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IMPLEMENTATION OF HIERACHICAL TEMPORAL MEMORY FOR STOCK PREDICTION

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Abstract: Nigerian Stock Exchange is the institution empowered by the Nigerian law to Manage and regulates the activities of the Nigerian capital market and therefore a key player role as they set the rules of the game despite the volatile and unpredictable nature of the market. The use of machine learning algorithms to predict the future values and other variables in the market through the use of time series data has proven to be of immense advantage to market players globally in the last two decades. In this work, the time serial movement of stock prices over a period of time extracted from daily official list of Nigeria Stock Exchange is used to predict the future values of other variables through the use of time series data and moving average methodology. Digital signal processing based on a biological neural network called Hierarchical Temporal Memory (HTM) was used for stock price data encoding and predictions and show high performance accuracy.

Introduction

The stock exchange (market) or capital market is a place where stock and other securities are traded. A stock exchange is the body that runs a stock market. Some stock markets are not run by any major body, but are coordinated by their dealers (Nwanwu, 2004). The stock exchange helps companies generate capital. As a primary market, it provides an avenue for them to sell new shares and bonds to investors. The company can then use proceeds from the sales to expand their business, develop new products, buy new equipment etc. The stock markets also provide a means for investors to trade in the shares of companies they own among themselves.

The stock market is also a complex, no stationary, chaotic and non-linear dynamic system. Forecasting stock market, currency exchange rate, bank bankruptcies, under-standing and managing financial risk, trading futures, credit rating, loan management, bank customer profiling, and money laundering analyses are core financial tasks for data mining (Nakhaeizadeh et al., 2002). Some of these tasks such as bank customer profiling have many similarities with data mining for customer profiling in other fields. Stock market forecasting includes uncovering market trends, planning investment strategies, identifying the best time to purchase the stocks and what stocks to purchase. Financial institutions produce huge data sets that build a foundation for approaching these enormously complex and dynamic problems with data mining tools. Potential significant benefits of solving these problems motivated extensive research for years. One of the most important problems in modern banking and finance is the need for an efficient ways to summarize visualize and manage the volatile nature of the stock market activities to give investors useful information about the market investment decisions. The enormous amount of valuable data generated by the stock market has attracted researchers to explore this problem domain using different methodologies

The study also aims to determine regression model that would accurately predict the future closing price of stock market using hierarchical temporal memory (HTM) algorithms. The objective is to prospect an accurate forecast that will be calculated using regression analysis.

Related Works

As part of a stock market analysis and prediction system consisting of an expert system and clustering of stock prices, data is needed. Stock markets are recently triggering a growing interest in the physicists' community. Basaltoa et al (2005) apply a pair wise clustering approach to the analysis of the Dow Jones index companies, in order to identify similar temporal behavior of the traded stock prices. The objective of this attention is to understand the underlying dynamics which rules the companies' stock prices which particularly useful in giving insight in to the stock market index and groups of companies sharing a similar temporal behavior.

Muh-Cherng et al (2006), presented a stock trading method by combining the filter rule and the decision tree technique. The filter rule have been widely used by investors to generate candidate trading points which are subsequently clustered and screened by the application of a decision tree algorithm. When compared to previous literature that applied such a combination technique, this research shows distinction in incorporating future information into the criteria for clustering the trading points.

In another study in Taiwan and NASDAQ, the stock markets were used to justify the proposed method. Experimental results show that the proposed trading method outperformed both the filter rule and the previous method (Muh-Cherng et al., 2006).

Jie and Hui (2008) also carried out a study on prediction of distressed listed stock companies important to both listed companies and investors. They presented a data mining technique that combines attribute-oriented induction, information gain, and decision tree, which is suitable for preprocessing financial data and constructing decision tree model for financial distress prediction.

Methodology

The methodology deployed in this research is the moving average and regression analysis using the hieratical temporal memory (HTM) algorithm on time series data obtained from the daily activity summaries (equities) published by Nigerian stock exchange to predict future stock prices in the capital market.

