2nd Augmented Intelligence and Interaction (AII) Workshop Tensor Transform for Memory-Efficient AI Operations on Parallel Architectures



Outline

- AI edge: distributed intelligence
- Tensor transform for memory-efficient operations
- Implementation results
- Conclusion

Internet-of-AI-Things



Where Should Computing be Located?

- Data from Internet: big data
- Data from IoT: Ultra-big data!
- AI on the cloud?
- AI on the edge?



Distributed Intelligence

AI Edge



Deep Learning Ecosystem

Application	AI, Classification, etc				
Framework	<i>Caffe, TensorFlow</i> , etc				
Library Language	<i>cuDNN, OpenCL</i> , etc	Memory efficient is the most important target			
Hardware	GPU, CPU	for optimization			

Unroll: Fast and Simple



cuBLAS

Formulation of Unrolling



 $U(\mathbf{A})_{\mathbf{p},\mathbf{a}} = \mathbf{A}_{\mathbf{x}}, \text{ where } x_i = \sum_j \delta_{i,d_j} (k_j s_j + o_j)$



Unrolling: Where and Who?

- Where the unrolling operation is employed?
 - Everywhere in optimized parallel computing systems!
 - CPU, GPU, DSP, VPU, ASIC
- Who will execute unrolling in a system
 - General purpose processors: the software developers need to handle it
 - VPU and ASIC: it is embedded in the hardware for specific applications





Efficient Blackbox: Unroll as Last as Possible



Naïve Unrolling



Unroll at Shared Memory



Unroll Upon Computation



Can we code with unrolled matrix, but as fast as direct implementation?



Useful Unrolling Framework Requires

- Formulation of unrolling
- Build algorithms by unrolling
 - DNN
 - CV, ML
 - ...
- Memory efficient unrolling
 - GPUs
 - ASICs

MERIT Memory Efficient Ranged Inner-product Tensor transform

UMI (Unrolled Memory Inner-Products) Operator

- You simply write code for
 - Describing the unroll pattern and
 - Defining what to do for each row.
- Efficient blackbox make you code fast.



Memory Efficient Unrolling

- Smooth dataflow must consider:
 - 1. DRAM reuse
 - 2. Bank conflict
- Both can be analyzed by the formula:

$$U(\mathbf{A})_{\mathbf{p},\mathbf{a}} = \mathbf{A}_{\mathbf{x}}$$
, where $x_i = \sum_j \delta_{i,d_j} (k_j s_j + o_j)$



UMI: Experimental Results

UMI blackbox

- CUDA version is available on Github
- Code reduction 2--4x
- Speed-up 1.4--26x
- Hardware implementation is coming soon

Baseline: OpenCV, Parboil and Caffe

Kernels	Note	Speed up
Separable	k = 3	0.35
filter	k = 30	1.42
Motion		6.51
estimation		
Forward	UMI $3 + 1s$	19.9
propagation	UMI $9 + 1s$	26.4
	UMI $3 + 2s$	1.80
	UMI $9 + 2s$	2.83
	cuDNN $3 + 1s$	100
	cuDNN 9 + 1s	109
	cuDNN $3 + 2s$	27.1
	cuDNN 9 + 2s	27.3

Ref: Y. S. Lin, W. C. Chen and S. Y. Chien, "Unrolled Memory Inner-Products: An Abstract GPU Operator for Efficient Vision-Related Computations," *ICCV 2017*.

ASIC Design

- TAU: 32-core parallel processor
- Scaled up linearly



Collect data and write to DRAM

Single-pipelined RISC for executing the arithmetic parts

Conclusion

- AI edge: distributed intelligence
- Memory access optimization is the key for efficient CNN computing
- Unrolling plays an important role for memory optimization, which can also benefit other operations
- A unrolling framework, tensor transform for memoryefficient operations, is developed to decouple unrolling operations
- Implementation results: code reduction 2--4x; speedup 1.4--26x

Using UMI Operator is...

Application	Patch Search	Neural Network	Nearest Neighbor	Misc.
Framework	UMI			
Library Language	Unroll Blackbox			
Hardware	NV. (C	IDIA UDA)	Custom Parallel Architecture	