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Deep Reinforcement Learning for Stock Behavior Prediction

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Abstract:

Stock market forecasting has long been both the most sought-after and the most dreaded occupation due to the high stakes involved. Since investors could lose a lot of money if they are wrong, a precise forecast is required. Once performed by trained stock behaviourists, this task is now as easy as clicking a button. Stock prediction is one of the many human abilities that technology has supplanted. This work proposes a combination of machine learning algorithms that, when trained on historical stock data, can identify patterns in market behaviour and make more accurate predictions about stock behaviour than a human expert with a wealth of knowledge in the field. In order to forecast even the most erratic stock price spikes, the suggested system employs Reinforcement Learning algorithms like DQN, Double DQN, and Duelling Double DQN. These algorithms have independently demonstrated to be the most effective, efficient, and productive in their respective fields. An investor in the stock market can relax now that

Keywords: Python; Django; JavaScript; MySQL; Flask; Stock Prediction; Reinforcement Learning algorithms

Introduction

Predicting stock prices has grown in popularity among young entrepreneurs and is providing a substantial income for those who dabble in the stock market today. The inability to accurately forecast the behaviour of stocks is the most annoying problem with stock prediction [5]. Despite the proliferation of algorithms for stock market prediction brought about by the ever-expanding fields of AI and ML, no better solution has been developed as of yet. This might be because of the stock market's wildly fluctuating behaviour, which is known for its unpredictability [6]. Here is where algorithms for Reinforcement Machine Learning come into play. It is well-known that Reinforcement Algorithms mimic the way the human brain works. Its architecture allows it to reflect on its actions, make adjustments, and apply those adjustments to future stock data of a similar kind [7-10]. The stock prediction mechanism of the Reinforcement Learning Algorithm is based on rewards, and the payouts are designed to increase regardless of how close the algorithm gets to the real results during training. Therefore, the algorithm may still interpret and apply its predictions to real-world data by predicting how close it is to the needed results, even if it fails to anticipate the correct number [12-15]. After being trained on a certain data set multiple times, the reinforcement learning algorithm is prepared to be tested, albeit this depends on the amount of data that is available. The actual world is a wonderful place to be. The reinforcement algorithm is unique in that it only requires a little amount of training on the training data set to function, even on highly unpredictable data sets. Stock predictions benefit from reinforcement learning. Q learning allows for the execution of various experiments [16-22]. Applying reinforcement learning will be easier if more research on the topic has progressed [24].

Objective

Developing a highly effective reinforcement learning algorithm for stock market prediction and producing a machine learning model with human-like behavior that is, one that learns from its mistakes and gains better decision-making abilities with each training is the goal.

Scope of Project

Along with supervised and unsupervised learning, there is also reinforcement learning in the realm of machine learning [25-31]. This learning system is built on agents. In a record-maximizing environment, an agent performs action. Unlike supervised learning, which relies on labelled data, reinforcement learning can function without it. Less historical data is still enough to make reinforcement learning work. In accordance with the policy determined for that activity, it computes the value using the value function. Using a Markov Decision Process as its model, reinforcement learning (MDP) [32-39]. As a reinforcement method, the deep-Q network is utilised by the suggested system to forecast the stock's behaviour. An approach for model-free reinforcement learning, a deep-Q network teaches an agent what to do in different situations based on the quality of those actions. Starting from the present state, the deep-Q network determines an optimal policy by maximising the anticipated value of the total reward over any successive steps. Therefore, in order to enhance the precision of the findings obtained from predicting stock behaviour, the suggested method employs double deep-Q learning [40-44].

Domain Explanation

To teach machine learning models to make a series of judgments, one uses reinforcement learning. With practise, the agent learns to succeed in a setting that is both complex and fraught with uncertainty [45-51]. Artificial intelligence encounters a scenario similar to a game in reinforcement learning. The computer solves the problem by using trial and error. The artificial intelligence is trained to follow the programmer's commands by providing it with incentives and punishments [52-57]. Its objective is to increase the overall benefit. Despite the designer dictating the game's rules (the reward policy), he offers no guidance to the model on how to win. From simple trial and error to complex strategies requiring superhuman abilities, the model is free to choose the optimal way to complete the task in order to maximise the reward [58-61]. The most successful method for hinting at a machine's creativity currently exists in reinforcement learning, which uses search and numerous trials. Running a reinforcement learning algorithm on a strong enough computer architecture allows artificial intelligence to learn from thousands of simultaneous gameplays, unlike humans [62-71].

