NLPR at Multilingual Opinion Analysis Task in NTCIR7

Kang Liu, Jun Zhao
National Laboratory of Pattern Recognition,
Institute of Automation, Chinese Academy of Sciences,
Beijing, 100190, China
{kliu, jzhao}@nlpr.ia.ac.cn

Abstract

This paper presents our work in the simplified Chinese opinion analysis task in NTCIR7. For identifying the subjective sentences, the domain adaptation technique was applied in our method, so that the data in NTCIR6 can be used for training subjective classifier. The evaluation results proves that the method proposed in this paper is effective. In extracting the opinion holder, we used the CRF model, which was combined with manual designed heuristics rules. For CRF model we not only extracted part-of-speech features, semantic class features, contextual features, but also some dependency features through parsing analysis. The evaluation results prove that the proposed method is effective for extracting opinion holders.

KeyWords: *NTCIR, Sentiment Analysis, Subjective Classification, Opinion Holder Extraction*

1. Introduction

Nowadays, opinion analysis has been a hot problem and attracted much attentions from researchers recently. Opinion analysis contains several tasks, including subjective text detection, polarity identification, opinion holder extraction etc.. Many researchers have proposed their methods for different tasks in opinion analysis based on different datasets. For evaluate and compare the different methods in multi-lingual opinion analysis, NTCIR7 proposed Multilingual Opinion Analysis Tasks (MOAT) tasks in this year. More descriptions of the task design are shown in the overview paper[25].

In NTCIR7, we participated in the two subtasks for simplified Chinese data: opinionated sentences identification and opinion holder extraction. In opinion sentences identification, because the provided training data is very small, when training subjective classifier, we not only used the training data in NTCIR7 simplified Chinese data, but also the traditional Chinese data in NTCIR 6 Opinion Analysis Pilot Task. The traditional Chinese data in NTCIR6 come from the United Daily News, China Times, China Times Express, Commercial Times, China Daily News, Central and Daily News. But the simplified Chinese data in NTCIR7 come from Xinhua News and Lianhe Zaobao. There is a domain difference between these two datasets. That is to say that training data hasn't the same distribution with the testing data, which can result in that the trained classifier cannot have good performance on the testing data if we directly use the training data in NTCIR 6. Therefore, we applied a domain adaptation technique to train a subjective classifier for identifying the opinionated sentences. For extracting opinion holder, we regarded it as a sequential labeling task and applied CRF model. For training it, we integrated some special features, like dependency features, contextual features, etc. After applying CRF model, we also use some manual designed rules to extract potential opinion holders for increasing recall. The details will be given below.

The reminder of this paper is organized as follows. In the section 2, we will give the related work about domain adaptation technique, subjective text detection and opinion holder extraction. In the section 3, we will give our domain adaptation method for subjective sentence detection in detail. In the section 4, the detail process for extraction opinion holder will be proposed. In the section 5, the evaluation results will be given. In the last section, we will give our conclusion.

2. Related Work

Many researches focused on identifying the subjective texts, like [9][20][15][16][23]. Wiebe[9] used a Naïve Bayes classifier to judge the sentence is subjective or objective. They used syntactic classes, punctuation, and sentence position as features. [15][16] used a sentimental dictionary to identify the subjective sentence. If a sentence contains one sentimental word, this sentence would be regarded as the subjective one. [21] shows that the adjective are useful for subjective classification.

For domain transferring, there are several researches about this problem [1][8][10][11][12][13][17][22]. Blitzer [13] proposed structural corresponding learning that defines new features for capturing the correspondence between features in two domains. Blitzer [12] applied this method in sentiment classification for four different domains and obtained better results than traditional learning methods. Jiang [11] proposed a two stages method. The first stage is generalization stage which looks for generalized features across domains and the second stage is the adaptation stage which picks up useful features specific to the target domain. Dai [22] gave a transferring naïve Bayes method. They used KL divergence between two different domains to estimate the trade off parameters in the EM iterative process. Hal Daumé III [8] proposed a graphic model in which they assumed that the data in source domain and target domain are generated from a mixture of a general distribution and a domain specific distribution. They used conditional expectation maximization algorithm to estimate the parameters in the model.

