Deep Learning Neural Network Approach to Beat Naive Stock Dealing Strategy

Hongzhen Xu, Jingming Cheng, Che-Yi Wu

Khoury College of Computer and Information Science
Northeastern University
Boston, MA
xu.hongzh, cheng.jingm,wu.chey@northeastern.edu
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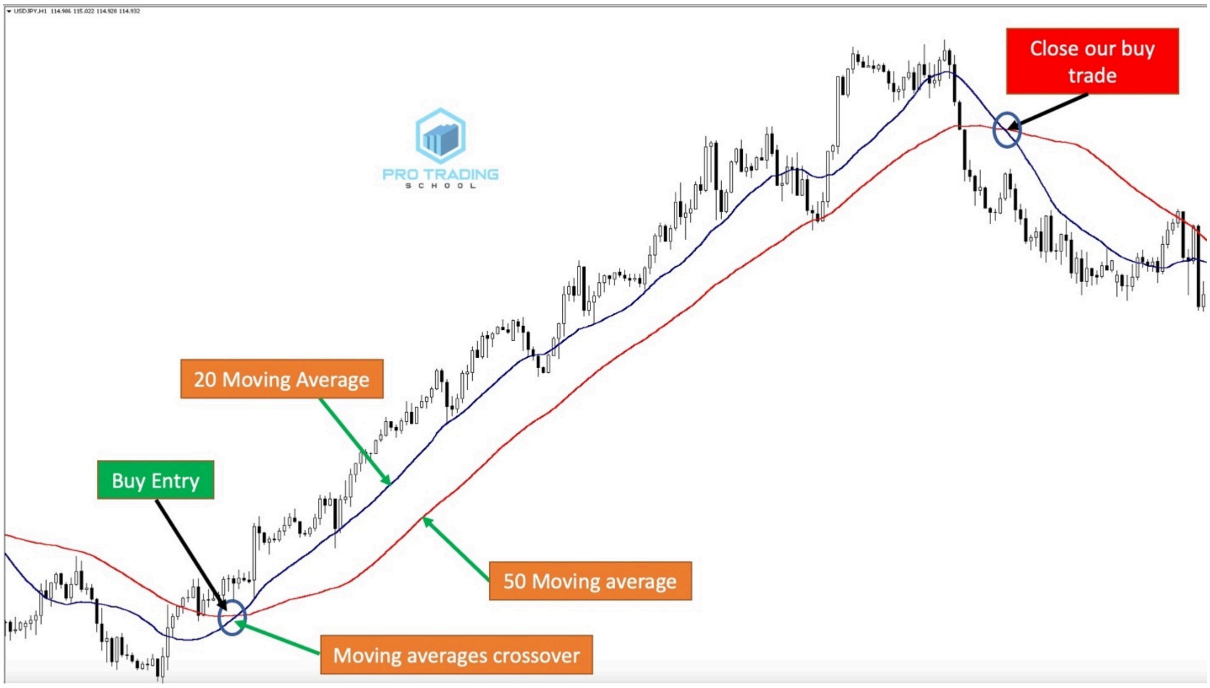
1. Objectives and significance (1-2 paragraphs)

