

Modeling Crime in Los Angeles

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ACMS40842

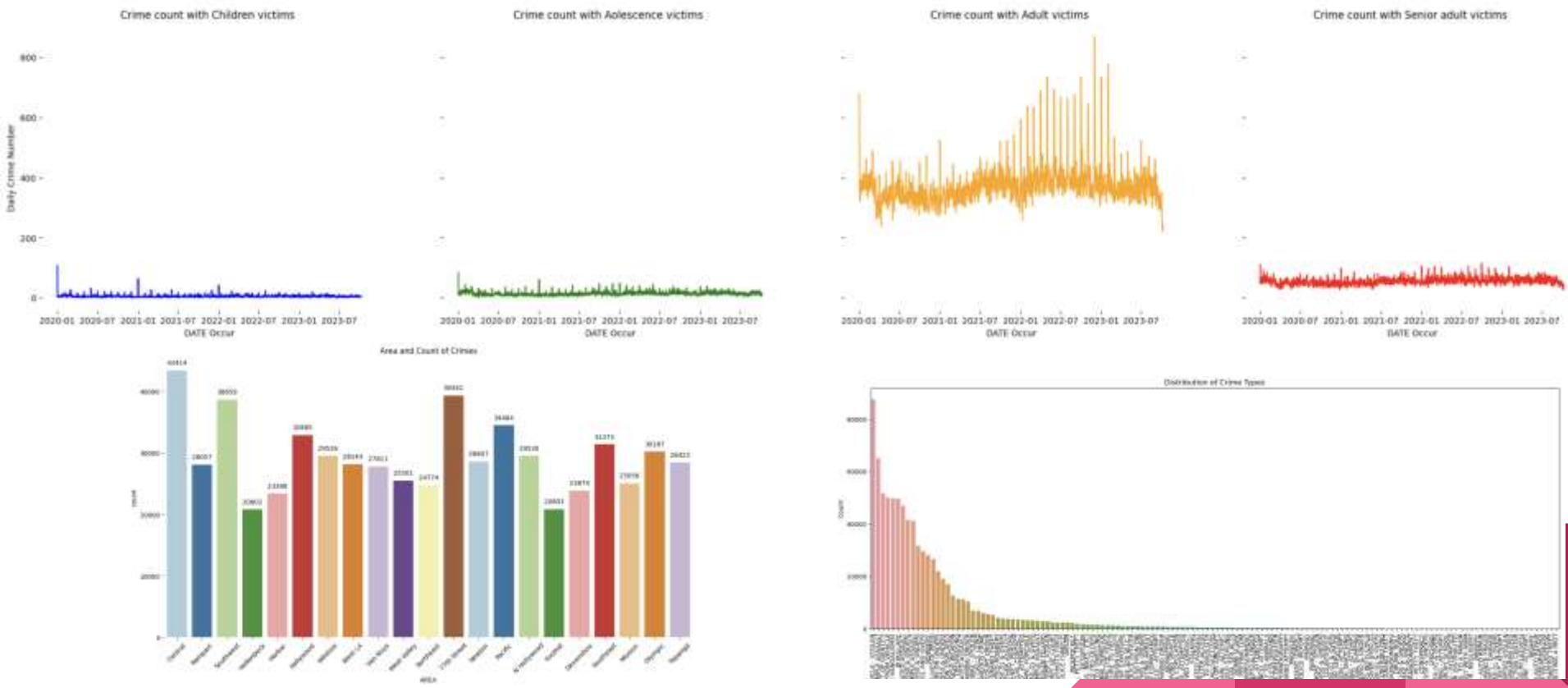
Background

- Los Angeles ranks 17th in crime rate for US cities with population >100,000
 - Highest among the biggest cities in the US (NYC, Chicago, Houston, Phoenix, Philadelphia)
- 3rd largest police department in US
 - \$1.74 billion budge
 - \$420 per resident
- One of the most diverse cities in the US
 - 50% latino, 11% asian, 10% black



Dataset Overview: 01/01/2020 - 10/08/2023 Over 700k Crime Case

Selected Features: Area, Crime Type, Victim Sex, Age & Descent, Exact Time



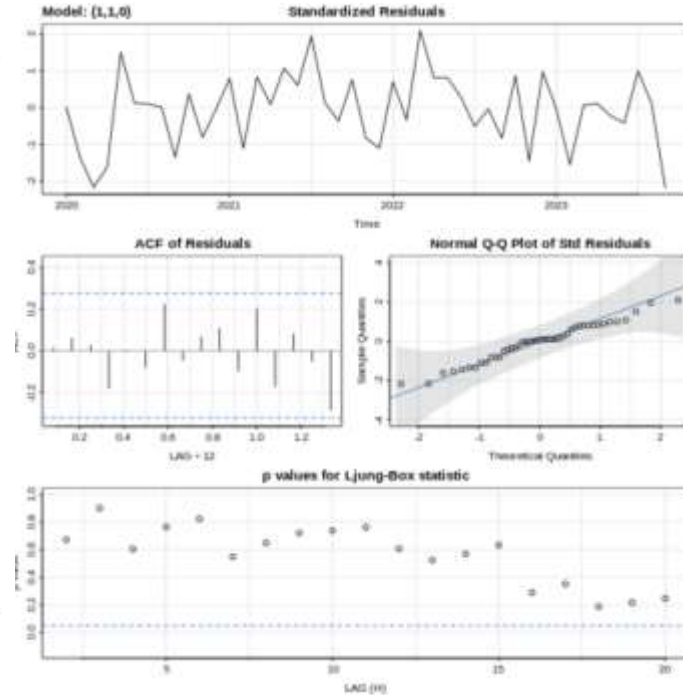
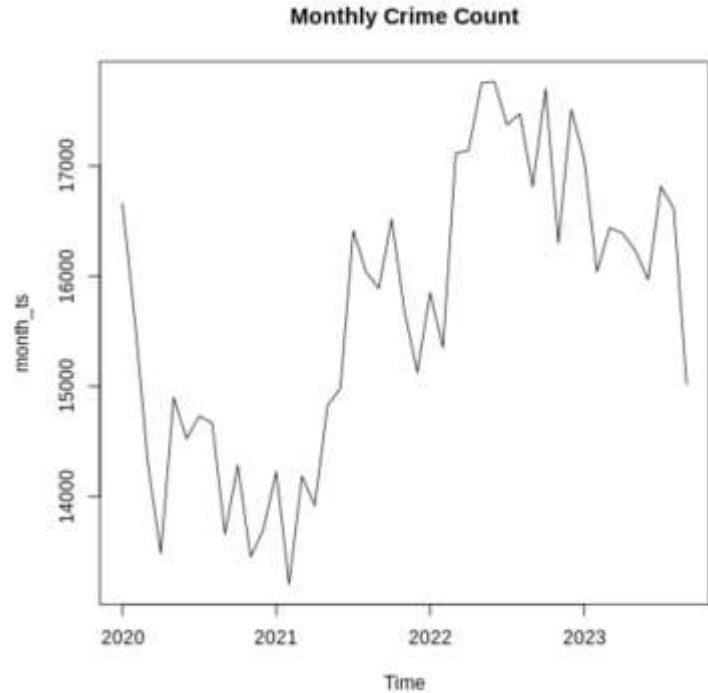
Research Questions

Examine how crime trends differ for different groups of victims.

- Enable policy makers to create more appropriate solutions to fighting crime
- Deeper understanding of who is most affected by crime
- Help the general public become aware of the possible crimes



Overall crime count model (monthly)



ARIMA(1,1,0)

