Research on Cross-Domain Sentiment Classification Model Based on Multi-Feature Fusion (Postprint)

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Abstract

[Purpose/Significance] Cross-domain sentiment classification remains a critical issue requiring focused research. [Method/Process] By leveraging sentiment-irrelevant words, cross-domain sentiment feature word clusters for source and target domains are constructed through spectral clustering algorithm; the sentiment word features obtained from spectral clustering, along with position features, keyword features, and part-of-speech features, are integrated into a logistic regression classification algorithm to implement a cross-domain sentiment classification algorithm based on multi-feature fusion; and validated using user review data. [Results/Conclusion] The research results demonstrate that the CDFF (Cross Domain pulse Four Factor) algorithm can effectively achieve cross-domain user sentiment classification, providing valuable reference for cross-domain sentiment classification research.

Full Text

Research on a Cross-Domain Sentiment Classification Model Based on Multi-Feature Fusion

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Abstract

[**Purpose/Significance**] Cross-domain sentiment classification remains a critical research problem that requires focused attention. [**Method/Process**]

Leveraging sentiment-irrelevant words, this study constructs cross-domain sentiment feature word clusters between source and target domains through spectral clustering algorithms. The sentiment word features obtained from spectral clustering are integrated with position features, keyword features, and part-of-speech features into a logistic regression classification algorithm to achieve a cross-domain sentiment classification algorithm based on multi-feature fusion. The model is validated using user review data. [**Result/Conclusion**] Research results demonstrate that the CDFF (Cross-Domain Four Factor) algorithm can effectively achieve cross-domain user sentiment classification, providing a valuable reference for cross-domain sentiment classification research.

Keywords: cross-domain sentiment classification; multi-feature fusion; spectral clustering; transfer learning

1 Introduction

The interactive behaviors of Internet users generate vast amounts of review data, such as customer reviews after purchasing products and Weibo user comments on hot topics. These interaction data implicitly contain users' sentiment tendencies toward certain entities, which holds significant practical value for constructing user interest models and generating recommendation results. Sentiment classification categorizes user sentiments into two classes—positive and negative—based on review data. While humans can easily infer a reviewer's sentiment from a comment, this task is considerably more challenging for machines. Furthermore, some review data does not explicitly express user sentiment, which further increases the difficulty of machine learning.

Numerous scholars have studied sentiment classification through semi-supervised learning approaches [1-3]. Some researchers have exploited the differences and complementarity between key sentences and detail sentences by applying extracted key sentences to both supervised and semi-supervised sentiment classification [2]. However, accurately identifying key sentences in reviews remains an issue requiring further investigation. Other researchers have achieved sentiment classification using large-scale unlabeled data and a small number of emotion words [3], which reduces the cost of manual data labeling but yields models that cannot be reused in other domains, necessitating domain-specific sentiment classification learning. Additional studies have focused on calculating sentiment degrees for emotional words [4], proposing fuzzy analytic hierarchy processes to measure sentiment intensity.

These methods' classification results depend heavily on manually labeled training data; higher quality training data yields higher classification accuracy. However, the reality is that manually creating labeled training data for each domain is costly, and labeling data for every domain is impractical. Consequently, some researchers have considered the domain-dependent nature of sentiment classification tasks [5], proposing cross-domain learning methods based on evaluation object categories to reduce data labeling requirements. Nevertheless, evaluation object categories are too coarse-grained and unsuitable for cross-domain sentiment classification across multiple domains [6].

Evidently, a classifier trained in one domain with high accuracy may not perform equally well in another domain. To address issues such as high domain dependency in sentiment classification algorithms and costly manual data labeling, this paper conducts an in-depth study of cross-domain sentiment classification. The research reveals that spectral clustering can reduce the distance between sentiment words across different domains. Building upon existing research, this study aims to bridge source and target domains using sentiment-irrelevant words, employ spectral clustering algorithms to cluster sentiment words from different domains together, and consider the fusion of relevant features to achieve cross-domain sentiment classification.

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2 Concept Definitions and Problem Description

This section provides formal definitions for concepts including domain, sentiment words, and cross-domain sentiment classification.

Definition 1 (Domain): A domain D represents a collection of entities or concepts in the real world. This can be understood as different product sections in a supermarket, such as food, stationery, and home appliances, or different disciplinary fields in a library. The granularity of domains can be abstract or fine-grained, depending on actual requirements.

Definition 2 (Sentiment Word): Given a specific domain, sentiment words are those that reflect user sentiment tendencies. These words are expressed through user phrases and can be extracted through sentence segmentation to form sentiment word sequences $[w_1, w_2, w_3, ..., w]$. This study does not consider the impact of sentiment word ordering in sentences on final sentiment classification but does consider the influence of sentiment word positions within statements. Each specific domain D has its own sentiment word library W (w W). Drawing on the bag-of-words concept, $c(w, x)$ represents the frequency of sentiment word w appearing in statement x.

