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Identifying Product Aspect Polarity by Product Review Classification with Dual Sentiment Analysis

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Abstract

Dual Sentiment Analysis has emerged as a crucial and active research field. It involves extracting sentiment from comments, feedback, or critiques, which serves as valuable indicators for various purposes. To address this, we propose a novel dual training algorithm that utilizes both original and reversed training reviews to develop a robust sentiment classifier. Additionally, we introduce a dual prediction algorithm that comprehensively assesses both aspects of a review for classification during testing. The proposed approach goes beyond traditional polarity (positive-negative) classification by extending the framework to a 3-class system, which includes neutral reviews. This enhancement allows for a more nuanced understanding of sentiment. By considering neutral reviews, we gain deeper insights into the sentiment landscape. Dual Sentiment Analysis plays a pivotal role in helping companies gauge the level of acceptance of their products and formulate strategies to improve product quality. Moreover, it empowers policymakers and politicians to gain valuable insights by analyzing public sentiments on policies, public services, and political issues.

Keywords

opinion mining, sentiment analysis, bag of words, negation analysis, review polarity, data mining.

1 Introduction

Every domain now has access to the internet, which is now a necessity in all spheres of life. People in the modern age post their reviews online. Large amounts of data are being stored for each and every minute of all these reviews. These evaluations are just as significant as purchasing the product. The account executive and the end users will benefit from the analysis of these reviews. Sentiment analysis has earned its identification and is used in classifying the reviews. Sentiment analysis, also called opinion mining, is the field of study that analyses people's opinions, sentiments, evaluations, appraisals, It has become known as sentiment analysis, and it is used to categorize the reviews. The study of sentiment analysis, also known as opinion mining, examines people's attitudes and feelings toward many types of entities, including goods, services, organizations, people, issues, events, subjects, and their attributes, attitudes. In addition to having additional names and slightly varied duties, it represents a huge problem field. Examples include opinion mining, opinion extraction, sentiment analysis, subjectivity analysis, affect analysis, emotion analysis, review mining, etc. However, sentiment analysis or opinion mining now encompasses them all. Both sentiment analysis and opinion mining are widely used in academia. They essentially represent the same academic discipline. Opinions themselves still have a fairly broad definition. The major focus of sentiment analysis and opinion mining is on opinions that explicitly or implicitly indicate positive or negative sentiments. In opinion mining, classification is crucial for doing an analysis. Choosing a hypothesis from a list of alternatives that best fits a collection of observations is done using a classification algorithm. Because they are major determinants of our behaviors, opinions play a crucial role in practically all aspects of human activity. The opinions of others are necessary whenever a decision needs to be made. In the real world, companies and organizations are constantly interested in the public's or consumers' perceptions of their goods and services. When someone needed advice in the past, they typically turned to their friends and relatives. Surveys, opinion polls, and focus groups were undertaken by businesses and organizations when they needed the opinions of the general public or customers. For years, marketing, public relations, and political campaign firms have made a fortune by gathering consumer and public opinion. Opinion summaries give an overview of articles' opinions by describing the degree, polarity, and correlations of various emotions. A customer can quickly learn how existing customers feel about a product via opinion summaries, and a product's manufacturer can learn why different demographics enjoy it or what they don't like about it. A seller's work may be very difficult or very simple. Based on the fact that the seller interprets the interests of the customer, the two mutually exclusive words determine the selling experience. It is impossible to collaborate on the genuine needs of the client and the product unless one is psychic or has the ability to enter another person's head. The correct product must be presented to the right customer, which is just as crucial as having the right product. here.