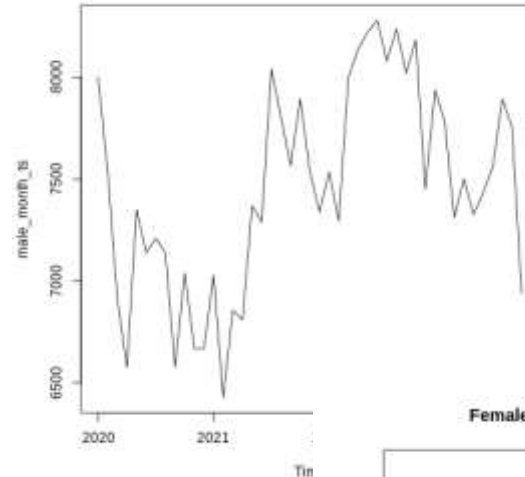
No seasonality

Segmented by Victims' Gender (Monthly): EDA

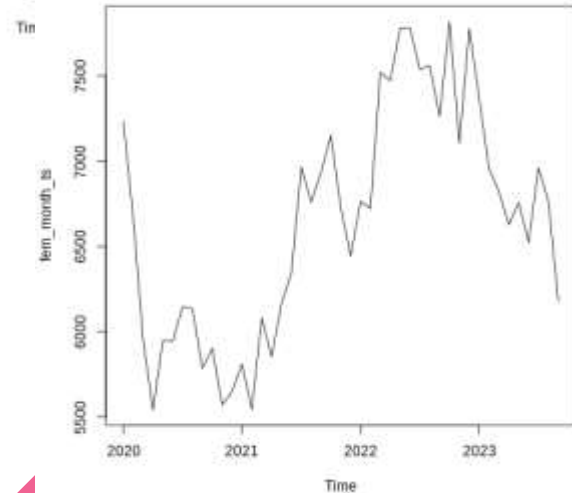


Largely similar, but enough differences to explore further

Male Victim Monthly Crime Count

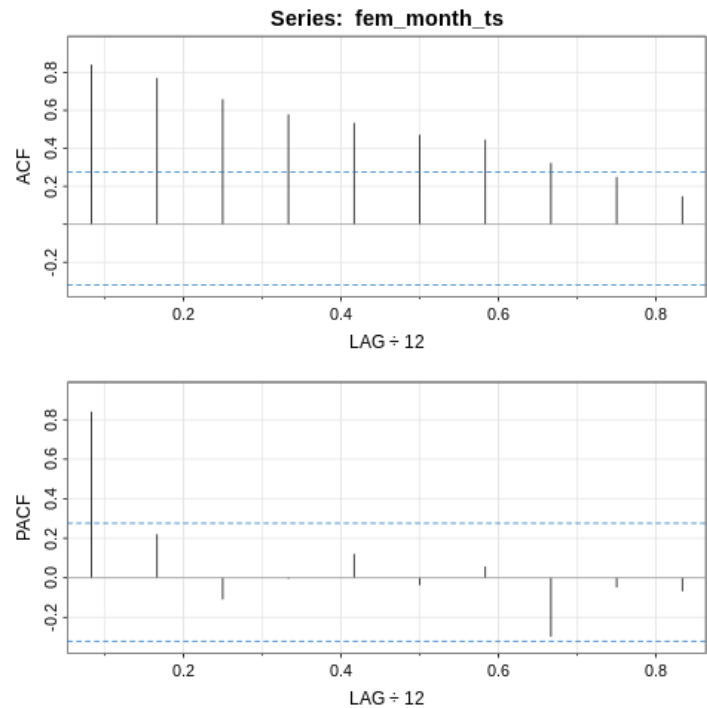


Female Victim Monthly Crime Count

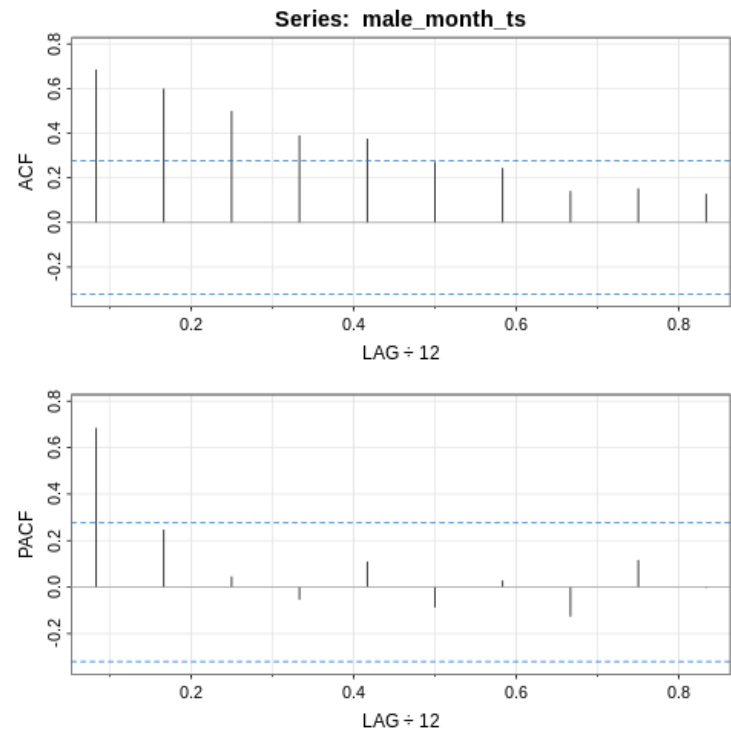


Segmented by Victims' Gender (Monthly): EDA

Female Victims



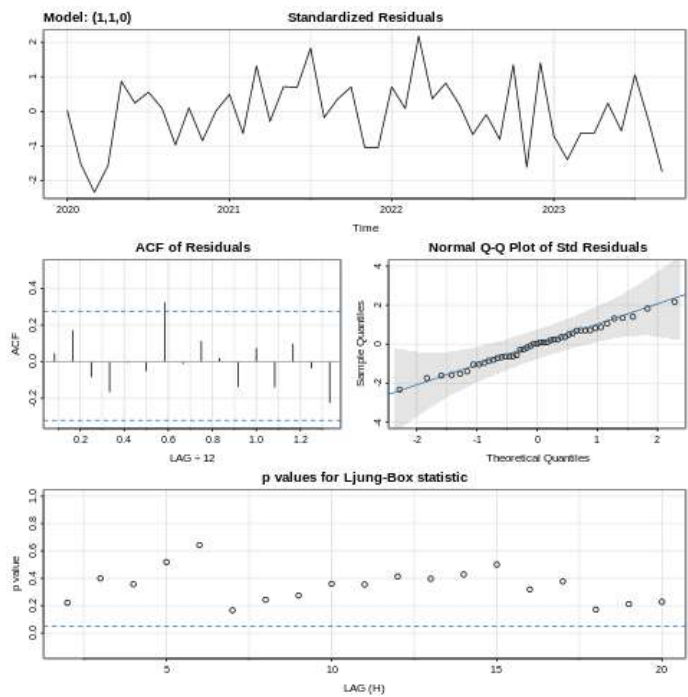
Male Victims



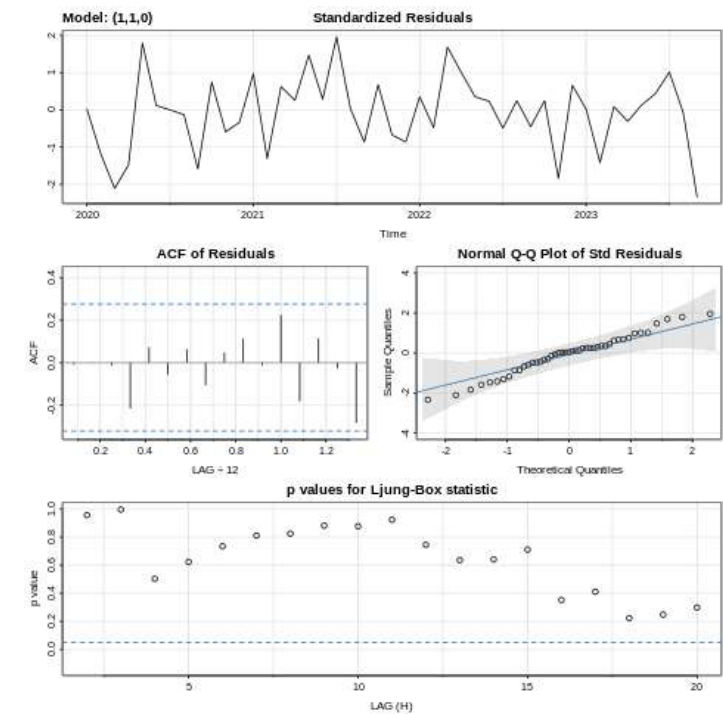
Indicate
AR(1)
Model

Segmented by Victims' Gender (Monthly): Model Selection

Female Victims: ARIMA(1,1,0)



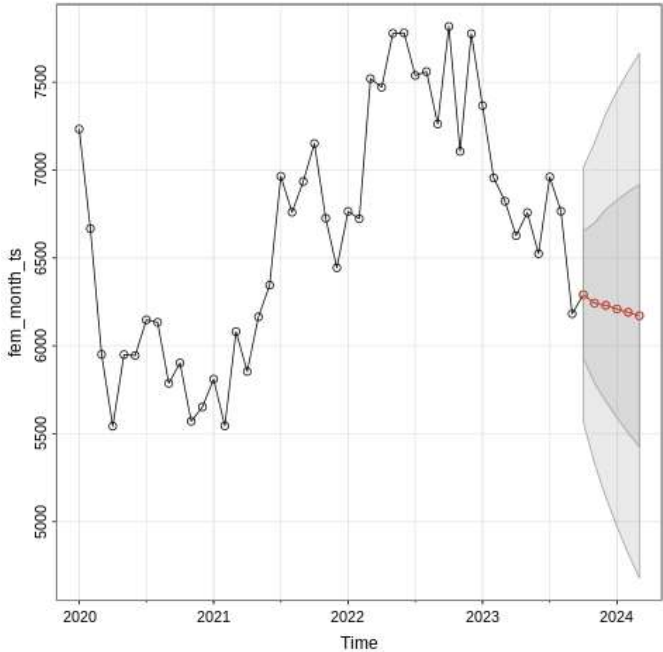
Male Victims: ARIMA(1,1,0)



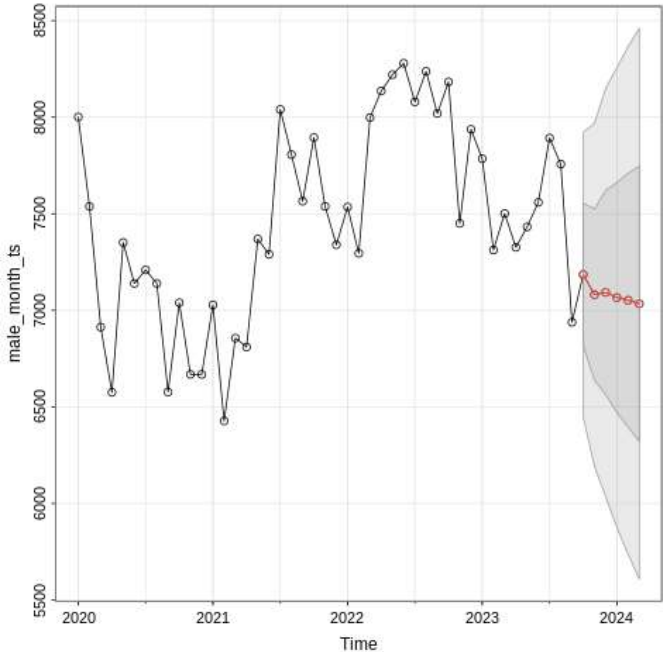
All
diagnostic
plots look
good

Segmented by Victims' Gender (Monthly): Forecasting

Female Victims:



