Enhance Cross-Domain Aspect-Based Sentiment Analysis by Incorporating Commonsense Relational Structure (Student Abstract)

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Figure 1: An example of providing the domain-shared commonsense relational structure for cross-domain ABSA.

Abstract

Aspect Based Sentiment Analysis (ABSA) aims to extract aspect terms and identify the sentiment polarities towards each extracted aspect term. Currently, syntactic information is seen as the bridge for the domain adaptation and achieves remarkable performance. However, the transferable syntactic knowledge is complex and diverse, which causes the transfer error problem in domain adaptation. In our paper, we propose a domain-shared relational structure incorporated cross-domain ABSA model. The experimental results show the effectiveness of our model.

Introduction

Aspect Based Sentiment Analysis (ABSA) aims to extract the aspect terms and predict the sentiment polarities of the extracted aspect terms. However, the performance of supervised models highly rely on large-scale labeled data. Thus, cross-domain ABSA, which aims to transfer knowledge from a rich labeled source domain to an unlabeled target domain, becomes a promising direction.

The main challenge for the cross-domain ABSA is the domain disparity since the aspect terms in different domains are almost disjoint. Facing this challenge, current methods (Gong, Yu, and Xia 2020) focus on extracting the domain-shared syntactic information to bridge the gap between domains. For example, the two cases: "*Great* **pizza** *for lunch place*" in *Restaurant* domain and "*The laptop has a* *nice* *screen*" in *Laptop* domain have the similar syntactic expression (i.e., "*great pizza*" and "*nice screen*") and share the syntactic pattern "*opinion terms*→*amod*→*aspect terms*". However, these domain-shared syntactic patterns lack of generalization and even cause the syntactic transfer error, since the language morphology and syntax are complex and diverse across domains. For instance, the case "*Windows being the* *main* **issue**" in *Laptop* domain also have the same syntactic pattern (i.e.,"*main*→*amod*→**issue**") and thus the 'issue' is wrongly recognized as the aspect term in Laptop domain for the current methods which rely on syntactic information.

To solve the syntactic transfer error problem, we propose a commonsense knowledge aware cross-domain ABSA
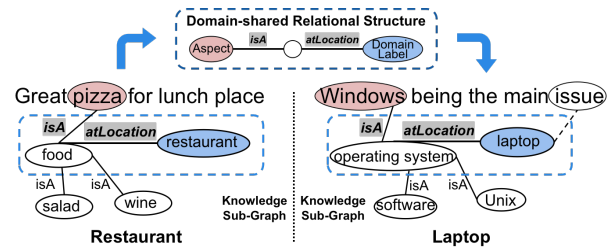
model. Augmenting neural model with external knowledge base (KB) has shown effectiveness in the coarse-grained sentiment analysis (Ghosal et al. 2020), but few efforts focus on the cross-domain ABSA using KBs. Though the aspect terms vary a lot across domains, the commonsense knowledge graph (e.g., *ConceptNet (Speer, Chin, and Havasi 2017)* can provide the domain-shared commonsense relational structure to bridge the gap between domains for the cross-domain aspect detection. As depicted in Figure 1, the aspects "*pizza*" and "*windows*" respectively link to a knowledge sub-graph which extracted from the *ConceptNet*. As we can observe, they share the same relational structure (i.e., "*IsA*"→"*AtLocation*") to the domain-label concept (i.e., "*restaurant*" or "*laptop*"). Instead, the term "*issue*" does not link the domain-label concept in the knowledge graph. Therefore, the domain-share relational structure information is beneficial to domain adaptation in cross domain ABSA.

Methodology

We propose a domain-shared relational structure incorporated cross-domain ABSA model (RSKGM). Our proposed model contains three parts.

