FasterMoE

Modeling and Optimizing Training of Large-Scale Dynamic Pre-Trained Models

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4, Apr, 2022 @ PPoPP'22

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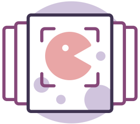
Pre-Trained Models

- The most popular DL model with **capability in multiple disciplines**.

Reading comprehension

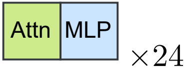
Conversation

Genome analysis



Computer vision

Trend of Pre-Trained Models: Giant Transformers



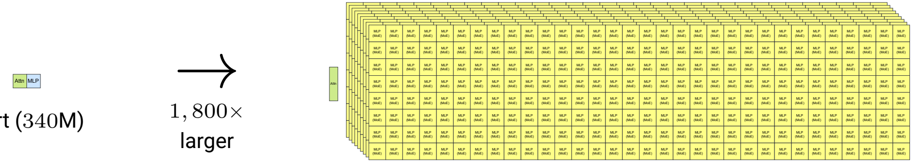
Transformer blocks in Bert[2] (340M Parameters)

- Massive computation for each input.
- Outstanding model capability.

[2] Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." (2018).

[3] Lepikhin, Dmitry, et al. "Gshard: Scaling giant models with conditional computation and automatic sharding." (2020).

Trend of Pre-Trained Models: Giant Transformers



Bert (340M) $\longrightarrow$ $1,800\times$ larger GShard (600B)

- GShard[3] is $1,800\times$ larger.
  - Significant improvement in model capability is observed.
- While GShard is only $1.5\times$ deeper, it adopts **Mixture-of-Experts (MoE)** structure, and employs $2,048$ experts in every MLP module.

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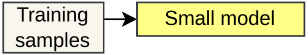
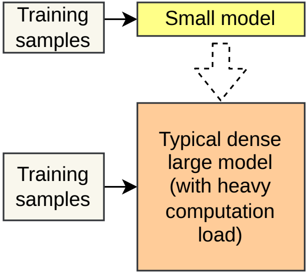
MoE: A New Structure to Enlarge Models



- Small models: limited capability

MoE: A New Structure to Enlarge Models



- Small models: limited capability; Dense large models: expensive computation.

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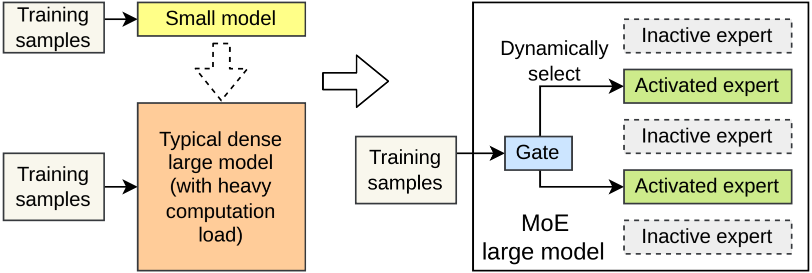
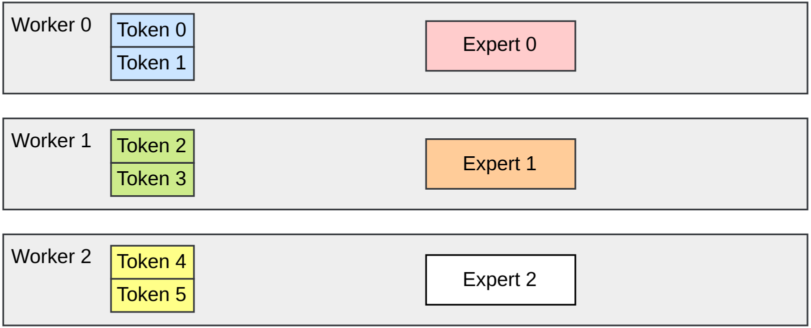


- Small models: limited capability; Dense large models: expensive computation.
- Mixture of **Experts**: Small models, selected by **Gate Module**.
  - The size of the model is enlarged, thus its capability is stronger.
  - The amount of computation remains small.

Expert Parallelism



- Both experts and training data (tokens) are distributed across all workers.

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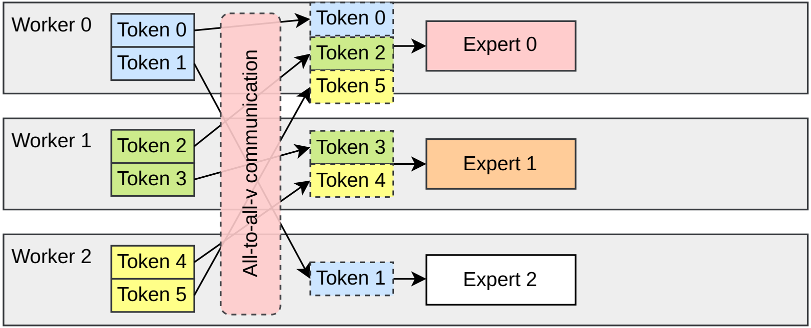

- Both experts and training data (tokens) are distributed across all workers.
- An `all-to-all` is performed to send tokens to their desired experts.

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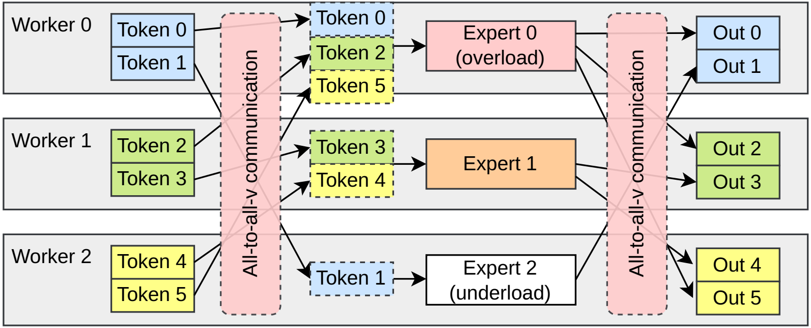

- Both experts and training data (tokens) are distributed across all workers.
- An `all-to-all` is performed to send tokens to their desired experts.
- Another `all-to-all` sends the experts' answers back into original sequences.

