Opinion Mining in Persian Language Using Supervised Algorithms

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Abstract

Rapid growth of Internet results in large amount of user-generated contents in social media, forums, blogs, and etc. Automatic analysis of this content is needed to extract valuable information from these contents. Opinion mining is a process of analyzing opinions, sentiments and emotions to recognize people's preferences about different subjects. One of the main tasks of opinion mining is classifying a text document into positive or negative classes. Most of the researches in this field applied opinion mining for English language. Although Persian language is spoken in different countries, but there are few studies for opinion mining in Persian language. In this article, a comprehensive study of opinion mining for Persian language is conducted to examine performance of opinion mining in different conditions. First we create a Persian SentiWordNet using Persian WordNet. Then this lexicon is used to weight features. Results of applying three machine learning algorithms Support vector machine (SVM), naive Bayes (NB) and logistic regression are compared before and after weighting by lexicon. Experiments show support vector machine and logistic regression achieve better results in most cases and applying SO (semantic orientation) improves the accuracy of logistic regression. Increasing number of instances and using unbalanced dataset has a positive effect on the performance of opinion mining. Generally this research provides better results comparing to other researches in opinion mining of Persian language.

Keywords: Opinion Mining; Persian; Supervised Algorithm; SentiWordNet.

1. Introduction

Nowadays, rapid growth in the number of Internet and social networks users, has paved the way of accessing people's opinions. Recognizing orientation of this opinion is easy for a human being, but since number of these opinions is increasing massively, it is impossible to analyze all of them manually.

Therefore opinion mining is required to automatically analysis these opinions and extract useful information from them.

"Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes"[1].

Opinions contain worthy information that are useful for both customers and organizations. For example, people express pros and cons of different aspects of a product in their opinions, so by analyzing them, others can be aware of different aspect of products before buying them. Opinion mining also lets companies improve products, resolve their weaknesses and acquire useful information about their rivals. The purpose of opinion mining is to obtain such information.

Different approaches have been developed for opinion mining. Most of these approaches were applied in English [2-4], Spanish [5-6] and Chinese [7-10]. Although Persian language is spoken in different countries, but there are few researches that consider opinion mining in Persian. Hence, in this article opinion mining in Persian language is investigated by applying standard machine learning techniques naive Bayes, SVM and logistic regression. For this purpose, opinion mining is experimented in different conditions. Also different features are incorporated to accomplish this task in a hotel domain. Up to now there are few researches in opinion mining for Persian language. So we decided to do a research in this field, studied different methods that are introduced in other languages and observed that a new lexicon can be produced for our purpose to do opinion mining in Persian language. The main reason that we conduct this research is to build Persian SentiWordNet and also to investigate the behavior of opinion mining in different conditions using this lexicon.

This article seeks to investigate:

1. The effect of weighting features by their semantic orientation.
2. The effect of instance number in Persian opinion mining.
3. The effect of unbalanced data set in Persian opinion mining.
4. Persian opinion mining using supervised algorithm.

The paper is organized as follows. Next section, presents basic concept of opinion mining. Section 3 presents related works on sentiment analysis. Lexicon creation and data preparation are described in section 4. Section 5 expresses experimental results. In conclusion section we present a summary of the article and results.

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2. Basic Concept

With rapid growth of social networks, forums, blogs and websites, the produced data is increasing rapidly. A part of this data is in a form of text. This text contains valuable information about different subjects. But raw text without analyzing hasn't any value and also the amount of this data is too huge. So this text data should be analyzed automatically to extract valuable information. Opinion mining is a field of study that used for this purpose.

Opinion is people's belief, idea and view point about different subjects.

Bing Liu [1] defines three general categorizations for opinion mining: Document-level, sentence-level, and phrase-level. In document-level a whole document is analyzed. In a sentence-level, sentence should be recognized and then be analyzed. In phrase-level, a phrase is identified and then its orientation is determined.

Researchers have introduced different methods for opinion mining. In general these methods are categorized in two categories: supervised and unsupervised methods. In supervised methods, there are Training and testing data to assign an appropriate class to given review and it requires labeled instances. Naïve Bayes, SVM and other supervised algorithm can be used here. But in unsupervised methods there are not any labeled instances. For example Turney [4] performs classification based on syntactic patterns.