2 Review of Literature

Polarity shift refers to a linguistic phenomenon that can invert the sentiment polarity of a text. One of the most crucial forms of polarity shift is negation, where adding a negation word, like "don't," before a positive statement like "I like this book" will reverse the sentiment from positive to negative. This poses a challenge for standard machine learning algorithms that often struggle to handle such polarity shifts when using Bag-of-Words (BOW) representation, as the opposite sentiment texts appear similar in this representation. Researchers have proposed various approaches to tackle the polarity shift problem, but many of them require complex linguistic knowledge or additional human annotations, making them less practical for widespread use. Some efforts have been made to address the problem without relying heavily on external resources, but the state-of-the-art results still fall short of being satisfactory. For instance, even the most promising improvements achieved so far are only around 2 percent on multi-domain sentiment datasets. In summary, handling polarity shift in sentiment analysis remains a challenging task, and while there have been attempts to address it using different techniques, finding an effective and practical solution is still an ongoing research area.

2.1 Sentiment Analysis of Product Review

Establish The internet is currently the best resource for learning, gathering ideas, and reading evaluations of goods and services. The Internet generates millions of reviews for every product. It is incredibly challenging to handle and comprehend such assessments due to their enormous size and number. Sentiment analysis is a branch of research that collects and comprehends opinions from reviews, identifying the polarity of those opinions, and using natural language processing (NLP), computational linguistics, and text analytics. Numerous algorithms exist in the sentiment analysis sector to address NLP issues. Several applications use each algorithm. We have displayed the taxonomy of the numerous sentiment analysis techniques in this system. Additionally, this system shows that Support vector machines (SVM) perform more accurately than Naive Bays and Maximum Entropy approaches. [1]

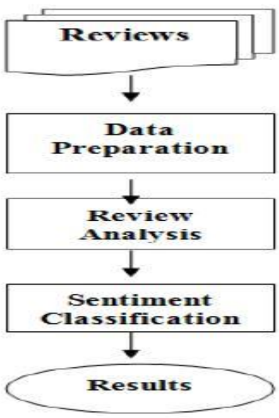

Fig. 01 The Sentiment Analysis process Model.

2.2 Weakly Supervised Joint Sentiment-Topic Detection from Text

By utilizing automated technologies, opinion mining and sentiment analysis seek to identify subjective information like opinions, attitudes, and sentiments represented in text. This method suggests a brand-new probabilistic modelling framework based on latent Dirichlet allocation (LDA) termed joint sentiment-topic (JST), which jointly extracts sentiment and topic from text. Reverse joint sentiment-topic model, which was created by flipping the order of topic generation and sentiment during the modelling process, is another joint sentiment topic model that is investigated. Results show that JST outperforms Reverse-JST when sentiment priors are included. The test results on data sets from five distinct domains are used to check this. The topics and topic sentiment that JST has identified are accurate and coherent. [2]

2.3 Dual Sentiment Analysis: Considering Two Sides of one Review

The most often used technique for modelling text in statistical machine learning approaches to sentiment analysis is the bag-of-words (BOW) approach. To solve this issue for sentiment categorization, we here offer a paradigm called dual sentiment analysis (DSA). First, by constructing a sentiment-reversed review for each training and test review, we suggest a novel data expansion strategy. Based on this, we suggest a dual training method to employ pairs of reversed and original training reviews to create a sentiment classifier and a dual prediction algorithm to categorize the test reviews by. by taking into account both sides of a review and expanding the DSA framework from a polarity (negative-positive) classification to a 3-class (positive-negative-neutral) classification.

As of right now, dual sentiment analysis is no longer dependent on an external antonym dictionary for review reversal because to the corpus-based method we proposed for creating a pseudo-antonym dictionary. Two goals, nine datasets, two antonym dictionaries, three classification algorithms, and two different types of characteristics are used in our extensive range of tests. [3]

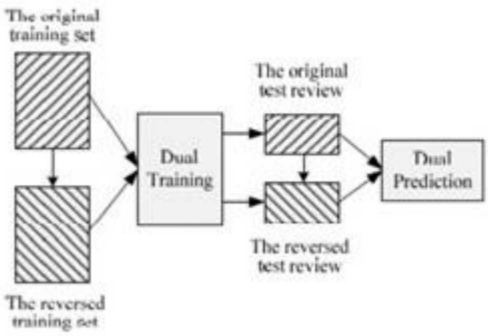

Fig.02. The process of dual sentiment analysis. The rectangle filled with slash denotes the original data, and the rectangle filled with backslash denotes the reversed data

