Class-Aware Visual Prompt Tuning for Vision-Language Pre-Trained Model

Yinghui Xing 1*, Qirui Wu 1*, De Cheng 2 †, Shizhou Zhang 1, Guoqiang Liang 1, Yanning Zhang 1

1National Engineering Laboratory for Integrated Aero-Space-Ground-Ocean Big Data Application Technology, School of Computer Science and Engineering, Northwestern Polytechnical University
2School of Telecommunications Engineering, Xidian University
dcheng@xidian.edu.cn

Abstract

With the emergence of large pre-trained vision-language model like CLIP, transferrable representations can be adapted to a wide range of downstream tasks via prompt tuning. Prompt tuning tries to probe the beneficial information for downstream tasks from the general knowledge stored in both the image and text encoders of the pre-trained vision-language model. A recently proposed method named Context Optimization (CoOp) introduces a set of learnable vectors as text prompt from the language side, while tuning the text prompt alone can not affect the computed visual features of the image encoder, thus leading to sub-optimal. In this paper, we propose a dual modality prompt tuning paradigm through learning text prompts and visual prompts for both the text and image encoder simultaneously. In addition, to make the visual prompt concentrate more on the target visual concept, we propose Class-Aware Visual Prompt Tuning (CA VPT), which is generated dynamically by performing the cross attention between language descriptions of template prompts and visual class token embeddings. Our method provides a new paradigm for tuning the large pre-trained vision-language model and extensive experimental results on 8 datasets demonstrate the effectiveness of the proposed method. Our code will be available soon.

Introduction

Recently, research in large-scale Vision-Language Models (VLM), such as CLIP (Radford et al. 2021), ALIGN (Jia et al. 2021), has achieved remarkable progress in representation learning (Desai and Johnson 2021; Zhang et al. 2020; He et al. 2016). Different from the traditional representation learning framework which usually trains the vision model with a fixed set of discrete labels and limits the visual recognition system to close-set visual concept, the vision-language model aims to align images with raw texts in the common embedding space by training on large-scale image-text pairs, which has become a promising alternative paradigm. Benefiting from huge amounts of image-text data, the pre-trained large-scale vision-language model is able to earn open-set visual concept generated from natural language, thus further allows zero-shot transfer to downstream tasks. Specifically, the vision-language model is composed

*These authors contributed equally to this work.
†Corresponding authors.

Figure 1: Visualization of the attention map of the image encoder. (a) Original Image. (b)Zero-Shot CLIP/CoOp. (c) Ours. The images are selected from OxfordPets, and Caltech101. The GT annotated object is marked by a red box. Best viewed in color.

of two components: the image encoder and the text encoder. When a new classification task arrives, one can synthesize the classifier by feeding the natural language description of the classes to the text encoder, then compute similarity between the “classifier” and the image features generated by the image encoder.

However, adapting these large vision-language models efficiently to downstream tasks demonstrates its own challenge. Recent studies show that “prompting” is a simple and effective way (Radford et al. 2021). While designing a proper prompt is a non-trivial task. It always requires domain expertise and takes significant amount of time for manually words tuning. Usually even with massive tuning, we could not yet guarantee that the obtained prompt is optimal for the downstream tasks.
Recent researches on prompt learning for vision representation are mainly inspired by some prompt tuning approaches in NLP (Shin et al. 2020; Jiang et al. 2020; Lester, Al-Rfou, and Constant 2021), e.g., the representative CoOp (Zhou et al. 2022b) and CoCoOp (Zhou et al. 2022a). These methods proposed to model learnable contexts in prompt using continuous representations, and then trained the model with these learnable prompts in an end-to-end way while keeping the pre-trained parameters fixed. Although these methods have achieved great success and show promising performance at present, they only learn prompts for the text encoder.

