OPINION CLASSIFICATION BASED INFORMATION CREDIBILTY ANALYSIS SYSTEM

Nasiya.C.Najeeb* and Sangeetha Jamal**

*Department of Computer Science and Engineering, Rajagiri School of Engineering and Technology, Kochi, India, Email: nasiya.nachu@gmail.com
** Department of Computer Science and Engineering, Rajagiri School of Engineering and Technology, Kochi, India, Email: sangeethajamal@rajagiritech.ac.in

ABSTRACT: Social media is currently a place where massive data is generated continuously. Nowadays, majority of the people share their opinions online. Hence, microblogging websites are rich sources of information which have been successfully leveraged for the analysis of sociopragmatic phenomena such as belief, opinion and sentiment in online communication. However, the unprecedented existence of such massive data acts as a double edged sword, one can easily get unreliable information from such sources,and it is a challenge to control the spread of false information either maliciously or even inadvertently. The information seeker is inundated with an influx of data. To cope with this , here we introduce a new method for automatically determining the opinion and to assess the credibility of the information. To identify an opinion (positive or negative) about a review, sentiment analysis is performed using Bing Liu's dictionary and to improve the accuracy of sentiment classification incrementers, decrementers and negation modifiers are considered. For assessing credibility a new method , "Automatic Helpfulness Classification", is introduced. The effects are proven by experiments using a large number of reviews and the accuracy obtained is more compared to existing methods.

KEYWORDS: Sentiment Classification, Incrementers, Decrementers, Negation modifiers, Information credibility.

INTRODUCTION

People use social media for communicating or for sharing newsworthy information’s. They use social media for almost every aspect of their lives, for example, for sharing opinions on the products they purchased or movies they watched. As a result, it is very common to read reviews and comments before purchasing a product or watching a movie. The main task of sentiment classification is to assign a category label (e.g., positive, negative, or neutral) to a piece of text.
Machine learning methods have been widely used for sentiment classification [7, 8]. The Bag-of-Words (BoW) model is the most widely adopted representation for sentiment classification, but other models, e.g., Bag-of-Concepts [9], do exist. BoW based methods assume the independence of words and ignore the importance of semantic and subjective information in natural language text.
Social media provides a huge amount of information for decision making, but the problem is to distinguish between credible and incredible information’s. In many cases, social media data is user generated and can be biased, inaccurate and subjective [25]. Furthermore, some people use social media to spread rumour and misinformation. Consequently, information in social media is not necessarily of equal value and we need to assess the credibility of the data before using it for decision making.
A few works have already been performed for assessing the credibility of information or for detecting false rumour information on twitter [1, 4]. Based on its characteristics , researchers mainly focus to specific features extracted from Twitter , such as the characteristics of the users who post messages , the length of a tweet and number of positive words in the text. There are some other works [2, 3, 6] which mainly focus to specific features of target WebPages, such as the amount of advertisement, the structure of web-page and the number of readers.

Here we propose an automated system that collects reviews automatically from IMDb and measures the credibility of a review and the author and also analyzes the sentiment of the review (i.e. positive, negative or neutral) by considering incrementers, decrementers and inverters.
The rest of this paper is organized as follows: Section 2 shows the works that are related to Sentiment Analysis and Information Credibility. Section 3 describes the problem statement. Section 4 explains framework for proposed system. Section 5 shows the experiment results and finally Section 6 concludes the paper.

RELATED WORKS

Sentiment Analysis

Sentiment Analysis is the process used to determine the attitude/opinion/emotion expressed by a person about a particular topic. The researches in the field of sentiment analysis started much earlier in 1990s, but the terms sentiment analysis and opinion mining were introduced in the year 2003 [10, 11].
The earlier work in the field was limited to subjectivity detection, interpretation of metaphors and sentiment adjectives [12, 13]. Pang et al. [7] classified movie reviews into positive and negative by using different classifiers, and the results showed that SVM combined with unigrams obtained the best performance. Liu et al. [14], extracted the features of the product. A summarization system has been built to show the users sentiment to every feature of the product. Ding et al. [15] presented a holistic lexicon based approach to analyze the sentiment of both explicit and implicit aspect of product, and realize an opinion mining system. Kim et al. [16], classified sentiment analysis at word and sentence level. According to Jindal et al. [17], comparative sentence was identified, and comparative relationships were extracted from the identified comparative sentence. Alexander et al. [18] focused on how to automatically collect a corpus for sentiment analysis and opinion mining purposes by using Twitter. A sentiment classifier is built to determine positive, negative and neutral sentiments for a document. Ohana et al. [19], applied SentiWordNet lexical resource in automatic sentiment classification. Wilson et al. [20] focused on the task of phrase-level sentiment analysis. They followed a two-tiered approach: detecting whether a phrase is polar or neutral. According to pak et al. [21], Twitter as a corpus has been automatically collected, and sentiment classifier has been built to determine sentiment polarity. Here, to enhance Sentiment Classification we consider incrementers,decrementers and inverters .

