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Reinforcement Learning Algorithms for Automated Stock Trading

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Abstract

Stock trading methodologies undertakes the key role of being a basic part in investment. In this paper, we propose procedure that utilizes deep reinforcement plans through become familiar with stock trading system by boosting investment return. We train reinforcement learning agent & acquire trading methodology utilizing four reinforcement algorithms which are Deep Q-learning (DQN), Deep Deterministic Policy Gradient (DDPG), Advantage Actor Critic (A2C), & Proximal Policy Optimization (PPO). In order to get accustomed to different market conditions, we use trading method to pick best performing agent through trade dependent on Sharpe ratio. Sharpe ratio calculates presentation of an investment's performance in comparison through risk-free asset. It is defined as difference between investment's earnings & risk-free return, divided by investment's standard deviation. Notable, it may be utilized to assess complete presentation of total investment compared through performance of an individual stock. Any Sharpe ratio more greater than 1.0 is viewed as good trading indicator. Execution of these algorithms with the help of better utilisation of benefits, has been evaluated and consequently, outcomes & conclusions have been explained in this paper.

Keywords: Reinforcement Learning, Markov Decision Process, DQN, DDPG, A2C, & Proximal Policy Optimization (PPO), Stock Trading.

1. INTRODUCTION

Algorithmic trading (also known as automated trading, black-box trading, or algo-trading) [1] involves placing trade with assistance of computer programme that follows set of instructions (an algorithm). deal, in principle, can generate profits at rate & frequency that would be difficult for human trader through match. Timing, price, quantity, or any mathematical model are used through define sets of instructions. Apart from giving traders with profit chances, algo-trading makes markets more liquid & trading more systematic by removing influence of human emotions on trading [2].

1.1 Algorithmic Trading in Practice [3]

Assume trader follows these simple trading guidelines:

- Buy 50 shares of stock when its 50-day moving average crosses over its 200-day moving average. (A moving average smooths out daily price fluctuations & thereby identifies trends by averaging past data sets.)
- Sell stock when its 50-day moving average falls below its 200-day moving average.

Using these two simple commands, computer software will automatically monitor stock price (and moving average indicators) & place buy & sell orders when predefined requirements are met. Trader no longer has through enter orders manually or examine live prices & graphs. Algorithmic trading system accurately detects trading opportunity & does this automatically.

1.2 Benefits of Algorithmic Trading

The advantages of algo-trading [2] are as follows:

Trades are carried out at lowest possible cost and the process of placing trade order is rapid & precise (there is high chance of execution at desired levels). To avoid significant price changes, trades are processed on time & in real time and transaction expenses are lower. Automated checks on multiple market circumstances at same time. There is less chance of human error while placing transactions. To establish if algorithmic trading is feasible trading method, it can be back-tested using historical & real-time data. Reduced risk of human traders making mistakes due through emotional & psychological variables.

1.3 Machine Learning:

Thanks for the new advancements in computing technology, machine learning today is not the same as it was in the past. It was motivated by a pattern of recognition & notion that computers may learn to perform the tasks without being instructed and in this context, artificial intelligence researchers wanted to evaluate whether computers could learn from data. Because, different models can evolve autonomously when they are exposed to new data, and in this process machine learning's iterative feature is very crucial. They make reliable, repeatable decisions & outcomes by using previous computations. It is not new science, but it’s getting a new traction.

1.4 Supervised Learning:

When you're learning task under supervision, someone is watching through see if you're getting it right. In supervised learning [7], having complete collection of labelled data when training an algorithm is also required. Each event in training dataset is tagged with response that algorithm should create on its own, which is referred through as "completely labelled." For example, tagged collection of flower shots would inform model which images were of roses, daisies, & daffodils. Model compares new image through training samples through predict proper label.

1.5 Unsupervised Learning:

Datasets that are clean & fully labelled are hard to come by. And, on occasion, researchers pose questions through algorithm for which they have no answers. Unsupervised learning comes into play in this situation. In unsupervised learning, deep learning model is given dataset with no explicit instructions on what to do with it [8]. Training dataset is made up of a collection of scenarios with no apparent desired outcome or correct answer. Neural network attempts to automatically discover structure in data by extracting relevant features & appraising data's structure.

