ProCC: Progressive Cross-primitive Consistency for Open-World Compositional Zero-Shot Learning

Fushuo Huo\(^1\), Wenchao Xu\(^1\), Song Guo\(^1\), Jingcai Guo\(^1\), Haozhao Wang\(^2\), and Ziming Liu\(^1\)
\(^1\)Department of Computing, The Hong Kong Polytechnic University
\(^2\)School of Computer Science and Technology, Huazhong University of Science and Technology

Abstract

Open-World Compositional Zero-shot Learning (OW-CZSL) aims to recognize novel compositions of state and object primitives in images with no priors on the compositional space, which induces a tremendously large output space containing all possible state-object compositions. Existing works either learn the joint compositional state-object embedding or predict simple primitives with separate classifiers. However, the former heavily relies on external word embedding methods, and the latter ignores the interactions of interdependent primitives, respectively. In this paper, we revisit the primitive prediction approach and propose a novel method, termed Progressive Cross-primitive Consistency (ProCC), to mimic the human learning process for OW-CZSL tasks. Specifically, the cross-primitive consistency module explicitly learns to model the interactions of state and object features with the trainable memory units, which efficiently acquires cross-primitive visual attention and avoids cross-primitive feasibility scores. Moreover, considering the partial-supervision setting (pCZSL) as well as the imbalance issue of multiple tasks prediction, we design a progressive training paradigm to enable the primitive classifiers to interact to obtain discriminative information in an easy-to-hard manner. Extensive experiments on three widely used benchmark datasets demonstrate that our method outperforms other representative methods on both OW-CZSL and pCZSL settings by large margins.\(^1\)

1. Introduction

Humans can extrapolate new concepts from previously learned knowledge. For instance, if the people are taught what the fried chip and toasted bread are, most of them can recognize the fried bread immediately. This ability is known as compositional generalization [1], which is one of the ultimate targets for artificial intelligence. In the literature, such a task is formulated as Compositional Zero-Shot Learning (CZSL). Concretely, the training set contains images with corresponding descriptions (primitives), i.e., state and object. The model is expected to recognize unseen compositions based on known primitives, which is non-trivial because object and state are semantically tangled, i.e., objects in different states often have different appearances, and states can vary greatly conditioned on different objects.

The major challenge behind the CZSL lies in how to model the interactions between state and object primitives and extrapolate seen compositions to unseen ones. Existing methods mainly focus on learning a shared embedding space for object-state compositions [17, 25, 32, 33] or compositional attribute and object classifiers [24, 31, 37, 47, 49].

However, the performances of these methods degrade to some extent [28, 29] as for the open-world setting (OW-CZSL), where there are no priors on the unseen compositions and the model must consider the whole possible compositions in terms of all objects and states. To deal with such a problem, existing mainstream methods utilize feasibility constraints on the composition embedding [28, 29] or independently predict simple state and object primitives [16]. While [28, 29] somewhat rely on different word embedding methods and embedding dimensions also matter. The straightforward but effective method [16] predicts the state and object primitives while ignoring the interaction and consistency between two primitives. So external knowledge is introduced to eliminate less feasible compositions, while it is cumbersome to select proper external knowledge for the varying datasets.

To address aforementioned problems, we propose Progressive Cross-primitive Consistency (ProCC) network to recognize compositions in the open-world setting and a more realistic setting (i.e., partial supervision), aiming at attaining cross-primitive consistency during easy-hard recognition progress, as shown in Figure 1. Specifically, following the route of the human learning process, we first learn to classify objects, which is easier than recognizing states because the same state varies greatly conditioned on objects and related contexts, i.e., ancient castle / ancient coin, and different states are sometimes less feasible composed

\(^1\)The Codes will be released.
Figure 1. The overall concept of our method. Following the principle of ‘forest before trees’ [10], human feedforward hierarchy underlies implicit processing for initial vision at a glance, and feedback connections add details to explicit vision with scrutiny. As for composition generalization learning, humans first learn to recognize overall objects, then gradually identify the scrutiny attribute of objects, i.e., state, and finally reasonably compose the object and state primitive. Inspired by this, we aim to progressively recognize the object and state primitives and guide the network to discriminative information conditioned on learned knowledge via the CPC module.

with the same object, i.e., old dog / ripe dog. Then, with the learned knowledge of object primitive, we sequentially classify state primitives conditioned on guided object features via Cross-Primitive Consistency (CPC) module, excavating discriminative information. Finally, we finetune the whole network conditioned on each other prior knowledge. The ProCC network achieves the cross-primitive consistency by adjusting the visual attention via the CPC module, without the aid of external knowledge like Word2vec [30], Glove [35], Conceptnet [42] etc. Also, the progressive training paradigm effectively model the interactions of primitives via trained features in pCZSL and alleviates the imbalance (over/under-fitting) learning of state and object classifiers compared with the jointly training.

In summary, our contributions are four-fold:

1) We propose a novel Progressive Cross-primitive Consistency (ProCC) network, mimicking the human learning progress of recognizing the state and object compositions without external knowledge.

