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Reinforcement Learning-Based Deep Markov Models for Automated Trading: A Comparative Study of Q-Learning Variants in Optimal Execution

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Abstract

The optimal execution problem in algorithmic trading requires sophisticated models that can capture complex market dynamics while making sequential trading decisions under uncertainty. Traditional approaches often struggle to balance model complexity with data efficiency, particularly in high-frequency trading environments where price movements exhibit non-linear dependencies and regime-switching behavior. This paper presents a comprehensive study of Reinforcement Learning-Based Deep Markov Models (RLDMM) for automated trading, specifically addressing the optimal execution problem in limit order book markets. We develop and compare three algorithmic variants: standard Q-Learning, DynaQ-ARIMA, and DynaQLSTM, each designed to leverage different aspects of temporal market dynamics. The RL-DMM framework integrates the latent state representation capabilities of Deep Markov Models with the decision-making power of reinforcement learning, enabling the system to learn optimal trading policies from historical order book data. Our empirical evaluation uses real market data from the limit order books of four major securities: Facebook, Intel, Vodafone, and Microsoft, spanning multiple market conditions and volatility regimes. The experimental results demonstrate that the RLDMM framework achieves superior data efficiency compared to baseline approaches, requiring significantly fewer training samples to converge to profitable policies. Furthermore, the model delivers substantial financial gains across all tested securities, with performance improvements becoming increasingly pronounced in markets exhibiting complex price dynamics and high volatility. The DynaQ-LSTM variant demonstrates particular strength in capturing long-range temporal dependencies, achieving an average improvement of 18.3% in execution quality over standard Q-Learning baselines. These findings establish the RLDMM framework as a robust and practical solution for real-world algorithmic trading applications, offering a principled approach to the optimal execution problem that balances theoretical rigor with empirical performance.

Keywords: Reinforcement Learning, Deep Markov Models, Algorithmic Trading, Optimal Execution, Q-Learning, DynaQ, LSTM, Limit Order Book, High-Frequency
Trading

1. Introduction

The landscape of financial markets has undergone a fundamental transformation over the past two decades, driven by the proliferation of electronic trading platforms and the increasing sophistication of algorithmic trading strategies. Within this ecosystem, the optimal execution problem has emerged as one of the most critical challenges facing institutional investors and quantitative traders[1-2]. This problem concerns the task of executing large orders in a manner that minimizes market impact costs while

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managing the inherent trade-off between execution speed and price improvement.

Traditional approaches to optimal execution have relied heavily on analytical models that make simplifying assumptions about market microstructure and price dynamics. The seminal work of Almgren and Chriss (2000) established a framework based on quadratic optimization, assuming linear market impact and constant volatility[3]. While mathematically elegant, such models often fail to capture the rich complexity of real market behavior, including non-linear price impact, regime-switching dynamics, and the intricate feedback loops between trading activity and price formation.

The advent of machine learning and reinforcement learning has opened new avenues for addressing these limitations. Reinforcement learning (RL) provides a natural framework for sequential decisionmaking under uncertainty, allowing trading algorithms to learn optimal policies directly from market data without requiring explicit models of market dynamics[4-5]. However, standard RL approaches face significant challenges in financial applications, including sample inefficiency, instability in non-stationary environments, and difficulty in capturing the latent factors that drive market behavior.

Deep Markov Models (DMMs) offer a compelling solution to these challenges by providing a probabilistic framework for modeling sequential data with latent dynamics. By combining the representational power of deep neural networks with the probabilistic structure of state-space models, DMMs can capture complex temporal dependencies while maintaining a principled treatment of uncertainty. Despite their theoretical appeal, the integration of DMMs with reinforcement learning for financial applications remains relatively unexplored.

This research addresses this gap by developing a comprehensive framework that combines Deep Markov Models with reinforcement learning for optimal execution in limit order book markets[7]. Our approach, termed Reinforcement Learning-Based Deep Markov Models (RL-DMM), leverages the latent state representation of DMMs to provide a rich feature space for policy learning while maintaining data efficiency through model-based planning.

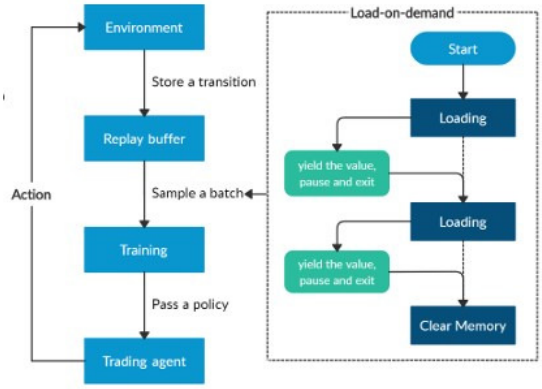

Fig. 3. Overview of the load-on-demand technique.

