Learning from Unknown for Open-Set Test-Time Adaptation

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Abstract

Deep learning models often struggle to maintain performance when the training and testing data come from different distributions. Test-time adaptation (TTA) addresses this by adapting a pre-trained model to an unlabeled target domain under distribution shifts. A more challenging setting is open-set TTA (OSTTA), where the target domain may contain unknown samples outside the source classes. Existing OSTTA methods primarily detect and discard such unknowns, relying only on known samples for adaptation. In this work, we argue that unknown samples can also provide valuable cues for improving adaptation. We propose LU-OSTTA (learning from unknown for OSTTA), a simple yet effective framework that leverages both in-distribution and semantically useful out-of-distribution samples. Our approach introduces: (i) a class-conditioned dynamic energy threshold to separate OOD samples more reliably, (ii) an optimal transport-based pseudo-label refinement to mitigate noise under distribution shifts, and (iii) an adaptive prototype weighting strategy that emphasizes semantically aligned target samples while down-weighting harmful ones. Extensive experiments on CIFAR-C and Tiny-ImageNet-C benchmarks demonstrate that LU-OSTTA consistently outperforms state-of-the-art TTA and OSTTA methods, highlighting the benefits of utilizing rather than discarding unknown samples.

1. Introduction

Deep learning has emerged as a key solution for computer vision tasks when the training and testing data are derived from the same distribution. However, in real-world settings, this assumption often does not hold due to discrepancies between the training and test samples [6, 20, 38]. This is primarily because train (source) and test (target) data are collected from different distributions. Moreover, target data can be corrupted during online batch adaptation.

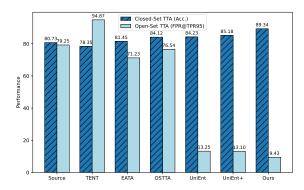


Figure 1. Existing TTA methods exhibit performance degradation when unknown classes are included, while OSTTA methods handle open-set distributions more effectively but still fall short. Our method significantly improves performance in the open-set setting. We compare Source [77], TENT [64], CoTTA [66], EATA [52], OSTTA [34], UniEnt [20], and UniEnt+ [20] on CIFAR-10-C.

To address these limitations, test-time adaptation (TTA) [4,50,66,75,80,82] methods provide a holistic solution by enhancing the learning capabilities of a source model without requiring access to the source data, thereby improving robustness and consistency. They also help mitigate inherent privacy concerns during deployment.

Test-Time Training [3, 19, 45, 62] introduces an auxiliary rotation prediction task that is self-supervised. However, it offers a source-free learning facility but requires altering the source training protocol, which eventually limits the practicability of the fully test-time adaptation task. Distribution shift can happen often, but further model tuning is not usually feasible due to lack of labels in target domain and computational resources. Meanwhile, TTA offers online adaptation of unlabeled target data without explicit fine-tuning [7]. Existing TTA methods are based on entropy minimization, where models adopt the samples that contribute to lower entropy. However, if the model encounters open classes during adaptation, the performance usually degrades.

On the other hand, out-of-distribution (OOD) detection [17,18,43,56] aims to detect samples not fully related to the training samples. But, models tend to classify OOD data as

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one of the in-distribution (ID) data that hinders the predictive performance [21,49]. Existing methods are focused on dealing with covariate shift instead of semantic shift. Following recent literature, semantic shift refers to "out of the semantic spaces". In this work, we define *unknown samples* as those exhibiting semantic shift, while known samples include both ID and covariate-shifted variants.

Motivation. In practical deployment, the target domain often contains strong unknown OOD samples. Existing OSTTA methods [20, 34] mainly attempt to separate or discard such samples. However, we argue that not all unknowns are harmful: certain unknown samples can provide valuable semantic cues, reducing prediction entropy in ways similar to known samples. Prior works overlook these semantically useful unknowns, discarding them indiscriminately. As shown in Fig. 1, source models fail to adapt effectively under both closed- and open-set conditions. Standard TTA methods [52, 64] degrade in open-set scenarios due to incorrect normalization statistics and ineffective OOD filtering. OSTTA methods [20, 34] improve robustness but still underperform, as they cannot distinguish helpful unknowns from harmful ones. This motivates us to explicitly leverage semantically useful unknown samples for more effective open-set adaptation.

