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Comparative Study of Customer Ratings Analysis Algorithms

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***Abstract*: Reviewing online applications and services is now becoming a trend and is highly important as the world is progressing towards digital platform of everything it has become easier to use the services and also to decide which app is to be used and which not. Customer reviews for any online platform business is must and is very essential for its growth. Analyzing ratings and reviews allows a strategist to act according to the market needs and to overcome the shortcomings in the services and in the products. There can be n ways of analyzing the ratings and reviews, the process of data analysis comes under the data mining techniques.**

Data mining is the process of analyzing hidden patterns of data according to different perspectives for categorization into useful information, which is collected and assembled in common areas, such as data warehouses, for efficient analysis, data mining algorithms, facilitating business decision making and other information requirements to ultimately cut costs and increase revenue.

***Keywords*: Customer Review Ratings, Online Ratings, Digital Platforms, Application Reviews, Data Mining.**

1. Introduction

Information coming directly from customers about the satisfaction or dissatisfaction they feel with a product or a service. Customer comments and complaints given to a company are an important resource for improving and addressing the needs and wants of the customer. The information is procured through written or oral surveys, online forms, emails, letters, or phone calls from the customer to the company.

In electronic commerce, product reviews are used on shopping sites to give customers an opportunity to rate and comment on products they have purchased, right on the product page. Other consumers can read these when making a purchase decision. Often, the company will include a URL on printed literature or e-mail marketing to invite customers to review their service after a transaction has been completed.

Feedback is essential to the working and survival of all regulatory mechanisms found throughout living and non-living nature, and also in man-made systems such as education and economic system. Feedback is a two-way flow as its inherent all interactions, between human-to-human, human-to-machine or machine-to-machine. In an organization, feedback is the information sent to an entity about its prior behavior so that the entity may change its behavior to achieve the desired result.

Feedback occurs when an environment reacts to an action or undesirable behavior. For example, 'customer-feedback' is the buyers' reaction to a firm's products and policies, and 'operational feedback' is the internally generated information on the firm's performance. Response to stimuli is considered as a feedback only if it brings about a change in the recipient's behavior.

Feedback is data from customer about their perceptions & experiences as your customer. The feedback is gathered directly by company or outsourced and gather by market research firms (Third party). Feedback can take different forms and it usually covers a wide range of topics about the organization. The feedback data collected by the user are broadly evaluated by the two methodologies: quantitative & qualitative information. Quantitative and qualitative techniques provide a tradeoff between breadth and depth, and between generalizability and targeting to specific (sometimes very limited) populations [1].

Quantitative information (Numerical rating) is obtained from various research methods such as surveys conducted by mail, questionnaires, phone in person or over the internet on various social sites. The quantitative methodology uses a structured approach for collecting the feedback. The structured method for collecting feedback suffers from many draw backs. The surveys include questionnaires about the product and they deals only yes/no format. The questionnaires feedback received from the customer are invaluable in terms of making the organization successful. The customer feedback is the most important of all and all you need is to analyze it correctly. Numerical rating is provided to every answer and based upon the numerical analysis the result are formed. The numerical results are not enough sufficient to tell us the actual disadvantages of the organization, the scope and area of improvement where the organization is lagging behind.

The structured methods of collecting the feedback deals with the following challenges such as 1) might not get the careful feedback. 2) Wording can bias client's response 3) doesn't get the full story 4) good surveys questions are hard to write and they take considerable time to develop and sone 5) suggestions and opinions are not asked 6) data may provide a general picture but lack depth. The quantitative methodology is not enough sufficient for providing a solution to all these challenges and for overall development of the organization.

The qualitative information is obtained during interviews with human participants, often in video or audio tape and may be transcribed into written forms. The qualitative methodology uses an unstructured approach for collecting the feedback. The unstructured approach provides the user with free space to write their opinions, suggestions about the organization in the user friendly language. The textual feedback along with numerical ratings for a particular product can be obtained from various E-Commerce website such as Epinions.com, Cnet.com, amazon.com etc. The common methods are blogs posted by customer, emails, documents on the web, tweets, customer comments, customer reviews written after experiencing the product services and so on. The analysis of freely expressed customer's feedback is an excellent alternative to conventional survey techniques used in quantitative information [1].

2. Literature survey

The prediction of star ratings (e.g., ratings ranging from 1 to 5 stars) has been the focus of many academic and business applications to date. In particular, review rating prediction, also known as sentiment rating prediction, is a task that deals with the inference of an author's implied numerical rating, i.e. on the prediction of a rating score, from a given written review [2], [3]. Recommendation systems, for instance, often suggest products based on star ratings of similar products previously rated by other users.

Yet analysing a textual review is a much more difficult task than guessing the rating by only considering other available numerical scores. This is why not only classifying sentiment [4], [5] but also predicting rating scores has captured the attention of the sentiment analysis community in the last few years. For example, Pang and Lee apply classification and regression, supervised learning techniques to rate movie reviews [6], and Goldberg and Zhu extend their approach by applying a graph-based semi-supervised learning algorithm that achieves better performance [7]. Tang and co-authors follow a similar approach [8], and present a neural network-based method that considers not only the review texts but also author information. They claim that their method "performs better than several strong baseline methods which only use textual semantics." Li and co-authors go beyond the review texts and their authors, and add information also about the product that is reviewed, by modelling all three features using a three-dimensional tensor [9]. Then, they apply tensor factorisation techniques and optimise their model using gradient descent. Their results outperform other similar approaches. Furthermore, Qu et al. introduce the bag-of-opinions representation for which their method learns rating scores from domain-independent corpora using constrained ridge regression [10].

