Domain Adaptation for Sentiment Analysis: A Survey

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Abstract

Domain adaptation is a useful technique to combat the problem of data scarcity. It has been used for multiple NLP tasks like part of speech tagging, dependency parsing, named entity recognition *etc*. Cross-domain sentiment analysis (CDSA) is one such application of domain adaptation where classifier is trained on one domain (referred as '*source domain*') and tested on another domain (referred as '*target domain*'). In this paper, we investigate various challenges and techniques for CDSA. We also address the problem of selecting suitable source domain for a particular target domain in CDSA.

1 Introduction

Sentiment analysis (SA) deals with automatic detection of opinion orientation in text (Liu and others, 2010). Domain-specificity of the sentiment of words is a well-known challenge to sentiment analysis (Pang et al., 2008). A popular example is the word '*unpredictable*' that is positive for a book review (as in '*The plot of the book is unpredictable*') but negative for an automobile review (as in '*The steering of the car is unpredictable*').

Cross-domain sentiment analysis (CDSA) helps to apply sentiment information learned on a source domain to a particular target domain. The need for CDSA arises in two scenarios:

- **Insufficient Data** - When there is not enough data for the target domain to have a sentiment classifier of its own
- **Unlabelled Data** - When data in target domain is not labelled. Labelling of data is both expensive and time-consuming task

Multiple techniques have been proposed to improve classification accuracy for the task of CDSA. In this paper, we look at these techniques in detail. The rest of the paper is organised as follows. In section 2, we look at various challenges to CDSA. We then investigate techniques for CDSA in section 3 which is followed by the discussion on source domain selection for CDSA in section 4. Finally, we conclude the paper in section 5.

2 Challenges to CDSA

Sentiment classification accuracy takes a hit when we use a cross-domain classification model since the target domain comes from a different distribution compared to the source domain. There are some challenges one needs to consider before building a cross-domain sentiment classifier. Following are the challenges faced by CDSA:

1. **Sparsity** - The problem of sparsity emerges when target domain contains words or phrases that are not present in source domain or appear very few number of times. If the words are polar [1], it further adds to the severity of the problem.

2. **Feature Divergence** - The features used by the classifier to learn sentiment in the source domain might not align well or mismatch with those in the target domain (Pan et al., 2010). Therefore, the classifier fails to generalise on the target domain resulting in poor performance.

3. **Chameleon Words** - The context in which a word appears can heavily affect its meaning and polarity. Therefore, there are some polar words which are domain-specific.

[1]Polar words are those words which express an opinion. For example, *Good* is a polar word.

Challenge	Example
Sparsity	*Delicious* is a significant word for Food domain but will be hardly present in Movie domain. Similarly, *Engaging* will is significant for Movie domain but is not expected to be present in Food domain
Feature Divergence	Food and Movie domains are quite distant domains in terms of the topics they discuss. They will use different words (features) to express sentiment
Chameleon Words	*Poignant* is positive in Movie domain whereas negative in many other domains viz Beauty, Clothing etc

Table 1: Examples for CDSA challenges

These can be referred as '*Chameleon Words*' which change their polarity across domains. (Sharma and Bhattacharyya, 2013) use χ^2 test to find out domain-dedicated polar words. The authors use multiple thresholds based on χ^2 value for a word to detect if it is polar for a domain. hamilton-etal-2016-inducing combine domain-specific word embeddings with a label propagation framework to induce accurate domain-specific sentiment lexicons using small sets of seed words

Table 1 shows the examples for these challenges to CDSA.

3 Techniques for CDSA

In recent years, several techniques have been proposed to perform the task of CDSA. In this section, we look at some of these techniques in detail and provide a summery in figure 1.

3.1 Feature Alignment

We looked at how feature divergence between source and target domain poses a challenge to CDSA. (Pan et al., 2010) provide a technique to mitigate feature divergence using a spectral feature alignment (SFA) algorithm. SFA aligns domain-specific words from different domains into a single cluster by employing domain independent words as a bridge. SFA constructs a bipartite graph to represent co-occurrence relationship between domain-specific words and domain-independent words. The idea is that if two domain-specific words have connections to more common domain-independent words in the graph, they tend to be aligned together with higher probability. Similarly, if two domain-independent words have connections to more common domain-specific words in the graph, they tend to be aligned together with higher probability. (Lin et al., 2014) later enhanced SFA through addition of shorthand notated words and n-gram form. They train a SVM-based binary classifier on Amazon reviews that takes into account the similarity between domains during sentiment classification.