Our Approach. Motivated by these observations, we propose LU-OSTTA, a framework that handles unknown-class samples often encountered in real-world deployment. Instead of solely detecting and rejecting harmful samples during adaptation, our method leverages semantically useful unknown samples through a weighted mechanism for openset adaptation. To enhance robustness in open-set settings, we introduce a dynamic energy threshold (DET), a classconditioned variant of the energy threshold that dynamically adjusts on a per-class basis to better distinguish between weak and strong OOD samples. Since noisy labels are common under distribution shift and further increased when OOD samples are encountered during test time, we propose employing optimal transport (OT) to refine pseudo labels by aligning teacher and student predictions, thereby alleviating noise due to the open-set setting. To further separate and exploit semantically helpful unknowns, we propose an adaptive prototype weighting strategy, which maintains source and target prototype memory banks, and assigns semantic weights based on similarity to source prototypes. We incorporate contrastive loss with entropybased regularization to ensure that only semantically useful and informative unknown samples contribute to adaptation, while down-weighting strong OOD samples. Lastly, to demonstrate the effectiveness of our proposed approach, we conducted comprehensive experiments under the openset protocol described in [20].

Contributions. In summary, our main contributions are:

• We identify a critical limitation of prior works: dis-

- carding all unknown samples ignores their potential to enhance adaptation. We instead propose leveraging semantically helpful unknowns for improved open-set performance.
- We introduce a dynamic energy threshold (DET) that performs class-conditioned thresholding, enabling more reliable separation of known and unknown samples. We further refine pseudo-labels via optimal transport, improving supervision under distribution shift.
- We design an adaptive prototype weighting mechanism that emphasizes semantically aligned unknown samples while down-weighting harmful ones during adaptation.
- Our method is evaluated on multiple open-set TTA protocols, where it exhibits significantly higher performance compared to other OSTTA and TTA methods.

2. Related Work

Test-Time Adaptation. Test-time adaptation (TTA) [52,53, 64, 75] is a promising direction in domain adaptation research. TTA aims to generalize to unseen target domains using a pre-trained source model. Unlike traditional domain adaptation, TTA does not assume that the source and target data come from the same distribution. A notable entropyminimization-based TTA method, TENT [64], minimizes prediction entropy to update the affine parameters γ and β in batch normalization, thereby improving model adaptation. Based on this criterion, the entropy minimization loss function becomes the sole objective for updating batch normalization layers. EATA [52] introduces a sample selection strategy that excludes high-entropy samples from adaptation. SAR [53] adopts gradient-based sample selection, encouraging model weights to converge toward flat minima with small gradients. DeYO [35] further argues that entropy alone is insufficient for robust adaptation and proposes object-destructive transformations as an additional filtering step. In contrast to sample selection, some TTA methods [14,47,51,63] focus on improving the optimization objective so that all samples can contribute to adaptation. Other approaches, such as refining pseudo labels [16, 46] or batch normalization [54], have also demonstrated strong TTA performance. Recently, open-set TTA (OSTTA) has gained attention due to its practical significance. OSTTA methods [20, 34] account for the possibility that target data may contain unknown samples. These approaches detect both covariate-shifted in-distribution (csID) and out-ofdistribution (csOOD) data, and adapt only the csID samples to achieve robust OSTTA. Another work, ODS [83], considers label shift for open-world TTA. Moreover, TTA has been widely applied across diverse tasks, including object detection [5, 32, 57], action recognition [70], superresolution [15, 81], visual question answering [42, 68], and video understanding [1,40,78], demonstrating its versatility as a practical solution.

OOD Detection. Out-of-distribution (OOD) detection is essential for building safe machine learning systems, as it enables the identification of samples that fall outside the training distribution. This capability is crucial for anomaly detection, open-set recognition, novelty detection, and detecting covariate domain shifts [8,28,72]. OOD detection methods can be broadly categorized into several directions [72]. Post-hoc methods [61, 65] improve OOD detection without modifying pre-trained models. Other approaches, such as ReAct [60], adjust model activations to yield more informative energy scores. A widely used baseline is softmaxbased detection, where prediction entropy is computed from the softmax output. Temperature scaling further calibrates model uncertainty by rescaling logits [60], while Generalized Entropy (GEN) [44] enhances softmax-based scoring. Another line of work leverages additional outlier data for OOD detection [31,71,79]. OE [26] encourages low model confidence for OOD samples, whereas WOODS [31] exploits unlabeled "wild" data to improve detection performance. Gradient-based approaches, such as ODIN [39] and MDS [36], apply input perturbations during inference as a pre-processing step to improve OOD discrimination. Grad-Norm [29] and Approximate Mass [22] instead use gradient norms to define OOD scores. More recently, test-time OOD detection has emerged as a way to improve robustness [73, 74]. AUTO [73] introduces a test-time modification strategy using stochastic gradient decent to reduce model confidence on potential OOD samples. OODD [74] proposes a dynamic OOD dictionary that accumulates OOD features during test time to enhance detection.

