ADAPTIVE AND GENERATIVE ZERO-SHOT LEARNING

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ABSTRACT

We address the problem of generalized zero-shot learning (GZSL) where the task is to predict the class label of a target image whether its label belongs to the *seen* or *unseen* category. Similar to ZSL, the learning setting assumes that all class-level semantic features are given, while only the images of seen classes are available for training. By exploring the correlation between image features and the corresponding semantic features, the main idea of the proposed approach is to enrich the semantic-to-visual (S2V) embeddings via a seamless fusion of adaptive and generative learning. To this end, we extend the semantic features of each class by supplementing image-adaptive attention so that the learned S2V embedding can account for not only inter-class but also intra-class variations. In addition, to break the limit of training with images only from seen classes, we design a generative scheme to simultaneously generate *virtual* class labels and their visual features by sampling and interpolating over seen counterparts. In inference, a testing image will give rise to two different S2V embeddings, seen and *virtual*. The former is used to decide whether the underlying label is of the unseen category or otherwise a specific seen class; the latter is to predict an unseen class label. To demonstrate the effectiveness of our method, we report state-of-the-art results on four standard GZSL datasets, including an ablation study of the proposed modules.

1 INTRODUCTION

Different from conventional learning tasks, zero-shot learning (ZSL) by Lampert et al. (2009); Palatucci et al. (2009); Akata et al. (2013) explores the extreme case of performing inference only over samples of unseen classes. To make the scenario more realistic, generalized zero-shot learning (GZSL) (Chao et al., 2016; Xian et al., 2017) is subsequently proposed so that inference can concern samples of both seen and unseen classes. Nevertheless. the learning setting in ZSL/GZSL is essentially the same where sample classes are divided into two categories, *seen* and *unseen*, but only those samples of seen classes are accessible to training. In addition, each of all the classes under consideration is characterized by semantic features such as attributes (Xian et al., 2018b) or text descriptions (Zhu et al., 2018) to specify and relate seen and unseen classes.

The lack of training samples from unseen classes has prompted generative approaches (Chen et al., 2018; Felix et al., 2018; Kumar Verma et al., 2018; Mishra et al., 2018) to creating synthetic data from semantic features of unseen classes. The strategy could enable learning semantic-visual alignment on unseen classes implicitly, and thus improves the ability to classify unseen classes. However, such generative models are indeed trained on seen samples, and the quality of synthesized unseen samples is predominantly influenced by seen classes. If the number of training samples of each seen class is small, it is hard for generative models to adequately synthesize samples of unseen classes, leading to unsatisfactory zero-shot learning. To better address the issue, we propose to synthesize visual and semantic features of *virtual* classes rather than those of the unseen classes. An interesting analogy is that childhood experience and relevant study (Greene, 1995) suggest the behavior of using human imagination to produce new object concepts could assist our cognitive capability. To mimic people utilizing imagination for exploring new knowledge, we create *virtual* classes by the integration of past "experience" (seen classes). In detail, we extend the mixup technique by Zhang et al. (2018) to generate *virtual* classes, with a subtle difference that mixing is conducted on the semantic features (in addition to the visual ones), rather than the class label vectors.

In ZSL/GZSL, each seen or unseen class is typically described by a single semantic feature vector. The practice is useful in differentiating different classes in a principled way, but may not be sufficient

to reflect the inter-class and intra-class visual discrepancies, not to mention the ambiguities caused by different backgrounds, view orientations, or occlusion in images. The concern of inefficient class-level representation can also be observed from how the semantic feature vectors are constructed. Take, for example, the Attribute Pascal and Yahoo (`aPY`) dataset (Farhadi et al., 2009), where each instance is annotated by 64 attributes. The semantic features of each class in `aPY` are obtained by averaging the attribute vectors of all its instances. We are thus motivated to introduce an image-adaptive class representation, integrating the original semantic features for inter-class discrimination with an image-specific attention vector for intra-class variations.

With the addition of *virtual* training data and the image-adaptive class representation, our method is designed to learn two classification experts: one for seen classes and the other for unseen classes. Both experts project the image-adaptive semantic feature vectors to the visual space and use cosine similarity to find the class label most similar to the given visual feature vector. The seen expert is trained with the provided training (seen) data, while the class prediction is over all possible classes, including seen and unseen. In inference, if its predicted class is not within the seen category. The testing sample is deemed to be from the unseen category, whose label is then decided by the unseen expert. The unseen expert is trained with the *virtual* data only, and the process indeed resembles meta-learning. However, the effectiveness of meta-learning is boosted by the design of the image-adaptive mechanism in that fine-tuning is not needed in performing zero-shot classification over unseen classes. We characterize the main contributions of this work as follows.

- Instead of generating synthetic data of unseen classes, we propose to yield *virtual* classes and data by mixup interpolations. The *virtual* classes of synthetic data can then be seamlessly coupled with meta-learning to improve the inference on unseen testing samples.
- We introduce the concept of representing each class with image-adaptive semantic features that could vary among intra-class samples. While the adaptive mechanism improves classifying the seen classes, it manifests the advantage in boosting the effect of meta-learning over *virtual* data to zero-shot inference over unseen classes.
- We demonstrate state-of-the-art results of zero-shot learning over four popular benchmark datasets and justify the design of our method with a thorough ablation study.

