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Algorithmic Finance Approach in Media Stock Analysis

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ABSTRACT: *Literature is scanty on how to understand the dynamics of media stock and Factors that affect them. An algorithm with variables accounting for changes is developed. This algorithm will help in generating automatic trade signals and to create superior profits vis a vis individual speculation. Algorithmic trading improves market efficiency with higher liquidity and better price discovery. It improves the informative-ness of the quotes. Focus on control or regulatory structure is also addressed on media stocks. The relative superiority of supervised and unsupervised learning is undertaken.*

KEY WORDS: *Media stocks, algorithmic design, eigen vector, covariance matrix, control theory, hidden markov, trading rules.*

I. INTRODUCTION

Media stocks are becoming a key factor in stock market analysis in the context of a burgeoning knowledge economy. While fundamentals will help explain the movement of robust economic and financial factors, stock market analysis and technical analysis will justify results, positive or negative and throw interpretative light on fundamentals. Algorithmic approach is being used frequently to show whether mathematical/ algebraic manipulation can help factor in more relevant variables along with a control structure for regulatory freedom that is available to regulators.

II. LITERATURE REVIEW

Fischer,Thomas (2011), News Reaction in Financial Markets within a Behavioral Finance Model with Heterogeneous Agents Algorithmic Finance 1 (2011) 123–139 IOS Press
The paper introduces the phenomenon of under reaction and overreaction in the market by using heterogeneous agent model[a] and stability in the prices are assessed using control theory. The basic model in this assumes two agents chartist and fundamentalist whose demand functions are arrived at by using mean variance portfolio optimizations[c]. Different agents differ in their weights which is derived by multinomial logit model [see appendix]. The expectation of chartists and fundamentalist are modeled based on knowledge of true fundamental value and moving average rule respectively[d].

The classical control theory is then applied to the model with several simplification to take care of non-linearity[e]. When variables are observed in frequency domain, we get for first order fundamentalist system. Under reaction stronger when

- Price adjustment[b] speed is low
- Low aggressiveness of fundamental agent
- High overall risk aversion

For second order chartist system
1) Under reaction
- Low Price adjustment speed
- Low aggressiveness of fundamental agent
- High overall risk aversion

- Low aggressiveness of chartist agent

2) Overreaction

- High Price adjustment speed
- Low liquidity

3) Instability

- High price adjustment speed
- High chartist aggression
- Low overall risk aversion

[a] exhibit bounded rationality and heterogeneous beliefs
[b] Finite price adjustment speed assumed
[c] Zero net supply in market clearing
[d] Degree of rationality in choosing a strategy taken into consideration while framing demand function
[e] Continuous time function assumed for simplifying calculations.

Wieland Cristian, Westerhoff Frank H. (2003) <u>Exchange rate dynamics, central bank interventions and chaos control methods</u> Journal of Economic Behavior & Organization Vol. 58 (2005) 117–132

The paper shows the usefulness of chaos control algorithms in improving the effectiveness central bank intervention in controlling the exchange rates[a]. It basically goes into 3 different chaos control methods namely OGY (ott-Grebogi-yorke), DFC (delayed feedback control), and CF (constant feedback) [see appendix]. The two strategies studied here are "leaning against the wind" and "targeting long run fundamentals".

The performance of central bank is measured through volatility [see appendix] and distortion.

OGY : Small wisely chosen swift kicks in the form of intervention tends to bring it near the desired unstable periodic orbit[b]. The level of intervention in the small neighborhood is determined using the intervention level of the central bank. However, leaning against the wind fails to calm down the exchange rates.

DFC : The feedback [see appendix] perturbation applied is proportional to the deviation of the current state of the system from one period in past so that the control signal[c] vanishes when stabilization is achieved.

CF : It simply varies the strength of the constant signal fed[c] in the system in the form of intervention of bank. Choice of the type of signal positive or negative depends on the response of the system to the previously applied signal. Thus it helps a nation in carrying out "beggar thy neighbor" policy [see appendix].

[a] The exchange rate p for period t + 1 is given as pt+1 = pt + cE[pt],
[b] Periodic orbit which is dynamically unstable.
[c] Intervention from central bank in this case.

Feldman Todd (2011), <u>Behavioral biases and investor performance</u> Algorithmic Finance 1 (2011) 45–55 IOS Press

This paper shows the different behavioral traits that force person to trade excessively and simultaneously underperform in the market. Agent based approach has been used with each agent having different alpha[a].

Four different groups of investor has been assumed with each having its different risk assumption.

Group 1:

a) uses mean variance approach
b) long run averages

Group 2:

a) heavily weight current return
b) Recency bias[see appendix]

Group 3:

a) more affected by losses
b) loss averse[see appendix]

Group 4:
a) hold on loss, sell wins
b) disposition effect[see appendix]

II. RESULTS:

Group 4 trades most and 1 least. Even Group 2 trades more than Group 1.
But Group 1 outperforms other groups in terms of long term return.

Louis K.C. Chan, Josef Lakonishok, and Bhaskaran Swami Nathan (2007), Industry Classifications and Return Comovement Financial Analysts Journal Volume 63 (56-70)

The paper takes a look into industry based classification of the stocks and the co-movement of returns associated. It considers two basic systems GICS [see appendix] and Fama French system (based on SIC [see appendix])

[a] ratio of portfolio holding of the agent.

Authors talks about various method of homogeneous stock grouping of which he claims industry affiliation being the most popular one. GICS being the system that takes not only operational characteristics but investors perception also into consideration while classifying the industry.

The methodology adopted here is that coincident movement of stock prices of the group is measured by pairwise correlation [see appendix] In-group[a] and that of the Out-group[b]. Averaging of correlation[c] is done over the group and then values obtained are used for arriving at the conclusion.

The results thus obtained were that co-movement in returns were stronger for large companies. Even the contaminations due to trading issues are less likely. GICS classification was found to be better due to more diversity of industry classification. This was observed through the contrast in in and out industry correlation.

Rachana Sharma (2012) Algorithmic Trading: A Study The international journal RJSITM: Volume: 01 (23-28)

The paper introduces us with the growth of algorithmic trading in India. It describes certain common algorithms used in the markets such as arrival price, time weighted average price (TWAP)[[see appendix] ,volume weighted average price (VWAP)[see appendix], market-on-close (MOC), and implementation shortfall. It also throws some light on basic strategies that are used for developing the algorithm such as pair trading, delta neutral, arbitrage mean reversion and scalping. Author emphasizes on developing state of algorithm as the main challenge however she raises concern over certain aspects like lack of visibility, unfair advantages to the institutional investors, and selection of appropriate algorithm. She then compares Algorithms with human saying that they cannot replicate the gut feel element of human nature wherein they decide on the strategy on whether to be more aggressive or subdued. Also human reaction to an unexpected situation is better than an algorithm.

Domowitz Ian (2005), The Cost of Algorithmic Trading: A First Look at Comparative Performance

Algorithmic Trading: Precision, Control, Execution Institutional Investor, Inc. (1-23)

[a] $\rho_{iI} = \frac{\sum_{j \in I, j \neq i} \rho_{ij}}{N-1}$, pairwise correlations between stock i's return and the return on each of the other members of its industry.

[b] $\phi_{iI} = \frac{\sum_{j \notin I} \rho_{ij}}{K-N}$. The average pairwise correlation between stock i's return and the returns of all other stocks not in its industry.

[c] $\bar{\rho}_I = \frac{\sum_{i=1}^{K} \rho_{iI}}{K}$ $\bar{\phi}_I = \frac{\sum_{i=1}^{K} \phi_{iI}}{K}$ Average correlation between a stock and other stocks

The author in this paper talks about media, its relation with finance and how it has penetrated into the market affecting the volatility. The importance of media has increased in recent time due to technological advances .the introduction of derivatives trading, multi-channel TV and pressure on the state to provide appropriate condition has fueled its growth. The growth of finance can also be observed by the number of financial publication, reporting of finance in mainstream media, and large scale advertising of financial products.

Media has also been dressing up financial news into entertainment so that more and more views gets attracted. Now the audience are more heterogeneous than before with greater level of literacy. Audiences are now more actively entering into information gathering industry.

Author concludes saying that finance has become more per formative rather than a continuous activity of rational entity

W. H. Laverty, M. J. Miket and I. W. Kelly (2002), Simulation of Hidden Markov Models with EXCEL
Journal of the Royal Statistical Society. Series D (The Statistician), Vol. 51, No. 1(2002), pp. 31-40, Wiley

The paper illustrates the simulation of equation that are used for hidden markov model[Ref] in excel. The functions of excel is slightly limited when compared to other high end software that are designed specifically for carrying out extensive calculation. However through this paper author has not only provided valuable aid for learning but also it has led understanding of basic of excel concept and to probability concepts.

