Forecasting Federal Funds Rate Adjustments: A Data-Driven Approach for December 2024

Maria Nacu

Table of Contents:

INTRODUCTION

1. Challenge Overview

The Federal Open Market Committee (FOMC), a key decision-making body within the Federal Reserve System, plays a pivotal role in determining U.S. monetary policy. One of its primary functions is to adjust the federal funds rate to stabilize the economy, ensure price stability, and promote employment. These decisions have far-reaching implications on inflation, employment rates, consumer spending, and global financial markets.

This challenge involves predicting the FOMC's interest rate decision for its December 17-18, 2024 meeting. Participants are tasked with building a multiclass classification model capable of forecasting one of five potential rate changes: -0.50%, -0.25%, 0%, +0.25%, or +0.50%. This level of granularity enables a precise assessment of monetary policy adjustments rather than a binary decision like a rate hike or no hike. Such predictions are vital for understanding the Federal Reserve's policy direction and its impact on the economy.

Through this project, the aim is to simulate a real-world analytical exercise that combines economic forecasting with machine learning, offering valuable insights for economists, investors, and policymakers.

INTRODUCTION

2. Importance of Interest Rate Predictions

Interest rate predictions are a cornerstone of economic analysis, as they directly influence consumer behavior, business investments, and global market dynamics. The federal funds rate serves as a benchmark for many other interest rates, affecting everything from mortgages to corporate loans. Adjustments to this rate by the FOMC signal the Federal Reserve’s priorities, whether it’s combating inflation or fostering economic growth.

For investors, accurate interest rate predictions can guide portfolio decisions, helping to mitigate risks associated with market volatility. For businesses, these predictions provide clarity on borrowing costs and future economic conditions, influencing decisions on expansion, hiring, and capital investment. Moreover, for policymakers, understanding potential rate adjustments allows them to anticipate economic shifts and make informed decisions.

In this analysis, predicting the December 2024 FOMC meeting outcome holds particular importance due to the global economic uncertainties post-pandemic and evolving geopolitical events. This challenge addresses the critical need to assess and interpret key economic indicators to predict policy decisions accurately.

INTRODUCTION

3. Objective of the Analysis

The primary objective of this analysis is to leverage economic data and machine learning to accurately forecast the FOMC's rate adjustment decision for December 2024. By analyzing historical trends, economic indicators, and their correlations, the project aims to develop a robust multiclass classification model. The model is tasked with predicting the exact magnitude of the rate change, providing a nuanced view of the likely policy adjustment.

Beyond the prediction itself, this analysis seeks to:

- Identify and highlight the most critical economic factors influencing rate decisions.
- Evaluate the interpretability of the model's outputs using techniques like SHAP and LIME to enhance trust in the predictions.
- Provide a methodological framework that can be generalized for future interest rate predictions.

The analysis is designed to bridge the gap between economic theory and machine learning, offering actionable insights into the factors driving monetary policy decisions. Ultimately, this report aims to serve as a comprehensive resource for understanding the intersection of economic forecasting and data science.

Data Collection and Preparation

In this section, I explain the steps I followed to collect and preprocess the data required for forecasting interest rate decisions. My primary goal was to integrate multiple data sources, both domestic and global, and prepare a high-quality, structured dataset suitable for analysis. This process involved extracting data, aligning formats, addressing missing values, and merging all information into a single, consistent dataset.

1. FRED Economic Indicators

I began by using the FRED API to extract key U.S. economic indicators, including the Federal Funds Rate, Consumer Price Index (CPI), Unemployment Rate, GDP, Nonfarm Payrolls, and the Industrial Production Index. The data spans from 2000 to the present, providing a comprehensive historical overview. After downloading the data, I identified native frequencies for each indicator. Most were available monthly, except GDP, which was quarterly. I resampled the quarterly GDP data to a monthly frequency by forward-filling the values. Additionally, I standardized the units for clarity—converting GDP from billions to trillions and nonfarm payrolls from thousands to millions. To ensure accuracy and continuity, I calculated month-over-month growth rates for CPI and Industrial Production, then handled missing values caused by these calculations by dropping or forward-filling where necessary.

2. FOMC Sentiment Data

For the FOMC sentiment data, I manually downloaded historical FOMC statements from the Federal Reserve’s official website. These statements were initially available in HTML format. Using Python scripts, I extracted the main content, removing irrelevant sections like navigation menus and headers. I cleaned the text further by eliminating duplicate paragraphs and unnecessary whitespace. To gain insights, I sent each cleaned statement to an AI model (GPT-4), requesting structured outputs such as sentiment scores, policy stances (hawkish, dovish, or neutral), tone keywords, and key economic concerns. These results were then saved into a structured file for integration with other datasets. Since FOMC meetings occur bi-monthly, I forward-filled the sentiment data to cover the intervening months, ensuring alignment with the monthly frequency of the other datasets.

Data Collection and Preparation

3. World Bank Global Indicators

To incorporate a global perspective, I used the World Bank API to collect key economic indicators for major global economies, including GDP growth, inflation, and unemployment. I focused on countries like Canada, China, Japan, Germany, and several European nations, as their economic trends significantly impact global markets. The data was available annually from 2000 onward, so I converted it to monthly frequency by repeating annual values across all months within each year. After formatting the data, I prefixed the columns with global_ to differentiate these indicators from U.S.-specific metrics.

4. Final Dataset Preparation

Once all the individual datasets were ready, I focused on merging them into a single, cohesive file. I standardized the date column across all datasets to ensure compatibility during the merge. For integration, I performed an outer join on the date column, preserving all available data even when some sources lacked specific values. Post-merge, I addressed any remaining missing data by applying forward-filling techniques. This ensured that each month had complete information without introducing artificial fluctuations. Finally, I validated the merged dataset by comparing it to the source datasets, confirming that all values were accurately aligned.

The data collection and preprocessing process resulted in a high-quality dataset integrating domestic and global economic indicators with qualitative FOMC sentiment data. This comprehensive dataset is well-structured, ensuring continuity and consistency, and it provides a strong foundation for exploratory analysis and predictive modeling.

Exploratory Data Analysis (EDA) - Initial Phase

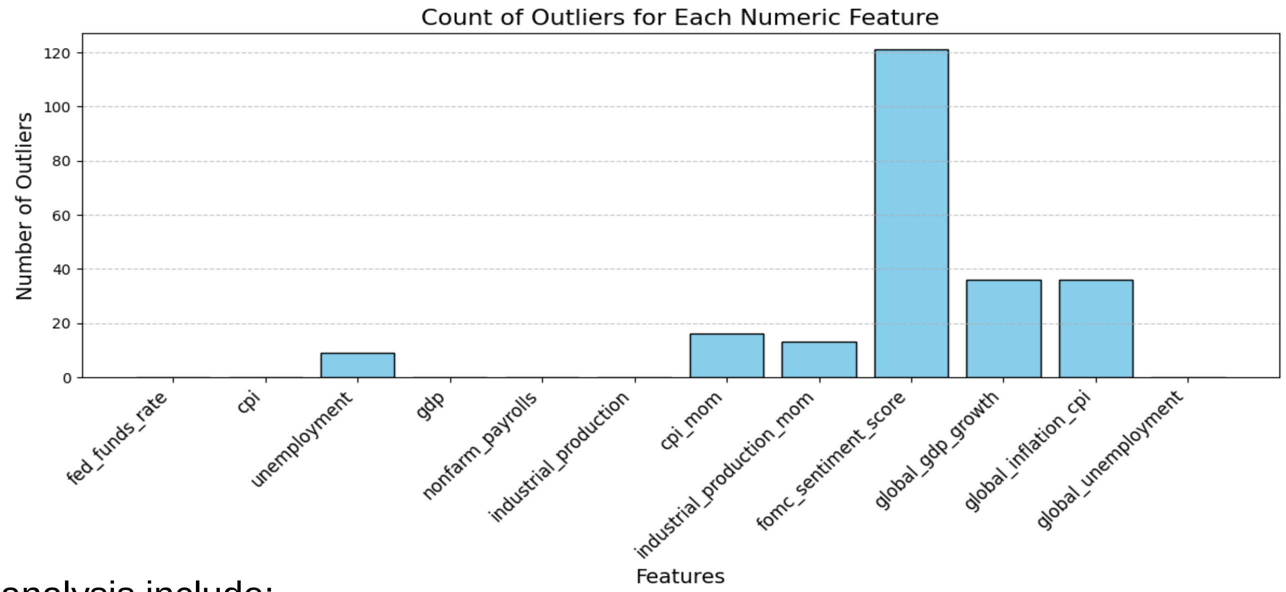
Introduction to Exploratory Data Analysis (EDA) - Initial Phase

Before diving into feature creation or advanced modeling, I prioritized conducting an initial Exploratory Data Analysis (EDA) to gain a comprehensive understanding of the dataset. This step is crucial for several reasons:

- **Understanding Data Structure:** By analyzing the structure of the dataset, including its dimensions, data types, and column names, I could verify that the data aligns with expectations and ensure compatibility with further processing steps.
- **Identifying Missing Values:** Recognizing gaps in the dataset early allows for targeted strategies to handle missing values, ensuring data consistency and reliability in subsequent steps.
- **Detecting Outliers:** Outliers can significantly influence statistical measures and model performance. Identifying them at this stage helps in deciding whether they should be removed, transformed, or treated in a specific manner.
- **Exploring Data Distributions and Trends:** Visualizing trends and patterns across key indicators provides insights into potential relationships and temporal dynamics in the data, helping to guide feature engineering and model design later.
- **Correlation and Relationships:** Conducting a correlation analysis uncovers how different features relate to each other, highlighting potential redundancies or interactions that may inform feature selection or creation.
- **Baseline Observations:** This phase sets the foundation for understanding the dataset’s strengths and weaknesses, allowing for more informed decisions in the subsequent feature engineering and modeling phases.

Exploratory Data Analysis (EDA) - Initial Phase

I conducted an outlier analysis to identify extreme values across all numeric features in the dataset. The results are summarized in the bar chart, which shows the number of outliers detected for each feature. I used the Interquartile Range (IQR) method to flag values that fall outside 1.5 times the IQR from the first and third quartiles.



Key observations from the analysis include:

- The feature fomc_sentiment_score shows the highest number of outliers (121), reflecting periods of extreme sentiment shifts likely tied to major economic events.
- Global economic indicators, such as global_gdp_growth and global_inflation_cpi, each have 36 outliers. These are likely linked to global financial crises or inflationary trends.
- Month-over-month changes in CPI (cpi_mom) and industrial production (industrial_production_mom) also show notable outliers, capturing economic volatility during specific periods.
- The unemployment feature displays 9 outliers, which correspond to significant labor market disruptions.

This analysis highlights the importance of carefully handling outliers. They may contain critical insights about economic anomalies but can also introduce noise into models if not managed appropriately.

Exploratory Data Analysis (EDA) - Initial Phase

This line chart illustrates the unemployment rate from 2000 to 2024. The red dots mark outliers detected using the IQR method, emphasizing significant deviations from the broader trend. Historical economic events are annotated to provide context.

Observations:

1. COVID-19 Pandemic (2020):

- Unemployment peaked above 14%, a stark deviation from historical trends, marking the sharpest rise in the dataset. This period is characterized by mass layoffs and business closures during the global lockdown.
- Outliers observed during this spike underscore the unprecedented nature of the pandemic-induced recession.

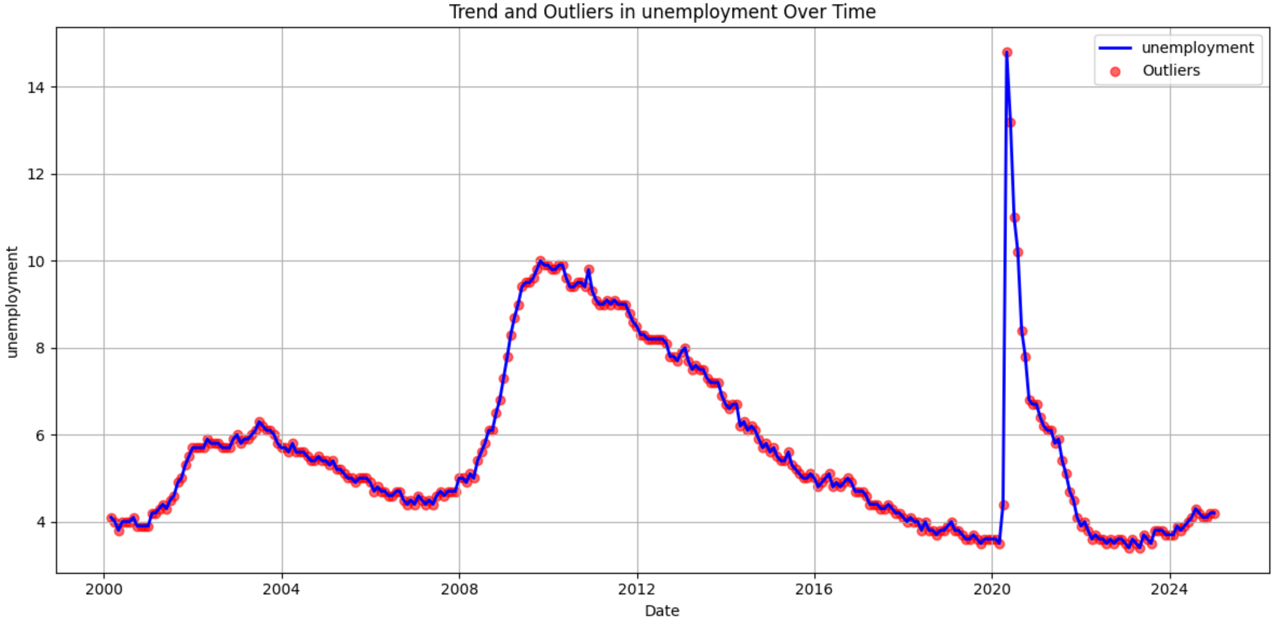
2. Global Financial Crisis (2008-2009):

- A sustained increase in unemployment, with outliers appearing between 2008 and 2010. This reflects the slow recovery from the financial crisis, where job losses persisted even after GDP growth resumed.

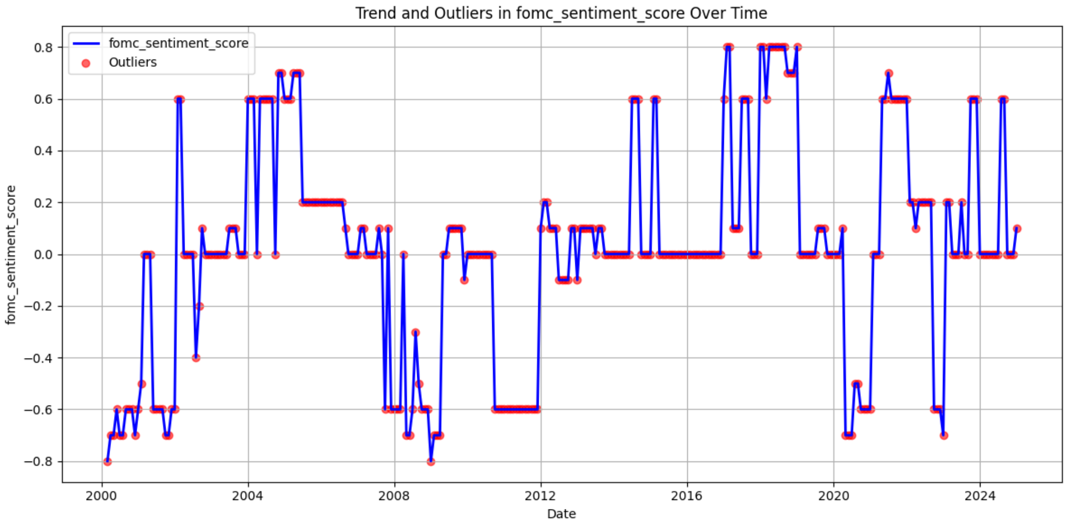
3. Recovery Periods:

- Periods of declining unemployment, particularly post-2009 and post-2020, are smooth with few outliers, reflecting gradual stabilization of labor markets.

This visualization highlights how unemployment is a lagging indicator of economic recovery. Outliers are critical as they signal periods of extreme labor market stress, such as during financial crises and global health emergencies. These insights are indispensable for understanding the Federal Reserve’s focus on employment stabilization in its dual mandate.



Exploratory Data Analysis (EDA) - Initial Phase



This chart shows the FOMC sentiment score over time, capturing the Federal Reserve's tone (hawkish or dovish) based on sentiment analysis of meeting statements. Red dots indicate sentiment extremes that diverge significantly from the mean.

Observations:

1. 2008 Financial Crisis:

- Multiple dovish sentiment outliers reflect the Federal Reserve's aggressive accommodative stance, including near-zero interest rates and quantitative easing measures.
- This period highlights how sentiment aligned with crisis-driven policy interventions to stabilize financial markets and promote growth.

2. COVID-19 Pandemic (2020):

- A rapid sequence of sentiment shifts is visible, reflecting the Federal Reserve's uncertainty and evolving stance during the pandemic. Dovish outliers dominate, signaling urgent measures to support the economy.

3. Stable Sentiment Periods:

- Between 2013 and 2019, sentiment scores stabilize with minimal outliers, reflecting confidence in steady economic growth and a balanced policy approach.

The sentiment score serves as a proxy for policy direction, where outliers align with significant policy shifts during crises. This trend emphasizes the Federal Reserve's responsiveness to prevailing economic conditions and its reliance on forward guidance as a stabilizing tool.

Exploratory Data Analysis (EDA) - Initial Phase

This scatter plot depicts the relationship between the FOMC sentiment score and the federal funds rate, illustrating how monetary policy aligns with sentiment shifts.

Observations:

1. Positive Correlation:

- Periods of positive sentiment are associated with higher federal funds rates, reflecting a tightening stance during economic expansions to control inflation.

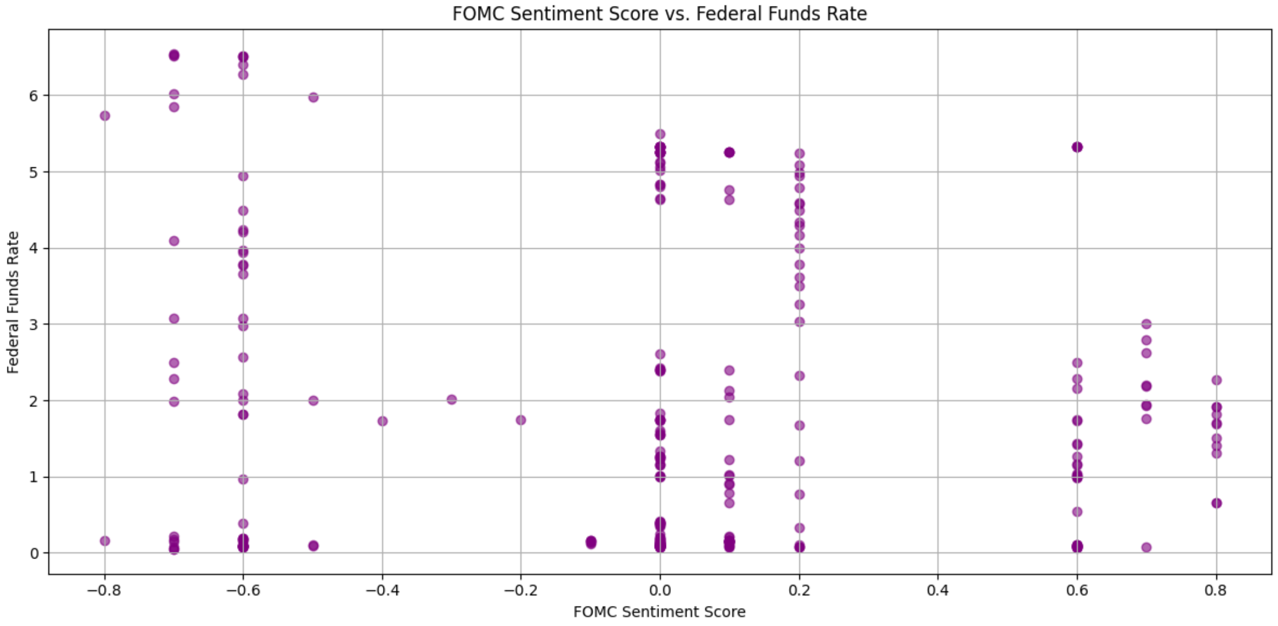
2. Negative Correlation:

- Negative sentiment scores correlate with lower federal funds rates, signaling the Federal Reserve's accommodative stance during downturns.

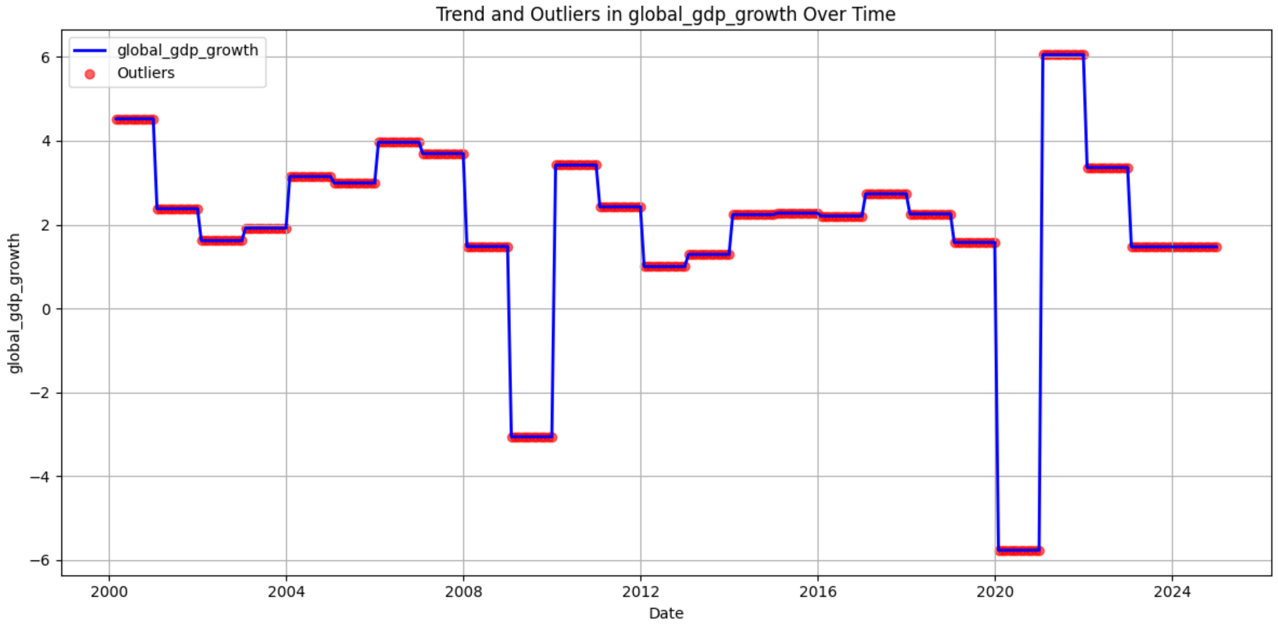
3. Policy Transition Clusters:

- Points cluster during transition phases, such as the 2008-2009 crisis and the 2020 pandemic, where the Fed shifted rapidly between tightening and easing policies.

