Piper:
Multidimensional Planner for DNN Parallelization

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NEURAL INFORMATION PROCESSING SYSTEMS

Zillion-dollar question: how to train DNNs efficiently?

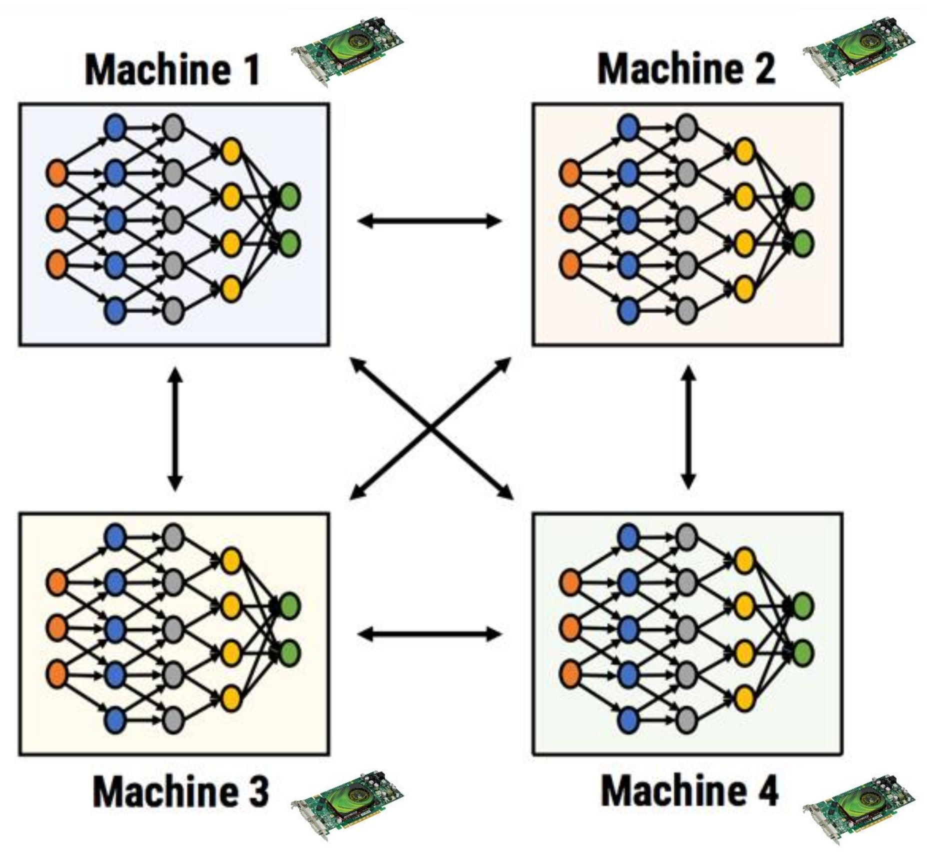
Dimension 1:

Data parallelism:

- Replicate model on every worker
- Train on disjoint samples

But:

- Communication (weight resync) can be expensive
- SOTA models are huge and don't fit on a single worker



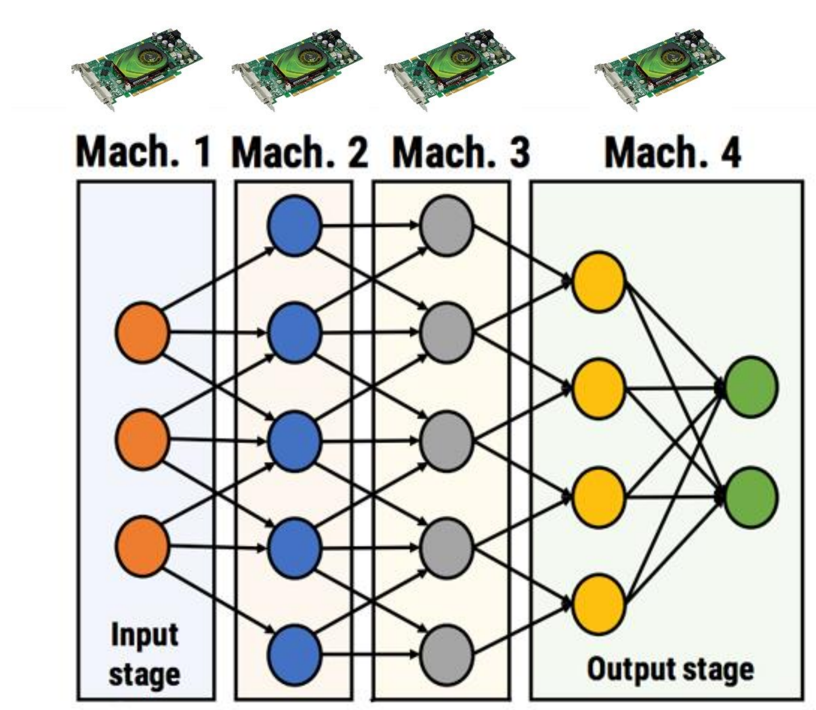
Dimension 2:

Model parallelism:

- Partition the model
- Transfer intermediate activations between workers

To get high worker utilization, use **pipelining:**

- Once the first sample goes to Machine 2, Machine 1 can start processing the second sample, etc.

