Survey on Product Review Sentiment Classification and Analysis Challenges

Mubarak Himmat, Naomie Salim

Faculty of Computing
Universiti Teknologi Malaysia
81310 UTM Skudai-Johor, MALAYSIA
barakamub@yahoo.com, naomie@utm.com

Abstract. There is no doubt that the process of using the internet to post comments and to get others' comments has become a common daily practice on the Web. Nowadays, a huge amount of information is available on the internet .The data which is posted by users and customers who visit these websites every day contain significant information. Some companies ask their customers about a product or services, for feedback analysis and to evaluate the satisfaction ratio of their products and services. The reviews by customers of products are rapidly growing. This paper provides ground knowledge and covers the most important scholarly papers and research that have been done in the area of sentiment analysis and the classification of opinion. This work presents opinion definitions and more detailed opinion classifications, and explains the related topics. This review will provide an introduction to the most common and significant information related to sentiment analysis, and it will answer many questions that have been asked in opinion mining, analysis, classifications and challenges.

Keywords: Opinion mining, Text mining, Sentiment classification, Customer reviews.

1 Introduction

The development of the internet and its applications and the wide use of it technologies has created a mania for using the internet. Nowadays, most users and customers are becoming familiar and comfortable with the internet’s applications and these increases with each day. The development that occurred in the generation and the fourth generation of mobile phone technology has helped and increased the wide use of the internet by people all over the world. People now share information, opinions and reviews rapidly, within few moments. Now, when you want to know information about any specific items, you do not need to ask others as in the past to get their opinion. You needn't follow the advertisements of companies, for these contain many fakes, and they contains information that also more over the truth to gain and attract

T. Herawan et al. (eds.), *Proceedings of the First International Conference on Advanced Data and Information Engineering (DaEng-2013)*, Lecture Notes in Electrical Engineering 285, DOI: 10.1007/978-981-4585-18-7_25,

customers. If want to get true information that is based on experience, you must get the information from real users who are using or used the product or service before. You just seek the reviews of people of the specific target and you will find huge information and reviews that spread and are available on the online selling products' websites, firm's websites, forums, social media and so forth. The growth of opinion has generated a good ground for opinion mining and sentiment analysis. The products manufacturers need to find out the customers' viewpoints about their products for feedback and enhancement reasons. There are many works which focus on opinion mining analysis [1-6] generating a summary of the product reviews [3, 7-13] and opinion analysis that have been attracting many researchers recently.

In this paper, we present a discussion and examine the works that have been done for opinion mining of products and general opinion classification. We also provide the series development, what and how to support the knowledge discovery of internet text mining. What is opinion and how is it classified, how can it be extracted and how is it analysed and classified? The rest of this paper will be classified as follows. Firstly, an introduction, then defining opinion and sentiment analysis, and then sentiment classification and discussing the sentiment analysis level, followed by a conclusion.

2 Opinion Mining

Recently, opinion mining has become one of the rich data mining fields. The review of the customers has significant information as we mentioned above. This lets many researchers try to work in this area using data mining techniques and methods and by applying new techniques within Natural Language Processing (NLP) tools, and modified tools of text analysis and summarisation.

The term sentiment analysis was used for the first time in 2003 with [14] when they evolved a Sentiment Analyser (SA) that extracts sentiment (or opinion) about a subject from online text documents, but really much research had been done on sentiment and topic detection before that date[1, 15, 16].

3 Sentiment Analysis and Classification

Opinion definition: opinion mining and sentiment analysis can be described as the process of automatically extracting and analysing the opinions, sentiments, thoughts and feelings of opinion writers on a specific target. This target could be a product, some issue like politics, economics, events, phenomena, services, etc.).[16] define sentiment to be a personal positive or negative feeling.[2, 4, 5, 10-12, 15, 17-19]have works on sentiment analysis and they focus on classifying each customer review as positive, negative and neutral.

