

A Case Study in Time-Series Forecasting: Sector Rotation



By Young Han

Project Overview

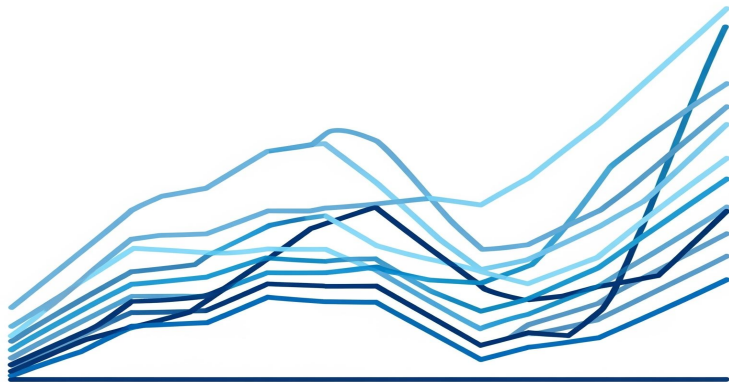
Objective:

To develop and validate a quantitative model that ranks the 11 US sector ETFs based on predicted next-month performance

The ultimate aim is to test if this active strategy can outperform a passive SPY benchmark

Why it matters:

- Provides a data-driven investigation into a popular active investment strategy for investors
- Highlights the challenges of beating the market
- Reveals how models can be biased by the market environment



Dataset

Source:

Daily price data from Yahoo Finance

Macroeconomic data from FRED

Scope:

15 years of data covering 11 sector ETFs, benchmarks, and economic indicators

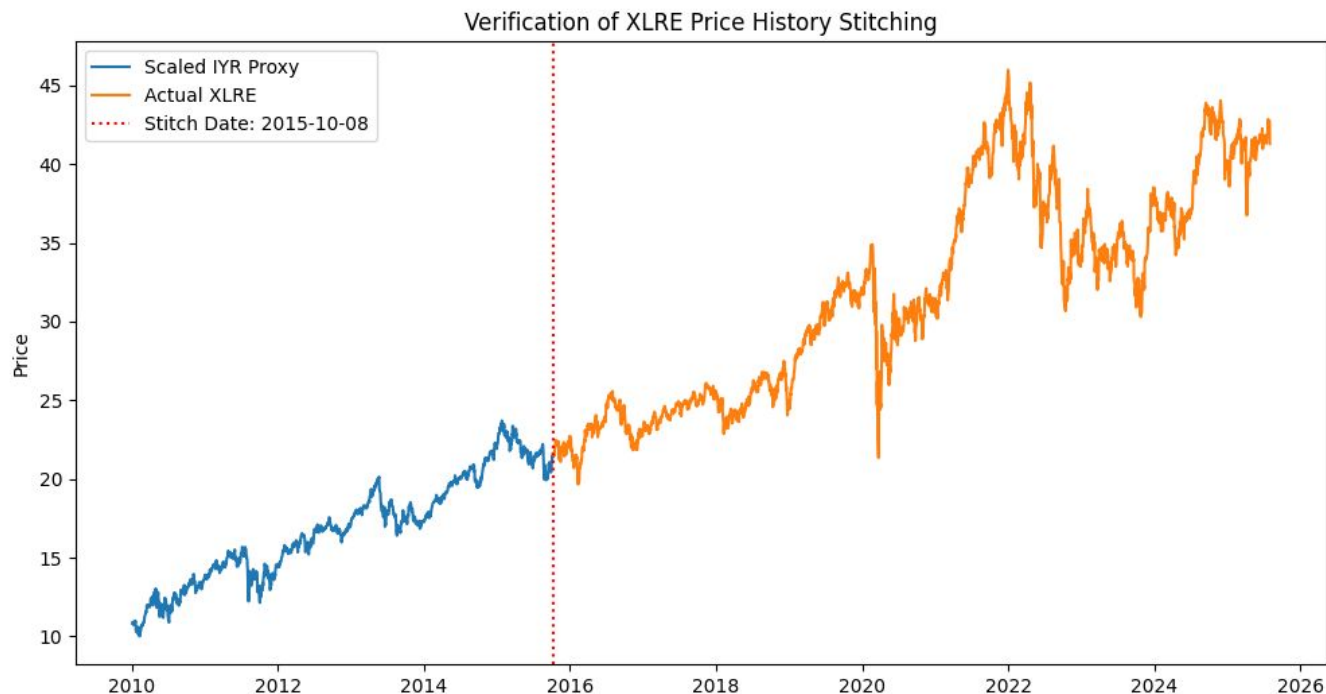
Preprocessing step:

Addressing missing data for newer ETFs by creating a continuous price history



The Data & The First Hurdle

- Like many real-world dataset, part of the data was incomplete (XLRE, XLC)
- Solved this problem by finding highly correlated 'proxy' datasets and using them to backfill the missing history



Feature & Target Engineering

How the Model sees the Market

Input features: What just happened?

