Prediction of Financial Performance Using Genetic Algorithm and Associative Rule Mining

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Abstract— The proposed system introduces a new genetic algorithm for prediction of financial performance with input data sets from a financial domain. The goal is to produce a GA-based methodology for prediction of stock market performance along with an associative classifier from numerical data. This work restricts the numerical data to stock trading data. Stock trading data contains the quotes of stock market. From this information, many technical indicators can be extracted, and by investigating the relations between these indicators trading signals can discovered. Genetic algorithm is being used to generate all the optimized relations among the technical indicator and its value. Along with genetic algorithm association rule mining algorithm is used for generation of association rules among the various Technical Indicators. Associative rules are generated whose left side contains a set of trading signals, expressed by relations among the technical indicators, and whose right side indicates whether there is a positive ,negative or no change. The rules are being further given to the classification process which will be able to classify the new data making use of the previously generated rules. The proposed idea in the paper is to offer an efficient genetic algorithm in combination with the association rule mining algorithm which predicts stock market performance.

Keywords— Genetic Algorithm, Associative Rule Mining, Technical Indicators, Associative rules, Stock Market**, Numerical Data, Rules**

INTRODUCTION

Over the last decades, there has been much research interests directed at understanding and predicting future. Among them, to forecast price movements in stock markets is a major challenge confronting investors, speculator and businesses. How to make a right decision in stock trading extracts many attentions from many financial and technical fields. Many technologies such as evolutionary optimization methods have been studied to help people find better way to earn more profit from the stock market. And the data mining method shows its power to improve the accuracy of stock movement prediction, with which more profit can be obtained with less risk.

Applications of data mining techniques for stock investment include clustering, decision tree etc. Moreover, researches on stock market discover trading signals and timings from financial data. Because of the numerical attributes used, data mining techniques, such as decision tree, have weaker capabilities to handle this kind of numerical data and there are infinitely many possible ways to enumerate relations among data.

Stock prices depend on various factors, the important ones being the market sentiment, performance of the industry, earning results and projected earnings, takeover or merger, introduction of a new product or introduction of an existing product into new markets, share buy-back, announcements of dividends/bonuses, addition or removal from the index and such other factors leading to a positive or negative impact on the share price and the associated volumes. Apart from the basic technical and fundamental analysis techniques used in stock market analysis and prediction, soft computing methods based on Association Rule Mining, fuzzy logic, neural networks, genetic algorithms etc. are increasingly finding their place in understanding and predicting the financial markets.

Genetic algorithm has a great capability to discover good solutions rapidly for difficult high dimensional problems. The genetic algorithm has good capability to deal with numerical data and relations between numerical data. Genetic algorithms have emerged as a powerful general purpose search and optimization technique and have found applications in widespread areas.

Associative classification, one of the most important tasks in data mining and knowledge discovery, builds a classification system based on associative classification rules. Association rules are learned and extracted from the available training dataset and the most suitable rules are selected to build an associative classification model. Association rule discovery has been used with great success in domains such as market basket analysis but it finds an even wider domain of applications when used in combination with other classification and predictive approaches.

Classification is a well-known task in data mining that aims to predict the class of an unseen instance as accurately as possible. While single label classification, which assigns each rule in the classifier the most obvious label, has been widely studied, little work has been done on multi-label classification. Most of the work to date on multi-label classification is related to text categorization. In existing associative classification techniques, only one class label is associated with each rule derived, and thus rules are not suitable for the prediction of multiple labels. However, multi-label classification may often be useful in practice.

Although associative classification has better prediction accuracy than traditional classification approaches, it has a weak capability of handling numerical data and its relations. To improve the capability of handling numerical data in associative classification, there are two issues that must be addressed, including constructing a suitable relation representation method of numerical data and building associative classifiers from numerical data with suitable relation representations. The major contributions of this study are to propose a simple yet powerful structure for relation representation of numerical data in associative classification problem and to improve the capability of handling numerical data in associative classification.

Constructing fast and accurate classifiers for large data sets is an important task in data mining and knowledge discovery. There is growing evidence that merging classification and association rule mining together can produce more efficient and accurate classification systems than traditional classification techniques.

