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Bank Customer Classification in Indonesia: Logistic Regression Vis-à-vis Artificial Neural Networks

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Abstract: This paper aims to identify factors distinguish Islamic and conventional bank customers in Indonesia. It tries to relate between bank customers' religiosity, assessment upon certain factors such as bank performance, bank advertisement and main reasons of using banking services towards their decision on which bank they had joined. Logistic regression and neural networks models are used to answer the research questions based on 520 customers reside in Jakarta. Data collection is done through a direct survey using self administered questionnaire. The results from logistic regression and neural networks models demonstrate that *shariah* compliant issues, customers' awareness on the fatwa announced by National *Ulama* Council on the impermissibility of bank interest, safety of fund as main reason of using banking services and customers' perception on bank advertisement are the significant factors which classify the bank customers in Indonesia. Nonetheless, neural network classifies better than logistic regression.

Key words: Neural networks · Classification · Bank customers · Logistic regression · Indonesia

INTRODUCTION

Banking in Indonesia has had a long history. Since colonial rule, it has been widely established foreign banks from both countries Dutch and other foreign countries as well as several local banks. Entering the time of independence, the government of the Republic of Indonesia began to establish state banks such as Bank Negara Indonesia (BNI), Bank Rakyat Indonesia (BRI), Bank Industri Negara (BIN) and the Postal Savings Bank. In addition to banks government, at that time also has operated several national private banks, foreign banks, rice barns, village banks and credit foundation. All banks, both government and private sector banks, continues to grow until the next period.

In 1992, competition between banks continued with the emergence of Bank Muamalat Indonesia (BMI), the first Islamic bank in Indonesia. Unlike the conventional banks, BMI was the only bank that could survive without any aids given by the government during the 1997 financial crisis. In fact, as the only Islamic bank in Indonesia until 1999, BMI was able to achieved capital adequacy ratio up to 12%, recorded as the highest among banks in Indonesia during the crisis.

Since that time, people start learning and patronizing Islamic banks. As a result, up to December 2011, there are 11 Islamic commercial banks with 1215 branches and 23 Islamic windows of conventional banks with 262 branches. The number of Islamic rural banks also increased significantly from 92 in 2006 to 153 in 2010. In total, there are 1,877 branches of Islamic banks spread around Indonesia to meet the needs of Muslims in the country. This is evidence that Islamic banking market share is growing further.

In this situation, when many banks operate side by side and the competition becomes more intensive, a better marketing strategy is needed by banks in order to gain more profit in their businesses. One of the best strategies is by being able to recognize the characteristics and patronize behavior of their customers. Therefore, this paper is aimed at providing an insight upon factors affecting bank patronize behavior of individuals, in the case of Indonesia.

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Literature Review: The study on customer's decision to patronize a specific bank has been done quite extensively. [1-3], for instance, identify bank's reputation as the main factor in determining customers' decision in using conventional banks' services, while [3, 4-6] say that profitability factors and service quality, such as low service charges and high interest rates, are the major reasons why customers chose a particular bank. [7] investigates the banking behavior of poor people in South Africa and found that a bank which can offer more beneficial products for its customers will have more opportunity to be chosen. Many more similar studies under conventional banking framework can be found but most of them had identified the same factors although the degree of importance of these factors might be different.

In contrast to the large number of studies in patronage behavior under the conventional banking framework, which could reach hundreds, similar study within the Islamic banking framework is inadequate [8]. The study done by [9] in Jordan is said to be the first study in the area. [9] utilizes self-administered questionnaire to gather information from 434 Jordanian individual customers, about their bank selection criteria. The result shows that instead of religiosity, other factors like rate of return, facilities and services provided and the bank reputation have appeared the main factors influencing individual customer to patronize Islamic bank.

In Malaysia, [10] studies the selection criteria of Muslim and non-Muslim customers in patronizing a particular bank. They have found that the most important factor considered by Muslims when selecting their financial institutions is "fast and efficient service" and this factor was ranked second by non-Muslims. The factor of "friendliness of bank personnel" is considered as the most important factor by non-Muslims and is ranked third by Muslim customers. The implication is that Islamic bank should not over emphasize and rely on, the religion factor as a strategy in its effort to attract more customers.

However, using profile analysis and non-parametric test, [11] find that the most important factors for the use of Islamic bank services are religion followed by profitability. In addition, [12] investigates the impact of selected economic variables on deposits level in the Islamic and conventional banking systems in Malaysia. They found that customers of conventional banks behave in conformity with the savings behavior theories. In contrast, most of these theories are not applicable to Islamic banking customers. Therefore, there is a possibility that religious belief plays an important role in the banking decisions of Muslim customers.

