ENHANCING NEAR OOD DETECTION IN PROMPT LEARNING: MAXIMUM GAINS, MINIMAL COSTS

Anonymous authors
Paper under double-blind review

ABSTRACT

Prompt learning has shown to be an efficient and effective fine-tuning method for vision-language models like CLIP. While numerous studies have focused on the generalisation of these models in few-shot classification, their capability in near out-of-distribution (OOD) detection has been overlooked. A few recent works have highlighted the promising performance of prompt learning in far OOD detection. However, the more challenging task of few-shot near OOD detection has not yet been addressed. In this study, we investigate the near OOD detection capabilities of prompt learning models and observe that commonly used OOD scores have limited performance in near OOD detection. To enhance the performance, we propose a fast and simple post-hoc method that complements existing logit-based scores and can be easily applied to any prompt learning model without change in architecture or model re-training while keeping the same classification accuracy. Our method boosts existing prompt learning methods' near OOD detection performance in AUROC by up to 11.67% with minimal computational cost. Comprehensive empirical evaluations across 13 datasets and 8 models demonstrate the effectiveness and adaptability of our method[1].

1 INTRODUCTION

Pre-trained vision-language models such as ALIGN (Jia et al., 2021) and CLIP (Radford et al., 2021) have shown outstanding visual-text understanding by learning to align image features and textual features of a large-scale image-text dataset via contrastive learning. Consequently, CLIP naturally excels at zero-shot image classification, utilising a class name as natural language text instead of arbitrarily numbered category. For instance, cosine similarity between encoded image feature of an image and encoded textual feature of "a photo of a [CLASS]." with a class name as "[CLASS]" can perform zero-shot classification without requiring any additional classification head. Logits with different class names can then be transformed to probabilities by using the softmax function.

While CLIP's zero-shot capabilities are impressive, recent studies have highlighted its sensitivity to prompt wording. For instance, Zhou et al. (2022b) demonstrated that small variations in prompt structure (e.g., "a photo of a [CLASS]" vs. "a photo of [CLASS]") can lead to significant accuracy drops, sometimes exceeding 5% on standard benchmarks like Caltech101 (Fei-Fei et al., 2004). This observation has led to an emerging research direction of prompt learning for few-shot classification with vision-language models (Zhou et al., 2022b;a; Yao et al., 2023; Zhu et al., 2023; Khattak et al., 2023a;b), which optimises continuous context vectors in the word-embedding space, eliminating the need for handcrafting prompts.

Although existing methods have shown success in this area, the majority focus primarily on enhancing classification accuracy, leaving the equally important task of out-of-distribution (OOD) detection underexplored. OOD detection is crucial for real-world, safety-critical applications such as autonomous driving, healthcare, and industrial automation, where models must perform reliably under unfamiliar or unexpected conditions. In these applications, excelling in in-distribution (ID) classification is not enough. Models must also be capable of detecting and effectively handling OOD samples. Here, we focus on the more challenging task of *near OOD detection* (Yang et al., 2023;

[1]Codes are available at `https://anonymous.4open.science/r/near-OOD-prompt-learning-25D1`

2022; Zhang et al., 2023b; Fort et al., 2021; Ren et al., 2021; Winkens et al., 2020). Near OOD detection refers to a scenario where OOD samples share the same domain as ID samples but have different label space (e.g., both ID and near OOD samples are flower images with no overlapping classes).

In this paper, we focus on developing a post-hoc method to enhance near OOD detection performance for prompt learning methods in vision-language models without the need to retrain them. To the best of our knowledge, only a few existing works address related problems, and none of them address this specific problem directly. Specifically, Bai et al. (2023); Miyai et al. (2023) investigated far OOD detection, where OOD samples come from completely different domains. However, these methods are not post-hocs, which require to train the models from scratch. In addition, near OOD tasks are out of their consideration. Existing logit-based OOD scores, such as MaxLogit score (Hendrycks et al., 2022) or Energy score (Liu et al., 2020), which estimate a model's confidence in its predictions, can be applied to our case in a post-hoc manner. However, these scores are not specifically designed for vision-language models like CLIP where overlapping score distributions between ID and OOD samples often result in poor detection performance, especially in the near OOD tasks.

We address the above problem by proposing a simple yet novel and effective approach, which introduces a new logit-based score named Marginal Logit Score (MLS), computed from the output logits of an existing method. Tailored for vision-language models, the key idea of MLS is measuring the difference between the existing logit scores and a new complementary score named Context score. MLS creates clearer separation between ID and near OOD samples, leading to substantial performance gains. Notably, our method does not require any change to the model architecture and does not involve retraining, making it highly efficient and adaptable. Table 1 demonstrates the performance gain of MLS when used with existing methods.

Table 1: Improvement of near OOD AUROC using MaxLogit score with our method on 1-shot Caltech101 (Fei-Fei et al., 2004) with wall-clock time measured for the method. Refer to Section 5 for details.

Model	△ AUROC	Computation Time (s)
CoOp (Zhou et al., 2022b)	+2.66	0.988
CoCoOp (Zhou et al., 2022a)	+5.05	1.703
IVLP (Khattak et al., 2023a)	+3.79	1.055
KgCoOp (Yao et al., 2023)	+7.09	0.989
ProGrad (Zhu et al., 2023)	+5.90	0.994
MaPLe (Khattak et al., 2023a)	+5.74	0.974
PromptSRC (Khattak et al., 2023b)	+6.09	1.005
LoCoOp (Miyai et al., 2023)	+10.57	1.153

We validate our method across 13 diverse datasets and 8 state-of-the-art prompt learning models. Our experiments show that our framework improves near OOD detection performance by up to 11.67% in terms of AUROC, without affecting the classification accuracy of the underlying models. This demonstrates the versatility and effectiveness of our approach in real-world applications.

2 BACKGROUND

2.1 CONTRASTIVE LANGUAGE–IMAGE PRE-TRAINING (CLIP)

Contrastive Language–Image Pre-training (CLIP) (Radford et al., 2021), a pre-trained vision-language model learned to align 400 million image-text pairs, is renowned for its powerful zero-shot image classification performance. It measures cosine similarity between image feature of an unseen image and textual feature of a text prompt formatted as "a photo of a [CLASS]" where [CLASS] is the name of a class in a label space of interest. Formally, given an image $I \in \mathbb{R}^{H\times W\times 3}$ with H being the height and W being the width and a text prompt $T =$ "a photo of a [CLASS]", a classification logit is computed by $\langle \mathrm{Enc_I}(I), \mathrm{Enc_T}(T)\rangle$ where $\langle\cdot,\cdot\rangle$ is cosine similarity, $\mathrm{Enc_I}(\cdot)$ is an image encoder, and $\mathrm{Enc_T}(\cdot)$ is a text encoder. The image encoder can be either ResNet (He et al., 2016) or Vision Transformer (ViT) (Dosovitskiy et al., 2021), and the text encoder is Transformer (Vaswani et al., 2017). For the brevity of notation, we omit the notations of the encoders for the remainder of the paper.

2.2 PROMPT LEARNING OF CLIP

Prompt learning of CLIP was first introduced by Zhou et al. (2022b) through Context Optimization (CoOp), which adapts popular prompt learning techniques from the natural language processing (NLP) field to CLIP. It addresses the issue of CLIP's classification being sensitive to the prompt's prefix (e.g., a large performance gap between when using "a photo of a [CLASS]" and "a [CLASS]") by optimising the prefix with few-shot samples. CoOp learns M continuous context vectors $V = \{V_1, V_2, \cdots, V_M\}$ within word-embedding space where $V_i \in \mathbb{R}^D$ is the i^{th} vector with D being the word-embedding dimension. The learnable prompt is formalised as $P = \{V_1, V_2, \cdots, V_M, C\}$ where $C \in \mathbb{R}^D$ is the word-embedding of a class name appended to the context vectors. The classification logit of i^{th} class is then computed by $\langle I, P_i \rangle$ where P_i is the learnable prompt with the i^{th} class name. The probability is estimated by the softmax function as $p(y = i|I, P_i) = \frac{\exp(\langle I, P_i \rangle/\tau)}{\sum_{k=1}^{K} \exp(\langle I, P_k \rangle/\tau)}$ where K is the total number of classes and τ is the temperature scale. Cross-entropy loss is then minimised to learn the context vectors. Note that the only learnable parameters that are common among different prompt learning models are the M context vectors. Since the introduction of CoOp, a number of subsequent works have aimed to improve its ID accuracy and generalisability with modifications in model architecture or additional loss terms (See Section 4). The aim of the paper is to develop a post-hoc approach that improves near OOD detection performance while being agnostic to base prompt learning models.

2.3 Near Out-Of-Distribution Detection

OOD detection is largely categorised as far OOD detection and near OOD detection based on the distribution shift between an ID test dataset and an OOD dataset along with difficulty of detection (Ren et al., 2021; Fort et al., 2021; Yang et al., 2021; 2022; Zhang et al., 2023b). Far OOD datasets have covariate shift in images (i.e., OOD samples are from domains that differ from the training set), and near OOD datasets which are more challenging to detect involve semantic shift (i.e., OOD samples are drawn from the same domain as the training set but belong to previously unseen label classes). Near OOD detection is also synonymous with fine-grained OOD detection (Zhang et al., 2023a) and hard OOD detection (Li et al., 2024; Ming et al., 2022).

In this paper, we study near OOD detection via prompt learning of CLIP, a new research problem to which no existing methods are tailored. Given a trained CLIP prompt learning method, we focus on post-hoc approaches that compute a score from the logits of the method to determine whether a given image is from ID or from OOD, which can be written as:

$$g\left(I; \{P_i\}_{i=1}^{K}, \alpha\right) = \begin{cases} 1 & S\left(I; \{P_i\}_{i=1}^{K}\right) \geq \alpha \\ 0 & S\left(I; \{P_i\}_{i=1}^{K}\right) < \alpha \end{cases} \tag{1}$$

where $g(\cdot)$ is a OOD detector, α is the threshold, and $S(\cdot)$ is a score function. By convention, the ground truth label is 1 for ID samples and 0 for OOD samples.

3 Method

3.1 Problem Setting

We focus on a near OOD detection problem for prompt learning models of CLIP, which is to detect whether a given image I_{test} is from the ID test dataset $\mathcal{D}_{test}^{ID}$ of (I_{test}^{ID}, y^{ID}) pairs or a near OOD dataset $\mathcal{D}_{test}^{nearOOD}$ of $(I_{test}^{nearOOD}, y^{nearOOD})$ pairs where $y^{ID} \in \{1, \cdots, K\}$ is the ID label with K classes and $y^{nearOOD} \in \{1, \cdots, L\}$ is the near OOD label with L classes. The ID dataset and the near OOD dataset contain the same types of images (i.e., no covariate shift in images) but have no overlapping classes (i.e., $y^{ID} \cap y^{nearOOD} = \varnothing$). Without loss of generality, we assume that the context vectors V have already been fine-tuned using a prompt learning model with a few-shot ID training dataset and only consider post-training stage in a post-hoc manner.

3.2 Motivation

Energy and MaxLogit scores are two widely-used scores in the OOD detection literature (Liu et al., 2020; Hendrycks et al., 2022; Yang et al., 2021; Sun et al., 2022; Yang et al., 2022; Zhang et al., 2023b; Han et al., 2022; Sun et al., 2021). In our prompt learning context, these scores can be used to measure a model's confidence from the output logits (i.e., cosine similarity between image and textual features), based on the assumption that ID samples typically have higher scores than OOD

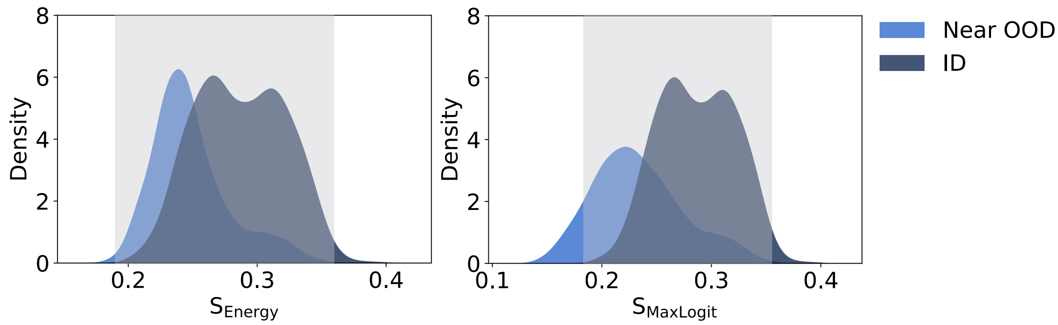


Figure 1: Density plots of Energy scores (left) and MaxLogit (right) computed with CoOp (Zhou et al., 2022b) on Flowers102 (Nilsback & Zisserman, 2008). Large regions of ID and near OOD samples overlap, which are highlighted by shaded boxes.

samples. Specifically, we have:

$$\textbf{Energy Score} \quad S_{\text{Energy}} = \tau \log \sum_{i=1}^{K} \exp\left(\langle I, P_i \rangle / \tau\right) \tag{2}$$

$$\textbf{MaxLogit Score} \quad S_{\text{MaxLogit}} = \max_i \langle I, P_i \rangle \tag{3}$$

Energy score can be viewed as an approximation of MaxLogit score when $\tau = 1$ as $\max_i \langle I, P_i \rangle \leq \log \sum_{i=1}^{K} \exp\left(\langle I, P_i \rangle\right) \leq \max_i \langle I, P_i \rangle + \log K$.

Although these logit-based scores have been commonly used for OOD detection, they perform sub-optimally in near OOD tasks. This is because near OOD samples often generate logit distributions that closely resemble those of ID samples, causing significant overlap between their score distributions. Figure 1 demonstrates this with a real-world dataset in the near OOD setting, where the overlap makes it difficult to distinguish between the two, leading to poor detection performance.

3.3 Proposed Score Function

Our objective is to develop a post-hoc method that improves MaxLogit and Energy scores to enhance near OOD detection for any CLIP-based prompt learning model with minimal learning cost.

3.3.1 Context Score and Marginal Logit Score

We first introduce the concept of **Context Score** $S_{\text{Context}} = \langle I, V \rangle$, which represents the cosine similarity between the image feature and the textual feature from the context vectors *without* any class name. The intuition is that the context vectors capture the general features of the model without associating images with any specific class and this score reflects how well the image aligns with these generic and non-class-specific features. The key insight is that for ID samples, the model should have a strong class-specific association, and therefore the Context score should be relatively low. Conversely, for OOD samples, the model's uncertainty should result in a higher Context score. Given a prompt learning method, Context score can be easily obtained by adding an additional label class with no class name (i.e., extending K classes to $K + 1$ classes).

We argue that Context score is a valuable complement to MaxLogit or Energy score, especially when the difference between these scores is leveraged. Ideally, when a model is given an ID image, it confidently predicts that the image belongs to a specific ID class, resulting in high Energy or MaxLogit score which represents the model's confidence. In contrast, its Context score is much lower, as it is calculated using a prompt lacking the ground-truth class name. This creates a large gap between the original score and the Context score.

Conversely, when the model is given a near OOD image, MaxLogit or Energy score is small as the model is uncertain about the image belonging to any ID class. As a result, the gap between the original score and Context score is much smaller. This difference between Energy or MaxLogit

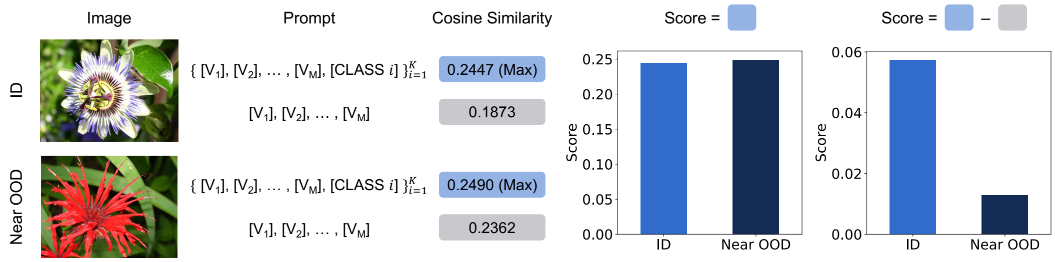


Figure 2: An example illustrating the effectiveness of MLS using ID and near OOD samples from Flowers102 (Nilsback & Zisserman, 2008) with the MaxLogit score shown in blue and the Context score shown in grey. While the MaxLogit score between the ID image and the near OOD image is not distinguishable (left bar plot), MLS which subtracts Context score from MaxLogit score is much more distinguishable (right bar plot).

score and Context score can be viewed as an alternative score, which we name *Marginal Logit Score (MLS)* defined as:

$$\textbf{Marginal Logit Score (Energy)} \quad S_{\text{MLS-E}} = S_{\text{Energy}} - S_{\text{Context}} \tag{4}$$

$$\textbf{Marginal Logit Score (MaxLogit)} \quad S_{\text{MLS-M}} = S_{\text{MaxLogit}} - S_{\text{Context}} \tag{5}$$

To demonstrate the effectiveness of MLS, we present an ID image and a near OOD image from Flowers102 (Nilsback & Zisserman, 2008) in Figure 2, with MaxLogit scores highlighted in blue and Context scores in grey. The MaxLogit score for the OOD sample is higher than that for the ID sample, indicating the model's failure to differentiate between the two. However, when the Context score is subtracted from the MaxLogit score, MLS is higher for the ID sample, showing that the model can successfully distinguish between the two samples.

We further illustrate its geometric interpretation in Figure 3a and Figure 3b where MaxLogit score and MLS-M are plotted at y-axis and Context score is plotted at x-axis. Geometrically, subtracting Context score from MaxLogit score is the same as applying vertical shearing transformation (Lax, 2007) to the samples, which essentially reduces the overlapping area highlighted by shaded boxes. With the MaxLogit score, the near OOD AUROC is 0.785 which is increased to 0.879 when evaluated with MLS-M.

3.3.2 Margin Scale

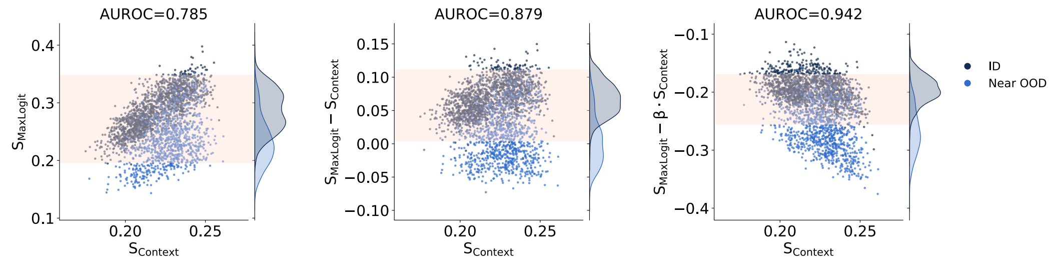
While the simple subtraction of the Context score improves OOD performance, its fixed margin limits adaptability across different models and datasets. To address this, we introduce a coefficient β termed *margin scale* that controls the amount of reduction of Context score from MaxLogit or Energy score in a more flexible manner:

$$\textbf{Marginal Logit Score (Energy)} \quad S_{\text{MLS-E}} = S_{\text{Energy}} - \beta \cdot S_{\text{Context}} \tag{6}$$

$$\textbf{Marginal Logit Score (MaxLogit)} \quad S_{\text{MLS-M}} = S_{\text{MaxLogit}} - \beta \cdot S_{\text{Context}} \tag{7}$$

In Figure 3c, we show that if the margin scale is applied, the near OOD AUROC is improved from 0.879 (equivalent to $\beta = 1$) to 0.942 ($\beta = 2.2$). To further demonstrate the importance of β to the base prompt learning models, we show how the near OOD performance in AUROC of different models varies with different β in Figure 4, where $\beta = 0$ represents the case of the original score without the context score and $\beta = 1$ is MLS without the margin scale. One can see that the value of β significantly affects the performance with all the prompt learning models.

This naturally opens a question on how to set β properly. If we were given the OOD samples, we could simply choose the value of β that minimises the near OOD performance. However, such an approach is impractical for real-world applications where near OOD samples are unavailable before deployment. To address this, we propose to estimate the margin scale by only using *few-shot ID training samples*. Initially, MaxLogit score and Context score in Figure 3a exhibit positive correlation, leading to significant overlap in the density distributions of ID and near OOD samples. When the near OOD detection AUROC is maximised, as shown in Figure 3c, this correlation is



(a) S_{MaxLogit} (b) $S_{\text{MLS-M}}$ $(\beta = 1)$ (c) $S_{\text{MLS-M}}$ $(\beta = 2.2)$

Figure 3: (a) MaxLogit score, (b) MLS-M without β, and (c) MLS-M with β of test ID and near OOD samples with respect to Context scores. Areas where ID samples and near OOD samples overlap are highlighted with shaded boxes. All scores are computed using MaPLe (Khattak et al., 2023a) on Caltech101 (Fei-Fei et al., 2004). See Appendix A.4 for additional demonstrations with different models and datasets.

minimised, resulting in reduced overlap between the distributions. Thus, we formulate this problem as finding the margin scale that minimises the correlation between MaxLogit or Energy score and Context score.

We propose approximating this correlation using the covariance matrix of a bivariate normal distribution fitted with MLS and Context scores computed from the training samples. A key advantage of this approach is its computational simplicity and the availability of a closed-form solution via maximum likelihood estimation. By leveraging this, we find the margin scale that zeros out the off-diagonals of the covariance matrix of the fitted bivariate normal distribution.

Lemma 3.1. *Given N scalar observations $\{\hat{x}_i\}_{i=1}^N$ and $\{\hat{y}_i\}_{i=1}^N$, we define two variables $x = \hat{x}$ and $y = \hat{y} - \beta \cdot \hat{x}$. The scale parameter β that zeros out the covariance of two variables (i.e., the off-diagonals of a covariance matrix) which is approximated by maximum likelihood estimation is:*

$$\beta = \frac{\sum_{i=1}^N (\hat{x}_i - \mu_{\hat{x}})(\hat{y}_i - \mu_{\hat{y}})}{\sum_{i=1}^N (\hat{x}_i - \mu_{\hat{x}})^2} \tag{8}$$

where $\mu_{\hat{x}} = \frac{1}{N}\sum_{i=1}^N \hat{x}_i$ and $\mu_{\hat{y}} = \frac{1}{N}\sum_{i=1}^N \hat{y}_i$.

By using Lemma 3.1 with $\hat{y}$ being the MaxLogit score or Energy score and $\hat{x}$ being the Context score, the margin scale can be easily estimated with ID training samples (see Appendix A.1 for proof of the lemma). This scale estimation needs to be conducted only once after training finishes. Figure 4 shows the estimated margin scale in red dotted lines, demonstrating that our estimation is close to the value that results in the best performance. In addition to good accuracy, our method is a close-form estimation that only takes a small number of ID training samples with little computational cost.

4 Related Work

Vision-Language Models Vision-language models have significantly advanced in recent years, bridging the gap between visual and textual data. Early approaches, such as image captioning models (Karpathy & Fei-Fei, 2015; Wang et al., 2016; You et al., 2016), typically used convolutional neural networks (CNNs) to extract visual features and recurrent neural networks (RNNs) to generate descriptive text. The advent of transformers (Vaswani et al., 2017) handling long-range dependencies more effectively and contrastive learning (Oord et al., 2018) revolutionised this field. Notably, ALIGN (Jia et al., 2021), CLIP (Radford et al., 2021), and LiT (Zhai et al., 2022) leveraged a contrastive learning framework that aligns image and text embeddings in a multimodal space, allowing for zero-shot learning capabilities and impressive generalisation to unseen tasks and datasets. In this work, we leverage the powerful vision-language model CLIP and extend its near OOD capability.

CLIP-based Prompt Learning Despite the remarkable zero-shot performance of CLIP, CLIP shows inherently unstable classification accuracy that varies by wording of prompt. To mitigate this

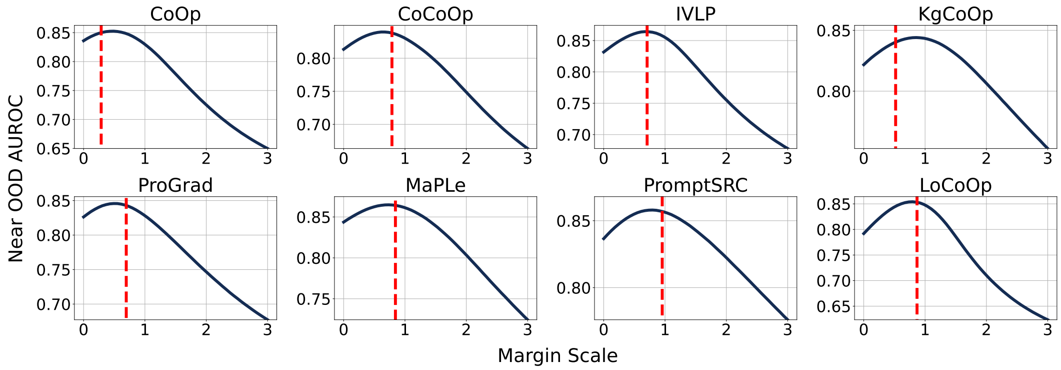


Figure 4: Near OOD detection AUROC using MLS-M vs. margin scale β for CoOp (Zhou et al., 2022b), CoCoOp (Zhou et al., 2022a), IVLP (Khattak et al., 2023a), KgCoOp (Yao et al., 2023), ProGrad (Zhu et al., 2023), MaPLe (Khattak et al., 2023a), PromptSRC (Khattak et al., 2023b), and LoCoOp (Miyai et al., 2023) on 16-shots UCF101 (Soomro et al., 2012). The margin scale is approximated by Eq.(8), shown as red dotted lines.

issue, CoOp (Zhou et al., 2022b) was proposed to optimise a prompt in word embedding space, leveraging prompt learning from the NLP literature. CoCoOp (Zhou et al., 2022a) identified that CoOp has limited generalisation and proposed to condition image features to the learnable prompt. Subsequently, many studies have proposed different techniques to improve the generalisation (Yao et al., 2023; Zhu et al., 2023; Khattak et al., 2023a;b). While its generalisation has been largely improved, its OOD detection has been overlooked. LoCoOp (Miyai et al., 2023) proposed a OOD regularisation to improve OOD detection performance. Nevertheless, no study has addressed near OOD detection of prompt learning models.

OOD Detection An early work of Hendrycks & Gimpel (2017) utilised the maximum softmax probability (MSP) as a score to identify OOD samples. Another notable work is Out-of-DIstribution detector for Neural networks (ODIN) (Liang et al., 2018) which extends MSP by introducing temperature scaling and input pre-processing to enhance separation of the scores from ID samples and OOD samples. Similar to ODIN, Mahalanobis (Lee et al., 2018) score also uses input pre-processing in addition to measuring distance in feature space. Delving into a more challenging task of near OOD detection, several studies analysed benchmarks of pre-trained networks in near OOD detection (Yang et al., 2023; 2022; Zhang et al., 2023b; Fort et al., 2021), and different training methods and score functions were proposed for near OOD detection (Ren et al., 2021; Winkens et al., 2020). Despite significant advancements in OOD detection for traditional classifier-based neural networks, many existing methods are not directly applicable to CLIP-based prompt learning models, which lack classifier heads. Furthermore, since these models do not update their image encoders during fine-tuning, many distance-based methods that rely on image features become ineffective.

5 Experiments

5.1 Experimental Settings

Datasets Following previous works of CLIP-based prompt learning models (Zhou et al., 2022a; Khattak et al., 2023a; Yao et al., 2023; Zhu et al., 2023; Khattak et al., 2023a;b; Miyai et al., 2023), we use 11 publicly available datasets of ImageNet (Deng et al., 2009), Caltech101 (Fei-Fei et al., 2004), OxfordPets (Parkhi et al., 2012), StanfordCars (Krause et al., 2013), Flowers102 (Nilsback & Zisserman, 2008), Food101 (Bossard et al., 2014), FGVCAircraft (Maji et al., 2013), SUN397 (Xiao et al., 2010), DTD (Cimpoi et al., 2014), EuroSAT (Helber et al., 2019), and UCF101 (Soomro et al., 2012). A common task of these works involves training models on half of the label classes (e.g., base classes) and evaluating them on the other half classes (e.g., new classes) to measure base-to-new generalisation. We reframe this task as a near OOD detection problem. Specifically, the models trained on base classes are tested with a dataset where half of the samples belong to the base classes (ID) and the other half to new classes (near OOD). The task is to detect whether each test image

Table 2: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	80.74	81.84	+1.09
CoCoOp	81.09	82.74	+1.65
IVLP	81.12	84.34	+3.23
KgCoOp	80.84	83.12	+2.28
ProGrad	79.77	82.35	+2.58
MaPLe	81.06	83.94	+2.88
PromptSRC	83.85	85.77	+1.92
LoCoOp	77.55	81.74	+4.18

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.78	94.66	+0.88
CoCoOp	94.85	95.14	+0.29
IVLP	94.55	94.70	+0.15
KgCoOp	94.21	94.21	+0.01
ProGrad	93.62	94.67	+1.04
MaPLe	94.20	94.35	+0.16
PromptSRC	94.52	95.32	+0.80
LoCoOp	93.10	94.56	+1.46

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	88.27	90.12	+1.85
CoCoOp	85.80	89.02	+3.22
IVLP	85.50	90.53	+5.03
KgCoOp	83.64	90.06	+6.42
ProGrad	82.96	88.85	+5.89
MaPLe	85.91	91.53	+5.62
PromptSRC	84.94	90.56	+5.62
LoCoOp	76.08	87.75	+11.67

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	86.22	88.73	+2.52
CoCoOp	89.58	92.28	+2.69
IVLP	88.84	91.94	+3.10
KgCoOp	89.94	92.64	+2.69
ProGrad	87.82	89.60	+1.78
MaPLe	87.40	91.00	+3.60
PromptSRC	90.80	93.45	+2.65
LoCoOp	84.44	89.19	+4.75

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	91.36	91.59	+0.22
CoCoOp	92.43	92.99	+0.57
IVLP	90.43	92.98	+2.56
KgCoOp	92.77	93.27	+0.51
ProGrad	91.52	92.63	+1.11
MaPLe	91.39	92.85	+1.47
PromptSRC	92.88	94.24	+1.35
LoCoOp	88.24	91.94	+3.70

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	90.83	91.99	+1.16
CoCoOp	87.93	89.41	+1.48
IVLP	86.20	88.45	+2.25
KgCoOp	87.61	91.12	+3.52
ProGrad	89.27	91.41	+2.14
MaPLe	86.05	88.34	+2.29
PromptSRC	91.10	92.61	+1.51
LoCoOp	86.17	88.59	+2.42

(g) Food101

	MaxLogit	MLS-M	△
CoOp	86.70	87.91	+1.21
CoCoOp	90.52	91.63	+1.10
IVLP	89.70	91.87	+2.18
KgCoOp	89.87	92.12	+2.25
ProGrad	88.60	91.05	+2.45
MaPLe	89.10	92.00	+2.89
PromptSRC	90.94	92.11	+1.17
LoCoOp	84.87	90.12	+5.25

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	55.99	56.97	+0.97
CoCoOp	52.60	55.04	+2.45
IVLP	58.47	64.16	+5.69
KgCoOp	57.82	57.46	-0.36
ProGrad	53.69	55.67	+1.97
MaPLe	52.18	56.93	+4.74
PromptSRC	60.63	62.50	+1.87
LoCoOp	50.99	56.12	+5.13

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	75.78	76.75	+0.97
CoCoOp	76.32	78.29	+1.97
IVLP	77.13	79.60	+2.46
KgCoOp	76.45	77.91	+1.46
ProGrad	75.52	77.67	+2.15
MaPLe	77.62	79.73	+2.11
PromptSRC	78.51	80.70	+2.19
LoCoOp	73.97	78.00	+4.02

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	68.90	69.60	+0.69
CoCoOp	65.10	67.17	+2.07
IVLP	64.99	67.93	+2.94
KgCoOp	63.79	68.17	+4.39
ProGrad	62.90	66.96	+4.06
MaPLe	64.80	67.79	+2.99
PromptSRC	69.09	70.38	+1.29
LoCoOp	66.63	69.05	+2.42

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	67.94	67.83	-0.11
CoCoOp	66.87	66.76	-0.10
IVLP	65.56	70.62	+5.06
KgCoOp	62.41	65.66	+3.25
ProGrad	68.96	69.71	+0.75
MaPLe	71.18	72.28	+1.09
PromptSRC	75.22	74.97	-0.25
LoCoOp	66.72	67.85	+1.13

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	82.17	83.65	+1.48
CoCoOp	81.32	84.02	+2.70
IVLP	80.26	84.55	+4.29
KgCoOp	81.26	84.06	+2.80
ProGrad	81.21	83.71	+2.50
MaPLe	80.81	84.25	+3.45
PromptSRC	83.19	85.43	+2.24
LoCoOp	76.28	82.54	+6.26

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	84.05	85.76	+1.71
CoCoOp	89.91	92.49	+2.58
IVLP	88.17	91.10	+2.93
KgCoOp	90.26	92.77	+2.52
ProGrad	83.94	89.08	+5.13
MaPLe	87.79	91.81	+4.02
PromptSRC	91.36	93.97	+2.60
LoCoOp	84.69	90.22	+5.53

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	77.67	78.30	+0.63
CoCoOp	80.99	81.44	+0.45
IVLP	84.69	88.01	+3.32
KgCoOp	80.94	81.14	+0.20
ProGrad	77.01	79.55	+2.55
MaPLe	85.35	88.35	+3.01
PromptSRC	86.82	88.78	+1.96
LoCoOp	76.03	76.67	+0.64

belongs to the ID dataset or the near OOD dataset. In addition, we include CIFAR10 (Krizhevsky et al., 2009) and CIFAR100 (Krizhevsky et al., 2009), which are standard near OOD detection benchmarks (Ren et al., 2021; Fort et al., 2021; Yang et al., 2021; 2022; Zhang et al., 2023b). For CIFAR10 and CIFAR100, we use all classes and evaluate with a test dataset consisting of both CIFAR10 test samples and CIAFR100 test samples, following the literature.

