

PGADA: Perturbation-Guided Adversarial Alignment for Few-shot Learning Under the Support- Query Shift

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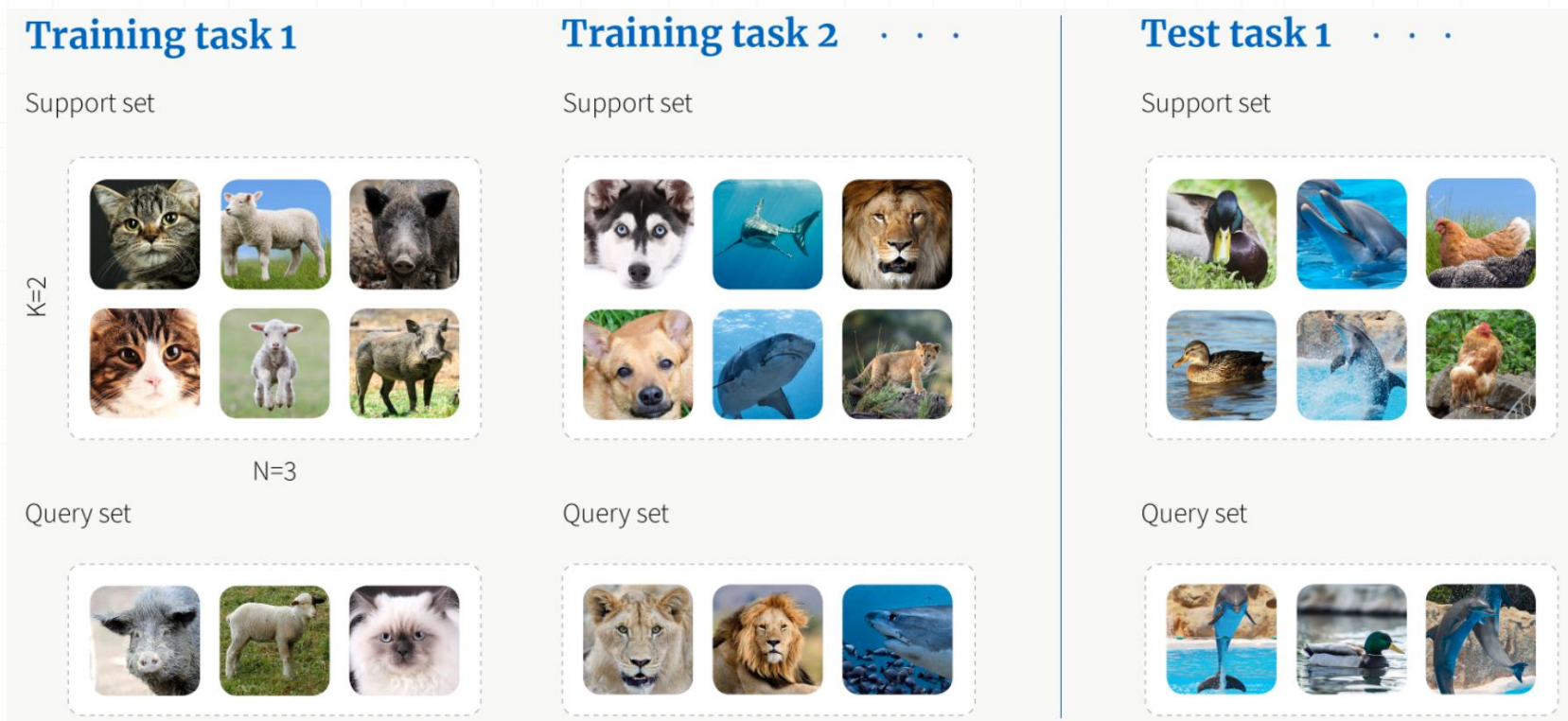
Outlines

- ◆ Background
- ◆ Challenges
- ◆ Motivation
- ◆ Methodology
- ◆ Result
- ◆ Conclusion



Background

◆ Few-shot Learning (FSL)



