Domain-Aware Generalized Zero-Shot Learning

Yuval Atzmon
Bar-Ilan University,
yuval.atzmon@biu.ac.il

Gal Chechik
Bar-Ilan University, NVIDIA Research,
gal.chechik@biu.ac.il

Abstract

Generalized zero-shot learning (GZSL) is the problem of learning a classifier where some classes have samples, and others are learned from side information, like semantic attributes or text description, in a zero-shot learning fashion (ZSL). A major challenge in GZSL is to learn consistently for those two different domains. Here we describe a probabilistic approach that breaks the model into three modular components, and then combines them in a consistent way. Specifically, our model consists of three classifiers: A "gating" model that softly decides if a sample is from a "seen" class and two experts: a ZSL expert, and an expert model for seen classes. We address two main difficulties in this approach: How to provide an accurate estimate of the gating probability without any training samples for unseen classes; and how to use an expert predictions when it observes samples outside of its domain.

The key insight in our approach is to pass information between the three models to improve each others accuracy, while keeping the modular structure. We test our approach, Domain-Aware GZSL (DAZL) on three standard GZSL benchmark datasets (AWA, CUB, SUN), and find that it largely outperforms state-of-the-art GZSL models. DAZL is also the first model that closes the gap and surpasses the performance of generative models for GZSL, even-though it is a light-weight model that is much easier to train and tune.

1. Introduction

Generalized zero-shot learning (GZSL) [8] is the problem of learning to classify samples from two different domains of classes: seen classes, trained in a standard supervised way from labeled samples, and unseen classes, learned from external knowledge, like attributes or natural language, in a zero-shot-learning fashion. GZSL poses a unique combination of hard challenges: First, the model has to learn effectively for classes without samples (zero-shot), it also needs to learn well for classes with plenty of samples, and finally, the two very different regimes should be combined in a consistent way in a single model. GZSL can be viewed as an extreme case of classification with unbalanced classes, hence solving the last challenge can lead to better ways to address class imbalance, which is a key problem in learning with real-world data.

The three learning problems described above operate in different learning setups, hence combining them into a single model is challenging. Here, we propose an architecture with three modules, each focusing on one problem. At inference time, these modules share their prediction confidence in a principled probabilistic way, to reach an accurate joint decision.

One natural instance of this general architecture is using a hard mechanism of gating. Given a test sample, the gate assigns it to one of two domain expert classifiers: "seen" classifier trained as a standard supervised classifier, or "unseen" classifier trained in a zero-shot-learning fashion [45]. The specific class is then predicted by the assigned classifier, ignoring the expert of the other domain. Here we study a more general case, which we call “GZSL-mixture”. In GZSL-mixture, both "seen" and "unseen" classifiers are applied to each test sample, and their predic-
tions are combined in a soft way by the gating classifier. More specifically, predictions can be combined in a principled way using the law of total probability: 
\[ p(\text{class}) = p(\text{class}|\text{seen})p(\text{seen}) + p(\text{class}|\text{unseen})p(\text{unseen}). \]

Unfortunately, softly combining expert decisions raises several difficulties. First, when training a gating module, it is hard to provide an accurate estimate of the probability that a sample is from the “unseen” classes, since by definition no samples have been observed from that class. Second, when using a soft combination of the two expert models, each expert may behave irregularly when observing images from outside its own domain, typically producing falsely confident spurious predictions that can confuse the GZSL-mixture model.

We address these issues in two ways. First, we show how to train a gating mechanism to recognize the domain based on the distribution over class predictions. The idea is to simulate the softmax response to samples of unseen classes using a held-out subset of training classes, and represent expert predictions in a class-independent way. Second, we introduce a Laplace-like prior \cite{33} over softmax outputs in a way that uses information from the gating classifier. This additional information allows the experts to estimate class confidence more robustly.

This combined approach, which we name domain-aware generalized zero-shot learning (DAZL, pronounced Dazzle) has significant advantages. It can incorporate any state-of-the-art zero-shot learner as a module, as long as it outputs class probabilities; It is very easy to implement and apply (code provided) since it has very few hyper-parameters to tune; Finally, it outperforms competing approaches (including most recently published), on all the three GZSL benchmarks (SUN, CUB, AWA). Our main novel contributions:

- A new soft approach to combine decisions of seen and unseen classes for GZSL.
- A new “out-of-distribution” (OOD) classifier to separate seen from unseen classes; and a negative result, showing modern OOD classifiers have limited effectiveness on ZSL benchmarks.
- New state-of-the-art results on GZSL for all three main benchmarks, SUN, CUB, AWA. DAZL is the first model that is comparable or better than generative models for GZSL, while being easy to train.
- A characterization of GZSL approaches on the seen-unseen accuracy plane.

