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ARTIFICIAL NEURAL NETWORKS FOR CLASSIFICATION OF SOUVENIR DESIGNS

KOMSAN SURIYA[1], JANETTE WALDE[2]
Faculty of Economics[1]
Chiang Mai University
Chiang Mai, 50200, Thailand
suriyakomsan@yahoo.co.th

Department of Statistics, Faculty of Economics and Statistics[2]
University of Innsbruck
Innsbruck, A-6020, Austria

ABSTRACT. *The study constructs an Artificial Neural Networks (ANNs) for indicating successful souvenir designs with the evaluation on two issues. First, it evaluates the effect of pre-processing methods which are logit, discriminant analysis, principal component analysis and the search tree on the accuracy of the prediction. Second, it compares the performance of the model-free method, ANNs, and the fixed model method, logit. The accuracy rate is the multiplication between the hit ratio among the predictions of success and the overall hit ratio. The data are from 160 souvenir designs and 1,276 international tourists who visit Chiang Mai. The best pre-processing method is logit plus the search tree. The best architecture of ANNs is the model with one hidden layer including 3 neurons, logistic sigmoid transformation functions, and the training by Conjugate Gradient algorithm. The accuracy rate is 85.92 percent. The best ANNs yields a better accuracy rate than logit around 1.92 percentage points.*

Keywords: Artificial Neural Networks; Classification; Souvenir; Product Design; Product Development

1. Introduction. Souvenir production strengthens the economy of Upper Northern Thailand. It yields around USD 270 million per year to this second poorest region of the country (Suriya and Srichoochart, 2007). It also helps the poor in community-based tourism villages to get out of poverty (Suriya, 2010).

Souvenir design is crucial for the success of its commercialization. Although the region is famous for its authenticity embedded in the souvenir designs which are important for the buying decision of consumers (Shen, 2011), it needs an advanced technology to indicate successful designs to avoid wasteful production costs. Artificial Neural Networks (ANNs) is a hope for this task. It can extract knowledge from large data sets (Shobha and Sharma, 2005) or even from small data sets (Walde et al, 2004).

ANNs serves two purposes in general. First, it forecasts time series, e.g. Filik, Gerek and Kurban (2011 and 2009); Ma, Lu and Han (2011); Xue and Watada (2011); Kuo, Hu and Chen (2009). Second, it classifies matters in engineering issues, e.g. Cai, Zhao and Zhang

(2011); Li, Liu and He (2011); He, et al (2010); Li et al (2010 and 2005); Yu, Yan and Li (2010); Vachkov (2006); Machowski and Marwala (2005); Motoki, Koakutsu and Hirata (2005). Moreover, ANNs is useful for the classification in medical aspects, e.g. Tanprasert and Tanprasert (2011); Takeda, Shiraishi and Sanechika (2007); Kim et al (2006). Finally, it classifies consumer's decision in marketing issues, e.g. Li, Liu and Yang (2011); Wang, Chen and Zhang (2010); Chou, et al (2009) and Suriya and Prukrudee (2006).

This study tries to construct Back Propagation Artificial Neural Networks to classify successful and unsuccessful souvenir designs in the market of international tourists visiting Upper Northern Thailand. It focuses on two issues. First, As Bishop (2005) mentioned that an appropriate pre-processing method could lift the accuracy rate for the prediction of ANNs, the study evaluates the effect of pre-processing methods which are logit, discriminant analysis, principal component analysis and the search tree on the accuracy of the prediction. Second, it compares the performance of the model-free method, ANNs, and the fixed model method, logit.

2. Experiments on Pre-Processing Methods. The base case of the experiment is ANNs without pre-processing method. There are four experiments to evaluate the effects of pre-processing methods on the accuracy of ANNs' prediction; logit, discriminant analysis, principal component analysis and the search tree.

Each experiment will construct Back Propagation ANNs with one hidden layer. It will investigate the effects of different sigmoid transformation functions, tansig and logsig. It will figure out the performance using different training algorithm, Levenberg-Marquardt (LM), Conjugate Gradient (CGF) and Scaled Conjugate Gradient (SCG).

The training and validation sets are balanced between successful and unsuccessful souvenir designs. There are 80 and 30 designs in each set. However, the testing set is imbalanced with only 9 successful designs out of 50 designs.

The optimal number of neurons in the hidden layer can be obtained by varying the number from 2 to 15 and measuring the Mean Squared Error (MSE) of each model. Then, the model with minimum MSE will indicate the optimal number of neurons.

