Foreign Exchange Rate Prediction between Indonesian Rupiah and U.S. Dollar Using Transductive Learning

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***Abstract* — Purchasing goods or services produced in United States would force Indonesian company or investor to purchase U.S. dollar, and vice versa. The drastically changes of the foreign exchange rate between Indonesian rupiah and U.S. dollar would significantly affect the good's price. Those facts motivated many studies focused on the exchange rate prediction. Various algorithms have been developed in which data mining has received arising attentions. The aim of this study is to evaluate the transductive learning to forecast the U.S. dollar price from Indonesian rupiah price. Compared to inductive learning, transductive learning is expected to perform better in prediction task. Tomorrow price of U.S. dollar could be difficult to be predicted because the tomorrow price would drastically increase or decrease. Using transductive learning, only small training data set is analyzed to determine the appropriate rule for prediction result. Since the rule is obtained from only small subset of training data, not from the whole, the rule is not generalized as which is applied by inductive learning approach. The result of the small subset of the training data would be used to find the best result of prediction.**

***Index Terms* — exchange rate prediction, inductive learning, nearest neighbor, transductive learning.**

I. INTRODUCTION

In the last few years, there are various methods that have been introduced and applied to forecast the value of foreign exchange rate [1] [2] [3]. Nonetheless these methods are basically can be categorized as inductive learning which is concerned to the creation of a model from all available data, representing the entire problem space [4]. Yet, this approached is useful when a general problem solution is needed in an approximate form and it has been proven to give good accuracy output for time-series prediction. This has been demonstrated by a study conducted by [5] that used neural network to predict the daily foreign exchange rate of the U.S. dollar compared to the German Mark.

In this study, we seek to determine the tomorrow's price of the Indonesian rupiah compared to the U.S. dollar using transductive learning, which have been introduced by Vapnik [6]. Compared to inductive learning, transductive learning is more appropriate for application focused on a specific case or vector, not on the model. This is very relevant to the movement of foreign exchange rate data where the changes of values tend to be specific from time to time. According to Bosnic et al., transductive inference refers to the common principle which states that when solving a given problem one should avoid solving a more general problem as an intermediate step [4].

Preliminary results generated from a study using K-Nearest Neighbour (K-NN) and Weighted K-Nearest Neighbour show that personalized models predicts stock index values in the shorter term with a reasonable degree of accuracy [7]. Therefore we expect to develop a new transductive algorithm for time-series prediction. We expect that the algorithm will provide better prediction for fluctuative time-series data as it has been stated by Kasabov [8]. In addition we aim that proposed algorithm would acquire the ability to reveal repeating similar patterns from the past as well.

II. TRANSDUCTIVE LEARNING

Transduction is defined as an inference principle that takes a training sample and aims at estimating the values of a discrete or continuous function only at given – unlabelled – points of interest from input space, as opposed to the whole input space for induction [9]. This approach, which is usually used to solve the classification problem, is also defined in contrast with inductive inference as a method used to estimate the value of a potential model (function) only for a single point of space (that is, a new data vector) by utilizing additional information related to that vector [4]. Based on this characteristic, transductive inference would be more appropriate to be applied in a data set where a single solution could not be used to answer all problems which emerge in the whole problem set.

In their experiment [8], have implemented the transductive learning on a real data set from a medical institution to solve an identification and prediction problem, and it was found that the new method performed better compare to the use of inductive inference. Additionally, structural information of unlabeled data was also revealed in the study.

A. K-Nearest Neighbour

A transductive model is created "on the fly" for each new input vector and this individual model is based on the closest data samples to the new sample taken from a data set. K-Nearest Neighbour (K-NN) is the simplest and most widely used approaches to transductive learning, where for every new sample data, the nearest K samples are derived from a data set using a distance measure to define similarity between new data set and data sample, and a voting scheme is implied to define the class label for the new sample. Euclidean distance is usually chosen as the distance measure, defined in the following formula:

$$\left(\sum_{i=1}^{n} |x_i - y_i|^2\right)^{1/2} \qquad (1)$$

In the K-NN method, the output value y_i for new vector x_i is calculated as the average of the output values of K nearest sample from data set D_i. The following steps describe about K-NN algorithm:

- **Step 1**: The training examples are vectors in a multidimensional feature space. The space is partitioned into regions by locations and labels of the training samples.
- **Step 2**: A point in the space is assigned to the class c if it is the most frequent class label among the k nearest training samples. Usually Euclidean distance is used as the distance measure; however this will only work with numerical values. In cases such as text classification another metric, such as the overlap metric (or Hamming distance) can be used. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.
- **Step 3**: When new test sample (whose class is not known) is represented as a vector in the feature space, distances from the new vector to all stored vectors are computed and k closest samples are selected.
- **Step 4**: Classify the new vector based on the most common class amongst the K nearest neighbors.

