Predicting Federal Reserve Interest Rates Using Machine Learning and Sentiment Analysis

Abstract

The Federal Reserve's interest rate decisions significantly influence macroeconomic stability, affecting the financial markets, investments, and household finances. Traditionally, interest rate decisions have been made by analyzing certain economic indicators like the unemployment rate, inflation rate, and GDP. However, in recent years the traditional models have not been considered sufficient and enhanced to capture the fed decision in the interest rate policies. So, to increase the accuracy and interpretability of future economic conditions specifically with interest rates, the combination of sentiment analysis of unstructured textual data such as Federal Reserve economic reports and members' speeches and meeting minutes, and traditional numerical data analysis would help to enhance the accuracy of the predictions. This research proposes a hybrid machine learning framework integrating both textual and numerical data to predict Federal Reserve interest rate decisions. Separate pipelines will preprocess and analyze the numerical and textual data using machine learning models (such as Random Forest, Gradient Boosting, and BERT). The outputs from these two pipelines will be combined through ensemble modeling techniques to improve predictive accuracy. This innovative approach not only enhances the understanding of interest rate decisions but also provides valuable insights for policymakers, investors, and the public, ensuring a comprehensive analysis of economic trends.

Keywords

Federal Reserve, Interest Rate Prediction, Machine Learning, Sentiment analysis, Economic Indicators, Fed Policy, Economic News and Report Analysis, Ensemble Techniques

Introduction

The Federal Reserve's interest rate decisions have been a crucial tool for macroeconomic stability, impacting a broad spectrum of financial and economic activities, from investments to household finances. Historically, interest rate decisions have been guided by quantitative economic indicators such as the ten-year bond rate, inflation rate, unemployment rate, and market indices [1]. However, recent research has suggested that the increasing availability of unstructured textual data like economic reports, news, and articles can be used to capture economically meaningful information [11]. Text mining techniques, such as sentiment analysis, allow researchers and policymakers to extract valuable information from unstructured text, providing a deeper understanding of underlying economic trends and sentiment. For example, the words and language that Federal Reserve members used during the meetings and speeches might signal or give clues for future policy decisions, and interpreting these subtle cues can complement the traditional economic indicators in the decision-making process [10].

This research seeks to address gaps in the current literature by expanding to include both qualitative and quantitative data for more accurate predictions of Federal Reserve policies and decisions due to which the policymakers, investors, and the common public can be aware of the future risks and conditions.

A. Benefits of Study

The benefits of this study will be significant in the economic and financial areas. For policymakers, it will provide an innovative approach to refine monetary policy through a better understanding of the factors driving interest rate decisions. Financial institutions and investors will get predictive insights that can guide them with better investment and risk mitigation strategies associated with sudden policy changes. The public, in turn, will benefit from increased transparency and a deeper understanding of the economic environment. This study also contributes to the academic literature by addressing the existing gap in models that often analyze numerical and textual data in isolation, instead proposing an ensemble approach that reflects the complexity of modern economic conditions.

B. Research Questions

This research aims to answer the following questions:

- How can machine learning models improve the prediction of Federal Reserve interest rate decisions using key economic indicators (such as inflation, GDP, Bond yields, Consumer Price Index (CPI), Producer Price Index (PPI), Job Openings, and Labor Turnover Survey (JOLTS), unemployment rate, and market indices (S&P 500, NASDAQ and Volatility Index (VIX))?
- What role does sentiment analysis of Fed members' speeches and meetings, economic news, reports and articles play in understanding interest rate decisions?
- Can combining selected economic indicators with sentiment analysis improve the predictive accuracy of interest rate decision models, and how effective is this integration?

C. Scope of the Project

This research focuses on building a machine learning framework that integrates numerical economic indicators with textual sentiment analysis for predicting Federal Reserve interest rate decisions. The study will investigate key economic indicators, such as inflation, GDP, Bond yields, Consumer Price Index (CPI), Producer Price Index (PPI), Job Openings and Labor Turnover Survey (JOLTS), unemployment rate, and market indices, alongside textual data from economic news, reports, and articles, Federal Reserve members' speeches and meeting reports. By combining these data sources, the study aims to develop an ensemble approach that utilizes the strengths of both numerical and textual analysis in predicting interest rate decisions such as whether rates will be increased, decreased by how many points, or held steady. However, the research will not extend to examine the broader economic consequences of these decisions, such as their effects on inflation, employment, or economic growth, nor will it explore other Federal Reserve policies like quantitative easing or asset purchasing programs.

