GENERALIZED DEEP REINFORCEMENT LEARNING FOR TRADING

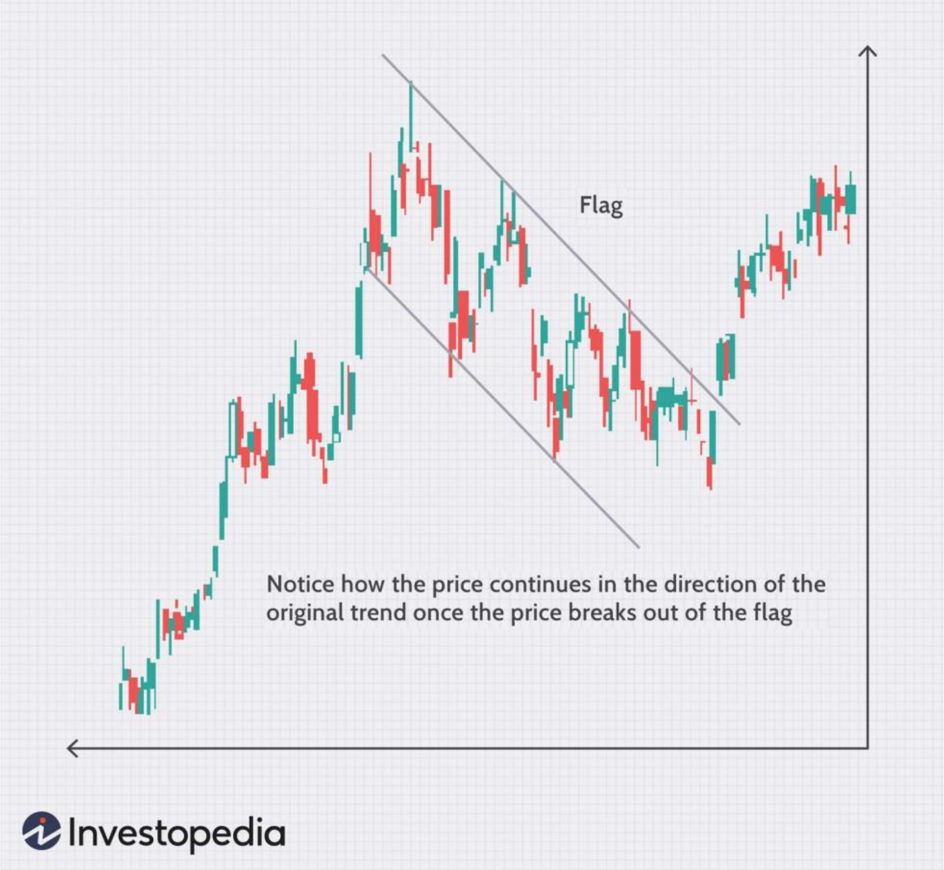
Junyoung Sim; Benjamin Kirk

INTRODUCTION

Efficient Market Theory vs Wall Street

Quants (i.e., technical analysis)

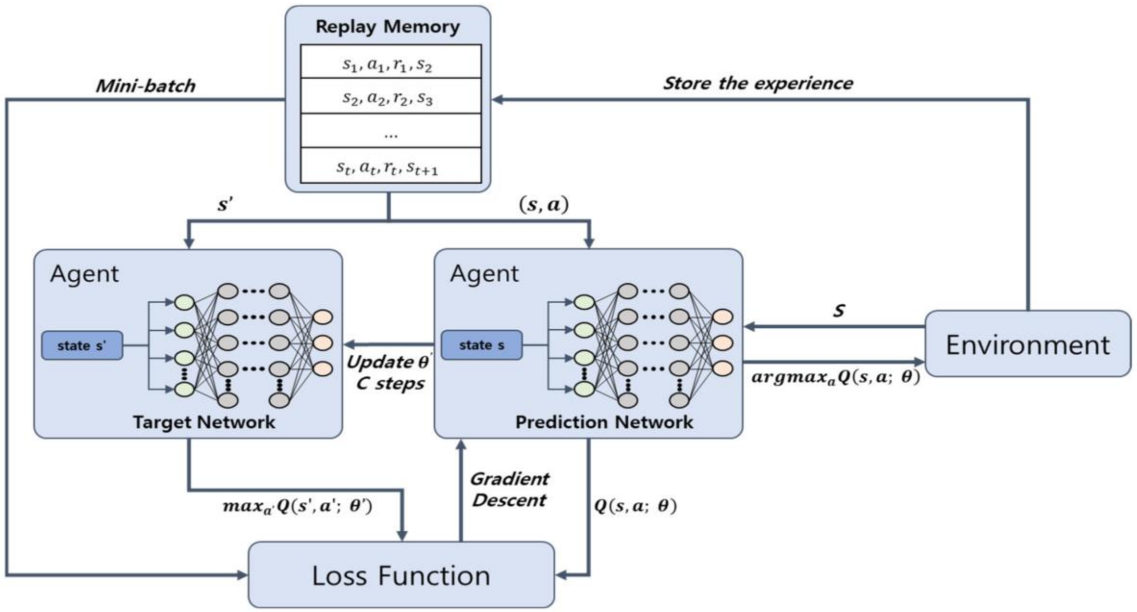
Simple Charts to Artificial Intelligence