Models We use 8 prompt learning models: CoOp (Zhou et al., 2022b), CoCoOp (Zhou et al., 2022a), IVLP (Khattak et al., 2023a), KgCoOp (Yao et al., 2023), ProGrad (Zhu et al., 2023), MaPLe (Khattak et al., 2023a), PromptSRC (Khattak et al., 2023b), and LoCoOp (Miyai et al., 2023), all of which uses ViT-B/16 (Dosovitskiy et al., 2021) for the visual encoder and Transformer (Vaswani et al., 2017) for the text encoder. We follow their training details to train them with 16, 8, 4, 2, and 1-shot settings using 3 random seeds (see Appendix A.2 for implementation details). For each model, we use MaxLogit score, Energy score, and MCM (Ming et al., 2022) score as baselines where MCM is the state-of-the-art score for CLIP. As our focus is on the post-hoc method

Table 3: Near OOD AUROC (↑) and FPR95 (↓) of prompt learning models averaged over 13 datasets using MaxLogit score, Energy score, MLS, and MCM.

	AUROC ↑					FPR95 ↓				
	MaxLogit	Energy	MCM	MLS-M	MLS-E	MaxLogit	Energy	MCM	MLS-M	MLS-E
CoOp	80.74	80.44	79.41	**81.84**	81.71	58.23	59.45	63.70	**54.85**	55.37
CoCoOp	81.09	80.53	79.28	**82.74**	82.74	55.78	57.49	63.76	**51.67**	51.90
IVLP	81.12	80.49	80.95	84.34	**84.40**	55.65	57.66	60.05	**48.58**	49.19
KgCoOp	80.84	80.14	79.82	83.12	**83.23**	57.16	59.69	62.20	**51.52**	51.90
ProGrad	79.77	78.79	79.91	**82.35**	81.93	60.07	62.74	62.89	**54.02**	55.34
MaPLe	81.06	80.39	80.54	83.94	**83.99**	55.58	57.82	60.68	**48.36**	48.76
PromptSRC	83.85	83.48	82.34	85.77	**85.88**	49.65	51.86	55.86	**44.60**	45.15
LoCoOp	77.55	75.94	79.22	**81.74**	81.25	64.89	69.07	63.37	**55.76**	57.80

directly applicable to fine-tuned prompt learning models without requiring near OOD samples, we exclude other scoring methods that require OOD samples, modifications of training procedures, or architecture changes in models.

5.2 Experimental Results

We report average AUROC and false positive rate (FPR) of near OOD samples when true positive rate (TPR) of ID samples is at 95% with 16, 8, 4, 2, and 1-shot settings and 3 randoms seeds. Refer to Appendix A.3 for results of individual few-shot settings with standard deviations across the random seeds. In Table 2, we compare near OOD detection AUROC using the MaxLogit score and MLS-M score. Positive improvements in AUROC are observed in 100 out of 104 evaluations (i.e., 13 datasets$\times$8 models) when MLS-M is used.

On average, the largest improvement was observed with LoCoOp, the recent prompt learning model for OOD detection. The same results for Energy score are shown in Table 12. Similar to MaxLogit score, AUROC is improved in 101 out of 104 evaluations when using Energy score. Refer to Table 6 and Table 13 for FPR95.

Table 3 shows a comparison between MaxLogit score, Energy score, MLS-M, MLS-E, and MCM, in terms of both AUROC and FPR95 averaged across 13 datasets. The MLS-M and Energy score outperform MCM in both AUROC and FPR95. When MLS-M and MLS-E are compared, MLS-M outperforms MLS-E for the half of the models in AUROC and all models in FPR95. This highlights that the proposed scores are better scores for near OOD detection tasks than MCM, and MLS-M is better than MLS-E. Refer to Table 21 and Table 22 for the results of all datasets.

6 Discussion

Comparison with MCM As discussed in Section 5.2, MLS outperforms MCM in AUROC and FPR95 averaged across 13 datasets. We notice that MCM outperforms these scores in a few datasets. We analyse this difference from the perspective of dataset distance. As MCM is the state-of-the-art OOD detection score for far OOD detection, MCM is expected to outperform as the dataset distance between an ID test dataset and a near OOD dataset increases. We empirically validate this assumption by measuring the dataset distance by Optimal Transport Dataset Distance (OTDD) (Alvarez-Melis & Fusi, 2020) which is shown in Figure 5. For each dataset, we measure the distance between the ID test dataset and the near OOD test dataset. The density is then plotted, with blue indicating areas where MLS performs better and grey indicating areas where MCM performs better. While MLS outperforms across a wide range of distance, it excels when the distance decreases. MCM, on the other hand, tends to outperform as the distance increases. Nevertheless, MLS outperforms in the majority of cases, resulting in superior average performance.

Application to MCM A straightforward extension of our method is the application of the post-hoc process to the MCM score (i.e., $S_{\text{MLS-MCM}} = S_{\text{MCM}} - \beta \cdot S_{\text{Context}}$). The differences in AUROC and FPR95 with MCM and MLS-MCM are presented in Table 19 and Table 20. While it improves performance with MCM on most datasets, some datasets exhibit a decline in performance. This decline is due to the lack of a positive correlation between MCM and the Context score, which was observed with logit-based scores in Figure 3. Figure 6 further demonstrates the differing relationships between the score and the Context score. This discrepancy primarily arises from the softmax normalisation, where MCM only considers the relative magnitude of logits between classes, allowing non-maximum logits to unexpectedly change the relationship.

Application to Far OOD Detection Although our method is not designed for far OOD detection, it can be potentially applied to the area. Following the OOD literature of CLIP (Ming et al., 2022; Miyai et al., 2023; Wang et al., 2023; Jiang et al., 2024), we use ImageNet as an ID dataset and iNaturalist (Van Horn et al., 2018), SUN (Xiao et al., 2010), Places (Zhou et al., 2018), and Texture (Cimpoi et al., 2014) as far OOD datasets. We leverage the fine-tuned models in our experiments and show AUROC results in Table 23 and FPR95 results in Table 24 in Appendix A.3.5. The post-hoc framework is effective for both MaxLogit score and Energy score, improving AUROC and FPR95 in 126 out of 128 evaluations where MLS outperforms MCM in a half of evaluations. This aligns with the near OOD results, being effective across various models and OOD datasets. The limited performance also aligns with our observation in Figure 5 that MCM can be more effective when the dataset distance between ID and OOD datasets increases. However, far OOD detection is beyond our focus.

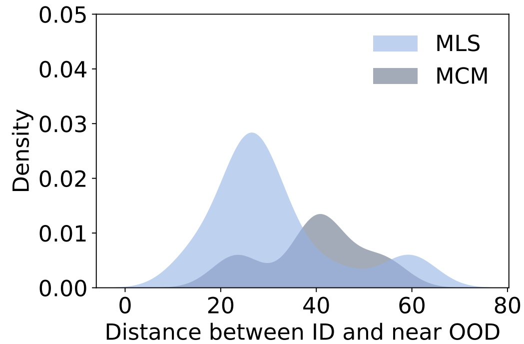


Figure 5: Density plot of dataset distance between the ID test dataset and near OOD dataset measured with OTDD. Datasets where MLS outperforms are highlighted in blue, while those where MCM outperforms are highlighted in grey.

Comparisons with More OOD Methods In our experiments, we intentionally excluded OOD methods that require access to OOD samples during training, retraining the prompt learning models, or those incompatible with the fine-tuned CLIP-based prompt learning models. This is because our main contribution is a new score specifically designed for few-shot prompt learning models without these requirements. For example, ODIN (Liang et al., 2018) is not a suitable baseline as it requires access to OOD samples for hyperparameter tuning. Similarly, LogitNorm (Wei et al., 2022) needs to be trained with a specific loss function, requiring the retraining of prompt learning models with modified training objectives. Distance-based scores, such as Mahalanobis distance (Lee et al., 2018) and relative Mahalanobis distance (RMD) (Ren et al., 2021), were originally designed for traditional classifiers and are therefore incompatible with few-shot prompt learning models. For example, to compute RMD in our case, only image features can be used while the textual features are ignored. As the prompt learning models do not update their image encoders while fine-tuning, RMD will be the same regardless of prompt learning model used. Therefore, these scores are not suitable for our problem. However, we provide comparisons with LogitNorm and RMD in Appendix A.3.8 for readers interested in the comparisons.

7 Conclusion

In this work, we address few-shot near OOD detection of CLIP-based prompt learning models. To enhance existing logit-based scores, we propose a simple and fast post-hoc method applicable to any prompt learning model. Without changing training procedures of the existing models nor compromising classification accuracy, our method effectively enhances near OOD AUROC and lowers FPR95 for 8 recent prompt learning models across 13 real-world datasets. While our method is broadly applicable across various prompt learning models, the degree of improvement can vary depending on the underlying model characteristics. Some models may not see as substantial a benefit, particularly if their inherent logit distributions already exhibit strong separability between ID and OOD samples.

REFERENCES

David Alvarez-Melis and Nicolo Fusi. Geometric dataset distances via optimal transport. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 21428–21439. Curran Associates, Inc., 2020.

Yichen Bai, Zongbo Han, Changqing Zhang, Bing Cao, Xiaoheng Jiang, and Qinghua Hu. Id-like prompt learning for few-shot out-of-distribution detection. *arXiv preprint arXiv:2311.15243*, 2023.

C.M. Bishop. *Pattern Recognition and Machine Learning*. Information science and statistics. Springer (India) Private Limited, 2013. ISBN 9788132209065.

Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101 – mining discriminative components with random forests. In David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars (eds.), *Computer Vision – ECCV 2014*, pp. 446–461, Cham, 2014. Springer International Publishing. ISBN 978-3-319-10599-4.

Mircea Cimpoi, Subhransu Maji, Iasonas Kokkinos, Sammy Mohamed, and Andrea Vedaldi. Describing textures in the wild. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2014.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 248–255, 2009. doi: 10.1109/CVPR.2009.5206848.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2021.

Li Fei-Fei, R. Fergus, and P. Perona. Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories. In *2004 Conference on Computer Vision and Pattern Recognition Workshop*, pp. 178–178, 2004. doi: 10.1109/CVPR.2004.383.

Stanislav Fort, Jie Ren, and Balaji Lakshminarayanan. Exploring the limits of out-of-distribution detection. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, volume 34, pp. 7068–7081. Curran Associates, Inc., 2021.

Songqiao Han, Xiyang Hu, Hailiang Huang, Minqi Jiang, and Yue Zhao. Adbench: Anomaly detection benchmark. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 32142–32159. Curran Associates, Inc., 2022.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

Patrick Helber, Benjamin Bischke, Andreas Dengel, and Damian Borth. Eurosat: A novel dataset and deep learning benchmark for land use and land cover classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 12(7):2217–2226, 2019. doi: 10.1109/JSTARS.2019.2918242.

Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. In *International Conference on Learning Representations*, 2017.

Dan Hendrycks, Steven Basart, Mantas Mazeika, Andy Zou, Joseph Kwon, Mohammadreza Mostajabi, Jacob Steinhardt, and Dawn Song. Scaling out-of-distribution detection for real-world settings. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pp. 8759–8773. PMLR, 17–23 Jul 2022.

Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 4904–4916. PMLR, 18–24 Jul 2021.

Xue Jiang, Feng Liu, Zhen Fang, Hong Chen, Tongliang Liu, Feng Zheng, and Bo Han. Negative label guided ood detection with pretrained vision-language models. *arXiv preprint arXiv:2403.20078*, 2024.

Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015.

Muhammad Uzair Khattak, Hanoona Rasheed, Muhammad Maaz, Salman Khan, and Fahad Shahbaz Khan. Maple: Multi-modal prompt learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 19113–19122, June 2023a.

Muhammad Uzair Khattak, Syed Talal Wasim, Muzammal Naseer, Salman Khan, Ming-Hsuan Yang, and Fahad Shahbaz Khan. Self-regulating prompts: Foundational model adaptation without forgetting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 15190–15200, October 2023b.

Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei. 3d object representations for fine-grained categorization. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV) Workshops*, June 2013.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Peter D Lax. *Linear algebra and its applications*, volume 78. John Wiley & Sons, 2007.

Kimin Lee, Kibok Lee, Honglak Lee, and Jinwoo Shin. A simple unified framework for detecting out-of-distribution samples and adversarial attacks. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018.

Tianqi Li, Guansong Pang, Xiao Bai, Wenjun Miao, and Jin Zheng. Learning transferable negative prompts for out-of-distribution detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 17584–17594, June 2024.

Shiyu Liang, Yixuan Li, and R. Srikant. Enhancing the reliability of out-of-distribution image detection in neural networks. In *International Conference on Learning Representations*, 2018.

Weitang Liu, Xiaoyun Wang, John Owens, and Yixuan Li. Energy-based out-of-distribution detection. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 21464–21475. Curran Associates, Inc., 2020.

Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft. *arXiv preprint arXiv:1306.5151*, 2013.

Yifei Ming, Ziyang Cai, Jiuxiang Gu, Yiyou Sun, Wei Li, and Yixuan Li. Delving into out-of-distribution detection with vision-language representations. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 35087–35102. Curran Associates, Inc., 2022.

Atsuyuki Miyai, Qing Yu, Go Irie, and Kiyoharu Aizawa. Locoop: Few-shot out-of-distribution detection via prompt learning. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine (eds.), *Advances in Neural Information Processing Systems*, volume 36, pp. 76298–76310. Curran Associates, Inc., 2023.

Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing*, pp. 722–729, 2008. doi: 10.1109/ICVGIP.2008.47.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

Andres Palechor, Annesha Bhoumik, and Manuel Günther. Large-scale open-set classification protocols for imagenet. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pp. 42–51, January 2023.

Omkar M Parkhi, Andrea Vedaldi, Andrew Zisserman, and C. V. Jawahar. Cats and dogs. In *2012 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3498–3505, 2012. doi: 10.1109/CVPR.2012.6248092.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 8748–8763. PMLR, 18–24 Jul 2021.

Jie Ren, Stanislav Fort, Jeremiah Liu, Abhijit Guha Roy, Shreyas Padhy, and Balaji Lakshminarayanan. A simple fix to mahalanobis distance for improving near-ood detection. *arXiv preprint arXiv:2106.09022*, 2021.

Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.

Yiyou Sun, Chuan Guo, and Yixuan Li. React: Out-of-distribution detection with rectified activations. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, volume 34, pp. 144–157. Curran Associates, Inc., 2021.

Yiyou Sun, Yifei Ming, Xiaojin Zhu, and Yixuan Li. Out-of-distribution detection with deep nearest neighbors. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pp. 20827–20840. PMLR, 17–23 Jul 2022.

Grant Van Horn, Oisin Mac Aodha, Yang Song, Yin Cui, Chen Sun, Alex Shepard, Hartwig Adam, Pietro Perona, and Serge Belongie. The inaturalist species classification and detection dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.

Cheng Wang, Haojin Yang, Christian Bartz, and Christoph Meinel. Image captioning with deep bidirectional lstms. In *Proceedings of the 24th ACM International Conference on Multimedia*, MM '16, pp. 988–997, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 9781450336031. doi: 10.1145/2964284.2964299.

Hualiang Wang, Yi Li, Huifeng Yao, and Xiaomeng Li. Clipn for zero-shot ood detection: Teaching clip to say no. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 1802–1812, October 2023.

Hongxin Wei, Renchunzi Xie, Hao Cheng, Lei Feng, Bo An, and Yixuan Li. Mitigating neural network overconfidence with logit normalization. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pp. 23631–23644. PMLR, 17–23 Jul 2022.

Jim Winkens, Rudy Bunel, Abhijit Guha Roy, Robert Stanforth, Vivek Natarajan, Joseph R Ledsam, Patricia MacWilliams, Pushmeet Kohli, Alan Karthikesalingam, Simon Kohl, et al. Contrastive training for improved out-of-distribution detection. *arXiv preprint arXiv:2007.05566*, 2020.

Jianxiong Xiao, James Hays, Krista A. Ehinger, Aude Oliva, and Antonio Torralba. Sun database: Large-scale scene recognition from abbey to zoo. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 3485–3492, 2010. doi: 10.1109/CVPR.2010.5539970.

Jingkang Yang, Kaiyang Zhou, Yixuan Li, and Ziwei Liu. Generalized out-of-distribution detection: A survey. *arXiv preprint arXiv:2110.11334*, 2021.

Jingkang Yang, Pengyun Wang, Dejian Zou, Zitang Zhou, Kunyuan Ding, WENXUAN PENG, Haoqi Wang, Guangyao Chen, Bo Li, Yiyou Sun, Xuefeng Du, Kaiyang Zhou, Wayne Zhang, Dan Hendrycks, Yixuan Li, and Ziwei Liu. Openood: Benchmarking generalized out-of-distribution detection. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 32598–32611. Curran Associates, Inc., 2022.

Jingkang Yang, Kaiyang Zhou, and Ziwei Liu. Full-spectrum out-of-distribution detection. *International Journal of Computer Vision*, 131(10):2607–2622, 2023.

Hantao Yao, Rui Zhang, and Changsheng Xu. Visual-language prompt tuning with knowledge-guided context optimization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 6757–6767, June 2023.

Quanzeng You, Hailin Jin, Zhaowen Wang, Chen Fang, and Jiebo Luo. Image captioning with semantic attention. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

Xiaohua Zhai, Xiao Wang, Basil Mustafa, Andreas Steiner, Daniel Keysers, Alexander Kolesnikov, and Lucas Beyer. Lit: Zero-shot transfer with locked-image text tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 18123–18133, June 2022.

Jingyang Zhang, Nathan Inkawhich, Randolph Linderman, Yiran Chen, and Hai Li. Mixture outlier exposure: Towards out-of-distribution detection in fine-grained environments. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pp. 5531–5540, January 2023a.

Jingyang Zhang, Jingkang Yang, Pengyun Wang, Haoqi Wang, Yueqian Lin, Haoran Zhang, Yiyou Sun, Xuefeng Du, Kaiyang Zhou, Wayne Zhang, Yixuan Li, Ziwei Liu, Yiran Chen, and Hai Li. Openood v1.5: Enhanced benchmark for out-of-distribution detection. *arXiv preprint arXiv:2306.09301*, 2023b.

Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(6):1452–1464, 2018. doi: 10.1109/TPAMI.2017.2723009.

Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Conditional prompt learning for vision-language models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 16816–16825, June 2022a.

Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Learning to prompt for vision-language models. *International Journal of Computer Vision*, 130(9):2337–2348, 2022b.

Beier Zhu, Yulei Niu, Yucheng Han, Yue Wu, and Hanwang Zhang. Prompt-aligned gradient for prompt tuning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 15659–15669, October 2023.

A Appendix

A.1 Proof of Lemma

We provide the proof of Lemma 3.1. For completeness of proof, we duplicate the lemma here.

Lemma A.1. *Given N scalar observations $\{\hat{x}_i\}_{i=1}^N$ and $\{\hat{y}_i\}_{i=1}^N$, we define two variables $x = \hat{x}$ and $y = \hat{y} - \beta \cdot \hat{x}$. The scale parameter β that zeros out the covariance of two variables (i.e., the off-diagonals of a covariance matrix) which is approximated by maximum likelihood estimation is:*

$$\beta = \frac{\sum_{i=1}^N (\hat{x}_i - \mu_{\hat{x}})(\hat{y}_i - \mu_{\hat{y}})}{\sum_{i=1}^N (\hat{x}_i - \mu_{\hat{x}})^2} \tag{9}$$

where $\mu_{\hat{x}} = \frac{1}{N}\sum_{i=1}^N \hat{x}_i$ and $\mu_{\hat{y}} = \frac{1}{N}\sum_{i=1}^N \hat{y}_i$.

Proof. It is well known that maximum likelihood estimation (MLE) of bivariate normal distribution for N observations of variables x and y results in (Bishop, 2013):

$$\mu_x = \frac{1}{N}\sum_i x_i, \quad \mu_y = \frac{1}{N}\sum_i y_i \tag{10}$$

$$\Sigma = \begin{bmatrix} \sigma_{xx} & \sigma_{xy} \\ \sigma_{xy} & \sigma_{yy} \end{bmatrix} = \frac{1}{N}\sum_i \left(\begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix} \right) \left(\begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix} \right)^T \tag{11}$$

$$\sigma_{xy} = \frac{1}{N}\sum_i (x_i - \mu_x)(y_i - \mu_y) \tag{12}$$

where μ_x and μ_y are the means of x and y, and Σ is the covariance matrix. We let $x = \hat{x}$ and $y = \hat{y} - \beta \cdot \hat{x}$ and find β that makes $\sigma_{xy} = 0$. By rewriting σ_{xy} in terms of $\hat{x}$ and $\hat{y}$, we obtain β as:

$$\sigma_{xy} = \frac{1}{N}\sum_i (\hat{x}_i - \mu_{\hat{x}})(\hat{y}_i - \beta \cdot \hat{x}_i - \mu_{\hat{y}} + \beta \cdot \mu_{\hat{x}}) = 0 \tag{13}$$

$$\beta = \frac{\sum_i (\hat{x}_i - \mu_{\hat{x}})(\hat{y}_i - \mu_{\hat{y}})}{\sum_i (\hat{x}_i - \mu_{\hat{x}})^2} \tag{14}$$

The resulting β is the ratio of covariance of $\hat{x}$ and $\hat{y}$ to variance of $\hat{x}$. □

A.2 Implementation Details

We follow the officially released training guidelines for each prompt learning model using the same configuration files. The only additional line of code required is `beta=(((y-y.mean())*(x-x.mean())).sum())/(((x-x.mean())**2).sum())` to estimate the margin scale in Eq.(8). The overall algorithm is summarised in Algorithm 1. Table 4 shows common hyperparameters which are the number of epochs, batch size, and context vectors initialisation. Refer to their officially released codes for other model-specific hyperparameters. All models were trained on a single NVIDIA GeForce RTX 3090 GPU with PyTorch framework. The temperature scaling is 0.01 for the Energy score and 1 for the MCM score.

Algorithm 1: MLS Computation

Input: Few-shot training dataset of N image-label pairs of $\{I_i, y_i\}_{i=1}^N$ where $y_i \in \{1, \cdots, K\}$ with K classes, a test image I_{test}, a fine-tuned prompt learning model with learned context vectors V.

for I_i, y_i **do**
    Compute and store MaxLogit score S_{MaxLogit} or Energy score S_{Energy} by Eq.(3) and Eq.(2).
    Compute and store Context score S_{Context}.
end for
Estimate margin scale β by Eq.(8)
Compute MLS by Eq.(7) and Eq.(6)

Table 4: Training details of the prompt learning models..

	# Epochs	Batch Size	Context Vectors Initialisation
CoOp	50 (ImageNet) 200 (Others)	32	"a photo of a"
CoCoOp	10	1	
IVLP	5	4	
KgCoOp	100	128	
ProGrad	200	32	
MaPLe	5	4	
PromptSRC	20	4	
LoCoOp	50	32	16 vectors drawn from $\mathcal{N}(0, 0.02)$

A.3 Additional Experimental Results

We provide additional experimental results other than the results in the main section.

A.3.1 MaxLogit Score

We provide average AUROC and FPR95 across 13 datasets using MaxLogit in Table 5 and Table 6. Note that Table 5 is duplicated for completeness of this Section. From Table 7 to Table 11, average AUROC across 3 random seeds with standard deviations are reported for each few-shot setting. While overall improvements are observed across different few-shot settings, slight performance degradations are observed in EuroSAT and CIAFR10 at 1-shot. This is because of insufficient training samples used to find the optimal margin scale where EuroSAT and CIFAR10 have 5 classes and 10 classes in their training datasets respectively.

Table 5: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	80.74	81.84	+1.09
CoCoOp	81.09	82.74	+1.65
IVLP	81.12	84.34	+3.23
KgCoOp	80.84	83.12	+2.28
ProGrad	79.77	82.35	+2.58
MaPLe	81.06	83.94	+2.88
PromptSRC	83.85	85.77	+1.92
LoCoOp	77.55	81.74	+4.18

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.78	94.66	+0.88
CoCoOp	94.85	95.14	+0.29
IVLP	94.55	94.70	+0.15
KgCoOp	94.21	94.21	+0.01
ProGrad	93.62	94.67	+1.04
MaPLe	94.20	94.35	+0.16
PromptSRC	94.52	95.32	+0.80
LoCoOp	93.10	94.56	+1.46

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	88.27	90.12	+1.85
CoCoOp	85.80	89.02	+3.22
IVLP	85.50	90.53	+5.03
KgCoOp	83.64	90.06	+6.42
ProGrad	82.96	88.85	+5.89
MaPLe	85.91	91.53	+5.62
PromptSRC	84.94	90.56	+5.62
LoCoOp	76.08	87.75	+11.67

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	86.22	88.73	+2.52
CoCoOp	89.58	92.28	+2.69
IVLP	88.84	91.94	+3.10
KgCoOp	89.94	92.64	+2.69
ProGrad	87.82	89.60	+1.78
MaPLe	87.40	91.00	+3.60
PromptSRC	90.80	93.45	+2.65
LoCoOp	84.44	89.19	+4.75

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	91.36	91.59	+0.22
CoCoOp	92.43	92.99	+0.57
IVLP	90.43	92.98	+2.56
KgCoOp	92.77	93.27	+0.51
ProGrad	91.52	92.63	+1.11
MaPLe	91.39	92.85	+1.47
PromptSRC	92.88	94.24	+1.35
LoCoOp	88.24	91.94	+3.70

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	90.83	91.99	+1.16
CoCoOp	87.93	89.41	+1.48
IVLP	86.20	88.45	+2.25
KgCoOp	87.61	91.12	+3.52
ProGrad	89.27	91.41	+2.14
MaPLe	86.05	88.34	+2.29
PromptSRC	91.10	92.61	+1.51
LoCoOp	86.17	88.59	+2.42

(g) Food101

	MaxLogit	MLS-M	△
CoOp	86.70	87.91	+1.21
CoCoOp	90.52	91.63	+1.10
IVLP	89.70	91.87	+2.18
KgCoOp	89.87	92.12	+2.25
ProGrad	88.60	91.05	+2.45
MaPLe	89.10	92.00	+2.89
PromptSRC	90.94	92.11	+1.17
LoCoOp	84.87	90.12	+5.25

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	55.99	56.97	+0.97
CoCoOp	52.60	55.04	+2.45
IVLP	58.47	64.16	+5.69
KgCoOp	57.82	57.46	-0.36
ProGrad	53.69	55.67	+1.97
MaPLe	52.18	56.93	+4.74
PromptSRC	60.63	62.50	+1.87
LoCoOp	50.99	56.12	+5.13

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	75.78	76.75	+0.97
CoCoOp	76.32	78.29	+1.97
IVLP	77.13	79.60	+2.46
KgCoOp	76.45	77.91	+1.46
ProGrad	75.52	77.67	+2.15
MaPLe	77.62	79.73	+2.11
PromptSRC	78.51	80.70	+2.19
LoCoOp	73.97	78.00	+4.02

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	68.90	69.60	+0.69
CoCoOp	65.10	67.17	+2.07
IVLP	64.99	67.93	+2.94
KgCoOp	63.79	68.17	+4.39
ProGrad	62.90	66.96	+4.06
MaPLe	64.80	67.79	+2.99
PromptSRC	69.09	70.38	+1.29
LoCoOp	66.63	69.05	+2.42

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	67.94	67.83	-0.11
CoCoOp	66.87	66.76	-0.10
IVLP	65.56	70.62	+5.06
KgCoOp	62.41	65.66	+3.25
ProGrad	68.96	69.71	+0.75
MaPLe	71.18	72.28	+1.09
PromptSRC	75.22	74.97	-0.25
LoCoOp	66.72	67.85	+1.13

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	82.17	83.65	+1.48
CoCoOp	81.32	84.02	+2.70
IVLP	80.26	84.55	+4.29
KgCoOp	81.26	84.06	+2.80
ProGrad	81.21	83.71	+2.50
MaPLe	80.81	84.25	+3.45
PromptSRC	83.19	85.43	+2.24
LoCoOp	76.28	82.54	+6.26

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	84.05	85.76	+1.71
CoCoOp	89.91	92.49	+2.58
IVLP	88.17	91.10	+2.93
KgCoOp	90.26	92.77	+2.52
ProGrad	83.94	89.08	+5.13
MaPLe	87.79	91.81	+4.02
PromptSRC	91.36	93.97	+2.60
LoCoOp	84.69	90.22	+5.53

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	77.67	78.30	+0.63
CoCoOp	80.99	81.44	+0.45
IVLP	84.69	88.01	+3.32
KgCoOp	80.94	81.14	+0.20
ProGrad	77.01	79.55	+2.55
MaPLe	85.35	88.35	+3.01
PromptSRC	86.82	88.78	+1.96
LoCoOp	76.03	76.67	+0.64

Table 6: Near OOD FPR95 (↓) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	58.23	54.85	-3.38
CoCoOp	55.78	51.67	-4.11
IVLP	55.65	48.58	-7.07
KgCoOp	57.16	51.52	-5.64
ProGrad	60.07	54.02	-6.05
MaPLe	55.58	48.36	-7.22
PromptSRC	49.65	44.60	-5.05
LoCoOp	64.89	55.76	-9.12

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	31.02	26.40	-4.62
CoCoOp	26.76	23.85	-2.92
IVLP	27.23	24.54	-2.70
KgCoOp	29.84	27.45	-2.39
ProGrad	32.73	27.40	-5.33
MaPLe	29.87	26.09	-3.79
PromptSRC	27.89	22.82	-5.07
LoCoOp	36.95	28.94	-8.01

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	38.42	29.90	-8.52
CoCoOp	42.22	33.02	-9.20
IVLP	45.94	30.97	-14.97
KgCoOp	49.33	28.80	-20.53
ProGrad	56.38	39.35	-17.02
MaPLe	44.44	28.30	-16.14
PromptSRC	43.79	25.83	-17.96
LoCoOp	69.02	37.02	-32.00

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	51.60	45.90	-5.70
CoCoOp	42.47	35.89	-6.58
IVLP	48.28	40.88	-7.40
KgCoOp	47.06	35.52	-11.54
ProGrad	50.75	51.94	+1.19
MaPLe	50.86	42.87	-7.99
PromptSRC	42.14	38.08	-4.06
LoCoOp	54.57	48.65	-5.92