Open-Set Domain Adaptation. Open-Set Domain Adaptation (OSDA) addresses the challenge of unknown classes that exist in the target domain but are absent in the source domain. The goal of OSDA is to reduce the distribution gap between source and target domains while simultaneously detecting unknown classes. Existing approaches [41, 58, 59, 67] typically group unknown-class samples together and transfer knowledge from known classes for alignment. For example, OSBP [59] employs pseudo labels to guide classifier learning while rejecting unknown samples during source-target alignment. STA [41] introduces a weighting mechanism that distinguishes between known and unknown samples, gradually adjusting their importance for feature alignment. OVANET [58] adopts a one-vs-all classifier to model inter- and intra-class distances, minimizing sample entropy to better detect unknown samples. UADAL [30] proposes a segregation strategy to identify samples that are far from the source distribution. Finally, OSLPP [67] learns a discriminative common subspace between source and target features and progressively selects unknown-class samples to improve model training.

Discussion. While TTA, OOD detection, and OSDA have each advanced robustness under distribution shifts, they face limitations when unknown samples appear during adaptation. Existing OSTTA approaches primarily reject unknowns, thereby discarding potentially useful semantic information. While OOD detection is effective at detecting OOD data, do not integrate such samples into adaptation. On the other hand, OSDA assumes access to source data and is not suited for fully test-time settings. Our work addresses this gap by introducing a framework that leverages semantically helpful unknown samples, refines pseudo labels under distribution shift, and adaptively weights prototypes to enable more effective open-set test-time adaptation.

3. Method

3.1. Preliminary

Task Definition. During test-time adaptation, a source model adapts to a target domain with n_t samples in the test set \mathcal{D}_t , which were not observed in the source domain. Let a source domain with labeled samples $\mathcal{D}_s =$ $\{(x_i^s, y_i^s)\}_{i=1}^{n_s}$ and target domain only has unlabeled samples $\mathcal{D}_t = \{(x_i^t)\}_{i=1}^{n_t}$, as y_t^i is not available during testing. Additionally, we designate C_s to be the representative to source classes and C_t to be the target classes. In closedset TTA settings, C_s is equal to C_t . While in open-set TTA, $|\mathcal{C}_s| < |\mathcal{C}_t|$ always holds, where $\mathcal{C}_s \subset \mathcal{C}_t$, and $\mathcal{C}_t \setminus \mathcal{C}_s$ is called unknown classes. So, given a model f_{θ} , pre-trained on \mathcal{D}_s , aims to adapt \mathcal{D}_t without accessing the target labels. Specifically, given a mini-batch \mathcal{B} from the test set, the goal is to adapt samples from known classes C_s and also adapt classes from C_t that are weak OODs but considered as unknown.

Framework Overview. To address the open-set test-time adaptation (OSTTA) problem, we propose a framework, LU-OSTTA, which leverages both in-distribution and outof-distribution samples under distribution shifts that often encountered in the target domain. An overview of the framework is illustrated in Fig. 2. LU-OSTTA is composed of three key modules: (1) dynamic-energy threshold, (2) OT-based pseudo-label refinement, and (3) adaptiveprototype weighting. First, the dynamic-energy threshold enables fine-grained separation between in-distribution and OOD samples by adjusting thresholds on a per-class basis, preventing over-reliance on a global cutoff. Next, the OT-based pseudo-label refinement calibrates noisy pseudolabels caused by distribution shifts through distributionlevel alignment between teacher and student predictions. Finally, the adaptive-prototype weighting emphasizes semantically aligned target samples while down-weighting highly uncertain ones, ensuring that only informative OOD samples contribute to adaptation. Our framework effectively utilizes semantically useful unknown samples rather than discarding them, leading to more robust and efficient online adaptation under open-set conditions. Further descriptions of the proposed modules are discussed below.

3.2. Dynamic-Energy Threshold for OOD Detection

OOD sample detection is a binary classification problem that provides a boundary between in- and out-of-distribution samples. However, previous methods [25, 49, 69] rely on softmax scores to distinguish between these samples. But models have the tendency to assign arbitrarily high confidence for OOD samples. Energy-based scores overcome this limitation [9,43] by mapping each sample as a scalar that is lower for ID-data but higher for OOD data. Here, a density function of data p(x) that has a low likelihood score can be considered as an OOD sample. Energy of a given input (x,y) is E(x,y) = -f(x) where f(x) is a discriminative neural classifier. Free energy function is defined as $E(\mathbf{x};f) = -T \cdot \log \sum_{i}^{K} e^{f_i(\mathbf{x})/T}$, where T is the softmax temperature. Based on the energy free function, OOD detection is defined as:

$$g(\mathbf{x}; \tau, f) = \begin{cases} 1, & \text{if } -E(\mathbf{x}; f) > \tau, \\ 0, & \text{otherwise.} \end{cases}$$
 (1)

