Project 2

2022-12-04

Names

Stacy Meng, Sammy Park, Neha Pavuluru, Anika Sharma

Library Setup:

Here, we are importing the necessary libraries.

```
require("knitr")
```

```
## Loading required package: knitr
```

```
sourcedir <-"C:/Users/Neha/Documents/SYS4021/RCode"
opts_knit$set(root.dir = sourcedir)
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.1.3
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(mtsdi)
```

```
## Warning: package 'mtsdi' was built under R version 4.1.3
```

```
## Loading required package: gam
```

```
## Warning: package 'gam' was built under R version 4.1.3
```

```
## Loading required package: splines
```

```
## Loading required package: foreach
```

```
## Warning: package 'foreach' was built under R version 4.1.3
```

```
## Loaded gam 1.22
```

```
## mtsdi 0.3.5
```

```
library(MTS)
```

```
## Warning: package 'MTS' was built under R version 4.1.3
```

```
library(ggplot2)
library(ggpubr)
```

```
## Warning: package 'ggpubr' was built under R version 4.1.2
```

```
##
## Attaching package: 'ggpubr'
```

```
## The following object is masked from 'package:forecast':
##
##     gghistogram
```

```
library(ggfortify)
```

```
## Warning: package 'ggfortify' was built under R version 4.1.3
```

```
## Registered S3 methods overwritten by 'ggfortify':
##   method                 from
##   autoplot.Arima         forecast
##   autoplot.acf           forecast
##   autoplot.ar            forecast
##   autoplot.bats          forecast
##   autoplot.decomposed.ts forecast
##   autoplot.ets           forecast
##   autoplot.forecast      forecast
##   autoplot.stl           forecast
##   autoplot.ts            forecast
##   fitted.ar              forecast
##   fortify.ts             forecast
##   residuals.ar           forecast
```

```
library(tseries)
```

```
## Warning: package 'tseries' was built under R version 4.1.3
```

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

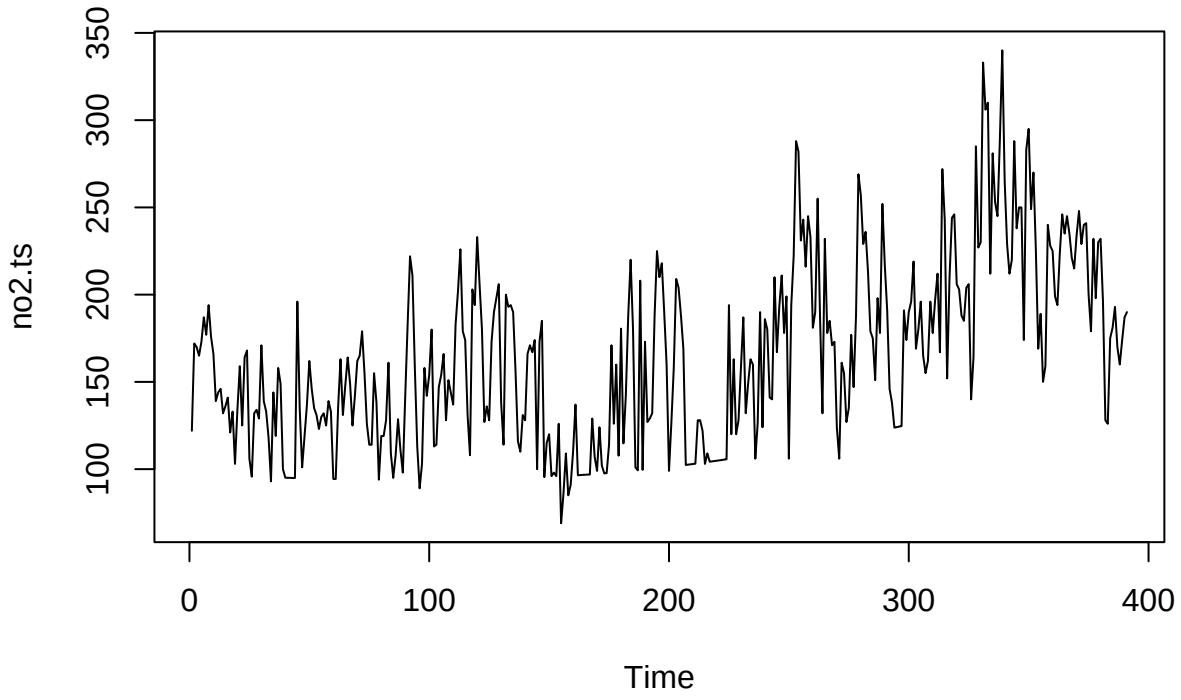
Imputing Data

```
setwd(sourcedir)

airquality = read.csv('AirQualityUCI.csv')

# replace -200 with NA
airquality[airquality == -200] <- NA

# convert integer type to numeric
intcols = c(4,5,7,8,9,10,11,12)
for(i in 1:length(intcols)){
  airquality[,intcols[i]] <- as.numeric(airquality[,intcols[i]])
}

setwd(sourcedir)

# create new data frame with just CO and NO2
AQdata = airquality[,c(3,10)]

# impute missing air quality data
f <- ~ CO.GT. + NO2.GT.
t <- c(seq(1,dim(AQdata)[1],1))
i <- mnimput(f, AQdata, eps=1e-3, ts=TRUE, method='gam',
             ga.control=list(formula=paste(names(AQdata)
                                           [c(1:2)],'~ns(t,2)')))

# set airquality to imputed data
AQdata <- i$filled.dataset

# aggregate to daily maxima for model building
dailyAQ <- aggregate(AQdata, by=list(as.Date(airquality[,1],"%m/%d/%Y")),
                     FUN=max)
```

