FINSEARCH MID-TERM REPORT

Using Deep Reinforcement Learning to Optimize Returns

Group – H9

Mentor: Prerak Contractor

Mentees: Raghav Rander
Naveen Gowda
Praveen Saharan

Relative Advantages and Disadvantages of Traditional and Reinforcement Learning-Based Algorithms:

The field of artificial intelligence has witnessed rapid advancements over the years, resulting in the development of various algorithmic paradigms to address different problem domains. Two prominent approaches are traditional algorithms and Reinforcement Learning (RL) based algorithms. This note aims to explore the relative advantages and disadvantages of each approach, shedding light on their strengths and limitations.

Traditional algorithms have been the backbone of many AI applications, offering several compelling advantages. One of their key strengths is determinism, where the same input will consistently produce the same output, making them reliable and predictable. This property is crucial in domains where certainty and reproducibility are critical, such as in financial systems or safety-critical environments.

Another advantage of traditional algorithms lies in their simplicity. These algorithms are typically well-established and widely understood, making them easier to implement and debug. Furthermore, traditional algorithms often come with rigorous mathematical proofs, ensuring their correctness under specific conditions.

Moreover, traditional algorithms possess broad applicability across various problem domains. Due to their deterministic nature and well-defined rules, they can be applied to a wide range of tasks, from image processing to natural language processing, without the need for extensive modification.

However, traditional algorithms have their drawbacks. One significant limitation is the requirement for manual feature engineering. Extracting relevant features from raw data demands domain expertise and can be a labor-intensive process. Additionally, manual feature engineering can lead to suboptimal performance, as certain relevant features might be overlooked.

Reinforcement Learning (RL) Algorithms: Adaptability, Autonomous Feature Extraction, and Scalability

Reinforcement Learning (RL) algorithms are a type of machine learning approach that focuses on decision-making in dynamic environments. RL has gained popularity due to several advantageous characteristics.

One key strength of RL algorithms is adaptability. These algorithms can learn from experience and improve their performance over time, making them suitable for tasks where the optimal strategy might change or is unknown at the beginning. This adaptability allows RL algorithms to handle complex and dynamic problem domains effectively.

Moreover, RL algorithms offer autonomous feature extraction. Unlike traditional algorithms, RL agents can automatically learn relevant features from raw data, reducing the need for manual feature engineering. This characteristic is particularly valuable in scenarios where feature engineering is challenging or infeasible, such as computer vision tasks with high-dimensional input data.

Furthermore, RL algorithms are scalable and can handle large state and action spaces, making them suitable for complex real-world problems.

Trade-offs with RL algorithms

Despite their advantages, RL algorithms come with certain trade-offs. One major concern is sample inefficiency. Training an RL agent often requires a substantial number of interactions with the environment, which can be time-consuming and computationally expensive. This becomes a significant drawback in applications where obtaining data is expensive or risky, such as in medical trials or robotics.

Additionally, RL algorithms require a delicate balance between exploration and exploitation. Exploration is necessary to discover optimal strategies, but excessive exploration can lead to slow learning and reduced performance. Striking the right balance is challenging and often requires careful tuning.

Moreover, RL models can be inherently complex, making them less interpretable than traditional algorithms. In critical applications where understanding the decision-making process is essential, the lack of interpretability can be a significant drawback.

In conclusion, both traditional algorithms and RL-based algorithms offer unique advantages and disadvantages that must be considered when choosing the appropriate algorithmic paradigm for different problem domains. Traditional algorithms provide determinism, simplicity, and broad applicability but necessitate manual feature engineering and may lack adaptability. On the other hand, RL algorithms offer adaptability, autonomous feature extraction, and scalability but may suffer from sample inefficiency, exploration-exploitation challenges, and reduced interpretability.

Understanding these trade-offs is vital for practitioners and researchers to make informed decisions and select the most suitable algorithmic approach based on the specific requirements and characteristics of the problem at hand. Future advancements in AI may bridge the gaps between these paradigms, leading to hybrid approaches that combine the best of both worlds.

Code:

The code includes an LSTM model which predicts the price of NIFTY50 for the future.
LSTM model has been chosen since it is widely used for time series type of data and gives best possible results in such scenarios.
It has been trained on the NIFTY50 data from Jan 2010 to Jun 2019 and tested on the NIFTY50 data from Jul 2019 to Jul 2022.
Some parameter tuning has been tried to reduce the RMSE. Though it increases the computation and time required to train, for now we have a decent trade-off between the two. Hence, the model is pretty accurate and can be used for the later half of the project.

Individual Contribution:

Praveen Saharan: Literature review about RL and traditional algorithms. Comparative study and documenting the findings.

Naveen Gowda: Finding the dataset for NIFTY50, pre-processing and exploring different RL algorithms.

Raghav Rander: Building and training the LSTM model.

Github Repository: https://github.com/raghavrander/Finsearch

Future Work:

- Including actions for buying, selling and holding based on the predictions generated
- Creating ARIMA model and comparing it with the LSTM
- Testing the models and optimizing the parameters for maximum returns