Information Credibility Analysis

Assessing credibility is an important part of research on mass communication. Castillo et al. [2] discussed the information credibility of news propagated through Twitter. They used users profile information, network information, and users behaviour (tweets and retweets) to assess the credibility of tweets. Barbier and Liu [22] proposed a method to find provenance paths leading to sources of the information to evaluate its credibility. Qazvinian et al. [23] explore three categories of features including content-based, network-based and microblogs specific memes. And they studied the effectiveness for correctly identifying rumours. Ratkiewicz et al. [24] build the Truthy system to automatically classify tweet credibility by mining, visualizing, mapping, classifying, and modelling massive streams of public microblogging events. In this paper, we develop an automated credibility analysis system for movie reviews collected from IMDb, which classifies credible and not credible reviews.

PROBLEM STATEMENT

Given reviews R of a movie A, determine whether R is positive or negative and also check the credibility of R and then give a rating for A based on the percentage of positive reviews of A.

PROPOSED METHODS

Our goal in this work is to perform Information Credibility Analysis along with Sentiment Analysis. To achieve this we divide our work into 4 modules.

Data Collection

This work uses an automated data collection method for collecting reviews. Here we collect movie reviews automatically from IMDb. Only the reviews made by IMDb users are collected.

Sentiment Classification

We performed Sentiment Classification to recognize whether a review is positive or negative. Before classification, the reviews were pre-processed using NLTK Toolkit. In this phase, we used Bing Lius [5] Sentiment dictionary which contains almost 6800 words. Using the dictionary, word matching is performed for each word in a review and then each sentiment word is enriched with tags <positive> or <negative>. After dictionary tagging, sentiment score of each review is calculated.

$$sentiment\_score = \frac{\sum_{i=0}^{t} w_i}{W_n}$$

where, w is the score of a sentiment word in a review, t is the total sentiment words in a review and $w_n$is the total number of words in a review.
In majority of the existing works, even though they consider inverters (negation modifiers) they don't consider incrementers and decrementers while calculating sentiment score. Here to improve the accuracy of sentiment classification, incrementers and decrementers are also considered with negation modifiers.
Inverters are those words which reverse the polarity of a sentence, for example, consider the sentence “the movie was not interesting”. Here the word "not” changes the positive polarity of the sentence into negative polarity.
People usually use incrementers in reviews to express their emotion deeply. Presence of the words like ‘very ’, ‘really’ and ‘extremely ’ in negative and positive sentences make the adjective and adverb stronger. But this effect is not considered during the score calculation in existing methods. A decrementer is used to reduce the emotional context of a word. Words like ‘barely’, ’less’ are examples for decrementers.

Table. 1. Handling Incrementers, Decrementers and Negation modifiers in Positive and Negative Sentences

Previous Word	Next Word	Score
Negation Modifier	Adjective/Adverb [positive]	Negative
Negation Modifier	Adjective/Adverb [negative]	Positive
Incrementer	Adjective/Adverb [positive]	High Positive
Incrementer	Adjective/Adverb [negative]	High Negative
Decrementer	Adjective/Adverb [positive]	Low Positive
Decrementer	Adjective/Adverb [negative]	Low Negative

Information Credibility Assessment

There are few works considering user expertise for assessing the credibility of information. Here a new method,“Automatic Helpfulness Classification”, (i,e determining the number of people for whom the review was helpful) is introduced . In this method, a score is calculated for each review by determining the number of people who found the review useful.

$$Review\_score = \frac{\alpha}{\alpha + \beta}$$

where, **α** = number of people who found the review useful, **β** = number of people who did not find the review useful.
The value of review_score obtained was between 0 and 1. Only the reviews which has a score greater than 0.5, was classified as credible.
In many cases a username is the only information we have as a reviews source. But here apart from username,
other profile information such as the Account membership age, Total number of reviews made by the author dated till now are also collected. To make our Credibility Assessment more accurate, we also considered the above said author information, which shows the expertise of an author. For instance, an author is expected to be a kind of expert if he is a member in IMDb for a long period and also makes reviews on movies frequently. Hence the decision for assessing the credibility of information was made by setting threshold values for 3 factors i.e. review_score, account membership age and total reviews made. If the values of these 3 factors are greater than the threshold value for a review, then that review is considered to be credible.

Rating System

Majority of the existing works use Average Rating (the sum of all reviews divided by the number of total reviews) for rating a movie. But here we propose a new method of movie rating. This rating system represents the percentage of reviews that are positive for a given movie. As per this system a movie is categorized into 4:

Excellent If the positive reviews make up 80% or more, the film is considered “excellent”.
Good A film is categorized as “good” if its positive reviews are between 50%-79%.
Average A film is categorized as “average” if its positive reviews are between 30%-49%.
Bad If the positive reviews are less than 30%, the film is considered “bad”.

