Opinion Based Quality Evaluation Using Social User's Context by Aspect Rating.

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***Abstract* - People frequently use reviews on online communities to learn about others opinion and to express their own opinions. While a rating can be good indicator for the opinion, text reviews are usually more elaborate. Generally on online communities they focus mainly on overall opinions, it's difficult to predict about the product/service quality. Overall rating usually represents the evaluation but cannot predict the rating accurately. So this model proposed for aspect based rating. Take, an example, in movie rating overall rating does not provide clear predication, so separate consideration for different aspects of a movie review & rating provides better predication of quality evaluation of a movie. The separate consideration of movie review can be cast, director, story and music etc. This model is used to conduct quality evaluation by providing different aspects of the product/service. The quality evaluation using different aspects can be calculated using the following concepts. First, take the review from customer and split overall review into sentences using the concept "Parsing". Parsing is used to remove stop words like is, a, an, the etc. Next, important aspects are identified from the reviews. Then pros & cons of the sentence are classified using sentiment classification. Finally fuse aspects and their pros & cons into a unified model, apply Aspect Rating algorithm to this model to explore the quality of a product/service.**

Keywords— Opinion, Aspect Review, Sentiment Classification, Aspect Rating algorithm.

I. INTRODUCTION

Over the recent year there is quick growth and emergence of e-commerce technology, inspire customer to buy online products and express their opinions on product and services. Due to the evolution many e-commerce websites are available, hence result into more and more number of products are sold on the internet. Thousands of products from various dealers have been offered online. In order to feel customer more pleasant and more secure about online shopping, it has become a conventional practice for online dealers to enable their customers to write reviews on product aspects that they have purchased. Consumers commonly seek quality information from online consumer reviews prior to purchasing a product. The first generation of recommender systems with traditional collaborative filtering algorithms mostly focused on only ratings. They neglect the significance of service quality. Quality of service is also important in recommender systems. High quality services should be recommended more easily. Thus, this paper focuses on how to evaluate the quality of service. Reading text reviews is also time consuming. For this project, we propose probabilistic aspect ranking algorithm helps for rating product or service based on aspect reviews. This method accurately finds the rating of a product or service. We propose a product aspect ranking framework to automatically identify the important features of products from online consumer reviews. While a product may have hundreds of aspects, we argue that some aspects are more important than the others and have greater influence on consumers' purchase decisions. Take *IPhone 3GS* as an example, some aspects like "*battery*" and "*speed*," are more important than the others like "*moisture sensor*". In our proposed work, based on consumer reviews of product first we recognize the important features of product. Then we classify the sentiment on that aspect by sentiment classification. This can be done at three levels of extraction which are Document level, Sentence level and Aspect level. Sentiments represent any viewpoints of consumer such as like or desirable (positive), dislike or undesirable (negative) and may be neutral viewpoint. For example, the sentence '*I love the story but not the music*' is divided into '*I love the story*' and '*I do not love the music*'. After dividing the sentence into separate clauses, a contextual sentiment score toward each movie aspect (e.g. story or music aspect) is calculated. The sentence '*this is superb*' has a higher sentiment score than the less positive sentence '*this is good*'. However, for a new item, we cannot simply average the few ratings available and accept it as accurate. So it is urgent to address quality evaluation for products and services. Sometimes users give ratings as well as reviews. But normally Quality of a product and service are based on overall rating. And this rating considered from overall reviews. The biggest difference between with related works is that previous research has focused on quality based on user's text recommendation, while quality evaluation based on aspect is our concern.

The main contributions are shown as follows:

We address the issue of quality evaluation and proposed by exploring social users' contextual information based on aspects. It will benefit users and services providers to know the quality of the services with the help of aspect based ratings and reviews from worldwide users.

1. We are going to identify user reviews. Reviews are normally contains lots of user's opinion based on

product. Now split the overall reviews into sentences & words. Stop words are removed from the review.

2. Important aspects are identified from the user opinions. Sentiment classification aims to classify the given text to one or more predefined sentiment categories. Such as Positive, Negative, Neutral. Based on the categories scores are generated. The classifier is used to predict the sentiment on each aspect.
3. This proposed product aspect ranking framework, which will identify the important aspect of product from online consumer reviews. The important aspects are commented again and again in consumer review and the consumers opinions on the important aspects are greatly influence their overall opinions on the product. The overall opinion in a review is an aggregation of the opinions given to specific aspects in the review, and various aspects have different contributions in the aggregation.

That is, the opinions on (un)important aspects have strong (weak) impacts on the generation of overall opinion. Aspect rating algorithm fuse aspects and aspect level to find sentiment scores to explore product or service quality.

