Affective-feature-based Sentiment Analysis using SVM Classifier

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***Abstract*—Based on the methods of the traditional topic-based text classification, machine learning method was performed to the coarse-grained sentiment classification of reviews. Sentiment classification involved a lot of problems. In this paper, the sentiment Vector Space Model (s-VSM) was used for text representation to solve data sparseness. In addition, the critical issues of the sentiment classification, i.e. the selection of classification algorithms, the determination of feature selection method and the selection of feature dimension, are verified by experiments. Furthermore, in order to consider the entire corpus contribution of features and each category contribution of features, the feature selection method of Chi-square Difference between the Positive and Negative Categories (CDPNC) was proposed. It combined DF with CHI and had the better performance. Experiments showed that the Macro-F and Micro-F achieved 90.18% and 90.08% respectively.**

***Key words*—Reviews; Sentiment classification; Machine learning; Classification algorithm; Feature selection**

I. INTRODUCTION

With the expansion of Web2.0 and e-commerce, the amount of online reviews has reached an unprecedented volume growth. People would like to write reviews for some aspects of the product, on which some relevant opinions are positive, and some are negative. These comments for merchants and buyers have great commercial value. Nevertheless, the large number of reviews is in unstructured text format that is difficult to record customer opinions automatically. As a result, there had been a burst research in the area of opinion mining and sentiment analysis due to the important application value.

Sentiment analysis is part of the opinion mining and refers to determining orientation of text reviews positive or negative. Depending on the granularity of context analysis, sentiment analysis can be divided into word level, sentence level and document level [1].

Currently, there are three main branches in sentiment analysis: machine learning-based, corpus-based and lexicon-based [2], [3], [4]. The former adapts machine learning technique to classify reviews into positive classification and negative classification, which is used to the sentiment analysis at sentence level and document level. The corpus-based method is based on the analysis of the syntactic connection between words in corpus [4], [5], which is semantic association and co-occurrence information, and the method is used to the sentiment analysis at sentence level. The lexicon-based method uses semantic relation to sentiment analysis based on the dictionary [6], [7] (such as WordNet, HowNet), which is used to the sentiment analysis at word level. All of these methods have their own advantages and disadvantages respectively. Machine learning-based method is strongly dependent on the size and quality of training data, which require human intervention. Corpus-based method relies on syntactic or co-occurrence patterns as well as an initial seed list of subjective words to identify other subjective words and their orientations in a large corpus. Lexicon-based method often highly relies on expert-defined dictionaries of subjective words. Nevertheless, current researches showed that machine learning-based method performed well in sentiment analysis [8].

In this article, we study the problem of coarse-grained sentiment classification with the machine learning method. Specifically, we investigate how to build a classifier with machine learning method to assist coarse-grained sentiment classification well.

II. SENTIMENT ANALYSIS PROCESS

The aim of sentiment analysis is discovering the emotional orientation of user reviews automatically. It is distinctively different from traditional text mining in that the latter focuses on topic mining (e.g. sports, economic) whereas sentiment analysis is much complex than those for topic mining. Sentiment analysis can be considered as a binary-classification process which is to classify customer reviews into two classifications [9]. Those classifications are positive and negative. A classification process of sentiment analysis based on machine learning method is depicted in Fig1[10].

978-1-5090-1915-1/16/$31.00 ©2016 IEEE

The classification process of sentiment analysis based on machine learning is made up of training and testing section. The detailed work flows: Firstly, pre-processing the training corpus. And extracting the feature from the training corpus according to predefined feature templates; Secondly, weighting feature item with Term Frequency and Inverse Documentation Frequency (TF-IDF) and representing the reviews text with the sentiment vector space model (s-VSM); Thirdly, building a classifier with support vector machine (SVM); Finally, using the classifier to sentiment classification of test corpus. In this process, the key techniques of sentiment analysis involve feature item weighting, feature selection, text representation and classifier algorithm selection.

