Question: How to **generate potential outlier labels** for OOD detection **without auxiliary data**? 🤔

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Envisioning Outlier Exposure by Large Language Models for Out-of-Distribution Detection

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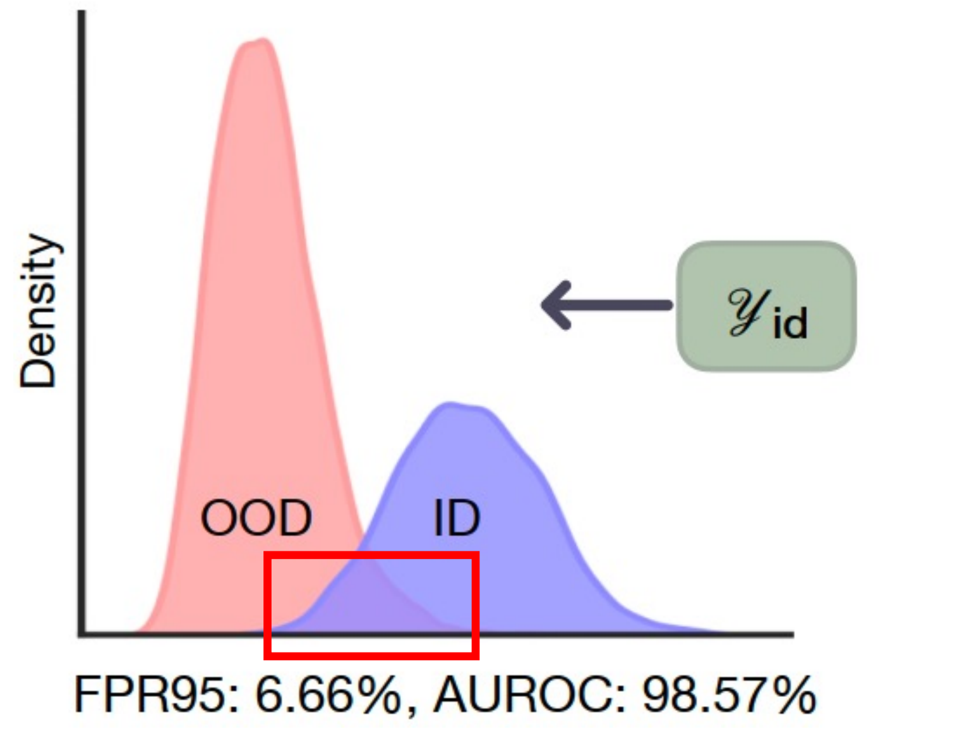
Paper Code

Background: Zero-shot OOD Detection

Given a pre-trained model, ID classes $\mathcal{Y}_{\text{id}}$ are defined by the classification task of interest, instead of the classes used in pre-training.

OOD detector: $G_\lambda(x;\mathcal{Y}_{\text{id}},\mathcal{I},\mathcal{T}) = \begin{cases} \text{ID} & S(x) \geq \lambda \\ \text{OOD} & S(x) < \lambda \end{cases}$

