A Recommender System for Online Consumer Reviews

Research-in-Progress

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Abstract

Online consumer reviews have helped consumers to increase their knowledge about different products/services. While most previous studies try to provide general models that predict performance of online reviews, this study notes that different people look for different types of reviews. Hence, there is a need for developing a system that that is able to sort reviews differently for each user based on the ratings they previously assigned to other reviews. Using a design science approach, we address the above need by developing a recommender system that is able to predict the perceptions of each user regarding helpfulness of a specific review. In addition to addressing the sorting problem, this study also develops models that extract objective information from the text of online reviews including utilitarian cues, hedonic cues, product quality, service quality, price, and product comparison. Each of these characteristics may also be used for sorting and filtering online reviews.

Keywords: Online consumer reviews, recommender system, review helpfulness

Introduction

Online consumer reviews (OCR) have helped consumers to increase their knowledge about different products/services and choose the ones that best suit their needs. A recent study finds that online reviews are the second most-trusted source of product information after recommendations from family and friends (Nielsen 2012). On the other hand, online reviews are more user-oriented compared to vendor-generated product descriptions because they show different usage scenarios for products and assess them from the user's perspective (Chen and Xie 2008). Thus, some people have suggested that consumers who write online reviews serve as "sales assistants" for online retailers (Chen and Xie 2008). While many products have thousands of online reviews, many of those reviews do not receive any attention from consumers because of the way online reviews are sorted. One the other hand, sorting online reviews by their perceived helpfulness may bias the perceptions of future readers. Hence, previous research has called for improved methods for sorting online reviews (Salehan and Kim 2014).

The process of analyzing online reviews can be broken into two steps: (1) the decision to read the review, and (2) the actual processing of the information in the review that leads to the decision to whether or not use it based on its perceived helpfulness (Ahluwalia 2000). Previous research has looked at how users read and process online reviews and the factors that influence consumers' perceptions of helpfulness of online reviews. Review extremity (Chevalier and Mayzlin 2006), sentiment (Salehan and Kim 2014), length of a review (Chevalier and Mayzlin 2006; Salehan and Kim 2014), proportion of product-descriptive statements, and proportion of reviewer-descriptive statements (Schindler and Bickart 2012) are among the most important predictors of helpfulness of online reviews. While most of the previous studies aim at providing a generalized model that explains how consumers process online reviews, other studies suggest that different people have different motivations for reading online reviews. People use online reviews as additional source of information, to gain reassurance about the choice they have already made, to know about what other consumers are thinking, and also as primary source of information prior to a product purchase (Bailey 2005). Hence, one can conclude that different people are looking for different information in online reviews and thus make their decisions regarding helpfulness of a review based on their informational needs. As a result, one cannot develop a universal model that is able to predict the perceptions of all consumers regarding helpfulness of online reviews. This leads to the need for a system that is able to predict the perception of each consumer separately.

Recommender systems are "software agents that predict the interests or preferences of individual users for products and make recommendations accordingly" (Xiao and Benbasat 2007, p. 137). The recommendation is usually made based on the attributes of the user or his/her preference for other products he/she has used before. This study aims at developing a recommender system for online reviews that is able to predict the perception of each user regarding the helpfulness of online reviews. Using a machine learning approach, we provide predictive models that measure different attributes of a review including hedonic cues, utilitarian cues, product quality, service quality, price, and comparison with similar products. Then, we develop a recommender system that will be later validate using online reviews rated by human subjects. The proposed recommender system can be used by online vendors to sort online reviews differently for each user. The remaining parts of this paper are organized as follows. We start with the theoretical background of this study. Then we proceed with the proposed predictive model. Later, we show the preliminary results of the study and discuss its potential contributions. Finally, we discuss the future steps to be taken as well as our limitations.

