Once Read is Enough: Domain-specific Pretraining-free Language Models with Cluster-guided Sparse Experts for Long-tail Domain Knowledge

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Introduction

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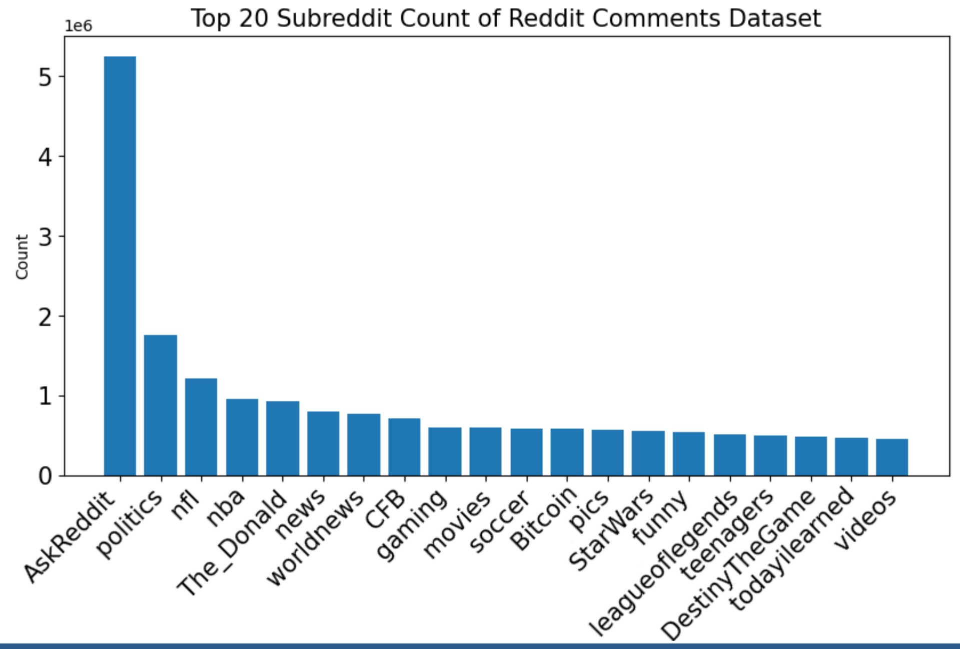
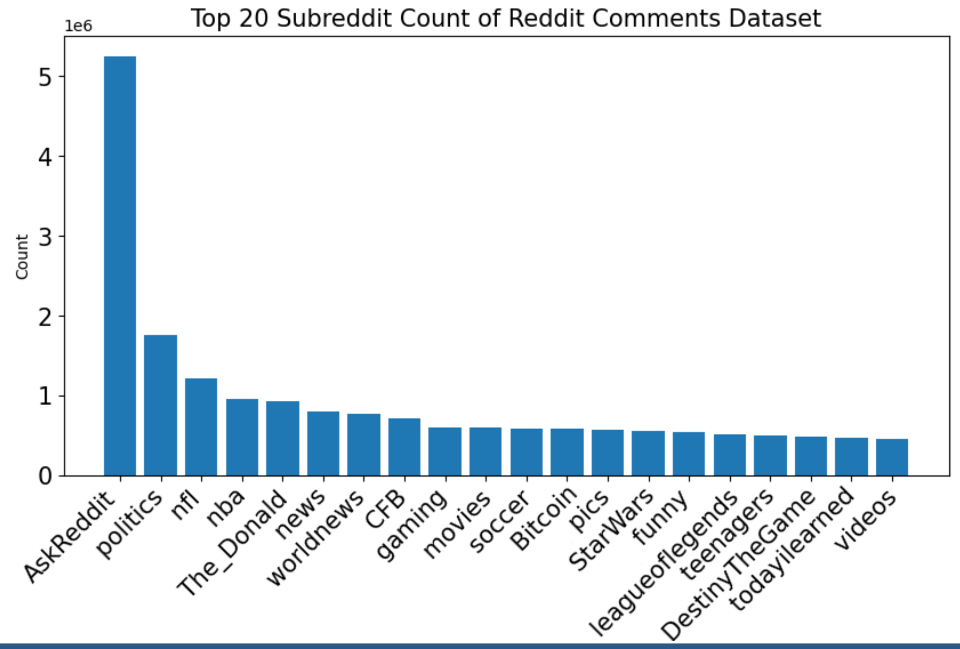
- Domain-specific information appears significantly less frequently than general knowledge, or long-tail.



