Domain Adaptive Few-Shot Open-Set Learning

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Abstract

Few-shot learning has made impressive strides in addressing the crucial challenges of recognizing unknown samples from novel classes in target query sets and managing visual shifts between domains. However, existing techniques fall short when it comes to identifying target outliers under domain shifts by learning to reject pseudo-outliers from the source domain, resulting in an incomplete solution to both problems. To address these challenges comprehensively, we propose a novel approach called Domain Adaptive Few-Shot Open Set Recognition (DA-FSOS) and introduce a meta-learning-based architecture named DAFOS-Net. During training, our model learns a shared and discriminative embedding space while creating a pseudo-open-space decision boundary, given a fully-supervised source domain and a label-disjoint few-shot target domain. To enhance data density, we use a pair of conditional adversarial networks with tunable noise variances to augment both domains' closed and pseudo-open spaces. Furthermore, we propose a domain-specific batch-normalized class prototypes alignment strategy to align both domains globally while ensuring class-discriminativeness through novel metric objectives. Our training approach ensures that DAFOS-Net can generalize well to new scenarios in the target domain. We present three benchmarks for DA-FSOS based on the Office-Home, mini-ImageNet/CUB, and DomainNet datasets and demonstrate the efficacy of DAFOS-Net through extensive experimentation.

Motivation

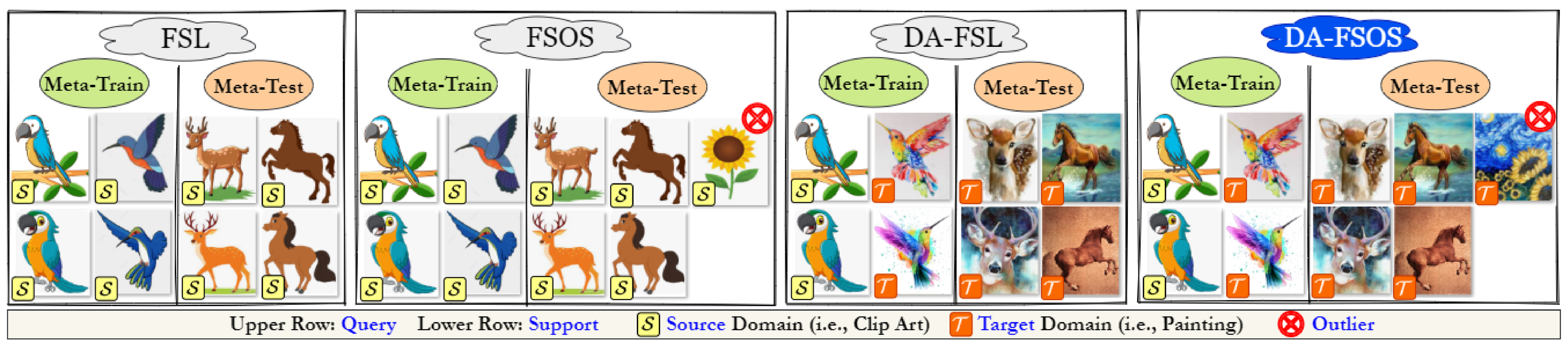


Figure 1. DA-FSOS tackles the challenges of both Domain Adaptive Few-Shot Learning (DA-FSL) and Few-Shot Open-Set Learning (FSOS) by integrating them into a unified framework. In training phase, the model observes a fully-supervised source domain $\mathcal{S}$ and a sparsely-supervised target domain $\mathcal{T}$, where the labels of both domains are disjoint. However, during testing, the model encounters a few-shot support set of new *known* classes from $\mathcal{T}$, while the test query set contains unlabeled samples from both the known and previously unknown classes.

Contributions

The present study investigates the following objectives:

- Novelty 1: An episodic training strategy to develop a domain-agnostic open-set classifier.
- Novelty 2: A generative feature augmentation scheme that produces diversified known and pseudo-unknown class samples for both domains from few-shot training samples.
- Novelty 3: A metric loss to ensure class compactness and discriminativeness for both domains.
- Novelty 4: A prototypical batch-norm alignment-based global domain adaptation.
- Novelty 5: Extention of standard DA-FSOS to generalized DA-FSOS protocol.

