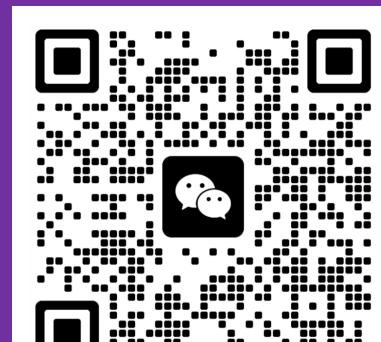


MoETTA: Test-Time Adaptation Under Mixed Distribution Shifts with MoE-LayerNorm



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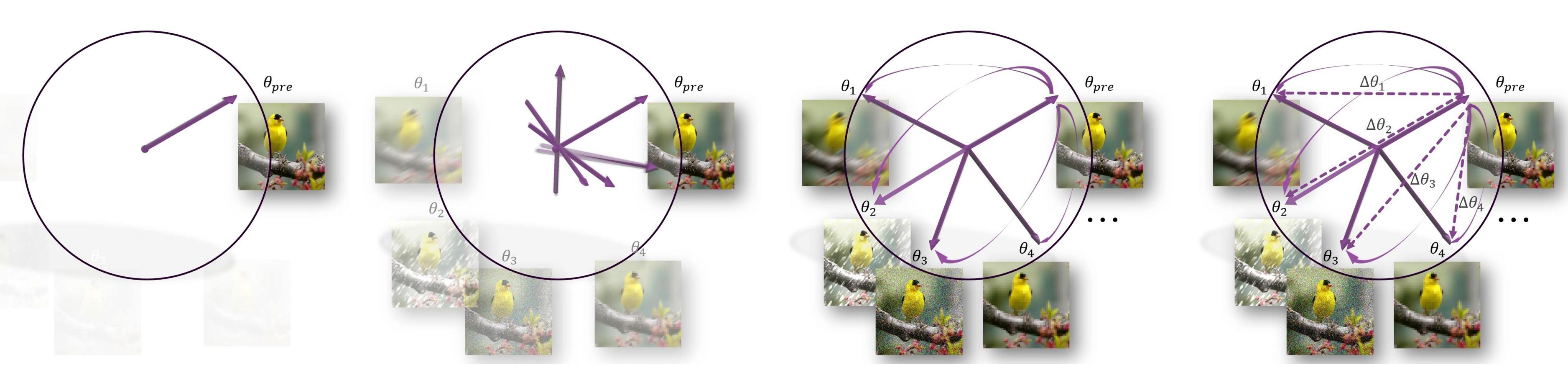
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* Work completed during an internship at Tsinghua University.