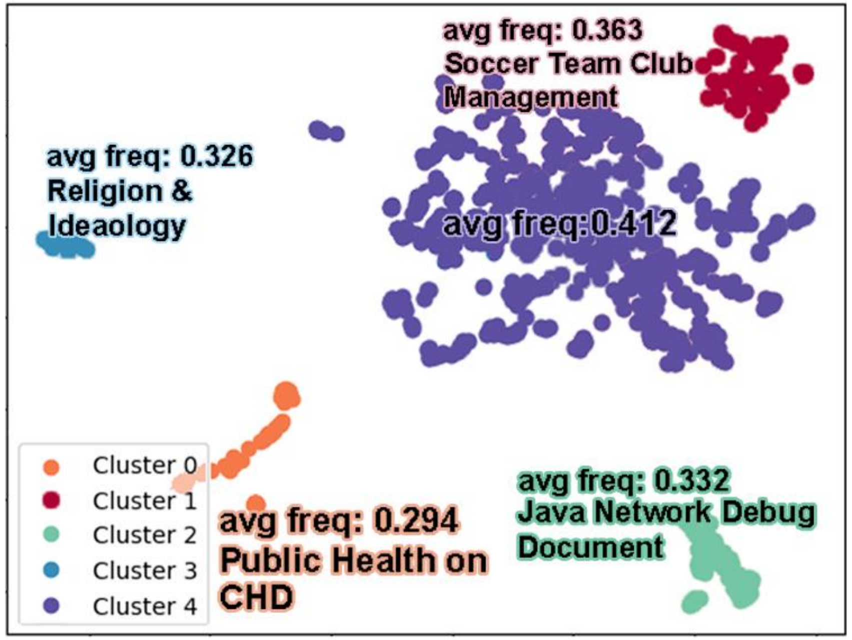
Analysis

- Data domains show a long-tail distribution.



Analysis

- Data domains show a long-tail distribution.
- Lower frequency score for domain-specific data
  - Frequency score is defined as average token frequency in a sentence
  - Low-frequency score data are considered long-tail



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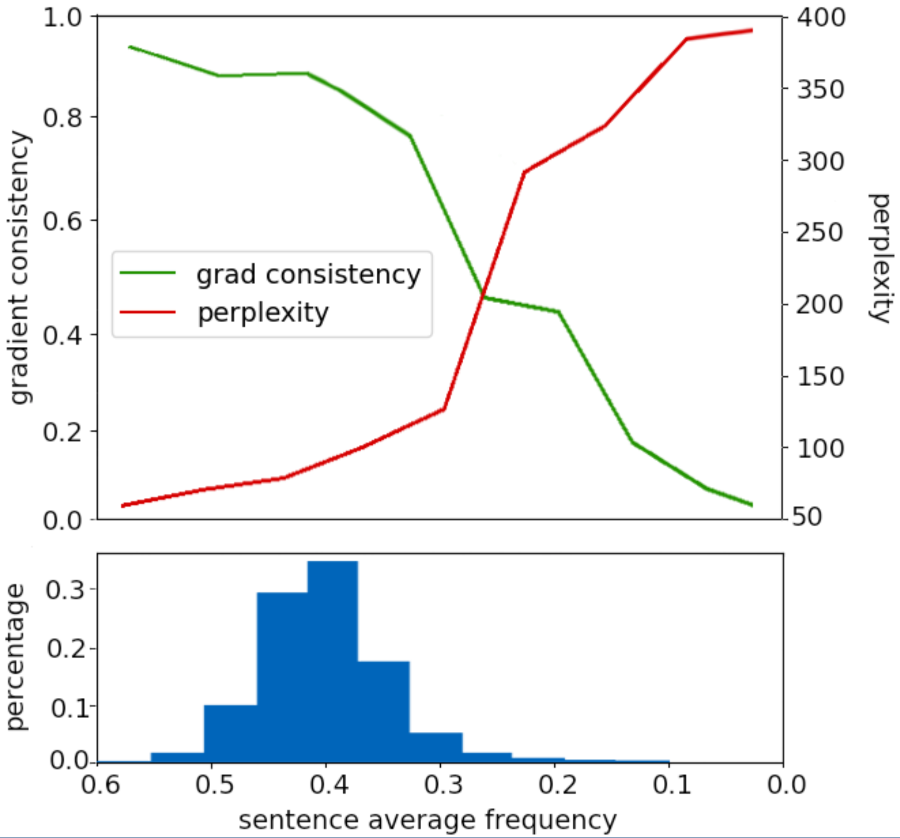
- Lower frequency score for domain-specific data
- Data with lower frequency show lower gradient consistency and higher perplexity



