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

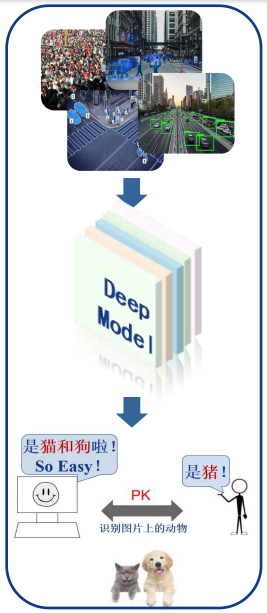
Xinxing He, Yuan Yuan, Zhiyu Jiang*
School of Computer Science and Center for OPTical IMagery Analysis and Learning (OPTIMAL),
Northwestern Polytechnical University, Xi'an, Shaanxi, P.R. China

Layout

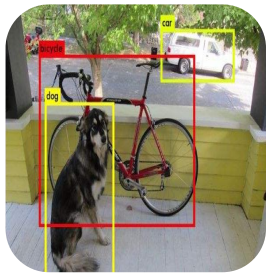
- Background
- Related Works
- Method
- Experiments
- Conclusions

Background

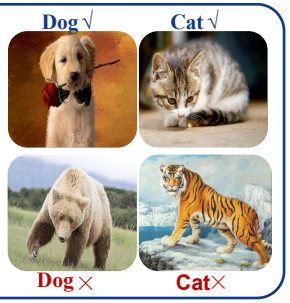
"Awkward Situation" of Deep Learning



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



The generalization ability of the model is disappointing

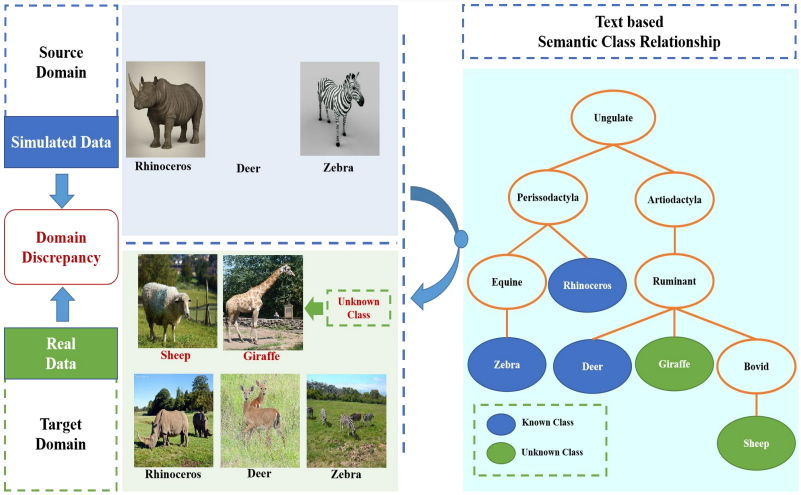


Humans Can Learn New Concepts Quickly

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

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