In Indonesia, Bank Indonesia [13] together with Bogor Agricultural University (IPB) conducted a series of Islamic bank selection surveys covering West, Central and East Java as well as West Sumatera and South Kalimantan from 2000 until 2005. The total number of respondents was approximately 7,000. The results indicate that the main factors in customers patronizing Islamic banks are level of education, service quality and convenience. Religiosity comes after those two factors.

Based on the previous studies and reasons given above, we therefore formulate our hypotheses as follows:

H1: Religiosity such as considering shariah compliant issue and paying zakat and shadaqah regularly significantly classify bank customer in Indonesia;
H2: Awareness upon the fatwa announced by National Ulama Council (MUI) regarding the impermissibility of bank interest significantly classify bank customer in Indonesia;
H3: Level of education significantly classify bank customer in Indonesia;
H4: Perception towards profitability given by Islamic banks significantly classify bank customer in Indonesia;
H5: Perception towards safety of fund provided by Islamic banks significantly classify bank customer in Indonesia;
H6: Perception towards facilities & services provided by Islamic banks significantly classify bank customer in Indonesia;
H7: Perception towards conveniences given by Islamic banks significantly classify bank customer in Indonesia;
H8: Perception towards Islamic banks' advertisements significantly classify bank customer in Indonesia;

MATERIALS AND METHODS

Data Collection: A total of 800 questionnaires were randomly distributed to bank customers. As many as 400 questionnaires were distributed to Islamic bank customers and remaining 400 questionnaires were distributed to conventional bank customers. However, some questionnaires are not fulfilled correctly and hence only 272 questionnaire from Islamic bank customers and 248 from conventional bank customers can be included in the analysis. Thus there are 520 questionnaires included in the analysis.

Table 1: Variables included in the model

Variable	Description
Y	1: Islamic bank's customer 0: Conventional bank's customer
X_1	Respondent knows/aware about the fatwa released by MUI ➜ 1: Yes; 0: No
X_2	Level of Education ➜ 1: University; 0: High school and below
X_3	Give charity/*shadaqah* regularly➜ 1: Yes; 0: No
X_4	Pay Zakat regularly➜ 1: Yes; 0: No
X_5	Profitability offered is the reason for choosing a bank➜ 1: Yes; 0: No
X_6	Safety of fund during financial crisis is the reason for choosing a bank➜ 1: Yes; 0: No
X_7	Facilities and services provided is the reason for choosing a bank➜ 1: Yes; 0: No
X_8	Convenience is the reason for choosing a bank➜ 1: Yes; 0: No
X_9	*Shariah* compliant is the reason for choosing a bank➜ 1: Yes; 0: No
X_{10}	Bank's advertisement is the reason for choosing a bank➜ 1: Yes; 0: No

Logistic Regression: This paper aims to investigate relationship between individual's attributes like education level and perceptions upon bank performances, facilities and attributes with their preferences in patronizing a bank in Indonesia. The dependent variable is binomial whereby code 1 means he patronized Islamic banks and code 0 means he patronized conventional banks for the time when they responded (Table 1).

In order to overcome the limitations in the distributions of the dependent variable, binary logistic regression has been widely utilized. Generally, binary logistic regression depicts the relationship between binomially distributed dependent variable with its explanatory variables by taking the logarithm of both sides of equation. The dependent variable is denoted by p, the probability of certain event happens.

The relationship tested in this study is described in equation (1) and (2).

$$p = \exp[a + b_1x_1 + b_2x_2 + ... + b_{10}x_{10}]/(1 + [a + b_1x_1 + b_2x_2 + ... + b_{10}x_{10}]) \quad (1)$$

$$\log(p/1-p) = a + b_1x_1 + b_2x_2 + ... + b_{10}x_{10} \quad (2)$$

Artificial neural networks (ANN): [13] provides the definition of Neural Networks as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It acquires knowledge through a learning process and stores the knowledge acquired in interneuron connection known as synaptic weights. Due to these two functions, for many scientists, Neural Networks resembles the human brain.

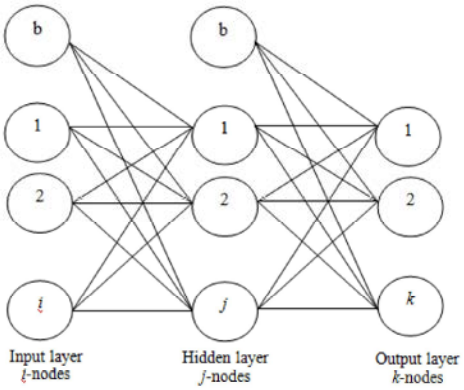

Fig. 1: Three layer ANN with biases

The work of a neural network is fundamentally based on a set of processing elements that are distributed in a few hierarchic layers which are input, hidden and output layers. The function of input, hidden and output layers are to process received information in real-time application from samples, to process and extract the data into meaningful information and generate conclusions respectively. Each layer consists of one or several nodes or neurons. Thus, after the tasks were done in every layer, the results will be passed to all of the neurons in the next layer, providing a feed-forward path to the output layer (Figure 1).

