S'MoRE: Structural Mixture of Residual Experts for Parameter-Efficient LLM Fine-Tuning

Code: https://github.com/ZimpleX/SMoRE-LLM

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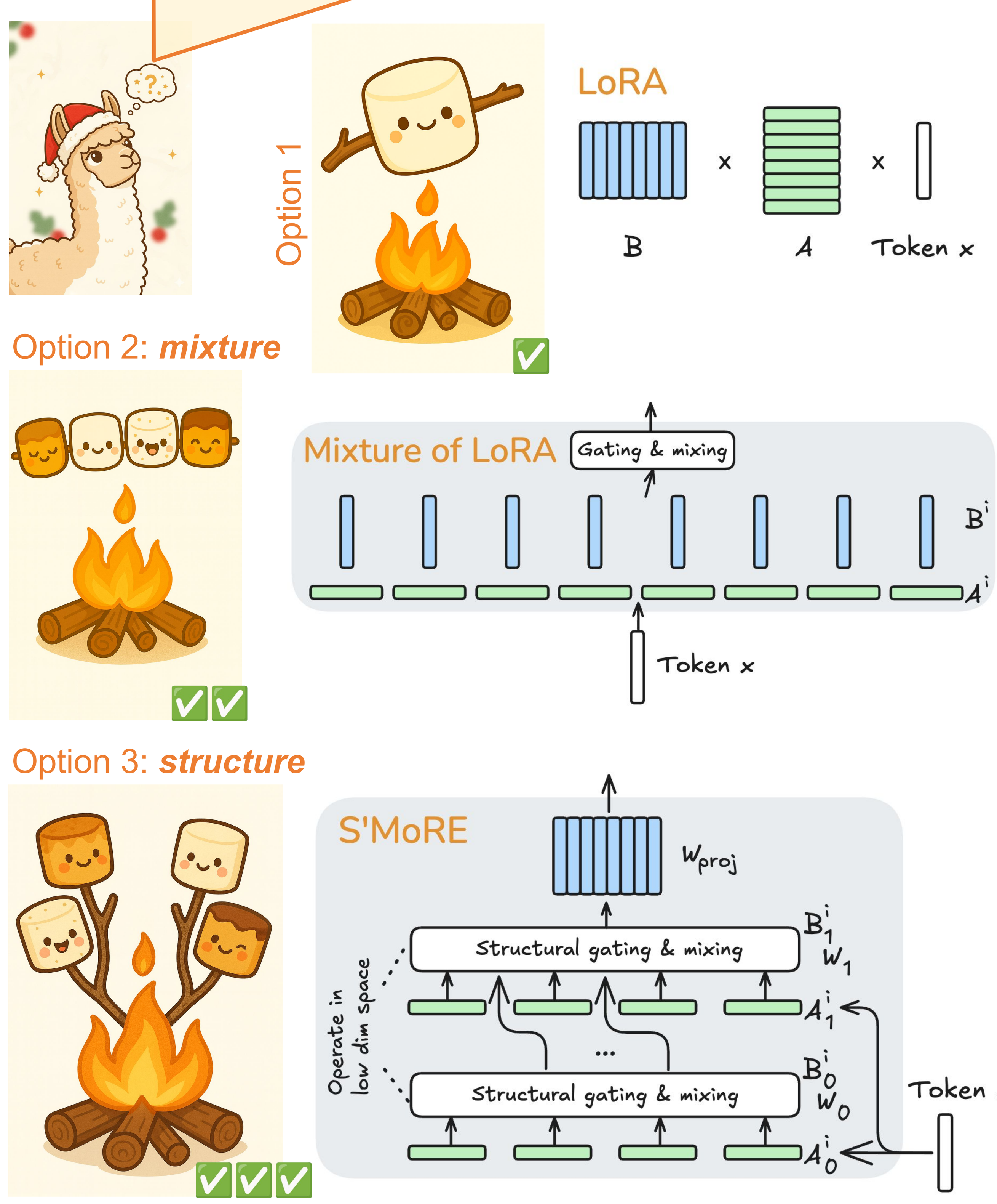
Meta MRS

NEURAL INFORMATION PROCESSING SYSTEMS

s'more /ˈsmoː(ː)ɹ/: a dessert consisting usually of toasted marshmallow and pieces of chocolate bar sandwiched between two graham crackers.