Literature Review and Theoretical Background

Online customer reviews play a critical role in purchase decision making of consumers. Many customers use OCR to make better decisions. As a result, businesses encourage customers to write reviews to enhance customers' satisfaction (Somprasertsri and Lalitrojwong 2010). OCR are written by consumers on retail websites to express their opinions and experiences with products and services (Somprasertsri and Lalitrojwong 2010). Writing OCR is a common practice among online shopping customers (Tsur and Rappoport 2009). Customers who write reviews have information about the product due to past, present, or even future experiences (Krishnamoorthy 2015; Rose, Hair and Clark 2011). Information provided by OCR ranges from comprehensive, detailed, and insightful to only prejudiced feelings or facts (Tsur and Rappoport 2009).

While OCR has become a crucial part of purchase decision making for online users (Chevalier and Mayzlin 2006), the information overload hinders the true link between information seeking and optimized decision making (Baum and Spann 2014). For example, it is shown that most customers only read less than 10 reviews (Anderson 2014). As a result, an online customer's decision making is usually based on limited numbers of reviews (Kuan, Hui, Prasarnphanich and Lai 2015). To facilitate decision making using OCR, many mechanisms and tools have been developed and introduced on the e-commerce websites. For example, overall star rating of the product or helpfulness of customer reviews have been recently proven to be influential in comforting users' decision making.

Predictors of Helpfulness of Online Consumer Reviews

OCR can be characterized by different measures. Customer purchase behavior is influenced by the content of online reviews (Chevalier and Mayzlin 2006). Previous studies have introduced variables such as numerical star rating, review length, review extremity, and review sentiment to predict performance of OCR (Chevalier and Mayzlin 2006; Hu, Koh and Reddy 2014; Kuan et al. 2015; Mudambi and Schuff 2010; Sridhar and Srinivasan 2012; Vermeulen and Seegers 2009). In addition to these measures, in an e-commerce environment other factors such as the overall star rating of all customer reviews of a product or reviewer popularity can influence decision making process (Korfiatis, García-Bariocanal and Sánchez-Alonso 2012).

Different measures, such as purchase intention (e.g., Park, Lee and Han 2007), readership (e.g., Salehan and Kim 2014), and sales revenue (e.g., Chevalier and Mayzlin 2006; Hu et al. 2014; Liu 2006), have been used by previous studies to predict performance of online reviews. Helpfulness is the most widely used measure for prediction of performance of online reviews (e.g., Baek, Ahn and Choi 2012; Cao, Duan and Gan 2011; Mudambi and Schuff 2010; Salehan and Kim 2014). Because review helpfulness represents the users' perceived value of a review (Connors, Mudambi and Schuff 2011), it facilitate users' decision making (Cao et al. 2011). More helpful reviews have stronger effect on purchasing behavior than less helpful reviews (Chen, Dhanasobhon and Smith 2008).

Review helpfulness is usually determined by readers. Review helpfulness ratings are the perceived usefulness of customer reviews voted as helpful by customers (Connors et al. 2011). They are designed to facilitate decision making process for customers. Review helpfulness is determinant of performance of online reviews (Salehan and Kim 2014). For example, Chevalier and Mayzlin (2006) showed how improvement in consumer reviews of books on Amazon.com yielded to sale growth. They also found total number of reviews positively influence the product sale. Other study showed purchase decision making in online shopping environment is influenced by helpfulness of OCR (Cao et al. 2011). Deviation of a review from overall ratings given by all other reviewers inversely influence perceived helpfulness of it (Danescu-Niculescu-Mizil, Kossinets, Kleinberg and Lee 2009). Although the actual determining factor of review helpfulness is the content of the review (Chan 2015), most of the previous studies ignored the importance of content and they focused more on non-textual factors such as star ratings or reviewer popularity.