Outline of the Paper

Challenge 1

Stragglers due to load imbalance

Challenge 2

Inefficient coarse-grained operators

Challenge 3

Network congestion

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Stragglers due to load imbalance

→ **Optimization 1**
Expert shadowing

Challenge 2
Inefficient coarse-grained operators

→ **Optimization 2**
Smart fine-grained schedule

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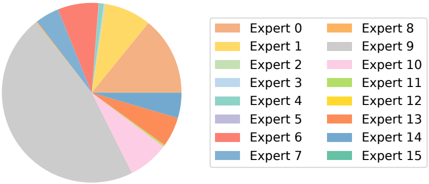
Performance Modeling
DDL-Roofline: Characterization of distributed DL workloads.

Challenge 1: Imbalanced Assignment



- Expert selection can be severely imbalanced.

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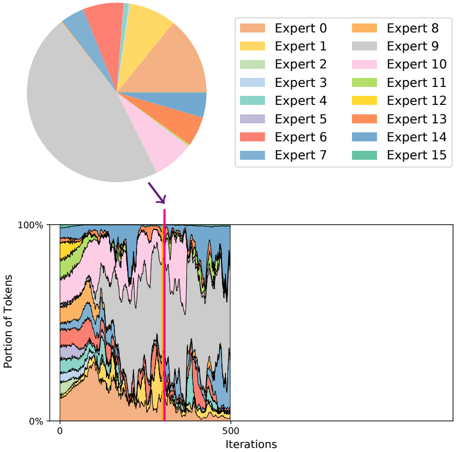

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- The distribution changes between iterations.

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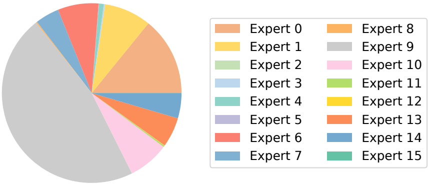

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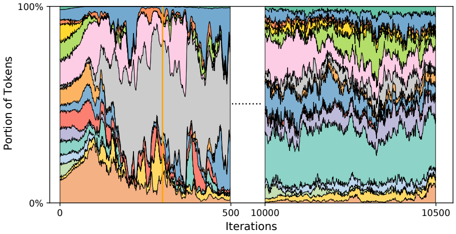
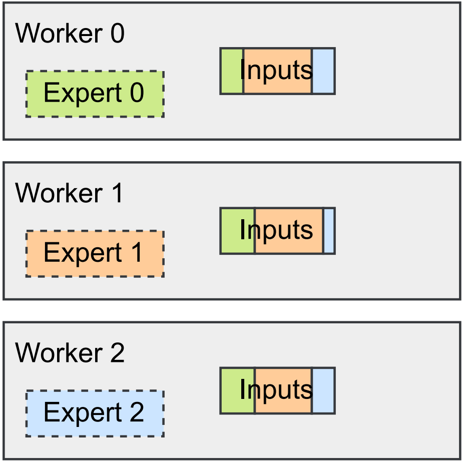


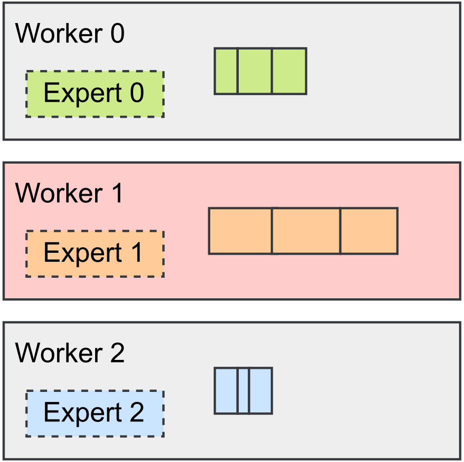
- The distribution changes between iterations.
- The skew varies a lot throughout the training process.

Expert Shadowing



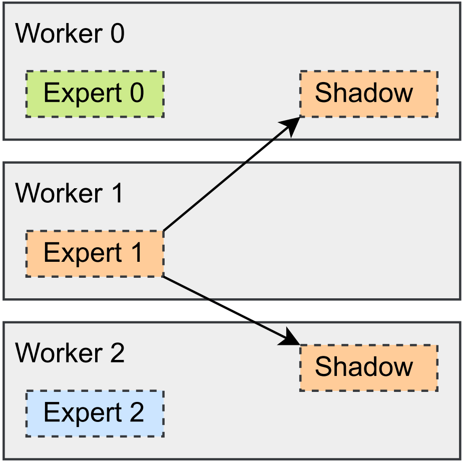
- Expert 1 is very popular.

Expert Shadowing



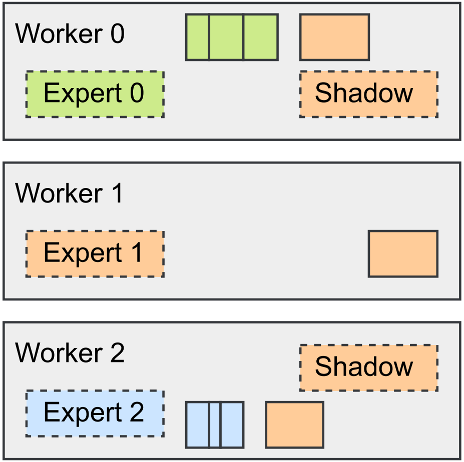
- Expert 1 is very popular.
- Worker 1 is a **straggler**.

Expert Shadowing



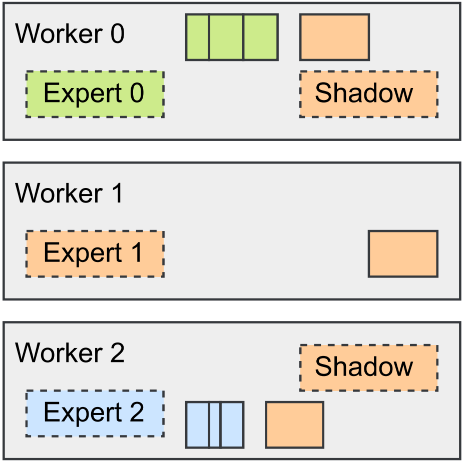
- **Shadow** expert 1 by broadcasting its parameters.

