ZKG INTERNATIONAL
ISSN: 2366-1313

CUSTOMER REVIEW RATING SYSTEM BASED ON FEATURES AND VOTES

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ABSTRACT: The purpose of this study is to leverage user reviews and votes to provide comprehensive evaluations of specific features of mobile products. Decisions made by manufacturers and potential clients will be influenced by the findings of this assessment procedure. This rating system provides more information about the product than ratings that solely consider the product. While feature-level rankings give precise information about the benefits and drawbacks of the product, product-level assessments are excessively general. Finding out whether customers think favorably or unfavorably of features is crucial. This method notifies both the manufacturer and the client of product modifications and potential sales. Customers' preferences for features vary widely. At the feature level, ratings can be used to tailor purchases to individual preferences. We looked at ratings and reviews left by customers on Amazon for a variety of mobile devices. We employ feature-tailored sentiment analysis to do this. We did a detailed analysis of 108 features from more than 4000 mobile devices that can be bought online. It gives manufacturers the opportunity to improve their products and gives consumers the ability to make more specialized purchases. Our analysis has a wide range of applications, such as recommender systems, consumer research, and other pertinent fields.

KEYWORDS:Feature Level Rating, Customer Reviews, Review Votes, Sentiment Analysis and User Feedback.

1. INTRODUCTION

Because so many people utilize the Internet these days, people are too busy to purchase at physical establishments. Online product reviews are a great way for consumers to make decisions.

Unfortunately, the majority of these online reviews are unclear and focus exclusively on the products. Even though you can compare costs and product ratings, some consumers may still choose to purchase items based on other characteristics. To learn what other users thought about the aspects of the product that piqued their attention, they typically have to read the entire comments section. It can be challenging for consumers to choose the best cell phone when there are numerous options available for the same product, like cell phones. These reviews nearly invariably highlight the product's shortcomings from the perspective of the manufacturer. A product's creator can learn how to improve it by reading reviews that focus only on its features. Because of these advantages, we would like to create a grading system that is based on attributes. Features can be rated by customers in the same manner as items.

It is not a good idea to have one review every product as there may be too many of them. features or attributes. Giving ratings based on reviews and votes that previous customers have previously provided is far preferable.

Every line in the reviews has an associated feeling that can be positive, negative, or neutral. Because the phrases may be divided up, we can also identify the sentences that discuss a certain feature

ISSN: 2366-1313

of the product and then calculate the sentiment scores across those sentences. These mood scores along with the review votes can be used to create a feature-based rating system, as illustrated in Fig. 1. However, creating a feature-level grading system of this type is not difficult.

We must first decide what qualities we are looking for in an object. Another issue is that several people could refer to the same thing by different names. To create a single feature, these various components must be assembled. Second, preprocessing of the data is necessary since some of the review notes might contain typos, non-English terminology, or other problems. The third task is to determine the best way to combine the sentiment ratings and review votes to assign the appropriate grade to each feature. A word frequency table is created using all of the customer reviews for a certain product, such as a cell phone. This, at least in part, aids in our determination of the features that the product possesses. Following that, every word sharing a characteristic is assigned to a category. Then, the most frequent word within each category is chosen to serve as the emblem. We refer to these characters as feature words.

And that's it! We employ several preparatory procedures to remove unnecessary data, correct the remaining data, and arrange the data in a file.

For every evaluation, there are various lines; only the most significant ones are retained. A sentiment analyzer converts valuable sentences into mood scores. These figures are then modified to reflect the ratings. For scores that fall within a particular range, a grade is assigned. Since each view has a different value, the final ratings are determined by summing the ratings of all significant sentences possessing a particular quality .The weights assigned to each item are determined by the votes cast on it. These are new additions.

We have a feature-based ranking system that we create using votes and consumer feedback. We examine over 4,000 phones that are available online in order to assign these phones a score of 108. We introduce new approaches for obtaining and completing opinion scores: vote-aware cumulative rating and vote-aware final rating measures. This means that even in the absence of real-world data, we can test our strategy by examining consumer ratings for our phone overall and comparing them to feature ratings. The outcomes are striking and validate the effectiveness of our approach.

