barrier is reached

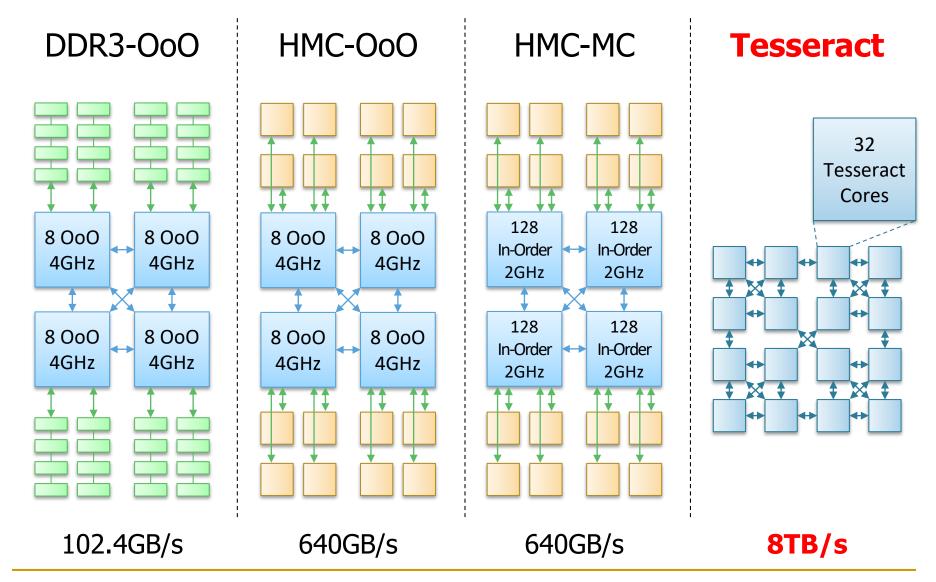


put(w.id, function() { w.next_rank += value; })

