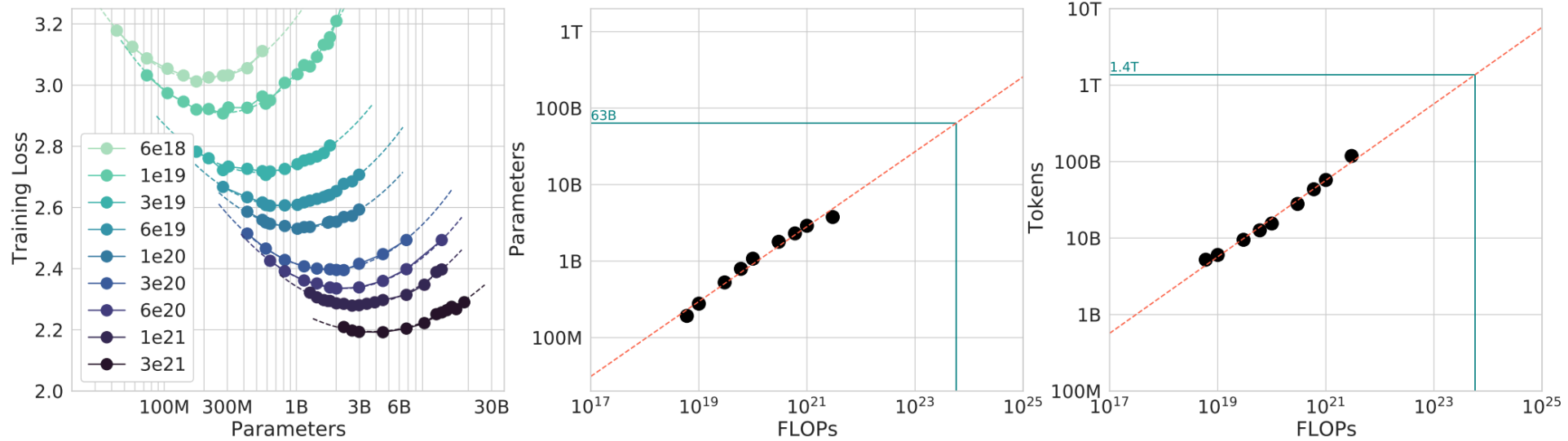


Course 5: Language Models at Inference Time

Introduction

Background

Scaling language models (LMs) is the go-to solution to achieve greater performance [1].



Background

- The more you scale, the more compute you need at inference.
- Hardware costs can hinder LLMs if no optimization is done.
- Not all optimization techniques are born equal...

What are the different responses to the trade-off between an LLM performance and an LLM throughput?

Content

1. More About Throughput?
 - a. Prompt pruning, when KV caching is not enough
 - b. Speculative decoding
 - c. Layer skip: self speculative decoding
2. More About Performance?
 - a. Retrieval augmented generation (at inference)
 - b. Test-time compute
3. More About "Balance"?
 - a. Mixture of experts

More About Throughput?

Prompt pruning: when KV caching is not enough

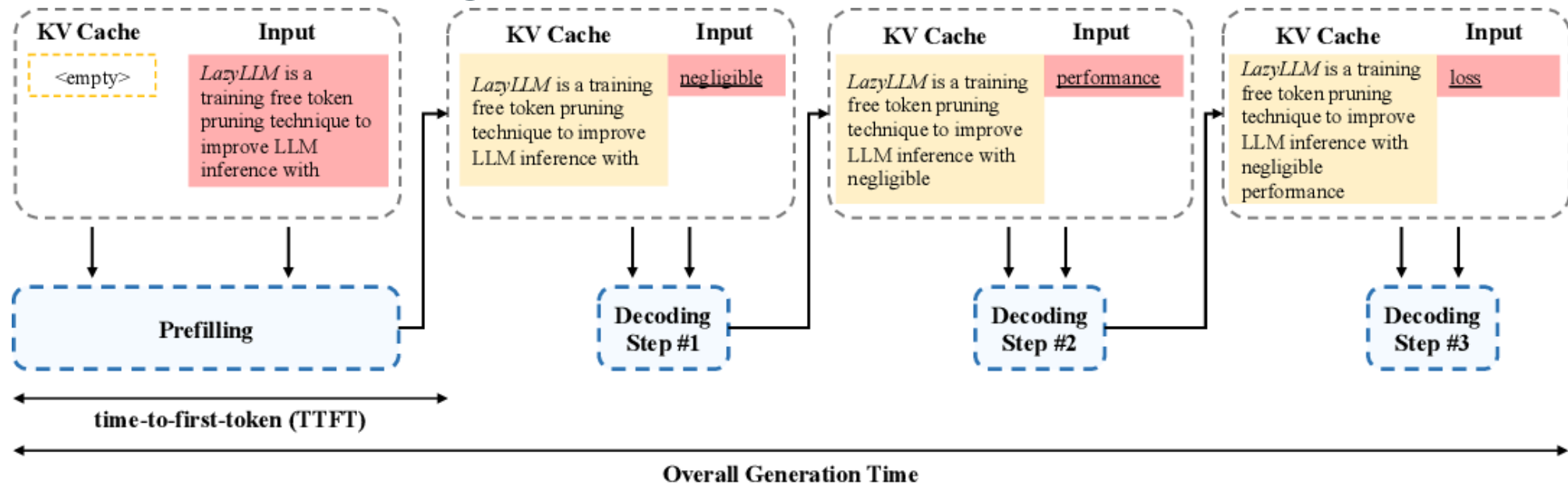
Attention matrices need to be calculated for every token constituting an LLM's prompt, leading to latency.

- On LLaMa2-70b models, given a long prompt, 23% of the total generation time is accounted for the time to first token (TTFT).
- KV caching is of no-use in that context...

How to reduce that TTFT with minimum performance loss?

Prompt pruning: when KV caching is not enough

When does KV caching comes into play?



The above example assume that your model is aware of LazyLLM [2] via its training data.

Prompt pruning: when KV caching is not enough

Not all tokens are useful to understand/answer the prompt.

