

An Automated Guided Model For Integrating News Into Stock Trading Strategies

Pallavi Parshuram Katke¹, Ass.Prof. B.R.Solunke²

¹Solapur University, N B Navale Sinhgad College of Engineering, Keganon, Solapur, 413255
pallavikatke9.nbnscoe@gmail.com

²Solapur University, N B Navale Sinhgad College of Engineering, Keganon, Solapur, 413255
b_solunke@rediffmail.com

Abstract: The proposed automated model represents merging news into stock trading strategies using genetic programming. Events are retrieved from news in free text. The introduced model can be tested by deriving trading strategies based on technical indicators and impacts of extracted events. The trading strategies take the form of system that combine technical indicators with a news variable and revealed through the use of genetic programming. The news variable contains in the best trading policy, indicating the added value of news for predictive purposes and validating our proposed model for automatically merging news in stock trading strategies.

Keywords: Technical indicator, Historical data, Genetic Programming, Optimal Trading Strategies

1. INTRODUCTION

Financial markets are driven by information. Stock market prediction is popular subject in the area of finance. Due to business growth, it has attracted often aid from educator to economics sector. It is impossible to give the prediction of prices of stock market because of stock prices are changed continually every second. Market stock prediction has ever been a subject of curiosity for most investors and business analyst. In today's information driven area more persons try to maintain record up-to-date with the present progress by reading informative news items on the internet. The content of news items shows past, current, and upcoming circumstances and thus news contains valuable information for different reasons. Being aware of ongoing marketplace situations is of paramount importance for investors and traders, who require to creating knowing decisions that could have an evidentiary impact on definite aspects specified as profits and marketplace perspective. It requires to do automatically mining news items by means of computers that would alleviate effort that are required for manually processing of news messages.

In this First, present previous work on the relationship between news and the stock market, and the type of events that are proven to influence stock prices. Next, provide an quantitative investigation of the relationship between news messages and the stock market. later, take the technical indicators that use for deriving stock trading strategies. After that introduce model for automated trading based on news results of validating the framework.

2. RELATED WORK

Wijnand Nuij, Viorel Milea, Frederik Hogenboom, Flavius event extraction from news articles & only logical operators was used for generating trading strategies. Jethro Borsje, Frederik Hogenboom and Flavius Frasinca[2] establish lexico-semantic patterns and lexico-syntactic patterns process for mining of financial event from RSS news feeds. Jordy Sangers, Wouter IJntema [3] makes the use of text rule based method that uses lexico semantic pattern for learning ontology instances from text that helps domain

experts for maintaining ontology population process. G.F. Knolmayer and M.A. Mittermayer [4] applied several prototypes for predicting the short-term market reaction to news based on text mining techniques. Prototype build up by Wthrich et al. Cho99[5], ChWZ99[6], WCLP98][7]. This prototype tries to guess the 1-day trend of five major equity indices such as the Dow Jones, the Nikkei, the FTSE, the Hang Seng, and the Straits Times. The Prototype build up by Lavrenko et al.

3. SYSTEM ARCHITECTURE

The below fig 1. Shows architecture of proposed system for merging news in stock trading strategies. The model assumes that events have been mined from news articles and are available together with the date on which the events took place.

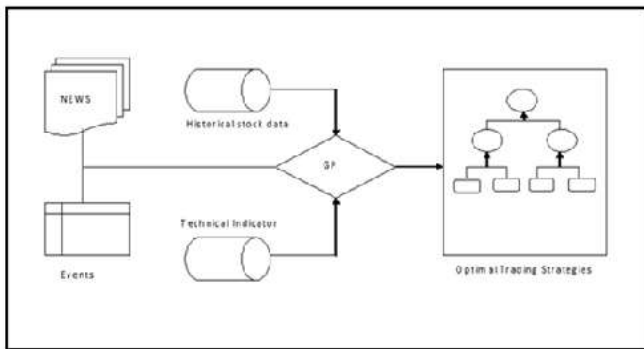


Figure 1: System Architecture

Additionally, already defined impact should be allocated to each event, allowing the news message to be added in the trading strategies. Technical trading indicators used in trading strategies generated through genetic programming. The indicators consist the simple moving average (SMA), the Bollinger band (BB), the exponential moving average (EMA), the rate of change (RoC), momentum (MOM), and moving average convergence divergence (MACD). The alternative for these indicators is depend on their widespread use in technical trading .For finding the optimal trading strategies, by using genetic programming. Genetic programming is a method where the possible solutions are presented as computer programs instead of numerical values encoded some other way. Initializing from starting population, genetic programs try to improve the fitness of individuals over consecutive generations through a

