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Building an online purchasing behavior analytical system with neural network

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Abstract

With the rapid growth of the worldwide online sales, it is very important to analyze the factors influencing online purchasing behaviors. The analysis of the data on online customers has not been given adequate effort. The difficulty of accurate assessment of online customer behaviors is due to its complexity, disorganized knowledge about it, and the lack of effective and valid tools to measure and predict it.

The technology of data mining has provided the opportunity to extract interesting knowledge from large amount of data. Since the back-propagation neural network (BPNN) is one of the most powerful general nonlinear modeling techniques, we have built a back office analytical system based on it and returned our classification and prediction results back to the consumer. The purpose of the research is to develop a system to help better understand customer online purchasing behaviors and to assist the customer relationship management campaigns of e-business enterprises. The system aims to classify online customers and predict their purchasing behaviors according to their demographics and attitudes toward online shopping.

The data used for model building and testing was collected through a website. A group of students at City University of Hong Kong participated in the data collection process to provide their online shopping behaviors. To evaluate the performance of the proposed system, we compare it with other mature classification tools, namely, K-means clustering and multiple discriminate analysis (MDA) tools. The results show better precision with the designed system.

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1 Introduction

In the past few years, information technology and the World Wide Web have created lots of innovations in the area of business. More and more businesses and organizations are collecting high quality data on a large scale. The huge amount of data can be a gold mine for business management. It is, therefore, increasing important to analyze the data. However, timely and accurately processing tremendous data analysis in traditional methods is a difficult task. The ability to analyze and utilize massive data lags far behind the capability of gathering and storing it. This gives rise to new challenges for businesses and researchers in the extraction of useful information.

1.1 Data mining

Data mining is different from traditional statistical analysis. It is aimed at finding unsuspected relationships which are of interest or value to the database owners [2]. Data mining does not compete with traditional statistical methods in basic statistical tasks. However, it should offer better solutions in advanced problems than traditional statistical methods could accomplish. To meet these challenges, research into artificial intelligence becomes imperative [1]. New generations of computational techniques and tools are required to support data mining [3] or knowledge discovery in databases. Data mining methods and algorithms extract useful regularities from large data archives, either directly in the form of "knowledge", characterizing the relations between the variables of interest, or indirectly as functions that allow to predict, classify or represent regularities in the distribution of the data [4].
Various applications have illustrated how data mining algorithms can be applied and made useful. One of them is to use back- propagation neural network (BPNN) to process classification and prediction.

1.2 Neural network

BPNN is one of the most popular artificial neural networks (ANNs). It is well known for its capability of performing complex mappings between input and output data. It can often provide outputs of adequate accuracy over a limited range of input conditions, with the advantage of requiring a lot less computation than other models. BPNN can be applied to different types of problems: classification of objects, modeling of functional relationships, storage and retrieval of information, and representation of large amounts of data.
Numerous previous studies have applied BPNN techniques to solve classification problems. Approaches that use BPNN for work piece classification problems are proposed in [14]. Financial classification problems have been reported to be solved in [15,17]. Patuwo et al.[18] study the two-group classification problem. The BPNN is also been used to solve detection and classification of flaws problems in concrete structure [21]. Ripley [19] provides a thorough review for classification applications. In the paper, an unseen holdout sample is correctly

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classified. A new method is introduced to automatic classify infrared spectra [20]. Their research investigates three fundamental questions relative to classification problems: (1) the appropriate neural network architecture, (2) the appropriate sample sizes, and (3) the accuracy of a neural network classifier compared to the classical statistical methods.
To date, little attention has been paid on the application area of online customer behavior studies. This may because it is a little difficult to use an appropriate BPNN model to analyze a large-scale customer dataset. When the attributes of the customers are ill defined, or ill structured, finding valuable patterns will be difficult and complex.

