A Factor Rotation Strategy Based on Two-Stage Machine Learning Approach

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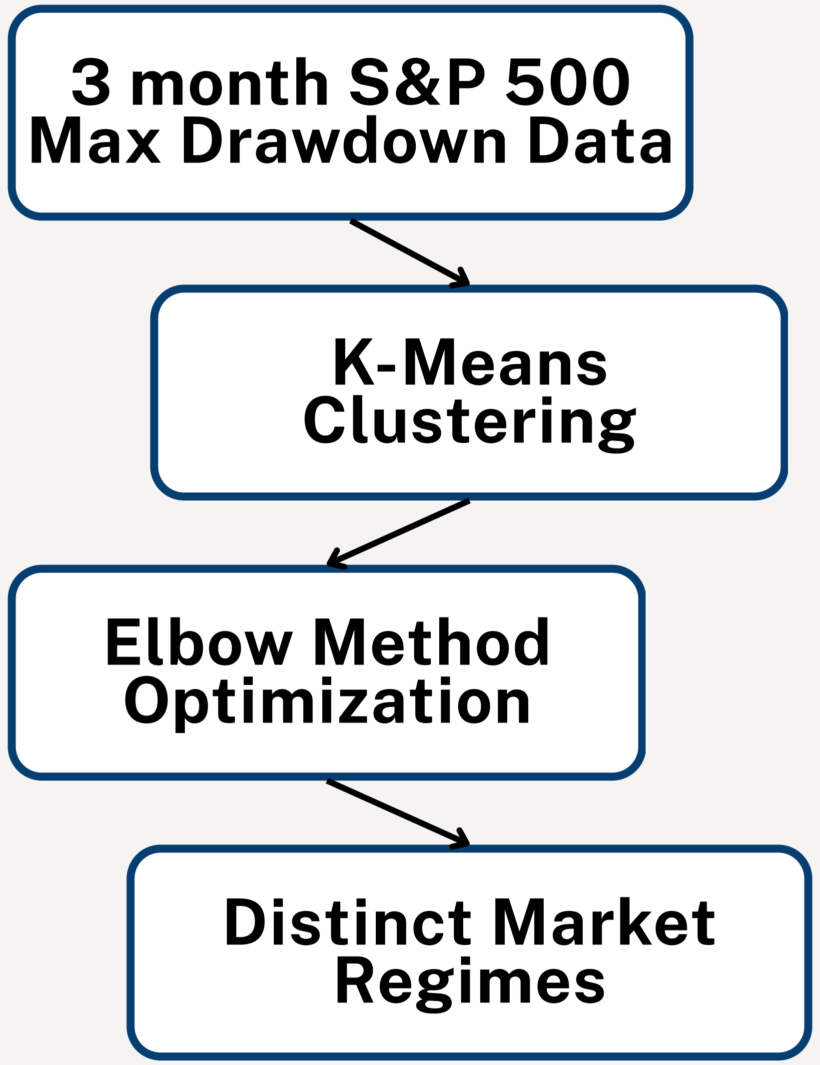
Content:

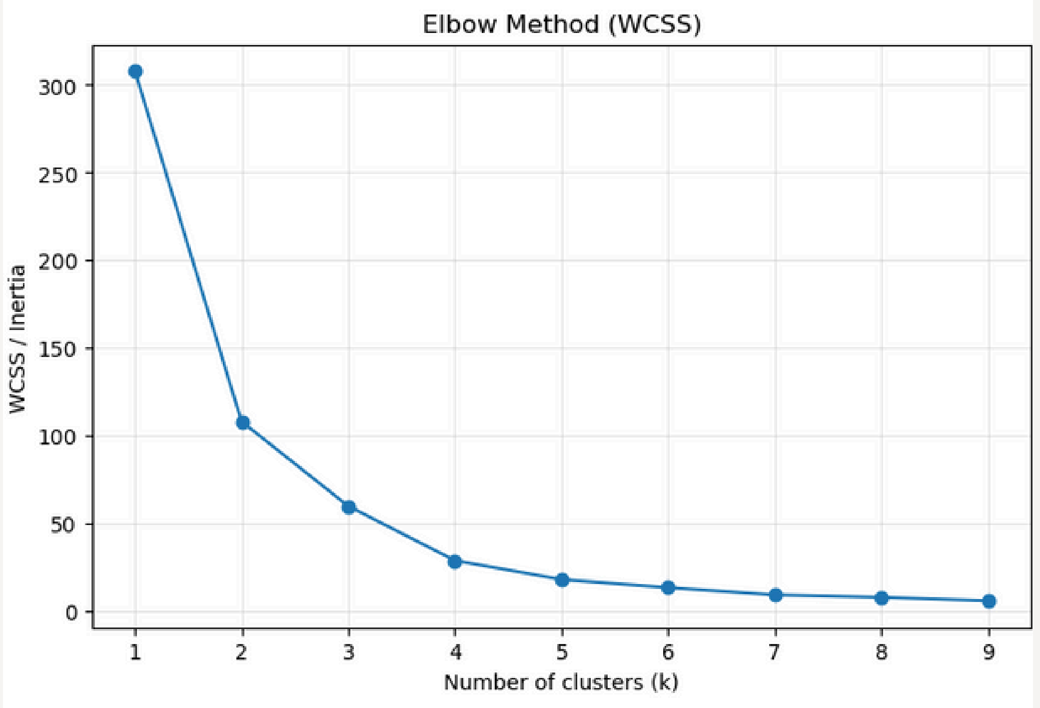
Part 1: Introduction and Working Hypothesis

