Volume 5, Issue 3, July 2018 ISSN: 2348-8565 (Online)
International Journal of Modern Engineering and Research Technology
Website: http://www.ijmert.org Email: editor.ijmert@gmail.com

A Novel Approach to Enhance Rating of Product Review Using Multiple Online Retailers

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ABSTRACT

Now a day's internet is most important and valuable source of learning, getting ideas as well as review also. In internet we can find any product and its reviews that it is positive or negative and use full information. This has inspired research in product rating opinion mining and sentiment analysis to develop methods for automatically detecting emotions, opinions, and other evaluations from texts. Many methods of sentiment analysis for reviews like lexicon based sentiment analysis, machine learning based sentiment analysis, supervised and unsupervised sentiment analysis are under research. Online shopping is the most comfortable way to shop in this new world of technology. Here we are interested in product rating. In product rating most of the researches are focused on sentiment or opinion oriented product rating.

People post reviews after buying the products and rate it in the scale of 1 to 5.Specific model of product is available in different online retailers. Always it seems that different online retailer shows different rating for same model of product. It is very difficult to determine actual rating of product. So unified rating based on multiple online retailers is presented here.

Keywords:— *PWAR-Proposed Weighted Average Rating, OR - Online Retailer, AVGR- Average rating, C -Credibility Score, SEO- Search engine optimization*

I. INTRODUCTION

Online shopping websites have shown immense growth in their popularity over the last few years. People find online shopping a more convenient platform for advertising and purchasing of products. Often, consumers purchase products from an online retailer and later remark about it by posting outcomes of the products in the form of Ratings and Reviews.

1.1 Introduction to Product Rating

A product rating is often a value assigned by the consumer to elicit the information about the product quality or product performance. Rating can be numeric, graphic or descriptive. A numeric rating system is the simplest one, where a rater marks a number to indicate the extent up to which the feature is present in a product (see figure 1 A graphical rating system uses picture response categories that stress on visual communication (see figure 2. A descriptive rating system uses a set of verbal phrases to indicate level of product performance (see figure 3).

Figure 1: An Example of Numerical Rating System

Figure 2: An Example of Graphical Rating System

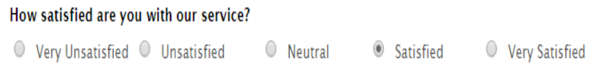

Figure 3: An Example of Descriptive Rating System

Figure 4: Example of 5 star rating system

Among all of the rating systems, a 5-star rating system (see figure 1 can be seen everywhere, which is being used by almost all popular retailers like Amazon, eBay, Flipkart etc. A 5-star rating system allows a user to mark his judgment about a product's performance on a scale of 1 to 5 in the form of stars which adds visual appeal to the rating system. A star rating system helps a user to make complex decision. For example, suppose a user likes to shop for shoes online, then he may want to know the shoe's fitting. A descriptive rating system saying "good- fit", "bad-fit" or a graphical "thumbs-up", "thumbs-down" would not be much helpful in guiding the decision. Whereas, a 4 to 5 star rating would quickly land him on selecting a perfect pair of shoes.

1.2 Introduction to Product Reviews

Stars ratings are often accompanied by reviews. Reviews are free text posted by customers to elicit the information about the product. These reviews further aid deeper considerations of a product such as product quality, customer satisfaction and product performance. Reviews are often biased from human sentiments and social or cultural factors. Yet, text reviews plays an important role in affecting a product's market value.

1.3 Importance of Product Ratings

These Ratings and Reviews posted online are an important source of information intended to both business owners as well as consumers. Lackermair et al [9] conducted a survey and found that 85.57% participants admitted that they look for online reviews and ratings before buying an online product. This is exactly the case of our society where our decision about making an online purchase, signing up for a service or even visiting a place of business is always influenced by online reviews, customer feedbacks, star ratings, rankings in discussion forums etc.

Ratings serve many different purposes for different products, different applications and different customers. For some applications like Amazon and ebay, ratings can be utilized to help customers making purchase decision and providing personal recommendations whereas in some applications like hotels and restaurants ratings can be utilized to get user feedbacks and provide long time offerings.