Alvaro Carteay and Sebastian Jaimungal (2011)Modeling Asset Prices for Algorithmic and High Frequency Trading Forthcoming, Applied Mathematical Finance, SSRN (121-149)
In this paper author points out how the intraday dynamics of market has changed .the microstructure of the market is now different each and every second. This has also led to need of developing new algorithmic trading strategies. For this she has used hidden markov model to capture different states in which market can be at any time. These states are also important from the point of view of price change. Author has chosen 7 different stocks to show not only the change in the frequency of trading but also change in the fundamentals. HMM in this respect has advantage over other models as it also captures probabilities of states with zero price revision.

HENRIK HULT AND JONAS KIESSLING (2010) ALGORITHMIC TRADING WITH MARKOV CHAINS Department of Mathematics, KTH,Stockholm, Sweden
Author in this paper uses markov chains to study the evolution of the entire order book to design and understand optimal algorithmic trading strategies. The order book changes rapidly due to high number of and frequent orders being executed. Since these orders can be observed, it gives opportunity to use markov chain process to find out an efficient algorithm out of it. The author finally goes on to find that this method of optimization provides significant improvement in expected price for buying. He follows a method whereby parameters are selected and calibrated using historical data, optimal strategies are developed and then used to make trading decisions. Not only market buy/sell order but cancel order also play an important role.

Jeff Bilmes (2002) What HMMs Can Do UWEE Technical Report Number (UWEETR-2002-0003) January 2002

This paper mainly deals with finding new model that is better than hidden markov model in terms computational requirements as well as noise insensitivity. It starts by praising HMM, and displaying its capabilities but later turns towards reasoning its ability thoroughly. He shows its advantages in artificial speech recognition. He starts off with formal definition of HMM, then he compiles a list of properties that may or may not apply to HMM. Finally he concludes by presenting several alternatives to HMM.

12. Md. Rafiul Hassan and Baikunth Nath, **StockMarket Forecasting Using Hidden Markov Model: A New Approach** Computer Science and Software Engineering The University of Melbourne, Carlton 3010, Australia

This paper shows the usage of HMM[appen] for forecasting prices of specific market. Author has used airlines stocks. Further he adds the usage of HMM for predicting needs training of data. HMM interpolates the nearby values to forecast the future values. He further adds to it the advantages of HMM such as

• HMM has strong statistical foundation

• It is able to handle new data robustly

• Computationally efficient to develop and evaluate

• It is able to predict similar patterns efficiently

He concludes by appreciating the statistical foundation of HMM and expects future development in collaboration with artificial intelligence.

Patrik Idvall, Conny Jonsson(2008) **Algorithmic Trading Hidden Markov Models on Foreign Exchange**
Department of Mathematics, Linkoping's University January 2008

Hidden markov model are used as a tool to forecast movements of time series data. Author points that out as one of the field along with other fields of application in the beginning. Further improvements in HMM are depicted like Gaussian mixture Model to enhance its prediction capability where one for each state assign a set of single Gaussians that are weighted together to replicate the density function of the stochastic process. Author has conducted his analysis on foreign exchange data and compared the results with Sharpe ratio.

He goes through derivation of HMM from Bayes theorem. He also thoroughly explains the chain problem. The three fundamental problems of decoding the chain, training and getting the most expected path has also been addressed. Extensions are also suggested here but later on he concluded that these extension are not of much advantage.

Barbara Resch, **Hidden Markov Models** Signal Processing and Speech Communication Laboratory Inffeldgasse 16c

Author in this paper explains the hidden markov by taking some basic examples of weather change pattern and how to predict the future weather. Additionally he has explained the Viterbi algorithm[appen] that is used to predict the sequence. The different orders of markovian chain have been dealt in this paper. The various terminology like transition probabilities emission probabilities and prior probabilities have been explained. He has also used trellis diagram to familiarize readers to the concept.

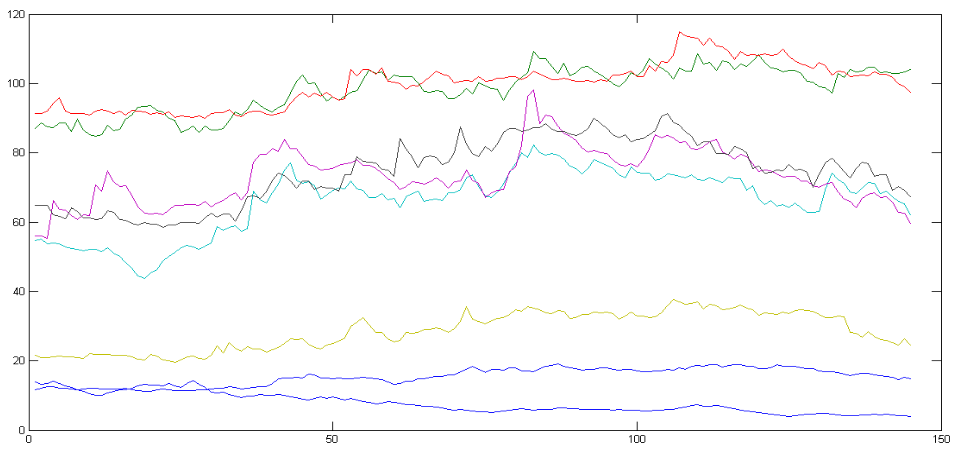
III. METHODOLOGY:

Principal component analysis is used to factor in more relevant variables form data sets. Then a hidden markov is used to generate trading rules.

IV. DATA PROCESSING AND ANALYSIS

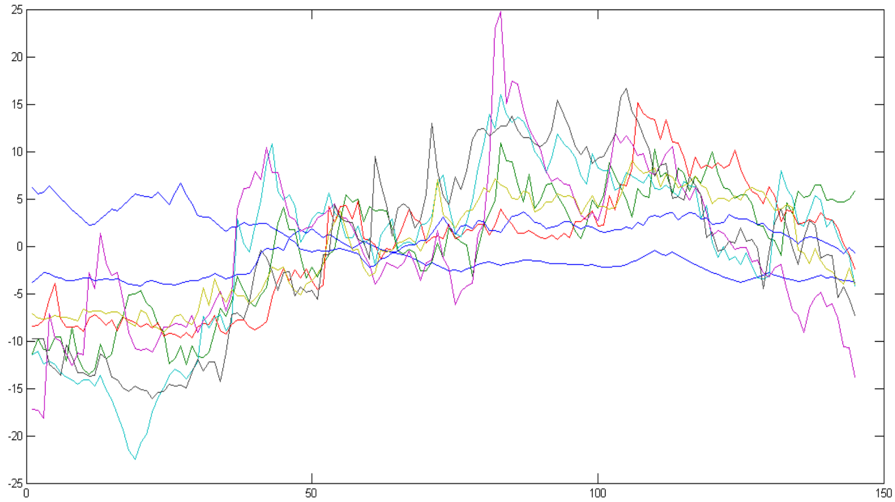
Step 1:
Applying principal component analysis:

The actual data is distributed as given in the figure. Therefore for applying PCA. The data is centered first which is: the mean of the each data column is subtracted from each variable.



DATA plotted versus time SOURCE:BSE India

The data so obtained after centering is



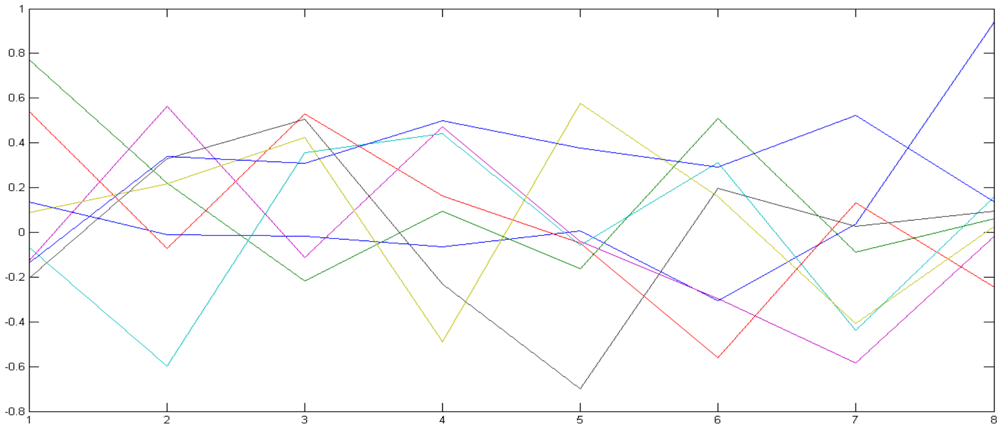
Centered DATA plotted versus time SOURCE:BSE India