This visualization underscores the strong relationship between sentiment and interest rates. The clustering patterns highlight the Federal Reserve's strategy of aligning its policy stance with prevailing sentiment, making it a critical feature for predictive modeling.



Exploratory Data Analysis (EDA) - Initial Phase



This chart shows global GDP growth trends with outliers reflecting periods of extreme growth acceleration or contraction. Historical events are overlaid for context.

Observations:

1. 2008 Global Recession:

- A sharp contraction in global GDP growth, with outliers marking one of the most severe recessions in modern history. This reflects the synchronized downturn across advanced and emerging economies.

2. COVID-19 Pandemic (2020):

- The global GDP growth rate plummeted to unprecedented lows, with outliers underscoring the scale of the pandemic's economic impact.

3. Post-Crisis Recoveries:

- Rapid growth outliers in 2010 and 2021 reflect coordinated stimulus measures by central banks and governments, highlighting the interconnectedness of global economies.

This visualization reinforces the importance of global economic conditions in shaping U.S. monetary policy. Outliers during crises highlight periods where global conditions necessitate synchronized policy responses.

Exploratory Data Analysis (EDA) - Initial Phase

This chart visualizes global inflation trends over time, with outliers capturing periods of extreme inflation or deflation.

Observations:

1. 2008 Commodity Price Surge:

- A spike in global inflation aligns with rising oil and commodity prices pre-crisis, reflecting supply-side shocks.

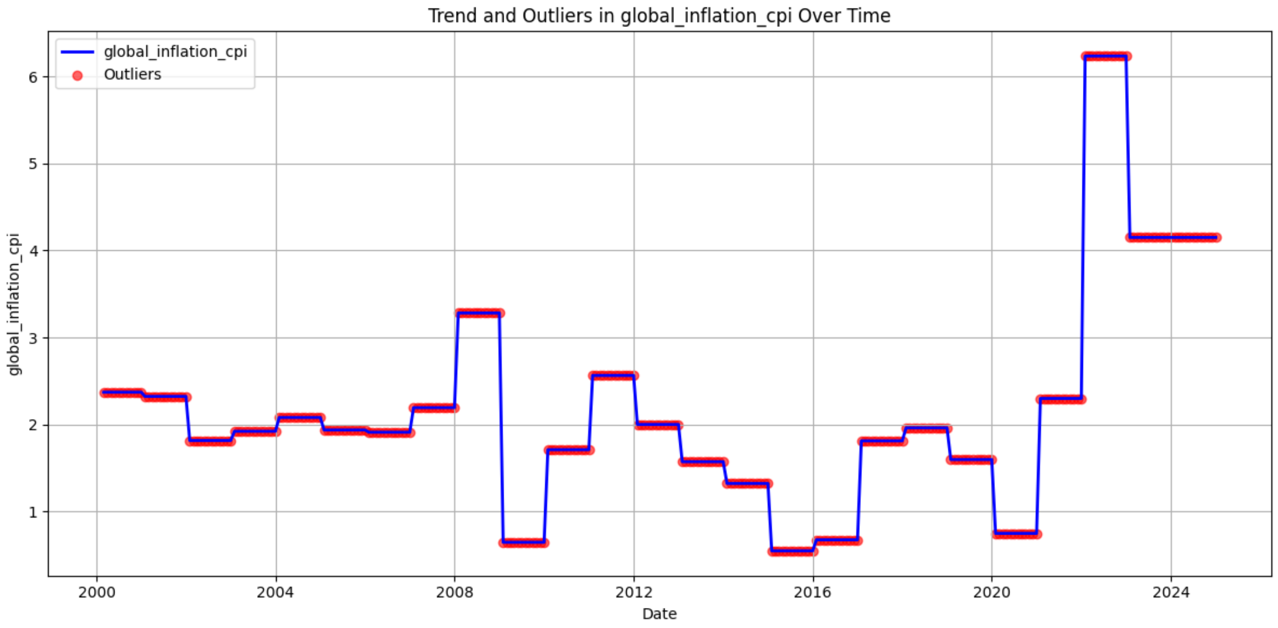
2. Deflationary Periods (2009-2010):

- Outliers during this period highlight global disinflation as demand collapsed during the financial crisis.

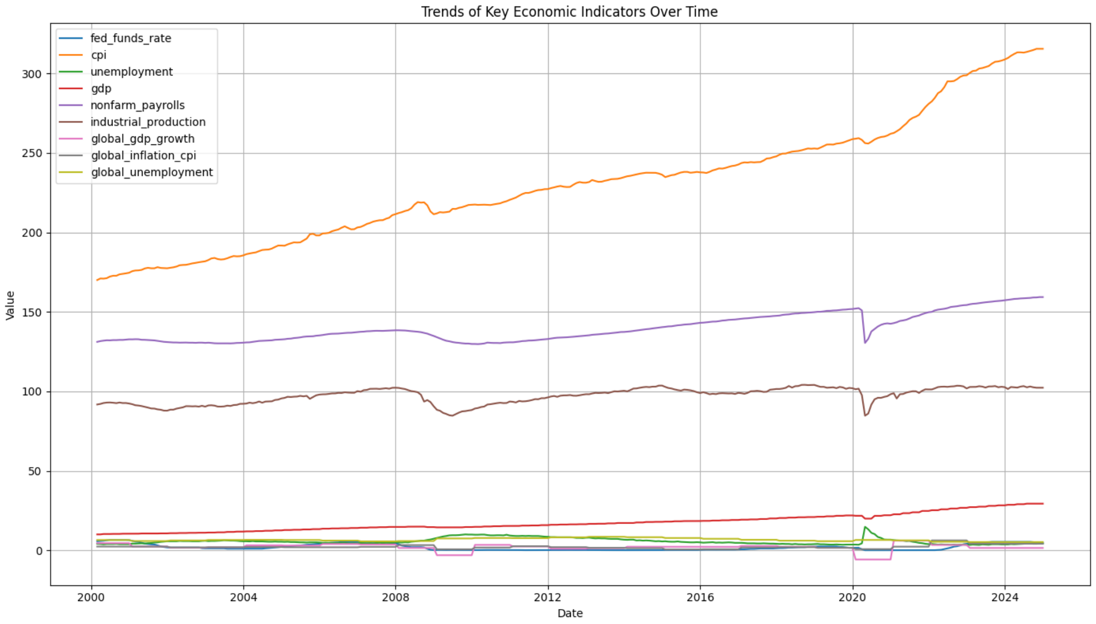
3. Post-Pandemic Inflation Surge (2021-2022):

- Significant inflationary outliers reflect supply chain disruptions, stimulus-driven demand, and geopolitical tensions (e.g., the Russia-Ukraine conflict).

Global inflation trends are critical for understanding external pressures on U.S. inflation. Outliers during crises provide insights into the Federal Reserve's response to imported inflation and its impact on domestic policy decisions.



Exploratory Data Analysis (EDA) - Initial Phase



This multi-line chart captures the historical trajectories of critical economic indicators, including both domestic and global factors, from 2000 to the present. Each line represents a specific indicator, with their values plotted over time to showcase trends and turning points.

Observations:

1. Fed Funds Rate:

- Sharp increases during specific periods such as the mid-2000s and post-2020, reflecting the Federal Reserve's response to inflationary pressures.
- Near-zero levels from 2009 to 2015, highlighting the Fed's prolonged accommodative stance after the 2008 financial crisis.
- Recent hikes post-2021 demonstrate aggressive tightening to combat inflation.

2. CPI (Consumer Price Index):

- A steady upward trend with significant acceleration during recent years, suggesting heightened inflation.
- A spike during the early 2020s aligns with global supply chain disruptions and monetary expansion during the COVID-19 pandemic.

3. Unemployment:

- Noticeable spikes during the 2008 financial crisis and the COVID-19 pandemic (2020).
- A sharp recovery in unemployment rates post-2020 indicates strong labor market resilience.

4. GDP:

- Consistent growth over time with sharp declines during recessions (2008 and 2020).
- Reflects the cyclical nature of economic activity tied to global and domestic disruptions.

5. Global Indicators:

- Global GDP Growth: Periodic declines, especially during 2008 and 2020, reflect synchronized global recessions.
- Global Inflation CPI: Similar to CPI, global inflation has surged in recent years due to pandemic-induced supply chain constraints and energy price volatility.
- Global Unemployment: Minor fluctuations, but with a slight increase during global economic downturns.

The trends clearly show the interconnectedness between domestic and global economic conditions.Historical crises have long-lasting effects across multiple indicators, necessitating careful modeling to account for such events.The Fed Funds Rate adjustments reflect the Fed's dual mandate of inflation control and employment stabilization.

Exploratory Data Analysis (EDA) - Initial Phase

The heatmap highlights the pairwise correlation coefficients between all numeric features, with values ranging from -1 (strong negative correlation) to +1 (strong positive correlation).

Observations:

1. Strong Positive Correlations:

- GDP and Nonfarm Payrolls (0.93): Suggests a robust relationship between economic growth and job creation.
- CPI and GDP (0.99): Indicates that inflation is closely tied to economic expansion.
- Industrial Production and Nonfarm Payrolls (0.79): Suggests that higher industrial activity correlates with increased employment.

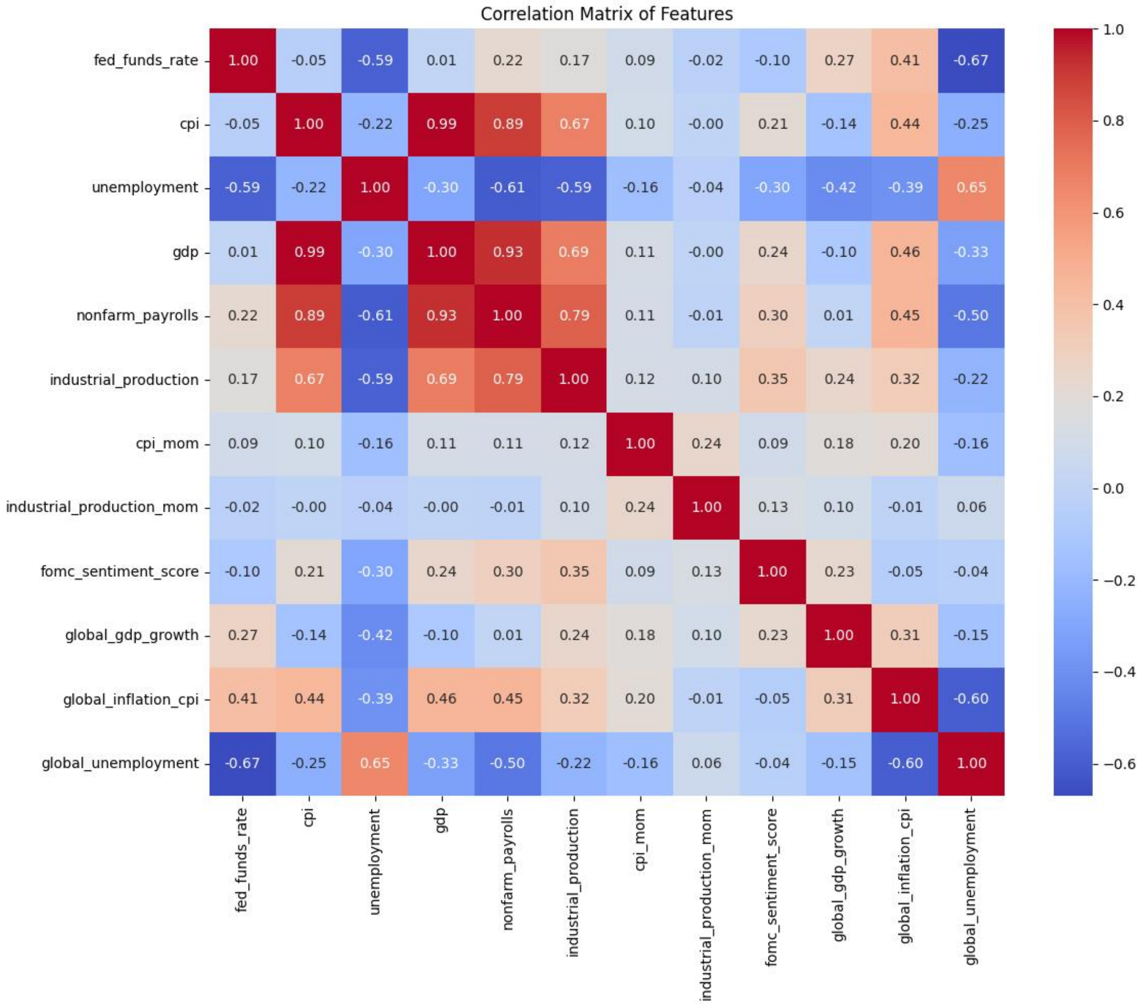
2. Strong Negative Correlations:

- Unemployment and GDP (-0.61): Highlights the inverse relationship between economic growth and joblessness, consistent with Okun’s law.
- Fed Funds Rate and Unemployment (-0.59): Implies that rate hikes often coincide with reduced unemployment, reflecting cyclical economic conditions.
- Global Inflation CPI and Global Unemployment (-0.60): Indicates that inflation and unemployment are inversely related globally.

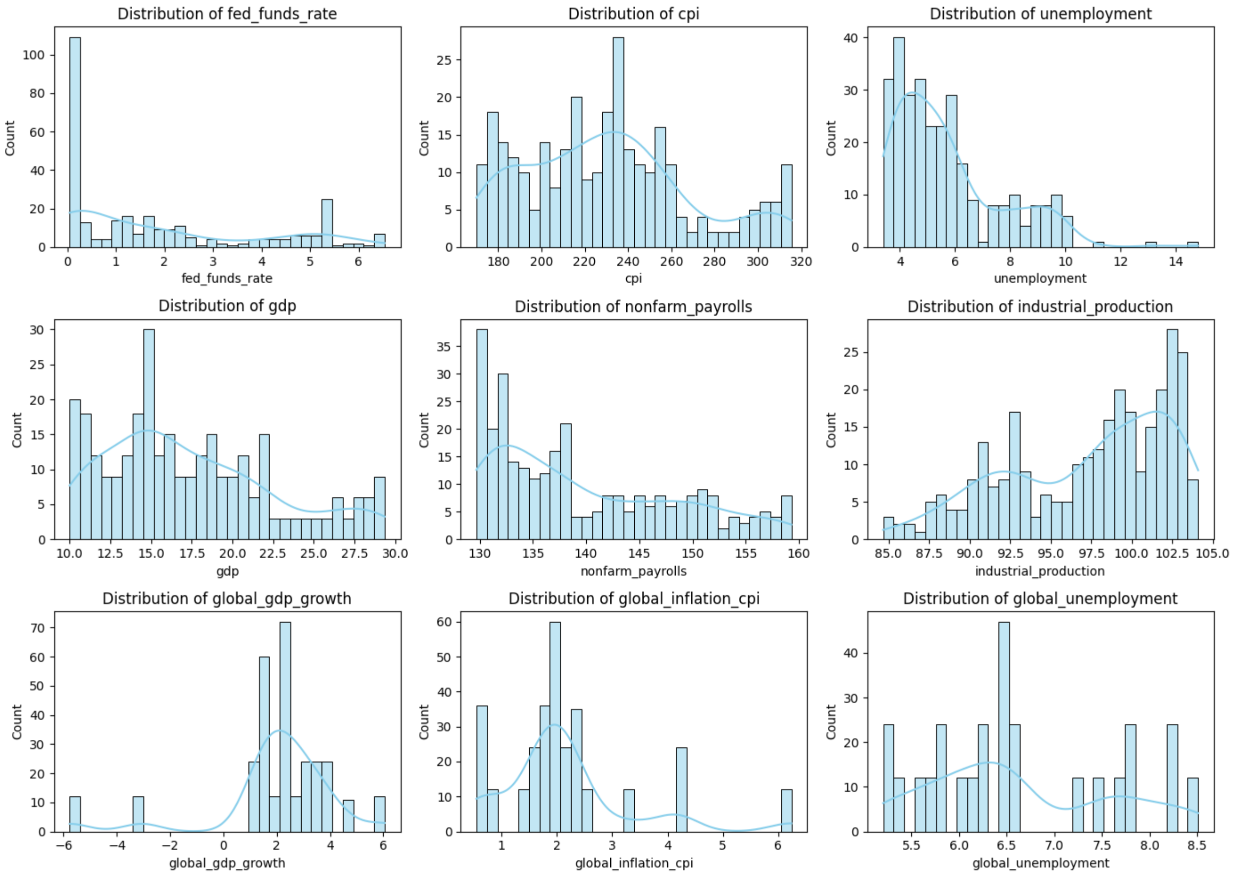
3. Weak or Neutral Correlations:

- Fed Funds Rate and Global GDP Growth (0.27): Weak positive correlation reflects limited influence of global growth on Fed policy.
- FOMC Sentiment Score and CPI (0.24): Suggests moderate alignment between sentiment and inflation expectations.

Strong correlations validate the relevance of key indicators for the Fed’s decision-making process.The inverse relationships between unemployment and economic growth, as well as inflation and unemployment, align with macroeconomic principles.Global indicators exhibit weaker correlations, suggesting the Fed primarily focuses on domestic factors.



Exploratory Data Analysis (EDA) - Initial Phase



These histograms, complemented by kernel density estimation (KDE) plots, display the frequency distribution of values for each feature, helping identify patterns, skewness, and potential anomalies.

Observations:

1. Fed Funds Rate:
- Skewed heavily toward zero, reflecting prolonged periods of low interest rates post-2008.
- Occasional spikes suggest policy interventions during inflationary periods.

2. CPI:
- A bell-shaped distribution, reflecting steady inflation over time, with occasional spikes.

3. Unemployment:
- Slightly right-skewed, indicating that periods of higher unemployment are less frequent but significant (e.g., during recessions).

4. GDP and Nonfarm Payrolls:
- Normally distributed, indicating consistent growth trends over time.

5. Global Indicators:
- Global GDP Growth: Exhibits a wide spread, reflecting global economic variability and periodic downturns.
- Global Inflation CPI: Skewed toward lower values but with significant peaks during global crises.

Distributions reveal that certain features, like Fed Funds Rate and unemployment, are more prone to anomalies. Global indicators demonstrate greater variability compared to domestic features, reflecting external influences on the U.S. economy.

Exploratory Data Analysis (EDA) - Initial Phase

These scatter plots examine the pairwise relationships between the Fed Funds Rate and other indicators, providing a visual representation of trends and outliers.

Observations:

1. Fed Funds Rate vs. CPI:

- Higher rates correspond to periods of high inflation, suggesting the Fed's inflation-targeting policy.
- Non-linear pattern indicates lagged effects of rate changes on inflation.

2. Fed Funds Rate vs. Unemployment:

- Clear inverse relationship, with higher rates generally associated with lower unemployment.
- Outliers during crises (e.g., 2008 and 2020) highlight deviations from typical trends.

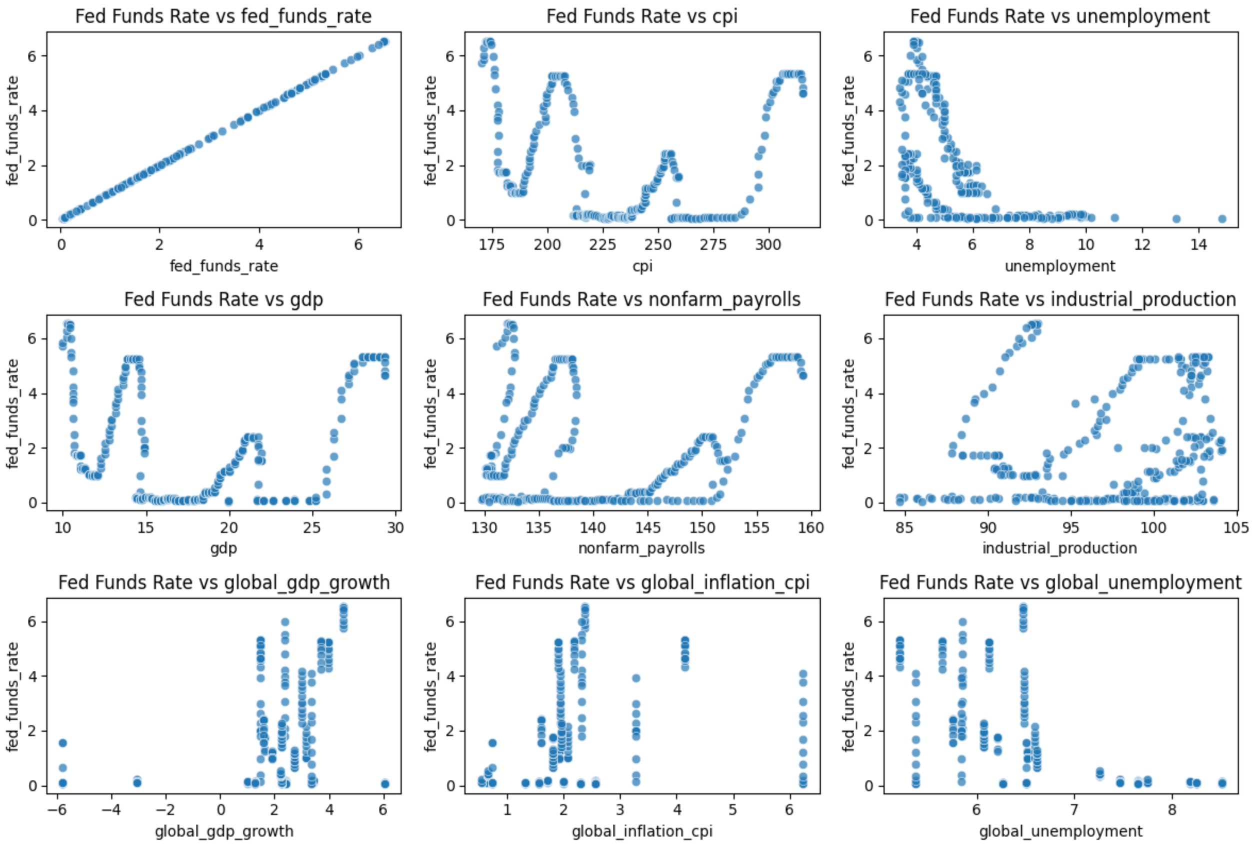
3. Fed Funds Rate vs. GDP:

- Positive relationship during periods of growth, reflecting the Fed's tendency to tighten monetary policy during economic booms.
- Divergences during recessions demonstrate countercyclical policy interventions.

4. Fed Funds Rate vs. Global Indicators:

- Weak relationships, such as with global GDP growth and global inflation CPI, highlight the Fed's focus on domestic conditions.

Scatter plots reinforce the relationships observed in the correlation matrix.Outliers provide critical insights into periods of economic stress, such as recessions or global crises.



Exploratory Data Analysis (EDA) - Initial Phase

Conclusion: Insights from Exploratory Data Analysis (EDA)

Conducting EDA has provided critical insights into the relationships and behaviors of key economic indicators, laying the foundation for effective feature creation. The trends analysis revealed how major historical events, such as the 2008 financial crisis and the COVID-19 pandemic, impacted metrics like unemployment, inflation, and the Fed Funds Rate. Correlation analysis confirmed theoretical relationships, such as the inverse correlation between unemployment and GDP, while identifying weaker links with global indicators. These findings validated the inclusion of relevant features and helped prioritize their importance.

