

## Supplementary Material of “Prompt Optimization Meets Subspace Representation Learning for Few-shot Out-of-Distribution Detection”

### A Notation

We use the following notation throughout the paper:  $x$ ,  $\mathbf{x}$ , and  $\mathbf{X}$ , represent a scalar, a vector, and a matrix, respectively.  $x_i$  denote the  $i$ th entry of the vector  $\mathbf{x}$ .  $\|\mathbf{x}\|_2$  mean the Euclidean norm.  $\mathbf{X}^{-1}$  means the inverse of a matrix  $\mathbf{X}$ .  $\mathbf{X}^\top$  denote transpose of the matrix  $\mathbf{X}$ .  $\mathbf{I}_M$  denotes an identity matrix of size  $M$ .

### B Additional Experiments

Figure 1 shows histogram plots of the OOD detection score computed for our method SubCoOp across four OOD datasets. The experiments are conducted using the ImageNet-1K dataset as the ID data, and the GL-MCM score is employed as the OOD detection score. Notably, the overlap between ID and OOD distributions is small across the OOD datasets, highlighting the ID-OOD separability achieved by our method.

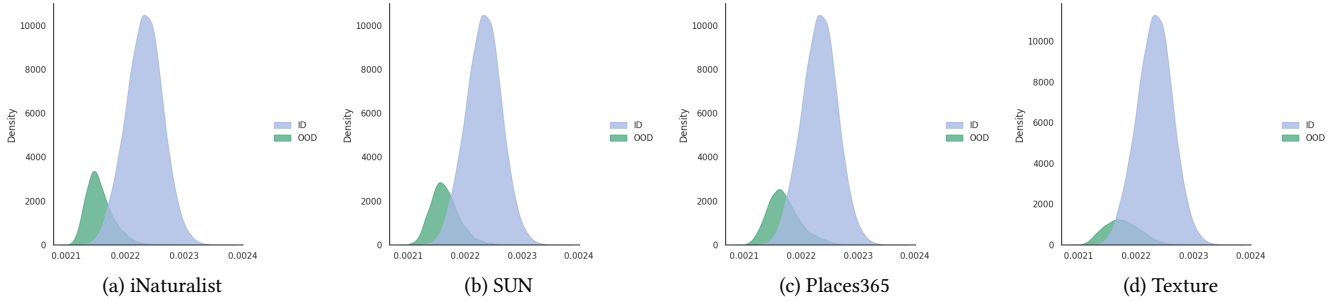


Figure 1: OOD score distribution histograms for different OOD datasets with ImageNet-1k ID dataset.

We present the ID classification performance of different methods in Table 1. Zero-shot and post-hoc methods achieve 66.7% ID accuracy on ImageNet-1K, while prompt tuning methods such as CoOp, NegPrompt, LSN, and LoCoOp improve it to around 72%. Our SubCoOp method achieves a comparable 71.63% ID accuracy while offering the best OOD detection performance.

Table 1: ID classification accuracy (%) with ImageNet-1k dataset

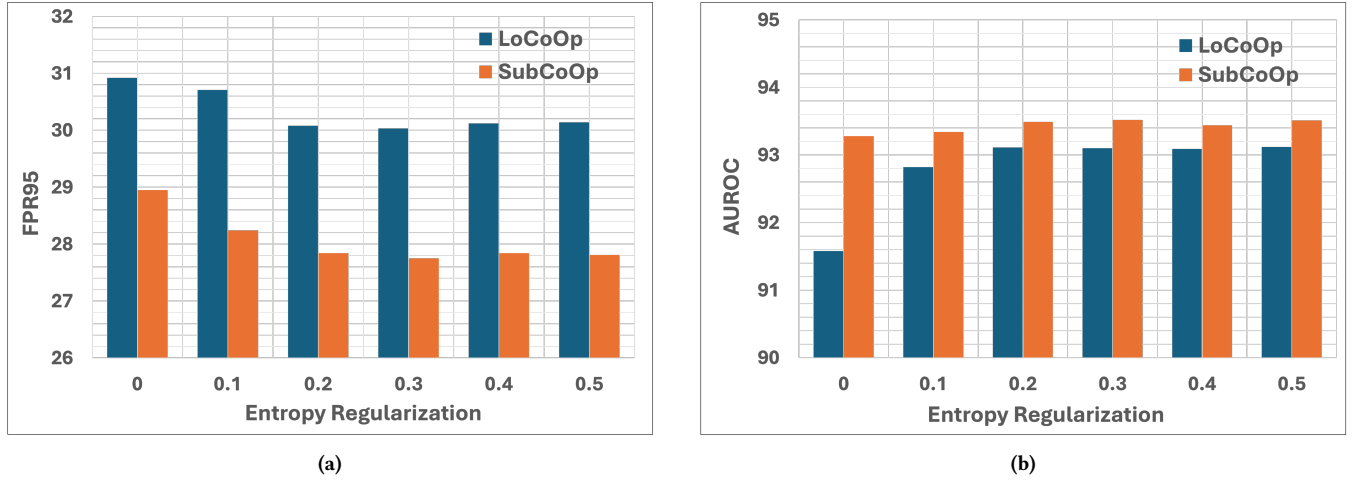
Method	ID Accuracy
<i>Zero-shot methods</i>	
MCM	66.7
GL-MCM	66.7
<i>CLIP-based post-hoc methods</i>	
MSP	66.7
ODIN	66.7
Energy	66.7
ReAct	66.7
MaxLogit	66.7
<i>Prompt tuning based methods</i>	
CoOp	71.93
NegPrompt	71.93
LSN	71.93
LoCoOp	71.43
SubCoOp	71.63

