

Learning to Prompt Knowledge Transfer for Open-World Continual Learning

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Abstract

This paper studies the problem of continual learning in an open-world scenario, referred to as Open-world Continual Learning (OwCL). OwCL is increasingly rising while it is highly challenging in two-fold: i) learning a sequence of tasks without forgetting knowns in the past, and ii) identifying unknowns (novel objects/classes) in the future. Existing OwCL methods suffer from the adaptability of task-aware boundaries between knowns and unknowns, and do not consider the mechanism of knowledge transfer. In this work, we propose Pro-KT, a novel prompt-enhanced knowledge transfer model for OwCL. Pro-KT includes two key components: (1) a prompt bank to encode and transfer both task-generic and task-specific knowledge, and (2) a task-aware open-set boundary to identify unknowns in the new tasks. Experimental results using two real-world datasets demonstrate that the proposed Pro-KT outperforms the state-of-the-art counterparts in both the detection of unknowns and the classification of knowns markedly.¹

Introduction

Continual learning (CL, a.k.a lifelong learning) is a new paradigm of machine learning that typically learns a large number of tasks sequentially without forgetting knowledge gained in the past and uses the knowledge to help new task learning (Wang et al. 2019; Ke, Liu, and Huang 2020). This paper concerns the problem of CL for a sequence of classification tasks, where each task involves a set of classes to classify. To date, most existing methods, even the most recent counterparts such as (Guo, Liu, and Zhao 2023; Smith et al. 2023), assume that the sets of training classes and test classes are the same in the past or future tasks, referred to as *closed-world assumption* (Fei and Liu 2016). However, the closed-world assumption is often invalid in practice as the real world is an open environment where it frequently happens that some tasks contain new classes that are unseen in past tasks. For example, the previous task had only learned cats and dogs, but now a new task is to classify a set of birds. In this work, we study CL with *open-world assumption*, where test data include unknowns or novel classes.

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¹Code released at <https://github.com/YujieLi42/Pro-KT>.

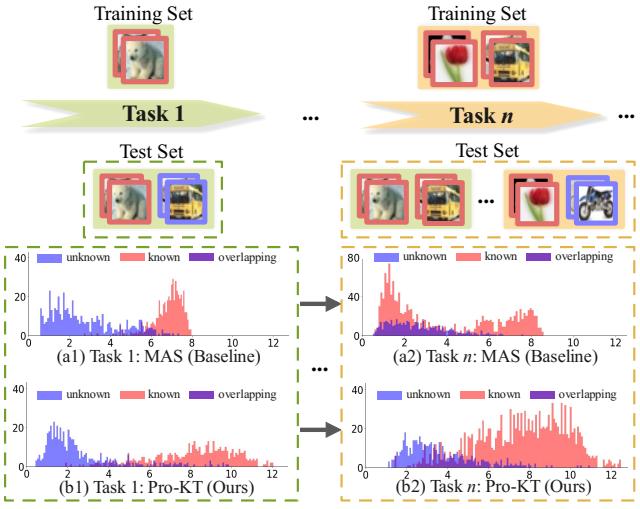


Figure 1: An example of our motivation. **Top:** A setting of OwCL that learns a sequence of tasks, where the training data of Task n have new classes versus Task 1 and the test data of each task may have unknowns versus its training data. **Bottom:** Evaluation results of MAS (a typical CL baseline) and Pro-KT (ours) on Task 1 and Task n , respectively. The evaluation is to evaluate all test data after learning each task. Note, the x -axis shows the unscaled class-maximum logits of samples, and the y -axis shows the number of samples. The area of overlap denotes the performance of partitioning knowns and unknowns (*less is better*).

Continual learning in an open world or simply *Open-world Continual Learning* (OwCL) is appealing yet challenging in recent years. Fig. 1 illustrates an example of our motivation. Specifically, the scenario refers to an OwCL setting, assuming the training data of Task n have new classes (i.e., *rose* and *bus*) and both the test data of Task 1 and Task n have novel objects (e.g., *bus* in Task 1 and *motorbike* in Task n) that are not seen in the training data. As shown in Fig. 1 (a1) and (b1), both MAS (Aljundi et al. 2018) (a typical CL baseline) and our method can distinguish the unknowns from knowns in Task 1 (*the first task*). However, as shown in Fig. 1(a2) and (b2), MAS fails to exploit previous unknowns (e.g., *bus* in Task 1) to help Task n , leading to the

issue of *performance degradation* on Task n . Our method can separate the knowns from unknowns for Task n . Our main motivation here is to learn knowledge for both knowns and unknowns from previous tasks and later use the knowledge to formulate an open-set boundary between knowns and unknowns for new tasks.