From the perspective of conventional visual recognition, a typical vision model can be roughly divided into two parts, namely a feature extraction module and a classifier. Similarly, the process of feeding the text prompt into the text encoder can be viewed as the synthesis of a classifier, and the image encoder extracts the visual features. Assume that the large scale pre-trained vision-language models have already captured all the knowledge (visual concepts) for the downstream tasks. What the prompting mechanism actually do is to query the suitable information, which is beneficial to the downstream tasks, from the pre-trained model. As shown in Figure 1 for an input image with multiple visual objects (concepts), e.g., the first case contains a person and a motorbike, and the image encoder will extract all the visual features of the objects, i.e., the attention maps of Zero-Shot CLIP and CoOp highlight on both the person and motorbike. However, the downstream task requires the output class label to be “motorbike”—the groundtruth annotation. CoOp actually tries to enable the model to output “motorbike” by adjusting the “classifier” alone, while keeping the given highlighted “person” and “motorbike” visual features unchanged. There is a consensus in vision community that—features matter (Girshick et al. 2014)! Therefore, we believe that adopting prompt tuning for the text encoder alone while directly utilizing the fixed image encoder for the downstream task is sub-optimal. In this paper, we introduce the visual prompts in the image input space, and propose a dual modality prompt tuning paradigm through learning text prompts and visual prompts for both the text and image encoder simultaneously, aiming at adapting the pre-trained model to downstream tasks via adjusting both the “classifier” and “visual features”.

Specifically, for the visual prompt tuning in the image encoder, we introduce only a small amount of trainable parameters in the image input space while keep the pre-trained image encoder fixed. Our extensive experimental results demonstrate that the visual prompt tuning is superior to the previously proposed context prompts. In addition, to make the visual prompt concentrate more on the target visual concept, we further propose the Class-Aware Visual Prompt Tuning mechanism, where the Class-Aware Visual Prompt is dynamically generated by performing the cross attention between language descriptions of template prompts and visual class token embeddings. Finally, we propose the overall prompt tuning mechanism to simultaneously learn the text and visual prompts, to make the pre-trained model better transfer to the downstream task. As shown in Figure 1 it greatly demonstrates that tuning the pre-trained models with visual and text prompts shows more focused visual attention area.

The main contributions of this paper can be summarized as follows:

- The proposed method demonstrates a new paradigm for tuning the large pre-trained vision-language model by simultaneously learning the visual and text prompts from both ends of text and image encoder.
- To encourage the visual prompts to concentrate more on the target visual concept, we further propose the Class-Aware Visual Prompt Tuning mechanism by performing cross attention between language descriptions of template prompts and visual class token embeddings.
- Extensive experimental results on eight datasets demonstrate the effectiveness of the proposed method, and show superiority to other prompt-tuning approaches by a large margin.

Related Work

Vision-Language Pretrained Models

Learning visual representations under the supervision of natural language has been demonstrated to be effective and attracting lots of attention (Chen et al. 2020; Jia et al. 2021; Li et al. 2021; Radford et al. 2021). For vision-language models, the image-text matching and the cross-modal contrastive learning are two important issues. In CLIP (Radford et al. 2021), two encoders related to the vision and language modalities are designed, and these image and text embeddings are then aligned using the straightforward dot product. Similarly, ALIGN (Jia et al. 2021) also utilizes a dual-encoder architecture, but it projects the image and text embeddings to the same semantic space to calculate the similarity scores between vision and language modalities, which makes the vision-language interaction more efficient. Both of them are pre-trained on a large-scale image-text datasets with the contrastive loss, and can be transferred to downstream task. In order to boost the performance of CLIP to downstream tasks, CLIP-Adapter (Gao et al. 2021) introduces feature adapters on either visual or language branch and fine-tunes them on the few-shot classification task. Zhang et al. (Zhang et al. 2021) further proposed a Training-Free CLIP-Adapter (TIP-Adapter), which creates the weights by a key-value cache model constructed from the few-shot training set. Without any training process, TIP-Adapter is more efficient than CLIP-Adapter. As an alternative framework to reduce the gap between objective forms of model pre-training and fine-tuning, prompt-based learning becomes a hot topic in both natural language process and computer vision communities. However, the discrepancy between two different modalities brings the difficulties in tuning the prompt. (Zhou et al. 2022b) proposed a context optimization (CoOp) strategy to automatically learn the optimal prompts, which greatly boosts the recognition accuracy. Our work also focuses on transferring the pre-trained vision-language model to downstream tasks through prompting.
Moreover, Class-Aware Visual Prompt is proposed to enable prompt and visual prompt for vision-language model. For this purpose, we introduce both the text clues in visual features. Our work proposes a dual modality tune the prompts in the text encoders and neglect the age to improve the generalization ability of CoOp. Both of CoOp by learning an input-conditional token for each image sample, CLIP has predicted. (Zhu et al. 2022) proposed a novel prompt tuning step which could hamper the general knowledge. For vision-language models (Jia et al. 2021), the text information while the image encoder can either be a transformer such as ViT (Dosovitskiy et al. 2021).

