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Collaboratively Improving the Performance of Multi-Domain Sentiment Classifiers for Multiple Domains

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ABSTRACT: This paper presents a Collaborative multi-domain sentiment classification approach at the same time to train the sentiment classifiers for multiple domains. When the labelled data is scarce, the sentiment information in different domain is shared to train more accurate and robust sentiment classifiers for each domain. Global one and Domain specific one are the two components of the specific classifier of the each domain. When the model is capture the general specific knowledge and is shared by various domain, and it is the global model. When the model is capture the specific sentiment expression in each domain, and it is the Domain specific model, and also extract domain-specific sentiment knowledge from both labelled and unlabelled samples in each domain and it is used to enhance the learning of domain-specific. To estimate the similarities between domains into regularization over the domain-specific sentiment classifiers. This is used to encourage the sharing of sentiment information the similar domains. To measure the domain similarities, explored the two kinds of domain similarities. One is based on textual content and other is based on sentiment expressions. To solve this model we introduce two efficient algorithm, one is Experimental results on benchmark datasets, this algorithm show that can effectively improve the performance of multi-domain sentiment classification and another one is significantly outperform baseline methods.

KEYWORDS: Single domain classification, Query By Commitee, All Mixed Classification

I. Introduction

Sentiment classification becomes more and more important with the rapid growth of user generated content. However, sentiment classification task usually comes with two challenges: first, sentiment classification is highly domain-dependent and training sentiment classifier for every domain is inefficient and often impractical; second, since the quantity of labelled data is important for assessing the quality of classifier, it is hard to evaluate classifiers when libelled data is limited for certain domains.

To address the challenges mentioned above, we focus on learning high-level features that are able to generalize across domains, so a global classifier can benefit with a simple combination of documents from multiple domains. In this paper, the proposed model incorporates both labelled and unlabelled data from multiple domains and learns new feature representations. Our model doesn't require labels from every domain, which means the learned feature representation can be generalized for sentiment domain adaptation. In addition, the learned feature representation can be used as classifier since our model defines the meaning of feature value and arranges high-level features in a prefixed order, so it is not necessary to train another classifier on top of the new features. Empirical evaluations demonstrate our model outperforms baselines and yields competitive results to other state-of-the-art works on the benchmark dataset.

With the rapid growth of user-generated content, such as product reviews and microblogs, sentiment analysis and opinion mining have become more and more important as they address the problem of analyzing user's opinions, emotions, sentiments and attitudes. The applications of sentiment analysis have been found in almost every business and social domain (Liu, 2012; Bollen et al., 2011; Ku et al., 2006). Document-level sentiment classification predicts sentiment polarities for a given document or review.

The large number of reviews not only help customers make better decisions but also make it possible yet challenge for product manufacturers to keep track opinions of the products (Hu and Liu, 2004). While machine learning techniques provide interesting methods for analyzing sentiments (Turney, 2002; Go et al., 2009; Pang et al., 2002), challenges also arise certain limitations for the development of sentiment classification. For example, sentiment expression is highly domain-dependent (Pang and Lee, 2008), but training sentiment classifier for every domain is inefficient and often impractical. Simply combining data from different domains may not contribute to a generalized classifier for every domain, as users express the same sentiment in different domains using different words, or even express different sentiment using same words.

For example, a user would prefer computer or car to "run fast" but not wish to use battery "die fast" or to see watch "move fast". A book or a movie can attract people by "unpredictable" endings but "unpredictable" economic trends scare away investors. In addition, certain domains don't have enough labeled data for building the classifier, which makes it indispensable to transfer knowledge between different domains.

A common observation is, even though sentiment expression is domain-dependent and various words are isolated by domain categories, there are always domain-independent words expressing general sentiment polarities. In traditional sentiment domain adaptation that focuses on one domain to another domain, such words are usually ´ defined as pivot features (Blitzer et al., 2006; Blitzer et al., 2007; Pan et al., 2010). Existing works have focused on generating new feature representations for pivot features so that classifiers trained on new features can generalize well across domains.