2 Related Work

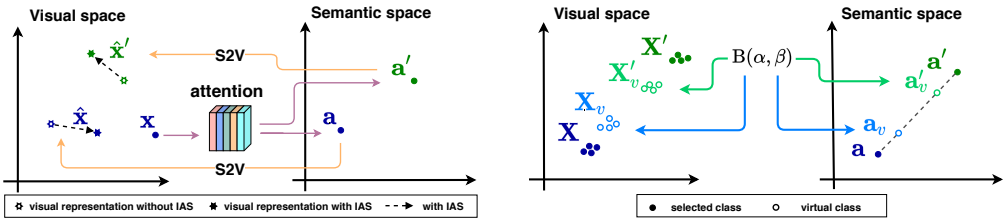
We review related works in this section. First, we study generative approaches for ZSL/GZSL that synthesize unseen images for training. To improve GZSL performance, we couple proposed *virtual* class generation with meta-learning for mimicking the inference scenario. Finally, we discuss attention approaches that extract discriminating features from images to help classification.

2.1 Generative Approaches for ZSL/GZSL

Arguably one of the most important problems in ZSL/GZSL is to prevent models from being biased to seen classes. Generative approaches (Chen et al., 2018; Felix et al., 2018; Kumar Verma et al., 2018; Mishra et al., 2018; Schonfeld et al., 2019; Paul et al., 2019; Xian et al., 2019) tackle the problem by synthesizing visual features of unseen classes from their semantic features with generative models like Generative Adversarial Networks (GAN; Goodfellow et al., 2014) or Variational Autoencoders (VAE) (VAE; Kingma & Welling, 2014). The synthetic visual features act as pseudo-examples of unseen classes, and effectively reduce the ZSL/GZSL problem to a supervised learning one.

One key issue behind generative approaches comes from the insufficient amount of data to learn a good generative model. As a consequence, some semantic features that seem important during training may be cause overfitting, and others that seem less important can be dropped. Therefore, many works propose new constraints or losses to preserve semantic features and regularize the generative model. For instance, (Chen et al., 2018) avoids the dropping of semantic information by disentangling the semantic space into two subspaces, one for classification and the other for reconstruction; Felix et al. (2018) enforces visual-semantic feature consistency by requiring synthesized visual features to reconstruct semantic features accurately.

Even with the new constraints or losses, the success of generative approaches still highly depends on whether there is enough data/variation in the seen classes to synthesize diverse visual features.



(a) Adaptive learning (b) Generative learning

Figure 1: Overview of AGZSL. The same color reflects the same class association between visual features and attributes. (a) Image-adaptive mechanism (marked as purple) based on $\mathbf{x}$ yields proper attention to adapt the semantic features of $\mathbf{a}$ and $\mathbf{a}'$ so that their S2V embedding (marked as orange) displays the desired effects in $\hat{\mathbf{x}}$ (attracted to $\mathbf{x}$) and in $\hat{\mathbf{x}}'$ (repelled from $\mathbf{x}$). (b) We generate *virtual* classes from a pair of classes of semantic features $\mathbf{a}$ and $\mathbf{a}'$ with selected weights λ via beta distribution $\mathrm{B}(\alpha, \beta)$. $\mathbf{X}_v/\mathbf{X}'_v$ and $\mathbf{a}_v/\mathbf{a}'_v$ represent visual and semantic features of *virtual* classes.

Otherwise, those features will be too close to the few seen classes and cannot help ZSL/GZSL much. For example, in `AWA2` dataset (Xian et al., 2018a), the unseen samples of "rat" are easily misclassified as seen classes of "mouse" or "hamster" because synthetic visual features for "rat" is doomed to be confused with seen visual features of those similar classes. The phenomenon inspires us to generate synthetic visual features for not only the given unseen classes but also the *virtual* unseen classes. These *virtual* classes provide a wider spectrum of support for unseen scenarios to improve ZSL/GZSL performance.

Besides, we combine the idea of meta-learning (Vinyals et al., 2016; Finn et al., 2017) with *virtual* classes in our training phase for the unseen expert. The most closely related works in ZSL are Li et al. (2019b); Yu et al. (2020); Verma et al. (2020); Sung et al. (2018); Hu et al. (2018). Verma et al. (2020) combines meta-learning and generative models to conquer limits in generative models. Li et al. (2019b) mimics the inference scenario by randomly selecting seen classes as "fake" new classes in each episode. Yu et al. (2020) randomly splits seen classes into two sets to train and refine the model. In contrast, we simulate the ZSL inference scenario in each episode by creating *virtual* classes from seen classes with mixup. With the training scenario closer to the inference setting in ZSL, our model achieve better S2V embedding on unseen classes and obtain state-of-the-art ZSL performance on most datasets. Besides, Sung et al. (2018) learns a deep distance metric to classify samples. Hu et al. (2018) utilizes the correction module to assist classification. On the contrary, our model do not have to learn complex relationship between classes and additional assistant module to achieve good performance.

2.2 ATTENTION

Attention mechanism is widely used on ZSL (Ji et al., 2018; Xie et al., 2019; Huynh & Elhamifar, 2020; Min et al., 2020; Liu et al., 2019). Highlighting important local features and reducing noisy features influence generates a better mapping between visual and semantic domains. Ji et al. (2018) proposes S^2GA which utilizes semantic features to focus on most informative visual local features. (Xie et al., 2019) employs AREN and ACSE to pay attention to the most important region in images. Huynh & Elhamifar (2020) applies dense attribute-attention to find the most discriminating image part and embedding them to semantic features individually. DVBE (Min et al., 2020) utilizes spatial and channel attention to maximize inter-class margin. Although the attention to visual features proved usable by the above works, seldom work mention the importance of attention on semantic features. In the ZSL setting, each class only contains one semantic feature, so the intra-class variance loses in the semantic feature. For example, sometimes the object is occluded partly in the image or in the front of different backgrounds, and a unique semantic feature is hard to reflect this variance. Thus, attention to semantic features is also very important in ZSL. The most similar work is LFGAA (Liu et al., 2019) who pays attention to the semantic prediction of samples. Different from LFGAA, we put attention on discriminating dimensions of semantic features and map them to the visual domain. The effect of our proposed attention is to attract a visual representation of ground true class and repel others. Besides, the other difference between us and LFGAA is the shortcut in the attention model.