			Accumulated # of Token Computed
LLM	Iteration #1 (Prefilling)	LazyLLM is a training free token pruning technique to improve LLM inference with negligible	13
	Iteration #2	LazyLLM is a training free token pruning technique to improve LLM inference with negligible performance	14
	Iteration #3	LazyLLM is a training free token pruning technique to improve LLM inference with negligible performance loss	15

LazyLLM	Iteration #1 (Prefilling)	LazyLLM is a training free token pruning technique to improve LLM inference with negligible	4
	Iteration #2	LazyLLM is a training free token pruning technique to improve LLM inference with negligible performance	6
	Iteration #3	LazyLLM is a training free token pruning technique to improve LLM inference with negligible performance loss	7

Prompt pruning: when KV caching is not enough

How to effectively choose tokens to prune out?

Transformer's attention represents more abstract concept as the computation is done deeper in its layers [3].

The last attention matrices play an important role in the decision boundaries computed by a transformer-based LM [4].

Prompt pruning: when KV caching is not enough

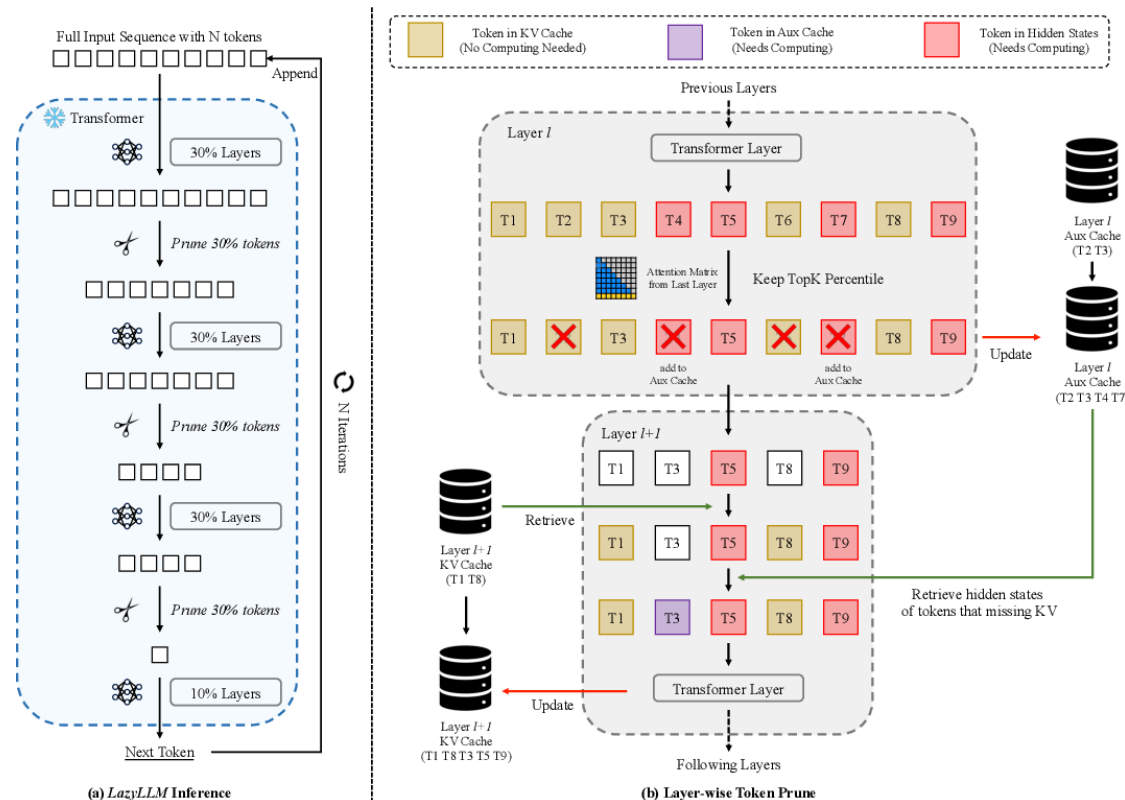
For a given token i , the attention matrix compute the probability of a token $j \leq N$ attending to i accross all H attention heads of a model. This process is repeated accross the $l \leq L$ layers of a model.

The importance of an input token i , at a given layer l can now be computed as

$$s_i^l = \frac{1}{H} \sum_{h=1}^H \sum_{j=1}^N A_{h,i,j}^l$$

Prompt pruning: when KV caching is not enough

We do not want to have too few tokens and some of them can become relevant later in the decoding process



Prompt pruning: when KV caching is not enough

Drawbacks:

- Marginal gain in performance with relatively short prompts.
- Drop in performance in code completion (no stop-words to drop?).

Speculative decoding

An **LLM** can **predict multiple tokens in a single forward pass** :

- **Speculative decoding** [5] allows an LLM to "**guess**" future tokens while generating current tokens, **all within a single forward pass**.
- By running a draft model to predict multiple tokens, the main model (larger) only has to verify the predicted tokens for "correctness".

Speculative decoding

1. **Prefix:** [BOS]
2. **Assistant:** [BOS] The quick brown sock jumps
3. **Main:** [BOS] The quick brown fox / sock jumps
4. **Assistant:** [BOS] The quick brown fox jumps over the crazy dog
5. **Main:** The quick brown jumps over the lazy / crazy dog
6. ...

