Hybrid Option Valuation: PINN Models Informed by Black-Scholes and Alternative Data Sources

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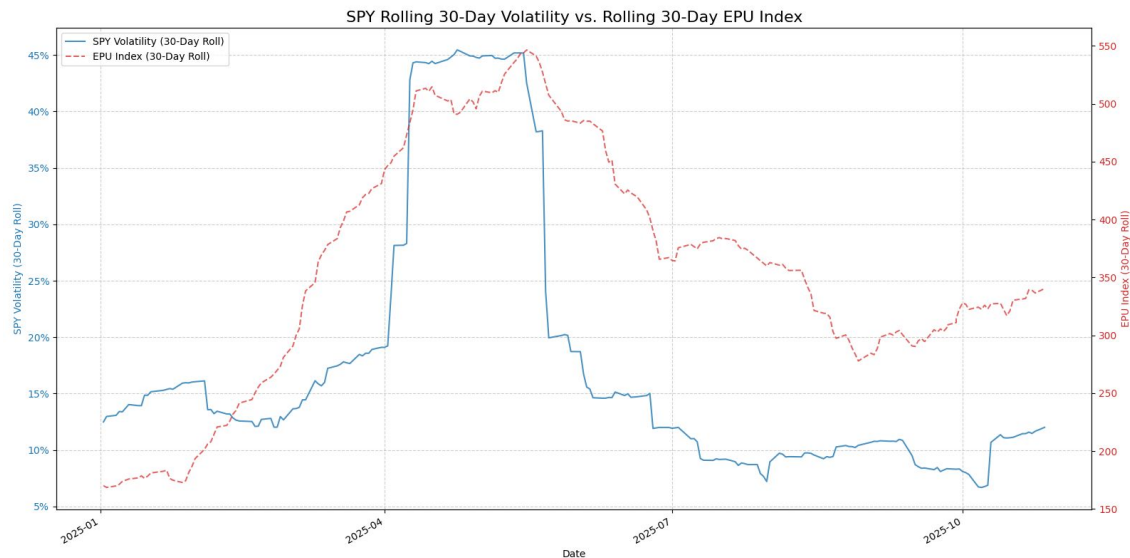
Topics

1. Background

Introduction

- Valuation of stock options is critical to finance

- Models such as Black-Scholes equation provide a theoretical framework for option pricing

- Advances in mobile technology have made "alternative data" sources (e.g. social media sentiment and web traffic) accessible for financial modeling

SPY Rolling 30-Day Volatility vs. Rolling 30-Day EPU Index

Problem Definition

Current Limitations

- Traditional models lack real-time adaptability and struggle with market shocks

- Purely data-driven models may ignore financial theory and overfit

Research Objective

- Build a model that predicts option prices accurately and robustly

- Incorporate both market behavior (through alternative data) and theoretical principles (through Black-Scholes)

2. Methods

PINN Model

Physics-Informed Neural Networks (PINNs)

- Neural nets trained to satisfy PDE constraints (e.g. Black-Scholes) as part of their loss function

