## GenASM: A Low-Power, Memory-Efficient **Approximate String Matching Acceleration** Framework for Genome Sequence Analysis

Damla Senol Cali<sup>1</sup> Carnegie Mellon University (dsenol@andrew.cmu.edu)

Gurpreet S. Kalsi<sup>2</sup>, Zulal Bingol<sup>3</sup>, Lavanya Subramanian<sup>2</sup>, Can Firtina<sup>4</sup>, Jeremie Kim<sup>1,4</sup>, Rachata Ausavarungnirun<sup>5,1</sup>, Mohammed Alser<sup>4</sup>, Anant Nori<sup>2</sup>, Juan Gomez-Luna<sup>4</sup>, Amirali Boroumand<sup>1</sup>, Allison Scibisz<sup>1</sup>, Sreenivas Subramoney<sup>2</sup>, Can Alkan<sup>3</sup>, Saugata Ghose<sup>6,1</sup>, and Onur Mutlu<sup>4,1,3</sup>









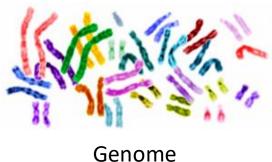






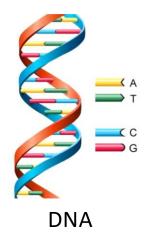


## Genome Sequencing



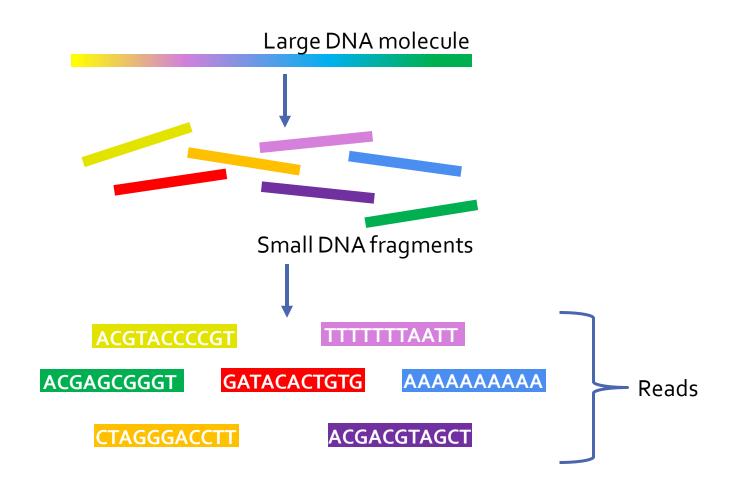


□ Genome sequencing is the process of determining the order of the DNA sequence in an organism's genome.



- ☐ Genome sequencing is pivotal in:
  - Personalized medicine
  - Outbreak tracing
  - Evolution
  - Forensics

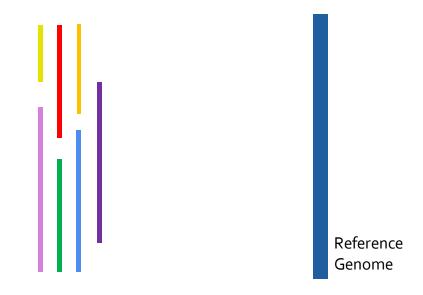
## Genome Sequencing (cont.)

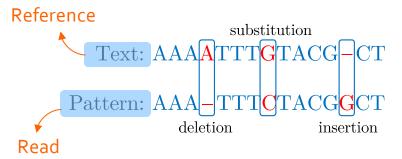


# Genome Sequence Analysis

- ☐ Genome sequence analysis requires:
  - 1) Taking small DNA fragments from an organism
  - 2) Reorganizing them into the entire genome
- Success of all medical and genetic applications critically depends on:
  - Existence of computational techniques that can process and analyze the enormous amount of sequence data quickly and accurately
- ☐ Effectively leveraging genome sequencing as a tool:
  - Requires very high computational power
  - Requires processing a large amount of data
  - Bottlenecked by the current capabilities of computer systems

# Read Mapping





- Read mapping is the method of aligning reads against a reference genome to detect matches and variations.
  - One of the key components of genome sequence analysis.
- Goal is to identify the original location of each read in the reference genome.
- Sequenced genome may not exactly map to the reference genome
  - Reason: mutations, variations, sequencing errors
- Multiple steps of read mapping must account for these errors.