Feature categories:

- **Momentum:** “How has the price changed over the last n month?”
- **Volatility:** “How bumpy was the ride recently?”
- **Macro context:** “What was the overall market environment like?”

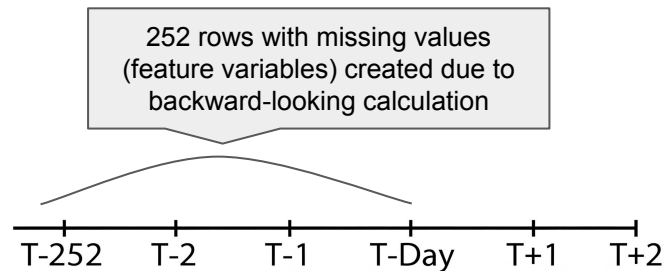
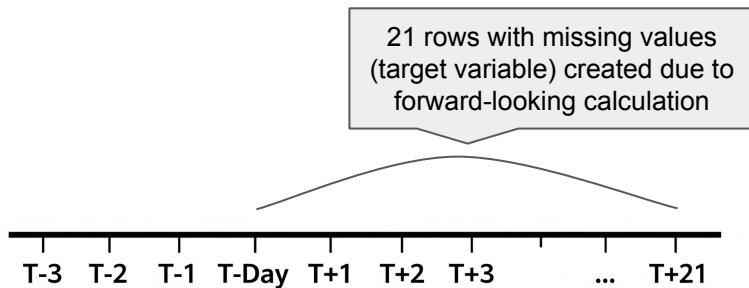
Target variable: What happened next?

- Step 1: Predict Absolute Performance
 - The actual performance over the next 21 trading days (absolute return)
- Step 2: Rank for Relative Strength
 - Individual predictions are ranked against each other to identify the top 3 expected performers
 - Final rankings is the signal used for the portfolio strategy

Final Data Preparation

Data Cleaning

- The forward and backward looking features naturally create NA values at the start and end of the dataset
- Incomplete rows were removed for the model training



- The final analytical window for the project:
From January 2011 to June 2025

Method

T-2 Timeline

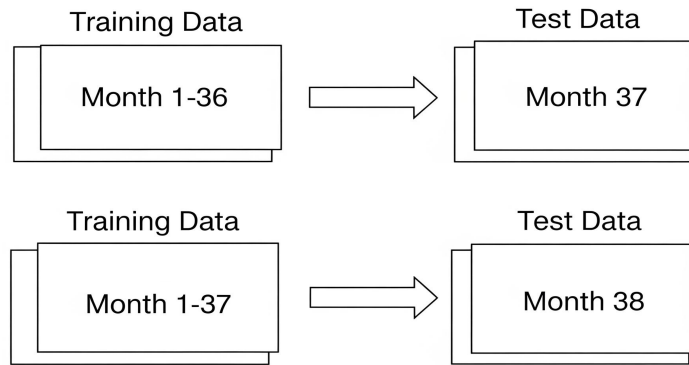
To prevent look-ahead bias, predictions were made on the second to the last business day of the month (T-2).

Example: for predicting September 2025

Prediction on August 27, 2025 (T-2)

