Implicit Non-linear Similarity Scoring for Recognizing Unseen Classes*

Yuchen Guo†, Guiguang Ding†, Jungong Han‡, Sicheng Zhao†, Bin Wang†
†School of Software, Tsinghua University, Beijing 100084, China
‡School of Computing & Communications, Lancaster University, UK
{yuchen.w.guo,jungonghan77,schzhao}@gmail.com, {dinggg,wangbins}@tsinghua.edu.cn

Abstract

Recognizing unseen classes is an important task for real-world applications, due to: 1) it is common that some classes in reality have no labeled image exemplar for training; and 2) novel classes emerge rapidly. Recently, to address this task many zero-shot learning (ZSL) approaches have been proposed where explicit linear scores, like inner product score, are employed to measure the similarity between a class and an image. We argue that explicit linear scoring (ELS) seems too weak to capture complicated image-class correspondence. We propose a simple yet effective framework, called **I**mpli**c**it **N**on-lin**e**ar **S**imilarity **S**coring (ICINESS). In particular, we train a scoring network which uses image and class features as input, fuses them by hidden layers, and outputs the similarity. Based on the universal approximation theorem, it can approximate the true similarity function between images and classes if a proper structure is used in an implicit non-linear way, which is more flexible and powerful. With ICINESS framework, we implement ZSL algorithms by shallow and deep networks, which yield consistently superior results.

1 Introduction

Image classification is an active research topic in artificial intelligence, machine learning and computer vision communities [Bishop and others, 2006]. Recently, the emergence of deep convolutional neural networks has led to tremendous progress for this task and even achieved surpassing-human-level performance [He *et al.*, 2016]. But it should be noted the success of current techniques for image classification heavily relies on a large number of labeled training samples for each class. However, collecting a large number of labeled training samples is challenging and expensive in real-world scenarios, like Web image classification, because the number of images for each classes follows a long-tail distribution [Changpinyo *et al.*, 2016] so that many classes have limited, or even no labeled exemplar. In addition, many new concepts emerge every day and it is difficult to collect labeled data for them. In these cases, the recognition model has to recognize classes which are unseen before. Therefore, how to train image recognition models that is capable of generalizing well for unseen classes, i.e., zero-shot learning, has recently become a hot research topic and is an open issue [Xian *et al.*, 2017].

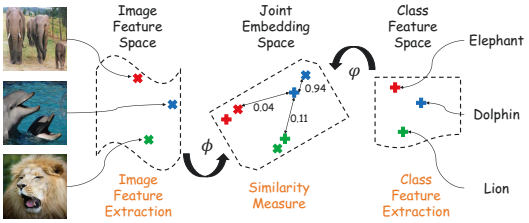


Figure 1: The basic framework of existing ZSL approaches.

The basic idea of ZSL is to learn a function to measure the correspondence/similarity between an image and a class using seen classes which have sufficient labeled images, and then transfer the similarity function to unseen ones. If an image is very similar to a class, it is likely to belong to this class. We summarize the framework in Figure 1. Each image is represented by a feature vector (image feature extraction), like deep feature [Donahue *et al.*, 2014]. Each class is also given a feature vector (class feature extraction), like the word2vec output using the class name as input or the class attributes [Lampert *et al.*, 2014]. Then the key step is to construct an image feature projection function ϕ and a text feature projection function φ to map them into a joint embedding space such that the similarity between them can be directly measured. The joint embedding space can be the image feature space [Guo *et al.*, 2017], the class feature space [Socher *et al.*, 2013], or a new latent space [Akata *et al.*, 2016]. After the joint embedding step, the similarity between an image and a class can be measured directly in this space, where the explicit linear scoring is widely adopted, for example, inner product similarity [Romera-Paredes and Torr, 2015; Zhang and Saligrama, 2016; Xian *et al.*, 2016]. Because the seen classes and unseen classes are related and similar, although different, the function learning on seen classes can work well on unseen classes. In this way, the model is able to recognize unseen classes based on the transferred knowledge.

*This work was supported by the National Natural Science Foundation of China (No. 61571269, 61701273), and the Project Funded by China Postdoctoral Science Foundation (No. 2017M610897).
Corresponding authors: Guiguang Ding and Bin Wang.