Definition 3 (Sentiment Classification): Given a domain, sentiment classification divides statements x into sentiment categories y (positive: $y = 1$ or negative: y = -1) based on overall semantic expression. Statements with labeled sentiment categories constitute training data (x, y), while unlabeled statements are called prediction data.

Definition 4 (Cross-Domain Sentiment Classification): Given two different domains—a source domain (D) and a target domain (D)—assume the source domain contains a labeled dataset ($[x\ , y\ ], i\ \ 1, 2, ..., n$) and the target domain contains an unlabeled dataset ($[x\ ], j\ \ 1, 2, ..., n$). If a classifier can accurately predict the unlabeled dataset in the target domain through training on the source domain, such classification is called cross-domain sentiment classification.

Cross-domain sentiment classification must address domain dependency issues. Specifically, sentiment word expressions in adjacent domains are similar, but in practice, users typically post domain-specific comments for different domains. Table 1 lists user comments from Sina Weibo on hot topics related to movies and society. User comment phrases explicitly or implicitly express certain sentiments about the comment subjects, thereby revealing users' sentiment tendencies toward current topics. Sentiment-bearing words are highlighted in bold, such as positive sentiment words "exciting," "intense," and "awesome," and negative sentiment words "painful" and "torturous." However, sentiment words differ across domains. For example, negative sentiment words in the movie domain include "clichéd" and "chaotic," while positive sentiment words in the social domain include "reasonable." Words like "clichéd," "chaotic," and "reasonable" are domain-related, whereas "since" and "after all" are domain-irrelevant.

Additionally, position features, keywords, and part-of-speech features must be considered in sentiment classification. Generally, the last few sentiment features in a comment statement most effectively express the reviewer's sentiment. Moreover, if transitional keywords such as "but," "after all," or "I think" appear, the reviewer's sentiment expression may shift. Finally, most words expressing user sentiment are adjectives or adverbs. Therefore, besides sentiment features, these feature factors must also be considered in sentiment classification.

Based on the above analysis and relevant research, this study proposes a cross-domain sentiment classification framework, as shown in Figure 1 [Figure 1: see original paper]. The target domain sentiment feature words are obtained according to labeled data. However, in reality, such labeled data is scarce or nonexistent, requiring partial manual labeling. By leveraging sentiment-irrelevant words and spectral clustering algorithms, this study constructs cross-domain sentiment feature word clusters between source and target domains. The sentiment word features obtained from spectral clustering are integrated with position features, keyword features, and part-of-speech features into a logistic regression classification algorithm to achieve a cross-domain sentiment classification algorithm based on multi-feature fusion.

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3 Cross-Domain Sentiment Classification Model

This study draws upon Lin et al.'s sentiment classification method based on sentiment key sentence extraction [2]. However, rather than extracting key sentences, this research applies feature scoring from that work to final sentiment classification. The model considers sentiment features (i.e., domain sentiment words), position features, keyword features, and part-of-speech features. Among these, sentiment features are obtained through multi-domain spectral clustering, while part-of-speech features exclude words irrelevant to sentiment classification, thereby achieving cross-domain sentiment classification. The sentiment classification considering these four features can be expressed by Formula (1), where each comment data point comprises four attribute features. Classification is achieved by calculating feature scores, which weakens the impact of feature space on cross-domain classification. p_0 is the bias term, and p_1, p_2, p_3, p_4 are parameters that can be trained from training data.

Formula (1) calculates values that cannot directly express sentiment classification (positive or negative). Therefore, Formula (2) is introduced to achieve cross-domain sentiment classification.

At this point, function *ø* maps the value domain of *f(x)* to between 0 and 1, thereby achieving sentiment classification.

3.1 Sentiment Feature Words

The sentiment tendency of a reviewer can generally be determined from sentiment feature words in comment phrases. In sentiment classification, sentiment feature words typically carry greater weight. The key challenge in cross-domain classification is that different domains have different sentiment feature spaces, ultimately preventing classifiers trained in the source domain from being effectively applied to the target domain. Therefore, this study employs domain-irrelevant words as a bridge [6] and uses spectral clustering methods to achieve cross-domain sentiment word transformation, obtaining a new sentiment word feature space. In this space, the sentiment feature word score for comment phrase x is calculated through Formula (3).

Each comment phrase x requires word segmentation and stop word removal. *positive(w)* represents the *j*-th word in the *i*-th comment statement corresponding to a sentiment word in the clustering set, where the word represents a positive sentiment tendency in the cluster. *negative(w)* represents the *j*-th word in the *i*-th comment statement corresponding to a sentiment word in the clustering set, where the word represents a negative sentiment tendency in the cluster. n is the total number of words in the comment phrase after stop word removal.