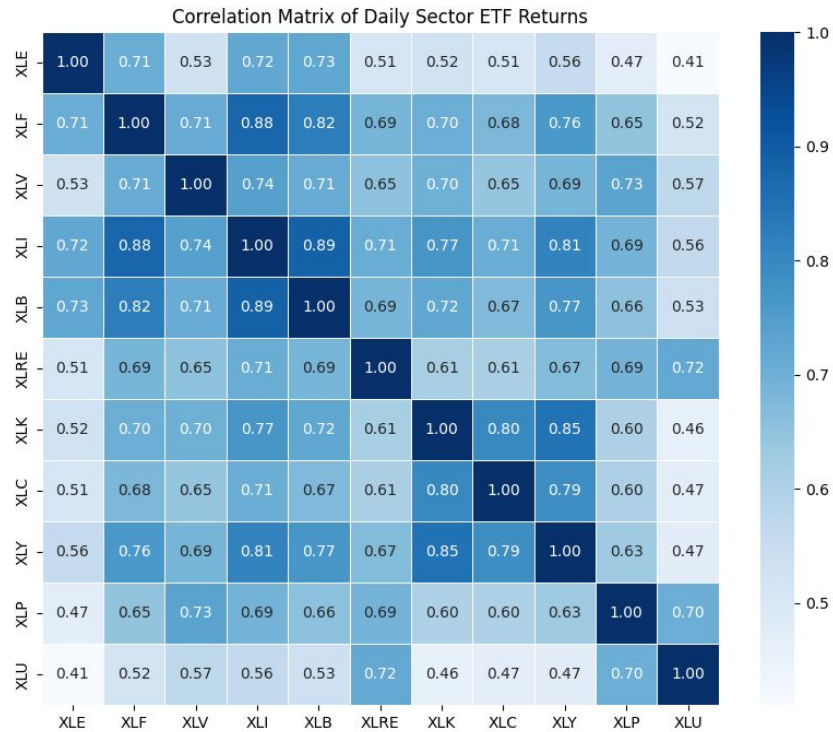
Execution on August 29, 2025 (T-Day)

Walk-Forward Validation

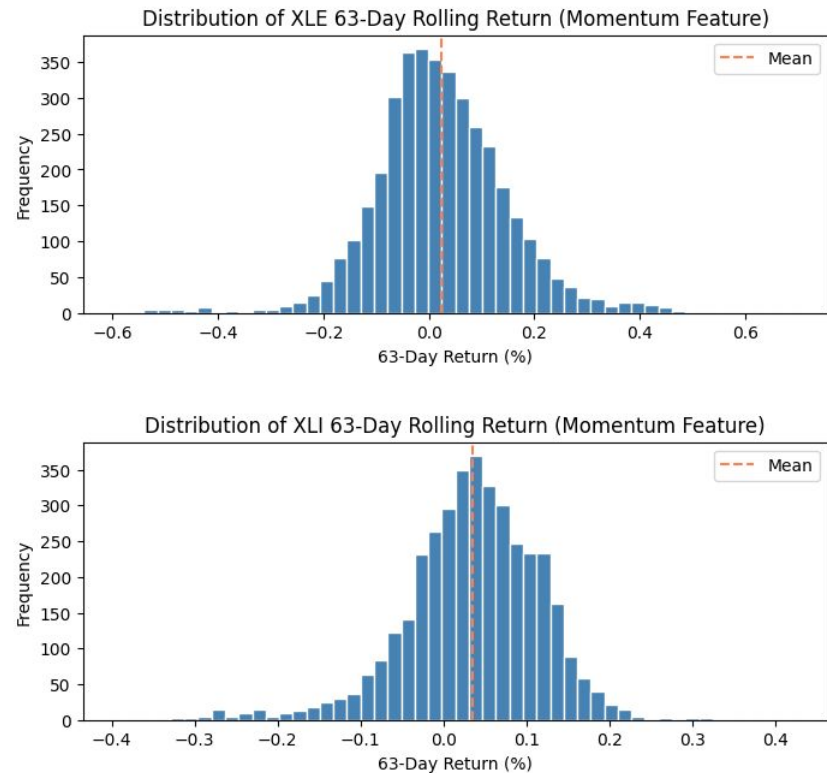


- For time-series, a standard train-test split lets the model see the future
- The method used: **Walk-Forward Validation**
- Training begins with the first 36 months and goes all the way until current month

