南京航空航天大學
NANJING UNIVERSITY OF AERONAUTICS AND ASTRONAUTICS

PMAL: Open Set Recognition via Robust Prototype Mining

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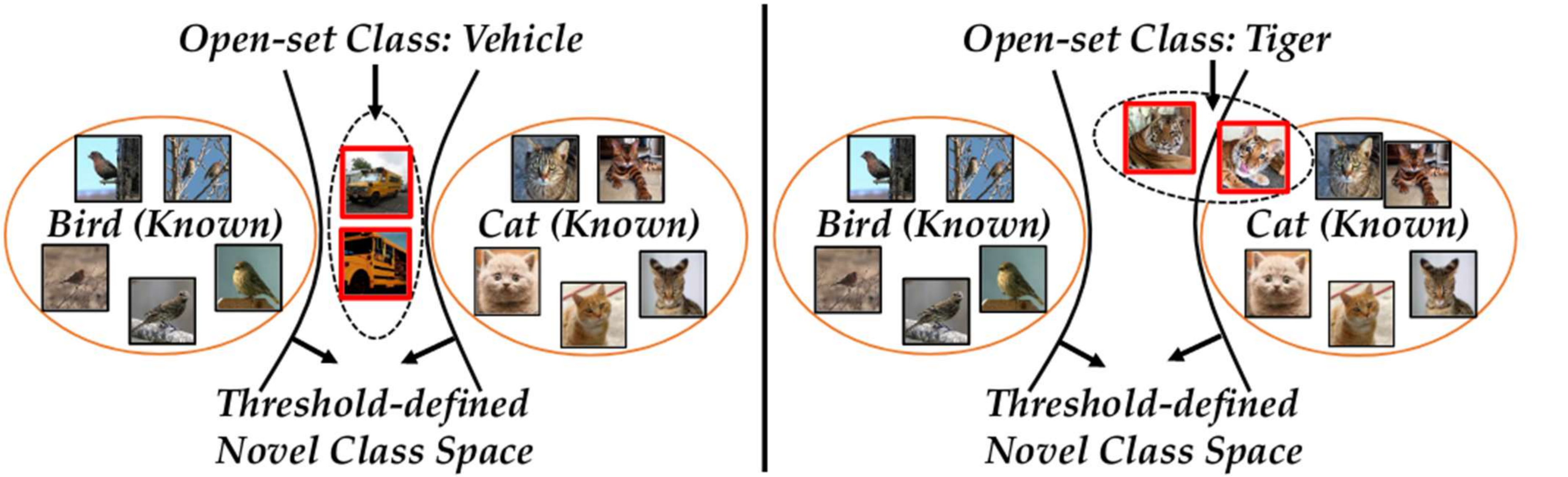
Background

