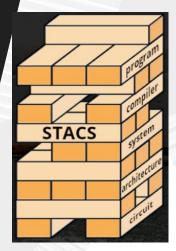


Working from Both Ends to Bridge the Gap Between Silicon and Human Cognition

High Throughput Computing - July 2024

Ranganath (Bujji) Selagamsetty Robert Klock Joshua San Miguel Mikko Lipasti



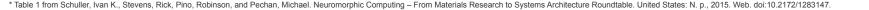


Outline

• Neuromorphic computing: the bridge between silicon and biology

- Top-down: Drawing inspiration from the auditory cortex for DNS
 Broad design exploration of network parameters (CHTC GPUs)
- Bottom-up: Improving current CPU architectures for stochastic workloads
 - Characterisation of Random Number Generation schemes (CHTC CPUs)

• Future Work and Opinions



Neuromorphic Computing

- "The opportunity lies in combining the best of biology and silicon"
- Approaches from different directions:
 - Top-down: understand the brain for better algorithms
 - Bottom-up: accelerate existing computing systems for cognitive programs

	Biology	Silicon
Speed	1 msec	1 nsec
Size	1µm - <mark>1</mark> 0µm	10nm - 100nm
Voltage	~ 0.1V	V _{dd} ~1.0V
Neuron Density	100K/mm ²	5k/mm ²
Reliability	80%	< 99.9999%
Synaptic Error Rate	75%	~ 0%
Fan-out (-in)	10 ³ -10 ⁴	3-4
Dimensions	Pseudo 3D	Pseudo 3D
Synaptic Op Energy	~ 2 fJ	~10pJ
Total Energy	10 Watt	>>10 ³ Watt
Temperature	36C - 38C	5C - 60C
Noise effect	Stochastic Resonance	Bad
Criticality	Edge	Far





Top-down: Study Auditory Cortex for DNS

- Speech denoising is a non-trivial, popular task
 - Microsoft DNS
 - Intel N-DNS
- ANNs struggle, ears are proficient
 - Look to human anatomy for inspiration
- What inspiration can we glean from the brain?
 - Rich data encoding from the pinna...
 - Energy efficiency from temporal computing in spiking neural networks...