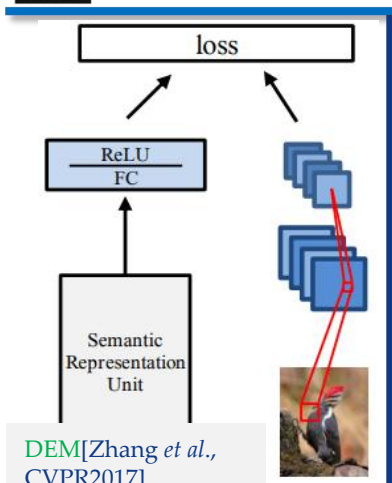
Autonomous Reconnaissance

Intelligent Service

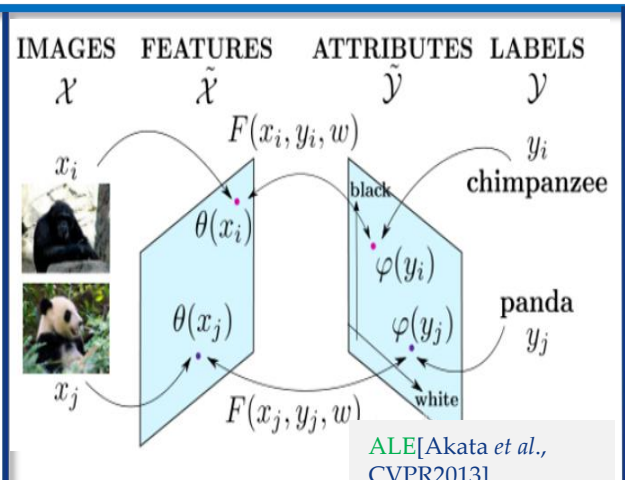
Automatic Driving

Related Works

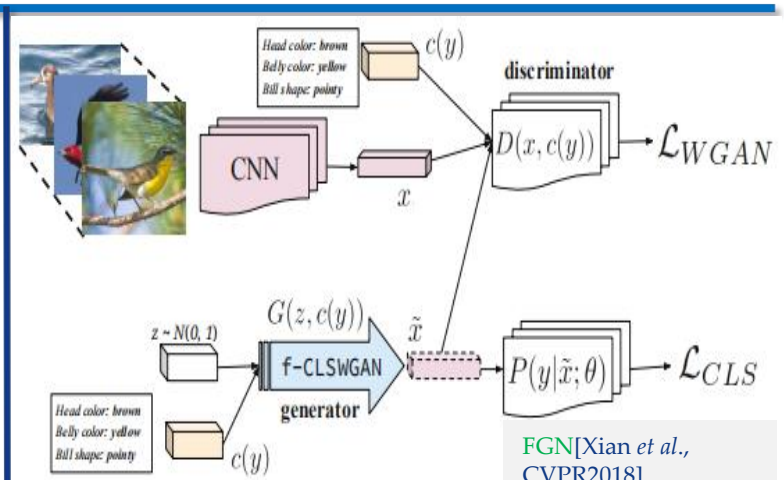
Identification of Unknown Classes



DEM[Zhang *et al.*, CVPR2017]



ALE[Akata *et al.*, CVPR2013]



FGN[Xian *et al.*, CVPR2018]

AESA[Romeraparedes *et al.*, ICML2015]
LEIC[Akata *et al.*, PAMI2016]
LCRN[Sung *et al.*, CVPR2018]
• • •

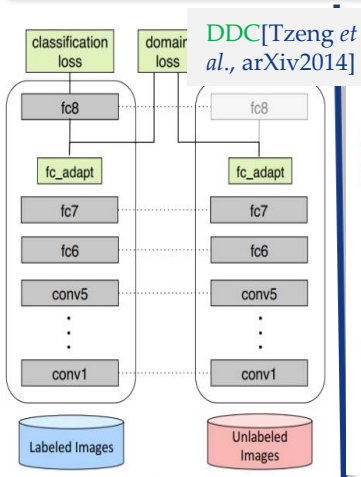
Based on Metric Learning → **Based on Compatibility Learning** → **Based on Generation Model**

RRHZ[Shigeto *et al.*, ICML2015]
LAD[Zhang *et al.*, CVPR2017]
PSE[Changoinyo *et al.*, ICCV2017]
• • •

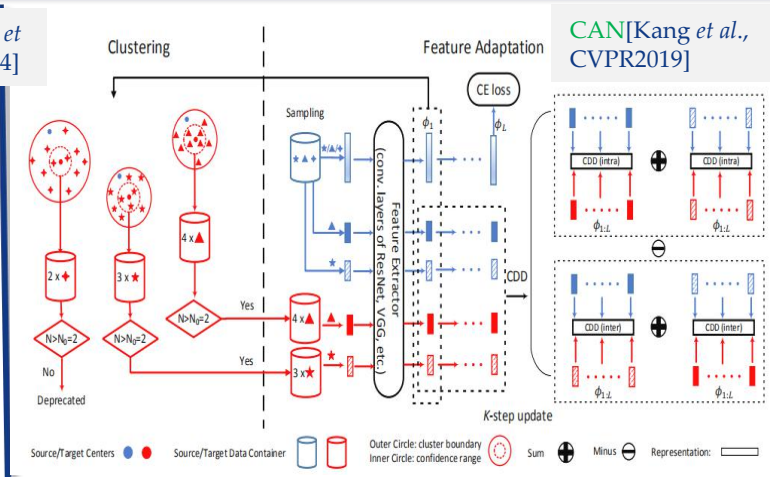
AGAZ[Zhu *et al.*, CVPR2018]
FGN[Xian *et al.*, CVPR2018]
JAZRLK[Qin *et al.*, AAAI2020]
• • •

