2000

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Eija Koskivaara
Turku School of Economics and Business Administration, eija.koskivaara@tukkk.fi

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Eija Koskivaara
Turku Centre for Computer Science TUCS, and
Turku School of Economics and Business Administration
P.O.Box 110, FIN-20521 Turku, Finland
Eija.Koskivaara@tukkk.fi

***Abstract*-The aim of this study is to investigate the impact of various pre-processing models on the forecast capability of artificial neural network (ANN) when auditing financial accounts. Hence, the focus of this paper is on the pre-processing of the data. ANNs are selected for auditing purposes because they are capable of learning complex, non-linear underlying relationships. Therefore, they are used to model the dynamics and the relationships between account values in order to find unexpected fluctuations. This study uses a multi-layered neural network with the backpropagation algorithm. The artificial neural network model used in this study was built by using the financial statements of 31 manufacturing companies over four years. The values of the accounts were regarded as a time-series. The data were pre-processed in four different ways. Firstly, all the data were scaled linearly. Secondly, the data were pre-processed linearly on a yearly basis. Thirdly, the data were pre-processed linearly on a company basis. And fourthly, the data were pre-processed on a yearly and company basis. The best results were achieved when all the data were scaled either linearly or linearly on a yearly basis.**

I. INTRODUCTION

Auditing is a part of the control processes in organisations. One purpose of auditing is to examine and observe the creditability of the account values, and that they give a true and fair view of the company. This means that an auditor has to examine financial accounts or related financial information of an entity. However, manual auditing can never cover all the evidence entirely and in detail, except in very small companies. Auditing of financial accounts and other financial information is often made with the help of analytical review procedures. Analytical review procedures are defined as an evaluation of financial information studying plausible relationships among both financial and non-financial information. Analytical review techniques in the literature are generally classified as non-quantitative or judgmental such as scanning, simple quantitative such as trend, ratio and reasonableness test, and advanced quantitative such as regression analysis and neural networks. However, techniques such as regression analysis have attracted little use in the auditing practice [1][2]. Moreover, the research of auditor judgement and decision-making has focused on revealing the limitations of human auditors [3][4]. These research findings have concluded that developing tools to overcome these limitations might enhance auditors' effectiveness and/or efficiency [5]. Indeed, a growing dimension in today's auditing is that a large amount of audit material, e.g. receipts and accounting records, is increasingly displayed only electronically. Naturally this kind of information also has to be audited. Furthermore, the American Institute of Certified Public Accountants (AICPA) Committee believes that major changes are currently under way involving both the kinds of information with which auditors are involved and the nature of that involvement. They describe this as a shift from an old audit paradigm to a new audit paradigm. This shift is also referred to as a transformation from audit to assurance. It also means that auditors have more and more varying kind of work to do than they had earlier. The report about the future of the financial statement audit is found on the homepage of AICPA (http://www.aicpa.org). These are some reasons why auditors need more or maybe different kind of support systems.

We are investigating the possibility to develop a support system, which uses an artificial neural network (ANN), for auditing financial accounts. We think that an ANN is suitable for these kinds of problems and will be one of the emerging technologies in this millennium [6]. Many ANN models are being developed in a wide variety of business fields [7][8]. Auditing as an application area for ANNs is also emerging [9][10][11][12][13][14][15][16][17][18][19]. As far as we know, ANNs are not yet used in practice within auditing.

The aim of this study is to get further evidence of the capability of an ANN to forecast and recognise patterns when auditing financial accounts. Therefore, the focus is on the development and evaluation of an ANN as a new audit method. The ANN architecture category and the prediction model for predicting and recognising patterns in this study is similar to the one in Koskivaara's [18] study. The difference is that we have more accounts, and in addition we have the number of staff turnover as variables. Furthermore, we have more companies in the study, because our aim is to build an ANN-based support system which forecasts and recognises patterns in financial accounts within one business line. In particular, we are focusing on the impact of various pre-processing models on the forecast capability of an ANN when auditing financial accounts.

The rest of the paper is organised as follows. First, a brief description of the multi-layer feedforward ANN method will be given. Then, the models used in prediction and pattern recognition will be specified. Finally, results and outlines for further research directions in this area will be presented.

