NC STATE UNIVERSITY

Interest Rate Change Forecasting: A Machine Learning Approach

FIM 500 - Risk Management in Commercial Banks

December 2, 2024

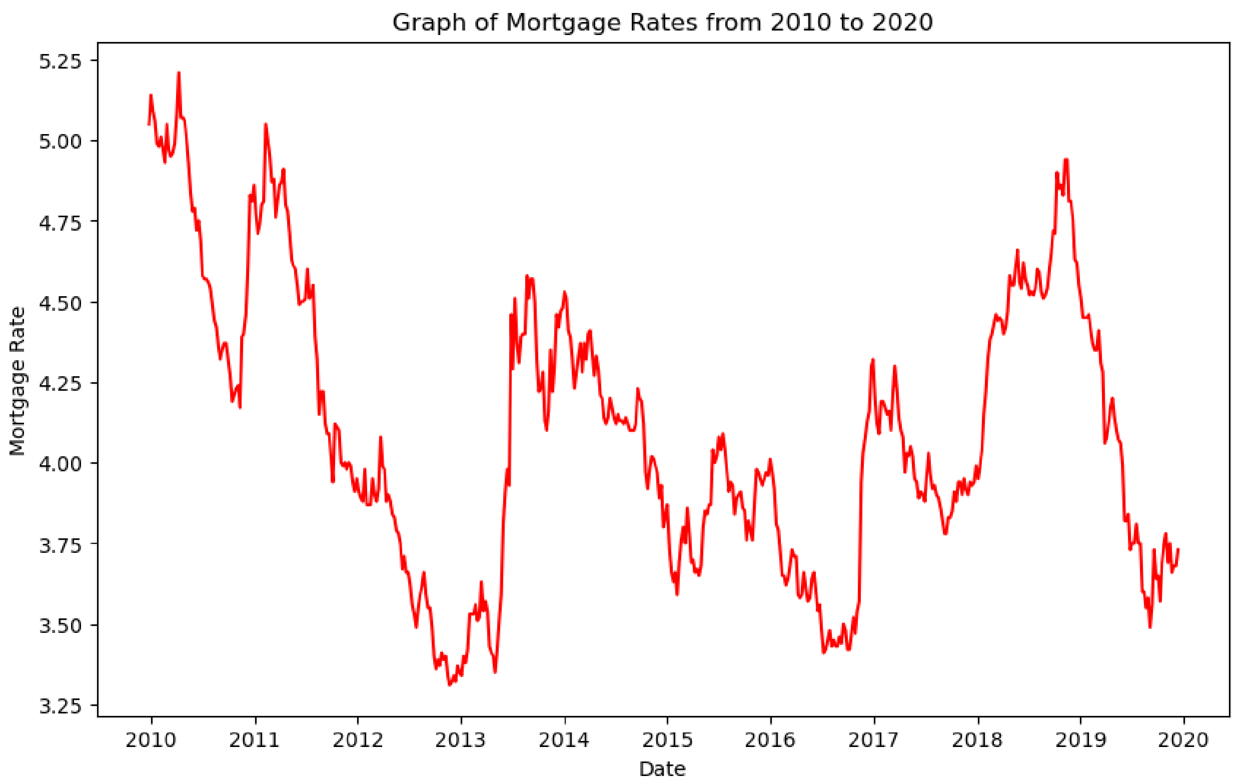
Jinjia Peng

Abstract

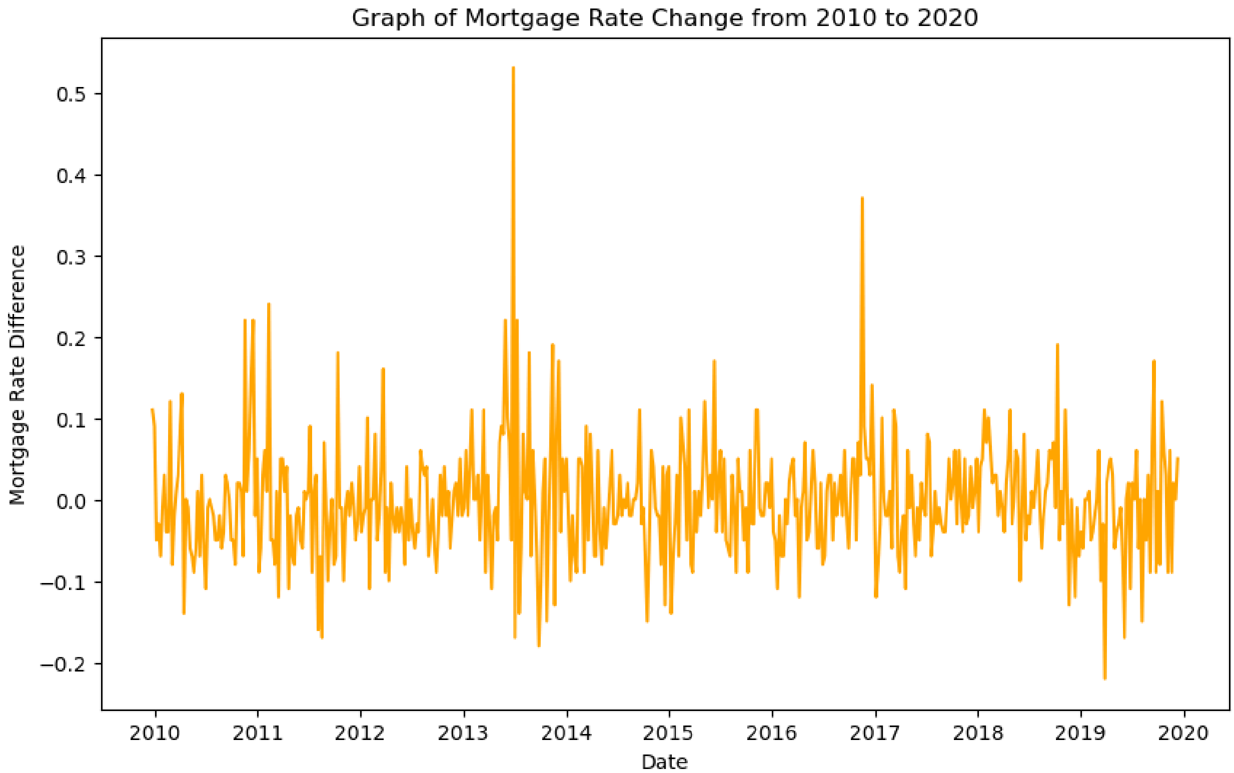
In real life, there are many factors that might affect the change of the interest rate. This project aims to find the potential factors that cause a direct or indirect effect on the **change of the 30-Year Fixed Rate Mortgage Average** (updated weekly) in the United States. The algorithms will involve multiple machine learning methods including XGBoost, Classification method, and some time series analysis. The goal is to discover potential patterns of the data sets, and their relationship with the interest rate.