Few-Shot Learning

Background

◆ Support-Query Shift Few-shot Learning (SQS-FSL)

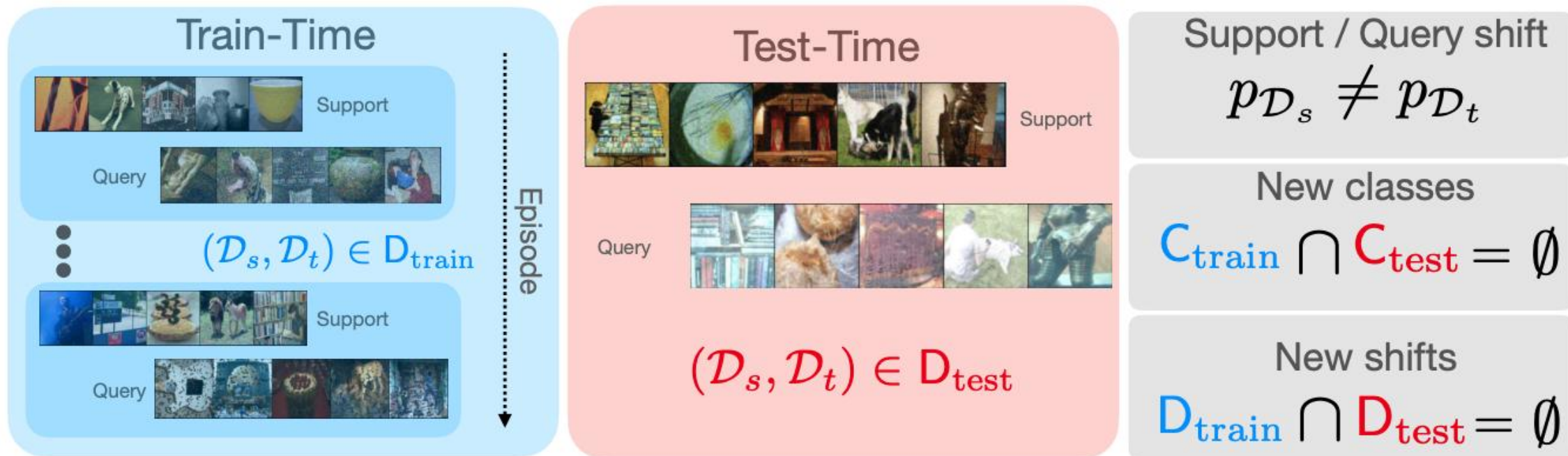


FSL



SQS-FSL

Challenges



Motivation

- ◆ Theoretical foundation
- ◆ A robust feature from images
- ◆ A better alignment plan for the support and query set