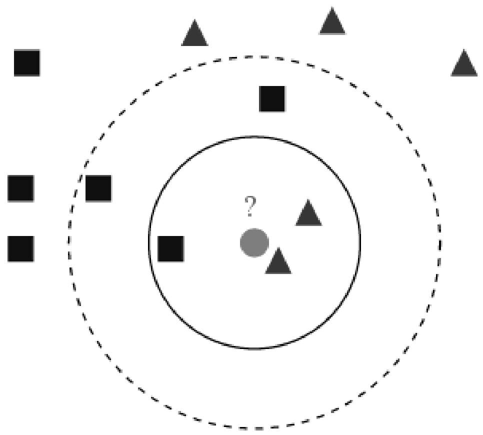

Figure 1. Example of *k*-NN classification. The test sample (circle) should be classified either to the first class of squares or to the second class of triangles. If *k = 3* it is classified to the second class because there are 2 triangles and only 1 square inside the inner circle. If *k = 5* it is classified to first class (3 squares vs. 2 triangles inside the outer circle).

Result of KNN depends significantly to the value of k, and the best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but it make boundaries between classes less distinct. Nevertheless the accuracy of the K-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance.

B. Polynomial Regression based Transductive Learning

The basic idea in our proposed algorithm is to merge K-NN method with regression. Implementation of regression analysis in transductive learning has been successfully used by [9], which concern on prediction reliability in regression and achieves good results.

In this study, three degrees of regression function are applied, which are linear regression, quadratic regression, and cubic regression. The following steps describe in detail about our algorithm:

- **Step 1**: Define partition data value as the different value between data point. If there is N point of training data, then the new partition will contain total (N-1) data point.
- **Step 2**: Segment the new partitioned data into L points for each block B. Suppose we have T points new partitioned training set, then the number of block B will be derived by as formula below:

$$B = (T - L) + 1 \qquad (2)$$

The first block consists of first data point until L^{th} data point, for the next block (second block) will consist of second data point until (L^{th} data point + 1), and so on.

- **Step 3**: For each block in the segmented data, generate the three regression functions, which are linear, quadratic and cubic regression function.
- **Step 4**: For each block in the segmented data, find the most fit regression function by comparing the y value of regression function to its real value using Euclidean distance.
- **Step 5**: After creating the pattern for each block using polynomial regression analysis, then reveal the most appropriate pattern (B_α) in the segmented data compared to the last pattern (B_T) in the training set to predict the point (T + 1). In this step, the nearest K pattern is achieved using Euclidean distance.

$$B_{\alpha} = \{B_1,\ldots,B_k\} \tag{3}$$

- **Step 6**: From those nearest K patterns, find the next value for every nearest pattern (y_α). y_i is derived from the last value of block (B_i + 1).

$$y_{\alpha} = \{y_1,\ldots,y_k\} \tag{4}$$

- **Step 7**: Calculate the average value from y_α as described as the following formula:

$$Y_{output} = \sum y_\alpha / k \tag{5}$$

- **Step 8**: The result of predicting value (T + 1) will be generated from addition between the last value (T) of training set and different result value Y_{output}.

$$X_{(T+1)} = X_T + Y_{output} \tag{6}$$

- **Step 9**: In the last step, the Root Mean Squared Error (RMSE) is applied to calculate how accurate the result is compared to the real value from test set. The RMSE formula is described as follow:

$$r = \sqrt{\frac{\sum x^2}{n}} \tag{7}$$

where x_1, x_2, $x_3 \ldots x_n$ are the errors at n reference points, and n value is similar defined as k value.

III. RESULT AND ANALYSIS

To test the performance of our proposed algorithm, we have conducted experiments using two data sets of foreign exchange rates which are: (1) the Indonesian rupiah compared to the U.S. dollar and (2) the U.S. dollar compared to the European euro. First data set span from 24th January 2001 to 31th May 2009 (2135 records), and the second data set covers the period of 9th December 1996 to 25th August 2008 (3039 records).

From both datasets, the last 14 data points have been selected as our test set and the remaining data points are defined as training set. The 14 points of the predicted value and test set value are calculated to generate RMSE value as the result. The following tables show the RMSE values from both datasets by selecting 10 different of k values (1 - 10).

Table 1. Prediction result using modified nearest neighbor as transductive learning. Different 10 RMSE values by selecting 10 different k values (1-10).

K	RMSE IDR – USD	RMSE USD - EUR
1	137.995342	0.007490
2	108.280060	0.006945
3	87.616136	0.006660
4	94.701717	0.007042
5	92.989508	0.006685
6	89.780619	0.006588
7	96.038766	0.006387
8	99.039241	0.006461
9	91.115389	0.006564
10	90.136848	0.006750

From the results showed in Table 1, it can be observed that as in K-NN, our method depends quite significantly on the value of *k* as well. Different value of *k* will lead to the different level of accuracy in the prediction result.

Using value of *k* which generates the best RMSE value as shown in Table 1, results of prediction value and test set value for data set 1, exchange rate between IDR and USD are illustrated in Table 2 and Figure 2.