2.1 3.1. Opinion Definitions

Opinion has two definitions. The first one is provided by [14]and the second is modified and redefined by [6]. Here we will examine the two definitions and the development of that definition that happened.

2.2 3.1.1 Defining Opinion as Quadruple

This definition was given by [3]. They divided the opinion into four major basic components (g_i, so_{ijkl}, h_i, t_l),

Where

- g_i is a target
- so_{ijkl} is the sentiment value of the opinion from opinion holder h_i of target g_i at time t_l. So_{ijl} is positive, negative or neutral, or a rating score.
- h_i is an opinion holder.
- t_l is the time when the opinion is expressed.

Opinion Definition: An opinion is a quadruple, (g, so, h, t), where g is the opinion (or sentiment) target, s is the sentiment about the target, h is the opinion holder and t is the time when the opinion was expressed. Let us look at the following example.

E.g. "(1) *I bought a Sony Mobile phone two weeks ago. (2) I really like It. (3) I have captured a clear nice image. (4) The sound voice is good. (5) My friends said it needs not a lot of money to buy it."*

The above opinion example describes the opinion components and demonstrates that opinion analysis is not an easy way in the real practice of online reviews of products, services, for the complexity target description, because of the implicit and indirect expression. For example, in sentence (3), the opinion target meant here is "picture quality of Sony mobile", but the sentence does not mention that directly. It indicates it by the following sentence: "*a clear nice image"* and this case will usually be found. Case 1 actually leads to new definitions of opinion by it the entities of the target. To know clearly which aspect of the product is the opinion about and what is the sentiment of the opinion holder on specific aspects.

2.3 3.1.2 Defining Opinion as Quintuple

An opinion is defined as a quintuple component [6](e_i, a_{ij}, s_{ijkl}, h_k, t_l) where

- e_i is the name of an entity.
- a_{ij} is an aspect of e_i.
- s_{ijkl} is the sentiment on aspect a_{ij} of entity ei.
- h_k is the opinion holder.
- t_l is the time when the opinion is expressed by h_k.

The sentiment s_{ijkl} is positive, negative, neutral, or expressed with different strength/intensity levels, e.g. 1 to 5 stars, as used by most review sites on the Web. When an opinion is on the entity itself as a whole, the special aspect GENERAL is used to denote it. Here, e_i and a_{ij} together represent the opinion target. This definition can be considered more accurate, especially in product and services opinions because any product has different component or aspects and it is not fair to judge the product at all by the overall opinion. Sometimes the opinion holder's sentiment is varied from one aspect to another.

3.2 Opinions' Sentences General Classification.

Just as general the opinion sentences can be classified into to two main classes, a fact which expresses factual information from sentences, and subjective that expresses the opinion holder's attitude and sentiment. Each class is derived to subclasses. Figure 1 illustrates the General Classifications of opinions' Sentences.

