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Quick Decision Making To Achieve The Competitive Edge: Significance Of Decimated Data For Forecasting The Stock Market

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Abstract

Since computers have been used to trade stocks on the trading floor, the stock markets have changed. Traditional bookmakers have been replaced by online portfolio management algorithms so that stocks and shares can be bought and sold quickly in competitive market. But because these algorithms need so much processing, it is hard to speed up the process and make computers profitable at the same time. By reducing the speed at which stock data is delivered to the computers that make quick decisions, the computational load can be reduced. Online algorithms for predicting the stock market and optimizing the portfolios may use decimated data if certain statistical conditions are met. We proposed decimated version of the algorithm to forecast the stock market prices for quick decision making and resource allocation. The proposed algorithm's performance is maintained if decimation rates are chosen in accordance with certain theoretical conditions derived from data analysis, and real-world stock market data supports the result.

Keywords: Portfolio, Machine Learning, OLMAR, D-OLMAR, Stock, Online Trading.

Introduction

The main goal of portfolio selection, which is a major area of research in computational finance and applied financial engineering, is to find the best way to spread wealth across a group of assets that is as good as possible. Capital Growth Theory (Kelly, 1956) and Mean Variance Theory (Markowitz, 1959) are the two basic schools of thought that have been utilized in this study. In contrast to capital growth theory, mean variance theory focuses on a single time period, with the objective of generating the maximum feasible expected rate of increase for the portfolio. Even though both theories are capable of handling the task of selecting a portfolio, the latter theory is better suited to the "Online" state, which includes a variety of time periods and is the subject of this study. The growth of information technology has helped speed up the trading industry in a big way. Consider high-frequency trading, in which buying and selling can be done in as little as a few seconds or as long as a day. On the other hand, intraday data comes in much faster and is much bigger than low-frequency data. This means that high-speed sensors and techniques need to be used. Due to how quickly it works, though, high-frequency trading requires a quick response to how market participants act. Otherwise, the chance would be lost. Investors who are human are sometimes able to see opportunities, but they move too slowly to take advantage of them when they come up. Due to its two defining traits, high frequency trading necessitates unique methodologies and applications. As a direct result, it is riskier and harder to guess how volatile prices will be in the future.

High-frequency data and sequential time intervals help people make decisions in the trading world of today, which is full of high-frequency data. This brings the purchasing and selling decision-making processes to a close in time frames varying from seconds to days. Because of this, we need fast computing and parallel calculations if we want to get rid of human biases and limits. In order to monitor and understand market behavior, the contemporary trading phenomenon needs lightning-fast speed and reaction. Although expert judgement and exposure can only visualize opportunities or risks, they allow for correct responses in today's fast-paced trading market. What influences the stability of networks inferred from a system's dynamical behavior? Co-movement networks can become unstable in a system because of internal or external shocks that change the way the network is put together. So, there is a trade-off between the worry about high dimensionality and the ability to find times when factual data is volatile. The problem of high dimensionality is mitigated by the mixing of volatile and quasi periods in longer time series. Shorter time series, however, can more precisely identify uncertain times. High dimensionality was a problem that (Bhachech et al., 2022) introduced, making it challenging to estimate the underlying linkages. They investigated the reasons for network instability when there are no external irregularities using high-frequency multivariate financial data. The topological characteristics captured by centrality ordering are extremely unstable, even during such calm periods. The outcomes of multivariate simulations of normal distribution and fat-tailed random processes tailored for financial data demonstrate the importance of sample size frequencies and the incidence of anomalies. What, then, affects the networks' stability when it is inferred from a system's dynamical behavior? The topological properties of co-movement networks can become unstable in a system if it gets a shock from the inside or the outside. According to the connectionist viewpoint, because of the basic environment, economists predict that assets in connected businesses will behave similarly. Corporations operating in the same industrial chain are also linked in some way, as illustrated in **Figure 1.** Market participants cannot pay close attention to all assets. Stock prices will underreact to firm-specific information as a result of the limited attention, perhaps influencing unmentioned firms as well.