method inspired by normal evolution. During this course individuals are altered, usually depend on their fitness values, by merging them with other individuals called crossover, or by slightly changing some parts of the individual with a already defined probability called mutation. The used genetic programming algorithm for determining the optimal trading strategies is presented in below Algorithm.1. The algorithm start from a random initial population of trees, and create new populations of trading strategies by applying crossover and mutation on the population from the preceding iteration. Crossover contains choosing two trading strategies, and finding two random crossover points. after that the subtrees created under the crossover point are swapped between the two trading strategies, therefore resulting in two new rules that are inserted to the new population. Mutation relates to the technical indicators included in a trading strategy, and consists of a slight change in the parameters of the arbitrarily selected technical indicator. The ending condition for the algorithm relates to the enhancement in the best solution found, thus when the optimal solution cannot be improved in a number of generations, the algorithm ends.

4. METHDOLOGY

4.1 Event Information Extraction

The event information extraction from the news messages is based on recognizing a predefined set of events as well as the affiliated entities. In this work we investigate unsupervised techniques for extracting and clustering complex events from news articles [9]. For clustering events we are using their generalized representation obtained by disambiguating events to concepts defined in knowledge bases.

4.2 Technical trading indicators

This section focuses on the technical trading indicators used in trading strategies generated through genetic programming. The indicator included in the study as simple moving average (SMA),the Bollinger band (BB) , the exponential moving average (EMA) , the rate of change (RoC), momentum (MOM), Weighted moving average (WMA) , Adaptive moving average (AMA) and

moving average convergence divergence (MACD). The choice for these indicators is based on their widespread use in technical trading.

4.3 Genetic Algorithm

Requirements:

- $a \geq 0$: minimum improvement
- $b > 0$: maximum times of no improvement
- $c > 0$: population size
- $0 < d \leq e$: number of parents
- $0 \leq f \leq 1$: mutation probability
- 1: $g = \text{generateRandomPopulation}(\gamma)$
- 2: $\text{hold} = -\infty$, $\text{hnew} = \text{calcFitness}(g)$, $i = 0$
- 3: while $i < b$ do
- 4: $\text{addIndividual}(g', \text{getBest}(g, \text{hnew}))$
- 5: while $|g'| < |g|$ do
- 6: $\theta = \text{selectRandomParents}(g, \text{hnew}, \rho)$
- 7: $\vartheta = \text{crossOver}(\theta)$
- 8: $\vartheta' = \text{mutate}(\vartheta, f)$
- 9: $\text{addIndividual}(g', \vartheta')$
- 10: end while
- 11: $g = g'$, $\text{hold} = \text{hnew}$, $\text{hnew} = \text{calcFitness}(g)$
- 12: if $\text{hnew} - \text{hold} \leq a$ then
- 13: $i = i + 1$
- 14: else if $i > 0$ then
- 15: $i = 0$
- 16: end if
- 17: end while
- 18: return g

The employed above genetic programming algorithm for determining the optimal trading strategies is presented above. We start from a random initial population of trees, and generate new populations of trading strategies by applying crossover and mutation on the population from the previous iteration. Crossover consists of selecting two trading strategies, and determining two random crossover points, i.e., one for each tree. Next, the sub trees generated under the crossover point are exchanged between the two trading strategies, thus resulting in two new rules that are added to the new population. Mutation only relates to the technical indicators included in a trading strategy, and consists of a slight change in the parameters of the randomly selected technical indicator.

5. EXPERIMENTAL RESULTS

5.1 Buy signal:

Following snapshots illustrates the results achieved of buy signals.

In the figure 2 the trading strategies of Infosys is calculated for one day period. By considering one day period include events as a relevant variable, with generated returns of 4.0% to 8.6%.The all indicators is included in all the rules, confirming the performance achieved.