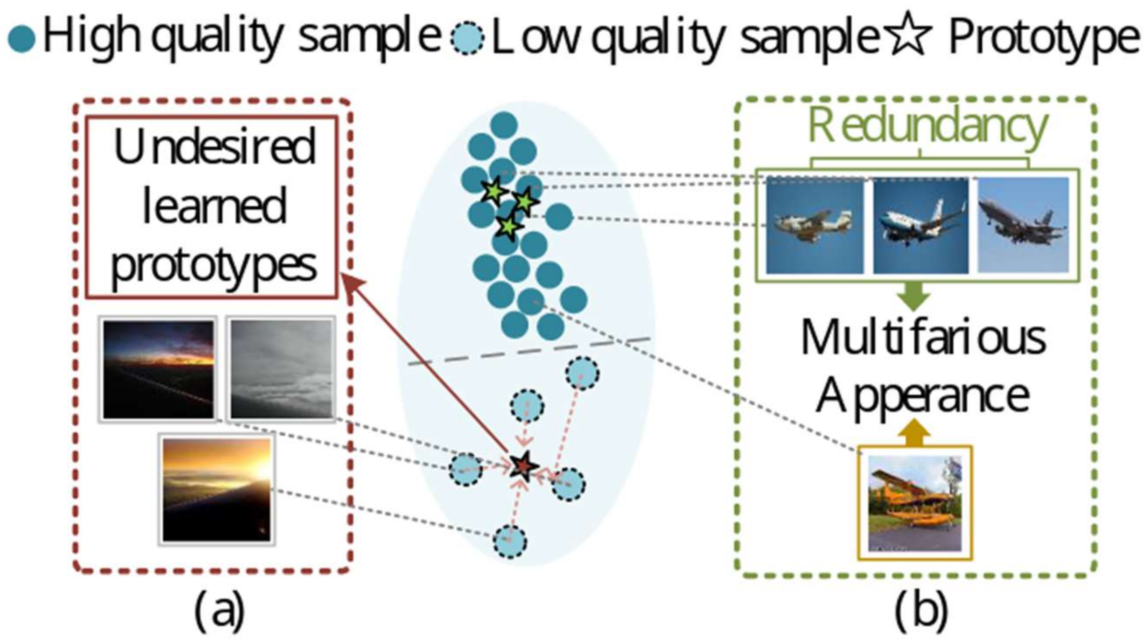
- **Open Set Recognition**

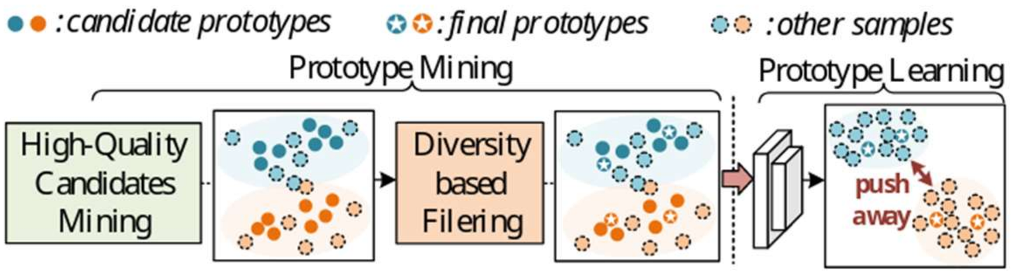


Motivation

Two typical Problems:

- Undesired learned prototypes close to feature space of low-quality samples
- Redundancy in similar prototypes and lack of diversity





Methods

- **Model uncertainty**

the noise of parameters in deep neural networks

- **Data uncertainty**

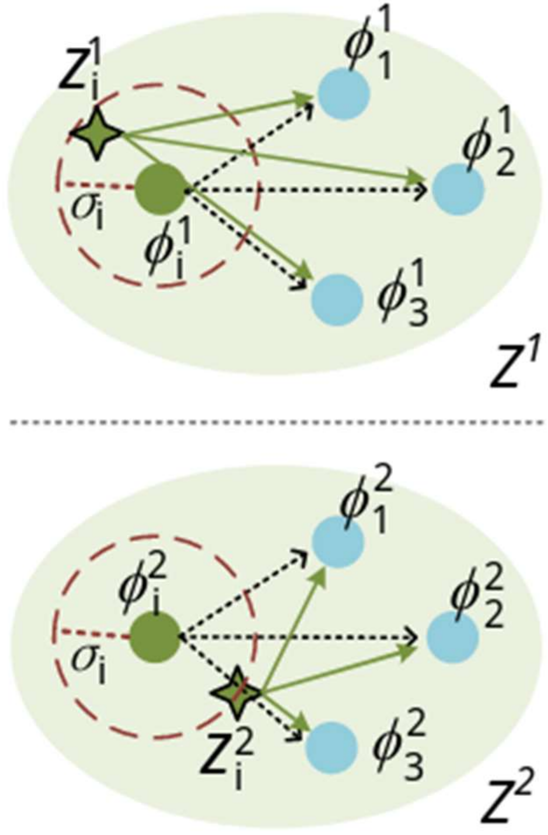
the inherent noise in input data (the low quality of image and the label noise)