Architecture and Meta-Learning of DAFOS-NET

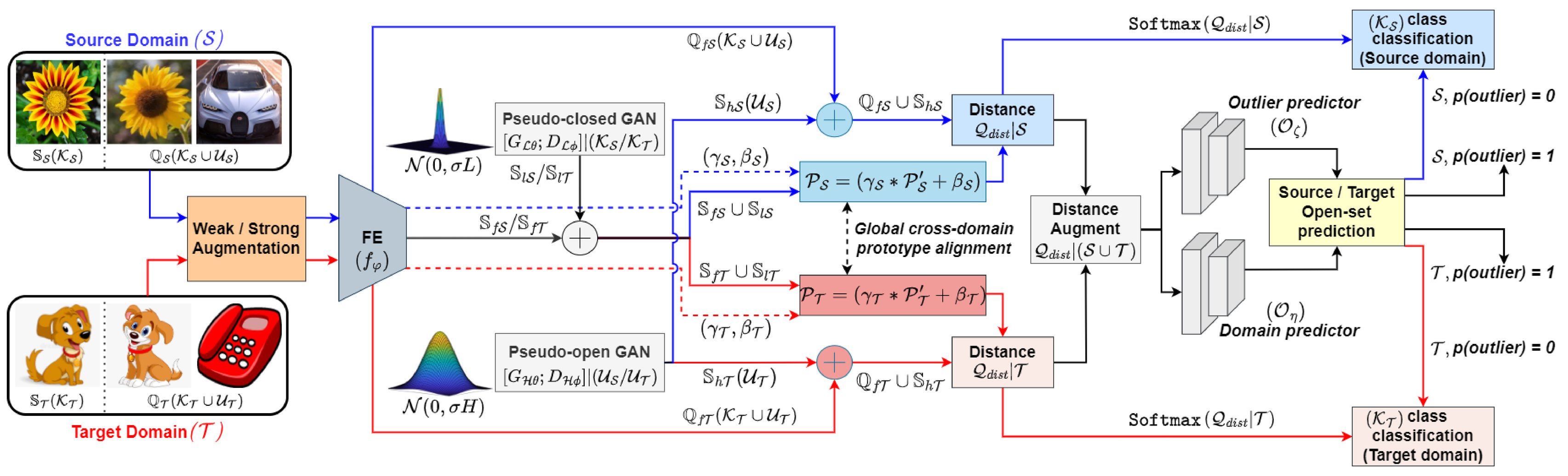


Figure 2. In each episodic training, Support $\mathbb{S}_\mathcal{S}(\mathcal{K}_\mathcal{S})/\mathbb{S}_\mathcal{T}(\mathcal{K}_\mathcal{T})$ and Query samples $\mathbb{Q}_\mathcal{S}(\mathcal{K}_\mathcal{S} \cup \mathcal{U}_\mathcal{S})/\mathbb{Q}_\mathcal{T}(\mathcal{K}_\mathcal{T} \cup \mathcal{U}_\mathcal{T})$ from $\mathcal{D}_s$ and $\mathcal{D}_d$ with $\mathcal{K}_\mathcal{S}/\mathcal{K}_\mathcal{T}$ known and $\mathcal{U}_\mathcal{S}/\mathcal{U}_\mathcal{T}$ pseudo-unknown classes are considered from $\mathcal{S}$ and $\mathcal{T}$. The domain and class conditional GANs $(G_{\mathcal{L}\theta}, D_{\mathcal{L}\phi})$ and $(G_{\mathcal{H}\theta}, D_{\mathcal{H}\phi})$ separately synthesize features for the known and pseudo-unknown classes. The augmented support sets $\mathbb{S}_{f\mathcal{S}} \cup \mathbb{S}_{l\mathcal{S}}$ and $\mathbb{S}_{f\mathcal{T}} \cup \mathbb{S}_{l\mathcal{T}}$ are used to produce the class prototype embeddings $\mathcal{P}'_\mathcal{S}$ and $\mathcal{P}'_\mathcal{T}$ for both the domains, which are aligned through the learnable domain-specific batch-norm parameters $(\gamma_\mathcal{S}, \beta_\mathcal{S})$ and $(\gamma_\mathcal{T}, \beta_\mathcal{T})$. Finally, a pair of domain-agnostic classifiers $(\mathcal{O}_\zeta, \mathcal{O}_\eta)$ are deployed for the purpose of domain and inlier/outlier class predictions for the query samples.

