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Sentiment Analysis: Automation of rating for review without Aspect Keyword Supervision

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Abstract: ***Customers put more trust on user rating and review on the product in an online environment. In cases, rating and reviews written by the user does not match which leads to the confusion for the customer to make decisions. These sentiments so called reviews written by users or critics are to be analyzed in order to give exact rating for the product to clear the customer confusion about the product. The work proposes the new method for analyzing the exact rating for the product. The goal of the algorithm is to obtain the rank of the aspect keywords included in the review written by users or critics. In the work, aspect keywords and seed words are considered manually. The algorithm, Boot-strapping method: rating analysis for aspect segmentation (RAAS) is applied on the review collected. The algorithm detects the values for the aspect keywords. The values for the entire aspect keywords in the review is obtained and summed up to acquire the rating for product. As the rating for the product is obtained, a tagline is given which describes the product is satisfying or not which clears the customers confusion for purchasing the product.***

Keywords: Text Mining, Review Mining, Opinion and sentiment analysis, Aspect Identification, summarization**.**

1. Introduction

In online environment, customer put more trust on user or critics rating and review on the product. In these cases, rating and reviews written by the user or critics does not match which leads to the confusion for the customer to make decision. These sentiments so called reviews are to be analyzed in order to give exact rating for the product to clear the customer confusion about the product. To help customers in making analyze the product, it is necessary to understand the reviews on a particular product based on the aspect words in the reviews. To this end, recent work on opinion mining has attempted to perform fine-grained sentiment analysis: in most work, the proposed algorithms are able to identify sentiment orientation or ratings on specific topical aspects, leading to useful detailed opinion summaries [1]. The paper focuses on analyzing the rating for the product automatically without Aspect Keyword Supervision.

2. Related Work

With the rapid growth of e-commerce, more and more products are sold on the Web, and more and more people are also buying products online. In order to improve customer satisfaction and shopping experience, it has become a common practice for online vendors to enable their customers to review or to express opinions on the products that they have purchased. In the web era, more and more people express their opinions on all kinds of entities, including products and services, which in turn help not only customers make informed decisions but also merchants improve their services. The rapid growth of such opinionated text data on the web, such as user reviews, raises interesting new challenges for text mining communities and leads to many studies on extracting information from reviews [2, 3, 4], sentiment analysis [5, 6, 7] and opinion summarization [1, 3, 8, 9]. With more and more common users becoming comfortable with the Web, an increasing number of people are writing reviews. As a result, the number of reviews that a product receives grows rapidly. Some popular products can get hundreds of reviews at some large merchant sites. Furthermore, many reviews are long and have only a few sentences containing opinions on the product. This makes it hard for a potential customer to read them to make an informed decision on whether to purchase the product. If he/she only reads a few reviews, he/she may get a biased view. The large number of reviews also makes it hard for product manufacturers to keep track of customer opinions of their products. For a product manufacturer, there are additional difficulties because many merchant sites may sell its products, and the manufacturer may (almost always) produce many kinds of products [10].

Sentiment analysis is the task of detecting subjectivity in natural language. Approaches to this task mainly draw from the areas of natural language processing, data mining, and machine learning. In the last decade, the exponential growth of opinionated data on the Web fostered a strong interest in the insights that sentiment analysis could reveal. For example, companies can analyze user reviews on the Web to obtain a good picture of the general public opinion on their products at very little cost. While the first efforts in sentiment analysis were directed towards determining the general polarity (positive or negative) of a certain sentence or document, the interest has recently shifted towards a more qualitative analysis, that aims to detect the different aspects of a topic towards which an opinion is expressed. For example, we may be interested in analyzing a movie review to capture the opinions of the reviewer towards aspects such as the plot, the cinematography, or the performance of a specific actor. The most challenging part in aspect-based sentiment analysis is that a system needs to detect the relevant aspects before these can be associated with a polarity [11].

