**ABSTRACT**

Zero-Shot Learning (ZSL) is a classification task where we do not have even a single training labeled example from a set of unseen classes. Instead, we only have prior information (or description) about seen and unseen classes, often in the form of physically realizable or descriptive attributes. Lack of any single training example from a set of classes prohibits the use of standard classification techniques and losses, including the popular crossentropy loss. Currently, state-of-the-art approaches encode the prior class information into dense vectors and optimize some distance between the learned projections of the input vector and the corresponding class vector (collectively known as embedding models). In this paper, we propose a novel architecture of casting zero-shot learning as a standard neural-network with crossentropy loss. During training our approach performs soft-labeling by combining the observed training data for the seen classes with the similarity information from the attributes for which we have no training data or unseen classes. To the best of our knowledge, such similarity based soft-labeling is not explored in the field of deep learning. We evaluate the proposed model on the four benchmark datasets for zero-shot learning, AwA, aPY, SUN and CUB datasets, and show that our model achieves significant improvement over the state-of-the-art methods in Generalized-ZSL and ZSL settings on all of these datasets consistently.

1 Introduction and Previous Works

Supervised classifiers, specifically Deep Neural Networks, need a large number of labeled samples to perform well. Deep learning frameworks are known to have limitations in fine-grained classification regime and detecting object categories with no labeled data [1][2][3][4]. On the contrary, humans can recognize new classes using their previous knowledge. This power is due to the ability of humans to transfer their prior knowledge to recognize new objects [5][6]. Zero-shot learning aims to achieve this human-like capability for learning algorithms, which naturally reduces the burden of labeling.

In zero-shot learning problem, there are no training samples available for a set of classes, referred to as unseen classes. Instead, semantic information (in the form of visual attributes or textual features) is available for unseen classes [7][8]. Besides, we have standard supervised training data for a different set of classes, referred to as seen classes along with the semantic information of seen classes. The key to solving zero-shot learning problem is to leverage trained classifier on seen classes to predict unseen classes by transferring knowledge analogous to humans.

Early variants of ZSL assume that during inference, samples are only from unseen classes. Recent observations [3][9][10] realize that such an assumption is not realistic. Generalized ZSL (GZSL) addresses this concern and considers a more practical variant. In GZSL there is no restriction on seen and unseen classes during inference. We are required to discriminate between all the classes. Clearly, GZSL is more challenging because the trained classifier is generally biased toward seen classes.
In order to create a bridge between visual space and semantic attribute space, some methods utilize embedding techniques [2, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23] and the others use semantic similarity between seen and unseen classes [24, 25, 26]. The embedding based models follow three various directions: mapping visual space to semantic space [2, 11, 12, 13, 14], mapping semantic space to the visual space [15, 16, 27, 28], and finding a latent space then mapping both visual and semantic space into the joint embedding space [17, 18, 19, 20, 21, 22, 23]. While semantic similarity based models intend to represent each unseen class as a mixture of seen classes.

The loss functions in embedding based models only have training samples from the seen classes. For unseen classes, we do not have any samples. It is not difficult to see that this lack of training samples biases the learning process towards seen classes only. One of the recently proposed techniques to address this issue is augmenting the loss function with some unsupervised regularization such as entropy minimization over the unseen classes [29].

Another recent methodology which follows a different perspective is deploying Generative Adversarial Network (GAN) to generate synthetic samples for unseen classes by utilizing their attribute information [30, 31, 32]. Although generative models boost the results significantly, it is difficult to train these models. Furthermore, the training requires generation of large number of samples followed by training on a much larger augmented data which hurts their scalability.

Our Contribution: We propose a traditional fully connected neural network architecture with cross-entropy loss for the problem of GZSL/ZSL. There are two key differences which allow such a model to predict unseen classes accurately without even having a single training example. The Softmax layer consists of nodes for all the classes, including the seen and the unseen. Besides, the weights in the final layer comprise of the attributes themselves and are non-trainable. In particular, the weight vector for node corresponding to class \( i \) is the given attribute vector for class \( i \) in the problem of ZSL and it does not change over the course of training.