Core Challenge

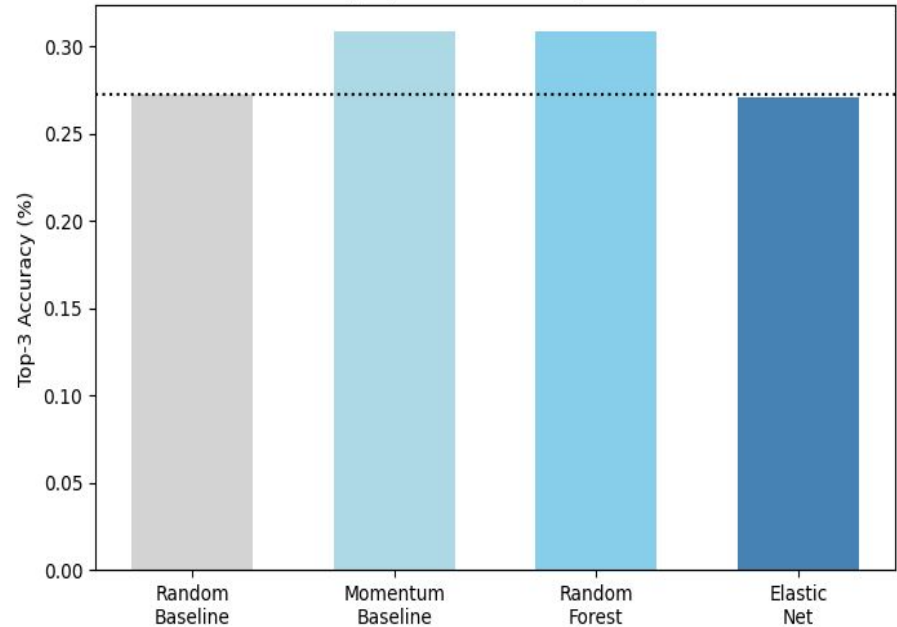


All sectors tend to move together,
exhibiting high multicollinearity



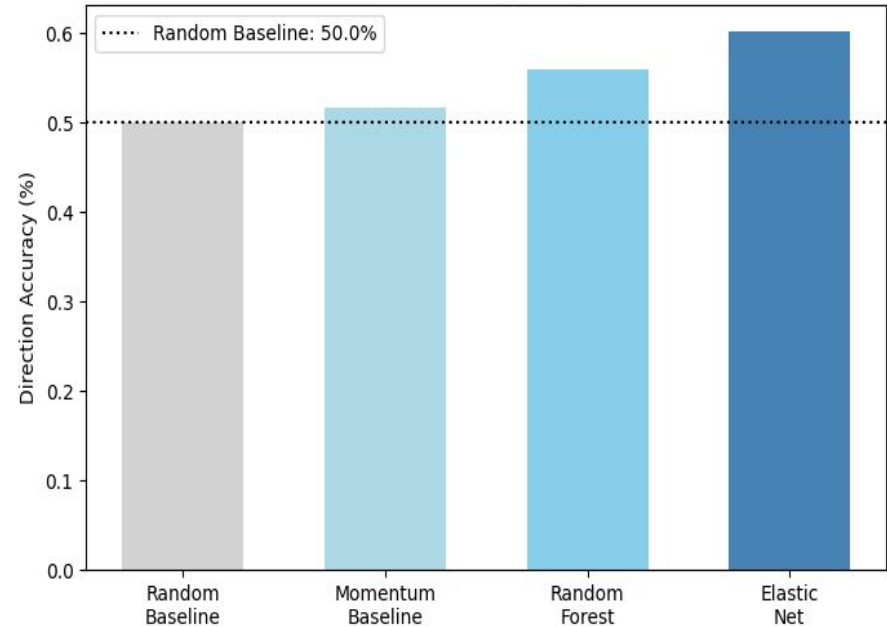
Results: The Models Failed

Ranking Top-3 ETFs Accuracy Comparison



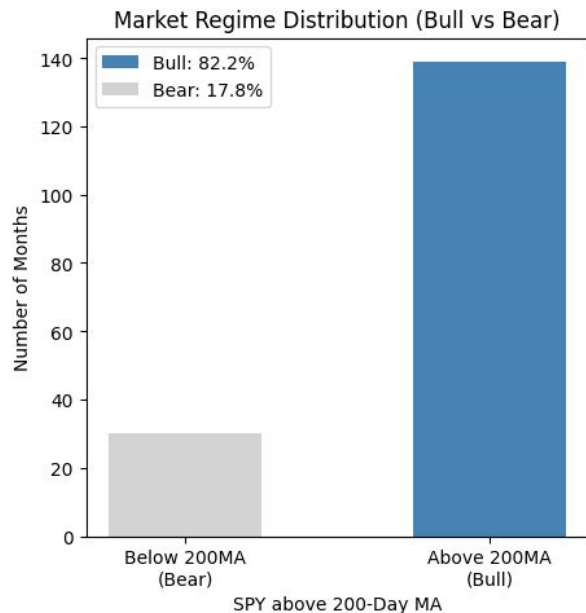
