ThorEMore

Optimizing Adaptive Reinforcement Learning for Stock Trading: Smaller and Faster Models

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Problem Statement

Theme and Objectives	Optimizing Adaptive Reinforcement Learning for Stock Trading: Smaller and Faster Models

Excessive Model Size: The current Reinforcement Learning (RL) model is too large, making it inefficient for real-world deployment.

Long Training Time: Training the model **takes too long**, delaying experimentation and making iterative improvements difficult.

Lack of Pretrained Models: No existing pretrained models can be used as a baseline, **requiring training from scratch every time**.

Innovation Overview

Smaller & Faster AI Model

- Traditional AI models for stock trading are **large and slow**, but we've made ours **smaller** and more efficient.
- By **reducing unnecessary parts** of the model, it runs faster while still making smart trading decisions.

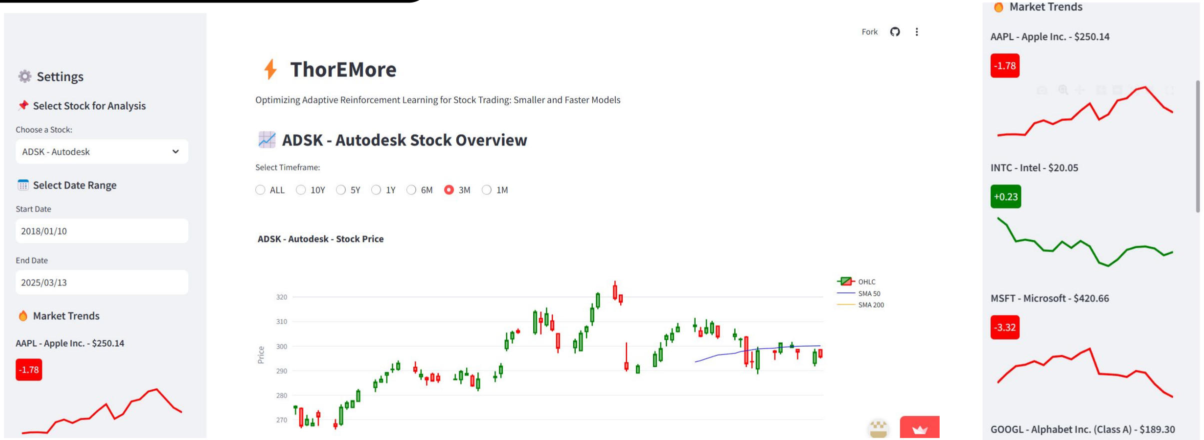
Model Download & Accessibility

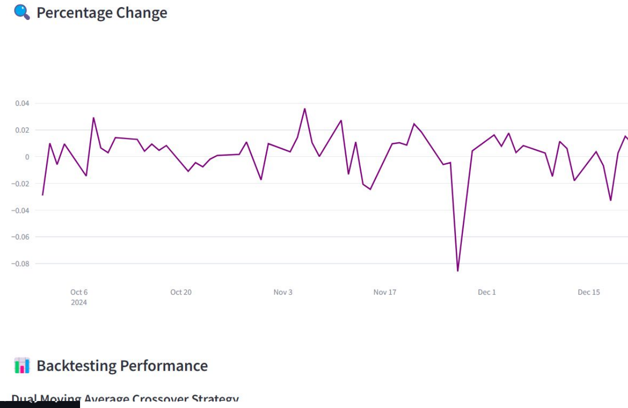
- Users can **download and deploy** our optimized RL model, allowing them to integrate it into their own trading strategies.
- The **lightweight** design ensures **compatibility with personal computers** and cloud-based environments, making it accessible to both retail traders and researchers.

Interactive Learning Platform

- We provide a **web-based interactive platform** where users can play, experiment, and learn how our RL model operates in stock trading.
- Users can **test different trading scenarios**, observe model behavior, and gain insights into financial market dynamics.