II. RELATED WORKS

A. *Service quality evaluation by exploring social users' contextual information*

An empirical methodology is proposed to conduct quality evaluation by improving overall rating of services in[1]. The concepts 'rating confidence' which denotes the trust worthiness of user ratings. Information entropy is utilized to calculate user rating's confidence. Several features of rating of the service are considered to evaluate the quality. These features include Spatial, Temporal, and Sentiment features. Spatial refers to location, Temporal indicates the timing, and sentiment denotes major view points of the service. Lastly, a unified model is proposed to calculate an overall confidence by fusing user rating confidence and spatial-temporal, sentiment features. The basic idea is that different users have different levels of confidence in the evaluation. User's profiles are changing at different places and different times. User rating's confidence is higher when a user is very far away from the rated item. Thus rating's confidence is increasing over time, and increasing with review sentiment in [1].

B. *Personalized recommendation combining user interest and social circle*

The three social factors personal interest, interpersonal interest similarity, and interpersonal influence are proposed. It can fuse into a unified personalized recommendation model based on probabilistic matrix factorization. The factor of personal interest can make the Recommended System (RS) recommend items to meet users' individualities, especially for experienced users. We conduct a series of experiments on three rating datasets: Yelp, Movie Lens, and Douban Movie. Experimental results show the proposed approach outperforms the existing RS approaches.

[2] Concentrate on probabilistic grid factorization with thought of elements of informal community. In the accompanying, we quickly survey some significant attempts to this paper, including the fundamental network factorization model with no social variables, the CircleCon model with the component of interpersonal trust values and the Social Contextual (ContextMF) model with interpersonal impact and individual inclination.

C. *Recommendation via user's personality and social contextual*

The algorithm used in [3] is

BaseMF: This model is the basic matrix factorization approach proposed in without consideration of any social factors.

CircleCon: This method is proposed including four variants: CircleCon1, CircleCon2a, CircleCon2b, and CircleCon3. It improves the accuracy of BaseMF and SocialMF by introducing the inferred trust circle of social network.

ContextMF: This method improves the accuracy of traditional item-based collaborative filtering model in influence-based model and by taking both interpersonal influence and individual preference into consideration.

D. *Rating prediction based on social sentiment from textual reviews*

The sentiment-based rating prediction method (RPS) is proposed in [4] to improve prediction accuracy in recommender systems. Firstly, we propose a social user sentiment measurement approach and calculate each user's sentiment on items/products. Secondly, we not only consider a user's own sentiment attributes but also take interpersonal sentiment influence into consideration. Then, we consider product reputation, which can be inferred by the sentiment distributions of a user set that reflect customers' comprehensive evaluation. At last, we fuse three factors-user sentiment similarity, interpersonal sentiment influence, and item's reputation similarity into our recommender system to make an accurate rating prediction. Our experimental results show the sentiment can well characterize user preferences, which help to improve the recommendation performance.

E. *Service objective evaluation via exploring social users' rating behaviors*

The model is to solve service objective evaluation by deep understanding of social users are proposed in [5]. As we know, users' tastes and habits are drifting over time. We conduct a series of experiments based on Yelp datasets. In this paper, we propose an issue about service overall and objective evaluation. To solve this problem, Traditional rating prediction methods are introduced, including methods based on biases and based on matrix factorization model. Here, we list compared methods as follows: Basic Method, Basic Biases, Biases based on taxonomy, Circle con, PRM, Item based. Yelp is a local directory service with social networks and user reviews. It combines local reviews and social networking functionality to create a local online community. Secondly, Yelp encourages user interactions through various forms, and pays a good reward to the active users.

III. METHODOLOGY

In this paper we proposed aspect based quality evaluation. We start with an overview consisting of four main components: (a) Data set collection; (b) Parsing review; (c) Aspect identification and Sentiment classification; (d) Aspect Rating algorithm.

A. Data Set Collection

User reviews are collected for data set. Phone product ASUS ZENFONE 3 is taken for experiment. The specifications of the product are listed. User can give their opinion or view point as reviews. Reviews are usually represents the quality of a product based on aspects. In data collection, the user can give their reviews using email id. We create a dataset by collecting reviews for Asus Zenfone 3 with feedback for the past year. The reviews about the product contain various features and their viewpoints (i.e.) pros and cons. The reviews are stored in a database.

