Mixture of Experts

CS 5624: Natural Language Processing

Spring 2025

https://tuvllms.github.io/nlp-spring-2025

Tu Vu

VIRGINIA TECH.

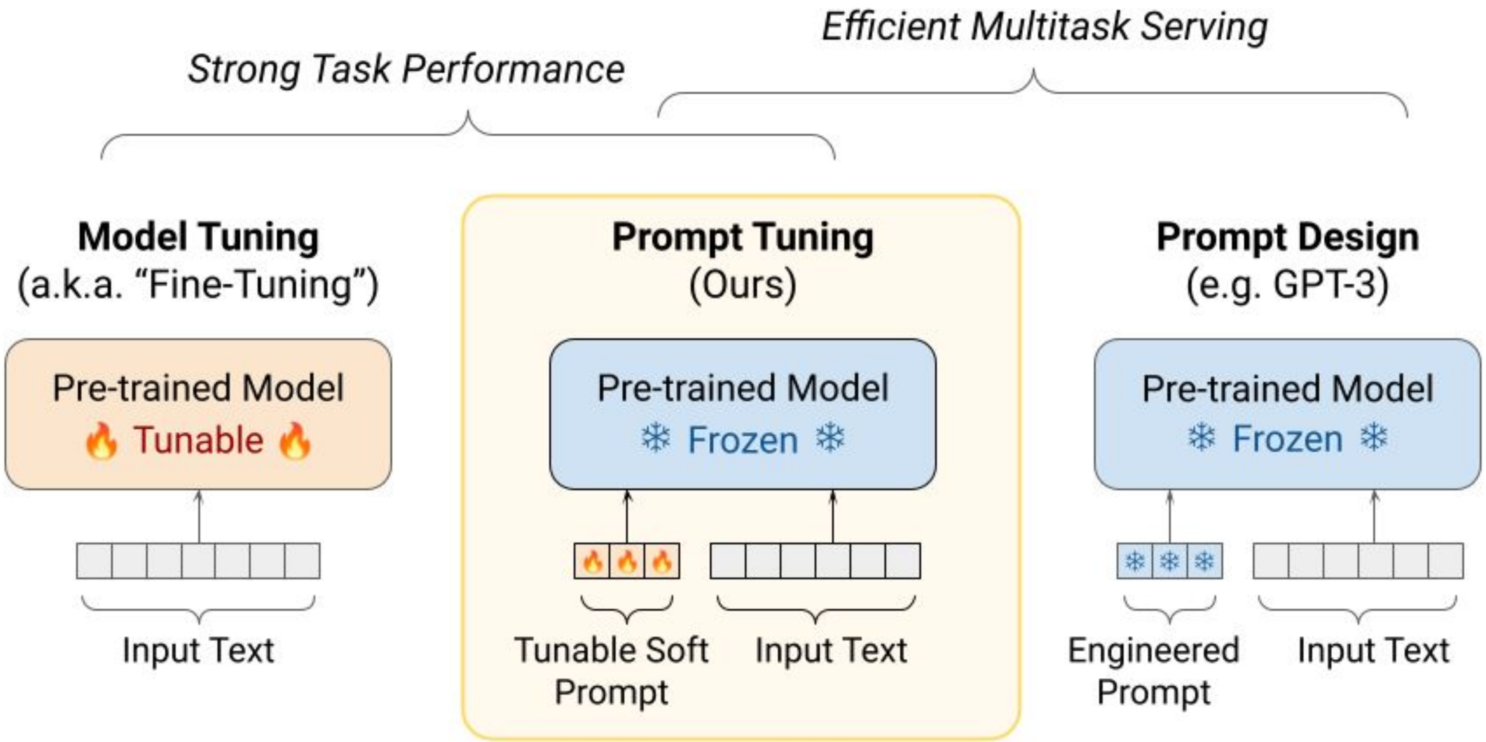
Logistics

- Quiz 2 & Homework 2 are postponed
- We are sending out feedback on final project proposals
- Please email us at cs5624instructors@gmail.com

More on benefits of parameter-efficient tuning

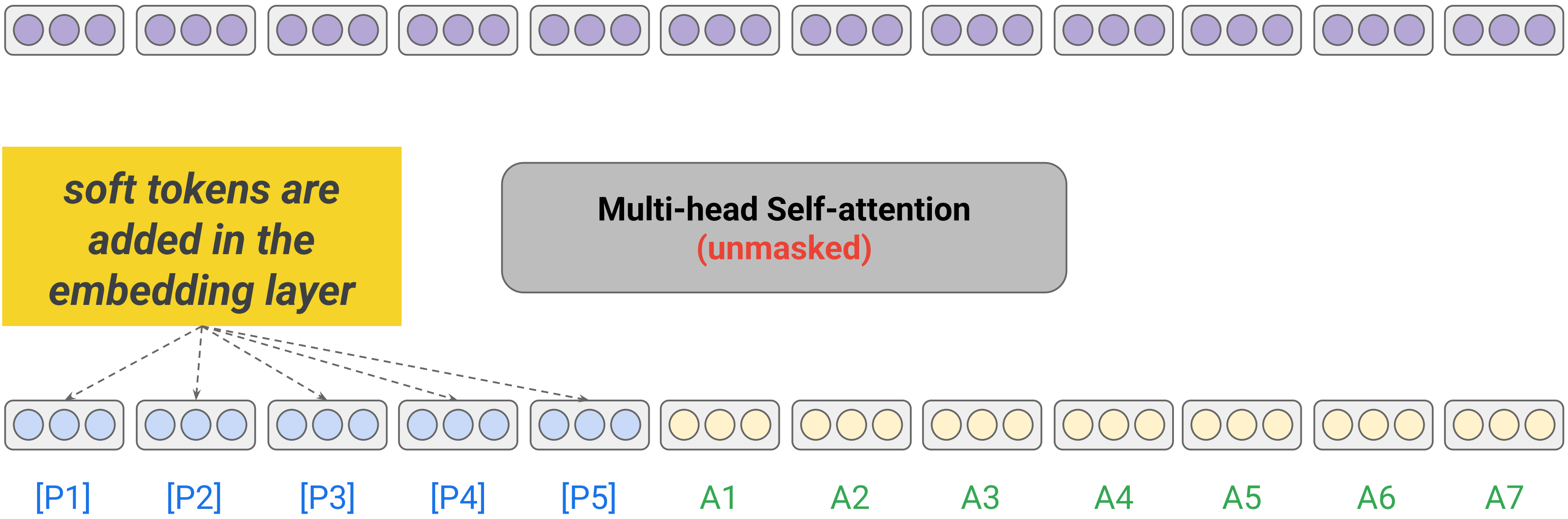
- Parameter-efficient transfer learning
- Multimodal learning
- Security & privacy