1.1 Observation and Contribution

As reviewed in the survey [Xian *et al.*, 2017], we have two important observations. Firstly, existing works pay most attention to learn the projection functions ϕ and φ. Secondly, explicit linear scoring is widely used for similarity measure. In fact, the similarity measure plays an important role in ZSL and finding or approximating the true similarity function between images and classes should be an important learning goal. However, it seems similarity measure has not gained adequate attention but a simple linear one is utilized for convenience. For example, the similarity function in many ZSL approaches [Frome *et al.*, 2013; Norouzi *et al.*, 2013; Socher *et al.*, 2013; Akata *et al.*, 2015; Kodirov *et al.*, 2015; Romera-Paredes and Torr, 2015; Zhang and Saligrama, 2015; Akata *et al.*, 2016; Xian *et al.*, 2016] can be summarized as:

$$f(x, y) = \phi(x)W\varphi(y)^T \quad (1)$$

where x and y denote an image and a class, $f(x, y)$ is the similarity function, ϕ and φ are the image-specific and class-specific embedding functions, and W is the linear compatibility parameters. Different approaches may have different choices for these functions. We need to point out although one may utilize non-linear functions for ϕ and φ, these functions can be regarded as the feature extraction functions so that generally f is still linear similarity with explicit scoring.

The simpleness of explicit linear scoring makes it easy to optimize. However, the true similarity function between images and classes is intuitively more than a linear one. Different datasets and scenarios may also have different functions. So explicitly defining a linear similarity function by human knowledge is sometimes not the best choice. On the other hand, using implicit non-linear similarity scoring seems more reasonable and practical. Motivated by this idea, we propose a ICINESS framework for ZSL. In particular, as stated by the *universal approximation theorem*, a feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of $\mathbb{R}^n$ under mild assumptions on the activation function. Inspired by it, we adopt a neural network to approximate the true similarity function $F(x, y)$. The network uses image and class features as input and output a similarity score directly. In this way, we do not need to specify the definition of f and let the network learn it automatically. In addition, it can learn non-linear similarity function. Obviously, ICINESS is more flexible and powerful than the explicit linear scoring in Eq. (1), which can better approximate the true function F. Moreover, based on ICINESS, it is easy to implement shallow or deep networks to make fully use of the advantages of neural network. We make the following contributions:

1. Different from the explicit linear similarity scoring in many ZSL approaches, we propose a novel implicit non-linear similarity scoring (ICINESS) for ZSL. Based on the universal approximation theorem, we use a neural network to implicitly approximate the non-linear similarity between images and classes, which can be more powerful and flexible.

2. Based on ICINESS, we implement shallow and deep networks. In practice, many existing ZSL approaches can be regarded as a special linear case of ICINESS but our work can deal with more complicated non-linear similarity functions.

3. We conduct extensive experiments on several benchmark datasets. The experimental results demonstrate consistent accuracy improvement over existing approaches for (generalized) ZSL, which validates the effectiveness of ICINESS.

2 Preliminary and Related Work

2.1 Problem and Notation

The problem of ZSL is defined as follows. we have two disjoint class sets $\mathcal{C}^s = \{c_1^s, ..., c_{k_s}^s\}$ and $\mathcal{C}^u = \{c_1^u, ..., c_{k_u}^u\}$ denoting seen classes and unseen classes respectively with $\mathcal{C}^s \cap \mathcal{C}^u = \emptyset$, where k_s and k_u are the number of classes in seen set and unseen set. From the image perspective, a training image set $\mathcal{D}^s = \{x_1^s, ..., x_{n_s}^s\}$ is given where each image x_i^s is associated with one seen class $y_i^s \in \mathcal{C}^s$. We uses $\{x_i^s, y_i^s\}_{i=1}^{n_s}$ to learn the similarity function between images and classes. At the test stage, an image x^u is given and our goal is to predict its class in the unseen classes $y^u \in \mathcal{C}^u$, which is the standard setting of ZSL. In the generalized ZSL (GZSL) [Xian *et al.*, 2017], an image x^t is given. Different from standard ZSL, x^t is from $\mathcal{C}^s \cup \mathcal{C}^u$. To enable similarity measure between images and classes, each class $c \in \mathcal{C}^s \cup \mathcal{C}^u$ has a feature vector $a_c \in \mathbb{R}^q$, which can be class attribute vector [Lampert *et al.*, 2014] or word2vec [Socher *et al.*, 2013].

