Forecasting Report 2

Tyler Campbell

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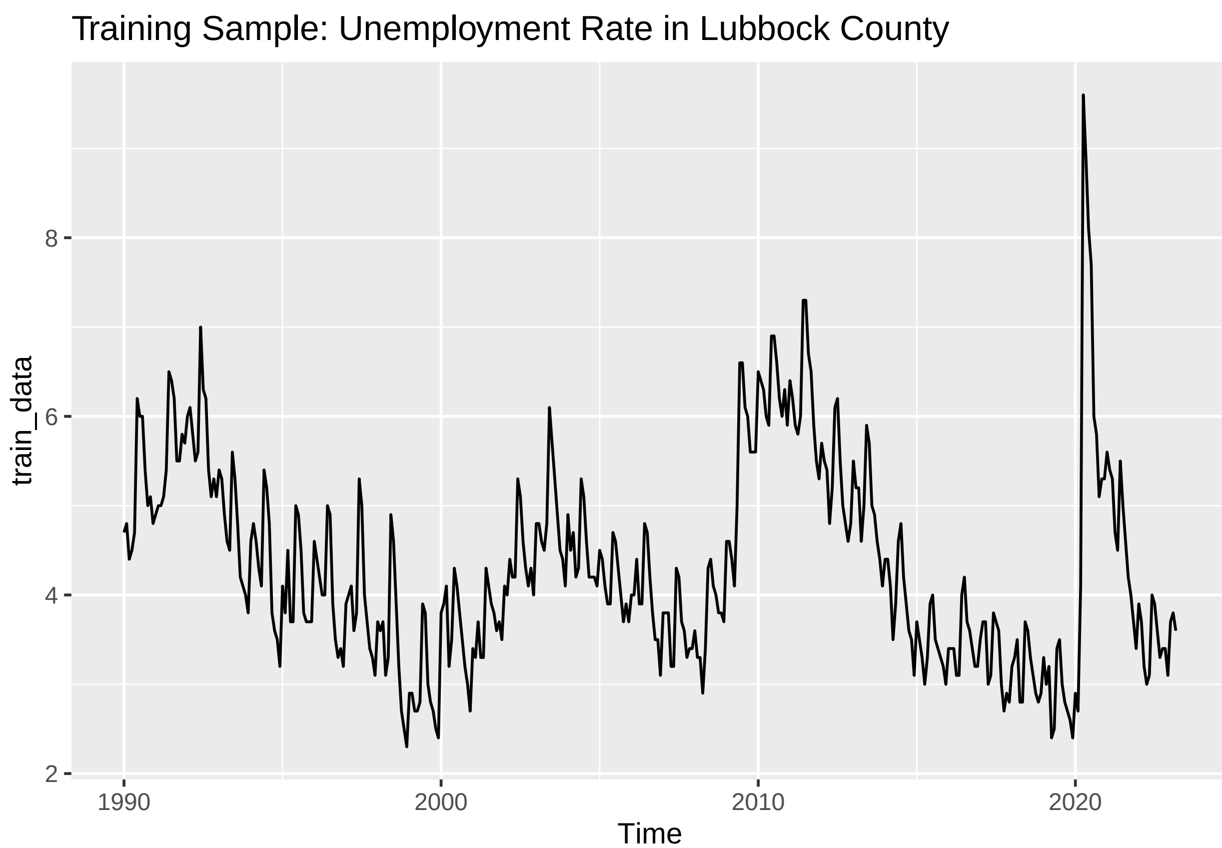
Introduction

