Algorithmically Trading like a Human with GPT-J

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Abstract—The abstract goes here.

I. INTRODUCTION

Algorithmic trading has become the dominant way of buying and selling securities. In the U.S. stock market, algorithms account for 70-80% of trading volume [1]. The next generation of trading algorithms use neural networks to improve prediction accuracy. However, current opinion states neural networks can only increase efficiency by about 10% and that neural networks are not capable of inventing winning trading ideas [2]. We theorize that neural networks are capable of much more. By scaling the number of network parameters into the billions, training the network on a massive dataset which captures the complexities of human behavior, and then making inferences from current and by feeding the network with current news and opinons we believe that neural networks can model the world accurately enough to discover winning, novel trade ideas. Thankfully, the creators of GPT-J have already created such a neural network [3]. GPT-J is a transformer network [4] that has been trained on an 825GiB language modelling data set called The Pile [5]. We propose that with adequate fine-tuning and well engineered prompts, GPT-J can learn to trade like a human by reading the news, social media, and other sources such as SEC filings.

In this paper we will first implement a trading algorithm based on GPT-J, then we will evaluate the algorithm's prediction accuracy and compare it to the accuracy of similar algorithms. Finally, we will evaluate the real-world profitability of the algorithm using both backtesting and live market data.

In summary, as algorihmic traders seek to employ increasingly competitive and complex trading algorithms, we intend to evaluate the viability of using GPT languange models to drive trading decisions. To achieve this goal we must first implement a trading algorithm based on GPT-J, then evaluate the accuracy of the algorithm's predictions, and finally evaluate the real-world profitability of the algorithm.

The contents of this paper are as follows: First we will explore competing algorithms and methods and how they compare with ours in section 2. Then we will describe our algorithm in section 3. Finally, we will evaluate our algorithm's accuracy and profitability using both backtesting and live market data in section 4.

II. BACKGROUND & RELATED WORKS

Many neural network structures and methods have been used to create trading algorithms. Some types include:

- Recurrent neural networks (RNNs) & Long short-term memory (LSTMs) [6][7].
  These are the most widely used network architectures for trading [8]. An LSTM trained on 900,000 sequences of length 30 days of Chinese stock market data yeilded an improvement of 12.9% in prediction accuracy over a random guess [9].
- Convolutional Neural Networks (CNNs) [8]
  CNNs can be used by converting time-series data into images [10]. Or they can be used to extract sentiment features from text [11].
- Deep reinforment learning (DRN).
  - Deep Q-learning [12] [13].
  - Deep robust reinforcement learning [14].
- Conventional deep learning [15].
- Transformer networks [16].

Most relevent to our work are methods that incorperate sentiment analysis of news sources. Mehta et al. (2021) evaluated a sentiment analysis methods and found that LSTMs could properly classify news tweets as indicative of positive or negative price movement with an accuracy of 92% correct [7]. Nan & Zaiane (2020) found that adding sentiment analysis to a Deep-Q learning algorithm could improve the sharpe ratio of the agent by a factor greater than 2 in their test cases. [13].

By our estimation, the vast majortity of previous works involving sentiment analysis used a pre-processing step to extract sentiment from the news, and then embedded those features into a time-series dataset. News sources were often limited to headlines, tweets and small snippits because of the memory limitations of RNN sentiment classifiers. With the indruduction of large transformer networks [4], capable of processing large amounts of text like OpenAi's GPT-3 [17] or GPT-J [18], we believe a new class of trading network can be created. Our method will encode the current world state in a large text-input wich combines sentiment, real-world facts, and stock price data into a single input. We believe that this new network can be trained to learn to trade like a human.

III. EXECUTION PLAN

A. Requirements & Goals

1) Functional requirements (user stories):

- As finance researchers, we want to quantify the ability of news releases, SEC filings, and social media posts to move stock prices.
- As AI researchers, we want to evaluate the viability of using GPT-J as a stock movement indicator so that we can understand the power of GPT-J to understand complex real-world interactions.
- As algorithmic traders, we want to evaluate the viability of using GPT-J as a stock movement indicator so that I can make more-informed trading decisions.

2) Non-functional requirements:

- We will evaluate the correlations between the following items:
  a) The release of SEC filings for company X and large movements in the stock price of company X.
  b) The release of news stories mentioning company X and large movements in the stock price of company X.
  c) The posting of tweets or other social media posts mentioning company X and large movements in the stock price of company X.
- We will evaluate the best ways of formatting prompts for GPT-J to increase output accuracy and consistency across varying inputs. Some options might include:
  a) Providing a form for GPT-J to fill out appended to the end of the input data.
  b) Asking GPT-J a direct question appended to the end of the input data.
  c) Appending a universe current stock prices to the beginning of the input.
  d) Appending multiple news stories from the past days and weeks at the beginning of the input.
- We will deploy the best model from my previous evaluations and test it on live stock market data. I will compare the model's performance against market indices like the S&P 500.

IV. IMPLEMENTATION

V. CONCLUSION

The conclusion goes here.

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Fig. 1. Execution Flow

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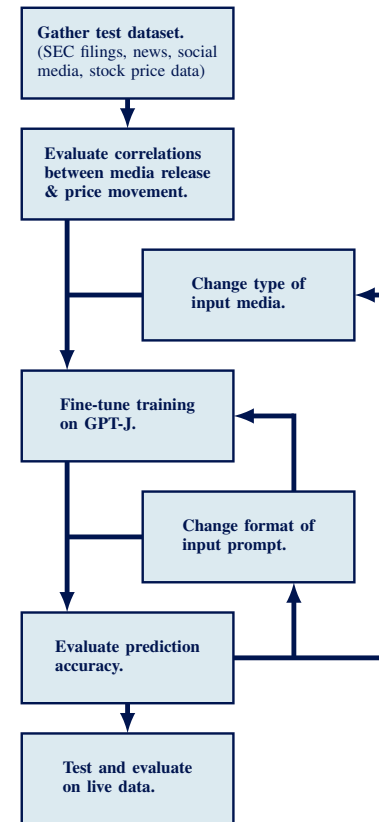
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