The Web has an overwhelming amount of reviews of products, restaurants, books, and many other types of tangibles and intangibles. In those reviews, people praise and criticize a variety of aspects of the target of the review, such as the waiting time of a restaurant or the noise level of a vacuum cleaner. Although some Websites (e.g., TripAdvisor) are specifically designed for user reviews with a predefined evaluation form, most users express their opinion in online communities and personal blogs using plain text without any structure [12].

Figure 1: A Sample Hotel Review [13].

The work by Hongning Wang, Yue Lu, ChengXiang Zhai on Latent Aspect Rating Analysis without Aspect Keyword Supervision is experimented on Hotel review data and MP3 player data. In the paper, the algorithm proposed is Latent Aspect Rating Analysis (LARA) which refers to the task of inferring both opinion ratings on topical aspects (e.g., location, service of a hotel) and the relative weights reviewers have placed on each aspect based on review content and the associated overall ratings.

LARA approach does not concentrate on pre-specified aspect by keywords. Concurrently LARA mines 1) latent topical aspects, 2) ratings on each identified aspect, and 3) weights placed on different aspects by a reviewer.

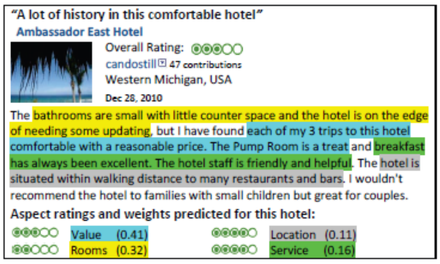

Figure 2: Sample output of LARA [1].

The paper Automatically Detecting and Rating Product Aspects from Textual Customer Reviews by Wouter Bancken, Daniele Alfarone and Jesse Davis proposes a new approach to aspect-based sentiment analysis. The goal of the algorithm is to obtain a summary of the most positive and the most negative aspects of a specific product, given a collection of free-text customer reviews. The approach starts by matching handcrafted dependency paths in individual sentences to find opinions expressed towards candidate aspects. Then, it clusters together different mentions of the same aspect by using a WordNet-based similarity measure. Finally, it computes a sentiment score for each aspect, which represents the overall emerging opinion of a group of customers towards a specific aspect of the product. The approach does not require any seed word or domain-specific knowledge, as it only employs an on-the-shelf sentiment lexicon. We discuss encouraging preliminary results in detecting and rating aspects from on-line reviews of movies and MP3 players [11]. In the paper "Consumers' Sentiment Analysis of Popular Phone Brands and Operating System Preference Using Twitter Data: A Feasibility Study" by Kin Fun Li , Neville, S.W., illustrate the potential of sentiment analysis of Twitter data to gauge users' response to popular smart phone brands and their underlying operating systems.
The work objective is to investigate whether the tweets available on the web are sufficient to gain useful insight about the performance of popular smart phone brands, their battery life, screen quality, and on the perceived performance of the phones operating systems. The results of the work show that although the Twitter data does provide some information about users' sentiments to the popular smart phone brands and their underlying operating systems, the amount of data available for different brands varies significantly [15].

The paper "Opinion mining from user reviews" by Sundararajan R , Deshpande C, Mishra P; discourses about extracting opinions from the user reviews is semi-automatic, in the sense that it requires some amount of expert assistance. Expert assistance is required for building the domain knowledge for the system, so as to make the system learn about the domain specific words. The proposed system, using domain knowledge, identifies and extracts the opinions for a given product. These extracted opinions include the opinion words, their polarity in from of weights and for which feature these opinions was provided and system aggregates the extracted opinions them for better display [16]. In this paper, new algorithmic sentiment analysis approach is proposed. In RAAS model aspect keywords are extracted manually from the reviews written on mobile dataset which is effective and more efficient.

3. Methodology

A major challenge in solving the problem of analyzing the rating for the product is that here in the work, aspect keywords are extracted manually. And another challenge is to discover the weight placed by a user or critic on each aspect keyword. To solve these challenges, an algorithm Boot-strapping method: rating analysis for aspect segmentation (RAAS) model is proposed in order to discover the values for each aspect keyword and the total rank for the entire review. Thus, overall approach consists of two stages, which is discussed further in detail.