Also different feature weighting method can be used to weight features in supervised algorithms such as Terms and their frequency, Part of speech and Sentiment words and phrases.

In this research opinion mining in document level is experimented and supervised methods are applied. We also used Sentiment word as feature weighting method.

3. Related Works

Up to now, different approaches are developed in the field of opinion mining. There are two main approaches, unsupervised and supervised approaches.

One of the first approaches in opinion mining applied average of phrases' SO in a document for classifying document as recommended or not recommended[4]. In this approach semantic orientation of a phrase is defined as a difference of its dependency with "excellent" and "poor". This dependency is number of hits calculated from a search engine.

Pang and Lee applied different Machine learning algorithms SVM, maximum entropy and naive Bayes with different features [3]. They showed that using unigram and present-absent as features achieve better results and SVM performs better than other algorithms. Zhang et al. [11] examined opinion mining by applying SVM, naive Bayes and character based N-gram model. Their findings showed that SVM and character based approaches outperform naive Bayes approach.

There are some approaches that applied lexicon based opinion mining. Taboada et al. [12] proposed a lexicon based approach that called semantic orientation calculator (SO-CAL). In this method, they used dictionary of words that contains words and their orientation. SO-CAL considers negation and strength too. They showed that SO-CAL has a consistent performance across different domains. Hung and Lin [13] used SentiWordNet and SVM for sentiment analysis. They observed that using objective words, can improve the performance of opinion mining, In Their method, if an objective word appears more in positive sentences, it got a positive score and if it appears more in negative sentences it got a negative score.

Martina and Finin [14] introduced new feature, Delta TF-IDF[1]. This feature is the difference of word's TF-IDF scores in the positive and negative training corpora. Using Delta TF-IDF has improved accuracy.

Tan and Zhang [15] applied four different feature selection methods and five learning method for sentiment analysis of Chinese language. They showed that IG (information gain) performs best for feature selection and SVM outperforms other algorithms for sentiment classification.

Beside this approaches, some researches use clustering-based approach for classification of document [16-17,2]. "The clustering-based approach is able to produce basically accurate analysis results without any human participation, linguist knowledge or training time" [17].

Basari et al. [18] introduced a method for improving SVM in sentiment analysis. Their method is combination of SVM and Particle swarm optimization (PSO). PSO is used for improving SVM parameters. Vinodhini and Chandrasekaran [19] applied Principal Component Analysis to decrease dimensionality problem in SVM.

There are few researches that have been conducted on sentiment analysis for Persian language. Shams et al. [20] proposed a method that is combination of unsupervised LDA [2] -based approach and PersianClues lexicon. This approach applied machine translation to translate MPQA[3] lexicon [21] and used Latent Dirichlet allocation for opinion mining. Their method achieved about 80 percent of accuracy.

Hajmohammadi and Ibrahim [22] used SVM for sentiment analysis in Persian. The experimental results showed that, SVM performs better than naive Bayes and unigram outperform bigram and trigram for feature selection.

Saraee and Bagheri [23] proposed a new feature called Modified Mutual Information (MMI) for Persian opinion mining. They examined different features and applied naive Bayes as a classifier. The results showed that MMI outperform MI (mutual information) as a feature selection method.

[1] Term Frequency–Inverse Document Frequency
[2] Latent Dirichlet Allocation
[3] Multi-Perspective Question Answering

4. Methodology

This section expresses different phases of opinion mining in this research as is shown in figure 1. Since in this article, opinion mining is performed using a lexicon, the first phase dedicate to create a lexicon. In next phase, required data for opinion mining is collected and then collected data are pre-processed. In the classification phase, reviews are classified in positive or negative classes. In last phase, different problems are investigated. Detailed descriptions of these phases are expressed as follows.

4.1 Persian Sentiwordnet Creation

There are different lexicons that can be used for annotating word's semantic orientation, but most of them are developed for other languages especially for English. Each of these lexicons has different mechanism for showing semantic orientation. For example, in SentiWordNet [24], each word contains three scores between [-1,1] and each score stands for positive, negative and objective orientation. Bing Liu [25] is a lexicon that contains two lists of positive and negative words. MPQA is a subjectivity lexicon that shows word's SO as positive or negative and also its subjectivity.