Speculative decoding

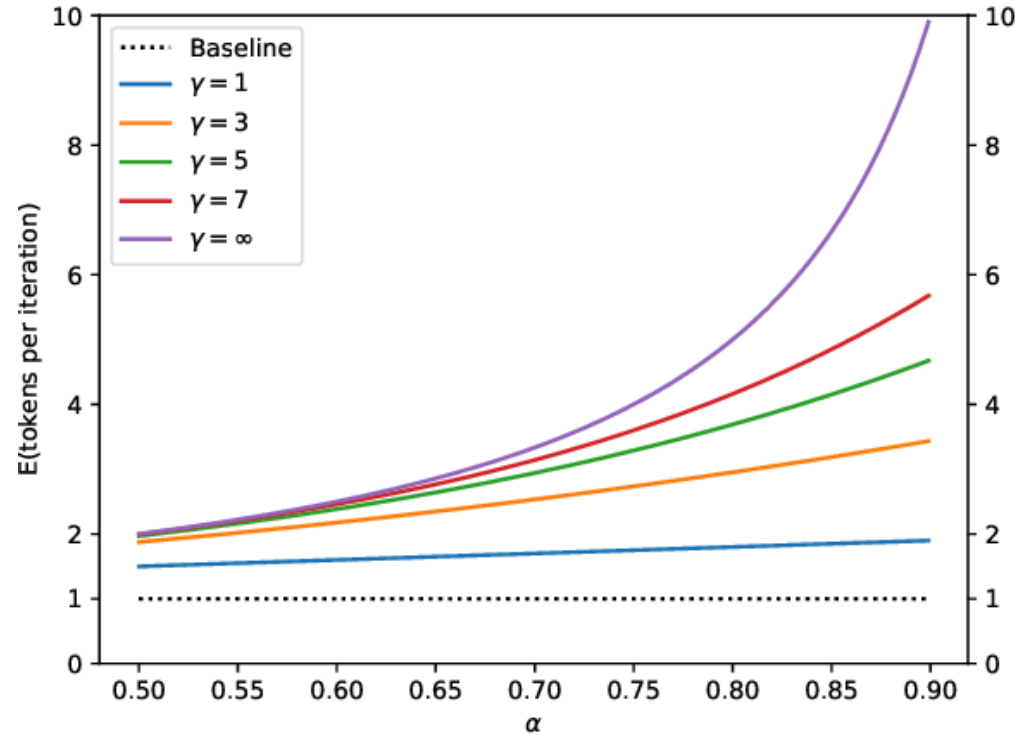
The main model just verifies that the distribution $q(x)$, computed by the assistant is not too far from the distribution $p(x)$ it computes within a forward pass.

The expected number of tokens generated within one loop of speculative decoding can be theoretically formulated as:

$$E(\#generated_tokens) = \frac{1 - \alpha^{\gamma+1}}{1 - \alpha}$$

Which is the forward passes' reduction factor.

Speculative decoding



The expected number of tokens generated via speculative decoding as a function of α for various values of γ .

Speculative decoding

In order **to take the most out of speculative decoding**, the distance between $q(x)$ and $p(x)$ **needs to be minimal**.

How to reduce the distance between $q(x)$ and $p(x)$ when the assistance model is smaller?

- Quantization
- Distillation
- Over-training on the same dataset as the main model

Layer skip: self speculative decoding

Speculative decoding comes with two inconveniences:

- Loading two models in memory
- Making sure the assistant model outputs a token distribution as close as possible to the main model

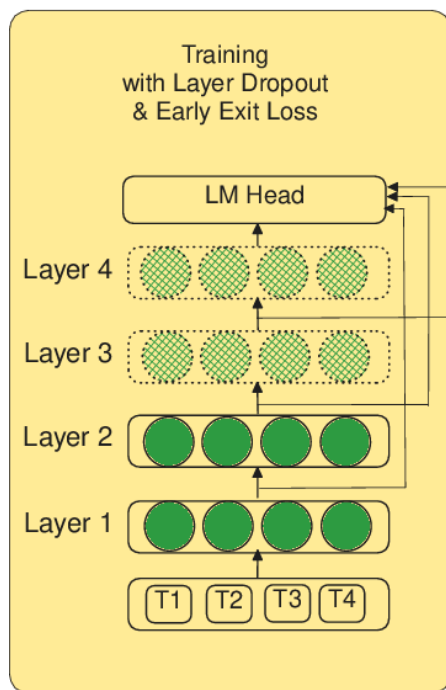
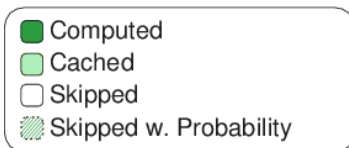
Layer skip: self speculative decoding

Why not let the main model do the speculation itself?

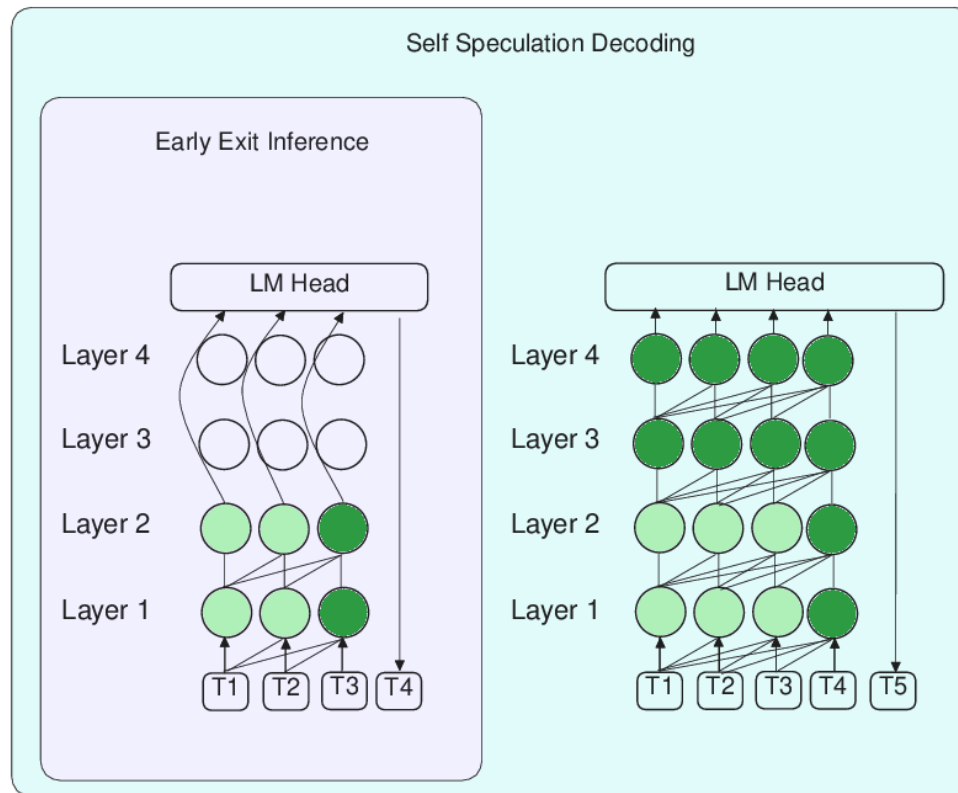
Transformer models are believed to be **over-parameterized** and the **last layers specialized** on computing the decision boundaries **before projecting on the LM head**. Maybe we can make **each layer able to project on the LM head**, thus skipping layers [6] and allowing for an **early exit** at inference [7].