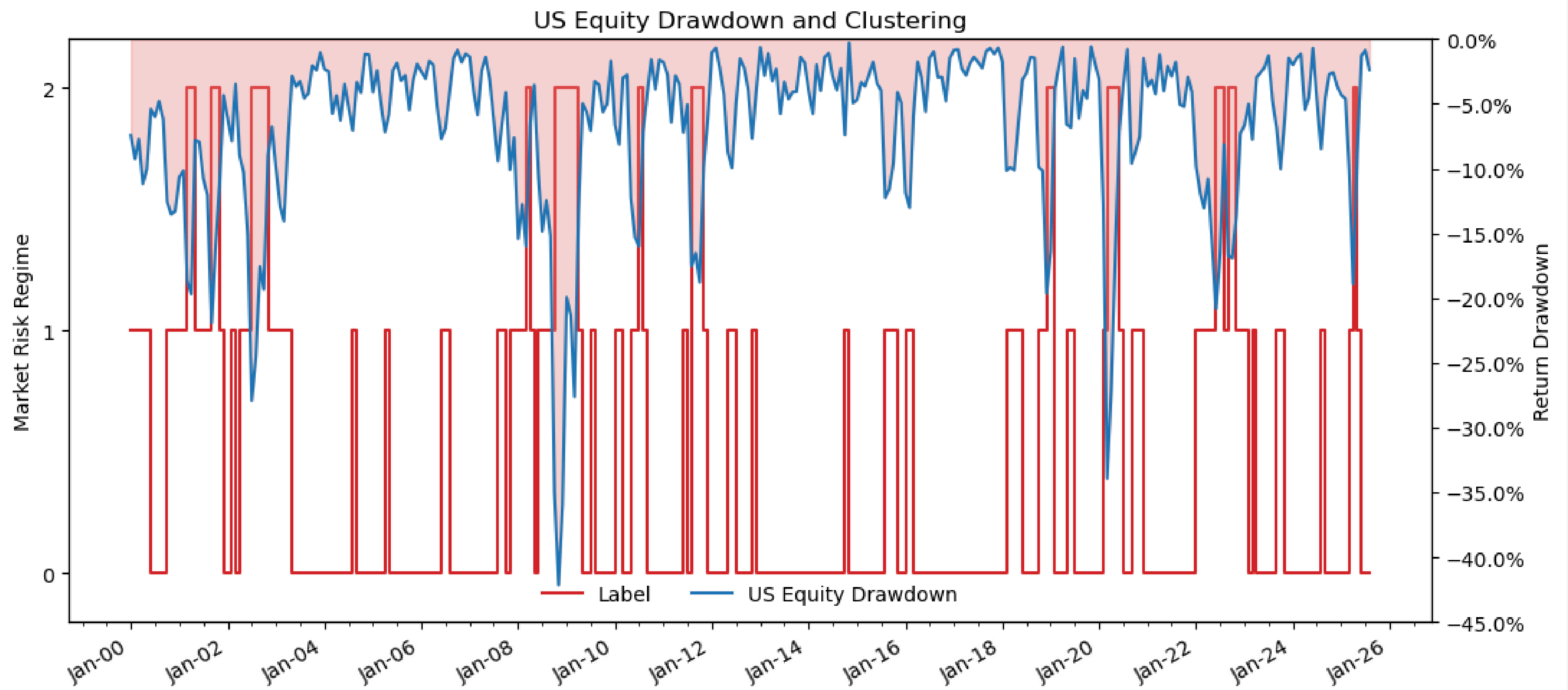
- **Introduction:**
  - In recent decades, factor investing has received sustained and widespread attention in the field of quantitative investment. Unlike most studies that focus on the long-term returns of individual factors, we focus on the relative performance among factors. Specifically, we use a two-stage model to predict how factors perform relative to each other under different market conditions.

- **Working hypothesis**:
  - Using K-means to identify the number of existing market states, and then applying classification models to predict the current state of the market based on financial turbulence and macroeconomic indicators, provides a reliable foundation for machine-learning-based factor rotation investing. In other words, conditional on these predicted regimes, supervised ensemble learning models can better identify next-period factor outperformers than naive benchmarks, ultimately leading to higher risk-adjusted portfolio returns.

Part 2: Stage One, Market Regime Clustering and Prediction







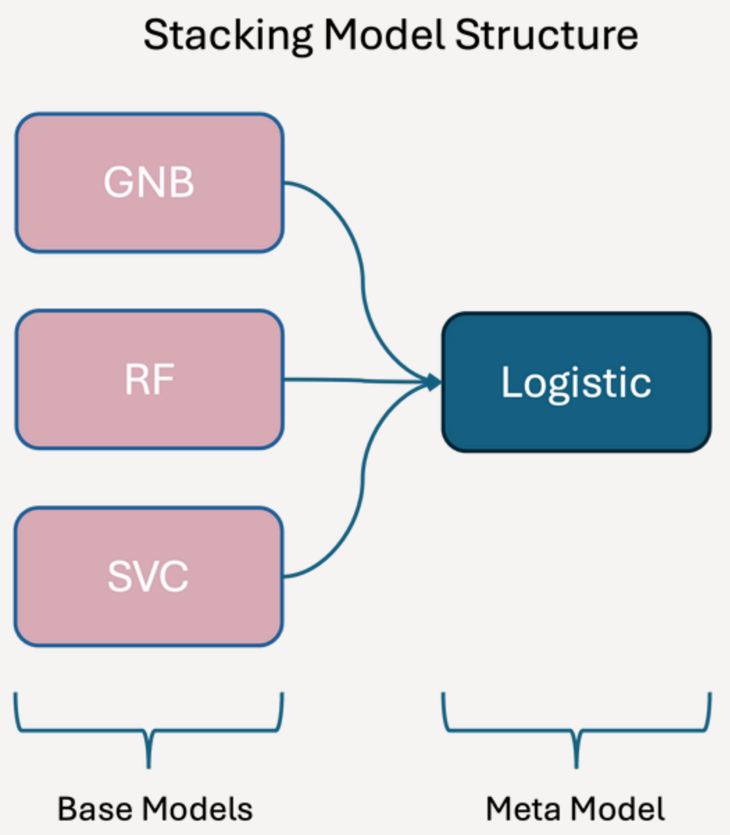
Stage 1 — Determining Types of Market Regime

