Final Capstone Project:

Algorithmic Stock Trading System

Group 6: Nathan Metheny, Javon Kitson, Adam Graves

University of San Diego

AAI-590: Capstone Project

Professor: Anna Marbut

April 15, 2024

Introduction

Our objective is to demonstrate the application of Deep Reinforcement Learning (DRL) in the domain of algorithmic stock trading. By leveraging advanced machine learning techniques, we aim to develop a system capable of taking a range of input matrix and then making informed trading decisions autonomously. This system is designed to adapt dynamically to the fluctuating stock market while aligning with the personalized risk tolerance of each user. This involves the creation of a model that can analyze investors portfolio data, calculate a risk factor that is attached to each individual's portfolio, historical stock data, understand market trends, and execute trades with the goal of maximizing returns. The demonstration will cover the setup, training, and evaluation of the DRL model, showcasing its potential to outperform traditional trading strategies.

In the core of our system, each trader's portfolio is analyzed to determine a unique risk factor, which is pivotal in customizing the trading strategy. This risk factor is derived from a comprehensive analysis of the individual's past trading history, financial goals, and risk tolerance. It serves as a critical input to the DRL algorithm, ensuring that the trading decisions not only pursue profitability but also conform to the individual's risk appetite. This approach allows our system to manage the portfolio proactively, executing trades that optimize returns while mitigating risk exposure in line with the trader's preferences, and regulatory bodies.

Integrating the individual risk factor into the DRL framework involves training the model to recognize and react to market signals in the context of the user's risk profile and thus the restrictions. The model's reference behavior is designed to balance risk and reward efficiently, guiding the trading algorithm to make decisions that align with the expected risk-adjusted returns. This integration ensures that the system remains robust and responsive, capable of navigating market volatilities while adhering to the risk constraints.

In addition to the technical implementation, we will explore the theoretical foundations of reinforcement learning and its suitability for financial markets. This includes discussing the challenges of applying DRL in a highly volatile environment, such as stock trading, and the strategies used to mitigate these risks. Our demonstration aims to provide a comprehensive overview of how deep reinforcement learning can be utilized to innovate in the field of stock trading, offering insights into both its capabilities and limitations.

Data Summary

The dataset used in this Deep Reinforcement Learning Stock Trading is a paid a licensed dataset from Firstrate Data.

Data Information:

FREQUENCY	DATE RANGE	NUMBER OF TICKERS
1-minute, 5-minute, 30-minute, 1-hour 1-day	Jan 2005 - Mar 2024 (see below dates for each ticker)	10120 Tickers

The bundle comprises 1-minute/5-min/30-min/1-hour intraday data as well as daily end-of-day data for:

7531 most liquid US stocks (includes all active Russell 3000, S&P500, Nasdaq 100, and DJI stocks)

- 2527 most liquid ETFs
- 460 delisted stocks

Both stocks and ETFs are adjusted for splits/dividends, out-of-hours trades are included.

Demonstration comprises historical stock data, including open, high, low, close prices, and volume for a selection of stocks over a specified period. This data is essential for training our DRL model, allowing it to learn and make predictions about future stock movements based on past trends. The dataset includes a diverse range of stocks from various sectors, ensuring a comprehensive learning experience for the model. The period covered by the dataset is from [start_date] to [end_date], encompassing 10,120 stocks. We have structured the system to train and trade on a subset of the dataset that corresponds with the predefined groupings within the stock market (SP 100, DOW 30, NAS 100, etc.). This rich dataset serves as the foundation for our demonstration, enabling the DRL model to simulate trading strategies and evaluate their performance in a controlled, paper trading environment. To enhance the predictive capabilities of our Deep Reinforcement Learning (DRL) model and provide a more nuanced understanding of the stock market dynamics, we augment select variables within our dataset. This augmentation process involves creating new variables or modifying existing ones to include derived metrics, such as moving averages, volatility indicators, and technical analysis signals. These augmented variables offer additional insights into market trends, momentum, and potential reversal points, which are crucial for making informed trading decisions.

In addition we have the portfolio data which is derived from our system input by the paid clients. In this the system builds an account that has some feature engineering to build a risk factor that will be part of the trading model.

Background Information

Current popular algorithmic stock trading systems, such as TradeStation (tradestation.com), have been based on the ability to predict the trading price of the stock on a day-to-day basis. As they advanced, they had the ability to go deeper into the prediction at a certain point of time. The foundation of this was the ability to trade on the condition of the limit price entered.