Layer skip: self speculative decoding

Legend



Train using Layer Dropout + Early Exit Loss....



... enables inference with subset of layers with higher accuracy...

... and we can improve accuracy by verifying and correcting with remaining layers

Layer skip: self speculative decoding

The hidden state of a token t , at layer $l + 1$ is stochastically given by

$$x_{l+1,t} = x_{l,t} + M(p_{l,t}) \times f_l(x_{l,t})$$

Where M is a masking function with a probability of skipping

$$p_{l,t} = S(t) \times D(l) \times p_{max}$$

$$D(l) = e^{\frac{l \times \ln(2)}{L-1}}$$

$$S(t) = e^{\frac{t \times \ln(2)}{T-1}}$$

Layer skip: self speculative decoding

How is the loss computed?

$$\mathcal{L}_{total} = \sum_{l=0}^{l=L-1} \tilde{e}(t, l) \times \mathcal{L}_{CE}$$

Where $\tilde{e}(t, l)$ is a normalized per-layer loss scale

$$\tilde{e}(t, l) = \frac{C(t, l) \times e(l)}{\sum_{i=0}^{i=L+1} C(t, i) \times e(i)}$$

Layer skip: self speculative decoding

$$C(t, l) = \begin{cases} 1 & \text{if there is no early exit at layer } l \\ 0 & \text{otherwise} \end{cases}$$

e is a scale that increases across layers, penalizing later layers, as predicting in later layers is easier.

$$e(l) = \begin{cases} \sum_{i=0}^{i=l} i & \text{if } 0 \leq l \leq L - 1 \\ L - 1 + \sum_{i=0}^{i=L-2} i & \text{if } l = L - 1 \end{cases}$$

Layer skip: self speculative decoding

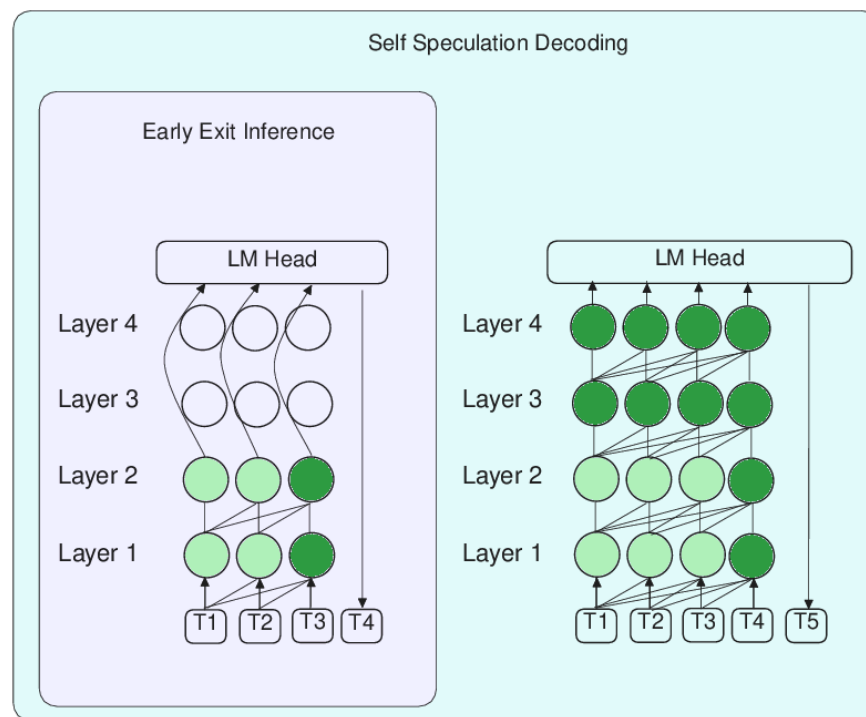
How does this change inference?

Legend

- Computed
- Cached
- Skipped
- ▨ Skipped w. Probability



Train using Layer Dropout + Early Exit Loss....



... enables inference with subset of layers with higher accuracy...

... and we can improve accuracy by verifying and correcting with remaining layers

More About Throughput?

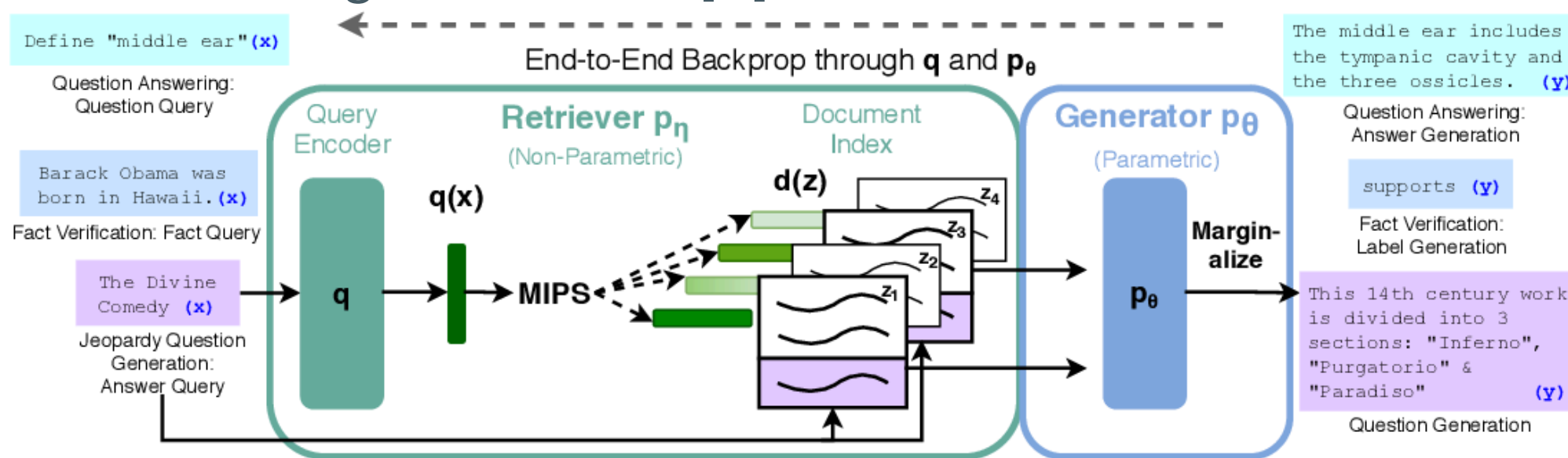
Layer skip: self speculative decoding

- 10% speed-up
- A single KV cache => low memory overhead
- The main model is still competitive when the last transformer layer is used for prediction despite a different training technique.

