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A Study on Sentiment Analysis

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Abstract

Sentiment Analysis is a new interrelated field of Natural Language Processing, Computational Linguistics and Text Mining. It analyzes emotion, attitude, and sentiment of people. Sentiment Analysis has a wide range of application in e-commerce. In this paper, we studies about 15 research papers of earlier models in this field. Authors of different papers choose different domain for their experimental data like hotel, product, service etc. We studies about approaches used in earlier research and try to make a conclusion and roadmap of further research.

Keywords

Sentiment Analysis, Opinion Mining, Sentiment lexicon, Fuzzy Sets, Classifier

I. Introduction

Sentiment Analysis deals with identifying the sentiment or opinions expressed by the users in the review. When purchasing a product for the first time as usually needs to choose between several products with similar characteristics. The best way to choose the almost suitable product is to rely upon the opinions of others. Product review by another customer plays an important role in our decision-making process. Consider a student who wants to buy a book,(s)he first looks for comments and reviews about the book on the web. The person, who has read the book, comments about the book and his experience on the web. The author gets feedback from the customers through these reviews to improve their books and their market.

Sentiment lexicon also called opinion word plays very important role in Sentiment Analysis. Generally, adjective followed or preceded by adverb is detected as opinion word or phase. So, Parts-of-Speech taggers is used to detect adjective and nearest adverb from a review. Some sentiment word directly show positive sense like good, excellent, great etc. similarly, some word also show negative sense like bad, poor, terrible etc. Sometimes adjective with adverb phase also write down sentiment, like, "not so bad", here "bad" is a negative sentiment word, but, it proceeds by another negation adverb, so real sentiment indicates positive. But challenging task is to treat such type of sentiment phase where no adjective is found, like, "up to the mark", "value for money" etc. Detection of sentiment from this type of phase, is challenging area of research. We discuss various kind of research area in sentiment analysis.

Sentence level Sentiment Analysis is comparatively easy task. If direct sentiment lexicon is fined in that particular review sentence, then it becomes very easy to detect real sentiment. Sometimes in review, we find only one word or phase, that show satisfaction of customer. But if no direct sentiment or phase inside the review and whole sentence show the real sentiment, then it becomes very hard to detect by machine.

Document level Sentiment Analysis is really tough job. Here whole opinion document considered as a single unit. Getting all sentiment lexicon from that review, summarize the score of sentiment, taking average of that will show real sentiment. For this kind of approach, Sentiment Analysis will be treated as regression type problem. But after getting real sentiment from document, system detects it is positive, negative or neutral, then, Sentiment Analysis will be treated as classification type problem.

Detecting Sarcastic review is also a very challenging job. Generally sarcastic review show negative opinion. But in review, we can find one or more positive word, like, "what a great book! I can't understand a single concept". A positive word "great" is there, but real sense of review is very negative. This type of problem is a part of sentiment subjectivity detection.

Comparative opinion detection is a field of study in Sentiment Analysis. "product x is better than product y", this type of review actually does not show any positive or negative sense about product "x" or "y". it only shows one product is better than another. But this type of review will be helpful to choose best product. If we get 10 comparative review of 4 toothpaste, then easily we can select best toothpaste out of four.

Spam opinion detection is also very hard. Sometimes if representative of that product, offer so many positive review or competitor provides many negative review, then it will be hard to detect proper information about that product. Manually detection of spam opinion is very hard, so it is too difficult to write algorithm about that.

II. Sentiment Analysis Approaches

Jusoh and Alfawareh applied Fuzzy Sets for Opinion Mining[2]. They used fuzzy lexicon and fuzzy sets in deciding the degree of positive and negative. They considered each opinion word as a linguistic variable and constructed a term set for that variable like if PRICE is a linguistic variable, then corresponding term set will be T(PRICE)= {cheap, moderate, expensive}. They used sentence tokenization on review and extract sentiment word from review. The possibility theory had been utilized in deciding the degree level of each positive or negative Sentiment Word. If sentiment word was negative then assigned negative fuzzy set to that word, otherwise assigned positive fuzzy set. Then calculated degree of sentiment and visualized the output.

