Domain Generalized Few-Shot Image Classification Via Meta Regularization Network

Min Zhang[1,2], Siteng Huang[2], Donglin Wang[2]

[1]Zhejiang University, [2]Westlake University

How Humans Learn?

Can we enable the computer to explicitly learn priors from previous experience that lead to efficient new task learning?

— Meta-learning

Humans generalize experience from learned tasks

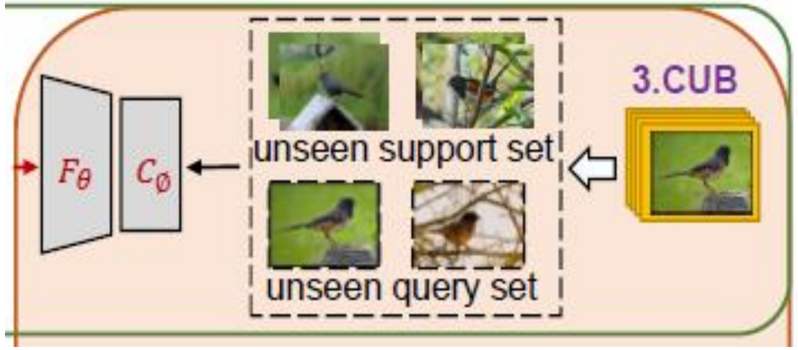
Humans learn to learn

Meta-learning with Fewer Tasks

Ideal Scenario

Meta-training phase

Prior



Meta-testing phase

Real-world Scenario

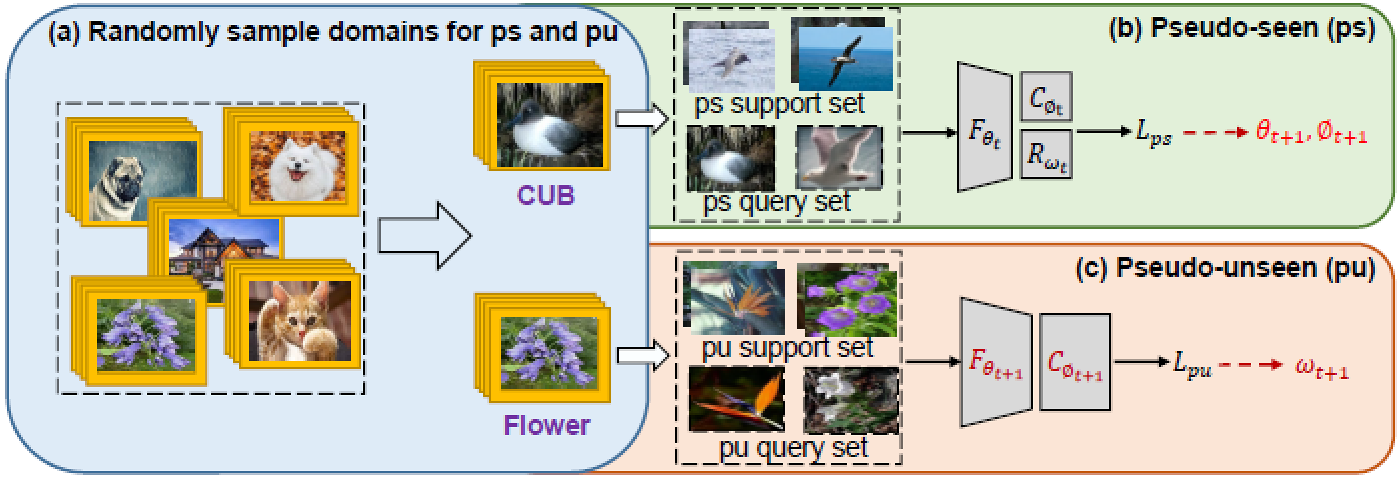
Meta-training phase

Fail to generalize due to domain shifts

Meta-testing phase

Overcoming domain generalized few-shot image classification via the MRN

We propose **meta regularization network (MRN)**, which aims to learn a **domain-invariant discriminative feature space** by using a learning to learn update strategy.

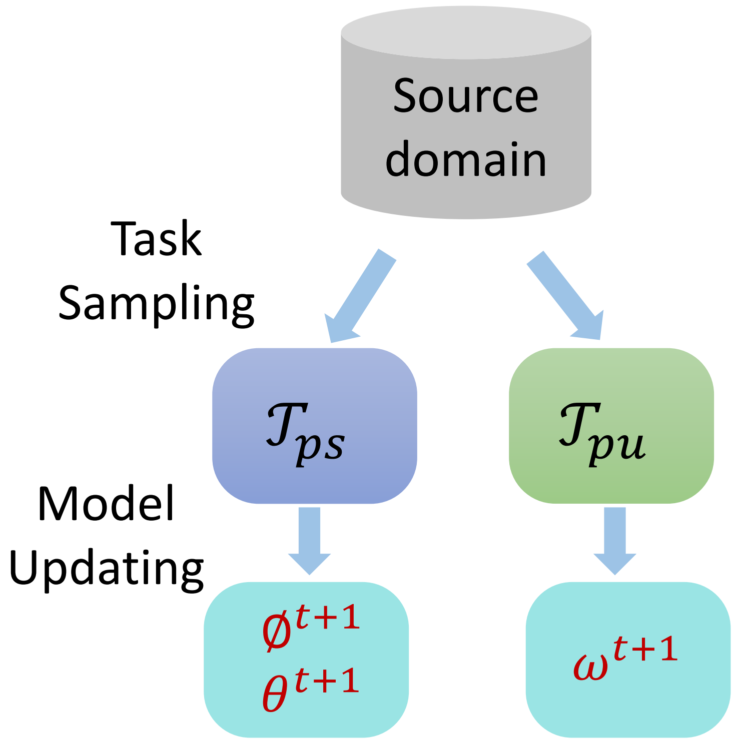


Solution: Overview

How can we learn domain-invariant feature sapce?