Existing method: Using only closed-set ID classes



FPR95: 6.66%, AUROC: 98.57%

We wonder 🤔

1) if this issue arises because the pre-trained VLMs are not strong enough

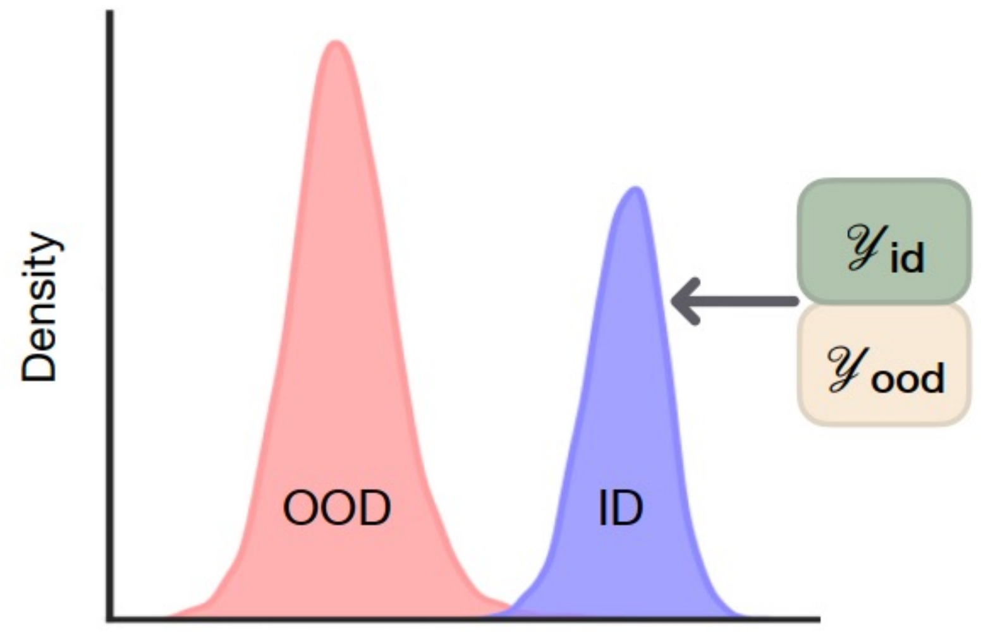
or

2) if it is attributable to the usages of these pretrained models, e.g., an exclusive reliance on closed-set ID classes

ID dataset: CUB-200-2011, OOD dataset: Places

Motivation

Ground truth: Incorporating with actual OOD class labels (unavailable)

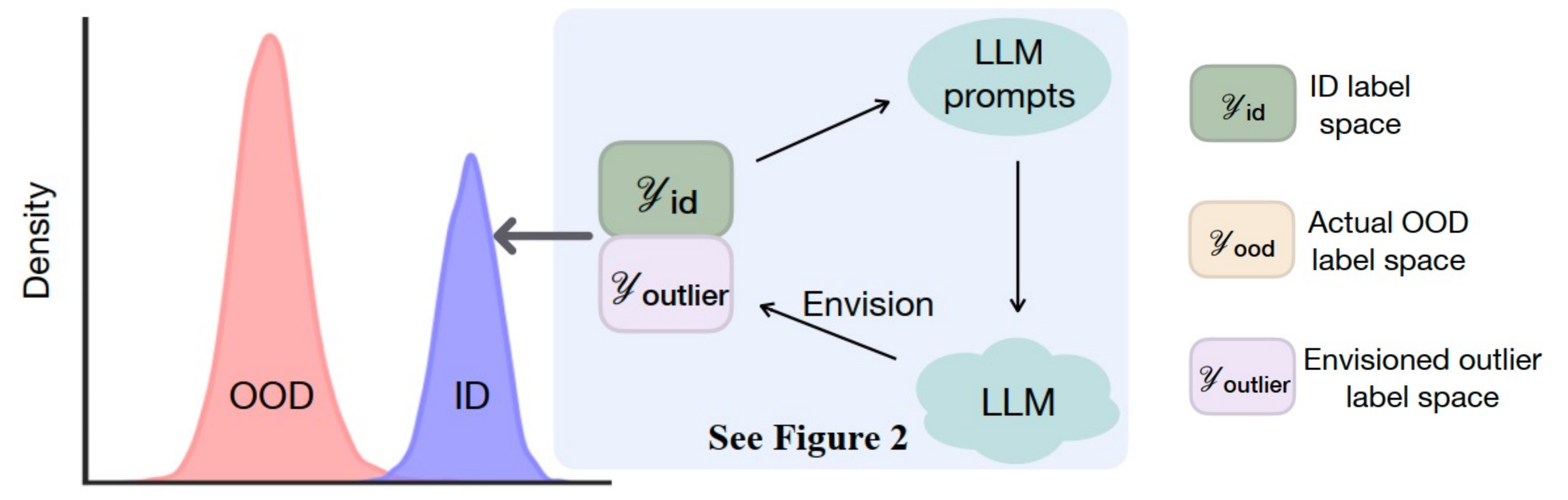


FPR95: 0.29%, AUROC: 99.93%

Building a text-based classifier with only closed-set labels largely restricts the inherent capability of VLMs

We can employ LLMs to envision potential outlier class labels for OOD detection since LLMs know the visual features of lots of categories

EOE (Ours): Incorporating with envisioned outlier classes


Density
OOD
ID
$\mathcal{Y}_{\text{id}}$
$\mathcal{Y}_{\text{outlier}}$
LLM prompts
LLM
Envision
See Figure 2
$\mathcal{Y}_{\text{id}}$ ID label space
$\mathcal{Y}_{\text{ood}}$ Actual OOD label space
$\mathcal{Y}_{\text{outlier}}$ Envisioned outlier label space

FPR95: 0.37%, AUROC: 99.88%

Method: Envisioning Outlier Exposure

Design principle: Guide LLM to generate the desired outlier class label based on the visual similarity rule

Q: I have gathered images of K distinct categories: $\mathcal{Y}_{\text{id}}$. Summarize what broad categories these categories might fall into based on visual features. Now, I am looking to identify L classes that visually resemble these broad categories but have no direct relation to these broad categories. Please list these L categories for me.