- Goal: Determine optimal number of unique market regimes
- K-Means clustering provides unique market regimes.
- Elbow method optimizes the number of market regimes.
- Data segmented into subdata corresponding to each regimes.

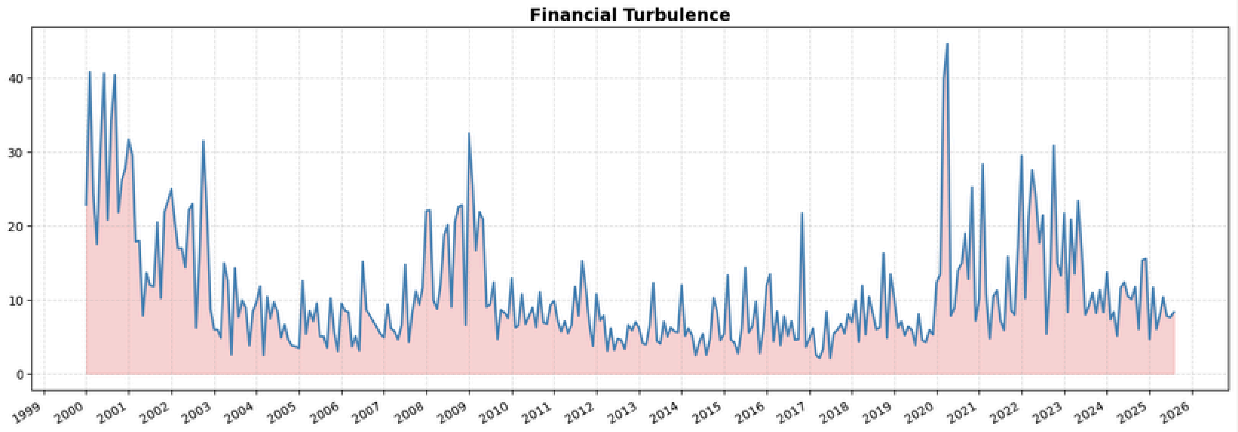
Feature Engineering: Financial Turbulence Creation, Lagged Features, PCA

