Mixture of Experts

Robots in Disguise, 28th August 2024

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Overview

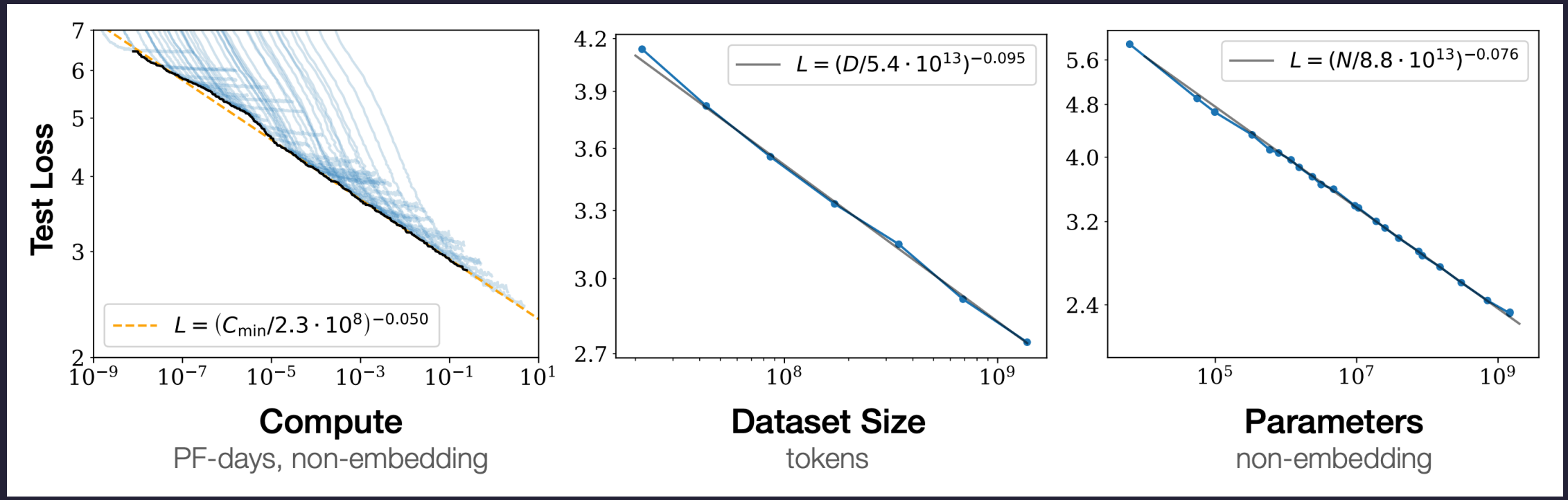
- Motivations for M.o.E
- How M.o.E works
- Challenges / Solutions
- Dynamics of experts

Motivation

- How do we scale models / train better models?
- **More parameters** (GPT3) vs. **more data** (Chinchilla) - *vs. better data (Llama 3)*
- Scaling parameters/data quantity → better models . . .
- . . . but scaling parameters/data quality → more compute

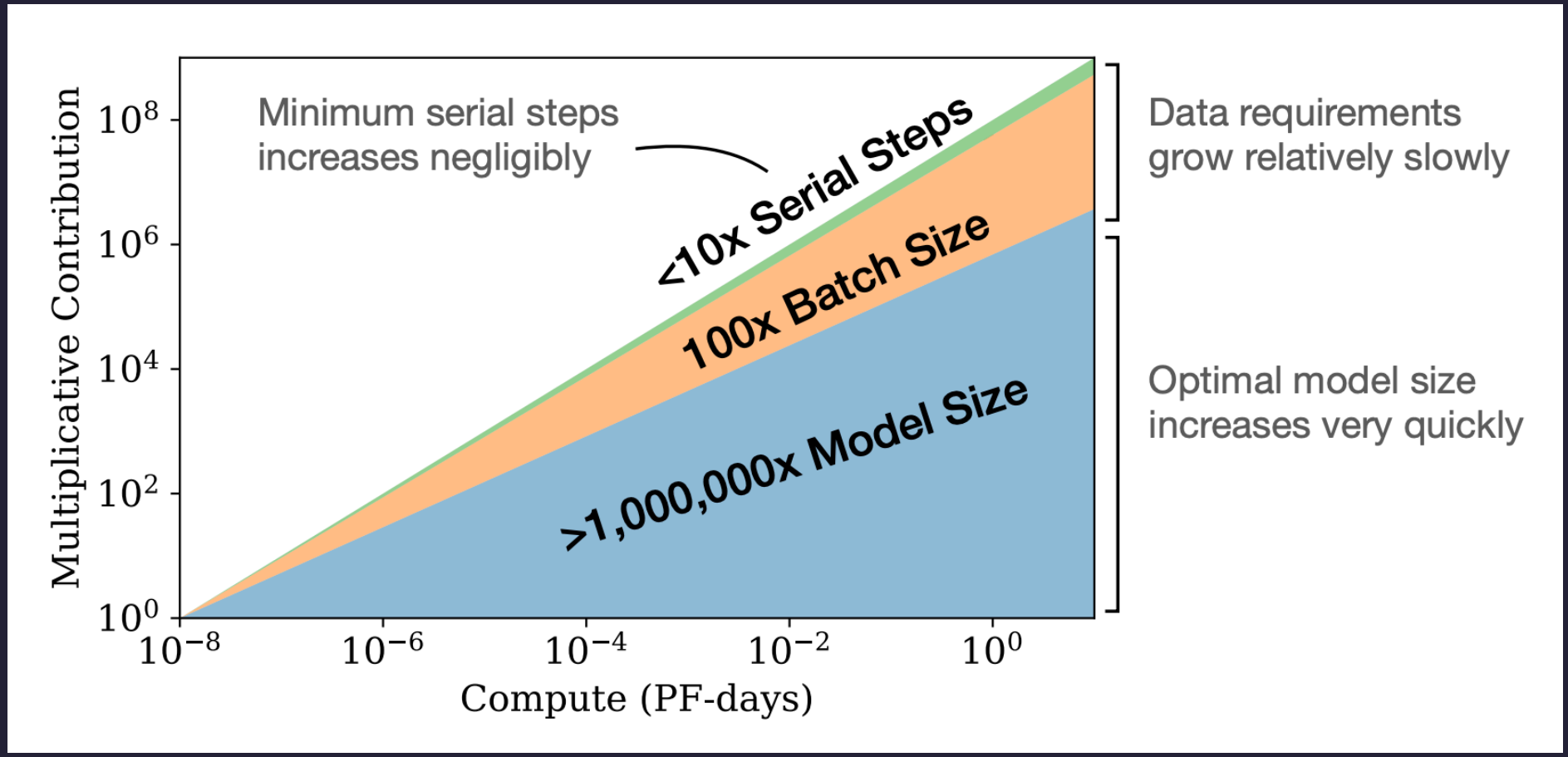
"Language Models are Few-Shot Learners", Brown et al., 2020,
"Training Compute-Optimal Large Language Models", Hoffman et al., 2022,
"The Llama 3 Herd of Models", Dubey et al., 2024

