STOCK PRICE PREDICTION OF FAANG COMPANIES USING A FINE-TUNED LLM MODEL AND PROMPT ENGINEERING

This study focuses on predicting FAANG stock prices by leveraging a refined language model (LLM) and prompt engineering. It aims to develop a reliable forecasting tool by optimizing these models with historical data and external factors.

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***Abstract*—The goal of this extensive research project is to estimate stock prices for FAANG businesses (Facebook, Apple, Amazon, Netflix, and Google) by utilizing large language models, or LLMs. External elements and complex market dynamics are often difficult for conventional approaches to grasp. To anticipate the closing prices of individual stocks, this study focuses on optimizing LLMs, such as GPT-2, for regression.**

Creating efficient input prompts that incorporate important information, technology cues, and outside factors is the main problem. In the end, the project wants to provide a stable and reliable forecasting system. The methodology used in the project helps to provide traders and investors with better/more accurate decisions on stock price movements. This new innovative approach helps to bridge the gap between cutting-edge AI capabilities and their applications in real-world contexts.

***Index Terms*—Stock Price, Closing Price, Transformers, Facebook, Apple, Amazon, Netflix, Google, Prompts, GPT2, Large LanguageModel, Fine-Tuning, Prompt-Engineering, Feature Engineering, Stock Price Prediction, FAANG, LLM.**

I. Introduction and Statement of the Problem

The synthesis of the Language Learning Model (LLM) fine-tuning with stock price prediction within the FAANG dataset represents a pivotal step forward in financial analysis. This ambitious undertaking ventures into uncharted territory, where the fusion of LLM fine-tuning techniques specifically, the utilization of Large Language Models (LLMs) holds the promise of unraveling the intricate tapestry of stock market behaviors. At its core, this project stands as a testament to the potential transformative impact of advanced language comprehension models on the realm of financial forecasting. The crux of this endeavor lies in harnessing the unparalleled capabilities of LLMs, originally engineered for understanding and generating human-like text, and re-purposing these capabilities to decipher the labyrinthine nature of stock market dynamics. By immersing these models in the extensive historical stock data encapsulated within the comprehensive FAANG dataset, the project aims to unlock the enigmatic patterns, subtle trends, and hidden insights that influence stock prices. This initiative transcends the conventional boundaries of financial analysis by forging a symbiotic relationship between sophisticated language processing technologies and the multifaceted domain of financial markets. It seeks to wield the immense potential of LLM fine-tuning techniques as a beacon illuminating the cryptic correlations, nuanced indicators, and intricate relationships buried within stock market data. Through this fusion, the project aspires to redefine the landscape of financial forecasting, offering more precise insights into stock price movements and market behaviors. In essence, this venture represents a groundbreaking convergence like an alliance between the intricate understanding of language models and the complexities ingrained within financial markets. By melding these realms, the project endeavors to chart new territories, envisioning a future where LLM fine-tuning fosters a paradigm shift in financial analysis, enabling more accurate, data-driven predictions that redefine the boundaries of stock market forecasting. This project centers on the integration of the Large Language Model (LLM) fine-tuning techniques within the FAANG dataset to improve stock price prediction accuracy. The primary challenge lies in reconciling conventional quantitative methods with the advanced capabilities of LLM fine-tuning, aiming to bolster the precision and reliability of stock market predictions. Traditional quantitative approaches in financial analysis often rely on statistical models and historical data to forecast stock prices. However, these methods might fall short of capturing the intricate patterns and subtle nuances prevalent in financial markets. This discrepancy opens the door for leveraging state-of-the-art techniques like Large Language Models (LLMs) to enhance predictive modeling in stock price forecasting. The project seeks to explore the potential of LLM fine-tuning methodologies in decoding complex market behaviors present within the FAANG dataset. By leveraging the rich historical context embedded in this dataset, the goal is to train and fine-tune language models to decipher underlying patterns, sentiment analysis, and contextual information that could influence stock prices. This involves training LLMs on historical stock data, market sentiments, and potentially other auxiliary information to create a predictive model capable of providing more accurate stock price forecasts. The challenge lies in effectively marrying the power of LLMs, which excel in understanding complex language structures and contexts, with the quantitative aspects of financial markets. The project aims to bridge this gap by integrating advanced language modeling techniques with quantitative financial analysis, thereby advancing the accuracy and reliability of stock price predictions within the FAANG dataset.