Table 2 presents an ablation study on the impact of subspace-based regularization in the SubCoOp framework across four OOD datasets. Without either regularization term, the model shows the weakest OOD detection performance. Adding only the ID regularization (see (??)) improves separability by aligning ID features with the prompt-induced subspace. The OOD regularization (see (??)) alone also offers limited improvement. The best performance is achieved when both regularizations are applied, confirming the benefit of jointly modeling ID and OOD feature projections for enhanced detection.

**Table 2: Performance comparison with subspace regularization parameters utilizing ID dataset ImageNet-1k. Here,  $\checkmark$  indicates that the corresponding regularization term ( $\lambda_2$  or  $\lambda_3$ ) is applied, while  $\times$  denotes that it is set to zero.**

$\lambda_2$	$\lambda_3$	iNaturalist		SUN		Places		Texture		Average	
		FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$
$\times$	$\times$	18.70 $\pm$ 2.12	96.09 $\pm$ 0.38	22.83 $\pm$ 0.98	95.12 $\pm$ 0.07	34.78 $\pm$ 3.47	91.52 $\pm$ 0.63	43.75 $\pm$ 0.22	89.81 $\pm$ 0.33	30.02 $\pm$ 1.70	93.14 $\pm$ 0.35
$\checkmark$	$\times$	17.12 $\pm$ 1.31	96.47 $\pm$ 0.19	21.54 $\pm$ 1.06	95.36 $\pm$ 0.25	31.16 $\pm$ 3.15	91.74 $\pm$ 0.59	43.04 $\pm$ 1.25	89.75 $\pm$ 0.31	28.22 $\pm$ 1.69	93.33 $\pm$ 0.33
$\times$	$\checkmark$	15.44 $\pm$ 1.04	96.71 $\pm$ 0.18	22.52 $\pm$ 1.37	94.95 $\pm$ 0.38	32.64 $\pm$ 2.28	91.83 $\pm$ 0.62	42.79 $\pm$ 2.36	89.65 $\pm$ 0.42	28.35 $\pm$ 1.76	93.29 $\pm$ 0.70
$\checkmark$	$\checkmark$	14.33 $\pm$ 0.76	96.99 $\pm$ 0.08	22.14 $\pm$ 1.96	95.10 $\pm$ 0.44	32.04 $\pm$ 2.82	92.07 $\pm$ 0.61	42.35 $\pm$ 3.04	89.87 $\pm$ 0.53	27.72 $\pm$ 2.15	93.51 $\pm$ 0.42

Figure 2 compares the OOD detection performance of LoCoOp and SubCoOp under different entropy regularization weights using FPR95 and AUROC metrics on ImageNet-1k dataset. SubCoOp consistently outperforms LoCoOp, achieving lower FPR95 and higher AUROC across all regularization settings.

**Figure 2: Performance Analysis of our proposed method with different entropy Regularization weights.**

We highlight our OOD detection performance on the ImageNet-100 dataset in Table 3. Similar to the results on ImageNet-1K, our method achieves the best OOD detection performance compared to state-of-the-art approaches.

**Table 3: Result analysis of FPR95 and AUROC scores (%) on various OOD datasets with ID dataset ImageNet-100.**

Method	iNaturalist		SUN		Places		Texture		Average	
	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$	FPR $\downarrow$	AUROC $\uparrow$
CoOp	23.70 $\pm$ 6.29	96.67 $\pm$ 0.57	21.30 $\pm$ 6.00	96.53 $\pm$ 0.51	25.75 $\pm$ 2.37	95.28 $\pm$ 0.42	19.39 $\pm$ 1.27	96.85 $\pm$ 0.16	22.54 $\pm$ 3.98	96.33 $\pm$ 0.42
LoCoOp	11.30 $\pm$ 10.01	97.99 $\pm$ 0.46	13.90 $\pm$ 7.35	96.92 $\pm$ 0.29	20.57 $\pm$ 10.13	95.50 $\pm$ 0.39	17.23 $\pm$ 8.56	96.16 $\pm$ 0.52	15.75 $\pm$ 9.01	96.64 $\pm$ 0.42
SubCoOp	5.03 $\pm$ 1.93	98.83 $\pm$ 0.28	9.70 $\pm$ 0.98	98.03 $\pm$ 0.23	15.06 $\pm$ 0.32	96.73 $\pm$ 0.07	16.59 $\pm$ 0.58	97.59 $\pm$ 0.31	11.60 $\pm$ 0.95	97.80 $\pm$ 0.22