LLaMA's Question: How to make a unique s'more for everyone using limited ingredients?



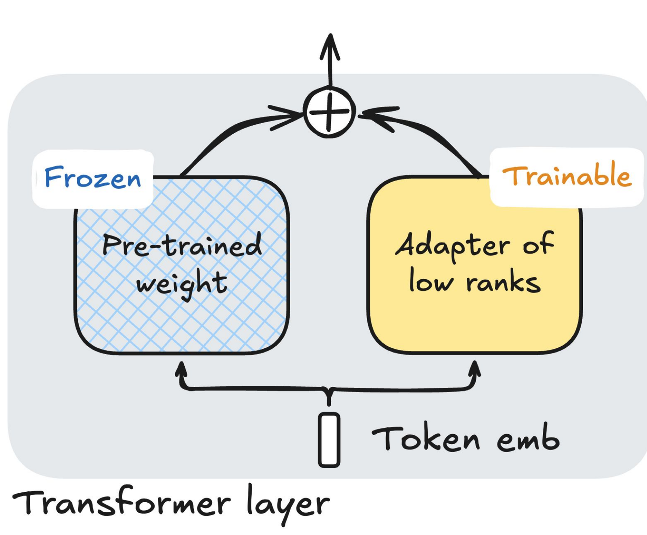
Comparison on the 3 options of adapters:

- Similar **efficiency**: same parameters of ▭ & ▯
- Higher **expressivity**: LoRA < Mixture of LoRA < S'MoRE (measured via *structural flexibility*)

Problem Setup

Parameter-efficient fine-tuning (PEFT) on pre-trained LLM

- Adapt to downstream tasks
- Freeze pre-trained weight; Update low-rank adapter parameters

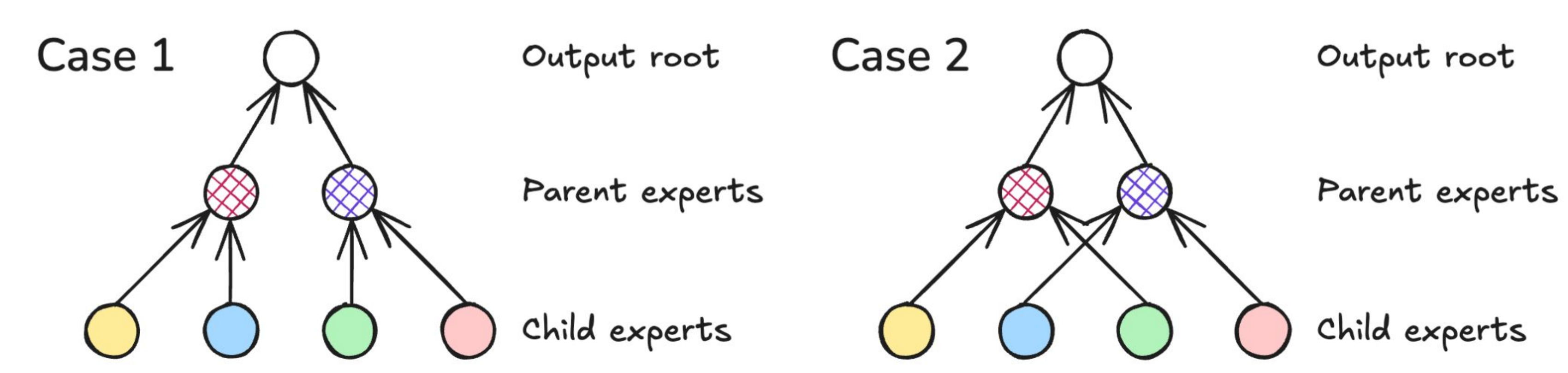


How Does Structure Help?