2.2 Related Work

As reviewed before, existing ZSL approaches adopt explicit linear similarity scoring, which can be generally formulated as Eq. (1). The difference is how to choose the embedding functions. Akata *et al.* [2016], Frome *et al.* [2013], Akata *et al.* [2015], Romera-Paredes and Torr [2015], and Kodirov *et al.* [2017] directly adopted identity function ($g(x) = x$) for ϕ and φ. The difference is the loss function used to learn W. Socher *et al.* [2013] utilized a simple two layer neural network for ϕ, identity function for φ and identity matrix for W. Fu *et al.* [2015] adopted a Markov absorbing chain, while Lampert *et al.* [2014] employed probabilistic classifier predictions to construct function ϕ. Zhang and Saligrama [2015] used class independent transformation for ϕ and sparse coding for φ. Norouzi *et al.* [2013] proposed to use class probability prediction for ϕ and semantic relatedness for φ. In the synthesized classifier approach [Changpinyo *et al.*, 2016], a complicated projection was constructed for φ but finally it still used Eq. (1) for similarity measure. In some recent data synthesis approaches [Guo *et al.*, 2017], a reconstruction based algorithm is used to project class features into image feature space for directly linear similarity measurement. In summary, though many ZSL approaches may have linear or non-linear functions for ϕ and φ, they essentially have linear function for similarity measure between images and classes.

3 Implicit Non-linear Similarity Scoring

3.1 General Framework

Previous approaches adopt image specific function ϕ and class specific function φ which consider the information from the corresponding side only, and they need to define a specific linear similarity function by human knowledge as in

Eq. (1). Due to these limitations, they are not flexible enough and too simple to capture the complicated relationship between images and classes. To address these limitations, a model is expected that takes into account the knowledge from both image and class and captures non-linear image-class relationship. Since the non-linear similarity is hard to define, the model should approximate it in an implicit way. Fortunately, it is observed that feed-forward neural network is able to approximate non-linear similarity function implicitly. Specifically, based on the universal approximation theorem, a feed-forward network with hidden layers can approximate continuous functions on compact subset of $\mathbb{R}^n$ under mild assumptions on the activation function, which has been discussed theoretically [Cybenko, 1989; Hornik, 1991] and applied to a wide range of real-world applications [Krizhevsky *et al.*, 2012; Sengupta *et al.*, 2016]. Inspired by it, we propose a framework ICINESS to implicitly learn the non-linear similarity function for ZSL, as illustrated briefly in Figure 2. In particular, after the feature extraction step for images and classes, we propose to directly fuse image and class features by a few fully connected layers which take both image feature and class feature as input. Then an activation function such as $\tanh$ is applied to each unit. The fused features are then connected to an output unit which gives the similarity score for the image-class pair.

It is easy to see the difference from existing approaches. Firstly, suppose the true similarity function is F, existing approaches need to define manually a similarity f explicitly which is likely to be different from F. On the other hand, ICINESS utilizes feed-forward neural network to directly approximate F **implicitly** without defining f, which is more flexible. Secondly, existing approaches basically adopt linear similarity. On the contrary, ICINESS directly adopts non-linear activation function, which is capable of capturing **non-linear** similarity, which is more powerful. Thirdly, existing approaches process image feature and class feature in a disjoint way such that the relationship between them is not fully explored, while ICINESS adopts a fully connected layer to fuse both features before similarity scoring such that it can better connect image and class features for similarity scoring. Based on these three advantages, ICINESS is able to better explore the cross-modality similarity between image feature and class feature than the explicit linear scoring framework.

3.2 Loss Function and Optimization

Given a training image-class pair $\{x, y\}$ as input, ICINESS will finally output a similarity score (after a $\mathrm{sigmoid}$ function) $\hat{s} \in [0, 1]$. The ground truth target is defined as $s(x, y) = 1$ if image x belongs to class y, or 0 otherwise. One simple way to define the loss function is to use a binary classification (similar/dissimilar) loss, like the cross-entropy loss below:

$$\mathcal{L}(x, y) = -s(x, y) \log \hat{s}(x, y) - (1 - s(x, y)) \log(1 - \hat{s}(x, y)) \quad (2)$$

Compared to the regression based loss function [Romera-Paredes and Torr, 2015; Zhang and Saligrama, 2016; Xian *et al.*, 2016; Guo *et al.*, 2016], classification based loss directly optimizes the ZSL goal: judging whether an image-class pair is similar. It is simple to adopt a regression based loss like $\|s - \hat{s}\|^2$ as the loss function. In the experiments, we will show that the classification based loss performs much better.