We add a shortcut to prevent the model from over-fitting on training data and retain discriminating dimensions for unseen class classification.

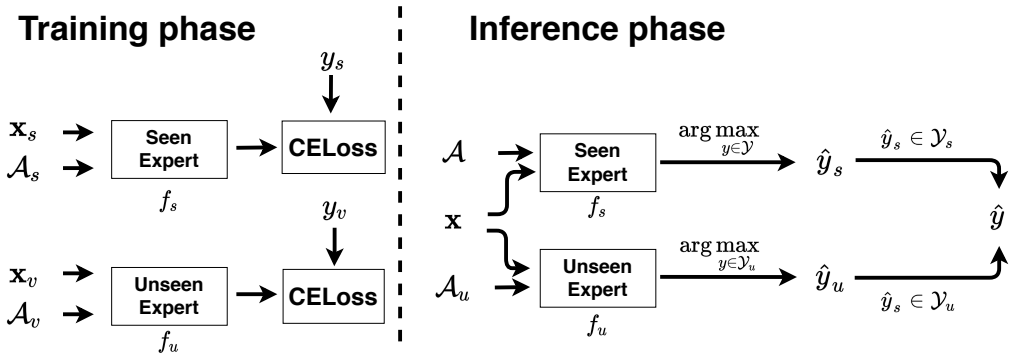


Figure 2: The proposed seen and unseen experts. In the learning phase, the seen expert f_s is trained with seen visual features $\mathbf{x}_s$, seen semantic features $\mathcal{A}_s$, and corresponding class labels y_s, while the unseen expert f_u is trained via meta-learning with *virtual* data. In the inference phase, given a testing sample $\mathbf{x}$, f_s is additionally fed with all semantic features $\mathcal{A}$, and f_u only with unseen semantic features $\mathcal{A}_u$. The decision rule leading to the class label $\hat{y}$ is based on (2). Note that in both training and inference stages, the image-adaptive mechanism to semantic features is carried out.

3 METHOD

We coin the proposed method as AGZSL in that its main idea is the fusion of Adaptive and Generative mechanisms in solving ZSL/GZSL. (See Figure 1.) We describe below the details of AGZSL.

3.1 NOTATIONS AND FORMULATION

We denote training data as $\mathcal{D} = \mathcal{D}_S \cup \mathcal{D}_U$ where $\mathcal{D}_S = \{(\mathbf{x}_s \in \mathcal{X}_s, \mathbf{a}_s \in \mathcal{A}_s, y_s \in \mathcal{Y}_s)\}$ comprises seen data and $\mathcal{D}_U = \{(\mathbf{a}_u \in \mathcal{A}_u, y_u \in \mathcal{Y}_u)\}$ includes unseen class labels y_u and the corresponding semantic/attribute feature vectors $\mathbf{a}_u$. The dimensions of visual features and semantic features are respectively expressed as $\mathbf{x} \in \mathbb{R}^d$ and $\mathbf{a} \in \mathbb{R}^k$, while the number of total classes is n. We also assume that the seen category $\mathcal{Y}_s$ and the unseen category $\mathcal{Y}_u$ are disjoint, i.e., $\mathcal{Y}_s \cap \mathcal{Y}_u = \emptyset$ and $\mathcal{Y}_s \cup \mathcal{Y}_u = \mathcal{Y}$. Besides, we define $\mathcal{A}_s \cup \mathcal{A}_u = \mathcal{A} \in \mathbb{R}^{k\times n}$ as semantic features of all classes. Finally, the *virtual* data via mixup interpolations is denoted as $\mathcal{D}_V = \{(\mathbf{x}_v \in \mathcal{X}_v, \mathbf{a}_v \in \mathcal{A}_v, y_v \in \mathcal{Y}_v)\}$. As we explain later, y_v is simply a new label of *virtual* class, rather than from label interpolation as in Zhang et al. (2018).

To perform the classification task, we explore the similarity correlations in the visual domain and consider semantic-to-visual (S2V) embeddings. Analogous to COSMO (Atzmon & Chechik, 2019), our method includes seen and unseen experts, f_s and f_u, to classify testing samples as shown in Figure 2; however, the algorithmic designs are fundamentally different. The novel component of our method is the introduction of Image-Adaptive Semantics (IAS) in both experts to expand the spectrum of S2V embeddings. Specifically, in training, IAS diversifies the total mappings of S2V embedding from the number of different semantic vectors/classes to the number of samples. Its effect is twofold. First, it boosts the classification performance of the seen expert. Second, it generalizes the meta-learning of the unseen expert with *virtual* data and yields good performance in the inference of samples from unseen classes. Given a testing sample $\mathbf{x}$ in inference, we apply the two learned experts by

$$\hat{y}_s = \arg\max_{y\in\mathcal{Y}} f_s(\mathbf{x}, \mathcal{A}) \quad \text{and} \quad \hat{y}_u = \arg\max_{y\in\mathcal{Y}_u} f_u(\mathbf{x}, \mathcal{A}_u)\,. \tag{1}$$

To decide the class label $\hat{y}$ of $\mathbf{x}$, we use the seen expert to discriminate whether the sample is from the seen category. If it is the case then $\hat{y}$ is decided by f_s, and otherwise by f_u. That is, we have

$$\hat{y} = \begin{cases} \hat{y}_s & \text{if } \hat{y}_s \in \mathcal{Y}_s\,, \\ \hat{y}_u & \text{otherwise.} \end{cases} \tag{2}$$

