Deep Learning Framework for Option Pricing

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Research Questions

- How well does Black Scholes price SPY American calls across maturities & strikes?
- Can a Multilayer Perceptron leverage only end-of-day data plus historical volatility to beat Black-Scholes out-of-sample?
- To what extent do unconstrained neural networks violate no arbitrage conditions when pricing American options?

Dataset

- End of Day data collected from Delta Neutral
- Ranging from February 2012 to May 2024
- Adjusted returns data recorded from Yahoo Finance
- Dividends collected from State Street Global Advisors

Model: Inputs

S: Underlying price
K: Strike price
T: Time to expiry (in years)
r: 3-month risk-free rate
σ: 63-day historical volatility (annualized)
q: Dividend yield (rolling dividends)
is_ex_date: 1 if ex-dividend date, else 0

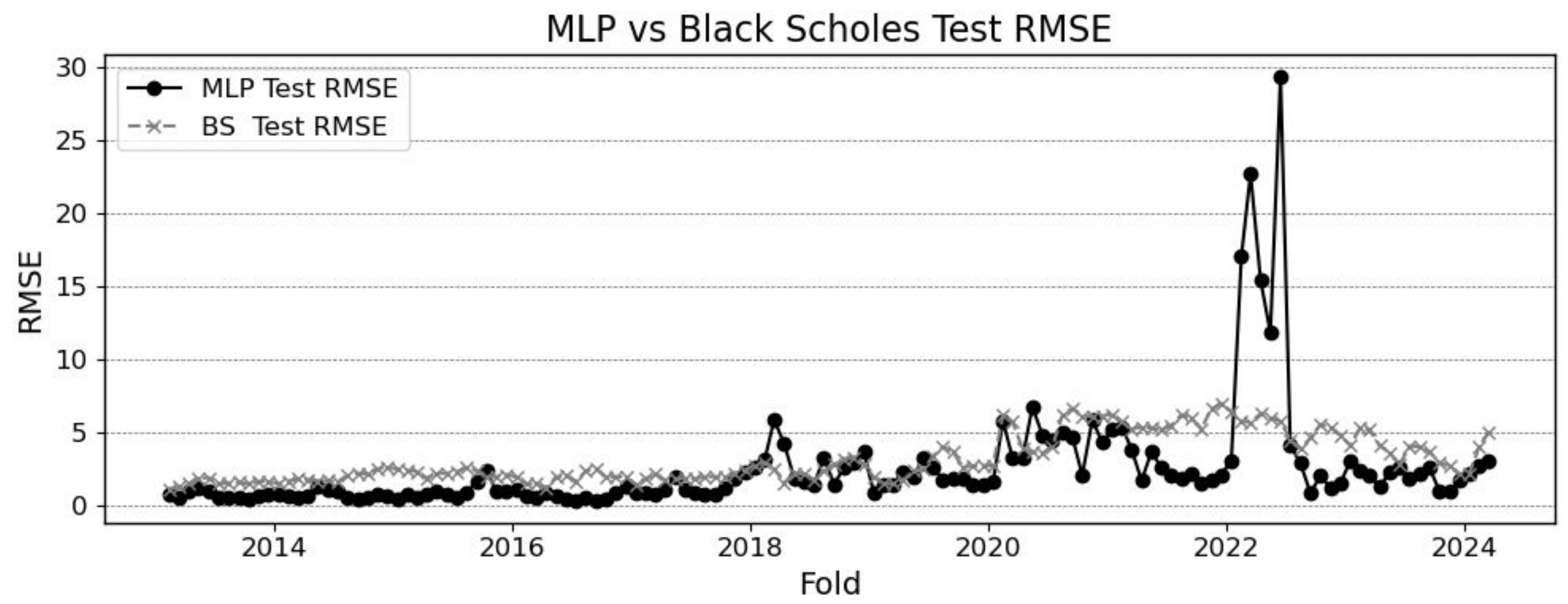
MLP Architecture

Component	Specification
Input features	$S, K, T, r, \sigma_{63}, q, exdate$
Hidden layers	3
Hidden units	10, 10, 10
Activation	Logistic (sigmoid)
Output	Linear
Training procedure	Walk-forward with 12-month train / 2-month test
Validation split	80/20 (no shuffling) within training window
Early stopping	Immediate stop when validation MSE increases
Epochs (max)	500
Regularization	L_2 penalty, $\alpha = 1 \times 10^{-4}$
Optimizer / Engine	MLPRegressor (scikit-learn, random_state=42)
Target	Option midpoint price (bid + ask)/2