Next we find out the covariance matrix

8.712678	**-16.1528**	**-14.8668**	**-19.7982**	**-9.59943**	**-12.8634**	**-20.8053**	**-6.24903**
-16.1528	43.70523	35.87588	47.11569	31.55942	29.28417	48.66163	13.95813
-14.8668	35.87588	41.0498	38.42098	25.96126	31.11942	45.19926	13.96647
-19.7982	47.11569	38.42098	82.69685	55.71067	39.25421	75.88563	18.87618
-9.59943	31.55942	25.96126	55.71067	63.47724	29.17569	53.72267	12.77449
-12.8634	29.28417	31.11942	39.25421	29.17569	29.45039	45.12726	12.77348
-20.8053	48.66163	45.19926	75.88563	53.72267	45.12726	88.04748	20.17886
-6.24903	13.95813	13.96647	18.87618	12.77449	12.77348	20.17886	6.249111

This covariance matrix is used to find out the Eigen vectors and Eigen values [see appendix] the plot of Eigen vector is as follows:

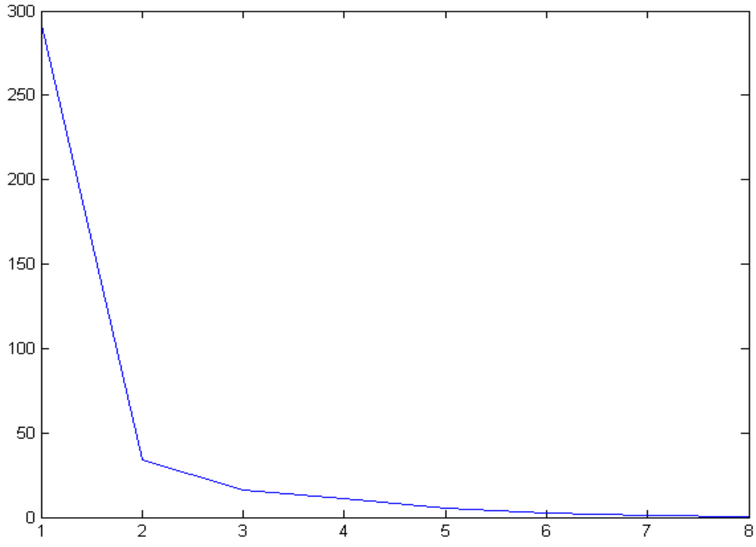
The Eigen values gives variance captured by that particular Eigen vector:



Eigen vector plotted versus time SOURCE:BSE India

To find the number of components to be included we have created a screen plot[append] and a cumulative percentage of variance captured by each of them.

In scree plot we take vectors till we observe the first shoulder. Since this is observed at 2nd component therefore we take 2 vectors as our feature vector.



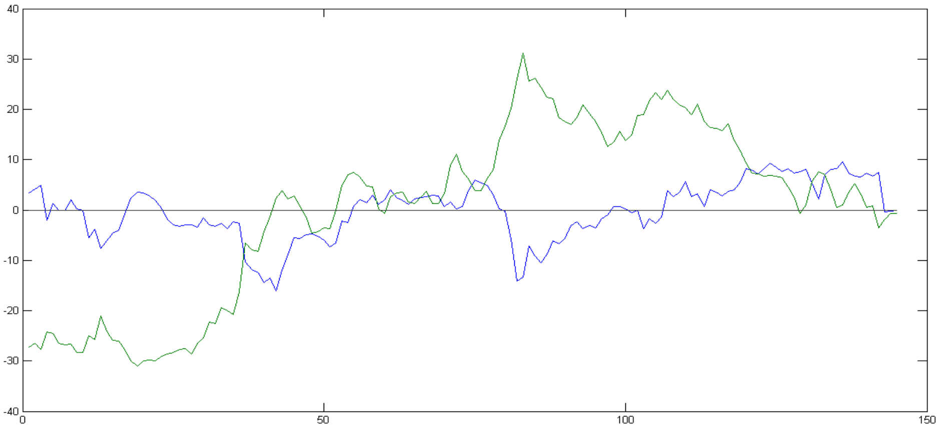
The % of variance captured by it is given by

Cum. Eigen value	Cumulative %
293.1557544	80.67275909
326.8911224	89.95630608
343.0592009	94.40555696
354.2048331	97.47269411
359.4493539	98.91591995
361.7485525	99.54863035
362.9599175	99.8819827
363.3887792	100

Cumulative% plotted vs. No. of components

Hence, we see that the first two component when arranged in decreasing order captures 89.95% variance. These are known as feature vector.

The plot of data on the first two component is:



Principal component plotted versus time

Step 2:

Using the hidden Markov model, forecasting data so obtained:

This is done using the statistic toolbox of Matlab and functions like

[seq,states] = hmmgenerate (len, TRANS, EMIS)

PSTATES = hmmdecode(seq,TRANS,EMIS)

[TRANS,EMIS] = hmmestimate(seq,states)

[ESTTR,ESTEMIT] = hmmtrain(seq,TRGUESS,EMITGUESS)

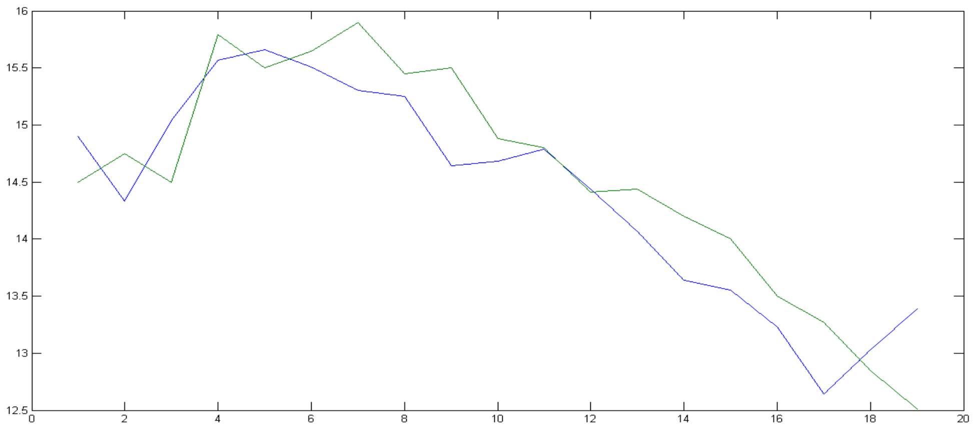
STATES = hmmviterbi(seq,TRANS,EMIS)

Where trans and emis are transition and emission matrix respectively[appen.]

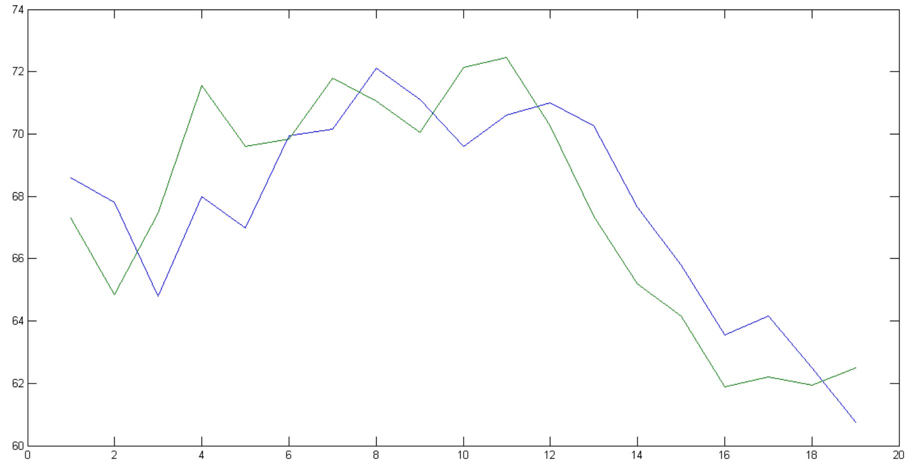
The data from 1 Aug 2012 to 28th Feb is used for training the model in hmmtrain function. This is then used in hmmviterbi to find out the most probable state. It is then fed in to hmmgenerate to generate the future sequence of data. Then hmmestimate finds out Tran and emis based on the next iteration. This whole process is repeated until we get the complete sequence of forecasted data.