2) We present a Cross-Primitive Consistency (CPC) module consisting of cross-primitive memory units to model the interactions of classifiers to focus the discriminative visual attention conditioned on each other, guiding the model to generalize to feasible compositions.

3) The progressive training paradigm alleviates the negative effect of invalid cross-primitive interactions in pCZSL without other cumbersome pseudo-label methods, as well as the imbalance issue of learning multiple tasks.

4) Comprehensive experimental results on three large-scale datasets for OW-CZSL and pCZSL tasks demonstrate the effectiveness of our proposed approach, which outperforms the state-of-the-art methods.

2. Related Work

Compositional zero-shot learning. Compositional Zero-shot Learning (CZSL) aims to recognize the state and object from the images, and even the state-object compositions are not ever seen in the training datasets. Different from typical zero-shot learning [5, 6, 13, 23, 26, 46], which aims to utilize attributed vectors or inherent semantic descriptions to recognize unseen instances, The main challenge of CZSL is modeling the relation and affordance of states and objects, generalizing this capability to unseen compositions. Existing methods mainly deal with CZSL in two ways. The first way is inspired by Biederman’s Recognition-By-Components theory [3] and Hoffman’s part theory [11]. For instance, Misra et al. [31] learns a transformation between individual classifiers of states and objects. Other representative methods learn a hierarchical decomposition and composition of the state and object primitives [48], model objects to be symmetric under attribute transformations [25], and learn independent prototypical representations of visual primitives then propagated prototype via a compositional graph [39]. The second way tries to learn the joint representation of the state-object compositions from given images [17, 25, 32, 33]. Similarly, [25] enforces symmetries in the representation of objects given their state transformations. Graph network is also employed to enforce the compositional information transfer from seen to unseen compositions. Nagarajan et al. [33] regard attribute as the operator and model each state as a linear transformation of objects. [17] exploit the self-attention mechanism to discover the complex interdependency structure between compositions and propagate it to unseen ones. Differently, causality-based methods [2,49] explore decomposable objects and state representations.

These methods perform well on the close-world CZSL, while suffering from severe degradation for the open-world setting [16,28,29], where the output space has not imposed any limit. Mancini et al. [28] compute feasibility scores (i.e., cosine similarity) between visual features and compositional embeddings to reduce the output space. Then they further inject the feasibility scores both at the loss level and within the graph connections [29]. [16] follows the Visual Product [31] and predicts state and object primitives independently with non-linear feature extractors. To refine the
relation between independent primitives, Conceptnet [42] is introduced as the external knowledge. We revisit the Visual Product and achieve cross-primitive consistency in an easy-hard learning manner, avoiding the external knowledge in [16] and cumbersome word embeddings in [28, 29].

**Multi-task consistency.** Our method predicts state and object primitives and therefore has a close relationship to Multi-Task Learning (MTL) [38, 44]. A rich body of work [22, 27, 40, 51] study the relation and consistency between tasks in MTL. Saha et al. [40] encodes the relationships between semantic segmentation and depth prediction to improve model performance. Zamir et al. [51] learns with cross-task consistency and leads to more accurate predictions and out-of-distribution generalization. [27] proposes the consistency loss to jointly train multiple tasks to benefit each other, reducing the need for labeled data. [22] further solve the partial-supervision MTL task via cross-task consistency in joint space. However, different from [22, 27], which apply strong cross-task consistency constraints to the decision level in terms of dense prediction tasks, we apply soft cross-primitive consistency in the feature level for sparse prediction tasks, avoiding over-fitting degradation.

**Conditional model.** To mitigate the domain diversity or informatively adjust feature weight, some conditional model has been proposed [7, 8, 36, 52, 54]. For instance, Perez et al. [36] develops an image feature modulation method conditioned on input words for visual reasoning. Zhao et al. [8] predicts a set of adaptive weights from conditional inputs to formulate specific filters, which facilitates parameter learning across different conditions for few-shot learning. The conditional model is also employed in the image restoration tasks [7, 52], which learn the conditional vector to control the enhancement degree. Recently, Zhou et al. [54] generated the input-conditional token from given images to improve the generalization ability of the pre-trained vision-language model. Inspired by them, the Cross-Primitive Consistency (CPC) module of ProCC can also be viewed as the layers conditioned on state and object primitives, which facilitates the model generalizing to new compositions with high feasibility.

