

arxiv.org/abs/ 2408.15901

Nexus: Specialization meets Adaptability for Efficiently Training Mixture of Experts

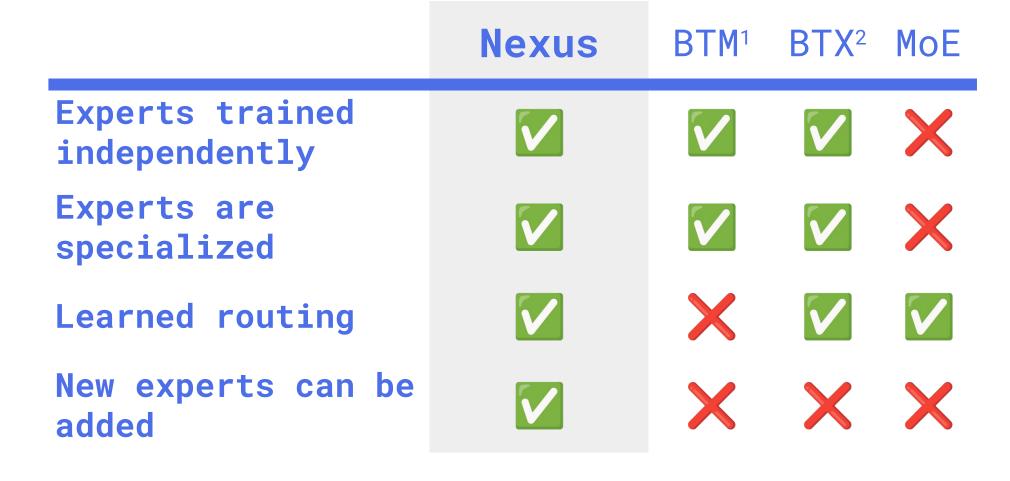
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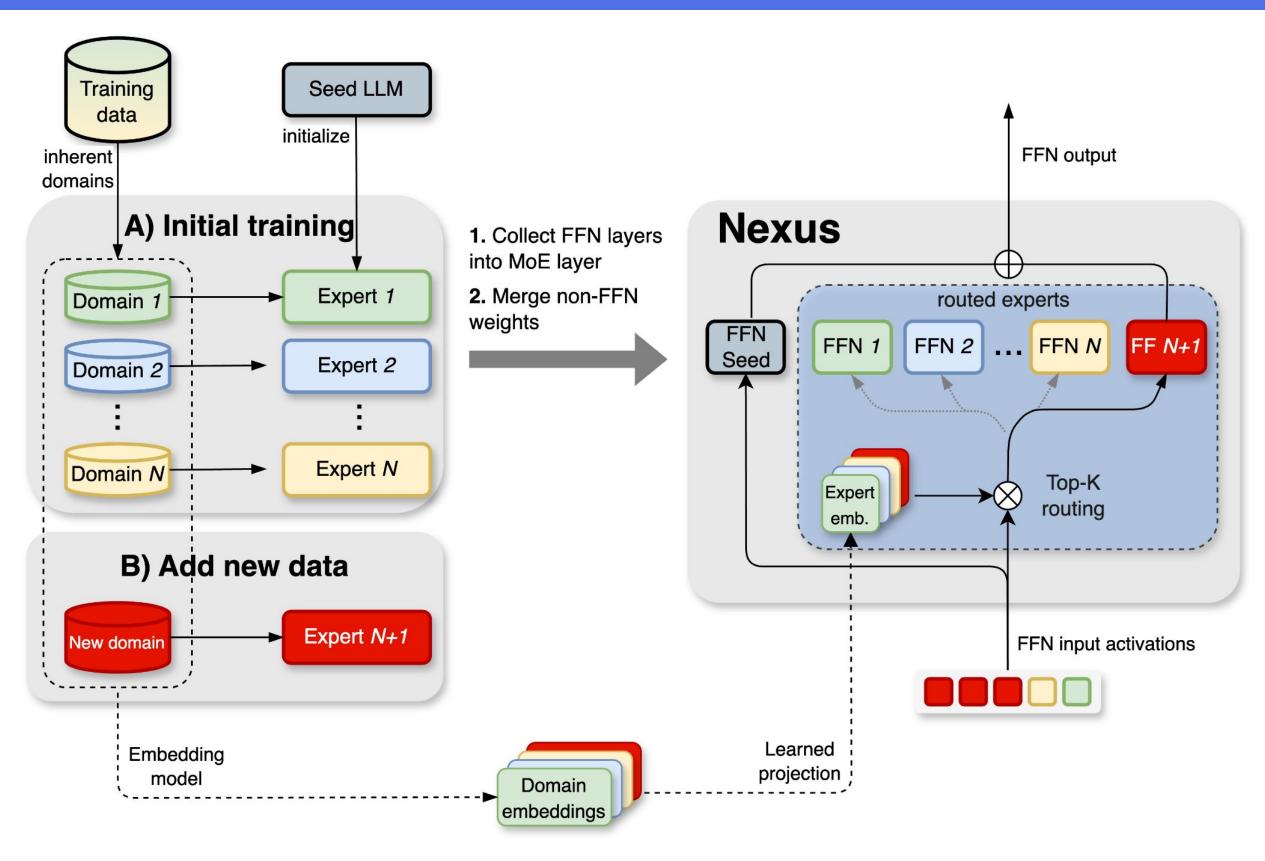
> ¹Cohere For Al ²Cohere ³University of Oxford *Work done as part of the Research Scholar Program