In Persian language, there is not such a lexicon. Shams et al [20] used machine translation to translate existing MPQA lexicon to Persian and developed a new lexicon named Persianclues.

We use existing English SentiWordNet for creating Persian SentiWordNet. Since each word in SentiWordNet has positive, negative and objective score, it didn't need to calculate this score. These scores were used for our Persian lexicon.

In this article, opinion mining is performed by applying combination of SentiWordNet and supervised algorithms. For this purpose Persian SentiWordNet is developed. English SentiWordNet has created by attaching positive and negative sentiment scores to WordNet synsets[1] [26]. In fact each word in SentiWordNet has an equivalent in WordNet. Therefore for creating Persian SentiWordNet a WordNet is required. Second version of Persian WordNet [27] is applied for developing a Persian SentiWordNet. Persian WordNet contains words in the form of noun, verb, adverb and adjective. Each synset contains some information such as part of speech, glossary and example of word usage. Beside this information, each synset has an equivalent in English WordNet. Since each word in the English SentiWordNet has an entry in English WordNet, this equivalent can be used to map each word in the Persian WordNet to English SentiWordNet. By considering this equivalent, Persian SentiWordNet is developed in three steps:

1. All words in Persian WordNet doesn't have equivalent in English WordNet, so only those words that have English equivalent are chosen. By searching automatically in Persian WordNet, 15904 synsets that have an equivalent were extracted. The problem with Persian WordNet is that some synsets have more than one English equivalent. For example word "خوب" (good) has five equivalent. For solving this problem, average of all equivalents for each synset, is calculated for its SO.
2. In the second step, all extracted synsets from the first step are mapped to their equivalent in English SentiWordNet and SO of them are retrieved. Each word may have multiple SOs in SentiWordNet. So average of these entire SOs was defined as the word's SO. In table 1 example of extracted words are shown. As you can see some words such as rain have only one equivalent and some words such as bad have more than one equivalent so we use average sentiment of these equivalents as a final sentiment. So final positive, negative and objective score of "bad" is 0.0416, 0.75 and 0.2083 respectively.
3. Retrieved verbs from Persian WordNet are in the infinitive form. So stemming is required and NLP[2] tool [28] is applied for stemming these words.

4.2 Data Description

To assess the opinion mining performance, data are collected from Persian website www.hellokish.com using Mozenda [3] web crawler. The extracted reviews from Hellokish are related to hotel domain. 1805 negative and 4630 positive reviews about hotels were collected and each of them contains an opinion about hotel, its date, writer, an option that shows it is recommend or not and percentage of satisfaction. For our purpose only opinion and its recommendation option are collected. Since each opinion contains recommendation option, this option is used as a class indicator.

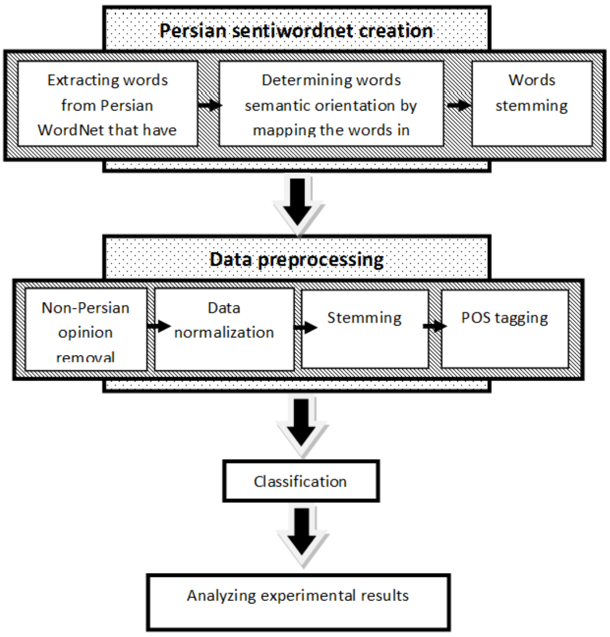

Fig. 1. Different phases of Persian opinion mining

[1] Sets of cognitive synonyms

[2] Natural Language Processing
[3] Mozenda is web crawler software

4.2.1 Data Pre-processing

Pre-processing is the process of cleaning and preparing the text for classification [29]. Keeping extra sections may increase dimensionality of classification. There are different pre-processing tools that can be applied according to our requirement. In this paper, the pre-processing has four steps. We use NLP tool [28] for step two to four.