In this work, we aim at designing an OwCL model that accumulates the knowledge gained in the past and uses the knowledge to help divide the test data into knowns and unknowns/opens, especially for enlarging the open-set boundary between knowns and unknowns. After learning each new task, the newly seen classes are subsequently treated as knowns for new tasks. Our main ideas are *knowledge transfer* and *prompt learning*. However, there are two major challenges. (1) *Knowledge Stability*: When a new task is largely dissimilar from the previous tasks, the newly acquired knowledge might contradict the existing knowledge. (2) *Knowledge Plasticity*: Once the ground-truth data of unknowns appear in the subsequent tasks, the model needs to update the corresponding unknown samples as knowns.

To address the aforementioned challenges, we propose a novel **Prompt-enhanced Knowledge Transfer** (Pro-KT) method. Pro-KT delineates an innovation of prompt learning for OwCL, a novel plug-and-play prompt bank for knowledge transfer, and two adaptive threshold selection strategies for determining the open-set boundary. Specifically, to address challenge (1), we create a prompt bank designed to encode knowledge through the use of prompts. These prompts serve as instructions for directing the model in task execution. By flexibly selecting prompts from the proposed prompt bank, Pro-KT can facilitate effective knowledge transfer with both task-generic and task-specific knowledge across diverse tasks. To address challenge (2), we design two adaptive threshold-selection strategies for determining the open-set detection boundary. Through these strategies, the open-set decision boundary will be updated according to the newly learned knowledge continually so as to handle knowledge plasticity.

Our main contributions are summarized as follows:

- This paper delves into knowledge transfer via prompt learning for OwCL. We propose a novel prompt bank for rehearsal-free knowledge transfer that delineates a new paradigm for representing, accumulating and transferring knowledge.
- We propose a novel task-aware open-set boundary to distinguish unknowns from knowns, based on two adaptive threshold-selection strategies. Thus, the model is able to accumulate and revise the knowledge learned from unknowns, ensuring knowledge plasticity for OwCL.
- Extensive experiments on two sets of real-world datasets demonstrate that the proposed Pro-KT outperforms baseline methods markedly on a large range of evaluation tasks. Case study and visualization results further show Pro-KT’s effectiveness in tackling OwCL.

Related Work

There are two closely related research topics: *Open-world Continual Learning* and *Prompt Learning*.

Open-world Continual Learning. OwCL is a synergistic integration of continual learning (Zenke, Poole, and Ganguli 2017) and open-world learning (Bendale and Boutil 2015). In a nutshell, OwCL aims at learning on the job in the open world with the goal of recognizing unknowns and incrementally learning them without catastrophic forgetting so that a model will become more and more knowledgeable for future learning. There are mainly two OwCL settings: 1) *Task-incremental* OwCL, where the classes (if any) in the tasks may or may not be disjoint, and 2) *Class-incremental* OwCL, where each task has a set of non-overlapping classes. In this work, we concern about the setting of class-incremental OwCL.

Dang et al. (2019) designed an open-set classifier for identifying new classes based on the extreme value theory and further proposed an ensemble classifier for open-set incremental learning. Joseph et al. (2021) presented a solution for identifying unknown categories without forgetting learned classes based on contrastive clustering and energy-based unknown identification. Kim et al. (2023) theoretically demonstrated the necessity of novelty detection for class-incremental continual learning. Liu et al. (2023a) introduced a prospective framework, SOLA, to facilitate autonomous continual learning through steps including novelty detection, adapting new tasks on the fly, and incremental learning.

However, the above-mentioned methods do not consider knowledge representation and integration schemes for OwCL. In addition, there is a lack of effective methods concerning the representation, accumulation, and update of knowledge for unknowns.

Prompt Learning. With the development of large-scale pre-trained models, prompt learning (Zhou et al. 2022; Khatatk et al. 2023; Gu et al. 2022; Wang et al. 2022b) is an emerging technique that deploys pre-trained models in a parameter-efficient and data-efficient way (Liu et al. 2023b). It applies a fixed function to guide a pre-trained model so that the pre-trained model achieves additional instructions to perform downstream tasks (Lester, Al-Rfou, and Constant 2021; Li and Liang 2021). Owing to the advantages of prompts, prompt-based continual learning methods show strong protection against forgetting by learning insertable prompts rather than modifying or constraining encoder parameters directly (Smith et al. 2023).

Prompt learning has been investigated recently for continual learning, such as L2P (Wang et al. 2022b), DualPrompt (Wang et al. 2022a) and CODA (Smith et al. 2023). However, the existing prompt learning-based methods have certain limitations. For example, L2P requires a single prompt pool to be updated after every new task, resulting in performance degradation for a long sequence of tasks. DualPrompt learns a set of task-specific prompts and a unique global prompt without considering knowledge transfer across tasks. CODA includes an end-to-end attention mechanism to decompose prompts, while learning a large number of prompts and increasing the prompt length to achieve effective results. What’s more, existing prompt-based methods follow the closed-world assumption, thereby lacking the capability to identify unknowns within an open-world context.

