## Improving performance for Matrix Multiplication in CUDA

## We started off with Sparse Matrices



- Various representation formats of Sparse Matrices – COO, CSR, CSC, ELLPACK.
- Sequential algorithm for COO & CSR

## Switched from Sparse to Dense Matrices

- For the CUDA implementation of Sparse Matrix multiplication, we started with simple dense matrix multiplication.
- Main task: Understand and compare Throughput oriented design (GPU) and Latency oriented design (CPU).
- Stuck to Matrix multiplication as the application – utilize the availability of SIMD.

# Understanding the impact on performance

- Understanding the thread organization for CUDA
- CUDA Memories
- Use of GPU and CPU together to further enhance the performance.

## Thread Organization

- Utilizing all the available threads in Streaming Multiprocessor of FERMI
  - Max number of resident threads per multiprocessor – 1536
  - Max number of blocks per multiprocessor 8
  - Max number of threads per block 512
- Identified the optimum number of threads per block and blocks per grid.
  - 16\*16 is the optimum number of threads per block to achieve max performance.

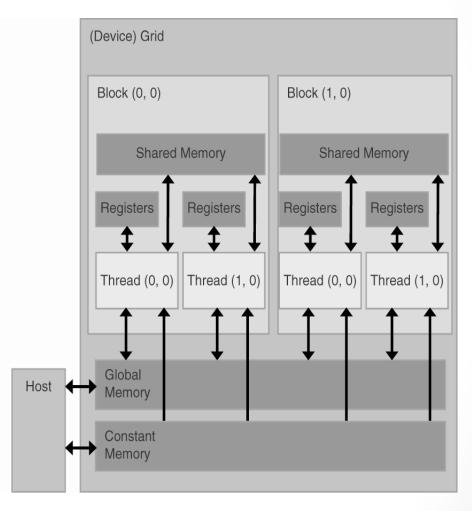
### **CUDA Memories**

#### Device code can:

- R/W per-thread registers
- R/W per-thread local memory
- R/W per-block shared memory
- R/W per-grid global memory
- Read only per-grid constant memory

#### Host code can

 Transfer data to/from per-grid global and constant memories

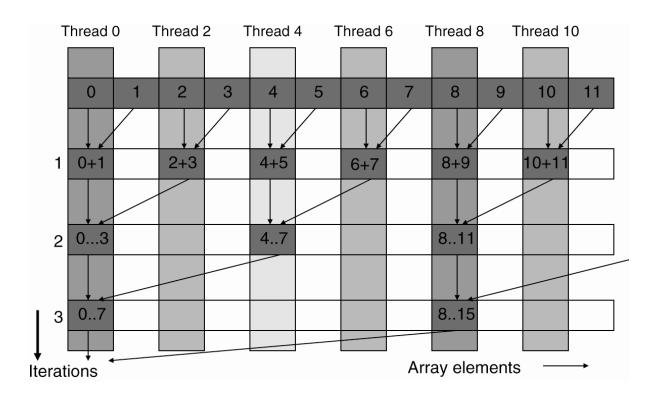


### **CUDA Memories**

- Global memory resides in device memory(DRAM) which is much slower to access than shared memory
- Tiling the data, is a way to achieve higher performance to take advantage of shared memory.
- Access the Global memory once and save it in the shared memory and utilize the same.

## Reduction

 A reduction algorithm extracts a single value from an array of values.



## CPU and GPU together

- Can CPU perform reduction better than GPU?
- Moving the vector multiplication result from GPU to CPU and perform reduction on CPU.