Forecasting Crime in the City of Raleigh, NC

Group 4:

Jisoo Han, Lexi Lin, Bonny Mathew, Stepan Ochodek

Date: March 12, 2025

Agenda

- Problem Statement
    - Data Description
- Executive Summary
- Exploratory Data Analysis
- Methodology and Results
    - Univariate
    - Multivariate
- Extensions

Crime thrives in the shadows; data and foresight bring it to light

Goal: Build a model that forecasts the crime rate in the city of Raleigh, NC over a 12 month horizon.

Why it matters:

- **Public Safety** – Helps government and citizens understand public safety climate
- **Resource Allocation** – Ensures police and emergency services are deployed effectively.
- **Policy Making** – Informs government decisions on crime prevention strategies.
- **Community Awareness** – Keeps residents informed and engaged in crime reduction.
- **Economic Impact** – Reduces costs related to crime and improves business confidence.
- **Justice System Efficiency** – Helps courts and correctional facilities prepare for trends.

Possible Drivers of Crime

Predictive policing models using historical crime data and AI improved crime prevention by up to 25% in U.S. cities - Perry et al. (2010 and 2013, Rand Corporation).

Crime data should be looked at in conjunction with other factors

<u>Primary Dataset</u>

- **Source:** City of Raleigh Police Department
- **Observations:** ~550 000 (timestamps, then aggregated to daily, monthly and yearly counts)
- **Time Period:** June 2014 – December 2024 (2024 is used as primary test period)
- **Number of variables:** 23 variables
- **Some of the main variables:** Case Number, District, Crime Type, Reported Hour/Date, Latitude/Longitude

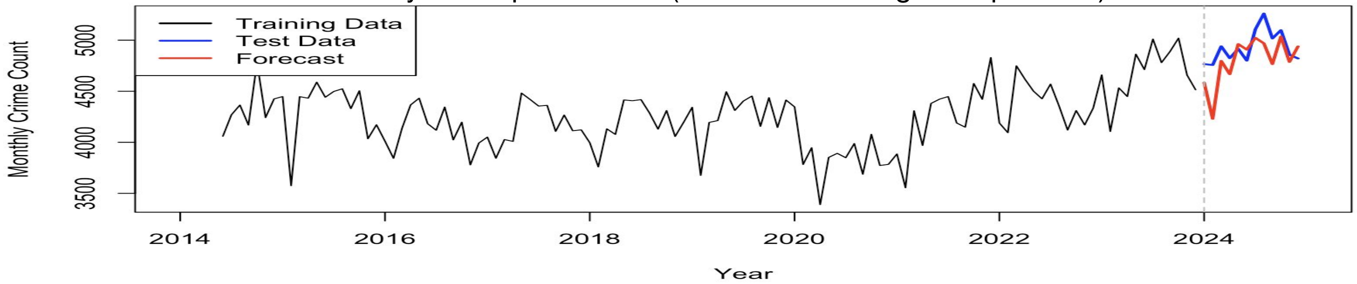
<u>Additional Datasets:</u>

- **Weather:** Precipitation, average monthly temperature **(**Source: National Weather Service)
- **Socioeconomic:** Unemployment rate in Raleigh area **(**Source: Bureau of Labor Statistics)

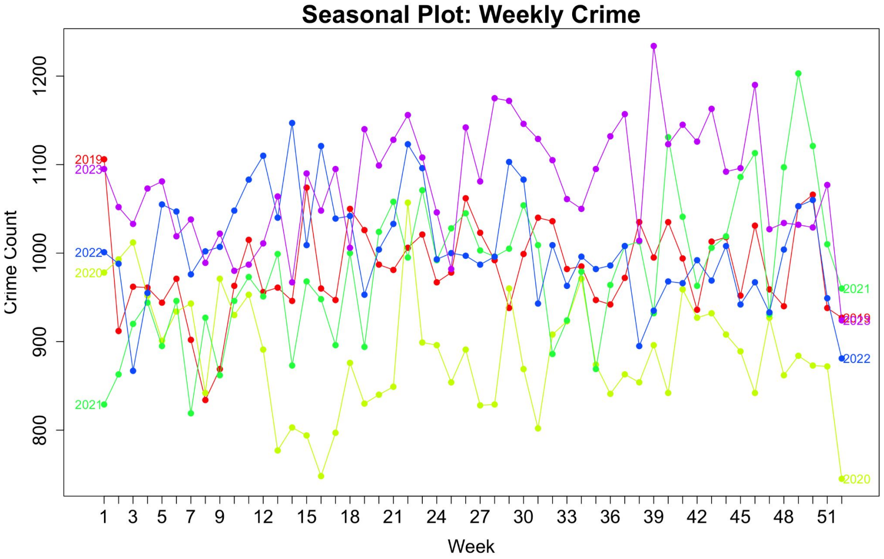
High-level Overview

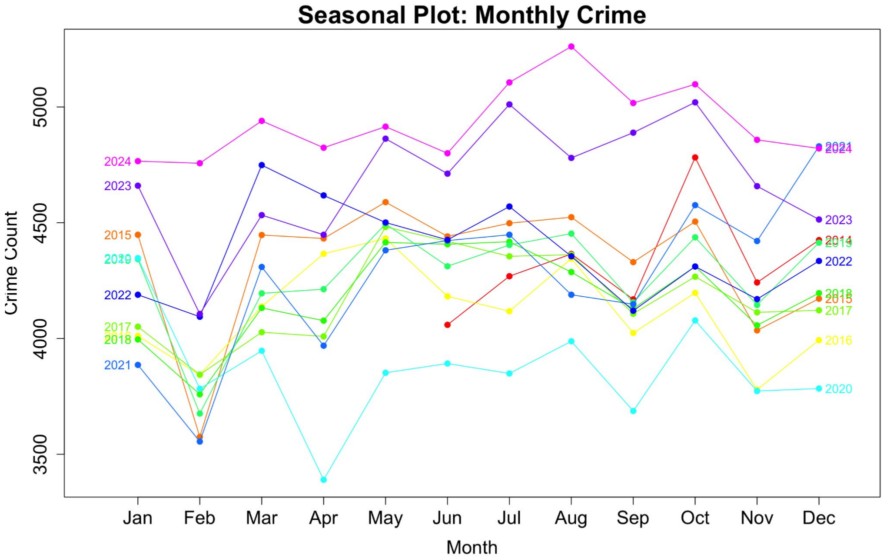
Method (Model)	Mean	Naive	S. Naive	Drift	ETS	BSTS	Holt Winters'	ARIMA Errors	VAR
Time Structure	Daily	Weekly	Monthly	Yearly					
Drivers	Time Structure	Average Temperature	Precipitation	Crime Type	Unemployment Rate				

Monthly VAR Specification (Crime and Average Temperature)



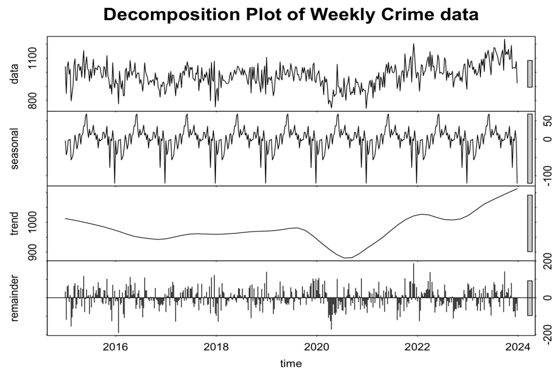
Monthly crime data depicts a stable pattern unlike weekly

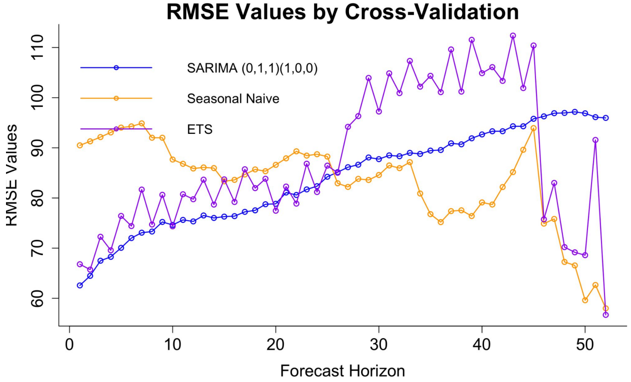




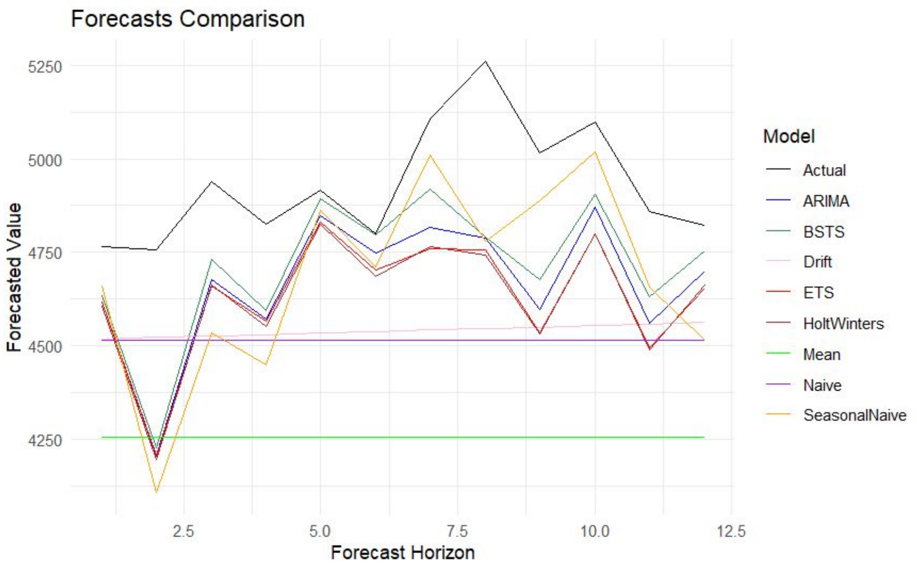
Weekly forecasts perform well for short-term horizons