II. ANN For Forecasting

We will focus on a particular structure of an ANN, the multi-layer feed-forward network, which is the most popular and widely used network paradigm in forecasting. We will present a brief description of it here. More details and applications of ANNs can be found in standard textbooks on ANNs [20][21][22][23][24].

The basic element of an ANN is a *neuron*. A neuron has many *input* vectors and one *output* vector. Fig. 1 presents an artificial neuron with three inputs and one output. The *transfer function* transforms the inputs into the output. The inputs are *weighted* within the transformation process.

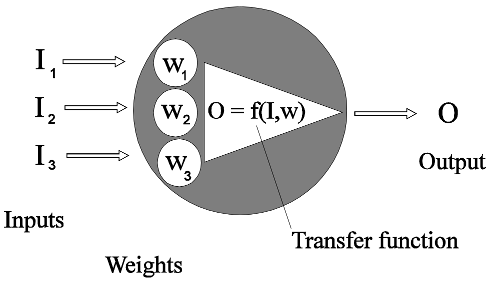

Fig. 1. Simple structure of an artificial neuron

An ANN is typically composed of layers of neurons. The first layer and the last layer within an ANN are called input and output layers, respectively. The inner layers (one or more) are known as *hidden* layers. The output of each neuron in a given layer, except the output layer, is fed as an input to every neuron of the next layer. Fig. 2 shows a feed-forward ANN with three layers.

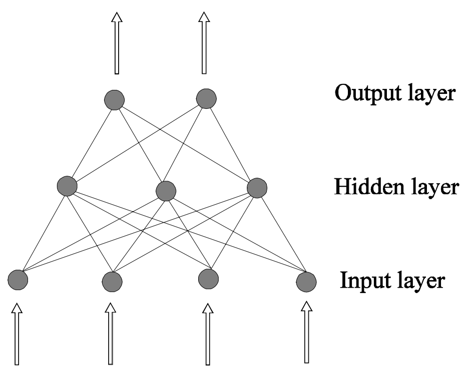

Fig. 2. Structure of a multi-layered neural network

In designing an ANN model, one must determine the following network architecture variables:

- *The number of input neurons*
- *The number of hidden layers and hidden neurons*
- *The number of output neurons*
- *Transfer or activation function*
- *Training algorithm*
- *Pre- and post-processing*
- *Training sample and test sample*
- *Performance measures*

The number of input neurons: The number of input neurons corresponds to the number of variables in the input *vector* used to forecast future values.

The number of hidden layers and hidden neurons: The hidden neurons in the hidden layer allow neural networks to detect the feature, to recognise the pattern in the data, and to perform complicated non-linear mapping between input and output variables. When the relationship between the input and output variables is non-linear, a hidden layer helps in extracting higher level features and facilitates the generalisation of outputs.

The number of output neurons: The number of output neurons is directly related to the problem under study.

Transfer or activation function: In practice, only a small number of activation functions is used [25]. These include the sigmoid (logistic) function, the hyperbolic tangent function, the sine or cosine function, and the linear function. The sigmoid transfer function is the most popular choice.

Training algorithm: During training, the weights of a network are iteratively modified to minimize the overall mean or total squared error between the desired and actual output values. Neural networks receive their *intelligence* through this training, which is also called *learning*. Although there are number of learning algorithms to train an ANN, the *backpropagation* paradigm has become the most popular one for prediction and classification problems [26]. It operates on a multilayered network like the one in Fig. 2. The backpropagation algorithm has two important parameters, the *learning rate* and *momentum*. The learning rate affects the speed in which the network settles on a solution by allowing us to regulate how much the error decreases at each iteration. Momentum is another way to increase the speed of convergence: when calculating the weight change at each iteration, we add a fraction of the previous direction. This additional term tends to keep the weight changes moving in the same direction.

Pre- and post-processing: The input data should be in such a form that a neural network can process it, this means numeric values. Furthermore, the numeric input values may be pre-processed in a way that the network's learning task is easier. In many practical applications, the choice of pre-processing will be one of the most significant factors in determining the performance of the ANN. One commonly used pre-processing method is data normalisation. Pre-processing is always performed before the training process begins. Sometimes the output data are also processed. This is called post-processing, which is the inverse of the pre-processing transformation.