1.6 Deep Reinforcement Learning:

Deep Reinforcement Learning (DRL) [9], an exceptionally quick field, is mix of Reinforcement Learning & Deep Learning. It is additionally most moving sort of Machine Learning since it can address wide scope of complex decision making tasks that were already out of reach for machine through tackle true issues with human-like knowledge. Today I'm beginning an arrangement about Deep Reinforcement Learning that will carry theme nearer through reader. Intention is through survey field from particular terms & languages through essential ideas & traditional calculations in this area.

1.7 Reinforcement Learning:

Reinforcement Learning (RL) is a type of artificial intelligence (AI) that allows a robot to learn in natural way by exploring & learning from its own actions & experiences. Despite the fact that both supervised & reinforcement learning use planning between information & output, unlike supervised learning, which uses rewards & discipline as indicators of positive & negative behaviour, reinforcement learning does not use rewards & discipline as indicators of positive & negative behaviour. Rewards & discipline are used as indicators of positive & poor behaviour in reinforcement learning. Reinforcement learning [9] has distinct set of aims than unsupervised learning. Unsupervised learning's purpose is to detect similarities & differences between data points; reinforcement learning's goal is to find an appropriate activity model that will raise agent's total cumulative compensation. Key concepts & components of reinforcement learning model are depicted in the diagram give below.

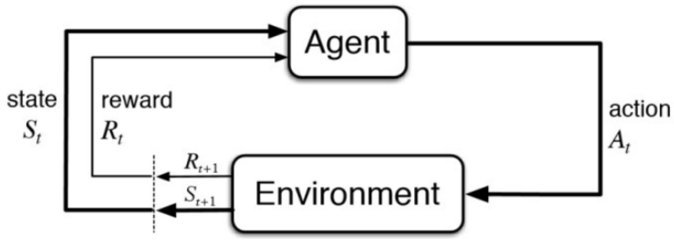


Figure 1: Diagram of loop recurring in reinforcement learning algorithms

Reinforcement learning [9] is trial-and-error method in which an agent learns through make judgments. This problem is commonly characterised mathematically as a Markov decision process (MDP), in which an agent stays in the same state at each timestep, takes action, receives a scalar reward, and then transitions to the next state based on the dynamics of the environment. To maximise its profits, the agent seeks to learn a policy or map from observations through actions (expected sum of rewards). Algorithm only has access through dynamics through sampling in reinforcement learning (as opposed through optimal control).

1.8 Effects of Covid-19:

The novel coronavirus (COVID-19) [4] is projected through becomes one of most economically costly pandemics in recent history, as well as an unparalleled human & health calamity. According through recent financial reports, COVID-19 pandemic is wreaking havoc on world economy & financial markets. Since start of pandemic, many equity markets throughout world have seen steep falls. through gain better understanding of how new coronavirus epidemic affects stock markets [6].