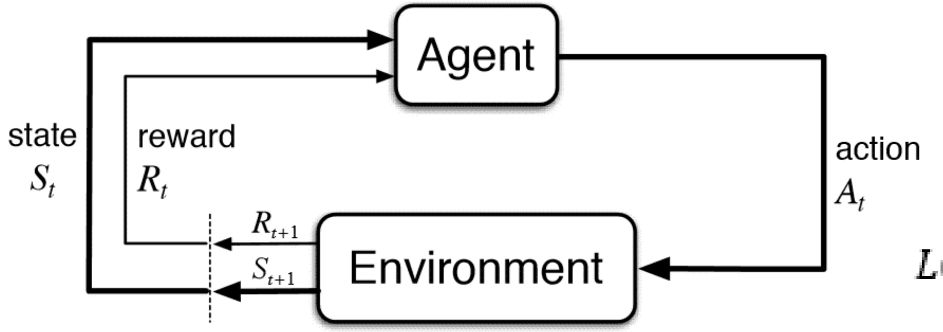
BACKGROUND

Deep reinforcement learning is a subfield of deep learning that uses reinforcement learning optimization techniques.

Reinforcement learning is the process of optimizing an agent's reward-maximizing behavior when given certain states in a Markov Decision Process.



$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k R_{t+1+k} \mid s, a\right]$$



$$Q^*(s,a) = r + \gamma \max_{a'} Q(s', a'; \theta_{i-1})$$

$$L(\theta_i) = [Q^*(s,a) - Q(s,a;\theta_i)]^2 = \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_{i-1})\right) - Q(s,a;\theta_i)\right]^2$$

LITERATURE REVIEW

Overreliance on technical indicators; **no cross-market correlations are utilized** in the state space.