Su, Qi, et al. proposed mutual reinforcement approach to deal with the feature-level opinion mining problem[3]. Clustering was done on product features and opinion words simultaneously and iteratively by fusing both their content information and sentiment link information. under the same framework, based on the product feature categories and opinion word groups, they constructed the sentiment association set between the two groups of data objects by identifying their strongest n sentiment links. POS tagger used to detect sentiment word and product features. Using sentiment word and product features they derived association rule to detect hidden sentiment. Finally sentiment scoring was done. They took automobile reviews (in Chinese) as experimental dataset. In result, they achieved 81.90% precision.

Sarmento et al proposed and evaluated a method for automatically creating a reference corpus for training text classification procedures for mining political opinions in user-generated content.

A sentiment lexicon and a small library of syntactic-semantic patterns where polarity-bearing adjectives or nouns may occur, used as linguistic resources. They manually developed a set of syntactic-semantic patterns,
describing typical elementary constructions related to
the expression of opinion about named entities (NE).

R1 [NE] [V cop] [Art ind] [Nh hum] [A−/+] (e.g. "S´ocrates ´e um pol´ıtico trai¸coeiro" / "S´ocrates is a treacherous politician")
R2 [NE] [V ser] [Art ind] [(A−/+□N−/+)] (e.g. "Menezes ´e um oportunista","MFL ´e uma desgra¸ca" /"Menezes is an opportunist", "MFL is a disgrace")
R3 [NE] [V cop] [A−/+] (e.g. "S´ocrates est´a nervoso"/"S´ocrates is nervous")
R4 [Art def] [A−/+] [(do□da□dos□das)] [NE] (e.g. "O aldrab˜ao do S´ocrates" / "The liar of S´ocrates"). Results show that the precision of identifying negative opinions (89%) is significantly higher than the precision of identifying positive opinions (60%). For negative opinions they chose rules R1B (83 correct cases / 12.6% support) and R2B (179 correct cases / 27.6% support), henceforth mentioned as R1B and R2B, respectively. For positive opinions, they opted for Rule R1B (81 correct cases / 28.9% support), henceforth mentioned as R1B+.
Maharani proposed two approaches for opinion mining[5]. A. Lexical based Opinion Mining Design B. Machine Learning based. For Lexical based Opinion Mining, author cleaned the data first, then used parts-of-speech tagger to detect adjective, adverb, verb. Each sentiment score is acquired from lexical database for Indonesian language which referred to English SentiWordNet. For Machine Learning based approach, author used four different classifiers namely- SVM, Multinomial Naive Bayes, k-NN and Maximum Entropy. Before trained the classifier, several NLP techniques like data cleaning, stemming, POS tagging, tokenization and term weighting using subjective weights on Indonesian lexical database were done. The result indicated that, out of all techniques, accuracy of SVM classifier was best. It became more than 81% accurate whereas accuracy of Lexical based Opinion Mining Without stemming was 74.59% and With Stemming 67.06%.
Banic et al used Big data and sentiment analysis together[6]. They collected hotel review data from some popular travel website like tripadvisor.com, hotels.com, laterooms.com, booking.com, the tripadvisor.com. n-gram model used for chunking. They paid special attention to hotel name and title of review of that hotel. Duplicated review was not considered for evaluation. When information retrieved from dataset, information not retrieved previously was considered only. They build a dictionary based on words and phrases used in hotel review. They extracted every sentiment word from review and converted into Bag-of-Word. Every word is marked with category and calculated score. Evaluation of Result show that more than 70 percent of terms are positive grade 3 (referring to very good) between 70 percent and 30 percent positive terms grade 2 (referring to average) less than 30 percent positive terms grade 1(referring to bad) .