Scaling Laws



"Scaling Laws for Neural Language Models", Kaplan et al., 2020

Scaling Laws



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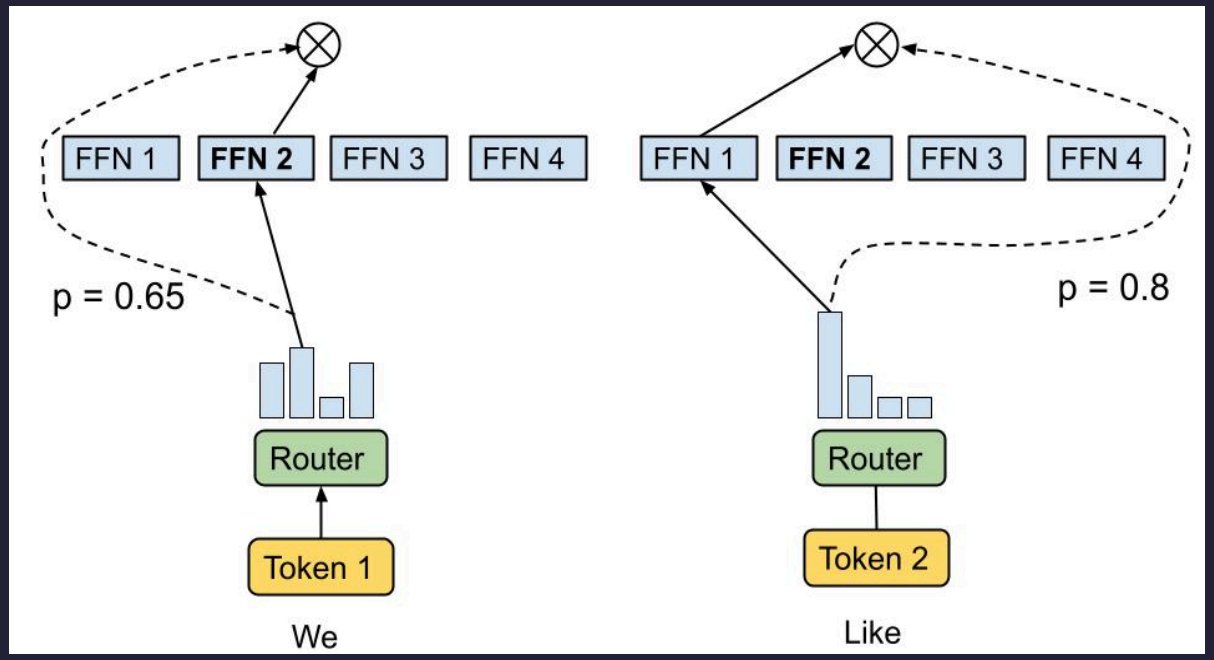
How can we scale model size without scaling compute linearly?

Mixture of Experts

Replacing "dense" feed forward layers with multiple parallel "expert" networks, accompanied by a gating network or "router".



Mixture of Experts

- Each input (token) is routed to some number of "expert" subnetworks, outputs of chosen experts are combined.
- Gating layer / router is another set of trainable weights.
- Individual experts learn from different inputs.
- Experts deal with individual tokens, other layers (attention) handle sequence-level info.

Mixture of Experts

- Introducing **SPARSITY** - replacing dense FF layer with set of networks where only N components are active at any time.
- More trainable parameters + smaller number of active parameters.
- E.g. Mixtral 8 x 7B (i.e. a 56B* model) only ever requires 2 experts i.e. compute for 2x7=14B params (actually 12B because some parameters are shared)
- Decoupling computational cost and parameter count.

History

- First introduced in 1991 by Jacobs et al.
- MoEs as the whole model explored in SVMs, Gaussian Processes, etc.
- Applied as components of deep networks in 2013 by Eigen et al.
- Applied to LSTMs in 2017 by Shazeer et al., producing 137B parameter LSTM.
- Applied to Transformers in SwitchTransformers (Fedus et al., 2021) (Encoder-Decoder) and GLaM (Du et al, 2021) (Decoder only), producing >1T parameter models.
- GPT4 - 16 x 111B MoE model?
- Mixtral - open-source 8 x 7B MoE model (later released 8 x 22B)
- Gemini 1.5 - >1.5T param MoE model?

"Adaptive Mixtures of Local Experts", Jacobs et al., 1991; "Learning Factored Representations in a Deep Mixture of Experts", Eigen et al., 2013; "Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts Layer", Shazeer et al., 2017; "Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity", Fedus et al., 2021; "GLaM: Efficient Scaling of Language Models with Mixture-of-Experts", Du et al., 2021; "Mixtral of Experts", Jiang et al., 2023

Fundamentals

- The output for a given input is the **sum of the outputs of the chosen experts (E), weighted by the value of the gating function (G) for each of the n experts.**

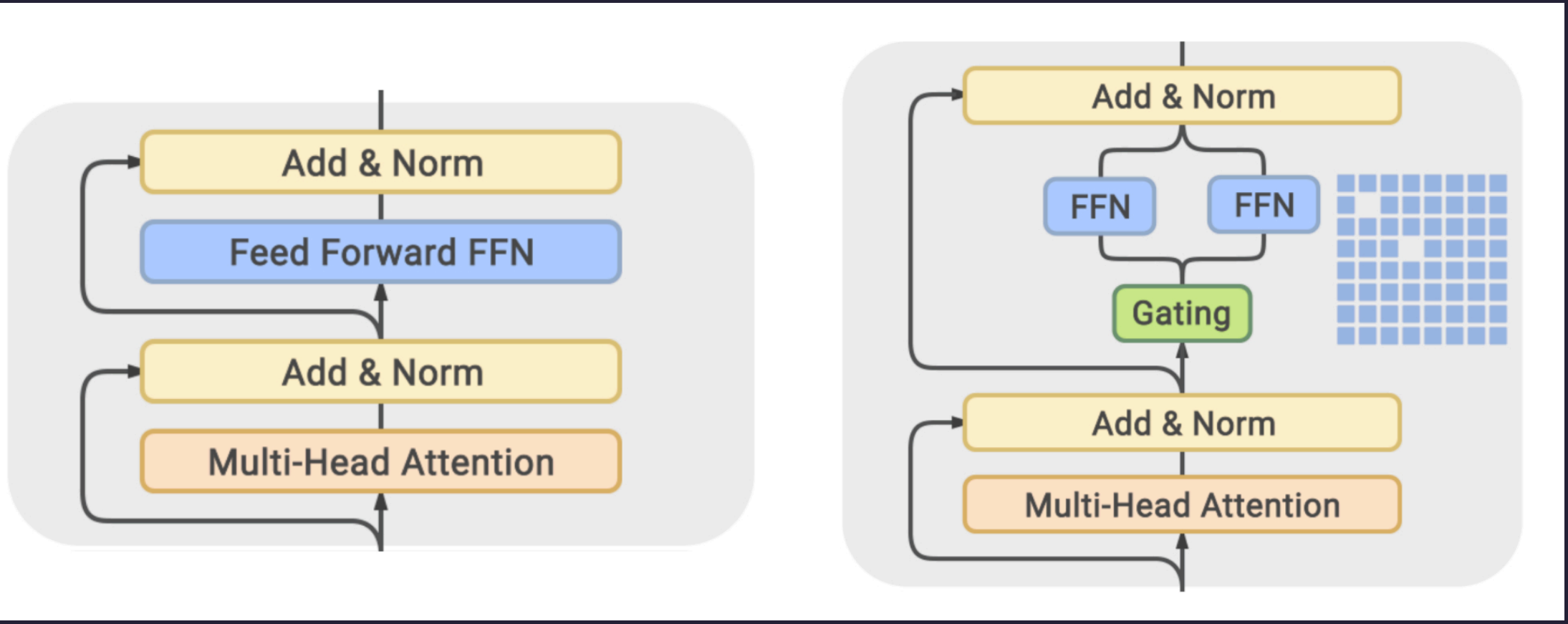
$$y = \sum_{i=1}^{n} G(x)_i E_i(x)$$

- In its most basic form, the gating function is a simple network that selects the top-K experts for a given token x, with a softmax function.