The forecasts for the two principal components that were obtained in PCA is given:

Actual (Green) Vs. Forecast (blue) graph for TV TODAY (March)



Actual (Green) Vs. Forecast (blue) graph for Zee News (March)



Similarly forecasts for all other firms were obtained and returns were calculated accordingly:

Step 3:

For calculating the return certain assumption were made and a simple trading rule was followed:

Assumptions:

[1] The return is calculated for the month of March.
[2] Transaction is executed only once in a day.
[3] Buyer can sell/buy only 1 share at a time. (Even if he sells more than 1 share at a time we only need to multiply our calculation with that fixed value).
[4] It is assumed that cost of equity for media industry (print/non-print) is fixed at 12.33% per annum.
[5] Broker charges fixed rate of .55% of the selling/buying value as a transaction cost.
[6] Buying/selling value is assumed to be the average price of scrip for that month.
[7] If the price is expected to decrease in future then trader can short-sell thereby earning profit.

Trading rule: A filter of 2% is used for executing the trading signal. That is if the actual value of the next day is 2% more or less than the forecasted value then only trade is executed. It is carried out at the end of each day.

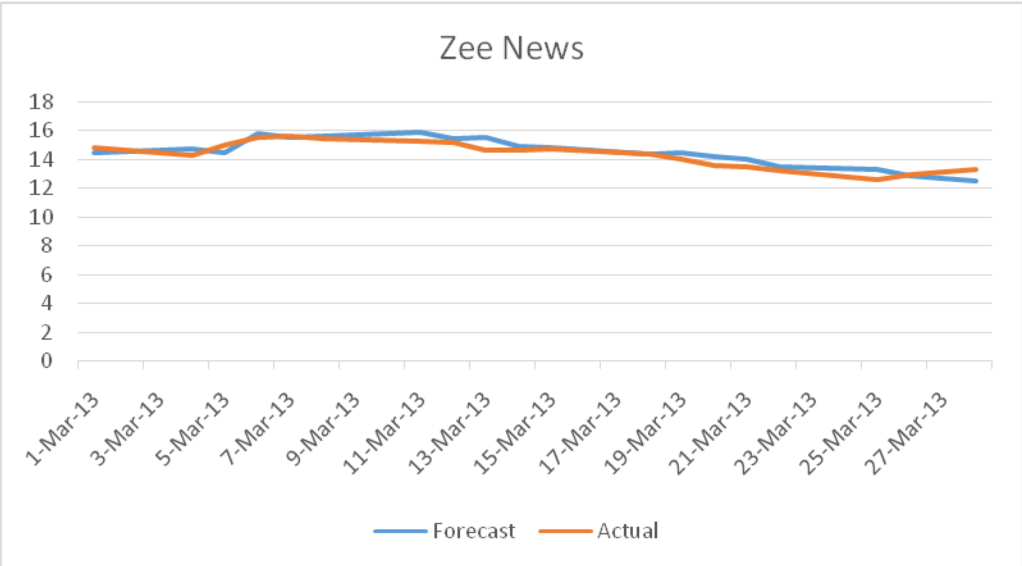
The blue band here denotes that filter rule is followed and individual made a gain from it whereas red band denotes loss due to incorrect forecasting.

Hence we see that if the (expected % change) is of the same sign as the (actual change) then it is profit for the trader whereas they being of opposite sign means loss. As the observation was opposite to that of expectation.

ZEE NEWS:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	14.5	14.9	-1.01	-0.57
4-Mar-13	14.75	14.33	1.19	0.71
5-Mar-13	14.5	15.04	4.99	0.53
6-Mar-13	15.79	15.57	-0.45	0.09
7-Mar-13	15.5	15.66	-0.06	-0.15
8-Mar-13	15.65	15.51	2.51	-0.21
11-Mar-13	15.9	15.3	0.98	-0.05
12-Mar-13	15.45	15.25	1.64	-0.61
13-Mar-13	15.5	14.64	1.64	0.04
14-Mar-13	14.88	14.68	0.82	0.11
15-Mar-13	14.8	14.79	-2.57	-0.35
18-Mar-13	14.41	14.44	0.00	-0.37
19-Mar-13	14.44	14.07	0.92	-0.43
20-Mar-13	14.2	13.64	2.64	-0.09
21-Mar-13	14	13.55	-0.37	-0.32
22-Mar-13	13.5	13.23	0.30	-0.59
25-Mar-13	13.27	12.64	1.66	0.39
26-Mar-13	12.85	13.03	-3.99	0.36
28-Mar-13	12.51	13.39		

Gain	0.88	%gain	15.33%
loss	0.3		
Brokerage	0.396		
total gain	0.396		

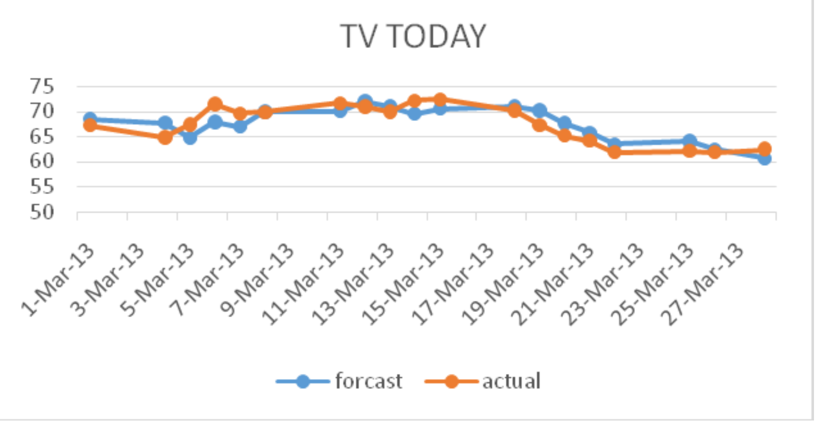


All figures in Rs. SOURCE:BSE India

TV TODAY:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	68.6	67.3	0.74	-2.45
4-Mar-13	67.8	64.85	-0.08	2.6
5-Mar-13	64.8	67.45	0.82	4.1
6-Mar-13	68	71.55	-6.36	-1.95
7-Mar-13	67	69.6	0.50	0.25
8-Mar-13	69.95	69.85	0.43	1.95
11-Mar-13	70.15	71.8	0.42	-0.75
12-Mar-13	72.1	71.05	0.07	-1
13-Mar-13	71.1	70.05	-0.64	2.1
14-Mar-13	69.6	72.15	-2.15	0.3
15-Mar-13	70.6	72.45	-2.00	-2.2
18-Mar-13	71	70.25	0.00	-2.9
19-Mar-13	70.25	67.35	0.45	-2.15
20-Mar-13	67.65	65.2	0.92	-1.05
21-Mar-13	65.8	64.15	-0.94	-2.25
22-Mar-13	63.55	61.9	3.63	0.3
25-Mar-13	64.15	62.2	0.48	-0.25
26-Mar-13	62.5	61.95	-1.94	0.55
28-Mar-13	60.75	62.5		

Gain	4.45	%gain	47.32%
loss	0.03		
Brokerage	1.486		
total gain	2.664		



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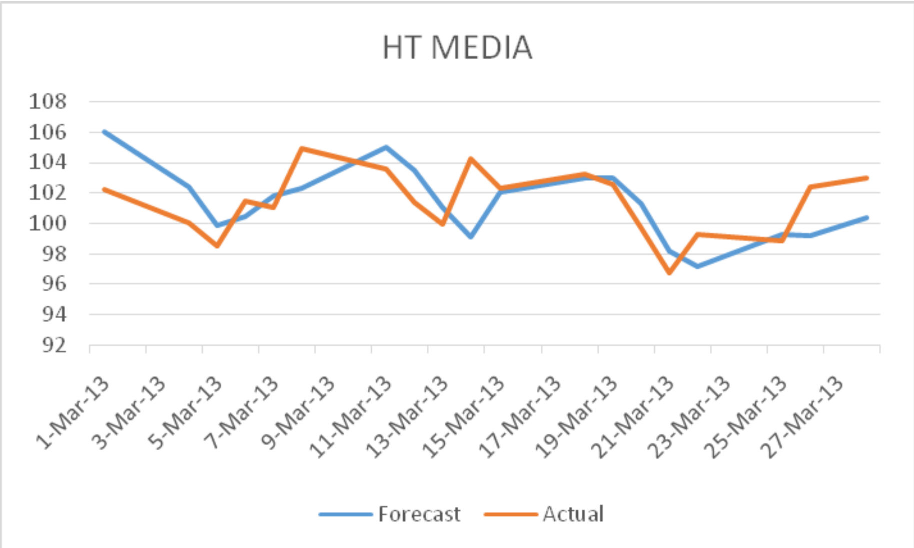
HT MEDIA:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	106	102.2	0.20	-2.2
4-Mar-13	102.4	100	-0.15	-1.5
5-Mar-13	99.85	98.5	1.93	2.95
6-Mar-13	100.4	101.45	0.34	-0.4
7-Mar-13	101.8	101.05	1.24	3.85
8-Mar-13	102.3	104.9	0.10	-1.35
11-Mar-13	105	103.55	-0.05	-2.2
12-Mar-13	103.5	101.35	-0.35	-1.45
13-Mar-13	101	99.9	-0.80	4.35
14-Mar-13	99.1	104.25	-2.11	-1.95
15-Mar-13	102.05	102.3	0.64	0.9
18-Mar-13	102.95	103.2	-0.19	-0.65
19-Mar-13	103	102.55	-1.27	-2.85
20-Mar-13	101.25	99.7	-1.50	-3
21-Mar-13	98.2	96.7	0.47	2.55
22-Mar-13	97.15	99.25	0.00	-0.45
25-Mar-13	99.25	98.8	0.40	3.55
26-Mar-13	99.2	102.35	-1.95	0.6
28-Mar-13	100.35	102.95	-100.00	-1.64