### 3. Approach

#### 3.1. Problem formulation

Compositional Zero-Shot Learning (CZSL) aims to recognize the composition of two primitive concepts, i.e., an state (e.g., tiny) and an object (e.g., dog). Given $S$ and $O$ as two sets of states and objects, we compose a set of possible state-object pairs, i.e., $C = S \times O = \{(s, o) | s \in S, o \in O\}$. Formally, given a training set $D^u = \{(i, c) | i \in I^u, c \in C^u\}$, where $I^u$ is an training image set, and $C^u$ is the corresponding state-object labels. The close world CZSL follows the generalized ZSL [46] that the test sample comes from either seen ($C^s$) or unseen ($C^u$) composition ($C^s \cup C^u$). For the Open-World CZSL (OW-CZSL) setting [28], there assumes no prior on the set of testing compositions. It means the model must consider the full compositional space ($C$), which is much larger than $C^s \cup C^u$. Consequently, the unseen compositions are $C_u = C \setminus C^s$. OW-CZSL introduces a more practical setting while bringing more challenging problems: 1) It is hard to generalize from small seen compositions to large unseen compositions. 2) There are a large number of less feasible compositions in the full composition space ($C$), confusing the prediction models. Recently, [16] proposes a new practical setting, i.e., only training with one of the state and object annotations, named partial-supervision CZSL (pCZSL). Formally, for the training set $C^s$, The relation of the partial label of state and object primitives can be formulated as: $\{(s, u) \cup \{u, o\} = C^u\}$, where $u$ indicates unlabeled primitives. Consequently, the test set in pCZSL has the full output composition space ($C$) like OW-CZSL, while the training set in pCZSL does not have the composition knowledge about any state-object pairs. Therefore, the joint training strategy may fail due to lacking the explicit supervision to learn how states interact with objects and vice-versa.

#### 3.2. Progressive Cross-primitive Consistency

Most CZSL methods [2, 25, 28, 29, 32, 33, 37, 41] explicitly modulate the interactions of states and objects to improve the generalization ability. While it is less effective for OW-CZSL and pCZSL due to large output space and missing labels. Some methods [15, 16] follow the Visual Product [31] that independently predict the state and object primitives, disregarding compositional nature. Following the route of [15, 16, 31], we propose Progressive Cross-primitive Consistency (ProCC) network while achieving cross-primitive consistency. Also, like the human learning process, ProCC trains the network in an easy-hard manner, which dynamically models interactions between state and objects, alleviating the negative influence of no explicit supervision on both states and objects in pCZSL and imbalance issues of MTL. Figure 2 shows the framework of the proposed approach.

In the following subsections, we revisit the Visual Product and introduce a cross-primitive consistency module and progressive learning strategy.

**Revisit Visual Product.** In a nutshell, given an image $i$, CZSL wants to model the joint probability distribution $p(s, o|i)$. The visual product simplifies this as:

$$p(s, o|i) \approx p(s|i) \times p(o|i) \quad (1)$$

In this way, Visual Product treats the states and objects independently only from the visual cues, without side information (i.e., word embeddings). Concretely, the image
During inference, we predict the output composition as:

\[
f_\theta(i) = \arg \max_{(s,o) \in C} \varphi_s(\omega(i), s) \times \varphi_o(\omega(i), o) \tag{5}\]

where \(C\) represents all the state-object composition pairs in OW-CZSL. As the search space is huge, Visual Product is more effective than previous methods, which aim to produce discriminative state-object embeddings \([15, 16]\). Recently, \([15, 16]\) expanded the visual product and equipped the classifiers with multi-layer perceptrons (MLP) to excavate discriminative features. Also, external knowledge \([42]\) is employed in \([16]\) to estimate the feasibility scores of compositions. Here, we explicitly model the composition interactions via Cross-Primitive Consistency (CPC) module during the training procedure, without external knowledge. Also, considering the pCZSL setting and unbalanced multi-task learning (i.e., recognizing state is more challenging than object), where joint training may obtain sub-optimal results, the progressive learning strategy is proposed to deal with it in an easy-hard manner.

**Cross-primitive consistency module.** Visual Product methods independently predict compositions via Equation 1, which ignores the fact that the feasibility of state-object compositions is heavily conditioned on each other. The more practical compositional probability can be modeled as follows:

\[
p(s, o|i) \approx p(s|i, f_o(i)) \times p(o|i, f_s(i)) \tag{6}\]

where \(f_o(i)\) and \(f_s(i)\) are intermediate features of the object and state primitives. It is non-trivial to directly model the relationship between objects and states due to the diverse semantic entanglement and a large amount of possible compositions. We integrate the feasibility reasoning into the trainable Cross-Primitive Consistency (CPC) module, which facilitates interactions between two classifiers to explore informative visual attention conditioned on feature representations of each primitive. Specifically, the features extracted by the encoder (\(\omega\)) are fed to multi-layer perceptron (MLP) (i.e., \(\varphi_o\) and \(\varphi_s\)) to enhance the feature representation. Take the object-state primitive consistency \((C_{o\rightarrow s})\) module for example, as shown in Figure 3, intermediate features from \(\varphi_{o-1}\) and \(\varphi_{o-2}\) are fed to \(\varphi_{s}\) to interact with state features. However, direct modulation
where \( \text{CAM}_c \) means the class activation map that leads to the classification of an image to class \( c \). \( f_k(x, y) \) and \( \omega^c_k \) stand for the activation of unit \( k \) in the last layer at spatial location \((x, y)\) and the weight corresponding to class \( c \) for unit \( k \). Here, \( \omega^c_k \) is the final layer of the MLP \( (i.e., \phi_{3-3} \text{ and } \phi_{x-3}) \), which has been modulated by the CPC modules. Figure 4 shows some visualization examples with (w/) and without (w/o) CPC module. As the encoder is pre-trained for the object classification task, most CAMs for the object classifier can locate and recognize the proper attention regions. However, the CAMs for the state classifier vary greatly as state primitives are conditioned on the object primitive and related contexts. For the “tiny dog” and “large dog” compositions, the CPC module drives the model to focus on the discriminative regions that a dog with a small head compared with other objects tends to classify to the “tiny” otherwise classify to “huge”. For more abstract compositions, “broken bridge” and “ripe banana” compositions, the state primitives heavily depend on the object primitives otherwise may induce less feasibility compositions. The state of “broken” is mainly reflected in the curvatures of the bridge and the “ripe” primitive of the banana displays the black spots on the surface. Overall, the CPC module enables the efficient adjustment of visual attention conditioned on mutual primitives.

