A Fuzzy Decision Support Method for Customer Preferences Analysis based on Choquet integral

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Abstract—The explosion of the Web 2.0 platforms, with massive volume of user generated data, has presented many new opportunities as well as challenges for organizations in understanding consumer's behavior to support for business planning process. Feature based sentiment mining has been an emerging area in providing tools for automated opinion discovery and summarization to help business managers with achieving such goals. However, the current feature based sentiment mining systems were only able to provide some forms of sentiments summary with respect to product features, but impossible to provide insight into the decision making process of consumers. In this paper, we will present a relatively new decision support method based on *Choquet* Integral aggregation function, *Shapley* value and *Interaction Index* which is able to address such requirements of business managers. Using a study case of Hotel industry, we will demonstrate how this technique can be applied to effectively model the user's preference of (hotel) features. The presented method has potential to extend the practical capability of sentiment mining area, while, research findings and analysis are useful in helping business managers to define new target customers and to plan more effective marketing strategies.

I. INTRODUCTION

Decision making is one of the common tasks that many of us face in daily life. An action that people do naturally to support decision making process is to seek opinion from others. With the advances of Internet technology, the way that people communicate, express their view or seek opinions has been significantly changed by the online communication. With the explosion of Web 2.0 platforms such as *blogs*, *discussion forums*, *peer-to-peer networks*, and various other types of *social media*, the world has seen a revolution in social media which makes the use of social network web sites number one activity on the Web [1]. Information available on the Web has been indeed representing a potential gold-mine for companies to identify products and features which consumers are most interested in and how consumer's focus changes in response to a new advertisement campaign. Therefore, a clear overview of customer profiles has been considered as a key factor in accurate planning and decision making which are preliminary conditions for the success of today's business [2].

However, it is exactly the quality of massive volume of data that makes online information so powerful, also makes it hard to discover the sentiments contained inside. *Sentiment Mining* has emerged to be a powerful tool to deal with this issue by providing tools for automated opinion discovery and summarization [3]. As the matter of fact that people usually

make purchasing decision for a particular product based on a number of criteria such as the product features or their own preferences, the understanding of people's opinion expressed on each product feature is crucial. *Feature based sentiment mining*, a branch of *Sentiment Mining*, has grown out of this need [4]. The technique in this area is able to provide automatic discovery and summarization of opinion from online reviews with respect to product features [5]. For instance, features of a camera that people can express opinion on include *picture quality*, *size*, *battery life*, *price*, etc. The expressed opinion can be in one of the pre-determined polarities (*positive*, *neutral*, and *negative*) [4] or rating inferences such as *scores* and *stars* [6]. A feature based sentiment summary system can help evaluating review comments and report the number of positive/negative comments of features or overall score of the products [3]. In this way, users can have an overall picture of what other people opinions are, without wasting time to read all available reviews.

Despite great efforts were made in this area, the current sentiment summary systems are unable to provide insight into consumer's behavior. More specifically, a customer may give low rating on the *battery life* and the *size* for a camera but still purchase it as they like its *picture quality*. The identification of the key features, which significantly influence customer's decision making process, can provide business managers with guidance on what features to improve and how to promote the sale of their products. Unfortunately, the current feature based *sentiment summary systems* are only able to provide summary of sentiment from reviews, but do not allow to effectively evaluate the importance of each feature in relation to customer's preference.

In fact, the issue of modeling consumer's behavior with respecting to multiple criteria such as product features can be formulated into a *multi-criteria decision making* (MCDM) problem [7], which is usually supported by techniques such as the *Fuzzy Decision Support System* (FDSS) [8]. For instance, Ngai and Wat developed a FDSS for risk assessment in e-commerce development [9], Grabish and Roubens applied aggregation function, a fuzzy decision support technique, to MCDM for game theory [10]. Lu et al. proposed a multi-criteria group decision-making method to evaluate non-woven cosmetic product prototypes [11]. Recently, Ma et al. implemented a FDSS, called *Decider*, to increase the level of overall satisfaction for the final decision across the groups of

respondents [7]. Recently, more advanced FDSS for MCDM have also been created [12]–[14]. Therefore, it would be advantageous to consider those techniques to extend the practical capability of *feature based sentiment mining* in helping business managers to understand the MCDM process of consumers.