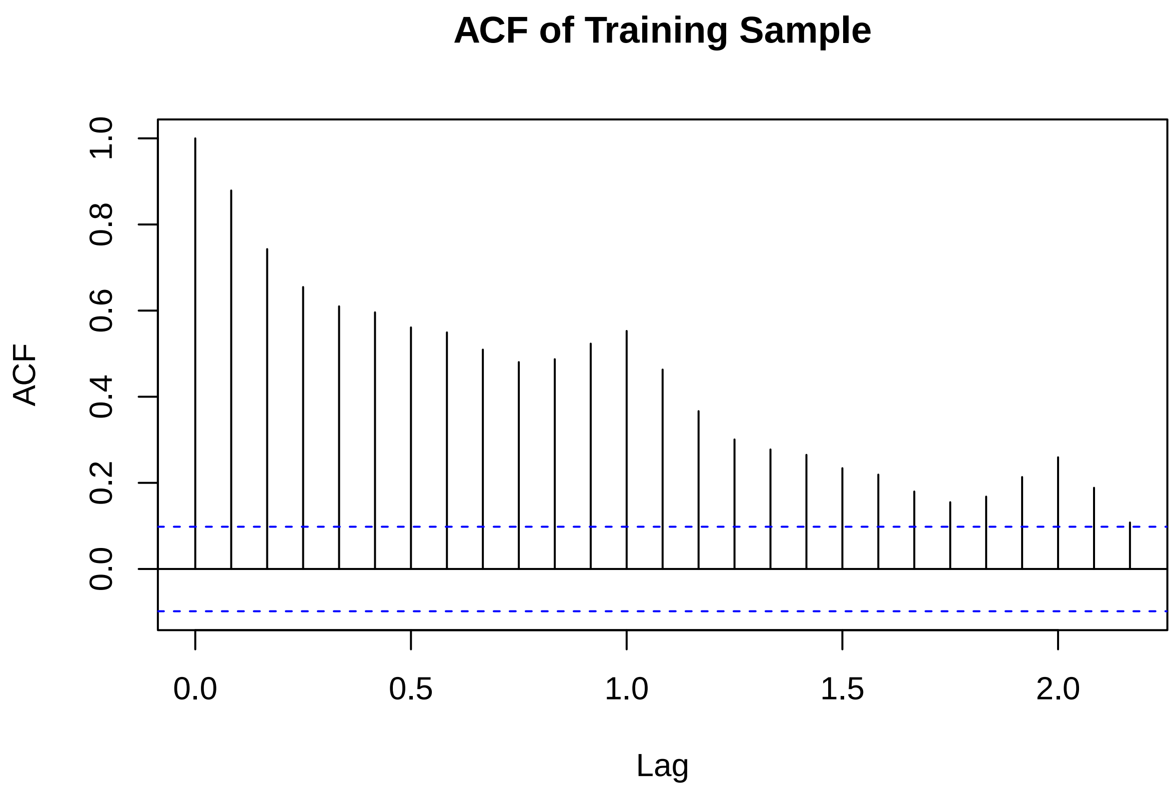
In this report, I analyze the monthly unemployment rate for Lubbock County, Texas, using time series forecasting techniques. The goal is to build an effective predictive model that can capture the underlying patterns in the data and compare its performance against a simple naive forecast. To do this, I divided the available data into a training sample and a test sample, applied stationarity tests, selected and estimated the best-fitting time series model, and generated one-step-ahead forecasts for the test period. I then evaluated the forecast accuracy using both visual plots and statistical measures to see if the model offered meaningful improvements over the naive benchmark.