Formulation of Metric Objectives

- Known-class compactness loss:

$$\mathcal{L}_{C|(\mathcal{S}\cup\mathcal{T})} = \mathbb{E}_{q\in\mathbb{Q}_f(\mathcal{K})\cup\mathbb{S}_f\cup\mathbb{S}_l}\left[-\log\frac{e^{-d(q,\mathcal{P}^l)}}{\sum_{k=1}^{\mathcal{K}} e^{-d(q,\mathcal{P}^k)}}\right] \tag{1}$$

- Prototype diversification loss:

$$\mathcal{L}_{PD} = \sum_{k=1}^{|\mathcal{K}_\mathcal{S}|}\left[\|\mathcal{P}^k_\mathcal{S} - q_{Pos|\mathcal{S}}\|_2^2 - \|\mathcal{P}^k_\mathcal{S} - q_{Neg|\mathcal{S}}\|_2^2 + \alpha\right]_+ + \sum_{k=1}^{|\mathcal{K}_\mathcal{T}|}\left[\|\mathcal{P}^k_\mathcal{T} - q_{Pos|\mathcal{T}}\|_2^2 - \|\mathcal{P}^k_\mathcal{T} - q_{Neg|\mathcal{T}}\|_2^2 + \alpha\right]_+; \tag{2}$$

- Global cross-domain prototype alignment loss:

$$\mathcal{L}_{Align} = \frac{\sum_{k=1}^{|\mathcal{K}_\mathcal{S}|}(\gamma_\mathcal{S} \times \mathcal{P}'^k_\mathcal{S} + \beta_\mathcal{S})}{|\mathcal{K}_\mathcal{S}|} - \frac{\sum_{k=1}^{|\mathcal{K}_\mathcal{T}|}(\gamma_\mathcal{T} \times \mathcal{P}'^k_\mathcal{T} + \beta_\mathcal{T})}{|\mathcal{K}_\mathcal{T}|}; \tag{3}$$

- Outlier detection loss:

$$\mathcal{L}_{OUT} = \mathbb{E}_{q\in\{\mathbb{Q}_{f\mathcal{S}}\cup\mathbb{Q}_{f\mathcal{T}}\cup\mathbb{S}_{h\mathcal{S}}\cup\mathbb{S}_{h\mathcal{T}}\}}\left[-\sum_{i=1}^{2} t_i log(\mathcal{O}_\zeta(\mathcal{Q}_{dist})_i)\right] \tag{4}$$

- Domain prediction loss:

$$\mathcal{L}_{DC} = \mathbb{E}_{q\in\{\mathbb{Q}_{f\mathcal{S}}\cup\mathbb{S}_{h\mathcal{S}}\cup\mathbb{Q}_{f\mathcal{T}}\cup\mathbb{S}_{h\mathcal{T}}\}}\left[-\sum_{i=1}^{2} c_i log(\mathcal{O}_\eta(\mathcal{Q}_{dist})_i)\right] \tag{5}$$

- Total loss: $\mathcal{L}_{FE} = \lambda_1 \cdot \mathcal{L}_C + \lambda_2 \cdot \mathcal{L}_{PD} + \lambda_3 \cdot \mathcal{L}_{Align} + \lambda_4 \cdot \mathcal{L}_{OUT} + \lambda_5 \cdot \mathcal{L}_{DC}$

Regularized closed-open feature hallucination

Anti-open-close mode collapse loss: To ensure a controlled generation of diverse open and closed space features for both the domains by $G_{\mathcal{H}\theta}$ and $G_{\mathcal{L}\theta}$, respectively, using inputs $z_l \in \mathcal{N}(0, \sigma L)$ and $z_h \in \mathcal{N}(0, \sigma H)$, it is essential to avoid generating identical $s_h \in \mathbb{S}_h$ and $s_l \in \mathbb{S}_l$ for similar z_l and z_h inputs to the cGANs. To this end, we propose the anti-open-close mode collapse loss ($\mathcal{L}_{AOCMC}$) during the optimization of the open-space cGAN parameters ($\mathcal{H}\theta, \mathcal{H}\phi$) in $\mathcal{L}_h$, which is as follows,

$$\mathcal{L}_{AOCMC} = \min_{G_{\mathcal{H}\theta}, D_{\mathcal{H}\phi}} 1 + \log\frac{1 - (\cos(z_l, z_h)) + \epsilon}{1 - (\cos(s_l, s_h)) + \epsilon} \tag{6}$$