where τ is the energy threshold and g(x) is the OOD detector. The threshold is derived carefully from the indistribution data for better OOD detection and separability [43]. However, a fixed global threshold can eliminate too many unlabeled samples which can potentially be useful OOD samples. Moreover, naively eliminating OOD samples can eventually negatively affect the model's performance, especially in class-imbalance settings. To address this limitation, we propose a *dynamic-energy threshold* that can dynamically adjust the threshold on a per-class basis. To achieve this, we apply a class-conditioned energy statistics (μ_c, σ_c) , and define a class-conditioned threshold,

$$\tau_c = \mu_c + \beta \sigma_c \tag{2}$$

where β is a scaling hyperparameter. Given a test sample x with a pseudo label \hat{y} . We assign a soft weight based on its normalized energy:

$$w_c(\mathbf{x}) = \exp\left(-\gamma \cdot \frac{E(\mathbf{x}; f) - \mu_c}{\sigma_c + \varepsilon}\right)$$
 (3)

where γ is a hyperparameter that controls the sharpness of down-weighting, and ε enforces numerical stability. This weighting strategy ensures low energy samples such as ID-samples obtain higher weights while OOD-samples are down-weighted rather than fully rejected by other works [20,37]. Finally, our adaptation incorporates these dynamic weights into the unsupervised loss:

$$\mathcal{L}_{dyn}(\theta) = \frac{1}{\sum_{\mathbf{x} \in \mathcal{B}_t} w_{\hat{y}}(\mathbf{x})} \sum_{\mathbf{x} \in \mathcal{B}_t} w_{\hat{y}}(\mathbf{x}) \cdot \ell(\mathbf{x}; \theta)$$
(4)

Our dynamic thresholding based on the energy score allows the model to retain useful OOD samples that are semantically aligned with source classes, while rejecting extreme outliers. As a result, it can adaptively balance between ID samples and extracting useful information from OOD data instead of just rejecting them during test-time adaptation.

3.3. Optimal Transport for Refined Pseudo Labels

In TTA setting, unreliable pseudo labels often occur due to dynamic distribution shifts in the test set. However, models often show higher confidence in OOD samples, but that can be incorrect. Higher confidence leads to noise during adaptation that hinders the model's performance. Taking inspiration from OT due to its success in domain adaptation tasks [2, 10, 11, 55], we propose Optimal Transport based **P**seudo-Label refinement (**OTPL**) strategy. Let $p_T(\mathbf{x})$ and $p_S(\mathbf{x})$ be the predictive distributions of a teacher and student model respectively. In general setting, consistency regularization is enforced to ensure similarity between $p_T(\mathbf{x})$ and $p_S(\mathbf{x})$ on unlabeled target samples. We leverage OT to align the teacher and student distributions instead of minimizing their discrepancy for each sample. Given a cost function $C(p_T, p_S)$ that minimizes their disagreement, we compute OT coupling such as:

$$\min_{T \in \Pi(p_T, p_S)} \langle T, C \rangle + \varepsilon H(T) \tag{5}$$

where $T \in \mathbb{R}_+^{n \times m}$ is the transport plan, $\Pi(p_T, p_S)$ denotes the set of couplings with marginals p_T and p_S , and H(T) is the entropy regularizer. This formulation is efficiently solved with the Sinkhorn algorithm [13]. Distribution-level alignment between teacher and student predictions is achieved by OT plan T. Thus, we define refined pseudo-labels as:

$$q(\mathbf{x}_i) = \sum_{j} T_{ij} \tag{6}$$

where $q(\mathbf{x}_i)$ represents a smoothed distribution over classes that aligns both teacher and student predictions. These refined labels alleviate the risk of overconfidence in model predictions and ensure correct pseudo-labels. Furthermore, the student model is then optimized with KL divergence loss between its prediction and the OT refined pseudo-labels:

$$\mathcal{L}_{OT} = \mathbb{E}_{\mathbf{x} \sim \mathcal{D}_t} \text{ KL} (p_S(\mathbf{x}) \parallel q(\mathbf{x}))$$
 (7)

This ensures the student model remains consistent with the teacher while having better and calibrated pseudo-labels.

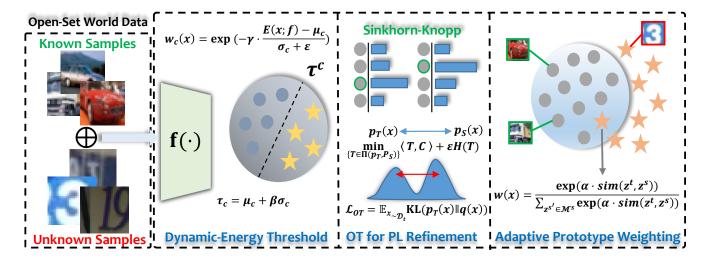


Figure 2. An overview of our *learning from unknown* OSTTA (LU-OSTTA) method. Real-world data can contain unknown samples during testing. Our framework deals with these unknown samples, and learn useful information from them to improve open-set adaptation performance. We identify known and unknown samples, then refine noisy pseudo labels. Lastly, we learn semantically useful unknown samples via a weighted contrastive objective.

