From Processing-in-Memory to Processing-in-Storage (PrinS)



Smith-Waterman: Local Sequence Alignment



- The Smith-Waterman (S-W) algorithm finds regions with Proven to be optimal
- > Every "match", "mismatch" & "gap" inside the pair of sequences has a score
- > S-W is based on dynamic programming \checkmark Fills a $m \times n$ matrix \checkmark Has a quadratic computational complexity $O(m \cdot n)$
- ✓ We implemented the scoring step more computationally demanding



Advisor: Prof. Ran Ginosar

Moving large amounts of data takes a lot of

performance we **must bring processing**

Resistive Content Addressable Memory (ReCAM): A Prins Device



PrinS Application: DNA Local Sequence Alignment In-ReCAM S-W

•

"highest similarity" between two sequences (DNA or protein)

> Two main steps in the algorithm: (1) scoring and (2) traceback

Parallel S-W

Matrix-fill order is on the main diagonal

> The entire antidiagonal is calculated in parallel Antidiagonal per group of ReCAM columns

We search for the maximal score





Roman Kaplan In collaboration with: Dr. Leonid Yavits

- Every score is a 32-bit integer = 32 ReCAM bitcells
- DNA sequence is stored in 2 columns (2 bits per base-pair)
- Sequence B shifts down at the beginning of an iteration









Simulations: ReCAM vs. OpenDedup

- ➢ ReCAM was simulated with a cycleaccurate simulator
- ReCAM size = 256GB
- Frequency = 1GHz
- > Opendedup was executed on a highend server for comparison: 4×8 octacore CPU, 64GB of RAM and 800GB SSD drive
- **ReCAM** has 100× higher throughput than deduplication with RAM+CPU
- Energy consumption is similar or lower for the common block sizes (4 & 8KB)





Entire ReCAM crossbar array can be GBs in size divided to

- separate ICs
- E.g., IC can be 256MB is size
- 256MB = 8M rows
- Future technology might allow TBs of storage
- > In-situ processing:
 - Bit-wise logic
 - Algebraic operations
- ✓ Column-shift
- Row-wise comparison
- CAM operations (explained in 'In-Storage Deduplication' below)

Bit-cell switching time can allow for a GHz operational frequency

Simulations

- Cycle-accurate simulator: 8GB of storage @500MHz
- Compared to multi-accelerator state-of-the-art solutions: FPGA, Xeon Phi and GPU

ReCAM (iteration end)

		A	В	
		<i>a</i> ₁	<i>b</i> ₆	
5,1	4,1	<i>a</i> ₂	b_5	
5,2	4,2	<i>a</i> ₃	<i>b</i> ₄	
5,3	4,3	<i>a</i> ₄	<i>b</i> ₃	
5,4	4,4	a_5	<i>b</i> ₂	
5,5		<i>a</i> ₆	b_1	
		a ₇		
		<i>a</i> ₈		
				-

Performance Compared to State-of-the-Art

	Hot C C			
Accelerator	FPGA	Xeon Phi	GPU	ReCAM
Performance (TCUPS)	6.02	0.23	11.08	52.68
# of ICs	128	4	384	32
Publication	L.Wienbrandt. The FPGA-based High-Performance Computer RIVYERA for Applications in Bioinformatics. In <i>Language</i> , <i>Life</i> , <i>Limits: 10th CiE</i> , pages 383- 392. Springer 2014.	Y. Liu and B. Schmidt. 2014b. SWAPHI: Smith-Waterman protein database search on Xeon Phi coprocessors. In <i>IEEE</i> <i>ASAP</i> . 184–185.	Sandes, E. F. O., et al. "CUDAlign 4.0: Incremental Speculative Traceback for Exact Chromosome-Wide Alignment in GPU Clusters." IEEE	

Future: Deep Learning

Next Work

> Nowadays Deep Learning for large nets is done in cloud

- > No energy figures reported, main concern is performance
- Deep Learning has two parts: (1) Feedforward (2) Backpropagation Each requires different set of tools

Main Questions

- Which instruction set?
- Do we need new modules? (E.g., sum) reduction)
- Will we be able to solve larger problems with PrinS?