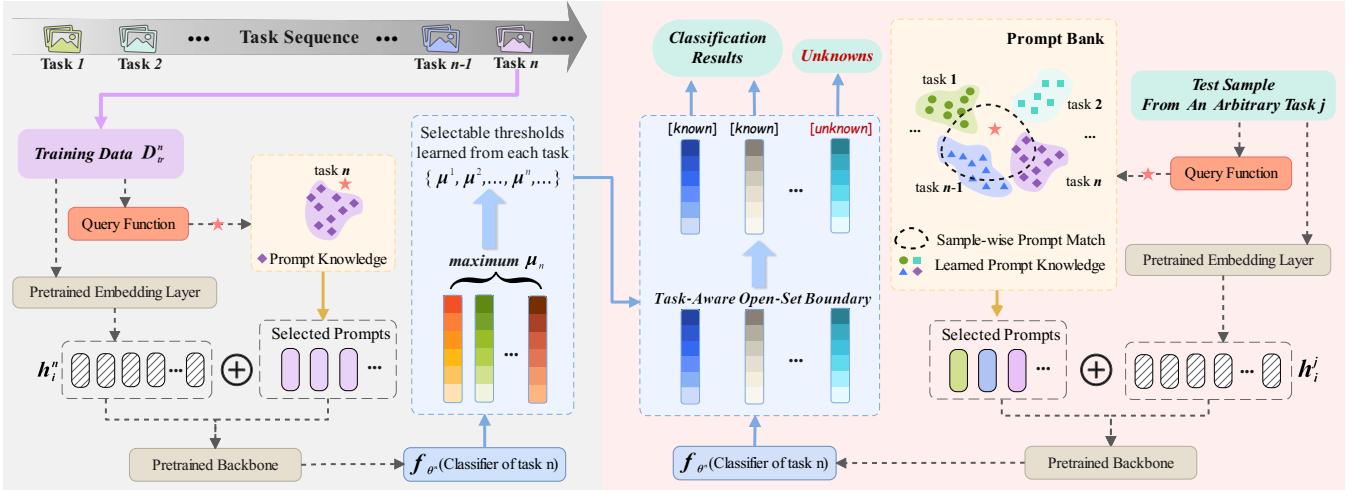


Figure 2: Illustration of the overall framework (**Left**: Training phase, and **Right**: Test phase). [Best viewed in color]

Remarks. As aforementioned, typical continual learning makes the closed-world assumption, which is often invalid in practice as the real world is an open environment that is full of unknowns or novel objects. Although there are several attempts with the open-world assumption, OwCL is still a highly challenging research problem. Most existing OwCL methods suffer from misinterpreting, assembling, or revising incorrect knowledge, without focusing on knowledge transfer. Our method, Pro-KT, addresses these limitations with prompts to encode knowledge and learns to prompt knowledge transfer for OwCL. Pro-KT buffers knowledge in a more intelligent and succinct rehearsal-free mechanism. The details of the proposed method will be clear shortly.

Methodology

In this section, we first clarify the research problem and the overall framework. Then we elaborate on two key components of the proposed Pro-KT: (1) *prompt bank*, and (2) *task-aware open-set boundary*. Finally, we conclude the overall objective function. Before going further, let us make a notational convention used throughout the paper. We will use superscripts to denote task identifiers (task IDs) for a sequence of tasks (e.g., T^1, \dots, T^n).

Problem Statement. Given a sequence (possibly never-ending) of tasks, our OwCL problem is that during continual learning if a learner encounters any novel objects in the test, the learner should detect them as ‘unknowns’. Then, suppose the learner approaches the ground truths for these ‘unknowns’ in a new task, the ‘unknowns’ will be evolved as knowns. What’s more, the learner should incrementally learn on the job – namely, *recognizing unknowns and incrementally learning them without catastrophic forgetting for new task learning*. Note that the training data from the previous tasks may be not accessible again for training new tasks. Briefly, we define our problem as follows:

Problem Definition. At any point in time, the learner has learned n tasks. Each task T^n has its training data D_{tr}^n . When faced with a new task T^{n+1} with its training data

D_{tr}^{n+1} , the purpose of our OwCL problem is that the learner 1) detects unknowns from new tasks, 2) annotates unknowns as knowns along with time, and 3) classifies previous classes without forgetting.

Architecture. Fig. 2 illustrates the overall framework of the proposed Pro-KT, comprising the *training* and *test* phases.

