Beyond Seen Primitive Concepts for Attributes-Objects Compositional Learning

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Abstract

Learning from seen attribute-object pairs to generalize to unseen compositions has been studied extensively in Compositional Zero-Shot Learning (CZSL). However, CZSL setup is still limited to seen attributes and objects, and cannot generalize to unseen concepts and their compositions. To overcome this limitation, we propose a new task, Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL), where unseen attributes, objects, and unseen compositions are evaluated. To show that OV-CZSL is a challenging yet solvable problem, we propose three new benchmarks based on existing datasets MIT-States (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW-CZSL (Saini, Pham, and Shrivastava 2022; Pham et al. 2021), along with new baselines and evaluation setup. We use language embeddings and external vocabulary with our novel neighborhood expansion loss to allow any method to learn semantic correlations between seen and unseen primitives.

Introduction

Attributes explain the semantic properties of objects and are essential for efficient in-the-wild object recognition (Farhadi et al. 2009; Lampert, Nickisch, and Harmeling 2009; Bertasius and Torresani 2020). For instance, an unseen image of `dog` can be identified for its novel attributes, "a fluffy brown dog" even if the breed is unknown. However, data annotation for object-attribute is prohibitively expensive. It is challenging to scale annotated data because: (1) labels for each attribute and object are required individually, and (2) annotated data is required for all possible object-attribute compositions. Prior works (Misra, Gupta, and Hebert 2017; Isola, Lim, and Adelson 2015; Yu and Grauman 2014) circumvent the first challenge by assuming a limited vocabulary of attributes and objects ('seen' primitives) and focus primarily on the second challenge of unseen compositions, which is referred to as Compositional Zero-Shot Learning (CZSL). However, dealing with unseen attributes, unseen objects, and unseen compositions together is still an open problem. In this paper, we propose a new task, *Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL)*, which attempts to address aforementioned challenges simultaneously, (1) dealing with unseen attributes and unseen objects, and (2) recognizing unseen attribute-object compositions.
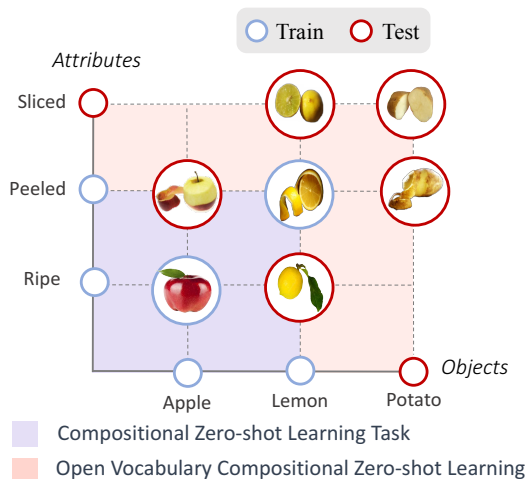

Figure 1: We propose a new task, Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL), that expands upon Compositional Zero-shot Learning (CZSL). CZSL focuses on evaluating unseen compositions `ripe lemon`, `peeled apple` of seen attributes (`ripe`, `peeled`) and seen objects (`apple`, `lemon`), using training samples (`ripe apple`,`peeled lemon`). The novel OV-CZSL is trained with the same data as CZSL. However, it can be evaluated on unseen attributes (`sliced`), objects (`potato`) and their unseen compositions. These unseen compositions also include seen attribute-unseen object (`peeled potato`), unseen attribute-seen object (`sliced lemon`) and unseen attribute-unseen objects (`sliced potato`).

Recognizing unseen classes (Zero-shot learning) and composing unseen relations between primitive seen classes (compositional learning) are both well known challenges in computer vision. Towards a more generic understanding of the unseen concepts, we introduce OV-CZSL that bridges the gap between ZSl and CZSL. Drawing inspiration from neuroscience, humans prototype and learn abstract concepts (fruit) while learning concrete concepts (apple, banana) (Zeithamova et al. 2019) (also known as concept learning). For instance, we can associate visually similar concepts (apple, orange) as an abstract concept(fruit), by linking them via language semantically. By extending this
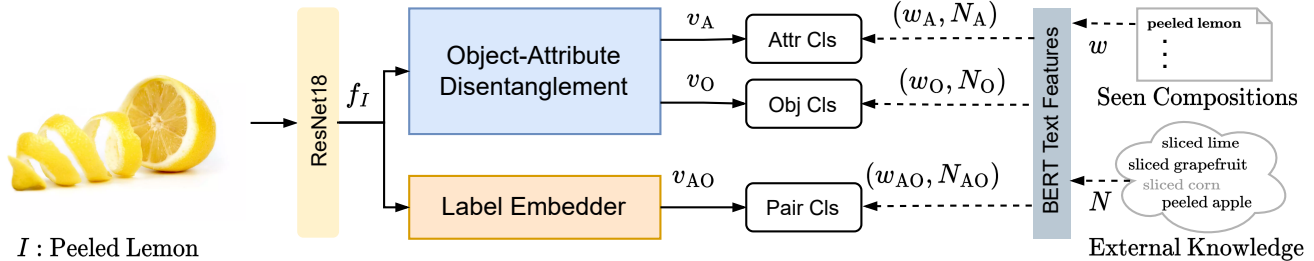
Figure 2: System Overview: ResNet18 (He et al. 2016a) is used as visual feature extractor. Label Embedder embeds the image feature v_{AO} along with BERT (Devlin et al. 2019) textual feature for the pair w_{AO}. Object-Attribute Disentanglement module separates visual features into attributes and objects as v_A and v_O. Moreover, along with target labels for attribute w_A, object w_O, and pair w_{AO}, we use neighbors for all of these from the semantic embedding space (N_A, N_O and N_{AO} respectively). We use cosine similarity loss, along with novel *Neighborhood expansion loss* to solve the task of OV-CZSL.

idea, with a seen concept `peeled lemon`, we can relate `lemon` with another vegetable, *e.g.* `potato`. Even though an image of `peeled potato` is never seen; by understanding the concept of `peeled`, we can extrapolate what `peeled potato` would look like (Figure 1). Accordingly, we leverage seen attributes and objects, along with external knowledge, to semantically associate and learn new concepts and their compositions.