3.2 Structured Correspondence Learning (SCL)

(Blitzer et al., 2006) introduced SCL algorithm to induce correspondences between features from different domains. SCL uses pivot features to correlate and discover features from different domains. The model is developed by measuring the distance between two distributions, one in the source and one in the target domain, by using hypothesized distance measures based on divergence. blitzer-etal-2007-biographies extended SCL and proposed a model named Structured Correspondence Learning-Mutual Information or SCI-MI model. They incorporate SCL to sentiment classification. This model selects pivot models using mutual information between a feature (unigram or bigram) and a domain label. The most recent use of SCL to the best of our knowledge is by Yu and Jiang (2016). They use SCL to induce sentence embeddings while learning the classifier.

3.3 Topic Modelling

Topic modelling provides unsupervised learning of sentiment classifier. It uses clustering techniques. (Zhou et al., 2015) provide topical correspondence transfer (TCL) algorithm to learn domain-specific information from different domains in a common space. As we discussed, text classification faces the problem of feature divergence and high dimensional feature space. This problem is addressed by Onan et al. (2016) using Latent Dirichlet allocation (LDA) for topic modelling to aid sentiment classification. Recent use of topic modelling using LDA for CDSA is by

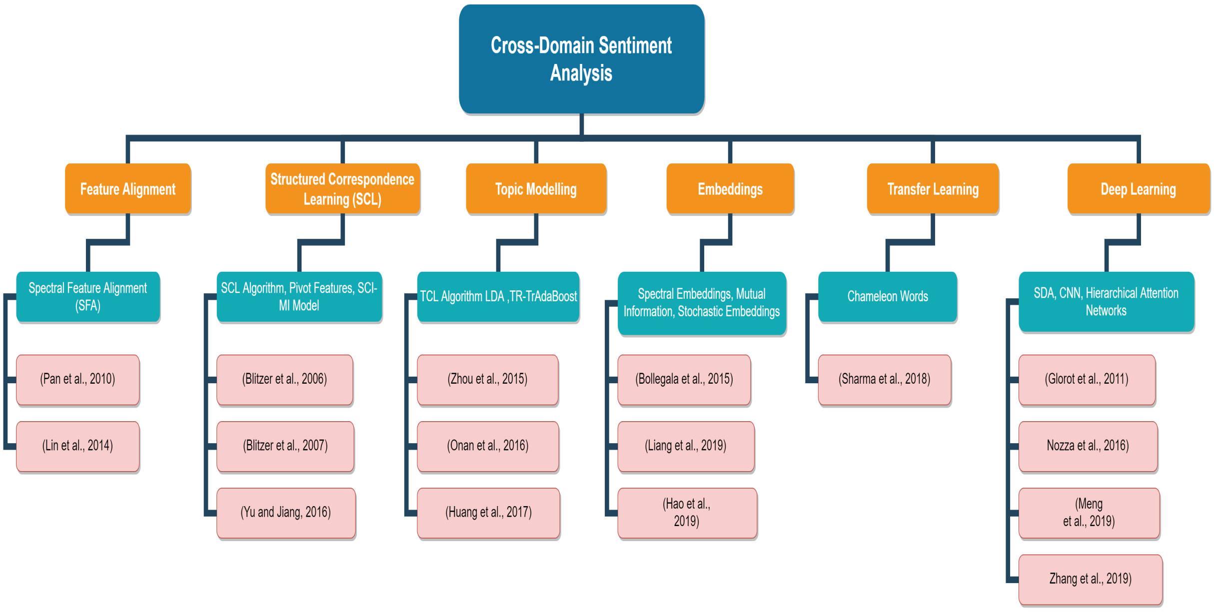

Figure 1: CDSA Techniques

Huang et al. (2017). They provide a boosting-based learning framework named TR-TrAdaBoost for cross-domain sentiment classification. The central idea is to capture the latent semantic structure by extracting the topic distribution of documents, so as to embed both domain-specific and shared information of documents.

3.4 Embeddings

Multiple models have been proposed to leverage either word or sentence embeddings for the task of CDSA. Bollegala et al. (2015) propose an unlabelled cross-domain sentiment classification method using spectral embeddings where both the words and the documents are projected into the same lower-dimensional sentiment sensitive embedding. Three objective models are jointly optimized by enforcing three requirements; domain-independent features (known as *pivots*), friend closeness and enemy dispersion of the source domain labeled documents and local geometry among the documents. Logistic regression with l_2 regularisation is used as the binary sentiment classifier. The latest contribution to word embeddings-based approach to CDSA is by Liang et al. (2019) and Hao et al. (2019). Liang et al. (2019) use SKIPGRAM model to learn embeddings for source domain and use them to train embeddings on target domain. A transfer coefficient is used as constraint to objective of SKIPGRAM while training embeddings for target domain. This coefficient is calculated using mutual information with pivots having strong polarity orientation. Hao et al. (2019) use mapping of the word polarity and occurrence information at low computational costs. They use stochastic embedding technique to train cross-domain embeddings for both words and reviews.