Gain	1.95	%gain	16.49%
loss	0		
Brokerage	0.557		
total gain	1.393		



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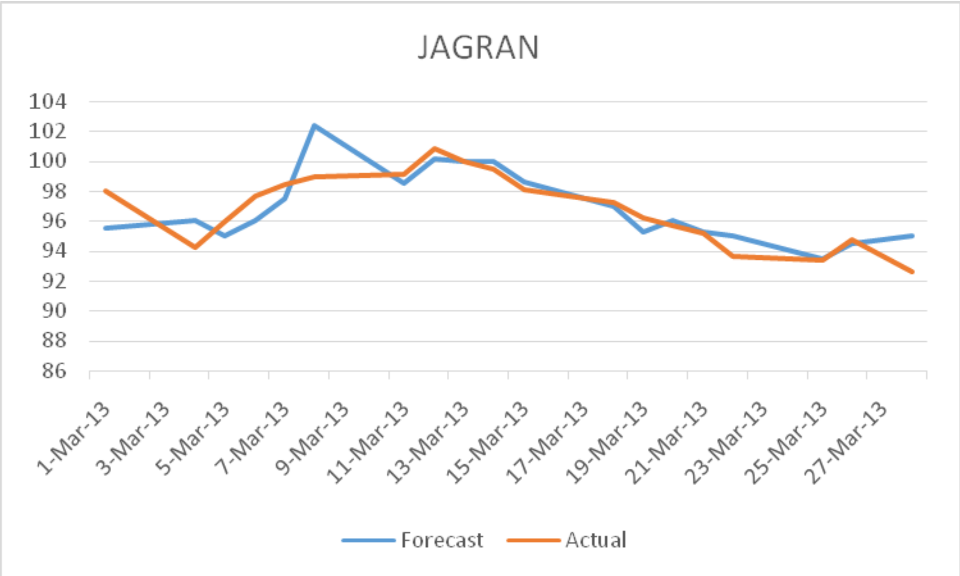
JAGRAN:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	95.5	98.05	-2.09	-3.75
4-Mar-13	96	94.3	0.74	1.7
5-Mar-13	95	96	0.05	1.7
6-Mar-13	96.05	97.7	-0.20	0.75
7-Mar-13	97.5	98.45	4.01	0.5
8-Mar-13	102.4	98.95	-0.45	0.15
11-Mar-13	98.5	99.1	1.06	1.75
12-Mar-13	100.15	100.85	-0.84	-0.85
13-Mar-13	100	100	0.00	-0.55
14-Mar-13	100	99.45	-0.85	-1.35
15-Mar-13	98.6	98.1	-1.12	-0.8
18-Mar-13	97	97.3	-2.06	-1.05
19-Mar-13	95.3	96.25	-0.21	-0.55
20-Mar-13	96.05	95.7	-0.47	-0.45
21-Mar-13	95.25	95.25	-0.26	-1.55
22-Mar-13	95	93.7	-0.27	-0.3
25-Mar-13	93.45	93.4	1.18	1.4
26-Mar-13	94.5	94.8	0.21	-2.15
28-Mar-13	95	92.65		

Gain	5.3	%gain	45.88%
loss	0		
Brokerage	1.597		
total gain	3.703		

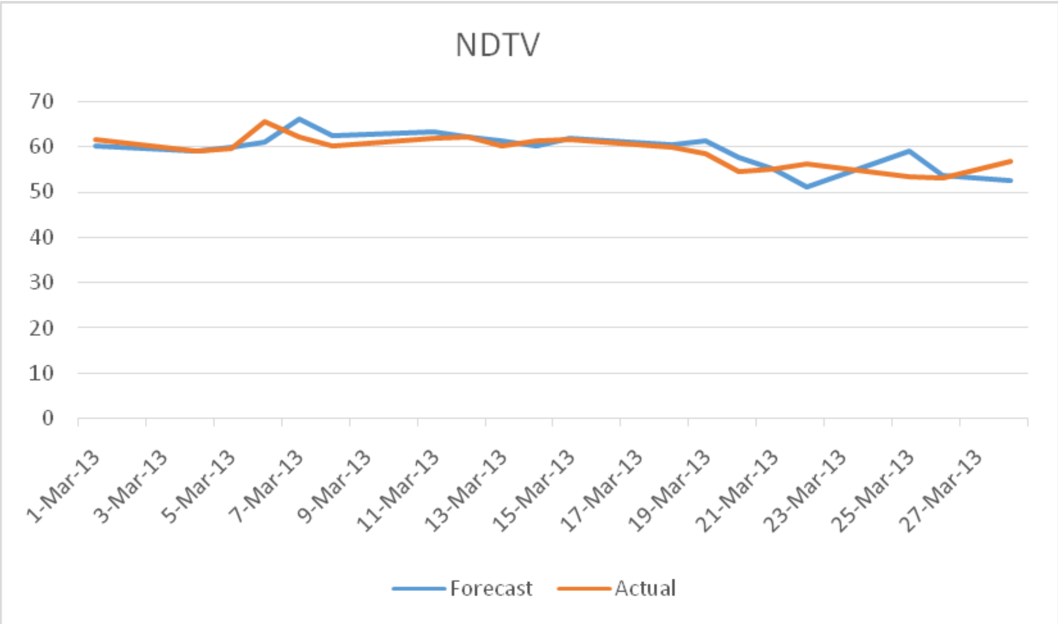


All figures in Rs. SOURCE:BSE India

NDTV:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	60.1	61.6	-4.22	-2.6
4-Mar-13	59	59	1.69	0.7
5-Mar-13	60	59.7	2.18	5.95
6-Mar-13	61	65.65	0.91	-3.45
7-Mar-13	66.25	62.2	0.56	-1.85
8-Mar-13	62.55	60.35	5.05	1.6
11-Mar-13	63.4	61.95	0.32	0.25
12-Mar-13	62.15	62.2	-1.37	-1.9
13-Mar-13	61.35	60.3	0.00	1.1
14-Mar-13	60.3	61.4	0.90	0.3
15-Mar-13	61.95	61.7	-1.78	-1.7
18-Mar-13	60.6	60	2.08	-1.35
19-Mar-13	61.25	58.65	-1.62	-4.1
20-Mar-13	57.7	54.55	0.82	0.6
21-Mar-13	55	55.15	-7.52	1
22-Mar-13	51	56.15	5.08	-2.65
25-Mar-13	59	53.5	0.19	-0.35
26-Mar-13	53.6	53.15	-1.13	3.8
28-Mar-13	52.55	56.95	-100.00	-56.95