Question 1

We start by extracting the NO2 values from dailyAQ and converting them to a time series. The plot of the time series values can be seen in Figure 1.

```
#making this a time series
no2.ts <-ts(dailyAQ$NO2.GT.)

#Figure 1:
plot(no2.ts)
```

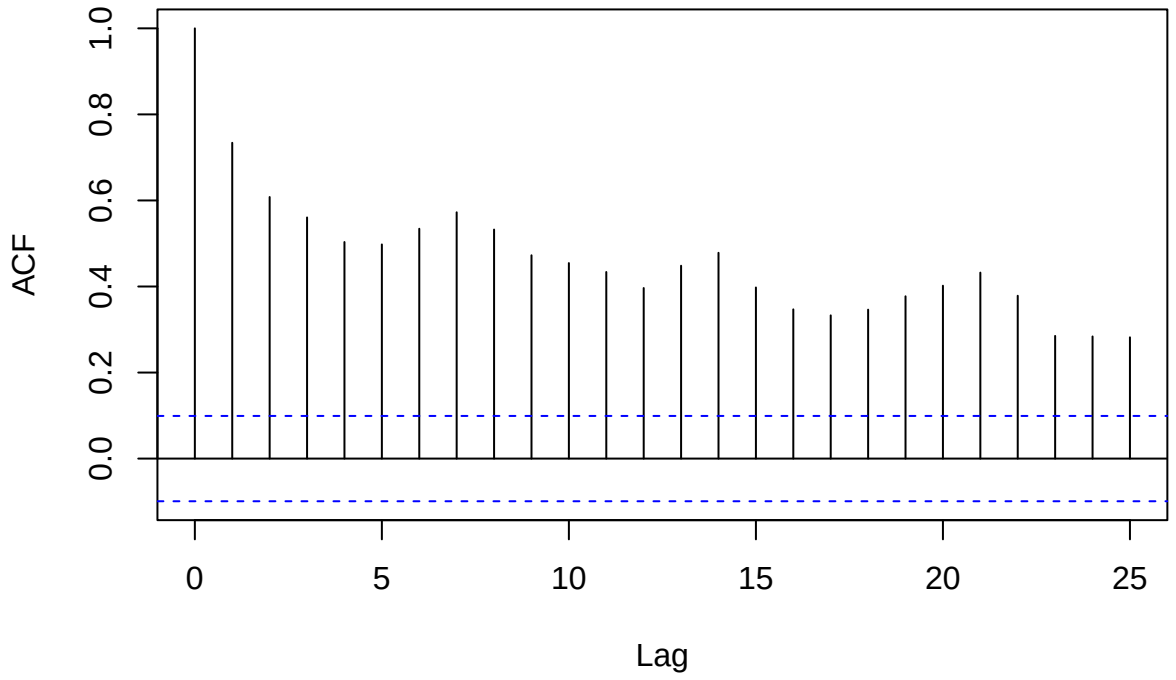



```
fig.dim = c(8, 6)
```

(a) Here, we're discovering and modeling any seasonal components. To test for seasonality, we can use the acf command. There seems to be seasonality since the graph exhibits sinusoidal decay. Based on the ACF plot (Figure 2) of the NO2 time series, it can be observed that the ACF is a decreasing sinusoidal with a peak occurring roughly every 7 day, which indicates a weekly seasonality. In the periodogram (Figure 3), the observed period of the first, largest peak is 192 days, however this data may be attributed to red noise as the second largest peak has a period of 7 days and better supports the results of the ACF.

```
#acf chart -> displays sinusoidal decay, peaks every 7 days indicating weekly seasonality

#Figure 2:
no2.acf <- acf(no2.ts, plot=FALSE)
plot(no2.acf, main = "Figure 2: ACF of NO2 Time Series")
```