ThorEMore


Settings
Select Stock for Analysis
Choose a Stock:
ADSK - Autodesk
Select Date Range
Start Date
2018/01/10
End Date
2025/03/13
Market Trends
AAPL - Apple Inc. - $250.14
-1.78
Fork
ThorEMore
Optimizing Adaptive Reinforcement Learning for Stock Trading: Smaller and Faster Models
ADSK - Autodesk Stock Overview
Select Timeframe:
ALL 10Y 5Y 1Y 6M 3M 1M
ADSK - Autodesk - Stock Price
OHLC
SMA 50
SMA 200
Price
Market Trends
AAPL - Apple Inc. - $250.14
-1.78
INTC - Intel - $20.05
+0.23
MSFT - Microsoft - $420.66
-3.32
GOOGL - Alphabet Inc. (Class A) - $189.30


Percentage Change
0.04
0.02
0
−0.02
−0.04
−0.06
−0.08
Oct 6
2024
Oct 20
Nov 3
Nov 17
Dec 1
Dec 15
Backtesting Performance
Dual Moving Average Crossover Strategy


Value
Sharpe Ratio -39.0711
Drawdown 0.1716
Metrics Explanation
Sharpe Ratio: Measures risk-adjusted return. A higher value indicates better risk-adjusted performance.
Drawdown: Represents the maximum drop from a peak before recovery, indicating downside risk.
$189.30

ThorEMore

ThorEMore is an **AI-powered adaptive trading system** using **Reinforcement Learning** integrated with **LSTMs** to predict market trends, optimize portfolios, and adapt to changing conditions. This model will focus on NASDAQ 100 market index.

Technical Overview

What makes our approach **different**?

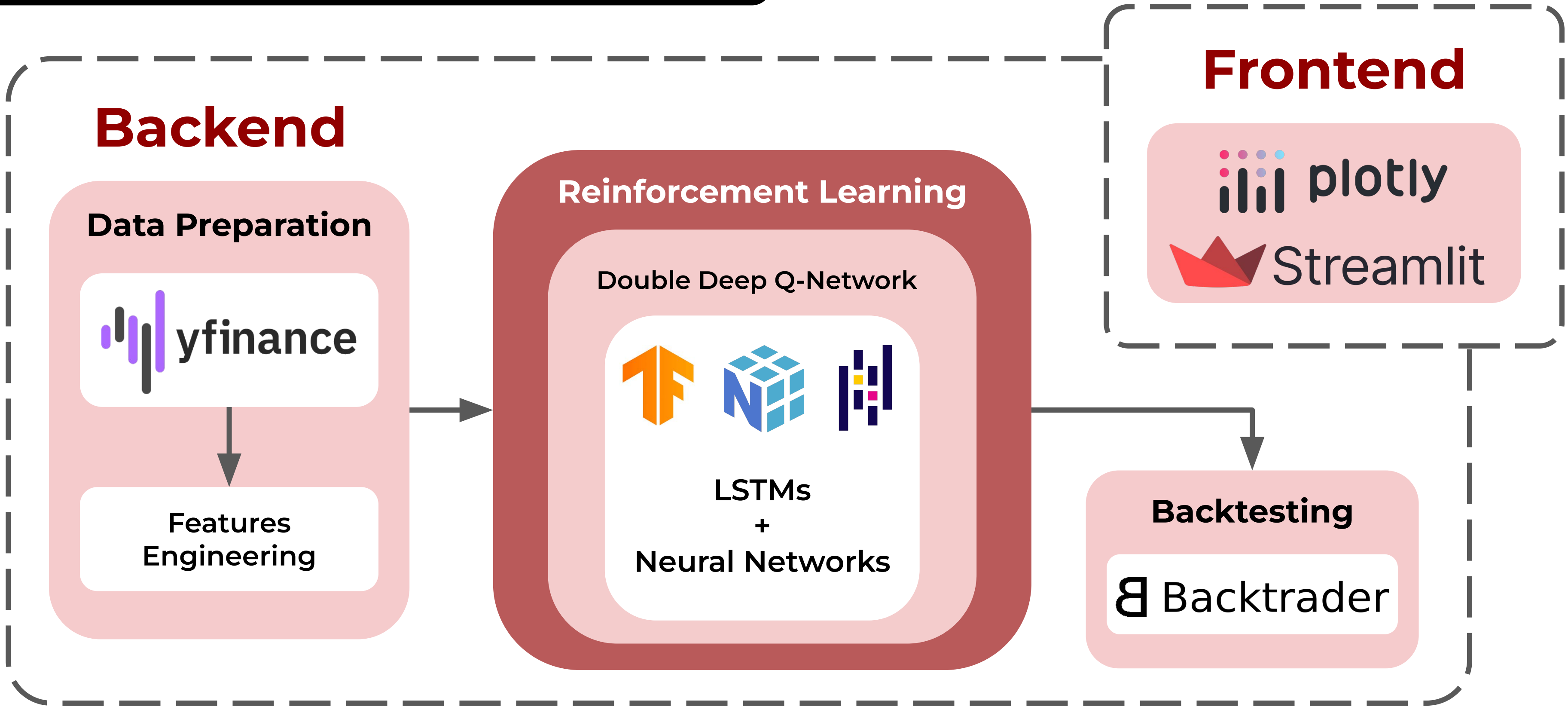
Adaptive Learning Models:

Long Short-Term Memory Networks (LSTMs): Recognizes sequential patterns in market data.
Reinforcement Learning (RL): Continuously adapts to new market conditions.

