Source-free Domain Adaptation for Aspect-based Sentiment Analysis

Zishuo Zhao, Ziyang Ma, , Zhenzhou Lin, Jingyou Xie, Yinghui Li, Ying Shen
School of Intelligent Systems Engineering, Sun Yat-Sen University
Tsinghua Shenzhen International Graduate School, Tsinghua University

Motivations

Unsupervised Domain Adaptation (UDA) task aims to transfer knowledge learned from labeled source domain datasets to unlabeled target domains on the assumption that samples from the source domain are freely accessible during the training period. However, this assumption can easily lead to privacy invasion issues in real-world applications, especially when the source data involves privacy-preserving domains such as healthcare and finance.

Contribution

(1)To the best of our knowledge, we are the first to explore domain adaptation for the ABSA task without access to source domain data.

(2)We propose the SFABSA framework, encompassing both feature-based adaptation and pseudo-label-based adaptation.

(3)Experimental results show that our framework achieves competitive results compared to the state-of-the-art results.

Method

In transfer learning, SF-ABSA aims to transfer knowledge learned from labeled source domain datasets to unlabeled target domains with privacy protection

Feature-Based Domain Adaptation：

Feature extraction：

extract the characteristics of their head entities and tail entities.

$$h_i^{head} = \tanh(W_1 h_i + b_1),$$

$$h_i^{tail} = \tanh(W_2 h_i + b_2),$$

Then the model predict their dependencies :

$$m_{ij} = [h_i^{head}; h_j^{tail}; h_i^{head} - h_j^{tail}; h_i^{head} \cdot h_j^{tail}],$$

$$p_{ij}^{dep} = softmax(W_{dep} m_{ij} + b_{dep}),$$

Dependency Relation Prediction：

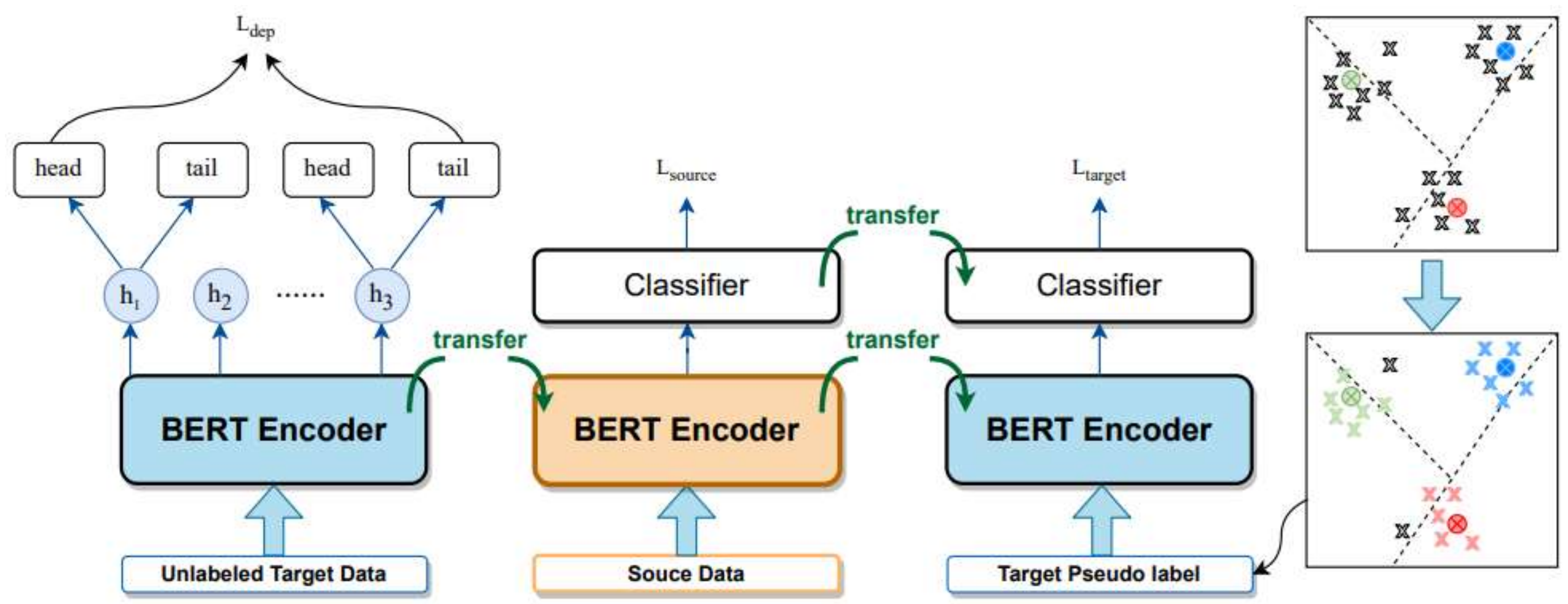
using MLM task, we make the model embed the target domain feature space

$$L_{dep} = \sum_{X^t} \sum_i^T \sum_j^T \mathbb{I}(ij)\, CrossEntropy\left(p_{ij}^{dep}, y_{ij}^{dep}\right),$$