**Progressive learning strategy.** However, jointly training the state and object classifiers may induce two issues: 1) When it comes to the more practical setting, partial supervision Compositional Zero-Shot Learning (pCZSL), where only the partial label, not both, is available [16]. The missing label makes the joint training strategy invalid to model the interactions between the state and object primitives. A naive way of learning from such partial supervision is to update the parameters of state and object classifier only based on the available labels, which lacks the interaction information across primitives via the CPC module. Recent method [16] estimates the missing labels via pseudolabeling [20] as well as utilizes the external knowledge [42]. The challenge of missing labels also exists in the standard MTL task that the traditional updating rule will give inferior results due to the missing annotations [18, 22, 34, 44]. Some typical solutions propose hard knowledge distillation [18], alternative optimization strategy [34], and learning in the joint pairwise task spaces [22]. However, compared with the MTL task, the missing label issue matters more to the CZSL task, as the object and state primitives are heavily tangled. 2) Also, classifying attributes is more challenging than objects [16, 41]. This is due to the fact that image encoder \( \omega \) is pre-trained for object classification, not for the more semantic state classification. Meanwhile, the state primitive is highly conditioned on the object classification results. Therefore, joint training makes the object classifier over-fitting or makes the state classifier under-fitting.
Algorithm 1: Training procedure of ProCC.

```
Input: Training data \( D^s = \{ (i, c) | i \in I^s, c \in C^s \} \), pre-trained \( \omega \), learning rate \( \lambda_1, \lambda_2, \lambda_3 \)
Output: Optimal \( \varphi_o, \varphi_s, \text{CPC: } \varphi_{o \rightarrow s}, \varphi_{o \rightarrow s} \)
1 Initialize: \( \varphi_o, \varphi_s, \varphi_{o \rightarrow s}, \varphi_{o \rightarrow s} \)
2 Stage 1: // train \( \varphi_o \)
3 while not converged do
4 Sample a batch from \( D^s \) as images \( (i_k)_{k=1}^n \) with their object labels \( (o_k)_{k=1}^n \);
5 for samples in the batch do
6 Compute \( \ell_{\text{obj}} \) via Equation 2.;
7 Update \( \varphi_o \leftarrow \varphi_o + \lambda_1 \nabla_{\varphi_o} \ell_{\text{obj}} \)
8 end
9 end
10 Stage 2: // train \( \varphi_s \) and \( \varphi_{o \rightarrow s} \)
11 while not converged do
12 Sample a batch from \( D^s \) as images \( (i_k)_{k=1}^n \) with their state labels \( (s_k)_{k=1}^n \);
13 for samples in the batch do
14 Compute \( \ell_{\text{state}} \) via Equation 3.;
15 Update \( \varphi_{s \rightarrow o} \leftarrow \varphi_{s \rightarrow o} + \lambda_2 \nabla_{\varphi_{s \rightarrow o}} \ell_{\text{state}} \)
16 end
17 Stage 3: // finetune \( \varphi_o, \varphi_s, \varphi_{o \rightarrow s}, \) and \( \varphi_{o \rightarrow s} \)
18 while not converged do
19 Sample a batch from \( D^s \) as images \( (i_k)_{k=1}^n \) with their object and state labels \( (o_k, s_k)_{k=1}^n \);
20 for samples in the batch do
21 Compute \( \ell_{\text{visprod}} \) via Equation 4.;
22 Update \( \varphi_{\text{total}} \leftarrow \varphi_{\text{total}} + \lambda_3 \nabla_{\varphi_{\text{total}}} \ell_{\text{visprod}} \)
23 end
24 end
25 end
```

To enable the full interaction of state and object primitives and alleviate the imbalance issue of MTL, we propose a progressive learning strategy, mimicking the easy-hard learning process shown in Figure 1. Concretely, with the features from the encoder \( \omega \), we first train the object classifier \( \varphi_o \) with given labels via \( \ell_{\text{obj}} \), to obtain trained object features from classifier \( \varphi_{o \rightarrow i} \). Then we sequentially train the state classifier \( \ell_{\text{state}} \) conditioned on well-trained object features \( \varphi_{o \rightarrow i} \) through the CPC module \( \varphi_{o \rightarrow s} \), to interact and adjust the visual attention. Finally, with the pre-trained object and state classifier, we fine-tune the state and object classifiers as well as CPC modules conditioned on the mutual information. We utilize this training protocol both in the OW-CZSL and pCZSL settings. During the easy-hard recognition progress, our method enables the interactions of cross primitives in the pCZSL setting without external knowledge and alleviates imbalance issue with the early stop strategy at each stage. The detailed training procedure of our network can refer to Algorithm 1.