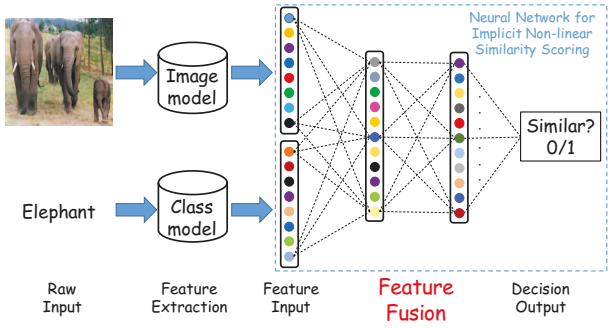


Figure 2: The proposed ICINESS framework. We fuse image and class features in a non-linear way and approximate the image-class similarity by a neural network based universal approximate theorem.

Ranking based loss is also widely used in ZSL. In fact, it is expected not only the similarity to its own class $\hat{s}(x_i, y_i)$ is large, but also larger than any other classes $y \neq y_i$. Fortunately, it is also very easy to adopt ranking loss in ICINESS. For example, we can adopt triplet loss:

$$\mathcal{L}(x_i, y_i) = \sum_{y \neq y_i} \max(0, \hat{s}(x_i, y) - \hat{s}(x_i, y_i) + \lambda) \quad (3)$$

where λ is a positive margin parameter, we use $\lambda = 0.1$ here.

Based on back-propagation algorithm, it is easy to optimize the network by minimizing the loss function. Specifically, the partial derivative of the cross-entropy loss with respect to $\hat{s}$ is:

$$\frac{\partial \mathcal{L}}{\hat{s}(x, y)} = -\frac{s(x, y)}{\hat{s}(x, y)} + \frac{1 - s(x, y)}{1 - \hat{s}(x, y)} \quad (4)$$

The partial derivative of the triplet loss with respect to $\hat{s}$ is:

$$\frac{\partial \mathcal{L}}{\hat{s}(x_i, y_i)} = -\mathbb{I}(\hat{s}(x_i, y) - \hat{s}(x_i, y_i) + \lambda \geq 0) \quad (5)$$

$$\frac{\partial \mathcal{L}}{\hat{s}(x_i, y)} = \mathbb{I}(\hat{s}(x_i, y) - \hat{s}(x_i, y_i) + \lambda \geq 0) \quad (6)$$

where $\mathbb{I}(z) = 1$ if z is true, or 0 otherwise. Since ICINESS adopts basic neural network operations, like $\mathrm{convolution}$ layer, $\mathrm{fully\ connected}$ layer, $\mathrm{sigmoid}$, and ReLU, it is easy to back-propagate the gradient of loss functions through the network, especially with well-established neural network tools, like $\mathrm{TensorFlow}$. Then we can use batch-based stochastic gradient descent algorithm to optimize network parameters.

3.3 Implementation

ICINESS is a general framework and flexible. In this paper, we implement a shallow and a deep networks based on it.

Shallow Network. We can view ICINESS as a purely similarity scoring model which takes image feature and class feature as input and output a score. In this case, the "image model" and "class model" in Figure 2 are fixed and we only need the output of them. For example, the image model can be a pre-trained deep convolutional neural network, like ResNet [He *et al.*, 2016] which we use the 2048-dim top-layer pooling units' output as image feature. The class model can be the $\mathrm{word2vec}$ tool which gives a 300-dim feature

vector using the class name as input, or the class attribute vector [Lampert *et al.*, 2014]. Then with the image feature and class feature as input (the left layer in the blue box in Figure 2), we uses a hidden layer in which each unit is fully connected to both image and class features, followed by an activation function, like $\tanh$. Then all the hidden units are fully connected to the output layer which gives the similarity score $\hat{s}(x, y)$. Because the image and class features are given, the network only needs to train hidden fully-connected layers, which can be fast. In our experiment, we find out that this simple shallow network yields state-of-the-art performance.

