Mixture of Adversarial LoRAs: Boosting Robust Generalization in Meta-Tuning

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Background & Motivation

- Grounded on large-scale pre-trained models, meta-tuning helps models quickly adapt to new tasks in few-shot scenarios.
- Meta-tuning on single domain **yields marginal OOD improvements** over pre-trained models.
- Meta-tunning suffers from **vulnerability in adversarial attacks and common visual corruptions** under distribution shifts.

Contributions

- We propose **AMT**, a novel **adversarial meta-tuning** approach for enhancing the robust generalization of pre-trained vision transformers across diverse domains.
- We construct the **adaptive robust LoRAPool** by injecting the adversarial perturbations on the **inputs, singular values and vectors of the weight matrices** under varying perturbation budgets during meta-tuning.
- The discriminative components of the pool are integrated into the pre-trained model via a simple yet effective **test-time merging mechanism** for task adaptation.

Adaptive Robust LoRAPool

- **Generate Adversarial Query Set:** Use PGD to generate adversarial query images with different robustness strength.

$$\max_{\|\delta\|_\infty \le \epsilon_i} \mathcal{L}(f_\theta(\mathcal{S}, x_q+\delta), y_q)$$
$$\delta \leftarrow \Pi_{\epsilon_i}\left(\delta + \alpha\cdot \mathrm{sign}\left(\nabla_\delta \mathcal{L}(f_\theta(\mathcal{S}, x_q+\delta), y_q)\right)\right) \quad (1)$$

- **Adversarial Perturbation on Singular Values and Vectors**

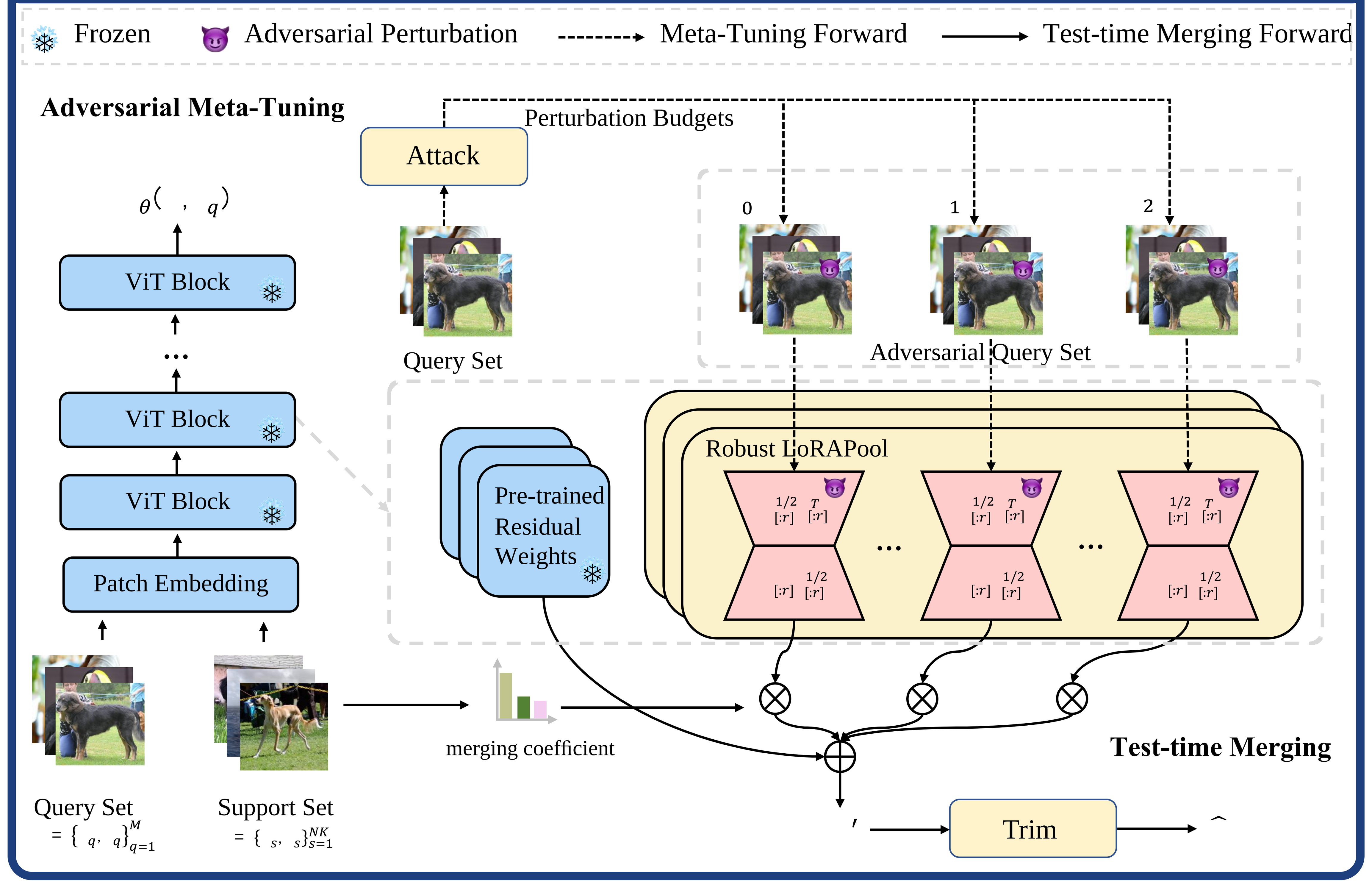
Initialize LoRA parameters with the SVD results and freeze the residual part.