2. Related Work

Zero-shot learning (ZSL): ZSL attracted significant interest in recent years \cite{25, 56, 54, 15, 7, 49, 35, 41, 3, 63, 58, 48, 57, 28, 61, 46, 9, 27, 53, 36, 4, 20, 32, 11, 24, 29, 21, 10, 59}. As our ZSL module, we use LAGO \cite{6}, a state-of-the-art approach which estimates \(p(\text{class}|\text{image})\) by learning an AND-OR group structure over attributes that describe a class.

Generalized zero-shot learning (GZSL) is a realistic task that extends ZSL to make predictions when test data has both seen and unseen classes. GZSL methods can be viewed as belonging to one of two groups. First, are GAN or VAE based models that use generative data-augmentation to synthesize feature vectors of unseen classes, and use them in training \cite{55, 12, 5, 34, 65}. The second group does not use data augmentation and is usually evaluated separately \cite{47, 63, 16, 62, 31, 45, 8}. To date, methods that include data-augmentation strongly outperform those who do not.

Among previous GZSL approaches, several are closely related to DAZL. First, CMT \cite{45} uses a hard gating mechanism to assign a sample to one of two domain experts. Second, CS \cite{8} suggested calibrating between seen and unseen class scores, by subtracting a constant value of all seen class scores. Third, DCN \cite{31}, calibrates seen and unseen prediction scores by making seen class scores less confident and unseen score more confident. This is achieved using temperature scaling \cite{18} and an entropy regularization term for the ZSL loss.

Detecting out-of-distribution (OOD) samples: Our approach to soft-gating builds on developing an out-of-distribution detector, where unseen images are treated as “out-of-distribution” samples. There is a large body of work on 1-class and anomaly detection which we do not survey here. In this context, the most relevant recent work includes \cite{17, 30, 50, 43}. \cite{17} detects an OOD sample if the largest softmax score is below a threshold. \cite{30} scales the softmax “temperature” \cite{18} and perturbs the input with a small gradient step. \cite{43} represents each class by multiple word-embeddings and compares output norms to a threshold. \cite{50} trains an ensemble of models on a set of “leave-out” classes, with a margin loss that encourages high-entropy scores for left-out samples.

We tested \cite{17, 30, 50} on the ZSL benchmarks and observed that a perturbation \cite{30} hurts OOD detection and that the loss of \cite{50} overfits on the leave-out classes. We discuss possible explanation of these effects in Section 7.3.

Mixture of experts (MoE): In MoE \cite{19, 60, 44} a sample is first classified by a gating network, which assigns weights to “expert” classifiers. Then the sample is classified by multiple experts, whose predictions are combined by the gating weights. Our GZSL-Mixture differs from standard MoEs by: (1) Modules are independently trained, ensuring that each module is an expert of its own domain. (2) The gating module is trained on held-out unseen training classes. (3) The gating module is based on the prediction scores of two experts rather than on sample features.
3. Generalized Zero-Shot Learning

We start with a formal definition of zero-shot learning (ZSL) and then extend it to generalized ZSL (GZSL).

In zero-shot learning (ZSL), a training set \( \mathcal{D} \) has \( N \) labeled samples: \( \mathcal{D} = \{ (x_i, y_i), i = 1 \ldots N \} \), where each \( x_i \) is a feature vector and \( y_i \in S \) is a label from a seen class \( S = \{1, 2, \ldots |S|\} \).

At test time, a new set of samples \( \mathcal{D}' = \{ x_i, i = N + 1 \ldots N + M \} \) is given from a domain of unseen classes \( \mathcal{U} = \{ |S| + 1, \ldots |S| + |U|\} \). Our goal is to predict the correct class of each sample. As a supervision signal, each class \( y \in S \cup U \) is accompanied with a class-description vector \( a_y \) in the form of semantic attributes \([25]\) or natural language embedding \([40, 65, 45]\). The crux of ZSL is to learn a compatibility score for samples and class-descriptions \( F(a_y, x) \), and predict the class \( y \) that maximizes that score. In probabilistic approaches to ZSL \([25, 26, 52, 45, 6, 31]\) the compatibility function assigns a probability for each class \( p(y = y|x) = F(a_y, x) \), with \( y \) viewed as a random variable for the label \( y \) of a sample \( x \).

**Generalized ZSL:** While in ZSL test samples are drawn from the unseen classes \( Y \in U \), in GZSL, samples are drawn from either the seen or unseen domains: \( Y \in S \cup U \).

