Beyond Forecasts: Deep Learning for Direct Portfolio Optimization

-Training LSTMs to Maximize Sharpe Ratio from Market Data

Daksh Agarwal

Nishika Kakrecha

The Traditional Hurdle & A New Path

For decades, portfolio optimization relied on predicting future returns, which is difficult and often unreliable. Models like MPT can fail to account for real-world risks like crashes or 'fat-tail' events.

What if a system could learn investment strategies directly from market history—focusing on how to respond to patterns, rather than predicting the future?

Our Vision: We set out to build and test a deep learning system using LSTMs that learns to allocate assets with the specific goal of maximizing risk-adjusted performance, measured by the Sharpe Ratio.

Our Strategy: End-to-End Learning & Focused Assets

The CORE Idea: Our end-to-end LSTM, trained on historical data, directly generates next-day portfolio allocations via self-adjusting optimization to maximize the Sharpe Ratio.

Why skip forecasts? Directly optimizing portfolio performance, not forecast accuracy, leads to better results and lets the model uncover complex patterns we might miss.

Smart Asset Selection: Instead of grappling with thousands of stocks, we built our portfolio using a curated set of four diversified ETFs, providing exposure across key market segments:

1. **VTI (Stocks):** Capturing the broad US equity market.
2. **AGG (Bonds):** Representing the stability of the US aggregate bond market.
3. **DBC (Commodities):** Offering diversification through raw materials.
4. **VIX (Volatility):** A tool often used for hedging or capturing market stress.

Crafting the Input: Data Prep & Feature Engineering

Feeding the LSTM: We used a rolling window of the past 50 trading days to give the model rich sequential context.

Rich Features: Each day's price and return data for all assets lets the LSTM learn both trends and momentum.

Essential Preprocessing: We cleaned, forward-filled, and standardized returns to ensure all features are comparable for effective learning.

Ready for Learning: The result is a structured 3D dataset perfectly formatted for the LSTM

The Brains of the Operation: LSTM Architecture

Why LSTMs? They're built to learn from sequences and remember what matters, making them ideal for financial data.

Softmax Activation: This converts outputs into positive weights that sum to 100%, enabling a fully invested, long-only portfolio.

Building the Network:

