LLM Sys

Large models with Mixture-of-Experts

Lei Li

Carnegie Mellon University
Language Technologies Institute

Outline

- Transformer Mixture-of-Expert Model
  - Switch Transformer architecture
  - Scalable training: expert parallelism (GShard)
- Deepspeed MoE Improvement
  - Pyramid-Residual MoE
  - Scaling MOE inference in Deepspeed
  - Performance
- Deepseek MoE (V3 model)
  - code walkthrough

Motivation: Scaling for Dense model is hard

- Background: Compute is the primary challenge of training massive models.

Model	Model Size	Hardware	Days to Train
Megatron-LM GPT-2	8.3B	512 V100 GPU	9.2 days
OPT	175B	992 A100 GPU	56 days
MT-NLG	530B	2200 A100 GPU	60 days
PaLM	540B	6144 TPU v4	57 days

Mixture of Experts (MoE) is a promising path for improved model quality without increasing training cost.

Need for Mixture of Expert Models(MoE)

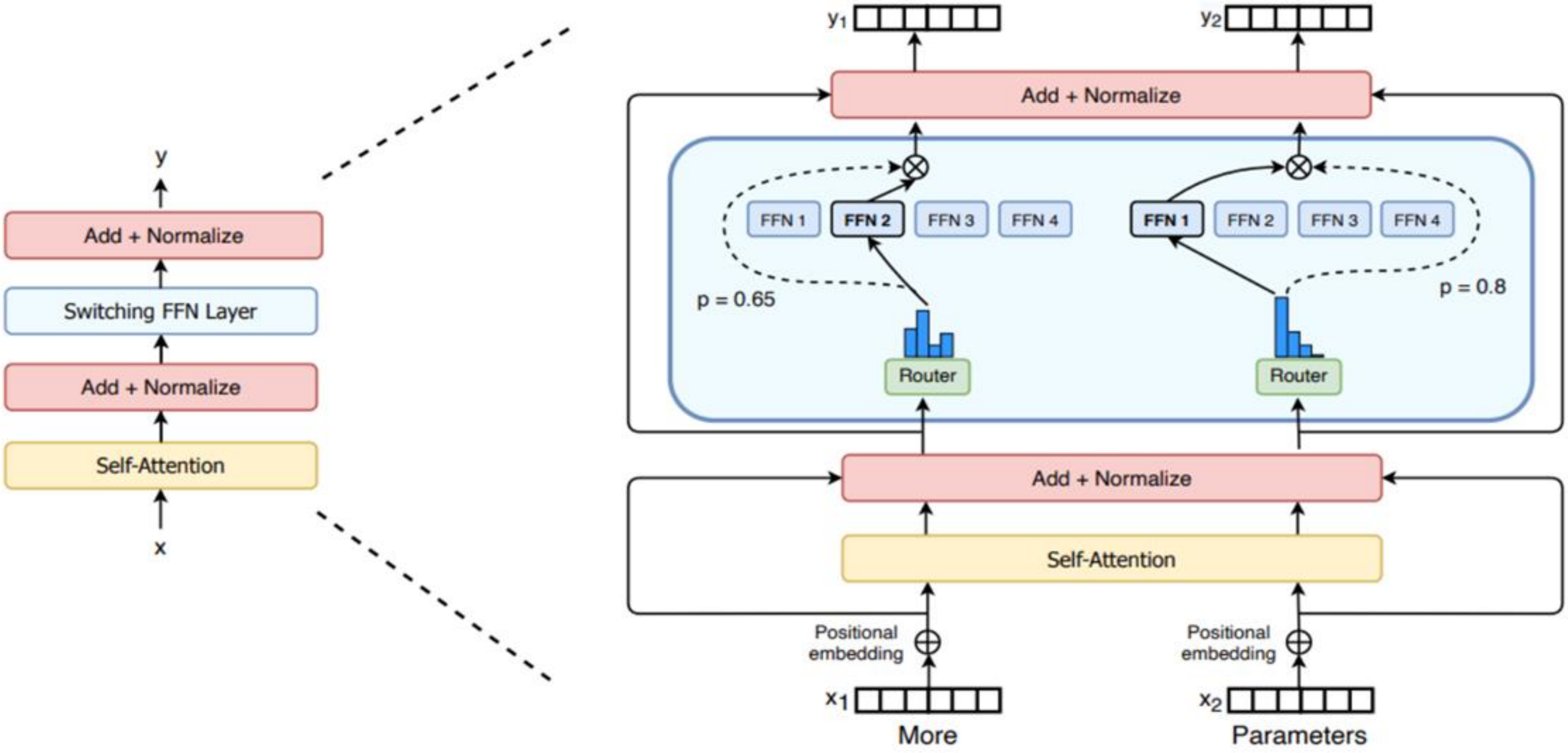
- Dense model is hard to scale, while MOE scales to larger models
- MOE pretraining is much faster vs. dense models
- MOE is faster in inference compared to a model with the same number of parameters

Mixture of Expert Model

- Replacing Transformer’s FFN with
  - multiple small experts, each expert is a neural network (e.g. FFNs)
  - a gating network to choose which expert to activate based on input token
- Not to be confused with Mixture-of-Expert learning, which is a learning algorithm to learn the weighted average of predictor models

Transformer MoE (Switch Transformer)

one token is only passed through one selected FFN



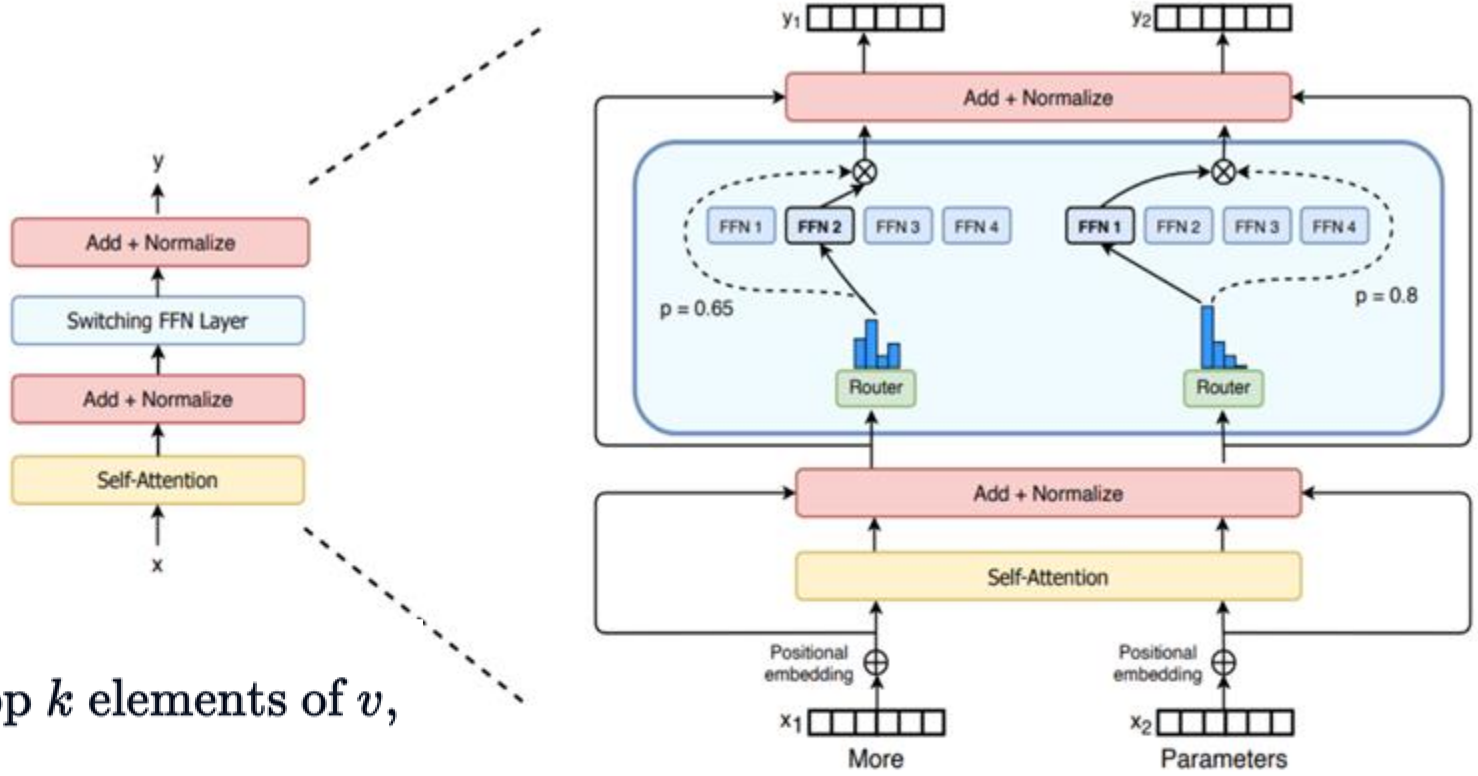
Fedus et al. Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity. JMLR 2022.