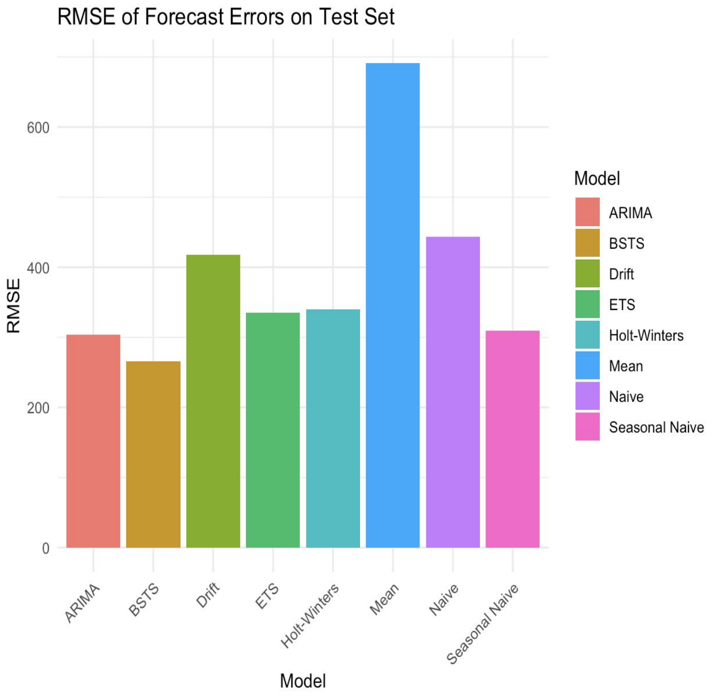
- **Train period:** 2015/1-2023/52
  Test period: 2024/1-2024/52
- **Behavior:** The weekly aggregated crime data indicates upward trend and yearly seasonality
- **Models tested:** ARIMA, SARIMA, ETS, SNaive, BSTS & Holt Winters
- **Winning Model on Test data:** SNaive (based on model evaluation metrics like RMSE, MAE and MAPE)
- **Winning Model after Cross-Validation:** SARIMA(0,1,1)(1,0,0)[52] for short-term(< W28) and SNaive for mid-term(>W28 &<W48) and SNaive & ETS for long-term(>W48).





Monthly Aggregate by a single Train/Test found BSTS outperform all benchmarks





Train: 2014/6 - 2023/12 | **Test:** 2024/1 - 2024/12

Differencing: D=1, d =1

Non-Stationary: Upward trend, 12-month seasonality

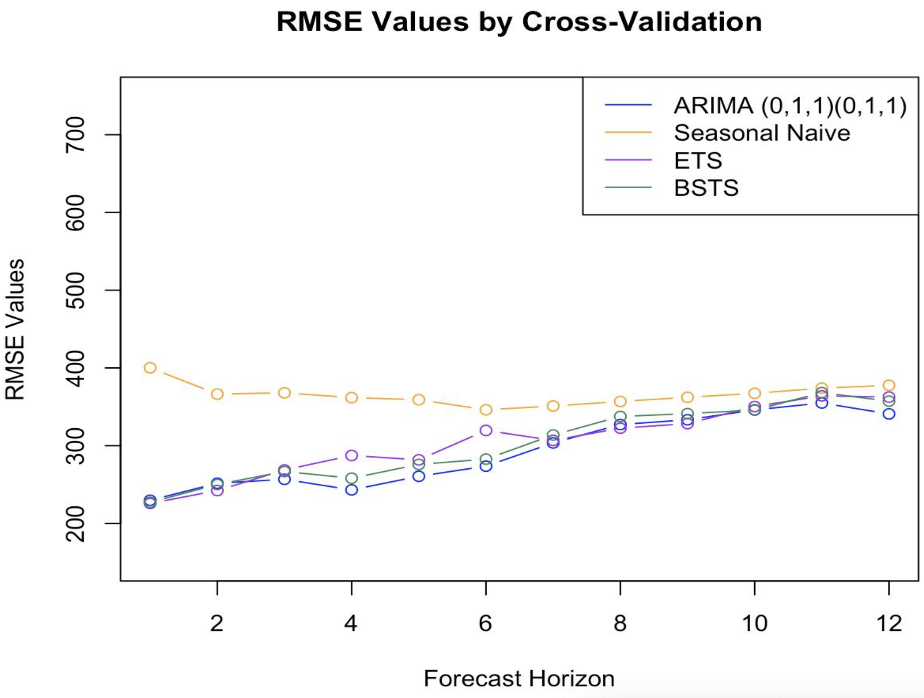
Model residuals: Resemble WN

Monthly Aggregate Cross-Validations Show Characteristics of Short-Term Models on Non-Stationary Data

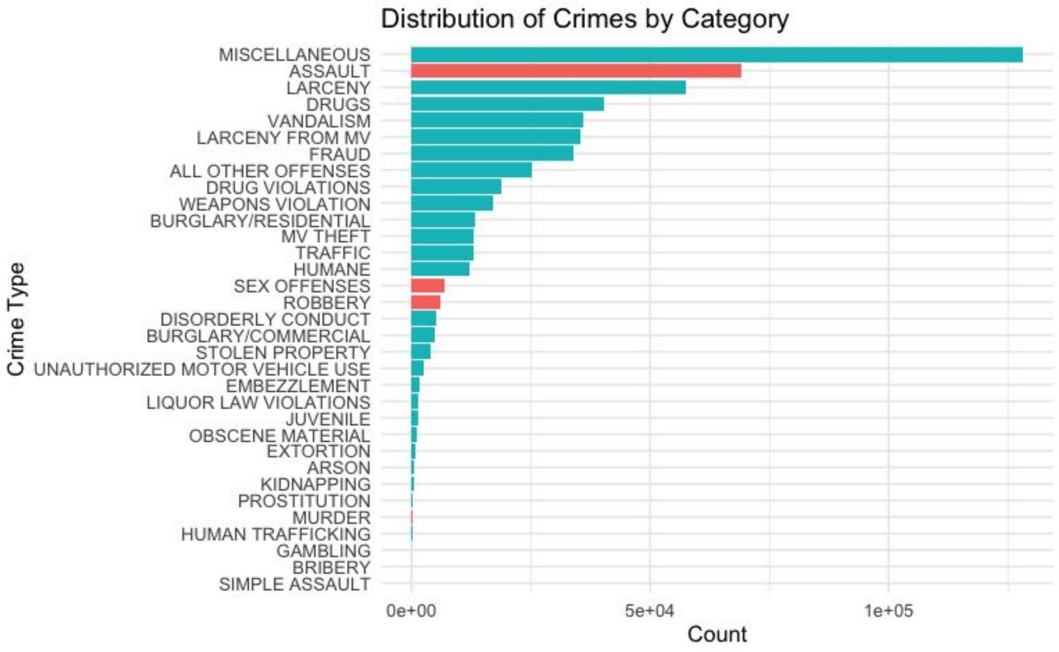
Cross-Validation

- ➢ Performed CV on the three top models and the best benchmark method
- ➢ Rolling window of length 90
- ➢ h = 12

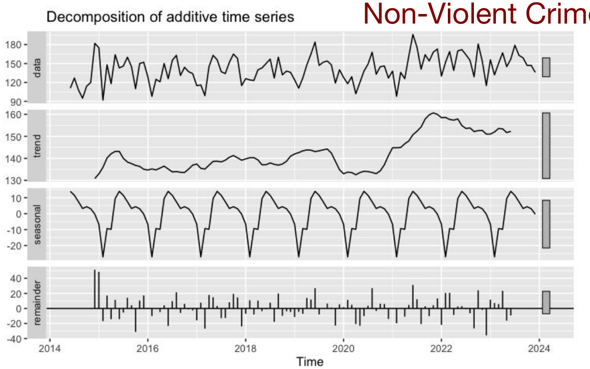
While the three advanced models demonstrate higher accuracy for short-term forecasting, their returns diminish at longer horizons



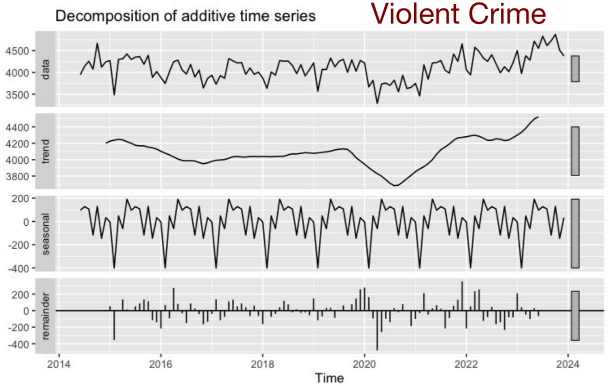
Does separating out by crime type yield better results?



Non-Violent Crime

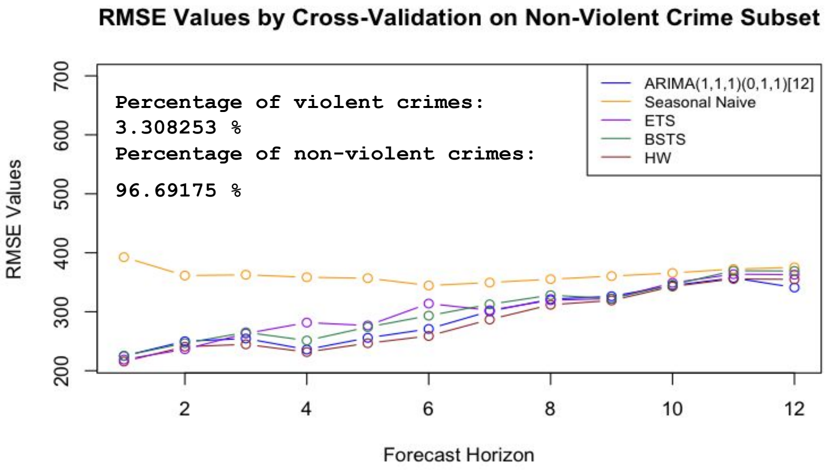


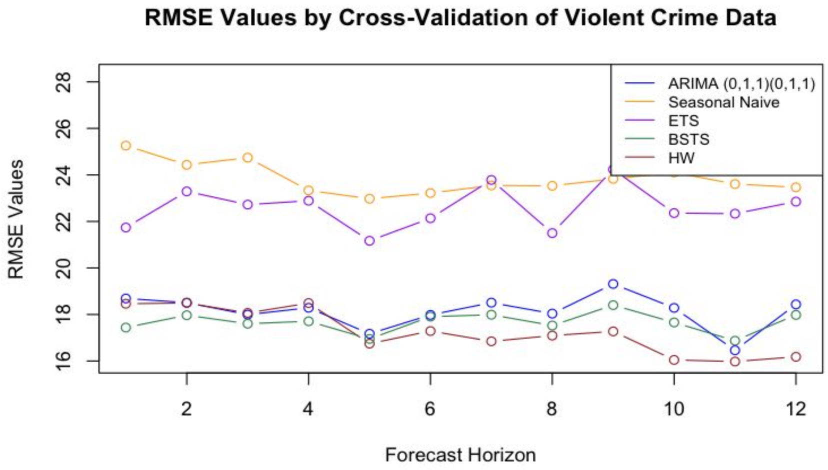
Violent Crime



Used definitions from FBI's Uniform Crime Reporting (UCR) Program to filter violent vs. nonviolent, https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/violent-crime

