Open Set Domain Recognition via Attention-Based GCN and Semantic Matching Optimization

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Layout

- Background
- Related Works
- Method
- Experiments
- Conclusions
Background

“Awkward Situation” of Deep Learning

The process of data annotation is time-consuming, laborious and biased

The generalization ability of the model is disappointing

Humans Can Learn New Concepts Quickly

Okapi: with zebra stripe, four legs, face like deer

It is Okapi!
**Background**

**Open Set Domain Recognition**

- **Task**: Specifically classify each sample in the practical unlabeled target domain, which consists of all known classes in the simulative labeled source domain and target-specific unknown categories.

- **Motivation**: Considering that the domain discrepancy between the target domain and the source domain has restricted the ability to generalize of current approaches which may transfer biased classification rules from known to unknown categories.

**Application Fields**

- Autonomous Reconnaissance
- Intelligent Service
- Automatic Driving
Related Works

Identification of Unknown Classes

Based on Metric Learning
- RRHZ [Shigeto et al., ICML2015]
- LAD [Zhang et al., CVPR2017]
- PSE [Changoinyo et al., ICCV2017]

Based on Compatibility Learning
- AESA [Romeraparedes et al., ICML2015]
- LEIC [Akata et al., PAMI2016]
- LCRN [Sung et al., CVPR2018]

Based on Generation Model
- AGAZ [Zhu et al., CVPR2018]
- FGN [Xian et al., CVPR2018]
- JAZRLK [Qin et al., AAAI2020]
Related Works

Reduce Domain Discrepancy

Based on Non-Adversarial Methods
DDC [Tzeng et al., arXiv2014]
SVDA [French et al., ICLR2018]
CAN [Kang et al., CVPR2019]

Based on Generative Adversarial Networks
ADDA [Tzeng et al., CVPR2018]
STA [Liu et al., CVPR2019]
AADA [Su et al., CVPR2020]

ADDA [Tzeng et al., CVPR2018]
KASE [Qing et al., arXiv2019]
Related Works

Existing Issues on Open Set Domain Recognition

- Ignore the effect of category similarity on knowledge transfer
- Various unknown classes distract the domain invariant feature learning
Method

Network Architecture

Source Domain
- Known Class
- Unknown Class
- Data Path
- CNN
- Supervision

Target Domain
- Additional Classes to Construct Full Path
- Word Vectors

Backbone Classification Network
- Joint Training

Attention-based GCN
- $h'_1 = H \ast W$

Semantic Matching Optimization
- Correct Pairs
- Noisy Pairs
- Labeled Source
- Unlabeled Target

Predict
- Rabbit
- Sheep
- Tiger

OPTIMAL, Xi’an, China
Method

Attention-based GCN for Knowledge Propagation

We first build a graph with \( n \) nodes where each node represents a distinct class. Attention mechanism is performed on these nodes. The attention coefficient is computed as

\[
\hat{\alpha}_{i,j} = f_a(W \times h_i, W \times h_j).
\]

After obtaining attention coefficient, the final output features of every node is expressed as

\[
\mathbf{z}_i = \sum_{j \in n_i} \hat{\alpha}_{ij} \times W \times h_j.
\]

By minimizing the loss from the \( m \) classes with abundant supervision to estimate the network parameter for the attention-based GCN. The loss is

\[
L_{init} = \frac{1}{m} \sum_{i=1}^{m} (z_i - w_i)^2.
\]
Method

Semantic Matching Optimization

For each sample in the target domain, the feature distance is calculated between it and each sample in the source domain. Then the source sample with the minimum distance is selected as its optimal pair. Semantic consistency is utilized to filter out such noisy matching. The filter function is

\[ I = \begin{cases} 
1, & d(p^s_i, p^t_i) < \tau, \\
0, & \text{else.} 
\end{cases} \]

After filtering out the noisy matching, the domain discrepancy loss can be measured as

\[ L_d = \sum_i d(f^s_i, f^t_i) \times I. \]
Experiments

Experimental Settings

<table>
<thead>
<tr>
<th>Datasets</th>
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<th>I2AwA_2</th>
<th>I2CIFAR</th>
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Evaluation Criteria

- Top1 Classification Accuracy of Known Categories
- Top1 Classification Accuracy of Unknown Categories
- Top1 Classification Accuracy of All Categories

Several Images of I2AwA Dataset

Source Domain

Target Domain
## Experiments

### Experimental Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>I2AwA_1</th>
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Conclusions

Attention-based GCN can effectively improve the unknown classes to learn more discriminating feature representations and further obtain more accurate visual classifier.

Make full use of category similarity on knowledge transfer.

Semantic matching optimization can achieve good performance on domain invariant feature learning in the presence of distractions from various unknown categories.

Minish the domain gap measured on the optimal matching pair.
Thanks!

Q&A

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