# ISyE 6402 Project

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11/04/2022

## Part II - ARIMA Modelling

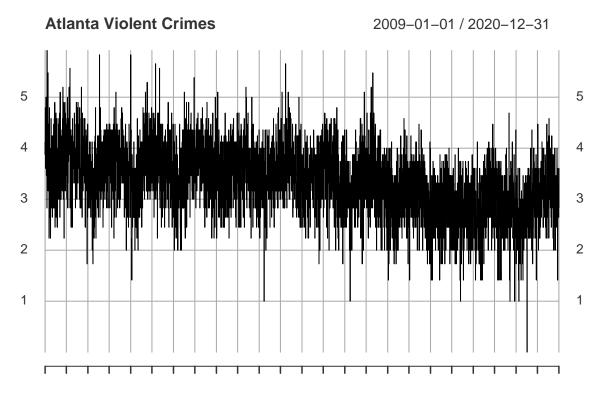
```
library(zoo)
library(xts)
library(lubridate)
library(mgcv)
library(lmtest)
```

#### Load data

```
## Atlanta
atl.v.df <- read.csv("atl_violent_final.csv", head = TRUE)</pre>
atl.v.df$occurance_count <- sqrt(atl.v.df$occurance_count)</pre>
atl.p.df <- read.csv("atl_prop_final.csv", head = TRUE)</pre>
atl.p.df$occurance_count <- sqrt(atl.p.df$occurance_count)</pre>
colnames(atl.v.df) <- c("Date", "violentCrime")</pre>
colnames(atl.p.df) <- c("Date", "propertyCrime")</pre>
atl.df <- merge(atl.v.df, atl.p.df)</pre>
atl.df$Date <- as.Date(atl.df$Date, "%Y-%m-%d")
atl.df <- atl.df[atl.df$Date <= "2020-12-31", ]
atl.df <- na.locf(atl.df)
## New York City
nyc.v.df <- read.csv("nyc_violent_final.csv", head = TRUE)</pre>
nyc.v.df$occurance_count <- sqrt(nyc.v.df$occurance_count)</pre>
nyc.p.df <- read.csv("nyc_prop_final.csv", head = TRUE)</pre>
nyc.p.df$occurance_count <- sqrt(nyc.p.df$occurance_count)</pre>
colnames(nyc.v.df) <- c("Date", "violentCrime")</pre>
colnames(nyc.p.df) <- c("Date", "propertyCrime")</pre>
nyc.df <- merge(nyc.v.df, nyc.p.df)</pre>
nyc.df$Date <- as.Date(nyc.df$Date, "%Y-%m-%d")</pre>
nyc.df \leftarrow nyc.df[nyc.df$Date >= "2009-01-01", ]
nyc.df <- na.locf(nyc.df)</pre>
```

#### Plot Time Series

```
## ATL TS
atl.v.ts <- ts(atl.df$violentCrime, start = 2009, freq = 365.25)
plot(xts(atl.df$violentCrime, atl.df$Date), main="Atlanta Violent Crimes", lwd=1)</pre>
```

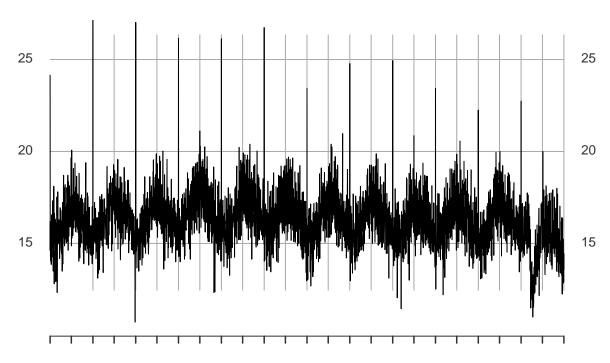


Jan 01 2009 Jan 01 2011 Jan 01 2013 Jan 01 2015 Jan 01 2017 Jan 01 2019 Dec 31 2020

```
## NYC TS
nyc.v.ts <- ts(nyc.df$violentCrime, start = 2009, freq = 365.25)
plot(xts(nyc.df$violentCrime, nyc.df$Date), main="NYC Violent Crimes", lwd=1)</pre>
```



#### 2009-01-01 / 2020-12-31



Jan 01 2009 Jan 01 2011 Jan 01 2013 Jan 01 2015 Jan 01 2017 Jan 01 2019 Dec 31 2020