Holt-Winters and BSTS especially accurate for violent crime





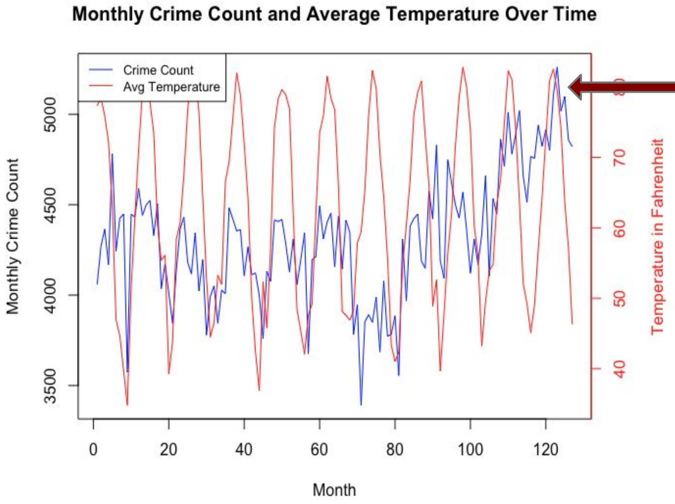
Non-Violent Crime Monthly Data (left) shows very similar model performance as the full monthly crimes dataset:

- SARIMA, and BSTS models are recommended for shorter-term forecasts, due to their higher accuracy and reliability
- For longer forecast horizons, the Seasonal Naive model is a more computationally efficient choice as its performance is on par with more complex models.

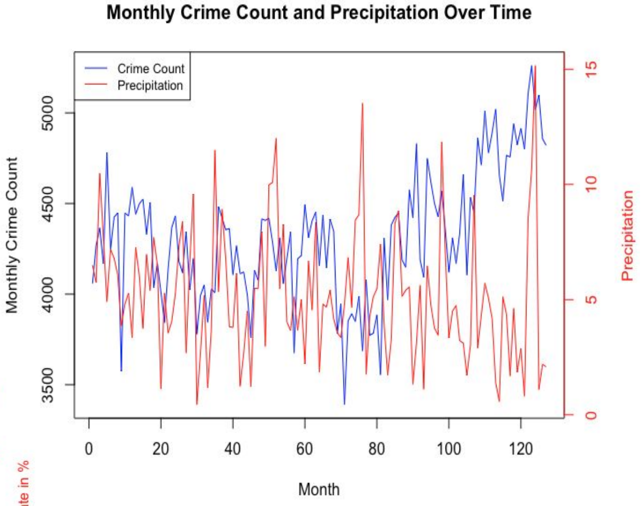
Violent Crime Monthly Data (right):

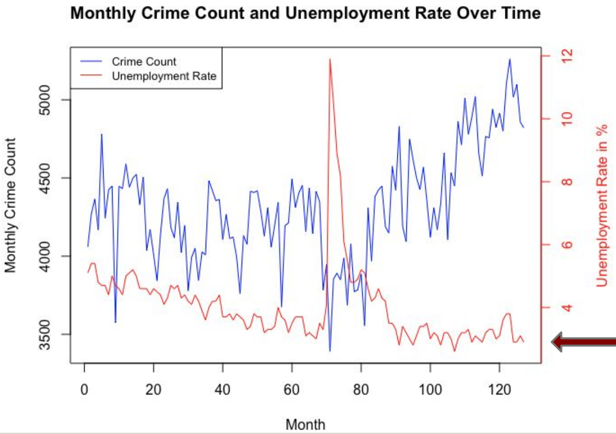
- HW and others like BSTS and SARIMA perform much better than sNAIVE or ETS throughout the forecast horizons

Multivariate Analysis - Monthly, Average Temperature, Precipitation and Unemployment Rate



Increases in average temperature appear to be associated with higher crime





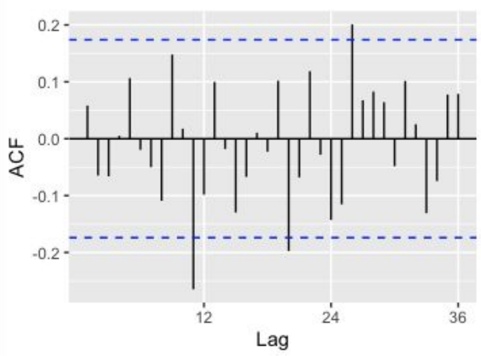
Post covid, conceptually not intuitive since lower unemployment leads to higher crime

Multivariate Analysis - ARIMA Error Model

Higher avg. temperature -> more crime | **Precipitation sign intuitive but not significant** | **Unempl. rate significant, but wrong sign**

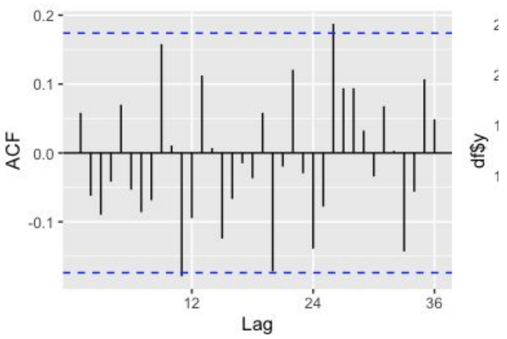
Average Monthly Temperature

```
Series: df_monthly_multi_avg_temp
Regression with ARIMA(0,1,1)(2,0,0)[12] errors

Coefficients:
          ma1    sar1    sar2    xreg
      -0.5122  0.3307  0.2982  8.8784
s.e.   0.0926  0.0916  0.0942  2.8344

sigma^2 = 40255:  log likelihood = -847.52
AIC=1705.04   AICc=1705.54   BIC=1719.22
```



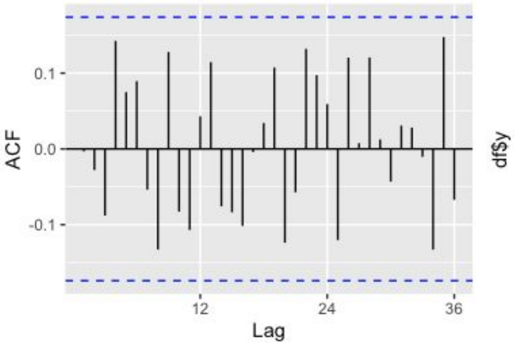
Precipitation

```
Series: df_monthly_multi_prcp
Regression with ARIMA(0,1,1)(2,0,0)[12] errors

Coefficients:
          ma1    sar1    sar2     xreg
      -0.4969  0.3680  0.2950  -2.3068
s.e.   0.0937  0.0896  0.0938   5.6573

sigma^2 = 43230:  log likelihood = -852.38
AIC=1714.75   AICc=1715.25   BIC=1728.93
```



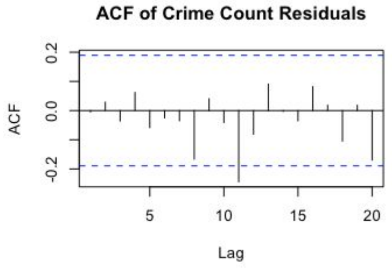
Unemployment Rate

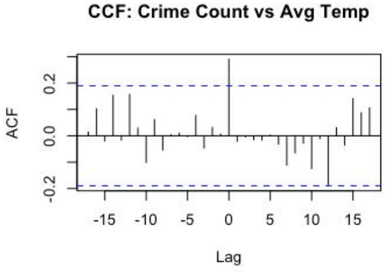
```
Series: df_monthly_multi_unemploy_rate
Regression with ARIMA(0,1,2)(0,1,1)[12] errors

Coefficients:
          ma1      ma2     sma1      xreg
      -0.4869  -0.1601  -0.8676  -82.8113
s.e.   0.0929   0.0878   0.1659   17.9518

sigma^2 = 30454:  log likelihood = -756.5
AIC=1523   AICc=1523.55   BIC=1536.68
```

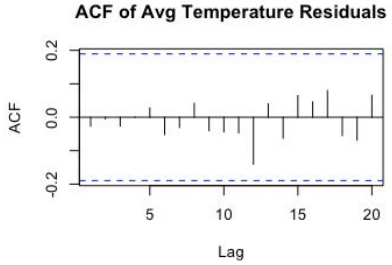


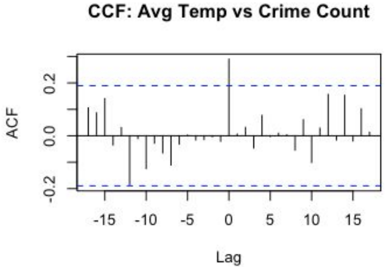
Multivariate Analysis - VAR Model (with Average Temperature)

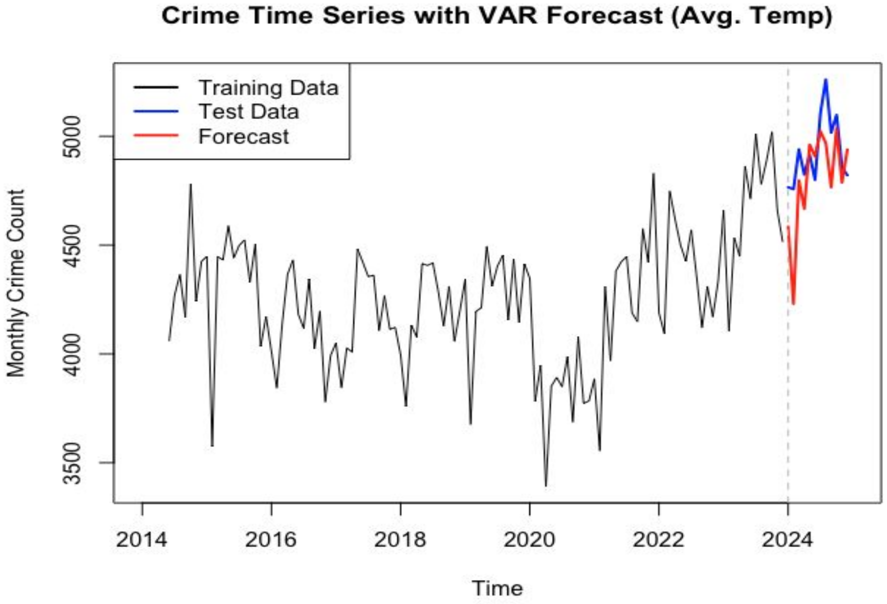
VAR Residuals generally resemble white noise