More About Performance?

Retrieval augmented generation (at inference)

The goal of retrieval augmented generation (RAG) is to give access to updated knowledge to a model [8].



RAG's intricacies will be discussed in another chapter.

Retrieval augmented generation (at inference)

RAG-sequence model

$$p_{\text{RAG-sequence}}(y|x) \approx \sum_{z \in \text{top-}k} p_{\eta}(z|x) \prod_i^N p_{\theta}(y_i|x, z, y_{1:i-1})$$

RAG-token model

$$p_{\text{RAG-token}}(y|x) \approx \prod_i^N \sum_{z \in \text{top-}k} p_{\eta}(z|x) p_{\theta}(y_i|x, z, y_{1:i-1})$$

Retrieval augmented generation (at inference)

- Although conditioned on retrieved knowledge, output may be a hallucination.
- Most of RAG's performance depends on the chunking method and the retriever.

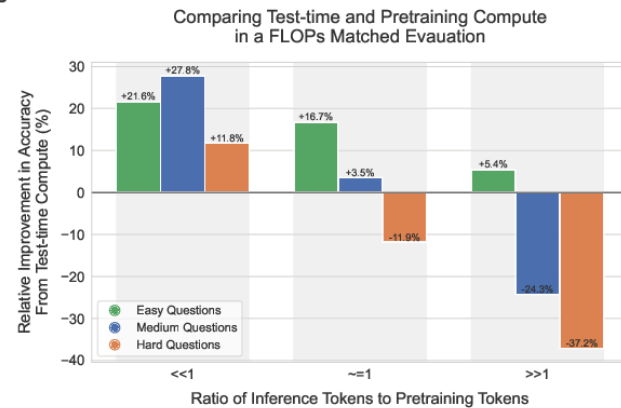
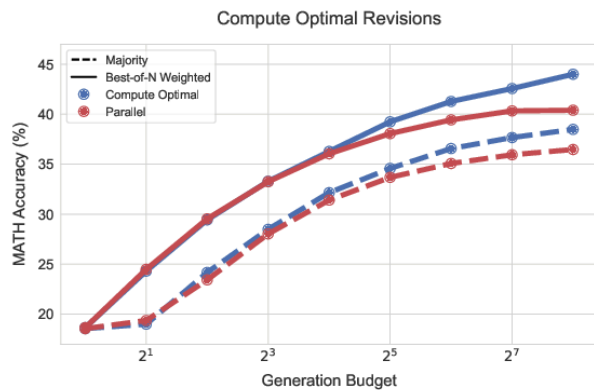
Test time compute

The goal is to **allocate more compute at inference** to "**natively**" **incorporate chain-of-thought** like decoding.

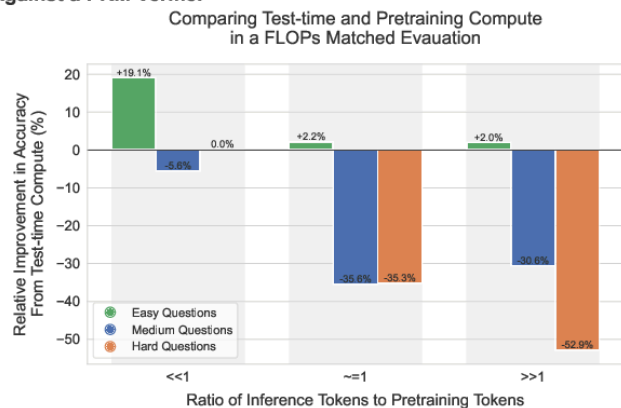
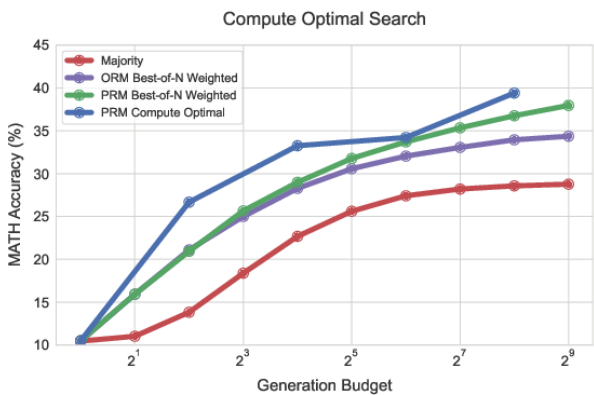
The hypothesis is that **models have good reasoning capabilities** but standard **decoding processes hinder them**.