In the *training*, samples are first projected with a query function. Pro-KT then learns a new set of prompts and accumulates them into the prompt bank. Next, each training sample is enhanced by chosen prompts, and all these prompt-enhanced embeddings are fed into the pre-trained backbone. The prompt-enhanced final representations are then fed into a trainable classifier. After that, we learn an adaptive threshold for the task-aware open-set boundary, based on the softmax entropy of the prompt-enhanced final representation. During the *testing* phase, after the projection of test samples, prompts are drawn from the prompt bank employing a sample-wise matching mechanism. This mechanism facilitates the transfer of both task-specific and task-generic knowledge. The enriched embeddings are then forwarded to the unified classifier, yielding unscaled logits scores. Pro-KT then detects samples as either **[known]** or **[unknown]** based on the task-aware open-set boundary, guided by adaptive thresholds.

Prompt Bank

We propose to use a prompt bank for knowledge transfer. Specifically speaking, we use prompts to encode both task-generic and task-specific knowledge and retain the prompts in a prompt bank. The prompts stored in the prompt bank are later transferred to new tasks for problem-solving, which further assures knowledge stability in OwCL. Given the current task T^n with its training data $D_{tr}^n = \{(\mathbf{X}^n, \mathbf{Y}^n)\}$, the learner achieves a prompt set $(p_1^n, \dots, p_i^n, \dots)$ for this task. Then, the learner stores this portion of knowledge together with the knowledge learned from previous tasks into the

prompt bank:

$$\begin{aligned} \mathbf{P} &= \bigcap_{n=1}^N (\mathbf{p}^1, \dots, \mathbf{p}^n, \dots, \mathbf{p}^N) \\ &= \{(p_1^1, p_2^1, \dots, p_M^1), \dots, \\ &\quad (p_1^n, p_2^n, \dots, p_M^n), \dots, (p_1^N, p_2^N, \dots, p_M^N)\}, \end{aligned} \quad (1)$$

where N is the total number of tasks, and M is the number of prompts learned from each task. $p_i^j \in \mathbb{R}^{L_p \times D_e \times NM}$ denotes the i -th prompt in task j , where L_p is the token length, and D_e is the embedding dimension. The prompt bank encourages comprehensive knowledge transfer with task-specific knowledge and task-generic knowledge.

However, a critical problem is how to encode and select the most useful prompting knowledge. Inspired by the key-value pair-based query strategy in L2P (Wang et al. 2022b), we propose to associate each prompt as a value with a learnable key. Specifically, given the task T^n , we perform a key-query pair for the sample-wise prompt matching:

$$(\mathbf{k}^n, \mathbf{p}^n) = (k_1^n, p_1^n), \dots, (k_M^n, p_M^n), \quad (2)$$

where $\mathbf{p}^n = \{p_m^n\}_M$ and $\mathbf{k}^i = \{k_m^i\}_M$. Then, after learning task T^N , the key-query pairs stored in the prompt bank can be formulated as:

$$(\mathbf{K}, \mathbf{P}) = \{(\mathbf{k}^1, \mathbf{p}^1), (\mathbf{k}^2, \mathbf{p}^2), \dots, (\mathbf{k}^N, \mathbf{p}^N)\}. \quad (3)$$

Next, we devise a more automatic knowledge transfer protocol via a sample-wise prompt matching mechanism, where the sample itself elects the most valuable/appropriate prompts as auxiliary knowledge from the prompt bank. Given an arbitrary input x_i^n from task T^n , we first apply the pre-trained projection layer \mathbf{Q}_x to map the initial input to a new feature space \mathbb{R}^{D_e} :

$$\mathbf{h}_i^n = \mathbf{Q}_x \cdot x_i^n. \quad (4)$$

Then, we apply the pre-trained projection layer as the query function \mathbf{Q}_x to lookup the top-K keys by solving the following optimization problem:

$$\underset{[1, K]}{\operatorname{argmin}} \sum_{j=1}^N \text{dis}(\mathbf{h}_i^n, \mathbf{k}^j), \text{ with } \mathbf{k}^j = \{k_m^j\}_M. \quad (5)$$

In such a method, the encoded input sample \mathbf{h}_i^n can find top-K keys by searching the top-K minimum distance (we use cosine similarity in this work) between prompt keys without any task identifier. After this, the input embedding \mathbf{h}_i^n is thus extended by the subset $\mathbf{P}_{S_K} \subset \mathbf{P}$ of prompt knowledge from the prompt bank:

$$\mathbf{h}'_i^n = \mathbf{h}_i^n \oplus \mathbf{P}_{S_K}, \quad (6)$$

where \oplus denotes the dimension-wise concatenation. The size of the subset P_{S_K} is K , which is smaller than M .

Since unknown samples may appear in the test, these enhanced embeddings will then be exploited to learn an adaptive detection boundary to distinguish knowns and unknowns for each task.