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Neural **T**angent **K**ernel: $\boldsymbol{\Theta}(\mathcal{X}, \mathcal{X}) = J_{\boldsymbol{\theta}}(\mathcal{X}) J_{\boldsymbol{\theta}}(\mathcal{X})^{\top}$, where Jacobian $J_{\boldsymbol{\theta}} = \nabla_{\boldsymbol{\theta}} f(\mathcal{X}; \boldsymbol{\theta})$

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PCA on NTK: $\boldsymbol{\Theta} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^\top = \sum_{i=1}^{n} \lambda_i \mathbf{u}_i \mathbf{u}_i^\top$, and $\mathbf{u}_{max}$ corresponds to the max eigenvalue

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Gradient **C**onsistency: $GC_{\theta}(X') = \dfrac{\mathbf{g}_{\boldsymbol{\theta}}(\mathcal{X}) \cdot \mathbf{g}_{\boldsymbol{\theta}}(\mathcal{X}')}{\|\mathbf{g}_{\boldsymbol{\theta}}(\mathcal{X})\| \|\mathbf{g}_{\boldsymbol{\theta}}(\mathcal{X}')\|}$

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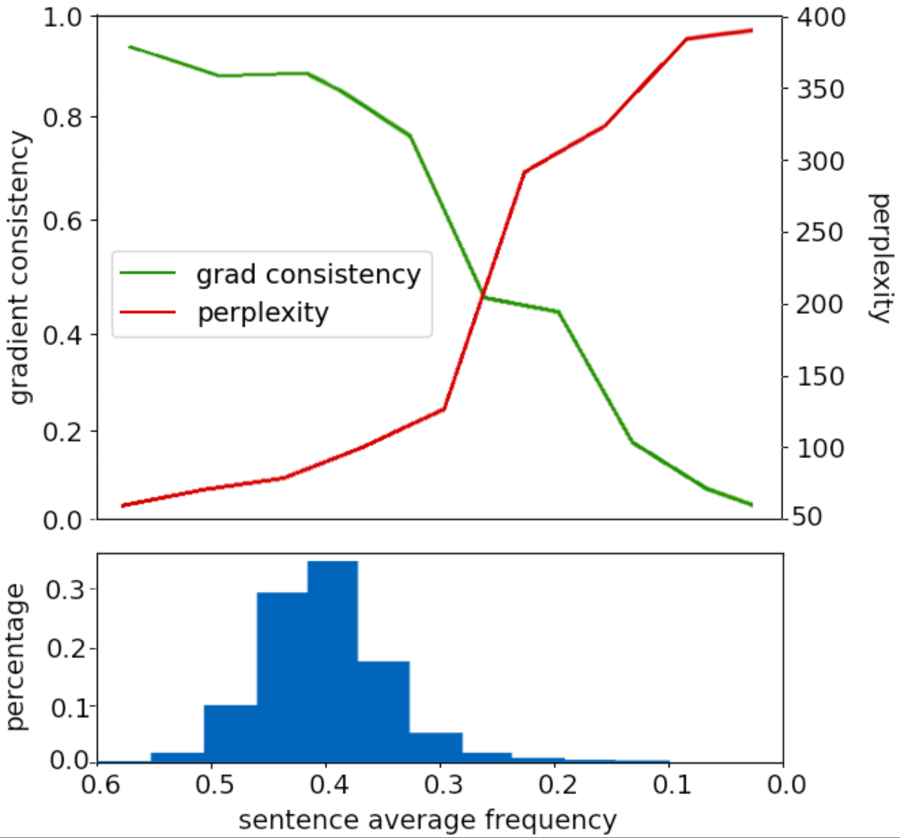