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Mixture of Experts from Specialized LMs

- ? How can we best upcycle specialized dense models into an MoE model?
- ? How can an MoE router adapt to new experts after the initial training?
- **Current MoEs are limited in different ways:**





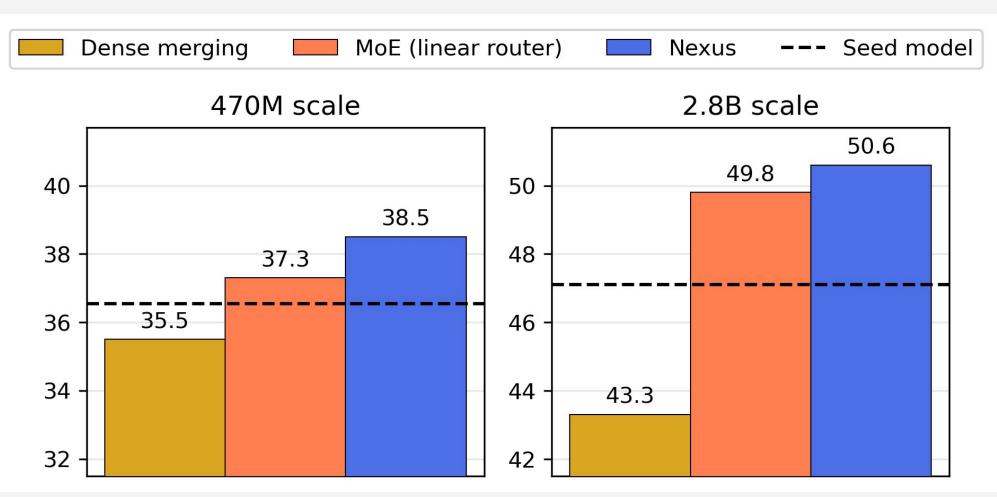
Contributions of Nexus

Efficient parallel, asynchronous expert training
Experts truly **specialized** on individual domains
Adapt to new experts after initial training without catastrophic forgetting

Our vision: In an ecosystem with many open-source finetunes of the same base model (e.g. Llama 3), use Nexus to quickly assemble your personalized MoE, and extend it anytime with new domains!