Task-Aware Open-Set Boundary

In this section, we elaborate on how to formulate a boundary between the knowns and unknowns and its adaptability to each task during the OwCL process. To address this issue, we devise two adaptive open-set detection threshold selection schemes for determining such a boundary.

In training, the prompting knowledge stored in the prompt bank is learned from the training data of each task with ground-truth labels. However, it is essential to use the knowledge gained from the knowns to identify unknown samples. We propose to learn a threshold on the softmax entropy of the prompt-enhanced embeddings and then utilize the knowledge acquired from the known entities to determine an open-set boundary between knowns and unknowns.

After training task T^n , the prompt-enhanced training sample \mathbf{h}'_i^n is fed into a pre-trained backbone f_{pr} . The final representation is fed into a trainable classifier f_{θ^n} :

$$\text{prob}_i^n = f_{\theta^n}(f_{pr}(\mathbf{h}'_i^n)), \quad (7)$$

where the prob_i^n is the maximum value of unscaled softmax entropy of the training sample \mathbf{h}'_i^n .

Then, we determine the open-set detection threshold μ by computing the mean of all the training samples $\{\text{prob}_1^n, \dots, \text{prob}_i^n, \dots\}$ from task T^n :

$$\mu^n = r \cdot \frac{1}{|\mathbf{X}^n|} \sum_{i=1}^{|\mathbf{X}^n|} \text{prob}_i^n, \quad (8)$$

where $|\mathbf{X}^n|$ denotes the total number of training samples and r denotes the deviation degree. Subsequently, the obtained open-set detection threshold of task T^n is stored with the previously learned thresholds. In such a manner, the model has the ability to deliver a suitable threshold from $[\mu^1, \dots, \mu^n]$ for the testing phase.

During the test phase, to determine whether a test sample x_i^j from an arbitrary task T^j is known or not, we design two simple but efficient strategies to choose the most appropriate threshold for the open-set detection boundary.

There are two scenarios. The first scenario is that the task identifiers (task IDs) are available in the test. Therefore, the model directly adapts the corresponding threshold via its task ID j :

$$x_i^j : f_{\theta^n}(\mathbf{h}'_i^j) \leq \mu^j \rightarrow [\text{unknown}], \\ \text{otherwise, } \rightarrow [\text{known}]. \quad (9)$$

The second scenario is that the task IDs are unavailable in the test. During OwCL, the model is incrementally learning new tasks, resulting in an accumulation of knowledge in the prompt bank. Hence, in this scenario, our model alternatively selects the latest threshold learned from the current task T^n for the open-set detection boundary:

$$x_i^j : f_{\theta^n}(\mathbf{h}'_i^j) \leq \mu^n \rightarrow [\text{unknown}], \\ \text{otherwise, } \rightarrow [\text{known}]. \quad (10)$$

After this, if a sample is detected as an unknown object, the model then annotates the sample with *[unknown]* for future tasks. If a sample is detected as one of the *[known]* objects, the model then classifies the sample with one of the known classes.

Objective Function

In the training of task T^n , the prompt bank first learns M prompts in total with the corresponding keys. The prompt bank (\mathbf{K} , \mathbf{P}) stores all the prompt knowledge learned from T^1 to T^n . Then, the known samples link to top-K prompt keys by Eq. (5) and extend with auxiliary knowledge by Eq. (6). The open-set detection boundary is also updated through the proposed threshold-setting strategies.

Finally, we formally formulate the overall objective function as follows:

$$\min_{\theta^n, (\mathbf{k}^n, \mathbf{p}^n)} \{ \mathcal{L}(f_{\theta^n}(f_{pr}(\mathbf{h}'^n), \mathbf{y}^n) + \lambda \sum_{i=0}^M dis(\mathbf{h}^n, k_i^n) \}, \quad (11)$$

where the \mathbf{h}^n refers to the set of training samples projected embeddings. The first term is the softmax cross-entropy loss, and the second term is a surrogate loss to pull the selected keys closer to the corresponding query features. λ is a trade-off parameter to balance the two terms. As previously noted, during the training phase of task T^n , we exclusively update the prompt set p^n , and during the testing, we select prompts from the entire prompt bank \mathbf{P} .

Experiments

Experimental Setup

Implementations. In our experiments, we remove the labels of the classes in the training set of the next task (i.e., $T^{(n+1)}$) and treat them as unknowns in the test set for the current task (i.e., T^n). Besides, we followed the general setting in the CL community, i.e., randomly shuffled the task order five times for both Split CIFAR100 (with 10 tasks) and 5-datasets (with 5 tasks). The results presented throughout this manuscript are the mean results of five random shuffles.