While conducting this research, we might face the challenges of acquiring real-time data, consistent textual data for sentiment analysis, and relying on historical data that may not be fully able to capture present and future dynamics. By addressing these limitations and challenges, this research aims to represent a significant step forward in understanding the complex factors influencing Federal Reserve interest rate decisions.

Literature Review

Historical Insights into Federal Reserve Policies

Miron (1986) investigates the connections between financial panics, seasonal fluctuations in nominal interest rates, and the establishment of the Federal Reserve (Fed) in 1914 [9]. The study evaluates pre-Federal Reserve conditions, where seasonal fluctuations in loan demand created instability, often concluding in widespread banking crises. Miron states that the establishment of the Federal Reserve shifted the paradigm of financial markets and conditions, as open market operations stabilized interest rate volatility, significantly mitigating the frequency of financial panics.

Based on historical data, Miron further illustrates how policy innovations in the early 20th century minimized risks. He argues that the Federal Reserve's ability to anticipate market demand for liquidity played a significant role in economic recovery post-crises. However, the paper also talks about the Fed's occasional missteps, such as delayed responses to emerging economic threats, which worsened downturns during the Great Depression.

Miron also emphasizes that financial panics had real, negative impacts on the economy, citing evidence of lower average GNP growth, higher growth volatility, and longer business cycles during panic years. The reduction in these negative outcomes following the Fed's establishment suggests that its policies substantially benefited the overall economy.

In the end, Miron concludes that the foundation of the Fed has helped minimize the fluctuations of interest rates and also the financial markets and economic conditions.

Role of Interest Rate

Benjamin (2020) talks about the detailed role of interest rates in shaping economic activities and financial markets [6]. He highlights that interest rate influences the key aspects of macroeconomics such as consumption, investment, inflation, and exchange rates.

Benjamin (2020) illustrates that interest rates affect borrowing and spending behaviors, directly impacting the supply and demand chain. For instance, an increase in interest rate tends to lower consumer spending and investment, while a decrease in interest rate stimulates them.

The paper emphasizes the dual role of interest rates as both a tool for monetary policy and a signal of economic conditions. The Federal Reserve manipulates the interest rates to gain stabilization of the economy and minimization of inflation and unemployment rate.

Furthermore, the paper talks about the interconnection of the interest rate globally. It talks about how changes in interest rates in major nations like the United States, affect the capital flows, exchange rates, and monetary policies in other countries. This demonstrates the importance of interest rates in stabilizing or disrupting the global economy.

Economic Indicators and Interest Rate

Zakhidov (2023) provides insights into the economic indicators, their analysis, and the role of the Federal Reserve in stabilizing the interest rates [12]. Zakhidov talks about the various aspects of economic activities, ranging from GDP growth, unemployment rates, and inflation figures to consumer spending patterns. Economic indicators like these could serve as barometers of economic health, providing analysts, policymakers, and decision-makers with vital information for strategic planning and risk management.

The Federal Reserve of the United States plays an important role in setting the interest rates that directly impact economic activity. And the economic activities and numbers do directly impact the decisions that are made by the Fed for interest rate decisions. The process and cycles are correlated to each other.

Furthermore, Zakhidov illustrates the example of Uzbekistan's economy to provide and demonstrate the relationship among the economic indicators like GDP, inflation, investor and business sentiment analysis, financial markets, and interest rates. He mentions how an increase in GDP correlates with performance in stock market indices and interest rate decisions.

Zakhidov offers Machine learning techniques that help to analyze the complex relationships between economic indicators and Federal Reserve interest rate decisions. However, Zakhidov has not explicitly mentioned the specific machine learning algorithm to train the model on historical data to identify patterns and make predictions about future economic outcomes. He includes, that we can train the model on a dataset of historical economic indicators and Federal Reserve interest rate decisions and use it to predict future interest rate decisions based on projected economic conditions.

In conclusion, Zakhidov highlights that building the model and analyzing the historical data and patterns unlocks and ensures investors, businesses, and policymakers and helps them make decisions that significantly minimize the risk and instability.

Machine Learning Enhancements in Financial Forecasting

Kiley (2020) talks about the different Machine learning techniques that can be used to build a robust model that can improve the financial condition indices (FCI) to predict economic activity (specifically the unemployment rate) and interest rates [8]. Kiley argues that traditional FCIs often rely on linear relationships between economic indicators like financial markets and interest rates. These kinds of approaches are very unlikely to capture the non-linear relationships and dynamic nature of the present situation of the economy. So, Kiley introduces the machine learning techniques including the LASSO regression and Random Forest, to capture the complexities.