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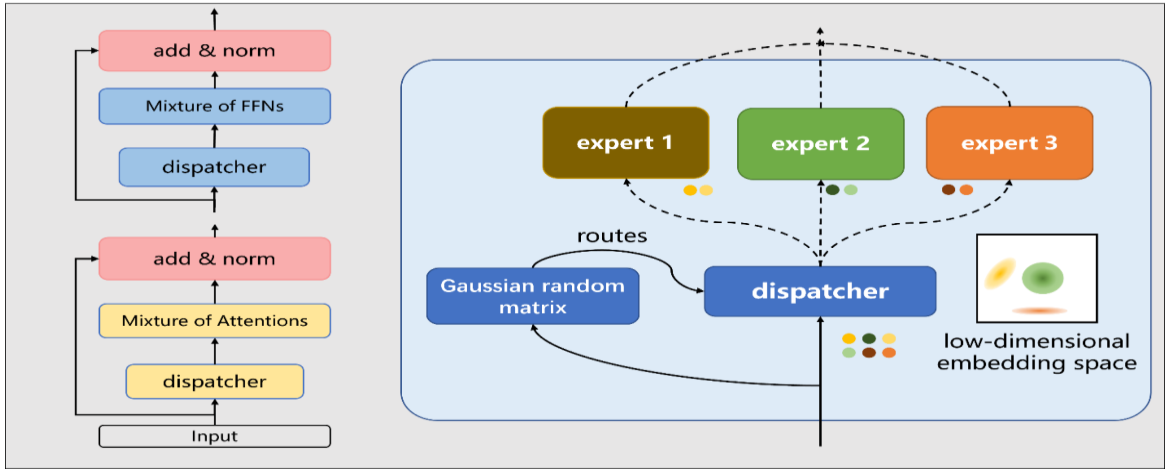

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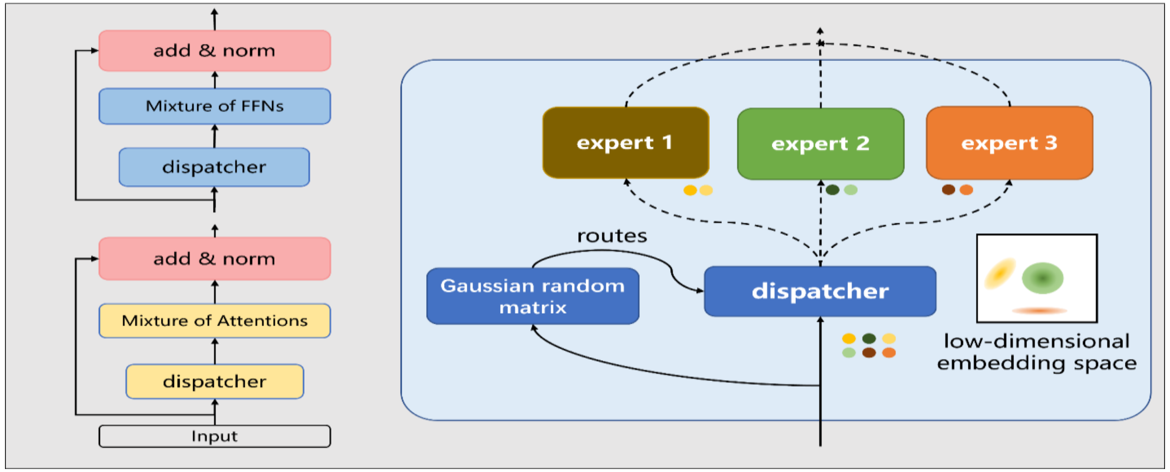

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  - **Update Clusters**: update center $c_i^{t+1} = \alpha \cdot c_i^t + (1-\alpha) \cdot v'$