In this paper, we follow the motivation of using new feature representations (Bengio et al., 2012) to bridge domain divergence and transfer knowledge among domains. The idea of proposed work is to learn a high-level feature space where three constraints are enforced: the model can incorporate multiple domains with both labeled and unlabelled data; the high-level feature space maximizes the margin between sentiment polarities; the high-level feature can represent original features well so that two feature space can be transformed to each other through a shared parametric matrix. Some of the key characters of the proposed model are:

1. Given multiple domains, our model can leverage sentiment similarity between instances across different domains regardless of the dissimilarity between domains. This is achieved by maximizing the distance between sentiments and minimizing the distance between domains in the high-level feature space.
2. Compared with one domain(source) to another domain(target) schema, our model collaborates all possible domains with both labeled and unlabeled data, which is a more generic framework and caters for better transfer across domains.
3. Our model directly maximizes the margin of sentiment polarities in the learned feature space. This is achieved by exploiting non-linear transformation with sigmoid function and aligning instances to pseudo-sentiment centroids.
4. Unlike traditional representation learning method which involves two stages: learning representation and building classifier, the new feature space learned by our model can be taken as classifier by itself. This is achieved through setting the order of learned high-level features and defining the meaning of feature values. As a result, it is not necessary to train another classifier on top of the new features.
5. We extend autoencoder (Vincent et al., 2010) by incorporating sentiment polarities. Unlike existing semi-supervised autoencoder (Liu et al., 2015; Socher et al., 2011) that needs another layer for labels, our model introduces pseudo-sentiment centroids, which can be prefixed and selected without fine-tuning.

In-Domain Sentiment Analysis

For sentiment analysis of user generated content, traditional works have focused on textual content and dictionaries based approaches (Taboada et al., 2011; Hu and Liu, 2004; Pang and Lee, 2008). Pang et al. (2002) built sentiment classifier to predict sentiment polarities of movie reviews. Hu et al. (2013) exploited contextual emotional signals for effective sentiment analysis in an unsupervised manner. Tumasjan et al. (2010) evaluated and analyzed Twitter messages with the political sentiment to predict the popularity of parties. Bollen et al. (2011) explored how Twitter

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mood patterns can identify economic events. Other trends of sentiment analysis are based on visual content (Siersdorfer et al., 2010; Borth et al., 2013) and multi-modalities (Socher et al., 2011). All these works consider training and testing data are within the same domain or following similar distributions.

Knowledge Transfer and Leveraging Multiple Domains

Knowledge-based sentiment analysis have been explored in (Mukherjee and Liu, 2012; Liu, 2014; Chen et al., 2013a; Chen et al., 2013b; Chen et al., 2013c). However, they have focused on aspect term extraction as opposed to sentiment polarity extraction which is the focus of this work. Another thread is to transfer sentiment knowledge across domains. It is usually defined as domain adaptation.

It utilizes the knowledge learned from one domain, referred as the source domain, to solve tasks in another domain, referred as the target domain. Studies have focused on re-weighting features that cross domains using feature embeddings to convert word feature to vector feature or generating new feature representations that align domain-specified features onto a generalized feature space which can bridge domain divergence (Blitzer et al., 2006; Cheng and Pan, 2014). Blitzer et al. (2007) proposed Structural Correspondence Learning by selecting pivot feature and creating correlations between the pivot and non-pivot features.

Pan et al. (2010) introduced a bipartite graph based approach to connect domain-independent features and domain-specific features. Xiao et al. (2013) proposed supervised word clustering, which assumed that a document was composed of latent (topical) clusters and used expectation-maximization algorithm to find those clusters to transform documents from bag-of-words representation to clusters representation.

Domain Adaptation in Sentiment Classification

Early studies on sentiment classification mainly focus on the single-domain setting [Pang et al., 2002; Turney, 2002]. For detailed discussion on this setting, please refer to [Pang and Lee, 2008]. As for cross-domain sentiment classification, [Aue and Gammon, 2005] pioneer the studies. Although they fail to propose an effective solution, they highlight the importance and difficulty of cross-domain sentiment classification.

Subsequently, [Blitzer et al., 2007] successfully develop a domain adaptation approach, named SCL, for sentiment classification, with the main idea to bridge the knowledge between the source and target domains using some pivotal features. More recently, [He et al., 2011] employ a topic model, called joint sentiment-topic model (JST), and [Bollegala et al., 2011] create a sentiment sensitive thesaurus, to perform cross-domain sentiment classification. Results from these studies demonstrate comparable performance to SCL. Unlike above studies, our study pioneers active learning on cross-domain sentiment classification, which greatly improves the adaptation performance with the help of a small amount of labeled data in the target domain.

QBC-based Selection Strategy

Query by Committee (QBC) is a group of active learning approaches that employ many copies of “hypotheses” (e.g., coming from randomized learning algorithms) to select an unlabelled example at which their classification predictions are maximally spread [Freund et al., 92]. In our setting, we first use the source classifier Sf and the target classifier Tf to collaboratively select label-disagreed samples as the selection candidates. Then, we rank the label-disagreed samples according to their uncertainty values by the source classifier. Finally, we select the top-N uncertainty samples as the newly-added data for human annotation.

