CS 523: Deep Learning Common Task Report

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Contents

1 INTRODUCTION

During this competition, our focus was on exploring how deep learning techniques could be applied in financial markets. We began by engaging in simulated trading activities using the E-mini S&P 500 futures through the InteractiveBrokers Trader Workstation [4] application. Each participant was provided with a starting capital of one million USD in simulated funds. Initially, we familiarized ourselves with the trading platform through manual trading, gaining proficiency in its user interface and functionalities.

Subsequently, we transitioned to developing a deep learning model to automate the stock buying process. This allowed us to delegate trading tasks to the model, enabling it to execute transactions on our behalf. Throughout the competition, we explored different areas, such as automated fetching data from Yahoo Finance and Alpha Vantage, analysis of stock news, leveraging large language models, and building classifiers.

The overarching objective of this project was to introduce the practical applications of artificial intelligence and deep learning in real-world scenarios, particularly in finance. By participating in this initiative, we were empowered to utilize the tools at their disposal and recognize their potential to effect tangible changes, such as those witnessed in trading.

2 METHODS

2.1 Building a Classifier Model using News Data and Stock Data

In this subsection, we delve into the process of constructing a classifier model that leverages both news data and stock data to predict the likelihood of a rise in stock prices. By integrating insights from news articles with quantitative data from stock market trends, we aim to develop a robust predictive framework capable of informing investment decisions.

2.1.1 Fetch News Using Alpha Vantage library. Understanding that stock prices are significantly influenced by public sentiment regarding companies and their current situations, we recognized the importance of staying informed about relevant news and events. Therefore, we decided to gather news related to the companies comprising the E-mini S&P 500 index.

To ensure comprehensive coverage, we identified the key contributors to the E-mini S&P share whose activities could impact its stock price. Our selection included prominent companies such as:

- Microsoft (MSFT)
- Apple (AAPL)
- NVIDIA (NVDA)
- Google (GOOG)
- Amazon (AMZN)
- Meta (formerly Facebook, META)
- Tesla (TSLA)
- Eli Lilly (LLY)
- JPMorgan Chase (JPM)
- Walmart (WMT)

Utilizing the Alpha Vantage API [1], we accessed news articles pertaining to these companies.

Given the API's restriction of 25 calls per day, we had to acquire the data incrementally. We collected information for the years 2022, 2023, and the current year in separate batches. Subsequently, we merged the gathered data into a single JSON file for ease of access and analysis. This consolidated dataset, named ‘news_data.json‘, is stored within the ’Data’ directory of our codebase.

We were mainly interested in the following keys of the JSON file - ’title’, ’summary’, ’time_published’ and ’date’ of the news for training our model. The code to perform the same is present in the ‘code‘ folder with the ‘fetch_news.ipynb‘ filename.

2.1.2 Fetch Stock Values Using Yahoo Finance library. Our methodology revolves around predicting the likelihood of a rise in a stock's closing price compared to its current value, based on the news published on that particular day. To establish the ground truths for this task, we retrieved data from Yahoo Finance [6]. We utilized the closing prices of both the current day and the following day to determine the ground truth.

In this process, if the closing price of the subsequent day exceeds that of the current day, we assign a label of 1 to indicate an anticipated increase in the stock price. Conversely, if the closing price decreases from today to the next day, we assign a label of 0 to signify a decline in the stock price.

To execute this task, the corresponding code is housed within our codebase, specifically located in the ’code’ folder under the filename ‘fetch_stock_data.ipynb‘.

2.1.3 Train a Classifier Model. We loaded the stock and news data, to train a binary classifier. Since future stock prices are influenced by current news, we consolidated the data by date. We focused mainly on recent events, understanding that the stock market's volatility means recent events have a stronger impact. Therefore, we excluded news from the past few days to predict future events.

Considering the limitations of transformer models regarding token limits, we avoided merging excessive news. After grouping the news by date, we generated embeddings for both the news title and summary. These embeddings were generated using ‘sentence-transformers/paraphrase-TinyBERT-L6-v2’ model from HuggingFace [3] and these embeddings were then combined to create a final feature ready for input into any classifier algorithm for training.