Training sample and test sample: The data set used in network development is divided into a training sample and a testing sample. The training sample is used to build the network. Swingler [24] states that the training may be stopped when one or more of the following criteria have been satisfied: 1) The average training error has reached a predetermined target value. 2) The average training error no longer falls, or falls by an insignificant amount. 3) The average independent test error starts to rise, indicating the onset of overfitting. After training, the ANN model is tested against the records of a test sample that have not been previously met with the network. For these records, the desired output is known. The output generated for each record of this test sample is checked against the desired output for that record. There can be many performance measures for an ANN model, such as modelling time, training time or development costs. The most important performance measurement is the prediction accuracy it can achieve beyond the training data.

Performance measures: An accuracy measure is often defined in terms of a forecasting error which is the difference between the actual/desired and the predicted value. The most frequently used are the mean absolute deviation (MAD), the sum of squared error (SSE), the mean squared error (MSE), the root mean squared error (RMSE), and the mean absolute percentage error (MAPE) [25].

III. The Prediction Model Used in This Study

Our aim is to build an ANN-based support system, which will forecast and recognise patterns in financial accounts within one business line. The system could assist in the audit decision by giving a suggestion that could either be "no further audit required" or "further audit required". The accounts in financial statements are regarded as a time-series and the aim is to observe the dynamics and the relationships between the accounts. The goal is to predict the value of a certain account for a short time in the future. The feed-forward network can be applied directly to such problems [27].

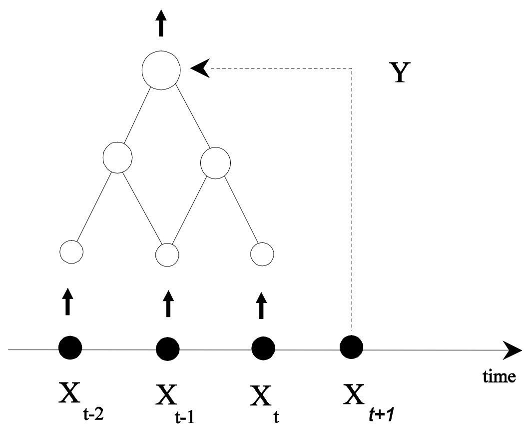

Fig. 3. Generating a set of training data for a feed-forward ANN. [27]

We can take a set of account values from a number of periods, for example two successive periods x_{t-2}, x_{t-1} and x_t to be the input vector of a network and use the next value x_{t+1} as the target value as illustrated in Fig. 3. This is called *one-step ahead* prediction. In the *multi-step ahead* prediction the outputs of the neural network are cycled around the inputs of the network, then predictions can be made for further points. By moving along the time axis we can create a training data set consisting of many sets of input vector values with corresponding target values [27].

The one-step ahead prediction model was selected for this study because our aim is to forecast the account values for a short time in the future. This also means that all the input values are based on real data.

IV. Monitoring The Financial Accounts of One Line of Business with A Neural Network

An ANN is a new possible method to be used in the analytical review process. An auditor needs to determine whether a financial statement is free of material errors and this can be done through an analytical review process [28]. For example, an auditor compares an estimated expected value with the actual value to identify those accounts where further audit testing seems to be needed. Our aim is to observe the dynamics and the relationships between accounts in one line of business and in that way monitor if there are unusual fluctuations. Furthermore, we are investigating four different ways to pre-process the data.

We will test the prediction model described above with a multi-layer feed-forward neural network. The study is based on the financial statements of 31 manufacturing companies over four years (1993-1998), all in the same line of business. The companies were picked from one bigger database. The limited companies with a turnover of over 3 million Finnish marks (~0.5 million euros) were accepted. Next we will give further information about the selection criteria of the variables. The variables and their averages and medians in thousand FIMs are presented in Table 1.

Variables

The reasons for selecting the above accounts for our models are as follows:

Net sales and other business earnings are significant values to predict. From the management's point of view it is better if the prediction value is lower than the actual value because then there are fewer disappointments. From the auditor's point of view this might raise doubts about whether all sales are recorded if the actual value is much below the prediction value.

Materials + change in inventory together should tell the total use of material during a certain period. The value should be in alignment with the net sales as these are manufacturing companies.

External service is quite a significant cost for some companies.

