Co-Representation Network for Generalized Zero-Shot Learning

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Introduction

➢ Classic Deep CNN

➢ Transfer Learning
  • Few-Shot Learning
  • One-Shot Learning

• Zero-Shot Learning (ZSL)

Source space (Seen Classes)
Semantic space (Attributes, word2vecs)
Target space (Unseen Classes)

Predict

Data requirements decrease

Generalized ZSL (GZSL)

Conventional ZSL (CZSL)
Bias Problem

Existing Embedding Models for GZSL

• Visual Space to Semantic Space
• Visual & Semantic Space to a Latent Space
• Semantic Space to Visual Space

Bias Problem

Unseen samples are easily classified into similar seen classes.

e.g. Zebra → Horse

Average per-class top-1 accuracy in % on unseen classes of various models following CZSL settings and GZSL settings

### Our Model

#### Co-Representation Network (CRnet)

1. A cooperation module for visual feature representation (our main contribution).

2. A pre-trained CNN (Resnet-101) for feature extraction.

3. A relation module for similarity output, i.e. the classification.

Algorithm

➢ Initialization Algorithm

Perform **K-means Clustering** on the semantic space.

Semantic vectors: \( s^s_m \)

Clustering center: \( \bar{s}_k \)

Expert module \( k \):

\[
f_k(s^s_m; \bar{s}_k) = \text{relu} \left( W_k(s^s_m - \bar{s}_k) + b_k \right)
\]

➢ Cooperation Module

Sum the outputs of expert modules.

\[
f(s^s_m) = \sum_{k=1}^{K} \text{relu} \left( W_k(s^s_m - \bar{s}_k) + b_k \right)
\]
Algorithm

➢ Relation Module

Concatenate feature anchor $\tilde{v}^s_m$ (output of cooperation module) and image feature $v^s_i$ as the input.

Two-layer perceptron with Sigmoid.

Ground-truth:

$$l(v^s_i, \tilde{v}^s_m) = \begin{cases} 1, & y^s_m = y_i \\ 0, & y^s_m \neq y_i \end{cases}$$

• When the model converges, cooperation module divides the semantic space into several parts.

• Semantic vectors located in different parts are projected by several different expert modules.

➢ Training

Objective function:

$$\arg\min_{w_f, w_g} \sum_m \sum_i (g(v^s_i, \tilde{v}^s_m) - l(v^s_i, \tilde{v}^s_m))^2 + \alpha ||w_f||^2 + \beta ||w_g||^2$$

End-to-end manner.
## Benchmark Results

<table>
<thead>
<tr>
<th>Method</th>
<th>AwA1 As</th>
<th>AwA1 Au</th>
<th>AwA1 H</th>
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<td>CRNet (Ours)</td>
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<td>35.3</td>
<td>68.4</td>
<td>32.4</td>
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</tbody>
</table>
Bias Problem

Unseen anchors distribute too close to seen anchors in the embedding space used for classification.

Local Relative Distance (LRD)

We propose the LRD as a metric for bias problem.

$$e(\vec{v}_1, \vec{v}_2) = \left( \frac{\sum_{q=1}^{Q} (\vec{v}_{1q} - \vec{v}_{2q})^2}{\sigma_q^2} \right)^{\frac{1}{2}}$$

$$\text{LRD}(\vec{v}_j^u) = \frac{e(\vec{v}_j^u, \vec{v}_j^{e(j)})}{e(\vec{v}_j^{e(j)}, \vec{v}_j^{e(j)})}$$

Larger LRD means a more uniform embedding space, i.e. slighter bias problem.

1-d semantic space to 1-d visual embedding space:

$$p \left( \text{LRD}(\vec{v}_{1q}^u) > \text{LRD}(\vec{v}_{1q}^u) \right) > \frac{s^2 - s^1}{s^2 - s^1} = 0.5$$

- High local linearity results in larger LRD.
- Cooperation module actually learns a piecewise linear function of $K+1$ pieces with high local linearity.

$\mathbf{f_G}$: General fitting curve; $\mathbf{f_{CR}}$: Fitting curve of CRnet

$S$: semantic space; $V$: visual embedding space.
Contrast Experiments

➢ Relation Network (RN)

A two-layer perceptron instead of cooperation module is used.

Contrast Experiments

Results

Compared with RN, CRnet achieves:

• More Sparse and Discriminative Features

• More Uniform Embedding Space (Larger LRD)

![Figure 4. Visualization of the feature anchors of CRnet (above) and RN (below) well-trained on AwA2. The first 300 dimensions’ normalization results of the feature anchors of 40 unseen classes and 10 seen classes are presented.]

Table 3. Average LRD of all unseen class anchors for RN and CRnet on various datasets.

<table>
<thead>
<tr>
<th></th>
<th>AwA1</th>
<th>AwA2</th>
<th>CUB</th>
</tr>
</thead>
<tbody>
<tr>
<td>RN</td>
<td>0.711</td>
<td>0.756</td>
<td>0.831</td>
</tr>
<tr>
<td>CRnet</td>
<td>0.835</td>
<td>0.956</td>
<td>0.843</td>
</tr>
</tbody>
</table>

![Figure. Bar chart of per-class Bias Rate and per-class Error Rate of RN and CRnet on AwA2. Bias Rate: The rate in % of misclassification into the closest seen class; Error Rate: Per-class classification Error Rate in %.]

• Slighter Bias Problem
Co-representation network

- Decomposition method for projecting semantic space to visual embedding space.
- Cooperation module for representation and learnable relation module for classification.

✓ Training in an end-to-end manner.

✓ Slighter bias problem leads to a good performance on GZSL.

Other advantages:

✓ Simple structure with high expandability.

✓ No need for semantic information of unseen classes during training (compared with generative models)

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