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	32.58	31.62	-0.97
CoCoOp	28.76	27.18	-1.58
IVLP	33.89	26.07	-7.82
KgCoOp	29.06	27.77	-1.29
ProGrad	32.44	28.42	-4.02
MaPLe	30.75	26.05	-4.70
PromptSRC	26.27	22.88	-3.38
LoCoOp	41.93	31.83	-10.10

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	40.02	36.14	-3.87
CoCoOp	50.27	45.51	-4.76
IVLP	54.62	49.00	-5.62
KgCoOp	56.18	43.15	-13.03
ProGrad	44.28	38.84	-5.44
MaPLe	54.00	47.94	-6.07
PromptSRC	38.96	34.33	-4.63
LoCoOp	52.83	46.72	-6.12

(g) Food101

	MaxLogit	MLS-M	△
CoOp	54.00	49.48	-4.52
CoCoOp	41.85	37.57	-4.28
IVLP	44.36	35.63	-8.74
KgCoOp	44.42	35.98	-8.44
ProGrad	48.58	40.02	-8.57
MaPLe	45.70	35.26	-10.44
PromptSRC	39.21	34.61	-4.60
LoCoOp	58.93	42.34	-16.59

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	83.67	82.75	-0.92
CoCoOp	84.31	81.95	-2.36
IVLP	79.19	75.35	-3.84
KgCoOp	79.80	79.98	+0.18
ProGrad	84.79	81.38	-3.41
MaPLe	81.98	80.73	-1.25
PromptSRC	76.62	75.53	-1.08
LoCoOp	86.36	83.58	-2.78

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	71.81	69.50	-2.31
CoCoOp	70.74	65.62	-5.12
IVLP	69.31	63.76	-5.55
KgCoOp	70.46	67.17	-3.29
ProGrad	73.83	68.12	-5.71
MaPLe	68.72	63.34	-5.38
PromptSRC	66.85	61.55	-5.30
LoCoOp	76.47	67.24	-9.24

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	85.34	85.16	-0.18
CoCoOp	88.48	87.50	-0.98
IVLP	87.08	87.11	+0.03
KgCoOp	88.52	86.93	-1.59
ProGrad	87.78	87.55	-0.23
MaPLe	88.85	86.81	-2.04
PromptSRC	84.52	83.56	-0.97
LoCoOp	84.51	83.94	-0.57

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	85.12	85.20	+0.08
CoCoOp	82.25	82.38	+0.13
IVLP	81.16	73.84	-7.32
KgCoOp	82.08	82.30	+0.22
ProGrad	81.61	82.31	+0.70
MaPLe	75.22	68.41	-6.81
PromptSRC	65.95	65.83	-0.12
LoCoOp	81.91	80.88	-1.03

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	55.64	50.12	-5.53
CoCoOp	57.04	50.37	-6.67
IVLP	56.96	47.71	-9.26
KgCoOp	54.77	50.16	-4.61
ProGrad	57.39	48.84	-8.55
MaPLe	57.16	49.27	-7.89
PromptSRC	51.62	46.17	-5.45
LoCoOp	67.38	55.38	-11.99

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	53.49	49.45	-4.04
CoCoOp	37.07	29.79	-7.28
IVLP	39.00	30.87	-8.13
KgCoOp	38.30	30.85	-7.45
ProGrad	52.48	40.59	-11.90
MaPLe	40.75	30.00	-10.75
PromptSRC	30.54	22.74	-7.80
LoCoOp	51.96	36.97	-14.99

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	74.33	71.48	-2.85
CoCoOp	72.96	71.09	-1.88
IVLP	56.39	45.86	-10.54
KgCoOp	73.27	73.66	+0.39
ProGrad	77.89	67.49	-10.40
MaPLe	54.19	43.60	-10.59
PromptSRC	51.05	45.82	-5.23
LoCoOp	80.71	81.44	+0.73

Table 7: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M with 16-shots.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	82.82±10.81	83.86±10.79	+1.03±1.08
CoCoOp	81.51±12.87	83.65±11.76	+2.14±2.32
IVLP	83.46±10.49	87.48±8.02	+4.02±3.96
KgCoOp	81.41±12.12	84.08±11.38	+2.67±2.38
ProGrad	81.76±11.56	83.83±11.66	+2.07±2.43
MaPLe	83.83±10.89	86.35±10.06	+2.52±1.97
PromptSRC	85.76±9.23	87.52±9.07	+1.76±1.55
LoCoOp	79.26±11.23	82.30±12.45	+3.05±3.61

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.81±0.23	95.38±0.27	+1.57±0.05
CoCoOp	94.90±0.30	95.15±0.80	+0.25±0.94
IVLP	94.46±0.15	94.58±0.47	+0.12±0.42
KgCoOp	94.31±0.05	94.18±0.27	-0.14±0.32
ProGrad	94.14±0.18	94.97±0.06	+0.82±0.15
MaPLe	94.66±0.51	94.70±0.55	+0.04±0.29
PromptSRC	94.66±0.21	95.60±0.18	+0.93±0.25
LoCoOp	93.70±0.10	94.96±0.36	+1.26±0.45

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	89.75±0.81	91.38±1.11	+1.63±1.18
CoCoOp	87.12±1.14	89.94±1.19	+2.82±1.92
IVLP	87.69±1.59	93.21±1.75	+5.52±1.82
KgCoOp	84.05±0.05	90.34±0.33	+6.29±0.38
ProGrad	82.24±2.23	89.63±0.49	+7.40±2.15
MaPLe	87.88±0.79	93.06±1.46	+5.18±1.97
PromptSRC	84.68±0.22	90.55±0.15	+5.86±0.14
LoCoOp	78.82±1.57	88.71±0.60	+9.89±1.44

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	85.22±1.19	86.66±1.64	+1.45±0.46
CoCoOp	90.93±0.76	93.54±0.23	+2.61±0.69
IVLP	91.15±1.82	93.74±1.33	+2.59±0.73
KgCoOp	90.28±0.28	92.16±0.97	+1.88±0.80
ProGrad	87.42±1.41	88.59±0.73	+1.17±0.98
MaPLe	90.02±0.45	94.16±1.27	+4.14±1.28
PromptSRC	91.64±0.33	94.70±0.45	+3.06±0.19
LoCoOp	84.20±3.06	89.18±1.21	+4.98±2.46

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	93.53±0.21	93.44±0.22	-0.09±0.16
CoCoOp	91.29±1.69	92.82±0.80	+1.52±1.08
IVLP	90.49±1.37	93.21±1.09	+2.72±0.33
KgCoOp	92.95±0.20	93.47±0.06	+0.51±0.21
ProGrad	93.25±0.06	94.04±0.13	+0.80±0.08
MaPLe	91.44±1.47	93.23±0.33	+1.78±1.50
PromptSRC	93.84±0.18	95.35±0.14	+1.51±0.13
LoCoOp	89.08±1.19	92.10±1.80	+3.02±0.94

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	94.30±0.63	94.66±0.57	+0.36±0.07
CoCoOp	89.42±0.75	91.10±0.05	+1.69±0.80
IVLP	90.63±2.80	92.62±1.65	+1.99±1.16
KgCoOp	90.03±0.40	93.09±0.43	+3.05±0.37
ProGrad	90.72±0.89	93.03±0.23	+2.32±0.68
MaPLe	89.76±0.79	91.43±1.17	+1.67±0.58
PromptSRC	94.40±0.18	95.69±0.07	+1.29±0.24
LoCoOp	87.05±1.89	89.98±0.29	+2.92±2.19

(g) Food101

	MaxLogit	MLS-M	△
CoOp	88.67±0.17	90.13±0.18	+1.46±0.13
CoCoOp	90.54±0.55	92.43±0.76	+1.89±0.24
IVLP	90.40±0.78	92.81±0.52	+2.41±1.29
KgCoOp	90.26±0.03	92.80±0.05	+2.54±0.04
ProGrad	90.36±0.33	92.68±0.21	+2.31±0.13
MaPLe	90.79±0.89	93.10±0.49	+2.30±0.51
PromptSRC	91.36±0.25	92.63±0.22	+1.26±0.07
LoCoOp	85.50±1.17	91.49±0.65	+6.00±1.61

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	55.40±1.81	56.30±1.88	+0.90±1.39
CoCoOp	49.94±2.22	57.15±3.04	+7.21±4.00
IVLP	59.68±1.37	71.67±1.42	+11.99±0.11
KgCoOp	57.08±0.46	57.12±1.48	+0.04±1.10
ProGrad	54.58±0.63	54.13±4.16	-0.45±4.07
MaPLe	56.37±4.94	61.55±5.18	+5.18±0.32
PromptSRC	64.57±1.65	66.79±1.95	+2.22±1.25
LoCoOp	52.39±1.93	49.20±3.56	-3.19±2.24

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	78.28±0.50	79.55±0.69	+1.27±0.28
CoCoOp	77.26±0.48	79.28±0.50	+2.01±0.35
IVLP	77.80±0.44	80.69±0.27	+2.89±0.71
KgCoOp	77.35±0.10	78.83±0.18	+1.47±0.23
ProGrad	77.06±1.03	79.49±0.85	+2.42±0.28
MaPLe	78.20±1.74	80.68±0.66	+2.48±1.12
PromptSRC	79.60±0.10	82.05±0.47	+2.45±0.37
LoCoOp	75.80±0.33	79.85±0.46	+4.05±0.72

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	74.05±1.15	74.30±1.40	+0.24±0.27
CoCoOp	66.24±1.28	69.63±1.46	+3.40±1.75
IVLP	67.09±1.68	71.16±0.76	+4.07±1.01
KgCoOp	65.47±0.65	71.38±0.52	+5.92±0.31
ProGrad	63.89±1.41	68.36±1.45	+4.47±1.16
MaPLe	67.14±2.96	70.89±2.12	+3.75±1.77
PromptSRC	71.98±0.74	73.59±0.71	+1.62±0.61
LoCoOp	68.15±0.66	72.60±0.68	+4.45±0.74

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	71.85±1.25	73.46±2.66	+1.61±1.55
CoCoOp	68.61±2.90	68.29±3.18	-0.32±0.36
IVLP	74.19±2.37	86.13±3.09	+11.94±3.57
KgCoOp	62.66±0.41	69.75±1.17	+7.09±0.89
ProGrad	75.98±1.94	76.16±1.80	+0.18±0.19
MaPLe	80.80±0.94	82.17±1.90	+1.37±1.12
PromptSRC	80.02±2.66	79.75±2.54	-0.27±0.26
LoCoOp	68.62±5.75	69.66±5.80	+1.04±0.55

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	83.64±0.49	85.37±0.51	+1.73±0.95
CoCoOp	82.76±1.14	85.17±0.81	+2.41±0.56
IVLP	82.48±2.21	86.65±0.37	+4.16±1.93
KgCoOp	82.08±0.13	85.01±0.62	+2.92±0.51
ProGrad	82.06±0.46	84.03±0.63	+1.97±0.22
MaPLe	83.00±0.94	84.81±1.10	+1.81±0.27
PromptSRC	84.17±0.61	86.03±0.67	+1.85±0.23
LoCoOp	78.50±1.08	84.35±1.15	+5.85±2.01

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	90.39±0.84	90.60±0.76	+0.20±0.26
CoCoOp	93.84±0.18	93.95±0.38	+0.10±0.40
IVLP	93.01±1.30	93.10±1.66	+0.09±0.45
KgCoOp	93.46±0.12	93.86±0.12	+0.40±0.03
ProGrad	92.94±0.40	93.30±0.28	+0.36±0.16
MaPLe	94.24±0.58	94.26±0.79	+0.02±0.43
PromptSRC	95.13±0.09	94.88±0.35	-0.24±0.29
LoCoOp	92.34±0.70	91.13±0.46	-1.21±0.59

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	77.81±0.91	78.93±1.06	+1.12±1.78
CoCoOp	76.76±1.06	79.06±1.14	+2.31±0.94
IVLP	85.87±0.90	87.68±2.39	+1.81±1.55
KgCoOp	78.28±0.43	81.07±0.32	+2.79±0.51
ProGrad	78.21±0.48	81.40±0.68	+3.19±0.47
MaPLe	85.48±0.77	88.50±2.08	+3.01±1.34
PromptSRC	88.83±0.25	90.21±0.13	+1.38±0.38
LoCoOp	76.19±1.57	76.73±1.77	+0.54±1.17

Table 8: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M with 8-shots.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	81.60±11.10	82.84±11.08	+1.24±1.01
CoCoOp	81.48±12.41	83.33±11.93	+1.85±1.55
IVLP	82.20±11.80	85.11±10.87	+2.91±3.80
KgCoOp	80.97±12.22	83.38±11.86	+2.40±2.18
ProGrad	80.39±12.37	82.96±12.03	+2.58±2.37
MaPLe	82.67±12.39	85.32±12.13	+2.64±3.29
PromptSRC	85.44±9.45	87.36±8.88	+1.92±1.70
LoCoOp	79.25±10.77	82.96±10.27	+3.71±4.19

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.40±0.29	95.13±0.43	+1.73±0.70
CoCoOp	94.87±0.55	95.74±0.18	+0.87±0.42
IVLP	94.22±1.03	94.18±0.62	-0.04±1.53
KgCoOp	94.29±0.04	94.04±0.38	-0.25±0.36
ProGrad	93.82±0.61	94.99±0.22	+1.17±0.60
MaPLe	93.76±1.36	94.51±1.07	+0.76±0.40
PromptSRC	94.64±0.19	95.54±0.09	+0.90±0.13
LoCoOp	92.60±0.52	94.22±0.53	+1.61±0.44

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	88.88±0.91	90.54±1.21	+1.66±0.85
CoCoOp	85.61±1.96	88.06±2.40	+2.46±1.43
IVLP	88.03±1.47	92.33±1.21	+4.31±0.55
KgCoOp	83.63±0.18	89.80±0.18	+6.17±0.03
ProGrad	83.99±1.42	89.25±1.18	+5.26±1.51
MaPLe	87.09±0.76	92.06±0.89	+4.97±1.59
PromptSRC	85.04±0.34	90.68±0.54	+5.64±0.49
LoCoOp	77.58±2.53	89.72±1.09	+12.14±2.80

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	86.69±1.96	89.06±1.86	+2.37±0.13
CoCoOp	90.96±0.62	93.07±0.16	+2.11±0.61
IVLP	90.40±0.59	92.21±0.56	+1.81±0.86
KgCoOp	90.21±0.16	92.49±0.33	+2.28±0.28
ProGrad	87.01±1.27	89.19±1.74	+2.18±0.47
MaPLe	89.00±0.59	92.25±1.20	+3.25±0.77
PromptSRC	91.60±0.19	93.92±0.35	+2.32±0.21
LoCoOp	85.70±2.63	89.51±1.11	+3.80±2.38

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	92.30±0.62	93.03±1.10	+0.73±0.56
CoCoOp	92.64±1.14	93.27±1.34	+0.63±0.56
IVLP	89.63±1.84	93.38±1.22	+3.75±2.47
KgCoOp	92.90±0.11	93.35±0.14	+0.46±0.06
ProGrad	92.93±0.90	93.25±0.61	+0.32±0.41
MaPLe	92.40±0.68	93.10±1.00	+0.70±0.32
PromptSRC	92.94±0.24	94.42±0.85	+1.49±0.68
LoCoOp	88.81±0.48	92.42±1.02	+3.61±1.23

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	92.28±0.46	93.00±0.50	+0.72±0.07
CoCoOp	88.33±0.08	89.32±0.22	+0.99±0.30
IVLP	88.07±4.61	88.71±4.29	+0.63±0.32
KgCoOp	88.36±0.20	92.26±0.37	+3.90±0.37
ProGrad	90.46±0.19	92.43±0.46	+1.98±0.50
MaPLe	87.04±0.98	88.53±0.79	+1.49±0.72
PromptSRC	93.37±0.38	94.81±0.27	+1.44±0.12
LoCoOp	88.52±2.42	90.72±1.72	+2.20±0.71

(g) Food101

	MaxLogit	MLS-M	△
CoOp	87.71±1.08	88.22±1.11	+0.51±0.18
CoCoOp	91.19±0.48	91.74±0.62	+0.55±0.24
IVLP	89.41±1.46	92.28±0.29	+2.87±1.44
KgCoOp	89.85±0.10	92.00±0.29	+2.15±0.32
ProGrad	89.28±0.37	91.03±0.45	+1.75±0.36
MaPLe	90.50±0.81	92.68±0.24	+2.17±0.94
PromptSRC	91.36±0.30	92.47±0.37	+1.10±0.36
LoCoOp	86.12±1.73	89.93±1.12	+3.80±0.75

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	55.53±5.96	56.84±5.79	+1.30±1.43
CoCoOp	53.41±1.06	55.94±2.55	+2.54±2.25
IVLP	59.95±5.12	65.22±4.95	+5.26±10.02
KgCoOp	57.14±1.06	57.48±0.42	+0.33±1.41
ProGrad	55.17±1.98	55.92±6.71	+0.75±5.07
MaPLe	48.85±8.17	53.45±14.82	+4.60±9.94
PromptSRC	63.32±0.71	68.18±1.55	+4.86±1.54
LoCoOp	56.10±7.22	62.22±9.93	+6.11±3.34

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	76.77±1.16	77.77±0.76	+1.00±0.47
CoCoOp	76.74±0.43	79.67±1.02	+2.93±1.39
IVLP	78.34±0.12	80.45±0.88	+2.12±0.81
KgCoOp	76.89±0.17	78.52±0.31	+1.63±0.35
ProGrad	76.17±0.28	79.14±0.62	+2.97±0.77
MaPLe	79.09±1.04	80.51±0.98	+1.42±0.17
PromptSRC	79.25±0.23	81.65±0.44	+2.40±0.31
LoCoOp	75.00±1.06	78.96±0.98	+3.96±1.14

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	71.45±0.53	72.10±1.04	+0.64±0.55
CoCoOp	65.53±0.61	68.34±0.42	+2.81±0.33
IVLP	67.23±0.52	69.55±0.50	+2.33±0.07
KgCoOp	63.45±0.50	67.91±1.17	+4.46±0.88
ProGrad	62.05±1.25	67.22±1.00	+5.17±0.37
MaPLe	66.90±1.49	70.91±1.83	+4.01±0.52
PromptSRC	70.78±1.16	71.82±1.05	+1.05±0.10
LoCoOp	68.50±0.52	70.79±0.33	+2.29±0.60

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	68.76±3.30	69.45±3.03	+0.69±0.28
CoCoOp	67.22±4.14	67.82±4.22	+0.60±0.40
IVLP	62.81±11.25	70.59±14.90	+7.78±3.79
KgCoOp	62.47±0.59	66.72±2.87	+4.26±3.46
ProGrad	64.62±2.32	67.46±0.83	+2.84±2.26
MaPLe	79.49±3.93	83.54±6.27	+4.05±2.44
PromptSRC	81.33±5.10	81.35±5.33	+0.02±0.25
LoCoOp	68.44±1.29	71.60±5.16	+3.16±3.89

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	83.55±0.94	85.42±0.73	+1.87±0.73
CoCoOp	82.64±1.02	85.35±0.48	+2.71±0.57
IVLP	81.35±1.72	86.23±1.34	+4.88±1.19
KgCoOp	81.75±0.34	84.93±0.41	+3.19±0.50
ProGrad	80.40±2.13	85.18±1.87	+4.78±0.32
MaPLe	81.06±0.69	84.41±0.65	+3.35±1.24
PromptSRC	84.54±0.84	86.81±0.95	+2.27±0.17
LoCoOp	75.23±2.13	83.62±0.92	+8.39±1.65

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	88.11±2.48	88.12±2.73	+0.01±0.26
CoCoOp	92.96±0.58	93.38±0.92	+0.42±0.43
IVLP	92.27±1.15	93.34±0.78	+1.07±0.43
KgCoOp	93.33±0.01	93.67±0.16	+0.34±0.14
ProGrad	92.31±0.54	92.71±0.70	+0.40±0.28
MaPLe	93.54±0.44	93.97±0.47	+0.43±0.20
PromptSRC	94.92±0.47	94.75±0.45	-0.16±0.31
LoCoOp	91.96±1.27	88.62±3.55	-3.34±3.08

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	75.41±0.95	78.30±0.46	+2.89±0.57
CoCoOp	77.14±1.36	81.60±0.63	+4.45±1.23
IVLP	86.85±0.73	87.94±0.63	+1.09±0.45
KgCoOp	78.39±0.44	80.69±0.94	+2.30±1.23
ProGrad	76.86±0.64	80.76±1.26	+3.90±0.76
MaPLe	86.01±0.50	89.21±0.23	+3.19±0.31
PromptSRC	87.67±0.69	89.33±0.83	+1.66±0.18
LoCoOp	75.70±0.75	76.16±2.61	+0.46±1.86

Table 9: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M with 4-shots.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	81.06±11.11	82.10±11.35	+1.04±1.56
CoCoOp	81.45±12.10	83.09±12.43	+1.63±2.06
IVLP	81.14±12.63	84.08±12.27	+2.94±2.39
KgCoOp	80.69±12.01	83.03±12.20	+2.34±2.02
ProGrad	80.58±11.41	82.50±11.50	+1.92±1.76
MaPLe	80.76±11.98	83.53±11.47	+2.78±3.03
PromptSRC	84.27±9.89	86.10±9.92	+1.83±1.54
LoCoOp	78.52±11.12	81.57±11.62	+3.06±4.44

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.83±0.51	95.14±0.22	+1.31±0.70
CoCoOp	95.32±0.02	95.73±0.05	+0.41±0.04
IVLP	95.03±0.13	95.45±0.25	+0.42±0.14
KgCoOp	94.20±0.08	94.29±0.08	+0.10±0.03
ProGrad	93.84±0.40	94.63±0.31	+0.79±0.19
MaPLe	93.94±1.47	93.77±0.69	-0.16±0.86
PromptSRC	94.57±0.13	95.40±0.29	+0.82±0.24
LoCoOp	93.24±0.26	94.86±0.15	+1.62±0.35

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	90.33±1.75	91.76±2.61	+1.42±1.39
CoCoOp	86.87±1.08	89.49±0.16	+2.62±1.15
IVLP	84.15±0.90	91.65±0.68	+7.51±1.56
KgCoOp	83.66±0.10	90.14±0.62	+6.48±0.58
ProGrad	84.42±1.03	88.66±1.52	+4.24±1.81
MaPLe	85.04±3.59	91.26±1.94	+6.22±4.19
PromptSRC	85.28±0.44	90.60±0.34	+5.32±0.27
LoCoOp	76.00±1.81	87.91±1.29	+11.91±0.60

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	87.50±1.91	89.59±1.72	+2.09±0.20
CoCoOp	89.60±0.93	92.90±0.68	+3.30±1.49
IVLP	89.53±1.52	93.28±0.55	+3.75±1.13
KgCoOp	90.07±0.08	93.18±0.28	+3.11±0.32
ProGrad	87.64±1.19	89.51±1.52	+1.87±0.33
MaPLe	86.47±2.51	91.28±1.59	+4.81±1.47
PromptSRC	90.75±1.02	93.93±1.02	+3.18±0.32
LoCoOp	86.18±1.10	89.77±1.27	+3.59±1.05

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	91.17±1.22	91.43±1.03	+0.26±0.36
CoCoOp	93.30±0.68	93.57±0.56	+0.27±0.23
IVLP	92.00±1.03	92.85±1.03	+0.85±0.01
KgCoOp	92.81±0.07	93.38±0.17	+0.57±0.14
ProGrad	92.38±1.00	92.86±0.75	+0.48±0.54
MaPLe	91.86±1.10	92.96±0.71	+1.10±1.19
PromptSRC	92.77±0.19	93.82±0.28	+1.05±0.39
LoCoOp	87.34±1.74	91.59±0.34	+4.25±2.02

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	91.86±1.63	93.13±1.28	+1.27±0.97
CoCoOp	87.75±1.53	89.30±0.74	+1.55±1.04
IVLP	86.85±1.79	88.54±1.03	+1.69±0.91
KgCoOp	86.91±0.26	90.44±0.01	+3.53±0.27
ProGrad	88.87±1.85	91.37±1.52	+2.50±0.87
MaPLe	85.57±2.40	87.96±1.68	+2.38±1.30
PromptSRC	91.72±0.23	92.92±0.73	+1.19±0.50
LoCoOp	87.15±0.57	89.05±0.72	+1.90±0.65

(g) Food101

	MaxLogit	MLS-M	△
CoOp	86.74±1.38	87.79±1.03	+1.05±0.40
CoCoOp	90.61±0.90	91.88±0.41	+1.27±0.50
IVLP	89.44±0.59	92.16±0.73	+2.72±0.63
KgCoOp	89.57±0.21	92.25±0.17	+2.68±0.27
ProGrad	87.78±0.58	90.72±0.16	+2.94±0.50
MaPLe	88.95±1.02	92.03±0.69	+3.08±1.55
PromptSRC	90.74±0.15	92.06±0.35	+1.32±0.21
LoCoOp	84.36±2.01	90.44±1.29	+6.08±1.32

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	56.85±1.73	57.84±2.90	+1.00±2.88
CoCoOp	54.94±2.06	53.40±1.26	-1.54±2.98
IVLP	56.56±7.89	60.45±11.15	+3.88±3.74
KgCoOp	57.62±1.51	56.08±1.55	-1.54±0.51
ProGrad	54.14±2.94	54.24±3.66	+0.10±0.96
MaPLe	51.02±0.95	57.51±4.12	+6.49±5.03
PromptSRC	61.21±2.47	62.69±3.58	+1.48±2.30
LoCoOp	52.51±3.97	54.96±8.63	+2.45±9.18

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	76.73±0.94	77.27±0.56	+0.54±0.38
CoCoOp	76.24±0.84	78.52±0.33	+2.28±0.99
IVLP	77.36±1.27	79.48±0.67	+2.11±0.90
KgCoOp	76.60±0.44	77.76±0.54	+1.16±0.10
ProGrad	75.84±1.03	77.43±1.27	+1.58±0.86
MaPLe	78.33±0.74	79.93±0.40	+1.61±0.95
PromptSRC	78.59±0.36	80.44±0.29	+1.86±0.61
LoCoOp	73.59±1.03	78.12±0.62	+4.53±0.64

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	68.35±0.34	69.74±0.64	+1.39±0.70
CoCoOp	64.22±1.22	66.23±0.16	+2.01±1.06
IVLP	65.12±0.45	67.49±0.99	+2.37±0.68
KgCoOp	63.09±0.23	66.45±0.68	+3.36±0.46
ProGrad	63.40±1.51	67.36±1.72	+3.96±0.77
MaPLe	64.63±0.99	66.06±0.55	+1.43±1.03
PromptSRC	68.39±1.39	70.29±1.02	+1.90±0.69
LoCoOp	67.92±1.34	69.50±0.85	+1.58±0.58

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	67.51±2.56	66.19±2.93	-1.32±1.80
CoCoOp	68.85±2.31	69.49±2.06	+0.64±0.96
IVLP	60.33±7.70	65.49±9.60	+5.16±2.58
KgCoOp	62.92±0.27	66.84±0.41	+3.92±0.20
ProGrad	74.47±1.09	74.59±2.97	+0.12±1.89
MaPLe	69.89±4.69	69.99±4.37	+0.10±0.58
PromptSRC	77.62±0.65	78.29±1.08	+0.66±0.45
LoCoOp	70.17±5.93	69.65±5.67	-0.52±0.63

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	81.09±1.53	82.52±1.91	+1.43±0.95
CoCoOp	81.34±1.17	84.59±1.22	+3.25±1.91
IVLP	80.78±1.59	84.87±1.46	+4.10±0.84
KgCoOp	80.78±0.22	83.99±0.30	+3.22±0.27
ProGrad	81.07±1.02	83.00±0.40	+1.93±1.29
MaPLe	81.35±0.32	86.21±1.05	+4.85±1.21
PromptSRC	84.07±0.51	86.77±0.99	+2.70±1.15
LoCoOp	78.33±0.78	83.19±1.89	+4.86±1.34

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	87.12±2.56	87.29±2.73	+0.17±0.24
CoCoOp	92.67±0.76	93.13±0.69	+0.45±0.17
IVLP	91.92±1.84	92.81±1.31	+0.89±0.54
KgCoOp	92.78±0.29	93.39±0.39	+0.61±0.11
ProGrad	89.36±0.43	90.10±1.12	+0.75±0.76
MaPLe	87.53±6.17	88.19±4.69	+0.66±1.82
PromptSRC	92.74±1.69	92.86±1.83	+0.13±0.16
LoCoOp	90.93±2.17	87.70±2.18	-3.23±1.33

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	74.64±1.74	77.60±2.69	+2.96±1.48
CoCoOp	77.19±1.06	81.91±1.30	+4.72±1.41
IVLP	85.72±0.61	88.55±0.76	+2.83±0.29
KgCoOp	77.99±0.45	81.21±0.38	+3.22±0.28
ProGrad	74.28±0.12	77.97±1.46	+3.69±1.52
MaPLe	85.28±0.74	88.79±0.58	+3.51±0.33
PromptSRC	87.04±0.65	89.17±1.09	+2.13±0.94
LoCoOp	73.01±1.23	73.71±2.24	+0.71±1.11

Table 10: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M with 2-shots.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	80.05±11.11	81.19±11.05	+1.14±1.59
CoCoOp	80.76±12.16	82.12±12.60	+1.35±1.70
IVLP	80.12±11.76	82.87±10.97	+2.75±2.35
KgCoOp	80.83±11.54	83.13±11.49	+2.30±2.01
ProGrad	79.43±11.87	82.07±11.48	+2.64±2.91
MaPLe	80.49±11.63	83.42±11.27	+2.92±2.35
PromptSRC	83.18±10.43	84.99±10.53	+1.82±1.58
LoCoOp	76.28±12.95	80.62±11.92	+4.34±4.81

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	94.19±0.39	94.39±0.14	+0.20±0.25
CoCoOp	94.31±0.34	94.52±0.27	+0.21±0.08
IVLP	94.86±0.67	94.65±0.24	-0.21±0.50
KgCoOp	94.15±0.17	94.32±0.35	+0.17±0.18
ProGrad	93.22±0.29	94.76±0.25	+1.54±0.26
MaPLe	94.50±0.71	94.45±0.32	-0.05±0.55
PromptSRC	94.48±0.20	94.95±0.19	+0.48±0.20
LoCoOp	92.89±0.56	94.31±0.07	+1.42±0.54

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	88.02±1.73	89.90±1.19	+1.88±1.20
CoCoOp	85.33±0.73	88.48±0.99	+3.15±0.28
IVLP	84.50±1.75	88.55±2.19	+4.04±2.52
KgCoOp	83.72±0.41	89.78±0.36	+6.06±0.06
ProGrad	83.67±2.53	90.32±2.56	+6.64±2.43
MaPLe	85.89±1.69	91.87±0.61	+5.98±1.71
PromptSRC	85.33±0.27	90.50±1.32	+5.17±1.50
LoCoOp	72.52±4.07	86.38±1.65	+13.85±3.56

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	86.15±3.09	89.19±3.57	+3.05±0.49
CoCoOp	87.40±1.25	91.23±0.94	+3.83±0.41
IVLP	84.75±1.68	89.58±1.17	+4.83±1.67
KgCoOp	89.65±0.42	92.68±0.53	+3.04±0.22
ProGrad	88.70±0.71	89.82±0.46	+1.12±1.11
MaPLe	86.04±1.41	89.19±2.52	+3.15±2.74
PromptSRC	89.91±0.38	92.48±0.71	+2.57±0.42
LoCoOp	82.02±2.93	89.14±1.05	+7.12±2.67

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	90.78±0.94	91.06±1.11	+0.28±0.71
CoCoOp	92.91±0.91	92.77±1.00	-0.14±0.14
IVLP	90.53±1.63	92.85±0.46	+2.32±1.23
KgCoOp	92.55±0.05	93.08±0.39	+0.53±0.44
ProGrad	89.29±1.35	91.70±1.04	+2.41±0.61
MaPLe	90.47±1.41	93.26±0.38	+2.78±1.69
PromptSRC	92.49±0.37	93.75±0.45	+1.26±0.59
LoCoOp	87.43±2.72	91.69±1.86	+4.26±0.96