Transformer MoE (Switch Transformer)

- Gating network (G) learns which experts (E) to send a part of the input:

$$G_\sigma(x) = \text{Softmax}(x \cdot W_g)$$

$$y = \sum_{i=1}^{n} G(x)_i E_i(x)$$



Top-k gating:

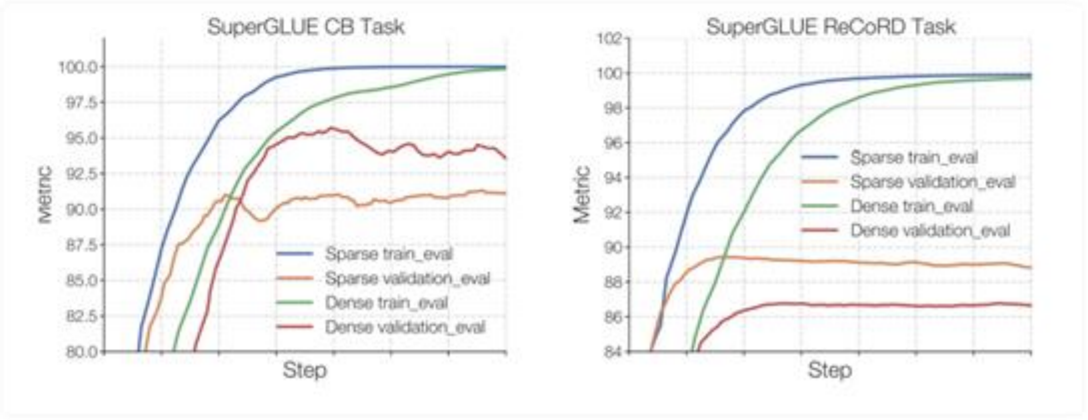
$$\text{KeepTopK}(v, k)_i = \begin{cases} v_i & \text{if } v_i \text{ is in the top } k \text{ elements of } v, \\ -\infty & \text{otherwise.} \end{cases}$$

$$G(x) = \text{Softmax}(\text{KeepTopK}(H(x), k))$$

Fedus et al. Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity. JMLR 2022.

MOE Challenges

- MoE tends to over-fit during fine-tuning
- Inference:
  - High memory requirements: All parameters must be loaded into RAM,
  - Example: Mixtral 8x7B functions as a 47B parameter model (not 56B), since only FFN layers act as experts, while other parameters are shared.



In the small task (left), we can see clear overfitting as the sparse model does much worse in the validation set. In the larger task (right), the MoE performs well. This image is from the ST-MoE paper.

What does an Expert network learn?

- Encoder experts tend to specialize in token groups or shallow concepts (e.g., punctuation, proper nouns).
- Decoder experts exhibit less specialization.
- In multilingual setups, experts do not specialize in specific languages due to token routing and load balancing.

Expert specialization	Expert position	Routed tokens
Sentinel tokens	Layer 1	been <extra_id_4><extra_id_7>floral to <extra_id_10><extra_id_12><extra_id_15> <extra_id_17><extra_id_18><extra_id_19>...
	Layer 4	<extra_id_0><extra_id_1><extra_id_2> <extra_id_4><extra_id_6><extra_id_7> <extra_id_12><extra_id_13><extra_id_14>...
	Layer 6	<extra_id_0><extra_id_4><extra_id_5> <extra_id_6><extra_id_7><extra_id_14> <extra_id_16><extra_id_17><extra_id_18>...
Punctuation	Layer 2	, , , , , , , , , - , , , , ,).)
	Layer 6	, , , , , : . : , & , & & ? & - , , ? , , , . <extra_id_27>
Conjunctions and articles	Layer 3	The the the the the the the the the The the the the the the The the the the
	Layer 6	a and and and and and and and or and a and . the the if ? a designed does been is not
Verbs	Layer 1	died falling identified fell closed left posted lost felt left said read miss place struggling falling signed died falling designed based disagree submitted develop
Visual descriptions *color, spatial position*	Layer 0	her over her know dark upper dark outer center upper blue inner yellow raw mama bright bright over open your dark blue
Proper names	Layer 1	A Mart Gr Mart Kent Med Cor Tri Ca Mart R Mart Lorraine Colin Ken Sam Ken Gr Angel A Dou Now Ga GT Q Ga C Ko C Ko Ga G
Counting and numbers *written and numerical forms*	Layer 1	after 37 19. 6. 27 I I Seven 25 4, 54 I two dead we Some 2012 who we few lower each

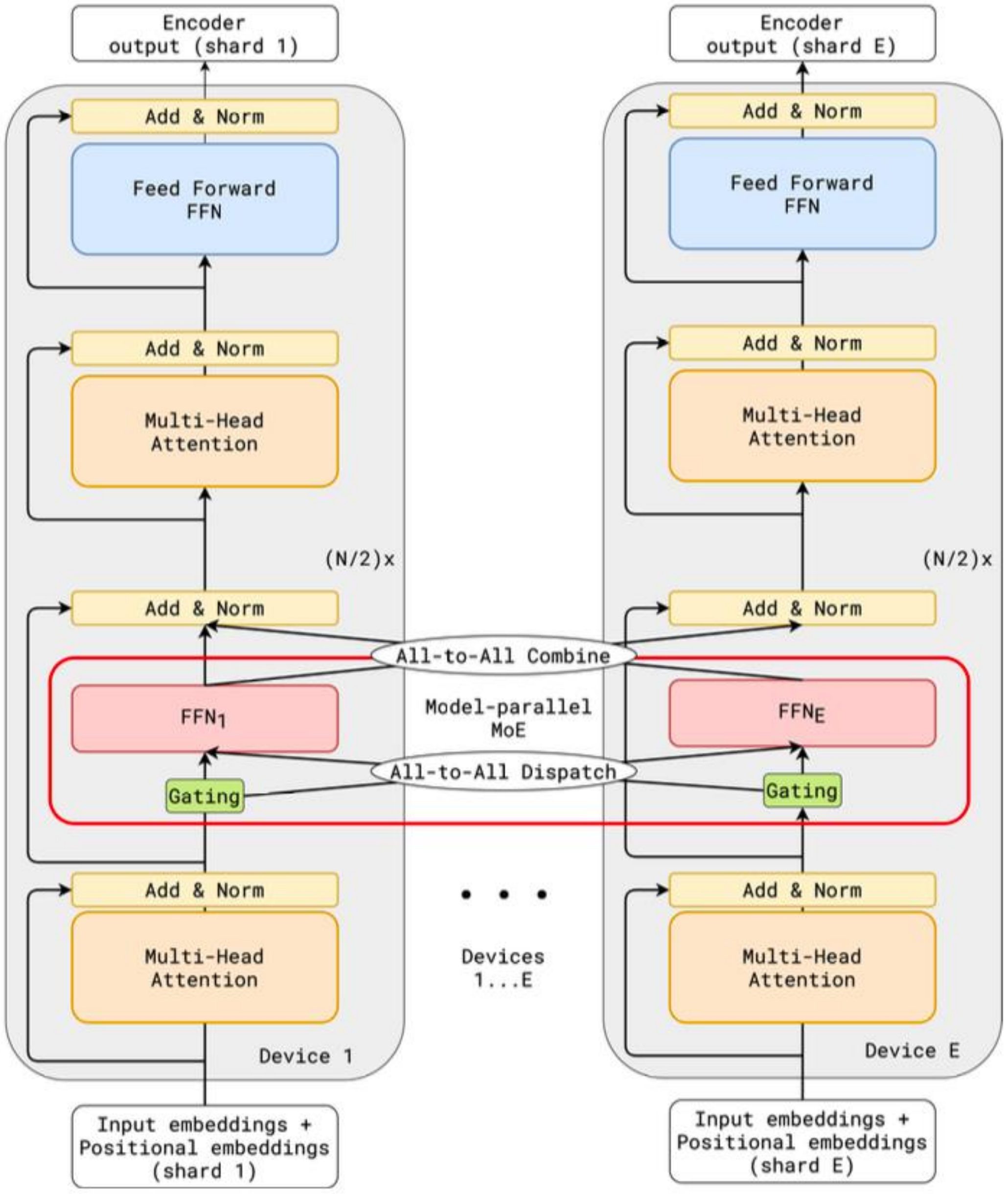
Table from the ST-MoE paper showing which token groups were sent to which expert.

