ANALYZING CHANGES IN HOTEL CUSTOMERS' EXPECTATIONS BY TRIP MODE

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ABSTRACT

With the emergence of Web 2.0, electronic word of mouth (eWOM) shared through social networking sites has become the primary information source for many travelers. An enormous quantity of reviews has been posted by customers, and has become a valuable means by which hoteliers can better understand customer satisfaction and expectations. Efforts have been made to analyze these parameters in terms of customers' backgrounds. Although customer expectations vary according to background, whether or not this is still the case across different trip modes remains unknown. In this study, an eWOM dataset was obtained from an online source and sentiment mining used to improve its quality by imputing missing values. A complete analysis of customer profiles and their contrast by trip mode was then conducted using association rule mining. The empirical results demonstrate differences in both customer expectation and satisfaction when the same traveler engages in different trip modes.

Keywords: eWOM, Customer Expectation, Sentiment Mining, Contrast Analysis, Association Rule, Data Mining

1. INTRODUCTION

When planning a trip, deciding which hotel to stay in is an essential but complicated decision-making process. To evaluate accommodation alternatives, people tend to seek information from others, either by talking to travel agents or seeking the opinions of family members or friends. Such information gathering is known as word of mouth (WOM) (Liao et al., 2010). With the rapid development of Internet technology since the 1990s (Coffman and Odlyzko, 1998), a new type of WOM, electronic WOM (eWOM), has emerged. Social media channels such as blogs, forums, and review sites have evolved as eWOM communication networks (Cheng and Zhou, 2010b), where ratings and advice from travelers can be shared freely over the Internet. Cheng and Zhou (2010a) confirm that eWOM has a significant effect on consumers' purchase decisions. Due to its flexibility, hoteliers can easily get customer feedback and evaluations through ratings, reviewer comments, and pictures posted online.

eWOM posts usually share the traveler's experiences and report their level of satisfaction with the hotel. Many people read these posts to gather extra information when planning a trip, and may even follow the advice given by them (Gretzel and Yoo, 2008; Ye, Law, Gu, and Chen, 2011). Service, location, price, room facilities, sleep quality, and cleanliness are factors a trip planner will commonly take into account when evaluating a hotel that he/she has not visited (Choi and Chu, 2001; Lockyer, 2005; Shergill and Sun, 2004). McCleary and Weaver (1993) show that travel purpose is a significant factor in hotel selection for those traveling on business, and Chu and Choi (2000) confirm this is also important to general travelers. However, diverse conclusions can be drawn from respondents of different backgrounds. Ananth et al. (1992) show that price and quality are the most important hotel factors; whereas Israeli (2000) finds that cleanliness is the top-rated attribute.

In addition, researchers have studied the relationship between customers' expectations of a hotel and personal factors such as gender, age, educational level, income, nationality, and purpose of stay. Their findings show that expectations do vary depending on customer background (Ariffin and Maghzi, 2012). Customers with different attributes may have different expectations, although it is not necessarily the case that similar customers will share the same expectations, especially in different trip contexts. However, the relationship between trip mode and customer expectations is still unknown.

Some studies use factor analysis to identify the importance of hotel attributes (Choi and Chu, 2001; Chu and Choi, 2000; Saleh and Ryan, 1992; Ananth et al., 1992; Yuksel, Kilinc, and Yuksel, 2006; Ariffin and Maghzi, 2012). However, the associations between customers' demographic attributes and their satisfaction with different hotel factors cannot be well defined using factor analysis alone. Surveys are the main data collection technique used, often resulting in small datasets. The Internet, which can be seen as a new source of data, has generated a significantly large amount of customer feedback and hence provides an opportunity to perform more reliable and informative analysis. However, there is a need for a technique that can fully utilize the large amount of available data, as well as identify the associations between customers' demographic attributes and their satisfaction with different hotel factors. Moreover, missing values in Internet evaluation data are often unavoidable, so a method for filling in these missing values is also required.

Over the past decade, data mining has emerged as an important technique for analyzing large volumes of data efficiently and accurately. It has found several effective applications across various research areas, and the hospitality industry is no exception. For example, Rong, Li, and Law (2009) use self-organizing maps to compare travelers who purchase online hotel services with those who only browse without purchasing. Min, Min, and Eman (2002) also use data mining techniques to profile repeat customers, as well as to identify those with a high churn rate. Given that online review data are on a large scale and come in transactional format, association rule mining has been identified as a particularly suitable technique to analyze hidden patterns. It has been widely used to identify associations between customers' behavior and factors such as traveler profile (Li, Law, Rong, and Vu, 2010). As mentioned previously, missing values in datasets collected from the Internet, such as online reviews with missing ratings for some hotel attributes, are common. Recently, sentiment mining has emerged as a technique for extracting opinions expressed as text. It has been successfully used in many studies to identify opinion information from text-based review comments (Pang and Lee, 2008; Miao, Li, and Dai, 2009; Wang, Lu, and Zhai, 2010). Therefore, sentiment mining is another technique that could be used to fill in the missing values in online review data.

In the present study, data mining techniques are employed to answer the central research question: How do satisfaction and expectations vary for customers with the same backgrounds but with different trip modes?

The rest of the paper is organized as follows. In Section 2 we present background information and review related work, before setting out the problem definition and research objectives. In Section 3, we describe the dataset, analysis strategy, and methodology. Section 4 presents the results of the analysis and discusses their implications. Section 5 concludes the paper.

2. BACKGROUND

In this section, we review existing studies on customer satisfaction, and present the factor analysis methods they use. We then identify the research problems and state the research goals.

