A real time clustering and SVM based price-volatility prediction for optimal trading strategy

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ABSTRACT

Financial return on investments and movement of market indicators are fraught with uncertainties and a highly volatile environment that exists in the global market. Equity markets are heavily affected by market unpredictability and maintaining a healthy diversified portfolio with minimum risk is undoubtedly crucial for any investment made in such assets. Effective price and volatility prediction can highly influence the course of the investment strategy with regard to such a portfolio of equity instruments. In this paper a novel SOM based hybrid clustering technique is integrated with support vector regression for portfolio selection and accurate price and volatility predictions which becomes the basis for the particular trading strategy adopted for the portfolio. The research considers the top 102 stocks of the NSE stock market (India) to identify set of best portfolios that an investor can maintain for risk reduction and high profitability. Short term stock trading strategy and performance indicators are developed to assess the validity of the predictions with regard to actual scenarios.

1. Introduction

The global financial markets are again fraught with uncertainties at every level of investment and over every possible investment vehicle. Recent developments like down grading of US credit rating by Standards and Poor’s (S and P) from the embellished AAA to a prudent AA+ and ongoing Euro credit crunch involving massive government debts have forced several countries into tailspin and the contagion has heavily affected many economies around the world, taking the investors by surprise and proving even their worst case predictions wrong. The implication of such astounding events could be seen in the massive price surge in the global gold markets whereas a complete opposite scenario evolved astounding events could be seen in the massive price surge in the US equity, stock and commodities market which was global gold markets whereas a complete opposite scenario evolved.

The fallacy lies in the predictions and decisions based only upon price movements of the indices or individual stock in the market and the technical analysis for the various strategies for a range of investment vehicles. The concept of risk or volatility takes a very important meaning in this context. Determining the standard deviation or variance of a particular asset class or its derivative becomes absolutely crucial in giving a holistic view of the market uncertainties existing. The structural exogenous changes in the market are extremely hard to predict, hence the analysis used in this piece of research focuses on giving an investor a robust tool that can accurately gauge the mood of the market and the asset under consideration which becomes crucial in formulating a trading strategy that matches the risk averseness or risk empathy of individual investors or conglomerates. Over reaction is extremely dangerous at arriving at investment decisions which becomes the cornerstone of formulating analytical or heuristic solutions towards strategy formulation that can hedge against such paranoia upon any disruptive influence. As no model is fool proof, the performance should be gauged by real time complemented by a weakened dollar and an even frailer euro. An overwhelming majority of investors and investment institutions tend to formulate their strategies based on extrapolating simple recent trends and calculate the portfolio return-risk trade-off to formulate an optimal one.

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portfolio return and risk analysis on a daily basis which gives an
investor to choose a set of classes that will diversify the risk which
aims to maximize or more correctly optimize the returns in lieu
with his targeted value [1].

The work presented here focuses on devising an optimal
portfolio of risky asset or asset clusters which will present an
investor to assess the risk-return involved in selection. The model
is applied for all the tradable stocks in the National Stock Exchange
(NSE) of India, which provides alternative derivative instruments
like index futures and options. The work chooses Indian stock for
the analysis because of the high beta of the Indian economy and
where distortion effects of financial failures can be studied amidst
a favorable environment for long term and short term investments
fueled by genuine economic growth. The work envisages a
complete predictive module that can accurately forecast the prices
and the inherent volatilities associated with the asset types, which
are first clustered based upon their risk and return profiles. A
hybrid SOM (Self-Organizing Maps) using K means clustering is
used for clustering the stocks whereas Support Vector Regression
(SVR) is used to predict the future price and volatility for short
trading cycles for better forecasts. Based on the results, a trading
strategy module is articulated which selects the best strategy for
trading under the implied uncertain scenario in the market
indicated by the forecasts. As stated earlier, more than the
accuracy in predicting the actual prices and volatilities, what
becomes important is the relative direction of the movements
and a definite range of values that the model can propose based
upon the different strategy that an investor chooses based upon
his risk aversion. Existing work which incorporates clustering
techniques [2,3] and advanced statistical and data mining techniques
[4] have undergone several transformations for better pre-
dictive ability. At the moment of writing, the authors have no
knowledge of an assimilated coupled system which uses both
clustering and predictive techniques linked to strategy selection
for stock market portfolio.