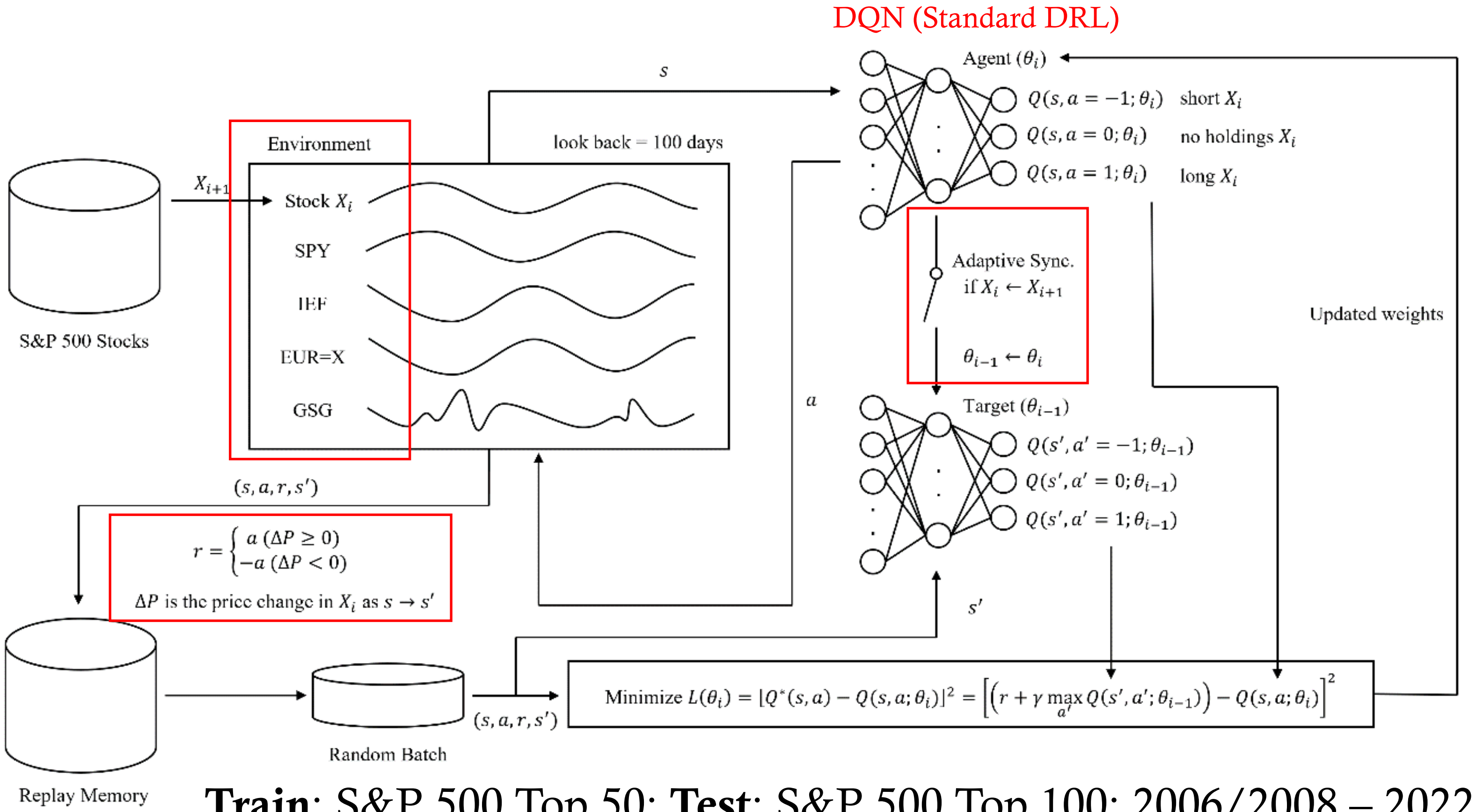
Continuous reward functions overfit to the volatility of certain stocks and limit the scope of generalization.

Fundamental challenges in deep reinforcement learning **are not discussed**.

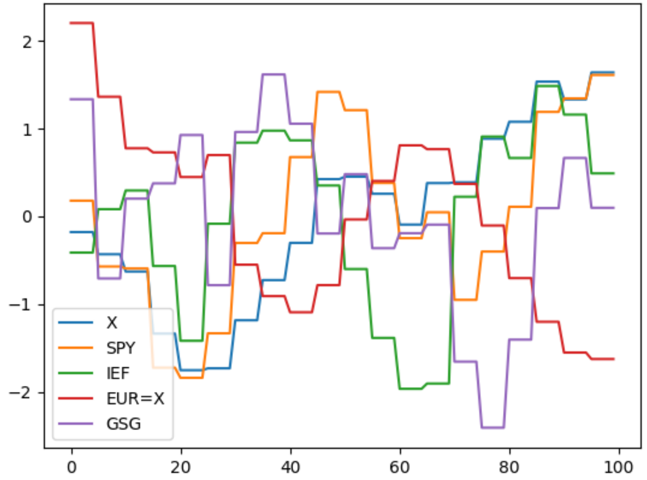
Complex models make it difficult to academically discern the factors contributing to performance improvements and alpha generation.

Proprietary concerns lead to **lack of open-sourcing**.

METHODOLOGY



Train: S&P 500 Top 50; **Test**: S&P 500 Top 100; 2006/2008 – 2022



Multivariate state space of the financial market discretized through piecewise aggregate approximation (PAA).

PAA not applied in original research.

X (Any stock of interest held in the S&P 500)
SPY (S&P 500 Index Fund ETF)
IEF (10-year treasury bond)
EUR=X (Euro/USD exchange rate)
GSG (S&P GSCI Commodities ETF)

RESULTS

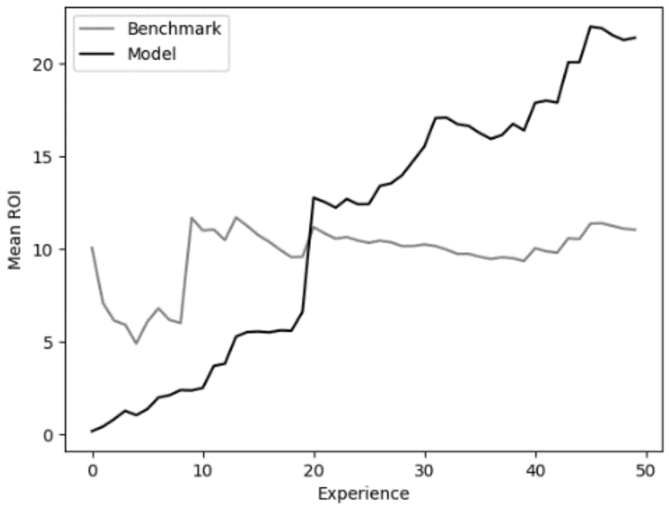


Figure 2. Cumulative mean return-on-investment of the trading model and 100% long-strategy benchmark as the trading model gained experience in trading the top 50 holdings of the S&P 500.