2. EXISTING SYSTEM

Sentiment analysis has long been the focus of extensive scholarly research. It has several uses, including as e-commerce, sports, politics, and health. As demonstrated in and, sentiment analysis of consumer feedback in e-commerce can reveal a wealth of information about the products. Wiliam et al. used sentiment analysis to investigate the patterns of mobile brand mentions on Twitter. Instead of focusing on specific characteristics, the study is limited to the mobile platform as a whole. Nandal et al. limited their effort to a specific set of objects and features. Sadhasivam and Kalivaradhan accomplished this through assembly, whereas Nadal et al. used SVM, a supervised learning method.

This article attempts to do something unprecedented in previous research by using these user reviews to assign ratings to up to 108 features of the over 4,000 mobile phones sold online, in addition to including review opinions. Furthermore, we achieve this in an unsupervised manner rather than a supervised or only loosely supervised one by using the lexical strategy to generate sentiment ratings for sentences. For the same reason, Zhang et al. investigated digital televisions and cameras, which is similar to our study.

However, they only consider ten features. Bafna, Toshniwal, and exclusively tested the Canon camera, iPhone 4s, and MP3 player.

However, we review over 4,000 goods and make suggestions. However, to the best of our knowledge, this is the only article that incorporates review votes into a feature-specific rating system.

Disadvantages

ISSN: 2366-1313

- Less effective recommender systems are a feature of the present system.
- On big datasets, text mining for sentiment analysis is not supported by this system.

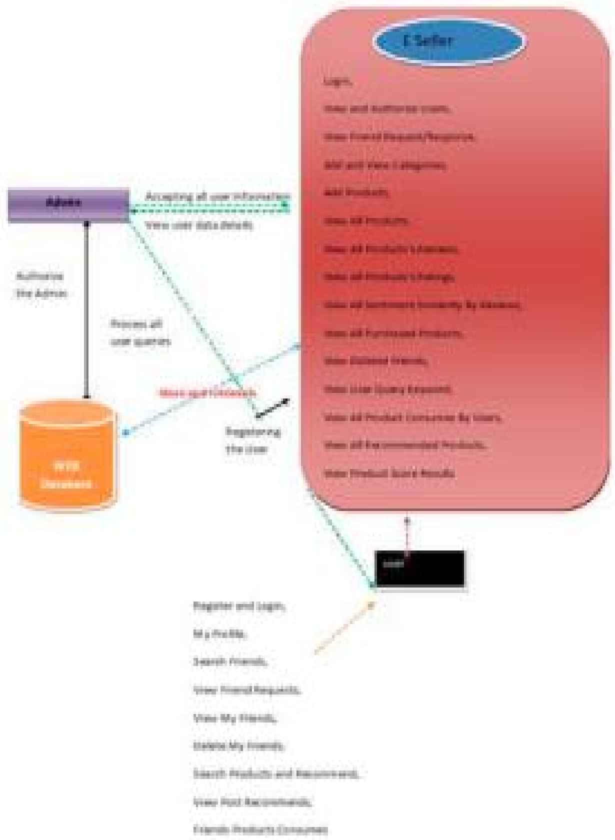
3. PROPOSED SYSTEM

The suggested system contributions are as follows. Following user assessments and review votes, the system creates a feature-level rating system that awards feature ratings. The system collects these assessments for up to 108 characteristics on over 4,000 mobile phones sold online. The methodology suggests a novel method for calculating and concluding emotion scores: measurements of vote-aware cumulative and final ratings. Despite the lack of empirical data, we can still assess the effectiveness of our method by comparing the eventual evaluations of our phone feature to the cumulative ratings provided by our clients. The astounding results support the efficacy of our methods.