### ARIMA Fitting and Forecasting

Test set = 2022 data (from Jan 1 2022 - end) Training Set = All previous data

#### Test Train Split

```
## X-axis points converted to 0-1 scale, common in nonparametric regression
scaler <- function(ts) {
   ts.pts = c(1:length(ts))
   ts.pts = c(ts.pts - min(ts.pts))/max(ts.pts)
   return(ts.pts)
}

train.ind = c(1:which(atl.df$Date == "2020-12-24"))

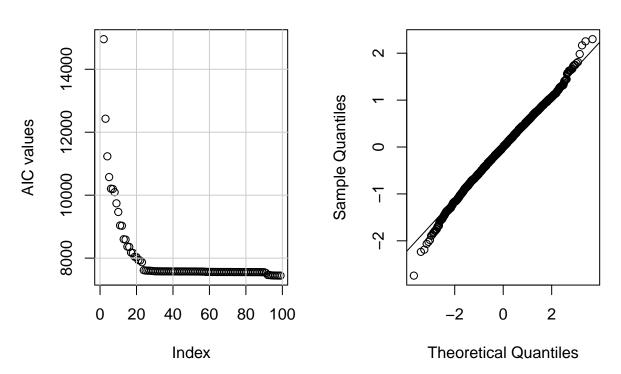
atl.train <- atl.df[train.ind, ]
atl.test <- atl.df[-train.ind, ]
nyc.train <- nyc.df[train.ind, ]
nyc.test <- nyc.df[-train.ind, ]</pre>
```

```
atl.v.train <- ts(atl.train$violentCrime, start = 2009, freq = 365.25)
# Function to train ARIMA (p, d, q) Model
test_modelA <- function(ts, p, d, q) {</pre>
  mod = arima(ts, order = c(p, d, q), method = "ML")
  current.aic = AIC(mod)
  df = data.frame(p, d, q, current.aic)
  names(df) <- c("p","d","q","AIC")</pre>
  # print(paste(p,d,q,current.aic,sep=" "))
  return(df)
}
# Daily TS ARIMA (p, d, q) Fitting
atl.v.orders = data.frame(Inf, Inf, Inf, Inf)
names(atl.v.orders) <- c("p", "d", "q", "AIC")
for (p in 0:6) {
  for (d in 1:2) {
    for (q in 0:6) {
      possibleError <- tryCatch(</pre>
        atl.v.orders <- rbind(atl.v.orders, test_modelA(atl.v.train,p,d,q)),</pre>
        error = function(e) {e}
      if (inherits(possibleError, "error"))
    }
  }
}
atl.v.orders <- atl.v.orders[order(-atl.v.orders$AIC), ]
atl.v.ord <- atl.v.orders[nrow(atl.v.orders), ]</pre>
atl.v.orders[(nrow(atl.v.orders)-3):nrow(atl.v.orders), ]
a) Atlanta Violent Crime
##
      рdq
                 AIC
## 64 4 1 6 7447.722
## 63 4 1 5 7446.246
## 77 5 1 5 7445.795
## 92 6 1 6 7444.383
# (4, 1, 5)
# ARIMA Fitted Model
atl.v.arima = arima(atl.v.train, order = c(atl.v.ord$p, atl.v.ord$d, atl.v.ord$q), method='ML')
atl.v.arima
##
## Call:
## arima(x = atl.v.train, order = c(atl.v.ord$p, atl.v.ord$d, atl.v.ord$q), method = "ML")
##
```

```
## Coefficients:
##
                               ar3
                                        ar4
                                                 ar5
                                                         ar6
                                                                          ma2
            ar1
                      ar2
                                                                 ma1
##
         -1.1225 -0.3773 -0.3921 -1.1573 -0.9477 0.0141 0.1946 -0.6814
        0.0030
                 0.0189 0.0041
                                   0.0063 0.0121 0.0162
                                                                          NaN
## s.e.
                                                                 NaN
##
            ma3
                   ma4
                             ma5
                                      ma6
##
         0.0177 0.7870 -0.1302 -0.9152
## s.e. 0.0027 0.0023
                             NaN
##
## sigma^2 estimated as 0.3186: log likelihood = -3709.19, aic = 7444.38
coeftest(atl.v.arima)
##
## z test of coefficients:
##
         Estimate Std. Error z value Pr(>|z|)
##
## ar1 -1.1225315 0.0030037 -373.7120 < 2.2e-16 ***
## ar2 -0.3772850 0.0189106 -19.9510 < 2.2e-16 ***
## ar3 -0.3921351 0.0040757 -96.2130 < 2.2e-16 ***
## ar4 -1.1573128  0.0063224 -183.0501 < 2.2e-16 ***
## ar5 -0.9477160 0.0120690 -78.5246 < 2.2e-16 ***
## ar6 0.0140929 0.0161628
                                0.8719
                                          0.3832
## ma1 0.1945653
                         \mathtt{NaN}
                                   NaN
                                             NaN
## ma2 -0.6813645
                                   NaN
                                             NaN
                         {\tt NaN}
## ma3 0.0176602 0.0027154
                                6.5036 7.841e-11 ***
## ma4 0.7869956 0.0022825 344.8023 < 2.2e-16 ***
## ma5 -0.1302488
                         {\tt NaN}
                                   NaN
                                             NaN
## ma6 -0.9152075
                                             NaN
                         {\tt NaN}
                                   {\tt NaN}
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
par(mfrow=c(1,2))
plot(atl.v.orders$AIC, ylab="AIC values", main="ATL Violent Crime AIC Values")
grid(lty=1, col=gray(0.8))
qqnorm(resid(atl.v.arima))
qqline(resid(atl.v.arima))
```