**Notation:** Below, we denote an unseen class by \( Y \in U \) and a seen one by \( Y \in S \). Given a sample \( x \) and a label \( y \) we denote the conditional distribution that a class is seen by \( p(S) = p(Y \in S|x) \), or unseen \( p(U) = p(Y \in U|x) = 1 - p(Y \in S|x) \), and the conditional probability of a label by \( p(y) = p(Y = y|x) \), \( p(y|S) = p(Y = y|Y \in S, x) \) and \( p(y|U) = p(Y = y|Y \in U, x) \). For brevity, our notation drops the conditioning on a sample \( x \).

4. Our approach: Domain-Aware ZSL

We now describe a probabilistic approach that breaks the model into three modular modules. The key idea is that these modules exchange information to improve each others accuracy. By the law of total probability

\[
p(y) = \sum_{S \in S} \frac{p(y|S)p(S)}{p(U)} \cdot \frac{p(U)}{p(U)}.
\]

This formulation decomposes GZSL into three sub-tasks that can be addressed separately. (1) \( p(y|S) \) can be estimated by any model trained to classify seen \( S \) classes, whose prediction we denote by \( p^S(y|S) \). (2) Similarly, \( p(y|U) \) can be computed by a model classifying unseen \( U \) classes, namely a ZSL model, whose prediction we denote by \( p^{ZS}(y|U) \). (3) Finally, the two terms are weighted by \( p(S) \) and \( p(U) = 1 - p(S) \), which can be computed by a gating classifier, whose prediction we denote by \( p^\text{Gate}(y) \), that is trained to distinguish seen from unseen classes. Together, we obtain a GZSL mixture model:

\[
p(y) = p(y|S)p^\text{Gate}(S) + p(y|U)p^\text{Gate}(U)
\]

A hard variant of Eq. (2) was introduced in \([45]\), where the gating mechanism makes a hard decision to assign a test sample to one of two expert classifiers \( p^{ZS} \) or \( p^S \). Unfortunately, although conceptually simple, using a soft mixture model raises several problems.

First, combining models in a soft way means that each model contributes its beliefs even for samples from the "other" domain. This tend to damage the accuracy because multiclass models tend to assign most of the softmax distribution mass to very few classes, even when their input is random noise \([17]\). For instance, when the unseen classifier is given an input image from a seen class, its output distribution tends to concentrate on a few spurious classes. This
4.2. Domain-Aware Laplace Smoothing

One approach to build an OOD detector, is to train a classifier on in-distribution data, and detect an image as out-of-distribution if the largest softmax score is below a threshold [17, 30, 50].

Here we improve over this approach by training a network on top of the softmax output of the two experts, with the goal of discriminating \(\mathcal{U}\) images from \(\mathcal{S}\) images. Intuitively, this can improve the accuracy of the gating module because the output response of each expert is different depending if an image is from \(\mathcal{U}\) or \(\mathcal{S}\). Since no samples from \(\mathcal{U}\) are available, we create a hold-out set of classes from \(\mathcal{S}\), which are not used for training, and use them to estimate the output response of the expert classifiers over images of unseen classes. Below, we refer to this set of classes as \textit{unseen-classes-for-training}.

This raises a challenge: The \textit{unseen-classes-for-training} are different than \textit{test} classes. Therefore, at test time, the unseen expert has a different output layer than during training: It corresponds to new (test) classes, with possibly a different dimension. To avoid dependence on the identity and order of unseen-classes-for-training, we use a representation that is invariant to specific classes, by taking the top-K softmax scores (for a small K) and sort them. We call this process \textit{top-K pooling}, which is a generalization of max-pooling, as they are equivalent for K=1.

A detailed architecture is shown in Figure 2. This approach has two benefits, it allows the model to generalize to new unseen classes, and it achieves robustness through top-K pooling.

4.2. Domain-Aware Laplace Smoothing

As we described above, probabilistic classifiers tend to assign most of the softmax mass to very few classes, even when a sample does not belong to any of the classes in the vocabulary. Intuitively, when given an image of out-of-vocabulary class as input, we would expect all classes to obtain a uniformly low probability, since they are all "equally wrong". To include this prior belief into our model we borrow ideas from Bayesian parameter estimation. Consider the set of class-confidence values as the quantity that we wish to estimate, based on the confidence provided by the model (softmax output scores). In Bayesian estimation, one combines the data (here, the predicted confidence) with a prior distribution (here, our prior belief).

Specifically, for empirical categorical (multinomial) data, \textit{Laplace smoothing} [33] is a common technique to achieve robust estimate with limited samples. It amounts to adding "pseudo counts" uniformly across all classes, and functions as a prior distribution over classes. We can apply a similar technique here, and combine the predictions with an additive prior distribution \(\pi^{\text{alt}} = p_0(y|\mathcal{U})\). This yield

\[
p^\lambda(y|\mathcal{U}) = (1-\lambda) p(y|\mathcal{U}) + \lambda \pi^{\text{alt}}, \tag{3}
\]

where \(\lambda\) weighs the prior, and \(\pi^{\text{alt}}\) is not conditioned on \(x\).

