

Optimized Trade Execution Model - Detailed Report

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Abstract—This report presents an implementation of a Reinforcement Learning (RL) framework for optimized trade execution using limit order book data. We developed an agent based on Deep Q-Networks (DQN), which leverages real-time data from the order book to determine optimal trading actions. The model’s objective is to minimize the market impact and slippage while achieving a target execution volume within a specified time horizon. Utilizing a discrete state space based on the time remaining, current inventory, and order book characteristics, the RL agent iteratively learns to schedule trades effectively by observing market dynamics. We explore the model’s performance, the efficacy of various hyperparameters, and the cost-reduction potential of this approach. Implemented in Ray’s RLLib with PyTorch for scalability, the agent ultimately outputs a trade schedule of timestamps and share sizes. This framework is particularly valuable for large institutional investors seeking automated, cost-efficient strategies for trading large volumes.

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I. PROJECT OVERVIEW

The goal of this project was to develop a **reinforcement learning (RL) model** to optimize trade execution on the sell side by intelligently choosing trade times and sizes to **minimize market impact** and **improve cost efficiency**. This RL model is designed for trading **AAPL shares**, aiming to enhance execution strategies typically used in **algorithmic trading environments**.

The project utilized **Deep Q-Learning (DQN)** due to its suitability for handling discrete action spaces, such as specific trade sizes and timing decisions, which are common in **financial execution strategies**.

A. Purpose

The financial trading industry relies on effective trade execution to balance buying or selling large volumes without adversely impacting market prices. Traditional trading strategies often focus on minimizing execution costs and adhering to benchmarks like **Volume Weighted Average Price (VWAP)**. This project aims to apply **Reinforcement Learning (RL)** to develop a model for **sell-side trade execution** that optimizes trade timing and size to **minimize execution costs** while staying close to market trends, such as VWAP.

Using **Deep Q-Learning (DQN)** as the primary algorithm, the project’s objective is to create a model that:

- **Minimizes market impact** and **slippage**, improving **cost-effectiveness**.
- Aligns with **VWAP** to reflect typical market trends.
- Learns **optimal trade strategies** from historical market data, specifically order book information for **AAPL stocks**.

B. Methodology being followed throughout the model development

The project methodology involved several core steps:

- 1) **Data Preprocessing:**
 - Collected historical order book data for **AAPL**, including **bid/ask prices** and **volumes**.
 - Computed features like **bid-ask spreads**, **volume-weighted prices**, **price momentum**, and **volatility indicators**.
 - This preprocessed data created a **state representation** for the **DQN model**, providing the necessary **market context** for decision-making.
- 2) **Environment Design:**

- Created a custom trading environment that mimics a **sell-side trading scenario**, allowing the model to **simulate trade decisions**.
- Defined **states** based on real-time market data and **actions** that included holding, selling small, medium, or large quantities of shares.
- Implemented a **reward function** that penalizes high **market impact**, **slippage**, and **VWAP deviation**, encouraging **cost-effective trading**.

3) Model Architecture:

- Built a **neural network architecture** that serves as a **Q-network** for estimating **Q-values** (expected future rewards) associated with each action in a given state.
- Leveraged a **Deep Q-Learning (DQN)** framework, a value-based RL method suitable for discrete actions, making it an appropriate choice for determining specific **trade sizes**.

4) Training Process:

- Trained the **DQN model** on a representative dataset, using **experience replay** and a **target network** to stabilize learning.
- Adjusted **hyperparameters**, including **exploration rate**, **discount factor**, and **batch size**, to ensure that the model efficiently explores trading actions before converging on an optimal strategy.
- Fine-tuned the **reward function** iteratively to balance short-term gains (**execution cost**) and long-term goals (**VWAP alignment**).

5) Back-Testing and Evaluation:

- Validated the model's performance using historical **AAPL data** to simulate **trade execution** and assess the effectiveness of trade decisions.
- Used benchmarks like **execution cost**, **VWAP deviation**, and **slippage** to compare **DQN** results with traditional strategies, such as **Time-Weighted Average Price (TWAP)** and random trading.