For extracting opinion holder, [15][20][24] are related to our work. Kim [20] used FrameNet and Semantic Role Labeling to find opinions and their holders. Ruifeng Xu [16] treated the nearest named entity before the opinion operator as the opinion holder in a subjective sentence. Our work is closely related with [15][24]. They both used CRF model to extract opinion holder. Ruihong Huang [15] used lexical features, POS features, semantic class features and opinion trigger features. Yejin Choi [24] not only used the features mentioned above, but also dependency tree features.

3. Opinion Identification based on Domain Adaptation

3.1 Data Preprocessing

Before detecting opinions, we used our own NER tools [25] to recognize the named entities in each sentence, by which we can also obtain the part-of-speech of each word. After that, we used parsing tool [6] to get the dependency relation among the words in each sentence. Those are the preparation for feature extraction. We would describe the process of feature extraction in detail in the following section.

For extracting features, we also built two dictionaries: opinion operator lexicon and opinion word lexicon. The concept of opinion operator and opinion word is the same as [16]. The opinion operators are verbs, which can denote an opinion event. The following table lists some examples about opinion operator.

Table 1. Some examples of opinion operator

表示(express)，认为(believe)，说(say)，坚称(persist)，盛赞(praise)，建议(suggest)，提出(propose)，宣称(declare)，表明(indicate)，称(state)，预测(predict)，声称(claim)，指出(point)，承认(confess)，要求(request)，宣布(announce)，明示(know)，预期(think)，……

The opinion word lexicon contains verb, adjectives and some adverbs, in which each opinion word expresses the polarity about some topic.

Table 2. Some examples of opinion words

小气(stingy)，大(big)，美丽(beautiful)，漂亮(pretty)，温柔(gentle)，好看(good looking)，失望(disappointed)，竟然(unexpectedly)，不足(insufficient)，没落(decline)，不景气(depression)，恶名昭彰(notorious)，退步(degenerate)，减少(reduced)，增加(increase)，抵制(resist)，……

The lexicon of the opinion operator comes from the corpus of NTCIR 6. We extracted all words which are tagged as <OPINION_OPR> in the corpus. The lexicon of the opinion word comes from three sources. The first source is the corpus of NTCIR 6. All words, which are labeled as <OPINION_OPR> and <SENTIMENT_KW>, are regarded as the opinion word. The second source is the sentiment dictionary which is provided by National Taiwan University. There are 11,088 words in this dictionary. The third source is HowNet[1], which has 8,938 subjective words.

3.2 Domain Adaptation

Based on these two lexicons, we train a subjective classifier. The size of simplified Chinese training data in NTCIR7 is small, which has only 424 sentences. For training subjective classifier, this training data is not sufficient. Therefore, we used the data in NTCIR6. The traditional Chinese data in NTCIR6 come from the United Daily News, China Times, China Times Express, Commercial Times, China Daily News, Central and Daily News. They come from the different domain compared with the data in NTCIR7. If we directly use the data in NTCIR6, it may result in the decrease of the performance because the distribution of these two domains is different. Therefore, we use a domain adaptation technique for identifying subjective sentences, which is similar to [10].

We have labeled dataset D_s of the source domain D_s with the probabilistic distribution $p_s(\cdot)$, the labeled dataset $D_{t,l}$ and unlabeled testing dataset $D_{t,u}$ of the target domain D_t with the probabilistic distribution $p_t(\cdot)$. The joint distribution function $p(x, y; \theta)$ of documents x, classes y and parameters θ is defined. Our goal is to obtain a good estimate of θ^* by optimizing the following likelihood function under the distribution of $p_t(\cdot)$. The optimization object is given as follows:

$$\theta = \arg\max_{\theta} \int \sum_{y} p_t(x, y) \log p(y / x; \theta) dx$$

$$= \arg\max_{\theta} \int p_t(x) \sum_{y} p_t(y / x) \log p(y / x; \theta) dx$$

[1] http://www.keenage.com/

For the source dataset D_s, we assume $p_s(y/x)$ approximate $p_t(y/x)$. Therefore, for different dataset D_s, $D_{t,l}$ and $D_{t,u}$, the above optimization object can be rewritten as the following formula, which is also mentioned in [10]:

$$\theta = \arg\max_{\theta}[\sum_{i=1}^{N_s} \lambda_i \log p(y_i^s / x_i^s;\theta)$$
$$+\lambda^{t,l}\sum_{i=1}^{N_{t,l}} \log p(y_i^{t,l} / x_i^{t,l};\theta)$$
$$+\lambda^{t,u}\sum_{i=1}^{N_{t,u}}\sum_{y} \alpha(y)\log p(y_i^{t,l} / x_i^{t,l};\theta)$$
$$+\log p(\theta)]$$

where N_s, $N_{t,l}$ and $N_{t,u}$ denote the size of the source labeled dataset, the target labeled dataset and the target unlabeled dataset, respectively.

The first part in the above formula is estimated in the source dataset, where $\lambda_i = \frac{p_t(x_s)}{p_s(x_s)}$. λ_i reflects the difference between two domains. For computing this value, we assume that the words are independent of each other and use the following formula to approximate it based on the unigram language model:

$$\frac{p_t(x_s)}{p_s(x_s)} = \frac{\prod_{w\in x_s} p_t(w)}{\prod_{w\in x_s} p_s(w)} \approx \frac{\prod_{w\in x_s} p(w/D_t)}{\prod_{w\in x_s} p(w/D_s)}$$

where w is the word in the instance. $p(w/D_i)$ can be estimated in each domain by $N(w,D_i)/N_{D_i}$, where $N(w,D_i)$ denotes the count of w in domain D_i, $i\in\{s,t\}$ and N_{D_i} denotes the count of all words in this domain.

The second part is estimated in the target labeled dataset and the third part is estimated in the target unlabeled dataset. This part is similar to the semi-supervised method. $\alpha(y)$ denotes the probability of labeling an instance as y. Many semi-supervised method can be used here. In our experiment, we use SVM as our model of $p(y/x;\theta)$. So for the selection of $\alpha(y)$, we directly use the transductive SVM method. $\lambda^{t,l}$ and $\lambda^{t,u}$ reflect the weight of the instance in target domain. As the same to [10], we will make them lager than λ_i, because we must put the more attentation on the target domain.

For using $p_s(y/x)$ to approximate $p_t(y/x)$, we use the small target labeled dataset to remove potentially uncorrected source labeled instance. We use the training data in NTCIR 7 simplified Chinese dataset to train a classifier and apply it on the labeled dataset in NTCIR 6. For misclassified instance, we select top 80% uncorrected instance and set λ_i of them to be zero. And others is set one. Then we will use domain adaptive method to train a classifier on the both dataset.

3.3 Features for Identifying Subjective Sentences

To train a subjective classifier, we must develop some special features for indicating opinion. Here, we mainly use the following features:

Table 3. Features for identifying subjective sentences

Features	Description
Adj. Verb.	The adjective and verb occurred in the sentence.
Named Entities	All named entities occurred in the sentence
Opinion Word	The word occurred in the opinion word dictionary
Dependency Features	The special dependent structure occurred in the parsing tree of the sentence
Other Features	All idioms occurred in the sentence

"美国/LOC (USA) 国防部长/n (defense minister) 柯恩/PER (Kern) 今天/TIM (today) 在/p (at) 澳洲/LOC (Australia) 堪培拉/LOC (Canberra) 表示/v (said)"