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	90.03±0.97	91.44±0.84	+1.42±0.29
CoCoOp	87.50±0.44	89.01±0.96	+1.51±1.01
IVLP	82.42±0.56	85.94±0.68	+3.52±0.21
KgCoOp	86.51±0.58	90.60±0.44	+4.08±0.17
ProGrad	88.22±1.50	91.20±0.53	+2.98±1.59
MaPLe	84.55±0.54	87.98±0.22	+3.43±0.46
PromptSRC	89.06±0.30	90.76±0.41	+1.70±0.24
LoCoOp	86.04±1.21	87.79±0.65	+1.75±0.64

(g) Food101

	MaxLogit	MLS-M	△
CoOp	84.32±0.55	85.60±1.02	+1.28±0.63
CoCoOp	90.19±1.03	91.17±1.08	+0.98±0.34
IVLP	90.08±0.26	91.09±0.45	+1.01±0.66
KgCoOp	89.77±0.31	91.94±0.33	+2.17±0.11
ProGrad	87.31±2.18	90.08±0.53	+2.77±1.69
MaPLe	86.87±0.33	91.34±0.36	+4.48±0.64
PromptSRC	90.62±0.54	91.64±0.59	+1.02±0.22
LoCoOp	84.15±0.34	89.87±0.39	+5.71±0.72

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	55.74±1.10	57.73±2.73	+1.99±3.42
CoCoOp	52.84±1.55	51.58±2.72	-1.26±2.25
IVLP	56.78±3.46	61.06±2.52	+4.28±1.69
KgCoOp	60.16±2.21	59.39±2.44	-0.77±0.44
ProGrad	52.61±1.01	56.25±5.57	+3.64±6.10
MaPLe	55.94±1.28	60.17±3.89	+4.22±3.82
PromptSRC	60.38±3.63	62.18±4.82	+1.80±2.49
LoCoOp	46.36±1.48	55.36±6.99	+9.00±5.61

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	74.08±0.32	75.16±0.62	+1.08±0.55
CoCoOp	75.78±0.47	77.19±0.08	+1.41±0.46
IVLP	76.86±0.69	78.73±0.81	+1.87±0.71
KgCoOp	76.06±0.10	77.26±0.53	+1.20±0.61
ProGrad	75.05±0.82	76.26±0.48	+1.22±0.41
MaPLe	76.87±0.15	78.95±0.71	+2.08±0.56
PromptSRC	77.91±0.20	80.19±0.31	+2.28±0.27
LoCoOp	72.91±0.71	77.06±0.87	+4.15±0.18

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	66.73±1.35	67.52±1.39	+0.79±0.53
CoCoOp	65.31±0.34	66.43±0.86	+1.12±0.79
IVLP	63.97±0.99	66.74±0.74	+2.77±1.15
KgCoOp	63.98±0.51	67.32±1.14	+3.34±1.20
ProGrad	62.75±0.94	66.94±0.43	+4.19±0.67
MaPLe	63.76±2.01	66.17±1.20	+2.41±1.25
PromptSRC	67.63±0.24	68.20±0.30	+0.57±0.20
LoCoOp	63.60±0.41	65.62±1.23	+2.02±0.82

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	69.45±3.44	68.88±3.68	-0.58±0.38
CoCoOp	68.72±4.97	69.27±5.04	+0.55±0.89
IVLP	62.65±1.90	66.29±3.59	+3.63±4.77
KgCoOp	63.15±0.24	67.37±1.54	+4.22±1.70
ProGrad	68.21±5.43	69.67±3.82	+1.46±2.18
MaPLe	65.05±5.56	68.44±6.25	+3.38±1.21
PromptSRC	71.63±0.73	72.92±0.91	+1.29±1.61
LoCoOp	63.36±2.81	66.60±4.99	+3.24±2.39

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	82.56±1.23	83.75±0.47	+1.19±0.77
CoCoOp	79.81±0.89	82.60±0.71	+2.80±0.38
IVLP	78.07±0.27	82.26±0.57	+4.18±0.40
KgCoOp	80.67±0.15	82.96±1.30	+2.30±1.19
ProGrad	81.13±0.67	84.09±0.61	+2.96±0.21
MaPLe	80.17±0.71	83.26±1.24	+3.09±0.54
PromptSRC	82.14±0.69	84.13±0.19	+1.99±0.65
LoCoOp	74.83±3.00	82.08±2.14	+7.25±0.87

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	86.90±0.17	86.61±0.59	-0.29±0.45
CoCoOp	93.11±0.38	93.36±0.41	+0.24±0.08
IVLP	92.90±0.41	92.94±0.13	+0.04±0.53
KgCoOp	93.17±0.07	93.54±0.06	+0.37±0.05
ProGrad	88.24±0.35	87.03±1.63	-1.21±1.41
MaPLe	93.02±0.44	92.72±0.42	-0.30±0.83
PromptSRC	93.88±0.11	94.33±0.28	+0.45±0.19
LoCoOp	92.70±0.80	88.96±1.85	-3.73±2.64

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	71.71±1.18	74.21±0.75	+2.50±1.84
CoCoOp	76.71±0.95	79.91±2.15	+3.20±1.41
IVLP	83.15±1.72	86.63±1.02	+3.48±0.71
KgCoOp	77.28±0.43	80.48±0.31	+3.20±0.50
ProGrad	74.20±1.65	78.77±1.67	+4.56±2.70
MaPLe	83.27±1.28	86.61±0.90	+3.34±2.09
PromptSRC	85.83±0.39	88.86±0.45	+3.03±0.19
LoCoOp	72.81±1.34	73.16±1.43	+0.36±0.82

Table 11: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MaxLogit score and MLS-M with 1-shot.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	△
CoOp	77.78±11.44	78.69±11.97	+0.92±2.15
CoCoOp	79.70±13.00	81.26±12.66	+1.56±2.54
IVLP	80.00±10.91	82.27±11.08	+2.26±3.19
KgCoOp	80.19±12.35	81.98±12.90	+1.79±2.74
ProGrad	78.26±12.72	80.32±12.20	+2.06±2.87
MaPLe	78.86±13.76	81.13±13.97	+2.27±4.69
PromptSRC	81.56±12.17	82.81±13.06	+1.25±2.45
LoCoOp	76.37±12.38	79.56±11.73	+3.19±5.99

(b) ImageNet.

	MaxLogit	MLS-M	△
CoOp	93.65±0.21	93.26±0.76	-0.39±0.96
CoCoOp	94.85±0.39	94.57±0.57	-0.28±0.92
IVLP	94.18±0.49	94.64±0.57	+0.45±0.89
KgCoOp	94.07±0.12	94.24±0.29	+0.16±0.23
ProGrad	93.09±0.63	93.99±0.40	+0.90±0.24
MaPLe	94.12±0.62	94.32±0.40	+0.19±0.44
PromptSRC	94.23±0.49	95.10±0.29	+0.87±0.22
LoCoOp	93.09±0.52	94.46±0.28	+1.37±0.47

(c) Caltech101.

	MaxLogit	MLS-M	△
CoOp	84.37±2.48	87.03±1.50	+2.66±1.47
CoCoOp	84.06±0.95	89.11±1.24	+5.05±1.93
IVLP	83.13±2.65	86.92±2.13	+3.79±2.12
KgCoOp	83.14±0.02	90.23±0.24	+7.09±0.25
ProGrad	80.48±0.51	86.38±3.52	+5.90±3.09
MaPLe	83.66±2.91	89.39±1.00	+5.74±3.28
PromptSRC	84.36±0.32	90.45±0.51	+6.09±0.81
LoCoOp	75.46±2.62	86.03±2.08	+10.57±0.86

(d) OxfordPets.

	MaxLogit	MLS-M	△
CoOp	85.54±1.64	89.17±2.00	+3.63±1.51
CoCoOp	89.03±1.15	90.64±0.09	+1.61±1.10
IVLP	88.39±1.71	90.89±0.15	+2.50±1.58
KgCoOp	89.51±0.24	92.67±1.14	+3.16±0.93
ProGrad	88.35±2.29	90.89±1.62	+2.54±0.88
MaPLe	85.46±4.88	88.10±2.63	+2.64±2.25
PromptSRC	90.11±0.68	92.23±0.50	+2.12±1.16
LoCoOp	84.09±2.60	88.34±1.97	+4.25±3.66

(e) StanfordCars.

	MaxLogit	MLS-M	△
CoOp	89.04±1.69	88.99±1.70	-0.05±0.54
CoCoOp	91.98±0.63	92.54±0.46	+0.56±0.75
IVLP	89.48±0.68	92.62±1.57	+3.14±0.89
KgCoOp	92.62±0.12	93.08±0.21	+0.46±0.13
ProGrad	89.73±2.12	91.28±0.91	+1.54±1.24
MaPLe	90.75±0.79	91.73±0.13	+0.98±0.69
PromptSRC	92.38±0.60	93.83±0.44	+1.45±0.27
LoCoOp	88.53±2.24	91.90±0.25	+3.37±2.39

(f) Flowers102.

	MaxLogit	MLS-M	△
CoOp	85.67±1.94	87.73±2.37	+2.06±0.69
CoCoOp	86.67±0.55	88.32±0.52	+1.65±0.14
IVLP	83.04±2.91	86.47±1.49	+3.42±1.61
KgCoOp	86.21±0.08	89.22±0.80	+3.01±0.84
ProGrad	88.11±0.73	89.02±0.97	+0.91±0.44
MaPLe	83.34±1.97	85.81±2.41	+2.46±0.47
PromptSRC	86.95±0.70	88.89±1.25	+1.94±0.55
LoCoOp	82.06±1.53	85.38±2.01	+3.32±0.84

(g) Food101

	MaxLogit	MLS-M	△
CoOp	86.05±1.60	87.82±2.12	+1.77±0.54
CoCoOp	90.07±0.75	90.91±0.37	+0.84±0.73
IVLP	89.15±1.82	91.01±0.78	+1.86±1.17
KgCoOp	89.88±0.14	91.58±0.47	+1.70±0.56
ProGrad	88.27±1.64	90.75±1.42	+2.48±1.10
MaPLe	88.40±0.68	90.83±0.75	+2.43±0.59
PromptSRC	90.59±0.12	91.76±0.16	+1.17±0.08
LoCoOp	84.22±3.05	88.87±1.10	+4.66±2.67

(h) FGVCAircraft.

	MaxLogit	MLS-M	△
CoOp	56.46±1.55	56.13±4.61	-0.33±3.69
CoCoOp	51.86±2.42	57.14±5.02	+5.29±3.96
IVLP	59.36±1.26	62.40±4.31	+3.04±3.42
KgCoOp	57.11±1.22	57.23±3.26	+0.12±2.04
ProGrad	51.97±1.64	57.80±3.36	+5.83±3.69
MaPLe	48.73±7.71	51.97±5.93	+3.24±13.20
PromptSRC	53.69±2.55	52.67±1.32	-1.02±3.51
LoCoOp	47.61±4.93	58.87±6.44	+11.26±9.05

(i) SUN397.

	MaxLogit	MLS-M	△
CoOp	73.03±1.27	73.99±2.01	+0.95±0.77
CoCoOp	75.58±0.29	76.79±0.55	+1.21±0.26
IVLP	75.31±0.70	78.63±0.77	+3.32±1.46
KgCoOp	75.35±0.08	77.19±0.14	+1.84±0.22
ProGrad	73.48±0.56	76.04±0.67	+2.57±0.20
MaPLe	75.59±1.31	78.56±0.92	+2.97±0.44
PromptSRC	77.19±0.99	79.17±0.71	+1.98±0.32
LoCoOp	72.56±1.04	75.99±0.86	+3.43±0.26

(j) DTD.

	MaxLogit	MLS-M	△
CoOp	63.93±1.09	64.32±0.70	+0.40±0.79
CoCoOp	64.23±0.39	65.22±1.19	+0.99±0.87
IVLP	61.56±1.52	64.71±1.91	+3.16±0.85
KgCoOp	62.95±1.40	67.80±0.89	+4.85±0.51
ProGrad	62.44±1.61	64.92±1.94	+2.48±0.50
MaPLe	61.56±0.70	64.89±0.47	+3.33±0.97
PromptSRC	66.69±1.81	67.99±2.73	+1.30±0.98
LoCoOp	65.00±1.05	66.74±0.67	+1.74±0.62

(k) EuroSAT.

	MaxLogit	MLS-M	△
CoOp	62.12±4.42	61.19±4.11	-0.93±0.61
CoCoOp	60.92±3.46	58.94±3.27	-1.98±1.72
IVLP	67.81±4.12	64.61±5.13	-3.21±5.92
KgCoOp	60.86±1.13	57.60±2.80	-3.26±1.67
ProGrad	61.51±1.14	60.65±3.08	-0.86±4.18
MaPLe	60.69±7.74	57.24±10.24	-3.45±4.26
PromptSRC	65.51±4.26	62.56±2.38	-2.95±1.87
LoCoOp	63.02±4.28	61.75±6.38	-1.27±2.61

(l) UCF101.

	MaxLogit	MLS-M	△
CoOp	79.98±1.30	81.17±0.71	+1.19±0.69
CoCoOp	80.07±1.01	82.40±0.35	+2.32±1.18
IVLP	78.63±1.72	82.75±0.78	+4.12±2.11
KgCoOp	81.02±0.88	83.41±1.66	+2.39±0.84
ProGrad	81.39±1.95	82.26±1.92	+0.87±0.13
MaPLe	78.44±0.58	82.58±0.49	+4.14±0.29
PromptSRC	81.02±0.85	83.40±0.99	+2.38±0.14
LoCoOp	74.53±1.82	79.48±2.15	+4.95±0.33

(m) CIFAR10.

	MaxLogit	MLS-M	△
CoOp	83.06±1.34	81.77±0.90	-1.29±1.60
CoCoOp	90.85±2.48	90.01±2.16	-0.84±0.59
IVLP	87.01±6.32	86.81±3.85	-0.20±3.51
KgCoOp	93.01±0.38	91.78±1.72	-1.23±1.61
ProGrad	87.62±4.43	86.07±4.47	-1.55±2.03
MaPLe	92.41±1.38	92.43±2.35	+0.02±1.21
PromptSRC	93.62±0.39	92.59±2.13	-1.02±1.78
LoCoOp	89.29±1.17	82.42±10.55	-6.87±9.46

(n) CIFAR100.

	MaxLogit	MLS-M	△
CoOp	68.18±1.23	70.43±3.00	+2.24±2.90
CoCoOp	76.01±1.44	79.86±1.91	+3.85±0.47
IVLP	83.00±0.54	87.04±0.30	+4.04±0.72
KgCoOp	76.77±0.66	79.69±1.55	+2.92±0.91
ProGrad	70.90±2.52	74.08±1.77	+3.18±1.24
MaPLe	82.03±2.21	86.88±0.88	+4.85±2.34
PromptSRC	83.99±0.11	85.91±0.89	+1.92±0.82
LoCoOp	73.40±1.57	74.07±1.22	+0.67±0.54

A.3.2 Energy Score

We provide the same results of Table 5 to Table 11 using Energy score in Table 12 to Table 18.

Table 12: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	80.44	81.71	+1.27
CoCoOp	80.53	82.74	+2.21
IVLP	80.49	84.40	+3.91
KgCoOp	80.14	83.23	+3.09
ProGrad	78.79	81.93	+3.14
MaPLe	80.39	83.99	+3.60
PromptSRC	83.48	85.88	+2.40
LoCoOp	75.94	81.25	+5.31

(b) ImageNet.

	Energy	MLS-E	△
CoOp	93.73	94.83	+1.10
CoCoOp	94.76	95.30	+0.54
IVLP	94.50	94.94	+0.44
KgCoOp	94.05	94.41	+0.36
ProGrad	93.46	94.79	+1.33
MaPLe	94.07	94.58	+0.51
PromptSRC	94.46	95.56	+1.10
LoCoOp	92.25	94.53	+2.28

(c) Caltech101.

	Energy	MLS-E	△
CoOp	87.31	89.48	+2.17
CoCoOp	84.19	88.04	+3.85
IVLP	84.08	89.85	+5.77
KgCoOp	80.39	88.79	+8.39
ProGrad	80.60	87.60	+7.00
MaPLe	84.52	90.95	+6.43
PromptSRC	82.59	89.70	+7.11
LoCoOp	71.45	86.09	+14.65

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	85.91	88.62	+2.71
CoCoOp	88.93	92.01	+3.08
IVLP	88.27	91.67	+3.40
KgCoOp	89.25	92.28	+3.03
ProGrad	87.54	89.51	+1.97
MaPLe	86.66	90.64	+3.98
PromptSRC	90.38	93.29	+2.90
LoCoOp	82.90	88.44	+5.54

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	91.37	91.66	+0.29
CoCoOp	92.56	93.17	+0.62
IVLP	90.45	93.24	+2.79
KgCoOp	92.85	93.43	+0.59
ProGrad	91.34	92.55	+1.21
MaPLe	91.53	93.14	+1.62
PromptSRC	92.97	94.47	+1.51
LoCoOp	87.93	92.16	+4.23

(f) Flowers102.

	Energy	MLS-E	△
CoOp	90.12	91.51	+1.40
CoCoOp	86.76	88.89	+2.13
IVLP	84.51	87.44	+2.93
KgCoOp	85.78	90.51	+4.74
ProGrad	87.51	90.37	+2.86
MaPLe	84.45	87.40	+2.95
PromptSRC	89.92	91.86	+1.93
LoCoOp	83.73	87.14	+3.41

(g) Food101.

	Energy	MLS-E	△
CoOp	86.32	87.70	+1.38
CoCoOp	90.09	91.44	+1.35
IVLP	89.22	91.73	+2.51
KgCoOp	89.29	91.96	+2.67
ProGrad	87.93	90.90	+2.98
MaPLe	88.43	91.84	+3.41
PromptSRC	90.59	91.97	+1.38
LoCoOp	82.51	89.45	+6.94

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	58.92	59.98	+1.06
CoCoOp	57.28	61.61	+4.33
IVLP	63.66	71.01	+7.35
KgCoOp	66.07	66.68	+0.61
ProGrad	57.15	59.58	+2.43
MaPLe	57.03	63.37	+6.33
PromptSRC	68.80	70.34	+1.54
LoCoOp	55.31	61.06	+5.75

(i) SUN397.

	Energy	MLS-E	△
CoOp	75.10	76.19	+1.09
CoCoOp	75.10	77.36	+2.27
IVLP	76.17	79.03	+2.86
KgCoOp	74.80	76.54	+1.74
ProGrad	74.00	76.48	+2.48
MaPLe	76.65	79.09	+2.44
PromptSRC	77.26	79.91	+2.65
LoCoOp	71.27	76.23	+4.96

(j) DTD.

	Energy	MLS-E	△
CoOp	68.35	69.16	+0.81
CoCoOp	63.75	66.27	+2.52
IVLP	63.94	67.25	+3.31
KgCoOp	61.31	66.69	+5.38
ProGrad	60.84	65.22	+4.38
MaPLe	63.54	66.92	+3.38
PromptSRC	67.56	69.27	+1.71
LoCoOp	65.29	68.07	+2.78

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	67.54	67.49	-0.06
CoCoOp	66.12	65.99	-0.13
IVLP	63.89	69.72	+5.83
KgCoOp	62.36	66.24	+3.88
ProGrad	68.19	69.10	+0.90
MaPLe	70.02	71.94	+1.93
PromptSRC	74.40	74.30	-0.10
LoCoOp	66.04	67.80	+1.77

(l) UCF101.

	Energy	MLS-E	△
CoOp	81.31	82.96	+1.65
CoCoOp	79.65	82.92	+3.27
IVLP	78.96	83.84	+4.88
KgCoOp	79.04	82.76	+3.72
ProGrad	79.39	82.30	+2.91
MaPLe	79.38	83.45	+4.07
PromptSRC	81.77	84.56	+2.79
LoCoOp	73.63	81.13	+7.50

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	82.84	84.86	+2.02
CoCoOp	88.08	91.91	+3.83
IVLP	86.40	90.40	+3.99
KgCoOp	88.09	91.93	+3.84
ProGrad	81.61	87.96	+6.35
MaPLe	85.68	91.07	+5.38
PromptSRC	89.76	93.41	+3.65
LoCoOp	81.33	89.26	+7.93

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	76.84	77.75	+0.91
CoCoOp	79.64	80.73	+1.09
IVLP	82.35	87.05	+4.70
KgCoOp	78.54	79.78	+1.23
ProGrad	74.71	78.76	+4.05
MaPLe	83.17	87.49	+4.32
PromptSRC	84.76	87.83	+3.07
LoCoOp	73.54	74.83	+1.28

Table 13: Near OOD FPR95 (↓) of prompt learning models over 13 datasets using the Energy score and MLS-E.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	59.45	55.37	-4.08
CoCoOp	57.49	51.90	-5.59
IVLP	57.66	49.19	-8.47
KgCoOp	59.69	51.90	-7.80
ProGrad	62.74	55.34	-7.41
MaPLe	57.82	48.76	-9.07
PromptSRC	51.86	45.15	-6.71
LoCoOp	69.07	57.80	-11.27

(b) ImageNet.

	Energy	MLS-E	△
CoOp	33.04	26.96	-6.08
CoCoOp	29.16	24.69	-4.47
IVLP	29.40	24.78	-4.62
KgCoOp	33.09	28.35	-4.74
ProGrad	35.87	28.41	-7.46
MaPLe	32.34	26.52	-5.82
PromptSRC	30.06	22.97	-7.09
LoCoOp	45.33	32.02	-13.31

(c) Caltech101.

	Energy	MLS-E	△
CoOp	42.21	32.07	-10.15
CoCoOp	48.28	36.22	-12.06
IVLP	51.35	34.09	-17.26
KgCoOp	61.27	34.10	-27.17
ProGrad	65.31	45.11	-20.20
MaPLe	49.42	31.23	-18.19
PromptSRC	52.12	28.81	-23.30
LoCoOp	80.74	44.34	-36.40

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	52.87	46.91	-5.95
CoCoOp	45.06	37.87	-7.18
IVLP	50.67	43.75	-6.92
KgCoOp	49.07	38.01	-11.06
ProGrad	51.49	52.73	+1.23
MaPLe	53.88	45.57	-8.30
PromptSRC	44.32	39.70	-4.62
LoCoOp	58.27	52.35	-5.92

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	32.23	30.96	-1.27
CoCoOp	28.37	26.83	-1.54
IVLP	33.75	25.40	-8.34
KgCoOp	28.62	27.05	-1.57
ProGrad	32.69	28.19	-4.49
MaPLe	30.20	25.29	-4.91
PromptSRC	26.11	22.29	-3.82
LoCoOp	42.86	31.34	-11.52

(f) Flowers102.

	Energy	MLS-E	△
CoOp	42.18	37.55	-4.63
CoCoOp	53.82	46.99	-6.83
IVLP	59.10	51.31	-7.79
KgCoOp	62.44	45.23	-17.21
ProGrad	49.71	43.54	-6.17
MaPLe	58.30	50.79	-7.52
PromptSRC	42.84	36.78	-6.06
LoCoOp	59.87	51.74	-8.14

(g) Food101

	Energy	MLS-E	△
CoOp	55.28	50.05	-5.23
CoCoOp	43.18	37.95	-5.23
IVLP	45.66	35.66	-10.00
KgCoOp	46.71	36.35	-10.36
ProGrad	50.78	39.99	-10.79
MaPLe	47.53	35.38	-12.15
PromptSRC	40.21	34.84	-5.36
LoCoOp	65.29	44.22	-21.06

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	81.31	80.09	-1.22
CoCoOp	81.38	76.55	-4.83
IVLP	75.61	69.78	-5.83
KgCoOp	72.11	72.30	+0.18
ProGrad	82.41	78.20	-4.21
MaPLe	78.68	75.01	-3.67
PromptSRC	69.47	69.00	-0.48
LoCoOp	83.64	79.53	-4.11

(i) SUN397.

	Energy	MLS-E	△
CoOp	73.24	70.54	-2.69
CoCoOp	73.55	67.30	-6.25
IVLP	71.54	65.08	-6.46
KgCoOp	74.01	70.02	-3.99
ProGrad	76.75	70.20	-6.56
MaPLe	71.20	64.64	-6.56
PromptSRC	69.99	63.56	-6.43
LoCoOp	81.12	71.02	-10.10

(j) DTD.

	Energy	MLS-E	△
CoOp	86.00	85.21	-0.79
CoCoOp	88.92	87.58	-1.34
IVLP	87.86	87.82	-0.04
KgCoOp	88.49	86.42	-2.08
ProGrad	88.90	88.31	-0.59
MaPLe	89.53	87.31	-2.22
PromptSRC	86.43	84.32	-2.11
LoCoOp	85.52	85.52	+0.01

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	85.49	85.25	-0.24
CoCoOp	82.05	81.58	-0.47
IVLP	81.29	74.34	-6.96
KgCoOp	82.60	79.15	-3.45
ProGrad	82.91	82.99	+0.09
MaPLe	76.75	67.28	-9.47
PromptSRC	67.18	66.27	-0.91
LoCoOp	82.06	79.99	-2.07

(l) UCF101.

	Energy	MLS-E	△
CoOp	56.84	51.16	-5.68
CoCoOp	58.31	50.90	-7.41
IVLP	58.72	48.52	-10.20
KgCoOp	56.41	50.89	-5.52
ProGrad	59.53	50.75	-8.78
MaPLe	58.65	49.51	-9.14
PromptSRC	53.91	47.33	-6.58
LoCoOp	70.46	57.05	-13.41

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	56.82	51.62	-5.20
CoCoOp	41.65	30.48	-11.17
IVLP	43.38	32.73	-10.65
KgCoOp	45.90	33.20	-12.70
ProGrad	58.65	43.18	-15.47
MaPLe	46.10	31.57	-14.53
PromptSRC	35.64	24.13	-11.51
LoCoOp	60.82	39.74	-21.08

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	75.30	71.41	-3.89
CoCoOp	73.60	69.70	-3.90
IVLP	61.31	46.22	-15.08
KgCoOp	75.27	73.58	-1.69
ProGrad	80.70	67.79	-12.91
MaPLe	59.11	43.73	-15.38
PromptSRC	55.95	47.00	-8.95
LoCoOp	81.91	82.49	+0.59

Table 14: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E with 16-shots.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	82.67±10.20	83.84±10.18	+1.17±1.20
CoCoOp	81.21±12.20	83.70±10.99	+2.49±2.54
IVLP	83.25±9.90	87.55±7.60	+4.30±4.05
KgCoOp	81.02±11.18	84.36±9.84	+3.34±2.72
ProGrad	80.90±11.25	83.32±11.27	+2.42±2.81
MaPLe	83.60±10.11	86.54±9.03	+2.94±2.28
PromptSRC	85.53±8.47	87.67±8.19	+2.13±1.90
LoCoOp	78.03±10.52	81.70±11.89	+3.67±4.56

(b) ImageNet.

	Energy	MLS-E	△
CoOp	93.74±0.33	95.56±0.27	+1.82±0.06
CoCoOp	94.85±0.32	95.38±0.75	+0.53±0.90
IVLP	94.49±0.16	94.84±0.50	+0.36±0.48
KgCoOp	94.15±0.05	94.39±0.25	+0.24±0.30
ProGrad	94.03±0.13	95.15±0.09	+1.12±0.14
MaPLe	94.64±0.55	95.00±0.51	+0.36±0.42
PromptSRC	94.64±0.21	95.88±0.16	+1.25±0.22
LoCoOp	93.06±0.25	95.10±0.29	+2.04±0.54

(c) Caltech101.

	Energy	MLS-E	△
CoOp	89.02±0.89	90.88±1.16	+1.87±1.31
CoCoOp	85.89±1.40	89.16±1.35	+3.27±2.20
IVLP	86.56±1.70	92.84±1.90	+6.27±2.02
KgCoOp	80.89±0.06	89.13±0.43	+8.24±0.49
ProGrad	79.45±2.82	88.37±0.45	+8.92±2.73
MaPLe	86.60±0.87	92.58±1.67	+5.98±2.16
PromptSRC	82.29±0.19	89.74±0.16	+7.44±0.11
LoCoOp	74.46±1.75	87.26±0.73	+12.80±1.62

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	84.87±1.44	86.40±1.96	+1.52±0.54
CoCoOp	90.51±0.79	93.43±0.31	+2.92±0.70
IVLP	90.80±1.97	93.60±1.41	+2.80±0.80
KgCoOp	89.58±0.21	91.70±1.01	+2.12±0.89
ProGrad	87.13±1.50	88.41±0.68	+1.28±1.05
MaPLe	89.43±0.65	93.96±1.35	+4.53±1.38
PromptSRC	91.23±0.29	94.58±0.45	+3.36±0.20
LoCoOp	82.84±3.33	88.48±1.24	+5.64±2.74

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	93.48±0.19	93.41±0.20	-0.07±0.18
CoCoOp	91.39±1.69	92.97±0.86	+1.58±1.07
IVLP	90.53±1.54	93.44±1.29	+2.90±0.30
KgCoOp	93.03±0.23	93.61±0.08	+0.59±0.25
ProGrad	93.03±0.10	93.90±0.13	+0.86±0.06
MaPLe	91.51±1.54	93.46±0.20	+1.95±1.50
PromptSRC	93.86±0.16	95.49±0.13	+1.63±0.18
LoCoOp	88.72±1.18	92.35±1.87	+3.63±0.92

(f) Flowers102.

	Energy	MLS-E	△
CoOp	93.69±0.72	94.14±0.65	+0.45±0.08
CoCoOp	88.15±1.05	90.26±0.13	+2.11±0.99
IVLP	89.67±3.16	91.96±1.95	+2.28±1.22
KgCoOp	87.91±0.45	92.03±0.53	+4.12±0.43
ProGrad	88.36±1.15	91.54±0.28	+3.18±0.87
MaPLe	88.72±0.83	90.62±1.40	+1.90±0.67
PromptSRC	93.36±0.19	94.96±0.13	+1.59±0.30
LoCoOp	84.27±2.11	87.83±0.61	+3.56±2.63

(g) Food101

	Energy	MLS-E	△
CoOp	88.26±0.17	89.91±0.19	+1.65±0.13
CoCoOp	90.04±0.56	92.29±0.80	+2.25±0.30
IVLP	89.87±1.04	92.63±0.48	+2.76±1.48
KgCoOp	89.71±0.06	92.76±0.03	+3.04±0.06
ProGrad	89.78±0.36	92.64±0.27	+2.87±0.10
MaPLe	90.26±1.07	93.01±0.63	+2.74±0.50
PromptSRC	91.05±0.24	92.49±0.21	+1.44±0.07
LoCoOp	83.07±1.58	90.78±0.93	+7.71±2.00

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	58.67±1.68	59.64±1.78	+0.98±1.53
CoCoOp	54.18±2.15	62.75±2.43	+8.57±3.29
IVLP	64.80±2.11	75.75±0.99	+10.95±1.23
KgCoOp	65.66±0.55	67.11±1.28	+1.45±0.74
ProGrad	58.30±0.53	58.03±4.57	-0.28±4.51
MaPLe	61.47±5.81	68.17±4.95	+6.71±1.30
PromptSRC	71.61±1.30	74.28±2.01	+2.67±0.91
LoCoOp	56.94±2.18	52.02±3.01	-4.92±2.79

(i) SUN397.

	Energy	MLS-E	△
CoOp	77.47±0.49	78.91±0.71	+1.45±0.29
CoCoOp	76.14±0.51	78.46±0.49	+2.31±0.37
IVLP	76.77±0.53	80.07±0.26	+3.30±0.78
KgCoOp	75.66±0.09	77.43±0.22	+1.76±0.27
ProGrad	75.33±1.06	78.14±0.99	+2.81±0.32
MaPLe	77.24±1.89	80.02±0.76	+2.79±1.18
PromptSRC	78.24±0.09	81.28±0.58	+3.04±0.49
LoCoOp	73.04±0.30	77.96±0.65	+4.92±0.89

(j) DTD.

