A recommender System for Restaurant Reviews Based on Consumer Segment

Emergent Research Forum Paper

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Abstract

Previous research shows that consumers use online reviews for a variety of reasons. For many products/services, there are a large number of reviews which makes it difficult for consumers to decide which reviews to pay attention to. Hence, previous research has suggested that online reviews websites can provide a customized review sorting system for each individual consumer. Consequently, drawing upon five consumer segments as well as 10 restaurant characteristics found in the literature, we propose a content-filtering recommender system that evaluates individual online reviews and assigns a numeric score to each review for each of the five consumer segments. The numeric scores can later be used to sort online reviews for individual consumers according to their taste for restaurants.

Keywords

Restaurant reviews, Yelp.com, recommender system, consumer segment.

Introduction

Online consumer reviews have thrived as they provide significant value to both consumers and businesses. Majority of consumers now read online reviews of the product or brand before making a purchase decision (Salehan and Kim 2016). More and more businesses are monitoring and responding to online customer reviews, not only to obtain customer feedback and suggestions, but also to build brand and increase revenue and sales (Anderson and Magruder 2012; Luca 2016).

Many products/services have a large number of reviews (Salehan and Kim 2016). However, consumers find some reviews more useful than others. Hence, a large body of literature investigates predictors of review usefulness (e.g., Connors, Mudambi and Schuff 2011; Mousavizadeh, Koohikamali and Salehan 2015; Mudambi and Schuff 2010; Salehan and Kim 2016). Previous research shows that different consumers use online reviews for a variety of reasons (Bailey 2005). On the other hand, there are a large number of reviews for many products/services which makes it difficult for consumers to decide which reviews to pay attention to (Salehan and Kim 2016). Hence, previous research has suggested that online reviews websites can provide a customized review sorting system for each individual consumer (Salehan, Mousavizadeh and Koohikamali 2015).

In the context of restaurant reviews, Yüksel and Yüksel (2002) identify five segments of consumers: value seekers, service seekers, adventurous food seekers, atmosphere seekers. The study also identifies 10 different restaurant characteristics and shows that each consumer segments puts different weights on each of these characteristics. For example, adventurous food seekers sought tasting new, interesting and local dishes, and are less concerned with the nutritiousness and healthiness of food as the healthy food seekers. Atmosphere seekers desired a pleasant dining ambience and a good time, and less concerned with the service quality as the service seekers, or menu diversity as the value seekers. Interestingly, menu
diversity is found to have a negative association with the overall satisfaction of service seekers, meaning the more diverse the menu, the less satisfaction it may create for this consumer group (Yüksel and Yüksel 2002).

Drawing upon the recommendations by Salehan et al. (2015) and using the five consumer segments as well as 10 restaurant characteristics provided by Yüksel and Yüksel (2002), we propose a content-filtering recommender system that evaluates individual online reviews and assigns a numeric score to it for each of the five consumer segments. The numeric scores can later be used to sort online reviews for individual consumers according to their taste for restaurants. The remaining part of this paper is organized as follows. First, we will review the related literature. Next, we discuss our methodology. Finally, we conclude with the expected contributions of this study.

**Literature Reviews**

**Factors of Restaurant Reviews**

Restaurant experiences consist of both tangible products and intangible services components (Bojanic and Drew Rosen 1994). Restaurant service providers not only interact with their customer through price, quality, and variety of food but also through quality and speed of service and dining environment. A customer’s experience with an unpleasant service environment may negatively affect his/her cognitive, emotional, and physiological response, which in turn may negatively influence his/her prospects about people/restaurant staff or product/food there (Yüksel and Yüksel 2002). Therefore, customer review of restaurant experience is a complex process that involves processing a multitude of factors. Identifying dimensions and attributes contributing to customer satisfaction in restaurants can provide practical knowledge for restaurant management to improve their service quality and customer satisfaction.

While restaurant attributes such as product quality, service quality, menu diversity, price, and value affect customer reviews (López and Farzan 2015; Pettijohn, Pettijohn and Luke 1997; Yüksel and Yüksel 2002), external factors such as demographics and weather can also influence reviews significantly (Bakhshi, Kanuparthy and Gilbert 2014). Furthermore, consumers are more responsive when a rating contains more information, when a restaurant has a higher number of reviews, or when the reviewers are certified as “elite” by Yelp.com. However, consumers do not use all available information from reviews to make the decision for restaurant selection (Luca and Zervas 2016). Users are able to detect reviews written by knowledgeable locals, and they perceive them as more useful and trustworthy (López and Farzan 2015).

**Segment-specific Satisfaction**

Most of previous studies explored customer satisfaction in an aggregate market, assuming that customer satisfaction factors work generically across populations. Yüksel and Yüksel (2002), however, suggest that different market segments focus on different sets of benefits and satisfaction factors. Based upon survey data from 449 tourists who dined at independent none-fast-food restaurants, Yüksel and Yüksel (2002) identified five customer clusters using factor and cluster analysis: (a) value seekers, (b) service seekers, (c) adventurous food seekers, (d) atmosphere seekers, and (e) adventurous food seekers. Then, using factor analysis of customers’ perceived performance ratings, they identified 10 food service evaluation factors: (1) service quality, (2) product quality, (3) menu diversity, (4) hygiene, (5) convenience and location, (6) noise, (7) service speed, (8) price and value, (9) facilities, and (10) atmosphere. Finally, by regressing the subjects’ satisfaction scores on the factor scores of performance perception, they found that the performance of segment-level prediction of customers’ overall satisfaction was better than aggregate market prediction. The study demonstrated that satisfaction drivers of different market segments vary. In fact, even though product quality, service quality, and menu diversity are among the common important factors across all segments, there was no single factor shared by all segments. Table 1 shows the details of the five market segments and their evaluation factors (Yüksel and Yüksel 2002).

