

GPU accelerated partial order multiple sequence alignment for long reads self-correction

19th IEEE International Workshop on High Performance Computational Biology,
May 18, 2020,
New Orleans, Louisiana USA

Francesco Peverelli:

francesco1.peverelli@mail.polimi.it

Steven Hofmeyr: shofmeyr@lbl.gov

Lorenzo Di Tucci:

lorenzo.ditucci@polimi.it

Aydın Buluç: abuluc@lbl.gov

Marco Domenico Santambrogio:

marco.santambrogio@polimi.it

Leonid Oliker: loliker@lbl.gov

Nan Ding:

nanding@lbl.gov

Katherine Yelick: kayelick@lbl.gov



POLITECNICO
MILANO 1863



Third generation sequencing

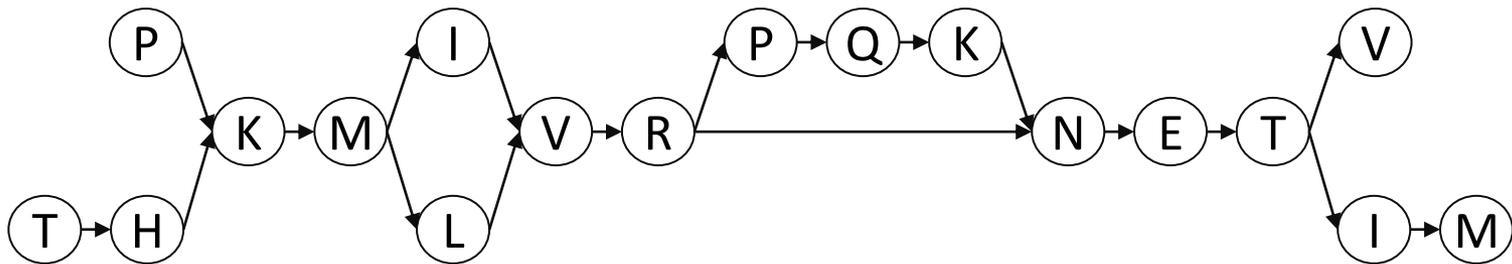
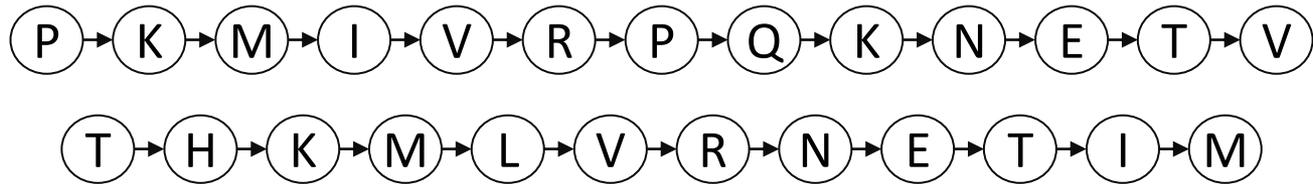
- provides much **longer reads** allowing more precise **contig and haplotype assembly** and **structural variant calling**
- the **error rate** of these sequences is **significantly higher (10-20%)** compared to their second generation counterparts (0.2%)
- therefore, **error correction** is included as a preliminary step in genome analysis
- many self-correction tools (e.g. RACON, CONSENT) rely on **Partial Order (PO) Multiple Sequence Alignment (MSA)** to identify the consensus sequences

Contributions

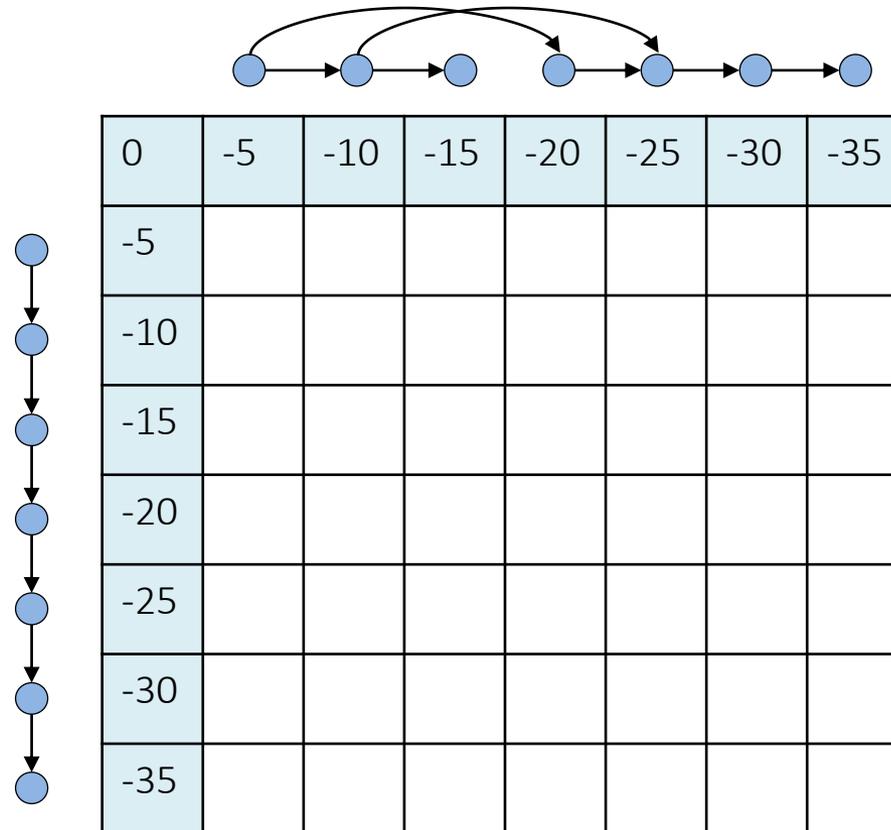
- A **GPU implementation** of the PO alignment algorithm that achieves up to **6.5x speedup** compared to the software version run on two 2.3 GHz **16-core Intel Xeon Processors E5-2698 v3** with 64 CPU threads
- An extension of the **Roofline model analysis** for **GPUs** presented in [1], to evaluate the performance of our implementation on the **NVIDIA Tesla V100**
- The **integration** of our kernel with **CONSENT**, a state of the art long read self-correction tool obtaining up to **8.5x speedup** of the error correction module

[1] N. Ding and S. Williams, “An instruction roofline model for gpus,” 2019 IEEE/ACM Performance Modeling, Benchmarking and Simulation of High Performance Computer Systems (PMBS), 2019.

