LLM Optimization

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Mixture of Experts

Slides adapted from William Fedus and Barret Zoph

Motivation

- The trend is to bigger models
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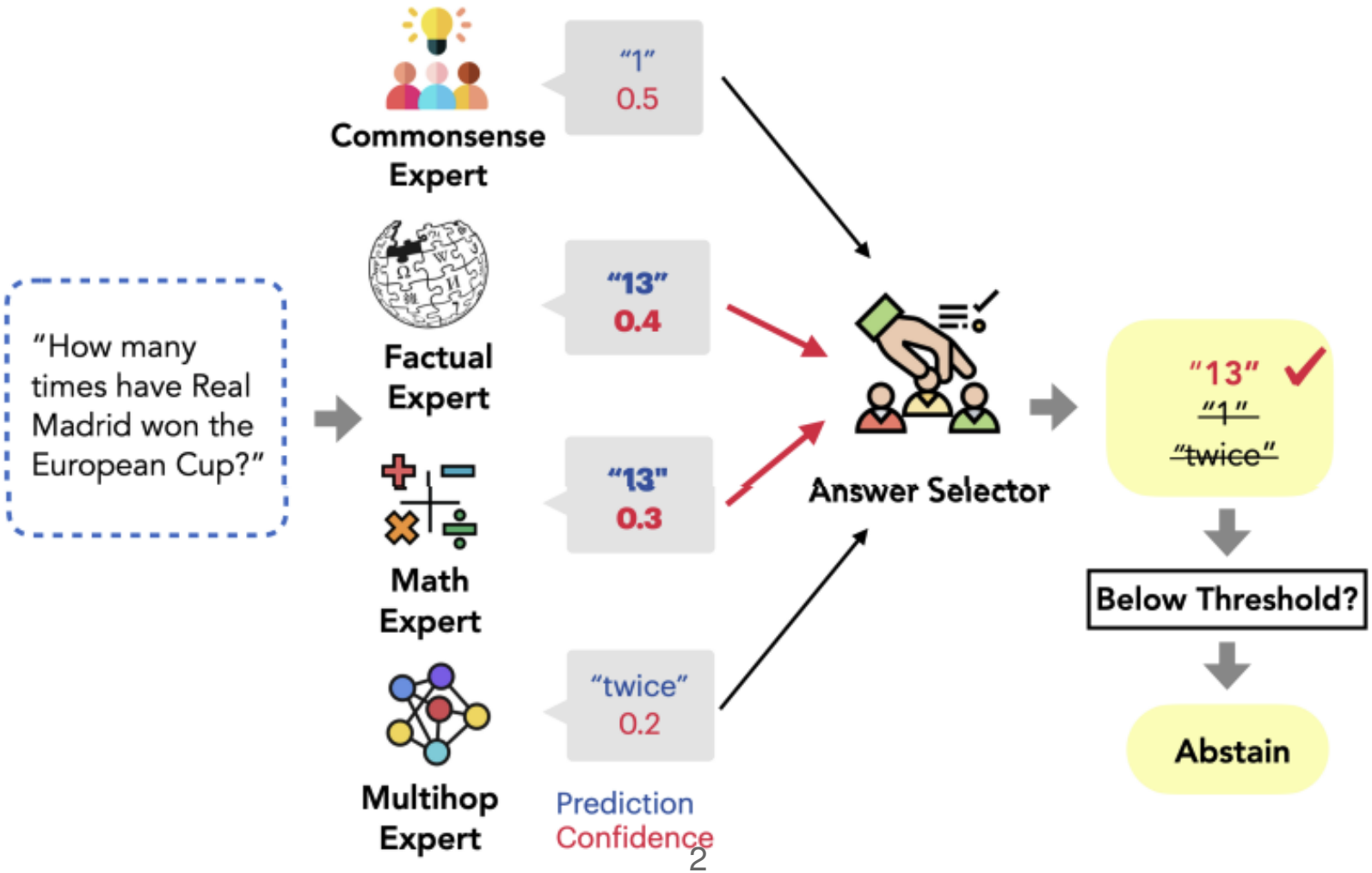

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Getting MoRE out of Mixture of Language Model Reasoning Experts

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Why is it a good idea?