Motivation

◆ Theoretical foundation

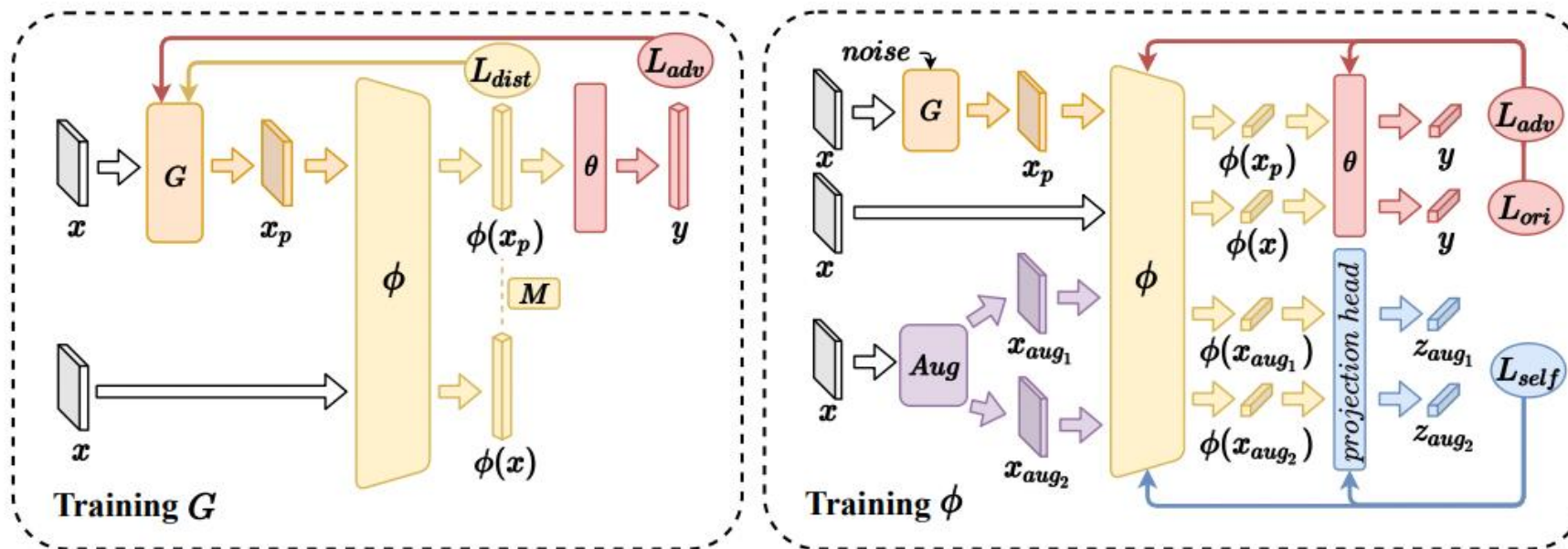
Theorem 1. *The error of the transported embedding is*

$$E[\|\hat{\phi}(x_{s,i}) - \hat{\phi}_{\sigma}(x_{s,i})\|_2^2] = \sqrt{d(\sigma_s^2 + \sigma_q^2)},$$

where $\hat{\phi}_{\sigma}(x_{s,i})$ is the transported embedding from the perturbed distribution $W_{\sigma}(\mu_s, \mu_q)$. $W_{\sigma}(\mu_s, \mu_q) := W(\mu_s * \mathcal{N}_{\sigma_s}, \mu_q * \mathcal{N}_{\sigma_q})$ denotes the original support and query set distributions μ_s and μ_q being perturbed with Gaussian noises σ_s and σ_q , and $*$ is the convolution operator.

