Efficient Algorithms for Device Placement of DNN Graph Operators

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NEURAL INFORMATION PROCESSING SYSTEMS

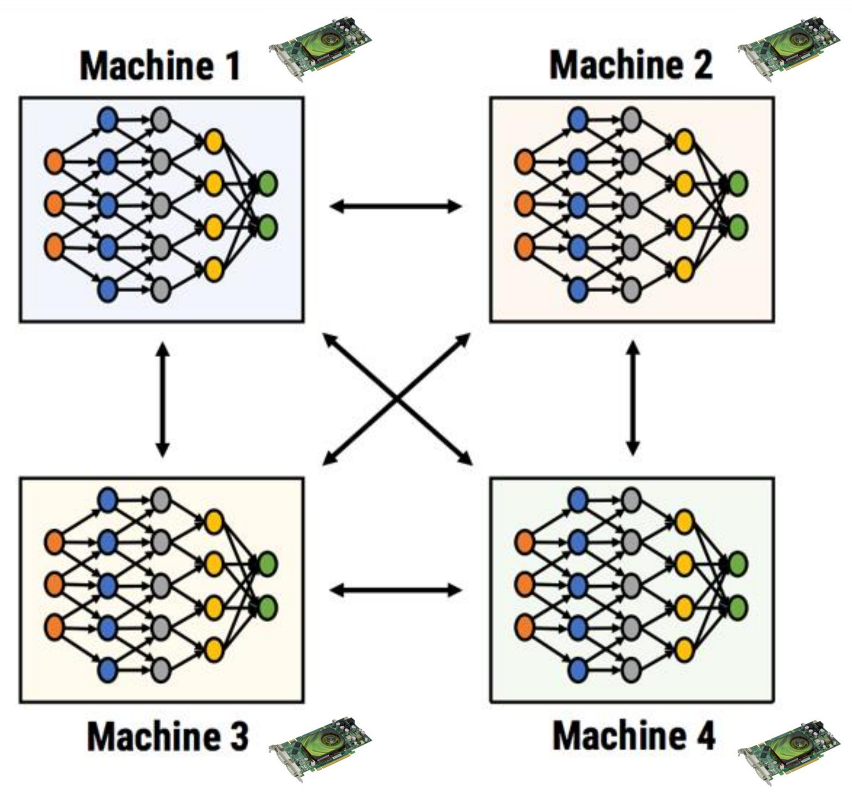
How to train DNNs efficiently?

Data parallelism:

- Replicate model on every worker
- Train on disjoint samples

But:

