

Survey on Product Recommendation Using Customer Reviews Based on Opinion Mining

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ABSTRACT: These days e-commerce is becoming more popular, the number of customer reviews for online products is growing rapidly. For a popular product, there can be many numbers of reviews. This makes it tough for a customer to read every review in order to get as much data and to make a decision on purchasing. To solve this problem, a lot of research is being carried out in Opinion Mining. Through the Opinion Mining, It is possible to know about contents of whole product reviews. Traditionally research on Natural Language Processing was applied to the Opinion Mining area in early stage. Recently, the computational statistics are applied to handle massive volume of reviews. This survey, suggests various methods for summarization of product reviews using the user's opinion, feature occurrences, and the rate of review in order to improve the performance of existing methods. These methods help in handling massive volumes of reviews in a short time efficiently. In this paper we discuss about various papers that deals with summarization of reviews. Techniques like, Summary process using scoring, Maximum Entropy model, Word weight classification, Vector feedback approach, prediction strength of opinion words.

CATEGORIES AND SUBJECT DESCRIPTORS: Opinion mining, Traditional natural language processing.

KEYWORDS: Summary process using scoring, The Maximum entropy model, Word weight classification, Vector feedback, Prediction of strength of opinion words.

I. INTRODUCTION

E-commerce is weighing more importance compared to conventional shopping methods. In the view of letting the customers to express their opinions and have discussions on web, many e-commerce websites often let their customers to rate and review the products after purchasing and hence product review gradually becomes a habit for some customers. As a consequence, the number of product reviews grows rapidly, and helpful reviews are likely to be rare in consecutive online review pages. This enormous amount of reviews makes it hard for customers to read them all before making final decisions of purchasing. It also makes it difficult for sellers to keep track on customers' opinions and improve their products.

Opinion mining also called sentiment analysis is a process of finding users opinion about particular topic helps in summarizing the opinions of customers. It involves opinion information retrieval, opinion classification and opinion aggregation. It is one of the booming research topics nowadays [1] [2]. Opinion mining can be used for product feedback analysis, and for decision making to users. Opinion retrieval is a process of collecting opinion text from review websites. Opinion text is subjective information in review, blog, tweet, micro-blog, comment etc.

This paper presents various methods used in process of opinion summarization. Such comparison will be helpful to find methods that best suits for required scenarios in opinion mining.

II. OPINION MINING

With the rapid growth of web technologies, which facilitate people to contribute rather than simply receive information, a large amount of review texts are generated and become available online. These user-generated opinion

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rich contents are credible sources of knowledge which can not only help users make better judgments but assist manufacturers of products in keeping track of customer sentiments.

However, with tens and thousands of reviews being generated everyday on almost everything, e.g., sellers, products, and services, at various websites, it has become increasingly difficult for an individual to manually collect and digest the reviews of his/her interest. As such, opinion mining has become an active area of research in the past few years, and has produced some important results. Online reviews have been shown to be second only to word-of-mouth in a study which compares the factors influencing purchase decisions. Therefore, online reviews can be very valuable, as collectively such reviews reflect the “wisdom of crowds” and can be a good indicator of a product’s future sales performance.

Opinion mining is a type of Natural Language Processing (NLP) for tracking the sentiment or thinking of the public about a particular product. Opinion mining, which is also called sentiment analysis, involves building a system to collect and examine opinions about the product made in blog posts, comments, reviews or tweets. Automated opinion mining often uses machine learning, a component of artificial intelligence. An opinion mining system is often built using software which is capable of extracting knowledge from examples in a database and incorporating new data to improve performance over time. The process does deep parsing of the data in order to understand the grammar and sentence structure used.

Opinion mining is a relatively recent discipline which studies the extraction of opinions using Artificial Intelligence and/or NLP techniques. More informally, it's about extracting the opinions or sentiments when given a piece of text. Opinion mining provides a great source of unstructured information especially opinions which may be useful to others, like companies, rival competitors and other consumers.

III. RELATED WORK

SUMMARY PROCESS USING SCORING

Summarization of product reviews is partitioned into several processes. Figure 1 shows all processes of summarization method proposed by Jung-Yeon Yang, Jaeseok Myung, and Sang-goo Lee. This chapter explains each process of these processes [3].