By using high-frequency and real-time financial data, the study outperforms the traditional models and methods in predicting short-term economic and interest rate fluctuations.

The model that this study provided states that market volatility and equity prices have significant weight in the prediction and can be considered as the key drivers for the economic condition activity and interest rate decisions.

Kiley's findings in this study illustrate that traditional methods and models should be transformed into new models which helps to highlight better precision and accuracy than the traditional models. The paper advocates that there should be a closer collaboration between economists and data scientists to develop frameworks that integrate present needs, domain expertise with computational power. This study provides a fine blueprint for applying Machine Learning to refine Federal Interest rate predictions, building the way for adaptive economic policies.

Textual Data to Improve Financial Crisis Identification

Chen et al. (2023) illustrate the approach to predicting financial crises by applying text mining and machine learning to qualitative data [3]. Most of the traditional models solely focused on numerical indicators like GDP, unemployment rate, and other economic indicators. So, Chen et al. (2023) built a model that deals with textual information from economic reports, news articles, and social media. He used models like support vector machines (SVMs) and random forests to analyze sentiment and thematic trends which helps to uncover the patterns that often precede the market disruptions.

The study suggests that the textual data can serve as early warning signals for financial crises and instability. For example, terms like "bank" and "credit" were highly influential and correlated with the model's identification of the 2008 crisis. This demonstrates the understanding that the 2008 crisis was related to a banking-driven crisis.

Similarly, the model identified the COVID-19 pandemic as a financial crisis, highlighting the terms like "government", "unemployment" and "financial support". This showcases the ability of the model to detect the different types of crises.

In this study, Chen et al. (2023) have demonstrated the importance and value of interdisciplinary methods in economic forecasting. The study expands the ways and techniques that can be used to decode the complex market economic structures by integrating natural language processing (NLP). This helps the Fed, investors, businesses, and policymakers to identify real-time trends and consumer sentiments and make decisions respectively.

Methodology

This study will use a hybrid approach combining machine learning and sentiment analysis to predict Federal Reserve interest rate decisions. The framework will integrate economic theory and data science techniques. The research will leverage both numerical economic indicators and textual data to create a comprehensive prediction framework, providing a unique mixture of traditional and modern approaches. The methodology involves data collection, preprocessing, feature engineering, model development, and evaluation, ensuring a robust and reliable analysis.

The economic data such as inflation, GDP, Bond yields, Consumer Price Index (CPI), Producer Price Index (PPI), Job Openings and Labor Turnover Survey (JOLTS), and the unemployment rate will be collected from trusted sources like the Federal Reserve Economic Data (FRED) [5]. The textual data like economic reports, Federal Reserve members' speeches, and meeting minutes, will be collected from the Federal Reserve's official archives and publicly available websites [4].

To process these data, two separate pipelines will be developed: one for the numerical economic data and another for the textual data. The numerical data pipeline will use machine learning models like Linear Regression, Random Forests, and Gradient Boosting (such as XGBoost, and LightGBM) as shown in Figure 1. These models will analyze trends and relationships among economic indicators to predict interest rate decisions.

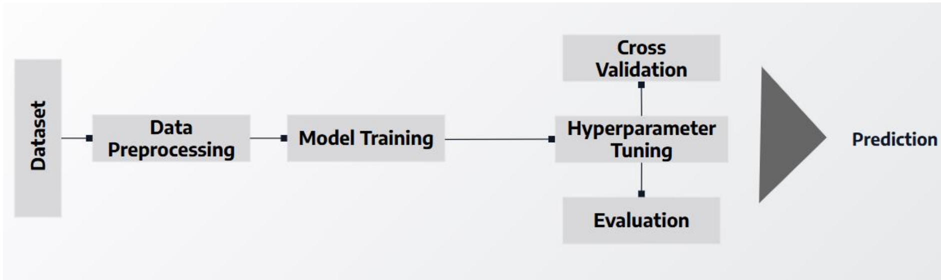

Figure 1. Numerical data pipeline

The textual data pipeline will focus on sentiment analysis and semantic understanding. Preprocessing techniques like tokenization and stop-word removal will be used to prepare the text for analysis. For the embeddings, advanced natural language processing (NLP) models like transformer-based architectures like BERT or RoBERTa combined with machine learning classifiers like dense neural networks or LSTMs will be used for the sentiment analysis as shown in Figure 2.

