

Deep Learning (hopefully faster)

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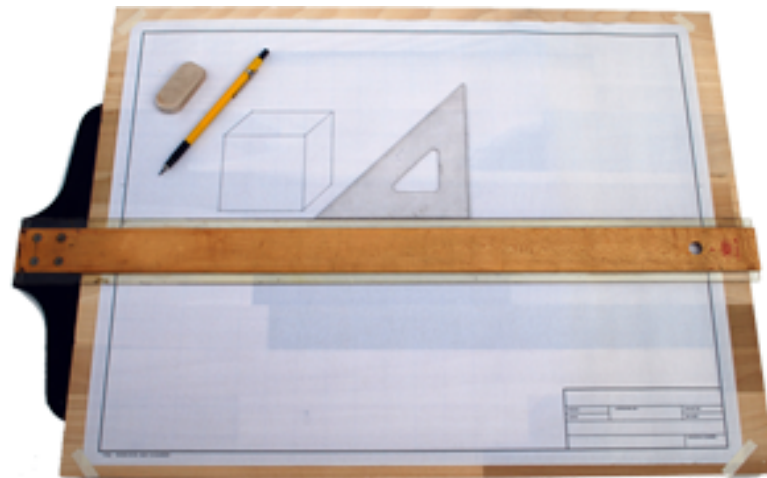
Scope

- AI and Deep Learning depend heavily on systems for training and deployment.
 - Many many tools to solve systems problems.



Scope

- Focus on making models train faster.
 - Huge topic! Best to see a ton of ideas over time.
- This talk: conceptual tools to help DL practitioner strategize and decide what to do next.

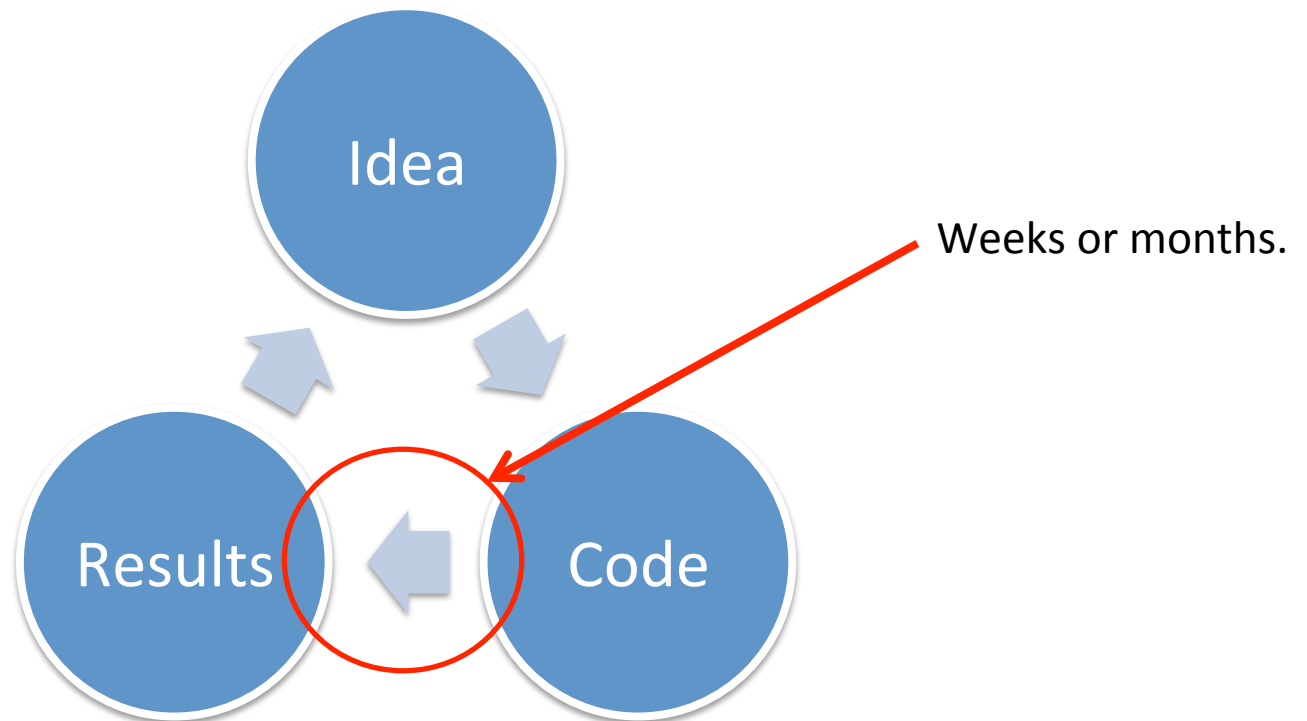


Overview

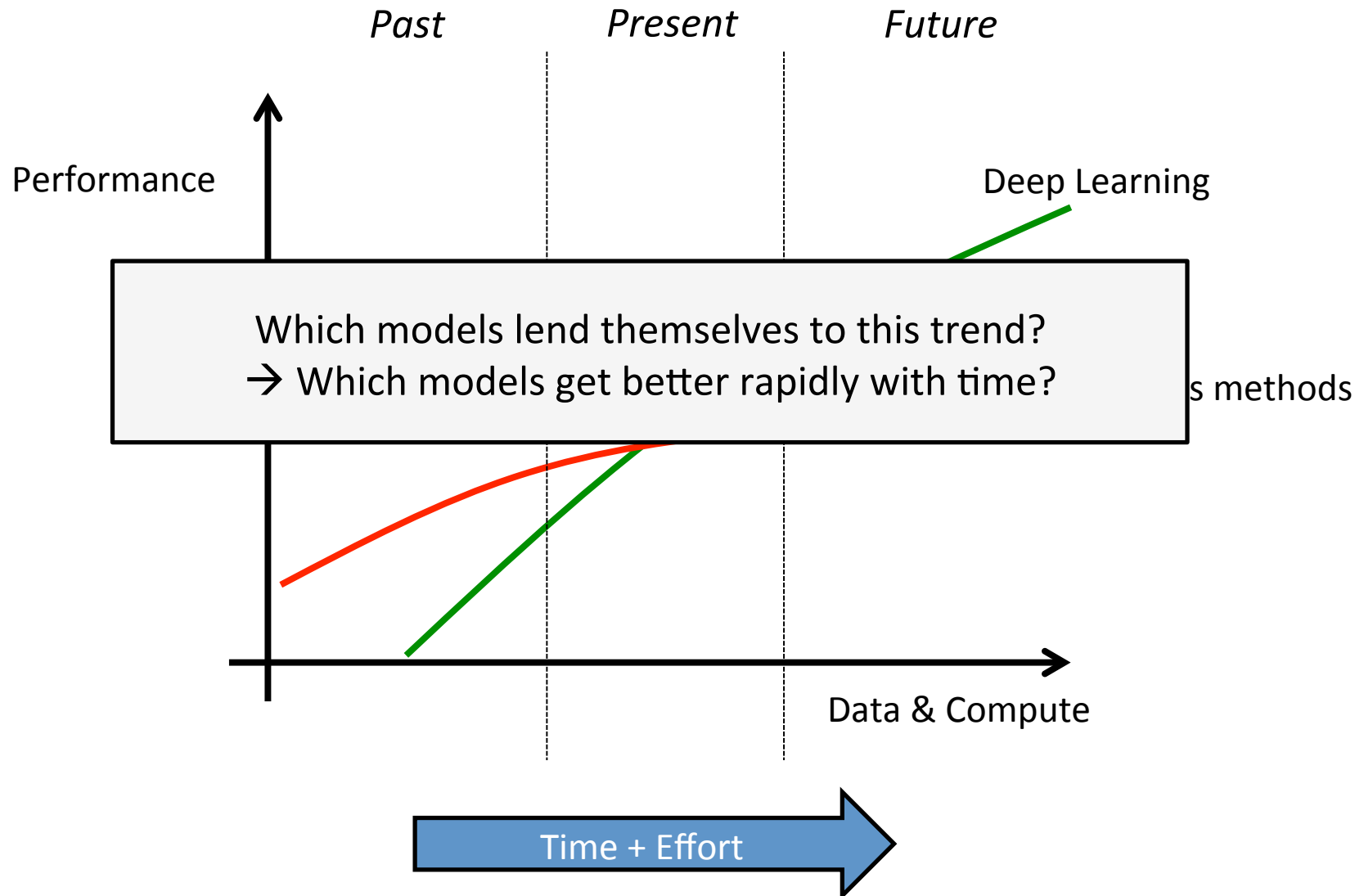
- Basic motivations & approach
- Single node: 1 GPU or 1 CPU.
- Multiple nodes.

Cycle time argument

- DL / ML research involves guided exploration.
 - We want shorter overall experiment time (wall time) so that we can make faster research progress!



Scaling argument

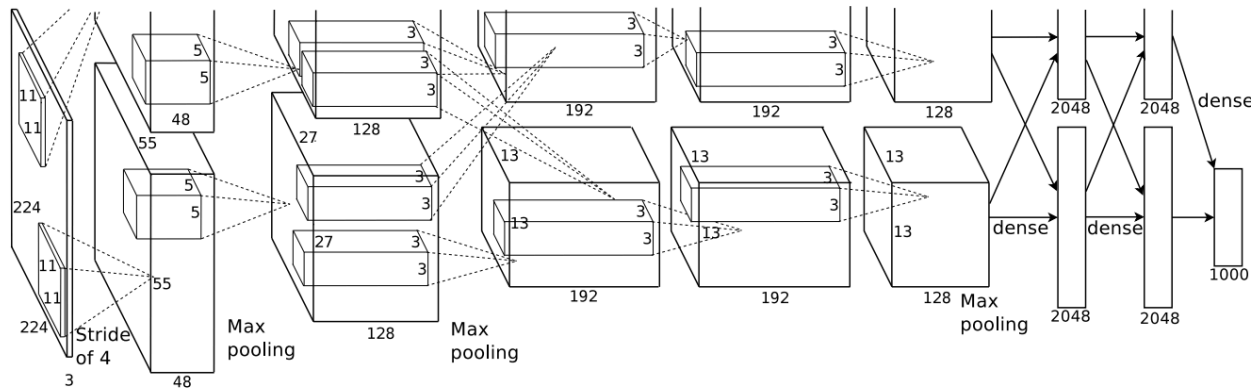


Approach

- Several ways to try to make system faster.
 - Change the software.
 - Change the hardware.
 - Change the model / algorithm.
 - Hard to chase systems+accuracy at once.
 - We'll talk about performance modeling: Basic idea applicable to all of these decision processes.
 - We'll work some examples.

Workload

- Most DL workloads built on common operations:



Convolution with small filters: $r = \text{conv}(\text{filters}, \text{data})$

Point-wise nonlinearities: $r = \max(0, z)$

Dense linear/affine operations: $r = A * z + b$

Reductions: $Z = \text{sum}(p)$

...

Workload

- Given *fixed* problem size, we will work on maximizing *throughput*.
 - Rate at which operations are completed.

$$\text{Throughput} = (\text{\#operations}) / (\text{running time})$$

If #operations is a constant → Same as minimizing running time.

Caveat

- Throughput doesn't consider convergence time.
 - Convergence depends on hyperparameters, etc., not systems.
- If you're trying to make changes to model or hyperparameters, beware:
 - Throughput is gameable.
 - E.g., Minibatching:
 - Bigger minibatch = higher throughput!
 - But not always best wall time for whole experiment.

SINGLE NODE PRINCIPLES

Setting goals

- While thinking through speed and systems issues, best question to keep asking:
 - How much could be gained? (Is it worth it?)
- To answer: need to be able to assess potential gain.
 - Go for biggest, cheapest gains.
 - Keep going until you hit diminishing returns.

The speed of light

➤ Your baseline is not how slow your current code runs.

- 10x speedup over slow code would be great.
- How do you know if you can get 10x?
- How do you know if there's more to do?