The outcome of numerous agents buying and selling an index is the stock market. Agents may be more likely to buy or sell in markets with obvious trends or behave more erratically in times of great uncertainty, depending on their beliefs and the state of the economy. By measuring the level of randomness, we can therefore learn more about the general behaviors of stock market participants. A market is said to be somewhat predictable if it consistently follows the same price patterns, and completely random if the patterns do not repeat and participants cannot predict their next move. Randomness is generally defined as the absence of patterns. However, human behavior is still having limitation, it is possible to predict market movements using price patterns. But this is a subjective phenomenon rather than an objective one. The researchers, generally, with backgrounds in both computer science and finance are drawn to the enthralling task of financial forecasting to generate a range of perspectives. The fundamental environment, according to the connectionist viewpoint, will cause assets in related industries to behave similarly. Companies that share a manufacturing supply chain are also related in some way.

Figure 2 depicts this pattern, in which financial markets frequently lag behind actual economic activity. When relating macroeconomic conditions to asset returns, accurate economic data is critical. (Kwon, 2022) explored the yield spread between the 10-year treasury yield and the effective federal funds rate, using the five leading variables as macro indicators: the credit spread between the 10-year treasury yield and the yield on Moody's Baa corporate bonds, the four-week moving average of initial unemployment claims, the total number of building permits, and the CBOE Volatility Index (VIX).

This historical pattern, from the National Bureau of Economic Research, with shaded areas denoting recessionary periods (NBER). No matter how long or persistent, every economic cycle eventually showed recurring patterns, with expansions followed by contractions. Particularly, the peak-to-trough decline of the macro indicator was largely consistent with previous NBER recessionary periods, such as the 2007–2008 Global Financial Crisis and the most recent COVID–19 pandemic.

This study focusses on the objectivity based when it considers certain financial market movements with predetermined thresholds. This concept is supported by (Cover, 1991) wherein the construction of portfolio is re-balanced up to a specific level at optimum log return. According to Cover's famous theorem, the long-term yield of a properly chosen "universal" portfolio is almost as good as the best retrospectively chosen constant rebalanced portfolio. The rebalancing rule is no longer required to be constant but may change depending on the state of the stock market because he used the market portfolio as the numeraire. A comparison to the numeraire portfolio using a stochastic stock market model is added to this model-free result. Therefore, a properly chosen "universal" portfolio constructed using only historical and current asset prices does not significantly outperform the Cover's insight "wisdom of hindsight". The relevant optimality criterion in this case is the asymptotic growth rate of the portfolio. In this context, the following are the key issues confronting today's high-speed, high-frequency Financial Markets:

- Voluminous financial instruments
- Decision making in multiple time frames
- Human behavioral biases

This study makes effort to remove the impediment that causes problems when dealing with numerous financial instruments such as hedge fund management, quantitative trading, and automated wealth management. However, because these methods are computationally demanding, they pose a considerable barrier to process acceleration and the economic viability of computer equipment. Increasing the rate at which stock data is supplied to decision-making systems reduces the computing strain on the computers. The proposed algorithm's prediction ability is tested under some statistical conditions using the most recent empirical data. This article will therefore go into detail about the sample size and the frequency rate at which it will be taken.