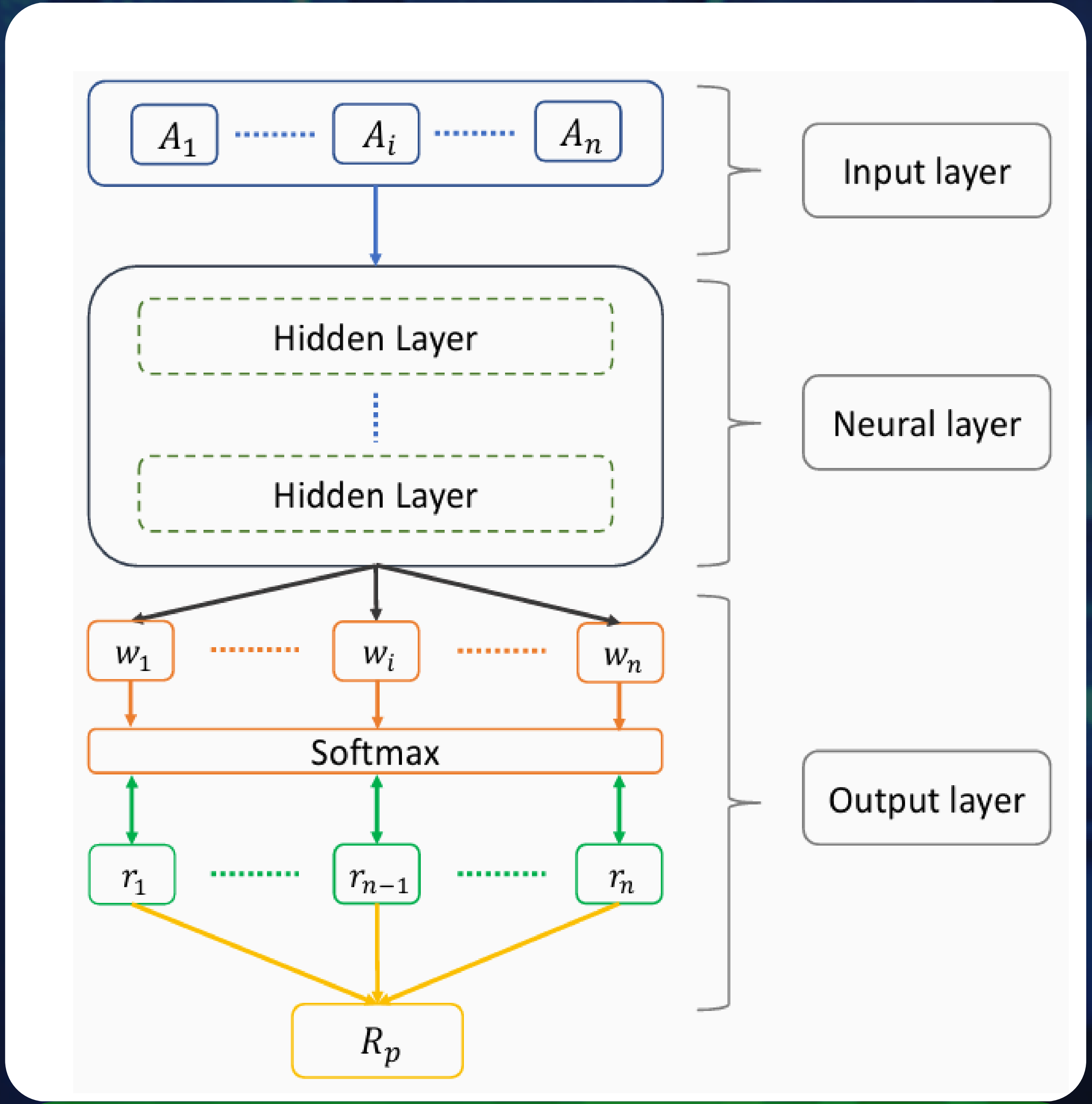
Our architecture consists of:

1. An input layer receiving the 50-day sequences.

2. Stacked LSTM layers (64 units then 32 units) responsible for processing the temporal patterns.

3. A Dropout layer sits between them to prevent the network from merely memorizing the training data (overfitting).

4. The crucial final output layer is a Dense layer with 4 neurons, one for each asset.



Model architecture schematic. Overall, our model contains three main building blocks: input layer, neural layer and output layer.

The Secret Sauce: Sharpe Ratio as the Loss Function

Aligning Training: We use a custom loss to maximize Sharpe Ratio, focusing on risk-adjusted returns instead of generic errors.

How it Guides Learning?
(sharpe ratio loss):

During training, the loss computes portfolio returns and the Sharpe Ratio from proposed weights and actual returns.

The optimizer minimizes the Negative Sharpe Ratio, guiding the LSTM to maximize risk-adjusted performance.