The models failed at their primary goal

Direction Accuracy Comparison



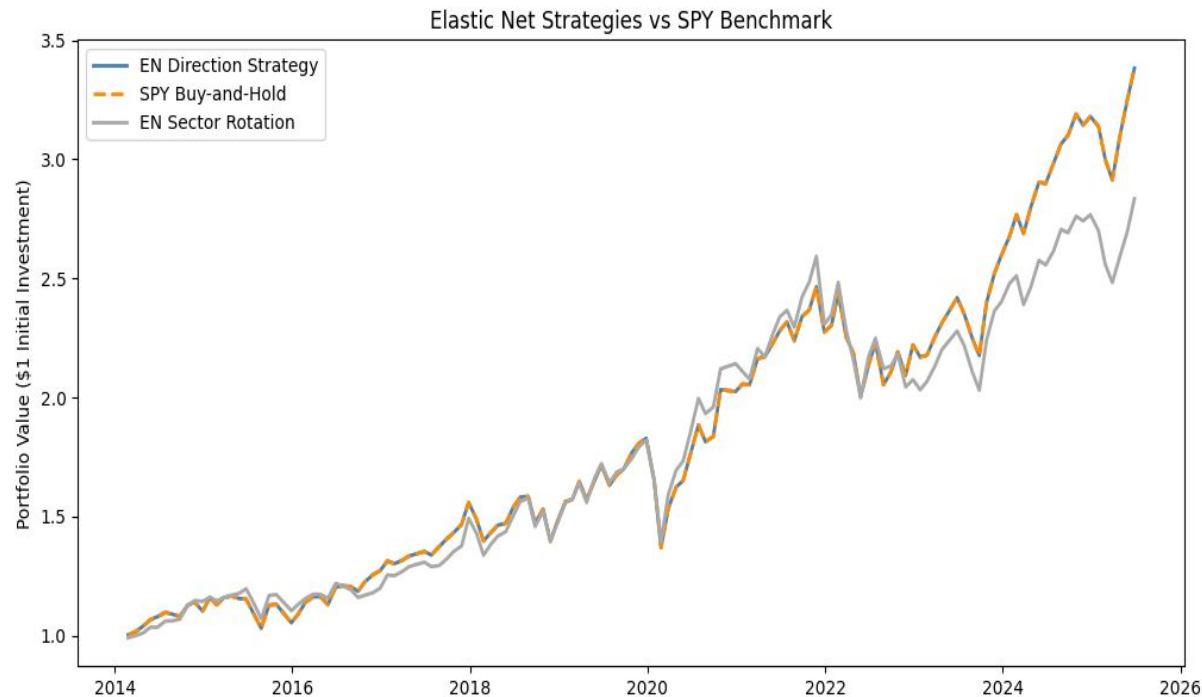
A suspicious result with direction accuracy

The “Lazy” Model

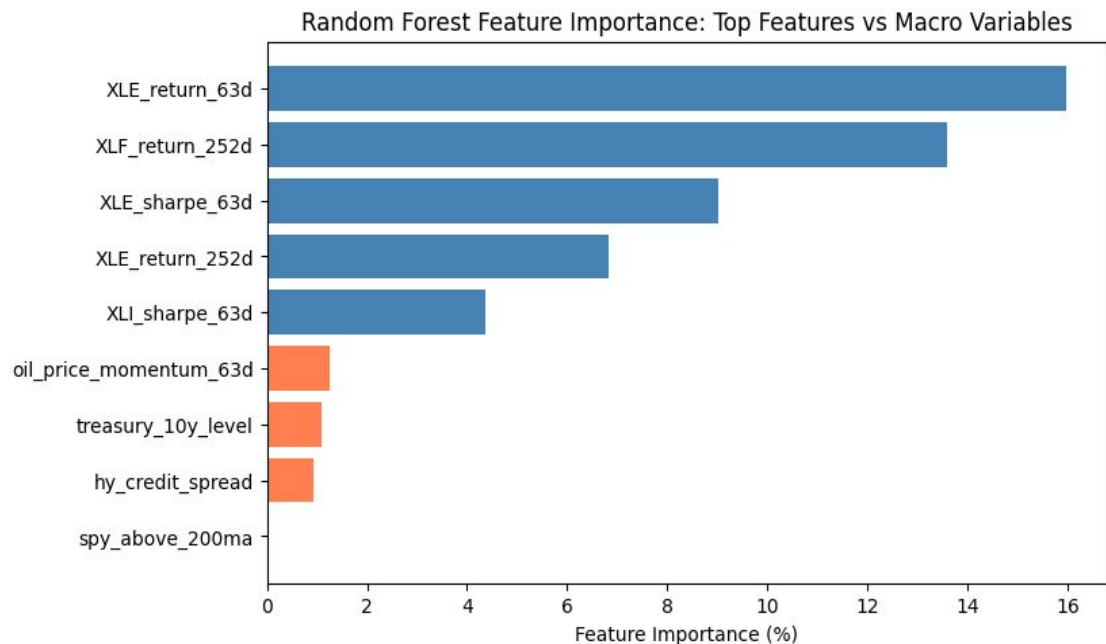


The model was trained on a dataset where the market was in a “**Bull**” regime **82.2%** of the time

