Custom Hardware Accelerators for Statistical Inference for Machine Learning



Rob A. Rutenbar

Bliss Professor & Head Department of Computer Science University of Illinois at Urbana-Champaign

A Talk Across Two Domains....

Custom Accelerators



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Machine Learning

Truth in Advertising Disclaimer..

1245 - 1330 Neuromorphic system software OS/R expert: no suggestions yet Post Moore's Law Rob Rutenbar, UIUC CS Chair, ""Custom Hardware Accelerators for Statistical Inference in Machine Learning"

Today's talk

- Neuromorphic....? Perceptual Al apps
- System software + OS/R? Gates, flips flops, SRAM, wires...
- Post-Moore's Law
 - Expert...?
- End-of-Roadmap & Beyond
- (TBD....)



Accelerator Architecture: *Why*?

Simple idea: Your app is too slow, or power hungry in software, so build *custom* hardware, *optimize* everything.

Ex: Speech Recognition





Accelerator Architectures: Why Now?



MOORE'S LAW

- 40+ yrs, every 2 years, transistors 2x smaller
- And faster, cheaper...
- Law close to its end

The "stack" people/social oplications transistors physics

ATTN RISES

- Investment, interest moves up the stack
- Good for us in R&D

My talk is this part of the stack



Hot Accelerator Areas



Bitcoin mining



High-freq trading



Two broad "styles" of accelerators



ASIC

Application Specific IC Performance: Best Cost: Worst



Configured

FPGA

Field Programmable Gate Array (i.e., reconfig) Performance: Good Cost: Cheap



Why FPGA Accelerators are Very Hot



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- Moore's Law over...
- Intel needs "Plan B"
- 2017: FPGA+CPUs all over data centers
- Upshot: Everybody can start building custom accelerators

Al Opportunity Area: Machine Learning (ML)

- Our apps can show us stuff, not understand stuff
- ML breakthroughs in recognition, classification



Activity Across Wide Spectrum

In Enterprise space





In Mobile space





In "hype" space

DAVEY ALBA BUSINESS 01.15.15 2:24 PM

ELON MUSK DONATES \$10M TO KEEP AI FROM TURNING EVIL



Elon Musk, Tesla Chairman, Product Architect and CEO, speaks at the Automotive News World Congress in Detroit, Tuesday, Jan. 13, 2015. © Paul Sancya/AP

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Practical Reality: ML is Huge Area

Saying "We do ML" like saying "We do Math"...

Critical to focus on "useful chunks" of ML domain



ML: Inference on Graphical Models

Important core ML technique, wide set of apps

- Nodes encode what we observe/know, how much we believe it
- Edges encode relationships (joint dependencies/affinities)
- Inference algorithms solve for "most likely" labels @ nodes



ource for graph, montage: Carsten Rother, Microsoft Research Cambridge, ICCV'09 Source for pose est: Pushmeet Kohil, Microsoft Research Cambridge, ibPRIA'11



Inference **How**: Belief Propagation (BP)

- In BP, a node propagates belief to neighbors, iteratively via messages
 - Message: Based on what I know now, what do I tell to my neighbor?
 - Belief: What do I believe about labels based on my neighbors?"

Over-emphasized!



- Good: BP on a tree converges
 - Most likely labels can be found after all inward/outward message passing is done
- Bad: BP on loopy graph might not



Stereo Matching as BP Inference



Our BP: Sequential Tree-Reweighted (TRW-S)

- Idea: Decompose a loopy graph to a set of trees, do inference sequentially across trees, recombine "right"
 - [Kolmogorov PAMI'06]: Empirically v. good on loopy case; slow



Recombine "smart": Outcome[p] = weighted sum from decomp

Problem: Sequential, across decomposed chains. Bad (really bad) for hardware. Need a fix...



