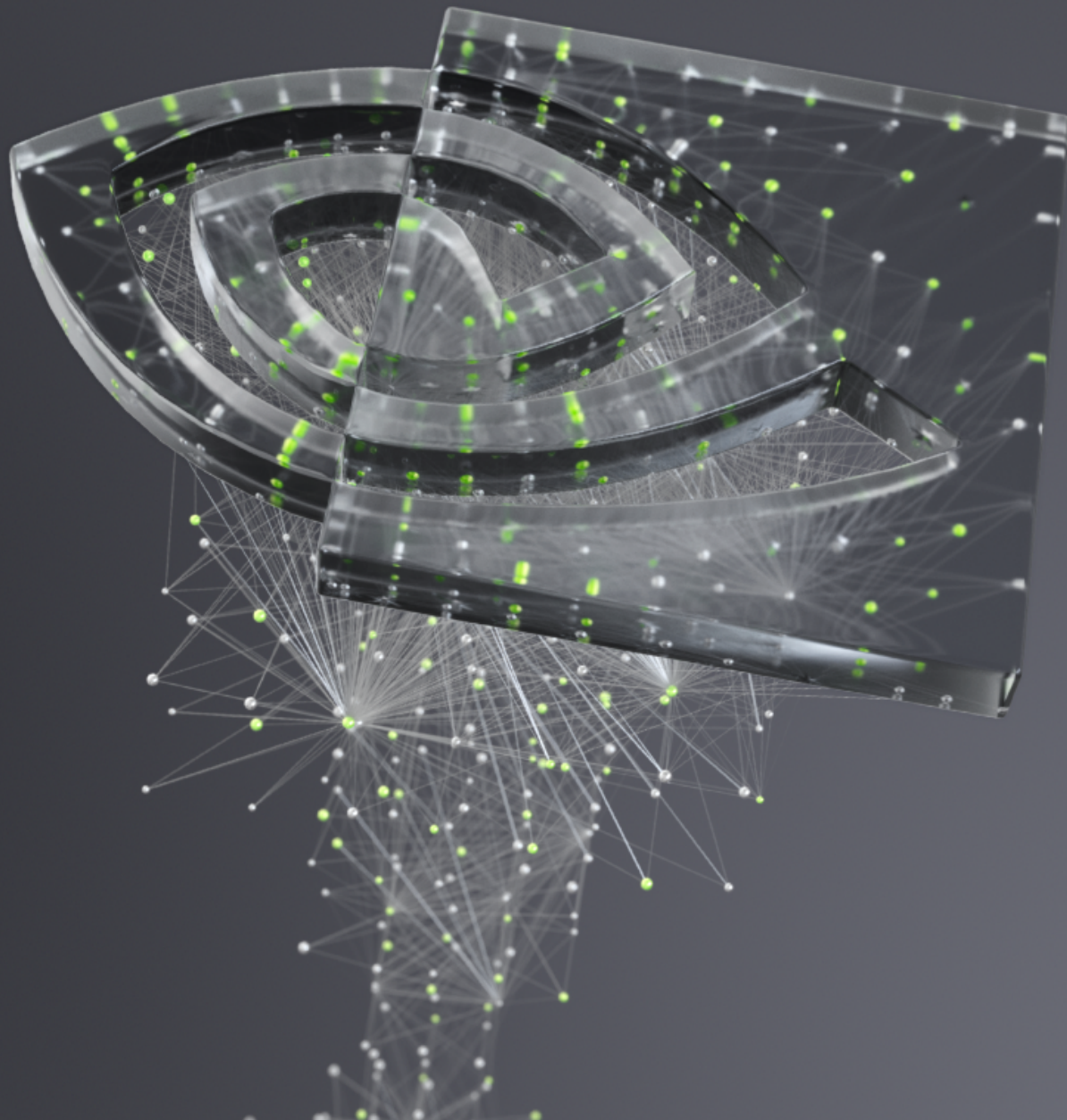




# GPU PERFORMANCE ANALYSIS

Bob Crovella, 8/18/2020





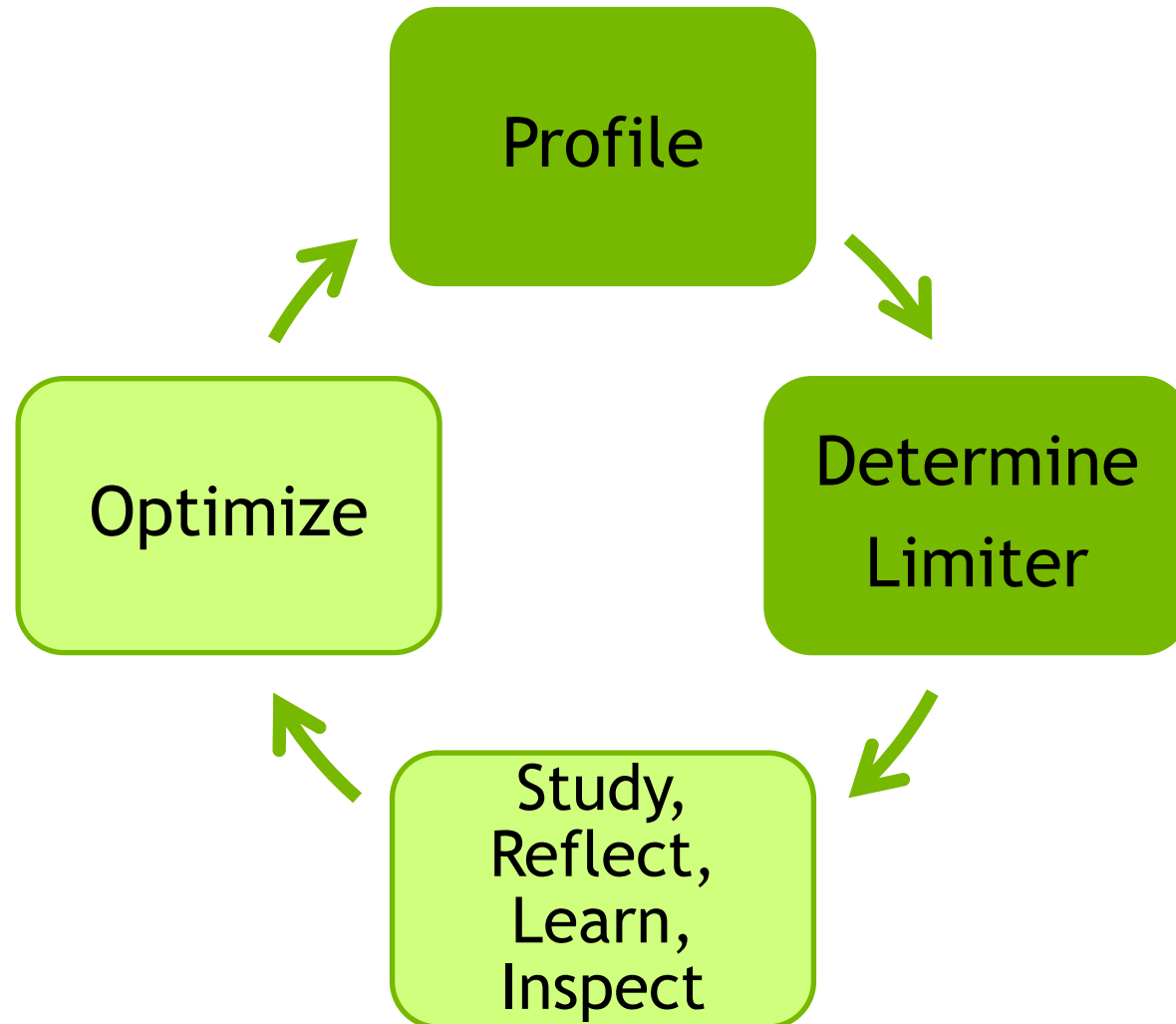
# AGENDA

- Analysis Driven Optimization
- Understanding Performance Limiters
- Metrics Review
- Memory Bound Analysis
- Compute Bound Analysis
- Future Sessions
- Further Study
- Homework