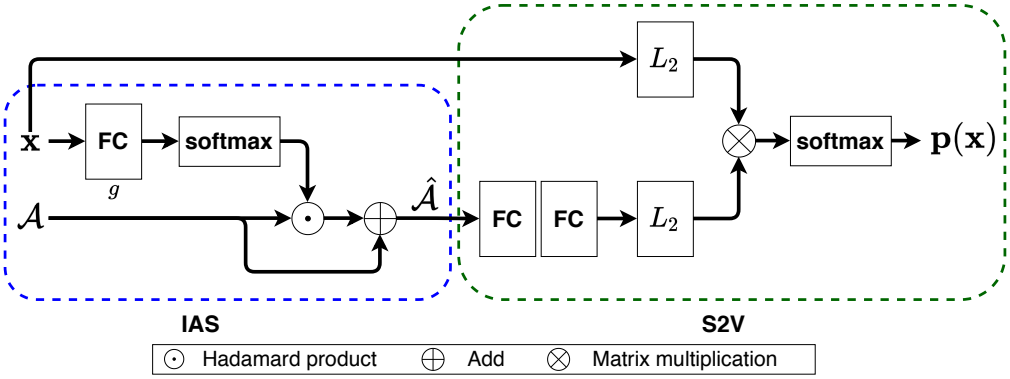


Figure 3: The architectures of IAS and S2V (FC: linear layer, L_2: L_2-normalization).

3.2 Image Adaptive Semantics (IAS)

As ZSL/GZSL assumes one semantic feature vector for each class, the conventional semantic-to-visual architecture leads to one single class-level visual feature vector, which is common to all samples of the same class. To learn such a single embedding vector with the constraint of being simultaneously similar to all visual features of samples from the same class tends to yield unsatisfactory classification outcomes in that it simply ignores the intra-class variations in visual features.

Diversifying semantic-to-visual embeddings with IAS establishes the core of our model as shown in Figure 3. To realize the concept, the network module learns to map image-adaptive semantic features to the corresponding visual features, according to the cosine similarity. To this effect, IAS leverages the given visual features $\mathbf{x}$ to focus on discriminative dimensions of the respective semantic features. Specifically, we apply IAS to obtain modified semantic features $\hat{\mathcal{A}}(\mathbf{x}) \in \mathbb{R}^{k\times n}$ by

$$\hat{\mathcal{A}} = \mathcal{A} + \mathcal{A} \odot \mathrm{softmax}(g(\mathbf{x})), \tag{3}$$

where $\mathrm{softmax}(g(\mathbf{x})) \in \mathbb{R}^k$ represents using an linear layer g to predict semantic attention and $\odot$ denotes Hadamard product to combine attention and semantic features. Note that the shortcut implementation in (3) is pivotal as the softmax function often puts high attention weights on sparse dimensions and draw others near to zero. Without the shortcut, the modified $\hat{\mathcal{A}}$ would miss some part of semantic features and degenerate the classification performance. Also, it is worthy to point out that compared to LFGAA (Liu et al., 2019), our method pays attention to the semantic features of classes, not the semantic prediction of the model. With (3), the process to drive the image-adaptive class-level visual features $\mathcal{V}(\mathbf{x})$ can be expressed by

$$\mathcal{A} \in \mathbb{R}^{k\times n} \xmapsto[\text{IAS}]{\mathbf{x}\in\mathbb{R}^d} \hat{\mathcal{A}}(\mathbf{x}) \in \mathbb{R}^{k\times n} \xmapsto[\text{S2V}]{} \mathcal{V}(\mathbf{x}) \in \mathbb{R}^{d\times n}. \tag{4}$$

Once we have obtained the class-level visual features, we then use the cosine similarity and softmax to calculate the probability of each class. We have the class probability of prediction on $\mathbf{x}$:

$$\mathbf{p}(\mathbf{x}) = f(\mathbf{x}, \mathcal{A}) = \mathrm{softmax}(\exp(\sigma \times \cos(\mathcal{V}(\mathbf{x}), \mathbf{x}))), \tag{5}$$

where σ is learnable scale and f is indeed the general form of an classification expert. We conclude by stating that the Cross-Entropy(CE) loss is adopted to update the model:

$$\mathcal{L}_{\mathrm{CE}} = -\sum\nolimits_{\mathbf{x}} \log p_y(\mathbf{x}), \tag{6}$$

where $p_y(\mathbf{x})$ is the predicted probability of ground-truth label.

3.3 Seen Expert

The objective of seen expert f_s is to recognize seen classes and otherwise decide whether a testing sample belongs to unseen classes in inference phase. In zero-shot learning, especially GZSL, the capability to single out testing samples of unseen classes is crucial to the classification performance. If

one can establish reasonable split mechanisms such as in Min et al. (2020) and Chen et al. (2020), the more challenging GZSL would be simplified into ZSL. For example, COSMO (Atzmon & Chechik, 2019) utilizes Confidence Base Gating to discriminate between seen and unseen classes, while DVBE (Min et al., 2020) considers the entropy threshold. In our formulation, the seen expert learns to predict all possible classes, including seen and unseen, although the training data assume only seen class labels. That is, f_s is trained to map (image adaptive) seen semantic features to their corresponding visual features. Such optimization can be thought of as one-category anomaly detection over only seen classes. Thus, in inference, if the highest cosine similarity value by the seen expert f_s is not yielded by one of the seen classes, the testing sample is considered *abnormal* from the unseen category and its classification should be decided by the unseen expert discussed next.