LITERATURE SURVEY

Dow Jones Industrial Average

The Dow Jones Industrial Average also called the Industrial Average, the Dow Jones, the Dow Jones Industrial, the Dow 30, or simply the Dow, is a stock market index, and one of several indices created by Wall Street Journal editor and Dow Jones & Company co-founder Charles Dow. It was founded on May 26, 1896, and is now owned by Dow Jones Indexes, which has its majority owned by the CME Group.The Dow Jones Industrial Average is simply the average value of 30 large, industrial stocks. It is an index that shows how 30 large publicly owned companies based in the United States have traded during a standard trading session in the stock market. It is the second oldest U.S. market index after the Dow Jones Transportation Average, which was also created by Dow.

Technical Indicators in Stock Market

A Technical Indicator [1] is a series of data points that are derived by applying a formula to the price data of a security. Price data includes any combination of the open, high, low or close over a period of time. Some indicators may use only the closing prices, while others incorporate volume and open interest into their formulas. The price data is entered into the formula and a data point is produced. A technical indicator offers a different perspective from which to analyze the price action. Indicators serve three broad functions: **to alert, to confirm and to predict.**

The Technical Indicators used in this papers are:

SMA--Simple Moving Average: A simple, or arithmetic, moving average that is calculated by adding the closing price of the security for a number of time periods and then dividing this total by the number of time periods. A simple moving average is formed by computing the average price of a security over a specific number of periods

EMA--Exponential Moving Average Calculation: EMA reduce the lag by applying more weight to recent prices. The weighting applied to the most recent price depends on the number of periods in the moving average. There are three steps to calculating an exponential moving average. First, calculate the simple moving average.

MACD--Moving Average Convergence-Divergence: MACD indicator is one of the simplest and most effective momentum indicators available. The MACD turns two trend-following indicators, moving averages, into a momentum oscillator by subtracting the longer moving average from the shorter moving average. As a result, the MACD offers the best of both worlds: trend following and momentum.

CCI: The Commodity Channel Index (CCI) is a versatile indicator that can be used to identify a new trend or warn of extreme conditions. In general, CCI measures the current price level relative to an average price level over a given period of time. CCI is relatively high when prices are far above their average. CCI is relatively low when prices are far below their average.

Williams %R: Williams %R is a momentum indicator that is the inverse of the Fast Stochastic Oscillator. Also referred to as %R, Williams %R reflects the level of the close relative to the highest high for the look-back period.

Stochastic Oscillator: The Stochastic Oscillator is a momentum indicator that shows the location of the close relative to the high-low range over a set number of periods. It doesn't follow price, it doesn't follow volume or anything like that. It follows the speed or the momentum of price. As a rule, the momentum changes direction before price.

RSI- Relative Strength: Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. RSI oscillates between zero and 100.

ROC—Rate of Change: The Rate-of-Change (ROC) indicator, which is also referred to as simply Momentum, is a pure momentum oscillator that measures the percent change in price from one period to the next. The ROC calculation compares the current price with the price "n" periods ago. The plot forms an oscillator that fluctuates above and below the zero line as the Rate-of-Change moves from positive to negative.

LIBOR: The London Interbank Offered Rate is the average interest rate estimated by leading banks in London that they would be charged if borrowing from other banks. It is usually abbreviated to Libor or LIBOR, or more officially to BBA Libor (for British Bankers' Association Libor) or the trademark bba libor. It is the primary benchmark, along with the Euribor, for short term interest rates around the world.

Genetic Algorithm

The Genetic Algorithm was proposed in 1975 and its framework is based on a direct analogy to Darwinian natural selection and mutations in biological reproduction [2]. It belongs to a category of heuristics known as the stochastic method, which employs randomized choice operators in the search strategy [3]. The appeal of GAs comes from their simplicity and elegance as strong search algorithms, as well as their ability to discover good solutions rapidly for difficult high-dimensional problems. The genetic algorithm is a popular method which has been applied in different data mining tasks, such as clustering [4]. Selection, crossover, and mutation are the three major GA operations.