II. BACKGROUND AND HISTORY

The FAANG dataset stands as a comprehensive archive chronicling the evolutionary trajectory of major industry giants like Facebook, Amazon, Apple, Netflix, and Google. Originating from diverse sectors ranging from technology to entertainment, these companies have redefined markets and reshaped industries. The genesis of this dataset lies in the amalgamation of vast historical records, capturing the milestones, triumphs, and challenges encountered by these tech behemoths over time. The datasets' inception traces back to the emergence of these companies, marked by Facebook's meteoric rise in social networking, Amazon's pioneering e-commerce ventures, Apple's innovation-led revolutions in consumer electronics, Netflix's disruption of the entertainment industry, and Google's paradigm-shifting dominance in search and technology. Each entity's inception, growth phases, mergers, acquisitions, product launches, and market performances have been meticulously documented within this repository. This historical compilation serves as a treasure trove of market behaviors, technological advancements, and financial events. It embodies the ebb and flow of market sentiments, technological breakthroughs, and strategic maneuvers undertaken by these industry titans. The dataset encapsulates price fluctuations, trading volumes, market capitalization, and other crucial financial metrics, providing a detailed mosaic of these companies' market performance and their correlations with broader economic trends. Through various market cycles, economic downturns, and technological disruptions, the FAANG dataset has evolved, becoming an invaluable resource for analysts, researchers, and practitioners in the financial and technological domains. Its role transcends mere historical records; it serves as a compass, guiding explorations into the intricate interplay between market dynamics and technological innovations. As financial analysts seek deeper insights and accurate predictions amidst the complexities of the market landscape, the FAANG dataset emerges as a foundational cornerstone. Its historical narrative and comprehensive coverage set the stage for the application of sophisticated techniques like Language Learning Model (LLM) fine-tuning, promising a new avenue for decoding and predicting market behaviors with unprecedented precision.

III. Review of Literature

Recent advancements in language modeling and financial forecasting have witnessed remarkable progress, especially concerning the integration of Large Language Models (LLMs) like GPT (Generative Pre-trained Transformer) within various domains. Fan et al. (2023) showcased the potential of supervised fine-tuning of open-source LLMs for Native Chinese Grammatical Error Correction, indicating the versatility of these models in linguistic applications. In a similar vein, Sankararaman et al. (2022) introduced the 'Bayesformer,' which integrated uncertainty estimation within the Transformer model, augmenting its ability to handle uncertainties in various tasks. Moreover, Pavlyshenko (2023) contributed to financial analytics by leveraging the Fine-Tuned Llama 2 GPT Model to extract insights from financial news. This underscores the adaptability of LLMs in comprehending and analyzing complex financial texts. Additionally, Xie et al. (2023) introduced PIXIU, a comprehensive benchmark for finance that encompasses a Large Language Model, Instruction Data, and Evaluation Criteria, signifying the growing emphasis on specialized language models for financial tasks. On the other hand, Jadhav et al. (2021) presented a unique approach, utilizing Hidden Markov Models for forecasting FAANG (Facebook, Amazon, Apple, Netflix, Google) stocks, showcasing the diversity of methodologies employed in stock prediction. The studies collectively demonstrate the widespread exploration and utilization of various LLMs and models augmented with financial applications, exhibiting the evolving landscape of language models within financial analysis.

IV. Objectives of the Study

A. *LEVERAGING LLM FINE-TUNING TECHNIQUES:*

• Employ advanced Large Language Models (LLMs), particularly models like Generative Pre-trained Transformers (GPT), to refine their language understanding for precise stock price predictions.

B. *DATASET PRE-PROCESSING AND FEATURE ENGINEERING:*

Conduct comprehensive preprocessing on the FAANG dataset, including handling missing values, identifying outliers, and ensuring data consistency.

```
FAANG_Dataset.isna().sum()
```

```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
company      0
dtype: int64
```