Since the output of one layer is an input to the following layer, the output of the network can be exhibited as in equation 3 [14]. Whereas Z is the output of the network, F is the transfer function in the output node, $W_{ij}^{(1)}$ and $W_j^{(2)}$ are connection weights from input layer (node i) to hidden layer (node j) and from hidden layer (node j) to output layer, respectively.

$$Z = F\left(\sum_{j=1}^{J} W_j^{(2)} \bullet U_j\right) = F\left(\sum_{j=1}^{J} W_j^{(2)} \bullet F_j\left(\sum_{i=1}^{I} W_{ij}^{(1)} \bullet X_i\right)\right) \quad (3)$$

The computation of synaptic weights, which is connecting neurons in one layer to other neurons in its adjacent layer, is known as training process. It is started by randomly choosing a number for synaptic weights and processes the data inputs.

Afterward, the network generate estimated output which will be compared with actual output and calculate the error subsequently. The value of the synaptic weights will be adjusted accordingly in order to minimize the network mean squared error.

Recently, many disciplines have adopted neural network methods to solve variety of research questions and objectives. It has been recognized in the literature that regression and neural network methods have become competing model-building methods ([14-17]). Neural network methods have also been used in the areas of prediction and classification.

RESULTS AND DISCUSSIONS

Descriptive Analysis: Respondents who are Islamic banks' customer total 272 (52%) and for conventional banks' customer total 248 (48%). There are 83.1% of the respondents are aware of the fatwa announced by MUI and that 79.2% and 75.8% respectively pay zakat and shadaqah regularly. Table 3 also shows that 57.3% of the respondents' level of education are university graduate while the rest are high school graduate and below. Therefore, it is believed that respondents involved in this study are educated and have enough knowledge on banking.

Logistic Regression: The overall percentage correct of 75 percent shows that the logit model is quite accurate predicting bank patronage behavior. However, the percentage of incorrect classification which is equal to likelihood to produce Type I error is quite high for both Islamic bank customer and conventional bank customer classification. The type I error is 20.6 percent and 29.8 percent for Islamic and conventional bank customer respectively (Table 3).

The estimated logistic regression developed in equation (2) is as shown in Table 4. The results show that 5 out of 10 explanatory variables have survived through this method of examination. Sorted by rank of marginal effect or relative contribution upon the model, shariah compliant is placed as the variable with highest impact towards bank patronage behavior in Indonesia followed by safety of fund reason, awareness on fatwa on impermissibility of bank interest, bank advertisement and performance of facilities and services.

From the odd-ratios provided by logistic regression, a customer who considers the shariah compliant issues before patronizing a bank is having possibility to become an Islamic bank customer 14 times greater than those with the opposite characteristic. Meanwhile, a customer who says that "safety of fund during the crisis" is his reason when choosing a bank is having possibility to become an Islamic bank customer 5.5 times greater than those who says differently. Similarly, the likelihood to patronize an Islamic bank for a customer who is aware about the fatwa on the impermissibility of bank interest is 5.3 times greater than who does not aware.

Table 2: Descriptive statistic

	Variable	Freq.	%
X_1	Knows the fatwa of MUI	432	83.1
	Does not know	88	16.9
X_2	University	298	57.3
	High school and below	222	42.7
X_3	Gives charity/*shadaqah* regularly	412	79.2
	Does not give charity/*shadaqah* regularly	108	20.8
X_4	Pays zakat regularly	394	75.8
	Does not pay zakat regularly	126	24.2
X_5	Profitability :yes	26	5
	Profitability: no	494	95
X_6	Safety: yes	362	69.6
	Safety: no	158	30.4
X_7	Facilities & Services provided: yes	280	53.8
	Facilities & Services provided: no	240	46.2
X_8	Convenience: yes	142	27.3
	Convenience: no	378	72.7
X_9	*Shariah* compliant: yes	104	20
	Shariah compliant: no	416	80
X_{10}	Bank's advertisement: yes	362	69.6
	Bank's advertisement: no	158	30.4

Table 3: Classification result using logistic regression

	Predicted		
Observed	Conventional	Islamic	% Correct
Conventional	174	74	70.2%
Islamic	56	216	79.4%
Overall Percent			75.0%