	Energy	MLS-E	△
CoOp	73.46±1.11	73.78±1.37	+0.32±0.30
CoCoOp	64.88±1.32	68.81±1.39	+3.93±2.01
IVLP	66.08±1.73	70.45±0.85	+4.37±1.00
KgCoOp	62.52±0.75	69.68±0.49	+7.15±0.46
ProGrad	61.18±1.21	65.78±1.57	+4.61±1.22
MaPLe	66.07±3.15	70.26±2.28	+4.19±2.02
PromptSRC	70.23±0.69	72.32±0.79	+2.09±0.69
LoCoOp	66.54±0.84	71.23±0.91	+4.69±0.82

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	71.11±0.80	72.98±2.62	+1.87±1.90
CoCoOp	67.77±3.30	67.38±3.57	-0.39±0.30
IVLP	72.49±2.75	85.82±2.86	+13.34±3.57
KgCoOp	62.59±0.31	70.32±1.20	+7.73±0.99
ProGrad	74.04±2.13	74.19±2.13	+0.15±0.09
MaPLe	79.57±1.14	81.41±2.37	+1.84±1.48
PromptSRC	78.87±2.45	78.58±2.27	-0.29±0.27
LoCoOp	67.22±5.88	68.64±5.90	+1.41±0.55

(l) UCF101.

	Energy	MLS-E	△
CoOp	82.77±0.52	84.74±0.62	+1.98±1.08
CoCoOp	81.32±1.02	84.19±0.56	+2.87±0.64
IVLP	81.30±2.34	85.95±0.24	+4.64±2.18
KgCoOp	79.79±0.09	83.61±0.82	+3.82±0.73
ProGrad	79.94±0.49	82.33±0.97	+2.39±0.49
MaPLe	81.63±1.04	83.84±1.25	+2.21±0.32
PromptSRC	82.61±0.58	84.96±0.67	+2.35±0.25
LoCoOp	75.72±1.15	82.57±1.31	+6.85±2.26

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	90.39±0.84	90.60±0.76	+0.20±0.26
CoCoOp	93.84±0.18	93.95±0.38	+0.10±0.40
IVLP	93.01±1.30	93.10±1.66	+0.09±0.45
KgCoOp	93.46±0.12	93.86±0.12	+0.40±0.03
ProGrad	92.94±0.40	93.30±0.28	+0.36±0.16
MaPLe	94.24±0.58	94.26±0.79	+0.02±0.43
PromptSRC	95.13±0.09	94.88±0.35	-0.24±0.29
LoCoOp	92.34±0.70	91.13±0.46	-1.21±0.59

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	77.81±0.91	78.93±1.06	+1.12±1.78
CoCoOp	76.76±1.06	79.06±1.14	+2.31±0.94
IVLP	85.87±0.90	87.68±2.39	+1.81±1.55
KgCoOp	78.28±0.43	81.07±0.32	+2.79±0.51
ProGrad	78.21±0.48	81.40±0.68	+3.19±0.47
MaPLe	85.48±0.77	88.50±2.08	+3.01±1.34
PromptSRC	88.83±0.25	90.21±0.13	+1.38±0.38
LoCoOp	76.19±1.57	76.73±1.77	+0.54±1.17

Table 15: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E with 8-shots.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	81.38±10.64	82.77±10.65	+1.39±1.17
CoCoOp	81.16±11.79	83.44±10.96	+2.28±1.87
IVLP	81.92±11.35	85.27±10.31	+3.34±3.78
KgCoOp	80.61±11.35	83.71±10.47	+3.10±2.60
ProGrad	79.71±12.08	82.65±11.65	+2.93±2.57
MaPLe	82.29±11.58	85.45±11.08	+3.16±3.24
PromptSRC	85.28±8.51	87.53±8.05	+2.26±1.90
LoCoOp	78.06±10.24	82.63±9.46	+4.57±4.78

(b) ImageNet.

	Energy	MLS-E	△
CoOp	93.29±0.22	95.34±0.45	+2.05±0.64
CoCoOp	94.78±0.62	95.89±0.09	+1.11±0.56
IVLP	94.18±1.20	94.51±0.61	+0.34±1.68
KgCoOp	94.16±0.03	94.22±0.43	+0.05±0.41
ProGrad	93.68±0.72	95.14±0.25	+1.47±0.71
MaPLe	93.56±1.53	94.72±0.96	+1.16±0.63
PromptSRC	94.57±0.20	95.81±0.08	+1.24±0.14
LoCoOp	91.81±0.61	94.26±0.56	+2.45±0.52

(c) Caltech101.

	Energy	MLS-E	△
CoOp	87.86±1.05	89.96±1.31	+2.09±1.00
CoCoOp	84.16±2.29	87.06±2.75	+2.90±1.66
IVLP	86.96±1.63	91.78±1.38	+4.82±0.57
KgCoOp	80.33±0.24	88.50±0.27	+8.17±0.15
ProGrad	81.78±1.73	88.09±1.39	+6.31±1.76
MaPLe	85.75±1.21	91.54±1.09	+5.79±2.12
PromptSRC	82.61±0.45	89.88±0.67	+7.27±0.55
LoCoOp	73.11±2.77	88.20±1.08	+15.10±2.96

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	86.31±2.02	88.83±1.92	+2.53±0.15
CoCoOp	90.57±0.75	92.98±0.16	+2.41±0.70
IVLP	89.92±0.68	91.94±0.65	+2.02±0.89
KgCoOp	89.48±0.16	92.12±0.35	+2.64±0.35
ProGrad	86.58±1.15	89.05±1.69	+2.47±0.54
MaPLe	88.42±0.71	92.02±1.36	+3.60±0.83
PromptSRC	91.19±0.27	93.77±0.38	+2.58±0.24
LoCoOp	84.20±3.03	88.73±1.24	+4.53±2.83

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	92.24±0.57	93.06±1.08	+0.82±0.58
CoCoOp	92.83±1.12	93.50±1.37	+0.67±0.58
IVLP	89.48±2.02	93.57±1.33	+4.09±2.67
KgCoOp	92.97±0.10	93.51±0.13	+0.54±0.06
ProGrad	92.76±0.97	93.15±0.67	+0.39±0.44
MaPLe	92.47±0.69	93.24±1.05	+0.77±0.36
PromptSRC	93.02±0.22	94.64±0.83	+1.62±0.68
LoCoOp	88.46±0.57	92.62±1.03	+4.17±1.25

(f) Flowers102.

	Energy	MLS-E	△
CoOp	91.48±0.50	92.37±0.52	+0.89±0.11
CoCoOp	87.02±0.02	88.32±0.43	+1.30±0.45
IVLP	86.79±4.78	87.59±4.46	+0.80±0.32
KgCoOp	86.43±0.09	91.65±0.48	+5.22±0.49
ProGrad	88.67±0.30	91.35±0.56	+2.68±0.67
MaPLe	85.83±0.77	87.63±0.67	+1.81±0.82
PromptSRC	92.24±0.37	94.05±0.23	+1.81±0.14
LoCoOp	86.09±2.83	88.96±2.00	+2.87±0.84

(g) Food101

	Energy	MLS-E	△
CoOp	87.40±1.19	87.98±1.22	+0.58±0.21
CoCoOp	90.81±0.62	91.47±0.75	+0.66±0.30
IVLP	88.77±1.69	92.09±0.36	+3.32±1.67
KgCoOp	89.28±0.13	91.85±0.42	+2.57±0.43
ProGrad	88.63±0.47	90.80±0.54	+2.18±0.45
MaPLe	89.99±1.07	92.60±0.29	+2.61±1.17
PromptSRC	91.03±0.27	92.31±0.43	+1.28±0.45
LoCoOp	83.90±2.11	88.93±1.64	+5.03±0.63

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	58.51±6.36	59.92±6.08	+1.41±2.28
CoCoOp	58.61±1.00	63.19±3.58	+4.58±3.21
IVLP	65.14±5.72	71.74±2.69	+6.60±8.26
KgCoOp	65.74±0.96	67.61±0.96	+1.87±1.73
ProGrad	58.66±2.45	60.02±7.36	+1.36±5.42
MaPLe	53.69±8.20	59.43±14.57	+5.74±8.67
PromptSRC	71.14±0.43	75.76±0.58	+4.61±0.83
LoCoOp	60.78±7.50	67.63±9.05	+6.85±3.06

(i) SUN397.

	Energy	MLS-E	△
CoOp	76.02±1.27	77.14±0.85	+1.12±0.50
CoCoOp	75.58±0.45	78.93±1.13	+3.35±1.56
IVLP	77.43±0.18	79.94±0.97	+2.51±0.94
KgCoOp	75.27±0.18	77.23±0.45	+1.96±0.44
ProGrad	74.63±0.37	78.07±0.63	+3.45±0.86
MaPLe	78.23±1.20	79.91±1.13	+1.69±0.20
PromptSRC	77.94±0.24	80.88±0.55	+2.93±0.36
LoCoOp	72.28±1.21	77.06±1.26	+4.77±1.50

(j) DTD.

	Energy	MLS-E	△
CoOp	70.79±0.49	71.54±1.12	+0.74±0.63
CoCoOp	63.93±0.38	67.29±0.37	+3.36±0.19
IVLP	66.04±0.36	68.68±0.39	+2.64±0.10
KgCoOp	60.85±0.26	66.50±1.25	+5.65±1.13
ProGrad	59.71±1.04	64.97±0.88	+5.26±0.60
MaPLe	65.47±1.47	69.84±1.95	+4.37±0.60
PromptSRC	69.00±1.03	70.36±1.04	+1.36±0.05
LoCoOp	66.91±0.80	69.47±0.47	+2.57±0.48

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	67.67±3.77	68.53±3.37	+0.86±0.45
CoCoOp	65.60±3.79	66.79±3.74	+1.19±0.73
IVLP	61.18±10.79	69.72±15.85	+8.54±5.16
KgCoOp	62.19±0.52	67.08±3.15	+4.89±3.56
ProGrad	63.62±2.46	66.39±0.81	+2.78±2.66
MaPLe	77.01±4.54	83.09±6.48	+6.07±2.26
PromptSRC	80.14±4.58	80.46±4.80	+0.32±0.21
LoCoOp	66.85±0.86	71.13±4.97	+4.28±4.19

(l) UCF101.

	Energy	MLS-E	△
CoOp	82.79±1.00	84.92±0.78	+2.14±0.76
CoCoOp	81.08±1.02	84.27±0.40	+3.19±0.76
IVLP	79.97±1.70	85.60±1.40	+5.63±0.99
KgCoOp	79.53±0.41	83.58±0.46	+4.05±0.62
ProGrad	78.41±2.14	83.91±2.00	+5.50±0.14
MaPLe	79.75±0.93	83.65±0.55	+3.90±1.41
PromptSRC	83.12±0.90	85.94±0.98	+2.82±0.27
LoCoOp	72.75±2.31	82.37±1.28	+9.62±1.61

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	88.11±2.48	88.12±2.73	+0.01±0.26
CoCoOp	92.96±0.58	93.38±0.92	+0.42±0.43
IVLP	92.27±1.15	93.34±0.78	+1.07±0.43
KgCoOp	93.33±0.01	93.67±0.16	+0.34±0.14
ProGrad	92.31±0.54	92.71±0.70	+0.40±0.28
MaPLe	93.54±0.44	93.97±0.47	+0.43±0.20
PromptSRC	94.92±0.47	94.75±0.45	-0.16±0.31
LoCoOp	91.96±1.27	88.62±3.55	-3.34±3.08

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	75.41±0.95	78.30±0.46	+2.89±0.57
CoCoOp	77.14±1.36	81.60±0.63	+4.45±1.23
IVLP	86.85±0.73	87.94±0.63	+1.09±0.45
KgCoOp	78.39±0.44	80.69±0.94	+2.30±1.23
ProGrad	76.86±0.64	80.76±1.26	+3.90±0.76
MaPLe	86.01±0.50	89.21±0.23	+3.19±0.31
PromptSRC	87.67±0.69	89.33±0.83	+1.66±0.18
LoCoOp	75.70±0.75	76.16±2.61	+0.46±1.86

Table 16: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E with 4-shots.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	80.96±10.65	82.10±10.96	+1.15±1.67
CoCoOp	81.06±11.56	83.05±11.69	+1.99±2.22
IVLP	80.84±12.25	84.23±11.72	+3.39±2.85
KgCoOp	80.36±11.15	83.31±10.95	+2.95±2.45
ProGrad	79.95±10.93	82.21±10.85	+2.26±1.91
MaPLe	80.39±11.25	83.76±10.48	+3.37±3.27
PromptSRC	84.22±8.81	86.37±8.78	+2.15±1.78
LoCoOp	77.45±10.27	81.35±10.79	+3.90±5.10

(b) ImageNet.

	Energy	MLS-E	△
CoOp	93.77±0.52	95.28±0.21	+1.50±0.71
CoCoOp	95.25±0.06	95.87±0.11	+0.62±0.10
IVLP	95.03±0.05	95.60±0.17	+0.57±0.20
KgCoOp	94.03±0.07	94.47±0.07	+0.43±0.08
ProGrad	93.72±0.37	94.73±0.26	+1.01±0.22
MaPLe	93.79±1.60	94.00±0.70	+0.21±0.95
PromptSRC	94.49±0.11	95.67±0.24	+1.18±0.23
LoCoOp	92.51±0.31	94.90±0.13	+2.39±0.40

(c) Caltech101.

	Energy	MLS-E	△
CoOp	89.67±1.88	91.35±2.71	+1.67±1.55
CoCoOp	85.37±1.02	88.46±0.33	+3.09±1.23
IVLP	82.49±1.10	91.07±0.79	+8.57±1.87
KgCoOp	80.41±0.10	88.88±0.74	+8.47±0.69
ProGrad	82.12±1.31	87.22±1.70	+5.10±1.99
MaPLe	83.52±4.07	90.61±1.95	+7.09±4.68
PromptSRC	82.95±0.45	89.72±0.36	+6.77±0.30
LoCoOp	71.40±2.18	86.42±1.52	+15.02±0.79

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	87.32±2.01	89.57±1.80	+2.26±0.22
CoCoOp	88.88±1.08	92.69±0.75	+3.81±1.65
IVLP	88.91±1.64	93.05±0.53	+4.14±1.27
KgCoOp	89.34±0.08	92.86±0.31	+3.52±0.35
ProGrad	87.25±1.22	89.33±1.55	+2.08±0.34
MaPLe	85.70±2.55	91.03±1.49	+5.33±1.64
PromptSRC	90.31±0.99	93.77±0.99	+3.46±0.32
LoCoOp	84.77±1.22	88.96±1.47	+4.19±1.08

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	91.15±1.35	91.46±1.09	+0.31±0.42
CoCoOp	93.45±0.67	93.80±0.54	+0.35±0.30
IVLP	92.10±1.07	93.13±1.07	+1.03±0.06
KgCoOp	92.92±0.11	93.56±0.19	+0.65±0.16
ProGrad	92.22±1.02	92.77±0.75	+0.55±0.61
MaPLe	92.09±1.08	93.29±0.71	+1.20±1.21
PromptSRC	92.88±0.20	94.09±0.33	+1.22±0.42
LoCoOp	86.92±1.81	91.75±0.44	+4.83±2.07

(f) Flowers102.

	Energy	MLS-E	△
CoOp	91.32±1.85	92.79±1.47	+1.47±1.14
CoCoOp	86.33±1.79	88.59±0.54	+2.26±1.32
IVLP	85.48±2.02	87.61±1.04	+2.13±1.12
KgCoOp	85.19±0.47	89.96±0.09	+4.77±0.38
ProGrad	87.02±2.01	90.27±1.66	+3.25±1.06
MaPLe	83.84±2.69	86.96±1.59	+3.12±1.74
PromptSRC	90.48±0.17	92.09±0.82	+1.61±0.65
LoCoOp	84.97±0.79	87.66±0.73	+2.69±0.88

(g) Food101

	Energy	MLS-E	△
CoOp	86.33±1.54	87.58±1.09	+1.25±0.51
CoCoOp	90.04±1.32	91.66±0.73	+1.62±0.62
IVLP	88.91±0.68	92.08±0.74	+3.17±0.71
KgCoOp	88.93±0.26	92.11±0.17	+3.18±0.28
ProGrad	86.91±0.76	90.44±0.15	+3.53±0.66
MaPLe	88.27±1.22	91.90±0.72	+3.63±1.80
PromptSRC	90.37±0.14	91.94±0.40	+1.57±0.26
LoCoOp	81.84±2.30	90.01±1.67	+8.17±1.13

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	59.53±1.10	60.54±3.45	+1.01±3.31
CoCoOp	59.21±2.05	58.83±2.44	-0.38±4.13
IVLP	61.99±8.45	67.41±11.46	+5.43±4.79
KgCoOp	66.06±1.05	65.16±1.56	-0.90±1.01
ProGrad	57.70±2.93	58.64±3.91	+0.94±1.11
MaPLe	55.95±1.39	64.26±3.44	+8.31±4.31
PromptSRC	69.46±2.71	70.66±2.79	+1.19±1.34
LoCoOp	57.42±3.96	60.08±9.93	+2.66±9.23

(i) SUN397.

	Energy	MLS-E	△
CoOp	76.15±0.98	76.74±0.56	+0.59±0.43
CoCoOp	75.10±0.98	77.71±0.31	+2.61±1.09
IVLP	76.42±1.31	78.87±0.72	+2.45±1.04
KgCoOp	74.99±0.39	76.35±0.54	+1.36±0.16
ProGrad	74.40±1.10	76.22±1.36	+1.81±0.97
MaPLe	77.45±0.88	79.31±0.52	+1.85±1.06
PromptSRC	77.43±0.33	79.65±0.42	+2.22±0.71
LoCoOp	70.75±0.99	76.45±0.65	+5.70±0.61

(j) DTD.

	Energy	MLS-E	△
CoOp	67.82±0.29	69.37±0.74	+1.55±0.74
CoCoOp	62.92±1.15	65.30±0.10	+2.38±1.06
IVLP	63.93±0.52	66.58±1.12	+2.64±0.82
KgCoOp	60.68±0.24	64.77±0.88	+4.09±0.65
ProGrad	61.17±1.47	65.56±1.81	+4.39±1.02
MaPLe	63.47±0.98	65.11±0.45	+1.64±1.15
PromptSRC	66.75±1.28	69.09±0.80	+2.34±0.87
LoCoOp	66.84±1.42	68.70±0.99	+1.86±0.66

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	67.49±3.02	66.17±3.58	-1.31±1.75
CoCoOp	67.69±1.96	68.18±2.08	+0.49±0.72
IVLP	58.42±8.07	64.08±10.84	+5.66±3.42
KgCoOp	62.82±0.26	67.44±1.00	+4.62±0.76
ProGrad	74.08±0.89	74.19±2.60	+0.12±1.74
MaPLe	68.42±5.44	69.97±4.80	+1.55±0.89
PromptSRC	77.36±0.86	78.11±1.36	+0.75±0.56
LoCoOp	69.77±4.99	69.54±5.02	-0.23±0.76

(l) UCF101.

	Energy	MLS-E	△
CoOp	80.10±1.53	81.59±1.90	+1.49±1.01
CoCoOp	79.68±1.26	83.47±1.38	+3.79±2.20
IVLP	79.58±1.87	84.16±1.72	+4.58±0.93
KgCoOp	78.52±0.23	82.86±0.30	+4.34±0.37
ProGrad	79.12±1.21	81.29±0.23	+2.17±1.39
MaPLe	79.79±0.36	85.53±1.24	+5.74±1.36
PromptSRC	82.62±0.65	85.95±1.04	+3.33±1.37
LoCoOp	75.77±1.05	81.68±2.47	+5.91±1.60

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	87.12±2.56	87.29±2.73	+0.17±0.24
CoCoOp	92.67±0.76	93.13±0.69	+0.45±0.17
IVLP	91.92±1.84	92.81±1.31	+0.89±0.54
KgCoOp	92.78±0.29	93.39±0.39	+0.61±0.11
ProGrad	89.36±0.43	90.10±1.12	+0.75±0.76
MaPLe	87.53±6.17	88.19±4.69	+0.66±1.82
PromptSRC	92.74±1.69	92.86±1.83	+0.13±0.16
LoCoOp	90.93±2.17	87.70±2.18	-3.23±1.33

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	74.64±1.74	77.60±2.69	+2.96±1.48
CoCoOp	77.19±1.06	81.91±1.30	+4.72±1.41
IVLP	85.72±0.61	88.55±0.76	+2.83±0.29
KgCoOp	77.99±0.45	81.21±0.38	+3.22±0.28
ProGrad	74.28±0.12	77.97±1.46	+3.69±1.52
MaPLe	85.28±0.74	88.79±0.58	+3.51±0.33
PromptSRC	87.04±0.65	89.17±1.09	+2.13±0.94
LoCoOp	73.01±1.23	73.71±2.24	+0.71±1.11

Table 17: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E with 2-shots.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	79.88±10.72	81.13±10.73	+1.25±1.73
CoCoOp	80.48±11.52	82.25±11.63	+1.77±1.74
IVLP	79.75±11.35	83.11±10.12	+3.35±2.75
KgCoOp	80.47±10.84	83.35±10.44	+2.88±2.41
ProGrad	78.86±11.41	81.87±11.07	+3.02±3.25
MaPLe	80.20±10.89	83.68±10.41	+3.48±2.64
PromptSRC	82.99±9.69	85.12±9.76	+2.14±1.75
LoCoOp	75.13±12.35	80.57±10.96	+5.44±5.58

(b) ImageNet.

	Energy	MLS-E	△
CoOp	94.23±0.46	94.56±0.19	+0.33±0.27
CoCoOp	94.20±0.38	94.73±0.29	+0.53±0.10
IVLP	94.80±0.70	94.90±0.23	+0.10±0.55
KgCoOp	94.01±0.18	94.58±0.28	+0.56±0.10
ProGrad	93.00±0.30	94.86±0.24	+1.87±0.32
MaPLe	94.34±0.81	94.63±0.23	+0.29±0.62
PromptSRC	94.46±0.16	95.25±0.18	+0.79±0.23
LoCoOp	92.01±0.72	94.18±0.17	+2.17±0.57

(c) Caltech101.

	Energy	MLS-E	△
CoOp	87.05±1.86	89.19±1.14	+2.14±1.37
CoCoOp	83.71±0.91	87.54±1.14	+3.83±0.28
IVLP	82.89±2.19	87.62±2.42	+4.73±2.85
KgCoOp	80.43±0.39	88.42±0.39	+7.99±0.12
ProGrad	81.49±2.78	89.30±2.72	+7.81±2.94
MaPLe	84.73±1.85	91.47±0.64	+6.75±1.89
PromptSRC	83.15±0.36	89.57±1.49	+6.41±1.80
LoCoOp	67.65±4.62	84.35±2.10	+16.70±4.18

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	85.82±2.98	89.09±3.50	+3.26±0.53
CoCoOp	86.48±1.05	90.84±0.82	+4.37±0.30
IVLP	83.94±1.84	89.19±1.36	+5.25±1.88
KgCoOp	89.06±0.45	92.42±0.59	+3.36±0.30
ProGrad	88.59±0.72	89.84±0.48	+1.25±1.12
MaPLe	85.18±1.66	88.66±2.71	+3.48±3.03
PromptSRC	89.54±0.38	92.33±0.80	+2.79±0.46
LoCoOp	80.35±3.33	88.62±1.51	+8.27±2.97

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	90.82±0.93	91.21±1.08	+0.39±0.80
CoCoOp	93.11±0.99	93.01±1.08	-0.10±0.13
IVLP	90.64±1.66	93.14±0.51	+2.50±1.24
KgCoOp	92.64±0.07	93.24±0.37	+0.60±0.42
ProGrad	89.08±1.43	91.68±1.05	+2.60±0.73
MaPLe	90.52±1.62	93.65±0.26	+3.13±1.81
PromptSRC	92.57±0.43	93.98±0.44	+1.41±0.59
LoCoOp	87.21±2.59	92.03±1.78	+4.82±0.97

(f) Flowers102.

	Energy	MLS-E	△
CoOp	89.39±1.03	91.05±0.92	+1.65±0.34
CoCoOp	86.69±0.68	89.06±0.95	+2.37±1.43
IVLP	80.13±1.23	84.73±0.67	+4.60±0.56
KgCoOp	84.67±0.55	90.18±0.38	+5.51±0.23
ProGrad	86.54±1.70	90.38±0.68	+3.84±1.91
MaPLe	82.72±0.76	87.12±0.21	+4.40±0.68
PromptSRC	87.93±0.38	90.10±0.45	+2.17±0.27
LoCoOp	83.93±1.67	86.67±0.85	+2.74±1.21

(g) Food101

	Energy	MLS-E	△
CoOp	84.00±0.44	85.45±0.95	+1.45±0.68
CoCoOp	89.85±1.08	91.07±1.15	+1.23±0.39
IVLP	89.78±0.22	90.94±0.57	+1.16±0.77
KgCoOp	89.16±0.42	91.76±0.44	+2.60±0.10
ProGrad	86.64±2.46	89.99±0.49	+3.35±1.99
MaPLe	85.91±0.46	91.15±0.30	+5.24±0.73
PromptSRC	90.31±0.51	91.53±0.62	+1.22±0.24
LoCoOp	81.81±0.50	89.49±0.27	+7.69±0.76

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	58.16±0.90	60.28±3.37	+2.12±3.84
CoCoOp	57.39±1.46	58.44±2.68	+1.05±2.38
IVLP	61.97±4.29	69.19±2.28	+7.22±2.16
KgCoOp	68.05±1.85	67.95±1.71	-0.10±0.39
ProGrad	55.95±1.16	59.68±6.81	+3.73±6.80
MaPLe	61.81±0.97	67.97±3.44	+6.16±3.07
PromptSRC	67.39±3.22	69.02±3.91	+1.64±1.99
LoCoOp	50.10±1.99	61.06±6.93	+10.97±6.16

(i) SUN397.

	Energy	MLS-E	△
CoOp	73.46±0.35	74.67±0.70	+1.21±0.61
CoCoOp	74.54±0.61	76.14±0.22	+1.60±0.53
IVLP	76.05±0.70	78.27±0.96	+2.22±0.84
KgCoOp	74.45±0.16	75.87±0.63	+1.41±0.74
ProGrad	73.52±0.79	74.90±0.47	+1.37±0.43
MaPLe	75.84±0.05	78.26±0.67	+2.42±0.71
PromptSRC	76.71±0.13	79.41±0.36	+2.70±0.36
LoCoOp	70.28±0.64	75.49±0.98	+5.21±0.38

(j) DTD.

	Energy	MLS-E	△
CoOp	66.18±1.37	67.09±1.37	+0.91±0.55
CoCoOp	64.06±0.20	65.47±1.14	+1.41±1.11
IVLP	63.06±1.22	66.37±0.81	+3.31±1.26
KgCoOp	61.72±0.30	65.84±1.29	+4.12±1.44
ProGrad	61.17±0.96	65.97±0.32	+4.80±0.67
MaPLe	62.53±1.74	65.49±0.73	+2.96±1.30
PromptSRC	66.17±0.12	67.04±0.12	+0.87±0.17
LoCoOp	62.43±0.38	64.85±1.41	+2.42±1.03

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	69.04±4.15	68.32±4.46	-0.73±0.56
CoCoOp	68.27±5.42	68.24±5.32	-0.04±0.14
IVLP	60.75±1.27	65.01±3.98	+4.27±4.75
KgCoOp	62.98±0.32	67.79±1.51	+4.81±1.81
ProGrad	67.28±5.69	69.20±4.12	+1.92±2.58
MaPLe	63.82±4.56	67.53±7.31	+3.71±2.94
PromptSRC	70.07±0.67	71.91±2.06	+1.84±1.73
LoCoOp	62.99±2.58	67.56±5.05	+4.57±2.96

(l) UCF101.

	Energy	MLS-E	△
CoOp	81.62±1.38	82.97±0.68	+1.34±0.79
CoCoOp	78.09±1.09	81.44±0.81	+3.35±0.43
IVLP	76.70±0.25	81.43±0.43	+4.73±0.57
KgCoOp	78.47±0.10	81.53±1.52	+3.07±1.45
ProGrad	79.42±0.61	82.78±0.77	+3.36±0.27
MaPLe	78.87±0.45	82.52±0.99	+3.64±0.55
PromptSRC	80.85±0.86	83.30±0.17	+2.45±0.73
LoCoOp	72.37±3.29	80.97±2.80	+8.60±0.58

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	86.90±0.17	86.61±0.59	-0.29±0.45
CoCoOp	93.11±0.38	93.36±0.41	+0.24±0.08
IVLP	92.90±0.41	92.94±0.13	+0.04±0.53
KgCoOp	93.17±0.07	93.54±0.06	+0.37±0.05
ProGrad	88.24±0.35	87.03±1.63	-1.21±1.41
MaPLe	93.02±0.44	92.72±0.42	-0.30±0.83
PromptSRC	93.88±0.11	94.33±0.28	+0.45±0.19
LoCoOp	92.70±0.80	88.96±1.85	-3.73±2.64

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	71.71±1.18	74.21±0.75	+2.50±1.84
CoCoOp	76.71±0.95	79.91±2.15	+3.20±1.41
IVLP	83.15±1.72	86.63±1.02	+3.48±0.71
KgCoOp	77.28±0.43	80.48±0.31	+3.20±0.50
ProGrad	74.20±1.65	78.77±1.67	+4.56±2.70
MaPLe	83.27±1.28	86.61±0.90	+3.34±2.09
PromptSRC	85.83±0.39	88.86±0.45	+3.03±0.19
LoCoOp	72.81±1.34	73.16±1.43	+0.36±0.82

Table 18: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the Energy score and MLS-E with 1-shot.

(a) Average over 13 datasets.

	Energy	MLS-E	△
CoOp	77.68±10.89	78.75±11.51	+1.08±2.34
CoCoOp	79.42±12.18	81.51±11.59	+2.09±2.95
IVLP	79.62±10.43	82.58±10.29	+2.96±3.38
KgCoOp	79.88±11.50	82.26±11.74	+2.38±3.14
ProGrad	77.86±12.21	80.27±11.67	+2.41±3.09
MaPLe	78.46±13.27	81.19±13.11	+2.73±5.06
PromptSRC	81.76±10.60	83.23±11.69	+1.47±3.32
LoCoOp	75.17±11.73	79.38±10.84	+4.22±6.61

(b) ImageNet.

	Energy	MLS-E	△
CoOp	93.63±0.19	93.42±0.82	-0.21±1.00
CoCoOp	94.72±0.50	94.62±0.52	-0.10±0.96
IVLP	94.02±0.58	94.86±0.50	+0.84±0.99
KgCoOp	93.88±0.11	94.41±0.30	+0.53±0.25
ProGrad	92.87±0.67	94.08±0.47	+1.21±0.21
MaPLe	94.00±0.71	94.53±0.44	+0.53±0.39
PromptSRC	94.17±0.49	95.21±0.32	+1.04±0.17
LoCoOp	91.88±0.55	94.21±0.21	+2.33±0.43

(c) Caltech101.

	Energy	MLS-E	△
CoOp	82.95±2.81	86.02±1.74	+3.07±1.81
CoCoOp	81.84±1.15	87.99±1.30	+6.15±2.32
IVLP	81.47±3.02	85.94±2.46	+4.47±2.40
KgCoOp	79.90±0.14	88.99±0.16	+9.09±0.30
ProGrad	78.15±0.45	85.03±3.93	+6.88±3.49
MaPLe	82.01±2.96	88.55±1.13	+6.53±3.62
PromptSRC	81.94±0.44	89.58±0.54	+7.65±0.98
LoCoOp	70.62±2.79	84.24±2.65	+13.62±1.42

(d) OxfordPets.

	Energy	MLS-E	△
CoOp	85.22±1.81	89.19±2.02	+3.97±1.71
CoCoOp	88.24±1.31	90.13±0.36	+1.89±1.23
IVLP	87.79±1.80	90.55±0.14	+2.77±1.66
KgCoOp	88.80±0.21	92.32±1.21	+3.52±1.04
ProGrad	88.13±2.30	90.92±1.65	+2.79±0.89
MaPLe	84.55±5.20	87.52±2.77	+2.97±2.43
PromptSRC	89.65±0.69	91.97±0.56	+2.32±1.25
LoCoOp	82.36±2.92	87.42±2.17	+5.06±4.41

(e) StanfordCars.

