INNOVATIVE TECHNOLOGICA
METHODICAL RESEARCH JOURNAL
ISSN: 2776-0987 Volume 4, Issue 4 April 2023

MACHINE LEARNING TECHNIQUES FOR STOCK PREDICTION

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Machine Learning

Annotation:
Most stock traders nowadays depend on Intelligent Trading Systems which helpthem in predicting prices based on various situations and conditions, thereby helping them in making instantaneous investment decisions.

Keywords: Algorithm, Machine Learning, condition, investment, stock prices, method.

INTRODUCTION

In this paper, we discuss the Machine Learning techniques which have been applied for stock trading to predict the rise and fall of stock prices before the actual event of an increase or decrease in the stock price occurs. In particular the paper discusses the application of Support Vector Machines, Linear Regression, Prediction using Decision Stumps, Expert Weighting and Online Learning in detail along with the benefits and pitfalls of each method. The paper introduces the parameters and variables that can be used in order to recognize the patterns in stock prices which can be helpful in the future prediction of stocks and how Boosting can be combined with other learning algorithms toimprove the accuracy of such prediction systems.

MATERIALS AND METHODS

The EMH hypothesizes that the future stock price is completely unpredictable given thepast trading history of the stock. There are 3 types of EMH's: strong, semi-strong, and weak form. In the weak EMH, any information acquired from examining the stock's history is immediately reflected in the price of the stock.

RESULTS AND DISCUSSION

We now take a brief look at the attributes and indicators that are normally used in thetechnical analysis of stock prices:

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Indicators can be any of the following:

Moving Average (MA) : The average of the past n values till today.

Exponential Moving Average (EMA) : Gives more weightage to the most recent valueswhile not discarding the older observation entirely.

Rate of Change (ROC) : The ratio of the current price to the price n quotes earlier.n is generally 5 to 10 days.

Relative Strength Index (RSI): Measures the relative size of recent upward trends againstthe size of downward trends within the specified time interval (usually 9 – 14 days).

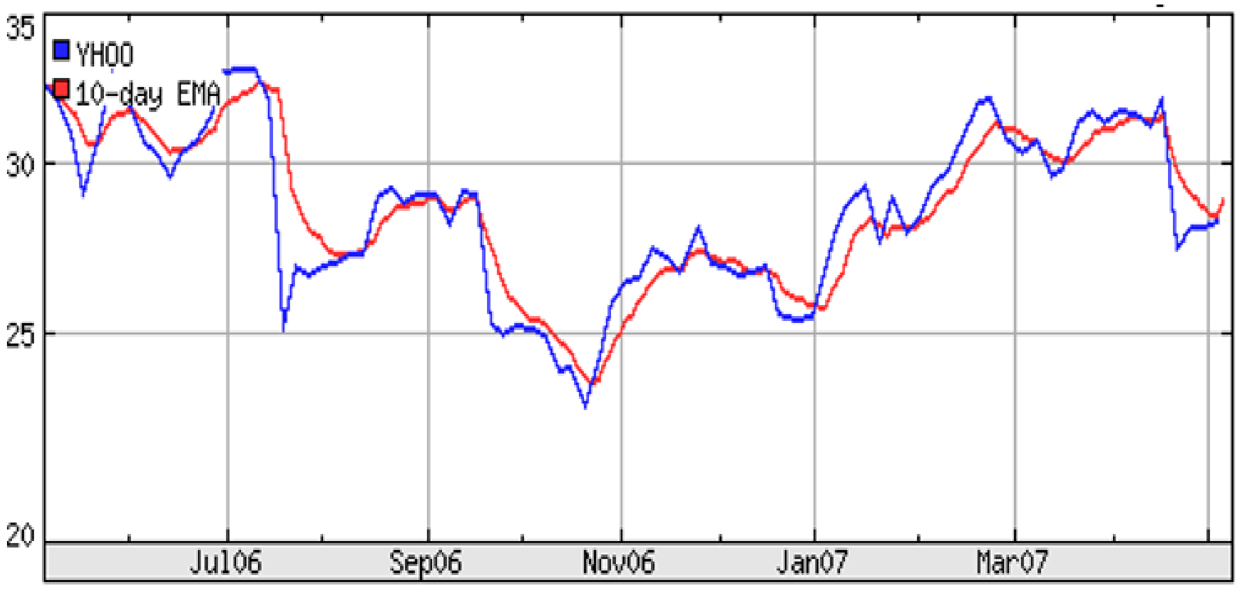
For this Project, the EMA was considered as the primary indicator because of its ability to handle an almost infinite amount of past data, a trait that is very valuable in time seriesprediction (It is worth noting that the application of other indicators might result in betterprediction accuracies for the stocks under consideration).

