Exploiting Polarity Features for Developing Sentiment Analysis Tool

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Abstract This paper proposes a system known as: SentiFinder (Sentiment Finder), a tool for sentiment analysis of amazon data to identifying the intensity of sentiments either positive or negative. The proposed system is based on our previous comprehensive experiments which we have been doing since more than a year. To identify a Sentiment of a comment/review, one need to analyze polarity features present in the natural language text. Different researchers have utilized different polarity features like adjectives, verbs, and adverbs. To conduct this study a comprehensive dataset has been acquired which contains 53,258 from Amazon. We extracted verbs, adverbs, and adjectives and evaluated them. It is found that adverb, adjectives, and verb combination can achieve the nest accuracy when trained on a specific settings of Random Forest Classifier and Gradient Boosting Classifier. This paper explains the lessons learned from the literature and followed by the findings and it gives an input to build a scalable system: SentiFinder.

Key words: Sentiment analysis. Polarity features extraction. Tagging.

1. Introduction

The growth of social web offers a huge amount of user generated data like opinions about products. People's opinions have moved from traditional commerce to e-commerce in the past few years. Companies have enabled users to share their opinions online about products in order to create more traffic and increase in sales. The reviews are increasing at a faster rate because mostly customers share their opinions about the products on the web. Therefore, sentiment analysis aims to automate the process of reviews based on opinion summarization of reviews like positive, negative, or neutral. In this research, SentiFinder tool is proposed to identify the sentiments either positive or negative that restricts on adjectives, adverbs, and verbs using Random Forest Classifier and Gradient Boosting Classifier. These are main tasks which focus on: (1) identifying the intensity of sentiments either positive or negative using SentiWordNet, (2) (i) polarity features extraction adjectives, adverbs, and verbs alone, (ii) Adjective-Adverb Combination (AAC), Adjective-Verb Combination (AVC), Adverb-Verb Combination (AVC), and Adjective-Adverb-Verb Combination (AAVC) at sentence-level after applying POS (Parts-of- Speech) tagging.

Related work is reviewed in section 2. Methodology of proposed tool is discussed in section 3, and the results come in Section 4, and discussion of research findings is concluded in section 5.

2. Related Work

The current sentiment analysis focuses on the classification of polarities like positive, negative, and neutral in the reviews that express sentiments. Some previous studies on sentiment analysis focus on sentence level sentiment polarities using a BOW (bag-of-word) model to address and solve the polarity shift problem [1] by detecting, modifying, and removing negation from the text. This paper also deals with opinion features. A technique proposed [2] to find the common used terms in online reviews and Unsupervised approach/Natural language processing (NLP) is used that automatically extract meanings of a text from natural language [3, 15, 10, 11], and uses corpus based approach to determine the sentiments in patterns of words to find the co-occurrence which also uses resources/lexicon like SentiWordNet[1], Wikictionary[2], to find the emotional similarities between words. This approach is used to determine the words sentiments by using antonyms and synonyms. A sentence level sentiment analysis is proposed [5] using online product reviews to identify the negative sentences and sentiment score computation. Sentiment analysis have been done on different levels like document level, aspect level and sentence level. A SentiWordNet algorithm [6] was proposed to find the polarity at sentence level. POS (Parts- of-Speech) tagger is used to determine polarity of text by proposing a new

1 sentiwordnet.isti.cnr.it/
2 https://en.wiktionary.org

SentiWordNet algorithm. On document level an Adverb-Adjective-Noun-Verb (AANV) combinations is proposed [7]. AANV technique is based on the analysis of adverbs, adjectives, abstract nouns, and categorized verbs. This technique defines a set of general axioms. Entropy, Conditional Entropy, and Information Gain concepts have been used to evaluate the proposed system. AAC (Adjective-Adverb Combination) in sentiment analysis plays an important role and Adverb-Adjective-Noun (AAN) [8] combination proposed and it provides better results than using AAC only. AAC [9] gives high Pearson correlations than previously used techniques. Another technique is proposed [10] to find the polarity of a sentiment at sentence level by AVA combinations. Adverbs and adjectives combination technique is used to extract the opinion [11] at the sentence level. A manually scored adjectives and adverbs [12] sum based scoring method is used in sentiment analysis, while using a template based method [13] to set values of sentiments at a degree of [-2, 10] scale is also proposed. Using linguistic feature, verb class information is performed and the online Wikipedia dictionary [14] is used for identifying the polarity of adjectives. The framework Hu04 [15], which summarizes online users reviews by extracting opinions on product features and classifies them as positive or negative opinions.

