Rough Sets for Predicting the Kuala Lumpur Stock Exchange Composite Index Returns

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ABSTRACT

This study aims to prove the usability of Rough Set approach in capturing the relationship between the technical indicators and the level of Kuala Lumpur Stock Exchange Composite Index (KLCI) over time. Stock markets are affected by many interrelated economic, political, and even psychological factors. Therefore, it is generally very difficult to predict its movements. There are extensive literatures available describing attempts to use artificial intelligence techniques; in particular neural networks and genetic algorithm for analyzing stock market variations. However, drawbacks are found where neural networks have great complexity in interpreting the results; genetic algorithms create large data redundancies. A relatively new approach, the rough sets are suggested for its simple knowledge representation, ability to deal with uncertainties and lowering data redundancies. In this study, a few different discretization algorithms were used at data preprocessing. From the simulations and result produced, the rough sets approach can be a promising alternative to the existing methods for stock market prediction.

Keywords

Financial Analysis, Index Fund, Continuous Attributes, Data Mining, Discretization

1.0 INTRODUCTION

Stock markets are affected by many interrelated economic, political, and even psychological factors. Therefore, it is generally very difficult to predict the movements of stock markets. People tend to invest in index fund because of its diversification, lower risk and being less random (Yao et al., 1999). Index funds are similar to mutual funds based on an index to mirror its performance (Investopedia.com, 2003). An index fund's return is the total return of the portfolio minus the fees an investor pays for management and fund expenses. Indices are statistical indicators used for tracking the overall performance of stocks in the market. KLCI is one of the major index funds available in Malaysia.

Technical analysis assumes that stock market moves in trends and these trends can be captured and used for forecasting. The technical analyst use tools as charting patterns and technical indicators to acquire some recurring patterns and turning points in the market behavior that are predictable. Nowadays, traders no longer rely on statistical techniques to provide information about the future of markets but rather use a variety of new techniques to obtain multiple signals. Neural networks, genetic algorithms, and fuzzy sets are some common artificial intelligent methods that are often used to produce trading signals.

The concept of a neural network is to mimic the complex processing of a biological brain. Among the models developed was a network predicting the Standard & Poors 500 stock exchange by (Gately, 1996). His studies achieved 93.3% probability of predicting a market rise and an 88.07% probability of market. Neural network approaches are classified as non-causal modeling. The prediction rules are implicitly represented in the network. They cannot be extracted such that humans can interpret them (Golan and Ziarko, 1995). Induction algorithm used encapsulates information like the number of repetition it made and when a concept is learned.

Research has also been conducted with genetic algorithms as training approach for neural networks (Margarita, 1992). Genetic algorithms are based on the evolution of plants and animals. However, we still have problems choosing the number of generations and may cause huge data redundancies.

Thus, rule based methods such as fuzzy theory and rough sets are being proposed in numerous applications of predicting the stock market. This approach was suggested due to its simple knowledge representation, strong ability to deal with vagueness or uncertainties and the ability in lowering data redundancies.

(Bazan et al., 1994) discussed trading system building problem using the rough set theory. In his work, 15 market indicators were collected and the problem was focused on how to deduce the rules that map the financial indicators at the end of a given month on to the stock price changes a month later. The preliminary results seemed to be below satisfactory with a classification accuracy of 44%.

(Baltzersen, 1996) also did some research on the Total Index of the Oslo Stock Exchange (OSE) using the rough sets theory. His studies came out with classification accuracy varies from 25% to 45%.

(Shen, 2002) conducted another interesting study to predict economical developments using rough set theory. His studies demonstrated the 'columnizing' method for converting temporal information into an Information System and seven market indicators as feature selection. Also in his studies, WARS (Weighted Accumulated Reconstruction Series), a trend-following indicator, has been found to be able to track market changes accurately. Four market indices are chosen as subjects and the results shows that the rough set approach did find the inherent rules of the financial market and its classification accuracies were able to reach as high as 76.1%.

Based on numerous studies conducted and their successful results, there is good reason and high probability that stock market prediction using the rough sets approach is applicable and promising.