For consumers, ratings and reviews can be helpful in deciding how much a business can be trusted. Higher ratings and more positive reviews shows a higher trust of customers on a particular business [11]. Ratings helps a customer to get the "worlds-view" on a product, helps him in guiding purchase decision and helps him in providing better system generated recommendations. For business owners, Product ratings are important because they reveal how well a product is adopted by the users and thus help in making future business decisions. Rating helps the business owner to better understand a customer's individual preferences and thus motivates them to provide a more personalized user experience. For example, in applications like Netflix, the more a customer rates, the better the system adapts his personal taste and makes suggestions.

That is the reason why almost all popular retailers are implementing onsite product rating functionality.

1.4 Factors Affecting the Product Rating

There are many factors that affect the actual rating of a product. Some of the major factors are described here:

Number of reviews: The number of reviews has a direct impact on a products rating. Rating does not purely indicate a product quality, instead it is a function of customer expectation and customer satisfaction [13]. With a product, each user's experience is unique; therefore his rating may be biased from his individual level satisfaction. Therefore, any customer tends not to believe in the rating given by few users. But the same customer tends to believe on rating if given by a large number of users. Such rating which is an aggregate of all its ratings is called as average rating. A user is more likely to purchase a product which has a higher average rating [11]. A product having 3 star rating from fifty users is more likely to be purchased than a product having 5 star rating from two users.

History of Retailer: For any business owner, winning its customer's trust is especially vital to retain its customers over time. What keeps consumer trust over long time is the quality of products and the increasing establishment and reputation of that retailer. It is human nature to go back to something which is more familiar and holds positive experiences. Therefore, a well- established retailer with considerable long history behind it, have a large number of loyal customers who stick to it over years. People like to sell or buy from a retailer with long history or old established rather than the newer ones and therefore, tends to believe in its ratings.

***Credibility Score*:** Credibility is all about reliability of any retailer. A higher Credibility score signifies that the source of information is reliable. People should trust on the ratings and reviews coming from a website having higher credibility score. There are many tools readily available on the web to measure the size and credibility score of any retailer such as Alexa Ranking, Web of Trust, Moz Bar, Ghostery and Quantcast etc. Every tool has its own benefits and shortcomings. These tools evaluate the credibility score on the basis of various factors such as website traffic, website's audience information, page ranks, content appropriateness, security concern, technical structure and social impact etc. Therefore the choice of using a tool completely depends on the given task and application.

II. Related Work

Overview of Research Techniques Used Earlier

Ali et al. [1] employed the use of Support Vector Machine and Co-reference resolution for sentiment analysis. SVM classification works on overall users‟ opinion. The training set is basically an X: Y relation

which x is score of an opinion word and y is whether that score is positive or negative. The input we gave to SVM is basically a score of an opinion word about a feature in a review. Their model is capable of identifying anaphors using co-reference resolution module and SVM. But they were unable to detect sarcastic reviews and also the advertisements links entered by the user.

In [2], Jagbir et al proposed an advancement of the previous model based clustering algorithm. The analysis is done in a multi layered iterating manner. It uses two algorithms to carry out the analytical review classification. This model is based on comparison of 6 mobile phones (Sony z1, Sony M4, Samsung s6 edge, Samsung A5, Nokia Lumia 920, Nokia Lumia 1020). Messages representing disgust, hate were studied under this model. The camera, screen, battery and other aspects have been compared in this model. But they were unable to identify of sarcasm or anaphors.

Shivprasad T K et al., [3] describes in his paper about many methods of review mining sentiment analysis and taxonomy of various sentiment analysis. First one is document sentiment analysis in which we analyze whole documents and give a review for overall document but there is a drawback that we can use it only for single entity. Second one is aspect level in this it use fine- grained sentiment analysis and differentiate what user actually want and what don't and give the result in negative or positive form. Sentiment level opinion mining base on two thing first one subjective and second one objective.

In 2017[14] B. Baby and S. Murali presented system that can recommend trust and distrust relations is needed. In the proposed system a user can validate the trustworthiness of a user by submitting a trust evaluation request to the system. The system takes the reviews of the particular user and measure the quality by extracting different features. The system will then calculate trust score of the user and based on the trust score classify the user as either trustworthy or as untrustworthy. The classification is performed using Naive Bayesian classifier. The system can help users to create web of trust containing trustworthy users in online product recommendation sites.