2.4 Dual Sentiment Analysis and Opinion Mining

This idea refers to the area of research that examines how written language conveys sentiments, people's ideas, assessments, attitudes, and emotions. Natural language processing is one of the most active fields of study for this approach, which is also extensively researched in data mining, web mining, and text mining. Due to its significance to business and society at large, this research has application in fields other than management sciences, including computer science and social sciences. With the growth of social media, including reviews, forum discussions, blogs, microblogs, Twitter, and social networks, sentiment analysis is becoming more and more important. We have a lot of subjective info that has been digitally stored and is accessible. Since opinions are fundamental to practically all human activities and are significant determinants of our behaviors, these systems are being utilized in the social domain and in every organization. When faced with a choice, we frequently look for other people's perspectives in order to inform our perceptions and ideas about reality as well as the decisions we make. Not just for people, but also for companies, this is true. [4]

3 Proposed System Architecture

In this paper, we propose a simple yet efficient model, called dual sentiment analysis (DSA), to address the polarity shift problem in sentiment classification. By using the property that sentiment classification has two opposite class labels (i.e., positive and negative), we first propose a data expansion technique by creating sentiment-reversed reviews. The original and reversed reviews are constructed in a one-to-one correspondence. Thereafter, we propose a dual training (DT) algorithm and a dual prediction (DP) algorithm respectively, to make use of the original and reversed samples in pairs for training a statistical classifier and make predictions. In DT, the classifier is learnt by maximizing a combination of likelihoods of the original and reversed training data set. In DP, predictions are made by considering two sides of one review. That is, we measure not only how positive/negative the original review is, but also how negative/positive the reversed review is. We further extend our DSA framework from polarity (positive-negative) classification to 3-class (positive-negative-neutral) sentiment classification, by taking the neutral reviews into consideration in both dual training and dual prediction. To reduce DSA's dependency on an external antonym dictionary, we finally develop a corpus-based method for constructing a pseudo-antonym dictionary. The pseudo-antonym dictionary is language-independent and domain-adaptive. It makes the DSA model possible to be applied into a wide range of applications.

Several approaches have been proposed to address polarity shift without relying on complex linguistic analysis or additional annotations. For instance, [7] introduced a method that first classifies each sentence in a text into a polarity-unshifted part and a polarity-shifted part based on specific rules. Then, these two parts are represented as separate bags-of-words for sentiment classification. Building upon this, [2] further developed a technique to distinguish the shifted and unshifted text by training a binary detector. Classification models are subsequently trained on each of these two parts, and an ensemble of two component classifiers is used to provide the final polarity of the entire text. In a similar vein. [4] proposed a sentence polarity shift algorithm that identifies consistent sentiment polarity patterns and utilizes only the sentiment-consistent sentences for sentiment classification.

These approaches demonstrate efforts to handle polarity shift in sentiment analysis while avoiding the need for intricate linguistic analysis or extra human annotations. By employing various methods for identifying and dealing with polarity shifts, researchers aim to enhance sentiment classification accuracy and address the challenges posed by linguistic phenomena like negation.

The system consists of three major steps:

3.1 Reviews Extraction

i. Creation of user interface and uploading videos

ii. Word clustering

iii. Pre-processing

3.2 Reviews Evaluation

i. Selection of hypotheses set

ii. Classification experimentation (field and laboratory).