Esuli and Sebastiani tried to detect whether a given term is positive or negative or no subjective value at all[7]. They used semi-supervised learning approach where only a small set of training data were labeled by human. Rest of training data were unlabelled. That set of data should be labeled automatically. They used General Inquirer (GI) lexicon (Stone et al., 1966) for experiment. Training set is obtained by expanding initial seed sets by means of WordNet lexical relations. They used three learning approaches to the problem of distinguishing between Positive, Negative, and Objective terms. First approach was a two stage classification approach, where first classifier specifies whether the term was subjective or objective and second classifier places subjective term. Second approach was also a two stage approach, where first classifier specifies term is positive or not positive, second classifier specifies term is negative or not negative. Third approach specified learning of ternary classifier.
Priyanka and Gupta identified best features namely N-gram features, POS based features and features based on the lexicon SentiWordNet from review for sentiment analysis[8]. They proposed a methodology which divided into preprocessing, Feature Extraction and Model Building. In preprocessing step, POS Tagger detected some incorrect word and it is corrected by using Regular Expression. Spell checking are performed by spell-checker. In Feature Extraction phase, N-gram feature, POS Tag based feature and SentiWordNet based feature were identified. Finally in Model Building phase, they used Support Vector Machine for Binary Classification. a highest accuracy of 95.0884% has been obtained when combing N-gram, POS and SWN-PS. The model has been able to produce a highest accuracy of 91.9% among the entire feature combinations when experimented on small dataset and 95% on the large dataset.
Boiy and Moens applied machine learning approach to sentiment analysis in multilingual Web texts[9]. They considered opinion recognition as a supervised classification task. From every sentence of review, they extracted sentiment features using state-of-art algorithm. Each sentence treated as a feature vector. For stemming, they used Snowball as stemmer, which implements Porter's algorithm. Negation detection was done by n-gram approach. They also paid attention to Discourse features like ''but'', ''despite'', ''although''. They combined classifiers in a pipelined cascaded way in a pipelined cascaded way. when two or more classifiers recognize the example unanimously above a threshold certainty in a certain class, the classification is accepted. Aggregation and combination rules of different classification models might be learned from a training set. The result shows that the Maximum Entropy (ME) and Support Vector Machine (SVM) classifiers (numbers in bold) outperform the Multinomial Nai¨ve Bayes (MNB) classifier (confidence level C99.5%, the difference in performance between ME and SVM was not statistically significant), when using unigram features combined with subjectivity analysis. Improvements resulting from subjectivity analysis had a confidence level C90% for SVM and C99.5% for MNB and ME.
Wang and Zhou used MRA(mutual reinforcement approach) to improve the accuracy of the mining results[10]. They crawled reviews from website and done some preprocessing using popular NLP techniques like POS tagging, stop word elimination, word stemming using Porter stemmer, to reduce noisy information from review. Then they used nouns and noun phrase as website feature words. They considered adjective as opinion word and identified their sentiment orientation based on WordNet. After the completion of the previous steps, they get two sets of association objects: the set of feature words F= {f1, f2…fm} and the set of opining words O= {o1, o2…on}. A m*n link weight matrix R= [rij] which contains all the pairwise weights between set F and O is then constructed. They set the weight rij by the co-appearance frequency of fi and oj in clause level.
Tian et al focused on mining opinion from Chinese review sentences using Natural Language Processing, obtaining comprehensive

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evaluation of product and ranking product in some feature or in all features[11]. Several resources used like HowNet "Sentiment Mining Lexicon(beta)"(released at 2007.10.22) to get static polar words, Product ontology processed from http://product.it168.com/. They extracted each ontology word from review and map them using syntactic parser to find the dependency. They searched each word in modified word lexicon and polar word lexicon, to calculate context polarity. Then they mapped context polarity to product feature object. In result, they got high precision, 76% , when number of text is 58, and comparatively low recall, 39%.