Rx	Freq	Tree
4.7	28.0	((BBI(SMA-CLOSE))
4.7	28.0	(CLOSE<0.14)
4.7	28.0	(EMA<=BB)
4.7	28.0	(LOW<=BB)
4.4	27.0	((0.43<=MACD)>=(CLOSE<=0.59))
4.4	27.0	((0.93<=(OPEN+0.49))
4.4	27.0	((0.28&&Roc)
3.9	25.0	(BB>(OPEN-0.44))
3.9	25.0	(LOW<0.69)(EMA)
3.9	25.0	(Momentum+(Roc<=EMA))
3.9	25.0	((VOLUME<=SMA<=EVENT)
3.9	24.0	((0.19<=(SMA<=EVENT))

Figure 2: Optimal strategies of buy signal if stocks are

held 1 day

In the figure 3 the trading strategies of Infosys is calculated for three days period. By considering three days period including events as a relevant variable, with generated returns of 2.7% to 9.6%.The all indicators is included in all the rules, confirming the performance achieved.

Rx	Freq	Tree
4.7	29.0	((0.55<0.27)((0.87<=OPEN)
4.7	29.0	((0.79+EMA)((EMA&&CLOSE))
4.7	29.0	(Roc&&(HIGH*0.94))
4.2	28.0	((HIGH<=0.34)(BB)
4.2	27.0	((BB&&0.82&&(0.66<=VOLUME))
4.2	27.0	(HIGH)(SMA<0.01))
4.2	27.0	(OPEN&&0.49)
4.2	27.0	(0.64)((0.87*VOLUME))
4.2	26.0	((MACD)(0.47)((0.70HIGH))
4.2	26.0	(0.76-CLOSE)
3.9	25.0	((VOLUME=MACD)*EVENT)
3.9	25.0	((0.13-OPEN)&&HIGH)

Figure 3: Optimal strategies of buy signal if stocks are

held 3 day

In the figure 4 the trading strategies of Infosys is calculated for five days period. By considering the five days period including events as a relevant variable, with generated returns of 4.9% to 11.9%.The all indicators is included in all the rules, confirming the performance achieved.



Figure 4: Optimal strategies of buy signal if stocks are

held 5 day

5.2 SELL signal

Following snapshots illustrates the results achieved of sell signals.

In the figure 5 the trading strategies of Infosys is calculated for one day period. By considering one day period including events as a relevant variable, with generated returns of -6.5% to -26.5%.The momentum indicators is included in maximum rules, confirming the performance achieved.

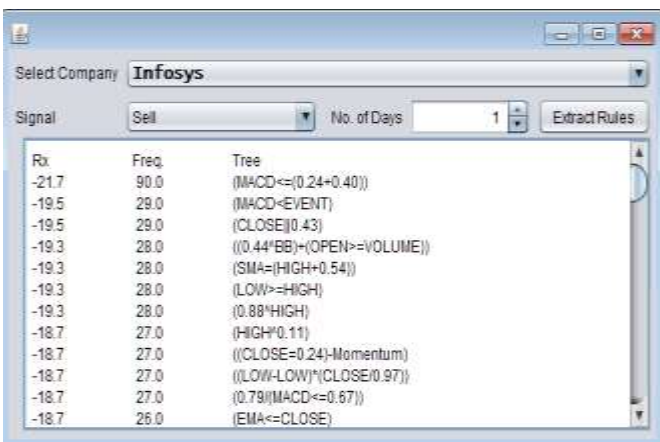


Figure 5: Optimal strategies of sell signal if stocks are

held 1 day

In the figure 6 the trading strategies of Infosys is calculated for three days period. By considering three days period including events as a relevant variable, with generated returns of -8.1% to -43.1%.The momentum indicators is included in maximum rules, confirming the performance achieved.



Figure 6: Optimal strategies of sell signal if stocks are

held 3 day

In the figure 7 the trading strategies of Infosys is calculated for five days period. By considering five days period including events as a relevant variable, with generated returns of -12.4% to -32.5%.The momentum indicators is included in maximum rules, confirming the performance achieved.