$$G(x) := Softmax(TopK(x \cdot W_g))$$

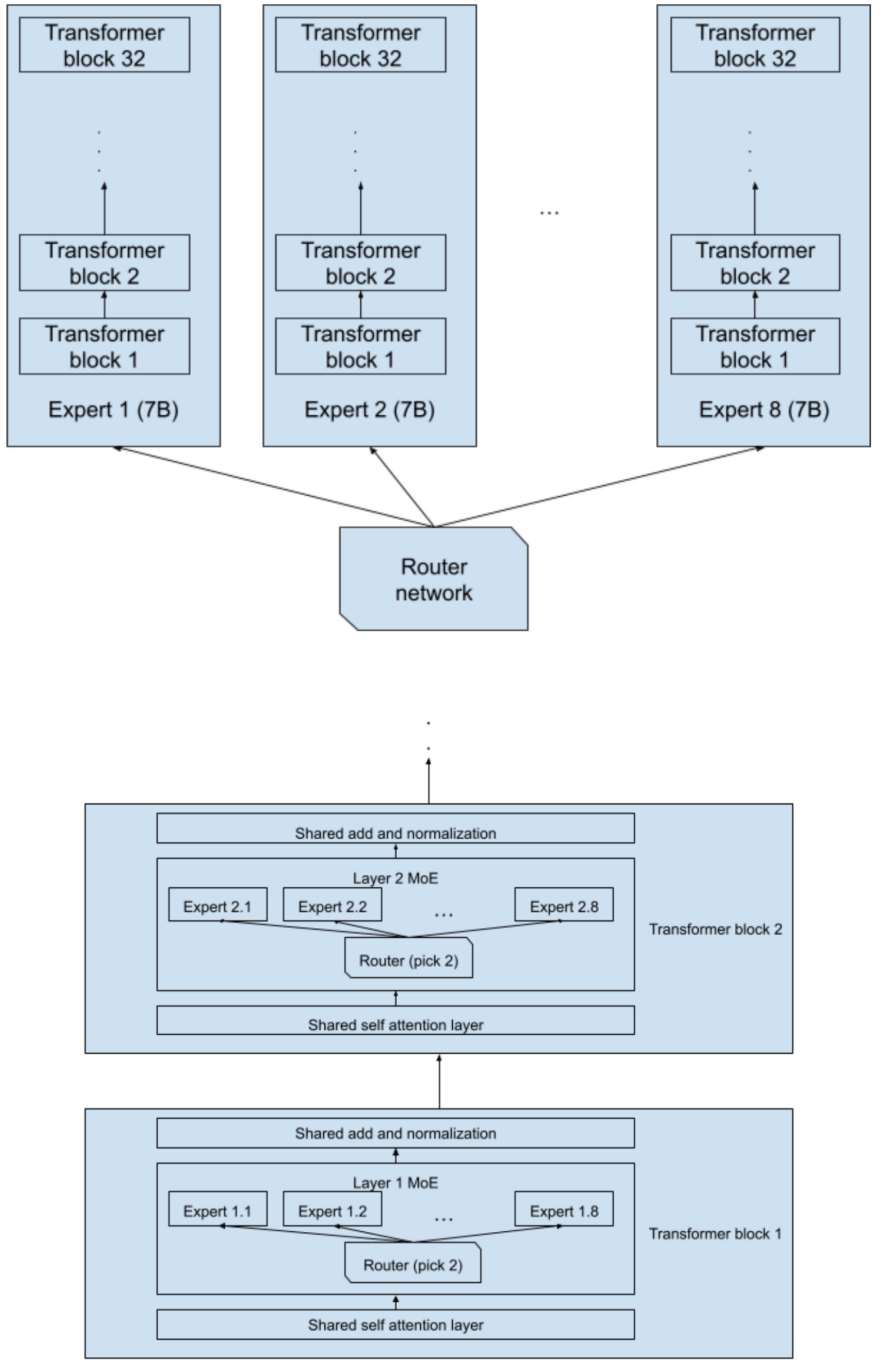
Transformer Architecture

- Replace FFN within transformer block with gating network and expert FFNs
- Some replace every transformer block (Mixtral), some every other (GLAM).



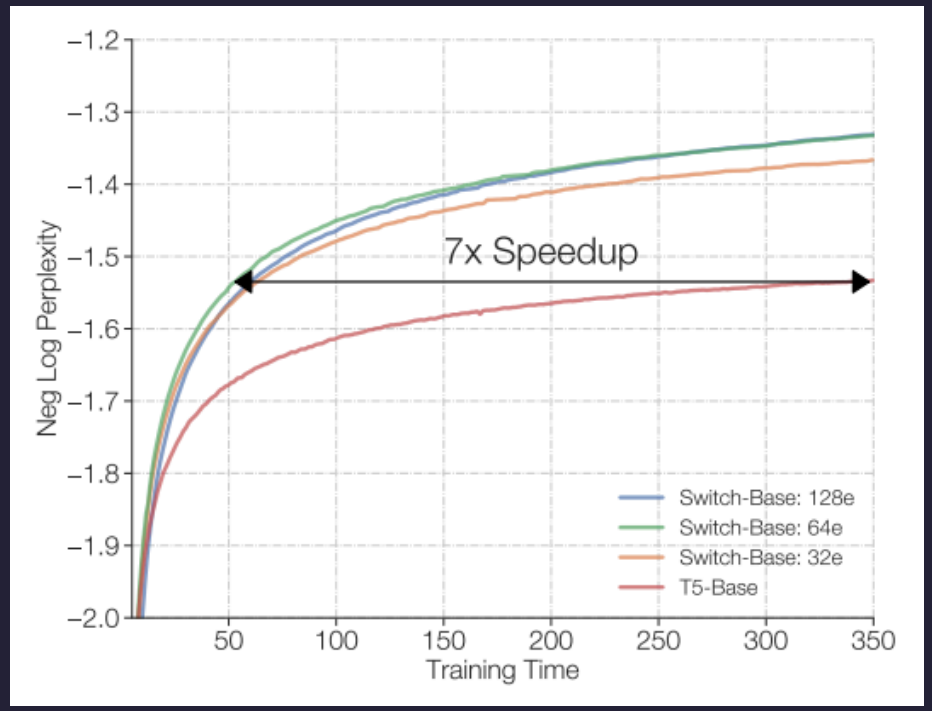
"Mixtral 8 x 7B"

