Prediction of Earnings per Share for Industry

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Abstract: Prediction of Earnings Per Share (EPS) is the fundamental problem in finance industry. Various Data Mining technologies have been widely used in computational finance. This research work aims to predict the future EPS with previous values through the use of data mining technologies, thus to provide decision makers a reference or evidence for their economic strategies and business activity. We created three models LR, RBF and MLP for the regression problem. Our experiments with these models were carried out on the real datasets provided by a software company. The performance assessment was based on Correlation Coefficient and Root Mean Squared Error. These algorithms were validated with the data of six different companies. Some differences between the models have been observed. In most cases, Linear Regression and Multilayer Perceptron are effectively capable of predicting the future EPS. But for the high nonlinear data, MLP gives better performance.

1 INTRODUCTION

Even though financial market analysis requires knowledge, intuition and experience, the automation process has been growing steadily because of the availability of large Finance data. There is a growing evidence to research in the fields of data mining and machine learning and their applications to Computational finance industry.

In a mature finance industry, a company that takes the dominant position in the industry earns greater profits because of better ways of handling its economic scale and market power (San Ong et al., 2010).

Evaluation of stocks of a company to buy or sell is an important decision to be made by the investors of a company. Nowadays, when huge amounts of data are made available with the advent of technology, this decision does not become any easier without the help of some model. Thus determining the best model directly affects the investment decisions for a company.

EPS is considered as one of the most important of the profitability metrics of a company. It represents the returns delivered by the company for each outstanding share of common stock. It is a major indicator for investors to purchase stocks. Price Earnings (PE) ratio is obtained by dividing the stock price by EPS. The EPS used here can be current or future earnings. EPS over past quarters as well as "forward" forecasted quarters is most frequently used in the calculation of PE ratio of a company. Comparison of a stock's current PE with those of its competitors or with its own average multiple over three to ten years gives useful information about hopeful future profits, investment in the company and also if a possible bargain has happened. Investment into a stock depends on the current PE ratio: Is it too high or low compared with the PE ratio of the stock's peers, industry or aggregate market?

This paper proposes three regression models to predict EPS: (1) Statistical Regression Model using Linear Regression (LR) (2) Neural network (NN) regression using Multilayer Perceptron (MLP) and (3) Neural network regression using Radial Basis Function (RBF). For construction of these models, 56-quarter EPS data are employed. The experimental results indicate that LR and MLP models outperform the RBF models, except for the high nonlinear data, where MLP gives better performance.

If one has huge and complex dataset, data mining can be carried out on it keeping in mind a particular problem and goal of discovering insights and predict future accurately. Formally, Data Mining or Knowledge Discovery in Databases (KDD), is the process of intelligent analysis of large amounts of data, also called as big data to explore consistent patterns and relationships among variables. This can

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be seen in Figure 1. The patterns found are in the form of models and are validated by subjecting them to new datasets. This process is called as deployment of the models. Data mining involves building models to detect patterns which then are used to predict situations. It is the amalgamation of different fields like Statistics, Information systems, Applied Machine learning, Data engineering, Database Systems, Artificial intelligence and Genetic Algorithms. Knowledge discovery process is being applied by various industries for fraud detection, bankruptcy prediction, marketing campaigns, forecasting high-risk clients and improving production processes, to name a few. Application of data mining in the area of finance is becoming more amenable since large financial datasets are becoming available.

Data mining takes inspiration from Machine learning which involves building and applying the models or algorithms to predict the future without any real explanation of any reasoning of the real causes of relationships. Machine learning takes from statistics but stresses more on accuracy of prediction. Various unsupervised or supervised machine learning techniques can be applied in the process of data mining.

Predictive data mining identifies very complex and generic model(s) which are then used to predict the response of new data sets. Prediction is a form of data analysis used to extract models to predict future data trends and get better understanding of the data. Prediction learns a mapping or function, y = f (X), where X is the input and y is the continuous output to model the relationship between X and y.

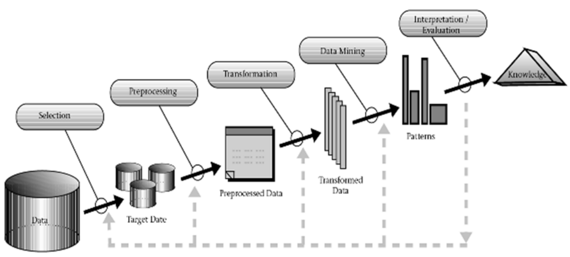

Figure 1: Data Mining as a step in the process of Knowledge Discovery (Fayyad et al., 1996).

