Learning to Compose Diversified Prompts for Image Emotion Classification

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Abstract
Contrastive Language-Image Pre-training (CLIP) represents the latest incarnation of pre-trained vision-language models. Although CLIP has recently shown its superior power on a wide range of downstream vision-language tasks like Visual Question Answering, it is still underexplored for Image Emotion Classification (IEC). Adapting CLIP to the IEC task has three significant challenges, tremendous training objective gap between pretraining and IEC, shared suboptimal and invariant prompts for all instances. In this paper, we propose a general framework that shows how CLIP can be effectively applied to IEC. We first introduce a prompt tuning method that mimics the pre-training objective of CLIP and thus can leverage the rich image and text semantics entailed in CLIP. Then we automatically compose instance-specific prompts by conditioning them on the categories and image contents of instances, diversifying prompts and avoiding suboptimal problems. Evaluations on six widely-used affective datasets demonstrate that our proposed method outperforms the state-of-the-art methods to a large margin (i.e., up to 9.29% accuracy gain on EmotionROI dataset) on IEC tasks, with only a few parameters trained. Our codes will be publicly available for research purposes.

1 Introduction
Image Emotion Classification aims to extract emotions evoked in images. Previous methods approach this challenging but essential task by first loading a backbone that initialized on datasets of fixed label sets (i.e., ImageNet), then designing various architectures or gating, attention mechanisms to compose discriminate emotion features. Benefiting from the powerful feature composition ability of deep learning, these methods have achieved great success [Zhao et al., 2021a].

Recently, vision-language pre-training such as CLIP has emerged as a promising alternative [Radford et al., 2021]. The main idea is to align images and raw text using two separate encoders. Compared to traditional vision-only pretraining methods, the large-scale, easily accessible training data and diverse natural language descriptions enable CLIP to learn more fine-grained open-set visual concepts. Benefiting from these broader ranges of visual concepts, CLIP has strong generalization ability, and some more recent work has shown that it can be readily transferred to downstream language-vision tasks with greatly improved performance. Adapting these recent techniques to IEC can be highly valuable, given that hu-
man emotion is highly abstractive and figuring out emotions carried in images requires a deep understanding of various details and concepts, but only a fixed set of concepts can be accessed by traditional vision pretraining methods [Zhao et al., 2021b].

However, adapting CLIP to IEC has three significant challenges. (1) **Tremendous gap between pretraining and IEC:** Unlike language-vision tasks, IEC has only image data during model training (as depicted in (a) (b) shown of Figure 1), which is dramatically different from CLIP training scenarios, making it difficult to effectively utilize rich knowledge entailed in CLIP.

(2) **Suboptimal prompts:** CLIP proposed to manually design text prompts to transfer knowledge to downstream tasks. However, we observe that a slight change in wording can make a massive difference in performance, as illustrated in (c) (d) of Figure 1.

(3) **Shared invariant prompts:** Some work in NLP treat prompts as sequences of virtual tokens [Li and Liang, 2021] and learns prompts automatically by parameterizing these tokens [Lester et al., 2021], avoiding the suboptimal problem to some extent [Liu et al., 2021]. However, these methods employed shared prompts across all instances, regardless of the fact that instances of different categories share similar features while also have their own distinct characteristics. As shown in (e) of Figure 1, although the left picture and the middle one are from different categories, there are some associations between them, i.e., the color. While the middle and the right ones come from one category, they have their own peculiarities.

To tackle the above three challenges, we propose a novel Prompt Tuning method with Diversified Prompt Composition (PT-DPC) based on CLIP, which can learn to compose unique prompts for each image. Specifically, we treat prompts as a sequence of tunable virtual tokens and obtain text representations by inputting them to the text encoder of CLIP. These virtual tokens are trained end-to-end and can condense the signal from a labeled dataset, with CLIP weights fixed. We further condition these virtual tokens on the classes and image contents of instances. More specifically, we employ different virtual tokens for each class to obtain class-specific prompts. Then we integrate image contents with all class-specific prompts to compose diversified prompt, forming an instance-specific prompt and capturing associations between possible classes.

We evaluate our model on six widely used image emotion classification benchmarks, namely, FI8, EmotionROI6, EmotionROI2, FL6, FL2, Twitter I, Twitter II. Experimental results show that our model outperforming state-of-the-art methods by a large margin. For example, our method achieves 92.9% absolute accuracy gain on EmotionROI6 dataset.