In 2017[15] Y. Liu, W. Zhou described the prosperity of online rating system makes it a popular place for malicious vendors to mislead public's online decisions, whereas the security related studies are lagging behind. In this paper, we develop a quantile regression model to investigate influential factors on online user choices and reveal that the promotion effect on products' market outcomes is determined by not only the attacker's manipulation power but also the specific property of the target product and the market self-exciting power. Inspired by these findings, we propose a novel iterative rating attack and validate its effectiveness through experiments.

In 2016 [16] Xiaodong Fu, Kun Yue, Li Liu, Lijun Liu, presented a method to understand Manipulating online ratings of a product, in terms of both volume and value, can substantially influence its market performance, but the profits of a particular strategy can vary across products and might not be maximized by the highest rating values.

In 2017 [17] Chuan Zhang, Liehuang Zhu, Chang Xu worked on Trust. Trust plays an important role in helping social network user make appropriate decision from abundant social information about products. A variety of social review information (e.g. ratings, voting and tags) emerge with the huge number of products on the Web. How they are utilized for searching and finding appropriate item is investigated. In this paper we propose a user credibility calculation method, which calculates user's credibility through his previous review information. By evaluating facets of every review, an integrated numerical value which denotes the reviewer's credibility can be calculated. This value can be used to rank products, further to help user making appropriate decision. Experiments on social book search database show that this calculation method improves effectively accuracy of recommended items . In [18] 2017 naïve Bayes algorithm can be used in review rating system. In 2014 [19] rakhya's method is tried to use in review rating system. In 2016 [20] prism method is tried to use in rating system.

In 2015 [21] y. Zeng, y. Zhu worked on review manipulation. Online review plays an important role when people are making decisions to purchase a product or service. It is shown that sellers can benefit from boosting their product review or downgrading their competitors' product Review. Dishonest behaviour on reviews can seriously. Affect both buyers and sellers. In this paper, we introduce a novel angle to detect dishonest reviews, called equal rating opportunity (ero) evaluation. The proposed ero evaluation can detect embedded.

III. METHODOLOGY

In this paper, we are proposing an innovative scheme to generate enhanced rating of a product. When a product of a particular model is available at multiple online retailers, the customers of each retailer give ratings for that product. These ratings may be different on each retailer's website due to different number of reviewers who have rated the product on the retailer's website. This difference in the number of reviewers may negatively impact the actual rating. For example, suppose for a product P, an online retailer R1 shows rating = 4.4 based on 100 reviewers and another retailer R2 shows rating = 2.5 based on 1000 reviewers, the normal average rating will be:

Normal average rating for retailer R1=

44/100 = 0.044 and, Normal average rating for retailer R2 =2.5/1000 = 0.0025

Even though the average rating by retailer R1 is greater than that showed by retailer R2, it is not much likely to be believed by new customers since it involves only 100 reviewers. The average rating given by retailer R2 is less than R1, but still the new customers are more likely to believe on this rating since it involves 1000 reviewers which are much greater than 100 reviewers.

Thus, we can generate a unified rating for a particular product which we call as "Weighted Average Rating" using the information of both the retailers as shown in figure 5.

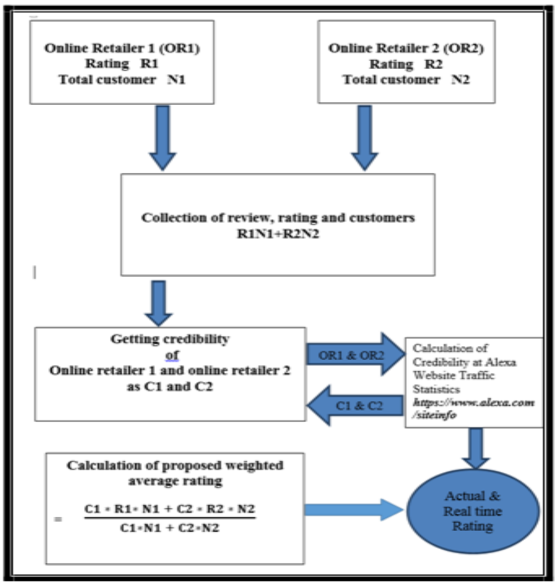

Figure 5. Block Diagram of Proposed Work

Algorithm: Algorithm to find Accurate & Real time Rating

Input: Online retailers OR1 & OR2, Product to buy P, rating of product P on OR1 and OR2 as R1 and R2, no of customers on OR1 and OR2 as N1 & N2, Credibility of OR1 & OR2 as C1 & C2

Output: Proposed Weighted Average Rating (PWAR)