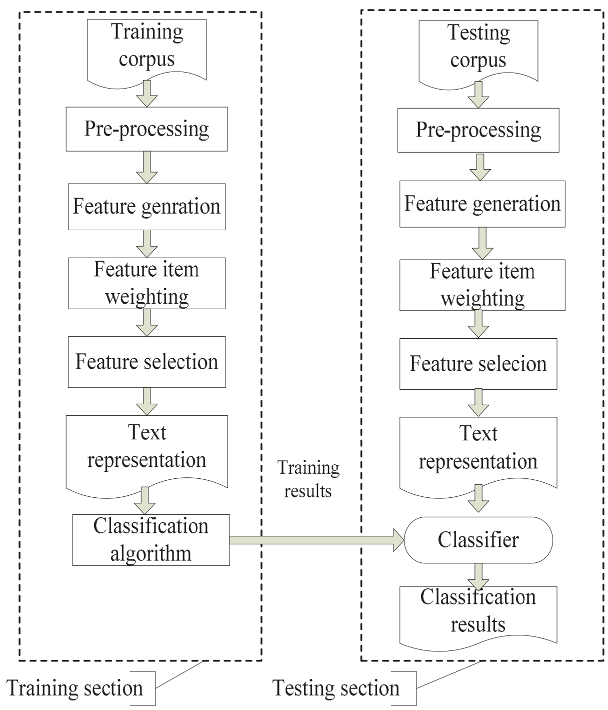

Fig.1. The classification process of sentiment analysis based on machine learning

III. Sentiment analysis based on machine learning method

A. Feature item weighting

Generally, each vector component is assigned a value related to the estimated importance of the word in customer reviews and the feature item weighting can be used to measure the importance of the feature word. Traditionally, this weight was assigned using Boolean weighting, Term frequency, Term Frequency–Inverse Document Frequency (TF-IDF) et al. [11].

Actually, Boolean weighting method cannot give expression to contribution customer reviews. Although Term frequency weighting method can reflect contribution in customer reviews, it ignores the contribution of low frequency feature. Some of feature words appear infrequently, but it makes great contribution to sentiment analysis. At present, TF-IDF is the most common weighting method used to describe documents. The TF-IDF function weights each vector component (each of them relating to a word of the vocabulary) of each document on the following basis. First, it incorporates the word frequency in the document. Thus, the more a word appears in a document (e.g., its TF, term frequency is high) the more it is estimated to be significant in this document. In addition, IDF measures how infrequent a word is in the collection. This value is estimated using the whole training text collection at hand. Accordingly, if a word appears frequently in the text collection, it is not considered to be particularly representative of this document (since it occurs in most documents; for instance, stop words). In contrast, if the word is infrequent in the text collection, it is believed to be very relevant for the document. TF-IDF is commonly used in text classification to compare a query vector with a document vector using a similarity or distance function such as the cosine similarity function as shown in the Equation (1) [12]:

$$w_{ik} = \frac{tf_{ik} * \log(N / n_k)}{\sqrt{\sum_{k=1}^{n} \left(tf_{ik} * \log(N / n_k)\right)^2}} \quad (1)$$

In the Equation (1) above, where tf_{ik} is the frequency of word t_k in document d_i, N is the number of documents in the text collection and nk is the number of documents where word t_k occurs. Normalization to unit length is generally applied to the resulting vectors.

B. Feature selection

Feature selection is an inevitable part of sentiment analysis. It is aiming at extract a small subset of feature from the problem domain while retaining a suitably high accuracy in representing the original features. In recent years, a lot of feature selection methods have been proposed such as Mutual Information (MI), Chi-Squared (CHI), Document Frequency (DF), Information Gain (IG), Cross Entropy (CE) and so on [13]. Among them, Feature selection methods of DF, IG, CE only consider feature words to the contribution of the whole training corpus, but MI, CHI only consider feature words to the contribution of categories. Nevertheless, the importance of feature words must be comprehensive consideration, and both the contribution to the whole corpus and the contribution to each category must be considered [14].