This OT-based pseudo-label refinement method jointly ensures calibration and consistency between pseudo-labels while preventing noisy labels that often occur during distribution shifts. It also ensures class-level structure in the target domain due to down-weighting unreliable predictions. It is worth mentioning that the OT-based refinement strategy complements our dynamic-energy thresholding because pseudo-labels are retained after prior class-conditioned thresholding, further calibrated to guide the adaptation process effectively.

3.4. Adaptive-Prototype Weighting

Even though dynamic-energy thresholding and OT-based refinement enforce utilization of better pseudo labels and OOD samples for adaptation. But there are some target samples that can be highly uncertain and far from the source classes. Naively rejecting them can diminish the potential of utilizing unknown samples. On the other hand, utilizing them directly for adaptation can cause the risk of negative transfer due to the mismatch between known and unknown classes [41]. To address this challenge, we introduce an *adaptive-prototype weighting* mechanism that selectively emphasizes target samples based on their semantic proximity to source prototypes. We maintain source and target memory banks \mathcal{M}^s and \mathcal{M}^t to store prototypes respectively.

$$\mathcal{M}^{s} = [m_{1}^{s}, m_{2}^{s}, \dots, m_{N_{s}}^{s}],$$

$$\mathcal{M}^{t} = [m_{1}^{t}, m_{2}^{t}, \dots, m_{N_{s}}^{t}]$$
(8)

Here, feature vector of x_i is stored in m_i , and updated after each batch with a momentum v.

$$m_i \leftarrow v m_i + (1 - v) \mathbf{f}_i \tag{9}$$

We perform k-means clustering to get clusters $C_s = [c_1^s, c_2^s, \ldots, c_{N_s}^s]$ and $C_t = [c_1^t, c_2^t, \ldots, c_{N_t}^t]$ on \mathcal{M}^s and \mathcal{M}^t [76]. We also retrieve normalized source and target prototypes $\{\mu_j^s\}_{j=1}^{N_s}$ and $\{\mu_j^t\}_{j=1}^{N_t}$. Using the source model, we extract features \mathbf{f}_i and compute similarity distribution between \mathbf{f}_i and $\{\mu_j^t\}_{j=1}^n$ (which is similar for $\{\mu_j^s\}_{j=1}^n$ too):

$$\mathcal{P}_{i,j}^{s} = \frac{\exp(\mu_{j}^{t} \cdot \mathbf{f}_{i}/\tau)}{\sum i = 1^{k} \exp(\mu_{j}^{t} \cdot \mathbf{f}_{i}/\tau)}$$
(10)

where τ is temperature parameter. This distribution captures how well a sample aligns with different target clusters. As target domain samples are unlabeled and far from the source distribution due to shift, it is hard to find which target sample contains semantically useful information among OOD. To address this, we compute a semantic weight w(x) for each target OOD sample ${\bf x}$ based on its similarity with source prototypes:

$$w(\mathbf{x}) = \frac{\exp(\alpha \cdot \sin(z^t, z^s))}{\sum_{z^{s'} \in \mathcal{M}^s} \exp(\alpha \cdot \sin(z^t, z^{s'}))},$$
 (11)

where z^t and z^s are the target and source embeddings. And α is a scaling factor. This weighting enforces target samples that are close to the source prototype as candidates during adaptation. To align target samples with the source prototype, we enforce contrastive loss with $w(\mathbf{x})$:

$$\mathcal{L}_{con} = -\frac{1}{|\mathcal{B}_t|} \sum_{\mathbf{x} \in \mathcal{B}_t} w(\mathbf{x}) \cdot \log \frac{\exp\left(\sin(z^t, z^s)/\tau\right)}{\sum_{z^{s'} \in \mathcal{M}^s} \exp\left(\sin(z^t, z^{s'})/\tau\right)},$$
(12)

This ensures that semantically useful OOD samples contribute during adaptation, while highly uncertain samples are down-weighted. Finally, to prevent mode collapse, and ensure balanced predictions across class, we add an entropy regularizer:

$$\mathcal{L}_{\text{ent}} = -\frac{1}{|\mathcal{B}_t|} \sum_{\mathbf{x} \in \mathcal{B}_t} \sum_{c=1}^K p(c|\mathbf{x}) \log p(c|\mathbf{x}), \quad (13)$$

Here, \mathcal{L}_{con} and \mathcal{L}_{ent} ensure that semantically useful OOD samples guide the adaptation process while avoiding mode collapse and maintaining diverse decision boundary.