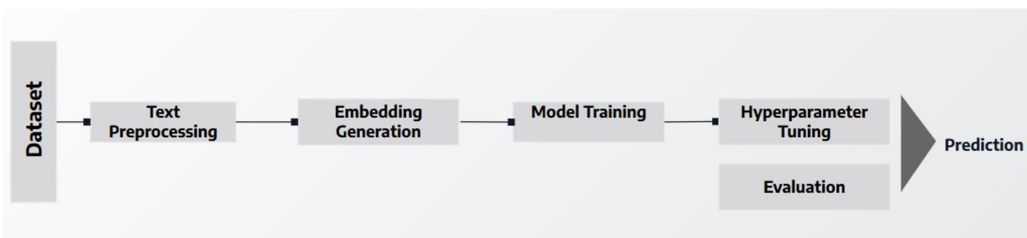

Figure 2. Textual data pipeline

The outputs from both pipelines will be integrated using an ensemble modeling approach. Ensemble strategies like stacking or weighted averaging can be used to combine insights from numerical and textual data to enhance prediction accuracy. Python programming will be used for model development tools with its libraries like Scikit-learn, TensorFlow, and NLTK.

Evaluation of Results

We will be splitting the dataset into 70-10-20 ratios for training, validation, and testing respectively. The model performance will be evaluated using metrics like accuracy, F1-score, and RMSE or MSE (based on the situation).

Furthermore, we will compare the prediction of the model with the historical data from the Federal Reserve Bank to ensure the model's accuracy. We will also compare the combined model with individual traditional models to see the enhancement in model performance and accuracy.

Ethical Considerations

This research will use publicly available data, such as economic indicators and textual data from Federal Reserve members' speeches and meeting minutes which ensures that no confidential information is used. If the study plans to use the ethically concerned data, it will be addressed by anonymizing data sources where necessary and adhering to relevant data protection regulations like GDPR and CCPA [7] [2].

There are no conflicts of interest to disclose. The research findings will be published and shared transparently, ensuring that any biases in the data or models are disclosed. Additionally, to prevent the misinterpretation and misuse of the results, particularly by policymakers or investors, various precautions will be taken such as methodology, assumptions, and limitations of the study will be well documented to ensure transparency and reproducibility. The research will have a clear disclaimer that the predictions are probabilistic and not deterministic. Efforts will be made to contextualize the model's predictions within the broader scope of traditional economic analysis, emphasizing their complementary role rather than positioning them as definitive solutions. Ethical oversight will involve consultations with experts and committees to assess potential risks and mitigate unintended social or economic consequences.

Through these measures, the research aims to provide valuable insights while minimizing the risk of harm or misapplication.

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Appendix I

Anticipated Funding Requirements

For this research, the funding requirements are expected to be minimal as publicly available data and open-source tools (like Python and its libraries like Scikit-learn, TensorFlow, and NLTK) will be used. However, the following costs may be anticipated:

- Computing Resources: Access to cloud services like AWS, Google Cloud, or Microsoft Azure for training and deploying machine learning models. Estimate cost: $200 - $500
- Publication Fees: Costs for publishing the research findings in peer-reviewed journals and at conferences. Estimated cost: $1000 - $5000
- Conferences: Participation in academic conferences to present research results. Estimated cost: $1000 - $1500 (registration and travel expenses).

Potential Funding sources include:

- Graduate research grants from the university.

Anticipated IRB and Other approvals

The research involves publicly available datasets, including numerical economic data and textual data (Federal Reserve speeches and meeting minutes). Since the study does not involve human subjects or private data, IRB approval may not be required. However, consultation with the university will be conducted to confirm compliance with ethical research standards.

Thesis/APP Committee

The following faculty members are proposed for the thesis/APP committee:

1. Chairman: Dr. Rajeev Bukralia, expertise in data science
2. Member: Dr. Naseef Mansoor, expertise in Machine Learning
3. Member: Dr. Deepak Sanjel, expertise in Statistics

Appendix II

Tentative Timetable for Completion of the Thesis/APP

Research Project/Thesis/APP Stage	Completion Target Date
Literature review	01/15/2025
Finalize research questions	02/15/2025
Finalize the thesis/APP committee	03/20/2025
Construct research design	04/30/2025
Conduct experiment/gather data	05/30/2025
Analyze data	07/15/2025
Draft thesis to advisor(s)	08/20/2025
Schedule defense	10/20/2025
Final thesis submission for signatures:	11/25/2025