**Stock Movement Prediction Using Market Features and Unsupervised Learning**

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A pie chart with different colored circles

AI-generated content may be incorrect.**Introduction**

The Standard & Poor’s 500 Index (S&P 500) is a list of the 500 largest publicly traded companies in the United States, considered to broadly represent the country’s overall economy. Figure 1 shows the various market sectors that comprise the S&P 500. Virtually every mutual fund compares its performance against the S&P 500 as a benchmark, and the goal of every financial advisor and brokerage firm is to *beat* the return of the S&P 500.

We attempt to use various techniques to evaluate the historical performance each ticker within the S&P 500, analyze it, and produce a prediction of little movement, or strong movement either up or down. By adjusting the features we analyze and our methodology, we are able to achieve 70% accuracy in our test sets, indicating our model is able to glean valuable momentum information regarding the present day market.

Figure 1.

The benefit of finding such information is that traders will be able to leverage the model to make better investment decisions and would build wealth more quickly than the “buy and hold” technique often used in index fund focused strategies. Our model assumes that markets have both high frequency fluctuations and lower frequency trends, and that both may be captured by evaluating the daily returns over various time periods. Our market takes simple indicators and runs it through a survey of models, which provide multiple perspectives on the same dataset, in essence allowing the user to build a comprehensive view. As a result, the different models will provide better performance than one singular model in varying market conditions.

**Previous Work**

Qiu et al [1] incorporate an Artificial Neural Network (ANN) to analyze the Japanese stock market and attempts to predict the final market movement using various technical indicators. Bolos et al (2025) [2] evaluate the impact of k-means clustering on portfolio optimization, this study groups enterprises based on profitability, liquidity, and solvency indicators. Qiu’s model broke down the stocks into two categories, and evaluated them separately. The categories contained simple metrics and hybrid (long term) metrics. Our model incorporates both together to improve performance. Bolos’ k-means clustering places each stock into groups of “high performing” or “stable” groups, but does not necessarily predict what tomorrow’s market will do.

Kumbure et al. [3] employed a three-hidden-layer MLP architecture with optimized hyperparameters to predict stock market trends, achieving directional accuracy rates of 70.36% on technology company data when trained on technical indicators and fundamental analysis features. Their architecture utilized three hidden layers with systematic optimization and reported that "the hybrid model successfully predicts the short-term stock trends" with superior performance compared to traditional regression baselines. While our model is similar in architecture, we attempt to balance out the data to capture the significant movers in the minority class of tickers.

Similarly, research in computational economics has investigated neural network approaches for S&P 500 stock market prediction using comprehensive feature engineering, finding that MLPs trained on technical analysis indicators exhibited improved performance compared to models using individual feature types. Studies report that technical analysis-based neural networks achieved accuracy values around 85.384% for S&P 500 companies, with the models demonstrating conservative prediction behavior that prioritizes precision over sensitivity in identifying significant market movements, particularly when predicting minority-class events such as substantial price increases [4].

Momeni et al.’s [5] k-means technique was to divide businesses from three industries listed on the Tehran Stock Exchange in 2012 into two groups: high performing and low-performing organizations. Financial ratios chosen through expert interviews were used for the clustering; in descending order, the most important indicators were Return on Assets (ROA), Earnings Per Share (EPS), Return on Equity (ROE), Profit to Sales Ratio, and Operating Profit Margins. Our model chooses to remain simple in its indicators, which should capture the overall market perception of a company’s health, encapsulating features such as EPS, ROE, and P/S ratio.

**Methods**

**A group of different colored squares

AI-generated content may be incorrect.**

Figure . The program pipeline

The program is built as a pipeline that provides outputs at each step, allowing the user to choose the model that performs the best. The first step is checking for a current feature set, or downloading a new one. If building a new data set, the program uses the YFinance library to interface with the Yahoo Finance API to the data for all tickers within the S&P 500. The list of tickers comes from Wikipedia. The program then organizes each data set into a Pandas dataframe before writing it all to a csv. This csv is saved in the data folder.

The first step in data analysis is via PCA analysis. We load the csv and perform the final data cleaning techniques. Our model uses a maximum time horizon of 120 days to capture the overall trend of the model in the past 4 months. If a ticker has not been active for the that long, that data is blank. To ensure missing data does not skew the model, we drop all rows with missing data. This ensures all data is for tickers that have been active for at least 4 months. We also separate the file into a features set and the target set. The target is the 1 day return percentage, and the features are all of the others. We drop columns that cannot contribute, such as the date of the data, the ticker label, the actual adjusted close, etc. After scaling the data, we perform a fit and transform on the dataset and save it to a .csv file. Rather than determine the exact number of components, we leverage sklearn’s ability to capture 95% of the variance.