The contributions of this work are summarized as follows:

- We propose a novel prompt tuning method, PT-DPC, addressing three challenges of adapting the CLIP model to the IEC task. To our best knowledge, this is the first work to introduce a prompt tuning method for image emotion classification tasks.
- To avoid suboptimal problems for the fixed prompt tuning of CLIP, we propose a diversified prompt composition by utilizing both image contents and all class-specific virtual tokens.
- The experimental results on six popular affective image datasets demonstrate that our proposed framework can outperform the state-of-the-art methods for emotion classification.

2 Related Work

Our work is closely related to image emotion classification and prompt tuning methods.

**Image Emotion Classification**

Image emotion classification is usually formulated as an emotion feature extraction problem. Learning discriminative emotion features will facilitate classification performance. To approach this task, previous methods utilized hand-crafted features [Zhao et al., 2014] [Borth et al., 2013]. Later on, CNNs or other alternative architectures like attention, transformer [Chen et al., 2014] [You et al., 2015] [Deng et al., 2021] that pretrained on a fixed set of labels were proposed to boost classification performance. In addition to designing new architectures, researchers also tried to boost classification performance by incorporating additional information such as salient regions [Wu et al., 2021], label transfer probabilities [Rao et al., 2019], or intensity information [Zhang and Xu, 2020]. All the above approaches employ a fixed set of labels as supervised signals to learn visual concepts. In contrast, we use CLIP, which employs language as supervised signals, to learn more fine-grained visual concepts.

**Prompt Tuning Method in NLP**

With the application of large-scale pre-trained language models such as BERT [Devlin et al., 2018] and GPT [Brown et al., 2020], many downstream applications have achieved significant improvements by finetuning on top of the pre-trained models. However, due to the large scale of model parameters, finetuning brings a large computational and storage burden. Instead of finetuning on the full model, Prompt tuning methods transfer knowledge entailed in large pre-trained models by designing a textual prompt to reformulate downstream tasks to look more like pretraining tasks. This reduces the gap between pretraining and downstream tasks, making the knowledge entailed in pretraining models can be transferred to downstream tasks easily with only a few annotation examples. Therefore, how to get a text prompts becomes a key issue in prompt tuning. Currently, prompt tuning methods can be roughly divided into two categories: manually crafted and automatically learned. While manually crafting prompts [Brown et al., 2020] [Radford et al., 2021] is intuitive, creating and experimenting with these prompts takes time and experience, even experienced prompt designers may fail to manually discover optimal prompts [Jiang et al., 2020]. To automate prompt engineering, [Li and Liang, 2021] [Lester et al., 2021] [Zhou et al., 2021] parameterized the prompts by treating prompts as virtual tokens and perform prompting directly in the embedding space.

Our proposed model lies in the second line of work. Instead of using a shared prompt for all instances, we condi-
3 Methodology

Figure 2 shows the overview of our PT-DPC framework. We will introduce it from three aspects: task definition, diversified prompts composition, and training.

3.1 Task Definition

A CLIP model carries two separate encoders, image encoder $\mathcal{M}_{\text{img}}$ and text encoder $\mathcal{M}_{\text{txt}}$. And two preprocessors of image and text inputs are $E_I$ and $E_T$ respectively. Normally, when a CLIP model is deployed on the image classification task, it is given a image $x$ with its corresponding label $y \in Y$ as input, where $Y = \{y_1, y_2, ..., y_C\}$ includes all $C$ categories of the dataset to which $x$ belongs. $f_{\text{img}}(E_I(x))$ is the representation of $x$ which obtained by $\mathcal{M}_{\text{img}}$. And $f_{\text{txt}}([E_T(p_i); E_T(y^{(i)})]) (i \in [1, C])$ are obtained by $\mathcal{M}_{\text{txt}}$, where $p_i$ is a prompt which is consisted of a series of tokens to compose the input of text encoder by concatting with the class embedding $E_T(y^{(i)})$. $S$ means the computation of cosine similarity as Eq 1.

$$S(a, b) = \frac{a \cdot b}{\|a\|\|b\|}.$$  \hspace{1cm} (1)

Then the classification result $y_{\text{pred}}$ is formed as Eq 2.

$$y_{\text{pred}} = \arg\max \arg\max_i S(f_{\text{img}}(E_I(x)), f_{\text{txt}}([E_T(p_i); E_T(y^{(i)})])))$$

$$= \arg\max \arg\max_i \frac{f_{\text{img}}(E_I(x)) \cdot f_{\text{txt}}([E_T(p_i); E_T(y^{(i)})])}{\|f_{\text{img}}(E_I(x))\|\|f_{\text{txt}}([E_T(p_i); E_T(y^{(i)})])\|}.$$  \hspace{1cm} (2)

We aim to find a text prompt $p_i$ to maximize the likelihood of $P(y_{\text{pred}} = y | p_i)$. Generally, $p_i$ is manually crafted, which may cause the suboptimal problem. Inspired by [Li and Liang, 2021], we parameterize $p_i$ by $\theta$ that can be updated, which avoiding the suboptimal problem.

