Abstract

A student-operated restaurant has to balance the achievement of its objectives as a profit generator and as a learning centre. This unique characteristic distinguishes a student-operated restaurant from other types of restaurants. This study aims to build a model to predict overall customer satisfaction in a student-operated restaurant. The input variables consist of 32 dining service attributes, which are derived from DINESERV factors. Data was collected using a close-ended questionnaire and was distributed using a convenience random sampling approach. A neural network model and a logistic regression model were built to predict overall customer satisfaction.

The result shows that the best neural network model built in this study was the MLP neural network model with two hidden layers. The correct classification rate of this model was 80.65% and 69.81% for the training and testing data set. The top three important attributes that influence overall customer satisfaction are customer satisfaction toward service, responsive service and excellent service.

In addition, the best logistic regression built in this study was a stepwise approach. This model had a correct classification rate at 73.39% and 69.17% for training and testing data set. The result of logistic regression shows that two significant dining attributes that influence overall customer satisfaction are customer satisfaction with service quality and food quality. Based on the correct classification rate, this study concludes that a neural network model has a better performance to predict overall customer satisfaction than a logistic regression model. However, a neural network model may not be the best model to determine the most significant input variable toward an output variable since it cannot be proven using a statistic method.

Keywords: customer satisfaction, neural network; logistics regression; student-operated restaurant

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1. Introduction

In the current economic decreasing, the restaurant industry sales are expected to exceed $1.5 trillion in 2009 - a 2.5 percent increase over 2008. This number represents 4% of the U.S. gross domestic product and employing 9% of the U.S. workforce (National Restaurant Association, 2009). In restaurant industries, customers are not only consuming tangible goods, such as food and drink, but also intangible services. Thus, establishing a good relationship between customer and frontline employee of a food service organization is a key factor to create a positive experience (Jaksa, Robert, & John, 1999). As other food and beverage outlets, a student-operated restaurant has to generate profit in order to cover its expenses. However, a student-operated restaurant has different characteristics from other types of restaurants. Other than as a profit generator, a student-operated restaurant also functions as a learning centre. To optimize the learning function, students experience job rotations regularly in order to make each student be an expert on various skills. Moreover, a student-operated restaurant is also operated by different students in each semester. The unique characteristics of this restaurant make it have a higher complexity to be analyzed than other types of restaurants.

This study aims to predict customer satisfaction, which is represented by the overall customer satisfaction level. Overall customer satisfaction is driven by customer perception toward the performance of dining satisfaction factors. These factors are derived from the DINESERV factors (Jaksa, Robert, & John, 1999; Stevens, Knutson, & Patton, 1995). Since the previous studies by Anderson & Sullivan (1993) and Kamakura, Mittal, De Rosa, & Mazzon, (2002) posit that an overall satisfaction shows a diminishing sensitivity toward dining attribute performance, this study applies a neural network model to classify customer satisfaction based on their perceived value toward the performance of the DINESERV factors.

The remainder of this paper is organized as follows. Section 2 reviews the literature on measuring customer satisfaction and neural network application. Section 3 explains the methodology used in this study including data collection and experiment processes, neural network models, and the performance metric used in this study. The following part explains the experimental results. Finally, the Section 5 of this paper describes the conclusion of this study.

2. Literature Review

Literatures that discuss studying the relationship between the performance levels of attributes and overall customer satisfaction can be classified into two groups. First group explains that the relationship between attribute level and overall satisfaction is linear and symmetric (Mittal, Ross, & Baldasare, 1998; Oliver, 1997). Linear relationship means that an increase in attribute level at a certain level leads to an increase of overall satisfaction at the same level and the decreasing of attribute level on a certain degree will lead decreasing overall satisfaction proportionately. The other group states that the relationship between attribute level and overall satisfaction is nonlinear and asymmetric (Anderson & Sullivan, 1993; Kamakura, et al., 2002; Mittal & Kamakura, 2001). That is, the impact of a certain increase is not equal to the impact of the same amount of decrease. That difference is not only in the term of level (size) but also in the term of direction (Anderson & Mittal, 2000).

Statistical methods and neural network are two main methods used to predict customer satisfaction. Some research applied statistical method, such as Eskildsen & Nussler (2000) who predicts customer satisfaction in several companies in Denmark by using partial least square, and Gustafsson & Johnson (2004) conducted customer research in pharmacy industry and employed multiple regressions and partial least square. In addition, Lariviere (2008) conducted a study of customer satisfaction in a financial service company and used structural equation model to analyze data. On the other hand, other studies employed neural network to predict customer satisfaction. These studies argued that the relationship between attribute level and overall satisfaction is nonlinear and asymmetric. Thus, statistical method, which depends on assumptions of linearity and non-collinearity between input variable, is not capable to perform well. Therefore, neural network has better capability to model customer satisfaction since neural network has the ability to deal with any non-linear functions, multi-collinearity within the input variable and capable to analyze data with any distribution (Lin, 2007). Two main areas of the application of neural networks in customer research studies are to determine the most critical attribute that influence customer satisfaction (W. Deng, 2007; W. J. Deng, Chen, & Pei, 2008; W. J. Deng, Kuo, & Chen, 2008) and to predict overall customer satisfaction (Behara, Fisher, & Lemmink, 2002; Lin, 2007). Furthermore, research that compare statistical method and neural
network to predict customer satisfaction have shown that neural networks perform better than statistical methods (Gronholdt & Martensen, 2005; West, Brockett, & Golden, 1997).