Srivastava1 et al focused on binary grammatical relation or dependency (BGD)of words ,the pattern in which each word in a sentence possesses grammatical corporations with other words for correct utterance of meaning[12]. They collected over 400 hundred reviews (220 of cell phone and 180 of digital camera) from amazon.com and epinion.com. They used SENTWORDNET 1.0.1 to get Domain Independent Opinion Words. Only adjective was considered for that purpose. They divided opinion words into three types, namely "PPPOW"- prior priority positive opinion words (e.g. excellent, brilliant, good, etc.), "PPNOW"- prior priority negative opinion words (e.g. bad, difficult, etc.), and "CPOW" represents contextual polarity opinion words (e.g. large, big, thick, etc.). "CPOW" is assigned to those opinion words, which generally adopt polarity from context (i.e. from reviews). Noun POS detected as explicit product features. They divided the complete process of features extraction into three categories:

1. Identification of features using EPFS and SDs (i.e.feature by feature and SDs).
2. Identification of features using IFTC and SDs.
3. Identification of features using SDs having opinion

words (i.e. features by opinion words and Sds). Where EPFS is Explicit Product Feature seeds, SDs are Stanford Typed Dependencies, IFTC is Implicit Feature Tag Corpus. They used following idea for resolving semantic orientation of an opinion word was that if two opinion words were conjoined with cooperative conjunction (e.g. "and" etc) then the opinion word with unknown polarity, adopts the same polarity of the prior polarity opinion word conjoined with it. Similarly, if two opinion words were conjoined with contrary conjunction (e.g. "but", "although", "while", etc), then the opinion word with unknown polarity, adopts the reverse polarity of the prior polar. Finally they determined strength of sentiment in a sentence.

Jędrzejewski and Morzy proposed a method is based on the ratio of term occurence frequency in documents assigned to positive and negative classes, for calculating the semantic orientation of a term[13]. They proposed a scoring function

$$score(t) = \begin{cases} p_t - 1 & , \text{iff } p_t \geq 1 \\ -\left(\frac{1}{p_t} - 1\right) & , \text{iff } p_t < 1 \end{cases}$$

where

$$p_t = \frac{p(t|C_P)+\varepsilon}{p(t|C_N)+\varepsilon}$$

where, pt is the raw semantic orientation of the term t, $p(t|C_P)$ and $p(t|C_N)$ are conditional probabilities of occurences of the term t in documents from positive and negative classes, respectively, and ε is a small positive value controlling for terms that appear in only one class.

Siering developed a two-stage approach that connects text mining with sentiment analysis to predict the stock price impact of company-specific news[14]. They acquired a dataset which consists of a large number of financial news articles. For supervised machine learning approach, they labeled the dataset. Then they used dictionary to detect opinion word. They make use of one out of three local support vector machine (SVM) classifiers, i.e. SVMPOS, SVMNEUT and SVMNEG for Subsequent to a document preprocessing, which is a major task in Text Mining. The classifier was chosen according to the sentiment of the document under consideration which can either be positive (POS), neutral (NEUT) or negative (NEG). Training of all classifier should done by subsequent positive, negative and neutral document. Additionally, they make use of a fourth classifier, SVMCOMPLwhich is a global classifier that is trained on all news articles which are contained in the dataset and represents a classical text mining setup. Result shows that, for Class positive, Precision is lower than Recall, for Class negative Precision is higher than Recall.

Sing, Sarkar and Mitra developed an Algorithm for Sentiment Analysis Based on Adverb-Adjective-Noun
Combinations[15]. They classified degree of adverb into five different categories: 1. Adverbs of affirmation: such as absolutely. 2. Adverbs of doubt: such as possibly, probably. 3. Strong intensifying adverbs: such as astronomically. 4. Weak intensifying adverbs: such as barely. 5. Negation and Minimizers: such as not. We proposed a way of scoring adjective on a scale of -1 (maximally negative) to + 1 (maximally positive) . For scoring of adjective between -1 to +1 depending upon domains described above they presented two axioms: Axiom1: Depending upon SentiWordNet positive and negative polarity and and also on the domain the adjective belongs to, w e map them in the scale of -1 to + 1. Axiom2: Same adjective may belongs to different domain. But then those adjectives will be scored differently depending upon their domains they belong to. They proposed two algorithm Unary ANN algorithm and Binary ANN Algorithm, where ANN stands for adverb-adjective-noun. They achieved higher Pearson correlations 0.495217881.