	Energy	MLS-E	△
CoOp	89.17±1.70	89.18±1.69	+0.01±0.54
CoCoOp	91.99±0.73	92.58±0.37	+0.59±0.76
IVLP	89.48±0.55	92.92±1.53	+3.43±0.99
KgCoOp	92.69±0.10	93.24±0.17	+0.55±0.12
ProGrad	89.62±2.18	91.26±0.93	+1.63±1.28
MaPLe	91.06±0.93	92.08±0.24	+1.02±0.69
PromptSRC	92.52±0.47	94.18±0.30	+1.66±0.29
LoCoOp	88.34±2.38	92.03±0.27	+3.69±2.48

(f) Flowers102.

	Energy	MLS-E	△
CoOp	84.70±2.03	87.21±2.66	+2.51±0.84
CoCoOp	85.61±0.63	88.20±0.53	+2.59±0.11
IVLP	80.49±3.74	85.33±1.89	+4.84±2.03
KgCoOp	84.69±0.36	88.76±1.03	+4.07±1.05
ProGrad	86.98±0.75	88.34±1.07	+1.36±0.56
MaPLe	81.17±2.31	84.68±3.01	+3.51±0.71
PromptSRC	85.61±0.92	88.09±1.66	+2.48±0.75
LoCoOp	79.39±1.42	84.59±2.18	+5.20±1.08

(g) Food101

	Energy	MLS-E	△
CoOp	85.62±1.78	87.58±2.38	+1.96±0.62
CoCoOp	89.73±0.89	90.73±0.24	+0.99±0.81
IVLP	88.76±2.17	90.89±0.91	+2.14±1.39
KgCoOp	89.35±0.21	91.33±0.65	+1.97±0.70
ProGrad	87.67±1.79	90.64±1.43	+2.96±1.31
MaPLe	87.72±0.98	90.56±0.84	+2.84±0.69
PromptSRC	90.21±0.12	91.58±0.12	+1.37±0.14
LoCoOp	81.94±3.22	88.04±1.50	+6.10±3.09

(h) FGVCAircraft.

	Energy	MLS-E	△
CoOp	59.73±2.43	59.49±5.99	-0.25±4.21
CoCoOp	57.01±2.68	64.83±3.99	+7.81±3.17
IVLP	64.42±1.74	70.97±5.40	+6.54±3.98
KgCoOp	64.85±1.17	65.58±3.35	+0.74±2.21
ProGrad	55.12±1.86	61.51±2.60	+6.40±2.98
MaPLe	52.24±9.93	57.00±5.71	+4.76±14.41
PromptSRC	64.39±2.64	61.96±5.31	-2.43±6.59
LoCoOp	51.32±7.65	64.50±3.27	+13.18±8.77

(i) SUN397.

	Energy	MLS-E	△
CoOp	72.41±1.26	73.47±2.07	+1.06±0.86
CoCoOp	74.11±0.24	75.57±0.64	+1.46±0.40
IVLP	74.16±0.73	77.99±0.88	+3.83±1.60
KgCoOp	73.65±0.13	75.85±0.15	+2.20±0.27
ProGrad	72.12±0.57	75.09±0.67	+2.97±0.19
MaPLe	74.47±1.59	77.94±1.17	+3.47±0.48
PromptSRC	75.98±1.06	78.35±0.77	+2.37±0.35
LoCoOp	69.97±0.93	74.18±0.84	+4.21±0.29

(j) DTD.

	Energy	MLS-E	△
CoOp	63.49±0.91	64.01±0.75	+0.52±0.95
CoCoOp	62.98±0.54	64.51±1.40	+1.52±0.98
IVLP	60.59±1.37	64.18±1.78	+3.59±0.89
KgCoOp	60.76±1.29	66.67±0.88	+5.91±0.46
ProGrad	60.96±1.56	63.81±1.94	+2.85±0.61
MaPLe	60.16±1.09	63.91±0.52	+3.75±0.92
PromptSRC	65.66±1.40	67.55±2.69	+1.89±1.39
LoCoOp	63.76±0.92	66.10±0.60	+2.34±0.49

(k) EuroSAT.

	Energy	MLS-E	△
CoOp	62.39±4.19	61.44±3.94	-0.96±0.62
CoCoOp	61.28±3.47	59.37±3.06	-1.91±1.79
IVLP	66.60±3.49	63.96±5.02	-2.64±4.86
KgCoOp	61.21±0.83	58.57±2.99	-2.63±2.20
ProGrad	61.96±1.16	61.51±4.02	-0.45±5.17
MaPLe	61.26±6.96	57.71±8.88	-3.54±3.44
PromptSRC	65.55±4.74	62.45±2.70	-3.10±2.07
LoCoOp	63.35±4.19	62.14±6.91	-1.21±3.25

(l) UCF101.

	Energy	MLS-E	△
CoOp	79.25±1.33	80.57±0.71	+1.32±0.81
CoCoOp	78.08±1.14	81.23±0.28	+3.15±1.41
IVLP	77.24±1.68	82.06±0.86	+4.82±2.30
KgCoOp	78.88±0.97	82.21±1.98	+3.33±1.06
ProGrad	80.03±1.83	81.16±1.73	+1.14±0.19
MaPLe	76.88±0.38	81.71±0.46	+4.84±0.53
PromptSRC	79.62±0.96	82.63±1.13	+3.01±0.21
LoCoOp	71.54±1.89	78.06±2.52	+6.52±0.63

(m) CIFAR10.

	Energy	MLS-E	△
CoOp	83.06±1.34	81.77±0.90	-1.29±1.60
CoCoOp	90.85±2.48	90.01±2.16	-0.84±0.59
IVLP	87.01±6.32	86.81±3.85	-0.20±3.51
KgCoOp	93.01±0.38	91.78±1.72	-1.23±1.61
ProGrad	87.62±4.43	86.07±4.47	-1.55±2.03
MaPLe	92.41±1.38	92.43±2.35	+0.02±1.21
PromptSRC	93.62±0.39	92.59±2.13	-1.02±1.78
LoCoOp	89.29±1.17	82.42±10.55	-6.87±9.46

(n) CIFAR100.

	Energy	MLS-E	△
CoOp	68.18±1.23	70.43±3.00	+2.24±2.90
CoCoOp	76.01±1.44	79.86±1.91	+3.85±0.47
IVLP	83.00±0.54	87.04±0.30	+4.04±0.72
KgCoOp	76.77±0.66	79.69±1.55	+2.92±0.91
ProGrad	70.90±2.52	74.08±1.77	+3.18±1.24
MaPLe	82.03±2.21	86.88±0.88	+4.85±2.34
PromptSRC	83.99±0.11	85.91±0.89	+1.92±0.82
LoCoOp	73.40±1.57	74.07±1.22	+0.67±0.54

A.3.3 MCM Score

We show the effectiveness of our method with MCM measured by average AUROC and FPR95 across 13 datasets in Table 19 and Table 20, where $S_{\text{MLS-MCM}} = S_{\text{MCM}} - \beta \cdot S_{\text{Context}}$. Also, we compare the correlation between scores and the Context score using MaxLogit and MCM in Figure 6.

Table 19: Near OOD AUROC (↑) of prompt learning models over 13 datasets using the MCM score and MLS-MCM.

(a) Average over 13 datasets.

	MCM	MLS-MCM	△
CoOp	79.41	81.31	+1.90
CoCoOp	79.28	82.59	+3.31
IVLP	80.95	84.48	+3.53
KgCoOp	79.82	83.31	+3.49
ProGrad	79.91	81.81	+1.90
MaPLe	80.54	83.81	+3.27
PromptSRC	82.34	85.49	+3.15
LoCoOp	79.22	80.36	+1.14

(b) ImageNet.

	MCM	MLS-MCM	△
CoOp	93.48	94.48	+0.99
CoCoOp	94.16	94.93	+0.77
IVLP	93.68	94.18	+0.50
KgCoOp	93.84	94.30	+0.46
ProGrad	93.20	94.08	+0.88
MaPLe	93.42	93.97	+0.56
PromptSRC	94.46	95.30	+0.84
LoCoOp	93.23	93.81	+0.59

(c) Caltech101.

	MCM	MLS-MCM	△
CoOp	92.57	92.42	-0.15
CoCoOp	90.71	90.27	-0.44
IVLP	91.35	91.56	+0.21
KgCoOp	91.08	90.83	-0.26
ProGrad	91.16	91.15	-0.01
MaPLe	91.32	91.92	+0.61
PromptSRC	91.27	90.93	-0.34
LoCoOp	91.02	90.97	-0.04

(d) OxfordPets.

	MCM	MLS-MCM	△
CoOp	85.75	88.59	+2.84
CoCoOp	86.85	91.41	+4.56
IVLP	87.51	91.01	+3.50
KgCoOp	88.35	92.51	+4.16
ProGrad	86.86	88.12	+1.26
MaPLe	86.31	90.39	+4.08
PromptSRC	88.69	93.24	+4.55
LoCoOp	86.56	87.12	+0.56

(e) StanfordCars.

	MCM	MLS-MCM	△
CoOp	82.61	88.62	+6.01
CoCoOp	83.77	91.30	+7.53
IVLP	84.75	92.66	+7.91
KgCoOp	83.38	92.41	+9.03
ProGrad	84.23	90.32	+6.09
MaPLe	83.80	92.13	+8.33
PromptSRC	84.64	93.85	+9.21
LoCoOp	82.83	88.23	+5.40

(f) Flowers102.

	MCM	MLS-MCM	△
CoOp	90.08	90.79	+0.71
CoCoOp	84.56	88.24	+3.69
IVLP	87.31	89.33	+2.02
KgCoOp	87.00	91.50	+4.50
ProGrad	89.66	90.80	+1.14
MaPLe	86.07	88.84	+2.77
PromptSRC	90.61	92.96	+2.35
LoCoOp	86.98	87.05	+0.07

(g) Food101.

	MCM	MLS-MCM	△
CoOp	85.65	87.72	+2.07
CoCoOp	89.05	91.64	+2.59
IVLP	88.71	92.07	+3.36
KgCoOp	89.41	92.30	+2.89
ProGrad	88.29	90.88	+2.59
MaPLe	88.96	92.22	+3.26
PromptSRC	89.39	92.45	+3.06
LoCoOp	88.29	90.05	+1.76

(h) FGVCAircraft.

	MCM	MLS-MCM	△
CoOp	41.22	52.57	+11.35
CoCoOp	37.53	57.00	+19.47
IVLP	40.70	65.75	+25.05
KgCoOp	37.83	58.34	+20.51
ProGrad	40.66	50.54	+9.88
MaPLe	38.94	58.04	+19.10
PromptSRC	39.89	61.58	+21.69
LoCoOp	38.94	50.03	+11.09

(i) SUN397.

	MCM	MLS-MCM	△
CoOp	78.86	78.83	-0.03
CoCoOp	79.97	80.13	+0.17
IVLP	80.41	80.74	+0.33
KgCoOp	80.25	80.37	+0.12
ProGrad	79.63	79.68	+0.06
MaPLe	80.21	80.72	+0.52
PromptSRC	81.71	82.03	+0.32
LoCoOp	79.75	79.72	-0.03

(j) DTD.

	MCM	MLS-MCM	△
CoOp	69.89	70.03	+0.14
CoCoOp	66.96	67.41	+0.45
IVLP	69.26	69.24	-0.02
KgCoOp	68.88	69.11	+0.23
ProGrad	68.21	68.17	-0.04
MaPLe	68.39	68.62	+0.23
PromptSRC	71.40	71.45	+0.05
LoCoOp	69.76	69.82	+0.06

(k) EuroSAT.

	MCM	MLS-MCM	△
CoOp	67.49	65.33	-2.16
CoCoOp	63.63	63.24	-0.39
IVLP	68.85	67.28	-1.58
KgCoOp	62.17	62.20	+0.03
ProGrad	66.93	65.91	-1.02
MaPLe	69.72	67.60	-2.13
PromptSRC	72.57	68.61	-3.96
LoCoOp	63.23	61.57	-1.66

(l) UCF101.

	MCM	MLS-MCM	△
CoOp	84.05	84.83	+0.78
CoCoOp	83.95	84.82	+0.86
IVLP	83.46	85.01	+1.55
KgCoOp	84.55	85.22	+0.67
ProGrad	85.03	85.40	+0.37
MaPLe	83.34	84.78	+1.44
PromptSRC	85.11	86.47	+1.36
LoCoOp	83.57	83.77	+0.20

(m) CIFAR10.

	MCM	MLS-MCM	△
CoOp	87.12	86.88	-0.24
CoCoOp	92.69	92.76	+0.08
IVLP	91.42	91.80	+0.38
KgCoOp	93.15	93.25	+0.10
ProGrad	90.09	89.84	-0.25
MaPLe	92.15	92.31	+0.17
PromptSRC	94.05	93.88	-0.17
LoCoOp	91.44	87.77	-3.68

(n) CIFAR100.

	MCM	MLS-MCM	△
CoOp	73.55	75.89	+2.34
CoCoOp	76.76	80.47	+3.71
IVLP	84.92	87.57	+2.65
KgCoOp	77.74	80.63	+2.89
ProGrad	74.89	78.60	+3.70
MaPLe	84.42	88.00	+3.58
PromptSRC	86.67	88.70	+2.02
LoCoOp	74.22	74.77	+0.55

Table 20: Near OOD FPR95 (↓) of prompt learning models over 13 datasets using the MCM score and MLS-MCM.

(a) Average over 13 datasets.

	MCM	MLS-MCM	△
CoOp	63.70	57.48	-6.21
CoCoOp	63.76	53.62	-10.14
IVLP	60.05	49.23	-10.83
KgCoOp	62.20	51.85	-10.35
ProGrad	62.89	56.22	-6.67
MaPLe	60.68	49.00	-11.68
PromptSRC	55.86	46.13	-9.73
LoCoOp	63.37	60.63	-2.74

(b) ImageNet.

	MCM	MLS-MCM	△
CoOp	32.74	26.85	-5.89
CoCoOp	30.51	24.63	-5.89
IVLP	31.20	26.31	-4.89
KgCoOp	31.99	27.10	-4.89
ProGrad	34.16	29.29	-4.88
MaPLe	32.58	27.27	-5.31
PromptSRC	28.77	22.81	-5.97
LoCoOp	35.06	31.97	-3.09

(c) Caltech101.

	MCM	MLS-MCM	△
CoOp	24.16	24.43	+0.27
CoCoOp	31.48	31.77	+0.28
IVLP	31.33	29.16	-2.17
KgCoOp	27.22	27.34	+0.12
ProGrad	33.36	33.33	-0.04
MaPLe	32.98	27.50	-5.48
PromptSRC	26.36	25.61	-0.75
LoCoOp	30.81	30.76	-0.05

(d) OxfordPets.

	MCM	MLS-MCM	△
CoOp	55.23	46.74	-8.49
CoCoOp	53.26	40.67	-12.59
IVLP	50.43	43.36	-7.08
KgCoOp	51.32	36.12	-15.20
ProGrad	54.48	55.72	+1.25
MaPLe	52.24	42.94	-9.30
PromptSRC	49.69	38.07	-11.62
LoCoOp	53.91	53.14	-0.77

(e) StanfordCars.

	MCM	MLS-MCM	△
CoOp	64.30	41.26	-23.05
CoCoOp	63.84	34.19	-29.65
IVLP	59.38	27.69	-31.69
KgCoOp	64.69	31.72	-32.97
ProGrad	62.17	37.12	-25.06
MaPLe	62.20	28.56	-33.64
PromptSRC	59.71	24.71	-35.01
LoCoOp	64.56	46.73	-17.83

(f) Flowers102.

	MCM	MLS-MCM	△
CoOp	45.66	42.85	-2.81
CoCoOp	62.92	52.14	-10.79
IVLP	55.70	48.98	-6.72
KgCoOp	57.90	40.86	-17.04
ProGrad	46.41	42.20	-4.22
MaPLe	57.83	49.43	-8.40
PromptSRC	43.15	34.45	-8.70
LoCoOp	54.17	53.85	-0.32

(g) Food101

	MCM	MLS-MCM	△
CoOp	64.07	53.69	-10.38
CoCoOp	55.24	39.39	-15.86
IVLP	56.66	35.87	-20.79
KgCoOp	54.18	36.14	-18.04
ProGrad	58.86	43.43	-15.43
MaPLe	54.93	35.68	-19.24
PromptSRC	54.50	35.58	-18.91
LoCoOp	56.78	45.80	-10.97

(h) FGVCAircraft.

	MCM	MLS-MCM	△
CoOp	96.60	87.13	-9.47
CoCoOp	97.73	79.83	-17.90
IVLP	96.33	73.45	-22.89
KgCoOp	97.50	79.50	-18.00
ProGrad	96.26	86.77	-9.49
MaPLe	97.15	79.37	-17.78
PromptSRC	96.76	75.93	-20.83
LoCoOp	97.11	89.01	-8.10

(i) SUN397.

	MCM	MLS-MCM	△
CoOp	67.98	68.17	+0.18
CoCoOp	65.10	64.27	-0.83
IVLP	65.20	63.57	-1.62
KgCoOp	64.31	63.76	-0.55
ProGrad	66.65	66.43	-0.23
MaPLe	65.25	63.02	-2.24
PromptSRC	62.12	60.91	-1.21
LoCoOp	65.51	65.60	+0.09

(j) DTD.

	MCM	MLS-MCM	△
CoOp	87.99	86.66	-1.33
CoCoOp	90.93	89.61	-1.32
IVLP	88.19	87.42	-0.77
KgCoOp	88.74	87.37	-1.37
ProGrad	89.19	88.90	-0.29
MaPLe	89.07	87.79	-1.28
PromptSRC	83.29	83.18	-0.11
LoCoOp	87.82	86.76	-1.06

(k) EuroSAT.

	MCM	MLS-MCM	△
CoOp	87.62	86.12	-1.49
CoCoOp	90.61	86.67	-3.94
IVLP	82.81	80.20	-2.60
KgCoOp	89.72	87.54	-2.18
ProGrad	86.46	84.96	-1.50
MaPLe	77.79	74.61	-3.18
PromptSRC	78.29	82.00	+3.71
LoCoOp	90.22	87.44	-2.78

(l) UCF101.

	MCM	MLS-MCM	△
CoOp	61.80	54.14	-7.65
CoCoOp	63.33	50.41	-12.93
IVLP	59.62	47.81	-11.81
KgCoOp	58.62	50.47	-8.14
ProGrad	59.14	51.74	-7.41
MaPLe	63.36	49.15	-14.21
PromptSRC	56.65	47.04	-9.62
LoCoOp	61.10	57.06	-4.04

(m) CIFAR10.

	MCM	MLS-MCM	△
CoOp	53.53	52.71	-0.83
CoCoOp	37.02	31.98	-5.04
IVLP	38.67	31.04	-7.63
KgCoOp	35.12	32.46	-2.66
ProGrad	45.00	42.88	-2.12
MaPLe	36.95	29.19	-7.76
PromptSRC	27.73	23.03	-4.70
LoCoOp	37.78	54.39	+16.62

(n) CIFAR100.

	MCM	MLS-MCM	△
CoOp	86.40	76.54	-9.86
CoCoOp	86.82	71.48	-15.35
IVLP	65.16	45.08	-20.08
KgCoOp	87.26	73.61	-13.65
ProGrad	85.42	68.06	-17.37
MaPLe	66.44	42.43	-24.00
PromptSRC	59.12	46.33	-12.79
LoCoOp	88.94	85.63	-3.31

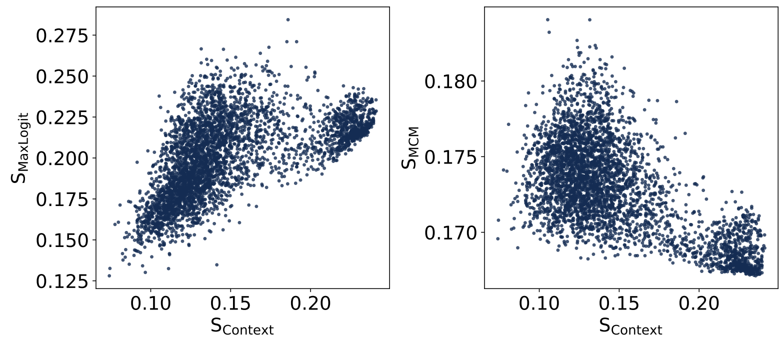


Figure 6: Comparison of MaxLogit (left) or MCM score (right) vs. Context score for near OOD samples with IVLP Khattak et al. (2023a) on EuroSAT Helber et al. (2019). MaxLogit score shows positive correlation with the Context score while MCM score lacks the correlation.

A.3.4 Score Comparison

In the main section, average AUROC and FPR95 of different scores are compared in Table 3. Here, we provide the individual's dataset results averaged across 16, 8, 4, 2, and 1-shot with 3 random seeds in Table 21 and Table 22.

Table 21: Near OOD AUROC (↑) of prompt learning models across 13 datasets using the MaxLogit score, the Energy score, MLS-M, MLS-E, and MCM.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	80.74	**81.84**	80.44	81.71	79.41
CoCoOp	81.09	**82.74**	80.53	82.74	79.28
IVLP	81.12	84.34	80.49	**84.40**	80.95
KgCoOp	80.84	83.12	80.14	**83.23**	79.82
ProGrad	79.77	**82.35**	78.79	81.93	79.91
MaPLe	81.06	83.94	80.39	**83.99**	80.54
PromptSRC	83.85	85.77	83.48	**85.88**	82.34
LoCoOp	77.55	**81.74**	75.94	81.25	79.22

(b) ImageNet.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	93.78	94.66	93.73	**94.83**	93.48
CoCoOp	94.85	95.14	94.76	**95.30**	94.16
IVLP	94.55	94.70	94.50	**94.94**	93.68
KgCoOp	94.21	94.21	94.05	**94.41**	93.84
ProGrad	93.62	94.67	93.46	**94.79**	93.20
MaPLe	94.20	94.35	94.07	**94.58**	93.42
PromptSRC	94.52	95.32	94.46	**95.56**	94.46
LoCoOp	93.10	**94.56**	92.25	94.53	93.23

(c) Caltech101.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	88.27	90.12	87.31	89.48	**92.57**
CoCoOp	85.80	89.02	84.19	88.04	**90.71**
IVLP	85.50	90.53	84.08	89.85	**91.35**
KgCoOp	83.64	90.06	80.39	88.79	**91.08**
ProGrad	82.96	88.85	80.60	87.60	**91.16**
MaPLe	85.91	**91.53**	84.52	90.95	91.32
PromptSRC	84.94	90.56	82.59	89.70	**91.27**
LoCoOp	76.08	87.75	71.45	86.09	**91.02**

(d) OxfordPets.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	86.22	**88.73**	85.91	88.62	85.75
CoCoOp	89.58	**92.28**	88.93	92.01	86.85
IVLP	88.84	**91.94**	88.27	91.67	87.51
KgCoOp	89.94	**92.64**	89.25	92.28	88.35
ProGrad	87.82	**89.60**	87.54	89.51	86.86
MaPLe	87.40	**91.00**	86.66	90.64	86.31
PromptSRC	90.80	**93.45**	90.38	93.29	88.69
LoCoOp	84.44	**89.19**	82.90	88.44	86.56

(e) StanfordCars.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	91.36	91.59	91.37	**91.66**	82.61
CoCoOp	92.43	92.99	92.56	**93.17**	83.77
IVLP	90.43	92.98	90.45	**93.24**	84.75
KgCoOp	92.77	93.27	92.85	**93.43**	83.38
ProGrad	91.52	**92.63**	91.34	92.55	84.23
MaPLe	91.39	92.85	91.53	**93.14**	83.80
PromptSRC	92.88	94.24	92.97	**94.47**	84.64
LoCoOp	88.24	91.94	87.93	**92.16**	82.83

(f) Flowers102.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	90.83	**91.99**	90.12	91.51	90.08
CoCoOp	87.93	**89.41**	86.76	88.89	84.56
IVLP	86.20	**88.45**	84.51	87.44	87.31
KgCoOp	87.61	**91.12**	85.78	90.51	87.00
ProGrad	89.27	**91.41**	87.51	90.37	89.66
MaPLe	86.05	**88.34**	84.45	87.40	86.07
PromptSRC	91.10	**92.61**	89.92	91.86	90.61
LoCoOp	86.17	**88.59**	83.73	87.14	86.98

(g) Food101

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	86.70	**87.91**	86.32	87.70	85.65
CoCoOp	90.52	**91.63**	90.09	91.44	89.05
IVLP	89.70	**91.87**	89.22	91.73	88.71
KgCoOp	89.87	**92.12**	89.29	91.96	89.41
ProGrad	88.60	**91.05**	87.93	90.90	88.29
MaPLe	89.10	**92.00**	88.43	91.84	88.96
PromptSRC	90.94	**92.11**	90.59	91.97	89.39
LoCoOp	84.87	**90.12**	82.51	89.45	88.29

(h) FGVCAircraft.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	55.99	56.97	58.92	**59.98**	41.22
CoCoOp	52.60	55.04	57.28	**61.61**	37.53
IVLP	58.47	64.16	63.66	**71.01**	40.70
KgCoOp	57.82	57.46	66.07	**66.68**	37.83
ProGrad	53.69	55.67	57.15	**59.58**	40.66
MaPLe	52.18	56.93	57.03	**63.37**	38.94
PromptSRC	60.63	62.50	68.80	**70.34**	39.89
LoCoOp	50.99	56.12	55.31	**61.06**	38.94

(i) SUN397.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	75.78	76.75	75.10	76.19	**78.86**
CoCoOp	76.32	78.29	75.10	77.36	**79.97**
IVLP	77.13	79.60	76.17	79.03	**80.41**
KgCoOp	76.45	77.91	74.80	76.54	**80.25**
ProGrad	75.52	77.67	74.00	76.48	**79.63**
MaPLe	77.62	79.73	76.65	79.09	**80.21**
PromptSRC	78.51	80.70	77.26	79.91	**81.71**
LoCoOp	73.97	78.00	71.27	76.23	**79.75**

(j) DTD.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	68.90	69.60	68.35	69.16	**69.89**
CoCoOp	65.10	**67.17**	63.75	66.27	66.96
IVLP	64.99	67.93	63.94	67.25	**69.26**
KgCoOp	63.79	68.17	61.31	66.69	**68.88**
ProGrad	62.90	66.96	60.84	65.22	**68.21**
MaPLe	64.80	67.79	63.54	66.92	**68.39**
PromptSRC	69.09	70.38	67.56	69.27	**71.40**
LoCoOp	66.63	69.05	65.29	68.07	**69.76**

(k) EuroSAT.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	**67.94**	67.83	67.54	67.49	67.49
CoCoOp	**66.87**	66.76	66.12	65.99	63.63
IVLP	65.56	**70.62**	63.89	69.72	68.85
KgCoOp	62.41	65.66	62.36	**66.24**	62.17
ProGrad	68.96	**69.71**	68.19	69.10	66.93
MaPLe	71.18	**72.28**	70.02	71.94	69.72
PromptSRC	**75.22**	74.97	74.40	74.30	72.57
LoCoOp	66.72	**67.85**	66.04	67.80	63.23

(l) UCF101.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	82.17	83.65	81.31	82.96	**84.05**
CoCoOp	81.32	**84.02**	79.65	82.92	83.95
IVLP	80.26	**84.55**	78.96	83.84	83.46
KgCoOp	81.26	84.06	79.04	82.76	**84.55**
ProGrad	81.21	83.71	79.39	82.30	**85.03**
MaPLe	80.81	**84.25**	79.38	83.45	83.34
PromptSRC	83.19	**85.43**	81.77	84.56	85.11
LoCoOp	76.28	82.54	73.63	81.13	**83.57**

(m) CIFAR10.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	84.05	85.76	82.84	84.86	**87.12**
CoCoOp	89.91	92.49	88.08	91.91	**92.69**
IVLP	88.17	91.10	86.40	90.40	**91.42**
KgCoOp	90.26	92.77	88.09	91.93	**93.15**
ProGrad	83.94	89.08	81.61	87.96	**90.09**
MaPLe	87.79	91.81	85.68	91.07	**92.15**
PromptSRC	91.36	93.97	89.76	93.41	**94.05**
LoCoOp	84.69	90.22	81.33	89.26	**91.44**

(n) CIFAR100.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	77.67	**78.30**	76.84	77.75	73.55
CoCoOp	80.99	**81.44**	79.64	80.73	76.76
IVLP	84.69	**88.01**	82.35	87.05	84.92
KgCoOp	80.94	**81.14**	78.54	79.78	77.74
ProGrad	77.01	**79.55**	74.71	78.76	74.89
MaPLe	85.35	**88.35**	83.17	87.49	84.42
PromptSRC	86.82	**88.78**	84.76	87.83	86.67
LoCoOp	76.03	**76.67**	73.54	74.83	74.22

Table 22: Near OOD FPR95 (↓) of prompt learning models across 13 datasets using the MaxLogit score, the Energy score, MLS-M, MLS-E, and MCM.

