Mixture of Experts meets Instruction Fine Tuning

Paper

- https://arxiv.org/pdf/2305.14705.pdf

Why was it made

- Says that llm are computationally expensive
- Mixture of experts reduces computational overhead
- Proposed model Combines instruction fine tuning and Mixture of experts

Mixture of Experts

- Idea that language models can be **decomposed into smaller, specialized sub-models**, or "experts", that focus on distinct aspects of the input data, thereby enabling more efficient computation and resource allocation
- However typical Moe leads to lower performance
- But its better if they use **both** instruction tuning and MoE

Model architecture

- Replaces every feedforward layer in transformer with MoE layer
    - Similar to Switch transformer (https://arxiv.org/pdf/2101.03961.pdf)
- Each MoE layer consists of a collection of independent feed-forward networks as the **'experts'**.
    - Interesting that its a layer with networks
    - Only a subset of those experts is used which reduces computation
- Gating function uses softmax activation over the experts
    - Models a probability distribution
    - Distribution indicates how well experts can handle the input
- The gating network is **trained** to only use the best 2 experts for each **token** of an input sequence
- During inference, the learned gating network dynamically picks the two best experts for each token
- For an MoE layer with E experts, it provides O(E^2) different combinations of feed-forward networks instead of one in the classic Transformer architecture,
- final learned representation of a token will be the weighted combination of the outputs from the selected experts.

Instruction fine tuning recipe

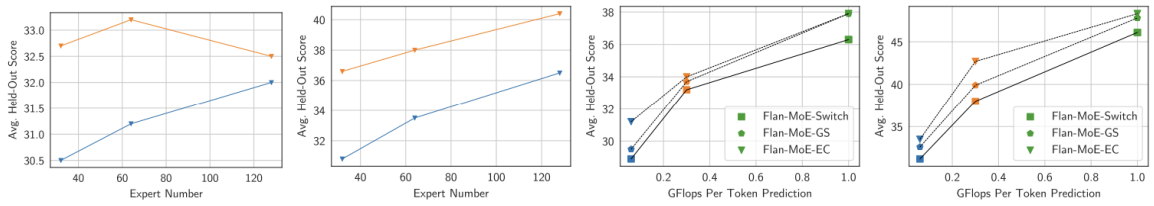
- fine-tune FLAN-MOE using the **prefix language model objective** on the FLAN collective dataset
    - Prefix language model objective is
    - https://blog.research.google/2021/10/introducing-flan-more-generalizable.html
- Uses the auxiliary loss during training
    - They tested both router Z loss and balancing loss. Balancing loss was better [ON CERTAIN TASKS]
        - **Mismatched** auxiliary loss and routing strategy could mean **lower performance**
- All model parameters are trained

Experiment Details

- In the context of instruction fine tuning
- Compares Flan-Moe to T5 models
    - T5 models are encoder-decoder model pre-trained on a multi-task mixture of unsupervised and supervised tasks and for which each task is converted into a text-to-text format
- Trained on 1,836 finetuning tasks
    - FLAN-MOE had lower flops
- Evaluated on both zero shot and few shot tasks
- Results: **The model FLAN-ST32B, comprising a total of 32 billion parameters, only utilizes 32.1 GFLOPs per token, which amounts to merely one-third of the computational power required by a FLAN-PALM62B model**
- Additionally, **all the routers combined account for less than 4 million parameters**

Expert Number

- The performance of FLAN-MOE models has been observed to scale with the number of experts included in the architecture to a certain threshold.

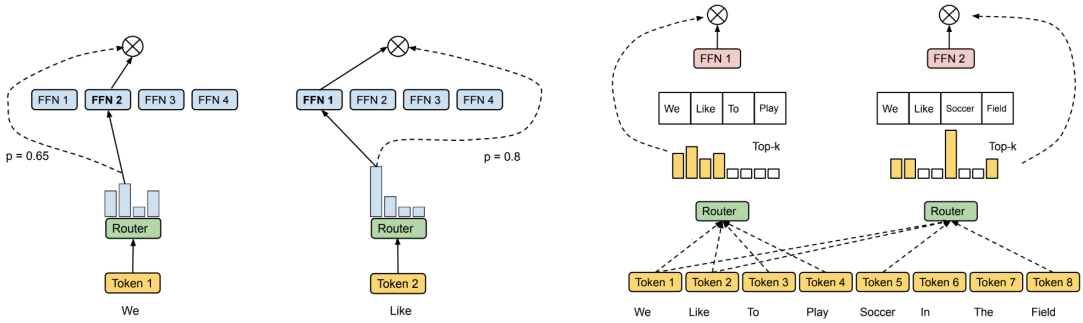


(a) Scaling (MMLU) (b) Scaling (BBH) (c) Routing (MMLU) (d) Routing (BBH)

Figure 4: Average few-shot performance of FLAN-MOE models over the 57 MMLU tasks and 23 BBH tasks. (Different color represents different dense model sizes.)

Routing Strategy

- **routing strategy intelligently distributes input data among multiple specialized experts**
- Important for maximizing the utilization of the model's capacity while minimizing the risk of **overfitting**
- two trending strategies
    - **token-choice** [23] which lets the **token select** the top-K experts
    - **expert-choice** [55] which lets the **experts select** the top-K tokens.
- FLAN-Switch: checkpoints from Switch Transformer top-1 token-choice gating
- FLAN-GS: GShard top-2 token-choice gating
- FLAN-EC: expert choice top-2 gating (FLAN-EC) models pre-trained on the same GLaM dataset
    - Probably based off https://arxiv.org/abs/2202.09368 ?
    - Instead of letting tokens select the top-k experts, we have experts selecting the top-k tokens



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    - Conventional vs non conventional moe
    - "We propose a very simple yet effective routing method we are calling expert choice. Unlike conventional MoE where tokens select one or two top-scoring experts, our method lets each expert pick the top-k tokens. Our method guarantees perfect load balancing, allows a variable number of experts for each

token, and achieves substantial gains in training efficiency and downstream performance as demonstrated in our experiments”

- “It is noteworthy that the performance gap between the token choice and expert-choice models can be bridged when we incorporate advanced auxiliary loss and pre-training strategy as exhibited in ST-MOE “

Random notes

- Seemingly flan-moe == flan-St

More Learning

- https://github.com/XueFuzhao/awesome-mixture-of-experts

Reference Papers

- https://blog.research.google/2021/10/introducing-flan-more-generalizable.html
- https://arxiv.org/abs/2202.09368
- https://arxiv.org/pdf/2310.06825.pdf
- https://arxiv.org/pdf/2101.03961.pdf
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- https://huggingface.co/blog/moe#what-is-sparsity
- https://github.com/mistralai/mistral-src/blob/main/tutorials/classifier.ipynb
- https://www.databricks.com/blog/introducing-mixtral-8x7b-databricks-model-serving
- https://arxiv.org/pdf/2210.11416.pdf
- https://huggingface.co/blog/moe#what-is-a-mixture-of-experts-moe
- https://arxiv.org/abs/2202.09368 mixture of expert with expert route choice
- https://arxiv.org/abs/2101.03961 Switchhead

Questions

- How are networks in the MoE layer initialized ?
- Which routing strategy did they introduce in Flan-MOE?