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Feature Transfer Through New Statistical Association Measure for Cross-Domain Sentiment Analysis

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Abstract: With the outgrowth of user-based web content, individuals can freely express their opinion in many domains. However, this would imply a huge cost to annotate training data for a large number of domains and prevent us from exploiting the information shared across various domains. As a result, cross-domain sentiment analysis is a challenging NLP task due to feature divergence and polarity divergence. However, to tackle this issue, this study presents a new model for cross-domain sentiment classification. This model is based on transferring features between source and target domains vice versa, using a Union of Conditional Probability (UCP) association measure. A Naive Bayes (NB) classifier and three feature selection methods (Information gain, Odd ratio, Chi-square) are used to evaluate the proposed model. Experimental results show that our model's results were very promising and encourages us to further pursue this research.

Key words: Sentiment analysis, cross-domain sentiment analysis, co-occurrence calculation methods, sentiment thesaurus, Malaysia

INTRODUCTION

Due to a large amount of textual information, opinion mining and sentiment analysis has been gaining strong interest from practitioners and researchers across the web (Moslmi *et al*., 2015; Balahur and Jacquet, 2015; Balahur and Ortega, 2015; Bertola and Patti, 2016; Fersini *et al*., 2016; Habernal *et al*., 2014; Omar *et al*., 2013; Piryani *et al*., 2017; Saif *et al*., 2016; Severyn *et al*., 2016; Vinodhini and Chandrasekaran, 2017; Xia *et al*., 2016). The aim of sentiment analysis is to classify text as describing positive sentiment or negative sentiment. Classification of text polarity form the huge amount of human generated textual data will help in garnering rich behavioural information from different domains like movie reviews, political news reviews and product reviews (Moslmi *et al*., 2015; Omar *et al*., 2014; Singhal *et al*., 2015; Yusof *et al*., 2015). The technical challenge in sentiment analysis is that it is highly domain dependent. A method performing well in one domain might underperform in another domain. In the machine learning area the latter issue also known as cross domain classification performs well only with labelled documents and hence is highly domain sensitive.

Many researchers for cross-domain sentiment analysis (Blitzer *et al*., 2007; Blitzer *et al*., 2006; Li *et al*., 2009; Pan *et al*., 2010) have differentiated between independent features and domain specific features and regarded the independent features as a bridge to align domain-specific features either by clustering or another suitable method. These researches were based on the rationale that the independent features have the same polarity in different domains. Nonetheless, in a real world scenario this assumption can be wrong as a word can have different sentiment polarities in different domains. For e.g., consider the Book domain, in a sentence like "It is too easy for senior students" the word "easy" can have a negative polarity indicating that Book is not suitable for senior students but only for junior students. Now this same word "easy" will mostly have a positive polarity in the Electronics domain, e.g., in the sentence "This device is easy to operate". This pole difference is called 'polarity divergence'. However, researchers like Blitzer *et al*. (2007), Bollegala *et al*. (2012), Li *et al*. (2009) and Pan *et al*. (2010) have argued that such polarity divergence is very rare and hence the authors in this work have not considered it. Moreover, the authors agree that polarity divergence though rare is present in some cross-domain tasks.

The main aim of this study is to build a new model for cross-domain sentiment classification based on transferring features between source and target domain. A new model is proposed based on using a union of conditional probability association measure.

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Table 1: An overview of earlier cross-domain classification researches

Researchers (year)	ML/NLP	Algorithms	Dataset	Classifier
Blitzer *et al.* (2006)	POS	SCL	Amazon	SVM
Blitzer *et al.* (2007)	POS	SCL-MI	Amazon	SVM
Xue *et al.* (2008)	TF and IDF	PLSA	Use Net news article, SRAA and Newswire articles	SVM and NBC
Li and Zong (2008b)	N-gram method	Feature level fusion	Amazon	LIBSVM
Guo *et al.* (2009)	LaSA and LDA	MI	Wikipedia, Chinese newspapers	PRM classifier
Wang *et al.* (2008)	TF and IDF	MI	Newsgroup and SRAA	NBC
Paltoglou and Thelwall (2010)	TF and IDF	SMART and BM25 tf.idf variants	Amazon, movie dataset from new groups	SVM and NBC
Jakob and Gurevych (2010)	POS	CRF Algorithm	Amazon	SVM
Huang and Yates (2010)	CRF	HHM based model	Wall street Journal	ME