MoE routing problem

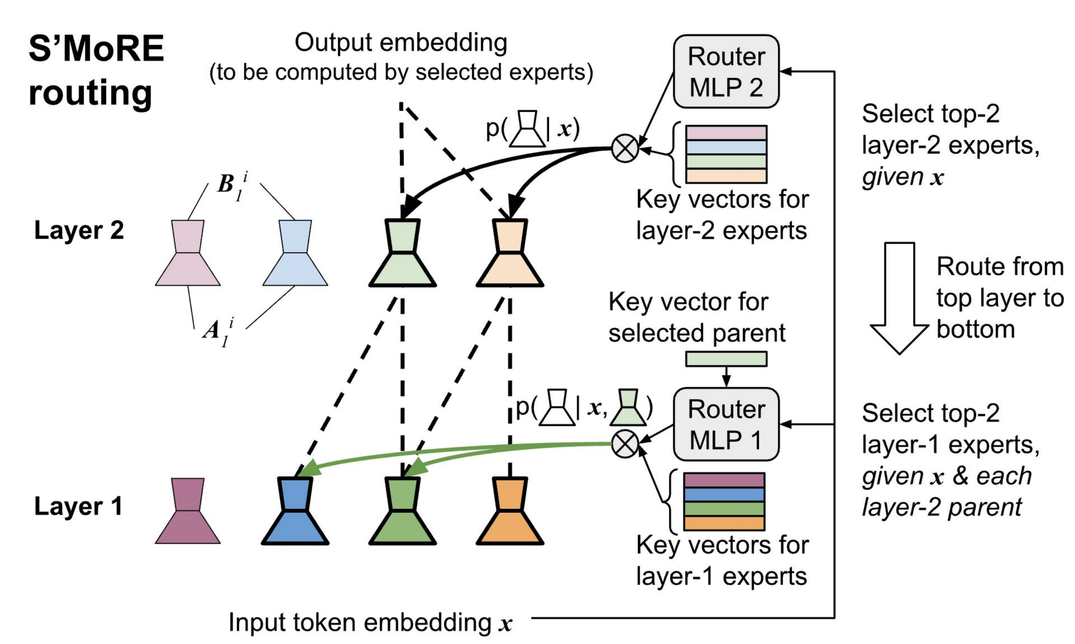
- What experts to activate? ⇒ Existing works
- How to connect activated experts? ⇒ S'MoRE & structural scaling

The **same** set of experts can form **exponentially many** different structures!



S'MoRE Routing

- Hierarchical routing (**top-down**)
- Router computes conditional probability by
  - active ancestors
  - input token
- "Token-expert" similarity based on key-query dot product
- Query embedding: by Router's compact MLP
- *Key* embedding: learnable for each residual expert



S'MoRE Layer Propagation

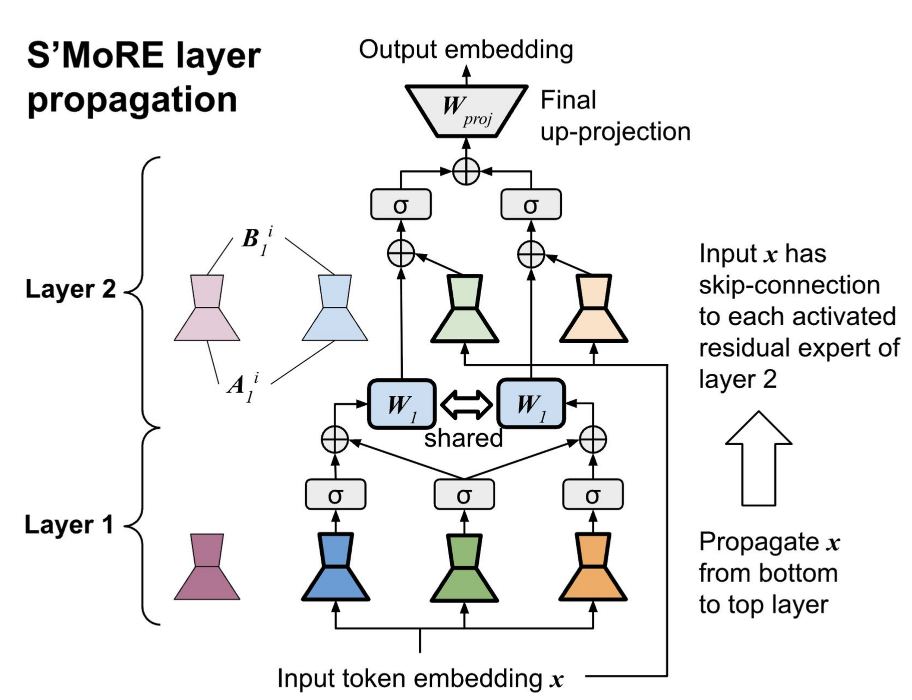
Current layer output — Token emb (skip connect) — Previous layer output