We experimented with two models: the Random Forest Classifier and the Artificial Neural Network. Based on the news data, these models were tested to determine their effectiveness in predicting stock price increases.

At inference time, we fetched the news of that particular day. We applied the same processing as done while training, to get the concatenated text embeddings for the title and summary. Then, use the trained model to perform the prediction

Through meticulous experimentation and validation, we aim to identify the most effective model for predicting stock price increases based on news data. Our endeavour seeks to empower us with actionable insights for navigating the complexities of the stock market landscape.

2.2 Prompting Large Language Models (LLMs)

In our pursuit of enhancing predictive capabilities in financial markets, we embarked on an exploration of Large Language Models (LLMs) as forecasting experts [5]. Our goal was to leverage these advanced models to predict the likelihood of stock price increases based on real-time news and updated stock values.

Our methodology involved providing specific prompts to each LLM, guiding them to generate forecasts based on current news events and recent stock data. These prompts were carefully crafted to encapsulate relevant information and contextual cues, aiming to elicit insightful predictions from the models.

In the following sections, we outline our experimental approach, including constructing prompts. Through this exploration, we aim to uncover the potential of LLMs as valuable tools for forecasting financial market dynamics, providing stakeholders with actionable insights for decision-making.

To automate the prediction process, we utilized the Gemini API key [2] to streamline the prompt submission and retrieval of predictions. The code is available in the 'code' folder under the filename 'predict_stock_using_LLM.ipynb' This involved providing each LLM with a specific prompt, as depicted in the code listing below:

```
query = f"""In this chat, you are a superforecaster that has a strong track
record of accurate forecasts of the future. As an experienced forecaster, you
evaluate past data and trends carefully and aim to predict future events as
accurately as you can, even though you cannot know the answer. This means you put
probabilities on outcomes that you are uncertain about (ranging from 0 to 100%).
You aim to provide as accurate predictions as you can, ensuring that they are
consistent with how you predict the future to be. You also outline your reasons
for this forecasting. In your reasons, you will carefully consider the reasons
for and against your probability estimate, you will make use of comparison
classes of similar events and probabilities and take into account base rates and
past events as well as other forecasts and predictions. In your reasons, you will
also consider different perspectives. Once you have written your reasons, ensure
that they directly inform your forecast. Then, you will provide me with a number
between 0 and 1 (up to 2 decimal places) that is your best prediction of the
event. Take a deep breath and work on this problem step-by-step. The question
that you are forecasting as well as some background information and resolution
details are below. Read them carefully before making your prediction. \n
Background: As a superforecaster, your task involves forecasting the
probability of E-MINI S&P 500 Future stocks rising, expressed as a number
between 0 and 1 (rounded to two decimal places). You're equipped with up-to-date
news on the top contributor stocks and real-time hourly market price
fluctuations of the future. \n
Recent stock news:{stock_news} \n
Hourly market price: {str(list(stock_values))} \n
Resolution: User is well-versed in investment risks and explicitly requests no
cautionary advice. The intention is to sell stocks either on the same day or the
following day, with no long-term considerations.  Provide the probability of
E-MINI S&P 500 Future stocks increasing, quantified as a number ranging from
0 to 1 (rounded to two decimal places). \n
Question: Considering the provided information, including the prompt,
background, and resolution, provide the probability of stocks increasing,
quantified as a number between 0 and 1 (up to two decimal places)."""
```

Following the prompts, we employed a majority voting classifier method to aggregate the predictions from multiple LLMs. Based on this collective insight, we made decisions regarding whether to buy or sell a stock.