Problem Statement and Two Straightforward Approaches

Standard sentiment classification tasks aim to seek a predictor f (also called a classifier) that can classify a document (represented as a vector x) into one of the defined n categories (denoted as {c1. . . cn}). In sentiment classification, the categories usually include two kinds of sentiment orientation: positive and negative. To train the classifier f, a set of labeled samples called training data need to be collected. Most existing studies assume that these training samples are all coming from one single domain. Multi-domain sentiment classification aims to seek a predictor which can classify

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documents from multiple domains. Formally, there are m different domains which are indexed by k = {1. . . m} and a sample from the k-th domain is denoted as xk.

To handle this new task, two straightforward approaches can easily be proposed. The first one, called single domain classification (SDC), makes use of the training data drawn from the l-th domain to train a single domain classifier fl (l = 1, 2. . . m) that is used to predict the reviews from the same domain. That is to say, the classifiers are individually trained and tested using the training and testing data from each domain. The second one, called all-mixed classification (AMC), simply mixes all the training data from all domains to train a common classifier fcommon with the mixed training data. The classifier fcommon is used to classify the reviews regardless of their domains. Note that this approach is called feature-level fusion in [12]. The architectures of these two approaches are shown in Fig.1 and Fig.2 respectively.

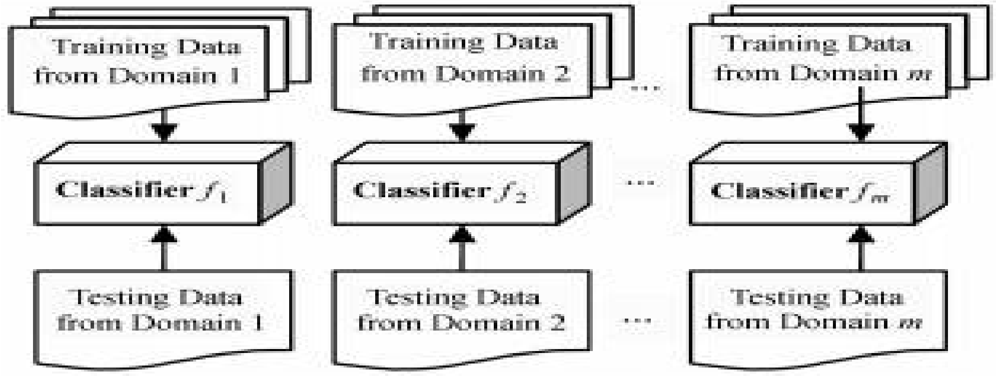

Fig.1. Architecture of single domain classification (SDC).

We believe that both these two approaches are not very competent and the reasons are as follows. On one side, general sentiment text often shares similar expressions independent of domains and thus reviewers sometimes use similar words or even sentences to deliver their positive or negative opinions on reviews cross different domains. For example, the word of “worthless” can always be used for negatively reviewing any products while the word of “perfect” is usually found in the positive reviews of many domains. Given the training data from multiple domains, we can certainly use all the data to better learn global sentiment classification information.

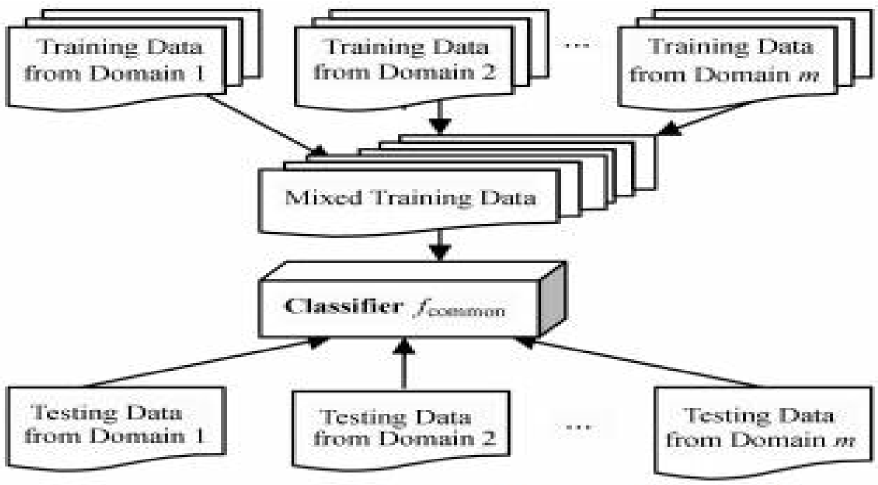

Fig.2. Architecture of all-mixed classification (AMC).

