

Learning Unknowns from Unknowns: Diversified Negative Prototypes Generator for Few-Shot Open-Set Recognition

Supplementary Materials

.1 Better Negative Prototype

Firstly, in Figure 1, we provide a more comprehensive illustration than the main text Figure 6. It can be observed that existing Negative-Prototype-Based FSOR models indeed suffer from the issue of erroneously approximating negative prototypes to known class representations, thus failing to model unknown samples. Our model effectively addresses this issue.

We further complement our analysis with Figure 7 in the paper to illustrate why our approach of “learning unknowns from unknowns” leads to superior negative prototype generation. In Figure 7, it can be observed that the negative prototypes generated by the ATTG model for different datasets are completely separated. This is because the approach of generating negative prototypes based on known sample information leads to distinct and separate negative prototypes when input samples differ. In contrast, our model first generates representations of the unknown space, and then uses only these learned representations in downstream tasks to generate negative prototypes. This approach, which is not directly linked to current input information, results in negative prototypes that are less influenced by input samples, but instead are more generalizable and difficult to distinguish, as depicted in Figure 7. Additionally, it can be observed that the coverage range of the negative prototypes generated by our model is greater than that of the ATTG model. This subjective analysis explains why our approach to negative prototype generation is superior to existing methods.

On an objective level, we provide the FSOR task performance of various models involved in plotting Figure 7 on two datasets, as shown in Table 1. It can be seen that the performance of our DNPG model on both datasets is significantly better than that of the ATTG model. Furthermore, comparing the performance on the training dataset with that on the new dataset also reveals that the performance drop of our model when transferred to a new dataset is smaller than that of other models. This objectively demonstrates that our approach to generating negative prototypes leads to better FSOR model performance.

Table 1: 5-way 5 shot test results on TieredImageNet and CIFAR-FS, using ATTG, GEL, and DNPG(ours) trained on TieredImageNet. Δ indicates degradation of the model’s effect before and after the model is migrated to test on CIFAR-FS, and smaller values indicate a more robust model.

Algorithm	TieredImageNet		CIFAR-FS		$\downarrow \Delta$	
	Acc	AUROC	ACC	AUROC	ACC	AUROC
ATT-G	84.54 \pm 0.67	78.84 \pm 0.76	72.64 \pm 0.73	61.39 \pm 0.68	11.9	17.5
GEL	83.55 \pm 0.72	81.06 \pm 0.72	62.19 \pm 0.71	61.60 \pm 0.63	21.4	19.4
DNPG	84.71\pm0.69	83.20\pm0.64	73.87\pm0.72	71.12\pm0.66	10.9	12.8

Table 2: Our model is compared with the state-of-the-art model ATT-G [1] on the miniImageNet dataset with the addition of three types of noise, evaluating the 5-way 5-shot classification performance.

	blur	digital	extra	Average
TANE-G [1]	45.98 \pm 0.66	54.23 \pm 0.76	36.75 \pm 0.67	45.65
DNPG(ours)	49.98\pm0.68	58.39\pm0.70	39.39\pm0.69	49.25

.2 Model Robust

We further show the robustness of our model under different conditions. Firstly, we evaluated the FSOR task performance of our model, DNPG, and the ATTG model (one of the Negative-Prototype-Based SOTA FSOR models) on the miniImageNet dataset with the addition of three types of noise. The results are shown in Table 2. It can be observed that our model outperforms the ATTG model significantly on datasets with various added noise. This is because the process of generating negative prototypes in the ATTG model heavily relies on the information of the known class samples, and the addition of noise greatly affects the quality of input samples, thus leading to poor quality negative prototypes. On the other hand, our model, by severing the direct connection between input information and negative prototype generation, is less affected. Furthermore, we present the FSOR task performance of our model and the ATTG model under different numbers of classes, as depicted in Table 3. It can be seen that our model consistently outperforms the ATTG model across various class configurations. Additionally, we observe that as the number of known and unknown classes increases, the superiority of our model over the ATTG model also increases. This further illustrates that our model is capable of generating more generalized negative prototypes, enabling better performance in FSOR tasks with varying numbers of classes.

.3 Storage and Computational Expenses

Our model needs to reserve an open weight for each base class. When the number of base classes is 64 and the dimensionality of the negative prototype features is 640, the additional parameter count is approximately 40,000. In contrast, the TANE-G [1] model has a parameter count of 27,198,124. This means that the storage overhead of our model is only increased by 0.14% compared to the TANE-G model.