Undoubtedly, reinforcement learning is a state-of-the-art technology with game-changing potential. But that's not always the case. However, it appears that reinforcement learning is the most probable method for imbuing a computer with creativity, since the pursuit of novel, inventive approaches to completing tasks constitutes creativity. This has already occurred: AlphaGo, a programme developed by DeepMind, beat Lee Sedol, a top human player, by playing moves that were once thought to be faults. So, reinforcement learning could be the next big thing in artificial intelligence [72-83].

Using Models vs. Model-Based: Environmental dynamics simulation is what the model represents. With the current state s0 and action a, the model learns the transition probability T(s1|(s0, a)) to the next state s1. Once the agent has learnt the transition probability, it will be able to use its present state and actions to determine the likelihood of entering a specific state. On the other hand, when the state and action spaces (S * S * A, in a tabular configuration) expand, model-based algorithms become unworkable [84-89].

However, model-free algorithms learn new information by trial and error. Consequently, there's no need to worry about storage space for all the possible states and actions. This class includes all of the algorithms that will be covered in the following section [90].

The difference between an on-policy and off-policy agent is that the former learns the value from its current policy-derived action, while the latter learns it from an action a* received from a different policy. Such an approach is considered greedy in Q-learning (Figure 1).

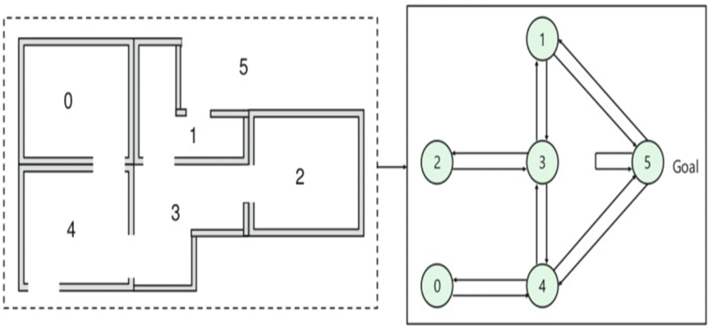


Figure 1: Q-Learning Outlook

The process of policy iteration is cyclical, going from evaluating policies to improving them. Using the greedy policy that was derived from the last policy enhancement, policy evaluation calculates the value function V. Conversely, after each state, policy improvement revises the policy to include the action that maximises V. The revised formulas take the Bellman Equation as their starting point [91-101].

Value Iteration

There is just a single component in Value Iteration. It keeps the value function V up-to-date using the Optimal Bellman Equation. Using an argument-max function for all states, the optimal policy can be easily calculated after the loop converges. You can tell it's a model-based algorithm because both of these methods need you to know the transition probability p.

Q-learning: Learn function $Q : \mathcal{X} \times \mathcal{A} \rightarrow \mathbb{R}$

Require:

Sates $\mathcal{X} = \{1, \ldots, n_x\}$

Actions $\mathcal{A} = \{1, \ldots, n_a\}$, $\quad A : \mathcal{X} \Rightarrow \mathcal{A}$

Reward function $R : \mathcal{X} \times \mathcal{A} \rightarrow \mathbb{R}$

Black-box (probabilistic) transition function $T : \mathcal{X} \times \mathcal{A} \rightarrow \mathcal{X}$

Learning rate $\alpha \in [0, 1]$, typically $\alpha = 0.1$

Discounting factor $\gamma \in [0, 1]$

procedure QLEARNING($\mathcal{X}$, A, R, T, α, γ)

Initialize $Q : \mathcal{X} \times \mathcal{A} \rightarrow \mathbb{R}$ arbitrarily

while Q is not converged **do**

Start in state $s \in \mathcal{X}$

while s is not terminal **do**

Calculate π according to Q and exploration strategy (e.g. $\pi(x) \leftarrow \arg\max_a Q(x, a)$)