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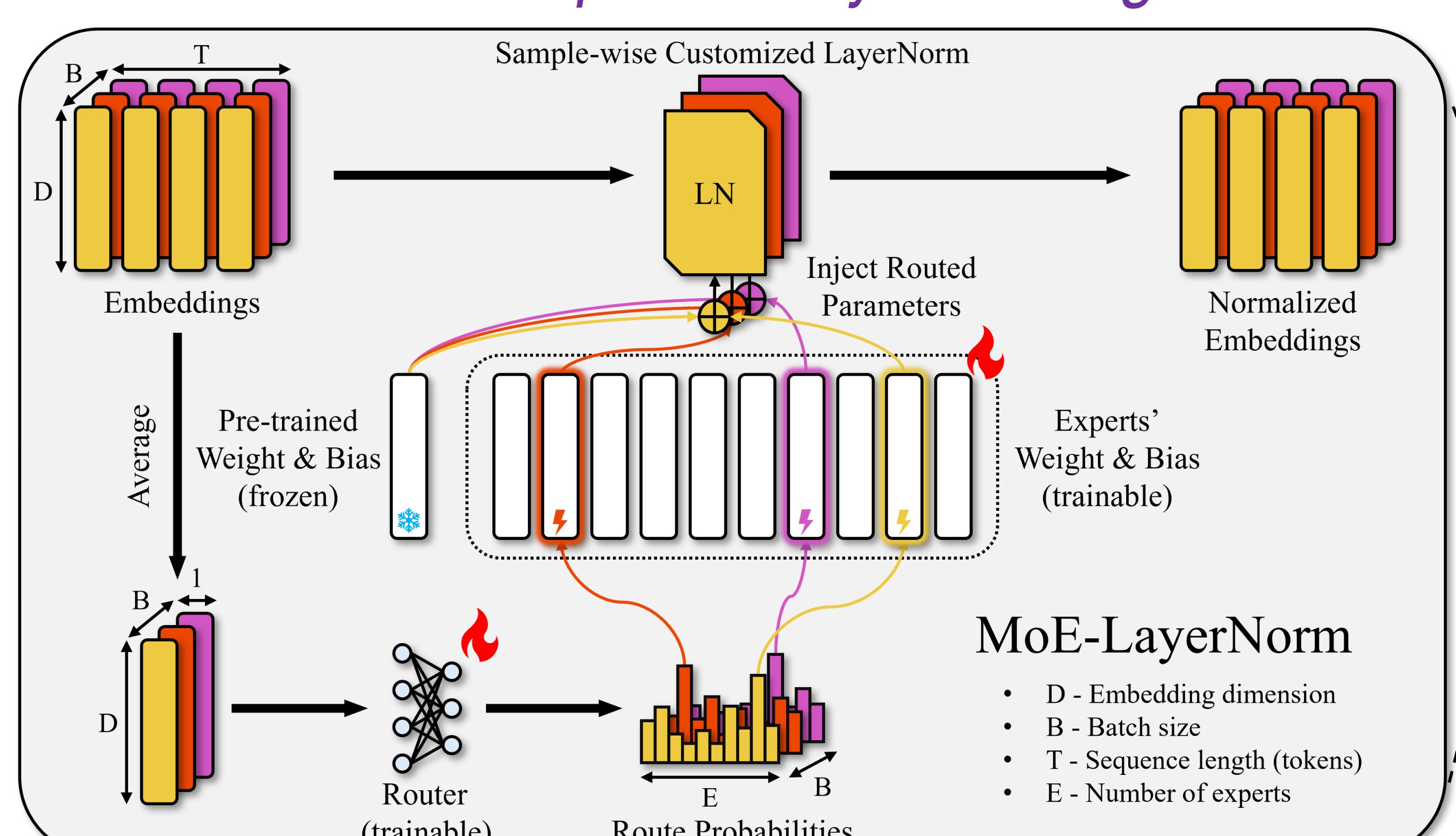
Motivation

Illustration of Adaptation Process Under Mixed Distribution Shifts



Domain-Specific gradient signals can be inconsistent or even conflicting.

