Prompting Large Pre-trained Vision-Language Models For Compositional Concept Learning

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Abstract

This work explores the zero-shot compositional learning ability of large pre-trained vision-language models (VLMs) within the prompt-based learning framework and propose a model (PromptCompVL) to solve the compositional zero-shot learning (CZSL) problem. PromptCompVL makes two design choices: first, it uses a soft-prompting instead of hard-prompting to inject learnable parameters to reprogram VLMs for compositional learning. Second, to address the compositional challenge, it uses the soft-embedding layer to learn primitive concepts in different combinations. By combining both soft-embedding and soft-prompting, PromptCompVL achieves state-of-the-art performance on the MIT-States dataset. Furthermore, our proposed model achieves consistent improvement compared to other CLIP-based methods which shows the effectiveness of the proposed prompting strategies for CZSL.

1 Introduction

In this paper, we investigate a previously formulated compositional learning problem, compositional zero-shot learning (CZSL), which requires the agent to recognize novel compositional attribute-object (attr-obj) pairs by composing previously learnt primitive concepts. For example, in Fig. 1, after learning the primitive concepts, sliced and apple, CZSL expects the agent to recognize sliced apple which has not been observed during training time.

The main challenge of CZSL is the distribution-shift between the training and test data which causes the learnt models overfit the seen compositions. Previous works usually construct a shared embedding space and add different constraints to regularize the space for compositional concept learning (Nagarajan and Grauman, 2018; Naeem et al., 2021; Mancini et al., 2021). In this work, we attempt to solve the CZSL problem from the lens of prompting large vision-language models. We propose a model, called PromptCompVL, to explore the compositional learning ability of current VLMs.

The core idea of PromptCompVL is to inject learnable pieces, including the soft-prompting layer and the soft-embedding layer, to CLIP (Radford et al., 2021) for compositional learning. In particular, soft-prompting layer is used to replace the CLIP’s hard-prompting vectors in order to increase CLIP’s capacity and reprogramming it for CZSL by adjusting the soft-prompting vectors. Moreover, soft-embedding layer is introduced to replace CLIP’s original vocabulary embedding layer to address the compositional concept learning challenge. We use the soft-embedding layer to encode the primitive concepts and update the concept embedding through observing different combinations during training time. The role of soft-embedding is similar to verbalizer in the general prompt-learning framework (Liu et al., 2021a).

The advantages of this work can be summarized as follows: 1) Inherited from prompting methods, PromptCompVL is a parameter-efficient learning framework which can improve CZSL using VLMs without the overhead of fine-tuning the entire model. 2) Different from previous prompting architecture, PromptCompVL introduces two learnable components, soft-embedding and soft-prompting.
simultaneously, to address CZSL problems. In particular, it introduces the soft-embedding layer to address the compositional challenge and the soft-prompting layer to improve the VLMs’ flexibility to fit CZSL tasks. 3) PromptCompVL achieves SOTA result on MIT-States dataset and shows consistent improvements compared to other CLIP-based methods on both MIT-States and UT-Zappos datasets.

2 Preliminaries

CLIP (Radford et al., 2021) is a powerful Vision-Language model which uses contrastive loss to learn a joint embedding space and align images and texts within the constructed space. CLIP consists of three components: 1) a text encoder to summarize text into a vector. It uses BERT (Devlin et al., 2018) as its text encoder, 2) an image encoder to transform image into a vector. The image encoder can be ResNet (He et al., 2016) or ViT (Dosovitskiy et al., 2020), 3) a loss function, which is contrastive loss to update the text and image encoders. In PromptCompVL, we use and fix the pre-trained text and image encoders and solve CZSL by adding the learnable soft-prompting and soft-embedding layers detailed in Sec. 4.1.