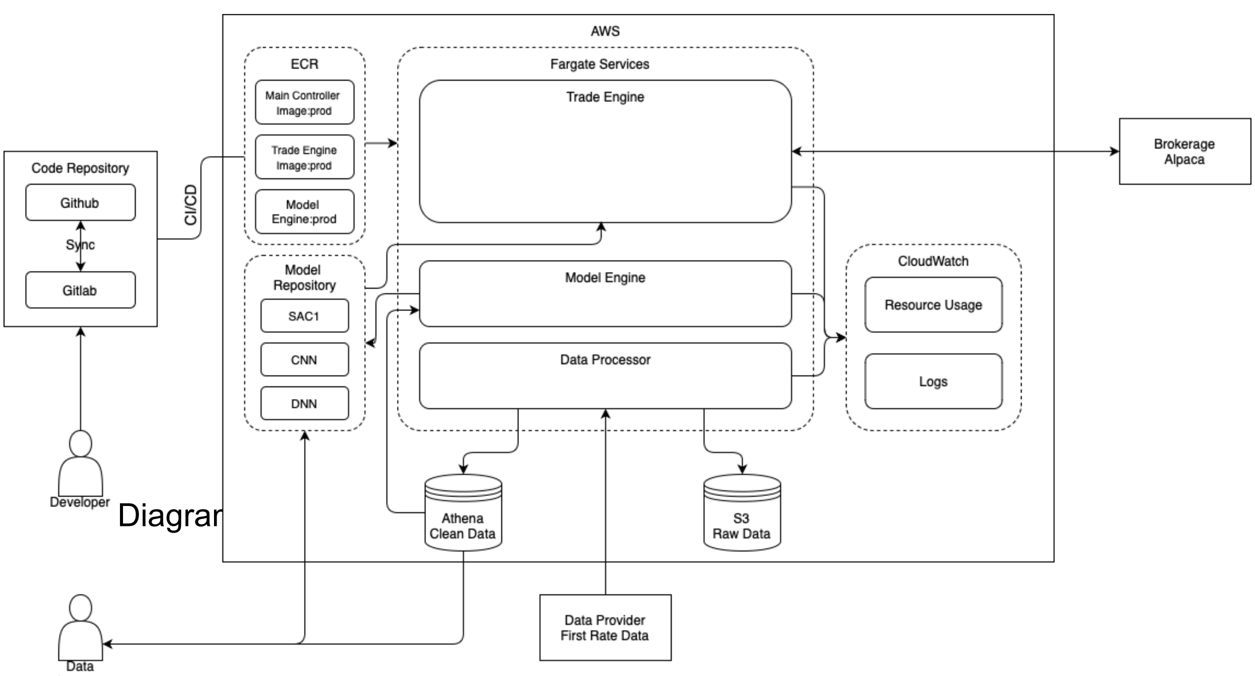
With our system we aim to alleviate the need to trade by a limit price and build a better algorithm that will rely on our DRL AI model and have the ability to trade at market price and still be successful.

To enhance the predictive capabilities of our Deep Reinforcement Learning (DRL) model and provide a more nuanced understanding of the stock market dynamics, we augment select variables within our dataset. We break this down into two sets of logical variables; one is the trading variables and the second is the portfolio variables. This augmentation process involves creating new variables or modifying existing ones to include derived metrics, such as moving averages, volatility indicators, and technical analysis signals, trading strategies, and constraints. These augmented variables offer additional insights into market trends, momentum, strategies, and potential reversal points, which are crucial for making informed trading decisions.

By incorporating these augmented variables, our DRL model can analyze not only the raw historical stock data but also the underlying patterns and relationships between different market indicators and alignment to the investor's strategies. This enriched dataset allows the model to capture a more comprehensive picture of the market, leading to improved accuracy in predicting future stock movements and optimizing trading strategies. The augmentation process is carefully designed to ensure that the new variables are relevant, non-redundant, and contribute positively to the model's learning process, thereby enhancing its overall performance in the stock trading demonstration.

