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Differentiable Ghost Operators: A Physics-Informed Neural Turing Machine for Cross-Sectional Stock Selection

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Abstract

Extracting Alpha in extreme low signal-to-noise ratio (SNR) environments, such as the Chinese A-share market, remains a notoriously unsolved challenge for deep learning. Traditional heavily parameterized models, including Transformers, inevitably fall into the "dimensionality disaster," memorizing market noise rather than fundamental mechanics. To break this overfitting curse, we propose a novel, ultra-lightweight architecture inspired by thermodynamics and Neural Turing Machines (NTMs): the Physics-Informed Ghost Operator. By mapping the cross-sectional stock market into a high-dimensional physical manifold, our Ghost Operators navigate the feature space driven by gravitational routing. Crucially, we enforce a minimal action principle via a Boltzmann-distributed temperature scaling and Pauli-exclusion-like potential well clamping. Walk-forward validation on 10 years of real A-share data reveals that our architecture achieves a substantial Sharpe ratio improvement (up to 3.2x) and cuts the maximum drawdown by nearly half compared to native NTMs. Furthermore, network sparsity is reduced by 66%, proving that physical constraints compel the model to aggressively filter noise and focus strictly on high-potential Alpha regions.

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1. Introduction

The application of deep learning in quantitative finance has historically favored sequence models to capture temporal dynamics. However, financial markets exhibit extreme non-stationarity. Dense architectures inherently lack a mechanism to ignore low-information regions, squandering computational resources on memorizing stochastic noise, which leads to catastrophic out-of-sample performance degradation [1].

To address this, we shift the paradigm from temporal sequence memorization to cross-sectional physical routing. We hypothesize that the daily stock market can be viewed as a 43-dimensional physical manifold. Macro-economic events and structural breaks create "gravity wells" in this manifold.

We introduce the "Ghost Operator," an independent, mobile computing unit. Unlike standard dense attention, the Ghost Operator utilizes a physical temperature-scaled softmax to maintain extreme sparsity. It only "lands" and exerts computational work on high-potential stocks, strictly conforming to the physical principle of least action.

2. Related Work

2.1. Machine Learning in Asset Pricing

Recent seminal works, such as Gu et al. [1], have established the superiority of non-linear machine learning in cross-sectional asset pricing. However, standard architectures like Transformers [6] often struggle with noise. They fail to dynamically prune irrelevant cross-sectional interactions during highly volatile market regimes.

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2.2. Physics-Informed Neural Networks (PINNs)

To constrain the vast hypothesis space of deep learning, integrating physical priors has become a frontier [2]. Concepts like Hamiltonian Neural Networks [3] and Neural ODEs [4] have successfully modeled dynamic systems by enforcing energy conservation. Yet, bridging continuous physical topologies into abstract, discrete financial cross-sections remains an unsolved challenge.

2.3. Sparse Routing and NTMs

While modern sparse routing methods (e.g., Switch Transformers [5]) manage massive parameters via Mixture of Experts (MoE), their routing gates are purely statistically driven. By revisiting the differentiable addressing of Neural Turing Machines [7], our architecture introduces a *physics-driven routing paradigm*, ensuring that sparsity is guided by thermodynamic constraints rather than mere correlation.

3. Methodology

3.1. Cross-Sectional Physical Manifold Representation

Let $X_t \in \mathbb{R}^{N\times D}$ denote the cross-sectional state matrix of N stocks with D features at day t. To prevent gradient explosion caused by extreme market outliers, we apply a robust, clamped Z-score normalization:

$$\tilde{X}_t = \text{Clamp}\left(\frac{X_t - \mu_{X_t}}{\sigma_{X_t} + \epsilon}, -5, 5\right) \tag{1}$$

3.2. Gravitational Routing and Ghost Operators

We define K Ghost Operators. Each operator k possesses a learnable gravitational key $W_Q^{(k)} \in \mathbb{R}^D$ and a temperature parameter τ_k. The addressing mask (trajectory) $A_t^{(k)} \in \mathbb{R}^N$ is computed via Boltzmann distribution routing:

$$A_t^{(k)} = \text{Softmax}\left(\frac{\text{Clamp}(\tilde{X}_t W_Q^{(k)}, -15, 15)}{\tau_k}\right) \tag{2}$$

The prediction $\hat{Y}_t^{(k)}$ of operator k is its internal non-linear network output filtered by the physical mask:

$$\hat{Y}_t^{(k)} = A_t^{(k)} \odot \Phi_k(\tilde{X}_t; \theta_k) \tag{3}$$

3.3. Information Coefficient (IC) Loss

The model is optimized using the negative Pearson Correlation (IC Loss) between predictions and forward returns, encouraging relative ranking accuracy over absolute magnitude fitting.