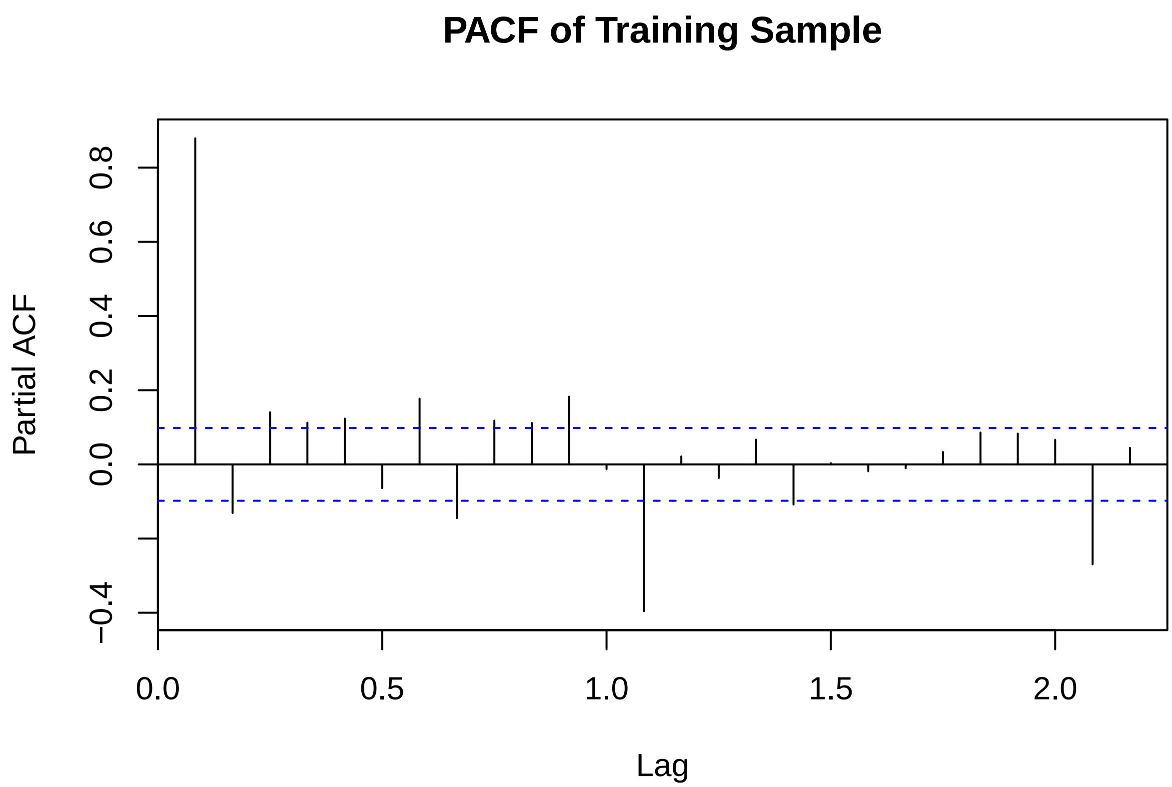
Data Preparation

```
## # A tibble: 6 x 2
##   observation_date TXLUBB3URN
##   <chr>                 <dbl>
## 1 1/1/1990                4.7
## 2 2/1/1990                4.8
## 3 3/1/1990                4.4
## 4 4/1/1990                4.5
## 5 5/1/1990                4.7
## 6 6/1/1990                6.2
```



Training Sample: Unemployment Rate in Lubbock County
train_data
8
6
4
2
1990
2000
2010
2020
Time


ACF of Training Sample
ACF
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
Lag



In this section, I prepared the time series data for the unemployment rate in Lubbock County, Texas, which spans from 1990 to 2025. I split the data into a training set ending in March 2023 and a test set starting in April 2023, leaving two years for testing. The time series plot shows visible trends and seasonal fluctuations, particularly around periods like the 2008 recession and the COVID-19 shock, where sharp spikes in unemployment appear. The correlogram plots (ACF and PACF) confirm that the series has a slow decay in the autocorrelations, which signals the presence of a trend component that should be carefully accounted for when modeling.