Related Works

The literature claims that the main objective of applied financial econometrics is to allocate wealth among a group of assets. Traditional finance, Mean Variance Approach presented by (Markowitz, 1959) , investigated this problem based on the single time period, however, Capital Growth Theory/Optimal investment strategy, also known as Kelly criterion, (Kelly, 1956) focus on many dynamics of investment situations considering attractive proprieties. Both theories are largely concerned with optimizing portfolio selection. In contrast, the successor hypothesis, which focuses on long-term phenomena of investment strategies, guarantees a gain in wealth over and beyond any other investment plan that does not converge to it. There is also the risk ruin ability, which exists, which has the virtue of asymptotically minimizing the predicted time to reach a given amount of wealth. Because of the implication of logarithmic utility of wealth at the end of each time interval, this strategy is considered to as more risk tolerant in the literature; as a result, the relative risk aversion would be equal to one. This approach was further developed by (William T Ziemba & Ziemba, 2008) and (Maclean et al., 2010) where the expected logarithm of final wealth over time were maximized. Thus, if the Kelly investor plans forever, he will not only get the most final wealth, but also all of it. In the short run, log is the most dangerous utility function to use because it has almost no Arrow-Pratt risk aversion. It is very easy to overbeat when the data is uncertain. However, a small percentage of the time, a series of bad scenarios combined with the large bets recommended by the Kelly criterion results in massive losses. In gambling, (Thorp, 1997) introduced, long-term compounders should consider using the Kelly criterion to asymptotically maximize the expected compound growth rate of their wealth. Lower functions may be preferred by investors with a lower risk tolerance for the intermediate term. Compounders should avoid using a higher fraction in the long run (this is known as "over betting"). As a result, if future probabilities are uncertain, long-term compounders should limit their investment fraction even further to avoid over betting. (Hausch et al., 2008) in sports beating strategies developed a model to show that profits are not the result of chance, but rather of correctly identifying market inefficiencies. The number of possible bets in any given race is reduced to three or fewer by side calculations, making the actual optimizations quite simple. The model was tested on Santa Anita and Exhibition Park data using exact and approximate solutions (which allow the system to operate at the track given the limited time available for placing bets) and was found to produce significant positive profits, and (W T Ziemba, 2005) in portfolio investment strategies, assess and validate Warren Buffett's superiority. This study emphasized the need to devise a new metric. He explained the log bettor at the limit accumulates wealth over time, so this is one candidate that is most likely related to the Kelly approach to investment evaluation. (Chang et al., 2018) observed the irrational behavior and characterized it in their study by weekly purchases of TWSE stocks followed by weekly sales of the same stocks. The market status for each week was determined using RSI (Risk Seeker), and it was then classified into six categories. The significant effects of irrational behavior were investigated in the top 150 stocks. The stock pool contains all 150 stock securities, the initial data period runs from 1-4 2002 to 6-15 2012, and the back-testing period runs from 6-15 2012 to 5-9 2014. The generation of 5000 weekly scenarios for stock returns that exhibit significant irrational behavior. The back-testing period lasts 100 weeks in total. (Chang et al., 2018) investigated this human behavior variation during decision making in their study, where SF1 (Safety First) outperforms its rivals, with the exception of the standard deviation, where the Market performs slightly better. These results indicate that RS1 (Risk Seeker) and SF1 outperform their competitors. Additionally, in terms of total return over 100 weeks, RS1 (SF1) exceeds RS2 (SF2), MV (Mean Variance), and Market.

The choice of sample frequency was found to be the main flaw in the algorithms described above. A single algorithm does not decide the sample frequency parameter. In short, for machine learning algorithms to work well, they need exact sample sizes and frequencies. In this article, we will look at the "Online" method and how it may be utilized to address the problem of portfolio optimization with accuracy and speed while incurring the least amount of administration expenses and time. (AlQabbany & Azmi, 2021) investigated the mechanisms for creating an accurate and effective prediction model based on stream learning algorithm using the concept drift within the random forest domain. The use of big data has grown in importance in the machine learning environment to forecast the stock market. Big data analytics' ground-breaking capabilities have changed many facets and methods of integrating technology in today complex financial environment. Concept drift is therefore a serious problem in applications of predictive analysis. Effective management of drifting concepts is necessary given the nature of stream learning environments. They proposed an efficient algorithm which can be roughly modeled after a Poisson distribution when the amount of data is large, as in stream learning. Even at longer time scales, there has been evidence of high entropy. Twenty SSE 50 index stocks, including the five with the highest and lowest entropies in daily data as well as the same selection in five-minute high-frequency financial data, were used by (S. Li & Lin, 2020). To counteract the impact of multi-scale on entropy calculation and stock selection, they used a coarse-graining algorithm with various amplification ratios (range from 0 to 20). The high entropy stocks and low entropy stocks were chosen by calculating the mean and median for the coarse-graining dataset. Both the median and average values were used to select the stocks. They provided Plz, a Lempel-Ziv estimator-derived information-theoretic predictability estimator for financial time series. By lowering the uncertainty of future values, the Plz quantifies the contributions of past values in the time series. The findings strongly imply that after removing overlapping stocks, five-minute high-frequency price changes are more predictable than daily price changes. The results show that daily price changes are less predictable than price changes that happen every five minutes. Using the EEMD-FFH prediction method, they also found some links between being able to predict something and being able to predict it accurately. Empirical evidence in this case demonstrates a strong positive correlation between these two concepts, proving that data with higher frequency has better predictive accuracy. In short, taking everything into account, it's likely that the optimal growth theory is the best way to solve the problems that came up during the portfolio optimization selection criteria small window size data set. The concepts of competitive analysis presented by (S. Li & Lin, 2020) approximation of the output of mathematical equations by (S. Li & Lin, 2020) and the minimization of human error biases by (S. Li & Lin, 2020), for the selection of a small window size data set with accurate prediction ability of the population, have a major consideration in this article. The small window size data set is helpful for the selection of an online portfolio algorithm with low scale and high frequency trading data, in light of the lower costs. Similarly the idea of forecasting of financial time series using single stock by (Huang et al., 2011). and (Koolen & Vovk, 2014) has also linked with this article. However, this research ignored the Markowitz Mean Variance portfolio theory (Stuart & Markowitz, 1959) which is based on a single period (batch) portfolio selection (with the exception of some extensions) (Jiang & Liang, 2017) and (Xing et al., 2018).

