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AN INTELLIGENT DECISION SUPPORT SYSTEM FOR FINANCIAL MARKETS

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Abstract: The automated computer programs using data mining and predictive technologies do a fare amount of tradesin the markets. Data mining is well founded on the theory that the historic data holds the essential memory for predicting the future direction. This technology is designed to help investors discover hidden patterns from the historic data that have probable predictive capability in their investment decisions. The prediction of stock markets is regarded as a challenging task of financial time series prediction. Data analysis is one way of predicting if future stocks prices will increase or decrease. In this paper we discuss the rule base system to automated trading ofstock which calculates the risk and profit involved in trading of a particular stock based on the patterns present in the historic data.

I. INTRODUCTION

The stock market can be viewed as a specific data mining and artificial intelligence problem, of knowledge and data representations for exploration, classification and forecasting. The movement in the stock exchange depends on capital gains and losses and most people consider the stock market erratic and unpredictable. However, patterns that allow the prediction of some movements can be found. Stock market analysis deals with the study of these patterns. It uses different techniques and strategies, mostly automatic that trigger buying and selling orders depending on different decision making algorithms. It can be considered as an intelligent treatment of past and present financial data in order to predict the stock market future behaviour.

Predictive modeling can help investors strategize their investment funds smarter. Investors no longer have to base their investment decisions totally on their “gut feelings” but can use factual data to assist in making better investment judgments. Predictive modeling is a form of data mining. Data mining is a computational intelligence discipline that contributes tools for data analysis, discovery of new knowledge, and autonomousdecision making. The task of processing large volume of data has accelerated the interest in this field.
Predictive patterns from quantitative time series analysis willbe invented fortunately, a field known as data mining usingquantitative analytical techniques is helping to discoverpreviously undetected patterns present in the historic data todetermine the buying and selling points of equities. Whenmarket beating strategies are discovered via data mining,there are a number of

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potential problems in making the leapfrom a back-tested strategy to successfully investing in futurereal world conditions.

II. SOLUTION ARCHITECTURE

The architecture of a solution is complex, and includes many elements. The reason for this is that a proposed solution is an amalgamation of many different systems. Integration of diverse elements is its primary concern, and to accomplish this integration, many different systems and processes are necessary.

The solution consists of the following architectural components, which includes the datamart in its infrastructure [12]:

- *Data models:*We are using the an extended data model as discussed in the[12]
- *Data acquisition:* We are accessing the data from the yahoo and nsewebsites
- *Aanalysis:* Includes the infrastructure required to support user queries and analysis.

III. DATA MODEL

The data used in this paper was obtained from the different websites like yahoo finance,nseindia and MSN. The daily data of the each stock with the attributes open, low ,high and close prices and fundamental data like ROC, ROA EPS are downloaded from the open sources. The datamart consists of the daily stock prices of the 700 stocks of 10 years from the year jan’2000 to the aug’2011 and also fundamental data of each stock annually.

IV. USER ANALYSIS

The most popular indicator is the moving average. Thisshows the average price over a period of time. For a 3 daymoving average you add the closing prices for each of the 3days and divide by 3. The most common averages are 3,5, 10, 13, 26,50,100, and 200 days. Longer time spans are less affectedby daily price fluctuations. A moving average is plotted as aline on a graph of price changes. When prices fall below themoving average they have a tendency to keep on falling. Conversely, when prices rise above the moving average theytend to keep on rising.