Table 4: Estimated coefficients and odd-ratios by logistic regression

ariable	B	Std. Error	p-value	Exp (B)
Shariah Compliant (X_9)	2.646	.407	.000	14.097
Safety (X_6)	1.718	.248	.000	5.576
Fatwa (X_1)	1.682	.310	.000	5.374
Advertisement (X_{10})	.667	.244	.006	1.948
Facilities&Services (X_7)	.526	.216	.015	1.692
Profitability (X_5)	.382	.468	.415	1.464
Shadaqah (X_3)	.289	.272	.288	1.335
Convenience (X_8)	.041	.249	.868	1.042
Zakat (X_4)	-.059	.263	.823	.943
Education (X_2)	-.256	.219	.244	.774

Hosmer and Lemeshow chi-square statistic = 6.774; df = 8; p-value = 0.561

Table 5: Classification result using ANN

		Predicted		
Sample	Observed	Conventional	Islamic	Correct %
Training (60% data)	Conventional	120	36	76.9%
	Islamic	33	138	80.7%
	Overall	46.8%	53.2%	78.9%
Testing (40% data)	Conventional	72	20	78.3%
	Islamic	17	84	83.2%
	Overall	46.1%	53.9%	80.8%

Table 6: Importance of independent variables by ANN

Independent Variable	Importance	Normalized Importance
Shariah Compliant (X_9)	.264	100.0%
Fatwa (X_1)	.166	63.0%
Safety (X_6)	.133	50.2%
Shadaqah (X_3)	.088	33.4%
Advertisement (X_{10})	.079	30.0%
Zakat (X_4)	.074	27.8%
Facilities&Services (X_7)	.069	26.2%
Profitability (X_5)	.057	21.8%
Education (X_2)	.035	13.3%
Convenience (X_8)	.034	12.7%

Of the question whether the model is fit or not is explained by the Hosmer and Lemeshow goodness-of-fit test. From the result of Hosmer and Lemeshow test, whereby shi-square statistic is 6.774 with degree-of-freedom is 8 and p-value is much greater than 0.05, we can conclude that goodness of fit test is valid for this model.

Artificial Neural Netwroks: Due to adopting the nonlinear functions, it is very difficult for neural networks to explain in simple terms the algebraic relationship between the dependent variable and independent variables. Furthermore, unlike regression model, the learned output or synaptic weights could not be explained and tested. Therefore, only the classification rates and the relative contribution factors are presented in Table 5 and Table 6 respectively.

The classification process done by neural networks exhibits better ability to learn and memorizes the pattern corresponding to customers' choice on bank type. It is done using one hidden layer and seven units determined automatically by estimation algorithm. The activation function used is softmax function which will take a vector of real-valued arguments and transforms it to a vector whose elements fall in the range (0, 1) and sum to 1. This function is most appropriate when the dependent variable is categorical. Neural networks result has higher overall percentage correct on customers' choice predictions than the logit model. Generally, neural networks perform better in classifying bank customers in Indonesia (Table 5).

Neural networks model uses the same numbers of independent variables as the logit model for the input layer neurons. The relative contribution factors presented in Table 6 show a medium level of consistency across the models. To recall the result from logit model, the first five and significant variables are Shariah Compliant (X9), Safety (X6), Fatwa (X1), Advertisement (X10) and Facilities & Services (X7) respectively. However, the independent variable importance built by neural networks is slightly different in ranks. Although X9, X1, X6, X10 are different in ranks, they are still the most importance variables in predicting customer decision to patronize a bank using neural networks model. Thus, these four variables must be considered and set as high priority factors by practitioners due to their strong impact on customers' decision on patronizing banks in Indonesia.

CONCLUSION

This study aims to provide factors distinguish between Islamic bank customers and conventional bank customers, particularly in Indonesia, using logistic regression and artificial neural networks models. Under both models, out of 10 explanatory variables, 4 are chosen as most importance factors which can be used to distinguish bank customers in Indonesia i.e. Shariah Compliant (X9), Safety (X6), Fatwa (X1) and the Bank's Advertisement (X10). It means that 3 out of 8 hypotheses are statistically proven.

Overall percentage correct of logit model classification upon the customers' group is 75 percent while neural networks model is 80.8 percent. In this regard, neural networks model is better off compared with logit model. However, the synaptic weights of neural networks model are very difficult to be interpreted and hence the relationship between dependent and independent variables is very difficult to be explained. Logit model takes this situation as its strength for researchers to utilize it.

Future researches can be directed in many ways such as (i) applying the same idea and method of analysis in different cities or countries, (ii) using different methods to demonstrate the robustness and the consistency of the results and (iii) comparing the Islamic bank patronage behavior of several countries simultaneously to find the similarities and differences.

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