In this section, we first revisit CLIP, and provide some basic concepts, namely text prompt and visual prompt, to facilitate the introduction of the proposed method. Then, we elaborate the proposed dual modality prompt tuning paradigm in detail, and finally provide the loss function during training process.

**Contrastive Language-Image Pre-training Model**

Contrastive language-image pre-training (CLIP) model aims to align image feature space and text feature space which enables the model to have the capability of zero-shot transfer to downstream tasks. CLIP is composed of two encoders, one is designed for image and the other is for text. The text encoder adopts a transformer (Vaswani et al. 2017) to encode the text information while the image encoder can either be a CNN model like ResNet (He et al. 2016), or be a vision transformer such as ViT (Dosovitskiy et al. 2021).

With a tremendous number of 400 million pairs of image-text samples, CLIP is trained under the contrastive learning framework, where the associated image and text are treated as positive samples, while the non-associated samples as negative samples. After that, the entire parameters of the pre-trained CLIP model are kept frozen to downstream tasks without any fine-tuning. In downstream tasks, a handcrafted prompt is fed into the text end to synthesize a zero-

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**Figure 2: Overall architecture of our proposed method. It consists of three learnable components: text prompt, visual prompt and class-aware visual prompt generated from Class-Aware Visual Prompt Tuning (CA VPT) module whose detailed architecture is illustrated in Figure 3.**

**Prompt Learning**

Prompt learning originated from the community of NLP (Shin et al. 2020; Jiang et al. 2020; Liu et al. 2021), and originally refers to the application of a fixed function to the input tokens, which provides an instruction about the task to the model. In computer vision community, prompt learning is explored both in the visual models (Jia et al. 2021; Wang et al. 2022; Babag et al. 2022) and the vision-language models (Radford et al. 2021; Zhou et al. 2022a; Rao et al. 2022; Zhu et al. 2022), where visual prompt tuning (VPT) (Jia et al. 2022) achieved significant performance gains with only a small amount of additional parameters, i.e., prompts, in the input space. For vision-language models, CoOp (Zhou et al. 2022b) brings continuous prompt optimization from downstream data to adapt the pre-trained vision-language model. But CoOp may introduce improper prompt tuning steps which could hamper the general knowledge probing. In order to improve the generalization ability of CLIP, (Zhu et al. 2022) proposed a novel prompt tuning method, ProGrad, to deal with the conflicts between each tuning step and the general knowledge CLIP has predicted. Conditional CoOp (CoCoOp) (Zhou et al. 2022a) extends CoOp by learning an input-conditional token for each image to improve the generalization ability of CoOp. Both of them tune the prompts in the text encoders and neglect the clues in visual features. Our work proposes a dual modality prompt tuning paradigm, which introduces both the text prompt and visual prompt for vision-language model. Furthermore, Class-Aware Visual Prompt is proposed to enable the image feature to pay more attention to the target foreground object.

**Methodology**

In this section, we first revisit CLIP, and provide some basic concepts, namely text prompt and visual prompt, to facilitate the introduction of the proposed method. Then, we elaborate the proposed dual modality prompt tuning paradigm in detail, and finally provide the loss function during training process.
shot linear classifier by embedding the class names of the target dataset. Taking the classification task as an example, “[CLASS]” token can firstly be extended by a template, such as “a photo of [CLASS]”. Then the sentence is treated as a prompt and is encoded by the text encoder to derive a weight vector $w_i$, $(i = 1, ..., K)$, where $K$ is the total number of categories. At the same time, image features $x$ are obtained by the image encoder. The prediction probability can be calculated by

$$p(y = i | x) = \frac{\exp (\text{sim}(x, w_i)/\tau)}{\sum_{j=1}^{K} \exp (\text{sim}(x, w_j)/\tau)}, \quad \text{(1)}$$

where $\text{sim}(\cdot, \cdot)$ represents the computation of cosine similarity, and $\tau$ is the temperature coefficient learned by CLIP.