1. Selection of online retailer 1 & online retailer 2
2. Selection of product P
3. Set OR1 -> online retailer 1
4. Set OR2 -> online retailer 2
5. Set P -> product
6. Set OR1.P>R1 -> Rating of product on online retailer 1
7. Set OR1.P>N1 -> No of customers on online retailer 1
8. Set OR2.P>R2 -> Rating of product on online retailer 2
9. Set OR2.P>N2 -> No of customers on online retailer 2
10. Get C1= Alexa[OR1]
11. Get C2= Alexa[OR2]
12. Set OR1.C1 ->C1
13. Set OR2.C2 ->C2
14. Float Z1=C1*R1*N1
15. Float Z2=C2*R2*N2
16. Float Z3=C1*N1
17. Float Z4=C2*N2
18. Float Z5=Z3+Z4
19. Float Z6=Z1+Z2
20. Float Z7=Z6/Z5
21. Return Z7 as PAWR

The Key Information that we have used in our proposed method are given below:

1. Rating given by retailers: Online retailers provide 5 star rating for each product on their website. Often, people look for ratings on different retailers" website since the same product may be available at different retailers. For example, among all the people who have bought the mobile "Samsung J7" online, some of them might have bought it from Amazon.com, some might have bought it from Flipkart.com and others might have bought it from Snapdeal.com. In such situation, it is not a good idea to trust the ratings provided by a single retailer and ignore others. Therefore, we have incorporated multiple retailers" ratings in our proposed method of generating enhanced rating. This enables the generation of the global rating for a particular product.

Number of reviewers: The rating for a particular product is highly dependent on the number of its reviewers. Among all the customers who have bought a product, only some of them posts online ratings. Then the number of reviewers is the total number of customers who have rated a product online. This information is provided by all the retailers on their website along with the product rating. The number of reviewers has a direct impact on the actual rating of a product. Let us assume that a product has an average of 3 star rating from sixty reviewers on one retailer's website and a 5 star rating from 10 reviewers on another retailer's website. Then any customer will believe on rating given by sixty reviewers instead of the rating given by only ten reviewers. Therefore, we have incorporated the total number of reviewers from multiple retailers to generate the enhanced rating for a particular product. This enables the generation of a rating which is more reliable and correct.

Credibility Score of retailers: generated using tool and age of retailer. Harnessing all the information gathered above, we can now generate the enhanced rating for a particular product.

Let, n = Number of retailers in consideration (n = 1, 2, 3… n),

Rn= Rating given by retailer n,

Nn= Number of reviewers of retailer n, Cn =

credibility score of retailer n. Then, Weighted Average Rating

$$= \frac{\Sigma\, Cn\ Rn\ Nn}{\Sigma Cn\ Nn} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Again, consider the Example given before.

For any product P, retailer R1 shows rating

= 4.4 based on 100 reviewers and retailer R2 shows rating = 2.5 based on 1000 reviewers. The credibility score of Retailer R1comes out to be 0.6 and the credibility score of retailer R2 be 0.4. Then, the Weighted Average Rating for the product P will be calculated as: Proposed Weighted Average Rating

$$\text{PWAR}= \frac{C1 * R1 * N1 + C2 * R2 * N2}{C1 * N1 + C2 * N2}$$

$$= \frac{0.6 * 4.4 * 100 + 0.4 * 2.5 * 1000}{.6 * 100 + .4 * 1000}$$

= 2.7(rounding off to the first place after decimal)

Calculation of credibility of website:-To find credibility of website we use Alexa Ranking system.

How to read the metrics: Alexa ranks websites in an ascending order based on their amount of traffic, starting with Google on number 1, followed by Facebook on 2nd and YouTube on 3rd place. A huge number of websites are listed in an endless and ever growing ranking.

Where to find it: By creating an official account at www.alexa.com or by installing the Alexa toolbar you can check any website's Rank. You can also use a third-party app such as Open SEO Stats, which includes the value for the Alexa Ranking Position for each visited website. Alexa ranking system uses popularity, engagement (daily time on site), search traffic, visitors uniqueness and audience geography.

4) Alexa's Traffic Rankings

Alexa's traffic estimates and ranks are based on the browsing behaviour of people in our global data panel which is a sample of all internet users.