DF simply measures in how many documents the word appears, which performs easier than Mutual Information. And the experiment proved that CHI performed better than MI, not only so, CHI is the common statistical test that measures divergence from the distribution expected if one assumes the feature occurrence is actually independent of the classification value. As a statistical test, it is known to behave erratically for very small expected counts, which are common in text classification both because of having rarely occurring word features, and sometimes because of having few positive training examples for a concept. Considering that sentiment analysis is a binary-classification problem, DF and CHI cannot consider feature words to the contribution of both the whole training corpus and the Categories. As s result, in this paper, on the basis of DF and CHI, we propose a feature selection algorithm [10], CHI-square Difference between the Positive and Negative Categories (CDPNC), which is expressed in the Equation (2):

$$CDPNC(t_i, c_n, c_p) = p(t_i) * | CHI(t_i, c_n) - CHI(t_i, c_P) | \tag{2}$$

In the Equation (2) above, where $p(t_i)$ is the frequency of word t_i in training corpus. $CHI(t_i,c_n)$ is CHI-square of the word t_i and negative-classification training text. $CHI(t_i,c_p)$ is CHI-square of the word t_i and positive- classification training text.

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C. Text representation

The traditional vector space model (VSM) is used for text representation in text topic classification. The main idea of VSM is to put each text into a vector. Each feature item of the text $D(t_1, t_2, \ldots, t_n)$ is composed of words or phrases, which can be seen as each dimension of the corresponding vectors. The weight of each feature item corresponds to a numerical representation of the text representation. Thus, the document $D(t_1, t_2, \ldots, t_n)$ is a vector in the coordinate system, and $(w_1, w_2, \ldots, w_n)$ is the corresponding coordinate values. But VSM is unsuited to sentiment analysis [15]. Firstly, the feature selection algorithm can be for feature extraction, no matter what kind of feature selection algorithm, but it cannot remove unemotional words based on VSM; Secondly, customer reviews are usually short texts, feature extraction based on keywords and can lead to serious data sparseness problem. Sentiment-related words are the important characteristic to distinguish positive and negative in sentiment analysis, and the emotional orientation of customer reviews express the feelings mainly through the sentiment-related words, which are emotional nouns, adjectives, verbs, adverbs, etc. Thus, we propose the sentiment vector space model(s-VSM) for sentiment analysis with the sentiment-related words as feature words. The s-VSM model is presented as follows, $D(t_1,w_1,t_2,w_2,\ldots,t_n, w_n)$ (for short $D(w_1,w_2,\ldots, w_n)$).

The main idea of s-VSM is to put each review into a vector. Each feature item of the document is composed of sentiment-related words, which can be seen as each dimension of the corresponding vectors $T(t_1, t_2, \ldots, t_n)$. The weight of each feature item corresponds to a numerical representation of the text representation [16]. Thus, the document $D(t_1, t_2, \ldots, t_n)$ is a vector in the coordinate system, and $(w_1, w_2, \ldots, w_n)$ is the corresponding coordinate values. The example of s-VSM is shown in Fig2.

In figure 2, file format is as follows: <Label> <Index1>:<Value1> <Index2>:<Value2>……,< Label > represents the classification[10], which is a integer, and 1 signifies the negative classification, 2 signifies the positive classification. <Index> represents the feature word ID, which is unique and start from 0 in the training corpus. <Value> represents the feature weighting, which is the TF - IDF Value of feature word.