In this paper, we will introduce a relatively new fuzzy decision support technique, based on an aggregation function named *Choquet Integral* [15] into *feature based sentiment mining*. This technique is able to address the requirement of business managers in utilizing *sentiment mining systems* to support their business planning process. Using a fuzzy measure toolbox, named *fntools*, which was recently developed by Beliakov [16], we will present how FDSS can be applied to assess user preferences from product reviews collected from web sites. Our study case is an application in Tourism and Hospitality industry, particularly for Hotel industry in Singapore.

Having introduced the research motivation, the rest of the paper is organized as follows; Section II provides a brief overview of *feature based sentiment mining*, together with a critical review of existing works which applied FDSS into sentiment mining area. Section III introduces the concept of aggregation function together with the *fntools* toolbox that we use in this study. After that, Section IV describes our data collection, experiment design, and analysis of result finding. Section V summarizes this research and provides a vision on future research directions.

II. PRELIMINARY

A. Feature Based Sentiment Mining

The research of *feature based sentiment mining* was originally formulated by Hu [4], and is composed of the following four subtasks:

- 1) Identifying product features from review comments;
- 2) Identifying opinion words regarding product features;
- 3) Determining the polarity of opinion words;
- 4) Polarity determination of review regarding product features.

Since then, many researchers have been trying to improve the accuracy and efficiency of existing *sentiment summary systems*. Some works focused on improving the discovery of product features to explore in more details the aspect on which people express their opinions [17]–[19]. Others focused on identification of opinion words [20], [21], or special words, phrases and language constructs which have impacts on opinions [22]. While some attempted to improve accuracy in determining the sentiment polarity of sensitive words [5], or review text [23], [24].

In view of practical application, a number of attempts have been made to support user decision making process by creating *sentiment summary systems*. Some of the systems can show the numbers of positive and negative reviews [4], [25], or display them in percentage with respect to opinions about products (*cameras, mobile phones, etc.*) [18]. Others

are designed to summarize and show the overall rating on each feature about products [26], [27]. Users are also able to visualize the sentiment scores of different products in the same figure and this makes it easy for product comparison [28].

B. Fuzzy System for Sentiment Mining

The literature of sentiment mining have witnessed a number of attempts in using fuzzy system concepts to predict sentiment. Huettnner and Subasic hand-crafted a cognitive linguistic model for *affection* sentiments based on fuzzy logic [29]. Later on, they manually constructed a lexicon associating words with affection categories which can specify *intensity* (strength of affect level) and *centrality* (degree of relatedness to the category), then classified documents by fuzzy sets [30]. In recent works, Azrifah et al. proposed a fuzzy logic model to perform semantic classifications of customer's reviews into one of the classes: *very weak, weak, moderate, very strong and strong* by combinations of adjective, adverb and verb to increase the accuracy of lexicon approach [31]. Leung et al. used fuzzy string matching by regular expressions when identifying negation words [32]. In other works, the concept of aggregation function was applied in determining the orientation of opinion expressed on each feature [33]. Aggregation functions such as *average* and *sum* were also applied to calculate sentiment score of a document based on score of each term [34].

C. Problem definition and research objectives

In view of feature based sentiment mining applications, a major shortcoming of existing works in designing the *sentiment summary systems* is that the output information was highly concentrated on supporting decision making process of individuals. Organizations, companies and business managers who want to make use of these systems in business planning processes still face significant barriers. Namely, business managers would want to know what aspects of products are most concerned by consumers in order to improve and promote the sale of their products. Besides, it is important for business managers to be able to identify their target customers in designing marketing strategy, thus, they would want to know about *the preference of different target customers*. Such information is helpful for business managers to design marketing strategies which are more focus and effective. Existing works were not paying much attention to these aspects, and no significant attempt was made to satisfy such requirements.

For fuzzy system application, the properties of fuzzy set and aggregation function have been used in some sub-tasks of sentiment mining area. However, no specific application was found in supporting decision making process of business managers in the field of *feature based sentiment mining*. Besides, other properties of fuzzy measures such as *Shapley value* and *Interaction Index* have not found their application in this area yet, while their properties appear to be promising: *Shapley value* can be used to measure overall importance of each feature in contribution to final decision; while *Interaction*

Index can measure the interaction between features in decision making process [10].