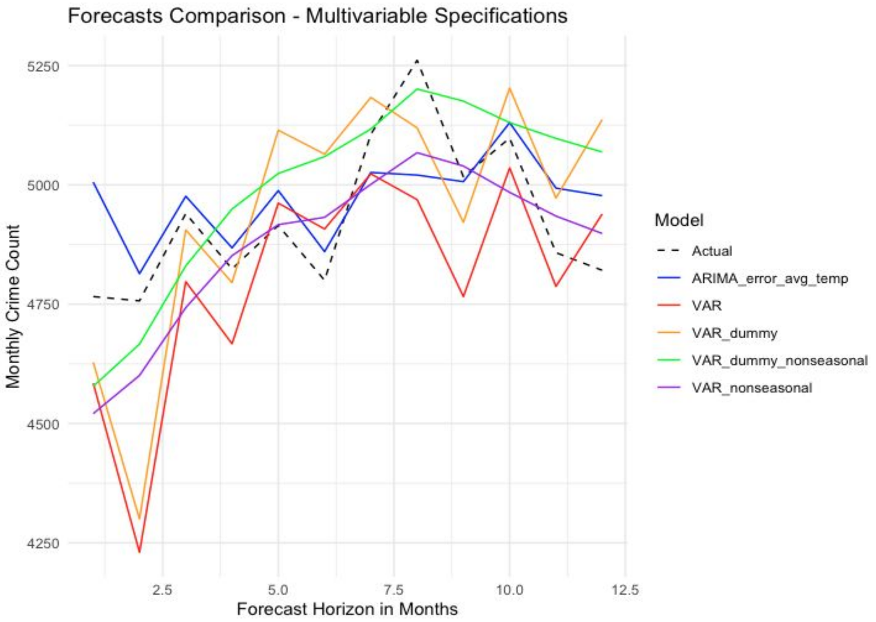


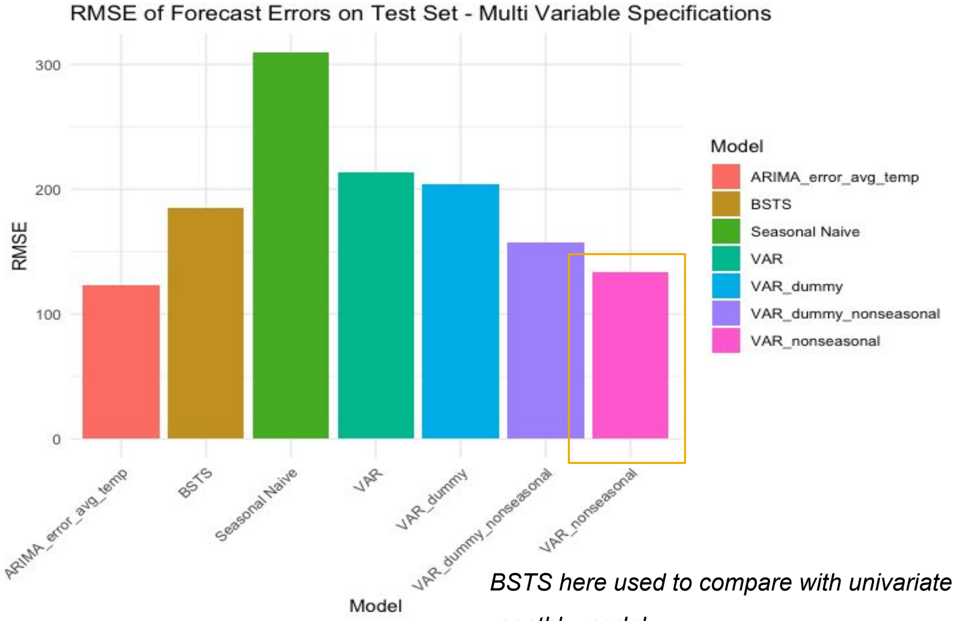


Precipitation and unemployment rate specifications not intuitive as in the previous case

Multivariate Analysis Comparison - Monthly with avg. temperature outperforms, non seasonal VAR outperforms

- Non Seasonal VAR chosen as the best model after being tested on multiple test years, ARIMA errors model with average temperature proved to be unstable on different tests samples





BSTS here used to compare with univariate monthly model

Conclusion

- **Overall: The monthly VAR model with average temperature** was concluded to be the most accurate model to forecast crime rates.
- **Short Term Forecasts**
  - Monthly: SARIMA, BSTS, ETS thrived in short-term forecasts but struggled at longer forecast horizons.
  - Weekly: SARIMA model performs well in the short-term but in the long term benchmark seasonal naive method performs better.
- **Type of Crime:** Holt Winters and BSTS models perform especially well for violent crime.

Extensions

- Ensemble Methods
- More details daily data specifications (Fourier Analysis or other methods)
- Exploring other dimensions of the data further:
  - Spatial effects
  - Type of crime

Thank you!

Appendix: Table of Contents

- Contributions……………………………………………………………………...slide 20
- Univariate Weekly Analysis………………………………………………….....slide 21 - 24
- Univariate Monthly Analysis……………………………………………………slide 25 - 30
- Violent vs. Nonviolent Crime Analysis…………………………………………slide 31 - 35
- Stationarity and Variance Checks……………………………………………….slide 36
- References…………………………………………………………………….......slide 37

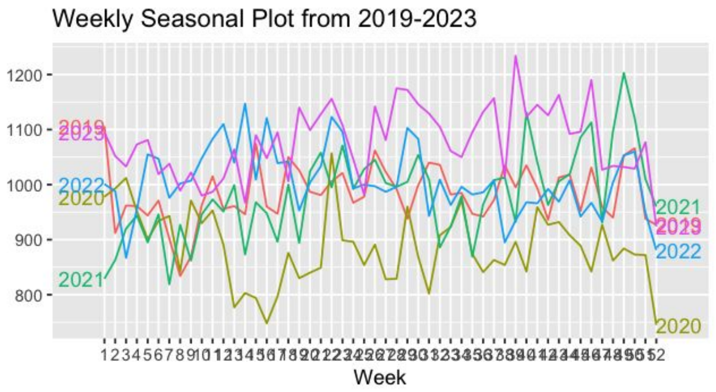
Appendix: Contributions

- Jisoo: Univariate Violent/Nonviolent Monthly Analysis, EDA, Presentation
- Bonny: Univariate Weekly Aggregate Analysis, EDA, Presentation
- Lexi: Univariate Monthly Aggregate Analysis, Overall Modeling Framework, Presentation
- Stepan: Multivariate Analysis + BSTS specification, EDA, Presentation

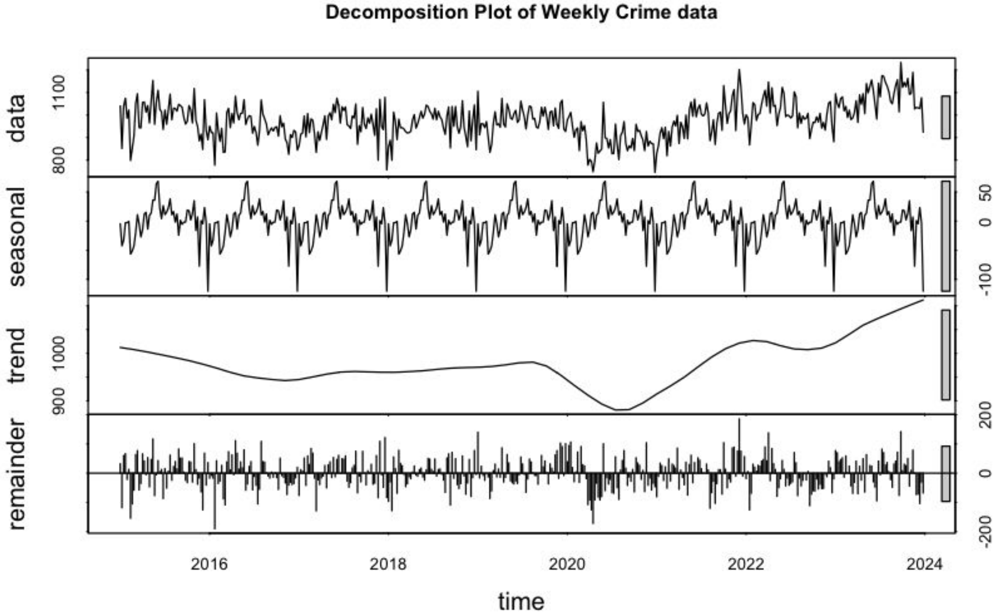
Appendix: Weekly Crime data indicates upward trend and yearly seasonality

Train/Test Split:

- Train: 2015/1 - 2023/52
- Test: 2024/1 - 2024/52

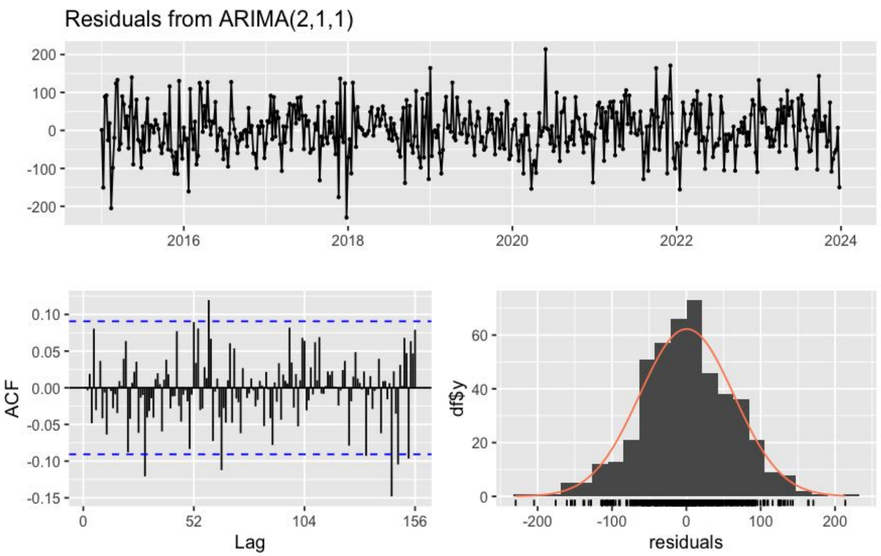


Seasonal plot depicts some yearly pattern.