Data Preprocessing

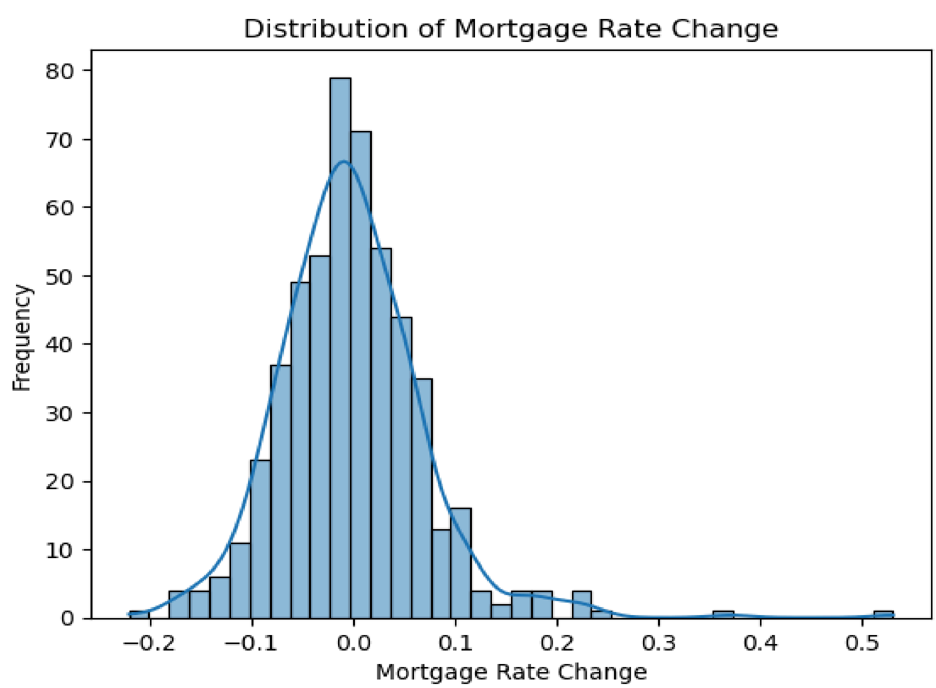
First, the time period of this analysis is decided between 2010 and 2020. The reason is that this period is relatively stable for analysis purposes. The graph of the mortgage rate is shown in the picture below.



Next, the graph of the change in the interest rate is attached below.