Expert Shadowing



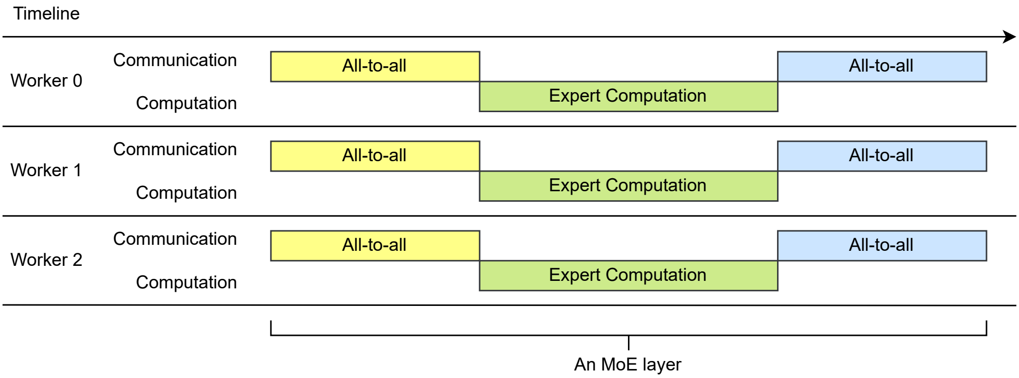
- **Shadow** expert 1 by broadcasting its parameters.
- It becomes more balanced.

Expert Shadowing



- We select shadow experts before every MoE layer, guided by a **performance predictor**. (detailed in the paper)

Challenge 2: Inefficient Coarse-grained Operators



- Each MoE layer involves computation between 2 `all-to-all`s.

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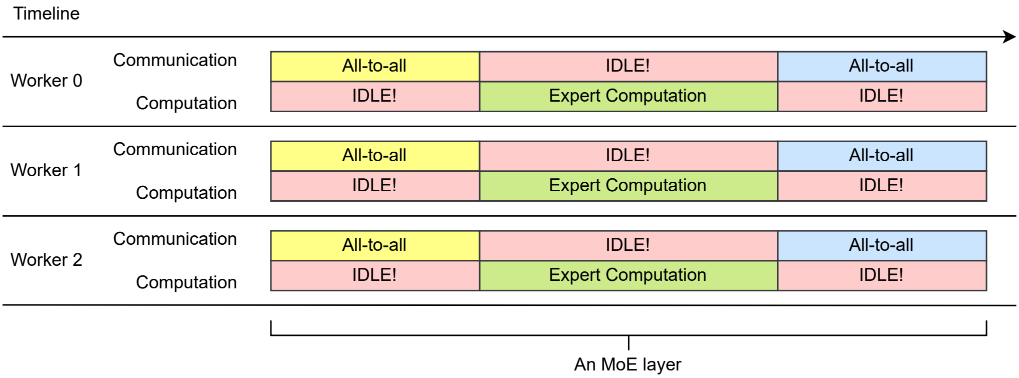
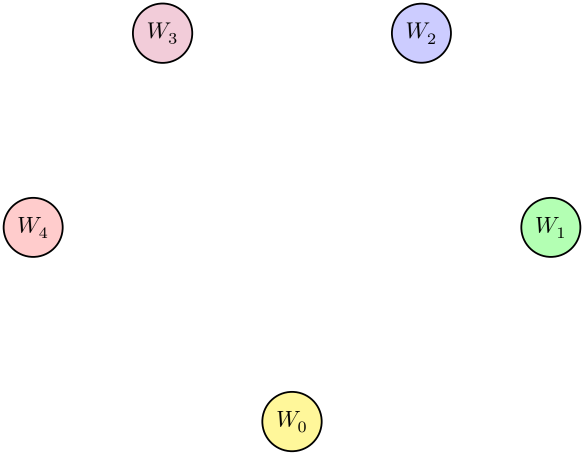


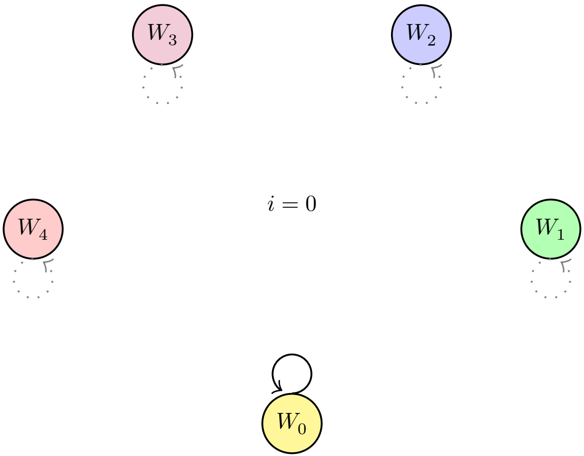
- There is always some hardware idling.

Pair-wise Exchange Algorithm for All-to-all



- n steps for n workers.
- At time step i, W_j:
  - Sends to $W_{(j-i) \bmod n}$
  - Receives from $W_{(j+i) \bmod n}$

Pair-wise Exchange Algorithm for All-to-all



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- Example: 5 workers
  - For W_0:
    - Receives from W_0

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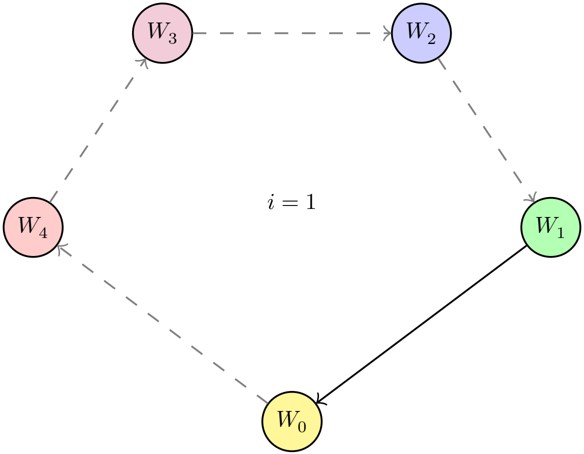

