DIVERGENCE-ENHANCED KNOWLEDGE-GUIDED CONTEXT OPTIMIZATION FOR VISUAL-LANGUAGE PROMPT TUNING

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ABSTRACT

Prompt tuning vision-language models like CLIP has shown great potential in learning transferable representations for various downstream tasks. The main issue is how to mitigate the over-fitting problem on downstream tasks with limited training samples. While knowledge-guided context optimization (Yao et al., 2023; 2024) has been proposed by constructing consistency constraints to handle catastrophic forgetting in the pre-trained backbone, it also introduces a potential bias toward pre-training. This paper proposes a novel and simple Divergence-enhanced Knowledge-guided Prompt Tuning (DeKg) method to address this issue. The key insight is that the bias toward pre-training can be alleviated by encouraging the independence between the learnable and the crafted prompt. Specifically, DeKg employs the Hilbert-Schmidt Independence Criterion (HSIC) to regularize the learnable prompts, thereby reducing their dependence on prior general knowledge, and enabling divergence induced by target knowledge. Comprehensive evaluations demonstrate that DeKg serves as a plug-and-play module can seamlessly integrate with existing knowledge-guided methods and achieves superior performance in three challenging benchmarks.

1 INTRODUCTION

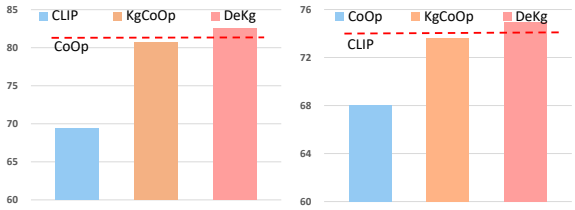
Large-scale vision-language models (VLMs) like CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021) have demonstrated excellent capabilities in zero-shot recognition and generalization representation. Unfortunately, the large model sizes, high computational resource requirements, and massive trainable data restrict their deployment on real vision-language tasks. To address this problem, a new paradigm of prompt tuning has been proposed and attracted increasing attention in recent years (Radford et al., 2021; Zhou et al., 2022b).

Prompt tuning (Zhou et al., 2022b) aims to optimize a limited set of dynamic continuous prompt representations with the end-to-end objective function, i.e., the cross-entropy loss, to transfer the pre-trained knowledge of VLMs to targeted tasks. These methods are less than optimal due to challenges in determining what should be preserved and what should be adapted for downstream tasks. For example, in the base-to-new generalization task, as shown in Figure 1, CoOp(Zhou et al., 2022b) can achieve a significant performance improvement over the manually prompted method CLIP(Radford et al., 2021) on base (seen) classes, yet is inferior on new (unseen) classes in the same dataset. This suggests that the prior general knowledge may be distorted by the limited task-specific labeled data, causing fine-tuned models to deviate from the pre-trained VLMs and leading to overfitting issues.

The overffitting issues can be attributed to the lack of regularization in the latent space to model the prior general knowledge for the unseen class distribution (Yao et al., 2023). Since the frozen CLIP (Radford et al., 2021) coupled with crafted prompts exhibits robust abilities to unseen classes, indicating that the pre-trained backbone serves as a valuable source of prior knowledge for each class, recent works (Yao et al., 2023; Zhu et al., 2023a;b; Yao et al., 2024) all construct a novel constraint term by enforcing the consistency between the learnable and crafted prompts, called knowledge-guided context optimization (KGCO). However, despite the benefits of regularization in preventing catastrophic forgetting, KGCO tends to be biased toward the pre-trained model, es-

pecially when the data distribution of the target task differs from that of the pre-trained data. For example, as shown in Figure 1, KgCoOp (Yao et al., 2023) improves CoOp on new classes but degrades on base classes, mainly due to the bias of the learnable prompts toward the representations of the pre-trained CLIP. Overall, an effective prompt tuning method should address the contradiction problem between catastrophic forgetting in fine-tuning and bias in pre-training.

In this work, we propose a novel method, called Divergence-enhanced Knowledge-guided Prompt tuning (**DeKg**). We aim to maintain the advantage of knowledge-guided context optimization but alleviate the contradiction problem between catastrophic forgetting and bias towards general knowledge. Specifically, we introduce a novel constraint by employing the Hilbert-Schmidt Independence Criterion (HSIC) regularization. The proposed constraint encourages the learnable prompts to maintain a consistent yet independent relation with general knowledge, optimizing the balance between adapting general knowledge and fine-tuning for targeted tasks. As shown in Figure 1, DeKg overcomes the weakness of KgCoOp, performing best on both base classes and new classes.



(a) Base class performance. (b) New class performance.

Figure 1: Performance comparison of DeKg with prompt tuning methods (CLIP/ CoOp, KgCoOp (baseline method), and DeKg (Ours)) under base-to-new generalization setting. We measure average accuracy on the base classes (a) and new classes (b) over 11 datasets. The red dotted line indicates the performance of CoOp for base classes and the zero-shot CLIP for new classes.

Our contributions can be summarized as follows:

- We tackle an inherent issue of knowledge-guided context optimization in overly biasing general knowledge in pre-training, and propose a novel HISC-based regularization method DeKg for encouraging independence between the learnable and the crafted prompts.
- DeKg integrates seamlessly with existing knowledge-guided methods. Compared to the baselines, DeKg not only introduces divergence between the learnable and crafted prompts but also enhances differentiation between learnable prompts for distinct classes.
- Extensive experiments demonstrate the superiority of the proposed method in three challenging benchmarks: base-to-new generalization, cross-dataset generalization, and few-shot learning.