Male Victims



Decreasing prediction

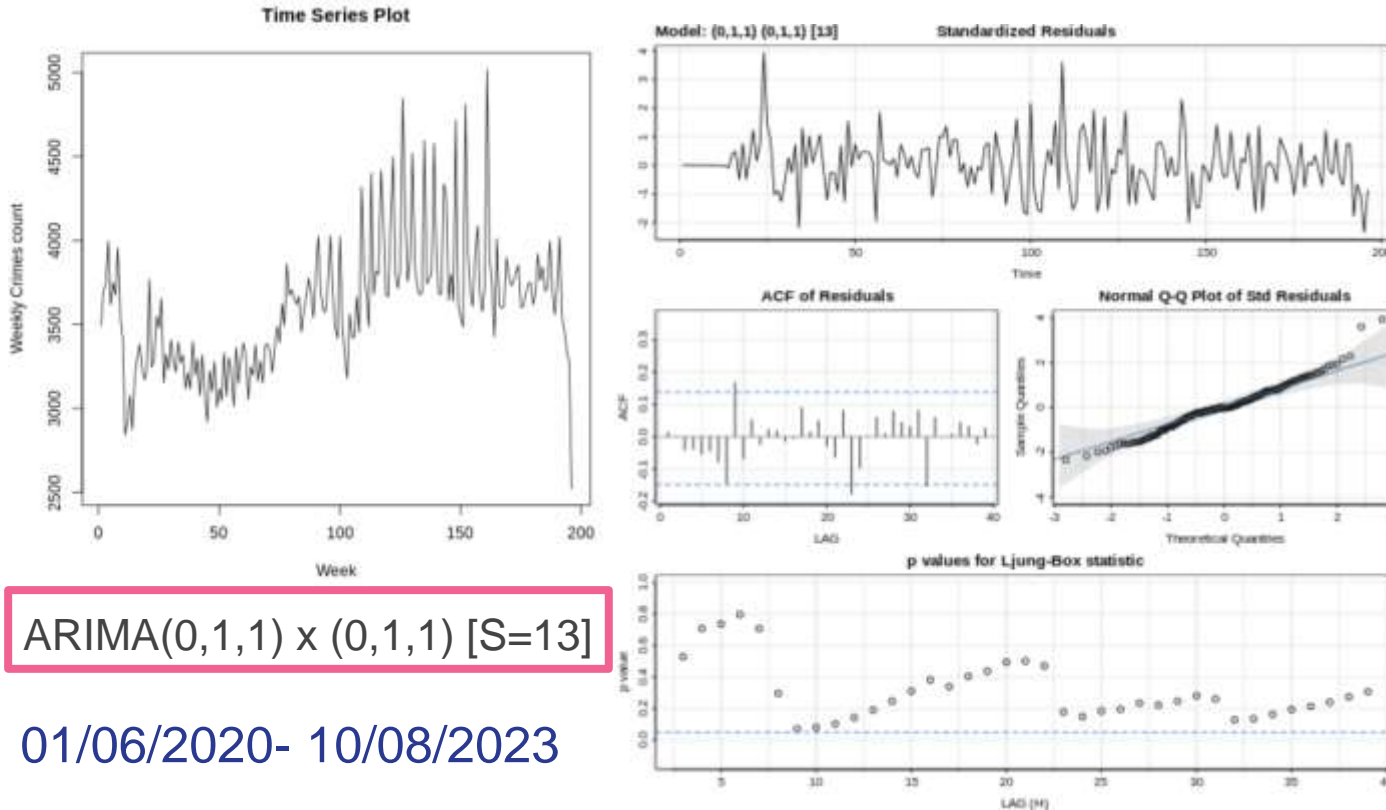
Summary of monthly trend

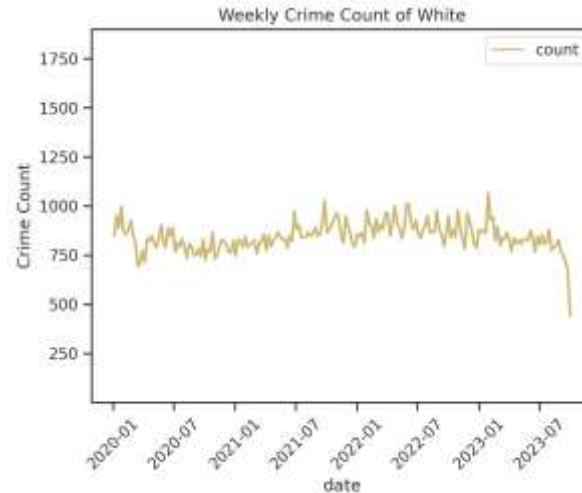
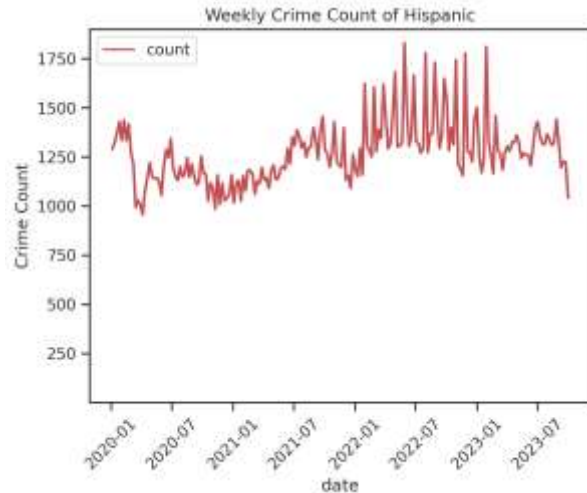
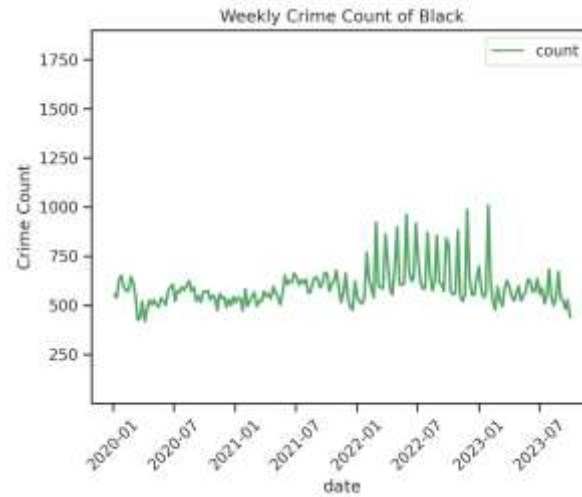
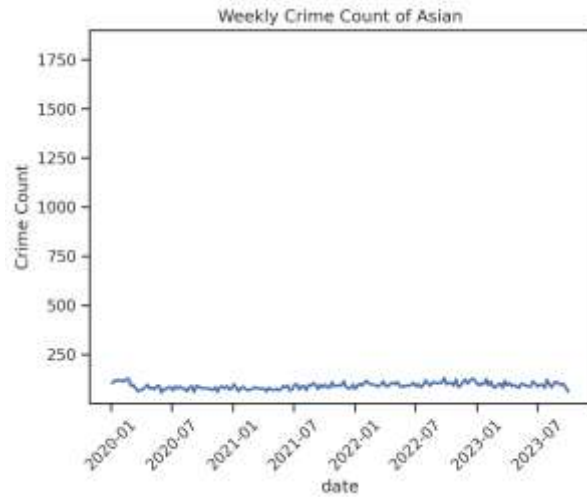
No difference in crime count trends toward male and female victims

- Efforts aimed to reduce crime against males or females may be effective in reducing crime overall
- Analysis into type of crime, area, etc may be more insightful when dealing with gender of victim

Overall crime count model (weekly)

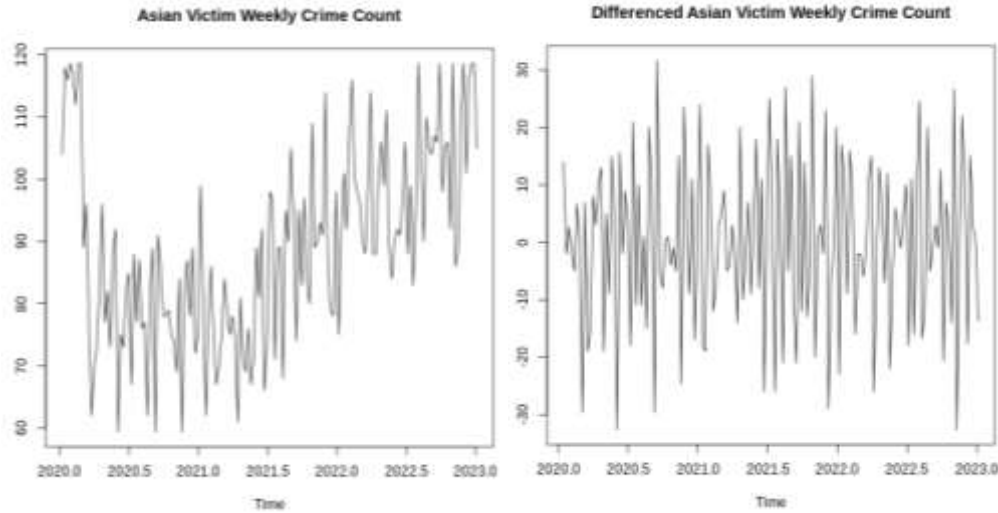
3 months
seasonality



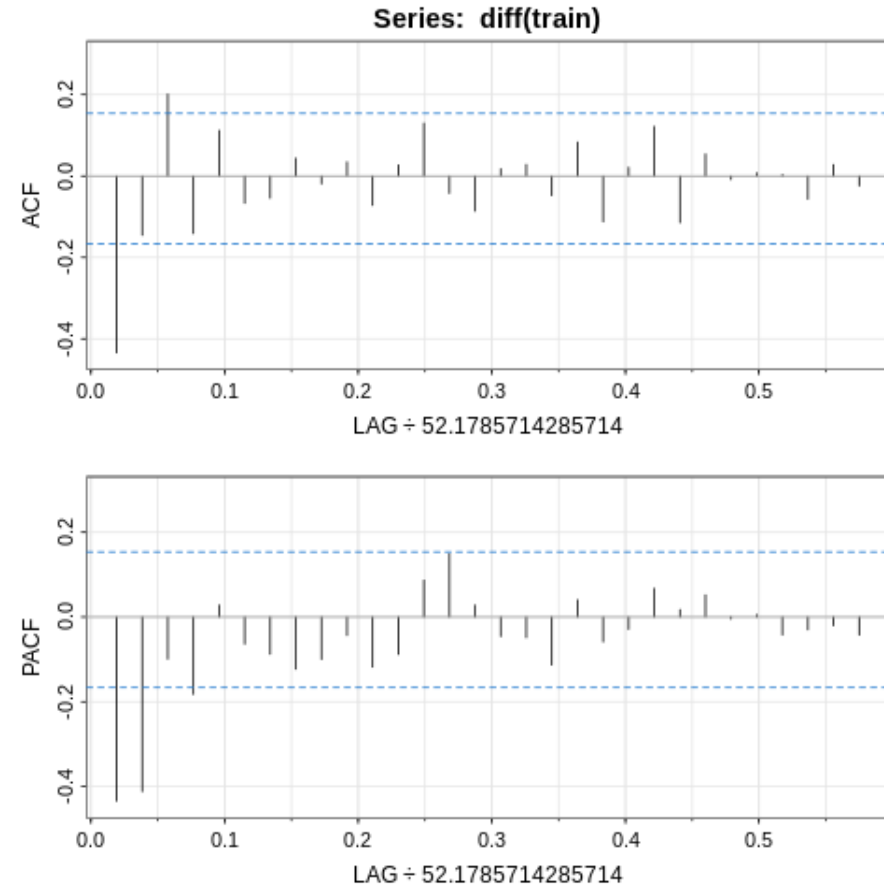


Victim Descent
Obvious
differences in
average counts
Possibly different
trends and
seasonality

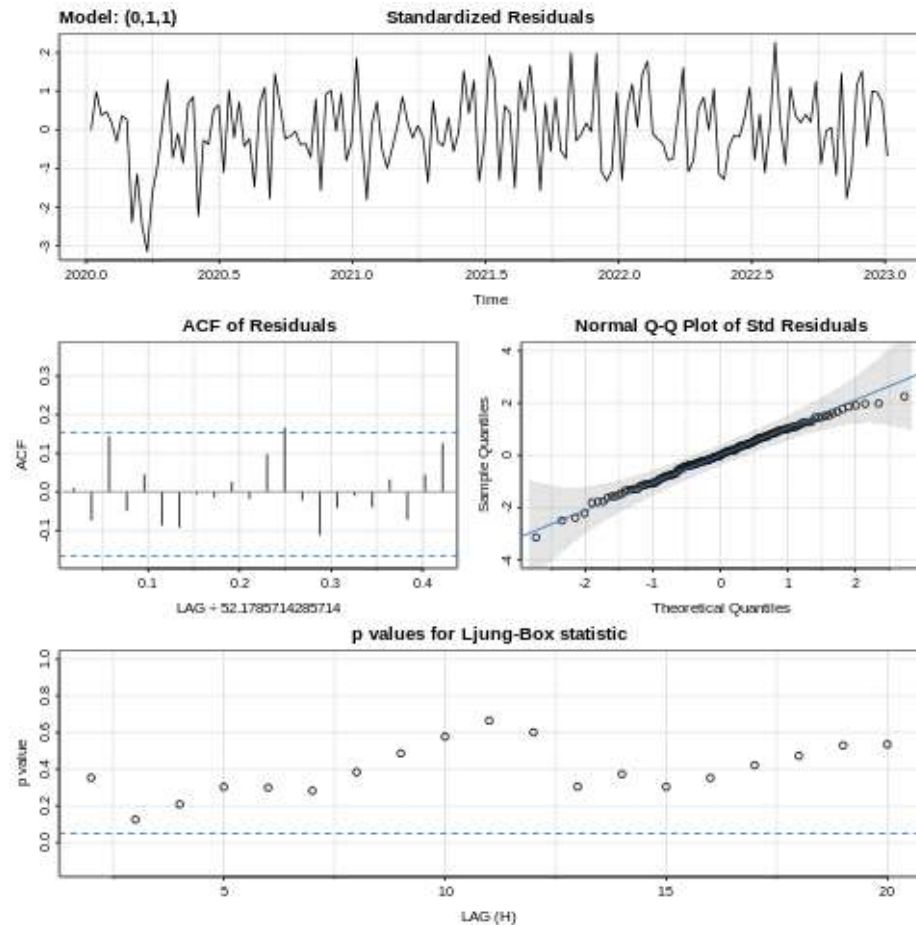
Weekly Asian Victim Crime Count



No seasonality
Possible Model: $ARIMA(0,1,1)$



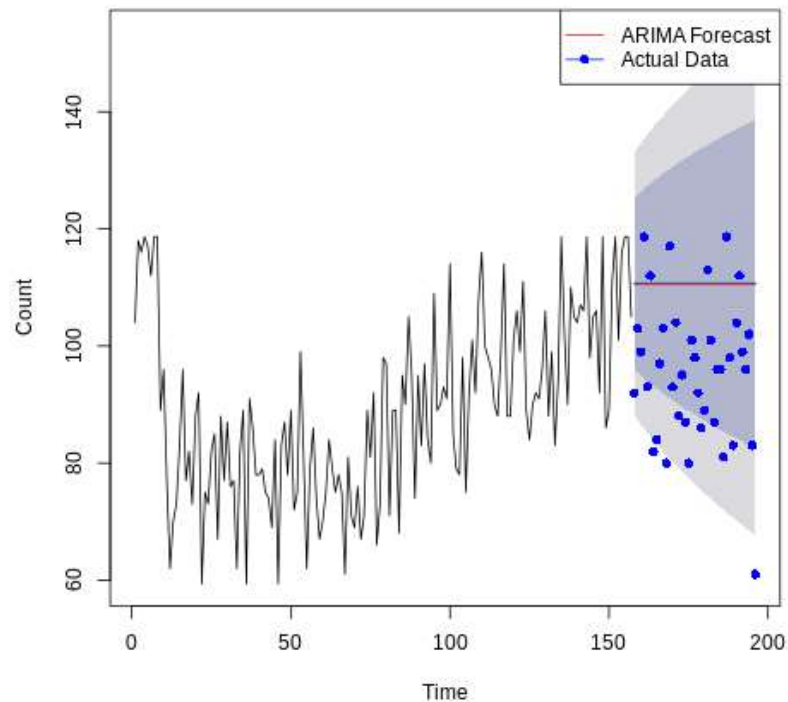
Weekly Asian Victim Crime Count



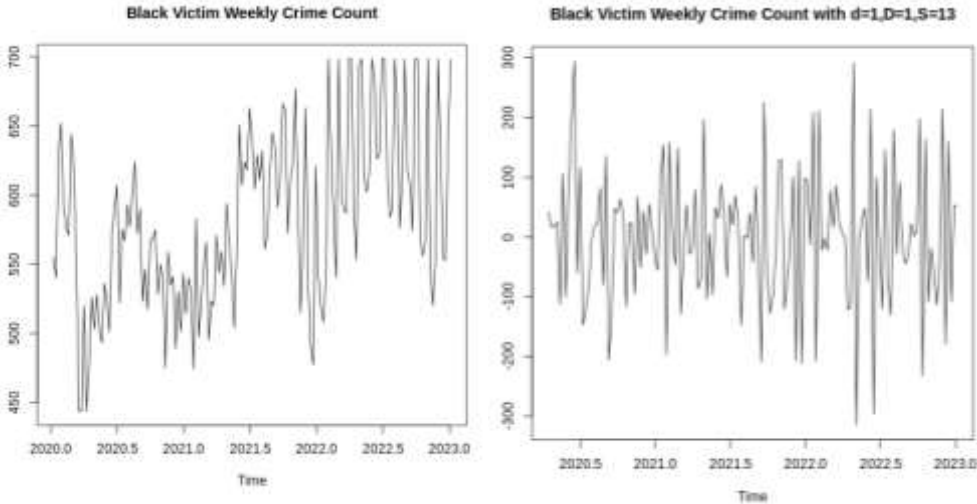
ARIMA(0, 1, 1)