The speed of light

- Baseline is the *fastest your code can ever run*.
 - I.e., maximum potential *throughput*.
 - This is “the speed of light” for your system.
 - 0.5c is pretty good. Potential ~2x speedup left.
 - 0.8c is very good. Only ~1.25x speedup left.
 - Usually costs more effort to go faster if already close to speed of light.
 - Also: could be time to buy more GPUs.

The speed of light

- Your baseline is not how slow your current code runs.
 - Your “baseline” is the *fastest it can ever run*.
 - This is “the speed of light” for your system.

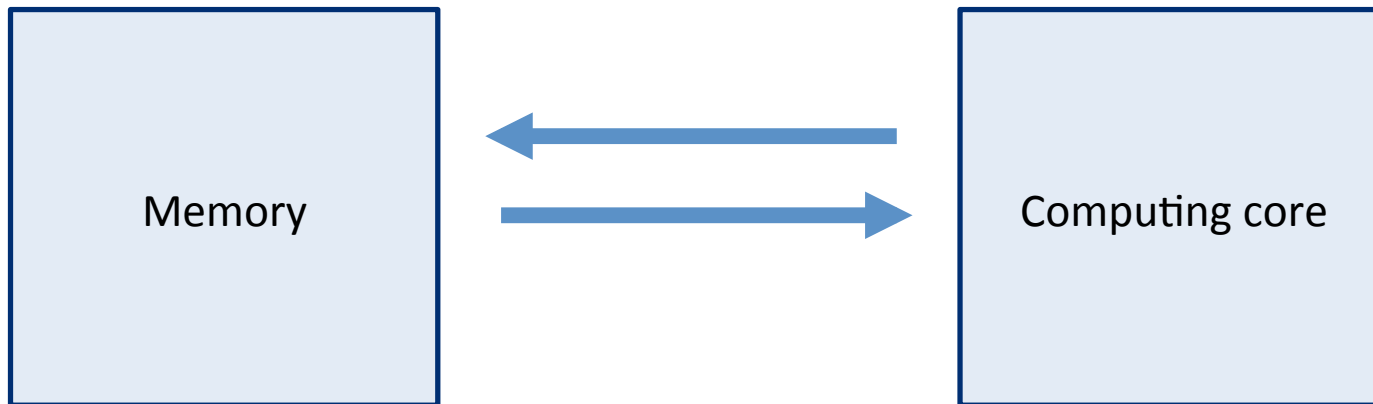
Goal: for single node, quickly estimate speed of light for DL operations.

Performance modeling

- Given a fixed computation to perform, how do we estimate maximum potential throughput?
 - Hard to do in general. Modern processors are complicated!
- We'll use a simple scheme that is quick and will give you intuition.

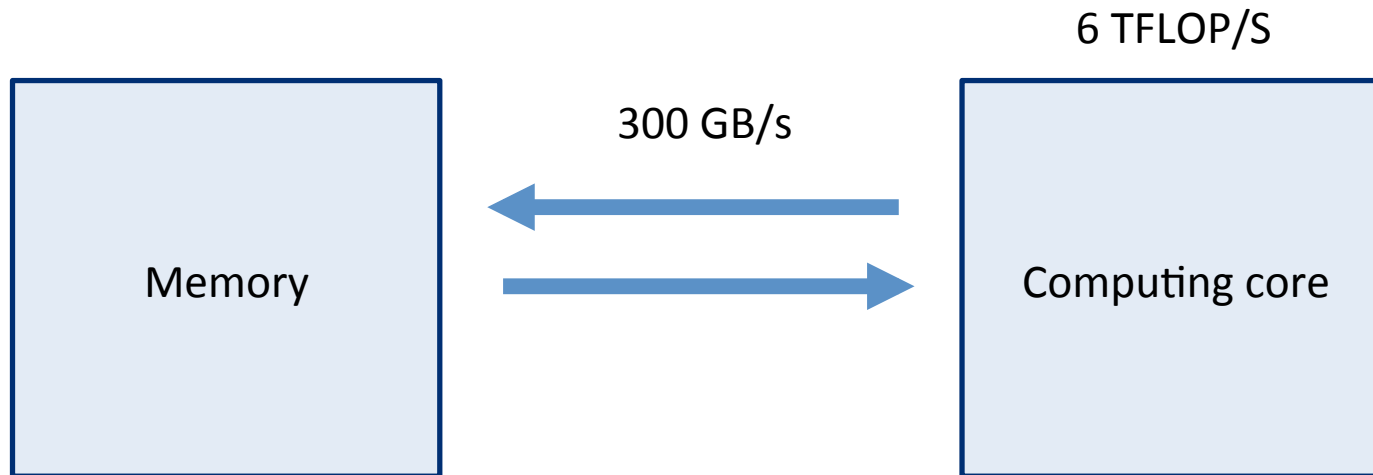
Model of a compute node

- Represent computation and memory only.
 - Only represents two key hardware limitations:
 - Total computation system can perform.
 - Total bandwidth available to memory.



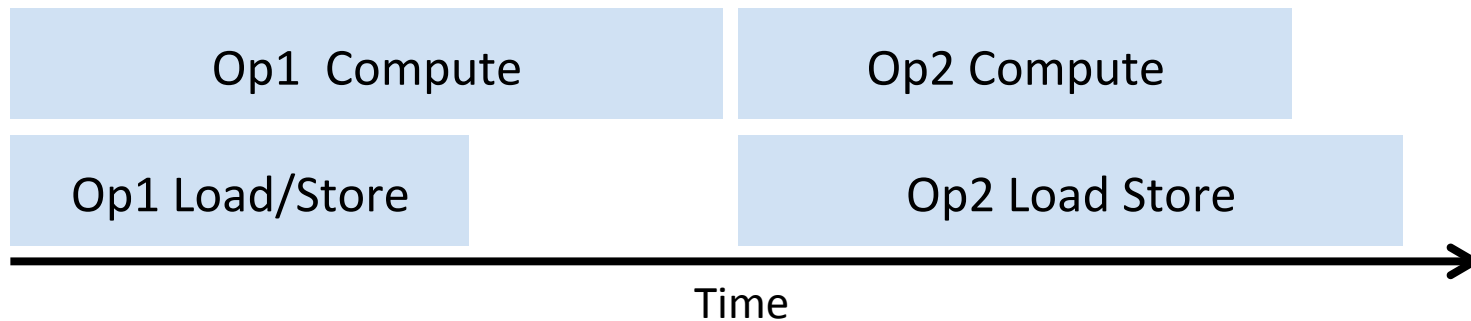
Model of a compute node

- Example: GPU circa 2015
 - Computing limit: ~ 6 TFLOP/S
 - Memory bandwidth: ~ 300 GB/s
 - **Key assumption:** we can always stream memory simultaneously with computation.



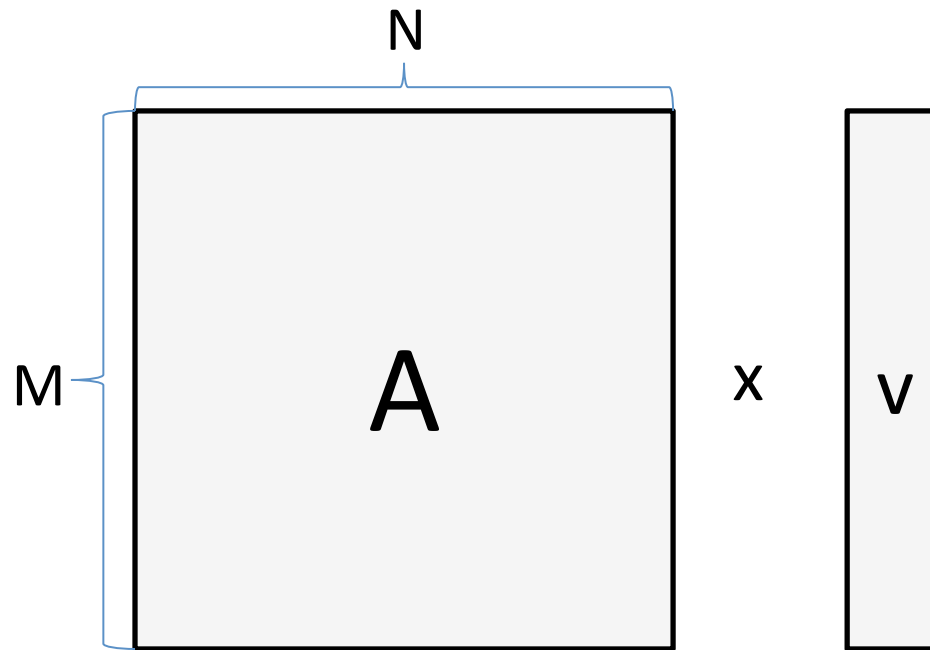
Model of a compute node

- If we run a sequence of operations, timeline might look like:



Example: Matrix-vector multiply

Compute: $A v$ for single-precision operands.



How much data do we need to load from memory?

$$4 \text{ bytes} \times (MN + N)$$

How much data do we need to store to memory?

$$4 \text{ bytes} \times M$$

How many FLOPs?

$$M (2N - 1) \approx 2MN$$

Example: Matrix-vector multiply

For $M=1024$ and $N=512$, what is the best possible throughput (in operations per second)?

Memory: $4 \text{ bytes} \times (1024 \times 512 + 512 + 1024) = 2.1\text{e}6 \text{ bytes}$

FLOPs: $2 \times 1024 \times 512 = 1\text{e}6 \text{ FLOPs}$

Running time = $\max\left\{ \frac{2.1\text{e}6 \text{ bytes}}{(300\text{e}9 \text{ bytes/s})}, \frac{1\text{e}6 \text{ FLOPs}}{(6\text{e}12 \text{ TFLOP/s})} \right\}$

= $\max\{ 7\mu\text{s}, 0.16\mu\text{s} \}$

Even substantial change in this number is irrelevant.

The *effective throughput* is $(1\text{e}6 \text{ FLOPs} / 7\mu\text{s}) = \mathbf{142 \text{ GFLOPs}}$

Arithmetic intensity

- A key quantity related to throughput is the arithmetic “intensity”:

$$\text{Intensity} = (\# \text{ arithmetic ops}) / (\# \text{ bytes to load or store})$$