Figure 1 Summary Process

The figure 1 describes the overall process of the summarization of reviews. The first process after collecting the review is the word extraction based on POS tagging also the frequency and pattern based rules. The next step is to classify the extracted content using sentimental analysis techniques. Later the sentimental polarity of opinion words is recognised and also the feature co-occurrence is emphasised. The final step is to score those polarised content for better judgement of the reviews.

SCORING

In this method, the summarization of review is expressed by showing the score of each product feature. Feature occurrences, rate of reviews, feature co-occurrence information and sentimental polarities of opinion words in order to

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calculate the score of each product feature is used. The method defines some factors which have an effect on the own score of features. And through the experiments, the performance is shown.

METHODS FOR THE SCORING

Method 1: Using occurrence of features

When the score of features is calculated, number of occurrence is one of the important factors. If a reviewer mentioned specific product feature in the review then it means that he think that feature is more important than others. So, it has to reflect the occurrence of features as a weight when the score is calculated. The weight is calculated through the equation (1),

$$\text{Weight (feature)} = 2^{-1-\text{occurrence (feature)}} \quad (1)$$

If the product feature is mentioned, the scope of a weight is from 0 to 2. Weight is used as the opinion strength in the scoring equation,

if SP(fi,Rj) is positive,

$$\text{ownScore}(fi,Rj) = \text{rate}(Rj) * (1 + \text{Pneg}(Rj)) * \text{weight}(fi)$$

if SP (fi,Rj) is negative

$$\text{ownScore}(fi,Rj) = \text{rate}(Rj) * (1 - \text{Ppos}(Rj)) * \text{weight}(fi)$$

(1 ≤ i ≤ number of features, 1 ≤ j ≤ number of reviews)

In the equation SP (fi,Rj) means the sentimental polarity of the ith feature in the jth review. Ppos(Rj) and Pneg(Rj) is the percentage of positive opinions or negative opinions in the jth review.

Method 2: Using opinion words

In order to estimate the own score of product features; consider the opinion words with other factors. Prior methods use only opinion words using NLP. But those methods don't consider the union of NLP and other approaches. In order to overcome weak points of NLP for the summarization of product reviews, opinion words to score product features with a rate, feature occurrence is used. At first, the method classifies the sentimental polarity of the opinion words which describes the product feature. And then, the distribution of the sentimental polarity and strength of the opinion is used and then in order to compute the strength of an opinion the weight of the feature is used.

In O1 case, it just considers the distribution of a sentimental polarity of an opinion word on the same product feature. If the number of positive opinions is more than the number of negative opinions then the score of the product feature is high. The equation (2) is as follows,

$$\text{Score(feature)} = (\text{MaxR} - \text{MinR}) * P_{\text{pos}}(\text{feature}) + \text{MinR} \quad (2)$$

MaxR and MinR mean the maximum rate and the minimal rate of the review system. In case of O2 method, it is assumed that the rate of review is derived from the combination of several opinions about features. Because the rate of review is an explicit score which represents a reviewer's overall opinion, the method use this to score the product feature. For example, in the Figure, if the rate of R1 is 4 then it is derived from many positive features and negative features. f4 and fn has a bad influence upon the overall valuation of the product. On the other hands, f1, f2, and f6 may have a higher score than the rate of R1. That is, the positive opinion makes the rate of review high and the negative opinion makes the rate of review down.

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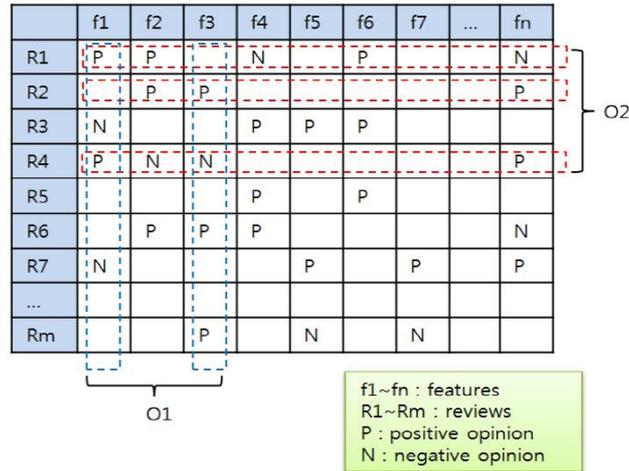


Figure 2 Opinion Words.