In MRN, we learn a domain-invariant feature space by using a learning to learn update strategy with three steps:

1. Randomly pick two tasks $\mathcal{T}_{ps}$ and $\mathcal{T}_{pu}$ (ps is pseudo-seen and pu is pseudo-unseen domains)
2. $\mathcal{T}_{ps}$ is used to update the model parameters F_{θ} and $C_{\emptyset}$ with the MRN loss L_{mrn} and cross-entropy loss L_{ce}
3. Remove the MRN from the framework and use the updated model to calculate the loss of $\mathcal{T}_{pu}$ to update the MRN



Experiments: Overview

- Q1: Does the MRN improves the performance of meta-learning methods?

- Q2: How is its performances compared with state-of-the-art approaches?

- Q3: How do different regularization, *i.e.*, L1-norm or L2-norm, affect the performance?

Q1: Does the MRN improves the performance of meta-learning methods?

Four datasets

miniImageNet; CUB-200-2011; tieredImageNet; CIFAR-FS

The leave one-domain0-out setting is adopted to select an unseen domain.

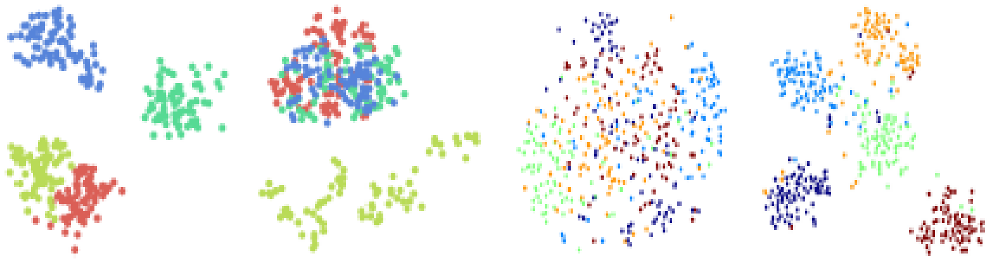
Table 1. Classification average testing accuracy (%)

5-way	MRN	*mini*ImageNet		*tiered*ImageNet		CUB-200-2011		CIFAR-FS	
		1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
MAML [3]		35.18	45.82	30.83	45.91	30.96	42.28	35.62	37.28
MAML [3]	✓	45.30 (+10.12)	62.33 (+16.51)	42.59 (+11.76)	59.83 (+13.92)	35.42 (+4.46)	47.63 (+5.35)	39.27 (+3.65)	48.61 (+11.33)
Prototypical Network [6]		47.72	64.83	43.50	58.04	39.47	55.36	38.87	54.41
Prototypical Network [6]	✓	53.77 (+6.05)	68.05 (+3.22)	46.67 (+3.17)	64.23 (+6.19)	42.32 (+2.85)	60.83 (+5.47)	41.33 (+2.46)	58.91 (+4.50)

Q2: How is its performances compared with state-of-the-art approaches?

Table 2. Average accuracy (%) comparison to state-of-the-arts.

5-way	Backbone	*mini*ImageNet 1-shot	*mini*ImageNet 5-shot	*tiered*ImageNet 1-shot	*tiered*ImageNet 5-shot	CUB-200-2011 1-shot	CUB-200-2011 5-shot	CIFAR-FS 1-shot	CIFAR-FS 5-shot
Relation Network LFT [16]	ResNet10	55.23±0.14	72.56±0.81	48.75±0.89	63.24±0.91	45.67±0.78	64.75±0.47	44.79±0.31	60.12±0.45
Matching Network LFT [16]	ResNet10	56.01±0.31	73.45±0.65	49.31±0.21	65.41±0.45	45.12±0.65	65.14±0.74	45.98±0.31	59.12±0.34
ProtoNet MRN (ours)	ResNet10	**56.99±0.61**	**75.16±0.48**	**50.31±0.12**	**68.23±0.47**	**48.32±0.45**	**66.85±0.31**	**47.23±0.18**	**64.52±0.25**



(a) MAML (b) MRN (c) MAML (d) MRN

Fig. 3. The t-SNE visualization of the embedding distributions learned by MAML without (a)/(c) or with (b)/(d) the MRN. The model is tested on *tiered*ImageNet datatset.

Q3: Ablation study

Table 3. Average testing accuracy (%).

5-way-1-shot	*mini*ImageNet	*tiered*ImageNet	CUB-200-2011	CIFAR-FS
L_1	48.18±0.37	44.83±0.57	39.96±0.45	38.62±0.55
L_2	48.63±0.35	45.95±0.38	40.06±0.42	38.79±0.58
Flatten	52.98±0.38	46.23±0.37	**43.21±0.46**	**42.63±0.54**
MLP	**53.77±0.61**	**46.67±0.68**	42.32±0.62	41.33±0.59
5-way-5-shot	*mini*ImageNet	*tiered*ImageNet	CUB-200-2011	CIFAR-FS
L_1	64.82±0.47	59.91±0.47	55.28±0.58	56.28±0.58
L_2	65.23±0.37	58.98±0.37	56.32±0.42	55.78±0.48
Flatten	67.95±0.35	63.06±0.35	60.01±0.41	57.98±0.69
MLP	**68.05±0.56**	**64.23±0.75**	**60.83±0.44**	**58.91±0.55**

Takeaways

- Learning a domain-invariant feature space can improve generalization in few-shot image classification under domain generalization setting.

- MRN achieves this by a learning to learn update strategy and is compatible with any meta-learning algorithms.

Thanks

Q & A