2.1. Studies of Customer Satisfaction

Customer satisfaction means the evaluation of the relationship between customer expectations and the actual performance of services; a customer is satisfied when hotel services meet or exceed his/her expectations (Oliver, 1997).

Customer satisfaction plays a crucial role in the hospitality business, and so considerable efforts have been made to find ways to maintain and improve it (Yuksel and Yuksel 1990; Oliver and DeSarbo, 1988; Parasuraman, Zeithaml, and Berry, 1988). Cronin and Taylor (1992) examine different service sectors, with their empirical results showing that customer satisfaction significantly influences purchase intention in different sectors.

Customer satisfaction has also been proven to have a strong positive relationship with customer loyalty. A loyal customer is defined as one who repurchases from the service provider when there are alternatives, and who will recommend it or provide positive WOM to others (Getty and Thompson, 1994; Kandampully and Suhartanto, 2000).

Despite its importance, customer satisfaction is not a universal measurement, because different customers can have different degrees of satisfaction with the same service (Pizam and Ellis, 1999). The evaluation of the service is subject to the customer's experience, evaluation criteria, and the context and circumstances (Eccless and Durand, 1997). Dolnicar (2002) identifies expectations and disappointments for business travelers. Mok and Armstrong (1998) analyze travelers from five different countries, and show that travelers from different cultural backgrounds have significantly different expectations. Though prior studies confirm that customers' backgrounds influence their expectations and satisfaction, customers with the same attributes may still have different expectations when their experience takes place in an alternative context, such as will be the case across different trip modes. For example, a group of similar travelers could have high expectations of service when on a business trip, while being less sensitive to service levels when they are traveling independently.

2.2. Factor Analysis in Prior Studies

Researchers have attempted to identify and measure the importance of hotel factors in order to enhance customer satisfaction and analyze hotel selection intentions. Factors such as location, price, cleanliness, and facilities have a strong influence on hotel selection (Lockyer, 2005). As well as these traditional elements, new factors have been identified such as silence in rooms and air conditioning (Merlo and João, 2011). Choi and Chu (2001) employ exploratory factor analysis (EFA) and show that value, service quality, and room quality are the most important determinants of hotel guests' satisfaction. Ariffin and Maghzi (2012) use factor analysis with Varimax rotation to explore the relationships between customers' expectations of hotel factors and their personal attributes such as gender, age, educational level, income, purpose of stay, and nationality. Chu and Choi (2000) also use this method as a dimensionality reduction technique, and apply factors derived from an Importance-Performance Analysis to compare their importance in hotel selection for business and leisure travelers. Their results show that business travelers are more concerned about the room and front desk, whereas security is the top-rated issue for leisure travelers.

Factor analysis can be divided into two categories: EFA and confirmatory factor analysis (CFA). The difference is that EFA explores the underlying structure of a set of variables, whereas CFA determines whether a predefined expectation can be met, such as the loadings of measured variables. Most studies use EFA to measure the importance of variables based on factor loadings, which represent those original variables and their respective factors. In such studies, a factor is considered significant if the factor loading is equal or greater than 0.5 and its eigenvalue is equal to or greater than 1. Other studies employ classical factor analysis methods (Saleh and Ryan, 1992; Ananth et al., 1992; Yuksel et al., 2006; Ariffin and Maghzi, 2012). Such methods can identify the importance of variables, but the associations between them cannot be well defined.

2.3. Problem Definition and Research Objective

Prior studies have explored which hotel factors are relevant to customer satisfaction (Gundersen, Heide, and Olsson, 1996) and influence hotel selection (Israeli, 2000; Chu and Choi, 2000; Reisinger and Turner, 1997). However, different customers (such as those who are and are not price sensitive) may be influenced by different factors (Petrick, 2005). Efforts have been made to identify associations between customers' background and their satisfaction and expectations (Ariffin and Maghzi, 2012). However, similar customers may have different expectations in different contexts, depending on factors such as the season and any festivals in the destination. Trip mode, as a context, has usually been treated as one of the ordinary personal factors, on the same footing as gender, age, or income. However, people may have different expectations of hotels when they are traveling with different partners (such as family, friends, or as a couple) or for different purposes, such as business or leisure. However, no study has so far studied the effect of trip mode on customer expectations.

As mentioned above, many studies use factor analysis, which cannot analyze the associations between customer demographic attributes and their satisfaction with hotel factors. In other words, such work can identify the influence of hotel factors on customer satisfaction, but there is no way to use it to explain how the latter varies according to demographic attribute or trip mode. To fill this gap, the first goal of this study is therefore to analyze how customer expectations change with trip mode for groups of customers from the same background.

Existing studies mainly use surveys to collect data, which is expensive and often generates a limited sample size. With the development of information technology, another source of customer feedback is the ratings data generated online. Traditionally, rating systems have been administered by government organizations, tourism associations, or commercial bodies. However, the development of Internet technology and social networking has allowed various online rating systems to emerge which enable consumers to provide direct feedback. Compared with editorial recommendations, consumers prefer to rely on the opinions of peers who have similar interests (Smith, Menon, and Sivakumar, 2005). Data from online rating systems vary in format, capturing different hotel factors and using different scales. They normally adopt common conventions like a 5-point rating scale, and common hotel factors such as room, service, and location.

However, the design of rating systems generally varies across sites. For example, the hotel rating system of TripAdvisor (www.tripadvisor.com) uses six factors; value, location, room, cleanliness, sleep quality, and service. In contrast, Expedia (www.expedia.com) uses four factors: cleanliness, service, room, and hotel condition. Other systems only generate a single overall rating with no breakdown for individual attributes, such as VirtualTourist (www.virtualtourist.com). Furthermore, the same basic rating system may change its design over time. For example, the factor of check-in/front desk was originally included in TripAdvisor's rating scheme, but in 2011 was replaced by the factor sleep quality.