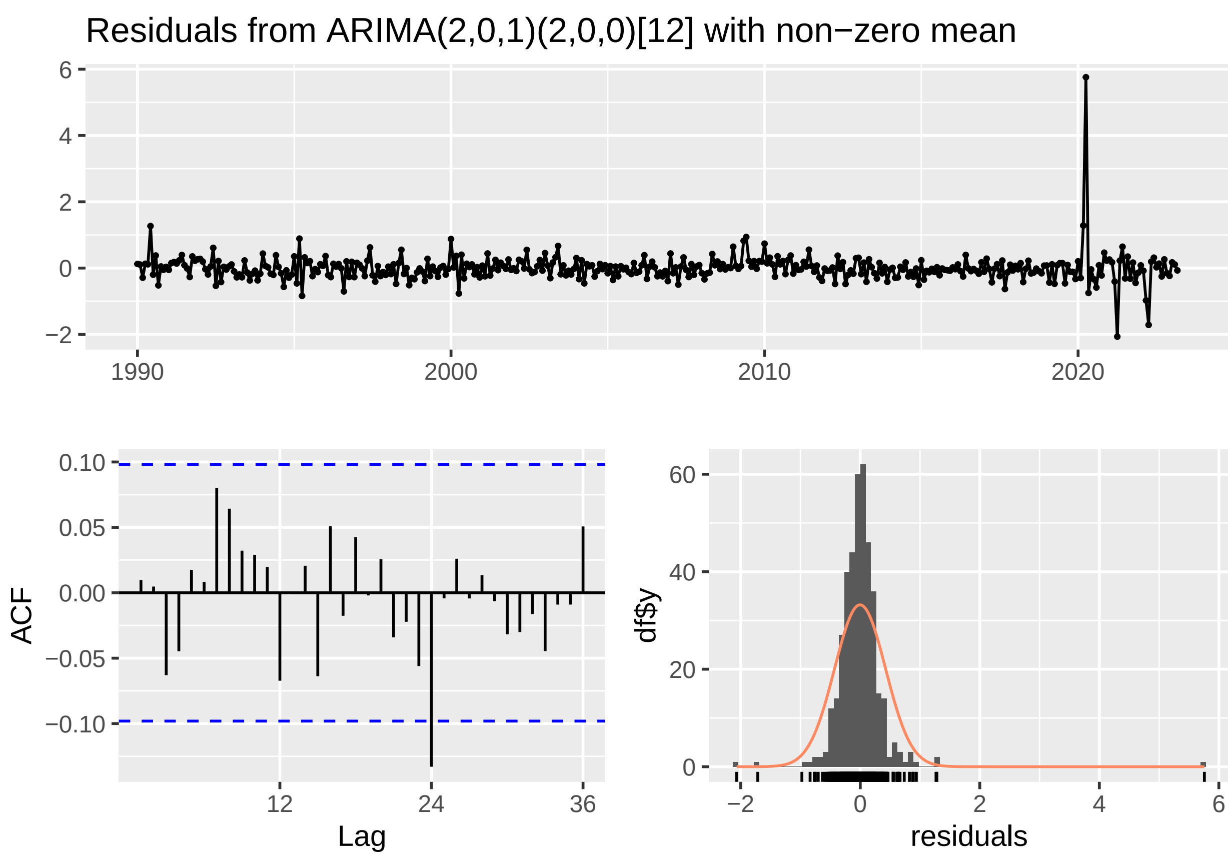
Stationarity Test

```
##
##  Augmented Dickey-Fuller Test
##
## data:  train_data
## Dickey-Fuller = -3.4383, Lag order = 7, p-value = 0.04864
## alternative hypothesis: stationary
```

Using the Augmented Dickey-Fuller (ADF) test, I tested whether the unemployment rate series was stationary. The test produced a p-value of about 0.048, which is below the 0.05 threshold, allowing me to reject the null hypothesis of a unit root and conclude that the series is trend-stationary. This result was important because it guided my decision to fit an ARMA-type model without differencing, instead of an ARIMA model, as the deterministic trend could be captured directly within the modeling framework.

Model Estimation

```
## Series: train_data
## ARIMA(2,0,1)(2,0,0)[12] with non-zero mean
##
## Coefficients:
##          ar1     ar2     ma1    sar1    sar2    mean
##       0.1956  0.6014  0.8576  0.3564  0.3161  4.2997
## s.e.  0.0761  0.0728  0.0518  0.0474  0.0477  0.5397
##
## sigma^2 = 0.1841:  log likelihood = -229.65
## AIC=473.3   AICc=473.59   BIC=501.23
##
## Training set error measures:
##                        ME      RMSE       MAE      MPE     MAPE      MASE
## Training set -0.003345437 0.4258304 0.2324948 -0.79624 5.424149 0.3443378
##                     ACF1
## Training set 0.009759738
```