Similarly, for the seen distribution, we set \(p^\lambda(y|\mathcal{S}) = (1-\lambda)p(y|\mathcal{S}) + \lambda \pi^{S}\). When no other information is available we set the prior to the maximum entropy distribution, which is the uniform distribution \(\pi^{\text{alt}} = 1/\text{(#unseen classes)}\) and \(\pi^{S} = 1/\text{(#seen classes)}\).

**Domain-Aware Adaptive Prior**

How should the prior weight \(\lambda\) be set? In Laplace smoothing, adding a constant pseudocount has the property that its relative weight decreases as more samples are available. Intuitively, this means that \textit{when the data provides strong evidence, the prior is weighted more weakly}. We adopt this intuition for making the trade-off parameter \(\lambda\) adaptive. Intuitively, if we believe that a sample \textit{does not} belong to a seen class, we smooth the seen classifier outputs (Figure 1). More specifically, we apply domain-aware prior by replacing the constant \(\lambda\) with our belief about each domain (for \(p'(y|\mathcal{U})\) set \(\lambda = p(\mathcal{U})\):

\[
p'(y|\mathcal{U}) = p(\mathcal{U})p(y|\mathcal{U}) + (1-p(\mathcal{U}))\pi^{\text{alt}} = p(y,\mathcal{U}) + (1-p(\mathcal{U}))\pi^{\mathcal{U}}. \tag{4}
\]

Similarly \(p'(y|\mathcal{S}) = p(\mathcal{S})p(y|\mathcal{S}) + (1-p(\mathcal{S}))\pi^{S}\). In practice, we use the ZS model estimation for \(p(y,\mathcal{U})\), and the gating model estimation for \(p(\mathcal{U})\), yielding \(p'(y|\mathcal{U}) = p[ZS(y,u)] + (1-p^{\text{Gate}}(\mathcal{U}))\pi^{\mathcal{U}}\) and similarly for \(p'(y|\mathcal{S})\).

The resulting model has two interesting properties. First, it reduces hyper-parameter tuning, because prior weights are determined automatically. Second, smoothing adds a constant value to each softmax score, hence maintains the class that achieves the maximum of each individual expert, but at the same time affects their combined prediction in Eq. (2).
5. Details of our approach

Our approach has three learning modules: A model for seen classes, for unseen classes, and for telling them apart.

**A model for unseen classes.** For a ZSL module, we use LAGO [6], currently a state-of-the-art model for several ZSL benchmarks. LAGO predicts $p^{ZS}(y|x)$ by learning an AND-OR group structure over attributes. We retrained LAGO according to the GZSL split (Figure 3), keeping hidden the test samples of seen classes.

**A model for seen classes.** For seen classes, we train a logistic regression classifier to predict $p^S(y|x)$. We used LBFGS solver [13] with the default aggressiveness hyperparameter ($C=1$), because the number of weights (∼10-50) is much smaller than the number of training samples (∼thousands). We tune the decision threshold and softness of the gating model by adding constant bias $\beta$ and applying a sigmoid with $\gamma$ gain, on top of its scores:

$$p(S|x) = \sigma\{\gamma[\text{score} - \beta]\}$$

(5)

$\gamma$ and $\beta$ were tuned using cross validation.

6. Experiments

We tested DAZL on three generalized zero-shot learning benchmark datasets: CUB, AWA and SUN.

**CUB:** We first tested DAZL in a task of fine-grained classification of bird-species using CUB-2011 [51]. CUB has 11,788 images of 200 bird species. Each species described by 312 semantic attributes (like wing-color-olive, wing-pattern-stripes, beak-shape-curved). It has 100 seen training classes, 50 unseen validation and 50 unseen test classes.

**AWA:** The second dataset, Animals with Attributes (AWA) [25], consists of 30,475 images of 50 animal classes. Classes and attributes are aligned with the class-attribute matrix of [37, 22], using a vocabulary of 85 attributes (like white, brown, stripes, eat-fish). It has 27 seen training classes, 13 unseen validation and 10 unseen test classes.

**SUN:** The third dataset, SUN [38], is a dataset of complex visual scenes, having 14,340 images from 717 scene types and 102 semantic attributes. It has 580 seen training, 65 unseen validation and 72 unseen test classes.

6.3. Cross-validation

For selecting hyper-parameters for DAZL, we make additional two splits: GZSL-val and Gating Train / Val. See Figure 3 for details.