Far OOD prompt

A: These L categories are:

Figure 3: LLM prompt for far OOD detection, consisting of both the contents of **Q** and **A**.

Q: Given the image category y_i, please suggest visually similar categories that are not directly related or belong to the same primary group as y_i. Provide suggestions that share visual characteristics but are from broader and different domains than y_i.

Near OOD prompt

A: There are l classes similar to y_i, and they are from broader and different domains than y_i:

Figure 4: LLM prompt for near OOD detection.

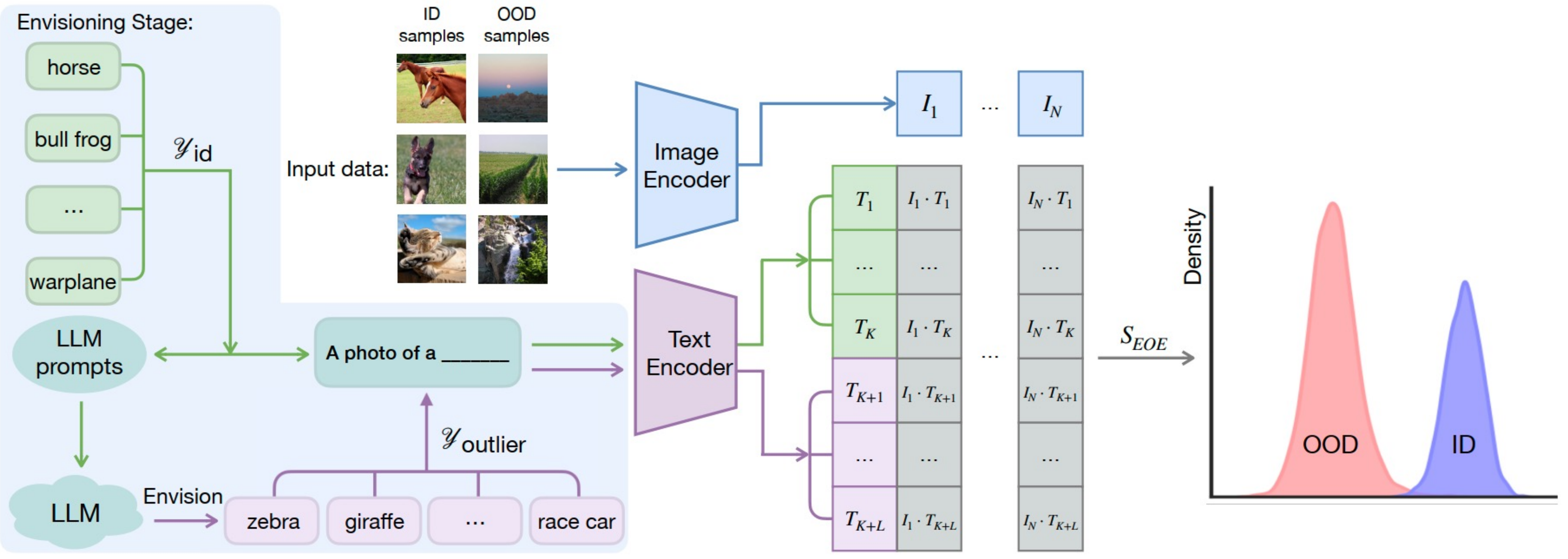
Q: I have a dataset containing K different species of *class-type*. I need a list of L distinct *class-type* species that are NOT present in my dataset, and ensure there are no repetitions in the list you provide. For context, the species in my dataset are: $\mathcal{Y}_{\text{id}}$.

Fine-grained OOD prompt

A: The other L *class-type* species not in the dataset are:

Figure 5: LLM prompt for fine-grained OOD Detection.

