HMM-Based Market Regime Detection with RL for Portfolio Management

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***Abstract* — This paper studies the impact of combining a Hidden Markov Model (HMM) with a Reinforcement Learning (RL) framework, implemented within FinRL, to enhance algorithmic trading. Our objective is to improve trading performance and realism by dynamically adapting to market regimes. Leveraging a portfolio of 30 Dow Jones stocks, we analyze the impact of regime awareness by comparing hybrid RL-HMM agents to standard FinRL algorithms. We observe that RL-HMM outperforms baseline models in Sharpe Ratio, annual returns, and other risk-adjusted performance metrics.**

***Index Terms* — Reinforcement Learning, Hidden Markov Model, FinRL, Market Regimes**

I. INTRODUCTION

Algorithmic trading has progressed significantly with the rise of deep reinforcement learning. Yet, most RL-based strategies are limited by their inability to detect or react to shifting market conditions. To overcome this, we propose a hybrid model that incorporates market regime identification using an HMM into the RL trading pipeline. Our contributions include:

- Integration of HMM with RL agents for regime-aware trading.
- Extension of the FinRL framework with regime-switching logic.
- Comparative analysis with traditional RL models: A2C, PPO, SAC, TD3, and DDPG.

II. RELATED WORKS

RL algorithms such as PPO, A2C, SAC, DDPG, and TD3 have shown promise in financial markets. Meanwhile, HMMs have been applied for market regime detection, but not for decision-making. Our study bridges this gap by embedding regime awareness directly into the observation space of RL agents.

III. METHODOLOGY

A. *Market Regime Detection*

Hidden States:

Engaged (Δ=1): Market follows predictable trends; RL-driven trading is effective.

Lapse (Δ=0): Market is noisy/unpredictable; conservative actions are preferred.

Observable States: Economic indicators (interest rates, inflation, tariffs), market news (VIX, indices), sector trends (industry shocks), and company fundamentals (earnings reports, insider trading) are used as input features.

HHMs for multiple Regimes:

Markov chain with hidden states, $X = (X_t : t = 0, \dots, n)$, and an observable a vector process $Y = (Y_t : t = 0, \dots, n)$, whose outcomes are directly affected by the outcomes of X the process X satisfies the Markov property

$$P(X_t | X_{t-1}) = P(X_t | X_{t-1}, \dots, X_0)$$

Additionally, the output independence property $P * (Y_t | X_t) = P(Y_t | X_t, \dots, X_0)$ The hidden state "emit" the observable Y.

Actions & Rewards:

Actions: Buy, Sell, Hold}

Rewards: Profit/Loss, Sharpe Ratio, risk-adjusted returns

B. Model Dynamics

HMM-Based Regime Switching: Gaussian HMM

A Hidden Markov Model (HMM) is defined as a quintuple $(H,\ O,\ T,\ \Psi,\ \Pi)$. The variables H, T and Π define the behavior of the market chain (X_t), while O and Ψ specify the observable process Y_t

- H: Set of hidden market states. In our case, we consider two regimes: {0: Bearish, 1: Bullish}.
- O: Observable states that include economic indicators, market news, sector trends, and company fundamentals.

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- T: Transition probability matrix, where $T_{ij} = P(X_{t+1} = j|X_t = i)$, for $i, j \in$ H.
- Ψ: Emission probability matrix, $\psi_{ik} = P(Y_t = k|X_t = i)$, where $i \in H, k \in O$.
- Π: Initial probability distribution, $\pi_i = P(X_0 = i)$.

Observable Process

The observable process Y_t is composed of four components: $Y_t = (E_t, M_t, S_t, C_t)$, where:

- E_t: Economic indicators (e.g., interest rates, inflation, fiscal stimulus, Fed announcements, tariffs).
- M_t: Market news (e.g., VIX, major indices, geopolitical events).
- S_t: Sector news (e.g., industry-specific shocks like tech regulation or oil supply).
- C_t: Company-specific data (e.g., earnings, insider trading, analyst upgrades/downgrades).

Gaussian Emissions

The return vector Y is assumed to be normally distributed conditional on the hidden state:

$$Y_t|X_t = x \sim N(\mu_x, \Sigma_x), x \in \{0,1\}$$

Estimates of the mean and covariance are computed using historical data:

- Mean: $\mu_x = \frac{1}{N_x}\sum_{t:X_t=x} Y_t$
- Covariance: $\Sigma_x = \frac{1}{N_x}\sum_{t:X_t=x}(Y_t - \mu_x)(Y_t - \mu_x)^T$

Where N_x is the number of observations assigned to state x.

Emission Probability

The emission probability for observation k given hidden state i is: $\psi_{ik} = P(Y_t = k|X_t = i) = N(k; \mu_i, \Sigma_i)$

Parameter Estimation

The HMM parameters T, Ψ, and Π are estimated from historical data using the Baum-Welch algorithm, a variant of the Expectation-Maximization (EM) method.

C. Estimating HMM Parameters

Proximal Policy Optimization (PPO) for HMM-Based Trading

To integrate reinforcement learning, PPO algorithm was employed. PPO-HMM model dynamically adjusts trading strategies based on hidden market state inferred from HMM.