3.2 Diversified Prompts Composition

Following [Lester et al., 2021], we initialize the class-specific prompts $p_{c(i)}$ by a template $s$, which are processed by the tokenizer and embedding of the original CLIP model. Then the task target comes to train the parameters of $p_{c(i)}$ to maximize the likelihood of $P(y_{\text{pred}} = y | p_{c(i)})$. However, just like the part (e) in the Figure 1, there are significant differences among the content of different affective images even though they are in the same class. So the prompt should not be the same for
different images. Thus we propose a diversified prompt composition method to combine the instance-content feature with class-specific, as shown in Figure 3.

The initial parameters are the same for different categories. The effect on different initialization will be discussed in the Section 4.4. After the initialization of class-specific prompt $p_c(i)$, we get $C$ series of $L$-long class embedding which are marked as $p_c(i)(j)$ ($j \in [1, L]$). Each token has same dimension with the input and the output feature of the CLIP model. We take a similarity calculation between the output feature of the image and each virtual token to get a similarity score as weight multiply with each virtual token. Then we get the diversified prompt $p_d$, as the Eq 3.

$$p_d(j) = \sum_{i=1}^{C} S(f_{img}(E_{I}(x)), p_c(i)(j)) p_c(i)(j)$$

$$= \frac{C}{\sum_{i=1}^{C} \|f_{img}(E_{I}(x))\| \|p_c(i)(j)\|} f_{img}(E_{I}(x)) p_c(i)(j),$$

where $p_d(j)$ is the $j$-th virtual token of the diversified prompt $p_d$.

After composing the full diversified prompt by concatenating the $p_d$ with each class embedding $y^{(i)}$. Then the follow-up process is same as former.

### 3.3 Training

$$y_{pred} = \arg \max \frac{S(f_{img}(E_{I}(x)), f_{txt}(|E_T(p_d); E_T(y^{(i)})|))}{f_{img}(E_{I}(x)) \|f_{txt}(|E_T(p_d); E_T(y^{(i)})|)\|}$$

The final prediction $P(y_{pred})$ is obtained as Eq 4. The full model can be trained by maximizing the likelihood of $P(y_{pred} = y|p_d)$ via backpropagation, while the parameters of whole original CLIP model are fixed, only applying gradient updates to $p_d$. Cross-entropy loss is widely used in classification problems due to its advantages of fast convergence and not falling into local optimum solutions. We also adopt cross-entropy loss as classification loss to update and optimize the model, as Eq 5.

$$Loss = -\frac{1}{N} \sum_{i=1}^{N} y^{(i)} \log \frac{e^{y^{(i)}}}{\sum_{j=1}^{C} e^{y^{(j)}}}.$$  

### 4 Experiments and Analysis

#### 4.1 Datasets

We perform experiments on four datasets with six settings, including Flickr and Instagram(FL), EmotionROI, FL, EmotionROI, Twitter I, and Twitter II. Following previous studies [Yang et al., 2018a], we adopt accuracy as the metric to evaluate our proposed method and use the same dataset split for fair comparisons.

- FL [You et al., 2016] is consisted of 23,308 pictures distributed in 8 imbalanced emotion categories from Flickr and Instagram, two popular social media platforms. Since these 8 categories can be divided into two categories according to polarity such as positive (amusement, awe, contentment, excitement) and negative (anger, disgust, fear, sadness), we also conduct experiments on binary classification setting to facilitate the comparison with work that only performs binary classification, which called FL2.
- EmotionROI [Peng et al., 2016] has 6 balanced categories of affective images, which contains 1980 images from Flickr. Since these 6 categories can also be divided into two categories (positive: joy, surprise, negative: anger, disgust, fear, sadness), we also evaluate our method on both six-category setting and binary setting, which called EmotionROI2.
- Twitter I [You et al., 2015] is a dataset with two categories. It has 1,269 images in total, all of them are from the Twitter platform.
- Twitter II [Borth et al., 2013] is a small-scale dataset that contains 603 images of two different categories.