Moreover, the same hotel factor may have slightly different meanings across different rating systems. For example, Wang et al. (2010) examine a dataset collected from TripAdvisor, where room and sleep quality are offered for rating at the same time. However, other research may use datasets which contain a rating for room but not sleep quality (Chu and Choi, 2000). The meaning of the room rating is therefore different in these two cases, as in the first case users will tend to exclude sleep quality when giving feedback on the room (as it can be assessed separately) whereas in the second case the room evaluation will include a consideration of sleep quality. Moreover, traditional rating systems can only offer a limited number of user options. Therefore, it is impractical to include all possible aspects of a hotel and decompose all factors into sub-factors, that is, to deconstruct the factor of room into sub-factors such as room size, silence in rooms, room comfort, and room facilities.

In addition, another limitation of online rating systems is the absence of rating information. It is often not compulsory for a customer to provide ratings for all factors. Taken together with the inherent limitations of rating systems design, it is therefore not guaranteed that the data collected from various online sources will be complete or properly organized. It is therefore essential to preprocess it before embarking on further analysis. One of the important tasks to accomplish as part of this is to fill in the missing values.

To overcome this barrier, the second goal of this study is to utilize the sentiment mining technique to extract opinions from text-based review comments, and use these to fill in the missing values of the review data.

The main contributions of this work are therefore as follows:

- We define trip mode as an important context category and analyze customer expectations of the hotels they stayed in based on their self-selected trip modes.
- We use a data preprocessing method based on sentiment mining to fill the missing values in the hotel review dataset.
- We develop a rule mining algorithm to contrast positive and negative associations and detect the change in customer expectations when different trip modes are selected.

3. METHODOLOGY

To explore the relationship between trip mode and customer expectations of different hotel factors, a dataset with ratings for all hotel factors is required. This data can be partially collected from review sites. However, there will be many missing values as not all review sites provide, and not all customers complete, ratings for all hotel factors. Therefore, sentiment mining is used to extract and fill in those missing values.

Once the completed dataset with ratings for all hotel factors has been constructed, the method of Contrast Targeted Positive and Negative Rules Mining (CTR) is employed to identify contrast and frequent patterns. An overview of the framework is given in Figure 1. The two methods employed in the framework are described in the following sections.

*****Please Place Figure 1 Here*****

3.1. Data Preprocessing Based on Sentiment Mining

With the emergence of Web 2.0, an interactive experience has been provided to end users through technologies such as blogs, forums, Wikis, and review sites, none of which were possible in the static Web 1.0 environment. These social media applications have enabled users to express their opinions freely and to retrieve information from each other's views. A massive amount of text-based content has been created in the form of review comments. Typically, a user review may contain both ratings and text-based comments, where ratings across thousands of reviews can be easily aggregated. However, it is not an easy task to extract and aggregate information from text-based comments. The naïve method needs human experts to read through them and perform an analysis, which is impractical, if not impossible, when the dataset consists of thousands of comments. To remove the need for humans to carry out such time-consuming work, sentiment mining has emerged as a technique to enable computers to read and understand text. It has been successfully applied to various areas including tourism. Applications include ranking product reviews (Miao et al., 2009), finding spam reviews including fakes and irrelevant advertisements (Jindal and Liu, 2008), automatically identifying reasons for positive and negative online reviews (Kim and Hovy, 2006), identifying product features (Popescu and Etzioni, 2005), and extracting opinions from hotel reviews (Wang et al., 2010).

In this study, sentiment mining was used to extract positive/negative opinions of each hotel factor from the review comments. This was achieved using the following approach.

3.1.1 Part-Of-Speech (POS) Tagging

For all review comments, the POS Tagger developed by Toutanova, Klein, Manning, and Singer (2003) was used to mark each word as the corresponding part of speech (that is, noun, verb, and adjective) according to its definition and context. The POS Tagger has been reported to achieve 97% accuracy on a standard dataset of newspaper stories (Toutanova et al., 2003) and has been employed in various applications such analyzing textbook (Tanawongsuwan, 2010) and movie (Na, Thet, and Khoo, 2010) reviews.

3.1.2 Hotel Factors Classification

Based on the results of POS tagging, the most frequently used nouns were identified and a list of keywords for each hotel factor extracted from them, such as the keyword “staff” for the factor service. Each review comment was then split into sentences, which could be further classified into a hotel factor if they contained one or more relevant keywords. Only words marked as nouns by POS Tagger were used for hotel factor matching, and one sentence could be classified in multiple factors if it matched more than one keyword.

3.1.3 Positive/Negative Opinions Detection

After all the sentences in all review comments had been labeled for hotel factors, SentiWordNet 3.0 (Baccianella, Esuli, and Sebastiani, 2010) was then used to calculate the positivity, negativity, and subjectivity scores for each word in each sentence, based on its definition and POS tag. Only the positivity and the negativity scores were retained and summed to generate overall scores for each word, which were then summed in turn to give an overall score for the sentence. Finally, for each review comment, the score for each hotel factor was calculated based on the scores of all sentences relevant to it. The final score ranged from −1.0 to 1.0, where a higher value indicates a positive opinion, and a score of 0 indicates that either the neutral opinion or the hotel factor is missing from the review comments (that is, no review comment is relevant to that factor).