Partial order graph alignment

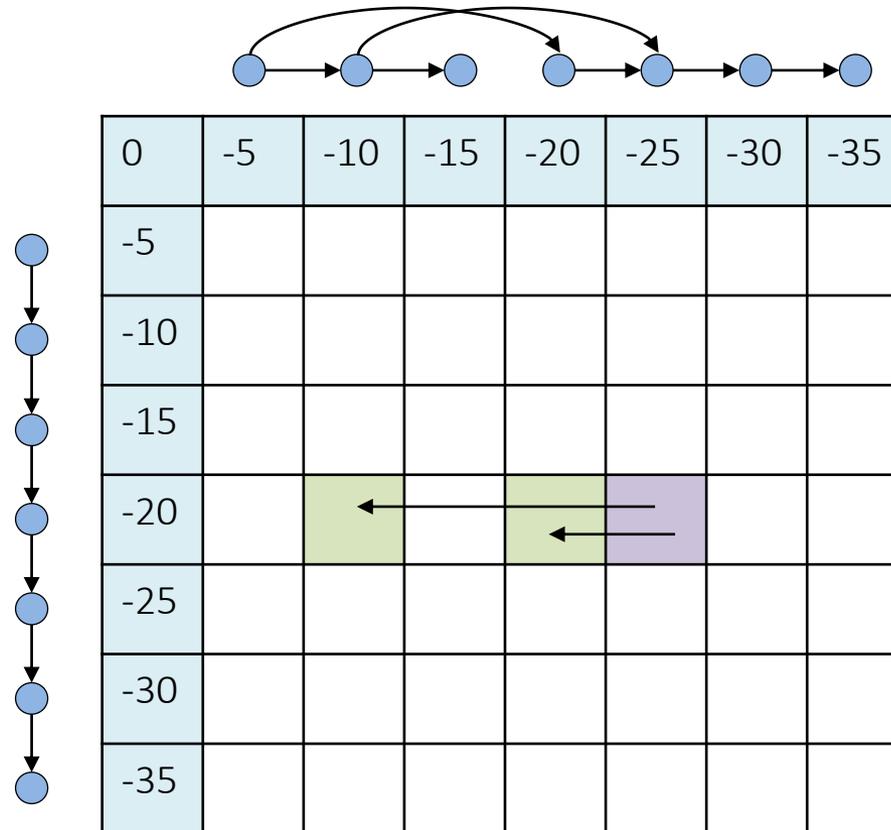


Partial Order Alignment



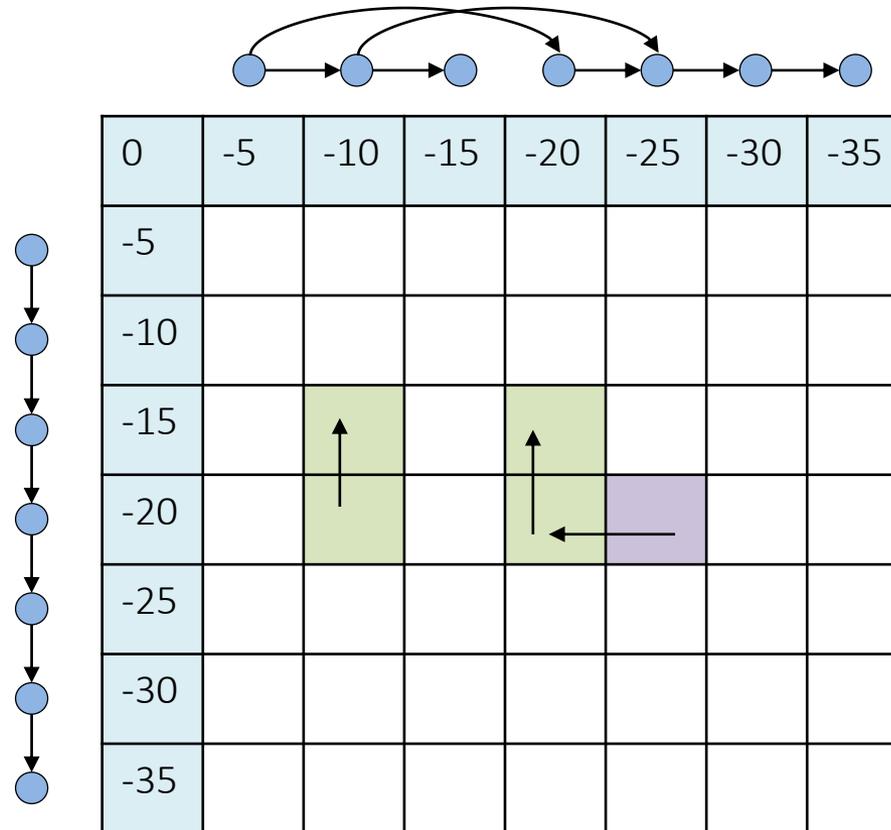
Similarly to sequence alignment, a scoring matrix is used to identify the optimal alignment between the PO graphs

