Impact of Crypto Market on Stock Market: A Study Using Deep Reinforcement Learning

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***Abstract*— Literature indicates the existence of a correlation between the stock market and the crypto market [8]–[10]. However, to the best of our knowledge, no studies have demonstrated the impact of the crypto market on the stock market (and vice versa) observed in Return on Investment (ROI). For this study, we select popular entities: Standard and Poor's (S&P) 500 (stock), Bitcoin, and Ethereum (crypto) and perform two case studies: i) ROI on the stock market using pure stock market parameters, and ii) ROI on the stock market using a mixture of stock and crypto market parameters. We implemented Advantage Actor to a critic (A2C) and Proximal Policy Optimization (PPO) for both cases and study the impact of Bitcoin and Ethereum on the stock market. We use rolling correlation of 14 days between the cryptocurrencies and stock market to include it as one of a parameter of stock market. The best total reward of $25067.91 was observed using only the stock market parameters so we conclude that using correlation between crypto market and stock market alone will not have remarkable impact on the ROI.**

***Index Terms*—Stock market, Crypto market, Actor-Critic, Proximal Policy Optimization, Deep Reinforcement Learning**

I. Introduction

Algorithm trading is enlarging the financial investment market. The correlation between trading volume and good point returns has been studied extensively for both Stock and Crypto markets. Also, the parallel use of the stock and crypto market might create a great impact on our ROI. Existing works are inadequate to explain its impact. Thus, we approach Deep Reinforcement Learning (DRL) to observe the ROI on the stock market with and without incorporating its correlation with the crypto market as one of the parameters to automate trading in the financial market.

In simple terms, Stock trading is defined as buying and selling of shares in the financial market. Whereas, the Crypto market is nothing but the stock market in the digital world. Crypto is known for its high volatility and rapid price fluctuations, which can result in significant gains or losses. ROI is a metric to evaluate the performance of an investment by comparing the current value of an asset to its original value. The formula to calculate ROI is given as, $R = (V_f - V_i)/V_i$, where R, V_f, and V_i represent returns, final value, and initial value, respectively.

For reproducibility, the code is available at: https://github.com/siddhi47/rl-project.

In this paper, we study the impact of crypto trading in a complicated and dynamic stock market by using DRL algorithms of the actor-critic family which are Proximal Policy Optimization (PPO), and Advantage Actor-Critic (A2C).

The paper is structured as follows: The literature review is introduced in Section II. The experimental setup is described in Section III. We explain the results and analysis in Section IV. The discussion and conclusions are included in Section V.

II. Literature Review

In November 2021, the overall value of digital assets, such as cryptocurrencies, reached a dollar 3 trillion, matching the size of the global stock market [1]. To automate trading, researchers have used historical data from the stock and cryptocurrency markets. The approaches like statistical analysis and time series analysis are introduced to find the correlation between Crypto and Stock markets. In the time series, Researchers analyze the time-dependent data of cryptocurrency and stock market indices, looking at their patterns and trends. Changes in correlation have been noticed as a result of particular situations or events, like COVID, the Russian invasion of Ukraine, and the crypto winter [1]. In academia, there are multiple strategies that have been applied to machine learning, and deep learning for predicting the stock and crypto market with popular algorithms like SVM, Random Forest, RNN, and LSTM by comparing the results from different models. However, to the best of our knowledge, no studies have demonstrated the impact of the crypto market on the stock market (and vice versa) observed in ROI both by using and not using Machine learning.

RL provides a flexible framework that can adapt to dynamic environments, capture nonlinear relationships, consider long-term returns, and incorporate risk management techniques. These benefits make RL a potentially more effective way than

This paper is a part of the Applied Reinforcement Learning course at the University of South Dakota.

conventional ones for obtaining ROI in the stock and cryptocurrency markets, enabling more complex decision-making. To gain ROI in the stock and cryptocurrency markets, researchers have used a variety of reinforcement learning (RL)-based strategies, including Q-learning, DQN, Policy gradients, etc. This learning strategy trains an agent on a single stock or asset and uses Deep Q-learning (DQN) and its improvements, for example, to solve a discrete action space issue [4]–[6]. The goal of the critic-only technique is to identify the best action-selection strategy that, given the current situation, maximizes the projected future reward using a Q-value function. Instead of creating a state-action value table, DQN approximates functions by minimizing the difference between the estimated Q-value and the target Q-value over a transition. The primary drawback of the critic-only strategy is that it can only be applied to discrete and finite state and action spaces, which makes it impractical for a sizable stock portfolio.