2 Related Work

Vision-Language Models (VLMs) pre-trained on large-scale image-text association pairs through self-supervised methods have exhibited impressive performance in various visual tasks (Radford et al., 2021; Jia et al., 2021). Despite the powerful generalization capacities, the enormous size of these models makes it challenging to fine-tune the entire models for downstream tasks, particularly when dealing with few-shot data. Such a trend raises the essential need to study different adaptation approaches, where prompting has been shown to be one of the simple and effective strategies.

Prompt Tuning for VLMs: Prompting was initially proposed in the domain of Natural Language Processing (NLP) (Lester et al., 2021; Li & Liang, 2021), providing textual instructions to the task input for distilling task-relevant knowledge. For example, CLIP (Radford et al., 2021) utilizes a collection of crafted templates "a photo of a [CLASS]" as textual inputs for category-wise embeddings, and demonstrates exceptional zero-shot image recognition capabilities. However, building a proper predefined prompt requires domain-specific knowledge and enormous time. To circumvent this, a series of methods that automate learning embeddings at the input tokens, known as soft prompts, have emerged for fast adaptation to various downstream tasks. CoOp (Zhou et al., 2022b) optimizes the prompt content by a continuous set of learnable vectors that are used as input to the text encoder alongside the class name. However, the prompts are learned by minimizing the classification error on a training set within the given base classes, resulting in weak generalization on new classes. Co-

CoOp (Zhou et al., 2022a) further expands by constructing conditional prompts on specific image instances. However, such methods have a worse generalization than CLIP on the same task to the unseen classes. In addition to the textual prompt tuning, MaPLe (Khattak et al., 2023a) conducts the visual-textual prompt tuning by jointly conducting the prompt tuning on the visual and text encoders.

Knowledge-guided Prompt Tuning: To ensure that learnable prompts retain essential general textual knowledge contained in frozen CLIP, ProGad (Zhu et al., 2023a), and KgCoOp (Yao et al., 2023) all constrained the consistency between the learnable prompt and the crafted prompt by employing a novel constraint term. Specifically, ProGad tries to optimize the learnable prompts with the aligned direction generated by the crafted prompts. KgCoOp adopts the Euclidean distance to minimize the discrepancy between textual embeddings generated by learned prompts and crafted prompts. PromptSRC (Khattak et al., 2023b) presents a self-regulating approach to prompt learning, overcoming overfitting and improving generalization by leveraging mutual agreement, prompt self-ensembling, and textual diversity. Later, TCP (Yao et al., 2024) constructs an embedding module to inject the class-level textual knowledge into the learnable prompt tokens. While existing prompt learning techniques have boosted the generalization ability by applying consistency constraints on the textual input between learnable and crafted tokens, they exhibit limited capability to capture specific knowledge. To mitigate this limitation, we propose a novel textual prompting method that incorporates consistency and diversity to enhance the generalization and discriminative capabilities of the learnable tokens.

3 METHODOLOGY

In this paper, we seek a more general prompting to empower the capabilities of capturing task-specific information without forgetting task-agnostic general knowledge. Our method is built upon the framework of knowledge-guided context optimization (Yao et al., 2023), which enforces a consistency constraint between the learnable and crafted prompts to distill knowledge from the frozen encoders, thus defying catastrophic forgetting. However, relying too much on pre-trained knowledge may hurt downstream knowledge and degrade performance. To mitigate this limitation, we propose a new method based on the Hilbert-Schmidt Independence Criterion (HSIC) regularization.

3.1 REVISITING KNOWLEDGE-GUIDED CONTEXT OPTIMIZATION

CLIP (Radford et al., 2021) is a fundamental Vision-Language Model, offering a zero-shot transfer strategy by pre-training the visual backbone and textual encoder on 400M large-scale image-text pairs through contrastive learning. Benefiting its robust generalization capabilities to new classes, the frozen text embeddings $\{\mathbf{w}_i^{clip}\}$ of the crafted prompt " a photo of a [class]" can be a valuable source of prior general knowledge[1], where the " [class]" is replaced by i-th class name. However, general knowledge is less able to accurately describe downstream tasks, mainly without considering the task-specific knowledge of each task.

To obtain discriminative target task knowledge, a set of learnable prompts $\mathbb{T} = \{\mathbf{t}_1, \mathbf{t}_2, \ldots, \mathbf{t}_M\}$ is designed for generating task-specific textual embeddings of all classes, where M is the length of tokens. Similar to CLIP, the corresponding class token $\mathbf{c}_i$ is concatenated with the learnable tokens for generating the textual token $\mathbf{w}_i = \{\mathbf{t}_1, \mathbf{t}_2, \ldots, \mathbf{t}_M, \mathbf{c}_i\}$. Then the textual embeddings of all classes can be optimized by minimizing the contrastive loss between the given image's embedding $\mathbf{x}$ and its class embedding $\mathbf{w}_y$, which formulates as:

$$\mathcal{L}_{ce} = \frac{1}{N} \sum_{(\mathbf{x},y)\in\mathcal{D}_s} \frac{exp(sim(\mathbf{x}, \mathbf{w}_y)/\tau)}{\sum_{i=1}^{N_c} exp(sim(\mathbf{x}, \mathbf{w}_i)/\tau)}, \tag{1}$$

where $\mathcal{D}_s$ denotes the seen dataset, N is the number of training images, N_c is the number of classes, $sim(\cdot)$ represents the cosine similarity, and τ refers to a temperature parameter frozen in CLIP.