Methodology

Online Trading-Back Ground of Strategies

(B. Li et al., 2015) **and** (Hoi et al., 2021) summarized the literature about the critique on current algorithms: The Follow the Winner strategy, which is based on the Regret Bound Theory, boosts the weights of more successful stocks in theory, but its actual performance is not particularly impressive. Contrary to actual evidence, this theory claims that relative prices follow an i.i.d. pattern. Wealth is shifted from winner to loser, according to the Follow the Loser strategy, which is based on the mean reversion principle. It explains how price swings gradually settle back to their averages or means. However, actual research disputed the assertion of high cumulative returns, this theory broke the i.i.d. assumption in real markets, and this concept also does not apply to short-term data, such as daily data.

Pattern-matching approaches include non-parametric sequential investment strategies as well as the usage of winner and loser algorithms. Pattern matching and optimization are the two stages of this algorithm. There is no attempt made by this algorithm to cope with recurrent patterns. Several base expert's strategies are included in the Meta-Learning Algorithms that are mostly related with the FoF theory and are armed from the same strategy class or from separate classes. This feature, on the other hand, comprises a complex mathematical simulation, which is a significant plus.

Empirical studies show that extremes in a stock's price range, both up and down, are transient, and that the mean reversion phenomena tend to be followed by stock price relatives. Even though existing mean reversion algorithms can achieve acceptable empirical performance on a wide range of real data sets, they usually assume a single-period mean reversion assumption that is not always satisfied, leading to subpar performance on some real data sets. This is due to the fact that the assumption relies on mean reversion occurring periodically. The assumption is based on the finding that mean reversion always occurs over the same time frame. Multiple-period mean reversion, also known as the moving average reversion (MAR), was proposed by (B. Li et al., 2015) along with a new online portfolio selection (OLPS) strategy exploiting MAR using potent online learning techniques and given the term online moving average reversion (OLMAR).

Extension in Online Moving Average Reversion (OLMAR)}

As this study mainly focus the Online Moving Average Reversion (OLMAR) and proposed the decimated version called D-OLMAR algorithm. Therefore, there is need to briefly describe the formulation of OLMAR and then its extension.

The vast majority of formulations that are now on the market conform to the conventional practice of Kelly-based portfolio selection (Kelly, 1956) and (Thorp, 1997). To provide a greater level of detail, a portfolio manager will make a projection for $\overline{X}_{t+1}$ based on k probable values, which include $\overline{X}^1_{t-1}, \dots, \overline{X}^1_{t+1}$ in addition to the probabilities that are associated with them $\rho 1, \dots, \rho k$. It is essential to bear in mind that each $\overline{X}_{t+1}$ represents a unique alternative combination vector of individual price relative estimates. It is also crucial to keep this fact in mind. Constructing a portfolio with the objective of getting the best feasible predicted log return is the next step for him or her to take.

Considering the limitations discussed by (B. Li et al., 2015) and (Hoi et al., 2021)of mean reversion algorithms, proposed multiple time period mean reversion algorithms, named Moving Average Reversion (MAR). Wherein, OLMAR assume that $\overline{p}_{t+1} = \overline{p}_{t-1}$ will revert to moving average (MA), where MA_t represent the moving average consistency till the end of period t. Further, it observes the long-term trend and thus overcomes the drawbacks of existing mean reversion algorithms.