We used cross-validation to optimize the $Acc_H$ metric over $\beta$ and $\gamma$ of Eq. (5) on the GZSL-Val set. We tuned these hyper parameters by first taking a coarse grid search, and then making a finer search around the best performing values for the threshold. Independently, we used framework for comparing zero-shot methods, and we follow it here. Our evaluation uses its features, cross-validation splits, and evaluation metrics for comparing to the state-of-the-art approaches as baselines.

**Evaluation Metrics** By definition, GZSL aims to perform well in two different sub-tasks: classify seen classes and classify unseen classes. The standard GZSL evaluation metrics therefore combine accuracy from these two sub-tasks. Following [54] we report the harmonic mean of $Acc_{tr}$ - the accuracy over seen classes, and $Acc_{ts}$ - the accuracy over unseen classes (see Eq. 21 in [54])

$$Acc_H = 2 \frac{Acc_{ts}Acc_{tr}}{Acc_{ts} + Acc_{tr}}.$$  

(6)

As a second metric, we compute the full seen-unseen accuracy curve using a parameter to sweep over the decision threshold. Like the precision-recall curve or ROC curve, the seen-unseen curve provides a tunable trade-off between the performance over the seen and unseen domains.

Finally, we report the Area Under Seen-Unseen Curve (AUSUC) [8].
DAZL, through a series of ablation experiments. We then study in more depth the properties of generative methods. We compare DAZL with 17 leading GZSL methods. These include widely-used baselines like ESZSL [42], ALE [1], SYNC [7], SJE [2], DEVISE [14], recent published approaches RN [47], DEM [63], ICINESS [16], TRIPLE [62], Kernel [61], and methods that provide interesting insight into the method, including CMT [45], DCN [31], LAGO [6], and CS [8] that we reproduced using LAGO as a ZSL module.

Recent work showed that generating synthetic samples of unseen classes using GANs or VAEs [55, 12, 5, 65] can substantially improve generalized zero-shot learning. The recent literature considers this generative effort to be orthogonal to modelling, since the two efforts can be combined [31, 6, 64, 16, 62]. Here we compare DAZL directly both with the approaches listed above, and with generative approaches TCLSWGAN [55], cycle-(U)WGAN [12], SE-GZSL [5]. Interestingly, we find that DAZL closes the gap and sometimes surpasses generative methods.

### 7. Results

We first describe the performance of DAZL on the test set of the three benchmarks and compare it with baseline methods. We then study in more depth the properties of DAZL, through a series of ablation experiments.

Table 1 describes the test accuracy of DAZL and all compared methods over the three benchmarks. Compared with non-generative models, DAZL improves the harmonic accuracy $Acc_H$ by a large margin for all three datasets: 63.9% vs 47.3% in AWA, 41.1% vs 30.3% in SUN and 51.8% vs 47% in CUB.

In addition, DAZL closes the performance gap with generative approaches. It wins in AWA (63.9% versus 61.5%) and SUN (41.1% versus 39.4%), and loses by a small margin for CUB (51.8% versus 53%).

Interestingly, when DAZL uses LAGO as its ZSL module, it reaches state-of-the-art performance although LAGO alone performed poorly on the generalized ZSL task.

#### 7.1. The seen-unseen plane

By definition, the GZSL task aims to perform well in two different metrics: accuracy on seen classes and on unseen classes. It is therefore natural to compare approaches by their performance on the seen-unseen plane. This is important, because different approaches may select different operating-points to trade seen and unseen accuracy.

In Figure 4, we provide a full Seen-Unseen curve (blue dots) that shows how DAZL trades-off the metrics. We compare it with a curve that we computed for the CS-LAGO baseline (orange dots) and also shows the results (operation-points) reported for the compared methods. For plotting the curves, we sweep over the decision threshold ($\beta$) of the gating network, trading its true-positive-rate with its false-negative-rate. In blue-square we show our operating point that was selected with cross-validation by choosing the best $Acc_H$ on GZSL-Val set.

An interesting observation is that different types of models populate different regions of the Seen-Unseen curve. Generative models (X markers) tend to favor unseen-classes accuracy over accuracy of seen classes, while non-generative models (triangles) tend to favor seen classes. Importantly, DAZL can be tuned to select any operation point along the curve, and achieve better or equivalent performance at all regions of the seen-unseen plane.

Finally, the Area Under Seen-Unseen Curve (AUSUC) scores are 53.2, 23.9, 36.5 for AWA, SUN, CUB with DAZL and 43.4, 16.3, 34.3 for AWA, SUN, CUB with CS-LAGO.

#### 7.2. Ablation experiments

To understand the contribution of the different modules of DAZL, we carried ablation experiments that quantify the benefits of the domain-aware gating model and domain-aware Laplace smoothing.