The key novelty of our approach is using soft-labeling that enables the training data from the seen classes to also train the unseen class. We directly use attribute similarity information between the correct seen class and the unseen classes to create a soft unseen label for each training data. As a result of this soft labeling, training instances for seen classes also serve as soft training instance for the unseen class without increasing the training corpus. This soft labeling leads to implicit supervision for the unseen classes that eliminates the need for any unsupervised regularization such as entropy loss in [29].

Soft-labeling along with cross-entropy loss enables a simple MLP network to tackle GZSL problem. Our proposed model, which we call Z-Softmax, is simple (unlike GANs) and efficient (unlike visual-semantic pairwise embedding models) approach which outperforms the current state-of-the-art methods in GZSL and ZSL settings on four benchmark datasets with a significant margin.

2 Problem Definition

In zero-shot learning problem, a set of training data on seen classes and a set of semantic information (attributes) on both seen and unseen classes are given. The training dataset \( D = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n \) includes \( n \) samples where \( \mathbf{x}_i \in \mathbb{R}^d \) is the visual feature vector of the \( i \)-th image and \( \mathbf{y}_i \in \mathbb{R}^C \) is the one-hot-encoded true label. All samples in \( D \) belong to seen classes \( S = \{1, \cdots, C_S\} \) and during training there is no sample available from unseen classes \( U = \{1, \cdots, C_U\} \). The total number of classes is \( C = C_S + C_U \). Semantic information or attributes \( \mathbf{a}_i \in \mathbb{R}^a \), are given for all \( C \) classes and the collection of all attributes are represented by attribute matrix \( \mathbf{A} \in \mathbb{R}^{a \times C} \).

In the inference phase, our objective is to predict the correct classes (either seen or unseen) of the test dataset \( D' \). The classic ZSL setting assumes that all test samples in \( D' \) belong to unseen classes \( U \) and tries to classify test samples only to unseen classes \( U \). While in a more realistic setting i.e. GZSL, there is no assumption about correct classes of test data \( D' \) and we aim at classifying samples in \( D' \) to either seen or unseen classes \( S \cup U \).

3 Proposed Methodology

3.1 Network Architecture and Training Strategy

The overall proposed methodology is shown in Figure 1. We map visual space to semantic space (\( \tilde{a} \)), then compute the similarity score (\( s \)) between true attributes and the attribute/semantic representation of the input (\( \mathbf{x} \)). Finally, the similarity score is fed into a Softmax, and the probability of all classes are computed. Figure 2 depicts the details of our proposed network. For the visual features as the input, for all four benchmark datasets, we use the extracted visual features by a pre-trained ResNet-101 on ImageNet provided by [3]. We do not fine-tune the CNN that generates the visual features unlike model in [29]. In this sense, our proposed model is also fast and straightforward to train.
Semantic Similarity Based Softmax Classifier for Zero-Shot Learning

A P

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mapping

Figure 1: The overall framework of the proposed Z-Softmax classifier. Semantic representation $\tilde{a}$ is obtained via a visual-to-semantic mapping of visual features $x$. Similarity scores (dot-products) of $\tilde{a}$ and all class attributes $A$ are calculated and passed through a Softmax to produce all class probabilities.

Figure 2: Architecture of the proposed MLP for Z-Softmax classifier. Layers #1 and #2 provide the nonlinear embedding $g_W(\cdot)$ to map visual features to attribute space and their weights $W_1, W_2$ are learned by SGD. The output layer with non-trainable weights $A$, basically calculates dot-products of semantic representation of the input and all class attributes simultaneously.

As Figure 2 illustrates our architecture, first a nonlinear mapping $g_w(\cdot)$ is employed to transfer visual features $x$ (e.g. CNN extracted image features) to semantic domain, $g_w(x)$. Then, consistency (similarity) between semantic representations and class attributes is calculated by dot-product $\langle g_w(x), a \rangle$. As the result, a zero-shot classification task can be accomplished by assigning the class with the maximum value of consistency measure (dot-product) to the image instance. We propose to pass consistency scores of all seen and unseen classes through Softmax to produce class probabilities and tackle GZSL problem. In our proposed framework, $g_w(\cdot)$ is a multi-layer perceptron (MLP) embedding with trainable parameters given by $W$ (Figure 2).