1.3 Online customer behavior

The fast growth of electronic commerce (EC) has the potential to influence the economy. In order to promote EC, it is important to study individual customers' online behaviors. Lots of research papers have been published on the topics of business to consumer (B2C) E-commerce and online shopping [5,6,24]. The relationship between consumers' lifestyles and online purchasing has been fully investigated [22]. The reason of why some consumers are online shoppers while other are not is described [23]. In the paper, consumer's convenience and risk perception are suggested to decide the consumers' channel choice. Regression methods have been applied to study the initial effects and relationships between consumer attitudes and Internet-based e-shopping [7]. The analysis shows that the life content of products, transaction security, price, vendor quality, IT education and Internet usage significantly affect the willingness to shop over the Internet.
The purpose of this study is to establish a classification system that applies data mining technology to perform the whole analytical process by implementing BPNN. The classification ability of BPNN, K-means clustering and multiple discriminant analysis (MDA) methods are compared based on real-word data sets from an online survey. We suggest that the BPNN model is more accurate and robust than other methods. It can be regarded as an aid tool for profiling good customers, performing market segmentation, and improving the results of direct-marketing campaigns.

2 Model development

In our research, data mining processes are employed to create the whole model. Five major steps are carried. Firstly, the goal of the model is described and the problem defined in advance. Secondly, customers' behavior data is collected. Thirdly, the data is pre-processed. The data is normalized and scaled in order to minimize noise. Fourthly, the data is transformed in order to feed to the model. Fifthly, an appropriate BPNN classification model which has the ability to capture the hidden information in the data is built by experimenting with various architectural and training parameters. Finally, the result is interpreted to help

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decision making. Each stage is fully studied in our system to ensure accuracy and validity of the results.
The whole data mining process of our system is depicted as follow figure1:

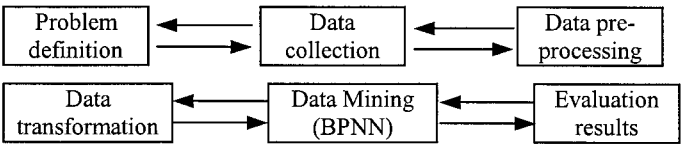


Figure1: Data mining process of our BPNN model system

2.1 Problem formulation

In this stage, information requirements are identified to be fulfilled with BPNN based data mining technology. The online purchasing features of customers are based on previous research studies on the Internet and e-shopping behaviors. The initial question in our research is to classify the customers according to their different features of purchasing behaviors.

2.2 Data collection

The data used in this study is collected via an online survey conducted by City University of Hong Kong on April 2001. Real-world data sets are used in this research because they are the best test of the accuracy of the respective classification algorithms in real-world situations. The supporting features are all derived from our earlier discussion of online customer behavior studies. To group online customers, all possible features are collected. The survey contains four sections: purchasing behaviors, general demographics, opinions on purchasing, and security and privacy of transactions. Following the standard approach [8], we measure the variables in terms of a Likert-type scale ranging from 1 to 5 with the following equivalences, "1": "not important" or "strongly disagree"; "2": "slightly important" or "slightly agree"; "3": "neutral"; "4": "important" or "agree"; and "5": "very important" or "strongly agree". Only those customers who are able to participate in web surveys are considered. This bias is exactly what is desired of the data of marketers on the web since it provides them with data about actual online users. The sample is therefore, restricted to Internet users.
The features of each of the data sets are summarized in table 1. One hundred and eighty six customer profiles are gathered and one hundred and sixty three are useful after reprocessing. Each data set represents a consumer profile. Twenty-eight variables are obtained.

Table1: Survey Items

Purchasing behavior
1.Money spend on online purchasing in the past six months
2.Frequency of making online purchases from web-based vendors

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3.Frequency of using WWW browser
4.Amount of time using WWW browser
General demographics
1.Age
2.Gender
3.Major
4.Amount of household income
5.Internet-related skill and training in computer applications
6.Level of education
Opinions on purchasing
1.E-vendors offer better prices
2.E-vendors offer more variety of products
3.E-vendors offer good quality of products
4.E-vendors offer satisfactory product guarantees
5.Delivery services of e-vendors are better
6.E-vendors offer more attractiveness of special rewards and discounts
7.Design of the web stores are attractive and friendly
8.Web stores are easier to search interesting information
9.E- vendors offer more useful information about choices
10.E-vendors offer easier way to cancel order with Web vendor
11.E-vendors offer easier way of checking out process
12.It is easier to contact e-vendors
13.E-vendors provide better customer service and after-sale support
14.E-vendors are more reliable (reputation / big size)
15.It is more efficient to manage my time when making purchase from e-vendors
16.It save more time when making a purchasing from e-vendors
Security and privacy
1.It is riskier to make purchases or banking over Internet
2.it is important to protect privacy when making purchases from e-vendors

2.3 Data pre-processing

The quality of data is a key points in the whole system. It is often necessary to pre-process the data before analysis. In this stage, the noisy, erroneous, and incomplete data are removed. For error detection, the out-of-range values are automatically identified and removed by the system. Idiosyncratic error and conflict values such as the "purchased online" and the "amount spent online" records are deleted from the research data sets. Part of the missing values in the datasets are made up with using the "average of values" technique. The others, with lots of missing values, are removed completely. All the data are documented in a meta-dictionary for reference purposes.