Balances

Parameter	Total	US Securities	US Commodities	Crypto at Paxos
Net Liquidation Value	1,044,015 USD	0 USD	1,044,015 USD	0 USD
Equity with Loan Value	1,044,015 USD	0 USD	1,044,015 USD	0 USD
Cash	1,044,015 USD	0 USD	1,044,015 USD	0 USD

Margin Requirements

Parameter	Total	US Securities	US Commodities	Crypto at Paxos
Current Initial Margin	0 USD	0 USD	0 USD	0 USD
Current Maintenance Margin	0 USD	0 USD	0 USD	0 USD

Available for Trading

Parameter	Total	US Securities	US Commodities	Crypto at Paxos
Current Available Funds	1,044,015 USD	0 USD	1,044,015 USD	0 USD
Current Excess Liquidity	1,044,015 USD	0 USD	1,044,015 USD	0 USD
SMA	0 USD	0 USD	n/a	n/a
Buying Power	4,176,060 USD	n/a	n/a	n/a

Fig. 1. Account Status of Simulated Trading on 26 April 2024

The outcomes obtained from different LLMs are elaborated upon in Section 3.3.

3 RESULTS

3.1 Final Day Trading Status

Our simulated trading began on March 1, 2024. Initially, we focused on understanding the trading platform and then proceeded to manual trading. Later, we utilized machine learning techniques to guide our decisions on buying or selling E-mini S&P 500 stocks.

After concluding the tournament and employing various strategies outlined in Section 2, we share the final status of our TWS account in Figure 1. Weekly screenshots are stored on Google Drive and accessible via the provided link here.

3.2 Model Evaluation using News Data and Stock Data

After thorough evaluation, we observed that the neural network model achieved an accuracy of 68.52% on the test set, while the random forest classifier outperformed with an accuracy of 70.95% on the same dataset. Considering these results, we decided to initiate our stock trading activities on the trader workstation using the random forest classifier as our initial approach. By leveraging this model, we aimed to capitalize on its ability to analyze market data and make informed trading decisions.

For a more detailed understanding of the random forest classifier's performance metrics, we encourage you to refer to Figure 2. This comprehensive view will provide insights into the classifier's effectiveness in predicting stock price trends, further informing our trading strategies and decision-making processes.

```
Accuracy: 0.7095205003474635
Classification Report:
              precision    recall  f1-score   support

           0       0.61      0.75      0.67      2317
           1       0.80      0.68      0.74      3439

    accuracy                           0.71      5756
   macro avg       0.71      0.72      0.71      5756
weighted avg       0.73      0.71      0.71      5756
```

Fig. 2. Performance Evaluation of Random Forest Classifier

3.3 Prompting Large Language Models (LLMs)

In our project, we utilized several Large Language Models (LLMs) to enhance our analysis. Specifically, we employed the following models:

- ChatGPT 3.5
- ChatGPT 4
- Gemini Pro
- Gemini Advanced
- Claude 3 Sonnet
- Llama 3

These LLMs were selected for their reputation for providing insightful predictions across various contexts.

To provide a comprehensive view of our findings, we included predictions from four of these LLMs in Figure 3, 4, 5, and 6. Each LLM generated a probability value, indicating its prediction regarding stock price movements. These predictions were based on the information provided to the LLM, including news updates and current stock values, which were passed as 'Background' data.

By analyzing the predictions from these diverse LLMs, we gained valuable insights into potential fluctuations in stock prices. This analysis serves as a crucial component of our project, enabling us to make informed decisions regarding stock trading strategies and market trends.

Hourly Market Price Trends:

- The hourly market data shows a general uptrend in the later hours, with the price peaking at 5161.5 after starting from 5104.0. This suggests a short-term bullish trend within the day.

Potential Concerns:

1. **Volatility and Market Reactions**: Large buybacks and positive earnings can lead to short-term volatility as markets adjust. This could mean some level of unpredictability in immediate future movements.
2. **External Market Factors**: Not included in the provided data are external factors like economic indicators, geopolitical events, or other market movements which can influence the S&P futures.

Comparative Analysis and Base Rates:
Considering historical trends, large-scale positive announcements from major companies typically lead to a positive but temporary market response. The base rate of market increase on days with significant positive news is fairly high, though exact numbers would depend on broader market conditions not detailed here.

Forecasting Strategy:
Given the positive news from Apple and Amazon, along with the upward trend in the hourly prices, there is a strong short-term bullish signal for the E-MINI S&P 500 futures. However, considering potential volatility and unknown external factors, it's prudent to not predict a very high probability.