**Text Prompt and Visual Prompt**

**Text Prompt.** It is known that hand-crafted prompt for CLIP model may take a lot of time and expertise for word tuning as a slight change in wording may lead to a significant performance degradation. Motivated by prompt tuning in NLP models, CoOp (Zhou et al. 2022b) introduces a set of tunable word embedding vectors to learn machine-favorable prompt for the text end which we call text prompt. Let $\{u_1, u_2, ..., u_M\}$ denote $M$ learnable context vectors, and the word embedding of the text token is represented by $c_i$, $(i = 1, ..., K)$, then the prompt for the $i$th class can be denoted as $t_i = \{u_1, u_2, ..., u_M, c_i\}$. By forwarding $t_i$ into the text encoder $g(\cdot)$, we can obtain a classification weight vector for the $i$th visual concepts. The corresponding prediction probability can be calculated by

$$p(y = i | x) = \frac{\exp (\text{sim}(x, g(t_i))/\tau)}{\sum_{j=1}^{K} \exp (\text{sim}(x, g(t_j))/\tau)}, \quad \text{(2)}$$

where $x$ represents the extracted image features, and $g(\cdot)$ denotes the text encoder.

**Visual Prompt.** For vision-language models, there are two encoders for visual and language modalities. Tuning text prompt alone is not enough to reduce the gap between pre-trained and downstream tasks, thus leads to sub-optimal results. Motivated by the visual prompt tuning (VPT) (Jia et al. 2022) proposed for tuning vision transformers, we introduce visual prompt into the image encoder of CLIP model. The image patches $\{I_j \in \mathbb{R}^{3 \times h \times w} | j \in \mathbb{N}, 1 \leq j \leq N_p\}$ are firstly embedded into a $d$-dimensional latent space

$$e^d_0 = \text{Embed}(I_j), \quad e^d_0 \in \mathbb{R}^d, j = 1, 2, ..., N_p. \quad \text{(3)}$$

Let $E_l = \{e^d_i \in \mathbb{R}^d | j \in \mathbb{N}, 1 \leq j \leq N_p\}$ and $P_l = \{p^d_i \in \mathbb{R}^d | i \in \mathbb{N}, 1 \leq i \leq P\}$ represent a collection of image patch embeddings and visual prompts for the $l$th transformer layer. Suppose $s_l \in \mathbb{R}^d$ is a learnable class token in image encoder, which is different from the text class token used in the text prompt that the latter is a category-related word embedding. There are also two versions of visual prompt, VPT-Shallow and VPT-Deep. For VPT-Shallow, the image class token is combined with the image patch embeddings and the visual prompts to be taken as the input of the first transformer layer, i.e.,

$$[s_l, Z_l, E_l] = \Phi_1([s_{l-1}, P_{l-1}, E_{l-1}]), \quad l = 2, 3, ..., L, \quad \text{(4)}$$

where $Z_l \in \mathbb{R}^{P \times d}$ represents the image features of the $l_{th}$ transformer layer $\Phi_l$.

For VPT-Deep, prompts are introduced to each of the transformer layer, that is,

$$[s_l, \cdot, E_l] = \Phi_l([s_{l-1}, P_{l-1}, E_{l-1}]), \quad l = 1, 2, ..., L. \quad \text{(5)}$$

Generally, the performance is positively correlated with the prompt depth, therefore, we utilize the VPT-Deep in our model. $s_l$ is then projected by a linear projection layer $LP$ to obtain the final image feature. For simplicity, the whole process of image feature extraction can be represented by

$$\hat{x} = f([s_0, P_0, E_0]), \quad \text{(7)}$$

where $f(\cdot)$ denotes the image encoder. On combining the visual prompt, Equation (2) becomes

$$p(y = i | \hat{x}) = \frac{\exp (\text{sim}(\hat{x}, g(t_i))/\tau)}{\sum_{j=1}^{K} \exp (\text{sim}(\hat{x}, g(t_j))/\tau)}, \quad \text{(8)}$$

**Class-Aware Visual Prompt Tuning**

As shown in Figure 4, although visual prompt can implicitly make the VLM concentrate on the target visual concept, we further propose Class-Aware Visual Prompt Tuning (CAVPT) to explicitly enhance the concentration effect on the classes of the downstream tasks. Class-Aware Visual Prompt is generated dynamically by performing the cross attention between language descriptions of template (hand-crafted) prompts, i.e., “a photo of a [CLASS]”, and visual class token embeddings, where top-$K_N$ text class token

![Figure 3: The detailed architecture of the proposed Class-Aware Visual Prompt Tuning (CAVPT) module.](image-url)
[CLASS] are filtered out according to the zero-shot inference results.