In the following, the utilization of the rough set theory to forecast the Kuala Lumpur Stock Exchange Composite Index (KLCI) is focused. The remainder of the paper is organized as follows. In section 2, we describe the general methodology of rough set theory. In section 3 and 4, we describe the preprocessing of data and the discretization algorithms used. In section 5 and 6, the performance of the proposed approach is reported by experiment results. We will evaluate the discretization methods, the appropriate range of data use for induction, and the efficiency of the decision attributes to generated buy-hold-sell signals. Section 7 will conclude this study.

2.0 THE PROCESS & MOVING SIMULATION

Rough sets refer to a mathematical concept in set theory, used to represent uncertainties in data. The main steps of the rough set approach are data discretization, mapping information to decision system, computing reducts, discovering, and verifying decision rules.

The process of stock market data classification and analysis in which we are concerned is shown in Figure 1.

For predicting the KLCI, first, raw stock market data that consists of a day's close, high, low, open and volume is collected. Several technical indicators' values are derived from the raw data and shall be used as conditional attributes for classification rules. Before mapping the temporal information system into decision system, all numeric attributes are discretized.

Then, training data are separated from the testing data. Usually, a few numbers of objects at the end of the raw data is used as testing data and data before the testing data are used for training. Using ROSETTA, reducts or a minimal selection of attributes is calculated from the training data, and trading rules are subsequently been generated.

These trading rules are used to classify the testing data. Algorithms for generating rules can be adjusted to produce better classification rules. This process iterates until it meets certain classification accuracy.

For prediction of an economic system, such as stock prices, in which the prediction rules are changing continuously, learning and prediction must follow the changes. In this system, prediction is done by simulation while moving the objective learning and prediction periods. The moving simulation predicts as in Figure 2.

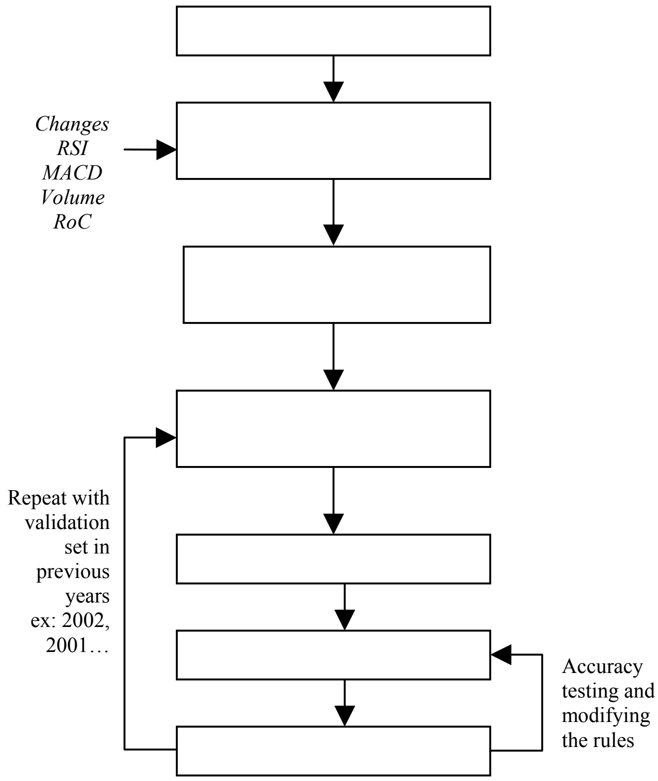

Figure 1: The process of stock market data classification and analysis

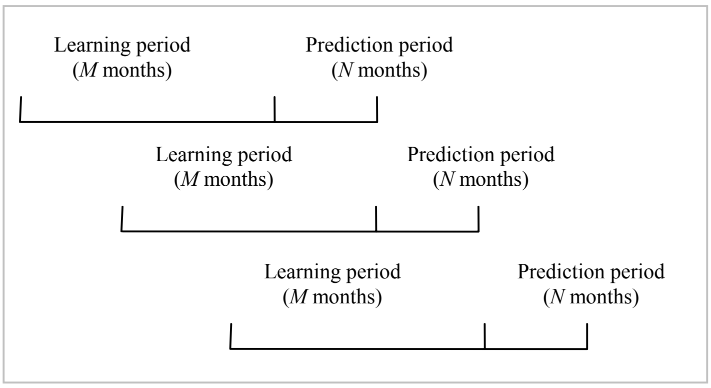

Figure 2: The moving simulation

3.0 DATA & ATTRIBUTES SELECTIONS

The historical daily data of KLCI between January 2001 and August 2003 were used in this research. The data includes a day's close, high, low, open, and volume.