On the other hand, we noticed that a recent work by Wang et al. [27] has a similar objective to our study in terms of weighting the features to analyze reviewer's rating behavior and preferences. An assumption of their work is that the overall rating is generated based on a weighted combination of the latent ratings over all the aspects, where the weights are to model the relative emphasis that the reviewer has placed on each aspect when giving the overall rating. However, this assumption is not close to reality, where the criteria are often not independent, and *positive* or *negative* interactions may exist among them. For instance, two or more features may refer basically to the same concept, the combination of input features such as the *weighted means* would double count the scores of those features. Therefore, such assumption may not be able to explore fully and model accurately the decision making process of consumers.

With the aim of addressing above limitations, we present an application of a new fuzzy decision support technique into *feature based sentiment mining*. This can help developing better *sentiment summary systems*, which provide better support for business managers in their planning process. In the context of Hotel industry, the objectives of this work could be seen as following:

- Introducing a new technique into *feature based sentiment summary system* which is able to evaluate the importance of features in product (hotel) rating process of consumers. Reviewer's profiles such as *background* and *travel type* will also be considered and reported.
- Exploring the usage of some metrics in fuzzy system such as *Shapley value* and *Interaction Index*, and evaluate their effectiveness in sentiment mining application of hotel industry.
- Demonstrating the advantage of the presented method in modeling the *multi-criteria decision making* process in consideration to criteria dependence, which is more practical for real life application.

III. METHODOLOGY

In this section, we firstly present the concept of aggregation function and fuzzy measures, then we describe how *Shapley value* and *Interaction Index* can be computed from fuzzy measures. After that, we will provide a brief introduction to the *fntool* toolbox which provides calculation functions for these metrics.

A. Aggregation Functions

Aggregation is the process of combining several inputs into a single representative output. Typically, the inputs and outputs are considered on the unit interval $[0, 1]$. Formally, an aggregation function can be defined as a function with $n > 1$ arguments, $f : [0, 1]^n \rightarrow [0, 1]$ with the following properties:

$$f(a_1, a_2, \dots, a_n) = 0, \text{ if } a_i = 0, \forall i \quad (1a)$$

$$f(a_1, a_2, \dots, a_n) = 1, \text{ if } a_i = 1, \forall i \quad (1b)$$

$$x \leq y \text{ implies } f(x) \leq f(y), \forall x, y \in [0, 1]^n \quad (1c)$$

Eq. (1a) and (1b) present the boundary conditions of this aggregation function. Eq. (1c) specifies the monotonicity condition with respect to the inputs, the partial order of vectors " $\leq$ " is understood component-wise. Besides, another property of aggregation functions is called *averaging*, which bounds its value by $\min(x) \leq f(x) \leq \max(x), \forall x \in [0, 1]^n$.

Two well-known aggregation functions are the *weighted arithmetic mean* (WAM) and the *ordered weighted averaging* (OWA) operator [35], [36]. However, the disadvantage of these methods is that they are only able to take into account relative weighting of individual inputs, while the MCDM process is usually performed under the relative influence within groups (coalitions). Therefore, we use another type of aggregation function named *Choquet Integral*, which is defined with respect to a fuzzy measure taking into account the interplay of non-independent criteria, and can thus handle this issue [37].

B. Fuzzy Measures

The computation of *Choquet* integrals is based on a fuzzy measure. Here we provide an introduction to its concepts. Let set $N = \{1, 2, \dots, n\}$. A discrete fuzzy measure is a set function $v : 2^N \rightarrow [0, 1]$ which is monotonic (i.e. $v(A) \leq v(B)$ whenever $A \subset B$) and satisfies $v(\emptyset) = 0$ and $v(N) = 1$. Since subset $A \subseteq B$ can be considered as a *coalition*, $v(A)$ is able to represent the importance or weight of this coalition. Note that, the monotonicity condition implies that its weight does not decrease when adding new elements to a coalition.

The discrete *Choquet* integral with respect to a fuzzy measure v is given by

$$C_v(x) = \sum_{i=1}^n x_i [v(\{j | x_j \geq x_i\}) - v(\{j | x_j \geq x_{(i+1)}\})] \quad (2)$$

where $x_1, x_2, \dots, x_n$ is a non-decreasing permutation of the input x , and $x_{(n+1)} = \infty$ by convention.

C. Shapley Value

Since the *Shapley* value measures the overall importance of each element in terms of its contribution to the score of each coalition, it can measure better the importance of each feature in contribution to multi-criteria decision making problem.

