# CS 6120: Equities Trading Strategy using Aspect Based Sentiment Analysis

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## Abstract

This research investigates the use of social media sentiment analysis combined with traditional market indicators to enhance equities trading strategies. By analyzing Reddit posts from the WallStreetBets subreddit, sentiment predictions are integrated with indicators such as price trends and moving averages to inform trading decisions. The study employs transformer-based models, notably GPT-Neo, for sentiment classification, which demonstrated superior performance. The resulting strategy, tested over 18 months, yielded a return of 8.87%, showcasing the potential of integrating sentiment analysis with conventional trading metrics to improve market strategies

## 1 Introduction

The increasing influence of social media on financial markets has opened new avenues for leveraging user-generated content to enhance trading strategies. Platforms like Reddit, particularly the WallStreetBets subreddit, have become hubs for retail investors to share opinions and discuss market trends, significantly influencing stock prices. This research aims to integrate sentiment analysis of these social media discussions with traditional market indicators to develop a robust equity trading strategy. We employ an aspect-based sentiment analysis approach, classifying Reddit posts into positive, negative, or neutral sentiments using a pre-trained Part-of-Speech (POS) tagger to extract nouns and transformer-based models such as GPT-2, BERT, and GPT-Neo. By combining these sentiment predictions with traditional trading indicators, we aim to construct a trend-following strategy capable of adapting to market dynamics. This study highlights the value of integrating social media sentiment with conventional metrics and underscores the practical application of advanced natural language processing (NLP) techniques in financial decision-making.

## 2 Background/Related Work

The integration of sentiment analysis into trading strategies has been explored extensively, enhancing financial decision-making. Kumar and Shankar (2021) demonstrated the potential of using sentiment from social media to predict market movements, focusing on Reddit's WallStreetBets subreddit. Our work builds on this by employing advanced transformer models for sentiment classification and integrating these insights with traditional trading indicators. Chen et al. (2022) utilized aspect-based sentiment analysis (ABSA) in financial contexts, focusing on news articles. Zhang et al. (2020) proposed a Deep Q-Network model incorporating composite sentiment scores from multiple investor types. Our study specifically analyzes retail investor sentiment from social media. Liu et al. (2019) introduced a multimodal approach to ABSA by integrating text and image data. In contrast, our research focuses solely on textual data from Reddit posts, leveraging advanced NLP techniques to capture nuanced sentiments relevant to equities trading. Our research advances this field by targeting retail investor sentiment and integrating it with traditional market indicators to enhance trading strategies.

## 3 Data

### 3.1 Data for Sentiment Prediction

The Reddit dataset consists of ~50k posts from the WallStreetBets subreddit, encompassing four key classes: date, title, body, and sentiment. Preprocessing began with handling missing values by dropping rows with missing titles and replacing empty body entries with "No content." Text



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cleaning involved removing special characters, mentions, URLs, and numbers, converting all text to lowercase, and eliminating single-character words and excessive spaces. A pre-trained Part-of-Speech (POS) tagger extracted noun aspects from the cleaned text, which were then concatenated with contextual data using the separator tags [SEP] to indicate the end of the aspect and the start of the context, additionally to indicate the start of the aspect [CLS] tag was used. The data was then tokenized using a pre-trained tokenizer model. This processed dataset was used for sentiment classification, with the resulting predictions integrated with traditional trading indicators to guide buy and sell decisions in the trading strategy.

### 3.2 Data for Trading Strategy

Our trading strategy utilized financial data from Yahoo Finance and sentiment data from Reddit posts, covering September 2020 to September 2022. This timeframe was chosen to match the availability of Reddit sentiment data. We focused on Amazon (AMZN), Tesla (TSLA), and GameStop (GME) due to their frequent mentions on the *WallStreetBets* subreddit and significant volatility, notably GameStop in January 2021.The dataset included daily open and close prices, trading volume, and a 100-day Simple Moving Average (SMA) of closing prices to identify price trends. Sentiment predictions from Reddit posts were integrated by determining the daily mode of sentiments—positive, negative, or neutral. This integration allowed us to incorporate social media-driven retail investor sentiment into our trading decisions, complementing traditional market indicators.

