Sharif University of Technology
Computer Engineering Department

MSc Thesis

Deep Zero-Shot Learning

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supervised by

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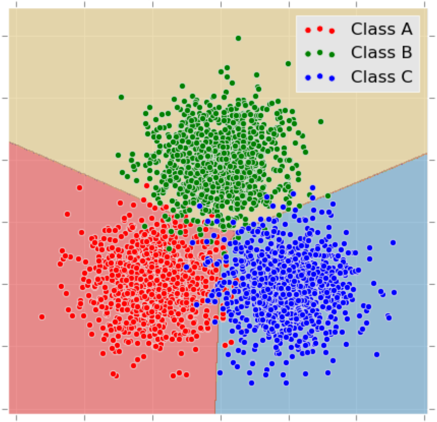
Plan

Plan

Introduction

Standard Supervised Learning Paradigm: Discover the pattern for each class from abundant labeled samples.

- Using SVM, Decision Tree, KNN, etc.



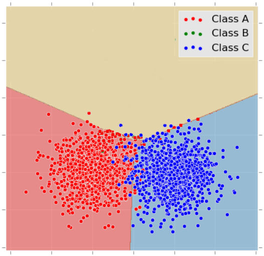
Extening the Standard Paradigm

Sometimes samples from all classes is not available

- Example: Novel Categories, Fine-grained classification.

Zero-Shot Learning addresses the problem of classification.

when no training sample is available for some classes.



Extening the Standard Paradigm

Identifying Classes without Samples:

- Each category is identified some *auxiliary information* also called *signature*.
- Examples of class signatures include:
  - Attribute Vectors
  - Text Articles
  - Category Names
- Signatures exist for all classes.

Extening the Standard Paradigm

As a sample, an animal species like Zebra can have these signatures:

- The Vector (four legs, fast, striped, gallops, non-domestic, ...).
- The Wikipedia Entry for zebra.
- The word *'Zebra'* itself.

Problem Definition

At training time:

- there are N_s labeled samples: $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N_s}$.
- These samples are from n_s classes that are called *seen classes*.
- Class signatures C_s for seen classes is also available.
- There are also n_u classes with no labeled sample. These are called *unseen classes.*
- It is assumed in most works that signatures of unseen classes, C_u, is also available.

Problem Definition

At test time:

- N_u samples from unseen classes are presented: $\{(\mathbf{x}_i)\}_{i=N_s+1}^{N_s+N_u}$.
- The Goal is to classify test samples into unseen categories.
- In other words finding

$$\arg\min_{\mathbf{y}^*{}_i} \mathbf{y}^*{}_i \neq \mathbf{y}_i, \quad i = N_s + 1, \ldots, N_s + N_u$$

Solution Steps

Most existing solutions for zero-shot learning consist of these three steps:

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Prior Works

Existing works can be categorized by the semantic space they use:

- Space of signatures (Attribute Prediction).
- Space of images.
- A third space.

We review some selected works from each category.

Attribute Prediction

- A large body of work in zeroshot learning belongs to this category.
- The mapping from signature space is considered identity mapping.
- Attribute Estimator/Classifier are learned on train images (standard supervised problem).
- The Estimator/Classifier is used on test images to find $\mathbf{c}_i^*$ for image $\mathbf{x}_i$
- $\mathbf{x}_i$ is assigned to class with most similar signature:

$$\ell(\mathbf{x}_i) = \underset{j=n_s+1\ldots,n_s+n_u}{\arg\min} \; distance(\mathbf{c}_i^*, \mathbf{c}_j)$$

Examples from this category include:
[Akata et al., 2013, Jayaraman and Grauman, 2014, Lampert et al., 2009]

Mapping to Image Space

- In training time, Learn a mapping from class signatures to image space:

$$\phi : \mathbb{R}^a \rightarrow \mathbb{R}^d$$

- This can bee seen predicting linear one-vs-all classifier for each class from its signature.
- In test time, classify test images using classifiers predicted from unseen class signatures.
- Assign each sample to class whose classifier produces maximum score:

$$\ell(\mathbf{x}) = \operatorname*{arg\,max}_{j=n_s+1\ldots,n_s+n_u} \langle \phi(\mathbf{c}_j), \mathbf{x} \rangle \tag{1}$$