Prediction: constant trend

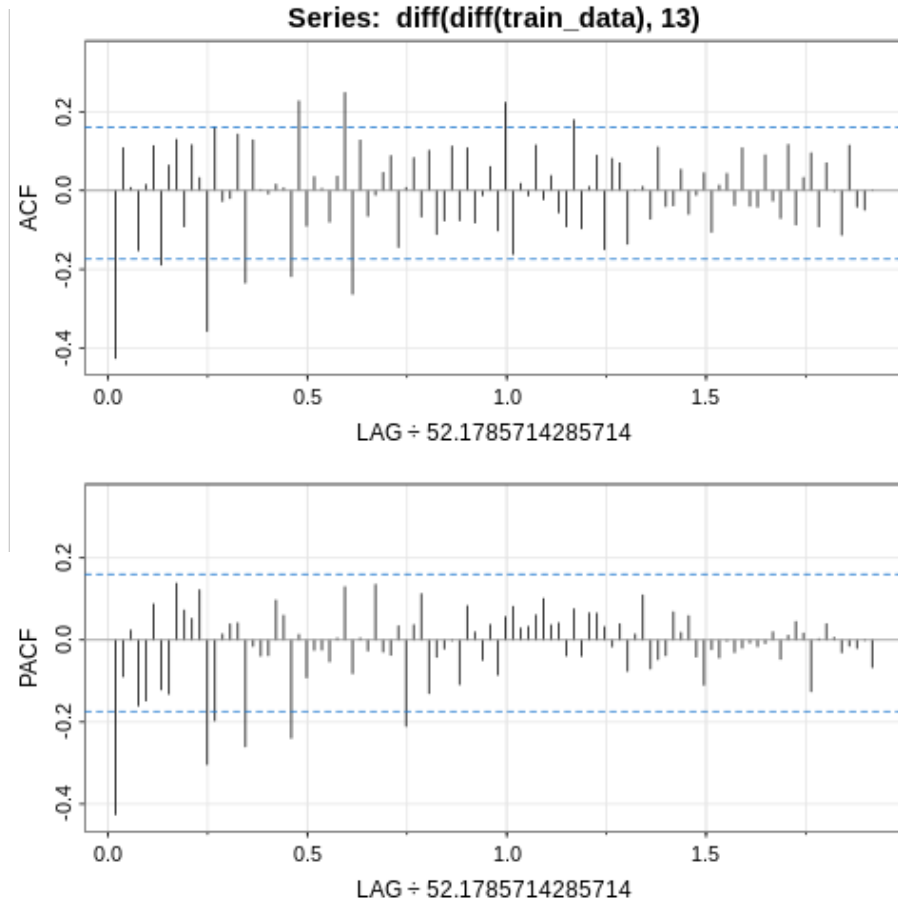
ARIMA Forecast with Actual Data



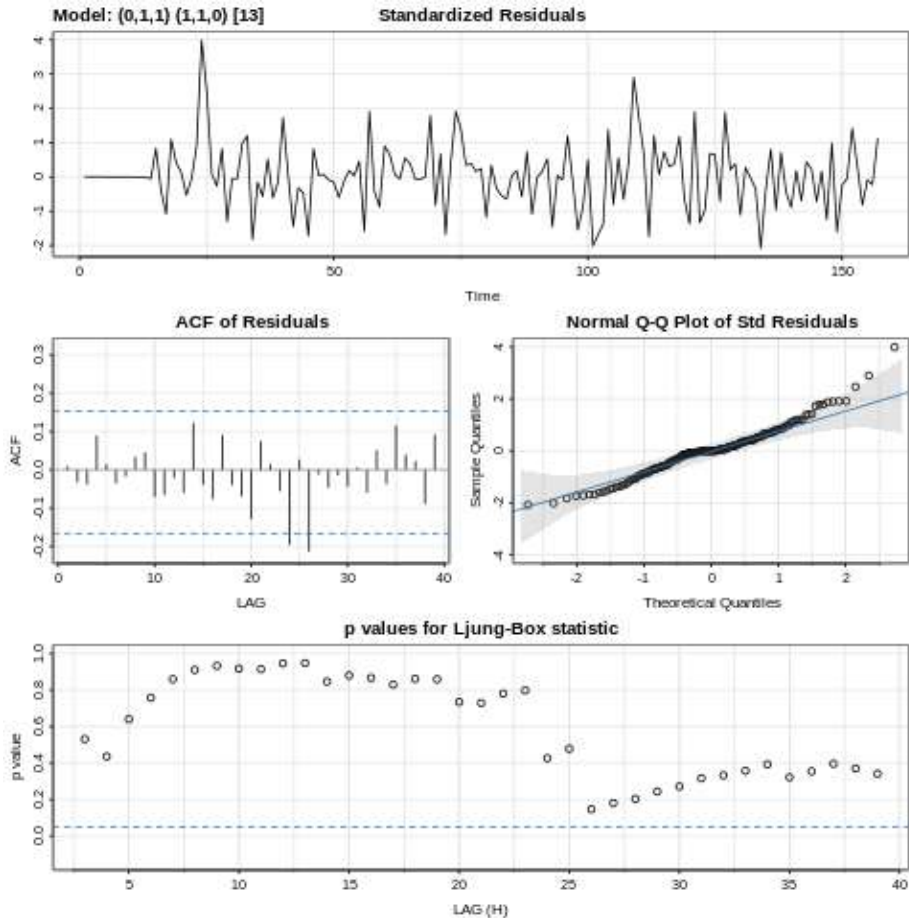
Weekly Black Victim Crime Count



Seasonality with $S=13$
Possible Model: MA(1), undetermined
for seasonal component



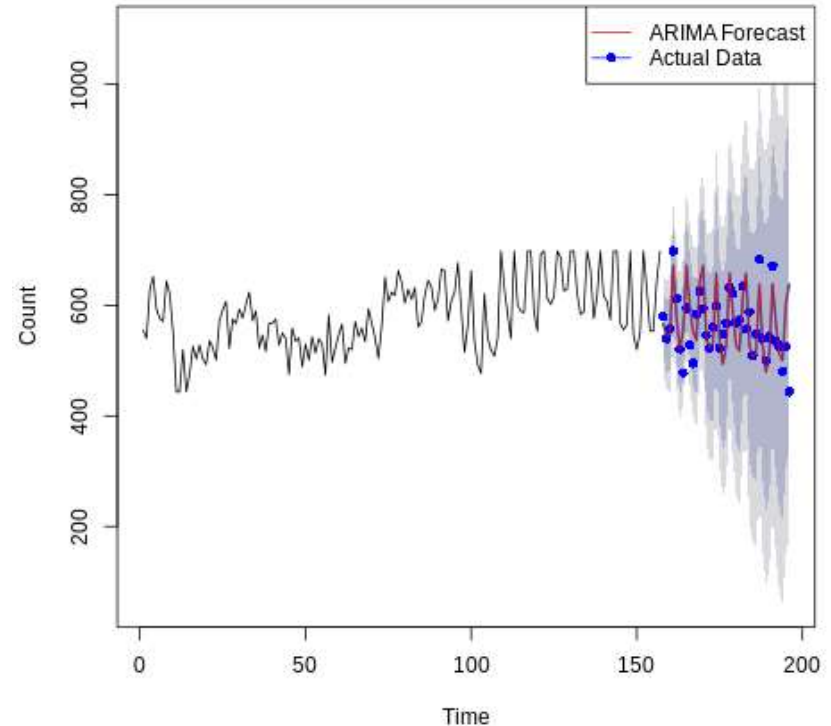
Weekly Black Victim Crime Count



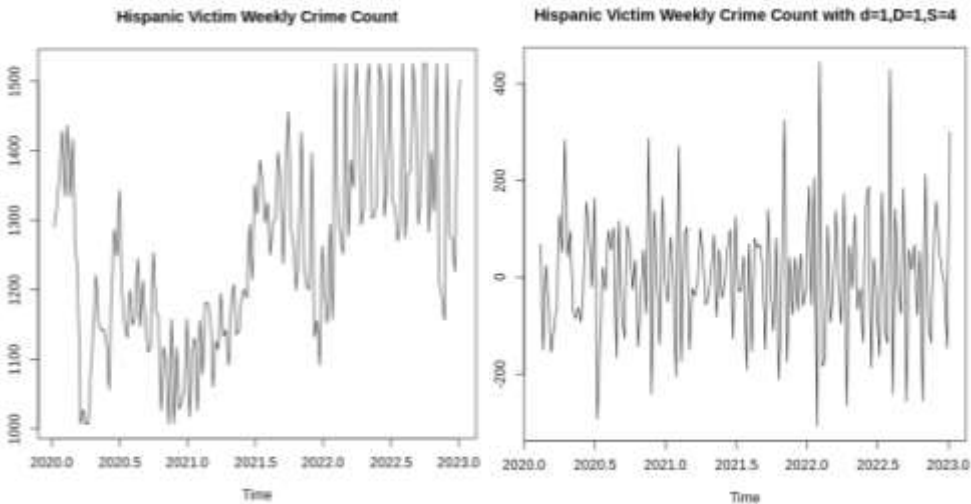
$$ARIMA(0, 1, 1) \times (1, 1, 0)_{13}$$