(a) Average over 13 datasets.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	58.23	**54.85**	59.45	55.37	63.70
CoCoOp	55.78	**51.67**	57.49	51.90	63.76
IVLP	55.65	**48.58**	57.66	49.19	60.05
KgCoOp	57.16	**51.52**	59.69	51.90	62.20
ProGrad	60.07	**54.02**	62.74	55.34	62.89
MaPLe	55.58	**48.36**	57.82	48.76	60.68
PromptSRC	49.65	**44.60**	51.86	45.15	55.86
LoCoOp	64.89	**55.76**	69.07	57.80	63.37

(b) ImageNet.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	31.02	**26.40**	33.04	26.96	32.74
CoCoOp	26.76	**23.85**	29.16	24.69	30.51
IVLP	27.23	**24.54**	29.40	24.78	31.20
KgCoOp	29.84	**27.45**	33.09	28.35	31.99
ProGrad	32.73	**27.40**	35.87	28.41	34.16
MaPLe	29.87	**26.09**	32.34	26.52	32.58
PromptSRC	27.89	**22.82**	30.06	22.97	28.77
LoCoOp	36.95	**28.94**	45.33	32.02	35.06

(c) Caltech101.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	38.42	29.90	42.21	32.07	**24.16**
CoCoOp	42.22	33.02	48.28	36.22	**31.48**
IVLP	45.94	**30.97**	51.35	34.09	31.33
KgCoOp	49.33	28.80	61.27	34.10	**27.22**
ProGrad	56.38	39.35	65.31	45.11	**33.36**
MaPLe	44.44	**28.30**	49.42	31.23	32.98
PromptSRC	43.79	**25.83**	52.12	28.81	26.36
LoCoOp	69.02	37.02	80.74	44.34	**30.81**

(d) OxfordPets.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	51.60	**45.90**	52.87	46.91	55.23
CoCoOp	42.47	**35.89**	45.06	37.87	53.26
IVLP	48.28	**40.88**	50.67	43.75	50.43
KgCoOp	47.06	**35.52**	49.07	38.01	51.32
ProGrad	**50.75**	51.94	51.49	52.73	54.48
MaPLe	50.86	**42.87**	53.88	45.57	52.24
PromptSRC	42.14	**38.08**	44.32	39.70	49.69
LoCoOp	54.57	**48.65**	58.27	52.35	53.91

(e) StanfordCars.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	32.58	31.62	32.23	**30.96**	64.30
CoCoOp	28.76	27.18	28.37	**26.83**	63.84
IVLP	33.89	26.07	33.75	**25.40**	59.38
KgCoOp	29.06	27.77	28.62	**27.05**	64.69
ProGrad	32.44	28.42	32.69	**28.19**	62.17
MaPLe	30.75	26.05	30.20	**25.29**	62.20
PromptSRC	26.27	22.88	26.11	**22.29**	59.71
LoCoOp	41.93	31.83	42.86	**31.34**	64.56

(f) Flowers102.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	40.02	**36.14**	42.18	37.55	45.66
CoCoOp	50.27	**45.51**	53.82	46.99	62.92
IVLP	54.62	**49.00**	59.10	51.31	55.70
KgCoOp	56.18	**43.15**	62.44	45.23	57.90
ProGrad	44.28	**38.84**	49.71	43.54	46.41
MaPLe	54.00	**47.94**	58.30	50.79	57.83
PromptSRC	38.96	**34.33**	42.84	36.78	43.15
LoCoOp	52.83	**46.72**	59.87	51.74	54.17

(g) Food101

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	54.00	**49.48**	55.28	50.05	64.07
CoCoOp	41.85	**37.57**	43.18	37.95	55.24
IVLP	44.36	**35.63**	45.66	35.66	56.66
KgCoOp	44.42	**35.98**	46.71	36.35	54.18
ProGrad	48.58	40.02	50.78	**39.99**	58.86
MaPLe	45.70	**35.26**	47.53	35.38	54.93
PromptSRC	39.21	**34.61**	40.21	34.84	54.50
LoCoOp	58.93	**42.34**	65.29	44.22	56.78

(h) FGVCAircraft.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	83.67	82.75	81.31	**80.09**	96.60
CoCoOp	84.31	81.95	81.38	**76.55**	97.73
IVLP	79.19	75.35	75.61	**69.78**	96.33
KgCoOp	79.80	79.98	**72.11**	72.30	97.50
ProGrad	84.79	81.38	82.41	**78.20**	96.26
MaPLe	81.98	80.73	78.68	**75.01**	97.15
PromptSRC	76.62	75.53	69.47	**69.00**	96.76
LoCoOp	86.36	83.58	83.64	**79.53**	97.11

(i) SUN397.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	71.81	69.50	73.24	70.54	**67.98**
CoCoOp	70.74	65.62	73.55	67.30	**65.10**
IVLP	69.31	**63.76**	71.54	65.08	65.20
KgCoOp	70.46	67.17	74.01	70.02	**64.31**
ProGrad	73.83	68.12	76.75	70.20	**66.65**
MaPLe	68.72	**63.34**	71.20	64.64	65.25
PromptSRC	66.85	**61.55**	69.99	63.56	62.12
LoCoOp	76.47	67.24	81.12	71.02	**65.51**

(j) DTD.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	85.34	**85.16**	86.00	85.21	87.99
CoCoOp	88.48	**87.50**	88.92	87.58	90.93
IVLP	**87.08**	87.11	87.86	87.82	88.19
KgCoOp	88.52	86.93	88.49	**86.42**	88.74
ProGrad	87.78	**87.55**	88.90	88.31	89.19
MaPLe	88.85	**86.81**	89.53	87.31	89.07
PromptSRC	84.52	83.56	86.43	84.32	**83.29**
LoCoOp	84.51	**83.94**	85.52	85.52	87.82

(k) EuroSAT.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	**85.12**	85.20	85.49	85.25	87.62
CoCoOp	82.25	82.38	82.05	**81.58**	90.61
IVLP	81.16	**73.84**	81.29	74.34	82.81
KgCoOp	82.08	82.30	82.60	**79.15**	89.72
ProGrad	**81.61**	82.31	82.91	82.99	86.46
MaPLe	75.22	68.41	76.75	**67.28**	77.79
PromptSRC	65.95	**65.83**	67.18	66.27	78.29
LoCoOp	81.91	80.88	82.06	**79.99**	90.22

(l) UCF101.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	55.64	**50.12**	56.84	51.16	61.80
CoCoOp	57.04	**50.37**	58.31	50.90	63.33
IVLP	56.96	**47.71**	58.72	48.52	59.62
KgCoOp	54.77	**50.16**	56.41	50.89	58.62
ProGrad	57.39	**48.84**	59.53	50.75	59.14
MaPLe	57.16	**49.27**	58.65	49.51	63.36
PromptSRC	51.62	**46.17**	53.91	47.33	56.65
LoCoOp	67.38	**55.38**	70.46	57.05	61.10

(m) CIFAR10.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	53.49	**49.45**	56.82	51.62	53.53
CoCoOp	37.07	**29.79**	41.65	30.48	37.02
IVLP	39.00	**30.87**	43.38	32.73	38.67
KgCoOp	38.30	**30.85**	45.90	33.20	35.12
ProGrad	52.48	**40.59**	58.65	43.18	45.00
MaPLe	40.75	**30.00**	46.10	31.57	36.95
PromptSRC	30.54	**22.74**	35.64	24.13	27.73
LoCoOp	51.96	**36.97**	60.82	39.74	37.78

(n) CIFAR100.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	74.33	71.48	75.30	**71.41**	86.40
CoCoOp	72.96	71.09	73.60	**69.70**	86.82
IVLP	56.39	**45.86**	61.31	46.22	65.16
KgCoOp	**73.27**	73.66	75.27	73.58	87.26
ProGrad	77.89	**67.49**	80.70	67.79	85.42
MaPLe	54.19	**43.60**	59.11	43.73	66.44
PromptSRC	51.05	**45.82**	55.95	47.00	59.12
LoCoOp	**80.71**	81.44	81.91	82.49	88.94

A.3.5 Far OOD Detection

We provide additional far OOD detection results of AUROC and FPR in Table 23 and Table 24 respectively.

Table 23: OOD detection AUROC (↑) averaged over 16, 8, 4, 2, and 1 few-shot settings with 3 random seeds.

(a) Places.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	96.22	**96.78**	+0.56	95.80	96.65	+0.85	95.92
CoCoOp	**96.90**	96.79	-0.11	96.50	96.51	+0.01	96.21
IVLP	95.79	**96.01**	+0.22	95.18	95.77	+0.60	95.97
KgCoOp	96.67	**96.91**	+0.24	96.12	96.74	+0.62	96.30
ProGrad	95.21	**96.05**	+0.84	94.52	95.76	+1.25	95.30
MaPLe	**96.61**	96.52	-0.09	96.00	96.11	+0.11	96.26
PromptSRC	96.54	**96.59**	+0.05	96.00	96.20	+0.21	96.40
LoCoOp	94.67	**97.10**	+2.43	91.59	96.45	+4.86	96.57

(b) SUN.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	96.49	97.88	+1.39	95.69	97.62	+1.93	**97.94**
CoCoOp	98.17	**98.47**	+0.30	97.64	98.21	+0.57	98.30
IVLP	97.61	98.20	+0.58	96.98	97.97	+0.99	**98.33**
KgCoOp	97.50	**98.47**	+0.96	96.61	98.29	+1.68	98.33
ProGrad	96.51	**97.73**	+1.22	95.60	97.35	+1.75	97.65
MaPLe	97.91	**98.54**	+0.63	97.13	98.21	+1.07	98.42
PromptSRC	97.63	98.11	+0.48	96.88	97.64	+0.76	**98.44**
LoCoOp	95.38	**98.94**	+3.56	90.79	98.20	+7.40	98.80

(c) Texture.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	93.38	93.74	+0.36	92.51	93.07	+0.56	**96.66**
CoCoOp	94.79	95.29	+0.50	93.72	94.51	+0.79	**96.99**
IVLP	93.32	95.49	+2.17	91.78	94.90	+3.12	**97.09**
KgCoOp	93.59	96.30	+2.71	92.03	95.90	+3.86	**96.62**
ProGrad	91.36	94.22	+2.86	89.72	93.37	+3.65	**96.73**
MaPLe	93.36	93.89	+0.52	91.73	92.64	+0.91	**97.50**
PromptSRC	92.69	94.52	+1.83	90.94	93.52	+2.58	**96.81**
LoCoOp	93.18	96.16	+2.98	89.80	94.82	+5.02	**96.96**

(d) iNaturalist.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	94.58	97.23	+2.65	92.66	96.28	+3.62	**97.86**
CoCoOp	97.02	**97.65**	+0.63	95.61	96.58	+0.97	97.52
IVLP	95.98	97.88	+1.91	93.74	96.89	+3.15	**98.26**
KgCoOp	97.05	**98.49**	+1.44	95.61	98.00	+2.39	97.96
ProGrad	92.90	96.04	+3.14	90.46	94.73	+4.27	**97.39**
MaPLe	95.80	97.60	+1.80	93.43	96.25	+2.82	**98.32**
PromptSRC	96.37	96.76	+0.38	94.41	95.01	+0.60	**98.44**
LoCoOp	93.41	**98.46**	+5.05	87.11	97.08	+9.97	97.95

Table 24: OOD detection FPR95 (↓) averaged over 16, 8, 4, 2, and 1 few-shot settings with 3 random seeds.

(a) Places.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	17.58	**13.56**	-4.01	20.90	14.42	-6.48	16.40
CoCoOp	13.01	**12.92**	-0.09	15.41	14.09	-1.33	14.78
IVLP	17.82	**15.32**	-2.50	22.14	16.67	-5.47	15.41
KgCoOp	14.43	**12.46**	-1.97	18.32	13.33	-4.99	14.34
ProGrad	22.47	**16.28**	-6.19	28.38	17.85	-10.52	18.51
MaPLe	15.37	**14.01**	-1.37	19.35	16.74	-2.62	14.32
PromptSRC	14.88	**13.77**	-1.11	18.70	16.04	-2.66	13.77
LoCoOp	27.58	**11.05**	-16.52	53.58	14.25	-39.33	12.43

(b) SUN.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	19.44	**10.06**	-9.38	26.66	11.60	-15.06	10.24
CoCoOp	8.37	**6.39**	-1.98	11.64	7.18	-4.46	8.15
IVLP	10.77	7.92	-2.86	15.85	9.35	-6.50	**7.49**
KgCoOp	12.98	**6.81**	-6.17	20.58	7.32	-13.26	7.77
ProGrad	19.14	**10.37**	-8.77	27.60	12.33	-15.28	11.37
MaPLe	9.67	**5.91**	-3.76	15.09	7.69	-7.40	7.10
PromptSRC	11.48	8.37	-3.11	17.35	11.28	-6.08	**6.84**
LoCoOp	29.82	**3.76**	-26.06	64.29	7.80	-56.49	4.51

(c) Texture.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	35.02	31.39	-3.63	43.04	37.32	-5.72	**17.29**
CoCoOp	26.11	23.14	-2.96	36.68	29.31	-7.37	**15.31**
IVLP	33.43	20.25	-13.18	43.80	24.40	-19.40	**13.70**
KgCoOp	33.06	18.30	-14.76	46.06	22.26	-23.79	**17.23**
ProGrad	42.31	28.67	-13.64	54.27	36.97	-17.30	**16.12**
MaPLe	35.20	29.43	-5.77	47.83	40.47	-7.36	**12.49**
PromptSRC	37.51	26.90	-10.61	52.59	36.40	-16.19	**15.64**
LoCoOp	39.95	19.69	-20.25	68.07	32.19	-35.87	**14.72**

(d) iNaturalist.

	MaxLogit			Energy			MCM
	Original	MLS-M	△	Original	MLS-E	△	
CoOp	32.70	13.64	-19.07	48.16	20.24	-27.93	**9.38**
CoCoOp	14.03	**9.68**	-4.35	24.75	16.71	-8.04	12.13
IVLP	22.51	8.85	-13.66	39.50	15.17	-24.33	**7.28**
KgCoOp	14.76	**5.76**	-9.00	25.50	8.60	-16.90	9.32
ProGrad	43.71	21.29	-22.42	58.34	32.44	-25.90	**13.93**
MaPLe	23.97	10.38	-13.58	42.23	19.62	-22.62	**6.76**
PromptSRC	19.38	16.03	-3.35	33.65	29.98	-3.67	**5.87**
LoCoOp	51.09	**6.17**	-44.92	85.97	18.46	-67.51	8.85

A.3.6 COMPARISON WITH ZERO-SHOT CLIP OOD DETECTION

Although our work is specifically designed for few-shot prompt learning CLIP models and is not comparable to zero-shot CLIP OOD detection models, we here provide a comparison with CLIPN (Wang et al., 2023) in Table 25. Following the original setting, we use the maximum softmax probability as an OOD score. Note that MLS cannot be applied to CLIPN as it is a zero-shot model which lacks the context vectors.

Table 25: Near OOD AUROC (↑) and FPR95 (↓) of prompt learning models and CLIPN averaged over 13 datasets.

	AUROC ↑			FPR95 ↓		
	MLS-M	MLS-E	MCM	MLS-M	MLS-E	MCM
CoOp	**81.84**	81.71	79.41	**54.85**	55.37	63.70
CoCoOp	**82.74**	82.74	79.28	**51.67**	51.90	63.76
IVLP	84.34	**84.40**	80.95	**48.58**	49.19	60.05
KgCoOp	83.12	**83.23**	79.82	**51.52**	51.90	62.20
ProGrad	**82.35**	81.93	79.91	**54.02**	55.34	62.89
MaPLe	83.94	**83.99**	80.54	**48.36**	48.76	60.68
PromptSRC	85.77	**85.88**	82.34	**44.60**	45.15	55.86
LoCoOp	**81.74**	81.25	79.22	**55.76**	57.80	63.37
CLIPN	N/A	N/A	79.64	N/A	N/A	64.44

A.3.7 IMAGENET PROTOCOL RESULTS

In addition to 13 datasets used in the main experiments, we also provide experimental results on ImageNet Protocol (Palechor et al., 2023) in Table 26. We follow the four-split setting used by Li et al. (2024).

Table 26: OOD AUROC (↑) of 8 prompt learning models averaged over 4 ImageNet protocol datasets using the MaxLogit score, the Energy score, MLS-M, MLS-E, and MCM.

	MaxLogit	MLS-M	Energy	MLS-E	MCM
CoOp	96.46	**96.74**	96.43	96.72	91.11
CoCoOp	97.42	**97.69**	97.34	97.65	93.77
IVLP	97.19	**97.60**	97.03	97.50	94.35
KgCoOp	97.34	**97.57**	97.24	97.50	94.09
ProGrad	96.84	**97.20**	96.73	97.12	93.18
MaPLe	**97.48**	**97.48**	97.38	97.23	94.16
PromptSRC	97.57	**97.73**	97.49	97.66	94.61
LoCoOp	96.59	**97.19**	96.15	96.94	93.76

A.3.8 OTHER OOD SCORES

We intentionally excluded OOD scores that require model retraining, architectural modifications, access to OOD samples, or those that are incompatible with fine-tuned prompt learning models. For examples, LogitNorm (Wei et al., 2022) requires training a model with its dedicated training loss to use the score, and relative Mahalanobis distance (RMD) (Ren et al., 2021) is intended to be used with a traditional classifier which has a classifier head. Even if RMD is applied to image features of the CLIP prompt learning models, all prompt learning models output the same RMD score as their image networks are not optimised during fine-tuning. Nonetheless, we provide experimental results of LogitNorm and RMD in Table 27, using 12 datasets excluding ImageNet with 16, 8, 4, and 2-shot settings. For LogitNorm, we trained the prompt learning models with LogitNorm loss substituting the original cross entropy loss. Following the original setting in (Wei et al., 2022), we used the temperature scale of 0.04 and calculated the maximum softmax probability score.

Table 27: Near OOD AUROC (↑) of prompt learning models averaged over 12 datasets with LogitNorm and RMD scores.

	MLS-M	MLS-E	MCM	LogitNorm	RMD
CoOp	**80.77**	80.61	78.24	77.55	57.58
CoCoOp	**81.71**	81.70	78.04	77.86	57.58
IVLP	83.48	**83.52**	79.89	79.56	57.58
KgCoOp	82.20	**82.30**	78.65	77.38	57.58
ProGrad	**81.32**	80.86	78.80	77.16	57.58
MaPLe	83.07	**83.11**	79.47	78.39	57.58
PromptSRC	84.97	**85.08**	81.33	80.28	57.58
LoCoOp	**80.67**	80.14	78.05	77.52	57.58

A.4 Additional Demonstrations

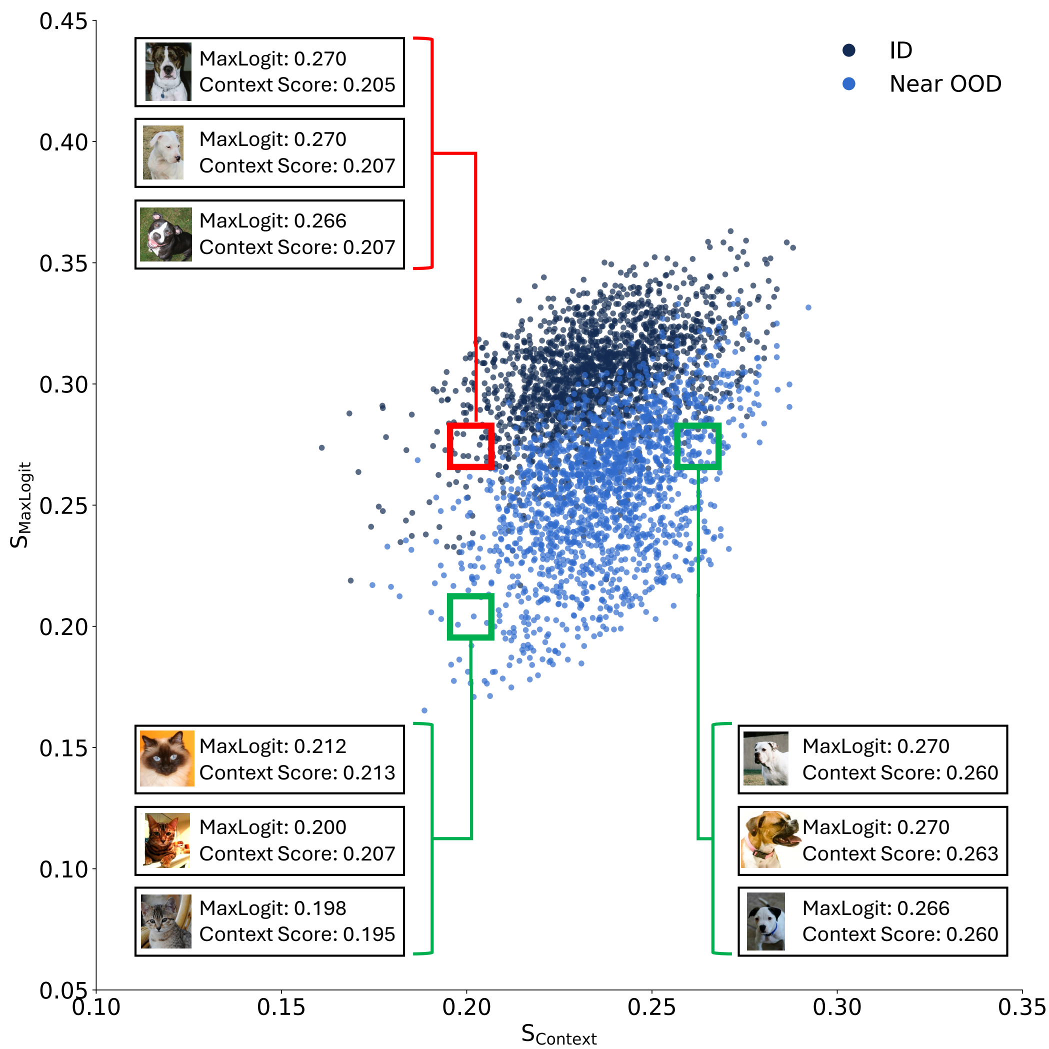


Figure 7: Comparisons of MaxLogit score and Context score computed by MaPLe (Khattak et al., 2023a) on OxfordPets (Parkhi et al., 2012) (16-shot). Three ID images from the red box are shown, and six OOD images from two green boxes are shown.

In Figure 7, ID and OOd examples with MaxLogit score and Context score are plotted.We also provide additional plots of Figure 3a with all prompt learning models and datasets used using 16-shot setting.

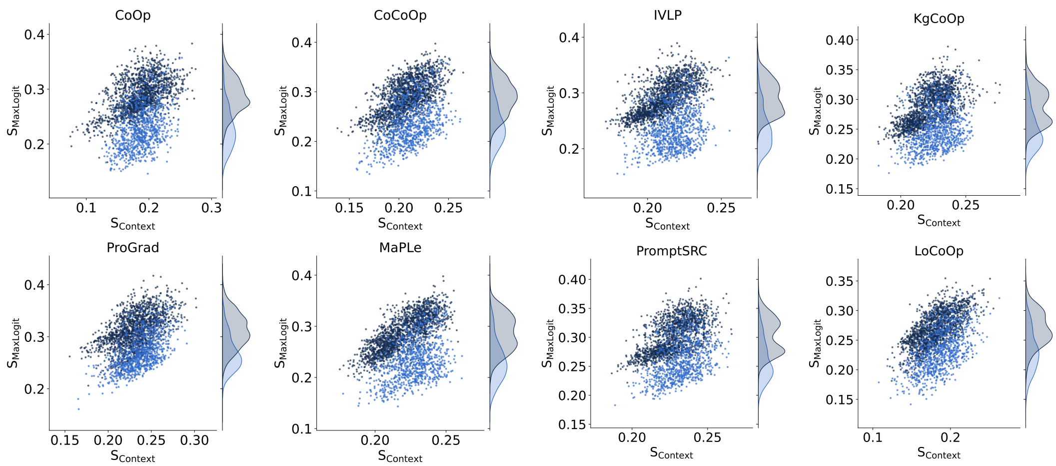


Figure 8: Additional demonstrations of the relationship between MaxLogit score and Context Score using Caltech101 (16-shots) with different prompt learning models.

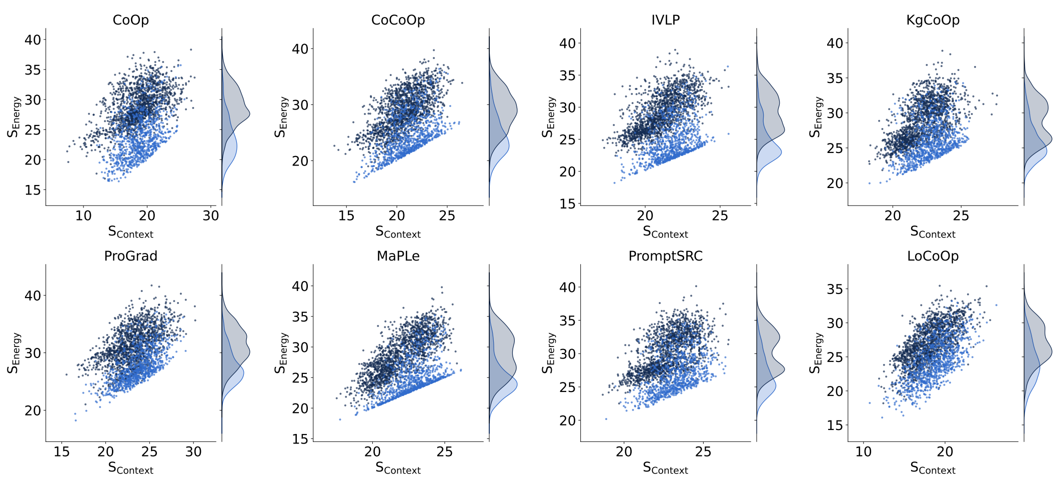


Figure 9: Additional demonstrations of the relationship between Energy score and Context Score using Caltech101 (16-shots) with different prompt learning models.

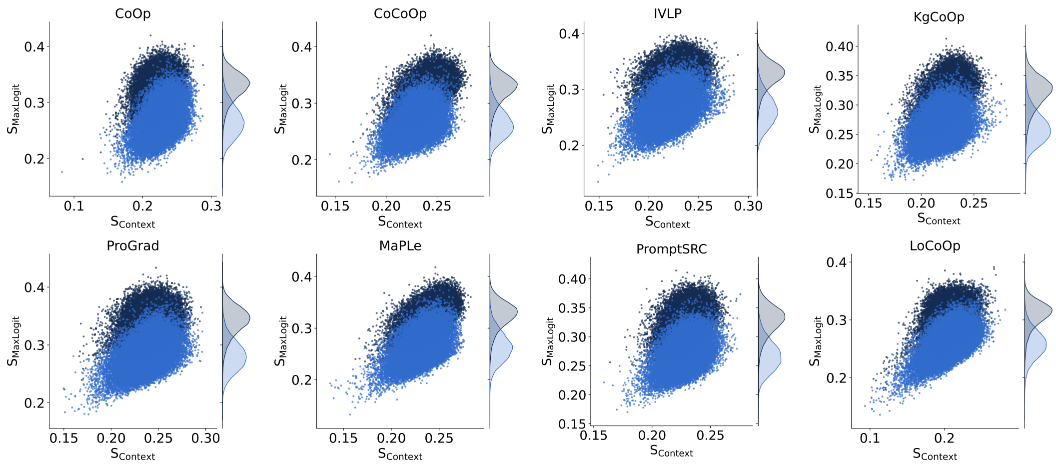


Figure 10: Additional demonstrations of the relationship between MaxLogit score and Context Score using ImageNet (16-shots) with different prompt learning models.

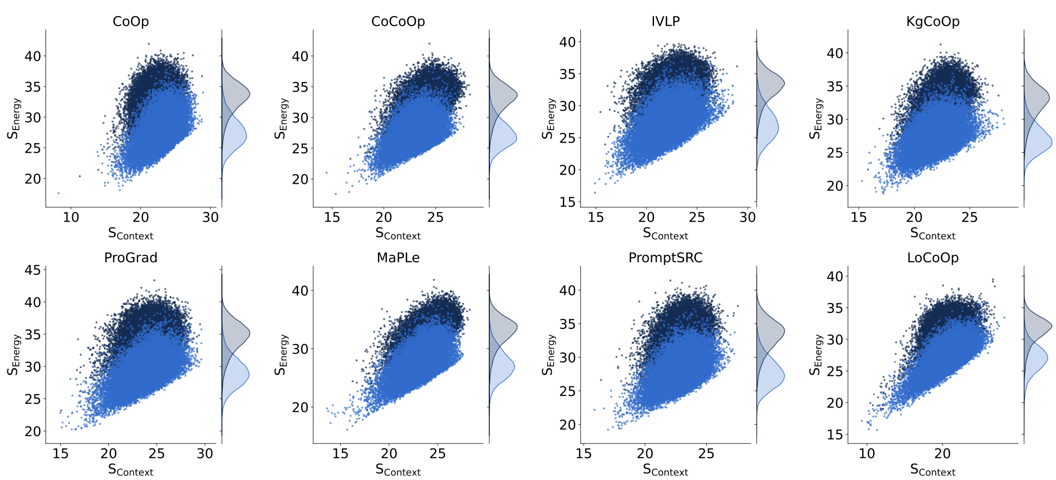


Figure 11: Additional demonstrations of the relationship between Energy score and Context Score using ImageNet (16-shots) with different prompt learning models.

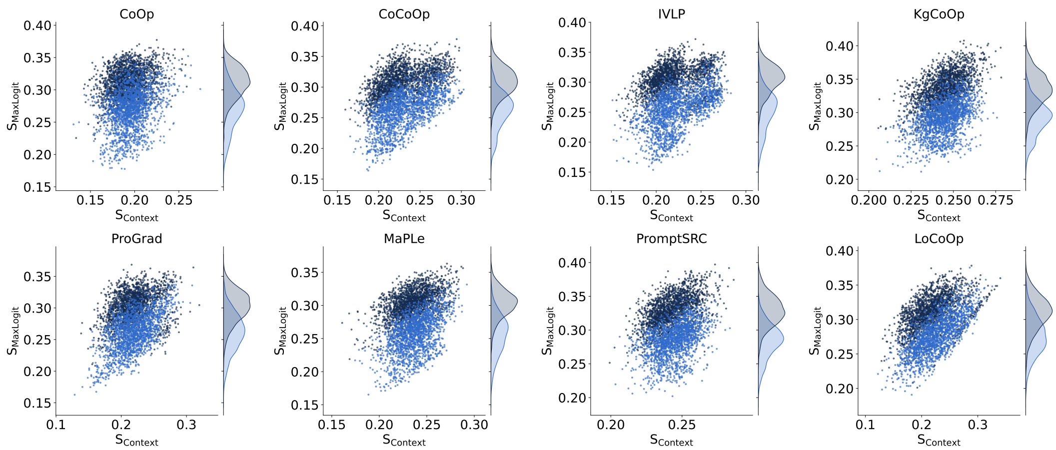


Figure 12: Additional demonstrations of the relationship between MaxLogit score and Context Score using OxfordPets (16-shots) with different prompt learning models.

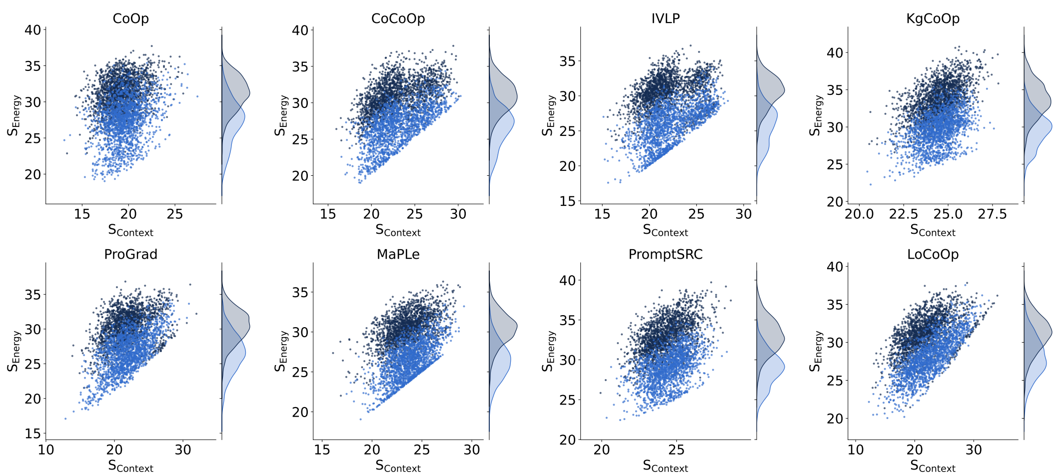


Figure 13: Additional demonstrations of the relationship between Energy score and Context Score using OxfordPets (16-shots) with different prompt learning models.

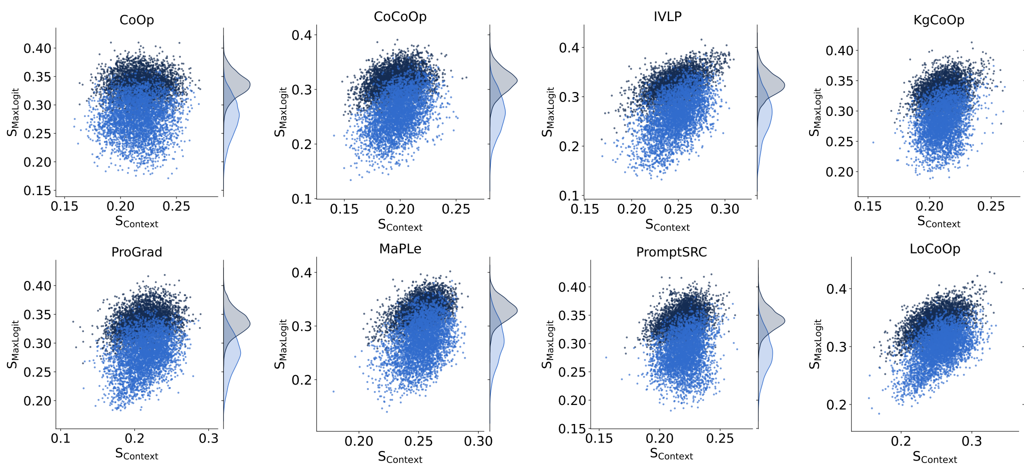


Figure 14: Additional demonstrations of the relationship between MaxLogit score and Context Score using StanfordCars (16-shots) with different prompt learning models.