The Figure 2 shows two different cases, O1 and O2, in which used opinion words. In the product review, reviewer says his opinion for each product feature. There are many reviews on the same product. In all product reviews, many features are mentioned. But every feature is not mentioned in every product review. The above figure shows this situation. In the product reviews, the unit of the opinion is not a document or review, but each product feature. So, the distribution of opinions can be expressed like in figure using the sentiment classification.

Method 3: Using co-occurrence among features

With an occurrence of a feature, concern is the co-occurrence between features in order to calculate the score of product features. Additionally, rate of the review is used to estimate the score with co-occurrence information. In order to calculate the score of features, we compute an association value between a feature and a rate using the equation (3).

$$association(f_i, k) = \sum_{j=1}^{NF} (Pco(f_i, f_j) * Pscore(f_j, k)) \begin{cases} 1 \leq i \leq NF \\ 1 \leq k \leq 5 \end{cases} \quad (3)$$

In the equation (3), f is a product feature and k is grade of rate. NF means the number of product features that are extracted. Pco(fi,fj) is a probability of co-occurrence between features, and Pscore(fj,k) is a probability of feature occurrences when the rate of review is k. After the computation of an association, computation of the score of the product feature that is based on association values of the feature is done.

$$score(f_j) = \frac{\sum_{k=1}^5 (k * association(f_j, k))}{\sum_{k=1}^5 association(f_j, k)} \quad (4)$$

Through the equation (4), Estimation of the score of product features is expressed in 5-scale. Then it is found out whether the co-occurrence information is a proper factor through experiments.

THE MAXIMUM ENTROPY MODEL:

The Maximum entropy (ME) was first described by Jayne in and more recently in a draft manuscript available on the Web. The maximum entropy model is a framework for integrating information from many heterogeneous information sources for classification. This model implements the intuition that the best model is the one consistent with the set of constraints imposed by the evidence but otherwise is as uniform as possible as proposed by Gamgarn Somprasertsri, Pattarachai Lalitrojwong [4].

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The maximum entropy approach has in recent years been used for a wide variety of classification problems in natural language processing, such as sentence boundary detection, information extraction, and part-of-speech tagging. In study of Nigam, Lafferty and McCallum found that maximum entropy worked better than Naïve Bayes' classification for their classification. Unlike Naïve Bayes' machine learning, maximum entropy makes no independence assumptions about the occurrence of features

For this work, maximum entropy model is used to extract product features from online product reviews. This task can be re-formulated as a classification problem, in which the task is to observe some syntactic dependency and context information $x \rightarrow X$ and predict the class $y \rightarrow Y$. Design classes such as product feature and non-product feature can be done. Implementation classifier $c: X \rightarrow Y$ with a conditional probability model by simply choosing the class y with the highest conditional probability p in the context x .

$$C(x) = \arg \max p(y|x)$$

The conditional probability $p(y|x)$ is defined as follows

$$p(x|y) = \frac{1}{Z(x)} \prod_{i=1}^k \alpha_i^{f_i(x,y)}$$

$$Z(x) = \sum_y \prod_i \alpha_i^{f_i(x,y)}$$

Where y refers to the outcome, x is the history (or context), k is the number of features and $Z(x)$ is a normalization factor to ensure that $\sum [p(y | x)]=1$. Each parameter α_i corresponds to one feature f_i and can be interpreted as a weight for that feature. Generalized Iterative Scaling (GIS) algorithm to estimate parameters α_i or weights of the selected features is used.

Under the maximum entropy framework, the probability for a class y and object x depends solely on the features that are active for the pair (x, y) , where a feature is defined here as a function $f: X * Y \rightarrow \{0,1\}$ that maps a pair (x, y) to either 0 or 1. The feature is defined as follows:

$$f_y(x,y) = \begin{cases} 1, & \text{if } y' = y \text{ and } cp(x) = \text{true} \\ 0, & \text{otherwise} \end{cases}$$

Where $cp(x)$ is contextual predication that returns true or false, corresponding to the presence or absence of useful information in some context or history $x \in X$.

