Aspect-Opinion Sentiment Alignment for Cross-Domain Sentiment Analysis (Student Abstract)

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Abstract

Cross-domain sentiment analysis (SA) has recently attracted significant attention, which can effectively alleviate the problem of lacking large-scale labeled data for deep neural network based methods. However, exiting unsupervised cross-domain SA models ignore the relation between the aspect and opinion, which suffer from the sentiment transfer error problem. To solve this problem, we propose an aspect-opinion sentiment alignment SA model and extensive experiments are conducted to evaluate the effectiveness of our model.

Introduction

Sentiment analysis (SA) is a task of automatically assigning sentiment polarity to the text data like movie reviews. Currently, deep neural network based SA models achieve remarkable performance, nevertheless suffer from the lack of large-scale labeled data. To alleviate this problem, the task of cross-domain SA recently extracts significant attention, which transfers the knowledge from the label-rich source domain to the label-scarce target domain.

The main challenge of the cross-domain SA is the discrepancy between the source and target domains (e.g., the different expressions of users' emotion across domains). Facing this challenge, many studies (Ghosal et al. 2020) are proposed to extract the domain-invariant features (e.g., the opinion terms '*great*' and '*fast*' which are shared across domains, as shown in Figure 1). They are often based on the key assumption that the domain-invariant features also share the same sentiment polarities in both source and target domains. However, it is often violated in many realistic scenarios and causes the sentiment transfer error. For instance shown in Figure 1, the opinion term '*fast*' expresses negative sentiment when describing the aspect term '*batteries*' in *Electronic* domain, while is positive sentiment for the aspect term '*machine*' in *Kitchen* domain. The sentiment polarity of '*fast*' relies on its described aspects and wrongly transferred into *Kitchen* domains. Therefore, the sentiment of domain-invariant opinion features not only depend on the domain they are in but also depend on the aspects they describe.

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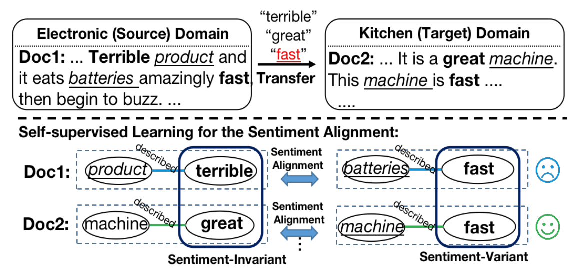

Figure 1: An example for Aspect-Opinion Sentiment alignment Cross-domain Document-level Sentiment Analysis

According to our observation, the aspect-opinion pairs in a document-level review almost share the sentiment polarity, as shown in Figure 1. The sentiment of aspect-opinion pair (e.g., "*fast*↔*battery*") can be derived by its contextual aspect-opinion pairs (e.g., "*terrible*↔*product*" in Figure 1). Based on this observation, the sentiment transfer errors can be corrected by learning the sentiment alignment relationship among the aspect-opinion pairs. For example shown in Figure 1, existing methods assume that the domain-invariant features (i.e., "*fast*") share the sentiment polarities across domains and the aspect-opinion pair "*fast*↔*machine*" is wrongly transferred as negative sentiment in target domain. Leveraging the sentiment alignment features among aspect-opinion pairs (e.g., the two aspect-opinion pairs "*great*↔*machine*" and "*fast*↔*machine*" share the sentiment polarity), the aspect-opinion pair "*fast*↔*machine*" can be corrected as positive sentiment according to its sentiment-aligned pairs "*great*↔*machine*" which is sentiment-invariant across domains. Therefore, to solve the sentiment transfer error problem, we propose a self-supervised sentiment alignment learning model which effectively captures the sentiment alignment features among aspect-opinion pairs.

Methodology

We propose an aspect-opinion sentiment alignment cross-domain SA model (AOAKM) containing three parts.