EMA (t) = EMA (t-1) + alpha * (Price (t) - EMA (t-1))Where, alpha = 2/ (N+1), Thus, for N=9, alpha = 0.20

In theory, the Stock Prediction Problem can be considered as evaluating a function F attime T based on the previous values of F at times t-1,t-2,t-n while assigning corresponding weight function w at each point to F.

F (t) = w1*F (t-1) + w2*F (t-2) + ... + w*F (t-n)

The technical analysis charts below show how the EMA models the actual Stock Price.



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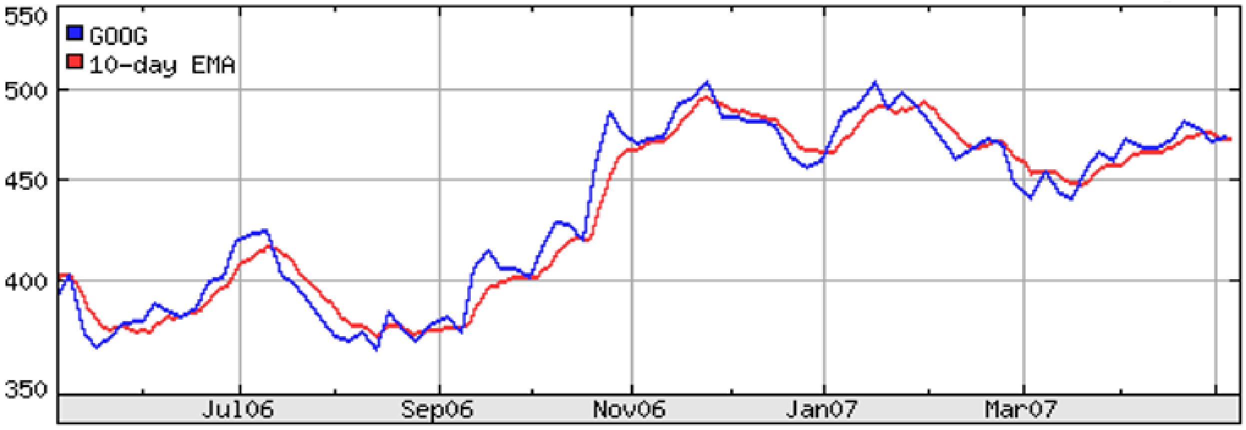

For this experiment, the historical data was downloaded from the yahoo finance section.In particular, the stock prices of two companies were studied, namely Google Inc. (GOOG) and Yahoo Inc. (YHOO)

The dataset available has the following attributes:

Date Open High Low Close Volume Adj. Close

Intuitively, based on the EMH, the price of the stock yesterday is going to have the mostimpact on the price of the stock today. Thus as we go along the time-line, data-points which are nearer to today's price point are going to have a greater impact on today's price. For a time-series analysis we can take the Date as the X-Axis with integer values attached to each date, such that the most recent Date Tag in the dataset gets the highest value and the oldest Date Tag gets the lowest value.

We add one more attribute to the above attributes, this attribute will act as our label for predicting the movements of the stock price. This attribute will be called "Indicator" andwill be dependent on the other available attributes. For our experiments we use the EMA(Exponential Moving Average) as the indicator function.

This is a list of top research analysts based on the accuracy of earnings estimates on

GOOG, according to StarMine. Analysts that appear here are limited to those coveringGOOG for a significant period of time. Learn More.

Total Ranked Analysts: 31

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EPS ACCURACY FOR GOOG - Trailing Two Fiscal Years and Four Quarters

Top-Ranked Analysts	GOOG	Overall	Research	Reports
Westerfield, Leland BMO Capital Markets	★★★★★			
Wolk, Marianne Susquehanna Financial Group	★★★★★	★★★★★		
Rohan, Jordan RBC Capital Markets	★★★★★			
Jain, Pratik First Global Stockbroking Ltd.	★★★★★			
Squali, Youssef Jefferies & Co.	★★★★★	★★★★★		
Garcia, Denise A. G. Edwards & Sons, Inc.	★★★★★			
Quarles, Christa Thomas Weisel Partners	★★★★☆	★★★★☆		
Brown, Derek Cantor Fitzgerald	★★★★☆	★★★★☆		

CONCLUSION

Of all the Algorithms we applied, we saw that only Support Vector Machine combinedwith Boosting gave us satisfactory results. Linear Regression gave lower mean squarederrors while predicting the EMA pattern.
Another technique which looks promising but which we did not cover the evaluation ofwas Expert Weighting. More recently, the linguistic analysis of Financial News Resultsto predict stocks has been a topic of extensive study.

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