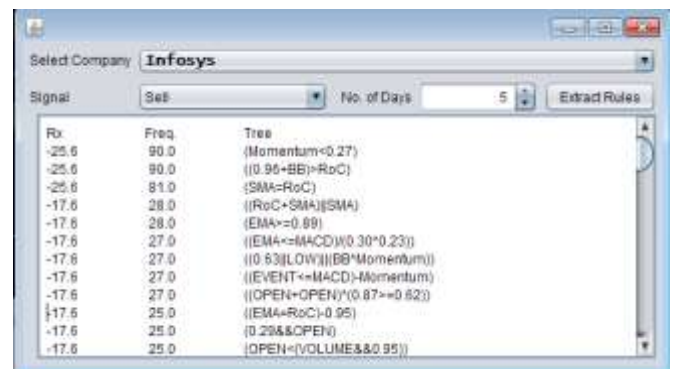


Figure 7: Optimal strategies of sell signal if stocks are

held 5 day

6. CONCLUSION AND FUTURE WORK

This automated news guided model has been design and implemented by merging news into stock trading strategies. The result indicates that the inclusion of news into stock trading strategies can be achieved by extracting the events from the text of the news messages and associating an impact with these events. The trading strategies that consider may include any number of technical trading indicators. The news variable is quantified based on the events extracted from the text of news messages and the assignment of an expert defined impact to each of these events. The results indicate that adding the news variable to each of the indicators generates higher returns than when each of the variables

indeed can lead to higher returns, thus making it worthwhile to employ trading rules that, next to technical indicators make use of the events that are relevant for a certain company.

The future work includes instead of genetic programming an evolutionary method can be used for faster calculation and also improve the event extraction method.

REFERENCES

- [1] Wijnand Nuij, Viorel Milea, Frederik Hogenboom, Flavius Frasincar, and Uzay Kaymak ,An Automated Framework for Incorporating News into Stock Trading Strategies. IEEE transactions on knowledge and data engineering, VOL. 26, NO. 4, APRIL 2014
- [2] J. Borsje, F. Hogenboom, and F. Frasincar, Semi Automatic Financial Events Discovery Based on Lexico-Semantic Patterns, Int'l J. Web Eng. and Technology, vol. 6, no. 2, pp. 115-140, 2010.
- [3] W. IJntema, J. Sangers, F. Hogenboom, and F. Frasincar, A Lexico-Semantic Pattern Language for Learning Ontology Instances From Text, J. Web Semantics: Science, Services and Agents on the World Wide Web, vol. 15, no. 1, pp. 37-50, 2012.
- [4] M.-A. Mittermayer and G.F. Knolmayer, Text Mining Systems for Market Response to News: A Survey, technical report, Institute of Information Systems University of Bern.
- [5] Cho, V.: Knowledge Discovery from Distributed and Textual Data. Dissertation Hong Kong University of Science and Technology. Hong Kong 1999.
- [6] Cho, V.; Wüthrich, B.; Zhang, J.: Text Processing for Classification. In: Journal of Computational Intelligence in Finance 7 (1999) 2, pp. 6-22.
- [7] Wüthrich, B.; Cho, V.; Leung, S.; Peramunetilleke, D.; Sankaran, K.: Zhang, J.; Lam, W.: Daily Prediction of Major Stock Indices from Textual WWW Data. In: Proceedings 4th ACM SIGKDD Int. Conference

on Knowledge Discovery and Data Mining. New York 1998, S. 364-368.

- [8] W. IJntema, J. Sangers, F. Hogenboom, and F. Frasincar, "A lexico-semantic pattern language for learning ontology instances from text," Journal of Web Semantics: Science, Services and Agents on the World Wide Web, vol. 15, no. 1, pp. 37-50, 2012.
- [9] Delia Rusu and James hadson, "Unsupervised Techniques for Extracting and Clustering Complex Events in News", Association for Computational Linguistics, June 22-27, 2014.

Author Profile



Pallavi P. Katke , received B.E degree in Computer Science & Engineering in 2010 from BMIT, Solapur University, Maharashtra, India and pursuing the M. E.

degree in

Computer Science and Engineering in N B N Sinhgad College Engineering Solapur University,Solapur,India. She

is doing her dissertation work under the guidance of Mr.B.R

Solunke, Professor in N B N Sinhgad College Of Engineer- ing Solapur University,Solapur, India. Her research area is Genetic Programming



Mr. B. R. Solunke, received the B.E degree in Computer Science and Engi-neering India and M. Tech degree in

Computer Science and Technology. He is having 12 year teaching

exper-

ience and one year industrial experience.He is presently working as an Professor N B N Sinhgad College Of Engineering Solapur University,Solapur. His research interests include Distributed system, Advance database system and compiler construction.