- Penalizes deviations from the Black-Scholes equation during training
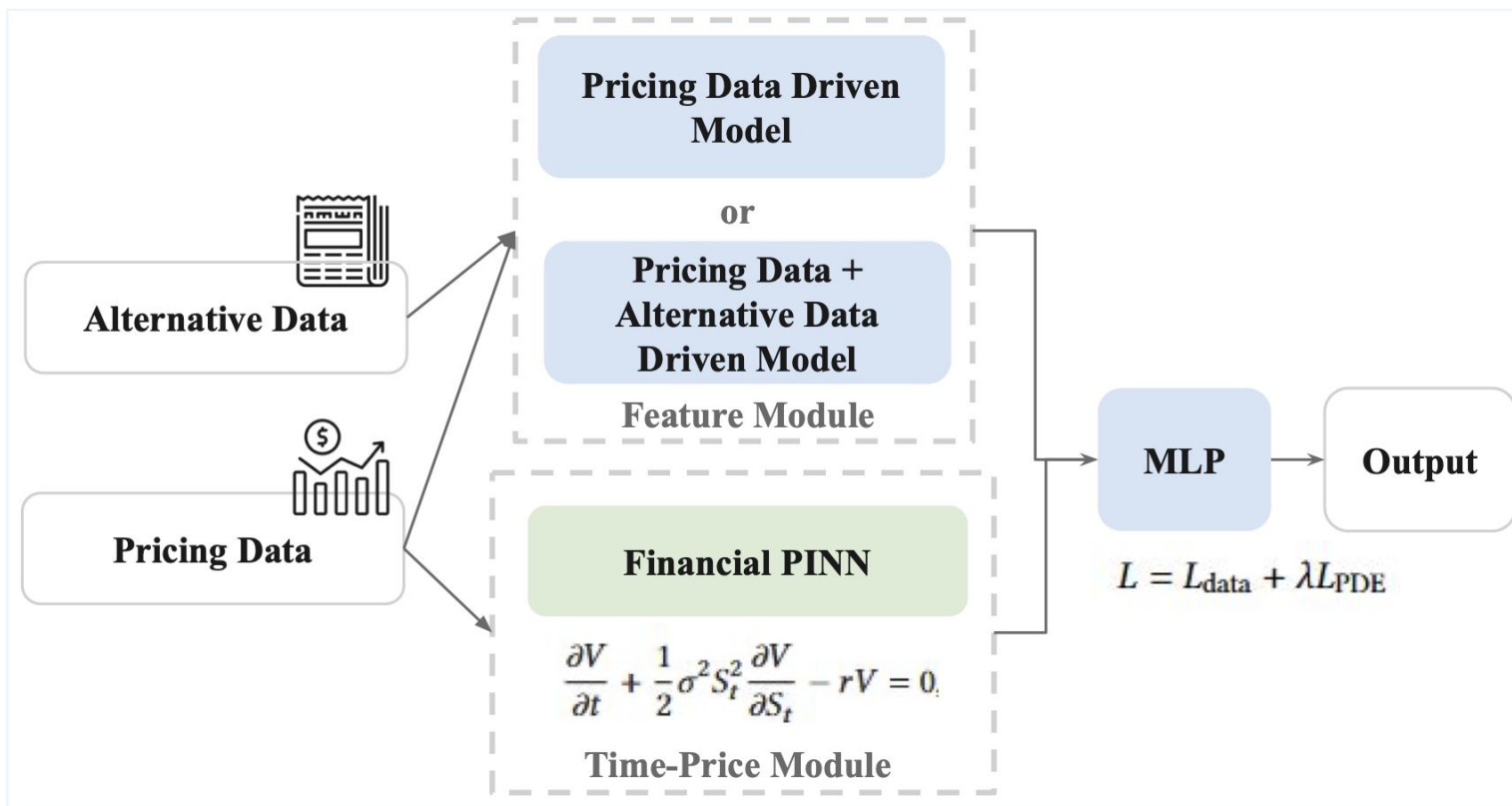
Advantages

- Enforces realistic option price behavior (no-arbitrage, correct exercise boundaries)

- Combines pure financial theory and empirical data

Knowledge Transfer Mechanism

- **Pure Data-Driven Module:** Approaches like MLPs, LSTMs, GRUs trained only on market data and alternative features

- **Pure Black-Scholes Module:** Classic theoretical pricing using only financial parameters (volatility, interest rate, etc.)

- **Transfer Learning Approach**

  - Hybrid models jointly train on financial and alternative data

  - Use knowledge transfer to guide data-driven networks using PINN-derived constraints

Framework

3. Data & Experiments

Data Sources

Traditional Data

- Daily S&P 500 (SPY ETF) data including close prices, trading volumes, implied volatility, strike prices, expiration dates

- Extracted via Yahoo Finance and Alpha Vantage API

Alternative Data

- Economic Policy Uncertainty Index (EPU) from news articles tracking policy & event impacts

- Tech sentiment from S&P-related news articles and commentaries (sentiment scored via FinBERT financial language model)

Experiment Methodology

Testing

- Time-Price Module: PINN

- Baseline Feature Module: Pure data-driven (MLP, Gated LSTM) approach with traditional data

- Enhanced Feature Module: Data-driven model with alternative data (MLP or LSTM variants)