4. Experiments

Datasets. We conduct experiments on three widely-use datasets including UT-Zappos [50], MIT-States [14], and C-GQA [31]. UT-Zappos is a dataset for the shoes and has 50025 images. It contains 12 object classes and 16 state classes, with 83 seen compositions and a total of 192 compositional spaces. MIT-States has 53753 images with 115 state classes and 245 object classes. The seen and all output compositions are 1,262 and 28,175, respectively. C-GQA is the largest dataset that contains 186,577 images with 413 state classes and 674 object classes. It contains 5,592 seen compositions and a full output space of 278,362 compositions, which makes it the most extensive for the OW-CZSL.

Evaluation Metrics. For the OW-CZSL, we follow the splits of [16, 28, 29] and evaluate based on the generalized settings, where the test samples are from both seen and unseen compositions. Considering the performance of the model with different bias factors for the unseen compositions, we vary the bias on the seen composition \( (C^s) \) during the test phase and report the performance as best seen \( (S) \), best unseen \( (U) \), best harmonic mean \( (HM) \), and the Area Under the Curve \( (AUC) \). For the pCZSL, following [16], we remove the label and calculate the metrics on the full output composition space \( (C) \). As we can not access the full-labeled seen compositions \( (C^s) \), we do not subtract any bias on \( C^s \). Therefore, we use the seen \( (S) \) and unseen \( (U) \) as well as accuracy harmonic mean \( (HM) \) metrics.

Baselines. For the OW-CZSL setting, we compare ProCC with other OW-CZSL methods, including Compositional Cosine Logits (CompCos) [28], Knowledge Guided Simple Primitives (KGSP) [16], and Compositional Cosine Graph Embeddings (Co-CGE) [29]. CZSL methods are also compared, including Label Embed+ (LE+) [31], Attributes as Operators (AoP) [33], Task Modular Networks (TMN) [37], SymNet [25], and Compositional Graph Embeddings (CGE) [32]. For the pCZSL setting, ProCC are compared with KGSP [16] as well as standard (OW-)CZSL methods like CGE [32], CompCos [28], and Co-CGE [29], which are state-of-the-art (OW-)CZSL methods respectively. They all adopt the same missing label protocol as us.

Implementation Details. Following the standard practices in the CZSL, we utilize the pre-trained ResNet-18 [9] without updating parameters as the feature encoder \( \omega \) to extract 512-dimensional feature vector. Following [16, 32], each classifier is composed of Multi-Layer Perceptrons (MLP) with three layers with dimensions 768, 512, and the number of output classes, respectively, and comprise Layer Normalization [21] and Dropout [43]. To be consistent with other methods, we randomly augment input images with random crop and horizontal flip. We use PyTorch to im-
implement our network and optimize it with Adam [19] with default settings. The batch size is 256, and the learning rate is $5.0 \times 10^{-5}$ for the first two stages and $1.0 \times 10^{-5}$ for the third stage. For the UT-Zappos, MIT-States, and C-GQA datasets, the total training time is approximately 1, 3, and 5 hours for 40/80/20, 50/100/25, and 50/100/25 epochs for three stages, respectively, with the early stop strategy.

### 4.1. Open-World CZSL (OW-CZSL)

The results of the Open-World Compositional Zero-Shot Learning (OW-CZSL) setting are illustrated in Table 1. In general, closed-world CZSL methods achieve inferior performance, especially in two large datasets (i.e., C-GQA and MIT-States), due to the large cardinality of the output space. ProCC outperforms previous methods on almost all metrics in terms of three datasets. Concretely, as for the most comprehensive dataset, i.e., C-GQA, the proposed method exceeds the previous SOTA methods, especially for best harmonic (HM) metrics (3.4→3.8; ↑12%), which means that ProCC has the better ability to recognize both the seen and unseen compositions. Also, in the validation sub-dataset, our method supersedes the best baseline (i.e., KGSP) by a large margin in two overall evaluation indexes (i.e., HM: 13.2→16.1: ↑22%; AUC: 2.9→4.0: ↑38%). As for the MIT-States dataset, our method also has comparative results. Notably, we achieve the best performance on $U$ metric, which validates the generalization ability of ProCC. For UT-Zappos, it is specially designed for shoes and is relatively simpler than others. ProCC consistently outperforms others, i.e., $S$: 59.3→62.2; $U$: 47.2→48.0; HM: 39.1→39.9; AUC: 22.9→23.6.

Remarkably, previous methods, including TMN [37], AoP [33], SymNet [25], CompCos [28], CGE [32], Co-CGE [29] also utilize word embedding methods to encode the word expression, which already contains semantic knowledge of similar objects and attributes for composition learning [41]. Recent advanced Visual Product based method [16] employs more complex classifiers (with hidden layers of 768 and 1024) than ours as well as uses external knowledge to eliminate the less feasibility compositions. We predict the state and object primitives with more lightweight classifiers and explicitly model the cross-primitive interactions to learn the relationship between primitives without external knowledge. Therefore, our method is a more effective method to deal with the large output composition space in the OW-CZSL task.