Table 2: The most common baseline methods used by previous researchers

Methods	Algorithm	Researcher (year)
Structured correspondence learning	SCL	Blitzer *et al.* (2006)
SCL mutual information	SCL-MI	Blitzer *et al.* (2007)
Partially supervised cross-collection LDA	PSCCLDA	Bao *et al.* (2013)
Spectral feature alignment	SFA	Pan *et al.* (2010)
Latent semantic analysis	LSA	Cohn and Hofmann (2001)
Transfer probabilistic latent semantic analysis	TPLSA	Xue *et al.* (2008)
Collaborative Dual-PLSA	CDPLSA	Zhuang *et al.* (2010)
Manifold	Manifold	Zhou *et al.* (2004)
Non-negative matrix tri-factorization	NMTF	Li *et al.* (2009)
Transfer component analysis	TCA	Li *et al.* (2012)
Majority class classifier	MC	Majority class classifier
Multi-label consensus training	MCT	Li and Zong (2008a)
Senti rank	SentiRank	Wu *et al.* (2009)
Traditional supervised classifier	Porto	-

Literature review: In this study, we give an overview of the earlier researchers in cross-domain sentiment analysis. Groups of classifiers trained on different source domains were used in the early days of domain adaptation (Li and Zong, 2008a). TPLSA was developed by (Xue *et al*., 2008) to include both unlabeled and labelled data. This learning is done via a joint probabilistic model and documents in test and training domains are bridged using hidden variables. The basis of TPLSA is the concurrent decomposition of contingency tables related with information of term occurrence in both training and test domain documents leading to the identification of prime topics in both domains. Heterogeneous transfer learning approach was proposed by (Wang *et al*., 2009). In this method, learning performance is increased if data can be denoted in feature spaces such that there is no communication between the data in these spaces. Collaborative Dual-PLSA was developed by Zhuang *et al*., 2010) to concurrently capture both domain distinction and commonality among multiple domains. Word concept and document class are the two latent aspects of their model. Table 1 summarize some of the earlier researches in cross-domain sentiment analysis.

To the purpose of evaluate the previous proposed methods; the researchers have used many baseline methods to evaluate their researches. The most common baseline methods that have been used are Structured Correspondence Learning (SCL) (Blitzer *et al*., 2006), SFA (Pan *et al*., 2010) and SCL Mutual Information (SCL-MI) (Blitzer *et al*., 2006). Table 2 shows the summary of baseline methods have been used in different researches during past years.

MATERIALS AND METHODS

The main aim of this phase is to automatically create a thesaurus which can be used to transfer feature vectors of the source and target domains. We aim to design a new method to calculate co-occurrences between features which is typically used in characterizing a word's distributional context. This method is based on the union of the conditional probability of features' occurrences. Figure 1 represents the Cross-Domain Sentiment Thesaurus (CDST) model for the automatic construction of the thesaurus. The following describes each of the processes involved:

Pre-processing: In the pre-processing stage (Duwairi and Orfali, 2014) various NLP techniques are applied. The pre-processing consists of four steps: tokenization, normalization, stop word removal and stemming. All reviews go through a pre-processing stage. In the normalization process; diacritics and noisy characters are removed. Secondly, in this phase certain stop-words that occur commonly in all reviews are removed to avoid misclassifying the reviews. Finally, the last stage of the pre-processing involves a stemming process that proposed by (Porter, 1980).