Elastic Net Strategies vs SPY Benchmark (Buy and Hold Strategy)

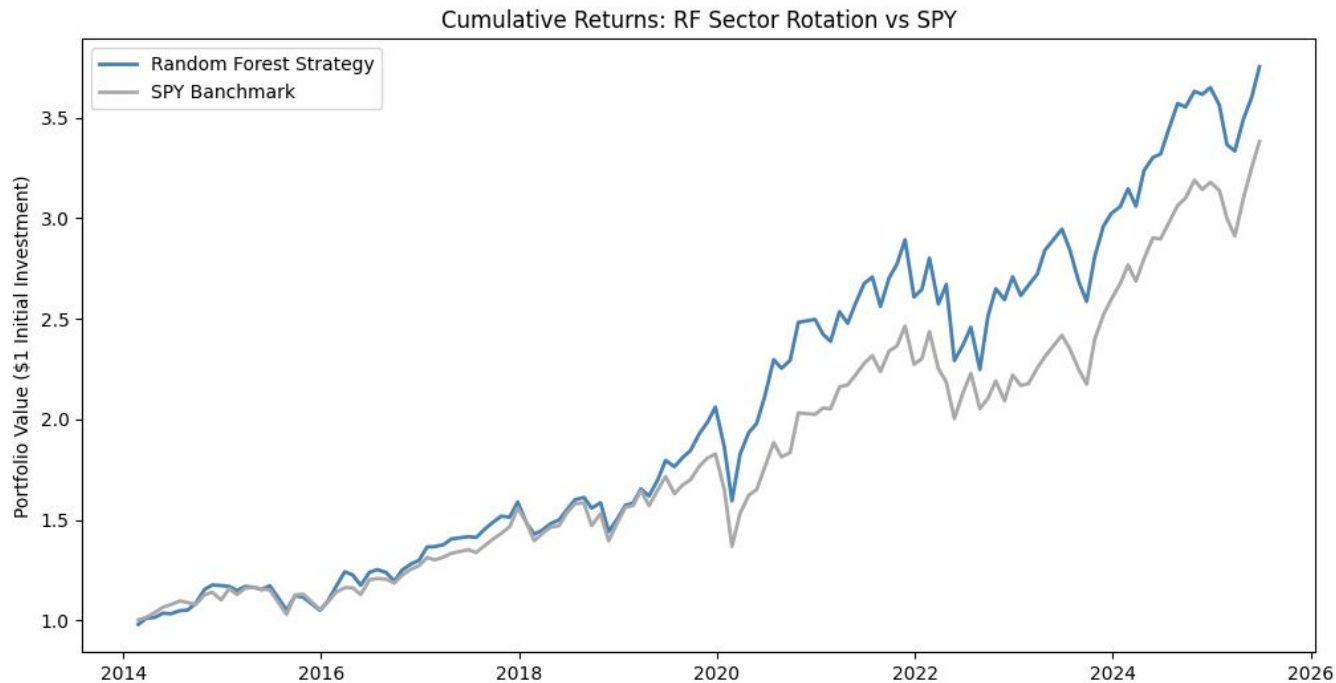


The “Obsessed” Model



- Random Forest model found strong signals - almost exclusively in the energy sector
- 3 of the top 5 features are related to XLE (energy sector)
- Macroeconomic features show little to no importance

The Verdict: Simulating the Outcome



The Random Forest strategy appeared to slightly outperform the SPY benchmark

The result came from a flawed XLE-obsessed model

The model failed to produce a viable, real-world investment strategy

Conclusion

- The linear model became “lazy,” simply following the market’s 82% bull market regime while ignoring features
- The random forest model became “obsessed,” overly relying on highly volatile patterns of the energy sector (XLE) while ignoring other sectors
- This project demonstrated how easily models can be misled by environmental biases and feature characteristics

Future work:

- Engineer more sophisticated features
- Develop a strategy focused on a smaller, less correlated portfolio of sectors
- Build a dedicated model for the energy sector (XLE) to leverage its strong patterns

Reference list

Dataset: Yahoo Finance, FRED

Libraries: scikit_learn, pandas, numpy, seaborn, matplotlib

Thank you!