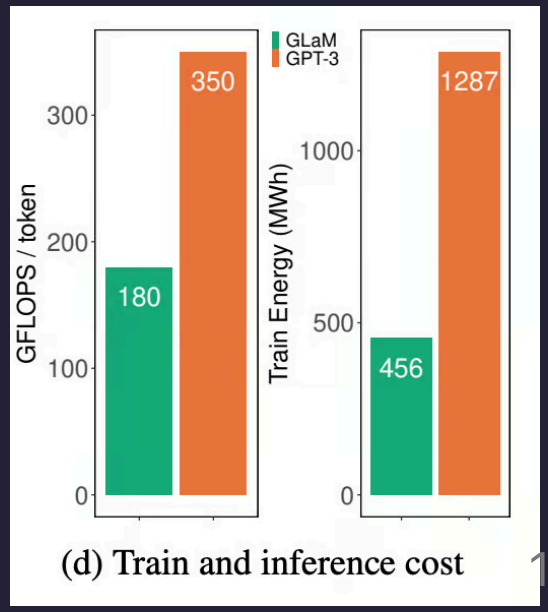
- **NOT 8 separate 7B models**
- "8 x 7B" refers to the fact that it's the same architecture as Mistral 7B but each FFN layer is replicated 8 times.
- 8 expert FFNs in each of 32 transformer blocks, i.e. 256 individual FFNs.
- 2 experts active per layer $\rightarrow$ 28 possible combinations per layer $\rightarrow$ 32 layers $\rightarrow$ effectively $2 \cdot 10^{46}$ unique models
- Token representations evolve throughout layers.



Impact

- Sparsity, conditional computation
- Well suited for distributed computing
- 7 x speedup in pre-training vs. dense model (SwitchTransformers)
- GLaM outperforms GPT-3 on 6/7 benchmarks on 1/3 of the compute budget
- GPT4: ~280B params and ~560 TFLOPs in MoE architecture vs. ~1.8T params and ~3,700 TFLOP for dense equivalent
- Gemini 1 vs 1.5 (1.5 pro ~ 1.0 ultra, with less compute, 1.5 pro outperfoms 1.5 pro)
- Distilling from MoE models retains 30-40% of sparsity gains





"Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity", Fedus et al., 2021
"GLaM: Efficient Scaling of Language Models with Mixture-of-Experts", Du et al., 2021

Challenges

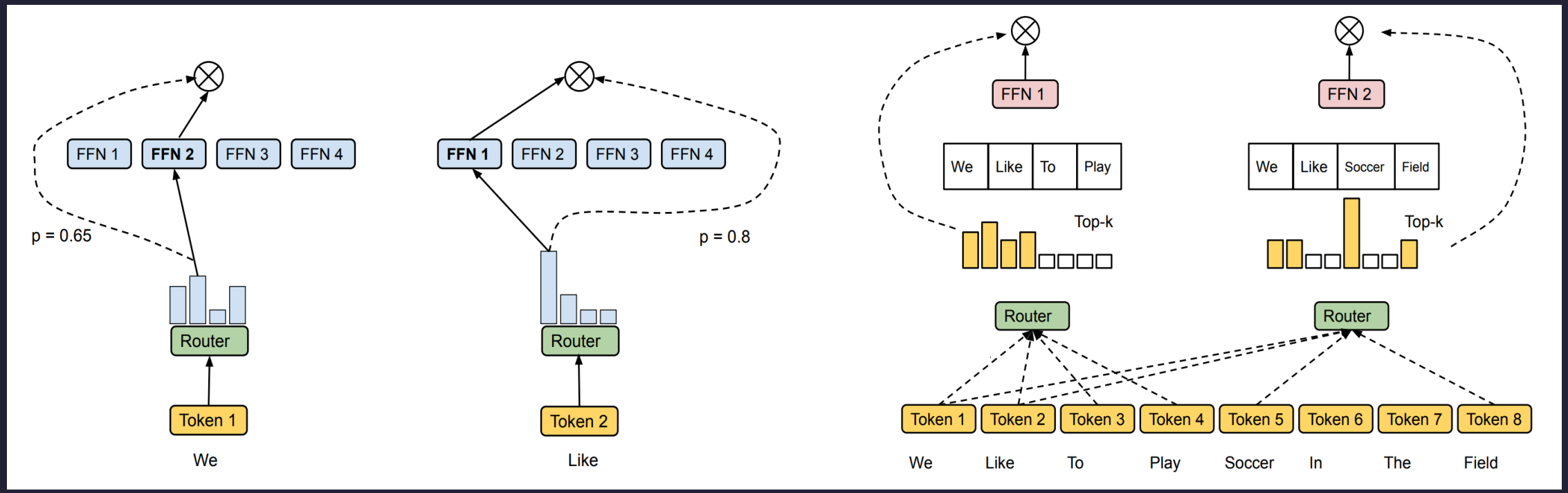
- (Still need to lead the whole model into memory)
- Load balancing
- Instability
- Overfitting
- Fine-tuning

Routing

Load Balancing: How do we stop the gating network from routing all tokens to the same expert(s)?

- **Expert Capacity**: threshold of how many tokens each expert can process. Any further tokens are sent to next layer / dropped
  - Sparse models are robust to dropping tokens: Dropping 10-15% ~ dropping < 1%
- **Auxiliary Loss**: loss added to encourage groups of tokens to evenly distribute across experts. Can contribute to instability
- **Z-Loss**: Penalise large logits entering gating network. Improve stability with no quality degradation
- **Expert Choice Routing**: Let experts pick top-k tokens. Enables tokens to be routed to **variable** number of experts

