Modelling shares choice to enter in a portfolio using artificial neural networks (ANN)

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Introduction
Shares choice to enter a portfolio is a special topic in finance and management and is very interesting to be discussed by both practitioners and academics. Shares choice to enter in a portfolio is very important for a Fund Manager when he manages his client’s fund. When a Fund Manager does not properly choose the share, it will affect target return and Investors will redeem their fund and looking the good performance. Share choice to enter a portfolio is a process to build a portfolio. Good shares portfolio consists of many shares that have good performance from the past and in the future. Research for shares choice becomes very important because the result will make the fund be sought by investors as a good investment. Good shares in a portfolio is a power to Fund Manager to sell it and investor to become large to buy the fund.

Markowitz [7] introduced a method of shares choice to enter a portfolio using risk and return. Elton et al. introduced an alternative to choose a share to enter a portfolio. The method is known as Excess Return to Beta which is using risk (beta) and returns. Wallingford [17] used the Single-Index, Multi-Index, and Full-Covariance Model to choose a share to enter a portfolio. Saaty et al. [15] stated that the Analytical Hierarchy Process (AHP) can be used to choose a share to enter a portfolio. AHP was developed by Saaty in 1970. Khaksari et al. [5] supported Saaty et al.’s research to use AHP to choose share to
enter into a portfolio. Jones [4] introduced a network analysis to build a portfolio. Reily and Brown ([13], 272) stated that an optimal portfolio is an efficient portfolio to have the highest utility for the investor’s certainty.

Previous research used risk and return to choose a share enter in a portfolio, but it never discusses characteristics of the companies whose shares were entered into a portfolio, for example, market capitalization and financial ratio company. Farrell [3] investigated stock to enter in a portfolio using homogeneous stock grouping. Based on some previous researches, Common stocks tend to group naturally, according to their price behavior [8] and also P/E [10]. Wainscott [16] found that the changing of correlation between assets will significantly affect mixed-asset portfolio from one period to another period. Peritt and Lavine [11] stated that asset allocation is very important to build a portfolio. Marmer [9] explored an efficient frontier for Canadian’s Portfolio. Fama and French [2] explored another factor to affect portfolio return. Reinganum [14] did research and stated that market capitalization has an impact on managing portfolio. Manurung [6] used the Logit Method to choose a share to enter into a portfolio using financial ratios.

Shares choice to enter in a portfolio is still developed for research, especially to explore new methods. Recently, a research on Shares choice to enter in a portfolio was conducted using Artificial Neural Networks (ANN). Ashwood [1] explored ANN as a method to predict stock prices in shares portfolio, with a result of better than 50% accuracy for almost all of the stocks and portfolios tested. Rasekhschaffe and Jones [12] used Machine Learning to select stocks for building portfolio using deep neural networks (DNN). This paper explores the usage of ANN to choose a share to enter in a portfolio using financial situation data of several Indonesian companies.

Meanwhile, big data techniques, especially the volume of data, can be used in modeling shares choice to gather data to use as training and testing data for the ANN. Zhang et al. [18] stated that ANNs can extract features from raw data while big data provides tremendous training samples for the ANN, creating a mutual reinforcement. Thus, the use of big data is beneficial to improve this experiment in the future.

**Proposed methods**
The algorithms used for building the ANN was supervised stochastic learning with backpropagation and steepest gradient descent, with bias nodes at the hidden and output layer. The 31 data rows gathered were split into 80% training set and 20% test set. The model of the ANN was as shown in Fig. 1.

The ANN takes 15 input data, X, of attributes associated with a company’s financial situation:

- Cash Ratio (X1)
- Current Ratio (X2)
- Cash T. Assets (X3)
- Cash Debt US$ (X4)
- Free CF Debt US$ (X5)
- Debt US$ Equity (X6)
- MV E Debt US$ (X7)
• Sales T. Assets (X8)
• Net Inc. T. Assets (X9)
• Net Inc. Equity (X10)
• Operational Profit (X11)
• R E T. Assets (X12)
• EBIT T. Assets (X13)
• Debts T. Assets (X14)
• Free CF T. Assets (X15).