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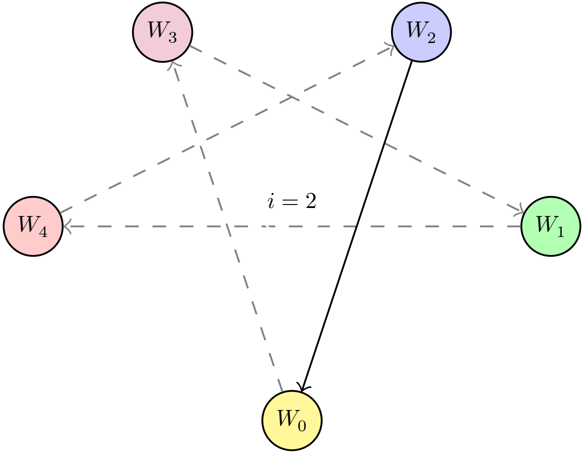

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    - Receives from W_2

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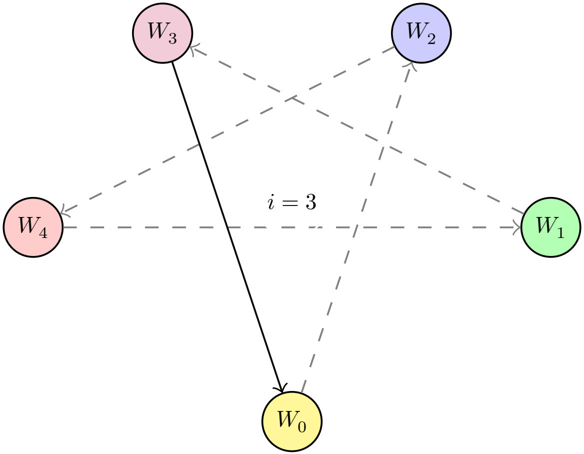

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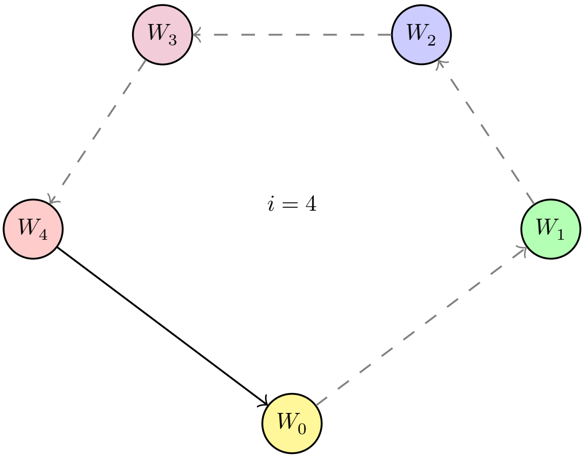

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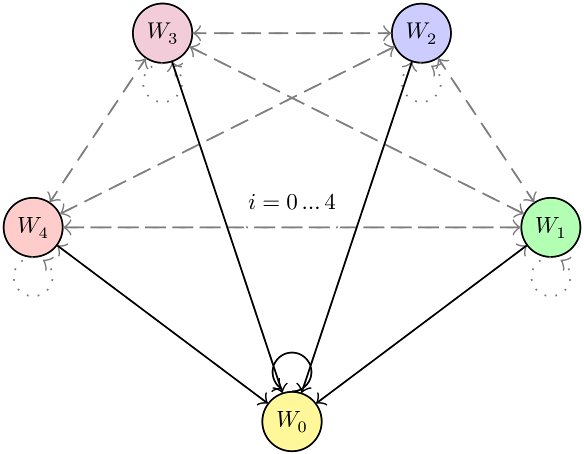

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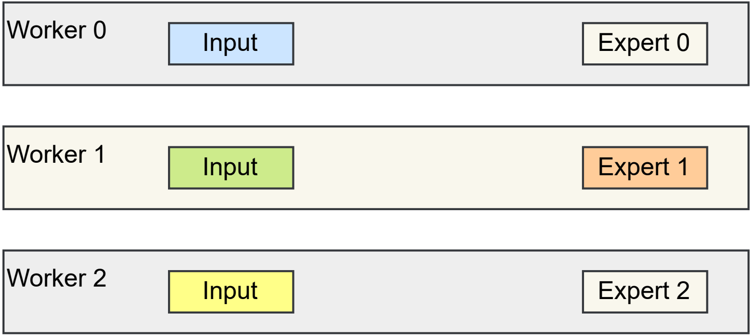
  - For W_0:
    - Receives from W_0
    - Receives from W_1
    - Receives from W_2
    - Receives from W_3
    - Receives from W_4
    - All data received.

Smart Scheduling: Fine-grained Task Split-up



- Take worker 1 for example, expert 1 on it has to process input on worker $0, 1, 2$.

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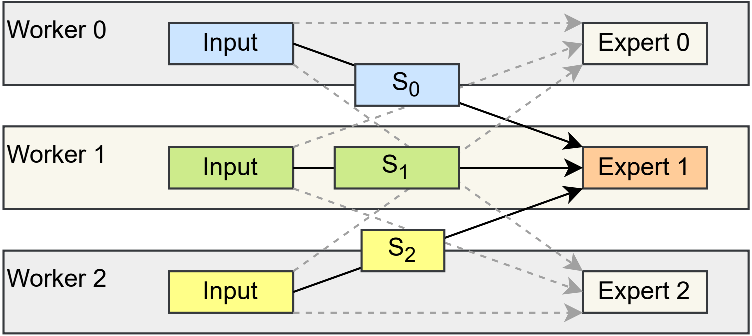

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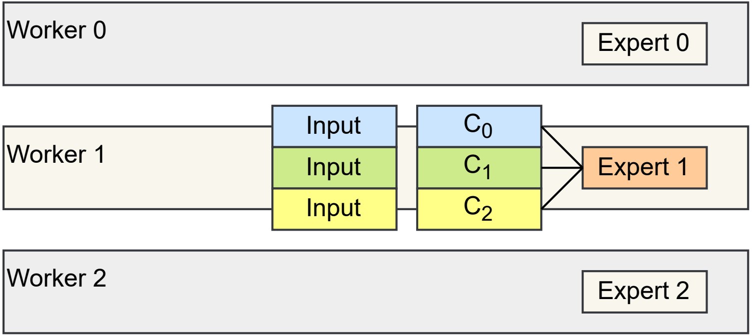