Soft prompt tuning



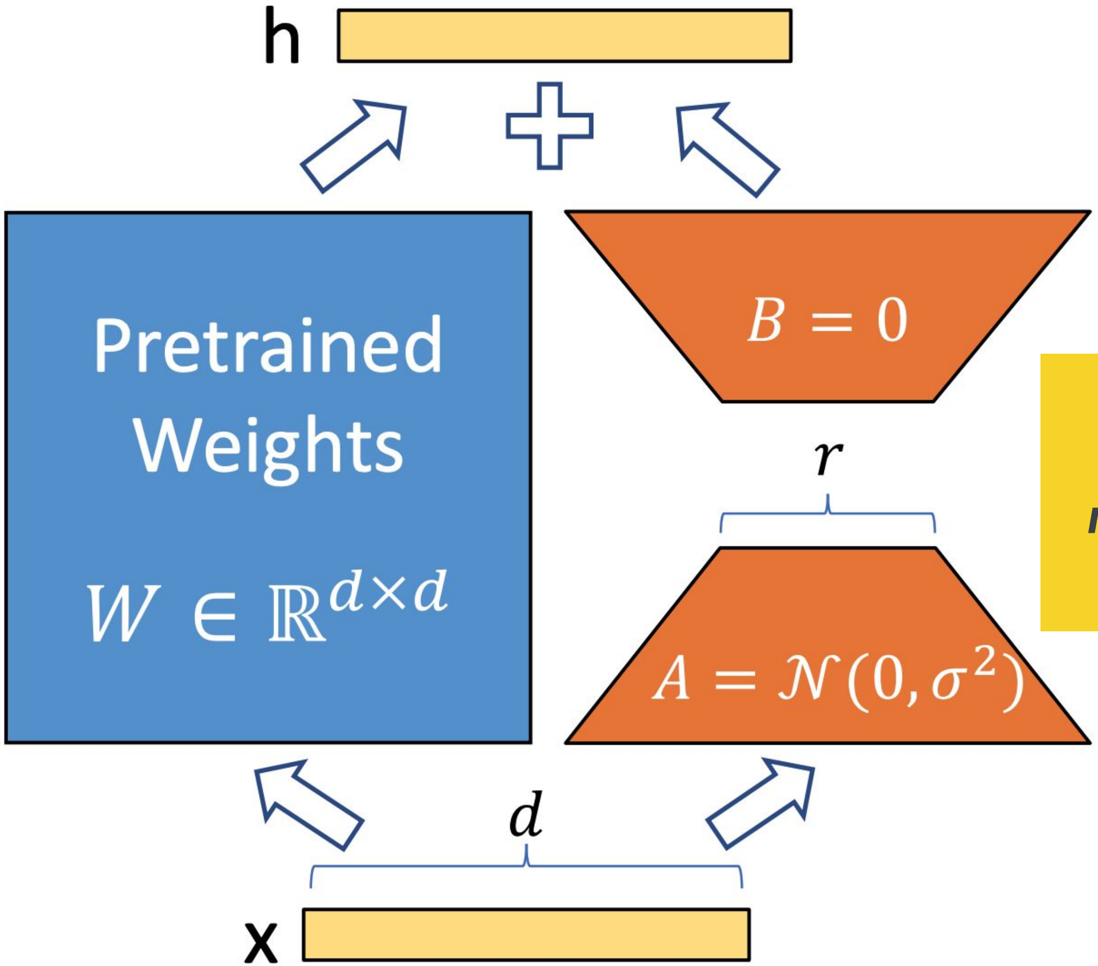
[*"The Power of Scale for Parameter-Efficient Prompt Tuning" by Lester et al. (2021)*]()

Soft prompt



soft tokens are added in the embedding layer
Multi-head Self-attention
(unmasked)
[P1]
[P2]
[P3]
[P4]
[P5]
A1
A2
A3
A4
A5
A6
A7

LoRA



Only rank decomposition matrices A and B are trained

Journal of Machine Learning Research 23 (2022) 1-40 Submitted 8/21; Revised 3/22; Published 4/22

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

William Fedus*
LIAMFEDUS@GOOGLE.COM

Barret Zoph*
BARRETZOPH@GOOGLE.COM

Noam Shazeer
NOAM@GOOGLE.COM

Google, Mountain View, CA 94043, USA

The Bitter Lesson

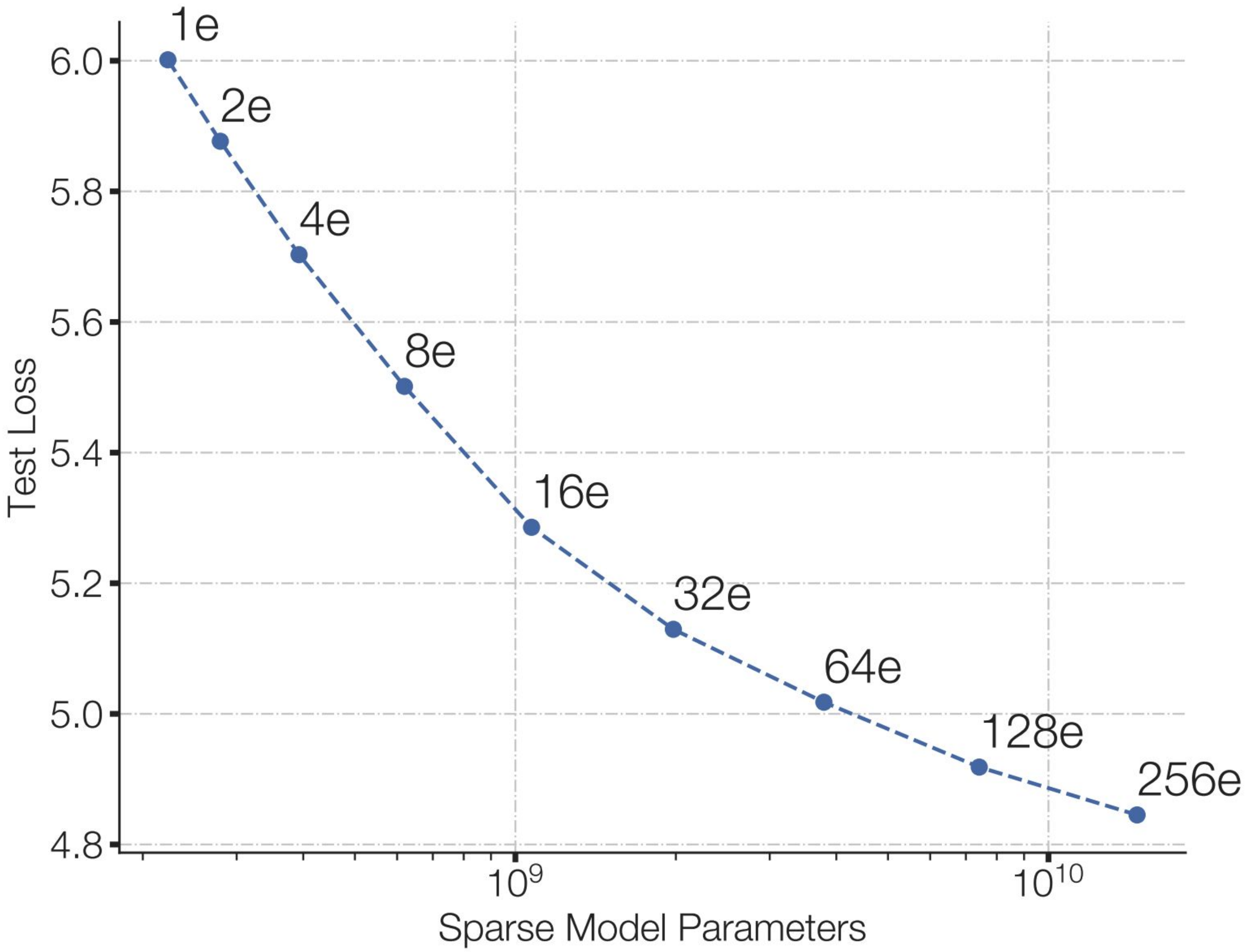
"The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin."