Zero-shot learning studies (Wang, Ye, and Gupta 2018; Ghosh et al. 2020; Gao, Zhang, and Xu 2019; Han et al. 2021), mostly uses external language and map unseen concepts close to semantically similar seen concepts. For OV-CZSL, we utilize pre-trained language embeddings (BERT (Devlin et al. 2019)), to acquire semantically organized knowledge. Similar to CZSL, we learn a joint image and language embedding space to deal with unseen compositions. Within this embedding space, we expand the neighborhood around seen concepts to correlate different concepts and expand our vocabulary. Similar to query expansion in image retrieval (Xie et al. 2014; Dibia 2020; He et al. 2016b), we enforce the visual feature of semantically similar linguistic concepts to be close in the embedding space. This helps in training the image encoder to recognize visually and semantically similar concepts that it has never seen before (Wang, Ye, and Gupta 2018). We propose a new regularizing loss function, *Neighborhood Expansion Loss*, to perform this vocabulary expansion efficiently. Henceforth, we propose new benchmarks for the OV-CZSL task, building on three standard attribute-object datasets MIT-States (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022). As shown in Figure 1(b), we expand on the CZSL task, to create more challenging sets for evaluating OV-CZSL, which includes a mixture of seen and unseen compositions of seen and unseen attributes and objects. We also propose a *Neighborhood Expansion Loss* that helps train our model to generalize efficiently on unseen pairs, while maintaining the seen pair accuracy of the existing models. To summarize, our contributions are as follows:

• We propose a challenging and practical extension on CZSL, Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL), for learning compositions beyond the seen attributes and objects.
• We create three new benchmarks for MIT-states (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW (Pham et al. 2021; Saini, Pham, and Shrivastava 2022) for OV-CZSL, along with an efficient evaluation setup.
• We also propose an approach for OV-CZSL, which utilizes plug-and-play *Neighborhood Expansion Loss* to regularize training and generalize to unseen concepts and compositions.

Problem Setup

OV-CZSL is motivated by in-the-wild recognition, where it is infeasible to train on all possible objects and attributes for learning their compositions. To compare it with ZSL and CZSL setups, we discuss the train and test splits for these. Zero-shot Learning (ZSL) has distinct seen labels used for training and unseen labels used for testing. For attributes, we represent the seen and unseen sets as A and A^* respectively. Similarly, ZSL for objects will have O and O^* for seen and unseen sets, respectively. Compositional Zero-Shot Learning (CZSL) deals with unseen compositions of seen attribute and seen object pairs. Training set for CZSL is seen pairs (AO) and test set is unseen compositions of seen object and attribute classes, $(AO)^*$. By definition, there is no overlap between train and test sets in both ZSL and CZSL.

The goal for Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL) is to recognize attributes and objects beyond its seen vocabulary (hence it's open vocabulary). During training, only a set of compositions of seen attributes and objects AO are used. For testing, we evaluate on compositions of seen attribute-unseen object AO^*, unseen attribute-seen object A^*O, unseen attribute-unseen object A^*O^* and a set of unseen compositions of seen attributes and objects $(AO)^*$. The unseen test set for OV-CZSL is $\{AO^*, A^*O, A^*O^*, (AO)^*\}$. Hence, the formulation is OV-CZSL can be considered as a generalized combination of ZSL and CZSL tasks.

Related Work

Zero-shot learning. Different from ZSL, Generalized Zero-shot Learning (GZSL) has distinct seen labels used for
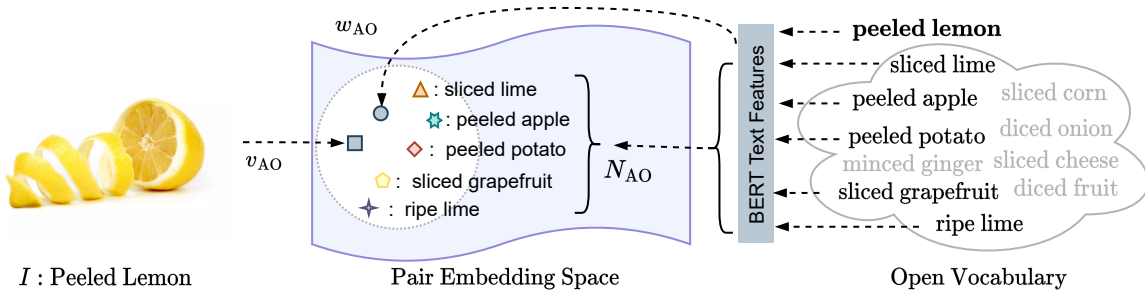
Figure 3: *Neighborhood Expansion Loss*. In the pair embedding space, we embed visual feature v_{AO} close to w_{AO}. Further, we use $k = 5$ neighbors of correct label w_{AO}, and make their word embeddings closer to the visual embedding v_{AO} as well. This gives our model the ability to generalize to unseen compositions.

training and evaluated on both seen and unseen labels during testing. Most works use auxiliary attribute descriptions of the object classes, for ZSL of objects (Wang, Ye, and Gupta 2018; Han et al. 2021; Ghosh et al. 2020; Narayan et al. 2020). Other works use word embeddings and pre-computing semantic features from Wikipedia et al., for identifying attributes or objects on commonly used datasets (AwA (Lampert, Nickisch, and Harmeling 2014), CUB (Wah et al. 2011), SUN (Patterson and Hays 2012), ImageNet (Deng et al. 2009)). In summary, there is no datasets and papers zero-shot attribute classification, along with zero-shot object classification and along with composition of attributes-objects.