Partial Order Alignment



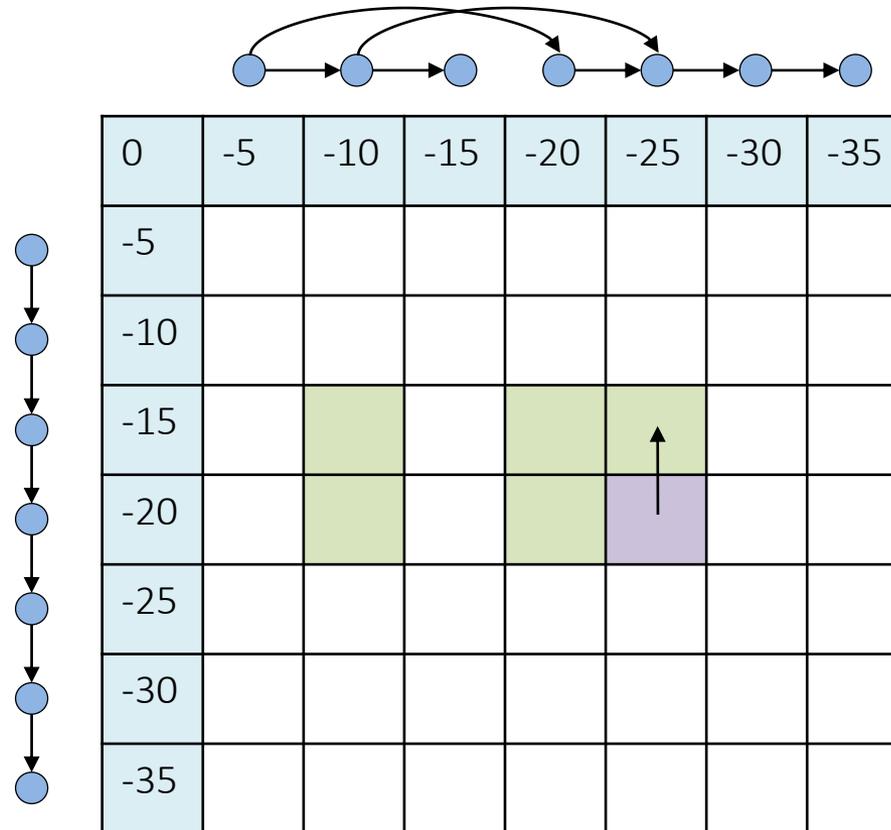
Cell to score at current iteration
 Scoring dependencies
 Dependency arc

Partial Order Alignment



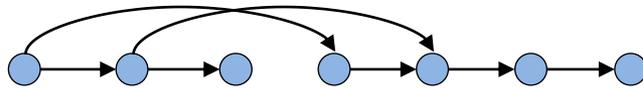
- Cell to score at current iteration
- Scoring dependencies
- Dependency arc

Partial Order Alignment



Cell to score at current iteration
 Scoring dependencies
 Dependency arc

Partial Order Alignment



	0	-5	-10	-15	-20	-25	-30	-35
-5								
-10								
-15								
-20								
-25								
-30								
-35								

All the **white cells** are possible **scoring dependencies** for the current cell for a generic PO pair

- Cell to score at current iteration
- Scoring dependencies
- Dependency arc

PO alignment implementation

	t0	t1	t2	t3	
0	-5	-10	-15	-20	-25
-5					
-10					
-15					
-20					
-25					

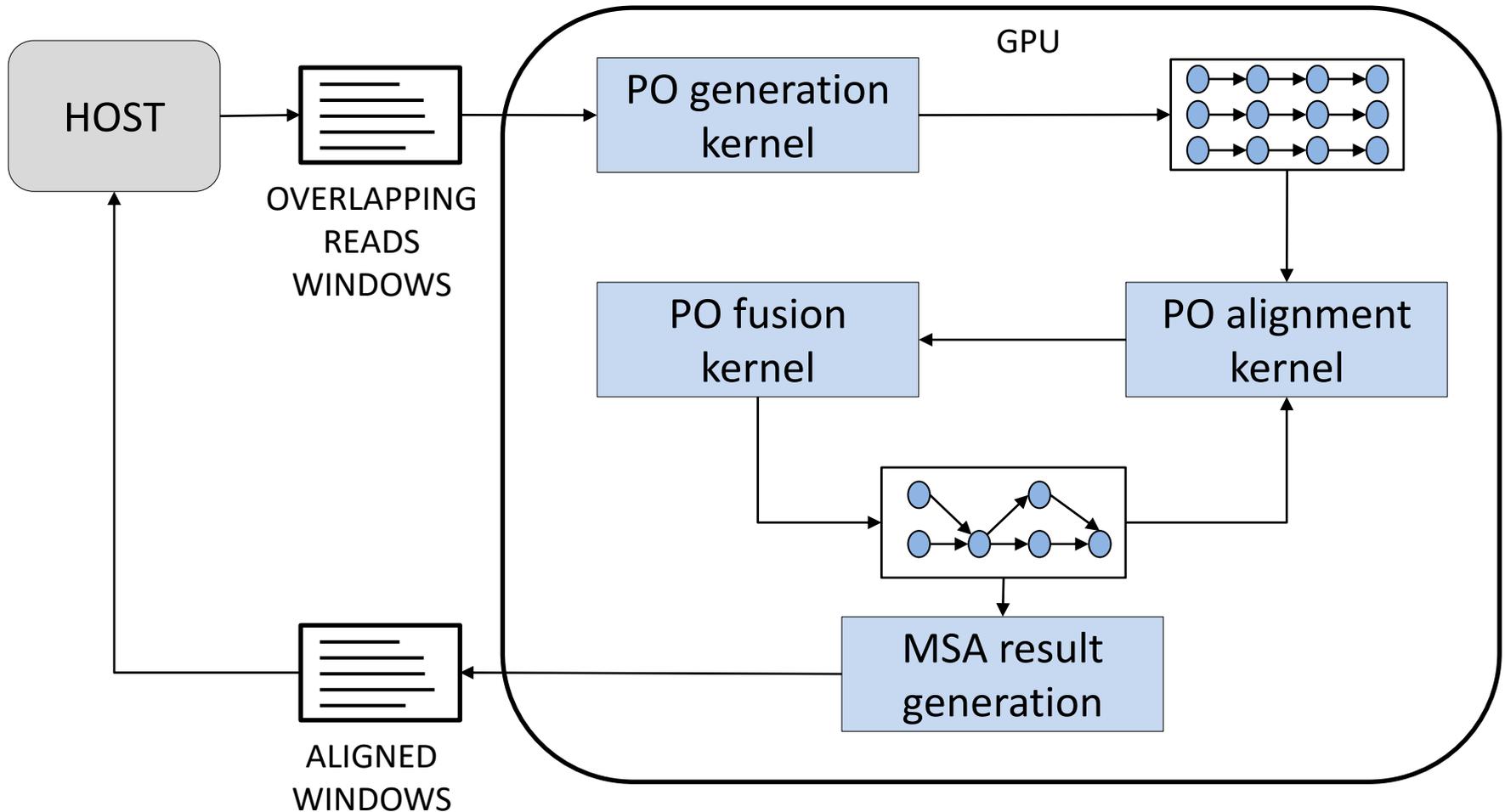
The table illustrates the PO alignment implementation. The first row and first column are highlighted in light blue. The main diagonal cells (from (0,0) to (-25,-25)) are highlighted in light orange. Arrows point from the labels t0, t1, t2, and t3 to the first column, the first row, the main diagonal, and the main diagonal respectively.