Neural network model is one of data mining techniques. Garver (2002) indicated that data-mining techniques has capability to perform better than traditional statistical techniques since data mining techniques are able to mitigate several assumption of statistical techniques, such linearity, multi-collinearity, and normal distributed data. Garver (2002) proposed the use of decision tree and neural network models to investigate customer behavior. In addition, Bounsaythip & RUNsala (2001) described many data mining techniques to model customer behavior. This study illustrated the application of K-Nearest neighbors, SOM, neural network, and decision tree to model customer behavior. It also pointed out advantages and limitations of each data mining technique.

Although many studies have applied data mining techniques to model customer behavior, none of these studies takes place in a teaching restaurant. A teaching restaurant is a unique business since students operate the restaurant. This type of restaurant also has to gain profit and maximize the learning rate of students. This study uses neural network models to forecast customer satisfaction in a teaching restaurant. The reason is that a neural network model is a supervised learning model and suitable for classification purposes. The models use customer perceived value toward attribute performance of DINESERV as input variable and use overall customer satisfaction as output variable. This study compares some neural network architecture available on PASW Modeler 13, such as multilayer perceptrons (MLP), radial basis function (RBF), quick, dynamic, prune and exhaustive prune method in order to find out the best neural network architecture for this study.

Finally, since many study pointed out that the limitation of the neural network is its inability to explain the relationship between input and output variable, this study conducted sensitivity analysis to explore the causal relationship between input and output as proposed by Sharda & Delen (2006). This study determined the most important attribute to be improved based on both variable (attribute) importance resulted from the model and the sensitivity of this attribute.

3. Method

3.1. Data Collection

This study used data that were collected through a sampling survey in Fajar Teaching Restaurant at Universitas Negeri Malang by distributing a closed-ended questionnaire to customer. The questionnaire consists of 6 parts: 1) questions of customer dining pattern, 2) customer perceived value toward dining attribute, 3) customer perception on their overall customer satisfaction, 4) customer retention and word-of-mouth, 5) customer perceived value on the student performance, and 6) customer demographic data.

This study used the second and the third part of the questionnaire only. Both of these parts used seven-points the Likert type scale. On the customer perceived value toward dining attributes, 1 refers to strongly disagree to the statement and 7 refers to strongly agree to the statement. On the customer perception of the overall satisfaction, 1 refers to strongly dissatisfied and 7 refers to strongly satisfied.

There were 257 valid responses used in this study out of 308 responses received from the survey. Invalid responses are caused by missing values on more than 25% of questions. Among 257 valid responses is not found any missing value. Thus, there is no treatment on replacing missing value on the data.

3.2. Data and Variable Definitions

The independent variables used in this study were derived from DINESERV factors, which cover food quality, service quality, price, convenience, and ambience. Based on frequency distribution of the data, the customer perceived value on scale 1 -3 has a small percentage compared to other point of scale. In average, the cumulative percentage on scale 1 to 3 is only 8.38%, which is ranged from 3.1% (friendly greeting) and 24.9% (music entertainment). Furthermore, the customer perception of overall satisfaction is ranged from 3 to 7. Thus, this study needs to transform the independent and dependent variable. Customer perceived value, which is ranged from 1 to 3, is transformed to 3. Thus, in the neural network model, there was only 5 point of scale: 3 to 7 point. This model contained 32 input variables and 1 output variable. The input and output variable names are shown in Table 1.
3.3. Neural Network Model

The first step to build the model is to divide collected data into three parts: training, validation, and testing data. Training data comprised of 50% of data, while validation and testing comprised of 30% and 20% of data. Random seed was used to generate each type of data. The neural network model was built in IBM SPSS Modeler. Based on the misclassification rate on testing data, this study found that MLP architecture showed the best performance. Since, this study had found that the best architecture was MLP, then the next phase was to find the best topologies of MLP. After several trials, for this study’s problem domain, two hidden layers MLP architectures consistently generated better prediction than a single hidden layer. This study assigned 32 processing elements (PE’s) in the input layer and assigned 20 and 10 PE’s to the first and second layers respectively.