3.4 UNSEEN EXPERT

So far we have stated the objective of the unseen expert f_u is to classify the labels of those that cannot be decided by the seen expert, as in (2). To resolve the dilemma of zero-shot setting, we apply meta-learning to train f_u over *virtual* classes by mixup interpolations. The exact number of *virtual* classes in each episode is decided by the pilot study (Li et al., 2019b), and an ablation study in appendix is provided to analyze its effect on the performance of zero-shot classification. To begin with, in each episode we randomly select m pairs of seen classes. Then, we create m *virtual* classes out of these pairs by mixup. The semantic and visual features for these *virtual* classes are defined as

$$\mathbf{a}_v = \lambda\, \mathbf{a}_i + (1-\lambda)\, \mathbf{a}_j, \tag{7}$$

$$\mathbf{x}_v = \lambda\, \mathbf{x}_i + (1-\lambda)\, \mathbf{x}_j, \tag{8}$$

where $\mathbf{a}_i$ and $\mathbf{a}_j$ are semantic features of paired classes, and $\mathbf{x}_i$ and $\mathbf{x}_j$ are randomly chosen from visual samples of the paired classes. Following Zhang et al. (2018), $\lambda \in [0, 1]$ is sampled from the beta distribution. We then define a new *virtual* class y_v, with $\mathbf{a}_v$ as semantic features, to be associated with *virtual* visual features $\mathbf{x}_v$. Previous generative models (Schonfeld et al., 2019; Xian et al., 2019) synthesize unseen samples by GAN/VAE or their variants. In comparison, the proposed meta-learning has at least three advantages for ZSL. First, the small number of classes in some datasets, such as 50 in AWA2, may fall short to provide sufficient support set such that the generative model is hard to be optimized, while episodic meta-learning over *virtual* classes can overcome this problem. Second, some part of semantic features which are important to classify unseen classes do not have enough training classes in the datasets. With mixup semantic features as *virtual* classes, our model can learn underlying discriminating semantic features well. Third, the fusion of image-adaptive mechanism and meta-learning is flexible. As a result, we do not need online fine-tuning in applying the unseen expert f_u yielded by meta-learning to predict the label of unseen class for testing samples.

4 EXPERIMENT

4.1 EXPERIMENTAL SETTING

Datasets. In GZSL, there are four widely used benchmark datasets for evaluation, which are `AWA2` (Xian et al., 2018a), USCD Birds-200-2011 (`CUB`) (Welinder et al., 2010), `SUN` (Patterson & Hays, 2012), and `aPY` (Farhadi et al., 2009). `AWA2` contains 37K images and 50 kinds of animals with 85-dimension attributes. `CUB` consists of 11K images and 200 bird species described with 312-dimension attributes. `SUN` is composed of 14K images 717 classes labeled with 102-dimension attributes. `aPY` includes 15K images and 32 different classes with 64-dimension attributes. The attributes of class in datasets will be taken as the semantic features in our work. We follow existing GZSL works (Min et al., 2020; Li et al., 2019b) and extract 2048-dimensional visual features for each image by the ResNet101 backbone (He et al., 2016) pretrained on ImageNet-1K. We then split the data into seen and unseen classes according to the benchmark procedure from Xian et al. (2017).

Evaluation. We evaluate our approach for both ZSL and GZSL settings. For the ZSL setting, the average per-class top-1 accuracy (**T**) on unseen classes is taken as the evaluation metric. For GZSL (Xian et al., 2017), the evaluation metrics include seen classes accuracy **S**, unseen class accuracy **U**, and their harmonic mean $\mathbf{H} = (2\mathbf{U} \cdot \mathbf{S})/(\mathbf{U} + \mathbf{S})$.

Table 1: GZSL results on four datasets. All compared methods utilize ResNet101 as the backbone for fairness. Notation "*" means the method fine-tunes the backbone to match the characteristic of datasets.

	AWA2				CUB				SUN				aPY			
	ZSL	GZSL			ZSL	GZSL			ZSL	GZSL			ZSL	GZSL		
	T1	U	S	H	T1	U	S	H	T1	U	S	H	T1	U	S	H
SP-AEN	58.5	23.3	90.9	37.1	55.4	34.7	70.6	46.6	59.2	24.9	38.6	30.3	24.1	13.7	63.4	22.6
DLFZRL	60.9	-	-	45.1	51.9	-	-	37.1	42.5	-	-	24.6	38.5	-	-	31.0
PSR	63.8	20.7	73.8	32.3	56.0	24.6	54.3	33.9	61.4	20.8	37.2	26.7	38.4	13.5	51.4	21.4
CDL	-	-	-	-	54.5	23.5	55.2	32.9	63.6	21.5	34.7	26.5	43.0	19.8	48.6	27.1
PQZSL	-	-	-	-	-	53.2	51.4	46.9	-	35.1	35.3	35.2	27.9	64.1	64.1	38.8
f-VAEGAN-D2*	70.3	57.1	76.1	65.2	72.9	63.2	75.6	68.9	65.6	50.1	37.8	43.1	-	-	-	-
LsrGAN	-	54.6	74.6	63.0	-	48.1	59.1	53.0	-	44.8	37.7	40.9	-	-	-	-
TF-VAEGAN*	73.4	55.5	83.6	66.7	74.3	63.8	79.3	70.7	**66.7**	41.8	51.9	46.3	-	-	-	-
OCD-CVAE	71.3	59.5	73.4	65.7	60.9	44.8	59.9	51.3	62.1	44.8	42.9	43.8	-	-	-	-
ZSML Softmax	76.1	58.9	74.6	65.8	69.6	60.0	52.1	55.7	60.2	-	-	-	**64.1**	36.3	46.6	40.9
GXE	71.1	56.4	81.4	66.7	54.4	47.4	47.6	47.5	62.6	36.3	42.8	39.3	38.0	26.5	74.0	39.0
E-PGN	73.4	52.6	83.5	64.6	72.4	52.0	61.1	56.2	-	-	-	-	-	-	-	-
Relation Net	64.2	30.0	93.4	45.3	55.6	38.1	61.1	47.0	-	-	-	-	-	-	-	-
Correlation Net	-	-	-	-	45.8	41.9	-	-	-	-	-	-	-	-	-	-
LFGAA+Hibrid	68.1	27.0	93.4	41.9	67.6	36.2	80.9	50.0	62.0	18.5	40.0	25.3	-	-	-	-
AREN*	66.9	54.7	79.1	64.7	72.5	63.2	69.0	66.0	60.6	40.3	32.3	35.9	39.2	30.0	47.9	36.9
COSMO	-	-	-	-	-	44.4	57.8	50.2	-	44.9	37.7	41.0	-	-	-	-
DVBE*	-	62.7	77.5	69.4	-	64.4	73.2	68.5	-	44.1	41.6	42.8	-	37.9	55.9	45.2
ours	73.8	65.1	78.9	71.3	57.2	41.4	49.7	45.2	63.3	29.9	40.2	34.3	41.0	35.1	65.5	**45.7**
ours*	**76.4**	69.0	86.5	**76.8**	**77.2**	69.2	76.4	**72.6**	66.2	50.5	43.1	**46.5**	43.7	36.2	58.6	44.8