Examples from this category include:
[Elhoseiny et al., 2015, Reed et al., 2016]

Mapping to a middle Space

- In training time mappings $\theta(\mathbf{c})$ and $\phi(\mathbf{x})$ are learned.
- The mapping should map image $\mathbf{x}$ close to its true signature $\mathbf{c}$
- And with a margin from other signatures.
- In this way we expect θ and ϕ to map signature and samples of same unseen classes also close to each other.
- Space of seen classes has been a successful choice for middle space

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Semi-supervised Zero-shot Learning

- Use Unsupervised information in structure of unlabeled images.
- This information helps finding better mappings
- Semi-supervised methods can alleviate *domain shift problem* by using unlabeled samples.

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Domain shift problem

- Attributes are represented with different visual features in different classes.
- Mapping Learned on seen classes would not do as good on unseen classes.

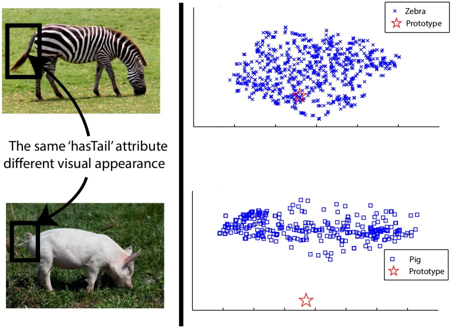

Figure: Different visual representation of attribute "has tail" [Fu et al., 2014].

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Proposed Methods

Here we present four proposed methods for the problem of zero-shot Image Classification.

In our methods we consider class signatures of type attribute vectors.

- Attribute Prediction with Multi-task Deep Neural Networks.
- Mapping to Histograms of Seen Classes with Deep Neural Network.
- Independent Embedding and Clustering
- Joint Embedding and Clustering

Multi-task Neural Network

We propose a network architecture for attribute prediction from images. The network:

- predicts for train and test images at the same time (hence multi-task).
- can mitigate the domain shift problem that appears when only samples from seen classes is used.
- uses 17 layers from famous VGG-19 network [Simonyan and Zisserman, 2014] for feature extraction.
- is trained fast using Stochastic gradient descent algorithms family.

Multi-task Neural Network

Let f denote the mapping modeled by the multi-task network.

Then $\hat{\mathbf{c}}_i = f(\mathbf{x}_i)$ would be attributes predicted by network for $\mathbf{x}_i$

We learn f such that:

$$\underset{f}{\text{minimize}} \frac{1}{N_s} \sum_{i=1}^{N_s} loss(\hat{\mathbf{c}}_i, \mathbf{c}_{y_i}) + \frac{\gamma}{N_u} \sum_{i=N_s}^{N_s+N_u} \Big(\min_{j=n_s,\ldots,n_s+n_u} loss(\hat{\mathbf{c}}_\mathbf{i}, \mathbf{c}_\mathbf{j}) \Big). \quad (2)$$

The second term enforces that prediction for test samples to be close to an unseen class signature

Therefore, mitigating domain-shift problem

Multi-task Neural Network

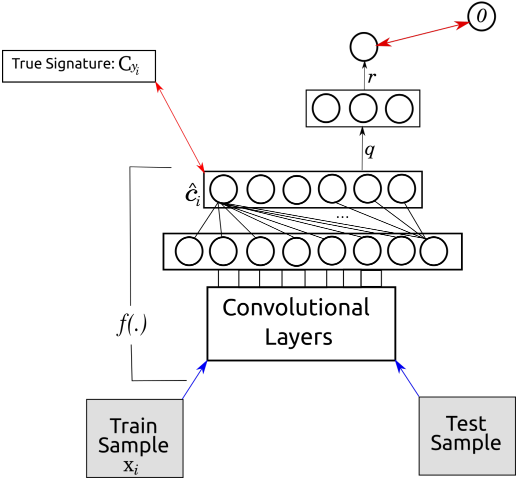


Figure: Proposed Multi-task network Architecture

Multi-task Neural Network

The second term in Eq. (2) is modeled by two layers, q and r:

$$\big(q(\mathbf{v})\big)_j = \|f(\mathbf{v}) - \mathbf{c_j}\|_2^2\,, \tag{3}$$

$$r(\mathbf{z}) = \min_{j=1\ldots n_u} (\mathbf{z})_j. \tag{4}$$

- The $j-$th element of q shows distance of prediction made by network to signature of $j-$th unseen category.
- r selects the minimum element of its input
- Hence using q and r successively produces distance of prediction to nearest unseen class signature.
- This is exactly same as the second term in Eq. (2)