Scalable Training of MoE: Expert Parallelism

- For every other Transformer layer, replace FFN with Gated Experts

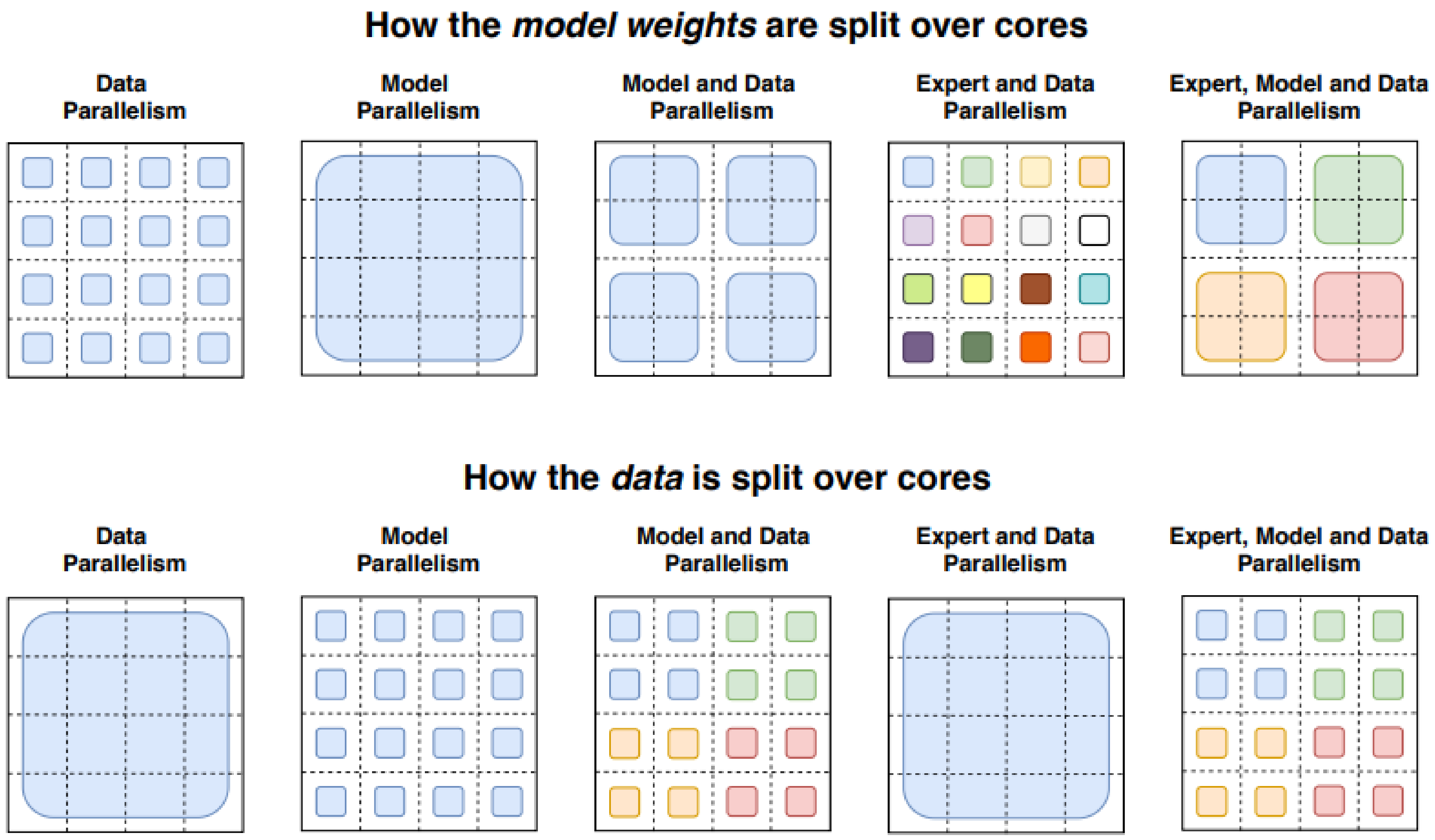
- Keep one Expert on one worker device

- Replicate all other network components in all devices



Lepikhin et al. GShard: Scaling Giant Models with Conditional Computation and Automatic Sharding. ICLR 2021.

Expert Parallelism + Data/Model Parallelism



Fedus et al. Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity. JMLR 2022.

Outline

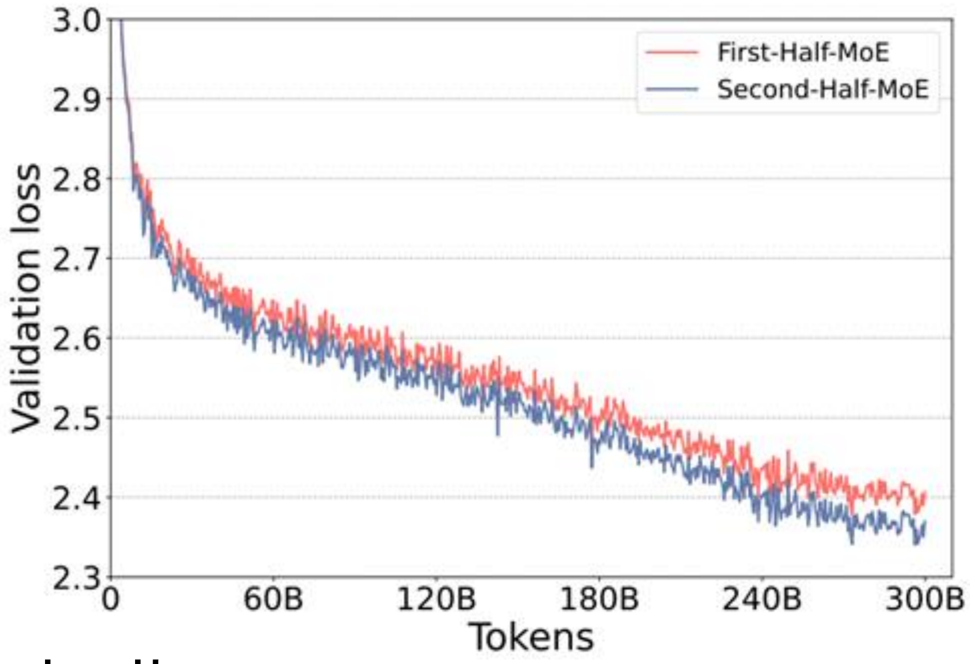
- Transformer Mixture-of-Expert Model
  - Switch Transformer architecture
  - Scalable training: expert parallelism (GShard)
- Deepspeed MoE Improvement
  - Pyramid-Residual MoE
  - Scaling MOE inference in Deepspeed
  - Performance
- Deepseek MoE (V3 model)
  - code walkthrough

Pyramid-Residual-MoE (in DeepSpeed)

Pyramid-MOE:
last two layers 2x routing experts

Residual-MOE:
(one) shared expert and
(one/multiple) routing experts

PR-MoE: where to put MoE?



Intuition: In CV, deeper layers learn more objective specific representations

Question: Are all the MOE layers equally important?

Experiment: Put MoE layers in the (first/sec half layers of the model and leave the other half of layers identical to dense model

-> **Phenomenon**: Deeper layers benefit more from large number of experts

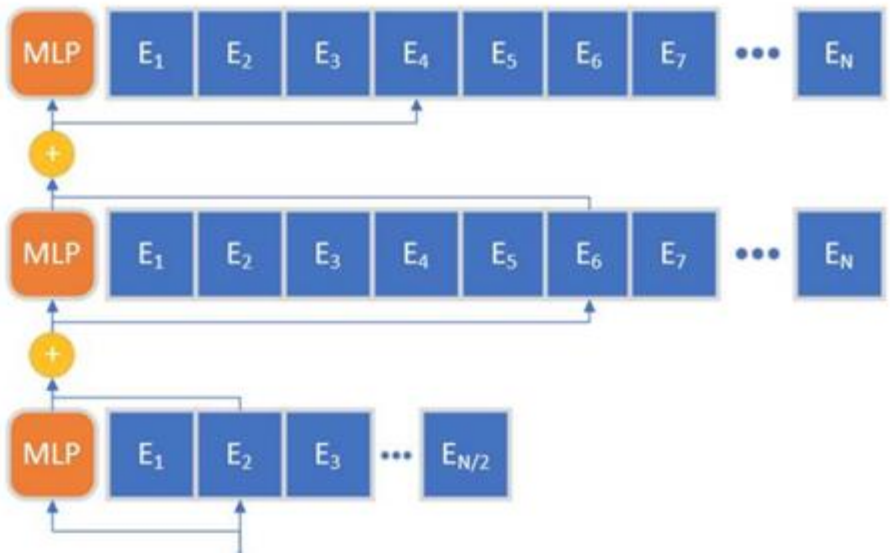
PR-MoE: Intuition 2

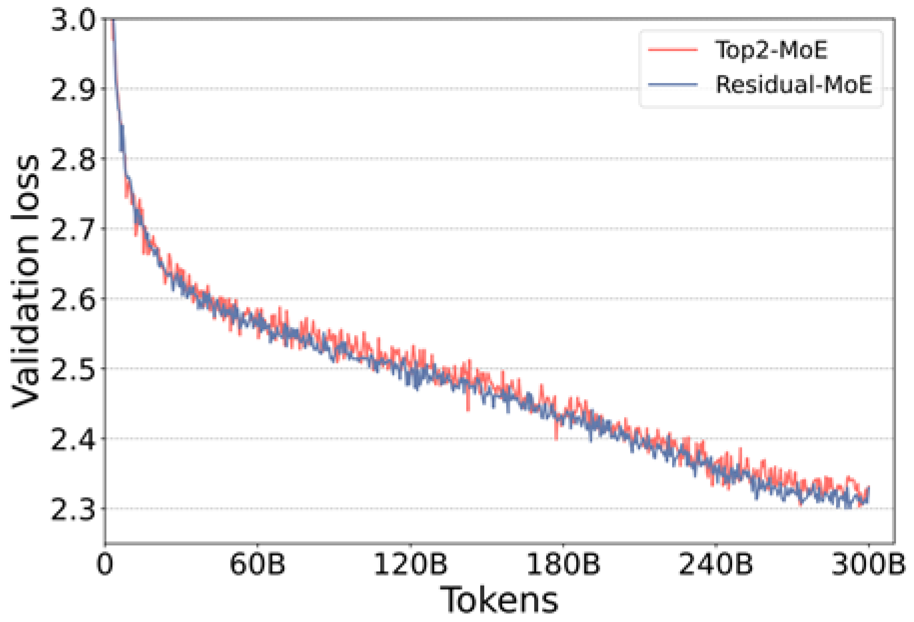
More experts (more memory) and more expert capacity (higher latency) can help improve generalization.