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Apparently, SDC approach is often difficult to capture adequate information for sentiment classification due to the limited scale training data in one single domain. Using the data from other domains is possibly to get more global sentiment classification information which might be missing in the in-domain data. On the other side, each domain has its own character on expressing sentiment information. For example, the term “quiet” is very informative in the kitchen product reviews but provides no sentiment information in some other domains like books or DVDs. Unfortunately, AMC approach neglects or weakens local information for sentiment classification on each domain. In brief, we believe that a better approach to multi domain sentiment classification must take into account both global and local sentiment classification information from the multi-domain training data.

II. LITERATURE SURVEY

Literature survey is the most important step in software development process. Before developing the tool it is necessary to determine the time factor, economy and company strength. Once these things are satisfied, then the next step is to determine which operating system and language can be used for developing the tool. Once the programmers start building the tool the programmers need lot of external support. This support can be obtained from senior programmers, from book or from websites. Before building the system the above consideration are taken into account for developing the proposed system.

The major part of the project development sector considers and fully survey all the required needs for developing the project. For every project Literature survey is the most important sector in software development process. Before developing the tools and the associated designing it is necessary to determine and survey the time factor, resource requirement, man power, economy, and company strength. Once these things are satisfied and fully surveyed, then the next step is to determine about the software specifications in the respective system such as what type of operating system the project would require, and what are all the necessary software are needed to proceed with the next step such as developing the tools, and the associated operations.

2.1.1 RECOGNIZING CONTEXTUAL POLARITY IN PHRASE-LEVEL SENTIMENT ANALYSIS

This paper presents a new approach to phrase-level sentiment analysis that first determines whether an expression is neutral or polar and then disambiguates the polarity of the polar expressions. With this approach, the system is able to automatically identify the contextual polarity for a large subset of sentiment expressions, achieving results that are significantly better than baseline.

2.1.2 A SENTIMENTAL EDUCATION: SENTIMENT ANALYSIS USING SUBJECTIVITY SUMMARIZATION BASED ON MINIMUM CUTS

Sentiment analysis seeks to identify the viewpoint(s) underlying a text span; an example application is classifying a movie review as thumbs upor thumbs down. To determine this sentiment polarity, we propose a novel machine-learning method that applies text-categorization techniques to just the subjective portions of the document. Extracting these portions can be implemented using efficient techniques for finding minimum cuts in graphs; this greatly facilitates incorporation of cross-sentence contextual constraints.

2.1.3 IDENTIFYING EXPRESSIONS OF OPINION IN CONTEXT

While traditional information extraction systems have been built to answer questions about facts, subjective information extraction systems will answer questions about feelings and opinions. A crucial step towards this goal is identifying the words and phrases that express opinions in text. Indeed, although much previous work has relied on the identification of opinion expressions for a variety of sentiment-based NLP tasks, none has focused directly on this important supporting task. Moreover, none of the proposed methods for identification of opinion expressions has been evaluated at the task that they were designed to perform. We present an approach for identifying opinion expressions that uses conditional random fields and we evaluate the approach at the expression-level using a standard sentiment corpus. Our approach achieves expression-level performance within 5% of the human interannotator agreement.

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2.1.4 Q-WORDNET: EXTRACTING POLARITY FROM WORDNET SENSES

This paper presents Q-WordNet, a lexical resource consisting of WordNet senses automatically annotated by positive and negative polarity. Polarity classification amounts to decide whether a text (sense, sentence, etc.) may be associated to positive or negative connotations. Polarity classification is becoming important for applications such as Opinion Mining and Sentiment Analysis, which facilitates the extraction and analysis of opinions about commercial products, on companies' reputation management, brand monitoring, or to track attitudes by mining online forums, blogs, etc.

Inspired by work on classification of word senses by polarity (e.g., SentiWordNet), and taking WordNet as a starting point, we build Q-WordNet. Instead of applying external tools such as supervised classifiers to annotated WordNet synsets by polarity, we try to effectively maximize the linguistic information contained in WordNet, thereby taking advantage of the human effort put by lexicographers and annotators. The resulting resource is a subset of WordNet senses classified as positive or negative. In this approach, neutral polarity is seen as the absence of positive or negative polarity. The evaluation of Q-WordNet shows an improvement with respect to previous approaches. We believe that Q-WordNet can be used as a starting point for data-driven approaches in sentiment analysis.