An axiomatic linguistic AAC classification [18] proposed to calculate the scoring of both adjectives and adverbs. A framework [19] proposed with semantic web and natural language processing. A standard AI framework [20] based on opinion summary application built to communicate, exchange, and resolve conflicting opinions in distributed scenarios. A tool named RAID [21] proposed for then opinion frames extraction from the reviews. RAID uses natural language processing tools for sentiment analysis to classify opinions from the text based on a technique that merges the scores of several features. A set of unsupervised approaches [22] uses for the mining of aspects from the given sentence. A unified approach to opinion analysis proposed to identify the sentiments expressed by adjectives, adverbs, and verbs combinations [23].

A multi-domain approach [24] calculate the polarity of the opinion. Sentilo [25], an upgraded novel sentic computing system merges NLP technology with knowledge. It effectively uses resources such as SentiWordNet SenticNet, and the SentiloNet for the identification of resource of annotated verbs. SHELLFBK system [26] applies a supervised learning for information retrieval. The proposed algorithm find the dependency the index is then classified into polarity and the domain it belongs.

Though much work has been done and conducted in sentiment analysis covering the Adjective-Adverb-Verb-Noun combinations but no research focuses on this area on a comprehensive dataset i.e. (i) feature evaluation of adjectives, adverbs, and verbs alone, (ii) Adjective-Adverb Combination (AAC), Adjective-Verb Combination (AVC) , Adverb-Verb Combination (AVC), and Adjective-Adverb-Verb Combination (AAVC) at sentence level and to identify the intensity of these polarity features and classifies them either as positive or negative. Polarity feature extraction improves the performance and also provides the more precise results to the customers who want to purchase the product online.

3. SentiFinder A Tool for Sentiment Analysis

Amazon receives millions of user's reviews per day and these reviews turned into a gold mine for the companies to analyze their brands by mining the sentiments of product reviews. We present a feature extraction process based on natural language processing with the use of a training corpora SentiFinder, a system for feature extraction from users' opinions and our focus is on feature extraction restricted to adjective, adverb, and verb. The system also accounts for the classification of reviews either positive or negative. The feature extraction process receives text as an input containing users' opinions, and returns the extracted features (adjective, adverb, and verb).

We present a feature extraction model which gathers reviews from amazon and thus give a site of business intelligence. In proposed framework, sentiment analysis tool consists of number of steps: which include data processing, stops word removal, tokenization, stemming, parts-of-speech tagging, word sense disambiguation and classification. SentiFinder is a tool which utilizes Random Forest classifier and Gradient Boosting Classifier to classify amazon data based on intensity of sentiments either positive or negative. SentiFinder enables the users to extract the polarity features and restrict to adjectives, adverbs, and verbs, recognize the sentiments they express, and then classify them according to their polarity as shown in Figure 1 and further details about the system will be described in the following sections.;