The paper is structured as follows. The next section discusses
about the existing literature existing in our field of application.
The following section introduces the complete clustering, prediction
and strategy selection module methodology and the various
algorithms involved at each stage. This methodology is then tested
and analyzed for performance on the stocks of the NSE for a given
trade cycle. The paper concludes with a definitive discussion on
the scope of work and the existing shortcomings that can become
a future area of research. The lists of all references appear
thereafter.

2. Literature review

In this section, related work in clustering techniques, regres-
sion models and trading strategies are discussed which sets the
stage for the problem addressed in this paper.

2.1. Clustering techniques

For the past few decades clustering techniques has been used
to assort varied data sets but it is only in the later 1990s when
clustering techniques were exploited on financial data. Conven-
tional partitive and hierarchal algorithms evolved into their
genetic hybrids like GA–K-means. These were extensively used
for market segmentation [5]. In case of financial data, clustering
algorithms has also been used to cluster time series data. Clust-
ering of the time series facilitates a better regression model for
future prediction [6] as it considerably reduces the noise of a non-
stationary time series, like that of a stock price.

Though there are numerous partitive and agglomerative clus-
tering algorithms SOM has emerged as one of the more popular
choice in clustering multi-dimensional data, as analyzed by
Shahapurkar and Sundareshan [7]. SOM use artificial neural net-
works for cluster data and helps mapping multi-variate data on a
2-D space as shown by [8]. The complexity of these clustering
algorithms are proportional to amount of data fed, thereby heavily
increasing the computational time for the clustering operation. In
our case data is both noise prone and exhaustive.

To eliminate the noise and subsequently improve the computa-
tion time Vesanto and Alhoniemi [9] proposed a novel two level
abstraction to cluster the Self Organizing Map. Their experiments
hinted that clustering the SOM is a more computationally effective
approach than directly clustering the data set. On the other hand
SOM helps to visualize higher dimensional data sets on a 2-D
space, which will be helpful if we increase the dimensions
representing a stock to more than 2. There have been efforts to
create a portfolio using different single layer clustering methods
[10], but to the best of our knowledge, the proposed two layers is
yet to be implemented for generating an optimal portfolio. The
two stage subroutine – first using SOM to produce the prototypes
that are then clustered in the second stage – is found to perform
well when compared with direct of the data and to reduce the
computation time A research by Canetta et al. [11] also concludes
the same.

A few articles like [12–14] compared different clustering
techniques to find the optimal number of clusters and to validate
the results. The results obtained from the clustering techniques
have been validated.

2.2. Regression model

Over the last few years growing number of researchers are
studying the price and volatility movement of different kinds
of financial instruments. Academicians and corporate researchers
are trying their best to formulate methods to predict the future
economic market and devise an effective trading system to
maximize the profit [15].

Before the introduction of computational intelligence tradi-
tional statistical techniques such as multivariate regression, auto-
regressive integrated moving average (ARIMA) [16], generalized
autoregressive conditional heteroskedasticity (GARCH) [17] were
being used for forecasting. They are unable to produce significant
result as stocks data are generally complex and noisy in nature. To
correct the problem artificial intelligence techniques such as
Generic Algorithms, Artificial Neural Networks (ANN) were pro-
posed to approach this problem. Researchers are now inclining
towards Support Vector Machine (SVM), first suggested by Vapnik
[18] to improve the forecast [6,19]. Most comparison results of
show that SVM surpasses ANN in terms of prediction performance
[20]. This is due to less complex structure of SVR and due to the
implementation of structural risk minimization principle. SVR
attempts to minimize the upper bound of generalization error
wheras in ANN empirical risk minimization principle is imple-
mented which seeks to minimize misclassification error or devia-
tion of the solution from the test data. Also there is lesser chance
of over fitting with SVM as it is global optimum whereas ANN may
generate only local optimal solutions [21,22]. A convex quadratic
optimization is used to get the solution for the SVM where a
Karush–Kuhn–Tucker (KKT) statement molds the necessary and
sufficient conditions for a global optimum [23]. On the other hand,
in case of ANN even a well optimized algorithm may not be able
attain global optimum within finite process time [24].