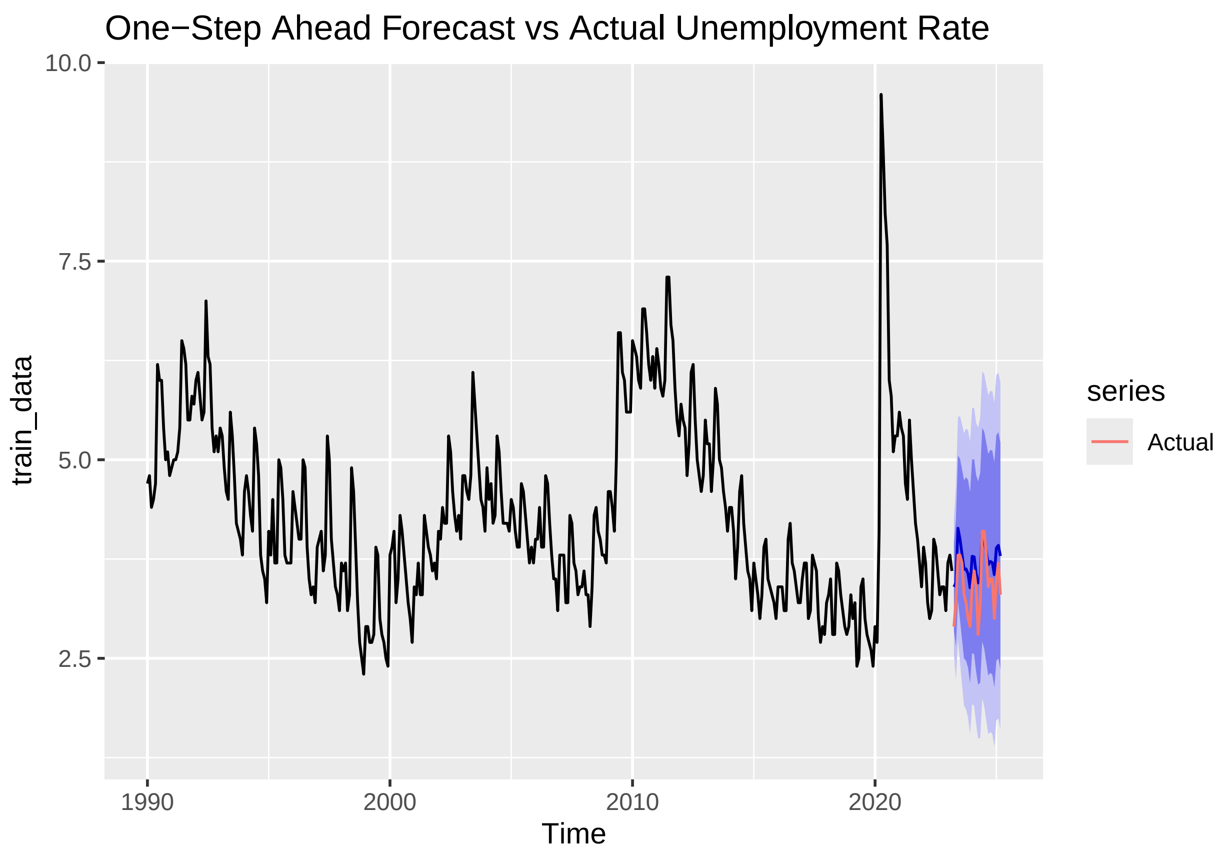



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,0,1)(2,0,0)[12] with non-zero mean
## Q* = 23.442, df = 19, p-value = 0.2185
##
```