### Problem & Our Goal

- Multiple steps of read mapping are essentially a series of *approximate* (i.e., *fuzzy*) *string matches*
- Approximate string matching makes up a significant portion of read mapping (i.e., more than 70%).
- ☐ One of the key bottlenecks of the entire genome analysis pipeline.

### **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

### Outline

- □ Background
- Motivation
- **□ASM** with Bitap Algorithm
- ☐ GenASM: ASM Acceleration Framework
- ☐ Use Cases of GenASM
- **□** Evaluation
- □ Conclusion

# Bitap Algorithm

- We have focused on the Bitap algorithm¹,²
  - → Reason: Bitap algorithm can perform ASM with fast and simple bitwise operations, which makes it amenable to acceleration
- Step 1: Preprocessing
  - For each character (A, C, G, T), generate a pattern bitmask
  - Indicates if character exists at each position of the pattern.
- Step 2: Searching (Edit Distance Calculation)
  - Compare all characters of the text with the pattern by using:
    - Pattern bitmasks
    - Set of bitvectors that hold the status of the partial matches
    - Bitwise operations

[1] R. A. Baeza-Yates and G. H. Gonnet. "A new approach to text searching." *Communications of the ACM*, 1992.

[2] S. Wu and U. Manber. "Fast text searching: allowing errors." Communications of the ACM, 1992.

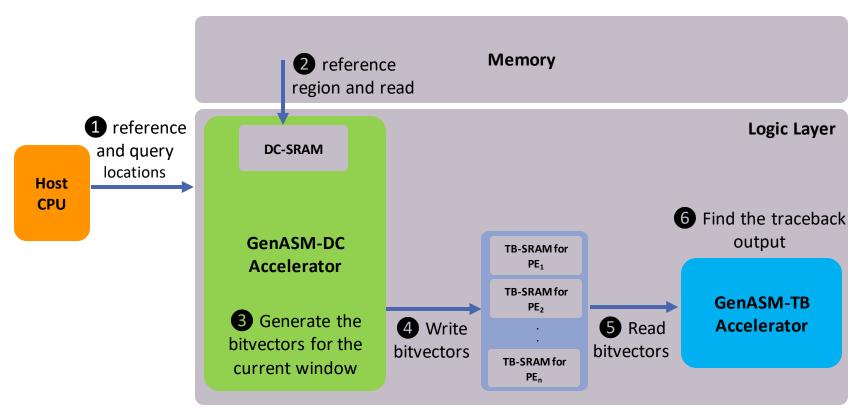
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### **GenASM**

- Approximate string matching (ASM) acceleration framework based on the Bitap algorithm
- ☐ Includes optimized ASM algorithm and new hardware
  - Highly-parallel Bitap with small memory footprint
  - Bitvector-based novel algorithm to perform traceback
    - Finding the sequence of matches, substitutions, insertions and deletions, along with their positions
  - Processing-in-Memory (PIM) accelerator for Bitap and traceback
  - □ Optimized for both 1) short yet accurate and 2) long but noisy reads