Many researchers have explored and proposed variations of actor-critic algorithms for financial tasks, including stock and cryptocurrency trading. Using an actor-only strategy has been done in [2], [3], [7]. The notion is that the agent itself immediately learns the best course of action. Instead of learning the Q-value, the neural network instead learns the policy. The probability that an action will be taken is what makes up the policy, which is essentially a strategy for a certain situation. In order to avoid the dimensionality curse and increase trade efficiency, recurrent reinforcement learning is introduced in [2]. The continuous action space environments can be handled by the actor-only method.

In [13], the authors have used gym-style environments to study data-driven financial reinforcement learning. Some research [14], [15], [16] and [17] suggest using DRL for automated portfolio optimization and stocktrading. The research has produced some interesting findings and promising results. [17] uses an empirical approach to demystify the black-box nature of deep neural networks to produce explainable portfolio management methods.

Some researches [18] and [19] suggests that there is a correlation between the stock market and the crypto market. Findings in [19] reveal that the shock from the stock market also influenced the volatility of bitcoin during covid-19. In this research, the authors discovered the returns of the SP 500 significantly affected the bitcoin returns using quantile regression techniques. In [18], the authors shed light on the importance of studying volatile cryptocurrencies with the help of well-understood and massively adopted financial assets like foreign exchange and stock by constructing the correlation matrices and asset trees.

III. Experimental Setup

A. Environment

1) States: We used two independent continuous states representing parameters of stock market and stock with crypto as shown in Figure 2. Five parameters in the first state included balance, closing price, number of shares held, and two technical indicators: Moving Average Convergence/Divergence (MACD), and Relative Strength Index (RSI). Similarly, an additional parameter (Pearson correlation coefficient) was added which was separately computed between each crypto and S&P 500 (stock). The details of correlation computation is provided in Section III-C.

2) Rewards: Agent received one of the two rewards (profit or loss) at the end - no reward was provided to the agent in the middle of trading.

3) Actions: For a single stock, the action space was defined as $-1, \ldots + 1$, where positive 1, negative 1 and 0 represented a strong buy, strong sell, and hold, respectively. To avoid the model from using all balances during a strong buy or sell signal, we limited a single trade to 200 units of stock. For instance, in a strong signal of +1, the total number of stocks bought would be $1 * 200 = 200$, whereas in case of a weaker buy signal like 0.2, the total number of stocks bought will be $0.2 * 200 = 40$. Selling works in a similar way.

For our experiment, we began with $100,000 as the initial balance with 200,000 time steps. The number of time steps defines the number of samples taken for training.

Fig. 1. Training and testing on different market trends.

B. Dataset

Two publicly available datasets: cryptocurrency (Bitcoin and Ethereum) [1] and Standard and Poor (S&P) 500[2] were used in this study. Both data consisted of historical data from August 2017 to March 2023 that were structured in the Open, High, Low, Close, and Volume (OHLCV) format. The OHLCV format enabled efficient analysis and interpretation of the data. The datasets provided daily price movements for the crypto assets and daily performance information for the stock market.