Forman et al. (2008) evaluated online review helpfulness on Amazon. Their findings indicate that reviews containing self-descriptive information about the author are perceived more helpful compared to anonymous ones. They also showed that reviewer expertise and attractiveness, as two dimensions of source credibility, are significantly related to the perceived helpfulness of a review. The reason is that people tend to seek advice from expert sources when making purchase decisions because they believe experts provide more accurate information (Willemsen, Neijens, Bronner and de Ridder 2011). Helpfulness of a review could also be determined by measuring its length or readability (Eastin 2001; Kuan et al. 2015), or by more complex characteristics such as valence, sentiment, and argument style. Readability of a text is the minimum level of education required to understand it (Korfiatis, Rodríguez and Sicilia 2008). Length and readability of a review both positively influence its perceived helpfulness (Kuan et al. 2015). Zhu et al. (2014) found that perceived helpfulness of hotel reviews on Yelp was related to central and peripheral cues of the argument. Cao et al. (2011) conducted a text mining approach to show determinants of helpfulness of OCR. The found that basic characteristics of a review (e.g., posting date, extremeness), stylistic characteristics (e.g., average number of words in a sentence), and semantic characteristics (e.g., overall semantic of a review) influence the number of helpfulness votes of a review. In addition to content (central) cues, peripheral cues such as review extremity and expertise claims influence helpfulness of a review (Kuan et al. 2015).

Valence of OCR is another important characteristic that influences the perceived helpfulness of OCR (Kusumasondjaja, Shanka and Marchegiani 2012). Negativity and positivity connotation or orientation of a review is defined as review valence (Basuroy, Chatterjee and Ravid 2003; Kusumasondjaja et al. 2012). Positive reviews have higher impact on purchase decision making than negative reviews (Zhu and Zhang 2010) while more negative reviews perceived more helpful (Kuan et al. 2015). Hu et al. (2009) found negative reviews contain more clear information than positive reviews. However, the effect of negative reviews diminishes over time (Basuroy et al. 2003).

Review augmentation is another important predictor of helpfulness of OCR. Review augmentation refers to the arguments that support the statements written in OCR and make them more persuasive (Price, Nir and Cappella 2006; Willemsen et al. 2011). Argument density and diversity positively influence helpfulness of OCR (Willemsen et al. 2011). Another important variable in this concept is review extremity. Review extremity is the difference of star rating of a review from average voted star ratings (Mudambi and Schuff 2010). It can also be defined as the difference between star rating and the middle star rating, usually 2.5 on a 5 star scale (Basuroy et al. 2003; Heitmann, Lehmann and Herrmann 2007). Previous research shows that extreme information are more influential than moderate arguments (Skowronski and Carlston 1987). For example, one-star reviews are perceived more helpful than 3-star reviews (Cao et al. 2011). Moreover, extremely negative reviews (i.e., one-star reviews) hurt sales (Chevalier and Mayzlin 2006).

In addition to the review content, the reviewer itself should also be considered. Ngo-Ye et al. (2014) showed reviewer engagement is an important predictor of review helpfulness. Reviewer's recency, frequency, and monetary value can capture a reviewer's engagement. Useful reviews are usually written by reviewers with more effort and involvement. In an study by Zhu et al. (2014), it is shown that reviewer expertise and reviewer's online attractiveness positively influence perceived helpfulness of reviews.

Review helpfulness is operationalized as the ratio of positive votes and overall votes on helpfulness of a review (Kim, Pantel, Chklovski and Pennacchiotti 2006). Helpfulness ratio can be between 0 and 1, the greater the value the more helpful it is perceived to be (Liu et al., 2007). Some researchers also consider reviews as either helpful or not helpful by operationalizing it as a binary variable (Forman et al. 2008).

Recommender Systems

Recommendation agents (RAs) "are software agents that elicit the interests or preferences of individual users for products, either explicitly or implicitly, and make recommendations accordingly" (Xiao and Benbasat 2007, p. 137). One of the most important applications of these agents is in the e-commerce context. These agents have been used to make recommendations of suited products or vendors to the customers and provide a type of mass customization on the internet (Ansari et al. 2000; Detlor and Arsenault 2002; Grenci and Todd 2002; O'Keefe and McEachern 1998). According to Xiao and Benbasat (2007) there are different categorizations of RAs methods including: (1) content filtering vs. collaborative filtering vs. hybrid, (2) compensatory vs. non-compensatory, and (3) feature-based vs. needs-based vs. hybrid.