These data were chosen based on several incidents happened that affected not just local markets but also globally. Those incidents include periods during the economic crisis suffered globally spanning across 2001 to 2002. The United States of America declared war against Iraq on March 2003. This has also more or less affected Malaysian economy.

Furthermore, the Severe Acute Respiratory Syndrome (SARS) epidemic started on April 2003 seriously damaged business and tourism around the Malaysia. By capturing investors' trends and psychologies of various conditions, the rule extracted would be more robust and able to forecast better regardless of any condition happening in the future.

Four parameters were used for the information table. They are 20-40-15 days moving average convergence-divergence (MACD), 40-days relative strength index (RSI), 15-days volume rate of change (VROC) and 3-days trend. These parameters are common stock market trend indicators. All the parameters values are derived from the original stock market data and smoothed.

3.1 Trend 3-days

The 3-days trend is a string parameter where its value is either 'Gd' or 'Gu' for going down and going up. The trend was determined using the below formula:

IF [Close $_{today}$ – Close $_{3\ days\ ago}$] > 0 (1)
THEN decision = '*Gu'*
ELSE decision = '*Gd'*

3.2 Moving average convergence-divergence 20-40-15 days

The 20-40-15 moving average convergence-divergence (MACD) consists of two lines that are derived from three exponential moving averages (EMA). The MACD line is the difference between a 20-day EMA and a 40-day EMA; the signal line is a 15-day EMA of the MACD line. To fit into the information system, a MACD histogram is created by subtracting the signal line from the MACD line.

To compute an EMA, first, determine the number of days. A value will be given to every day as weightings. The most recent days will have higher values. Then, weighted values are derived by multiplying closed values with its associated weightings. The EMA is the average sum of all derived values.

3.3 Relative strength index 40-days

Relative strength index (RSI) compares the relative strength of price gains on days that close above the previous days close to price losses on days that close below the previous day's close.

$$RSI = 100 - \frac{100}{1 + RS} \tag{2}$$

Average Gain = Total Gains / 40 days
Average Loss = Total Losses / 40 days
RS = Average Gain / Average Loss

The formula for RSI is shown above where RS is the average of positive closing changes for a specified number of days divided by the average of negative closing changes for the same number of days.

3.4 Volume rate of change 15-days

The 15-days VROC was calculated from 20-days EMA volume. The formula is based on the basic rate of change oscillator, where V_0 equals the most recent volume and V_n equals the volume n days ago.

$$VROC = \frac{V_0 - V_n}{V_0} \times 100\% \tag{3}$$

3.5 Decision attribute

The decision attribute determines the future direction of the data sets. For investors, prediction results of just either UP or DOWN are considered pointless. Instead, investors are expecting more prediction results that are able to tell how much the market is going up or down so that they can plan their investment strategies to obtain the maximum profit.

Therefore, the rate of change for average 4 days in the future is used as our decision attribute. These rates of change values are subsequently grouped into four intervals:

$$ROC = \frac{average(\text{4 days ahead}) - close(\text{today})}{close(\text{today})} \times 100 \tag{4}$$

$$\text{decision} = \begin{cases} [-\infty,\ -2.0)\ where\ ROC < -2.0 \\ [-2.0,\ 0.0)\ where\ -2.0 \le ROC < 0.0 \\ [0.0,\ 2.0)\ where\ 0.0 \le ROC < 2.0 \\ [2.0,\ \infty)\ where\ ROC \ge 2.0 \end{cases}$$

The decision attributes can be interpreted as follows. For example, a person bought KLCI for RM 1000.00 at a closed value of 624.21. If the index is predicted at [0.0, 2.0), KLCI will go up in the next four days in average from 0% to as much as 2%. If that person sells its investment within these four days, the profit he gets is equal or less than RM 20. If the index is predicted [-∞, -2.0), KLCI will go down in the next four days for at least 2%. If that person sells its investment within these four days, he will lose RM 20 or more.

The decision attribute can be used in some buy-hold strategy. When a market has been predicted declining for at least 3 days consecutively, it indicates that the future market is bearish; and the price per unit is getting lower. Long-term investors can choose whether to start buying or wait for the last buying signal. The last buying signal appears the moment when a market is predicted to rise after declining for a few days consecutively. At this time, the price per unit should be the lowest before it starts climbing again.