$$\boldsymbol{x}_{\ell+1}^{i} = \sum_{n\in\mathcal{N}_{\ell}^{i}} \alpha_{\ell}^{i,n} \cdot \sigma\left(\boxed{\boldsymbol{B}_{\ell}^{n}\cdot\boldsymbol{A}_{\ell}^{n}}\cdot\boldsymbol{x} + \boxed{\boldsymbol{W}_{\ell}}\cdot\boldsymbol{x}_{\ell}^{n}\right)$$

Active children experts — Router weights — Residual (low rank) experts — Shared weights

Neighbor aggr. — Transformation

- Selected experts form a residual tree
- Token emb propagates: leaves → root
- Each layer: aggregation + transformation ⇒ GNN
- Craft each layer's output dim for parameter & computation efficiency
- σ & W theoretically ensures expressive power



Summary of Theoretical Properties

Parameter & computation efficiency:

- Similar to vanilla LoRA

Recovering MoE baseline:

- By simply setting activation σ as identity

Expressive power w.r.t. "**structural flexibility**" Γ ⇒ Graph isomorphism test

- *Definition*: Given token, Γ = num distinct outputs that different expert structures can generate

Table 1: Overhead Δ compared with the main computation cost $2\cdot d\cdot d_L$

r_ℓ	L	d_L	$2\cdot d\cdot d_L$	Δ	Overhead ratio
8	2	64	0.5M	0.005M	1.0%
	3	96	0.8M	0.014M	1.8%
	4	128	1.0M	0.031M	2.9%
16	2	128	1.0M	0.020M	2.0%
	3	192	1.6M	0.057M	3.6%
	4	256	2.1M	0.123M	5.9%

(i.e., 1-layer MoE)

Theorem 3.3. *The structural flexibility of* $\boxed{\text{MoMOR}}$ *is upper-bounded by* $\Gamma_{\text{MoMOR}} = \max_{\boldsymbol{x},\Theta} \texttt{dist}(\boldsymbol{x};\Theta) \leq \binom{s_{L-1}}{f_{L-1}}\cdot\prod_{\ell=0}^{L-2}\left(\sum_{i=f_\ell}^{\min\{\boxed{F_\ell},s_\ell\}}\binom{s_\ell}{i}\right)$.

Sum over fanout

Theorem 3.4. *Setting* $\sigma(\cdot)$ *as an MLP, there exists some* Θ' *such that the structural flexibility of* $\boxed{\text{S'MoRE}}$ *is:* $\Gamma_{\text{S'MoRE}} = \min_{\boldsymbol{x}} \texttt{dist}(\boldsymbol{x};\Theta') = \prod_{\ell=0}^{L-1}\binom{s_\ell}{f_\ell}^{\boxed{F_{\ell+1}}}$, *where we define* $F_L := 1$.

Exponent over fanout

Experiments

Setup

- 7 benchmarks
- 2 model families & 3 model scales
- 3 gating types
- 4 or 8 total number of experts