Methodology

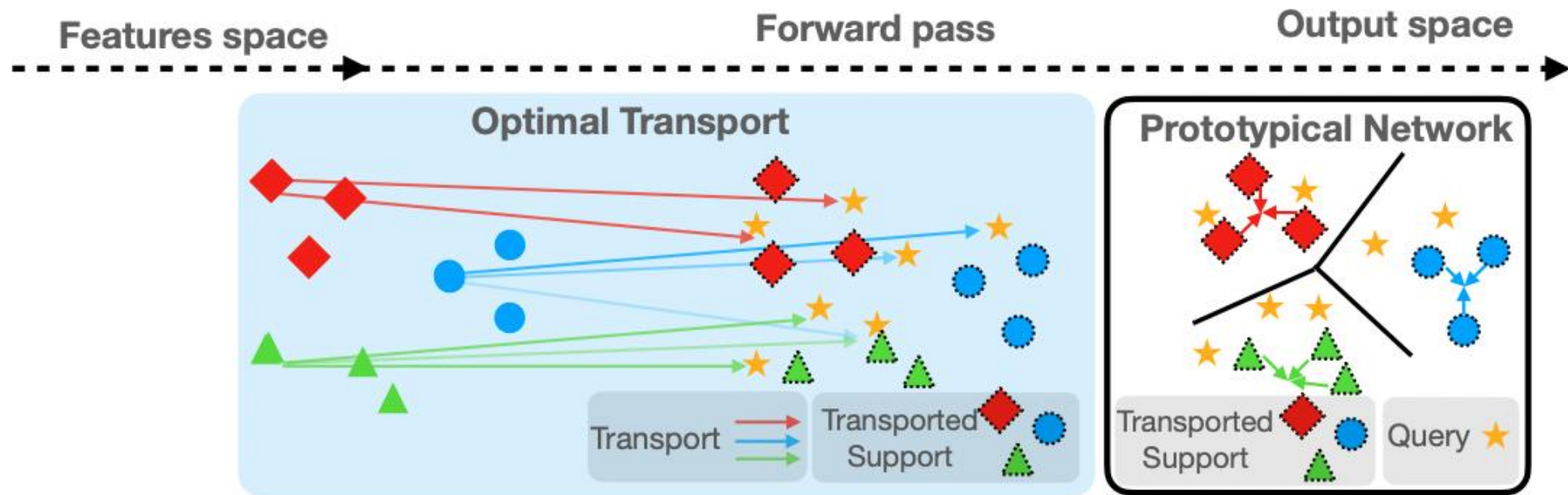
◆ A robust feature from images



$$\min_{\phi, \theta} L_{ori} + \lambda_1 L_{adv} + \lambda_2 L_{self},$$

Methodology

- ◆ A better alignment plan for support and query set



Methodology

- ◆ A better alignment plan for support and query set

$$\pi^* = \arg \min_{\pi} \sum_{\substack{x_{s,i} \sim \hat{\mu}_s \\ x_{q,j} \sim \hat{\mu}_q}} \beta w(x_{s,i}, x_{q,j}) \pi(x_{s,i}, x_{q,j}) + (1 - \beta) \pi(x_{s,i}, x_{q,j}) \log \pi(x_{s,i}, x_{q,j}),$$

Result

Dataset	CIFAR100				miniImageNet				FEMNIST
	8-target		16-target		8-target		16-target		1-target
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot
Few-shot Learning									
MatchingNet [30]	30.71 \pm 0.38	41.15 \pm 0.45	31.00 \pm 0.34	41.83 \pm 0.39	35.26 \pm 0.50	44.75 \pm 0.55	37.20 \pm 0.48	44.22 \pm 0.52	84.25 \pm 0.71
ProtoNet [26]	30.02 \pm 0.40	42.77 \pm 0.47	30.29 \pm 0.33	42.52 \pm 0.41	36.37 \pm 0.50	47.58 \pm 0.57	35.69 \pm 0.45	46.29 \pm 0.53	84.31 \pm 0.73
TransPropNet [21]	34.15 \pm 0.39	47.39 \pm 0.42	34.20 \pm 0.40	44.31 \pm 0.38	24.10 \pm 0.27	27.24 \pm 0.33	25.38 \pm 0.30	28.05 \pm 0.30	86.42 \pm 0.76
FTNET [10]	28.91 \pm 0.37	37.28 \pm 0.40	28.66 \pm 0.31	37.37 \pm 0.33	39.02 \pm 0.46	51.27 \pm 0.45	39.70 \pm 0.40	52.00 \pm 0.37	86.13 \pm 0.71
TP [2]	34.00 \pm 0.46	49.71 \pm 0.47	35.55 \pm 0.41	50.24 \pm 0.39	40.49 \pm 0.54	59.85 \pm 0.49	43.83 \pm 0.51	55.87 \pm 0.42	93.63 \pm 0.63
Adversarial Data Augmentation									
MixUp [34]	37.82 \pm 0.47	52.57 \pm 0.47	38.52 \pm 0.42	53.33 \pm 0.40	42.98 \pm 0.54	57.22 \pm 0.48	43.64 \pm 0.48	57.33 \pm 0.42	97.22 \pm 0.46
CutMix [33]	39.36 \pm 0.48	54.76 \pm 0.48	40.05 \pm 0.44	55.44 \pm 0.40	35.50 \pm 0.52	45.50 \pm 0.56	35.78 \pm 0.48	44.85 \pm 0.52	96.89 \pm 0.49
Autoencoder [24]	39.05 \pm 0.50	53.24 \pm 0.47	39.82 \pm 0.44	53.88 \pm 0.40	45.36 \pm 0.56	57.69 \pm 0.51	45.65 \pm 0.52	57.39 \pm 0.44	96.53 \pm 0.43
AugGAN [16]	39.54 \pm 0.50	53.05 \pm 0.47	39.50 \pm 0.45	53.42 \pm 0.39	44.65 \pm 0.55	57.55 \pm 0.50	44.91 \pm 0.49	57.10 \pm 0.42	96.42 \pm 0.52
MaxEntropy [36]	38.14 \pm 0.40	51.02 \pm 0.56	38.21 \pm 0.34	51.33 \pm 0.52	48.21 \pm 0.36	57.67 \pm 0.63	48.99 \pm 0.21	59.01 \pm 0.44	97.19 \pm 0.51
MaxUp [13]	34.84 \pm 0.44	47.51 \pm 0.46	35.20 \pm 0.40	47.63 \pm 0.39	37.62 \pm 0.55	48.65 \pm 0.58	38.13 \pm 0.50	49.19 \pm 0.51	96.48 \pm 0.53
Ours									
PGADA (ProtoNet)	42.16 \pm 0.52	56.52\pm0.47	42.73\pm0.46	56.83\pm0.40	55.44 \pm 0.61	67.34\pm0.49	55.69 \pm 0.62	66.90\pm0.50	97.98\pm0.40
PGADA (MatchingNet)	42.25\pm0.53	50.98 \pm 0.45	42.60 \pm 0.45	51.80 \pm 0.39	56.15\pm0.61	63.08 \pm 0.49	56.12\pm0.57	63.61 \pm 0.45	97.96 \pm 0.39