1.0 0.8 0.6

0.4

0.2

0.0 -0.2 -0.4 -0.6

0.75

0.00 -

-0.25

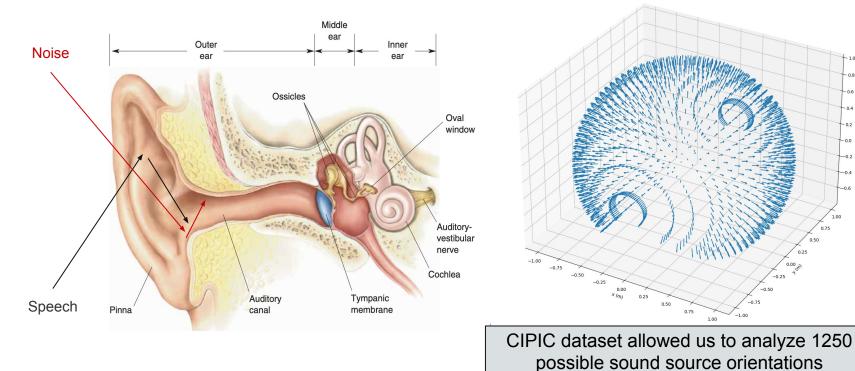
-0.50

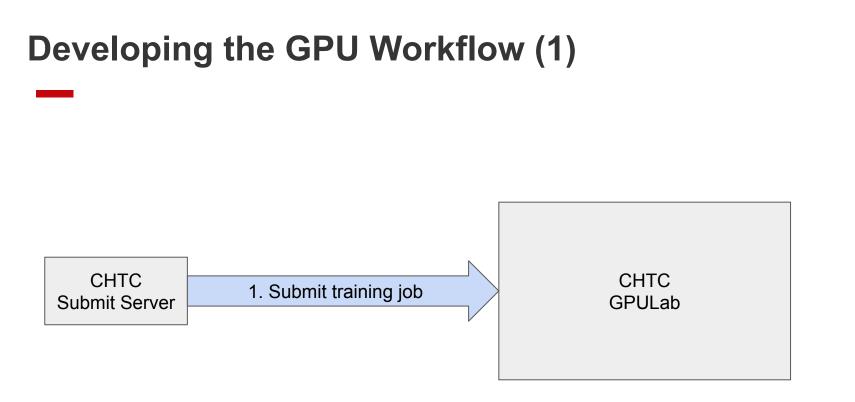
-1.00

1.00

Speech & Noise Position for Denoising

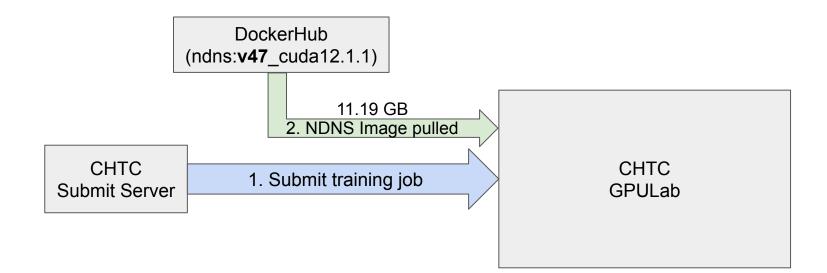
Source Positions





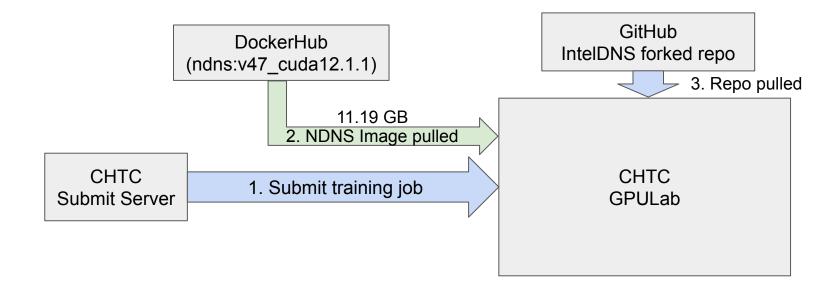


Developing the GPU Workflow (2)



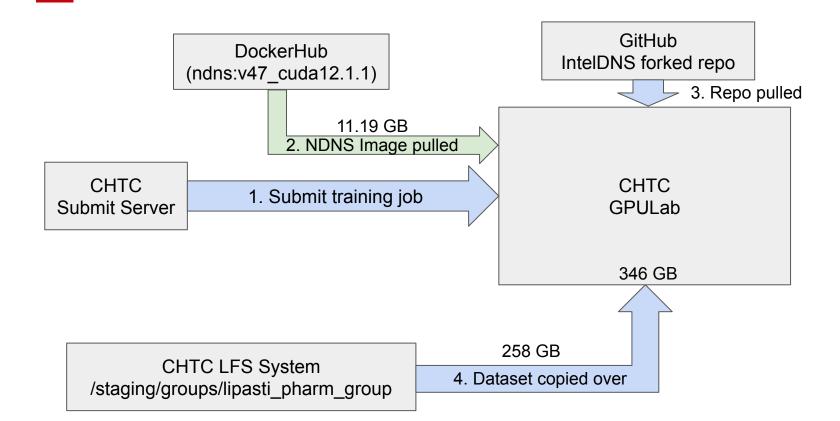


Developing the GPU Workflow (3)