Alexa's Traffic Ranks are based on the traffic data provided by users in Alexa's global data panel over a rolling 3 month period. Traffic Ranks are updated daily. A site's ranking is based on a combined measure of Unique Visitors and Page views. Unique Visitors are determined by the number of unique Alexa users who visit a site on a given day. Pageviews are the total number of Alexa user URL requests for a site. However, multiple requests for the same URL on the same day by the same user are counted as a single Pageview. The site with the highest combination of unique visitors and pageviews is ranked #1. Additionally, we employ data normalization to correct for biases that may occur in our data. Using

Alexa ranking system we prepare a table given below

Table 1: Alexa Decision Table

Cases	Value of C1	Value of C2
If Alexa ranking of online retailer O1 is greater than online retailer O2	60%	40%
If Alexa ranking of online retailer O2 is greater than online retailer O1	40%	60%
online retailer O1 is equal to online retailer O2	Not Possible in Alexa Ranking	

IV. Results and Discussion

To simulate our proposed work we have to select a product and has to describe its review according to traditional review system and our proposed raring system. Further we will go for comparison. To favour our proposed rating system two different case studies will be taken and demonstrated.

Case Study 1

Product name: Moto E4 Plus

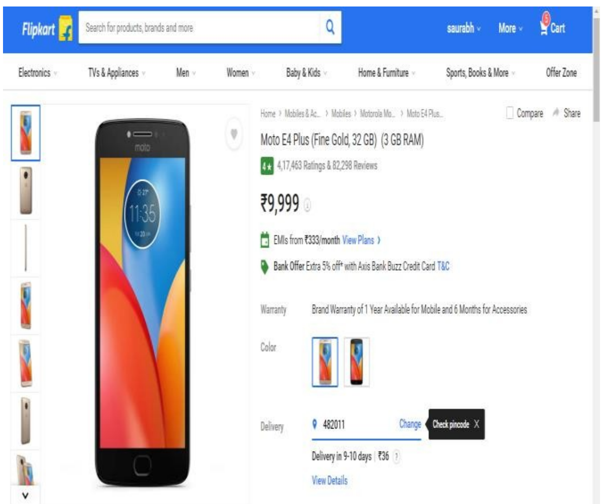

Figure 6 : Motorola E4 plus rating in flipkart.com

In figure 6 it is clearly shown that in flipkart.com rating of Motorola e4 plus is 4 with 417463 customers.82998 customer shave written reviews. But our focus is on rating only.

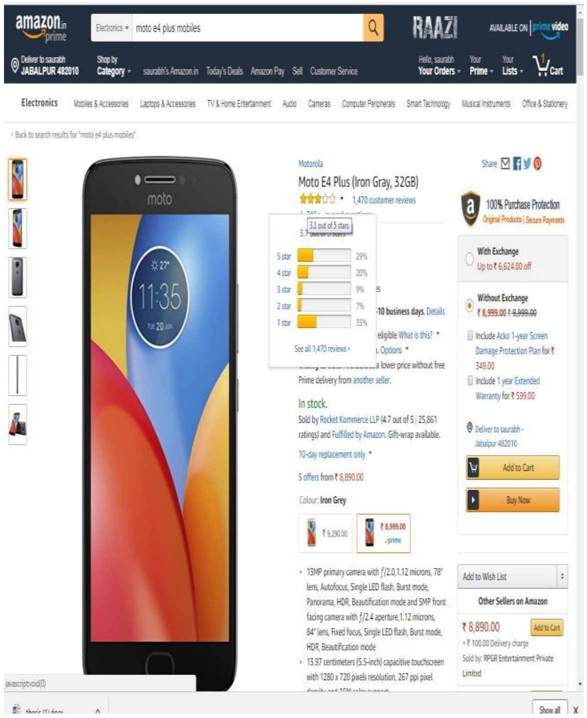

Figure 7: Motorola E4 plus rating in Amazon.in

In figure 7 it is clearly shown that in Amazon.in rating of Motorola e4 plus is 3.1 with 1470 customers.

Calculation using traditional method:-

In traditional method normal average of both online retailerare taken for product Motorola e4 plus.

Average rating (avgr) = (R1+R2)/2 = (4+3.1)/2 = 3.55

Calculation using Proposed method:-

First we calculate Alexa rating of two online retailers Amazon.in and Flipkart.com using online tool [https://www.alexa.com/siteinf].