2.4 Data transformation

Data transformation is performed in terms of normalizing the data, i.e. map the original values onto the numerical range [0,1] prior to insertion into the input-layer of the classification and prediction. The numerical range [0,1] is important as our BPNN system employed the binary sigmoid function. Linear normalization is carried out with respect to the maximal and minimal values by using the equation (1):

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$$y = \log\left(\frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}\right) \quad (1)$$

2.5 BPNN model development

2.5.1 Validation of our system

There always exists the possibility that after running the system, valuable information cannot be discovered over real world datasets. It is, therefore, necessary to make certain whether the problem is coming from the quality of the data or the constructed system. In order to verify it, the output of our BPNN model was compared with results from the K-means clustering statistical approach. The two models were applied to a typical statistical dataset. As there are four variables in the data sets, the topology of the BPNN classification model is four neurons in the input layer, two neurons in one hidden layer, and three neurons at output layer. Each of the 150 datasets is grouped into one of the three different types. The output table 2 shows the results and validates the applied BPNN.

Table2: Result of BPNN and K-means cluster models

Class	Max	Min	Mean	SD	BPNN error	K-means error
Type1	0.0385	0.0084	0.0218	0.0169	0	0
Type2	0.8202	0.3649	0.5331	0.1132	2	2
Type3	0.9978	0.7192	0.9389	0.064	0	1

2.5.2 Back-propagation neural classification architecture

The BPNN model [9,16] is used to build up the classification system. As shown in figure 2, it is composed of three layers. Since many of the utilization of BPNN models in classification issues are constrained generally within the adoption of continuous or ratio variables, we developed our analytical system based on the categorical values of variables. For the purpose of practical implementation, all variables are scaled to lie between 0 and 1 before training and classification. The number of input neurons in the input layer is 28, in accordance with the selected input variables. The number of neurons in the hidden layer, selected as 12, was found to be appropriate for the present problem under investigation. A cascade learning process [13] is applied to determine the number of neurons in the BPNN hidden layer. The cascade learning process begins with an empty hidden layer and adds neurons to this layer one at a time until there is no further improvement in network performance. The network has three neurons in the output layer, and the desired outputs are (1,0,0), (0,1,0) and (0,0,1), respectively. The weights are initialized randomly. This study uses the sigmoid activation function as recommended by [10], equation (2)

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$$f(x) = \frac{1}{1+\exp(-x)} \in [0,1] \qquad (2)$$

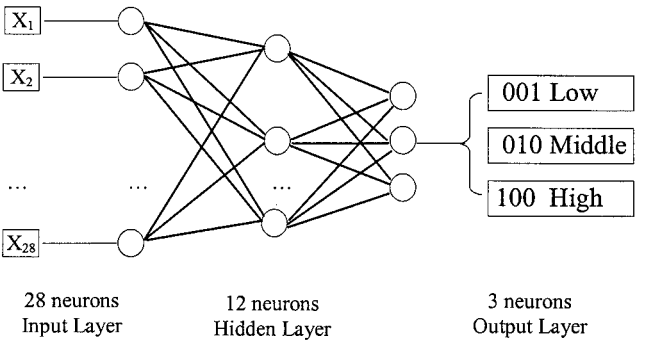


Figure 2: The three-layer BPNN model

2.5.3 Network Training

Training is the learning process, in which the input and output data are repeatedly presented to the network. BPNN needs to be trained in order to build up its classification mechanism. A training algorithm [9] was performed to determine the best set of weights for the network with a high level of classification accuracy. Similar problems have been discussed in the two papers [9, 11]. One major factor affecting the accuracy of BPNN classification models is the convergence criteria. In our model, two convergence criteria are used. Either the classification error of the learning sample falls below a threshold or the error does not show any relevant change after some duration of learning epochs. One of the stop criterion used is based on mean squared error (MSE), equation (3)

$$MSE = [\sum (E_i - O_i)^2]/n \qquad (3)$$

Where, O_i is the actual output for each data set i; E_i is the corresponding expected value; n is the whole dataset number. The training was ended when the change of MSE was less than 0.05% in three consecutive sessions. This method avoids the undesired effect that more frequent classes in the overlap region is classified correctly at the expense of those less frequent. The other criterion is the learning epoch. To explore the impact of it, the classification accuracy was repeatedly assessed by different sets of learning epoch. The highest classification accuracy achieved is then identified on both the training and test sets. This