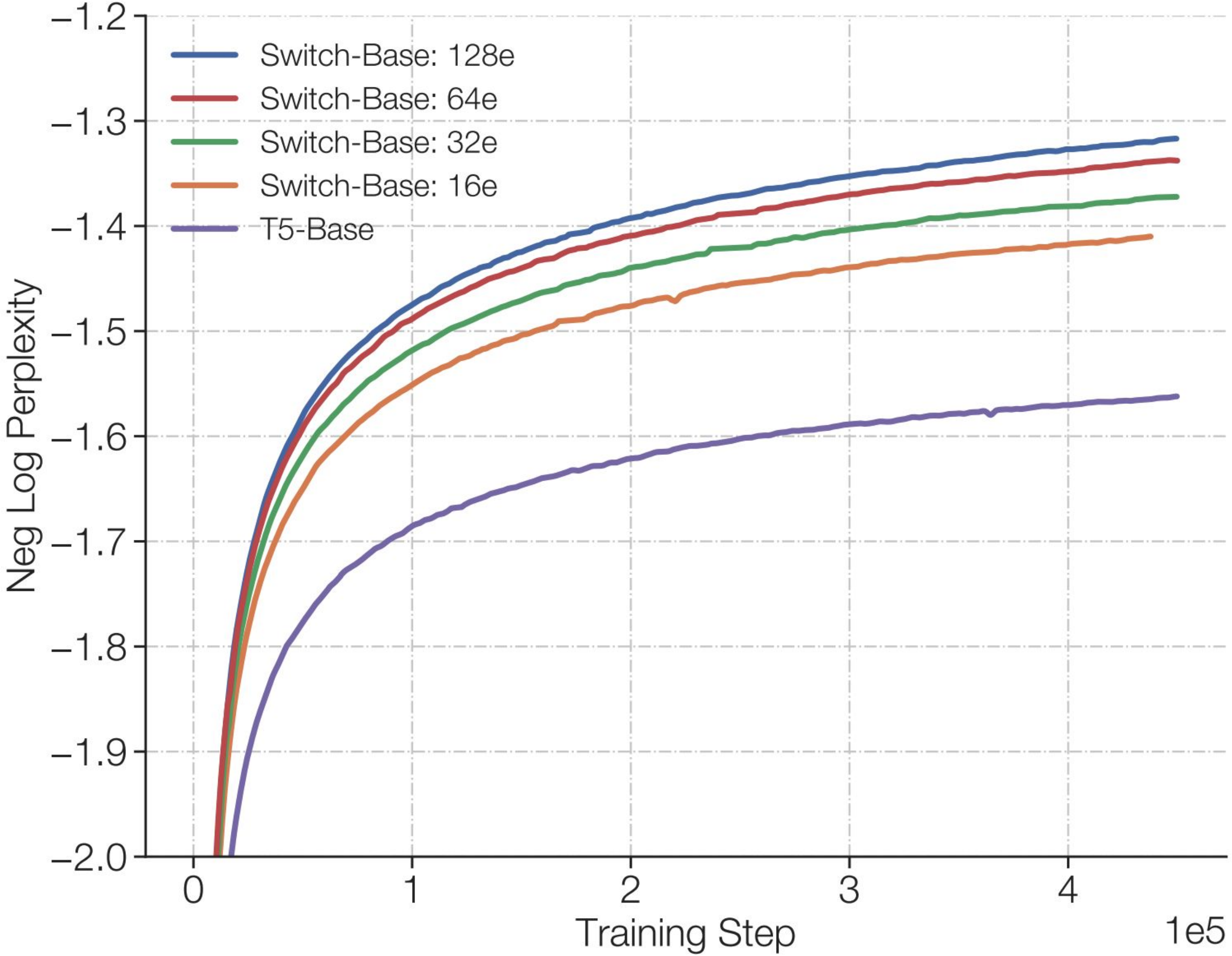
Rich Sutton, 2019

Simple architectures—backed by a generous computational budget, data set size and parameter count—surpass more complicated algorithms

Switch Transformers

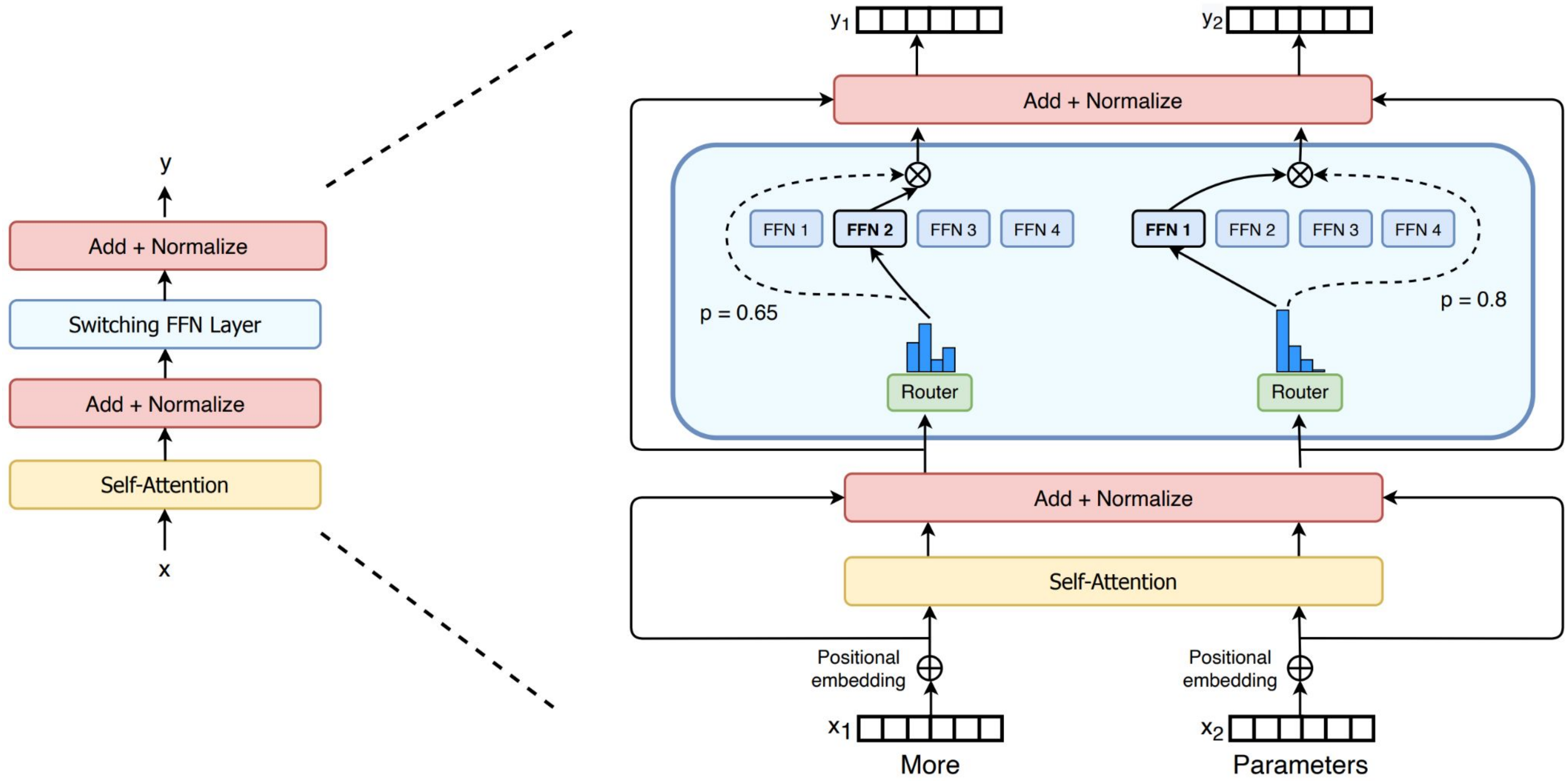
- Vanilla Transformer
  - densely-activated
- Switch Transformer
  - sparsely-activated expert model
  - with an outrageous number of parameters—but a constant computational cost (!)
  - pretraining up to *trillion* parameter models and achieving a 4x speedup over the T5-XXL (11B)


1e
2e
4e
8e
16e
32e
64e
128e
256e
6.0
5.8
5.6
5.4
5.2
5.0
4.8
Test Loss
10^9
10^{10}
Sparse Model Parameters


Switch-Base: 128e
Switch-Base: 64e
Switch-Base: 32e
Switch-Base: 16e
T5-Base
Neg Log Perplexity
−1.2
−1.3
−1.4
−1.5
−1.6
−1.7
−1.8
−1.9
−2.0
0
1
2
3
4
Training Step
1e5

Switch Transformers

The layer operates independently on the tokens



Mixture of Expert Routing

The MoE layer takes as an input a token representation x and then routes this to the best determined top-k experts, selected from a set $\{E_i(x)\}_{i=1}^N$ of N experts.