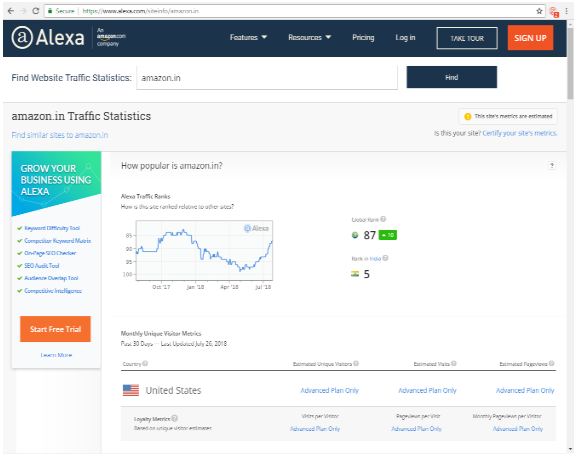

Figure 8: Alexa ranking of Amazon.in

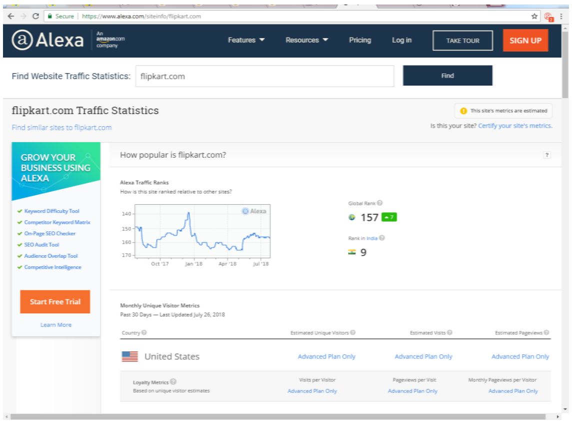

Figure 9: Alexa ranking of Flipkart.com

It is shown using figure 8 and figure 9 that Alexa ranking of Amazon.in is 87 and Alexa ranking of Flipkart.com is 157. So credibility of Amazon.in (c1) is 60% and credibility of Flipkart.com (c2) is 40%.

Using equation 1 here R1= 3.1, C1=.60, N1= 1470

R2= 4.0, C2=.40, N2= 417463

Proposed Weighted Average Rating

$$= \frac{C1 * R1 * N1 + C2 * R2 * N2}{C1 * N1 + C2 * N2}$$

$$= \frac{.60 * 3.1 * 1470 + .40 * 4.0 * 417463}{1470 + 417463}$$

= 3.99

Comparison Chart

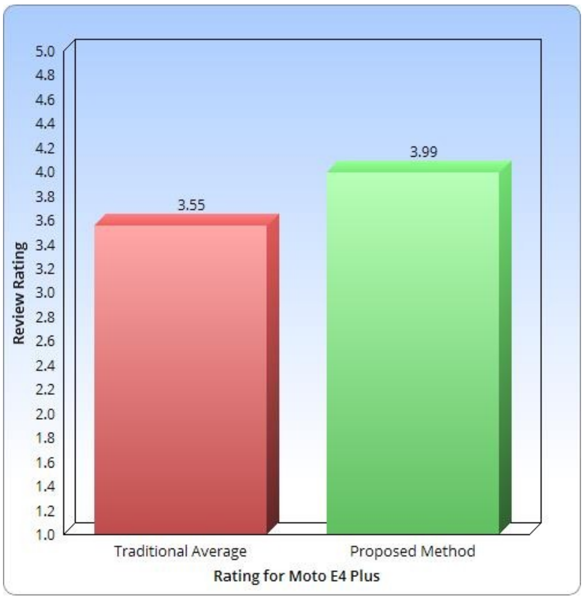

Figure 10: Comparison Chart for Moto E4 Plus

In Figure 10 it is shown clearly that using traditional average rating is 3.55 but using PAWR it is 3.99. Here variation of 0.44 in positive side shows that product is better hence it gives more chance to buyer to get it Also it is good for seller.