### 4.2. Partial-supervision CZSL (pCZSL)

As for the more challenging setting, partial-supervision CZSL (pCZSL), the challenges come from not only the huge output composition space but also the missing labels. The results of ProCC and previous SOTAs are reported in Table 2. We can see that our method achieves state-of-the-art performance compared with previous CZSL, OW-CZSL, and pCZSL methods. Concretely, for the largest dataset, C-GQA, the performance of SOTAs on pCZSL severely degrades compared with OW-CZSL, even for KGSP, which is equipped with the pseudo label and external knowledge. Our method consistently exceeds them both on validation and testing datasets. For the MIT-States dataset, our method surpasses the second-best method in terms of HM metrics by a large margin (i.e., val: 5.3→5.8; ↑9%; test: 4.4→4.8: ↑9%). For the simplest dataset, UT-Zappos, our method also has the best performance. Note that we do not use any external knowledge like Word2vec [30], Glove [35], Conceptnet [42], and other semi-supervised learning tech-

| Method       | C-GQA     | MIT-States | UT-Zappos |
|--------------|-----------|------------|-----------|
|              | Test      | Test       | Test      |
|              | HM        | AUC        | S         | U         | HM        | AUC        | S         | U         | HM        | AUC        |
| TMN [37]     | NA        | NA         | NA        | NA        | NA        | 2.1        | 0.2       | 12.6      | 0.9       | 1.2       | 0.1       | 21.2      | 9.2       | 55.9      | 18.1      | 21.7      | 8.4       |
| AoP [33]     | NA        | NA         | NA        | NA        | NA        | 3.2        | 0.3       | 16.6      | 5.7       | 4.7       | 0.7       | 23.4      | 10.1      | 50.9      | 34.2      | 29.4      | 13.7      |
| LE+ [31]     | 9.3       | 1.8        | 19.2      | 0.7       | 1.0       | 0.08       | 5.3        | 0.5       | 41.2      | 2.5       | 2.7       | 0.3        | 26.6      | 14.3      | 60.4      | 36.5      | 30.5      | 16.3      |
| VisProd [31] | 10.5      | 2.0        | 24.8      | 1.7       | 2.8       | 0.33       | 7.2        | 1.0       | 20.9      | 5.8       | 5.6       | 0.7        | 28.8      | 15.4      | 54.6      | 42.8      | 36.9      | 19.7      |
| SymNet [25]  | 12.3      | 2.5        | 26.7      | 2.2       | 3.3       | 0.43       | 8.0        | 1.2       | 21.4      | 7.0       | 5.8       | 0.8        | 32.5      | 16.7      | 53.3      | 44.6      | 34.5      | 18.5      |
| CGE [32]     | 12.8      | 2.8        | 28.3      | 1.3       | 2.2       | 0.30       | 8.3        | 1.8       | 29.6      | 4.0       | 4.9       | 0.7        | 34.5      | 18.9      | 58.8      | 46.5      | 38.0      | 21.5      |
| CompCos [28] | 12.0      | 2.4        | 28.4      | 1.8       | 2.8       | 0.39       | 8.4        | 1.5       | 25.4      | 10.0      | 8.9       | 1.6        | 32.5      | 18.1      | 59.3      | 46.8      | 36.9      | 21.3      |
| Co-CGE [29]  | 12.3      | 2.7        | 28.7      | 1.6       | 2.6       | 0.37       | 8.4        | 2.1       | 26.4      | 10.4      | 10.1      | 2.0        | 34.8      | 19.2      | 60.1      | 44.3      | 38.1      | 21.3      |
| KGSP [16]    | 13.2      | 2.9        | 26.6      | 2.1       | 3.4       | 0.44       | 7.9        | 1.4       | 23.4      | 7.0       | 6.7       | 1.0        | 33.2      | 19.8      | 58.0      | 47.2      | 39.1      | 22.9      |
| **Ours**     | **16.1**  | **4.0**    | **29.0**  | **2.6**   | **3.8**   | **0.54**   | **8.6**    | **1.9**   | **27.6**  | **10.6**  | **7.8**   | **1.6**    | **36.5**  | **22.4**  | **62.2**  | **48.0**  | **39.9**  | **23.6**  |

Table 1. The state-of-the-art comparisons of C-GQA, MIT-States, and UT-Zappos datasets in the OW-CZSL setting. We report the best seen ($S$) and best unseen ($U$) accuracy and best harmonic mean (HM) on the test sub-dataset. $S$, $U$, and HM metrics are also reported on the validation sub-dataset. The best and second-best results are **bold** and underlined.
### 5. Conclusion

In this paper, we propose a method named Progressive Cross-primitive Consistency (ProCC) network for both OW-CZSL and pCZSL tasks. The simple but effective Cross-Primitive Consistency module drives the network learning to predict feasible object and state primitives conditioned on mutual information. Also, the progressive learning strategy significantly avoids the negative influence of the pCZSL setting and imbalance issue of MTL in an easy-hard learning manner with pre-trained classifiers. Comprehensive experiments on OW-CSZL and pCZSL settings illustrate superior performance compared with other state-of-the-art methods.
References