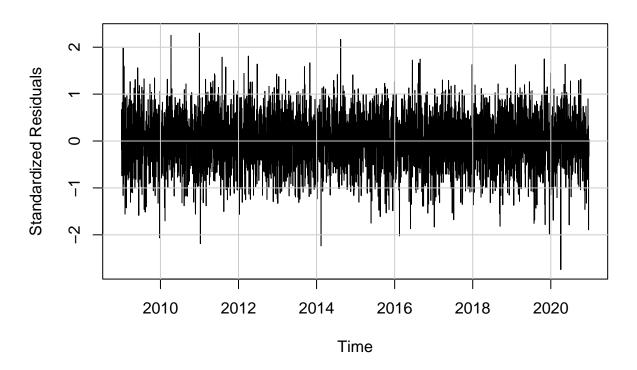
## **ATL Violent Crime AIC Values**

# Normal Q-Q Plot



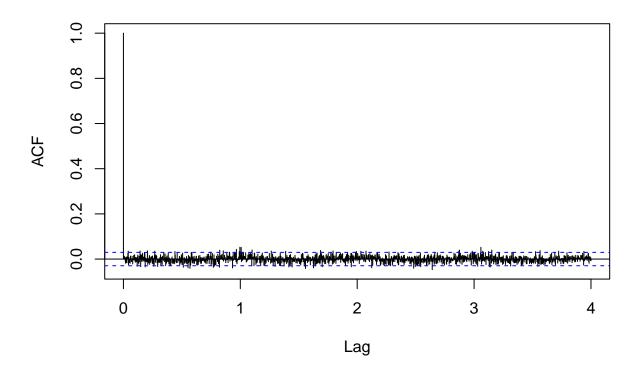
```
par(mfrow=c(1,1))
plot(residuals(atl.v.arima), ylab='Standardized Residuals', main="ATL Violent Crime ARIMA Residuals")
grid(lty=1, col=gray(0.8))
```

# **ATL Violent Crime ARIMA Residuals**



acf(residuals(atl.v.arima), lag.max = 365.25\*4, main="ACF of ATL Violent Crime ARIMA Residuals")

