Domain Generalized Few-Shot Image Classification Via Meta Regularization Network

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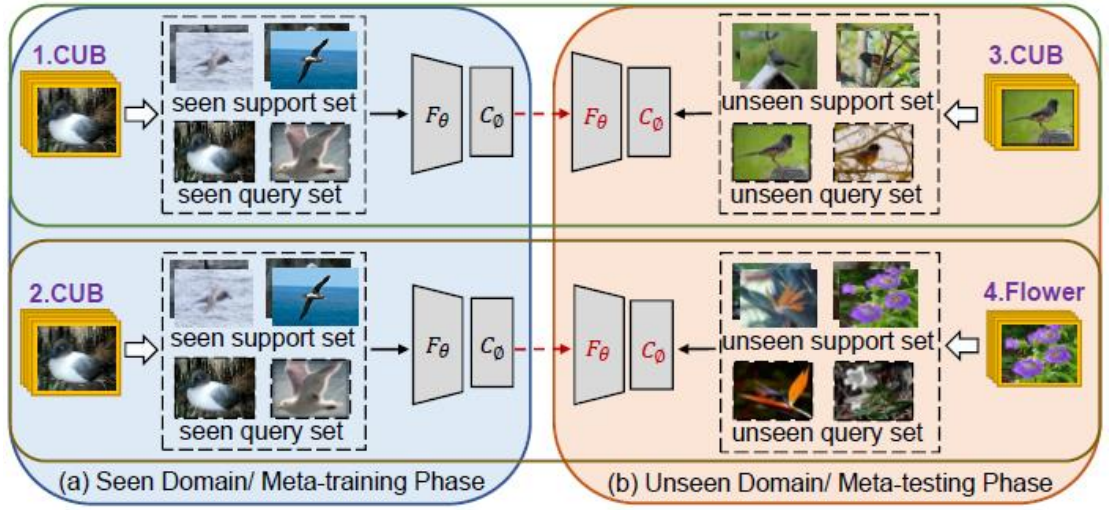
Background

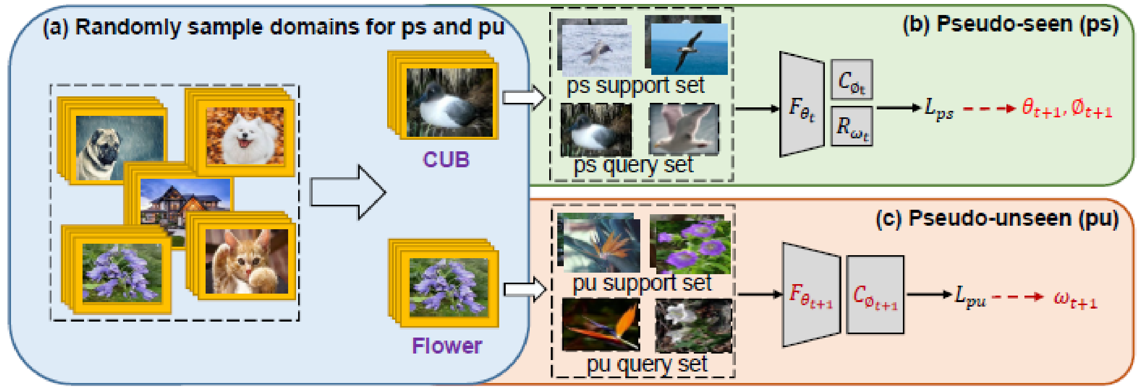


Abstract We design an Meta Regularization Network (MRN) to learn a domain-invariant discriminative feature space, where a learning to learn update strategy is used to simulate domain shifts caused by seen and unseen domains. The simulation trains the model to learn to reorganize the feature knowledge acquired from seen domains to represent unseen domains. Extensive experiments and analysis show that our proposed MRN method can significantly improve the generalization ability of various meta-learning methods to achieve state-of-the-art performance in domain generalized few-shot learning.

Challenges

- If testing episodes are sampled from the same domain as training episode (*e.g.*, the training and testing episodes are the same dataset in Figure (a): 1.CUB→(b): 3.CUB), the updated model has a good performance.
- However, If testing episodes are given from a different domain like Figure (a): 2.CUB → (b): 4.Flower, the learned model cannot quickly adapt to unseen domains, resulting in poor performance.
- Solving the DGFSL problem remains a challenge for different label spaces between the training and testing phases.

Approach



1. We propose the meta regularization network (MRN) to adjust the feature encoder F_θ to learn a domain-invariant feature space. Intuitively, the F_θ equipped with the MRN can produce more diverse feature distributions, which improves the generalization ability of the classifier C_ϕ.

2. How to integrate the MRN with the feature encoder? Inspired by multi-tasks learning, we introduce an additional regularization loss generated by the MRN, combined with a few-shot learning loss to optimize the model. .

3. We use a learning to learn update strategy to optimize the proposed MRN. Specifically, two non-overlapping episodes from different domains are randomly sampled in each meta-training iteration. One is used to update the model using the summation of the two loss. The other tests the performance of the updated model and then feeds it back to the MRN. Furthermore, the MRN is updated based on this feedback to improve the performance of the model in the next iteration.

Experimental Results

Extensive experiments show that our light-weight module can significantly improve meta-learning approaches to achieve SOTA. More details can be found in https://2022.ieeeicassp.org/papers/accepted_papers.php

Table 1. Classification average testing accuracy (%)

5-way	MRN	*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
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)

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**

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**

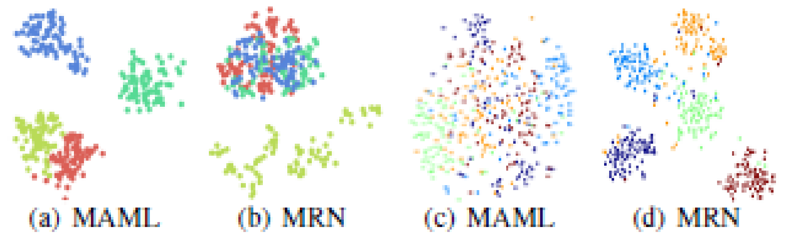


Fig. 3. The t-SNE visualization of the embedding distributions learned by MAML without (a)/(c) or with (b)/(d) the MRN. The model is tested on *tiered*ImageNet datatset.

Conclusion The MRN is presented to assist the feature encoder to learn a domain-invariant feature space through simulating various feature distributions extracted from the different domains. A learning to learn update strategy is used to optimize the MRN. From extensive experiments, we demonstrate that our method can handle the domain generalized few-shot image classification problem, and shows an improvement to achieve new SOTA.