Datasets. We experiment on two commonly-used and publicly-available datasets, namely **Split CIFAR100** (Krizhevsky, Hinton et al. 2009) and **5-datasets** (Ebrahimi et al. 2020). The Split CIFAR100 dataset is sampled from the CIFAR100 by dividing the original CIFAR100 into 10 tasks, where each task contains 10 disjoint classes. Since the 10 tasks are sampled from the same dataset, they exhibit certain similarities. The 5-datasets comprises five distinct image classification datasets: TinyImagenet, NotMNIST, CUB200, Fashion-MNIST and CIFAR10. Each dataset represents an individual task.

Baselines. Since OwCL involves continual learning with novelty detection (Kim et al. 2023), we evaluate two tasks: (1) *Unknown Detection* and (2) *Known Classification*.

- **Unknown Detection:** We compare Pro-KT against the following seven baseline methods: *OpenMax* (Bendale and Boult 2015), *MSP* (Hendrycks and Gimpel 2016), *MCD* (Yu and Aizawa 2019), *EnergyBased* (Liu et al. 2020), *Entropy* (Chan, Rottmann, and Gottschalk 2021), *MaxLogits* (Basart et al. 2022) and *ODIN* (Liang, Li, and Srikant 2018).

- **Known Classification:** We compare Pro-KT with the following nine continual learning methods: *EWC* (Kirkpatrick et al. 2017), *MAS* (Aljundi et al. 2018), *DER++* (Buzzega et al. 2020), *GEM* (Lopez-Paz and Ranzato 2017), *LwF* (Li and Hoiem 2017), *HAT* (Serra et al. 2018), *UCL* (Ahn et al. 2019), *L2P* (Wang et al. 2022b) and *DualPrompt* (Wang et al. 2022a).

Metrics. For unknown detection, we use the average area under the curve (AUC_N) and average false positive rate (FPR_N) (Chan, Rottmann, and Gottschalk 2021) as metrics. AUC_N is the average area under the receiver operating characteristic (ROC) curve across all past tasks, providing a comprehensive measure of open detection performance over N tasks. FPR_N reports the average error rate of misclassifying unknown samples into known categories.

For known classification, we employ average final accuracy (A_N) and average forgetting rate (F_N) (Wang et al. 2022b) as metrics. A_N is the average final accuracy concerning all past classes over N tasks. F_N measures the performance drop across N tasks, offering valuable information about plasticity and stability during OwCL.

Main Results

Dataset	Methods	AUC_N	FPR_N
Split CIFAR100 (10 tasks)	OpenMax	49.99	50.06
	MSP	50.29	52.18
	MCD	50.17	70.37
	EnergyBased	49.66	71.86
	Entropy	49.56	51.17
	MaxLogits	52.63	74.99
	ODIN	50.81	52.64
	Pro-KT w/o task IDs	<u>91.01</u>	<u>41.31</u>
	Pro-KT	92.69	39.71
5-datasets (5tasks)	OpenMax	60.09	84.23
	MSP	51.22	87.96
	MCD	50.60	98.62
	EnergyBased	49.38	87.99
	Entropy	39.49	96.34
	MaxLogits	66.78	73.12
	ODIN	49.63	97.91
	Pro-KT w/o task IDs	<u>82.76</u>	<u>50.05</u>
	Pro-KT	88.60	45.70

Table 1: Results(%) regarding unknown detection. We report the results over 10 tasks for Split CIFAR100 (10 classes per task) and 5 tasks for 5-datasets.

Results on Unknown Detection. Table 1 shows the results of unknown detection. From the results, we can see that the baselines perform poorly on the OwCL problem, indicating that these algorithms struggle to maintain satisfactory open detection performance after learning a sequence of tasks. In contrast, Pro-KT consistently outperforms all compared methods across various configurations, as evident from both the AUC_N (increased) and FPR_N (decreased). Moreover, we examine the performance under different open detection threshold learning strategies. By comparing the AUC_N for Pro-KT without task IDs, we observe a performance drop of the basic Pro-KT when task identifiers are agnostic in the

Backbone	Method	Split CIFAR100 (10 tasks)			5-datasets (5 tasks)		
		$A_N(\uparrow)$	$Diff(\downarrow)$	$F_N(\downarrow)$	$A_N(\uparrow)$	$Diff(\downarrow)$	$F_N(\downarrow)$
ResNet32	<i>Upper-bound</i>	72.99	-	-	93.59	-	-
	EWC	34.16	38.83	36.20	51.25	42.34	42.06
	GEM	24.93	48.06	42.04	39.06	54.53	56.47
	LwF	16.73	56.26	51.62	36.18	57.41	59.19
	DER++	31.03	41.96	22.63	45.59	48.00	47.82
	HAT	30.43	42.56	36.73	37.00	56.59	51.35
	UCL	29.77	43.22	31.99	31.71	61.88	58.89
	MAS	29.58	43.41	22.14	49.59	44.00	33.90
ViT	<i>Upper-bound</i>	86.07	-	-	80.59	-	-
	LwF	71.93	14.14	6.89	19.02	61.57	44.23
	MAS	76.71	9.36	13.02	65.13	15.46	13.5
	L2P	80.63	5.44	10.93	69.06	11.59	9.53
	DualPrompt	83.18	2.89	8.42	70.14	10.45	10.11
	Pro-KT	84.07	2.00	5.43	71.70	8.89	5.19