3.5 Transfer Learning

Transfer learning is at the heart of domain adaptation. It is very important to identify what information should be transferred from source domain to target domain while performing CDSA. Sharma et al. (2018) present a novel method to perform this task. They propose that words that do not change their polarity and significance represent the useful information that can be transferred across domains for CDSA. The χ^2 test is used to identify and exclude words that change their polarity orientation (Chameleon Words as discussed before) from the source domain to the target domain. The authors also provide a weighted ensemble of the classifiers that enhances the cross-domain classification performance.

3.6 Deep Learning

Deep learning has proved to be very useful for various NLP tasks. Similar is the case with CDSA. Deep networks extract common features and concepts between source and target domain. These features are then used to train the classifier. One of the initial use of deep learning for CDSA is by Glorot et al. (2011). They extract high level features with the help of a Stacked Denoising Auto-encoder (SDA) with rectifier units. The stochastic gradient descent is used to train the SDA in a greedy layer-wise manner. The classifier is then trained on the source domain data which is labelled. Nozza et al. (2016) use a combination of deep learning and ensemble methods. Deep leaning aids feature extraction and ensemble methods are used to reduce the amount of generalization errors across domains. Some of the latest advances in deep leaning methods for CDSA are by Meng et al. (2019) that use a transfer learning method based on the multi-layer convolutional neural network (CNN) and Zhang et al. (2019) that proposes a hierarchical attention generative adversarial network for CDSA.

4 Source Domain Selection for CDSA

It is vital to select a suitable source domain for a particular target domain. A source domain with high feature divergence with the target domain negatively affects the performance of CDSA. For example, *'Clothing'* domain will be a more suitable source domain for *'Shoe'* domain compared to *'Book'* domain because of relatively high feature and concept overlapping.

schultz2018distance present a method for source domain selection as a weighted sum of similarity metrics. They use statistical classifiers such as logistic regression and support vector machines. To the best of our knowledge, this is the first work in this direction. The proposed method is a linear combination of well-known distance functions between probability distributions supported on the source and target domains. They call this method CMEK, named after the metrics used to find out the distance between available choices of the source domain and the given target domain. The CMEK method trains source domain selection model using these distance metrics. The four metrics chosen are (i) χ^2 test, (ii) Maximum Mean Discrepancy (MMD) distance function, (iii) Earth Mover's Distance (EMD) and, (iv) Kullback-Leibler Divergence (KLD). Selection based on the linear combination of these four metrics, the constant, and $\xi(\mathbb{P})$ is referred to as the CMEK selection model:

$$
\begin{aligned}
d(\mathbb{P},\overline{\mathbb{P}}_x) = \beta_1\chi^2(\mathbb{P},\overline{\mathbb{P}}_x) + \beta_2 MMD(\mathbb{P},\overline{\mathbb{P}}_x) + \\
\beta_3 EMD(\mathbb{P},\overline{\mathbb{P}}_x) + \beta_4 KLD(\mathbb{P},\overline{\mathbb{P}}_x) \\
+\beta_5\xi(\mathbb{P}) + \beta_0
\end{aligned} \tag{1}
$$

where $\mathbb{P}$ and $\overline{\mathbb{P}}$ are source and target domain distributions respt. with marginals $\mathbb{P}_x$ and $\overline{\mathbb{P}}_x$. $\xi(\mathbb{P})$ denotes in-domain error and β_i is weight coefficient. β_0 is a constant.

They experiment on two datasets; (i) homogeneous data consisting of Amazon reviews in 20 domains each having 5000 positive and 5000 negative reviews. (ii) heterogeneous data consisting of 13 domains each having different number of reviews. The authors report a probability of selecting best source domain for homogeneous dataset as 0.6 and 0.385 for heterogeneous dataset. The CMEK model is limited by it's computational requirements as distance metrics like Earth Mover's Distance are quite expensive to compute.

5 Conclusion and Future Work

Over the years, domain adaptation has proved to be a vital technique to address the problem of data scarcity for various NLP tasks including sentiment analysis. Multiple methods have been proposed to improve the performance of CDSA. We discussed some of these methods in this paper. All these methods more or less try to tackle the challenges we discussed. We also looked at the importance of selecting a suitable domain for a particular target domain.
For future research in this area, we see the following possibilities:

- Develop methods that take into account the conceptual relatedness of source and target domains
- Device deep networks that can filter out useful information to transfer from source domain to target domain
- Training of rich cross-domain word embeddings
- Develop metrics to predict cross-domain classification error

- Develop computationally feasible methods to select suitable source domain for a target domain
- Use of text similarity-based metrics to measure relatedness of source and target domains

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