The modeling of five futures of Chicago Mercantile Market was
done by [25] using SVM. They also compared the performance
with multlayer back-propagation (BP) neural network models to

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find that SVM outperforms the latter one. SVM was used by [21] to predict the daily change of price of Korea Composite Stock Price Index (KOSPI). Further the SVM model was compared with case-based reasoning (CBR) and back-propagation neural network (BPN) where SVM outperformed the other two. Prediction of weekly movement trend of NIKKEI 225 Index was carried out using SVM [26]. To evaluate the forecasting ability of SVM, its performance was compared with those of Linear Discriminant Analysis, Quadratic Discriminant Analysis and Elman Back propagation Neural Networks (NN). SVM outperformed other methods in the experiment. A combining model by integrating SVM with the other classification methods was also proposed in the paper. Gavrishchaka and Banerjee [27] addressed the problem of volatility forecasting from high-dimensional stock market. SVM-based volatility model was comparable often superior to the established volatility prediction models for instance GARCH and its generalizations. Forecasting of S&P CNX NIFTY Market Index of the NSE was carried out by Kumar and Thenmozhi [28] using SVM and Random Forest Regression. In the test SVM was superior to Random Forest, ANN in addition to traditional methods like ARIMA. The empirical studies in the Hong Kong securities market substantiate that the ANN and SVR approaches noticeably shrink the average forecast errors and accordingly improve the forecasting accuracy. A nonparametric approach based on ANN and SVM along with improved conventional option pricing technique was presented to forecast option prices from the Hong Kong securities market [29]. Results showed significant improvement in forecasting accuracy with ANN and SVR based models. The performance on literature case studies of SVM regression is measured against other advanced learning methods such as the Radial Basis Function, the traditional Multilayer Perceptron model, Box–Jenkins autoregressive-integrated-moving average and the Infinite Impulse Response Locally Recurrent Neural Networks [22]. The comparison shows that in the analyzed cases, SVM comparable to and in most cases outperforms the other techniques. Classical methods like ARMA and GARCH, requires huge sample size for better prediction leading to a reduced original sample size for higher order models [30]. They also showed that SVM and Back propagation (BP) performs better than the ARMA model in the deviation measurement criteria. Experiments also show that SVM outperforms both finite mixture of ARMA-GARCH and BP models in deviation performance criteria [31].

More recent studies have been targeting a hybrid SVR approach to improve the forecast performance of SVR [32,33]. Signal processing techniques like wavelet transform and nonnegative matrix factorization helps in improving the forecasts.

The forecasts obtained from the Support Vector Regression model, provides closing prices and volatility values for the next 15 days. These values formed the platform for formulating the trading strategy to maximize profit.

2.3. Trading strategy

A great deal of work has been published over the past decade on Stock market trading strategies. Most of these strategies are either plagued down by lags, as it is in the case of Candle stick strategy, or is fit for long term investments, like the case of momentum trading. The strategy that we propose is based on the analysis of two trading days, which gives it an advantage over the other strategies keeping in mind the present turmoil in the financial markets. A decision matrix is also prepared to help the trader take decisions.

The short term trading strategy is ideal for unstable markets. The detailed methodology is discussed in the next section.

3. Methodology

Through the literature survey it is found that the problem of formulating optimal trading strategies in a volatile environment can be tackled more efficiently with the help of clustering and prediction methodologies. It involves three discrete steps which are incorporated in the formulation of the final trading strategy for different market conditions. It is discussed below in the following section.

3.1. Clustering

The first step of the solution involves clustering of stocks listed in NSE based on their Logarithmic Returns and Daily Underlying Volatilities. Clustering is a method of unsupervised learning to partition a data set into a set of clusters. This paper proposes a two layer abstraction to cluster the stocks using SOM followed by K-means clustering of the SOM as shown in Fig. 1. The first level, SOM, comprises of a 2-D neural network with neighborhood relations among the neurons. The Input vectors are connected to the output layers but the neurons are not inter-connected. SOM is suited for clustering and mapping of higher dimensional data on 2-D plots, proving to be ideal in the case of multi-dimensional market data. The visualization obtained from SOM fails to infer quantitative description of the data parameters, thereby promoting the need for another clustering algorithm for proper interpretation of the SOM prototypes. The prototypes obtained represent the local averages of the data belonging within a particular radius of that prototype. These local averages are further used as the data set for the second level of clustering.