A brief mathematical introduction of Simple Moving Average strategy proposed by Li, B et al. is as follows;

Simple Moving Average Reversion: MAR-I

$$\overline{X}_{t+1}(\omega) = \frac{SMA_t(\omega)}{\rho_t} = \frac{1}{\omega}\left(\frac{\rho_t}{\rho_t} + \frac{\rho_{t-1}}{\rho_t} + \cdots + \frac{\rho_{t-\omega+1}}{\rho_t}\right)$$

$$= \frac{1}{\omega}\left(1 + \frac{1}{X_t} + \ldots\ldots + \frac{1}{\bigodot_{i=0}^{\omega-2} X_{t-1}}\right)$$

where SMA is Simple Moving Average, ω is the window size, ρ is the price vector and relative change in prices are shown by x and $\odot$ denotes the element-wise product.

OLMAR capture the Creamer's basic idea of passive aggressive (PA), (Creamer, 2007) to explain the moving average reversion. In simple words, PA incorporate the previous output if the classification found correct and adopt aggressively approaches in case of incorrect classification.

OLMAR Algorithm

The OLMAR optimization problem presented by (Creamer, 2007) is given as;

$$b_{t+1} = arg_{b\in\Delta_m} \min \frac{1}{2}|b - b_t|^2 \quad \boldsymbol{s.t.} \quad b.\check{x}_{t+1 \geq \epsilon}$$

where $\check{x}_{t+1}$ is the next price relative which is inversely proportional to last price relative $\check{x}_t$. In particular, they implicitly assume that next price $\check{p}_{t+1}$ will revert to last price $\check{p}_{t-1}$, as follows;

$$\check{x}_{t+1} = \frac{1}{x_t} \xrightarrow{yields} \frac{\check{p}_{t+1}}{p_t} = \frac{p_{t-1}}{p_t} \xrightarrow{yields} \check{p}_{t+1 = \check{p}_{t-1}}$$

and b_t represents a portfolio vector which is an investment in the market for the $t-th$ periods, i.e $b_t = b_t\ (x_1^{t-1})$ and $b_1^n{}_{= (b_1 \ldots\ldots b_n)}$.

As earlier discussed, the basic idea of this study is the decimation process explored in the of study of (de Cheveigné & Nelken, 2019) due to challenges faced in the today voluminous trading of high speed and high frequency instruments. The extended version of this model was proposed by (Ingber & others, 2020) using multiple and sequential time period to avoid or minimize the human biases errors. Like lowpass filtering a signal and produce some samples from the population (Soleymani & Paquet, 2020). If this process continues without the lowpass filtering concept, it's called down sampling. The core motivation behind this study for decimation is to reduce the cost of processing, time saving and prompt response to the quick opportunities, which create in today fast-moving market. Therefore, the use of a lower sampling rate usually results in a cheaper and quick implementation. We modified the OLMAR algorithm for decimation process. However, it does not ensure aliasing degree and produces a shift invariant signal representation explored by (T. Li et al., 2002).

The term "decimated" refers to the process of resampling the original ("undecimated") data at a lower sampling rate. Therefore, compared to undecimated data, decimated data will have a lower sampling rate. This algorithm refereed D-OLMAR, can be stated as;

D-OLMAR Algorithm

$$\mathrm{b}_{t+1} = \arg_{\mathrm{b}\,\epsilon\,\Delta_m} \min \frac{1}{2}\ \|\mathrm{b} - \mathrm{b}_t\|^2 \quad \mathbf{s.t.}\ \ \check{\mathbf{b}}\,.\,\mathbf{y}_{\mathbf{t+1}} \geq \boldsymbol{\epsilon}$$

Where $\mathbf{y_{t+1}}$ is the decimated version of $\mathbf{x_{t+1}}$ which is $\mathbf{y_{t+1}} = \mathbf{x}(\ (\mathbf{t+1})\mathbf{M})$ and $\mathbf{y_{t+1}}$ is the moving average of $\check{\mathbf{y}}_{\mathbf{t+1}}$

Assumption

We need the following optimizations for Decimated OLMAR algorithm.

- The given stock data preserve the ergodicity property for a given window size.

- The down sampling factor is chosen such that the first order moment remains constant.