- The PO graph is represented as and **edge list** stored in **shared memory**, plus a sequence of characters
- Each thread computes a cell of the current antidiagonal by looping over all the predecessors
- The scoring matrix is **stored by antidiagonals** for **coalesced memory access**

CHALLENGES

1. The dependencies of each cell change for different PO graphs, either pre-compute them or **store** the entire alignment matrix in memory (we chose the latter option)
2. The memory space required **changes** during the iterative alignment procedure -> allocate **enough memory statically** for each alignment

PO Multiple Sequence alignment

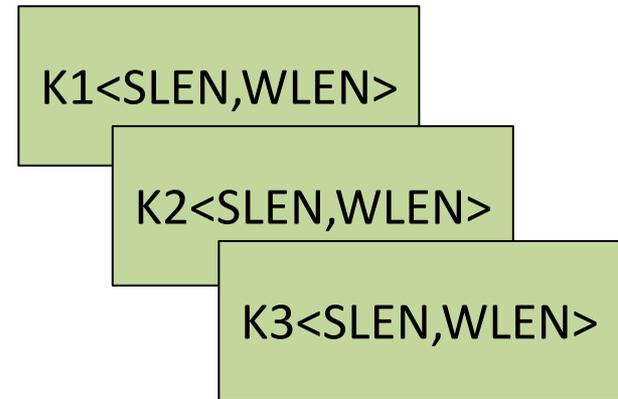


Each **CUDA block** operates on an **independent window of reads**. The whole **MSA task** is performed **in parallel** on up to 150,000 blocks

Kernel selection

CHALLENGE:
Reduce **excess static memory allocation** for the alignment scoring matrix and MSA result

SOLUTION:
Choose between **multiple kernels** at **runtime** depending on the **size and number** of sequences



Depending on the kernel selected and the device global memory capacity we can compute a **different number of blocks**

SLEN: maximum initial length of the sequences for each MSA task

WLEN: maximum number of sequences in the window for each MSA task

Roofline model analysis

- Given the specific nature of the parallelism in the alignment algorithm, we propose a theoretical ceiling in terms of **GWarpIntInstructions/s**:

$$IntF_{max} = \frac{1}{D} \sum_{k=1}^D \frac{F_{INT} \cdot N_k \cdot B}{\lceil T \cdot B / \min(INT_C, T \cdot SM \cdot MB) \rceil}$$