Deep Network. The shallow network uses pre-trained and fixed image and class models. In fact, we can also train or fine-tune them in ICINESS in an end-to-end manner. In particular, for image model, we adopt ResNet-101 as the base architecture where its top-layer pooling units (we directly use its output as image feature in shallow network) are connected to the hidden fusion layer. As for class feature, we can also use a neural network as class model. In this work, we adopt another fully connected hidden layer to class model. In addition, to relieve the computational burden, we still use the $\mathrm{word2vec}$ or class attribute features as raw input of a class. Since the image and class models are fine-tuned, they generate more powerful features, which is able to better fit the data.

For feature fusion, we can use only one hidden layer as briefly shown in Figure 2, which leads to a simple model and is easy to train, or two (or more) hidden layers which is harder to train but can approximate more complicated similarity function. In the experiments, we will show the difference.

3.4 Discussion

Interestingly, we observe that many existing ZSL approaches turn out to be a specific case of ICINESS if proper activation function is utilized. For example, suppose x is the image feature and a is the class feature for y. The similarity function for many linear models [Romera-Paredes and Torr, 2015; Akata *et al.*, 2016; Kodirov *et al.*, 2017] can be written as:

$$f_{linear}(x, a) = xWa' = \sum_{m=1}^{q} a_m (x \cdot W_{*m}) \tag{7}$$

where a_m is the m-th element in vector a, W_{*m} is the m-th column in matrix W. Now suppose we have $3 * q$ hidden units, where the r-th unit is connected to input features with a weight $T^r \in \mathbb{R}^{d+q}$ where the first d weights correspond to the image feature and the last q weights correspond to the class feature. Then we can set the weights in T as follows:

$$T_j^r = \begin{cases} w_{jr};\ \forall r = 1, ..., q,\ \forall j = 1, ..., d \\ 1;\ \forall r = 1, ..., q,\ j = d + r \\ w_{j(r-q)};\ \forall r = q + 1, ..., 2q,\ \forall j = 1, ..., d \\ 1;\ \forall r = 2q + 1, ..., 3q,\ j = d + r - 2q \\ 0; \text{otherwise} \end{cases} \tag{8}$$

Then suppose we use square function as the activation function for each hidden unit, and the weights connected to output unit are 1 for the first q hidden units, and -1 for the last $2q$ units. We can compute the pre-activation output as follows:

$$\begin{aligned} \mathcal{O} =& \sum_{r=1}^{q} (T^r \cdot [x, a]')^2 - \sum_{r=q+1}^{3q} (T^r \cdot [x, a]')^2 \\ =& \sum_{r=1}^{q} (T^r_{1,...,d} \cdot x' + T^r_{d+1,...,d+q} \cdot a')^2 \\ & - \sum_{r=q+1}^{3q} (T^r_{1,...,d} \cdot x' + T^r_{d+1,...,d+q} \cdot a')^2 \\ =& \sum_{r=1}^{q} ((x \cdot W_{*r}) + a_r)^2 - \sum_{r=1}^{q} (x \cdot W_{*r})^2 - \sum_{r=1}^{q} a_r^2 \\ =& \sum_{r=1}^{q} 2a_r (x \cdot W_{*r}) = 2 f_{linear} \end{aligned} \tag{9}$$

which indicates the output of the network is equivalent to linear similarity score. In fact, if the projections ϕ and φ are linear [Zhang and Saligrama, 2015; Norouzi *et al.*, 2013], i.e., $\phi(x) = xP$ and $\varphi(a) = aR$, we can define $W_{net} = PWR'$ and define a network by Eq. (8) using W_{net}. This network is equivalent to the original similarity function. For which adopt non-linear projections [Socher *et al.*, 2013; Changpinyo *et al.*, 2016], we can also regard their transformation functions as a feature preprocessing step for ICINESS which is analogous to the deep implementation of ICINESS.

	AwA2	aPY	SUN	CUB
#seen class	40	20	645	150
#(train) seen sample	23,527	5,932	10,320	7,057
#(test) seen sample	5,882	1,483	2,580	1,764
#unseen class	10	12	72	50
#unseen sample	7,913	7,924	1,440	2,967
#class attributes	85	64	102	312

Table 1: The statistics of datasets.