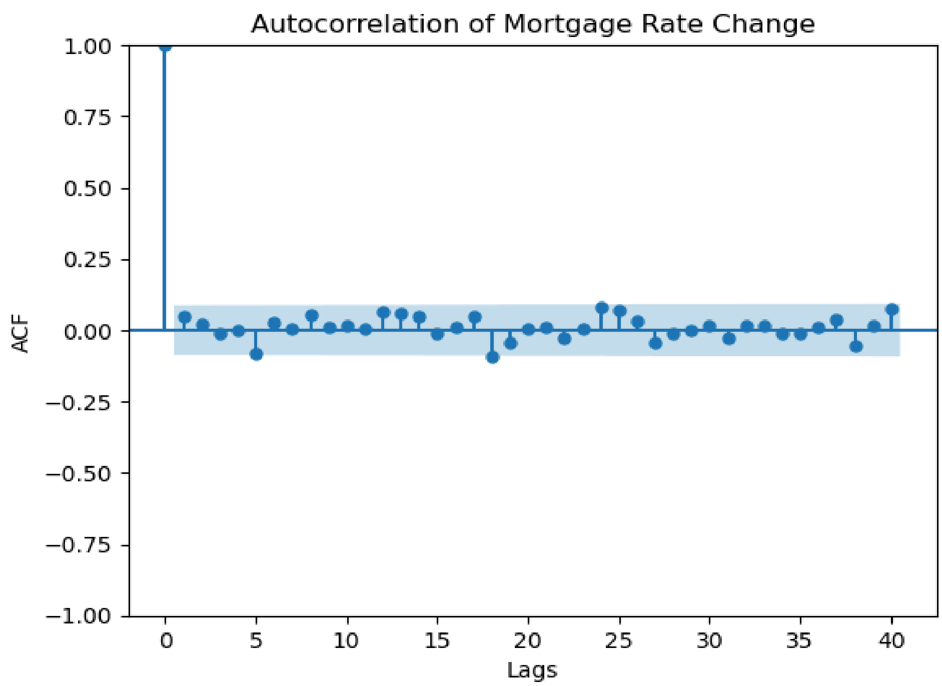


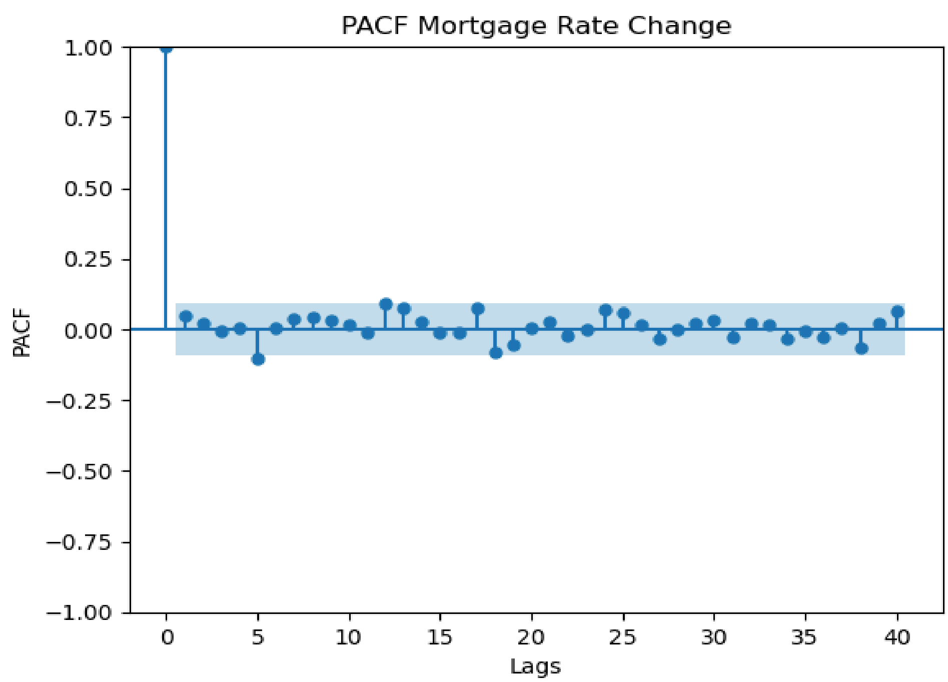
Observe that the distribution of the change is close to a normal distribution, with a few outliers. This is great news. In the data analysis steps, outliers are removed by considering the range of the valid data inside [Q1-1.5 IQR, Q3+1.5 IQR].



Times Series Approach

First, check the impact of the past lags. Observed that the values in the graph are close to zero, meaning that the time series values do not depend significantly on their lagged values. If the ACF is close to zero, the observations are likely independent of one another, meaning that the change in Mortgage Rate Change in each time period are not necessarily related to each other.





Assumption: The time series of the Mortgage Rate Change might be a white noise process, which means:

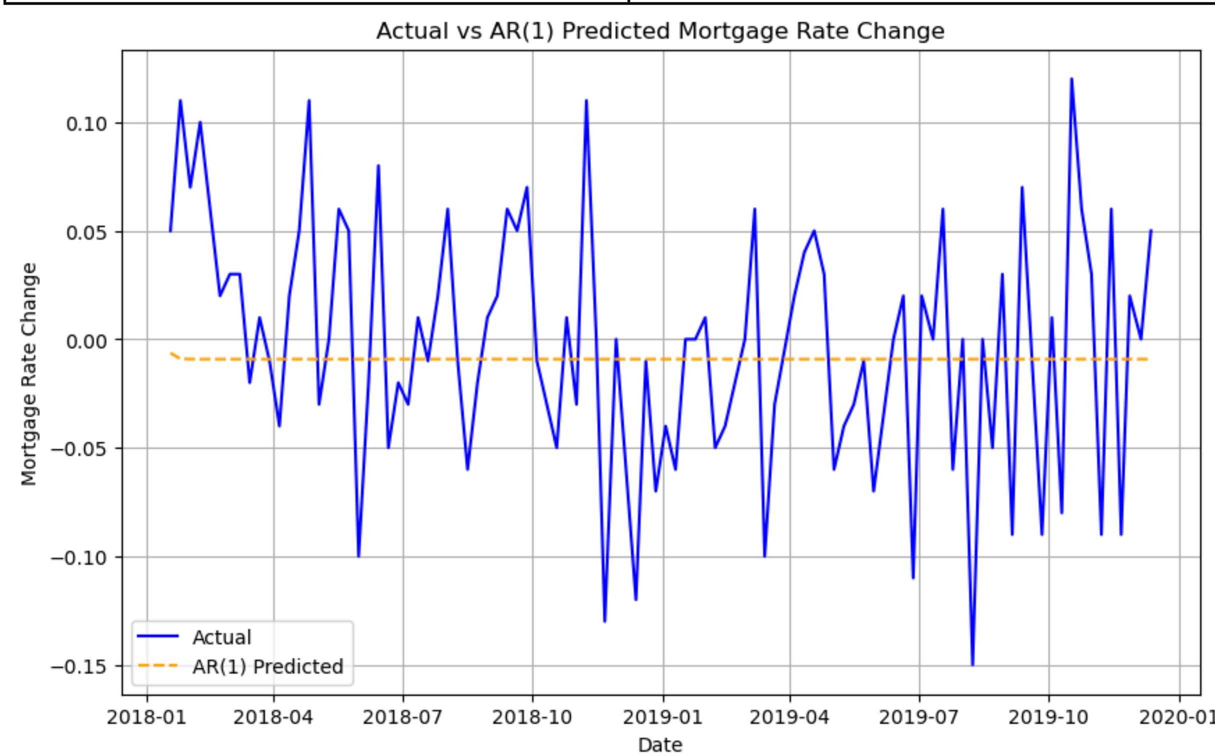
- It consists of random, independent observations with no discernible pattern.
- The mean and variance are constant over time, but there is no predictable structure.

Verification: To further assess, the Ljung-Box test, a statistical test used to determine whether a time series is random or exhibits autocorrelation, is being performed. It resulted in a p-value of 0.59, which shows that the series is more close to a random state.

AR(1)

Splitting the data into a training set (80%) and a testing set (20%). Starting with AR(1) Model, which only consider the lag effect of one previous data point, the statistical result of the testing set is shown below:

MAE	0.04580
MSE	0.00328

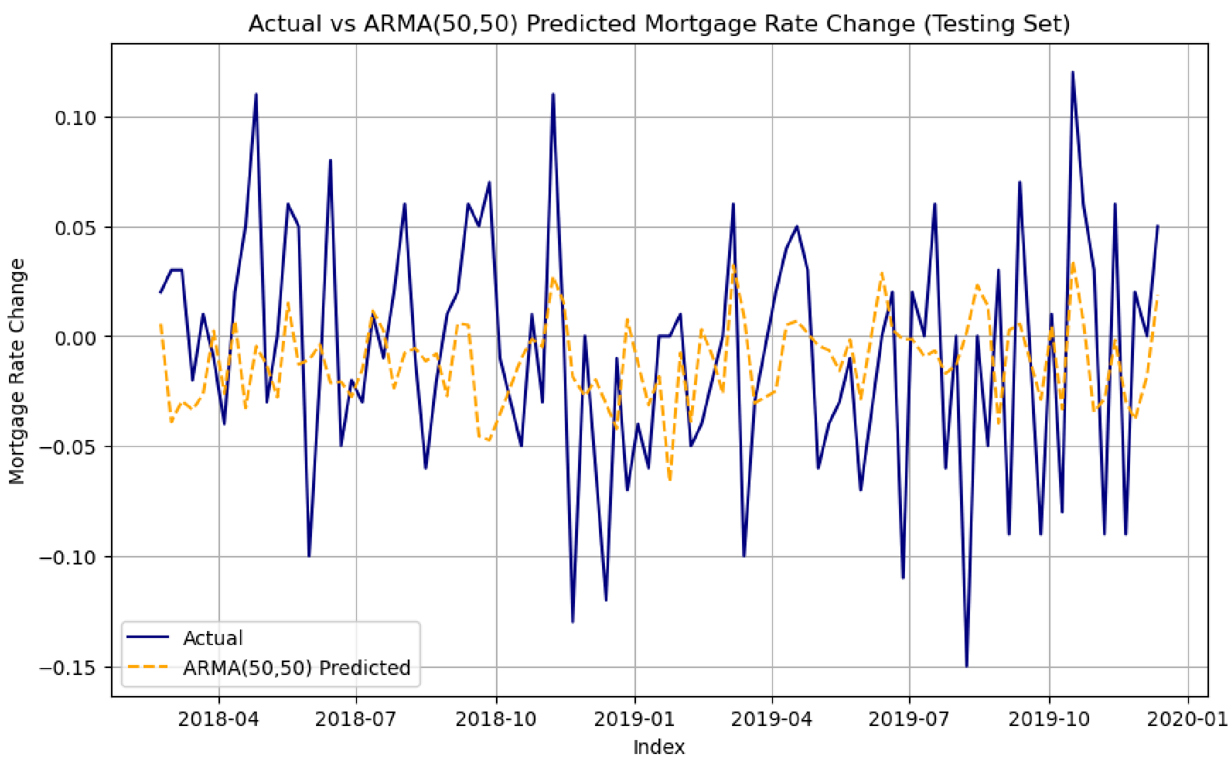


Observation: The model performs poorly on the testing set, that it did not capture the movements of the change in Mortgage Rate.