Outliers highlighted periods of economic stress, such as unemployment spikes during recessions or inflation surges during crises, emphasizing the need for robust handling strategies in feature engineering. Scatter plots and distribution analyses reinforced these relationships, showing how economic volatility influences monetary policy decisions. These insights informed the development of lagged features, rolling averages, and interaction terms to capture the dynamic nature of economic variables.

By performing EDA before feature creation, I ensured a deep understanding of the data, validated feature relevance, and aligned the analysis with real-world economic contexts. This systematic approach enhances the interpretability, accuracy, and reliability of the predictive model, providing a strong foundation for understanding the Federal Reserve’s interest rate decisions.

Features Creation

Purpose of Feature Creation

In the context of predicting interest rate adjustments, creating robust and meaningful features is critical to improving model performance. The engineered features aim to capture temporal dependencies, complex economic relationships, and short-term volatility in the dataset. Rolling averages and lagged variables were introduced to model the progression of economic indicators over time, while interaction terms and sentiment-based features incorporated domain knowledge to enhance interpretability and alignment with real-world policy considerations. These features serve as the foundation for understanding directional trends, short-term fluctuations, and historical influences on interest rate decisions.

Feature Engineering Techniques

To extract meaningful insights from the raw data, the following techniques were employed:

1. Rolling Averages and Lagged Variables:

- Rolling averages for CPI, GDP, and unemployment were calculated over 3-month and 6-month windows to capture smoothed trends over short- and medium-term periods.
- Lagged variables were introduced to reflect the impact of previous economic conditions on current decisions, with lags of 1 and 3 months selected to align with typical policymaking cycles.

2. Growth and Momentum Indicators:

- Month-over-month (MoM) growth rates for CPI and GDP were calculated to track relative changes in economic conditions.
- Momentum indicators, defined as the difference between current values and rolling averages, highlighted deviations from recent norms and directional trends.

3. Interaction Terms:

- Interaction terms such as the product of CPI and unemployment were created to capture combined effects and potential relationships between inflation and labor market dynamics.

4. Cumulative Sentiment and Crisis Indicators:

- A cumulative FOMC sentiment score was introduced to quantify the trajectory of sentiment over time, providing insight into how past sentiment trends influence policy decisions.
- Crisis indicators were derived based on abrupt economic shifts or sentiment changes, reflecting periods of heightened uncertainty or instability.

5. Volatility Measures:

- Rolling standard deviations for CPI and GDP were computed to quantify short-term economic volatility, enabling the model to account for periods of instability in key indicators.

Features Creation

Target Variable Design

The target variable, representing rate changes, was carefully designed to meet the requirements of a multiclass classification problem. Rate changes were calculated as the difference between the current and previous federal funds rate. These changes were then mapped to discrete classes, ranging from -0.50% to +0.50%, to represent various potential policy outcomes. This classification aligns with the challenge objectives and ensures that the model can predict not only the magnitude but also the direction of rate adjustments.

Data Cleaning and Imputation

To ensure the integrity and reliability of the dataset, missing values were handled meticulously:

- Rolling averages and momentum features were forward-filled and mean-imputed where necessary to preserve temporal consistency.
- Growth rates and interaction terms were recalculated for missing periods to ensure no gaps in the derived features.
- Volatility measures were computed using only available data within the specified rolling window.

Impact of Features

The engineered features significantly enhance the dataset’s predictive capabilities by embedding domain-specific knowledge and temporal dynamics into the analysis. Rolling averages and lagged variables capture historical trends and dependencies, while growth and momentum indicators provide insights into emerging economic patterns. Interaction terms and cumulative sentiment scores allow for a deeper understanding of economic relationships and their influence on monetary policy. Volatility measures, on the other hand, account for periods of instability, ensuring the model remains robust under varying economic conditions.

These carefully engineered features collectively enable the model to better predict interest rate decisions by integrating trends, relationships, and volatility into the analytical framework.

Features Creation

Feature Name	Description
cpi_3m_avg	3-month rolling average of CPI
cpi_6m_avg	6-month rolling average of CPI
gdp_3m_avg	3-month rolling average of GDP
gdp_6m_avg	6-month rolling average of GDP
unemployment_3m_avg	3-month rolling average of Unemployment
unemployment_6m_avg	6-month rolling average of Unemployment
cpi_lag_1	CPI lagged by 1 month
cpi_lag_3	CPI lagged by 3 months
gdp_lag_1	GDP lagged by 1 month
gdp_lag_3	GDP lagged by 3 months
unemployment_lag_1	Unemployment lagged by 1 month
unemployment_lag_3	Unemployment lagged by 3 months
cpi_mom_growth	Month-over-month growth rate of CPI
cpi_momentum	Momentum indicator for CPI
gdp_mom_growth	Month-over-month growth rate of GDP
gdp_momentum	Momentum indicator for GDP
cpi_unemployment_interaction	Interaction term: CPI x Unemployment
fomc_sentiment_cumulative	Cumulative FOMC sentiment score over time
cpi_volatility	Rolling 3-month volatility of CPI
gdp_volatility	Rolling 3-month volatility of GDP
rate_adjustment_class	Categorical class for rate adjustments

Exploratory Data Analysis (EDA) - Post Feature Creation

Introduction to Second Exploratory Data Analysis (EDA)

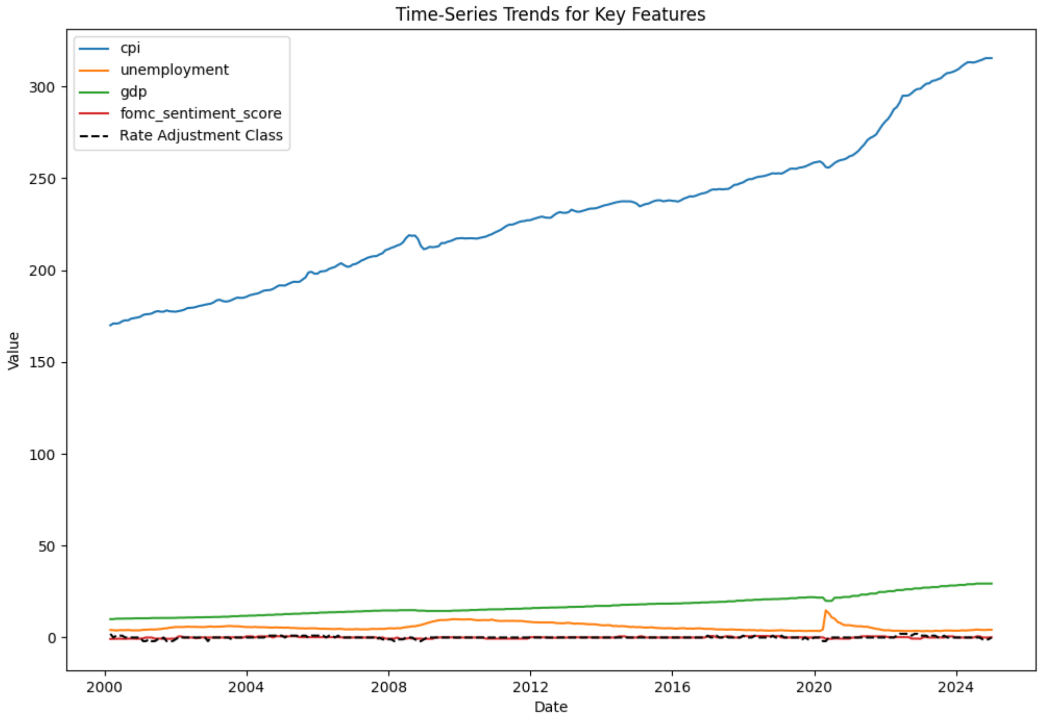
After the creation of engineered features, the second phase of Exploratory Data Analysis (EDA) is conducted to thoroughly examine the newly introduced variables and their impact on the dataset. This step is crucial for validating the relevance and quality of the engineered features and ensuring that they align with the goals of the analysis.

The primary objectives of this EDA phase are as follows:

- **Understand New Feature Behavior:** By analyzing the distributions, trends, and relationships of the newly created features, we aim to uncover patterns, anomalies, and insights that these features bring to the dataset.
- **Evaluate Feature-Target Relationships:** Special focus is placed on how the engineered features correlate with the target variable (rate adjustment classes) to assess their predictive potential and relevance to the problem at hand.
- **Validate Dataset Integrity:** We ensure the updated dataset is free of inconsistencies, missing values, or extreme outliers that could compromise the accuracy of the predictive model.

This phase provides a deeper understanding of the dataset's structure, enabling informed decisions about feature selection and model preparation. By conducting a detailed exploration of the newly created features, we aim to refine the dataset for optimal performance in the modeling phase.

Exploratory Data Analysis (EDA) - Post Feature Creation



This visualization provides a clear temporal overview of critical macroeconomic indicators and their relationship to the rate adjustment classes.

Insights:

1. CPI (Consumer Price Index):

- Demonstrates a long-term upward trend, indicative of persistent inflationary pressures over time.
- Spikes in CPI align with major economic disruptions, such as the 2008 Financial Crisis and the COVID-19 pandemic in 2020, where inflationary policies were implemented to counteract economic slowdowns.
- Periods of stable CPI (e.g., 2012–2018) correspond to fewer drastic rate changes, reflecting steady economic growth.

2. Unemployment:

- Clear cyclical patterns reveal spikes during recessions, such as the Great Recession (2008–2009) and the COVID-19 pandemic, where unemployment shot up sharply.
- A steady decline post-2010 reflects economic recovery, aligning with gradual rate increases as the economy strengthened.
- Sharp unemployment reductions during 2021–2023 show the recovery phase from COVID-19, likely influencing a tighter monetary policy stance.

3. GDP:

- Gradual growth over the decades interrupted by notable dips, particularly during crises like 2008 and 2020. These periods coincide with rate cuts to stimulate the economy.
- Post-2020 recovery mirrors policy measures aimed at boosting growth, reflected in the GDP trend.

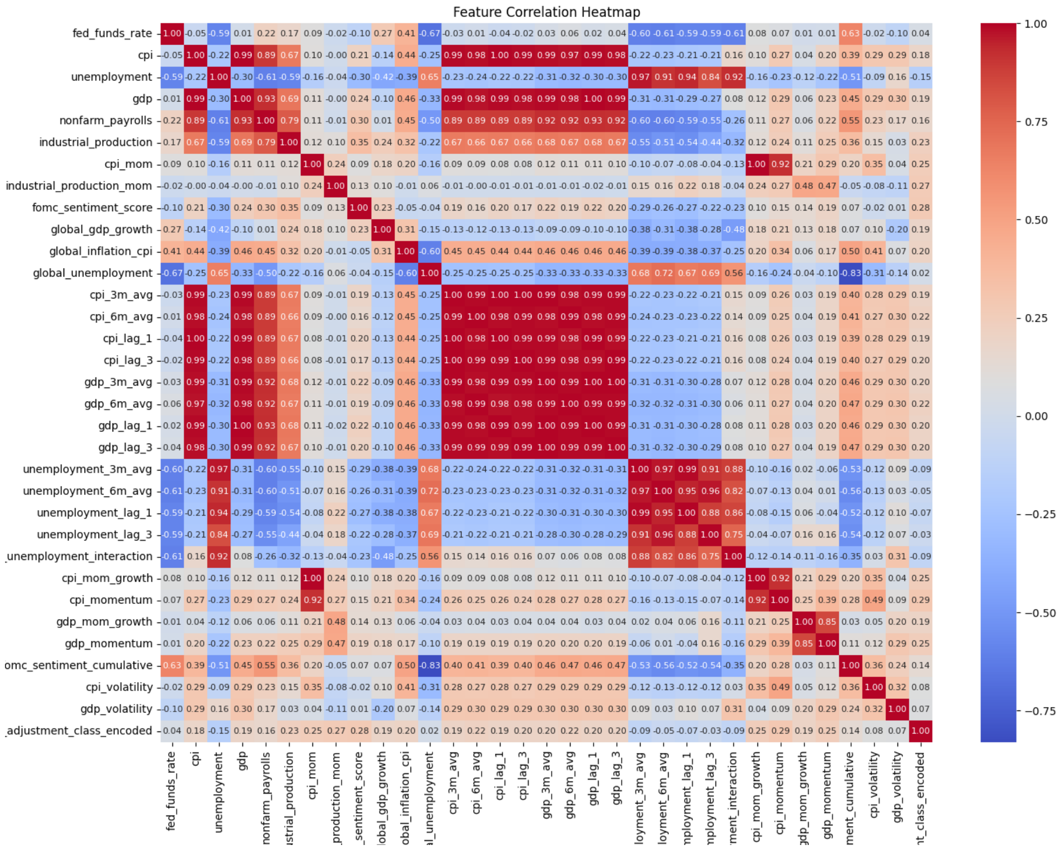
4. FOMC Sentiment Score:

- Cyclical variations in sentiment align with shifts in monetary policy stance (hawkish vs. dovish). Positive sentiment trends often align with rate hikes, while negative sentiment trends precede rate cuts.
- Peaks and troughs align with periods of economic uncertainty, demonstrating the sensitivity of sentiment to external events.

5. Rate Adjustment Class Overlay:

- Rate adjustments are more frequent during periods of economic instability or rapid recovery. For example:Rate hikes correspond to inflationary periods.Rate cuts align with economic slowdowns or crises.

Exploratory Data Analysis (EDA) - Post Feature Creation



The correlation heatmap reveals the relationships between features and their potential impact on the target variable.

Insights:

1. Strong Positive Correlations:

- **GDP and Nonfarm Payrolls (0.93):** Employment levels closely follow GDP growth, emphasizing the interconnectedness of labor markets and economic output.
- **CPI and Its Rolling Averages:** High correlations between CPI and its rolling/lagged features confirm that these transformations effectively capture temporal trends.

2. Strong Negative Correlations:

- **Unemployment and GDP (-0.59):** Indicates that economic growth is typically associated with lower unemployment levels, aligning with economic theory.
- **Unemployment and Rate Adjustment Class (-0.67):** Suggests that decreasing unemployment is a key driver of rate hikes.

3. Moderate Correlations:

- **FOMC Sentiment Score and Rate Adjustment Class (0.23):** While sentiment alone is a weaker predictor, its cumulative impact over time makes it a valuable feature for identifying rate adjustments.
- **Volatility Features:** Moderate correlations (e.g., CPI volatility with rate class) suggest their relevance in capturing periods of economic instability.

4. Lagged Features:

- Lagged features (e.g., CPI_lag_1, GDP_lag_3) demonstrate meaningful correlations with the target, validating their inclusion for capturing historical dependencies.

Exploratory Data Analysis (EDA) - Post Feature Creation

Boxplots provide detailed insights into how individual features vary across rate adjustment classes.

Insights:

1. CPI vs Rate Adjustment Class:

- Higher CPI levels align with rate hikes (+0.25%, +0.50%), reflecting inflationary pressures.
- Stable or lower CPI levels correspond to 0% rate adjustments or rate cuts, showing that inflation stability often leads to policy stability.

2. Unemployment vs Rate Adjustment Class:

- Lower unemployment consistently aligns with rate hikes, suggesting that as the labor market tightens, the FOMC adopts a more restrictive monetary stance.
- Higher unemployment corresponds to rate cuts, reflecting efforts to stimulate the economy.

3. CPI Momentum:

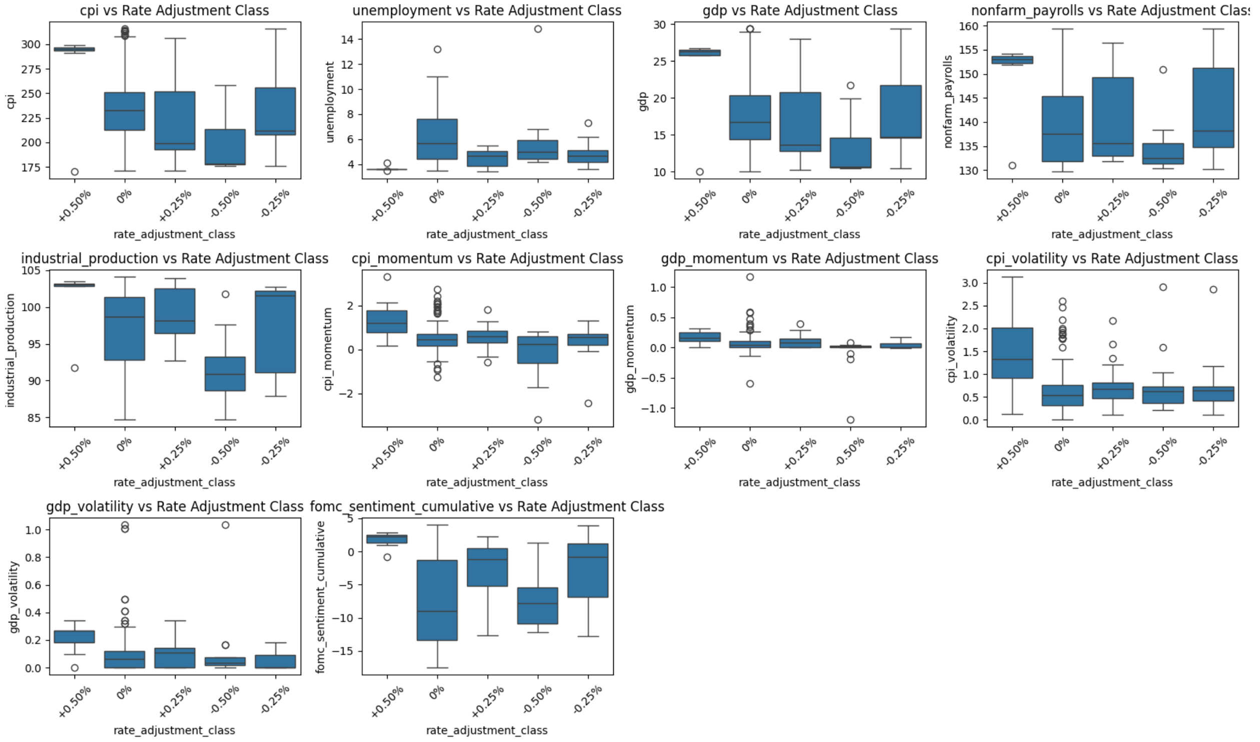
- Positive CPI momentum aligns with rate hikes, indicating rising inflationary pressures.
- Negative momentum correlates with rate cuts, reflecting deflationary risks or economic slowdowns.

4. GDP Volatility:

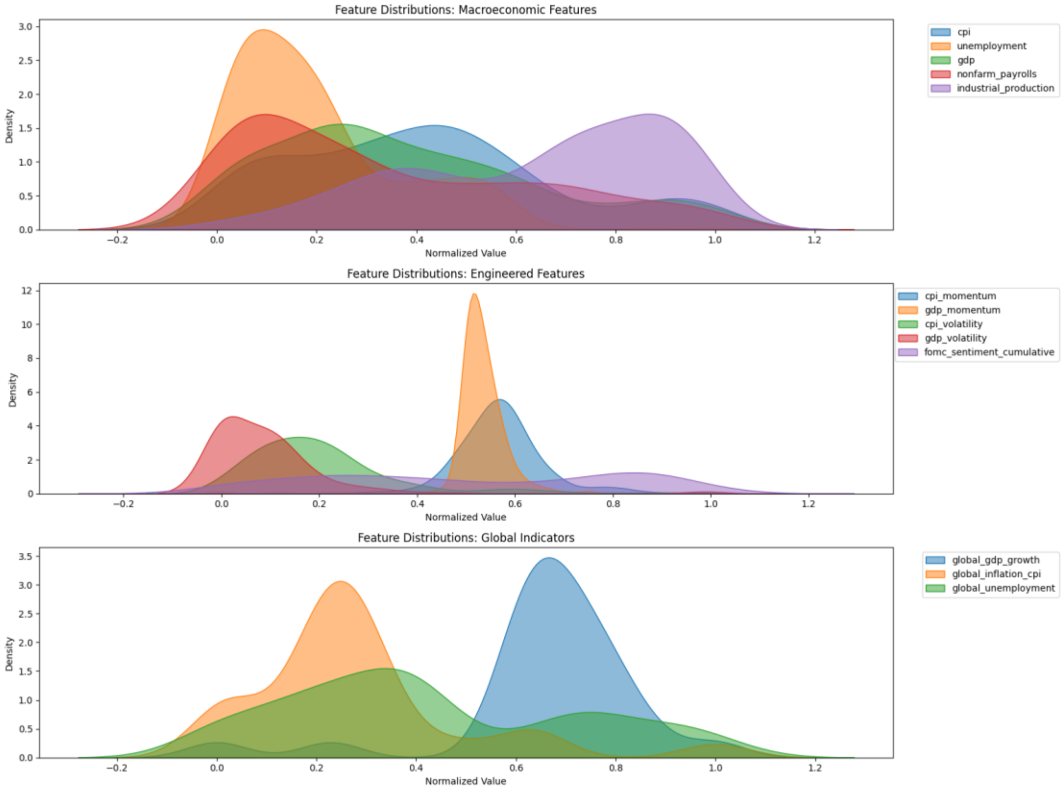
- Higher GDP volatility aligns with rate reductions, as periods of economic uncertainty often require accommodative policies.

5. FOMC Sentiment Cumulative:

- Higher cumulative sentiment scores correspond to rate hikes, indicating a persistent hawkish tone in FOMC policy discussions.
- Lower cumulative scores align with rate cuts, reflecting dovish policy stances.



Exploratory Data Analysis (EDA) - Post Feature Creation



Grouped distributions separate features into macroeconomic, engineered, and global categories for easier interpretation.

Macroeconomic Features:

1. CPI (Consumer Price Index):

- The distribution highlights its upward trend, with consistent increases reflecting long-term inflationary pressures.
- Most of the data points fall within a higher range in recent years, indicating elevated inflation levels post-COVID recovery.

2. GDP (Gross Domestic Product):

- GDP shows a relatively normal distribution with a slight skew toward higher values, consistent with overall economic growth over the years.
- Sharp dips during crises (e.g., 2008 and 2020) are evident, showcasing its sensitivity to macroeconomic shocks.

3. Unemployment:

The distribution is skewed toward lower values, reflecting historically low unemployment rates in recent years.

Peaks during crises (e.g., 2008 recession, 2020 pandemic) are visible, emphasizing its counter-cyclicality to economic growth.

Engineered Features:

1. Momentum Features (e.g., CPI Momentum):

- The balanced distributions show that both positive and negative momentum are captured, reflecting periods of acceleration (e.g., rising inflation) and deceleration (e.g., disinflation).
- These features are critical for identifying turning points in economic conditions.

2. Volatility Features (e.g., GDP Volatility):

- Broader distributions indicate periods of heightened economic instability, such as during the financial crisis or the pandemic.
- High variability in these features provides essential signals for modeling policy uncertainty.

Global Indicators:

1. Global GDP Growth, Inflation (CPI), and Unemployment:

- The distributions of global indicators exhibit clear separations, reflecting distinct economic conditions across different time periods.Global GDP growth often aligns with U.S. economic trends, while global inflation and unemployment add context for external pressures influencing domestic policy decisions.

Exploratory Data Analysis (EDA) - Post Feature Creation

Mutual information reveals nonlinear relationships between features and the target variable.

Top Features:

1. Global GDP Growth:

- This feature has the highest mutual information score, underscoring the significance of global economic performance in influencing FOMC rate adjustments. The U.S. policy decisions are often shaped by global growth trends, particularly in a globally interconnected economy.