$$T = \left\lceil \frac{N_k}{T_s} \right\rceil \cdot T_s$$

INT_C = number of integer FUs

F_{INT} = frequency of an integer FU

SM = streaming multiprocessors

T_s = number of threads scheduled

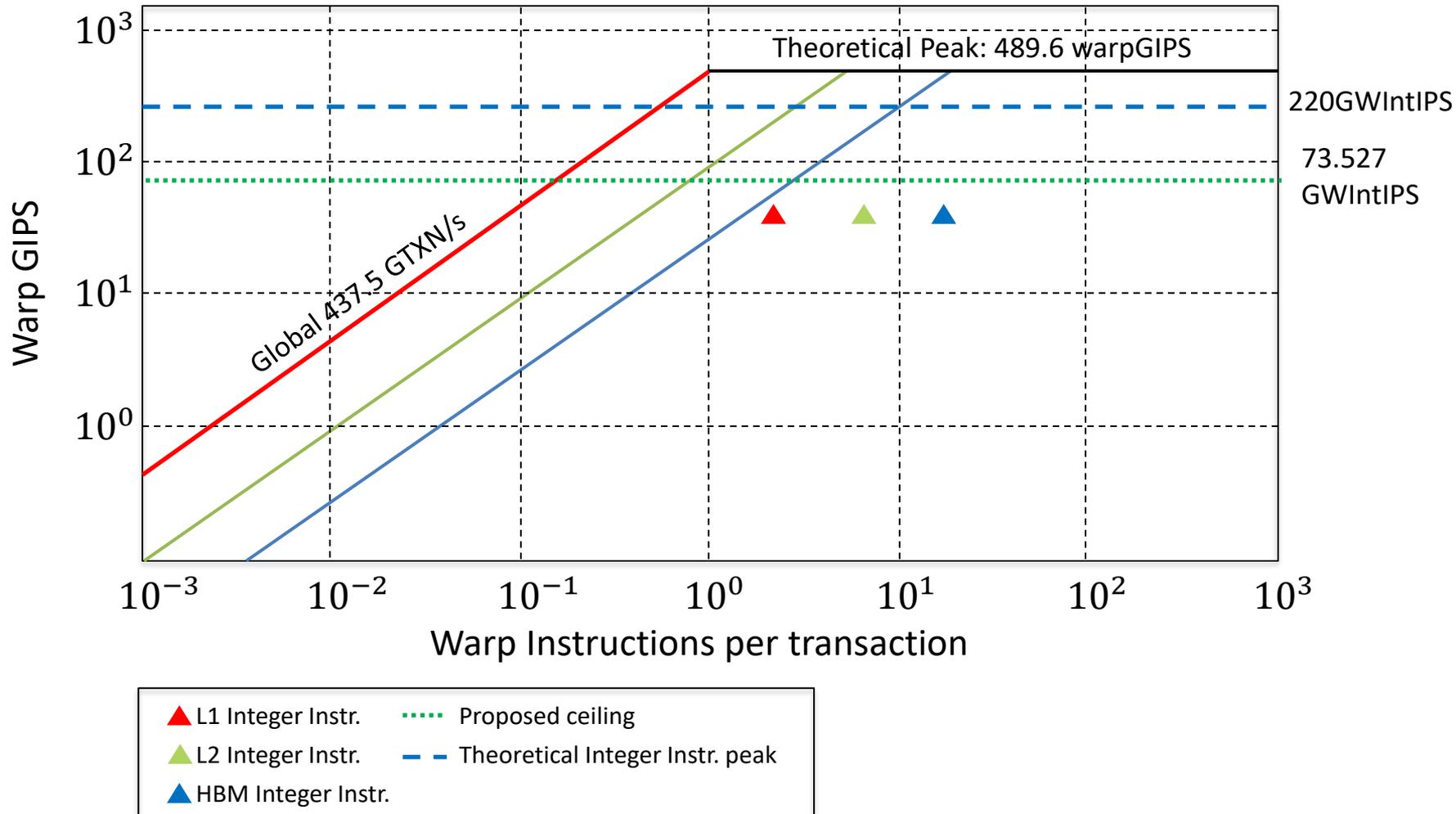
B = number of blocks scheduled

MB = max blocks per SM