Zhang and co-authors delve deeper into the polarity2 of a review by stating that "it might not be appropriate to use overall ratings as ground-truth to label the sentiment orientations of review texts, as users tend to act differently when making overall ratings and expressing their true feelings on detailed product aspects or features" [11]. This means that rating predictors should consider the subtle differences between review texts as a whole, and reviews of individual aspects. [12] and [13] come to the same conclusions, and affirm that textually derived ratings are better predictors than numerical star ratings. In their experiments, Zhang and co-authors first let three annotators manually label the polarity orientation of sample reviews from a restaurant dataset and then compare them against automatically generated annotations using unsupervised review-level sentiment classification [11]. Afterwards, the annotators label not reviews as a whole but their aspects or features individually. Again, the results are compared to those obtained with the methods the authors propose, showing the inconsistency between textual reviews and numerical ratings when the latter do not consider phrase-level sentiment polarity. Gupta and co-authors also apply supervised learning with a multi-aspect rating prediction for textual reviews of restaurants [14]. They consider numerical ratings for aspects like food, service, and overall experience, inter alia, as well as considering the interdependence of aspects for around eight sentences per review on average. Orimaye and co-authors introduce a sentence-level polarity correction [15]. Their technique identifies sentences with inconsistent polarities that are handled as outliers and, as such, are discarded from the reviews. This approach might not be convenient for mobile app reviews, where the length of subjective phrases might be about two words long on average, and the reviews are not long enough either [16]. Discarding information in the case of mobile apps would introduce an extra bias to the problem.

Sänger [16] introduces an aspect-based opinion mining of mobile apps ratings that extends Klinger and Cimiano's work [17], [18]. According to Sänger, Klinger and Cimiano's approach was chosen because it deals with fine-granular aspect-based opinion mining, its implementation is open-sourced (see https://bitbucket.org/rklinger/jfsa), and it is suitable for mining text written in German, as is the case of the dataset he uses (see next section). Sänger concludes that such a technique is also appropriate for analysing mobile app reviews; he both adapts and validates Klinger and Cimiano's work for such reviews.

Sänger's approach serves as the background to, and the basis for, the work presented here. It is worth mentioning, however, that the goal of the work presented in this paper is not to deal with aspect identification nor with sentiment classification; but assuming that these tasks are performed before the star ratings are predicted. A complement to Sänger's work, in other words. Thus, unlike other approaches that identify aspects or classify sentiment at a fine-granular level, like most of the works reviewed above (e.g. [6]–[8], [13], [17], to cite but a few), the idea of our approach is to provide a method for predicting star ratings based solely on available annotated, fine-granular opinions.

Correctly identifying customer needs and satisfying them with fine-tuned product attributes is the foremost challenge for customer driven product developers. In the front-end product development process, product development teams have to come up with multiple candidates, and evaluate them to sort out the most appropriate one [19]. For maximizing the consumer's satisfaction, it is better to have as many design alternatives as possible, but in a practical sense, we eventually need to single out the most suitable design to minimize cost involved in product design, modification, and development.

In this selection process, it is important to have a systematic decision supporting method to choose the best design, which is accurately addressing customer requirements at a given future time step. Proper candidate selection at the front-end design phase will ensure better product performance at the market, and it will reduce design change cost, which increases exponentially alongside the product design and development process, by minimizing the changes in latter stages. [1].

The most popular and widely used technique in industry to elicit customer preferences is conjoint analysis [20-21] and discrete choice analysis [21-22]. These traditional ways of assessing the customer preferences consist of consumer surveys, interviews with consumers and deriving utility, value or the probability of selection, which are time consuming, complex and expensive exercises. Although conjoint analysis and discreet choice analysis provides time variant models in theory, real applications or case studies are difficult to find due to the highly complex nature of time variant models and difficulties in gathering data.

The relationship between attributes and experts' ratings is obtained through Projections to Latent Structures (PLS) technique, using the competitive product data from the product market, for each time step. A multivariate analysis is carried out to screen the unimportant variables and again models are formulated for each time step using selected variables. This time series of ratings models is then used to formulate the future ratings model which is used to obtain the rating predictions for design alternatives.

The ratings of experts from reliable organizations are taken as the overall perceived values of the products, in this study. Experts' ratings are a reliable source that can be used to represent the degree of customer satisfaction, due to the fact that product reviewers are more aware of various product offerings and technological advances compared with average customers [23]. Hence, it is used as the metric for the degree of customer satisfaction.

3. Conclusion

The above studied methods are analytical study of analyzing customer reviews and ratings through different methodologies. Collecting customer feedback shows you value their opinions. By asking your clients for feedback you communicate that their opinion is important to you. You involve them in shaping your business so they feel more attached to your company. Listening to their voice helps you create stronger relations with them.

Analyzing customer feedback is highly important for any business and acting upon them is equally important too, in this paper the importance of the customer feedback has been discussed and the existing algorithms have been studied to improve the way of analyzing customer feedback ratings.

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