Through this process, positive/negative opinions on each hotel factor can be extracted from the available review comments. If an opinion on a factor is missing from the review data, the extracted positive/negative opinions can then be used to approximate the ratings for different factors.

3.2. Change-Detecting Model Based on CTR

In this section, we introduce the basic concept of association rule mining, followed by the CTR method proposed by Law, Rong, Vu, Li, and Lee (2011).

3.2.1 Association Rule Mining

This is a data mining technique for discovering interesting relationships between multiple attributes in a dataset. The relationship is precisely defined in the form of an association rule. Given a transactional dataset T = $\{t_1, t_2 \ldots t_n\}$ where n is the number of transactions, the set $I = \{i_1, i_2 \ldots i_m\}$ contains the m possible items which appear in the transactional dataset T. A, B $\subseteq$ I are two nonempty item-sets, and $A \cap B = \emptyset$. With the above notation, a typical association rule can be written as $A \Rightarrow B$. The item-set A on the left is the antecedent of the rule, and the item-set B on the right is its consequent. Association rules can be constructed from the dataset T by following two steps:

Identify frequent item-sets. Not all possible item-sets A and B will be capable of forming association rules, where the support of A∪B must be greater than a user-specified minimum support value δ_S. The support of A∪B is defined as follows.

$$(3.1) \qquad supp(A \cup B) = \frac{number\ of\ transactions\ that\ contain\ A\ \cup B\ in\ T}{total\ number\ of\ transactions\ in\ T}$$

If the support of A∪B is greater than the user-specified minimum support δ_S, A∪B is called a frequent item-set. A frequent item-set is a set of items appearing together frequently in the dataset, where the support value indicates the frequency. The algorithm will identify all possible frequent item-sets from T.

Generate strong rules. A large number of association rules can be derived from the frequent item-sets, where the significance of correlation between antecedent and consequent are different. To identify association rules with significant correlation, the measurement confidence can be used. This is defined as follows:

$$(3.2) \qquad conf(A \Rightarrow B) = \frac{supp(A \cup B)}{supp(A)}$$

Association rules with high confidence are considered as strong rules, which indicate a strong relationship between the antecedent and the consequent.

3.2.2 Contrast Targeted Positive and Negative Rules

For traditional association rule mining, frequent item-sets extracted based on user-specified minimum support δ_S are considered to be interesting. However, in the CTR method, infrequent item-sets are also of interest, as they can be used to construct negative association rules (Law et al., 2011). As mentioned previously, a typical association rule is in the form of $A \Rightarrow B$, which indicates the association between the antecedent and the consequent. Negative association rules, on the other hand, are in the form of $A \Rightarrow \neg B$. Furthermore, a CTR mining algorithm can target one or more specific attributes, which avoids generating uninteresting (or less applicable) rules.

Another, more important, difference is that the CTR mining algorithm can be used to contrast multiple datasets, whereas traditional association rule mining can only be applied to a single dataset. As our goal in this work was to contrast five trip modes in terms of customer satisfaction with hotel factors, the original review data was divided into five sub-datasets according to trip mode, and the CTR mining algorithm applied to discover precise associations between customers' attributes and their expectations of hotel factors, then to contrast these across the five trip modes.

A set of targeted positive/negative rules can be generated from the sub-datasets of the five trip modes. For illustration purposes, we describe the CTR mining algorithm on two datasets D_i and D_j, where the datasets have the same attributes. One or more attributes will be selected as the target attributes for contrasting, and their possible values are target values denoted as T_i, which will be the consequent of the association rules to be generated. The CTR mining is then accomplished through the following major steps:

Interesting Item-sets Identification. Given the original datasets D_i and D_j together with target values T_1, T_2, T_3… all possible level-1 item-sets are extracted. With the user-specified minimum support δ_s, level-1 item-sets can be divided into candidate interesting positive item-sets $A_i^{(k)} \cup T_j$, if $\text{supp}(A_i^{(k)} \cup T_j) \geq \delta_s$; and candidate interesting negative item-sets $A_i^{(k)} \cup \neg T_j$, if $\text{supp}(A_i^{(k)} \cup \neg T_j) \geq \delta_s$.

These two candidate item-sets will be further divided into interesting positive item-sets $F^{(k)}$ and interesting negative item-sets $I^{(k)}$ based on the user-specified criteria of leverage, which is a measure of the interestingness of item-sets. The leverage for candidate interesting positive item-set $\mathbf{A \cup T}$ is calculated as $\left|\text{supp}(A \cup T_j) - \text{supp}(A)\text{supp}(T_j)\right|$; and the leverage for candidate interesting negative item-set is calculated as $\left|\text{supp}(A \cup \neg T_j) - \text{supp}(A)\text{supp}(\neg T_j)\right|$.

The interesting negative item-sets will be retained without change, whereas interesting positive item-sets will be used to generate higher level item-sets. Combining all the interesting item-sets for both positive and negative item-sets will generate the interesting item-sets.