Intuition: Extra experts can help correct the "representation" of the first one

Experiment: doubling the capacity (Top2) vs fixing one expert and varying the second expert (Residual)

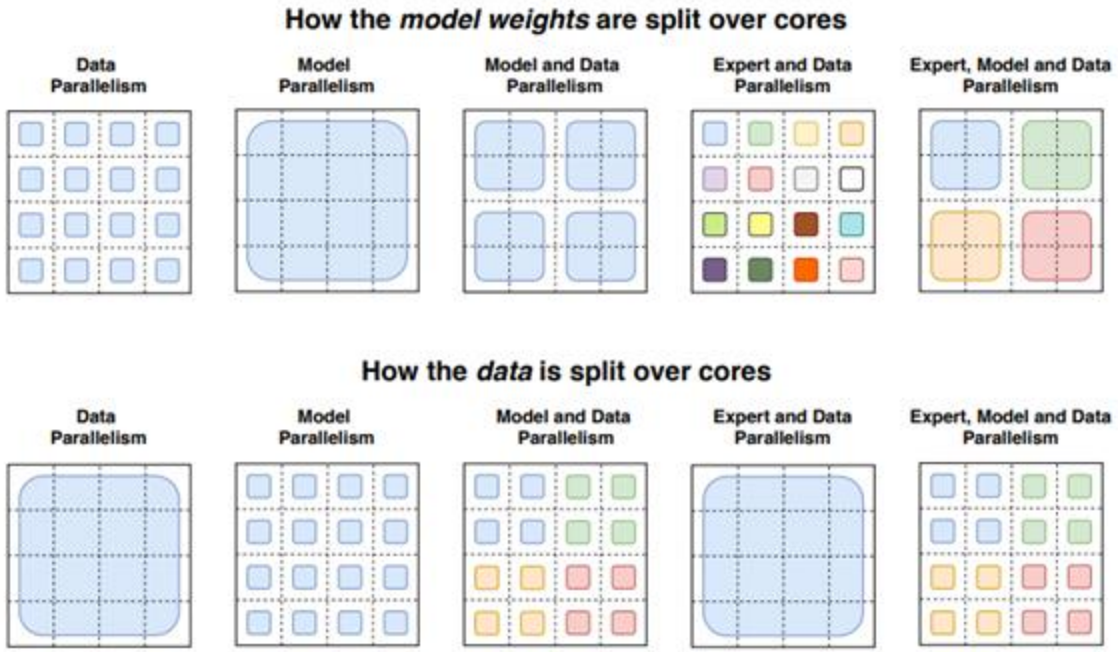
-> **Phenomenon**: on par generalization, training Residual-MoE is 10% faster





PR-MoE: Training System Design

- MOE training: Data parallelism + Expert parallelism
- Challenge: PR-MoE is Pyramid shaped, no optimal expert parallelism
- parallelize smallest number of experts: multiple experts per GPU, reduced batch size and increased memory requirement
- parallelize largest number of experts: load balancing problem



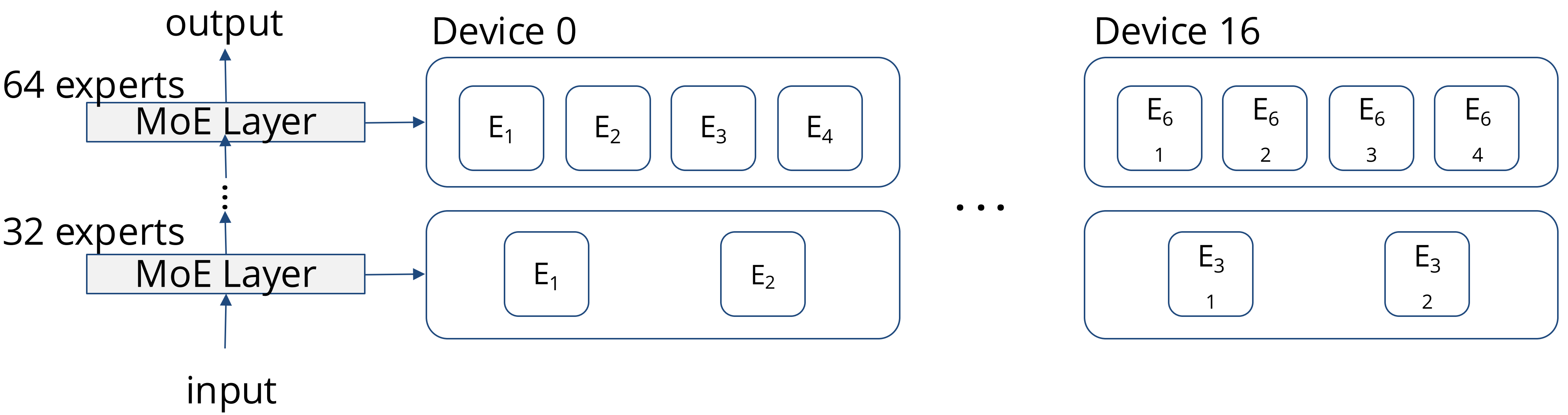
PR-MoE: Multi-expert and Multi-data Parallelism Support

Provide flexible training for different parts of the model with different expert and data parallelism degree

- MoE layer API allows different number of experts and a different expert parallelism degree for each MoE layer.

ep_size="desired expert-parallel world size"

deepspeed.moe.layer.MoE(hidden_size=input_dim, expert=ExpertModule(), **num_experts**=[..], **ep_size**=ep_size, **use_residual**=True)



Benefits of PR-MOE

- extend MoE to decoder-only models

- Reduced model size and improved parameter efficiency with Pyramid-Residual-MoE (PR-MoE) Architecture and Mixture-of-Students (MoS)

- Faster and cheaper MoE inference at scale

DeepSpeed-MOE Inference System

- MoE inference performance depends on:
  - overall model size
  - overall memory bandwidth

- DeepSpeed-MOE: Optimize the inference system by maximizing the achievable memory bandwidth

- Performance
  - 7.3x better latency compared to baseline MOE system
  - 4.5x faster and 9x cheaper MoE inference compared to quality equivalent dense models

MoE inference performance

- Best Case: Active only single expert at each MoE layer during inference, which is equivalent to dense model.

- Worst Case: Active entire MOE model’s parameters, making it challenging to achieve short latency and high throughput.

- Optimization:
  - group and route all tokens with the same critical data path together to reduce data access per device and achieve maximum aggregate bandwidth;
  - Optimize communication scheduling with parallelism coordination;
  - Optimize transformer and MoE related kernels to improve per-device performance;

Data Parallelism and Tensor-slicing (Non-Expert Params)

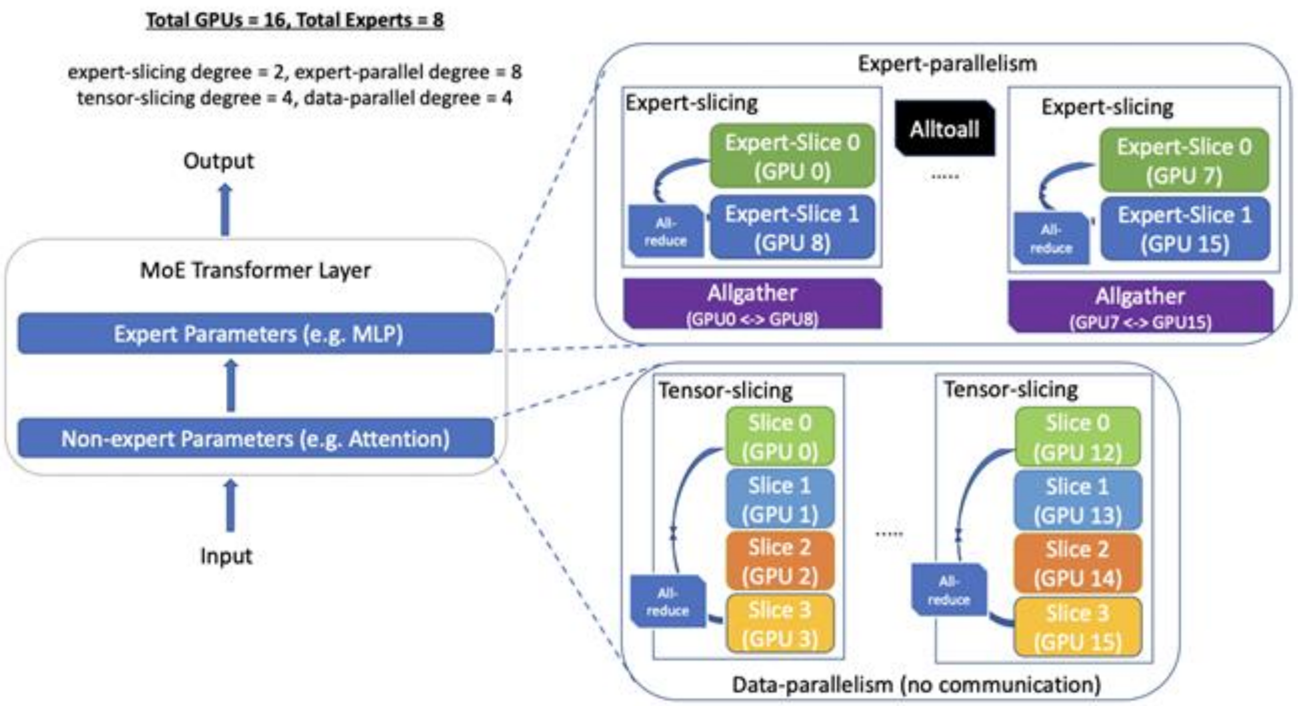


Figure 7: DS-MoE design that embraces the complexity of multi-dimensional parallelism for different partitions (expert and non-expert) of the model.