## **ACF of ATL Violent Crime ARIMA Residuals**



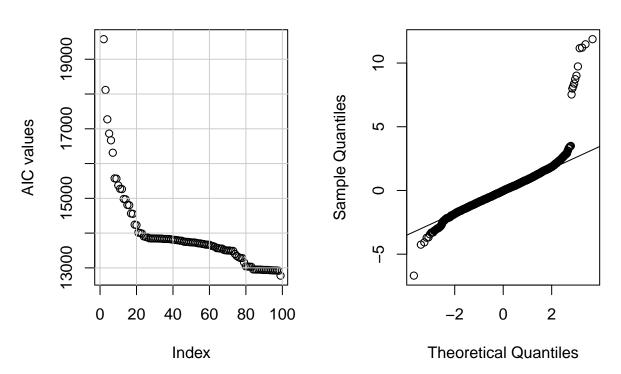
```
nyc.v.train <- ts(nyc.train$violentCrime, start = 2009, freq = 365.25)</pre>
# Daily TS ARIMA (p, d, q) Fitting
nyc.v.orders = data.frame(Inf, Inf, Inf, Inf)
names(nyc.v.orders) <- c("p", "d", "q", "AIC")</pre>
for (p in 0:6) {
  for (d in 1:2) {
    for (q in 0:6) {
      possibleError <- tryCatch(</pre>
        nyc.v.orders <- rbind(nyc.v.orders, test_modelA(nyc.v.train,p,d,q)),</pre>
        error = function(e) {e}
      )
      if (inherits(possibleError, "error"))
        next
    }
  }
nyc.v.orders <- nyc.v.orders[order(-nyc.v.orders$AIC), ]</pre>
nyc.v.ord <- nyc.v.orders[nrow(nyc.v.orders), ]</pre>
nyc.v.orders[(nrow(nyc.v.orders)-3):nrow(nyc.v.orders), ]
```

```
b) NYC Violent Crime
     p d q
## 50 3 1 6 12927.23
## 36 2 1 6 12925.04
## 75 5 1 3 12917.33
## 78 5 1 6 12777.38
# (5, 1, 6)
# ARIMA Fitted Model
nyc.v.arima = arima(nyc.v.train, order = c(nyc.v.ord$p, nyc.v.ord$d, nyc.v.ord$q), method='ML')
nyc.v.arima
##
## Call:
## arima(x = nyc.v.train, order = c(nyc.v.ord$p, nyc.v.ord$d, nyc.v.ord$q), method = "ML")
## Coefficients:
##
                     ar2
                             ar3
                                      ar4
                                               ar5
                                                       ma1
                                                               ma2
                                                                       ma3
##
        -0.1967 -0.6381 -0.6443 -0.1982 -0.9945 -0.6922 0.4495 0.0965
## s.e.
         0.0014
                 0.0028
                          0.0008
                                   0.0014 0.0030
                                                   0.0099 0.0122 0.0119
##
                    ma5
                            ma6
            ma4
##
        -0.3790
                 0.8030
                        -0.8615
                         0.0128
## s.e.
         0.0078 0.0136
##
## sigma^2 estimated as 1.078: log likelihood = -6376.69, aic = 12777.38
coeftest(nyc.v.arima)
##
## z test of coefficients:
         Estimate Std. Error z value Pr(>|z|)
##
## ar1 -0.19667899 0.00137986 -142.535 < 2.2e-16 ***
## ar2 -0.63811043  0.00278659 -228.993 < 2.2e-16 ***
## ar3 -0.64431184  0.00075258 -856.137 < 2.2e-16 ***
## ar4 -0.19822549  0.00142030 -139.566 < 2.2e-16 ***
## ar5 -0.99451186  0.00300954 -330.453 < 2.2e-16 ***
## ma1 -0.69217334 0.00989389 -69.960 < 2.2e-16 ***
## ma2 0.44948699 0.01224785 36.699 < 2.2e-16 ***
## ma3 0.09654115 0.01189662
                               8.115 4.858e-16 ***
## ma5 0.80303644 0.01361195
                              58.995 < 2.2e-16 ***
## ma6 -0.86151688 0.01281810 -67.211 < 2.2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
par(mfrow=c(1,2))
plot(nyc.v.orders$AIC, ylab="AIC values", main="NYC Violent Crime AIC Values")
grid(lty=1, col=gray(0.8))
qqnorm(resid(nyc.v.arima))
```

qqline(resid(nyc.v.arima))