Content filtering method create recommendations based on the attributes that a customer prefers. An example for these RAs is Active Buyer Guide and My Simon. Collaborative filtering RAs generate recommendations as a linear weighted combination of like-minded people's preferences. Collaborative filtering method has been used by Amazon, MovieLens, and etc. The hybrid method is a combination of the two methods. (Ansari et al. 2000; Xiao and Benbasat 2007). Compensatory methods recommend based on the relative importance of the attributes for an individual while the non-compensatory RAs generate the recommendation based on the attributes which are important for an individual (Knijnenburg et al. 2011). Finally, feature-based RAs generate recommendation based on the features that an individual likes while needs-based recommendation systems create the recommendation by using the individuals' needs. The hybrid method combine both features and needs to generate the recommendation (Xiao and Benbasat 2007).

One of the most prevalent issues in developing recommender systems is the cold start problem. Cold start happens when the system wants to recommend an item that has not been rated in the community by anyone before (Schein, Popescul, Ungar and Pennock 2002). Collaborative filtering, as one of the most common methods in developing recommender systems, cannot solve this problem (Ghabayen and Noah 2014). Recommender systems recommend products based on other users' explicit or implicit preferences (Lam, Vu, Le and Duong 2008). Therefore, to decide about recommending a product to a consumer, the the product should have been rated by other users. Previous research suggests several approaches to address this problem. One prevalent solution is adopting a hybrid approach between content-based matching and collaborative filtering. In this approach, the recommender system rates those items that have not been rated before based on the available rates for similar items. The item similarity is determined based on content-based information, i.e., the attribute information. An example of attribute information is a list of actors for a movie (Schein et al. 2002). Thus recommender system may find the similar items based on the similarity of their attributes and then use the ratings of those items to estimate rate of unrated items.

The Proposed Predictive Model

The basic idea of this study is to develop a systems that is able to recommend reviews for each individual person based on their previous behavior toward online reviews. In other words, the system will be able to predict how likely it will be for a specific person to like a specific review which we call "likelihood of helpfulness". Later, the system will be able to sort the reviews for that person based on the "likelihood of helpfulness" of individual reviews. The review that has the higher score will stand on the top and other reviews will be sorted in a descending order.

The first step to design such a recommender system is to identify factors that significantly predict helpfulness of online reviews. We checked the previous literature to find a set of factors that influence review helpfulness. Table 1 shows the preliminary results of literature analysis.

Table 1 - Predictors of helpfulness

Factor	**Study**
Numerical star rating	Mudambi and Schuff (2010)
Review length	Eastin (2001); Kuan et al. (2015)
Review extremity	Chevalier and Mayzlin (2006); Hu et al. (2014); Kuan et al. (2015); Mudambi and Schuff (2010); Sridhar and Srinivasan (2012); Vermeulen and Seegers (2009)
Longevity	Salehan and Kim (2014)
Sentiment	Salehan and Kim (2014)
Reviewer popularity	Korfiatis et al. (2012)
Number of self-descriptive statements	Forman et al. (2008)
Reviewer expertise and attractiveness	Forman et al. (2008)
Readability	Eastin (2001); Kuan et al. (2015)
Central cues, Peripheral cues	Zhu et al. (2014)
Argument density and diversity	Willemsen et al. (2011)
Reviewer engagement	Ngo-Ye and Sinha (2014)

The next step is to pick a set of factors that we use to recommend reviews to individuals. Previous literature shows a large number of factors that significantly predict helpfulness. However, in this study we will be limited to factors that can be measured by automated systems. For example, length, longevity, and review extremity can be easily calculated by software programs. However, reviewer expertise and attractiveness, argument density and diversity, and reviewer engagement cannot be easily measured by software programs. On the other hand, the authors also added a group of factors that are likely to be important including service quality, product quality, price, comparison, review comprehensiveness, hedonic cues, and utilitarian cues. Table 2 shows the selected factors and their definitions.

