Multi-level Optimization of Matrix Multiplication for GPU-equipped Systems

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Outline

- Matrix Multiplication Problem
- Motivation
- AMD Cypress GPU
- DGEMM Implementation
 - Part 1: DGEMM Kernel
 - Part 2: DGEMM for Large Matrices
- Conclusions

Matrix-Matrix Multiplication

• GEMM (General Matrix Multiplication) is a fundamental linear algebra routine

 $C \leftarrow AB + C, C \leftarrow A^TB + C, C \leftarrow AB^T + C, C \leftarrow A^TB^T + C$

• Existing DGEMM (Double-precision GEMM) implementations on GPU

– On Cypress: 472 GFlop/s;

87% of peak (544 Gflop/s) [Nakasato]

– On Fermi: 362 GFlop/s;70% of peak (515 GFlop/s) [Tan]

 [Nakasato] N. Nakasato (2010), "A Fast GEMM Implementation on a Cypress GPU," In the 1st International Workshop on Performance Modeling, Benchmarking and Simulation of High Performance Computing Systems (PMBS 10).
 [Tan] G. Tan, et al. (2011), High Performance DGEMM on NVIDIA, [Online], Available: <u>http://asl.ncic.ac.cn/dgemm/dgemm_nv.html</u> [accessed May 24, 2011].

Motivation

- DGEMM kernel with higher performance stability by considering memory access patterns.
- DGEMM for matrices whose required data size is larger than GPU memory capacity.

Optimization	Role
1st level	Building block for computation in each GPU thread
2nd level	Optimizing the memory access pattern in a group of GPU threads
3rd level	Maximizing the GPU utilization



AMD Cypress GPU (Radeon HD 5870)

- Evergreen GPU family launched in 2009
- 320 double-precision (DP) cores
 - 640 DP op/clock, using MAD (fused multiply-add) instruction
- DP peak perf.: 544 GFlop/s (=640 [op/clock] * 0.85 [GHz])



GPU Thread Scheduling

- Cypress GPU schedules a range of threads onto a group of DP cores.
 16 DP cores / group
- 64 threads are a unit of workload on a group.
 - Changing the order of thread assignment changes memory access patterns.



PART 1: DGEMM KERNEL

Layout Functions

• map a thread ID to the memory index.

• are based on space filling curves.







Z-Morton

X-Morton

U-Morton

Hilbert

Performance of $C \leftarrow A^T B + C$



Cache hit rate of $C \leftarrow A^T B + C$

Performance of $C \leftarrow A^T B$

PART 2: DGEMM FOR LARGE MATRICES

Using $C \leftarrow A^T B$ kernel

- Fastest kernel among all tested kernels.
- No need to send a matrix C to GPU.
- Load with transposition by CPU if necessary.
 - Example: $C \leftarrow AB$

Hiding data communication latency

- Reusing matrix blocks within the GPU and minimizing the amount of communication.
 - asymptotically sending 1 matrix block and receiving 1 matrix block during a DGEMM kernel execution on the GPU.
- Explicitly loading/storing matrix blocks to/from PCI Express memory.

Maximum Performance of $C \leftarrow AB + C$

CPU + 1 GPU

CPU + 2 GPUs

Core i7 960 CPU (4-core at 3.2 GHz) + Radeon HD 5870 GPUs Core i7 920 CPU (4-core at 2.67 GHz) + Radeon HD 5870 GPUs

Performance of $C \leftarrow AB + C$

Conclusions

- DGEMM for systems which contain AMD Cypress GPUs
- Effects of memory access patterns to the DGEMM kernel's performance
 - $C \leftarrow A^T B + C$ kernel with X-Morton layout shows the superior performance
- DGEMM for large matrices on hybrid CPU-GPU systems

 Max perf. (n≈30000): 472 GFlop/s (on CPU + 1 GPU), 921 GFlop/s (on CPU + 2 GPUs)
- Future work: optimizing DGEMM for non-square matrices and utilizing it to other linear algebra problems