## 4 Data

### 4.1 Sentiment Classification

Advanced transformer-based models were utilized for sentiment classification, integrating their predictions into a trend-following trading strategy. The models employed include BERT, GPT-2, and GPT-Neo, chosen for their ability to extract meaningful insights from textual data.

**Sentiment Classification Pipeline**

The pipeline begins with preprocessing Reddit posts from the *WallStreetBets* subreddit. This includes cleaning and Part-of-Speech (POS) tagging for aspect extraction. The processed posts are then input into the transformer models, which are fine-tuned specifically for sentiment classification tasks.

**Models Used**

- **BERT (Bidirectional Encoder Representations from Transformers)**: BERT is designed to analyze both left and right contexts of a word, making it effective for text classification (Devlin et al., 2019). It was fine-tuned on the *WallStreetBets* dataset, using embeddings from the [CLS] token for sentiment prediction. BERT's bidirectional nature enhances its understanding of complex linguistic structures in financial discussions.
- **GPT-2 (Generative Pre-trained Transformer 2)**: GPT-2 is a unidirectional model trained to predict the next token in a sequence, excelling at generating contextual embeddings (Radford et al., 2019). Adapted for sentiment classification by adding a classifier layer, GPT-2 captures subtle language patterns and idiomatic expressions common in social media stock discussions.
- **GPT-Neo**: This open-source implementation of the GPT architecture was selected for its scalability and adaptability (Black et al., 2021). It outperformed BERT and GPT-2, achieving the highest accuracy in sentiment classification, thus significantly enhancing the trading strategy's effectiveness. Its large model size and diverse training data allow it to capture complex relationships in financial text.

### 4.2 Trading Strategy

Our strategy uses price, volume, and the standard moving average (SMA) to guide trading decisions, employing both long and short positions. Going long involves buying a stock expecting a price rise, while going short means selling a stock not owned, intending to repurchase it at a lower price.



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- **Long Entry**: Initiate when price and volume exceed n-day SMAs, indicating upward momentum.
- **Long Exit:** Close when a target profit of n% is achieved.
- **Short Entry:** Initiate when price and volume fall below n-day SMAs, suggesting downward momentum.
- **Short Exit:** Cover when a target profit of n% is reached.
- **Stop Loss:** Set at m% to automatically close positions against adverse movements.

Parameters n (SMA look-back and target profit) and m (stop loss) are optimized using historical data, allowing the strategy to capitalize on trends while managing risks.

# 5 Methods

## 5.1 Sentiment Classification

In our experiment, we implemented aspect-based sentiment classifiers using pre-trained BERT, GPT-2, and GPT-Neo models. Each model architecture consisted of a frozen transformer base, a fully connected layer, ReLU activation, dropout, and an output layer. We used model-specific tokenizers to preprocess the input data. The dataset was split 50-30-20 for training, validation, and testing. For hyperparameter tuning, we experimented with different learning rates and optimizers. Training occurred on Google Colab with an NVIDIA T4 GPU for 10 epochs. We monitored training and validation accuracy and loss. For each transformer model, we selected the combination of hyperparameters that yielded the highest accuracy during training.

## 5.2 Trading Strategy

To evaluate our trading strategy's effectiveness, To evaluate the effectiveness of our trading strategy, we created a dataset that integrated sentiment predictions with trading metrics. For each date, the sentiment most frequently cited in Reddit posts was assigned as the daily sentiment. The trading strategy was implemented using the Backtrader API, allowing us to simulate trades over an 18-month period. We manually tested various configurations of target returns, stop loss values, and look-back periods for the simple moving average (SMA) to optimize performance. Through this process, we determined that a target return of 20%, a stop loss of 10%, and a 100-day look-back period for the SMA yielded the best results. This experimental setup demonstrates the practical application of integrating sentiment analysis with traditional market indicators in developing a robust trading strategy.