$$z(x_i) = \phi(x_i) + n(x_i),\ n(x_i) \sim \mathcal{N}(0, \sigma(x_i))$$

Definition 1. ***Embedding Topology Robustness.*** *Given a sample x_i, its relative position to other samples in embedding space Z is defined by 'embedding topology' as: $t(z_i) \triangleq (d_{\mathcal{M}}(z_i, z_1), ..., d_{\mathcal{M}}(z_i, z_N))$. Then the distance metric 'embedding topology robustness' is defined by:*

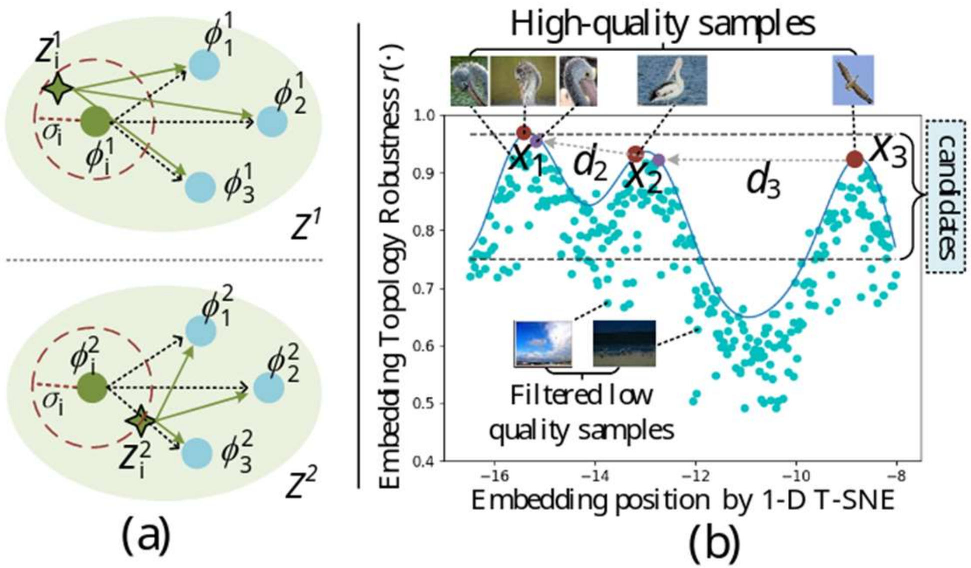
$$r(x_i) \triangleq exp(-||t(z_i^1) - t(z_i^2)||_2) \tag{7}$$

$$d_{\mathcal{M}}(z_i, z_j) = \sqrt{(z_i\text{-}z_j)\Sigma^{-1}(z_i\text{-}z_j)^{\mathrm{T}}}$$



(a)

Methods



- choose T prototypes by a greedy algorithm

$$P_k = \bigcup_{i=1}^{T} \{x_i \,|\, \max_{x_i \in C_k} \{ \min_{x_j \in C_k} d_{\mathcal{M}}(z_i, z_j) | r(x_j) > r(x_i) \} \}.$$

Algorithm 1: Filter Candidate Prototype Set with Diversity

Require: Candidate prototype set $C=\{C_i\}_{i=1}^{K}$; Class number K; Prototype number per class T;

Ensure: final prototype set $P=\{P_k\}_{k=1}^{K}$;

1: **for** $k = 1$ to K **do**
2: compute Mahalanobis distance matrix $D_k \in \mathbb{R}^{N_k \mathrm{x} N_k}$ in Z^1 (or Z^2), N_k is the candidate number in C_k;
3: initial a N_k-length array E with max value in D_k;
4: **for** $i = 1$ to N_k **do**
5: for i-th candidate $x_i \in C_k$, find its closest candidate x_j in C_k, where $r(x_j) > r(x_i)$, if exists, update E[i]=D_k[i,j];
6: **end for**
7: sort E in descending order, E_{ind} is the sorted index array;
8: **repeat**
9: add sample whose index is E_{ind}[0] in C_k into P_k, then remove E_{ind}[0] from E_{ind};
10: **until** the number of samples in P_k exceeds T
11: **end for**