$a \leftarrow \pi(s)$

$r \leftarrow R(s, a)$ $\triangleright$ Receive the reward

$s' \leftarrow T(s, a)$ $\triangleright$ Receive the new state

$Q(s', a) \leftarrow (1 - \alpha) \cdot Q(s, a) + \alpha \cdot (r + \gamma \cdot \max_{a'} Q(s', a'))$

$s \leftarrow s'$

return Q

There are issues with scalability in model-based algorithms. This difficulty is resolved using Q-learning: α denotes the rate of learning (i.e., how fast the goal is being approached) [102-106]. Value iteration has been a key component of Q-learning from the start. Nevertheless, the formula provided above substitutes for the revised equation. The consequence is that worrying about the likelihood of the changeover is no longer relevant. Take note that the subsequent action, a', is selected not to follow the present policy but to maximise the Q-value of the next state. So, Q-learning is an example of an off-policy technique [107-111].

State-Action-Reward-State-Action (SARSA)

SARSA is extremely similar to Q-learning. Being an on-policy algorithm is SARSA's main distinction from Q-learning. In other words, rather of learning the Q-value from the greedy policy, SARSA now learns it from the current policy's action in the following state s (t+1). This action is denoted as a (t+1). Two action selections are carried out, as seen in the pseudo-code above, which consistently adheres to the present policy [112-119]. When it comes to the next stage, Q-learning is free to do whatever it wants as long as it optimises the Q-value. That is why SARSA is an algorithm that operates on policies. Two action selections are executed in the pseudo code above, and they always adhere to the existing policy [120-125]. In comparison, Q-learning is unrestricted in its ability to optimise the Q-value for the subsequent state, regardless of the activity that follows. That is why SARSA is an algorithm that operates on policies.

Deep Q Network (DQN)

Despite its impressive power, Q-lack learning's of generalizability is its biggest flaw. By seeing Q-learning as a process of updating integers in a two-dimensional array (Action Space * State Space), it becomes similar to dynamic programming [126-131]. This means the Q-learning agent doesn't know what to do when faced with a state it has never encountered before. When it comes to unseen states, the Q-learning agent is unable to make value estimations. To address this issue, DQN introduces a Neural Network, which removes the need for a two-dimensional array.

In order to get a ballpark figure for the Q-value function, DQN uses a Neural Network. The current is the input to the network, and the associated Q-value for each operation is the output. The Atari game was DQN-powered by DeepMind in 2013 [132-139]. The input is a snapshot of the game as it is right now. It traversed multiple layers, some of which were fully linked and others convolutional. The result is the Q-value for all of the agent's possible actions. We are not going to cover the parameters in the Neural Network ($\boldsymbol{\theta}$), but the ώ is the same as the state s. So, the network's loss function is the squared error of the difference between the target Q-value and the network's output Q-value.

Literature Survey

According to Tsantekidis et al. [1], the use of machine learning techniques in financial trading has been on the rise as of late. Several quantitative trading programmes have focused on the ability to automatically extract patterns from past price data and reliably apply them going forward. However, establishing methods for financial trading that rely on machine learning is not an easy task. It involves designing targets and rewards with care and fine-tuning hyperparameters, among other things. On top of that, the majority of the current approaches fail to make good use of the data that is accessible across different types of financial instruments. In order to reduce the impact of the often-used profit-and-loss incentives, this article suggests a deep reinforcement learning-based strategy that guarantees the trading agent continuous rewards. The agent's performance in profit, Sharpe ratio, and maximum drawdown is greatly enhanced by employing a novel reward shaping strategy based on price trailing. Additionally, a meticulously crafted data preparation strategy is employed to educate the agent on various FOREX currency pairs, paving the way for the creation of market-wide RL agents and the utilisation of more potent recurrent deep learning models, all while avoiding the danger of overfitting. Using a difficult large-scale data set with 28 instruments supplied by Speedlab AG, the ability of the suggested strategies to improve different performance indicators is shown.