## GenASM Design



#### **GenASM-DC:**

generates bitvectors and performs edit

Distance Calculation

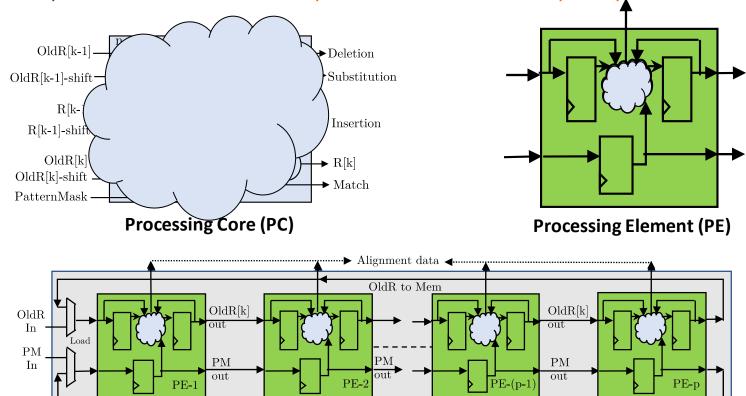
#### **GenASM-TB:**

performs TraceBack and assembles the optimal alignment

### GenASM-DC: Hardware Design

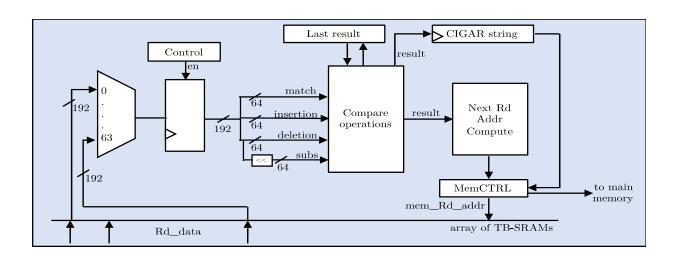
□ GenASM-DC Hardware Accelerator (HWA) is implemented as a linear cyclic systolic array.

Optimized to reduce memory bandwidth and memory footprint



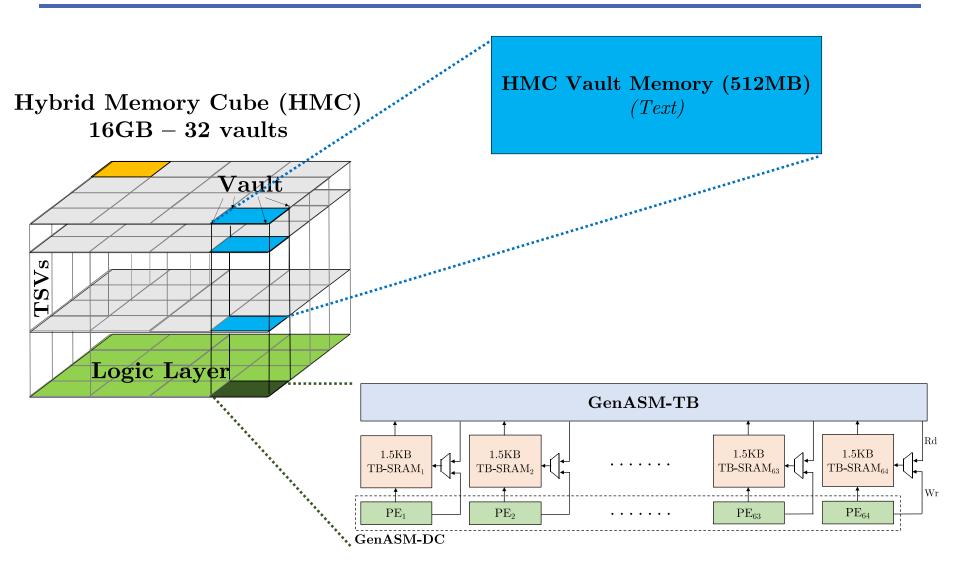
**Processing Block (PB)** 

## 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 computation and comparisons to find the traceback output for the current position
  - 3) Computes the next TB-SRAM address to read the new set of bitvectors