C. Correlation computation

The correlation between the cryptocurrency and stock value was calculated using the rolling function in Python with a lookback period of 14 days. Pearson correlation coefficient was used to measure the degree of the linear relationship between the two variables, which ranges from -1 to +1. A value of +1 or -1 indicates a perfectly positive or negative

[1] www.cryptodatadownload.com
[2] www.marketwatch.com

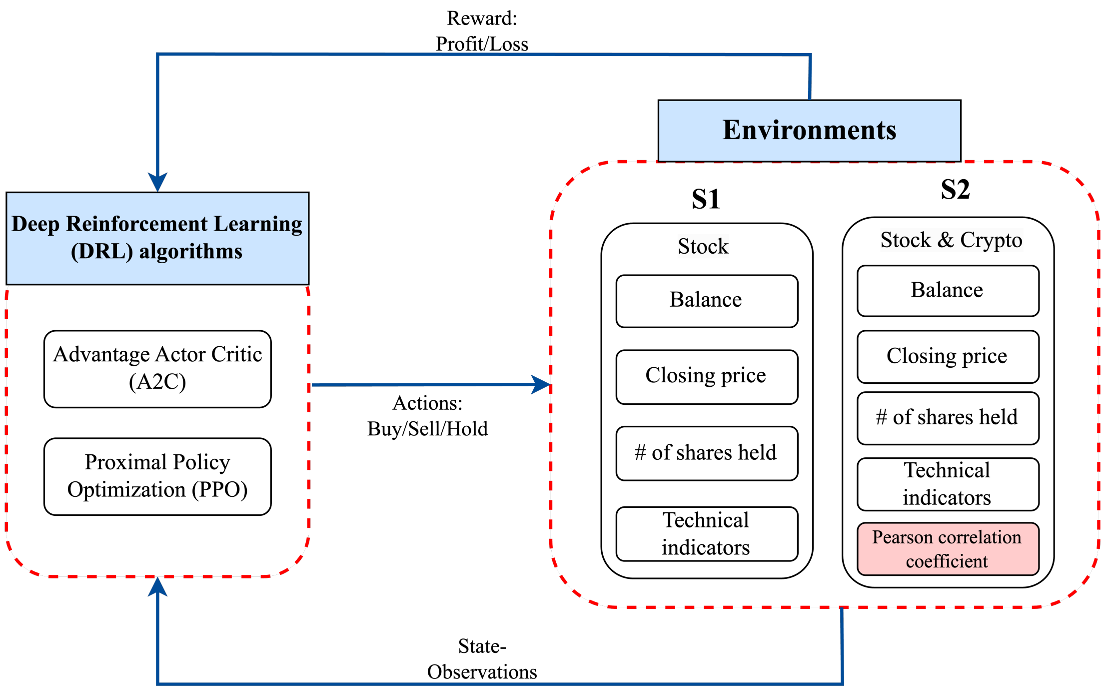

Fig. 2. Schema showing the proposed methodology to study the impact of crypto market on stock market.

correlation, respectively. The calculation of correlation is an important step in this research study as it enables the investigation of the relationship between these two assets, and the closer the correlation value is to +1 or -1, the stronger the correlation between the two datasets.

D. Implementation details

Three independent experiments were conducted by training the models on different market trends as shown in Figure 1. The idea was to study the effect of market trends on ROI. In Experiment 1, we trained the agent in data from 8/17/2017 to 1/1/2023 and tested it on three-month data (1/2/2023 - 3/29/2023). In Experiment 2, the data from 8/17/2017 to 1/1/2021, and data from 1/2/2021 to 3/29/2023 were used for training and testing, respectively. In Experiment 3, we used train data from 8/17/2017 to 1/1/2021 and tested it from 1/2/2021 - 3/29/2023.

For all the experiments, we implemented code in Python 3.9.0 using Docker to create an isolated environment. Docker allows deterministic building every time and ensures the exact environment every time. To allow containerization in an HPC (High-Performance Computer), we use software called Apptainer. Setting up the Apptainer definition file and Dockerfile both allows us to replicate training and testing environments across normal machines as well as HPCs. We used our personal computers for development and testing, whereas USD's Lawrence Supercomputing for training the models.

We further discuss the libraries used in this study:

1) Gymnasium: The Gymnasium [12] is a popular Python framework used in reinforcement learning capable of modeling RL environments. It has popular RL environments that are ready to use out of the box such as grid worlds, cart pole balance environments, etc. The gymnasium can also be used to create custom environments. We extend the gymnasium's environment to create a custom stock trading environment.