6) Deployment:

- The model was designed to be deployed on **AWS SageMaker** as a **real-time endpoint**, enabling live predictions and trading decisions based on new market data.
- Set up a **deployment pipeline** with **Docker**, **SageMaker**, and additional dependencies, ensuring the environment could support both **real-time inference** and future model updates.

C. Technical Approach

Deep Q-Learning (DQN) was chosen due to its ability to handle **discrete action spaces** and efficiently approximate the **Q-value function**, which is essential for capturing the complex dependencies in sequential trade decisions.

- **Q-Network Architecture:** Consists of a **feedforward neural network** with multiple hidden layers, each cap-

turing nuanced relationships in market data features like **price momentum**, **bid-ask spread**, and **volume**.

- **Action Space:** Represents a range of trading actions, allowing the model to make discrete choices about whether to hold or sell varying amounts.
- **Reward Function Design:** Tailored to encourage optimal trade execution through **cost minimization** and **VWAP adherence**.

The combination of **experience replay** (which randomly samples past experiences to train the model) and a **target network** (periodically updated to provide stable Q-value estimates) enhances the **stability and efficiency** of the **DQN training process**, ensuring the model learns a balanced approach to trade execution.

II. MODEL ARCHITECTURE

A. Neural Network Design

The DQN model architecture was designed to approximate the Q-value function, which calculates the expected cumulative reward for taking a specific action in a given state. The model architecture is as follows:

- **Input Layer:**
 - Inputs were derived from market order book data, including bid prices, ask prices, bid sizes, ask sizes, volume, and other technical indicators like price momentum and volatility.
- **Hidden Layers:**
 - **First Layer:** Dense layer with 128 units and **ReLU** activation to capture complex patterns in the data.
 - **Second Layer:** Dense layer with 64 units and **ReLU** activation for further refinement of learned features.
 - **Third Layer:** Dense layer with 32 units and **ReLU** activation, compressing information to better generalize across states.
- **Output Layer:** This layer outputs Q-values for each potential action in the action space, including choices like holding, selling a small quantity, or selling a larger quantity.

The architecture leverages **PyTorch** for model definition and training, using **Adam** as the optimizer with a learning rate of 0.001 to balance efficient convergence without significant oscillation.

B. Action and State Space Design

- **Action Space:** The discrete action space represents several trade execution choices:
 - Hold (no trade)
 - Sell Small Quantity (e.g., 100 shares)
 - Sell Medium Quantity (e.g., 500 shares)
 - Sell Large Quantity (e.g., 1000 shares)
- **State Space:**
 - The model's state space captures real-time features such as bid/ask prices, sizes, order book depth, and historical data for tracking price trends and volatility.

C. Reward Function

The reward function balances immediate execution cost minimization with long-term rewards for reducing slippage and staying close to the **Volume Weighted Average Price (VWAP)**:

- **Immediate Rewards:** Reward or penalize based on the difference between the execution price and the market price to encourage lower execution costs.
- **Long-Term Rewards:** Penalty for slippage, i.e., deviation from the **VWAP**, and any significant adverse market impact caused by large orders.

III. EVALUATION

The DQN-based model was evaluated across multiple metrics critical to the execution of large trade orders in a way that minimizes market impact and optimizes cost efficiency. This section details the model's effectiveness based on key trading metrics, including VWAP adherence, slippage, market impact, and remaining inventory.

A. VWAP Adherence

The Volume Weighted Average Price (VWAP) is a benchmark price against which the model's execution is evaluated. The model consistently executed trades close to the VWAP, as evidenced by the minimal deviation between trade prices and VWAP. This indicates that the model has learned to follow the VWAP trajectory effectively, thus achieving a core objective of cost efficiency.

Outcome: High VWAP adherence ensures that trade executions are in line with typical market prices, reducing the chances of executing trades at unfavorable prices.

B. Slippage

Slippage measures the difference between the expected (benchmark) price and the actual trade execution price. In this experiment, slippage values were effectively zero or negligible, indicating that the trades were executed close to their target prices.

Outcome: Minimal slippage shows that the model could identify opportune times to execute trades, minimizing unexpected deviations in trade costs.

