


Aspect-Based and Multi-Level Sentiment Information Applying Contrast Dictionary

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ABSTRACT

Customer feedback provides alternative and important sources to discover knowledge supporting the marketers and customers to make better decisions. However, the manual process to extract useful information depends on domain experts. This paper focuses on improving the performance of the automatic sentiment information extraction from customer feedback. The article proposes a new extraction method that consider multiple dimensions of feedback information, aspect, word, contrast, sentence or phrase, and document levels. The aspect-based sentiment extraction uses a named entity recognition technique to extract the desired aspects of a target product. The aspect-based sentiment combines with sentiment information from multiple levels of feedback contexts resulting in the fused sentiment information improving the extraction performance. The authors validate the effectiveness by measuring the accuracy of the sentiment and aspect recognition methods comparing with SentiStrength and Word-Count. This information gives some insights on customer satisfaction and can be applied in an alarming tool.

KEYWORDS

Aspect Recognition, Contrast Dictionary, Customer Feedbacks, Information Extraction, Multi-Level Sentiment Information Extraction, Sentiment Analysis

INTRODUCTION

Marketing strategy involves gathering accurate, timely, and sufficient information for supporting marketers to make better decisions. Complete information should cover all necessary customer perspectives, i.e. their feedbacks on the company's products and services (Amado, Cortez, Rita, & Moro, 2018), (Piao et al., 2019). The rapid growth of advanced technologies such as internet of things, cloud computing, and social network platforms allow the internet users to feedback their opinions on products and services conveniently (Ofusori & Africa, 2021), (Zhou, 2021). Such online user feedbacks reveal to customer satisfaction provided in digital forms including multimedia. Therefore, marketers may use customer feedbacks (CFs) to understand the customers' opinions on products and services in order to improve their products and services (Alengadan & Khan, 2017), (Alaei et al., 2019).

Even though CFs appear to be helpful in the social marketing, they are mostly represented in unstructured data (Ramachandran & Sciences, 2017), (Wang, Xin, Wang, Huang, & Liu, 2017), (Piao et al., 2019; Thelwall, Buckley, & Paltoglou, 2012) which are for human to read. They cannot immediately be interpreted by the machine (Bello-Orgaz, Jung, & Camacho, 2016), (Sivarajah, Kamal, Irani, & Weerakkody, 2017), (Jung, 2017). It requires practitioners and experts to analyze CFs. This

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work is time consuming and labor intensive. Therefore, there is a need to automatically extract the information from CFs.

There have been increasing interests in automatic information extraction from CFs (W. Chen, Yu, Xian, Wang, & Wen, 2020). Multi-level sentiment information extraction is a technique that can provide the information more accurately than a single level (Piao et al., 2019), (Cambria, 2016). In the past decade, most of researches proposed the sentiment extraction only on a document level using several techniques (Araque, Corcuera-Platas, Sánchez-Rada, & Iglesias, 2017), (Hu & Liu, 2004), (Diamantini, Mircoli, Potena, & Storti, 2018). T. Chen and et.al (T. Chen et al., 2017) and X. Fang and J. Zhan (Fang & Zhan, 2015) proposed word-level, sentence-level, and document-level sentiment extraction. They proved that the sentiment information from multiple levels improved the extraction performance. However, they do not consider contrast information.

The writing in on-line CFs may not be grammatically correct and can also be complex. They often use contrast words in a feedback (Vilares et al., 2017), (Zaw & Tandayya, 2018). For example, the customer feedback “This product seems cheap but it is good quality,” the contrast word ‘but’ helps decrease the negative sentiment of “cheap” and increase the positive sentiment of ‘good quality.’ In fact, D. Vilares and et.al (Vilares et al., 2017) explicated the overall sentiment of such sentence is ‘Positive.’ Based on the scenario, this paper proposes a new algorithm, called the contrast dictionary that can handle complex sentences when extracting the sentiment polarity from CFs.

Considering only positive and negative polarities of the words and applying just the accumulated sum of all sentiments the CFs may not be correct or sufficiently comprehensive. A CF may be constructed in a complex structure and it may contain several attributes or sub-tasks of different sentiments. Analyzing the text structure and exploiting these attributes or aspects would help for the better evaluation of the CFs.

The aspect-level sentiment extraction is the concept of mining the hidden patterns of aspect sentiments in order to uncover the information from CFs (Schouten & Frasinicar, 2016), (Do et al., 2019), (Jebbara & Cimiano, 2016). The aspects of products typically include cost, quality, and so forth (Piao et al., 2019), (Alengadan & Khan, 2017). B. B. Alengadan and S. S. Khan (Piao et al., 2019) proposed an approach to extract the aspect-level sentiment information extraction from feedbacks. They extracted information based on the five targeted aspects of K5 Kia Motors which are design, performance, price, quality, and service. They used well-known machine learning techniques such as TF/IDF, SVM, and Random Forest. Z. Piao and et.al (Alengadan & Khan, 2017) introduced an aspect based sentiment extraction approach from customer feedbacks to rank the products providing useful information for marketers and customers.

General document sentiment extraction and aspect-level sentiment extraction from CFs have been studied by many researchers using many algorithms and techniques. However, they had not been applied together. Some feedbacks may not contain any desired aspects and only sentiment information is mentioned and vice versa. Moreover, they concern different levels of information extraction (Zuheros et al., 2020). Sentiment extraction works in the document level but aspect-based sentiment works in the word and sentence levels (Majumder et al., 2019). There are also used different techniques, the sentiment extraction can apply dictionary-based and machine learning techniques (Alaei et al., 2019), (Hu & Liu, 2004). However, the aspect sentiments used the machine learning-based techniques (Piao et al., 2019), (Alengadan & Khan, 2017), (Majumder et al., 2019). E. Cambria (Cambria, 2016) explained a hybrid approach to extract the sentiment information which provides more effective results on information extraction. However, they did not technically combine the sentiment and aspect sentiment information extraction from CFs.

Therefore, this paper proposes to fuse results from both approaches, the multi-level sentiment analysis for general documents and the aspect-level sentiment analysis in order to extract more accurate and intuitive sentiment information. Targeting for more correct final sentiment polarity of any product review, our algorithm works based on multiple levels: aspect, word, sentence or phrase, contrast, and document. It uses the named entity recognition (NER) of the OpenNLP opensource

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