Encoding and predicting streaming stock price data

This phase performs online data capture to decipher the continual hidden causes that occur in the information generated by the moving average model. This is done using a biological machine intelligence neural network (BAMI-NN) called the Hierarchical Temporal Memory (HTM) currently developed in (Hawkins et al., 2016). In this study, the HTM spatial pooler is applied to the task of predicting the stock price from moving average phase; the proposed architecture is as shown in Fig.1.

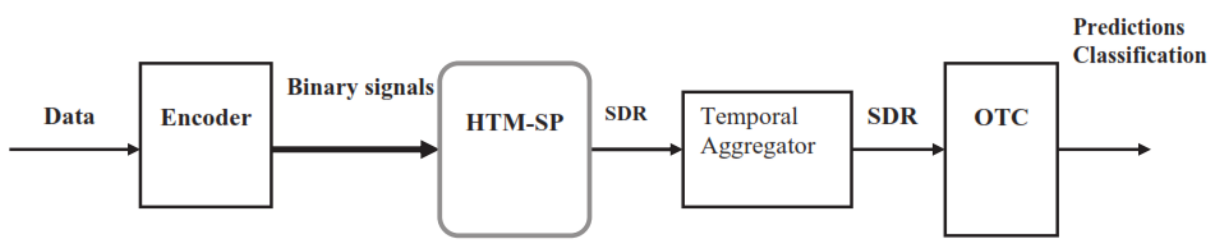

Figure 1**:** Proposed architecture for simulating the Stock Price Prediction

The mathematical details involved in the neural network processing are as follows:

Step 1: Form the set of Generative Mini-columns

A set of Spatial Pooler (SP) generative mini-columns comprising cortical neurons is initialized according to the rule in Eqn(1):

$$\Pi_i = \{ j \mid \mathrm{I}(x_j ; x_i^c, \gamma) \ \& \ \mathrm{Z}_{ij} < \rho \} \qquad (1)$$

Where,

j = HTM neuron location index in the mini-column

i = mini-column index

x_j = location of the *j*th input neuron (synapses) in the input space

x_i^c = location centre of potential neurons (synapses) of *i*th mini-column in a hypercube of input space

γ = edge length of x_j

ρ = fraction of inputs within the hypercube of input space that are potential connections

Z_{ij} = represents a uniformly distributed random number between 0 and 1

I = an indicator function

The indicator function I in Eqn(1) is described by Eqn(2):

$$\mathrm{I}(x_j ; x_i^c, \gamma) = \begin{cases} 1, & \text{if } x_j \subset x_i^c \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

Step 2: Form the binary synapses

A set of binary synapses W_{ij} is formed by conditioning using a permanence activation rule as in Eqn(3):

$$W_{ij} = \begin{cases} 1, & if \;\; D_{ij} \geq \theta_c \\ 0, & otherwise \end{cases} \qquad (3)$$

Where,

D_{ij} = independent and identically distributed (IID) dendrite synaptic permanence values from the *j*th input to the *i*th mini-column

θ_c = synaptic permanence threshold

The synaptic permanence values are conditioned by Eqn (4):

$$D_{ij} = \begin{cases} U(0,\ 1), & if \;\; j \in \Pi_i \\ 0, & otherwise \end{cases} \qquad (4)$$

Step 3: Overlap computation

Associations with input patterns (features) are created by computing feed-forward inputs to each generative spatial mini-column using a matching approach called the “overlap” - see Eqn (5):

$$o_i = b_i \sum_j W_{ij} z_j \qquad (5)$$

Step 4: Compute the activations

Using Eqn(5) the activations of each SP mini-column is computed as:

$$a_i = \begin{cases} 1, & if \;\; o_i \geq Z(V_i, 100 - s) \,\&\, o_i \geq \theta_{stim} \\ 0, & otherwise \end{cases} \quad (6)$$

Also,

$$V_i = \{o_i \mid j \in N_i\} \quad (7)$$

Where,

s = target activation density (sparsity)

Z = a percentile function

θ_{stim} = a stimulus threshold

Step 5: Learning

Learning is done by activating, deactivating and updating the permanence values via the synaptic connections:

$$\Delta D_{ij} = p^{+} D_{ij} \circ A^{t-1} - p^{-} D_{ij} \circ (1 - A^{t-1}) \quad (8)$$