In their deep reinforcement learning approach, Double DQN, proposed by Zuo et al. [2], an object detection strategy is taught to use an image window to identify which preset regions should be focused on. An action to search the target region is chosen using the first DQN in the Double DQN framework, and then that action is evaluated using the second DQN. By comparing the results of Double DQN with those of regular DQN, we can ensure that the procedure is effective. Double DQN shows promise in experiments, outperforming its predecessors in terms of recall and precision. The results demonstrate that the object may be located with minimal steps after analysing the amount of actions executed by the Double DQN agent. The results of a person detection experiment demonstrate the algorithm's remarkable adaptability.

Lawton and Corcoran [3] Using the frameworks of system analysis and the concepts of automatic control theory, talk about the architecture of trading algorithms and automated trading systems. Depending on the imbalance in the order book, several adjustments to the implementation of the trading algorithm are taken into account. This paper presents a number of methods and ideas for optimising, adapting, and parameter tweaking trading algorithms both online and offline through the use of trading process simulations.

In their study, Tsantekidis et al. shown [4] Financial time series forecasting is one of the oldest and most difficult issues in financial market research. Typically, investors will use statistical models to help them identify the best times to join or exit the markets (or even simple qualitative methods). Unfortunately, the accuracy of the models utilised for forecasting is significantly limited by the markets' intrinsic noise and stochasticity. Modern advances in electronic trading and the accessibility of massive amounts of data have paved the way for innovative machine-learning approaches that overcome some of the limitations of the aforementioned methodologies. Using massive amounts of high-frequency time-series data from Limit Order Books, this study suggests a recurrent neural network–based deep learning approach to price movement prediction. With the help of a massive dataset consisting of limit order book events, the suggested strategy is tested.

System Analysis

Existing System

A first: navigating the stock market using Reinforcement Learning. Many methods for predicting the stock market's performance have been developed and implemented thus far, but they typically only look forward one year, one month, one week, etc. Fbprophet, a library developed by Facebook that makes stock price predictions, is an example of this type of technology. In the past, algorithms for behaviour prediction have often been either supervised or unsupervised, or a hybrid of the two. The stock market is very unpredictable, so even if these algorithms are good at predicting, they may not be able to navigate stocks effectively. Therefore, these drawbacks are intended to be addressed by the existing system.

Proposed System:

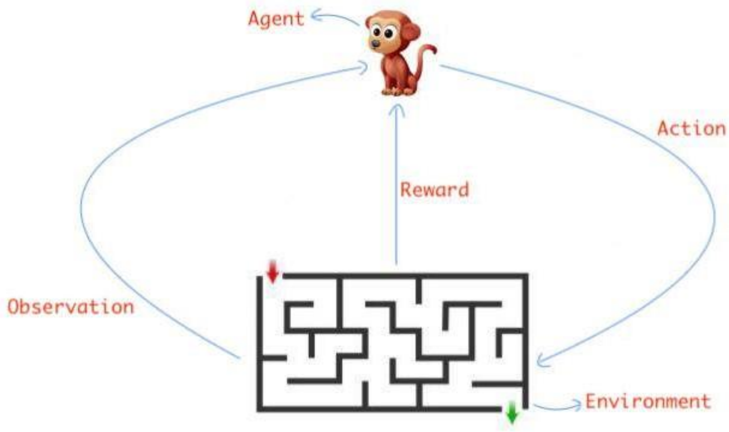
The suggested approach recommends analysing stock market data using a combination of machine learning algorithms like DQN, Double DQN, and Duelling Double DQN. Algorithms like these use reward shaping to gauge how near an outcome is. Even if the final outcome is not known, the algorithm will get closer and closer to it; this is the most important tactic. With the end, this aids in pattern deduction by preventing the algorithm from becoming overfit to the dataset. The subject of the stock market's excessive volatility is also covered here.

Data Wrangling

Collecting, sorting, and changing data in order to provide an analytical solution is known as data wrangling. "Munging" is another name for data cleansing. According to urban mythology, analytics professionals spend up to 80% of their time on data wrangling, leaving only 20% for actual modelling and exploration.

