Customer Analytics Using Multicriteria and Machine Learning: A Case Study on Foody Application Vietnam

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Abstract

Online platforms allow customers leave their opinions after using products or services. Data collected from customers is enormous. How to organize and transform the data to useful information is one of the most important work to improve future business strategies. This study focuses on customer analytics to define the potential certain groups of customers so restaurants can concentrate their efforts and to build a database system that includes a satisfaction rating scale in order to benefit in the customer's experience. This study applies a method combining machine learning (ML) techniques and multi-criteria decision making (MCDM), with the case study of customers on Foody Vietnam. Using the criteria rating data, the revised Fuzzy C-Means (RFCM) clustering technique builds descriptive modeling to discover customer segmentation while Random Forest (RF) technique builds predictive modeling to show satisfaction classification. Method Based on the Removal Effects of Criteria (MEREC) ranks the criteria that customers of each generated segment rate on the Foody platform, which are Location, Space, Quality, Service, and Price. The results give three segments of customers with different criteria ranking and a customer preference prediction. The study provides a better insight into customer understanding and therefore, helps restaurant owners in terms of improving overall customer experiences.

Keywords
Customer Analytics, Machine Learning, Multi-Criteria Decision Making, Revised Fuzzy C-Means, Random Forest

1. Introduction
Customer analytics is a process which a business uses all of customer data to understand better customer behavior. In the past companies focus only on VIP customers. But since the growth of service providers and products, companies change business strategies, trying to understand the needs of any customers to retain customer loyalty and increase market share (David and Galit, 2013). In a customer-centric economy, there is a trend to use analytic tools in customer relationship management to maximize customer value and decide on business strategy (Mirzaei and Iyer, 2014). In a competitive industry such as retails, customer analytics is considered one of the most controlling strategic weapons (Hossain and Yanamandram 2020). Customer analystics also promise to help the food and beverage industry perform much better (Shaeeali et al., 2020). For example, Ching and de Dios Bulos (2019) used different analytic techniques

analyzing data from Yelp to improve the restaurant's business performance; Akila and Shreedevi (2020) analyzed customers' opinions and comments on McDonald's website with the application of Machine Learning algorithms.

1.1 Problem statement
Foody Vietnam application (Foody.vn) is established in 2012 in Ho Chi Minh City and is considered a reliable network to search, review, and comment on different eating places such as restaurants, cafes, bars, karaoke shops, bakeries, coffee shops, etc. in Vietnam. Foody provides both website platforms and mobile apps for iOS, Android, and Windows Phone users to connect customers from all over the country and welcome them to all-sized eateries. So far Foody has over 300.000 locations over 1 million comments spread from different cities and provinces and approximately 39 million unique visitors. It is expected that Foody could utilize its massive amount of data to find approriate marketing strategy and enhance customer experience.

1.2 Objectives
This study applies machine learning techniques and multi-criteria decision making based on the data available from Foody Vietnam. The study helps Foody raise customer comprehension by looking at different customer segments, criteria that affect customer experiences, and suggesting approriate marketing strategies. The study also contributes to business and market research by delivering a new market segmentation technique.

2. Literature Review
2.1 Application of Machine learning techniques on Customer segmentation
In customer analytics, customer segmentation is one of the approaches that have been used to understand customers (David and Galit, 2013). The approach divides customers with the same characteristics into groups and each group has different attributes from the others in terms of preferences or behaviors. Many customer segmentation approaches using machine learning have been studied in various areas such as banking, retails, tourism, restaurants. For instance, Yuping et al. (2020) determined the latest trends of how customer segmentation is associated with individual credit evaluation by using Random Forest, Gradient Boosting Decision Tree, Logical Regression and BP Neural Networks. Zhou and Xu (2021) introduced a method of applying Web Mining, a new RFMT (Recency, Frequency, Monetary and Interpurchase Time) model, and Hierarchical Clustering to segment shopping customers on a retailer's website. Yadegaridehkordi et al. (2021) used dataset crawled from online ratings and reviews from TripAdvisor and applied K-means Clustering and Classification and Regression Tree to segment customers in the attempt of investigating travelers' choice attitude towards green hotels. Nilashi et al. (2021) worked on online reviews and applied Latent Dirichlet Allocation, Self Organizing Map and Classification and Regression Trees to understand what drove TripAdvisor customers in making decision about vegetarian restaurants.