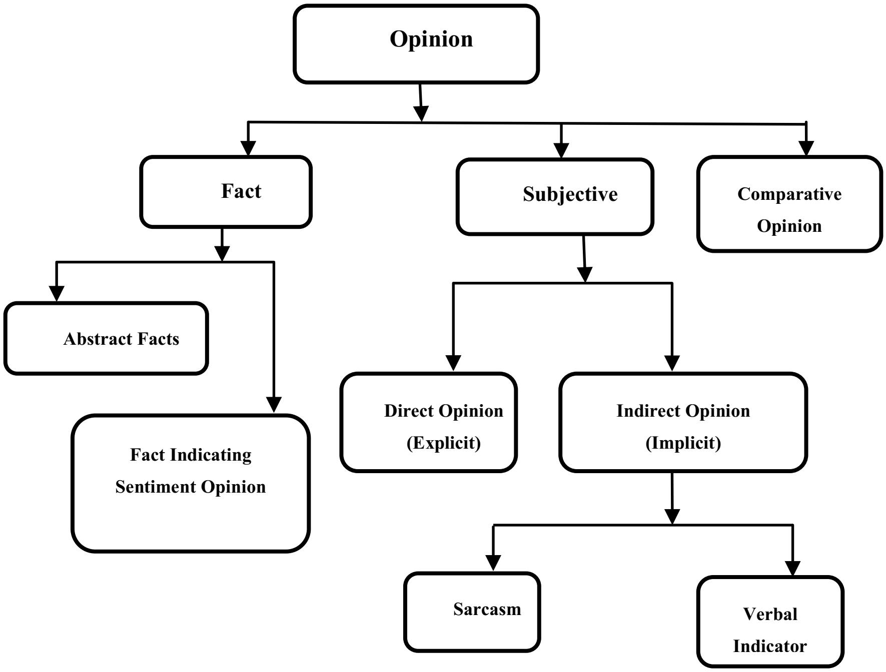

Fig .1 General Classifications of opinions' Sentences.

Within the below opinion example, we will demonstrate and discuss each class:

E.g. "*Proton Saga cars are made in Malaysia (1), and it has a very strong engine (2), its design is very beautiful (3) You do not need a lot of money to buy it (4)*".

3.3.1 Abstract Facts

To define the abstract fact let us look at the following example.

> E.g. *Proton Saga cars are made in Malaysia (1), and it has a very strong engine (2), its design is very beautiful (3). You do not need a lot of money to buy it (4).*

The first sentence, "*Proton Saga cars are made in Malaysia*", this sentence is not telling us the sentiment of the opinion holder, and it tells us about truth and facts "that the proton saga cars are made in Malaysia". When the sentence is not telling us about what the opinion holder really feels about the target, but just tells us some information and facts on that target we call this sentence a fact sentence.

3.3.2 The facts indicating sentiment

Sometimes facts can contain implicitly some sentiment. Let us examine the following opinion sentence: "*this kid is two years old, he has the ability to read and write*". This seems like a fact, because it talks about truth and fact, but it implicitly indicates that the kid is intelligent, for there are hidden sentiments in facts sometimes.

3.4 Subjective Opinions

The subjective opinion is the sentence that tells us what the opinion holder really feels about the product or target. Let us take a look at the second, third and fourth sentences."*It has a very strong engine* ","*its design is very beautiful", you need not a lot of money to buy it.*" These sentences are telling us about the sentiment of this opinion holder because he/she looks at the engine as being strong, and at the design as being beautiful, and this can be considered as his own opinion or sentiment, maybe someone else has a different opinion. The subjective opinion analysis has been more effective in sentiment analysis. For that reason,[20]identified subjective classification as a task that investigates whether a paragraph presents the opinion of its author or reports facts. Many researchers have shown that there is a very tight relation between subjectivity classification and sentiment classification[10, 11, 13, 17, 21, 22].and all these approaches are used to automatically assign subjective opinion.

3.4.1 Explicit opinion (Direct)

This type of opinion we can call explicit if a feature or any of its synonyms appears in a sentence. The feature could be identified as explicit or direct opinion. The explicit features are features which appear directly in a review, such as phone speed in the following sentence: "*The speed of the phone is slow*". The opinion that directly points to the target feature is called a direct opinion, e.g."It has a very strong engine"," its design is very beautiful" - these two sentences are direct opinions. The first sentence indicted to the engine feature, and the second sentence indicated directly to the design feature. This kind of sentiment is called a direct opinion[10, 12, 13, 18][10, 12, 13, 18] and these kinds of opinions provide good and easy analysis compared with others opinion classes.

3.4.2 Implicit opinions (Indirect)

The opinion has been called implicit if the feature or any of its synonyms do not appear in a sentence. The feature can be identified as explicit or an indirect opinion, such as "*my friend said that you lost your money by purchasing this phone*". Here the sentence is free of any feature or synonym of features, but the sentence indicates that it means the phone is bad.