Environment Setup

There is an agent and a setting accessible in reinforcement learning, a subfield of machine learning. In this scenario, the environment is merely a simulation or task, and the agent is an artificial intelligence system that attempts to complete the task by interacting with the environment. Here we can see the maze representing the environment in the diagram. Taking optimal actions is the



agent's goal as they attempt to solve this maze (Figure 2).

Figure 2: The Reinforcement Learning Environment

Training Agent

It is possible to train the agent in the environment using the train function after the environment and agent for reinforcement learning have been constructed. To set up the training, use the retraining options feature. Setting up a training option and then training an agent in a given environment is one example.

Training Algorithm

Apply action to the environment and obtain the next observation s" and the reward r.

Learn from the experience set (s, a,r,s').

Compute the next action a’ = μ(s’).
Update the current action with the next action (an←a’) and the current observation with the next observation (s←s’).
Plotting: For deep reinforcement learning algorithm creation, debugging, prototyping, and evaluation, plotting and visualisation are crucial. If you're having trouble writing code that generates good plots, the following suggestions may be useful.
System Study: After the issue has been defined and potential solutions have been considered, a feasibility study can be carried out. Analyzing the possible effects of a planned project or programme is what a feasibility study is all about. Checking the practicality of the suggested system is the goal. Below, we'll go over the three main components of a feasibility study that the suggested system goes through.
Technical Feasibility: To determine if the new system can be implemented with the available technical resources, technical feasibility analyses are conducted. In the event that they are unavailable, is it possible to upgrade them. The feasibility of the suggested system within the current system, without requiring any hardware support, is examined.
Economic Feasibility: It ascertains whether resources like time and money can be allocated to create the system. It also comprises buying new software, gear, and equipment. The creation, upkeep, and consumption of a software product should not break the bank. The organisation is able to allocate the necessary resources because the necessary hardware and resources are already in place.
Operational Study: Whether or not the necessary personnel are on hand to run the system after its installation is dependent on operational feasibility. The organisation already has all the necessary resources to install or deploy. Workers at the company don't have to have any prior experience with computers, but they will need training to utilise this programme. Not all of them will receive training. Also, the amount of training is little. On top of that, upper management will see the project's optimal feasibility.

Requirement Analysis And Specification

In a software development project, gathering requirements is the initial step. In order to come up with a novel product idea that no other software seller has thought of, the first step in gathering software requirements is to engage in creative brainstorming. In most cases, researching consumer wants and needs through surveys and market research leads to the development of new software products. An abstract concept that addresses a genuine need or problem can be materialised into a project with specific goals, a schedule, a budget, and a team during the requirements-gathering phase.
Gathering project ideas: Coming up with project ideas can be a great way to stretch yourself.

Collecting client needs and suggested remedies: Prioritize meeting the customer's specific requirements and resolving their issues.
Project justification: Finding out which projects have the best chance of contributing to the company's success is a crucial aspect of the requirements-gathering phase.
The submission of the request for proposal is a crucial step in the process by which upper management determines which initiatives are likely to be profitable and, therefore, deserving of funding for additional research and testing.
Establishing the team: Collaborative effort from a group of people is essential to the completion of any endeavour. Individuals such as the project's sponsor, manager, analysts, developers, dba, tw, QA, trainers, release managers, etc. make up the team.

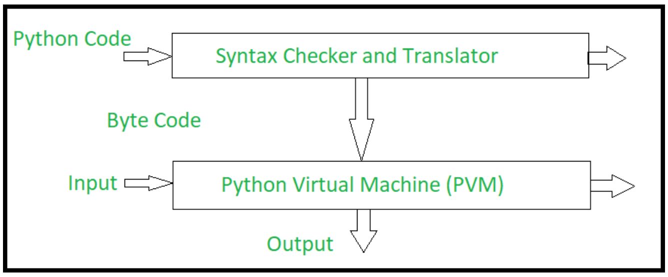
The analysis phase relies heavily on the Requirements Document (RD), which must first be prepared. Features of the product, a strategy for documentation and support, licencing considerations, and an overview of the requirements to achieve the project's goal are all part of it. Python, an interpreted, object-oriented, high-level language with dynamic semantics, is introduced in this introduction. Its dynamic typing, binding, and high-level built-in data structures make it a great choice for scripting and glueing together different components, as well as for Rapid Application Development. The emphasis on readability and the reduction in the cost of programme maintenance are both contributed by Python's basic and easy-to-learn syntax. Because of its modules and packages, Python promotes code reuse and software modularity. Both the source code and binary versions of the Python interpreter and standard library are freely distributable and accessible for use on all major platforms.