N_k = elements to compute at iteration k

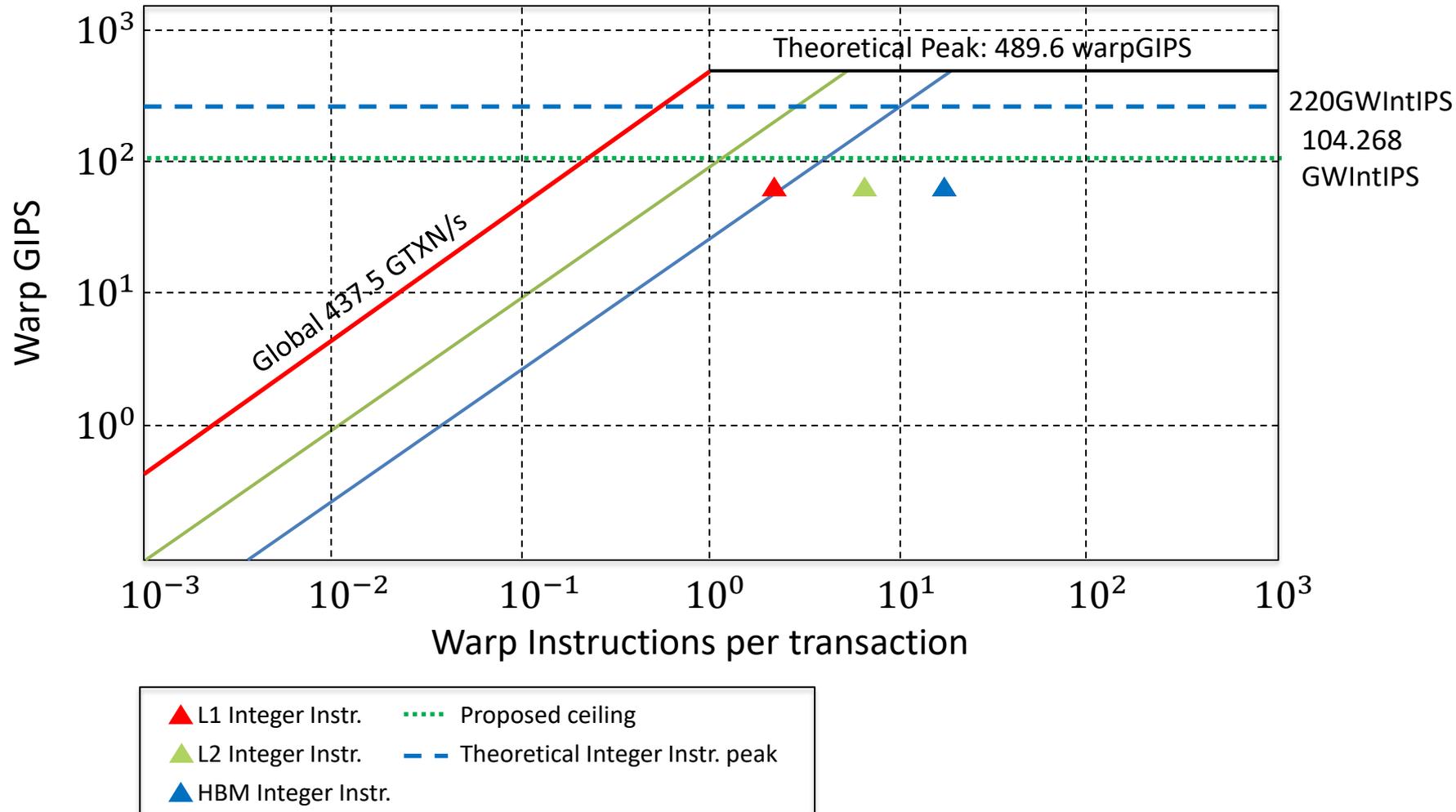
D = total iterations of the algorithm

Roofline model analysis



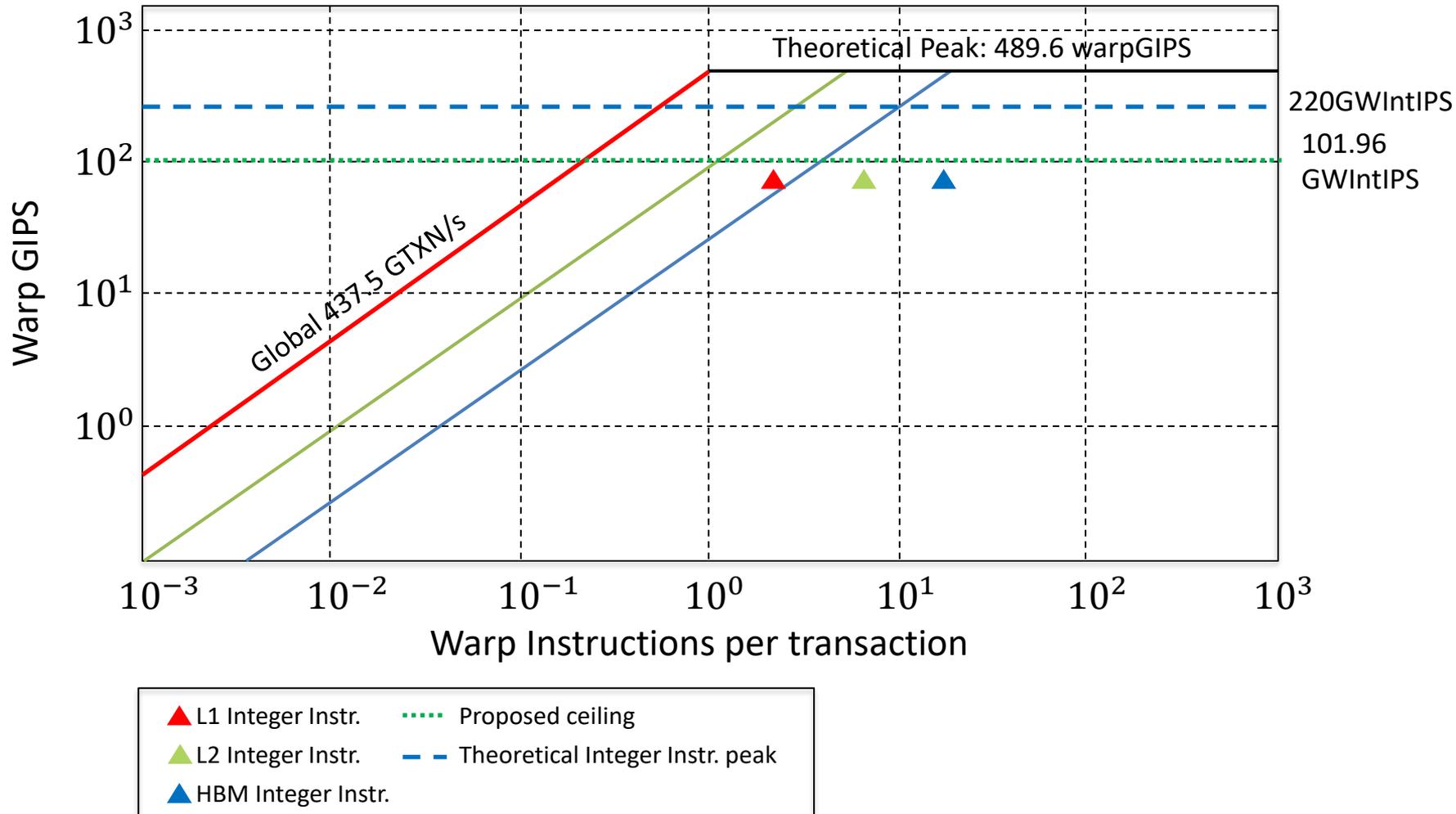
Roofline analysis for one GPU kernel for windows of between 1 and 32 sequences and sequences of 1-31 bp