Sometimes, the opinion holder does write and express his/her sentiment explicitly without writing the feature name, let's look at the last sentence of another example: "*you need not a lot of money to buy it*." This sentence indicates that the price of the car is cheap. But it does not mention the feature (price) directly, he assigned it explicitly. This kind of sentence is found in many reviews and it can be classified into two classes:

1. **Verbal indicator.**

The opinion holder writes and expresses his sentiment explicitly without writing the feature's name. Let us look at the last sentence of the four in the previous mentioned examples: "*you do not need a lot of money to buy it*." This sentence indicated that the price of the car is cheap, but he does not mention the price feature directly; he assigns it explicitly. This kind of sentence is quite difficult to understand using natural language processing and it has been expressed in many commented opinions.

2. **Sarcasm definition**

Sarcasm is defined as the use of irony to mock or convey contempt (http://oxforddictionaries.com/). It is the activity of saying or writing the opposite of what you mean, or of speaking in a way intended to make someone else feel stupid or show them that you are angry, as defined in (http://www.macmillandictionary.com/)or the use of unpleasant remarks intended to hurt a person's feelings, as defined in (the free English dictionary).

The sarcastic type of opinion is very popular and many opinion holders use it when they are not satisfied with the target. They describe their opinion by using joke or sarcastic expression [23]. Sarcasm (also known as verbal irony) is a sophisticated form of speech act in which the speakers provide enhancement of the semi-supervised sarcasm identification algorithm (S A S I).Their algorithm employs two modules, semi-supervised pattern acquisition for identifying, sarcastic patterns that serve as features for a classifier, and a classification stage that classifies each sentence to a sarcastic class. Convey their message in an implicit way. This type of opinion is very difficult to be explored by using the available natural language processing tools because there is no standard for the way of writing sarcasm and jokes. Below are two examples of sarcastic opinion sentences. Some work has been done in the area of sarcasm detection. This has investigated the impact of lexical and pragmatic factors on machine are investigate the impact of lexical and pragmatic factors on machine learning effectiveness for identifying sarcastic utterances.

E.g.1 "*I bought a new novel, it was expensive, it isn't interesting, but it's so good for the kindergarten*".

E.g.2."*It's great for a fun read or if you are looking for some funny material for gags or jokes".*

In the first example, the opinion holder posts an opinion about a new story book. The first sentence and second sentences are direct opinions, the book is expensive and not interesting. The third sentence at the first glance seems like a positive opinion, but really, when you take a deep look, you will find that the opinion holder here meant that the book is not good and it is better to be scaled for kids, and they are sarcastic that the contents of the book do not convince him.

In the second example, the opinion is telling us that the book is great for fun and for funny material, and this means the book's content is not important and not serious. But he does not indicate this directly. He uses a sarcastic expression.

3. Comparative Opinion

Opinion holders sometimes prefer to compare products with each other. The comparison opinion expresses the differences or similarities of the product or specific aspects or features by stating the preferences. E.g.: "Samsung galaxy II camera is better than the IPhone camera." [7] discussed different types of comparisons.

4 Sentiment Analysis Level

The process of opinion mining analysis can be classified into three general levels. Many works have done with researches. Here, we will try to describe each level.

4.1 Document level

At the document level, which is to obtain an overall opinion value for the whole document, the task of analysis at this level is classifying the opinion as the overall meaning, what is really the conclusion of sentiment that has been expressed, is it positive or negative sentiment. For example, if we have a product review, the system will determine the opinion in general whether the review as general evaluated positive, negative, or neutral sentiment. This kind of analysis is known as document-level sentiment classification.