CTR Extraction. Interesting item-sets can be used to construct association rules. The conditional-probability increment ratio (CPIR) introduced by Wu, Zhang, and Zhang (2004) is used to measure the significance of the rules. On dataset D_i, the CPIR for targeted positive rules is defined as:

$$(3.3) \quad CPIR(A_x^{(k)} \Rightarrow T_y, D_i) = \frac{p_{D_i}(T_y|A_x^{(k)}) - p_{D_i}(T_y)}{1 - p_{D_i}(T_y)}$$
$$= \frac{Supp_{D_i}(A_x^{(k)} \cup T_y) - Supp_{D_i}(A_x^{(k)})Supp_{D_i}(T_y)}{Supp_{D_i}(A_x^{(k)})(1 - Supp_{D_i}(T_y))}$$

and the CPIR for targeted negative rules is defined as:

$$(3.4) \quad CPIR(A_x^{(k)} \Rightarrow \neg T_y, D_i) = \frac{p_{D_i}(\neg T_y|A_x^{(k)}) - p_{D_i}(\neg T_y)}{1 - p_{D_i}(\neg T_y)}$$
$$= \frac{Supp_{D_i}(A_x^{(k)} \cup \neg T_y) - Supp_{D_i}(A_x^{(k)})Supp_{D_i}(\neg T_y)}{Supp_{D_i}(A_x^{(k)})(1 - Supp_{D_i}(\neg T_y))}$$

Using the CTR mining algorithm, a set of association rules can be extracted from the datasets. Each rule has the CPIR values for each dataset, where these indicate the strength of the association rules. Once the CPIR values have been calculated for each rule on each dataset, differences as well as similarities can be detected.

4. EXPERIMENT

To understand customers' satisfaction levels and expectations of hotel factors across different trip modes, we analyzed an online review dataset using sentiment mining and the CTR algorithm. The analysis was carried out in two steps. Firstly, we extracted the customer opinions from text-based review comments to fill in the missing values for hotel attribute ratings. Secondly, we identified the differences as well as the similarities in customers' satisfaction and expectations of hotel factors across different trip modes.

In this section, we describe the data collection and analysis, and present the details of the experimental settings.

4.1. Data Collection

A dataset containing reviews of 93 Melbourne hotels rated 4-star and above was collected from TripAdvisor (www.tripadvisor.com). The collected reviews had been posted between July 2006 and March 2012. After filtering out reviews without enough information on the customer's profile, the final dataset contained a total of 6,196 reviews. Each review contained ratings for some hotel factors, some text review comments, and customer profile information. The dataset consisted of the following sections.

Demographic Information: Demographic information about the reviewers was collected, including gender, age, and location. In this experiment, location information was converted into the following categories: Melbourne, Interstate, New Zealand, North America, South America, Europe, Africa, and Asia. The demographic attributes of reviewers are listed in Table 1.

*****Please Place Table 1 Here*****

Travel Information: Travel-related information included trip mode, motivation, travel style, registered period, number of reviews, and number of cities visited. In this dataset, five trip modes were defined; couple, business, solo, friends, and family. The registered year varied among reviewers, and this information was recorded using the registered period, which was the subtraction of the current year (that is, 2012) from the year the reviewer had registered with the site. Details of travel-related attributes and labels are given in Table 1.

Review Information: Review information included overall rating and scores for each of the six hotel factors: room, service, value, sleep quality, cleanliness, and location. Each rating was scored using a 5-point scale ranging from 1 (terrible) to 5 (excellent). The ratings were converted into binary format, where 4 (very good) and 5 (excellent) were considered positive, and 1 (terrible) to 3 (average) as negative. Hotel factors are listed in Table 2. The year the user registered was subtracted from the year of the review to give the registered period, which is a measure of the customer's experience in using review sites. Finally, a text-based review comment was presented for each review. Details of review attributes are given in Table 1.

*****Please Place Table 2 Here*****

4.2. Experiment Design

In the experiment, satisfaction overall and with each of the hotel factors was analyzed using the CTR mining algorithm. However, it is often not compulsory for reviewers to give ratings for all factors. As a result, the dataset contained many missing values. A more complete dataset will enable a more reliable analysis to be performed. Fortunately, customer opinions expressed in text-based review comments can be treated as an alternative to the missing values.

To extract opinions from the collected review comments and hence fill in missing ratings, a list of 593 keywords was defined to indicate the hotel factors. By applying the data preprocessing method described in section 3.1, positive/negative opinions of different hotel factors presented in the comments were extracted and used to fill in the missing values in the corresponding review.

Having thus filled in the missing values, the CTR mining algorithm was then applied to detect changes in customer expectations across the five different trip modes. The targeted attributes of the CTR mining algorithm were set to overall satisfaction plus satisfaction with each of the six hotel factors; cleanliness, location, room, service, sleep quality, and value, as shown in Table 2. Each factor was selected alternatively while the other five were treated as the conditioning attributes. The dataset was divided into five sub-datasets based on trip mode, and then the targeted positive/negative association rules generated using the CTR mining algorithm.

Considering the size and complexity of the dataset, the user-specified parameters were configured as follows; the support threshold was set as 0.05, and leverage threshold as 0.001. Note that the difference and ratio thresholds were not set in the experiment, because rules that have both significant and minor differences were considered interesting for the purposes of this study.

5. FINDINGS AND ANALYSIS

5.1. Filling in Missing Ratings by Sentiment Mining

Applying the sentiment mining method to the dataset enabled customer opinions on hotel factors to be extracted. The extracted positive/negative opinions were checked against the ratings given in the reviews, which had been converted into binary format. Only cases where opinions on a hotel factor were expressed in both ratings and review comments were included in the evaluation. Accuracy (Olson and Delen, 2008) was used to evaluate performance, and the evaluation result is given in Table 3. It can be seen that the two most frequently mentioned hotel factors were location and service; whereas cleanliness and sleep quality were not explicitly mentioned in most comments. As well as the fact that customers tended to mention certain factors in their review comments, another reason for this imbalance is the difficulty of defining keywords for some factors, such as cleanliness and sleep quality. Unlike other factors, opinions on these attributes were often expressed implicitly using adjectives; for example the word “beautiful” may indicate a positive opinion of room cleanliness. However, it is difficult to tell whether such adjectives actually do refer to the hotel factor in question.