![Fig. 1. Two levels of abstraction used to cluster stocks. Level 1: SOM and Level 2: K-means.](image-url)
The second level in the approach involves clustering using a partitive algorithm. Partitive algorithms like K-means partitions the data set into k-clusters, in which every prototype is clustered based on its closest mean. Results obtain from K-means represent clusters of prototypes, which in turn are a map of the underlying stocks. The optimal number of clusters is determined from various cluster validity indices. Indices calculated also hints an optimal clustering in this case, that is tabulated in Table 1.

This two level approach substantially reduces computation time in large data sets, because it is much lighter to cluster a set of epitomes. Consider clustering N samples using K-means. It involves making several clustering trials with different values for. The computational complexity is proportional to, involves making several clustering trials with different values for.

Table 1

<table>
<thead>
<tr>
<th>Index</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Silhouette</td>
<td>0.47904</td>
</tr>
<tr>
<td>Davies–Bouldin</td>
<td>0.50596</td>
</tr>
<tr>
<td>Calinski–Harabasz</td>
<td>66.9185</td>
</tr>
<tr>
<td>Dunn</td>
<td>2.4381</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.98224</td>
</tr>
</tbody>
</table>

3.2. Support vector machine

The second step of the solution involves regressing the time series of the stocks obtained from the first step and thereby prediction future values using Support Vector Machines. SVMs are very specific class of algorithms, characterized by usage of kernels, flatness of solution and capacity control obtained by acting on the number of support vectors. SVMs are learning machines which implements the structural risk minimization inductive principle to obtain good generalization on a limited number of learning data set.

Set of points in the network: \((x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\)

\[
h(x) = w^T \Phi(x) + b
\]

We define the above function taking into account:

\[
C \quad \text{penalty cost for deviation during training process}
\]

\[
F \quad \text{a feature space}
\]

\[
W \quad \text{a vector in } F
\]

\[
w^T w \quad \text{regularized term controlling the function capacity}
\]

\[
e \quad \text{an insensitive loss function as proposed by Vapnik [18]. It is the maximum error allowed during training of the dataset}
\]

\[
\xi_i^+ + \xi_i^- \quad \text{slack variables corresponding to the size of the excess deviations}
\]

\[
\Phi(x) \quad \text{a mapping function which maps each } x_i \text{ to a vector in } F
\]

In \(\epsilon\)-SVR the objective is to obtain a function \(h(x)\) that accounts for the most \(\epsilon\) deviation from the actually obtained target values in the training data set. The absolute errors are neglected as long as they are less than \(\epsilon\). Initially we consider the function to be a linear function for the sake of simplicity.

Based on SVM literature, the given optimization problem is formulated:

Minimize \(\frac{1}{2} w^T w + C \sum_{i} (\xi_i^+ + \xi_i^-)\)  \hspace{1cm} (2)

Subject to \(y_i - w^T \Phi(x_i) - b \leq \epsilon + \xi_i^+\)  \hspace{1cm} (3)

Subject to \(w^T \Phi(x_i) + b - y_i \leq \epsilon + \xi_i^-\)  \hspace{1cm} (4)

Subject to \(\xi_i^+, \xi_i^- \geq 0\)  \hspace{1cm} (5)

constant \(C > 0\) determines the offset between the flatness of \(f\) and the amount up to which deviations larger than \(\xi\) are tolerated. Thus the \(\xi\) can be deduced to another form considering the error weightage. \(\frac{1}{2} \| E \|_\Phi^2\) – insensitive loss function (Fig. 3).

The problem is solved using the KKT Conditions. SVR maps the training data set onto a feature space to enable non liner prediction. The parameters of \(\epsilon\)-SVR were optimized using both grid and pattern search algorithms. The parameters with the minimum Mean Absolute Percentage Error (MAPE) were chosen. MAPE is a measure of the accuracy of a method for constructing fitted time series values. The accuracy is expressed in terms of percentage. Finally the forecasts were compared with Neural Network model for the same.

\[
M = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right|\]

\[
\text{MAPE } A_i - \text{Actual}
\]

\[
F_i - \text{Forecast}
\]

The closing prices and Volatility predicted forms the basis of the different trading strategies, discussed in the next step.
3.3. Trading strategy