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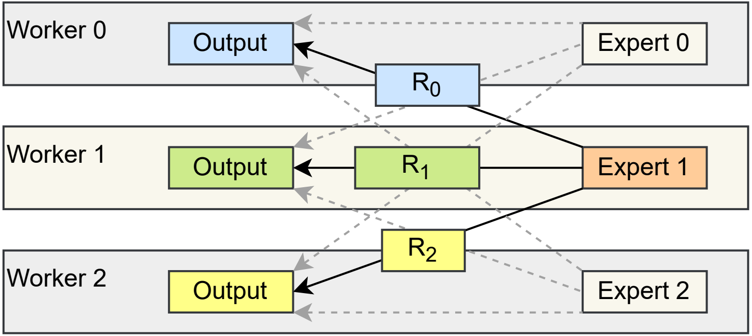

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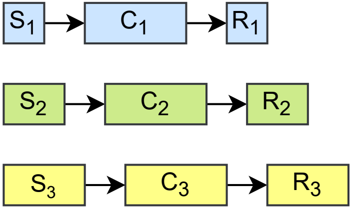
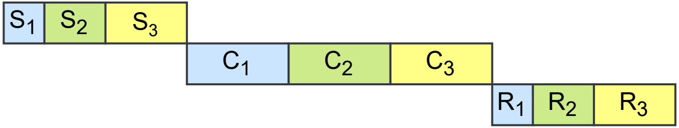
  - S_i: Worker i sends input to worker 1 (as a part of the first `all-to-all`).
  - C_i: The input from worker i is processed by expert 1 on worker 1.
  - R_i: Worker i retrieves output from worker 1 (as a part of the second `all-to-all`).

Smart Scheduling: Re-ordering Fine-grained Operations



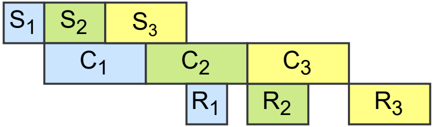
- Dependencies between S, C, R.

Smart Scheduling: Re-ordering Fine-grained Operations



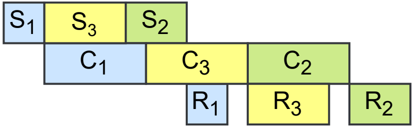
- Follow *Pair-wise Exchange algorithm* to organize Ss and Rs.
- Baseline: execute sequentially.

Smart Scheduling: Re-ordering Fine-grained Operations



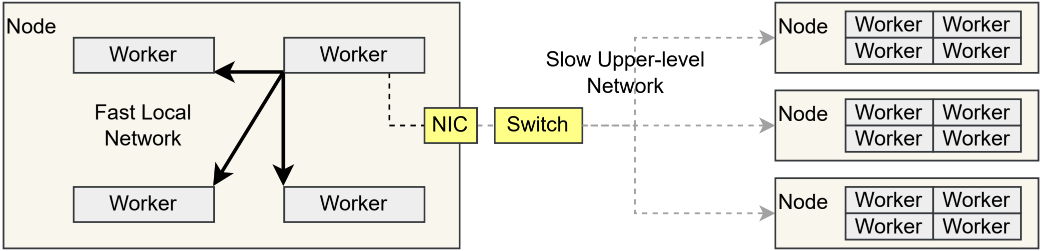
- Lower the latency: Perform C and R **as soon as possible**.

Smart Scheduling: Re-ordering Fine-grained Operations



- To maximize efficiency: (detailed in the paper)
  - Use a **group of workers**, instead of a single worker, as the granularity.
  - Minimize first S and last R by grouping heuristics.

Challenge 3: Congested Cross-node Connection



- Commonly, workers are in a tree-like topology, with lower upper-level bandwidth.

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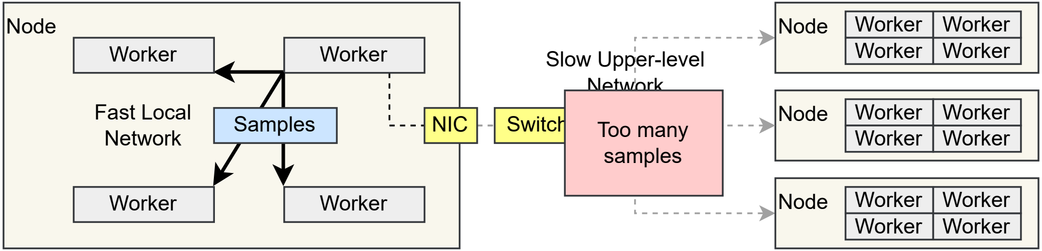
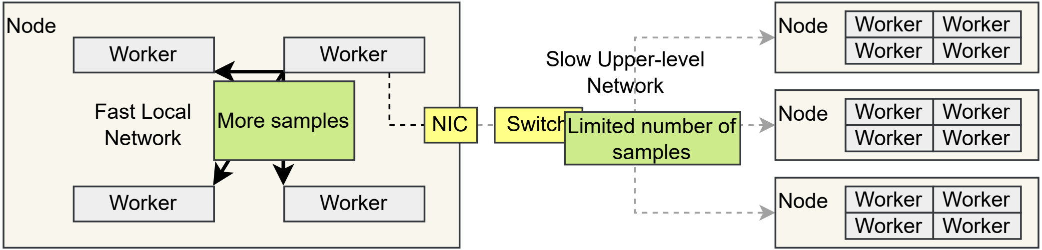


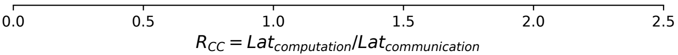
- Commonly, workers are in a tree-like topology, with lower upper-level bandwidth.
- With unconstrained expert selection, there is **congestion** in the slow connections.

Topology-aware Gates



- We design a **Topology-aware gate**.
  - Limit the number of tokens transmitted through upper-level links.
  - Redirect overfilling tokens to experts in the local node (for better data utilization).
  - **Specific gates shall be designed for different cases**.