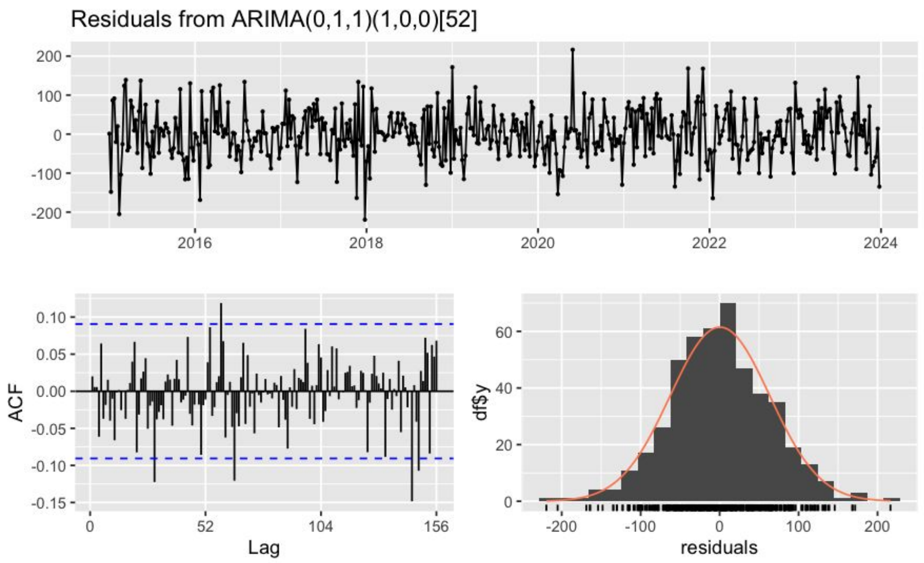


Decomposition plot indicates slight upward trend and seasonality pattern which repeats every year.

Appendix: SARIMA Model works better than ARIMA for weekly aggregate

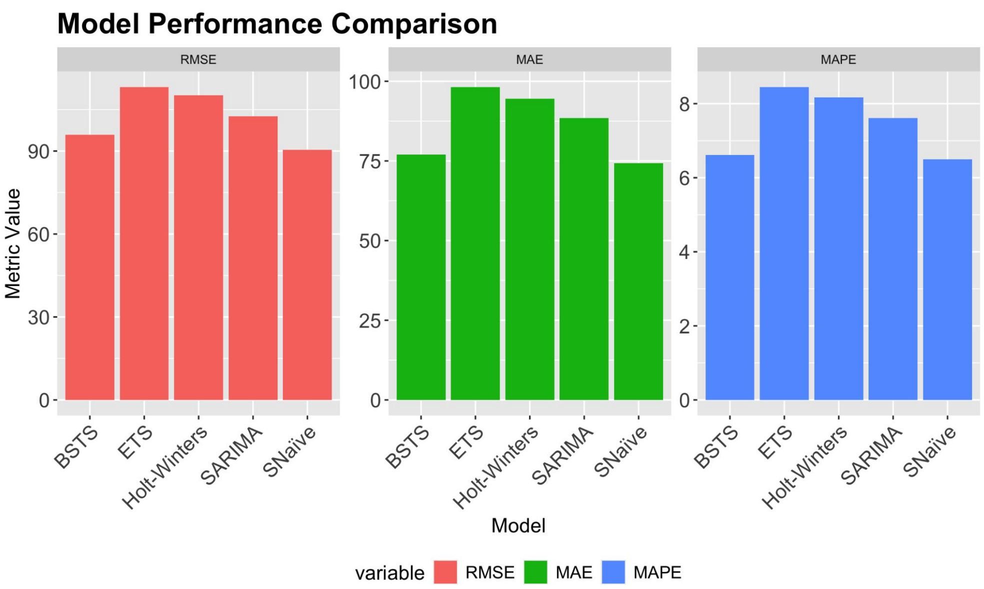


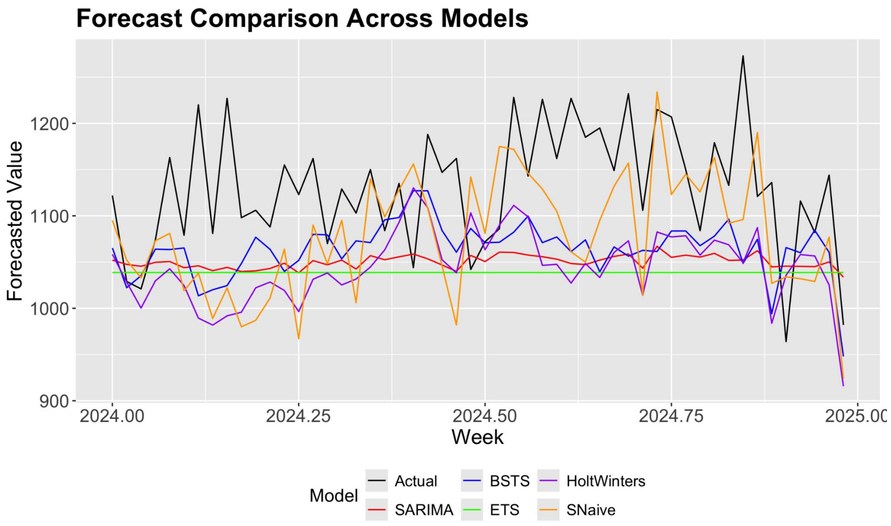
AIC = 5208.67 **RMSE** = 63.25254



AIC = 5202.77 **RMSE** = 62.94953

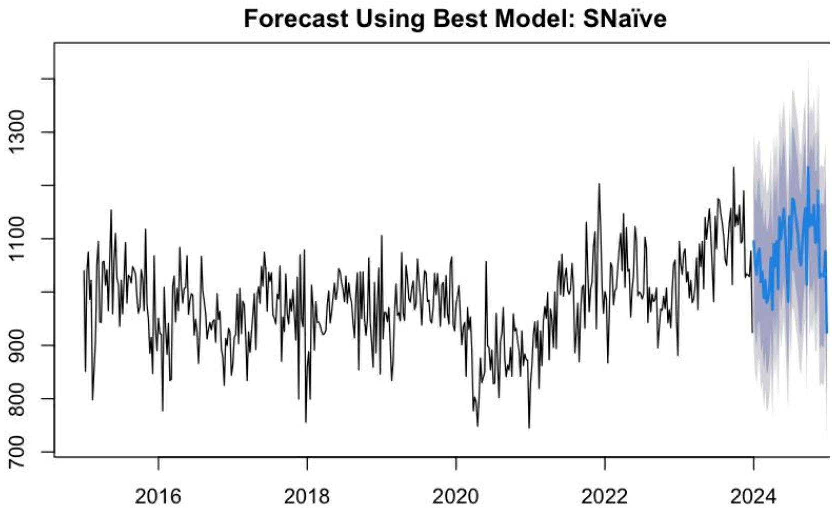
Appendix: SNaive works best in the long term



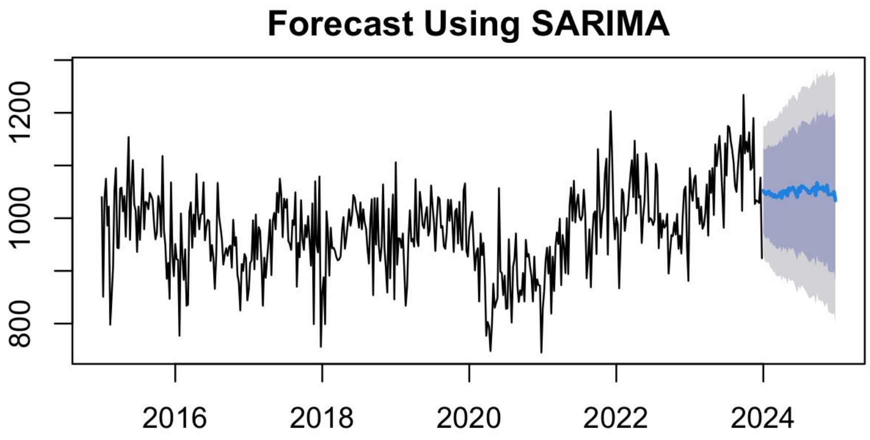


Model Performance metrics indicate SNaive to be the best model. The Forecast comparison also shows how SNaive performs better in the long term

Appendix: SARIMA works best in the short term based on the cross validation dataset



SNaive is the best forecast model based on test dataset



SARIMA is the best forecast model based on cross validation dataset in short term

Appendix: Univariate Monthly Aggregate Data Exhibits Clear Trend and Seasonality

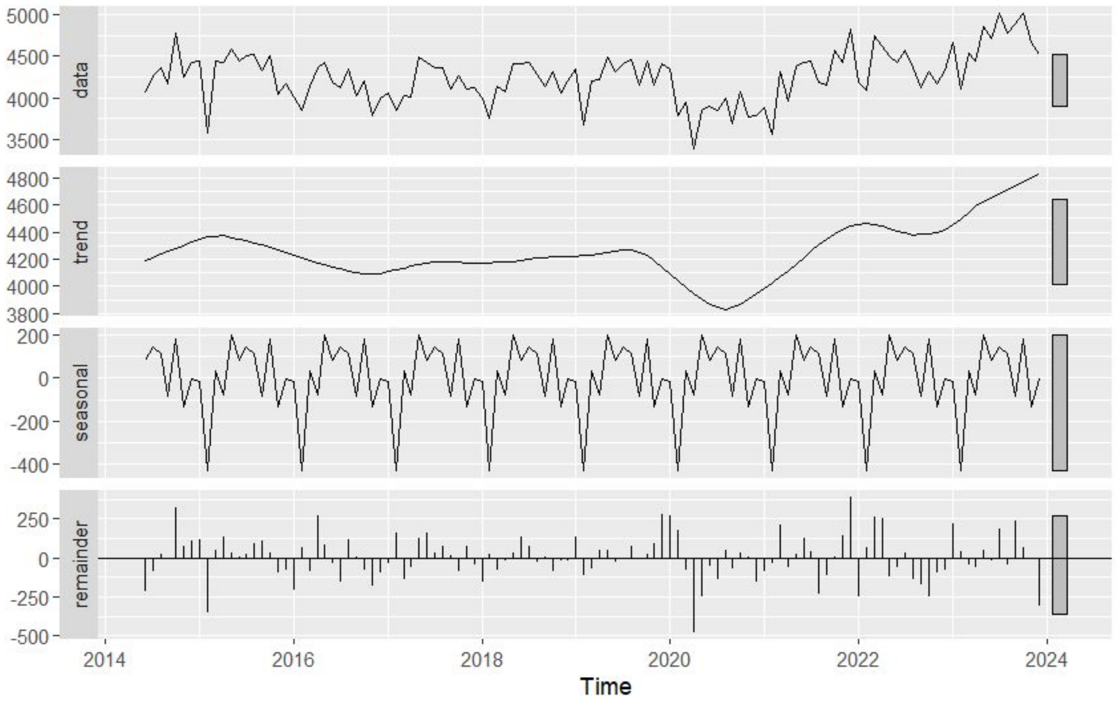
Train/Test Split:

Train: 2014/6 - 2023/12

Test: 2024/1 - 2024/12

Decomposition

➢ TS
➢ STL



Appendix: Univariate Monthly Aggregate ARIMA Models

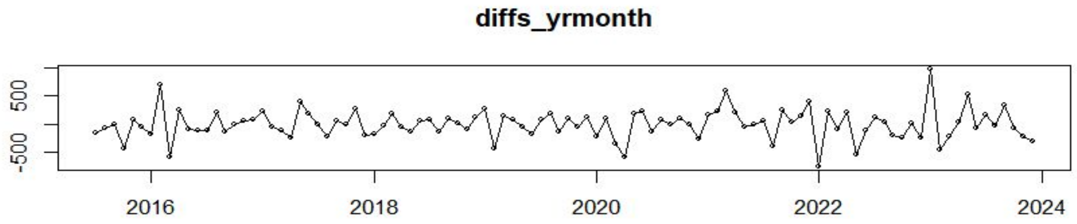
Applied Differencing d=1, D=1

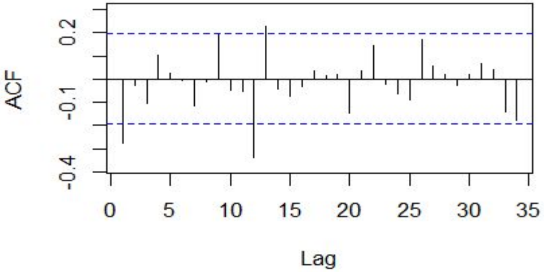
ARIMA(0,1,1)(1,1,0)[12]
ARIMA(1,1,0)(0,1,1)[12]
ARIMA(1,1,0)(1,1,0)[12]
ARIMA(0,1,1)(0,1,1)[12] - Best
Auto.arima:

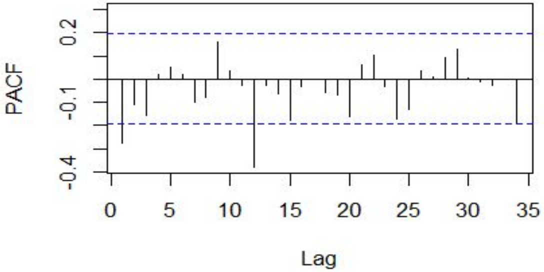
ARIMA(1,1,1)(0,1,1)[12]

AR/MA

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	x	x	x	x	o	x	o	o	o	o	x	o	o
1	x	x	o	x	x	x	x	o	o	o	o	x	x	o
2	o	x	o	o	o	o	o	o	o	o	o	x	o	o
3	x	o	o	o	o	o	o	o	o	o	o	x	o	o
4	x	o	o	o	o	o	o	o	o	o	o	x	o	o
5	x	x	o	o	o	o	o	o	o	o	o	x	o	o
6	x	x	x	o	o	o	o	o	o	o	o	x	o	o
7	x	o	x	o	o	o	o	o	o	o	o	x	o	o

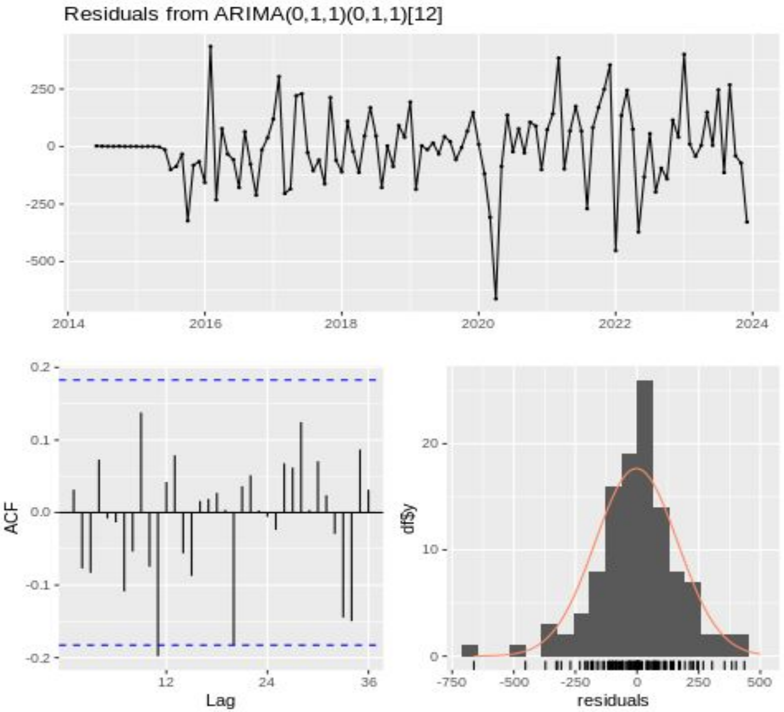


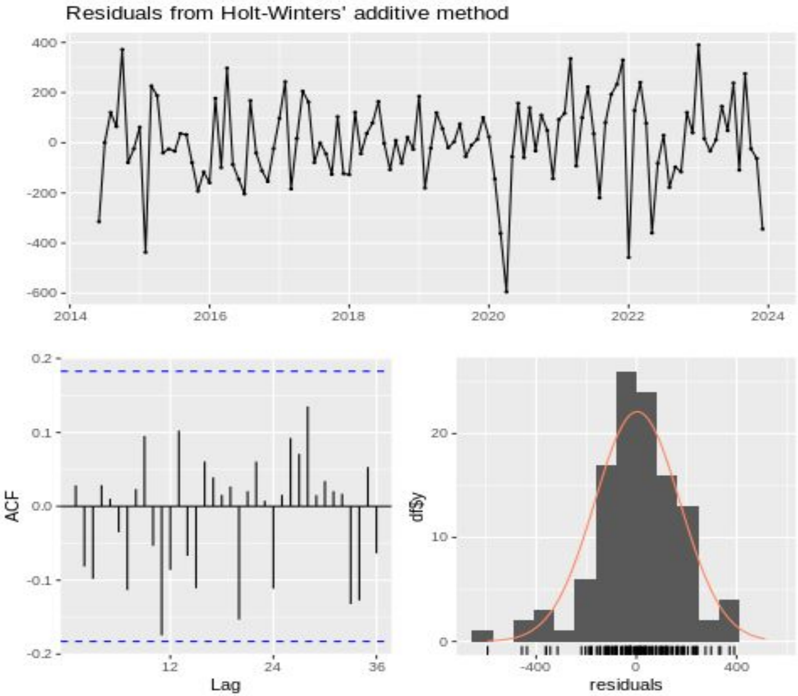




Appendix: Monthly Aggregate Model Residuals

ARIMA and Holt-Winters model residuals resemble a WHITE NOISE





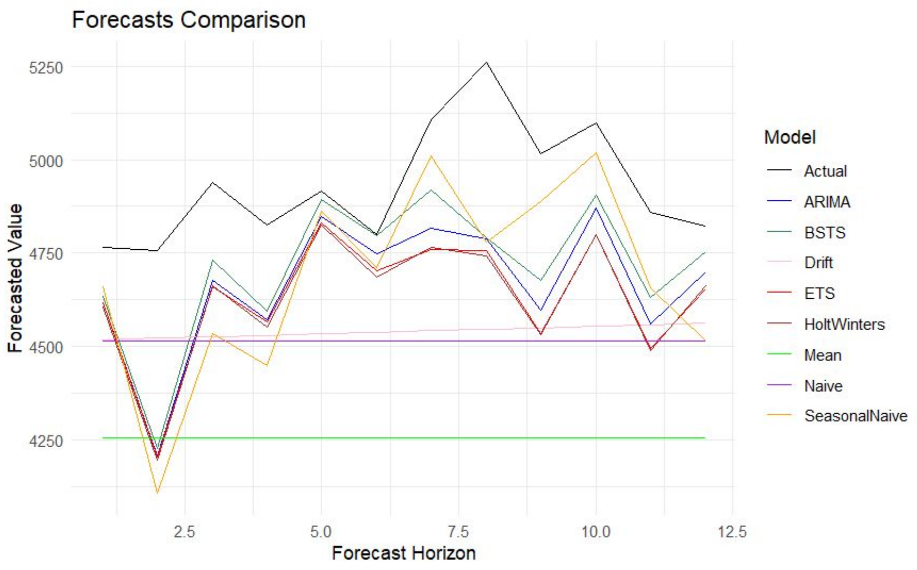
Appendix: Monthly Aggregate Models Perform Better than Benchmark Methods for Small Forecast Horizons