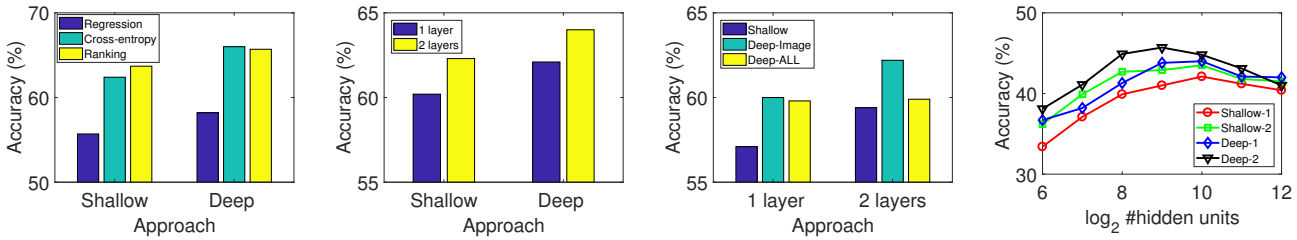
4 Experiment

4.1 Experiment Setting

Following [Xian *et al.*, 2017], we adopt 4 benchmark datasets for ZSL. The first is Animals with Attributes2 (AwA2) [Xian *et al.*, 2017] with 40 seen classes and 10 unseen classes. The second is aPascal-aYahoo (aPY) [Farhadi *et al.*, 2009] with 20 seen classes and 12 unseen classes. The third is SUN [Patterson and Hays, 2012] scene recognition dataset with 645 seen classes and 72 unseen classes. The last is CUB [Wah *et al.*, 2011] bird recognition dataset with 150 seen classes and 50 unseen classes. For each image, we use the $2,048$-dimensional output of the pre-trained ResNet-101 as image feature considering its efficacy [Tang *et al.*, 2017; Zhang *et al.*, 2017]. For each class, the attribute vector from each dataset is used as the class feature. The seen-unseen split is from Xian *et al.* [2017]. The statistics are in Table 1.

We consider two tasks. The first is standard ZSL, where a test sample is from $\mathcal{C}^u$ and the goal is to assign a label $c \in \mathcal{C}^u$ to the test sample. For ICINESS, the prediction is given by

$$\hat{c}(x) = \mathrm{argmax}_{c \in \mathcal{C}^u} \hat{s}(x, c) \tag{10}$$



(a) Loss function, AwA2 (b) #hidden layers, SUN (c) Architecture, CUB (d) #hidden units, aPY

Figure 3: The effect of loss functions, the number of hidden layers, architectures, and the number of hidden units.

where $\hat{s}(x, c)$ is the similarity score given by ICINESS. In this case, the performance is evaluated by the *average per-class top-1 accuracy* [Xian *et al.*, 2017] defined as follows:

$$ACC_{\mathcal{C}} = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \frac{\#\text{correct predictions in } c}{\#\text{samples in } c} \tag{11}$$

where $\mathcal{C} = \mathcal{C}^u$. We use all samples from the seen classes, including both train and test in Table 1, to train the network.

The second task is generalized ZSL (GZSL) where a test sample may come from both $\mathcal{C}^u$ and $\mathcal{C}^s$ and the goal is to assign a label $c \in \mathcal{C}^s \cup \mathcal{C}^u$ to the test sample. Because the model is likely to assign larger values to seen classes [Chao *et al.*, 2016], we slightly modify the prediction as follows:

$$\hat{c}_g(x) = \text{argmax}_{c \in \mathcal{C}^s \cup \mathcal{C}^u} \hat{s}(x, c) - \gamma \mathbb{I}(c \in \mathcal{C}^s) \tag{12}$$

where we simply use $\gamma = 0.1$ in this paper. In GZSL, the test data contains two parts. One is the unseen samples and the other is the test seen samples (the fourth row in Table 1). We only use the train seen samples (the third row in Table 1) as the training set. The harmonic mean of the accuracies on seen classes and unseen classes is used as evaluation metric:

$$H = \frac{2 \times ACC_{\mathcal{C}^s} \times ACC_{\mathcal{C}^u}}{ACC_{\mathcal{C}^s} + ACC_{\mathcal{C}^u}} \tag{13}$$

4.2 Implementation Details

To alleviate the difference between image feature's scale and class feature's scale, all features are all normalized to have unit length before feed into the network. For feature fusion, 512 hidden units are used for each hidden layer. For the deep implementation, we use ResNet-101 as the backbone for image model, which is pre-trained on ImageNet [Russakovsky *et al.*, 2015]. For each class, we use the attribute vector as input and adopt an one-hidden-layer network as the class model which has 512 hidden units and 128 output units with $\tanh$ as the activation function. In fact, because the manually defined attribute vector is itself a good class feature, we also consider to directly use the attributes as the input to the fusion network.