DDL-Roofline: Roofline for Distributed Deep Learning



- X-axis: $R_{CC} = \frac{Lat_{\text{computation}}}{Lat_{\text{communication}}}$

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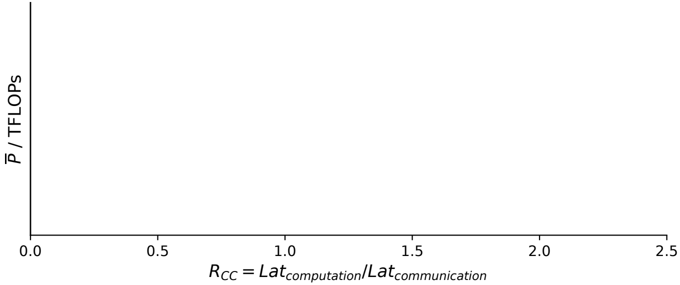

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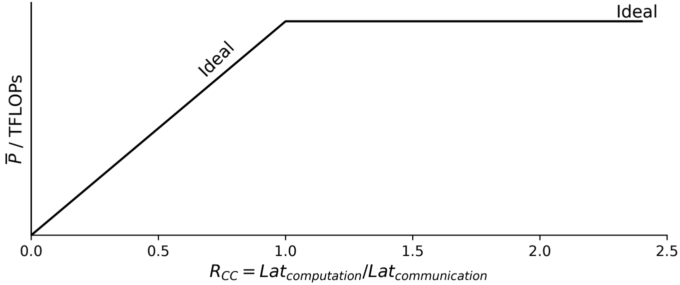

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  - Ideal: Computation and communication are **perfectly overlapped**.

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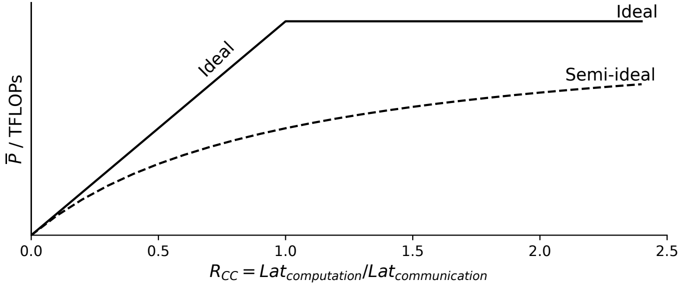

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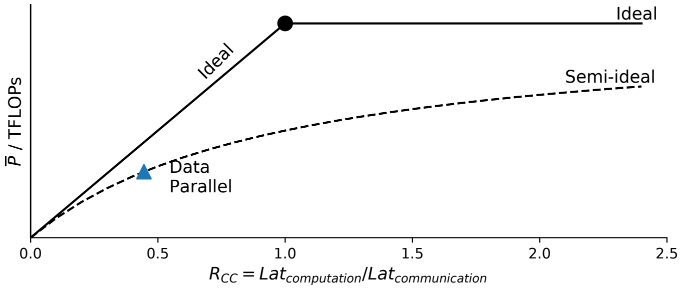
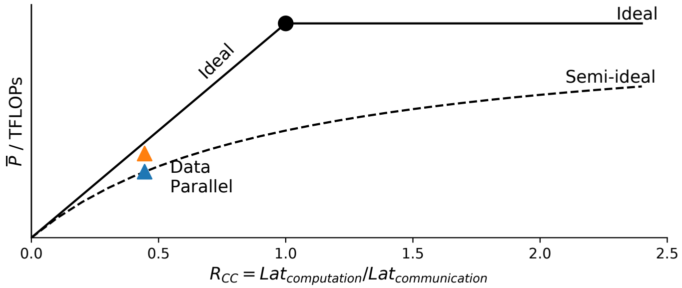
  - Semi-ideal: They are performed **sequentially**.



- Data parallelism: too much **communication overhead** of gradients for MoE.



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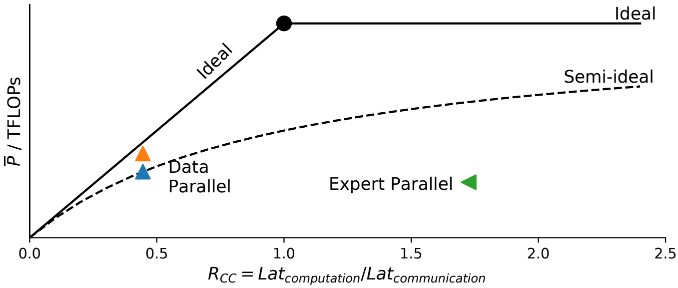

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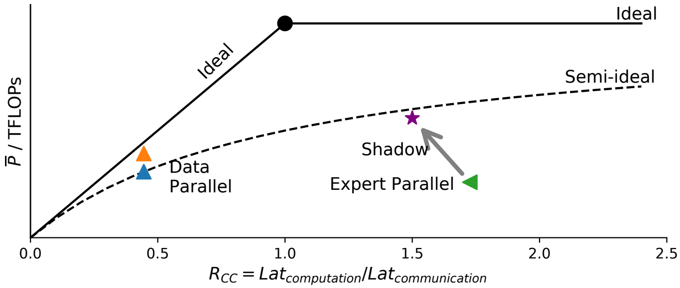

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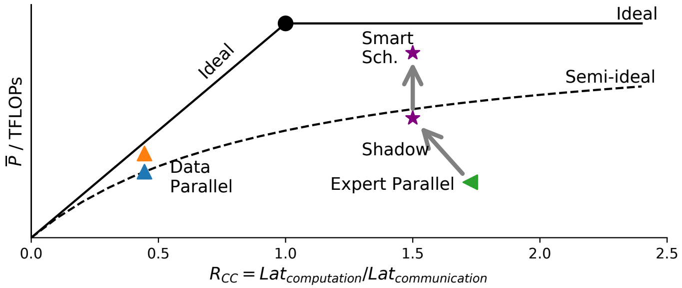

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  - **Smart schedule** overlaps communication with computation.