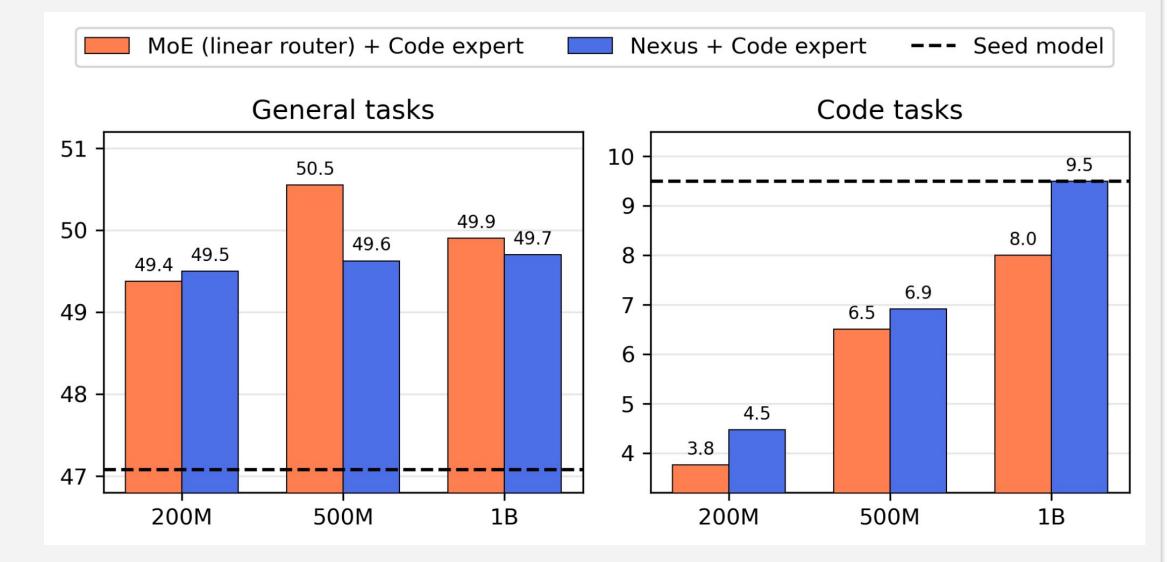
Methodology

- Train *n* dense experts (initialized from same pretrained model) on different datasets/domains (e.g. ArXiv, Books, C4, Wikipedia)
- Convert the dense models to a single Nexus model by **stacking** the dense model MLPs into an MoE layer and **averaging** all other params
- How do we know when to route to each expert?
 - 1. Baseline (BTX): train a router (linear proj.) for 40B tokens
 - 2. Nexus: use expert training data embeddings as informative prior! They capture the "knowledge" each expert has. Train for 40B tokens to learn a projection from data embedding space to model latent space, then route by choosing the most similar embedding to a token's latent representation



Nexus beats BTM and BTX for <u>pre-training</u>:

Nexus adapts better to <u>new experts</u>:



- 4 experts are initialized from a pretrained model and trained for 40B tokens on ArXiv, Books, C4, and Wikipedia
- Upcycling with Nexus outperforms both BTX and a full model averaging baseline on Knowledge, Science, Reasoning and MMLU downstream tasks (all compute and data matched)
- Nexus also beats training a dense model with the data/compute of all experts!
- For the new expert, a dense model is trained for 40B tokens on a new domain (Code), appended to the Nexus expert layer, and fine-tuned on all data for budgets of 200M/500M/1B tokens
- Nexus outperforms BTX on the new domain, and the gap increases with more finetuning

Q: Does Nexus add overhead for training/inference?

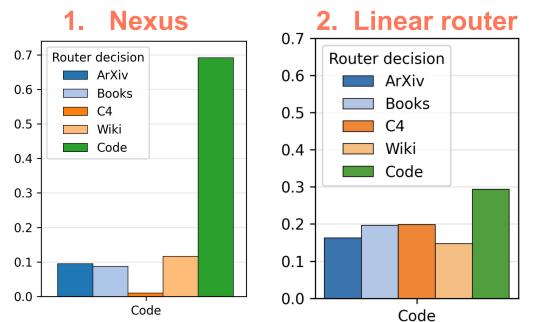
A: No, same complexity as vanilla MoE!

- Training: less than 1% additional parameters
- Inference: 0% overhead as expert embeddings can be precomputed!
 - Intuition: learned projection is a **hypernetwork** that computes the router weights, using the dataset embeddings as input. Only need to recompute when set of expert changes

Q: Is the routing in Nexus truly specialized?

A: Yes!

- Nexus assigns tokens more often to the expert specia-lized on that domain
- Comparison of routing distributions for code tokens:



References

Margaret Li, Suchin Gururangan, Tim Dettmers, Mike Lewis, Tim Althoff, Noah A. Smith, & Luke Zettlemoyer. (2022). Branch-Train-Merge: Embarrassingly Parallel Training of Expert Language Models.
Sainbayar Sukhbaatar, Olga Golovneva, Vasu Sharma, Hu Xu, Xi Victoria Lin, Baptiste Rozière, Jacob Kahn, Daniel Li, Wen-tau Yih, Jason Weston, & Xian Li. (2024). Branch-Train-MiX: Mixing Expert LLMs into a Mixture-of-Experts LLM.
Suchin Gururangan, Margaret Li, Mike Lewis, Weijia Shi, Tim Althoff, Noah A. Smith, & Luke Zettlemoyer. (2023). Scaling Expert Language Models with Unsupervised Domain Discovery.

Special thanks to John Lin, Tim Chung, Sylvie Shi, Arkady Arkhangorodsky, David Cairuz, Felipe Cruz Salinas, Milad Alizadeh, James Owers-Bardsley, and Viraat Aryabumi for their support!