Rigorous Testing: Training & Walk-Forward Validation

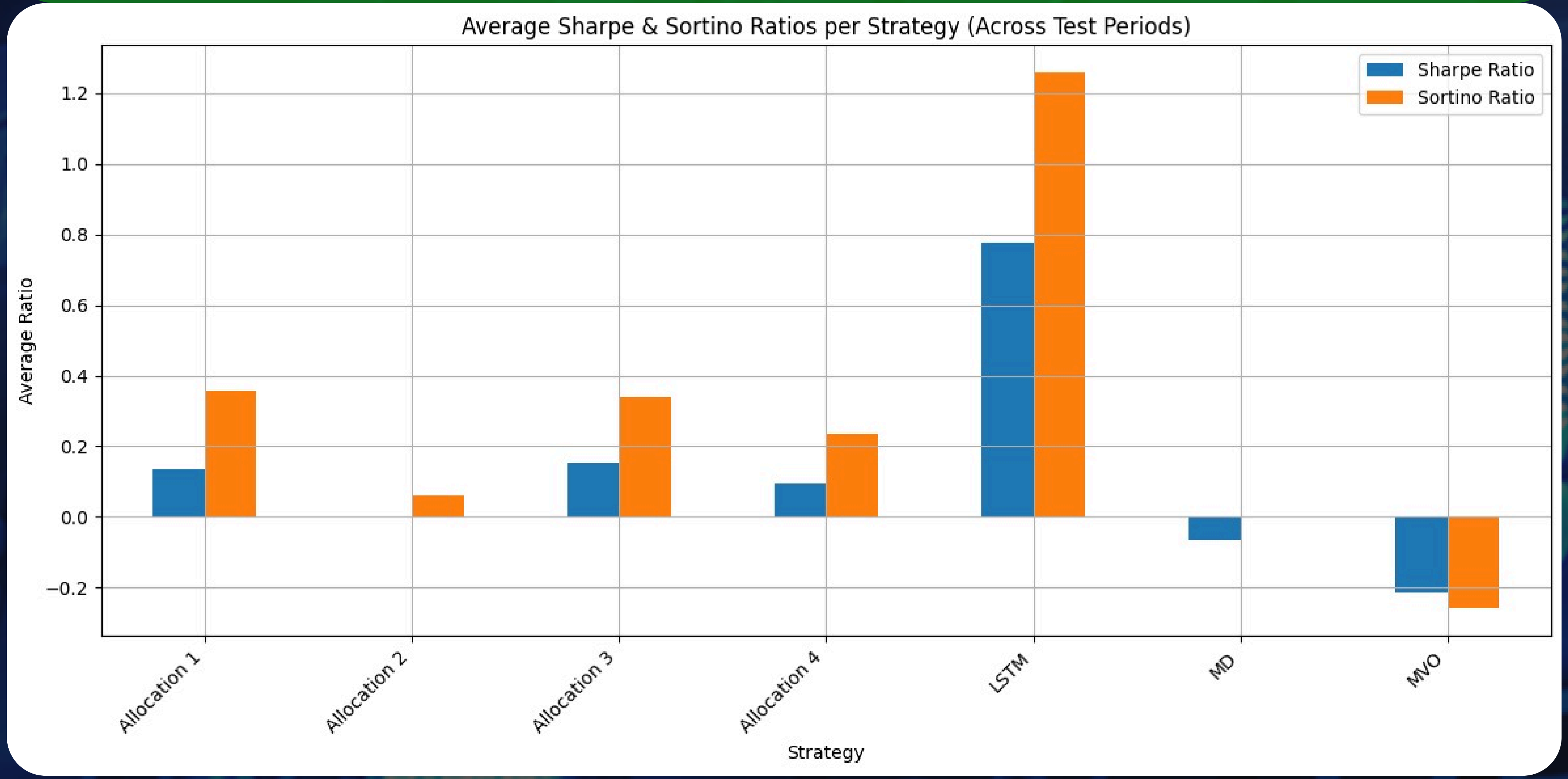
Learning Process: We trained the network with Adam optimizer using our Sharpe Ratio loss.

Realistic Evaluation: Walk-forward validation tests the model on unseen future data incrementally **(train through 2010 → test 2011, retrain through 2011 → test 2012)**, eliminating lookahead bias.

Benchmarks: Fixed weights (e.g., Equal) and daily-updated MVO strategies.