V. METHODOLOGY

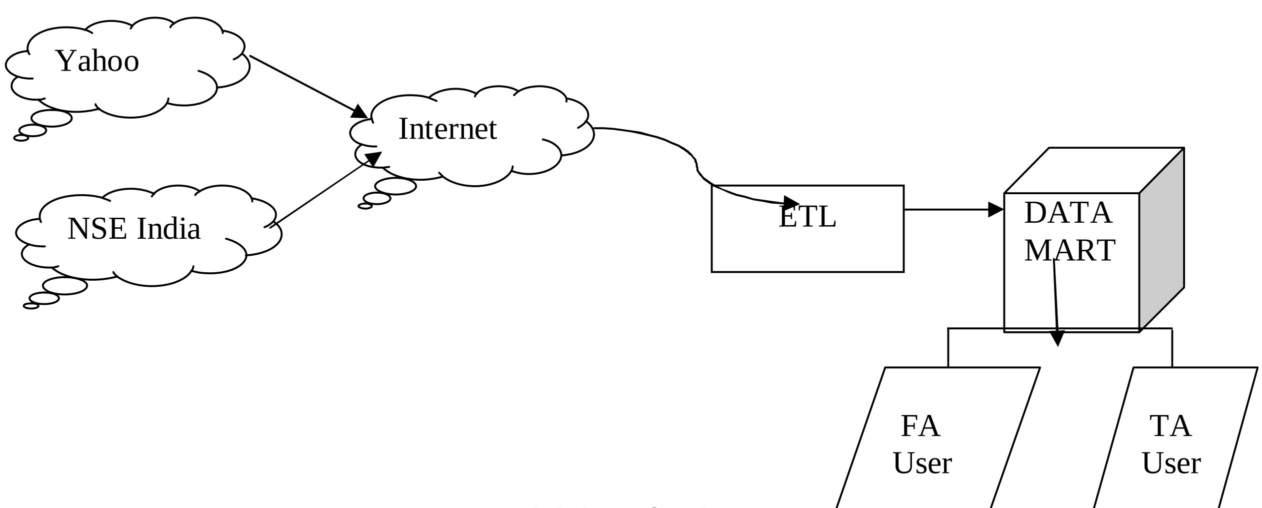

Fig1:Mehdology for decision

The trading rules will be formed based on the different moving averages and tested for different stocks on the historical data to validate the statistical patterns and rules. The rules which gives the more profit among the different combination of stocks which satisfies the rules will be selected and applied on the real time over a period.

The different rules formed are

- Close price > 200 DMA Buy and price <=200 DMA sell
- Close price > 200 DMA and >100DMA Buy and price <=200 DMA sell
- Close price > 200 DMA and >100DMA and >50DMA Buy and price <=200 DMA sell
- Close price > 200 DMA and >100DMA and >50DMA Buy and price <=50 DMA sell
- Close price > 200 DMA and >100DMA and >50DMA Buy and price <=100 DMA sell

VI. RESULTS

Rule	2010-2011(Annually)		
	p	c	%P
I	31217.68	499723.26	6.246993
II	33796.86	304691.91	11.09214
III	25943.44	619201.99	4.189818
IV	33666.01	285687.52	11.78421
V	26456.30	474145.86	5.579781

Rule	2007-2008(Annually)		
	P	C	%P
I	4701.004	350382.51	1.341678
II	9744.62	225103.65	4.328949
III	12040.41	405764.54	2.967339
IV	10712.50	199704.43	5.364178
V	13219.46	289501.98	4.566275
VI	16103.37	450700.27	3.572967

Rule	I quarter(2010-2011)		
	p	c	%P
I	5948.136	80454.535	7.393164
II	6399.24	41625.94	15.3732
III	8860.14	139143.37	6.367634
IV	6375.51	40801.51	15.62567
V	8859.84	106594.95	8.31169
VI	3626.68	199367.54	1.819093

Rule	II quarter(2010-2011)		
	p	c	%P
I	4557.374	85027.446	5.359886
II	4649.20	63921.16	7.273327
III	3867.42	106801.91	3.621113
IV	4745.82	57960.00	8.188099
V	3647.70	88318.84	4.130154
VI	3496.77	172058.60	2.032312

Rule	III quarter(2010-2011)		
	p	c	%P
I	8215.178	150493.2	5.458837
II	8644.14	101498.66	8.516509
III	11343.08	219077.08	5.177664
IV	8718.07	93596.66	9.314514
V	12532.27	148914.58	8.415743
VI	9260.05	289106.39	3.202989

Rule	IV quarter(2010-2011)		
	p	c	%P
I	12496.99	183748.08	6.801155
II	14104.29	97646.15	14.44428
III	1872.80	154179.64	1.21469
IV	13826.60	93329.34	14.81485
V	1416.49	130317.50	1.086952
VI	-3488.28	153404.26	-2.27391

The results show that in the financial year 2010-11 leads profit better than 2007-08, 2008-09 and 2009-10. In the quarterly based trading most of the rules leads to profit except the rule –VI in the fourth quarter.

VII. CONCLUSION

The traders can test their rules on the historic data and apply the same rules on to the real time stock market and traders will know how much risk has to take to get desired profit. This work can be extended further to quantify the risk for different trading rules on individual stocks.

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