3.5. Training Objective

During test-time adaptation, the student model f_{θ} is optimized on unlabeled target samples \mathcal{D}_t using a combination of dynamic-energy loss \mathcal{L}_{dyn} , OT-based pseudo-label refinement loss \mathcal{L}_{OT} , \mathcal{L}_{con} and \mathcal{L}_{ent} . For a target batch \mathcal{B}_t , the total training objective can be written as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{dvn}} + \lambda_{OT} \mathcal{L}_{OT} + \lambda_{\text{con}} \mathcal{L}_{\text{con}} + \lambda_{\text{ent}} \mathcal{L}_{\text{ent}}$$
 (14)

where λ is a hyperparameter that balances the contribution of all losses. Minimizing \mathcal{L}_{total} encourages the student model to adapt robustly to the target domain while leveraging potentially useful unknown samples instead of discarding them.

4. Experiments

4.1. Experimental Setup

Datasets. We follow previous TTA studies; we evaluate our method with commonly used corruption benchmark datasets: CIFAR-10-C, CIFAR-100-C, and Tiny-ImageNet-C [24]. Each of the datasets has 15 different corruptions with 5 severity levels from 1 to 5, and we use the highest level. Models pre-trained with clean source training data (CIFAR-10, CIFAR-100, and Tiny-ImageNet) are adapted to corrupted datasets. Following [20, 34], we apply the identical corruption to SVHN [48] and ImageNet-O [27] datasets, and create SVHN-C and ImageNet-O-C datasets to incentivize the open-set setting with unknown classes. All open-set samples were resized as the closed-set samples and to the same corruption level.

Evaluation Settings. We follow the common TTA protocol where the model is evaluated under continuously changing domains without resetting its parameters after adapting to

each domain. During inference, corrupted target samples are streamed in an online manner. For each mini-batch, the model first predicts the labels and updates its parameters using the same mini-batch. To construct the mini-batches, we sample an equal number of known (in-distribution) and unknown (out-of-distribution) samples to simulate the openset scenario. We adopt evaluation setup from [20]. We report the classification accuracy on known target samples to measure the adaptation performance. Second, to evaluate the separation of known and unknown samples, we report the area under the ROC curve (AUROC), false positive rate at 95% TPR (FPR@95) and the Open-Set Classification Rate (OSCR), which jointly measure classification and rejection performance across decision thresholds.

Implementation Details. We follow the previous standard TTA [52, 64] and OSTTA [20, 33] setups; we use WideResNet-40 for CIFAR benchmarks, pre-trained on a clean dataset using AugMix augmentation provided by RobustBench [12]. For Tiny-ImageNet-C, the ResNet-50 model is pre-trained on Tiny-ImageNet. During TTA, the Adam optimizer with a learning rate of 0.001 and a batch size of 200 is used for all experiments. Particularly, learning rate is set to 0.01 for TENT [64], EATA [52], CoTTA [66] and OSTTA [34].

4.2. Experimental Results

CIFAR Benchmarks. We conduct experiments on both CIFAR-10-C and CIFAR-100-C benchmarks, where the SVHN-C dataset is included as open-set unknown samples for evaluation. We compare our method with source-only, representative TTA methods, and OSTTA methods. As presented in Tab. 1, our method significantly improves performance across all metrics (Acc., AUROC, FPR@TPR95, and OSCR) in both closed-set and open-set TTA. This improvement is due to the inclusion of semantically useful unknown samples during adaptation. However, directly using the pre-trained source [77] model results in a significant drop in accuracy and a 69.82% higher FPR@TPR95 compared to our method, as it is unable to distinguish between known and unknown tasks in the CIFAR-10-C dataset. For example, our method improves TENT [64] by 10.99%, 33.77%, 85.44%, and 32.82% across the evaluation metrics, while it improves the best-performing open-set TTA method S-OSTTA [33] by 3.11%, 0.82%, 1.81%, and 3.71%, respectively. On the CIFAR-100-C dataset, our method also consistently exhibits better performance. In contrast, TENT [64] and OSTTA [33] show performance drops in the OSCR metric, as these models naively update parameters with unknown samples included, failing to achieve considerable performance. Finally, our consistent improvements suggest the effectiveness of selectively incorporating semantically useful unknown samples, rather than naively adopting them as in TENT [64] or OSTTA [34].

Table 1. Results of different methods on CIFAR-10/100-C benchmarks. (\uparrow) indicates that larger values are better, and vice versa. All values are percentages. We present Source, TTA methods, OSTTA methods, and Our method respectively. We underline the second best score, and best scores are in **bold**. And improvements (\pm) compared to the second best score are presented.