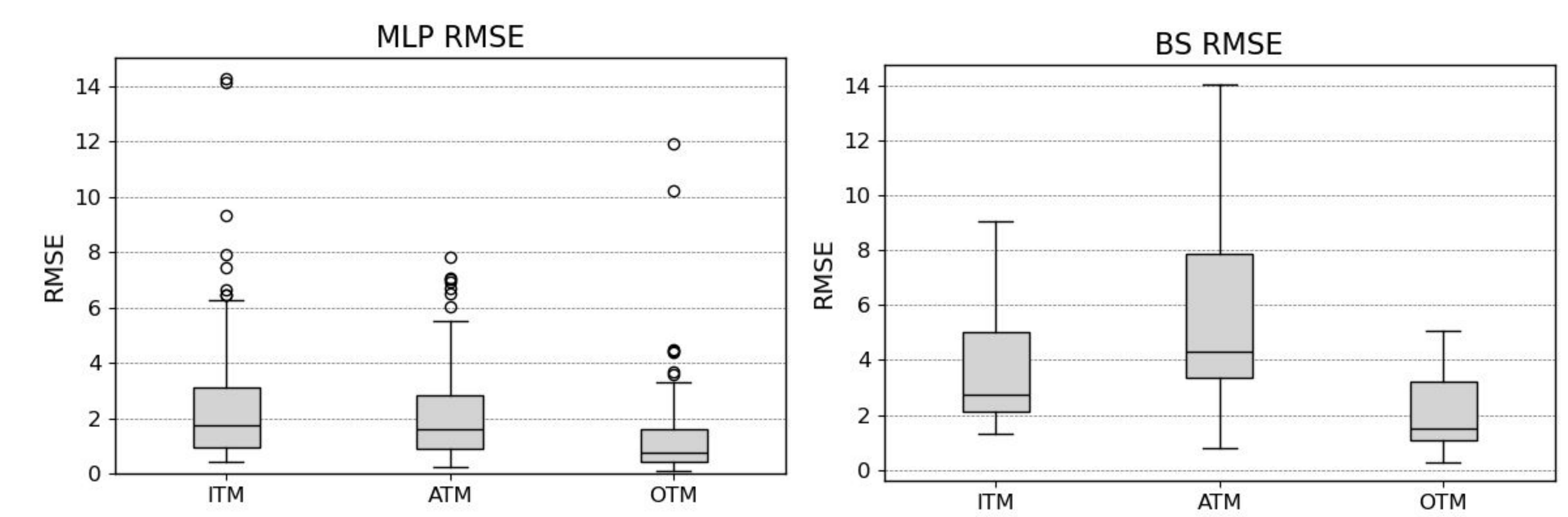
Results

Model	ITM RMSE	ATM RSMSE	OTM RMSE
MLP	2.898	2.847	1.712
BSM	3.580	5.601	2.071

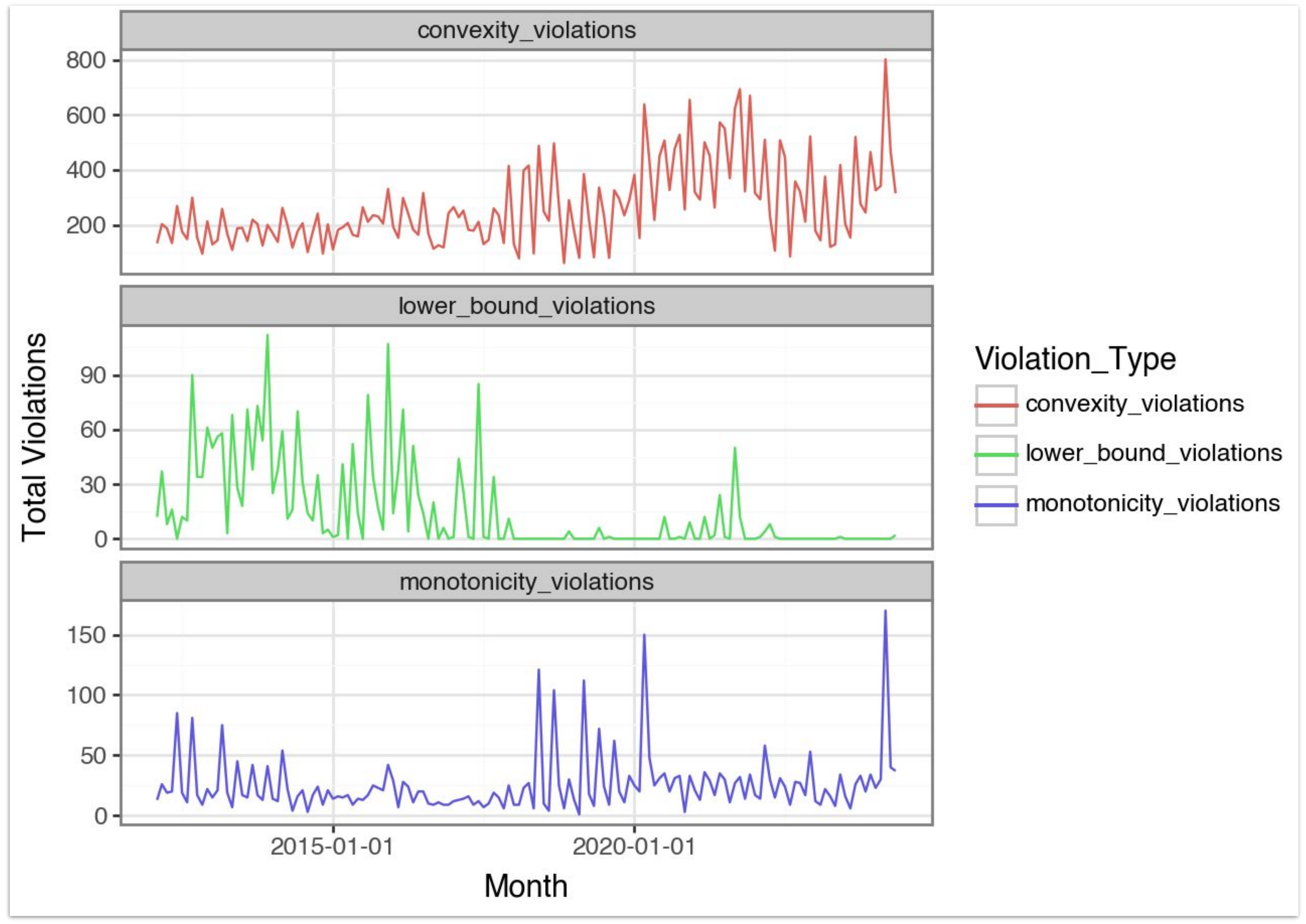
MLP vs Black Scholes Test RMSE



MLP vs Black Scholes RMSE Boxplots



Monthly No Arbitrage Violations



MLP Benefits

Why MLPs are better than Black Scholes for out of the money call prices

- MLPs can model without relying on rigid assumptions
- MLPs can incorporate more macroeconomic features
- MLPs learn the nonlinear pricing behavior of OTM calls

MLP Limitations

Why MLPs perform poorly in certain scenarios

- MLPs break fundamental no arbitrage assumptions
- MLPs fail to generalize under certain market conditions
- When MLPs fail, they may produce extreme outputs that could be risky in a live portfolio

Conclusions

- On average, MLPs outperform the Black Scholes model on pricing call options
- However, frequent violations of no arbitrage conditions undermine its reliability for real world option pricing
- MLPs performance degrades over regimes with extreme uncertainty
- Improved volatility forecasts would improve predictive performance
- A hybrid approach may be beneficial depending on the market regime

Next Steps

- Use realized volatility from intraday SPY prices
- Incorporate no arbitrage constraints into the MLP loss function

References

[1] B. Horvath, A. Muguruza, and M. Tomas. Deep learning volatility: a deep neural network perspective on pricing and calibration in (rough) volatility models. Quan-titative Finance, 21(1):11-27, 2021.
[2] F. Black and M. Scholes. The pricing of options and corporate liabilities. Journal of Political Economy, 81(3):637-654, 1973.
[3] J. H. Jang, J. Yoon, J. Kim, J. Gu, and H. Y. Kim. Deepoption: A novel option pricing framework based on deep learning with fused distilled data from multiple parametric methods. Information Fusion, 70:43-59, 2021.