3.3 Sentiment Visualization

The establishment of a web-based interface is required for the module's first stage. When a new account is created, the admin will log in and upload MP4 videos. The user will then log in and start watching videos. He will then provide reviews for the video, which the database will subsequently store. Word clustering and preprocessing are then used to process the saved reviews. With the use of classification, the content is refined during review evaluation into pertinent phrases and words. The basis for classification is supervised learning [6]. The system divides the user-provided words into positive, negative, and neutral categories. Words without any meaning are referred to as hypothetical words. Such words are analyzed using an iteratively induced hypothesis. The creation of a sentiment graph is the focus of the final module. It uses categorized reviews from the database as an input, which are then displayed graphically as the sentiment graph. The system's functional architecture is shown in Figure 3 below.

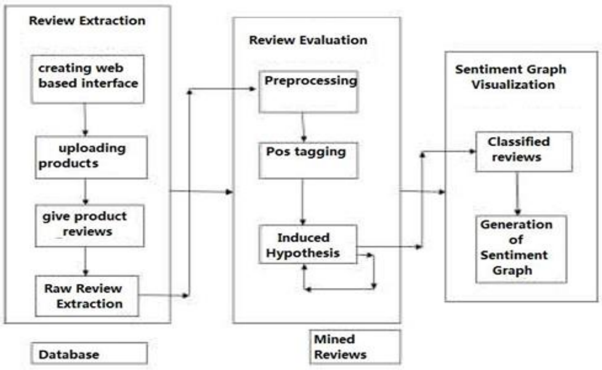

Fig. 03. System Architecture title.

4 Expected Outcome

In the future, anyone making a judgement will need to conduct a sentiment analysis as it will continue to be useful for calculating, recognizing, and conveying emotion in a variety of fields. Everyone will continue to benefit from being able to choose the greatest product when they wish to purchase one. By examining the products on the E-commerce site and deleting any that may be detrimental to the owner's business, the proposed system will continue to keep the company's standing in the market. The suggested approach will continue to perform a thorough analysis of the comments or reviews by looking for conjunction and negation terms, such as "no," "not," and similar expressions, in order to debunk the polarity of the review results. Businesses like Amazon.com or Snapdeal.com, as well as individuals who purchase the products, will continue to benefit from the suggested method to analyze the products being offered on their platform and make decisions appropriately.

In the coming years, a novel strategy for expanding data will be recommended to tackle the issue of shifting sentiment polarity in categorizing sentiments. This strategy will encompass the utilization of two sets of samples for both training and prediction, referred to as dual training and dual prediction. The DSA algorithm will introduce a selective data expansion method, leveraging evaluations from training data with higher sentiment levels as the foundation for data expansion.

The proposed system will maintain the company's market position by scrutinizing products on e-commerce platforms and removing any that could potentially harm the owner's business. Additionally, the suggested approach will continue to conduct a thorough analysis of comments and reviews, specifically focusing on conjunctions and negations like "no" and "not" to clarify the sentiment expressed in the reviews

5 Result

The proposed reseacrh has explored the field of dual sentiment analysis, aiming to improve the accuracy and effectiveness of sentiment classification by considering both positive and negative sentiments simultaneously. Through extensive research and experimentation, several key findings and contributions have been made. Firstly, a thorough review of existing literature on sentiment analysis highlighted the limitations of traditional single-polarity sentiment analysis techniques. The need for a more nuanced and comprehensive approach to sentiment analysis was evident, leading to the exploration of dual sentiment analysis. The research proposed and implemented a novel dual sentiment analysis architecture that incorporated both positive and negative sentiment classifiers. The architecture leveraged machine learning algorithms and feature engineering techniques to capture and analyze sentiment signals from textual data. The implementation demonstrated promising results, achieving higher accuracy and improved sentiment classification performance compared to single-polarity approaches. Furthermore, the research investigated various feature selection and representation techniques to enhance the sentiment analysis process. Feature selection methods such as information gain, chi-square, and mutual information were explored to identify the most informative features for sentiment classification. Additionally, feature representation techniques such as

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bag-of-words, n-grams, and word embeddings were employed to capture the semantic and contextual information of the text. The experimental evaluation of the dual sentiment analysis approach was conducted on datasets collected from e-commerce dummy platforms and online review platforms. The results demonstrated that the proposed approach outperformed traditional single-polarity methods in accurately identifying and classifying both positive and negative sentiments. The evaluation metrics, including precision, recall, and F1-score, indicated the superiority of the dual sentiment analysis approach.