2) FinRL: FinRL [13] is a popular Python framework for financial reinforcement learning. We leverage this framework to train two different models: PPO and A2C. FinRL uses stable baselines to train state-of-the-art reinforcement models. FinRL consumes the gymnasium's environment.

E. Performace metrics

Total reward: Total reward obtained from all the transactions.
Sharpe ratio: It is a measure of risk-adjusted return that compares the excess return of an investment to its standard deviation of returns. It provides a way to compare different investments' performance while accounting for the level of risk taken, and helps investors identify investments that offer the best trade-off between risk and return [20]. Closer the value to 1, better the Sharpe ratio.
Total cost: Transactional cost for each trade.
Annual return (%): Percentage of annual return.

F. Trading Algorithms

1) Advantage Actor Critic (A2C): A2C techniques are Temporal Difference (TD) methods that explicitly describe the policy apart from the value function in a distinct memory structure. It consists of an actor that controls how our agent behaves (policy-based method) and a critic that measures how good the action taken is (value-based method).

A2C is one of the popular model-free value and policy-based algorithms under the Actor-Critic family. Instead of using the action value function, it uses the advantage function as a critic. The main objective of using the advantage function is to get the extra reward by calculating the better action at a state compared to the average value of the state.

The advantage function is given as, $A(s,a) = Q(s,a) - V(s)$, where $Q(s,a) = Q$ is value for action a in the state s, and $V(s)$ is the average value of that state. Here, if $A(s,a) > 0$, our action will be better than the average value of that state, and if $A(s,a) < 0$, our action does worse than the average value of that state.

2) Proximity Policy Optimization (PPO) [11]: PPO avoids having too large policy updates by cautiously revising the policy. For this, we must calculate the ratio between the two policies in order to determine how much the present policy has changed in comparison to the previous one. To remove the incentive for the current policy to depart too much from the previous one, we trim this ratio in the range $[1-\epsilon, 1+\epsilon]$, hence the phrase "proximal policy term."

IV. Result and Analysis

The primary aim of this research was to study the impact of the cryptocurrency market on the stock market. Table II depicts the total reward, Sharpe ratio, total cost, and annual return observed on different experiments using A2C and PPO algorithms. Overall, A2C performed better than PPO in most of the cases, except in Experiment 1 when including correlation, which had comparable results. The best total reward of 25067.91 was observed in Experiment 3 using A2C with only the stock market parameters. Similarly, the A2C algorithm in Experiment 1 had the best Sharpe ratio (0.97) and annual return (14.41 %), whereas the least Sharpe ratio (0.04) and annual return (0.79%) was observed in Experiment 3 when using PPO. Both occurred when using pure stock market parameters.

Figure 3 and Figure 4 illustrate the trend of percentage change in reward including the transaction cost on test data when using pure stock market parameters and including the correlation of the stock market with the crypto market, respectively. Similar trends were observed in both algorithms. An increasing percentage change was observed until 2022-02, after which it started to decrease. In a pure stock market environment, a higher change in percentage occurred in the A2C algorithm with the highest (0.25) change occurring in January 2022. It was interesting to observe similar values in PPO and A2C when including the correlation as a parameter in the environment.

Our experiments suggest that we need more data with different price movements.

V. Discussion and Conclusion

The idea to choose correlation as the parameter was to study if the impact of the crypto market can be observed in the stock market in terms of ROI. Also, different time frame experiments were implemented to study if different market trends (bearish/bullish) affect overall trading. From our results, it is clear although a correlation exists between these two

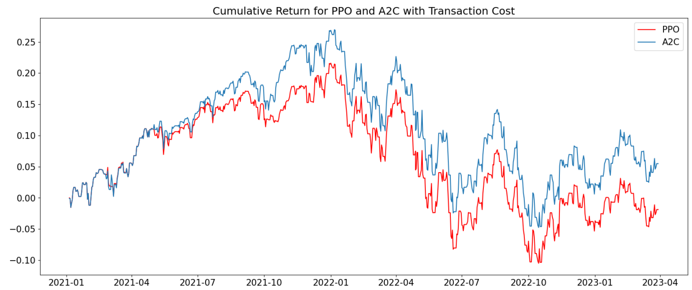

Fig. 3. Cumulative returns from 2020-01 to 2023-05 using pure stock market parameters on A2C and PPO.