Proof

The Lagrangian for the optimization problem of D-OLMAR is;

$$L(b,\lambda,\eta) = \frac{1}{2}\|b - b_t\|^2 + \lambda(\varepsilon - b.\breve{y}_{t+1}) + \eta(b.1 - 1)$$

where $\lambda \geq 0$ and η are the Lagrangian multipliers. Taking the gradient with respect to b and setting it to zero, we get;

$$0 = \frac{\delta L}{\delta b} = (b - bt) - \lambda\breve{y}_{t+1} + \eta_1 \Rightarrow b = b_t + \lambda\breve{y}_{t+1} - \eta_1$$

Multiplying both sides by 1^T, we get

$$1 = 1 + \breve{y}_{t+1}.1 - \eta_m \Rightarrow \eta = \lambda\bar{y}_{t+1}$$

where $\bar{y}_{t+1}$ denotes the average predicted price relative (market). Plugging the above equation to the update of b, we get the update of b;

$$b = b_t + \lambda(\breve{y}_{t+1} - \bar{y}_{t+1}.1)$$

To solve the Lagrangian multiplier, let us plug the above equation to the Lagrangian;

$$L\lambda = \lambda(\varepsilon - b_t . \breve{y}_{t+1}) - \frac{1}{2}\lambda^2 \|\breve{y}_{t+1} - \bar{y}_{t+1}\|^2$$

Taking derivative with respect to and setting to zero we get;

$$0 = \frac{\delta L}{\delta \lambda} = \lambda(\varepsilon - b_t . \breve{y}_{t+1}) - \lambda^2 \|\breve{y}_{t+1} - \bar{y}_{t+1}\|^2$$

$$\Rightarrow \lambda = \frac{\varepsilon - b_t . \breve{y}_{t+1}}{\|\breve{y}_{t+1} - \bar{y}_{t+1}\|^2}$$

Further projecting λ to $[0; \infty]$ we get

$$\lambda = \max\left\{0 \; \frac{\varepsilon - b_t . \breve{y}_{t+1}}{\|\breve{y}_{t+1} - \bar{y}_{t+1}\|^2}\right\}$$

Behavior of the Data before Simulation

The data sample and measurements that make up a study's dataset are summed up in a descriptive statistics" **Table 1**. It helps in the analysis of data. The mean, median, maximum, and minimum values of all three data sets indicate that we can classify the underlying companies based on their size and frequency of trading volume, like AMZN, AAPL and AMD, respectively, in ascending order. When compared to AAPL and AMD, the AMZN stock is more volatile. However, in a few clusters, the trading size of AAPL and AMD stocks is greater than that of AMZN stock. Similarly, the volatility was higher in the peak days of AAPL and AMD than in AMZN stock. **Figure X** represents the same price patterns of AMZN, AMD and AAPL stocks.

Simulation Results: D-OLMAR Results

Having proposed and proved the decimated version of OLMAR, i.e. D-OLMAR its appropriate to demonstrate the efficacy of the proposed algorithm on a set of real stock market data. For this purpose, fast moving data set of Amazon. com, Inc. (AMZN), Advanced Micro Devices Inc. (AMD) and Apple Inc. (AAPL) are selected from NASDAQ stock exchange. For rigorous testing of D-OLMAR a 2264 daily data from November 5, 2012 to November 5, 2021 have been downloaded from Yahoo Finance. Various D-OLMAR results are shown in **Table 2, 3 and 4** decimated window size of 1-5, 1-6 and 1-8 days. Result of performance parameters like, Final Value, Mean Value and Annualized return are consistent to this study. The result of risk and risk-adjusted (Sharpe, 1964)and other parameters are also consistent with proposed algorithms. It can be seen that the annualized return for five days decimation is much better than that of the decimation of six and eight days.

