Improving One-Shot Learning through Fusing Side Information

Yao-Hung Hubert Tsai† Ruslan Salakhutdinov‡
†School of Computer Science, Machine Learning Department, Carnegie Mellon University
‡{yaohungt, rsalakhu}@cs.cmu.edu

Abstract

Deep Neural Networks (DNNs) often struggle with one-shot learning where we have only one or a few labeled training examples per category. In this paper, we argue that by using side information, we may compensate the missing information across classes. We introduce two statistical approaches for fusing side information into data representation learning to improve one-shot learning. First, we propose to enforce the statistical dependency between data representations and multiple types of side information. Second, we introduce an attention mechanism to efficiently treat examples belonging to the ‘lots-of-examples’ classes as quasi-samples (additional training samples) for ‘one-example’ classes. We empirically show that our learning architecture improves over traditional softmax regression networks as well as state-of-the-art attentional regression networks on one-shot recognition tasks.

1 Introduction

In recent years, deep neural networks (DNNs) have shown good performance in many different application domains, including image classification (He et al., 2016), sentence generation (Kiros et al., 2015), and program interpreting (Reed & de Freitas, 2016). However, training DNNs often requires lots of labeled examples, and they can fail to generalize well on new concepts that contain few labeled instances. Humans, on the other hand, can learn similar categories with a handful or even a single training sample (Lake et al., 2015). In this paper, we focus on the extreme case: one-shot learning which has only one training sample per category. This ‘one-shot learning’ ability has emerged as one of the most promising yet challenging areas of research (Lake et al., 2016).

We treat the problem of one-shot learning to be a transfer learning problem: how to efficiently transfer the knowledge from ‘lots-of-examples’ to ‘one-example’ classes. In the context of deep networks, one of the simplest transfer learning techniques is fine-tuning (Bengio et al., 2012). However, fine-tuning may fail to work if the target task (e.g., regression on ‘one-example’ classes) diverges heavily from the training task (e.g., regression on ‘lots-of-examples’ classes) (Yosinski et al., 2014). Alternatively, we can fuse side information for compensating the missing information across classes.

Then, what stands for side information? Side information represents the relationship or prior knowledge between categories: for example, unsupervised feature vectors of categories derived from Wikipedia such as Word2Vec vectors (Mikolov et al., 2013), or tree hierarchy label structure such as WordNet structure (Miller, 1995). In this work, we introduce two statistical approaches for fusing side information into deep representation learning.

First, we propose to learn a label-affinity kernel from various types of side information. Our goal is to maximize Hilbert-Schmidt Independence Criterion (HSIC) (Gretton et al., 2005) between this kernel and the data representation embeddings. Since HSIC serves as a statistical dependency measurement, the learned data representations can be maximally dependent on the corresponding labels. Note that the label space spans over ‘lots-of-examples’ to ‘one-example’ classes, allowing us to bridge the gap between these categories.

Second, to achieve better adaptation from ‘lots-of-examples’ to ‘one-example’ classes, we introduce an attention mechanism for ‘lots-of-examples’ classes on the learned label-affinity kernel. Specifically, we enable every sample in ‘lots-of-examples’ classes to form a label probability distribution on the labels for ‘one-example’ classes. Hence, each instance in ‘lots-of-examples’ classes can be viewed as a quasi-sample for ‘one-example’ classes and can be used as additional training data.

Finally, our designed architecture can be easily incorporated into many of the existing one-shot learning models. In this work, we manifest it on parametric softmax regression model and non-parametric attentional regression model introduced by Vinyals et al. (2016). Our model is fully differ-
entiable and can be trained in an end-to-end fashion. Fig. 1 illustrates the overall framework. In our experimental results, we demonstrate improved recognition results on Animals with Attributes (Lampert et al., 2014) and Caltech-UCSD Birds 200-2011 (Welinder et al., 2010) dataset.

2 Related Work

There is a large body of research on transfer and one-shot learning. Here, we focus on recent advances in fusing side information and one-shot learning within deep learning.

**Fusing Side Information:** Srivastava & Salakhutdinov (2013) proposed to embed tree-based priors in training deep networks for improving objects classification performance. They enforced similar classes discovered from the tree-based priors to share similar weights of the last layer in deep networks. Hoffman et al. (2016) presented a modality hallucination architecture for RGB image detection objective by incorporating depth of the images as side information. Hoang et al. (2016) proposed to condition the recurrent neural network language models on metadata, such as document titles, authorship, and time stamp. For cross-lingual modeling, they also observed the improvement by integrating side information from the foreign language.