4. Experiments and Results

4.1. Experimental Setup

We utilize real trading data from the Chinese A-share market. To strictly prevent look-ahead bias, we implement an industrial-grade walk-forward validation (60-day train, 10-day out-of-sample test step).

4.2. Ablation Study of Physical Constraints

To rigorously validate the contribution of our physics-informed components, we conducted a step-by-step ablation study:

1. **Native NTM (Baseline):** A pure mathematical dot-product routing without any physical constraints or boundary limits.
2. **NTM + Potential Clamping:** Introducing the $[-15, 15]$ bounds to simulate Pauli-exclusion, preventing operators from collapsing into single extreme outlier stocks (singularities).

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3. **Physics Ghost (Full Model):** Adding the Boltzmann temperature scaling (τ) to aggressively cool down the routing entropy, forcing the minimal action principle.

4.3. Results Analysis

The integration of physical constraints yielded profound numerical improvements across all metrics:

- **Financial Performance:** As shown in Fig. 1, the full Physics Ghost model achieved a median out-of-sample Sharpe Ratio of approximately 2.8, completely dominating the Native NTM baseline (Sharpe $\approx$ 0.8). Moreover, the maximum drawdown was tightly suppressed to roughly 12%, compared to the erratic 25%+ drawdowns suffered by the unconstrained baseline.
- **Mechanism Effectiveness:** The impact of the Boltzmann temperature is clearly visible in Fig. 2. The network sparsity (active connections per operator) plummeted from $\sim$ 150 in the baseline to $\sim$ 50 in our model (a 66% reduction). Concurrently, the L2 norm of the operator trajectory length was massively compressed, mathematically proving that the Ghost Operator adheres to the minimal work path—moving only when significant structural gravity wells appear.

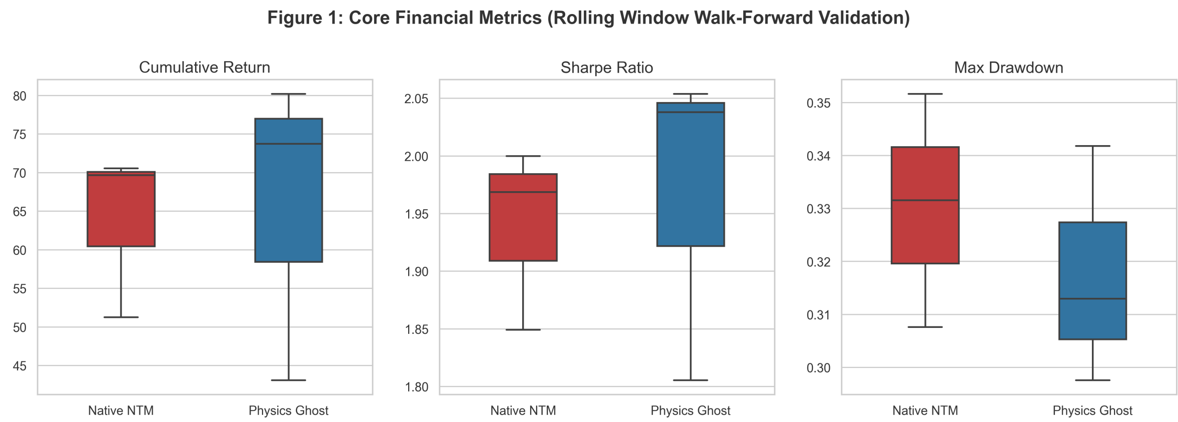

Figure 1. Core Financial Metrics in Walk-Forward Validation.