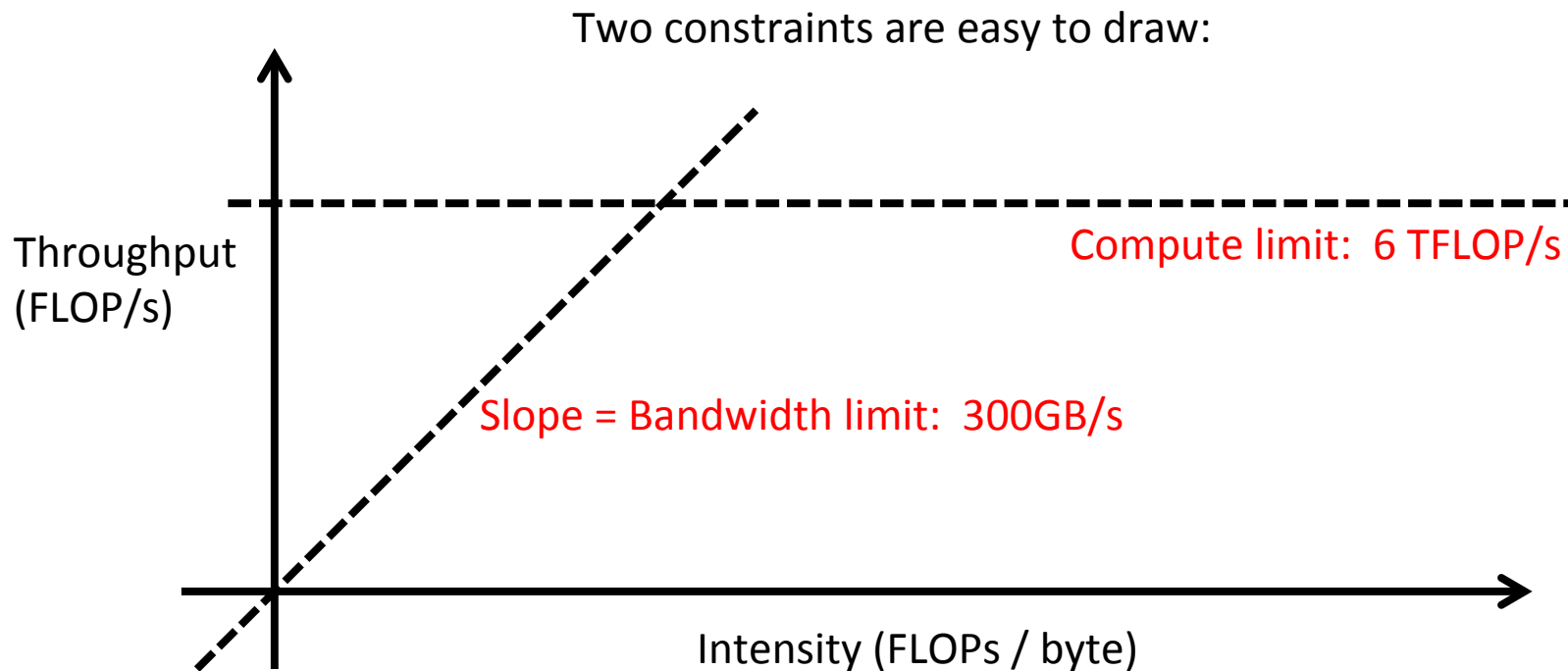
- E.g, for previous scenario, intensity is:

$$\text{Intensity} = (1\text{e}6 \text{ FLOPs}) / (2.1\text{e}6 \text{ bytes}) = 0.5 \text{ FLOPs/byte}$$

➤ Low intensity = bottlenecked on memory.

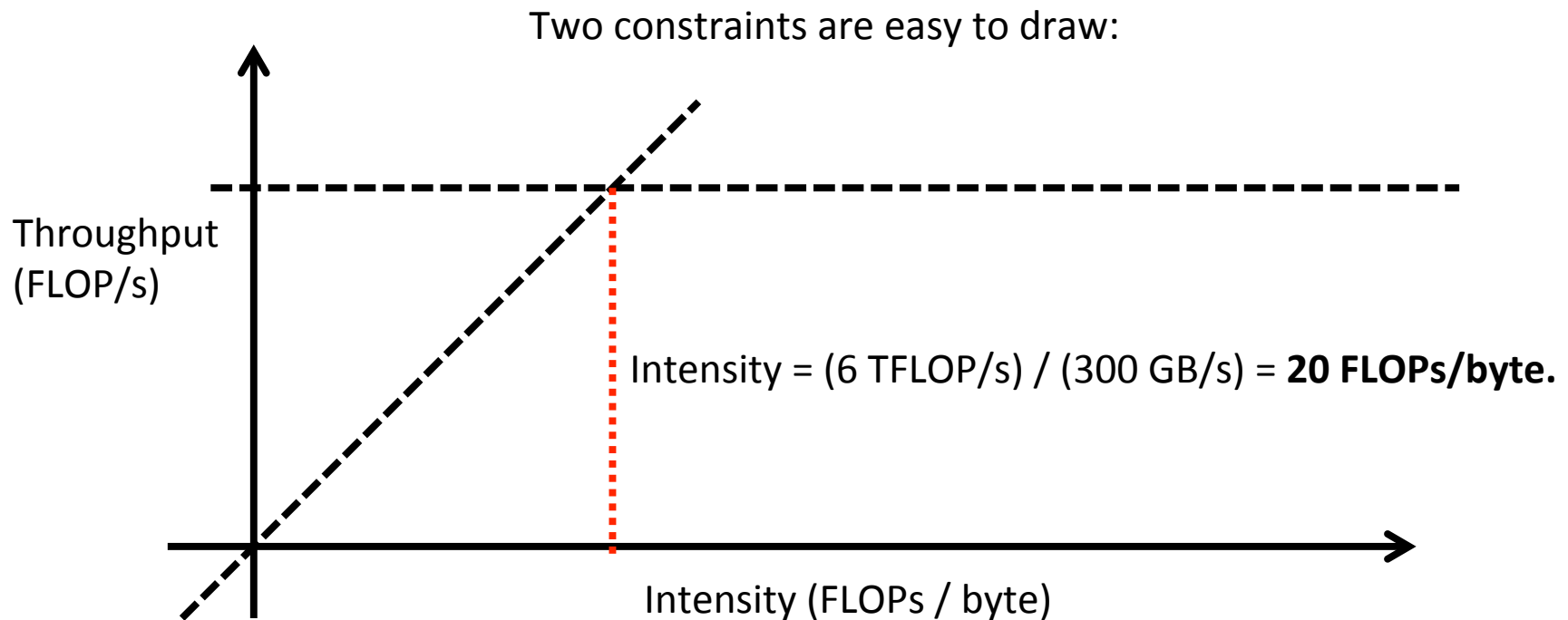
The “Roofline” model

- Williams, Waterson, Patterson 2009:
 - Visualize maximum throughput of our 2-part system as a function of intensity.



The “Roofline” model

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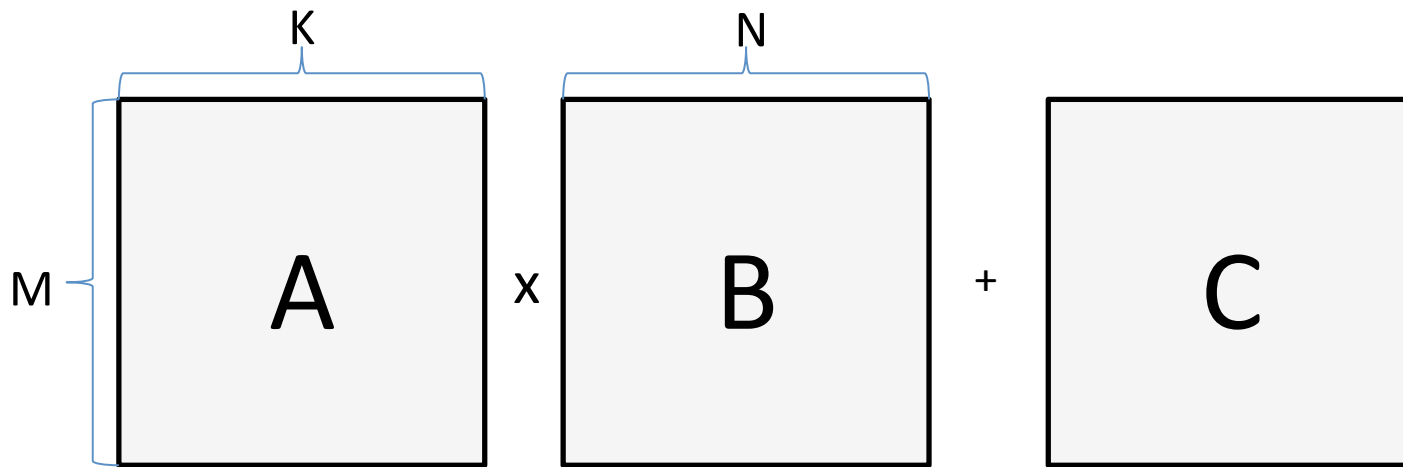


The “Roofline model”

- Easy to see relationship between memory-bound and compute-bound work.
 - Based on “theoretical” numbers: need intensity > 20 FLOPs/byte to be compute bound.
- Why is this useful to know?
 - Below 20 FLOPs/byte, compute is not constraining.

Example: matrix-matrix multiply

- Compute: $C = C + A B$ for single precision matrices.



Memory to load + store: 4 bytes \times (MK + KN + 2MN)

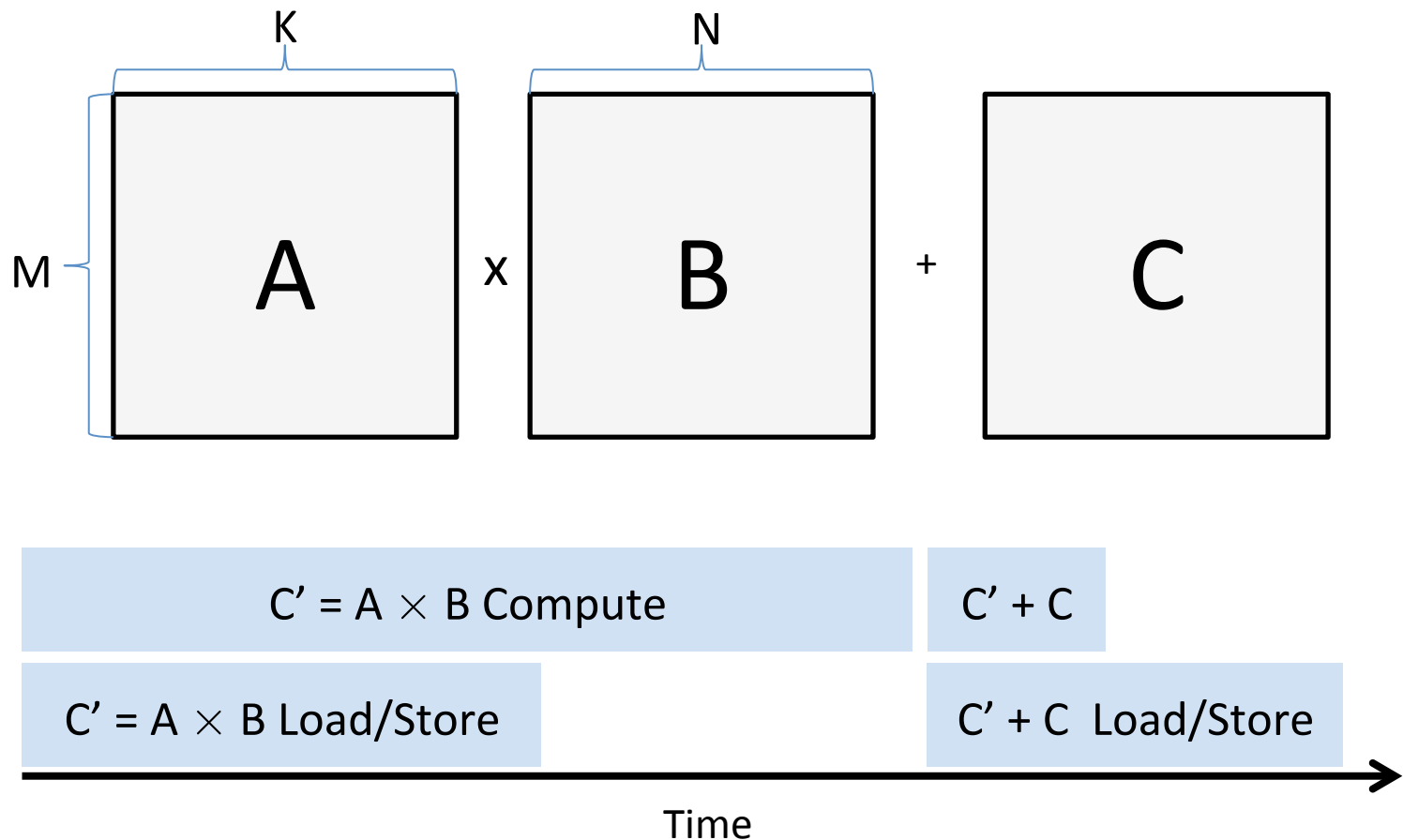
FLOPs to compute: $\approx 2 \times MKN$

For $M=K=N=512$:

Intensity = 64 FLOPs / byte (Should be compute-bound)