Gain	10.15	%gain	64.86%
loss	5		
Brokerage	1.952		
total gain	3.198		

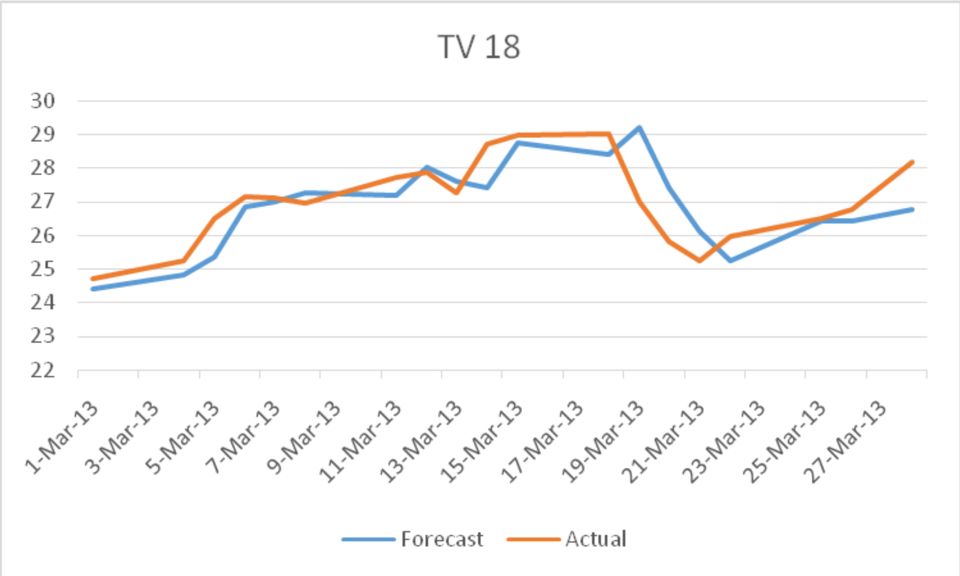


All figures in Rs. SOURCE:BSE India

TV 18:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	24.4	24.7	0.40	0.55
4-Mar-13	24.8	25.25	0.40	1.25
5-Mar-13	25.35	26.5	1.32	0.65
6-Mar-13	26.85	27.15	-0.55	-0.05
7-Mar-13	27	27.1	0.55	-0.15
8-Mar-13	27.25	26.95	0.93	0.75
11-Mar-13	27.2	27.7	1.08	0.15
12-Mar-13	28	27.85	-0.90	-0.6
13-Mar-13	27.6	27.25	0.55	1.45
14-Mar-13	27.4	28.7	0.17	0.25
15-Mar-13	28.75	28.95	-1.90	0.05
18-Mar-13	28.4	29	0.69	-2
19-Mar-13	29.2	27	1.48	-1.2
20-Mar-13	27.4	25.8	1.16	-0.55
21-Mar-13	26.1	25.25	0.00	0.7
22-Mar-13	25.25	25.95	1.73	0.55
25-Mar-13	26.4	26.5	-0.38	0.25
26-Mar-13	26.4	26.75	0.00	1.4
28-Mar-13	26.75	28.15		

No transaction within this period

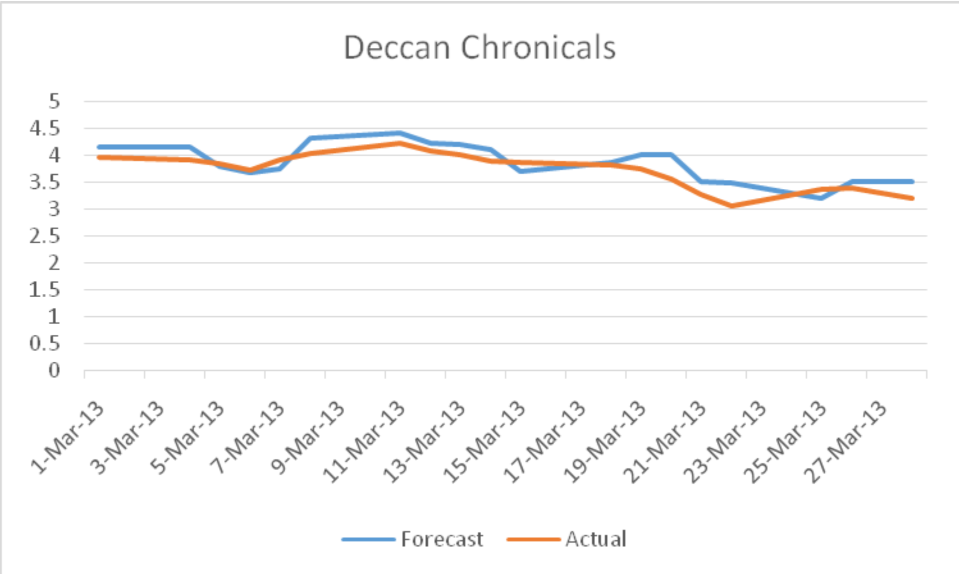


All figures in Rs. SOURCE:BSE India

Deccan Chronicles:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	4.15	3.96	4.80	-0.05
4-Mar-13	4.15	3.91	-2.81	-0.08
5-Mar-13	3.8	3.83	-3.92	-0.11
6-Mar-13	3.68	3.72	0.81	0.19
7-Mar-13	3.75	3.91	9.97	0.12
8-Mar-13	4.3	4.03	9.18	0.18
11-Mar-13	4.4	4.21	0.00	-0.13
12-Mar-13	4.21	4.08	2.94	-0.09
13-Mar-13	4.2	3.99	2.76	-0.12
14-Mar-13	4.1	3.87	-4.39	-0.02
15-Mar-13	3.7	3.85	0.00	-0.04
18-Mar-13	3.85	3.81	4.72	-0.06
19-Mar-13	3.99	3.75	6.40	-0.19
20-Mar-13	3.99	3.56	-1.69	-0.28
21-Mar-13	3.5	3.28	6.40	-0.22
22-Mar-13	3.49	3.06	4.58	0.3
25-Mar-13	3.2	3.36	4.17	0.02
26-Mar-13	3.5	3.38	3.55	-0.19
28-Mar-13	3.5	3.19	-100.00	-3.19

Gain	0.83	%loss	121.00%
loss	0.92		
Brokerage	0.2867		
total gain	-0.3767		

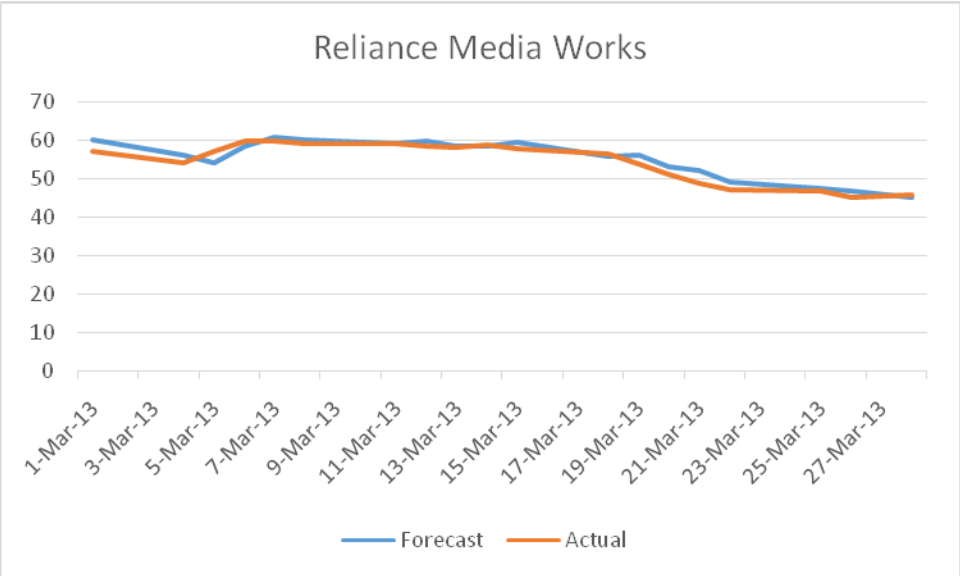


All figures in Rs. SOURCE:BSE India

RELIANCE MEDIA:

	Forecast	Actual	expected% change	Actual change
1-Mar-13	60	56.9	-1.58	-2.8
4-Mar-13	56	54.1	0.00	2.7
5-Mar-13	54.1	56.8	2.82	2.8
6-Mar-13	58.4	59.6	2.01	-0.15
7-Mar-13	60.8	59.45	0.93	-0.55
8-Mar-13	60	58.9	0.17	0.1
11-Mar-13	59	59	1.36	-0.6
12-Mar-13	59.8	58.4	0.17	-0.5
13-Mar-13	58.5	57.9	0.86	0.75
14-Mar-13	58.4	58.65	1.36	-0.95
15-Mar-13	59.45	57.7	-3.64	-1.45
18-Mar-13	55.6	56.25	-0.44	-2.55
19-Mar-13	56	53.7	-1.21	-2.65
20-Mar-13	53.05	51.05	1.86	-2.45
21-Mar-13	52	48.6	0.82	-1.45
22-Mar-13	49	47.15	0.11	-0.4
25-Mar-13	47.2	46.75	0.00	-1.65
26-Mar-13	46.75	45.1	-0.22	0.8
28-Mar-13	45	45.9		

Gain	4.25	%gain	70.79%
loss	0.15		
Brokerage	0.8961		
total gain	3.2		



OBSERVATION:

All figures in Rs. SOURCE:BSE India

Scrip	No. of transaction	% Gain
Deccan Chronicles	14	-121
TV 18	0	0
NDTV	6	64.86
JAGRAN	3	45.88
HT MEDIA	1	16.49
ZEE NEWS	5	15.33
TV TODAY	4	47.32
Reliance Media	3	70.79

CONCLUSION:

[1] We see that we almost always get positive returns and that too more than the market cost of equity (12.33%)

[2] In two cases of Deccan chronicles and TV 18 we see that we could not satisfy the investor. The possible explanation for this can be the excessive number of order executed in the case of Deccan chronicles and no orders executed for TV 18.