Comparison with other attribute prediction methods

Table: Multi-calss accuracy in form of average $\pm$ std

method	AwA	CUB-2011	aPY	SUNA
[Jayaraman and Grauman, 2014]	43.01 ± 0.07	-	26.02 ± 0.05	56.18 ± 0.27
[Lampert et al., 2009]	41.4	-	19.1	22.2 ± 1.6
[Lampert et al., 2009]	42.2	-	16.9	18.0 ± 1.5
[Akata et al., 2013]	37.4	18.0	-	-
Baseline network (1 layer)	56.78 ± 1.29	32.60 ± 0.82	24.57 ± 1.36	58.33 ± 1.52
Baseline network (2 layer)	52.14 ± 0.31	31.65 ± 0.41	22.56 ± 1.29	62.00 ± 2.64
Multi-task network (1 layer)	$\mathbf{74.52 \pm 1.93}$	$\mathbf{33.91 \pm 0.21}$	$\mathbf{33.10 \pm 1.36}$	$\mathbf{66.13 \pm 0.50}$
Multi-task network (2 layers)	57.10 ± 0.47	31.27 ± 0.87	22.32 ± 0.48	66.83 ± 1.52

Mapping to Histogram of Seen Classes

- Motivated by good performance of methods using historgram of similarity to seen classes as semantic space [Zhang and Saligrama, 2015].
- We present a deep neural network that maps images to this space.
- This network also uses convolutional layers from VGG-19 network.
- The network is a modification of a typical CNN used in standard supervised classification problems.

Mapping to Histogram of Seen Classes

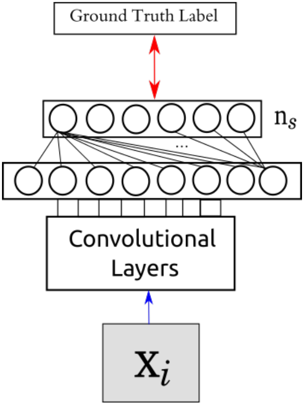


Figure: Proposed network architecture for mapping to histograms

Mapping to Histogram of Seen Classes

In Training Time:

- Labeled samples from seen classes is used.
- Activation function in last layer is softmax:

$$softmax(\mathbf{z})_j = \frac{e^{\mathbf{z}_j}}{\sum_k e^{\mathbf{z}_k}}, \quad j = 1, \ldots, n_s. \tag{5}$$

- Training criteria is correct label prediction of labeled samples.
- Let ϕ denote the mapping modeled by the network

$$\underset{\phi}{\text{minimize}} \sum_{i=1}^{N_s} \sum_{j=1}^{n_s} (\mathbf{y}i)_j \times log(\phi(\mathbf{x}_i)_j) + (1 - (\mathbf{y}i)_j) \times log(1 - \phi(\mathbf{x}_i)_j) \tag{6}$$

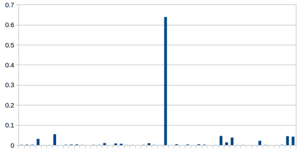
Mapping to Histogram of Seen Classes

In Test Time:

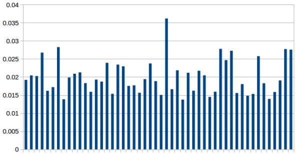
- Activation function in last layer is *temprature softmax*:

$$softmax_T(\mathbf{z})_j = \frac{e^{\mathbf{z}_j}/T}{\sum_k e^{\mathbf{z}_k}/T}, \quad T > 1, \quad j = 1, \ldots, n_s. \tag{7}$$

- The softmax layer is trained to produce distribution of true label which is a discrete delta function.
- When setting $T > 1$ the output becomes smoother.