On the other hand, when a market has been predicted to rise for at least 3 days consecutively, it indicates that the future market is bullish; and the price per unit is getting higher. These situations are favor to long-term investors whom have already bought a certain number of units earlier. They can choose whether to start selling or wait for the last selling signal. The last selling signal appears the moment when the market is predicted to decline after rising for a few days consecutively. At that time, the price per unit should be the highest before it starts to down again.

Buying signals are not necessarily appears at the end of a declining behaviour. Another type of buying signal appears when a market is predicted to climb very high such as the "[2.0, ∞)" attribute. Short-term investor will buy at a large volume and sell immediately the moment when the market is predicted to decline for the next few days.

The periods between the buying and selling signals indicates a hold. However, investors should always be aware that an index fund's return is the total return of the portfolio minus the fees an investor pays for management and fund expenses.

3.6 Decision table

Time series data are inter-related with each other. The value closed today is more or less affected by the values in the past. The decision table needs to have temporal effect which make every object relates to each other. Therefore, a window size of 3 days is used to create temporal effect in each object of the information system.

In the decision table, every object will have extra two columns for each attribute which holds attribute values of a day ago and a days before it. Finally, the information system has 12 columns of condition attribute and a column of decision attribute (Table 1).

Table 1: Decision table information

Features	Quantity
Instances	550
Continuous attributes	9
Discrete attributes	3
Decision Class	4

4.0 DATA DISCRETIZATION

Even though the rough set method is an appropriate knowledge-mining tool, it cannot be applied to generate rules from the continuous features unless they are first discretized. This requires a discretization method to pre-process the data.

4.1 Equal frequency binning

Binning algorithms are the simplest method to discretize a continuous valued attribute by creating a specified number of bins. In this study, the bins are created using equal frequency approach where an equal number of continuous values are placed in each bin. Then, each bin is associated with a distinct discrete value.

In this algorithm, the numbers of bins have to be first determined. This value can be attained from user or by a preset value. With the number of bins, we can determine the bin size by dividing the total number of objects with the total number of bins. Then, the objects will be sorted and searched through for cut points.

4.2 Modified chi2

The modified chi2 algorithm (Shen, 2002; Tay and Shen, 2002) applies the chi square statistic, which conducts a significance test on the relationship between the values of an attribute and its class. In phase 1, it begins with a large significance level, α for all numeric attributes to be discretized. Then, for each attribute, the following is performed:

1. Calculate the χ^2 value for every pair of adjacent intervals.
2. Merge the pair of adjacent intervals by considering the effects of the degree of freedom (Shen, 2002; Tay and Shen, 2002).

Merging continues until all pairs of intervals have χ^2 values exceeding the parameter determined by α. The above process is repeated with α decreased as long as the discretized data's inconsistency rate is above zero.

The phase 1 of chi2 is an automated version of Chi Merge (Kerber, 1992) with a loop that automatically increments the χ^2 threshold. A consistency checking is to make sure that chi2 automatically determines the proper χ^2 threshold that keeps the fidelity of the original data. The second phase refines the intervals. If any of the attributes consisting of any of the intervals can be further merged without increasing the inconsistency of training data above the given limit, then the merging phase is carried out.

When calculating the χ^2 values, if either R_i or C_j is 0. E_{ij} is set to 0.1. The default value for δ is zero assuming that the data set is consistent, and can be reset to any value between zero and one (Liu and Setiono, 1995; 1997).

4.3 Entropy MDLP

The entropy discretization is a supervised method (Dougherty et al., 1995; Fayyad and Irani, 1993). The entropy-based approach utilizes the minimum description length principle (MDLP) as a stopping criterion for the recursive algorithm.

This discretization first sorts all the examples by the attribute being discretized. Then, a recursive divide and conquer approach is used to create the discretization. The algorithm can be described as the following steps:

1. Choose the best cut point according to the entropy criteria
2. Evaluate of the cut point is significant according to the MDLP. If it is significant, then recursively call the discretization algorithm for each of the intervals split by the cut point.

5.0 EXPERIMENT

The decision tables are divided into several rule extraction sets (32, 125, 250, and 500 objects) which covers the period before May 27, 2003, and several validation set (20, 30, 40, and 50 objects) which covers the period after May 27, 2003.