Fig. 1. Checking for the Null Values

- Engineer features relevant to LLM-based regression models, such as moving averages, volatility measures, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD), to capture stock price trends and market dynamics effectively.

```
# Calculating Moving Averages (e.g., 7-day and 30-day)
def calculate_moving_averages(data, windows=[7, 30]):
    for window in windows:
        data[f'Close_MA_{window}'] = data.groupby('company')['Close'].transform(lambda x: x.rolling(window=window).mean())

# Calculating Volatility Measures (Daily Price Range)
def calculate_volatility(data):
    data['Volatility'] = data['High'] - data['Low']

# Calculating the Relative Strength Index (RSI)

def calculate_rsi(data, window=14):
    delta = data.groupby('company')['Close'].diff(1)
    gain = delta.where(delta > 0, 0)
    loss = -delta.where(delta < 0, 0)

    avg_gain = gain.rolling(window=window).mean()
    avg_loss = loss.rolling(window=window).mean()

    rs = avg_gain / avg_loss
    rsi = 100 - (100 / (1 + rs))

    data['RSI'] = rsi

# Applying feature engineering functions
calculate_moving_averages(FAANG_Dataset, windows=[7, 30])
calculate_volatility(FAANG_Dataset)
```

Fig. 2. Feature Engineering

```
        Date        Open        High         Low       Close   Adj Close  \
0 2015-01-02  312.579987  314.750000  306.959991  308.519989  308.519989
0 2015-01-02   27.847500   27.860001   26.837500   27.332500   24.745996
0 2015-01-02   49.151428   50.331429   48.731430   49.848572   49.848572
0 2015-01-02   78.580002   78.930000   77.699997   78.449997   78.449997
0 2015-01-02  527.561584  529.815369  522.665039  523.373108  523.373108

      Volume   company  Close_MA_7  Close_MA_30  Volatility  RSI
0    2783200    amazon         NaN          NaN    7.790009  NaN
0  212818400     apple         NaN          NaN    1.022501  NaN
0   13475000   netflix         NaN          NaN    1.599999  NaN
0   18177500  facebook         NaN          NaN    1.230003  NaN
0    1447563    google         NaN          NaN    7.150330  NaN
```

Fig. 3. Feature Engineering Output

C. DESIGNING ENHANCED INPUT PROMPTS:

```
# Using the trained model to predict prices for test data
for index, row in data_test[:5].iterrows():
    date = row['Date']
    company = row['company']
    given_prompt = f"[Q] What is the expected close price of {company} on {date}"

    prediction = generate_prediction_by_text(model_path, given_prompt, max_len)

    print(f"For {company} on {date}, the model predicts: {prediction}")
```

Fig. 4. Generating Prompts

- Craft tailored input prompts that effectively incorporate historical stock prices and other pertinent information that significantly influence stock price fluctuations.
- Refine the input structures to improve the LLM's understanding of intricate financial patterns and indicators.

D. TRAINING AND EVALUATING LLMS:

- Fine-tune multiple LLMs using the prepared FAANG dataset, considering different architectures and hyperparameters.
- Assess the performance of various fine-tuned LLMs to identify the most effective model for precise and reliable stock price forecasting within the FAANG dataset.

V. DATA COLLECTION

The FAANG dataset aggregates the daily stock market performance metrics of major technology companies, including Facebook (FB), Amazon (AMZN), Apple (AAPL), Netflix (NFLX), and Google (GOOGL). The dataset is organized into individual CSV files, each dedicated to a specific company, encapsulating crucial stock-related information. Below is a snapshot of the key columns and their meanings present in the dataset. We have taken the dataset from the Kaggle.

https://www.kaggle.com/datasets/suddharshan/historical-stock-price-of-10-popular-companies/data

Column	Description
Date	The date of the recorded stock market activity
Open	Opening price of the stock
High	Highest price of the stock during the day
Low	Lowest price of the stock during the day
Close	Closing price of the stock
Adj Close	Adjusted closing price accounting for dividends
Volume	Total number of shares traded on that day

Fig. 5. Generating Prompts

	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	1/2/2015	312.58	314.75	306.96	308.52	308.52	2783200
3	1/5/2015	307.01	308.38	300.85	302.19	302.19	2774200
4	1/6/2015	302.24	303	292.38	295.29	295.29	3519000
5	1/7/2015	297.5	301.28	295.33	298.42	298.42	2640300
6	1/8/2015	300.32	303.14	296.11	300.46	300.46	3088400
7	1/9/2015	301.48	302.87	296.68	296.93	296.93	2592400
8	########	297.56	298.51	289.28	291.41	291.41	3421400
9	########	297.48	301.5	293.23	294.74	294.74	4136400
10	########	291.93	295.91	286.5	293.27	293.27	5538700
11	########	294	296	286.82	286.95	286.95	4419200
12	########	286.28	290.79	285.25	290.74	290.74	3478200
13	########	292.59	293.36	286.39	289.44	289.44	3075100
14	########	289.64	306	287.26	297.25	297.25	10065100