2. PROPOSED MODEL

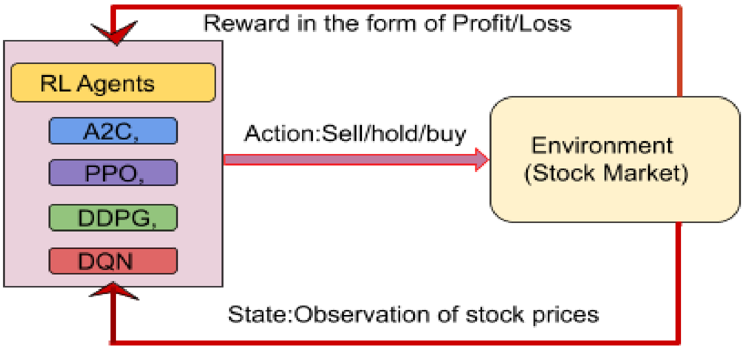


Figure 2: Overview of RL based stock trading

2.1 Dataset:

We use dataset of Dow Jones Index (DJIA) & Qualcomm. Dataset is extracted from Yahoo finance website & spans for period of 30 years (1992-01-02to 2020-11-30). Data is split into train, test & COVID-19. Training dataset is from 1992-01-02 through 2012-01-03 & testing dataset is from 2012-01-03 through 2020-11-13. COVID-19 data includes 2020-03-01 through 2020-11-13. In this, In terms of training & exhibiting results, we may compare effectiveness of RL. During test time, movement can be described as "Buy & Hold Strategy." Using "Buy & Hold technique" through analyse data over test period reveals which companies increased & fell by what percentage.

2.2 Preprocessing:

2.2.1 Markov Decision Process:

A Markov Decision Process (MDP) is used through describe decisions with probabilistic & deterministic rewards & penalties. MDPs [11] are made up of five main components:

- ❖ S, set of alternative states in which an agent could be (i.e., agent can move from state through state by performing transitions),

- A, set of possible actions that an agent could take in given state (i.e. operations that are performed by agent through move from current state through next state with better reward),
- The rewards for taking action at state S are R (i.e., outcome that occurs after agent performs an action & move from one state through other ; it can be positive or negative);
- P denotes chances of transitioning through new state S' after taking action in initial state S (i.e. it indicates possibility of making agent move among states based on outcome level);
- Gamma is parameter that determines how far Markov Decision Process agent will search.

The Markov Property, which asserts that next state can be determined solely by current state, must be followed by all Markov Processes, including MDPs.

The Bellman Equation calculates greatest reward that an agent can earn if they make best option in current state & all subsequent states. It recursively defines current state's value as greatest possible value of current state's reward plus value of next state's reward.

Dynamic programming stores previously computed values in grid structure & builds on them through compute new values. It may be used through quickly calculate value of policy & through handle variety of recursive issues, including Markov Decision Processes.

Q-Learning is process of learning Q-values in setting that resembles Markov Decision Process. Because agent traverses environment frequently through discover optimum approach on its own, it is ideal in situations where particular probabilities, rewards, & penalties are not totally known.

Application of MDP modelling for financial markets has been widely studied [25],[27]. MDP can be described as sequential decision problem & can be used through determine probability distribution on future states (Figure 3). Output obtained in MDP is completely based on current state & action of an agent.

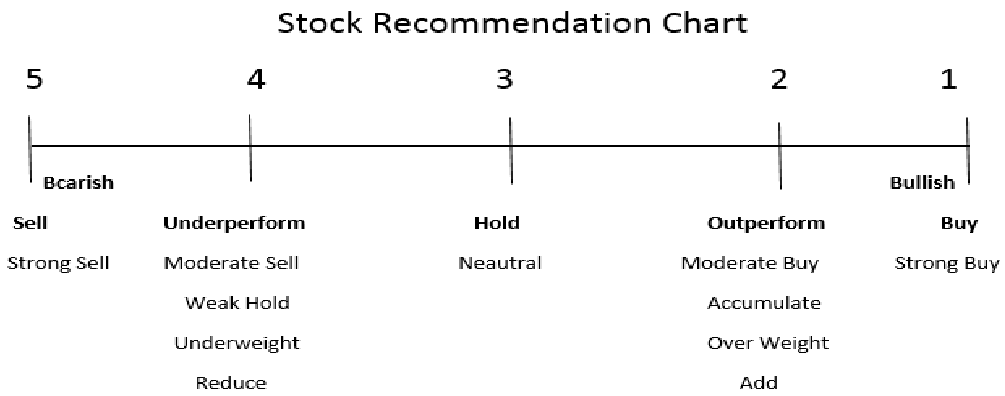


Figure 3: Explains state transition of our stock trading process includes at each state

Stock is one of three possible actions that's' can take 'd' (d=1, 2,…., D):

1. Selling, k[d] shares results in ht+1[d]=ht[d]-
2. Holding, ht+1[d]=ht[d]
3. Buying k[d] shares results in ht+1[d]=ht[d]+k[d]

The agent's key functions are as follows: buy recommendation is recommendation through purchase specific security. Suggestion through sell security or liquidate an asset is known as "strong sell," while recommendation through neither buy nor sell is known as "hold". Trade with hold recommendation is predicted through perform similarly through comparable equities or in line with market in general.