Despite delivering promising results, it can be observed the learned context is prone to overfitting to small training data and not generalizing to new classes (Zhou et al., 2022a), primarily because the context is fixed once learned and only optimized for specific classes, i.e., catastrophic forgetting for

[1]Following Yao et al. (2023), "general knowledge" in this work denotes the information contained in the pre-trained CLIP model.

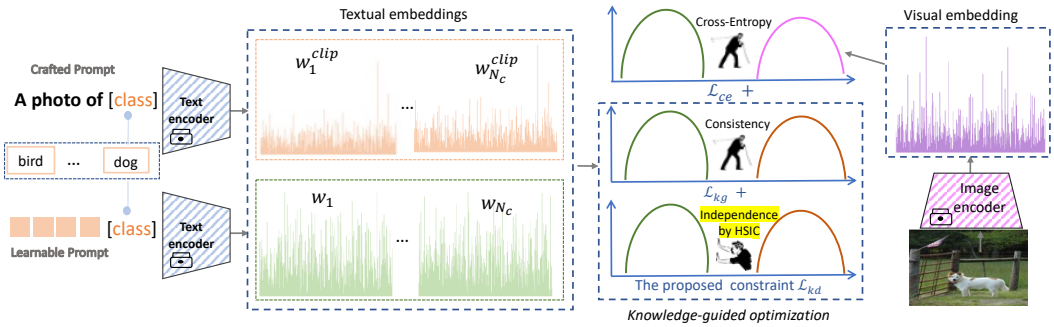


Figure 2: The knowledge-guided optimization framework of DeKg. $\mathcal{L}_{ce}$ is the cross-entropy loss, and $\mathcal{L}_{kg}$ is a consistency constraint. $\mathcal{L}_{kd}$ is a regularization term that uses the Hilbert-Schmidt Independence Criterion (HSIC) to encourage the independence between learnable and crafted prompts.

pre-trained knowledge. To exploit the prior general textual knowledge contained in the frozen CLIP for learnable tokens optimization, a simple yet efficient consistency constraint is added during the prompt tuning to prevent catastrophes forgetting (Yao et al., 2023), which can be expressed as

$$\mathcal{L}_{kg} = \|\mathbf{w}_i - \mathbf{w}_i^{clip}\|_2^2. \tag{2}$$

The consistency constraint enforces that the learnable tokens have similar distributions as the crafted prompts, suggesting the potential bias toward pre-training. The reason lies in the different data distributions of the different domains. Compared to the pre-trained VLMs, the training data of downstream tasks is extremely limited, resulting in the learnable context inevitably towards pre-trained knowledge distributions.

Overall, existing soft prompt learning methods still encounter substantial challenges, i.e., catastrophic forgetting and bias, leading to performance degradation.

3.2 Divergence-enhanced Knowledge-guided Context Optimization

The proposed framework is shown in Figure 2. Considering that the consistency between learnable tokens and general knowledge plays an important role in preventing catastrophic forgetting, we propose to add a new regularization to prevent current task-specific knowledge from being interfered with by prior general knowledge to some extent, i.e., encouraging the independence between the learnable and crafted prompts. Thus, the context optimization can be guided with divergence-enhanced prior general knowledge.

To constrain independence, Hilbert-Schmidt Independence Criterion (HSIC) is adopted to penalize the dependency between the learnable and crafted prompts. HSIC measures the degree of dependency, with lower values indicating stronger independence and higher values suggesting greater correlation. Formally, the learnable prompts of N_c classes are defined as $\mathbf{W} = \{\mathbf{w}_i\}_{i=1}^{N_c}$, and the corresponding crafted prompt is defined as $\mathbf{W}^{clip} = \{\mathbf{w}_i^{clip}\}_{i=1}^{N_c}$. HSIC between $\mathbf{W}$ and $\mathbf{W}^{clip}$ is empirically expressed from Gretton et al. (2005) as below:

$$\mathcal{L}_{kd} = \text{HSIC}(\mathbf{W}, \mathbf{W}^{clip}) = (N_c - 1)^{-2} tr(\mathbf{K}\mathbf{H}\mathbf{K}^{clip}\mathbf{H}), \tag{3}$$

where $\mathbf{K} \in \mathbb{R}^{N_c \times N_c}$, $\mathbf{K}^{clip} \in \mathbb{R}^{N_c \times N_c}$ with entries $\mathbf{K}(i,j) = k(\mathbf{w}_i, \mathbf{w}_j)$, $\mathbf{K}^{clip}(i,j) = k(\mathbf{w}_i^{clip}, \mathbf{w}_j^{clip})$, $k(.,.)$ is a kernel function; $\mathbf{H} = \mathbf{I}_{N_c} - \frac{1}{N_c}\mathbf{1}_{N_c}\mathbf{1}_{N_c}^T \in \mathbb{R}^{N_c \times N_c}$ is the centering matrix, which is used to remove the bias within each representations and focus on the inter-variable relationships; tr represents the trace of the matrix. In our implementation, we use the inner product kernel function, i.e., $\mathbf{K}^{clip} = \mathbf{W}^{clip^T}\mathbf{W}^{clip}$, and promising performance is achieved.