PACMAN
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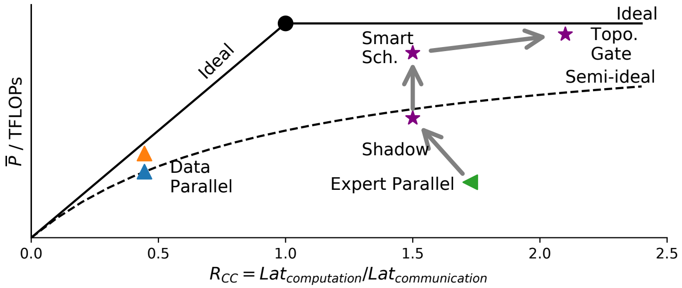

- Data parallelism: too much **communication overhead** of gradients for MoE.
  - Leap beyond semi-ideal by *overlapping*.
- Expert parallelism: less communication, but **load imbalance**.
- Our optimizations:
  - **Shadow** relieves load imbalance.
  - **Smart schedule** overlaps communication with computation.
  - **Topology-aware gate** reduces communication volume.

Implementation Details

- Based on *FastMoE*[4], a PyTorch-based MoE training framework.
  - With modified operators and customized gates.
- Using Megatron-LM[5] as transformer codebase.
- Open source at https://github.com/thu-pacman/fastermoe

[4] He, Jiaao, et al. "Fastmoe: A fast mixture-of-expert training system." (2021).
[5] Shoeybi, Mohammad, et al. "Megatron-lm: Training multi-billion parameter language models using model parallelism." (2019).

Baseline Systems for Comparison

Systems that support faithfully selecting top-k experts for each token

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Systems that require specific expert selection method

- *GShard*: A state-of-the-art MoE system. (*by Google*)
  - Limit capacity of each expert, and drop the overfilling input.
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  - Limit capacity of each expert, and drop the overfilling input.
  - Ported to PyTorch + NVIDIA with customized gate in *FastMoE*.
- *FairSeq + BASE Layers*: Another state-of-the-art MoE system. (*by Facebook*)
  - Run a matching algorithm over the input and expert score sheet for perfectly balanced assignment.

Evaluation Setup

Hardware

- *johnny* cluster: 16 `NVIDIA V100 PCIe` GPUs in 2 nodes.
- *trevor* cluster: 64 `NVIDIA V100 SXM2` GPUs in 16 nodes.

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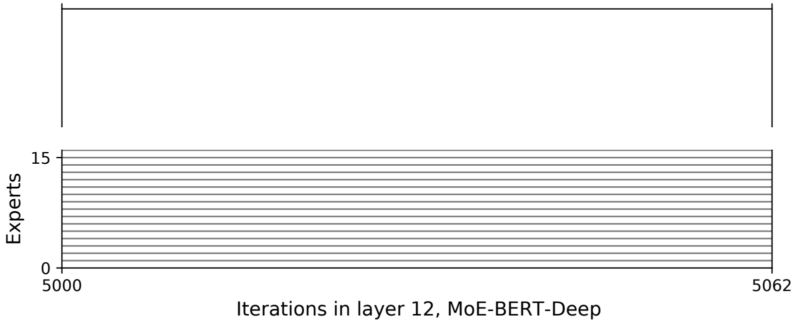
Models

- 4 MoE-Bert and 3 MoE-GPT models at different sizes.

Model name	Size	Layers	Experts	H	α	Cluster
MoE-GPT-S	0.86B	12	16	1024	2	johnny
MoE-GPT	3.42B			2048		
MoE-GPT-L	13.7B			4096		
MoE-BERT-Deep	1.71B	24	16	1024	2	johnny
MoE-BERT-Deep-L	27.4B			4096		
MoE-BERT-Wide	3.27B	12	64	1024	2	trevor
MoE-BERT-Wide-L	13.1B			2048		

Case Study of Expert Shadowing



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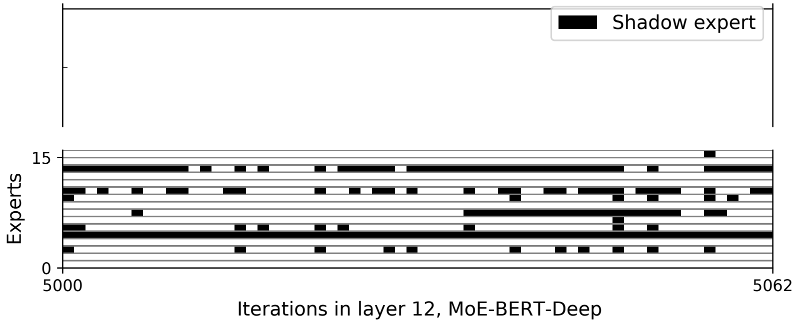

- Different experts are shadowed dynamically, according to different input.
  - On average, 19% experts are shadowed.

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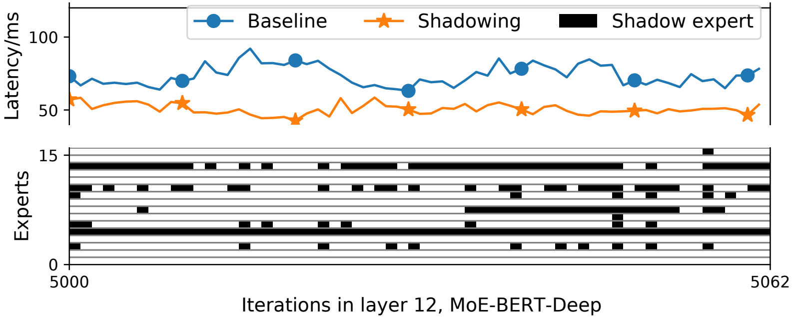
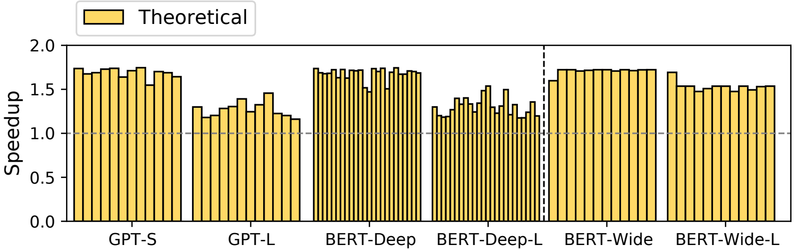


- Different experts are shadowed dynamically, according to different input.
  - On average, 19% experts are shadowed.
- End-to-end latency is effectively reduced.
  - Up to $1.97\times$ speedup in one iteration.