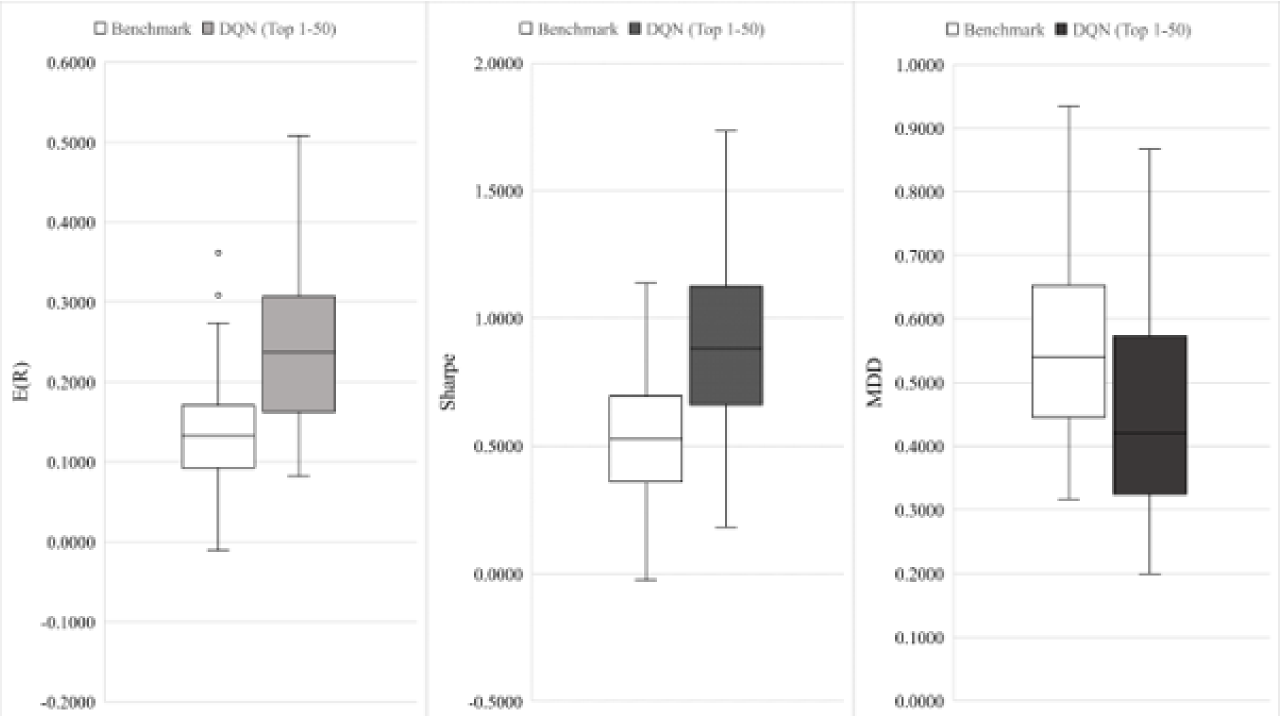


Figure 3. Comparing the distribution of annualized returns, Sharpe ratios, and maximum drawdowns of the trading model and the 100% long-strategy benchmark on the top 1st to 50th holding of the S&P 500 (trained).