ARMA(50,50)

Now consider the ARMA(50,50) model, which includes lags and errors up to 50 previous data points. In addition, independent features such as Mortgage Rate itself with lag effects up to 10 previous data points were also considered in the model building. The statistical result is described below:

MAE	0.04396
MSE	0.00296



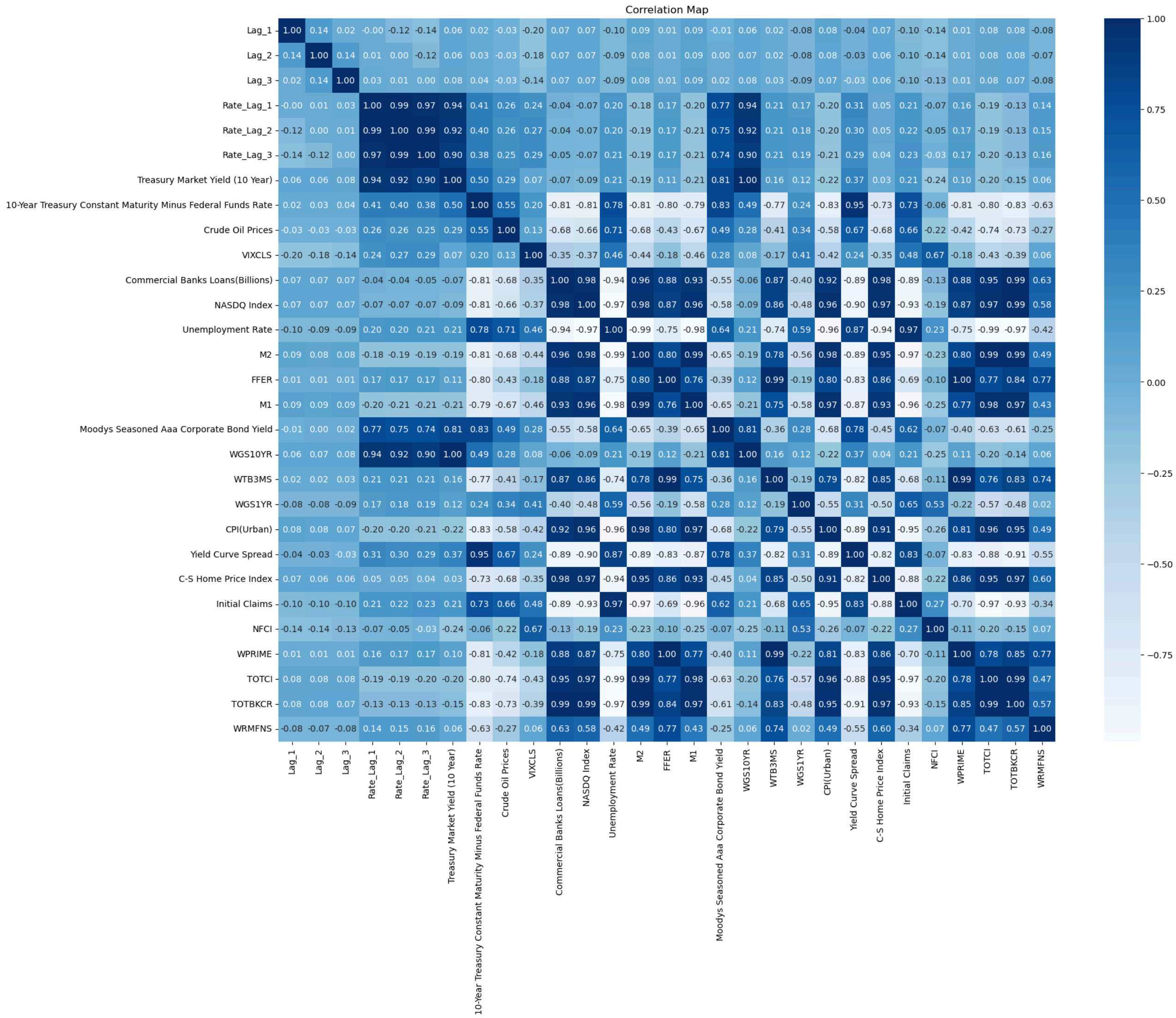
The statistical result is slightly improved, but it is still poorly performed on the testing set. The two time series approaches verified the assumption of the randomness of the data set, that it is indeed a white noise process. However, observe from either the statistical result or the graph, the new model with more lags involved more accuracy and moved better with the trend. This suggests that the data could have some nonlinear relationships, or other hidden patterns that the AR and ARMA model did not capture. Now, a new approach, that captures the non-linear relationship between data sets, might be a better fit.