Routing

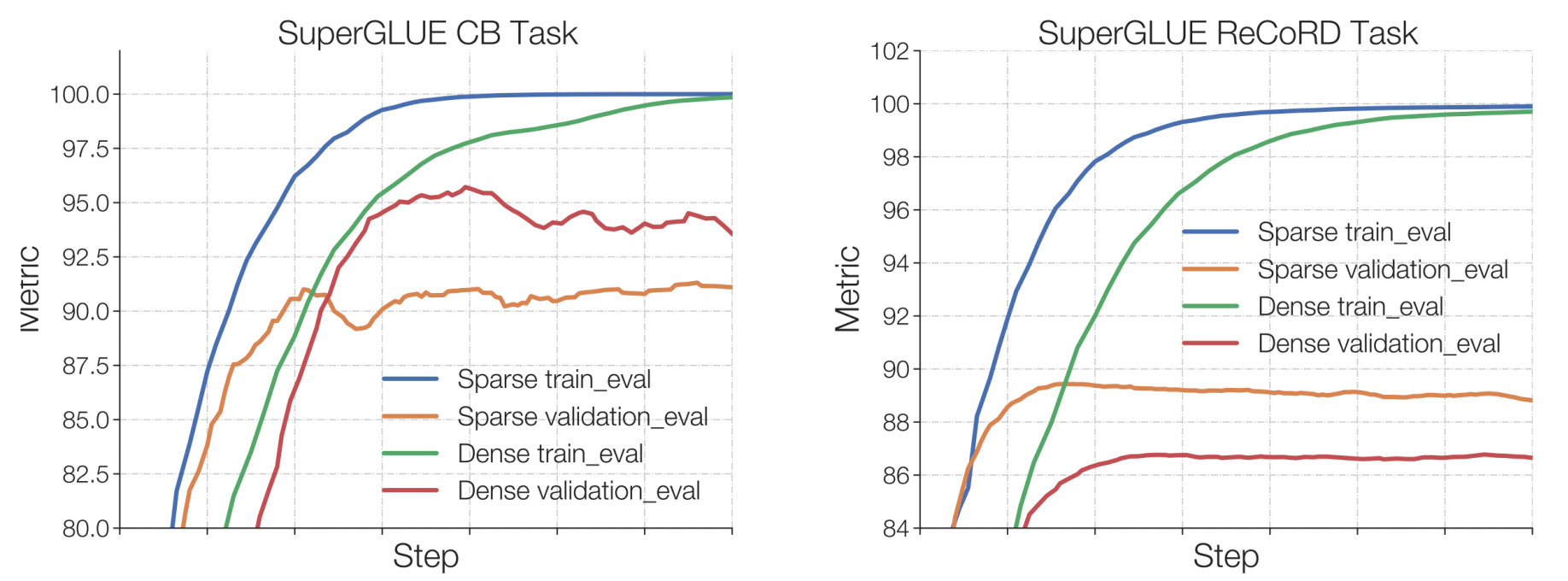

FFN 1
FFN 2
FFN 3
FFN 4
p = 0.65
Router
Token 1
We
FFN 1
FFN 2
FFN 3
FFN 4
p = 0.8
Router
Token 2
Like
FFN 1
We
Like
To
Play
Top-k
Router
Token 1
Token 2
Token 3
Token 4
Token 5
Token 6
Token 7
Token 8
We
Like
To
Play
Soccer
In
The
Field
FFN 2
We
Like
Soccer
Field
Top-k
Router

Training & Fine-tuning

- **Regularisation**: MoEs benefit from higher dropout in expert layers, lower dropout in shared layers.
- **Hyperparameter turing**: MoEs benefits from smaller batch sizes and higher learning rates $\rightarrow$ higher noise, better generalisation

Training & Fine-tuning

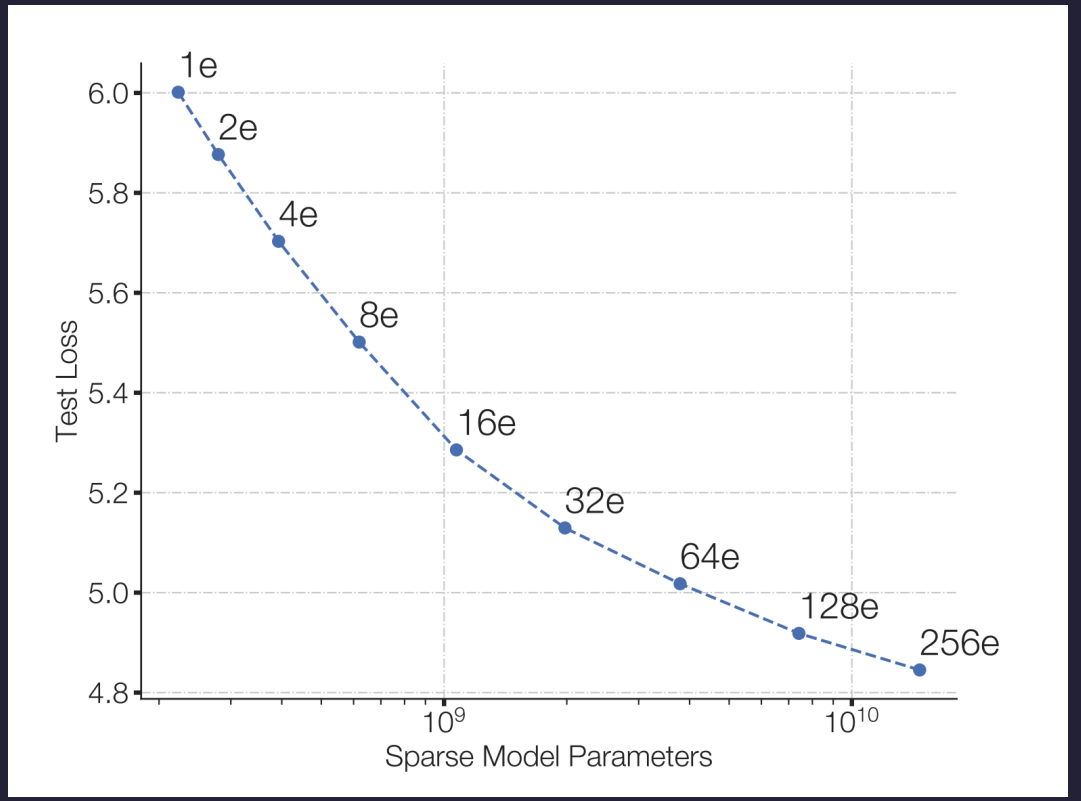
- MoEs learn more quickly than dense models, but also overfit more easily on smaller tasks / are "slower" at transferring knowledge.
- MoEs are generally **better at knowledge-heavy tasks** than dense models, worse at reasoning-heavy tasks.



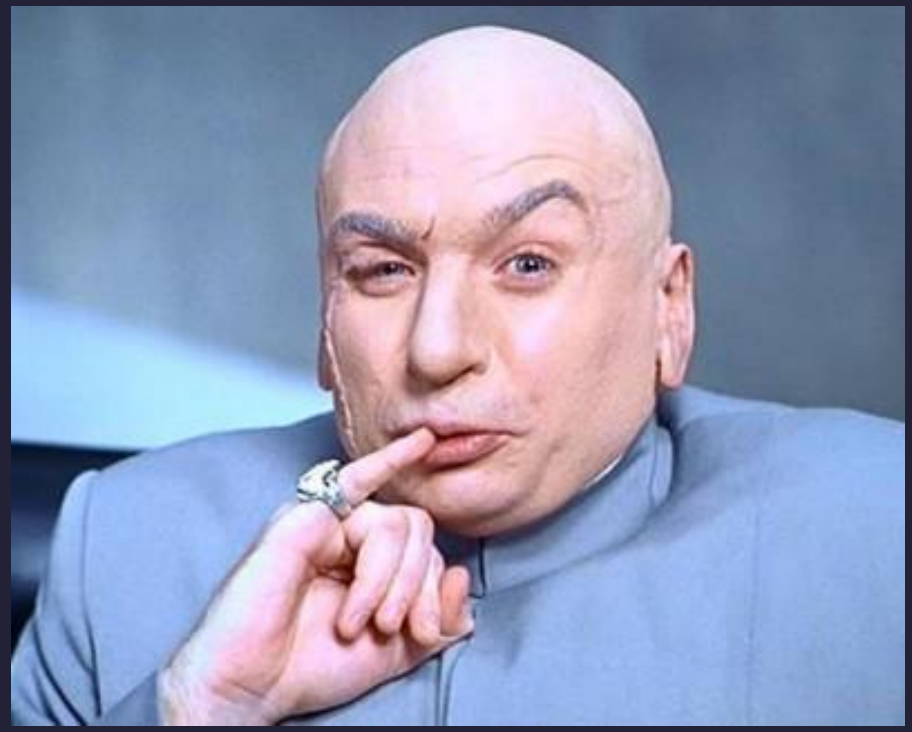
"ST-MoE: Designing Stable and Transferable Sparse Expert Models", Zoph et al., 2022

How many experts?