Compositional Zero-shot learning. Most recent works rely on joint embedding space for images and labels, with linguistic losses (Nagarajan and Grauman 2018; Purushwalkam et al. 2019; Mancini et al. 2022, 2021; Li et al. 2020; Yang et al. 2020; Lu et al. 2016). Nagarajan *et al.* (Nagarajan and Grauman 2018) proposed two scenarios for evaluation: (1) Closed world, where images are classified into only unseen pairs, and (2) Open world, where both seen and unseen pairs are used for evaluation. Moreover, (Mancini et al. 2021) proposed another Open world setting, where for M attributes and N objects, they consider all possible combinations of M x N pairs, which might or might not be part of seen and unseen pairs for evaluation. Note that, in this work, 'Open' refers to extra vocabulary it can generalize to, but the evaluation is done in a closed world setup only. None of the existing works learn to compose novel unseen compositions.

Open Vocabulary. Recently, the focus on using limited labels to learn unseen in-the-wild classes has grown tremendously. Sergio *et al.* (Guadarrama et al. 2014) first proposed the task of open vocabulary object retrieval using descriptive natural language phrases by combining category and instance-level recognition. Further, Hang *et al.* (Zhao et al. 2017) proposed an open-vocabulary framework for scene parsing, which built an image-text common embedding space using hierarchical semantic relations. Open vocabulary setup has evolved over time, for scene parsing (Guadarrama et al. 2014), object detection (Zareian et al. 2021; Shi et al. 2022; Gu et al. 2021; Ye et al. 2018; Du et al. 2022), and object segmentation (Ghiasi et al. 2021). Moreover, we want to emphasize that most Open-Vocabulary works use CLIP (Radford et al. 2021) in the pipeline, however using

CLIP (Radford et al. 2021) makes the setup not-ZSL, since CLIP has already seen most attributes and objects. Hence, we avoid using CLIP for our setup. To the best of our knowledge, this is the first work exploring Open Vocabulary for Compositional Zero-shot Learning (OV-CZSL), and proposing a new challenging benchmark. We compare with baselines for both tasks ZSL and CZSL for OV-CZSL.

Approach

In this section, we describe our method to tackle OV-CZSL. We emphasize that similar to ZSL, for solving OV-CZSL, the approach must balance the tradeoff between seen and unseen class accuracy. Existing works in CZSL consider only the composition of seen attributes and objects (Mancini et al. 2022, 2021; Purushwalkam et al. 2019; Saini, Pham, and Shrivastava 2022; Nagarajan and Grauman 2018), and fail to generalize on compositions of unseen classes. We recommend new baselines for future work in OV-CZSL.

Task Formulation

OV-CZSL focuses on learning to compose seen and unseen attributes and objects. Each image I, has an attribute label A and an object label O. We use $*$ to represent the unseen concepts, *i.e.* unseen attributes are A^* and unseen objects are O^*. Training labels are set of seen attribute-object pairs, represented by Y^s, where $Y^s = AO$. Similar to CZSL, we evaluate on seen attribute-objects yet unseen compositions $(AO)^*$. Further, with unseen attributes and objects, there are three combinations of labels: 1) seen attribute and unseen object AO^*, 2) unseen attribute and seen object A^*O, 3) unseen attribute and unseen object A^*O^*. The overall test set is denoted as Y^u, where $Y^u = (AO)^* \cup AO^* \cup A^*O \cup A^*O^*$. Note that train and test set compositions are mutually exclusive, *i.e.*, $Y^s \cap Y^u = \emptyset$.

Methodology

Our architecture is based upon common state-of-the-art baselines in CZSL (mostly OADis (Saini, Pham, and Shrivastava 2022)). We extract image and textual features using pre-trained networks (ResNet18 (He et al. 2016a) and BERT (Devlin et al. 2019) respectively). The pair embedder is LabelEmbedder (Nagarajan and Grauman 2018) (LE) and the Object-Attribute Disentanglement module is

Table 1: **Dataset Splits.** We denote $*$ for unseen concept, such that A and O are seen attribute and objects, whereas A^* and O^* denote unseen attributes and objects. AO and $(AO)^*$ are seen and unseen compositions or seen attributes and seen objects respectively. AO^* are seen attribute-unseen object pairs, A^*O are unseen attribute-seen object set and A^*O^* are the unseen attribute-unseen object pairs. We propose new benchmark splits for OV-CZSL on datasets MIT-states (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022).

Datasets	Attributes		Objects		Training Set	Validation Set	Test Set
	A	A^*	O	O^*	AO	$AO/(AO)^*/A^*O/AO^*/A^*O^*$	$AO/(AO)^*/A^*O/AO^*/A^*O^*$
MIT-states (Isola, Lim, and Adelson 2015)	84	31	182	63	955	236 / 105 / 126 / 177 / 44	289 / 130 / 157 / 218 / 50
C-GQA (Mancini et al. 2022)	311	102	504	170	4094	1012 / 447 / 525 / 517 / 147	1239 / 542 / 664 / 655 / 176
VAW-CZSL (Pham et al. 2021)	330	135	406	110	7142	1767 / 803 / 1420 / 1253 / 412	2161 / 982 / 1737 / 1532 / 504

from OADis (Saini, Pham, and Shrivastava 2022), as shown in Figure 2. The Disentanglement module separates the visual features for attribute and object.