Co-occurrence calculation method: Let us indicate the value of a feature w in the feature vector u representing a lexical element u by f(u, w). The vector u can be seen as a compact representation of the distribution of a lexical element u over the set of features that co-occur with u in the reviews. f(u, w) will be computed as the co-occurrence measure between a lexical element u and a feature w. The

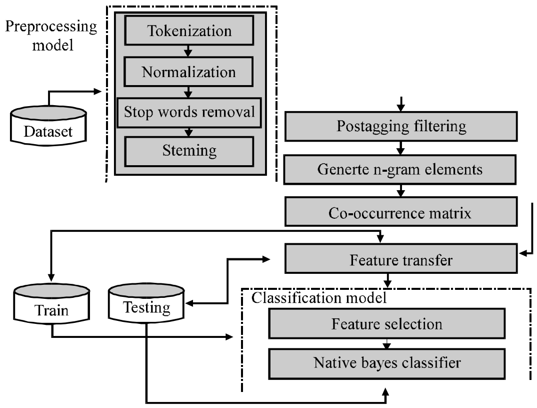

Fig. 1: Cross-Domain Sentiment Thesaurus (CDST) Model

calculation of our new method which we called the Union of Conditional Probability (UCP) can be done using the formula below:

$$f(u,w) = p(u \mid w) + p(w \mid u) = \frac{p(u \mid w)}{p(w)} + \frac{p(u \mid w)}{p(u)}$$

$$= \frac{p(u,w)\big(p(u)+p(w)\big)}{p(w)p(u)}$$

$$= \frac{\frac{c(u,w)}{N}\left(\frac{\sum_{i=1}^{n} c(i,w)}{N} + \frac{\sum_{j=1}^{m} c(u,j)}{N}\right)}{\frac{\sum_{i=1}^{n} c(i,w)}{N} \times \frac{\sum_{j=1}^{m} c(u,j)}{N}}$$

whereby, c(u, w) indicates the number of review sentences in which a lexical element u and a feature w take place simultaneously, n indicates the total number of lexical elements and m the total number of features. In addition, N indicates the numbers of reviews.

Feature transfer: In this phase, this research tries to transfer features between source and target domain. Given a co-occurrence matrix, we expand reviews from source domain using features from target domain. In addition, reviews from target domain are also expanded using features from source domain. The transfer or expansion algorithm works as follows. Firstly, each review from both source and target domains is pelleted into sentences and POS is assigned for each element then Bag Of Words (BOW) is generated. Afterwards, a global unigrams and bigrams list is created after calculating the co-occurrence matrix for all elements. Then for each element in the unigrams and bigrams list generated for this review, a set of most related words is retrieved. The most related words refer to all words in the co-occurrence matrix that have the highest co-occurrence values with the elements. After we get the most K related unigrams and bigrams elements, the review r is expanded by adding these elements to the review. We exclude all elements that belongs to the same review's domain from the list of the most related unigrams and bigrams, given the global unigrams and bigrams elements list that has been created in advance. Algorithm 1 shows the pseudo code of the feature transfer method.

Algorithm 1: the pseudo code of feature transfer method

```
Input: A review R from a domain D
Output: Expanded review R
For each R in D do
    Begin
              NEL = Generate N-gram elements (R)
          For each element e in NEL do
             Begin
                   CE = Get co-occurrence element (e)
             TCE = Get top K elements (CE)
                 NEL = NEL R TCE
             End For
          R = Expand- R (NEL,R)
    End
End
```

Classification phase: After the reviews are expanded from both source and target domains, a classification model based on Naive Bayes which is trained using expanded reviews from source domain is applied to expanded reviews from target domain. Before applying the classification model, a feature selection method was used to select important features from expanded reviews of the source domain.

Three effective feature selection methods were used, IG, Odd ratio and Chi-square (Moslmi *et al*., 2014) for feature selection. These methods compute a score for each individual feature and then select a predefined size for the feature set.

In this study, Naïve Bayes classifier method is used. This method is used due to its simplicity effectiveness and accurateness (Claster *et al*., 2010; Kang *et al*., 2012). The Naive Bayes (NB) algorithm is a popular machine learning technique for sentiment analysis. Given a collection of N reviews $\{r_j\}_1^N$ where each review is represented as a sequence of m terms, $r_j = \{t_1, t_2,...,t_m\}$ the probability of a document r_j occurring in classis $C_k \in$ {positive, nagative} is given as:

$$p(c_k \mid r_j) = p(c_k)\prod_{i=1}^{m} p(t_i \mid c_k)$$

where, $p(t/C_k)$ is the probability of term t occurring in a review of class C_k and $p(C_k)$ is the prior probability of a review occurring in class C_k. $P(t/C_k)$ and $p(C_k)$ are estimated from the training data.