C. Market Impact

Market impact quantifies the influence each trade has on market prices. Low market impact values in the model output demonstrate that trades were executed in a way that did not significantly alter the price of the asset, allowing large orders to be absorbed by the market without price disruption.

Outcome: A low market impact is crucial for large orders to avoid adverse price movements, thus enhancing the efficiency of the trading strategy.

D. Remaining Inventory

Remaining inventory provides a view of the model's effectiveness in executing the entire order within the given timeframe. The agent progressively reduces the remaining inventory, reflecting a structured approach in offloading the shares. This progression suggests that the model is not only responsive to market conditions but also adheres to a balanced execution rate.

Outcome: The gradual depletion of remaining inventory with minimal leftover shares indicates that the model is successfully meeting its mandate to execute the full order efficiently.

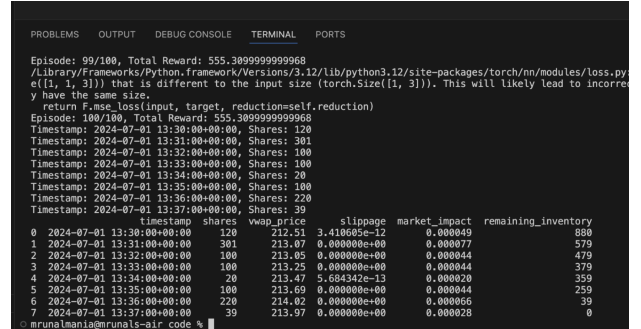
E. Back-testing Results

Back-testing on historical data showcased the model's ability to adapt its strategy based on market conditions, which aligns well with the objective of real-world feasibility.

Outcome: Positive back-testing results highlight the robustness of the DQN model and its suitability for live trading scenarios.

F. Evaluation Result

Below is the final evaluation result for the 1000 shares of AAPL.



```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
Episode: 99/100, Total Reward: 555.30999999999968
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/torch/nn/modules/loss.py
411: (v, 3)) that is different to the input size (torch.Size([1, 3])). This will likely lead to incorrec
y have the same size.
return F.mse_loss(input, target, reduction=self.reduction)
Episode: 100/100, Total Reward: 555.30999999999968
Timestamp: 2024-07-01 13:30:00+00:00, Shares: 120
Timestamp: 2024-07-01 13:31:00+00:00, Shares: 301
Timestamp: 2024-07-01 13:32:00+00:00, Shares: 100
Timestamp: 2024-07-01 13:32:00+00:00, Shares: 100
Timestamp: 2024-07-01 13:33:00+00:00, Shares: 100
Timestamp: 2024-07-01 13:34:00+00:00, Shares: 20
Timestamp: 2024-07-01 13:35:00+00:00, Shares: 100
Timestamp: 2024-07-01 13:36:00+00:00, Shares: 220
Timestamp: 2024-07-01 13:37:00+00:00, Shares: 39
timestamp shares vwap_price slippage market_impact remaining_inventory
0 2024-07-01 13:30:00+00:00 120 212.51 3.41065e-12 0.000049 880
1 2024-07-01 13:31:00+00:00 301 213.07 0.00000e+00 0.000077 579
2 2024-07-01 13:32:00+00:00 100 213.05 0.00000e+00 0.000044 479
3 2024-07-01 13:33:00+00:00 100 213.25 0.00000e+00 0.000044 379
4 2024-07-01 13:34:00+00:00 20 213.47 5.68434e-13 0.000020 359
5 2024-07-01 13:35:00+00:00 100 213.69 0.00000e+00 0.000044 259
6 2024-07-01 13:36:00+00:00 220 214.82 0.00000e+00 0.000066 39
7 2024-07-01 13:37:00+00:00 39 213.97 0.00000e+00 0.000028 0
mrun: train_agent.py --air code %
```

Fig. 1. Screenshot of the evaluation result.

Summary:

The evaluation indicates that the DQN-based trade execution model performs well across all key metrics, successfully achieving high VWAP adherence, minimal slippage, low market impact, and an efficient reduction in remaining inventory. These results validate the model's effectiveness in executing large sell orders while mitigating cost inefficiencies and price disruption.