(a) $T = 1$



(b) $T = 10$

Mapping to Histogram of Seen Classes

- Singanures are mapped to space of histogram by similarity of their signatures to signature of seen classes:

$$\theta_j(\mathbf{c}) = \frac{1}{\|\mathbf{c} - \mathbf{c_j}\|_2}, \quad j = 1, \ldots, n_s. \tag{8}$$

- finally prediction can be done using nearest neighbor (or our proposed compatibility function)

Independent Embedding and Clustering (IEaC)

Observation: There is a clustering structure in image space when features are extracted using Deep CNNs.

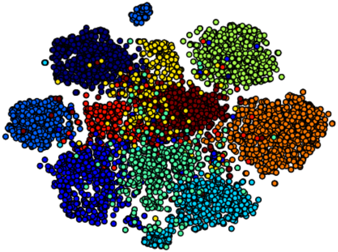


Figure: Samples of unseen classes from AwA dataset. Classes are shown in colors.

Independent Embedding and Clustering (IEaC)

Motivated by this observation we propose a novel compatibility function for zero-shot learning:

1. Cluster test samples.
2. Assign each cluster to an unseen class.
3. All items in a cluster inherit the label received by cluster

We have used two variation for the second step:

- Classify all samples and then use majority vote:
  used on output of two previous methods.
- Classify just cluster centers.
  we will present a method for this type.

Independent Embedding and Clustering (IEaC)

To assing label to cluster centers μ_k we propose:

- Embed class signatures to image space using linear mapping D from:

$$D = \underset{D}{\arg\min} \left\| X_s - DZ_s \right\|_{Fro}^2 + \alpha \left\| D \right\|_{Fro}^2 . \tag{9}$$

  X_s: matrix of train samples, Z_s true attribute vector for samples in X_s.

- Assign each μ_k to an unseen class using:

$$\ell(\boldsymbol{\mu_k}) = \underset{u=1,\dots,n_u}{\arg\min} \left\| \boldsymbol{\mu_k} - D\mathbf{c}_u \right\|_{Fro}^2 \tag{10}$$

Joint Embedding and Clustering (JEaC)

In the previous method:

- Classification Accuracy is bottlenecked by the clustering accuracy.
- Separate learning mapping and mapping prevents information flow.
- Each one is learned with a different criteria

To over come this shortcomings, we propose a *Joint Embedding and Clustering* method.

Joint Embedding and Clustering

The method is formulated as:

$$\min_{R,D} \|X_s - DZ_s\|_{Fro}^2 + \lambda \left\|X_u - DC_uR^T\right\|_{Fro}^2 + \eta \|D\|_{Fro}^2 , \qquad (11)$$
$$s.t. \quad R \in \{0,1\}^{N_u \times n_u}.$$

- The first term is same as in Eq. (9).
- The second term is essentially a clustering criteria. this will be more clear if re-written as:

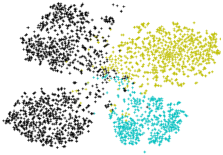
$$\sum_{n=N_s+1}^{N_s+N_u} \sum_{k=1}^{n_u} r_{nk} \|\mathbf{x_n} - D\mathbf{c_k}\|_2^2 .$$