[1] Yuval Atzmon, Jonathan Berant, Vahid Kezami, Amir Globerson, and Gal Chechik. Learning to generalize to new compositions in image understanding. arXiv e-prints, page arXiv:1608.07639, Aug. 2016. 1

[2] Yuval Atzmon, Felix Kreuk, Uri Shalit, and Gal Chechik. A causal view of compositional zero-shot recognition. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, NeurIPS, volume 33, pages 1462–1473, 2020. 2, 3

[3] Irving Biederman. Recognition-by-components: a theory of human image understanding. Psychological review, 94(2), 1987. 2

[4] Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. In L. Saul, Y. Weiss, and L. Bottou, editors, NeurIPS, volume 17, 2004. 8

[5] Jingcai Guo and Song Guo. A novel perspective to zero-shot learning: Towards an alignment of manifold structures via semantic feature expansion. IEEE TMM, 23:524–537, 2020. 2

[6] Jingcai Guo, Song Guo, Qihua Zhou, Ziming Liu, Xiaocheng Lu, and Fushuo Huo. Graph knows unknowns: Reformulate zero-shot learning as sample-level graph recognition. In AAAI, 2023. 2

[7] Jingwen He, Chao Dong, and Yu Qiao. Modulating image restoration with continual levels via adaptive feature modification layers. In CVPR, June 2019. 3, 5

[8] Jingwen He, Yihao Liu, Yu Qiao, and Chao Dong. Conditional sequential modulation for efficient global image re-touching. In ECCV, pages 679–695, 2020. 3, 5

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, June 2016. 6

[10] Shaul Hochstein and Merav Ahissar. View from the top: Hierarchies and reverse hierarchies in the visual system. Neuron, 36(5):791–804, 2002. 2

[11] D.D. Hoffman and W.A. Richards. Parts of recognition. Cognition, 18(1):65–96, 1984. 2

[12] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In CVPR, June 2018. 5

[13] Dat Huynh and Ehsan Elhamifar. Fine-grained generalized zero-shot learning via dense attribute-based attention. In CVPR, June 2020. 2

[14] Phillip Isola, Joseph J. Lim, and Edward H. Adelson. Discovering states and transformations in image collections. In CVPR, June 2015. 6

[15] Shyamgopal Karthik, Massimiliano Mancini, and Zeynep Akata. Revisiting visual product for compositional zero-shot learning. In NeurIPS Workshop, 2021. 3, 4, 8

[16] Shyamgopal Karthik, Massimiliano Mancini, and Zeynep Akata. Kg-sp: Knowledge guided simple primitives for open world compositional zero-shot learning. In CVPR, pages 9336–9345, June 2022. 1, 2, 3, 4, 5, 6, 7, 8

[17] Muhammad Gul Zain Ali Khan, Muhammad Ferjad Naem, Luc Van Gool, Alain Pagani, Didier Stricker, and Muhammad Zeshan Afzal. Learning Attention Propagation for Compositional Zero-Shot Learning. arXiv e-prints, page arXiv:2210.11557, Oct. 2022. 1, 2

[18] Dong-Jin Kim, Jinsoo Choi, Tae-Hyun Oh, Youngjin Yoon, and In So Kweon. Disjoint multi-task learning between heterogeneous human-centric tasks. In WACV, pages 1699–1708, 2018. 5

[19] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2015. 7

[20] Dong-Hyun Lee. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In ICML Workshop, 2013. 5, 8

[21] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. Layer Normalization. arXiv e-prints, page arXiv:1607.06450, July 2016. 6

[22] Wei-Hong Li, Xialei Liu, and Hakan Bilen. Learning multiple dense prediction tasks from partially annotated data. In CVPR, pages 18879–18889, June 2022. 3, 5

[23] Xiangyu Li, Zhe Xu, Kun Wei, and Cheng Deng. Generalized zero-shot learning via disentangled representation. AAAI, 35(3):1966–1974, May 2021. 2

[24] Xiangyu Li, Xu Yang, Kun Wei, Cheng Deng, and Muli Yang. Siamese contrastive embedding network for compositional zero-shot learning. In CVPR, pages 9326–9335, June 2022. 1

[25] Yong-Lu Li, Yue Xu, Xiaohan Mao, and Cewu Lu. Symmetry and group in attribute-object compositions. In CVPR, June 2020. 1, 2, 3, 6, 7

[26] Ziming Liu, Song Guo, Jingcai Guo, Yuan yuan Xu, and Fushuo Huo. Towards unbiased multi-label zero-shot learning with pyramid and semantic attention. IEEE TMM, 2022. 2

[27] Yao Lu, Soren Pirk, Jan Dlabal, Anthony Brohan, Ankita Pasad, Zhao Chen, Vincent Casser, Anelia Angelova, and Ariel Gordon. Taskology: Utilizing task relations at scale. In CVPR, pages 8700–8709, June 2021. 3

