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Synergetic Research Response Classifiers for Multiple Domains

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Abstract:
This project propose a collaborative multi-domain sentiment classification approach to train sentiment classifiers for multiple in domains simultaneously. In our approach, the sentiment information in different domains is shared to train more accurate and robust the sentiment classifiers for each domain when labeled data is scarce. Specifically, we decompose the sentiment classifier of each domain into two components, a global one and a domain-specific one. The global model can capture the general sentiment knowledge and is shared by various domains. The domain-specific model can capture the specific sentiment expressions in each domain. In addition, we extract domain-specific sentiment knowledge from both labeled and unlabeled samples in each domain and use it to enhance learning of domain-specific sentiment classifiers. Besides, we incorporate the similarities between domains into our approach as regularization over the domain- specific sentiment classifiers to encourage the sharing of sentiment information between similar domains. Two kinds of domain similarity measures are explored, one based on textual content and the other one based on sentiment expressions. Moreover, we introduce two efficient algorithms to solve the model of our approach. Experimental results on benchmark datasets show that our approach can effectively improve the performance of multi-domain sentiment classification and significantly outperform baseline methods.

Terms: Sentiment Classification, Multiple Domain, Multi- Task Learning.

I. INTRODUCTION

With the development of Web 2.0 websites, user generated content (UGC), such as product reviews, blogs, micro blogs and so on, has been growing explosively. Mining the sentiment information contained in the massive user generated content can help sense the public's opinions towards various topics, such as products, brands, disasters events, celebrities and so on, and is useful in many applications. For example, researchers have found that analyzing the sentiments in tweets has the potential to predict variation of stock market prices and presidential election results. Classifying the sentiments of massive microblog messages is also helpful to substitute or supplement traditional polling which is expensive and time-consuming. Product review sentiment analysis can help companies improve their products and services, and help customers make more informed decisions. Analyzing the sentiments of user generated content is also proven useful for user interest mining, personalized recommendation, social advertising, customer relation management, and crisis management. Thus, sentiment classification is a hot research topic in both industrial and academic fields. In many mainstream sentiment analysis methods, sentiment classification is regarded as a text classification problem. Supervised machine learning techniques, such as SVM, Logistic Regression and CNN, are frequently applied to train sentiment classifiers on labeled datasets and predict the sentiments of unseen texts. These methods have been used to analyze the sentiments of product reviews, micro blogs, and soon. However, sentiment classification is widely recognized as a domain-dependent problem. This is because in different domains different words are used to express sentiments, and the same word may convey different sentiments in different domains. For example, in the domain of electronic product reviews the word "easy" is usually positive, e.g., "this digital camera is easy to use." However, in the domain of movie reviews, "easy" is frequently used as a negative word. For instance, "the ending of this movie is easy to guess." Thus, the sentiment classifier trained in one domain may fail to capture the specific sentiment expressions of another domain, and its performance in a different domain is usually unsatisfactory. An intuitive solution to this problem is to train a domain specific sentiment classifier for each domain using the labeled samples of this domain. However, the labeled data in many domains is usually scarce. In addition, since there are massive domains involved in online user generated content, it is very costly and time-consuming to annotate enough samples for them. Without sufficient labeled data, it is quite difficult to train an accurate and robust domain-specific sentiment classifier for each domain independently. The motivation of our work is that although each domain has its specific sentiment expressions, different domains also share many common sentiment words. For example, general sentiment words such as "best", "perfect", and "worst" convey consistent sentiment polarities in various domains. Thus, training sentiment classifiers for multiple domains simultaneously and exploiting the common sentiment knowledge shared among them can help alleviate the problem of scarce labeled data and help learn more accurate sentiment classifiers for each domain. Motivated by above observations, in this paper we propose to train sentiment classifiers for multiple domains simultaneously in a collaborative way.In our approach, the sentiment classifier of each domain is decomposed into two components, i.e., a global one and a domain-specific one. The domain-specific sentiment classifiers are trained using labeled samples of one domain and can capture the domain-specific sentiment expressions. The global sentiment classifier is shared by all domains and istrained on the labeled samples from various domains to have better generalization ability. It can capture the general sentiment knowledge consistent in different domains. In addition, we extract prior general sentiment knowledge from general-purpose sentiment lexicons and incorporate it into our approach to guide the learning of the global sentiment classifier. Besides, we propose to extract domain specific sentiment knowledge for each domain from both limited labeled samples and massive unlabeled samples. The domain specific sentiment knowledge is used to enhance the learning of domain-specific sentiment classifiers in our approach. Moreover, since different pairs of domains have different sentiment relatedness. We propose to measure the similarities between domains and incorporate them into our approach to encourage the sharing of sentiment information between similar domains. Two kinds of domain similarity measures are explored, one based on the textual content, and the other one based on the sentiment word distribution. The model of our approach is formulated as a convex optimization problem. In order to solve it efficiently, we introduce an accelerated algorithm based on FISTA [18]. In addition, we propose a parallel algorithm based on ADMM [19] to further improve the efficiency of our approach when domains to be analyzed are massive. Extensive experiments were conducted on benchmark sentiment datasets. Experimental results show our approach can improve sentiment classification performance effectively and outperform state-of-the-art methods significantly. The major contributions of this paper are as follows:

- We propose a collaborative multi-domain sentiment classification approach (CMSC) based on multi-task learning to train sentiment classifiers for multiple domains simultaneously. It can exploit the sentiment relatedness between different domains and effectively alleviate the problem of scarce labeled data in each domain
- We propose to extract domain-specific sentiment knowledge for each domain by propagating the sentiment scores inferred from limited labeled samples along contextual similarities mined from massive unlabeled samples
- We propose to incorporate the similarities between domains into the collaborative learning process. In addition, we propose a novel domain similarity measure based on the sentiment expression distributions.
- We introduce an accelerated algorithm based on FISTA[18] to solve our model effectively by exploiting the "momentum" between iterations, and propose a parallel algorithm based on ADMM [19] to further improve its efficiency by computing at multiple parallel nodes.
- We evaluate our approach by conducting extensive experiments on the benchmark Amazon product review datasets. The experimental results show our approach can improve the sentiment classification accuracy by 2.74% in average compared with the best baseline method . This paper is an extended and improved version of our previous work in [20]. In this version, we have made many important improvements in both algorithm and experiment. First, besides the single-node version algorithm for solving the model of our approach, in this paper we propose a parallel version algorithm, which is more efficient when there are a large number of domains to be analyzed. Second, in this paper we propose to extract domain-specific sentiment knowledge by combining limited labeled samples with massive unlabeled samples, which is not considered in previous work. The domain-specific sentiment knowledge contains rich specific sentiment expressions used in each domain and can provide important prior information for learning domain-specific sentiment classifiers. It is also used in our approach to measure the similarities between different domains. Third, a large multi-domain sentiment dataset was added to the experiments to evaluate the performance of our approach more thoroughly. In addition, more experiments were conducted. For example, we conducted experiments to explore the influence of training data size on the performance of our approach to verify whether our approach can handle the problem of scarce labeled data by training sentiment classifiers for multiple domains collaboratively. We also conducted experiments to evaluate the time complexity of the proposed parallel algorithm and compare it with the single-node version algorithm. Besides, more detailed analysis and discussions on the experimental results are presented in this paper. Thus, compared with the previous version work [20], a large amount of new content has been added to this paper. The rest of this paper is organized as follows. In Section 2, we briefly review several representative related works. In Section3, we introduce two important components in our approach, i.e., domain-specific sentiment knowledge extraction and domain similarity measure. In Section 4, we presentour collaborative multi-domain sentiment classification approach as well as the optimization algorithms in detail. In Section 5, we report the experimental results on benchmark multi-domain sentiment datasets. In Section 6, we conclude this paper.

II. RELATED WORK

In this section, we briefly review several representative works on multi-domain sentiment classification and multi task learning.