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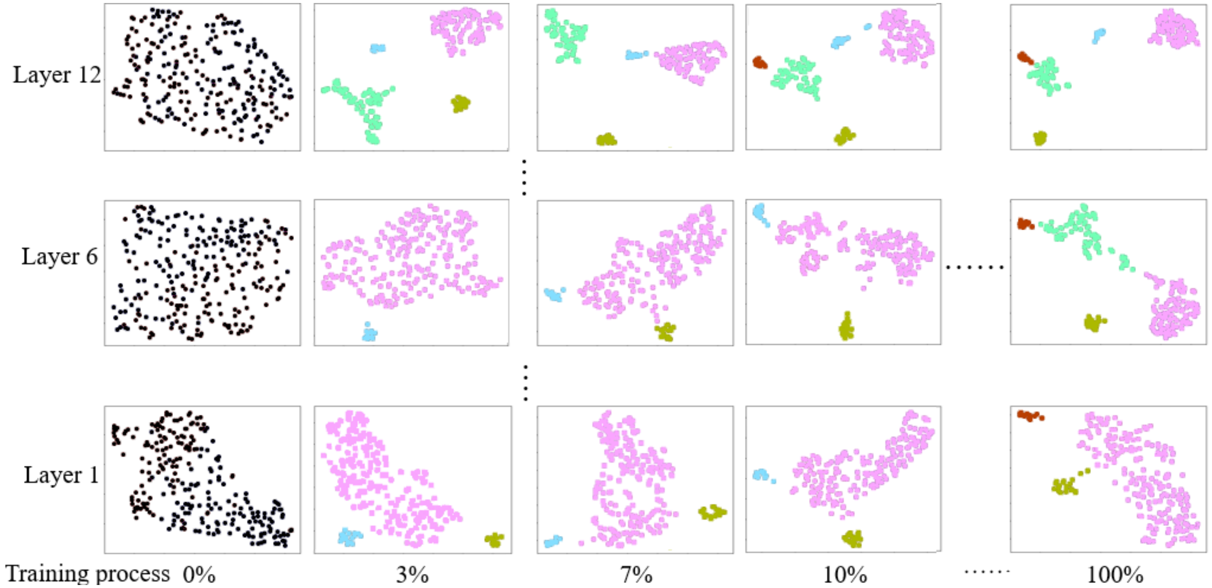
- Representation Cluster Structure
  - Emerge at early stage in training



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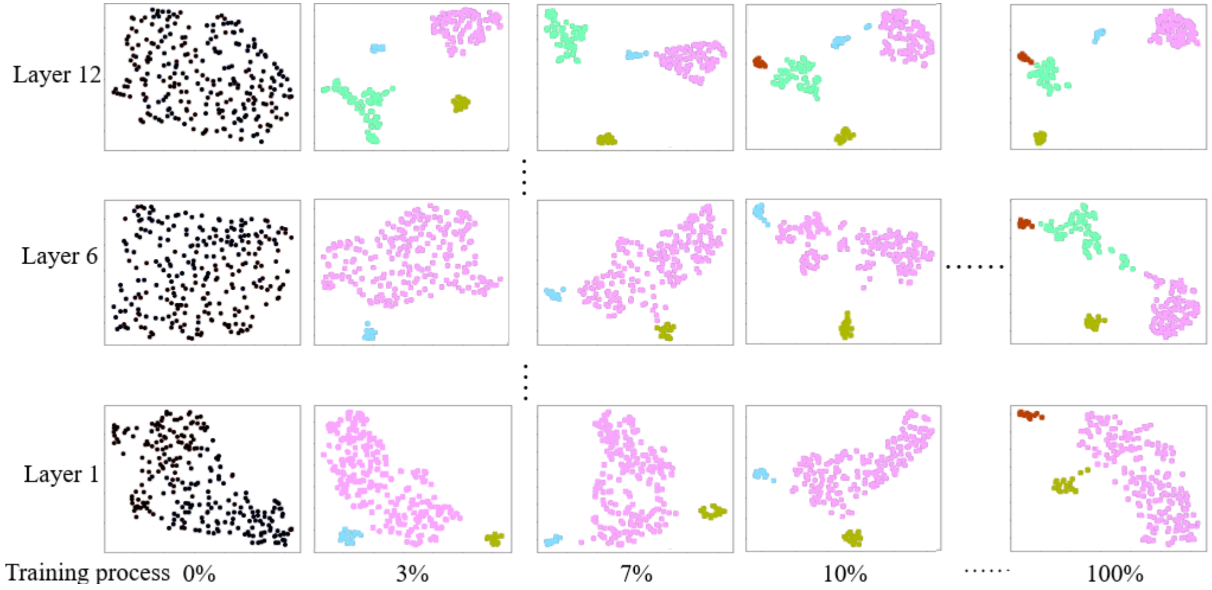