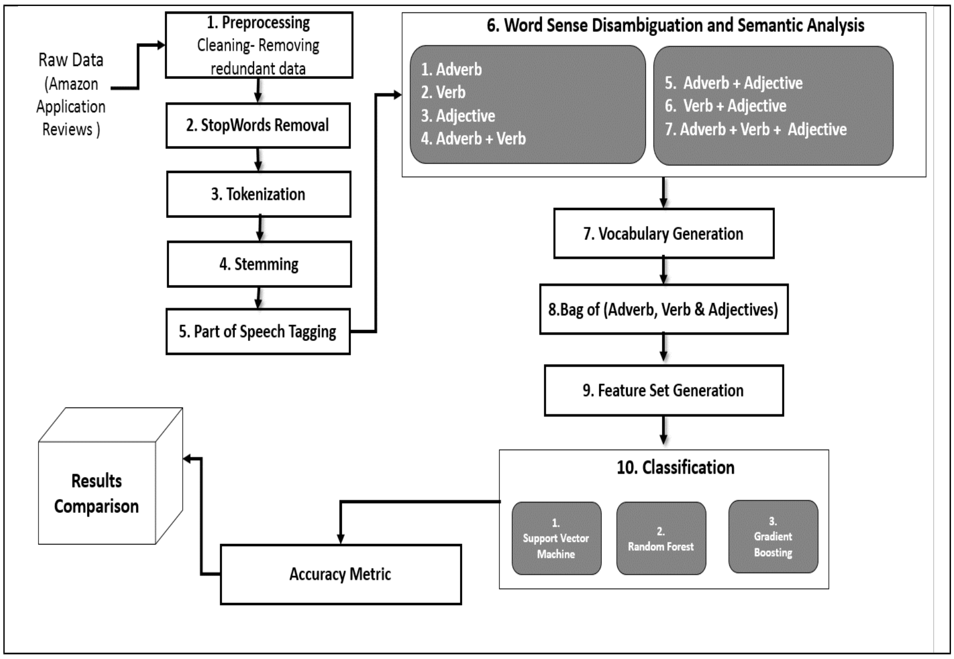

Fig 1 Block diagram of Polarity Features Extraction Model

3.1. Data Collection and Preprocessing

Reviews about office products are collected from online website jmcauley.ucsd.edu/data/amazon [16] are taken as the dataset. There are total 53,258 reviews in the dataset. This step mainly focus on data review as there are many useless special characters which can affect the sentiment analysis process. Hence we first clean all the special characters from our data set. Secondly, we removed the non-letters from each review. In this study, for simplicity, all punctuation periods, apostrophes, and hyphens, non-alphabetic characters like numbers and smileys are removed from the given dataset of reviews. After, performing all these steps all words in the review is converted into lowercase and then each word in the sentence is splited for further processing.

3.2. Stop Words Removal

We have to choose how to manage as often as possible happening words that don't convey much significance. Such words are called "stop words" in English they incorporate words, for example, *"a"*, "and", *"is",* and *"the"*. It is removed using Natural Language Tool Kit. This step is beneficial for better accuracy.

3.3. Tokenization

Tokenization is the process of breaking a sequence of strings into pieces such as phrases, symbols, words, and keywords called tokens. The process break the string in tokens.

For example *"Apple laptop is very good "*

Output *'Apple', 'laptop' 'is', 'very', 'good'.*

3.4. Stemming

The tokenized sentence is pass for further processing. Stemming is the process of removing morphological affixes from words. It is the process of reducing a word into its root form.

For example *'Look', 'looks' and 'looking'*

Output *Look*

3.5. Parts-of- Speech (POS) Tagging

The process of assigning a word to its grammatical category, in order to understand its role within the sentence is Parts-of-Speech (POS) tagging. We used Natural Language Tool Kit part-of- speech tagger. For instance let's take following review.

Review

"I ordered this DashMat for a specific vehicle, it was not the correct mat. I returned the original one and they sent me an exact duplicate of the wrong mat. I can't seem to get the correct one and therefore it sits in a box!!!!!! "

By applying ***Step 1-4*** will get the following output

"'ordered', 'dashmat', 'specific', 'vehicle', 'correct', 'mat', 'returned', 'original', 'one', 'sent', 'exact', 'duplicate', 'wrong', 'mat', 'seem', 'get', 'correct', 'one', 'therefore', 'sits', 'box'. " Now applying Part of Speech of Tagger will get the following ***output***

[('ordered', 'VBN'), ('dashmat', 'NN'), ('specific', 'JJ'), ('vehicle', 'NN'), ('correct', 'JJ'), ('mat', 'NN'), ('returned', 'VBD'), ('original', 'JJ'), ('one', 'CD'), ('sent', 'NN'), ('exact', 'NN'), ('duplicate', 'NN'), ('wrong', 'JJ'), ('mat', 'NN'), ('seem', 'VBP'), ('get', 'VB'), ('correct', 'JJ'), ('one', 'CD'), ('therefore', 'NN'), ('sits', 'VBZ'), ('box', 'NN')

Table 1 Parts-of-Speech Definition

Tagged	Definition
VB	verb, base form i.e. take
VBD	verb, past tense i.e. took
VBG	verb, gerund/present participle i.e. taking
VBN	verb, past participle i.e. taken
VBP	verb, present tense i.e. take
VBZ	verb, 3rd person singular i.e. takes
RB	adverb i.e. very, silently
RBR	adverb, comparative i.e. better
RBS	adverb, superlative i.e. best
JJ	adjective i.e. big
JJR	adjective, comparative i.e. bigger
JJS	adjective, superlative i.e. biggest

3.6. Word Sense Disambiguation and Semantic Analysis

This research focuses on different types of adjectives, adverbs, and verbs. So we restrict to adjectives, adverbs, and verbs from the tagged file which explained in the Table 1. Then, we make separate files for each combination as mentioned in Table 3.

Semantic of opinions are important in the given piece of text, words like adjectives, adverbs, and verbs are sometimes convey the opposite sentiment with the use of negation prefixes. It is difficult to identify such phrases from the text. We identified three types of phrases like negation-of-adjective (NOJJ), negation-of-adverb (NORB), and negation-of-verb (NOVB) as in the following algorithm.