#### 4.2 Implementation Details

We build our framework based on the CLIP-ViT-B/32 [Radford et al., 2021], which is trained on 400 million image-text pairs and reports impressive performance on several zero-shot downstream tasks. The text and image encoder of CLIP model are fixed during the whole experiment period, which have been already pre-trained on the large-scale datasets.

We employ the SGD optimizer to tune the trainable part with 0.1, 0.01, and 0.01 as the initial learning rate of different scale dataset, and a StepLR learning rate scheduler with 3 steps and 0.1 momentum.

All our experiments are carried out on an NVIDIA RTX3090 GPU with 32GB of CPU memory using PyTorch framework [Paszke et al., 2019]. Images are resized and center cropped to $224 \times 224$, channel converted, and data normalized by the preprocessor that the original CLIP project provides, with a batch size of 64 for 10 epochs.

#### 4.3 Performance on Image Emotion Classification

In this section, we review recent work on image emotion classification and draw comparisons with our method. There are two hand-craft-feature-based method, three CNN-based fine-tuning method, and few special-designed methods based on CNN backbone in recent years, including the SOTA methods of each dataset.

- In the early years, researchers explored emotion classification tasks in terms of hand-craft features at the image art level [Zhao et al., 2014] or using sentiment dictionary and simple classifiers [Borth et al., 2013].
- With the rise of deep learning method, the image emotion classification methods turned to use CNN as backbone, got better performance.
- DeepSentibank [Chen et al., 2014] employed CNNs to discover ANPs and realized visual sentiment concept classification.
Table 1: The Classification Accuracy of PT-DPC on different datasets comparing with baseline methods

| Method          | FL8    | EmotionROI6 | FL2    | EmotionROI2 | Twitter I | Twitter II |
|-----------------|--------|-------------|--------|-------------|-----------|------------|
| Zhao et al.     | 0.4613 | 0.3484      | 0.5842 | 0.7345      | 0.6792    | 0.6751     |
| SentiBank       | 0.4923 | 0.3524      | 0.5647 | 0.6618      | 0.6663    | 0.6593     |
| AlexNet         | 0.5813 | 0.4141      | 0.6863 | 0.7160      | 0.7324    | 0.7566     |
| VGGNet-16       | 0.6375 | 0.4546      | 0.7064 | 0.7225      | 0.7675    | 0.7999     |
| ResNet101       | 0.6616 | 0.5160      | 0.7576 | 0.7392      | 0.7813    | 0.7823     |
| DeepSentiBank   | 0.5154 | 0.4253      | 0.6154 | 0.7011      | 0.7125    | 0.7023     |
| PCNN            | 0.5616 | -           | 0.7534 | 0.7358      | 0.8254    | 0.7768     |
| MldrNet         | 0.6775 | -           | 0.7954 | 0.7899      | -         | -          |
| Zhu et al.      | 0.7303 | -           | 0.8426 | 0.8052      | -         | -          |
| Yang et al.     | -      | -           | 0.8635 | 0.8126      | 0.8865    | 0.8048     |
| WSCNet          | 0.7007 | 0.5825      | -      | -           | 0.8425    | 0.8135     |
| ECWA            | 0.7087 | 0.5909      | -      | -           | 0.8479    | 0.8167     |
| MSRCA           | 0.7260 | 0.5560      | 0.8740 | 0.8300      | -         | -          |
| Rao et al.      | 0.7546 | -           | 0.8751 | 0.8294      | -         | -          |
| Zhang et al.    | 0.7271 | 0.6041      | 0.9097 | 0.8510      | -         | -          |
| Wu et al.       | -      | -           | 0.8871 | 0.8429      | 0.8965    | 0.8268     |
| PT-DPC          | 0.7807 | 0.6970      | 0.9389 | 0.8855      | 0.9094    | 0.8250     |