Personnel costs (manufacturing) and other direct costs should be in alignment with production and the total use of material.

Sales margin is an important value at least from the prediction point of view as well as to see how much money is left to cover indirect costs and profit.

Personnel costs (administration) and other indirect costs are good values to see the overall trend of the costs in the company and in the line of business. These values should be predicted always and everywhere because these costs do not depend on sales.

Profit (total) is an interesting value at least from the prediction point of view. Furthermore, it is important to see that operation is profitable in the long run.

Average staff number should be in alignment with personnel costs.

Receivables are an interesting and important value to follow in order to know how much of the company's money is "outside". Moreover, the receivables have been taken into the model to illustrate how big the seeded fictitious sales must be before the model gives an alarm. In the case of fictitious sales, both net sales and receivables should go up.

Accounts payable are interesting and important values to follow, and they tell how much the company has to pay "outside". It should be in alignment with net sales and the total use of material.

Financial assets and *short-term liabilities* are taken into the model in order to calculate quick ratio (QR), which shows the liquidity of the company.

TABLE I
Variables

Variable	Averages	Median
1. Net sales	19076	9389
2. Other business earnings	113	11
3. Materials + change in inventory	8966	3591
4. External service	686	5
5. Personnel costs (manufacturing)	3046	2386
6. Other direct costs	295	141
7. Sales margin	6437	2761
8. Personnel costs (administration)	1633	756
9. Other indirect costs	1979	626
10. Operating margin	2825	1387
11. Profit (total)	1433	606
12. Average staff (number)	26	19
13. Receivables	2862	895
14. Financial assets	5381	1709
15. Accounts payable	1331	535
16. Short-term liabilities	4171	1833

The implementation environment is a Pentium PC. A commercial development package, Neuralyst, developed by Cheshire Engineering Corporation was selected for prototyping because of its user-friendly features. A multilayer architecture was selected for our study. Our aim is to predict future values based on prior values. The current study used the back-propagation algorithm described in Section II for training the networks. The data were pre-processed to a [0,1] range to make the network's learning task easier. This was done because the selected neural network works best when its inputs range from 0 to 1 [29]. This pre-processing is made in four different ways.

Four different pre-processing ways

Model A: *All* the data are scaled linearly. The reason for this is that we wanted to keep the existing dynamics and relationships between the variables. In the case where there are any trends and relationships between the years and companies the ANN model might recognise them. In this case all data should always be checked and maybe pre-processed before entering new data into the support system.

Model Y: The data are pre-processed linearly *on a yearly basis*. An assumption in this case is that it is easier for the ANN model to learn the dynamics and relationships between the variables if the year effect is minimised on a yearly basis pre-processing. In this case when the year or other selected period is closed there is no need for data re-pre-processing.

Model C: The data are pre-processed linearly *on a company basis*. Respectively, an assumption in this case is that it is easier for the ANN model to learn the dynamics and relationships between the variables if every company has its own sliding scale. All of the company's data should pre-process when new data are put into the support system.

Model C&Y: The data are pre-processed *on* a *yearly and company basis*. Correspondingly, an assumption in this case is that it easier for the ANN model to learn the dynamics and relationships between the variables if every company has its own sliding scale on a yearly basis. The data from the period are ready after one pre-processing.

Training and testing sets and the prediction model

The training data set consists of 25 companies and their financial statement values and other variables from four years. The remaining 6 companies and their financial statement values and variables were divided into the training and the testing set so that the first three years were put into the training set and the fourth year's variables were left for testing.

The ANN models were used to make a *one-step ahead* prediction described in Section III, for training and testing. Therefore, the training data were presented to the network in a chronological order. Our models use two previous years to predict a third one. This required 32 input data streams to represent the data from each of the 16 account values. Four additional input neurons indicate the year of the input variable. The input value of this neuron was set to one if the neuron corresponded to the year of the data, and otherwise to zero. An additional input neuron was added to indicate the company. To summarise, the model has 37 input data streams in the input layer, and 16 neurons in the output layer, one for each account variable.