$$\begin{aligned}\mathcal{L}_h &= \underset{G_{\mathcal{H}\theta}}{min}\,\underset{D_{\mathcal{H}\phi}}{max}\,\mathbb{E}_{s\sim\mathbb{Q}_{f\mathcal{S}/f\mathcal{T}}(\mathcal{U}_\mathcal{S}/\mathcal{U}_\mathcal{T})}[logD_{\mathcal{H}\phi}(s|\mathcal{U}_\mathcal{S}/\mathcal{U}_\mathcal{T})] + \mathbb{E}_{z_h\sim\mathcal{N}(0,\sigma H)}[log(1 - D_{\mathcal{H}\phi}(G_{\mathcal{H}\theta}(z_h|\mathcal{U}_\mathcal{S}/\mathcal{U}_\mathcal{T})]\\ &\quad + \mathcal{L}_{AOCMC}\\ \mathcal{L}_l &= \underset{G_{\mathcal{L}\theta}}{min}\,\underset{D_{\mathcal{L}\phi}}{max}\,\mathbb{E}_{s\sim\mathbb{S}_{f\mathcal{S}/f\mathcal{T}}}[logD_{\mathcal{L}\phi}(s|\mathcal{K}_\mathcal{S}/\mathcal{K}_\mathcal{T}))] + \mathbb{E}_{z_l\sim\mathcal{N}(0,\sigma L)}[log(1 - D_{\mathcal{L}\phi}(G_{\mathcal{L}\theta}(z_l|\mathcal{K}_\mathcal{S}/\mathcal{K}_\mathcal{T}))];\end{aligned} \tag{7}$$

Results and discussion

A. Standard DA-FSOSR evaluation

Table 1. The 5-way ($\mathcal{K} = 5$) 1 and 5-shot DA-FSOS performance comparison

Model	Paradigm	Office-Home Real-World to Clipart Acc(%)	Office-Home Real-World to Clipart AUROC(%)	MiniImageNet to CUB Acc(%)	MiniImageNet to CUB AUROC(%)	DomainNet Real to Clipart Acc(%)	DomainNet Real to Clipart AUROC(%)	DomainNet Real to Painting Acc(%)	DomainNet Real to Painting AUROC(%)	DomainNet Clipart to Painting Acc(%)	DomainNet Clipart to Painting AUROC(%)
		1-shot Evaluation									
PrototypicalNet	FSL	25.17	19.23	31.44	25.12	28.15	23.02	29.81	23.51	27.59	22.18
Metaoptnet	FSL	33.71	26.62	42.46	34.22	35.16	27.19	38.63	26.02	37.21	29.56
OpenMax	OSR	12.19	14.77	21.88	24.02	14.68	16.25	15.71	16.38	15.66	17.01
PEELER	FSOS	14.55	16.18	25.47	27.82	18.81	20.28	21.06	22.67	22.64	23.04
SnaTCHer	FSOS	20.36	22.15	31.33	32.18	23.79	25.17	24.43	25.64	25.18	24.56
OCN	FSOS	22.64	21.32	35.98	33.27	24.11	23.92	26.24	25.17	27.65	26.64
MORGAN	FSOS	33.92	35.15	40.62	37.45	33.15	32.43	34.89	33.45	39.22	38.07
AdaMatch	DA	30.31	27.29	45.82	36.26	34.53	30.36	33.27	29.71	30.84	26.34
DAPN	DA-FSL	31.86	25.28	47.82	38.76	38.44	29.73	41.65	33.21	43.49	35.27
NSAE	CDFSL	34.26	28.17	42.67	34.59	36.33	28.25	39.17	31.07	40.14	33.19
MORGAN + DAPN	-	36.22	38.12	41.12	40.46	36.58	34.41	38.75	36.19	41.77	39.45
DAFOS-Net [Ours]	DA-FSOS	51.79±0.67	50.54±0.54	49.25±0.62	50.17±0.28	52.42±0.37	54.84±0.36	55.06±0.34	54.16±0.33	56.21±0.21	57.26±0.49
		5-shot Evaluation									
PrototypicalNet	FSL	29.61	24.75	35.87	31.27	31.67	23.43	32.28	25.96	31.28	24.98
Metaoptnet	FSL	36.51	28.63	46.36	35.97	38.45	30.77	41.73	32.29	40.42	32.37
OpenMax	OSR	15.74	16.28	26.43	29.32	16.26	17.38	17.46	18.23	20.21	19.45
PEELER	FSOS	20.16	22.24	30.71	33.41	22.52	24.14	23.24	27.08	24.82	25.12
SnaTCHer	FSOS	23.12	25.12	34.28	35.13	26.13	27.16	26.71	28.16	28.41	26.72
OCN	FSOS	24.28	23.98	37.42	34.21	25.86	25.62	27.87	26.23	31.35	29.89
MORGAN	FSOS	35.31	37.43	42.04	39.82	36.25	34.44	38.32	36.44	42.05	39.86
AdaMatch	DA	36.67	30.48	46.15	39.19	37.91	31.21	35.37	31.34	33.57	28.38
DAPN	DA-FSL	34.55	27.32	49.55	41.23	40.47	31.42	44.29	35.68	45.57	38.75
NSAE	CDFSL	37.84	29.65	46.33	36.67	39.11	29.32	42.32	34.42	43.14	35.23
MORGAN + DAPN	-	39.52	40.68	45.55	44.26	40.64	41.45	40.27	39.26	45.81	42.26
DAFOS-Net [Ours]	DA-FSOS	54.44±0.29	57.72±0.18	58.51±0.32	59.73±0.43	55.09±0.64	60.67±0.48	59.03±0.25	56.08±0.67	59.66±0.28	60.55±0.31