Implementation



We design a new score function is to better distinguish between ID and OOD score distributions. First, the label-wise matching score is

$$s_i(x) = \frac{\mathcal{I}(x)\cdot\mathcal{T}(t_i)}{\|\mathcal{I}(x)\|\cdot\|\mathcal{T}(t_i)\|};\quad t_i \in \mathcal{Y}_{\text{id}} \cup \mathcal{Y}_{\text{outlier}}$$

The proposed OOD detection score function

$$S_{\text{EOE}}(x;\mathcal{Y}_{\text{id}},\mathcal{Y}_{\text{dood}},\mathcal{T},\mathcal{I}) = \max_{i\in[1,K]} \frac{e^{s_i(x)/\tau}}{\sum_{j=1}^{K+L} e^{s_j(x)/\tau}} - \max_{k\in[K+1,K+L]} \frac{\beta e^{s_k(x)/\tau}}{\sum_{j=1}^{K+L} e^{s_j(x)/\tau}}$$

Experiments

EOE can be effectively scaled to the ImageNet-1K dataset and is comparable to fine-tuning methods

Table 2: Zero-shot **far** OOD detection results for ImageNet-1K as ID dataset. The **black bold** indicates the best performance. The gray indicates that the comparative methods require training or an additional massive auxiliary dataset. Energy (FT) requires fine-tuning, while Energy is post-hoc.

Method	OOD Dataset								Average	
	iNaturalist		SUN		Places		Texture			
	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑
MOS (BiT)	9.28	98.15	40.63	92.01	49.54	89.06	60.43	81.23	39.97	90.11
Fort et al.	15.07	96.64	54.12	86.37	57.99	85.24	53.32	84.77	45.12	88.25
Energy(FT)	21.59	95.99	34.28	93.15	36.64	91.82	51.18	88.09	35.92	92.26
MSP	40.89	88.63	65.81	81.24	67.90	80.14	64.96	78.16	59.89	82.04
CLIPN	19.13	96.20	25.69	94.18	32.14	92.26	44.60	88.93	30.39	92.89
Energy	81.08	85.09	79.02	84.24	75.08	83.38	93.65	65.56	82.21	79.57
MaxLogit	61.66	89.31	64.39	87.43	63.67	85.95	86.61	71.68	69.08	83.59
MCM	30.92	94.61	37.59	92.57	44.71	89.77	57.85	86.11	42.77	90.77
EOE (Ours)	12.29	97.52	20.40	95.73	30.16	92.95	57.53	85.64	**30.09**	**92.96**
Ground Truth	-	-	-	-	13.24	96.96	24.29	95.04	-	-

For near OOD detection, EOE increases the average OOD performance by 2.13% in FPR95

Table 3: Zero-shot **near** OOD detection results. The **bold** indicates the best performance on each dataset, and the gray indicates methods requiring an additional massive auxiliary dataset.