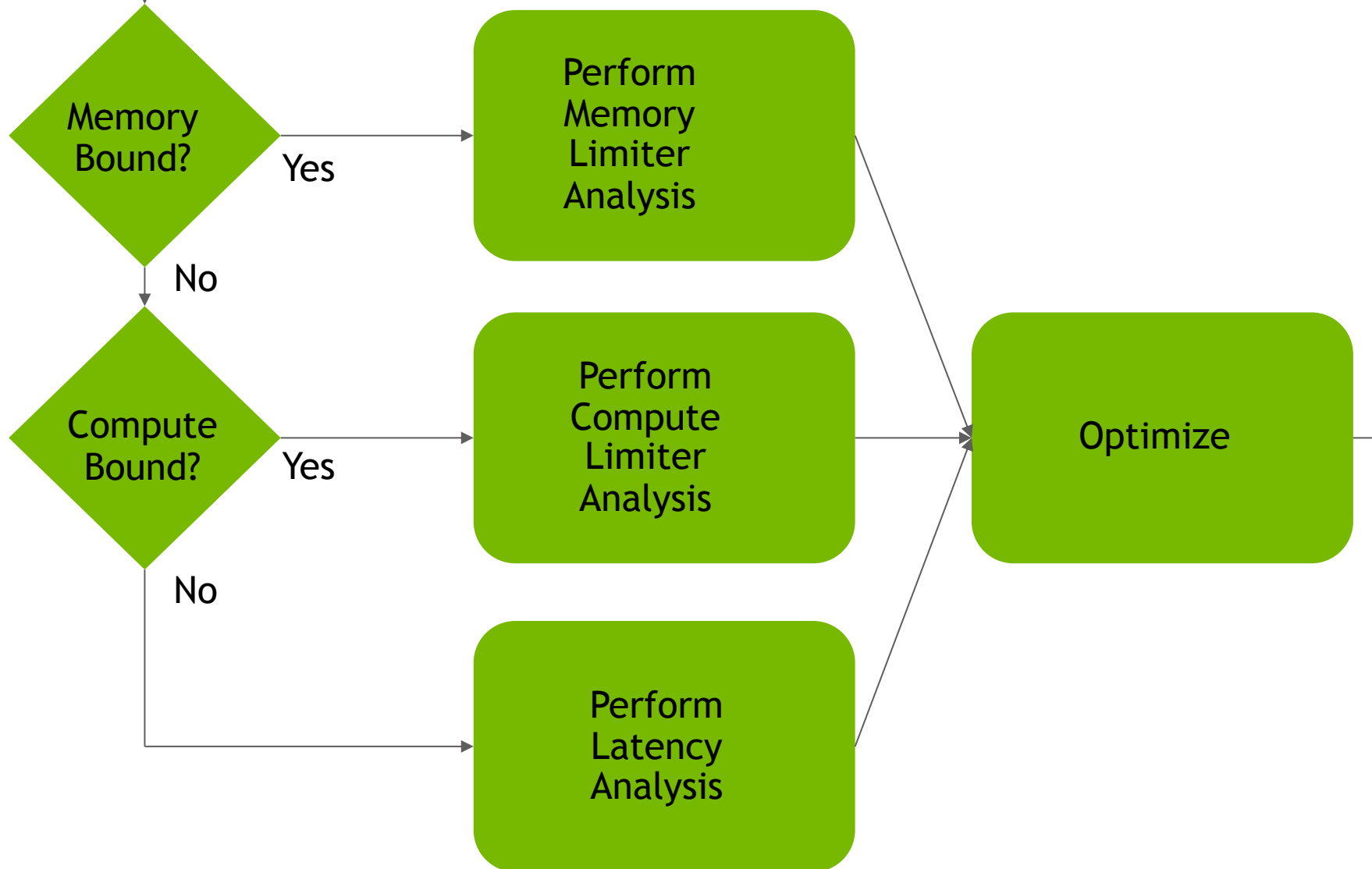
# REVIEW: TOP-LEVEL PERFORMANCE CODING OBJECTIVES

- ▶ Make efficient use of the memory subsystem
  - ▶ Efficient use of global memory (coalesced access)
  - ▶ Intelligent use of the memory hierarchy
    - ▶ shared, constant, texture, caches, etc.
- ▶ Expose enough parallelism (work) to saturate the machine and hide latency
  - ▶ Threads/blocks
  - ▶ Occupancy
  - ▶ Work per thread
  - ▶ Execution efficiency