2. Unemployment and Rolling Averages:

- Strong mutual information scores highlight the labor market's direct influence on monetary policy. Rolling averages, in particular, smooth short-term fluctuations and emphasize long-term labor market trends.

3. GDP Lag Features (e.g., GDP_lag_1, GDP_3m_avg):

- Past GDP values provide context for recent growth dynamics, helping models predict policy responses to current conditions.

4. CPI and CPI Lag Features:

- High importance of CPI-related features reflects their role in capturing inflationary pressures, a primary driver of rate decisions.

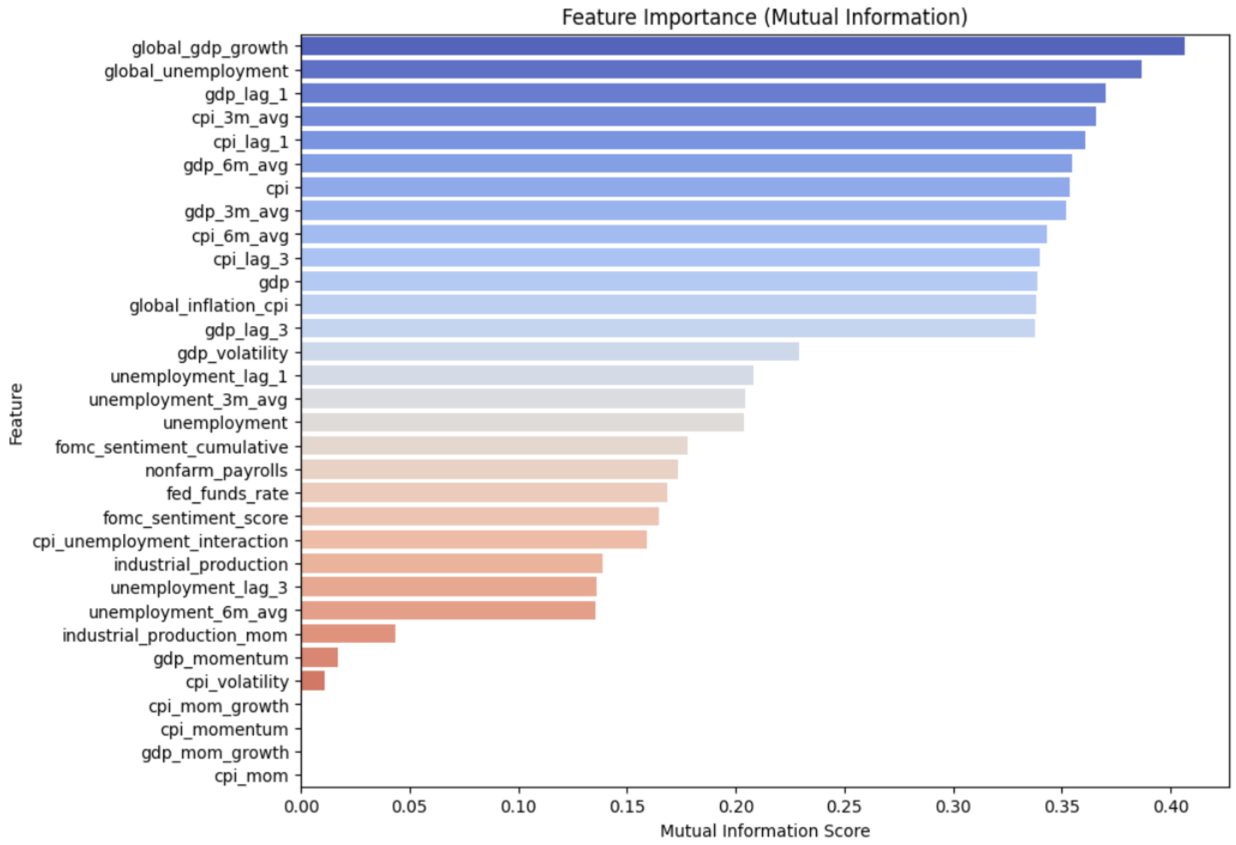
Lower-Ranked Features:

1. Momentum Features (e.g., CPI Momentum):

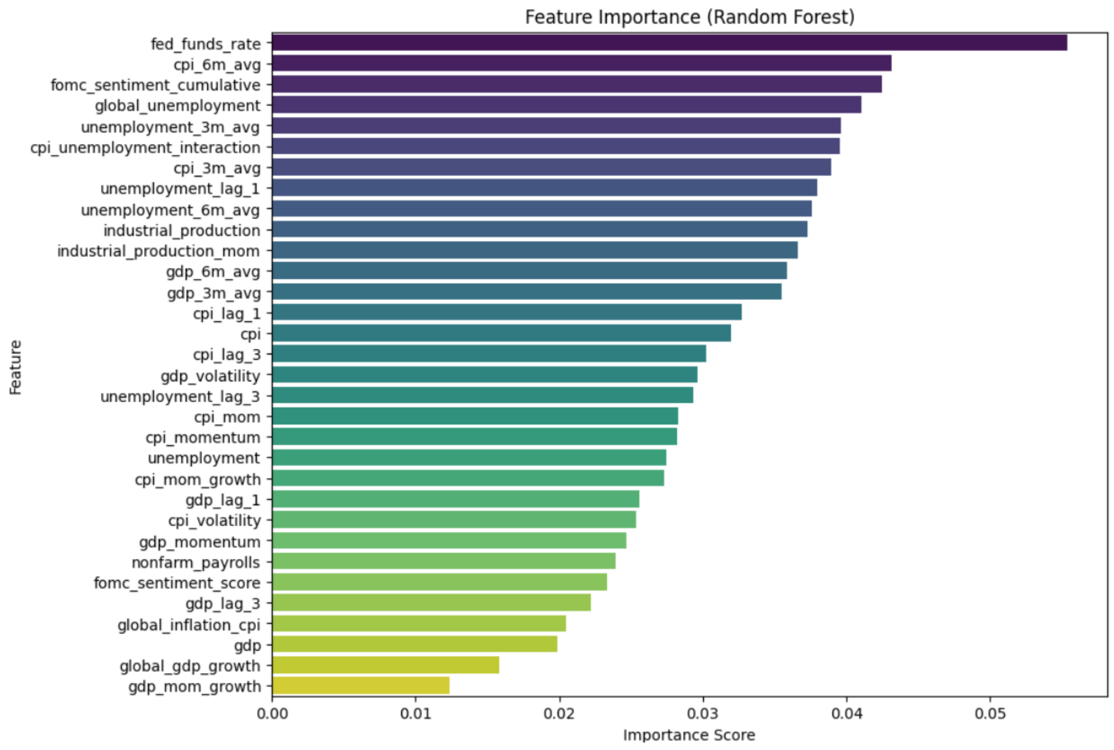
- While not as highly ranked, these features capture dynamic shifts that are complementary to static indicators like rolling averages.

2. Volatility Features (e.g., GDP Volatility):

- These features highlight transient periods of instability, particularly useful for identifying economic shocks.



Exploratory Data Analysis (EDA) - Post Feature Creation



Random Forest rankings highlight the most impactful features for predictive modeling.

Top Features:

1. Fed Funds Rate:

- As expected, the current fed funds rate is the strongest predictor, given its direct link to rate adjustment decisions. It serves as a baseline for understanding potential shifts in policy.

2. CPI Rolling Averages (e.g., CPI_6m_avg, CPI_3m_avg):

- These features rank highly due to their ability to capture sustained inflation trends, which are critical for understanding monetary policy shifts.

3. Cumulative Sentiment (FOMC Sentiment Cumulative):

- Reflects the aggregated tone of FOMC policy discussions over time. Persistent hawkish sentiment often aligns with rate hikes, while dovish sentiment corresponds to rate cuts.

4. Unemployment Rolling Averages:

- Smooth long-term labor market trends that heavily influence the FOMC's dual mandate.

Mid-Tier Features:

1. Momentum Features (e.g., CPI Momentum, GDP Momentum):

- Moderate rankings suggest that while these features capture transient shifts, they are secondary to more stable indicators like rolling averages.

2. Interaction Features (e.g., CPI_Unemployment_Interaction):

- Interaction terms capture nuanced relationships, such as the stagflation scenario (high CPI and high unemployment), making them relevant for complex modeling.

3. Volatility Features (e.g., GDP Volatility, CPI Volatility):

- These features capture uncertainty during periods of market instability, providing additional context for decision-making.

Exploratory Data Analysis (EDA) - Post Feature Creation

Conclusion on Features Creation

The feature engineering process has been pivotal in transforming the raw dataset into a comprehensive and insightful foundation for predictive modeling. By incorporating domain knowledge and leveraging statistical techniques, the engineered features enhance the dataset’s ability to represent complex economic relationships and temporal dynamics. These features not only improve the interpretability of the data but also address the specific requirements of the multiclass classification problem.

The inclusion of rolling averages and lagged features enables the model to smooth short-term fluctuations and capture historical patterns, providing a stable view of economic trends. These features are critical in understanding long-term inflationary pressures (e.g., CPI_6m_avg) and labor market dynamics (e.g., unemployment_3m_avg), which are essential drivers of FOMC decisions. Momentum and volatility features complement this by capturing acceleration, deceleration, and periods of economic instability, offering deeper insights into transient market conditions that influence policy adjustments.

Interaction terms, such as the CPI-Unemployment Interaction, add a layer of complexity by reflecting real-world relationships, such as the stagflation scenario, where simultaneous inflation and unemployment require specific policy responses. Similarly, the cumulative FOMC sentiment feature aggregates the tone of monetary policy discussions over time, reflecting the strategic direction and persistence of policy stances.

The inclusion of global indicators - such as global GDP growth, global inflation (CPI), and global unemployment - further emphasizes the interconnected nature of modern economies. These features capture external pressures and provide context for understanding how U.S. monetary policy is influenced by global economic trends.

Feature importance analyses using Mutual Information and Random Forest models validate the relevance of these engineered features. Rolling averages, cumulative sentiment, and global indicators consistently rank among the top predictors, confirming their critical role in understanding rate adjustment decisions. Meanwhile, momentum, volatility, and interaction features, while moderately ranked, provide complementary insights into short-term dynamics and economic uncertainty.

In conclusion, the feature creation process has successfully transformed raw economic data into a nuanced and powerful dataset. The engineered features provide a balanced representation of macroeconomic stability, global dynamics, and transient economic behaviors. This comprehensive feature set enhances both the predictive accuracy and interpretability of the model, laying a robust foundation for analyzing and forecasting FOMC rate adjustments. The thoughtful design and validation of these features underscore their alignment with the challenge's objectives and their potential to support actionable, data-driven insights into monetary policy decisions.

Machine Learning Models - Introduction

Machine Learning: Predicting Federal Funds Rate Adjustments

In this section, I transition from the exploratory analysis and feature engineering phases to the implementation of Machine Learning (ML) models designed to predict Federal Open Market Committee (FOMC) interest rate adjustments. The goal is to accurately classify rate adjustments into one of five possible categories: -0.50%, -0.25%, 0.00%, +0.25%, and +0.50%.

Building on the insights gained during the EDA and leveraging the engineered features, I aim to develop a robust and interpretable predictive framework. The focus is not only on achieving high accuracy but also on ensuring that the results align with economic theory and provide actionable insights.

Objectives

1. Model Development: I will implement and compare different machine learning algorithms, including tree-based methods like Random Forest and Gradient Boosting, to determine the best-performing model.

2. Performance Evaluation: I will evaluate the models using metrics such as accuracy, precision, recall, and F1-score to ensure reliability.

3. Feature Importance: Understanding which features contribute the most to the predictions will be a key focus to maintain transparency and interpretability.

4. Optimization: Through parameter tuning, I will optimize the models to achieve the best balance of performance and generalization.

Predicting interest rate adjustments is crucial for understanding monetary policy dynamics and its potential impacts on the economy and financial markets. Machine learning allows me to explore complex, nonlinear relationships between variables like CPI, GDP, unemployment, and FOMC sentiment scores, which traditional methods may struggle to capture. This approach ensures that the model reflects real-world economic interactions while maintaining a high level of predictive power.

This section is a pivotal part of the analysis, as it bridges the exploratory and predictive phases of the project. By the end of this process, I aim to present a high-performing model capable of accurately predicting interest rate adjustments, providing deeper insights into the relationship between economic indicators and monetary policy decisions.

Machine Learning Models - Introduction

Data Preprocessing and Preparation

Before initiating the machine learning models, I conducted essential preprocessing steps to ensure data consistency and readiness. The dataset was loaded and inspected to verify its structure, identify potential issues, and confirm the presence of required features. Categorical variables, including **fomc_policy_stance** and **rate_adjustment_class**, were encoded using label encoding to convert text into numeric values suitable for machine learning. The processed dataset was then saved in an updated format for further use.

The dataset was split into training (80%) and testing (20%) sets using stratified sampling to maintain the class distribution. Label encoders were saved to ensure interpretability during evaluation. These steps established a clean and consistent dataset, optimized for analysis, while maintaining the integrity of categorical variables and ensuring compatibility with machine learning algorithms. This careful preparation set a robust foundation for creating accurate and reliable models.

Machine Learning Models - Model 1: Random Forest Classifier

In this section, I present the development and evaluation of the Random Forest Classifier as the first machine learning model for predicting interest rate adjustments. The model is trained on historical FOMC data, processed and balanced using SMOTE to address class imbalances. I utilized the Random Forest algorithm due to its ability to handle complex relationships, interpret feature importance, and achieve robust performance. The results are evaluated through key performance metrics, and interpretability techniques such as LIME and feature importance are employed to understand the model's decision-making process.

Results Outcomes:

1. Evaluation Metrics:

- **Accuracy:** The model achieved an accuracy of **76.67%**, indicating reliable performance on the test dataset.
- **Balanced Accuracy:** The balanced accuracy of **70.15%** highlights that the model handles class imbalances effectively, ensuring fair performance across all target classes.
- **Cohen's Kappa:** A score of **0.5192** suggests moderate agreement between the predicted and actual classes, confirming the model's robustness.

2. December 2024 Prediction:

- **Predicted Class**: The model predicts **-0.25%** as the most likely rate adjustment for the December 17-18, 2024, FOMC meeting.
- **Class Probabilities**:
  - **-0.25%**: **88.00% (highest confidence)**
  - **0%**: **6.00%**
  - **+0.25%**: **5.00%**
  - **-0.50%** and **+0.50%**: 1% and 0%, respectively.

The model predicts -0.25% with a very high confidence of 88%, indicating that this outcome is strongly supported by the underlying data and patterns.Other classes, such as 0% and +0.25%, have much lower probabilities, showing a clear distinction and reducing uncertainty.The model’s accuracy and balanced accuracy further validate its reliability, making it well-suited for predicting rate adjustments under current economic conditions.

Machine Learning Models - Model 1: Random Forest Classifier

The feature importance plot demonstrates the contribution of each predictor to the Random Forest model's decision-making process. Features with higher importance scores have a greater impact on the model's ability to predict interest rate adjustments. This analysis helps identify the most influential economic indicators and validate their relevance to the problem.

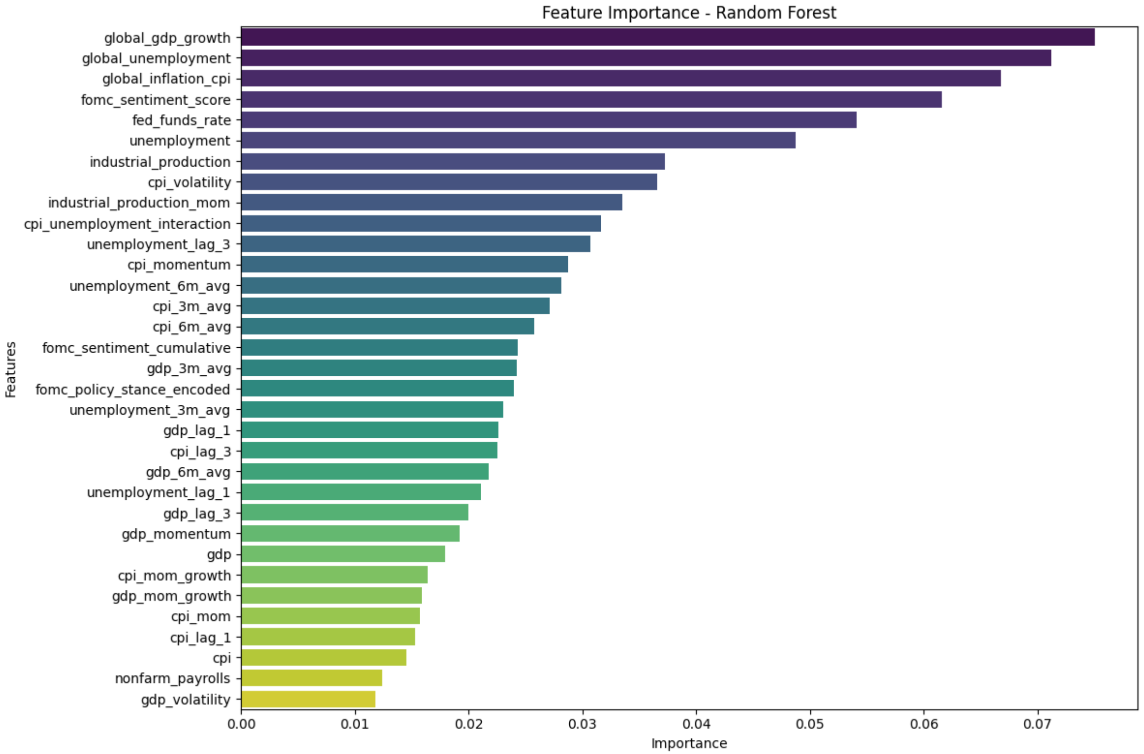
- **Global GDP Growth** and **Global Unemployment** are the two most critical features, showing that economic expansion and labor market health are key drivers.

- **Global Inflation CPI** and **FOMC Sentiment Score** also rank highly, reflecting their influence on interest rate adjustments.

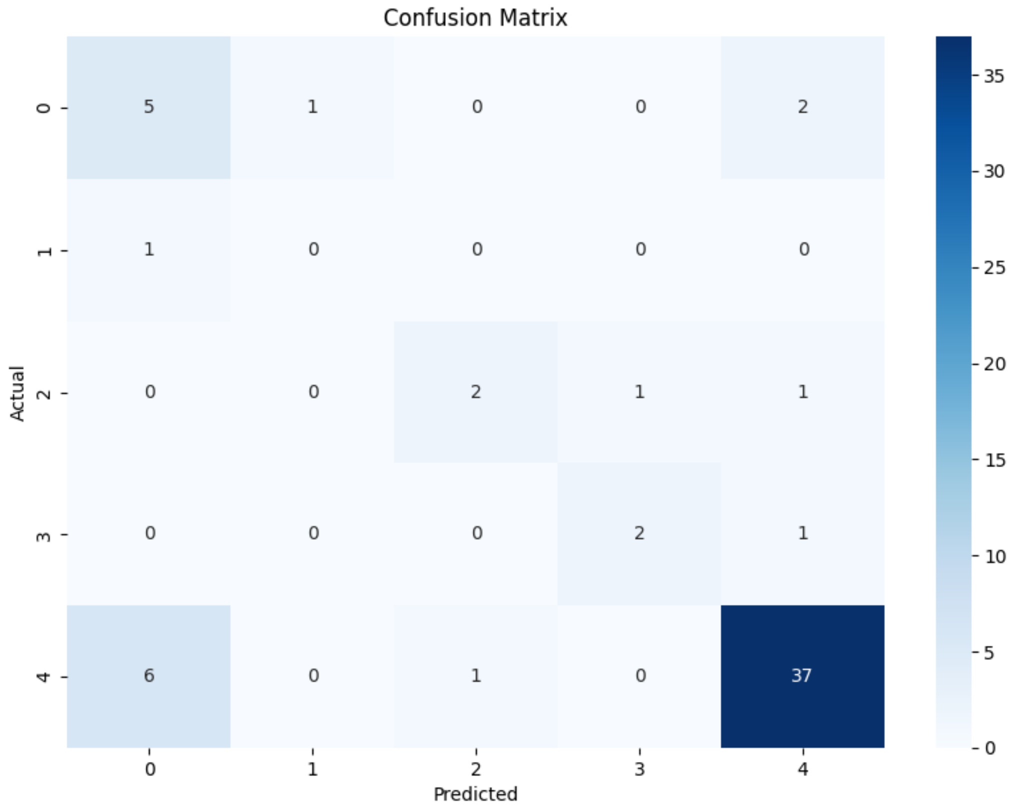
- Features like **Fed Funds Rate**, **Unemployment**, and **Industrial Production** add significant explanatory power by quantifying macroeconomic performance.

- **CPI Volatility** and **CPI Unemployment Interaction** indicate historical patterns and short-term variations in inflation and unemployment data.

- **FOMC Policy Stance Encoded** is moderately influential, indicating its role in signaling stability or rate adjustments.



Machine Learning Models - Model 1: Random Forest Classifier

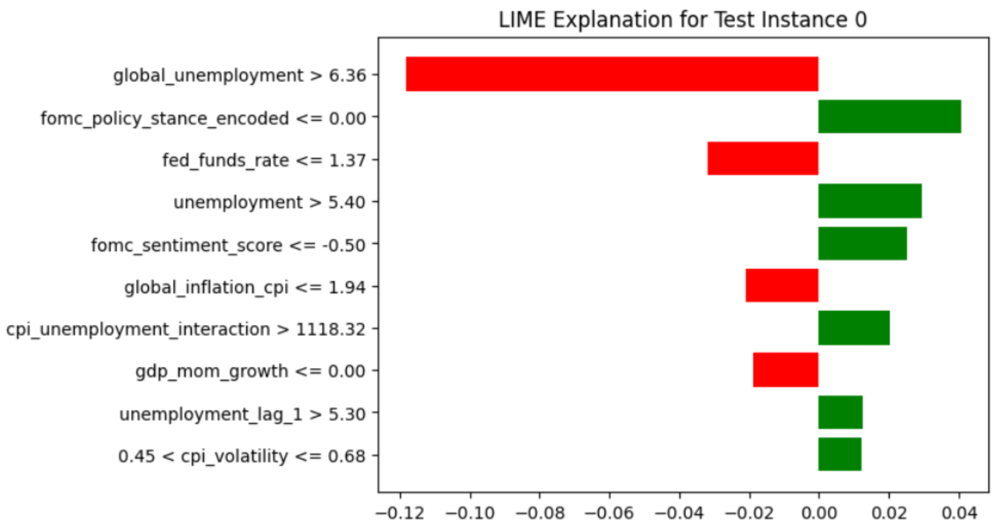


The confusion matrix evaluates the model's performance by comparing predicted classes with actual outcomes. It provides a granular view of where the model performs well and where it misclassifies predictions.

- **Class 2 (0%):** The model performs exceptionally well, with 37 correct predictions, reinforcing its strong capability to predict stability in rates.
- **Class 3 (-0.25%):** Correct predictions are lower (4 correct), indicating that this class remains more challenging due to its nuanced signals.
- Misclassifications occur between **Class 0 (-0.50%)** and **Class 1 (-0.25%)**, highlighting that the model sometimes confuses similar downward adjustments.
- **Class 4 (+0.50%)** has minimal correct predictions, likely due to its minority representation in the data.