For this study, only three types of discretization algorithms are tested. Four identical decision tables were constructed for different discretization methods as listed below.

- Rosetta's equal frequency binning algorithm
- Rosetta's entropy MDLP algorithm
- Customized equal frequency binning algorithm
- Customized chi2 algorithm

For this experiment, default settings are used when discretizing data using Rosetta. Three different bin sizes are used for the customized equal frequency-binning algorithm that is 5, 20, and 100 bins.

After discretizing, the number of cuts produced is shown in (Table 2). Equal frequency binning algorithm created the same number of cut points for each attribute, but chi2 have different cut points for each attribute. The entropy MDLP algorithm created a large number of cut points.

Table 2: Number of cut points for each attributes and average time (in seconds) required for discretizing each data samples

Data Samples	RSI	MACD	VROC	Time
EFB Rosetta	2	2	2	<1 sec
EFB 5 bin	4	4	4	<1 sec
EFB 20 bin	19	19	19	<1 sec
EFB 100 bin	99	99	99	<1 sec
Chi2	13-15	12-16	11-15	3 min 1 sec
Entropy Rosetta	308-330	293-319	315-321	2 min 27 sec

Proper reducts are computed from each of the samples using dynamic reducts with exhaustive calculation. Each set of reducts will subsequently be used to generate rules for classification.

5.1 Results of classification on real data

The classification results for each sample are shown in (Figure 3-6). Classification rules generated from the data discretized with the embedded equal frequency-binning algorithm performed the worst. Most of the classification accuracy falls below the acceptable ratio of 50%.

Similar to the former, the classification accuracy for the other three data discretized with 5, 20, and 100 equal frequency bins declines with more training data except for cases with 500 training objects. Among the three different bin sizes, the best bin size is five where rules created from its dataset notably classifies at a higher ratio compared with other data discretized with the same algorithm.

Lesser bins do not necessarily help in improving the classification result; the equal frequency-binning algorithm in Rosetta produced only two cuts points for each attribute in the data sets (Table 2). When rules were tested on a few samples of new objects, it performed badly. It is believed that the over-discretization caused too many information in the data get loss.

For the chi2 discretization algorithm, the classification ratio is better. Its classification pattern was different from the previous samples in most cases; the accuracy for all chi2-discretized data samples with different training sets remains higher than 50%. The chi2 discretization algorithm took about 3 minutes while the equal frequency binning discretization algorithm only takes less than a second to complete (Table 2). However, the chi2 discretization did not help to improve classification accuracy when applied on larger data, and this is probably because it is not suitable for very large data (Shen, 2002).

The entropy algorithm outperforms the equal frequency binning and chi2 algorithm. In contrast to the chi2 algorithm, the classification accuracy for entropy-discretized data increase proportional to the volume of training data. With 500 training objects, its rules could classify over than 80% of the testing data.

5.2 Results of moving simulation

Based on previous evaluations, we know that bigger training data improve the classification accuracy and the entropy MDLP is the best discretization algorithm for data preprocessing. Using the best algorithm and parameters, we apply our moving simulation with a series of data from 1999 to 2003.

Table 3: Prediction accuracies for moving simulation

Simulation	Training Period (500 days)	Testing Period (50 days)	Prediction Accuracy
1	6/4/1999 to 11/4/2001	12/4/2001 to 25/6/2001	88%
2	6/12/1999 to 2/1/2002	3/1/2002 to 20/3/2002	92%
3	6/9/2000 to 30/9/2002	1/10/2002 to 12/12/2002	98%
4	26/1/2001 to 18/2/2003	20/2/2003 to 2/5/2003	86%
		Average:	91%

All samples use 500 days before the testing period as training data. The first simulation examines the period between April 12, 2001 and Jun 25, 2001. During that year, Malaysia suffers from the economic crisis and KLCI records the lowest value over the past 4 years at 553.34 points. Most investors trade at a short-term basis. In just a few days, stock prices can rise as much as 5%; and dropped as much as 8%.

The second simulation classifies the period covering from January 3, 2002 to March 20, 2002. The recovery of the Malaysian economy gained momentum in 2002 amidst a more challenging external environment. The KLCI flaunt an upward trend and surpass 800 points in April that year. Malaysia benefited from some diversion of foreign investment flows, particularly through outsourcing activities and the relocation of design and product development operations by some foreign companies in the electronics industry (BNM, 2003).