2.2 Customer online reviews in the service business and restaurant
Customers these days tend to leave opinions on online media such as websites about certain products, services, restaurants, etc. (Akila and Shreedevi 2020; Hajli 2018; Huete-Alcocer, 2017). The appearance of social media simplifies the method of communication which involves sharing the experience, thoughts, and attitudes of customers with each other (Akila and Shreedevi 2020). In the case of Shopee Indonesia, a trending e-commerce channel in Southeast Asia, customer online reviews and ratings had a positive influence on purchase decisions, namely, 16,1% out of the total influence factors were contributed from the words and sharing experience of the buyers (Ardianti and Widiartanto 2019). In the on-demand food service context, customers' overall ratings in the review were measured to explore overall satisfaction. The performance of the drivers and ordering platforms were found to affect the overall satisfaction, and the higher the cost of the order the more possible customers leave the comments (Xu, 2021). In the restaurant business, Huifeng and Ha (2021) analyzed a survey of 274 respondents and the result showed that online customer reviews directly affect restaurant visit intention. Considering the factors that affect customers' revisit attention to restaurants, Yan and Chau (2015) based on 10,136 restaurant reviews from the online life community in China and concluded that food quality, price and value, service quality, and atmosphere played important roles on customer's decision.

3. Methods
The aim of this work is to deliver an approach in order to enhance customer understanding for the benefit of Foody, restaurant owners, and customer experience. In order to do so, we performed customer segmentation, criteria ranking,

and satisfaction prediction. The process is divided into three main phases with the Figure 1 showing the visualized process.

Phase 1: Applying a Revised Fuzzy C-Means (RFCM) method to cluster the customers into groups that have the same characteristics based on ratings.

Phase 2: Applying Method Based on the Removal Effects of Criteria (MEREC) to rank five criteria by segments to find out which criterion has the best performance and which does not.

Phase 3: Applying Random Forest (RF) to predict customers' satisfaction of a restaurant or eating place based on the ratings of the five criteria.