Table 1: Accuracy comparison of the three datasets with two types of baselines.

Result

Dataset	CIFAR100				miniImageNet				FEMNIST
	8-target		16-target		8-target		16-target		1-target
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot
PGADA	42.16 ± 0.52	56.52 ± 0.47	42.73 ± 0.46	56.83 ± 0.40	55.44 ± 0.61	67.34 ± 0.49	55.69 ± 0.62	66.90 ± 0.50	97.98 ± 0.40
Generator									
fixed G	38.58 ± 0.48	52.41 ± 0.47	39.26 ± 0.43	52.67 ± 0.39	43.50 ± 0.55	55.65 ± 0.50	43.48 ± 0.51	55.42 ± 0.43	96.41 ± 0.52
w/o noise	37.16 ± 0.47	50.12 ± 0.46	37.73 ± 0.41	50.50 ± 0.38	44.06 ± 0.56	56.97 ± 0.48	44.42 ± 0.49	56.96 ± 0.42	96.89 ± 0.48
w/o KL	37.30 ± 0.47	50.79 ± 0.46	37.91 ± 0.42	51.35 ± 0.39	44.22 ± 0.54	55.04 ± 0.49	44.21 ± 0.49	53.96 ± 0.41	96.49 ± 0.48
Regularized Optimal Transport (OT)									
w/o OT	35.76 ± 0.41	54.06 ± 0.45	35.66 ± 0.35	54.09 ± 0.38	44.30 ± 0.52	61.23 ± 0.53	44.15 ± 0.46	60.86 ± 0.48	94.03 ± 0.48
TP [2]	34.00 ± 0.46	49.71 ± 0.47	35.55 ± 0.41	50.24 ± 0.39	40.49 ± 0.54	59.85 ± 0.49	43.83 ± 0.51	55.87 ± 0.42	93.63 ± 0.63
TP w/o OT	33.07 ± 0.38	50.99 ± 0.44	32.96 ± 0.32	50.71 ± 0.37	38.07 ± 0.45	55.31 ± 0.51	37.94 ± 0.41	55.11 ± 0.44	91.84 ± 0.56
Self-supervised Learning (SSL)									
w/o SSL	39.33 ± 0.50	53.66 ± 0.47	40.31 ± 0.44	54.23 ± 0.40	47.96 ± 0.57	61.38 ± 0.49	48.70 ± 0.52	61.44 ± 0.43	97.07 ± 0.48

Table 2: The results of ablation studies.

Conclusion

- ◆ PGADA
 - ◆ Theoretical foundation
 - ◆ Clean representations
 - ◆ Accurate Alignment Plans



Thanks for your attention.