Define $\mathbf{A} = \mathbf{H}\mathbf{K}^{clip}\mathbf{H}$, Eq.(3) can be rewritten as follows:

$$\begin{aligned} \mathcal{L}_{kd} &= (N_c - 1)^{-2} tr(\mathbf{K}\mathbf{A}) \\ &= (N_c - 1)^{-2} \sum_{i,j} \mathbf{K}(i,j)\mathbf{A}_{i,j}. \end{aligned} \tag{4}$$

Notice that $\mathbf{A}$ is fixed because it is only related to the representations of the crafted prompts. Therefore, $\mathcal{L}_{kd}$ is only affected by $\{\mathbf{K}(i,j)\}$, which describe the relationship between the set of learnable prompts $\mathbf{W} = \{\mathbf{w}_i\}_{i=1}^{N_c}$. Thus the computation of HSIC is only related to $\mathbf{W} = \{\mathbf{w}_i\}_{i=1}^{N_c}$ without introducing any extra parameters.

Let us revisit the computation of $\mathcal{L}_{kd}$ in Eq.(4). It actually involves both intra-class relations (e.g., between $\mathbf{w}_i$ and $\mathbf{w}_i^{clip}$) and inter-class relations (e.g., between $\mathbf{w}_i$ and $\mathbf{w}_j$). Therefore, penalizing $\mathcal{L}_{kd}$ encourages both intra-class and inter-class independence.

Finally, we constrain the learnable prompts with both consistency and independence, which can be expressed as follows:

$$\mathcal{L} = \mathcal{L}_{ce} + \lambda\mathcal{L}_{kg} + \mu\mathcal{L}_{kd}, \tag{5}$$

where λ and μ are tradeoff hyperparameters encoding the belief degrees for consistency and expressiveness, respectively.

4 Experiments

In this section, we conduct extensive experiments on three widely-used benchmarks to evaluate the ability of base-to-new generalization, cross-data generalization, and few-shot learning, and demonstrate the effectiveness of the proposed method by comparing with strong vision-language prompt tuning baselines.

4.1 Experimental Setup

Dataset: For downstream tasks, we follow previous work (Radford et al., 2021; Zhou et al., 2022a;b), to conduct experiments on 11 representative image classification datasets, including ImageNet (Deng et al., 2009) and Caltech (Fei-Fei et al., 2004) for generic object classification; OxfordPets (Parkhi et al., 2012), StanfordCars (Krause et al., 2013), Flowers (Nilsback & Zisserman, 2008), Food101 (Bossard et al., 2014), and FGVCAircraft (Maji et al., 2013) for fine-grained visual categorization, EuroSAT (Helber et al., 2019) for satellite image classification, UCF101 (Soomro et al., 2012) for action recognization, DTD (Cimpoi et al., 2014) for texture classification, and SUN397 (Xiao et al., 2010) for scene recognition.

Baselines: First, to demonstrate that DeKg can embody the advantage of preserving both the general knowledge frozen in CLIP and task-specific knowledge, we compare the results of CLIP (Radford et al., 2021), CoOp(Zhou et al., 2022b), CoCoOp (Zhou et al., 2022a) and MaPLe (Khattak et al., 2023a) which only make use of general or task-specific knowledge, i.e., only use cross-entropy for prediction. Second, to show the significant advantage of enhancing task-specific knowledge, we compared with two baselines (KgCoOp (Yao et al., 2023), and ProGad (Zhu et al., 2023a)) which preserve the general knowledge by enforcing the consistency between the learnable tokens and crafted prompts. Besides, to highlight the importance of divergence guided by general knowledge and task-specific knowledge, we compared with PromptSRC (Khattak et al., 2023b) and TCP (Yao et al., 2024) which incorporates other strategies to consistency constraint, i.e., PromtSRC adds self-ensembling and textual diversity regularization, while TCP inserts class-specific knowledge into embeddings.

For the DeKg method which unifies the general knowledge preservation and divergence upon general-specific knowledge into one framework, four baselines, i.e., KgCoOp, ProGad, TCP, and PromtSRC, can be expanded by adding the HSIC regularization to produce the divergence by target knowledge with general knowledge preservation. In our experiments, only KgCoOp and TCP are adopted and expanded to generate the final learnable tokens, denoted as $\text{DeKg}_{\text{KgCoOp}}$ and DeKg_{TCP} respectively. The main reason for this is that, on one hand, ProGad aligns prompts with general knowledge of the gradient, while the others are directly aligned with the embeddings. On the other hand, PromptSRC includes visual prompts and textual prompts, while other baselines only include textual prompts.