*****Please Place Table 3 Here*****

For hotel factors including value, room, location, and service, the algorithm was able to extract positive/negative opinions from the comments with an accuracy of around 80%. The accuracy for cleanliness and sleep quality was below 70%, because of the difficulty in defining corresponding keywords precisely.

Considering that the extracted ratings had a reasonable accuracy, missing values in the original dataset were filled in using the opinions extracted from the comments. The original dataset had 3,474 missing values, of which 1,603 were filled in using this approach.

5.2. Contrasting Customer Expectations by Trip Mode

To conduct this analysis, the CTR mining algorithm was used to generate contrast targeted association rules for the hotels' overall rating as well as the five trip modes (business, couple, family, friends, and solo). Altogether, the CTR algorithm generated 1,357 association rules, of which 642 were positive rules indicating positive ratings and the remainder were negative. The maximum difference of 0.5205 on CPIR measurement was found on the factor of sleep quality, for at least one group of travelers with similar personal attributes. In addition, a 50% difference in expectations of sleep quality was found across different modes.

Table 4 reports an average difference of 0.1352 among the five trip modes for all six hotel factors. In addition, it is worth noting that the ratings indicate a significant difference of up to 0.7500 in overall satisfaction. This indicates that differences were found in both expectations and satisfaction when the same person was traveling in different trip modes.

*****Please Place Table 4 Here*****

We found that in different trip modes, a group of travelers with similar personal factors or travel experiences could have different expectations of the same hotel factors. These findings are expressed as the rules listed in Table 5 and may be summarized with respect to the hotel factors as follows.

Cleanliness: Expectations of the cleanliness of hotel rooms differed significantly in different trip modes. Senior travelers (over 50), agreed that they sought a clean environment when traveling with family, partner and friends, but on a solo trip, their expectations of cleanliness were much higher (Rule 1). Cleanliness was quite important when traveling with family for those travelers who identified themselves as active and experienced sharers (that is, they had posted a large number of reviews and had visited more than 10 different cities around the world) (Rules 2 and 3).

It is interesting to note that all the Melbourne-based travelers who had posted more than 50 reviews agreed that all the hotels they had stayed in were very clean (Rule 3). Travelers from European countries generally expected a clean environment more than those from other countries when traveling with friends (Rule 4). Melbourne travelers had higher expectations of cleanliness during business trips than other travelers, such that they usually gave lower ratings to this attribute when on business (Rule 5). However, travelers from both areas agreed that their hotels were clean and nice when they traveled alone.

Location: Most senior travelers picked hotels with good locations for all their nonbusiness trips (Rule 6). Convenient transportation and an advanced location can help a hotel to attract female customers traveling with friends (Rule 7). European travelers who splash out occasionally on travel showed more satisfaction with hotel locations on business and family trips (Rule 8).

Room: Young but experienced travelers were quite flexible in their selection of hotel rooms on solo trips (Rule 9). Europeans were not easily satisfied with hotel rooms when traveling with friends (Rules 10 and 11). Unlike Europeans, young Melbourne residents expected more of their rooms when they traveled with family, but were less concerned about this factor when traveling alone (Rule 12).

Service: Travelers in different age groups had different expectations of hotel services. Senior travelers said they had received the best service on family trips of all modes (Rule 13). In contrast, young travelers cared more about the quality of hotel services when they traveled alone or with family (Rule 14). There were also differences between Melbourne-based and European travelers. The former expected excellent service on their solo trips (Rules 15 and 16), but the latter wanted better service on their family trips (Rule 17).

Sleep Quality: Young European travelers said they only slept well on solo trips, such that they had high expectations of a good sleep environment for all other modes (Rule18). In contrast, senior travelers who had visited several cities enjoyed their best sleep on family trips, and only got enough rest on around 60% of their trips for business or with friends (Rule 19).

Value: Travelers who had visited more than 10 different cities agreed that they were quite satisfied with the value of the hotels they had stayed in for solo trips (Rules 20 and 21). People with less traveling experience cared less about price when traveling for business or with family rather than solo (Rule 22).

*****Please Place Table 5 Here*****

5.3 Common Customer Expectations across Trip Modes

While some customers' expectations varied among different trip modes, others did not change. These customers are identified in the association rules listed in Table 6. The profile and traveler behavior of these customers can be summarized with respect to the hotel factors as follows.

*****Please Place Table 6 Here*****

Cleanliness: Female travelers from Melbourne had consistently high satisfaction with cleanliness in all trip modes (Rule 23). The male travelers who prefer moderate life style also expressed positive opinions on cleanliness (Rule 24). Despite the gender factor, travelers who had visited many cities but whose reviews were limited also tended to be satisfied with cleanliness irrespective of trip mode (Rule 25).

Location: Some female travelers were experienced in online reviewing, having either used online review websites for a long time or having posted many reviews. This group said that hotel location had always met their expectations across all trip modes (Rules 26 and 30). Another group of female customers coming from interstate to Melbourne, including both experienced and inexperienced online users, also showed consistently high satisfaction with hotel location in all modes (Rule 27). When taking both genders into consideration, young travelers tended to be easily satisfied with hotel location regardless of trip mode, especially those who cared less about money but asked for the best service (Rule 28). This rule also applies to male travelers of different ages (Rule 29).

Room: As indicated by Rule 32, travelers who had spent neither too much nor too little were consistently satisfied with their hotel rooms if their primary motivation was just to have fun. Another group of travelers, identified in Rule 31, had visited many places, and posted many online reviews. This group also expressed consistent (although not high) satisfaction levels with hotel rooms in different trip modes.