Test time compute

Iteratively Revising Answers at Test-time



Test-time Search Against a PRM Verifier



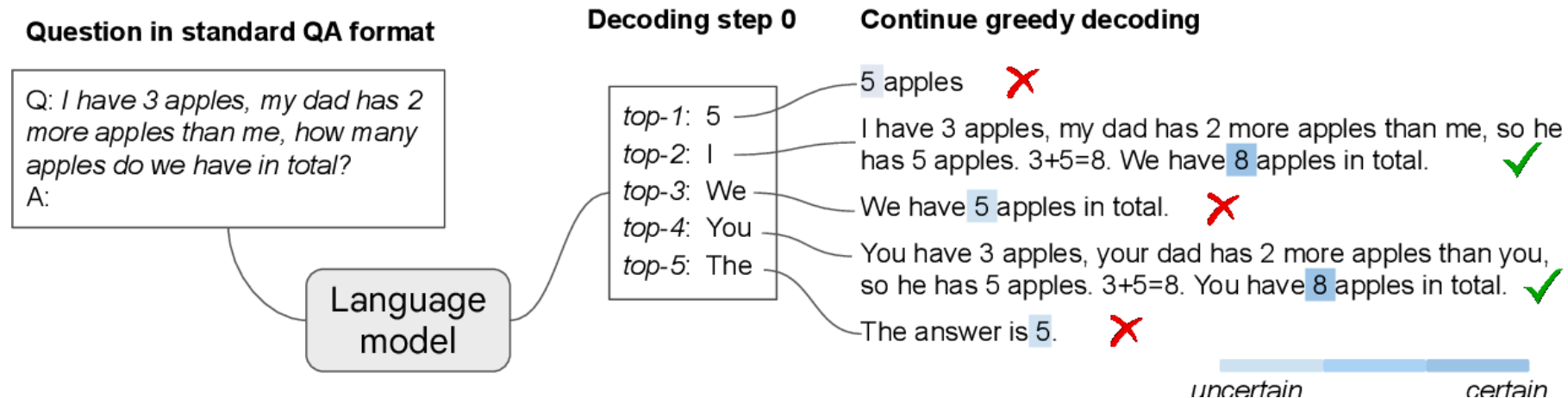
[9]

More About Performance?

Test time compute

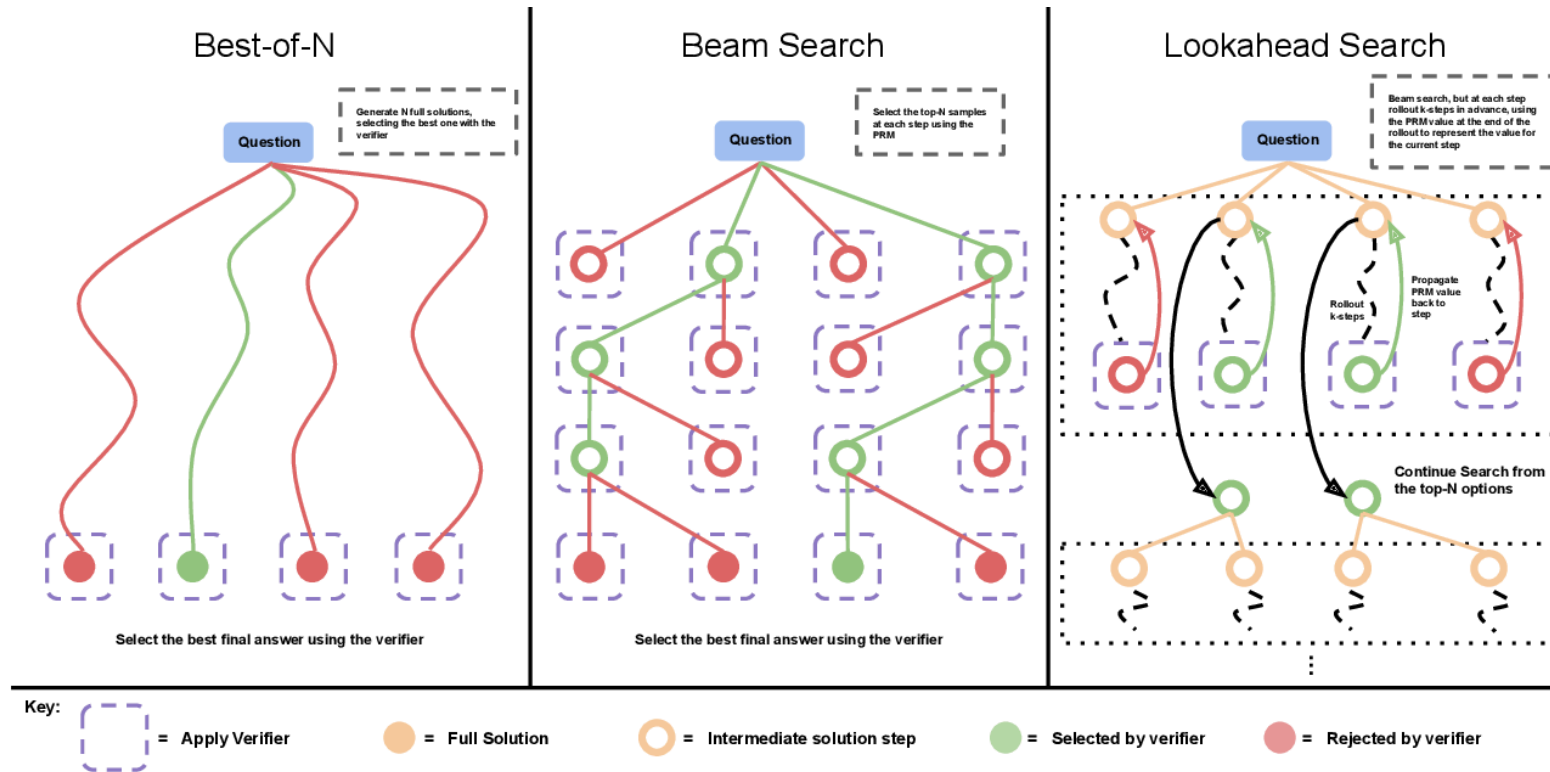
Search against verifiers [10]:

- Most decoding methods stem from greedy decoding.
- There is no "correct" way of selecting the first token when decoding.



test time compute

A reward model (verifier) selects the **best answer** based on a **systematic search method**:



Test time compute

Modifying proposal distribution:

Reinforcement learning-like techniques where a **model learns to refine its own answer** to reach the optimal one: look at **ReST** [12] and **STaR** [11].