Methods

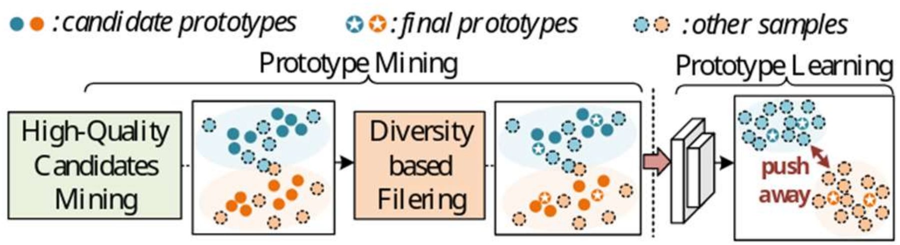
Prototype-based Space Optimization

$$\mathcal{L}_p = \frac{1}{N}\sum_{i=1}^{N}[d(z_i, z(P_m)) - d(z_i, z(P_u)) + \delta]_+,$$

$$P_u = \underset{P_k \in P \setminus P_m}{\arg\min}\,(d(z_i, z(P_k)))$$

m: the class it belongs to
u: the other close-set classes

$(x)_+ = \max(0,x)$



- Point to set distance by attention

$$d(z_i, z(P_k)) = 1 - \frac{{z_i}^{\mathrm{T}} z_i^{att}(P_k)}{|{z_i}^{\mathrm{T}}||z_i^{att}(P_k)|},$$

$$z_i^{att}(P_k) = SoftMax\left(\frac{z_i^{\mathrm{T}} z(P_k)}{\sqrt{d}}\right) z(P_k)$$

- Final loss

$$\mathcal{L} = \mathcal{L}_{cls} + \lambda_p \mathcal{L}_p,$$

Experiments

Table 1: Close set ACC and Open set AUROC on small datasets. '*' denotes implemented results and 'C' is short for 'CIFAR'.

Methods	Close set ACC						Open set AUROC					
	MNIST	SVHN	C10	C+10	C+50	TINY	MNIST	SVHN	C10	C+10	C+50	TINY
SoftMax	99.5	94.7	80.1	-	-	-	97.8	88.6	67.7	81.6	80.5	57.7
CPN (Yang et al.)	99.7	96.7	92.9	94.8*	95.0*	81.4*	99.0	92.6	82.8	88.1	87.9	63.9
PROSER (Zhou, Ye, and Zhan)	-	96.5	92.8	-	-	52.1	94.3	-	89.1	96.0	95.3	69.3
CGDL (Sun et al.)	99.6	94.2	91.2	-	-	-	99.4	93.5	90.3	95.9	95.0	76.2
OpenHybrid (Zhang et al.)	94.7	92.9	86.8	-	-	-	99.5	94.7	95.0	96.2	95.5	79.3
RPL-OSCRI (Chen et al.)	99.5*	95.3*	94.3*	94.6*	94.7*	81.3*	99.3	95.1	86.1	85.6	85.0	70.2
ARPL (Chen et al.)	99.5	94.3	87.9	94.7	92.9	65.9	99.7	96.7	91.0	97.1	95.1	78.2
RPL-WRN (Chen et al.)	99.6*	95.8*	95.1*	95.5*	95.9*	81.7*	99.6	96.8	90.1	97.6	96.8	80.9
PMAL-OSCRI	99.6	96.5	96.3	96.4	96.9	84.4	99.5	96.3	94.6	96.0	94.3	81.8
PMAL-WRN	**99.8**	**97.1**	**97.5**	**97.8**	**98.1**	**84.7**	**99.7**	**97.0**	**95.1**	**97.8**	**96.9**	**83.1**