2.1.5 DETERMINING THE SEMANTIC ORIENTATION OF TERMS THROUGH GLOSS CLASSIFICATION

Sentiment classification is a recent sub discipline of text classification which is concerned not with the topic a document is about, but with the opinion it expresses. It has a rich set of applications, ranging from tracking users' opinions about products or about political candidates as expressed in online forums, to customer relationship management. Functional to the extraction of opinions from text is the determination of the orientation of "subjective" terms contained in text, i.e. the determination of whether a term that carries opinionated content has a positive or a negative connotation. In this paper we present a new method for determining the orientation of subjective terms. The method is based on the quantitative analysis of the glosses of such terms, i.e. the definitions that these terms are given in on-line dictionaries, and on the use of the resulting term representations for semi-supervised term classification. The method we present outperforms all known methods when tested on the recognized standard benchmarks for this task.

2.1.6 IDENTIFYING TEXT POLARITY USING RANDOM WALKS

Automatically identifying the polarity of words is a very important task in Natural Language Processing. It has applications in text classification, text filtering, analysis of product review, analysis of responses to surveys, and mining online discussions. We propose a method for identifying the polarity of words. We apply a Markov random walk model to a large word relatedness graph, producing a polarity estimate for any given word. A key advantage of the model is its ability to accurately and quickly assign a polarity sign and magnitude to any word. The method could be used both in a semi-supervised setting where a training set of labeled words is used, and in an unsupervised setting where a handful of seeds is used to define the two polarity classes. The method is experimentally tested using a manually labeled set of positive and negative words. It outperforms the state of the art methods in the semi-supervised setting. The results in the unsupervised setting is comparable to the best reported values. However, the proposed method is faster and does not need a large corpus.

III. EXISTING SYSSTEM

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 micro blog messages is also helpful to substitute or supplement traditional polling, which is expensive and time-consuming.
Disadvantages: More Expensive, • Time consuming more.

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IV. PROPOSED SYSTEM

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. 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.

Advantages of the Proposed System :

- Speeding up the learning process by training sentiment classifiers for multiple domains in parallel at different computing nodes.
- A parallel algorithm to further improve its efficiency when domains to be analysed are massive.

V. SYSTEM ARCHITECTURE

Design is a multi- step that focuses on data structure software architecture, procedural details, algorithm etc… and interface between modules. The design process also translate the requirements into presentation of software that can be accessed for quality before coding begins. Computer software design change continuously as new methods; better analysis and border understanding evolved. Software design is at relatively early stage in its revolution.

Therefore, software design methodology lacks the depth, flexibility and quantitative nature that are normally associated with more classical engineering disciplines. However techniques for software designs do exit, criteria for design qualities are available and design notation can be applied.

DESIGN STRUCTURE

INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy. Input Design considered the following things:

- What data should be given as input?
- How the data should be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occur.

OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the
- Future.
- Signal important events, opportunities, problems, or warnings.

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- Trigger an action.
- Confirm an action.

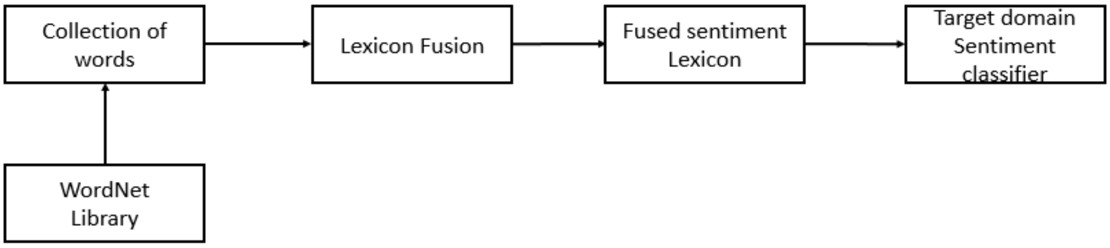

Fig. 3 : System Architecture

VI. Conclusion and Future Work

Sentiment classification is a domain specific problem i.e. classifiers trained in one domain do not perform well in others. At the same time, sentiment classifiers need to be customizable to new domains in order to be useful in practice such as the Web. Within this context, different studies have been emerging to tackle cross-domain sentiment classification. Moreover, most of the studies have been focusing on polarity although subjectivity is a much more complex linguistic phenomenon as explained in Boiy et al. (2007). For that purpose, we presented different experiments based on single-view, multi-view and semi-supervised learning algorithms, using high-level and low-level features, and the results can be viewed as very encouraging.

Sentiment analysis has wide area of applications and it also facing many research challenges. Since the fast growth of internet and internet related applications, the Sentiment Analysis become a most interesting research area among natural language processing community. A more innovative and effective techniques required to be invented which should overcome the current challenges faced by Sentiment Analysis.

FUTURE ENHANCEMENT:

In our future work, we will exploit more effective algorithms to improve the performances of the source and target classifiers. Mean while,we would like to adapt our active learning approach to other cross-domain tasks in natural language processing

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