[28] Massimiliano Mancini, Muhammad Ferjad Naem, Yongqin Xian, and Zeynep Akata. Open world compositional zero-shot learning. In CVPR, pages 5222–5230, June 2021. 1, 2, 3, 6, 7, 8

[29] Massimiliano Mancini, Muhammad Ferjad Naem, Yongqin Xian, and Zeynep Akata. Learning graph embeddings for open world compositional zero-shot learning. IEEE TPAMI, pages 1–1, 2022. 1, 2, 3, 6, 7, 8

[30] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In NeurIPS, volume 26, 2013. 2, 7

[31] Ishan Misra, Abhinav Gupta, and Martial Hebert. From red wine to red tomato: Composition with context. In CVPR, July 2017. 1, 2, 3, 6, 7, 8

[32] Muhammad Ferjad Naem, Yongqin Xian, Federico Tombari, and Zeynep Akata. Learning graph embeddings for compositional zero-shot learning. In CVPR, pages 953–962, June 2021. 1, 2, 3, 6, 7, 8

[33] Tushar Nagarajan and Kristen Grauman. Attributes as operators: Factorizing unseen attribute-object compositions. In ECCV, September 2018. 1, 2, 3, 6, 7
[34] Vladimir Nekrasov, Thanuja Dharmasiri, Andrew Spek, Tom Drummond, Chunhua Shen, and Ian Reid. Real-time joint semantic segmentation and depth estimation using asymmetric annotations. In ICRA, pages 7101–7107, 2019. 5

[35] Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In EMNLP, 2014. 2, 7

[36] Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron Courville. Film: Visual reasoning with a general conditioning layer. AAAI, 32(1), 2018. 3, 5

[37] Senthil Purushwalkam, Maximilian Nickel, Abhinav Gupta, and Marc’Aurelio Ranzato. Task-driven modular networks for zero-shot compositional learning. In ICCV, October 2019. 1, 3, 6, 7

[38] Caruana Rich. Multitask learning. Machine learning, 28(1):41–75, 1987. 3

[39] Frank Ruis, Gertjan Burghouts, and Doina Bucur. Independent prototype propagation for zero-shot compositionality. In NeurIPS, volume 34, 2021. 2

[40] Suman Saha, Anton Obukhov, Danda Pani Paudel, Menelaos Kanakis, Yuhua Chen, Stamatios Georgoulis, and Luc Van Gool. Learning to relate depth and semantics for unsupervised domain adaptation. In CVPR, pages 8197–8207, June 2021. 3

[41] Nirat Saini, Khoi Pham, and Abhinav Shrivastava. Disentangling visual embeddings for attributes and objects. In CVPR, pages 13658–13667, June 2022. 3, 5, 7

[42] Robyn Speer, Joshua Chin, and Catherine Havasi. Conceptnet 5.5: An open multilingual graph of general knowledge. In AAAI, page 4444–4451, 2017. 2, 3, 4, 5, 7

[43] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. JMLR, 15:1929–1958, JUN 2014. 6

[44] Simon Vandenhende, Stamatios Georgoulis, Wouter Van Gansbeke, Marc Proesmans, Dengxin Dai, and Luc Van Gool. Multi-task learning for dense prediction tasks: A survey. IEEE TPAMI, 44(7):3614–3633, 2022. 3, 5

[45] Qilong Wang, Banggu Wu, Pengfei Zhu, Peihua Li, Wangmeng Zuo, and Qinghua Hu. Eca-net: Efficient channel attention for deep convolutional neural networks. In CVPR, pages 11531–11539, 2020. 5

[46] Yongqin Xian, Christoph H. Lampert, Bernt Schiele, and Zeynep Akata. Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly. IEEE TPAMI, 41(9):2251–2265, 2019. 2, 3

[47] Ziwei Xu, Guangzhi Wang, Yongkang Wong, and Mohan S. Kankanhalli. Relation-aware compositional zero-shot learning for attribute-object pair recognition. IEEE TMM, 24;3652–3664, 2022. 1

[48] Muli Yang, Cheng Deng, Junchi Yan, Xianglong Liu, and Dacheng Tao. Learning unseen concepts via hierarchical decomposition and composition. In CVPR, June 2020. 2

[49] Muli Yang, Chenghao Xu, Aming Wu, and Cheng Deng. A decomposable causal view of compositional zero-shot learning. IEEE TMM, pages 1–11, 2022. 1, 2

[50] Aron Yu and Kristen Grauman. Fine-grained visual comparisons with local learning. In CVPR, June 2014. 6

[51] Amir R. Zamir, Alexander Sax, Nikhil Cheerla, Rohan Suri, Zhangjie Cao, Jitendra Malik, and Leonidas J. Guibas. Robust learning through cross-task consistency. In CVPR, June 2020. 3

[52] Fang Zhao, Jian Zhao, Shuicheng Yan, and Jiashi Feng. Dynamic conditional networks for few-shot learning. In ECCV, September 2018. 3, 5

[53] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. In CVPR, June 2016. 5

[54] Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Conditional prompt learning for vision-language models. In CVPR, pages 16816–16825, June 2022. 3, 5