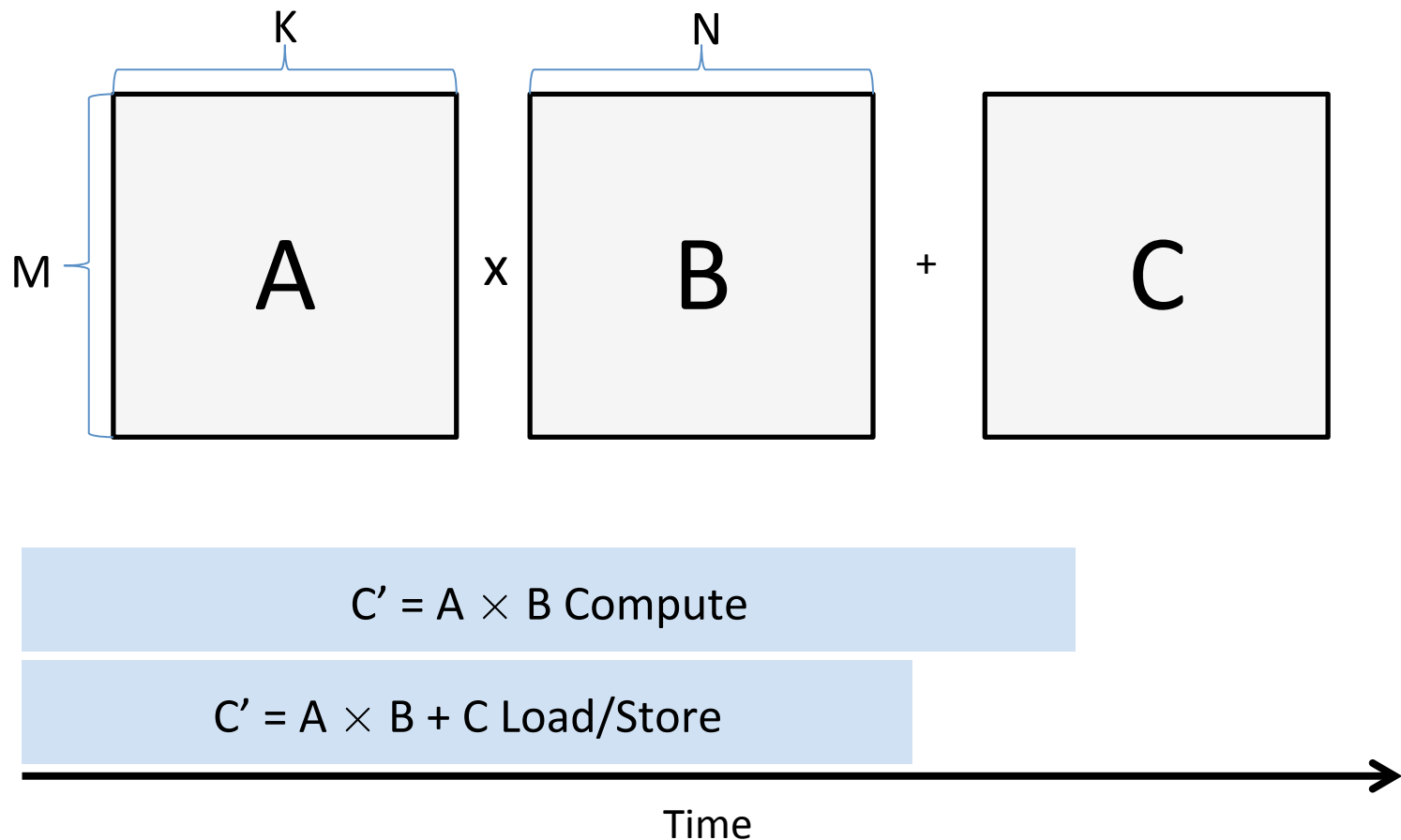
Example: matrix-matrix multiply

- Notice: we analyzed two operations as one.



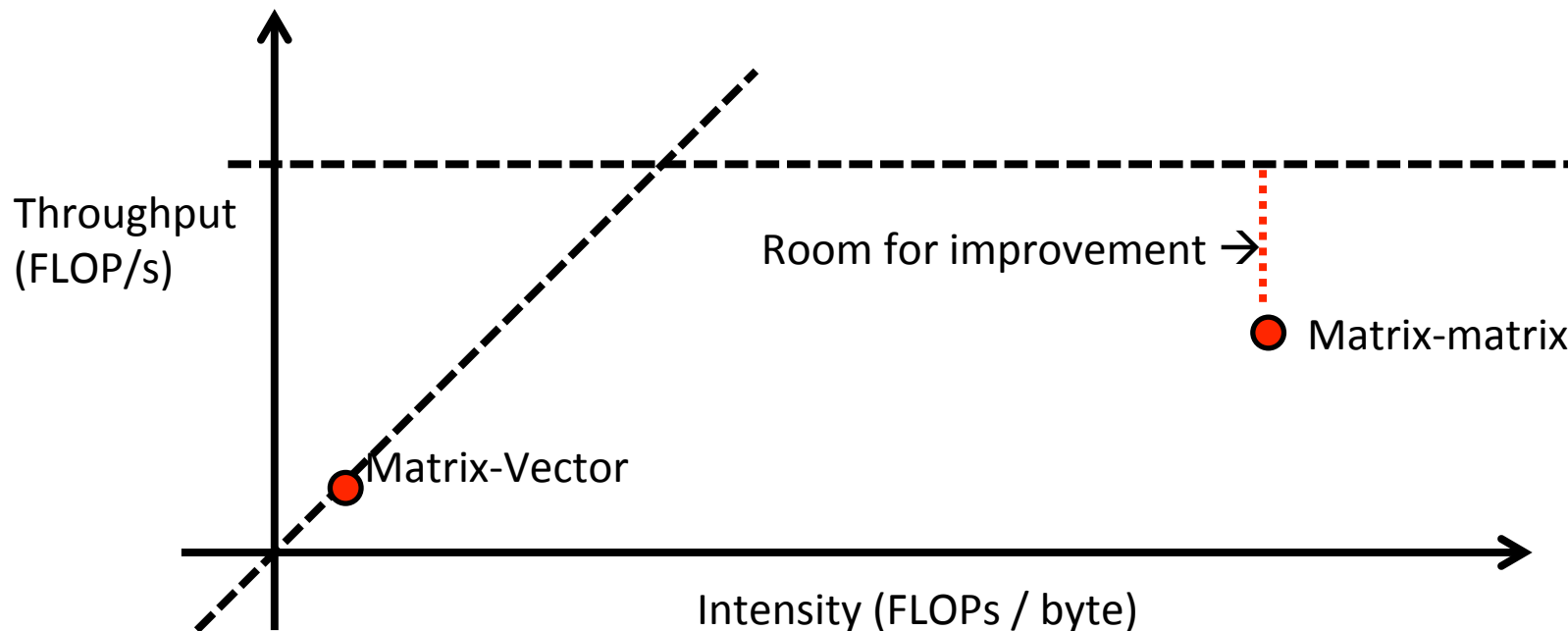
Example: matrix-matrix multiply

- Implicitly assuming we can overlap load/store of C to save time.



The “Roofline” model

- Roofline is the upper speed limit.
 - In practice, your code probably doesn’t reach it.
 - Pick the piece of code that:
 - (i) is responsible for most of running time.
 - (ii) has some headroom for improvement.



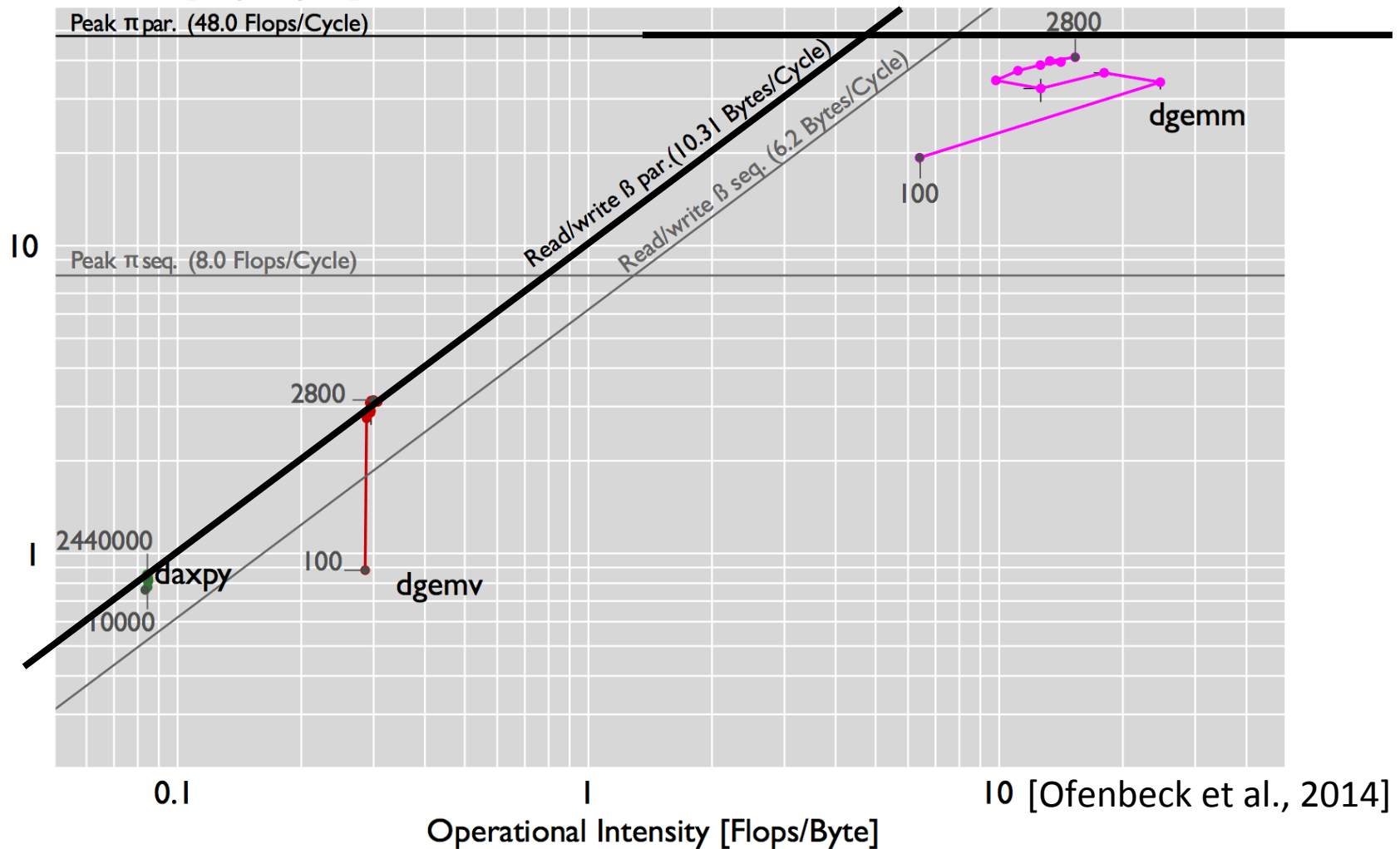
Roofline in practice

- Theoretical limit is hard to reach with fully generic code.
 - E.g., CuBLAS sgemm can achieve peak with large matrices, but tends to do badly for small matrices (bandwidth-bound).
 - Might need to sanity-check boundaries with small benchmarks.
 - E.g., Many Kepler GPUs could not achieve > 50% floating point peak using CUDA code.

Roofline in practice

- Often decent:

Performance [Flops/Cycle]



Summary

- Want to find maximum potential throughput (“speed of light”) to know best performance we can ever get.
 - Benchmark against this.
 - Factor speedup is nice; but not actionable.
- Use operational intensity and roofline model to quickly spec out what performance you might be able to achieve.