Experimental setup: Several experiments were conducted to evaluate the proposed model. Experiments were conducted on the Amazon dataset (Blitzer *et al*., 2006). This dataset includes four different domains (Book, DVDS, Electronics and Kitchen) and each domain has 2000 labled reviews 1000 reviews are negative and 1000 more reviews are positive. In all experiments, one domain is selected as a target domain while three domains are used as a source domain one by one. In each experiment, 1600 reviews (800 positive and 800 negative) are selected as a training data from source domain while 200 reviews (100 positives and 100 negatives) are selected as a test data. Experiments were conducted on the Amazon dataset that contains four domains, i.e., Book, DVD, Electronics and Kitchen. All experiments were evaluated using 5 fold cross-validation. To measure the performance of these classification methods, experimental results were sorted into the following: True Positive (TP) is the set of reviews that is correctly assigned to the given category, False Positive (FP) is the set of reviews incorrectly assigned to the category, False Negative (FN) is the set of reviews that is incorrectly not assigned to the category and True Negative (TN) is the set of the set of reviews correctly not assigned to the category. The F1 and Macro-F1 measures were employed. The following describe these matricies:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP}+\text{FN})}$$

$$F_1 = \frac{2\times\text{Recall}\times\text{Precision}}{(\text{Recall}+\text{Precision})}$$

$$F_1^{macro} = \frac{1}{m}\sum_{i=1}^{m} F_1(i)$$

RESULTS AND DISCUSSION

The purpose of this experiment is to evaluate the quality and usefulness of proposed model. Accordingly, four main parts of experiment have been done. In all experiments, one domain is selected as a target domain while the remaining three domains were used as a source domain one by one. In the first part, the Book domain is selected as target domain and the rest three domains, DVD, Electronics and Kitchen have been used as target domains, respectively. Table 3 shows the results of the NB classifier with the three feature selection methods (IG, Odd ratio, Chi-square). As it can be seen in Table 4, the best result achieved is when the electronics domain is used as a source domain and book as a source domain and chi-square feature selection with feature size 600.

Table 3: Performance (F-measure) of the Book as a target domain with NB classifiers

Feature size	200	400	600	800	1000	1200	1400	1600
DVD								
ODD	60.6	64.3	67.6	67.6	68.6	67.6	66.6	67.5
CHI	52.0	60.2	58.8	60.1	57.8	59.5	59.5	59.5
IG	42.3	35.8	35.1	41.4	42.7	47.3	50.8	50.4
Electronics								
ODD	64.0	66.5	64.5	63.0	62.0	62.0	62.0	62.0
CHI	57.4	64.4	71.5	62.9	67.9	65.4	57.3	58.4
IG	42.9	55.8	57.3	56.9	59.4	61.3	61.8	62.3
Kitchen								
ODD	67.8	64.4	64.9	66.4	66.8	66.8	66.8	66.8
CHI	59.4	59.5	65.8	61.9	67.3	64.1	62.5	64.8
IG	47.4	58.1	59.2	57.8	55.2	53.7	55.6	56.6

Table 4: Performance (F-measure) of the DVD as a target domain with NB classifiers

Feature size	200	400	600	800	1000	1200	1400	1600
Book								
ODD	63.4	70.6	70.1	70.1	70.6	69.0	69.5	71.1
CHI	64.1	67.1	71.5	72.1	72.2	74.3	74.1	71.3
IG	58.4	59.1	60.3	59.4	58.7	58.0	59.9	58.9
Electronics								
ODD	69.6	68.1	68.5	66.0	68.5	67.0	67.8	69.4
CHI	68.6	65.5	67.3	68.4	67.1	71.6	67.0	67.0
IG	59.4	52.2	49.1	50.0	54.6	55.1	56.2	56.4
Kitchen								
ODD	72.5	68.3	68.0	67.5	69.6	69.5	67.1	69.1
CHI	64.0	69.0	71.1	68.0	67.2	67.8	70.6	71.3
IG	52.2	55.9	57.9	60.4	66.9	61.0	61.5	65.4

In the second part, the DVD domain is selected as target domain and the rest three domains, book, electronics and kitchen have been used as target domains respectively. Table 4 shows that the highest performance obtained is with chi-square when the domain book is used as a source domain and the size of feature is 1200. In general, the results when the DVD is the target domain outperformed the results when the other domains are used as target domains.