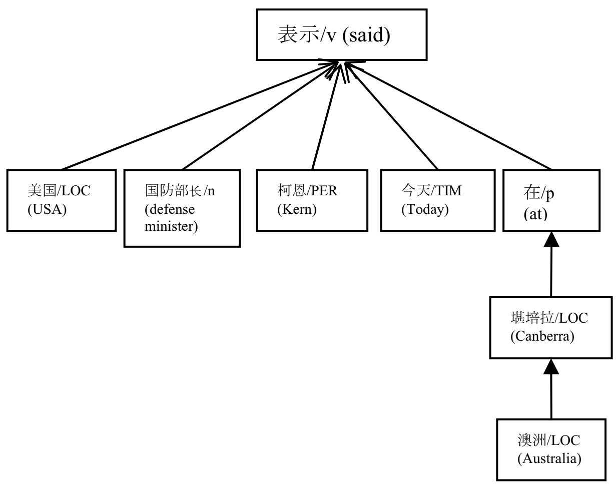

Figure 1. The parsing result

We use paring tools [6] to parse each sentence to obtain a dependency tree. When a word of the sentence occur in the opinion operate lexicon and there are a named entity dependent on this word, we believe that there is an opinion in this sentence. For example in figure1, "柯恩(Kern)" is a named entity and it is dependent on "表示(said)" in this dependency tree, while "表示(said)" is an opinion operate word. So there are dependency features which indicate an opinion. We also regard idioms as features, because in Chinese idiom idioms often express strong sentiment, like "十恶不赦(wicked to the extreme)", "美妙绝伦(prefect)"……

4. Extracting Opinion Holders based on CRF Model

As mentioned in section 1, we used CRF model to extract opinion holder in the subjective sentences which are extracted in section 3. After that, we used some heuristics rules to revise the extracted results for increasing the recall. In the following, we firstly introduce the CRF model. Then we explain the features which we used. Finally we will describe the used heuristics rules.

4.1 CRF Model

Conditional Random Fields (CRFs) [14] are undirected graphical models used to calculate the conditional probability of a set of labels given a set of input variables. We cite the definitions of CRFs in [14]. It defines the conditional probability proportional to the product of potential functions on cliques of the graph,

$$P_\lambda(Y \mid X) = \frac{\exp \lambda \cdot F(Y,X)}{\sum_y \exp(\lambda \cdot F(Y,X))}$$

where X is a set of input random variables and Y is a set of random labels. $F(Y,X)$ is an arbitrary feature function over its arguments, λ is a learned weight for each feature function

The training of CRFs is based on Maximum Likelihood Principle [7]. The log likelihood function is

$$L(\lambda) = \sum_k \left[\lambda \cdot F(Y_k, X_k) - \log Z_\lambda(X_k)\right]$$

Therefore, Limited-memory BFGS (L-BFGS) algorithm is used to find this nonlinear optimization parameters.

4.2 Features for Extracting Opinion Holders

To develop features, we consider them in the following principles: 1. Opinion holders are mostly named entities (Person, Organization or Location), noun phrases and pronouns. 2. Opinion holders are mostly connected with the opinion operate. 3. Opinion holders mostly occur in special position in the sentence. Based these three principles, we define the following features:

POS features: Based on our own POS tagger, the output of each word in the sentence would be taken into the feature set. If one word is labeled as noun or pronoun, it would be regarded as the potential opinion holder.

Semantic class features: Based on NER tools [25], we extract the named entities in a sentence. All the named entities are regarded as the candidates of the opinion holder.

Contextual Features: For extracting opinion holders, we must consider the contextual information around the opinion holder. Therefore, we defined the lexical features in a [-2,+2] window and their part-of-speech as the contextual features. If there are named entities in this window, we also find them out. We also believe that "colon (:)" is the strong indicator of the opinion holder. If it occurs in the behind of the token in the window, we extract it as a feature.