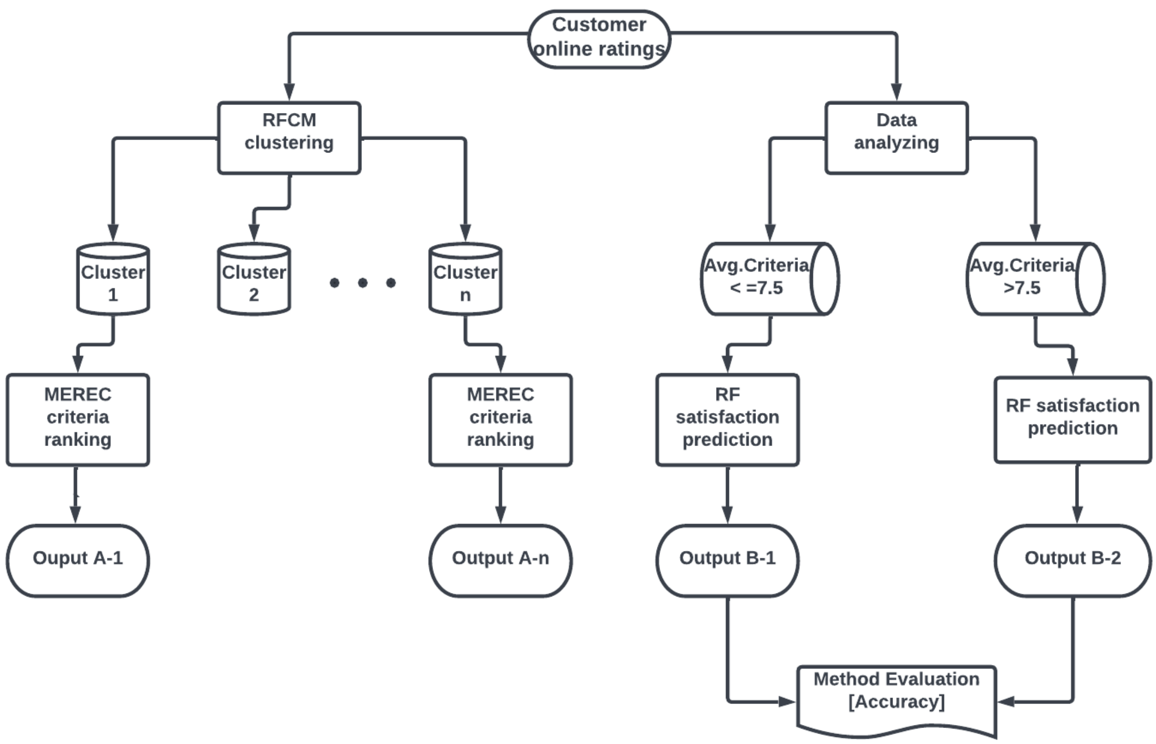

Figure 1. The Flowchart

3.1 Revised Fuzzy C-Means (RFCM)

Revised Fuzzy C-Means (RFCM) algorithm was developed by (Askari, 2021) based on Fuzzy C-Means (FCM) algorithm which was proposed by (Dunn, 1973) in 1973. FCM is a data clustering technique in which data points are grouped into different clusters. One data point will have a higher degree of belonging to one cluster than the others. However, FCM may perform inaccurate and misplace cluster centers due to the problem of noise and outliers, or when the sizes of the clusters are different leading to emerged centers of the small clusters to the larger clusters. RFCM was updated from the FCM to overcome its drawbacks. RFCM employs adaptive exponential functions to prevent the impacts of noise and outliers and adjusts constraints of the original algorithm to restrain large clusters from attracting centers of small clusters (Askari, 2021). Thus, there are two parts in the RFCM, the noise-resistant part (nrRFCM) and the size-insensitve part (siRFCM).

Size-insensitive part of RFCM (siRFCM)

- Objective function

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m} \left\|x_j - v_i\right\|_{A'}^{2} \quad , \sum_{k=1}^{c} u_{kj} = \rho_j(X, U) \tag{1}$$

- siRFCM algorithm

$Inputs: X, c, \varepsilon, m, \tau, p$
$U = rand(c, n)$

$for\ t = 1{:}\tau$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \ \forall i \in [1, c] \tag{2}$$

$$S_i = \frac{1}{|X|} \sum_{x_j \in A_j} \left(1 + \frac{u_{ij}}{|X|^p}\right) \ \forall i \in [1, c] \tag{3}$$

$$i = arg\, max_{r \in [1,c]}\left(u_{rj}\right) \ \forall j \in [1, n] \tag{4}$$

$$\rho_j = 1 - S_j \ \forall j \in [1, n] \tag{5}$$

$$\frac{\partial \rho_j}{\partial u_{ij}} = \begin{cases} -\frac{1}{|X|^{p+1}} \ if\ i = \ arg\, max_{r \in [1,c]}\left(u_{rj}\right) \\ 0 \qquad\qquad otherwise \end{cases} \ if\ \forall i \in [1, c], \forall j \in [1, n] \tag{6}$$

$$u_{ij} = \rho_j \left[\sum_{k=1}^{c} \left(\frac{\left(1 - \frac{\partial \rho_j}{\partial u_{kj}}\right) \left\|x_j - v_i\right\|_A^2}{\left(1 - \frac{\partial \rho_j}{\partial u_{ij}}\right) \left\|x_j - v_k\right\|_A^2} \right)^{\frac{1}{m-1}} \right]^{-1} \ \forall i \in [1, c], \forall j \in [1, n] \tag{7}$$

$if\ \left\|V^{(t+1)} - V^{(t)}\right\| \leq \varepsilon$

$stop$
$else$
end
end
$Outputs: U, V$

Noise-resistant part of RFCM (nrRFCM)

- Objective function

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m} f\left(\left\|x_j - v_i\right\|_{A'}^{2}\right), \sum_{k=1}^{c} u_{kj} = \varphi_j(X, U) \tag{8}$$