The paper is organized as follows. Next section reviews the literature on usage of EPS for stock price forecasting. Then, the methodology of the research along with the applied methods is introduced. Next section describes the dataset and experimental set up of the work. The experimental results of forecasting performance across the LR and NNs are compared in next section followed by conclusions of the work.

2 RELATED WORK

Prediction of Earnings per share forms the basis for stock price forecasting. Forecasting is s function approximation problem involving choosing a model and fitting its parameters to the data. This problem is complex because of stock price changes in time being highly nonlinear. Many artificial intelligence, soft computing and machine learning methods have been used wherein neural networks and regression show good results since they are robust against noise, can model nonlinear relationships and give good generalization performance.

Data mining and regression have long been researched upon to solve various problems. There are three types of Regression models such as Linear, Polynomial and Logistic Regression.

Regression modelling has many applications wherein the output is continuous such as in trend analysis, business planning, marketing, financial forecasting, time series prediction, biomedical and drug response modelling, and environmental modelling (Sajja and Akerkar, 2012).

Artificial neural networks (ANNs) are one of the most common supervised data mining techniques used by the industry for forecasting.

MLPs have been employed for prediction of stock prices and indexes on various stock markets, see: (Mostafa, 2010; Ince and Trafalis, 2008; Guresen et al., 2011). Similarly RBF neural networks were the topic of choice for same purpose in: (Shen et al., 2011; Chen et al., 2009; Yan et al., 2005). Use of RBFs along with various other data mining techniques can be found in (Guo et al., 2015; Sermpinis et al., 2013; Kara et al., 2011).

Other research regarding forecasting and prediction in the area of finance focuses on stock market, bankruptcy, fraud, credit scoring and business failures. Bankruptcy prediction attempts to predict bankruptcy and financial distress of public firms. It is one of the vast areas of finance research. Creditors and investors have always given importance to the evaluation of credit worthiness of firms.

A lot of them consider ANNs as the main technique of forecasting (Geng et al., 2015; Wong and Versace, 2012; Ravisankar et al., 2011; Pacelli et al., 2011; Du Jardin and Séverin, 2011; Ravisankar and Ravi, 2010; Hsieh and Hung, 2010; Esichaikul and Srithongnopawong, 2010; Wang et al., 2011; De Oliveira et al., 2011; Vaisla and Bhatt, 2010).The learning and predicting potential of the adaptive neuro-fuzzy inference system (ANFIS) model, a variant of ANN is used for stock market returns prediction in (Bagheri et al., 2014; Chen, 2013; Boyacioglu and Avci, 2010).

Classic economic model of regression is used to predict stock trends in (Olaniyi et al., 2011). To obtain n-day ahead volatility forecasts, the implied volatility may be parameterized within an ARCH model (Blair et al., 2010). Similarly Regression along with neural network was applied in (Saigal and Mehrotra, 2012) and along with support vector machines was investigated in (Kazem et al., 2013). Other research work using Regression can be found in (Serrano-Cinca and GutiéRrez-Nieto, 2013; Pan, 2012; Öğüt et al., 2012).

The observation is that models based on neural networks are suitable for stock market related forecasting. They are efficient at producing better results for trading systems with higher forecasting accuracy. The literature demonstrates that soft computing techniques have natural connection with classical statistics methods and have been used alongside conventional models. However, difficulties arise when defining the structure of the model (the hidden layers, number of neurons etc.). While determining the structure of the model trial and error procedures are still employed.

A company's stock price is mainly affected by Earnings Per Share (EPS) since the stocks vary according to EPS ratio. Researchers have investigated several methods to construct models taking help of EPS: (Patell, 1976) suggested that firms disclose more frequently when experiencing favourable earnings results and that earnings forecasts are, usually associated with positive returns. Financial distress prediction was the topic of study in (Chen and Du, 2009) wherein EPS was used as one of the inputs to neural networks.

A study involving financial ratios included EPS among others and showed that application of ensemble methods with diverse models have good predictive capacity and have good applications in the area of forecasting. PE ratio has been used in many research works: DJIA stock selection assisted by neural network (Quah, 2008). Few researchers have taken into consideration the EPS ratio as part of dataset. (Khirbat et al., 2013; Lai et al., 2009) used it for stock price forecasting and (Pan et al., 2011) used it for financial crisis prediction.