Dependency Features: As mentioned in section 3, we used our own parsing tool [6] to parse each subjective sentence. Then we can obtain a dependency tree for each sentence. We believe that the root of this dependency tree would be a verb, which cannot be a holder candidate. We assume there are some structure relationship between the opinion word and the opinion operate word. The opinion operate dictionary mentioned in section 3 are used to find the opinion operate word. If some word is dependent on the opinion operate word, we think this word will be the opinion holder. For the example in figure 1, the part-of-speech of "柯恩(Kern)", "国防部长(defense minister)" and "美国(USA)" is noun and they are dependent on "表示" in this dependency tree, while "表示" is an opinion operate word. At this reason, they may be the opinion holder in this sentence, while "堪培拉(Canberra)" and "澳洲(Australia)" are not. After that, we must record the distance from the opinion operate word to the opinion holder candidate, because we believe that the opinion holder cannot be too far from the opinion operate word.

Position Features: We recorded the word's position in the sentence, because we believe that the opinion holder often occurs in the beginning or end of the sentence. We divided the sentence into three parts and recorded the part to which the word belongs.

4.3 Finding Opinion Holder by Heuristics Rules

After identifying opinion holder with CRF model, we find that recall of the result is not high. Therefore, we designed several heuristics rules to extract potential opinion holders. They are shown in table 1. If there are no opinion holder extracted by CRF model in a sentence, these heuristics rules would be used.

Table 4. Rules for Extracting Opinion Holder

No.	Description
1	If the opinion operator occurs in the subjective sentences and is the root of dependency tree, the nearest named entity or the pronoun, which is dependent on the opinion operator, are regarded as the opinion holder.
2	If the opinion operator occurs in the clause of the subjective sentences, the nearest named entity or the pronoun, which is depend on the opinion operator, are regarded as the opinion holder.
3	The nearest named entity which occurs before the opinion operator in the subjective sentence.
4	The nearest noun which occurs before the opinion operator in the subjective sentence
5	The occurred named entity in the subjective sentence.
6	If there is no opinion holder in the subjective sentence, the "Post_Author" will be regarded as the opinion holder of this sentence.

More opinion holders would be extracted if the sentences satisfies any of the rules with the priority from 1to 6, which means that rule 1 has the highest priority and rule 6 has the lowest priority. Rule 1 is to find the opinion holder from the dependency relationship in the whole sentence. Rule 2 is the same to Rule 1, except that the dependency relationship is found in the clause rather than the whole sentence. Rule 3 and Rule 4 are to find the potential opinion holder which occurs before the opinion operator like "说 (say)". Rule 5 is practical because we believe that the named entity is probably to be a holder. Rule 6 is suitable for the situation that the opinion is expressed by the author of the post which has not been mentioned.

5. Evaluation Results and Discussion

We submitted four runs. The strict and lenient evaluation results are listed in the following table. The detail descriptions of these two evaluation method are given in [25], and we will not describe them here. In Run1, we applied the domain adaptation technique mentioned in section 3. In Run2, we only used the training files in NTCIR7 simplified Chinese corpus to train our classifier. In Run3, we used the whole training dataset which contains NTCIR7 simplified Chinese corpus and all data in NTCIR6 traditional Chinese corpus to train our classifier. In Run4, we used the training files in NTCIR7 simplified Chinese corpus to select the "correct" instance in NTCIR6 traditional Chinese corpus, then we combined them together and trained our subjective classifier. All evaluation results for identifying subjective sentences are given in table 5 and 6.

Comparing the results of Run3 with Run2, we can see that the performance would be worse, if we directly regarded the data in NTCIR6 as the training data. In the results of Run1, we can see that the domain adaptation method mentioned give the different weight to each instance in NTCIR6 and use the data in testing dataset to guide the training process. It proves that our methid can effectively make use of the training files came from the different domain. It can effectively increase the performance of our subjective classifier.

For extracting opinion holder, the method mentioned in section 4 was applied to the subjective sentence identified by subjective classifier. Therefore, for each run, different results of the opinion holder extraction are obtained. All results for each run are listed in table 7, 8, 9 and 10. Compared with other methods mentioned in [25], our method achieves the best performance on opinion holder extraction strict and lenient evaluation. We think that our results benefits from the following points. 1. The effectiveness of the CRF model. 2. The parsing features is useful for extracting opinion holder. 3. The manual designed heuristics rules are effective.