- nrRFCM algorithm

$Inputs: X, c, \varepsilon, m, \tau, p, \alpha$
$U = rand(c, n)$
$for\ t = 1{:}\tau$

$$s_{ij} = \left[\sum_{k=1}^{c} \left(\frac{\left\|x_j - v_i\right\|_A^2}{\left\|x_j - v_k\right\|_A^2} \right)^{\frac{1}{m-1}} \right]^{-1} \ \forall i \in [1, c], \forall j \in [1, n] \tag{9}$$

$$\omega_i^2 = \frac{\sum_{j=1}^{n} s_{ij}^{m} \left\|x_j - v_i\right\|_A^2}{\alpha \sum_{j=1}^{n} s_{ij}^{m}} \ \forall i \in [1, c] \tag{10}$$

$$u_{ij} = \varphi_j \left[\sum_{k=1}^{c} \left(\frac{\left(1-\frac{\partial \varphi_j}{\partial u_{kj}}\right) f\left(\left\|x_j - v_i\right\|_A^2\right)}{\left(1-\frac{\partial \varphi_j}{\partial u_{ij}}\right) f\left(\left\|x_j - v_k\right\|_A^2\right)} \right)^{\frac{1}{m-1}} \right]^{-1} \quad \forall i \in [1,c], \forall j \in [1,n] \tag{11}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m f'\left(\left\|x_j - v_i\right\|_A^2\right) x_j}{\sum_{j=1}^{n} u_{ij}^m f'\left(\left\|x_j - v_i\right\|_A^2\right)} \quad \forall i \in [1,c] \tag{12}$$

$if \left\|V^{(t+1)} - V^{(t)}\right\| \leq \varepsilon$
$stop$
$else$
end
end
$Outputs: U, V$

3.2 Method Based on the Removal Effects of Criteria (MEREC)

The MEREC introduced by Keshavarz-Ghorabaee et al., 2021 is used to calculate weights on criteria, which is a mandatory step in Multi-criteria decision-making (MCDM) approach. MEREC proposed a new perspective on determining objective weights of criteria. While some objective weighting methods such as Entropy, Standard Deviation, CRITIC (Criteria Importance Through Inner-criteria Correlation), SECA (Simultaneous Evaluation of Criteria and Alternatives) use the variations in different alternatives' performances concerning each criterion to determine weights, which means the more variation the bigger weights, MEREC defines its bigger weight when its removal leads to more effects on alternatives' aggregate performances.

MEREC algorthim

Step 1: Construct the decision matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1j} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2j} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} & \dots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nj} & \dots & x_{nm} \end{bmatrix} \tag{13}$$

Step 2: Normalize the decision matrix (N)

$$n_{ij}^x = \begin{cases} \frac{min_k x_{kj}}{x_{ij}} & if\ j \in \beta \\ \frac{x_{ij}}{max_k x_{kj}} & if\ j \in \mathcal{H} \end{cases} \tag{14}$$

Step 3: Calculate the overall performance of the the alternatives (Si)

$$S_i = ln\left(1 + \left(\frac{1}{m} \sum_j \left|ln\left(n_{ij}^x\right)\right|\right)\right) \tag{15}$$

Step 4: Calculate the performance of the alternatives by removing each criteria

$$S'_{ij} = ln\left(1 + \left(\frac{1}{m} \sum_{k,k \neq j} \left|ln\left(n_{ij}^x\right)\right|\right)\right) \tag{16}$$

Step 5: Compute the summation of absolute deviations

$$E_j = \sum_j \left|S'_{ij} - S_i\right| \tag{17}$$

Step 6: Determine the final weights of the criteria

$$w_j = \frac{E_j}{\sum_k E_k} \tag{18}$$

3.3 Random Forest (RF)

Random Forest introduced by Breiman 2001 is a machine learning algorithm which bases on Decision Tree (Breiman et al. 1984) and bagging (Breiman 1996). Decision Tree and Classification and Regression Tree (CART) is a series of splitting rules and addresses the classification problems by building the binary decision trees from the predictor variables to make the prediction (Breiman et al. 2017). However, CART tends to overfit the training data and can be non-robust which shows in a low accuracy. Random Forest was developed to overcome the drawbacks of CART. Random Forest uses bagging (bootstrap aggregation) and random feature selection. In general, Random Forest is a combination of many random independent Decision Trees.