2.1 Multi-Domain Sentiment Classification

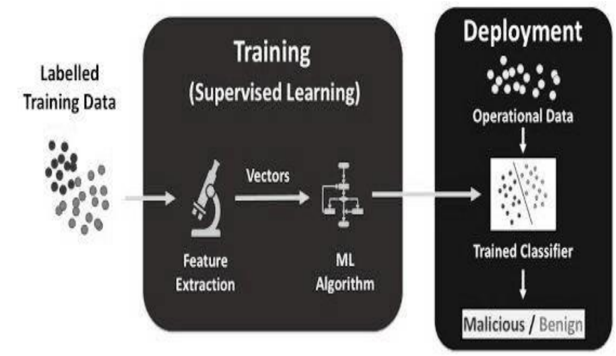
Sentiment classification has been widely known as a highly domain-dependent problem Different domains have different ways to express sentiments, and a sentiment classifier trained in one domain usually perform not very well in another domain. For example, "easy" is a positive word in Kitchen domain (e.g., "this fryer is very easy to use"). However, it is frequently used as a negative word in Movie domain (e.g., "the ending of this film is easy to guess"). Thus, the sentiment classifier trained in Movie domain cannot predict the sentiment of " easy" in Kitchen domain accurately. An intuitive method to solve this problem is training a domain specific sentiment classifier or building a domain-specific sentiment lexicon for each domain independently. For example, Pang etal. Built sentiment classifiers for movie reviews using machine learning techniques such as SVM and Naive Bayes based on the labeled data of this domain. Lu et al. proposed to construct a domain-specific sentiment lexicon by incorporating information from various sources in this domain, such as sentiment labels and linguistic heuristics. However, in many domains, the labeled data is usually in limited size and insufficient to extract accurate and robust sentiment information. In addition, since there are massive domains involved in online user generated content, it is expensive and time-consuming to manually annotate enough samples for each domain. A popular method to reduce the effort of manual annotation is using transfer learning to adapt the sentiment classifier from a source domain with sufficient labeled data to a target domain with scarce or no labeled data . Many cross domain sentiment classification methods belong to this kind .For example, Blitzer et al. proposed a sentiment domain adaption method based on Structural Correspondence Learning (SCL) algorithm. The core idea of SCL is finding correspondence among features from different domains by computing their associations with pivot features. Pan et al. proposed a spectral feature alignment (SFA) algorithm for cross domain sentiment classification to reduce the gap of sentiment expressions from different domains. He etal. Proposed to extract polarity-bearing topics based on a modified joint sentiment-topic (JST) model using data from both source and target domains. These topics are used to augment the feature representations of texts from both domains. Then a sentiment classifier is trained on labeled data in source domain and applied to unseen data in target domain. The assumption behind these cross domain sentiment classification methods is that there is sufficient labeled data in source domain while the labeled data in target domain is scarce or non-existent [16]. The goal of these methods is to adapt the sentiment knowledge extracted from the labeled data of source domain to target domain. However, in this paper we assume that the labeled data in each domain is insufficient, and our goal is to train an accurate and robust sentiment classifier for each domain in a collaborative way by exploiting the sentiment relatedness among these domains. Another line of research in multi-domain sentiment classification is sentiment classifier combination [15]. For example, Liet al. proposed to combine the classification results of sentiment classifiers trained in different domains to make final predictions. These methods can be regarded as integrating the sentiment knowledge from different domains at the classification stage, while in our approach the sentiment knowledge from different domains is shared at the learning stage in order to help train sentiment classifiers for each domain more accurately when labeled data is in sufficient. The experimental results validate that our approach is more effective in exploiting the sentiment knowledge of multiple domains than these sentiment classifier combination methods.

2.2 Multi-Task Learning

The approach proposed in this paper is based on multi-task learning. The aim of multi-task learning is to improve the generalization ability and prediction performance by learning multiple related tasks simultaneously and leveraging the common knowledge shared by these tasks appropriately . The main difference between different multi-task learning methods lies in how they model and incorporate the task relatedness. For example, Evgeniou and Pontil proposed a regularized multi-task learning method. In their method, the classification models of related tasks are constrained to be similar with their average model. Thus, in this method the relatedness between various tasks is introducedby the average model and the direct relations between these tasks are not taken into consideration. Liu et al. proposed a multi-task feature learning method . In their method, the classification models of related tasks are assumed to share the same sparse feature space, which is selected by group Lasso . However, this assumption may not hold in multi-domain sentiment classification scenario, since different features are used to express sentiments in different domains. In trace-norm regularized multi-task learning methods, the models from multiple related tasks are assumed to share a low-dimension A popular method to reduce the effort of manual annotation is using transfer learning to adapt the sentiment classifier from a source domain with sufficient labeled data to a target domain with scarce or no labeled data . Many cross domain sentiment classification methods belong to this kind. For example, Blitzer et al. proposed a sentiment domain adaption method based on structural correspondence learning (SCL) algorithm [13]. The core idea of SCL is finding correspondence among features from different domains by computing their associations with pivot features. Pan et al. proposed a spectral feature alignment (SFA) algorithm for cross domain sentiment classification to reduce the gap of sentiment expressions from different domains . He etal. proposed to extract polarity-bearing topics based on a modified joint sentiment-topic (JST) model using data from both source and target domains . These topics are used to augment the feature representations of texts from both domains. Then a sentiment classifier is trained on labeled data in source domain and applied to unseen data in target domain. The assumption behind these cross domain sentiment classification methods is that there is sufficient labeled data in source domain while the labeled data in target domain is scarce or non-existent [16]. The goal of these methods is to adapt the sentiment knowledge extracted from the labeled data of source domain to target domain. However, in this paper we assume that the labeled data in each domain is insufficient, and our goal is to train an accurate and robust sentiment classifier for each domain in a collaborative way by exploiting the sentiment relatedness among these domains. Another line of research in multi-domain sentiment classification is sentiment classifier combination [15]. For example, Liet al. proposed to combine the classification results of sentiment classifiers trained in different domains to make final predictions . These methods can be regarded as integrating the sentiment knowledge from different domainsat the classification stage, while in our approach the sentiment knowledge from different domains is shared at the learning stage in order to help train sentiment classifiers for each domain more accurately when labeled data is insufficient. The experimental results validate that our approach is more effective in exploiting the sentiment knowledge of multiple domains than these sentiment classifier combination methods.