Related Works

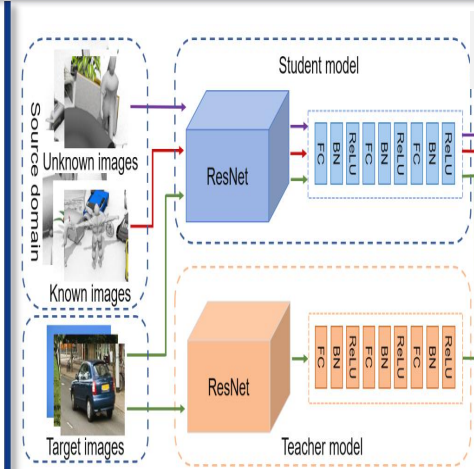
Reduce Domain Discrepancy



DDC[Tzeng *et al.*, arXiv2014]



CAN[Kang *et al.*, CVPR2019]



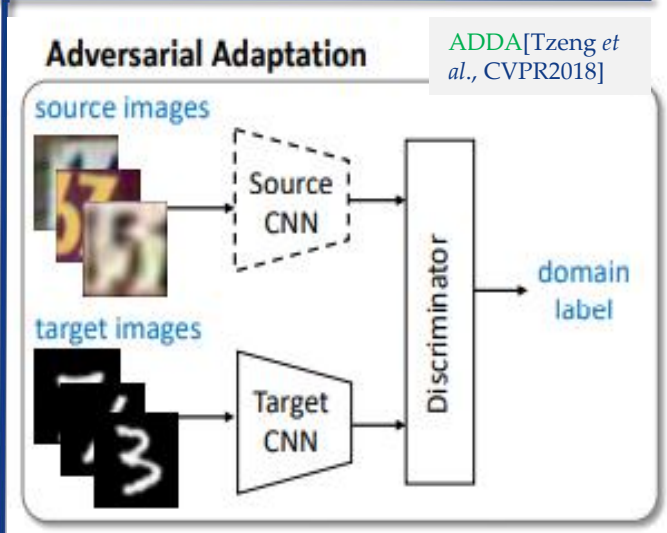
KASE[Qing *et al.*, arXiv2019]

ADDA[Tzeng *et al.*, CVPR2018]
STA[Liu *et al.*, CVPR2019]
AADA[Su *et al.*, CVPR2020]
• • •

Based on Non-Adversarial Methods

Based on Generative Adversarial Networks

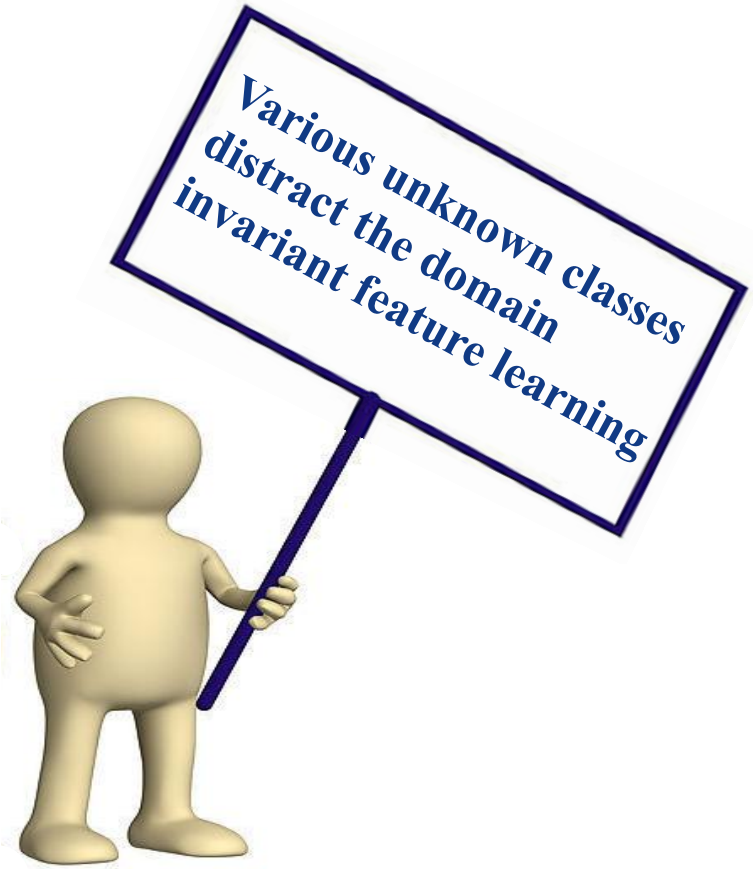
DDC[Tzeng *et al.*, arXiv2014]
SVDA[French *et al.*, ICLR2018]
CAN[Kang *et al.*, CVPR2019]
• • •