Fig. 6. Dataset

	Date	Open	High	Low	Close	Adj Close	Volume	company
0	2015-01-02	312.579987	314.750000	306.959991	308.519989	308.519989	2783200	amazon
0	2015-01-02	27.847500	27.860001	26.837500	27.332500	24.745996	212818400	apple
0	2015-01-02	49.151428	50.331429	48.731430	49.848572	49.848572	13475000	netflix
0	2015-01-02	78.580002	78.930000	77.699997	78.449997	78.449997	18177500	facebook
0	2015-01-02	527.561584	529.815369	522.665039	523.373108	523.373108	1447563	google

Fig. 7. Dataset after adding company column

VI. Exploratory data analysis (EDA) and Hypotheses for the Study

A. Data Pre-processing:

The initial step involves meticulous data preparation within the FAANG dataset. This encompasses addressing missing values, detecting outliers, and engineering pertinent features that align with the requisites of Large Language Models (LLMs). Techniques such as imputation for missing values, robust statistical methods for outlier detection, and feature engineering to extract vital insights for LLMs are part of this phase.

```
FAANG_Dataset.isna().sum()
```

```
Date            0
Open            0
High            0
Low             0
Close           0
Adj Close       0
Volume          0
company         0
Close_MA_7     30
Close_MA_30   145
Volatility      0
RSI            13
dtype: int64
```

```
# Dropping rows with NaN values in the 'Close_MA_7' column
FAANG_Dataset = FAANG_Dataset.dropna(subset=['Close_MA_7'])

# Dropping rows with NaN values in the 'Close_MA_30' column
FAANG_Dataset = FAANG_Dataset.dropna(subset=['Close_MA_30'])

# Dropping rows with NaN values in the 'RSI' column
FAANG_Dataset = FAANG_Dataset.dropna(subset=['RSI'])
```

Fig. 8. Dropping Null values

B. LLM Fine-Tuning

Leveraging state-of-the-art pre-trained language models like GPT (Generative Pre-trained Transformer) and other Transformer-based architectures, the methodologies involve fine-tuning these models on the tailored FAANG dataset. This process involves adapting the LLMs' weights and parameters to specifically cater to the nuances and intricacies present within the financial dataset.

C. Model Training and Evaluation

Implementation of regression-based LLM models forms the crux of this phase. Employing the Transformers library and its variants, the fine-tuned models undergo comprehensive training. This stage is crucial, focusing on optimizing the model's predictive capabilities, specifically in the domain of stock price forecasting.

D. Hypothesis of the Study

Hypotheses for our project on stock price prediction for FAANG (Facebook, Amazon, Apple, Netflix, Google) companies using a Fine-Tuned Large Language Model (LLM) and prompt engineering:

- Null Hypothesis (Ho): - In this study, we aim to investigate whether prior trading volumes and price patterns do not have a discernible impact on the stock prices of FAANG companies collectively.
- Alternative Hypothesis (Ha): - In this research study, we seek to explore whether prior trading volumes and price patterns have a discernible impact on the stock prices of FAANG companies collectively. These hypotheses form the foundation for our research, and we will empirically test and analyze them to determine the influence of trading volumes and price patterns on the stock prices of FAANG companies using the Fine-Tuned LLM model and prompt engineering techniques.