Table 1. Input and Output Variables Name

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Variable</th>
<th>Description</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Quality</td>
<td>Service Quality</td>
<td>Convenienc</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3a Menu Variation</td>
<td>3i Greeting</td>
<td>3x Aisle in service area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3b Taste</td>
<td>3j Helpful Waiter</td>
<td>3z Menu card</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3c Food Appeal</td>
<td>3k Responsiveness Waiter</td>
<td>Comfortable</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3d Food Temperature</td>
<td>3l Friendly service</td>
<td>3v Clean Environment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3e Freshness</td>
<td>3m Respectful Waiter</td>
<td>3w Comfortable Layout</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3h Food Quality</td>
<td>3n Excellent Service</td>
<td>3y Clean facility</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>3o Knowledge about food</td>
<td>Satisfaction</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3f Portion</td>
<td>3p Self Cleanliness</td>
<td>4a Satisfaction to food</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3g Price</td>
<td>3q Follow standard food</td>
<td>4b Satisfaction to service</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3r Skillful</td>
<td>4c Overall satisfaction</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>3s Direct respond to</td>
<td></td>
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<td></td>
<td>3t Fast service</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>3u Food service</td>
<td></td>
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</tbody>
</table>

3.4. Performance metrics

This study used a success rate to measure the predictive performance of the neural networks. The percent of a success rate is the aggregate ratio of total correct classifications for all classes to the total number of samples in a particular classification problem. A higher success rate indicates a better classification performance.

4. Result

4.1 Neural Network Results

Since the aims of this study is to build the best performance of a neural network model in order to find out the relationship between DINESERV attributes and overall customer satisfaction, this study chooses a neural network model with the highest percent success rate in both training and testing data as the model reference to get the DINESERVE attribute importance. The confusion matrix of the best model used in this study is shown at Figure 1. This matrix shows the percent of the success rate in training, testing and validating data. The confusion matrix shows that the neural network model built in this study fails to predict the overall customer satisfaction when customer feel dissatisfy (level3). The possible reason for this result is that the relatively small percentage of customer who feel dissatisfy. Total number of dissatisfy feeling is only 3.1% of total respondents.

Figure 1. Confusion Matrix and Percent Success Rate of the Best Neural Network Model
The neural network model also provides the input variable importance, which implies the effect of each attribute to overall customer satisfaction level. Based on the variable importance, this study concludes that the top three important variables are customer satisfaction with the service quality (4b), responsive service (3t) and excellent service (3u).

4.2 Comparison with Logistic Regression

One of the common statistic methods for estimating classification problem is the logistic regression. Since this problem has a five-level of output variable, thus a multinomial logistic regression was chosen. After several trials, this study found that the stepwise method resulted in the best correct classification rate compared to other methods such as backward, backward stepwise, and enter. The backward and enter method resulted in 100% correct classification for training data set, but had a lower correct classification for testing data set (<15%). This study chose the stepwise method, which had a higher average correct classification rate and 68% of correct classification rate for testing data set.

After determining the method of the logistic regression used to select input variables, this study conducted several runs to find out the best setting parameter of the stepwise logistic regression to obtain the highest accuracy model. The coincidence matrix obtained from the logistic regression model with the highest correct classification rate is shown in Figure 2.

Based on the variable importance, the logistic regression shows that there are only two significant input variables on this study: customer satisfaction with the service quality (4a) and customer satisfaction toward food quality (4b). In addition, the result of the confusion matrix shows that the logistic regression is not able to predict overall customer satisfaction at level 3 (customer feel dissatisfied).

<table>
<thead>
<tr>
<th>Partition</th>
<th>1_Training</th>
<th>2_Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>91 73.39%</td>
<td>92 69.17%</td>
</tr>
<tr>
<td>Wrong</td>
<td>33 26.61%</td>
<td>41 30.83%</td>
</tr>
<tr>
<td>Total</td>
<td>124</td>
<td>133</td>
</tr>
</tbody>
</table>

Figure 2. Confusion Matrix and Percent Success Rate of the Best Logistics Regression Model

5. Discussion and Conclusion

The results shows that the best neural network model gained from this study has a correct classification rate at 80.65% and 69.81% for the training and testing data set, while the best logistic regression gained from this study has a correct classification rate at 73.39% and 69.17% for the training and testing data set. Thus, based on the success-hit rate, this study concludes that the neural network performs better than the logistics regression model. However, both of these models show consistently a wrong prediction on customer satisfaction level when the actual customer response is at level 3 (dissatisfied). Some possible reasons for these are the relatively small percentage training data set that provides responses of customer satisfaction level 3. Based on the previous explanation in frequency distribution section, there is only 3.1% of total data chose customer satisfaction level 3. It means that there might be less than 3.1% of training data contains customer satisfaction level 3. Thus, the model created either a neural network or a logistics regression fail to predict customer satisfaction at level 3. The other possible reason is that the decision to collapse the customer satisfaction level 1 – 3 as the customer satisfaction level 3 possibly leads to unbalanced customer perception since the neutral level becomes customer satisfaction at level 5, which is not true for this case study. Last, this study needs more trials to find out the best-mixed parameter either topology setting and learning rate for the neural network model or the stepping procedure and significant thresholds for the logistics regression model.

The neural network model shows that the top three important variables that influence overall customer satisfaction are customer satisfaction with the service quality (4b), responsive service (3t) and excellent service (3u).
In contrast, logistic regression model shows that two significant input variables that influence overall customer satisfaction are customer satisfaction with the food quality (4a) and customer satisfaction with the service quality (4b). Based on this result, this study cannot conclude which input variable is the most important variable since each model results in a different priority list of input variables. Thus, this study concludes that neural network models provide a better prediction compared to a logistics regression. On the other hand, a logistics regression provides statistically significant input variables that influence output variables, although it has lower prediction accuracy.

Reference