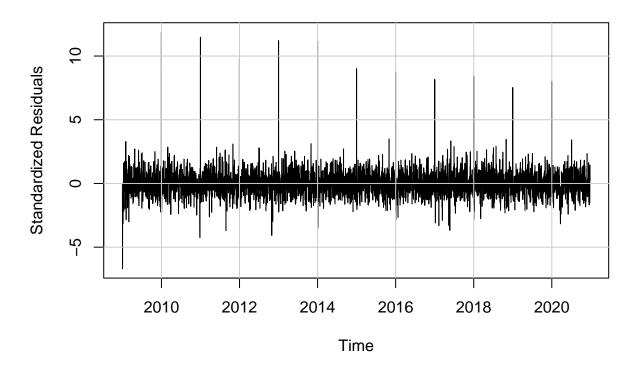
## **NYC Violent Crime AIC Values**

# Normal Q-Q Plot



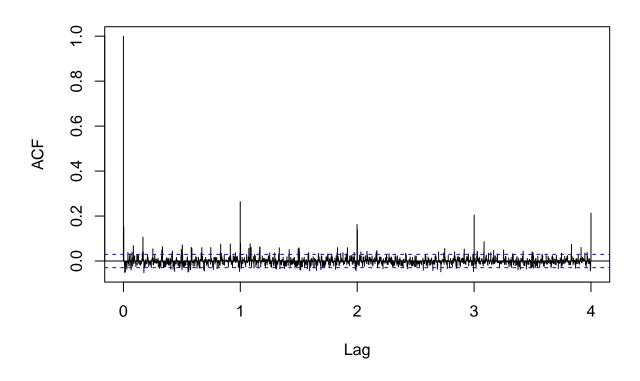
```
par(mfrow=c(1,1))
plot(residuals(nyc.v.arima), ylab='Standardized Residuals', main="NYC Violent Crime ARIMA Residuals")
grid(lty=1, col=gray(0.8))
```

# **NYC Violent Crime ARIMA Residuals**



acf(residuals(nyc.v.arima), lag.max = 365.25\*4, main="ACF of NYC Violent Crime ARIMA Residuals")

## **ACF of NYC Violent Crime ARIMA Residuals**

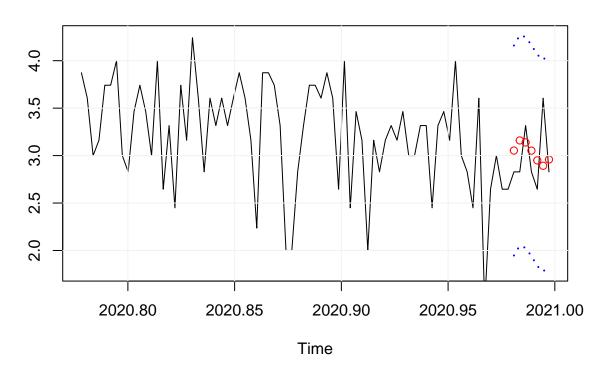


#### Residual Analysis

#### **Forecast**

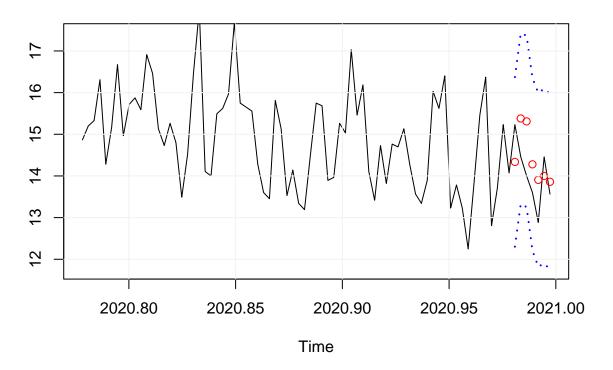
```
plot_forecast <- function(ts, out_pred, days_ahead, plot_title, conf) {</pre>
  n = length(ts)
  nfit = n-days_ahead
  timevol=time(ts)
  ubound = out_pred$pred+conf*out_pred$se
  lbound = out_pred$pred-conf*out_pred$se
  ymin = min(lbound, min(out_pred$pred))
  ymax = max(ubound, max(out_pred$pred))
  par(mfrow=c(1,1))
  plot(timevol[(n-80):n],ts[(n-80):n],type="1", ylim=c(ymin, ymax), xlab="Time",
       ylab="", main=plot_title)
  points(timevol[(nfit+1):n],out_pred$pred,col="red")
  lines(timevol[(nfit+1):n],ubound,lty=3,lwd= 2, col="blue")
  lines(timevol[(nfit+1):n],lbound,lty=3,lwd= 2, col="blue")
}
n.ahead <- nrow(atl.test)</pre>
## Forecast ATL Violent Crime
atl.v.pred <- as.vector(predict(atl.v.arima, n.ahead=n.ahead))</pre>
plot_forecast(atl.v.ts, atl.v.pred, n.ahead, conf=1.96, plot_title = "ATL Violent Crime Forecast")
grid(lty=1, col=gray(0.95))
```

## **ATL Violent Crime Forecast**



```
## Forecast NYC Violent Crime
nyc.v.pred <- as.vector(predict(nyc.v.arima, n.ahead=n.ahead))
plot_forecast(nyc.v.ts, nyc.v.pred, n.ahead, conf=1.96, plot_title = "NYC Violent Crime Forecast")
grid(lty=1, col=gray(0.95))</pre>
```