Advantages

- The system preprocesses customer review data, removing extraneous information and correcting errors so that it can provide organized data. We select the most essential lines from each review and keep them.
- You can improve the system's performance by applying web mining for mood analysis.

SYSTEM ARCHITECTURE



4.IMPLEMENTATION

ESeller

An active username and password for an ESellers account are needed to connect to this module. After a successful login, users can start doing things like watching and granting other users permission.Examine and respond to the friend request.Look through and add categories. Present the products.Examine each product, including reviews, ratings, sentiment similarity, purchased products, and friends who have been deleted.

View the user query's keyword. Get access to an extensive selection of products that consumers have used. See the full version. There are product ratings and suggested products listed.

Viewing and Authorizing Users

In this module, the administrator can view each user's information and provide them access to the login page. Information on the user, including their name, address, phone number, and email address.

Add and View Category as Domain

The administrator can create sections such as flicks, merchandise, and sports using this module.

Add Posts as Products

By choosing domains and adding post details like title, description, photographs, and uses, the administrator can add posts to this module.

View all Posts with Rating based on Ranks

This module gives the administrator access to every single posting he's made, including ratings, ranks, uses, descriptions, and images. Ratings are computed using ranks.

View User Query Keyword and Analyze the Query Subgroup

All search words entered by users, including exact matches and query subgroups, can be viewed and reviewed by the administrator. This includes matched posts as well as query subgroups.

View all Recommended Products

Any idea that users have shared with their friends can be seen by the editor right here. Pick a topic to see the suggested posts.

Categorize Users Based on Products Consumes with user Images

This functionality allows the administrator to see a list of all users who have liked and recommended a specific post. A visual graph is presented depicting the result when a specific post name is selected.

View Product Rank Results

The administrator can view the ranking of the products using a graph. A post's rank is determined by the amount of likes it receives.

User

In this module there are many users (n). Users must register before proceeding. The information of the user will be retained in the database after registration. He has to log in with the permitted login and password after registration is finished. Users can view their profiles, friend requests, friends, product consumption and suggestions, postings, and friend removals when they log in.

Viewing Profile Details

Users are able to access their personal profile information, including address, email, phone number, and profile photograph, through this module.

Search Friends, Request, and View Friend Requests, View all Friend Details

Users can send friend invitations, look through other users' profiles, and conduct name-based searches for other users. A vast amount of acquaintance data, including pictures and private details, is available to the user.

Search Query by keyword

The user can use this interface to perform a post search by entering a query keyword. There are two categories that display the results. One has precisely matched posts, while the other just comprises posts that fall within the category of the matched posts.

The user can convey their feelings to their acquaintances by rating posts and loving or disliking them.

View every post suggested by your friends.

This allows the user to examine every post suggested by one of his acquaintances. The user can check the specifics of a recommended post and see what their peers think about it.

View Your Friends Products Consumes details with their images

Users can view the particular details of their friends' product usage thanks to this functionality. A friend's unique design will be used to display information when they like or recommend a post.

5. CONCLUSION

We have developed a mechanism that uses review votes and user reviews to rank smartphones according to 108 features. For the benefit of consumers and product developers alike, we could provide ratings for over four thousand phones. Finding and extracting lines that contain our feature keywords is made easier if we first organize the raw data in an easily usable fashion.

We generated feature-level scores by applying sentiment analysis to these words. We compared the phones' performance in many areas to determine which ones were best suited for each function. We used the overall customer rating for the "phone" feature as our benchmark.It appears that our approach is effective. Our findings

ISSN: 2366-1313

indicate that the MAE is a meager 0.555. Approximately half a star. Accuracy of 52.3% is achieved when precise integer scores are provided. That's probably what's going to happen.
However, the accuracy increases to 93.8% if a one-star inaccuracy in an integer rate is acceptable. Nobody is keeping an eye on the method that was described. In our pursuit of better outcomes, we shall choose a supervised or a poorly supervised approach. The only way to accomplish this would be to categorize the current data according to each of our 108 attributes.

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