Model	Average-ACC
ACAN (Qu et al. 2019)	85.2
IATN (Zhang et al. 2019)	85.8
HATN-BERT (Li et al. 2018)	88.7
CoCMD (Peng et al. 2018)	82.4
KinGDOM (Ghosal et al. 2020)	84.0
BERT-DAAT (Du et al. 2020)	90.1
SENTIX (Zhou et al. 2020)	92.7
AOAKM	**93.7**

Table 1: Average accuracy (%) of comparison with current cross-domain SA models on the amazon-reviews dataset.

Aspect-Opinion Aware Graph Feature Learning

Knowledge Graph Constructon Inspired by the effectiveness of the knowledge-guided cross-domain SA (Ghosal et al. 2020), the aspect-opinion aware knowledge graph is constructed based on the *ConceptNet* for each domain. Specifically, for each review of the large-scale unlabeled data in each domain, the unique words belonging to *nouns*, *adjectives* and *adverbs* are extracted as the seeds concepts. Moreover, the *nouns* (or *adverbs*) and the *adjectives* concepts are connected as '*described*' relations if their dependency syntactic relation is "*nsubj*", "*amod*" or "*xcomp*", as shown in Figure 1. Finally, the seed concepts are used to filter the *ConceptNet* and create a sub-graph $G = (V, \Phi, R)$.

Graph Pre-training Two self-supervised tasks (i.e., relation classification task and sentiment alignment classification task) are designed to train the GCN-autoencoder, aiming to learn the background commonsense and the sentiment alignment features of the aspect-opinion pairs. Specifically, the relation classification task is designed with the negative sampling strategy, following Ghosal et al. 2020. Moreover, as shown in Figure 1, the aspect-opinion pairs in the same document review share the same sentiment information. Based on this observation, the sentiment alignment binary classification task is proposed to learn the sentiment alignment feature among aspect-opinion pairs. More specifically, given two aspect-opinion pairs (whose relations is "*described*"), a binary classification is performed to detect whether they have the same sentiment polarity (i.e., detect whether they are from the same document reviews). The R-GCN encoder is trained with the two cross-entropy losses:

$$\begin{aligned}\pounds_G = -\frac{1}{|T|} \sum_{(v_i, r_{i,j}, v_j, y) \in T} & (y \log s(v_i, r_{i,j}, v_j) + \\ & (1-y) \log(1 - s(v_i, r_{i,j}, v_j)))\end{aligned} \tag{1}$$

, where the triplets $(v_i, r_{i,j}, v_j) \in T$, $y \in \{0, 1\}$ and $s(v_i, r_{i,j}, v_j)$ denotes score function.

Sentence Encoder and Classifier

Given an instance x_q, the representation $\boldsymbol{x}_q$ is obtained by concatenating $\boldsymbol{x}_g$ and $\boldsymbol{x}_w$, where $\boldsymbol{x}_g$ and $\boldsymbol{x}_w$ are respectively obtained by R-GCN encoder and the pre-trained BERT encoder (Zhou et al. 2020). Finally, the probability of query instance q belonging to sentiment polarity category $c_i \in C$ can be measured by the fully-connected and softmax layer.

Experiment

Dataset We conduct experiments on the Amazon-reviews benchmark dataset (Ghosal et al. 2020) which ranges across four domains: Books (B), DVDs (D), Electronics (E), and Kitchen appliances (K). Thus, 12 cross-domain tasks can be conducted for the our experiments.

Experimental Results As shown in Table 1, our proposed model obtains the better performance than current proposed methods which suffer from the sentiment transfer error problem. Specifically, our model significantly outperforms the *KinGDOM* which also utilizes the external commonsense knowledge, evaluating that our proposed method enable effectively alleviate sentiment transfer error problem. Moreover, the language models (e.g., BERT) can obtain rich domain knowledge by pre-training large-scale unlabeled data, but they hardly capture the sentiment features of the aspect-opinion pairs. Comparing with *Sentix*, our model can obtain the better performance of cross-domain SA.

Conclusion

In this paper, we propose an aspect-opinion sentiment alignment cross-domain SA model to solve the sentiment transfer error problem suffered in current unsupervised methods. The experiment results show the effectiveness of our proposed model.

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