The Verdict: Performance Comparison

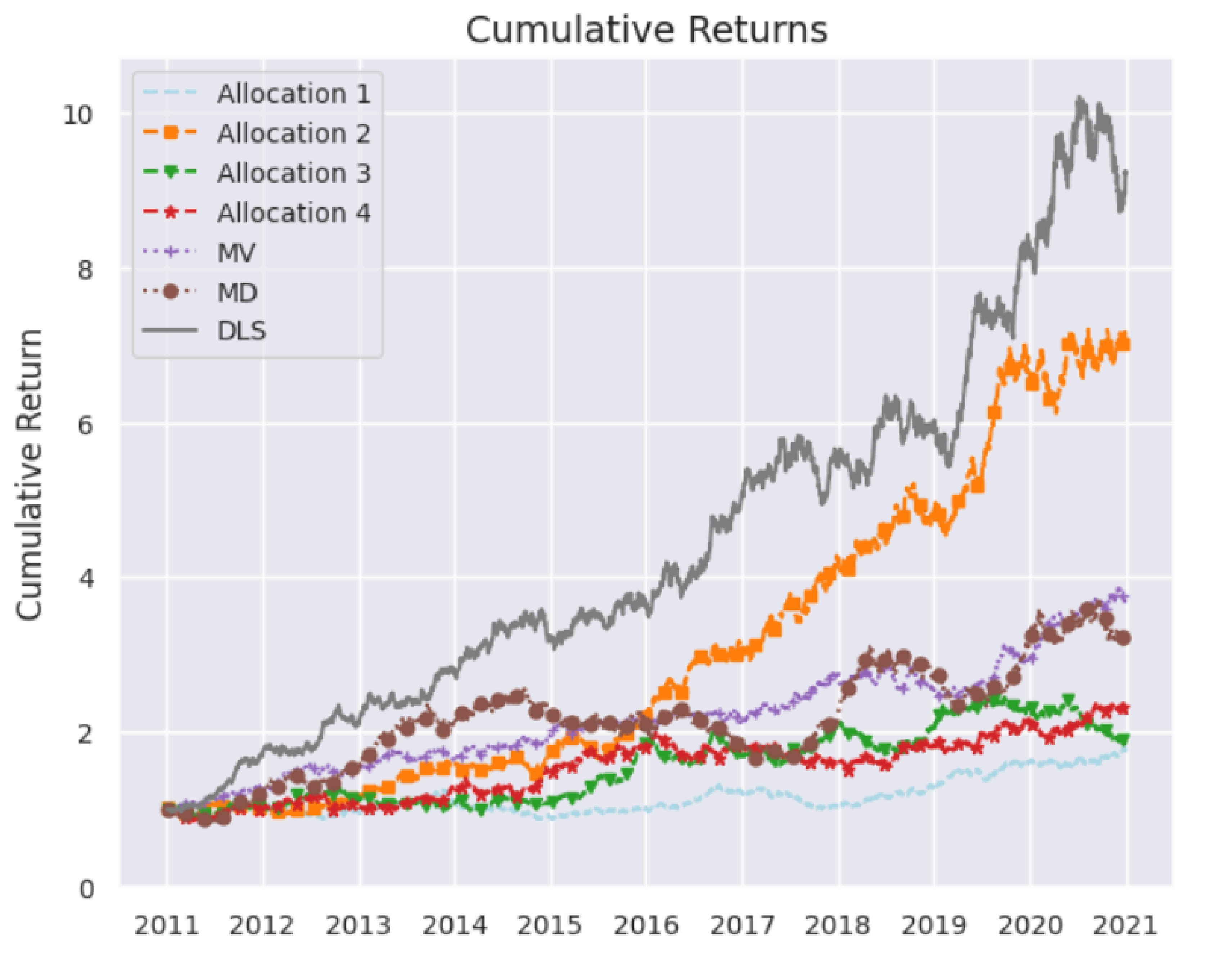
The Key Metric: We focused on the annualized Sharpe Ratio, averaged across all the walk-forward test periods, to judge risk-adjusted success.



Clear Results: The LSTM, trained to maximize Sharpe Ratio, outperformed both fixed allocation and traditional MVO strategies, showing clear benefits from its adaptive, data-driven approach.