As shown in Figure 3, feeding the template prompts with $K_N$ text class token [CLASS] into the text encoder produces $K_N$ text feature vectors $q_j \in \mathbb{R}^d, 1 \leq j \leq K_N$. After the mapping of a two-layer MLP, we can get $K_N$ query vectors $q_j \in \mathbb{R}^d, 1 \leq j \leq K_N$. The key and value vectors $k \in \mathbb{R}^d$ and $v \in \mathbb{R}^d$ are both obtained from the image class embedding vectors. Our proposed class-aware visual prompt $\tilde{p}_i \in \mathbb{R}^d$ for the $l_{th}$ layer is computed as

$$\tilde{p}_i = LP(LN(Softmax(Q^T_k)v) + [s_i]_{K_N}), 1 \leq j \leq K_N$$

where $LP$ denotes a linear projection layer, $LN$ denotes Layer Normalization, $s_i$ denotes the class token embedding vector corresponding to the $l_{th}$ layer of the image encoder and $[s_i]_{K_N}$ represents concatenating $K_N$ copies of $s_i$. $\tilde{p}_i$ is then fed into the $l_{th}$ transformer layer to take effect as a visual prompt.

To ensure the effect of the class-aware visual prompt, we additionally introduce a $K$-way classifier on top of the $K_N$ outputs of the $LN$ layer and cross entropy loss is enforced on the $K$-way logits

$$L_{ce}^{ca} = - \sum_i y_i \log p_i, 1 \leq i \leq K,$$

where $p_i$ denotes the $i_{th}$ logit, $K$ denotes the number of classes and $y$ denotes the one-hot coding for the output of the $LN$ layer which corresponds to the ground-truth target class, while for the outputs corresponding to other classes $y_i = \frac{1}{K}$. As the image class token embedding in deeper layers usually contains more semantic information, the Class-Aware Visual Prompt is only applied into the last few layers of the image encoder in our implementation.

**Training**

During training, the proposed method keeps the entire parameters of both the image and text encoder fixed, while optimizing the Text prompt, Visual prompt and the parameters for generating Class-Aware Visual Prompt. A Cross Entropy loss is adopted to minimize the distance between ground-truth annotation and the prediction probability computed by Equation (8).

$$L_{ce} = - \sum_i y_i \log p(y = i | \tilde{x}), 1 \leq i \leq K,$$

where $y$ denotes the ground-truth annotation and $p(y = i | \tilde{x})$ denotes the predicted probability from Equation (8). The total loss function combines the two cross entropy loss,

$$L_{total} = L_{ce}^{ca} + L_{ce}.$$  

**Experiments**

Datasets and Implementation Details.

To evaluate the effectiveness of our method, we conduct experiments on 8 classification datasets: EuroSAT (Heller et al. 2019), Caltech101 (Fei-Fei, Fergus, and Perona 2004), OxfordFlowers (Nilsback and Zisserman 2008), Food101 (Bossard, Guillaumin, and Gool 2014), FGVCAircraft (Maji et al. 2013), DTD (Cimpoi et al. 2014), Oxford-Pets (Parkhi et al. 2012), and StanfordCars (Krause et al. 2013). These datasets cover a variety of computer vision tasks, including image classification on generic objects, fine-grained categories, satellite and texture images.

Comparing with Baseline and Existing Methods

Existing representative prompt tuning methods include the remarkable CoOp method (Zhou et al. 2022b), and the CLIP model (Radford et al. 2021) itself used for zero-shot classification (i.e. Zero-Shot Clip). Therefore, we adopt these two models as our mainly compared methods.

As illustrated in the methodology part, the proposed dual modality prompt tuning paradigm contains three novel ingredients: 1) The fundamental visual prompt tuning design; 2) The class-aware visual prompt tuning module to guide the image encoder to obtain more discriminative image features; 3) The new model tuning paradigm by simultaneously learning the visual and text prompts from both sides of text and image encoders. To reveal how each ingredient contributes to the performance improvements, we conduct extensive ablation study to analyze different ingredients contained in the proposed model.

Specifically, we implement five variants of the proposed method as follows:

- **VPT-CLIP**, standards for introducing fundamental visual prompt into the primary CLIP model (Radford et al. 2021) to transfer pre-trained large model to the downstream tasks. Depending on the number of transformer layers involved in image encoder, we also design two variants of the VPT-CLIP model, namely VPT-CLIP-Shallow and VPT-CLIP-Deep.

- **VPT-CLIP-CAVPT**, standards for integrating the CAVPT module into the last layer of the image encoder in previous VPT-CLIP-Deep model architecture, to further improve the model attention.