ADDA[Tzeng *et al.*, CVPR2018]

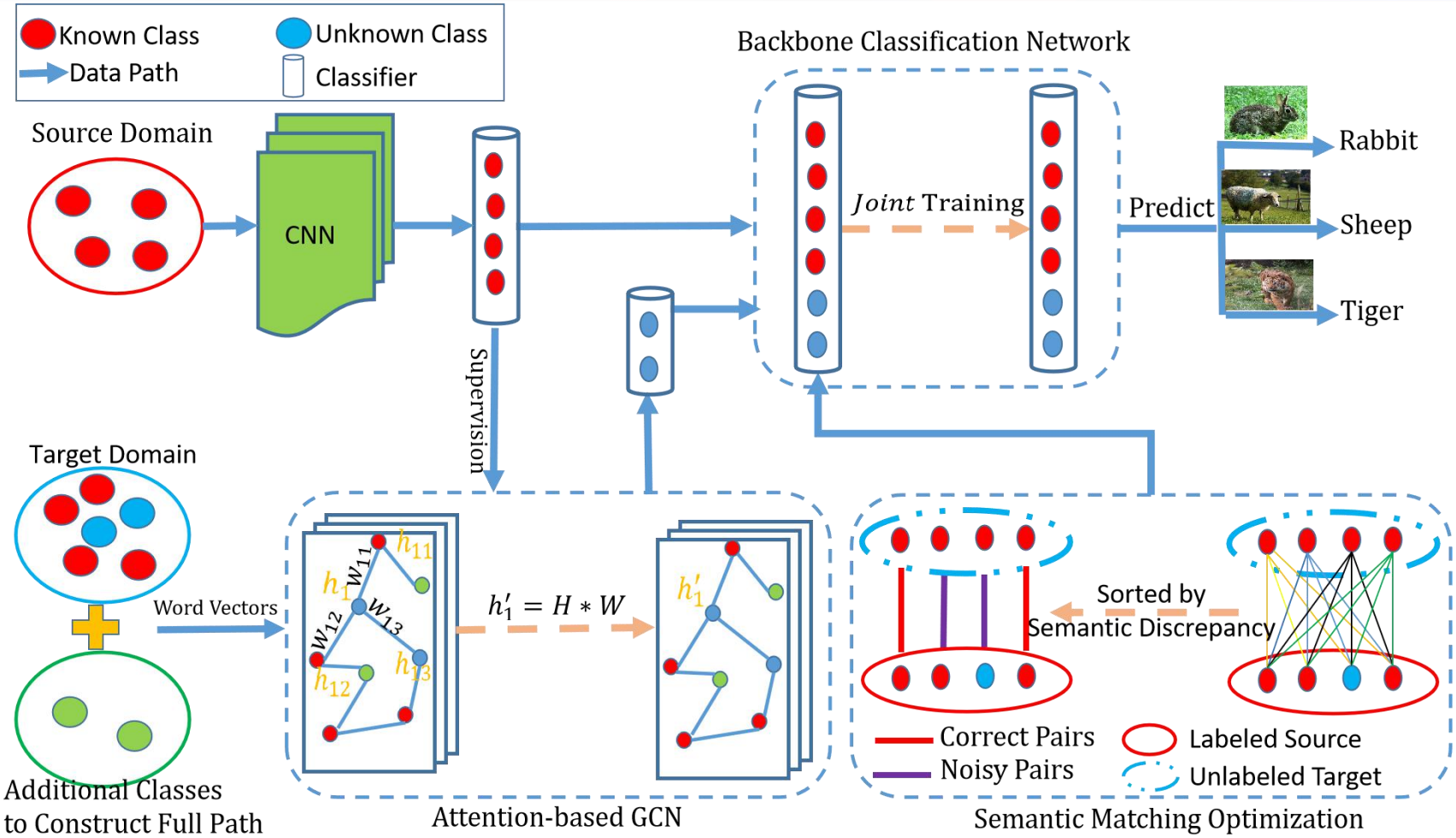
Related Works

Existing Issues on Open Set Domain Recognition



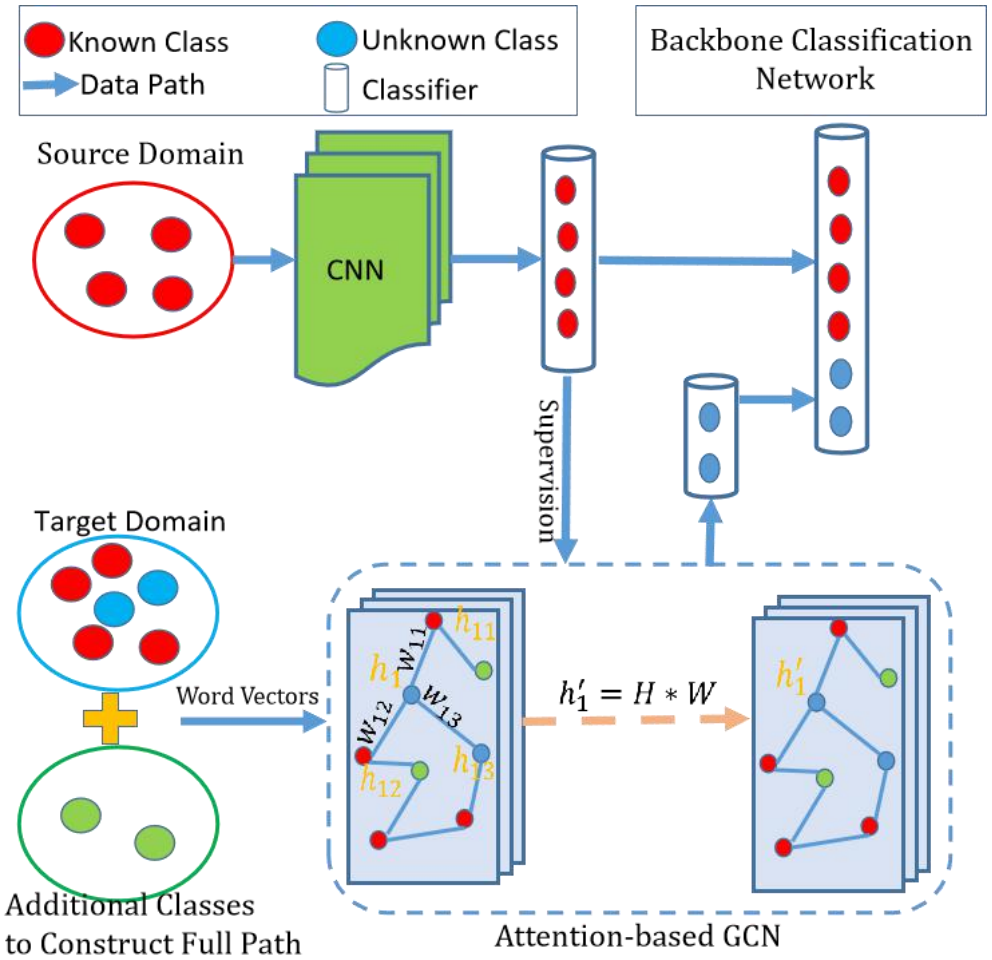
Method

Network Architecture



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

$$\partial_{i,j} = f_a(W \times h_i, W \times h_j).$$

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

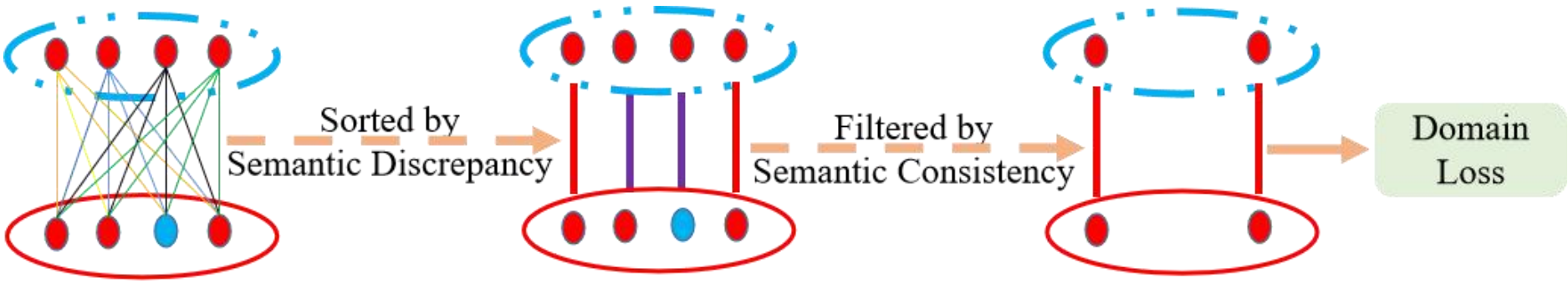
$$z_i = \sum_{j \in n_i} \partial_{ij} \times W \times h_j.$$

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 filiter function is