Python is a popular programming language among programmers due to its ability to enhance productivity. The iteration of edit, test, and debug is lightning quick because compilation is not involved. Because segmentation faults are never caused by bugs or improper input, debugging Python scripts is a breeze. On the contrary, an exception is raised if the interpreter finds a mistake. If the programme fails to handle an exception, the interpreter will display a stack trace. You may set breakpoints, step through the code line by line, inspect local and global variables, evaluate arbitrary expressions, and much more with a debugger that operates at the source level. One evidence of Python's reflective strength is the fact that it is used to write the debugger. However, thanks to the efficient edit-test-debug cycle, adding a few print statements to the source code is usually the easiest method to debug a programme.

The first step in writing the code is to have a Jupyter notebook. Notepad++, Atom, Sublime Text, Visual Studio Code, or any other text editor that the programmer is familiar with can also be utilised as part of an integrated development environment. We need a big dataset from the stock market.

Python is a Java-like object-oriented programming language. Interpreted languages are what Python is known as. Instead of the conventional long list of instructions used by functional programming languages, Python makes use of interchangeable code modules. It is known as "CPython" and it is the default Python implementation. It is the most popular and default version of Python.

Python does not translate its programmes into a form that hardware can understand, known as machine code. The process turns it into byte code. Python is not a machine language, but compilation does take place within it. Now it's in byte code, which the central processing unit



(CPU) cannot decipher. Therefore, a Python virtual computer, an interpreter, is necessary. To run the byte codes, the Python virtual machine is used (Figure 3).

Figure 3: Internal Working Of Python

New advances in computer vision and voice recognition have hinged on how well deep neural networks are trained using massive training sets. Training the best methods from raw inputs with lightweight updates based on stochastic gradient descent yields the best results. When trained with enough data, deep neural networks can frequently outperform human-created features in learning representations [11]. Our strategy for reinforcement learning is driven by these achievements. The goal is to build a deep neural network to handle RGB images efficiently by integrating a reinforcement learning technique with stochastic gradient updates. Such an approach can be built upon Tesauro's TD-Gammon architecture. The algorithm's interactions with the environment are used to draw on-policy samples of experience, st, at, rt, st+1, and at+1, and this design modifies the parameters of a network that estimates the value function (or by self-play, in the case of backgammon). Given that this method beat the top human backgammon players twenty years ago, one would expect that advancements in hardware, together with new designs for deep neural networks and scalable RL algorithms, may lead to even greater success.

A data-set D = e1,..., eN, which is pooled over many episodes into a replay memory, stores the agent's experiences at each time-step, et = (st, at, rt, st+1), in contrast to TD-Gammon and comparable online techniques. In the inner loop of the method, experience samples, denoted as e ~ D, are chosen at random from the stored pool of samples and subjected to Q-learning updates, also known as minibatch updates. The agent decides what to do next based on a -greedy policy after running experience replay. The Q-function operates on a representation of histories with a defined length that is generated by a function φ because it can be challenging to use histories of arbitrary length as inputs to a neural network. Here you can get the complete algorithm, which we refer to as deep Q-learning: (Figure 4).