Table 5. The lenient result for identifying subjective sentences

	Precision	Recall	F1
Run1	0.5822	0.7753	0.665
Run2	0.588	0.4842	0.5311
Run3	0.4551	0.5725	0.5071
Run4	0.5769	0.5639	0.5703

Table 6. The strict result for identifying subjective sentences

	Precision	Recall	F1
Run1	0.6096	0.892	0.724
Run2	0.6129	0.5501	0.5798
Run3	0.4197	0.637	0.506
Run4	0.5973	0.6459	0.6207

Table 7. The lenient result for extracting opinion holder

	Precision	Recall	F1
Run1	0.428571	0.42857	0.428571
Run2	0.449724	0.44972	0.449724
Run3	0.403738	0.40374	0.403738
Run4	0.429791	0.42979	0.429791

Table 8. The lenient result (recall based) for extracting opinion holder

	Precision	Recall	F1
Run1	0.2495	0.33226	0.28499
Run2	0.26446	0.21776	0.23885
Run3	0.18375	0.23114	0.20474
Run4	0.24795	0.24238	0.24513

Table 9. The strict result for extracting opinion holder

	Precision	Recall	F1
Run1	0.475862	0.47586	0.475862
Run2	0.482143	0.48214	0.482143
Run3	0.4689	0.4689	0.4689
Run4	0.471503	0.4715	0.471503

Table 10. The strict result (recall based) for extracting opinion holder

	Precision	Recall	F1
Run1	0.17186	0.40351	0.24105
Run2	0.16875	0.23684	0.19708
Run3	0.098	0.28655	0.14605
Run4	0.15582	0.26608	0.19654

6. Conclusions and Future Work

In this paper, we reported our method for NTCIR 7 Multilingual Opinion Analysis Tasks (MOAT). From the evaluation results, our method achieved a satisfactory performance. Our results in opinion identification subtask prove the effectiveness of domain adaptation technique mention in this paper. Also the favorable performance on opinion holder extraction proves that the selection of parsing features is useful and the method based on heuristics rules is also effective for opinion holder identification.

Furthermore, we can see that our results are still not satisfactory enough for practical application. We must devote to select more effective opinion features that can indicate the opinion in the sentences. It is an important part for our further research.

Acknowledgments

The work is supported by the National Natural Science Foundation of China under Grants no. 60673042, the Natural Science Foundation of Beijing under Grants no. 4073043 and the National High Technology Development 863 Program of China under Grants no. 2006AA01Z144.

References

[1] Alina A. and Sabine B. When Specialists and Generalists Work Together: Overcoming Domain Dependence in Sentiment Tagging. In Proc. of ACL-08. 2008.

[2] Alistair Kennedy and Diana Inkpen. Sentiment Classification of Movie Reviews Using Contextual Valence Shifters. Conputational Intelligence, 22(2), pages 110-125. 2006

[3] Anthony Aue and Michael Gamon. Customizing sentiment classifiers to new domains: a case study. In Proc. of the International Conference on Recent Advances in Natural Language Processing. Borovets, BG. 2005

[4] Bo Pang, Lillian Lee and Shivakumar Vaithyanathan. Thumbs up? Sentiment Classification using Machine Learning Techniques. In Proc. of Empirical Methods in Natural Language Processing (EMNLP). . 2002

[5] Bo Pang and Lillian Lee. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. In Proc. of the Association of Computational Linguistics (ACL). 2004

[6] Duan Xiangyu and Zhao Jun. Probabilistic Parsing Action Models for Multi-Lingual Dependency Parsing, In Proc. of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), Prague, Czech Republic, 940-946. 2007

[7] Fei Sha and Fernando Pereira. Shallow Parsing with Conditional Random Fields, Proc. of. HLT-NAACL 2003, Edmonton, Canada, pp. 213-220. 2003