[3] These two problems can be dealt with by adjusting the filter value.

[4] The general trend in the return on equity is around 40%. This is quite overoptimistic mainly because of the low transaction cost of 0.55% per sale value assumed.

[5] The two principal components of media industry ZEE NEWS and TV TODAY show an average return of 31.25% which sufficient enough for this algorithm comprising of HMM and filter rule to be used in this industry.

APPENDIX

DATA: All figures in Rs. SOURCE:BSE India

Date	Deccan Chronicals	HT MEDIA	JAGRAN	NDTV	Reliance Media Works	TV 18	Tv Today	Zee News
1-Aug-12	**13.95**	86.95	91.3	54.75	56.15	21.55	64.8	11.64
2-Aug-12	**13.3**	88.55	91.4	55.1	56.05	21.05	64.85	12.05
3-Aug-12	**13.55**	87.4	91.95	53.8	55.25	21	64.85	12.64
6-Aug-12	**14.2**	87.35	94.2	54.1	66.3	21.1	62.15	12.51
7-Aug-12	**13.5**	88.7	95.9	53.7	63.7	21.35	61.6	12.2
8-Aug-12	**12.85**	88.75	92.1	52.85	63.4	21.15	60.95	12.12
9-Aug-12	**12.25**	86.2	91.25	52.4	62	21.15	64.15	11.83
10-Aug-12	**11.65**	89.75	91.25	52.1	60.85	20.95	63	11.76
13-Aug-12	**11.1**	86.55	91.35	51.65	62.1	20.8	61.3	11.85
14-Aug-12	**10.55**	85.35	90.8	52.1	61.95	22	61.25	12.05
16-Aug-12	**10.05**	84.8	92.15	52.1	70.65	21.75	60.9	12.05
17-Aug-12	**10.15**	85.35	92.55	51.4	68.95	21.8	61	11.82
21-Aug-12	**10.65**	88	92.05	52.55	74.8	21.85	63.25	11.88
22-Aug-12	**11.15**	86.4	91.45	51.1	71.65	21.55	62.8	12
23-Aug-12	**11.7**	86.9	92	50.05	70.35	21.7	60.75	11.9
24-Aug-12	**11.55**	89.85	90.9	48.45	70.6	21.7	60.5	12.01
27-Aug-12	**12.1**	90.95	92.3	46.85	67.7	21.25	59.65	11.72
28-Aug-12	**12.7**	93.2	91.95	44.6	64.35	20.6	59.25	11.46
29-Aug-12	**13.3**	93.3	91.75	43.7	62.65	20.25	59.85	11.31
30-Aug-12	**13.1**	93.65	91.2	45.45	62.45	21.95	59.45	11.22
31-Aug-12	**13**	92.35	91.65	46.35	62.65	21.5	59.4	11.74
3-Sep-12	**12.9**	91.75	91.1	48.7	62.25	20.2	58.55	11.81
4-Sep-12	**13.54**	90.05	91.75	50.2	63.4	20	59.15	11.61
5-Sep-12	**12.87**	89.35	90.25	51.25	64.85	19.6	59.3	11.42
6-Sep-12	**12.23**	85.9	90.6	52.6	64.85	20.2	60	11.44
7-Sep-12	**13.45**	86.5	90.5	53.25	65.2	21.25	59.85	11.37
8-Sep-12	**14.48**	87.75	90.15	52.85	65.15	21.45	59.9	11.48
10-Sep-12	**13.26**	85.85	90.65	52.2	64.9	20.65	59.7	11.73
11-Sep-12	**12.25**	87.8	90.1	53	66.05	20.45	61.3	11.76
12-Sep-12	**11.03**	86.65	91.25	53.95	64.35	21.6	62.7	11.82

13-Sep-12	**10.84**	86.55	91.6	58.75	65.5	24.25	61.45	12.09
14-Sep-12	**10.9**	87.1	91.55	57.55	66.15	22.4	62.4	12.19
17-Sep-12	**10.36**	89.3	92.5	58.6	67.55	25.2	62.4	12.52
18-Sep-12	**9.85**	91.8	90.85	58.95	68.6	23.65	60.35	12.25
20-Sep-12	**9.36**	90.9	90.5	57.3	66.55	22.75	63.3	11.95
21-Sep-12	**9.82**	92.5	91.5	58.1	68.5	24.1	67.4	12.14
24-Sep-12	**9.85**	95.15	92	69.05	77.3	23.45	67.55	12.43
25-Sep-12	**10.34**	93.65	91.95	66.4	79.5	23.45	66.95	12.48
26-Sep-12	**9.98**	92.4	91.2	65.55	79.55	22.55	68.8	12.55
27-Sep-12	**10.12**	91.9	91	68.4	81.25	23.15	72.1	13.39
28-Sep-12	**10.22**	93.2	91.35	71.05	80.4	23.9	74.15	14.72
1-Oct-12	**10.16**	93.9	91.8	75.05	83.8	25.1	73.45	15.16
3-Oct-12	**9.71**	97.2	94.4	77	81.2	26.4	71.9	15.06
4-Oct-12	**9.49**	100.75	96.1	72.05	81.2	26.15	69.95	15.31
5-Oct-12	**9.03**	102.4	97.5	71.1	78.8	26.4	71.8	14.96
8-Oct-12	**8.73**	100.05	96.1	71.65	76.55	24.7	71.95	16.24
9-Oct-12	**9.12**	100.1	97.25	70.45	76.15	23.95	69.35	15.89
10-Oct-12	**9.53**	97.25	96.4	66.65	74.95	23.5	70.35	15.08
11-Oct-12	**9.15**	94.95	97.4	67.7	75.35	24.65	69.75	15.05
12-Oct-12	**9.6**	96.05	96.15	69.1	75.45	25	69.9	14.82
15-Oct-12	**9.13**	95.1	95.2	69.75	76.4	25.75	68.95	15.05
16-Oct-12	**8.71**	96.45	95.65	69.65	76.8	26.7	73.75	14.94
17-Oct-12	**9.1**	97.4	103.95	71.85	77.2	30	73.7	14.87
18-Oct-12	**8.67**	98	102.25	69.7	77.9	31.2	78.95	15.07
19-Oct-12	**8.34**	101.1	104	69.2	76.5	32.4	77.55	15.2
22-Oct-12	**7.93**	103.7	104.05	67.1	76.35	30.4	77.25	14.96
23-Oct-12	**7.54**	102.95	102.7	67.1	75.4	28.2	77.1	14.85
25-Oct-12	**7.91**	103.3	104.5	68.3	74.1	28.3	75.35	14.63
26-Oct-12	**8.3**	100.95	100.55	66.4	72.55	26.35	75	13.9
29-Oct-12	**8.06**	102.5	100.4	67	71.45	25.5	73.25	13.25
30-Oct-12	**7.78**	102	99.9	64.15	69.4	25.9	84.05	13.39
31-Oct-12	**7.46**	102.1	98.45	67.35	70.25	28.25	81.2	14.05
1-Nov-12	**7.29**	102	99.5	68.2	71.65	28.05	79	14.22
2-Nov-12	**7.2**	100.2	99.35	69.05	71.4	28.25	75.7	14.76
5-Nov-12	**6.96**	97.8	100.6	66	71.05	29	78.6	14.87