The genetic algorithm can be summarized as:

```
 Randomly generate Initial population;
Evaluate fitness of each chromosome in the population;
While (result doesn't achieve the goal)
{
    Perform selection operation;
    Perform crossover operation;
    Perform mutation operation;
    Evaluate fitness of each chromosome in the population;
 }
```

RELATED WORK

Ya-Wen Chang Chien, Yen-Liang Chen [5] presented a GA-based algorithm used to build an associative classifier that can discover trading rules on stock trading data with many numerical technical Indicators. Associative classifiers are a classification system based on associative classification rules. The main goal is to build associative classifiers from numerical data. This paper employs a GA-based method to mine from stock trading data the best k associative classification rules, and to build a classification system with high trading prediction accuracy from the best k associative classification rules. The GA–ACR algorithm incorporates the static capital allocation method to build an automatic stock trading system. Within this automatic stock trading system, trading signals for each stock can be discovered using the GA–ACR algorithm. The major contributions of this study is to propose a simple yet powerful structure for relation representation of numerical data in associative classification problem and to improve the capability of handling numerical data in associative classification.GA with phenotype encoding structure was employed to express relations between numerical data. To simplify the relationship between two numerical data and to express the common relations in stock trading problems, three relations were used to discover associative classification rules. Semantic roles (SR) were used to pre-prune rules with infeasible comparisons with technical indicators and the best k rules strategy was used to make the GA–ACR algorithm more efficient. The prediction accuracy of GA-ACR was extremely comparable to the data distribution method.

Ya-Wen Chang Chien , Yen-Liang Chen[6] proposed a phenotypic genetic algorithm (PGA) to overcome the weaknesses of Inductive Logic Programming (ILP) like: (1) weak capabilities in numerical data processing, (2) zero noise tolerance, and (3) unsatisfactory learning time with a large number of arguments in the relation and to strengthen the numerical data processing capabilities, a multiple level encoding structure is used that can represent three different types of relationships between two numerical data. To tolerate noise, PGA's goal of finding perfect rules is changed to finding top-k rules, which allows noise in the induction process. Finally, to shorten learning time, the semantic roles constraint were incorporate into PGA, reducing search space and preventing the discovery of infeasible rules. Stock trading data from Yahoo! Finance Online was used for the experiments. The results indicate that the PGA algorithm can find interesting trading rules from real data.

B. Manjula, R. Lakshman Naik and S.S.V.N. Sarma [7] presented a paper to track the trends of financial applications using genetic algorithm. The First stage is classifying the prone direction of the price for India cements stock price index (ICSPI) futures with several technical indicators using artificial intelligence techniques. And second stage is mining the trading rules to determined conflict among the outputs of the first stage using the evolve learning. This study intends to find good sets of rules which would have made the most money over a certain historical period. To mine reasonable trading rules using genetic algorithms for ICSPI future. They found trading rule which would have yield the highest return over a certain time period using historical data. These groundwork results suggest that genetic algorithms are promising model yields highest profit than other comparable models and buy-and-sell strategy. Experimental results of buying and selling of trading rules were outstanding. Although the trading systems that have worked well in the past seem to have a reasonable chance of doing well in the future, a more extensive validation process is required.

Preeti Paranjape-Voditel and Dr. Umesh Deshpande [16] presented a paper on Association Rule Mining (ARM) based Recommender system for the stock markets which deals with the prediction of individual stocks. The method uses ARM, fuzzy ARM, weighted fuzzy ARM, ARM with time lags, fuzzy ARM with time lags and weighted fuzzy ARM with time lags to predict relationships between stocks. The authors have used Association Rule Mining along with fuzzy classification methods to develop a Recommender system for the stock markets. Recommender System deals with the generation of Association Rules. The Recommender System handles inter-day as well as intra-day associations.

The system mines relationships between items or scrips. It does not recommend the scrips in isolation but in relation to the other existing scrips. The objective is to show good returns. The transaction files for this system were created by finding out the percentage rise/fall of certain scrip from its previous trading day's close. Thus a transaction will contain all the scrips which have risen/fallen by more than some minimum amount. The scrips of relevance are generated from the database by finding the frequent itemsets and then discovering the rules for all itemsets above some minimum support threshold. The association rules between scrips are positively or negatively correlated. These rules recommend to buy stock2 if stock1 is bought, if stock1 and stock2 exhibit positive correlation. If a negative correlation exists between them a rise in stock1 can trigger a sell stock2. Rules are generated on the individual frequent itemsets and only the strongest rules are chosen. The days on which the strongest rules occur gives the time lag for that particular rule.The system can be used for portfolio management, assumed that a portfolio has to be managed with the obvious intention of making a profit. The portfolio already contains scrips which can be replaced and the portfolio restructured or the portfolio can be created by initializing it with the scrips from different sectors. Then a time frame for monitoring is considered which is fixed. After periodic intervals association rules are generated and loss making stocks can be replaced by corresponding negatively correlated rising stocks of the same amount.