Roofline model analysis



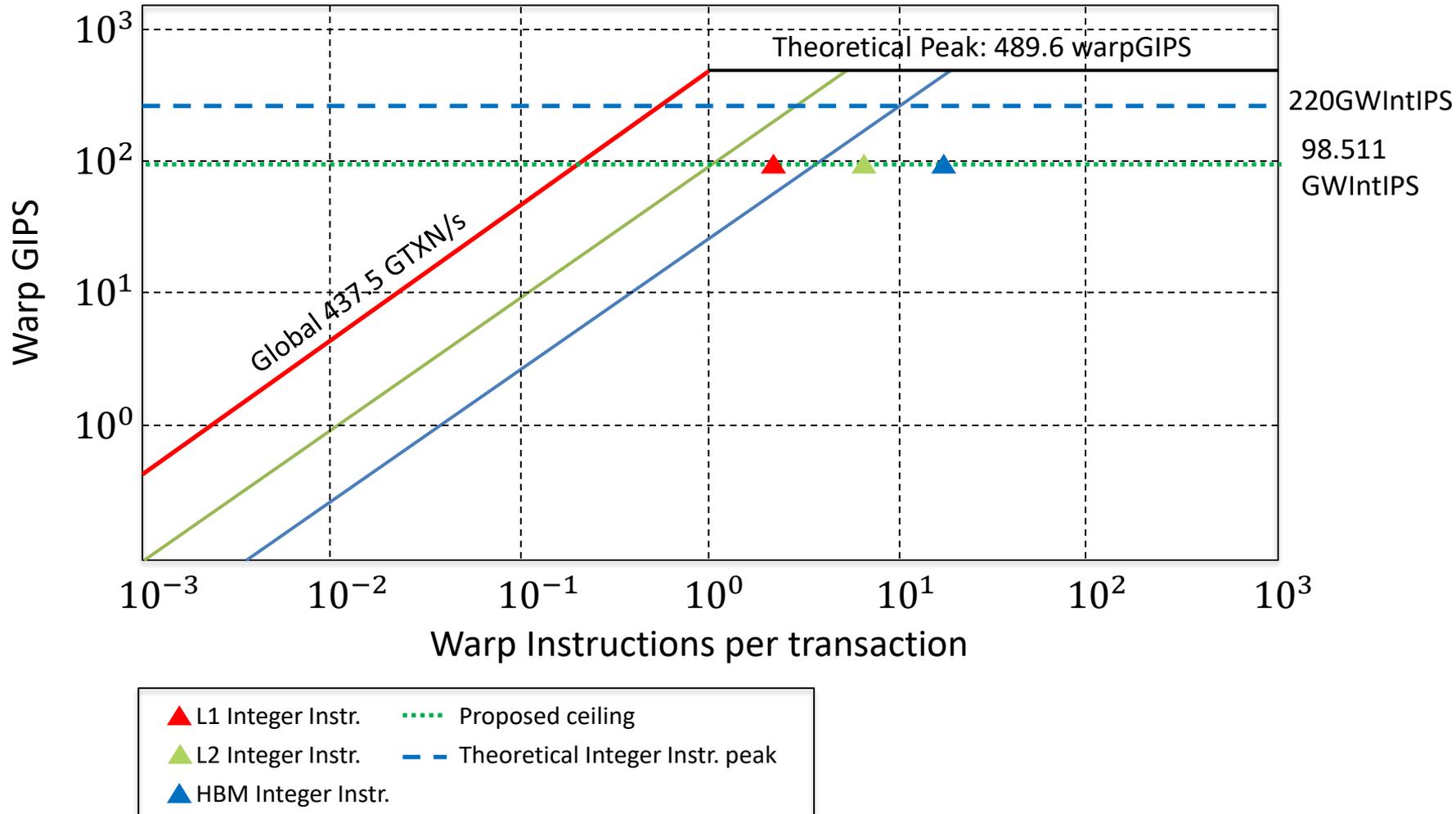
Roofline analysis for one GPU kernel for windows of between 1 and 32 sequences and sequences of 1-63 bp

Roofline model analysis



Roofline analysis for one GPU kernel for windows of between 1 and 32 sequences and sequences of 1-127 bp