The attribute matrix $A \in \mathbb{R}^{a \times C}$ includes both seen and unseen class attributes:

$$A = [a_1 | a_2 | \cdots | a_C]$$

The proposed method is a multi-class probabilistic classifier that produces a $C$-dimensional vector of probabilities $p$ for each sample $x_i$ as follows:

$$p(x_i) = \text{Softmax}\left(A^T g_w(x_i)\right)$$

Where $A^T g_w(x_i)$ is a $C$-dimensional vector of all consistency scores of an input sample. The following defines the similarity score (dot-product) between semantic representation of sample $x_i$ and attribute $a_k$:

$$s_{i,k} \triangleq \langle g_w(x_i), a_k \rangle$$
We propose soft labeling based on the similarity between semantic attributes. For each seen sample, we represent its

\[ p_k(x_i) = \frac{\exp(s_{i,k})}{\sum_{j=1}^{C} \exp(s_{i,j})} \]  

(4)

This Softmax as the activation function of the last layer of the network is calculated on the total number of classes \( C_S + C_U \). A natural choice to train a multi-class probabilistic classifier is the cross-entropy loss which we later show naturally integrates our idea of soft labeling. During training, we aim at learning the nonlinear mapping \( g_w(.) \) i.e. obtaining network weights \( W \) through:

\[ \min_W \sum_{i=1}^{n} L(x_i) + \lambda \|W\|_F^2 + \gamma \|W\| \]  

(5)

where \( \lambda \) and \( \gamma \) are regularization factors which are obtained through hyperparameter tuning, and \( L(x_i) \) represents the categorical cross-entropy loss for each training sample as defined below:

\[ L(x_i) = \sum_{k=1}^{C} y_{i,k} \log(p_k(x_i)) \]  

(6)

where \( C \) is the total number of classes \( C_S + C_U \).

The following is the unified crossentropy loss for each sample \( x_i \) (or \( x \) for simplicity) and its separated terms involving seen and unseen classes:

\[ L(x) = \sum_{k \in C_s} y_k^s \log(p_k^s) + \sum_{k \in C_u} y_k^u \log(p_k^u) \]  

(7)

Plugging in \( p_k^s \) and \( p_k^u \) as normalized versions of \( p_k^s \) and \( p_k^u \) into the above equation:

\[ L(x) = \sum_{k \in C_s} y_k^s \log(p_k^s) + \sum_{k \in C_u} y_k^u \log(p_k^u) + \text{Constant} \]  

(8)

We deploy similarity based soft labeling of unseen classes that allows us to learn both seen and unseen signatures simultaneously via the above-mentioned simple architecture.

3.2 Soft Labeling

In ZSL problem, we do not have any training instance from unseen classes, so the output nodes corresponding to unseen classes are always inactive during learning. Standard supervised training biases the network towards seen classes only. Moreover, the available similarity information between the seen and unseen attributed is never utilized.

We propose soft labeling based on the similarity between semantic attributes. For each seen sample, we represent its relationship to unseen categories by obtaining semantic similarity (dot-product) using the seen class attribute and all the unseen class attributes. In the simplest form, for every training data, we can find the nearest unseen class to the correct seen class label and assign a small probability \( q \) (partial membership or soft label) of this instance to be from the closest unseen class. Note, each training sample only contains a label which comes from the set of seen classes. With soft labeling, we enrich the label with partial assignments to unseen classes.

In a more general soft labeling approach, we propose assigning a distribution to all the unseen classes. A natural choice is to transform seen-to-unseen similarities (dot-product) to probabilities (soft labels) shown in Equation (9). The unseen distribution is obtained for each seen class by calculating dot-product of seen class attribute and all unseen classes’ attributes and squashing all these dot-product values by Softmax to acquire probabilities. In this case, we distribute the probability \( q \) among all unseen classes based on the obtained unseen distribution. This proposed strategy results in a soft label for each seen image during training, which as we show later helps the network to learn unseen categories.