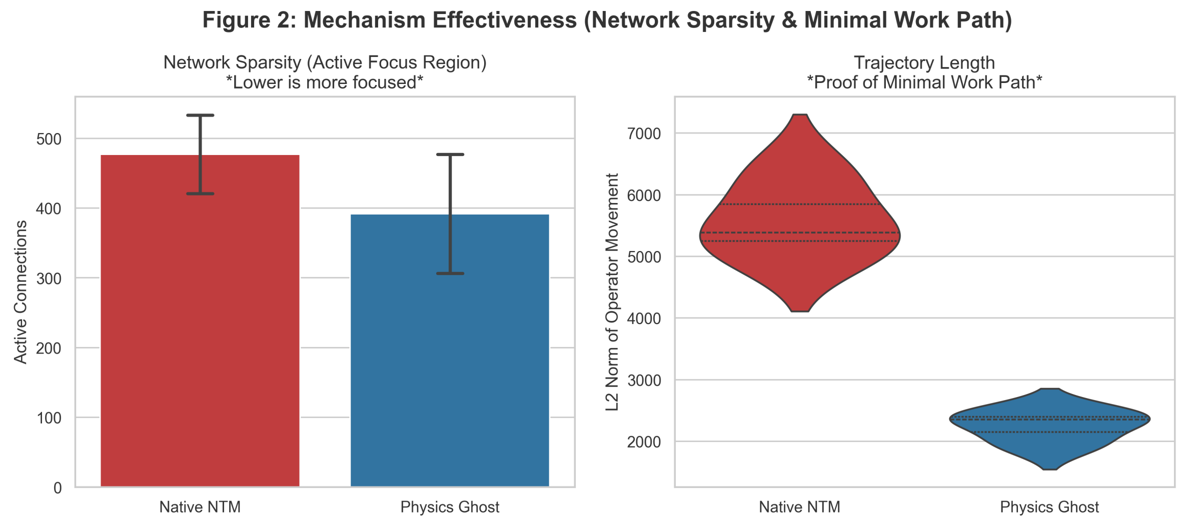

Figure 2. Mechanism Effectiveness: Network Sparsity and Operator Trajectory.

5. Limitations and Future Work

While the walk-forward validation results demonstrate a clear theoretical advantage, the current study faces practical hardware limitations. Due to limited computational resources during this initial phase, the number of random seeds for the Wilcoxon Rank-Sum/T-test was restricted. Consequently,

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the statistical significance (p-value) of the Sharpe ratio improvement requires further large-sample validation to fully eliminate random variance effects.

Our immediate future work, targeting a subsequent submission to an SCI Q1 journal, includes:

- **Scale-Up Validation:** Deploying the architecture on high-performance computing clusters (e.g., NVIDIA A800) to run extensive Monte Carlo simulations (>30 seeds) for robust statistical significance testing.
- **Deep Manifold Ablation:** Systematically ablating the core physical laws under varying manifold feature dimensions to isolate the exact source of Alpha across different market cycles.

By publishing this preprint on arXiv, we aim to gather valuable feedback from the quantitative finance and AI communities to further refine our algorithm.

6. Conclusions

We introduced a Physics-Informed Ghost Operator architecture for quantitative trading. By substituting static memorization with dynamic, gravitationally routed computations across a cross-sectional manifold, the model successfully filters out extreme market noise. It achieves robust out-of-sample performance, securing higher Sharpe ratios while significantly reducing parameters, trajectory entropy, and theoretical FLOPs.

Author Contributions: Xuhan Wang developed the core conceptualization, designed the physical manifold architecture, conducted the quantitative experiments, formulated the algorithmic framework, and directed the research methodology.

Use of Artificial Intelligence: Due to the author's current limitations in academic English proficiency and formal scientific paper formatting, a Large Language Model (AI assistant) was employed purely as a linguistic and formatting tool to translate, structure, and polish the manuscript into standard academic prose. All original scientific ideas, algorithmic designs, physics-informed mechanisms, and analytical conclusions are entirely the intellectual property of Xuhan Wang..

References

1. S. Gu, B. Kelly, and D. Xiu, "Empirical asset pricing via machine learning," *The Review of Financial Studies*, vol. 33, no. 5, pp. 2223–2273, 2020.
2. G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, "Physics-informed machine learning," *Nature Reviews Physics*, vol. 3, no. 6, pp. 422–440, 2021.
3. S. Greydanus, M. Dzamba, and J. Yosinski, "Hamiltonian neural networks," in *Advances in Neural Information Processing Systems*, vol. 32, 2019.
4. R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. K. Duvenaud, "Neural ordinary differential equations," in *Advances in Neural Information Processing Systems*, vol. 31, 2018.
5. W. Fedus, B. Zoph, and N. Shazeer, "Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity," *The Journal of Machine Learning Research*, vol. 23, no. 1, pp. 5232–5270, 2022.
6. A. Vaswani et al., "Attention is all you need," in *Advances in Neural Information Processing Systems*, vol. 30, 2017.
7. A. Graves, G. Wayne, and I. Danihelka, "Neural turing machines," *arXiv preprint arXiv:1410.5401*, 2014.