Plan

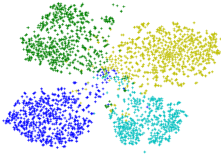
Experimental Results

method	AwA	CUB-2011	aPY	SUN
[Li and Guo, 2015]	38.2 ± 2.3	-	-	18.9 ± 2.5
[Schuurmans and Tg, 2015]	40.05 ± 2.25	-	24.71 ± 3.19	-
[Akata et al., 2015]	66.7	50.1	-	-
[Xian et al., 2016]	71.9	45.5	-	-
[Kodirov et al., 2015]	73.2	39.5	26.5	-
[Akata et al., 2015]	61.9	50.1	-	-
[Zhang and Saligrama, 2015]	76.33 ± 0.53	30.41 ± 0.20	46.23 ± 0.53	82.50 ± 1.32
[Zhang and Saligrama, 2016]	80.46 ± 0.53	42.11 ± 0.55	$\mathbf{50.35 \pm 2.97}$	$\underline{83.83 \pm 0.29}$
proposed (mapping to histograms)	76.50 ± 1.02	33.29 ± 0.21	47.46 ± 0.31	79.88 ± 0.42
proposed(IEaC - k-means)	86.34 ± 0.13	52.48 ± 0.60	48.03 ± 1.56	75.75 ± 1.06
proposed (IEaC - semisupervised)	$\underline{86.38 \pm 0.56}$	$\underline{53.10 \pm 0.43}$	48.52 ± 0.29	80.66 ± 0.76
proposed (JEaC- init D)	83.03	57.55	42.62	72.50
roposed (JEaC - init R)	$\mathbf{88.64 \pm 0.04}$	$\mathbf{58.80 \pm 0.64}$	$\underline{49.77 \pm 2.02}$	$\mathbf{86.16 \pm 0.57}$

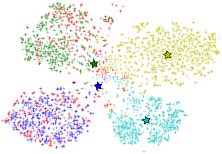
Demonstrating on Real Data



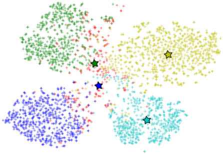
(a) seen/unseen



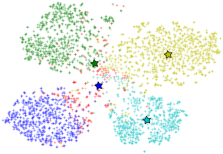
(b) ground truth



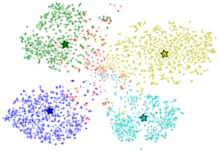
(c) nearest neighbor com-pabtibility



(d) IEaC (k-means)



(e) IEaC (semi-supervised)



(f) JEaC

Conclusion

In this presentation we:

- introduced the problem of zero-shot learning
- categorized and reviewed a selection on prior works
- proposed a Deep Neural network to predict attributes from images.
- proposed a Deep Neural network to map images to histogram of seen classes
- proposed a novel compatibility function and semi-supervised algorithm for zero-shot learning.
- used above propositions in an Independent Embedding and Clustering method
- extended our Independent Embedding and Clustering to do this steps jointly.
- Demonstrated performance of our methods through experiments.
- Discussed effect of different parts in our models by experimenting on a real dataset.

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A Sermi-Supervised Clustering Algorithm

Performance of proposed compatibility function depends on clustering.
We present a semi-supervised clustering algorithm matching assumptions of zero-shot Learning.
Formulated with an Optimization Problem:

$$\min_{R,\mu_{\mathbf{1}},\ldots,\mu_{\boldsymbol{k}}} \sum_{n=1}^{N_s+N_u} \sum_{k} r_{nk} \left\|\mathbf{x_n} - \mu_{\boldsymbol{k}}\right\|_2^2 + \beta \sum_{n=1}^{N_s} \mathbb{1}(\mathbf{r_n} \neq \mathbf{y_n}). \tag{12}$$

The first term is inherited from k-means clustering

The second term produces a penalty of β if a labeled instance from seen classes is assigned to cluster with different number.

Experimental Results for Clustering

method	AwA	CUB-2011	aPY	SUNA
k-means	65.93 ± 1.73	34.48 ± 1.00	65.37 ± 3.73	16.83 ± 0.76
Proposed semi-supervised clustering	70.74 ± 0.32	42.63 ± 0.07	69.93 ± 3.40	45.50 ± 1.32

Plug Proposed Compatibility Function to other methos

Table: Results for Multi-task Neural Network using two different compatibility functions

	AwA	CUB-2011	aPY	SUNA
Nearest Neighbor	74.52 ± 1.93	33.91 ± 0.21	33.10 ± 1.36	66.13 ± 0.50
Proposed Compatibility	74.68 ± 0.73	33.92 ± 0.07	38.26 ± 1.27	67.50 ± 0.00

Discussion

In IEaC:

- Using proposed clustering function based on clustering performs better than nearest neighbor compatibility.
- This is by taking in account the unsupervised information available in images space.

In JEaC:

- Keeps Strong points in IEaC
- Jointly learning cluster assignments and linear mapping improves results.
- Considers good clustering while learning the mapping.
- Considers proximity of cluster centers and mapping of signatures while assigning clusters.
- This mitigates Domain-shift problem