III. DOMAIN-SPECIFIC SENTIMENT KNOWLEDGE AND DOMAIN SIMILARITY

In this section, we introduce two important components that will be used in our collaborative multi-domain sentiment classification approach (CMSC). The first one is the domain-specific sentiment knowledge, which is mined from massive unlabeled samples and a small number of labeled samples. It can provide prior knowledge of the sentiment expressions used in each domain. The second one is domain similarity, which measures whether two domains share similar terms and sentiment expressions.



3.1 Domain-Specific Sentiment Knowledge Extraction

Every domain has many domain-specific sentiment expressions, which are not captured by general-purpose sentiment lexicons or sentiment datasets of other domains. For example, “quick” is a positive word in Kitchen domain (e.g., “It’s a quick and quiet way to clean up”). However, it is a neutral word in many sentiment lexicons, such as MPQA1 . Another example is “easy”, which is a positive word in Kitchen domain (e.g., "Hand washing is easy and quick") but frequently conveys negative sentiment in Movie domain (e.g., "The ending of this film is easy to guess"). Thus, we propose to extract domain-specific sentiment knowledge from the data of a specific domain. It is formulated as the sentiment expression distribution of this domain and can provide prior knowledge for learning domain-specific sentiment classifiers. Two kinds of data are combined to extract domain-specific sentiment knowledge for each domain. The first kind of data is the labeled samples, which are associated with sentiment labels and can be used to infer domain-specific sentiment expressions directly. A common observation in sentiment analysis field is that the words occur more frequently in positive samples than negative The textual content based domain similarity is motivated by the observation that although different topics and opinion targets are discussed in different domains, similar domains may share many common terms. For example, in both Smart Phone and Digital Camera domains, terms like "screen", "battery", and "image" are frequently used. In contrast, the probability of two far different domains such as Smart Phone and Book sharing many common terms is low. Thus, we propose to measure the similarity between domains based on their textual content. Inspired by the work in [38], here we select Jensen-Shannon divergence to measure the similarity of two domains based on their textual term distributions. Denote dm 2 RD_1 and dn 2 RD_1 as the term distribution vectors of domains m and n respectively, where D represents the dictionary size. Dmt 2 [0; 1] stands for the probability of term t occurring in domain m. Then the textual content based domain similarity between domains m and n is formulated as:

ContentSim(m; n) =1 - DJS(dm || dn)
=1 -1/ 2 (DKL(dm||d) + DKL(dn || d));

where d = 12 (dm + dn) is the average distribution, DJS(_) represents Jensen-Shannon divergence, and DKL(_) is the Kullback- Leibler divergence which is defined as:

DKL(p || q) =XDt=1p(t) log2p(t)/q(t)

Since the base of logarithm used in Eq. (5) is 2, DJS(dmjjdn) 2[0; 1]. Thus, the range of the textual content based domain similarity defined in Eq. (4) is also [0; 1].