The router variable W_r produces logits $h(x) = W_r \cdot x$, which are normalized via a softmax distribution over the available N experts at that layer. The gate value for expert i is given by:

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

The top-k gate values are selected for routing the token x. If T is the set of selected top-k indices, then the output computation of the layer is the linearly weighted combination of each expert's computation on the token by the gate value:

$$y = \sum_{i \in T} p_i(x) E_i(x)$$

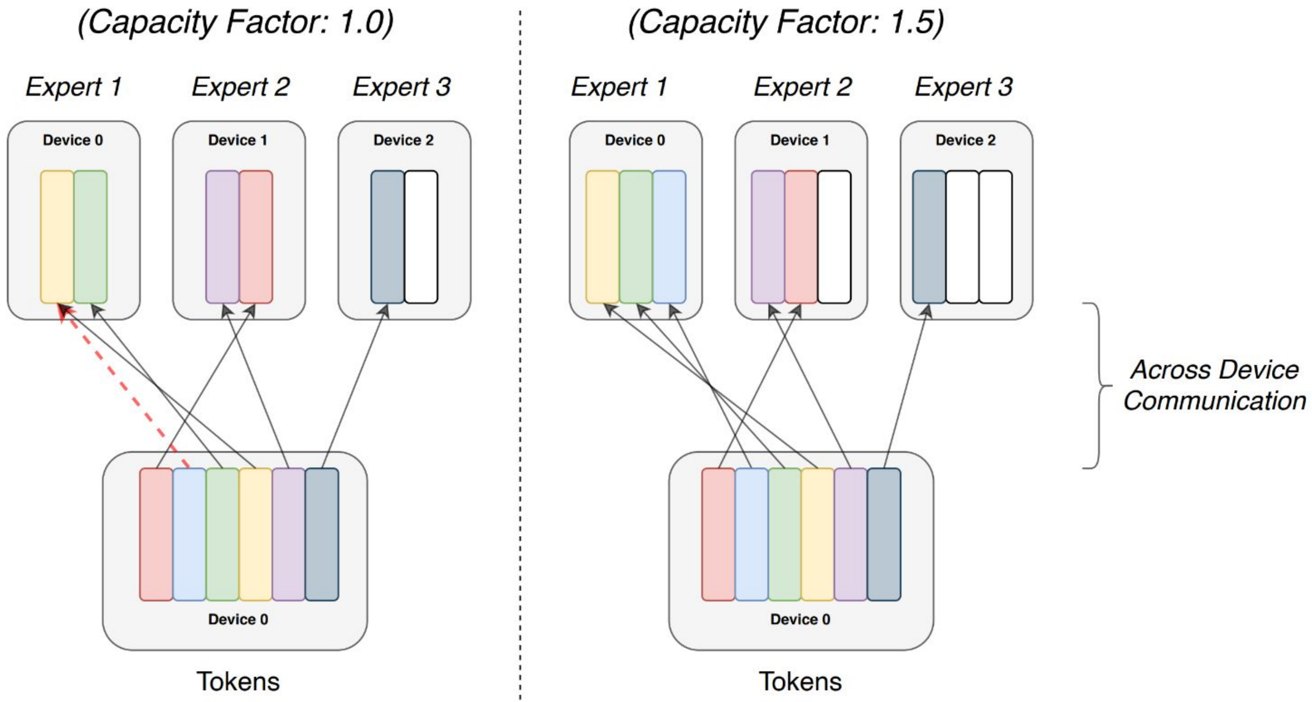
Rethinking Mixture-of-Experts

- Shazeer et al. (2017)
  - routing to *k > 1* experts
  - intuition: learning to route would not work without the ability to compare at least two experts
- Switch layer
  - routes to only a *single* expert
  - preserves model quality
  - reduces routing computation
  - performs better

$$\text{expert capacity} = \left(\frac{\text{tokens per batch}}{\text{number of experts}} \right) \times \text{capacity factor}$$

Terminology

- **Experts:** Split across devices, each having their own unique parameters. Perform standard feed-forward computation.
- **Expert Capacity:** Batch size of each expert. Calculated as
- (tokens_per_batch / num_experts) * capacity_factor
- **Capacity Factor:** Used when calculating expert capacity. Expert capacity allows more buffer to help mitigate token overflow during routing.



What would happen with the blue (dropped) token?

overflow

wasted computation & memory

An auxiliary load balancing loss

Given N experts indexed by $i = 1$ to N and a batch B with T tokens, the auxiliary loss is computed as the scaled dot-product between vectors f and P:

$$\text{loss} = \alpha \cdot N \sum_{i=1}^{N} f_i \cdot P_i$$

f_i: fraction of tokens to expert i

- ***For each token in the batch, check which expert got chosen.***
- ***Count how many times expert i was picked.***
- ***Divide by the total number of tokens T to get the fraction.***

P_i: router probability for expert i

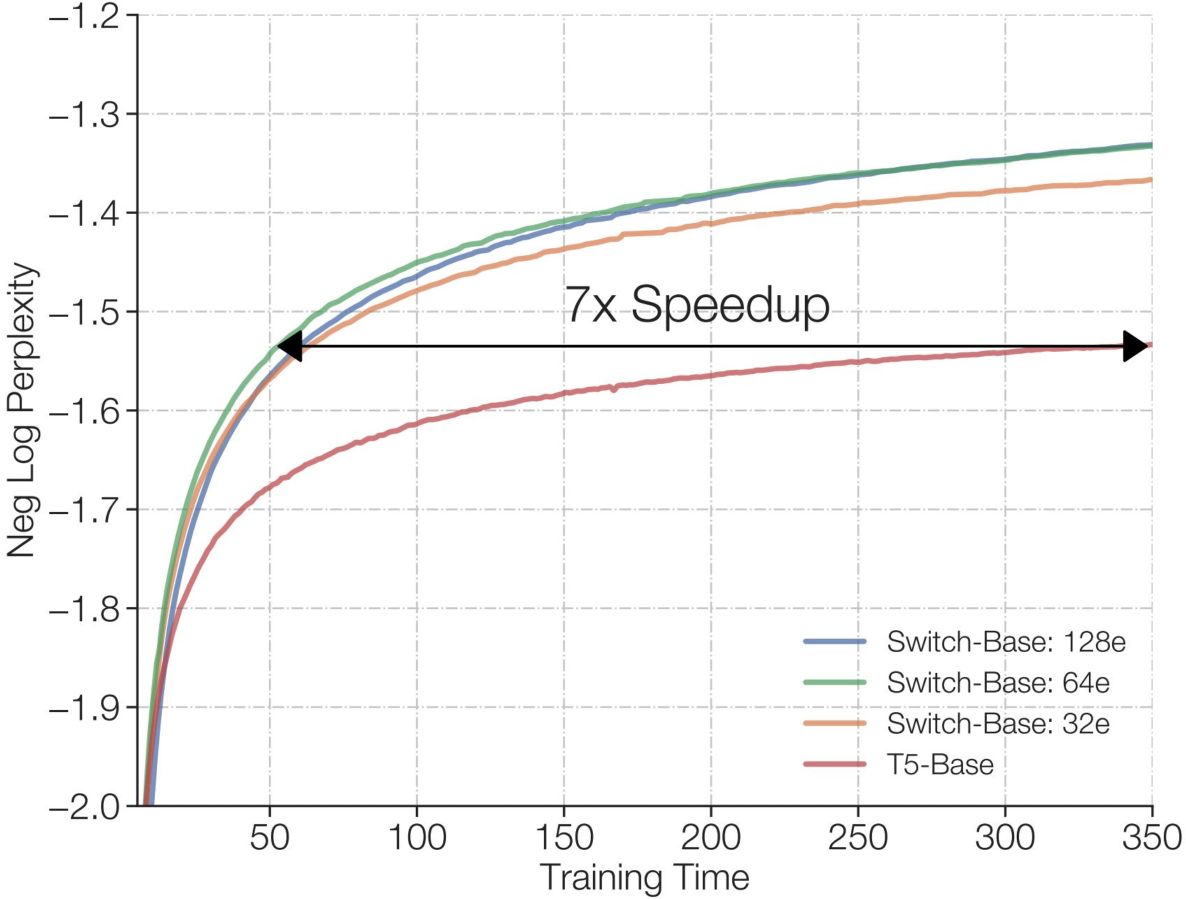
- ***The router assigns probabilities to each expert for every token.***
- ***For each token, take the probability that expert i i was preferred.***
- ***Average over all tokens.***

The auxiliary loss encourages uniform routing since it is minimized under a uniform distribution