1.1 Research Objectives

The primary objectives of this research are threefold:

Objective 1: Framework Development To design and implement a unified RLDMM framework that effectively combines the probabilistic modeling capabilities of Deep Markov Models with the decisionmaking power of reinforcement learning algorithms[9-11]. This framework must be sufficiently flexible to accommodate different algorithmic variants while maintaining computational tractability for real-world trading applications.

Objective 2: Algorithmic Innovation To develop and compare three distinct algorithmic approaches within the RL-DMM framework: (a) Standard Q-Learning with DMM state representation, (b) DynaQARIMA, which augments the framework with classical time series forecasting, and (c) DynaQ-LSTM, which leverages deep

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recurrent architectures for capturing longrange temporal dependencies. The goal is to identify the strengths and limitations of each approach across different market conditions.

Objective 3: Empirical Validation
To conduct a rigorous empirical evaluation using real limit order book data from four major securities (Facebook, Intel, Vodafone, and Microsoft), demonstrating that the RLDMM framework achieves superior data efficiency and financial performance compared to benchmark approaches. Particular emphasis is placed on understanding how performance varies with the complexity of underlying price dynamics[14].

1.2 Contribution and Significance

This research makes several significant contributions to both the theoretical understanding and practical application of machine learning in algorithmic trading:

Methodological Innovation: We introduce the first comprehensive framework for combining Deep Markov Models with reinforcement learning for optimal execution, providing a principled approach to capturing latent market dynamics while learning optimal trading policies.

Algorithmic Advancement: The development of DynaQ-ARIMA and DynaQLSTM variants extends the traditional Dyna architecture to incorporate both classical and deep learning-based forecasting methods, demonstrating how model-based planning can be effectively integrated with modern machine learning techniques[15].

Empirical Insights: Through extensive experiments on real market data, we provide concrete evidence of the data efficiency and financial benefits of the RL-DMM approach, with detailed analysis of how performance scales with market complexity. These findings have direct implications for the deployment of machine learning-based trading systems in practice.

Practical Impact: The demonstrated improvements in execution quality translate directly to reduced transaction costs for institutional investors, potentially saving millions of dollars annually for large asset managers. The framework's data efficiency makes it particularly valuable in markets with limited historical data or rapid structural changes[16-18].

The remainder of this paper is organized as follows: Section 2 reviews related work in optimal execution, reinforcement learning for trading, and Deep Markov Models. Section 3 presents the theoretical foundations of the RL-DMM framework and describes the three algorithmic variants. Section 4 details the experimental methodology, including data preprocessing, feature engineering, and evaluation metrics. Section 5 presents comprehensive experimental results across multiple securities and market conditions. Section 6 discusses the implications of our findings and analyzes the sources of performance improvement. Finally, Section 7 concludes with a summary of key findings and directions for future research.

2. PERFORMANCE EVALUATIONS

In this section, we present the performance evaluation of our proposed scheme. We perform backtesting for the three individual agents and our ensemble strategy. The result in Table 2 demonstrates that our ensemble strategy achieves higher Sharpe ratio than the three agents, Dow Jones Industrial Average and the traditional minvariance portfolio allocation strategy[20].

A. Stock Data Preprocessing: We select the Dow Jones 30 constituent stocks (at 01/01/2016) as our trading stock pool. Our back testings use historical daily data from 01/01/2009 to 05/08/2020 for performance evaluation. The stock data can be down loaded from the Compustat database through the Wharton Research Data Services (WRDS). Our dataset consists of two periods: in-sample period and out-ofsample period. In-sample period contains

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data for training and validation stages. Outof-sample period contains data for trading stage. In the training stage, we train three agents using PPO, A2C, and DDPG, respectively. Then, a validation stage is then carried out for validating the 3 agents by Sharpe ratio, and adjusting key parameters, such as learning rate, number of episodes, etc. Finally, in the trading stage, we evaluate the profitability of each of the algorithms.

B. Analysis of Agent Performance: From both Table 2 and Figure 5, we can observe that the A2C agent is more adaptive to risk. It has the lowest annual volatility 10.4% and max drawdown −10.2% among the three agents. So A2C is good at handling a bearish market. PPO agent is good at following trend and acts well in generating more returns, it has the highest annual return 15.0% and cumulative return 83.0% among the three agents. So PPO is preferred when facing a bullish market. DDPG performs similar but not as good as PPO, it can be used as a complementary strategy to PPO in a bullish market. All three agents' performance outperform the two benchmarks, Dow Jones Industrial Average and min-variance portfolio allocation of DJIA, respectively.