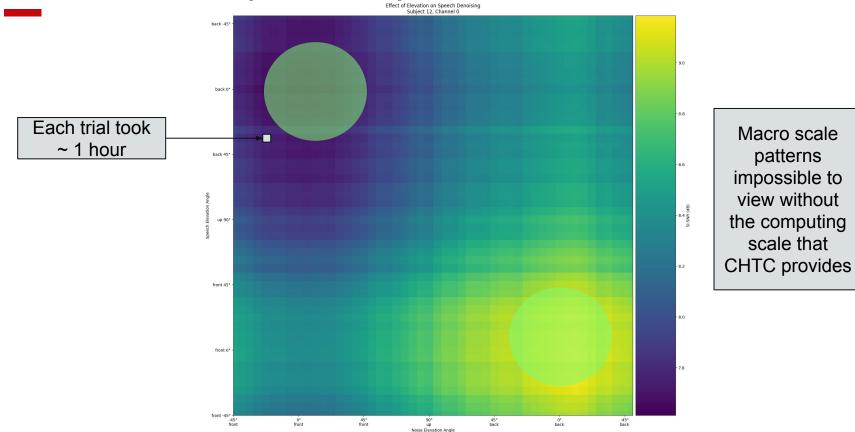


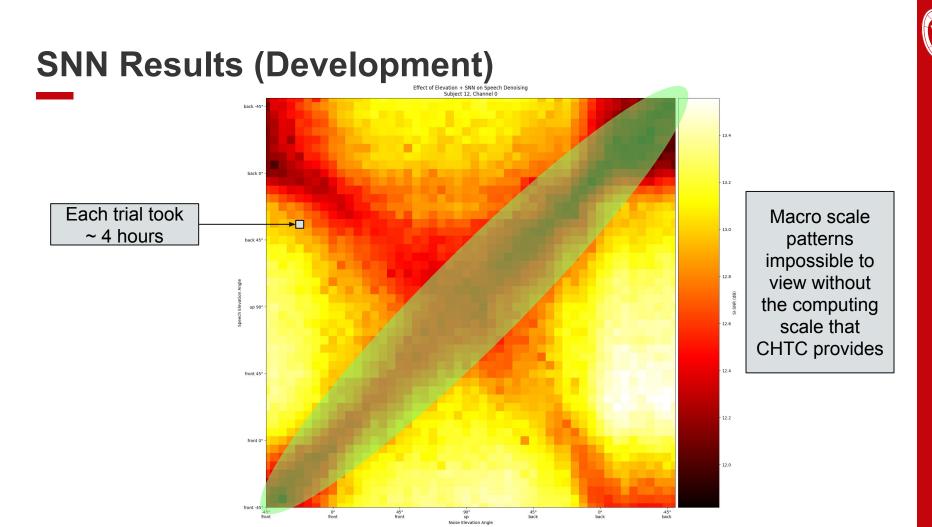


Developing the GPU Workflow (4)



Pinna Results (Baseline)

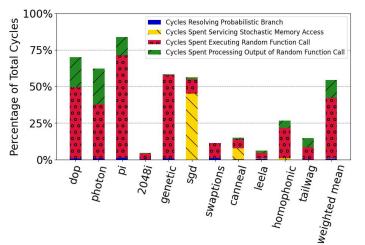






Bottom-up: Neuromorphic Workloads are Stochastic

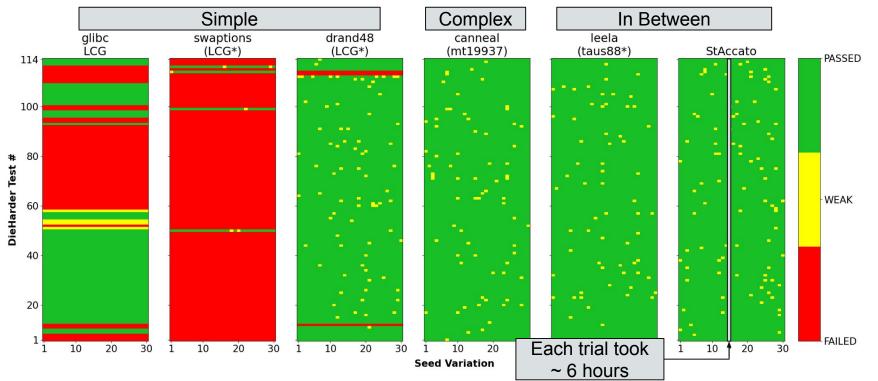
• Key Insight: random number generation and downstream, dependent operations are expensive



 To develop StAccato, a hardware *acc*elerator for *st*ochastic workloads, how can we compare RNG quality?

Dieharder

• Great, StAccato is better than simple RNG, but by how much?



13



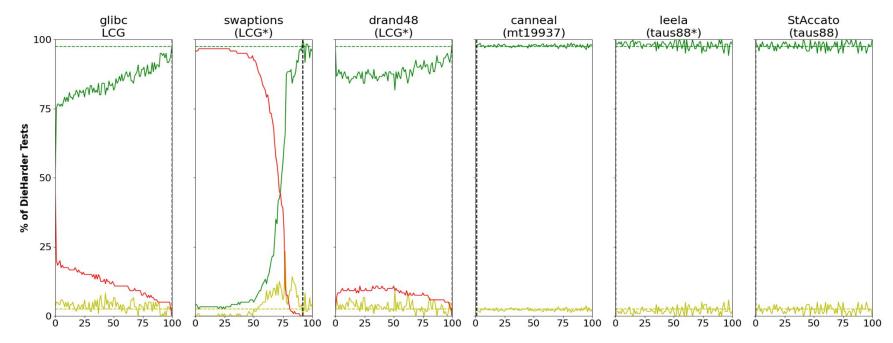
Scaling the Problem

- Throughput problem demanding large amounts of CPU hours, but minimal restrictions:
 - Lightweight docker image with Dieharder installed
 - Single requested CPU, 512MB memory, 1MB storage
 - ~need CPUs past 2011
- Workload is ideal for CHTC's ~40K CPU cores
 - Problem well defined in a single 34 line submit file (+config list)
 - Launched 6 RNGs x 5 trials per rate x 100 different rates from
 - ~2.1 compute years completed in ~3 weeks!

Comparative Dieharder Results

• StAccato is as good as the best of them!

The timeliness of this analysis was only possible via CHTC



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Current Outlook and Next Steps

Current Outlook:

- CHTC fairly easy to use and very flexible for a wide variety of studies
- Minor pain points using the GPU system
 - simultaneous profiling during GPU sim (resolved in an update)
 - non-deterministic crashes (only in < 6% of runs)
 - runtime variability for repeat tasks

• Next CHTC features to explore

- Checkpointing to support long running GPU sims (> a week)
- Thorough sweep of model hyper-parameters (width, depth, fft bins, etc.)
- Better coordination of job resources in allocation request and during runtime
- Desirable features from CHTC in the future
 - Vendor variety (AMD GPUs)



Thank You!