## **NYC Violent Crime Forecast**



#### **Prediction Evaluation**

```
mape <- function(y, y_pred) {
    mape <- mean(abs((y-y_pred)/y))
    return(mape)
}

pm <- function(obs, pred) {
    pm <- sum((pred-obs)^2)/sum((obs-mean(obs))^2)
    return(pm)
}

atl.v.mape <- mape(atl.test$violentCrime, atl.v.pred$pred)
atl.v.pm <- pm(atl.test$violentCrime, atl.v.pred$pred)

nyc.v.mape <- mape(nyc.test$violentCrime, nyc.v.pred$pred)

nyc.v.pm <- pm(nyc.test$violentCrime, nyc.v.pred$pred)

cat("ATL Violent:\nMAPE =", atl.v.mape, "\nPM =", atl.v.pm,
    "\n\nNYC Violent:\nMAPE =", nyc.v.mape, "\nPM =", nyc.v.pm)</pre>
```

```
## ATL Violent:
## MAPE = 0.0983468
## PM = 1.214297
```

```
##
## NYC Violent:
## MAPE = 0.05693062
## PM = 1.465883
```

### SARIMA Fitting and Forecasting

0.2237308 0.2588139

-0.2675961 0.4221474

-0.0172830 0.2352841

0.1847715 0.2500624

## sar2 0.9949347 0.0048703 204.2880

## sma2 -0.9874367 0.0061644 -160.1839

-0.0210306

-0.1915679

## sar1 0.0045851 0.0048716

## sma1 -0.0032469 0.0061744

-0.6177669 0.2789681 -2.2145

 $\mathtt{NaN}$ 

NaN

## ar5

## ma1 ## ma2

## ma3 ## ma4

## ma5

## ma6

## ---

0.8644

-0.6339

-0.0735

0.7389

0.9412

-0.5259

## Signif. codes: 0 '\*\*\* 0.001 '\*\* 0.01 '\* 0.05 '.' 0.1 ' ' 1

 $\mathtt{NaN}$ 

 ${\tt NaN}$ 

```
atl.v.sarima = arima(atl.v.train, order = c(5,1,6), seasonal = list(order =c(2,0,2), period=7), method=
atl.v.sarima
a) ATL Violent Crime
##
## arima(x = atl.v.train, order = c(5, 1, 6), seasonal = list(order = c(2, 0, 2),
       period = 7), method = "ML")
##
## Coefficients:
##
                      ar2
                                                ar5
                                                                  ma2
                                                                           ma3
             ar1
                               ar3
                                        ar4
                                                         ma1
##
         -0.3117
                  -0.2662 0.0083
                                    0.0132 0.2237
                                                     -0.6178
                                                              -0.021
                                                                       -0.2676
## s.e.
          0.2749
                                            0.2588
                                                      0.2790
                      {\tt NaN}
                               {\tt NaN}
                                    0.4509
                                                                  \mathtt{NaN}
                                                                        0.4221
                      ma5
                               ma6
                                      sar1
                                               sar2
                                                        sma1
                                                                  sma2
             ma4
##
         -0.0173 -0.1916
                            0.1848
                                    0.0046
                                             0.9949
                                                     -0.0032 -0.9874
        0.2353
                      NaN 0.2501 0.0049 0.0049
                                                      0.0062
## s.e.
                                                                0.0062
##
## sigma^2 estimated as 0.3164: log likelihood = -3697.65, aic = 7427.31
coeftest(atl.v.sarima)
##
## z test of coefficients:
          Estimate Std. Error z value Pr(>|z|)
##
## ar1 -0.3116551 0.2749122 -1.1337
                                            0.2569
## ar2 -0.2661876
                           \mathtt{NaN}
                                     {\tt NaN}
                                               NaN
        0.0083429
                                               {\tt NaN}
## ar3
                                     {\tt NaN}
                           NaN
## ar4
        0.0131595 0.4509087
                                 0.0292
                                          0.9767
```