Models Tested

- ARIMA
- BSTS
- Holt-Winters
- ETS

Benchmark Methods

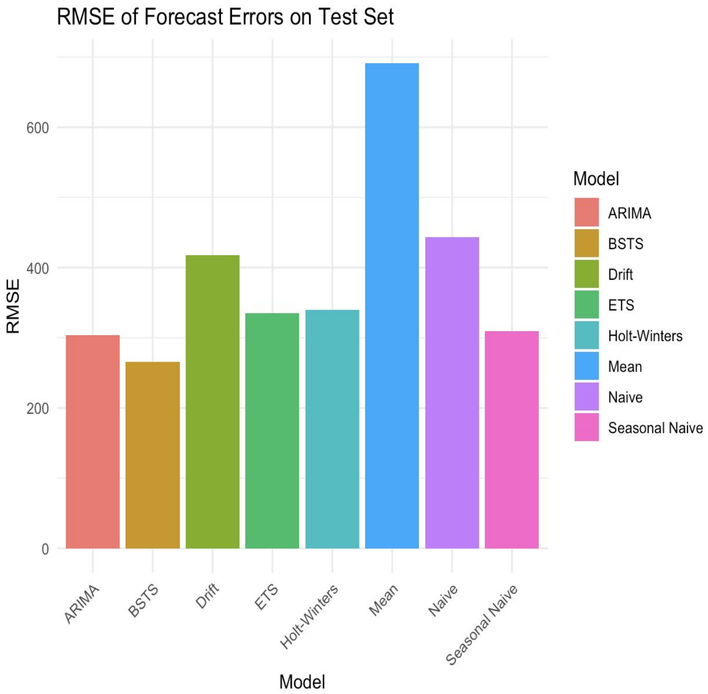
- Naive
- Seasonal Naive
- Mean
- Drift

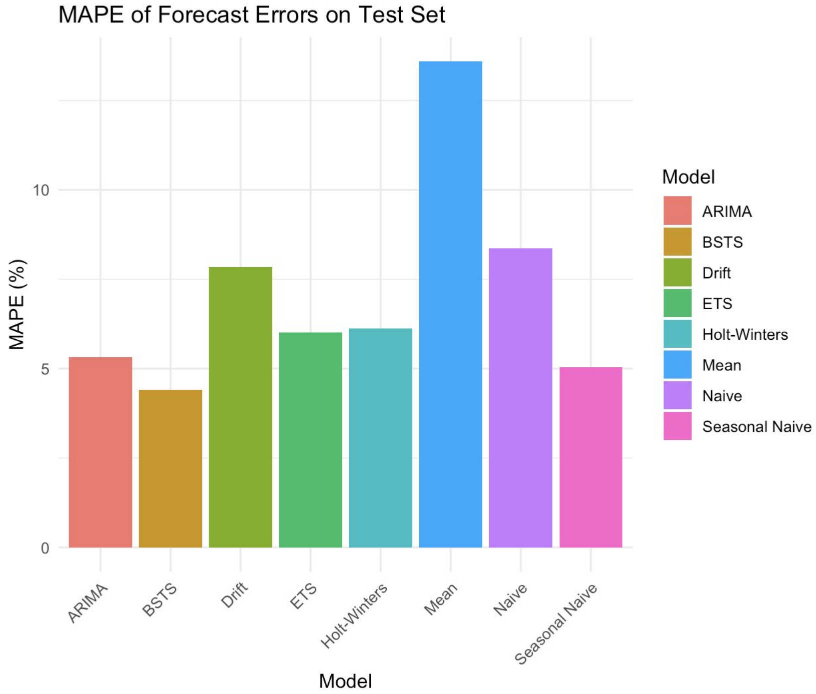


Appendix: Monthly Aggregate Model Evaluation shows BSTS and Seasonal Naive have the lowest Error Rate on a single Test Set

Best Models

1. BSTS
2. ARIMA
3. ETS
4. SNaive

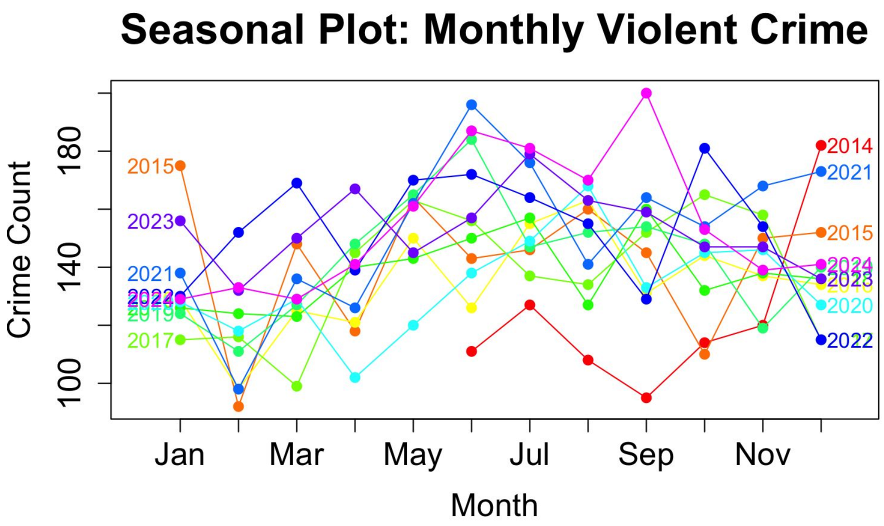


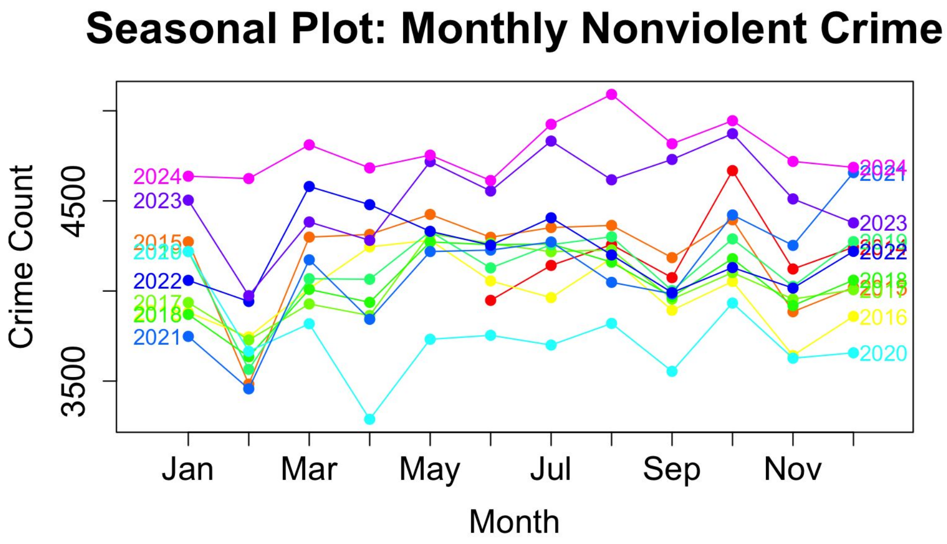


Appendix: Conclusions - Univariate Monthly Aggregate Analysis

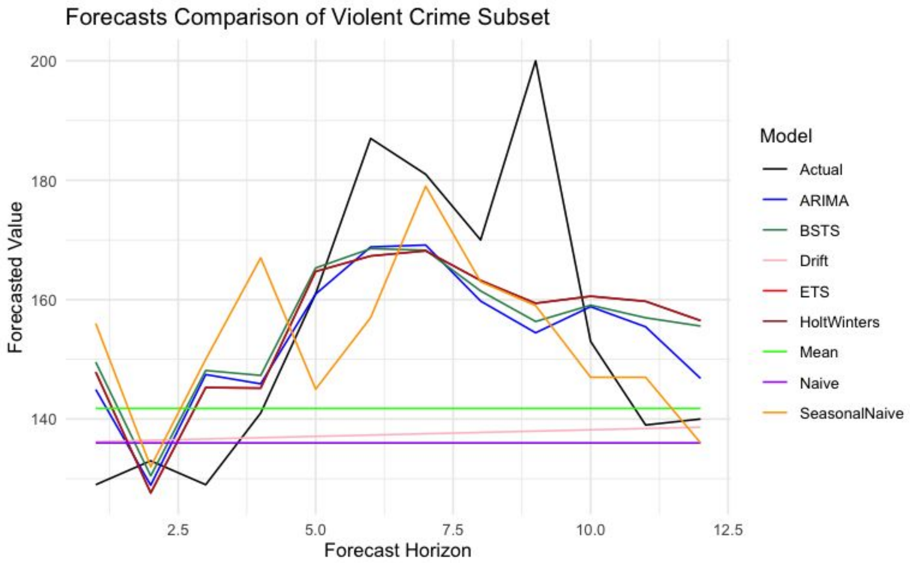
- SARIMA, ETS, and BSTS models perform well and produce comparable results for short-term forecast horizons (e.g., $h \leq 10$).
- As the forecast horizon increases ($h>10$), the accuracy of SARIMA, ETS, and BSTS models gradually declines. By $h=11$, the models show similar performance to the Seasonal Naive benchmark.
- For <u>shorter-term forecasts, SARIMA, ETS, and BSTS models are recommended</u> due to their higher accuracy and reliability.
- For <u>longer forecast horizons, the Seasonal Naive model is a more computationally efficient choice</u> as its performance is on par with more complex models.