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1 119:0.156152 126:0.230322 139:0.441715 173:0.156152 240:0.234512 243:0.299506 298:0.26054
1 132:0.185793 240:0.419884 298:0.233246 367:0.306869 417:0.182424 441:0.283362 453:0.23324
1 168:0.124295 328:0.275446 346:0.221450 457:0.105824 503:0.295275 530:0.131703 535:0.22145
1 243:0.498657 351:0.123583 358:0.255968 417:0.339269 451:0.288403 468:0.279713 492:0.13470
1 16:0.395817 120:0.215466 328:0.252982 356:0.279989 417:0.162866 535:0.203389 545:0.358301
1 65:0.354210 168:0.164538 243:0.345022 346:0.293148 457:0.280172 475:0.160365 530:0.348689
1 221:0.221310 243:0.434080 267:0.170997 358:0.222820 439:0.207193 475:0.100880 610:0.29084
1 142:0.359567 246:0.304186 350:0.265510 457:0.120302 498:0.428543 543:0.287583 656:0.26434
1 128:0.337129 168:0.158722 186:0.256703 314:0.429220 318:0.312763 377:0.481381 502:0.29957
1 132:0.129002 168:0.088782 243:0.186169 293:0.213069 318:0.174946 331:0.290765 356:0.21775
1 24:0.257110 26:0.177962 196:0.208372 337:0.177962 346:0.132115 358:0.159635 373:0.213067
1 58:0.441002 439:0.385639 457:0.164019 513:0.163107 520:0.444889 584:0.264915 680:0.403968
2 89:0.162934 171:0.231786 189:0.139736 243:0.575330 301:0.311382 429:0.167327 439:0.274613
2 141:0.144335 173:0.115706 243:0.221929 342:0.136388 414:0.190759 417:0.150993 439:0.63557
2 89:0.141166 144:0.265445 189:0.121067 243:0.249234 483:0.197600 606:0.212572 669:0.230722
2 168:0.134831 241:0.256810 243:0.282729 265:0.467495 292:0.314210 328:0.298794 439:0.26990
2 170:0.582590 194:0.149546 243:0.503657 417:0.171336 492:0.136059 517:0.135033 611:0.14125
2 89:0.111090 119:0.102257 145:0.068759 170:0.113435 171:0.079017 173:0.051128 186:0.075636
2 119:0.109160 193:0.224778 206:0.192885 243:0.628119 374:0.182136 439:0.199873 455:0.23268
```

Fig.2. Examples of sentiment vector space model

D. Classification Algorithm

Our aim in this work is to consider sentiment analysis as a special binary-classification (with the two "topics" being negative sentiment and positive sentiment). We experimented with three standard algorithms: Naive Bayes (NB) , K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and SVM classifier has been shown to be highly effective at sentiment analysis [17], generally outperforming the other algorithms. Support Vector Machine is a new machine learning technique developed on the basis of statistical learning theory, and it is the most successful realization of statistical learning theory. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible [18].

We use linear SVM for sentiment analysis. In the binary-classification, the basic idea is to find a linearly hyperplane as shown in Fig3, and features are classified by the linearly separated hyperplane with the negative and positive classification.

The optimal separating hyperplane problems can be expressed as the constrained optimization problem in the Equation (3):

$$\min \Phi(w) = \min_{w,b} \frac{1}{2}\|w\|^2 = \min_{w,b} \frac{1}{2}(w^T w) \tag{3}$$

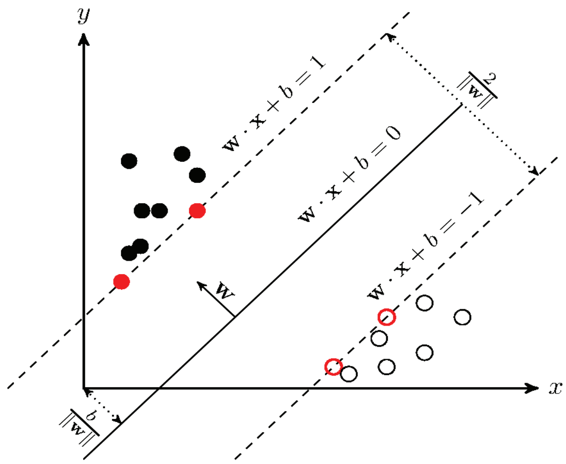

Fig.3. An illustration of the SVM method

When two kinds of sample is linear can be separated, it must meet the requirements as shown in the Equation (4):

$$\begin{aligned} (w \cdot x_i) + b &\geq +1 \quad for \;\; y_i = +1 \\ (w \cdot x_i) + b &\leq -1 \quad for \;\; y_i = -1 \end{aligned} \tag{4}$$

Where the y_i is either 1 or −1, indicating the negative and positive classification to which the point x_i belongs. Each x_i is a p-dimensional real vector. We want to find the maximum-margin hyperplane that divides the points having y_i =+1 from those having y_i =-1. Where "·" denotes the dot product and w the normal vector to the hyperplane.

Thus, the task of sentiment analysis can be formulated as discovering which side of the hyperplane of a test sample falls into, which means that for y_i =+1, $(w{\cdot}x_i)+b\geq 1$ then x_i falls into the positive sentiment, and for y_i =-1, $(w{\cdot}x_i)+b\leq -1$ then x_i falls into the negative sentiment.