The following results are based on experiments to find (train) the network architecture that minimised the RMSE between the target account balances and the predicted output balances. The transfer function is the sigmoid function. We built (trained) the neural network model to monitor the dynamics of variables in such a way that it accepts 5 % difference between the target (= real, desired) and the output (= the value the networks give) values. We varied both layers and numbers per layer to find the best results. The training tolerance has no effect on the learning algorithm. However, when the Neuralyst finds 100% right, as defined by training tolerance, it will stop training. After training the ANN models were tested. The testing data set consists of the previous year's variables from six companies. The output values were compared to the target values. Table 2 summarises the best-achieved prediction capability of the models.

TABLE 2
Test statistics of the models

	Model A	Model Y	Model C	Model C&Y
Layers	5	3	6	4
Neurons per Layer	37-32-26-20-16	37-27-16	37-33-29-25-21-16	37-27-16
Training Epochs	3002	4091	3627	2593
RMSE	0.0048932	0.069367	0.132907	0.187114
Number of Items	96	96	96	96
Number Right	91	89	61	61
Number Wrong	5	7	35	35
Percent Right	**95 %**	93 %	64 %	64 %
Percent Wrong	5%	7 %	36 %	36%

The neural network output and the test target values are scored as "right" if they are within the testing tolerance, which was 10 %. From table 2 we can see that Model A received the best results with five layers. 91 data items out of 96 are within the 10% testing tolerance whilst others are not. Model Y was almost as good. Models C and C&Y attained much lower results.

Another way to compare the models is to calculate the quick ratio (QR) in the testing period. The QR shows the liquidity of the company and its financial assets divided by short-term liabilities. From table 3 we can see the calculated QRs in the testing period and that they support the test statistics of the models. Model A is best followed by Model Y.

TABLE 3
Quick Ratio in the test period

QR	**Right**	**A**	Y	C	C&Y
Company 26	**0.8**	**1.0**	**1.0**	0.5	0.1
Company 27	**1.1**	1.6	0.8	**1.0**	2.1
Company 28	**1.3**	**1.3**	**1.3**	2.2	2.7
Company 29	**1.5**	1.2	**1.5**	0.8	1.3
Company 30	**1.1**	**1.1**	1.2	2.6	1.8
Company 31	**1.2**	**1.1**	2.4	1.5	0.6

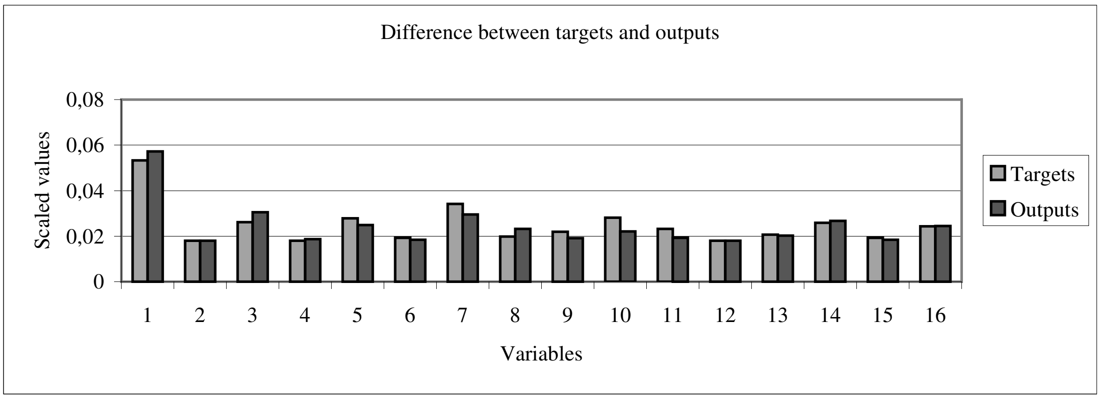

Fig. 4. Company 31, difference between target and output variables in the testing period

The columns in Fig. 4 show the difference between the target and the output values with Model A of Company 31's variables in the testing set. The difference values between targets and outputs are scaled and the number of the column equals the number of the variables in table 1.

The biggest differences are in:
(1) Net sales 7%
(3) Materials + change in inventory 17%
(5) Personnel costs (manufacturing) -11%
(7) Sales margin -14%
(8) Personnel costs (administration) 17%
(9) Other indirect costs -13%
(10) Operating margin -22%
(11) Profit -17%

The predicted output values of net sales (1) and materials + change in inventory (3) are bigger than the actual value.