Figure 3: Methodology flow diagram

3.1 Aspect Segmentation

The dataset is chosen for evaluation is a collection of data related to mobile phones. The various aspect keywords are battery, design, price, quality, display, software, camera and performance which can serve as ground-truth for quantitative evaluation of aspect rating prediction.

Aspect: An aspect Ai is a (typically very small) set of words that characterize a rating factor in the reviews. For example, words such as "price", "value", and "worth" can characterize the price aspect of a mobile phone [13].
Aspect Ratings: Aspect rating sd is a k dimensional vector, where the i^{th} dimension is a numerical measure, indicating the degree of satisfaction demonstrated in the review d toward the aspect Ai, and $sdi \in [rmin, rmax]$. A higher rating means a more positive sentiment towards the corresponding aspect [13].
Aspect Weights: Aspect weight αd is a k dimensional vector, where the i^{th} dimension is a numerical measure, indicating the degree of emphasis placed by the reviewer of review d on aspect Ai, where we require $\alpha di \in [0,1]$ and$\sum k$ i=1 αdi = 1 to make the weights easier to interpret and comparable across different reviews. A higher weight means more emphasis is put on the corresponding aspect [13].

3.2 Rating analysis for aspect segmentation (RAAS)

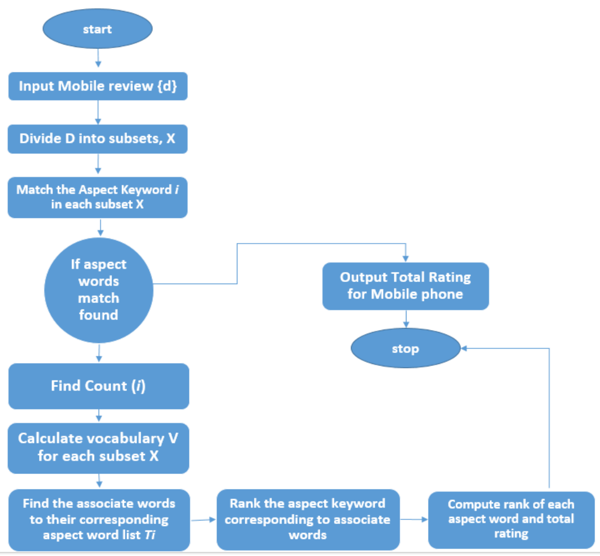

Figure 4: Rating analysis for aspect segmentation (RAAS) work flow

The Figure 4 gives work flow model of RAAS (Rating analysis for aspect segmentation) system. The workflow begins with taking input as review {d} and the review considered is subdivided into subsets, X. Matching aspect keywords are found in the subsets, then the frequency of occurrence of aspect words are calculated and stored in count variable. Associated words V for the aspect words are found and the ranking is determined for those words. Summing up all these word values gives rating for that particular aspect word. The flow is repeated for all the aspect keywords and the rating for the overall review is generated.

4. Implementation

4.1 Dataset and Preprocessing

The preprocessing steps:
1) Read the review collected; 2) Review is divided into subsets and corpus occurrence; 3) Converting words into lower cases; 4) removing punctuations, stop words, stripping whitespaces. Figure 4(a) and Figure 4(b) shows the sample review considered for preprocessing and the result after preprocessing [4].

Similar to its predecesseor, users can flick their wrists with the device in hand, to launch he camera. Though this isn't the most natural motion, it's pretty effective and useful. To activate the 4x digital zoom, you'll need to swipe up and down on the left side of the viewfinder; and to call up the menu wheel, you can swipe inward from the edges of the screen.

Figure 4(a): Sample review before preprocessing

similar predecesseor users flick wrists device handlaunch camera though natural motion pretty effective x digital zoom need swipe left side viewfinder menu wheel swipe inward edges screen

Figure 4(b): Sample review after preprocessing

4.2 Algorithm

Input: A review $\{d\}$, set of aspect keywords $\{T1$, 2,..., $Tk\}$, vocabulary V, selection threshold p and iteration step limit I.
Output: Rank of each keyword with aspect assignments and total rank.