Training Details: Our implementation is based on KgCoOp's (Yao et al., 2023) and TCP's (Yao et al., 2024) codes. To ensure a fair comparison, all experiments were conducted using the Vit-B/16 (Dosovitskiy et al., 2021) as the vision backbone and the context length set as 4. Additionally,

we maintained consistency with the corresponding baselines in $\text{DeKg}_{\text{KgCoOp}}$ and DeKg_{TCP} for random prompt initialization, training epoch, training schedule, and data augmentation settings. In our experiments, we set the ratio of λ/μ to 3/1 by grid search, which translates to λ being 6 and μ being 2. All experiments were carried out using the HYGON DCU-Z100L.

Table 1: Comparison with existing methods in the base-to-new generalization setting with ViT-B/16 as the backbone. The context length M is 4 for prompt-based methods with the 16-shot samples from the base classes. H: Harmonic mean.

Datasets		CLIP	CoOp	CoCoOp	MaPLe	KgCoOp	ProGrad	PromptSRC	TCP	$\text{DeKg}_{\text{KgCoOp}}$	DeKg_{TCP}
Regularization:		only cross entropy				consistency constraint		consistency constraint and other		consistency and indenpendence constraints	
Average	Base	69.34	82.64	80.47	82.28	80.73	82.48	84.26	84.13	82.59	**84.96**
	New	74.22	68.00	71.69	75.14	73.6	70.75	76.10	75.36	74.93	**76.38**
	H	71.70	74.61	75.83	78.55	77.0	76.16	79.97	79.51	78.57	**80.44**
ImageNet	Base	72.43	76.46	75.98	76.66	75.83	77.02	**77.60**	77.27	76.65	77.40
	New	68.14	66.31	70.43	70.54	69.96	66.66	**70.73**	69.87	69.66	69.20
	H	70.22	71.02	73.10	73.47	72.78	71.46	**74.01**	73.38	72.99	73.07
Caltech	Base	96.84	98.11	97.96	97.74	97.72	98.02	98.10	98.23	98.13	**98.64**
	New	94.00	93.52	93.81	94.36	94.39	93.89	94.03	94.67	95.09	**95.20**
	H	95.40	95.76	95.84	96.02	96.03	95.91	96.02	96.42	96.59	**96.89**
Pets	Base	91.17	94.24	95.20	**95.43**	94.65	95.07	95.33	94.67	95.00	94.47
	New	97.26	96.66	97.69	**97.76**	**97.76**	97.63	97.30	97.20	97.71	**97.76**
	H	94.12	95.43	96.43	**96.58**	96.18	96.33	96.30	95.92	96.34	96.09
Cars	Base	63.37	76.20	70.49	72.94	71.76	77.68	78.27	80.80	76.31	**81.18**
	New	74.89	69.14	73.59	74.00	75.04	68.63	74.97	74.13	**75.27**	74.75
	H	68.65	72.50	72.01	73.47	73.36	72.88	76.58	77.32	75.79	**77.83**
Flowers	Base	72.08	97.63	94.87	95.92	95.00	95.54	98.07	97.73	97.72	**98.58**
	New	**77.80**	69.55	71.75	72.46	74.73	71.87	76.50	75.57	74.04	75.18
	H	74.83	81.23	81.71	82.56	83.65	82.03	**85.95**	85.23	84.25	85.30
Food	Base	90.10	89.44	90.70	90.71	90.5	90.37	90.67	90.57	90.57	**90.73**
	New	91.22	87.50	91.29	**92.05**	91.7	89.59	91.53	91.37	91.95	91.55
	H	90.66	88.46	90.99	**91.38**	91.09	89.98	91.10	90.97	91.25	91.14
Aircraft	Base	27.19	39.24	33.41	37.44	36.21	40.54	42.73	41.97	39.08	**45.20**
	New	36.29	30.49	23.71	35.61	33.55	27.57	**37.87**	34.43	34.97	35.09
	H	31.09	34.32	27.74	36.50	34.83	32.82	**40.15**	37.83	36.91	39.51
SUN397	Base	69.36	80.85	79.74	80.82	80.29	81.26	**82.67**	82.63	81.19	82.52
	New	75.35	68.34	76.86	**78.70**	76.53	74.17	78.47	78.20	76.57	78.30
	H	72.23	74.07	78.27	79.75	78.36	77.55	**80.52**	80.35	78.81	80.35
DTD	Base	53.24	80.17	77.01	80.36	77.55	77.35	82.37	82.77	80.90	**83.80**
	New	59.90	47.54	56.00	59.18	54.99	52.35	**62.97**	58.07	58.21	59.66
	H	56.37	59.69	64.85	68.16	64.35	62.45	**71.75**	68.25	67.70	69.70
EuroSAT	Base	56.48	91.54	87.49	**94.07**	85.64	90.11	92.90	91.63	88.29	94.02
	New	64.05	54.44	60.04	73.23	64.34	60.89	73.90	74.73	72.69	**81.69**
	H	60.03	68.28	71.21	82.3	73.48	72.67	82.32	82.32	79.73	**87.42**
UCF101	Base	70.53	85.14	82.33	83.00	82.89	84.33	87.10	87.13	84.64	**88.06**
	New	77.50	64.47	73.45	78.66	76.67	74.94	78.80	80.77	78.04	**81.77**
	H	73.85	73.38	77.67	80.77	79.65	79.35	82.74	83.83	81.21	**84.80**

4.2 Performance Comparision & Analysis

4.2.1 Base-to-New Generalization

The base-to-new generalization setting aims to evaluate whether the models learned on base tasks can generalize to new tasks without unseen classes, i.e., a *category shift* exists between base and new tasks. Following the baselines, on each dataset, we first construct a base and new task by equally dividing the dataset into two groups, then perform prompt tuning on the base classes and test the learned model on both the base and new tasks. Table 1 presents the performance of different methods across 11 datasets with 16-shot samples, where the best and second results are marked in bold and underlined, respectively. For convenience, we refer to the classification accuracy of base tasks and new tasks as base accuracy and new accuracy, respectively. The harmonic mean (H) of base accuracy and new accuracy is also computed to demonstrate the generalization trade-off.