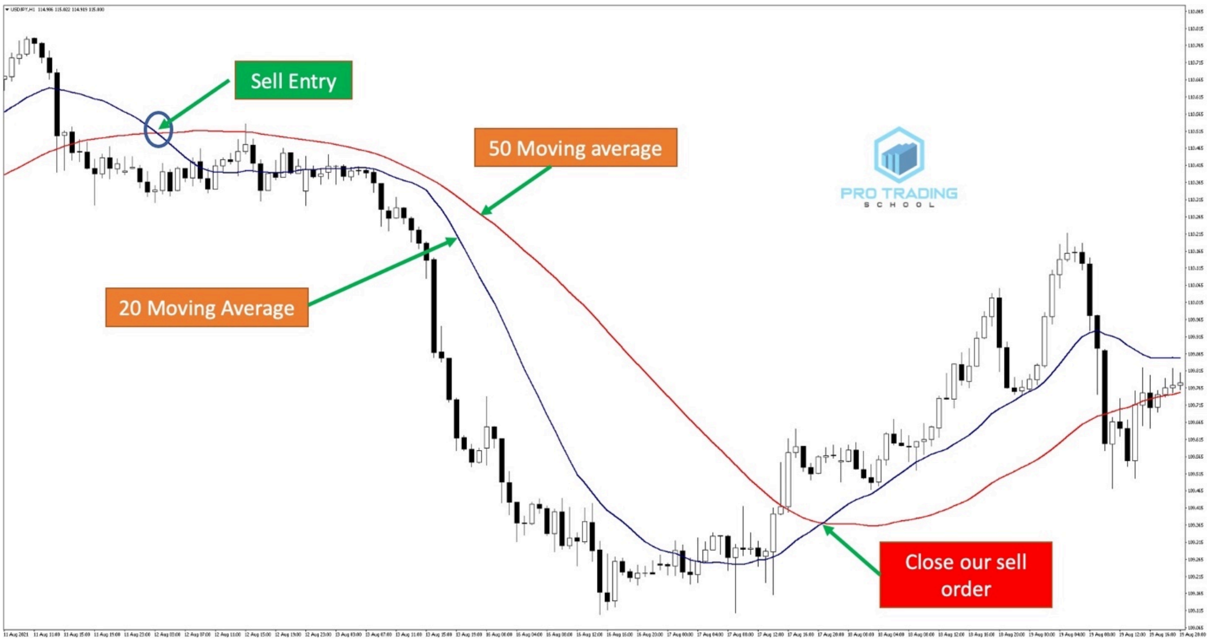
In stock market, there are many buy signals and sell signals for any stock. The goal of this project is to build a deep learning machine to give extent of certainty when these signals happen. The input of the neural network should be important and related features to stocks, and the output should be a float number between 0 and 1 representing the extent of certainty. This machine should not only fit one stock, but also be trained and tested on multiple stocks one by one.

It is important because most of the stock dealers in the world follow a simple and naive stock dealing strategy. This strategy is to look at plots of the price, the average price over the last period, and the the average price over the last period of a longer time frame. Then, the price crossovers and moving average crossovers become buy and sell signal. For example, if the current price surpasses the average price in last 30 days, it is interpreted as a buy signal; if the current price submerges below the average price in last 30 days, it is interpreted as a sell signal. If the average price of the last 7 days surpasses the average price of the last 30 days, it is interpreted as a buy signal; if the average price of the last 7 days submerges below the average price of the last 30 days, it is interpreted as a sell signal. The period frame length can be customized. This strategy is simple and naive, because the stock market is a complicated game that releases tricky signals. To evaluate the certainty of such signals, we decide to make a machine to give a second judge on the dealing signals.

The motivation is simple as well. Over the years, many families including Hongzhen's put money in stock market and the outcome is depressing. With the help of deep learning neural network, we believe we can make better decisions on dealing stock. This machine is just the first step. There will be more complicated factors, strategies and models to concern in the future.



pic1: example of moving average crossover-buy signal (Pro Trading School., 2024)



pic2: example of moving average crossover-sell signal (Pro Trading School., 2024)

2. Background(1-2 pages)

(a) Introduce all important concepts and background information.
Stock market prediction has long been a challenging area of research due to the complex and volatile nature of financial markets. Traditional strategies, like price and moving average crossovers, are often used by traders to generate buy and sell signals. However, these methods are considered simplistic and susceptible to market noise.

The project focuses on evaluating certainty in stock trading signals such as price crossovers (e.g., when the stock price crosses above or below a moving average). These signals are traditionally used by traders to make decisions, but they can be unreliable due to market fluctuations.Instead of using these signals at face value, this project employs a deep-learning neural network to assess the likelihood of their correctness. A deep learning model, through its ability to learn from large amounts of data, can provide a probabilistic judgment that enhances trading strategies.

"Stock Market prediction has been one of the more active research areas in the past, given the obvious interest of a lot of major companies."[1]

(b) Search the literature and describe previous work on this problem.