B. Liu, W. Hsu, Y. Ma [18] proposed the CBA (Classification based on association) algorithm which was one of the first associative classification algorithms that used an Apriori-based candidate generation step to build complete classification models from association rules. In the CBA algorithm, all class-association rules are extracted from the available training dataset, i.e. all the association rules containing the class attribute in their consequents. The most suitable rules are selected to build an associative classification model, which uses a default class to complete it. It relies on a single rule to classify data. This classifier builder uses a brute-force exhaustive global search, and yields better results than the C4.5 [19]. This framework integrates classification and association rule mining algorithm to build an accurate classifier for prediction from the set generated rules.

X. Yin, J. Han [22] proposed the CPAR (Classification based on Predictive association rules) algorithm was proposed after the CBA and CMAR algorithms. Using ideas taken from traditional rule-based classification methods (such as Quinlan's FOIL [23]), the CPAR algorithm avoids generating a large number of candidate rules by generating candidate rules directly from the training data. It is a compromise between exhaustive and greedy algorithms and combines the advantages of both. CPAR uses the best k rules, rather than all of a group's rules, to predict the class label of a new tuple. This avoids the influence of lower ranked rules and is much more efficient with large sets of training data. CPAR uses expected accuracy to evaluate each rule.

PROPOSED SYSTEM

The diagram below gives the overview of the project. The numerical Stock Market data: DJIA is being used. Stock trading data contains the quotes of stock market. From this information, many technical indicators can be extracted, and by investigating the relations between these indicators trading signals can discovered. Genetic algorithm is being used to generate all the relations among the technical indicator and its value. Along with genetic algorithm association rule mining algorithm is used for generation of association rules among the various Technical Indicators. Associative rules are generated whose left side contains a set of trading signals, expressed by relations among the technical indicators, and whose right side indicates whether there is a positive negative or no change. The rules are being further given to the classification process which will be able to classify the new data making use of the previously generated rules.

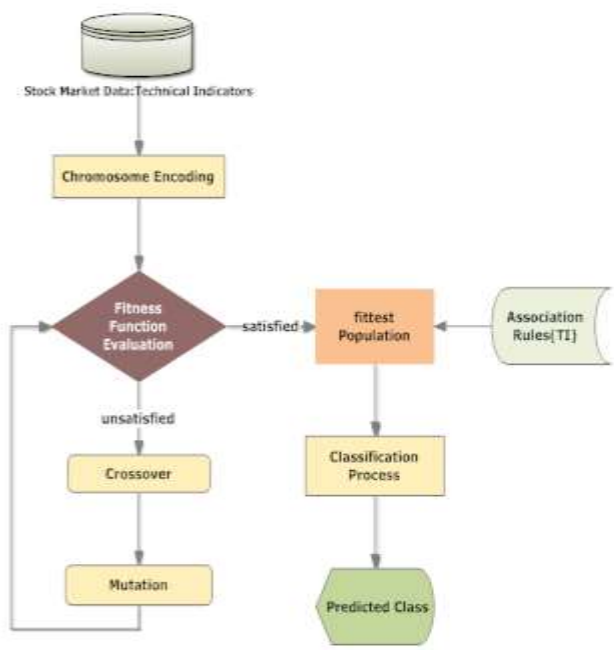


Figure 1 Flow of the system

Data Preprocessing

The first module deals with the collection of stock market data quotes of DJIA. The data is being collected from yahoo finance. After the data is being made available the technical indicators are being calculated using the stock market data quotes. The technical indicators used for the project are: RSI, EMA, MACD, k, ROC, CCI, William %R and LIBOR. In order to apply genetic algorithm to the data first the technical indicators are investigated and various relations are being generated between them which will help to discover trading signals. The three types of relations commonly used are:

- The value of attribute A < continuous value (eg: RSI<70)
- The value of attribute A > value of attribute B
- $A_t < A_{(t+1)}$ where t is the time

These relations are being used and various relations among the technical indicators are being generated. Now the data is being ready for the input to the next module.