System Architecture. Similar to OADis (Saini, Pham, and Shrivastava 2022), we use the second last layer before AveragePool of pre-trained ResNet18 (He et al. 2016a), for spatial features $f_I \in \mathbb{R}^{512 \times 49}$. The Label Embedder module (MLP) extracts final feature v_{AO} for pair embedding, with same dimension as the word embedding final feature w_{AO}, extracted from BERT (Devlin et al. 2019) Text Features (Figure 2). The disentanglement module separates the attribute and object visual features using backbone features for I, I_{attr} and I_{obj}, where I_{attr} is image with same attribute as I, and I_{obj} is an image with same object as I. I and I_{attr} are used to extract visual feature for attribute v_A. Similarly, visual feature for object v_O is extracted from I and I_{obj}. Using textual features (w_A and w_O), these visual embeddings for attributes and objects are regularized, *i.e.* given a seen image with label `peeled apple`, we push the visual embedding of this image closer to text embedding of the label. More details can be found in (Saini, Pham, and Shrivastava 2022). We use cross-entropy along with cosine similarity to get the final classification score for each attribute, object and pair, same as (Mancini et al. 2022). Let visual feature is v and text feature is w, y is the correct seen label, then the main classifier logits can be defined as (where δ is the temperature factor):

$$C(v, w) = \frac{e^{h(v,w)}}{\sum_{y \in Y^s} e^{h(v,y)}}$$

$$h(v, w) = \cos(v, w) = \delta \cdot \frac{v^T w}{\|v\| \, \|w\|} \quad (1)$$

Neighborhood Expansion Loss

Previous CZSL methods perform fairly well for OV-CZSL, however fail to generalize on totally unseen compositions set, *i.e.* A^*O^*. By using common techniques of data augmentation and learning rate decay leads to improved generalization on unseen compositions, but deteriorates performance on seen compositions. Hence the goal of novel *Neighborhood Expansion Loss* (NEL) is to balance the generalizability and learnability of the model. To achieve this, we leverage ideas from *label smoothing* and *label propagation*. Label smoothing is a regularization technique used to reduce overfitting. Although, as explained in (Yuan et al. 2020;

Müller, Kornblith, and Hinton 2019), it is not always helpful and often introduces noise in the system. We use label smoothing to make the model less confident with training classes, such that negative bias for unseen classes decreases, and the model does not overfit on seen classes. Further, to transfer knowledge from seen to unseen concepts, we use label propagation techniques (Zhou et al. 2003). It is a graph-based method for semi-supervised learning (Fergus, Weiss, and Torralba 2009; Shrivastava, Singh, and Gupta 2012). In a transductive setting, given labeled and unlabeled examples, label propagation defines a graph between samples, to connect unlabeled samples to potential labels. In our paper, we use neighbors from external knowledge sources (open vocabulary) to learn unseen pairs from seen pairs.

With traditional cross-entropy loss, the model only learns to minimize the distance between the the visual embeddings and text embeddings for each image and correct label (`peeled lemon`). However, for limited seen compositions, this strategy causes a negative bias against unseen pairs. In a way, it forces the model to never learn unseen pairs, since it is too confident for the correct label. To overcome this, we apply label smoothing, which reduces negative bias for unseen classes during training with NEL. Another problem is extending knowledge from seen to unseen compositions. For that, we use label propagation. For each seen pair, we find k nearest-neighbors N_k using word embeddings for labels (details in next section). These neighbors make the 'open-vocabulary' aspect of OV-CZSL. As shown in Figure 3, if seen pair is `peeled lemon`, we also learn visual embeddings for unseen compositions `sliced lime`, `peeled apple`, `peeled potato`, `sliced grapefruit` and `ripe lime` as well by minimizing the distance between visual feature for given image of `peeled lemon` with the textual embeddings of the 5 mentioned neighbors. This intuition is from human learning, that we can correlate similar looking objects using language, such as oranges are similar to lemons. With this new loss, we expand our vocabulary beyond seen classes, by correlating similar concepts using language priors. Note that these neighbors are weighted, and the distance between visual feature with its original label (`peeled lemon`) is smaller than distance with its neighbor embeddings. so that the correct label is still learnt with higher confidence than it's neighbors.

Let N represent the neighbor set of seen pair text embedding w. For M training labels, cross-entropy is defined as H where, y_m is 1 for the correct class and 0 for the rest. Label

Table 2: **Results on MIT-states (Isola, Lim, and Adelson 2015) and CGQA (Mancini et al. 2021).** We report Top 1 AUC, which balances % between seen and unseen compositions with different bias terms. HM is Harmonic Mean where maximum AUC is computed. Following (Purushwalkam et al. 2019), best accuracy values are reported for Seen AO and Unseen pairs $\{AO^*, A^*O, A^*O^*, (AO)^*\}$. All other accuracies for individual splits are computed with bias where HM is maximum. Our method with NEL loss outperforms previous methods on most unseen compositions.

	MIT-States									C-GQA								
Model	Test@1	HM	Seen	Unseen	AO	$(AO)^*$	A^*O	AO^*	A^*O^*	Test@1	HM	Seen	Unseen	AO	$(AO)^*$	A^*O	AO^*	A^*O^*
LE (Nagarajan and Grauman 2018)	1.01	7.64	16.29	9.46	10.24	11.38	5.98	4.15	2.87	1.17	8.39	19.37	8.36	10.76	6.51	9.53	2.67	1.08
CompCos (Mancini et al. 2021)	1.97	10.22	26.53	10.29	**14.32**	**21.09**	5.86	2.89	0.63	2.35	9.64	40.19	7.25	**21.19**	**20.24**	4.47	1.95	0.26
OADis (Saini, Pham, and Shrivastava 2022)	1.83	9.55	25.35	10.79	12.18	16.06	6.40	5.41	1.34	2.33	9.74	**42.88**	7.12	20.86	15.19	6.17	3.47	0.61
Ours	**2.41**	**10.94**	**29.02**	**11.13**	14.11	18.87	**8.24**	**5.49**	**3.54**	**3.18**	**12.11**	42.38	**9.77**	19.78	16.07	**12.86**	2.87	**3.04**

Table 3: **Results on VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022).** All measures are shown in Top 3 AUC. HM is Harmonic Mean where maximum AUC is computed. All other accuracies for individual splits are computed with bias where HM is maximum. Our approach outperforms previous baselines for unseen compositions.