Method		CIFAR-10-C			CIFAR-100-C			
	Acc.↑	AUROC↑	FPR@TPR95↓	OSCR↑	Acc.↑	AUROC↑	FPR@TPR95↓	OSCR↑
Source [77]	80.73	76.44	79.25	67.44	53.68	61.55	93.20	39.71
TENT [64]	78.35	64.79	94.87	55.92	55.71	66.23	93.89	41.34
CoTTA [66]	83.34	84.07	72.40	77.45	55.33	77.23	80.78	48.32
EATA [52]	81.45	83.76	71.23	72.56	60.78	<u>87.24</u>	94.88	42.28
OSTTA [34]	84.12	72.45	76.54	65.32	60.18	75.34	82.12	50.83
UniEnt [20]	84.23	95.45	13.25	83.45	59.45	92.21	23.24	57.31
UniEnt+ [20]	85.18	96.12	13.10	84.27	60.32	92.43	23.69	58.23
S-OSTTA [33]	86.23	<u>96.74</u>	<u>11.24</u>	<u>85.03</u>	<u>61.34</u>	<u>95.37</u>	23.75	<u>58.35</u>
Ours	89.34 _(+3.11)	98.56(+0.82)	9.43 _(-1.81)	88.74 _(+3.71)	64.76(+3.42)	97.67 _(+2.30)	20.34 _(-3.35)	62.45 _(+4.10)

Table 2. Results of different methods on Tiny-ImageNet benchmark. (†) indicates that larger values are better, and vice versa. All values are percentages. Notations are followed from Tab. 1.

Method	Tiny-ImageNet-C					
Method	Acc↑	AUROC↑	FPR@TPR95↓	OSCR↑		
Source [77]	22.14	54.86	93.32	16.12		
TENT [64]	28.56	48.10	95.32	19.41		
CoTTA [66]	30.12	57.24	81.78	23.45		
EATA [52]	32.92	58.31	83.66	25.64		
OSTTA [34]	37.46	55.78	93.78	27.67		
UniEnt [20]	37.23	56.02	91.25	27.98		
UniEnt+ [20]	38.00	57.12	90.34	28.43		
S-OSTTA [33]	<u>39.12</u>	<u>58.90</u>	<u>89.36</u>	<u>29.89</u>		
Ours	42.78(+3.66)	62.34(+3.44)	86.57 _(-2.79)	32.47(+2.58)		

Tiny-ImageNet Benchmark. We also conduct experiments on the Tiny-ImageNet benchmark, as presented in Tab. 2. Our method consistently outperforms all other approaches (Source, TTA, and OSTTA) across all evaluation metrics. In particular, it achieves performance gains of 3.66%, 3.44%, 2.79%, and 2.58% over the second-best method, S-OSTTA [33]. These improvements demonstrate that our proposed modules: DET, OT-PL Refinement, and APW play a crucial role in improving model performance by effectively leveraging helpful unknown samples for adaptation.

4.3. Further Analysis

Ablation Study. We verify the effect and contribution of each proposed component (DET, OTPL, APW) in Tab. 3. We use CIFAR-10-C as the closed-set and SVHN-C as the open-set datasets. Without known and unknown sample separation, the model intends to minimize the entropy of open-set samples, which leads to a severe performance drop in all metrics. Adding our dynamic-energy thresholding (DET) alone drastically improves performance due to its flexible class-conditioned known and unknown sample separation strategy, which indicates our proposed DET can well distinguish samples. Moreover, our OT-based pseudo-label refinement also proves effective as it improves all metrics by a large margin similar to DET. Combining both DET

and OTPL achieves similar results to other OSTTA methods such as UniEnt and UniEnt+. Finally, our adaptive prototype weighting further improves the overall results and outperforms all methods. This indicates that our APW incentivizes learning useful unknown samples, which helps achieve better performance and robustness.

Table 3. Ablation study of DET, OTPL and APW.

DET	OTPL	APW	Acc↑	AUROC↑	FPR@TPR95↓	OSCR↑
Х	Х	Х	64.23	61.33	96.31	48.42
✓	Х	Х	82.27	79.93	39.45	68.73
×	✓	Х	74.34	76.14	42.59	66.56
✓	✓	Х	83.45	95.61	14.56	83.11
✓	✓	1	89.34	98.56	9.43	88.74

Different Confidence Thresholds. Inspired by the experimental setting in [34], we evaluate our dynamic-energy threshold (DET) against other thresholding methods such as MSP [25], Max Logit [23], and Energy [43]. For the evaluation, we train TENT [64] and compare our DET with these methods. We include the SVHN-C dataset alongside CIFAR-10-C to ensure an open-set setting. From Tab. 4, we can see that across all evaluation metrics—AUROC, FPR@TPR95, and OSCR; our method shows superior performance. Another advantage is that using classconditioned energy statistics helps to immediately distinguish between known and unknown samples, whereas existing OOD methods require a large batch to determine the threshold with the AUROC score. Hence, our method is more flexible and better suited for OSTTA tasks.