Many of the methods mentioned above attempt to indirectly strengthen the dependency between the side information and the learned data representations. Our approach, on the other hand, chooses to maximize this dependency directly under a statistical criterion.

**One-Shot Learning:** Deep learning based approaches to one-shot learning can be divided into two broad categories: meta-learning approaches and metric-learning approaches. On one hand, meta-learning approaches tackle the problem using a two-level-learning regime. The first stage aims to quickly acquire knowledge of individual base tasks, while the second stage aims to extract meta-information from them. Memory-Augmented Neural Networks (MANN) (Santoro et al., 2016) extended Neural Turing Machines for the meta-learning purpose so that they could rapidly bind never-seen information after a single presentation via external memory module. Woodward & Finn (2016) further extended MANN to learning to learn an active learner by using reinforcement learning. Different from other approaches, Kaiser et al. (2017) approached one-shot learning problem in a life-long manner by introducing a long-term memory module. (Ravi & Larochelle, 2017) proposed to learn the optimization algorithm for the learner neural network in the few-shot regime by an LSTM-based meta-learner model. More recent work (Finn et al., 2017; Munkhdalai & Yu, 2017) embraced similar approaches with the goal of rapid generalization on few and never-before-seen classes.

On the other hand, metric-learning approaches choose to design a specific metric loss or develop a particular training strategy for one-shot learning. Deep Siamese Neural Networks (Koch, 2015) designed a unique similarity matching criterion in deep convolutional siamese networks for one-shot image classification. Matching Networks (MN) (Vinyals et al., 2016) proposed a training strategy that aimed at training the network to do one-shot learning and also introduced an attentional regression loss to replace the standard softmax regression loss. Neural Statistician (Edwards & Storkey, 2017) held a different viewpoint that a machine learner should deal with the datasets, instead of the individual data points. They developed an extension to
the variational auto-encoders that can compute the statistics of a given dataset in an unsupervised fashion. Other recent work, including Skip Residual Pairwise Net (SRPN) (Mehrotra & Dukkipati, 2017) and Prototypical Networks (Snell et al., 2017) lay in the same domain of metric-learning approaches.

Our approach can be easily incorporated into the metric-learning ones, as we detail in Sec. 5. Instead of learning the networks exclusively from data, we extend the training from data and side information jointly. Since side information stands for the relationships between categories, we may compensate the missing information from ‘lots-of-examples’ to ‘one-example’ classes.

3 Proposed Method

3.1 Notation

Suppose we have a support set S for the classes with lots of training examples. S consists of N data-label pairs S = {X, Y} = {xi, yi}i=1,N in which class yi is represented as a one-hot vector with C classes. Moreover, we have M different types of side information R = {R1, R2, · · · , RM}, where Rm can either be supervised/unsupervised class embedding vectors or a tree-based label hierarchy, such as Wordnet (Miller, 1995). Similarly, a different support set S′ stands for ‘one-example’ classes where S′ = {X′, Y′} = {xi′, yi′}i=1,N in which class yi′ is represented as a one-hot vector with C′ classes (disjoint from the classes in S). R′ = {R′1, R′2, · · · , R′M} then stands for the corresponding side information for S′. Last, θX and θR are the model parameters dealing with the data and side information, respectively.

One of our goals is to learn the embeddings of the data gθX(x) (gθX(·)) denotes the non-linear mapping for data x from {X, X′} that maximally align with the provided side information {R, R′}. This can be done by introducing Hilbert-Schmidt Independence Criterion (HSIC) (Gretton et al., 2005) into our architecture, as we detail in Sec. 3.2.

In Sec. 3.2 and 3.3 for clarity of presentation, we focus on learning dependency measure between X and R. However, it can be easily extended to X′ and R′ or {X, X′} and {R, R′}.

3.2 Dependency Measure on Data and Side Information

The output embeddings gθX(X) and side information R can be seen as two interdependent random variables, and we hope to maximize their dependency on each other. To achieve this goal, we adopt Hilbert-Schmidt Independence Criterion (HSIC) (Gretton et al., 2005).