- PCNN [You et al., 2015] purposed a novel progressive CNN architecture based on VGGNet.
- Yang et al. [Yang et al., 2018b] employed object detection technique to produce the “Affective Regions” and propose three fusion strategy to generate the final predictions on VGGNet.
- ResNet is also a widely-used CNN baseline structure. It is pre-trained on the ImageNet dataset [Deng et al., 2009] and fine-tuned after modifying its FC layer.
- Based on the backbone of ResNet101, the WSCNet [Yang et al., 2018a] realized the end-to-end image emotion classification by coupling the global and local features according to the detected salient regions in the image, which is the best method among the content-based image emotion classification task.
- To compare with the WSCNet, ECWA [Deng et al., 2021] purposed a emotion class-wise aware loss on the same backbone. Only finetuning the backbone, it got better performance on all datasets than WSCNet without any other structure.
- Zhu et al. [Zhu et al., 2017] explored a unified CNN-RNN architecture for visual emotion recognition.
- MldrNet [Rao et al., 2020] provided a CNN architecture based on AlexNet with side branch to utilize multi-level deep features.
- MSRCA [Zhang et al., 2022] proposed a novel multi-level sentiment region correlation analysis model.
- Due to some datasets have probabilities with its corresponding labels, [Rao et al., 2019] utilized the label probability of the affective images into a loss function for training to leverage the knowledge from such a large-scale pre-trained model. We employ a group of experiments to find out the role they play in overall performance, and show in Table 2.
- [Zhang and Xu, 2020] purposed an end-to-end network for IEC leveraging weakly supervised emotion intensity learning, achieved SOTA performance on FL2 and two categories types of EmotionROI dataset.
- Based on the object information in the detected image, [Wu et al., 2021] built a graph convolutional network based on the sentiment dictionary to explore relationship among the object in image, which made a better performance on the sentiment polarity classification datasets.

As can be seen from the Table 1, Early hand-craft feature methods were generally less effective, despite their better interpretability. With the rise of deep learning, the performance of deep feature methods on IEC is increasing with the network depth and the number of model parameters. As the exploration of IEC continues, more and more researchers focus on the extraction of information or external knowledge about the image is beneficial to improve the performance of sentiment classification. Therefore, the DPC method, which utilizes a large scale pre-trained model with richer knowledge, achieves competitive results on all six commonly used datasets, but fails to achieve the best performance on the TwitterII dataset due to the difficulty of training because of the small data scale of only 603 images total.

4.4 Ablation Study
The diversified prompt part combine the categories-specific information and the image-content information, which makes the prompt more precise to leverage the knowledge from such a large-scale pre-trained model. We employ a group of experiments to find out the role they play in overall performance, and show in Table 2.

The full model line is the normal version of PT-DPC that we have shown above. The version without instance-specific is that we obtain the prompt from the mean value of class-specific embedding without multiplying similarity weights from the corresponding image feature. The version with-
Table 2: Ablation Study Results of PT-DPC on Different Datasets

| Template       | FL_8 | EmotionROL_6 | FL_2 | EmotionROL_2 | Twitter I | Twitter II |
|----------------|------|--------------|------|--------------|-----------|------------|
| Full model     | 0.7807 | 0.6970       | 0.9389 | 0.8855       | 0.9094    | 0.8250     |
| w/o instance-specific | 0.7669 | 0.6919       | 0.9381 | 0.8737       | 0.8937    | 0.8167     |
| w/o class-specific | 0.7631 | 0.6481       | 0.9372 | 0.8788       | 0.8976    | 0.7667     |
| w/o instance-specific w/o class-specific | 0.7730 | 0.6380       | 0.9372 | 0.8771       | 0.8937    | 0.8083     |

As can be seen from the Table 3, a different initialization only brings a small changes while not relevant with special dataset. The Std show that there is only a few influence on different initialization method. Specially, it doesn’t take even any changes on the FL and TwitterII dataset with polarity classification. Though further tuning of the initialization words might help, it can still consider that PT-DPC is robust by different initialized templates.

4.6 Remaining Challenges

Although the successfully applying of large models has a strong effect on classification of semantically complex affective images. However, for datasets with small-scale and large domain biases, such as the TwitterII dataset, special design of domain adaptation is needed to more adequately bridge this gap.

In addition, there is not an either/or relationship between affective categories. So it could be considered to research more about the interclass relationships or LDL-related studies by PT-DPC or to exploit a more large-scale pre-trained model beyond CLIP.

5 Conclusion

In this paper, we first propose a general framework that adapting CLIP to the image emotion classification task, diversified prompt composing (PT-DPC), to effectively leverage the rich image and text semantics entailed in CLIP. Except for addressing the challenge of training objective gap, the PT-DPC automatically compose instance-specific prompts by conditioning them on the categories and image contents of instances, diversifying prompts and avoiding suboptimal problems. Compared with the state-of-the-art method, PT-DPC performs better in several widely-used datasets, including binary categories and multi-categories. Furthermore, research about the multimodal method is well popular, but there are still many cases alive with only one modal information. We hope that the ideas in this article can inspire other resource-constrained tasks like image emotion classification and develop more novel multi-modal methods for traditional single-modal tasks.
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