Service: Those travelers motivated by having fun, who were less experienced with online review sites or whose budget was limited, tended to be satisfied with service irrespective of trip mode (Rules 33 and 34).

Sleep Quality: Rule 35 identified a group of travelers whose motivation was to have fun and who frequently posted online reviews. This group of travelers claimed that they did not sleep well in any trip mode. Similar claims were made by female frequent reviewers (Rule 36).

Overall: Many female travelers were identified as being consistently satisfied with different hotel factors. In terms of satisfaction with overall hotel performance, another sub-group of female travelers aged 35-49 also tended to be consistently satisfied (Rule 37).

6. IMPLICATIONS AND CONCLUSIONS

eWOM, including blogs, forums, and review sites, contains rich information generated directly by customers, and so provides a good opportunity for hoteliers to understand their market. However, these user-generated data are often incomplete compared with the high-quality data collected using traditional survey methods. As a result, such raw data, which contains undiscovered knowledge, is often not capable of being immediately analyzed using traditional methods of enquiry. The sentiment mining approach presented in this paper has acted as a bridge between the incomplete raw data and the new methods of knowledge discovery, in this case the CTR technique.

The association rules generated by the CTR technique suggest that some customers with the same backgrounds had different expectations of hotel factors when in different trip modes. For example, older customers who did not care about money but wanted the best service had higher expectations of service when on business, but were less sensitive to it when traveling with family. The results also confirm that there were customers whose expectations of hotel factors did not change in any trip mode.

This research has made some meaningful contributions to knowledge. Firstly, it has presented a practical application of sentiment mining in the tourism context. A data preprocessing method based on sentiment mining has been tested for the newly emerging and widespread sources of eWOM online. The idea can be applied to future work which involves online review data. Secondly, but more importantly, we have defined trip mode as an important category and utilized a CTR algorithm to detect changes in customer expectations across trip mode.

This work has also generated a set of interesting rules using the CTR algorithm. Significant differences in customer expectations have been found for different trip modes. This study shows that customers with the same backgrounds had varied expectations of hotel factors in different trip modes. Groups of similar customers have been identified where some have shown significantly higher/lower expectations in certain modes; on the other hand, other groups have been identified with consistent expectations across all modes.

This study employed a dataset collected from a review site with some missing values, and imputed these ratings using text comments identified through sentiment mining. However, there is potential to improve the process of extracting opinions about sleep quality and cleanliness, given the difficulty in defining corresponding keywords. Therefore, a natural extension of this work would be to overcome this limitation by employing more sophisticated methods of sentiment mining, or by defining a more precise and comprehensive keyword list. By doing so, more association rules could be obtained and contrasted.

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Table

Table 1: Attributes in the Online Review Dataset

Attribute	Description	Possible values	Label
DEMOGRAPHIC ATTRIBUTES			
AGE	Age	1 (Under 24)	age1
		2 (25 – 34)	age2
		3 (35 – 49)	age3
		4 (50 – 64)	age4
		5 (65 years old or above)	age5
GENDER	Gender	1 (Male)	male
		2 (Female)	female
RESIDENCE LOCATION	Location of the residence	1 (Melbourne)	melbourne
		2 (Interstate)	interstate
		3 (New Zealand)	nz
		4 (Europe)	europe
		5 (Africa)	africa
		6 (South America)	samerica
		7 (North America)	namerica
		8 (Asia)	asia
TRAVEL EXPERIENCE ATTRIBUTES			
TRIP MODE	Trip mode	1 (Business)	business
		2 (Couple)	couple
		3 (Family)	family
		4 (Friends)	friends
		5 (Solo)	solo
TRAVEL MOTIVATION	Travel motivation	1 (For fun)	fun
		2 (For work)	work
		3 (Both fun and work)	workfun
TRAVEL STYLE	Travel style	1 (Middle of the road)	style1
		2 (Nothing but the best)	style2
		3 (Splurge occasionally)	style3
		4 (On a tight budget)	style4
		5 (Roughing it)	style5
ONLINE REVIEW EXPERIENCE ATTRIBUTES			
REGISTRATION PERIOD	Number of years since registration	0 (less than a year)	registered0
		1 (1 year)	registered1
		2 (2 years)	registered2
		3 (3 years)	registered3
		4 (4 years)	registered4
		5 (5 years or above)	registered5
NUMBER OF REVIEWS	Number of reviews posted by the reviewer	1 (1 review)	reviews1
		2 (2-10 reviews)	reviews2
		3 (11-50 reviews)	reviews3
		4 (51 or more reviews)	reviews4
NUMBER OF VISITED CITIES	Number of visited cities	1 (1 city)	cities1
		2 (2-10 cities)	cities2
		3 (11-50 cities)	cities3
		4 (51 or more cities)	cities4
REVIEW COMMENTS	Text-based review comments	Text	Text

Table 2: Hotel Factors

Attribute	Description	Label	
		Satisfied	Unsatisfied
OVERALL	Overall rating	overall	¬overall
HOTEL FACTORS	Individual rating for each hotel factor		
CLEANLINESS	The cleanliness of the hotel room	cleanliness	¬cleanliness
LOCATION	The location of the hotel	location	¬location
ROOM	The style and facilities in the hotel room	room	¬room
SERVICE	The quality of the hotel services	service	¬service
SLEEP QUALITY	The quality of sleep in hotel room	sleep	¬sleep
VALUE	The price of the hotel room	value	¬value