# ANALYSIS DRIVEN OPTIMIZATION



# ANALYSIS DRIVEN OPTIMIZATION



# TOP-LEVEL PERFORMANCE BEHAVIOR - LIMITERS

- ▶ Memory Bound - A code is memory bound, when the measured memory system performance is at or close to the expected maximum. (saturate memory bus)
- ▶ Compute Bound - A code is compute bound when the compute instruction throughput is at or close to the expected maximum.
- ▶ Latency Bound - One of the indicators for a latency bound code is when neither of the above are true.
- ▶ (Analysis-driven) Optimization uses the above determination to direct code refactoring efforts in the first stage.
- ▶ Limiting behavior of a code may change over the duration of its execution cycle.
- ▶ It's desirable to analyze small sections of code e.g. one kernel at a time



# METRICS FOR DETERMINING COMPUTE VS. MEMORY BOUND

<https://docs.nvidia.com/nsight-compute/NsightComputeCli/index.html#nvprof-metric-comparison>

## Latency metrics:

“sm efficiency”: `smsp__cycles_active.avg.pct_of_peak_sustained_elapsed`

## Memory metrics:

“dram utilization”: `dram__throughput.avg.pct_of_peak_sustained_elapsed`

“L2 utilization”: `lts__t_sectors.avg.pct_of_peak_sustained_elapsed`

“shared utilization”:

`l1tex__data_pipe_lsu_wavefronts_mem_shared.avg.pct_of_peak_sustained_elapsed`

## Compute metrics:

“DP Utilization”: `smsp__inst_executed_pipe_fp64.avg.pct_of_peak_sustained_active`

“SP Utilization”: `smsp__pipe_fma_cycles_active.avg.pct_of_peak_sustained_active`

“HP Utilization”: `smsp__inst_executed_pipe_fp16.avg.pct_of_peak_sustained_active`

“TC Utilization”: `sm__pipe_tensor_op_hmma_cycles_active.avg.pct_of_peak_sustained_active`

“Integer Utilization”:

`smsp__sass_thread_inst_executed_op_integer_pred_on.avg.pct_of_peak_sustained_active`

# MEMORY BOUND

- ▶ A code can be memory bound when either it is limited by memory bandwidth or latency. We will lump memory latency bound codes in with the general latency case.
- ▶ For a memory bandwidth bound code, we will seek to optimize usage of the various memory subsystems, taking advantage of the memory hierarchy where possible.
  - ▶ Optimize use of global memory
  - ▶ Under data reuse scenarios, make (efficient) use of higher levels of the memory hierarchy, and optimize these usages (L2 cache, shared memory).
  - ▶ Take advantage of cache “diversification” using special GPU caches - constant cache, read-only cache, texture cache/memory, surface memory.
- ▶ For a code that is memory bandwidth bound, we can compute the actual throughput vs. peak theoretical



# COMPUTE BOUND

- ▶ A code is compute bound when the performance of a particular type of compute instruction/operation is at or near the limit of the functional unit servicing that type
- ▶ Optimization strategy involves optimizing the use of that functional unit type, as well as (possibly) seeking to shift the compute load to other types
- ▶ For a code that is dominated by a particular type (e.g. single precision floating point multiply/add) we can compare the actual throughput vs. peak theoretical.