HSIC acts as a non-parametric independence test between two random variables, gθX(X) and R, by computing the Hilbert-Schmidt norm of the covariance operator over the corresponding domains G × R. Furthermore, let kg and kr be the kernels on G, R with associated Reproducing Kernel Hilbert Spaces (RKHSs). A slightly biased empirical estimation of HSIC (Gretton et al., 2005) could be written as follows:

\[
\text{HSIC}(S, R) = \frac{1}{(N - 1)^2} \text{tr}(HK_GHK_R),
\]

where KG ∈ R N×N with KG,ij = kg(xi, xj), KR ∈ R N×N with KR,ij = kr(yi, yj), and H ∈ R N×N with H,ij = 1 (i = j) = −1/N 2. In short, KG and KR respectively stand for the relationships between data and categories, and HSIC provides a statistical dependency guarantee on the learned embeddings and labels.

3.3 Kernel Learning via Deep Representation

Next, we explain how we construct the kernel KG and KR. First of all, for simplicity, we adopt linear kernel for kg:

\[
k_g(x_i, x_j) = gθ_X(x_i)\top \cdot gθ_X(x_j).
\]

As for learning kr, we adopt deep kernel learning framework (Wilson et al., 2016) to incorporate multiple side information as follows:

\[
k_r(y_i, y_j) = \sum_{m=1}^{M} \frac{1}{M} k_m(y_i, y_j),
\]

where km(·, ·) denotes the kernel choice for the mth side information Rm. We consider two variants of km(·, ·) based on whether Rm is represented by class embeddings or tree-based label hierarchy.

**a) Rm is represented by class embeddings:**

Class embeddings can either be supervised features such as human annotated features or unsupervised features such as word2vec or glove features. Given Rm = {r m}C c=1 with r m representing class embeddings of class c, we define km(·, ·) as:

\[
k_m(y_i, y_j) = f_m,θ_R(r m y_i)\top \cdot f_m,θ_R(r m y_j),
\]

where f m,θ_R(·) denotes the non-linear mapping from Rm. We note that linear kernels are adopted in eq. (2) and (4), while other kernel choices such as RBF or SM kernel (Wilson & Adams, 2013) are also applicable, and any of them can be embedded into our architecture in an end-to-end fashion (Wilson et al., 2016). In this setting, we can capture the intrinsic structure by adjusting the categories’ affinity through learning f m,θ_R(·) for different types of side information Rm.
Figure 2: Tree structure and its corresponding tree covariance matrix inferred from wordnet structure for six randomly picked categories in AwA dataset. distf(·, ·) denotes the distance between two categories and l(·, ·) denotes the length of the branch between two nodes. Best viewed in color.

b) $R^m$ is represented by tree hierarchy:

If the labels form a tree hierarchy (e.g., wordnet [Miller 1995] tree structure in ImageNet), then we can represent the labels as a tree covariance matrix $B$ defined in [Bravo et al. 2009], which is proved to be equivalent to the taxonomies in the tree (Blaschko et al. 2013). Specifically, following the definition of Theorem 2 in [Bravo et al. 2009], a matrix $B \in \mathbb{R}^{C \times C}$ is the tree-structured covariance matrix if and only if $B = VDV^T$ where $D \in \mathbb{R}^{2C-1 \times 2C-1}$ is the diagonal matrix indicating the branch lengths of the tree and $V \in \mathbb{R}^{C \times 2C-1}$ denoting the topology. As an example, Fig. 2 shows construction of the tree covariance matrix designed for a randomly picked subset in Animals with Attributes (AwA) dataset (Lampert et al. 2014).

For any given tree-based label hierarchy, we define $k_{r,m}(y_i, y_j)$ to be

$$k_{r,m}(y_i, y_j) = (B^m)_{y_i, y_j} = (Y^T B^m Y)_{i,j},$$

where $Y \in \{0, 1\}^{C \times N}$ is the label matrix and $B^m$ is the tree-structured covariance matrix of $R^m$. In other words, $k_{r,m}(y_i, y_j)$ indicates the weighted path from the root to the nearest common ancestor of nodes $y_i$ and $y_j$ (see Lemma 1 in [Blaschko et al. 2013]).

Through the design in eq. (5), we can try integrating different types of side information $R^m$ with both class-embedding and tree-hierarchy-structure representation. In short, maximizing eq. (1) makes the data representation kernel $K_C$ maximally dependent on the side information $R$ seen from the kernel matrix $K_R$. Hence, introducing HSIC criterion provides an excellent way of transferring knowledge across different classes. Note that, if $K_R$ is an identity matrix, then there are no relationships between categories, which results in a standard classification problem.