Table 2: Results(%) of known samples classification on Split CIFAR100 and 5-datasets. For the Split CIFAR100 dataset, we report the results over 10 tasks with 10 classes per task. For the 5-datasets, we report the results over 5 tasks where each dataset refers to a task. We used two backbones (i.e., ResNet32 and ViT) in the experiments.

test. This suggests that task-specific knowledge significantly enhances test performance in OwCL, and the utilization of task IDs further refines open detection boundaries.

The superior performance of our Pro-KT, especially in transferring knowledge from open data across tasks, underscores the success of our proposed prompt bank in accumulating and transferring knowledge. Overall, Pro-KT demonstrates substantial improvements in open detection performance, while effectively mitigating the selection of a promising threshold with adaptive strategies.

Results on Known Samples Classification. In this experiment, we evaluate the performance of known classification. In particular, Pro-KT does not require task identifiers for the classification of known samples, enabling its application in task-agnostic class-incremental settings. We also report the *Upper-bound*, i.e. the offline training of all tasks, which is usually regarded as the upper-bound performance a method can achieve (Wang et al. 2022b).

Table 2 shows the results on the Split CIFAR100 and 5-datasets, respectively. From the results, we can observe that our Pro-KT consistently outperforms other methods and yields SOTA performance. Besides, we observe that Pro-KT achieves higher A_N when ViT is the backbone compared to ResNet32. This is attributed not only to the powerful representation ability of large-scale pre-trained models but also to the adaptability of our prompt learning method for knowledge transfer to pre-trained models. Additionally, a relatively modest performance gap between baseline methods and the upper-bound result has been reported, highlighting the significant performance advantage of our method. It is noted that Pro-KT exhibits the lowest forgetting rate (F_N) after learning a sequence of tasks.

Additional Results

Task Effect. As shown in Fig. 3, we illustrate A_N and F_N as line plots to provide further insights into Pro-KT after learning each new task. The results demonstrate the Pro-

KT’s consistently high performance across tasks and its superiority over baselines with the number of tasks increasing. This demonstrates the effectiveness of our approach in mitigating performance decay and maintaining promising classification results compared to existing benchmarks. Thus, we emphasize the crucial role of knowledge transfer in addressing the OwCL problem.

Unknown Detection	Split CIFAR100		5-datasets	
	AUC_N	FPR_N	AUC_N	FPR_N
w/o task IDs	91.01	41.31	82.76	50.05
w/o AODB	50.02	87.63	46.78	88.90
Pro-KT	92.69	39.71	88.60	45.70
Known Classification	Split CIFAR100		5-datasets	
	A_N	F_N	A_N	F_N
w/o prompt bank	40.49	17.21	15.42	40.19
Pro-KT	84.07	5.43	71.70	5.19

Table 3: Ablation study on the variants of Pro-KT.

Ablation Study. To show the importance of each key component of Pro-KT, we conduct ablation studies on 1) task identifiers in determining the threshold, 2) the whole task-aware open-set boundary, and 3) the prompt bank. The results are shown in Table 3.

First, we remove the task identifiers in determining the threshold. The performance has a small drop (compared with the intact Pro-KT), suggesting that when tasks are diverse, adding task identifiers for the instruction of threshold choosing indeed facilitates knowledge sharing and mitigates interference between dissimilar tasks. Second, we eliminate the whole open-set boundary. As a result, the model does not have the ability of open detection, where the AUC_N value is only about 50, and the FPR_N is the highest. Finally, we ablate the entire prompt bank and directly fine-tune the pre-trained backbone and a trainable classifier for each task. The significant decrease in performance suggests that a naive fine-tuning suffers catastrophic forgetting in OwCL.