RF algorithm

Step 1: Create a bootstrapped dataset which has the same size as the original dataset and random datapoints.
Step 2: Create a decision tree with the created bootstrapped dataset using a subset of random variables.
Step 3: Repeat step 1&2 until reaching a satisfied number of decision trees.
Step 4: Calculate the accuracy of the latest Random Forest.
Step 5: Change the number of variables.
Step 6: Repeat step 3,4&5 until reaching the most accurate Random Forest.
Step 7: Final output is considered based on Majority Voting or Averaging

4. Data Collection and Data Analyzing

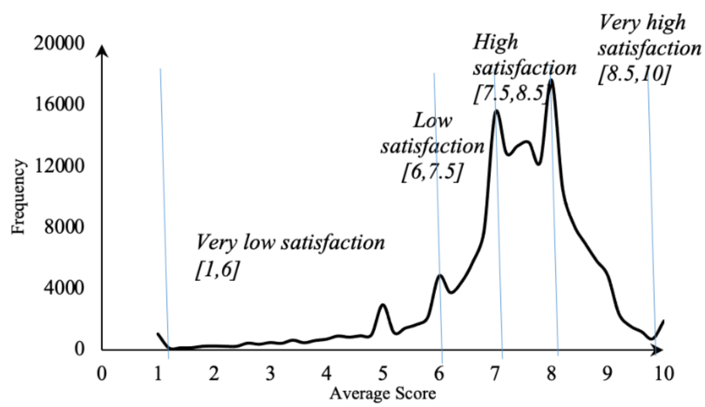

Figure 2. Characteristics of the full dataset

The data of 174,429 ratings collected from the app include five rating criteria: “Location”, “Space”, “Quality”, “Service”, “Price”. The average of the sum of five criteria of the full dataset is calculated. Category of satisfaction level is determined based on the “Leaf node” of the score data (Figure 2). The average score has a mean at 7.6 and a median at 7.3. Therefore, at the splitting point 7.5, the score is divided into two categories which are Low Satisfaction and High Satisfaction**.** For Low Category, the customers are considerd having “Very Low Satisfaction” if the average score is less than or equal to 6, and “Low Satisfaction” if the score between 6 to less than or equal to 7.5. For High Category, the splitting point for “High Satisfaction” and “Very High Satisfaction” is 8.5.

5. Results and Discussion

The RFCM technique results in three clusters or segmenst (Figure 3). There are 43.5% of customers belonging to segment 1, 8.8% segment 2 and 47.6% segment 3. Average score of segment 1 ranges from 7.2 to 10 with a peak at 8. Segment 2 occupies the smallest percentage, with scores ranging from 7.4 to 8.2 and a peak at 7.6. Segment 3 has the widest score range spreading from 1 to 7.6, and a peak at about 7.

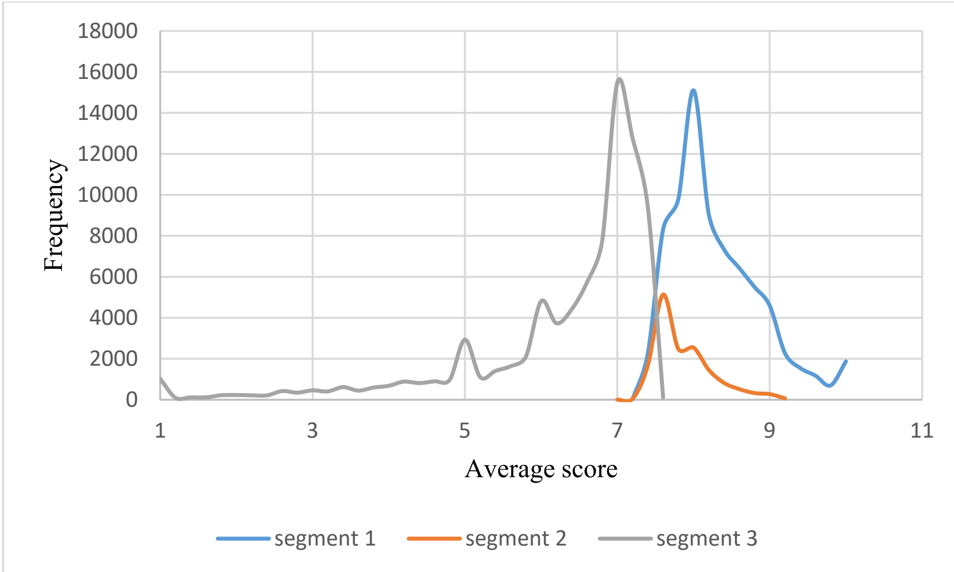

Figure 3. Characteristics of three segments

Table 1 shows the ranking of the criteria of performance. In segment 1, “Service” has the highest rank with 26.56 % in weight while in segment 2 and 3 “Location” has the highest rank. “Price”, “Space”, and “Service” receive the last place respectively for Segment 1, 2 and 3.