- **VLP-CLIP**, means the dual modality prompt tuning paradigm to simultaneously learn visual (V) and text (L) prompts for image and text encoders, where the text prompt
is designed the same as that in CoOp\cite{zhou2022coop}, and the visual prompt is exactly the same as VPT-CLIP-Deep.

- **VLP-CLIP-CAVPT**, represents that we further integrate the CAVPT module into image encoder of VLP-CLIP. That is to say, we additionally introduce the class-aware visual prompt into VLP-CLIP by VPT-CLIP-CAVPT, to further illustrate the effectiveness of the CAVPT module.

The overall evaluation results are shown in Table 1 which reports the classification accuracy on 8 datasets. The table includes experimental results of two baseline methods, i.e., Zero-Shot CLIP\cite{radford2021learning} and CoOp\cite{zhou2022coop}, and other five variants of the proposed method. Compared with all these methods, our final method VLP-CLIP-CAVPT achieves the top performances on average over the 8 datasets. The evaluation results shown in Table 1 can be summarized as follows.

- Comparing the VPT-CLIP-Deep with the CoOp method, we can conclude that tuning image encoder of the pre-trained large model through visual prompt can get better performance than tuning the text encoder by text prompt. Specifically, the VPT-CLIP-Deep surpasses CoOp method by a margin of 1.79% in term of classification accuracy on average over the 8 datasets.

- Comparing VPT-CLIP-CAVPT with VPT-CLIP-Deep, as well as VLP-CLIP-CAVPT with VLP-CLIP-Deep, we can clearly see that the proposed CAVPT module can help to improve the corresponding baseline methods by 0.62% and 0.16% on average over 8 datasets, respectively. This illustrates the effectiveness of the proposed CAVPT module, which can be used as a plug-and-play module for further application.

- Comparing VLP-CLIP-CAVPT with VPT-CLIP-Deep, as well as VLP-CLIP-CAVPT with VLP-CLIP-Deep, we can clearly see that the proposed CAVPT module can help to improve the corresponding baseline methods by 1.1% and 0.64% on average over 8 datasets, respectively. This implies that simultaneously learning visual and text prompts is very effective for tuning pre-trained large model to adapt to downstream tasks.

## Ablation Study

### Analysis of constraint on CAVPT module

In the proposed CAVPT module, we apply the cross-entropy loss to encourage the visual class token and the text feature to be aligned, so as to extract class-related features. In order to demonstrate the effectiveness of the constraint, we conduct extensive ablation study to reveal how this constraint influences the model performance. Specifically, we conduct experiments on top of the VPT-CLIP-CAVPT model, by optimizing the model with/without the cross-entropy loss on the CAVPT module. We denote this two variant model as VPT-CLIP-CAVPT(w/o loss) and VPT-CLIP-CAVPT(w/loss), re-

| Models          | EuroSAT | Caltech101 | Oxford Flowers | Food101 | FGVC Aircraft | DTD | Oxford Pets | Stanford Cars | Average |
|-----------------|---------|------------|----------------|---------|---------------|-----|-------------|---------------|---------|
| Zero-Shot CLIP  | 45.19   | 90.87      | 66.95          | 80.50   | 19.23         | 43.97| 87.49       | 60.55         | 61.84   |
| CoOp            | 83.11   | 94.82      | 95.06          | 78.24   | 33.81         | 67.22| 88.64       | 75.79         | 77.09   |
| VPT-CLIP-Shallow| 79.33   | 94.66      | 86.74          | 80.92   | 27.50         | 62.71| 89.36       | 64.56         | 73.22   |
| VPT-CLIP-Deep   | **92.34**| 95.01      | 93.95          | **81.14**| 39.60         | 66.80| 90.15       | 72.07         | 78.88   |
| VPT-CLIP-CAVPT  | 92.31   | **95.36**  | 95.64          | 81.12   | 40.49         | **68.68**| 90.30       | 72.12         | 79.50   |
| VLP-CLIP-Deep   | 91.84   | 94.96      | 96.39          | 77.16   | 42.95         | 67.99| 90.35       | 78.16         | 79.98   |
| VLP-CLIP-CAVPT  | 92.03   | 95.08      | **96.45**      | 77.12   | **43.59**     | 68.66| 89.72       | **78.48**     | **80.14**|

Table 1: Main Results of our models.

