Enhancing Sentiment Classification Performance Using Bi-Tagged Phrases



- Sentiment analysis is to extract the opinion of the user from of the text documents.
- Identifying the orientation of opinions from the text.
 - ▶ This movie was awesome . [Sentiment] ③
 - ► This movie was boring. [Sentiment] 😕

Applications !

- Helpful for Business in improving quality of the product based on users opinion.
- Help people in decision making.
- For government, know the opinion of people for a certain policy.
- For example:

Which model of a camera is liked by most of the users and which music is liked the most by people ? which laptop is best to purchase? etc.

Sentiment classification using machine learning

- The proposed approach consists of two phases.
- In the first phase, various features are extracted and feature selection methods are used to generate relevant sentiment-rich features.
- In the second phase, the relevant feature vector is passed to a machine-learning algorithm for sentiment classification.

Feature Engineering

- Two types of features are extracted:
 - unigrams and bi-tagged phrase.
- Bi-tagged phrases are extracted using POS-based fixed patterns and represent better indicators of sentiment information.
- Bi-tagged phrases conforming to certain pattern (as shown in Table I) are extracted.

Feature Engineering

► TABLE I. RULES FOR EXTRACTION OF BI-TAGGED PHRASES

S.No	First Word	Second Word
1	JJ/JJR/JJS	NN/NNS
2	RB/RBR/RBS	JJ/JJR/JJS
3	JJ/JJR/JJS	JJ/JJR/JJS
4	NN/NNS	JJ/JJR/JJS
5	RB/RBR/RBS	VB/VBD/VBN/VBG
6	VB/VBD/VBN/ VBG	NN/NNS
7	VB/VBD/VBN/ VBG	JJ/JJR/JJS
8	NN/NNS	RB/RBR/RBS
9	JJ/JJR/JJS	VB/VBD/VBN/VBG

- Initially, unigram and bi-grams are extracted from text.
- Next, bi-tagged phrase features are extracted.
- Further, prominent features are extracted using the IG feature selection method.
- Prominent features extracted from unigrams, bigrams and bi-tagged phrase are named as *PromUni* (prominent unigrams), *PromBi* (prominent bi-grams) and *PromBiTa* (prominent bi-tagged) features respectively

- The performance of unigram features increases when combined with bi-grams.
- Composite features are created using unigram with bigrams and unigrams with bi-tagged features namely ComUniBi and ComUniBiTa, respectively.
- Finally, PromUniBiTa feature set is created by combining prominent unigrams (PromUni) and prominent bitagged features (PromBiTa).

Feature Engineering

▶ Table 2. Description of the feature sets

Feature set	Feature extraction method		
Unigram	Unigrams		
Bi-gram	Bigrams		
Bi-tagged Phrases	Bi-tagged features as discussed		
ComUniBi	Composite of Unigrams and Bigrams		
ComUniBiTa	Composite of Unigrams and Bi-tagged features		
PromUni	Prominent unigram features using IG as Feature Selection		
PromBiTa	Prominent Bi-tagged features using IG as Feature Selection		
PromUniBiTa	Composite of Prominent unigram and prominent bi- tagged features		

Datasets

Movie Review Dataset (Pang B., and Lee L., 2004).

- http://www.cs.cornell.edu/People/pabo/movie-review-data/
- Dataset is consisting of 2000 reviews that contain 1000 positive and 1000 negative labeled reviews.

Experimental Setup

- Documents are initially pre-processed as follows: "NOT_" is concatenated to every word between negation words (no, not, never, isn't, didn't etc.) and punctuation marks following the negation word.
- Binary weighting scheme is used for representing text.
- Support Vector Machine (SVM) and Naïve Bayes (NB) classifiers are used for sentiment classification. The Weka tool is used for implementing the two classifiers.
- Evaluation is performed using 10-fold cross validation.
- Performance of all the feature vectors are reported using F-measure.

F-measure is used for performance evaluation

• $F - Measure = \frac{2*precision*recall}{(precision+recall)}$

- Precision for a class C is the fraction of total number of documents that are correctly classified to the total number of documents that classified to the class C.
- Recall is the fraction of total number of correctly classified documents to the total number of documents that belongs to class C.

Results

F-Measure (%) for various feature sets

Features	SVM	NB	Feature size	
Unigram	84.2	79.4	9045	
Bi-gram	78.8	73.5	6050	
Bi-tagged Phrases	75.3	71.8	4841	
ComUniBi	86.7	81.1	15095	
ComUniBiTa	87.6	82.3	13886	
PromUni	85.8	85.4	1130	
PromBiTa	86.5	73.7	1114	
PromUniBiTa	89.4	86.2	2244	

Comparison with existing methods

- Proposed method depends on the basic unigrams, simple bi-tagged phrases and IG which are easy to extract and computationally efficient as compared to other methods proposed in the literature for sentiment classification on movie review dataset.
- Proposed approach produces comparable results with very much less computational cost.

Paper	Approach	Best accuracy
Pang et al. (2004) [8]	Minimum cut algorithm, SVM	87.1
Prabowo et al. 2009. [9]	Hybrid SVM	87.3
O'keefee et al. 2009. [5]	SentiWordNet based features and feature selection with SVM,NB classifier	87.15
Ng et al.(2006) [13]	SVM with various features	90.5
Tu et al. (2012) [12]	Dependency forest based with MaxEnt	91.6
Abbasi et al., 2008 [1]	Genetic Algorithms (GA), Information Gain (IG), IG + GA	91.7
Proposed Approach	Unigrams, Bi- tagged phrases, IG	89.4

Table.3 Performance of Various Methods on Movie Review Dataset

Conclusion

- Main objective of this paper is to investigate the performance of the bitagged features for supervised classification.
- In this paper, Bi-tagged features are used in addition to unigrams for enhancing the performance of the sentiment classification.
- Experimental results show that composite feature of prominent unigrams and prominent bi-tagged features perform better than other features for movie review sentiment classification.
- The main reason for this observation is that that bigrams contains very important sentiment information but with lots of noisy features which surpass the effect of context and sentiment information.
- However, Bi-tagged phrases are the sentiment-rich bi-grams which contain only subjective information that is very important for sentiment classification.
- Experimental results show the effectiveness of the proposed method.

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Thank You