3.2 Part-of-Speech Features

Part-of-speech features are domain-independent. Although each domain has its specific feature space, the parts of speech in these spaces are identical. Literature indicates that adjectives and adverbs most effectively represent cross-domain review sentiment tendencies [7], while nouns are domain-related. Therefore, this study considers target domain part-of-speech features for sentiment classification. Following the approach of B. Pang et al. [1], the method first performs POS tagging on comment phrases; then extracts adjectives and adverbs from target domain comment phrases according to predefined rules; and finally calculates the part-of-speech weight score for each comment phrase using Formula (4).

Here, w equals the total number of adjectives and adverbs extracted from the i-th comment phrase according to predefined rules, and n equals the total number of words in the i-th comment phrase after removing comment phrases. This formula represents the proportion of adjectives and adverbs in comment phrases, i.e., the influence degree of adjectives and adverbs on sentiment classification.

3.3 Position Features

A comment statement may contain multiple positive and negative sentiment words, but the sentiment words most likely to express the reviewer's sentiment typically appear at the beginning or end of the comment. Therefore, the impact of position features in sentiment comments on sentiment classification must be considered. The position feature score can be calculated through Formula (5).

pos(w) represents the position of the j-th word in the i-th comment statement. The position feature follows a quadratic function, i.e., a parabolic curve, to highlight the importance of words at the beginning and end of sentences for sentiment classification. However, the difference from middle positions should not be too large, so the parabola should open widely to prevent excessive influence from end values on sentiment classification.

Where the following condition is satisfied: M represents the total number of characters in x . The middle position is the lowest point of the function, where calculated sentiment word scores are lower, while sentiment words at the beginning and end of comments receive higher scores. For short comment data where few feature words appear in sentences, making sentiment classification difficult, the influence of position features is weakened, and the value of c can be adjusted accordingly to modify position feature scores.

3.4 Keyword Features

In sentiment classification, keywords in evaluation phrases can reflect changes in reviewers' sentiment tendencies. Therefore, the impact of keyword features on sentiment orientation must be considered. This study summarizes 20 common keywords across multiple domains for experiments, including: "in summary," "I think," "however," "after all," "but," "since," etc. The calculation of keyword features is shown in Formula (6):

3.5 Cross-Domain Sentiment Classification Algorithm Based on Multi-Feature Fusion

To achieve cross-domain sentiment classification, this algorithm not only maps sentiment word feature spaces through spectral clustering algorithms but also integrates part-of-speech features, position features, and keyword features. A logistic regression classifier is trained on this new feature space. The specific algorithm steps are as follows:

Algorithm 1: Cross-Domain Sentiment Classification Based on Multi-Feature Fusion
Input: Source domain training data, small amount of target domain training data, number of clusters k
Output: Logistic regression classifier

Algorithm Steps:
Step (1) Remove stop words from the training dataset
Step (2) Apply spectral clustering algorithm to source domain training data and small amount of target domain training data to obtain k clusters
Step (3) Calculate sentiment feature word scores for the training dataset using Formula (3) based on spectral clustering results
Step (4) Calculate part-of-speech feature scores using Formula (4)
Step (5) Calculate position feature scores for the training dataset using Formula (5)
Step (6) Calculate keyword feature scores for the training dataset using Formula (6) according to the keyword dictionary
Step (7) Perform POS tagging on the training dataset and extract adverbs and adjectives
Step (8) Transform the training dataset, constructing a new training dataset D with sentiment words, position, keywords, part-of-speech, and sentiment as features
Step (9) Learn the values of parameters p_0, p_1, p_2, p_3, p_4 in Formula (1) through gradient descent using the new training dataset
Step (10) Input the parameters into Formula (2) to output the logistic regression classifier

Algorithm 2: Spectral Clustering Algorithm [8]
Input: Source domain training data, target domain training data, number of clusters k
Output: k clusters

Algorithm Steps:
Step (1) Construct a bipartite graph $G(V \quad V, E)$ based on domain-irrelevant and domain-related words, and calculate the weighted adjacency matrix $W^{n\ n}$ of the bipartite graph, where $W = m$ if $i \neq j$, otherwise $W = 0$
Step (2) Calculate the diagonal matrix D, where $D = \Sigma W$, and construct the graph Laplacian matrix $L = D^{-1\ 2} W D^{-1\ 2}$
Step (3) Compute the top k eigenvectors corresponding to the largest eigenvalues of Laplacian matrix L and construct the feature matrix $U = [u_1, u_2, ..., u]^{n}$
Step (4) Normalize the feature matrix U
Step (5) Apply the K-means algorithm on matrix U to cluster n points into k clusters
Step (6) Return k clusters