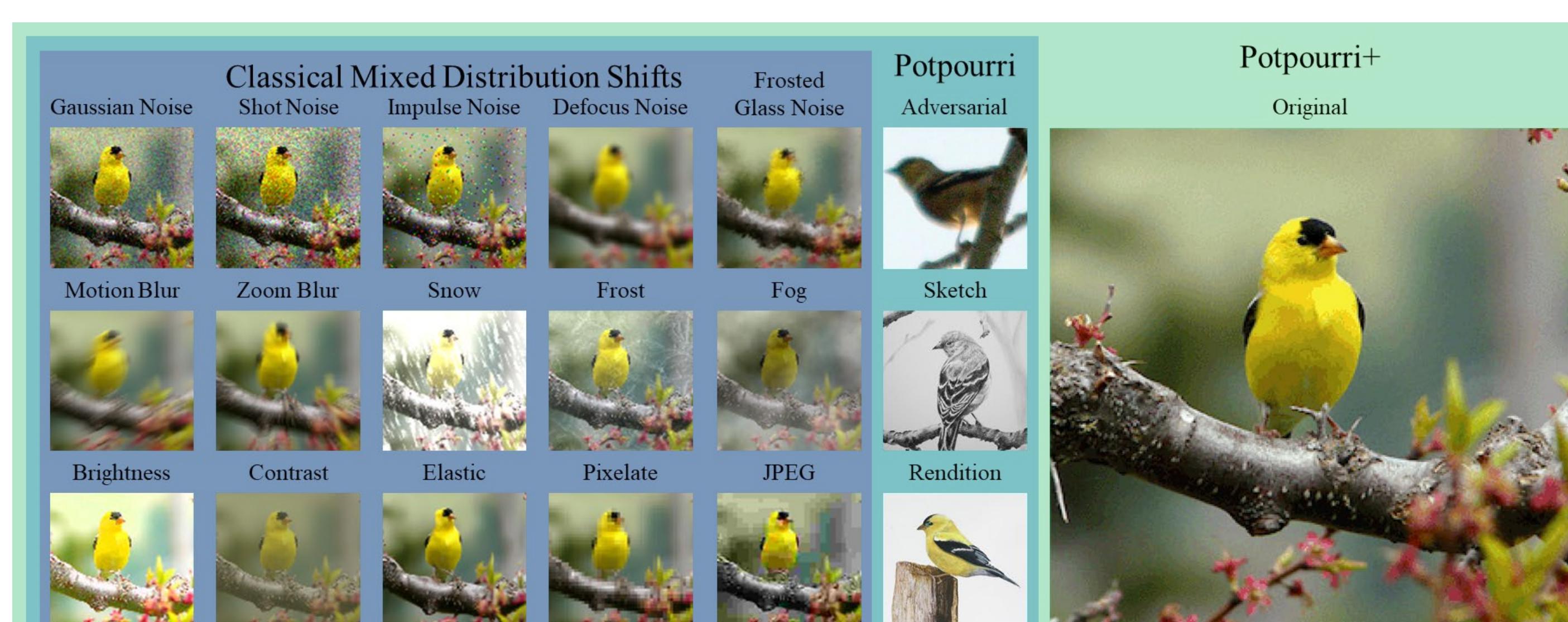
Leveraging a diverse set of experts to represent multiple adaptation solutions within one model is particularly advantageous for mixed distribution shifts.



Benchmark

Propose two more benchmarks

- Potpourri: More OOD samples