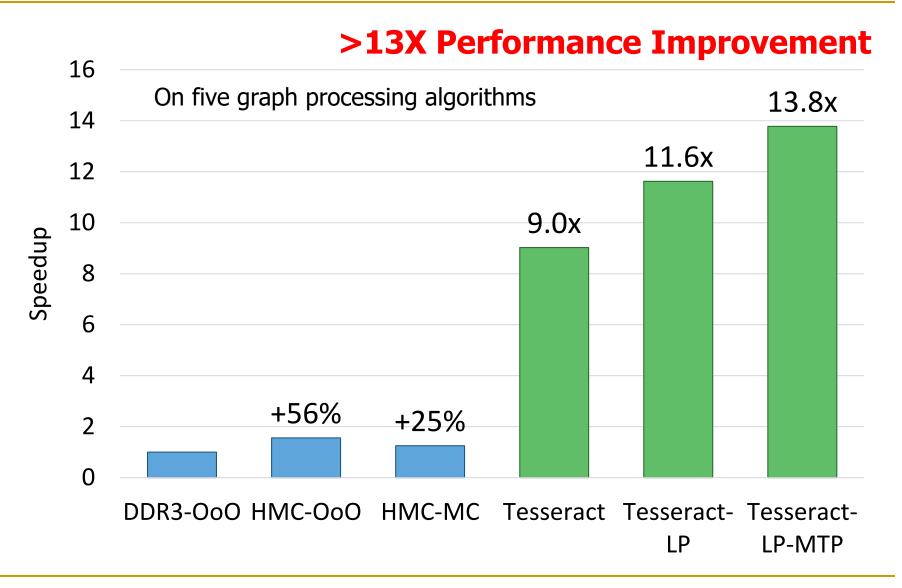
Tesseract System for Graph Processing



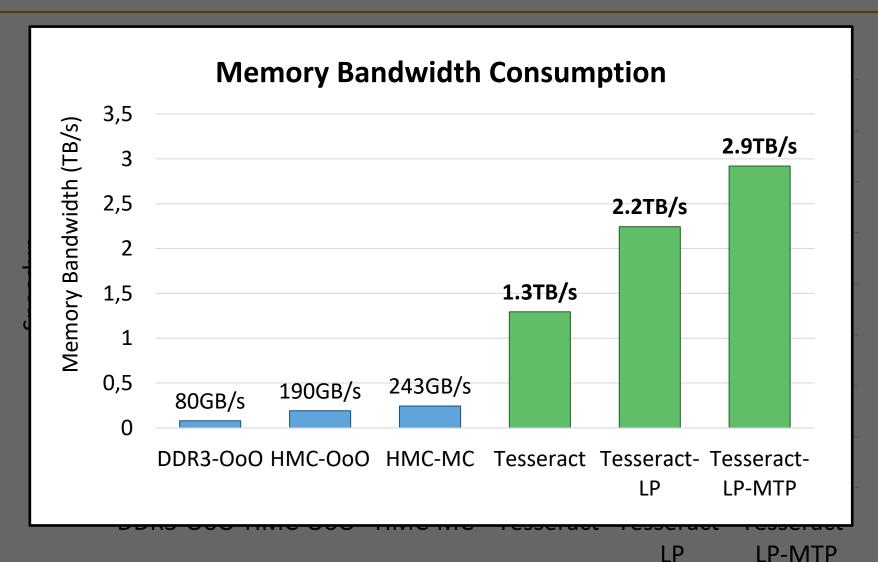
Evaluated Systems



Tesseract Graph Processing Performance

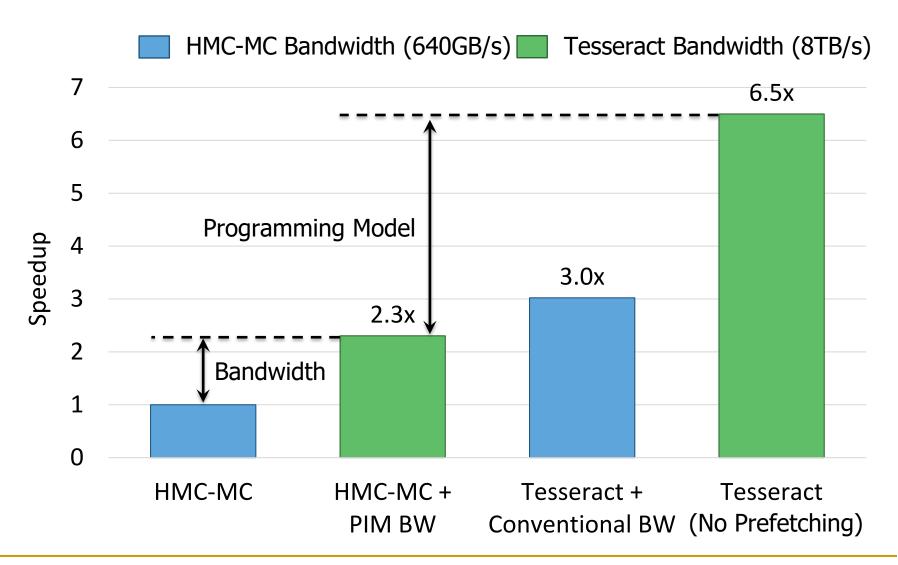


Tesseract Graph Processing Performance

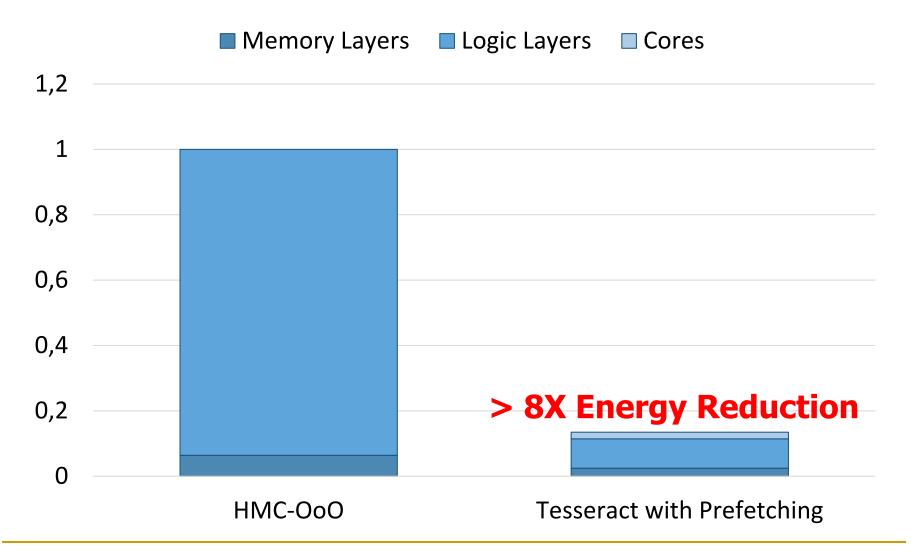


369

Effect of Bandwidth & Programming Model



Tesseract Graph Processing System Energy



SAFARI Ahn+, "A Scalable Processing-in-Memory Accelerator for Parallel Graph Processing" ISCA 2015.

More on Tesseract

 Junwhan Ahn, Sungpack Hong, Sungjoo Yoo, Onur Mutlu, and Kiyoung Choi,

"A Scalable Processing-in-Memory Accelerator for Parallel Graph Processing"

Proceedings of the <u>42nd International Symposium on</u> <u>Computer Architecture</u> (**ISCA**), Portland, OR, June 2015. [<u>Slides (pdf)</u>] [<u>Lightning Session Slides (pdf)</u>]

A Scalable Processing-in-Memory Accelerator for Parallel Graph Processing

Junwhan Ahn Sungpack Hong[§] Sungjoo Yoo Onur Mutlu[†] Kiyoung Choi junwhan@snu.ac.kr, sungpack.hong@oracle.com, sungjoo.yoo@gmail.com, onur@cmu.edu, kchoi@snu.ac.kr Seoul National University [§]Oracle Labs [†]Carnegie Mellon University

End of Backup Slides