IV. Experiments and Discussion

A. Experimental Setup

We use ChnSentiCorp corpus to evaluate our sentiment analysis method [19]. ChnSentiCorp is the Chinese sentiment analysis balance corpus offered by Dr Song-bo tan, which contains 4,000 annotated reviews (2,000 positive reviews and 2,000 negative reviews) on laptop computer. We select 70% reviews randomly from ChnSentiCorp corpus as training samples and the remaining 30% reviews as test samples.

We do experiments for classification algorithm, feature selection methods and the selection of the characteristic dimension respectively. To evaluate the results of experiment, we use Precision rate (P), Recall rate (R), F-measure (F), Macro-average (Macro) and Micro-average(Micro), in which P represents percentage of opinions assigned correct sentiment polarity against all opinions classified sentiment polarity , R represents percentage of opinions assigned correct sentiment polarity against all opinions annotated sentiment polarity, while the F-measure means a comprehensive evaluation, and it is the harmonic mean of precision and recall.

B. Experiment I: Quantitative evaluation on Classification algorithm

In order to verify the performance of the classifier in text sentiment classification, we do contrast experiments using the same feature selection algorithm with the same training data and test data. The experimental results of KNN, NB and SVM classifiers are shown in Table I.

TABLE I. RESULTS OF SENTIMENT CLASSIFICATION WITH CLASSIFIERS (KNN, NB, SVM) (%)

Classfier / Performance	KNN	NB	SVM
R-negative	78.223	65.505	75.167
P-negative	65.643	48.831	73.453
F-negative	71.383	55.952	**74.300**
R-positive	58.185	29.893	72.833
P-positive	72.345	45.902	74.573
F-positive	64.497	36.207	**73.693**
Macro-R	68.401	47.699	74.000
Macro-P	68.399	47.366	74.013
Macro-F	68.400	47.532	**74.006**
Micro-R	68.398	47.887	74.000
Micro-P	68.398	47.887	74.000
Micro-F	68.398	47.887	**74.000**

It can be seen from Table I that not only from a single classification evaluation index, the F-measures of positive classification and negative classification with SVM are the highest, and the performance ranking: SVM>KNN>NB; but also for the comprehensive evaluation index, the various performance of SVM is the highest, and the comprehensive evaluation index of performance ranking: SVM>KNN>NB.

In fact, in addition to using the MI feature selection methods for three classifiers experiments, we use the common feature selection methods about IG,CHI,CE. The classifier performance of each feature selection method is as follows, IG: SVM>KNN>NB, CHI: SVM>KNN>NB, CE: SVM >NB>KNN.

The experimental results show that the performance of SVM classifier is the best, regardless of the feature selection method, so the SVM classifier is used in text sentiment classification.

C. Experiment II: Quantitative evaluation on feature selection

In order to solve the high dimension of feature space and the sparsity of sentiment vector space model, we use feature selection algorithm to calculating each of feature value, and then choose to form feature vector from high to low. To verify the proposed feature selection method in text sentiment classification performance is best, we compare our method with the common feature selection methods of MI, IG, CHI and CE using SVM classifier. The results of contrast experiment are shown in Table II:

TABLE II. RESULTS OF SENTIMENT CLASSIFICATION WITH FEATURE SELECTION METHODS (KNN, NB, SVM) (%)

Feature selection / Performance	MI	IG	CHI	CE	CDPNC
R-negative	75.167	93.000	93.000	92.667	**93.500**
P-negative	73.453	86.916	86.781	86.470	**87.520**
F-negative	74.300	89.855	89.783	89.461	**90.411**
R-positive	72.833	86.000	85.833	85.500	**86.667**
P-positive	74.573	92.473	92.460	92.101	**93.023**
F-positive	73.693	89.119	89.023	88.678	**89.733**
Macro-R	74.000	89.500	89.417	89.083	**90.083**
Macro-P	74.013	89.695	89.620	89.285	**90.271**
Macro-F	74.006	89.597	89.518	89.184	**90.177**