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

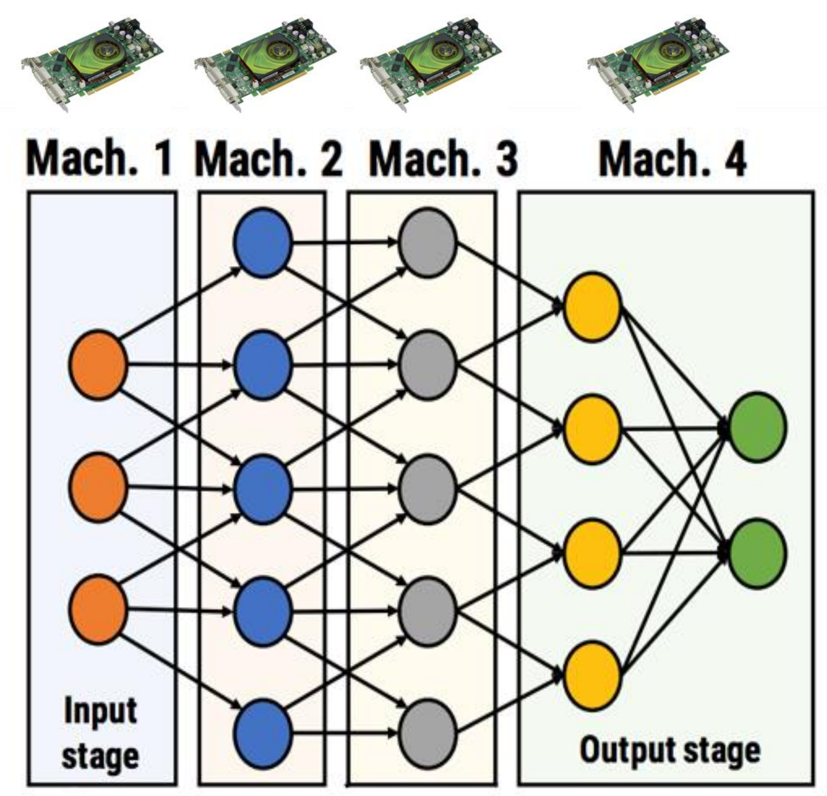


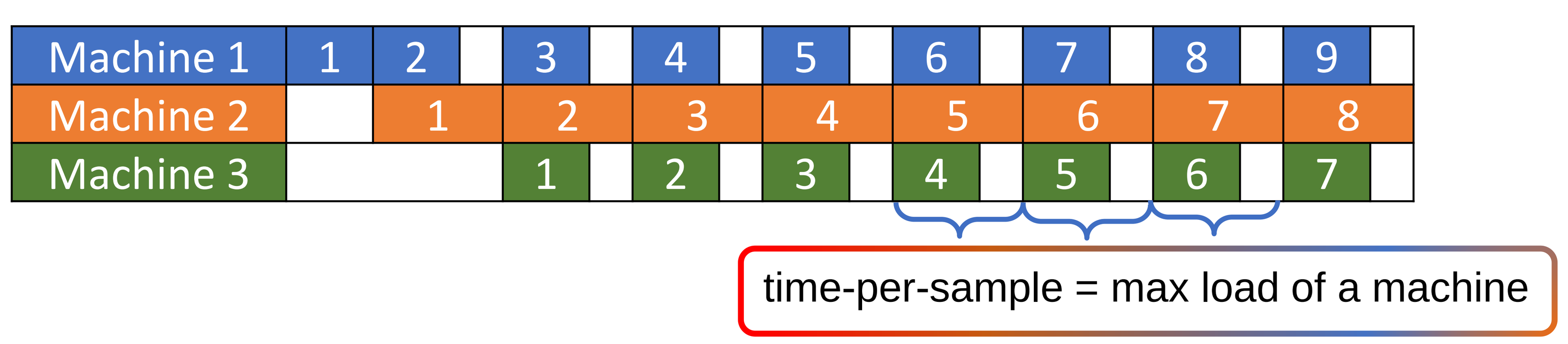
Instead use **model parallelism:**

- 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.
- For training (forward + backward pass), schedules were proposed by PipeDream and GPipe





How to split the DNN graph?

- Assign every node to a machine/device
- Problem called *device placement*
- Want to balance computation out, but also minimize communication
- Usually done by human experts; growing need for automated methods

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 [Mirhoseini et al., Spotlight] or MCMC [FlexFlow]
- Learn a placement policy and generalize to unseen graphs [Placeto, GDP, REGAL]
- Pros: realistic-by-definition performance model
- Cons: very expensive to evaluate cost of each partition tried; heuristics w/o guarantees

Approach 2 (ours):

- Build cost model that closely reflects real performance
- Solve resulting "offline" optimization problem with principled algorithmic techniques
- Previously done in PipeDream, but only for linear computation graphs (i.e. path-graphs)

Challenges:

- Formulate a correct (close-to-reality) cost model
- Resulting problem is highly non-trivial

Our contributions:

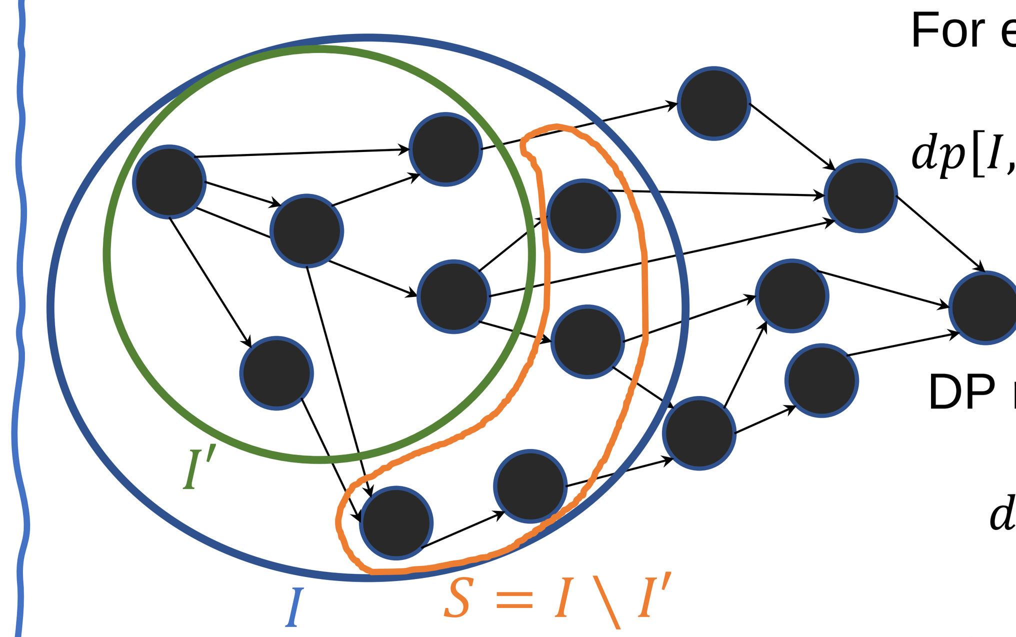
We isolate the structured combinatorial optimization problem at the core of device placement, for both training and inference