Prompt Learning is commonly used for transferring knowledge from pre-trained models to downstream tasks, especially in low-resource scenarios. Prompt Learning can be generally categorized into: 1) discrete/hard prompting which requires carefully engineered prompts and verbalizers to map the vocabulary-space to the label-space for downstream tasks (Liu et al., 2021b). 2) continuous/soft prompting which injects learnable prompts into VLMs and reprogram the VLMs for downstream tasks. PromptCompVL follows the soft-prompting line. Besides soft-prompting layer, PromptCompVL also adds soft-embedding layer to further improve CLIP’s compositional learning ability. Because CZSL has no training examples for novel attr-obj compositions, prompting large VLMs can help solve this zero-shot problem.

3 Problem Formulation

Here we formally define the CZSL task. Let $\mathbb{A} = \{a_0, a_1, \ldots, a_n\}$ be the attribute set and $\mathbb{O} = \{o_0, o_1, \ldots, o_m\}$ be the object set. The compositional label space $\mathbb{Y}$ is the Cartesian product of the attribute set and the object set, $\mathbb{Y} = \mathbb{A} \times \mathbb{O}$. At training time, we are given seen examples $\mathbb{S}_{\text{seen}} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$, where $x_i$ is an image and $y_i = (a_i, o_i)$ is its label from seen pair set $\mathbb{Y}_{\text{seen}} \subseteq \mathbb{Y}$. The goal of CZSL is to learn a function $f$ to assign an image a compositional label from the target set $\mathbb{Y}_{\text{target}} \subseteq \mathbb{Y}$. Based on different target set settings, CZSL can be categorized into: 1) Standard CZSL, where $\mathbb{Y}_{\text{target}} = \mathbb{Y}_{\text{unseen}}$ and $\mathbb{Y}_{\text{seen}} \cap \mathbb{Y}_{\text{unseen}} = \emptyset$, the target set only consists of unseen pairs introduced in (Nagarajan and Grauman, 2018); 2) Generalized CZSL, where $\mathbb{Y}_{\text{target}} = \mathbb{Y}_{\text{seen}} \cup \mathbb{Y}_{\text{unseen}}$, the target set consists of both seen and unseen pairs introduced in (Purushwalkam et al., 2019); 3) Open-world CZSL where $\mathbb{Y}_{\text{target}} = \mathbb{Y}$ where target set is all attr-obj combinations and is the most challenging case introduced in (Mancini et al., 2021). Following (Purushwalkam et al., 2019)’s pair split, we evaluate PromptCompVL using generalized CZSL as the close world and open-world CZSL as the open world detailed in Appendix A.

4 PromptCompVL

4.1 Architecture

The architecture of PromptCompVL is shown in Fig. 2. It has four components: text encoder, image encoder, soft-embedding layer and soft-prompting layer. As Fig. 3 shows, different from previous prompting strategies (Zhou et al., 2022; Nayak et al., 2022), we set both soft-prompting and soft-embedding as learnable parameters and we use these two soft layers to construct text input as Eq. 1.

\[
[SOS, v_1, v_2, \ldots, v_k, \text{attr}, \text{obj}, \text{EOS}] \quad (1)
\]

Text Context

- **Soft-embedding layer.** We update the embedding for each primitive concept under different combinations during training time. And this improve the model’s compositional ability. The soft-embedding layer is with size \(R^{(|a|+|o|) \times d} \), where \(|a|\) is the attribute number, \(|o|\) is the object number, \(d\) is the soft-embedding dimension.

- **Soft-prompting layer.** In this setting, by adding the soft-prompting parameters, we reprogram CLIP for different compositional learning datasets. We have \(k\) prompt vectors, each with dimension \(d\), i.e., \(v_i \in R^d, i \in 1, 2, \ldots k\).
Compositional Concepts:
• Old City
• New Shoe
• Broken Clock
• Small Dog
• …

Learnable Prompt Tokens
(soft prompt)

Learnable Attr./Obj. Embeddings
(soft embedding)

Text Encoder

Attr Emb.

Obj. Emb.

Forward Path

Backward Path

Image Encoder

Image Vector

Cos Score

Cos Score

Cos Score

Cross Entropy Loss

Pair_1 Vector

Pair_2 Vector

… …

Pair_N Vector

Learnable Parameters

Fixed CLIP Parameters

Figure 2: PromptCompVL Architecture. It consists of four components: image encoder, text encoder, soft-prompting layer and soft-embedding layer. The Soft-prompting and soft-embedding layers are learnable during training.