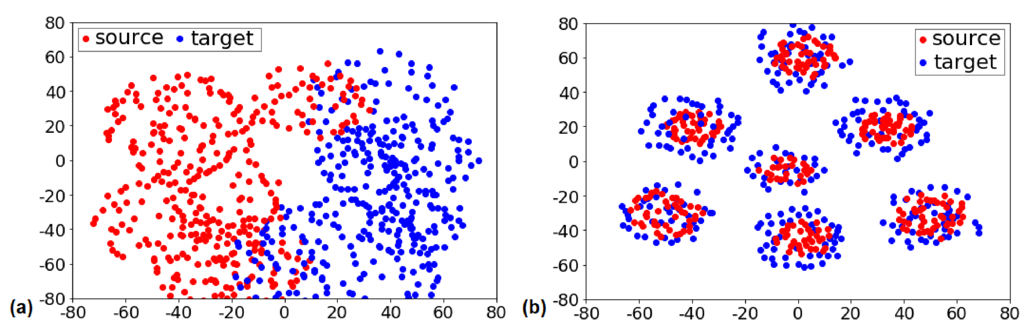
B. Generalized DA-FSOSR evaluation

Table 2. The 5-way 5-shot Generalized DA-FSOSR comparison against MORGAN, DAPN and MORGAN+DAPN

Dataset	MORGAN		DAPN		MORGAN+DAPN		DAFOS-Net	
	Acc(%)	AUROC(%)	Acc(%)	AUROC(%)	Acc(%)	AUROC(%)	Acc(%)	AUROC(%)
Office-Home (R → C)*	32.37±0.71	30.65±0.09	30.09±0.28	27.16±0.67	36.23±0.17	38.47±0.47	49.24±0.59	52.25±0.83
MiniImageNet to CUB	36.18±0.37	34.89±0.82	31.54±0.43	26.08±0.58	42.26±0.15	41.06±0.31	52.79±0.62	52.35±0.35
DomainNet (R → C)*	32.25±0.52	35.53±0.71	29.25±0.31	28.67±0.45	38.23±0.06	37.38±0.29	52.92±0.46	59.17±0.18

*R: RealWorld domain, C: Clipart domain

C. t-SNE visualization without and with domain adaptation



Conclusions

- Introduced a novel problem definition, DA-FSOS, to reject few-shot target domain outliers by learning to reject source domain outliers with large sample space.
- Developed a new framework, DAFOS-Net with a discriminative, domain-invariant embedding space while being able to reject target outliers in meta-testing.
- Proposed a new generative augmentation scheme, a domain-aware GCDPA loss, and a metric loss to assert discriminativeness.
- Extended the standard DA-FSOS protocol for a generalized case.
- In the future, the model can be evaluated by learning from multiple source domains.

Practical Applications

- In many applications, abundant synthetic data exist, while real-world images are often scarce. Real-world data annotation is costly with a high probability of unknowns during inference.
- Self-driving cars: By learning to identify known classes and reject outliers from the gaming environment, DA-FSOSR can assist self-driving cars in recognizing objects of interest (known / unknown) on the road, given limited real-world supervision.
- DA-FSOSR can be applied to novel animal species detection, unknown object rejection for land cover analysis, unknown virus detection in medical imaging, etc.

References

[1] Pal, Debabrata, et al. "MORGAN: Meta-Learning-based Few-Shot Open-Set Recognition via Generative Adversarial Network." In IEEE/CVF Winter Conference on Applications of Computer Vision. 2023.

Authors

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