We first compared variants of the gating model, then compare variants of the smoothing method, and finally, compare how these modules work together.

**Domain-Aware Gating:**

Table 2, provides out-of-distribution (OOD) metrics, including AUC, False-Positive-Rate at 95% True-Positive-
Figure 4: The Seen-Unseen curve for DAZL, compared with: (1) The curve of CS-LAGO [8] baseline, (2) 15 baseline GZSL models. Dot markers denote samples of each curve. Squares: DAZL cross-validated model and its LAGO-based baselines. Triangles: non-generative approaches, ‘X’: approaches based on generative-models. Generative models tend to trade the Accuracy of the Seen classes for the accuracy of the Unseen classes, while non-generative models tend to be biased toward the Seen classes. Importantly DAZL curve achieve better or equivalent performance compared to all methods, and allows to easily choose any operation point along the curve.

| METHOD / DATASET | AWA | SUN | CUB |
|------------------|-----|-----|-----|
| **NON-GENERATIVE MODELS** |     |     |     |
| ESZSL (Romera-Paredes, ICML 2015) | 6.6 | 11 | 12.6 |
| SJE (Akata, CVPR 2015) | 11.3 | 14.7 | 23.7 |
| SYNC (Changpinyo, CVPR 2016) | 8.9 | 7.9 | 11.5 |
| ALE (Akata, PAMI 2016) | 16.8 | 21.8 | 23.7 |
| DEM (Zhang, CVPR 2017) | 32.8 | 19.8 | 19.6 |
| KERNEL (Zhang, CVPR 2018) | 18.3 | 19.9 | 19.9 |
| ICINESS (Guo, IJCAI 2018) | - | - | - |
| TRIPLE (Zhang, TIP 2019) | 27 | 22.2 | 26.5 |
| RN (Sing, CVPR 2018) | 31.4 | - | 38.1 |
| **GENERATIVE MODELS** |     |     |     |
| SE-GZSL (Verma, CVPR 2018) | 56.3 | 40.9 | 41.5 |
| f-CLSWGAN (Xian, CVPR 2018) | 59.7 | 42.6 | 43.7 |
| CYCLE-(U)WGAN (Felix, ECCV 2018) | 59.6 | 47.2 | 47.9 |
| **DAZL AND BASELINES** |     |     |     |
| CMT (Socher, NIPS 2013) | 8.4 | 8.7 | 8.7 |
| DCN (Liu, NIPS 2018) | 25.5 | 25.5 | 28.4 |
| LAGO (Atzmon, UAI 2018) | 21.8 | 21.8 | 23.8 |
| CS-LAGO (Chao, ICCV 2016) with LAGO | 45.4 | 47.5 | 45.1 |
| DAZL (Ours) | 54.7 | 45.6 | 47.6 |

Table 1: Comparing DAZL with state-of-the-art GZSL non-generative models and with generative models that synthesize feature vectors, including most recent publications. $\text{Acc}_{\text{ts}}$ is the accuracy over seen classes, $\text{Acc}_{\text{tr}}$ is the accuracy over unseen classes and $\text{Acc}_H$ is their harmonic mean (Eq. (6)), which is the main metric used in GZSL. The baseline GZSL model for DAZL is LAGO [6]. CS-LAGO is a reproduced version of [8], with the LAGO baseline. DAZL improves $\text{Acc}_H$ over latest state-of-the-art by 35%, 35%, 10% relatively for AWA, SUN and CUB and over CS-LAGO [6, 8] by 17%, 38%, 6% relatively. Comparing with generative models, DAZL closes the non-generative:generative performance gap, and is comparable or better than these models, while is very easy to train.

Rate on Gating-Val and the $\text{Acc}_H$ metric on GZSL-Val.

We test the effect of temperature scaling and of domain-aware gating by comparing the following gating models: (1) DA-Gating-3 is our best domain-aware gating model, from Section 4.1 with temperature $T = 3$. (2) DA-Gating-1 is the same model with $T = 1$, revealing the effect of temperature scaling [30]. (3) DA-Gating-3 (w/o $p^{ZS}$) is like DA-Gating-3 without the inputs from the ZS expert, revealing the importance of utilizing information from both experts. (4) Max-Softmax-1 is a baseline gating model of [17], in-
Instead of domain-aware gating it discriminates by comparing the largest softmax score to a threshold. (5) Max-Softmax-3 is like Max-Softmax-1, but with $T = 3$. In these experiments, Laplace smoothing is disabled, to only quantify factors related to the gating model.

We find that both temperature scaling and domain-aware gating improves the quality metrics. Importantly, domain-awareness has a strong contribution to performance: The AUC increases from 88.3 to 92.6 for AWA, 61.4 to 73.6 for SUN and 73.6 to 79.3 for CUB.