6-Nov-12	**6.87**	97.5	102.1	66.5	71.65	29.15	79.1	15.38
7-Nov-12	**6.68**	97.95	103.65	66.6	72.85	29.6	78.65	15.55
8-Nov-12	**6.42**	97.6	102.65	66.3	71.6	29.05	76.55	15.55
9-Nov-12	**6.1**	95.7	102.25	68.45	69.8	28.15	77.35	16.04
12-Nov-12	**5.8**	95.7	100.15	68.6	71.65	29.35	80.15	16
13-Nov-12	**6.09**	96.7	100.65	69.4	71.95	31.3	87.6	16.79
15-Nov-12	**5.79**	98.6	100.9	72.85	75.05	35.65	82.5	17.62
16-Nov-12	**5.51**	97	100.55	73.7	72.15	32	79.9	18.5
19-Nov-12	**5.24**	100.25	102.1	70.4	71.1	31.4	78.95	17.58
20-Nov-12	**5.25**	99.35	100.55	67.55	67.2	30.6	81.9	16.72
21-Nov-12	**5.1**	98.7	100.85	67.15	68.6	31.6	80.6	17.54
22-Nov-12	**5.35**	98.45	101.55	68.8	69.25	32.35	82.6	17.6
23-Nov-12	**5.59**	95.15	101.45	70.95	69.45	32.45	85.85	17.23
26-Nov-12	**5.85**	98.05	102.1	74.45	74.7	33.5	86.95	18.07
27-Nov-12	**6.09**	100.45	102.1	76.95	75.85	34.85	87	17.98
29-Nov-12	**6.13**	101.85	101	80.15	82.4	34.35	86.25	17.1
30-Nov-12	**5.96**	103.1	101.95	78.65	96.4	35.75	86.7	17.07
3-Dec-12	**5.78**	109.2	103.65	82.2	98.15	35.1	87.3	16.9
4-Dec-12	**5.95**	107.3	102.75	80.15	88.45	34.85	87.3	17.7
5-Dec-12	**6.08**	107.2	102.05	79.3	90.85	33.75	88.35	18.55
6-Dec-12	**6.1**	104.85	101.1	79.85	90.55	33.6	86.85	18.7
7-Dec-12	**6.34**	102.95	101.1	79.4	87.8	34.5	86.05	19.05
10-Dec-12	**6.37**	105.95	101.45	78.25	85.8	34.3	86.1	18.55
11-Dec-12	**6.22**	102.3	101.05	76.2	84.7	32.25	85.45	17.9
12-Dec-12	**6.21**	103.15	100.65	75.4	83.65	32.55	85.1	17.8
13-Dec-12	**6.07**	104.75	100.6	74	81.3	33.35	85.6	17.25
14-Dec-12	**5.92**	105	100.95	75.6	80.25	33.3	86.95	17.5
17-Dec-12	**5.99**	103.6	100.5	78.05	80.65	34.15	90.05	17.55
18-Dec-12	**5.96**	102.5	101.1	77.05	80	33.85	88.4	18
19-Dec-12	**5.9**	101.3	100.65	76.45	79.85	34	87.05	18
20-Dec-12	**5.88**	99.85	102.4	75.55	78.05	33.6	85.15	17.55
21-Dec-12	**5.89**	99.15	102.4	73.65	76.7	32	84.25	17.25
24-Dec-12	**5.76**	100.75	102.95	72.75	76.15	33.05	85.15	17.55
26-Dec-12	**5.83**	103.15	103.5	75.95	76.9	34	83.3	17.45
27-Dec-12	**5.71**	102.3	101.9	74.45	76.05	32.9	83.9	17.1

28-Dec-12	**5.55**	103.75	101.95	74.15	78.05	32.85	84.05	16.9
31-Dec-12	**5.61**	107.15	105.1	74.2	81.25	32.55	85.25	16.95
1-Jan-13	**5.68**	105.7	103.6	72.1	85.3	32.75	86.4	17.15
2-Jan-13	**5.69**	104.6	106.35	72.5	84.35	33.95	90.35	17.15
3-Jan-13	**5.9**	103.25	106.1	74	85.05	35.95	91.25	17.45
4-Jan-13	**6.11**	101.4	108	73.6	84.25	37.7	88.8	17.25
7-Jan-13	**6.38**	104.4	114.95	73.25	83	36.95	87.85	17.95
8-Jan-13	**6.69**	103.6	113.8	72.85	83.15	36.35	86.25	17.6
9-Jan-13	**7.02**	103.5	113.35	73.75	81.25	36.55	84.9	18.45
10-Jan-13	**7.37**	108.55	113.15	72.3	80.9	36.95	82	18.7
11-Jan-13	**7.01**	105.65	111.05	72.15	81.9	34.95	83.15	18.5
14-Jan-13	**6.83**	106.05	113.1	72.7	83.15	36.25	83.3	18.9
15-Jan-13	**7.17**	103.9	110.8	72.05	83.95	35.95	79.7	18.95
16-Jan-13	**6.82**	106.55	110.65	71.4	80.2	34.85	79.85	18.25
17-Jan-13	**6.48**	106	109.15	73	79.35	35.05	79.5	18.65
18-Jan-13	**6.16**	104.15	107	72.55	78.3	35.45	81.9	18.95
21-Jan-13	**5.86**	105.7	109.15	72.5	79.55	36.1	81.1	18.9
22-Jan-13	**5.57**	105	108	69.15	78.85	35.1	80	18.35
23-Jan-13	**5.3**	106.55	108.3	70.45	76.95	34.75	75.55	18.4
24-Jan-13	**5.04**	108.3	108	66.6	74.5	33.15	76.1	17.75
25-Jan-13	**4.79**	106	108.55	65	75.05	33.75	74.1	17.85
28-Jan-13	**4.56**	104.5	108	66.15	74.75	33.7	74.3	17.95
29-Jan-13	**4.34**	104.3	108.35	64.75	73.95	33.4	75.1	18.8
30-Jan-13	**4.13**	103.35	109.95	65.15	73.1	34	74.9	18.4
31-Jan-13	**3.93**	103.75	107.9	64.3	73.25	33.55	76.55	18.35
1-Feb-13	**4.12**	103.75	106.6	65.5	73.3	34.55	75.15	18.35
4-Feb-13	**4.32**	102.8	105.55	64.1	71.8	34.8	75.3	18.05
5-Feb-13	**4.53**	100.55	105.2	62.85	71.95	34.55	74.4	17.7
6-Feb-13	**4.75**	100.45	104.25	62.75	70.6	34.35	70.1	17.85
7-Feb-13	**4.98**	99.1	106.05	63.05	70.15	33.4	73.9	17.15
8-Feb-13	**4.76**	98.9	105.15	69.35	71.05	32.5	77.1	16.9
11-Feb-13	**4.53**	97.3	102.4	74.2	71.5	32.6	78.55	16.85
12-Feb-13	**4.31**	102.85	103.55	72.3	68.8	33.05	76.6	16.55
13-Feb-13	**4.23**	101.75	103.4	71.3	66.7	32.8	74.5	16.2
14-Feb-13	**4.1**	104.15	102.05	68.65	66.1	28.2	72.7	15.7

15-Feb-13	**4.12**	103.45	102.25	68.35	64.3	27.95	75.4	16.25
18-Feb-13	**4.32**	103.6	102.55	69.8	66.9	26.85	77.3	16.4
19-Feb-13	**4.52**	104.75	102.25	71.5	67.95	28.4	76.85	16.35
20-Feb-13	**4.7**	104.8	103.3	71.1	68.55	27.1	73.35	16
21-Feb-13	**4.47**	103.15	102.65	68.2	67.05	26.25	73.7	15.75
22-Feb-13	**4.55**	103.25	102.6	69	67.35	26	73.6	15.45
25-Feb-13	**4.33**	103	101.7	67.3	65.8	25.25	69.15	15.2
26-Feb-13	**4.12**	103	100	65.95	62.75	24.65	70.3	14.6
27-Feb-13	**4.12**	103.25	99	65.25	62.7	26.35	69.1	15.3
28-Feb-13	**3.96**	104.1	97.4	62.05	59.6	24.65	67.3	14.75

CONVARIANCE MATRIX:

8.712678	**-16.1528**	**-14.8668**	**-19.7982**	**-9.59943**	**-12.8634**	**-20.8053**	**-6.24903**
-16.1528	43.70523	35.87588	47.11569	31.55942	29.28417	48.66163	13.95813
-14.8668	35.87588	41.0498	38.42098	25.96126	31.11942	45.19926	13.96647
-19.7982	47.11569	38.42098	82.69685	55.71067	39.25421	75.88563	18.87618
-9.59943	31.55942	25.96126	55.71067	63.47724	29.17569	53.72267	12.77449
-12.8634	29.28417	31.11942	39.25421	29.17569	29.45039	45.12726	12.77348
-20.8053	48.66163	45.19926	75.88563	53.72267	45.12726	88.04748	20.17886
-6.24903	13.95813	13.96647	18.87618	12.77449	12.77348	20.17886	6.249111

Eigen Value Matrix:**Error! Not a valid link.**

Eigen vectors:

-0.13748604	-0.205821768	0.088058	-0.12919	-0.06564	0.542803	0.772436	0.136705
0.339571377	0.328533177	0.216655	0.565276	-0.59703	-0.0726	0.220082	-0.01116
0.308978617	0.506276332	0.423626	-0.11335	0.356676	0.53049	-0.21671	-0.01764
0.500514006	-0.232230465	-0.48958	0.470383	0.441664	0.161972	0.096567	-0.06306
0.375985206	-0.701145855	0.576667	-0.04127	-0.05686	-0.04805	-0.16488	0.007182
0.293139092	0.19520635	0.158767	-0.29663	0.312518	-0.55917	0.509809	-0.30417
0.523947651	0.025896556	-0.40938	-0.58282	-0.43707	0.131975	-0.0873	0.038242
0.13412781	0.095262675	0.028505	-0.01704	0.158191	-0.24503	0.062496	0.939608

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