Prediction:
decreasing trend with seasonality

ARIMA Forecast with Actual Data

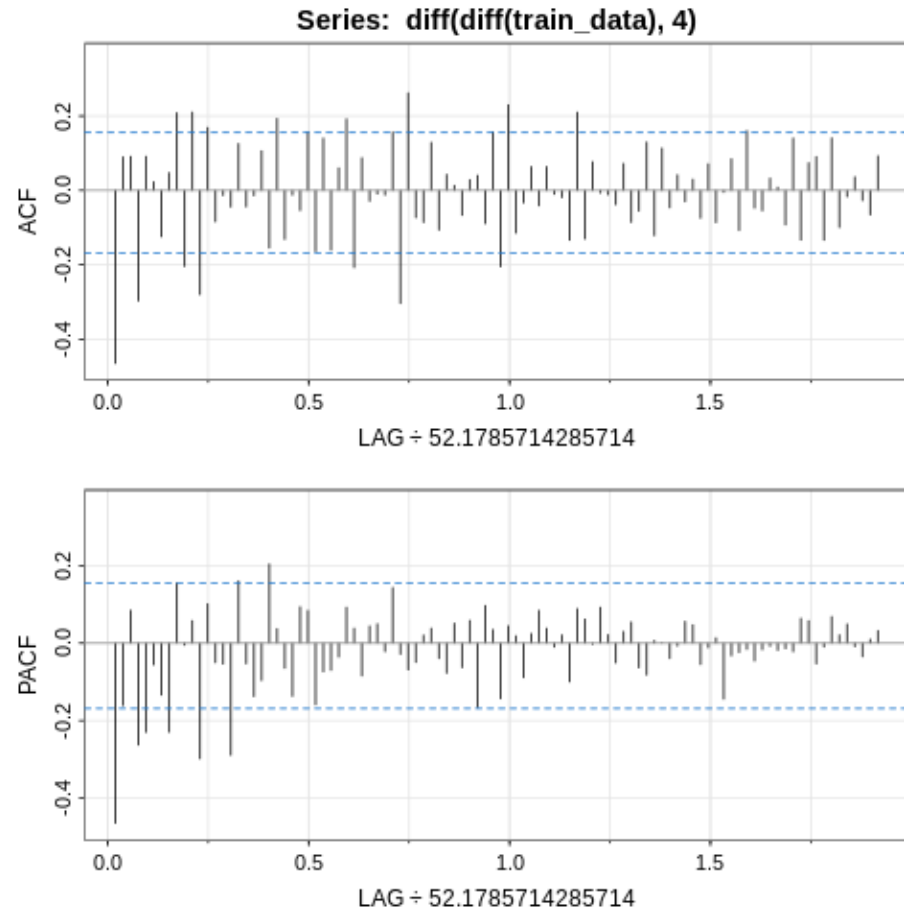


Weekly Hispanic Victim Crime Count

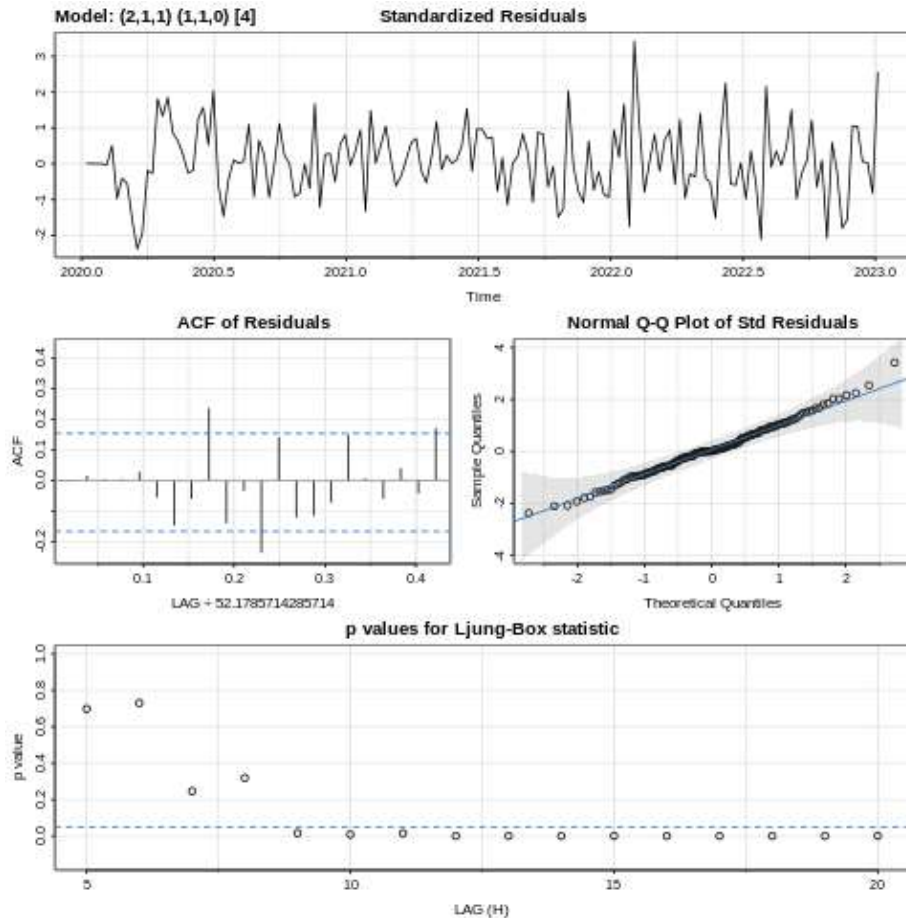


Seasonality with $S=4$

Possible Model: both seasonal and non-seasonal components cannot be determined from the ACF and PACF plot

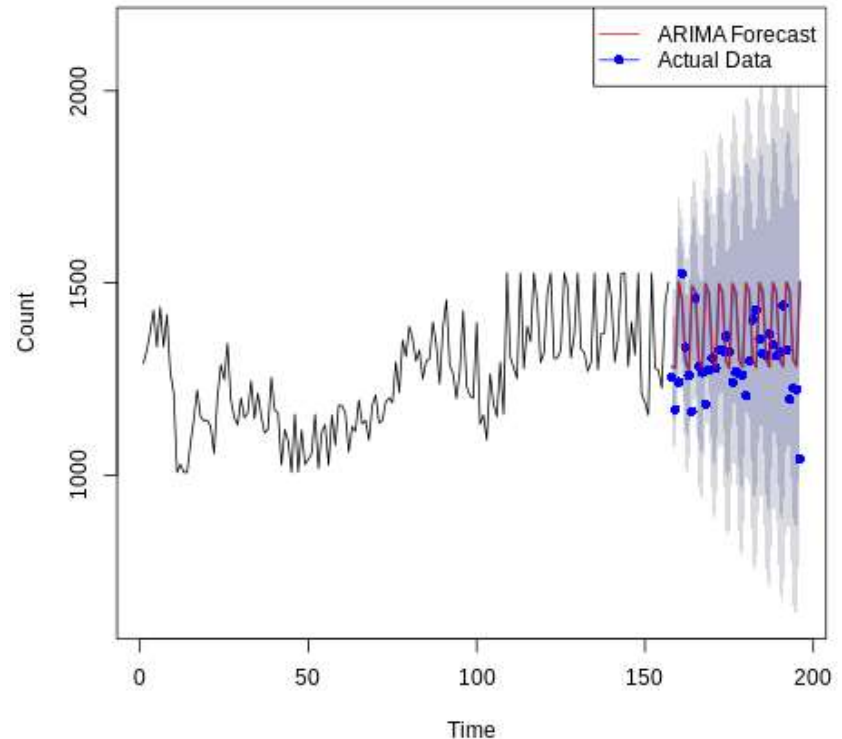


Weekly Hispanic Victim Crime Count

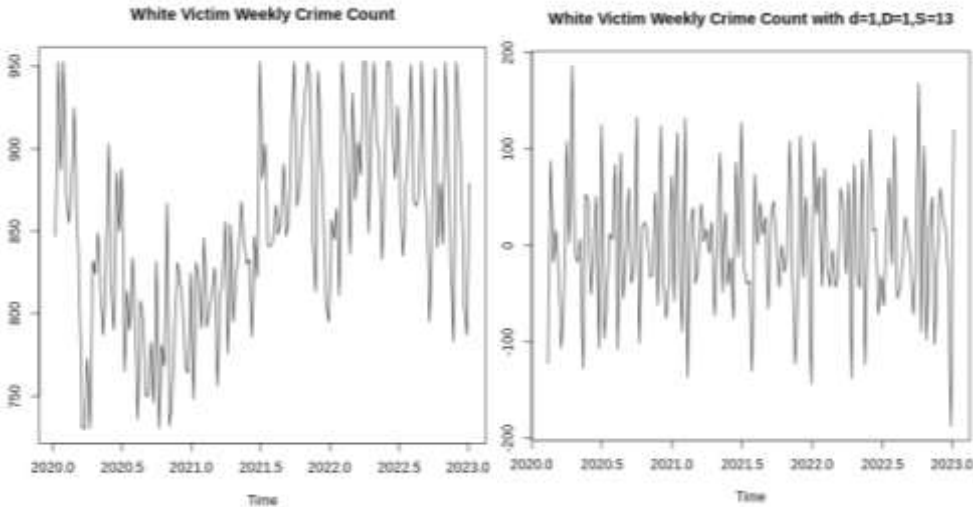


$$ARIMA(2, 1, 1) \times (1, 1, 0)_4$$

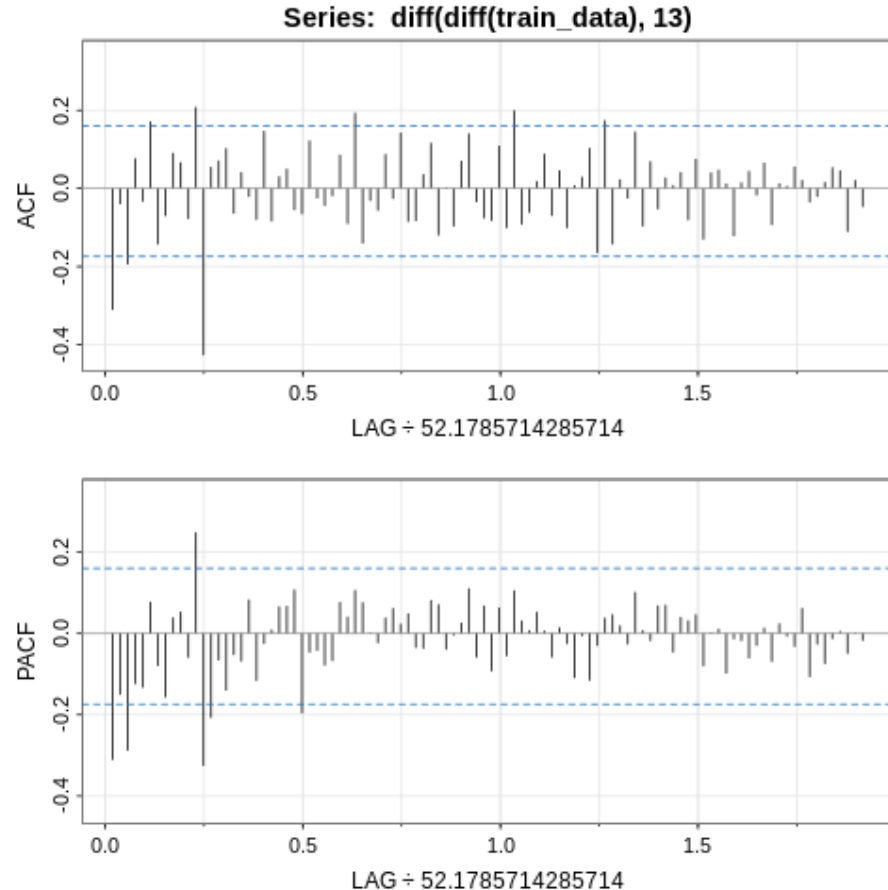
Prediction:
constant trend with seasonality
ARIMA Forecast with Actual Data



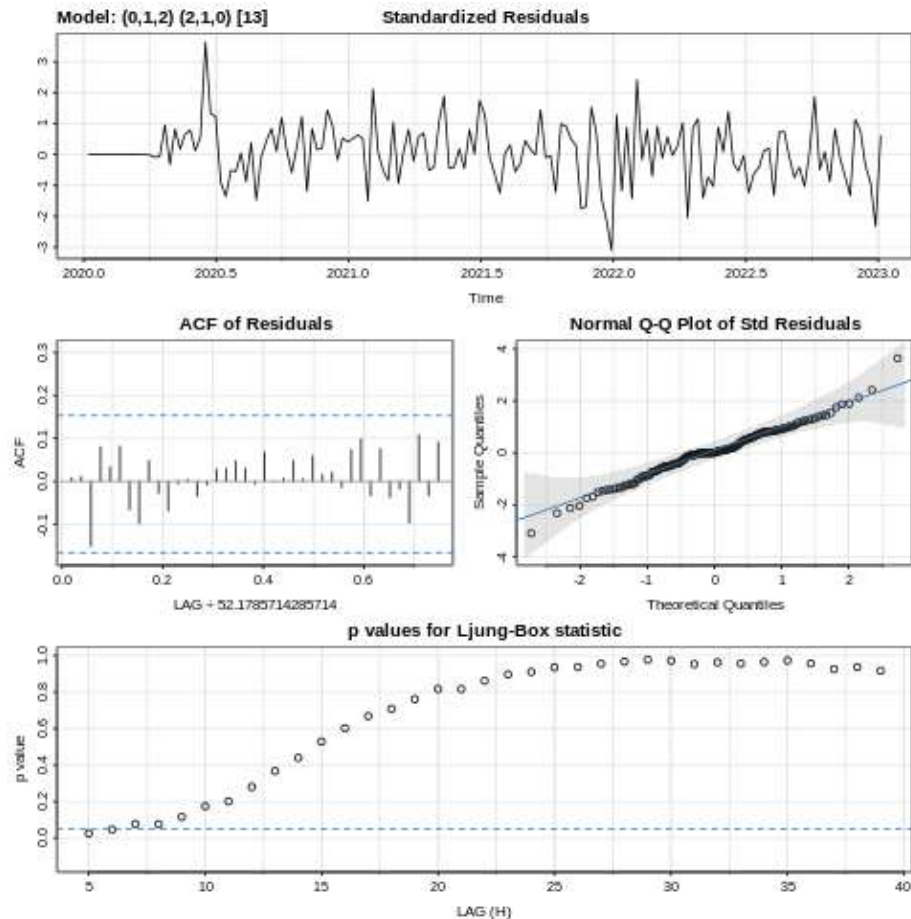
Weekly White Victim Crime Count



Seasonality with $S=13$
Possible Model: both seasonal
and non-seasonal components
cannot be determined from the
ACF and PACF plot