Our proposed model with distribution on unseen (DU) is referred to as Z-Softmax DU throughout the rest of the paper. The nearest unseen method is a special case of unseen distribution soft labeling where the probability of the nearest unseen class is \( q \) and the rest of unseen classes are assigned to zero. It is natural to implement two or three nearest unseen approach, however, a better strategy is to utilize a temperature parameter \( \tau \) on the similarity score. The temperature parameter \( \tau \), controls the flatness of the unseen distribution; higher temperature results in flatter distribution over unseen categories and lower temperature creates a more ragged distribution with peaks on nearest unseen classes.
A small enough temperature basically results in the nearest unseen approach. The Impact of temperature $\tau$ on unseen distribution is depicted in Figure 4a for a particular seen class. Soft labeling implicitly introduces unseen visual features into the network without generating fake unseen samples as in generative methods [30][31][32]. Hence our proposed approach is able to reproduce same effect as in generative models without the need to create fake samples and train generative models that are known to be difficult to train. Below is the formal description of temperature Softmax:

$$y_{i,k} = \frac{q \exp (s_{i,k}/\tau)}{\sum_{j=C_S+1}^{C_S+C_U} \exp (s_{i,j}/\tau)}$$

where $\tau$ and $q$ are temperature parameter and total probability assigned to unseen distribution, respectively. Also $y_{i,k}$ is the soft label (probability) of unseen class $k$ for training sample $x_i$. It should be noted that $q$ is the sum of all unseen soft labels i.e. $\sum_{k=C_S+1}^{C_S+C_U} y_{i,k} = q$.

Utilizing Equations 8 and 9, $y_k^u = q \bar{y}_k^u$, where $y_k^u$ are soft labels of unseen classes and $\bar{y}_k^u$ is the temperature softmax where $\sum_{k \in C_u} \bar{y}_k^u = 1$, we obtain the following:

$$\tilde{L}(x) = \sum_{k \in C_s} y_k^s \log \bar{p}_k^s + q \sum_{k \in C_u} \bar{y}_k^u \log \bar{p}_k^u$$

Hence minimizing $L(x)$ is equivalent to minimizing $\tilde{L}(x)$ which is the weighted sum of cross-entropy of seen classes and cross-entropy of unseen classes. Hyperparameter $q$ acts as a trade-off coefficient between seen and unseen cross-entropy loss (Figure 3). We can see that the regularizer is a weighted cross entropy on unseen class, which leverages similarity structure between attributes compared to uniform entropy function of [29].

### 3.2.1 Intuition

We illustrate the intuition with AwA dataset [7], a ZSL benchmark dataset, and its proposed seen-unseen split [3]. Consider a seen class *squirrel*. We compute unseen classes closest to the class *squirrel* in terms of attributes. We naturally find that the closest class is *rat* and the second closest is *bat*, while other classes such as *horse, dolphin, sheep, etc.* are not close. This is not surprising as *squirrel* and *rat* share several attribute. It is naturally desirable to have a classifier that gives *rat* higher probability than other classes. If we force this softly, we can ensure that classifier is not blind towards unseen classes due to lack of any training example.

From a learning perspective, without any regularization, we cannot hope classifier to classify unseen classes accurately. This problem was identified in [29], where they proposed entropy-based regularization in the form of Deep Calibration Network (DCN). DCN uses cross-entropy loss for seen classes, and regularize the model with entropy loss on unseen classes to train the network. Authors in DCN postulate that minimizing the uncertainty (entropy) of predicted unseen distribution of training samples, enables the network to become aware of unseen visual features. While minimizing uncertainty is a good choice of regularization, it does not eliminate the possibility of being confident about the wrong unseen class. Clearly, in our example above, the uncertainty can be minimized even when the classifier gives high confidence to an unseen class *dolphin* on an image of seen class *squirrel*. Furthermore, in many cases if several unseen classes are close to the correct class, we may not actually want low uncertainty. Utilizing similarity based soft-labeling implicitly regularizes the model in a supervised fashion. The similarity values naturally has information of how much certainty we want for specific unseen class. We believe that this supervised regularization is the critical difference why our model outperforms DCN with a significant margin.