- Hybrid Models: Combine PINN with baseline/enhanced feature modules using only financial or both financial & alternative data
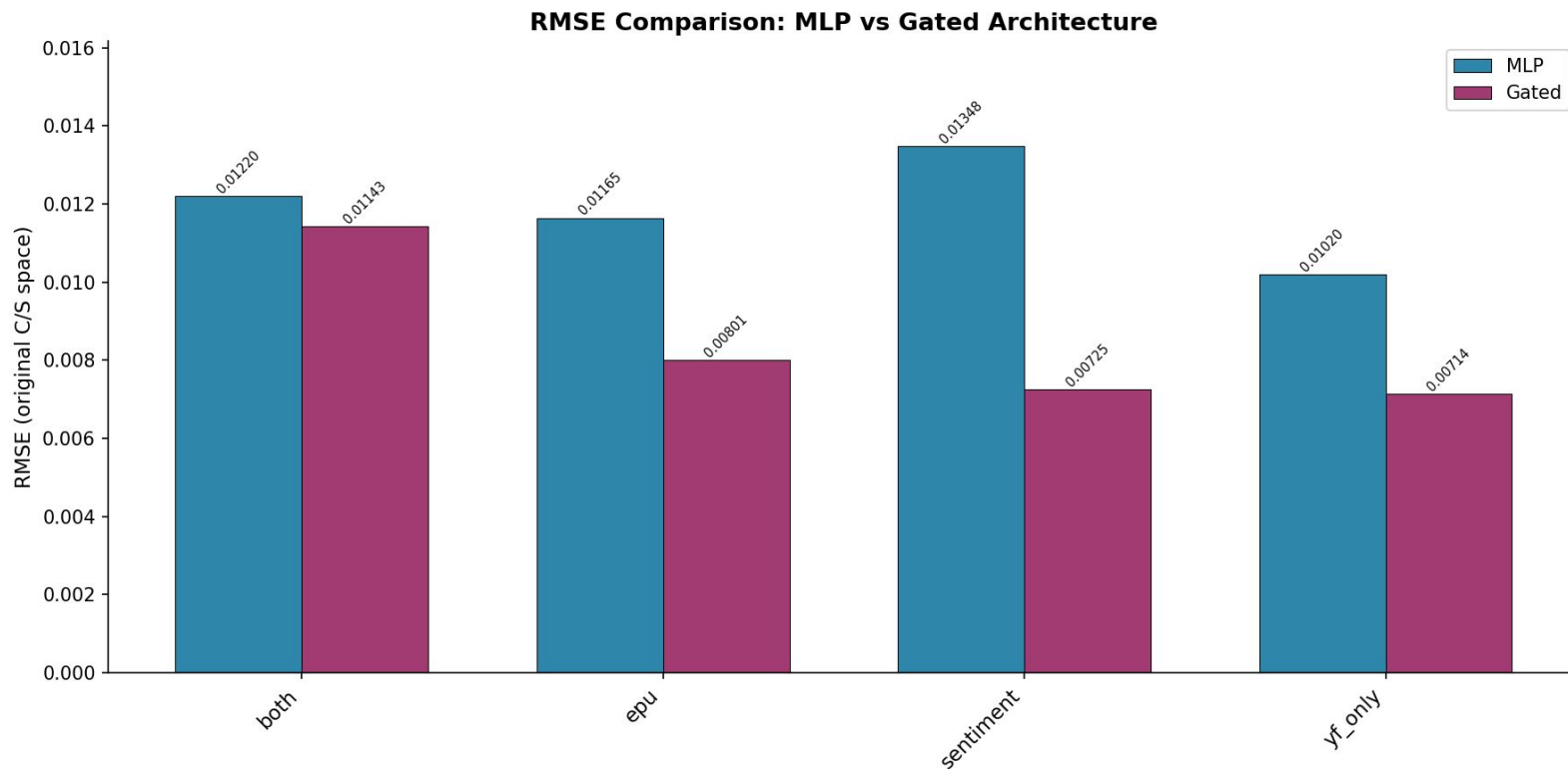
Metrics