Moreover, the research also delved into the interpretability aspect of dual sentiment analysis. Techniques such as sentiment lexicons, feature importance analysis, and sentiment intensity estimation were employed to provide insights into the sentiment classification process. These interpretability techniques not only enhanced our understanding of the sentiment analysis model but also provided explanations for the sentiment predictions made. The findings of this research have several implications for real-world applications. Dual sentiment analysis can be applied in various domains such as social media monitoring, customer feedback analysis, and brand reputation management. By accurately capturing and analyzing both positive and negative sentiments, organizations can gain deeper insights into public opinion, customer satisfaction, and sentiment trends. This can inform decision-making processes, marketing strategies, and product improvements. While this research has made significant contributions to the field of dual sentiment analysis, there are areas that warrant further exploration. The incorporation of domain-specific knowledge and contextual information could enhance the accuracy and relevance of sentiment analysis. Additionally, the integration of multi-modal data, including text, images, and videos, can lead to more comprehensive sentiment analysis models. In conclusion, the dual sentiment analysis approach presented in this thesis has demonstrated its efficacy in capturing the complexity of sentiment in text data. The research findings contribute to the advancement of sentiment analysis techniques, providing a foundation for further research in this field. The potential applications and implications of dual sentiment analysis are vast, offering valuable insights and opportunities for organizations to better understand and respond to sentiment in various contexts.

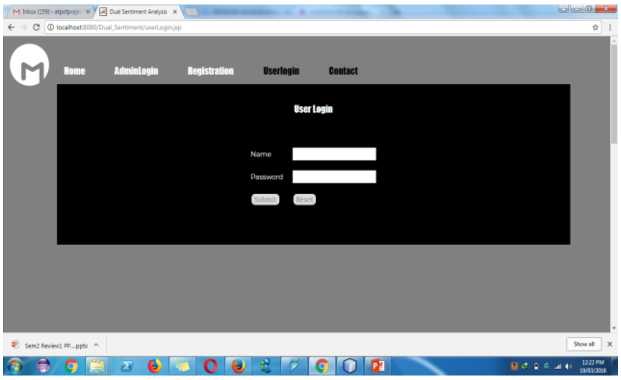

Fig. 04 Login Page.

User can login directly if he has already registered by giving correct credentials (Name and password). If user has forgot password then he can reset the password by clicking on reset button.

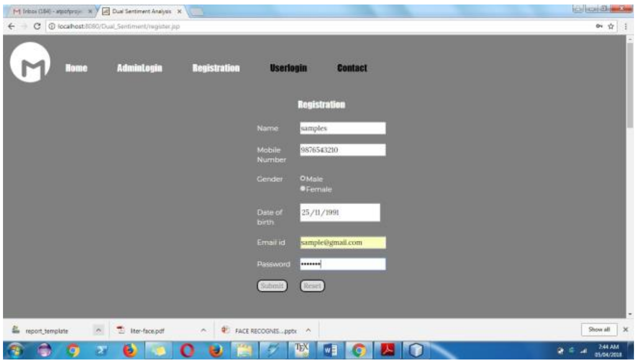

Fig. 05 Registration Page.

If there is someone who is using this first time then the person needs to get registered by providing all the required details. Then user can login and use the software.