Unlike standard decoding, **the model can backtrack to previous steps.**

Test time compute

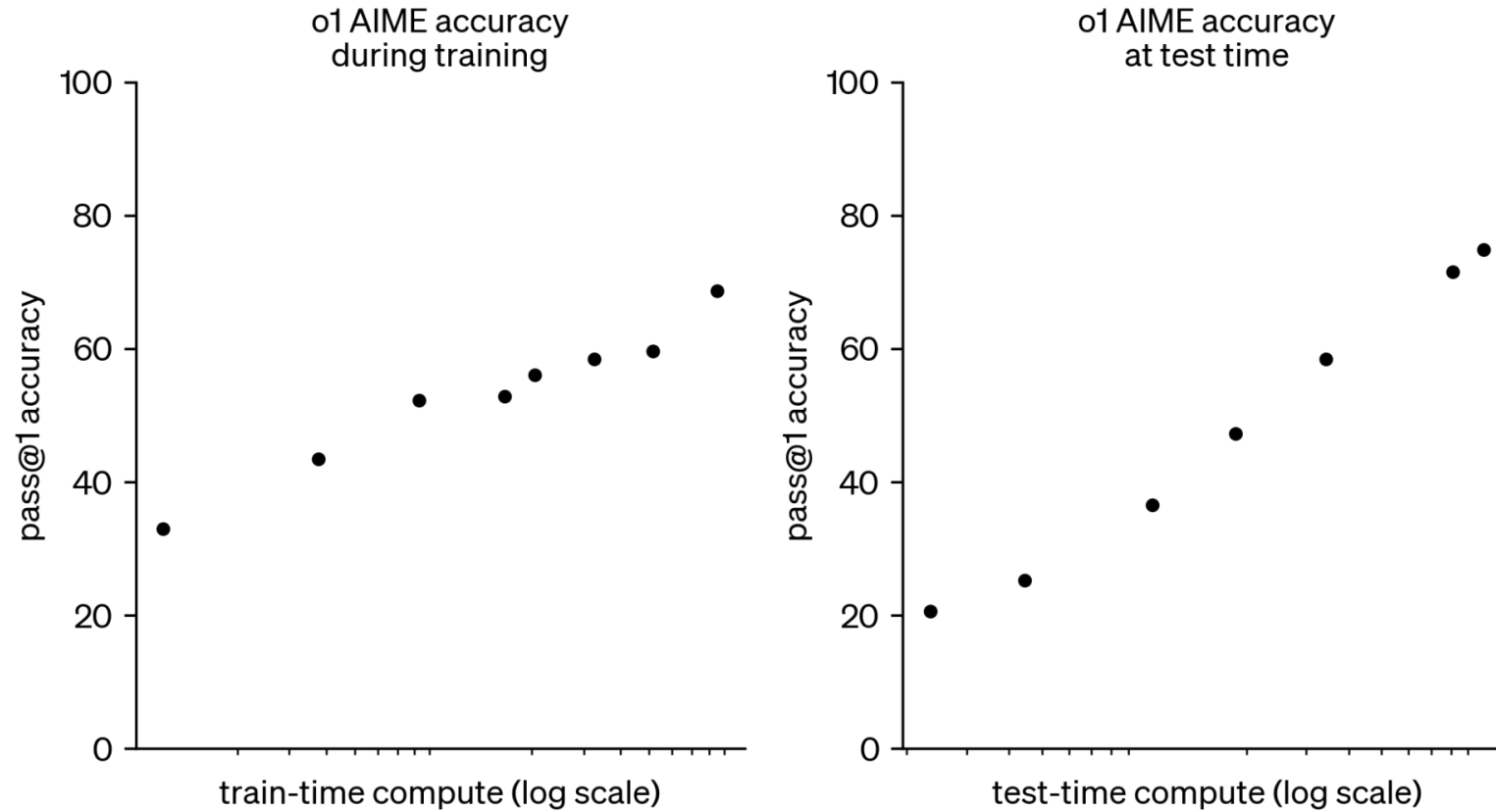
- Borrowing from **ReST**, one could **create candidate responses during inference** and **assess them against a task-specific quality metric** (without updating weights). The highest-quality candidates can then **guide token sampling**.
- **STaR's** multi-path reasoning generation and selection is applicable at test-time by **generating multiple answer paths** and **using consistency checks** or **reranking** to **choose the best response**.

Test time compute

Takeaways (DeepMind's scaling laws):

- Small models ($< 10b$) are better at answering easy questions when given more TTC than pretraining compute.
- Diminishing return on larger models with more TTC than pretraining compute.

Test time compute



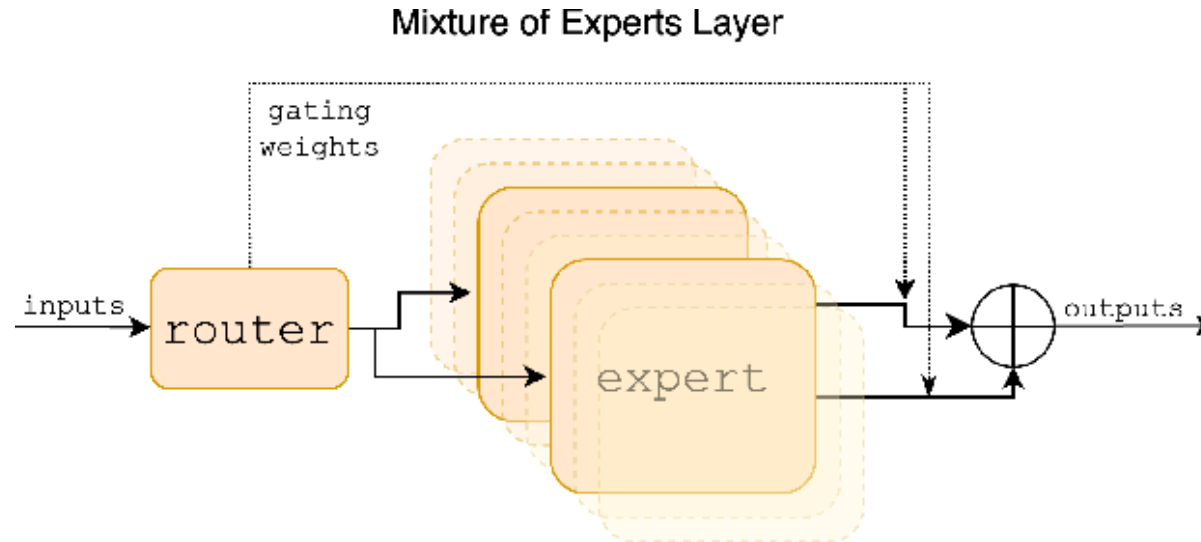
[13]

More About Performance?