Learnable Parameters

Forward Path

Backward Path

PromptCompVL

Figure 3: Different prompting strategies. PromptCompVL combines both soft-prompting and soft-embedding.

4.2 Pipeline

In this section, we will discuss the details of PromptCompVL’s components and the whole pipeline is outlined in Appendix B.

Text Encoder. Given the attr-obj label, 1) instead of using CLIP’s hard prompts, “a photo of”, we add the learnable soft-prompting vectors \([v_1, v_2, ..., v_k]\) before the attr-obj label, 2) we encode attr-obj label using the learnable soft-embedding layer instead of the CLIP’s fixed embedding layer, 3) after the above replacements, we extract and normalize EOS vector \(t_i\) after self-attention mechanism as the text representation using Eq. 2.

\[
x_i = \frac{\text{VisEnc}(x_i)}{||\text{VisEnc}(x_i)||}
\]

\[
t_i = \frac{T\text{xtEnc}_{\theta,\phi}(t_{a_i}, o_i)}{||T\text{xtEnc}_{\theta,\phi}(t_{a_i}, o_i)||}
\]

\[
\text{Sim}(x, t_i) = \exp\left(\frac{\text{Sim}(x, t_i)}{\tau}\right)
\]

\[
p(y | x) = \frac{\exp(\text{Sim}(x, t_i) / \tau)}{\sum_{i=1}^{K} \exp(\text{Sim}(x, t_i) / \tau)}.
\]

where \(\tau\) is a temperature hyper-parameter, \(\text{Sim}\) denotes cosine similarity and \(K\) is the number of attr-obj pairs in the training set.

4.3 Training

After obtaining attr-obj and image vectors following the aforementioned steps, we can calculate the class probability using the cosine similarity as Eq. 3. Finally, Cross-Entropy loss is used to update PromptCompVL’s soft-prompting parameters \(\theta\) and soft-embedding parameters \(\phi\) using the training dataset.

\[
\hat{y} = \arg \max_{t_i \in Y_{\text{target}}} \text{Sim}(t_i, x).
\]

4.4 Inference

Given an image, for each attr-obj pair in \(Y_{\text{target}}\), we construct the text input using the learnt soft-embedding and soft-prompting as the format of Eq. 1. After going through CLIP’s text and image encoders, we use cosine similarity to select the most relevant attr-obj pair as the compositional label of the given image as follows,
Table 1: Close and Open World results on UT-Zappos and Mit-States datasets. We report best seen accuracy S, best unseen accuracy U, best harmonic mean(HM) and area under the curve(AUC) for comparison.

Table 2: Dataset Split Statistics.
These results demonstrate potential advantages and limitations in applying CLIP-based prompting approaches to compositional concept learning in the future.

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A CZSL Settings

Fig. 4 shows the different target dataset choice in test phase. In our experiment, we select generalized CZSL as our close world setting and open-world CZSL as our open world setting used in recent works (Nayak et al., 2022; Mancini et al., 2021; Naeem et al., 2021).
B Pipeline

Algorithm B.1 PromptCompVL

1: Initialize PromptCompVL using the pre-trained CLIP’s text and image encoders.
2: Construct text input for attr-obj labels using Eq. 1.
3: Extract and normalize image/text vectors using CLIP’s image/text encoder using Eq. 2.
4: Calculate the class probability as Eq. 3 using the cosine similarity and update PromptCompVL’s soft-prompting layer $\theta$ and soft-embedding layer $\phi$ using Cross-Entropy loss.

C Feasibility Scores

| Dataset   | Feasibility Score |
|-----------|-------------------|
| MIT-States | 0.40691           |
| UT-Zappos  | 0.5299            |
| C-GQA      |                   |

Table 3: PromptCompVL’s Feasibility score for MIT-States and UT-Zappos which is tuned using the validation set.