- Potpourri+: Include ID samples



Methodology

Overall Loss Function

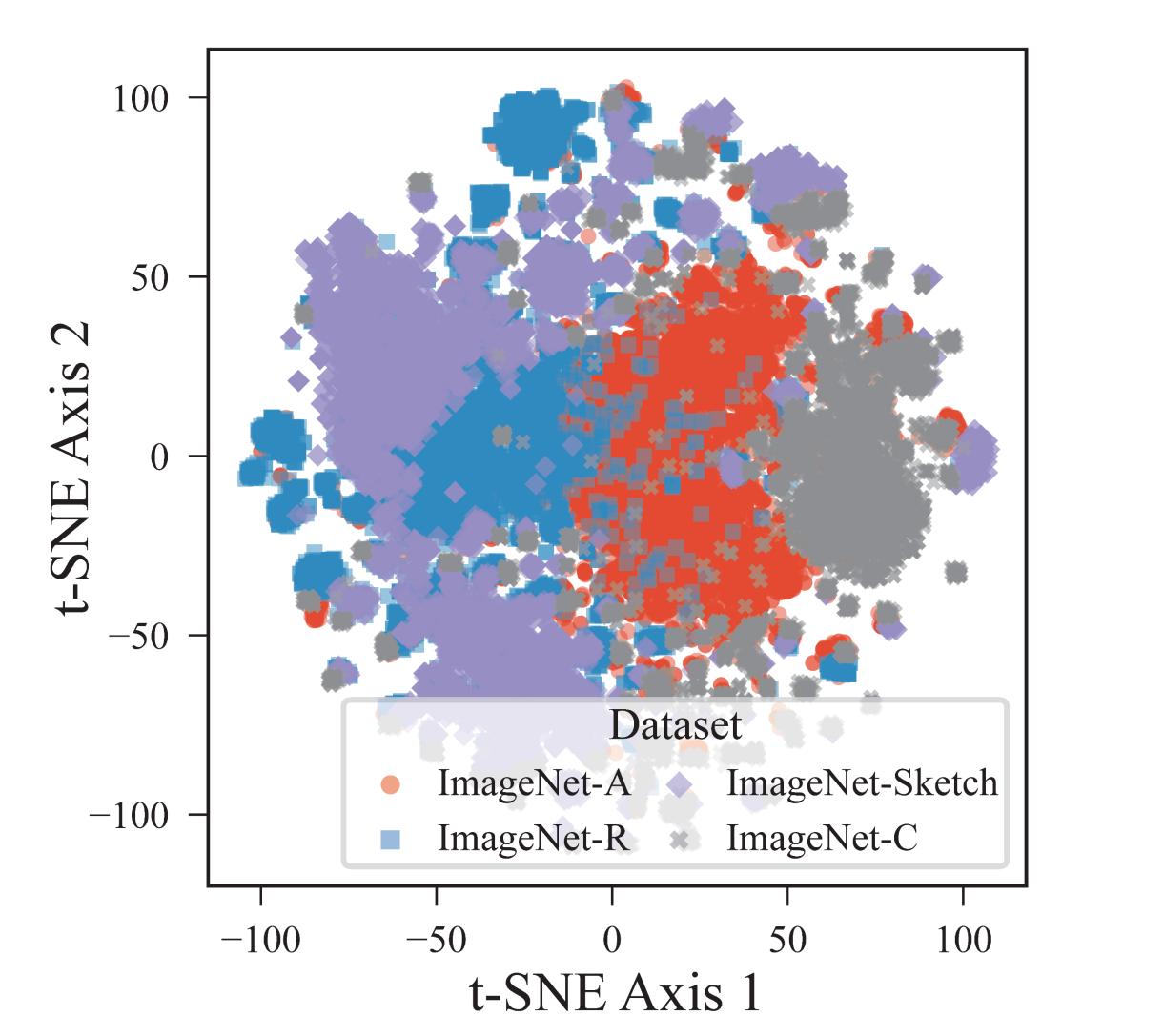
$$\frac{1}{|\mathcal{S}_t|} \sum_{x \in \mathcal{S}_t} \exp[E_0 - \text{Ent}(x)] \text{Ent}(x) + \alpha_t \sum_{i=1}^M \mathcal{L}_{\text{load balancing}}^i$$