The hidden layer, H, which consists of 8 nodes, then extracts features from these data and sends a signal to the output layer, Y. The result is the probability of the company being bankrupt or not. To calculate the accuracy of the model, the test set is fed into the trained network, and if the probability is above 70%, then the company is bankrupt \( Y=1 \), otherwise, it is not bankrupt \( Y=0 \). This output is then compared with the actual labels of the test set.

The equations used in this research are as follows:

Linear combinations:

\[
\hat{o}_j = \sum_{i=1}^{a} w_{ji} x_i + b_1
\]  

(1)
\[ p_l = \sum_{k=1}^{b} u_{kl} h_m + b_2 \]  \hspace{1cm} (2)

with: \( o_j, p_l \) as linear combination results for the hidden layer nodes and output layer nodes respectively; \( w_{ij} \) as weights from the input layer to the hidden layer; \( u_{kl} \) as weights from the hidden layer to the output layer; \( x_i \) as input nodes; \( h_m \) as hidden layer nodes; \( b_1, b_2 \) as biases of the hidden layer and the output layer respectively; \( i, k \) as the index of nodes in the input layer and the hidden layer respectively; \( j, l \) as the index of nodes in the hidden layer and the output layer respectively; \( a, b \) as the number of nodes in the input layer and the hidden layer respectively.

Sigmoid activation function:

\[ h_j = \frac{1}{1 + e^{-o_j}} \]  \hspace{1cm} (3)

\[ y = \frac{1}{1 + e^{-p_l}} \]  \hspace{1cm} (4)

with: \( h_j \) as the hidden layer nodes’ output; \( y \) as the output layer node’s output; \( o_j, p_l \) as linear combination results for the hidden layer nodes and output layer nodes respectively.

Mean squared error:

\[ E = \frac{1}{2} (t - y)^2 \]  \hspace{1cm} (5)

with: \( E \) as error (or loss); \( t \) as the target output; \( y \) as the output layer node’s output

Steepest gradient descent:

\[ w_{\text{new}} = w_{\text{old}} + \Delta w \]  \hspace{1cm} (6)

\[ \Delta w = -\alpha g_a(w) \]  \hspace{1cm} (7)

\[ b_{\text{new}} = b_{\text{old}} + \alpha (y - t) (1 - y) (y) \]  \hspace{1cm} (8)

with: \( w_{\text{new}} \) as the new weight value; \( w_{\text{old}} \) as the current weight value; \( \Delta w \) as the adjustment made to the current weight value; \( \alpha \) as learning rate \( g_a(w) \) as a function of weight; \( b_{\text{new}} \) as the new bias value; \( b_{\text{old}} \) as the current bias value; \( y \) as a vector of the output layer nodes’ output; \( t \) as a vector of the target output.

Chain rule for the hidden layer \( \rightarrow \) output weights (u):

\[ p_l = \sum_{k=1}^{b} u_{kl} h_m + b_2 \]
\[
\frac{\partial E}{\partial u} = \frac{\partial E}{\partial y} \frac{\partial y}{\partial q} \frac{\partial q}{\partial u}
\]

\[
\frac{\partial E}{\partial u} = (y - t)(1 - y)(y)(h_2)
\]  
\[
\text{(9)}
\]

with: \( g_u(u) \) as a function of the hidden layer → output layer weights; \( \frac{\partial E}{\partial u} \) as the partial derivative of Error against the hidden layer → output layer weights; \( \frac{\partial E}{\partial y} \) as the partial derivative of Error against the output layer; \( \frac{\partial y}{\partial q} \) as the partial derivative of the output layer against the output layer’s linear combination; \( \frac{\partial q}{\partial u} \) as the partial derivative of the output layer’s linear combination against the hidden layer → output layer weights.