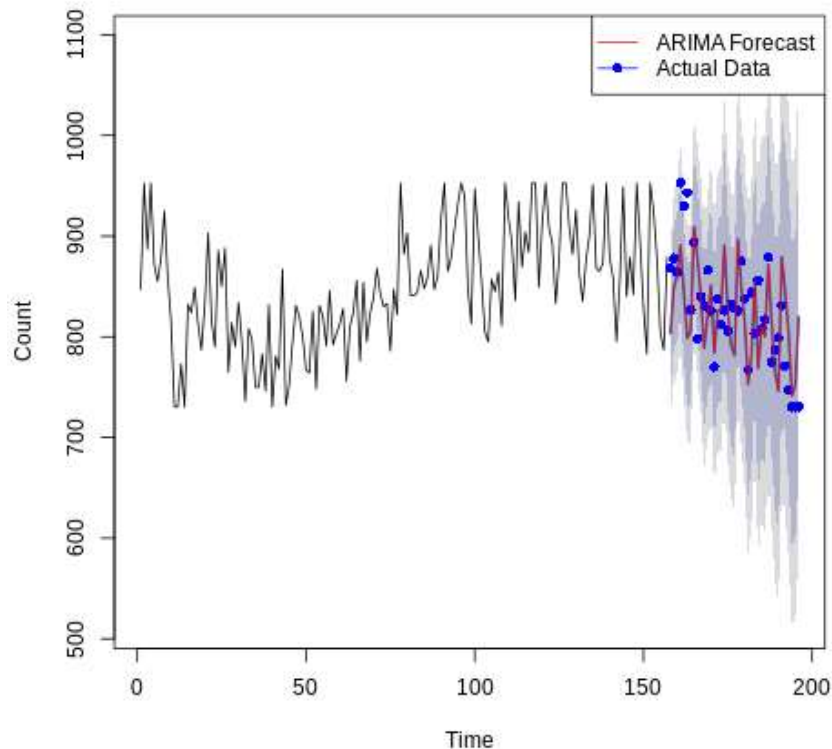
Weekly White Victim Crime Count



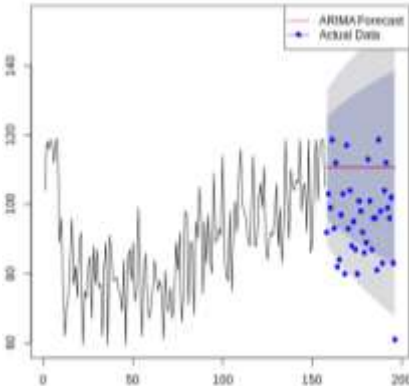
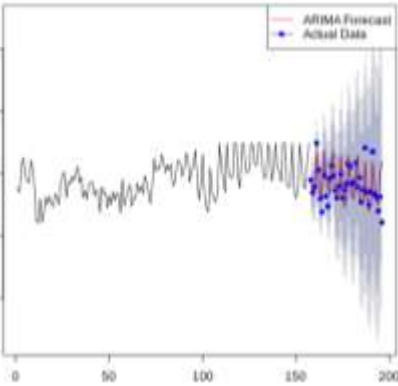
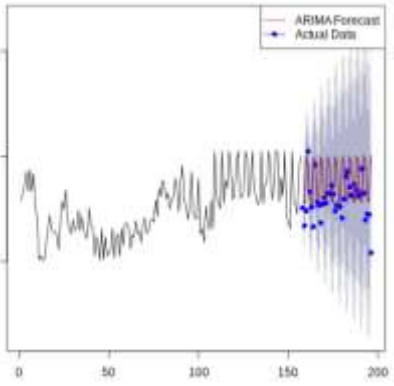
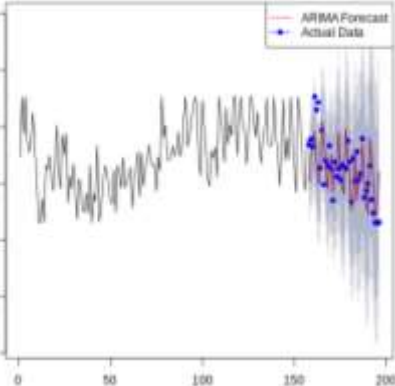
$$ARIMA(0, 1, 2) \times (2, 1, 0)_{13}$$

Prediction:
decreasing trend with seasonality

ARIMA Forecast with Actual Data

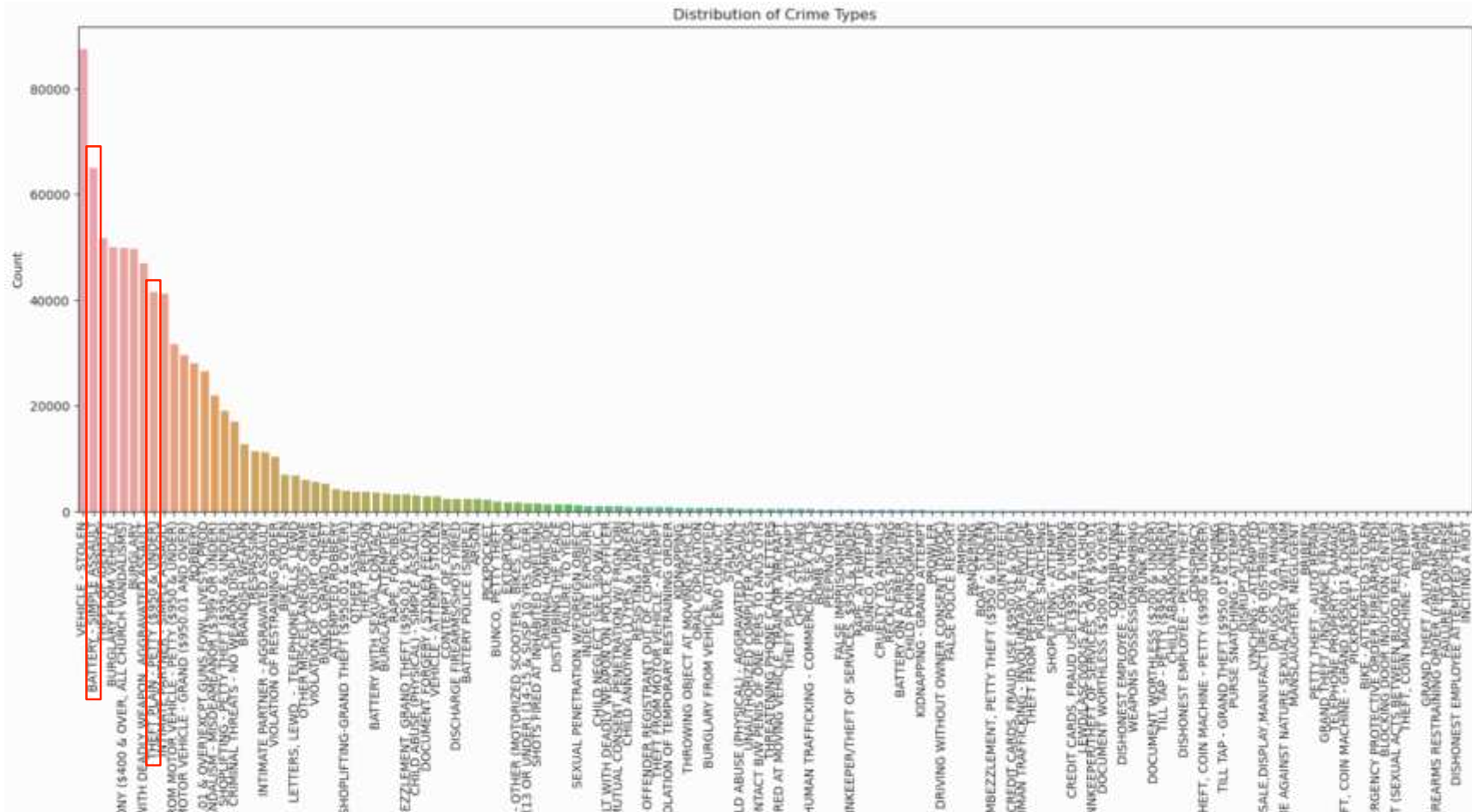


Models for different Victim Descent

Victim Descent	Asian	Black	Hispanic	White
Model Fitted	$ARIMA(0, 1, 1)$	$ARIMA(0, 1, 1) \times (1, 1, 0)_{13}$	$ARIMA(2, 1, 1) \times (1, 1, 0)_4$	$ARIMA(0, 1, 2) \times (2, 1, 0)_{13}$
Equation of Model	$x_t = x_{t-1} + w_t$ $-0.7364w_{t-1}$ $w_t \sim N(0, 131.8)$	$z_t = x_t - x_{t-1} - x_{t-13}$ $+ x_{t-14}$ $z_t = 0.474x_{t-13} + w_t$ $- 0.520w_{t-1}$ $w_t \sim N(0, 1996)$	$z_t = x_t - x_{t-1} - x_{t-4} + x_{t-5}$ $z_t = 0.2325x_{t-1} + 0.2727x_{t-2}$ $- 0.3278x_{t-4} + 0.0762x_{t-5}$ $+ 0.0894x_{t-6} + w_t - w_{t-1}$ $w_t \sim N(0, 10415)$	$z_t = x_t - x_{t-1} - x_{t-13} + x_{t-14}$ $z_t = -0.7113x_{t-13} - 0.3954$ $x_{t-26} + w_t - 0.5175w_{t-1}$ $- 0.1922w_{t-2}$ $w_t \sim N(0, 1850)$
39-week Prediction				