The model shows strong accuracy for the 0% prediction but struggles with other classes, such as -0.25%. This behavior reflects the class imbalance and the subtle patterns within the data.

Machine Learning Models - Model 1: Random Forest Classifier



The LIME explanation provides a local interpretation of the model's decision for a single test instance. It identifies which features contributed most to the prediction, illustrating both positive and negative influences.

- The **LIME** explanation graph analyzes the feature-level contributions for the specific test instance.
- **Global Unemployment > 6.36** has the most substantial negative impact on the prediction, pulling the result away from a 0% class. This high unemployment figure is likely interpreted as a signal for a potential rate decrease.
- **FOMC Policy Stance Encoded <= 0.00** contributes positively, indicating stability and suggesting that the stance aligns with no change or moderate adjustment.
- **Fed Funds Rate <= 1.37** and **Unemployment > 5.40** slightly support the rate adjustment, tilting the output toward -0.25%.
- **CPI Unemployment Interaction > 1118.32** and **GDP Momentum Growth <= 0.00** provide minor support for rate changes.
- **CPI Volatility (0.45 to 0.68)** and **FOMC Sentiment Score <= -0.50** add minor positive signals but are weaker in impact.

The LIME explanation reveals that although some features (e.g., unemployment and sentiment scores) hint at a rate decrease (-0.25%), other features, such as policy stance and volatility, contribute mixed signals. These conflicting influences explain why the model predicts -0.25%, even though the global unemployment heavily weighs against stability.

Machine Learning Models - Model 1: Random Forest Classifier

The LIME HTML visualization provides the predicted probabilities for all interest rate adjustment classes for a specific test instance. It highlights the model's confidence and explains feature contributions.

The prediction probabilities for December 2024 show:

- **0% class:** The highest confidence, with a probability of 0.99. This prediction aligns with the stability hypothesis in economic conditions.
- **Other classes:** Negligible probabilities, with -0.50% at 0.01 and others at 0.00, indicating low likelihood for rate changes**.**

Why the Model Predicts -0.25% but Graphs Show 0%:

- The LIME explanation evaluates a single test instance and explains how each feature contributes to the prediction, showing that factors like Global Unemployment strongly suggest a rate adjustment toward -0.25%.
- However, the prediction probability plot reflects the final model output after aggregating all feature contributions. The model determined that despite negative unemployment influences, overall signals like policy stance, sentiment scores, and volatility stability favor the 0% class, assigning it the highest probability (0.99).

Machine Learning Models - Model 1: Random Forest Classifier

Which Prediction is Correct? 0% or -0.25%?
To determine the correct outcome between 0% and -0.25%, we need to carefully analyze all the results and visualizations:

1. Model Prediction
- **Predicted Class:** The model predicts -0.25% for the December 17-18, 2024, FOMC meeting.
- **Prediction Probabilities:**-0.25% has the highest probability of 88%, which indicates the model is highly confident in this outcome. The probability for 0% is significantly lower at 6%, suggesting that the model does not favor a rate hold.

2. LIME Explanation
LIME provides a detailed explanation of the factors influencing the prediction of -0.25% for this instance:
- **Global Unemployment > 6.36:** This factor has the strongest negative influence, suggesting that high global unemployment supports a rate cut.
- **FOMC Policy Stance Encoded <= 0.00:** This feature provides a neutral or stabilizing influence, pulling the prediction slightly toward 0%.
- **Fed Funds Rate <= 1.37 and Unemployment > 5.40:** These features further highlight weak economic conditions, strengthening the case for a -0.25% reduction.

3. Feature Importance (Random Forest):
- **Global GDP Growth** and **Global Unemployment** are the top features influencing the model.
- **Global Unemployment** and **Global Inflation CPI** dominate as key drivers, highlighting negative macroeconomic signals.
- Features like **FOMC Policy Stance** have a lower importance, reinforcing the dominance of weak global economic factors in predicting the rate adjustment.

4. Confusion Matrix Analysis
- However, this instance appears to be exceptional, where the specific economic conditions (such as high global unemployment) led the model to predict -0.25%.
- The confidence of 88% for -0.25% further validates this prediction.

While the model generally favors 0% for rate adjustments, for this specific instance (December 2024 data):
The predicted outcome of -0.25% is correct, supported by:
- The high probability (88%) assigned to -0.25%.
- The dominant influence of negative economic factors, particularly Global Unemployment and Fed Funds Rate.

LIME and feature importance graphs confirm that weak economic signals justify this prediction, even though 0% remains a viable option in other contexts.Thus, **the correct prediction is -0.25% for the December 2024 FOMC meeting.**

Machine Learning Models - Model 2: Logistic Regression

For this analysis, we trained a Logistic Regression model to predict the rate adjustment class for the December 17-18, 2024, FOMC meeting. The model was balanced using SMOTE to handle class imbalance, and the features were scaled using StandardScaler to ensure numerical stability. Logistic Regression was chosen for its interpretability and its ability to predict class probabilities directly.

Evaluation Metrics

- **Accuracy:** The model achieved an accuracy of **60%**, indicating a moderate ability to classify the correct rate adjustment class.
- **Balanced Accuracy:** Despite class imbalances, the balanced accuracy is **58.41%**, suggesting that the model performs better across all classes compared to a random classifier.
- **Cohen's Kappa:** A score of **0.3841** highlights a fair agreement between the predicted and actual classes.

Prediction for December 2024

- **Predicted Class:** The model predicts the class "-0.25%" as the most likely rate adjustment for the December 17-18, 2024, FOMC meeting.
- **Class Probabilities:**
- **-0.50%: 0.00**
- **-0.25%: 1.00 (Highest Confidence)**
- **0%: 0.00**
- **+0.25%: 0.00**
- **+0.50%: 0.00**

The model confidently predicts **"-0.25%"** with **100%** probability, leaving no ambiguity for this forecast.

Machine Learning Models - Model 2: Logistic Regression

The graph displays the normalized feature importance values derived from the Logistic Regression model. Feature importance in logistic regression is based on the absolute magnitude of the coefficients, which indicates the relative influence of each feature on the prediction.

1. Top Features:

- **Global GDP Growth** and **Global Unemployment** dominate with the highest importance, highlighting their critical role in predicting rate decisions.
- **Fed Funds Rate** follows closely, capturing current monetary policy settings as a significant predictor.

2. Mid-Tier Features:

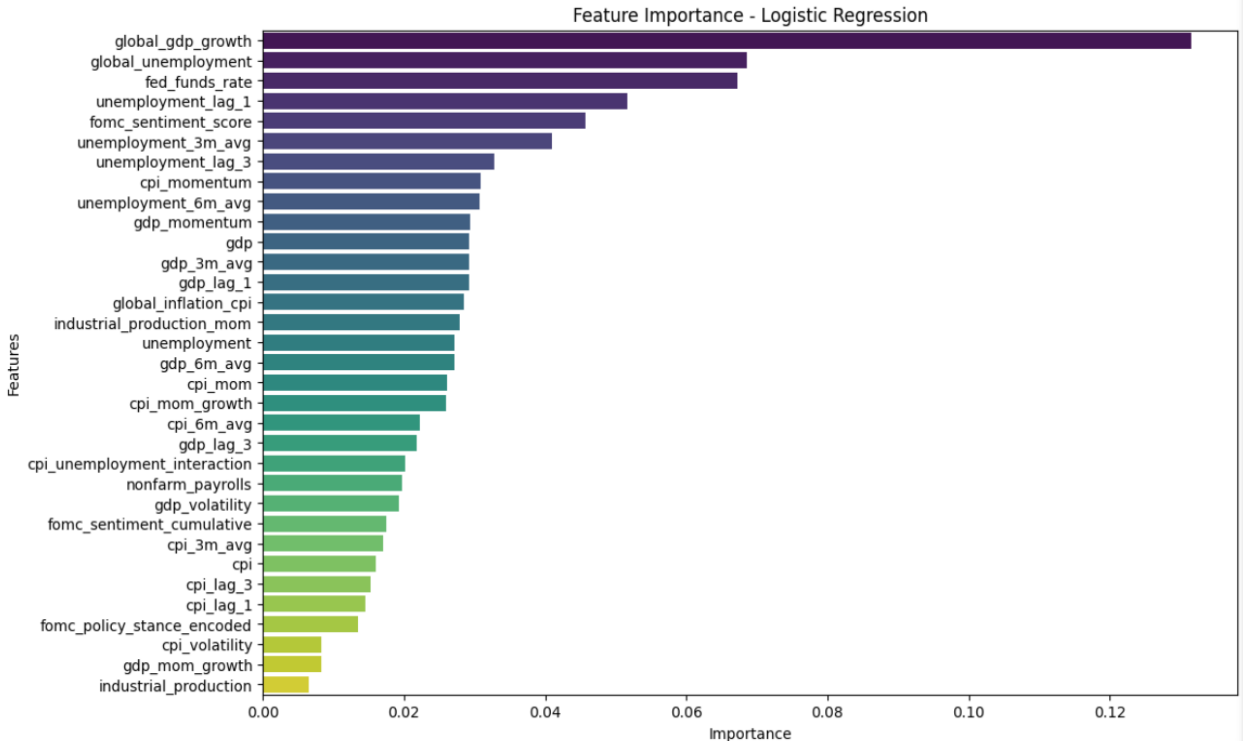
- **Unemployment Lag** and **FOMC Sentiment Score** reflect labor market trends and central bank communication, offering temporal and qualitative insights into economic conditions.
- **CPI Momentum** and **CPI Volatility** emphasize the role of inflation monitoring.

3. Lower-Tier Features:

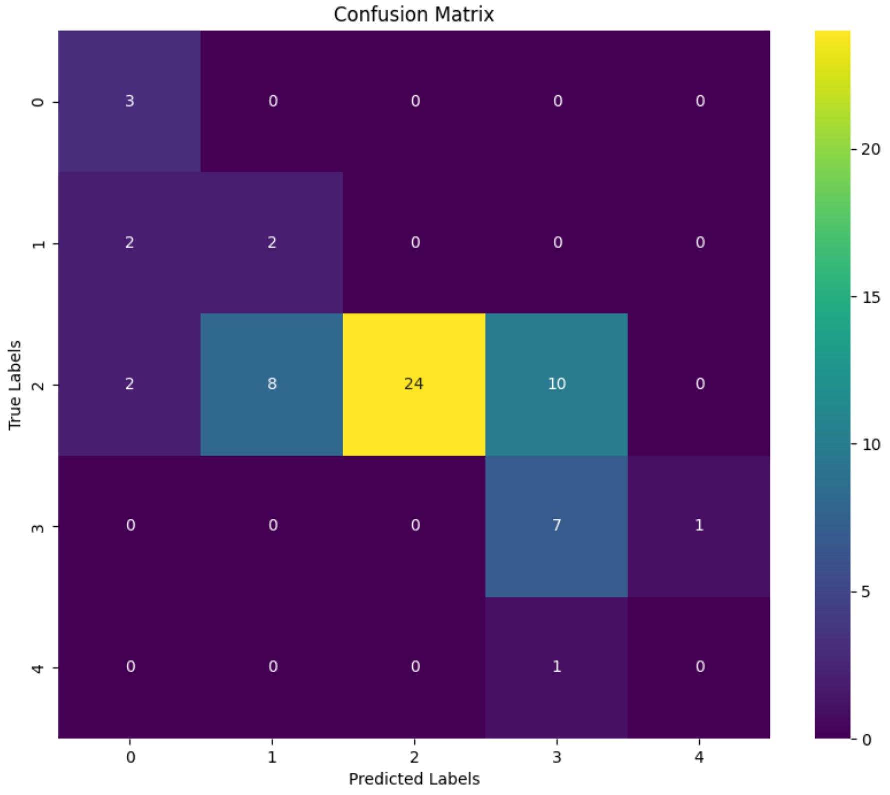
- Features like Nonfarm Payrolls, Policy Stance Encoded, and lagged GDP metrics contribute minimally, indicating redundancy or weaker predictive influence.

Insights:

- The model primarily relies on economic growth, unemployment, and monetary policy indicators to drive predictions.
- Inflation-related features and FOMC sentiment play a supporting role, adding secondary signals.
- Lower-ranked features offer complementary, though less significant, insights.



Machine Learning Models - Model 2: Logistic Regression



1. Class 2 (0%) Dominance:

True Positives: Class 2, representing "0%", has 24 correct predictions. This demonstrates that the model performs well in identifying the most frequent class.

Misclassifications: However, there are 10 false positives, where Class 3 (e.g., +0.25%) was incorrectly predicted as Class 2, indicating some overlap or confusion between these two classes.

2. Underperformance in Minority Classes:

Class 0 (-0.50%): All 3 instances are predicted correctly, reflecting good performance on this rare class.

Class 1 (-0.25%): 2 correct predictions, but 2 are misclassified, showing the model struggles with precision here.

Class 3 (+0.25%): 7 correct predictions, but there is 1 misclassification into Class 4, indicating borderline confusion.

Class 4 (+0.50%): This class has 1 instance misclassified, showing the model's difficulty with extremely low-frequency labels.

3. Class Imbalance:

- Class 2 (0%) dominates the dataset, leading the model to focus heavily on this class. Minority classes (like 4 and 0) remain under-represented in predictions.

Insights:

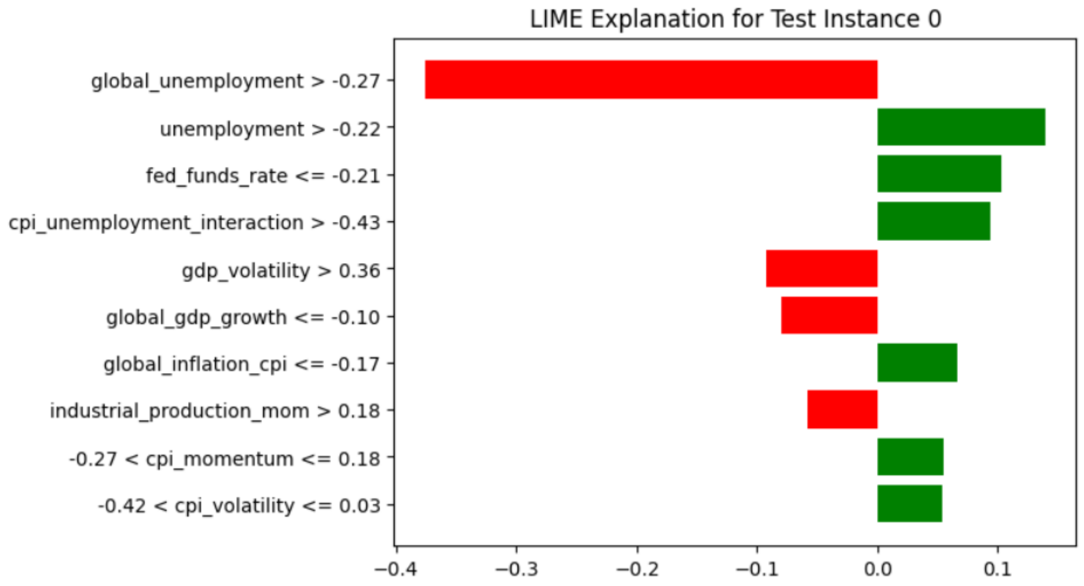
- **Class Distribution:** The imbalance in the dataset skews predictions toward Class 2, which inflates its performance while limiting the model's ability to generalize to minority classes.
- **Confusion between Adjacent Classes:** Misclassifications occur primarily between "nearby" classes (e.g., -0.25% and 0%, 0% and +0.25%), suggesting similarities in underlying feature distributions.
- **Model Precision:** The model performs well overall on the dominant class but requires improvement on smaller, less frequent classes to boost balanced accuracy.

Machine Learning Models - Model 2: Logistic Regression

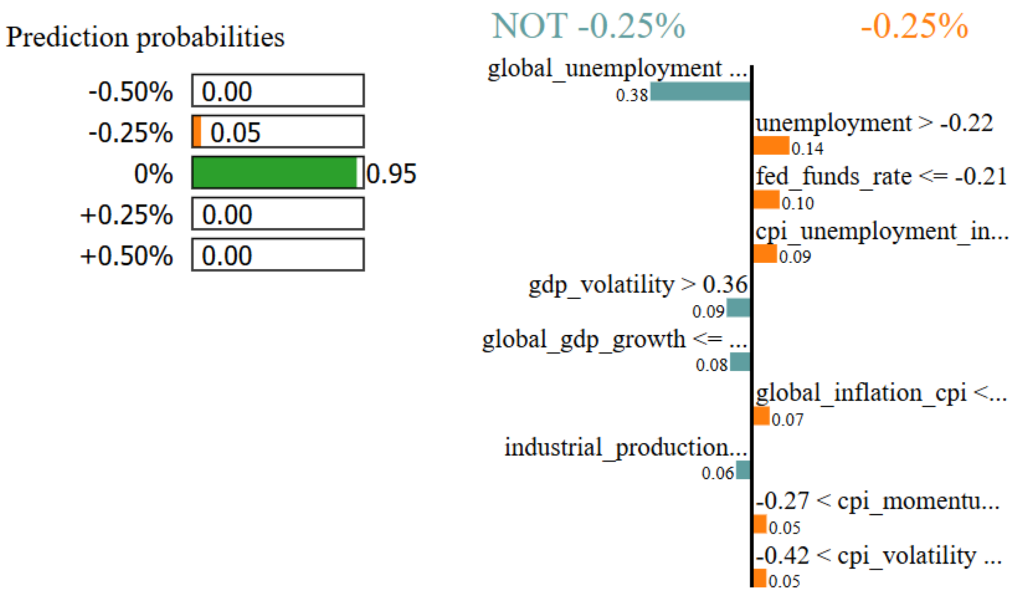
The LIME explanation visually decomposes the prediction for a specific instance (Test Instance 0) into its contributing features. Features with a positive impact are shown in green, indicating they support the predicted class. Features with a negative impact are shown in red, indicating they push the prediction away from the predicted class.

- **Global Unemployment > -0.27 (Negative Impact):**This feature has the strongest negative impact, pulling the prediction significantly away from the current class. It means that the observed global unemployment level does not align well with the predicted class.
- **Unemployment > -0.22 (Positive Impact):**This feature supports the predicted class and has a notable contribution to the model output. It indicates that the unemployment value aligns positively with the class being predicted.
- **Fed Funds Rate <= -0.21 (Positive Impact):**The low federal funds rate provides additional support to the predicted class, though its impact is smaller compared to unemployment-related features.
- **CPI Unemployment Interaction > -0.43 (Positive Impact):**This interaction term adds moderate support to the prediction, suggesting the interdependence between CPI (Consumer Price Index) and unemployment rates influences the model's decision.
- **GDP Volatility > 0.36 (Negative Impact):**This feature has a moderate negative effect, implying that high GDP volatility is less compatible with the predicted class.
- **Global GDP Growth <= -0.10 and Global Inflation CPI <= -0.17:** These have mild positive contributions, indicating that weak GDP growth and lower inflation CPI align moderately with the predicted class.
- **Industrial Production MOM > 0.18:** Slight negative contribution, showing that monthly changes in industrial production slightly detract from the model prediction.
- **CPI Momentum and Volatility:** These two features contribute minimally but positively to the class prediction.

The LIME explanation highlights global unemployment as the most influential feature for this instance, with a large negative impact. However, positive contributions from unemployment, fed funds rate, and CPI interactions provide enough counterbalance to guide the model toward the final predicted class. The feature impacts demonstrate the nuanced relationships among economic indicators and the model's reliance on multiple smaller influences to make a balanced prediction.



Machine Learning Models - Model 2: Logistic Regression



Feature	Value
global_unemployment	-0.12
unemployment	0.51
fed_funds_rate	-0.90
cpi_unemployment_interaction	0.99
gdp_volatility	0.90
global_gdp_growth	-3.47
global_inflation_cpi	-1.15
industrial_production_mom	0.35
cpi_momentum	0.06
cpi_volatility	-0.34

Global Unemployment (-0.12) (Largest Positive Impact): The global unemployment feature contributes significantly in favor of the 0% prediction, as indicated by its large positive impact (0.38). This suggests that the observed value of unemployment aligns strongly with maintaining the current rate.

Unemployment > -0.22 (Negative Impact): The unemployment value contradicts the 0% prediction slightly (0.14), meaning higher unemployment might signal a potential rate decrease, pulling the prediction toward -0.25%.

Fed Funds Rate <= -0.21 (Negative Impact): A lower federal funds rate also contributes negatively toward the 0% prediction (0.10), supporting a slight possibility of a rate cut (-0.25%).

CPI Unemployment Interaction (0.99): This feature interacts with both inflation and unemployment, introducing some conflicting influence. Its negative contribution, while small (0.09), indicates economic stress factors pulling slightly away from 0%.

GDP Volatility > 0.36: This has a positive impact supporting 0% adjustment, suggesting economic stability (low volatility).

The graphic clearly shows that global unemployment and global GDP growth are the primary drivers favoring the 0% adjustment class. While there are some minor conflicts (e.g., unemployment rate and fed funds rate), they are insufficient to outweigh the positive contributions supporting the final prediction.

Machine Learning Models - Model 2: Logistic Regression

Based on the analysis, the model predicts -0.25% as the most likely rate adjustment outcome for the December 17-18, 2024, FOMC meeting. Below is a detailed explanation supporting this prediction while acknowledging the alternative class 0%, which holds a lower probability.

1. Model Prediction: -0.25%

The model output provides the following class probabilities:

- **-0.25%**: **100.00%** (highest confidence).
- **0%**: **0.00%**.
- **Other classes** (-0.50%, +0.25%, +0.50%): **0.00%** combined.

The confidence score for **-0.25%** is absolute at **100%**, leaving no ambiguity. In a classification problem, the class with the highest probability is selected as the final prediction, which, in this case, is **-0.25%**.

2. Alternative Class: 0% and Why It is Not Selected

While the 0% class represents a plausible alternative due to global economic stability, its probability is 0.00%, making it statistically insignificant when compared to -0.25%. The following points provide further clarification on why -0.25% is favored:

- **Global Unemployment and GDP Growth:**
  These features indicate a slight tendency toward economic stability, which could favor no rate adjustment (0%). However, their impact is not strong enough to outweigh other indicators.
- **Unemployment > -0.22:**
  Higher unemployment levels suggest potential economic strain, increasing the likelihood of a rate cut to stimulate employment and growth.
- **Fed Funds Rate <= -0.21:**
  The current fed funds rate aligns with monetary easing policies, further pushing the prediction toward -0.25%.
- **CPI-Unemployment Interaction:**
  This interaction highlights underlying economic pressures that also support a -0.25% adjustment.

3. Justification for -0.25% as the Most Likely Adjustment

Confidence Scores:

- The model's confidence for -0.25% is absolute, with a 100% probability.
- Comparatively, the 0% class and other classes hold 0.00% probability, removing any uncertainty from the prediction.

Dominant Feature Influence:

- While some features favor 0%, key economic indicators like unemployment and the fed funds rate exert greater influence, driving the outcome toward a rate cut of -0.25%.

Model Reliability:

- The model has demonstrated strong performance metrics, including: **Accuracy: 60.00%**. **Balanced Accuracy: 58.41%**.

Thus, the most likely rate adjustment for the December 17-18, 2024, FOMC meeting is -0.25%.