$$\mathrm{I} = \begin{cases} 1, & d(p_i^s, p_i^t) < \tau, \\ 0, & else. \end{cases}$$

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

$$\mathrm{L_d} = \sum_i d(f_i^s, f_i^t) \times I.$$

Experiments

Experimental Settings

Datasets

		I2AwA_1	I2AwA_2	I2CIFAR
Source Domain	Classes	40	30	15
	Images	2970	1894	1130
Target Domain	Classes	50	50	45
	Images	37322	37322	22500

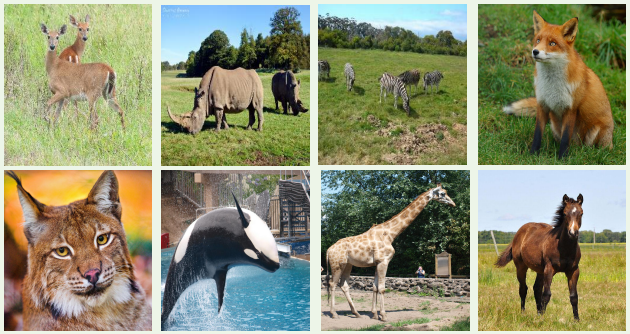
Evaluation Criteria

- 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

Dataset	I2AwA_1			I2AwA_2			I2CIFAR		
Method	Known	Unknown	All	Known	Unknown	All	Known	Unknown	All
zGCN	77.2	21.0	65.0	69.7	13.2	45.3	50.1	5.6	21.7
dGCN	78.2	11.6	64.0	74.3	4.3	43.9	59.9	3.1	22.1
adGCN	77.3	15.0	64.1	71.9	7.1	43.8	59.3	4.2	22.6
bGCN	84.6	28.0	72.6	77.8	19.7	52.6	65.3	9.3	27.9
pmd-bGCN	84.7	27.1	72.5	79.6	19.9	53.7	63.9	11.8	29.2
UODTN	84.7	31.7	73.5	77.9	24.1	54.5	64.2	13.6	30.4
AGCN-SMO	85.1	34.3	74.3	79.7	27.4	56.7	65.1	15.7	32.1

Conclusions

01

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.

02

Thanks!
Q&A

Xinxing He
Email: hexinxing0906@163.com

2021-01-13