- If you need a model to do x, easier to train that model than to train a massive model to do everything and x
- Users find it more interpretable
- Disagreements between models can help with calibration
- Cheaper to serve (smaller models can live on modest, smaller servers)

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Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity

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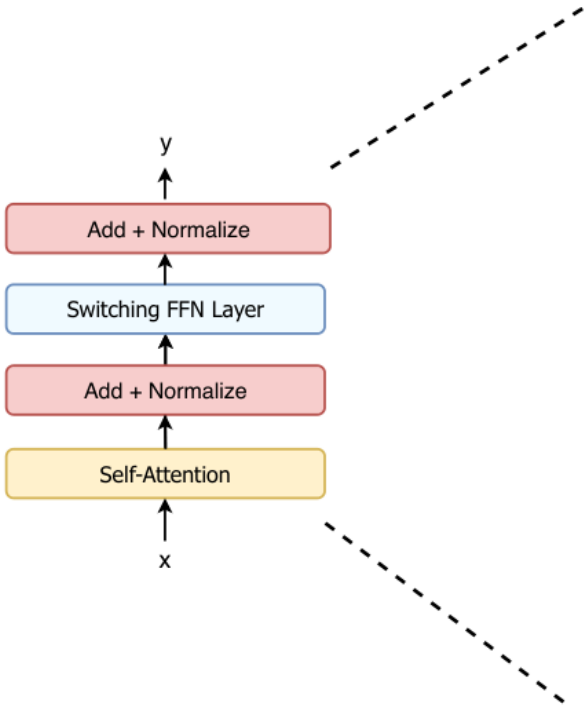
Going to the Token Level



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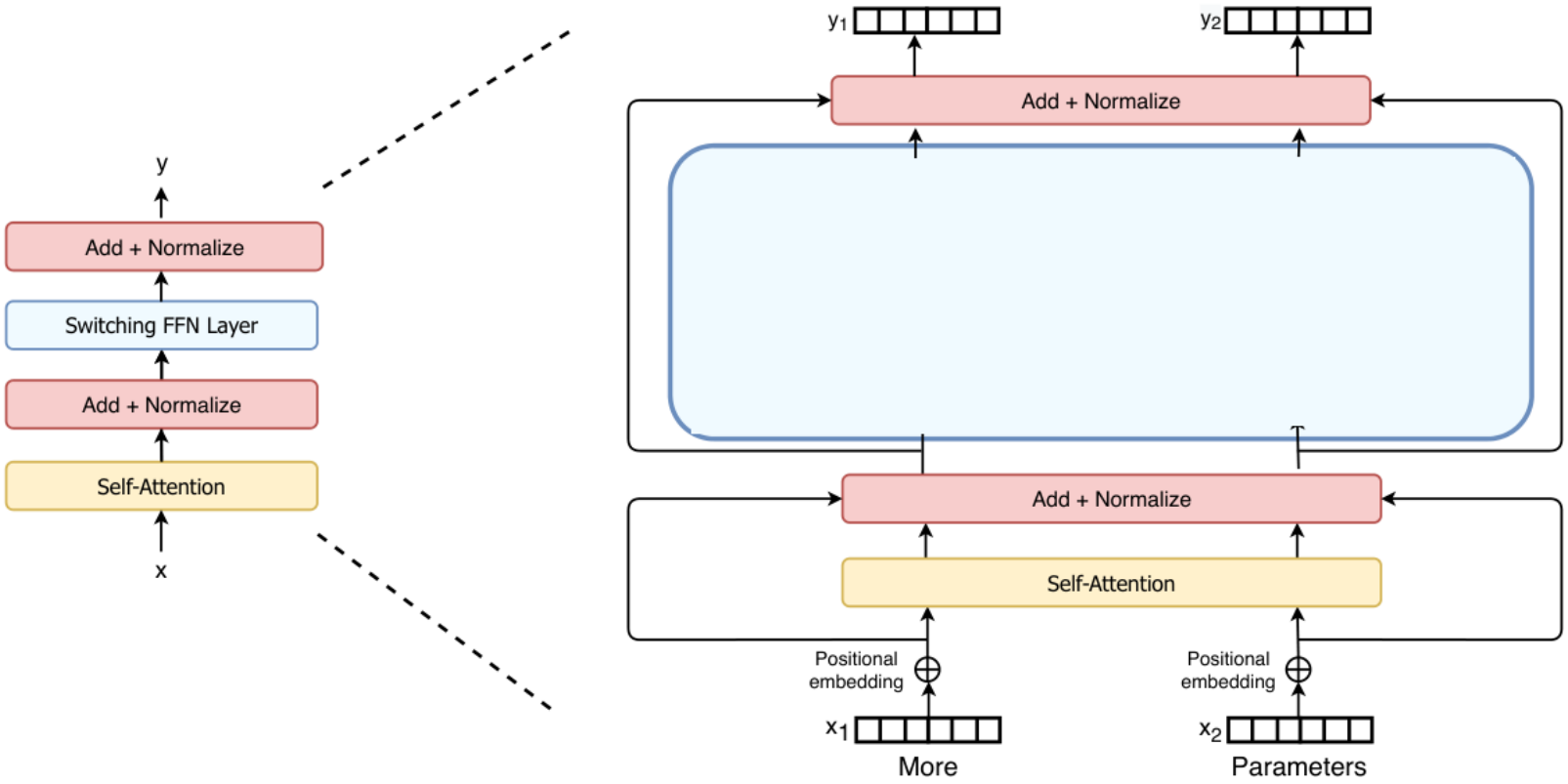