In (Han and Chen, 2007), a method of SVM was proposed with financial statement analysis for prediction of stocks using EPS as one of the finance parameters. EPS was used as a financial variable for financial crisis prediction in (Song et al., 2010). SVM and ANN models including PE ratio as one of the basic financial indicator give meaningful performance results for the stock selection (Timor et al., 2012). Many stock prediction, stock selection, financial crisis prediction and fraud detection studies have used EPS as part of the study: (Qiu, 2007; Jiang et al., 2009; Quah and Ng, 2007; Li and Wong, 2014; Arefin and Rahman, 2011; Rezaie et al., 2013).

Actual EPS forecasting was the topic of research in few studies. In an interesting study of Markov process model to forecast subsequent quarterly EPS values, the authors applied time independent transition probability matrices to predict EPS of IT companies (Rajakumar and Shanthi 2014).

It is seen that EPS forecasting using machine learning techniques is still a new area. Neural networks seem obvious choice to model nonlinear data, but need the decision about parameters, architecture and speed.

When a real problem needs to be solved, the goal is to find an approach as easy as possible with the performance as good as possible. Therefore, we select three models of LR, MLP and RBF for the EPS problem, and compare the suitability for the real data.

3 ALGORITHMS USED FOR THE PREDICTIVE PROBLEM

In order to find the best model for the predictive problem, we select Linear Regression (LR), Multilayer Perceptron (MLP) and Radial Basis Function (RBF) for the predictive problem.

3.1 Linear Regression

Regression is used to predict values in Data Mining. The process starts with a dataset where the target values are known and other attributes might be the predictors in predicting value of the target. While building the regression model, the algorithm which is a relationship between predictors and target estimates the target as a function of the predictors for each observation in the dataset. This model then can be applied to a dataset not seen by the model previously to determine target values.

Least squares regression, a standard approach to regression, finds a best-fitting line that minimizes the mean squared difference between the observed values and the fitted values.

The simplest regression model is the linear regression model, which represents the linear relations between independent (also called as x-variables or predictors) and dependent variables (y-variables, response variables or goal variables), as shown in formula (1).

$$f(X)= a0+a1x1+a2x2+a3x3+\ldots \quad (1)$$

3.2 MLP Architecture-Feedforward Neural Networks

Artificial Neural Networks (ANN) are universal approximators, and they are very popular with regression applications where they obtain a close relation to a continuous objective function. As they are data-driven, if a good training dataset is available, they provide good forecasting results.

It is comprised of a set of neural perceptrons. A Perceptron is a simplest neural network. It is a linear classifier, using sigmoid function as the activation function. A perceptron can be described with the following function:

$$u = \sum_{i=1}^{N} W_i\,(p) x_i^n(p) \quad (2)$$

$$v = f(u) = \frac{1}{1+e^{-\alpha(u-\theta)}} \quad (3)$$

where N is the total number of nodes in input layer, W_i is the weight vector connecting the neuron of the output layer for the pattern p.

Multilayer Perceptron (MLP) extends the concept of perceptron by adding one or more hidden layers of neurons. Neural network is usually used to extract patterns from complex data, as adaptive learning makes it easy to model complex data, and they do not assume about underlying probability density functions or any information regarding the modelling sample under consideration. Therefore, we investigate the multiple layer perceptron regression for the real predictive problem, and use classic backpropagation algorithm to train the neural network.

3.3 RBF Network Architecture

RBF network is one of the most popular neural networks and is a main competitor for MLP networks. RBFs are faster to train than MLPs of a similar size, as RBF is a feed forward neural network with a single hidden layer. But the number of hidden layer neurons required for RBF neural networks grows exponentially with the number of inputs. A unique feature of this network is the process that is performed in the hidden layer. Input layer sends the input value to each of the nodes in the hidden layer. Each node in the hidden layer (neurons) are characterized by a transfer function: *G*. Usually the transfer function uses radial basis functions (e.g. Gaussian functions in formula (4)) as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters (See formula (5)).

$$f(x) = a\,exp\left(-\frac{((x-b)^2)}{2c^2}\right) \quad (4)$$

$$GW = b \quad (5)$$

where W is the weight vector, linking the hidden layer to the output layer and b is the output.

To avoid overtraining of the network, 10-fold cross validation method is used. This method splits the data into 10 parts of equal size. In each of the 10 iterations, one part is used as testing set and remaining as training sets. At the end of 10 runs, overall performance is the average of all runs' results.