Within the realistic domain of an equity stock market and the portfolio generated from the above computational analysis, we consider a generic trading strategy for the trading space considered in the problem. We analyze the trading strategy from the view of a risk-averse trader or investor who tries to maximize his net returns focusing on minimizing the associated risk in the investment. The computational module deployed earlier gives a crystallized view of the market movements in the future, both in terms of price as well as the volatility associated. It is important to remember that throughout the entire scope of the study, only temporal effects of the time series data considered is studied. We refrain from going into long term investment strategy especially for volatile stocks like those considered simply because its erroneous on part of the researchers to not take into account dominant structural alterations that make equity markets unpredictable as they are. Instead the focus is on short term strategies (ranging from a week to a maximum of month) which take into account short term ripples and market tendencies to derive an investor strategy for the risky assets. Contrarian and momentum investment strategies are suited for longer time scales and we do not consider those strategies. Our strategy is based on a micro level strategy for the best portfolio (ranked) for each stock and its related performance based on the movement predictions. Markets are generally difficult to study owing to strong coupling between stocks, nonlinear investor response to news and imperfect dissemination of news among the investors rendering it highly inefficient, a marked deviation from traditional assumptions of market efficiency.

The investor considered has characteristic features like initial investment, target profit, stop loss price and time threshold being few of the most important ones. The investor’s target margins will be reflected in the transactions (buy–sell) made based on the limits set. A general view is given below in Fig. 4 which consists of the average, stop loss limit, target limit and investment horizon (15 days for the case considered). As long as the prices remain in between these goalposts, transactions made by an investor will be less based on the preferences and the situation in the market (not considering any external stimuli of structural characteristics). However when prices exceed the limits, it is an indication of selling stocks for various reasons in accordance with the escape position existing in the market. The volume of transaction is of paramount importance because it directly affects the profit–loss scenario of the overall investment horizon. Prescient knowledge of market indicating a bullish or bearish tendency is already available for the future through the predictions made earlier.

Generally there are periods of normal and frantic trading based on the market indications and transaction volume becomes a major factor then. Normal trading involves slow oscillating price movements and low volumes where owners are reluctant to short because prices are not attractive enough and buyers prefer to wait for even lower prices. Significant trading and volume increase (rally) is followed by a crash which is indicative of settlements. Demand is truly a stochastic variable and transaction will depend upon human interpretation of the market scenario.

In the model discussed below, every investor has an initial investment to make at the starting period for the portfolio chosen. All investors intend to get rich with minimum risk. Investor, with past price-volatility history, future short term predictions and incomplete news from the market. The transactions made are series of buy–sell events based on the prices existent at the particular time for each stock in the portfolio. For simplicity, volume considered is constant based on investor preference. The tendency to buy or sell is decided based upon a decision matrix (Fig. 5) based upon bullish or bearish indicators of prices and the movement of the volatility giving the investor a holistic view of the strategy he should use. The scale of the investments and its profitability can be gauged by the slope between a buy–sell pair. A steep slope implies high positive or negative impact of the transaction whereas a mild slope implies less impact on overall profitability. We define a few indices to gauge the relative performance of the strategy.

Further analysis of the performance can be gauged by the slope of buy–sell price transaction graph. It is assumed that volume involved is same, though in real cases we can derive values for volumes actually traded.

```
<table>
<thead>
<tr>
<th>Volatility</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIGH</td>
<td>HIGH</td>
</tr>
<tr>
<td></td>
<td>BUY</td>
</tr>
<tr>
<td>LOW</td>
<td>SELL</td>
</tr>
<tr>
<td></td>
<td>HOLD</td>
</tr>
</tbody>
</table>
```

Fig. 5. Proposed trading strategy.
4. Computational results and analysis

In this paper historical stock data (closing price and intra-day volatility) for the companies listed NSE was collected from NSE database and Yahoo finance. The closing prices and intra-day volatility data has been collected for 102 stocks for the horizon 2008–2011. We collected a fairly mixed data from various sectors and capital sizes. To model the functions the logarithmic returns and daily volatility were considered.

From the initial pool of 102, 31 poor performing stocks were eliminated to form the final data pool. The aforementioned two layer clustering algorithm was applied on the data pool to obtain clusters based on their Returns and Daily Underlying Volatility. The clusters with relatively higher performing stocks constituted the optimal portfolio and subsequently the underlying stocks were regressed. The underlying stocks are listed in Table 2.