Data-parallelism

Data-parallelism by creating non-expert parameter replicas processing different batches across nodes

Tensor-slicing

tensor-slicing within a node allowing for hundreds of billions of non-expert parameters by leveraging aggregate GPU memory, while also leveraging the aggregate GPU memory bandwidth across all GPUs within a node

Expert Parallelism and Expert-slicing (Expert Params)

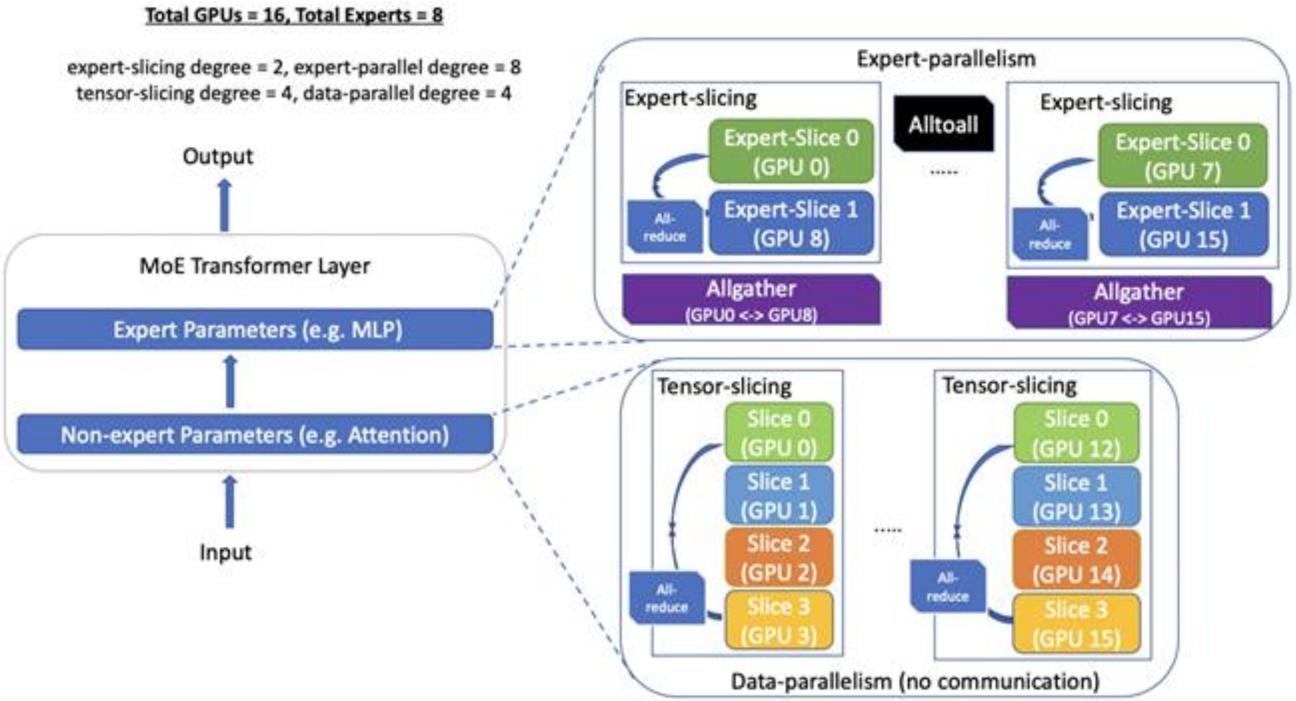


Figure 7: DS-MoE design that embraces the complexity of multi-dimensional parallelism for different partitions (expert and non-expert) of the model.

Expert Parallelism
Group all input tokens assigned to the same experts under the same critical data path, and parallelize processing of the token groups with different critical paths among different devices using expert parallelism.

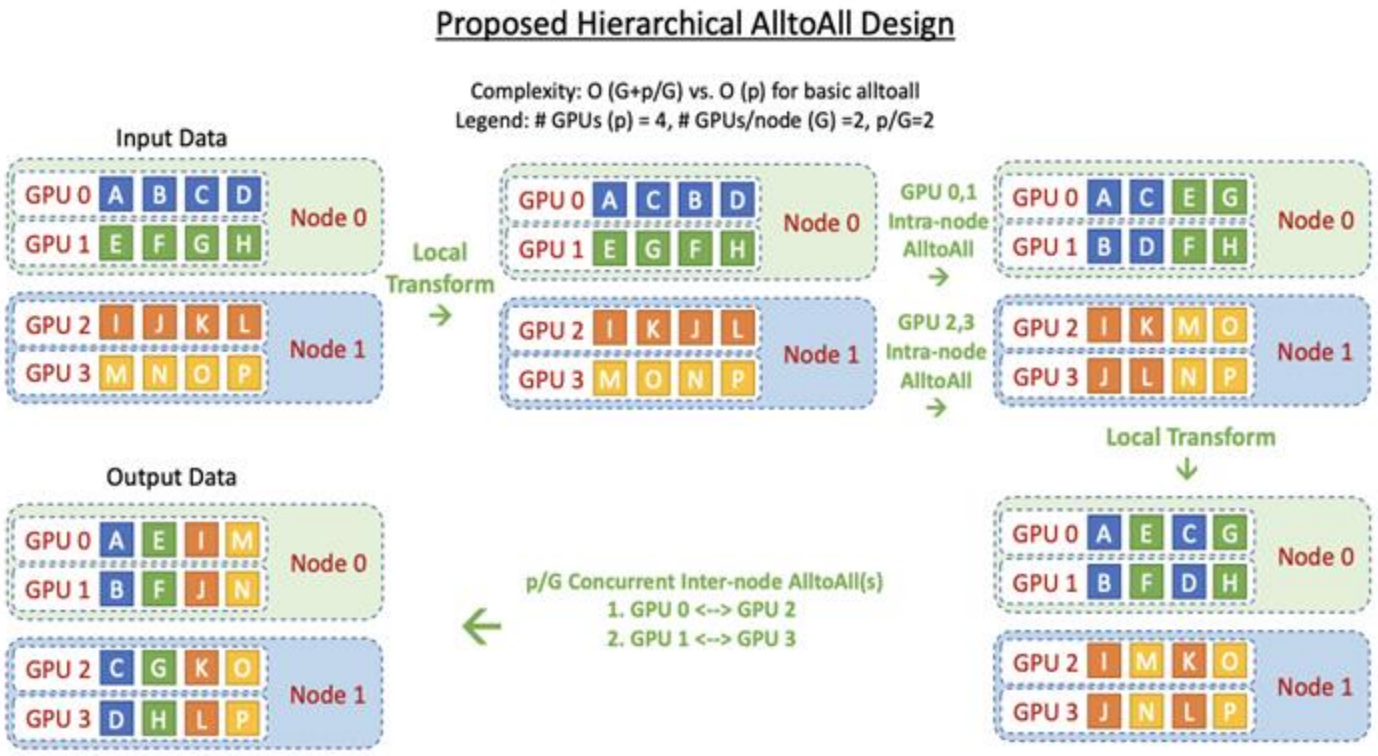
Expert Slicing
Partitions the expert parameters horizontally/vertically across multiple GPUs.

Optimized All-to-All Communication

- Expert parallelism requires all-to-all communication between all expert parallel devices; the latency increases linearly with the increase in devices
- custom communication interface using Microsoft SCCL
- Two optimizations:

- hierarchical all-to-all communication pattern: reduces the communication hops
- parallelism-coordinated communication optimization: schedules communications based on the model's parallelism strategy to minimize overhead.

Hierarchical All-to-all for communication



Implemented a hierarchical all-to-all as a two-step process with a data-layout transformation, followed by an intra-node all-to-all, followed by a second data-layout transformation, and a final inter-node all-to-all.

Reduces the communication hops from O(p) to O(G+ p/G)

G: number of GPUs in a node;
p: total number of GPUs

Highly Optimized Transformer and MoE Kernels

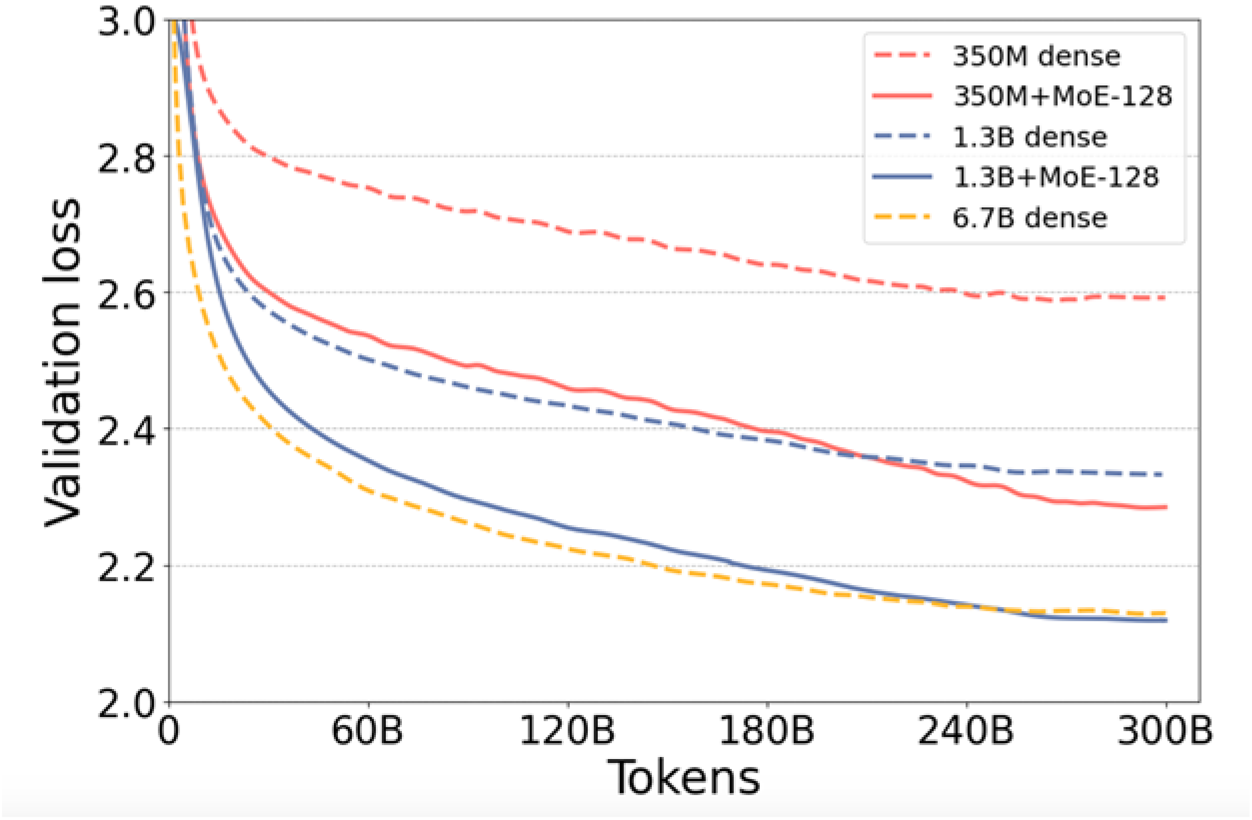
- Transformer: Leveraging DeepSpeed inference kernels for transformer layers