Where,

p^{+} = positive permanence value increment

p^{-} = negative permanence value increment

A^{t-1} = activation state at time step, t

Step 6: Classification

Classification may done in a temporal manner using a temporal version of Eqn(6) as below:

$$o_{j_t} = \sum_{j_t} W_{j_t}^{sp} W_{(k-N_c):j_t}^{sp}, \quad N_c < k \le j_t, \qquad (9)$$

Where,

N_c = Number of past sample SDRs used as context

k = size of the temporal aggregated (bivariate) sequence through time

j_t = a temporal aggregation index number

$W_{j_t}^{sp}$ = a bivariate SDRs after a temporal aggregation

The details involved in the neural network processing are as (Cui et al, 2017).The mathematical equation shows the various methods in their expression.

Results and Discussion

Data is an important resource for every program process. Data mined from the selected Banks were all documented. Documentation is very important in the development of any software or any system. This is because documentation makes the system to be open to all users, and if it is not well documented it becomes difficult in its usage. That is why the system documentation has to be included in the specification document of the systems.

Sample Implementation of Input/output Snapshots

Table 1 Top 20 Equities by Market Capitalization in January 2013

S/N	Equity	Market Cap. (Naira)	% of Equities Mkt. Cap
1	Dangote Cement Plc	2,383,966,985,959.50	23.38
2	Nigerian Breweries Plc	1,216,082,872,665.60	11.93
3	Guaranty Trust Bank Plc	723,124,073,533.68	7.09
4	Nestle Nigeria Plc	665,831,251,680.00	6.53
5	Zenith Bank Plc	643,628,122,613.00	6.31
6	FBN Holdings Plc	592,598,651,904.96	5.81
7	Guinness Nigeria Plc	432,153,177,067.00	4.24
8	Access Bank Plc	254,059,591,405.80	2.49
9	United Bank for Africa Plc	226,582,132,578.42	2.22
10	Flour Mills Nigeria Plc	209,896,442,321.10	2.06
11	Lafarge WAPCO Plc	196,604,800,262.00	1.93
12	Ecobank Transnational Incorporated Plc	172,099,357,157.00	1.69
13	Unilever Nigeria Plc	169,870,001,625.00	1.67
14	Union Bank Nigeria Plc	142,260,774,356.40	1.40
15	P Z Cussons Nigeria Plc	134,996,219,530.00	1.32
16	Stanbic IBTC Holdings Plc	131,100,000,000.00	1.29
17	Cadbury Nigeria Plc	100,134,021,120.00	0.98
18	Diamond Bank Plc	99,010,662,838.20	0.97
19	First City Monument Bank Plc	91,688,168,056.80	0.90
20	Fidelity Bank Plc	91,560,358,592.68	0.90
	Top 20 total	**8,677,247,665,267.14**	**85.11**

Table 2. Market Recap and Outlook of the Nigeria Stock Exchange for 2013

	2012	2013	% Change
Total Market Capitalization[7]	**N14.80 trillion $94.74 billion**	**N19.08 trillion $119.41 billion**	**28.92% 26.03% ($-terms)**
Equities Market Capitalization[8]	N8.98 trillion $57.49 billion	N13.23 trillion $82.80 billion	47.33% 44.03% ($-terms)
Bonds Market Capitalization	N5.82 trillion $37.26 billion	N5.85 trillion $36.561 billion	0.52%
NSE All Share Index	28,078.81	41329.19	47.19%
NSE Lotus Islamic Index	1,769.07	2863.12	61.84%
NSE Industrial Index	1403.63	2546.59	81.43%
NSE 30 Index	1,336.07	1907.17	42.75%
NSE Consumer Goods Index	838.97	1100.25	31.14%
NSE AseM Index	964.59	962.31	-0.24%
NSE Banking Index	339.63	447.84	31.86%
NSE Oil/Gas Index	152.92	339.88	122.26%
NSE Insurance Index	118.49	152.87	29.01%
Total Volume - Equities	89.15 billion	106.54 billion	19.51%
Total Value (Turnover) - Equities	N657.77 billion $4.21 billion	N1.04 trillion $6.51 billion	58.66% 54.57% ($-terms)
Avg. Daily Volume - Equities	359.50 million	426.16 million	18.54%
Avg. Daily Value (Turnover) - Equities[9]	N2.65 billion $16.96 million	N4.17 billion $26.10 million	57.36% 53.83% ($-terms)
Turnover Velocity - Equities (%)[10]	7.33	7.89	7.58%
[illegible]	[illegible]	[illegible]	

Table 3. Sample of stock prices the months of January 2007 to June 2011.