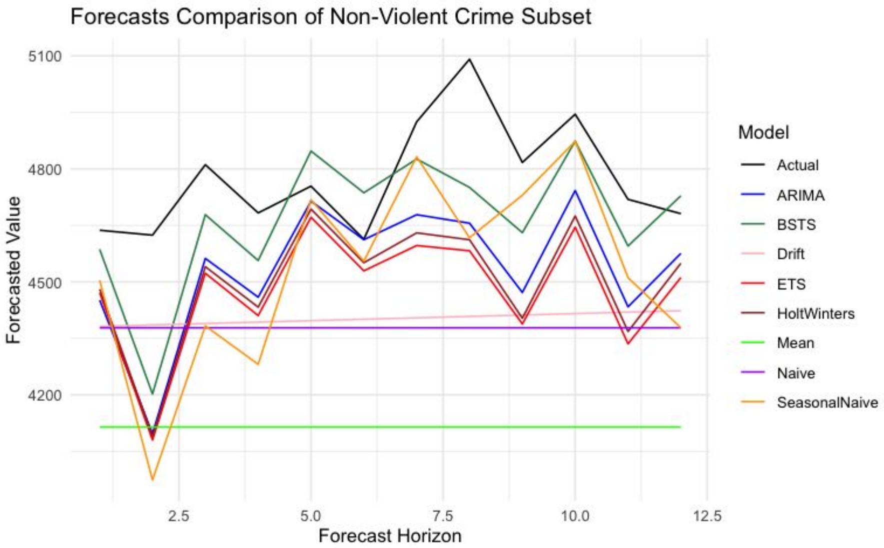
Violent vs Nonviolent



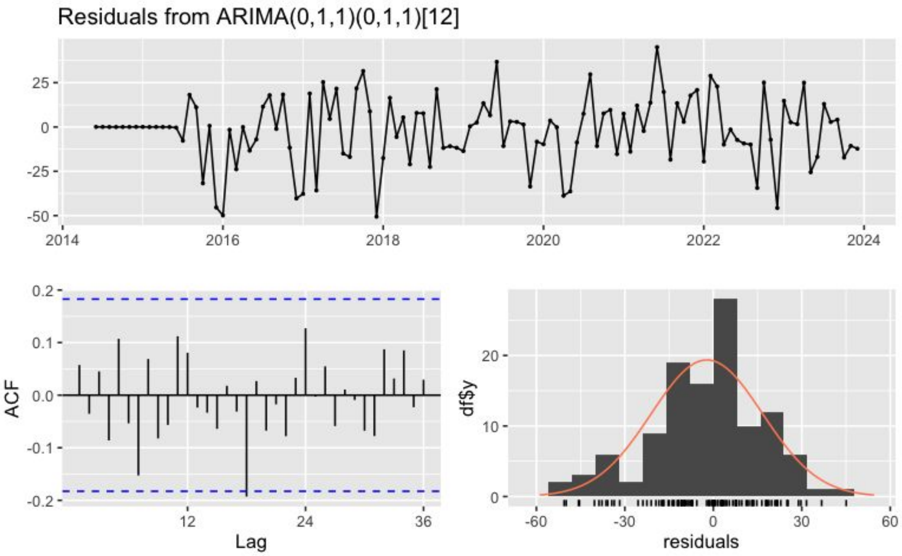


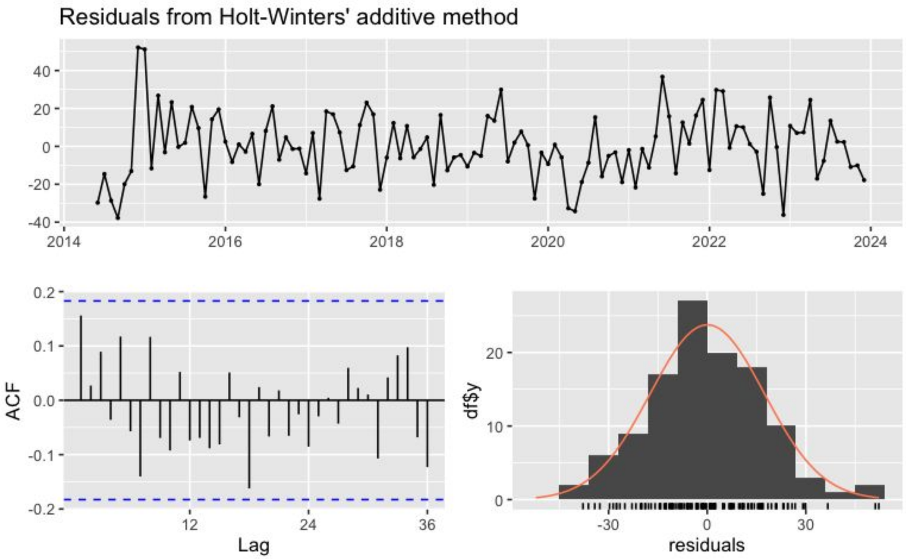
Univariate Analysis - Violent vs Nonviolent Model Comparison



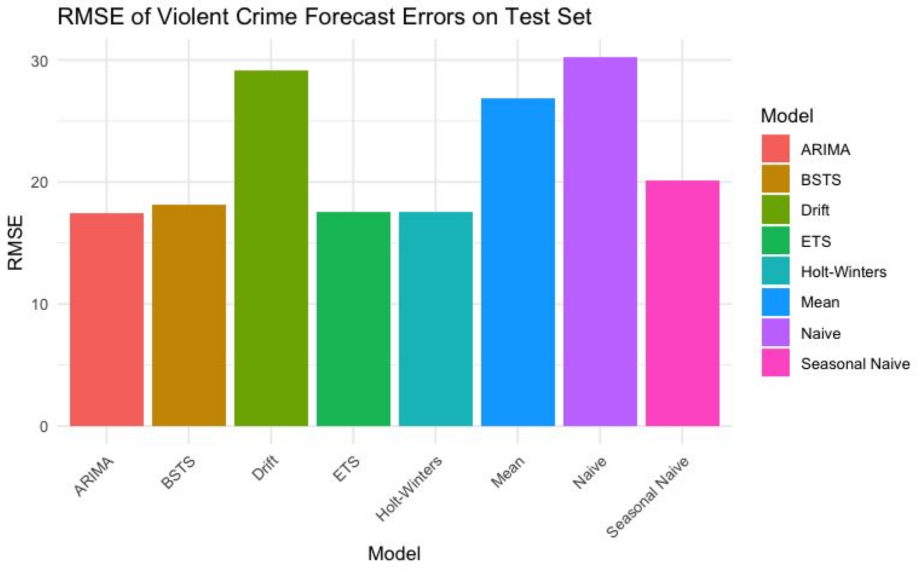


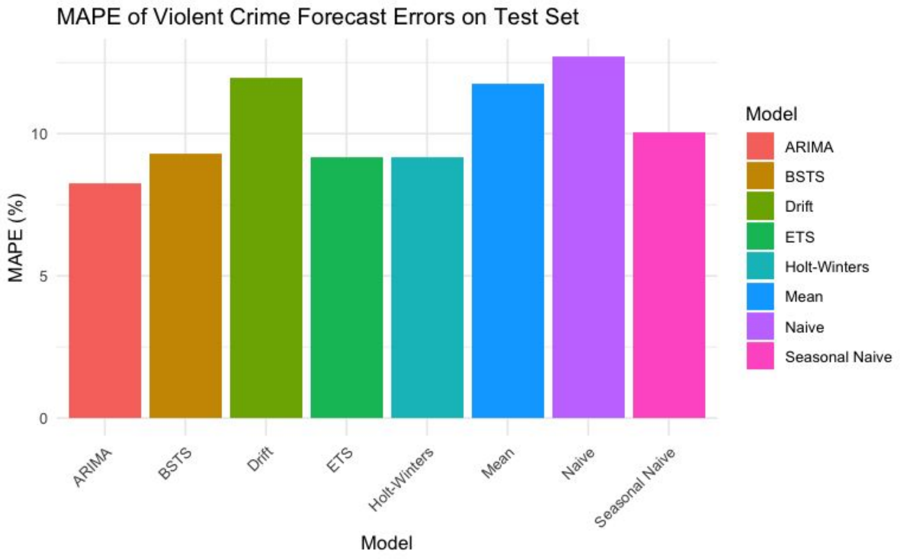
Violent vs Nonviolent Model Comparison



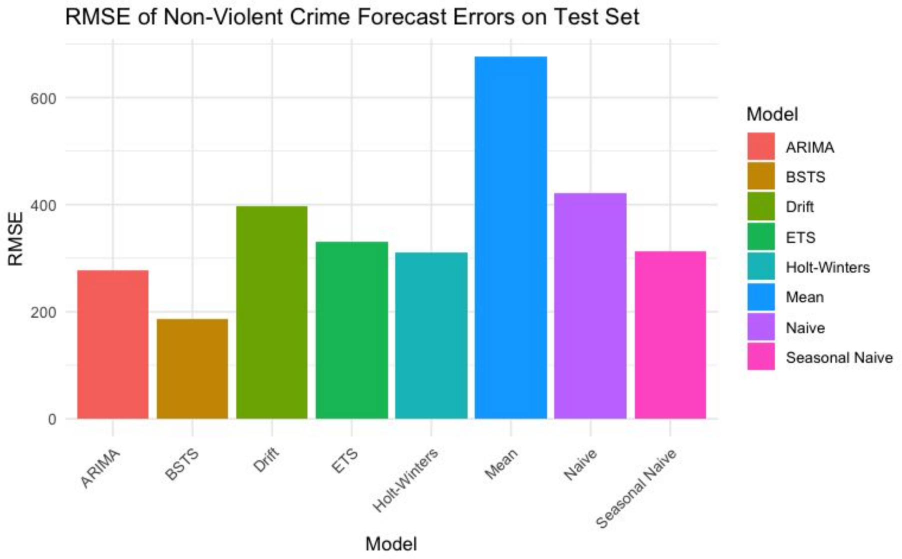


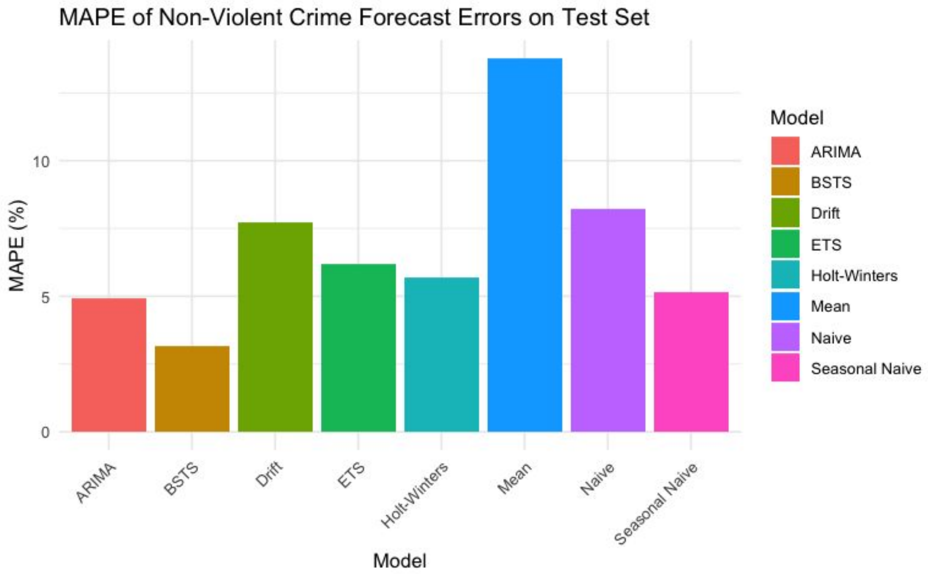
Appendix: Violent data subset forecast errors





Appendix: Nonviolent data subset forecast errors





Appendix: Stationarity and Variance Verification

- **Variance:** Box-Cox Transformation did not warrant variance transformation (lambda values close to 1)

- **Stationarity:** Stationarity checks performed; VAR specifications were run on differenced data (order 1) given that differencing was required.

References

Pearsall, Beth, “Predictive Policing: The Future of Law Enforcement?” National Institute of Justice Journal, No. 266, May 2010.

https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/violent-crime

https://www.weather.gov/wrh/climate?wfo=RAH

https://www.bls.gov/eag/eag.nc_raleigh_msa.htm