Discussion and Significance

It is well known that the most straightforward method for estimating statistical parameters uses the least squares method with linear functions. The problem with this strategy is figuring out how to recognize a linear observation. Estimation accuracy is a crucial concept in many fields, including medicine, the humanities, engineering, industry, economics, and others, as an objective viewpoint is necessary to support the industry's decision-making. The methods used to complete estimates, the variables that affect how estimation methods are chosen, and the current level of estimation accuracy are all pertinent data that should be collected. Recognizing that in business, "Time is Money," the dynamic choice mentioned here has shown to be a critical instrument for successfully applying to a wide range of managerial decisions involving time and money. We all create forecasts when making strategic judgments in the face of uncertainty. Although we may not believe we are forecasting, our actions and inactions are influenced by our expectations about the outcomes of our actions or inactions. Failure results from indecision and delays. In today's fast-paced trading environment, swift decision making is critical to success. Minor time delays in decision making can cause a slew of strategic issues in addition to financial losses. Market capture is now a science in addition to an art form. The more sophisticated algorithms that provide accurate predictions are gaining popularity in the investment industry. The results demonstrate that sampling size and frequency are critical for making timely decisions. The proposed approach is an attempt to reduce the time and cost elements involved in heavy mathematical simulation.

Shortcomings and Future Direction

Numerous relevant data sets are statistically excluded from the decimation process of the proposed algorithms, and various noises are produced. The stock price news release also has a time-profile and is only available for up to one day. While many announcements do not immediately affect the stock price, all announcements do over time. Additionally, the proposed decimated model is based on the mathematical operations of the algorithms it ignores the statistical aspects. These are the next steps for the researcher to take in order to create a filter that solves the problems mentioned above.

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Table 1: Descriptive Statistics

Sample: 11/05/2012 11/04/2021			
	AAPL	**AMD**	**AMZN**
Mean	49.67212	24.31467	65.20742
Median	36.03000	11.20000	47.23800
Maximum	156.6900	137.5000	186.5705
Minimum	13.94750	1.620000	11.03000
Std. Dev.	36.80723	30.23704	51.06249
Skewness	1.462030	1.507289	0.840546
Kurtosis	3.951821	4.083749	2.480278
Jarque-Bera	893.2062	969.3492	292.4602
Probability	0.000000	0.000000	0.000000
Sum	112606.7	55121.35	147825.2
Sum Sq. Dev.	3069914.	2071755.	5908319.
Observations	2267	2267	2267

Table 2: D-OLMAR performance-AMZN

Tools	**Amzn_1_5**	**Amzn_1_6**	**Amzn_1_8**
Final Value	0.7805	0.5760	0.7764
Mean Return of every Period	-3.4899e-04	-0.0013	-7.2048e-04
Annualized Return	-0.1288	-0.3077	-0.2018
Standard Deviation	0.0199	0.0193	0.0187
Annualized Standard Deviation	0.3151	0.3070	0.2963
Sharp Ratio	-0.5357	-1.1327	-0.8160

Calmar Ratio	-0.3064	-0.6718	-0.4551
Value at Risk	-0.2908	-0.9938	-0.4950
Maximum Drawdown	0.0265	0.0299	0.0286

Table 3. D-OLMAR performance-AMD

Tools	AMD_1_5	AMD_1_6	AMD_1_8
Final Value	0.7603	0.4730	0.4364
Mean Return of every Period	-2.4899e-04	-0.1011	-5.2328e-04
Annualized Return	-0.1078	-0.2066	-0.2438
Standard Deviation	0.0198	0.0191	0.0157
Annualized Standard Deviation	0.3461	0.3160	0.2543
Sharp Ratio	-0.5247	-1.1417	-0.7140
Calmar Ratio	-0.2056	-0.4728	-0.4321
Value at Risk	-0.2757	-0.8756	-0.3940
Maximum Drawdown	0.0255	0.0285	0.0288

Table 4. D-OLMAR performance-AAPL

Tools	AAPL_1_5	AAPL_1_6	AAPL_1_8
Final Value	0.6705	0.3460	0.1264
Mean Return of every Period	-4.3879e-04	-0.0010	-5.2148e-04
Annualized Return	-0.0888	-0.2067	-0.1017
Standard Deviation	0.0269	0.0383	0.0467
Annualized Standard Deviation	0.5122	0.2570	0.3863
Sharp Ratio	-0.4357	-1.5327	-0.7160
Calmar Ratio	-0.4064	-0.4718	-0.4251
Value at Risk	-0.3958	-0.8978	-0.5940
Maximum Drawdown	0.0155	0.0089	0.0266

Figure 1

An example of co-movement of connected stocks, (Reprinted from (Xing et al., 2018) with permission of the Springer Science Business Media B.V.,copyright (2017).