Model	Test@3	HM	AO	$(AO)^*$	A^*O	AO^*	A^*O^*
LE (Nagarajan and Grauman 2018)	1.49	8.27	15.62	10.48	5.79	2.78	0.98
CompCos (Mancini et al. 2021)	2.69	10.68	20.21	**20.58**	5.04	2.48	0.5
OADis (Saini, Pham, and Shrivastava 2022)	2.68	10.91	21.19	15.65	6.75	3.16	0.76
Ours	**2.91**	**11.35**	**23.02**	16.18	**7.86**	**3.37**	**1.36**

Table 4: **Comparison with ZSL baselines.** We show results on two ZSL baselines for seen and unseen attributes and objects. Using NEL significantly improves outperforms existing ZSL baselines.

Model	Emb.	A	A^*	O	O^*
SEKG (Wang, Ye, and Gupta 2018)	GloVe	**5.04**	**3.10**	5.19	**3.17**
	BERT	3.37	2.33	**5.72**	2.29
TF-VAEGAN (Narayan et al. 2020)	GloVe	**5.86**	**5.76**	**5.93**	**4.52**
	BERT	4.54	3.05	5.82	3.93
Ours	GloVe	20.75	13.67	32.19	7.86
	BERT	20.37	11.42	29.3	**10.07**

smoothing (Müller, Kornblith, and Hinton 2019) makes the model less confident for the correct label, by weighting the loss for correct label with a smoothing factor $\alpha < 1$. Thus cross-entropy between the modified targets y_m^{LS} and and the network's outputs C_m is minimized.

$$H(y, C) = \sum_{m=1}^{M} -y_m \log(C_m)$$
$$y_m^{LS} = y_m(1 - \alpha) + \alpha/M \quad (2)$$

The *Neighborhood Expansion* makes the target for actual label is weighted highest, and rest weights are distributed among neighbors, with least weights are assigned to other labels.

$$y_m^{NE} = y_m(1 - \alpha)T + y_k(1 - \alpha)(1 - T) + \alpha/(M + k)$$

where, k is the number of neighbors, y_k are labels for neighbors from open-vocabulary, T is smoothing term for label propagation (weighting neighbors) and α is smoothing term for label smoothing. Thus, *Neighborhood Expansion Loss* is a combination of label propagation and label smoothing. We use Cosine Similarity-based cross-entropy H classification loss and *Neighborhood Expansion Loss* for attribute, object, and pair embeddings, represented by Attr Cls, Obj Cls, and Pair Cls shown in Figure 2. Here, we elaborate on the Pair Cls loss:

$$\mathcal{L}_{AO} = H(y_{AO}, C(v_{AO}, w_{AO}))$$
$$\mathcal{L}_{AO}^{NE} = H(y_{AO}^{NE}, C(v_{AO}, w_{AO})) \quad (3)$$

We can define similar loss functions for Attr Cls and Obj Cls as well. For each embedding space, we use both losses, and overall objective function $\mathcal{L}$ is:

$$\mathcal{L}_{pair} = \beta_1 \mathcal{L}_{AO} + (1 - \beta_1)\mathcal{L}_{AO}^{NE}$$
$$\mathcal{L}_{attr} = \beta_2 \mathcal{L}_A + (1 - \beta_2)\mathcal{L}_A^{NE}$$
$$\mathcal{L}_{obj} = \beta_3 \mathcal{L}_O + (1 - \beta_3)\mathcal{L}_O^{NE}$$
$$\mathcal{L} = \mathcal{L}_{pair} + \gamma_1 \mathcal{L}_{attr} + \gamma_2 \mathcal{L}_{obj}. \quad (4)$$

Experimental Setup

Following CZSL works, we propose new splits for OV-CZSL on existing dataset MIT-States (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022). MIT-states (Isola, Lim, and Adelson 2015) is relatively small, is a popular choice for CZSL. It has 115 attributes, 245 objects, 1962 compositional pairs, and 53k images. C-GQA (Mancini et al. 2022) a larger dataset with 413 attributes, 674 objects and a total of $\sim 7k$ pairs and 39k images. VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022) is the largest of all, with 533 attributes, 543 objects, $\sim 15k$ (15785) pairs and 92k images. The scale for C-GQA and VAW-CZSL is similar, however, VAW-CZSL has more shared attributes among objects. C-GQA has more one-to-one attribute object pairing, without much sharing of attributes among objects. We do not use UT-Zappos (Yu and Grauman 2014) since it only has 16 attributes and 12 objects. **Dataset Splits.** Following the ZSL works (Han et al. 2021; Wang, Ye, and Gupta 2018), we split attributes and objects into 75-25% split for training and testing. Since we are using ResNet18 (He et al. 2016a) trained on Imagenet (Deng et al. 2009) as backbone for visual features, we make sure that attributes and objects common with Imagenet labels are part of training set (seen attributes and seen objects). This ensures that the unseen attributes and objects are truly zero-shot, and

Table 5: **Using NEL with other baselines**. We show effect of NEL for different baselines. All methods using NEL perform better for OV-CZSL splits.

Model	AO	$(AO)^*$	A^*O	AO^*	A^*O^*
LE (Nagarajan and Grauman 2018)	10.24	11.38	5.98	4.15	2.87
LE + NEL	10.65	6.11	5.61	4.09	7.71
	+0.4	-5.2	-0.3	-	+5.5
CompCos (Mancini et al. 2022)	14.32	21.09	5.86	2.89	0.63
CompCos + NEL	15.73	19.72	8.03	4.13	1.77
	+1.4	-1.3	+2.1	+1.24	+1.1
OADis (Saini, Pham, and Shrivastava 2022)	12.18	16.06	6.40	5.41	1.34
Ours (OADis+NEL)	14.11	18.87	8.24	5.49	3.54
	+2.9	+2.8	+1.8	-	+2.2
CLIP (Radford et al. 2021) (ZSL)	20.08	22.03	23.38	23.21	34.93
CLIP+ FT	25.89	22.03	24.87	25.60	34.50
CLIP+FT+NEL	25.97	23.06	25.90	25.70	36.45
	-	+1.0	+1.3	-	+2.0

are never seen. A set of valid compositions of seen attribute and object pairs becomes the training set Y^s. Test set, denoted as Y^u has unseen compositions of seen attributes and objects $(AO)^*$, as well as, other sets of seen and unseen attributes with unseen objects (AO^*, A^*O, A^*O^*). We further split Y^u 40-60%, to make validation and test splits, similar to CZSL. To evaluate learnability on seen compositions, test and validation split also have subset of Y^s. All split creations are random and are selected from 10 random splits, based on the balance between seen and unseen accuracies (refer supplementary). Table 1 shows statistics of the benchmark split.