B. Parsing Reviews

For parsing process, Reviews are taken from the database. Parsing refers to splitting or separation. Reviews are splitted into words and listed. Delimiter characters are removed while splitting. The delimiter characters are ‘ ’ , ‘.’ , ‘,’ , ‘:’ . For example, Camera quality is good. It is splitted as camera, quality, is, good. Next stop words are removed. Because the stop words are irrelevant for searching purposes if they occur frequently in the reviews. In order to save both space and time, these words are ignored at search time. Stop words are “ a, about, above, across, after, all, already, also, always, among, an, and, anything, are, area, as, ask, at, back, be, become, because, before, behind, being, best, between, big, both, but, came, cannot, do, down, differ, during, each, early, end, ever, enough, everything, face, fact, far, find, for, from, further, gave, general, get, got, have, herself, if, in, it, itself, just, keeps, know, last, like, long, make, might, more, mostly, must, need, never, next, other, out, over, put, really, say, shall, shows, so, sure, take, think, this, thought, therefore, two, until, etc., ”

C. Aspect Identification & Sentiment Classification

The parsing result finally contains the words which are aspects and their corresponding pros and cons. In aspect identification we detect the aspects related to the product asus zenfone 3. While a product may have hundreds of aspects, we argue only some particular important aspects than others. They have greater influence on consumers’ purchase decision and product development team. Consumers can conveniently make wise purchase decision by paying attentions on important aspects. However it is impractical to identify important aspects from numerous reviews manually. Thus, it becomes a compelling need to automatically identify the important aspects from consumer reviews. A straight forward solution for important aspect identification is to select the aspects that are frequently commented in consumer reviews as the important ones. For example, most consumers frequently criticize the bad signal connection of iphone 4, but they may still give high overall ratings to iPhone 4. In this paper we propose an effective approach to automatically identify the product aspects from reviews. We consider important aspects as the features that are frequently commented by consumers. These aspects are maintained in a database.

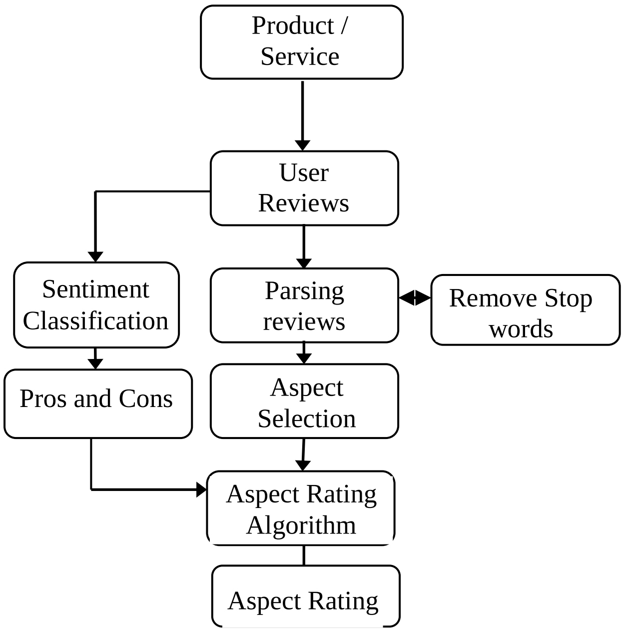

Fig 1. Data Flow Diagram

For sentiment classification, the aspects & their levels are compared. Sentiment analysis or opinion mining is a type of natural language processing used for tracking the mood or polarity of people about product aspect. For example, in the sentence ‘The quality is not good’, here the polarity of the word ‘good’ is positive while the polarity of the whole sentence is reversed because of the negation word ‘not’. Sentiment analysis is classified into three different level namely they are document level, sentence level, and entity-aspect level. Overall opinion is to be considered in document level whether opinion of particular sentence is to be considered in sentence level and focus is directly on opinion itself is called entity and aspect level. Sentiment classification used to classify the given text to predefined sentiment categories such as positive, negative, neutral. These reviews are taken from reviews based on corresponding aspects.

D. Aspect Rating Algorithm

We proposed a new model ‘Aspect rating algorithm’ which rate and evaluate the quality of a product based on each aspects. Aspect rating algorithm takes two input parameter. It generates short command and rating using sentiment scores. Sentiment scores are generated in sentiment classification through view points of the consumer about aspects of a product. The scores are varying for each aspect. Based on the scores the quality is evaluated and aspects are rated.

Algorithm: Aspect rating algorithm

Input: Consumer review corpus R, Each review $r \in R$,
Positive scores P and Negative scores N for all the
m aspects.
Output: Rating of aspects R_A
for each **m** aspect
update P and N from r=1 to $|R|$
if(P==0)
R_A = ‘Good’
if(N==0)
R_A = ‘Excellent’
ratio=P/N;
if (*ratio* >= 5)
R_A = ‘Excellent’
if (*ratio* == 4)
R_A = ‘Very good’
if (*ratio* == 3)
R_A = ‘Good’
if (*ratio* == 2)
R_A = ‘Not bad’
if (*ratio* == 1)
R_A = ‘Worst’
end for
Rate **stars** and display R_A

The aspect and score are input for the above algorithm. Result is the output of our model. Based on the input score value, the output is calculated.