Previous work in stock market prediction has extensively explored the use of machine learning techniques, such as Artificial Neural Networks (ANNs), Fuzzy Logic, and Support Vector Machines (SVMs), with mixed results due to the non-stationary, volatile nature of financial data. ANNs, while widely used, have demonstrated limited reliability. More recently, Hidden Markov Models (HMMs) were applied to stock market prediction, given their success in time-dependent analyses like speech recognition and ECG analysis. HMMs have been used to model stock data as financial time series, with notable applications including Shi and Weigend's work predicting financial trajectories and Hassal's integration of HMMs with fuzzy logic to improve accuracy. A similar approach was adopted by Nobakht et al., who used continuous HMMs to model daily stock indices, although their method focused on data pattern identification.
Studies such as those by Agrawal et al. (2013) and Adebiyi et al. (2014) explored both linear and nonlinear models for stock return prediction. While linear models have been found to

perform well in some cases, nonlinear models, including deep learning approaches, have also shown potential to outperform traditional methods, as highlighted in research by Thawornwong and Enke (2004) and Cao et al. (2005). However, the literature presents mixed results, with some nonlinear models not consistently outperforming their linear counterparts.

(c) If there exists previous work on the problem, describe what makes your work distinct or particularly interesting

Generalized Certainty Instead of Exact Prediction: While many existing studies focus on predicting stock prices or market trends directly (e.g., forecasting specific price movements), our approach seeks to predict the certainty of buy or sell signals as a probability. This probabilistic output (a float between 0 and 1) allows for flexibility in decision-making without requiring the system to predict exact prices, making it less sensitive to market noise and stock-specific volatility.

Loss Function Tailored to Signal Accuracy: Our method introduces a loss function that focuses on the correctness of the signal (buy/sell) rather than the profitability or the magnitude of price changes. This loss function, which penalizes the model based on its confidence in the signal rather than the actual financial gains, differs from the more traditional approaches that use mean squared error (MSE) or root mean squared error (RMSE). This makes our approach more adaptable across different stocks without requiring stock-specific tuning.

Cross-stock Applicability: Unlike some deep learning models designed for specific stock indices or limited to high-frequency trading data, our approach aims to be more generalized. The goal is to build a system that can generate signals across various stocks, without overfitting to individual stock behaviors or unique financial conditions.

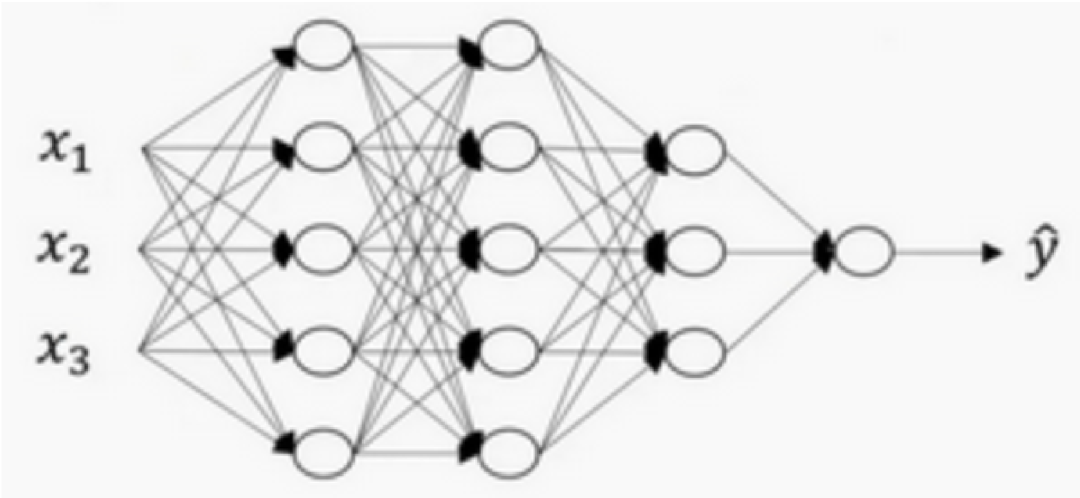
3. Proposed Approach(2-4 pages)

To feed the deep learning neural network, we need a lot of features of small number of stocks.

Most of them are public online and easy to be obtained such as in the treasury report of a specific company.

One specific API we use is the AlphaVantage API, which downloads the data of any business day of any stock for the last 20 years. The data includes timestamp, open price, high price, low price,close price, volume for each business day.