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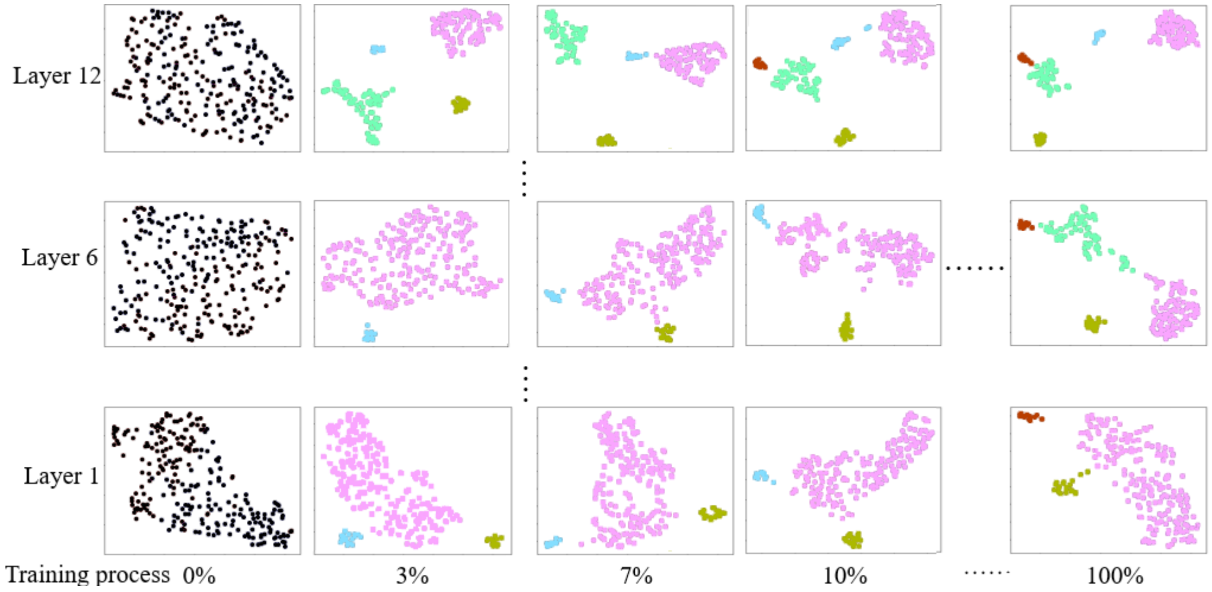
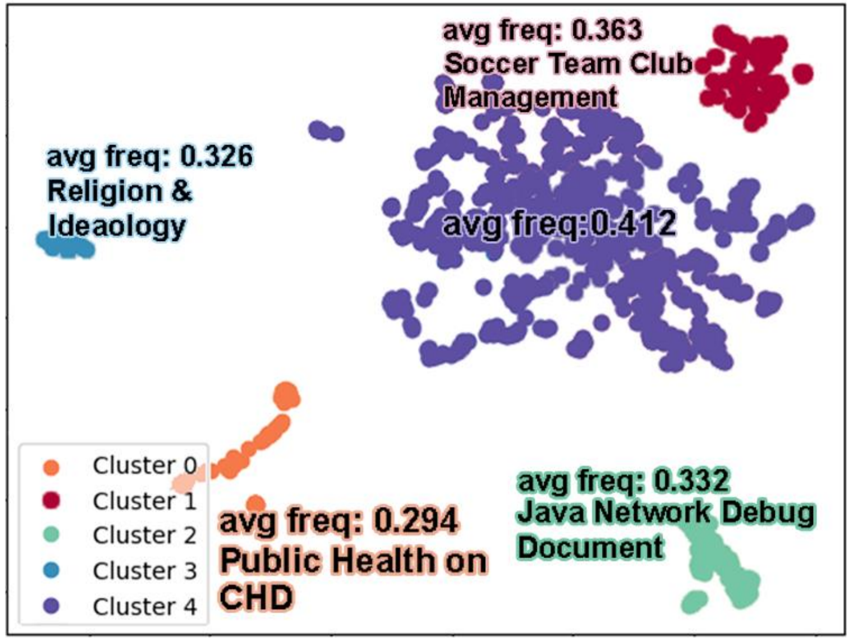
  - More clusters in deep layers than shallow layers.