# 6 Results

## 6.1 Sentiment Classification

For sentiment classification, upon running the experiments as described in section 5.1, we received the success metrics as shown in the Table 1. For both GPT-2 and GPT-Neo we got similar F1-Scores. However, since our dataset is balanced accuracy is a fair indicator to judge the performance of the models and compare them. Fig. 1 & 2 show the accuracy and loss learning curves respectively. As seen in the loss learning curve the direction of the training loss is still downward which and the gap between the curves might still decrease if the validation loss also decreases further in which case training for further epochs might help in getting a better accuracy. We got the best model performance for GPT-Neo for an $lr = 0.5$ and Adam optimizer.

| Model | Acc. | Precision | Recall | F1-Score |
|---|---|---|---|---|
| BERT | 71% | 68% | 70% | 67% |
| GPT-2 | 86% | 74% | 85% | 75% |
| GPT-Neo | 88% | 73% | 87% | 75% |

Table 1

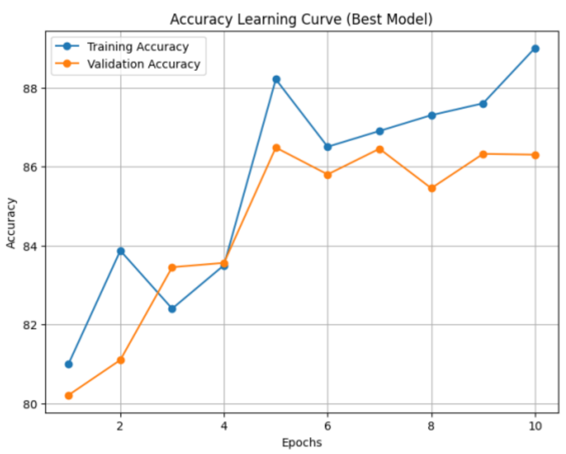


Figure 1


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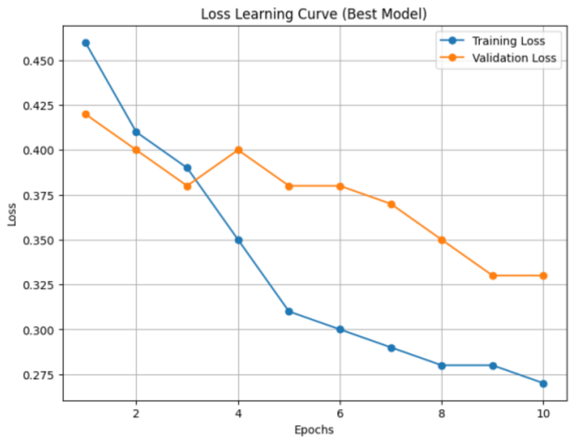


Figure 2

## 6.2 Trading Strategy

For the trading strategy combined with sentiment predictions we ran simulation with a starting portfolio value of $1000 and ran the simulation for 18 months and ended with around $1088.7 or 8.87% return. Fig. 3 shows the portfolio value over time which is the P&L chart for the strategy. The strategy provides a higher return compared to an annualized return of around 4% usually observed as a benchmark performance provided by government bonds, i.e. the bonds issued by the US government paying an interest on the deposit.

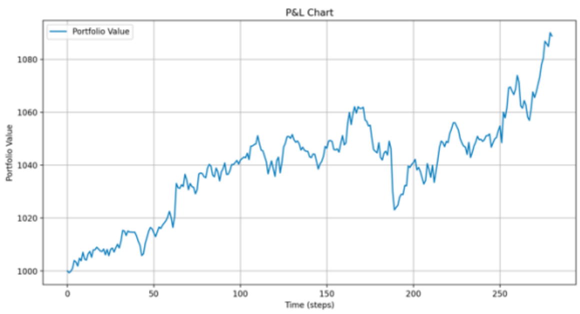


Figure 3

# 7 Conclusions

Currently, the strategy we developed is tested upon historical data through simulators, however, one of the limitations currently is that the continuous scraping and sentiment prediction on daily basis would be required to deploy the strategy in real time to take trades. It is also worth noting that the reddit posts might become irrelevant to the stocks currently chosen which might lead to the strategy failing. For sentiment prediction, we might want to try different methodologies other than aspect based classification such as leveraging knowledge graphs to enhance the prediction results and compare them with our current models.

# 8 References

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