Genetic Algorithm

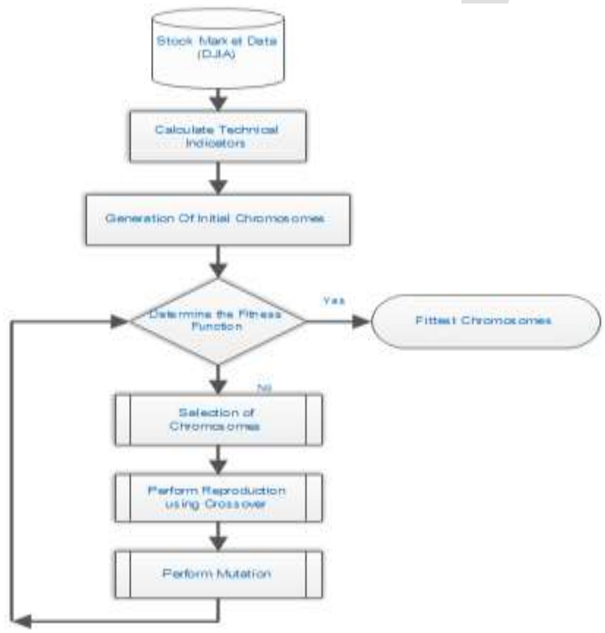


Figure 2 Genetic Algorithm

The genetic algorithm starts with the generation of initial chromosomes. Here, the chromosomes are represented as 64bits. The chromosome structure is as mentioned below:

RSI	EMA	MACD	K	ROC	CCI	William%R	LIBOR

Where each of the technical indicators mentioned is assigned 8bits each.

Relations generated from the technical indicators are

Technical Indicators	Rules
RSI	RSI>70 , RSI <30

EMA	EMA12>adj close, EMA26>adj close, EMA12>EMA26, EMA26>EMA12, EMA12(t)>EMA26(t-1), EMA26(t)>EMA12(t-1), EMA12 (t) > adj close (t-1), EMA26 (t) > adj close (t-1)
MACD	MACD>0, MACD>100, MACD>K, MACD>ROC, MACD(t) > K(t-1), MACD(t)>ROC(t-1), MACD>adj close, MACD(t)>adj close(t-1)
K	K>70, K(t-1)>70, K<30, K(t-1)<30, K(t-1)>K(t), K(t)>D(t-1), K(t-1)>D(t), K(t-1)>D(t-1)
ROC	ROC>3, ROC<-1, ROC>K, ROC(t)>k(t-1)
CCI	CCI>100, CCI>high, CCI>Low, CCI>adj close, CCI(t)>Adj close(t-1), CCI<-100
Williams %R	%R >ROC, %R>ROC(t-1), %R>-30, %R<-70, %R>adj close, %R>adj close(t-1)
LIBOR	LIBOR>0.7

Table 1 Technical Indicators relations

Each bit of the chromosome represents to the relations generated from the technical indicator. While generation of initial chromosome each bit in the chromosomes are assigned to either 1/0 depending upon the rules satisfy the data or not. Thus the initial chromosome is being generated.Now, the fitness function of each of the chromosomes is being calculated. And the chromosomes which are fit are being given to the next step. The next step is crossover function wherein the two chromosomes are randomly being selected and a crossover site is being chosen randomly and then the contents of the two chromosomes are being swapped forming two new chromosomes. If the chromosomes already exists they are deleted or otherwise the added to the final chromosome list.

The last step is the mutation function wherein specific amount of chromosomes which are being determined by mutation rate are undergone mutation where one random bit of the chromosome is being flipped if this results in a new chromosome then its being added to the final chromosome list. Now the final new chromosomes list in turn gives us the rules or relations of various technical indicators. This is being given as an input to the next module.

Association Rule Mining Algorithm

Figure 3 Flowchart for Association Rule Mining Algorithm

In this Module, the chromosomes generated are being assigned to the date and the class label. The class label is calculated using the stock market data.

Change = (Close-Open)

If Change>0 then class label is Positive

Change<0 then Negative and if Change=0 then the class label is No Change

The rules obtained from the Genetic Algorithm are being given to the Apriori Algorithm.

The Apriori Algorithm takes in the rules and generates all possible combination of frequent rules sets. During each iteration rules are being assigned to each of the class label and then the support count of the rule along with the class is being calculated. All the rules→class label set is being pruned which are below the Support and confidence threshold.

The support and confidence is being calculated as below:

Support (rule→class) = count (rule→class) / |total number of chromosome| *100

Confidence = support (rule→ label) / support (rule)

At the end of the module we are left with the all possible frequent combination of the rule set along with the class label. These sets of frequent rule will help us in classification of the new test data.

Prediction

In the Classification step, the new test data is being collected and is being given to the genetic algorithm to generate the initial set of chromosome. The chromosomes obtained will help us in obtaining the rules which can be used to predict the class label. The rules obtained from the new set of chromosomes are mapped against the rules obtained from the previous step i.e. association rule mining algorithm.