Let v be a fuzzy measure. The *Shapley* index for every input $i \in N$ is

$$\phi_i = \sum_{A \subseteq N/\{i\}} \frac{(n - |A| - 1)! |A|!}{n!} [v(A \cup \{i\}) - v(A)] \quad (3)$$

The *Shapley* value is the vector $\phi(v) = \phi_1, \dots, \phi_n$, and satisfies $\sum_{i=1}^n \phi_i = 1$.

D. Interaction Index

The *Interaction Index* is interpreted as the behavior of criteria in coalitions. Interaction index for every pair of input features $i, j \in N$ is defined as:

$$I_{ij} = \sum_{A \subseteq N \setminus \{i,j\}} \frac{(n - |A| - 2)! |A|!}{(n - 1)!} [v(A \cup \{i, j\}) - v(A \cup \{i\}) - v(A \cup \{j\}) + v(A)] \quad (4)$$

For any pair i, j , we have $I_{ij} \in [-1, 1]$. If i and j are positively correlated, then $I_{ij} < 0$. Similarly, if i and j are negatively correlated, then $I_{ij} > 0$. This measure is more than just the interaction between pairs of criteria by themselves. Each pair is considered in the presence of all coalitions. It may be that two criteria interact positively in isolation, but in larger groups they may contribute very little. Such behavior can be measured using *Interaction Index*.

E. FMTools

FMTools [16] is a software package implemented in C++ programming language for evaluating *Choquet* Integrals and performing operations on fuzzy measures. There are two main programs, fuzzy measure estimation and aggregation function, embedded in this toolbox.

Fuzzy measure estimation program learns the coefficients of a suitable fuzzy measure from observations by fitting Choquet integral to the data. The fitting is performed by minimizing the sum of absolute deviations between the predictions and observations, using linear programming techniques. The details are given in [15], [38]. Fuzzy measure estimation program is an executable named *fmfitting* which is compiled for MS Windows and Linux i386. It takes parameters from a configuration file. Some basic parameters for input file are N (the number of input argument), M (the number of data instances), *data`set* (name of file containing empirical data), *output* (name of output file). Given a data set containing M instances $x_1, x_2, \dots, x_M$, each instance x_i is composed by N inputs $x_{i1}, x_{i2}, \dots, x_{iN}$. Fuzzy measure v can be estimated from this data such that the corresponding *Choquet* Integral $f = C_v$ predicts the output y_k as close as possible in the least absolute deviation sense. The detailed description of optimization procedure for fuzzy measure estimation can be obtained from [16]. Then other values such as *Shapley* and *Interaction Index* can be computed following equations 3 and 4.

In general, the concepts of fuzzy measure and aggregation function have been utilized in some applications of decision making [10], [39]. *Choquet* Integral has also been used as an ordinal classifier in Journal Ranking application [40]. In this paper, we will focus on investigating the usage of *Shapley* value and *Interaction Index* in Hotel industry customer reviews analysis, which can address the shortcomings of existing feature based *sentiment summary systems*.

IV. STUDY CASE AND ANALYSIS

A. Data collection

The hotel review data set that we used in this study is collected from *TripAdvisor*¹, a well-known travel review web site which has been investigated in *Sentiment Mining* area [27], [41]. An advantage of this web site is that each review comment contains not only review text but also direct review rating for each hotel feature as well as an overall rating. Since our study focus on evaluating the importance of hotel features rather than sentiment prediction from review text, we only extract the hotel feature rating and overall rating from each review. The ratings for the hotels are in scale from 1 (*very disappointed*) to 5 (*very satisfied*), which includes value for money (*Value*), hotel location (*Location*), quality of sleep (*Sleep*), quality of room (*Room*), room cleanliness (*Cleanliness*), and additional service (*Service*). The hotel ratings and other reviewer demographic data such as traveler types (*business, family, couple*) and countries of origin are extracted automatically using a professional data extraction software, called *Visual Web Ripper*². The software navigated through all listed hotels in Singapore and extracted all review comments posted in year 2011. Note that, this is an automated process and some reviews did not provide rating for all 6 listed hotel features, and a number of data instances are with missing attributes. We removed all those missing data, and this left us with approximately 8790 records.