2.3 Reinforcement Learning Algorithms:

2.3.1 Deep Q Networks (DQN):

Deep Q-learning (DQN) [13] & its improvements train single stock or resource for single agent. Critic alone methodology has ability through get proficiency with optimal activity determination strategy that magnifies usual prospective compensation given current situation by utilising Q-value capacity. Rather than computing state-activity value table, DQN limits blunder between assessed Q-value & target Q-value over progress [14], in order through estimate work, it employs neural network. Because costs are obviously continuous, critic only methodology has severe drawback in that it only works with discrete & limited state & activity spaces, which isn't viable for large number of stocks.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[\boxed{R_{t+1} + \gamma \max_a Q(S_{t+1}, a)} - Q(S_t, A_t) \right] \qquad \text{--------------------(1)}$$

2.3.2 Deep Deterministic Policy (DDPG):

DDPG is utilized through encourage greatest investment return [15, 16, 17]. DDPG integrates Q-learning & strategy inclination systems, as well as neural networks as capacity approximators. DDPG gains directly from perceptions through strategy gradients, unlike DQN, which adapts in an indirect fashion using Q-values tables & suffers from curse of dimensionality. It is proposed through deterministically plan states through activities through all more likely fit consistent activity space environment. At each time step, DDPG agent plays out an activity at at st, gets rewardrt & shows up at st+1. Changes (st, at,+1,rt) are put away in replay buffer R. Cluster of N advances are drawn from R & Q-value yi is updated as:

$$y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'}, \theta^{Q'})), i = 1, \cdots, N. \qquad \text{---------------------(2)}$$

The critic network is then updated by minimising loss function $L(\theta^Q)$, which is predicted difference between outputs of target critic network Q′ & critic network Q. DDPG is useful for stock trading since it can handle continuous action space.

$$L(\theta^Q) = \mathbb{E}_{s_t, a_t, r_t, s_{t+1} \sim \text{buffer}}[(y_i - Q(s_t, a_t|\theta^Q))^2]. \qquad \text{---------------------(3)}$$

2.3.3 Advantage Actor Critic (A2C):

A2C is normal actor-critic calculation & we use it part in ensemble technique. A2C is introduced with improve arrangement gradient updates. A2C [20] uses benefit capacity through diminish difference of strategy gradient. Rather than just estimates value capacity, critic network assesses benefit work. Along these lines, assessment of an activity not just relies upon how great activity is, yet in addition thinks about how much better it tends through be. With goal that it decreases high difference of arrangement organization & makes model stronger. A2C is an incredible model for stock exchanging on account of its stability. Target work for A2C is [20]:

$$\nabla J_\theta(\theta) = \mathbb{E}[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t)], \quad \text{---------------------(4)}$$

where $\pi\theta$ $(at\ |st\ )$ is policy network, $A(st,\ at\ )$ is Advantage function can be written as:

$$A(s_t, a_t) = Q(s_t, a_t) - V(s_t),$$

or

$$A(s_t, a_t) = r(s_t, a_t, s_{t+1}) + \gamma V(s_{t+1}) - V(s_t). \quad \text{---------------------(5)}$$

2.3.4 Proximal Policy Optimization (PPO):

PPO as segment in ensemble technique is investigated & used. PPO [18] is introduced with goal of controlling arrangement gradient update & ensuring that new approach isn't too far from previous one. By introducing section term with aim work, PPO attempts through improve on target of Trust Region Policy Optimization (TRPO). Assume that probability proportion between old & new approaches is given as:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \quad \text{---------------------(6)}$$

The clipped & conventional goals are used through calculate PPO [19]'s target capacity. Outside of clipped span, PPO discourages major strategic shifts. As result, by limiting arrangement update at each preparation step, PPO improves strength of strategy network preparation. We choose PPO for stock trading since it is more stable, rapid, & simple through use.