Table 3: Evaluation of Positive/Negative Opinions Extraction

Dimension	No. of Positive Reviews	No. of Negative Reviews	No. of Correctly Classified Positive Reviews	No. of Correctly Classified Negative Reviews	Accuracy
value	2544	452	2158	141	0.7674
room	3720	529	3148	233	0.7957
location	4233	117	3488	39	0.8108
cleanliness	611	150	445	65	0.6702
sleep quality	122	51	94	19	0.6532
service	4378	572	3954	190	0.8372

Table 4: Customer Expectations of Hotel Factors against Trip Modes

Hotel Factor	Number of Generated Association Rules (Total)	(Positive)	(Negative)	Difference on CP IR (Maximum)	(Minimum)	(Average)
Cleanliness	173	99	74	0.5000	0.0284	0.1271
Location	114	67	47	0.4194	0.0164	0.1012
Room	192	105	87	0.4326	0.0071	0.1295
Service	222	114	108	0.5126	0.0170	0.1584
Sleep Quality	212	142	70	0.5205	0.0207	0.1473
Value	223	115	108	0.4028	0.0189	0.1505
Overall Rating	221	118	103	0.7500	0.0160	0.1576

Table 5: Association Rules of Contrast Customer Expectation against Trip Modes

Association Rule			Trip Mode					Difference	Ratio	Rule ID
			Business				Solo			
age4, style2	→	cleanliness	76.19	87.5	89.47	88.89	55.56	33.92	61%	Rule 1
cities3, reviews4	→	cleanliness	74.77	85.42	77.78	87.27	94.87	20.1	27%	Rule 2
cities4, melbourne	→	cleanliness	93.02	90.23	78.57	88.89	100	21.43	27%	Rule 3
europe, registered3	→	cleanliness	88.89	88.57	72.73	50	100	50	100%	Rule 4
melbourne, reviews4	→	cleanliness	75	91.6	92.31	87.1	100	25	33%	Rule 5
age4, registered1	→	location	78.67	91.06	90.32	100	100	21.33	27%	Rule 6
female, registered3	→	location	78.43	87.61	82.14	97.5	88.57	19.07	24%	Rule 7
europe, style3	→	location	91.67	87.69	92.73	73.91	83.33	18.81	25%	Rule 8
age2, reviews4	→	room	67.31	70.73	83.33	75.93	92.68	25.38	38%	Rule 9
europe, reviews3	→	room	76.54	81.36	74.51	38.1	69.57	43.26	114%	Rule 10
cities4, europe	→	room	79	74.38	67.27	52.63	85.71	33.08	63%	Rule 11
age2, melbourne	→	room	82.35	81.7	62.5	89.47	100	37.5	60%	Rule 12
age4, style2	→	service	59.52	79.17	94.74	88.89	77.78	35.21	59%	Rule 13
age2, registered5	→	service	86.96	77.42	55.56	85.71	50	36.96	74%	Rule 14
melbourne, registered2	→	service	85.71	78.75	86.96	83.33	50	36.96	74%	Rule 15
cities2, melbourne	→	service	88.89	80.49	77.14	94.12	42.86	51.26	120%	Rule 16
europe, registered5	→	service	86.67	79.1	60	100	83.33	40	67%	Rule 17
age2, europe	→	sleep	40.43	47.2	36.84	45.83	88.89	52.05	141%	Rule 18
age4, cities2	→	sleep	61.54	72.73	92	64.52	79.31	30.46	50%	Rule 19
cities4, europe	→	value	65	65.02	58.18	52.63	92.86	40.23	76%	Rule 20
cities3, registered4	→	value	61.9	74.23	76.32	88.24	100	38.1	62%	Rule 21
cities2, registered2	→	value	74.07	75.22	77.78	53.85	37.5	40.28	107%	Rule 22

Table 6: Association Rules of Common Customer Expectations across Trip Modes

Association Rule			Trip Mode					Difference	Ratio	Rule ID
			Business	Couple	Family	Friends	Solo			
female, melbourne	→	cleanliness	85.71	88.12	85.45	89.55	89.47	4.10	5%	Rule 23
male, style1	→	cleanliness	85.82	84.89	86.49	87.18	89.66	4.76	6%	Rule 24
cities3, registered1	→	cleanliness	86.32	85.48	88.89	88.00	90.91	5.43	6%	Rule 25
female, registered4	→	location	88.89	88.32	90.57	92.59	92.31	4.27	5%	Rule 26
female, interstate	→	location	84.86	89.30	86.47	89.38	88.24	4.53	5%	Rule 27
male, style3	→	location	83.43	88.12	88.14	83.54	83.33	4.80	6%	Rule 28
age2, style3	→	location	84.12	87.08	87.63	87.78	89.58	5.46	6%	Rule 29
female, reviews3	→	location	84.70	89.02	90.31	89.43	84.72	5.61	7%	Rule 30
cities3, reviews3	→	room	73.99	77.84	74.05	74.44	76.79	3.85	5%	Rule 31
fun, style1	→	room	79.09	76.26	80.98	81.42	76.62	5.15	7%	Rule 32
fun, style1	→	service	75.45	79.18	78.53	79.65	79.22	4.19	6%	Rule 33
fun,registered2	→	service	76.83	80.33	77.78	75.34	78.57	4.99	7%	Rule 34
fun, reviews2	→	sleep	62.12	61.80	59.64	61.47	60.38	2.48	4%	Rule 35
female, reviews3	→	sleep	57.65	59.39	57.27	60.98	61.11	3.84	7%	Rule 36
age3, female	→	overall	71.81	75.69	73.52	77.44	72.50	5.63	8%	Rule 37

Figure 1: Framework