Experiments

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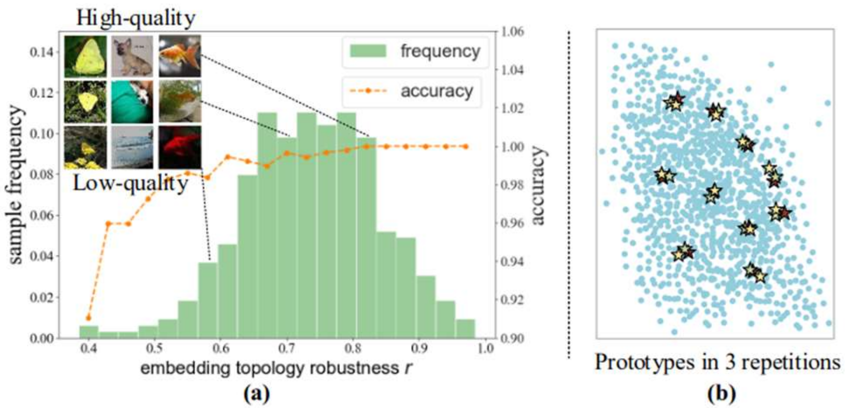
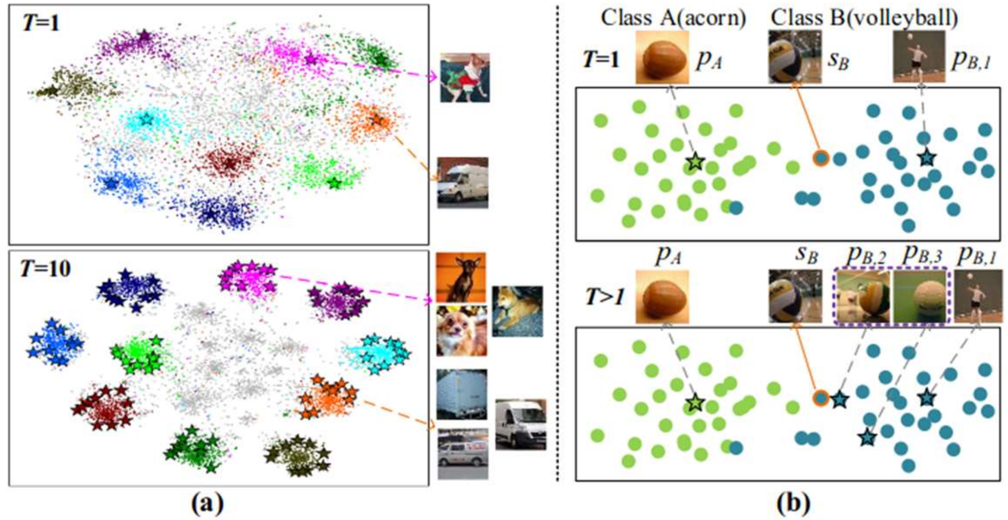


Figure 4: (a) Distribution of r; (b) Prototypes in embedding space (visualized by T-SNE) under 3 repetitions. Star in different color denotes prototypes in different repetition.



Experiments

Table 2: Comparisons on 3 large-scale datasets. We denote 'ImageNet' as 'IN' for simplicity.

Method	Close Set ACC			Open Set AUROC			Additional Params		
	IN-LT	IN-100	IN-200	IN-LT	IN-100	IN-200	IN-LT	IN-100	IN-200
Softmax	37.8	81.7	79.7	53.3	79.7	78.4	0	0	0
CPN	37.1	86.1	82.1	54.5	82.3	79.5	2M	0.2M	0.4M
RPL	39.0	81.8*	80.7*	55.1	81.2*	80.2*	2M	0.2M	0.4M
RPL++	39.7	-	-	55.2	-	-	4M	-	-
PMAL	**42.9**	**86.2**	**84.1**	**71.7**	**94.9**	**93.9**	0	0	0

Table 3: Ablations of each module on TinyImageNet.