Many works have been done at this level. [22]studied the effect of dynamic adjectives, semantically oriented adjectives, and gradable adjectives on a simple subjectivity and how they can be classified, and they proposed a trainable method for statistically combining two indicators of gradable. They proposed a system called Opinion Finder that automatically identifies the appearance of opinions, sentiments, speculations, and other private states in a text, via the subjective analysis, and applied machine learning techniques to address the sentiment classification problem for movie review data, and show how it can become effective. They there algorithms: Naive Bayes, classification, maximum entropy classification, and support vector machines. Work to address the rating inference problem, i.e. how to summarise a user review to a virtual rating from 0 to 5, or binary value (thumb up/down). They presented a graph based on a semi-supervised learning algorithm to resolve the rating inference problem. It inferred numerical ratings from unlabelled documents based on the sentiment expressed in the text. Concretely, they achieved and solved an optimisation problem to obtain good rating function over the whole graph that was created on the reviewer's data. They proved that, when limited labelled data is available, their method can achieve significantly better predictive accuracy over other methods. Das and Hu et al. (2007)studied sentiment classification for financial documents.

However, all the above works discovered the sentiment to represent the reviewer's overall opinion results, but did not find which features the reviewer actually preferred and liked and the one that they disliked. And in all the mentioned approaches, an overall negative sentiment on an object will not indicate that the reviewer dislikes every feature of the object.

4.2 Sentence level

In this kind of analysis level, the analysis will be concerned with the sentences and determining whether each sentence polarity (positive, negative, or neutral).Neutral means no opinion on the sentence. The sentence level of analysis is closely related to the subjectivity classification, which distinguishes sentences that express subjective views and objective sentences that express factual information from sentences. Many works, like[21], do subjective analysis. Work[3]identifies opinion sentences in each review and decides whether each opinion sentence is positive or negative[4, 5, 17, 19, 24].

4.3 Aspect or Feature-based level

As mentioned above, the usage of document level and sentence level analyses is not exactly determined and does not explore what exactly people like and dislike in a product's features. Aspect (feature) performs a perfect analysis in some cases. The feature based level [3], or aspect-based level as it has been called recently is directly looking at the opinion itself instead of an aspect of the target that is mentioned in each sentence, for opinion holders comment on different target features or aspects and it is not fair to judge an opinion at overall. For example, the sentence "*the Samsung mobile phone camera is fantastic (1), and it has a very nice design (2), the memory is not enough for many applications*". In this example we can…"We cannot say that the voice or the sentiment of the customers here is positive, because the first two sentences are positive opinions about the camera and design, but the last sentence is a negative opinion about the memory. In many comments on specific targets, opinions are described by target aspects or entities. Thus, the aim of the aspect level is to discover sentiments on each entity and/or their aspects that are mentioned throughout opinion sentences. The aspect-level is quite difficult. It really faces some challenges.[24] presented a how regular opinion expresses a sentiment only on a particular entity or an aspect of the entity, e.g. "*mobile battery is bad* ," which expresses a negative sentiment on the aspect battery of a mobile. [9] proposed a graphical model to extract and visualise comparative relations between products from customer reviews, with the interdependencies among relations taken into consideration[7]. They adapted the CRFs (Conditional Random Fields) model for accomplishing the feature-level of web opinion mining tasks for analysing online consumer reviews.

5 Conclusion

In this literature survey paper, we have illustrated a sentiment analysis approach and discussed sentiment analysis and classification in more detail. This work discusses many related problems, sentiment analysis and classification, subjectivity classification, and we found that the major challenges and the problems faced that need to be solved are the following challenges: the opinion holder has written and expressed their opinion without regard for the grammatical syntax and also there are many comment opinions which could include difficult sentences. Some comments also contain sarcastic expressions and this type of opinion is difficult to detect because there are no standards for sarcasm; it depends on human recognition. Also comparison sentence are used by many researchers, as we mentioned, but we also need more works. Slang and privation words are difficult to detect. Using comparison sentences also needs more work. But we think that the future of opinion mining will deal with the outstanding problems identified above. The work can be further extended to emerging areas like sarcasm and slang and privation words and comparisons analysis and detection using natural language processing tools and improving new tools.

Acknowledgement

We would like to thank the Ministry of Higher Education (MOHE) and Research Management Centre (RMC) at the Universiti Teknologi Malaysia (UTM) under Research University Grant Category (VOT Q.J130000.2528.02H99) for supporting this work."