Algorithm: for negation of tagged sentences

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1: for k/k + 1 for every tagged word
2: if k + 1 is a Negative Prefix
3: if adjective or adverb or verb tag in next pair
4: NOJJ ← (k, k + 2)
5: NORB ← (k, k + 2)
6: NOVB ← (k, k + 2)
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else
if adjective or adverb or verb tag in the pair after next
 NOJJ ← (k, k + 2, k + 4)
NORB ← (k, k + 2, k + 4)
NOVB ← (k, k + 2, k + 4)
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Adjectives, adverbs, and verbs scores are calculated by using SentiWordNet after applying POS tagging. Score of each adjective, adverb, and verb is calculated and stored in database. Now, combined the adjective-adverb words in a file, calculate the score and save the file, also applied this with adjective-verb words and adverb-verb words. Scoring of any word will be either -1 to +1 using Sentiwordnet polarity categorization. -1 is considered as negative polarity, 0 as neutral and +1 as positive as shown in table 1. Adjectives, adverbs, and verbs scores are calculated separately and then classified into two different intensities like positive and negative

Table 2 Sentiment score calculation and polarity classification

Word	Score	Sentiment
best	0.75	positive
appreciate	0.5	positive
Good	0.375	positive
serious	-0.75	negative
Same	-0.375	negative
long	-0.25	negative

3.7. Feature Set Generation

The Bag of adverbs, verbs and adjectives model generates a vocabulary. The vocabulary consists of the words which occurs frequently. Frequency is calculated by counting the number of times each word appears. For example, consider the following two sentences:

Sentence 1

"The cat sat on the hat"

Sentence 2
"The dog ate the cat and the hat"

From these two sentences, our vocabulary is as follows:

{The, cat, sat, on, hat, dog, ate, and}

To get our bags of words, we count the number of times each word occurs in each sentence. In **Sentence 1**, *"the"* appears twice, and *"cat", "sat", "on", and "hat"* each appear once, so the feature vector for **Sentence 1** is:

{The, cat, sat, on, hat, dog, ate, and}

Sentence 1
{2, 1, 1, 1, 1, 0, 0, 0}

Similarly, the features for **Sentence 2**

{3, 1, 0, 0, 1, 1, 1, 1}

In our dataset of instant videos from Amazon, we have a very large number of reviews, which will give us a large vocabulary. To limit the size of the feature vectors, we choose 5000 most frequent words (remembering that stop words have already been removed).

3.8. Classification

In this study, supervised machine learning model is implemented. Each review is a variable sequence of words and the sentiment of each review must be classified into positive or negative output class. The amazon review dataset contains 53,258 reviews for training and testing. The problem is to determine whether a given review has a different sentiment depending polarity of Table 2 mentioned features. Various methodologies have been practiced by different studies over the years starting from tree based classifier to neural network based approaches. We have chosen *Random Forest, Support Vector Machine and Gradient Boosting.* Input vector consist of 5000 features. Top feature represent most frequently occurring word. These feature consist of following types of grammatical words as explain below in Table 2.

Table 3 Feature Set

Set no.	Feature Set	Description
1.	Adverbs	Contain all types of Adverbs
2.	Verbs	Contain all types of Verbs
3.	Adjectives	Contain all types of Adjectives
4.	Adverbs + Verbs	Contain combination of Adverbs and Verbs
5.	Adverbs + Adjectives	Contain combination of Adverbs and Adjectives
6.	Verbs + Adjectives	Contain combination of Verbs and Adjectives
7.	Adverbs + Verbs+ Adjectives	Contain combination of Adverbs, Verbs & Adjectives

We used tree type of classifiers as explains below:

3.8.1. Random Forest

Random Forest is an adaptable machine learning strategy equipped for performing both regression and classification tasks. It is a type of ensemble learning method, where a weak tree model combines in a manner to form a powerful tree model. During classification of a new object, each tree model gives a classification and each tree classification is taken into account. After that finalized decision is made by taking the average of the different tree.

3.8.2. Support Vector Machine

Support Vector Machines are perhaps a standout amongst the most well-known and discussed machine learning algorithms. It remains in mainstream around the time they were created in the 1990s and keep on being the go-to technique for a high-performing algorithm with little tuning. It is a discriminative classifier, given labelled training data (supervised learning), the algorithm outputs an optimal hyper plane which categorizes new example. On the basis of this training, the algorithm is able to predict unknown input.