Source Model Generation：

Then we train the model on the source domain data by minimizing the cross entropy.

$$L_{source} = CrossEntropy\left(M_0(x_s), y^{label}\right)$$



Domain Adaptation with Self-supervised Pseudo-labeling：

First, predict the data of the target domain based on the source model:

$$y^t = argmax(\delta_k(M_s(x_t))),$$

Based on the predicted labels, calculate the center point of the category, then using the allocated pseudo labels, recalculate the center point and iterate through the loop:

$$A_k^{(m)} = \frac{\sum_{x_t \in X_t} \mathbb{I}(\hat{y}^t = k) * F_s(x_t)}{\sum_{x_t \in X_t} 1(\hat{y}^t = k)}, \quad A_k^{(0)} = \frac{\sum_{x_t \in X_t} \delta_k(M_s(x_t)) * F_s(x_t)}{\sum_{x_t \in X_t} \delta_k(M_s(x_t))},$$

$$\hat{y}^t = arg\min_k Dist(A_k^{(m)}, F_s(x_t)), \quad \hat{y}^t = arg\min_k Dist(A_k^{(0)}, F_s(x_t)),$$

Experiments

Method Comparison

Comparison results of different methods for Cross-Domain End-to-End ABSA based on Micro-F1.The table consists of three parts: (1) Source-Only; (2) Source-Required; (3) Source-Free

Methods	R→S	L→S	D→S	S→R	L→R	D→R	S→L	R→D	AVG
Source-Only									
BERT-Base (Devlin et al., 2018)	19.48	25.78	30.31	42.2	40.38	30.06	29.20	29.47	30.36
Source-Required									
Hier-Joint (Ding et al., 2017)	15.56	13.90	19.04	31.10	33.54	32.87	22.65	24.53	23.71
RNSCN (Wang et al., 2018)	20.04	16.59	20.03	33.21	35.65	34.60	18.87	33.26	26.09
AD-SAL (Li et al., 2019a)	28.01	27.20	26.62	41.03	43.04	41.01	27.04	35.44	33.71
BERT-DANN (Gong et al., 2020)	21.60	25.10	18.62	45.84	41.73	34.68	30.47	34.41	30.83
BERT-UDA (Gong et al., 2020)	33.12	27.89	28.03	47.09	45.46	42.68	**34.77**	34.93	35.98
CDRG (Indep) (Yu et al., 2021)	34.10	33.97	31.08	44.46	44.96	39.42	26.81	25.25	34.27
CDRG (Merge) (Yu et al., 2021)	35.14	**38.14**	37.22	47.92	**49.79**	**47.64**	33.69	27.46	**38.98**
Source-Free									
SF-ABSA (Feature-based only)	26.44	26.05	31.83	**48.78**	40.72	41.16	34.33	**36.64**	35.87
SF-ABSA (All)	**35.67**	29.62	**45.93**	44.62	44.23	35.43	34.01	28.56	37.14

Methods	R→S	L→S	D→S
Source-Required			
BERT-DANN (Gong et al., 2020)	21.60	25.10	18.62
BERT-UDA (Gong et al., 2020)	33.12	27.89	28.03
CDRG (Yu et al., 2021)	35.14	**38.14**	37.22
GCDDA (Li et al., 2022)	32.07	27.22	28.52
Source-Free			
SF-ABSA(our)	**35.67**	29.62	**45.93**

When the target domain is the Service domain dataset, the pseudo-label based approach has a significant effect on performance improvement, as shown in the Table.

Experiments Analysis

SHOT is a method in the field of computer vision, but it has a strong generalization ability and can be generalized to our ABSA task for comparison. m represents the number of times to iteratively calculate the category center.

Methods	BERT-Base	SHOT	SF-ABSA
R→S	42.2	26.52	**35.67**
L→S	20.99	17.00	**29.62**
D→S	13.64	10.45	**45.93**
S→R	42.2	37.95	**44.62**
L→R	39.14	33.57	**44.45**
D→R	30.06	26.94	**35.43**

Domain	m=1	m=2	m=3
R→S	**35.67**	31.61	30.72
L→S	**29.62**	25.12	25.68
D→S	**45.93**	41.98	40.56
S→R	**44.62**	41.79	41.32
L→R	**44.45**	42.54	40.19
D→R	**35.43**	32.15	31.08

Conclusions

In this paper, we explore the ABSA task of source-free unsupervised domain adaptation. We propose a joint framework of feature-based methods and pseudo-labeling methods. Our framework achieves comparable performance to conventional unsupervised domain adaptation methods under the premise of insufficient information and without access to source domain data. This demonstrates the superiority of our method under the source-free setting.