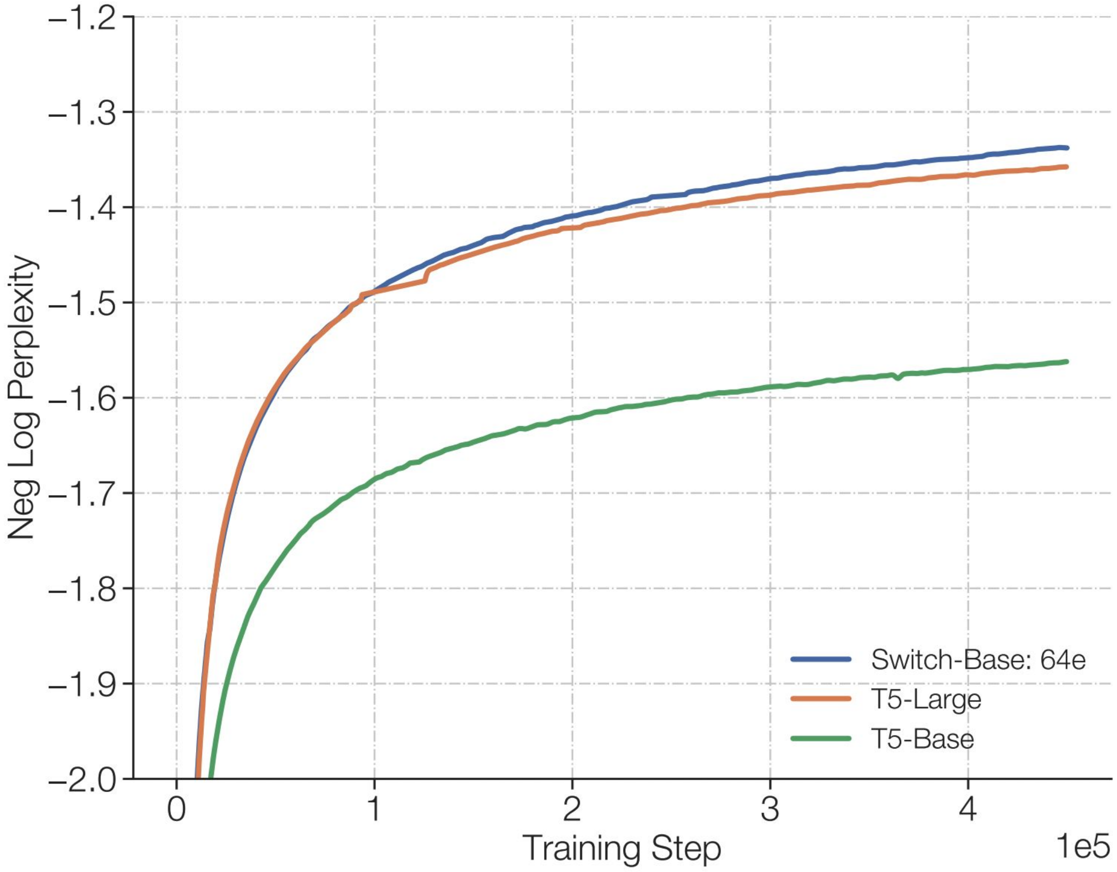
Lower standard dropout rate for non-expert layers, higher for expert feed-forward layers

Model (dropout)	GLUE	CNNDM	SQuAD	SuperGLUE
T5-Base (d=0.1)	82.9	**19.6**	83.5	72.4
Switch-Base (d=0.1)	84.7	19.1	**83.7**	**73.0**
Switch-Base (d=0.2)	84.4	19.2	**83.9**	**73.2**
Switch-Base (d=0.3)	83.9	19.6	83.4	70.7
Switch-Base (d=0.1, ed=0.4)	**85.2**	**19.6**	**83.7**	**73.0**

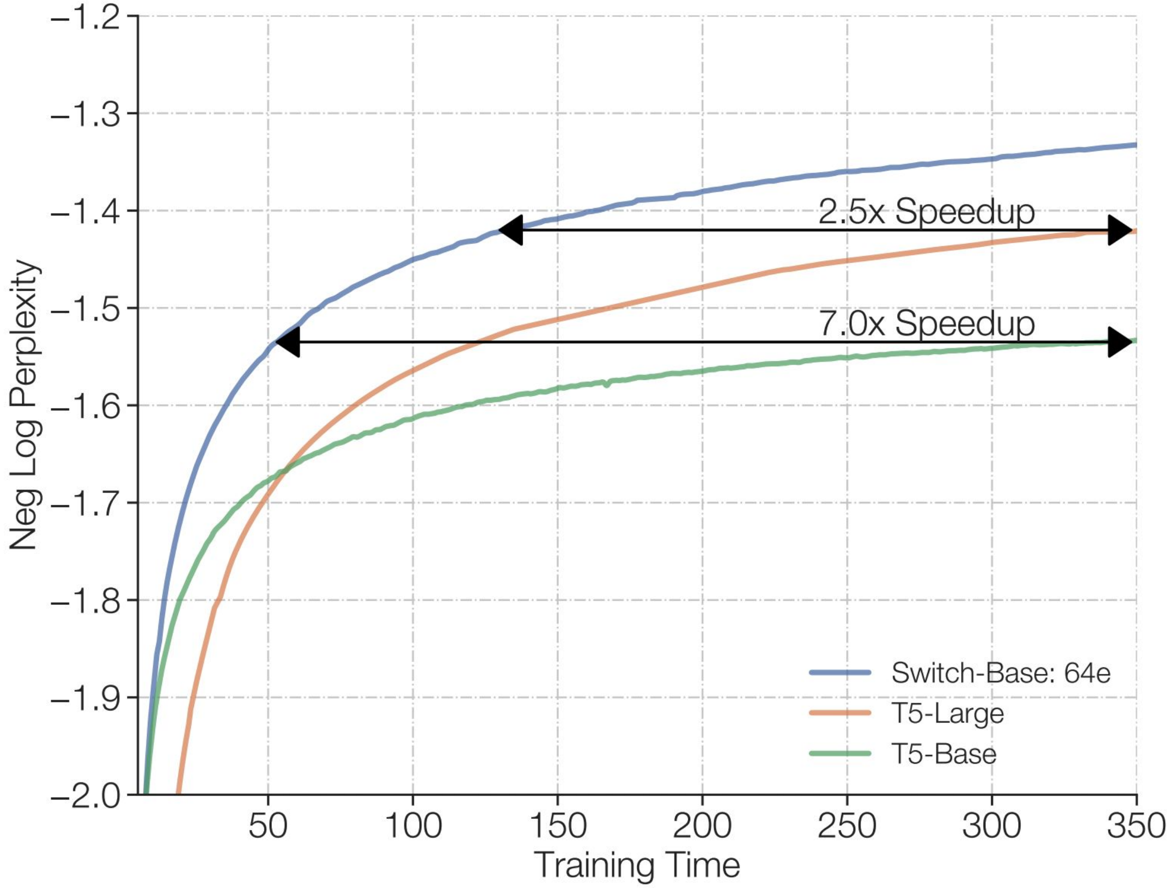
Speed advantage of Switch Transformer



Switch-Base is more sample efficient than T5-Large



Switch-Base is faster than T5-Large (2.5x speedup)



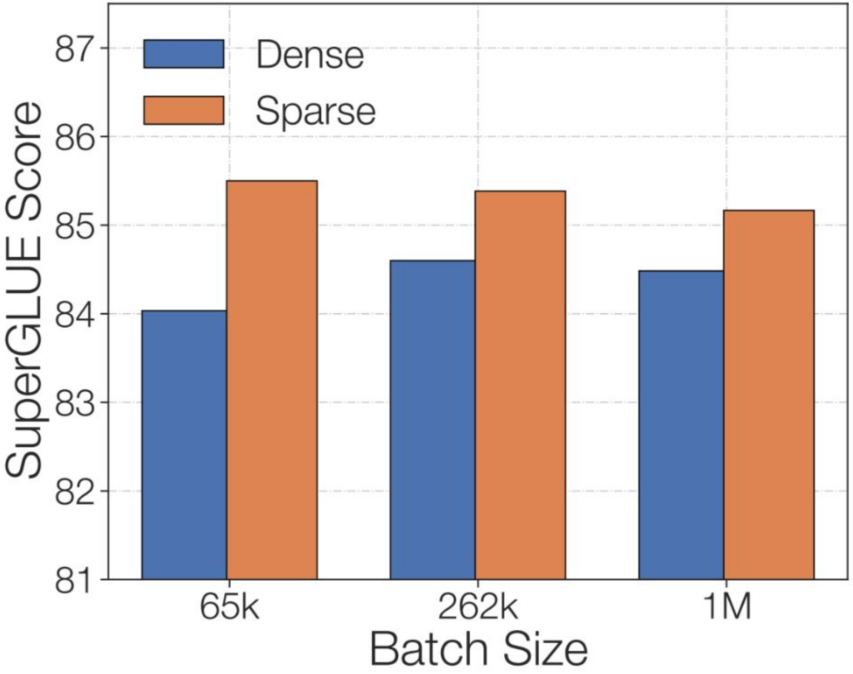
… and significant downstream improvements