Domain-shared Relational Structure Learning To capture the domain-shared relational structure features, each token (e.g., "*pizza*" and "*windows*" shown in Figure 1) of the unlabeled reviews is utilized to construct a knowledge sub-graph and then the graph autoencoder is trained based on the constructed graph to obtain the representation of each token. Specifically, given the token t of the sentence re-

view and the corresponding domain label (e.g., "*restaurant*" in Restaurant domain), the knowledge sub-graph G_t is extracted by collecting the knowledge paths between the token t and domain-label with less than n-hops in *ConceptNet* (e.g., "$pizza_{\{token\}} \rightarrow food \rightarrow restaurant_{\{domain\text{-}label\}}$ with 2 hops"). Therefore, each sentence review will be constructed as a knowledge graph G_s by combining multiple G_t. Moreover, the dependency relations between the terms in the sentence are also added into the graph G_s. Then, the graph autoencoder using the graph convolution network (GCN) is trained by giving the knowledge graph G_s for per unlabeled review in both source and target domains, aiming to capture the relational structure features by convolving the features of neighboring nodes.

$$\boldsymbol{o}_t^{l+1} = ReLU(\sum_{g \in N(t)} (W^l \boldsymbol{o}_g^l + b^l)) \qquad (1)$$

where $N(t)$ represents the neighborhood node of the token t; $\boldsymbol{o}_g^l$ denotes the hidden feature of node g at layer l; W^l and b^l are the learnable parameters. With the representation of nodes in G_s, the self-supervised relation classification task is conducted to optimize the graph autoencoder.

Syntactic Knowledge Learning   To learn the domain-shared syntactic knowledge, the BERT encoder (Gong, Yu, and Xia 2020) is introduced to obtain the representation of tokens. which is pre-trained with part-of-speech information and dependency relations of large-scale unlabeled reviews.

Features Fusion and Classification   Each token t in instance x is encoded by GCN encoder and BERT encoder to respectively obtain the concept-level commonsense features representation t_c and world-level syntactic feature representation t_s. Thus, the word representation $\boldsymbol{v}_t$ is obtained by concatenating t_c and t_s. Finally, the probability $\boldsymbol{p}_t$ of each token t belonging to unified tags can be measured by the full-connceted and softmax layer.

Experiments

Dataset   The dataset is taken from the Four Benchmark Datasets (Gong, Yu, and Xia 2020), namely Laptop(L), Restaurant(R), Device(D), Service(S).

Experimental Results   The evaluation results are obtained based on the test data from the target domain. Table 1 shows the comparison results of Average Micro-F1 score of 10 transfer cross-domain tasks in AE and ASBA with other baselines. With the domain-shared relational structure learning module, our model (i.e., RSKGM$_B$) almost outperforms all other baselines in terms of AE and ABSA. We analyse that our model effectively captures the domain-shared structural relation knowledge, which benefits extracting the aspect and predicting the sentiment polarity precisely. With the extended BERT$_E$, our model further boosts the average performance, which demonstrates our proposed model can effectively solve the syntactic transfer error problem.

Conclusion

In this paper, we propose a unified model for incorporating the commonsense relational structure and syntactic knowl-

Models	Avg	
	AE	ABSA
Hier-Joint(Ding, Yu, and Jiang 2017)	35.66	23.72
RNSCN(Wang and Pan 2018)	40.84	26.09
AD-SAL (Li et al. 2019)	43.91	33.71
BERT$_B$-UDA(Gong, Yu, and Xia 2020)	42.97	35.98
BERT$_E$-UDA	45.53	40.63
AHF (Zhou et al. 2021)	-	37.67
CDRG$_B$-Merge(Yu, Gong, and Xia 2021)	45.60	38.98
CDRG$_E$-Merge	50.00	43.46
RSKGM$_B$(Ours)	48.03	38.88
RSKGM$_E$(Ours)	**51.01**	**44.09**

Table 1: Comparison results for cross-domain Aspect Extraction (AE) and End2End ABSA based on Average Micro F1 of ten transfer pairs. $[X]_B$ adopts the uncased BERT$_{base}$ model pre-trained while $[X]_E$ adopts the BERT$_B$ pre-trained on large-scale product reviews.

edge. The domain-shared relational structure can be effectively utilized and alleviate the recognition error problem. Experimental results show that our method can effectively identify aspect terms and their sentiment polarities.

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