**Domain-Aware Smoothing:** Table 3 shows the contribution of domain-aware smoothing to $Acc_H$ on the validation set. In these experiments, gating is disabled, to only quantify factors related to the smoothing. (1) DAZL Smoothing corresponds to our model with adaptive smoothing, Eq. (4). (2) Const-Smoothing uses a constant smoothing weight $\lambda$ (Eq. 3) for all images. $\lambda$ was selected using cross validation. DAZL Smoothing shows superior performance to Const-Smoothing (AWA: 57.5% vs 55.4%, SUN: 39.9% vs 37.9%, CUB: 46.2% vs 45.8%) and even to not using smoothing at all ($\lambda = 0$).

Table 3: Ablation study for domain-aware smoothing. Showing $Acc_H$ on GZSL-Val set.

| Gating       | AWA | SUN | CUB |
|--------------|-----|-----|-----|
| DA-Gating-3  | 59.2| 92.6| 46.4|
| DA-Gating-1  | 56.4| 89.1| 57.2|
| DA-Gating-3 (w/o $p^{ZS}$) | 55.8| 88.5| 57.2|
| MAX-SMOTH-3  | 56  | 88.3| 58.4|
| MAX-SMOTH-1  | 55.3| 86.8| 67.7|

**Combining gating and smoothing:** Table 4 reports test-$Acc_H$ when ablating the main modules of DAZL:

(1) **Independent-Hard** is the simplest approach, applying Eq. (2) where the modules don’t exchange information, and the gating is hard decision over "Max of Softmax" [17]. It resembles reproducing CMT [45] but using LAGO as the ZSL model and Max-of-softmax gate. (2) **Independent-Soft** uses a soft gating following Eq. (5). (3) **DAZL Smoothing** uses domain-aware smoothing Eq. (4), and max-of-softmax gating. (4) **DAZL** is our best model, applying both domain-aware gating (Section 4.1) and smoothing.

We find that both domain-aware smoothing and domain-aware gating contribute to test accuracy. Comparing with Independent-Hard, DAZL shows a relative improvement from 58.3% to 63.9% on AWA, 35.5% to 41.1% on SUN and 44.6% to 51.8% on CUB. Domain-aware smoothing and domain-aware gating are weakly synergistic, providing a 3.6% relative improvement for CUB, 0.5% for AWA and 0.2% for SUN.

Importantly, accuracy of DAZL is comparable with state-of-the-art generative models. This is important because DAZL is much easier to train and tune than GAN-based approaches.

### 7.3. Negative Results for OOD Methods

Here we report negative results we encountered with state-of-the-art methods for out-of-distribution detection: ODIN [30] and Ensemble (Ensemble, [50]). We observed that taking a perturbation hurts OOD metrics with both these methods. In addition, in Ensemble, although quality metrics improved for the left-out training subsets during training time, the ensemble models learned to overfit the left-out subsets and failed to generalize to Unseen-Val set, better than using the baseline Max-Softmax-1. We believe it may be explained by two factors: (1) **Fine-grained datasets are harder**: CUB, SUN and AWA are fine grained datasets. For an un-trained eye, all their unseen samples may appear as in-distribution. E.g. only a few fine-grained details discriminate “Black Throated Blue Warbler” ($\in S$) of “Cerulean Warbler” ($\in U$). Therefore we believe that a perturbation would have a similar effect on images from $S$ or $U$. (2) **Shallow vs Deep**: In the standard GZSL protocol we use, each sample is represented as a feature vector extracted from a deep CNN pre-trained on ImageNet. We found that the best classifier for this data is a shallow logistic regression classifier. This is different than ODIN and Ensemble that make the perturbation along a deep network.

|          | AWA | SUN | CUB |
|----------|-----|-----|-----|
| Independent-Hard | 58.3| 35.5| 44.6|
| Independent-Soft  | 57.7| 38.3| 46.4|
| DAZL Smoothing    | 63.6| 41.2| 50  |
| DAZL (GATING & SMOTHING) | 63.9| 41.1| 51.8|
References

[1] Z. Akata, F. Perronnin, Z. Harchaoui, and C. Schmid. Label-embedding for image classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 2016.

[2] Z. Akata, S. Reed, D. Walter, H. Lee, and B. Schiele. Evaluation of output embeddings for fine-grained image classification. In *CVPR*, 2015.

[3] Z. Al-Halah and R. Stiefelhagen. How to transfer? zero-shot object recognition via hierarchical transfer of semantic attributes. In *WACV*, 2015.