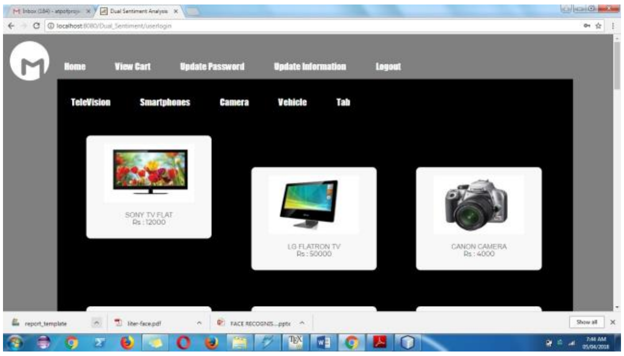

Fig. 06 Home Page.

After login we will get a home page with multiple products from which we can choose any and can move to review page.

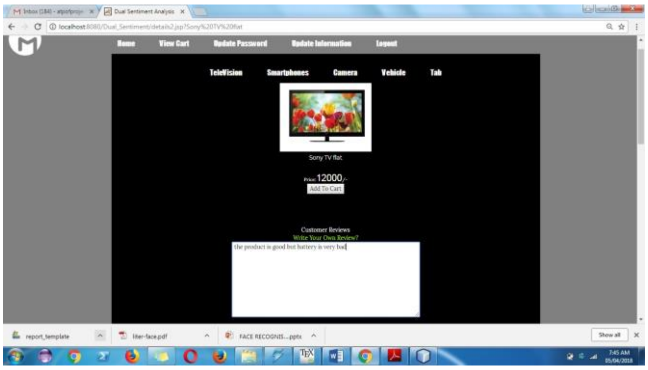

Fig. 07 Review Submitting Page.

After choosing the production on review page we can see the chosen product, its price and options like add to cart and enter your reviews. We can also see the already submitted reviews on the same page.

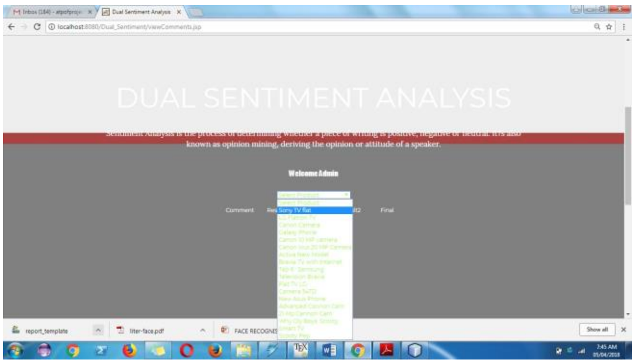

Fig. 8 Admin Home Page.

On admin page, admin can see all the product list. Admin can add or remove the products from user side also.

Fig. 09 Sentiment Polarity Page.

Sentiment polarity refers to the degree of positive, negative, or neutral sentiment expressed in a text or a document. The sentiment polarity of a document is usually measured on a scale ranging from highly positive to highly negative, with neutral sentiment falling in the middle. In the above image polarity is displayed for a battery performance in bot the positive and negative way.

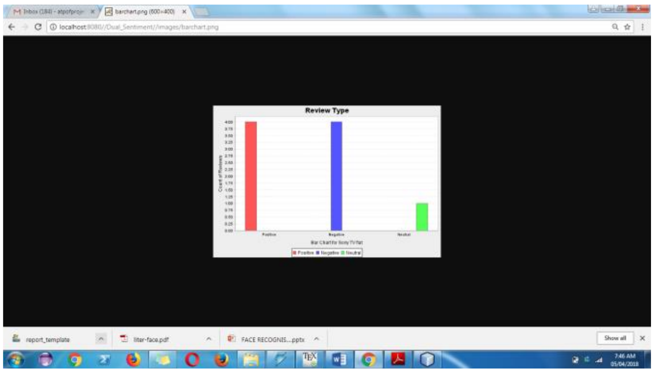

Fig. 10 Sentiment Polarity Graph.

The above graph shows graphical representation for all the positive, negative and neutral reviews.