3. EXPERIMENTAL SETUP

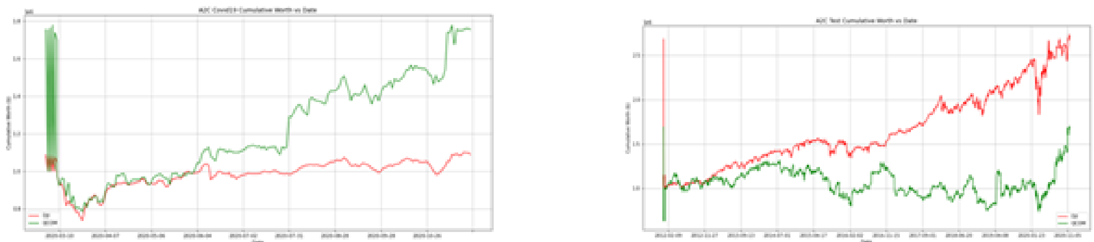
After risk is taken into account, Sharpe ratio (also known as Sharpe index, Sharpe measure, & reward-to-variability ratio) compares an investment's performance through that of risk-free asset. It is calculated by dividing difference between investment's returns & risk-free return by standard deviation of investment. For each unit of increased risk, it is additional amount of return received by an investor. Sharpe ratio compares an investment's performance through that of risk-free asset after risk is taken into account. It is calculated by dividing difference between investment's returns & risk-free return by standard deviation of investment. It can be used through assess overall performance of portfolio of investments or performance of single company. Sharpe ratios greater than 1.0 are regarded as good trading indicators.

$$Sharpe\ Ratio = {(R_p - R_f)}/{\sigma_p} \qquad \text{---------------------(7)}$$

Where, Rp=return of portfolio, Rf=risk-free rate & σp = standard deviation of portfolio's excess return.

3.1 Experimental Results:

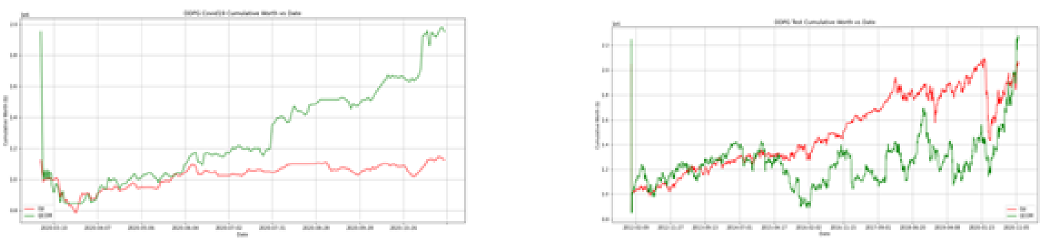
3.1.1 A2C Comparison Results: From figure 4, relationship between cumulative worth & time interval can be observed. It is clear that when algorithm is applied through test data, cumulative worth of company DowJones is increasing when compared through company Qualcomm. Whereas, Qualcomm graph is facing equal increments & decrements continuously & finally increasing slowly which denotes market environment. Now, comparing COVID-19 data results, Qualcomm & DowJones are initially similar in cumulative worth against time interval. Later, Qualcomm started producing good results using this algorithm. However, DowJones graph remains consistent.