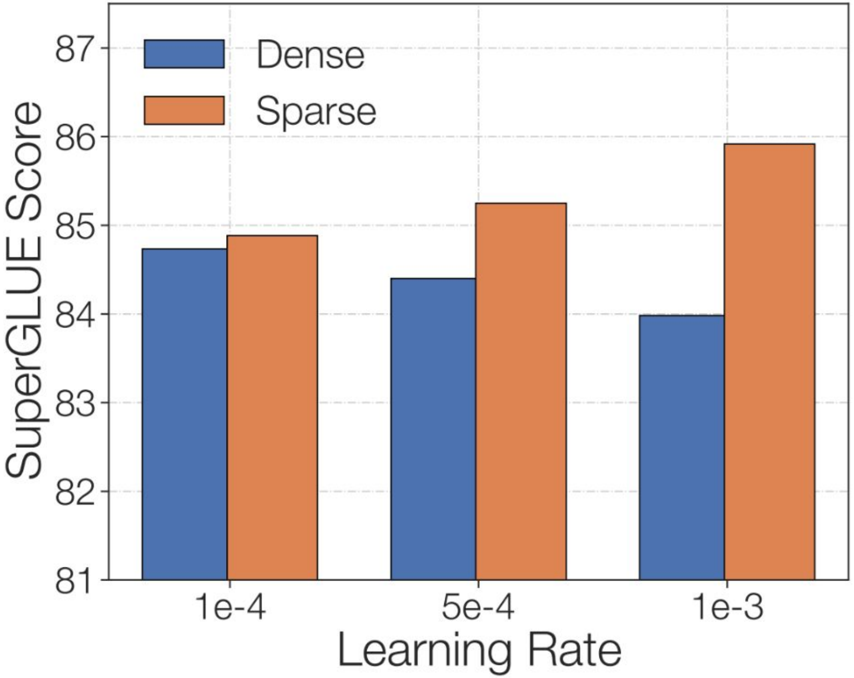
Model	GLUE	SQuAD	SuperGLUE	Winogrande (XL)
T5-Base	84.3	85.5	75.1	66.6
Switch-Base	**86.7**	**87.2**	**79.5**	**73.3**
T5-Large	87.8	88.1	82.7	79.1
Switch-Large	**88.5**	**88.6**	**84.7**	**83.0**

Model	XSum	ANLI (R3)	ARC Easy	ARC Chal.
T5-Base	18.7	51.8	56.7	**35.5**
Switch-Base	**20.3**	**54.0**	**61.3**	32.8
T5-Large	20.9	56.6	**68.8**	**35.5**
Switch-Large	**22.3**	**58.6**	66.0	**35.5**

Model	CB Web QA	CB Natural QA	CB Trivia QA
T5-Base	26.6	25.8	24.5
Switch-Base	**27.4**	**26.8**	**30.7**
T5-Large	27.7	27.6	29.5
Switch-Large	**31.3**	**29.5**	**36.9**

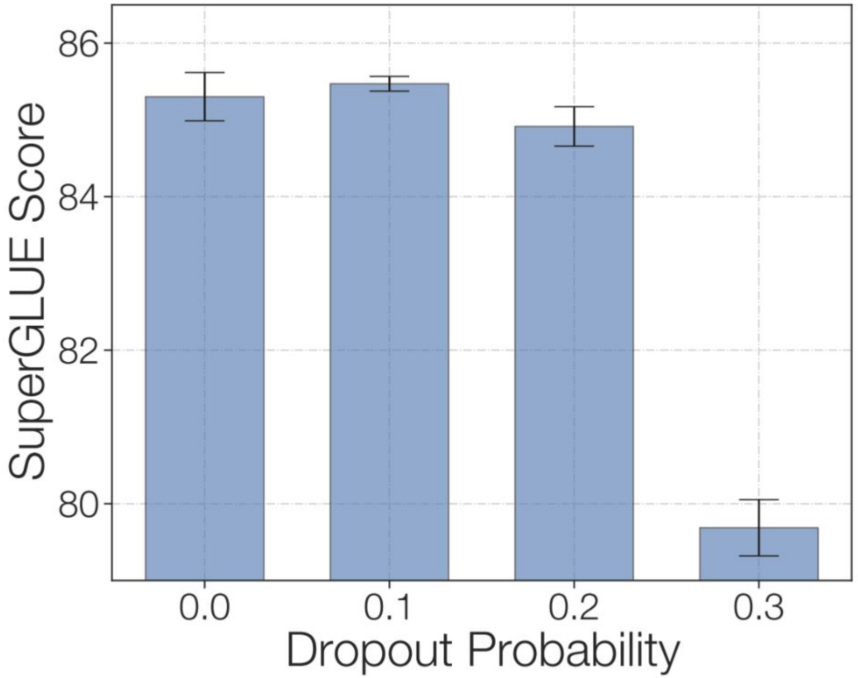
Sparse models benefit from small batch sizes and high learning rates

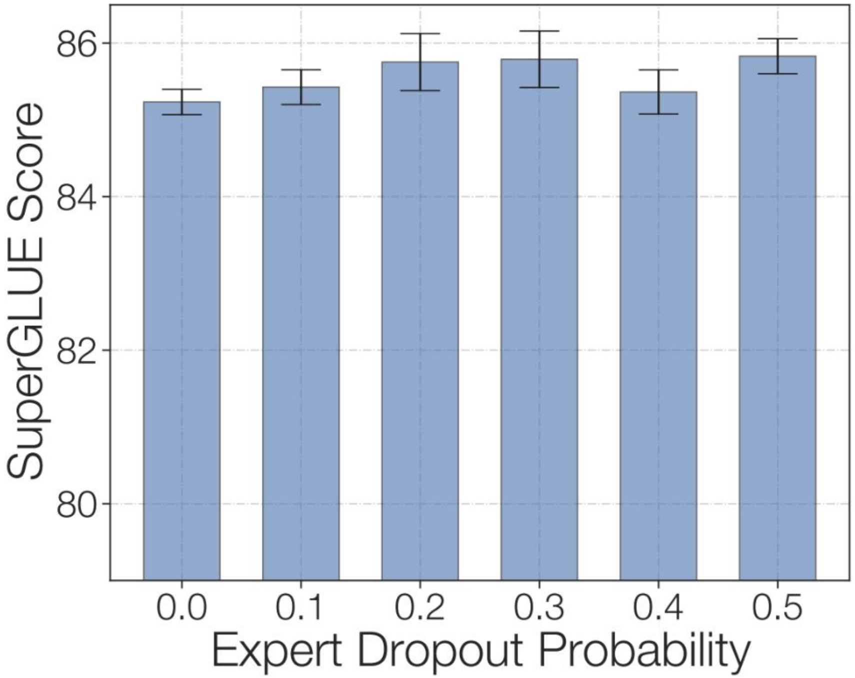




[“ST-MoE: Designing Stable and Transferable Sparse Expert Models” by Zoph et al. (2022)]

