Predicting Federal Reserve Interest Rate Decisions Using Macroeconomic Indicators

Brandeis Quant Club

Silas Brooks Hedstrom, Isaac Klar, Vishnu Murthy, Dante Sasso, Taj Scott, Adam Stepansky, Robert Sun, Massimo Valentino

Spring 2025

The Federal Reserve's interest rate decisions play a critical role in financial markets and the broader economy. This semester, members of Brandeis Quant Club undertook a project to analyze historical macroeconomic data and build a machine learning model capable of classifying Fed rate decisions as a hike, no change, or cut. The goal was twofold: to develop a deeper understanding of macroeconomic drivers of monetary policy and to apply quantitative methods in a collaborative, interdisciplinary setting.

Our project began with an extensive literature review and policy research phase, led by economics-focused members of the club. We examined Federal Open Market Committee (FOMC) statements, historical emergency meetings, and prior interest rate cycles, beginning in 1982. The team identified a wide range of potentially relevant indicators, including:

- Inflation indicators (CPI, PPI)
- Labor market statistics (unemployment rate, non-farm payrolls)
- Growth measures (GDP growth, consumer and government spending)

We curated this data from publicly available economic reports and compiled it into a structured CSV format for use in modeling. This phase not only built foundational macroeconomic literacy but introduced students to practical research workflows, data cleaning, and dataset construction.

Modeling Approach

After constructing the dataset and performing initial cleaning, we began the modeling phase with a clear objective: to classify Federal Reserve interest rate decisions as either a rate hike, rate hold, or rate cut using macroeconomic features. The modeling team experimented with several supervised learning algorithms and ultimately selected a Random Forest Classifier, which offered strong performance, robustness to noise, and intuitive interpretability through feature importance scores.

We used a 67/33 train-test split, stratified by class label to preserve balance. The final model was trained using the RandomForestClassifier from scikit-learn, with 10 decision trees and default parameters. It achieved a test accuracy of 86.32%, indicating a high level of predictive performance on unseen data.

Feature Selection and Evaluation

Feature engineering was an iterative and collaborative process. We began with a broad set of macroeconomic indicators, many of which were identified during the research phase by our economics-focused members. These included various measures of inflation, employment, and economic growth, as well as interest rate spreads and market signals.

Initial modeling runs helped us evaluate the predictive contribution of each feature using both accuracy metrics and feature importance scores from the Random Forest. In addition, we considered potential redundancy and overlap between variables, particularly among labor market and inflation indicators.

Based on these insights, we decided to exclude several features from the final model. These included:

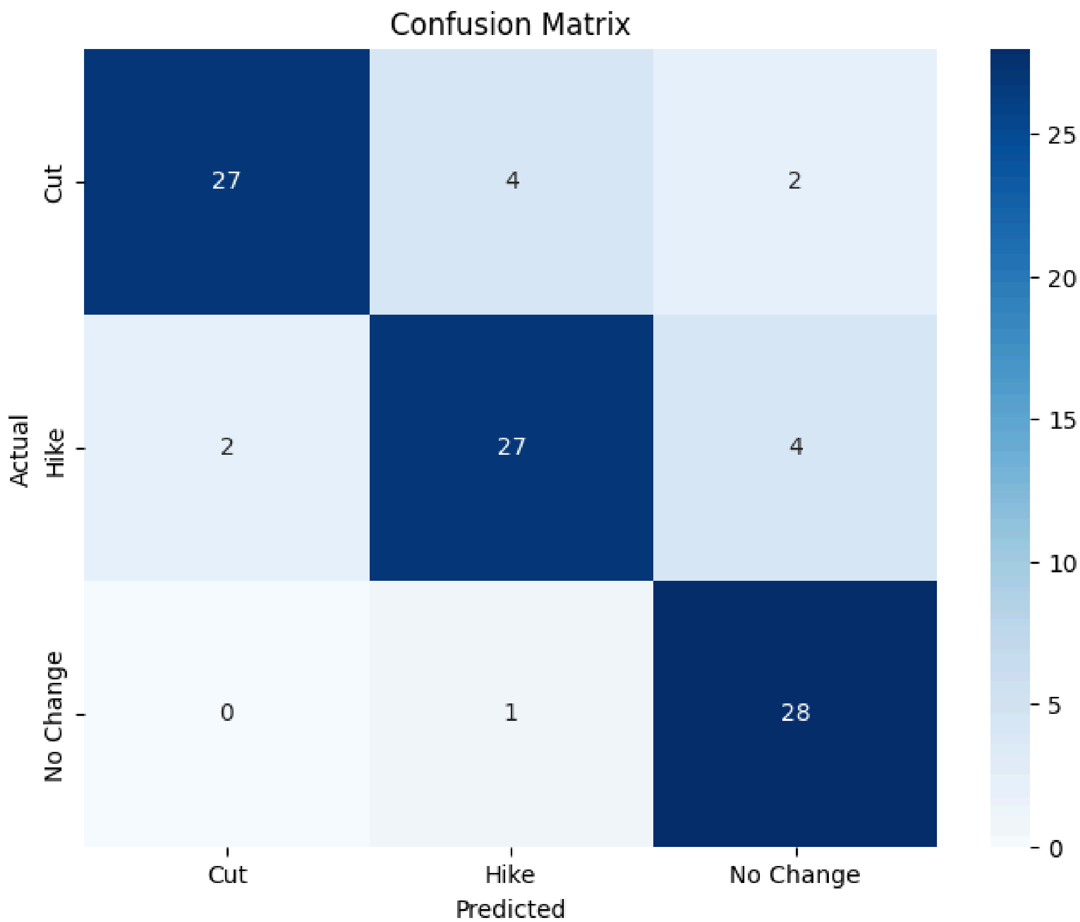
- Unemployment rate
- Initial claims
- Crude oil price