The third simulation classifies the period between October, 2002 and December, 2002. There are several mixtures of short-term trading patterns during this time. Part of the unstable buying and selling activities in November believed to be related to several terrorist attacks in the United States of America.

The last simulation examines the period covering from February 20, 2003 to May 2, 2003. During this time of the year, the United States of America declared war against Iraq on March. KLCI dropped as much as 36 points during the war. Then on April, the Severe Acute Respiratory Syndrome (SARS) epidemic regional outbreak seriously affected most of the tourism sectors and some business around the world.

Table 3 records the prediction accuracy for each individual simulation. The average prediction accuracy for all four samples is 91%.

6.0 DISCUSSION

From all the tests carried out, supervised discretization methods are more appropriate for discretizing stock market prediction data compared to unsupervised techniques. This is because the decision attributes work as the classification information and should be taken into consideration when discretizing the data.

To verify the effectiveness of the prediction system, a simulation of buying and selling of stock was done. Buying and selling was simulated by the one-point buying and selling strategy, so performance could be clearly evaluated. One-point buying and selling means all available money is used to buy stocks and means all stocks held are sold at a time. In the prediction system, buying and selling signals are interpreted as described earlier.

Trading signals within the 50 testing data (May 27, 2003 to August 4, 2003) are determined (Figure 7). Trading signals shown are divided by short-term signals and long-term signals. At the beginning, the prediction output could not determine the decision for day 1. Therefore, the first short-term buying signals could not be identified. On the other hand, the identified buying and selling signals are sufficient and accurate for the rest of the testing data.

In the simulation, RM1000 is used to buy KLCI each time the prediction system generates a long-buy or a short-buy signal. An administration fee of 2% is included in each selling transaction fee. Our simulation was able to generate an excellent profit ratio of 4.88% within 50 days that is as much as RM97.52 from RM2000 capital.

7.0 CONCLUSION

Several of techniques such as neural network have been utilized for analyzing stock market variations and achieved good result. Targeting at applying the rough sets theory to time series forecasting problem, a system was built to model the KLCI and to implement the whole process.

The first step is to convert the temporal information system to an information system, which can be processed using the traditional rough set model. Four well-established indicators are included to compose the information system. Each column corresponds to an indicator.

Secondly, the composed decision table is discretized separately using equal frequency binning, chi2 and the entropy based MDLP algorithm. The discretized decision table is subsequently sent to generate reducts and rules.

After the rules generation, new objects from the test data are classified using these rules. The results show that the rough set approach is able to find inherent rules of the financial market, but the most important thing is its prediction results were able to help users in their investment planning to gain maximum profits.

Finally, we believe that with more financial experience, this study will be able to generate results that are more promising.

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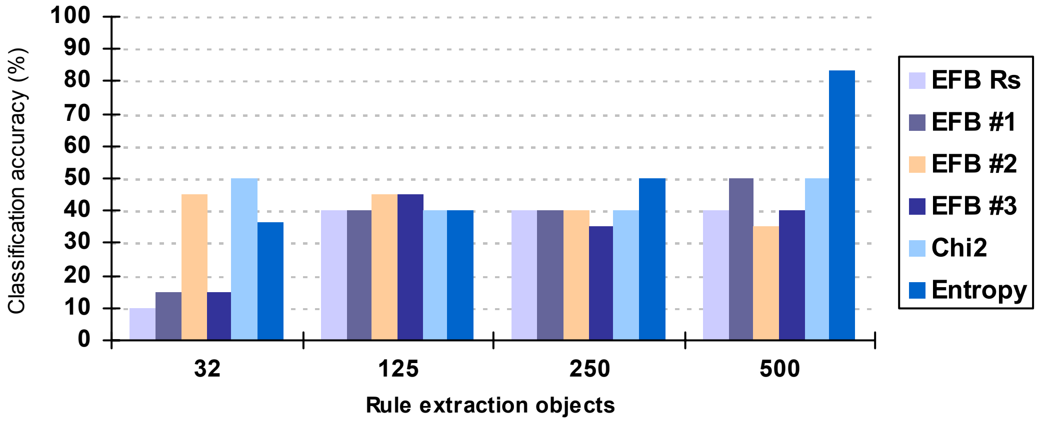