Table 1. Criteria ranking result

Segment	Criteria	Rank	Weight
1	Service	1	26.56%
	Location	2	25.92%
	Space	3	25.92%
	Quality	4	12.75%
	Price	5	8.59%
2	Location	1	25.94%
	Quality	2	25.46%
	Price	3	22.6%
	Service	4	16.77%
	Space	5	9.24%
3	Location	1	21.25%
	Space	2	20.18%
	Price	3	19.76%
	Quality	4	19.75%
	Service	5	19.06%

Figure 4 illustrates one of the 6 decision trees of the Low Satisfaction category's random forest while Figure 5 illustrates one of the 5 trees of the High Satisfaction category's random forest.

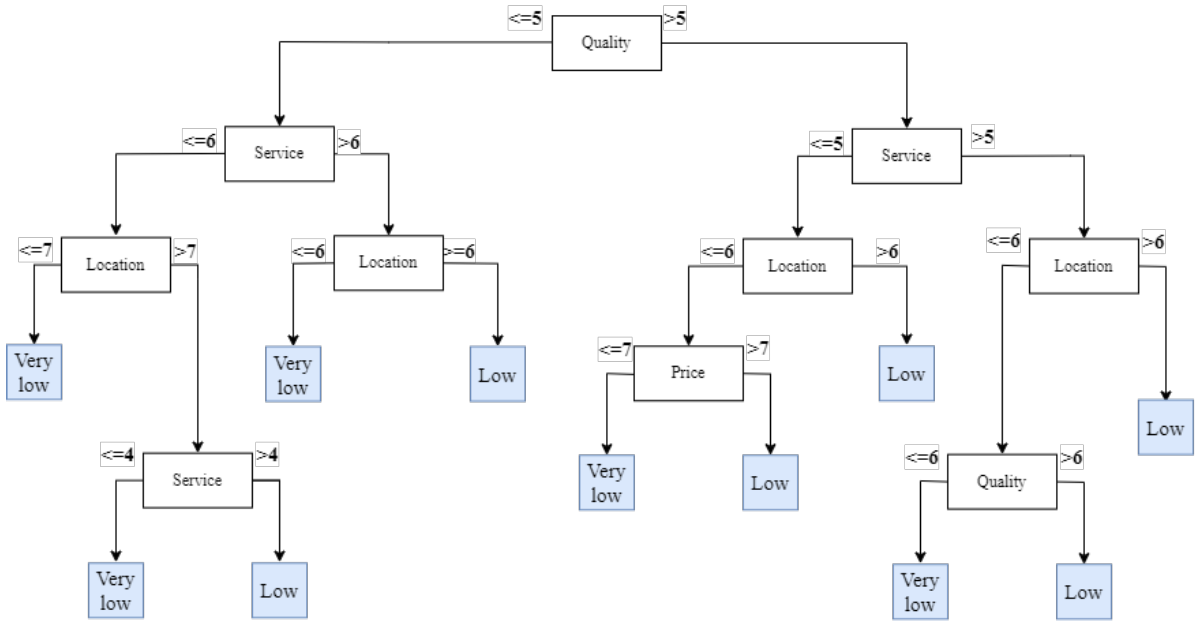

Figure 4. Random Forest for Low Satisfaction category

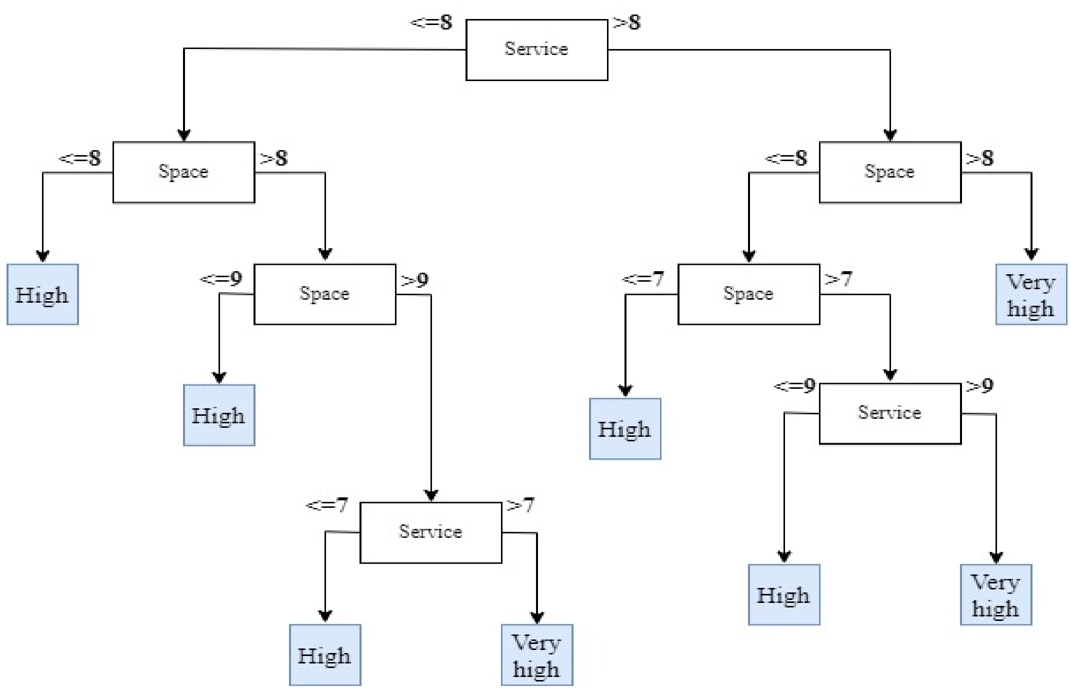

Figure 5. Random Forest for High Satisfaction category

Sensitivity test for Low & High Satisfaction category is performed with different numbers of trees and features in the Random Forest. By calculating the accuracy, Random Forest's result shows that for the Low Satisfaction category, the best result is given when there are 6 decision trees and 5 features with an accuracy of 93%. For the High

Satisfaction category, the Random Forest gives the best result when there are 5 decision trees and √5 features with an accuracy of 91% (Table 2).

Table 2. Sensitivity test for Low & High Satisfaction category

Number of trees	Number of features	Accuracy Low Satisfaction	Accuracy High Satisfaction
2	$\sqrt{5}$	83%	89%
3	$\sqrt{5}$	87%	90%
4	$\sqrt{5}$	84%	89%
5	$\sqrt{5}$	90%	**91%**
6	$\sqrt{5}$	86%	89%
2	$\log_2 5$	78%	85%
3	$\log_2 5$	81%	89%
4	$\log_2 5$	83%	88%
5	$\log_2 5$	80%	89%
6	$\log_2 5$	86%	89%
2	5	92%	89%
3	5	92%	89%
4	5	92%	90%
5	5	92%	90%
6	5	**93%**	90%

6. Conclusion

The study works on the customer analytics problem to help Foody business understand the customers, therefore, make a wise business decision as well as benefit customers with better service and experience since service is served distinctively. Different forms and promotional activities, different bundles and incentives can be used for different segments based on the unique needs and characteristics.

The work carries out three main phases including customer segmentation by applying Revised Fuzzy C-Means, criteria ranking by applying Method Based on the Removal Effects of Criteria, and customer satisfaction prediction by applying Random Forest.

The results suggest that segment 1 includes the group of customers that have best experience out of three segments, segment 2 includes the group of customers that have average experience from the restaurants and segment 3 includes the group of customers that have not-so-good experience. In terms of each segment, to improve customer experience, businesses can adjust the “Price” criterion for segment 1, create a better “Space” for segment 2 and provide better

"Service" for segment 3. With the predictive modeling created by Random Forest technique, when new customers approach the restaurant and give ratings on each criterion, restaurant owners can predict the satisfaction of the customers.

The future paper can continue to develop new methods to improve customer analytics problem. On top of that, instead of exploiting numeric online ratings, word reviews can be a great source of customer information to work on.

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