Chain rule for the input layer → hidden layer weights (w):

\[
g_u(w) = \frac{\partial E}{\partial w}
\]

\[
\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y} \frac{\partial y}{\partial q} \frac{\partial h}{\partial p} \frac{\partial p}{\partial w}
\]

\[
\frac{\partial E}{\partial w} = (y - t)(1 - y)(y)(u)(1 - h)(h)(x)
\]  
\[
\text{(10)}
\]

with: \( g_u(w) \) as a function of the input layer → hidden layer weights; \( \frac{\partial E}{\partial w} \) as the partial derivative of Error against the input layer → hidden layer weights; \( \frac{\partial E}{\partial y} \) as the partial derivative of the output layer’s linear combination against the hidden layer; \( \frac{\partial y}{\partial q} \) as the partial derivative of the hidden layer against the input layer’s linear combination; \( \frac{\partial q}{\partial w} \) as the partial derivative of the hidden layer’s linear combination against the input layer → hidden layer weights.

Meanwhile, the pseudocode of the algorithm used in this experiment is:
begin
import libraries
import dataset as X (features) and y (label)
normalize X
split dataset into training and test set
define ANN architecture
define learning rate as lr
define number of iterations as number_of_iter
initialize output_errors array
function train(X_train, y_train, lr, number_of_iter):
    initialize weight and biases randomly using numpy.random.randn()
    for iter in range(number_of_iter):
        store shuffled list of len(X_train) as r
        for i in r:
            reshape biases into vectors
            do forward pass
            reshape vector variables into matrices
            gradient descent backpropagation algorithm
            update weights and biases
        end for
    end for
    calculate mean of errors
    if iter is 0.1 * number_of_iter:
        report mean of errors
    end if
    return weights and biases
end function
function predict(X_test, weights and biases):
    initialize array y_pred
    for i in range(len(X_test)):
        do forward pass
    end for
    return y_pred
end function
initialize array new_ypred
for yp in y_pred:
    if yp > 0.7:
        yp = 1
    else:
        yp = 0
    end if
    new_ypred.append(yp)
end for
y_pred = new_ypred
initialize int trueCount = 0
for i in range(len(y_pred)):
    if y_pred[i] equals y_test[i]:
        add 1 to trueCount
    end if
end for
print trueCount/len(y_pred) * 100 as accuracy
print error vs. iteration graph
end

Experimental results
We used a total of 31 lines of data for training and testing. The data was split into
80% training set and 20% test set prior to executing the training algorithm using the
architecture defined in Fig. 1. It was trained with various learning rates: 0.5, 0.1 and
0.05. It was also trained with various amounts of iterations.
The test results can be seen in Fig. 2, while the error vs. iteration graph for each learning rate for 2000 iterations can be seen in Figs. 3, 4, 5.

**Discussion**

As can be seen in Fig. 2, the maximum accuracy of the model is 85.71%, with the results stabilizing on 2000 iterations. By comparing Figs. 3, 4, and 5, we can see that the smoothest, thus the most stable, graph is the one with 0.05 learning rate. From these results, we can say...
that the optimal parameters for the ANN has 0.05 learning rate and trained for over 2000 iterations.

**Conclusion**

The data in this research are real data from some Indonesian companies. With these results, it can be said that the data used can be used to predict which shares are best for a portfolio. The algorithms used for building the ANN were supervised stochastic learning with back-propagation and steepest gradient descent, with the optimal parameters of 0.05 learning rate trained over 2000 iterations. These algorithms run with these parameters were able to predict if a company will go bankrupt with good success, that is, with 85.71% accuracy. The
accuracy may be improved by obtaining more real data to be used in training the ANN, so it can learn from more examples. Big data techniques will be very helpful in this matter.

**Abbreviation**

ANN: Artificial neural network.

**Acknowledgements**

This work is supported by BINUS University.

**Authors' contributions**

Both authors read and approved the final manuscript.

**Funding**

No funding in this research.

**Availability of data and materials**

Not applicable.

**Competing interests**

The authors declare that they have no competing interests.

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**Received: 23 October 2019   Accepted: 21 February 2020**

**Published online: 09 March 2020**

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