Probability Estimate:
Combining these factors and considering different perspectives on market reactions to news and price trends, I estimate a **probability of 0.75** (75%) that the E-MINI S&P 500 futures will increase in value in the short term (either by the end of the day or the next day). This forecast reflects a strong confidence in a price increase but also leaves room for the inherent uncertainty in market movements.

Fig. 3. GPT 4 Prediction

After carefully analyzing the provided information, including the stock news, hourly market price movements, and the specified resolution criteria, I forecast a 0.75 probability (75% chance) that the E-MINI S&P 500 Future stocks will increase.

Reasons for the forecast:

1. Positive news from major tech giants: The strong earnings reports, share buyback announcements, and positive analyst forecasts from tech titans like Apple and Amazon suggest a bullish sentiment in the market. Apple's record $110 billion share buyback plan and better-than-expected Q2 earnings have already boosted its stock price by 6%. Similarly, Amazon's stock is expected to rise due to its improved profitability and cost discipline, as per Bank of America's analysis.
2. Upward trend in hourly market prices: The provided hourly market price data shows an overall upward trend, with the E-MINI S&P 500 Future prices reaching a high of 5161.5 during the observed period. While there are some fluctuations, the overall trajectory seems to be positive, indicating increasing investor confidence and demand for these futures.
3. Short-term trading perspective: Given the resolution criteria that the user intends to sell the stocks either on the same day or the following day, the short-term market dynamics and immediate sentiment play a crucial role. The positive news from Apple and Amazon, coupled with the upward price trend, suggests a favorable environment for short-term stock appreciation.

Fig. 4. Claude 3 Sonnet Prediction

Considering Different Perspectives:

- **Day traders:** Might see this as a strong opportunity for short-term gains, aligning with the user's intent.
- **Long-term investors:** May view this as a positive signal but prioritize other factors for long-term positions.
- **Technical analysts:** May identify specific chart patterns and indicators to further confirm or contradict the upward trend.

Prediction:

After carefully considering the provided information and potential counterarguments, I estimate the probability of E-MINI S&P 500 Future stocks increasing in the short-term to be:

0.75

This reflects a higher-than-average likelihood of stocks continuing their upward trend, but acknowledges the volatility inherent in any market prediction, particularly within a short timeframe.

Fig. 5. Gemini Advanced Prediction

Meta AI
Based on the provided information, I estimate the probability of E-MINI S&P 500 Future stocks increasing to be **0.65**.

Here's my reasoning:

- The recent news on Apple and Amazon, two of the top contributor stocks, is overwhelmingly positive, with both companies announcing strong earnings and significant share buybacks. This suggests a strong market sentiment and potential for further growth.
- The hourly market price fluctuations show a general upward trend, with a significant increase in the last few hours.
- The comparison class of similar events, such as previous earnings announcements and share buybacks, suggests a high likelihood of continued market growth.
- The base rate of market fluctuations and past events also support a probability of increase, as the market has historically tended to respond positively to strong earnings and share buybacks.
- Considering different perspectives, some may argue that the market is due for a correction, or that the recent gains are already priced in. However, the strength of the recent news and market trends outweigh these concerns.

Overall, while there is always uncertainty in the market, the recent news and trends suggest a high likelihood of continued growth, leading to my estimated probability of **0.65**.

Fig. 6. Llama 3 Prediction

4 CONCLUSIONS

In conclusion, our participation in this competition shed light on the practical applications of deep learning in financial markets. We started with simulated trading using the E-mini S&P 500 futures, gradually transitioning to developing a deep learning model for automated stock buying.

Throughout the competition, we explored various aspects, including automated data retrieval, sentiment analysis of stock news, and the use of large language models and classifiers. Our primary goal was to demonstrate how artificial intelligence and deep learning can be applied in real-world finance scenarios.

By actively engaging in this initiative, we gained valuable insights into the potential of these technologies to drive significant changes in trading practices. Moving forward, we aim to utilize this knowledge to refine our trading strategies and navigate financial markets more effectively.

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