Evaluation. We follow Generalized CZSL (Purushwalkam et al. 2019; Li et al. 2020; Saini, Pham, and Shrivastava 2022; Mancini et al. 2021) evaluation protocol, to evaluate on both seen and unseen pairs (Y^s, Y^u) with a scalar term used to overcome negative bias for unseen pairs. Since, the OV-CZSL task is already challenging, we use Closed world evaluation setup (mentioned in related work), where AUC is reported over only "valid" unseen pairs while ignoring the "invalid" pairs. Area Under the Curve (AUC) is computed between the accuracy on seen and unseen compositions with different bias and Harmonic Mean (HM), to balance the bias. We also report separately accuracy for each set $(AO, (AO)^*, AO^*, A^*O, A^*O^*)$ at the bias-term where HM is maximum. The seen pairs Y^s consist of AO whereas the unseen pairs Y^u are $\{AO^*, A^*O, A^*O^*, (AO)^*\}$. Following (Purushwalkam et al. 2019), best accuracy values are reported for seen and unseen pairs.

Neighborhood list. Since some datasets are small, and the testing pair labels might not be semantically similar to training pairs. To expand the vocabulary, we use external knowledge sources. In total, we use 2294 attributes/adjectives and 4090 objects aggregated from Visual Genome (Krishna et al. 2016), Flick30k (Young et al. 2014), COCO-captions (Chen et al. 2015), and LocalizedNarratives (Pont-Tuset et al. 2020). These attributes and object pairs make up $\sim$118650 compositions, as valid extra compositions we use for neighborhood search. We find 10 neighbors for each seen attribute and objects from the external source, using GloVe (Pennington, Socher, and Manning 2014) embeddings cosine similarity score. Using the neighbors for attribute and object, we find all possible compositions ($\sim$100) for each pair. The

compositions are then analyzed for validity using the external pair list described above. 10 valid compositions are chosen as neighbors for the seen pair. If the external pair list does not have any compositions, we only choose compositions of first 6 closest attributes and objects from the neighbor list. Hence, neighbor search is based on individual attribute and object, instead of pairs directly. More details on for neighbor search and hyperparameter sensitivity of NEL are explained in suppl.

Training Details. Following standard practice in CZSL (Nagarajan and Grauman 2018; Purushwalkam et al. 2019; Mancini et al. 2022, 2021), we use Frozen ResNet18 (He et al. 2016a), pre-trained on ImageNet (Deng et al. 2009) for image features (without finetuning) and BERT (Devlin et al. 2019) text embeddings for labels. A linear layer on top of BERT (Devlin et al. 2019) features is used for pair embeddings. We use image augmentations (random crop, horizontal flip) for all baselines and our method, like OADis (Saini, Pham, and Shrivastava 2022). For MIT-States (Isola, Lim, and Adelson 2015), the network is trained with Adam optimizer, with weight decay 1e-6, learning rate 3e-5 and decay at epoch 120 and 130. Smoothing factor $\alpha = 0.8$, temperature for cosine similarity $\delta = 0.05$, temperature for weights of neighbors $T = 0.5$, number of neighbors $k = 5$, weights for losses are $\beta_1 = 0.8, \beta_2 = \beta_3 = 0.95$, and $\gamma_1 = \gamma_2 = 0.05$. The model is trained for 150 epochs and best performance based on validation AO performance. More details are mentioned in suppl.

Results

CZSL Baselines

The main task for OV-CZSL is compositional learning for seen and unseen attribute-object pairs. Our architecture is most similar to OADis (Saini, Pham, and Shrivastava 2022), with embedding space and losses from LE (Nagarajan and Grauman 2018) and CompCos (Mancini et al. 2021). Hence we compare with these 3 baselines and show accuracy for each individual split. Other baselines for CZSL, (e.g. TMN (Purushwalkam et al. 2019), AttrOpr (Nagarajan and Grauman 2018), GraphEmb (Mancini et al. 2022)) are either outperformed by CompCos (Mancini et al. 2021) or perform poorly on unseen pairs (e.g. KG-SP (Karthik, Mancini, and Akata 2022), Symnet (Li et al. 2020)). Note that, even though the external open vocabulary may or may not have any lables from our test set, we explicitly do not include test classes in the external knowledge sources. Hence, baselines which have any test labels while training(GraphEmb (Mancini et al. 2022)) are not compared with, since they have use test lables while training.

Results on MIT-States and C-GQA. We report the AUC and harmonic mean (HM) for Top1 predictions on both datasets in Table 2. Seen and Unseen accuracy is the overall best accuracy without bias calibration. Interestingly, LE (Nagarajan and Grauman 2018) generalizes well on unseen compositions, but does not perform as well for seen compositions overall. Moreover, CompCos (Mancini et al. 2021) works the best for CZSL task, as its performance for AO and $(AO)^*$ remains unbeatable. However, it fails

Table 6: **Ablation for varying number of neighbors (k)**. We show how changing the number of neighbors can introduce noisy labels in the setup. For generalization to unseen classes, we need fewer neighbors (5 as shown here).

k	Val@1	Test@1	HM	AO	$(AO)*$	A^*O	AO^*	A^*O^*
1	2.67	2.21	10.46	15.16	17.46	8.02	4.41	2.21
3	2.69	2.18	10.39	**16.37**	16.71	7.67	4.47	2.21
5	**2.69**	**2.41**	**10.94**	14.11	**18.87**	**8.24**	**5.49**	**3.54**
7	2.65	2.24	10.44	15.16	17.67	8.09	4.50	2.37
10	2.60	2.16	10.35	13.79	18.33	8.01	4.61	2.14

Table 7: **Ablation on different Text Embedding**. We show effect of using different text embeddings for OV-CZSL. We observe that BERT (Devlin et al. 2019) improves the unseen compositions A^*O^* the most, hence we use BERT (Devlin et al. 2019) for our approach.