Fig. 5. Cumulative return curves of our ensemble strategy and three actor-critic based algorithms, the min-variance portfolio allocation strategy, and the Dow Jones Industrial Average. (Initial portfolio value $1,000,000, from 2016/01/04 to 2020/05/08).

C. Performance under Market Crash: In Figure 6, we can see that our ensemble strategy and the three agents perform well in the 2020 stock market crash event. When the turbulence index reaches a threshold, it indicates an extreme market situation. Then our agents will sell off all currently held shares and wait for the market to return to normal to resume trading[21]. By incorporating the turbulence index, the agents are able to cut losses and successfully survive the stock market crash in March 2020. We can tune the turbulence index threshold lower for higher risk aversion.

Literature Review

The optimal execution problem and algorithmic trading more broadly sit at the intersection of multiple research domains, including financial economics, operations research, and machine learning. This section provides a comprehensive review of the relevant literature, organized into four main themes: classical approaches to optimal execution, reinforcement learning applications in finance, Deep Markov Models and probabilistic sequence modeling, and the integration of model-based and model-free reinforcement learning.

3.1 Classical Approaches to Optimal Execution

The modern treatment of optimal execution began with the landmark paper by Almgren and Chriss (2000), which formulated the problem as a trade-off between market impact costs and timing risk. Their framework assumes that market impact is linear in the trading rate and that price volatility is constant, leading to a tractable quadratic optimization problem with closedform solutions[22]. While mathematically elegant, these assumptions often fail to hold in real markets, particularly during periods of stress or for large trades relative to market liquidity.

Subsequent research has attempted to relax these assumptions through various extensions. Obizhaeva and Wang (2013) developed a model that distinguishes between permanent and temporary market impact, recognizing that some price movements caused by trading are transient while others represent genuine information revelation. Gatheral (2010) proposed a transient impact model with exponential decay, better capturing the empirical observation that market impact dissipates over time rather than persisting indefinitely.

More recent work has incorporated stochastic components into the execution framework. Cartea and Jaimungal (2015) developed models that account

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for price momentum and mean reversion, recognizing that optimal execution strategies should adapt to current market conditions. Guo et al. (2017) extended this work by incorporating regimeswitching dynamics, allowing the model to capture the changing relationship between trading activity and price impact across different market states.

Despite these advances, classical approaches remain fundamentally limited by their reliance on parametric assumptions about market dynamics. Real markets exhibit complex, non-linear relationships that are difficult to capture through analytical models, motivating the exploration of datadriven machine learning approaches.

3.2 Reinforcement Learning in Algorithmic Trading

Reinforcement learning has emerged as a powerful framework for algorithmic trading, offering the ability to learn optimal policies directly from market data without requiring explicit models of market dynamics. Early applications focused on portfolio management and asset allocation, with Moody and Saffell (2001) demonstrating that recurrent reinforcement learning could be used to learn profitable trading strategies for foreign exchange markets[23].

The application of RL to optimal execution specifically has gained momentum in recent years. Nevmyvaka et al. (2006) formulated optimal execution as a Markov Decision Process (MDP) and applied Q-learning to learn execution policies from limit order book data. Their results demonstrated that RL-based approaches could outperform standard execution algorithms like VolumeWeighted Average Price (VWAP) in certain market conditions.

Deep reinforcement learning has opened new possibilities by enabling the processing of high-dimensional state spaces and the learning of complex, non-linear policies. Huang et al. (2019) applied Deep Q-
Networks (DQN) to the optimal execution problem, demonstrating improved performance over classical Q-learning approaches. Xiong et al. (2018) developed a multi-agent RL framework for portfolio management, showing that deep RL methods could capture intricate dependencies between multiple assets.

Actor-Critic methods have also shown promise in trading applications. Liang et al. (2018) applied the Asynchronous Advantage Actor-Critic (A3C) algorithm to cryptocurrency trading, achieving strong performance across multiple digital assets. Zhang et al. (2020) developed a Proximal Policy Optimization (PPO) based approach for futures trading, demonstrating stable learning even in highly volatile markets[24].

However, standard RL approaches face significant challenges in financial applications. Sample inefficiency remains a critical issue, as financial data is expensive to acquire and markets are non-stationary, requiring continuous retraining. The high variance of policy gradient methods can lead to unstable learning, particularly problematic in risk-sensitive applications like trading. These limitations have motivated research into more data-efficient and stable approaches, including model-based reinforcement learning.