Zuhui and Weiproposed to apply the mutual information method to mine the complicated features from online reviews, and extend features extraction from the conventional word bags to regular collocations[16]. They defined the mutual information of collocation feature words W and sentiment orientation O

$$\mathbf{MI}(W, O) = \log \frac{\mathbf{P}(W, O)}{\mathbf{P}(W) \times \mathbf{P}(O)}$$

Where P(W,O) is the joint probability distribution function of W and O , P(W) and P(O) is the marginal
probability distribution functions of W and O respectively. Average mutual information between two
feature words within the collocation can be defined as

$$\mathrm{AMI}(W_1, W_2) = \mathrm{P}(W_1, W_2)\log\frac{\mathrm{P}(W_2 \mid W_1)}{\mathrm{P}(W_2)} + \mathrm{P}(W_1, \bar{W}_2)\log\frac{\mathrm{P}(\bar{W}_2 \mid W_1)}{\mathrm{P}(\bar{W}_2)}$$
$$+\mathrm{P}(\bar{W}_1, W_2)\log\frac{\mathrm{P}(W_2 \mid \bar{W}_1)}{\mathrm{P}(W_2)} + \mathrm{P}(\bar{W}_1, \bar{W}_2)\log\frac{\mathrm{P}(\bar{W}_2 \mid \bar{W}_1)}{\mathrm{P}(\bar{W}_2)}$$

They used following Filtering strategy over extracted features

$$T_{w,o}(\lambda) = \begin{cases} 2(\lambda - \lambda \cdot P_w(o) + P_w(o)) - 1 & if(\lambda >= 0.85) \\ 2\lambda p_w(o) & if(\lambda < 0.85) \end{cases}$$

Where $P_w(o)$ can be estimated by MLE method over the whole corpora and the boundary value 0.85 can be captured from statistics of the corpora. Finally they incorporated all features which extracted, into sentiment analysis model.

III. Language And Platform

A. NLTK

Natural Language Toolkit(NLTK) is a widely used toolkit for Natural Language Processing. It incorporated with Python Programming Language. More than 50 corpora for different purposes, in build with it. Also NLTK provide an easy interface to access this corpus. It has suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning. Maximum research paper considered for this literature survey, used NLTK with Python.

B. WEKA

WEKA is a collection of Machine Learning algorithms with JAVA for Data Mining purpose. WEKA contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is helpful for building new machine learning algorithm. It is also an open-source software and licenced under GNU General Public License.

C. StanfordCoreNLP

It is also based on JAVA programming language. All available Natural Language Processing tools in StanfordCoreNLP, are written in JAVA. It also included the part-of-speech (POS) tagger, the named entity recognizer (NER), the parser, the coreference resolution system, and the sentiment analysis tools, and provides model files for analysis of English.

D. LingPipe

LingPipe is a Natural Language Processing toolkit based on Computational Linguistics widely used in Text Mining, Sentiment Analysis etc. It is also run in JAVA programming environment and also a free toolkit.

E. GATE

GATE (General Architecture for Text Engineering) is an open source software for text mining, computational linguistics and natural language processing. It is a JAVA suite. All NLP tools like tokenizer, POS tagger, named entity recognition included here. A separate information extraction unit called ANNIE with a set of all NLP tools included here.

IV. Conclusions and Future Direction

In this paper, we study previous research on Sentiment Analysis. If we consider Sentiment Analysis is a regression type problem, then we can choose fuzzy set. It is one of the best technique for that purpose. If we consider Sentiment Analysis is a classification type problem then we can choose semi-supervised learning or supervised machine learning approach. Small dataset is used for training in semi-supervised approach. Classifier is used for supervised machine learning approach. Out of all classifiers, Maximum Entropy Classifier produces overall good result, but Support Vector Machine (SVM) produce best result all time. In future, we will use SVM classifier for our further research.

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