Components		(a)	(b)	(c)	(d)	(e)	(f)
PM	High-Quality	✓		✓		✓	✓
	Diversity		✓		✓	✓	✓
EO	Point-to-Set			✓	✓		✓
AUROC		80.3	78.1	81.6	80.2	81.9	**83.1**

Experiments

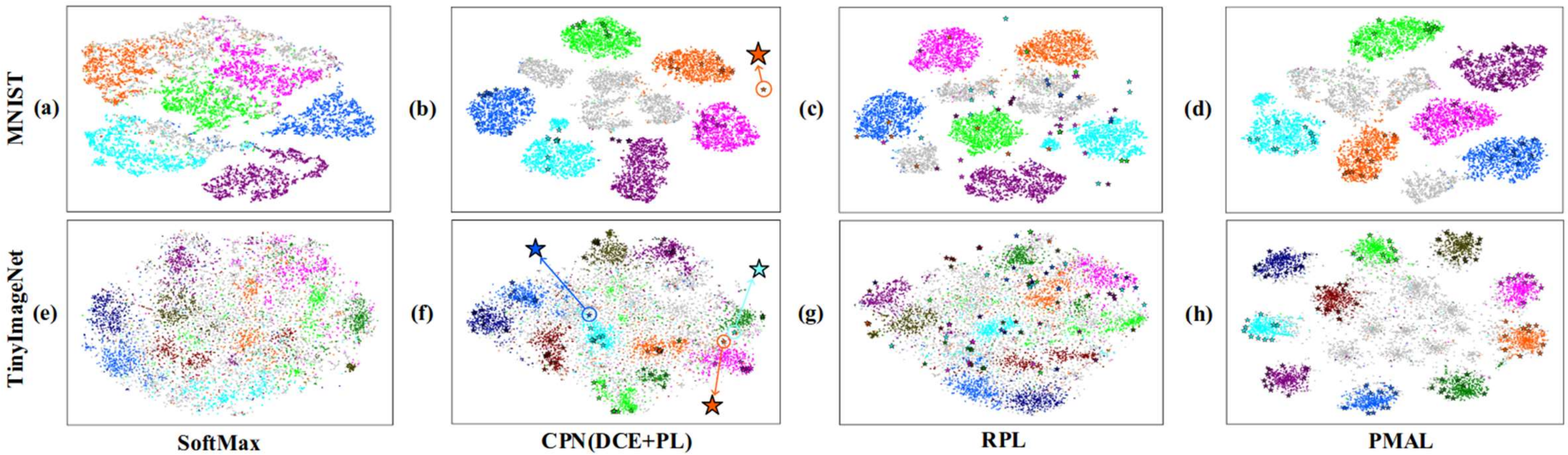
Table 4: Comparisons with other methods on the *quality* and *diversity* property.

Method	ACC	AUROC
(a)Probability	81.9	79.3
(b)Deep Ensembles	82.3	80.5
(c)MC-dropout	81.6	78.8
(a)Randomization	81.5	79.1
(b)Clustering	81.8	79.6
Ours	**84.7**	**83.1**

Table 5: AUROC under different hyper-parameters, including T,ϵ,U and δ.

T	1	5	10	20	30
AUROC	79.9	81.1	83.1	82.6	83.1
ϵ	0.1	0.3	0.5	0.7	0.9
AUROC	73.6	78.1	82.6	83.1	81.2
U	2	3	4	5	6
AUROC	83.1	83.3	83.2	83.0	83.3
δ	0.1	0.3	0.5	0.8	1.
AUROC	80.9	82.8	83.1	82.1	80.5

Experiments



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