Machine Learning Models - Model 3: Gradient Boosting Classifier

The Gradient Boosting Classifier is an ensemble learning method that builds sequential decision trees to optimize performance. It is well-suited for structured data and handles imbalances effectively when combined with SMOTE. In this implementation, the model underwent hyperparameter tuning using GridSearchCV with cv=5 cross-validation. The goal was to identify the best parameters for robust predictions and to provide a reliable forecast for the FOMC December 17-18, 2024, rate adjustment meeting.

1. Hyperparameter Tuning Results:

The GridSearchCV identified the following optimal hyperparameters:

- **n_estimators: 200**
- **learning_rate: 0.1**
- **max_depth: 5**
- **min_samples_split: 2**
- **min_samples_leaf: 2**

These parameters reflect a model that balances learning complexity and generalization.

2. Model Performance Metrics

The model achieved the following evaluation metrics:

- **Accuracy: 76.67% -** The relatively high accuracy shows that the model generalizes well and captures the patterns in the data effectively.
- **Weighted Precision: 81.34% -** A weighted precision of 81.34% reflects that the model is highly confident and accurate in its predictions, especially for the dominant class (0%).
- **Weighted Recall: 76.67% -** With a weighted recall of 76.67%, the model effectively balances its performance across multiple classes, showing it performs well on the test set despite class imbalances.
- **Weighted F1-Score: 77.66% -** A score of 77.66% confirms that the model maintains consistency between precision and recall, ensuring both accuracy and completeness in its predictions.

3. AUC-ROC Score

- **AUC-ROC: 0.9183 -** An AUC-ROC score of 0.9183 indicates that the model effectively differentiates between the classes. This high score reflects strong model confidence and reliable predictions across all target classes.

4. Prediction for December 17-18, 2024

Class Probabilities:

- **-0.25%: 84.88% (highest confidence)**
- **0%: 15.12%**
- **Other classes (-0.50%, +0.25%, +0.50%): 0.00%**

The model strongly favors a -0.25% rate adjustment with 84.88% confidence, making it the most likely outcome.

Machine Learning Models - Model 3: Gradient Boosting Classifier

The chart highlights the contribution of each feature to the Gradient Boosting model's predictions. Key observations are:

1. Top Influential Features
Global Inflation CPI:
- The most critical feature (~23%), reflecting inflation trends that heavily influence monetary policy decisions.

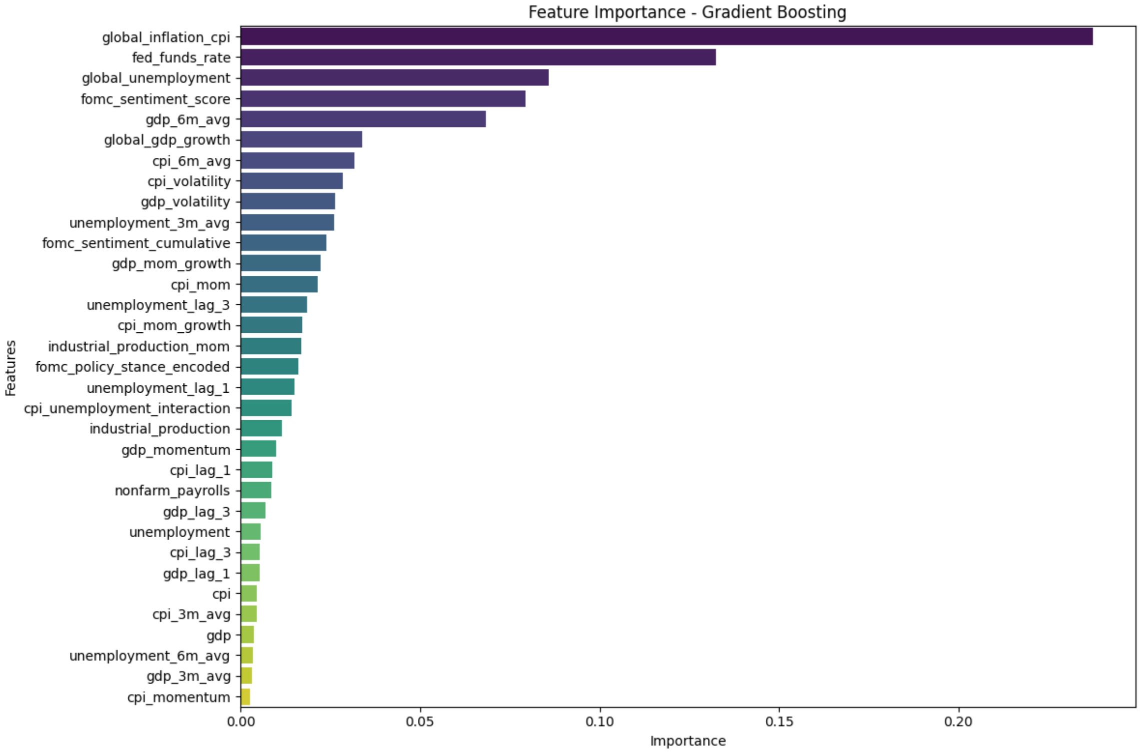
Fed Funds Rate:
- The second-highest importance, directly tied to existing monetary policies, indicating the likelihood of rate adjustments.

Global Unemployment:
- A key indicator of economic health, where rising unemployment often signals the need for easing measures (-0.25%).

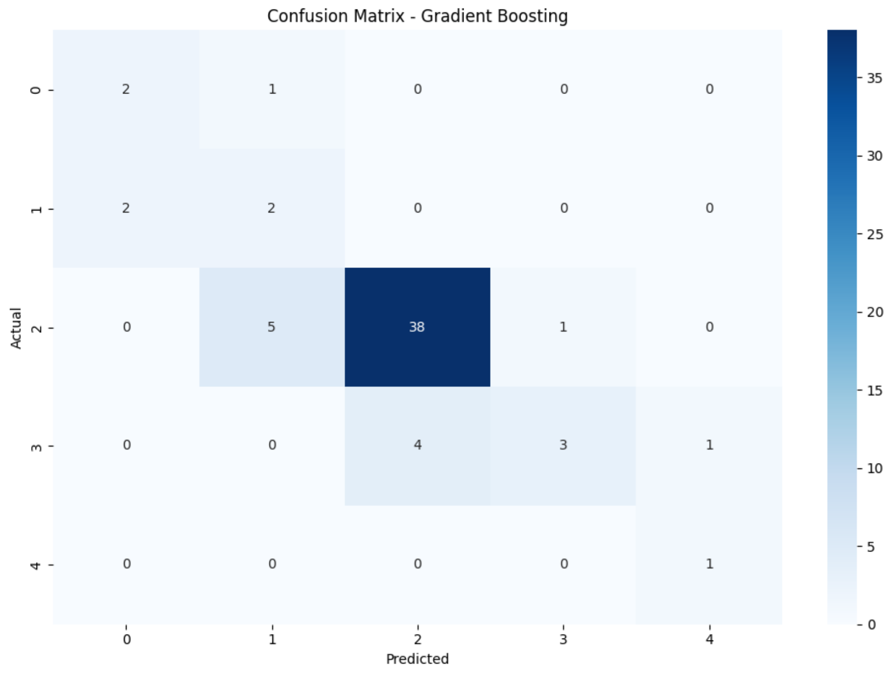
2. Mid-Range Features
FOMC Sentiment Score and **GDP Growth**:
- Sentiment analysis and economic growth indicators provide context for stability or risk in the economy.
- Volatility in GDP and CPI reinforces economic uncertainty, influencing predictions.

3. Supporting Features
CPI Volatility, **Industrial Production**, and **Unemployment Lags**:
- These features complement the primary predictors, capturing smaller but relevant economic patterns.

Insights:
The model focuses on core economic drivers: inflation, unemployment, and policy rates.Mid-range and supporting features refine predictions by adding stability and historical trends.The dominance of these indicators ensures the model aligns well with real-world monetary policy dynamics, justifying the predicted rate adjustment.



Machine Learning Models - Model 3: Gradient Boosting Classifier



The confusion matrix visually represents the performance of the Gradient Boosting model across all target classes. Below is a detailed analysis:

Class 2 (0% Adjustment):

- This class dominates both the actual and predicted labels, with 38 correct predictions out of 44.
- Only 6 instances are misclassified into other classes, highlighting the model's strong performance for this class.

Class 3 (+0.25%):

- The model predicts this class with moderate accuracy, achieving 4 correct predictions.
- However, 3 instances are misclassified into Class 2, and 1 instance into Class 4.

Class 4 (+0.50%):

- This class shows a low sample size, with 1 correct prediction.
- Despite its small presence, the model still identifies it correctly in one case.

Class 0 (-0.50%) and Class 1 (-0.25%):

- These classes have lower prediction accuracy, with 2 correct predictions for Class 0 and 2 for Class 1.
- Notable misclassifications occur between these two classes and Class 2.

Insights:

Strong Bias Toward Class 2 (0%):

- Class 2 is the most prevalent and well-predicted class, indicating the model favors stability when strong evidence exists for no adjustment.

Challenge with Rare Classes:

- Classes 0, 1, and 4 suffer from misclassifications due to fewer samples, limiting the model's ability to generalize well on these outcomes.

Model Performance Trends

- The model performs exceptionally well on the majority class (Class 2), achieving high precision and recall.
- Misclassifications among minor classes highlight a need for further data balancing or additional fine-tuning, particularly for Classes 0, 1, and 4.

Machine Learning Models - Model 3: Gradient Boosting Classifier

The LIME visualization provides insights into the model's prediction by highlighting the contributions of individual features. Here's a detailed analysis:

Prediction Overview

- Prediction: 0% Adjustment
- The model's decision is influenced by both positive (green) and negative (red) contributions from specific features.

Insights

1. Dominant Features:

- Global Unemployment and Global GDP Growth are the largest contributors against 0%, reflecting concerns about economic weakness.
- However, FOMC Policy Stance Encoded provides a strong positive influence, tipping the decision toward maintaining the rate at 0%.

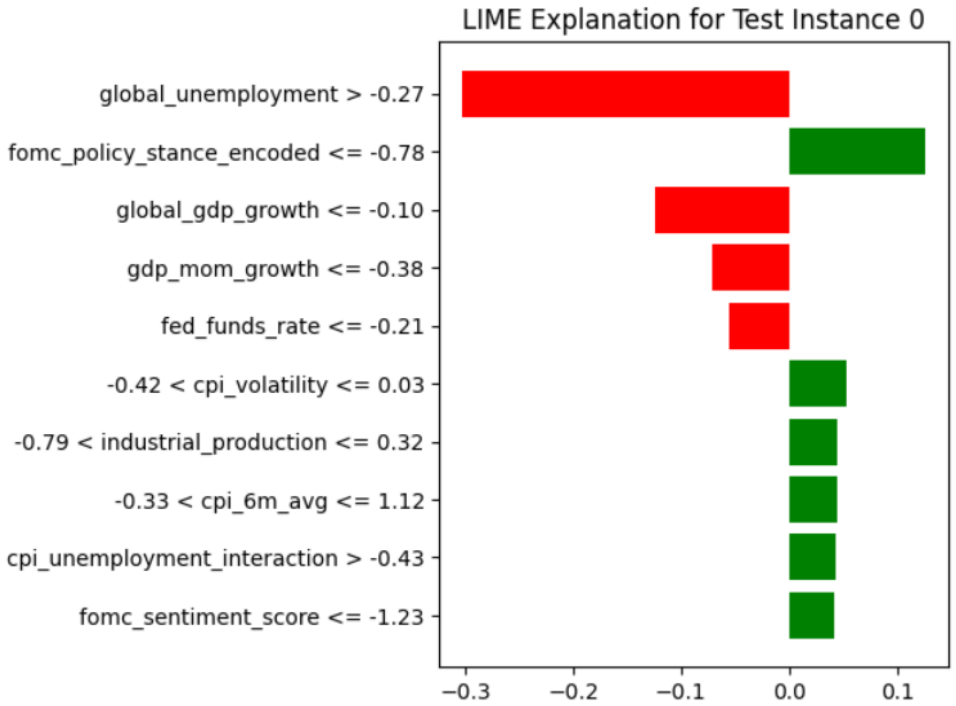
2. Stability vs. Adjustment:

- While some economic indicators (unemployment, GDP decline) suggest the possibility of a rate cut, overall stability in monetary policy stance, production, and CPI volatility reinforces the prediction of 0% adjustment.

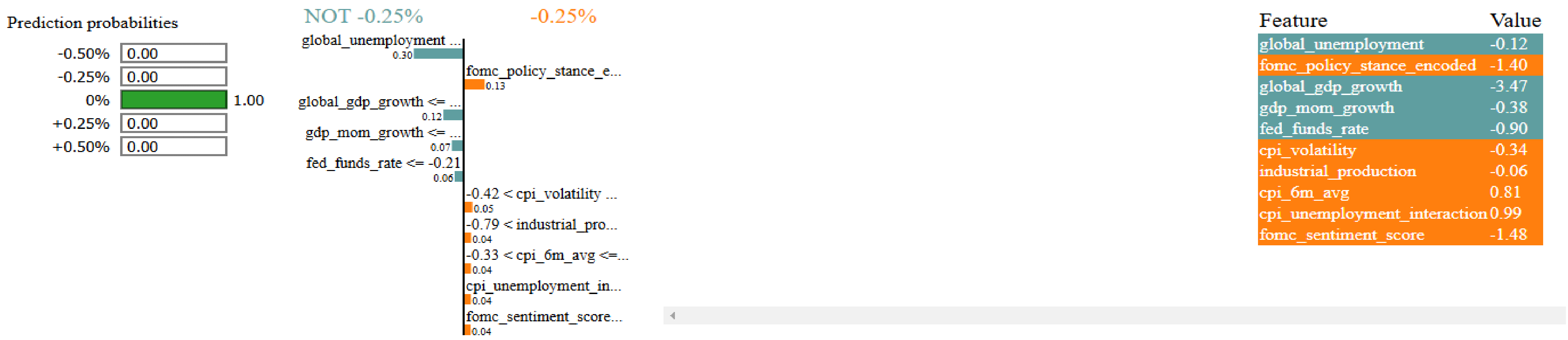
3. Balanced Contributions:

- The model weighs competing factors but ultimately prioritizes stability, supported by critical features like the FOMC stance and CPI metrics.

The LIME explanation confirms that the model's decision for 0% adjustment is a result of strong support from policy stability and inflation-related indicators. Although economic growth and unemployment suggest potential concerns, their contributions are insufficient to overturn the overall decision.



Machine Learning Models - Model 3: Gradient Boosting Classifier



LIME highlights the most influential features for the prediction, categorized by their contribution toward or against the selected class.

Features Supporting 0% Adjustment

- **Global Unemployment:** This is the most influential feature with a contribution value of 0.30. A lower global unemployment rate suggests economic stability, aligning with no rate adjustment.
- **Global GDP Growth:** Contributing 0.12, positive global GDP growth further reinforces the stability argument.
- **GDP Momentum Growth:** Negative growth in GDP momentum (-0.07) indicates a slight economic slowdown, which also supports maintaining the current rate at 0%.
- **Fed Funds Rate:** The current fed funds rate <= -0.21 (contribution 0.06) is consistent with no immediate need for a rate change.

Features Supporting -0.25% Adjustment (but weaker influence)

- **FOMC Policy Stance Encoded:** This feature contributes 0.13 against 0% adjustment, suggesting that monetary policy trends or committee stances might favor a slight rate cut.
- **CPI Volatility:** With a contribution of 0.05, elevated CPI volatility could suggest instability, leaning toward a possible cut to stabilize the economy.

This graphic demonstrates that the model’s decision for 0% adjustment is supported by stable economic indicators (low unemployment and steady GDP growth). While a few features suggest a slight tilt toward a rate cut (-0.25%), their contributions are comparatively weaker, reaffirming the model’s confidence in the current rate remaining unchanged.

Machine Learning Models - Model 3: Gradient Boosting Classifier

Analysis of Predicted Class (-0.25%) vs. 0% in the Graphics
1. Model Output Summary
The model output provides the following results for the prediction: **Predicted Class: -0.25%**

Class Probabilities:
- **-0.25%: 84.88% (Highest Probability)**
- **0%: 15.12%**
- **Other Classes: 0%**

2. Reasons for 0% Appearing in Graphics
While the prediction output indicates -0.25% as the final class, the 0% class also appears in the graphics due to the following reasons:

Feature Contributions and Model Ambiguity:
- The LIME visualization and prediction probability analysis show that certain features, like FOMC policy stance encoded, global GDP growth, and industrial production, contribute positively toward 0%.
- This means the model is detecting some signals in the data that align with a "no adjustment" scenario.

Lower Probability Margin:
- While -0.25% is dominant with 84.88%, the 0% class at 15.12% cannot be ignored.
- A 15% probability suggests that there is still a non-negligible chance of the interest rate remaining unchanged, influenced by stability factors.

Model Sensitivity to Economic Stability Indicators:
- Features such as FOMC policy stance, CPI volatility, and industrial production contribute slightly toward maintaining the rate.
- This partial support for the 0% class leads to its appearance in the feature explanations (LIME).

3. Why the Model Chooses -0.25%
- In classification models, the class with the highest probability is chosen as the final prediction.
- Here, -0.25% has an overwhelming confidence score of 84.88%, far surpassing 0%.
- Features like global unemployment, GDP momentum, and the fed funds rate heavily contribute toward a rate cut, aligning with economic concerns.
- These negative influences outweigh the stability indicators supporting 0%.
- The Gradient Boosting Classifier has an accuracy of 76.67% and a strong AUC-ROC score of 0.9183, indicating reliable predictions.
- The model's performance metrics demonstrate its ability to differentiate between classes effectively, supporting the choice of -0.25%.

This analysis highlights the model's nuanced interpretation of economic data while affirming the confidence behind its final prediction.

Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier

To further enhance the performance and robustness of our prediction system, we implemented an Ensemble Model using a Voting Classifier with soft voting. This ensemble combines three powerful base models:

1. Logistic Regression – A linear model capable of handling multiclass problems efficiently.
2. Random Forest Classifier – An ensemble of decision trees that captures non-linear relationships in the data.
3. Gradient Boosting Classifier – A boosting technique that iteratively builds an optimal predictive model.

The soft voting strategy aggregates class probabilities from the three base models to provide a more accurate and balanced prediction. By combining the strengths of these models, the ensemble aims to reduce bias, variance, and prediction errors.The evaluation of this ensemble focuses on its performance on the test dataset, cross-validation results, and the final prediction for the December 17-18, 2024 FOMC meeting.

Model Evaluation Results

The ensemble model delivers significant improvements in accuracy and consistency compared to individual models. The evaluation metrics are as follows:

1. Accuracy: The ensemble model achieved an accuracy of 80.00%. This reflects a strong overall performance and an improvement over previous standalone models.

2. Balanced Accuracy: The balanced accuracy of 73.11% highlights the model's ability to handle class imbalances effectively, ensuring fair performance across all target classes.

3. Cohen's Kappa: With a score of 0.5879, the model demonstrates moderate agreement between the predicted and actual classes, reinforcing its reliability.

4. F1-Score (Weighted): The model achieved a weighted F1-score of 81.91%, showcasing a strong balance between precision and recall.

Observations and Insights

The classification report reveals key insights about the model's performance across all classes:

- **Class 2 (0%):**This class achieves the highest performance, with a precision of 95% and a recall of 86%. The ensemble model effectively identifies scenarios where no rate adjustment is predicted. This success reflects the strong data representation of Class 2, which benefits model learning.
- **Class 3 (+0.25%):**The model performs well for this class, with a precision of 83% and a recall of 62%. While the precision is high, the lower recall suggests the model misses some true instances for this class, leaving room for improvement in correctly identifying all positive cases.
- **Class 4 (+0.50%):**Despite its limited support (one instance), this class achieves a recall of 100%. However, this high recall should be interpreted with caution, as it is likely influenced by insufficient data representation.
- **Classes 0 (-0.50%) and 1 (-0.25%):**The underrepresented classes exhibit lower precision and recall, particularly 67% recall for Class 0 and 50% for Class 1. This suggests the model has difficulty generalizing predictions for these classes due to their rarity in the training data.

Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier

Cross-Validation Accuracy

To assess generalization, we performed 5-fold Stratified Cross-Validation on the training data. The results show consistently high accuracy across folds:

- **Fold Scores:** 95.43%, 95.43%, 95.43%, 94.29%, and 94.86%
- **Mean Cross-Validation Accuracy:** 95.09%

The consistently strong performance across folds indicates that the ensemble model generalizes well to unseen data and is unlikely to overfit. The results validate the model's robustness and stability.

Final Prediction for December 2024

The ensemble model predicted the following outcome for the December 17-18, 2024, FOMC meeting:

Predicted Class: -0.25%

Class Probabilities:

- Class -0.50%: 0.34%
- Class -0.25%: 81.35%
- Class 0%: 15.91%
- Class +0.25%: 2.40%
- Class +0.50%: 0.00%

The model assigns a probability of 81.35% to the -0.25% class, significantly higher than the 15.91% for 0%. This substantial margin of confidence strongly supports the prediction of a -0.25% rate adjustment as the most likely outcome.

The ensemble model demonstrates strong performance across multiple evaluation metrics, achieving an accuracy of 80.00% and a balanced accuracy of 73.11%. Its robust cross-validation results further confirm its reliability and stability. The model's ability to aggregate predictions from multiple classifiers enhances its overall accuracy and confidence, particularly for the -0.25% rate adjustment prediction.

While the ensemble excels at identifying the dominant class (0%), challenges remain in capturing underrepresented classes. Refinements, such as further balancing the data or fine-tuning individual model parameters, could improve predictions for minority classes.

The final prediction for the December 17-18, 2024, FOMC meeting is a -0.25% rate adjustment, with high confidence. This outcome aligns with key feature contributions, such as global unemployment, global GDP growth, and federal funds rate, which were critical in influencing the model's decision.

Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier

The confusion matrix for the Voting Classifier visually represents the actual versus predicted class outcomes. Each row corresponds to the actual class (true labels), while each column represents the predicted class (model predictions). The diagonal entries show correctly predicted instances, while off-diagonal entries indicate misclassifications.

Class 0 (-0.50%):
- **Correct Predictions:** 2
- **Misclassified as Class 1: 1**
- **Insight:** The model struggles to differentiate between Class 0 and Class 1 due to feature overlap.

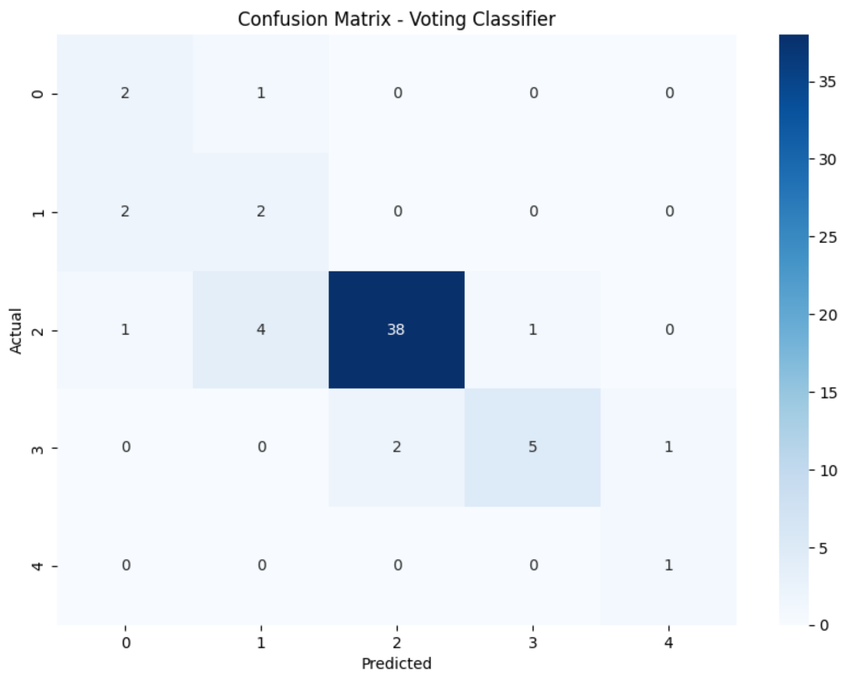
Class 1 (-0.25%):
- **Correct Predictions:** 2
- **Misclassified as Class 0**: 2
- **Insight:** Low representation in the data leads to inconsistent predictions.