The baseline model uses a logistic regression to classify the resultant behavior. It is broken down into three categories: strong downward movement, neutral, or strong upward movement. We define strong as being a 1.5% change or greater. Additionally, in this model we instantiate a random forest classifier, which provides better flexibility with non-linear groupings. A grid search pattern is first used to determine the optimum confidence thresholds for determining price change.

The PCA components are ingested by a K-means clustering algorithm, which will first determine the number of groups via the elbow method, and then groups each cluster. The results are output into csv and ingested into the final model, an MLP network. The MLP network consists of 3 hidden layers of size 128, 64, and 32, and incorporates a ReLu activation function. It trains off of the clustering data and provides a similar output: strong downward movement, neutral, or strong upward movement. At each stage of each model, the results are printed out and graphics provided to provide the user with statistical analysis of their performance.

**Dataset**

Our data set is the historical financial data of each of the 503 stocks that currently comprise the S&P 500. The python library Y Finance interfaces with Yahoo! Finance’s API and downloads a wealth of stock information requested by the user. In our model, we divide each stock into several feature sets: simple returns, Volatility, MACD, and RSI. We use the daily return percentage of various horizons: 1-5, 20, 60, and 120 day horizons. For training and testing historical data, the 1-day horizon becomes the target value. MACD computes a weighted average between a short time frame and a long time frame, giving traders a sense if the short term market movement coincides with long term movement, or contradicts it. The time frames we use for this are 12 days for short, 26 days for long term, and 9 day signal. Volatility is an indication of how much the stock may fluctuate in a given period. Higher volatility indicates potential large price swings, thus higher risk and reward. The RSI is a metric used to compare the speed and magnitude at which a stock’s price changes, and is used to determine if a stock is overbought (overvalued) or oversold (undervalued). We use RSI values of the previous 14 days.

**Results**

**Discussion**

**References**

[1] Qiu, Min, and Yi Song. “Predicting the Direction of Stock Market Index Movement Using an Optimized Artificial Neural Network Model.” PLOS ONE, vol. 11, no. 5, 2016, e0155133. PLOS, <https://doi.org/10.1371/journal.pone.0155133>.

[2] Boloș, M.-I., Rusu, Ș., Leordeanu, M., Sabău-Popa, C. D., Perțicaș, D. C., & Crișan, M.-I. (2025). K-Means Clustering for Portfolio Optimization: Symmetry in Risk–Return Tradeoff, Liquidity, Profitability, and Solvency. *Symmetry*, *17*(6), 847. https://doi.org/10.3390/sym17060847

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[4] Research in Computational Economics. "Stock Market Forecasting Using a Neural Network Through Fundamental Indicators, Technical Indicators and Market Sentiment Analysis." *Computational Economics*, 2024.

[5] Momeni, Mohseni, & Soofi. (2015). CLUSTERING STOCK MARKET COMPANIES VIA K- MEANS ALGORITHM. *Arabian Journal of Business and Management Review (Kuwait Chapter)*, *4*(5), 1–10. Retrieved from https://j.arabianjbmr.com/index.php/kcajbmr/article/view/815

**Appendix**

**Statement of Contributions**

1. **Introduction:**Provide a short background of the project (e.g., what kind of question is to be answered, and why this is of interest). Provide a short non-technical summary of your analysis.
2. **Methods:**Summarize the methodology used in your analysis and use mathematical formulas and notations.
3. **Dataset:** Identify a dataset to study, and describe literature related to the problem you are studying. If you are using an existing dataset, where did it come from and how was it used? What other similar datasets have been studied in the past and how?
4. **Results:**Show the results of your analysis.  Summarize the results with a small number of the most important figures or tables and keep the description short.
5. **Discussion:**What are the state-of-the-art (SOTA) methods currently employed to study this type of analysis? Are the conclusions from existing work similar to or different from your own findings? Why did the proposed model succeed or why did others fail (or if it failed, why did it fail)? What did you learn from this analysis? What additional steps could be potentially performed to improve your analysis?
6. **References:**Please only add references that are explicitly used in the text. Make sure that you cite the sources of data, and the associated claims. Use a consistent format and numbering scheme. Example:

      [1] Bob Smith, John Doe. My amazing method. In \_Proceedings of WWW 2024\_, Lyon France, 2024.

1. **Appendix:**Add links to the code repository, plots, and other relevant technical details that will help evaluate your work.
2. **Statement of contributions:**If you are working in a group of 2 or 3, your report should contain a short section at the end, stating that all group members contributed equally, and describing the contributions of each group member. You do not need to include this section if you are working alone. This section does not count towards the page limit.

**Note:**

* Your report should also include a link to a public GitHub repository containing the code used to produce your results. If you would like to not make your code public for any reason, you must instead submit your code as a zip file on Canvas.
* Your report should be written as a formal academic article. There should be no slang or jargon. Any claims you make should either be common knowledge (i.e. something we learned in the course), supported by a citation, or supported by your data/results. There should be no spelling or grammar mistakes.
* One submission per group is enough.