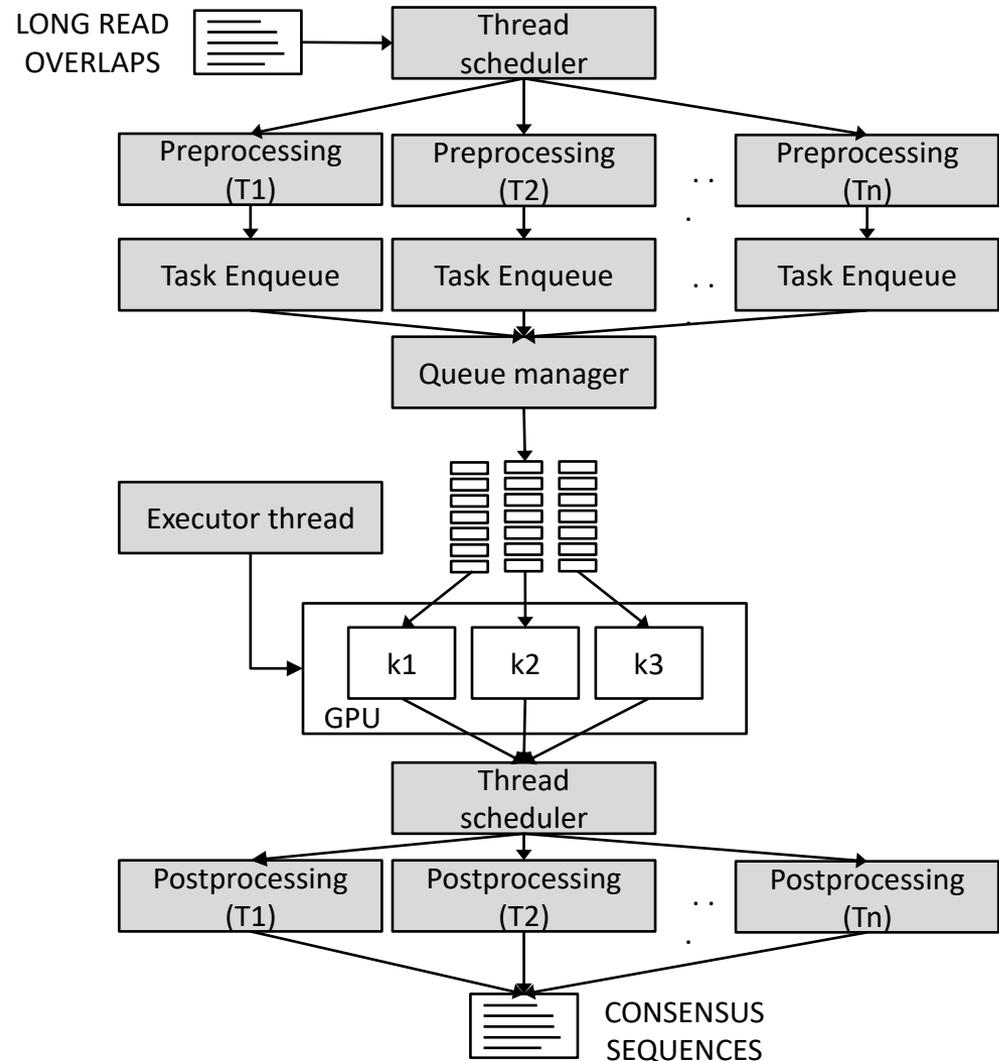
Roofline model analysis



Roofline analysis for one GPU kernel for windows of between 1 and 32 sequences and sequences of 1-255 bp

CONSENT integration

- The segmentation and correction strategy of CONSENT is split into three phases to create **batches of MSA tasks**
- Each thread is assigned to a **preprocessing and enqueue** task according to a round-robin policy
- The MSA tasks are enqueued in a **thread-safe queue**. Once the queue is full, the **executor thread** performs the accelerated MSA
- After the current batch of alignments has been performed, each thread is assigned to a **postprocessing** task to compute the final **consensus sequence** for the reads



Xeon E5 CPU performance comparison

Sequence size	Window size	CPU	Single thread speedup	64 threads speedup
1-32 bp	2-8	1 min 34s	35.31x	2.6x
32-63 bp	2-8	7 min 52s	82.15x	3.5x
64-127 bp	2-8	26 min 45s	121.28x	4.3x
128-255 bp	2-8	1h 42 min	192.13x	6.49x

Performance comparison of the PO alignment kernel executed on a **NVIDIA Tesla V100** against the CPU implementation of the BOA library [2] executed on a single thread and with 64 parallel threads on **two 2.3 GHz 16-core Intel Xeon Processors E5-2698 v3** with a total of 64 hardware threads. Each experiment was executed on **1.2 million windows of sequences**.

Sequence size: number of base pairs for each individual sequence in the MSA

Window size: number of sequences in the MSA procedure

[2] <https://github.com/Malfoy/BOA>

Skylake CPU performance comparison

Sequence Size	Window size	CPU	GPU	Speedup
1-32 bp	17-32	2 min 25s	1 min 7s	2.16x
32-63 bp	17-32	4 min 45s	1 min 57s	2.43x
64-127 bp	17-32	11 min 29s	4 min 19s	2.65x
128-255 bp	17-32	36 min 44s	12 min 55s	2.84x

Performance comparison of the PO alignment kernel against the CPU implementation of the BOA library executed with 80 parallel threads on **two Intel Xeon Gold 6148 ('Skylake')** running at 2.40 GHz. Both were executed on **3.2 million windows of sequences**.

Sequence size: number of base pairs for each individual sequence in the MSA

Window size: number of sequences in the MSA procedure

*A more complete version of this table is available in the paper

GPU state of the art comparison

Sequence size	Window size	Our kernel	Clara Genomics[1]	Speedup
1-255 bp	1-32	2 min 40s	15 min 42s	5.89x

[1] Clara Genomics run on single CUDA stream in MSA generation mode (same type of output as our implementation)

Sequence size	Window size	Our kernel	Clara Genomics[2]	Speedup
1-255 bp	1-32	2 min 40s	10 min 28s	3.92x

[2] Clara Genomics multi-batch benchmark in consensus generation mode (different type of output, but the most efficient way to run Clara Genomics, included for completeness)

All experiments are performed on a **NVIDIA Tesla V100** on **2 million windows** of sequences

CONSENT acceleration results

Dataset	Organism	Dataset size	CONSENT-GPU	CONSENT	Speedup
SRR10326407	E. Coli(30x)	151 Mbp	6 min 29s	34 min 36s	5.3x
SRR10326407	E. Coli(60x)	290 Mbp	16 min 44s	2h 26 min	8.5x
SRR7743079	D. Melanogaster (20x)	2.9 Gbp	2h 53 min	6h 17 min	2.18x
ERR3454401	S. Cerevisiae (30x)	386 Mbp	1h 6 min	23 min	2.86x
ERR3454401	S. Cerevisiae (60x)	756 Mbp	3h 0 min	1h 32 min	1.95x

Performance comparison of CONSENT and our GPU accelerated version. Both software were run on **two Intel Xeon Gold 6148 ('Skylake')** running at 2.40 GHz with **80 parallel threads**.

Conclusions

- We presented a **GPU accelerated** algorithm for **multiple sequence alignment** based on **partial order graphs** that outperforms the state-of-the-art CPU-based POA v2 alignment library for the targeted range of sequence and window lengths, achieving a speedup that ranges from **2.16x** to **6.49x**
- To evaluate the quality of the proposed GPU implementation, we have devised an extension of the **Roofline model for GPU** and we show that our kernel achieves near-optimal performance
- We have also shown that for the target range of sequences and window lengths we outperform the Clara Genomics PO alignment module by **5.89x** and **3.92x** for different execution modes on the NVIDIA Tesla V100 GPU

Contacts

For questions regarding this work, email
Francesco Peverelli: francesco1.peverelli@mail.polimi.it

Github repository:
<https://github.com/francesco-peverelli/CONSENT-GPU>



POLITECNICO
MILANO 1863