### 4 Experiment

We conduct comprehensive comparison of our proposed Z-Softmax NU and DU with the state-of-the-art methods for GZSL and ZSL settings on four benchmark datasets (Table 1). Our model outperforms the state-of-the-art methods on both GZSL and ZSL settings for all benchmark datasets.

#### 4.1 Dataset

The proposed method is evaluated on four benchmark ZSL datasets. The statistics for the datasets are shown in table [1]. Animal with Attributes (AwA) [7][8] dataset is a coarse-grained benchmark dataset for ZSL/GSZL. It has 30475 image samples from 50 classes of different animals and each class comes with side information in the form of attributes (e.g. animal size, color, specific feature, place of habitat). Attribute space dimension is 85 and this dataset has a standard split of 40 seen and 10 unseen classes introduced in [8]. Caltech-UCSD-Birds-200-2011 (CUB) [34] is a fine-grained ZSL benchmark dataset. It has 11,788 images from 200 different types of birds and each class comes...
with 312 attributes. The standard ZSL split for this dataset has 150 seen and 50 unseen classes \cite{17}. SUN Attribute (SUN) \cite{35} is a fine-grained ZSL benchmark dataset consists of 14340 images of different scenes and each scene class is annotated with 102 attributes. This dataset has a standard ZSL split of 645 seen and 72 unseen classes. attribute Pascal and Yahoo (aPY) \cite{36} is a small and coarse-grained ZSL benchmark dataset which has 14340 images and 32 classes of different objects (e.g. aeroplane, bottle, person, sofa, …) and each class is provided with 64 attributes. This dataset has a standard split of 20 seen classes and 12 unseen classes.

| Dataset | #Attributes | #Seen Classes | #Unseen Classes | #Images |
|---------|-------------|---------------|-----------------|---------|
| AwA     | 85          | 40            | 10              | 30475   |
| CUB     | 312         | 150           | 50              | 11788   |
| aPY     | 64          | 20            | 12              | 18627   |
| SUN     | 102         | 645           | 72              | 14340   |

4.2 Evaluation Metric

For the purpose of validation, we employ the validation splits provided along with PS \cite{3} to perform cross-validation for hyper-parameter tuning. The main objective of GZSL is to simultaneously improve seen samples accuracy and unseen samples accuracy i.e. imposing a trade-off between these two metrics. As the result, the standard GZSL evaluation metric is harmonic average of seen and unseen accuracy. This metric is chosen to encourage the network not be biased toward seen classes. Harmonic average of accuracies is defined in Equation 11 where $A_S$ and $A_U$ are seen and unseen accuracies, respectively.

$$A_H = \frac{2A_SA_U}{A_S + A_U} \quad (11)$$

| Method       | AwA | aPY | CUB    | SUN    |
|--------------|-----|-----|--------|--------|
|             | U   | S   | H      | U      | S      | H      | U      | S      | H      |
| DAP \cite{7} | 16.8| 76.1| 27.5   | 4.6    | 73.7   | 8.7    | 23.7   | 62.8   | 34.4   |
| ALE \cite{37} | 11.3| 74.6| 19.6   | 3.7    | 55.7   | 6.9    | 23.5   | 59.2   | 33.6   |
| SJE \cite{18} | 0.4 | 88.6| 0.8    | 0.0    | 91.2   | 0.0    | 1.6    | 72.2   | 3.1    |
| ConSE \cite{38} | 8.9 | 87.3| 16.2   | 7.4    | 66.3   | 13.3   | 11.5   | 70.9   | 19.8   |
| DeViSE \cite{29} | 13.4| 68.7| 22.4   | 4.9    | 76.9   | 9.2    | 23.8   | 53.0   | 32.8   |
| CMF \cite{20} | 0.9 | 87.6| 1.8    | 1.4    | 85.2   | 2.8    | 7.2    | 49.8   | 12.6   |
| ZSKL \cite{4} | 18.9| 82.7| 30.8   | 10.5   | 76.2   | 18.5   | 21.6   | 52.8   | 30.6   |
| DCN \cite{2} | 25.5| 84.2| 39.1   | 14.2   | 75.0   | 23.9   | 28.4   | 60.7   | 38.7   |