Table 2 - The factors used to characterize reviews

Factor	**Definition**
Numerical star rating	The number assigned by the author to the product (usually out of 5)
Review length	Number of words in the review
Review extremity	Deviation of numerical start rating from average star rating
Longevity	Number of days since the review was written
Emotional valence	The amount of positivity/negativity of the text of the review
Emotional arousal	The amount of emotional arousal (activation) in the text of the review

Total sentiment	The amount of all different types of sentiment in the text of the review
Reviewer popularity	The ranking of the reviewer on Amazon.com
Product quality	If the review talks about the quality of the product
Service quality	If the review talks about the quality of the service (e.g., delivery)
Price	If the review talks about the price of the product
Comparison	If the review compares the product to similar products
Review comprehensiveness	The degree to which the review talks about the product quality, service quality, price, and comparison of similar products
Hedonic cues	The amount of hedonic cues that exist in the review
Utilitarian cues	The amount of utilitarian cues that exist in the review

The final system will be able to automatically measure each of the above characteristics of a review and create a matrix similar to the one depicted in Table 3.

Table 3 - Review characteristics matrix

Factors	**Review 1**	**Review 2**	**Review 3**	**…**	**…**	**…**	**Review n**
Numerical star rating	1	5	3				2
Review length	100	20	180				550
Review extremity	1	3	2				1
Longevity	20	300	154				211
Emotional valence	+4	+3	-2				0
Emotional arousal	9	8	6				2
Total sentiment	10	12	6				2
Reviewer popularity	12000	660	77954				125
Product quality	1	1	0				1
Service quality	1	0	1				1
Price	1	0	1				0
Comparison	1	0	1				0
Review comprehensiveness	4	1	3				2
Hedonic cues	7	9	3				5
Utilitarian cues	2	6	8				9

The next step is to design the recommender core. We will design the system based on item-to-item collaborative filtering. In item-to-items filtering, the system will determine likelihood of helpfulness based on the helpfulness of similar reviews previously rated by the user. In this approach, to predict likelihood of helpfulness of review r_x for user i (r_{xi}), the system will first identify the top k reviews most similar to r_x which have already been rated by user i. Later, the system will calculate r_{xi} using weighted average of the scores for the top k similar reviews using the following equation:

$$r_{xi} = \frac{\sum_{j \in N\ (i;x)} S_{ij}.r_{xj}}{\sum_{j \in N\ (i;x)} S_{ij}}$$

Where S_{ij} is the similarity of reviews i and j.

Measurement

The first step in operationalizing the system is to develop the tools that measure different characteristics of reviews. Table 4 shows how we measure each characteristic and report descriptive statistics of our initial sample. The descriptive statistics are not reported for some measures because we did not measure those characteristics at this stage.

Table 4 – Measures used in this study				
Factor	**Measurement**	**Scale**	**Mean**	**Std. Dev**
Numerical star rating	The numerical rating assigned to the review	[1 , 5]	2.96	1.73
Review length	Remove punctuation, then (number of spaces +1)	[0, +∞]	106.8	138.3
Review extremity	$\lvert star\ rating - 3 \rvert$	[0, 2]	1.60	0.66
Longevity	Today's date – review date	[0, +∞]	785.8	628.4
Emotional valence	Using SentinStregth software	[-4, 4]	0.31	1.44
Emotional arousal	Affective Words for English lexicon	[0, +∞]	-	-
Total sentiment	Using SentinStregth software	[0, 8]	2.72	1.42
Product quality	Machine learning	Binary	67% = {1}	-
Service quality	Machine learning	Binary	20% ={1}	-
Price	Machine learning	Binary	24% ={1}	-
Comparison	Machine learning	Binary	18% = {1}	-
Review comprehensiveness	Service quality + Product quality + Price + Comparison	[0, 4]	1.30	0.97
Hedonic cues	Machine learning	[1, 10]	2.01	1.94
Utilitarian cues	Machine learning	[1, 10]	2.79	2.11