6 Conclusion

Sentiment analysis is useful for calculating, recognizing, and expressing sentiment in a variety of fields. Everybody benefits when they are able to choose the greatest product when they wish to purchase one. Sentiment analysis is crucial for businesses because it lets them know what their customers think about their goods. As a result, businesses can base judgments regarding their products on feedback from customers. As a result, businesses may release new goods and change the features of existing ones more quickly and effectively in response to client feedback. So with the implementation of sentiment analysis, it's clear that it can be used in following use-cases:

- Sentiment Analysis for Judgments: Sentiment analysis is the process of determining the sentiment or emotion expressed in a piece of text, such as product reviews or customer feedback. When individuals or businesses need to make judgments or decisions, analyzing the sentiment helps them better understand the overall tone and opinion of the text, which can influence their choices.
- Usefulness in Various Fields: Sentiment analysis has widespread applications in various fields. It can be used to calculate, recognize, and express sentiment in areas such as marketing, customer service, social media monitoring, public opinion analysis, and more. Understanding sentiments in these fields can lead to valuable insights and informed decision-making.
- Informed Product Choices: The passage suggests that sentiment analysis benefits everyone, as it helps individuals in selecting the best products when they intend to make a purchase. By analyzing the sentiments expressed in product

reviews, potential buyers can gauge the overall satisfaction or dissatisfaction of previous customers and make more informed choices.

• Feedback-driven Decisions: With sentiment analysis, businesses can make decisions based on customer feedback. They can use the sentiments expressed by customers to make improvements, launch new products, or modify existing ones to better align with customer preferences. This feedback-driven approach enables businesses to be more responsive to customer needs and demands.

In summary, sentiment analysis plays a critical role in making informed judgments and decisions across various fields. Businesses benefit greatly from understanding customer sentiments, as it helps them improve their products, make customer-driven decisions, and ultimately strengthen their market position. Meanwhile, consumers benefit from sentiment analysis as it empowers them to make more informed choices when purchasing products or services.

References

[1] Shivaprasad T K and Jyothi Shetty, "Sentiment Analysis of Product Reviews: A Review", International Conference on Inventive Communication and Computational Technologies (ICICCT 2017).

[2] Chenghua Lin, Yulan He, Richard Everson and Stefan Ruger, "Weakly Supervised Joint Sentiment-Topic Detection from Text", IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 24, NO. 6, JUNE 2012.

[3] Rui Xia, FengXu, Chengqing Zong, Qianmu Li, Yong Qi, and Tao Li, "Dual Sentiment Analysis: Considering Two Sides of One Review", IEEE TRANSACTIONS ON JOURNAL NAME, MANUSCRIPT ID, Citation information: DOI 10.1109/TKDE 2015. 2407371.

[4] Bing Liu, "Sentiment Analysis and Opinion Mining", http://www.morganclaypool.com /toc/hlt/1/1, Copyright ©2012 by Morgan & Claypool, DOI: 10.2200/ S00416ED1V01Y 201204HLT016, ISSN 1947-4040

[5] Abbasi, A. H. Chen, and A. Salem, "Sentiment Analysis in Multiple Languages: Feature Selection for Opinion Classification in Web Forums," ACM Trans. Information Systems, vol. 26, no. 3, pp. 1-34, 2008.digitaluniverse.

[6] A. Abbasi, S. France, Z. Zhang, and H. Chen, "Selecting attributes for sentiment classification using feature relation networks," IEEE Transactions on Knowledge and Data Engineering (TKDE), vol. 23, no. 3, pp. 447-462, 2011.

[7] I. Councill, R. MaDonald, and L. Velikovich, "What's Great and What's Not: Learning to Classify the Scope of Negation for Improved Sentiment Analysis," Proceedings of the Workshop on negation and speculation in natural language processing, pp. 51-59, 2010.

[8] 8. J. Li, G. Zhou, H. Wang, and Q. Zhu, "Learning the Scope of Negation via Shallow Semantic Parsing," Proceedings of the International Conference on Computational Linguistics (COLING), 2010.