Figure 3: Classification accuracy for different discretized samples on 20 testing data

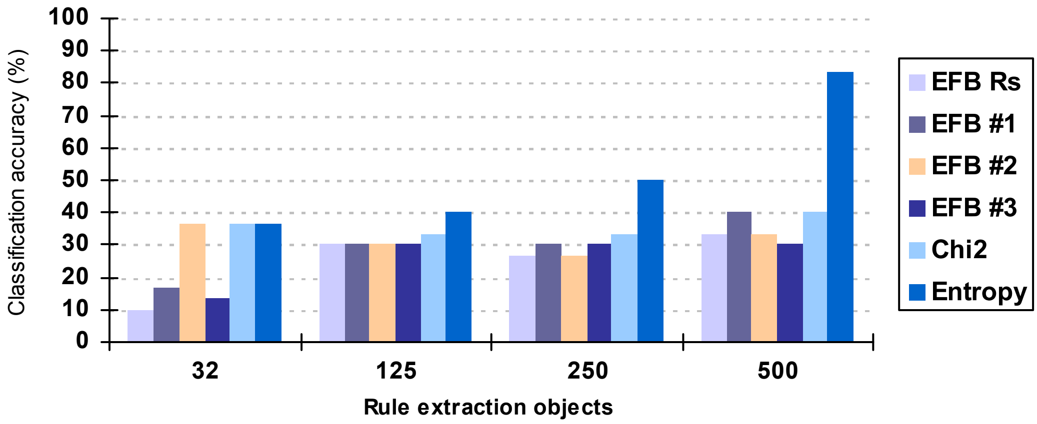

Figure 4: Classification accuracy for different discretized samples on 30 testing data

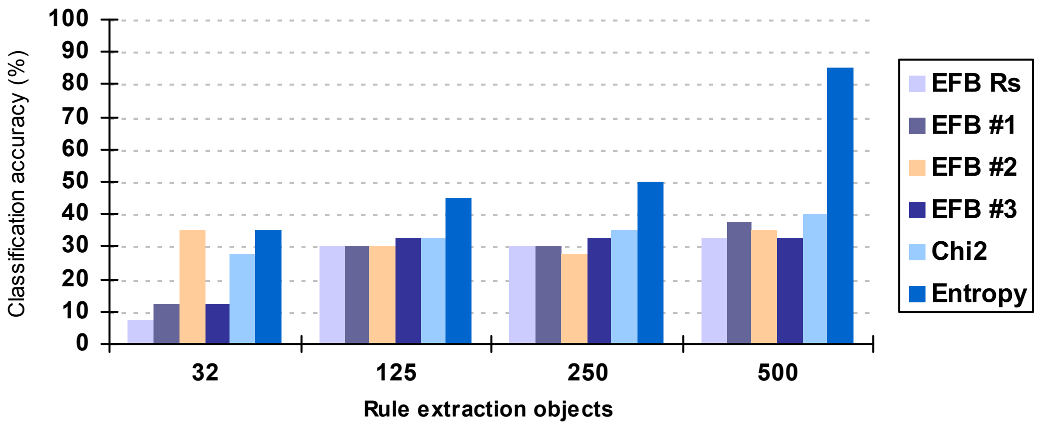

Figure 5: Classification accuracy for different discretized samples on 40 testing data