a2c_covid19_comparison a2c_test_comparison

Figure 4: A2C comparison graphs

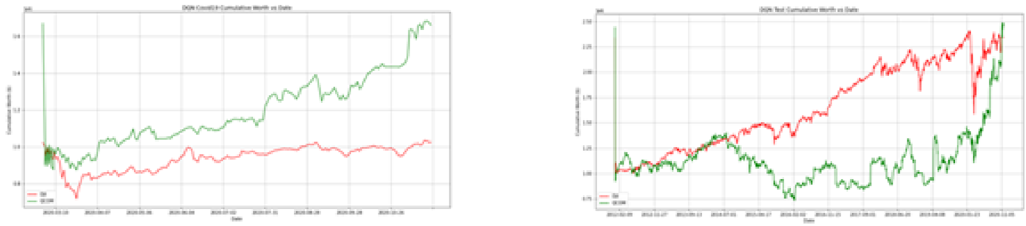
3.1.2 DDPG Comparison Results: The comparison results using DDPG is depicted in figure 7. When algorithm is applied on test data, initially, Qualcomm is showing comparatively better result than DowJones in terms of cumulative worth, but gradually DowJones starts increasing showing good results. Finally, Qualcomm captured upper cumulative worth. Now, coming through COVID-19 data, it is clearly displaying that Qualcomm company is making good result than that of DowJones right from initial point of considering graph results. Here, DowJones remains constant relatively as well.



ddpg_covid19_comparison ddpg_test_comparison

Figure 5: DDPG comparison graphs

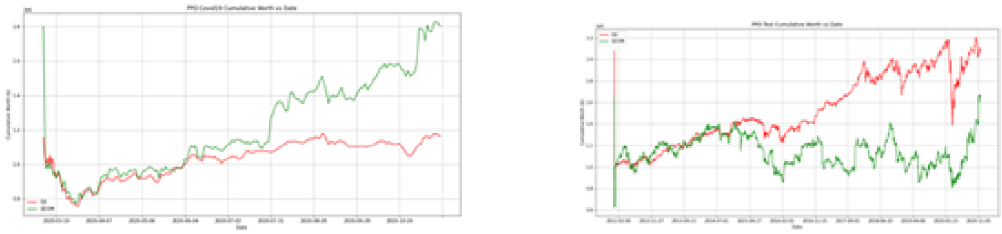
3.1.3 DQN Comparison Results: Figure 5 is displaying comparison results among test data & COVID-19 data when DQN algorithm is applied. Observing test data results, there is an initial spike in Qualcomm graph, but as time interval continues, DowJones starts producing better results whereas Qualcomm remains with numerous increments & decrements. Finally, Qualcomm after suffering lot of elevations & depressions, starts producing good result than DowJones. Now, by observing COVID-19 data, initially, two graphs are similar, but gradually, Qualcomm starts giving better results when compared through DowJones graph, & finally remains high. Here also, DowJones is yielding constant result.



dqn_covid19_comparison dqn_test_comparison

Figure 6: DQN comparison graphs

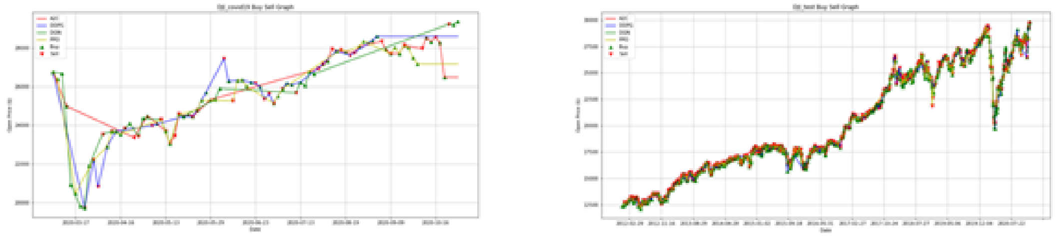
3.1.4 PPO Comparison Results: From figure.6, we can observe that when algorithm is applied on test data, both companies are producing similar graph values, but gradually DowJones starts yielding good result against Qualcomm company. Here, Qualcomm graph includes many increments & decrements that are due through market structure & investments. Comparing COVID-19 data, for some point of time, both are expressing similar result, however Qualcomm starts producing better results than DowJones that remains consistent.