Machine Learning Approach: XG Boost Prediction

Feature Selection: The features involved in the machine learning are:

10-Year Treasury Yield
10-Year Treasury Minus Federal Funds Rate Spread
Crude Oil Spot Price
CBOE Volatility Index (VIX)
Commercial Bank Loans and Leases (Billions)
NASDAQ Composite Index
Unemployment Rate
M2 Money Supply
Federal Funds Effective Rate
M1 Money Supply
Moody's Seasoned Aaa Corporate Bond Yield
10-Year Treasury Yield (Weekly)
3-Month Treasury Bill Yield (Weekly)
1-Year Treasury Yield (Weekly)
Consumer Price Index for Urban Consumers (CPI-U)
Yield Curve Spread
S&P/Case-Shiller Home Price Index
Initial Jobless Claims
National Financial Conditions Index (NFCI)
Prime Loan Rate (Weekly)
Total Consumer Credit Outstanding
Total Bank Credit Outstanding
Residential Fixed Investment as a Share of GDP (Weekly)
Mortgage Rate Lag_1
Mortgage Rate Lag_2
Mortgage Rate Lag_3
Mortgage Rate Change Lag_1
Mortgage Rate Change Lag_2
Mortgage Rate Change Lag_3

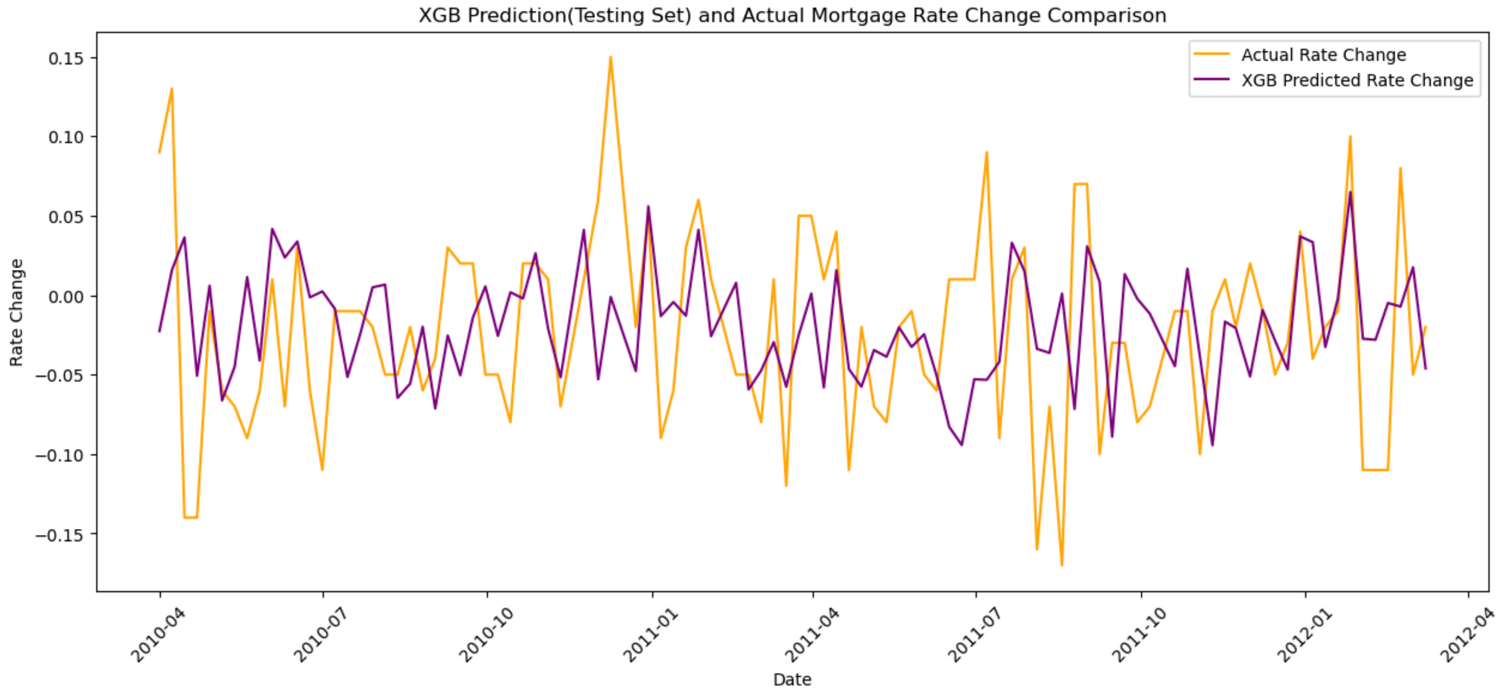
They are being split into a 60% training set, 20% validation set, and 20% testing set. The correlation chart of each feature, which shows how related they are to each other, are given:



In the picture, 1 means perfectly correlated to each other and -1 means perfectly correlated to each other.