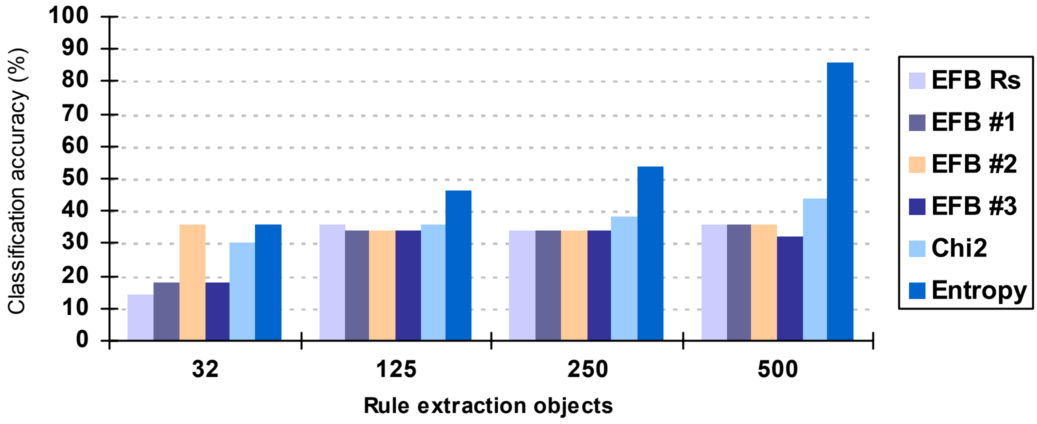

Figure 6: Classification accuracy for different discretized samples on 50 testing data

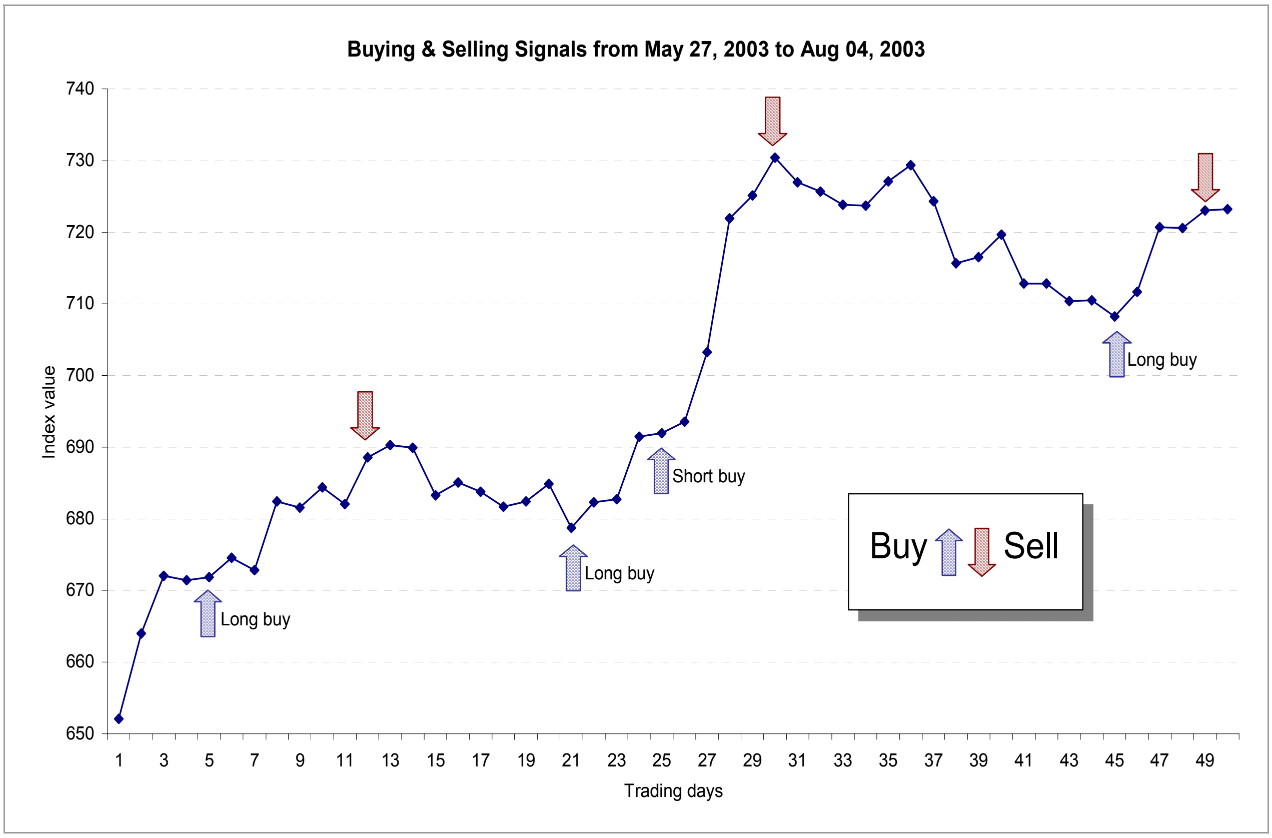

Figure 7: Buying and Selling Signals within KLCI 50 days (May 27, 2003 – Aug 4, 2003)