Table 1. Example of extracted words from Persian WordNet and SentiWordNet

Synonym in WordNet	Part of speech	Synonym in SentiWordNet	ID	Positive	negative	objective
دل‌خوش, دلخوش - بشاش - خوشحال, خوش حال - شاد	Adjective	happily, merrily, mirthfully, gayly, blithely, jubilantly	50297	0.5	0.25	0.25
تماشایی - دیدنی - زیبا - قشنگ	Adverb	beautifully, attractively	242006	0.375	0	0.625
باران, بارون - مطر	Noun	rain, rainfall	11501381	0	0	1
زباله - خاکروبه - آشغال	Noun	rubbish, trash, scrap	14857497	0	0.125	0.875
نامرغوب - بد - زشت - ناشایست - چرت - مزخرف - ناشایسته - ضعیف	Adjective	bad	1125429	0	0.625	0.375
		atrocious, abominable, awful, dreadful, painful, terrible, unspeakable	1126291	0	0.875	0.125
		inapprop riate	135718	0.125	0.75	0.125

- In the first step, all opinions that were written in English are detected and removed.
- In the second step, data are normalized. Informal words, intra-word spacing problems are corrected and Arabic letters are replaced by Persian ones. There are some letters in Persian that can be written with Arabic letters. For example letter “ی” is incorrectly written in Arabic as “ي”.
- In third step, words are stemmed.
- In the last step, all words are tagged with their POS[1]. Some words have more than one POS in different situations. Each POS may have different SOs in SentiWordNet. Therefore, POS tagging is required for determining words’ POS.

5. Experimental Results

This research is accomplished in document level and each opinion is considered as a document. We experiment opinion mining with three standard algorithms, naive Bayes, support vector machines and logistic regression for classifying documents in two positive and negative classes. Logistic regression and naive Bayes are run by default parameters.

LibSVM with linear kernel is applied for SVM. 5-fold cross-validation is performed for the experiments reported in this study. All three algorithms are run in weka[2].

Collected data are converted to a vector of words to be operative for classifier by using StringToWord filter in weka. Three feature weighting methods (TF[3], TF-IDF and present- absent) are applied to produce three different feature sets by setting feature’s frequency to three. At last, 1196 features are produced.

After that, SO of words are determined by using Persian SentiWordNet. Each word with its POS is looked up in Persian SentiWordNet. In SentiWordNet, each word has a positive, a negative and an objective score. Greater score was chosen so if the negative score is greater than the positive one, negative score is selected and vice a versa. For words that have equal positive and negative scores, zero is set as their SO. For those words that have more than one result in SentiWordNet, the average of all results as their SO is calculated.

To examine the result of opinion mining in different conditions, five hypotheses are defined. In each hypothesis, two cases are examined. The first case is related to classification of reviews before weighting by SO and the second case is related to classification after weighting by SO. In all hypotheses, a document is a vector of features and each feature is represented by a numeric value. Features have different values in different dataset according to the method of feature weighting. Four indexes were applied for evaluating classification. All these indexes were calculated in weka. Weka produces some indexes for evaluating a classification’s result. So we choose four of these indexes to analysis the classification results.

These four indexes are computed as follows in Weka:
Accuracy: number of Correctly Classified Instances
Precision = TP[4] / (TP + FP[5])
Recall = TP/ (TP+ FN[6])
F- Measure = 2 * Precision * Recall / (Precision + Recall)
Details of each hypothesis are expressed bellow:

1. Present-absent: When a word exists in a document it is represented by one and if it doesn’t exist it is represented by zero. Then this value is multiplied by word’s SO to create a new weight. Table 2 represents the results of these two cases. As it is shown in table 2, Using SO improves accuracy of logistic regression by 3.3 percent. But accuracy of SVM and NB decreases by 0.4 and 1.7 percent respectively. This reduction for SVM is not

[1] Part of Speech
[2] Weka is an open source machine learning software
[3] Term Frequency
[4] True Positive
[5] False Positive
[6] False Negative

significant. In both cases SVM gets better results comparing to other algorithms.