Implementation. Followed suggestion in Li et al. (2019b), we normalized the visual and semantic features into $[0, 1]$. The architecture of semantic-to-visual embedding contains two layers linear model with 1600 hidden units and utilize ReLU on the hidden and output layer. The seen and unseen experts are trained by Adam optimizer with a learning rate $5 * 10^{-5}$ and $5 * 10^{-4}$ respectively for all datasets. We apply 200,000 episodes to train unseen expert. In each episode, we randomly generated 16 or 20 (based on the dataset) *virtual* classes and 4 samples for each class. We follow setting in (Min et al., 2020) to fine-tune the backbone.

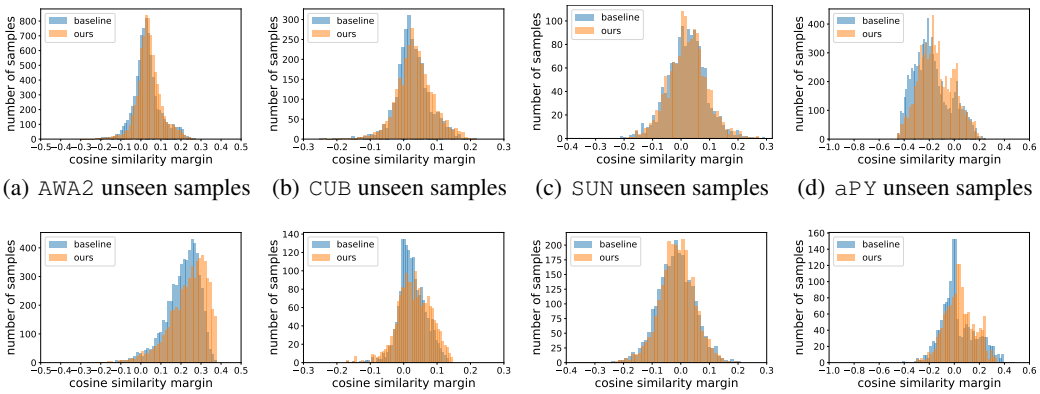
4.2 Comparing State-of-the-Art Approaches

We compare our method with 13 recent GZSL approaches. These contain SP-AEN (Chen et al., 2018), DLFZRL (Tong et al., 2019), PSR (Annadani & Biswas, 2018), CDL (Jiang et al., 2018), PQZSL (Li et al., 2019a), f-VAEGAM-D2 (Xian et al., 2019), LsrGAN (Vyas et al., 2020), TF-VAEGAN (Narayan et al., 2020), OCD-CVAE (Keshari et al., 2020) , ZSML Softmax (Verma et al., 2020), E-PGN (Yu et al., 2020), Relation Net (Sung et al., 2018), Correlation Net (Hu et al., 2018), GXE Li et al. (2019b), LFGAA+Hybrid (Liu et al., 2019), AREN (Xie et al., 2019), COSMO (Atzmon & Chechik, 2019), DVBE (Min et al., 2020). As shown in our Table 1, our method AGZSL achieves the best performance of GZSL on four datasets. The proposed AGZSL improves harmonic mean by 7.4% on AWA2, 1.9% on CUB, 0.2% on SUN, and 0.5% on aPY respectively. Among the compared approaches, DVBE searches entropy threshold τ and embedding model for the best harmonic means according to each dataset. In contrast to DVBE, without entropy threshold and specific model searching, our model achieves over 4% improvement on most datasets. The main reason is that AGZSL provides better visual discriminating representation for seen and unseen classes. Therefore, our model can separate seen and unseen correctly and achieve better performance in the harmonic mean. Notably, the AGZSL drop performance on aPY after fine-tuning backbone. The main reason is that the number of seen class and training images are fewest among the four datasets. After fine-tuning the backbone, the visual features over-fit on training samples and become less discriminating for correct classification.

Furthermore, generative models achieve higher performance on CUB and SUN, because there are many seen classes to synthesize better quality unseen sample in these two datasets. Compared to them, our model overcomes the influence of few seen classes and also achieves the best performance on AWA2 and aPY. Thus, the *virtual* classes are indeed helpful to classify unseen classes. Notably, ImageNet-1K used to pretrain backbone are very different from ZSL fine-grained databases, e.g., CUB and SUN. Thus, the harmonic mean improves a lot after fine-tuning the backbone on these two datasets.