Preliminary Results

We first tested the effect of hedonic cues and utilitarian cues on helpfulness of online review. The analysis show that both utilitarian cues ($b = 0.10$, $p < 0.01$) and hedonic cues ($b = 0.24$, $p < 0.001$) significantly influence helpfulness. Then, we tried to measure hedonic cues and utilitarian cues using a machine learning approach. Following the content analysis research process by Krippendorff (1980; 2012), we qualitatively hand coded 589 reviews to measure utilitarian cues, hedonic cues, product quality, service quality, price, and comparison variables. Four Master's students read all of the 589 Amazon customer reviews. To build our coding book two meetings were held to explain the above attributes to our coders. A different sample of reviews were randomly chosen by the authors and we did not use the reviews of the same product for our content coding purpose. The coders were unaware of the purpose of the study and did not know our proposed set of hypotheses. Moreover, we selected coders from four different departments. To reduce errors, the coders were given only 50 reviews to do the coding every even day.

Using the coded data, we trained 6 different Support Vector Machine (SVM) models with linear kernel to predict the 6 variables mentioned above. The results show 67.80% accuracy for utilitarian cues, 61.02% for hedonic cues, 73.29% for product quality, 77.97% for service quality, 86.44% for comparison, and 76.27% for price. We will continue optimizing the models until we get above 80% predictive accuracy for all models.

We also tested the performance of the recommender system. Sixteen undergraduate students were hired to rate 30 reviews of microwave ovens. The rating included classifying each review as either helpful or not helpful. Then 20 ratings were randomly selected to test the performance of the model. Because 70% of the ratings were helpful, we oversampled the unhelpful ratings to address the problem of imbalance in our dataset. To predict the rating user i assigns to review r_x (r_{xi}), we identified the top five reviews most similar to r_x. Euclidian distance was used to measure similarity. Later, we calculated the predicted value for r_{xi} using simple average of the scores for the top five similar reviews. The overall model shows 60% predictive accuracy.

Expected Contributions

While most of the previous studies try to provide general models that predict performance of online reviews, this study notes that different people look for different types of reviews. Hence, there is a need for developing a system that that is able to sort reviews differently for each user based on the ratings they previously assigned to online reviews. Using a design science approach, we address the above need by developing a recommender system that has the ability of predicting the perceptions of each user regarding helpfulness of a specific review. In addition to addressing the sorting problem, this study also develops models that extract objective information from the text of online reviews including utilitarian cues, hedonic cues, product quality, service quality, price, and product comparison. Each of these characteristics may also be used for sorting and filtering online reviews.

Limitations and Future Steps

We are currently trying to optimize the models that predict utilitarian cues, hedonic cues, product quality, service quality, price, and comparison. Initial results show that the model for utilitarian cues is highly dependent on product type. For example, the model that we trained, using a sample of reviews for microwave ovens, contains high loadings for words specific to the product such as cook, door, sensor, and light. Hence, the predictive model for utilitarian cues will have limited generalizability. The same may be true about hedonic cues but we do not expect it to be as severe. After all the models are trained, we will work on developing the recommender system.

Because the prediction task has a binary outcome (helpful / not helpful), a baseline system will perform at 50% predictive accuracy. Hence, if the designed system is able to perform above 50%, the prediction task can be marked as successful. A simple linear model tested by the authors shows 60% accuracy which is above the baseline. However, our goal is to optimize the model using a weighted average of the ratings to achieve higher levels of accuracy. We also plan to improve the algorithm used for calculating the similarity of the reviews. We will use different distance measures including cosine similarity, Manhattan distance, and Minkowski distance to optimize the similarity calculations (Perlibakas 2004).

This study does not address the problem of cold start. Future research may look at how content based approach may be used to determine ratings for new items. Moreover, the system will not be able to predict the behavior of new users. For such people, the reviews may be sorted based on aggregated helpfulness or by a most-recent approach.

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