These features were either closely correlated with other variables already in the dataset or did not significantly improve model performance when included. Removing them allowed the model to focus on more relevant signals without introducing noise or redundancy. The final model included the following features:

- 6-month Treasury bill minus Federal Funds rate
- Initial claims (4-week average)
- GDP (quarter-over-quarter and year-over-year)
- CPI and core CPI
- PPI
- Total nonfarm employees

After training, feature importance analysis showed that the spread between the 6-month Treasury bill and the Federal Funds rate was the most predictive variable. CPI, core CPI, and PPI also ranked highly, reinforcing the idea that inflation expectations are central to Fed decision-making. Labor market data, such as total nonfarm payrolls, added value but ranked lower than inflation and rate spread measures.

The confusion matrix shows that the model made accurate predictions across all three classes, with relatively few misclassifications. While the overall accuracy was strong, the model did occasionally predict one type of decision another. This reflects the complexity of monetary policy and the overlapping signals that can emerge from macroeconomic data. Despite this, the model demonstrated strong generalization and an ability to detect meaningful relationships between indicators and policy outcomes.



Key Takeaways

This project provided a rich learning experience for members of Brandeis Quant Club, especially those new to quantitative research and machine learning. Students with economics backgrounds developed greater technical fluency by engaging with tools like Python and scikit-learn, while computer science students deepened their understanding of economic theory and real-world financial policy.

Across the team, members learned how to:

- Interpret and contextualize macroeconomic indicators used in monetary policy
- Source, clean, and structure real-world economic data into usable formats
- Apply and evaluate machine learning models in a supervised classification setting
- Iterate on feature selection to improve model performance
- Analyze model outputs and understand their implications
- Communicate complex technical results in clear, accessible language

Beyond the technical skills, the project emphasized collaboration and the importance of combining domain expertise with data-driven approaches. Team members gained experience presenting their work, contributing to group decisions, and thinking critically about how models relate to real-world decision-making processes.

The experience also laid the foundation for deeper involvement in quant research. Several members expressed interest in taking on leadership roles in future projects or pursuing internships and careers in finance, data science, or economics. For many, this was their first exposure to building a full modeling pipeline from scratch. This project served as a hands-on experience that bridged the gap between classroom learning and applied analysis.

Conclusion and Future Work

While this model shows promising results, there is room to expand. Future iterations could explore more granular time-series features, incorporate sentiment analysis from FOMC statements, or apply models that better capture temporal dependencies such as long short-term memory networks (LSTMs). We also see potential in building out forecasting tools or testing alternative policy response frameworks under different macroeconomic scenarios.

Overall, this project served as both a learning experience and a practical demonstration of how economics and computer science can come together to tackle real-world problems. It strengthened our club's capabilities in quantitative analysis and opened the door for more advanced modeling work in future semesters.

Bibliography

- Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS, August 6, 2025.
- Federal Reserve Bank of St. Louis, 6-Month Treasury Bill Minus Federal Funds Rate [TB6SMFFM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TB6SMFFM, August 6, 2025.
- International Monetary Fund, Global price of Brent Crude [POILBREUSDM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/POILBREUSDM, August 6, 2025.
- University of Michigan, University of Michigan: Consumer Sentiment [UMCSENT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UMCSENT, August 6, 2025.
- U.S. Bureau of Economic Analysis, Gross Domestic Product [A191RP1A027NBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A191RP1A027NBEA, August 6, 2025.
- U.S. Bureau of Economic Analysis, Gross Domestic Product [A191RP1Q027SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A191RP1Q027SBEA, August 6, 2025.
- U.S. Bureau of Labor Statistics, All Employees, Total Nonfarm [PAYEMS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PAYEMS, August 6, 2025.
- U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, August 6, 2025.
- U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average [CPILFESL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPILFESL, August 6, 2025.
- U.S. Bureau of Labor Statistics, Producer Price Index by Commodity: All Commodities [PPIACO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PPIACO, August 6, 2025.
- U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, August 6, 2025.
- U.S. Employment and Training Administration, 4-Week Moving Average of Initial Claims [IC4WSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/IC4WSA, August 6, 2025.
- U.S. Employment and Training Administration, Initial Claims [ICSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/ICSA, August 6, 2025.

- Yoon, J., & Fan, J. (2024). Forecasting the direction of the Fed's monetary policy decisions using random forest. *Journal of Forecasting*, 43(7), 2848–2859. https://doi.org/10.1002/for.3144