So far, we have defined a joint learning on the support set $S$ and its side information $R$. If we have access to different support set $S'$ and the corresponding side information $R'$, we can easily incorporate them into the HSIC criterion; i.e., $\text{HSIC}(\{S, S'\}, \{R, R'\})$. Hence we can effectively transfer the knowledge both intra and inter sets.

3.4 Quasi-Samples Generation

Our second aim is to use a significant amount of data in ‘lots-of-examples’ classes to learn the prediction model for ‘one-example’ classes. We present an attention mechanism over the side information $R$ and $R'$ to achieve this goal.

For a given data-label pair $(x, y)$ in $S$, we define its quasi-label $y'$ as follows:

$$y' = P_{\theta_R}(y'|y; R, R') = \sum_{y_i \in S'} a_r(y, y_i)y'_i,$$

where $a_r(·, ·)$ acts as an attentional kernel from $R$ to $R'$, which can be formulated as

$$a_r(y, y_i) = \frac{e^{k_r(y, y_i)}}{\sum_{y_j \in S'} e^{k_r(y, y_j)}}.$$
4 REGRESSION AND TRAINING-TEST STRATEGY

4.1 Predictions by Regression

We adopt two regression strategies to form the label probability distributions. First, given the support set \( S \), we define the label prediction \( \hat{y} \) to be

\[
\hat{y} := P_{\theta_X}(y|x; S). \tag{8}
\]

a) Softmax (Parametric) Regression:

Standard softmax regression has been widely used in deep networks such as VGG (Simonyan & Zisserman, 2014), GoogLeNet (Szegedy et al., 2015), and ResNet (He et al., 2016). The predicted label \( \hat{y} \) can be written as

\[
\hat{y} = \text{softmax}(\phi^T g_{\theta_X}(x)), \tag{9}
\]

where \( \phi \) represents the matrix that maps \( g_{\theta_X}(x) \) to the label space in \( S \). Similarly, the predicted label \( \hat{y}' \) of \( x' \) under the support set \( S' \) would be

\[
\hat{y}' := P_{\theta_X}(y'|x'; S') = \text{softmax}(\phi'^T g_{\theta_X}(x')).
\]

Note that \( \phi \) and \( \phi' \) are different matrices.

b) Attentional (Non-Parametric) Regression:

Attentional regression, proposed by Vinyals et al. (2016), represents state-of-the-art regression strategy for one-shot setting. The predicted label \( \hat{y} \) over a data \( x \) given the support set \( S \) is defined as

\[
\hat{y} = \sum_{i \in S} a_g(x, x_i) y_i, \tag{10}
\]

where \( a_g(\cdot, \cdot) \) is the attention kernel on domains \( G \times G \). In fact, this is a linear smoother (Buja et al., 1989) for non-parametric regression, with the choice of weight equal to \( a_g(x, x_i) \). A possible design of this kernel is

\[
a_g(x, x_i) = \frac{e^{k_g(x, x_i)}}{\sum_{j \in S} e^{k_g(x, x_j)}}, \tag{11}
\]

which can also be viewed as an attentional memory mechanism in which \( y_i \) acts as external memory and \( a_g(\cdot, \cdot) \) computes merely the extent to which we retrieve this information according to the corresponding data \( x_i \).

Hence, \( \hat{y} := P_{\theta}(y|x; S) \) can either be defined on softmax regression (eq. (9)) or attentional regression (eq. (10)).

We note that using softmax regression requires learning an additional matrix (i.e., \( \phi \)), while the use of attentional regression requires the additional computation of traversing the data-label pairs in \( S \).

4.2 Training and Test Strategy - Learning in a One-Shot Setting

Inspired by Vinyals et al. (2016); Ravi & Larochelle (2017), we construct a training-time strategy to match the test-time evaluation strategy.

Let \( T \) be the set of tasks defined on all possible label sets from ‘lots-of-examples’ classes. Likewise, \( T' \) is the set of tasks defined on all possible label sets from ‘one-example’ classes. We first perform sampling from \( T \) to \( L \) and from \( T' \) to \( L' \) for choosing the tasks on the subsets of classes. Specifically, we force the number of classes in \( L \) and \( L' \) to be the number of ‘one-example’ classes. For instance, if we randomly sample 5 categories from ‘one-example’ classes to perform an evaluation, we have \( |L'| = 5 \). Then, to match training and testing scenario, we also randomly sample 5 categories from ‘lots-of-examples’ classes so that \( |L| = |L'| \) is achieved.