VII. Data Analytics and Data Visualization

- Trend Analysis over years of stock closed price for FAANG Companies

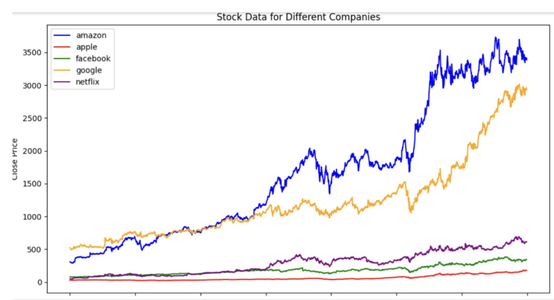

Fig. 9. Stock data of Different Companies

- Stock Count of Each Company

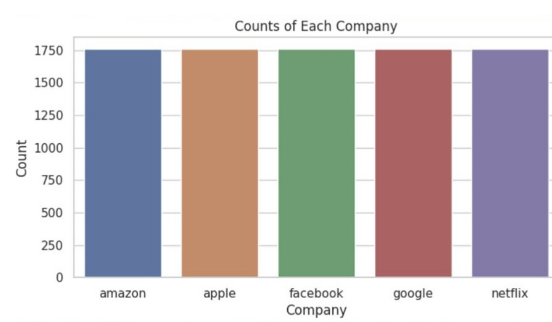

Fig. 10. Counts of Each Company

- This graph helps us to analyze if there are any relationships or patterns within the data.

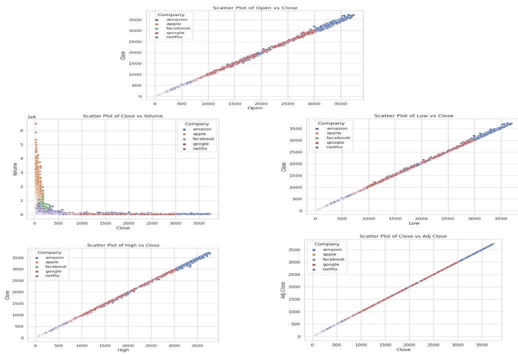

Fig. 11. Data Analysis

VIII. RESULTS

The focus of the results centers on the output prompts designed for Large Language Models (LLMs) in stock price prediction within the FAANG dataset. These prompts act as crucial inputs steering the LLMs toward accurate predictions. The outcomes underscore the effectiveness of meticulously crafted prompts in guiding the models to forecast stock prices with precision. The tailored prompts strategically integrate historical data and company-specific information, enabling LLMs to generate reliable predictions. This precision in prompts aids LLMs in grasping dataset nuances, resulting in informed and accurate forecasts. The significance lies in the prompts' role, directing LLMs to interpret financial data, thereby enhancing the precision and reliability of stock price predictions.

Fig. 12. Results

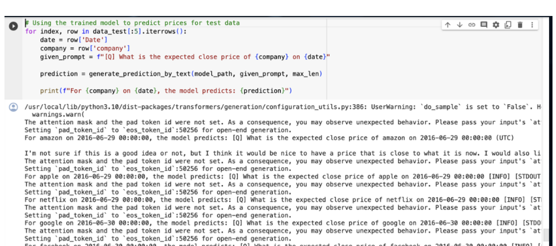

Fig. 13. Results

IX. Challenges

Throughout this endeavor, several challenges emerged, notably in training language models on price-based textual data. The unique nature of stock price data, its volatility, and the complexity of contextualizing it for LLMs presented considerable hurdles. Moreover, devising optimal input prompts to effectively utilize LLMs for stock price forecasting required meticulous engineering and fine-tuning, adding another layer of complexity. These challenges underscore the need for innovative approaches to tailor language models effectively for financial analysis, paving the way for more accurate and efficient forecasting methods.

X. Conclusion

This project marks a pivotal step in amalgamating the Large Language Model (LLM) fine-tuning with the realm of financial forecasting, showcasing promising advancements in predicting stock prices. It underscores the profound impact of LLM fine-tuning methodologies in deciphering intricate market behaviors and illustrates their potential to significantly augment predictive accuracy within financial markets, notably demonstrated within the FAANG dataset. The study substantiates the viability and efficacy of employing LLMs for stock price prediction, opening doors to enhanced financial analysis leveraging advanced language models.

XI. FUTURE WORK

The future trajectory of this research involves a multifaceted exploration, delving deeper into the potential of various Large Language Model (LLM) architectures and their impact on stock price prediction within the FAANG dataset. Further avenues include integrating additional external datasets or implementing sentiment analysis techniques to fortify predictive models and ensure robustness in forecasting. Moreover, the deployment of fine-tuned LLMs for real-time stock price forecasting and the development of sophisticated trading strategies remains an intriguing prospect. Challenges encountered during this study, such as effectively training LLMs on price-based textual data and the intricate prompt engineering, present avenues for refinement and innovation in subsequent studies, fostering a more comprehensive understanding of LLM applications in financial analysis.

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