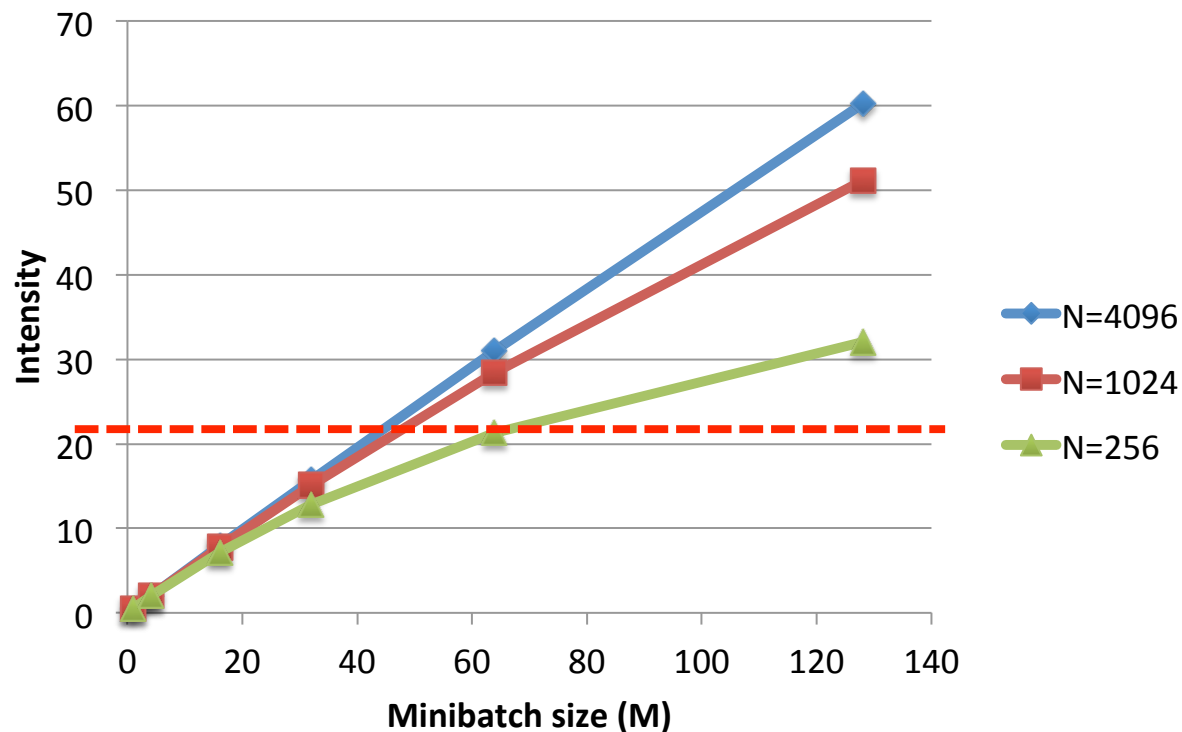
SINGLE NODE ISSUES

Minibatch size

- Common to process “minibatch” of examples.
 - Historically, minibatch size=1 has led to faster convergence. But this does not imply fastest experiment.
- What size should we use then?

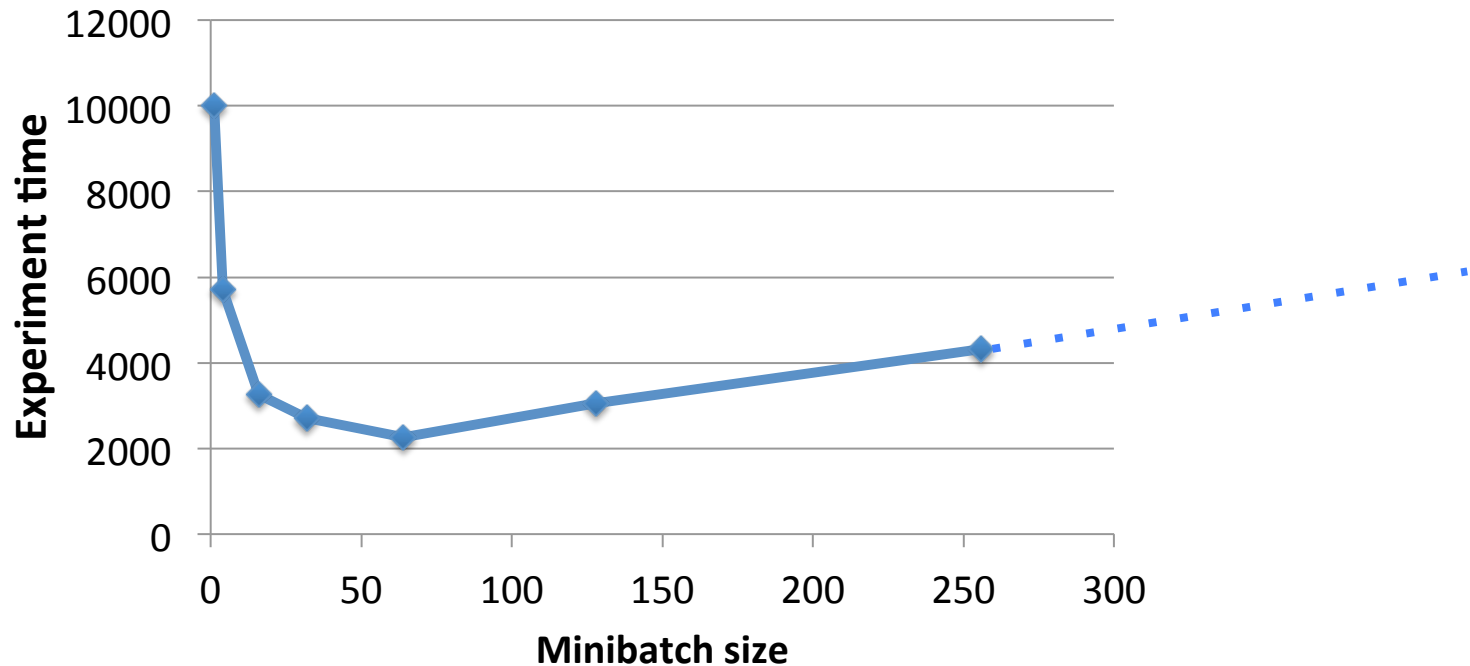
Minibatch size

- For DNN with $N \times N$ weights, minibatch size M :
 - Ops = $2N^2 M$, Memory = $4(N^2 + 2NM)$
 - Consider intensity for $M=1\dots1024$:



Minibatch size

- Below $\approx M=64$, operations are memory-bound.
 - Increasing M leads to sub-linear increase in compute time.
- Beyond 64, DNN operations will be compute-bound.
 - Increasing M further leads to linear increase in time.
- Effect: experiment time falls, then rises again with M .

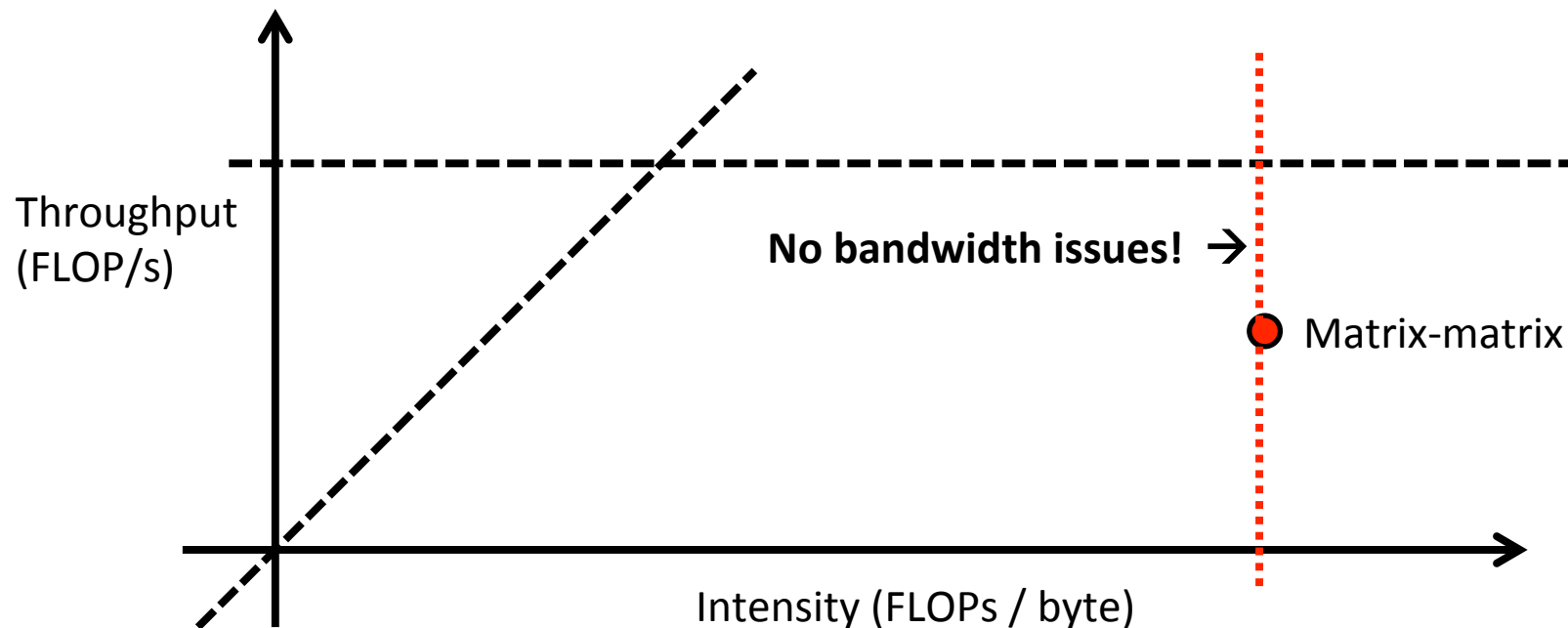


Moral of story

- For minibatch size:
 - Not much harm in raising until you are compute-limited; not much to gain beyond this point.
- In general, if you're *not* compute limited, there could be a free lunch in your future.
 - Bigger model = fit more data.
 - Bigger minibatch = faster convergence.

Optimizing software

- OK – your model is supposed to be compute limited now. But you're not achieving throughput you expect.
 - How do you make it fast?
 - Roofline model suggests some tactics over others.

