Supplementary Material for Learning Open Set Network with Discriminative Reciprocal Points

A Preliminaries

Our framework identifies open set learning problem by integrating multiple binary classification tasks (*one vs. rest*) into a multiclass recognition problem, by summing the expected risk defined in the paper category by category as:

$$\sum_{k=1}^{N} \mathcal{R}_\epsilon(\psi_k,\ \mathcal{S}_k \cup \mathcal{O}_k^{pos}) + \alpha \cdot \mathcal{R}_o(\psi_k,\ \mathcal{O}_k^{neg}) \tag{1}$$

which can be reformulated as:

$$\sum_{k=1}^{N} \mathcal{R}_\epsilon(\psi_k,\ \mathcal{S}_k \cup \mathcal{O}_k^{pos}) + \alpha \cdot \sum_{k=1}^{N} \mathcal{R}_o(\psi_k,\ \mathcal{O}_k^{neg}) \tag{2}$$

where $\psi_k : \mathbb{R}^d \mapsto \{0,1\}$ is a binary measurable prediction function, $\mathcal{S}_k$, $\mathcal{O}_k^{pos}$ and $\mathcal{O}_k^{neg}$ are known space, open positive space and infinite open negative space respectively. Minimizing the left part of plus sign in the Eq. (2) can be viewed as training multi binary classifiers for each category, with summing, leading to a multi-class prediction function $f = \odot(\psi_1, \psi_2, \ldots, \psi_N)$ for N-category classification, where $\odot(\cdot)$ is an integrating operation. Hereafter, we further replace ψ_k with f in the Eq. (2) and get the following formulation as:

$$\arg\min_{f \in \mathcal{H}} \{\mathcal{R}_\epsilon(f, \mathcal{D}_L) + \alpha \cdot \textstyle\sum_{k=1}^{N} \mathcal{R}_o(f, \mathcal{D}_U) \tag{3}$$

where $f : \mathbb{R}^d \mapsto \mathbb{N}$ is a measurable multi-class recognition function, $\mathcal{D}_L$ is all labeled data during training phase and $\mathcal{D}_U$ is potential unknown data. Minimizing the overall loss of the empirical classification risk and the open space risk simultaneously leads to be more distinguishable between known and unknown space.

B RPL++

The reciprocal point and the prototype are opposite and complementary. Here we simply combine the reciprocal point and the prototype. In addition to the reciprocal points, we added prototypes for known class k, denoted as $\mathcal{M}^k = \{m_i^k | i = 1, \ldots, C\}$ where C represents the index of the prototypes in each known class. Prototypes are initialized to the center of each known class. In the training phase of RPL, we add prototypes for training by *Prototype Loss* in [5]:

$$\mathcal{L}_{pl}(x;\theta,\mathcal{M}^k) = \frac{1}{C}\cdot\sum_{i=1}^{C}||f_\theta(x) - m_i^k||_2^2 \tag{4}$$

The overall loss function of RPL + GCPL combines RPL and *Prototype Loss* as:

$$\mathcal{L}(x;\theta,\mathcal{P},R,\mathcal{M}) = \mathcal{L}_c(x;\theta,\mathcal{P}) + \lambda\mathcal{L}_o(x;\theta,\mathcal{P},R) + \beta\mathcal{L}_{pl}(x;\theta,\mathcal{M}) \tag{5}$$

where β is a hyper-parameter of controlling the weight of *Prototype Loss* (PL). PL loss is used to reduce intra-class variance. The reciprocal point forms an excellent embedding space structure, then the prototype further narrow the intra-class distance so as to further divide the known classes and the unknown classes.

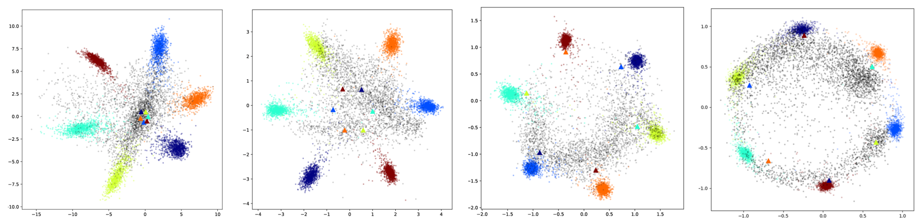
C Implementation Details

γ is set as 0.5 in all training phases. Reciprocal points are initialized by the random normal distribution and each margin is initialized with zeros. In experiments for out-of-distribution, λ is set to 0.1 in the training stage and we utilize the output after global average pooling (GAP) of WRN-40-4 as the feature. For open set identification, we add a global average pooling after the final convolution layer of the encoder. The dimension of the reciprocal point is consistent with the output of the GAP. Expect experiments with multiple reciprocal points, each known class is assigned one reciprocal point for training. β is set as 0.1 in the training phase by *RPL++*. We train all deep neural networks for 100 epochs with batch size 128 and momentum 0.9. The learning rate starts at 0.01 and is dropped by a factor of 0.1 in the training progress every 30 epochs. Apart from SGD optimizer used in ImageNet-LT, neural networks are trained with Adam optimizer [1].