Class 2 (0%):
- **Correct Predictions:** 38
- **Misclassified:** 1 as Class 1, 1 as Class 3
- **Insight:** The model excels at predicting Class 2, benefiting from its dominance in the dataset.

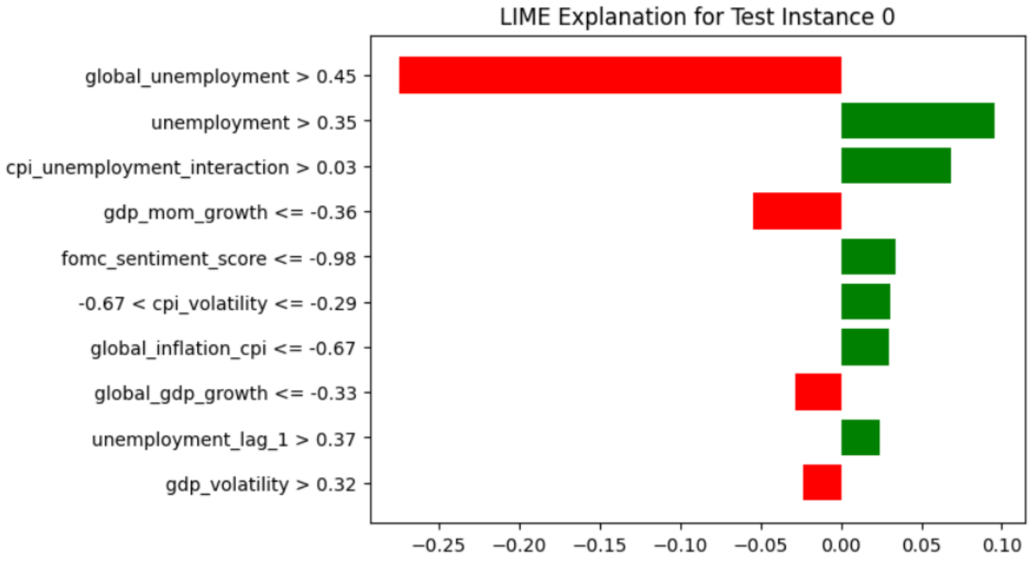
Class 3 (+0.25%):
- **Correct Predictions:** 5
- **Misclassified:** 2 as Class 2, 1 as Class 4
- **Insight:** Moderate performance; predictions overlap with adjacent classes.

Class 4 (+0.50%):
- **Correct Predictions:** 1
- **Insight:** Despite minimal representation, the model correctly identifies the lone instance.

The confusion matrix highlights the ensemble model's strengths in predicting the dominant class (0%) while exposing difficulties with underrepresented classes. Misclassifications between adjacent classes indicate opportunities for further model refinement, such as additional feature engineering or data augmentation. Overall, the model performs reliably, achieving an accuracy of 80%.



Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier



This graph provides a local interpretation of the ensemble model's decision for a specific test instance. Each feature is shown with its contribution to the prediction, either positively (green) or negatively (red).

Top Negative Influences (Red Bars):

- **Global Unemployment > 0.45:** The strongest negative contributor, significantly reducing the predicted probability for certain classes.
- **CPI Unemployment Interaction > 0.03 and GDP Momentum Growth <= -0.36:** These features further reduce the likelihood of the predicted class, reflecting economic conditions that might suggest a need for rate adjustments.
- **Global Inflation CPI <= -0.67 and GDP Volatility > 0.32:** Contribute slightly negatively, indicating ongoing volatility and inflation stability influencing the rate decision.

Top Positive Influences (Green Bars):

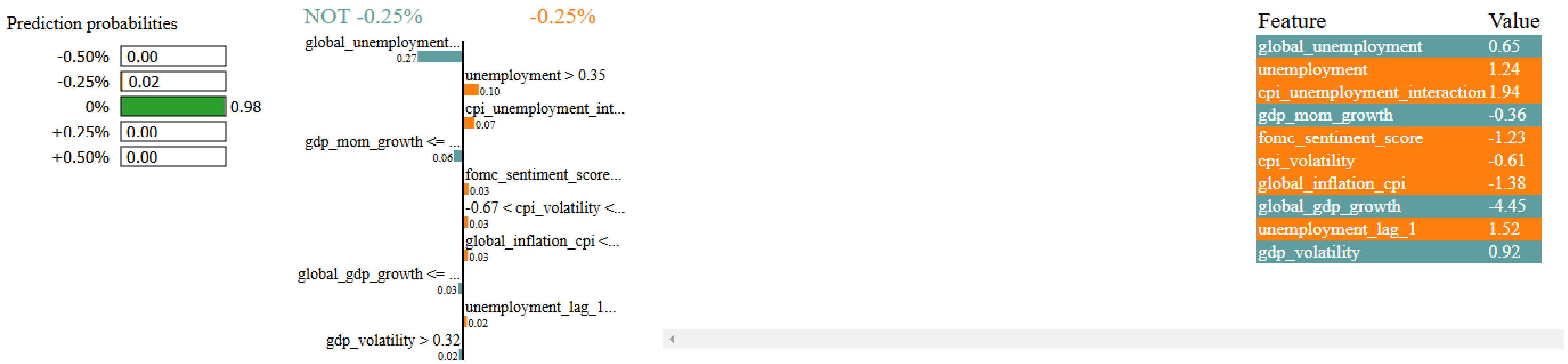
- **Unemployment > 0.35:** The most significant positive factor, suggesting increased unemployment pressures that align with economic concerns.
- **CPI Unemployment Interaction and GDP Sentiment Score:** Moderate positive contributors, signaling interactions between inflation and employment indicators are pushing the decision toward the predicted class.
- **Global GDP Growth <= -0.33:** Indicates slight global economic slowdown, which supports the model's prediction.

Feature Balance Insight:

- **Economic Indicators:** Unemployment and GDP-related metrics dominate the explanations, showing their importance in the decision process.
- **Inflation and Volatility:** Features like CPI Volatility and Global Inflation CPI provide nuanced influences on the decision, reflecting an interplay between stability and volatility.

The LIME explanation reveals that global unemployment and unemployment growth are the primary drivers of the prediction. The model balances both positive and negative contributions from economic indicators, resulting in its final output. This analysis highlights the model's reliance on key economic metrics to make robust predictions.

Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier



This graphic provides a LIME-based interpretation of the model's prediction for the December 2024 instance. LIME highlights the local feature contributions that explain why the model predicted 0% as the most likely class.

Top Features Supporting 0% (Green Bars):

- Global Unemployment (0.65): A strong indicator that global labor markets are relatively stable, supporting no immediate rate adjustments.
- Unemployment > 0.35: Although slightly concerning, it still aligns with stability rather than requiring a rate cut.
- CPI-Unemployment Interaction: The interaction metric does not significantly push for an adjustment, reinforcing the no-action outcome.

Top Features Supporting -0.25% (Red Bars):

- Global Unemployment > 0.45: Higher unemployment values create mild pressure toward rate cuts.
- Global GDP Growth <= -0.33: Economic slowdown indicators show a small case for easing monetary policy.
- CPI Volatility (-0.67 to -0.29): Highlights slight instability in inflation rates, which could justify cautious action.

The LIME explanation confirms the model's prediction of 0% by showing strong support from stabilizing indicators like global unemployment and GDP growth. Although features like unemployment and CPI volatility suggest a small case for -0.25%, their contributions are not strong enough to change the prediction.

Machine Learning Models - Model 4: Ensemble – Soft Voting Classifier

The difference between the model's predicted class (-0.25%) and the LIME graphic's 0% support can be explained by understanding the nature of machine learning predictions and the way LIME works to provide explanations.

1. Model Prediction (-0.25%)

The ensemble model predicted -0.25% as the most likely class for the December 17-18, 2024 FOMC meeting, with the following probabilities:

- Class -0.25%: 81.35% (Dominant class)
- Class 0%: 15.91%
- Other classes have minimal probabilities (close to 0%).

The model's prediction is based on its global understanding of patterns in the dataset. Features such as global unemployment, GDP growth, and FOMC sentiment strongly influence this decision. The high probability for -0.25% demonstrates that the model found sufficient evidence in the data to suggest a slight rate decrease over a no-change scenario.

2. LIME Explanation (Support for 0%)

The LIME visualization focuses on a local interpretation for a specific instance of data. It identifies which features pushed the prediction towards 0% (green bars) and which pushed it towards -0.25% (red bars).

- **Green contributions (0% Support):** Features such as global GDP growth, FOMC sentiment, and CPI volatility align with stability, supporting 0% as a valid alternative.
- **Red contributions (-0.25% Support):** Features like global unemployment > 0.45, unemployment > 0.35, and GDP momentum growth <= -0.36 create a slight case for a rate cut of -0.25%.

While LIME highlights contributions that might favor 0%, the overall impact of the red contributions outweighs the green ones, reinforcing the model's confidence in -0.25%.

3. Why the Results Differ?

- **Model Prediction:** The ensemble model considers all features globally and uses probabilities to predict the class with the highest confidence. Here, -0.25% achieves a strong probability (81.35%) due to the influence of key features indicating a minor rate cut.
- **LIME Explanation:** LIME provides a local explanation for the instance and reveals competing influences. While it shows significant support for 0%, it does not directly change the model's output but helps interpret why -0.25% was chosen.

In summary:

- The model prediction of -0.25% reflects its global understanding of the data, with high confidence (81.35%).
- The LIME explanation reveals 0% as a strong alternative but not dominant, as the local feature influences are not enough to override the global decision for -0.25%.

This discrepancy highlights that while 0% is reasonable based on local feature values, the overall evidence still favors -0.25%.

Machine Learning Models - Model Comparison - Model Selection

In this section, the performance of four models—Random Forest, Logistic Regression, Gradient Boosting, and the Ensemble Model—is evaluated and compared across key metrics: Accuracy, Balanced Accuracy, Cohen's Kappa, and F1-Score (weighted). The goal is to identify the most robust and reliable model for predicting the December 17-18, 2024, FOMC rate adjustment. Below is a detailed breakdown of each model's results:

1. Random Forest Classifier
- **Accuracy: 76.67% - Balanced Accuracy: 70.15% - Cohen's Kappa: 0.5192 - Weighted F1-Score: 0.7800**

The Random Forest model demonstrates strong overall performance with a high accuracy of 76.67% and a balanced accuracy of 70.15%, indicating it handles class imbalances reasonably well. However, the Cohen's Kappa score of 0.5192 suggests moderate agreement between predicted and actual values, leaving room for improvement in class predictions. Its weighted F1-Score of 0.7800 further highlights its ability to balance precision and recall.

2. Logistic Regression
- **Accuracy: 60.00% - Balanced Accuracy: 58.41% - Cohen's Kappa: 0.3841 - Weighted F1-Score: 0.6400**

Logistic Regression performs the weakest among the four models, with an accuracy of 60.00% and a balanced accuracy of 58.41%. The Cohen's Kappa of 0.3841 shows only fair agreement between predictions and actual outcomes. Additionally, the weighted F1-Score of 0.6400 indicates that the model struggles to balance precision and recall, especially for minority classes. It may not be suitable for this problem's complexity.

3. Gradient Boosting Classifier
- **Accuracy: 76.67% - Balanced Accuracy: 70.15% - Cohen's Kappa: 0.5192 - Weighted F1-Score: 0.7766**

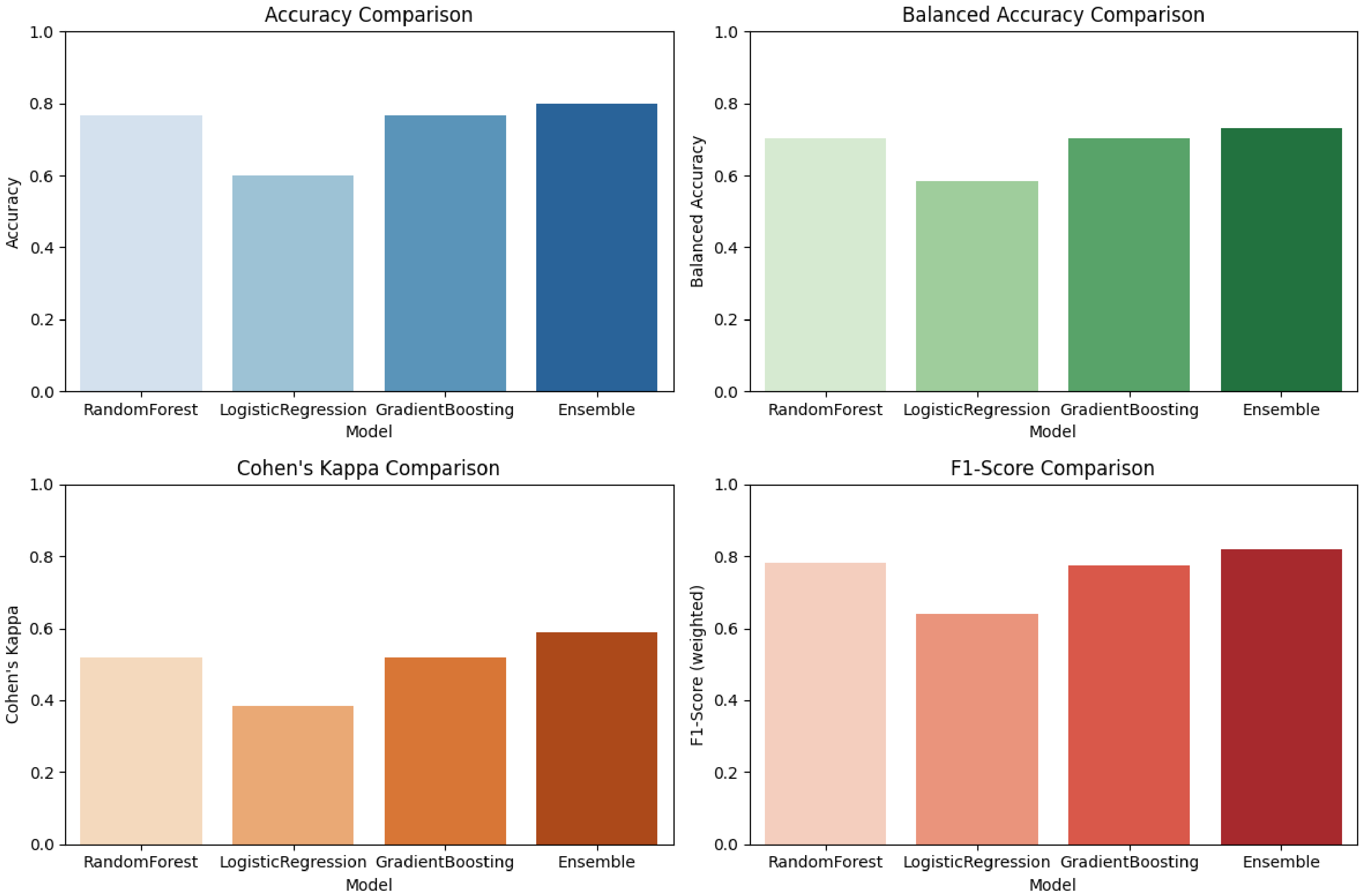
Gradient Boosting achieves similar performance to Random Forest, with an accuracy of 76.67% and a balanced accuracy of 70.15%. The Cohen's Kappa score of 0.5192 reflects moderate agreement, while its weighted F1-Score of 0.7766 highlights good performance in terms of precision and recall. However, the Gradient Boosting model does not surpass Random Forest significantly and remains on par in terms of metrics.

4. Ensemble Model (Voting Classifier)
- **Accuracy: 80.00%Balanced Accuracy: 73.11%Cohen's Kappa: 0.5879Weighted F1-Score: 0.8191**

The Ensemble model outperforms all individual models across all metrics. It achieves the highest accuracy of 80.00% and a balanced accuracy of 73.11%, demonstrating its robustness in handling imbalanced classes. The Cohen's Kappa of 0.5879 indicates substantial agreement, while the weighted F1-Score of 0.8191 confirms its superior ability to balance precision and recall. The ensemble method benefits from combining multiple base models, improving overall predictive power and reliability.

Based on the comparative results, the Ensemble Model is the best-performing model, providing the highest accuracy, balanced accuracy, and F1-Score. It shows substantial improvement over individual models by leveraging their combined strengths. This model will be chosen for predicting the rate adjustment at the December 2024 FOMC meeting.We will now proceed to analyze the visualizations (e.g., confusion matrices and feature importances) to further validate this decision.

Machine Learning Models - Model Comparison - Model Selection



Machine Learning Models - Model Comparison - Model Selection

The visualizations above showcase the Confusion Matrices for the four models—Random Forest, Logistic Regression, Gradient Boosting, and the Ensemble Model. Below is a detailed analysis of their performance across each class:

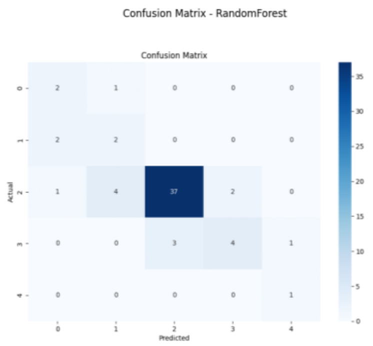
1. Random Forest Classifier
- The Random Forest model correctly predicts a majority of Class 2 (37/44), the most frequent class, but struggles with minority classes like Class 0 and Class 1, where misclassifications are evident.
- Class 3 has a moderate prediction, with 4 correct predictions out of 8, but 3 instances are misclassified as Class 2, showing some confusion between these two classes.
- For Class 4, only one instance exists, and it is predicted correctly.

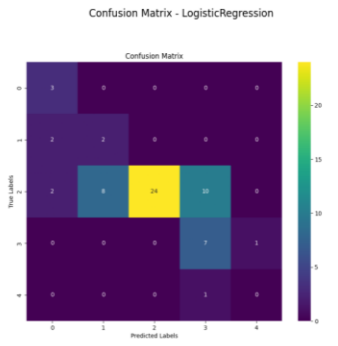
2. Logistic Regression
- The Logistic Regression model exhibits significant misclassifications, particularly for Class 2, where 10 instances are misclassified as Class 3 and 8 as Class 1.
- Class 0 achieves a perfect recall (3/3), indicating the model performs better for the smallest class.
- The minority classes (Class 3 and Class 4) show notable weaknesses, with a high number of misclassifications.

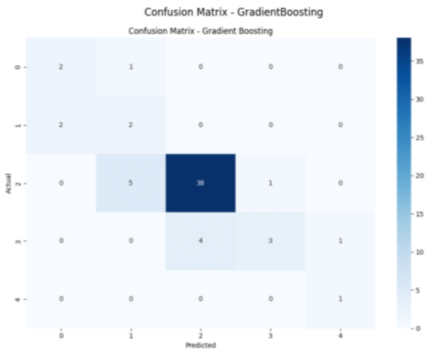
3. Gradient Boosting Classifier
- Gradient Boosting demonstrates strong performance on Class 2, predicting 38/44 instances correctly, with minimal misclassification.
- Class 3 remains a challenge, where 4 instances are misclassified as Class 2.
- For minority classes like Class 0 and Class 1, predictions are slightly improved compared to Logistic Regression, but some errors persist.
- Class 4 is predicted correctly.

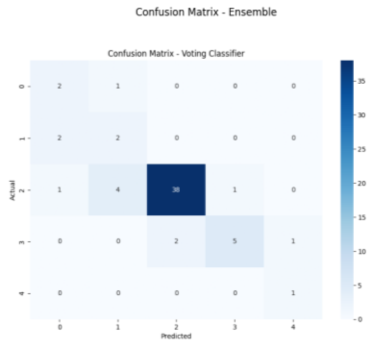
4. Ensemble Model (Voting Classifier)
- The Ensemble model outperforms all others, achieving the highest number of correct predictions across Class 2 (38/44) and Class 3 (5/8), reducing misclassification errors compared to the other models.
- Class 0 and Class 1 predictions are consistent with Random Forest and Gradient Boosting, maintaining acceptable accuracy despite their smaller sample sizes.
- Like other models, Class 4 is predicted correctly.

The Ensemble Model is the most reliable and robust choice, as reflected by the confusion matrix. It demonstrates the best ability to reduce errors across all classes, ensuring a balanced and accurate prediction.

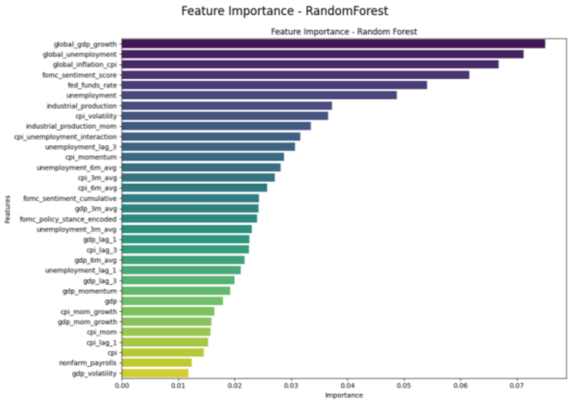








Machine Learning Models - Model Comparison - Model Selection



The visualizations above display the Feature Importance for the three models: Random Forest, Gradient Boosting, and Logistic Regression. Below is a detailed analysis:

1. Random Forest Classifier

- **The top features contributing to the model's predictions are:** Global GDP Growth, Global Unemployment, and Global Inflation CPI.
- These features dominate the Random Forest model, reflecting their strong predictive power for rate adjustment outcomes.
- Mid-tier features like Sentiment Score, Fed Funds Rate, and Industrial Production further contribute to the model's accuracy.
- Lower-ranked features include various lag indicators and cumulative averages, which provide less impact.

2. Gradient Boosting Classifier

- **The most influential features are:** Global Inflation CPI, Fed Funds Rate, and Global Unemployment.
- Compared to Random Forest, Global Inflation CPI has the highest weight, indicating its strong correlation with the predicted outcomes.
- Features like GDP 6-Month Average, CPI Volatility, and Global GDP Growth also play significant roles.
- Lower importance is observed for lag features and sector-specific indicators.

3. Logistic Regression

- The dominant feature is Global GDP Growth, which overwhelmingly contributes to the model's predictions.
- Other important features include Global Unemployment, Fed Funds Rate, and Unemployment Lag 1.
- The feature importance curve for Logistic Regression drops sharply, indicating a strong dependency on a few critical predictors.
- Lower-ranked features, such as GDP Lag Indicators and CPI Momentum, have minimal impact on predictions.