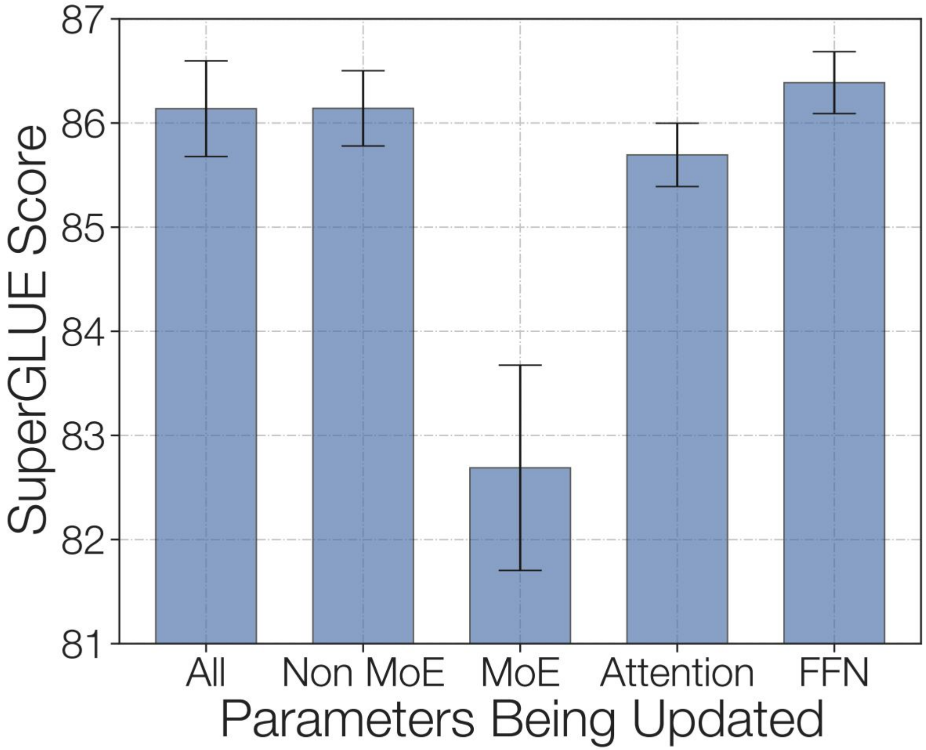
Sparse models benefit from high dropout rates





[“ST-MoE: Designing Stable and Transferable Sparse Expert Models” by Zoph et al. (2022)]

By freezing the MoE layers, we can speed up the training while preserving the quality



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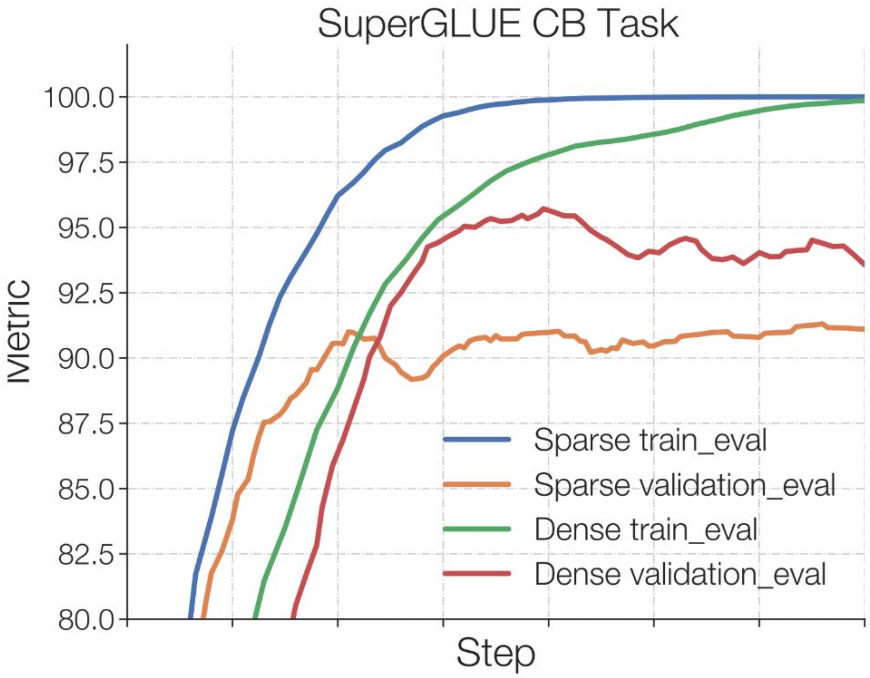
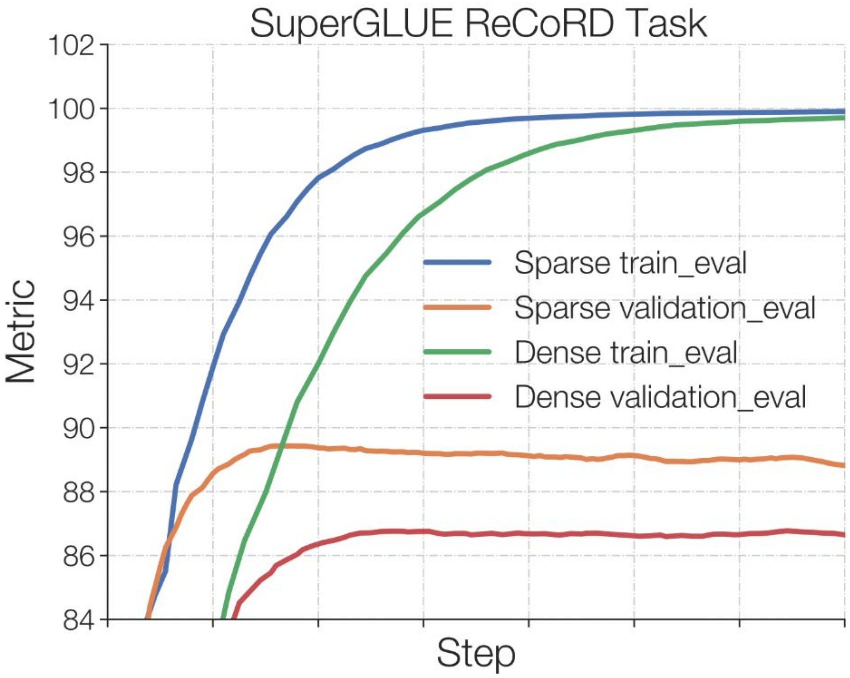
Sparse models are prone to overfit