# LATENCY BOUND

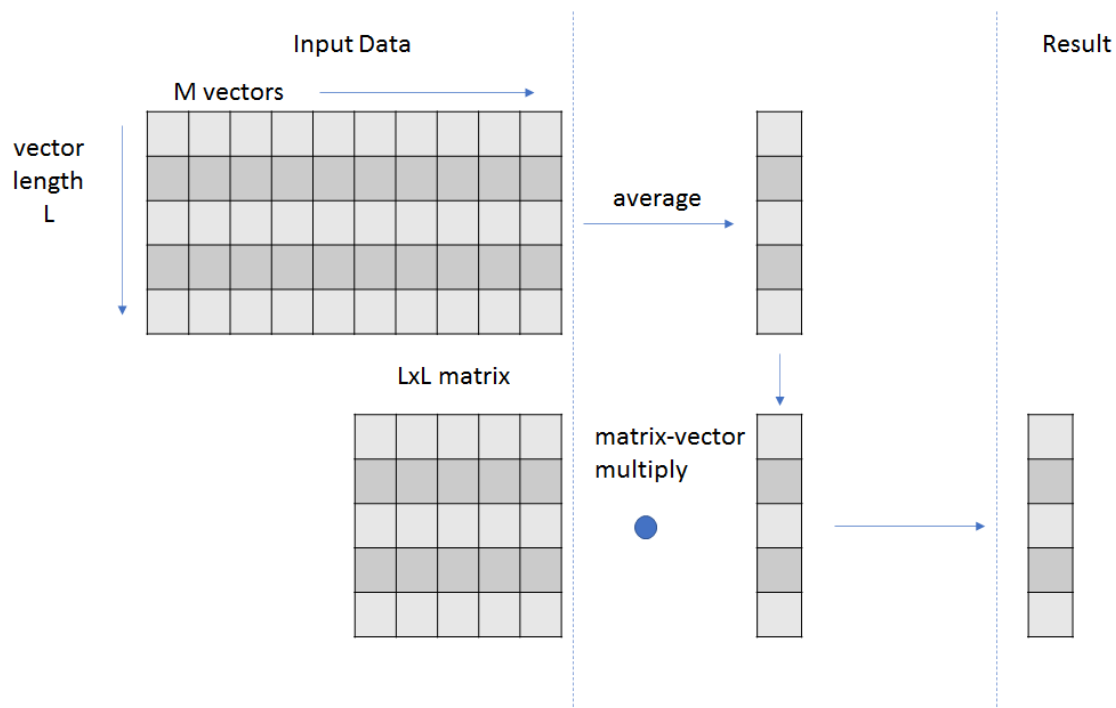
- ▶ A code is latency bound when the GPU cannot keep busy with the available/exposed parallel work.
- ▶ The general strategy for a latency bound code will be to expose more parallel work
  - ▶ Make sure that you are launching a large number of threads
  - ▶ Increase the work per thread (e.g. via a loop over input elements)
  - ▶ Use “vector load” to allow a single thread to process multiple input elements
  - ▶ Strive for maximum occupancy

# WHAT IS OCCUPANCY?

- ▶ A measure of the actual thread load in an SM, vs. peak theoretical/peak achievable
- ▶ CUDA includes an occupancy calculator spreadsheet
- ▶ Higher occupancy is sometimes a path to higher performance
- ▶ Achievable occupancy is affected by limiters to occupancy
- ▶ Primary limiters:
  - ▶ Registers per thread (can be reported by the profiler, or can get at compile time)
  - ▶ Threads per threadblock
  - ▶ Shared memory usage

# WALK-THRU

- What the code does:



This process is repeated  $N$  times, using  $N$  sets of input vectors, reusing the matrix, producing  $N$  result vectors.

# FUTURE SESSIONS

- ▶ Cooperative Groups

# FURTHER STUDY

- ▶ Analysis Driven optimization:

- ▶ <http://on-demand.gputechconf.com/gtc/2012/presentations/S0514-GTC2012-GPU-Performance-Analysis.pdf>
- ▶ [http://www.nvidia.com/content/GTC-2010/pdfs/2012\\_GTC2010.pdf](http://www.nvidia.com/content/GTC-2010/pdfs/2012_GTC2010.pdf)
- ▶ Google “gtc cuda optimization”