WORD WEIGHT CLASSIFICATION

In this classification process, Word Weight to calculate the strength of each word towards both orientations is used and Word Score to indicate the word strength of expressing sentiment according to its type is applied. In the phase of summarization process, the CHI-Square (X2) measure is employed to calculate the correlation of terms in the compound key phrase.

A. Word Weight

Here use of a frequency statistic value of a word-stem to weigh the strength of each word towards the sentiment in positive orientation and negative orientation is done. Then a weight value by comparing the strength for both orientations is obtained. Using stem but not the word itself is to make the result more precise and comprehensive. The weight equation of term t in data corpus c is given below,

$$\begin{aligned} \text{Weight}(t, c) &= \Delta(t) - \nabla(t) \\ &= \rho_{\text{pros}}(t) \cdot \delta_{\text{pros}}(t) - \rho_{\text{cons}}(t) \cdot \delta_{\text{cons}}(t) \\ &= f_{t,\text{pros}} / \max f_{\text{pros}} \cdot f_{t,\text{pros}} / f_{t,\text{corpus}} - f_{t,\text{cons}} / \max f_{\text{cons}} \cdot f_{t,\text{cons}} / f_{t,\text{corpus}} \end{aligned}$$

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Where

- $\Delta(t)$ is the strength of stem term t towards positive orientation, while $\nabla(t)$ is the strength of stem term t towards negative orientation.
- $\rho(t)$ is the weight of term t in an orientation set, and $\delta(t)$ is the capability of term t to stress a polarized feeling. The combination of the two can show the comprehensive strength of a term t towards one orientation in the whole corpus.
- $f_{t,pros}$ is the frequency of stem t presenting in the positive stem corpus, while $f_{t,cons}$ is the frequency of stem t appearing in the negative stem corpus. $Max\ f_{pros}$ is the maximum frequency of terms in positive stem corpus while $max\ f_{cons}$ is the maximum frequency of terms in negative stem corpus. $f_{t,corpus}$ is the frequency of stem t appearing in the whole training data corpus. Since $\rho(t)$ and $\delta(t)$ are all normalized, if $Weight(t, c)$ is larger than 0, this term tends to be a positive word. If $Weight(t, c)$ is less than 0, this term is more likely to be a negative one. In addition, if $Weight(t, c)$ is right equal to 0, then this term is neutral.

B. Word Score

Using the Word Weight is not enough for describing the strength of a word's orientation, since the word's linguistic type itself plays an important role in expressing the sentiment.

Related research found that adverb and adjective are the core types to express human sentiment although verb can show some polarized intention. For example, adjective "excellent" or adverb "horribly" expresses more sentiment than verb "like" or "hate". Conjunction like "however" or "but" usually leads a transformation of opponent feelings. However other types of words like noun, pronoun and article are neutral for most of the time. Based on these findings, a scoring algorithm is used to combine the linguistic feature of a word to its weight value.

It is calculated as follows.

$$Score(t, c) = Weight(t, c) \cdot Weight(t, type)$$

Where $Weight(t, c)$ is the weight of stem t in training data set, which is calculated above. $Weight(t, type)$ is a factor that is used to multiply the strength according to stem type. It is currently manually assigned according to research result mentioned and our experience after viewing plenty of reviews. Further sensitivity experiments showed that values in the vicinity (± 1) of the selected value larger than 3, rendered similar results. The stem type is according to WordNet Dictionary.

The pseudo code for calculation of type weight is as Algorithm

```

if type of  $t$  = 'adjective' or 'adverb'
then return (8)
else if type of  $t$  = 'verb'
then return (4)
else if type of  $t$  = 'conjunction'
then return (2)
else return (1)

```

C. CHI-Square (X^2)

In the summarization process, topical terms with their preterm and post-term co-occurrence collections are extracted from positive sentence set and negative sentence set separately. To estimate the importance of a term in a compound phrase, employment of CHI-Square (X^2) to calculate the degree of correlation between a topical term and its co-occurrence terms is done. The X^2 statistic measures the dependence of term t on the collection that can be compared to X^2 distribution with one degree of freedom to judge the extremeness. The X^2 measure is defined as

$$X^2(t) = \frac{N(ad-bc)^2}{(a+c)(b+d)(a+b)(c+d)}$$

where a is the frequency of term t in the collection; b is the frequency of term t outside the collection; c is the total frequency of terms in the collection except t ; d is the total frequency of terms outside the collection except t ; N is the total number of terms in document.