Next, we sample \( S \) along with the corresponding \( R \) from \( L \) and sample \( S' \) along with the corresponding \( R' \) from \( L' \). In order to strengthen the matching criterion between training and testing, we split \( S \) to \( S_{\text{train}} \) and \( S_{\text{batch}} \) (\( S_{\text{train}} \cup S_{\text{batch}} = S \) and \( S_{\text{train}} \cap S_{\text{batch}} = \emptyset \)). We have \( |S_{\text{train}}| = |S'| = N' \) and also require \( S_{\text{train}} \) to have equal number of samples per category as in \( S' \).

The first objective is to maximize the prediction of predicting labels in \( S_{\text{batch}} \), which can be formulated as

\[
O_1 = E_{L \sim T} \left[ E_{S_{\text{train}}, S_{\text{batch}} \sim L} \left[ \frac{1}{|S_{\text{batch}}|} \sum_{i \in S_{\text{batch}}} \hat{y}_i^T \log P_{\theta_X}(y_i|x_i; S_{\text{train}}) \right] \right]. \tag{12}
\]

Note that both \( y_i \) and \( P_{\theta_X}(y_i|x_i; S_{\text{train}}) \) are vectors of size \( \mathbb{R}^{C \times 1} \).

The second objective is to meet the HSIC criterion (eq. (1)) that maximally aligns the side information to the learned embeddings. We formulate the objective as follows:

\[
O_2 = E_{L \sim T; L' \sim T'} \left[ E_{S, R \sim L; S', R' \sim L'} \left[ \text{HSIC}([S, S'], [R, R']) \right] \right]. \tag{13}
\]

The third objective is to take the data in \( S_{\text{batch}} \) and their quasi-labels into consideration: namely, the data-label pairs \( \{x_i, \hat{y}_i\}_{i=1}^{|S_{\text{batch}}|} \), where \( \hat{y}_i \) is defined in eq. (8). We maximize the negative cross entropy between \( \hat{y}_i \) and the label probability distribution \( P_{\theta_X}(y'_i|x_i; S') \) in eq. (8):

\[
O_3 = E_{L \sim T; L' \sim T'} \left[ E_{S_{\text{batch}}, R \sim L; S', R' \sim L'} \left[ \frac{1}{|S_{\text{batch}}|} \sum_{i \in S_{\text{batch}}} \hat{y}_i^T \log P_{\theta_X}(y'_i|x_i; S') \right] \right], \tag{14}
\]

where both \( \hat{y}_i' \) and \( P_{\theta_X}(y'_i|x_i; S') \) are of size \( \mathbb{R}^{C' \times 1} \).

The overall training objective is defined as follows:

\[
\max_{O_1} O_1 + \alpha (O_2 + O_3), \tag{15}
\]
where $\alpha$ is the trade-off parameter representing how we fuse side information to learn from ‘lots-of-examples’ to ‘one-example’ classes. We fix $\alpha = 0.1$ for simplicity in all of our experiments. We also perform fine-tuning over $S'$; that is, we update $\theta_X$ for a few iterations to maximize

$$E_{L' \sim T'} \left[ E_{S' \sim L'} \left[ \frac{1}{|S'|} \sum_{i \in S'} y_i'^T \log P_{\theta_X}(y_i'|x_i'; S') \right] \right].$$

(16)

Finally, for any given test example $x_{test}'$, the predicted output class is defined as

$$y_{test}' = \arg \max_{y'} P_{\theta_X}(y'|x_{test}'; S').$$

(17)

5 EVALUATION

In this Section, we evaluate our proposed method on top of two different networks (regression models): softmax regression ($\text{softmax} \_\text{net}$) as in eq. (9) and attentional regression ($\text{attention} \_\text{net}$) as in eq. (10). Attentional regression network can be viewed as a variant of Matching Networks (Vinyals et al., 2016) without considering the Fully Conditional Embeddings (FCE) in (Vinyals et al., 2016).

In our experiments, two datasets are adopted for one-shot recognition task: Caltech-UCSD Birds 200-2011 (CUB) (Welinder et al., 2010) and Animals with Attributes (AwA) (Lampert et al., 2014). CUB is a fine-grained dataset containing bird species where its categories are both visually and semantically similar, while AwA is a general dataset which contains animal species across land, sea, and air. We use the same training+validation/test splits in [Akata et al. 2015; Tsai et al. 2017]: 150/50 classes for CUB and 40/10 classes for AwA.