The ϵ-SVR parameters for one of the stocks (GLAXO), along with its training data is shown in Table 3. Fig. 6 shows the plot between actual and predicted closing prices for the validation data space for GLAXO.

It has been stated earlier, that the optimal parameters for the SVR were found out by Grid and Pattern Search algorithms to minimize the Mean Absolute Percentage Error (MAPE). The behavior of the predicted value varies extensively with the change of parameters. In Table 4 MAPE and Root Mean Square Error (RMSE) for the underlying stocks are compared with the Neural Network model.

The results of the trading analysis are shown below. The stock taken is GLAXO from the best portfolio. The analysis is shown in Fig. 7. For GLAXO, three transactions were done based on the proposed trading strategy. The results are shown in Table 5.

If a total investment of 50,000 INR is assumed, the above transaction results in a return of 1.5% over the investment in a 15 day span. The strategies for other selected stocks with initial capital of 1000 stocks each are shown in Table 6. The obtained Return on Investments (ROI) for all the five stocks using the same strategy with the predictions obtained from Neural Networks and SVM has been compared in Table 7.

5. Conclusion

In this paper a clustering and prediction based short term trading strategy has been discussed. The model for classifying best

### Table 2
Optimal portfolio – highest performing stocks listed in National Stock Exchange (NSE).

<table>
<thead>
<tr>
<th>Name</th>
<th>Volatility × 10</th>
<th>Rate × 10⁶</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRIVENI</td>
<td>31.92331825</td>
<td>83.6908</td>
</tr>
<tr>
<td>GLAXO</td>
<td>12.15919784</td>
<td>77.8804</td>
</tr>
<tr>
<td>BHUSANSTL</td>
<td>29.7370912</td>
<td>57.0786</td>
</tr>
<tr>
<td>DR REDDY</td>
<td>18.64341629</td>
<td>53.702</td>
</tr>
<tr>
<td>HERO HONDA</td>
<td>19.99290779</td>
<td>48.54</td>
</tr>
</tbody>
</table>

### Table 3
SVM parameters and statistical data of training data for GLAXO.

- Mean target value for input data: 1289.6758
- Mean target value for predicted values: 1285.5683
- Variance in input data: 324357.5
- Correlation between actual and predicted: 0.998536
- Maximum error: 293.33115
- MAPE (Mean Absolute Percentage Error): 1.4246145
- Proportion of variance explained by model (R²): 0.99669

**Type of SVM model**: Epsilon-SVR.

**SVM kernel function**: Radial Basis Function (RBF).

**Epsilon = 0.001, C = 2000, Gamma = 8, P = 0.**
stocks at NSE and predicting the volatility of chosen stocks were formulated and analyzed. The model was developed in a generic fashion so it may be customized for most of the stock markets in the world. Two level of classification of different stocks was done by applying SOM on the pool of stocks and then applying K-Means clustering technique on the first layer of abstraction. Subsequently, SVR was applied on the clustered output for predicting price and volatility. Finally a user based decision system based on dynamic two-day price prediction was implemented.

Our work can find various applications in software development acting as investing guide to a target trader in a volatile market and investor’s technical information in financial markets. The clustering approach can also be used to tackle problems that have issues with noisy data set as in the case of multidimensional financial data.

In order to make this more suitable for front end solutions there are a few avenues of improvement that need to be addressed. The future work may include evaluating the performance of SVR and optimizing the computational time. SVMs sometimes account for poor scaling with the data size due to quadratic optimization algorithm and kernel transformation; furthermore the apt choice of the kernel parameters leads to extensive computation time through grid searches. Implementing heuristic approach in the intermediate steps to obtain the SVM parameters optimizes the solution. This will be another step towards arriving to a more real time accurate solution. We believe the next step of this problem is to investigate how to increase the accuracy and reliability by including the real world constraints before implementing it to real instances. A real life scenario of an effective trading system can be envisaged when this model can be integrated with a fundamental model which can take into account the market shocks and probability of external events which can then scale the parameters accordingly based on the probability of events. This will give more real time dynamic response to investor decisions rather based on just time series historical data as is used here.

References


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