Model	Gate	Method	ARC-c Acc.	ARC-c Param.	ARC-e Acc.	ARC-e Param.	CSQA Acc.	CSQA Param.	OBQA Acc.	OBQA Param.	Winogrande Acc.	Winogrande Param.	**Avg Acc.**	**Avg Param.**
LLaMA 3.2 1B		Base	32.54	0	66.31	0	23.67	0	43.80	0	50.75	0	43.41	0
		LoRA	36.27	0.004	74.78	0.002	63.80	0.063	71.20	0.031	50.59	0.008	59.15	0.022
	Dense	HydraLoRA (4)	35.93	0.006	73.54	0.023	66.34	0.002	71.60	0.023	50.75	0.012	59.63	0.013
		HydraLoRA (8)	35.93	0.012	72.31	0.007	62.08	0.042	71.60	0.012	50.99	0.012	58.58	0.017
		MixLoRA (4)	39.66	0.021	72.84	0.134	65.44	0.134	70.40	0.134	51.30	0.007	59.93	0.086
		MixLoRA (8)	39.32	0.021	74.78	0.270	66.42	0.069	69.60	0.134	51.14	0.037	60.25	0.106
		S'MoRE (2-2)	**40.00**	0.017	**75.31**	0.085	66.99	0.037	72.20	0.085	**52.01**	0.015	**61.30**	0.048
		S'MoRE (4-4)	39.66	0.017	74.43	0.085	**67.32**	0.045	**72.80**	0.202	**52.01**	0.168	61.24	0.103
	Noisy top-k	MixLoRA (4)	39.32	0.037	71.96	0.069	64.70	0.134	70.00	0.134	51.46	0.069	59.49	0.089
		MixLoRA (8)	37.97	0.069	72.84	0.270	65.03	0.134	70.80	0.270	51.46	0.069	59.62	0.162
		S'MoRE (2-2)	**39.66**	0.029	73.19	0.135	64.95	0.135	70.00	0.102	51.54	0.029	59.87	0.086
		S'MoRE (4-4)	**39.66**	0.037	**74.96**	0.135	**66.26**	0.102	**71.40**	0.135	**52.17**	0.273	**60.89**	0.136
	Switch	MixLoRA (4)	38.98	0.021	73.37	0.134	66.42	0.069	72.00	0.134	51.22	0.009	60.40	0.073
		MixLoRA (8)	39.32	0.021	73.72	0.069	65.85	0.134	71.80	0.134	51.30	0.021	60.40	0.076
		S'MoRE (2-2)	39.66	0.029	**74.78**	0.135	66.75	0.069	71.40	0.102	**52.25**	0.045	60.97	0.076
		S'MoRE (4-4)	**40.34**	0.021	**74.78**	0.168	**67.16**	0.202	**72.40**	0.085	52.09	0.021	**61.35**	0.099
LLaMA 3 8B		Base	80.34	0	89.77	0	70.35	0	73.80	0	59.91	0	74.83	0
		LoRA	81.69	0.028	91.36	0.028	81.00	0.028	87.00	0.028	81.77	0.028	84.56	0.028
	Dense	HydraLoRA (4)	**83.39**	0.013	91.53	0.160	81.82	0.013	88.20	0.082	83.82	0.160	85.75	0.086
		HydraLoRA (8)	81.69	0.079	91.53	0.015	81.49	0.024	86.60	0.015	84.14	0.297	85.09	0.086
		MixLoRA (4)	81.69	0.026	**92.24**	0.247	81.24	0.033	89.40	0.478	84.06	0.247	85.73	0.206
		MixLoRA (8)	82.37	0.132	91.71	0.247	81.00	0.033	88.60	0.075	85.40	0.478	85.82	0.193
		S'MoRE (2-2)	82.37	0.090	**92.24**	0.190	**81.90**	0.037	89.40	0.054	**88.24**	0.480	**86.83**	0.170
		S'MoRE (4-4)	82.71	0.190	91.89	0.247	**81.90**	0.033	**90.00**	0.076	85.48	0.247	86.40	0.157
	Noisy top-k	MixLoRA (4)	82.37	0.075	91.53	0.247	80.75	0.075	87.80	0.075	82.00	0.478	84.89	0.190
		MixLoRA (8)	**83.39**	0.950	91.53	0.247	80.67	0.075	88.40	0.247	83.19	0.478	85.44	0.399
		S'MoRE (2-2)	82.37	0.305	91.36	0.090	81.82	0.104	88.20	0.047	83.27	0.190	85.40	0.147
		S'MoRE (4-4)	82.37	0.104	**91.71**	0.305	**82.06**	0.047	**90.00**	0.480	**85.48**	0.714	**86.32**	0.330
	Switch	MixLoRA (4)	82.37	0.132	**92.95**	0.478	81.08	0.047	88.80	0.478	84.53	0.247	85.95	0.276
		MixLoRA (8)	82.03	0.033	91.71	0.132	81.24	0.047	88.60	0.247	85.95	0.950	85.91	0.282
		S'MoRE (2-2)	83.05	0.133	92.24	0.061	81.82	0.029	**89.80**	0.076	**86.42**	0.247	86.67	0.109
		S'MoRE (4-4)	**83.39**	0.076	92.42	0.305	**82.15**	0.047	**89.80**	0.305	85.87	0.305	**86.73**	0.208