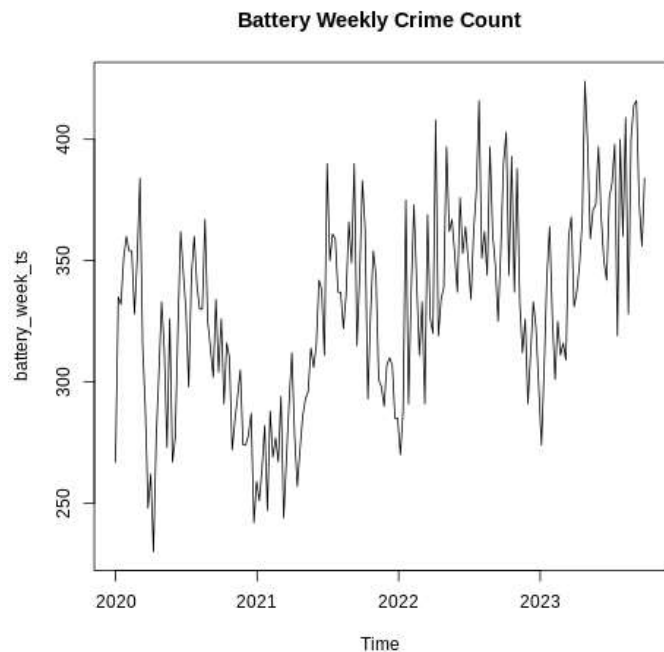
Segmented by Crime Type: EDA

210 Crime Types Overall

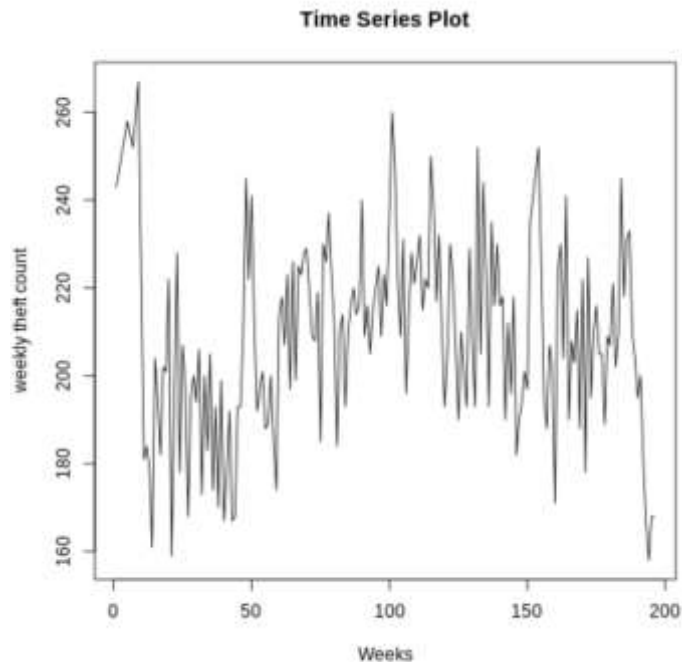


Segmented by Crime Type: EDA

Battery - Simple Assault

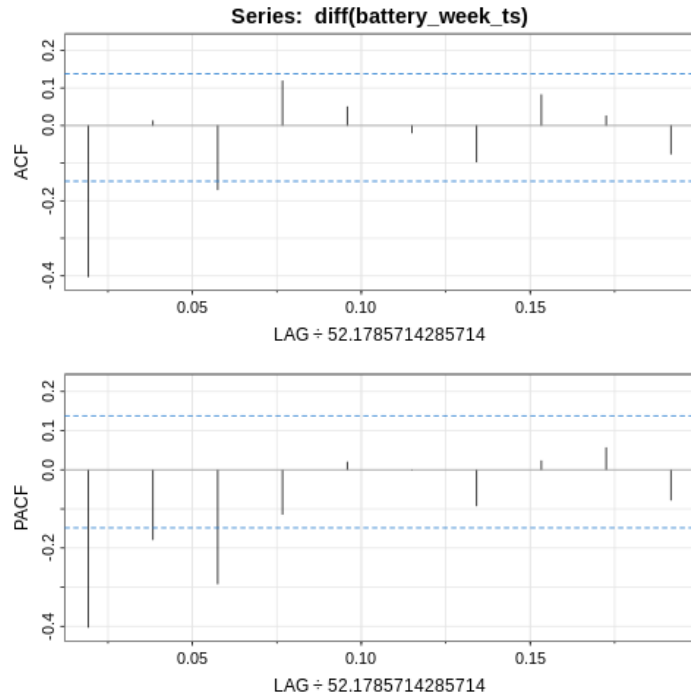


Theft - Plain (Under 950\$)

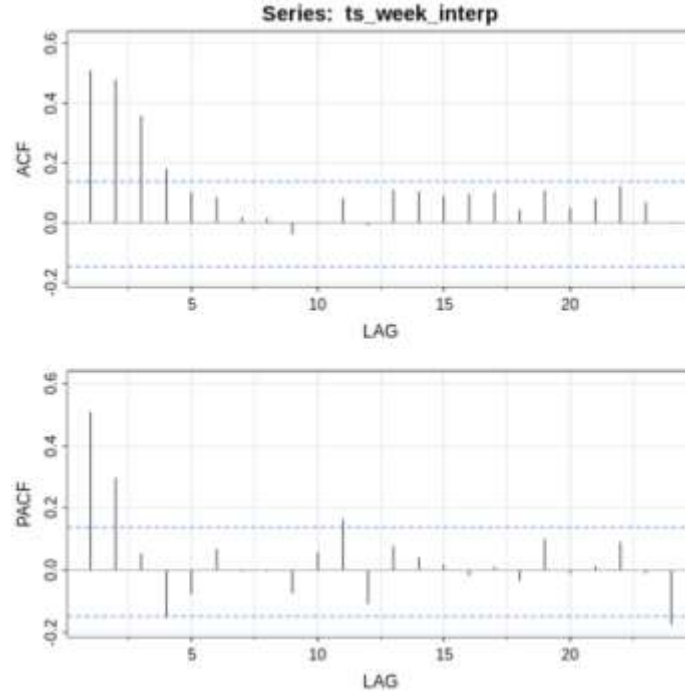


Segmented by Crime Type: EDA

Battery: possible MA(1) model

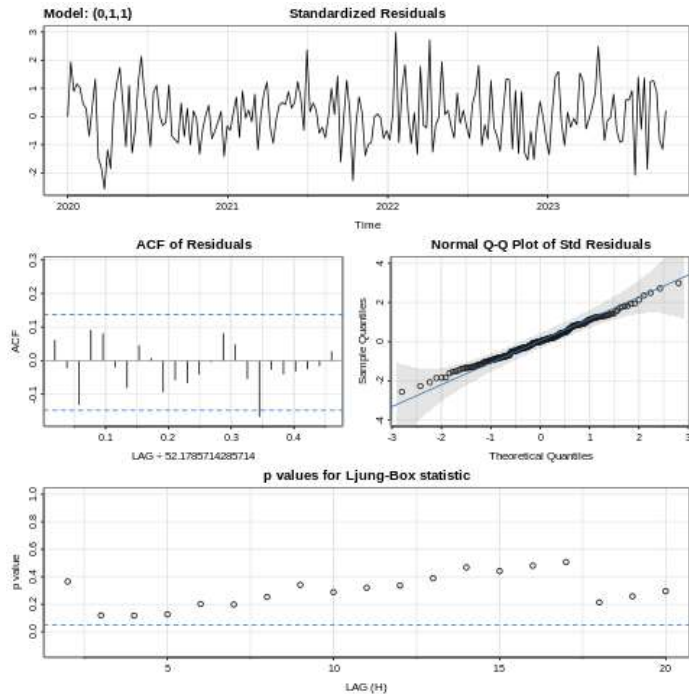


Theft : possible AR(2) model

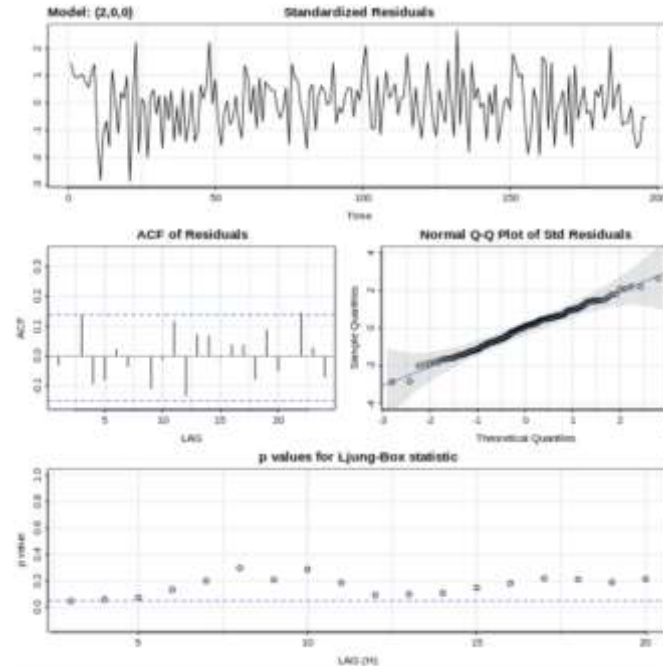


Segmented by Crime Type: Model Diagnostics

Battery: ARIMA(0,1,1)

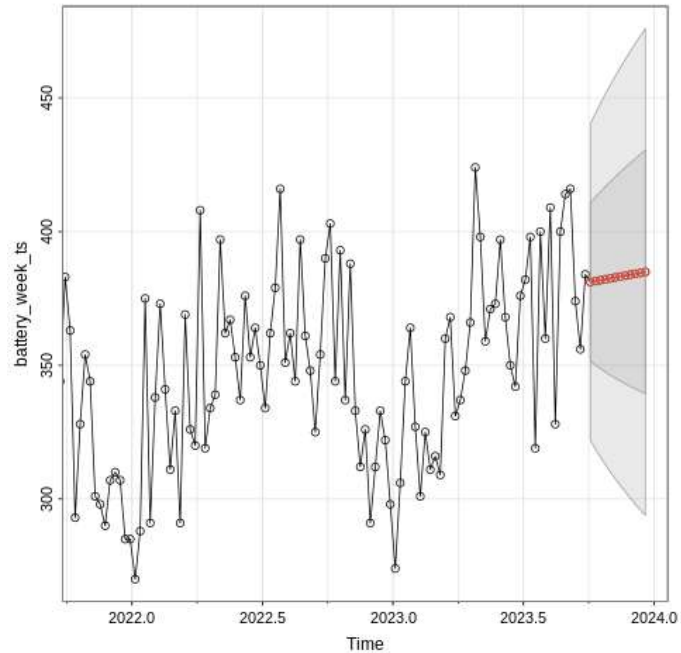


Theft: MA(2)

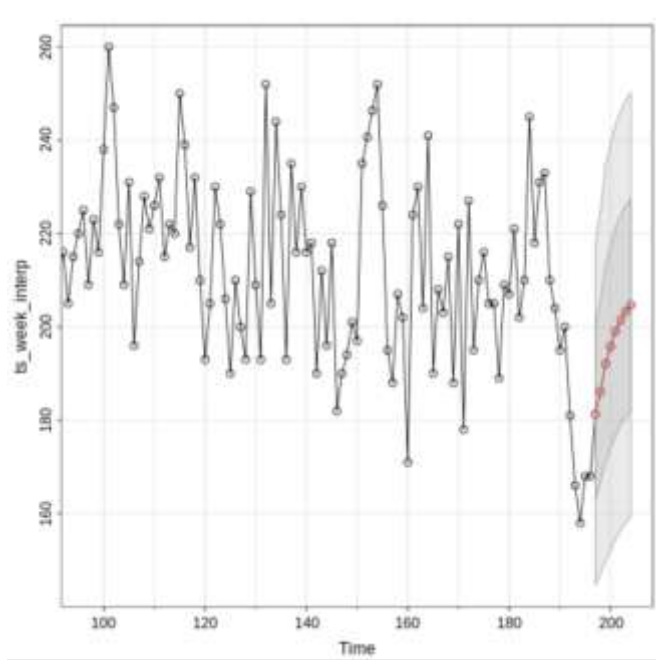


Segmented by Crime Type: Forecasting

Battery: slight increase 12 weeks ahead



Theft



Summary of Crime Type Trend

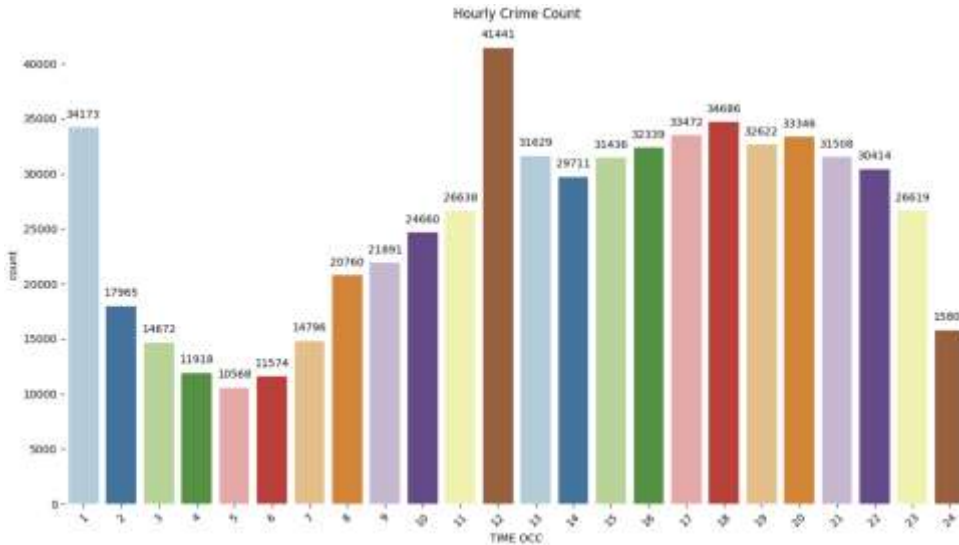
Difference in modeling the type of crime occurred