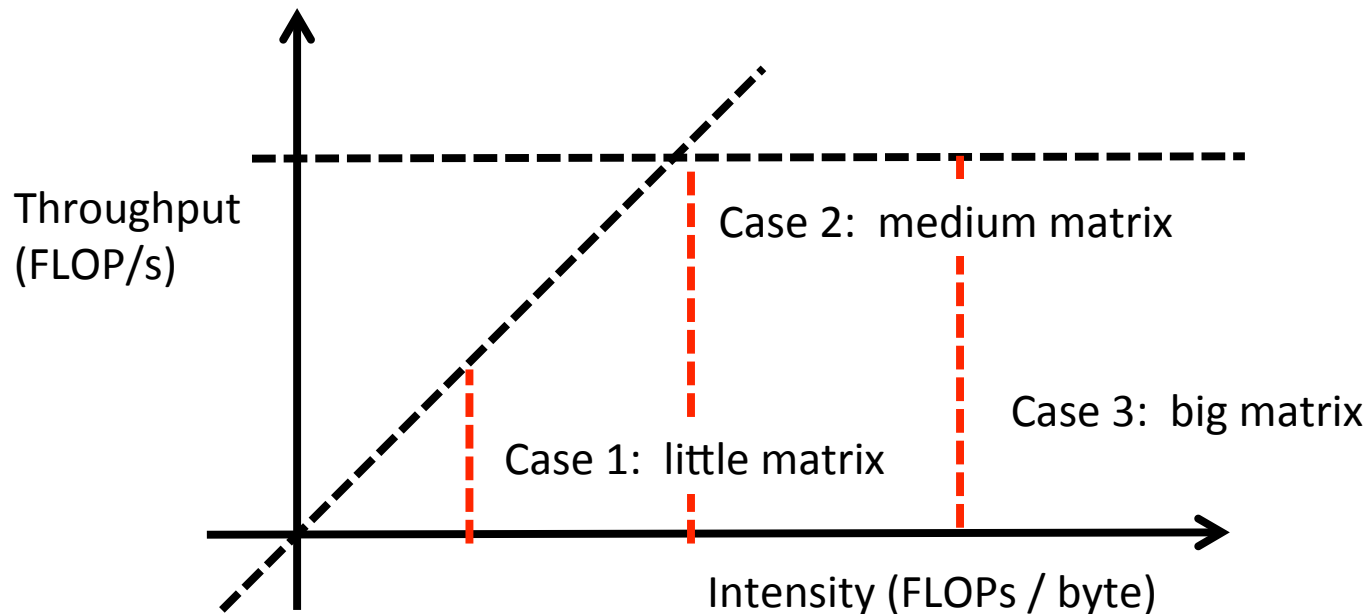


Things to try

- Low intensity workloads:
 - Try to increase intensity by accessing memory less.
(Try this first if you're in the "middle ground"!)
 - Look for data-reuse that will help you avoid redundant loading.
 - Focus on improving memory performance.
 - Sequential accesses on CPU / coalesced access on GPU.
 - Prefetch by hand.
- High intensity workloads:
 - Focus on improving compute performance.
 - Specialized instructions (SIMD, FMA = fused multiply add).
 - Adjust instruction mix.
 - Loop unrolling.

Note on code complexity...

- Very hard to write kernels that employ many optimizations at once.
 - And best optimization depends on problem parameters!
- Usually: dispatch problems into separate pieces of code optimized for different scenarios.



MULTINODE

Training with clusters

- To go very fast, we want to use many CPUs, GPUs, or many machines at once.
 - Relatively fewer tools and libraries to help.
 - It's not that easy to automate.
- Re-use some of analysis tools to guide your decisions on how to parallelize work.

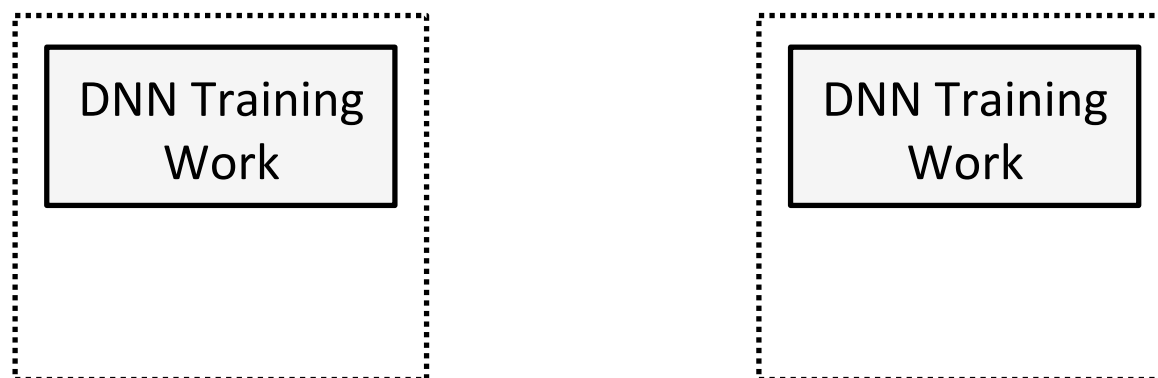
What can we hope to achieve?

- Ideal case: starting from single-node job, achieve higher throughput using more nodes for same job.



What can we hope to achieve?

- Starting from single-node job, achieve higher throughput using more nodes for same job.
(Ideally, 2x throughput.)



This is “strong scaling”: run same job in half the time.

What can we hope to achieve?

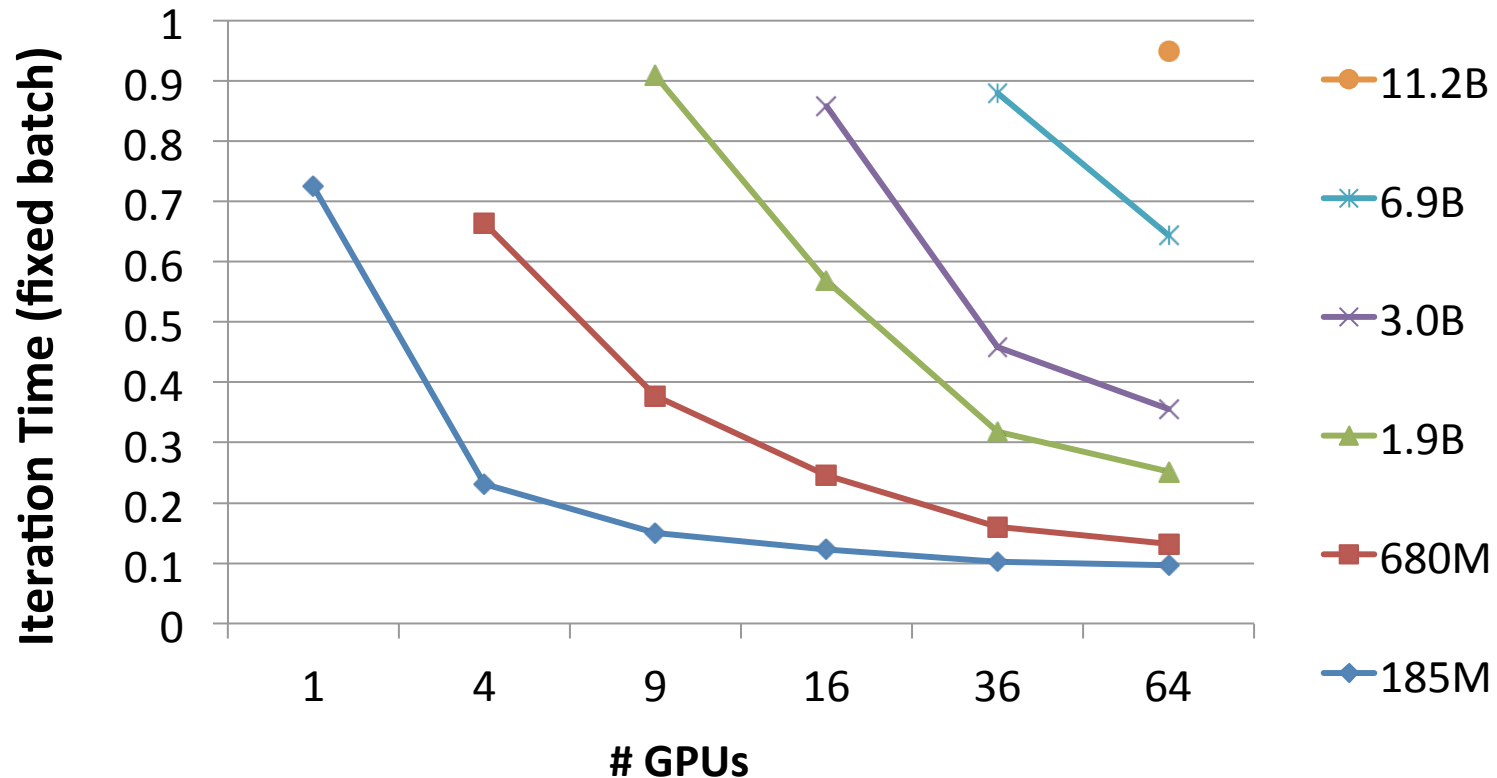
- Alternatively, we could parallelize *and* make workload larger (bigger model, bigger minibatch)



This is “weak scaling”: run larger job without slowing.

Example: weak scaling

Small network doesn't get faster with more GPUs.
But giant networks run about same speed.



[Coates et al., 2013]

Weak vs. strong

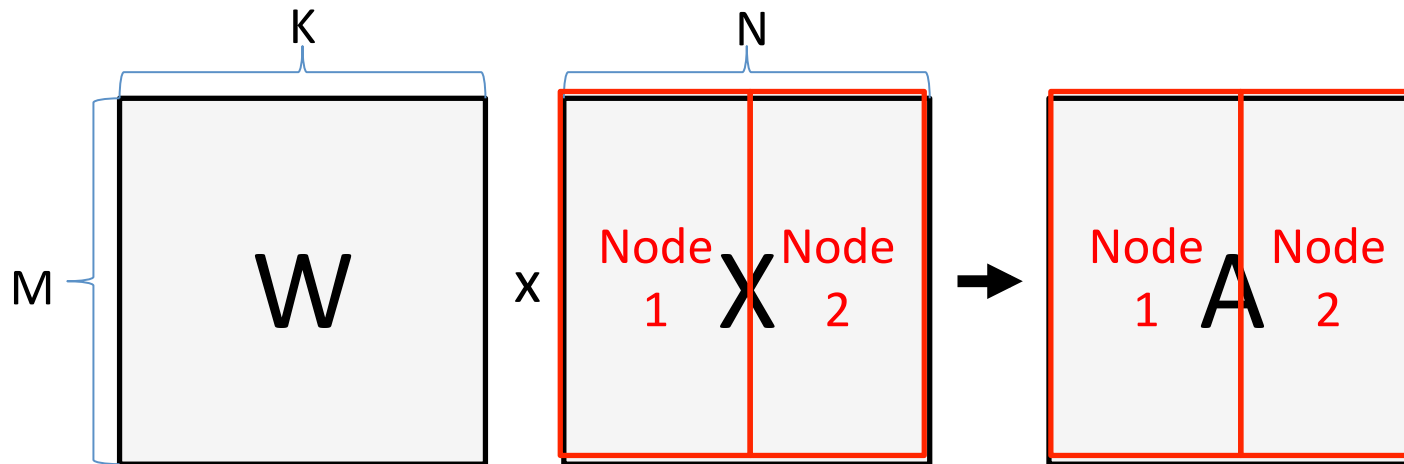
- If you can use a bigger model, or if a 2x increase in minibatch would help:
 - Job is a good candidate to scale up.
 - ***Recommend doing this first.***
- In practice:
 - Sometimes don't want a big net (e.g., data)
 - Minibatch size has already hit diminishing returns.
 - Want faster *cycle time* so we can learn quickly.
- What makes strong scaling difficult?

Performance modeling

- To understand this, need to analyze performance of multi-node system.
- First: let's partition work and just start by assuming infinite network bandwidth.

Example: Data Parallelism

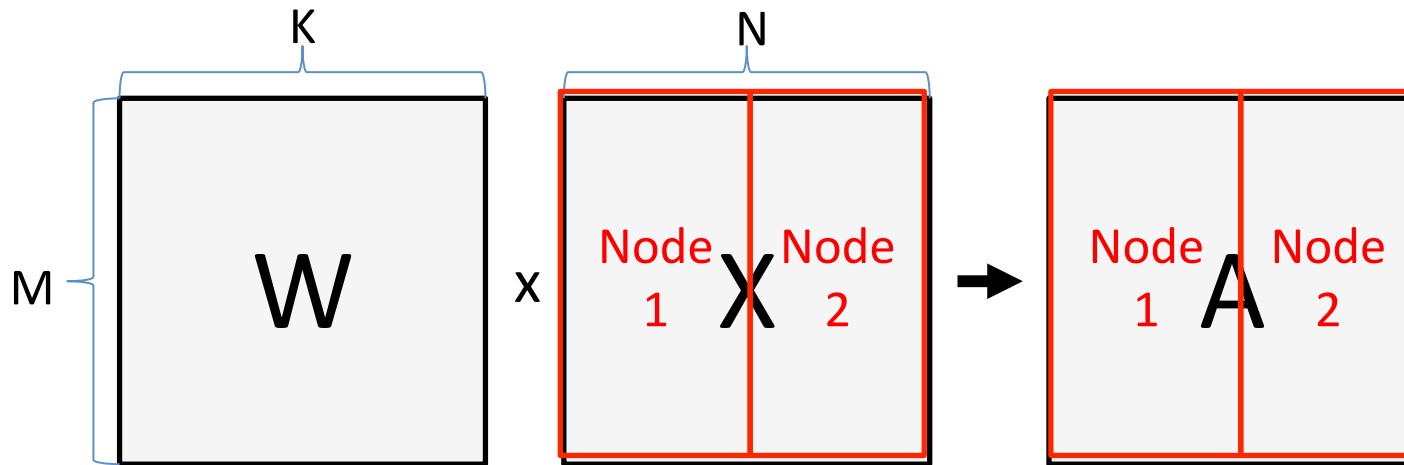
- Common practice: partition training job by splitting minibatch (X) in half.
 - Keep model (W) synchronized over network.