Z-Softmax NU | 34.5| 62.96| 44.5  | 21.2  | 59.5  | 31.0  | 34.8  | 45.5  | 39.4  | 40.0  | 26.8  | 32.1  |
Z-Softmax NU (std) | (1.9) | (1.9) | (1.4) | (4.1) | (1.4) | (4.4) | (0.47) | (0.46) | (0.31) | (1.1) | (0.75) | (0.42) |
Z-Softmax DU | 50.7| 75.8| 60.7   | 23.7   | 56.3   | 33.1   | 42.3   | 51.2   | 46.3   | 44.0   | 30.2   | 35.8   |
Z-Softmax DU (std) | (1.5) | (1)  | (1.3)  | (3.9)  | (1.4)  | (3.9)  | (0.7)  | (0.9)  | (0.4)  | (0.6)  | (0.3)  | (0.3)  |

4.3 Implementation Details

We utilized Keras \cite{40} with TensorFlow back-end \cite{41} to implement our model.

The input to the model is the visual features of each image sample extracted by a pre-trained ResNet-101 \cite{42} on ImageNet provided by \cite{3}. The dimension of visual features is 2048.

To evaluate Z-Softmax, we follow the popular experimental framework and the Proposed Split (PS) in \cite{3} for splitting classes into seen and unseen classes to compare GZSL/ZSL methods. Utilizing PS ensures that none of the unseen classes have been used in the training of ResNet-101 on ImageNet.

We cross-validate $r \in [10^{-2}, 10]$, $\text{mini-batch size} \in \{64, 128, 256, 512, 1024\}$, $q \in [0, 1]$, $\text{hidden layer size} \in \{128, 256, 512, 1024, 1500\}$ and $\text{activation function} \in \{\tanh, \text{sigmoid, hard-sigmoid, relu}\}$ to tune our model. Also we ran our experiments on a machine with 56 vCPU cores, Intel(R) Xeon(R) CPU E5-2660 v4 @ 2.00GHZ and 2 NVIDIA-Tesla P100 GPUs each with 16GB memory. The code is provided in the supplementary material.
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Figure 3: Plots of seen ($A_S$), unseen ($A_U$) and harmonic average ($A_H$) accuracies versus total probability ($q$) assigned to unseen classes are shown for all four ZSL datasets. The maximum obtained harmonic accuracy is also marked by ($\times$).

4.4 Generalized Zero-Shot Learning Results

To demonstrate the effectiveness of Z-Softmax model in GZSL setting, we comprehensively compare our proposed method with state-of-the-art discriminative GZSL models in Table 2. Since we use the standard split, the published results of other GZSL models are directly comparable.

We implemented two variants of soft labeling for our Z-Softmax model. In Z-Softmax NU, we assign a non-zero probability ($q$) to the nearest unseen class of the corresponding seen class of each training sample. The other version of our model is Z-Softmax DU, which distributes probability $q$ among the unseen classes based on their semantic similarity to seen classes. In Z-Softmax DU, the flatness/raggedness of unseen probability distribution is controlled by temperature parameter $\tau$. We report the accuracies of both Z-Softmax NU and DU in Table 2. To obtain statistically consistent results, the reported accuracies are averaged over 30 trials (using different initialization) after tuning hyper-parameters with cross-validation.

As reported in Table 2, unseen and harmonic accuracies of both variants of our model significantly outperform current state-of-the-art GZSL methods on all four benchmark datasets. Also the proposed Z-Softmax DU shows meaningful improvement over Z-Softmax NU, highlighting the advantage of soft labeling via similarity-based distribution. Overall, we could achieve a state-of-the-art performance on ZSL benchmark datasets while keeping the model simple and efficient.