Month	Open	High	Close	Normalized Open	Normalized High	Normalized Close
Jan-07	2240.5	2324.95	2244.45	0.48	0.46	0.48
Feb-07	2244.45	2439	2078.35	0.48	0.51	0.41
Jan-09	1125	1318.7	1305.5	0	0.008	0.08
Feb-09	1293	1324.95	1231.3	0.072	0.011	0.048
Mar-09	1211.3	1398	1324.1	0.037	0.044	0.088
Apr-11	3225	3316.85	2905.95	0.9	0.91	0.76
May-11	2924.7	2952.95	2791.85	0.77	0.75	0.71
Jun-11	2794	2915.95	2907.4	0.71	0.73	0.76

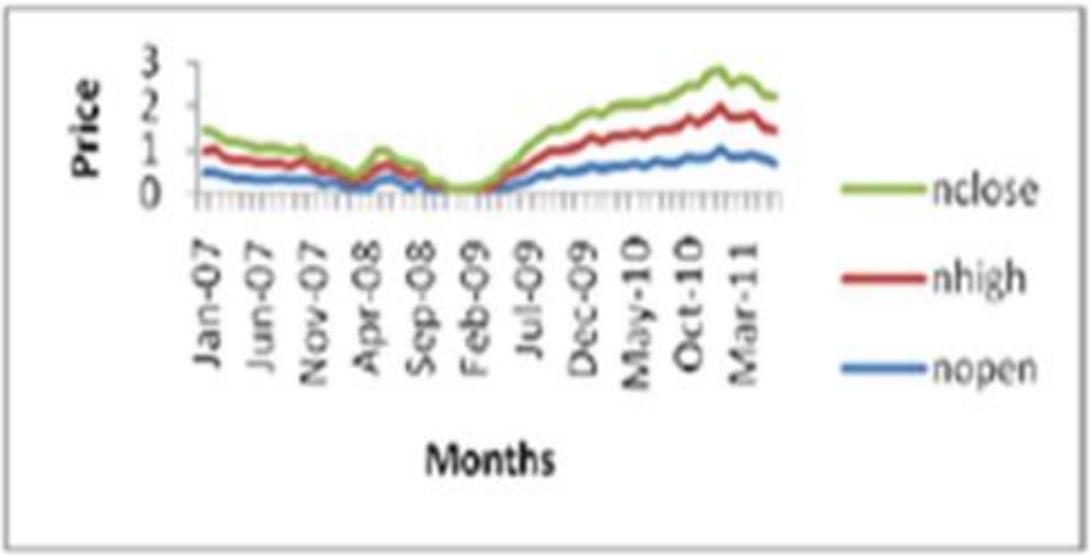

Figure 2: Opening and Closing Price of Stock Market against the Months of Year 2007 – 2011

Discussion of Results

As one of the predominant phases in the Knowledge Discovery (KDD) process data mining and its application in the predicting stock prices is of utmost importance to the research community as it ensures computational efficiency of the machine learning model deployed for stock prediction in the sense that the dataset used for training the predictive model is first extracted or mined from an enterprise database and then used for training and subsequent prediction by the model. The dataset used for this study was extracted from the Nigerian Stock repository made of an eighteen months summary of daily activities of published equities declared on the floor of the stock exchange.

Conclusion

We present data mining technique and develop tool for exploiting especially time series data in the Nigerian Stock Exchange (NSE). A prediction system based on Digital Signal Processing (DSP) algorithm called Hierarchical Temporal Memory (HTM) is proposed and has been built using data mining techniques to produce periodically forecasts about stock market prices. Our technique complement proven numeric forecasting method using regression analysis and technology taking input dataset for the stock prices from the months of January 2007 to June 2011.

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