Main observations

- Accuracy boost due to structural mixture
- Comparable parameter size due to low-dim aggr.
- Consistent gains across model families
- Structure improves *scaling* on math & coding

Table 4: Results on Gemma 2-9B. We evaluate on representative benchmarks due to limited resources.

Method	ARC-e Accuracy	ARC-e Param. (B)	CSQA Accuracy	CSQA Param. (B)	Winogrande Accuracy	Winogrande Param. (B)	HumanEval Pass@1	HumanEval Param. (B)	**Avg Acc. / Pass@1**	**Avg Param. (B)**
LoRA	79.72	0.289	85.91	0.145	87.06	0.145	43.29	0.072	74.00	0.163
MixLoRA (4)	85.54	0.059	85.83	0.096	88.79	0.169	43.29	0.096	75.86	0.105
MixLoRA (8)	83.07	0.168	85.83	0.096	89.19	0.315	44.51	0.168	75.65	0.187
S'MoRE (2-2)	86.24	0.042	**86.40**	0.169	**90.13**	0.169	44.51	0.096	76.82	0.119
S'MoRE (4-4)	**86.60**	0.169	86.32	0.060	**90.13**	0.315	**46.34**	0.060	**77.35**	0.151

Table 3: LLaMA 3-8B model Accuracy / Pass@1, and the best-performing models' trainable parameters (B).

Gate	Method	GSM8K Accuracy	GSM8K Param. (B)	HumanEval Pass@1	HumanEval Param. (B)
	Base model	55.95	0	26.22	0
	LoRA	59.97	0.014	43.29	0.014
Dense	HydraLoRA (4)	62.47	0.317	40.85	0.082
	HydraLoRA (8)	62.24	0.297	**44.51**	0.079
	MixLoRA (4)	61.11	0.132	39.02	0.026
	MixLoRA (8)	59.36	0.132	40.85	0.033
	S'MoRE (2-2)	62.40	0.104	42.07	0.090
	S'MoRE (4-4)	**65.20**	0.957	43.90	0.104
Switch	MixLoRA (4)	59.67	0.047	42.68	0.075
	MixLoRA (8)	61.56	0.247	39.63	0.247
	S'MoRE (2-2)	62.47	0.133	**45.73**	0.190
	S'MoRE (4-4)	**63.91**	0.957	42.07	0.090

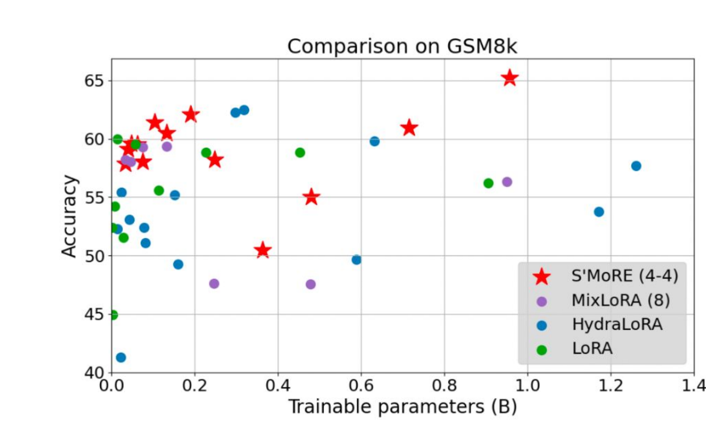


Figure 4: Change of accuracy w.r.t. trainable parameters, corresponding to models in Table 3.