Soft labeling employed in Z-Softmax gives the model new flexibility to trade-off between seen and unseen accuracies during training and come up with a higher value of $A_H$, which is the standard metric for GZSL. Assigned unseen soft labels (unseen probability $q$) in both NU and DU setting enables the classifier to gain more confidence in recognizing unseen classes, which in turn results in considerably higher $A_U$. As the classifier is now discriminating between more classes we get marginally lower $A_S$. However, balancing $A_S$ and $A_U$ with the cost of deteriorating $A_S$ leads to much higher $A_H$. This trade-off phenomenon is depicted in Figure 3 for all datasets. The flexibility provided by soft labeling is examined by obtaining accuracies for different values of $q$. In Figure 3a and 3b, by increasing total unseen probability $q$, $A_U$ increases and $A_S$ decreases as expected. From the trade-off curves, there is an optimal $q$ where $A_H$
Table 3: Zero-Shot Learning results under Proposed Split (PS) \cite{3} with ResNet-101 features \cite{42}.

| Method   | AwA | aPY | CUB | SUN |
|----------|-----|-----|-----|-----|
| DAP \cite{7} | 44.1 | 33.8 | 40.0 | 39.9 |
| ALE \cite{37} | 59.9 | 39.7 | 54.9 | 58.1 |
| SJE \cite{13} | 65.6 | 32.9 | 53.9 | 53.7 |
| ESZSL \cite{12} | 58.2 | 38.3 | 53.9 | 54.5 |
| ConSE \cite{35} | 45.6 | 26.9 | 34.3 | 38.8 |
| Sync \cite{39} | 54.0 | 23.9 | 55.6 | 56.3 |
| DeViSE \cite{20} | 54.2 | 39.8 | 52.0 | 56.5 |
| CMT \cite{2} | 39.5 | 28.0 | 34.6 | 39.9 |
| DCN \cite{29} | 65.2 | 43.6 | 56.2 | 61.8 |
| Z-Softmax DU | 68.8 | 53.1 | 59.8 | 61.9 |

Figure 4: The impact of temperature parameter $\tau$ for AwA dataset. (a) unseen soft labels (before multiplying $q$) produced by temperature Softmax Equation (9) for various $\tau$, (b) accuracies versus $\tau$ for proposed Z-Softmax DU classifier.

4.5 Zero-Shot Learning Results

We also evaluated our Z-Softmax DU model on ZSL setting where it the test data is assumed to be from the unseen class only. We observe in Table 3 that results have the same trend. Again Z-Softmax outperforms the state-of-the-art methods in ZSL framework on four benchmark datasets.

4.6 Illustration of Soft Labeling

Figure 4 shows the effect of $\tau$ and the consequent assigned unseen distribution on accuracies for AwA dataset. Small $\tau$ enforces $q$ to be concentrated on nearest unseen class while large $\tau$, spread $q$ over all the unseen classes and basically does not introduce helpful unseen class information to the classifier. The optimal value for $\tau$ is 0.2 for AwA dataset as depicted in Figure 4.b. The impact of $\tau$ on the assigned distribution for unseen classes is shown in Figure 4.a when seen class is *squirrel* in AwA dataset. Unseen distribution with $\tau = 0.2$, well represents the similarities between seen class (*squirrel*) and similar unseen classes (*rat, bat, bobcat*) and basically verifies the result of Figure 4.b where $\tau = 0.2$ is the optimal temperature. While in the extreme cases, when $\tau = 0.01$, distribution on unseen classes in mostly focused on the nearest unseen class and consequently the other unseen classes’ similarities are ignored. Also $\tau = 10$ flattens the
unseen distribution which results in high uncertainty and does not contribute helpful unseen class information to the learning.

5 Conclusion

We proposed a discriminative GZSL/ZSL classifier with visual-to-semantic mapping and cross-entropy loss. During training, while Z-Softmax learns a seen class, it is simultaneously soft labeled with the information about similar unseen classes based on semantic class attributes. Soft-labeling offers a trade-off between seen and unseen accuracies and provides the capability to adjust these accuracies based on the particular application. We achieve a state-of-the-art performance, for both ZSL and GZSL, on all four ZSL benchmark datasets while keeping the model simple and efficient.

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