Table 2. Data analysis from different 14 values of prediction value and real value for first dataset (k= 3).

TIME POINT (Day)	PREDICTED VALUE (Rupiah)	REAL VALUE (Rupiah)
1	12099.0	11980.0
2	11884.0	11990.0
3	11901.0	11980.0
4	12035.7	11958.0
5	12001.0	11979.0
6	11866.7	11900.0
7	11855.0	11833.0
8	11767.7	11760.0
9	11393.0	11435.0
10	11701.3	11530.0
11	11451.3	11530.0
12	11376.7	11495.0
13	11648.7	11530.0
14	11527.3	11575.0

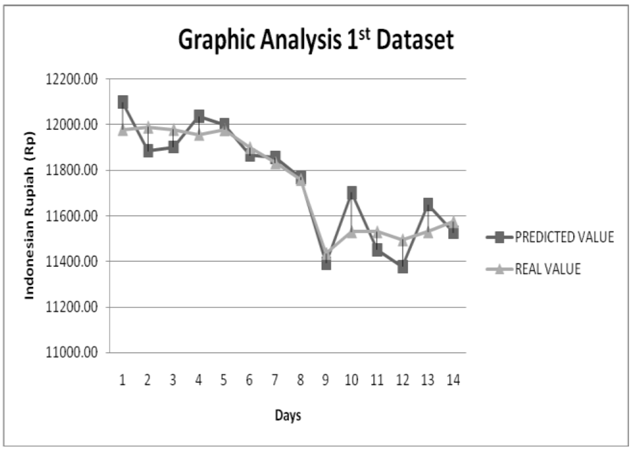

Figure 2. Graph analysis first dataset between predicted value and the real value in test set for IDR and USD.

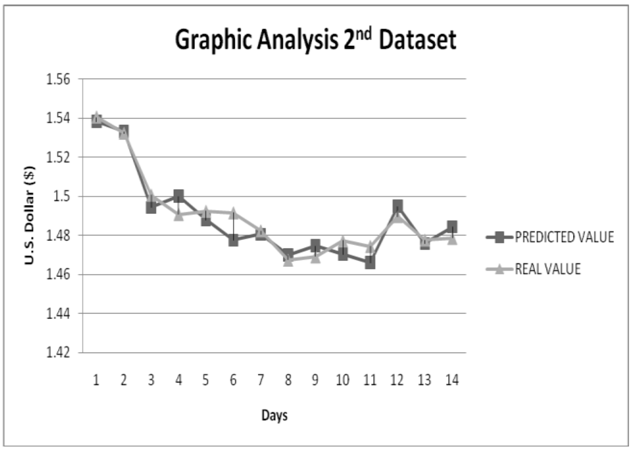

Figure 3. Graph analysis second dataset between predicted value and the real value in test set for USD and EUR.

Other results of prediction for data set 2, which is the exchange rate between USD and EUR are also illustrated in Table 3 and Figure 3.

Table 3. Data analysis from different 14 values of prediction value and test set value for second dataset by selecting k = 7.

TIME POINT (Day)	**PREDICTED VALUE (USD)**	**REAL VALUE (USD)**
1	1.53827	1.54040
2	1.53313	1.53220
3	1.49417	1.50060
4	1.49989	1.49080
5	1.48783	1.49240
6	1.47740	1.49160
7	1.48047	1.48240
8	1.46981	1.46750
9	1.47454	1.46920
10	1.47039	1.47730
11	1.46594	1.47450
12	1.49470	1.48970
13	1.47570	1.47770
14	1.48423	1.47860

By comparing the prediction value to the actual value from the test set for each data set, our proposed algorithm performs a high quality accuracy in predicting single time series data set as shown in Figure 2 and 3. Additionally, the algorithm also shows its robustness since it gives considerably comparable performance when applied to different data set.

As expected, our proposed algorithm is able to reveal similar patterns from the past that can be associated to latest pattern of movement using transductive learning, and then used them to predict future value. Other than that, we realized that the regression calculation for every block of training data always generalize cubic regression function as the most fit regression function rather than linear or quadratic regression function. Based on this finding, we assume that the higher regression function, the most fit regression function generalized.

IV. CONCLUSION AND FUTURE WORK

Results from the experiments conducted in this study indicated that our proposed algorithm provides high-quality accuracy in predicting movement of time-series data in particular exchange rate value between Indonesian Rupiah and United States Dollar. Additionally, by merging a traditional transductive learning, i.e. K-NN, with polynomial regression, the proposed algorithm is proficient to extract repeating patterns of exchange rate differences from the past.

As for future works, we would like to improve our proposed algorithm so it would be able to do prediction for multiple time series data. The basic idea is to modify our proposed algorithm so it would take into account information about exchange rate movement from other foreign exchange rates, and use this information to conduct a transductive inference through past data set. In addition we would like to conduct a comparative study to compare the performance of our proposed algorithm with the other time series prediction methods.

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