- MOE Specific Optimizations:
  - Optimizing the gating mechanisms
    - fuse the gating function into a single kernel
    - dense token-to-expert mapping table

- Result: over 6x reduction in MoE Kernel related latency

MOE Training Loss and Throughput

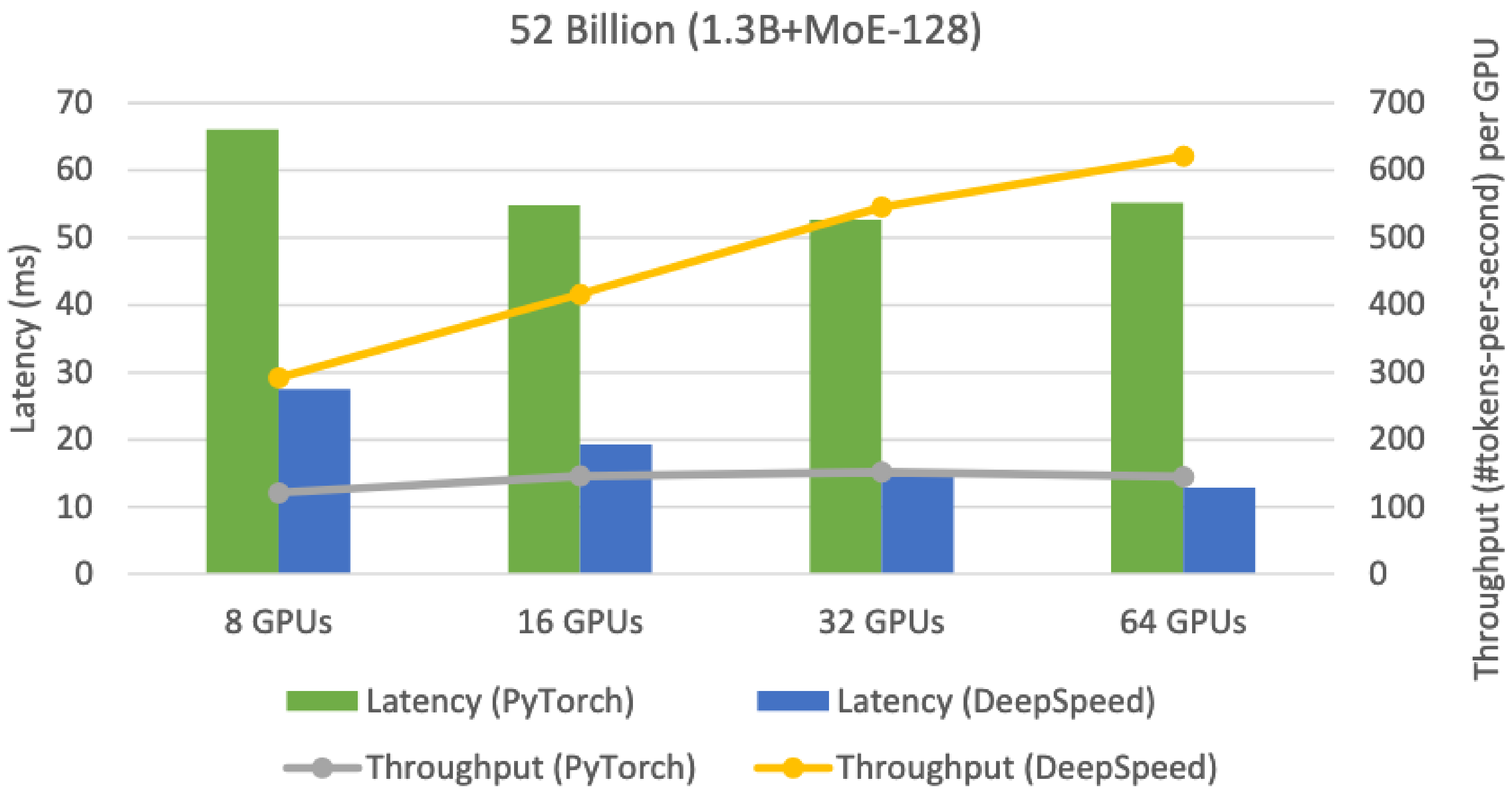
Token-wise validation loss curves for dense and MoE LLMs



	Training samples per sec	Throughput gain/ Cost Reduction
6.7B dense	70	1x
1.3B+MoE-128	372	5x

Training throughput (on 128 A100 GPUs) comparing MoE based model vs dense model that can both achieve the same model quality.

DeepSpeed MOE Inference Performance



DeepSpeed MOE Inference Performance

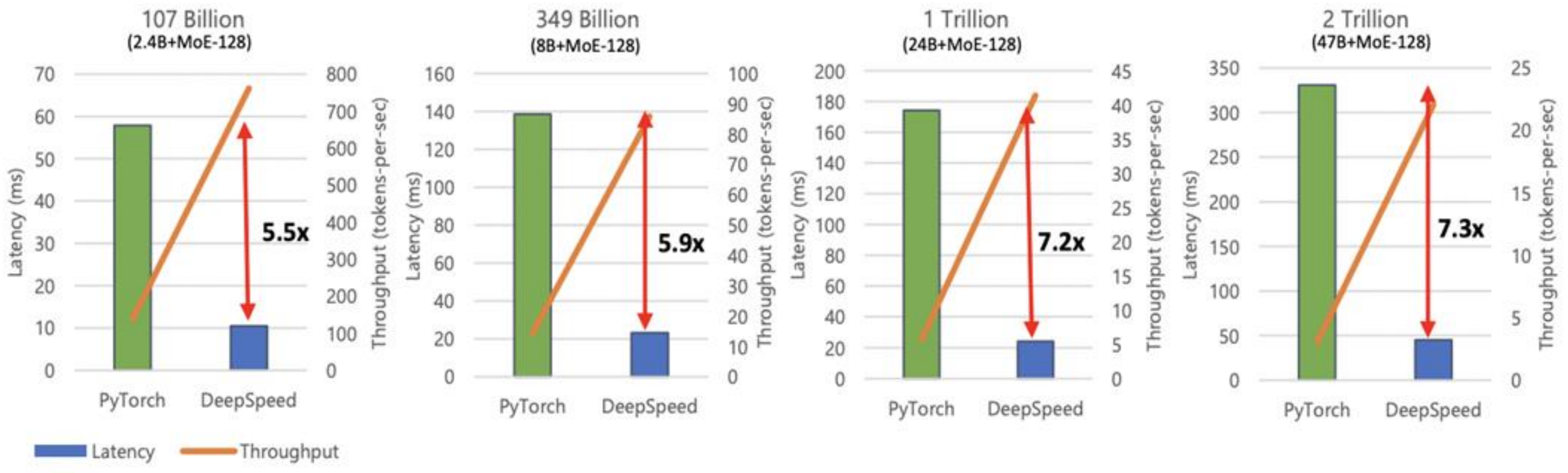


Figure 11: Latency and throughput improvement offered by DeepSpeed-MoE (Optimized) over PyTorch (Baseline) for different MoE model sizes (107 billion to 2 trillion parameters). We use 128 GPUs for all configurations for baseline, and 128/256 GPUs for DeepSpeed-MoE (256 GPUs for the trillion-scale models). The throughputs shown here are per GPU and should be multiplied by number of GPUs to get the aggregate throughput of the cluster.

MOE Zero-shot Performance

Zero-shot evaluation results on different benchmarks.