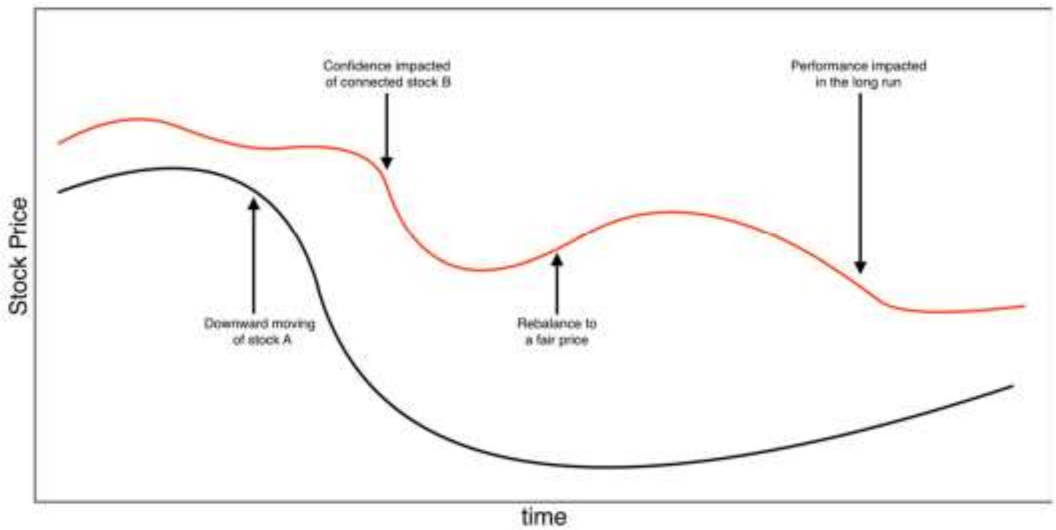

Figure 2

The trend of the macro index from January 1967 through October 2021, with NBER recession periods depicted by dark zones (Reprinted from (Kwon, 2022), distributed under the terms of the of Creative Commons Attribution (CC BY) license).

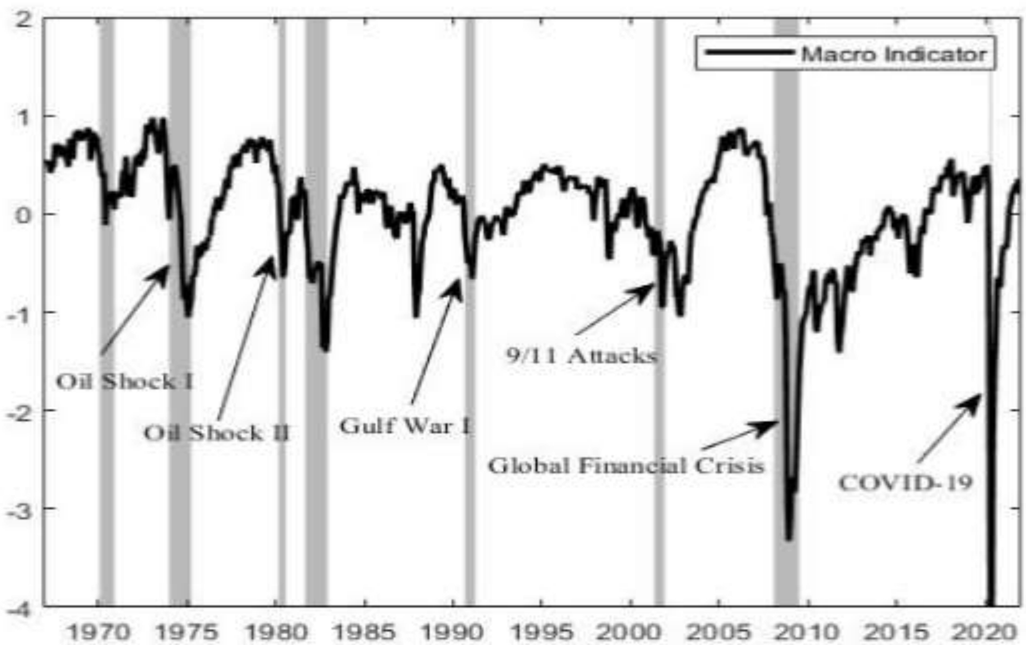

Figure 3

Historical Price Movement