Table 2: The effect of *virtual* classes and IAS for GZSL. We remove these two components as our baseline (b). In the ablation study, we add *virtual* classes (v) and IAS (I) step by step to show their effect on GZSL.

	AWA2				CUB				SUN				aPY			
	ZSL	GZSL			ZSL	GZSL			ZSL	GZSL			ZSL	GZSL		
	T1	U	S	H	T1	U	S	H	T1	U	S	H	T1	U	S	H
b	72.2	63.2	86.1	72.9	73.7	68.6	71.3	69.9	63.9	47.6	42.1	44.7	40.0	33.4	57.2	42.2
b+v	75.8	66.9	86.1	75.3	76.1	70.3	71.3	70.8	65.6	48.6	42.1	45.1	42.8	35.2	57.2	43.6
b+v+I	**76.4**	69.0	86.5	**76.8**	**77.2**	69.2	76.4	**72.6**	**66.2**	50.5	43.1	**46.5**	**43.7**	36.2	58.6	**44.8**



(a) AWA2 unseen samples (b) CUB unseen samples (c) SUN unseen samples (d) aPY unseen samples

(e) AWA2 seen samples (f) CUB seen samples (g) SUN seen samples (h) aPY seen samples

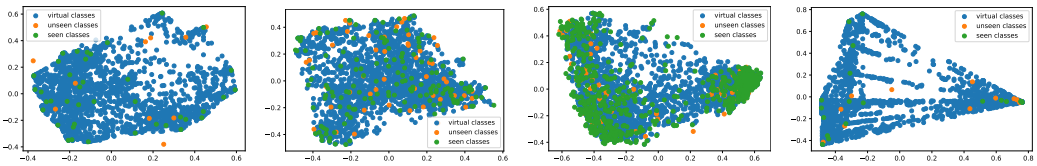
Figure 4: The cosine similarity margin between the correct class and other nearest class. The blue area depicts the cosine similarity margin of baseline without IAS and generative learning. On the other hand, the orange area represents the cosine similarity margin of ours. Most of the samples improve their margin in our methods, so our methods indeed are beneficial for GZSL.

4.3 Ablation Study

To qualify the benefits of virtul classes and IAS, we carry an ablation study on four datasets. We add each component step by step to show their effect. As shown in Table 2, the *virtual* classes improve ZSL accuracy extremely. ZSL improve 4.6% on AWA2, 2.4% on CUB, 1.7% on SUN, and 2.8% on aPY respectively. The result means that the *virtual* classes are advantageous for ZSL. After adding IAS to our model, seen and unseen accuracy simultaneously and improve averaged 1.5% H. The result exemplifies IAS can provide better semantic-to-visual embedding and achieve higher performance on GZSL.

4.4 Cosine Similarity Margin

Figure 4 illustrates the effect of our model. The cosine similarity margin means the distance between the correct class and the other nearest class. If the margin is negative, the model will predict the false class. Besides, a larger margin mean model has better embedding, so it can distinguish the correct class from others clearly. Thus, the positive and larger margin is a very important objective in GZSL. As the first row in Figure 4, the margin of unseen samples sift right on four datasets. It shows our methods provide better embedding on visual space and make the model easier to predict the correct class. Moreover, the second row in Figure 4 shows our methods improve the margin of seen samples dramatically on most datasets. The above experiment explains our models obtain a higher margin in most samples, so we achieve better performance on four datasets.



(a) AWA2 (b) CUB (c) SUN (d) aPY

Figure 5: The semantic features of virtual/seen/unseen classes

4.5 THE DISTRIBUTION OF VIRTUAL CLASSES

To explicitly exhibit the distributions of seen, unseen and virtual classes, we use PCA to map the class-wise semantic features to a two-dimensional space, as shown in Figure 5. The features of virtual classes scatter around seen classes, because we have used $\mathbf{B}(5,1)$ to generate virtual classes. Advantageously, some virtual classes are very close to unseen classes in the semantic domain and turn out to be helpful for enabling the unseen expert to classify samples of unseen classes. With meta-learning over these numerous virtual classes and samples, the proposed S2V can better learn the embedding between semantic and visual domains, and results in an effective unseen expert.

5 CONCLUSION

In this paper, we propose IAS and *virtual* classes to solve the ZSL/GZSL. To reflect the intra-class visual discrepancies, IAS emphasizes on the most discriminating dimension in semantic features according to each visual feature. On the other hand, we apply generative learning in our model to classify unseen samples. Different from previous generative models that synthesize unseen samples for training the model, we create *virtual* classes as unseen classes in the training phase. To imitate the ZSL inference scenario, we apply meta-learning with *virtual* classes. In our experiment, AGZSL is beneficial to tackle the ZSL/GZSL. Consequently, we achieve remarkable advantages over other methods on the ZSL/GZSL four benchmark datasets.