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Vector feedback

A. Architecture of the Recommendation Technique

The Architecture of the recommendation technique is depicted in figure below. This method is intended to evaluate the ranking system presented by providing a new users ranking and evaluating the system ranking with the new user ranking based on implicit user feedback using vector feedback technique. An arbitrary ranking of 5 different items each consist of 10 feedback in terms of five vectors is provided that convey the user log information and hence their activities are interpreted to score the products and finally ranking is done proposed by Shahab Saquib Sohail, Jamshed Siddiqui, Rashid Ali [5].

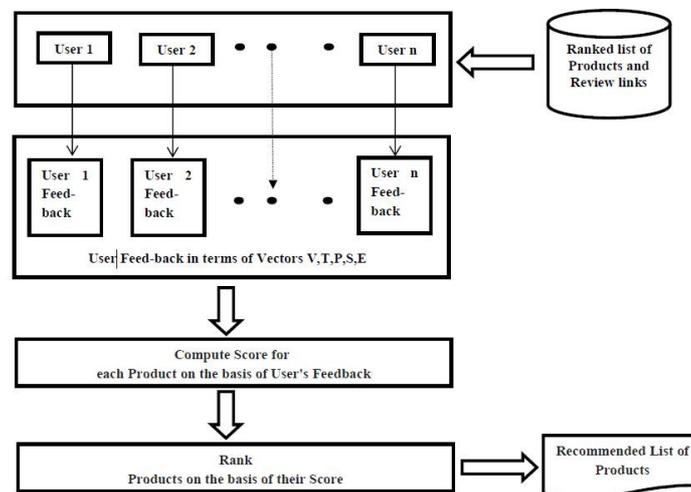


Figure 2: Architecture of Recommendation Technique

This is to characterize the feedback of the user by a five component vector (V, T, P, S, and E) which consists of the following:

- The sequence V in which the user visits the product reviews, $V = (V_1, V_2, \dots, V_N)$. If product i is the kth product visited by the user, then we set $V_i = k$.
- To know whether the user prints the reviews for product i, this is denoted by the Boolean P_i . This is denoted by vector (P_1, P_2, \dots, P_N) by P.
- Whether or not the user saves the reviews for product i. we denote it by the Boolean S_i . This is denoted by the (S_1, S_2, \dots, S_N) by S
- The time duration 't' for which the user remain on the page to browse the contents of the review. This is denoted by vector (T_1, T_2, \dots, T_N) by T.
- Whether or not the user e-mailed the reviews for product i to someone. This is denoted by the Boolean E_i . We Denote the vector (e_1, e_2, \dots, e_N) by E.

Each of these five components depicts the importance of a particular product in eyes of the user.

B. Vector Feedback

Five components are used as user feedback each having their significance in the recommendation process. V, T, P, S and E are respective components of the vector feedback as described. V has a value from 1 to 10 only if the user visits the review page of the products concerned, that shows which product is given priority by the user. If user visits particular products in very first browsing, v is assigned value '1'. If $V=0$, it means user does not visit the review page

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of the product, that implies user does not like the product. T is the time duration for which user remain visiting the review of the products. If a user does not visit the page then T also becomes '0'. S,P and E are Boolean values, either yes or no, 1 is assigned for yes and '0' for no. let us consider a user does not have a printer, obviously that user will not be able to take print, hence the value of p becomes '0'. In the same way if the review is not saved and emailed then S and E given values 0 respectively.

PREDICTION OF STRENGTH OF OPINION WORDS

A. Features Generation

Xinghua Hu and Bin Wu proposed the LDA (latent Dirichlet allocation) is used to find features that people are most interested in. It posits that each customer review is a document, and each document is a mixture of a small number of topics and that each word's creation is attribute to one of the document's topics. In order to ensure the accuracy of the process, association of rule mining of all features is used. Cross-validation the results with previous results, if the word or the phrase that occurs in the two mining results. It is regarded as a feature that customers are interested in. Then we need to identify sentiment word, these are words primarily use to express subjective opinions. Similarly, it is needed to find sentiment word that customers express their opinions about the product features, first we use LDA to find all the sentiment words, and then associate rule to mining the nearby adjective for each feature in the sentence is used, at last, in order to improve the precision, use of Cross-validation to remove the incorrect match is done [6].