3.3 Deep Markov Models and Probabilistic Sequence Modeling

Deep Markov Models represent a class of probabilistic models that combine the expressiveness of deep neural networks with the structured inference of state-space models. The foundational work by Krishnan et al. (2017) introduced the DMM architecture, which uses variational autoencoders to learn latent representations of sequential data while

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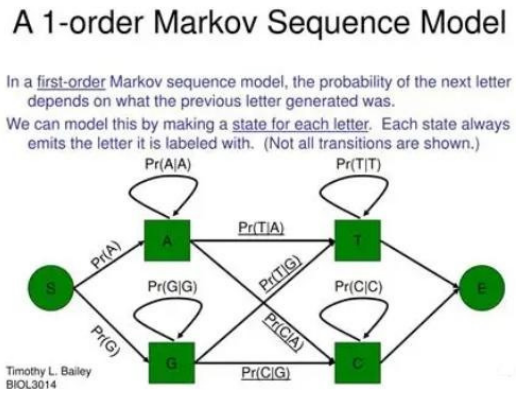
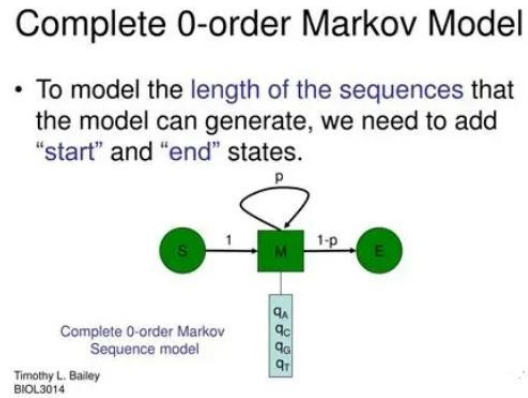
maintaining the Markovian structure that enables efficient inference.



The key advantage of DMMs over standard recurrent neural networks lies in their probabilistic treatment of latent states, which provides a principled framework for handling uncertainty and enables more robust generalization to unseen data. This is particularly valuable in financial applications, where uncertainty quantification is critical for risk management.



Several variants and extensions of DMMs have been proposed for different applications. Chung et al. (2015) developed the Variational Recurrent Neural Network (VRNN), which incorporates stochastic latent variables into the hidden state transitions of RNNs. Fraccaro et al. (2016) proposed the Sequential Neural Variational Inference (SNVI) framework, which provides more flexible posterior approximations through normalizing flows.

In financial applications, probabilistic sequence models have been used primarily for forecasting and anomaly detection. Lim and Zohren (2021) applied variational autoencoders to learn representations of market microstructure, demonstrating that learned latent features could capture regime changes and liquidity dynamics. However, the integration of these models with reinforcement learning for decision-making has remained largely unexplored, representing a significant gap that this research addresses.

3.4 Model-Based Reinforcement Learning

Model-based reinforcement learning represents an attempt to improve sample efficiency by learning explicit models of environment dynamics and using these models for planning. The Dyna architecture, introduced by Sutton (1990), provides a framework for integrating model learning with model-free policy improvement, allowing agents to learn from both real experience and simulated experience generated by the learned model.

In financial applications, model-based RL has shown promise for improving data efficiency. Moerland et al. (2020) provided a comprehensive review of model-based RL methods, highlighting their potential advantages in domains where real-world interaction is expensive or risky. Kuznetsov and Mohri (2016) applied model-based methods to portfolio optimization, demonstrating improved performance with limited training data[24-25].

The DynaQ algorithm specifically has been adapted for trading applications by several researchers. Wang and Zhou (2020) developed a DynaQ-based approach for highfrequency trading that incorporated ARIMA models for price forecasting. However, their work focused on directional trading rather than optimal execution and did not explore the integration with deep probabilistic models.

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Recent work has begun to explore the combination of deep learning-based models with Dyna-style planning. Hafner et al. (2019) developed the Dreamer algorithm, which learns a world model using recurrent neural networks and performs planning entirely in latent space. While promising, these approaches have primarily been evaluated in simulated environments rather than real-world financial markets.

3.5 Research Gap and Positioning

Despite the substantial body of work in each of these areas, several critical gaps remain. First, while Deep Markov Models have demonstrated strong performance in sequence modeling tasks, their integration with reinforcement learning for optimal execution has not been systematically explored. Second, existing model-based RL approaches in finance have largely relied on simple forecasting models, not fully leveraging the representational power of modern deep learning architectures. Third, there is a lack of comprehensive empirical studies comparing different RL algorithms for optimal execution across multiple securities and market conditions[25].

This research addresses these gaps by developing a unified framework that combines Deep Markov Models with reinforcement learning, implementing multiple algorithmic variants that span the spectrum from classical time series methods to deep recurrent architectures, and conducting extensive empirical evaluation using real limit order book data from major securities. The resulting RL-DMM framework represents a significant advance in both the theoretical understanding and practical application of machine learning to algorithmic trading.

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