3.8.3. Gradient Boosting

Grading boosting technique is used by major search engine companies, i.e. Google, Bing, Yandex and Yahoo. They used it for web page ranking, but it’s actually not limited to application domain and can be used for a variety of problems. Grading boosting classifier are models made out of different weaker models that are trained individually and each model prediction is combine. The combination of weak model that much exertion. This is an effective strategy and accordingly is extremely famous. Gradient boosting is a standout amongst most powerful techniques for building classification models. The idea is to combine weak leaner in such a way that overall model accuracy is optimal.

3.9. Evaluation and Results

In order to evaluate the proposed methodology and to classify the reviews in classed the standard formula of precision - recall is used.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Precision is calculated for those forms or forms which are correctly selected.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + True\ Negative}$$

Recall is calculated for those form or forms which are successfully selected. Furthermore, the F measure is calculated for these respective classes and simplifies the results. The results are discussed in the next section.

$$\text{F} - \text{measure} = 2 * \frac{Precision.Recall}{Precision + Recall}$$

Dataset used in this paper for evaluation of the work is the office product reviews. Dataset consists of 53,258 reviews. Evaluation measures are precision, recall, and f-measure and machine learning algorithms are used for testing the dataset. By using Random Forest and Gradient Boosting classifiers on verbs, adverbs, and adjectives, they achieved 0.81 precision as mentioned in Table 10. We also evaluated verbs, adverbs, and adjectives alone and also their combinations. The verbs, adverbs, and adjectives achieved the F –measure of 0.81. This means one should use the *Feature Set 7* to achieve better results. After the detail analysis, *Feature Set 7* remained one of the influential features and however, whenever they were combined or used alone with any of the other forms, the results fell down. This means the influence of *Feature Set 7* is highest to classify sentiments, however, using them with others reduce the F- measure due to reduction of overall scores. Results of all feature sets is mentioned as below;

Table 4 Feature Set 1- Adverbs

Feature Set 1	Random Forest	SVM	Gradient boosting
Precision	0.64	0.65	0.64
Recall	0.63	0.64	0.63
F-measure	0.63	0.63	0.62

Table 5 Feature Set 2- Verbs

Feature Set 2	Random Forest	SVM	Gradient boosting
Precision	0.63	0.63	0.62
Recall	0.63	0.64	0.63
F-measure	0.64	0.65	0.64

Table 6 Feature Set 3- Adjectives

Feature Set 3	Random Forest	SVM	Gradient boosting
Precision	0.74	0.74	0.72
Recall	0.74	0.74	0.72
F-measure	0.74	0.74	0.72

Table 7 Feature Set 4- Adverb and Verb Combination

Feature Set 4	Random Forest	SVM	Gradient boosting

Precision	0.75	0.74	0.7
Recall	0.75	0.73	0.7
F-measure	0.75	0.73	0.7

Table 8 Feature Set 5- Adverb and Adjective Combination

Feature Set 5	Random Forest	SVM	Gradient boosting
Precision	0.76	0.77	0.77
Recall	0.76	0.77	0.77
F-measure	0.76	0.77	0.77

Table 9 Feature Set 6- Verb and Adjective Combination

Feature Set 6	Random Forest	SVM	Gradient boosting
Precision	0.77	0.78	0.79
Recall	0.77	0.78	0.79
F-measure	0.77	0.78	0.79

Table 10 Feature Set 7- Adverb, Verb, and Adjective Combination

Feature Set 7	Random Forest	SVM	Gradient boosting
Precision	0.81	0.79	0.81
Recall	0.81	0.79	0.81
F-measure	0.81	0.79	0.81

5. Conclusion

In this research, SentiFinder tool is used for extracting polarity features from users' reviews and classified them into either positive or negative polarity for a comprehensive dataset of 53,258 office product reviews collected from amazon. Gradient Boosting and Random Forest classifiers gave 0.81 precision on Adjective-Adverb and Verb Combination. It is concluded that this research might help the companies to manage their online reputation and aid them to improve their products because understanding the preferences of customers can be highly valuable for any product development, marketing, and customer relationship management. Furthermore, the identification of context being represented in natural language could be a challenging task to achieve by the research community

In future, the impact of adjective, adverb, and verb types can be evaluated individually for the task of sentiment classification that whether the feature combination has strong polarity to detect the sentiments on other dataset or not. This approach can further applied on other datasets such as news articles and blogs. Furthermore, the identification of context being represented in natural language could be a challenging task to achieve by the research community.

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