More About "Balance"?

Mixture of experts

Replacing every FFN in a transformers with a MoE layer [14]?



Divide one FFN network with M parameters into N experts with $M' = \frac{M}{N}$ parameters each.

Mixture of experts



Mixture of experts

- Reduced computation during training and inference since we only need to run $1/N$ th of the FFN weights.
- Unstable during training: can struggle to generalize, thus prone to overfitting.
- Load balancing is crucial: we do not want a subset of experts to be under-utilized.

Mixture of experts

A learned gating network G decides which experts E to send a part of the input:

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

Where $G(x)_i$ denotes the n -dimensional output of the gating network for the i -th expert, and $E_i(x)$ is the output of the i -th expert network

Mixture of experts

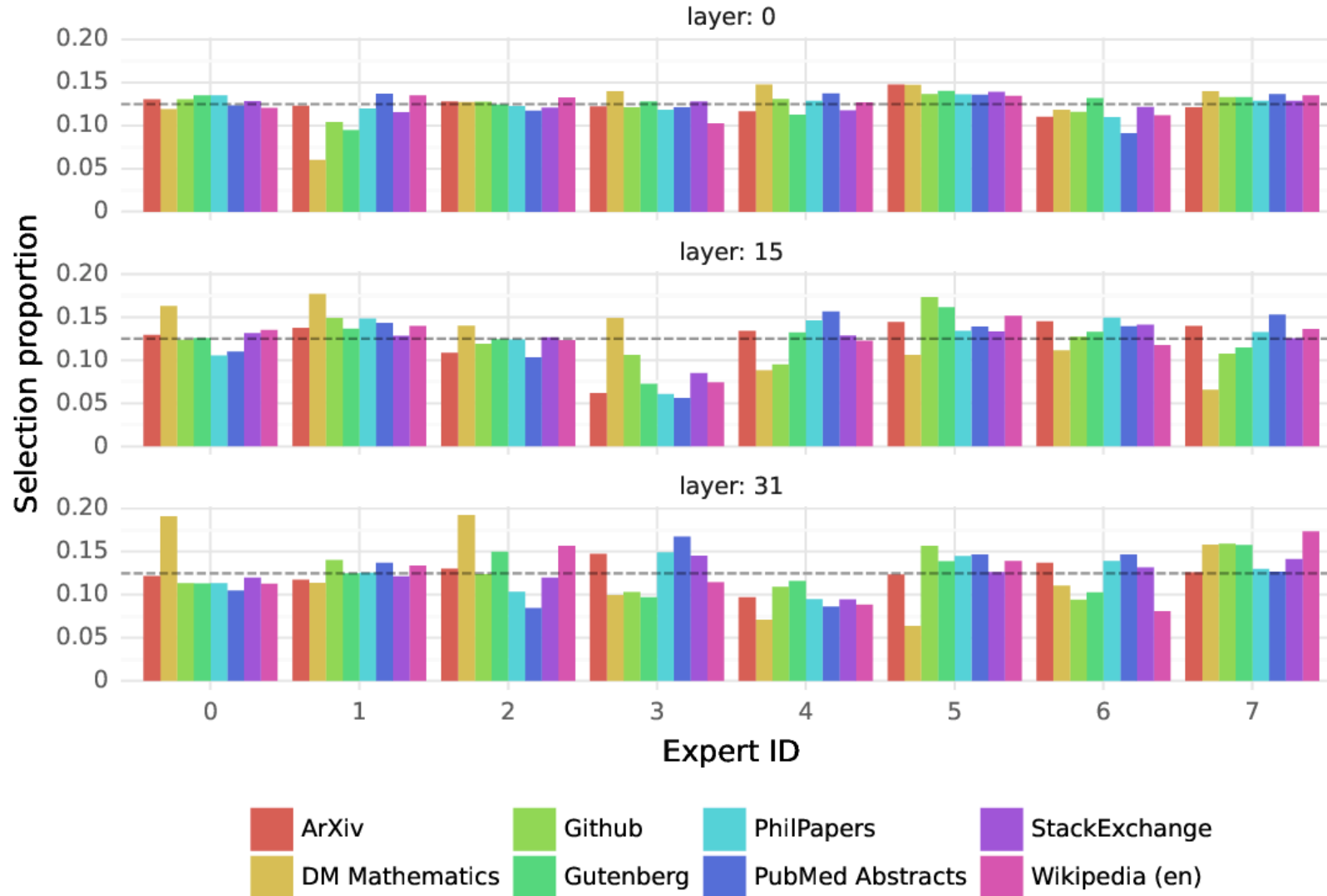
A popular gating function is the softmax function over the top- k logits.

$$G(x) := \text{softmax}(\text{top-}k(x \cdot W_g))$$

In order to have a sparse vector as output

$$\text{top-}k(x \cdot W_g) = \begin{cases} v_i & \text{if } v_i \text{ is in the top } k \text{ of } x \cdot W_g \\ -\infty & \text{otherwise} \end{cases}$$

Mixture of experts



More About "Balance"?

Mixture of experts

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.size(-1))
        gate_logits = self.gate(inputs_squashed)
        weights, selected_experts = torch.topk(
            gate_logits, self.args.num_experts_per_token
        )
        weights = nn.functional.softmax(
            weights,
            dim=-1,
            dtype=torch.float,
        ).type_as(inputs)
        results = torch.zeros_like(inputs_squashed)
        for i, expert in enumerate(self.experts):
            batch_idx, nth_expert = torch.where(
                results[batch_idx] == weights[batch_idx, i]
            )
            inputs_squashed[batch_idx] = expert(inputs_squashed[batch_idx])
        return results.view_as(inputs)
```

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

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

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

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

Layer 15

```
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.size(-1))
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        weights, selected_experts = torch.topk(
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        )
        weights = nn.functional.softmax(
            weights,
            dim=-1,
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        ).type_as(inputs)
        results = torch.zeros_like(inputs_squashed)
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Layer 31

```
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.size(-1))
        gate_logits = self.gate(inputs_squashed)
        weights, selected_experts = torch.topk(
            gate_logits, self.args.num_experts_per_token
        )
        weights = nn.functional.softmax(
            weights,
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Questions?

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