We implement the network in TensorFlow framework. Mini-batch based stochastic gradient descent is used to optimize network parameters with initial learning rate 0.01 and decrease it to 0.001 after 75k batches. The training stops after 100k batches. We use 128 image-class pair in each batch. In particular, a positive pair is given by an image and its ground truth class label. A negative pair is an image and a randomly sampled other class. In fact, because each image belongs to only one class, there are much more negative pairs. In this paper, we set the positive:negative ratio to $1:3$, i.e., for each positive class, we randomly sample 3 negative classes for an image in a batch. Therefore, each batch has 32 images and each image has 1 positive class and 3 negative classes, leading to 128 pairs in each batch. The weight decay is $5e-5$ and we use random flip and random rotate for data augmentation.

4.3 Ablation Study

Loss functions. We introduce the cross-entropy classification loss in Eq. (2) and ranking loss in Eq. (3). It is mentioned we can use pre-activation output for regression loss (squared Euclidean loss) like in previous works [Romera-Paredes and Torr, 2015; Zhang and Saligrama, 2016; Guo *et al.*, 2016]. We consider both shallow and deep implementations with one hidden layer. The ZSL accuracy on AwA2 dataset is utilized for evaluation. The comparison is shown in Figure 3(a). Obviously, the classification loss and the ranking loss perform better than the regression loss. In fact, the proposed scoring network attempts to yield large similarity scores for positive pairs and small similarity scores for negative pairs, instead of fitting a particular similarity score, which is more reasonable.

The number of hidden layers. For feature fusion, we can use one hidden layer for simpleness. One hidden layer is able to introduce non-linearity into similarity measure. Also we can adopt more hidden layers to increase the complexity of the model so that it can approximate more complicated similarity function between images and classes. Here we consider the difference between them. We also use shallow and deep implementations and SUN dataset. The results are given in Figure 3(b). It can be observed that two-layer networks achieve higher accuracy than one-layer networks. The superior performance of two-layer networks indicates that imposing more non-linearity is indeed useful for ZSL which is an evidence for the key assumption in this paper that the image-class similarity function is non-linear, which further indicates that the linear functions adopted in previous ZSL works seems too weak to capture the image-class similarity.

The architectures. In the shallow implementation, the image model and class model are fixed while only the fusion layers are tuned. In the deep implementation, we can simultaneously train all parts. In fact, the manually defined class attribute is an effective feature for classes. Therefore, it seems we do not need to train the class model. Instead, we can di-

	AwA2		aPY		SUN		CUB		Average	
	ACC	H	ACC	H	ACC	H	ACC	H	ACC	H
Norouzi *et al.* [2013]	44.5	1.0	26.9	0.0	38.8	11.6	34.3	3.1	36.13	3.93
Changpinyo *et al.* [2016]	46.6	18.0	23.9	13.3	56.3	13.4	55.6	19.8	45.60	16.13
Frome *et al.* [2013]	59.7	27.8	39.8	9.2	56.5	20.9	52.0	32.8	52.00	22.68
Socher *et al.* [2013]	37.9	15.9	28.0	19.0	39.9	13.3	34.6	8.7	35.10	14.23
Lampert *et al.* [2014]	46.1	0.0	33.8	9.0	39.9	7.2	40.0	3.3	39.95	4.88
Romera-Paredes and Torr [2015]	58.6	11.0	38.3	4.6	54.5	15.8	53.9	21.0	51.33	13.10
Xian *et al.* [2016]	55.8	20.0	35.2	0.2	55.3	19.5	49.3	24.0	48.90	15.93
Akata *et al.* [2015]	61.9	14.4	32.9	6.9	53.7	19.8	53.9	33.6	50.60	18.68
Akata *et al.* [2016]	62.5	23.9	39.7	8.7	58.1	26.3	54.9	34.4	53.80	23.33
ICINESS-S	**64.2**	**36.3**	**42.4**	**23.1**	**62.9**	**30.3**	**59.8**	**39.4**	**57.33**	**32.28**
ICINESS-D	**67.0**	**41.0**	**46.1**	**25.4**	**65.1**	**32.1**	**62.9**	**41.8**	**60.28**	**35.08**