3. Comparison between ANNs and Logit. This section will compare the performance of the predictions by ANNs and logit. The best ANNs from the previous section will compete with a logit model which includes all dichotomous input variables, -1 or 1. Logit will use only significant variables for its prediction. ANNs and logit model primarily use 18 input variables as listed in table 1.

The accuracy index is the multiplication between the hit ratio among the predictions of success and the overall hit ratio. Then divide it by 100 to make it as the percentage as follows:

$$\text{Accuracy rate} = (\text{Hit ratio among the predictions of success} \times \text{Overall hit ratio}) \div 100$$

The hit ratio among the predictions of success is when ANNs predicts that a souvenir design is successful and that prediction is correct. The overall hit ratio is the ratio of correct predictions to all predictions.

This measurement is to avoid the benefits from the strategies of predicting only successful, only unsuccessful and half successful outcomes. The more outcomes that the model dares to predict successful designs and correct, the higher accuracy index will be achieved.

TABLE 1. Description of input variables

	CODE	*DESCRIPTION*
1	HANDMADE	Made by hand
2	WOOD	Made of wood
3	CLOTH	Mode of clothe
4	SILVER	Made of silver
5	NATRMATR	Made of natural materials
6	NATURE	The design is inspired by nature
7	LANNA	Lanna (Northern Thai) style
8	THAI	Thai style
9	ELEPH	Contains something related to elephant
10	SMALL	Small size
11	LIGHT	Light weight
12	TOLERENC	Not fragile
13	ROUND	Round shape
14	FOLD	foldable
15	PACK	Sold more than 1 piece at a time
16	USE	Function, not just decoration
17	BODY	Usable with human body
18	COLLECT	Collectible as collections

Note: All variables are binary choices with the value of -1 and 1.

For the data collection, catalogues of 160 souvenir designs were presented to 1,276 international tourists in the domestic departure lounge at Chiang Mai International Airport. A tourist chose two favorite designs from the catalogue. Successful deigns were defined as the designs with more than 10 times of being chosen. The rest was classified as unsuccessful designs.

4. Results. The following section presents the results from the prediction of ANNs with variety of pre-processing methods.

4.1 Classification without Data Pre-Processing. ANNs without pre-processing method uses 18 input variables. The result in table 2 shows that the model yields only around 12.35 to 14.60 percent of accuracy. The best model in this class is ANNs with one hidden layer, 3 neurons, tan-sigmoid (tansig) transformation function in the hidden layer, the logistic sigmoid (logsig) transformation function in the output layer and training Levenberg-Marquardt (LM).

TABLE 2. The performance of ANNs without data pre-processing

Transformation function	Training	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
Tansig, Logsig	LM	23.54	62.02	14.60
Logsig, Logsig	LM	22.88	60.44	13.83
Tansig, Logsig	SCG	21.93	60.58	13.29
Logsig, Logsig	CGF	20.94	60.52	12.67
Tansig, Logsig	CGF	21.02	59.62	12.53
Logsig, Logsig	SCG	20.7	59.66	12.35

Source: Calculation using Matlab

4.2. Classification with Pre-Processing Using Logit. After using logit as the pre-processing method, ANNs improves its accuracy rate to 32.36 percent. The overall hit ratio of the model improves to around 80 percent. However, the hit ratio among the predictions of success is lower than 50 percent. The best ANNs in this class uses only 5 variables. It includes one hidden layer, 3 neurons, logistic sigmoid transformation functions in both hidden and output layer, and training with CGF algorithm.

TABLE 3. The performance of ANNs with data pre-processing using logit

Transformation function	Training	Inputs	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
Logsig, logsig	CGF	5	40.15	80.60	32.36
Tansig, logsig	CGF	5	40.11	80.02	32.10
Tansig, logsig	LM	5	38.27	80.24	30.71
Logsig, logsig	LM	5	33.87	80.36	27.22

Source: Calculation using Matlab

4.3. Classification with Pre-Processing Using Discriminant Analysis. ANNs with the discriminant analysis as the pre-processing method yields the lowest accuracy rate, 3.46 percent. Both the hit ratio among the predictions of success and the overall hit ratio are low.

TABLE 4. The performance of ANNs with data pre-processing using discriminant analysis

Transformation function	Training	Neurons	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
Logsig,logsig	CGF	5	15.95	21.72	3.46

Source: Calculation using Matlab

4.4. Classification with Pre-Processing Using Principal Component Analysis. The principal component analysis as a pre-processing method slightly improves the performance of ANNs. The accuracy rates are around 12.55 to 17.21 percent. Varimax is the best strategy among rotation strategies.