4 EXPERIMENTS

4.1 Data for the Experiments

The nature of the data used in this work is Estimates made by the market on Earnings per Share for a company. The data is captured multiple times in a quarter for 14 years. First, the records for EPS values were extracted separately for each company, and data for six companies were used in the experiments.

The problem domain is divided into two problems: Problem 1 and Problem 2. The EPS numeric data for six companies is chosen, which is organized in matrix as follows:

Problem 1: The EPS data is columnised such that previous four values are used to predict the fifth value.

In Table 1, x1-x4 are inputs of the model and y is the fifth value as the target.

Table 1: Format of the Data sample for Problem 1.

x_1	x_2	x_3	x_4	y
1	2	3	4	5
2	3	4	5	6
3	4	5	6	7
4	5	6	7	8
5	6	7	8	9

Table 2: Format of the Data sample for Problem 2.

x_1	x_2	x_3	x_4	y
1	2	3	4	6
2	3	4	5	7
3	4	5	6	8
4	5	6	7	9
5	6	7	8	10

Problem 2: The EPS data is columnised such that previous four values are used to predict the sixth value.
In Table 2, x1-x4 are the inputs of the model and y is the sixth value as the target.

4.2 Experiment Set up

(1) The purpose of the work is to find the best model for the EPS prediction problem. Therefore, we perform the experiments for the data from six companies, and compare the performance of the three models LR, MLP and RBF.
(2) The parameter selection process for each algorithm was carried out with the help of industry experts.
(3) All the experiments are run for the datasets using 10-fold cross validation.
(4) Experiment platform: We use WEKA as the experimental platform.

4.3 Performance Evaluation

In this study, Correlation Coefficient (r) and the root mean square error (RMSE) are used for the evaluation of performance of the models.

A correlation coefficient equal to zero indicates that there is no relationship between the variables; i.e. if one variable changes, the other may or may not change. A correlation of +1.00 or -1.00 indicates that the variables involved are perfectly associated positively or negatively. A higher correlation coefficient indicates better fitting to the data. It can be calculated with formula (6).

$$r = \frac{\sum_{i=1}^{n}(Y_{act} - \bar{Y}_{act})(Y_{est} - \bar{Y}_{est})}{\sqrt{\sum_{i=1}^{n}(Y_{act} - \bar{Y}_{act})^2 \, (Y_{est} - \bar{Y}_{est})^2}} \quad (6)$$

RMSE gives the measure of the difference between values predicted by the model and the real values. The lower RMSE indicates the higher accuracy. It can be calculated with formula (7).

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(Y_{est} - Y_{act})^2}}{n} \quad (7)$$

Where
n is the sample size
Y_{act} is the real observed value
Y_{est} is the predicted value
$\bar{Y}_{act}$ is the average of real observed value
$\bar{Y}_{est}$ is the average of predicted value from the model

5 RESULTS AND EVALUATION

The performance of all the models built by the three algorithms for Correlation Coefficient r and RMSE in WEKA is shown in figures below.

5.1 Problem 1

In Problem 1, we predict fifth value using previous four values. Figure 2 illustrates the Correlation coefficient obtained with the three models for Problem 1. From Figure 2 we can see that the three models obtained similar performance for all the companies except for Company 5, for which MLP is slightly better than LR and RBF. Also the Correlation Coefficient for Company 5 is lowest among all the six companies. It means the data for Company 5 is weakly linear. So MLP obtained better performance for Problem 1.

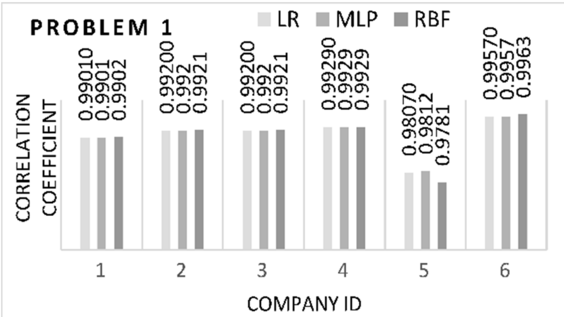

Figure 2: Correlation Coefficient obtained with the three models for Problem 1.

Figure 3 illustrates the RMSE obtained with the three models for Problem 1. Obviously it can be seen that RMSE for Company 4 is highest among all the companies. Although for all companies the three models obtained similar RMSE, for Company 5, MLP obtained the lowest RMSE compared with other two models for Problem 1. This is consistent with the Correlation Coefficient for Company 5 in Figure 2.