Method

- Representation Cluster Structure
  - Emerge at early stage in training
  - New small outlier cluster may emerge as training progress.
  - More clusters in deep layers than shallow layers
  - Long-tail data form small, outlier clusters.



Experiments

- Experiment Settings
  - Ours: Undergoes a pretrained phase, reading long-tail domain-specific data once.
  - Baselines: Pretrained on the same dataset and then continue-pretrained on domain-specific datasets.
  - Metrics： Accuracy on downstream domain-specific tasks.

Experiments

- Results-BERT(110M)

Table 1: Results of strategies applied on BERT

Models	Pretrain ppl	Overruling	Casehold	GAD	EUADR	SST2	average
BERT/med	37.00	86.67	50.51	67.09	84.23	66.86	71.07 ± 0.22
BERT/legal	37.00	86.67	50.93	66.83	84.79	65.14	70.87 ± 0.23
MoE/med	31.00	85.00	50.49	64.52	83.10	64.79	69.58 ± 0.20
MoE/legal	31.00	85.83	50.30	64.32	84.79	63.88	69.82 ± 0.19
Ours/MoA	28.25	86.62	**50.94**	**72.90**	90.09	66.60	73.43 ± 0.18
Ours/MoF	34.64	**89.10**	50.82	71.65	**91.23**	**67.98**	**74.16 ± 0.20**

BERT/med exhibited a severe forgetting issue and details will be discussed in the Appendix A.

Experiments

- Results-GPT(130M)

Table 2: Results of strategies applied on GPT

Models	Pretrain ppl	Overruling	Casehold	GAD	EUADR	SST2	average
GPT/med	55.59	88.33	49.82	71.56	84.23	73.90	73.57 ± 0.17
GPT/legal	55.59	89.17	50.58	71.69	81.69	74.50	73.53 ± 0.23
MoE/med	40.69	91.25	50.11	<u>72.77</u>	83.38	72.03	73.91 ± 0.12
MoE/legal	40.69	91.60	49.68	72.66	83.38	71.97	73.86 ± 0.23
Ours/MoA	42.99	<u>91.68</u>	<u>50.70</u>	71.75	**85.91**	<u>74.61</u>	<u>74.93 ± 0.08</u>
Ours/MoF	43.38	**93.33**	**51.26**	**73.30**	<u>85.63</u>	**76.00**	$\mathbf{75.90 \pm 0.19}$

Experiments

- Results-GPT(330M)

Our method also works well as model scaling up.

Table 3: Results of strategies applied on 330M GPT

Domain	Task	GPT/tuned	MoE/tuned	CSE/ w/o tune
academic	chem-prot	36.25	36.25	36.25
academic	MAG	63.22	64.91	**65.47**
academic	rct-20k	76.95	78.28	**80.15**
environment	clim. det.	78.94	79.90	**80.26**
environment	clim. sent.	66.81	68.31	**69.98**
financial	FPB	16.83	25.00	**40.11**

Experiments

- Results-GPT(330M)

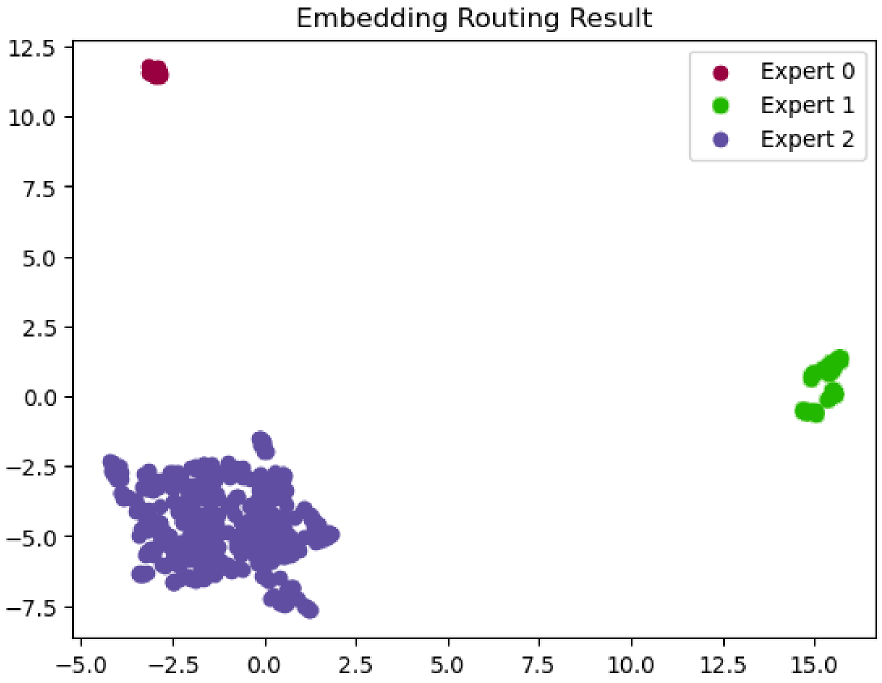
Our method learn long-tail domain knowledge without hurting the performance of general tasks.

