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This paper presents a streamlined hierarchical reinforcement learning framework for algorithmic trading that addre

Keywords: Hierarchical Reinforcement Learning, Algorithmic Trading, Market Regime Detection, LSTM, Archite

Introduction

Algorithmic trading has fundamentally transformed financial markets, enabling high-speed execution and the syste

This paper introduces a novel multi-agent system leveraging a Hierarchical Reinforcement Learning (HRL) framewo

Decompose Complexity: Break down the multifaceted problem of trading into manageable sub-problems, each handl

Integrate Diverse Intelligence: Combine the strengths of different machine learning paradigms – time-series forecast

Learn Adaptive Strategies with Integrated Risk Control: Employ reinforcement learning to enable agents to lea

Facilitate Scalability, Modularity, and Rigorous Validation: Allow for easier development, testing, and upgradin

The objectives of this paper are to:

Propose a detailed architecture for an advanced multi-agent HRL trading system, emphasizing its hierarchical structure

Describe the roles and interactions of specialized analytical and decision-making agents.

Outline a high-level mathematical formulation for the system's components, including its risk management layers.

Discuss practical implementation concepts, including data sourcing, technology stack, robust backtesting strategies, and

Explore potential challenges, recent advancements in related systems, and promising future research directions.

This work aims to provide a detailed blueprint for a next-generation trading system capable of sophisticated market ana

Related Work

The proposed system draws inspiration from several research areas:

Multi-Agent Systems (MAS) in Finance: MAS have been explored for simulating market dynamics, understanding

LSTM for Time-Series Forecasting: Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Netw

LLMs for Financial NLP: Large Language Models (LLMs) like BERT, GPT, and their derivatives have revolutionize

Gradient Boosting Machines in Trading: Gradient Boosting algorithms (e.g., XGBoost, LightGBM, CatBoost) are

Hierarchical Reinforcement Learning (HRL): HRL addresses the challenge of learning in complex environments w

Recent HRL Developments in Finance (2020-2024): Recent research has demonstrated significant advances in H

Multi-Agent Trading Systems (2021-2024): The field has seen substantial progress in multi-agent reinforcement le

Risk-Aware Reinforcement Learning (2021-2024): Recent research has significantly advanced risk management i

Recent Integrated Systems: More recent work on hierarchical policies and multi-agent RL (e.g., Option-Critic [9], F

Research Gaps and Positioning

While recent literature has made significant progress in individual areas—HRL for trading (Wang et al., 2020; Qin

Limited Integration: Existing work focuses on isolated components rather than comprehensive system integration

Single-Modal Input: Most HRL trading systems rely on price/volume data alone, missing textual and regime informa

Fragmented Risk Management: Risk measures are typically applied at single levels rather than integrated througho

Coordination Challenges: Multi-agent systems lack sophisticated information sharing mechanisms for coordinated d

Our Contribution: This work addresses these gaps by proposing the first comprehensive integration of specialized ana

Proposed System Architecture

Based on our empirical validation and complexity analysis, we propose a streamlined yet comprehensive architectur

Enhanced LSTM-based Market Intelligence Agent

The core analytical component consolidates multiple intelligence functions into a unified, efficient architecture:

Enhanced LSTM-based Time-Series and Regime Agent (ELTRA)

* **Role:** Provides comprehensive market intelligence including price forecasting, volatility prediction, and market regime

Streamlined Hierarchical Reinforcement Learning (HRL) Framework

Based on empirical validation results, we implement a focused two-level HRL architecture that eliminates unnecessa

HRL-L1: Strategic Portfolio Agent (SPA)

* **Role:** High-level agent responsible for portfolio-wide allocation decisions, risk management, and strategic positioning

HRL-L2: Execution Optimization Agent (EOA)

* **Role:** Specialized agent focused on optimal trade execution, market impact minimization, and short-term market dyn

Streamlined Communication and Coordination

The simplified architecture enables more efficient coordination with reduced communication overhead:

Enhanced Shared Knowledge Base (SKB): Centralized repository where ELTRA publishes market intelligence (pr

Direct Strategic-Execution Coordination: SPA directives (position targets, risk limits) are passed directly to EOA

Integrated Feedback Loops: Execution performance metrics from EOA (slippage, market impact, fill rates) feed bac

Risk-Integrated Communication: Risk constraints and portfolio limits are embedded in all communications, ensurin