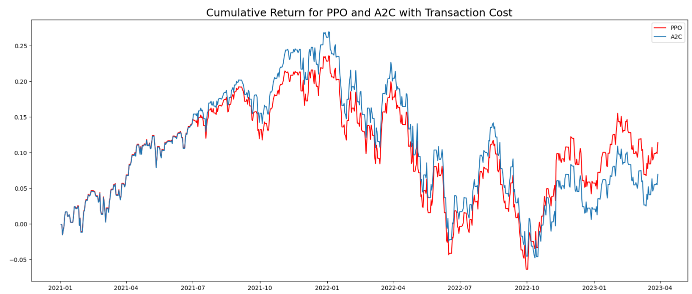

Fig. 4. Cumulative returns from 2020-01 to 2023-05 when including correlation with crypto market as a parameter on A2C and PPO.

markets, we did not find any remarkable impact on ROI. Our study shows that a model trained on a bullish market is not suitable for trading on a bearish market. So, future studies can explore using additional data that incorporates both trends. Furthermore, the A2C algorithm performed better in most of the experiments which might be because it minimizes the cost during the trades.

In this paper, we have explored the potential of using actor-critic-based algorithms such as PPO, and A2C to learn strategies for stock trading. The A2C algorithm performed better with minimal cost than PPO. With the purpose of finding the impact of crypto on the stock market, incorporating correlation with the Crypto market alone does not have a remarkable impact on automated trading of the stock market. Also, we noticed most of the trained portion had a bullish market whereas the tested portion had a bearish market.

For future work, it will be intriguing to investigate more complex ensemble models and deal with large-scale data to balance bullish and bearish trending cycles. One can explore more state space features like technical indicators based on the volume of trade, and the number of trade like the Trade Volume Index (TVI). Currently, we computed the correlation between two crypto and stock data based on the price of the assets. It will be interesting to experiment with correlation based on other factors like trade count and add and explore multiple correlation values. Also, incorporating other factors like causation [21] instead of correlation might allow us to have better insight on how crypto market is impacting stock market.

Cases	Training date (start - end)	Testing date (start - end)	Model	Total reward	Sharpe ratio	Total Cost	Annual Return (%)
Stock only	8/17/2017 - 1/1/2023	1/2/2023 - 3/29/2023	PPO	3976.55	0.91	198.25	12.95
			A2C	4420.41	**0.97**	292.92	**14.41**
Including correlation	8/17/2017 - 1/1/2023	1/2/2023 - 3/29/2023	PPO	3318.91	0.76	99.82	11.36
			A2C	3318.91	0.76	99.82	11.36
Stock only	8/17/2017 - 1/1/2021	1/2/2021 -3/29/2023	PPO	11408.89	0.29	1068.05	4.59
			A2C	23306.49	0.32	**99.69**	6.81
Including correlation	8/17/2017 - 1/1/2021	1/2/2021 - 3/29/2023	PPO	9321.15	0.19	1730.66	5.72
			A2C	23306.49	0.32	**99.69**	6.81
Stock only	8/17/2017 - 1/1/2020	1/2/2020 - 3/29/2023	PPO	-5139.23	0.04	2042.88	0.79
			A2C	**25067.91**	0.33	**99.69**	7.11
Including correlation	8/17/2017 - 1/1/2020	1/2/2020 - 3/29/2023	PPO	9321.15	0.19	1730.66	5.72
			A2C	23306.49	0.32	**99.69**	6.81

TABLE II

RESULTS SHOWING TOTAL REWARD, SHARPE, TOTAL COST, AND ANNUAL RETURN ON TEST DATA BEGINNING AT DIFFERENT TIMES.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to Dr. Rodrigue Rizk for his invaluable guidance and support throughout the entire Reinforcement Course. His expertise and mentorship have been instrumental in shaping the direction and quality of this work. We are particularly grateful for Professor Rizk's insightful feedback on our research methodology and his acceptance of this topic. Thank you for your unwavering support.

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