Emb	Test@1	HM	AO	$(AO)^*$	A^*O	AO^*	A^*O^*
GloVe	2.37	10.46	13.13	**19.11**	10.70	3.83	0.69
word2vec	2.37	10.68	13.82	17.46	10.61	4.19	1.13
fasttext	2.33	10.14	13.02	17.04	**10.93**	4.88	1.64
BERT	**2.41**	**10.94**	14.11	18.87	8.24	**5.49**	**3.54**

to generalize on compositions of unseen attributes or objects. OADis (Saini, Pham, and Shrivastava 2022) is somewhere in the middle but does not generalize as well on unseen compositions A^*O^*. Our proposed approach gets best of both world, as it performs close to CompCos (Mancini et al. 2022) and OADis (Saini, Pham, and Shrivastava 2022) for CZSL task and beats LE (Nagarajan and Grauman 2018) for unseen compositions, corresponding to A^*O, AO^* and A^*O^*. For C-GQA (Mancini et al. 2022), there are less attributes that share a common object (and vice-versa), which makes object-attribute disentanglement inefficient on this dataset. It relies more on backbone visual features (biased for objects), and performs well on A^*O than on AO^*. Our method with NEL surpasses most unseen sets with significant margin. Overall, in comparing CompCos and our method, for CZSL compositions AO and $(AO)^*$, the drop is accuracy is $< 4\%$ while the improvement in A^*O^* is almost 5 times, which is the most challenging split of unseen attribute-unseen object compositions.

Results on VAW-CZSL. This dataset created from multi-label VAW (Pham et al. 2021), and VAW-CZSL (Saini, Pham, and Shrivastava 2022) uses the least frequent labels for each image across the dataset. Hence top 1 predictions latch on to different attributes which are present in the image, but are not labeled. We show Top 3 AUC, HM and accuracy for this dataset. Similar variations in performance of baselines are obeserved for this dataset as well Table 3, *i.e.* CompCos performs better in $(AO)^*$ while our method outperforms all baselines in every other set.

ZSL Baselines

Zero-shot Learning (ZSL) for unseen attributes and objects is a by-product of OV-CZSL. Hence, we also compare with some baselines from ZSL. There are various ZSL methods, but most of them use pre-defined semantics for objects (Wang, Ye, and Gupta 2018; Ghosh et al. 2020), AwA (Lampert, Nickisch, and Harmeling 2014), CUB (Wah et al. 2011), Imagenet (Deng et al. 2009). Our work only relies on text label embeddings and visual features, therefore we compare with two recent works TF-VAEGAN (Narayan et al. 2020) and CE-GZSL (Han et al. 2021). Note that these works do not have any information about unseen test classes during training, which might or might not be part of external knowledge but are not explicitly added to the open vocabulary. These methods use semantic features, which we replace with GloVe (Pennington, Socher, and Manning 2014)

and BERT (Devlin et al. 2019) text embeddings. We show results for MIT-States (Isola, Lim, and Adelson 2015) as we observe similar pattern for other datasets as well. All the values are bias calibrated, to balance seen and unseen accuracy, for Top-1 predictions. Our proposed method outperforms common baselines in ZSL as well, with a significant margin. More details on why GloVe (Pennington, Socher, and Manning 2014) embeddings perform the best are explained in the next section.

Ablation Studies

We experimentally motivate the design choices as well as novelty aspect of our approach. All the experiments in this section are shown for MIT-States (Isola, Lim, and Adelson 2015) dataset. One of the most challenging set in OV-CZSL is A^*O^*, hence a lot of design choices are based mainly upon improving performance for this unseen split. We discuss more hyperparameters in suppl.

Neighborhood Expansion Loss. As the main contribution of this work is OV-CZSL and *Neighborhood Expansion Loss*, we explore if this loss can be used as plug-and-play for other baselines. In Table 5, third row for each model, shows the change caused by using NEL with respect to originally without NEL. red denotes negative change in value, green denotes the positive change and '-' represents no or change is less than ± 0.2. All methods with NEL improve significantly for A^*O^* split, whereas OADis (Saini, Pham, and Shrivastava 2022) improves for all splits. This is because NEL is applied for not just pair embedding space, but also for attribute and object spaces, which are not present for CompCos (Mancini et al. 2022) and LE (Nagarajan and Grauman 2018). Although, as mentioned earlier, CLIP (Radford et al. 2021) makes the setup not-ZSL, we still acknowledge the presence of such larger models and show the importance of NEL loss. The loss can be applied along with CLIP (Radford et al. 2021) loss function, and slightly improve generalization for the unseen compositions. Despite NEL being a small modification and the CLIP loss has more stronger impact, we show the potential to harness bigger models to generalize beyond seen classes. We expect similar boost for other Vision+Language models such as BLIP (Li et al. 2022) along with NEL, while showing results with CLIP (Radford et al. 2021) as a representative sample.