- Switch-C - 2,048/1
- GLaM - 64/2
- Mixtral - 8/2
- GPT4 - 16/2?
- Higher numbers of experts works better with hierarchical MoEs
- Diminishing returns after 256/512
- Properties of high number of experts consistent at smaller scale (2,4,8 experts)



"Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity", Fedus et al., 2021

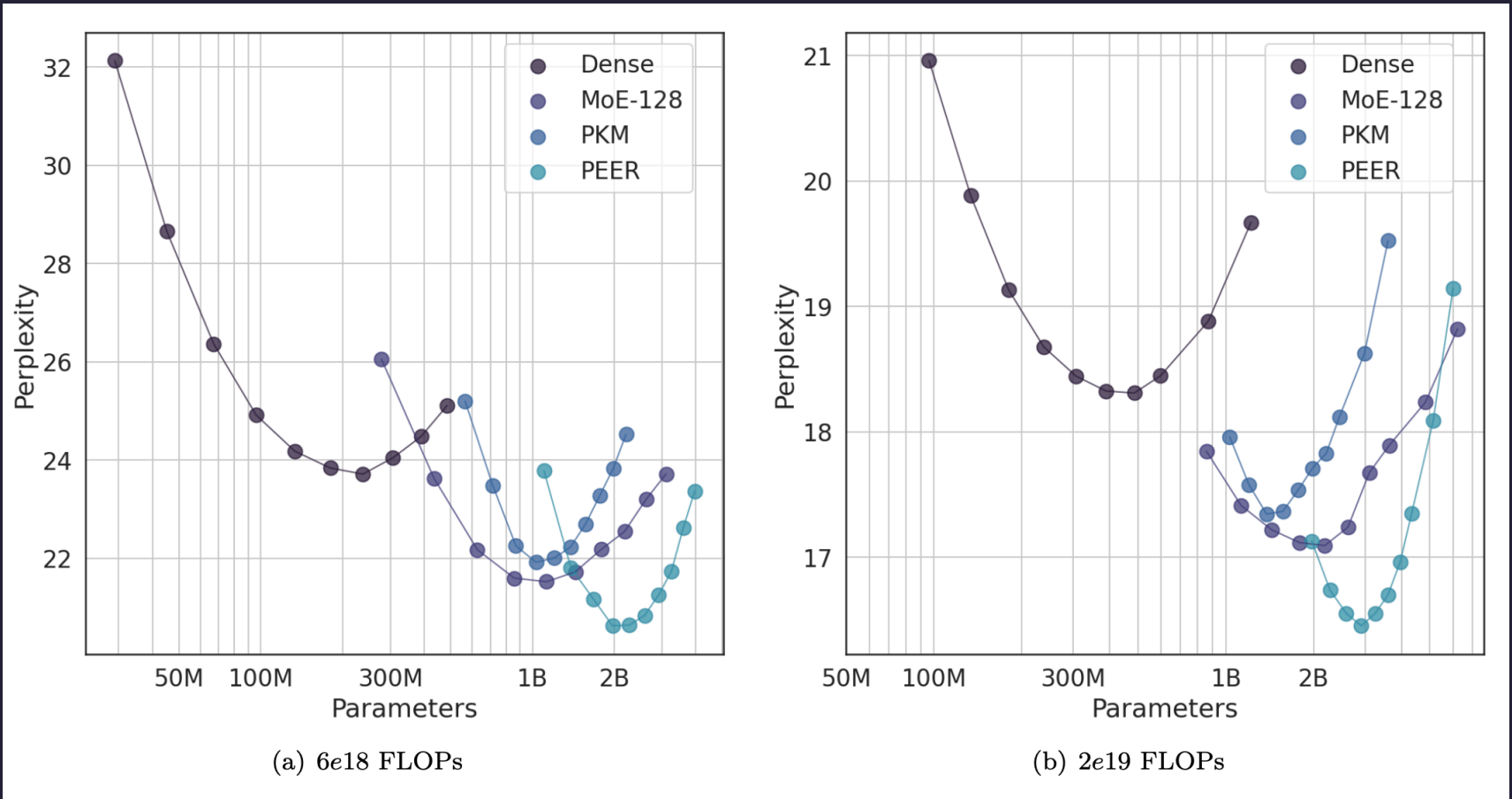


1 million experts

- We want to increase total number of trainable parameters but without increasing number of active parameters - so why not more, smaller experts?
- 1 million single neuron MLPs as experts
- Use multi-head retrieval to *"dynamically assembles an MLP with N neurons by aggregating N singleton MLPs retrieved from a shared repository"*
- Outperforms dense models and coarse MoE models on the same compute budget