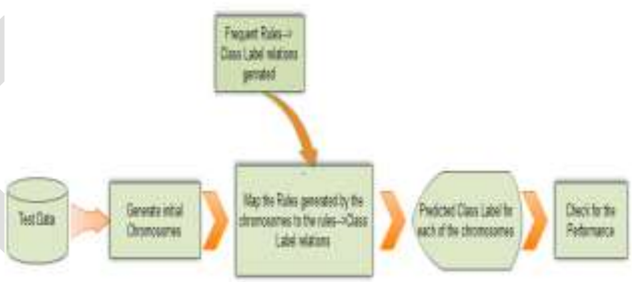
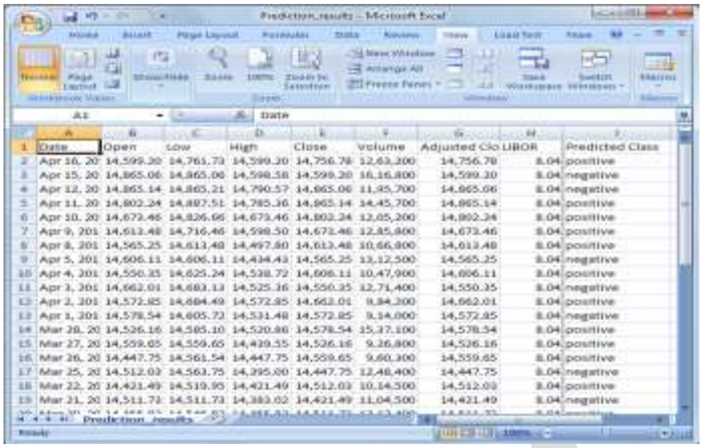


Figure 4 Flowchart for Prediction Process

The rule set which match the rules from the chromosomes are sorted out and checked against their class label. The prominent class label is being assigned to the new set of chromosome thus predicting the new class label for the test data.

RESULTS AND OBSERVATION

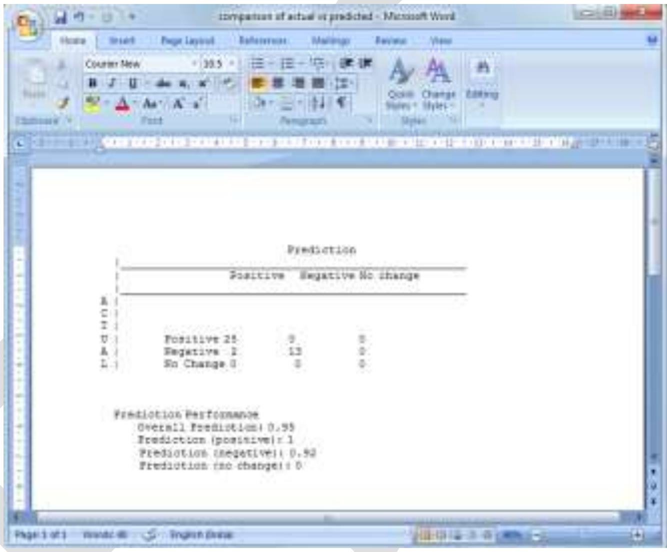
Training Data Set: DJIA from 30th December 2011 to 19th February 2013
Number of Chromosomes generated by the genetic Algorithm: 463
Association rule mining Algorithm generated 5-ruleset frequent rules with threshold of Support count as 40 and Confidence as 0.5
Total number of unique rule combination generated: 710
Test data set: 20st February 2013 to 16th April 2013 (40days)