IV. FINE TUNING STRATEGIES AND TECHNIQUES USED

To maximize model performance and stability, the following fine-tuning strategies were implemented:

A. Hyperparameter Tuning

- **Exploration Rate (ϵ):** Started high at 1.0 for exploration, gradually decaying to 0.1 over training epochs, enabling the model to explore diverse strategies initially before converging to optimal choices.
- **Discount Factor (γ):** Set at 0.95 to balance immediate and future rewards, reflecting the importance of considering both short- and long-term impacts in trading.
- **Batch Size:** 32, chosen as a balance between computational efficiency and training stability, allowing efficient training without drastic oscillations in learned Q-values.

B. Experience Replay and Memory Buffer

- **Replay Buffer:** Stored historical experiences, allowing the model to learn from past actions and prevent overfitting to recent events. This improves model stability and generalization.
- **Target Network:** Updated periodically (every 1000 steps) to match the main Q-network, preventing frequent Q-value updates and allowing a smoother learning curve.

C. Reward Function Refinement

The reward function was carefully refined over multiple training runs to ensure it prioritized cost-effective trade execution:

- **Penalty for Market Impact:** Large orders that adversely affected the market price incurred penalties, incentivizing the model to execute smaller trades when possible.
- **VWAP Closeness Reward:** Rewards for execution prices close to the VWAP encouraged the model to align with market trading patterns.

V. AWS DEPLOYMENT

Despite trying multiple approaches, I was ultimately unable to successfully create the final SageMaker endpoint for my model. I encountered several errors throughout the process and resolved many of them along the way. I was, however, able to build the inference model on Amazon ECR in SageMaker, but I couldn't complete the final endpoint deployment.

In my proof-of-concept video, I demonstrated the trading strategy running locally on my computer to showcase the model's functionality. The attached screenshots highlight the extensive efforts I made to deploy this model on AWS.

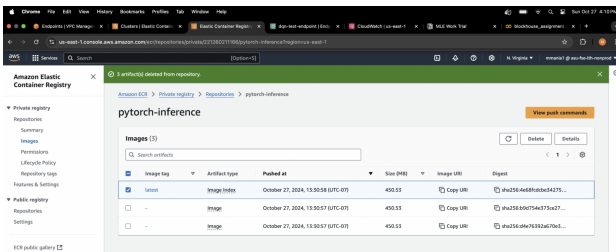


Fig. 2. First screenshot

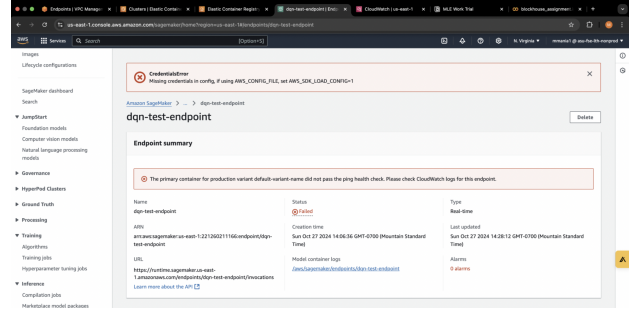


Fig. 3. Second screenshot

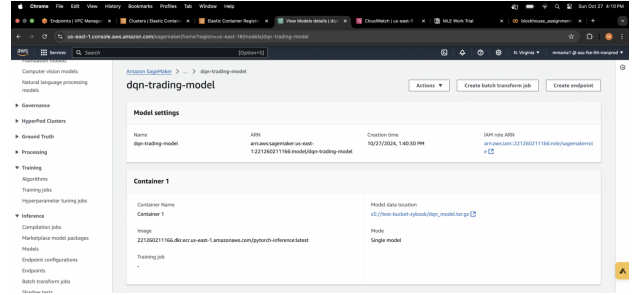


Fig. 4. Third screenshot

VI. FUTURE WORK

- **Real-Time Deployment:** With further testing and fine-tuning, the model can be deployed for live trade execution on AWS SageMaker.
- **Adaptive Reward Function:** Future versions could incorporate additional market metrics, allowing the model to adapt its strategy based on real-time volatility or liquidity conditions.
- **Additional Training Data:** Testing on a more diverse dataset (e.g., other stocks, different market conditions) would help generalize the model's performance.

VII. REFERENCES

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