"Mixture of A Million Experts", He.X, 2024

1 million experts

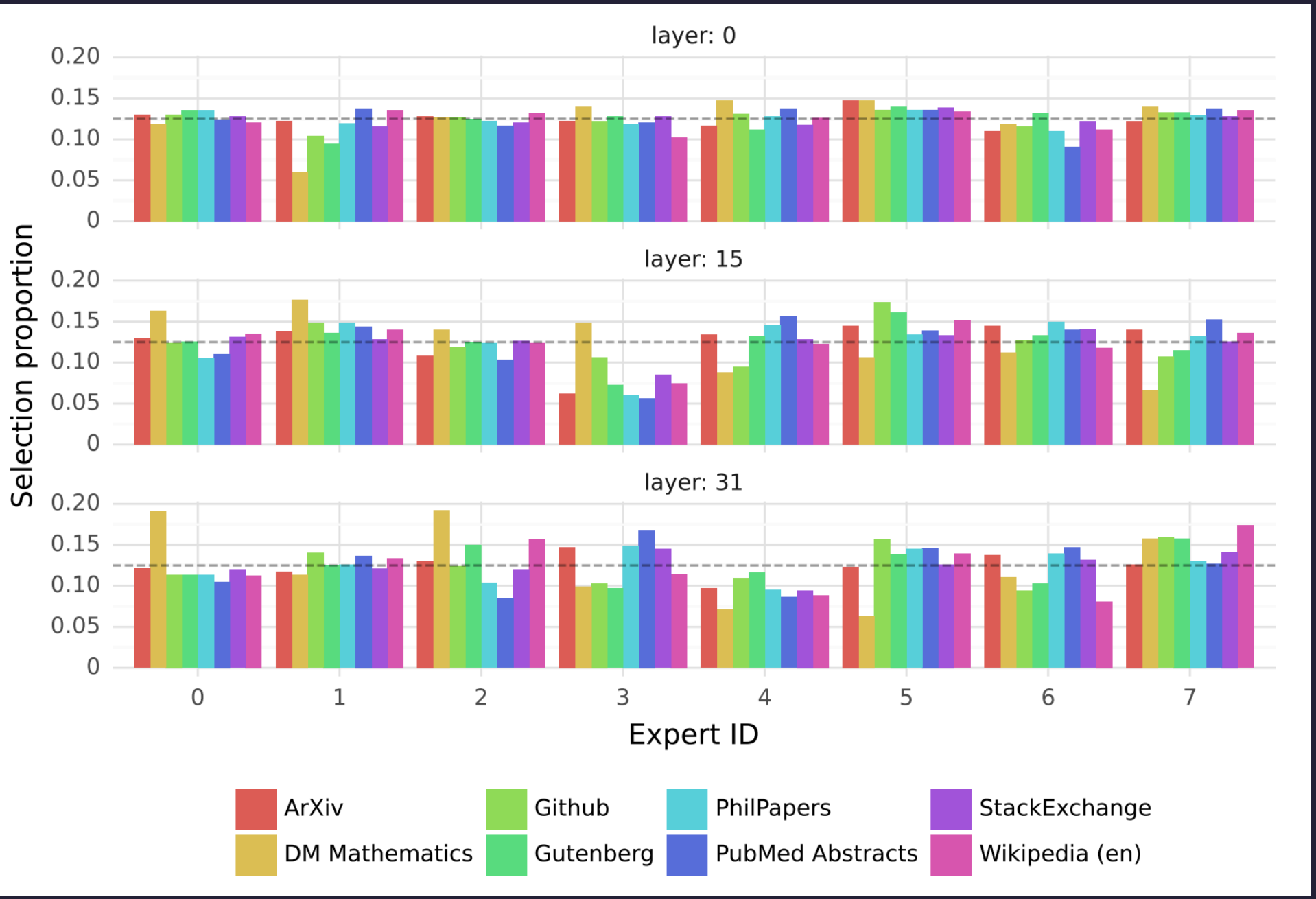


"Mixture of A Million Experts", He.X, 2024

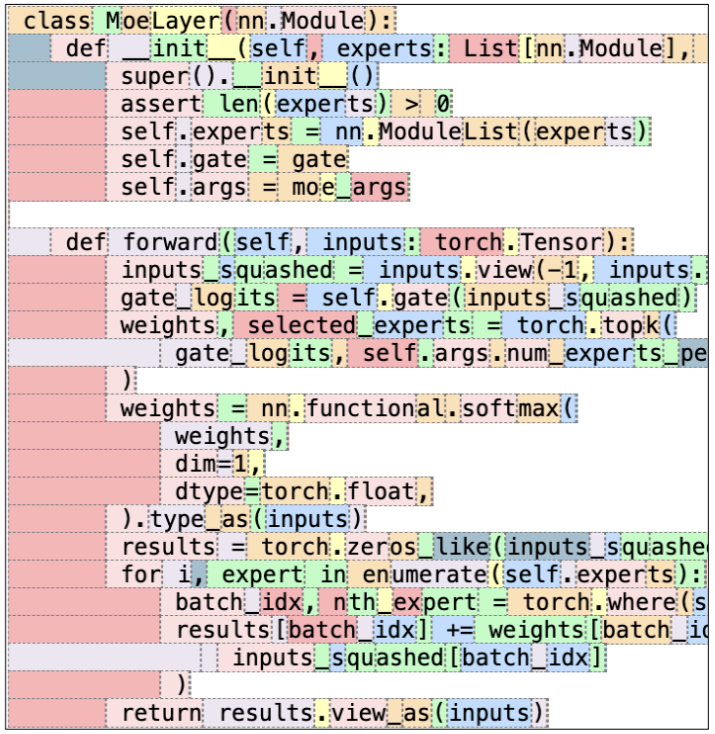
What are "experts" experts in?

- "Experts" conjures ideas of high-level specialisation
- The reality is **shallow** specialisation - token routing, load balancing prevents hi-level specialisation
- Expert selection more closely aligned with syntax than domain
- Levels of specialisation tends to differ across layers
- Consecutive tokens often assigned to the same expert - router is learning something about sequence information?

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


layer: 0
layer: 15
layer: 31
Selection proportion
0.20
0.15
0.10
0.05
0
0
1
2
3
4
5
6
7
Expert ID
ArXiv
DM Mathematics
Github
Gutenberg
PhilPapers
PubMed Abstracts
StackExchange
Wikipedia (en)

Layer 0



```
class MoeLayer(nn.Module):
    def __init__(self, experts: List[nn.Module],
        super().__init__()
        assert len(experts) > 0
        self.experts = nn.ModuleList(experts)
        self.gate = gate
        self.args = moe_args

    def forward(self, inputs: torch.Tensor):
        inputs_squashed = inputs.view(-1, inputs.
        gate_logits = self.gate(inputs_squashed)
        weights, selected_experts = torch.topk(
            gate_logits, self.args.num_experts_pe
        )
        weights = nn.functional.softmax(
            weights,
            dim=1,
            dtype=torch.float,
        ).type_as(inputs)
        results = torch.zeros_like(inputs_squashe
        for i, expert in enumerate(self.experts):
            batch_idx, nth_expert = torch.where(s
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            )
        return results.view_as(inputs)
```

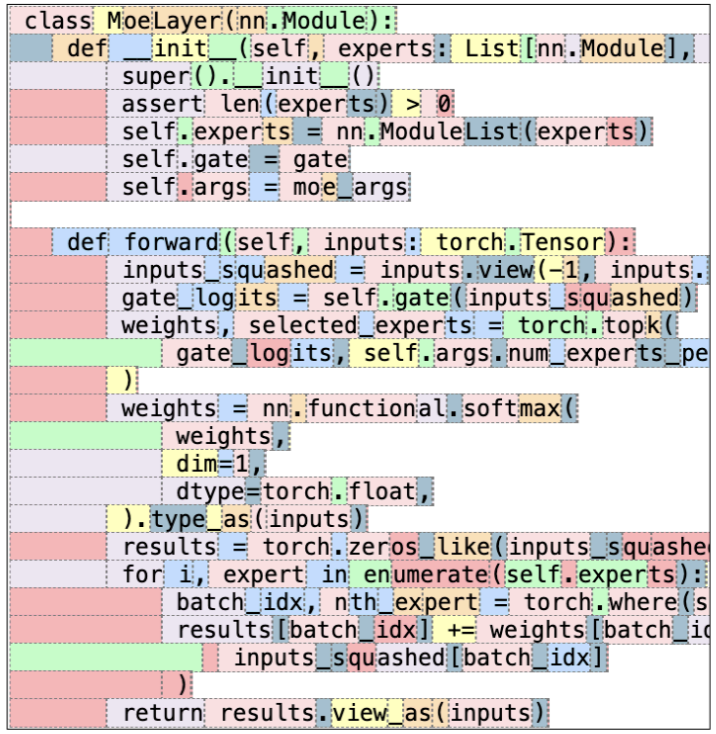
```
Question: Solve -42*r + 27*c = -1167 and 130*r
Answer: 4

Question: Calculate -841880142.544 + 411127.
Answer: -841469015.544

Question: Let x(g) = 9*g + 1. Let q(c) = 2*c +
Answer: 54*a - 30
```

```
A model airplane flies slower when flying into th
wind and faster with wind at its back. When launch
right angles to the wind, a cross wind, its ground
compared with flying in still air is
(A) the same (B) greater (C) less (D) either grea
or less depending on wind speed
```