ppo_covid19_comparison ppo_test_comparison

Figure 7: PPO comparison graphs

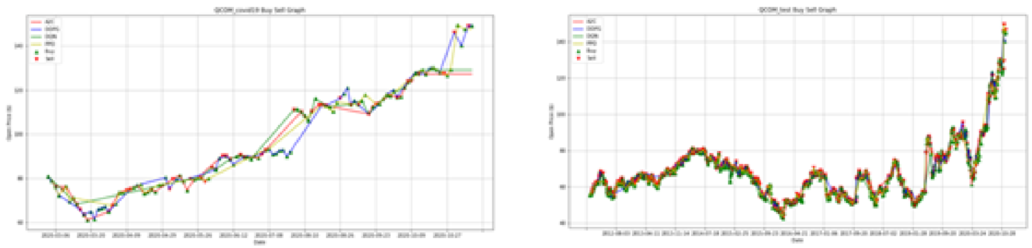
3.1.5 Dowjones Comparison Results: Consider DowJones results for all algorithms on test data & COVID-19 data. Results are evaluated against time & price of market state. Green indication denotes “sell” strategy & red indication denotes “buy” strategy. Observing test data, PPO algorithm is producing better output with numerous sell strategy points. Next algorithm that is giving good result is DQN. DDPG algorithm is yielding next good output. Finally, A2C is giving low result with many buy points. Now, comparing COVID-19 data, initially all algorithms produce similar outcomes but as time interval is extending, DQN algorithm becomes first through produce better result. DDPG stand next with numerous buy & sell points. PPO then produces consistent result with many sell points. Finally, A2C algorithm produces least result. From both graphs, it is clear that A2C is depicting low result in all situations, while PPO can be considered as better algorithm because of its consistency & buy sell points.



DJI_covid19_buy_sell_graph DJI_test_buy_sell_graph

Figure 8: DJI comparison graphs

3.1.6 Qualcomm Comparison Results: Considering figure 8, results of both test data & COVID-19 data can be observed. When test data on applying all algorithms is observed, algorithm that is producing better result is PPO as it is producing high graph ultimately as shown in figure. Next algorithm with good result is DDPG which is following path of PPO with numerous buy sell points. DQN becomes next through produce good result. A2C however produces less result. On comparing COVID-19 data, PPO & DDPG are yielding similar result where PPO algorithm is giving consistent when compared through DDPG. Next DQN is giving good result after PPO & DDPG. Finally, A2C is producing less result. From all observations, it can be concluded that PPO produces better result & A2C yields least outcome than all other algorithms.



QCOM_covid19_buy_sell_graph QCOM_test_buy_sell_graph

Figure 9: QCOM comparison graphs

Evaluation Metrics for Test Data (2012-01-03 through -2020-11-20)

Dowjones

Algorithm	PPO	DQN	DDPG	A2C
Sharpe Ratio	1.02	-0.61	-0.39	1.52

Qualcomm

Algorithm	PPO	DQN	DDPG	A2C
Sharpe Ratio	0.23	0.78	0.42	0.25

Evaluation Metrics for Covid-19 Data (2012-01-03 through -2020-11-20)

Dowjones

Algorithm	PPO	DQN	DDPG	A2C
Sharpe Ratio	1.12	1.03	~-1.2	-1.60

Qualcomm

Algorithm	PPO	DQN	DDPG	A2C
Sharpe Ratio	1.01	1.23	-0.78	1.89

4. CONCLUSION:

Before training reinforcement trading agent, we deliberately constructed environment through reproduce true exchanging which permits agent through perform collaboration & learning. In practical trading, different data should be considered, for instance verifiable stock costs, current holding shares, specialized indicators, etc. Our trading agent needs through acquire such data through environment, & make moves. In this paper, we have investigated capability of utilizing deep reinforcement algorithms which are Deep Q-learning (DQN), Deep Deterministic Policy Gradient (DDPG), Advantage Actor Critic (A2C), & Proximal Policy Optimization (PPO) agents through learn stock exchanging system. Through conform through various market circumstances, we utilize an exchanging technique through consequently choose best performing agent through exchange dependent on Sharpe ratio. Results show that our exchanging system beats four individual calculations.

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