4 Experimental Analysis and Results

4.1 Experimental Setup

To verify the model's effectiveness, this study implemented the CDFF algorithm using Java, based on Weka's logistic regression source code. For the dataset, the study utilized the word segmentation software interface ICTCLAS from the Institute of Computing Technology, Chinese Academy of Sciences (http://ictclas.org) and the open-source project IKAnalyzer, incorporating the Internet lexicon from Sogou Labs (http://www.sogou.com/labs/resources.html) and a stop word dictionary collected and compiled by this study to perform word segmentation and POS tagging on texts. The SVM algorithm used the standard toolkit light-SVM (http://svmlight.joachims.org) with a linear kernel function. Cross-domain sentiment word transformation was achieved through spectral clustering algorithms. Since sentiment feature scores depend on clusters, the experiment adjusted the clustering parameter k values to compare cross-domain sentiment classification effectiveness.

4.2 Experimental Results and Analysis

The dataset used in this study comprises balanced short review data from three domains—hotel, computer (laptop), and book—collected from online users (http://www.searchforum.org.cn/tansongbo/corpus-senti.htm). Each domain contains 2,000 positive and 2,000 negative reviews, totaling 12,000 balanced comment data points. The specific composition of the dataset is shown in Table 2 .

The correlation between domains is not particularly strong on the computer (laptop) dataset. To verify the algorithm's effectiveness, six cross-domain sentiment classification task schemes were adopted: Hotel→Computer, Hotel→Book, Computer→Hotel, Computer→Book, Book→Hotel, and Book→Computer, where the domain before the arrow represents the source domain and the domain after the arrow represents the target domain. The study compared the proposed CDFF algorithm with three other algorithms: Support Vector Machine (SVM), SFA (Spectral Feature Alignment), and SCL (Structural Correspondence Learning) [13]. Five-fold cross-validation was employed for each algorithm experiment, where data from each domain was randomly divided into five folds, with four folds used for training and one fold for testing each time. The average of the five classification results was taken as the final result.

Considering that the number of clusters in spectral clustering affects sentiment feature word scores, the experiment set the number of clusters to 5, 10, and 15 to measure their impact on sentiment classification. The results are shown in Table 3 .

From the cross-domain average accuracy values in Table 3, the experimental results of this algorithm are higher than those of the SFA algorithm. Sentiment classification accuracy increases with the number of clusters, but when $k =$

15, the accuracy improvement effect is no longer significant. However, when increasing from 5 to 10 clusters, classification accuracy improves, demonstrating that the number of spectral clusters affects cross-domain sentiment classification results.

In addition to sentiment feature words, this algorithm incorporates position features, keyword features, and part-of-speech features. To verify the effectiveness of adding these features, the number of clusters was fixed ($k = 10$), and these features were added sequentially to compare algorithm accuracy and observe the impact of different features on cross-domain sentiment classification. The results are shown in Table 4 .

Table 4 shows that cross-domain sentiment classification accuracy improves after sequentially adding part-of-speech features, position features, and keyword features. However, the contribution rate of each feature differs. The results indicate that the average contribution rates of position features and keyword features are greater than that of part-of-speech features. These two experiments validate that the cross-domain classification algorithm based on multi-feature fusion can improve sentiment classification accuracy.

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5 Summary and Outlook

Although humans can easily infer a reviewer's sentiment from a comment, this task is considerably challenging for machines. This study bridges source and target domains using sentiment-irrelevant words, employs spectral clustering algorithms to cluster sentiment words from different domains together, and applies the obtained feature sets from spectral clustering to calculate sentiment scores for target domain test data. Unlike traditional spectral clustering algorithms, this study also considers the impact of position features, part-of-speech features, and keyword features on final sentiment classification in cross-domain sentiment classification. The sentiment features obtained from spectral clustering are fused with position, part-of-speech, and keyword features to achieve cross-domain sentiment classification. Experiments on user review data validate the effectiveness of this algorithm for cross-domain user sentiment classification. Since the dataset selected in this study is relatively standard, but Weibo comment data exhibits considerable randomness with relatively novel domain-related words, cross-domain sentiment classification tailored to the characteristics of Weibo data will be a focus of future research.

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Author Contributions

Ju Chunhua: Proposed the cross-domain sentiment classification model based on multi-feature fusion, and contributed to paper writing and revision.
Zou Jiangbo: Implemented the cross-domain sentiment classification model algorithm based on multi-feature fusion, and contributed to paper writing, revision, and finalization.
Fu Xiaokang: Participated in model proposal and algorithm implementation, and contributed to paper writing and revision.

Note: Figure translations are in progress. See original paper for figures.