Compared with zero-shot CLIP, the baselines optimized with only cross-entropy loss, i.e., CoOp, CoCoOp, and MaPLe, achieve improvement on base classes but show inferior performance on new classes except Maple. This suggests that they overall tend to overfit the task-specific data distributions, losing the original generalization capability of the frozen CLIP model towards new tasks. Although KgCoOp alleviates the poor generalization problem in CoOp by preserving the prior general knowledge, it hardly outperforms CoOp in base accuracy in almost all benchmarks, i.e., KgCoOp has an average drop from 82.64% to 80.73% compared with CoOp, while ProGrad has a simi-

Table 2: Comparison in the cross-dataset Generalization the prompts from ImageNet(16-shot samples) with ViT-16/B, and evaluating on the other 10 datasets.

Datasets	CLIP	CoOp	MaPLe	PromptSRC	KgCoOp	ProGrad	TCP	DeKg$_{\text{KgCoOp}}$	DeKg$_{\text{TCP}}$
ImageNet	66.70	71.51	70.72	71.27	70.66	72.24	71.40	71.34	**72.33**
Caltech101	93.30	93.70	93.53	93.60	93.92	91.52	93.97	93.87	**94.73**
Pets	89.10	89.14	90.49	90.25	89.83	89.64	**91.25**	90.16	90.02
Cars	65.70	64.51	65.57	65.70	65.41	62.39	64.69	**65.91**	65.49
Flowers	70.70	68.71	72.20	70.25	70.01	67.87	71.21	70.6	**72.39**
Food101	85.90	85.30	86.20	86.15	86.36	85.40	**86.69**	86.37	86.59
Aircraft	24.90	18.47	24.74	23.90	22.51	20.16	23.45	23.37	**25.05**
SUN397	62.60	64.15	67.01	67.10	66.16	62.47	67.15	66.11	**67.19**
DTD	44.30	41.92	46.49	**46.87**	46.35	39.42	44.35	46.16	44.47
EuroSAT	48.30	46.39	48.06	45.50	46.04	43.46	**51.45**	43.15	51.37
UCF101	67.60	66.55	68.69	68.75	68.50	64.29	68.73	68.17	**68.78**
Avg.	65.24	63.88	66.30	65.81	65.51	62.71	66.29	65.33	**66.64**

lar trend. This suggests that the learnable context may be skewed towards the general knowledge frozen in the CLIP, due to the limited task-specific knowledge. In contrast, DeKg improves on both base and new classes over CLIP and CoOp. Specifically, DeKg$_{\text{TCP}}$ obtains an average gain of 2.32% (i.e., 84.96% vs 82.64%) over CoOp in base accuracy, and 2.16% (i.e., 74.22% vs 76.38%) over CLIP in new accuracy, respectively. Additionally, DeKg$_{\text{KgCoOp}}$ has a similar trend. This shows the benefits of DeKg by optimizing context explicit guidance by general and target knowledge which aid base and new classes respectively.

PromptSRC and TCP are two strong competitors because they both leverage task-specific knowledge and general knowledge together to improve generalization. Fortunately, DeKg$_{\text{TCP}}$ demonstrates improved performance for both base and new class recognition. Specifically, DeKg$_{\text{TCP}}$ outperforms PromptSRC on 8 out of 11 datasets in terms of base accuracy and almost half of the datasets in new accuracy. Additionally, DeKg$_{\text{TCP}}$ shows improvement over TCP in almost all 11 datasets. The main reason is that PromptSRC and TCP guide the prompt with the token alignment strategy, limited by handling domain shift in the test set. This demonstrates that DeKg$_{\text{TCP}}$ gains advantages by taking into account the textual embedding distribution with an independence constraint.

4.2.2 Cross-Dataset Generalization

To further demonstrate that the proposed model can bridge the distribution gap between the pre-training dataset and the downstream evaluation set for zero-shot generalization, we compare DeKg with baselines under the cross-dataset generalization. In this experiment, we follow the baselines to regard ImageNet as the source dataset and the other 10 dataset as target datasets, i.e., there is a *distribution shift* between the base and new tasks.

From the comparison results in Table 2, we can see that our DeKg$_{\text{TCP}}$ obtains the highest average performance among all baselines (66.64% vs 66.29% of TCP). By comparison, the performance on other datasets with distant and more fine-grained or specialized categories is much lower, such as Aircraft where the accuracy number is well below 30%. Nonetheless, DeKg$_{\text{TCP}}$ exhibits much stronger transferability than TCP with an average gain of 1.6% (i.e., 25.05% vs 23.45%) on Aircraft, as well as on most other fine-grained or specialized datasets. Additionally, DeKg$_{\text{KgCoOp}}$ achieves inferior performance to PromptSRC and TCP, mainly due to the inability to explicitly model the downstream class distribution.