B. Experiment Design

Since our target is to study the preference and profile of consumers, we divide our data set into a number of sub-data sets according to reviewer's travel types and regions. Let us assume that people from different continents would have different backgrounds [42]. Therefore, we group the regions according to reviewer's continents of origin. It is interesting that, the majority of people are from *North America, Europe, Asia* and *Oceania*, while very few people are from *South America* and *Africa*. Thus, we only consider those four continents in this study.

Besides, we would like to evaluate the performance of *Choquet* Integral against typical methods such as the *weighted arithmetic mean* (WAM), the *ordered weighted averaging* (OWA) and the unrestricted *linear model* (LM). These experiments are carried out on the collected Hotel data set using 10-fold cross validation strategy. We use the *root mean square error* (RMSE) to measure the prediction error of those algorithms:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2} \quad (5)$$

where y_i is the value of the i^{th} input instance to be predicted, and $f(x_i)$ is the predicted value of y_i .

¹<http://www.tripadvisor.com>

²<http://www.visualwebripper.com>

More importantly, we will demonstrate the advantage of *Choquet* Integral by analyzing the *interaction index* outputs between hotel features. Notice that the input data to *Choquet* Integral is in the range $[0, 1]$, therefore, we perform normalization for all the hotel rating scores into this range before fitting them into *fmfitting* function.

In order to achieve the above objectives, we will perform two major experiments on the collected data set: 1) *model evaluation* and 2) *profile study of travelers*. The *model evaluation* experiment will be performed on Hotel features for different types of travelers to evaluate algorithm's performance. Then, the *profile study of travelers* case will construct a detailed profile for Hotel features preference of travelers with respect to travel groups as well as their regions of origin. The description of the sub-data sets for these analysis are shown in Table I.

TABLE I: Structure of sub-data sets for each experiment

Study Case	Travel Type	Region	Size
1	Business	All 4 Continents	2579 instances
	Couple	All 4 Continents	4066 instances
	Family	All 4 Continents	1916 instances
2	Business	Asia	1210 instances
		Europe	581 instances
		North America	407 instances
		Oceania	381 instances
	Couple	Asia	1169 instances
		Europe	1389 instances
		North America	320 instances
		Oceania	1188 instances
	Family	Asia	951 instances
		Europe	309 instances
		North America	131 instances
		Oceania	525 instances

C. Result Analysis

1) *Model Evaluation*: In this section, we evaluate the performance of *Choquet* Integral (CI) against other algorithms (WAM, OWA and LM). We use the sub-data sets of the first study case for evaluation purpose. Each of the sub-data sets for different travel types (*business*, *couple*, and *family*) is randomly divided into 10 sets. The algorithms are applied on 9 sets and tested on 1 set, and this process is repeated 10 times according to 10-fold cross validation strategy. The RMSE values are recorded and shown in Table II.

TABLE II: RMSE values of the evaluated algorithms.

Travel Type	Regions	LM	RMSE Values		
			WAM	OWA	CI
Business	All 4 continents	0.0966	0.0966	0.0987	<u>0.0955</u>
Couple	All 4 continents	0.0928	0.0928	0.0950	<u>0.0917</u>
Family	All 4 continents	0.0933	0.0934	0.0947	<u>0.0931</u>

From Table II, OWA appears to be the algorithm with the highest RMSE values. Most importantly, *Choquet* Integral has outperformed all others algorithms with lowest RMSE values. This evidence supports the claim that *Choquet* Integral can model the input data better than other popular algorithms.

Even though, *Choquet* Integral outperformed other algorithms in fitting input data, it is necessary to verify the *Shapley*

value of *Choquet* in evaluating the importance (*weight*) of feature. For this purpose, we compare the output weights of *Choquet* and a popular feature weighting method (WAM). In this case, the entire sub-data sets are fitted into IC and WAM, output weights of two algorithms on Hotel features for different travel groups are shown in Figure 1.