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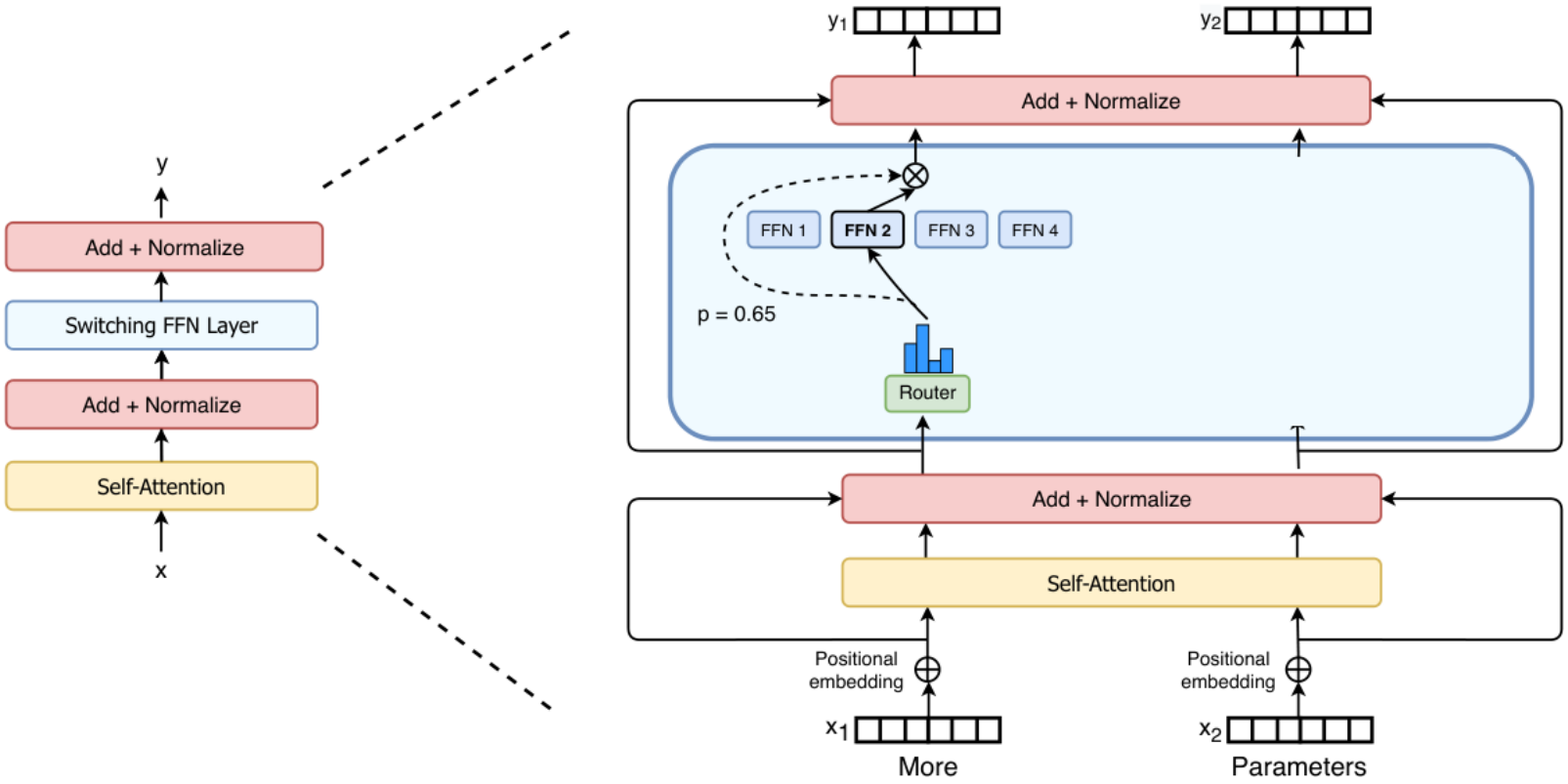