This system offers a standardized way for movie goers to examine film reviews. By looking at multiple reviews of the same movie and producing a score based on the percentage of favourable reviews that movie received, it helps users to directly compare films based on their critical reception. The main advantage of this system is that by looking at an aggregated review score rather than a specific review, the users are able to see what the whole critical or user community has thought about a movie, rather than the view of a single reviewer.

EXPERIMENT RESULTS

In this section, we present evaluation experiments of our method to demonstrate the efficiency. For experimentation, we collected online movie reviews automatically from IMDb. Here we chose 5 movies randomly, each with a maximum of 500 reviews. Pre-processing was performed on each reviews using NLTK toolkit . Word tokenizing and POS (part of speech) tagging was performed in the pre-processing stage.
We performed the Opinion Classification on two sets : set A containing all the collected reviews and set B containing only the credible reviews. The performance of the opinion classifier was calculated by using the equation given below.

$$\textbf{accuracy} = \frac{\textbf{number of systems correct outputs}}{\textbf{number of systems output}}$$

Table 2 shows the performance of the Opinion classifier and lists the accuracy obtained.

Table. 2. Performance of the Opinion Classifier

	Set A (all reviews)	**Set B (credible reviews)**
Total reviews	2500	1830
Accuracy	0.785	0.813

For determining the performance of the information credibility assessment, we compared the rating of different movies with and without considering credibility. Below diagram shows the rating of different movies with and without considering credibility based on our rating system.
We also compared our movie rating with IMDb rating to show how effective our Credibility Assessment is. Below table shows the comparison between our rating and IMDb rating.

Table. 3. Comparison of movie rating made with our system and IMDb rating

Movies	**Rating without credibility**	**Rating with credibility**	**IMDb rating (converted to percentage)**
A	80%	79%	81%(8.1/10)
B	74%	70%	75%(7.5/10)
C	30%	42%	24%(2.4/10)
D	72%	70%	75%(7.5/10)
E	53%	51%	55%(5.5/10)

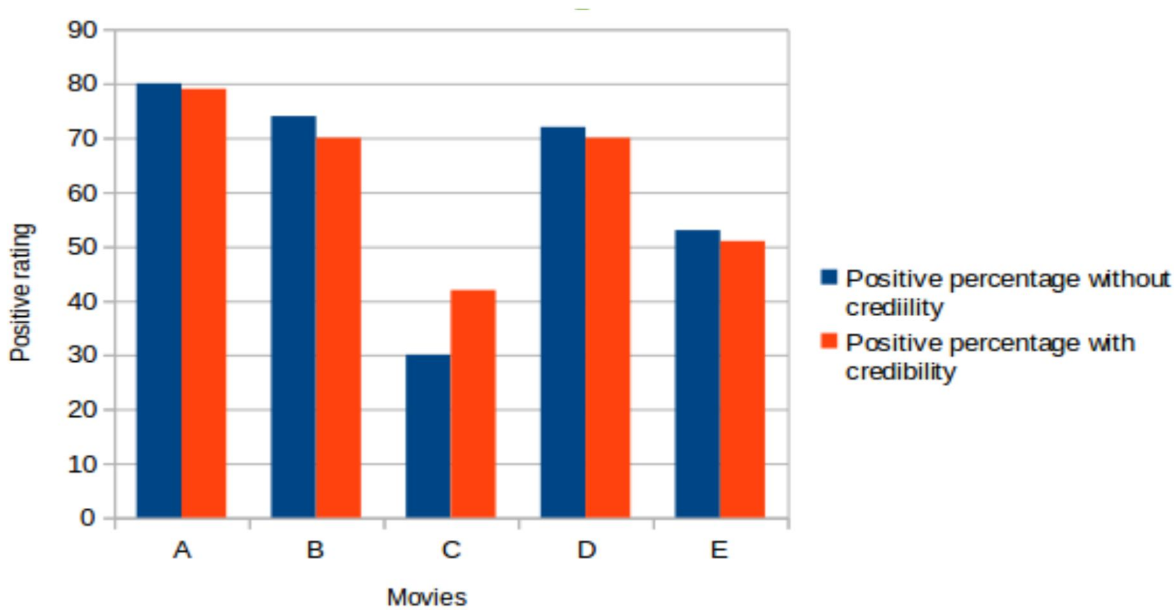

Figure. 1. Rating of different movies with and without considering credibility

CONCLUSION

In this article, we propose a general frame work to perform sentiment classification of movie reviews as well as to assess the credibility of reviews. To improve the sentiment accuracy compared to existing methods , we considered incrementers, decrementers and negation modifiers. To assess the credibility of information, 3 factors namely, review_score, account membership age of author and total number of reviews made by the author were considered.
This model can handle classification in an efficient manner compared to traditional methods. The experiment results show that proposed approach achieved a better accuracy rate.