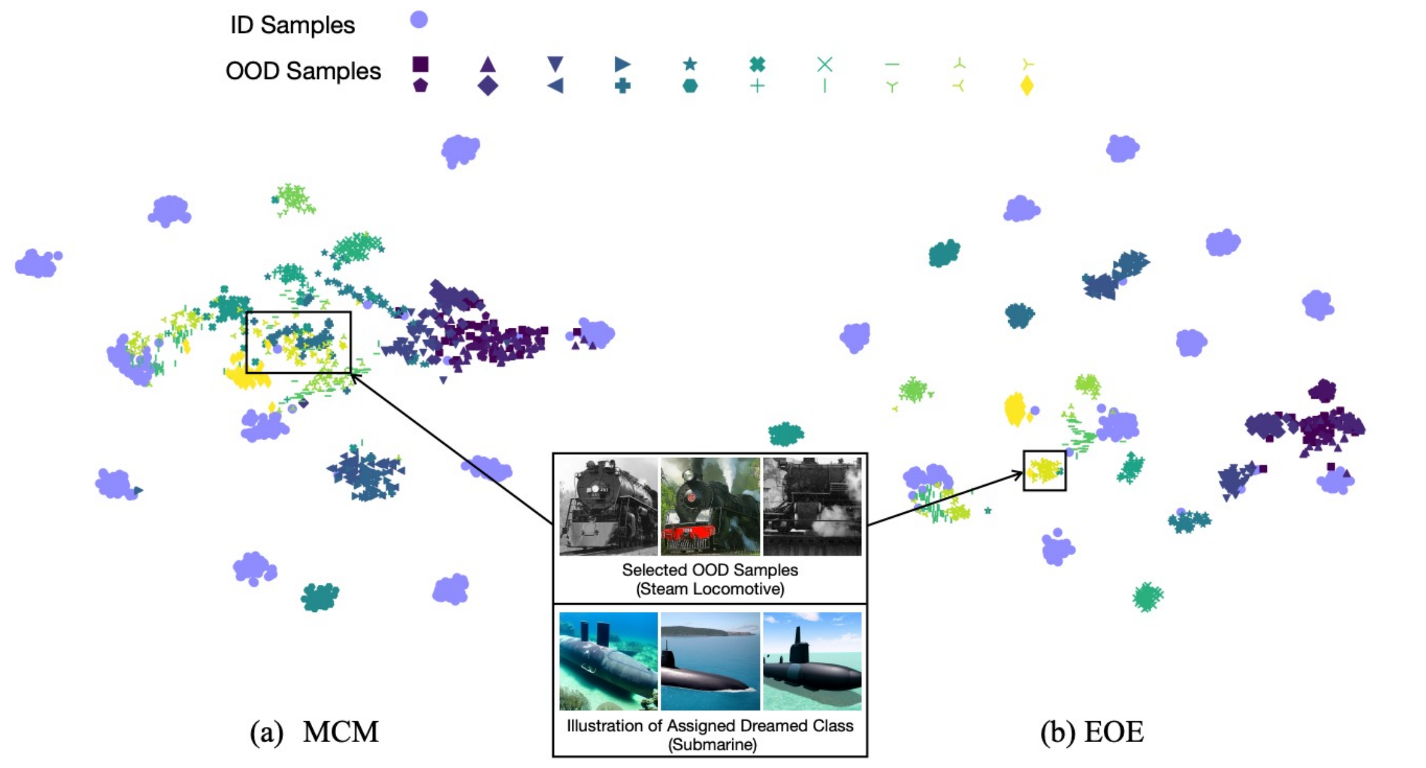
Method	ID OOD	ImageNet-10 ImageNet-20		ImageNet-20 ImageNet-10		Average	
		FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑
CLIPN		7.80	98.07	13.67	97.47	10.74	97.77
Energy		10.30	97.94	16.40	97.37	13.35	97.66
MaxLogit		9.70	98.09	14.00	97.81	11.85	97.95
MCM		5.00	98.71	17.40	97.87	11.20	98.29
EOE (Ours)		4.20	99.09	13.93	98.10	**9.07**	**98.59**
Ground Truth		0.20	99.80	0.20	99.93	0.20	99.87

For fine-grained OOD detection, EOE increases the average OOD performance by 3.59% in FPR95

Table 4: Zero-shot **fine-grained** OOD detection results. The **bold** indicates the best performance on each dataset, and the gray indicates methods requiring an additional massive auxiliary dataset.

Method	ID OOD	CUB-100 CUB-100		Stanford-Cars-98 Stanford-Cars-98		Food-50 Food-51		Oxford-Pet-18 Oxford-Pet-19		Average	
		FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑
CLIPN		73.54	74.65	53.33	82.25	43.33	88.89	53.90	86.92	56.05	83.18
Energy		76.13	72.11	73.78	73.82	44.95	89.97	68.51	88.34	65.84	81.06
MaxLogit		76.89	73.00	72.18	74.80	41.73	90.79	65.66	88.49	64.11	81.77
MCM		83.58	67.51	83.99	68.71	43.38	91.75	63.92	84.88	68.72	78.21
EOE (Ours)		74.74	73.41	76.83	71.60	37.95	91.96	52.55	90.33	**60.52**	**81.82**
Ground Truth		61.23	81.42	58.31	83.71	11.34	97.79	29.17	95.58	40.01	89.63

Without hitting the GT OOD, these potential outlier classes can still enhance performance in OOD detection



(a) MCM (b) EOE

Figure 8: T-SNE visualizations obtained by the classifier output. ID set: ImageNet-10; OOD set: ImageNet-20. We use distinct colors to represent different OOD classes. The illustrated envisioned OOD name is the class assigned with the corresponding cluster, and its examples are generated by Stable Diffusion (Rombach et al., 2022).