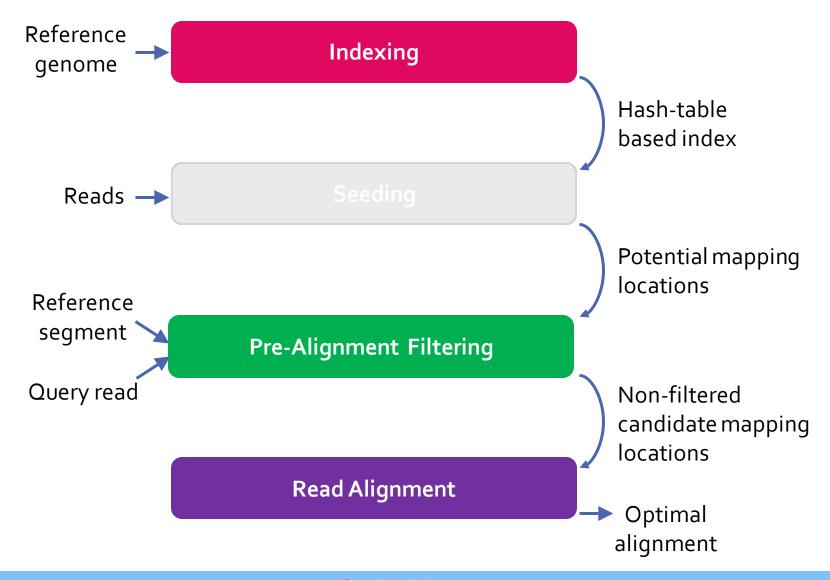
# GenASM: Overall System



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### Use Cases of GenASM



## Use Cases of GenASM (cont.)

### (1) Read Alignment Step of Read Mapping

- Also called *verification* or *seed-extension*
- GenASM can perform ASM between the query reads and the candidate regions and report the optimal alignment.

### (2) Pre-Alignment Filtering for Short Reads

- Filter out the dissimilar sequences
- GenASM can efficiently calculate the edit distance between the short read and the candidate text and decide whether it is above a user-defined threshold.

### (3) Edit Distance Calculation Between Any Two Sequences

- Fundamental operation in genomics
  - Measure the similarity or distance between two sequences
- o GenASM-DC is inherently an edit distance calculation accelerator
- We also discuss other possible use cases of GenASM in our paper:
  - o Hash-table based indexing, whole genome alignment, generic text search

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# **Evaluation Methodology**

- 16GB HMC-like 3D-stacked DRAM architecture
  - o 32 vaults
  - 256GB/s of internal bandwidth, and
  - o a clock frequency of 1.25GHz
- Datasets:
  - Simulated long read datasets (ONT and PacBio)
    - 10Kbp reads with 10-15% error rate
  - Simulated short read datasets (Illumina)
    - 100-250bp reads with 5% error rate

# Evaluation Methodology (cont.)

- ☐ For Use Case 1: Read Alignment, we compare GenASM with:
  - Two state-of-the-art read mappers: Minimap2¹ and BWA-MEM²
    - Compare GenASM only with the alignment steps of these mappers
    - Running on Intel® Xeon® Gold 6126 CPU (12-core) operating
       2.60GHz with 64GB DDR4 memory
  - Two state-of-the-art accelerators, Darwin<sup>3</sup> and GenAx<sup>4</sup>
    - Compare GenASM only with the alignment components of these accelerators (GACT for Darwin, SillaX for GenAx)
- [1] H. Li. "Minimap2: pairwise alignment for nucleotide sequences." In *Bioinformatics*, 2018.
- [2] H. Li. "Aligning sequence reads, clone sequences and assembly contigs with BWA-MEM." In arXiv, 2013.
- [3] Y. Turakhia et al. "Darwin: A genomics co-processor provides up to 15,000 x acceleration on long read assembly." In *ASPLOS*, 2018.
- [4] D. Fujiki et al. "GenAx: A genome sequencing accelerator." In ISCA, 2018.