$$A = U_{[:r]}\mathrm{diag}\left(S_{[:r]}^{1/2}\right)$$
$$B = \mathrm{diag}\left(S_{[:r]}^{1/2}\right)V_{[:r]}^T \quad (2)$$
$$W^{\mathrm{res}} = U_{[r:]}\mathrm{diag}(S_{[r:]})V_{[r:]}^T$$

Incorporate worst-case perturbation on A and B using gradient ascent.

$$\delta_A = \eta_1 \cdot \frac{1}{M}\sum_{q=1}^{M}\nabla_A \mathcal{L}\left(f_{W^{\mathrm{res}}+AB}(\mathcal{S}, x_q^{adv}), y_q\right) \quad (3)$$
$$A \leftarrow A - \eta_2 \cdot \frac{1}{M}\sum_{q=1}^{M}\nabla_A \mathcal{L}\left(f_{W^{res}+(A+\delta_A)B}(\mathcal{S}, x_q^{adv}), y_q\right)$$

Framework



Pseudo-code

Algorithm 1 Robust LoRAPools

```
Input: Source training domain D_tr^seen; pre-trained weight residual matrix W^res; P sets of attack configuration candidates;
Output: Adversarially meta-trained LoRAPool;

Initialize adversarial LoRAPool: φ = {}
for i = 1 to P (in parallel) do
    Sample the i-th set of ε_i, α_i from attack configuration candidates.
    Initialize the LoRA parameter AB via Eq. (2);
    while not converged do
        Sample a task T = {S, Q} ~ D_tr^seen.
        Generate adversarial query set Q_adv = {x_q^adv, y_q}_{q=1}^M with ε_i, α_i via Eq. (1)
        // Perturb singular value and vectors
        δ_A = η_1 · (1/M) Σ_{q=1}^M ∇_A L(f_{W^res+AB}(S, x_q^adv), y_q))
        δ_B = η_1 · (1/M) Σ_{q=1}^M ∇_B L(f_{W^res+AB}(S, x_q^adv), y_q))
        // Update AB via SGD
        A ← A − η_2 · (1/M) Σ_{q=1}^M ∇_A L(f_{W^res+(A+δ_A)B}(S, x_q^adv), y_q))
        B ← B − η_2 · (1/M) Σ_{q=1}^M ∇_B L(f_{W^res+A(B+δ_B)}(S, x_q^adv), y_q))
    end while
    φ = φ ∪ AB
end for
```