Stacking Ensemble Classification

Market Regime Prediction

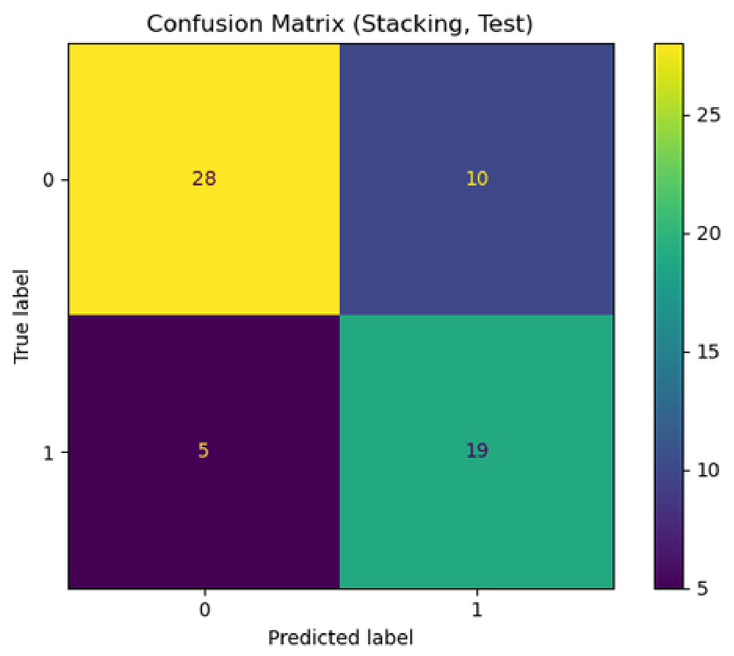


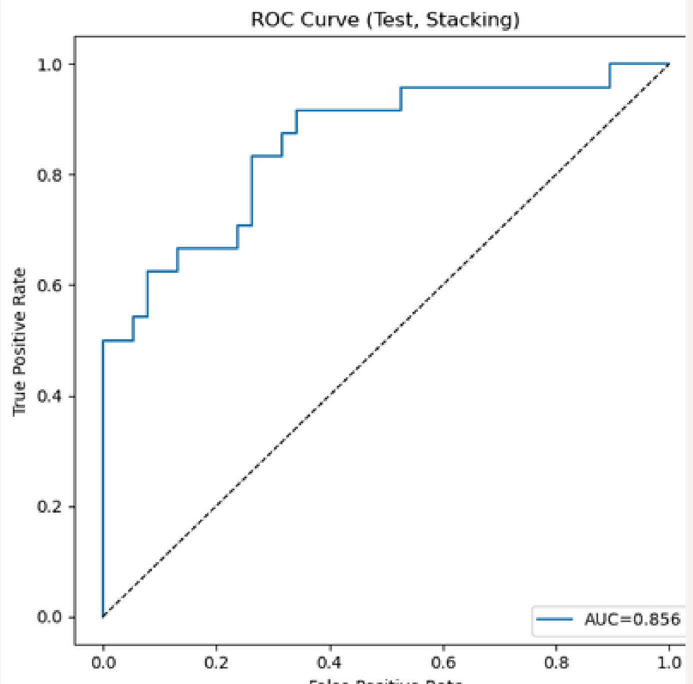
Macro Categories	Variables Considered for Machine Learning Testing
Inflation	Trailing ten-year annualized changes in core CPI Trailing one-year annualized changes in core CPI Sources: FRED, Federal Reserve Economic Data
GDP Growth / Business Cycle	US Real GDP Growth Sources: FRED, Federal Reserve Economic Data
Financial Condition	Risk Financial Condition Credit Financial Condition Leverage Sources: FRED, National Financial Conditions Index
Monetary Policy Expectations	Effective Federal Funds Rate Monetary Policy Expectations Sources: FRED, Federal Reserve Economic Data
Equity Earning Yield	Cyclically Adjusted PE Ratio (CAPE Ratio) Sources: Online Data Robert Shiller



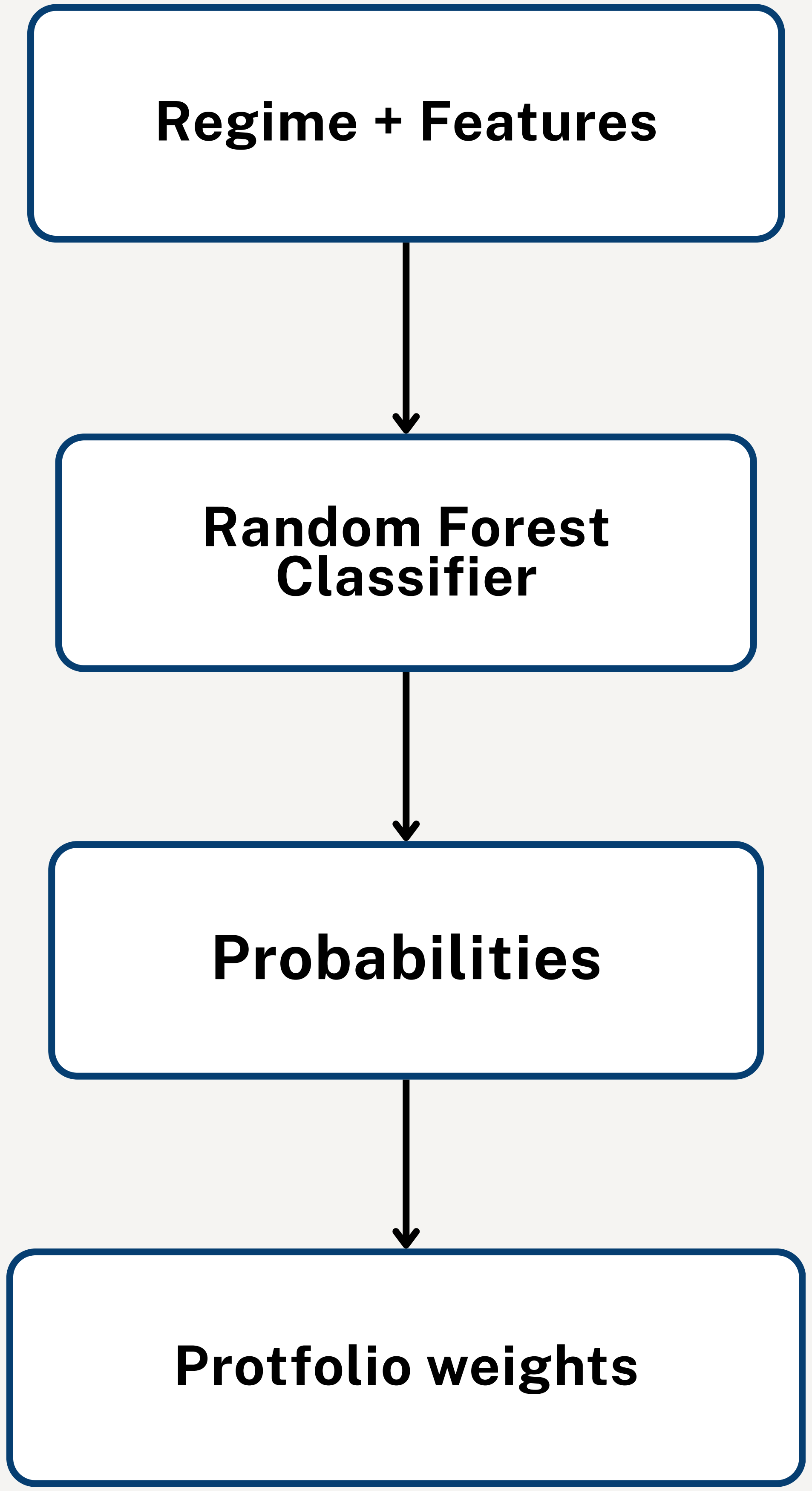
Stage 1 — Predicting Type of Market Regime

- Goal: Predict what the current market regime is
- Input features:
  - Macroeconomic variables
  - max drawdown $RollingDrawdown(t) = \frac{P_t - Max_{t-63 \le s \le t} P_s}{Max_{t-63 \le s \le t} P_s}$
  - financial turbulence $d_t = (y_t - \mu)\Sigma^{-1}(y_t - \mu)^T$
- Apply PCA: Multicolinearity issue
- Stacking Model: RF, SVC, GNB.
- Outputs market regime prediction.