Sample selection
 $\mathcal{S}_t = \{x | \text{Ent}(x) < E_{\max}^t \wedge x \in \mathcal{B}_t\}$

Dynamic threshold
 $E_{\max}^t = \begin{cases} E_{\text{avg}}^0, & t = 0, \\ E_{\max}^{t-1} \times \frac{E_{\text{avg}}^t}{E_{\text{avg}}^{t-1}}, & t \geq 1. \end{cases}$

Trade-off coefficient
 $\alpha_t = \begin{cases} \lambda \times E_{\text{avg}}^0, & t = 0, \\ \alpha_{t-1} \times \frac{E_{\text{avg}}^t}{E_{\text{avg}}^{t-1}}, & t \geq 1. \end{cases}$

Differentiable load balancing loss
 $\mathcal{L}_{\text{load balancing}} = N \times \sum_{i=1}^N F_i \times P_i,$
 $P_i = \frac{1}{|\mathcal{B}_t|} \sum_{x \in \mathcal{B}_t} p_i(x),$
 $F_i = \frac{1}{|\mathcal{B}_t|} \sum_{x \in \mathcal{B}_t} \mathbb{I}_{\{\arg \max_k p_k(x)=i\}}.$

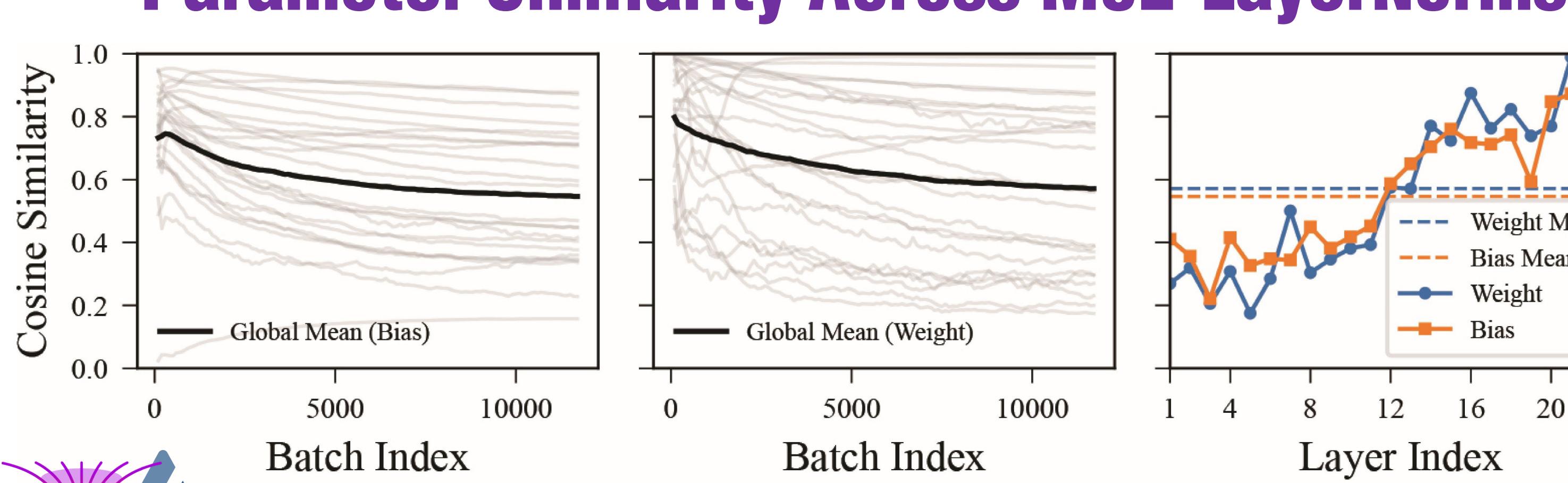


ViT CLS token t-SNE projection.

Robustness to Mixed Distribution Shifts

Model	Setting	Noadapt	Tent	EATA	CoTTA	SAR	DeYO	MGTTA	BECoTTA	Ours
ViT-B/16	Classical	55.52	63.20 _{0.08}	64.28 _{0.09}	60.53 _{0.57}	60.76 _{0.04}	63.97 _{0.04}	66.20 _{0.01}	61.57 _{0.08}	67.20 _{0.03}
	Potpourri	54.18	60.99 _{0.05}	61.99 _{0.11}	59.67 _{1.21}	58.71 _{0.03}	61.66 _{0.02}	62.98 _{0.26}	59.08 _{0.86}	65.12 _{0.08}
	Potpourri+	55.92	62.28 _{0.03}	63.17 _{0.06}	59.26 _{0.68}	59.99 _{0.07}	62.90 _{0.03}	64.35 _{0.07}	58.87 _{3.23}	66.15 _{0.06}
ConvNeXt-B (CNN Arch.)	Classical	54.81	58.88 _{0.06}	64.50 _{0.06}	59.65 _{0.04}	61.67 _{2.65}	64.32 _{0.03}	-	50.16 _{7.96}	67.40 _{0.02}
	Potpourri	53.91	58.23 _{0.05}	62.69 _{0.07}	58.57 _{0.00}	61.16 _{0.41}	62.46 _{0.07}	-	28.28 _{20.54}	65.70 _{0.05}
	Potpourri+	55.69	59.69 _{0.04}	63.94 _{0.07}	60.02 _{0.02}	62.72 _{0.10}	63.57 _{0.06}	-	48.92 _{9.35}	66.68 _{0.07}