PPO Algorithm with HMM

Input: Historical data (prices, economic indicators, market news, sector trends, company fundamentals)

Step 1: HMM Estimation

1. *Initialize μ_x, Σ_x, and transition probabilities T_{ij}.*
2. *Apply the Baum-Welch algorithm to estimate T, Ψ, Π.*
3. *Compute posterior probabilities $P(X_t = x|Y_t)$ using the Forward-Backward algorithm.*

Step 2: PPO Training

1. *Initialize PPO policy π_θ and value function V_ψ*
2. *For each trading episode:*
   a. Infer hidden state X_t using HMM.
   b. Construct state representation S_t using observable features Y_t.
   c. Sample action A_t (buy/sell/hold) from π_θ.
   d. Compute reward R_t based on Sharpe ratio and profit.
   e. Update policy π_θ using clipped surrogate objective: $L(\theta)=E[min(r_t(\theta)A_t, clip(r_t(\theta), 1-\varepsilon, 1+\epsilon)A_t)]$, where $r_t(\theta)$ the probability ratio between new and old policies.
3. *Update value function V_ϕ using squared loss: $L_V(\phi)=\sum_t\left(V_\phi(S_t) - R_t\right)^2$*

Step 3: Policy Execution

1. *At each decision point, infer X_t from HMM.*
2. *Execute action A_t from trained PPO policy.*
3. *Monitor risk-adjusted returns and refine model periodically.*

Actor-Critic (A2C), Soft Actor-Critic (SAC), and Deep Deterministic Policy Gradient (DDPG) Algorithm with HMM can be implemented likewise. These methods extend HMM-based market regime detection with reinforcement learning for optimized trading strategies.

IV. EXPERIMENTAL RESULTS

Comparison with FinRL Models

Model	Strengths	Limitations
RL-HMM	Adaptive market awareness	High complexity
PPO	Stable learning	Slower convergence
A2C	Efficient resource usage	Lower sample efficiency
SAC	Robust in stochastic markets	Computationally expensive
DDPG	Works in continuous spaces	Sensitive to hyperparameters
TD3	Reduces variance	Requires tuning

Fig. 1. Strengths and Limitations of FinRL Models in Financial Market Environments

Dataset:

Historical Stock Market Data: Dow 30 stocks (spanning from 2010 to 2025)

Features: Technical indicators, Volume, VIX-based volatility

Experimental Setup:

Train HMM on historical data (80% train, 20% test).

Use detected regimes as input features for RL agent.

Compare regime-aware RL strategy against: Standard RL trading model (without HMM).

Results:

	with HMM					without HMM				
Performance Metric	**A2C**	**DDPG**	**PPO**	**TD3**	**SAC**	**A2C**	**DDPG**	**PPO**	**TD3**	**SAC**
Annual Return	0.14	0.10	-0.02	0.11	0.12	0.11	0.08	0.19	0.07	0.16
Cumulative Returns	0.15	0.11	-0.03	0.12	0.13	0.12	0.09	0.20	0.08	0.17
Annual Volatility	0.16	0.12	0.17	0.14	0.14	0.13	0.13	0.16	0.12	0.14
Sharpe Ratio	0.75	0.72	-0.26	0.62	0.69	0.71	0.48	1.03	0.44	0.95
Calmar Ratio	1.06	1.51	-0.14	1.03	1.27	1.59	0.84	1.83	0.89	1.70
Stability	0.06	0.06	0.00	0.05	0.05	0.06	0.04	0.07	0.04	0.07
Max Drawdown	-0.13	-0.07	-0.18	-0.10	-0.09	-0.07	-0.10	-0.10	-0.08	-0.09
Omega Ratio	1.17	1.16	0.99	1.15	1.16	1.16	1.12	1.23	1.11	1.20
Sortino Ratio	1.21	0.95	-0.44	0.91	1.00	1.01	0.71	1.62	0.62	1.38
Skew	0.54	-0.60	0.39	0.26	0.18	-0.13	-0.12	0.98	-0.29	-0.15
Kurtosis	3.90	1.12	1.47	3.41	3.57	1.90	1.07	8.44	1.04	1.34
Tail Ratio	1.00	0.86	1.00	0.84	0.95	0.94	1.01	0.90	0.88	0.98
Daily VaR	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01

Fig. 2. Performance Comparison of RL Models With and Without HMM Integration

From the above table, we can observe that the RL-HMM strategy improves Sharpe and Sortino ratios for A2C, DDPG, and SAC. While PPO without HMM shows higher cumulative return, it does so at the cost of greater volatility and drawdowns, indicating a more aggressive yet risk-prone policy. In contrast, HMM-enhanced models maintain risk-adjusted returns with better stability, making them more suitable for institutional strategies.

V. CONCLUSION

This work demonstrates that incorporating HMM-based market regime detection into RL trading strategies improves both performance and risk control. While standard RL models can achieve high returns, they often lack robustness in volatile markets. RL-HMM fills this gap by guiding agents with hidden state awareness.

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