4.2.3 Few-shot Classification

To verify the model's ability to develop robust representations with a severely limited amount of downstream data, we follow the previous work(Yao et al., 2024) to train the model using K-shot labeled source images from each class and evaluate the testing domain with the same spaces as the training classes. A summary comparison of the 4-shot setting between the proposed DeKg and existing baselines appears in Table 3, from which can observe that: the proposed DeKg$_{\text{TCP}}$ achieves the best average performance than all baselines. In addition, the baselines KgCoOp and TCP have shown respective improvements with independence constraint (i.e., DeKg$_{\text{KgCoOp}}$ and DeKg$_{\text{TCP}}$) of the average gains of 0.64% (i.e, 75.12% vs 74.48%) and 0.44% (i.e, 77.06% vs 76.12%) across 11

Table 3: Comparison of few-shot learning with 4-shot samples.

	ImageNet	Caltech101	Pets	Cars	Flowers	Food101	FGVC	SUN397	DTD	EuroSAT	UCF101	Avg.
CLIP	66.70	93.30	89.10	65.70	70.70	85.90	24.90	62.60	44.30	48.30	67.60	65.37
CoOp	69.37	94.44	91.30	72.73	91.14	82.58	33.18	70.13	58.57	68.62	77.41	73.59
CoCoOp	70.55	94.98	93.01	69.10	82.56	86.64	30.87	70.50	54.79	63.83	74.99	71.98
MaPLe	70.67	94.30	92.05	68.70	80.80	**86.90**	29.03	71.47	54.73	54.87	73.70	70.66
ProGrad	70.21	94.93	93.21	71.75	89.98	85.77	32.93	71.17	57.72	70.84	77.82	74.21
PromptSRC	**70.80**	94.77	**93.23**	71.83	91.31	86.06	32.80	72.80	60.64	75.02	79.35	75.33
KgCoOp	70.19	94.65	93.20	71.98	90.69	86.59	32.47	71.79	58.31	71.06	78.40	74.48
TCP	70.48	95.00	91.90	**76.30**	94.40	85.3	36.20	72.11	63.97	77.43	80.83	76.72
$\text{DeKg}_{\text{KgCoOp}}$	70.24	94.97	93.1	72.24	90.5	86.88	32.88	72.33	61.05	72.65	79.43	75.12
DeKg_{TCP}	70.19	**95.21**	92.15	74.9	**95.21**	85.72	**37.02**	**72.85**	**64.24**	**79.16**	**81.05**	**77.06**

Table 4: Effect of the constraints in our model.

Method	Base	New	H
CoOp	82.63	67.99	74.60
$+\mathcal{L}_{kg}$	80.73	73.61	77.00
$+\mathcal{L}_{kd}$	**83.13**	69.87	75.93
$+\mathcal{L}_{kg}+\mathcal{L}_{kd}$(ours)	82.59	**74.93**	**78.57**

Table 5: Comparision of model complexity.

Method	Total Parameters(M)	H
KgCoOp	124.325	77.00
TCP	+0.329	79.51
$\text{DeKg}_{\text{KgCoOp}}$	+0	78.57
DeKg_{TCP}	+0.329	**80.44**

datasets. This demonstrates that optimizing the learnable prompts with independence and consistency constraints together is indeed beneficial.

Next, we will conduct more detailed investigations for DeKg. If there is no special statement, all reported results are averaged performance across over 11 datasets.

4.2.4 Ablation Study And Analysis

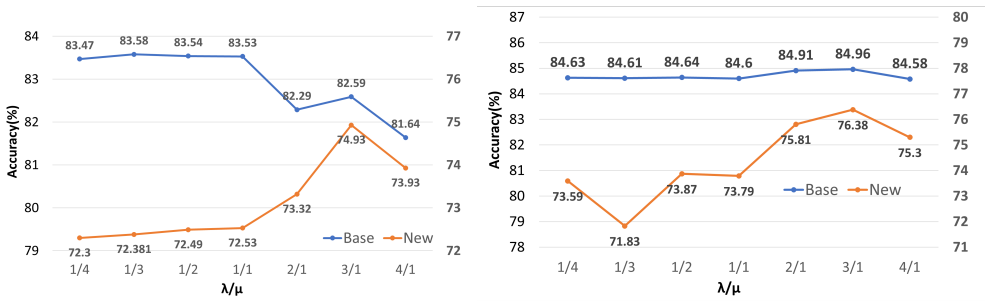
To investigate the learning process of DeKg, we conduct ablative analysis including as follows:

Effect of the constraints employed in DeKg: DeKg contains two key constraints, including the consistency constraint (i.e., $\mathcal{L}_{kg}$) and the independence constraint (i.e., $\mathcal{L}_{kd}$). We conduct a constraint-wise analysis by adding one or two of them to the baseline method CoOp. Table 4 shows the results. We can see that the baseline CoOp provides high base class performance but suffers from poor generalization. By incorporating $\mathcal{L}_{kg}$ alone, the performance of new classes increases significantly by 5.62% (i.e., 73.61% vs 67.99%), but the base class degrades from 82.63% to 80.73%. This suggests that $\mathcal{L}_{kg}$ explicitly enforces the prompts to capture generalizable features from frozen CLIP, or even overfitting to fail to capture task-specific knowledge. In contrast, incorporating $\mathcal{L}_{kd}$ leads improvements in both base and new classes compared with CoOp, indicating its ability in balancing model adaptation and generalization. It achieves the best performance in base classes but still legs behind KgCoOp in new classes. Finally, combining $\mathcal{L}_{kd}$ and $\mathcal{L}_{kg}$, DeKg achieves improvements in both base and new classes, leading to the average new class and harmonic mean gains of 6.94%(i.e., 74.93% vs 67.99%) and 3.97%(i.e., 78.57% vs 74.60%).