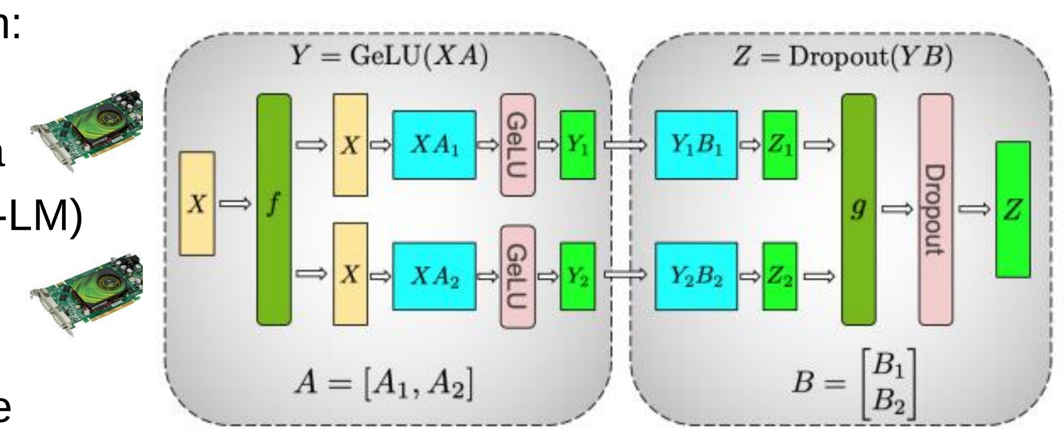


Dimension 3:

Tensor (model) parallelism (intra-layer):

Can also split individual layers and operators for the same microbatch/sample

- Think of matrix multiplication: many ways to split matrices
- Scheme proposed by nVidia for Transformers (Megatron-LM)



Advantages:

- does not increase batch size
  - with only data parallelism and pipeline model parallelism, batch size ≥ microbatch size · number of devices
- can have smaller memory usage
  - indispensable if single layer doesn't fit on 1 device

How to optimally partition the model and combine all dimensions?

Dimension 4:

Memory-saving optimizations such as activation recomputation

Prior work

Approach 1:

- Treat objective function as black box, e.g. measure time of 10 training steps
- Optimize it with generic heuristics such as Reinforcement Learning or MCMC
- [Mirhoseini et al. 2017, 2018]
  [Gao et al. 2018]
  [Addanki et al. 2019]
  [Zhou et al. 2019, 2020]
  [Paliwal et al. 2020]

Approach 2 (ours):

- Build cost model that closely reflects real performance
- Solve resulting "offline" optimization problem with principled algorithmic techniques
- [Jia et al. 2018, 2019]
  [Narayanan et al. 2019, 2020]
  [Tarnawski et al. 2020]

No prior work addresses the entire search space (with pipelining)

Our two-level approach

Huge search space,
incl. finding good tensor parallelism schemes
for *entire DNN operator graph*

this work

Find good tensor parallelism schemes for *individual layer types*

+

Combine them well, together with the other modes of parallelism

Beyond the scope of this work:
can use existing schemes
(e.g. Megatron-LM for Transformers),
human experts, or future algorithms

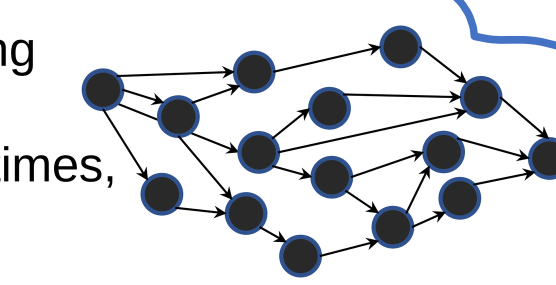
Our main contribution: Piper, an efficient algorithm for this problem

TODO

Piper algorithm

input

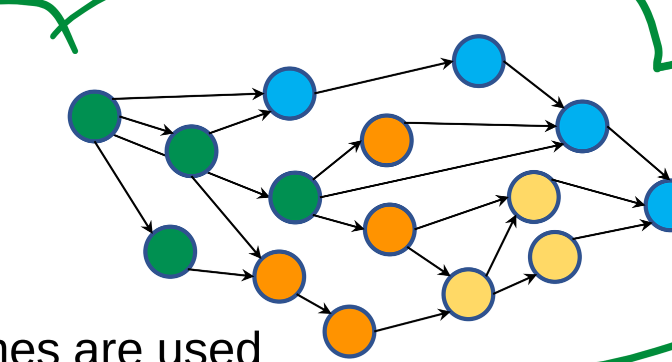
- Layer-granularity computation graph (DAG)
  - For each node (layer), a list of tensor parallelization schemes / memory-saving optimizations
  - Annotated with profiled / estimated runtimes, memory usage etc.
- Number of accelerators
- Memory, network, batch size constraints



dynamic programming

output

- Partitioning of DAG into *stages*
- For each stage:
  - Degree of data parallelism
  - Degree of tensor parallelism
  - Which tensor parallelism schemes are used
  - Which memory-saving optimizations are used



maximize throughput, subject to memory constraints

Our findings

- We evaluate Piper on several modern DNN workloads
- Piper is efficient
- Piper beats out planners from prior work (PipeDream, PipeDream-2BW)
  - Tensor parallelism very useful with very large number of devices
  - Heterogeneous stages are advantageous, even for very repetitive DNNs

Future work

- Piper can handle PipeDream and PipeDream-2BW schedules; TODO: take pipeline flushes into account
- Most importantly, solve **THIS** problem

Some figures courtesy of PipeDream / Megatron