2. Term frequency: In this hypothesis, Term frequency is investigated. Each number in the vector represents word's frequency in the document. Table 3 shows the results of classification. TF is defined as:

TF=log $(1+f_{ij})$ where f_{ij} is the frequency of the word i in document j. Using SO improves accuracy of logistic regression regressing by 3.4 percent.

Table 2. Classification results of present-absent feature

	results of classification after weighting by SO			results of classification before weighting by SO		
Result	SVM	NB	Logistic regression	SVM	NB	logistic regression
Accuracy	**85.9**	83.3	82	**85.5**	81.6	85.3
Precision	85.9	85.4	82.4	85.1	83	85
Recall	85.9	83.3	82	85.5	81.6	85.3
f-measure	85.9	83.9	82.2	85	82	85.1

Table 3. Classification results of term frequency feature

	results of classification after weighting by SO			results of classification before weighting by SO		
Result	SVM	NB	logistic regression	SVM	NB	logistic regression
Accuracy	**87**	80.1	82.4	**85.9**	79.7	85.8
Precision	86.9	82.1	82.8	85.6	80.8	85.5
Recall	87	80.1	82.4	85.9	79.7	85.8
f-measure	87	80.7	82.5	85.3	80.1	85.6

But accuracy of SVM and NB decreases by 0.4 and 1.1 percent respectively. This reduction for NB is not significant. In both cases SVM gets better results comparing to other algorithms.

3. Frequency–Inverse Document Frequency: This feature is defined as:

f_{ij}*log(number of documents /number of documents that has word i) where f_{ij} is the frequency of word i in document j. Table 4 shows the results of classification by applying this feature. Accuracy of Logistic regression improves by 3.2 percent when SO is considered. But accuracy of SVM and NB decreases by 1.6 percent. Like cases 2 and 3 SVM performs better than other algorithms.

In three above hypothesis, SVM and logistic regression achieve better results than naïve Bayes in most cases.

Accuracy of logistic regression improves about 3 percent by Appling SO. So it means that using SO has a positive influence on the performance of this algorithm.

4. Effect of number of instances: In this hypothesis, we try to investigate the effect of number of instances in the classification performance. The effect of this hypothesis is examined for term frequency feature. Table 5, shows the accuracy of classification. In both cases, number of positive and negative instances is equal.

By increasing number of instances, performance of classification increases too. Among these algorithms, SVM performs better even by decreasing number of instances. Observations show that, by decreasing the number of instances the accuracy of all algorithms decreases. But in most of cases, decrease in the accuracy of logistic regression is more than SVM and NB. Hence logistic regression is more sensitive to the number of instances.

It can be concluded that number of instances can affect classification performance and increasing number of instances has a positive effect on the performance of classification. SVM outperforms other algorithms by decreasing the number of instances. So Among these algorithms, SVM is more robots to the low number of instances.

5. Effect of unbalanced dataset: This Hypothesis investigates the effect of different number of positive and negative instances in the performance of opinion mining. In all cases total number of instances is equals 3600. Table 6 represents the accuracy of classification by using unbalanced dataset.

As table 6 shows, It is obvious that, unbalanced dataset, results in better performance for classification.

By increase in the difference between number of positive and negative instances, classification's accuracy improves too and it has a positive effect in opinion mining performance. In both cases SVM and logistic regression perform better than Naïve Bayes. Improvement in the results of SVM is more than other algorithms. This result confirm that when most of the instanced are belong to one class, the classifier assign a correct class to given sample.

Table 4. Classification results of TF-IDF feature

	results of classification after weighting by SO			results of classification before weighting by SO		
Result	SVM	NB	logistic regression	SVM	NB	logistic regression
Accuracy	**83.9**	80	82.1	**85.5**	81.6	85.3
Precision	84	80.8	82.4	85.1	83	85
Recall	83.9	80	82.1	85.5	81.6	85.3
f-measure	83.9	80.3	82.2	85	82	85.1