Optimization

Layer Optimization: Reduce layer from 76,035 to 65,000
Training Optimization: Adaptive model of sector can be used with its sector

Architecture Diagram

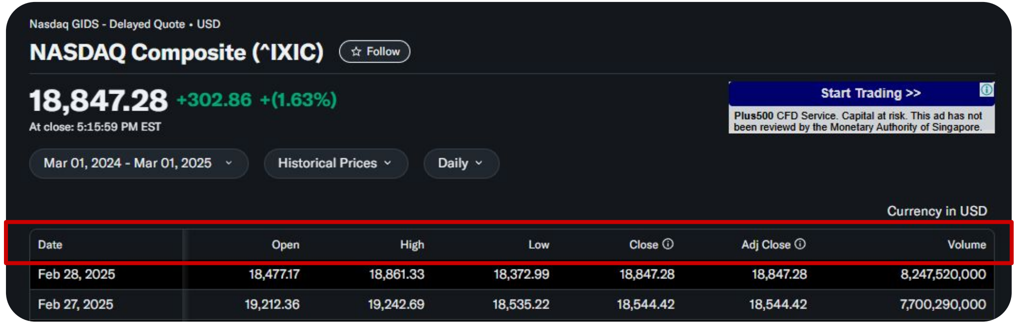


Training Methodology

1. Features Engineering

Based data from Yahoo Finance

- `Date, Open, Close, High, Low, Volume`



Date	Open	High	Low	Close	Adj Close	Volume
Feb 28, 2025	18,477.17	18,861.33	18,372.99	18,847.28	18,847.28	8,247,520,000
Feb 27, 2025	19,212.36	19,242.69	18,535.22	18,544.42	18,544.42	7,700,290,000

Additional data

- `Sector`: extract each **stock's sector** from table 4 in NASDAQ wikipedia (Nasdaq-100 - Wikipedia)
- `Dollar_vol_1m`: **average** of product of **volume and close price** in duration of 1 month
- `Return_{lag}d`: **average daily return** over lag days (in this project, we use 1 day, 1 week, 1 month, and 2 months)
- `Return_{lag}d_{t}lag`: average daily return over lag days **shift by t days**
- `Financial factors`: Relative Strength Index (RSI), Bollinger Bands, Average True Range (ATR), Moving Average Convergence/Divergence (MACD)
- `Target_{t}d`: **forward returns** in t days

Training Methodology

2. Model Training Process

Environment Setup

The agent interacts with this environment by making trading decisions **(buy, sell, hold)**

Experience Replay Buffer

The agent **stores past experiences** (state, action, reward, next state) in a buffer.

This **avoids training the model on highly correlated sequences**, improving stability.

Neural Networks in DDQN

1. **Main Q-Network** (Q) - Selects the best action.
2. **Target Q-Network** (Q') - Provides stable target values for updating the Main Q-Network.

TRAINING STEP

Random date to trade → Agent tries to trade for 1 year (252 days) after the desire date →

Agent action will base on ε-Greedy Policy → Store the current state in replay → Compute Target-Q → Update Q using Loss function → Update Target network periodically → Agent action will base on ε-Greedy Policy

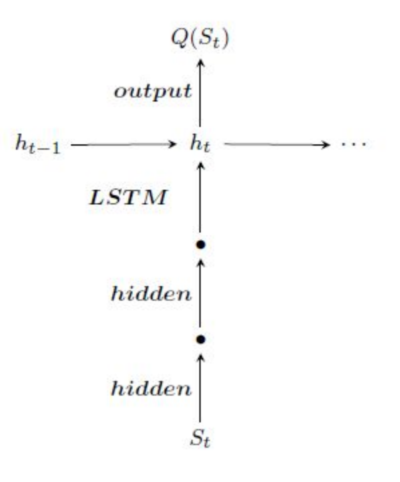
Training Methodology

3. Optimization

3.1 Layer Optimization

Before optimization : Hidden 1 (36) + Hidden 2 (256) + Hidden 3 (256) + output(3) = 75,000 ++ layers