For example, "overall this is a good camera with really good picture clarity", good is the effective opinion of picture clarity. Effective opinions will be useful when we predict the strength of opinion sentences. But, sometimes the opinion word is not the effective opinion of the feature, with our method, we can remove the incorrect one, for example, we get the set of features about the topics and the set of sentiment words through LDA and associate rule respectively:

Where $f = \{f_1, f_2, f_3, \dots, f_n\}$ represents the set of features, $s = \{a_1, a_2, a_3, \dots, a_n\}$ represents the set of sentiment words. We get a match that $\langle f_1, a_1, a_2 \rangle$ through association rule, but in LDA, a_1 is not exit, so the correct match is $\langle f_1, a_2 \rangle$ and if we get a match $\langle f_1, a_1, a_2 \rangle$ in LDA, according to associate rule, we can get the correct match $\langle f_1, a_1 \rangle$. The experiment results in section 5 confirm that our method is effective.

B. Predicting the strength of the Opinion words

In this paper we focus on the corpus formats that the reviewer is asked to give the grade in five stars and also write a detailed review, Jingdong.com uses this format. The web provides customers 10 levels of 5 stars to express the emotional intensity. We propose a method to calculate the strength of the sentiment words, we define the following terms: the number of all comments is_n , $g = \{g_1, g_2, g_3, \dots, g_n\}$ represents reviews grades, $s = \{s_1, s_2, s_3, \dots, s_t\}$, is the times that sentiment word appear in each grade, the corresponding weight is $w = \{w_1, -w_2, \dots, w_t\}$. We obtain the sentiment strength calculation formula of sentiment word:

$$s(word) = \frac{\frac{s_1}{n} * W_1 + \frac{s_2}{n} * W_2 + \dots + \frac{s_t}{n} * W_t}{s_1 + s_2 + \dots + s_t}$$

we use an example to illustrate our method, suppose that we want to predict the strength of "helpful" in the corpus, helpful occur total 100 times, 10 times in 5 stars (weight is 10), 5 times in 4.5 stars (weight is 9), 8 times in 2.5 stars (weight is 5), 1 times in 0 star (weight is 0), so we can obtain the strength of helpful:

$$s(helpful) = \frac{\frac{10}{100} * 10 + \frac{5}{100} * 9 + \frac{1}{100} * 5 + \frac{1}{100} * 0}{10 + 5 + 1 + 1} * 100 = 8.8$$

The result 8.8 is the strength of helpful, With this method we can obtain all the strength of the sentiment words, we divide the emotional intensity into six levels: positive(strength(9-10) 、 neutral(8) 、 weak(6-7)) and negative(strength(0-1) 、 neutral(2-3)、 weak(4-5)). We also consider whether there is a negation word such as "no" "not" "yet", appearing closely around the opinion word, if so the opinion orientation of the sentiment word is the opposite of its original orientation, such as "the telephone is not easy to use".

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C. Summary generation

After all the previous steps, we ready to generate the final fine-grained summary of reviews, all features are ranked according to the frequency of their appearances in the reviews.

The following shows an example summary for the feature “call quality” of a cell phone, the individual opinion sentences can be hidden using a hyperlink in order to enable the user to see a global view of the summary easily:

Product name: Samsung Galaxy SIII

Feature: call quality

Positive: 11

Strength: 9

The call quality, Music player, camera quality excel every existing phone on earth.

Call quality is very good.

The call quality is great and i haven't had a dropped call yet.

The call quality lives up to Samsung's past reputation. I found that the sound was crisp, the volume range was impressive, and the signal didn't fade a bit...neutral 2

My main concerns were call quality, app speed and battery life, the Galaxy SIII excels at all three.

Call quality is good.

Weak 0

Negative 2

Strength: 0

Neutral: 2

There will be a slight noise during a long time call. The cell phone may be a little hot after a long time use, if you call this time will have a sight echo.

Weak 0

IV. CONCLUSION

Above papers are used to discuss the various methods to summarize the reviews given by the consumers of the product. All the methods involve the calculation and research over the products which are already being used and which are familiar to market based on the feature of interest. One drawback of all the above summarizations is that the products which are new to market cannot be analysed since the product is gauged over one or the other basic factors.

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