[8] Hal Daumé III and Daniel Marcu. Domain Adaptation for Statistical Classifiers. Journal of Artificial Intelligence Research 26, pages 101-126. 2006

[9] J. Wiebe and E. Riloff. Creating subjective and objective sentence classifiers from unannotated texs. In CICLing. 2005

[10] Jin Jiang and ChengXiang Zhai. Instance Weighting for Domain Adaptation in NLP. In Proc. of the 45th Annual Meeting of the Association of Computational Linguistics (ACL), pages 264-271. 2007

[11] Jin Jiang and ChengXiang Zhai. A Two-stage Approach to Domain Adaptation for Statistical Classifiers. In Proc. of the 16th ACM International Conference on information and Knowledge Management (CIKM), pages 401-410. 2007

[12] John Blitzer, Mark Dredze and Fernando Pereira. Biographies, Bollywood, Boom-boxes and Blenders: Domain Adaptation for Sentiment Classification. In Proc. of the 45th Annual Meeting of the Association of Computational Linguistics (ACL), pages 440-447. 2007

[13] John Blitzer, Ryan McDonald and Fernando Pereira. Domain with Structural Corresponding Learning. In Empirical Methods in Natural Language Processing (EMNLP), pages 120-128. 2006

[14] J Lafferty, A McCallum, F Pereira. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings. ICML-01, pages 282.289. 2001

[15] Ruihong Huang, Longxin Pan and Le Sun. ISCAS in Opinion Analysis Pilot Task: Experiment with sentimental dictionary based classifier and CRF model. In Proc of the six NTCIR Workshop. May.2007, Japan. 2007

[16] Ruifeng Xu, Kam-Fai Wong and Yunqing Xia. Opinmine-Opinion Analysis Sytem by CUHK for NTCIR-6 Pilot Task. In Proc of the six NTCIR Workshop. May.2007, Japan. 2007

[17] Sandeepkumar Satpal and Sunita Sarawagi. Domain Adaptation of Conditional Probability Models via Feature Subsetting. In Proc. of the 11th European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD) . 2007

[18] Songbo Tan, Gaowei Wu, Huifeng Tang and Zueqi Cheng. A Novel Scheme for Domain-transfer Problem in the context of Sentiment Analysis. In Proc. of CIKM 2007

[19] S.-M. Kim and E. Hovy. Determining the Sentiment of Opinions. In Proc. of COLING 2004

[20] S.-M. Kim and E. Hovy. Extracting Opinions, Opinion Holders, and Topics Expressed in Online News Media Text. In Proceedings of ACL/COLING Workshop on Sentiment and Subjectivity in Text, Sydney, Australia. 2006

[21] V. Hatzivassiloglou and J. M. Wiebe. Effects of adjective orientation and gradability on sentence subjective In Proc. of the 18th International Conference on Computational Linguistics, Saarbrucken, Germany, 2000.

[22] Wenyuan Dai, Gui-Rong Xue, Qiang Yang and Yong Yu. Transferring Naïve Bayes Classifiers for Text Classification. In Proc. of AAAI. 2007

[23] Yejun Wu and Douglas W. Oard. NTCIR-6 at Maryland: Chinese Opinion Analysis Pilot Task. In Proc of the six NTCIR Workshop. May.2007, Japan. 2007

[24] Yejin Choi et al.. Identifying Sources of Opinions with conditional Random Fields and Extraction Patterns. In Proc of EMNLP 2006

[25] Yohei Seki, David Kirk Evans, Lun-Wei Ku, Le Sun, Hsin-His Chen and Noriko Kando. Overview of Multilingual Opinion Analysis Task at NTCIR-7. In Proc of the seven NTCIR Workshop. Dec.2008, Japan. 2008

[26] Youzheng Wu, Jun Zhao and Bo Xu. Chinese Named Entity Recognition Model Based on Multiple Features. In Proc. of the Joint Conference of Human Language Technology and Empirical Methods in Natural Language Processing, Vancouver, 2005