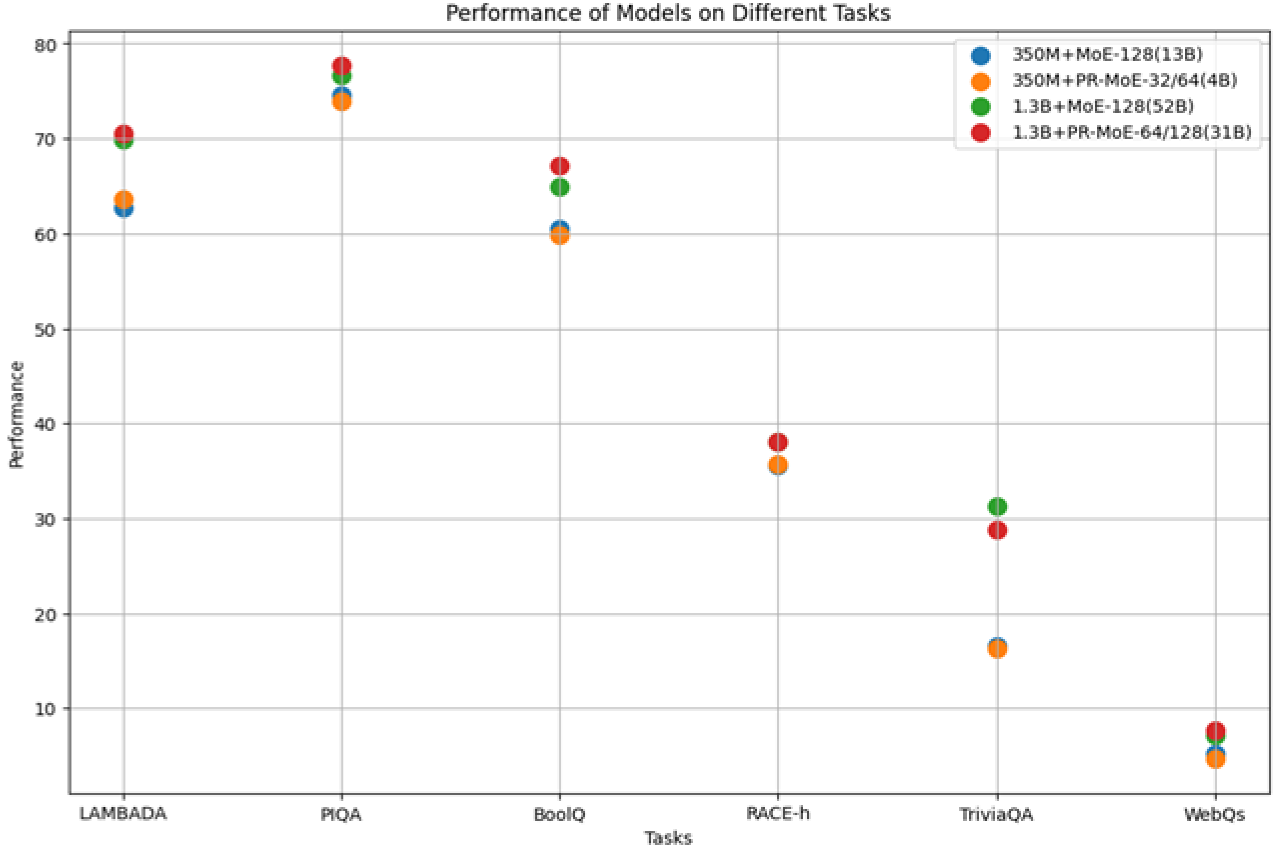
- 5x lower training cost to same accuracy using MoE
- 8x more parameters to same accuracy using MoE

Case	Model size	LAMBADA: completion prediction	PIQA: commonsense reasoning	BoolQ: reading comprehension	RACE-h: reading comprehension	TriviaQA: question answering	WebQs: question answering
Dense NLG:							
(1) 350M	350M	52.03	69.31	53.64	31.77	3.21	1.57
(2) 1.3B	1.3B	63.65	73.39	63.39	35.60	10.05	3.25
(3) 6.7B	6.7B	**71.94**	**76.71**	**67.03**	37.42	23.47	5.12
Standard MoE NLG:							
(4) 350M+MoE-128	13B	62.70	74.59	60.46	35.60	16.58	5.17
(5) 1.3B+MoE-128	52B	69.84	**76.71**	64.92	**38.09**	**31.29**	**7.19**

PR-MoE Performance (accuracy)

350M+PRMoE-32/64 vs 350M+MoE-128, 1.3B+PR-MoE-64/128 vs 1.3B+MoE128

comparable accuracy, **33% parameters** for 350M, **60% parameters** for 1.3B

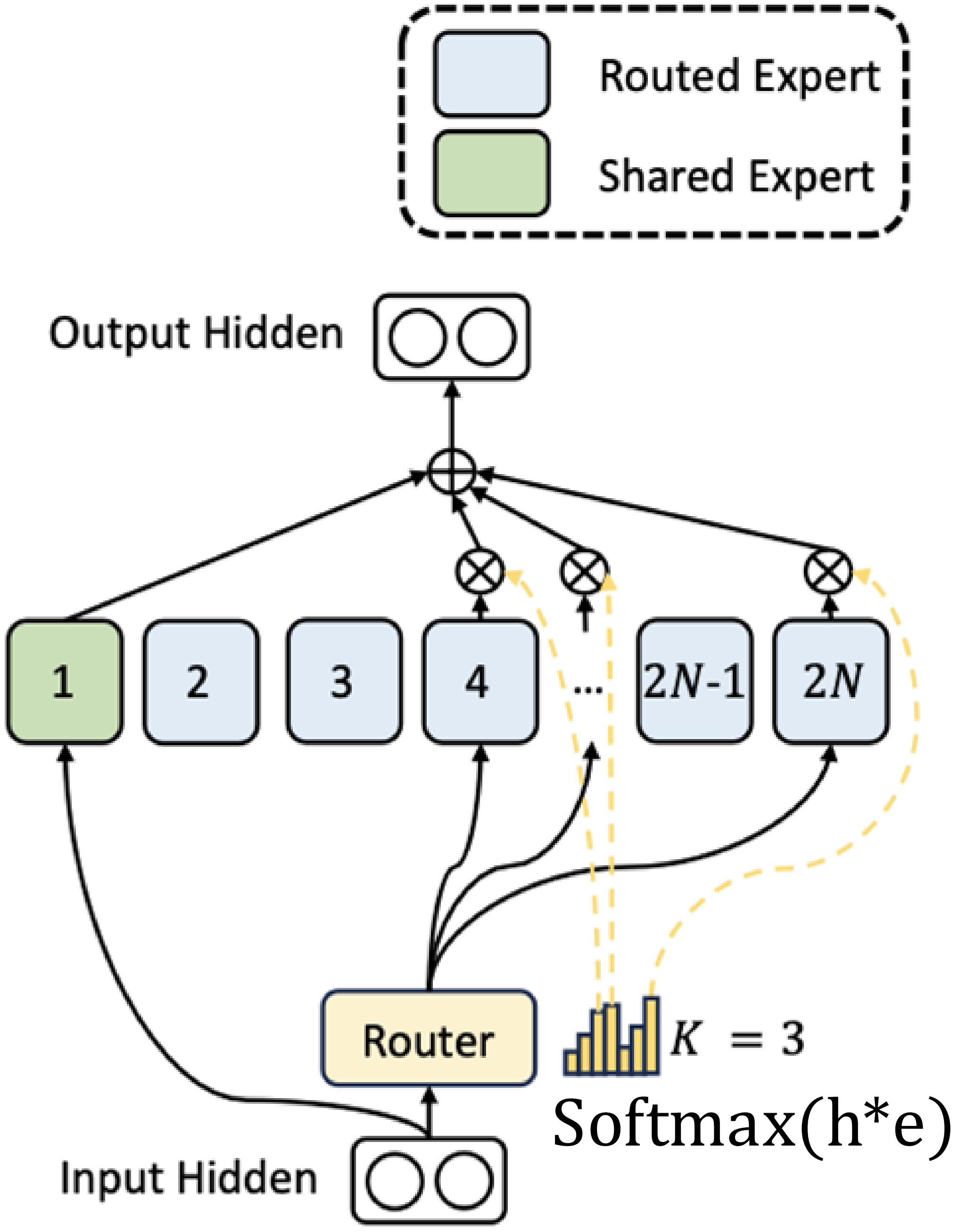


Outline

- Transformer Mixture-of-Expert Model
  - Switch Transformer architecture
  - Scalable training: expert parallelism (GShard)
- Deepspeed MoE Improvement
  - Pyramid-Residual MoE
  - Scaling MOE inference in Deepspeed
  - Performance
- Deepseek MoE (V3 model)
  - code walkthrough

DeepSeek MoE

- Fine-grained experts: each FFN is split to k smaller experts, total kN (N=original experts)
- shared experts + routing experts
- topk weighted average of routing experts (activating kM)



DeepSeek-MoE Benefits

- Performance Gains:
  - DeepSeekMoE 2B approaches the performance of its dense counterpart with the same number of total parameters.
  - DeepSeekMoE-16B achieves performance comparable to LLaMA2 7B, using only ~40% of the computations.