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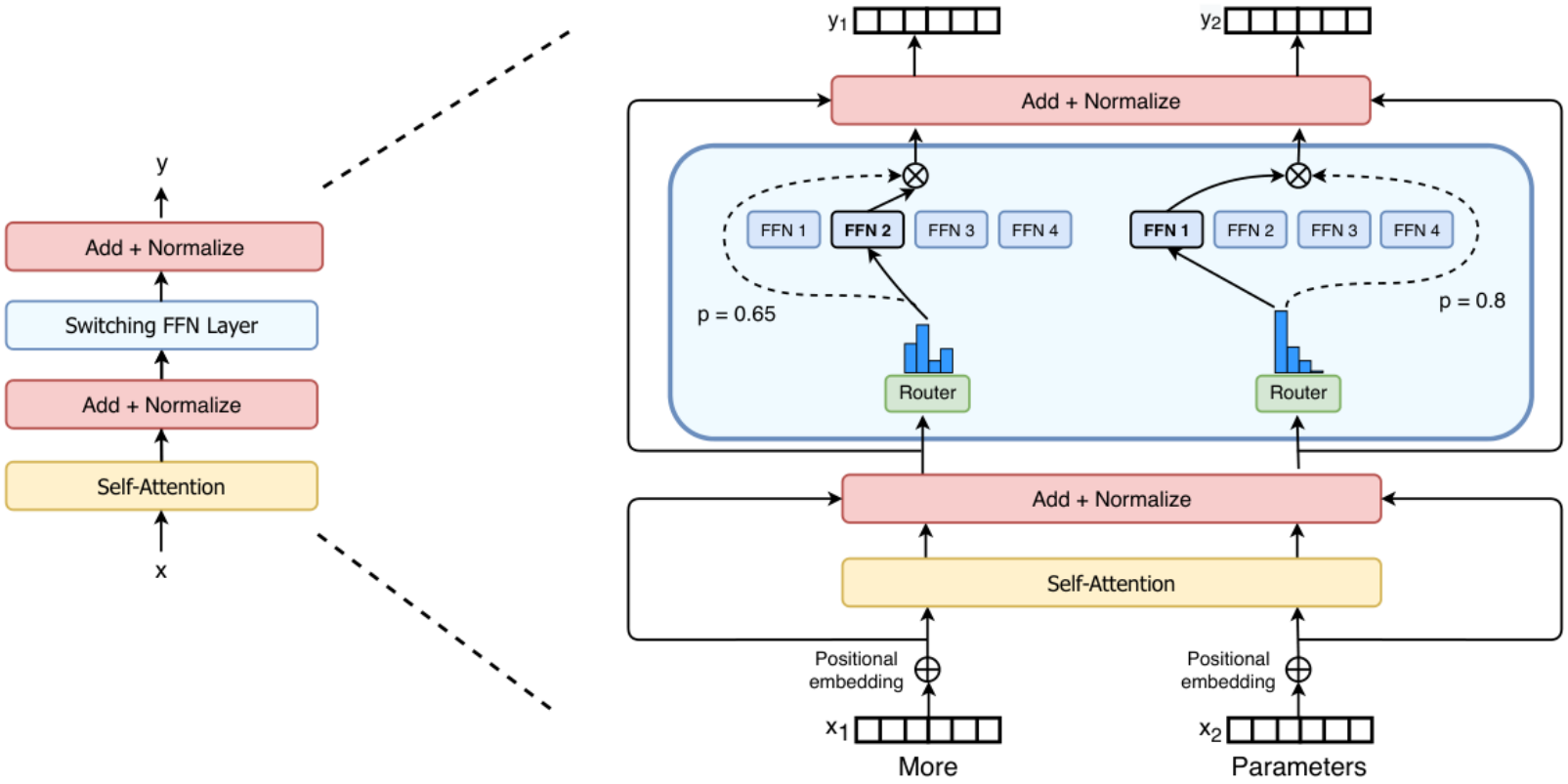

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Routing

The router variable W_r produces logits $h(x) = W_r \cdot x$ which are normalized via a softmax distribution:

$$p_i(x) = \frac{e^{h(x)_i}}{\sum_j^N e^{h(x)_j}}. \tag{1}$$

The top-k gate values are selected for routing the token x to linearly weight each expert's contribution

$$y = \sum_{i \in \mathcal{T}} p_i(x) E_i(x). \tag{2}$$

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- Given N experts indexed by $i = 1$ to N and a batch $\mathscr{B}$ with T tokens

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$$P_i = \frac{1}{T} \sum_{x \in \mathcal{B}} p_i(x). \tag{5}$$

Since we seek uniform routing of the batch of tokens across the N experts, we desire both vectors to have values of $1/N$.

Why can this help?

- Easier fine tuning (more on this later)
- Increase in overall scale
- Easier to distribute to more machines (Experts on different devices)

Wrapup

- Most major models are likely using mixture of experts
- It helps keep training scalable
- And allows to claim larger models
- It also leads to better results
- Helps address sparsity issue: most of models aren't useful for any particular example