The price crossovers and moving average crossovers during a given period can be obtained by using the program Hongzhen wrote during his study in CS5010 programming design paradigm course.



pic3: example of a DL neural network (wt168, 2024)

The proposed method is to build a deep learning neural network. The input is the features of the stock and the output is a float number between 0 to 1. Sigmoid activation function is ideal. We do not wish to predict the accurate stock prices because of the complexity of stock market. The only thing we get from the trained deep learning neural network is a percentage of certainty regarding the buy and sell signal.

When training, the loss function is built by comparing current stock price at current signal with the stock price at the next signal. If the signal is correct and the machine confirms (we make some money or avoid losing money), the loss is 0. If the signal is correct and the machine doubts, the loss is 1. If the signal is incorrect and the machine believe it is correct, the loss is 1. If the signal is incorrect and the machine doubts the signal, the loss is 0. We do not implement loss function based on benefit or benefit rate because each single stock is different in its circumstances. The machine should not work on single specific stock, but be more general usage possible. The boundary between machine confirmation and machine doubt is to be decided later.

The number of neural network layers depends on the number of features in the input. We haven’t agreed on the list of features yet, but will do more research to find important features.

Some candidate features include:

1) Financial Ratios and Metrics

Price-to-Earnings (P/E) Ratio

Earnings Per Share (EPS)

Price-to-Book (P/B) Ratio

Debt-to-Equity (D/E) Ratio

Return on Equity (ROE)

Return on Assets (ROA)

Return on Investment (ROI)

Free Cash Flow (FCF)

Gross Profit Margin

Operating Profit Margin

Net Profit Margin

Dividend Yield

Dividend Payout Ratio

Current Ratio

Quick Ratio

Interest Coverage Ratio

2) Economic Indicators

Gross Domestic Product (GDP) Growth Rate

Unemployment Rate

Consumer Price Index (CPI)

Producer Price Index (PPI)

Retail Sales Data

Consumer Confidence Index (CCI)

Purchasing Managers' Index (PMI)

3) Market and Stock-specific Metrics

Beta (Volatility measure relative to the market)

Sharpe Ratio (Risk-adjusted return measure)

Standard Deviation of Returns (Measure of stock's price volatility)

Moving Averages (50-day, 200-day) (Trend-following indicator)

Relative Strength Index (RSI) (Momentum indicator)

Market Capitalization

Volatility Index (VIX) (Market volatility indicator)

Depending on the computation power needed for the machine, we may use the Discovery clusters of Northeastern University.
To avoid overfitting, methods such as dropout or batch normalization are available.
One thing important to notice is that, we will not use temporal neural networks such as RNN, GRU or LSTM, because the temporal factor of a stock is disproved by many financial investment experts. In the book *A Random Walk Down Wall Street* by Burton G. Malkiel, he exemplifies the temporal prediction of a human is not better than a monkey throwing dart on the stocks. We use his words as the premise.

The evaluation strategy is to run the test data set on the machine and find out how many times the machine judge the signal correctly.
Specifically, we calculate accuracy measure in Statistics.
accuracy = correct_counter/num_test
accuracy=(TP+TN)/(TP+FP+TN+FN)
At last, we will compare the results using two different strategies on some stocks. The first strategy is to follow the naive crossover strategy just like most people. The second strategy is to use the machine as a second judge on each signal.

The expected outcome is that the second strategy makes much more money than the first strategy because of the power of neural network. The accuracy should be better than 60 percent. In case the initial idea fails, we will use the machine to judge a stock every ten days to decide on dealing instead of depending on the naive strategy signals.

4. Individual Tasks(1-3 paragraphs)

Hongzhen Xu: implement deep learning neural network, collect crossover signals, calculate accuracy, output the dates of each dealing decided by the machine, compare the results with naive strategy.

Jingming Cheng: search for related research papers and practical factors in stock market and suggest a list of features to group members. Collect the data for all features for each stock and make the data easy to import. Eg. Csv file

Che-Yi Wu: involve in discussions such as the architecture of deep learning network and list of features, support and substitute the other two members' tasks when facing obstacles in missions, main drafter of the final report.