IV. PERFORMANCE EVALUATION

Performance of aspect rating is analyzed in terms of ‘no of aspects’, ‘user feedback’ and ‘overall rating’. Overall rating does not predict the product quality. Because the overall ratings are given by testing team. The real quality is evaluated by users through their reviews. The overall consideration of review is also not clearly measured. It is very big process. So here we split the overall reviews into aspect base. It gives clear and detailed rating of a particular product. By this we can evaluate ‘n’ no of products as well as services. This method is applicable to service also. In service, for evaluation we are going to consider the features. E.g. various aspects of a movie are cast, director, story, music. Based on the features we rate the each aspect from consumer reviews. We take a phone product ASUS ZENFONE 3 for experiment.

ASUS ZENFONE 3

SPECIFICATIONS

Model Number	ZE552KL-1B032IN
Model Name	Zenfone 3
Color	White
SIM Type	Dual Sim
Hybrid Sim	Slot Yes
Sound Enhancements	5 Magnet Speakers for Upto 40% Better Performance Dual Internal Microphone with Asus
Display Size	5.5 inch
Resolution	1920 x 1080
Operating System	Android Marshmallow 6
Processor Type	Qualcomm Snapdragon 625 64-bit
Processor Core	Octa Core
Operating Frequency	GSM 850, 900, 1800, 1900; WCDMA - Bands (1/5/8), 4G LTE (FDD) - Bands (1/3/5/8), LTE (TDD) - Band 40 (VoLTE)
Internal Storage	64 GB
RAM	4 GB
Expandable Storage	2 TB
Primary Camera	16 megapixel
Secondary Camera	8 megapixel
Network Type	4G VOLTE, 3G, 2G
Internet Connectivity	4G, 3G, Wi-Fi
Bluetooth Version	4.2
Wi-Fi Version	802.11 b/g/n/ac
USB Connectivity	Yes
GPS Support	Yes
User Interface	Asus ZenUI 3.0
Removable Battery	No
Sensors	Accelerator, E-Compass, Gyroscope, Proximity Sensor, Hall Sensor, Ambient Light Sensor, RGB Sensor, IR Sensor, Fingerprint Scanner
FM Radio	Yes
Audio Formats	MP3
Battery Capacity	3000 mAh
Battery Type	Polymer

Fig 2. Features of Asus zenfone 3 product

The user purchasing the product can give their reviews about the product. We rate each aspect from the user review rather than tester rating. It is helpful to the new customer who wants to buy the product.

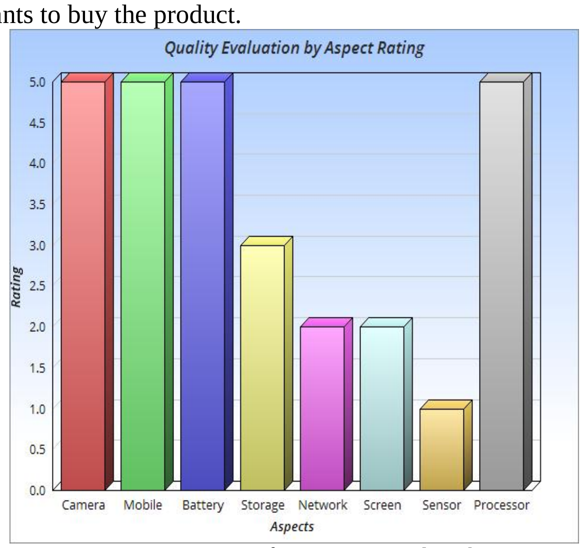

Fig 3. Execution of Aspect Rating Algorithm

This model is scalable. Because we consider all the user reviews including positive and negative feed backs to rate the product. At each time the rating is modified based on newly added reviews.

V. CONCLUSION AND FUTURE WORKS

In this paper, we have proposed a product aspect rating algorithm to predict quality for each aspect. We have to identify the important aspects of a product from online consumer reviews. Our assumption is that the important aspects of a product should be the aspects that are frequently commented by consumers. Based on this assumption, we have developed an aspect rating algorithm to identify the important aspects by simultaneously considering the aspect frequency and the influence of consumers' opinion given to each aspect on their overall opinion. In the future work, we can calculate rating by considering technical and critical reviews and by considering all features of a product. We can compare the features of various products and give the ratings based on comparison.

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