RESULTS

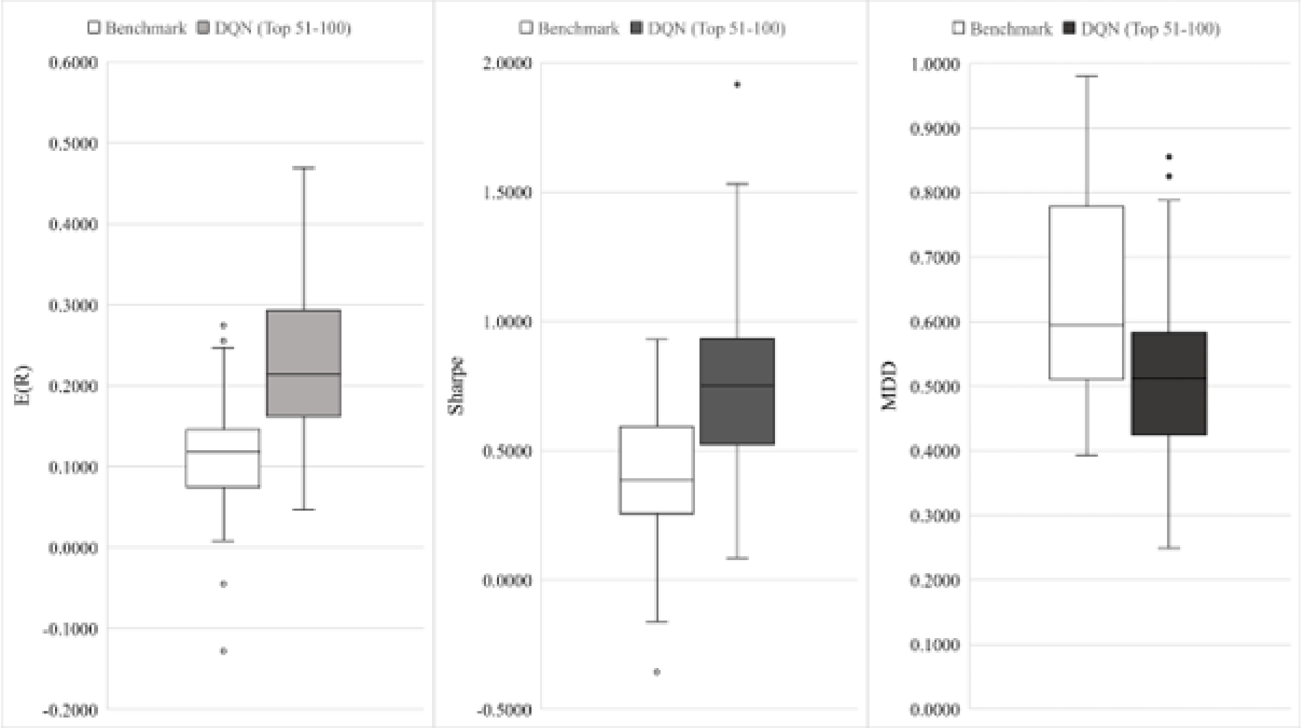
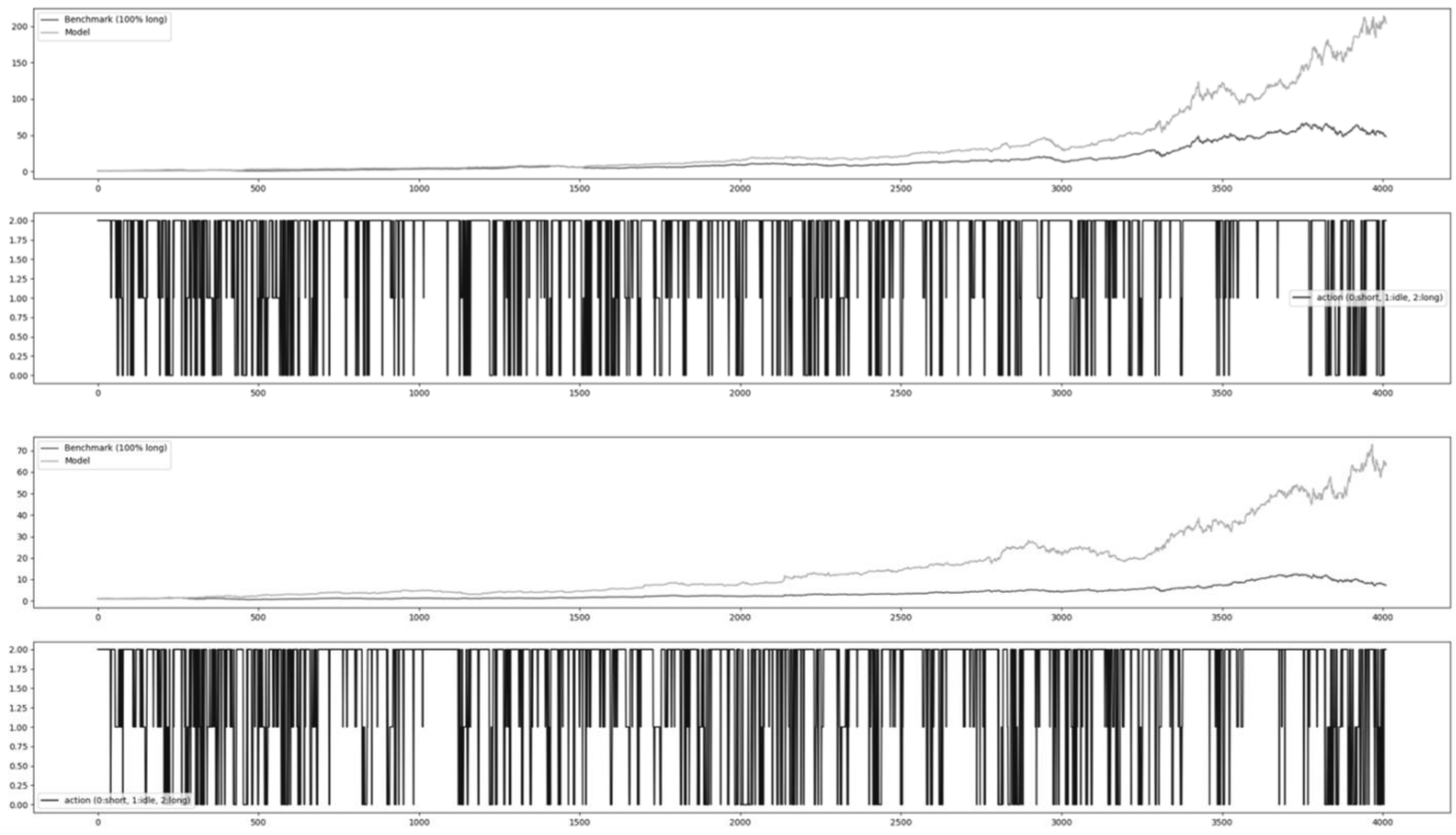