Fig. 1: Weights of Hotel Features estimated by Choquet Integral and WAM for different travel groups

From the Figure 1, we can see that there are some slightly differences between the weight of *Choquet* and WAM for all three data sets. However, the importance of each hotel features with respect to other features are relatively similar for both algorithms. More specifically, both *Choquet* and WAM evaluated features including the *value*, *room* and *service* to be significantly more important than other features in the case of *business* group and *couple* group. Besides, features including *location*, *sleep* and *cleanliness* are evaluated as slightly less important than the other features in the case of family group. These evidences indicate that *Choquet* Integral can preserve the relationship between feature's importance as the standard

TABLE III: Interaction Indices between Hotel Features for different Groups of Travelers

Travel Type	Interaction Index					
Business		Location	Sleep	Room	Cleanliness	Service
	Value	−0.017	−0.058	0.317	−0.058	−0.183
	Location		0.067	−0.058	0.067	−0.058
	Sleep			−0.100	−0.058	0.150
	Room				−0.100	−0.058
	Cleanliness					0.150
Couple		Location	Sleep	Room	Cleanliness	Service
	Value	0.017	0.156	−0.094	0.156	−0.233
	Location		−0.067	0.017	−0.067	0.100
	Sleep			0.044	−0.039	−0.094
	Room				−0.122	0.156
	Cleanliness					0.072
Family		Location	Sleep	Room	Cleanliness	Service
	Value	−0.108	0.058	0.142	0.142	−0.233
	Location		0.017	−0.066	−0.067	0.225
	Sleep			−0.067	−0.067	0.058
	Room				0.017	−0.025
	Cleanliness					−0.025

method WAM. Therefore, it is possible to use the weights that were generated by *Choquet* for feature evaluation purpose.

Analysis of Interaction Indices: Another advantage of *Choquet* Integral over the *weighted arithmetic mean* and the *ordered weighted averaging* operator is the ability of providing insight into the interaction between features. Here, we demonstrate such utility by analyzing the *interaction indices* between hotel features for different groups of travelers as shown in Table III. Note that, for a pair of features, a negative value represents a correlation or redundancy relationship, while a positive value represents a complementary effect.

From the pair-wise interaction of Hotel features in the Table III, we can see that, generally, most pairs show little interaction for all three groups of travelers. Even though, the *interaction indices* are expressing some interesting information as following:

- Most hotel feature pair in *business* groups show little interaction with each other as indicated by low interaction indices. Besides, *value for money* feature was found to have strong complementary effect with *room quality* (0.317), while, it is slightly redundant with *service* features. *Sleep quality* and *cleanliness* have considerably significant complementary effect with *service* feature as indicated by interaction index of 0.150.
- For people traveling as *couple*, *value for money* appears to have fairly high complementary effect with *sleep quality* and *cleanliness*, whereas, it is highly redundant with *service* feature. *Room quality* is slightly correlated with *cleanliness*, but complement with *service* feature.
- Similar to *couple* group, *value for money* feature is correlating with *service* feature for people traveling with *family* as shown by the *interaction index* of −0.233. In addition, *value for money* has significant complement effect with both the *room quality* and the *service* feature (0.142) Furthermore, it is interesting to see that *location* is highly compliment with *service* feature for this group.

2) *Profile study of Travelers:* The study of user profile is crucial for business managers in designing effective marketing

strategies. Thus, in this study case, we construct a profile for Hotel features preference of travelers with respect to travel groups and regions of origin. The sub-data sets for study case are input into *fmfitting* function. The *Shapley* values indicating the importance of hotel features are shown in Table IV

From the *Shapley* value in Table IV, the hotel preference profile of people traveling to Singapore can be constructed as following:

- **Business Group:** People from *Asia* care more about the features such as *value for money*, *room quality* and *services*, especially, *room quality* was the most concerned feature. For *European* and *Oceania* travelers, their preferred features are *room quality* and *service* as indicated with high *Shapley* values, particularly for *service*, it is highly considered by *Oceania* people (0.367). On the other hand, business people from *North American* countries are considering more the *value for money* and *sleep quality* features of hotel.
- **Couple Group:** It is interesting to see that *Asian* and *European* people are paying high attention to *value for money* feature when they travel with their partners. Besides, *European* people are also concerning more about *service* feature. For *North American* and *Oceania* couples, their preferred features are *room quality* and *service quality*, especially, *room quality* was most important to *North American* people (0.303). In general, most hotel features are having certain level of influence to the overall rating of people traveling as *couple* as shown with relatively significant *Shapley* values (above 0.1).
- **Family Group:** The importance of *value for money* feature remain significant for *Asian* people in this group, while, *European* people care more about *room quality*. Besides, the preference for *room quality* is still high for *North American* people (0.317). Most interestingly, *service quality* is the feature which has heavy effect on decision making process of people from all regions when traveling with *family*, particularly for *North American* and *Oceania* people.