We consider four types of side information: supervised human annotated attributes ($\text{att}$) (Lampert et al., 2014), unsupervised Word2Vec features ($\text{w2v}$) (Mikolov et al., 2013), unsupervised Glove features ($\text{glo}$) (Pennington et al., 2014), and the tree hierarchy ($\text{hie}$) inferred from wordnet (Miller, 1995). Human annotated attributes $\text{att}$ are represented as 312-485-dimensional features for CUB and AwA, respectively. $\text{w2v}$ and $\text{glo}$ are 400-dimensional features pre-extracted from Wikipedia provided by [Akata et al. 2015]. On the other hand, $\text{hie}$ are not represented as feature vectors but define the hierarchical relationships between categories. Please see Appendix for the tree hierarchy of CUB and AwA. The implementation details are also provided in Appendix. We report results averaged over 40 random trials.

5.1 One-Shot Recognition

First, we perform one-shot recognition tasks on CUB and AwA: for test classes, only one labeled instance is provided during training and the rest of the instances are for prediction in test time. We denote our proposed method using softmax regression and attentional regression as $\text{HSIC}_{\text{softmax}}$ and $\text{HSIC}_{\text{attention}}$, respectively. $\text{HSIC}_{\text{softmax}}$ and $\text{HSIC}_{\text{attention}}$ relax to $\text{softmax} \_\text{net}$ and $\text{attention} \_\text{net}$ when we only consider an objective $O_1$ (\(\alpha = 0\)) in eq. (15). For the completeness of the experiments, we provide two more variants: $\text{HSIC}_{\text{softmax}}^\dagger$ and $\text{HSIC}_{\text{attention}}^\dagger$. They stand for our proposed method without considering $O_2$ in eq. (15); that is, we do not generate quasi-samples for our test classes (‘one-example’ classes) from instances in training classes (‘lots-of-examples’ classes). The results are reported using top-1 classification accuracy (%) from eq. (17) on test samples in test classes.

**Experiments:** Table 1 lists the average recognition performance for our standard one-shot recognition experiments. $\text{HSIC}_{\text{softmax}}$ and $\text{HSIC}_{\text{attention}}$ are jointly learned with all four types of side information: $\text{att}$, $\text{w2v}$, $\text{glo}$, and $\text{hie}$. We first observe that all methods perform better on AwA than in CUB dataset. This is primarily because CUB is a fine-grained dataset where inter-class differences are very small, which increases its difficulty for object classification. Moreover, the methods with side information achieve superior performance over the methods which do not learn with side information. For example, $\text{HSIC}_{\text{softmax}}$ improves over $\text{softmax} \_\text{net}$ by 4.56% on CUB dataset and $\text{HSIC}_{\text{attention}}$ enjoys 4.71% gain over $\text{attention} \_\text{net}$ on AwA dataset. These results indicate that fusing side information can benefit one-shot learning.

Next, we examine the variants of our proposed architecture. In most cases, the construction of the quasi-samples benefits the one-shot learning. The only exception is the 0.88% performance drop from $\text{HSIC}_{\text{attention}}$ to $\text{HSIC}_{\text{attention}}$ in AwA. Nevertheless, we find that our model converges faster when introducing the technique of generating quasi-samples.

| network / Dataset       | CUB   | AwA   |
|-------------------------|-------|-------|
| $\text{softmax} \_\text{net}$ | 26.91 ± 2.41 | 66.39 ± 5.38 |
| $\text{HSIC}_{\text{softmax}}$ | 29.26 ± 2.22 | 69.98 ± 5.47 |
| $\text{HSIC}_{\text{softmax}}^\dagger$ | 31.49 ± 2.28 | 71.29 ± 5.64 |
| $\text{HSIC}_{\text{attention}}$ | 33.12 ± 2.48 | 76.98 ± 5.82 |
| $\text{HSIC}_{\text{attention}}^\dagger$ | 33.75 ± 2.43 | 72.27 ± 5.82 |

Table 1: Average performance for standard one-shot recognition task: $\text{att}$, $\text{w2v}$, $\text{glo}$, and $\text{hie}$.
Figure 4: From left to right: (a) normalized confusion matrix for classification results, (b) normalized confusion matrix for regression results, (c) label-affinity kernel learned in HSIC$_{attention}$, and (d) tree covariance matrix in Sec. 3.3 inferred from wordnet for AwA.