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However, these differences are in line. But if only the net sales were bigger an auditor might doubt whether all sales are recorded. The actual values of sales margin (7), operating margin (10), and profit (11) are bigger than the predicted output value. This indicates that the company attains better results than an average company in the same line of business. Personnel costs (manufacturing) (5) and other direct costs (6) also support this conclusion. However, personnel costs (administration) (8) do not support this conclusion.

We tested Model A by seeding fictitious sales into Company 31's data, which means that the net sales and receivables go up while the others remain at the initial level. The amount of the seeded error was 10 % of the average net sales. Fig. 5 shows that the target values of both net sales (1) and receivables (13) are clearly above the ANN output values.

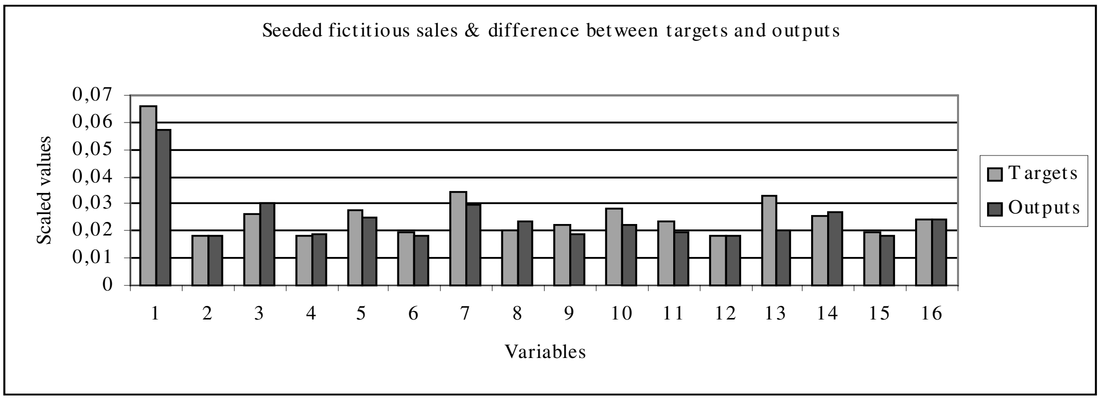

Fig. 5. Company 31, difference between target and output variables when seeding fictitious sales

V. Discussion and Further Research

We applied neural network technology to forecast and recognise patterns within one line of business when auditing financial accounts. The aim of this study is to get further evidence of the capability of an artificial neural network (ANN) to forecast and recognise patterns when auditing financial accounts. Therefore, the focus is on the development and evaluation of the ANN as a new audit method. We had both financial account values and other variables in our models. In particular, we focused on the impact of various pre-processing models on the forecast capability of an ANN when auditing financial accounts. The data were pre-processed in four different ways. Firstly, all the data were scaled linearly. Secondly, the data were pre-processed linearly on a yearly basis. Thirdly, the data were pre-processed linearly on a company basis. And fourthly, the data were pre-processed on a yearly and company basis. The best result was achieved when all the data were scaled linearly and linearly on a yearly basis. These two models give such encouraging results that it is worthwhile testing an ANN-based support system in a real audit situation. Before applying these kinds of methods in practice it has to be ensure that the results are stable enough. Comparing an ANN-model with other models such as regression analysis with the same data can do this.

However, pre-processing data on a company or on a yearly and company basis did not give as good results. One explanation for this might be that there were not enough data for learning the dynamics between variables. Another explanation might be that these pre-processing methods remove the existing dynamics and relationships between the variables within the business line. This has to be studied by using a larger data sample, i.e. data from more companies or by convincing that the sample data represent the whole population.

We think that neural network technology provides new opportunities for auditors and leads to improvements in the efficiency and effectiveness in auditing financial records, however, this has to be tested in further experiments. Moreover, the question arises how big the difference between the target value and output value might be without actions in the management or in the bookkeeping procedure. Furthermore, the question arises whether the neural network technology provides any improvement in the efficiency and effectiveness in auditing financial records. We plan to further apply the neural network technology to a real audit situation to get more results.

Acknowledgment

The author would like to thank Barbro Back for her comments and suggestions. Furthermore, the author would like to thank the company which provided the data for the study.

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