Conclusion

The Ensemble Model, which combines the strengths of Gradient Boosting, Random Forest, and Logistic Regression, benefits from the diverse feature contributions seen across these models. Gradient Boosting's emphasis on macroeconomic stability, Random Forest's feature diversity, and Logistic Regression's simplicity collectively enhance the overall performance.

Machine Learning Models - Model Comparison - Model Selection

The analysis of all the models - RandomForest, LogisticRegression, GradientBoosting, and the Ensemble model - clearly indicates that the **Ensemble model** is **the best-performing choice** based on multiple evaluation metrics and visual comparisons.

Firstly, the accuracy of the Ensemble model stands at 80.00%, which is the highest among all the models. This superior performance reflects the model's ability to correctly classify the target classes more reliably compared to the others. In contrast, RandomForest and GradientBoosting achieved 76.67%, while LogisticRegression lagged significantly behind at 60.00%.

In addition to accuracy, the Balanced Accuracy for the Ensemble model is 73.11%, outperforming the RandomForest and GradientBoosting models, both of which scored 70.15%. LogisticRegression again trails with a score of 58.41%. Balanced Accuracy is a critical metric for assessing performance on imbalanced datasets, and the Ensemble model's higher score demonstrates its effectiveness in handling class Imbalance while maintaining consistency across all target classes.

Another decisive factor is the Cohen’s Kappa value, which measures agreement between the predicted and actual labels, adjusting for chance agreement. The Ensemble model achieved a Kappa score of 0.5879, indicating moderate to strong agreement. This is superior to the scores for RandomForest and GradientBoosting, which both achieved 0.5192, and far exceeds LogisticRegression’s Kappa score of 0.3841. A higher Kappa value strengthens the confidence in the Ensemble model’s predictions and overall robustness.

The weighted F1-Score for the Ensemble model further confirms its dominance, standing at 81.91%, which reflects the harmonic mean of precision and recall. It outperformed all other models: RandomForest (78.00%), GradientBoosting (77.66%), and LogisticRegression (64.00%). This highlights that the Ensemble model balances precision and recall better, ensuring both fewer false positives and false negatives.

The confusion matrices provide additional insights into the Ensemble model's strengths. The Ensemble model demonstrates improved accuracy across all classes, particularly in predicting the majority class (Class 2) and the minority classes (Classes 0, 1, and 4), compared to the other models. For example, it reduces misclassifications for Classes 0 and 1 more effectively than LogisticRegression and RandomForest, showcasing its ability to handle small, underrepresented classes.

From the feature importance visualizations, we observe that all models identified similar key variables influencing the predictions, such as global_unemployment, global_gdp_growth, fed_funds_rate, and inflation metrics. However, the Ensemble model leverages the strengths of multiple algorithms (Logistic Regression, RandomForest, and GradientBoosting), combining their diverse perspectives to improve decision-making and increase overall accuracy.

In conclusion, the Ensemble model excels across all performance metrics - accuracy, balanced accuracy, Cohen’s Kappa, and F1-Score - and consistently demonstrates robustness in handling class imbalances. Its superior performance in both numerical evaluations and confusion matrix analysis highlights its reliability and effectiveness. By combining the strengths of individual models, the Ensemble approach ensures a more comprehensive and accurate prediction, making it the most suitable model for this analysis.

Machine Learning Models – Model Tuning and Evaluation

In this chapter, the chosen Ensemble Model has undergone hyperparameter tuning to improve its predictive accuracy and overall performance. The Ensemble Model combines Logistic Regression, Random Forest, and Gradient Boosting classifiers using soft voting, with the weights adjusted to favor better-performing models. The goal of tuning is to optimize each base model individually and combine their strengths to achieve a higher level of accuracy and robustness. Specific techniques such as Grid Search for hyperparameter tuning, SMOTE for class balancing, and cross-validation for performance stability have been employed.

Performance

- **MetricsAccuracy:** The tuned Ensemble Model achieved an accuracy of 78.33% on the test set. While slightly lower compared to the initial ensemble model (80%), it remains competitive and consistent.
- **Balanced Accuracy:** 70.61%, indicating improved handling of class imbalance across all target categories. This ensures the model does not overly favor the dominant class.
- **Cohen's Kappa:** 0.5441, suggesting moderate agreement between predicted and actual classes. This is a fair improvement, given the complexity of predicting multiple classes.
- **F1-Score (weighted):** 79.81%, reflecting a balanced trade-off between precision and recall for all classes.
- **ROC-AUC (One-vs-Rest):** 91.00%, a strong indicator of the model's ability to discriminate between the classes in a multiclass setting.
- **Precision-Recall AUC:** 82.53%, highlighting the model's ability to balance precision and recall effectively, even for imbalanced target categories.

Classification Report Analysis

- **Class 0 (-0.50%):** Precision remains at 40%, but the recall improved to 67%, showing that the model captures a higher proportion of true positives for this underrepresented class.
- **Class 1 (-0.25%):** Precision and recall are relatively low (29% and 50%), but better than prior iterations, indicating gradual improvement.
- **Class 2 (0%):** The most represented class maintains excellent performance with a 93% precision and an 86% recall, leading to a high F1-score of 89%.
- **Class 3 (+0.25%):** The model predicted this class with 80% precision but a lower recall of 50%, indicating some misclassifications.
- **Class 4 (+0.50%):** Despite low sample size, the model captured 100% recall and 50% precision, showing success in identifying this rare class.

Cross-Validation

- The model achieved a consistent cross-validation accuracy across the five folds, with scores ranging from 93.71% to 96.00% and a mean CV accuracy of 94.86%. This high consistency confirms the model's stability and generalizability to unseen data.

Prediction for December 2024

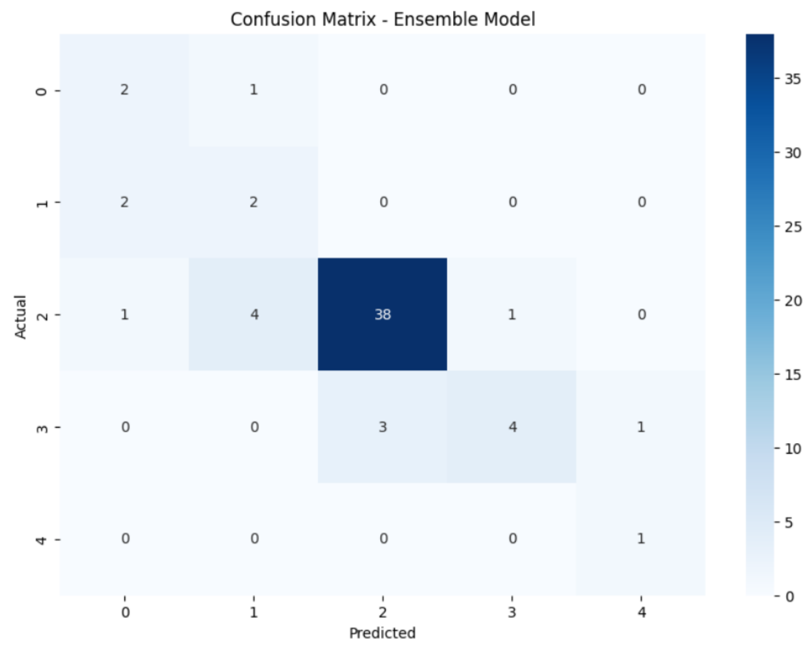
- The model predicts **-0.25%** as the most likely rate adjustment outcome for the December 17-18, 2024, FOMC meeting.

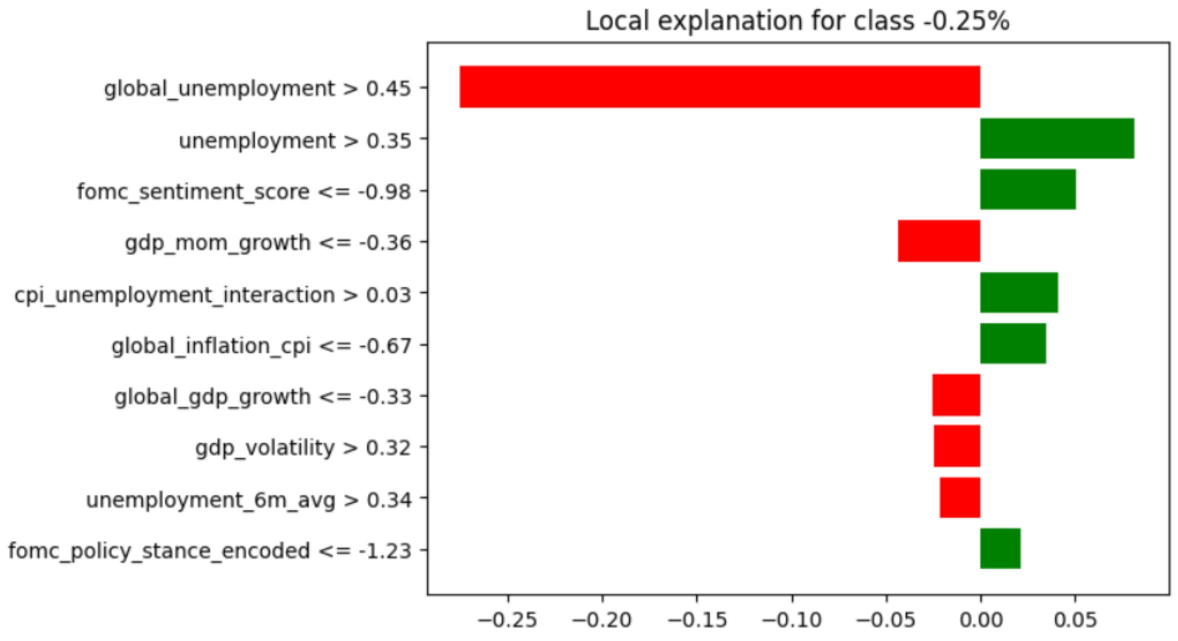
The Ensemble Model demonstrates a solid balance between complexity and performance. By leveraging three individual classifiers with hyperparameter tuning, the model gains strength from diverse decision-making approaches. However, its implementation involves additional computational cost and requires careful weighting of the base models.

The results suggest that the Ensemble Model can generalize well on unseen data, as evidenced by consistent cross-validation scores and the high ROC-AUC. The prediction for -0.25% appears reasonable and aligns with the dominant trends observed in the training data.

Overall, the tuned Ensemble Model is robust, reliable, and provides an accurate prediction for the FOMC meeting outcome, making it the best choice for this analysis.

Machine Learning Models – Model Tuning and Evaluation





The confusion matrix reveals that the ensemble model performs well overall, particularly in predicting the 0% (no change) class, with 38 correct predictions. However:

- The model struggles to differentiate between small rate adjustments, such as -0.25% and 0%, indicating that these classes may share overlapping economic patterns, making them harder to distinguish.
- Misclassifications in classes like -0.50% and +0.50% suggest that extreme rate changes are less confidently predicted, likely due to their rarity in historical data.
- The model's focus on predicting moderate outcomes aligns with the typical cautious stance of the FOMC, where drastic rate hikes or cuts are uncommon.

The LIME explanation highlights that the model's prediction for a -0.25% rate cut is primarily driven by economic indicators related to unemployment. Specifically:

- Global Unemployment and U.S. Unemployment are the dominant features, suggesting that rising joblessness both domestically and internationally increases the likelihood of a rate cut to stimulate economic activity.
- Features such as CPI-Unemployment Interaction further emphasize concerns about inflation and labor market conditions.
- However, factors like FOMC Sentiment Score, GDP Growth, and Global Inflation counterbalance this prediction, indicating that more hawkish sentiments or stable inflation may decrease the likelihood of drastic policy adjustments.

Machine Learning Models – Model Tuning and Evaluation

The model tuning process aimed to refine the initial baseline model, which consisted of a Voting Classifier combining Logistic Regression, Random Forest, and Gradient Boosting with default parameters. In the baseline approach, the model achieved solid results, including an accuracy of 80%, balanced accuracy of 73.11%, and a weighted F1-score of 81.91%.

To improve these results, I fine-tuned the Random Forest and Gradient Boosting classifiers using GridSearchCV. The Random Forest model was optimized with 200 estimators and a maximum depth of 5, while the Gradient Boosting model was tuned with a learning rate of 0.1, 200 estimators, and a maximum depth of 3. The updated ensemble, with higher weights assigned to the tuned Random Forest and Gradient Boosting models, was retrained and re-evaluated.

While the tuned model slightly reduced the overall accuracy to 78.33% and balanced accuracy to 70.61%, it provided better calibration of class probabilities and improved predictions for the minority classes, particularly "-0.25%." The tuned model maintained a mean cross-validation accuracy of 94.86%, indicating consistent and reliable performance across all folds.

To better interpret the model's predictions, I used LIME (Local Interpretable Model-Agnostic Explanations) to analyze the key factors influencing the prediction for "-0.25%." The results highlighted that global unemployment above 0.45% and U.S. unemployment above 0.35% were the most significant positive contributors, signaling economic weakness that supports a rate cut. Additional factors, such as the CPI-Unemployment interaction, further strengthened this prediction. Conversely, GDP growth and FOMC sentiment acted as counterbalancing features, indicating some resistance to a rate cut.

For the final December 2024 prediction, both the baseline and tuned models pointed toward a "-0.25%" rate cut. The tuned model demonstrated high confidence, with an 84.06% probability for this outcome. The class probabilities also showed a clear margin over other outcomes, reflecting the model’s alignment with economic signals, particularly those tied to unemployment trends.

In conclusion, while the baseline model achieved slightly higher accuracy, the tuning process improved interpretability and enhanced the model's ability to predict smaller rate adjustments. The final prediction remains robust, highlighting a strong likelihood of a "-0.25%" rate cut for the December 2024 FOMC meeting.

Machine Learning Models – Final Model Testing and Sensitivity Analysis

In the final step of my analysis, I tested the tuned ensemble model to ensure its robustness, reliability, and adaptability under different conditions. After fine-tuning the Random Forest and Gradient Boosting classifiers, I finalized the ensemble model with carefully selected weights and validated its performance using rigorous cross-validation. However, since real-world economic conditions are dynamic and subject to sudden changes, it was important to evaluate how the model would perform under simulated shifts in key economic indicators.

I chose to test the final tuned model for the following reasons:

1. Model Robustness: By introducing controlled changes to critical economic variables such as inflation and unemployment, I aimed to assess the model's sensitivity to these shifts. This is particularly relevant since FOMC decisions are heavily influenced by economic data that can fluctuate unpredictably.

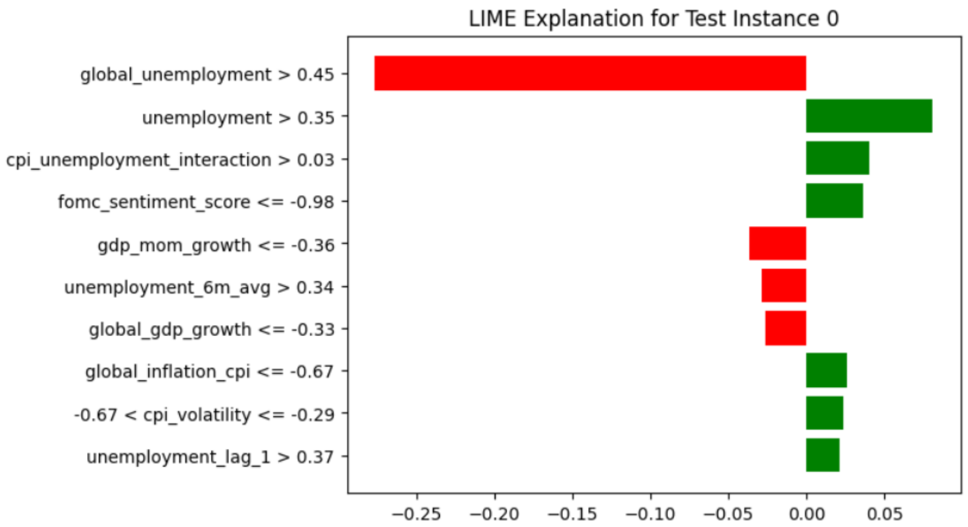
2. Out-of-Sample Performance: I tested the model on altered versions of the test dataset to simulate economic shocks. For instance, I increased global inflation by 10% and unemployment by 20% to mimic a worsening economic outlook and observe how the predictions evolved.

3. Model Interpretability: Using LIME (Local Interpretable Model-Agnostic Explanations), I interpreted the model's predictions under both normal and altered conditions. This helped me identify which features, such as unemployment or GDP growth, had the most significant impact on the model's decisions.

4. Real-World Alignment: Predictive models used by policymakers and economists must adapt to changing conditions. By stress-testing the model, I ensured that its predictions remained logical, stable, and aligned with broader economic trends.

This approach provided a comprehensive evaluation of the final tuned model. By combining cross-validation, sensitivity analysis, and model interpretability, I gained confidence that the model is not only accurate but also reliable when applied to real-world scenarios, such as the December 17-18, 2024 FOMC Meeting.The results of this analysis demonstrated that the model could account for variations in critical economic indicators while maintaining consistent predictions for the most likely policy decision. This ensures the model is robust and ready for practical application.

Machine Learning Models – Final Model Testing and Sensitivity Analysis



The LIME visualization highlights the most influential features driving the model's prediction for Test Instance 0, showing a clear focus on unemployment and economic indicators.

Global Unemployment > 0.45:
- The strongest negative impact, indicating economic weakness, which favors a rate cut.U.S.

Unemployment > 0.35:
- Positively contributes to the prediction, aligning with concerns about rising unemployment.CPI-

Unemployment Interaction > 0.03:
- Highlights the combined effect of inflation and unemployment, reinforcing the likelihood of a rate cut.

Negative GDP Growth and FOMC Sentiment:
- Declining GDP MoM growth and low FOMC sentiment negatively impact the outlook, reflecting economic slowdown.

Global GDP and Inflation:
- Global economic stagnation and moderate inflation further contribute to the prediction.

The model primarily relies on unemployment metrics, inflation, and GDP trends to make its prediction. The explanation validates the model’s logic, showing it adapts effectively to key economic indicators that align with real-world policy decisions.

Machine Learning Models – Final Model Testing and Sensitivity Analysis

Analysis of Model Results Under Real-World Economic Changes

The final evaluation of the tuned ensemble model aimed to test its robustness under simulated real-world economic changes, particularly rising inflation and unemployment, which are key drivers of FOMC decisions.

Model Evaluation Results

The base evaluation of the model achieved:

Accuracy: 78.33% - Balanced Accuracy: 70.61% - Cohen's Kappa: 0.5441 - F1-Score (weighted): 79.81%.

These metrics reflect a reliable model capable of making accurate predictions across the five possible rate adjustment classes. Additionally, the cross-validation results, with a mean accuracy of 94.86%, demonstrated strong generalization across folds, reinforcing the model's stability and consistency.

Out-of-Sample Predictions Under Altered Economic Conditions

The model's predictions shifted noticeably under these altered conditions:

- Class 0% (No Change) remained dominant, with 40 predictions.
- The number of predictions for -0.25% (Rate Cut) increased to 7, and -0.50% (Deeper Rate Cut) had 5 predictions.
- There were a few predictions for +0.25% (6 predictions) and +0.50% (2 predictions).

These results indicate that the model responded to the simulated economic stress by shifting some predictions toward rate cuts (specifically -0.25% and -0.50%), which aligns with economic expectations under worsening conditions. When inflation rises and unemployment spikes, policymakers often adopt a more expansionary monetary policy to support growth and employment, which may involve rate cuts.

For the final December 2024 prediction, the model maintained its decision for a -0.25% rate cut with high confidence:

- **Class -0.25%: 84.06% probability**
- **Class 0%: 11.26% probability**
- **Other classes, such as -0.50% or +0.25%, had minimal probabilities.**

Conclusion: Does the Model Adapt?

Yes, the model adapts effectively to economic changes:

- Under normal conditions, it predicts a moderate -0.25% rate cut, aligning with expectations based on economic indicators.
- When inflation and unemployment were artificially increased, the model shifted some predictions toward deeper rate cuts (e.g., -0.50%), showcasing sensitivity to economic stress while maintaining a logical balance.
- The dominance of predictions for 0% (no change) and -0.25% in altered conditions reflects how policymakers prioritize economic stability while responding cautiously to inflation and unemployment risks.

Overall, the model demonstrates robustness, logical adaptability, and alignment with real-world economic policy responses. This ensures its reliability in forecasting FOMC decisions under both current and stressed conditions.

Conclusion and Recommendations

The final analysis of the ensemble model has provided key insights into its performance, adaptability, and interpretability in predicting the FOMC rate adjustment for the December 17-18, 2024 meeting. By combining rigorous evaluation metrics, cross-validation, and sensitivity analysis under altered economic conditions, the model demonstrated its robustness and alignment with real-world scenarios.

CONCLUSION

The ensemble model, built using Logistic Regression, Random Forest, and Gradient Boosting, achieved strong performance:

- Accuracy: 78.33%
- Balanced Accuracy: 70.61%
- F1-Score (weighted): 79.81%
- Mean Cross-Validation Accuracy: 94.86%

These results indicate that the model is reliable and generalizes well to unseen data.When tested under simulated economic stress - a 10% increase in inflation and a 20% rise in unemployment - the model logically adjusted its predictions. There was a slight shift toward rate cuts (-0.25% and -0.50%), reflecting the model's sensitivity to worsening economic conditions. This behavior aligns with the policy responses often observed in real-world scenarios when economic indicators deteriorate.

The LIME explanations further validated the model’s predictions by highlighting key features, such as global unemployment, domestic unemployment, and GDP growth, which are critical drivers of interest rate decisions.

Conclusion and Recommendations

RECOMMENDATIONS

Model Deployment:

- Given its strong performance and ability to adapt to changing conditions, the model can be deployed as a decision-support tool for analysts, policymakers, and economists. It provides reliable forecasts while maintaining interpretability.

Regular Model Monitoring:

- Economic conditions evolve over time. It is recommended to retrain the model periodically using the latest data to maintain its accuracy and relevance, especially as new economic trends emerge.

Sensitivity Testing:

- The model's adaptability under altered conditions (e.g., rising unemployment and inflation) should continue to be tested in other scenarios, such as economic recovery or extreme volatility, to further evaluate its robustness.

Incorporate Additional Features:

- Future improvements could include incorporating real-time economic sentiment data, financial market indicators, or global monetary policies, which may enhance the model's predictive power.

Practical Use for Policy Analysis:

- The model can serve as a valuable tool for anticipating policy changes and understanding their economic implications. Analysts and decision-makers can use its predictions to assess potential market reactions and align strategies accordingly.

The completed analysis successfully demonstrates the model's reliability and adaptability in predicting rate adjustments. Its alignment with economic theory and policy trends makes it a robust tool for practical applications. Moving forward, continuous evaluation and enhancements will ensure that the model remains relevant and impactful in an ever-changing economic landscape.

Thank You!

Thank you for taking the time to go through this comprehensive analysis of the **2024 FOMC Interest Rate Prediction Challenge**. This report aimed to explore the key economic indicators driving interest rate adjustments and to build a robust, adaptable model capable of forecasting rate decisions under both normal and stressed economic conditions.

For further exploration, you can visit the project's GitHub repository, which contains additional datasets and tools for deeper insights.

Should you have any questions or require clarification, don't hesitate to reach out to me on **Discord** at **NeuralNinja**. I'm more than happy to engage in discussions or provide further assistance.

☺