**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). RAs are extensively used in the context of e-commerce. These agents are used to make
recommendations of suited products or vendors to customers and provide a type of mass customization on the internet (Ansari, Essegaier and Kohli 2000; Detlor and Arsenault 2002; Grenci and Todd 2002; O'keefe and McEachern 1998). RAs can be categorized in 3 different ways: (1) content filtering vs. collaborative filtering vs. hybrid, (2) compensatory vs. non-compensatory, and (3) feature-based vs. needs-based vs. hybrid (Xiao and Benbasat 2007).

<table>
<thead>
<tr>
<th>Restaurant Customer Segment</th>
<th>Evaluation Factors</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value Seekers</td>
<td>Product quality</td>
<td>A consumer group who tends to select restaurants that provide food value for money.</td>
</tr>
<tr>
<td></td>
<td>Service quality</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Menu diversity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Noise</td>
<td></td>
</tr>
<tr>
<td>Service Seekers</td>
<td>Product quality</td>
<td>A consumer group who sees the availability of quality service as the most important restaurant selection factor.</td>
</tr>
<tr>
<td></td>
<td>Service quality</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Menu diversity (negatively)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Service Speed</td>
<td></td>
</tr>
<tr>
<td>Adventurous food seekers</td>
<td>Service quality</td>
<td>A consumer group who sees the availability of local, new, and interesting food as the most important when selecting a restaurant, followed by the location of a restaurant.</td>
</tr>
<tr>
<td></td>
<td>Convenience location</td>
<td></td>
</tr>
<tr>
<td>Atmosphere seekers</td>
<td>Product quality</td>
<td>A consumer group who searches for restaurants that offer a friendly dining atmosphere and a good time.</td>
</tr>
<tr>
<td></td>
<td>Price and value</td>
<td></td>
</tr>
<tr>
<td>Healthy food seekers</td>
<td>Service quality</td>
<td>A consumer group who looks for restaurants that offer healthy food choices.</td>
</tr>
<tr>
<td></td>
<td>Product quality</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Facilities</td>
<td></td>
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<tr>
<td></td>
<td>Menu diversity</td>
<td></td>
</tr>
</tbody>
</table>

Table 1 - The market segments and their evaluation factors

Content filtering method creates recommendations based on preference of the user for certain attributes. An example of these RAs is the personal shopping bot at MySimon.com through the Active Buyer’s Guide. Collaborative filtering RAs generate recommendations based on preferences of like-minded people. The hybrid method consists of a combination of the two methods (Ansari et al. 2000; Xiao and Benbasat 2007). Compensatory methods permit tradeoffs between attributes allowing desirable attributes to compensate for less desirable attributes while non-compensatory RAs do not allow tradeoffs between attributes (Knijnenburg, Reijmer and Willemsen 2011). Finally, feature-based RAs provide recommendation by asking questions about product features the user prefers. Needs-based RAs, in contrast, are appropriate when users are not able to identify features but can describe their needs (Xiao and Benbasat 2007).

The Proposed Recommender System

This study develops a content-filtering recommender system based on the consumer input. In other words, for this system to perform, the consumer needs to choose one or all of the five consumer segments as their preference. This process can be done in two ways. For registered Yelp.com members, consumers’ preferences can be retrieved from their profile. For non-registered members, Yelp.com may ask consumers to select a set of those five segments to recommend the reviews that match the corresponding selected segments. We assume that a consumer selects a restaurant before checking the reviews. For instance, as reflected in Figure 1, consumers can sort reviews based on couple of options. Thus, our recommender system can augment the existing sorting mechanism in Yelp.com by recommending reviews based on the selected segments. In order to classify the reviews based on the segments in Table 1, we will deploy topic modeling using Latent Dirichlet Allocation (LDA) (Blei 2012; Debortoli, Junglas, Müller and vom Brocke 2016; Vakulenko, Müller and Brocke 2014). The LDA is a probabilistic model that assumes a review is a mixture of topics. We use the list of satisfaction factors in Table 1 as the list of topics that will appear across all the reviews. That means that after applying LDA on reviews, the percentage distribution of topics across the reviews will be determined. For instance, for a given review, the system may generate the following: 20% Food quality, 50% service quality, 10% menu diversity, and 20% price and value. By
doing so, we suggest the following equation to assign an appropriate score to reviews based on the taste of consumers reflected in Table 1.

$$\text{Score}_{ijc} = \sum \text{Topic}_{ijk} \times W_{kc}$$

where,

a) $\text{Score}_{ijc}$ denotes the score of review i in Restaurant j based for consumer C. Consumer C can select 1 or all the 5 segments.

b) $\text{Topic}_{ijk}$ denotes the weight of topic k in review i in restaurant j

$W_{kc}$ denotes the normalized weight of topic k for consumer C. $W_{kc}$ can be obtained by dividing the number of times topic k (i.e., satisfaction factors in table 1) appeared in the consumer C selected segments to the number of unique topics across selected segments. For instance, if a consumer selects value seeker and services seeker segments, the weight of product quality topic for this specific consumer will be $(2/5)$ or $40\%$ because product quality appears in both segments and there are five unique topics in the two segments (product quality, service quality, menu diversity, noise, and service speed). $W_{kc}$ will be zero if a topic doesn’t appear in the selected segments by consumers.

**Expected Contributions**

This study moves beyond describing the predictors of review usefulness and provides a practical method for classifying reviews and sorting them differently for each consumer based on their taste for restaurants. The provided solution is scalable and can be efficiently used by online restaurant review websites to reduce the search cost for their users. Using this study, consumers can indicate their preference in their profile and / or as part of their search query.

![Yelp Sort](image)

**Figure 1 – An example of sorting mechanism in Yelp**

**References**