Algorithm 2 Test-Time Merging

```
Input: Support set of meta-test task S = {x_i^s, y_i^s}_{i=1}^{NK}, pre-trained residual weight matrix W^res, adaptive robust LoRAPool φ = [A_1B_1, ..., A_PB_P]

for i = 1, ..., P (in parallel) do
    // Calculate the intra-class compactness
    C_i = (1/NK) Σ_{s=1}^{NK} γ(f_{W^res+A_iB_i}(x_s), p_{y_s})
    // Calculate the inter-class divergence
    V_i = (1/NK) Σ_{s=1}^{K} Σ_{c=1, c≠y_s}^{N} γ(f_{W^res+A_iB_i}(x_s), p_c)
end for
ζ_i = Top_k(exp(−β(1−(λC−(1−λ)V))))_i / Σ_{i=1}^k Top_k(exp(−β(1−(λC−(1−λ)V))))_i
W' = W_res + Σ_{i=1}^P ζ_i A_i B_i
// Singular Value Trimming
Ŵ = trim(W')
```

Experiments

Table 1. Few-shot classification clean accuracy (%) on Meta-Dataset in the 5-way 1-shot setting.

1-shot	Backbone	TTF	In-domain ImageNet	Out-of-domain Omglot	Acraft	CUB	DTD	QDraw	Fungi	Flower	Sign	COCO	Avg.
PM [12]	ViT-small	-	65.07	59.03	38.13	76.18	61.56	57.29	56.03	80.41	55.17	54.42	60.35
StyleAdv [86]	ViT-small	-	56.10	62.25	40.38	66.62	55.94	57.93	53.19	81.10	54.20	48.08	57.58
AMT	ViT-small	-	**68.80**	**71.95**	**42.90**	**79.95**	**62.99**	**59.62**	**59.06**	**85.37**	**63.78**	**57.14**	**65.16**
PMF [12]	ViT-small	Y	65.07	71.52	38.67	76.15	61.62	59.82	56.03	80.41	59.71	54.41	62.34
PMF+AMT-FT	ViT-small	Y	**68.80**	**77.83**	**42.90**	**79.95**	**63.77**	**63.72**	**59.06**	**85.37**	**63.87**	**57.37**	**66.26**
ATTNSCALE [59]	ViT-small	Y	63.66	72.51	40.09	73.59	61.04	60.26	54.88	82.52	59.91	55.10	62.36
ATTNSCALE+AMT-FT	ViT-small	Y	**68.80**	**79.43**	**42.90**	**79.95**	**63.08**	**65.66**	**59.06**	**85.37**	**64.13**	**58.24**	**66.66**

Achieve SoTA Performance with A Single Adversarially Meta-tuned Model

Table 2. Few-shot classification clean accuracy (%) on BSCD-FSL and fine-grained datasets in the 5-way 1-shot setting.

1-shot	Backbone	TTF	ChestX	ISIC	EuroSAT	CropDisease	CUB	Cars	Places	Plantae	Avg.
PM [12]	ViT-small	-	22.74 ±0.40	33.72 ±0.60	72.94 ±0.77	81.04±0.85	83.53 ±0.86	42.10 ±0.80	71.66 ±0.88	59.04±0.89	58.35
StyleAdv† [86]	ViT-small	-	**22.92±0.32**	33.05±0.44	72.15±0.65	81.22±0.61	84.01±0.58	40.48±0.57	72.64±0.67	55.52±0.66	57.75
AMT	ViT-small	-	22.39±0.39	**33.92 ±0.58**	**73.52±0.84**	**82.04 ±0.80**	**84.34 ±0.83**	**44.33 ±0.81**	**73.78±0.87**	**59.32 ±0.94**	**59.21**
PMF [12]	ViT-small	Y	21.73±0.30	30.36±0.36	70.74±0.63	80.79±0.62	78.13±0.66	37.24±0.57	71.11±0.71	53.60±0.66	55.46
StyleAdv-FT† [86]	ViT-small	Y	22.92±0.32	**33.99±0.46**	**74.93±0.58**	**84.11±0.57**	84.01±0.58	40.48±0.57	72.64±0.67	55.52±0.66	58.57
AMT-FT	ViT-small	Y	**23.23±0.40**	33.95±0.63	73.95±0.78	82.04±0.8	**84.34±0.83**	**46.06 ±0.80**	**73.83±0.89**	**59.32 ±0.94**	**59.59**

Improve Robustness Against Adversarial Attacks And Visual Corruptions Under Distribution Shifts

Table 3. Few-shot classification robustness against adversarial attacks under distribution shifts.