And we give **efficient algorithms** to find **optimal** splits:

Dynamic Programming Approach

Objective: maximize throughput

That is, minimize time-per-sample, which is the max load of any machine
(load = computation + communication)



For each downward-closed set I of nodes (*ideal*), compute:

$dp[I,k]$ = min max-load if splitting I onto k machines

DP recursion:

$$dp[I,k] = \min_{I' \subseteq I,\, I':\, ideal} \max(dp[I', k-1], load(I' \setminus I))$$

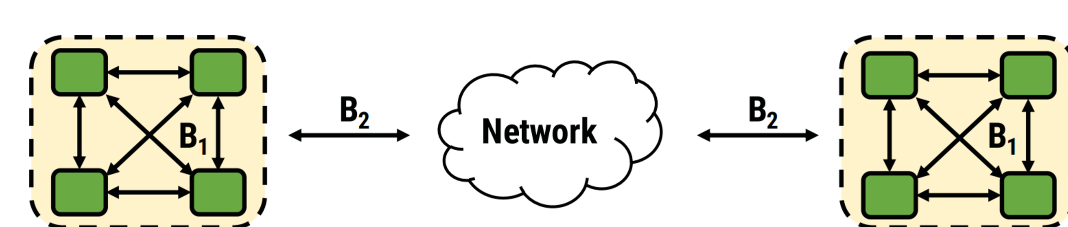
(I' is partitioned on $k-1$ machines, $I \setminus I'$ on 1 machine)

Notes:

- $S = I \setminus I'$ is a contiguous subgraph, and one gets *any* contiguous subgraph this way
- The function $load(S)$ can be arbitrary, should take computation and communication into account
  - Can set $load(S) = \infty$ if S doesn't fit on one device (OOM)
- Runtime is $O((\text{number of machines}) \cdot (\text{number of ideals})^2)$ – exponential in theory, good in practice

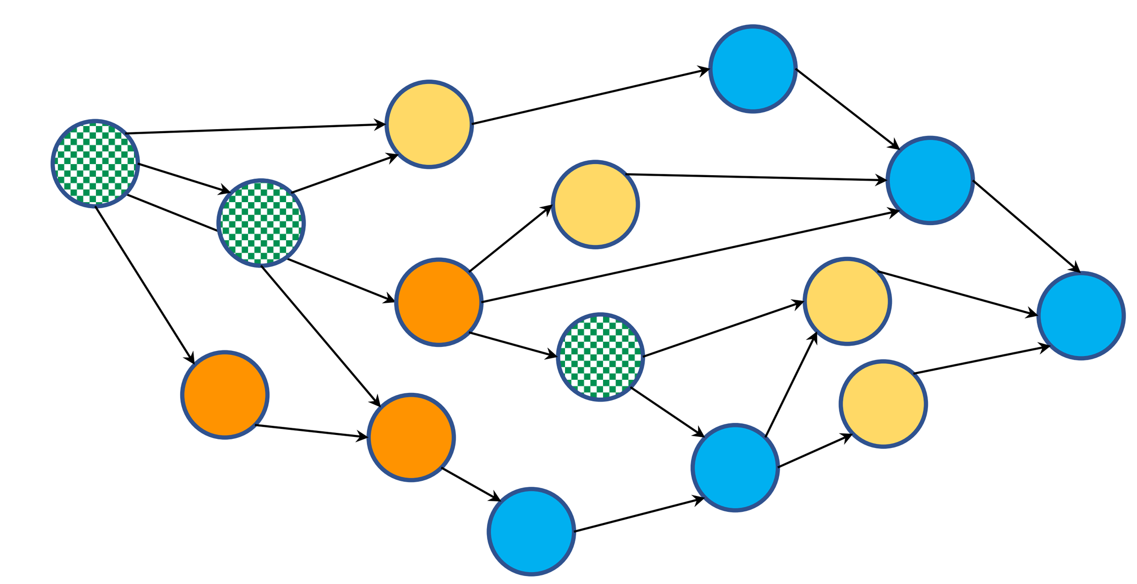
Yields a general framework; can also handle:

- Multiple device types
- Hybrid mode with data parallelism
- Hierarchical communication costs



Integer Programming Approach

that can find **non-contiguous splits**



- The green/checkered subgraph is *non-contiguous*
- Such splits are predicted to yield up to 27% higher throughput for some DNN workloads

Evaluation

- Several modern DNN workloads (BERT, GNMT, Inception, Resnet)
- We find provably optimal splits on operator-level graphs, within seconds to minutes
- Higher throughput than human experts, PipeDream, some other baselines

See paper at: https://arxiv.org/pdf/2006.16423.pdf

Some figures courtesy of PipeDream