In terms of computational expenditure, our model takes 142.8 seconds on an RTX3090 GPU to complete one epoch of 5-way 1-shot training (300 episodes) and testing (600 episodes) on the MiniImageNet dataset. In a similar experimental setup, the existing SOTA model TANE-G [1] requires 139.8 seconds. This indicates that our model exhibits a marginal 2% increase in computational costs compared to the TANE-G model.

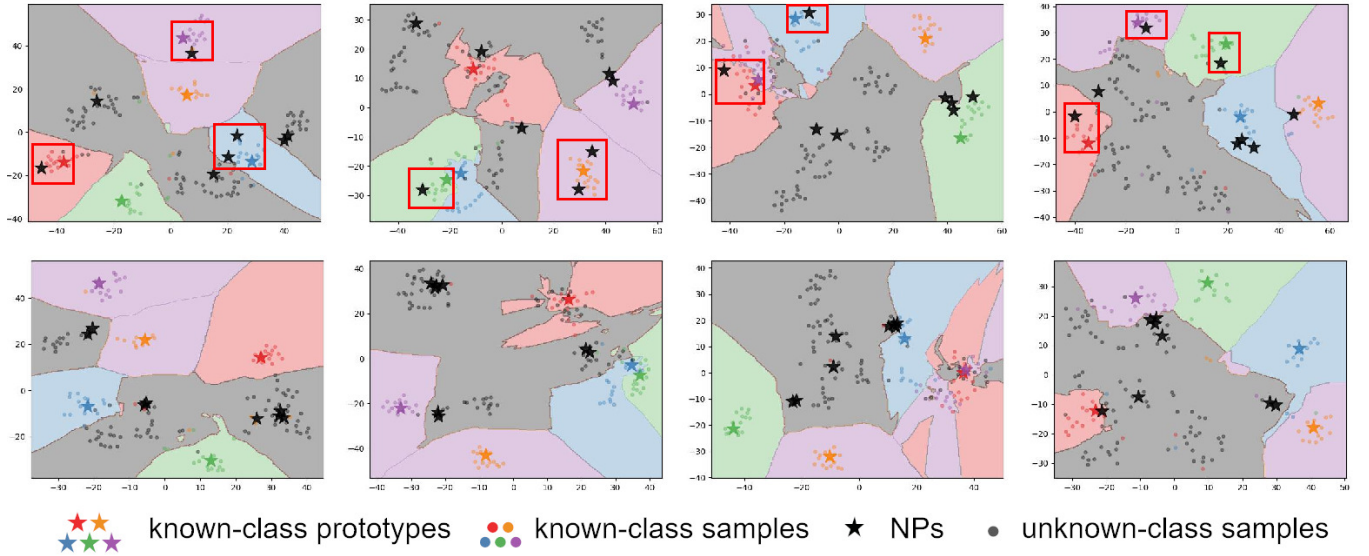


Figure 1: The visualization of the prototypes and NPs generated by one state-of-the-art method, ATTG (the first line) and our DNPG models (the second line) in the 5-way-5-shot FSOR task on the CIFAR-FS dataset. Each column corresponds to a specific episode. The NPs generated by ATTG incorrectly approximate the prototypes of known classes (highlighted in the red box). In contrast, the NPs generated by our model accurately model the space of unknown class samples (gray background area).

Table 3: The 5-way 1-shot performance of our model and an existing SOTA model TANE-G [1] on FSOR tasks under different class number settings.

Number of test classes	DNPG (ours)		ATT-G [1]		Δ	
	Acc	AUROC	ACC	AUROC	ACC	AUROC
5 novel + 5 unknown	68.83±0.85	73.62±0.79	67.33±0.85	72.11±0.78	1.50	1.51
6 novel + 6 unknown	64.81±0.75	71.52±0.71	63.30±0.76	70.02±0.71	1.51	1.50
7 novel + 7 unknown	61.13±0.71	70.56±0.69	59.71±0.72	68.86±0.68	1.42	1.70
8 novel + 8 unknown	58.30±0.64	69.19±0.59	56.75±0.64	67.43±0.60	1.55	1.76
9 novel + 9 unknown	55.54±0.60	68.62±0.56	54.04±0.62	66.78±0.56	1.50	1.84
10 novel + 10 unknown	52.89±0.54	68.19±0.53	51.63±0.55	66.11±0.53	1.26	2.08

REFERENCES

- [1] Shiyuan Huang, Jiawei Ma, Guangxing Han, and Shih-Fu Chang. 2022. Task-adaptive negative envision for few-shot open-set recognition. In *Proceedings of*

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