- Root Mean Squared Error (RMSE)
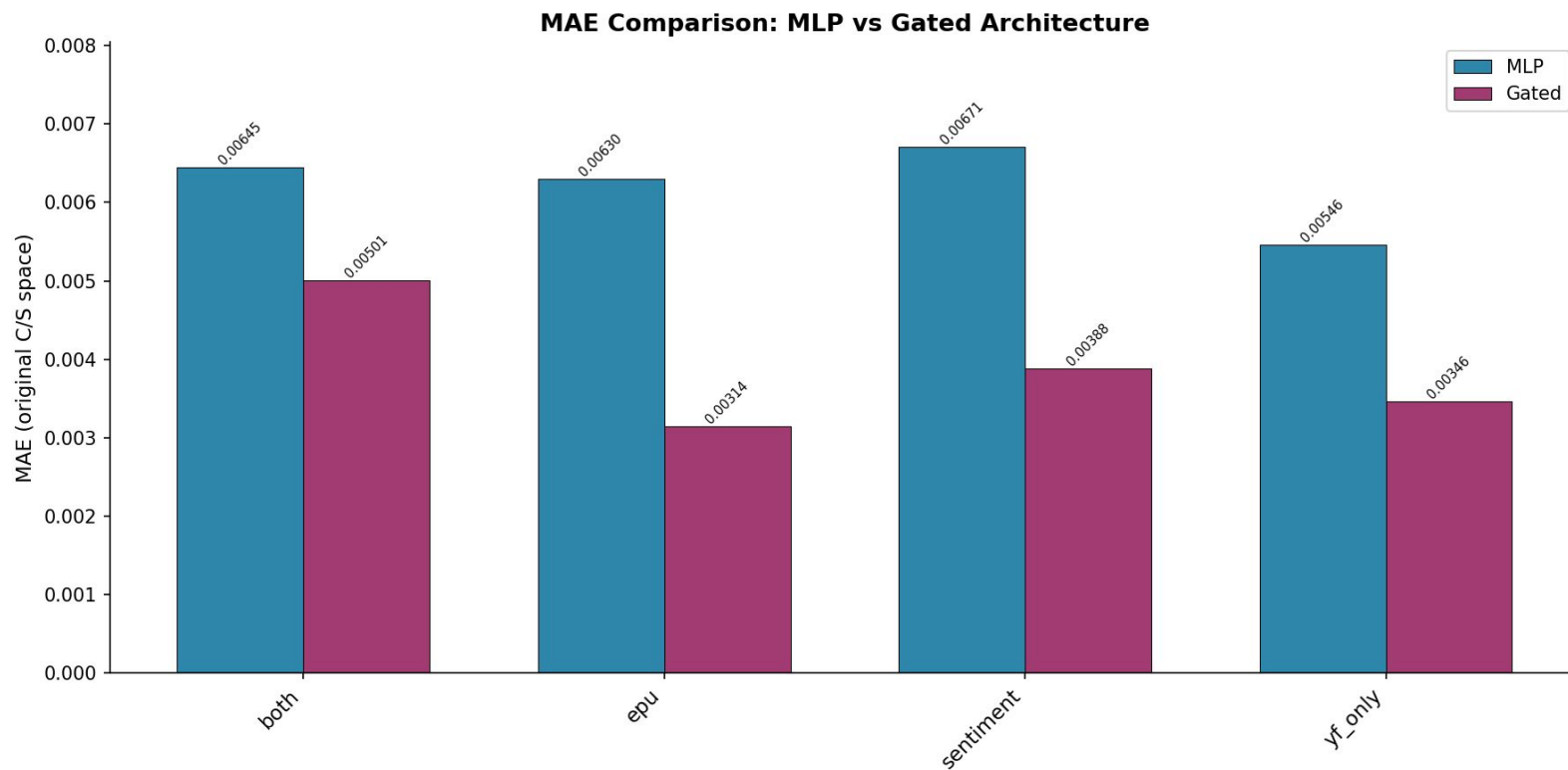
- Mean Absolute Error (MAE)