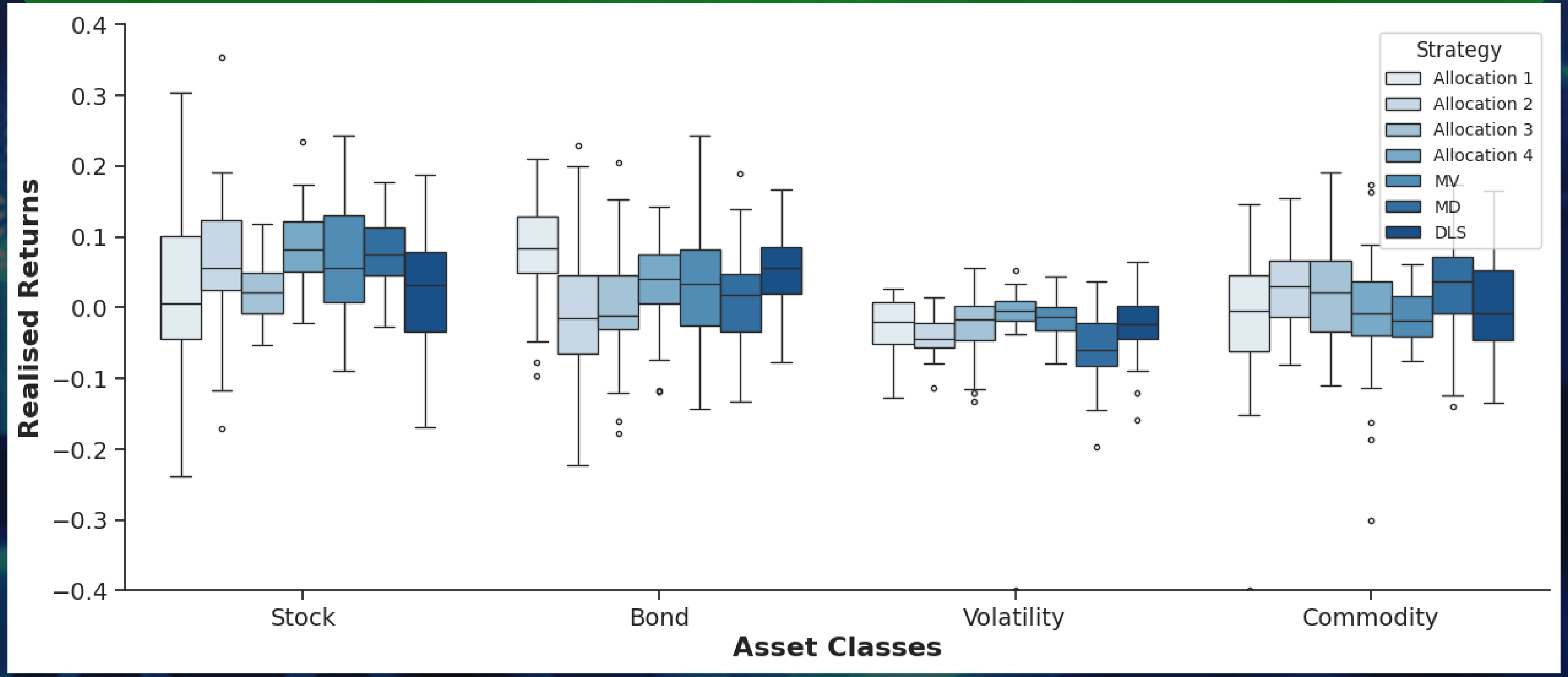
In Essence: The direct optimization approach proved capable of generating superior risk-adjusted returns within our testing framework.

Deeper Analysis: Return Characteristics & Consistency



Cumulative Return Plots: These charts illustrate the long-term growth trajectory of each investment strategy from 2011 to 2020, showing how an initial investment would have compounded over time based on the strategy's performance.

Realized Return Box Plot: This plot displays the return distributions (median, spread, outliers) for each strategy within the different asset classes (Stock, Bond, Volatility, Commodity), indicating performance consistency and risk.



Reflections: Discussion, Conclusion & Next Steps

What We Learned: LSTM optimized for Sharpe Ratio outperforms MVO, capturing complex patterns and handling input errors better.

Important Considerations: Dynamic strategies incur transaction costs, and deep learning models are less interpretable than simpler methods.

Conclusion: Our LSTM effectively learns high-performing portfolios by maximizing the Sharpe Ratio, offering a strong alternative to traditional methods.

Looking Ahead: Future work could try new architectures, add richer data, optimize for other risks, or factor in transaction costs.

QNA TIME!

THANK YOU!

FOLLOW US:

FEC_IITG

Instagram

Linkedin