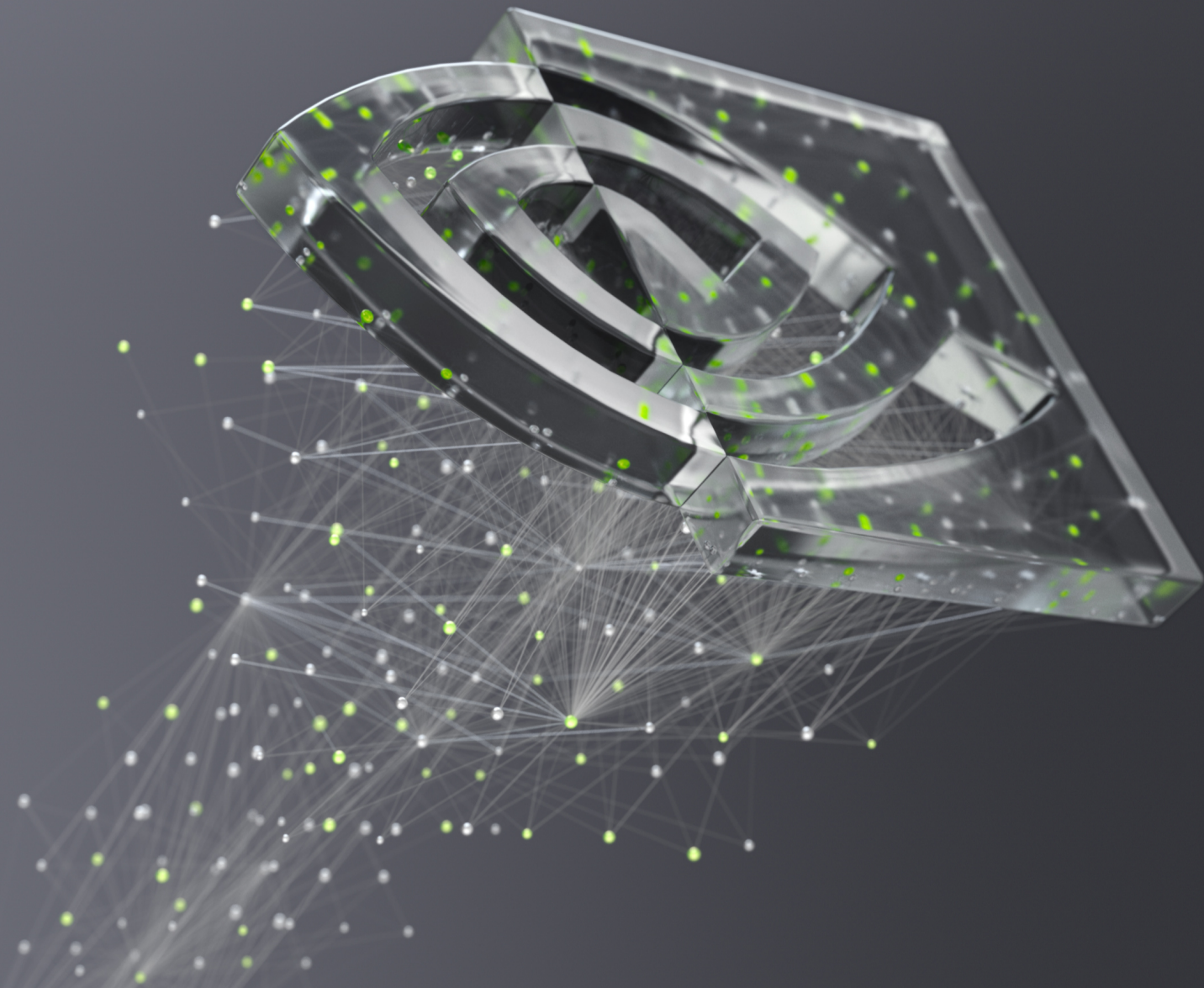
- ▶ New tools blogs:

- ▶ <https://developer.nvidia.com/blog/migrating-nvidia-nsight-tools-nvvp-nvprof/>
- ▶ <https://developer.nvidia.com/blog/transitioning-nsight-systems-nvidia-visual-profiler-nvprof/>
- ▶ <https://developer.nvidia.com/blog/using-nsight-compute-to-inspect-your-kernels/>

# HOMEWORK

- ▶ Log into Summit (ssh [username@home.ccs.ornl.gov](mailto:username@home.ccs.ornl.gov) -> ssh summit)
- ▶ Clone GitHub repository:
  - ▶ Git clone [git@github.com:olcf/cuda-training-series.git](https://github.com/olcf/cuda-training-series.git)
- ▶ Follow the instructions in the readme.md file:
  - ▶ <https://github.com/olcf/cuda-training-series/blob/master/exercises/hw7/readme.md>
- ▶ Prerequisites: basic linux skills, e.g. ls, cd, etc., knowledge of a text editor like vi/emacs, and some knowledge of C/C++ programming





**nvidia.**