Layer 15



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Layer 31

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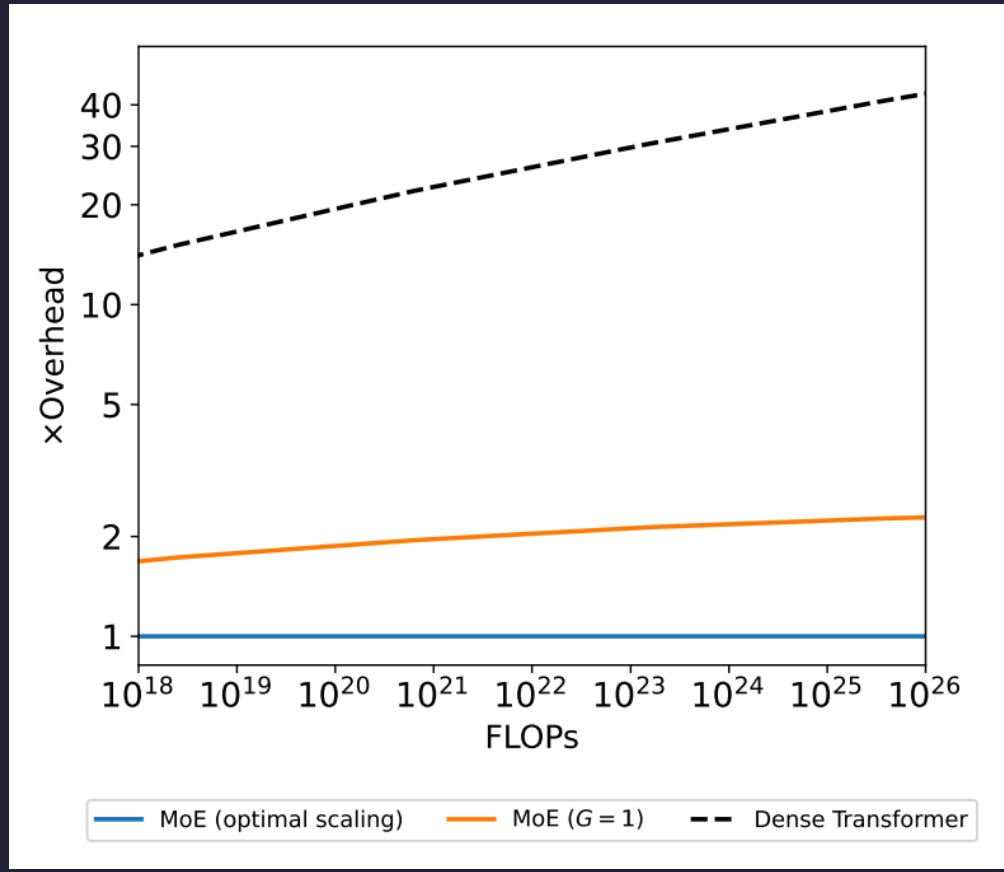
Scaling Laws

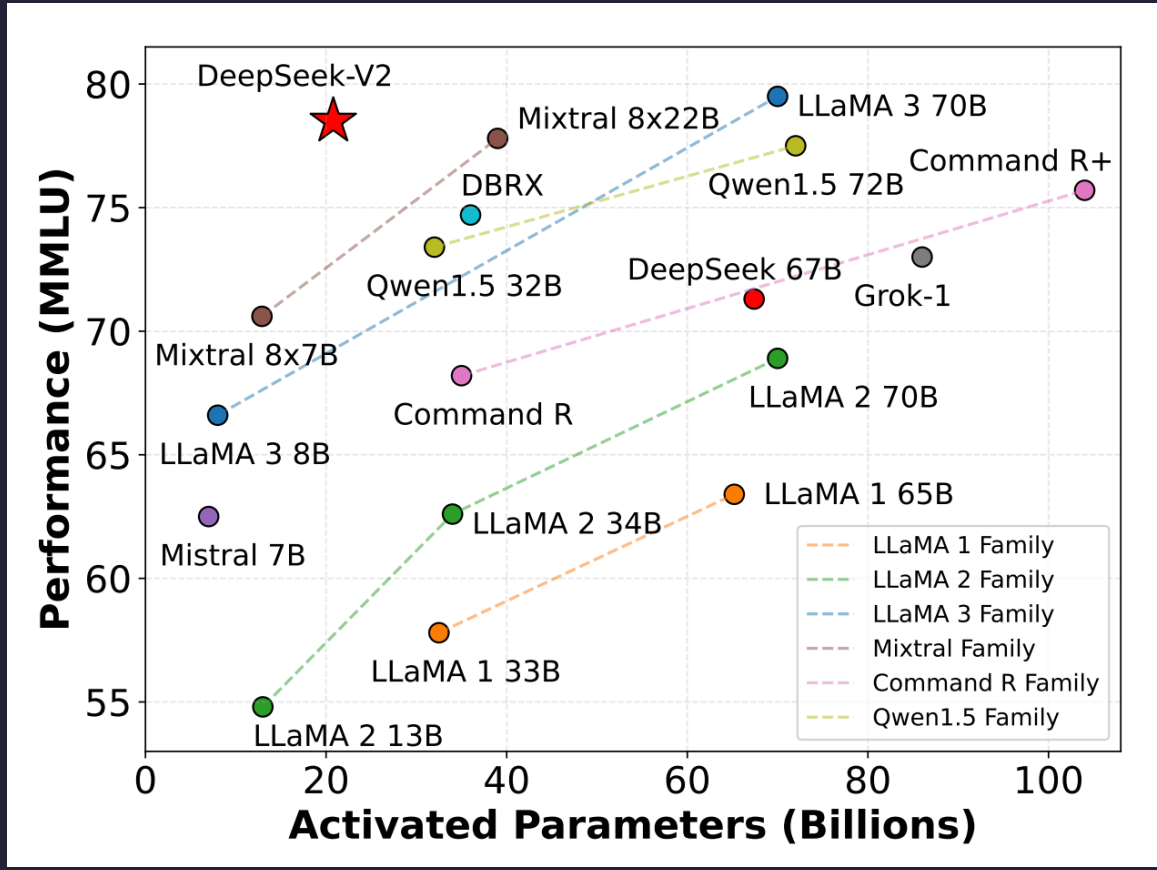
- MoEs are **always** more efficient than dense models
- Efficiency gap between dense and MoE models widens as we scale up the model size and training budget
- Performance declines when number of parameters in the routing mechanism **exceeds active parameters in actual experts**



"Scaling Laws for Fine-Grained Mixture-of-Experts Models", Krajewski et al., 2024

Looking forward

- **Lifelong learning** - freezing / adding new experts to deal with distributional shift over time while preserving existing knowledge
- Disentangling terminology: Mixture of Experts vs. Ensembles/Modular LLMs
- Dense models still relevant (Llama 3)
- There will always be another way to make gains - data quantity, data quality, compute efficiency



Thank you!

- Huggingface MoE Blog
- Nvidia MoE Blog
- Applying MoE in PyTorch
- Scaling Laws