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methodology minimizes errors due to over-training or under-training and to differences in convergence between training and test data.
In this system, the original sample is split into two distinct groups, namely, a training data with 99 items and a holdout data with 64 items. The model is trained using the former data set. The training and testing sample data sets are tested with different epochs as 1000, 3000, 6000 and 10,000. In the learning stage, the result shows that four different training epochs can all achieve a tolerance error of about 0.01, but the convergence speeds are quite different. The outcome indicates that a BPNN system with 12 nodes in one hidden layer and 10,000 epochs under random sampling methods has the best performance. We also tested our system with learning rates and momentums of 0.1 and 0.25. The result showed that 0.25 is better than 0.1. Table 3 gives the summary parameters in our BPNN model.

Table 3: the summary parameters in the BPNN model

BPNN Modeling	Parameters
Total patter	163
Training set	99
Test set	64
Pattern selection	Random
Initial weight	Random
Weight updates	Momentum with 0.1 and 0.25
Learning epoch	1000, 3000, 6000, 10,000
Hidden neurons	6,12,20

The comparisons of error curve with different parameters are displayed in figure 3. Curve1 is with 0.1 momentum, 6 hidden neurons and 1000 learning epoch; curve2 is with 0.25 momentum, 20 hidden neurons, and 6000 learning epoch; curve3 is with 0.25 momentum, 12 hidden neurons, and 10,000 learning epoch. Obviously, curve 3 performs best.

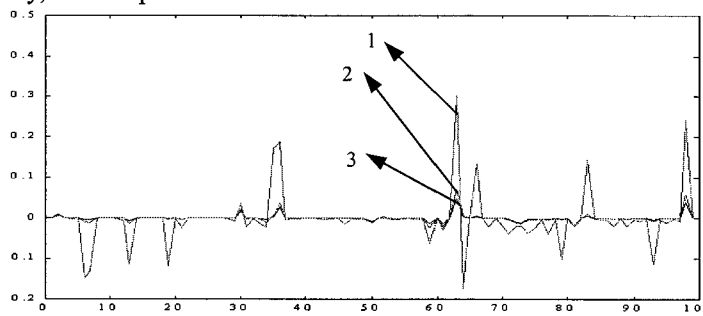


Figure 3: Error curves with different parameters

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2.5.4 Network Testing

After the network is trained, the holdout data is used as test data sets. It enters the network when the trained BPNN is used to test the predictive accuracy of the network. The testing of the network is carried out with the weight matrix and threshold values obtained from the previous training process. This 'train-and-test' procedure is conducted to predict the accuracy of the BPNN model. From the performance of the training process, the test model with 12 hidden neurons in one hidden layer and 10,000 epochs for the convergence criteria and 0.25 learning rate and learning momentum proved to be the most accurate. The procedure iterated five times with a new, randomly selected sample of 99 training data sets and 64 testing data sets each time. The Jackknife technique was used to generate the selected samples. It is a useful statistical procedure that produces unbiased estimates for the probability of misclassification [12]. The summary of the five iteration outcomes is calculated as the predictive accuracy rate of the model. The comparisons of the error curves with different testing samples are displayed in figure 4. Curve 1 is with sample3, curve 2 is with sample1 and curve 3 is with sample 5. Based on the results, sample 3 is selected as the best sample in our model.