3.2.2 Sentiment Expression Based Domain Similarity

The textual content based domain similarity introduced in previous subsection can measure whether two domains have similar word usage patterns. However, high similarity in textual content does not necessarily mean that sentiment words are used in similar ways in these domains. For example, both CPU and Battery belong to electronic hardware. In CPU domain, the word "fast" is usually positive. For instance, "Intel Core i7 is very fast." However, in Battery domain, the word "fast" is frequently used as a negative word (e.g., "This battery runs out too fast"). Thus, measuring domain similarity based on sentiment expressions may be more suitable for multi-domain sentiment classification task. Denote pm and pn as the sentiment word distributions of domains m and n respectively, which are extracted from both labeled and unlabeled samples according to previous subsection. Then the sentiment expression based domain similarity between domains m and n is defined as the cosine similarity of their sentiment word distributions:

SentiSim(m; n) = p^m _ p^n
kpmk2 _ kpnk2

Note that SentiSim(m; n) defined in Eq. (6) can be negative in theory, although the probability is very small. In this paper, we constrain that domain similarities should be non-negative. Thus, if the SentiSim score between a pair of domains is negative, then we set it to zero.

IV. AN ACCELERATED ALGORITHM

4.1 An Accelerated Algorithm

In this section, we introduce the FISTA based accelerated algorithm for our approach which can be conducted on a single computing node. As mentioned before, the optimization problem in our approach is nonsmooth. Although we can use subgradient descent method to solve it, the convergence rate of sub gradient method is O(1=pk) and is far from satisfactory, where k is the number of iterations. Thus, we propose to use the accelerated algorithm based on FISTA [18] . When f is smooth (such as squared loss and log loss). This algorithm has the same computational complexity as gradient method and subgradient method in each iteration, and at the same time has a convergence rate of O(1=k2), much faster than that of gradient method (O(1=k)) and subgradient method (O(1=pk)). Different from gradient method and subgradient method where current solution is computed using the last solution in each iteration, in FISTA the current solution is estimated using the last two solutions and the "momentum" between them is exploited to accelerate the optimization process [18]. In each iteration of FISTA, two kinds of points are sequentially updated. The first kind of point (denoted as search point) is a linear combination of last two solutions, which is defined as:

vk+1 =wk + ak(wk – w^{k-1}); Vk+1 =Wk + ak(Wk –W^{k-1}):

4.3 A Parallel Algorithm

When the domains to be analyzed are massive, it is inefficient to train sentiment classifiers for them on a single computing node due to the limit of memory and computational ability. Motivated by, here we propose a parallel algorithm based on Alternating Direction Method of Multipliers (ADMM) to solve our approach more efficiently. The domains in the same group are processed at the same node, and different groups are processed at different nodes. Denote Mg as the set of domains in group g. We keep a copy of w in each group and denote it as vg in group g. In addition, we also keep a copy ofW;m andW; n for each pair of domains m an, and denote them as vm;n and vn;m. Then the optimization problem in the model of our approach

vk+1m;n
= (Wk+1_;m + ukm;n) + (1 _)(Wk+1_;n + ukn;m); vk+1n;m
= (1 _)(Wk+1_;m + ukm;n) + _(Wk+1_;n + ukn;m);

V. CONCLUSION

This paper presents a collaborative multi-domain sentiment classification approach. Our approach can learn accurate sentiment classifiers for multiple domains simultaneously in a collaborative way and handle the problem of insufficient labeled data by exploiting the sentiment relatedness between different domains. In our approach, the sentiment classifier of each domain is decomposed into two components, a global one and a domain-specific one. The global model can capture the general sentiment knowledge shared by different domains and the domain-specific models are used to capture the specific sentiment expressions of each domain. We propose to extract domain-specific sentiment knowledge from both labeled and unlabeled samples, and use it to enhance the learning of the domain-specific sentiment classifiers. Besides, we propose to use the prior general sentiment knowledge in general-purpose sentiment lexicons to guide the learning of the global sentiment classifier. In addition, we propose to incorporate the similarities between different domains into our approach as regularization over the domain-specific sentiment classifiers to encourage the sharing of sentiment information between similar domains. A novel domain similarity measure based on sentiment word distributions is proposed. We formulate the model of our approach into a convex optimization problem. Moreover, we introduce an accelerated algorithm to solve the model of our approach efficiently, and propose a parallel algorithm to further improve its efficiency when domains to be analyzed are massive. Experimental results on benchmark datasets show that our approach can improve the performance of multi-domain sentiment classification effectively, and outperform baseline methods significantly.

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