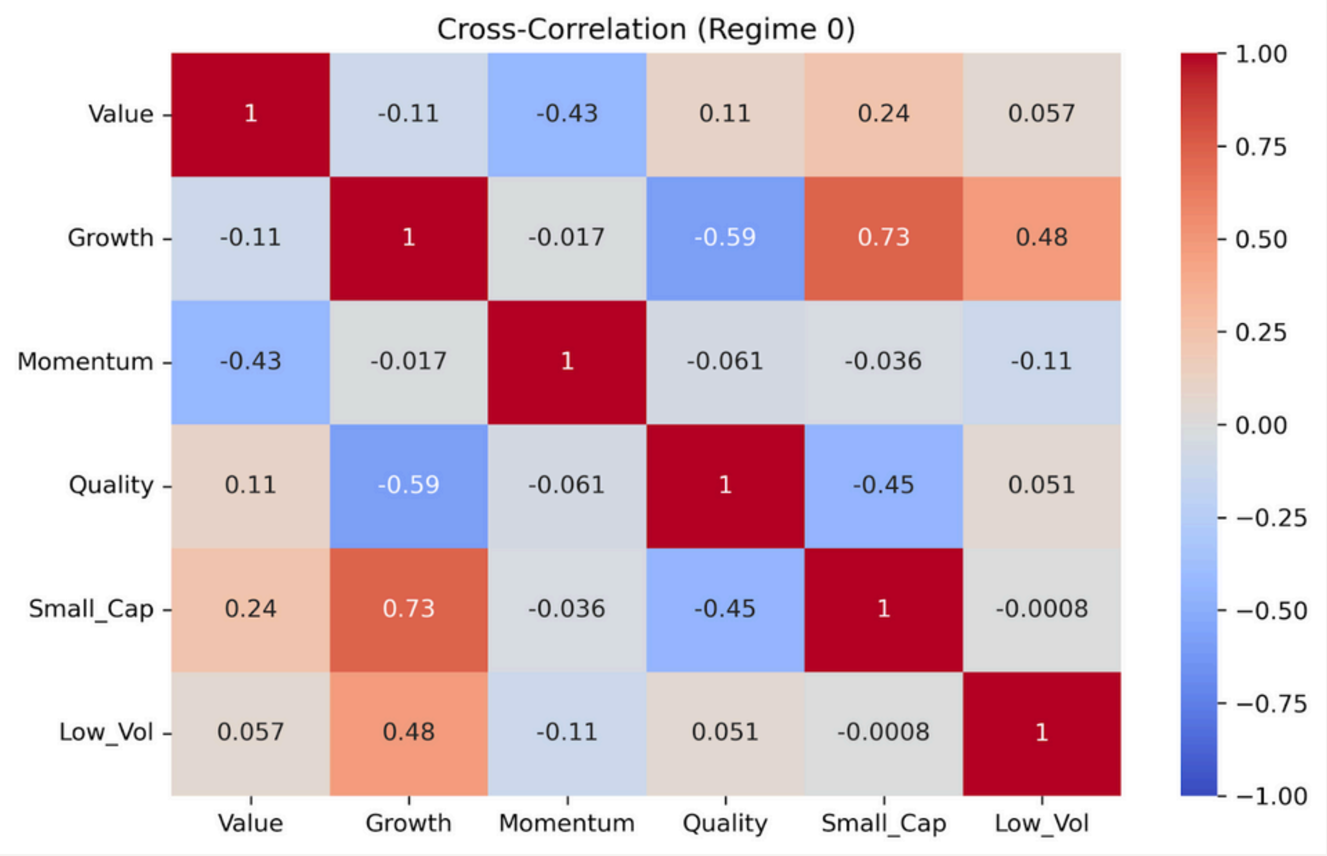


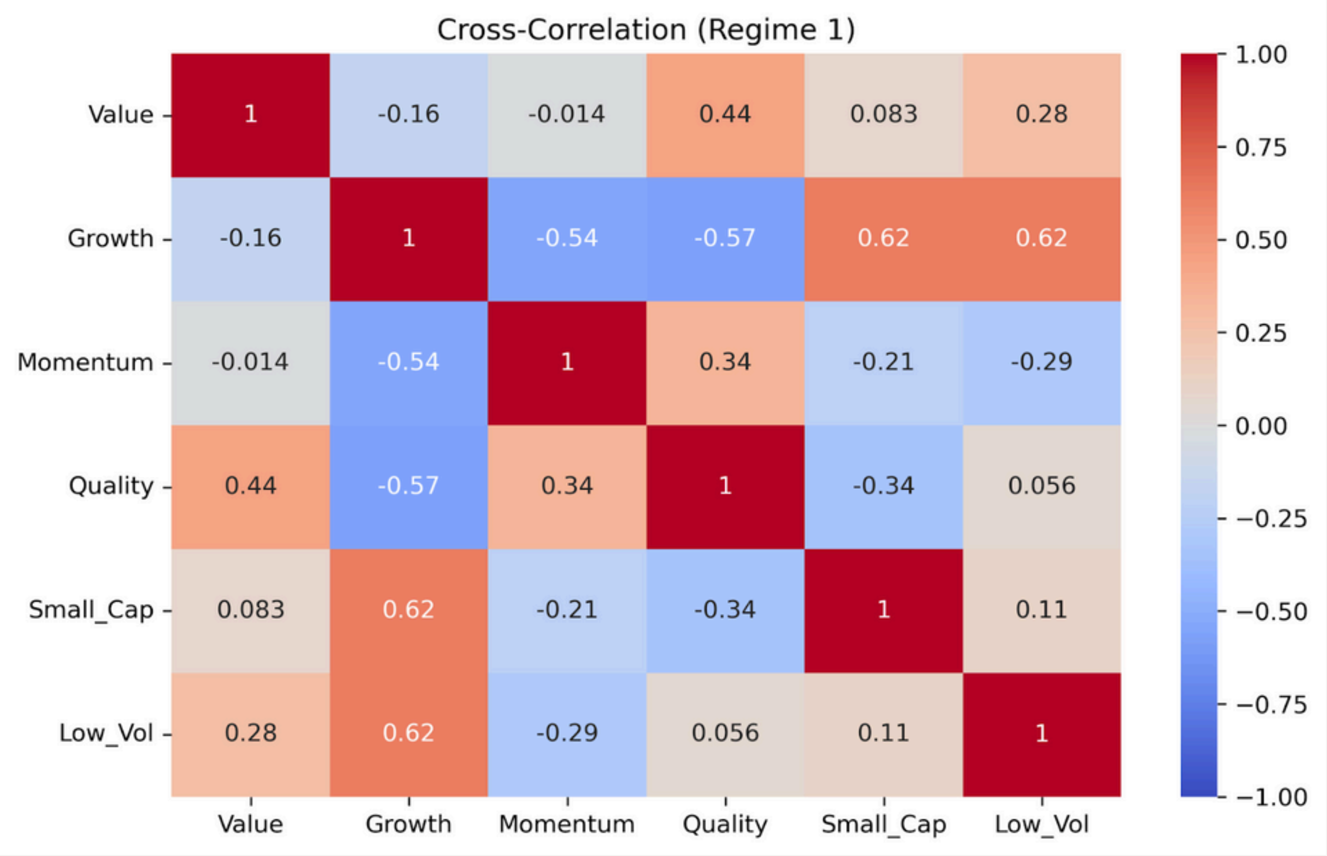
Part 3:
Stage Two, Outperformer Factor Prediction



Stage 2 — Predicting Factor Outperformance

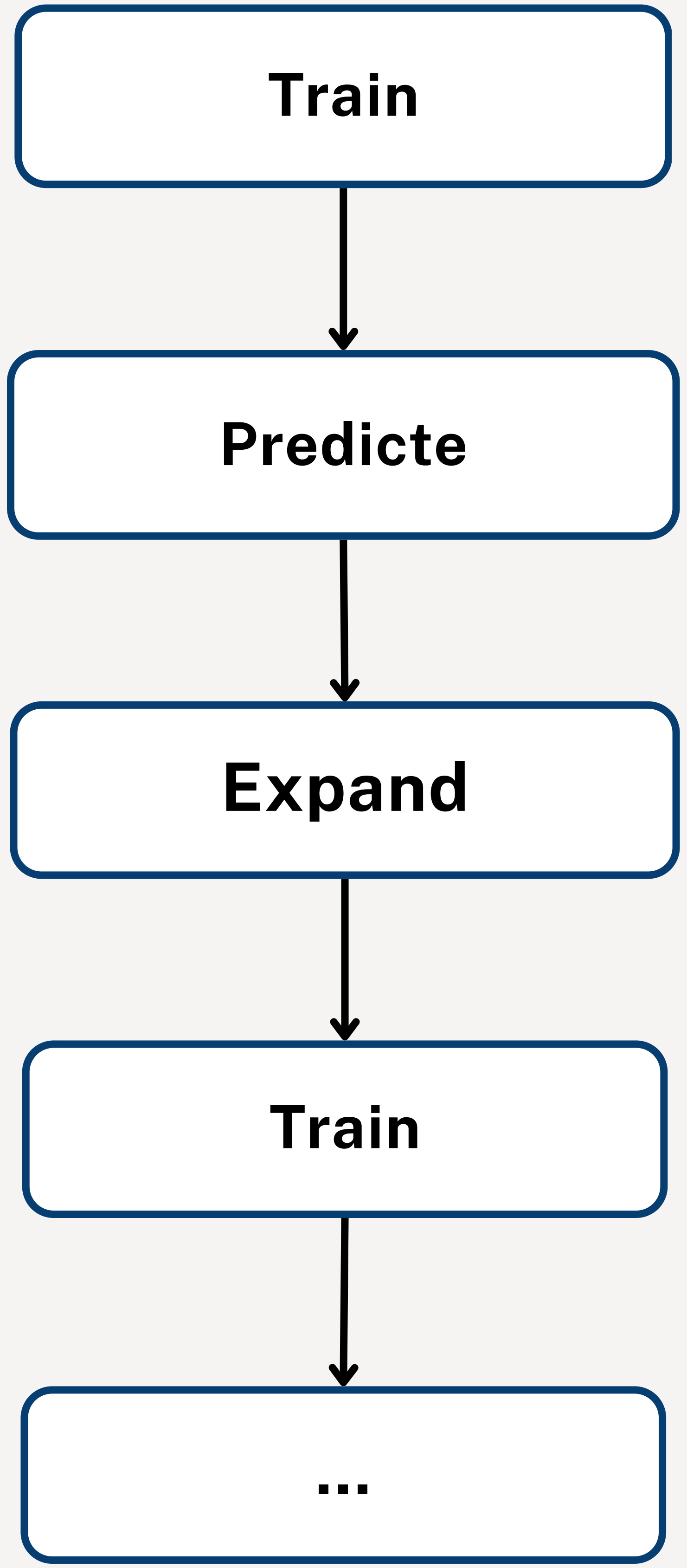
- Goal: predict which factor will outperform this month
- Random Forest model produces probability forecasts.
- Predictions conditioned on market regime.
- Probabilities later become portfolio weights.