Experimental Methods

High Level Diagram Flow:



Diagrar

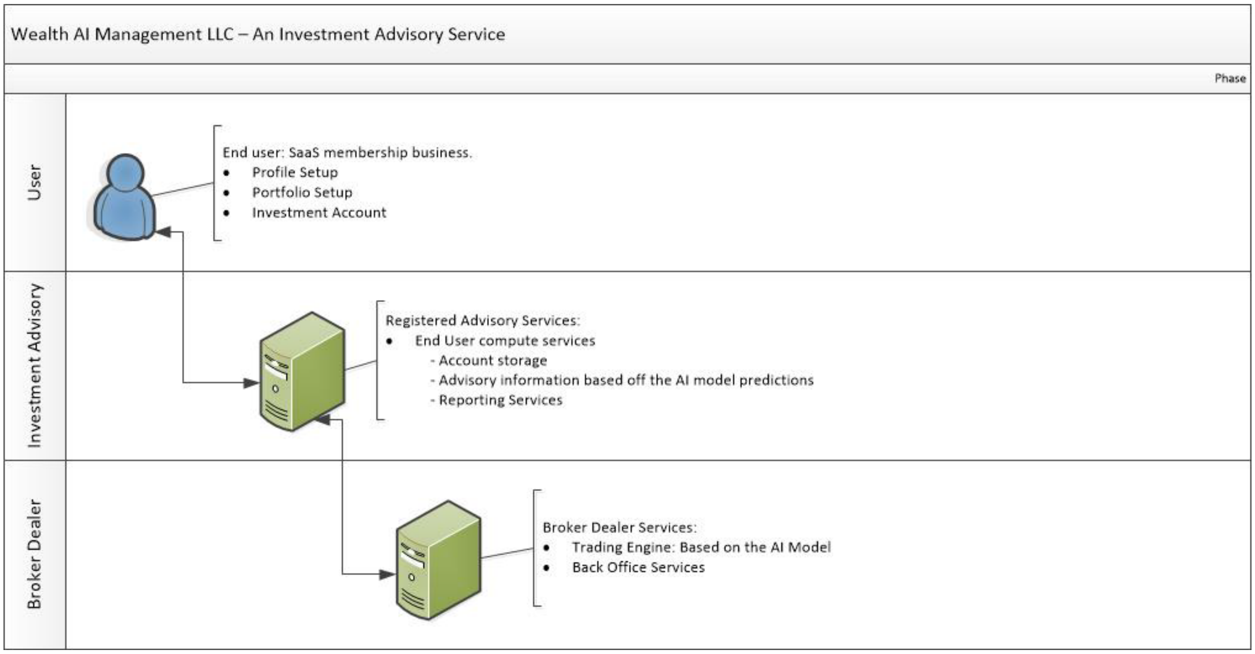


Diagram of Portfolio and Account Management

Portfolio Fields

- Name
- Social Security number or taxpayer identification number
- Address
- Telephone number
- E-mail address
- Date of birth
- Driver's license, passport information, or other government-issued identification
- Employment status and occupation
- Whether you are employed by a brokerage firm
- Annual income
- Other investments
- Financial situation and needs
- Tax status
- Investment experience and objectives
- Investment time horizon
- Liquidity needs and tolerance for risk
- Financial and trading record
- Net worth
- Trading experience
- Financial knowledge

Feature Engineering

From the Portfolio dataset we calculate logics to create a “Risk Factor”. This Risk Factor is taken into consideration in the constraints set upon the trading activity per the client. With a higher Risk Factor, the financial limits and stock volatility is limited accordingly.

Logical layer:

- Date of Birth needs to be calculated and then assigned a value 0-5. Calculate age. 21-29=0, 30-39=1, 40-49=2, 50-59=3, 60-68=4, 69+=5 (0-5)
- Networth: set to 0-10 based on the logic of: 100,000<= 0, 200,000<=1 …..1,000,000>=10
- The add the values of Networth+Trading experience+Financial knowledge
- Add these two rows above and the other yellow fields to get the "Liquidity needs and tolerance for risk" value

This is a value to be calculated into the model. The higher the value the lower the risk factor.

Results/Conclusion

This section of your final report should describe how your model performed and provide evidence for how your work did/did not support your experimental hypothesis or solve your chosen problem. The reader should be able to answer the following questions:

- How effective was your machine learning model at learning the task? e.g. Did the model overfit/underfit the training data? What does the training accuracy/loss curve look like for your model?
- If your project is focused on answering a research question, what evidence do you have to support or disprove your hypothesis?
- If your project is focused on solving a problem, how will your model performance affect the application of your model to that problem?
- Did your model training or performance bring about any unexpected results?
- If you were to continue this project, what would your next steps be? e.g., Would you continue to optimize your model or try other model architectures? Would you change or expand the data used in your model? What steps need to be taken to “productionize” your model

References

ffffffffffffff