System Diagrams

mermaid graph TD subgraph Analytical Intelligence ELTRA[Enhanced LSTM-based Time-Series & Regime Agent]
subgraph HRL Framework SPA[Strategic Portfolio Agent - HRL-L1] EOA[Execution Optimization Agent - HRL-L
subgraph Data Sources DS_Market[Market Data Feeds] DS_Macro[Macroeconomic Data] DS_Vol[Volatility Surfaces
DS_Market –¿ ELTRA DS_Macro –¿ ELTRA DS_Vol –¿ ELTRA DS_Technical –¿ ELTRA
ELTRA –¿ SKB[(Enhanced Shared Knowledge Base)] SKB –¿ SPA SKB –¿ EOA
SPA – Position Directives & Risk Constraints –¿ EOA EOA – Execution Performance Feedback –¿ SPA EOA – Ma
#f9f,stroke:#333,stroke-width:2px _Market fill:#lightgrey,stroke:#333 _Macro fill:#lightgrey,stroke:#333 _Vol fill:#
nalytical fill:#D6EAF8,stroke:#2874A6,stroke-width:2px; _strategic fill:#D1F2EB,stroke:#0E6655,stroke-width:2p
nalytical; _strategic; _execution;

Figure 1: Streamlined System Architecture. This diagram illustrates the simplified architecture with a single

mermaid graph TD subgraph ELTRA Internal Architecture Input[Multi-modal Market Data] –¿ SharedEncoder[Sh
ForecastHead –¿ Output1[Price & Volatility Forecasts] RegimeHead –¿ Output2[Regime Probabilities] ConfidenceH
subgraph HRL Coordination Flow SKB_Data[Enhanced SKB: Forecasts, Regimes, Confidence] –¿ SPA_Decision[SP
EOA_Execution –¿ Performance[Execution Metrics: Slippage, Market Impact] Performance –¿ SPA_Adaptation[SP
Output1 –¿ SKB_Data Output2 –¿ SKB_Data Output3 –¿ SKB_Data
ncoder fill:#E8F6F3,stroke:#0E6655,stroke-width:2px _Data fill:#FEF9E7,stroke:#B7950B,stroke-width:2px #FA
nfidenceHead heads; _Decision,EOA_Execution,Performance coordination;

Figure 2: Detailed Agent Architecture and Information Flow. This diagram shows the internal structure o

Mathematical Formulation (High-Level)

This section provides a conceptual mathematical framework for the agents and the HRL system.

Enhanced LSTM-based Market Intelligence Agent (ELTRA)

The core analytical component is formulated as a multi-task learning problem where a shared LSTM encoder proce

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Appendix A: Formal Risk Objectives, CVaR Estimation, and Constraints
A.1 Empirical VaR/CVaR Estimation
Given a sample of portfolio losses $\{L_i\}_{i=1}^N$ where $L_i = -r_{P,i}$ (negative returns), the empirical β-VaR and CVaR are:
Value at Risk (VaR): (65)

ath $\mathrm{VaR}_\beta = \inf\{\ell \in R : 1N \sum_{i=1}^N 1[L_i \leq \ell] \geq \beta\}, \quad \beta \in (0.9, 0.99).(65)$
Conditional Value at Risk (CVaR) - Tail Expectation: Let $\mathcal{I}_\beta = \{i : L\_i > \mathrm{VaR}\_\beta\}$ be the tail set. Then the emp

Alternative Rockafellar-Uryasev Formulation:

The Rockafellar–Uryasev objective admits the sample approximation

A.2 Mean–Variance with Transaction Costs
Let w be target weights and w^{prev} previous weights. With return vector r, covariance Σ, and linear cost $\lambda_T \|w - w^{prev}\|$

A.3 Portfolio Feasible Set and Risk Overlays
Define the feasible set $\mathcal{W}$ via hard constraints:
Corrected Portfolio Feasible Set:
Define the economically consistent feasible set $\mathcal{W}$ as:

Budget and Leverage Constraints:

where:
$w^+ \geq 0$: long positions
$w^- \geq 0$: short positions
c: cash position (can be negative if borrowing)
$L_{\max}$: maximum leverage ratio
Economic Consistency:
Total capital: $\mathbf{1}^\top w^+ + \mathbf{1}^\top w^- + c = 1$ (normalized)
Borrowing cost: $r_{borrow} \times \max(0, -c)$ per period
Short rebate: $r_{short} \times \mathbf{1}^\top w^-$ per period
Risk and Operational Constraints:

Turnover constraints can be imposed as $\|w - w^{prev}\|_1 \leq \tau\_\max$. These constraints are enforced by the L1 risk layer and
A.4 Numerical Example: Empirical VaR and CVaR
Let daily losses be $L = \{0.1$

text Order: 0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.9, 1.5, 2.5, 3.0 (%).
With $N = 10$, $\mathrm{VaR}_{0.95} \approx 2.5$

This illustrates the empirical estimate; in production, consider longer windows, exponential weights, or parametric/semi
A.5 Example of Portfolio Constraints (Matrices)
Assume 5 assets in 3 sectors: $S_1 = \{1, 2\}$, $S_2 = \{3\}$, $S_3 = \{4, 5\}$. Constraints:
text Budget: $1^T w = 1 Leverage : \|w\|_1 \leq 1.5 Per-asset : -0.1 \leq w_i \leq 0.3 Sector caps : w \leq 0.40, w \leq 0.30$