0.3873

0.0268 \*

0.5262

0.9414

0.3466

0.5990

NaN

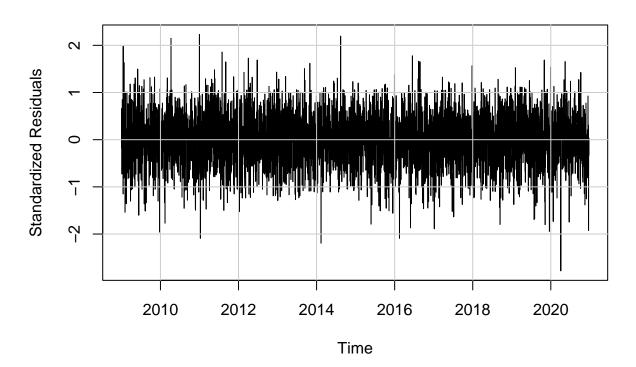
NaN 0.4600

<2e-16 \*\*\*

<2e-16 \*\*\*

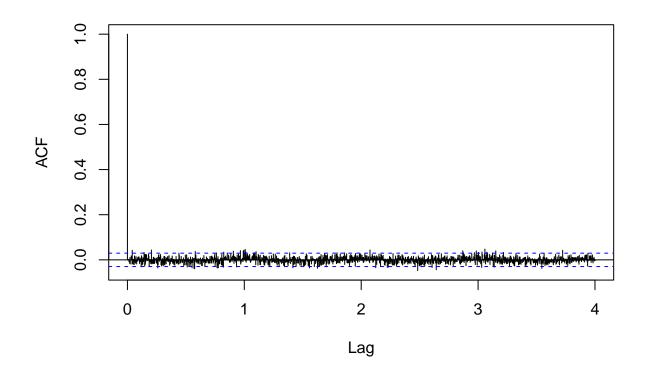
```
par(mfrow=c(1,1))
plot(residuals(atl.v.sarima), ylab='Standardized Residuals', main="ATL Violent Crime SARIMA Residuals")
grid(lty=1, col=gray(0.8))
```

## **ATL Violent Crime SARIMA Residuals**



acf(residuals(atl.v.sarima), lag.max = 365.25\*4, main="ACF of ATL Violent Crime SARIMA Residuals")

### **ACF of ATL Violent Crime SARIMA Residuals**



```
nyc.v.sarima = arima(nyc.v.train, order = c(5,1,6), seasonal = list(order =c(2,0,2), period=7), method='|
nyc.v.sarima
```

#### b) NYC Violent Crime

```
##
## arima(x = nyc.v.train, order = c(5, 1, 6), seasonal = list(order = c(2, 0, 2),
##
      period = 7), method = "ML")
##
## Coefficients:
##
                     ar2
                              ar3
                                       ar4
                                                ar5
                                                         ma1
         -0.6730 -0.4059 -0.6252
                                   -0.8598 -0.1270 -0.0660 -0.2456 0.2253
##
## s.e.
         0.1556
                  0.1121
                           0.1065
                                    0.1063
                                             0.0914
                                                      0.1543
                                                               0.1713 0.1620
##
           ma4
                    ma5
                             ma6
                                    sar1
                                            sar2
                                                     sma1
                                                              sma2
        0.3166 -0.6417
                         -0.2483 0.0110 0.9888 -0.0016 -0.9849
##
                 0.0911
                          0.0799 0.0074 0.0077
## s.e. 0.1202
                                                   0.0013
##
## sigma^2 estimated as 1.03: log likelihood = -6282.99, aic = 12597.98
coeftest(nyc.v.sarima)
```

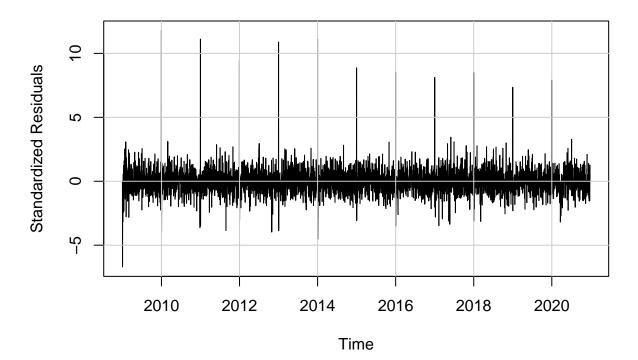
```
##
         Estimate Std. Error z value Pr(>|z|)
##
  ar1
       -0.6729602 0.1555966
                              -4.3250 1.525e-05 ***
       -0.4059085 0.1120734
                              -3.6218 0.0002925 ***
  ar2
        -0.6251983
                   0.1064586
                              -5.8727 4.288e-09 ***
  ar3
                              -8.0874 6.095e-16 ***
  ar4
        -0.8598435
                   0.1063188
##
  ar5
        -0.1270087
                   0.0913581
                              -1.3902 0.1644592
                   0.1543031
                             -0.4275 0.6690478
##
  ma1
        -0.0659577
  ma2
        -0.2456195
                   0.1712505
                             -1.4343 0.1514951
        0.2252845
                   0.1620041
                                1.3906 0.1643438
##
  ma3
        0.3166466
                   0.1201666
                                2.6351 0.0084122 **
##
  ma4
       -0.6417228
                  0.0910708 -7.0464 1.836e-12 ***
  ma5
        -0.2483220
                   0.0798663
                              -3.1092 0.0018758 **
  ma6
   sar1
        0.0109827
                    0.0074432
                                1.4755 0.1400684
        0.9888487
                   0.0077322 127.8868 < 2.2e-16 ***
                              -1.1728 0.2408931
  sma1 - 0.0015507
                   0.0013223
  sma2 - 0.9849050
                  0.0100829 -97.6810 < 2.2e-16 ***
##
##
                  0 '*** 0.001 '** 0.01 '* 0.05 '. ' 0.1 ' 1
## Signif. codes:
par(mfrow=c(1,1))
plot(residuals(nyc.v.sarima), ylab='Standardized Residuals', main="NYC Violent Crime SARIMA Residuals")
grid(lty=1, col=gray(0.8))
```