- What happens to workload on Node 1?

Example: Data Parallelism

	FLOPs	Memory	Intensity
Before:	$2 MKN$	$4(MK+KN+MN)$	$MKN/(2(MK+KN+MN))$
After:	MKN	$4MK + 2KN + 2MN$	$MKN/(2(2MK+KN+MN))$

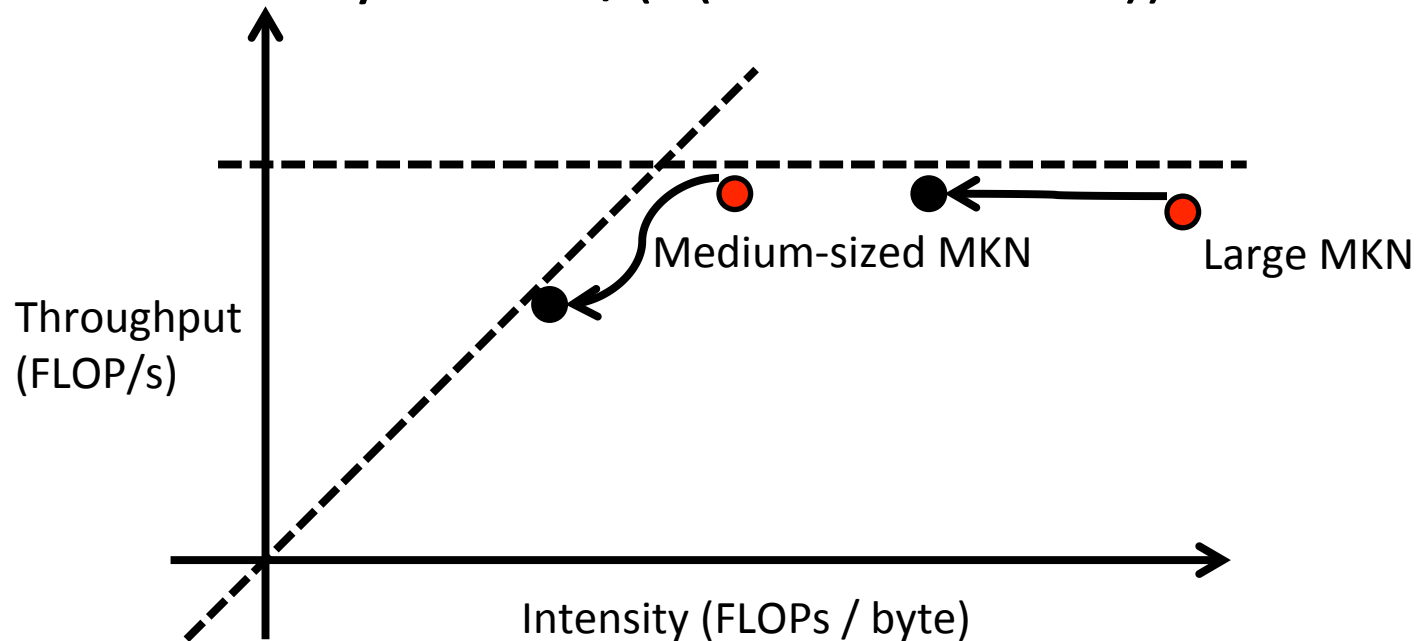


- Node 1 operational intensity falls!

Local throughput

- This may or may not cause a problem depending on size of model.

– Intensity = $MKN / (2(2MK + KN + MN))$



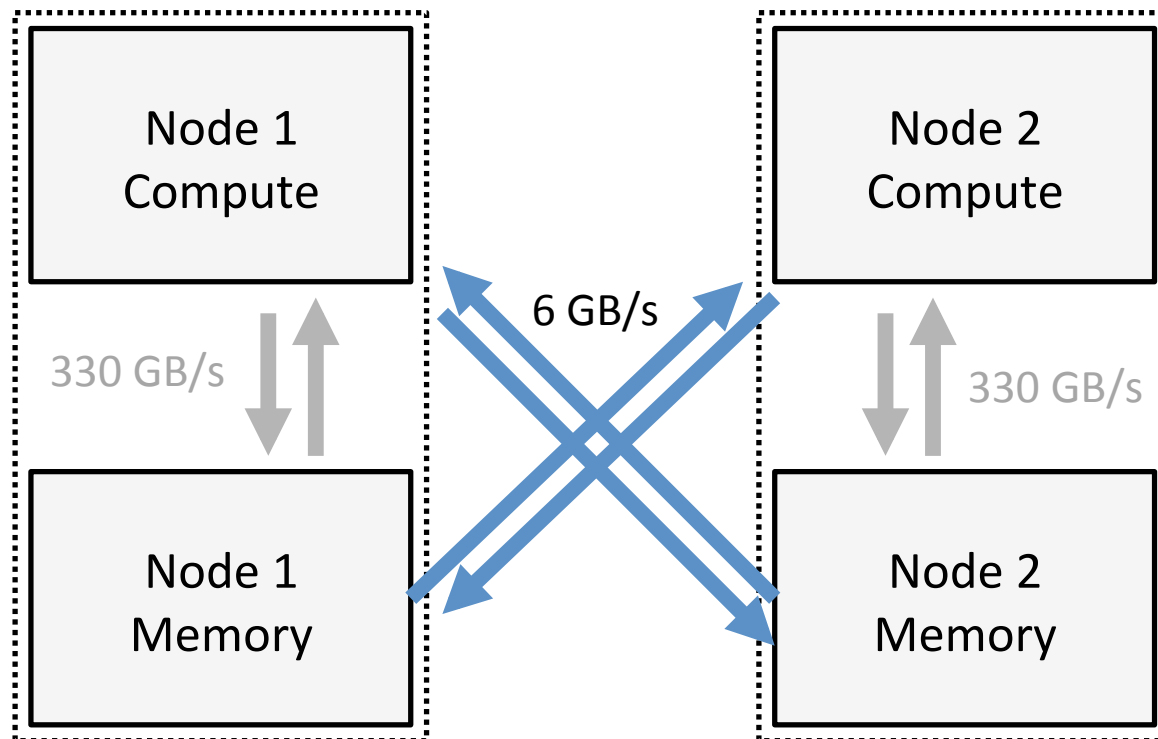
We'll assume that Node 1 can still run at max throughput.
Otherwise, need to prorate Node 1's throughput limit for any other analysis.

Performance Modeling

- Even with infinite network bandwidth, we might not be able to scale.
 - Have to be mindful of how distributing affects local node's efficiency.
- Next:
 - Assume local throughput is nice: 6 TFLOP/s
 - How do we analyze communication?

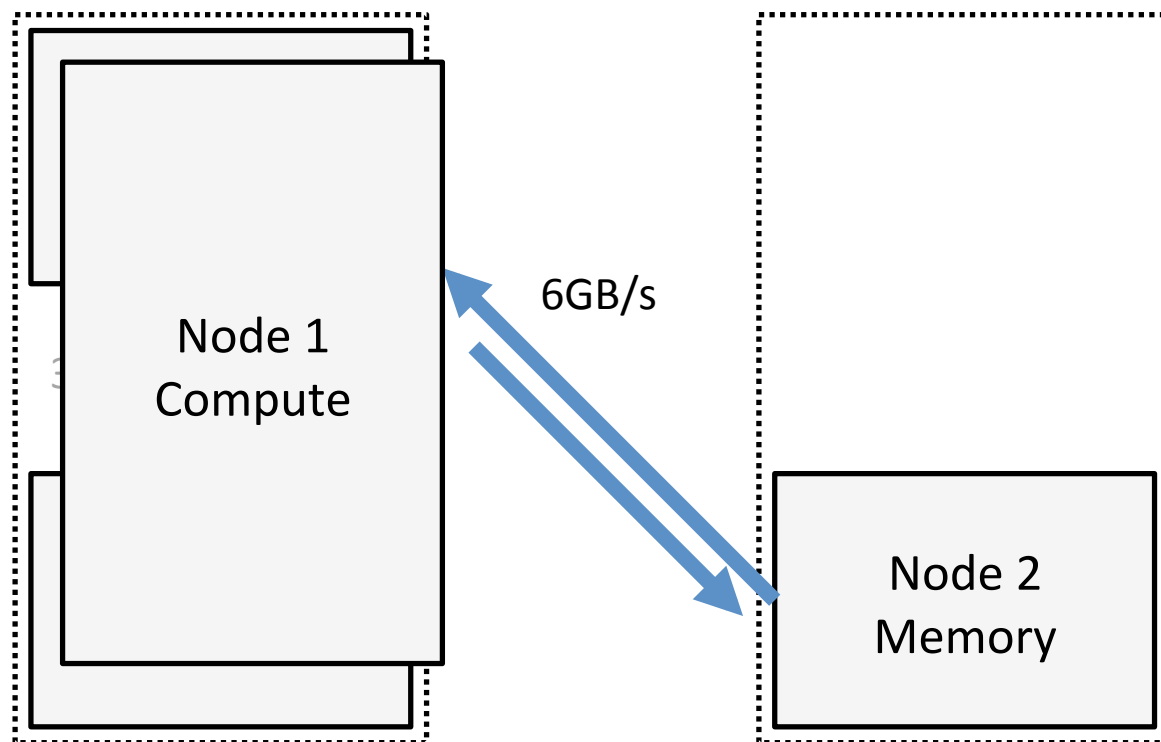
Performance modeling

- Approach we used to analyze operations for single node also useful for thinking about multiple nodes.
 - But make distinction between *local* and *remote* memory.



