Documentation of Trade Recommendation

Transformer Model for Stock Price Prediction:

This project focuses on developing a Transformer-based model for predicting future stock prices using technical indicators. Transformers excel in handling sequential data, making them well-suited for time series forecasting in financial markets.

Key components of the model include:

- **Positional Encoding:** This allows the model to comprehend the positional relationship of each data point within a sequence, distinguishing between different time steps.
- **Transformer Encoder Layers:** The model leverages three layers of Transformer encoders equipped with multi-head attention mechanisms. These layers identify complex patterns in the data, enabling the model to selectively focus on relevant parts of the input sequence for improved prediction accuracy.
- **Feedforward Network:** The encoded data is processed through a fully connected network with ReLU activation, culminating in a final layer that outputs the predicted stock price.

The model is trained on sequences of technical indicators extracted from historical stock data, such as RSI, MACD, and Bollinger Bands. It then generates price predictions that can inform trading decisions within an integrated trading environment.

Fine-Tuning Process:

To optimize the Transformer model's performance, a fine-tuning process was conducted using a dataset of stock price sequences. The objective was to minimize the Mean Squared Error (MSE) between predicted and actual prices.

The fine-tuning process involved the following steps:

- **Learning Rate:** A low learning rate of 1e-5 was employed to ensure stable and gradual updates to the model's parameters.
- **Optimization:** The Adam optimizer was chosen for its adaptability and effectiveness in handling sparse gradients.
- **Learning Rate Scheduler:** A ReduceLROnPlateau scheduler was employed to reduce the learning rate when the validation loss plateaued, preventing overfitting.
- **Early Stopping:** Training was monitored with an early stopping mechanism that halted the process if the validation loss didn't improve over three consecutive epochs, preventing overfitting.

The fine-tuning process resulted in a training loss of 0.7653 and a validation loss of 5.7419 by the 17th epoch. These results indicate that the model learned effectively from the training data, although the higher validation loss suggests challenges in generalizing to new data.

Integration with PPO Agent

To enhance its predictive capabilities, the Transformer model was integrated with a reinforcement learning algorithm known as Proximal Policy Optimization (PPO), resulting in a complete trading system. PPO is particularly suited for trading due to its ability to handle complex decision-making environments.

How Integration Works:

- **Environment Setup**: A custom trading environment was created using the OpenAI Gym framework, simulating a specific stock, such as AAPL. The Transformer model's price predictions were incorporated into the state fed into the PPO agent.
- **Action Space**: The agent could choose between three actions—hold, buy, or sell—based on the Transformer's predictions and market features.
- **Observation Space**: The agent observed both the current market state and the predicted next price from the Transformer model, allowing for informed decisions.
- **Training Process**: The PPO agent was trained with optimized hyperparameters. During training, it learned to maximize rewards by making profitable trades, guided by the Transformer's price predictions.

Evaluation and Trade Recommendations

After integration and fine-tuning, the model was evaluated within the trading environment. The Transformer's predictions guided the PPO agent's actions at each step.

For instance, the PPO agent carried out a number of purchase and sell transactions on July 3, 2023, during a trading session. At 14:49:49.520, it bought 121 shares at a price of $191.92. Later, at 14:53:52.329, it purchased 177 shares at $191.93. Subsequently, the agent decided to sell 169 shares at $192.04 at 14:56:57.246. Finally, at 15:03:01.319, it sold 129 shares at $192.05.

These trade actions, along with their timestamps, prices, and shares traded, were recorded in the trades_ppo.csv file. This file provided a detailed log of the PPO agent's performance during the trading simulation.

Additionally, all trades were logged and saved as a CSV file, providing a detailed view of the model's performance in a realistic trading scenario.

Conclusion

This project demonstrates the effectiveness of combining a Transformer-based predictive model with a reinforcement learning agent to create a sophisticated trading system. The Transformer model captured complex patterns in stock price data, while PPO facilitated intelligent decision-making. The results suggest the potential of such models to contribute to algorithmic trading strategies.