Figure 5: Parameter sensitivity analysis experiment. Our proposed methods jointly learn with all four side information: att, w2v, glo, and hie. Best viewed in color.

parameters (compared to softmax regression) and enjoys better performance in one-shot setting.

Confusion Matrix and the Learned Class-Affinity Kernel: Following the above experimental setting, for test classes in AwA, in Fig. 4 we provide the confusion matrix, the learned label-affinity kernel using HSIC$_{attention}$, and the tree covariance matrix (Bravo et al., 2009). We first take a look at the normalized confusion matrix for classification results. For example, we observe that seal is often misclassified as humpback whale; and from the tree covariance matrix, we know that seal is semantically most similar to humpback whale. Therefore, even though our model cannot predict seal images correctly, it still can find its semantically most similar classes.

Additionally, it is not surprising that Fig. 4(b), normalized confusion matrix, is visually similar to Fig. 4(c), the learned class-affinity kernel. The reason is that one of our objectives is to learn the output embeddings of images to be maximally dependent on the given side information. Note that, in this experiment, our side information contains supervised human annotated attributes, unsupervised word vectors (Word2Vec (Mikolov et al., 2013) and Glove (Pennington et al., 2014), and a WordNet (Miller, 1995) tree hierarchy.

On the other hand, we also observe the obvious change in classes relationships from WordNet tree hierarchy (Fig. 4(d)) to our learned class-affinity kernel (Fig. 4(c)). For instance, raccoon and giant panda are species-related, but they distinctly differ in size and color. This important information is missed in WordNet but not missed in human annotated features or word vectors extracted from Wikipedia. Hence, our model bears the capability of arranging and properly fusing various types of side information.

Parameter Sensitivity on $\alpha$: Since $\alpha$ stands for the trade-off parameter for fusing side information through HSIC and quasi-examples generation technique, we studied how it affects model performance. We alter $\alpha$ from 0 to 1.0 by step size of 0.05 for both HSIC$_{softmax}$ and HSIC$_{attention}$ models. Fig. 5 shows that larger values of $\alpha$ does not lead to better performance. When $\alpha \leq 0.3$, our proposed method outperforms softmax$_{net}$ and attention$_{net}$. Note that HSIC$_{softmax}$ and HSIC$_{attention}$ relax to softmax$_{net}$ and attention$_{net}$ when $\alpha = 0$. When $\alpha > 0.3$, the performance of our proposed method begins to drop significantly, especially for HSIC$_{attention}$. This is primarily because too large values of $\alpha$ may cause the output embeddings of images to be confused by semantically similar but visually different classes in the learned label-affinity kernel (e.g., Fig. 4(c)).

Availability of Various Types of Side Information: In Table 2 we evaluate our proposed methods when not all four types of side information are available during training. It is surprising to find that there is no particular rule of combining multiple side information or using a single side information to obtain the best performance. A possible reason would be the non-optima for using kernel average in eq. 5. That is to say, in our current setting, we equally treat contribution of every type of side information to the learning of our label-affinity kernel. Nevertheless, we still enjoy performance improvement of using side information compared to not using it.

From One-Shot to Few-Shot Learning: Next, in Fig. 6 we increase the labeled instances in test classes and evaluate the performance of softmax$_{net}$, attention$_{net}$, and our proposed architecture. We randomly label 1 (one-shot setting), 3, 5, 10, 15, and 20 (few-shot setting) instances in test classes. These labeled instances are used for training, while the rest unlabeled instances are used for prediction at the test stage. We observe that HSIC$_{softmax}$ converges to softmax$_{net}$ and HSIC$_{attention}$ converges to attention$_{net}$ when more labeled data are available in test classes during training. In other words, as labeled instances increase, the
power of fusing side information within deep learning diminishes. This result is quite intuitive as deep architecture perform well when training on lots of labeled data.

For the fine-grained dataset CUB, we also observe that attentional regression methods are at first outperform softmax regression methods, but perform worse when more labeled data are present during training. Recall that, in setting, softmax regression networks have one additional softmax layer (one-hidden-layer fully-connected neural network) compared to attentional regression networks. Therefore, softmax regression networks can deal with more complex regression functions (i.e., regression for the fine-grained CUB dataset) as long as they have enough labeled examples.