References

1. Turney, P.D. Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews. in Proceedings of the 40th Annual Meeting on Association for Computational Linguistics. 2002: Association for Computational Linguistics.
2. Yi, J., et al. Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques. in Data Mining, 2003. ICDM 2003. Third IEEE International Conference on. 2003: IEEE.
3. Hu, M. and B. Liu. Mining and summarizing customer reviews. in Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. 2004: ACM.

4. Kim, S.-M. and E. Hovy. Determining the sentiment of opinions. in Proceedings of the 20th international conference on Computational Linguistics. 2004: Association for Computational Linguistics.
5. Liu, B., Sentiment analysis: A multi-faceted problem. the IEEE Intelligent Systems, 2010.
6. Liu, B., Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies, 2012. **5**(1): p. 1-167.
7. Chen, L., L. Qi, and F. Wang, Comparison of feature-level learning methods for mining online consumer reviews. Expert Systems with Applications, 2012.
8. Aguwa, C.C., L. Monplaisir, and O. Turgut, Voice of the customer: Customer satisfaction ratio based analysis. Expert Systems with Applications, 2012.
9. Xu, K., et al., Mining comparative opinions from customer reviews for Competitive Intelligence. Decision Support Systems, 2011. **50**(4): p. 743-754.
10. Eirinaki, M., S. Pisal, and S. Japinder, Feature-based opinion mining and ranking. Journal of Computer and System Sciences, 2011.
11. Aurangzeb, K., B. Baharum, and K. Khairullah, Sentiment Classification from Online Customer Reviews Using Lexical Contextual Sentence Structure. 2011.
12. Lu, Y., et al., Exploring the sentiment strength of user reviews, in Web-Age Information Management. 2010, Springer. p. 471-482(2010).
13. Hu, M. and B. Liu. Mining opinion features in customer reviews. in Proceedings of the National Conference on Artificial Intelligence. 2004: Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.
14. Nasukawa, Tetsuya, and Jeonghee Yi. "Sentiment analysis: Capturing favorability using natural language processing." Proceedings of the 2nd international conference on Knowledge capture. ACM(2003)
15. Rajaraman, K. and A.-H. Tan, Topic detection, tracking, and trend analysis using self-organizing neural networks, in Advances in Knowledge Discovery and Data Mining. 2001, Springer. p. 102-107.
16. Pang, B., L. Lee, and S. Vaithyanathan. Thumbs up?: sentiment classification using machine learning techniques. in Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10. 2002: Association for Computational Linguistics.
17. Pang, B. and L. Lee, Opinion mining and sentiment analysis. 2008: Now Pub.
18. Zhan, J., H.T. Loh, and Y. Liu, Gather customer concerns from online product reviews–A text summarization approach. Expert Systems with Applications, 2009. **36**(2): p. 2107-2115.
19. Liu, B., Opinion mining and sentiment analysis. Web Data Mining, 2011: p. 459-526.
20. Tang, H., S. Tan, and X. Cheng, A survey on sentiment detection of reviews. Expert Systems with Applications, 2009. **36**(7): p. 10760-10773.
21. Wiebe, J.M., R.F. Bruce, and T.P. O'Hara. Development and use of a gold-standard data set for subjectivity classifications. in Proceedings of the 37th annual meeting of the Association for Computational Linguistics on Computational Linguistics(1999).
22. Hatzivassiloglou, V. and J.M. Wiebe. Effects of adjective orientation and gradability on sentence subjectivity. in Proceedings of the 18th conference on Computational linguistics-Volume 1.(2000)s.
23. Davidov, D., O. Tsur, and A. Rappoport. Semi-supervised recognition of sarcastic sentences in twitter and amazon. in Proceedings of the Fourteenth Conference on Computational Natural Language Learning. 2010: Association for Computational Linguistics.
24. Jindal, N. and B. Liu. Mining comparative sentences and relations. in Proceedings of the National Conference on Artificial Intelligence. 2006: Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.