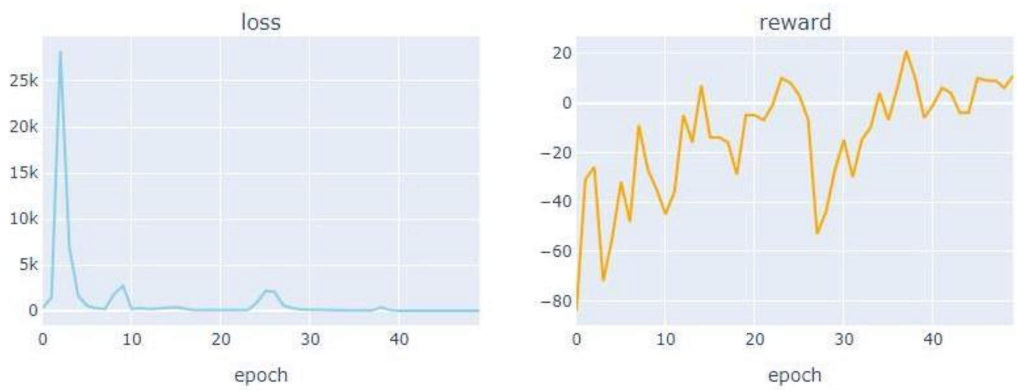


Figure 4: Double DQN Result

In comparison to the status quo of online Q-learning, this method provides significant benefits [23]. To start, there is more data efficiency because one experience step can be used in multiple weight updates. Second, significant correlations between data make direct learning from consecutive samples inefficient; randomising the samples breaks these correlations and minimises the variance of the updates. Third, the following data sample is used to train the parameters while learning on-policy, based on the present parameters. If the maximising action shifts to the left, for instance, samples from the left will predominate in the training set; likewise, if the maximising action shifts to the right, the training set will similarly undergo a shift. Parameters could diverge disastrously or become stuck in a bad local minimum; undesirable feedback loops are easy to imagine [25].

To prevent parameter oscillations or divergence and to smooth out learning, experience replay averages the behaviour distribution over several of its prior states. To learn from experience replay, one must learn off-policy (because our current parameters are different from the ones used to create the sample), which is why Q-learning is used. In actuality, the algorithm updates by evenly sampling from D and only keeps the most recent N experience tuples in the replay memory. The memory buffer constantly overwrites with recent transitions because of the finite memory size N, hence this approach is somewhat limited because it does not separate key transitions. The uniform sampling method also treats all replay memory transitions equally. A more nuanced approach to sampling, such prioritised sweeping, could place greater emphasis on transitions, the points at which the majority of learning occurs.

To solve the problem, it is necessary to employ two distinct Q-value estimators, each of which is utilised to update the other. These independent estimators allow us to generate unbiased Q-value estimates of the actions that were chosen by utilising the estimator that is opposite to the one we are using [3]. Through the process of disentangling our updates from biassed estimations, we are able to circumvent the maximising bias. As we can see, standard DQN has a tendency to dramatically overstate action values, which results in unstable training and policy that is of poor quality.

The standard DQN architecture makes use of convolutional layers in order to manage frames that are generated by games. After that, the network is cut in half, with one half being used to estimate the value of the state, and the other half being used to estimate the benefits of actions that are dependent on the state. In the final network module, the outputs of the state-value and advantage are incorporated once the two streams have been completed.

Taking such into consideration while also delivering accurate evaluations of the worth of the state and the rewards of action is a difficult task. Therefore, it is possible that combining these two variables in a naive manner could be harmful. The fact that V and A cannot be reconstructed in a unique manner from the naïve sum of the two makes it "unidentifiable" according to the Q value. Therefore, the final module of the neural network is where forward mapping is included in its implementation. In this way, the problem of identifying the maximum action will be resolved since the Q value for the action will be forced to equal V.

Conclusion

"Stock Behaviour Prediction Using Deep Reinforcement Learning Techniques" is an approach that suggests using RL to foretell how stocks will behave in the future. In order to achieve its impressive results, this system has integrated and optimised a number of machine learning techniques, including Deep Q-network, duelling double deep q-network, and double deep q-network. In addition to being a successful system overall, its accuracy rate of 73.3% is significantly greater than that of any prior stock prediction algorithm. An efficient forecast from the suggested system necessitates two processors and eight gigabytes of RAM, which uses up a lot of resources. In order to make the algorithm more suited for usage on home PCs, it can be improved in the future to employ batch processing and connect the results in such a way that the system processor consumption at any one time is significantly decreased. Attempts to improve this model's accuracy are also possible along the road

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