Effectiveness of Smart Scheduling



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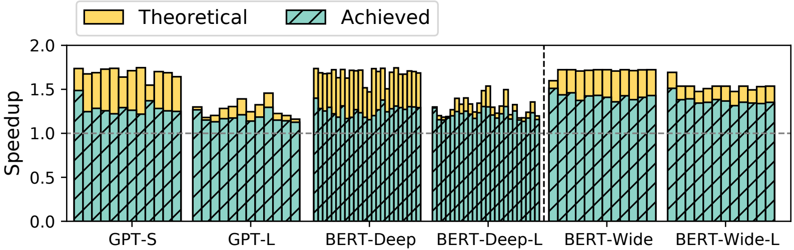
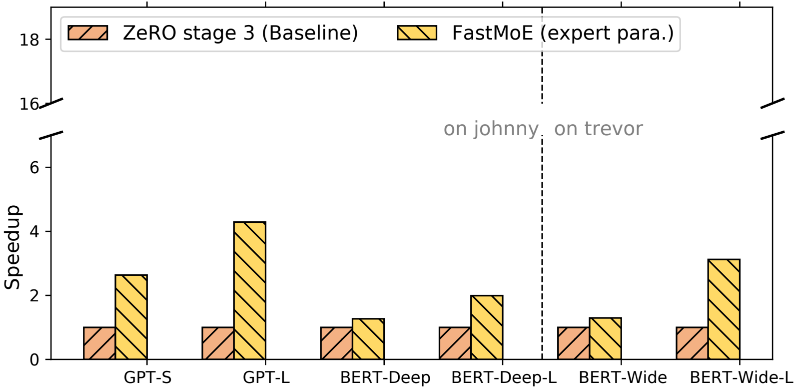


- Theoretical upper bound is computed by the performance predictor.
  - Up to $1.71\times$
- The schedule provides significant speedup.
  - Up to $1.42\times$ speedup achieved.
  - The effectiveness varies between models.

Speedup over FastMoE and ZeRO



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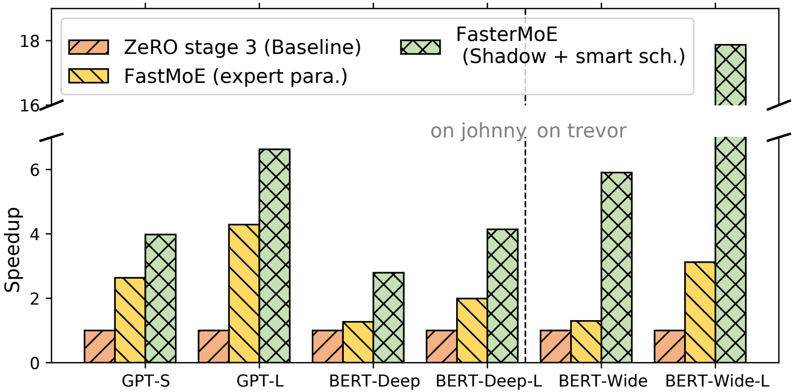
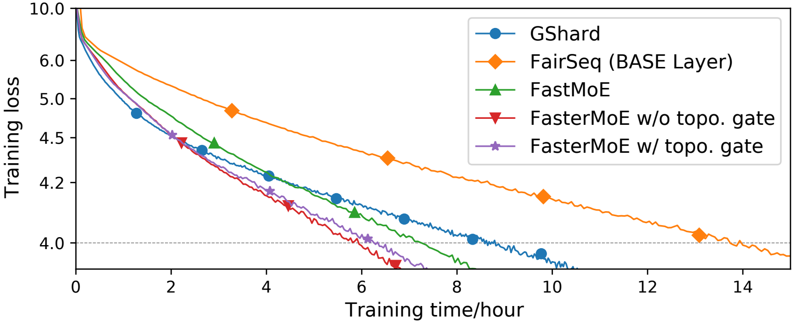


- More than $17\times$ speedup over *DeepSpeed + ZeRO* baseline.
- More than $5\times$ speedup over *FastMoE* baseline.

Convergence Speed w.r.t. GShard and BASE Layers



- Both baseline systems take significantly more steps to converge.
- Convergence speed is $1.37\times$ shorter than *GShard*, and $2.19\times$ shorter than *BASE Layers*.
- The topology-aware gate makes iterations 9.4% faster.

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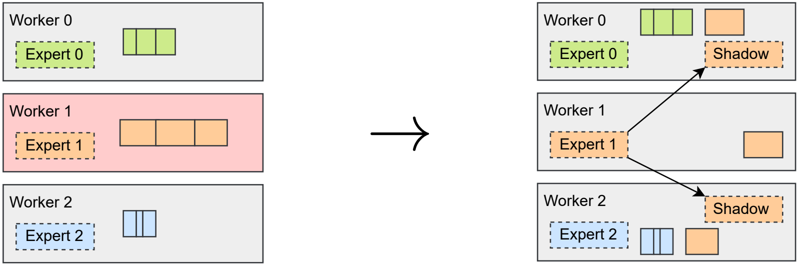

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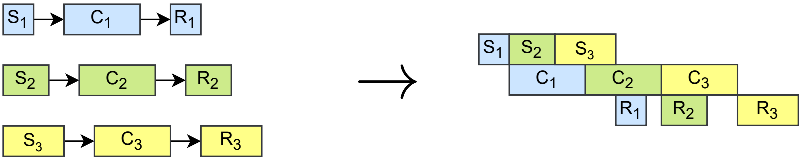

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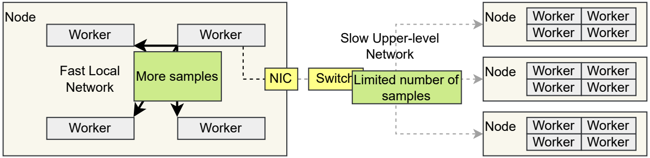

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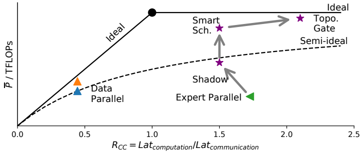
- All above are guided by the **DDL-Roofline** model.



The End

Thanks and Questions are Welcomed

- Contact: `hja20@mails.tsinghua.edu.cn`
- Source code: https://github.com/thu-pacman/FasterMoE