Textual Features. Textual features are the source of regularization and knowledge transfer, which makes these a crucial design decision. We observe that for zero-shot learning
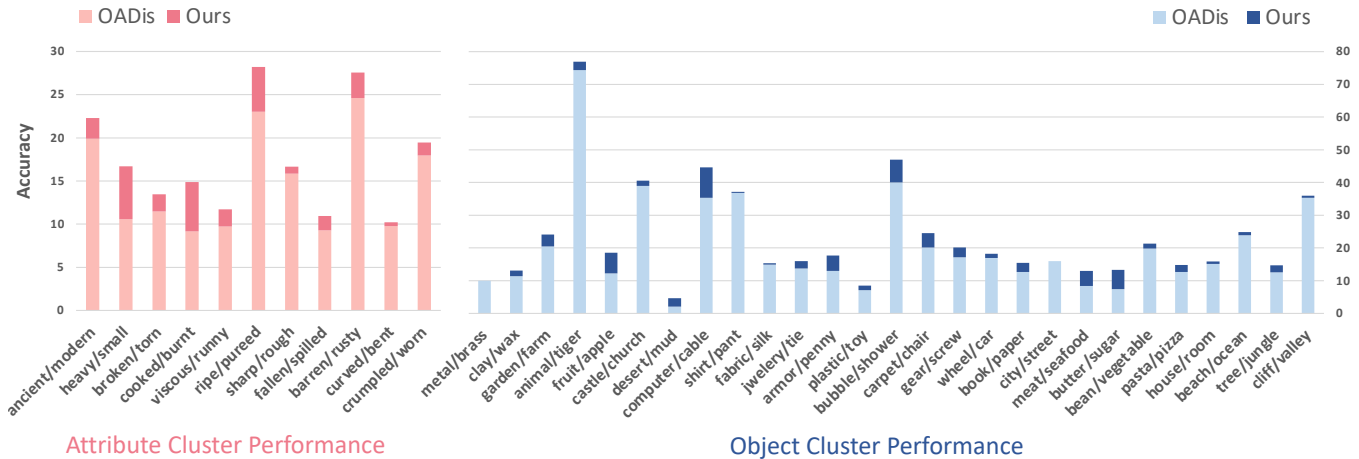
Figure 4: To show the impact of NEL, we cluster all attribute and object class labels for MIT-States (Isola, Lim, and Adelson 2015), and evaluate the accuracy for each cluster. These clusters have both seen (ancient, new, young) and unseen (modern, old) concrete concepts, such that each cluster has one abstract concept (time/age). Our model (OADis+NEL) shows either same or improved performance for attributes and object clusters, backing our hypothesis of NEL generalizes to unseen concrete concepts for the similar abstract concepts.

task, GloVe (Pennington, Socher, and Manning 2014) performs better than BERT (Devlin et al. 2019) embeddings. Since BERT is contextual embeddings, attribute-object embeddings from BERT are more helpful than GloVe. We also compare with other common word embeddings like Fast-text (Bojanowski et al. 2017) and word2vec (Mikolov et al. 2013) in Table 7. Most word embeddings perform better for unseen compositions of seen attributes-objects $(AO)^*$ and A^*O. We use BERT for all baselines of OV-CZSL since it outperforms for the most challenging set A^*O^*.

Number of Neighbors. Using too many noisy labels in label smoothing can affect the performance adversely (Yuan et al. 2020; Müller, Kornblith, and Hinton 2019). In our case, more neighbors can act as noisy labels. We experiment to find the ideal number of neighbors, as shown in Table 6. Among all numbers, our model achieves best performance using 5 neighbors on MIT-States (Isola, Lim, and Adelson 2015) and C-GQA (Mancini et al. 2022). For VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022), we use 10 neighbors for best performance.

How is NEL helping in learning abstract concepts?

Our inspiration for NEL is to learn to generalize similar concrete concepts (apple, banana) to all other abstract concepts (any fruits), such that if 1-2 fruits are seen in the training set, the model generalizes to other unseen fruits in the test set. To quantitatively verify this, we cluster all attributes and objects classes for MIT-states (Isola, Lim, and Adelson 2015), using k-nearest neighbors, along with a threshold cosine similarity of 0.4 across GLoVe (Pennington, Socher, and Manning 2014) features. We manually check the similarity between these label clusters and ignore the attributes and objects across clusters: (1) cluster size is less than 3 and (2) clusters which have classes that are only part of test set, without having any class in training set. Each cluster has some seen and unseen concepts. We compare OADis (Saini, Pham, and

Shrivastava 2022) and Our (OADis+NEL) model's accuracy for these clusters. Attributes are spread across 11 clusters, and objects are spit into 26 clusters. As shown in Figure 4, each cluster is represented with two labels from the cluster to disclose the abstract concept of the cluster. We observe that most clusters either show same or improved performance while using NET (for our model), across all attributes and objects. This shows that similar concepts are learnt together to generalize to unseen abstract concepts. However, this setup is still limited, such that the model cannot discriminate similar concepts `peel` from `slice` and `chop`, but can only learn these together closer in the visual+textual embedding space as `styles of cutting`.

Conclusion and Discussion

In the era of CLIP (Radford et al. 2021) and DALL-E (Ramesh et al. 2021), we emphasize that labeled data is still a bottleneck, which these bigger models dodge by extensively using all available labeled data. However, in limited data scenarios, we present a novel task Open Vocabulary-Compositional Zero-shot Learning (OV-CZSL), which not only focuses on learning unseen compositions of seen attributes and objects, but also can generalize to unseen attributes, unseen objects and their compositions. We propose new benchmark splits, backed by scientifically stable methods on existing datasets, MIT-states (Isola, Lim, and Adelson 2015), C-GQA (Mancini et al. 2022) and VAW-CZSL (Pham et al. 2021; Saini, Pham, and Shrivastava 2022). Any CZSL model (or even LLM) can be extended with Neighborhood Expansion Loss, for solving OV-CZSL, through semantic transfer from pre-trained language embeddings. However, open vocabulary compositional learning is still a challenging problem, with tremendous scope in improving benchmarks (datasets and evaluation). Therefore, we urge the community to further explore generalized compositional learning of attributes and objects.

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