After optimization: Hidden 1 (256) + Hidden 2 (256) + LSTM + output(3) = 65,000 ++ layers



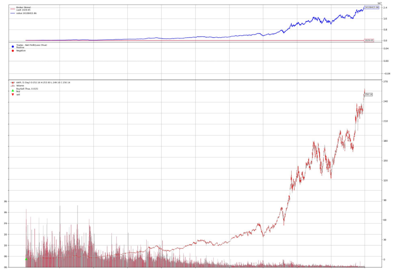
3.2 Training Optimization (Train by sector)

Reduced Training Complexity – Training an RL model on an entire market is computationally expensive due to high volatility and diverse patterns. By focusing on a specific sector (e.g., tech, healthcare, finance), the model learns more specialized patterns efficiently.

Faster Convergence – Since sector-based stocks share similar characteristics (e.g., growth trends, risk factors), the RL model trains faster as it doesn't need to generalize across vastly different industries.

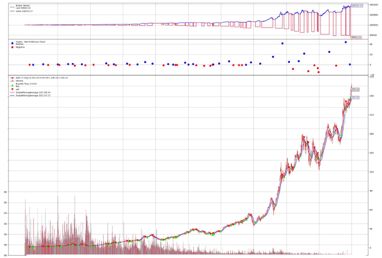
Performance - Backtesting & Testing

Buy and Hold



Sharpe Ratio: 0.8046097835557823
Max Drawdown: 60.75877896322654%

Double Moving Average Crossover



Sharpe Ratio: -54.60730192450425
Max Drawdown: 0.049178180794625465%

Our Trading Strategy

Competitive Edge & Market Potential

How ThorEMore Compares

Feature	Quant Hedge Funds	Retail Trading Bots	ThorEMore
Cost	High	Medium	Low
Accessibility	Limited	High	High
Model Complexity	High	Medium-High	Low-Medium

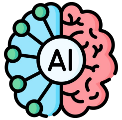
Business Applications

Financial AI Research & Development:

- A foundation for building advanced AI-powered trading tools.
- Supports innovation in risk management and portfolio optimization.

Retail Investors & Traders:

- Helps traders analyze trends, predict stock and refine strategies via an interactive website.
- Lightweight model runs efficiently on personal computers.



Stock Market Education & Training:

- Provides a hands-on AI trading experience for students and researchers.
- Downloadable model supports experimentation without high-end computing.

Impact & Scalability

SCALABILITY & GROWTH POTENTIAL

Expanding to Multiple Asset Classes:

- Beyond stocks, can adapt to crypto, forex, and commodities.
- Supports multi-market trading strategies.

API & Platform Integration:

- Deployable as a cloud-based API for hedge funds & fintech apps.
- Can be integrated into robo-advisors & trading platforms.

Automated Wealth Management Solutions:

- Retail & institutional investors can leverage AI-driven decision-making.
- Enables customized trading strategies for different risk profiles.

IMPACT

Faster & More Efficient Trading

- Reduces training time and inference latency, allowing for quicker decision-making in real-time markets.
- Improves scalability by enabling AI trading on personal computers and cloud-based systems.

Innovation in Financial AI

- Provides a lightweight, scalable foundation for future AI trading models.
- Encourages new developments in reinforcement learning for finance, leading to smarter, faster, and more ethical AI trading systems.

Increased Accessibility

- Enables retail traders, researchers, and small firms to leverage AI-powered trading without needing expensive hardware.
- The interactive platform makes AI trading more user-friendly and educational

Future Enhancements

ThorEMore is built to evolve—pushing AI trading beyond traditional markets!

Sentiment Analysis Integration

- Use Natural Language Processing (NLP) to analyze news, social media, and financial reports.
- Improve trade decisions by incorporating market sentiment & macroeconomic events.

High-Frequency Trading (HFT) Optimization

- Enhance real-time execution with low-latency infrastructure.
- Implement smart order routing & execution strategies to reduce slippage.

Multi-Asset Expansion

- Extend strategy to crypto, forex, commodities, and bond markets.
- Adapt risk models to different market structures & liquidity conditions.

Explainable AI (XAI) for Trading Decisions

- Develop transparent AI models to improve interpretability.
- Provide clear justifications for trades, enhancing trust in AI-driven strategies.

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