Fix: Streaming, 'Diagonal Order' Arch

Key: Diagonal ordering of all message pass → parallelism



Decoupled, streaming arch

- Launch/retire 1 pixel/clock
 - Complete label-set likelihood updates (~1Kb) for all labels
- Deep pixel pipeline
 - 14 stages deep
 - So: 14 pixels "in flight" / clock





Our Platform: Hybrid CPU+FPGA

Our platform: Convey HC-1

- Intel Xeon + four Xilinx Virtex 5 (XV5LX330)
- CPU-FPGA cache-coherent virtual memory system
- Max memory BW: 1Kbit/cycle(~20GB/sec)/FPGA (runs @150MHz)



Stereo Performance Result in FPGA

Video frame rate BP inference [ISFPGA'13]

Faster than competing software, GPU, ASIC published results



(Details: 1 Xeon + 4 FPGAs; 20 TRW-S iter's/frame; QVGA 20fps; Scene-change-detect with message-reuse 'warmstart')



But, Need to Get Beyond "Hello World"

- Valid criticism of point-accelerators: Narrow
- Problems with our current (Stereo) architecture:
 - Not configurable to other inference problems
 - Pipelined, but not scalable/parallel
 - Uses mem BW inefficiently if |Labels| not multiple of 16





New: Scalable/Configurable BP Arch

Not just a pipeline any longer: really parallel...



P Parallel processor elements (pixel streams)



Efficient new memory subsystem overlaps BW and computation, checks for data conflicts

Novel, Configurable Factor-Evaluation

unit removes the O(|labels|²) complexity



Aside: What Does "Configurable" Mean?



In vision, these pixel-to-pixel factors are called **Smoothness Costs**, reflect fact that pixels like to **agree**

- Essential fact
 - Standard forms for "cost fn's" for specific domains
 - We look at computer vision
- We want to "hardwire" most common template for fn's
- Unfortunate fact
 - Might have lots of labels
 - MAP BP comp's involve "MIN" op, quadratic in |Labels|



Fast Config Msg Passing: Jump Flooding

- Problem: BP msg computation quadratic in L=|Labels|
- Solution: Jump Flooding**
 BP msg approx = L log(L)
- Analogy: Like "FFT", smart order for arith & comparisons



**[Rong, Tan, ACM Symp Int 3D, 2006]

Configurable Jump-Flooding (JF-Unit) pipeline





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Positive Scalability Results

2, 4 PEs running (limited by Xilinx V5 size); sims 1-16 PEs

- Parameterized by "Bandwidth needed to feed P processors"
- If we can *feed* the architecture promising scalability



Execution Time vs (Mem BW for P processors)

Normalized Mem BW to Feed P Proc (mem blocksize B=4 fixed)



Results: Configurable BP Arch

12-40X faster than software (PE = 4)

- No loss of result quality
- 1st "custom HW" to run >1 "standard**" ML inference benchmarks



** Standard == *Middlebury*

Input Ground Truth TRW-SSW Config Engine



And Hardware BP Has Yet More Advantages

Dirty secret about "end-of-roadmap" & post-CMOS tech



When basic switch is ~100 atoms wide nothing is deterministic anymore

Every hardware behavior is a little smear of probability



New problem: Resilience on a Stochastic fabric



BP Resilience via Algorithmic Noise Tolerance

BP's iterative character is already quite resilient...

- ...but not enough on really nasty stochastic fabrics
- Studying Algorithmic Noise Tolerance (ANT) approaches





Big Result: BP Can Be Made Very Resilient

ANT "checker" HW && "pressure" from neighbor's beliefs





RIGHT





Smart Resilient Hardware



Even Better: Resilient \rightarrow Lower Power

Why? A reminder from EE side: Iron Law of Power





Resilient -> Lower Power

ANT mechanisms that "fix stuff" also handle low VDD



Summary

Doing ML in custom hardware:

- Academically challenging && industrially relevant
- Nice example of "cross over" from far ends of the computing space
- Especially relevant as FPGAs go "maintstream" in enterprise & HPC
- Big need to partner with OS/R experts to make these practical...
- Lots of interest in this line of work: intelligent systems