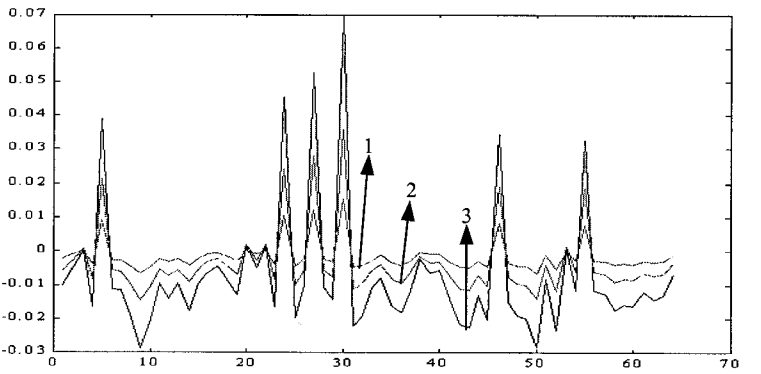


Figure 4: Error curves of different testing samples

2.5.5 Visualization of the results

To help decision making, a graphical window is used. The system provides good processing speed and the results are displayed in a comfortable user interface. It can be feasibly adopted in customized application systems. The visualization window of the input and output attributes are partly displayed in figure 5.

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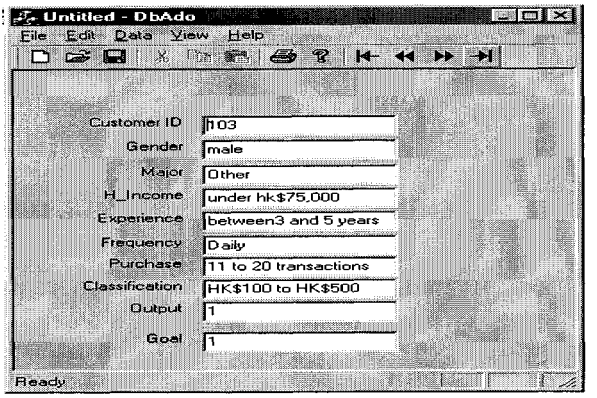


Figure 5: visualized input and output window

3 Results evaluation

Data mining typically uses an error rate to analyze the classification accuracy. The error rate is the percentage of correct classification of observations. As we define the criteria with 0.1 to be the accepted threshold, all of the data are accurately classified by our BPNN system. To test the effectiveness of our BPNN classification model, the result was compared with K-Means clustering and traditional multiple discriminate analysis (MDA) techniques. Pair wise t-tests are applied to assess the significance of the differences of the models. The results are reported in table 4. The Error rate of our BPNN system is zero; the error rate of K-means clustering is 34.36% with 56 misclassifications; the error rate of MDA is 7.36% with 12 misclassifications. As can be observed, the BPNN outperformed the K-means clustering and MDA technique at α=0.05 level. The reason for this may be because the MDA has very strict assumptions. Firstly, the MDA requires that the data set used to distinguish between variables must be linearly separable, and secondly, the relationship between variables make the value of each variables change accordingly. This has an impact on MDA. Thus, the complex properties of consumer behavior makes MDA a poor classification method compared with the BPNN model.

Table 4: Paired samples test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	S.D	Std. Error	Interval of the Difference				
					Lower	Upper			
Pair 1	NN-Km	-.8957	.9337	7.313E-02	-1.0401	-.7513	-12.248	162	.000
Pair 2	NN-MDA	6.135E-02	.2651	2.077E-02	2.034E-02	.1024	2.954	162	.004

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4 Conclusion

In this paper, we presented a BPNN classification model based on the data mining process procedures to analyze online customer purchasing behavior. Our research demonstrates that BPNN performs very well against two traditional statistical classification technologies, namely, K-means clustering and MDA on real-world data sets. The reliability and validity of the BPNN system are tested by comparing their classification ability with two different data sets (an external statistical data set and an online survey data set). The results indicate that the BPNN classification model has a higher classification accuracy and robustness than the alternatives used.

The findings of this study extend our knowledge of features influencing purchasing behavior from the conventional market to the Internet virtual market. From this study, it was found that each variable derived from our survey has played an important role to determine the classes of customers, i.e. all the features significantly influence the online customers to make purchase decisions. The resulting information can be used for more customized interaction between consumers and enterprises and better targeted marketing campaigns. However, although BPNN classification models have several advantages, they also have their limitations. The numbers of variables which can be input into the model are limited. In particular, the model cannot and should not entirely replace professional judgment. In addition, many new important qualitative variables may be difficult to incorporate into the model.