Figure 4. Comparing the distribution of annualized returns, Sharpe ratios, and maximum drawdowns of the trading model and the 100% long-strategy benchmark on the top 51st to 100th holding of the S&P 500 (untrained).

S&P 500 Top 100 Holdings (Mean Performance)				
	E(R)	**S(R)**	**Sharpe**	**MDD**
Benchmark	0.1251	0.3093	0.4044	0.5975
DQN	0.2375	0.3587	0.6622	0.4870

Statistics differ with PAA in state space (not applied in original research)

RESULTS


Benchmark (100% long)
Model
action (0:short, 1:idle, 2:long)
Benchmark (100% long)
Model
action (0:short, 1:idle, 2:long)

DISCUSSION/CONCLUSION

The proposed GDRL-based trading model **significantly outperforms** the 100% long-strategy benchmark, both trained and untrained without overfitting concerns.

Trading model makes **similar but different decisions** for each stock **based on how the historical data of a stock relates to core financial trends**.

Proposed adaptive synchronization enabled to **stabilize and track learning performance** on generalizing new experiences in trading each stock.

Use of **standard DQN** allows to conclude that the proposed Markov Decision Process (cross-market state space and discrete rewards) is the primary contributor to the trading model's profitability.

1. Stabilizing short-selling.
2. Applying more complex deep neural network architectures and testing other deep reinforcement learning algorithms.
3. Application to other types of securities.

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Fully independent work

Mr. Kirk as advisor

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Junyoung Sim
Ithaca High School

Benjamin Kirk
Ithaca High School

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PDF

ABSTRACT

This paper proposes generalized deep reinforcement learning with multi-variate state space, discrete rewards, and adaptive synchronization for trading any stock held in the S&P 500. Specifically, the proposed trading model observes the daily historical data of a stock held in the S&P 500 and multiple market-indicating securities (SPY, IEF, EUR=X, GSG), selects a trading action, and observes a discrete reward that is based on the correctness of the selected action and independent of the volatility of stocks. The proposed trading model's reward-maximizing behavior is optimized by using a standard deep q-network (DQN) with adaptive synchronization that stabilizes and enables to track learning performance on generalizing new experiences from each stock. The proposed trading model was trained on the top 50 holdings of the S&P 500 and tested on the top 100 holdings of the S&P 500 starting from 2006 to 2022. Experimental results suggest that the proposed trading model significantly outperforms the 100% long-strategy benchmark in terms of annualized return, Sharpe ratio, and maximum drawdown.

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CS = a tool for expression

Equitable CS education

Independent research-based, interdisciplinary curriculum (math, sciences, arts, etc)