Table 5. Effect of number of instances on the performance of classification

Results of classification after weighting by SO			Results of classification before weighting by SO			
Number of instances	logistic regression	NB	SVM	logistic regression	NB	SVM
83.0556	76.6111	72.6389	**81.6667**	3600	80.1389	75.5
83.4118	77	73.6176	**81.7941**	3400	80.1176	76.0882
83.25	77.375	71.4375	**82**	3200	79.9063	76.6563
83.4	77.0667	71.4667	**81.7**	3000	80.6667	77.2667
82.5714	76.75	69.75	**81.7857**	2800	79.3214	76.1786
82.3462	76.7308	67.7308	**81.8077**	2600	76.6154	75.9615
82.7083	77.5	67.4167	**80.9583**	2400	76.8333	75.9167
82.0909	76.7727	65.7273	**81.3636**	2200	76.2727	76.5909
83.4	77.65	66.65	**82.8**	2000	75.7	77.3
82.7778	77.7778	65.5556	**82.6111**	1800	74.7778	77.7222
83.125	76.5	67.25	**82.625**	1600	74.625	75.125
81.2857	78.2857	61.5714	**80.5**	1400	70.1429	76.1429
80.6667	76.25	66.25	**79.5**	1600	67.9167	73.5833
78.5	73.9	70.6	**76.8**	1000	64.6	74.1
78.25	78	77.125	**77.5**	800	65.875	77.125
79.1667	78.1667	78.8333	**77**	600	61	75.3333
78.25	70.5	73	**74.75**	400	66.75	69.5
63	**67**	66.5	**67.5**	200	63	64.5

Table 6. Effect of unbalanced dataset on the performance of classification

Results of classification after weighting by SO			Results of classification before weighting by SO				
SVM	NB	logistic regression	SVM	NB	logistic regression	Number of negative instances	Number of positive instances
83.8611	76.8889	73.9444	**82.4444**	76.1389	81.4167	1700	1900
84.1944	78.2222	74.4444	**82.0833**	76.6111	81.1667	1600	2000
84.6389	78.25	76.3333	**82.4167**	77.5833	81.5556	1500	2100
83.6667	79.25	75.25	**83.3333**	78.4722	81.9167	1400	2200
84.5556	79.5833	74.9722	**83.8611**	77.9722	81.5278	1300	2300
83.6667	79.25	75.25	**84.9722**	79.8611	83.0278	1200	2400
84.5556	79.5833	74.9722	**85.1944**	80.5278	83.7778	1100	2500
85.7778	79.8056	76.6389	**85.7222**	81.4167	84.5833	1000	2600
87.25	82.4722	79.1389	**86.5278**	81.9444	84.6944	900	2700
88.0556	83.1944	78.3611	**87.0833**	82.3333	85.6944	800	2800
89.5278	84.2222	78.25	**87.7778**	82.8333	85.6944	700	2900
89.6111	83.9444	78.9722	**88.6667**	82.5	86.0556	600	3000
86.1111	83.6667	81.1667	**90.1944**	83.1667	87.25	500	3100
91.7222	84.1667	82.7222	**91.5833**	82.1944	87.0833	400	3200

6. Conclusions

In this article, a comprehensive experiment of opinion mining was conducted in Persian language. Opinion mining was performed by applying combination of a Persian SentiWordNet and supervised algorithms SVM, logistic regression and Naive Bayes. Opinion mining is not performed in Persian language using SentiWordNet. So this lexicon is created to investigate its effect on opinion mining.

Therefore at the first phase a Persian SentiWordNet was created by applying Persian WordNet. For our purpose, the reviews from hotel domain were collected and defined some hypothesis to investigate the Persian opinion mining in different conditions. In the first three hypotheses, three feature weighting methods (present-absent, TF and TF-IDF) were applied. In the all hypotheses, features value was multiplied by their SOs. The results of classification by using these features were compared to results of classification before considering SO. SVM and logistic regression performed better than Naïve Bayes. By considering SO the accuracy of logistic regression improved by about 3 percent. By examining the effect of number of instances, we observed that increasing number of instances has a positive effect on the performance of opinion mining.

By decreasing number of instances, performance of all algorithms decreases too, but decrease in the performance of logistic regression was more than other algorithms and also SVM is more robust to low number of instances comparing Naïve Bayes and logistic regression. Using unbalanced dataset improved the classification results. In the future work, we want to investigate Persian SentiWordNet performance in other domains and also assess the performance of other approaches in the Persian opinion mining. By considering all of these results we can observe that SentiWordNet can gain acceptable accuracy.

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