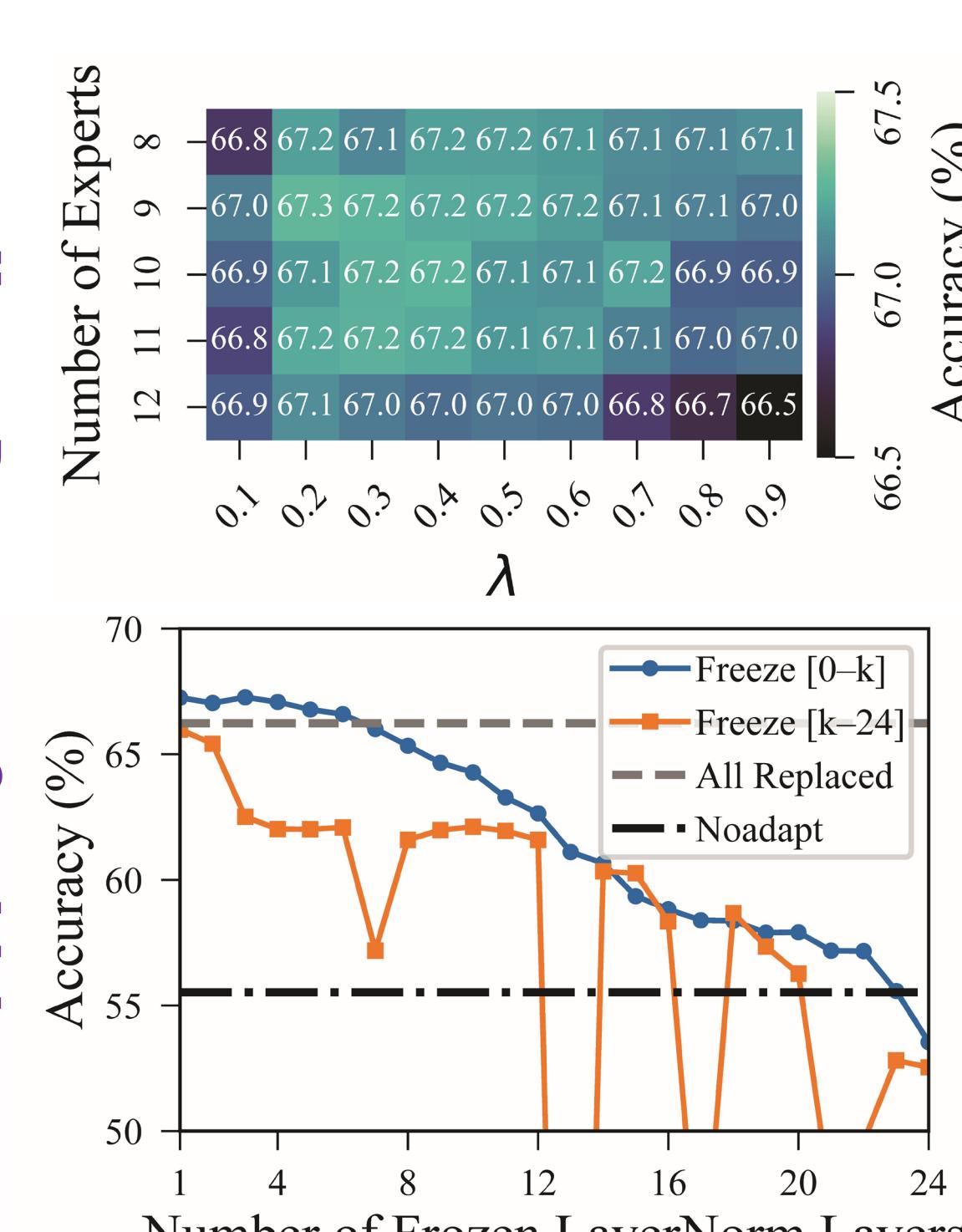
Evolution and Final-State Statistics of Expert Parameter Similarity Across MoE-LayerNorms



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Hyper-Parameter Sensitivity



Experiment

Computation efficiency comparison

Method	#Act. params per sample	#Fwd	#Bwd	Used time
Noadapt	0	100%	0%	100%
Tent	0.04M	100%	100%	226%
EATA	0.04M	100%	80%	239%
SAR	0.03M	199%	175%	440%
DeYO	0.04M	196%	53%	317%
CoTTA	86.42M	199%	100%	798%
MGTTA	2.80M	100%	100%	227%
BECoTTA	0.13M	100%	86%	334%
Ours	0.23M	100%	76%	247%

Ablation analyses

Method	Classical	Pot.	Pot.+	Avg.
Full method	67.25	65.14	66.21	66.20
Loss Components				
w/o Sample selection	67.04	64.01	57.61	62.89
w/o Entropy re-weight	62.86	60.51	61.79	61.72
w/o $\mathcal{L}_{\text{load balancing}}$	26.27	16.27	21.29	21.28
MoE Architecture				
w/o Grad to router	65.17	62.80	63.92	63.96
w/o Sample-wise router	28.69	28.60	24.96	27.42
w/o MoE-LayerNorm	22.38	17.94	26.93	22.42
w/o Layer-wise router	17.40	27.09	15.18	19.89