TABLE 5. The performance of ANNs with data pre-processing using principal component analysis

Rotations	Training	Neurons	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
Varimax	CGF	6	26.89	64.0	17.21
Quatimax	CGF	3	20.57	61.8	12.71
Equamax	CGF	7	21.16	60.0	12.70
None	CGF	12	21.41	58.6	12.55

Source: Calculation using Matlab

4.5. Classification with Pre-Processing Using the Search Tree. In search of the most important variables to the dependent variable, five significant input variables from logit are included into the experiments. Then the search tree will combine two variables and find the performance of using the pair as the input variables of ANNs.

TABLE 6. The performance of ANNs with data pre-processing using logit plus the search tree

Input variable 1	Input variable 2	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
Elephant	Small	50.00	82.00	41.00
Elephant	Tolerance	17.31	20.24	3.50
Elephant	Pack	20.37	26.60	5.42
Elephant	Collectible	100.00	85.92	85.92
Small	Tolerance	0.37	76.88	0.28
Small	Pack	0.77	76.04	0.59
Small	Collectible	0.00	78.08	0.00
Tolerance	Pack	17.91	24.02	4.30
Tolerance	Collectible	17.05	20.56	3.51
Pack	Collectible	19.53	26.40	5.16

Source: Calculation using Matlab

Note: The architecture of ANNs includes one layer with 3 neurons, logistic sigmoid (logsig) transformation functions and training CGF.

The pair of variables Elephant and Collect yields the highest hit ratio among the predictions of success as well as the overall hit ratio. Moreover, the accuracy rate is high, 85.92. This is the first model that the hit ratio among the predictions of success is 100 percent.

4.6. Comparison between ANNs and Logit. Logit model predicts the successful souvenir designs by using only 5 significant variables with their coefficients in that model. Table 7 presents the estimation results of logit models with all 18 input variables and only significant variables which are Elephant, Small, Tolerance, Pack and Collect.

TABLE 7. Estimation result from logit
(input values are in -1 and 1 while output variable is 0 and 1)

Variables	(1) Full model	Standard error	(2) Model with significant variables	Standard error
ELEPH	0.6591*	0.3610	0.6921**	0.3371
SMALL	0.4782*	0.2539	0.4749**	0.2054
LIGHT	-0.2012	0.5208		
TOLERENC	1.1444**	0.5760	0.9623*	0.5330
ROUND	-0.1316	0.3574		
FOLD	0.2586	0.2379		
PACK	-1.3564**	0.6811	-1.0810*	0.5892
USE	0.9950	0.7060		
BODY	0.0563	0.2117		
COLLECT	1.5482**	0.6790	0.6819**	0.3318
HANDMADE	-0.1309	0.2797		
WOOD	-0.0107	0.2356		
CLOTH	-0.2646	0.2613		
SILVER	0.3501	0.3582		
NATRMATR	0.1415	0.2337		
NATURE	0.2691	0.2199		
LANNA	0.6334	0.4823		
THAI	0.2944	0.5484		
C	-0.5067	1.0315	-1.5444**	0.7597

Source: Calculation using Eviews

Note: Number in the bracket is standard error.

*** Significant at 99%, ** Significant at 95%, * Significant at 90%

The performances of logit and the best ANNs are quite similar. ANNs is superior by only 1.92 percentage points. Their differences come from the overall hit ratio while both of them yields the same 100 percent of the hit ratio among the predictions of success.

TABLE 8. Comparison the performance of ANNs and logit

Model	Input variables	Specification	Hit ratio among the predictions of success	Overall hit ratio	Accuracy rate
The best ANNs	2 variables	One hidden layer with 3 neurons, logsig and training by CGF algorithm	100	85.92	85.92
Logit	5 significant variables	The values of input variables are either -1 or 1.	100	84.00	84.00

Source: Calculation using Matlab and Eviews

5. Discussions. ANNs without data pre-processing takes too much variables into the model. Most of these variables are proven that they give little information for the prediction. Logit helps improving the accuracy of the model by reducing the number of variable in a reasonable way. The signs of significant variables from logit model are explainable with stories in reality. The discriminant analysis and principal component analysis yields less accuracy rate than logit probably because they just reduce the number of variables but cannot explain the reasons behind the remaining variables.

ANNs using the search tree as the pre-processing method yields the best accuracy rate. However, the search tree does not work alone in this experiment. It uses significant variables from logit model. Therefore, it is a combination of logit and the search tree that makes ANNs superior than logit.

6. Conclusions. The best pre-processing method is logit plus the search tree. The best architecture of ANNs is the model which uses one hidden layer including 3 neurons, logistic sigmoid transformation functions, and the training by Conjugate Gradient algorithm. The accuracy index is 85.92 percent. The best ANNs yields a better accuracy rate than logit around 1.92 percentage points.

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