- Step 1: Review d divided into subsets, $X = \{x1, x2,...,xM\}$;
- Step 2: Match the aspect keywords in each subset of X and record the matching hits for each aspect i in $Count(i)$;
- Step 3: Calculate X measure of each word (in V);
- Step 4: Rank the words under each aspect with respect to their X value and join the top p words for each aspect into their corresponding aspect keyword list Ti;
- Step 5: If the aspect keyword is not matched go to Step6, else go to Step 2;
- Step 6: Output the Rank of each keyword with aspect assignments and compute total rank.

Specially, the basic workflow of the proposed Bootstrapping method: rating analysis for aspect segmentation algorithm is as follows: The review {d} based on the mobile dataset is collected from Androidauthority (*www.androidauthority.com*) is considered as input. From the review {d} obtained; discover the aspect keywords manually, for e.g.: "price", "camera" and "software" etc., which forms the aspect keywords input set {T1, T2,...Tk}, also the vocabulary V, selection threshold p and iteration step limit I are considered as inputs for the algorithm.

The input review {d} is divided to form subsets defined in set X = {x1, x2,..., xM}. From these subsets special characters, unwanted symbols and spaces are deleted. The matching aspect keywords in the subset X are discovered and also number of times the occurrences of these aspects are stored in count variable for each aspect word.

Then, the values for x are generated automatically which are stored in vocabulary V. Based on these auto generated values, ranks are computed for each aspect word according to the selection threshold p which is pre-defined for the aspect word. Likewise, ranking for all aspect words are collected and total is calculated which determines overall rating for the product. And if no matches for the aspect words are found in the review total ranking is built which will be less ranking for the product.

For example consider the review on the mobile phone HTC desire 820 "To start ... HTC phones are much better in many ways than other androids, and as for this phone, its smooth, fast and stable. Games and apps working great. Camera not as good as a 13MP should be, sound loud and clear. But 8G of memory is a huge limitation. Like A HUUUUUUGE limitation, soon your out of memory and mostly hard or can't root it, so no easy way to delete useless and memory eating logs and thumbs".

The review forms a {d} input. The review is sub divided to form subset X. From the subset X all the special characters, unwanted spaces, words are removed. Then, from the cleaned sentence, the matching aspect keywords are found. Here the matching aspect word is "camera" alone. The number of times the camera word is occurring in the review is counted and stored in count variable. In this case, the count value of camera would be '1'. For this aspect word, as pre-defined selection threshold p rank is generated. Finally the steps are repeated for all the aspect words found in the review and rank of each aspect word and total rank of for the product is computed. For the above explained example; the rank of word "camera" would be 6 and overall rating for the product would be 6/10 which says product is not satisfying.

5. Analysis and Inference

When customers comes online to purchase a mobile the various parameters he or she would consider are company, design, camera, price, speed, look and color etc. Hence based on these parameters users or critics write their reviews for the product. Considering all these parameters aspect words are extracted manually from the review and use them as input for processing rating. The aspect words are shown in table 1, where the selection threshold is set to p=0.5 [14].

Table 1: Showing aspect words extracted from review

Aspect Words from the review obtained
Battery
Design
Quality
Camera
Software
Display
Performance

Once the frequency of aspect words occurring in the review are found, the associate words related to aspect word are found applying the threshold limit of 0.5 [14]. The steps are repeated for all the aspect words extracted like design, camera, software, performance, display, battery including quality. Then, the variable holding the rating of each aspect word is considered and summed up to get the overall rating for the product. Once the overall rating is acquired, tagline is displayed which describes the nature of the product depending on the rating processed for each aspect word.