1-shot	Adv. TTF	In-domain ImageNet	Out-of-domain Omglot	Acraft	CUB	DTD	QDraw	Fungi	Flower	Sign	COCO	Avg.
PM [12]	-	23.22	7.74	5.37	22.38	25.39	1.11	12.79	24.99	2.23	10.20	13.54
StyleAdv [86]	-	16.76	15.25	5.95	17.70	25.75	1.43	14.78	30.75	3.07	9.63	14.11
AMT	-	**33.70**	**42.19**	**11.72**	**32.05**	**32.47**	**27.45**	**19.74**	**41.12**	**22.79**	**17.67**	**28.09**
PMF [12]	Y	23.22	31.77	18.35	22.65	25.39	30.99	23.20	38.93	25.86	23.69	26.41
AMT-FT	Y	**33.70**	**42.19**	**20.40**	**34.92**	**32.47**	**37.49**	**20.10**	**41.12**	**32.75**	**22.70**	**31.78**

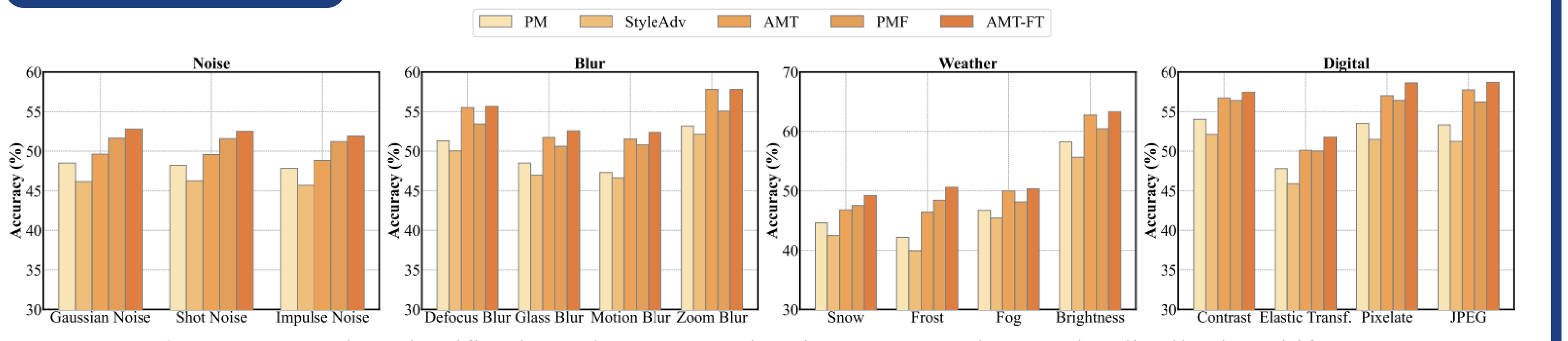


Figure 1. Few-shot classification robustness against image corruptions under distribution shifts.

Analysis

APQ	APSV	RLP	TTM	STr	In-domain INet	Out-of-domain Omglot	Acraft	CUB	DTD	QDraw	Fungi	Flower	Sign	COCO	Avg.
✗	✗	✗	✗	✗	65.07	59.03	38.13	76.18	61.56	57.29	56.03	80.41	55.17	54.42	60.35
✓	✗	✗	✗	✗	64.57	62.47	38.53	76.23	60.47	57.97	56.22	81.72	57.04	53.96	60.92
✓	✗	✓	✓	✗	65.56	63.92	39.74	76.06	61.73	58.64	55.99	80.93	56.96	54.28	61.38
✓	✗	✓	✓	✓	64.95	70.80	40.55	75.19	60.73	**59.66**	56.92	83.63	57.66	56.04	62.61
✓	✓	✓	✗	✗	67.95	62.16	39.13	79.27	61.77	58.75	56.59	79.74	55.45	54.63	61.54
✓	✓	✓	✓	✗	68.46	65.75	42.63	79.43	**63.10**	58.23	55.69	78.93	63.67	56.28	63.22
✓	✓	✓	✓	✓	**68.80**	**71.95**	**42.90**	**79.95**	62.99	59.62	**59.06**	**85.37**	**63.78**	**57.14**	**65.16**