[4] Y. Annadani and S. Biswas. Preserving semantic relations for zero-shot learning. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

[5] G. Arora, V.-K. Verma, A. Mishra, and P. Rai. Generalized zero-shot learning via synthesized examples. In *CVPR*, 2018.

[6] Y. Atzmon and G. Chechik. Probabilistic and-or attribute grouping for zero-shot learning. In *Proceedings of the Thirty-Fourth Conference on Uncertainty in Artificial Intelligence*, 2018.

[7] S. Changpinyo, W. L. Chao, B. Gong, and F. Sha. Synthesized classifiers for zero-shot learning. In *CVPR*, 2016.

[8] R. Chao, S. Changpinyo, B. Gong, and S. F. An empirical study and analysis of generalized zero-shot learning for object recognition in the wild. In *ICCV*, 2016.

[9] L. Chen, H. Zhang, J. Xiao, W. Liu, and S.-F. Chang. Zero-shot visual recognition using semantics-preserving adversarial embedding networks. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

[10] S. Deutsch, S. Kolouri, K. Kim, Y. Owechko, and S. Soatto. Zero-shot learning via multi-scale manifold regularization. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[11] Z. Ding, M. Shao, and Y. Fu. Low-rank embedded ensemble semantic dictionary for zero-shot learning. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[12] R. Felix, V. Kumar, I. Reid, and G. Carneiro. Multi-modal cycle-consistent generalized zero-shot learning. In *ECCV*, 2018.

[13] R. Fletcher. *Practical Methods of Optimization*. John Wiley & Sons, New York, NY, USA, second edition, 1987.

[14] A. Frome, G. Corrado, J. Shlens, S. Bengio, J. Dean, M. Ranzato, and T. Mikolov. Devise: A deep visual-semantic embedding model. In *NIPS*, 2013.

[15] Y. Fu, T. Xiang, Y.-G. Jiang, X. Xue, L. Sigal, and S. Gong. Recent advances in zero-shot recognition. *arXiv preprint arXiv:1710.04837*, 2017.

[16] Y. Guo, G. Ding, J. Han, S. Zhao, and B. Wang. Implicit non-linear similarity scoring for recognizing unseen classes. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*. International Joint Conferences on Artificial Intelligence Organization, 2018.

[17] D. Hendrycks and K. Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. In *ICLR*, 2017.

[18] G. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. In *NIPS Deep Learning and Representation Learning Workshop*, 2015.

[19] R. Jacobs, S. Nowlan, M. Jordan, and G. Hinton. Adaptive mixtures of local experts. *Neural computation*, 1991.

[20] D. Jayaraman and K. Grauman. Zero-shot recognition with unreliable attributes. In *NIPS*, 2014.

[21] N. Kaessliss, Z. Akata, B. Schiele, and A. Bulling. Gaze embeddings for zero-shot image classification. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[22] C. Kemp, J. Tenenbaum, T. Griffiths, T. Yamada, and N. Ueda. Learning systems of concepts with an infinite relational model. In *AAAI*, volume 1, 2006.

[23] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015.

[24] E. Kodirov, T. Xiang, and S. Gong. Semantic autoencoder for zero-shot learning. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[25] C. Lampert, H. Nickisch, and S. Harmeling. Learning to detect unseen object classes by between-class attribute transfer. In *CVPR*. IEEE, 2009.

[26] C. Lampert, H. Nickisch, and S. Harmeling. Attribute-based classification for zero-shot visual object categorization. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 36(3), 2014.

[27] C.-W. Lee, W. Fang, C.-K. Yeh, and Y.-C. Frank Wang. Multi-label zero-shot learning with structured knowledge graphs. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

[28] Y. Li, D. Wang, H. Hu, Y. Lin, and Y. Zhuang. Zero-shot recognition using dual visual-semantic mapping paths. In *CVPR*, 2017.

[29] Y. Li, D. Wang, H. Hu, Y. Lin, and Y. Zhuang. Zero-shot recognition using dual visual-semantic mapping paths. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[30] S. Liang, Y. Li, and R. Srikant. Enhancing the reliability of out-of-distribution image detection in neural networks. In *ICLR*, 2018.

[31] S. Liu, M. Long, J. Wang, and M. Jordan. Generalized zero-shot learning with deep calibration network. In *NIPS*, 2018.

[32] Y. Long, L. Liu, L. Shao, F. Shen, G. Ding, and J. Han. From zero-shot learning to conventional supervised classification: Unseen visual data synthesis. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[33] C. D. Manning, P. Raghavan, and H. Schütze. *Introduction to Information Retrieval*. Cambridge University Press, New York, NY, USA, 2008.

[34] A. Mishra, M. Reddy, A. Mittal, and H. A. Murthy. A generative model for zero shot learning using conditional variational autoencoders. In *WACV*, 2018.