Case Study 2

Product name: Fastrack Smartwatch Watch-SWD90059PP01

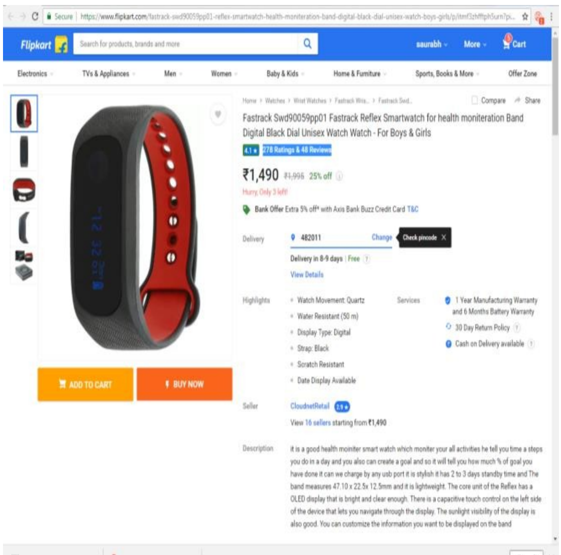

Figure 11: Fastrack Smartwatch Watch-SWD90059PP01 rating in flipkart.com

In figure 11 it is clearly shown that in flipkart.com rating of Fastrack Smartwatch Watch-SWD90059PP01 are 4.1 with 278 customers. In figure 1 1 it is clearly shown that in flipkart.com rating of Fastrack Smartwatch Watch- SWD90059PP01 are 4.1 with 278 customers.

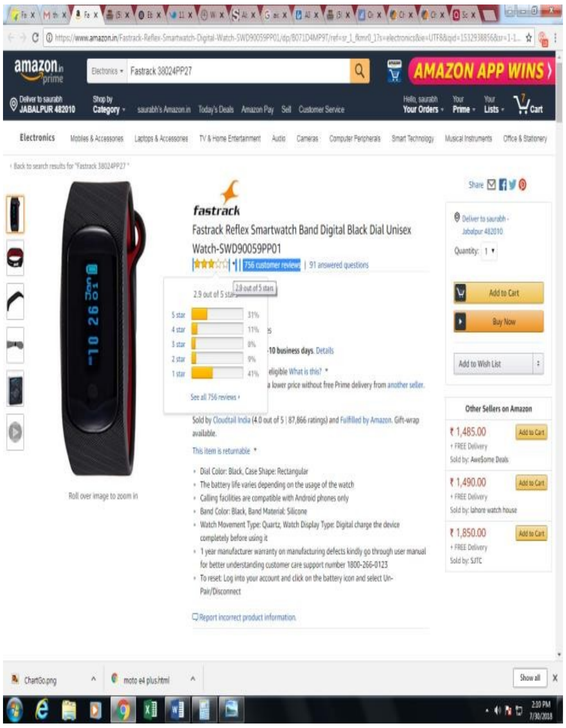

Figure 12: Fastrack Smart watch Watch-SWD90059PP01 rating in Amazon.in

In figure 12 it is clearly shown that in Amazon.in rating of Fastrack Smart watch Watchare2.9 with 756 customers. *Calculation* using traditional method:-

In traditional method normal average of both online retailer are taken for product Motorola e4 plus.

Average raring (avgr) = (R1+R2)/2 = (4.1+2.9)/2 = 3.5

Calculation using Proposed method:-

First we calculate Alexa rating of two online retailers Amazon.in and Flipkart.com using online tool [https://www.alexa.com/siteinfo].