Regime-Specific Random Forest Models

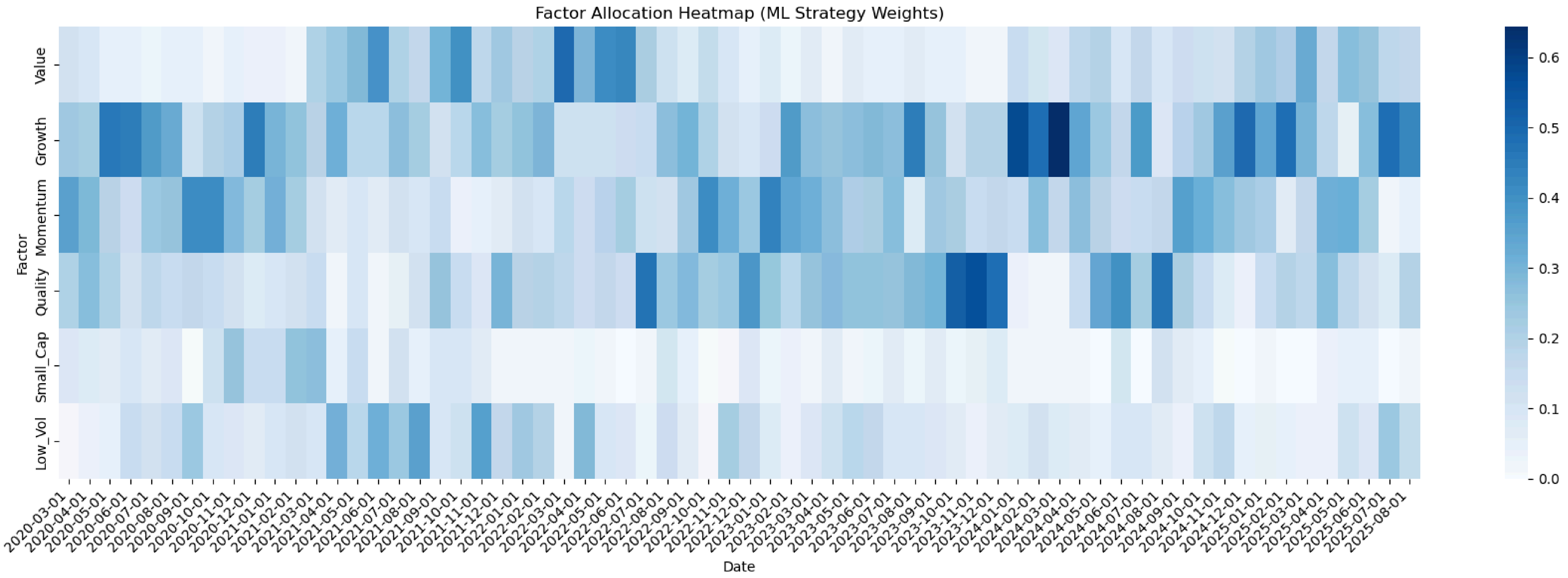
- RF trained separately for Regime 0 and Regime 1
- Factors behave differently under different risk environments.
- Model learns unique patterns per regime.



Expanding Rolling Training Window

- Train on all months up to time t.
- Predict factor performance for month t+1.
- Avoids leakage and improves stability.
- Matches “recursive real-time learning” setup in the base paper.

Probability-Based Predictions



- RF outputs: P(winning factor =f | regime, X)
- Convert to portfolio weights: $\omega_{f,t} = P(f,t)/\sum_j P(j,t)$
- Long only, weights sum to 1.

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FACTOR PREDICTION ACCURACY (Stage 2)
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Factor        Accuracy   Pred Count   Actual Win %
------------------------------------------------------------
Value           0.556          9          0.118
Growth          0.429         28          0.363
Momentum        0.267         15          0.206
Quality         0.273         11          0.127
Small_Cap       0.000          1          0.052
Low_Vol         0.500          2          0.134

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SUMMARY
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Overall Accuracy:   0.379
Random Baseline:    0.167
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Factor Prediction Accuracy

- ML accuracy significantly exceeds random baseline (≈16.7%).
- Growth, Momentum have highest accuracy and frequency.
- Small-Cap rarely wins → consistent with empirical returns.
- Value and Low Vol show moderate but meaningful predictability.