Comparision of Model Complexity: To better understand the benefits of the proposed DeKg, we examined the model complexity. As shown in Table 5, it can be observed that DeKg is an efficient method that performs better with the same model complexity of corresponding baselines. For example, $\text{DeKg}_{\text{KgCoOp}}$ shows an average improvement of 1.57% (i.e., 78.57% v 77.00%) over KgCoOp without adding any parameters. The main reason is that DeKg simply adds an efficient regularization for generating discriminative classifiers guided by better knowledge, i.e., optimizing the balance between adapting general knowledge and fine-tuning for targeted tasks.

Effect of Hyperparameter λ and μ: To further investigate the impact of consistency and independence constraints on model performance, we analyze the effect of hyperparameter λ and μ in the proposed model DeKg, i.e., λ controls the contribution of capturing general knowledge, and μ controls the divergence between task-specific knowledge and general knowledge. The effect of λ and μ on DeKg with KgCoOp and TCP (i.e., $\text{DeKg}_{\text{KgCoOp}}$ and DeKg_{TCP}) is shown in Figure 3a and Figure 3b, respectively. It can be seen that the performance of new tasks becomes better as λ/μ increases, indicating that the consistency constraint effectively captures the essential knowledge for new classes. The results reach the best when $\lambda/\mu = 3/1$ for both $\text{DeKg}_{\text{KgCoOp}}$ and DeKg_{TCP}. After that, the performance decreases because a larger ratio forces the learnable prompts to rely strongly on general knowledge, failing to capture task-specific information. The trend for base precision is

reversed. This result is reasonable because a larger ratio of λ/μ reduces the importance of task-specific knowledge, which is essential for base tasks.



(a) DeKg$_{\text{KgCoOp}}$ (b) DeKg$_{\text{TCP}}$

Figure 3: Effect of Hyperparameters λ and μ on DeKg$_{\text{KgCoOp}}$ and DeKg$_{\text{TCP}}$.

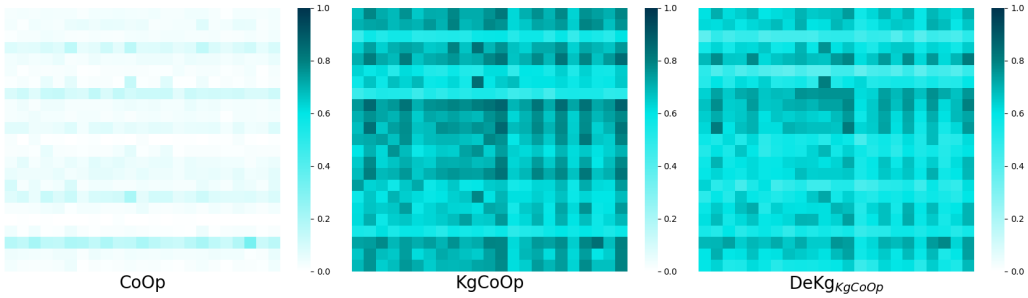


Figure 4: Visualization the HSIC between the prompt of W and W^{clip} in DTD dataset.

Visualization: To further explore the impact of independence on model performance, we examined the HSIC between learnable context and crafted prompts. In Figure 4, we observed that KgCoOp yielded very high values, indicating a strong reliance on general knowledge, thus resulting in poor performance on base tasks. Conversely, CoOp produced very low values, suggesting overfitting to the target task and limited generalization ability for new tasks. The values obtained by DeKg were moderate compared to the baselines, indicating a balance between not overfitting the target task and not being biased toward pre-training.

5 Conclusion

Knowledge-guided context optimization is a representative visual-language prompt tuning framework. It emphasizes the consistency between the learnable and crafted prompts to alleviate catastrophic forgetting, which boosts the generalization ability but degrades the few-shot learning ability in downstream tasks. In this paper, we introduce the method DeKg, introducing Hilbert-Schmidt Independence Criterion regularization for encouraging the intra-class independence between the learnable and crafted prompts and the inter-class independence between the learnable prompts. Extensive evaluations on three challenging benchmarks demonstrate that DeKg is an effective and efficient prompt tuning method. It can seamlessly integrate with existing knowledge-guided methods such as KgCoOp (Yao et al., 2023) and TCP (Yao et al., 2024), and significantly improve their performance without adding extra parameters. Especially, existing methods often struggle to keep a balance between the generalization ability and few-shot learning ability. In contrast, DeKg outperforms strong baselines on both base classes and new classes in base-to-new settings, and also obtains superior performance in cross-dataset generation and few-shot learning settings. In the future, we plan to incorporate DeKg to more visual-language prompt tuning frameworks and applications.

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