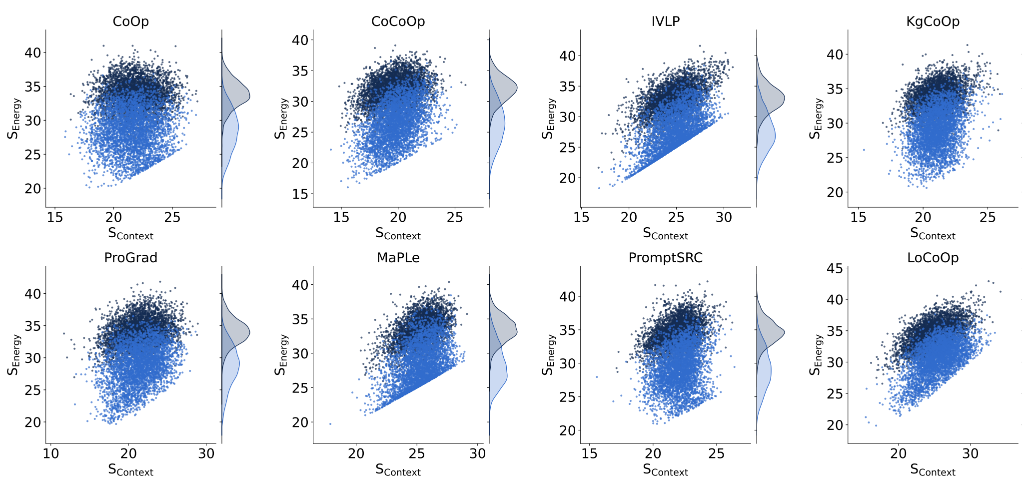


Figure 15: Additional demonstrations of the relationship between Energy score and Context Score using StanfordCars (16-shots) with different prompt learning models.

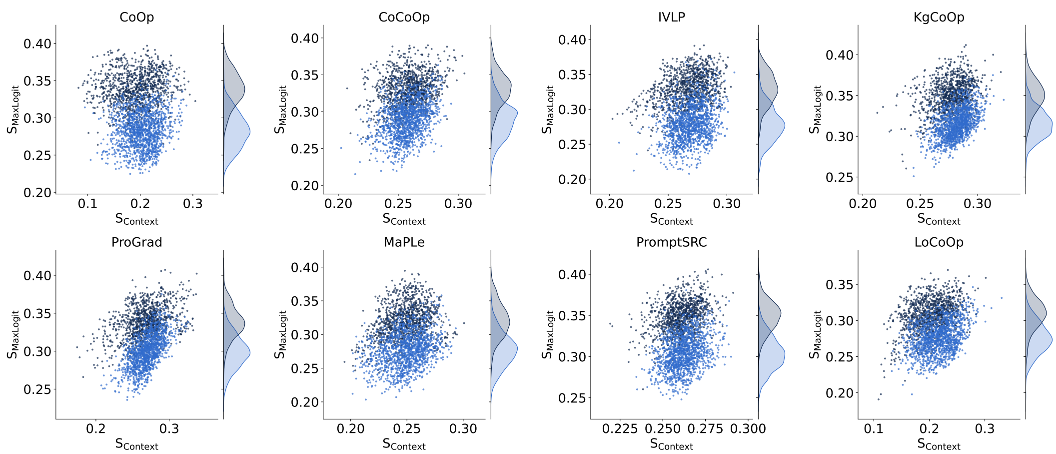


Figure 16: Additional demonstrations of the relationship between MaxLogit score and Context Score using Flowers102 (16-shots) with different prompt learning models.

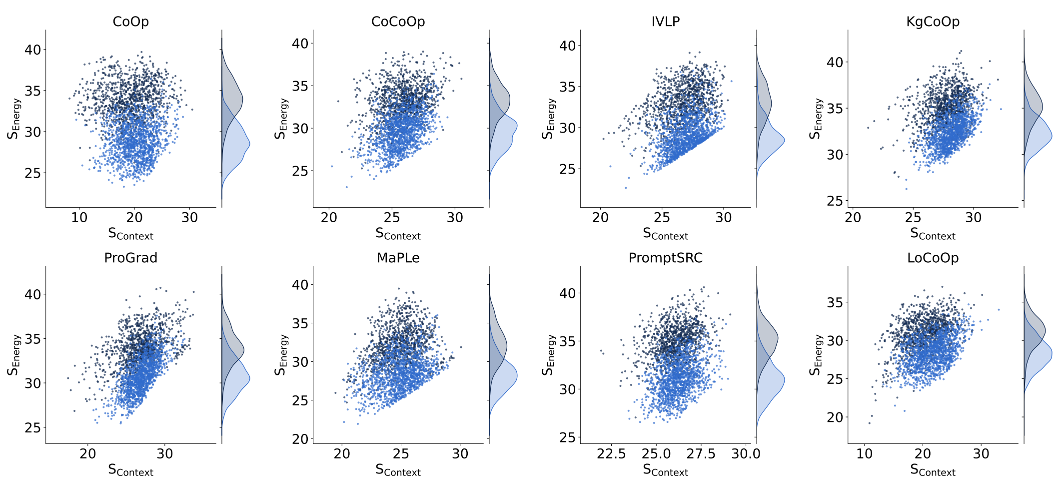


Figure 17: Additional demonstrations of the relationship between Energy score and Context Score using Flowers102 (16-shots) with different prompt learning models.

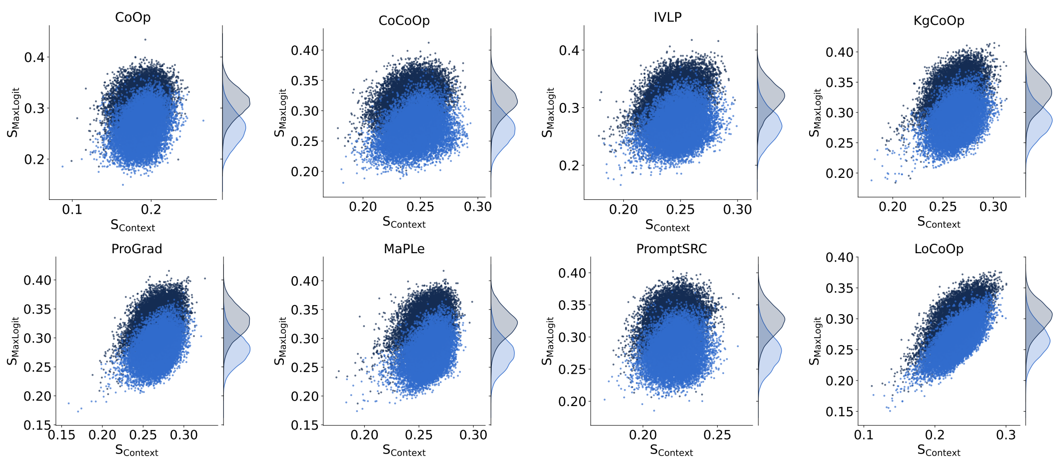


Figure 18: Additional demonstrations of the relationship between MaxLogit score and Context Score using Food101 (16-shots) with different prompt learning models.

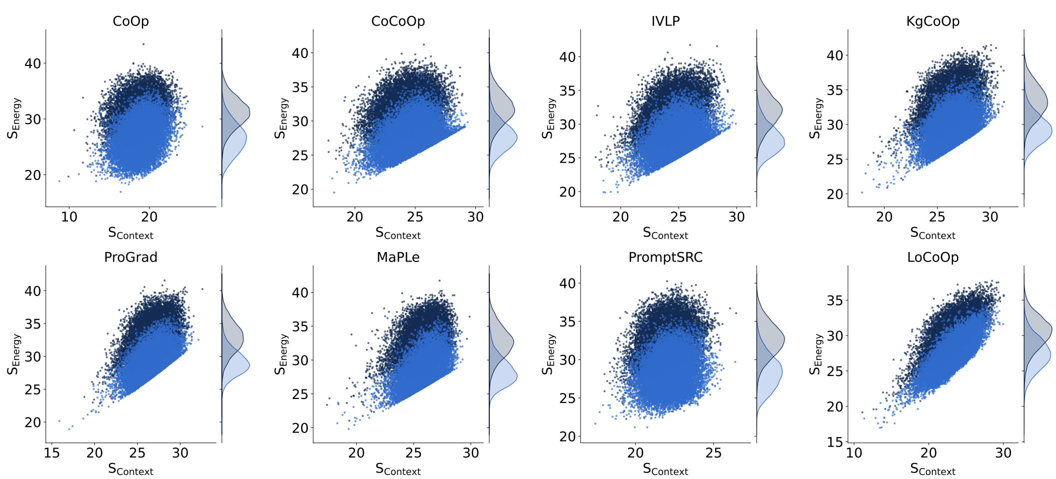


Figure 19: Additional demonstrations of the relationship between Energy score and Context Score using Food101 (16-shots) with different prompt learning models.

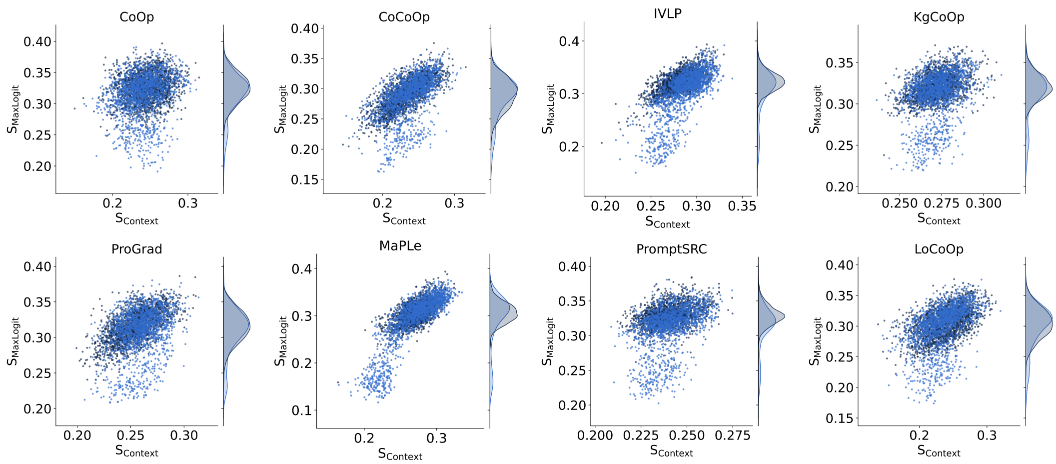


Figure 20: Additional demonstrations of the relationship between MaxLogit score and Context Score using FGVCAircraft (16-shots) with different prompt learning models.

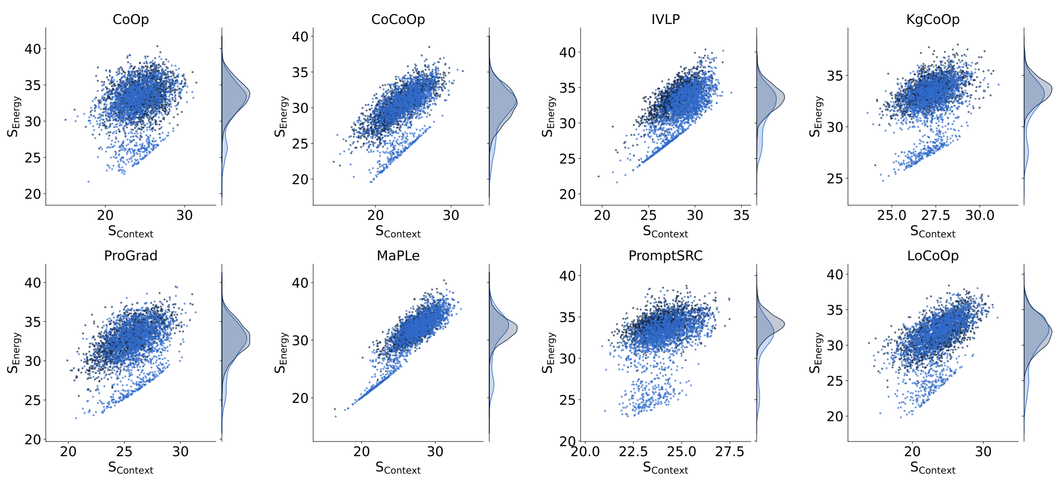


Figure 21: Additional demonstrations of the relationship between Energy score and Context Score using FGVCAircraft (16-shots) with different prompt learning models.

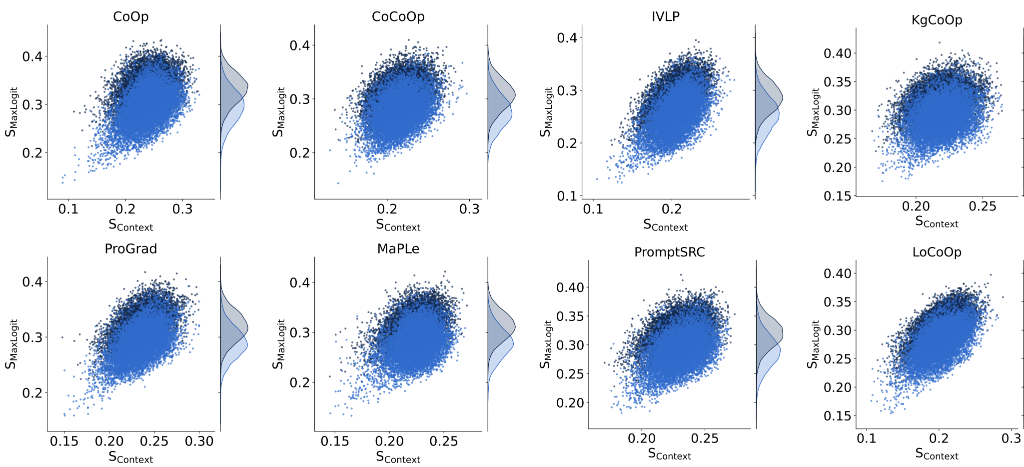


Figure 22: Additional demonstrations of the relationship between MaxLogit score and Context Score using SUN397 (16-shots) with different prompt learning models.

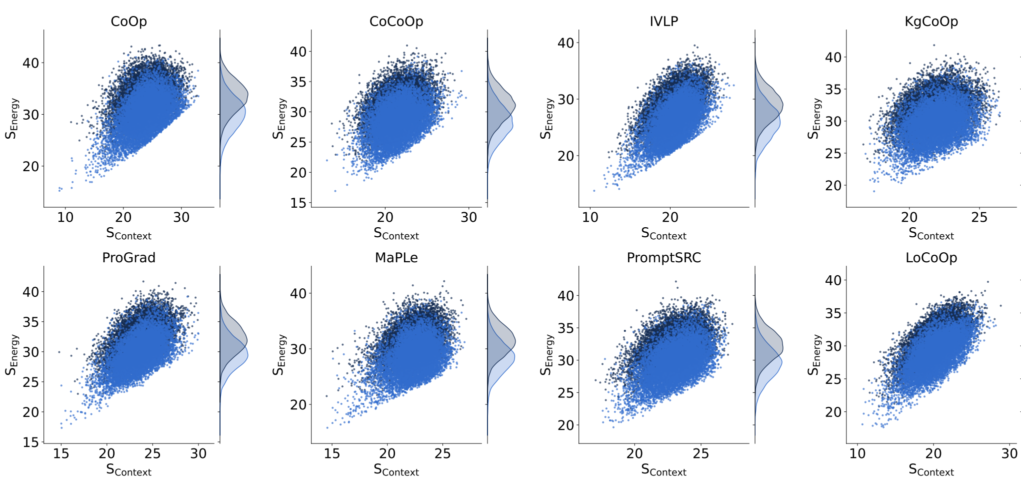


Figure 23: Additional demonstrations of the relationship between Energy score and Context Score using SUN397 (16-shots) with different prompt learning models.

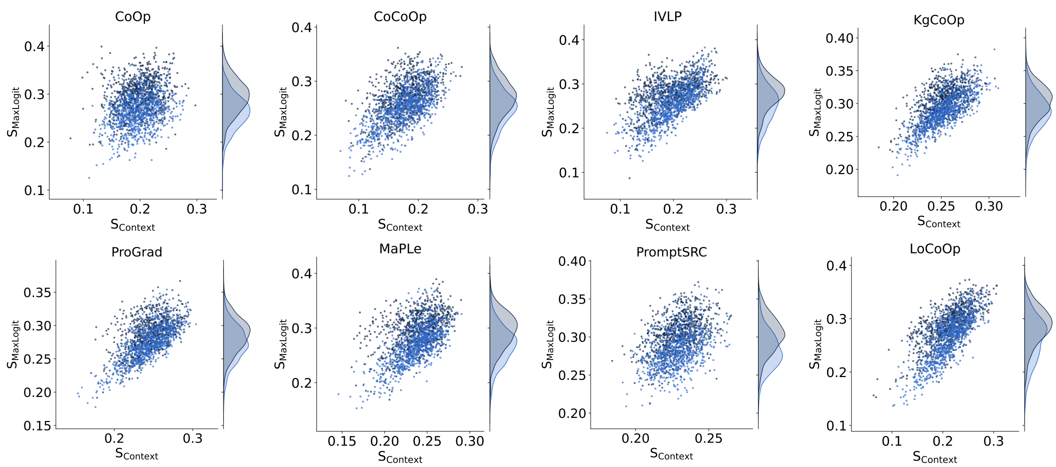


Figure 24: Additional demonstrations of the relationship between MaxLogit score and Context Score using DTD (16-shots) with different prompt learning models.

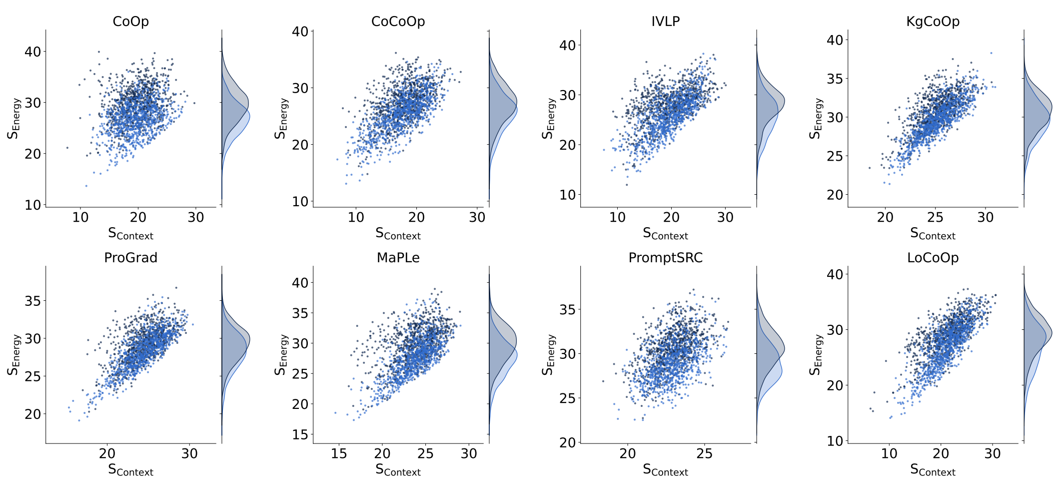


Figure 25: Additional demonstrations of the relationship between Energy score and Context Score using DTD (16-shots) with different prompt learning models.

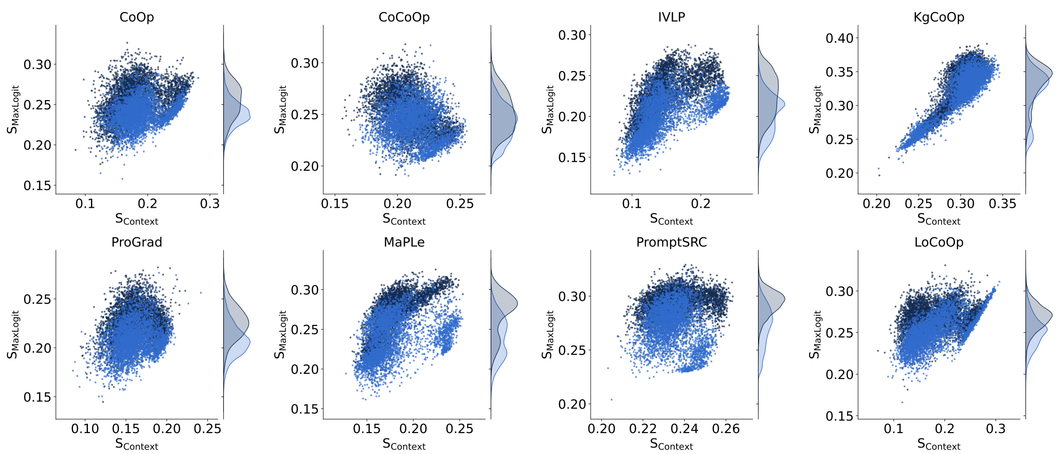


Figure 26: Additional demonstrations of the relationship between MaxLogit score and Context Score using EuroSAT (16-shots) with different prompt learning models.

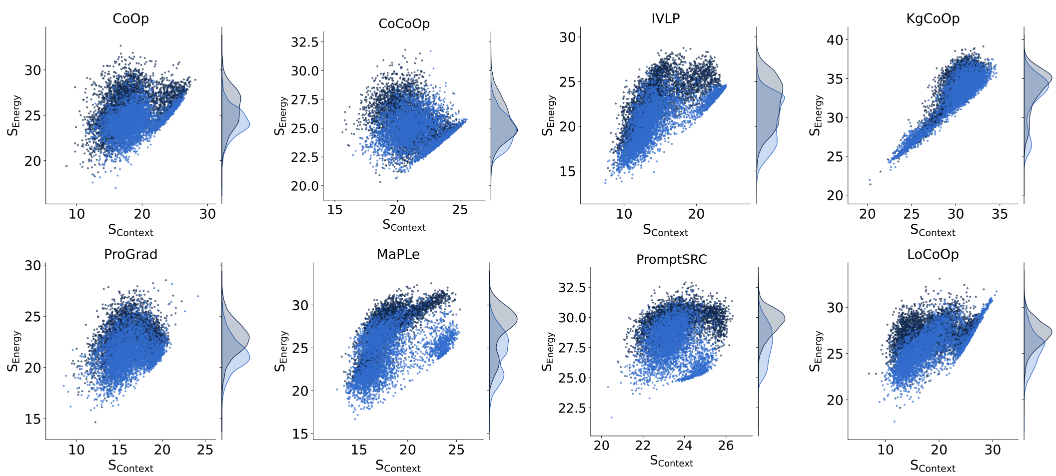


Figure 27: Additional demonstrations of the relationship between Energy score and Context Score using EuroSAT (16-shots) with different prompt learning models.

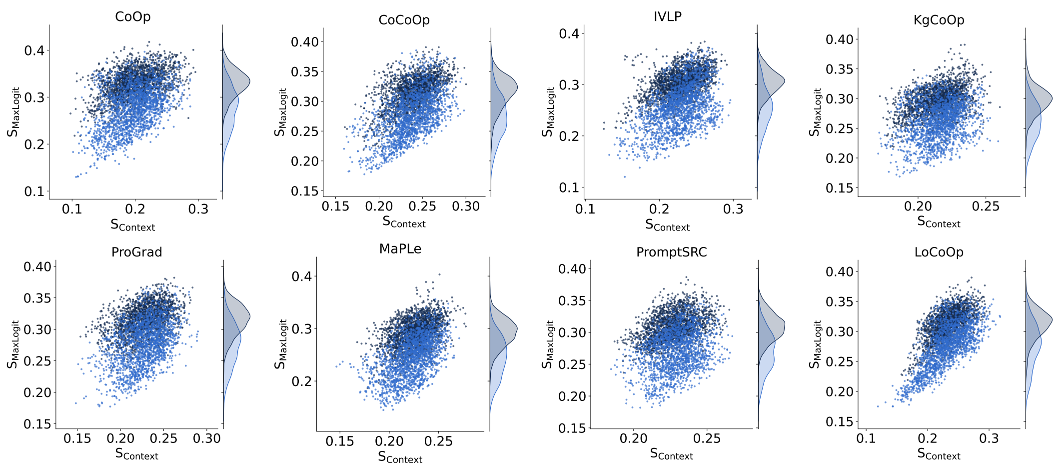


Figure 28: Additional demonstrations of the relationship between MaxLogit score and Context Score using UCF101 (16-shots) with different prompt learning models.

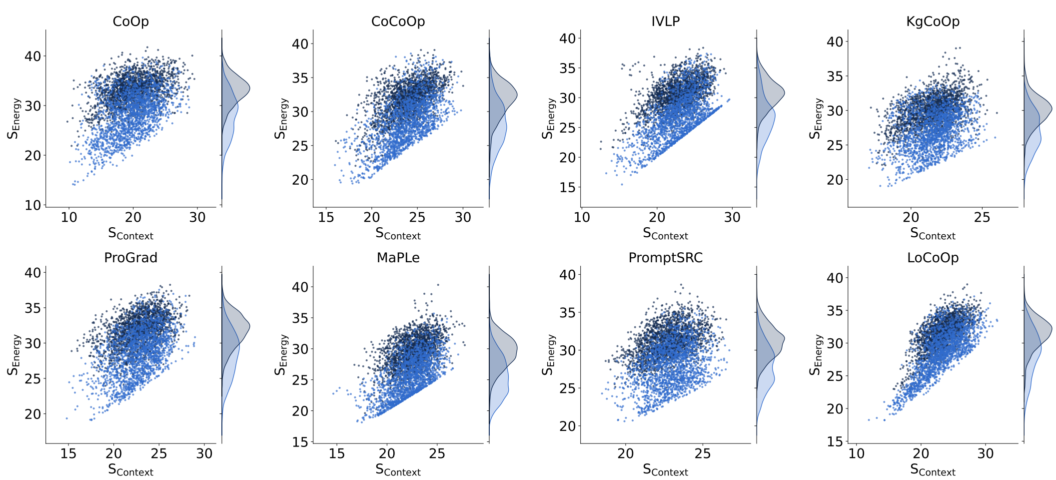


Figure 29: Additional demonstrations of the relationship between Energy score and Context Score using UCF101 (16-shots) with different prompt learning models.

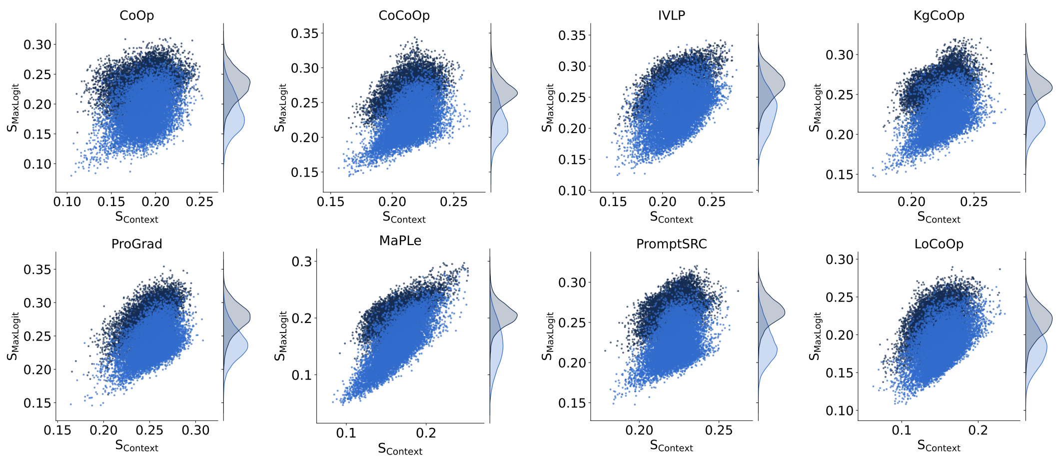


Figure 30: Additional demonstrations of the relationship between MaxLogit score and Context Score using CIFAR10 (16-shots) with different prompt learning models.

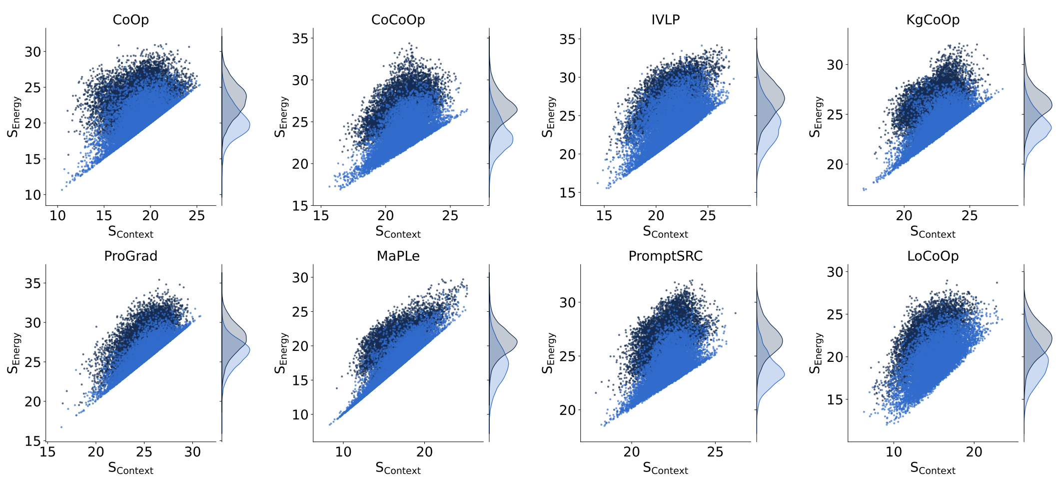


Figure 31: Additional demonstrations of the relationship between Energy score and Context Score using CIFAR10 (16-shots) with different prompt learning models.

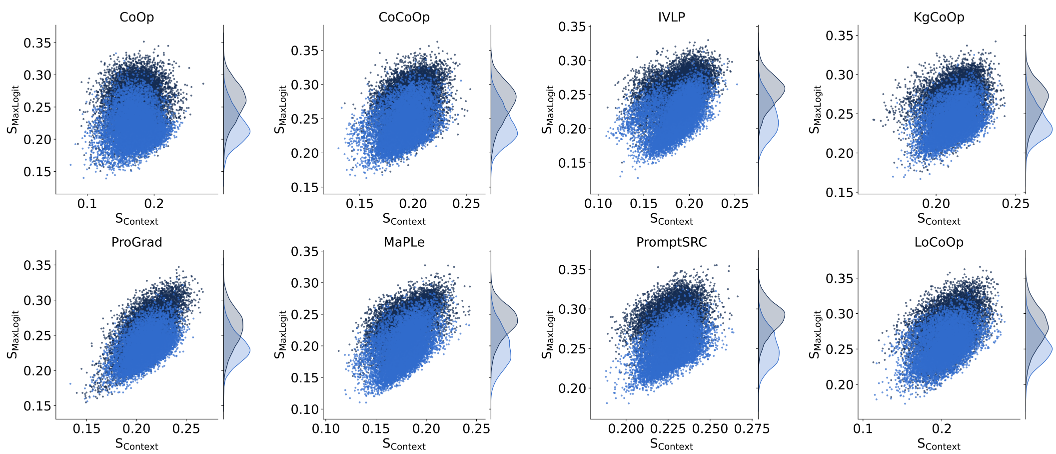


Figure 32: Additional demonstrations of the relationship between MaxLogit score and Context Score using CIFAR100 (16-shots) with different prompt learning models.

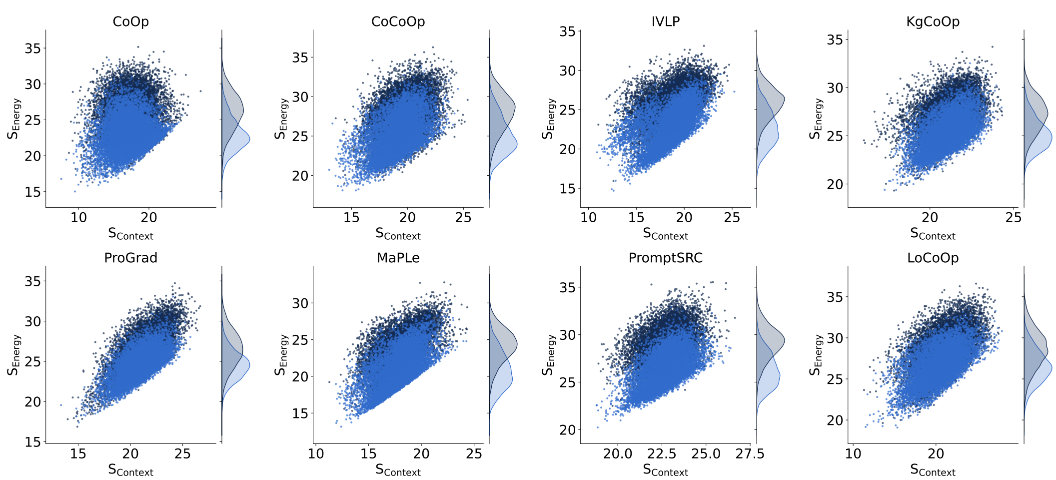


Figure 33: Additional demonstrations of the relationship between Energy score and Context Score using CIFAR100 (16-shots) with different prompt learning models.