Part 4:
Portfolio Simulation and Conclusion

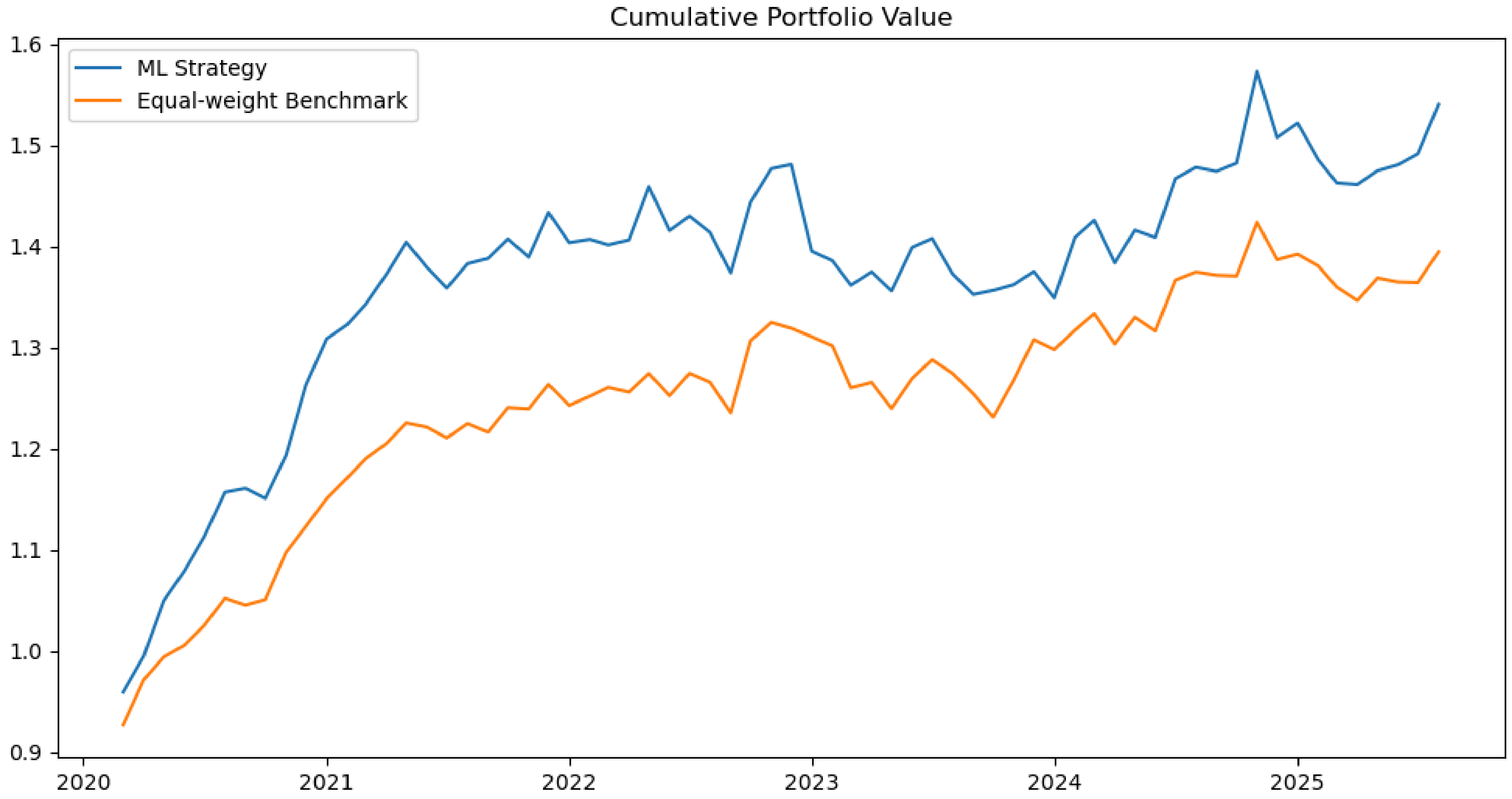
Portfolio Simulation

- **Benchmark: Equal-Weight (1/N) Portfolio**
  - → Allocates the same weight to all factors monthly.
  - → Represents simple diversification, no timing or prediction.

- **ML Strategy: Probability-Weighted Factor Portfolio**
  - → Convert predicted outperforming probabilities into portfolio weights:
    - $\omega_{f,t} = P(f,t)/\sum_{j} P(j,t)$
  - → Higher-confidence factors receive larger allocations.
  - → Dynamic monthly re-balancing based on new predictions.

Performance Comparison: ML vs Equal-Weight

- **Key highlights:**
  - Backtest period: Mar 2020 – Aug 2025
  - Final portfolio value: 1.54 (ML) vs 1.39 (Equal-Weight)
  - Total return: 54.0% vs 39.4%
  - Annualized return: 8.17% vs 6.23%
  - Sharpe ratio: 0.94 vs 0.86
  - Win rate: 63.6% vs 54.6%
  - Slightly higher volatility, compensated by stronger returns.



Most profits were generated between 2020 and June 2022.
Afterward, volatility increased slightly but profits remained stable.

Conclusion

Key Findings

- Hypothesis validation:
  - ML-based factor rotation strategy outperforms the baseline with higher returns and Sharpe ratio.
- Stage 1 insight:
  - Accurate market regime prediction provides useful signals for risk management.
- Model flexibility:
  - Flexible combination of classification models in both stages
  - Can integrate different factor styles to fit specific market segments

Limitations

- Lag issue:
  - Stage 1 depends on macroeconomic data (monthly / quarterly), causing data-frequency lag.
- Performance risk:
  - May underperform during fast market transitions or rapid regime shifts.

Thank You!