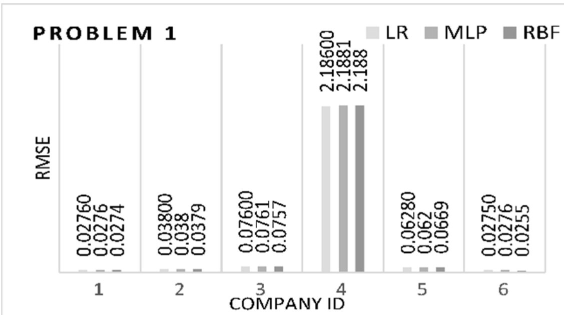

Figure 3: RMSE obtained with the three models for Problem 1.

5.2 Problem 2

Figure 4 illustrates the Coefficient of Correlation of six companies for Problem 2. From Figure 4, the performance in Correlation Coefficient for all the six companies for Problem 2 is similar to the performance for Problem 1. But all values for Problem 2 are lower than that of Problem 1. Company 5 still got the lowest Correlation Coefficient among all the companies. LR and MLP obtained better performance than RBF.

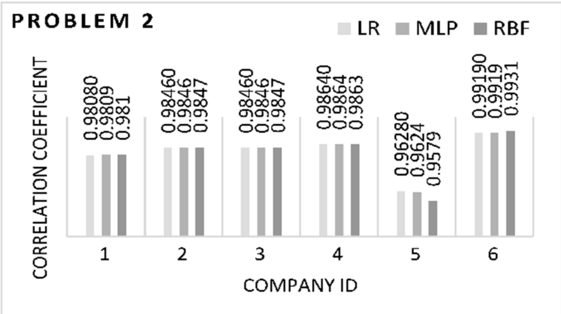

Figure 4: Correlation Coefficient obtained with the three models for Problem 2.

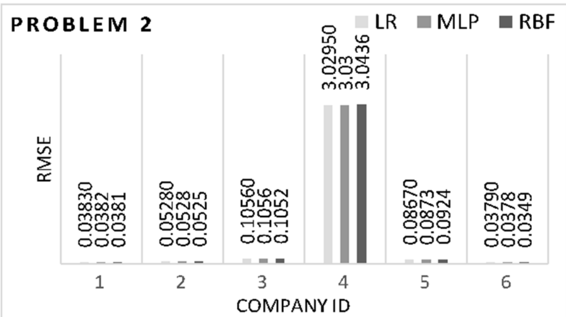

Figure 5: RMSE obtained with the three models for Problem 2.

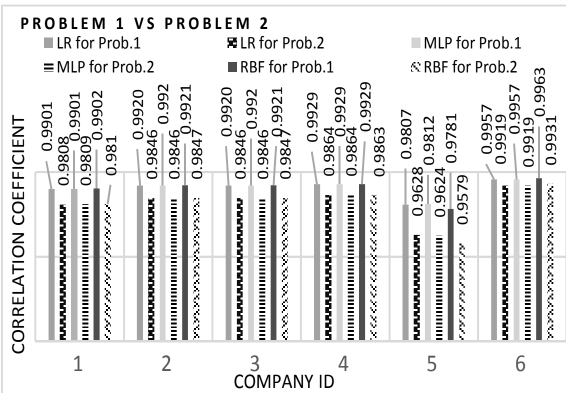

Figure 6: Correlation Coefficient for all the three models for six companies in both the problems.

From Figure 5, we can see that the RMSE of six companies for Problem 2 are similar to that for Problem 1. But the RMSE values of all companies for Problem 2 are larger than for Problem 1. For each company, the order of three models' performance in RMSE in Figure 5 is the same as the order of three models' performance in Correlation Coefficient in Figure 4 for Problem 2. The Coefficient of Correlation is consistent to the RMSE assessment.

In summary, Figure 6 illustrates all the Correlation Coefficients of six companies for Problems 1 and 2. It can be seen that the performance of the three models for Problem 1 is better than that for Problem 2. For company 5, which has high non-linearity, the MLP obtained the best performance.

6 CONCLUSIONS

In this paper, we employ three models (LR, MLP and RBF) to predict the change in the EPS of market firms with historical data. The experiments were carried out by running the three models on the data of six companies. We use the Correlation Coefficient and RMSE to assess the performance of the three models on the data of the six companies.

The experimental results show that MLP obtained best performance for high non-linear data. The performance in Correlation Coefficient is consistent to the performance in RMSE for the three models. The performance of the three models for Problem 1 is better than their performance for Problem 2. It means that we need to use different models for different data.

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