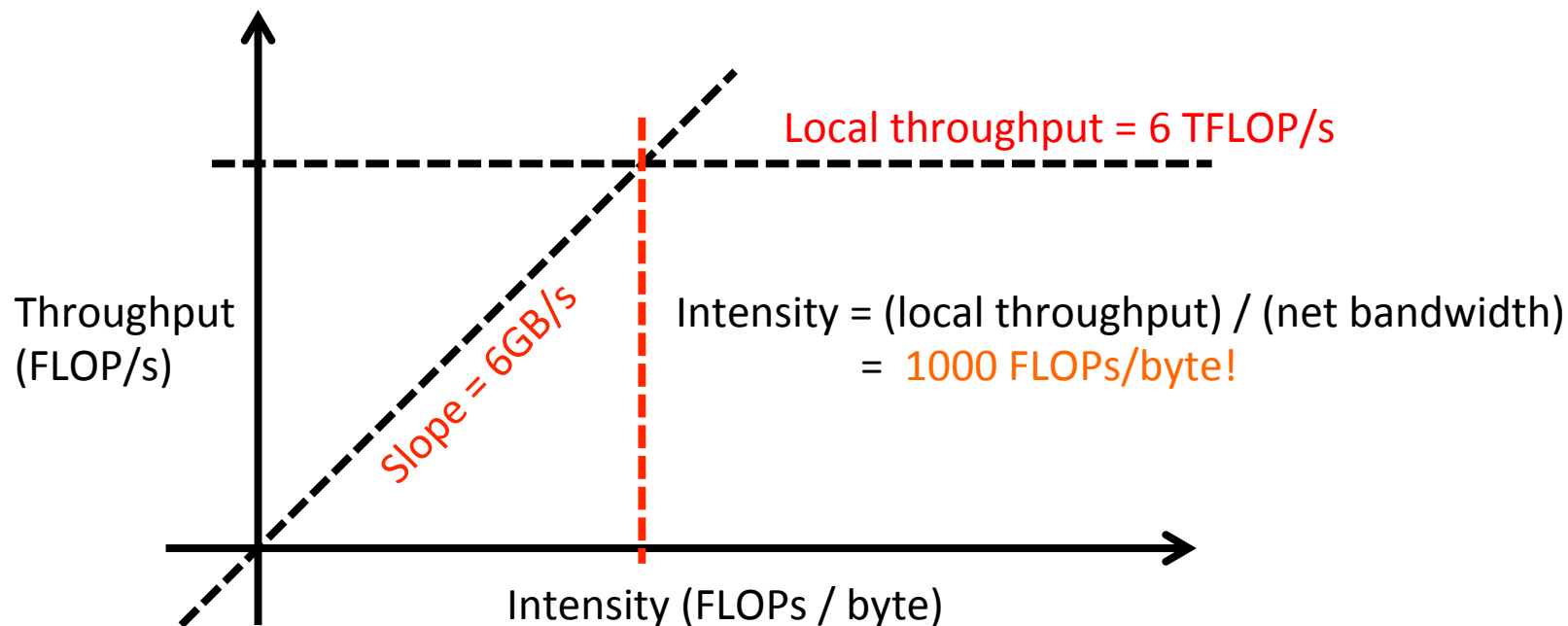
“Roofline” model

- Analyze performance of nodes in terms of their *local throughput* + bandwidth to *remote* data.



“Roofline” model

- Analyze performance of nodes in terms of their *local throughput* + bandwidth to *remote* data.



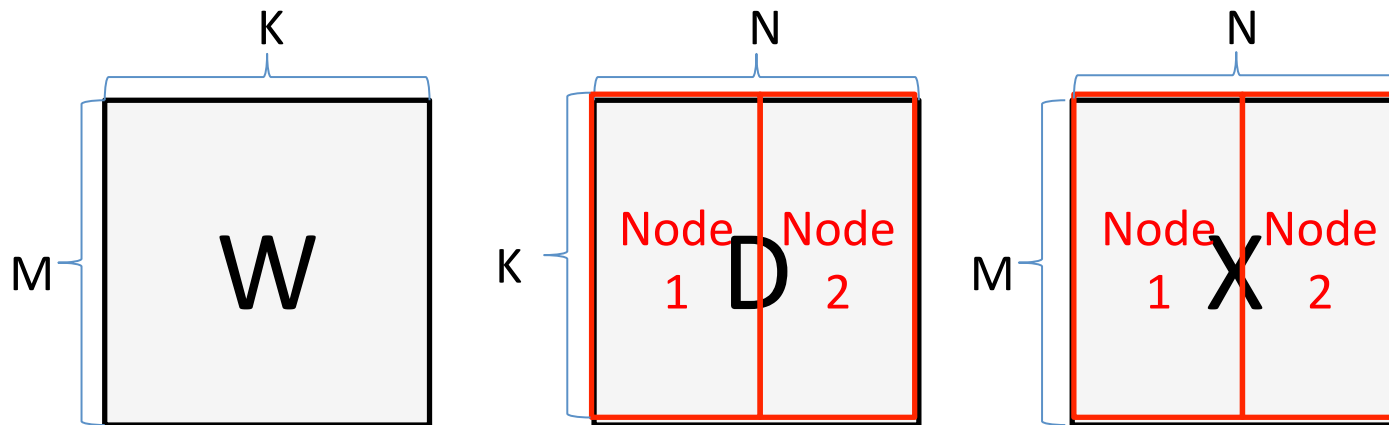
Note much higher intensity: need to do 1000 FLOPs locally (*at 6 TFLOP/s throughput*) for every 1 byte of network traffic.

Example: Data Parallelism

- What about gradient updates / communication?
- Analyze distributed operation for Node 1.

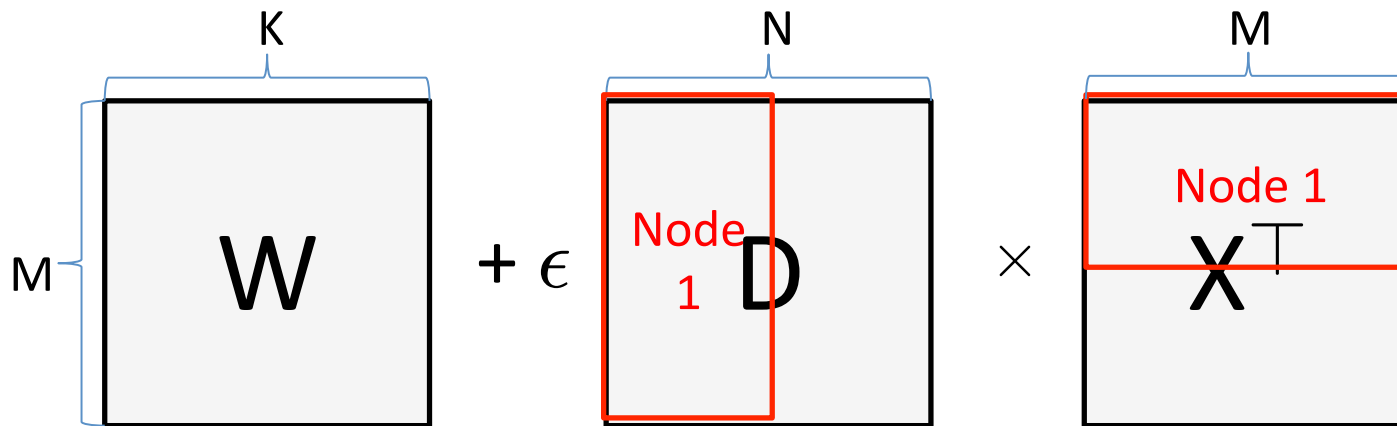
$$W = W + \epsilon D X^T$$

Send(W, Node 2)



Example: Data Parallelism

- Node 1 needs to perform computation on local portion of D , X and local copy of W .
- Send updated W to Node 2.



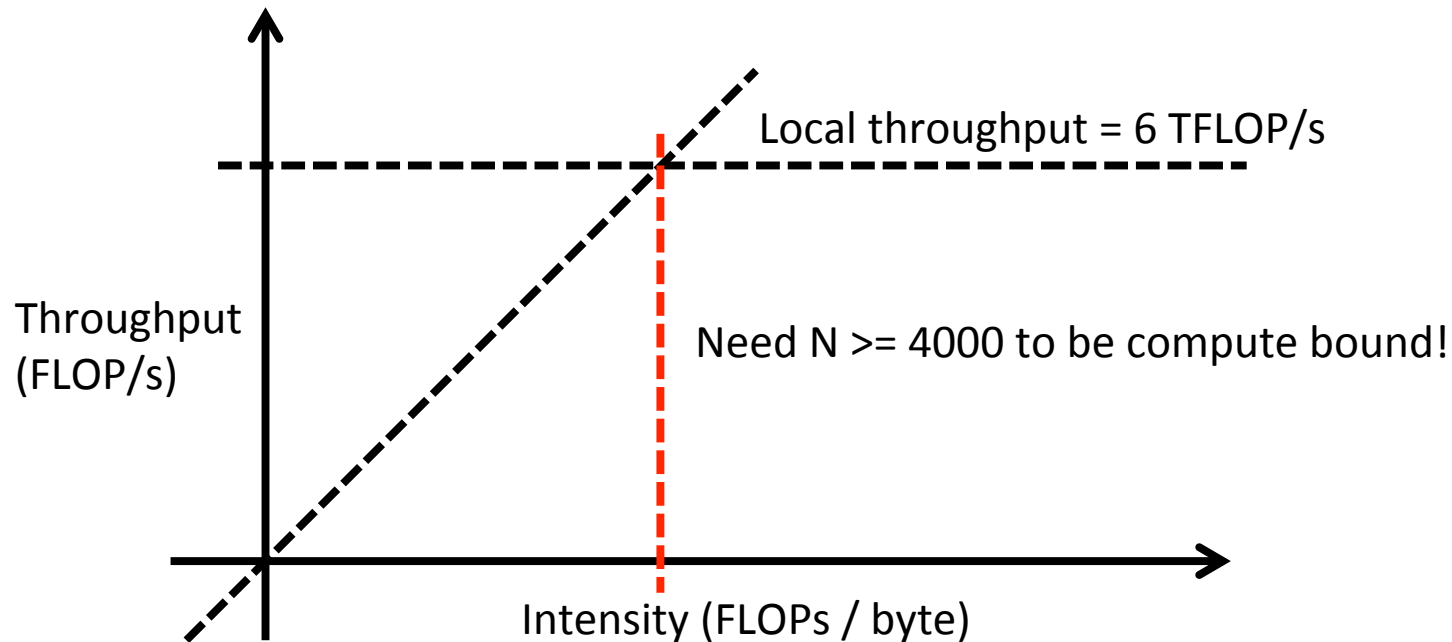
FLOPs	$MNK + 2MK$
Remote Memory	$4MK$
Overall Intensity	$(MNK + 2MK) / 4MK = N/4 + 1/2$



Number of FLOPs we can carry out on Node 1 per byte of network traffic.

Overall throughput

- How big does N need to be to achieve high overall throughput?
 - Overall intensity $\approx N/4$



Assumptions

- ...wait. We violated a modeling assumption:

Key assumption: we can always stream memory simultaneously with computation.

- But we introduced a dependency:

$$W = W + \epsilon D X^T$$

Send(W, Node 2)

- We can deal with this a few ways:
 - More analysis to overlap Send() with other ops.
 - Actually stream W while it's being computed.

Don't forget overlap assumption.
Optimize code to make it true.

Putting everything together

- Seen how partitioning affects our ability to scale.
 - Changes size/shape and intensity of local work.
 - Distribution introduces network bandwidth limit.
 - Use roofline to get a sense for both issues!

Putting everything together

- Suggested design process:
 1. Scale up weakly if you can. (Strong scaling is hard.)
 - I.e., Make your model + minibatch as large as practical before parallelizing.
 2. Choose a partition of the work and data over nodes.
 3. Estimate local node max throughput (via roofline or benchmarking)
 4. Use local throughput and cluster network bandwidth to create multi-node roofline model.
 5. Estimate overall max throughput of work on each node.
 6. Are you happy?
 - No: Go to next slide, or try new partition.
 - Yes: Go back to deep learning.

Optimization strategy

- Like single-node: find operations that use bulk of time.
- Hunt for partitioning scheme that has a lot of potential (i.e., high “speed of light”)
- Search for opportunities to increase communication+compute overlap.
- Judiciously apply hardware.
 - Compute limited: more GPUs / CPUs.
 - Bandwidth limited: faster network.
 - E.g., dual-rail connection, or 100G networks.

CONCLUSION

Key ideas

- Measure against the “speed of light”: the fastest your code could ever run.
- Use simple performance models to understand tradeoffs; identify approaches with high potential.
- Challenging part of multinode training is partitioning and communication.
 - Build intuition for good/bad schemes by trying out different choices and calculating max throughput.

Thank you!

Thanks: Greg Diamos & Bryan Catanzaro

References:

Coates, Huval, Wang, Wu, Ng, Catanzaro. “Deep Learning with COTS HPC.” ICML 2013.

Samuel Williams, Andrew Waterman, David Patterson. “Roofline: An Insightful Visual Performance Model for Multicore Architectures.”

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