- ARIMA(0,1,1) vs MA(2) indicate a more complex relationship with previous theft incidents compared to battery crimes
- Measures to prevent theft may be more difficult to predict the success of compared to battery

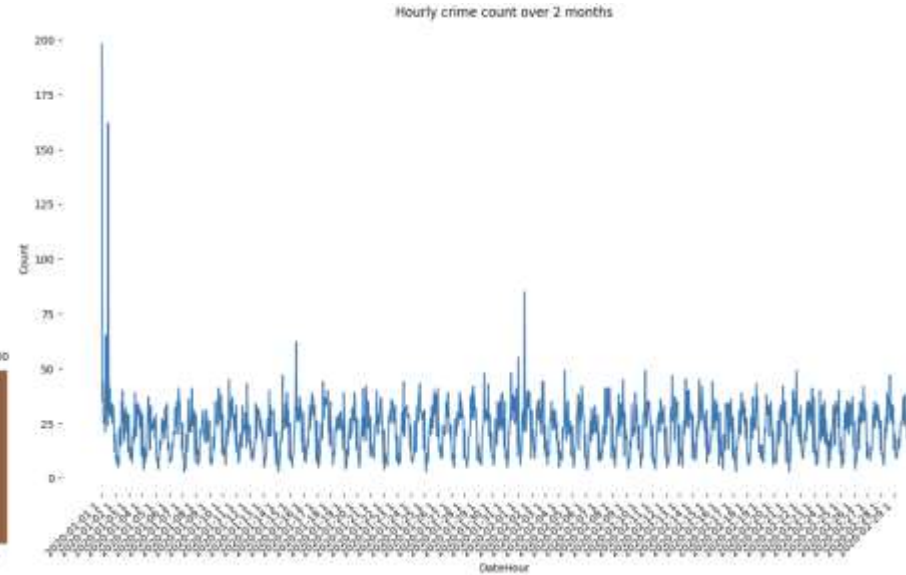


Segmented crime count model EDA (hourly)

01/01/2020 - 02/29/2020

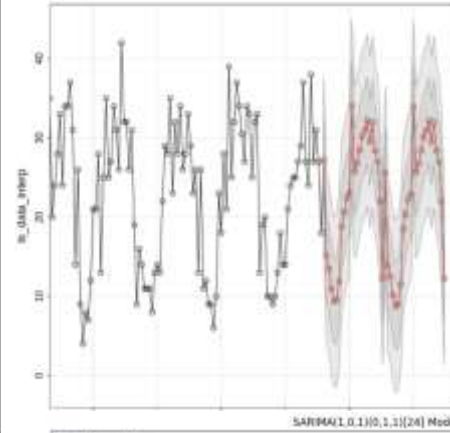
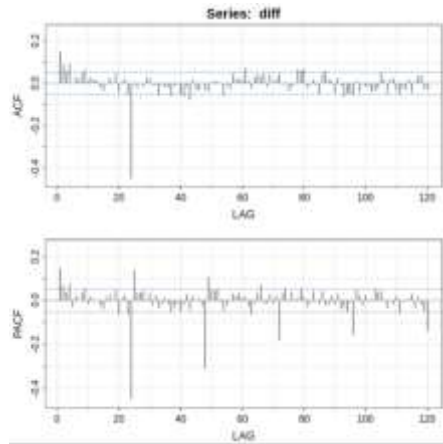
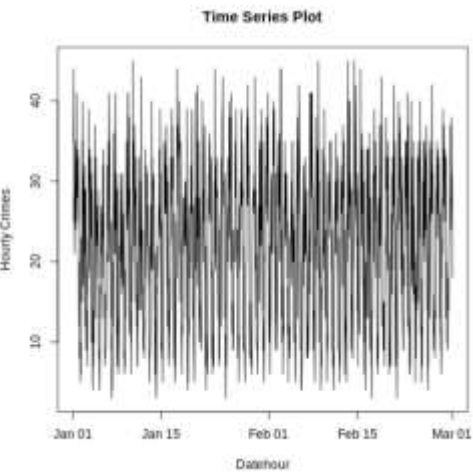


Overall Hourly Crime Count

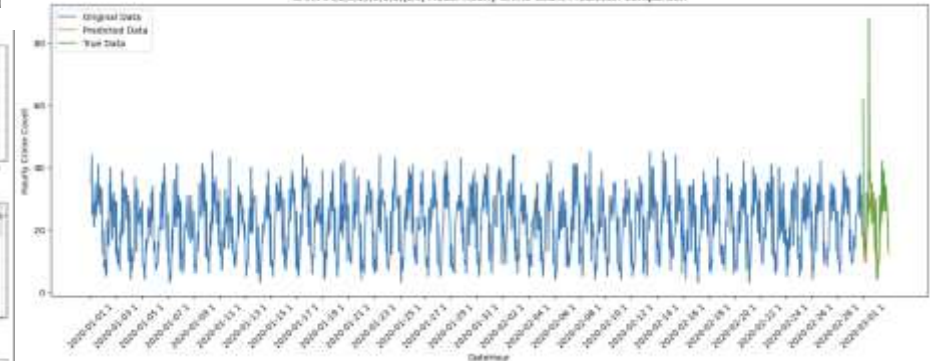
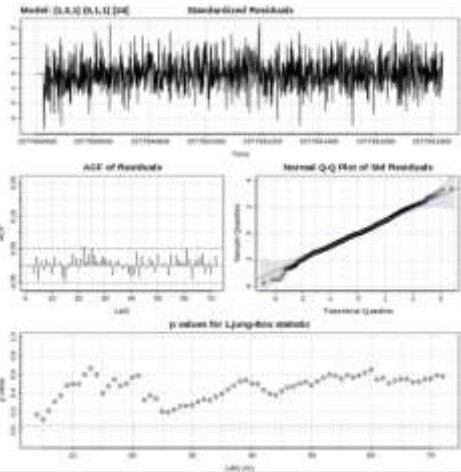
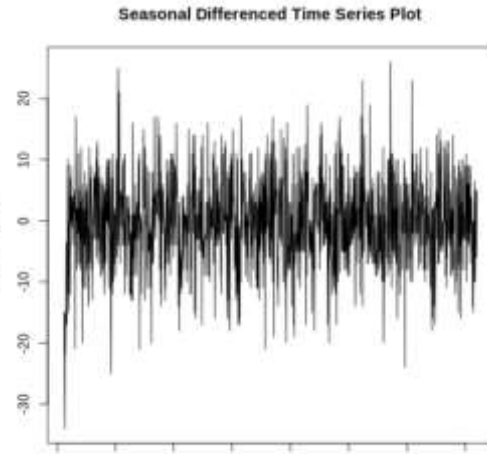


Hourly Crime Count over 2 months

Segmented crime count model fitting (hourly)



Apparent Seasonality



SARIMA(1,0,1)x(0,1,1) S=24

Question: - Is there a relationship between victim profile and crime info?
- Instead of overall crime count trend, can we predict a future crime within one hour time precision?

Proposed Solution: RNN model (Capture Sequential Dependencies)

- Using victim's profile (sex, age & descent) to predict crime area and type

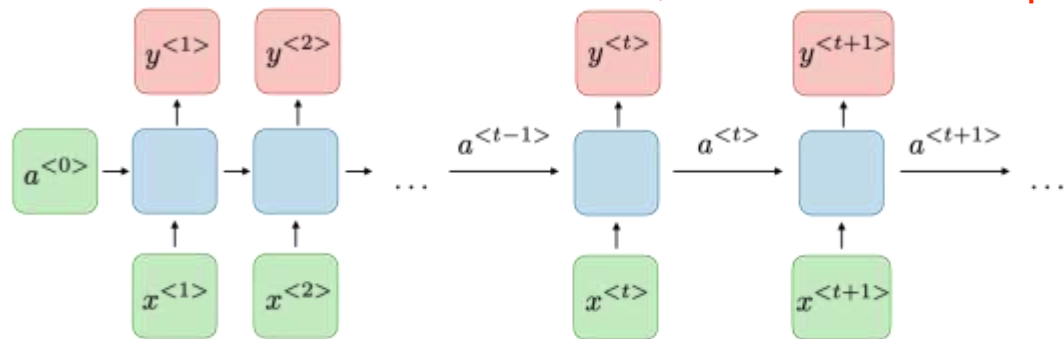
Data Pre-processing: 700k crime => 4k crime

- Rounding each crime time to the closest integer hour

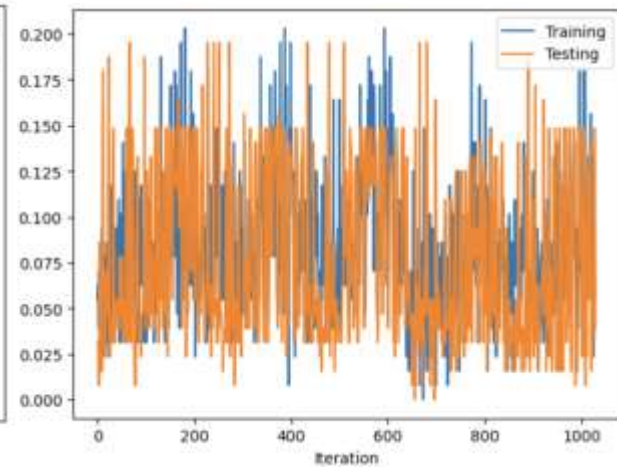
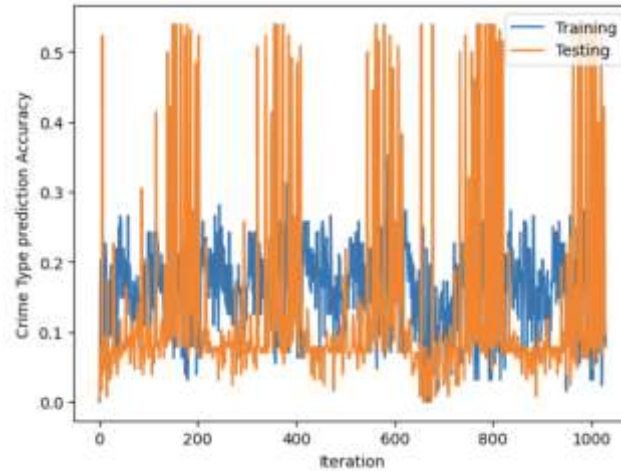
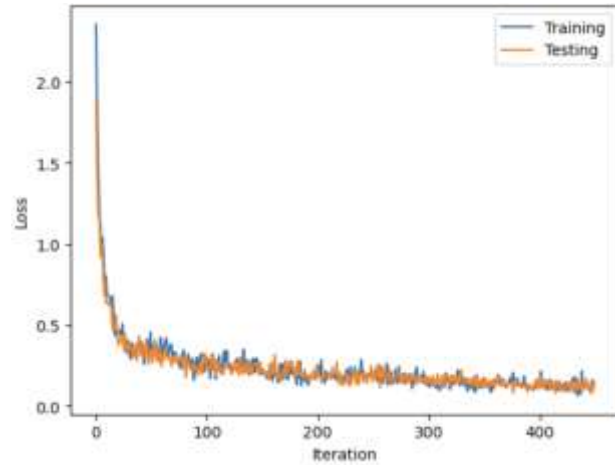
- Rounding each age to multiples of 5

- Use mode for each feature at the same rounding hour:

- Do not choose real crime, choose the most possible crime pattern



Training and Prediction Results



Take aways:

- Training is effective, best accuracies are good compared to untrained accuracies
- Model converges quickly (within each epoch), may be due to lack of data, and model is relatively complex (500 hidden neurons)
- Unbalanced class (crime type)
- Future analysis and models can be developed to predict crime more precisely

Q&A

ASK US ANYTHING!!!