DeepSeek V3 MoE (670B)

Vocab: 129,280

dimension=7168

num layer=61

num dense layer=3 (lowest)

num head = 128

dim ffn (inter dim)=18432

moe dim = 2048

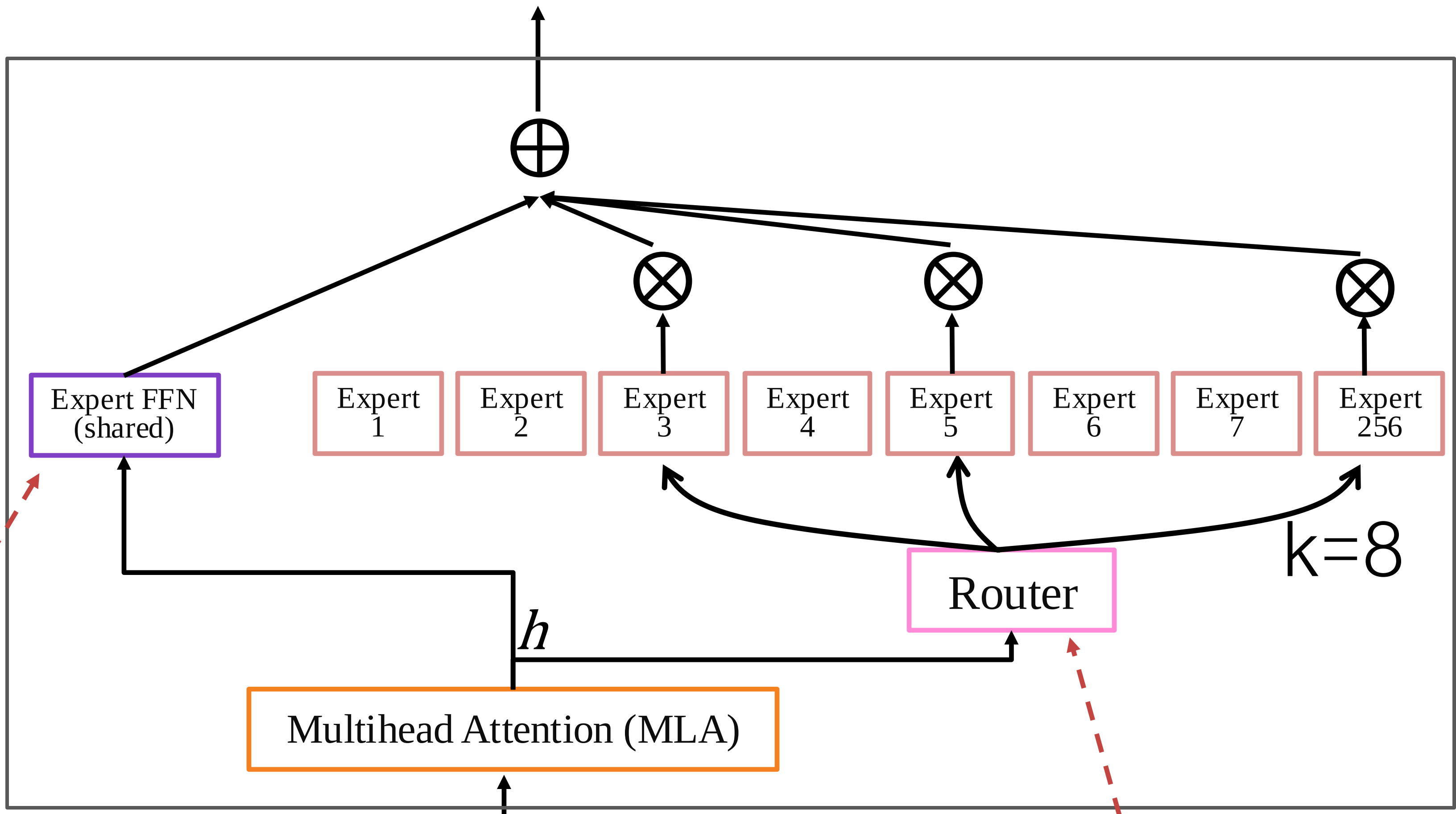
num shared experts = 1

num routed experts = 256

num activated experts = 8

num expert group=8

num limited group=4



$$\mathrm{FFN}_{SwiGLU}(x) = \left(Swish(x \cdot W_1) \odot (x \cdot W_2)\right) \cdot W_3$$

$$\mathrm{TopK}(\mathrm{Softmax}(h_t \cdot W), 8)$$

https://github.com/deepseek-ai/DeepSeek-V3/blob/main/inference/model.py

Load Balancing in Deepseek MoE

- Expert-Level Balance Loss (to avoid routing collapse to experts)

$$L_{ExpBal} = \alpha_1 \sum_{i=1}^{\#\text{experts}} f_i P_i$$

$$f_i = \frac{\#\text{experts}}{\#\text{activated\_experts}} \cdot \frac{\#\text{tokens to expert } i}{\#\text{tokens}} \qquad P_i = \frac{1}{\#\text{tokens}} \sum_{t=1}^{\#\text{tokens}} s_{i,t}$$

routing weight

- Device-level balance loss (balance computation across dev)

$$L_{DevBal} = \alpha_2 \sum_{j=1}^{\#\text{groups}} f_j P_j$$

$$f_j = avg\ f\ in\ group\ j) \qquad P_j = sum\ of\ P\ in\ group\ j$$

Deepseek V3 MoE Code Walkthrough

- https://github.com/deepseek-ai/DeepSeek-V3/blob/main/inference/model.py

Deepspeed MoE Code Example

```
import torch
import deepspeed
import deepspeed.utils.groups as groups
from deepspeed.moe.layer import MoE

WORLD_SIZE = 4
EP_WORLD_SIZE = 2
EXPERTS = 8

fc3 = torch.nn.Linear(84, 84)
fc3 = MoE(hidden_size=84, expert=self.fc3, num_experts=EXPERTS, ep_size=EP_WORLD_SIZE, k=1)
fc4 = torch.nn.Linear(84, 10)
```

https://www.deepspeed.ai/tutorials/mixture-of-experts/

Deepspeed MoE Code Example

```python
class MoE(nn.Module):
    """Initialize an MoE layer.

    Arguments:
        hidden_size (int): the hidden dimension of the model, importantly this is also the input and output dimension.
        expert (nn.Module): the torch module that defines the expert (e.g., MLP, torch.linear).
        num_experts (int, optional): default=1, the total number of experts per layer.
        ep_size (int, optional): default=1, number of ranks in the expert parallel world or group.
        k (int, optional): default=1, top-k gating value, only supports k=1 or k=2.
        capacity_factor (float, optional): default=1.0, the capacity of the expert at training time.
        eval_capacity_factor (float, optional): default=1.0, the capacity of the expert at eval time.
        min_capacity (int, optional): default=4, the minimum capacity per expert regardless of the capacity_factor.
        use_residual (bool, optional): default=False, make this MoE layer a Residual MoE (https://arxiv.org/abs/2201.05596) layer.
        noisy_gate_policy (str, optional): default=None, noisy gate policy, valid options are 'Jitter', 'RSample' or 'None'.
        drop_tokens (bool, optional): default=True, whether to drop tokens - (setting to False is equivalent to infinite capacity).
        use_rts (bool, optional): default=True, whether to use Random Token Selection.
        use_tutel (bool, optional): default=False, whether to use Tutel optimizations (if installed).
        enable_expert_tensor_parallelism (bool, optional): default=False, whether to use tensor parallelism for experts
        top2_2nd_expert_sampling (bool, optional): default=True, whether to perform sampling for 2nd expert
    """
```

https://github.com/microsoft/DeepSpeed/blob/master/deepspeed/moe/layer.py

Deepspeed MoE Code Example

```python
experts = Experts(expert, self.num_local_experts, self.expert_group_name)
self.deepspeed_moe = MOELayer(TopKGate(hidden_size, num_experts, k, capacity_factor, eval_capacity_factor,
                                       min_capacity, noisy_gate_policy, drop_tokens, use_rts, None,
                                       top2_2nd_expert_sampling),
                              experts,
                              self.expert_group_name,
                              self.ep_size,
                              self.num_local_experts,
                              use_tutel=use_tutel)
if self.use_residual:
    self.mlp = expert
    # coefficient is used for weighted sum of the output of expert and mlp
    self.coefficient = nn.Linear(hidden_size, 2)
```

https://github.com/microsoft/DeepSpeed/blob/master/deepspeed/moe/layer.py

Deepspeed MoE Code Example

```python
class Experts(nn.Module):

    def __init__(self, expert: nn.Module, num_local_experts: int = 1, expert_group_name: Optional[str] = None) -> None:
        super(Experts, self).__init__()

        self.deepspeed_experts = nn.ModuleList([copy.deepcopy(expert) for _ in range(num_local_experts)])
        self.num_local_experts = num_local_experts

        # TODO: revisit allreduce for moe.gate...
        for expert in self.deepspeed_experts:
            # TODO: Create param groups to handle expert + data case (e.g. param.group = moe_group)
            for param in expert.parameters():
                param.allreduce = False
                param.group_name = expert_group_name

    def forward(self, inputs: torch.Tensor) -> torch.Tensor:
        chunks = inputs.chunk(self.num_local_experts, dim=1)
        expert_outputs: List[torch.Tensor] = []

        for chunk, expert in zip(chunks, self.deepspeed_experts):
            out = expert(chunk)
            if isinstance(out, tuple):
                out = out[0]  # Ignore the bias term for now
            expert_outputs += [out]

        return torch.cat(expert_outputs, dim=1)
```

https://github.com/microsoft/DeepSpeed/blob/master/deepspeed/moe/experts.py

Summary

- LLM Mixture-of-Expert Model
  - Instead of a single dense FFN, using multiple FFNs (experts)
  - Routing network to select one/multiple experts
  - Shared-routed experts (deepspeed-MOE, deepseek MOE)
  - a few dense layers, then MOE (deepseek MOE)

- Scalable training/inference
  - expert parallelism: split experts and replicate non-expert (GShard)
  - all-to-all communication for expert output
  - load balancing: grouping and avoid collapse (deepseek)
  - optimized kernel for MoE

Reference

- Rajbhandari et al (2022). DeepSpeed-MoE: Advancing Mixture-of-Experts Inference and Training to Power Next-Generation AI Scale.

- Dai, D. et al. (2024). DeepSeekMoE: Towards Ultimate Expert Specialization in Mixture-of-Experts Language Models.