Different Number of Unknown Classes. We measure the performance under different numbers of unknown classes, as it is a crucial criterion to understand how the model is deviating when the number of unknown classes increases. In Tab. 5, we can see TENT [64], other methods have consistent fluctuations when the number of classes increases, hence complexity. However, our proposed

Table 4. Comparison of different methods on CIFAR-10-C. (\uparrow) indicates higher is better, (\downarrow) indicates lower is better.

Method	CIFAR-10					
Method	AUROC↑	FPR@TPR95↓	OSCR↑			
MSP [25]	48.08	93.34	42.90			
Max Logit [23]	50.51	90.67	45.66			
Energy [43]	51.25	90.89	47.76			
DET (Ours)	79.93	42.59	68.73			

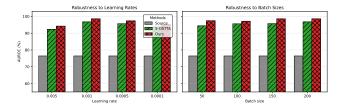


Figure 3. AUROC (%) on CIFAR-10-C with different learning rate and batch sizes, we compare our method with Source [77], S-OSTTA [33].

method has shown more robust and stabilized performance when the number of unknown classes increases.

Table 5. OSCR of different methods including ours on CIFAR-10-C under different number of unknown classes.

Method	2	4	6	8	10
Source	72.45	69.67	69.33	69.17	68.05
TENT	49.44	49.23	50.56	48.25	50.56
UniEnt+	78.45	78.46	78.51	78.34	76.98
S-OSTTA	80.34	79.26	79.76	80.00	78.28
Ours	84.12	83.44	83.33	83.67	83.00

Model Robustness to Hyper-Parameters. In real-world applications, models are often deployed on small devices. However, it is crucial to have a small batch size and set an optimal learning rate to stabilize performance. In Fig. 3, we can see our method can flexibly outperform S-OSTTA [33] even under a batch size of 50. On the other hand, the results do not fluctuate even across low to high learning rates. These findings demonstrate the scalability and robustness of our method when hyper-parameters are not optimal.

Different Ratios of Known and Unknown. We follow the setup from [20, 33, 34] to experiment with different ratios of known and unknown samples. But in the main experiments, it is set to 1:1. We consider an imbalanced data ratio between known and unknown samples. When the open-set dataset has a lower (0.1/0.5) ratio, or higher data ratio (1.5/2.0). In Tab. 6, we observe that the TTA method such as TENT [64] has a significant drop when we add a higher number of open-set data. In contrast, our method exhibits consistency and less sensitivity to different data ratios; hence it is more suitable in real-world applications where the data ratio is often imbalanced.

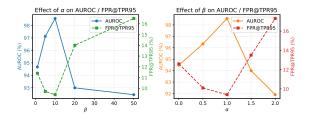


Figure 4. AUROC (%) and FPR@TPR95 on CIFAR-10-C with different α and β values.

Table 6. OSCR of different ratios of known and unknown on CIFAR-10-C.

Method	0.1	0.5	1.5	2.0
Source	40.00	40.3	38.97	38.18
TENT	47.76	44.27	44.89	41.79
UniEnt+	56.43	57.85	56.12	55.04
S-OSTTA	60.23	60.43	59.90	58.67
Ours	63.56	63.30	62.92	62.76

Per-batch Inference Time. TTA methods are often deployed in small devices, and they are often resource-intensive. In Tab. 7, we compare the inference latency per batch. As we can see our method achieved better OSCR than other high-performing methods while preserving similar inference time.

Ablation on α and β . We perform analysis for β and α values from eq. 2 and 11. In Fig. 4, we present the performance across different β and α values. We observe that β = 1.0 maintains the best performance, whereas α = 10 complements the performance on CIFAR-10-C. A larger β value can assume more target samples as in-distribution known samples, and vice versa. On the other hand, smaller α value is better when the target prototypes are noisier and classes are not well separated.

Table 7. Comparison of different methods for per-batch inference latency [33] on CIFAR-10-C.

Method			CIF	AR-10-C			
Wictiou	TENT	EATA	CoTTA	OSTTA	UniEnt	S-OSTTA	Ours
Inference Time (ms)↓	26.34	57.76	887.34	59.89	75.34	90.34	93.34
OSCR↑	55.92	72.56	77.45	65.32	83.45	85.03	88.74

5. Conclusion

In this paper, we address the challenging paradigm of open-set test-time adaptation (OSTTA). To tackle this setting effectively, we propose a simple yet effective framework, LU-OSTTA, which leverages both known and unknown samples during adaptation. Unlike previous methods that overlook unknown samples, our approach exploits them to improve adaptation. Specifically, we introduce a dynamic-energy threshold to separate known and unknown

samples in a class-conditioned manner. To mitigate the effect of noisy pseudo-labels, we employ an optimal transport (OT)—based pseudo-label refinement. Furthermore, we propose an adaptive prototype weighting strategy to ensure effective learning from semantically useful unknown samples. Extensive experiments across different settings demonstrate that our method consistently outperforms existing TTA and OSTTA approaches in the open-set settings.

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