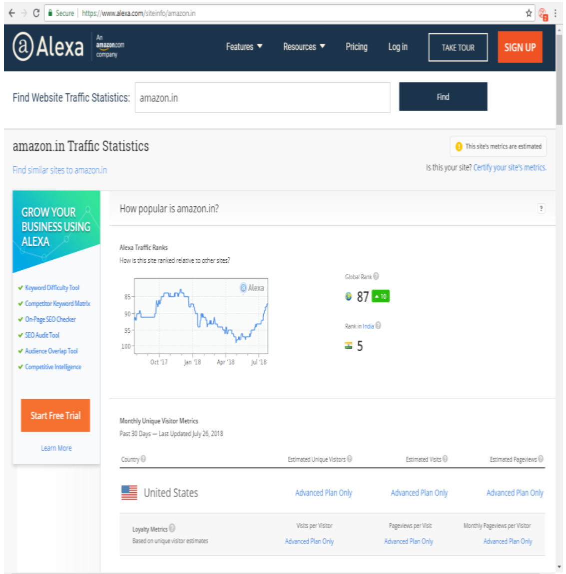

Figure 13: Alexa ranking of Amazon.in

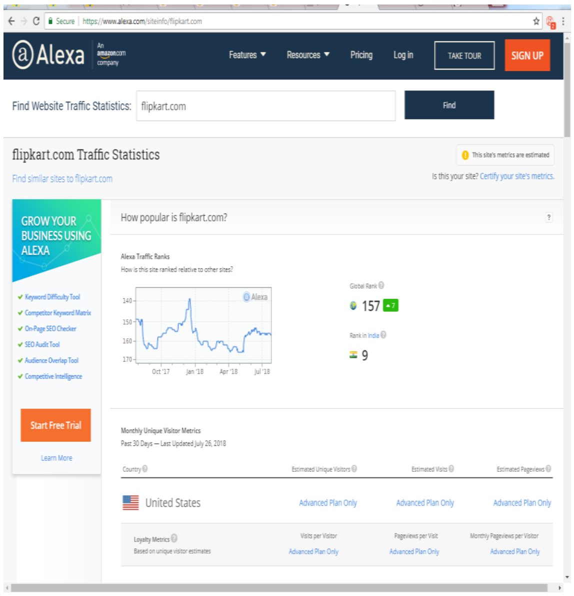

Figure 14: Alexa ranking of Flipkart.com

It is shown using figure 13 and figure 14 that Alexa ranking of Amazon.in is 87 and Alexa ranking of Flipkart.com is 157. So credibility of Amazon.in (c1) is 60% and credibility of Flipkart.com (c2) is 40%.

Using equation 1 here R1= 4.1, C1=.40, N1= 278

R2= 2.9, C2=.60, N2= 756

Proposed Weighted Average Rating

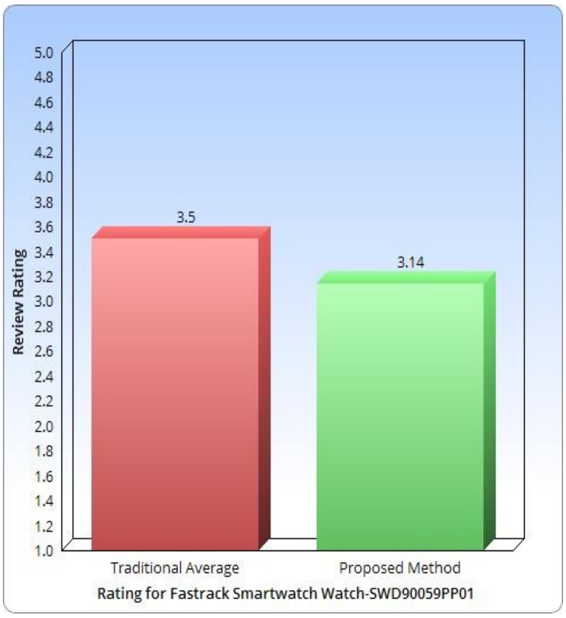

Figure 15: Comparison Chart for Fastrack Smart watch Watch-SWD90059PP01

In Figure 15 it is shown clearly that using traditional average rating is 3.5 but using PAWR it is 3.14. Here variation of 0.36 in negative side shows that product is worse hence it gives more chance to buyer to avoid it. So it is good for buyer.

After going through case study performed here, it is found that there is major difference between traditional average and proposed method. Proposed method gives rating more close accurate rating as it consist of credibility of online retailer along with balanced customer rating. It should be noted that slight fluctuation in rating affects major percent of selling of product.

Table 2: Comparisons of case studies

S.No	Name of Product	Traditional rating	Proposed Rating	Variation
1.	**Moto E4 Plus**	3.55	3.99	0.44
2.	**Fastrack Smart watch Watch-SWD90059P P01**	3.50	3.14	0.36

$$= \frac{C1 * R1 * N1 + C2 * R2 * N2}{C1 * N1 + C2 * N2}$$

$$= \frac{.40 * 4.1 * 278 + .60 * 2.9 * 756}{.4 * 278 + .6 * 756}$$

= 3.14

V. Conclusion and Future Scope

Accuracy in product rating helps customers to buy perfect model or product. Work presented here is just a beginning in this area. This work is done for two online retailers; it can be extended to multiple online retailers. A mobile APP can be launched which combine major familiar and popular online retailers with live data to show live product rating using my proposed rating.

A popular APP trivago is doing something similar to my work in area of hotel booking. But in review rating with multiple sellers, no combined single platform is available, so said area is open for further research.

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