5 Future works

In the future, new sources of data from real world company data sets will be gained. The validity of our BPNN will be confirmed with external data sets. To facilitate efficiency pattern discovery from the data, decision tree algorithms will be considered first to reduce key variables to fix input and output of our BPNN classification model. The output of BPNN system will be further analyzed by using Bayesian networks. The purpose of the Bayesian network is to predict what type of products customer will buy according to their historical purchasing behaviors and the classification of the customer.

References

[1]R.J. Brachman, T.Khabaza, W.Kloesgen, G.Piatetsky-Shapiro, E.Simoudis, Mining business databases, Communications of the ACM, 39 (11), pp.42-48, 1996.

[2]D.J. Hand, Data Mining: Statistics and more?, The American Statistician, 52(2), pp.112-118, 1998.

[3]U.Fayyad, G. Piatetsky-Shapiro, P.Smyth, The KDD process for extracting useful knowledge from volumes of data, Communications of the ACM, 39 (11), pp.27-34, 1996.

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ISBN 1-85312-925-9

[4]Yoshua Bengio, Joachim M.Buhmann, Mark J. Embrechts, Jacek M. Zurada, Introduction to the special issue on neural networks for data mining and knowledge discovery, IEEE transactions on Neural network, 11(3), pp.545-549, 2000.
[5]S.poon, P.M.C. Swatman, An exploratory study of small business Internet commerce issues, Information and Management, 35(1), pp.9-18, 1999.
[6]T.J. Strader, M.J. Shaw, Consumer cost differences for traditional and Internet markets, Internet Research, 9 (2), pp.82-92, 1999.
[7]Ziqi. Liao, Michael Tow Cheung, Internet-based e-shopping and consumer attitudes: an empirical study, Information and Management, 38(1), pp.299-306, 2001.
[8]C.Liu, K.P. Arnett, Exploring the factors associated with website success in the context of electronic commerce, Information and Management, 38(1), pp.23-33, 2000.
[9]Lippmann, R.P., An introduction to computing with neural networks, IEEE ASSP Magazine, pp.4-22,1987.
[10]Zahedi, F., Intelligent Systems for business: expert systems and neural networks, California: Wadsworth Publishing, 1994.
[11]C.Klawun, C.L. Wilkins, J.Chem, Information Computing Science, (34) pp.984,1994.
[12]Chen, K., & Church, B., Default on debt obligations and issuance of going-concern opinions. Auditing: A Journal of Practice and Theory, 11(2), pp. 30-49,1992.
[13]Neural Computing. Neural Ware, Pittsburgh, PA, 1991.
[14]Wu MC, Jen SR. A neural network approach to the classification of 3D prismatic parts. Int J Adv Manufact Technol(9), pp.123-128, 1996.
[15]Etheridge HL, Brooks RC, Neural networks: a new technology. The CPA Journal, pp.36-55, 1994.
[16]Martin T. Hagan, Howard B. Demuth, Mark Beale, Neural network design, PWS Publishing Company, pp.(11)1-43,1996.
[17]Salchenberger LM, Cinar EM, Lash NA, Neural networks: a new tool for predicting thrift failure, Decision Sciences, 23(4), pp.899-916, 1992.
[18]Patuwo E, Hu MY, Hung MS., Two-group classification using neural networks, Decision Sciences, 24(4), pp. 825-845, 1993.
[19]Ripley BD, Neural networks and related methods for classification, Journal of the Royal Statistical Society, 56(3), pp. 409-443, 1994.
[20]Plamen N. Penchev, George N. Andreev, Kurt Varmuza, Automatic classification of infrared spectra using a set of improved expert-based features, Analytica chimic Acta (388), pp.145-159, 1999.
[21]Yang Xiang, S.K. Tso. Detection and classification of flaws in concrete structure using bispectra and neural networks, NDT&E International, 35(1), pp.19-27, 2002.
[22]Bellman, S., Lohse, G.L., Johnson, E.J. Predictors of online buying behavior, Communications of the ACM, 42(12), pp. 32-38, 1999.

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ISBN 1-85312-925-9

[23]Amit Bhatnagar, Sanjog Misra, H. Raghav Rao, On risk, convenience, and internet shopping behavior, Communications of the ACM, 43(11), pp.98-105, 2000.
[24]Steve Elliot, Sue Fowell, Expectations versus reality: a snapshot of consumer experiences with Internet retailing, International Journal of Information Management (20), pp. 323-336, 2000.