Hypothesis

1. **The hybrid models perform better than the respective baseline models.**

2. **The Models with alternative data perform better than the models without.**
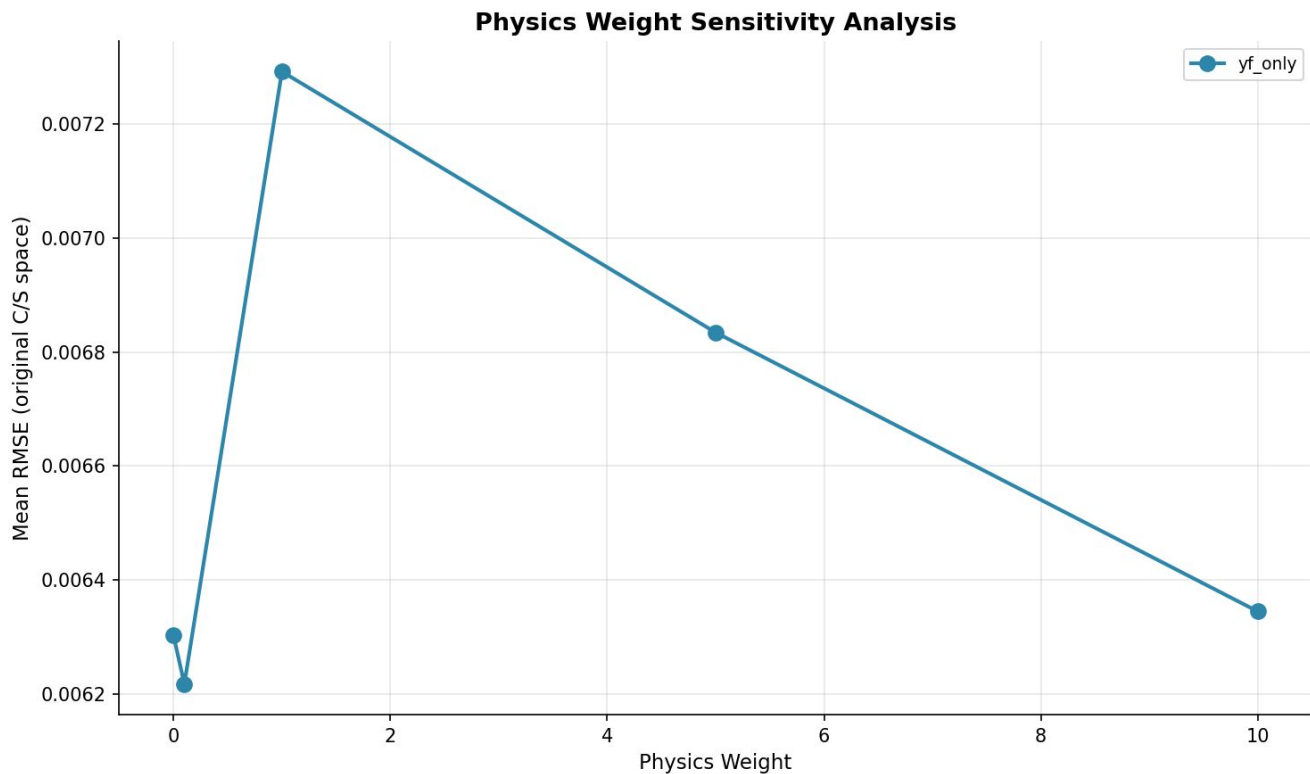
4. Results & Future Work

RMSE by Data Source

RMSE Comparison: MLP vs Gated Architecture

MAE by Data Source

MAE Comparison: MLP vs Gated Architecture

Physics Weight Sensitivity for Hybrid Model

Comparison of PINN+Feature Modules against baselines

Model	Data Config	Feature Count	RMSE (orig. space)
MLP Only	Traditional	5	0.01020
Gated LSTM Only	Traditional	5	0.00714
Gated LSTM only	Sentiment	8	0.00720
MLP + PINN	Traditional	5	0.00987
Gated LSTM + PINN	Traditional	5	0.00683
Gated LSTM + PINN	EPU	6	0.01718
Gated LSTM + PINN	**Sentiment**	**8**	**0.00566**
Gated LSTM + PINN	Both	9	0.01846

Conclusion

- The gated residual architecture consistently shows lower RMSE and MAE, especially with a single alternative data source added

- Physics-informed training provides marginal benefit in this data-rich setting, but combining it with feature modules yields additional performance gains

- Hybrid models show statistically significant improvements over purely data-driven approaches

- Alternative data improves results most when using market sentiment as a single source; Tech news sentiment is more effective than EPU

Future Work

- Develop sophisticated methods (e.g., attention-based networks) to better integrate multiple sources of alternative data and reduce conflicting signals

- Apply the hybrid PINN framework to assets with limited data, where regularization may provide greater benefits

- Evaluate models across additional assets, longer time periods, and varying market regimes, including major crashes and periods of low volatility

- Reduce training costs for PINN, explore scalable approaches and more efficient use of GPU resources

Q&A