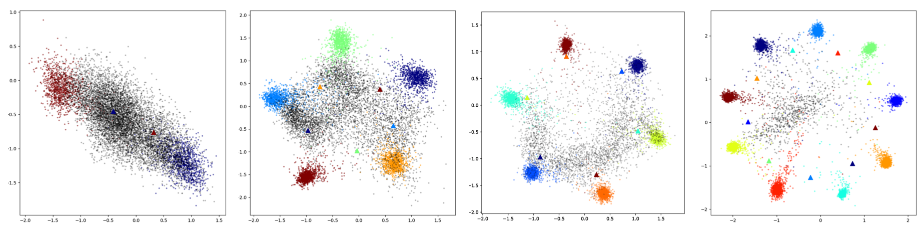
D Additional Results

D.1 Ablation Study

As shown in Fig.1, the reciprocal points are relative to the corresponding known classes in embedding space. The unknown samples are limited to the internal bounded space and all known classes are distributed around the periphery of the space. The size of the entire embedding space is limited by $\mathcal{L}_o$. However, with the increase in known classes, the entire embedding space should become larger for robust classification. Fig.1 (e)-(h) shows the distribution of features learned under different numbers of known classes. It can be seen through the axes that the known class distribution becomes wider with more known classes. Meanwhile, the margin R is also grown with more known classes. This phenomenon proves the rationality of the spatial distribution learned for multiclass.



(a) $\lambda = 0.001$ (b) $\lambda = 0.01$ (c) $\lambda = 0.1$ (d) $\lambda = 1$



(e) $N = 2$ (f) $N = 5$ (g) $N = 6$ (h) $N = 9$

Fig. 1. (a)-(d) The learned representations of RPL with different λ. The data is from MNIST by randomly sampling 6 known classes and 4 unknown classes. (e)-(h) The learned representations of RPL with different numbers of known classes. The data is from MNIST by randomly sampling K known classes and $10 - K$ unknown classes, where $\lambda = 0.1$. Colored triangles represent the learned reciprocal points of different known classes.

(a) $epoch = 0$ (b) $epoch = 100$

Fig. 2. (a)-(b) The learned representations of RPL in different training stages on Air-300. All classes are divided into two parts with 180 known classes for training and 120 novel unknown classes for testing respectively. Colored triangles represent the learned reciprocal points of different known classes.

Table 1. The results for long-tailed recognition.

Methods	All*	Head (80%) categories	Tail (20%) categories
Softmax	85.7	86.5	69.3
GCPL	84.5	85.4	66.2
RPL	**88.8**	**89.5**	**74.0**

As shown in Fig. 2(a) and 2(b), we provide the change of embedding features generated by t-SNE [2] on the Air-300. Compared with the initial features of neural network in Fig.2(a), the features of known and unknown classes are more obviously separated through RPL. We can notice that the reciprocal points are almost in the embedding space of unknown classes in Fig.2(b), which also proves that RPL can introduce the unknown information in the training process. It also produces the phenomenon that unknown classes are in the middle and the known category is distributed in outer space, which also proves the effectiveness of RPL for multiclass.

D.2 The Long-tailed Recognition

The long-tail experiments are to simulate real-world distribution so as to prove the effectiveness of RPL in practical application. The results prove that RPL is able to distinguish unknown categories in long-tail scenario. We further conduct classification experiments on the head (80%) categories and tail (20%) categories of Air-300 by using the same setting in the Sec 4.2. According to the results in Table 1, RPL is able to recognize unknowns while maintaining similar or even better classification performance.

D.3 Open Set Recognition

Table 2 shows the F-measure (or F1-scores) [3] trend under different Openness [4] in cifar100 averaged over ten randomized trials. In each trial, 15 categories are randomly selected as knowns and unknowns are randomly selected from the rest categories according to the Openness. We use ResNet18 as backbone networks and use the threshold of 0.1 for all methods. To evaluate all methods at a uniform threshold, all outputs are normalized by softmax function. The

Table 2. F1-scores against varying Openness with different baselines.

Openness	0.18	0.24	0.3	0.36	0.42	0.49
Softmax	59.0	49.5	41.1	33.4	26.8	20.2
GCPL	58.6	49.2	40.7	33.1	26.5	20.0
RPL	60.4	51.0	42.5	34.7	27.9	21.2
RPL++	**60.6**	**51.2**	**42.7**	**34.9**	**28.1**	**21.4**

Fig. 3. The overview of Air-300.

results show that RPL and RPL++ are superior to Softmax and GCPL as the Openness increasing.

References

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