## Key Results – Area and Power

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

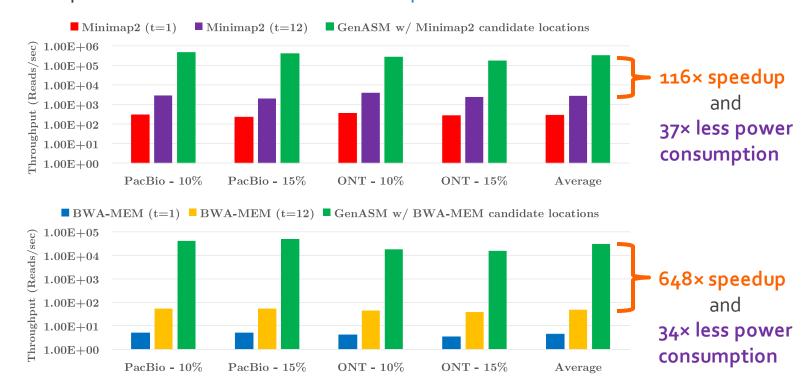
Component	Area (mm <sup>2</sup> )	Power (mW)
GenASM-DC (64 PE)	0.049	33.3
DC-SRAM (8KB)	0.013	9.2
GenASM-TB	0.016	4.0
TB-SRAMs $(64 \times 1.5 \text{KB})$	0.256	54.7
Total	0.334	101.2

- ☐ Total power consumption of all 32 vaults 3.24W
- Total area overhead of all 32 vaults is 10.69 mm²

# Key Results (Use Case 1) — Long Reads

#### Long Read Datasets:

Compared to 12-thread runs of Minimap2 and BWA-MEM:

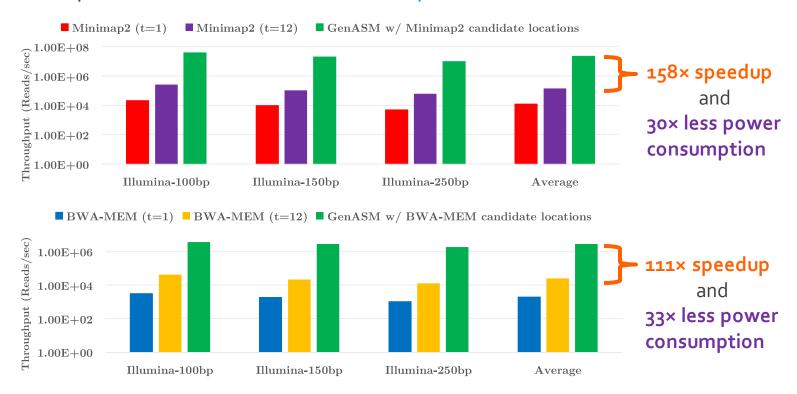


- Compared to Darwin-GACT:
  - 3.8× better throughput
  - 2.7× less power consumption

## Key Results (Use Case 1) – Short Reads

#### Short Read Datasets:

Compared to 12-thread runs of Minimap2 and BWA-MEM:



- Compared to GenAx-SillaX:
  - 1.9× better throughput
  - Comparable area and power consumption

# Key Results (Use Cases 2 & 3)

- □ Pre-Alignment Filtering for Short Reads
  - Use Case 2
  - 3.6× speedup vs. Shouji
  - GenASM also significantly improves the filtering accuracy
- Edit Distance Calculation
  - Use Case 3
  - 246 5668× speedup vs. Edlib
- ☐ See our MICRO 2020 paper for more details

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### Conclusion

#### Problem:

- Genome sequence analysis is bottlenecked by the computational power and memory bandwidth limitations of existing systems.
- o This bottleneck is particularly an issue for approximate string matching.
- **Goal:** Provide an approximate string matching (ASM) acceleration framework in order to accelerate multiple steps of genome sequence analysis

### **☐** Key Contributions:

- First to enhance and accelerate Bitap for ASM with genomic sequences
- GenASM: approximate string matching (ASM) acceleration framework
  - Co-design of our modified scalable and memory-efficient algorithms with low-power and area-efficient hardware accelerators
  - Evaluation of three different use cases of ASM in genomics: read alignment, edit distance calculation, and pre-alignment filtering.
- **Key Results:** GenASM is significantly more efficient for all the three use cases (in terms of throughput and throughput per unit power) than state-of-the-art software and hardware baselines.

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