	Date	Open	Low	High	Close	Volume	Adjusted Clo	LIBOR	Predicted Class
2	Apr 16, 20	14,599.20	14,761.73	14,599.20	14,756.78	12,63,200	14,756.78	8.04	positive
3	Apr 15, 20	14,865.06	14,865.06	14,598.58	14,599.20	16,16,800	14,599.20	8.04	negative
4	Apr 12, 20	14,865.14	14,865.21	14,790.57	14,865.06	11,95,700	14,865.06	8.04	negative
5	Apr 11, 20	14,802.24	14,887.51	14,785.36	14,865.14	14,45,700	14,865.14	8.04	positive
6	Apr 10, 20	14,673.46	14,826.66	14,673.46	14,802.24	12,05,200	14,802.24	8.04	positive
7	Apr 9, 201	14,613.48	14,716.46	14,598.50	14,673.46	12,85,800	14,673.46	8.04	positive
8	Apr 8, 201	14,565.25	14,613.48	14,497.80	14,613.48	10,66,800	14,613.48	8.04	positive
9	Apr 5, 201	14,606.11	14,606.11	14,434.43	14,565.25	13,12,500	14,565.25	8.04	negative
10	Apr 4, 201	14,550.35	14,625.24	14,538.72	14,606.11	10,47,900	14,606.11	8.04	positive
11	Apr 3, 201	14,662.01	14,683.13	14,525.36	14,550.35	12,71,400	14,550.35	8.04	negative
12	Apr 2, 201	14,572.85	14,684.49	14,572.85	14,662.01	9,84,200	14,662.01	8.04	positive
13	Apr 1, 201	14,578.54	14,605.72	14,531.48	14,572.85	9,14,000	14,572.85	8.04	negative
14	Mar 28, 20	14,526.16	14,585.10	14,520.86	14,578.54	15,37,100	14,578.54	8.04	positive
15	Mar 27, 20	14,559.65	14,559.65	14,439.55	14,526.16	9,26,800	14,526.16	8.04	positive
16	Mar 26, 20	14,447.75	14,561.54	14,447.75	14,559.65	9,60,300	14,559.65	8.04	positive
17	Mar 25, 20	14,512.03	14,563.75	14,295.00	14,447.75	12,48,400	14,447.75	8.04	negative
18	Mar 22, 20	14,421.49	14,519.95	14,421.49	14,512.03	10,14,500	14,512.03	8.04	positive
19	Mar 21, 20	14,511.73	14,511.73	14,383.02	14,421.49	11,04,500	14,421.49	8.04	negative

Figure 5 Prediction Results

The Prediction performance is being calculated by comparing the actual results to the predicted ones.



Prediction

ACTUAL	Positive	Negative	No change
Positive	25	0	0
Negative	2	13	0
No Change	0	0	0

Prediction Performance
Overall Prediction: 0.95
Prediction (positive): 1
Prediction (negative): 0.92
Prediction (no change): 0

Figure 6 Prediction Performance Results

The above figure gives the prediction performance of the application as compared to the actual results. From this it can be concluded that the overall prediction performance was 95%. Individually, The Positive Class Label showed 100% accuracy while Negative Class Label had 98% accuracy.

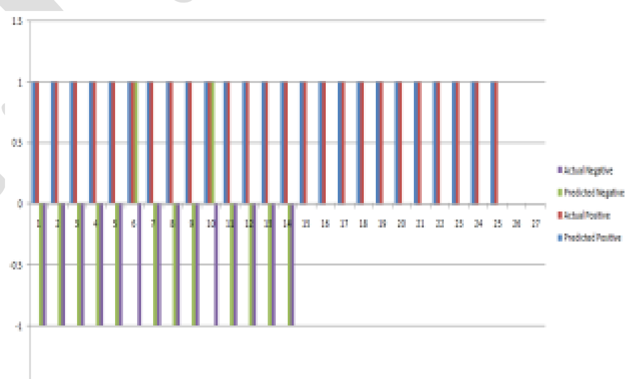


Figure 7 Prediction Performance Graph

The above Figure shows the prediction performance graph, which shows the predicted positive to the actual positive results and the predicted negative to the actual negative.

The x-axis of the graph shows the number of days and y axis represents the positive or the negative value. From the graph it can be concluded that twice the predicted negative result differed from the actual one.

CONCLUSION

A detailed Study was conducted on the DJIA stock market and the various technical indicators being used for Stock Market data which help in analysing the Stock Market.The Literature survey was conducted on Genetic Algorithm and Association rule Mining Algorithm and a combine approach was being implemented. As Association Rule Mining Algorithms cannot handle numerical data efficiently a modified Genetic Algorithm was being used for the representation of the stock market data and to generate rules among the various technical indicators. Association rule mining Algorithm help in generation of the frequent rule set along with the class label and then predict the class label for the new test data i.e. if it is positive, negative or no change.

Overall a new method was proposed for Stock Market Prediction using a combination of Genetic and Association rule Mining Algorithm which can handle numerical data.

The Prediction Performance was also being calculated and a comparison was carried out with the actual performance. The overall prediction process had 95% of accuracy.

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