```
## Model df: 5.   Total lags used: 24
```

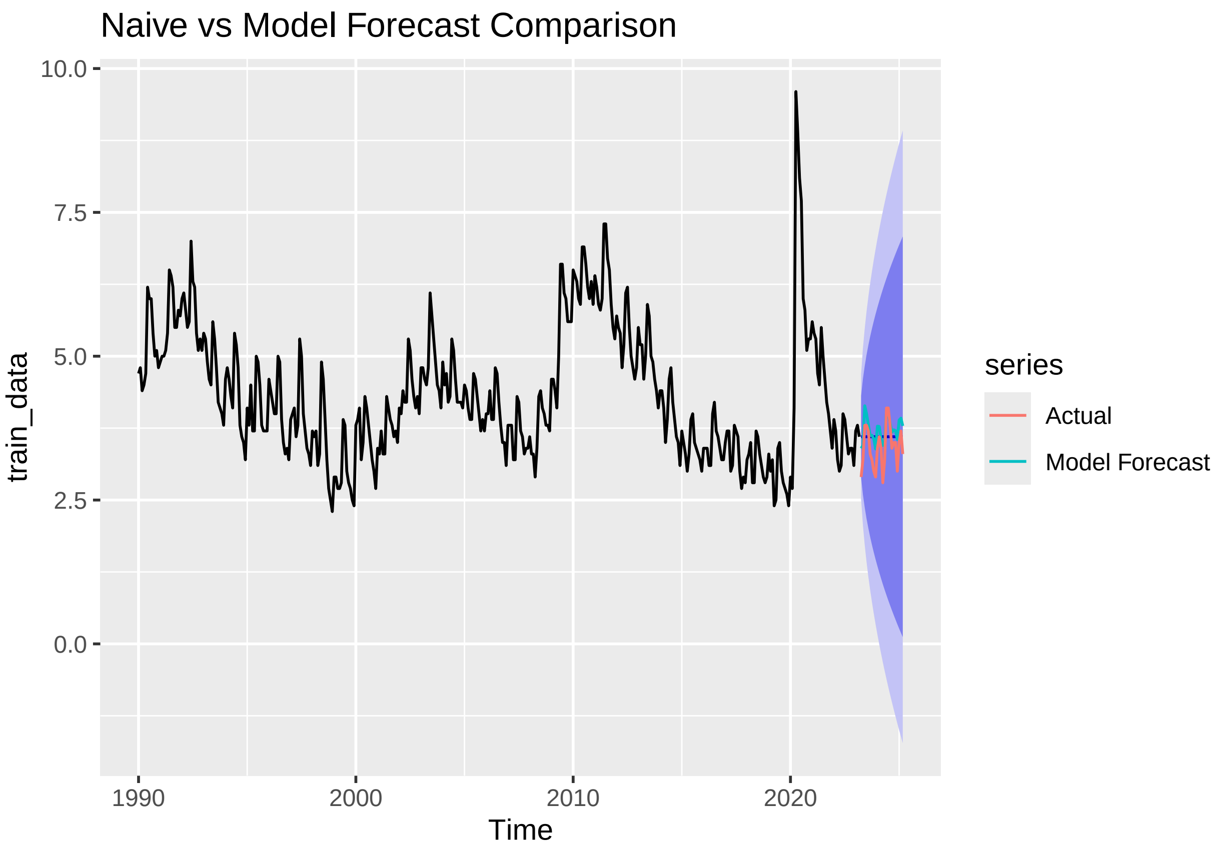
For the model selection, I used the auto.arima function with seasonal components enabled, which selected an ARIMA(2,0,1)(2,0,0)[12] model. The summary shows significant coefficients for AR, MA, and seasonal AR terms, which account for both short-term and seasonal dependencies in the data. I chose this model because it provided the best fit based on AIC and had residuals that looked like white noise in both the residual plots and the correlograms. This step was critical because a good model should leave no significant structure in the residuals, ensuring valid forecasts.

One-Step Ahead Forecast



Using the selected model, I generated one-step ahead forecasts for the test period and plotted them against the actual unemployment rates. The forecast plot shows that the model captures the general direction of the unemployment rate fairly well, with the actual values mostly falling within the 95% confidence intervals. This indicates that the model has reasonable predictive power, although occasional short-term deviations are expected, especially during economic events or shocks that are hard to predict.

Naive Forecast Comparison



To evaluate performance, I compared the model forecast against a naive forecast, which simply carries forward the last observed value. The comparison plot shows that the model forecast tends to track the seasonal and trend patterns better than the naive forecast, which flattens out unrealistically. Visually, the model forecast seems to align more closely with the actual values, particularly during periods of slight rises or falls, whereas the naive forecast lags behind and ignores any change direction.

Forecast Error and Loss Comparison

```
## Model Loss (MSE): 0.1239045
```

```
## Naive Loss (MSE): 0.1579167
```

```
##
##  Diebold-Mariano Test
##
## data:  model_errorsnaive_errors
## DM = -1.3596, Forecast horizon = 1, Loss function power = 2, p-value =
## 0.1872
## alternative hypothesis: two.sided
```

I calculated the quadratic loss (mean squared error) for both the model and the naive forecast. The model produced a lower MSE (0.1239) compared to the naive approach (0.1579), suggesting it was the more accurate method over the test period. However, the Diebold-Mariano test showed a p-value of 0.187, meaning the difference in predictive ability between the two forecasts is not statistically significant at standard confidence levels. This means that while the model looks better on average, we can't confidently say it outperforms the naive benchmark in a formal statistical sense over this particular test period.

Conclusion

Overall, this forecasting exercise showed that the ARIMA(2,0,1)(2,0,0)[12] model provided a reasonably good fit for the unemployment data, capturing both seasonal patterns and short-term dynamics. While the model produced lower forecast errors than the naive approach, the Diebold-Mariano test revealed that the difference in predictive ability was not statistically significant. This suggests that while advanced models can offer improvements, simple methods like naive forecasts still hold competitive ground, especially over short time frames. This project taught me the importance of model diagnostics, error evaluation, and understanding when complex models meaningfully outperform simpler alternatives.