Micro-R	74.000	89.500	89.417	89.083	**90.083**
Micro-P	74.000	89.500	89.417	89.083	**90.083**
Micro-F	74.000	89.500	89.417	89.083	**90.083**

The experimental results show that the CDPNC feature selection method is a combination of the method of DF and CHI, and the classification effect is superior to the other four feature selection methods.

D. Experiment III: Quantitative evaluation on feature dimension

The selection of feature dimension N selection will affect the classification performance. If the value of N is too large, it may cause too many noise features, but the value of N is too small and it may lead to the loss of useful information. So the selection of N is chosen to be fit for sentiment classification. Also using the above experimental data, we do the experiments about feature dimensions with CDPNC feature selection and SVM classifier. The experimental results are shown in Table III:

TABLE III. RESULTS OF SENTIMENT CLASSIFICATION WITH FEATURE DIMENSIONS (%)

Feature dimensions / Performance	300	500	1000	1500	2000	3000	5000
R-negative	93.500	**93.667**	93.500	93.167	92.500	92.333	91.667
P-negative	86.708	87.267	87.520	**87.893**	86.991	86.698	87.580
F-negative	89.976	90.354	90.411	**90.453**	89.661	89.427	89.577
R-positive	85.667	86.333	86.667	**87.167**	86.167	85.833	87.000
P-positive	92.948	93.165	**93.023**	92.730	91.993	91.800	91.259
F-positive	89.159	89.619	89.733	**89.862**	88.985	88.716	89.079
Macro-R	89.583	90.000	90.083	**90.167**	89.333	89.083	89.333
Macro-P	89.828	90.216	90.271	**90.312**	89.492	89.249	89.419
Macro-F	89.705	90.108	90.177	**90.239**	89.412	89.166	89.376

Micro-R	89.583	90.000	90.083	**90.167**	89.333	89.083	89.333
Micro-P	89.583	90.000	90.083	**90.167**	89.333	89.083	89.333
Micro-F	89.583	90.000	90.083	**90.167**	89.333	89.083	89.333

We can see that different N values from the experimental results of table 4, cause the different classification performance. The performance is not proportional to the value of the feature dimension N, and the moderate value of N is the best. The experimental results show that when the values of feature dimension N is 500, the recall rate of negative sentiment classification is to achieve the best, but when the values of feature dimension N is 1000, the precision rate of negative sentiment classification can reach the best. Nevertheless, the rest of the evaluation indexes are best when the value of feature dimension N is 1500.

V. Conclusions and Future work

In this paper, we consider text sentiment analysis as a binary-classification about positive and negative sentiment using the method based on machine learning. In order to solve the data sparseness problem, we put forward to use sentiment vector space model for the text representation. Considering feature words contribution to the whole corpus and each classification, we propose a feature selection algorithm, CHI-square Difference between the Positive and Negative Categories (CDPNC), which combines DF and CH, and the experimental results illustrate that the classification performance is superior to the other feature selection method. Then we study the selection of feature dimensions, contrast experiments show that is not proportional to the value of the feature dimension.

Sentiment analysis is a very challenging task. Since natural language expression is complicated and varies from time to time, no method can deal with every situation exhaustively. Although our proposed method perform well in sentence level and document level sentiment analysis, when we look at word level sentiment analysis, our proposed method fails, so we will use semantic analysis this to deal with it. And this will be our further works.

Acknowledgment

We would also like to thank Dr Tan Songbo from the Institute of Computing Technology, Chinese Academy of Sciences for the training and testing corpus. This work is funded by the Postdoctoral sponsored funds of Tsinghua University.

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