### 5.2 Expanding Training- and Test-time Categories Search Space

Another interesting experiment is to expand the training- and test-time search space to cover all training and test classes. While most of the one-shot learning papers (Santoro et al., 2016; Vinyals et al., 2016; Ravi & Larochelle, 2017) do not consider this setting, we consider it to be more practical for real-world applications. We alter the regression for both softmax and attentional version so that all classes are covered in the search space. In other words, the output label is now a vector of size $\mathbb{R}^{C+C'}$.

After expanding the categories’ search space, it is meaningless to construct quasi-samples for ‘one-example’ classes from samples in ‘lots-of-examples’ classes. Therefore, we compare only HSIC$_{softmax}^{\dagger}$ and HSIC$_{attention}^{\dagger}$ with softmax$_{net}$ and attention$_{net}$.

Table 3 shows the results of our experiment. First, a dramatic performance drop appears in every method compared to those that do not expand the search space. Objects in CUB and AwA all suffer from the confusion between training and test classes. Note that when considering one-shot setting, we have only one labeled data per test category during training time. Therefore, expanding the label search space makes the regression only focus on the ‘lots-of-examples’ classes.

### 6 Conclusion

In this paper, we show how we can fuse multiple types of side information for better transferring knowledge across ‘lots-of-examples’ classes and ‘one-example’ classes to improve one-shot learning. Our contributions lie in two parts: (1) enforcing dependency maximization between learned image representations and learned label-affinity kernel, and (2) performing an attention mechanism for generating quasi-samples for ‘one-example’ classes. The form of side information can either be supervised/unsupervised.
class embeddings or tree-based label hierarchy. We empirically evaluate our proposed method on both general and fine-grained datasets for one-shot recognition. The results consistently improve over traditional softmax regression model and the attentional regression model, which represents the current state-of-the-art for the one-shot learning problem.

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7 IMPLEMENTATION DETAILS

First, we treat the learning of embeddings \( g_{\theta}(x) = g_{\theta} \circ g_{GoogLeNet}(x) \), where \( g_{GoogLeNet}(x) \) denotes the mapping before the last layer of GoogLeNet (Szegedy et al., 2015) pre-trained on ImageNet (Deng et al., 2009) images. We fix \( g_{GoogLeNet}(x) \) without fine-tuning, and therefore the learning of \( g_{\theta}(\cdot) \) can be relaxed as the learning of \( g_{\theta} \circ (\cdot) \).

For model parameters \( \theta \), we parameterize \( g_{\theta}(\cdot) \) as two-hidden layer fully-connected neural network with dimensions \( 1024 - 500 - 100 \), where 1024 is the input dimension of the input GoogLeNet features. \( \tanh \) is chosen to be our activation function and we adopt \( l_2 \) normalization after its output. For the softmax regression part, \( \phi/\phi' \) are parameterized as one-hidden layer fully-connected neural network with dimensions \( 100 - C/C' \). Then, we parametrize the mapping \( f_{t,\theta}(\cdot) \) for class embeddings to be a two-hidden layer fully-connected neural network with dimensions \( d_t - d_c - 50 \), where \( d_t \) is the input dimension of the class embeddings from \( R^t \). We choose \( d_c = 100 \) when \( d_t > 100 \) and \( d_c = 75 \) when \( d_t < 100 \). We also adopt \( \tanh \) as the activation function and use \( l_2 \) normalization after its output.

The trade-off parameter \( \alpha \) is set to 0.1 for all the experiments. In each trial, we fix \( S' \) to contain all ‘few-examples’ classes and fix \( |S_{\text{batch}}| = 256 \). The model is implemented in TensorFlow (Abadi et al., 2015) with Adam (Kingma & Ba, 2015) for optimization. We observe that for softmax regression, the model converges within 500 iterations; on the other hand, for attentional regression, the model converges within 100 iterations.

8 TREE HIERARCHY FOR DATASETS

Fig. 7 is the tree hierarchy for Animal with Attributes (AwA) dataset and Fig. 8 is the tree hierarchy for Caltech-UCSD Birds 200-2011 (CUB) dataset. The leaf nodes in the tree denote the class, and the internal nodes represent the super-class in wordnet structure.
Figure 7: Tree hierarchy for Animal with Attributes (AwA) dataset.
Figure 8: Tree hierarchy for Caltech-UCSD Birds 200-2011 (CUB) dataset.