##

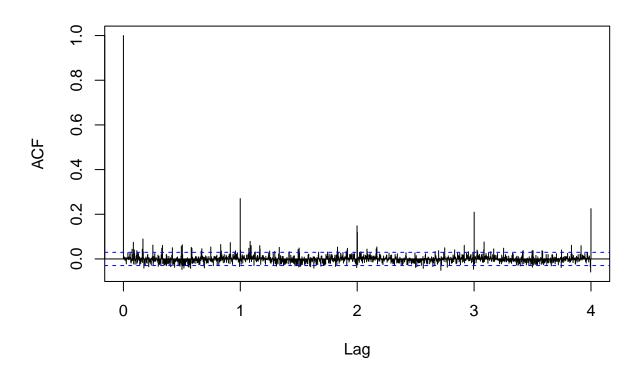
##

## z test of coefficients:

### **NYC Violent Crime SARIMA Residuals**



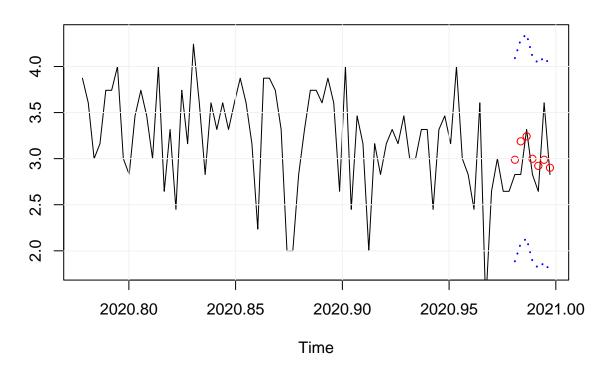
## **ACF of NYC Violent Crime SARIMA Residuals**



### Forecasting Analysis

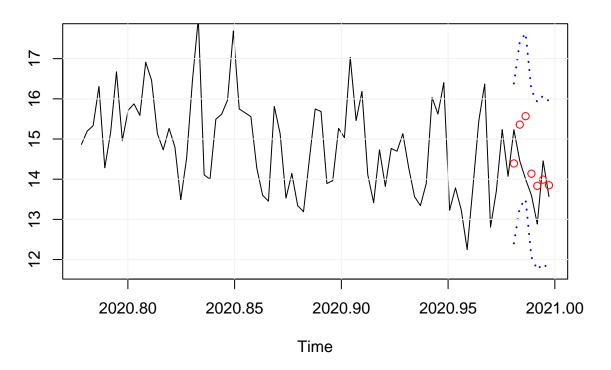
```
## Forecast ATL Violent Crime
atl.v.spred <- as.vector(predict(atl.v.sarima, n.ahead=n.ahead))
plot_forecast(atl.v.ts, atl.v.spred, n.ahead, conf=1.96, plot_title = "ATL Violent Crime Forecast")
grid(lty=1, col=gray(0.95))</pre>
```

## **ATL Violent Crime Forecast**



```
## Forecast NYC Violent Crime
nyc.v.spred <- as.vector(predict(nyc.v.sarima, n.ahead=n.ahead))
plot_forecast(nyc.v.ts, nyc.v.spred, n.ahead, conf=1.96, plot_title = "NYC Violent Crime Forecast")
grid(lty=1, col=gray(0.95))</pre>
```

## **NYC Violent Crime Forecast**



#### Evaluation

```
## ATL Violent:
## MAPE = 0.08107274
## PM = 0.9211366
##
## NYC Violent:
## MAPE = 0.05655839
## PM = 1.551702
```