Using XG Boost algorithm, the statistical result on the testing set is as follows:

MAE	0.04681
MSE	0.00321



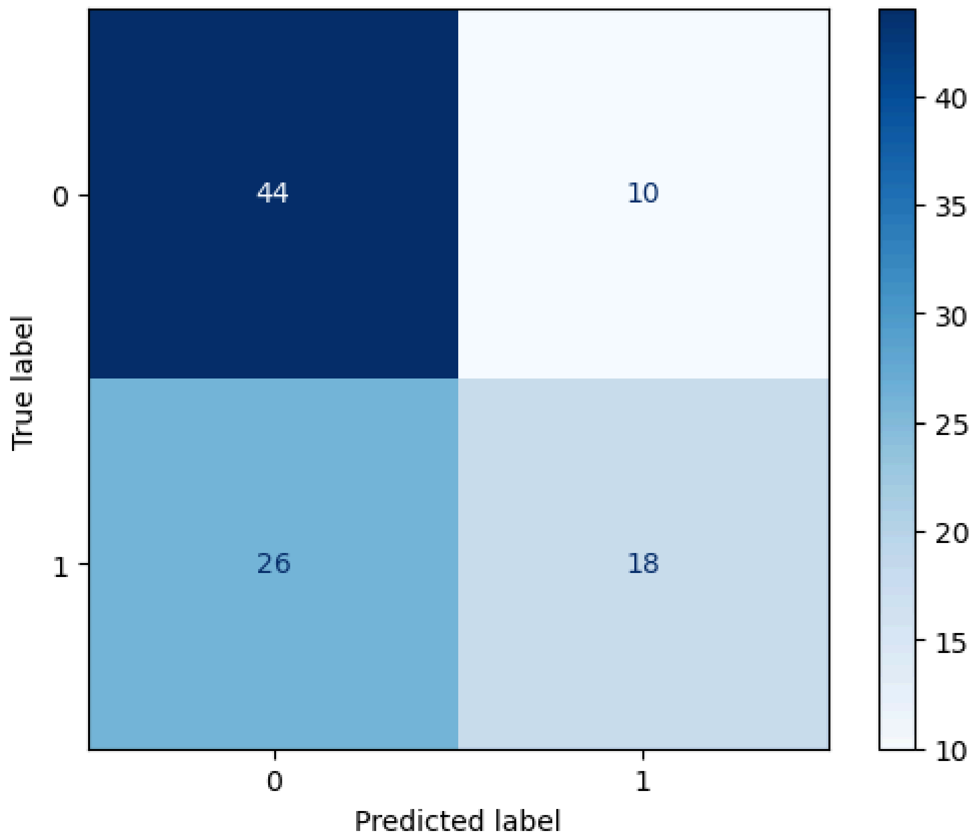
Observation: The performance on the testing was still not ideal because of the high MAE and MSE. This could happen due to the selection of the features, time interval, and the selection of the parameters of the algorithm. The graph suggests that the XGB algorithm captured some of the movements triggered by the features, but failed to capture the overall trend. If the actual change in value is difficult to predict, maybe straight predicting the rate going up or down would be another way to gain insights.

XG Boost Classification

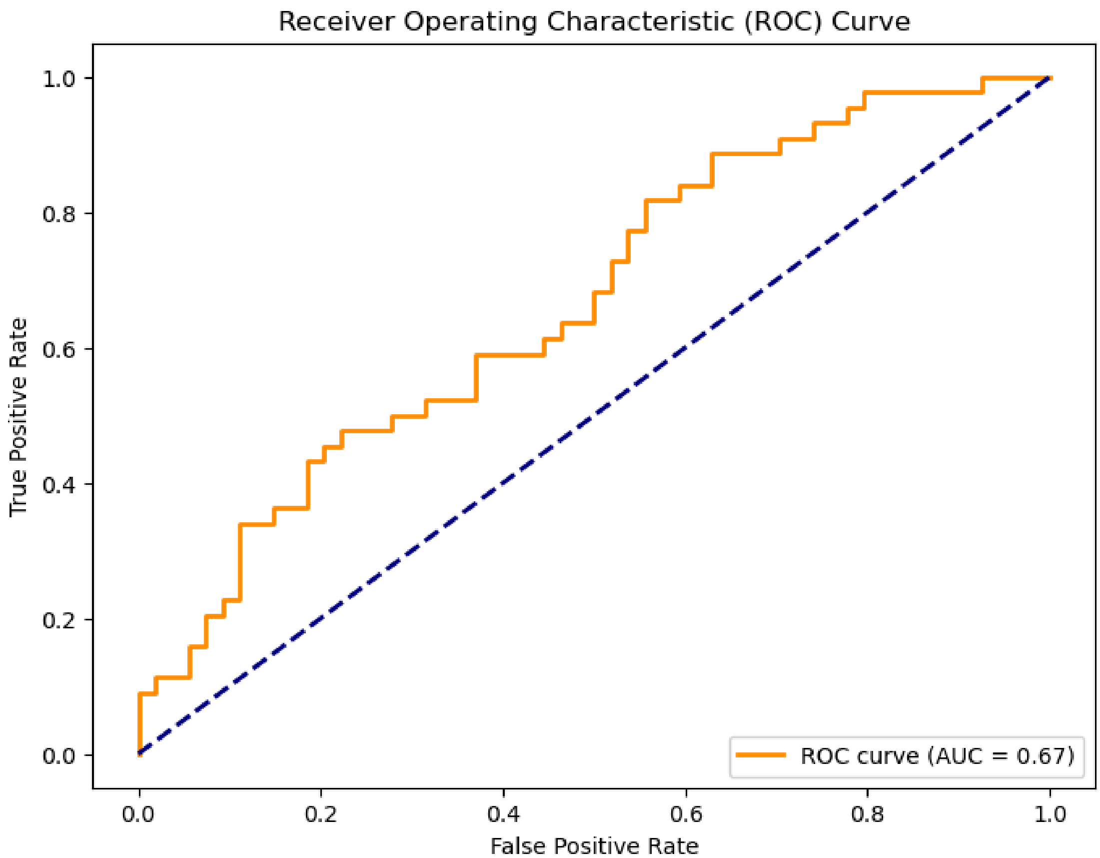
Assign 1 if the current rate is greater than the previous rate observed and 0 otherwise, now the problem turns into a classification problem. Using XG Boost Classification algorithm, the statistical result on the testing set is as follows:

	Precision	Recall	F1-score	Support
0	0.63	0.81	0.71	54
1	0.64	0.41	0.5	44

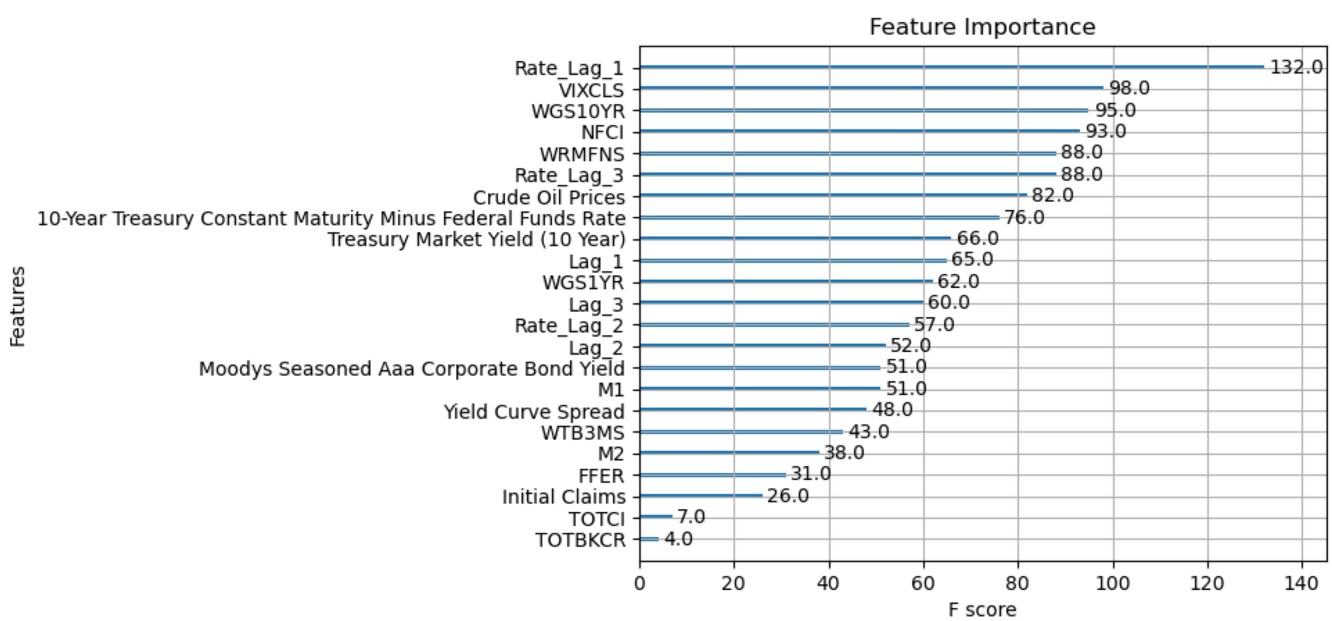
In the table, high F-1 scores for both 0 and 1 indicate that there are few false positives (instances incorrectly labeled as positive) and few false negatives (instances incorrectly labeled as negative) in predicting them. Higher F1-Score in 0 means that it is more accurate to predict the Mortgage Rate Change going down or unchanged compared to predicting it going up.



This table shows the actual value and the predicted result on the testing set. Here, the number of (0,0) and (1,1) are more than the number of (1,0) and (0,1), indicating that the model generates a relatively accurate prediction.



The area under the ROC curve also shows the prediction. The closer to 1, the better the result. Here, it has a value of 0.67, which means there is a 67% chance that the model correctly ranks a positive instance higher than a negative one.positive instance higher than a negative one.



This bar chart shows the weight that contributes the most to the prediction. Surprisingly, the Mortgage Rate Lag 1 (effect of the lag of 1 previous Mortgage Rate observation) has the most contribution, and the Total Bank Credit Outstanding has the least impact.

Conclusion

Undoubtedly, it was difficult to predict the change of interest rate. This happens because the interest rate tends to follow a random pattern that is hard to predict using algorithms. However, the features in this project provide useful insights on predicting the increase and decrease in the change of the value, where the closest previous observation could significantly affect the direction of the next observation. In the future, a better approach focusing on the random side might be more effective, such as Monte Carlo Simulation and Random Walks.

References

All economic data sources in this project were obtained from

FEDERAL RESERVE BANK of ST. LOUIS

FRED® ECONOMIC DATA | ST. LOUIS FED

https://fred.stlouisfed.org/