TABLE IV: Shapley values of Hotel Features rated by different Groups of Travelers

Travel Type	Region	Value	Location	Hotel Features			
				Sleep	Room	Cleanliness	Service
Business	Asia	0.250	0.042	0.108	0.258	0.142	0.200
	Europe	0.192	0.050	0.125	0.300	0.067	0.267
	North America	0.267	0.150	0.233	0.100	0.067	0.183
	Oceania	0.017	0.067	0.117	0.317	0.117	0.367
Couple	Asia	0.265	0.117	0.158	0.153	0.153	0.154
	Europe	0.225	0.075	0.125	0.158	0.142	0.275
	North America	0.150	0.067	0.114	0.303	0.150	0.217
	Oceania	0.100	0.100	0.183	0.217	0.133	0.267
Family	Asia	0.217	0.133	0.067	0.167	0.167	0.250
	Europe	0.142	0.125	0.167	0.233	0.117	0.217
	North America	0.092	0.092	0.042	0.317	0.117	0.342
	Oceania	0.100	0.203	0.119	0.092	0.186	0.300

D. Discussion

The above analysis of *Shapley* values and *interaction indices* have demonstrated that the presented fuzzy decision support system was able to provide hotel managers with a better understanding on travelers profiles and their preferences of hotel features. More specifically, they are able to create better business planning to improve hotel services by evaluating the importance of hotel features. Marketing strategy could be also improved with the profile construction for different travel groups from different regions. Consumer behavior was clearly understood through interaction index analysis of hotel features for people traveling with different purposes such as for business or for holiday with partner or family.

In view of sentiment mining application, this paper have considered the feature based sentiment mining under a new perspective which has not been implemented in existing sentiment systems. The presented fuzzy decision support method can provide more utility for feature based summary system in supporting organizations, companies and business managers in decision making process. The output result is easy to interpret and understand, and can thus be used directly by non-technical users. As this is general technique for modeling MCDM process, it can be applied into many areas such as retail industry for customer preferences about products, education industry for student preferences about course contents, politic for understanding the demand of people in society, etc. The presented study case for Hotels in Singapore has demonstrated its effectiveness in Tourism industry. Note that, although the assumption of this work is that the rating of opinion for each aspect should be available for review comments as on *TripAdvisor* web site. Such information can be mined directly from review text by applying other existing sentiment mining techniques when it is not already available. Therefore, the application of this method is not limited, and can be intergraded widely in most application of sentiment mining.

In view of fuzzy system area, this paper have demonstrated the usefulness of *shapley* value and *interaction index* with a real life application of tourism industry. Since, the presented aggregation function uses *Choquet* Integral which is able take into account the interplay of non-independent criteria and model the interaction between criteria. The MCDM process

of consumers can be modeled more accurately and closely to real life situation.

V. CONCLUSIONS

Due to the growth of internet technology and development of the Web 2.0, online environment has become an important channel for people around the world to seek and share opinions. This has presented a potential gold mine for businesses to construct profiles of target customers that support for their business planning process. *Feature based sentiment mining* has appeared to be a promising area to help business managers achieve such goals. However, existing summary systems were mainly designed to support for opinion seeking purpose under the perspective of individual users rather than organizations. Namely, existing summary systems were not focusing on answering questions such as *what are the key product features which are concerned most by people?*, and *what are the preferences of people from different backgrounds?*. Whereas, such information is particularly important for business managers to improve their products and create better marketing strategies.

In this paper, we have tackled those shortcomings of feature based sentiment summary systems by introducing a relatively new fuzzy decision support method which can model effectively the MCDM process of consumers. This is also the first attempt to explore the usage of *shapley* value and *interaction index* in application to Sentiment Mining area. This method was demonstrated to be better than other well-known techniques such as the *weighted arithmetic mean* and the *ordered weighted averaging*, since the use of *Choquet* Integral and fuzzy measure is not only able to model more accurately the nature of MDCM but also measure the interaction between criteria. With a case study for Hotel industry in Singapore, the result analysis have explored the advantages of this technique.

A natural extension of this work is to apply this technique into other areas (retail, education, politics, etc.) and take into account more aspects of discussed features in reviews. In view of sentiment mining application, online sentiment summary systems for business managers could also be developed to extend the benefits of sentiment mining in supporting decision making process for wider range of users.

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