250 examples



138k examples



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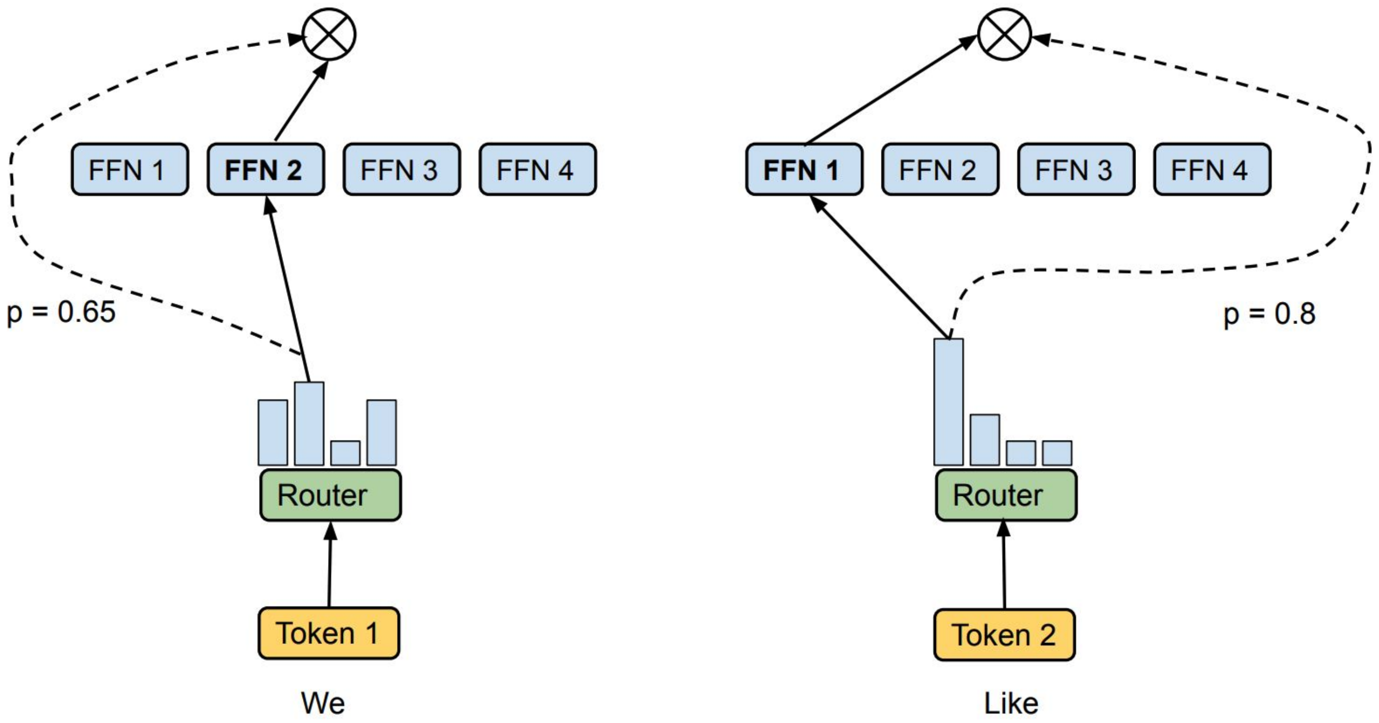
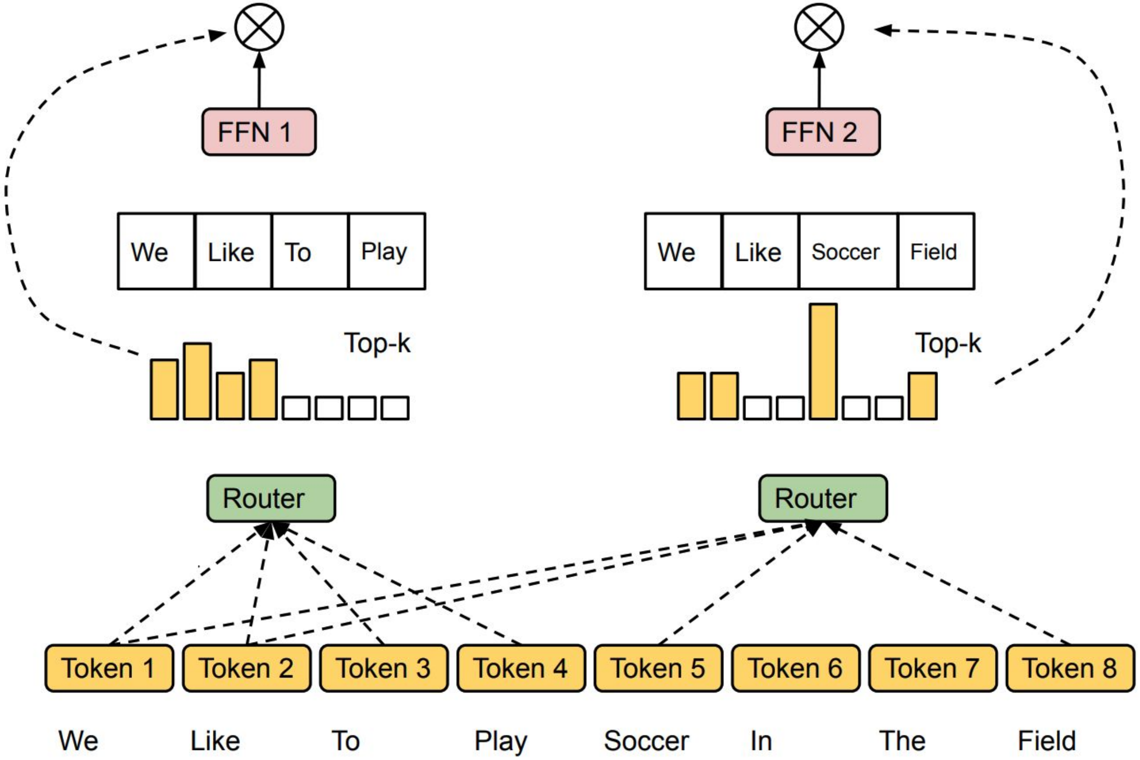
Token-choice routing



[“Mixture-of-Experts with Expert Choice Routing” by Zhou et al. (2022)]

Expert-choice routing



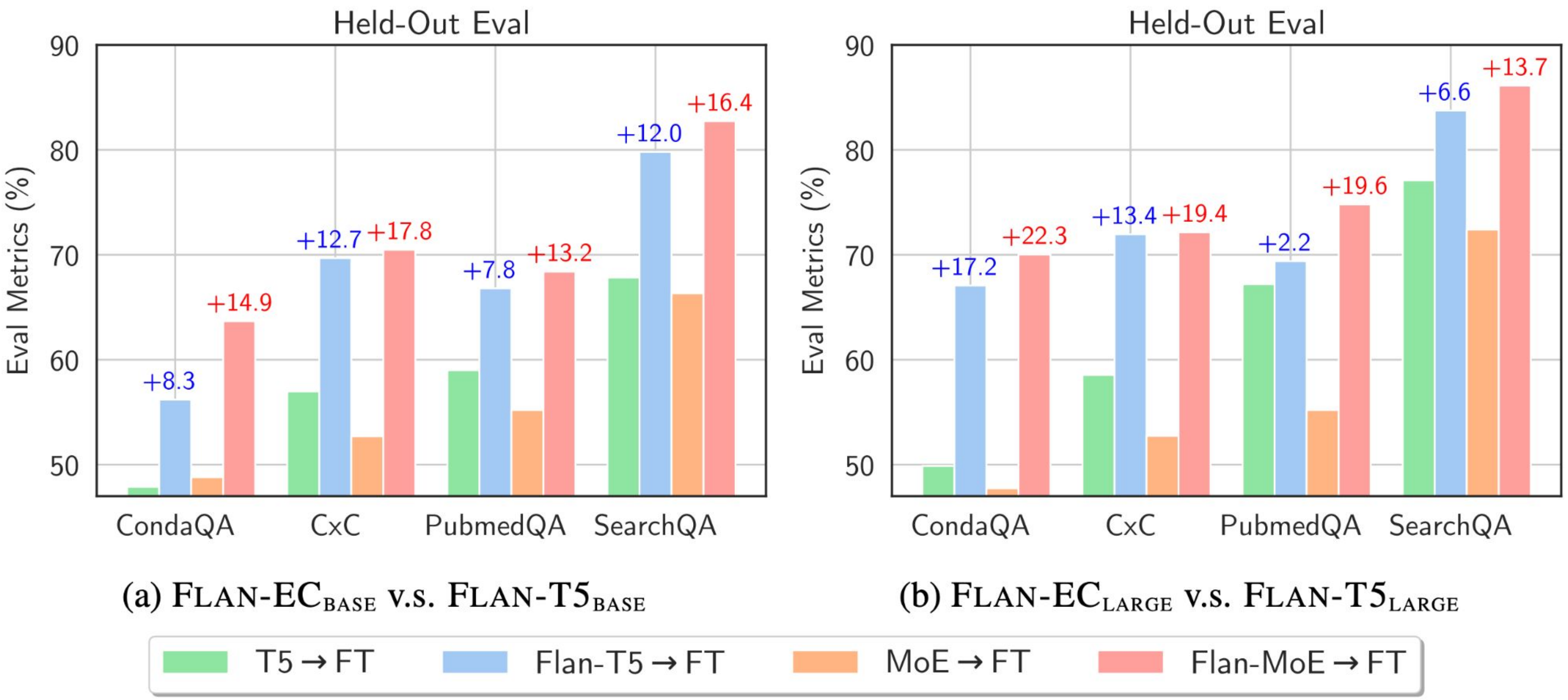
[“Mixture-of-Experts with Expert Choice Routing” by Zhou et al. (2022)]

Mixture-of-Experts Meets Instruction Tuning: A Winning Combination for Large Language Models

Sheng Shen[♮*] **Le Hou**[†] **Yanqi Zhou**[†] **Nan Du**[†] **Shayne Longpre**[⊤*] **Jason Wei**[†],
Hyung Won Chung[†] **Barret Zoph**[†] **William Fedus**[†] **Xinyun Chen**[†] **Tu Vu**[‡*],
Yuexin Wu[†] **Wuyang Chen**[§*] **Albert Webson**[†] **Yunxuan Li**[†] **Vincent Zhao**[†] **Hongkun Yu**[†]
Kurt Keutzer[♮] **Trevor Darrell**[♮] **Denny Zhou**[†]

[†]Google [♮]University of California, Berkeley [⊤]Massachusetts Institute of Technology
[‡]University of Massachusetts Amherst [§]The University of Texas at Austin

Mixture-of-Experts meets Instruction Tuning



(a) FLAN-EC$_{\text{BASE}}$ v.s. FLAN-T5$_{\text{BASE}}$ (b) FLAN-EC$_{\text{LARGE}}$ v.s. FLAN-T5$_{\text{LARGE}}$

When to use sparse MoEs vs dense models?

Thank you!