Table 8: Results of general tasks tested on GPT 330M trained with 20B tokens

Task	Domain	Freq. Score	Baseline(tuned)	MoE(tuned)	Ours(w/o tune)
COLA	general	0.389	69.10	69.10	**69.20**
QNLI	general	0.325	**60.17**	60.06	59.72
MRPC	general	0.343	70.18	71.75	**71.98**
QQP	general	0.380	73.28	74.47	**75.95**
SST2	general	0.327	74.50	72.03	**76.00**
average	general	-	69.45(-1.12)	69.48(-1.09)	**70.57**

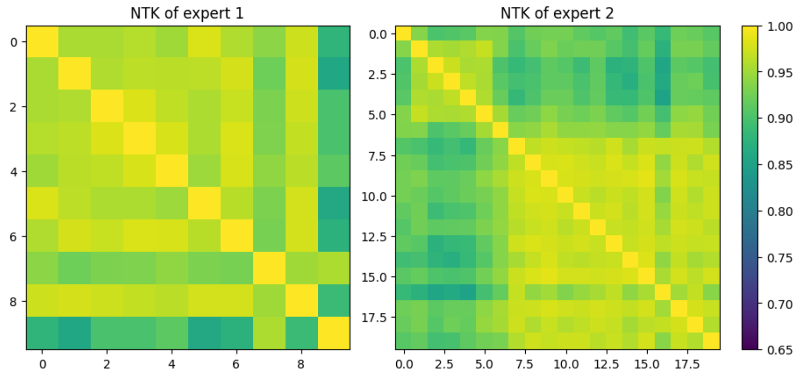
Experiments

- Representation Space Analysis
  - Cluster-guided correct dispatching

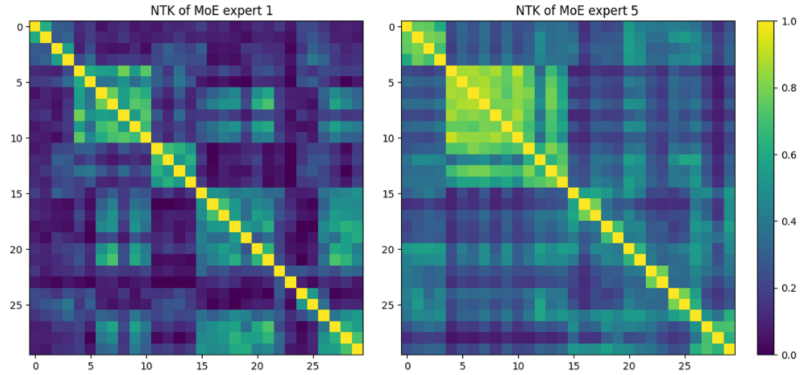


Experiments

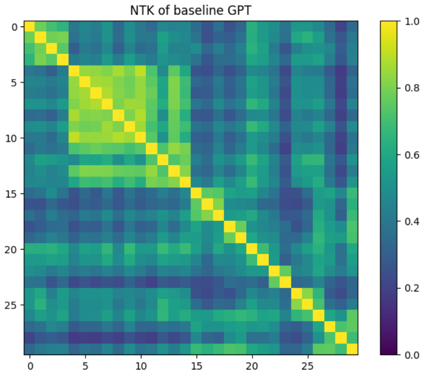
- Representation Space Analysis
  - Cluster-guided correct dispatching
  - Higher gradient consistency on each expert



Ours



MoE



baseline

Thank you!