Below, we list Jingming Cheng's and Che-Yi Wu's suggestions for finance, economics, statistics, and accounting metrics, along with financial statement data that are commonly used to analyze stock prices and assess investment value. This list is mostly contained in the items from the previous part proposed approach candidate features list. The actual features we will use are still in discussion, but we expect that a number of 20-30 features is demanded for using deep learning neural network.

Suggested list

1. Financial Metrics (from financial statements, measuring financial health)

- **Earnings per Share (EPS)**: Net income divided by total shares, indicating profitability per share.
- **Price-to-Earnings Ratio (P/E)**: Stock price divided by EPS, commonly used for valuation; a lower P/E may indicate undervaluation.
- **Price-to-Book Ratio (P/B)**: Stock price divided by book value per share, used to assess intrinsic value.
- **Book Value per Share**: The company's net asset value divided by total shares, representing liquidation value per share.
- **Cash Flow** (especially Free Cash Flow, FCF): Evaluates cash generated by operations, which shows liquidity and sustainability.
- **Gross Profit Margin and Net Profit Margin**: Measures the ratio of gross and net profit to revenue, evaluating profitability.
- **Debt-to-Equity Ratio**: Ratio of total liabilities to shareholder equity, assessing leverage and financial risk.

2. Economic Indicators

- **Gross Domestic Product (GDP)**: Measures national economic health and is correlated with stock market performance.
- **Interest Rates**: Influence borrowing costs and investment returns; typically set by

central banks (e.g., the Federal Reserve rate).

- **Inflation Rate (CPI)**: Shows the decline in currency purchasing power, impacting real stock returns.
- **Unemployment Rate**: Lower unemployment generally increases consumer spending, which can positively impact the stock market.
- **Balance of Payments**: Reflects a country's capital inflow and outflow, affecting exchange rates and, by extension, stocks.

3. Statistical Indicators (measuring volatility and market trends)

- **Volatility**: Often measured by standard deviation, it reflects the level of risk associated with the stock's price movements.
- **Beta Coefficient**: Indicates the relationship between a stock and overall market movement, assessing systematic risk.
- **Trading Volume**: Measures market participation; high volume often indicates market sentiment shifts.
- **Moving Averages (MA)**: Smooth price data to reveal trends and support/resistance levels over time.

4. Technical Market Indicators

- **Relative Strength Index (RSI)**: A value between 0 and 100, used to determine if a stock is overbought or oversold.
- **Bollinger Bands**: Comprised of a moving average and two standard deviation lines above and below it, indicating price volatility.
- **Momentum Indicator**: Measures the speed of price changes, useful for confirming trend direction.

5. Financial Statement Data

- **Revenue**: Total income over a specific period, indicating company size and market share.
- **Operating Income**: Profit after operating expenses, showing core business profitability.
- **Balance Sheet**: Includes current and non-current assets, current and long-term liabilities, showing asset structure and debt pressure.

- **Return on Equity (ROE) and Return on Investment (ROI)**: Measures the return for shareholders, commonly used to compare profitability across companies.

The study Factors Affecting Stock Prices in the UAE Financial Markets[4] shows that these factors influence stock market :
Earnings per Share (EPS): EPS reflects a company's profitability and is a crucial indicator for investors. A higher EPS generally signals higher potential returns, driving up stock prices and investment value. The study found EPS to be one of the most significant factors affecting stock prices, indicating investor preference for stocks with strong earnings potential.

Gross Domestic Product (GDP): Economic indicators like GDP show the broader economic health and impact corporate performance positively. The study observed that GDP positively influences stock prices, as a growing economy generally boosts corporate earnings, increasing stock demand and investment value.

Money Supply (MS): An increase in money supply can stimulate economic activity, thus enhancing corporate earnings and stock values. The study found that increased liquidity due to a higher money supply positively impacts stock prices.

Consumer Price Index (CPI): Inflation, as measured by CPI, was found to have a negative relationship with stock prices. High inflation increases costs, which may lower corporate profits and thus reduce stock prices and investment value.

Interest Rates (INT): Higher interest rates increase the cost of borrowing, which can reduce corporate profitability and investor returns. The study suggests that higher interest rates are generally associated with lower stock prices, affecting overall investment value negatively.

Note: we use the CS5010 project of Hongzhen Xu for collecting stock prices data and crossovers. The CS5010 project has no further help on this current project.

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