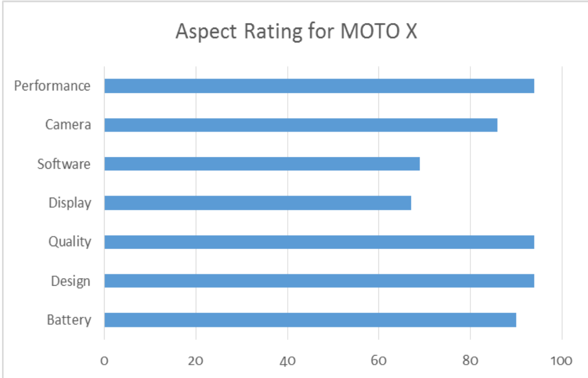

Figure 5: Graph showing the aspect word rating for Moto x mobile phone

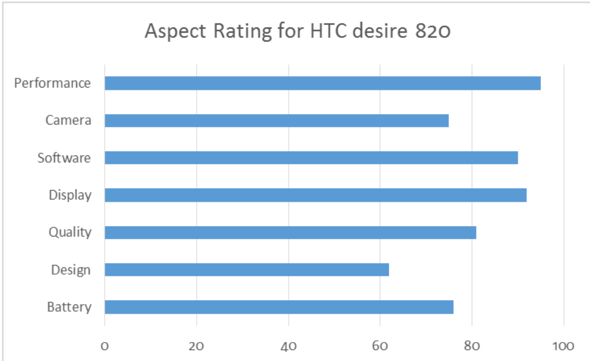

Figure 6: Graph showing the aspect word rating for HTC desire 820 mobile phone.

In the above figures, Figure 5 obtained aspect word rating the total score for the Moto X is computed which is 84 out of 100 and Figure 6 obtained aspect word rating the total score for the HTC desire 820 is computed which is 80 out of 100.

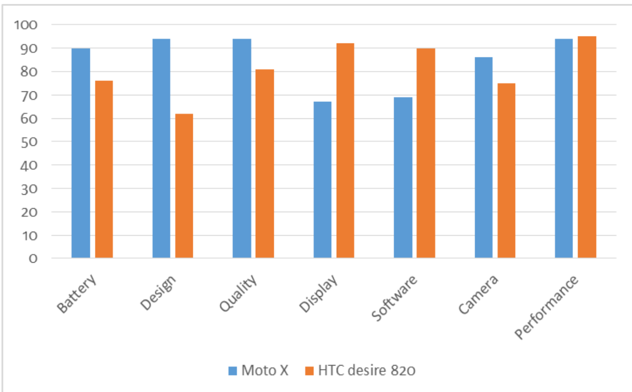

Figure 7: Graph comparing both HTC desire 820 and MOTO X aspect rating

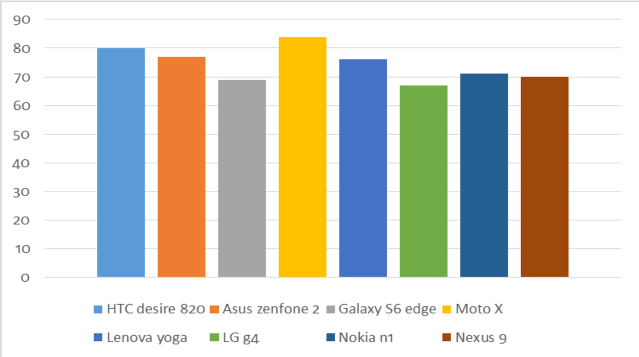

Figure 8: Graph comparing of HTC desire 820, Asus zenfone 2, Galaxy6 edge, Mot X, Lenovo yoga, LG g4, Nokia n1, Nexus 9 aspect rating.

In the above figures, Figure 7 shows the graph on the aspect rating values obtained for both MOTO X and HTC desire 820 and Figure 8 shows the graph drawn for the overall rating for three models of mobile phones, of HTC desire 820, Asus zenfone 2, Galaxys6 edge, Moto X, Lenovo yoga, LG g4, Nokia n1, Nexus 9.

6. Conclusion

In this paper, a new unified generative Boot-strapping method: Rating analysis for aspect segmentation (RAAS) is proposed. A Boot-strapping RAAS model explores the methodology to extract the exact rating for the product based on the aspect keywords collected manually from the reviews written by users or critics for the dataset containing the data related to mobile phones. And also, the paper process the comment on each aspect keyword and on the entire product which describes the product is satisfying or not to unclear the customer's confusion for purchasing the product.

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