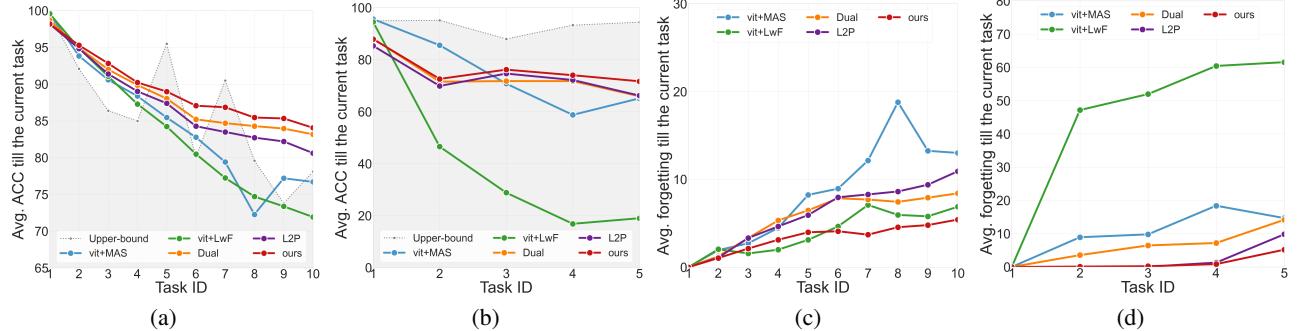


Figure 3: (a) and (b): Variation Curve of A_N on Split CIFAR100 and 5-datasets. (c) and (d): Variation Curve of F_N on Split CIFAR100 and 5-datasets.

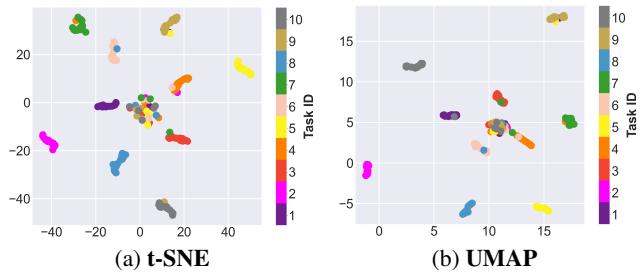


Figure 4: Visualization of the prompt bank via T-SNE and UMAP after training on all tasks (Split CIFAR100 dataset).

Visualization. To understand the mechanism of knowledge transfer and the different types of knowledge learned within the prompt bank, we visualize all the prompts using t-SNE (Van der Maaten and Hinton 2008) and UMAP (McInnes et al. 2018) on the dataset Split CIFAR100.

Specifically, we obtain the prompt bank from the final model after training on the sequence of all tasks T^1, \dots, T^N . The results are shown in Fig. 4, where each point represents a prompt. We observe that all the prompts are well-separated with different colors, indicating the model has learned task-specific knowledge. Besides, some prompts are automatically gathered in the center and these prompts are learned through different tasks, which indicates that the model has also learned task-generic knowledge. Hence, both task-specific knowledge and task-generic knowledge can be transferred across all tasks with the proposed prompt bank.

Parameter Sensitivity Analysis. Recall that there are three key parameters in our Pro-KT, i.e., M : the total number of prompts learned from each task, L_p : the length of a single prompt, and K : the selection size used to prepend the input. Hence, $M \times N$ decides the total size of the prompt bank. Fig. 5 shows the results on two datasets. We now analyze the impact of different parameter settings that could affect the proposed Pro-KT:

From the results in Fig. 5 (left-middle), we can see that an oversized selection size K may introduce knowledge underfitting, while L_p has little effect on performance. For the

total number of prompts for each task, we find that a reasonable capacity of the prompt bank is essential for encoding the task-common knowledge and task-specific knowledge. From the results in Fig. 5 (right), it was observed that in the Split CIFAR100 where the 10 tasks are similar, the effect of M on the performance was stable. However, in the 5-datasets where the 5 tasks were dissimilar, increasing M introduced irrelevant prompts, resulting in a decline in performance. Thereby, we safely conclude that when tasks are more dissimilar, the M is more sensitive.

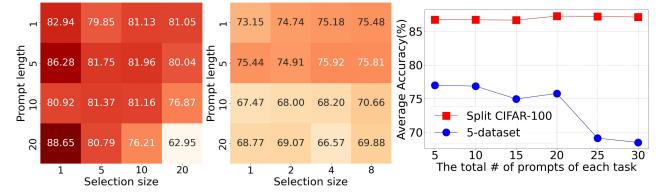


Figure 5: Left and Middle: A_N w.r.t prompt length L_P and prompt selection size K on both two datasets with $M = 25$. Right: A_N w.r.t. M (i.e., the total number of prompts of each task) with $L_P = 5$ and $K = 3$.

Conclusion

In this work, we proposed a prompt-based method (called Pro-KT) that achieves knowledge transfer via a novel prompt bank for open-world continual learning. Our Pro-KT involves a unique approach to representing task-specific and task-generic knowledge by attaching the complementary prompts to a pre-trained backbone. To determine a task-aware open-set boundary, we design two adaptive threshold-selection strategies, guided by the prompt bank. The experimental results demonstrate the effectiveness of our Pro-KT and its adaptability to different tasks.

Our future work includes: 1) integrating advanced clustering methods for the fine-grained classification of unknowns, and 2) exploring the forms of knowledge for unknowns and further using the knowledge to help future task learning.

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