In the third part, the electronics domain is selected as target domain whereas the rest three domains, book, DVD and kitchen have been used as target domains respectively. As it can be seen in Table 5, Kitchen domain achieved the best result as a target domain with odd ratio feature selection with 600 feature size.

In the last part of experiments, the kitchen domain is selected as target domain while the rest three domains, book, DVD and electronics have been used as target domains respectively. As the kitchen domain obtained the

Table 5: Performance (F-measure) of the electronics as a target domain with NB classifiers

Feature size	200	400	600	800	1000	1200	1400	1600
Book								
ODD	57.3	58.7	60.8	59.0	60.1	59.0	59.0	59.0
CHI	52.1	59.5	59.1	53.5	54.0	51.9	51.0	53.5
IG	38.8	40.5	40.7	40.5	40.9	42.8	43.2	43.6
DVD								
ODD	50.2	58.8	59.5	59.8	57.7	58.4	60.7	62.3
CHI	53.6	55.0	54.1	52.9	52.9	53.1	53.1	57.0
IG	42.3	35.5	35.9	40.2	41.7	41.7	44.2	45.8
Kitchen								
ODD	66.7	68.8	71.0	68.8	67.8	67.8	67.8	67.8
CHI	62.0	60.9	61.4	61.6	66.9	70.0	61.8	58.8
IG	47.4	49.5	51.7	55.0	55.9	58.4	59.2	61.5

Table 6: Performance (F-measure) of the kitchen as a target domain with NB classifiers

Feature size	200	400	600	800	1000	1200	1400	1600
Book								
ODD	57.0	56.8	59.6	56.8	56.3	56.8	56.8	56.8
CHI	50.2	61.0	66.0	63.4	61.9	49.8	49.4	50.0
IG	41.7	44.1	45.9	45.1	45.9	45.9	46.7	48.0
DVD								
ODD	54.9	61.1	62.2	61.9	62.5	60.8	62.0	63.0
CHI	53.6	58.8	60.7	63.8	63.2	59.2	58.6	59.4
IG	41.7	38.0	42.2	44.5	44.5	53.1	48.7	53.8
Electronics								
ODD	70.8	68.5	73.0	73.5	74.0	72.0	72.0	72.0
CHI	57.9	62.2	66.7	67.7	71.5	64.6	64.1	63.7
IG	42.0	51.0	52.9	55.6	61.0	59.3	58.4	59.0

best result as a source domain with electronics target domain as it cleared in Table 6, electronics domain achieved the best result when it used as a source domain and kitchen used as a target domain as it shown in Table 6. The result obtained with the same feature selection (Odd ratio) but different feature size (1000). In conclusion, depending on the feature used and feature size, the accuracy varies between 35.5 and 74.3%. Moreover, results vary depending on the domain used due to features divergence from one domain to another. Furthermore, the proportion of the presence of independent features differ from one domain to another and it affects the results and this explains the difference in results when the domain has been used reversely.

CONCLUSION

In this study, a new model for cross-domain sentiment classification has been proposed. This model is based on transferring features between source and target using a new proposed method called Union of Conditional Probability (UCP) association measure. Three feature selection methods (Information gain, Odd ratio, Chi-square) are used with a Naive Bayes (NB) classifier to evaluate the proposed model. The results show that the performance varies depending on the feature used and feature size. Moreover, results vary depending on the domain used, due to features divergence from domain to the other. Further experiments using more than one domain as a source domain and different classifiers will be tested and evaluated in our future work.

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