| Models              | EuroSAT | Caltech101 | Oxford Flowers | Food101 | FGVC Aircraft | DTD | Oxford Pets | Stanford Cars | Average |
|---------------------|---------|------------|----------------|---------|---------------|-----|-------------|---------------|---------|
| CAVPT(w/o loss)     | 92.16   | 95.22      | 94.05          | **81.13**| 39.69         | 67.12| 90.26       | **72.26**     | 78.99   |
| CAVPT(w/ loss)      | **92.31**| **95.36**  | **95.64**      | 81.12   | **40.49**     | **68.68**| **90.30**   | 72.12         | **79.50**|

Table 2: Ablation study on the loss applied in CAVPT.

| Models              | EuroSAT | Caltech101 | Oxford Flowers | Food101 | FGVC Aircraft | DTD | Oxford Pets | Stanford Cars | Average |
|---------------------|---------|------------|----------------|---------|---------------|-----|-------------|---------------|---------|
| 5                   | 92.31   | 94.90      | 94.83          | **95.36**| 95.26         |     |             |               | 92.13   |
| 10                  | 93.90   | 94.90      | 94.83          | **95.36**| 95.26         |     |             |               | 92.13   |
| 20                  | 95.64   | 94.59      | 94.02          | 94.05   | 94.06         |     |             |               | 92.13   |
| 50                  | **81.12**| 81.10      | 81.11          | 81.08   | 81.04         |     |             |               | 92.13   |
| 100                 | 38.27   | 40.18      | **40.49**      | 39.85   | 40.17         |     |             |               | 92.13   |
| FULL                | **68.68**| 68.01      | 67.77          | -       | -             |     |             |               | 92.13   |

Table 3: Ablation study on the length of input text class token in CAVPT.
We can clearly see that training CAVPT with cross-entropy loss helps to improve the average accuracy by a margin of 0.51%, compared with the corresponding baseline method VPT-CLIP-CA VPT (w/o loss). This greatly illustrates the efficiency of training CAVPT with such a constraint.

Analysis on the length of input text class tokens in CAVPT. As shown in Figure 3 and Equation (9), we need to select top-$K_N$ text class token as input to the CAVPT module, where $K_N$ is lower than the total number of classes in the dataset. In order to investigate the effect of the parameter $K_N$ on the model performance, we conduct comprehensive experiments with varying values of $K_N$, i.e., $\{5, 10, 20, 50, 100\}$, on top of the VPT-CLIP-CA VPT model, on all the 8 datasets. Generally speaking, the final results are not very sensitive to $K_N$. It achieves the best performance when setting $K_N = 5$ on half number of the datasets.

Visualization of the attention map. Visualization for the last layer of the trained model is shown in Figure 4, which helps understand the proposed method in-depth. Figure 4(a) is the original image with target object in the red bounding box. Figure 4(b) shows the attention maps of the baseline method Zero-shot CLIP/CoOp, as CoOp does not tune the image encoder. Figure 4(c) to (f) show the attention maps of four variants of our proposed method. We can clearly see that the Zero-shot CLIP usually focuses on most of the typical object areas in the image, while the VPT-CLIP-Deep focuses on the correct object area. This illustrate that VPT-CLIP-Deep learns more knowledge from the downstream tasks. When integrating the CAVPT module and simultaneously tuning the text and visual prompts for text and image encoder, we can find that the model gradually concentrates on the area of target object, especially for our final method “VLP-CLIP-CA VPT”. It concentrates more on the object of interest in the image, helping to learn more class-aware and distinct object features. Benefiting from the proposed CAVPT module, which is class-aware and contains more semantic information, the concentration effect on the classes of the downstream tasks can be greatly enhanced.

Conclusion

In this paper, we propose a new paradigm for tuning the large pre-trained vision-language model to downstream tasks by learning the visual and text prompts from both sides of text and image encoder simultaneously. We found that the visual prompt tuning is more effective to adapt the vision-language pre-trained model compared with the text prompt. Although visual prompt can implicitly tune the model to pay more attention on the target object belonging to the downstream classes, we explicitly encourage the visual prompts to concentrate more on the target visual concept and further propose Class-Aware Visual Prompt Tuning mechanism by performing cross attention between image class token embedding and language descriptions of template prompts. Extensive experimental results on eight datasets demonstrate the effectiveness of the proposed method, and show superi-
ority to other prompt tuning approaches by a large margin.

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