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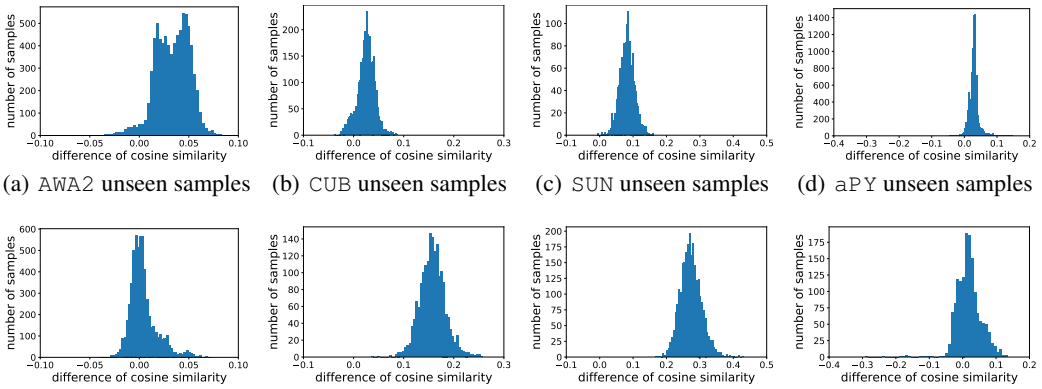
A APPENDIX

Table 3: The impact of shortcut in IAS on four datasets.

shortcut	AWA2				CUB				SUN				aPY			
	ZSL	GZSL			ZSL	GZSL			ZSL	GZSL			ZSL	GZSL		
	T	U	S	H	T	U	S	H	T	U	S	H	T	U	S	H
	23.9	13.0	30.0	18.2	23.3	17.0	45.8	24.8	42.1	22.5	20.3	21.4	30.5	14.9	4.7	7.1
√	**76.4**	69.0	86.5	**76.8**	**77.2**	69.2	76.4	**72.6**	**66.2**	50.5	43.1	**46.5**	**43.7**	36.2	58.6	**44.8**



(a) AWA2 unseen samples (b) CUB unseen samples (c) SUN unseen samples (d) aPY unseen samples

(e) AWA2 seen samples (f) CUB seen samples (g) SUN seen samples (h) aPY seen samples

Figure 6: The difference of cosine similarity between our model and baseline. In our experiment, most of the samples improve their embedding with IAS and *virtual* classes.

Shortcut in IAS Table 3 shows that shortcut in IAS improves performance a lot. The unseen class accuracy increase around 50% on AWA2 and SUN. Besides, the harmonic mean also enhances 20% to 60% on four datasets with the shortcut. The main reason is that the softmax usually puts high attention weight on few dimensions and decreases others near to zero. Thus, without shortcut, the model is prone to over-fitting on training data.

Cosine similarity enhancement Figure 6 illustrates better embedding for seen and unseen classes in our model. Since we apply cosine similarity to classify samples, the higher score means visual representation of each class is closer to their visual samples. The first row in 6 shows effect of our model on unseen classes. With generative learning and IAS, cosine similarity increase averaged 0.05 to 0.1 on different datasets. The increasing amount shows our model provides better visual-to-semantic embedding for unseen classes and samples are easier to classify correctly. Therefore, our model can achieve good ZSL performance. Besides, the second row in 6 illustrates the effect of IAS on seen classes. Most of the testing seen samples increase their cosine similarity around 0.02 on four datasets. With the IAS and *virtual* classes, the model can achieve better visual-to-semantic embedding on all classes and obtain better the generalized seen accuracy on four datasets.

***virtual* classes number per episode** To search the class number in each episode for best ZSL, we search 4 different numbers, i.e, 4,8,12, and 20 per episode. Table 4 shows that the best class number setting is related to the class number of classes. For example, the AWA2 and aPY which include fewer unseen classes obtain the best ZSL accuracy with 16 *virtual* classes. On the other hand, the CUB and SUN which include more unseen classes achieve the best performance with 20 *virtual* classes. The reason is that the advantage of meta-learning is to simulate inference scenarios while training (Li et al., 2019b). The *virtual* class number set closer to the unseen class number is favorable in the meta-learning setting. Therefore, the best *virtual* class number is different according to the unseen number of the dataset.

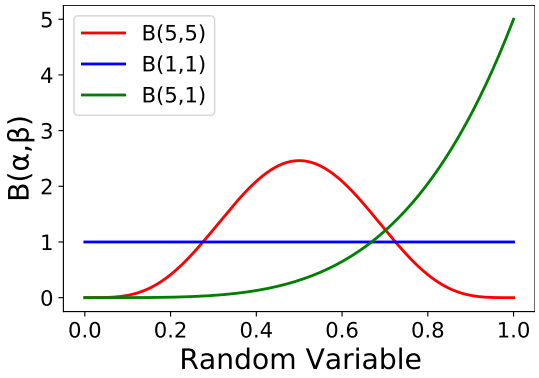


Figure 7: Beta distribution.

Table 4: ZSL accuracy w.r.t. *virtual* classes per episode.

k	AWA2	CUB	SUN	aPY
8	75.7	76.2	64.6	40.8
12	76.0	76.3	65.1	42.8
16	**76.4**	76.3	65.1	**43.7**
20	75.5	**77.2**	**66.2**	41.1

Table 5: ZSL accuracy w.r.t. beta distribution.

B(α,β)	AWA2	CUB	SUN	aPY
(5,5)	74.8	75.6	65.4	38.2
(1,1)	75.3	76.4	65.8	40.2
(5,1)	**76.4**	**77.2**	**66.2**	**43.7**

Effect of beta distribution on ZSL accuracy To explore the best beta distribution setting for ZSL, our experiments apply three different α and β sets. As shown in Figure 7, B(1,1) means *virtual* classes distribute uniformly between selected class pairs. Then, B(5,5) means most of the *virtual* classes distribute among the middle of selected class pairs. On the other hand, B(5,1) means most *virtual* classes distribute closer to one of the classes in selected class pairs. Table 5 demonstrates that B(5,1) achieves best performance on each dataset. In our speculation, the *virtual* classes created based on one class are closer to real-world classes. For example, the zebra is very similar to the horse in shape. Thus, the *virtual* classes distributing among seen classes enhance ZSL accuracy are very beneficial for training ZSL.