Table 2: (Generalized) zero-shot performance comparison on benchmarks. ZSL is evaluated by ACC and GZSL is evaluated by H.

rectly use the attribute vector as the input of fusion layers. Here we investigate the difference between them. In particular, we compare the shallow implementation (Shallow), deep implementation which uses attribute vector for fusion layers directly and only optimizes the image model (Deep-Image), and deep implementation which uses image and attribute attribute vector as raw input for image and class models which are both optimized (Deep-ALL). We use CUB dataset and the results are shown in Figure 3(c). The deep implementations are better than the shallow one. But we observe that Deep-ALL yields unstable performance while Deep-Image seems more robust. One possible reason is that there are thousands of images and only tens of classes. The class model is likely to overfit the data while the image model is not. Therefore, the fine-tuned image model may better fit the dataset and produce more powerful image feature which leads to better performance than Shallow. However, the overfitted class model may yield worse class feature than the attribute vectors. In the experiments introduced beforehand, we use Deep-Image.

The number of hidden units. Now we study the effect the number of units in each hidden layer to the performance. We use aPY, shallow and deep implementations with one or two hidden layers. The ZSL accuracy w.r.t. the number of hidden units is plotted in Figure 3(d). When increasing the number at first, performance gets better because more units lead to more powerful model so that it is capable of approximating more complicated non-linear similarity function. On the other hand, if the model has many hidden units (e.g., $1,024$), further increasing the number may degrade the performance because the model becomes too complicated to train. Using 512 units is a good trade-off between speed and accuracy.

4.4 Benchmark Comparison

We compare ICINESS to the related ZSL approaches on four benchmarks for ZSL and GZSL tasks. In particular, we use the shallow implementation with one hidden layer, denoted as ICINESS-S. It has the same input features as baselines. We also use the Deep-Image with two hidden layers, denoted as ICINESS-D. Both are trained with the cross-entropy loss.

The comparison is summarized in Table 2. ICINESS-S and ICINESS-D both achieve significant improvement over the other baseline approaches for all benchmarks and tasks.

In the experiment, ICINESS-S is almost the simplest implementation of ICINESS. It has the same input features as the baseline approaches, but significantly outperforms them. In particular, the ZSL ACC is improved by 3.53 and the GZSL H by 8.95 in average compared to the best baseline. The baseline approaches all adopt explicit linear scoring, while ICINESS defines the non-linear similarity function in an implicit way. The results clearly demonstrate the superiority of implicit non-linear scoring to explicit linear scoring. As discussed, the image-class similarity is complicated by nature. It is more reasonable to use a non-linear function than a linear one. However, it is quite difficult, if not impossible, to define the function manually. To address this issue, we propose to use a neural network to approximate the function. Based on the universal approximation theorem, neural network is capable of capturing non-linear functions to some extent. Because of this advantage, ICINESS-S achieves much better result.

By using more powerful architectures, ICINESS-D improves average ACC and H by 6.48 and 11.75 respectively compared to the best baseline, which demonstrates its efficacy. By using two hidden layers, ICINESS is able to approximate more complicated non-linear similarity functions. In addition, by fine-tuning the image feature model at the same time, more powerful image features are available. Both issues contribute to the extraordinary performance of ICINESS-D.

5 Conclusion

This paper focuses on zero-shot learning problem. We notice that existing ZSL approaches can be summarized into the same framework, explicit linear similarity scoring which explicitly defines a linear similarity function between images and classes. However, the image-class similarity is complicated by nature so that it seems not reasonable to simply define a linear one. We propose a novel, simple yet effective framework with implicit non-linear similarity scoring (ICINESS) which fuses image feature and class feature by hidden layers to output a similarity score by a network. Based on universal approximation theorem, the network can approximate the true non-linear similarity in an implicit way. We develop shallow and deep versions and we show that many existing ZSL approaches can be regarded as a special case of ICINESS. Experiments on four ZSL benchmarks demonstrate that ICINESS yields better results than the state-of-the-arts.

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