REFERENCES

[1] Y. Namihira, N. Segawa, Y. Ikegami, K. Kawai, T. Ka-wabe and S. Tsuruta, *High Precision Credibility Analysis of Information on Twitter*, Signal-Image Technology & Internet-Based Systems (SITIS), 2013 International Conference.

[2] C. Castillo, M. Mendoza, and B. Poblete, *Information credibility on twitter*, Proc. of the International Conference on World Wide Web, pp.675-684, ACM, 2011.

[3] YeKang Yang, Kai Niu, ZhiQiang He, *Exploiting the Topology Property of Social Network for Rumor Detection*, 12th International Joint Conference on Computer Science and Software Engineering (JCSSE), pp. 41-46, 2015.

[4] Ringel Morris, S.Counts, A.Roseway, A.Hoff and J.Schwarz. *Tweeting is believing? Understanding Microblog Credibility Perception*, .Proc. CSCW, (2012).

[5] Minqing Hu and Bing Liu. Mining *and summarizing customer reviews*. in Proceedings of ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2004). Aug 22-25, 2004, Seattle, Washington, USA.

[6] M. Wassmer and C. Eastman, *Automatic evaluation of credibility on the Web*, in Proc. of the American Society for Information Science and Technology, 42(1), 2005.

[7] B. Pang,, L. Lee, S.Vaithyanathan, *Thumbs up? Sentiment classification using machine learning techniques*, Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 7986, 2002.

[8] S. Tan, J. Zhang, An *empirical study of sentiment analysis for Chinese documents*, Expert Systems with Applications 34, pp. 2622-2629, 2008.

[9] E. Cambria, D. Rajagopal, D. Olsher, D. Das, *Big social data analysis*, R. Akerkar (ed.) Big Data Computing, ch. 13, pp. 401-414, Taylor & Francis, 2013.

[10] Nasukawa, Tetsuya and Jeonghee Yi, 2003, *Sentiment analysis: capturing favourability using natural language processing*, Proceedings of the K-CAP03, 2nd International Conference on knowledge capture.

[11] Dave et al, 2003, *Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews*, In Proceedings of the 12th International Conference on World Wide Web, WWW 2003, 519-528.

[12] Wiebe, Janyce et al, 1999, *Development and use of a gold-standard data set for subjectivity classifications*, Proceedings of the Association for Computational Linguistics (ACL-1999).
[13] WiebeJanyce, 2000, *Learning Subjective Adjectives from Corpora*, American Association for Artificial Intelligence (www.aaai.org).
[14] Hu Minqing, Liu Bing. *Mining and summarizing customer reviews*, Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York: ACM Press , 2004:168-177.
[15] Ding Xiaowen, LIU Bing, YU Philip S, et al. A *holistic lexicon-based approach to opinion mining*, Proceedings of the 2008 International Conference on Web Search and Data Mining. New York: ACM Press , 2008:231-240.
[16] Kim S-M, HOVY E, *Determining the sentiment of opinions*, Proceedings of the 20th International Conference on Computational Linguistics. Philadelphia: Association for Computational Linguistics,2004:1367.
[17] Jindal, Nitin, and Bing Liu. *Mining comparative sentences and relations*. AAAI. Vol. 22. 2006.
[18] Alexander Pak, Patrick Paroubek., *Twitter as a Corpus for Sentiment Analysis and Opinion Mining*, ELRA, L10-1263, 2010
[19] Ohana B, Tierney B. Sentiment classification of reviews using SentiWordNet, 9th. IT & T Conference. 2009: 13.
[20] Wilson, T.; Wiebe, J.; and Hoffmann P, *Recognizing contextual polarity in phrase-level sentiment analysis*. In Proceedings of HLTEMNLP, 347C354, 2005.
[21] Pak A, Paroubek P, *Twitter as a Corpus for Sentiment Analysis and Opinion Mining*, LREC. 2010.
[22] G. Barbier and H. Liu, *Information provenance in social media*. Social Computing,Behavioral-Cultural Modeling and Prediction, pp. 276-283,2011.
[23] V. Qazvinian, E. Rosengren, D. R. Radev, and Q. Mei. *Rumor has it:Identifying misinformation in microblogs*. In EMNLP, pp. 1589-1599,2011.
[24] Ratkiewicz, J., Conover, M., Meiss, M., Goncalves, B., Patil,S.,Flammini, A., and Menczer, F. *Truthy: Mapping the Spread of Astroturf in Microblog Streams*, WWW 2011.
[25] Mohammad-Ali Abbasi and Huan Liu, *Measuring User Credibilty in Social Media* , unpublished. (Unpublished manuscript)