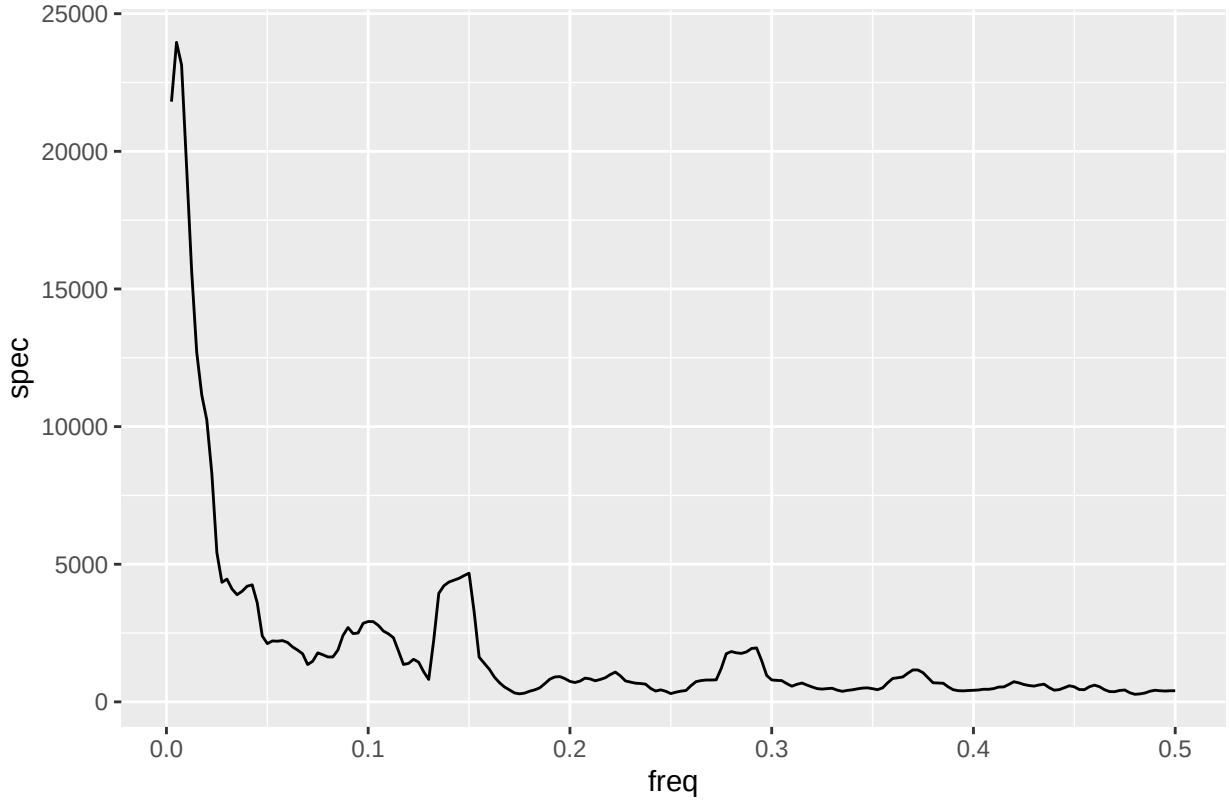
Figure 2: ACF of NO2 Time Series




```
#Periodogram for seasonality
pg.no2 <- spec.pgram(no2.ts,spans=9,demean=T,log='no',plot=F)

spec.no2 <- data.frame(freq=pg.no2$freq, spec=pg.no2$spec)
ggplot(spec.no2) + geom_line(aes(x=freq,y=spec), width=6, height=6) +
  ggtitle(" Figure 3: Smooth Periodogram of No2")
```

```
## Warning: Ignoring unknown parameters: width, height
```

Figure 3: Smooth Periodogram of No2




```
#Finding the peak
max.omega.no2<-spec.no2$freq[which(pg.no2$spec==max(pg.no2$spec))]

#Frequency of the peak
max.omega.no2
```

```
## [1] 0.005
```

```
#Period of the peak
1/max.omega.no2
```

```
## [1] 200
```

```
#Finding the periods of the next biggest peaks
sorted.spec <- sort(pg.no2$spec, decreasing=T, index.return=T)

sorted.omegas <- pg.no2$freq[sorted.spec$ix]
sorted.Ts <- 1/pg.no2$freq[sorted.spec$ix]

sorted.omegas[1:20] #peak of ~7.24 days around second peak
```

```
##  [1] 0.0050 0.0075 0.0025 0.0100 0.0125 0.0150 0.0175 0.0200 0.0225 0.0250
## [11] 0.1500 0.1475 0.1450 0.0300 0.1425 0.1400 0.0275 0.0425 0.1375 0.0400
```

```
#(frequency of around 0.15)
sorted.Ts[1:20]
```

```
##  [1] 200.000000 133.333333 400.000000 100.000000  80.000000  66.666667
##  [7]  57.142857  50.000000  44.444444  40.000000   6.666667   6.779661
## [13]   6.896552  33.333333   7.017544   7.142857  36.363636  23.529412
## [19]   7.272727  25.000000
```

We created a seasonal trend model which predicts the no2 time series based on time as well as accounting for sinusoidal seasonality. The model is statistically significant with a p-value of less than 2.2e-16. The coefficient for the time variable is 0.24817 which means that for every 1 increase in time, there should be about a 0.24817 increase in NO2 levels. The sine term is statistically significant indicating that there is a sinusoidal seasonal relationship between time and NO2 levels. Since we found that there was weekly seasonality, we decided to set the period to every 7 days.

Based on the graph of seasonal trend (Figure 4), we can see that there are seasons or a sinusoidal relationship between time and NO2 levels. We also ran diagnostics for the seasonal trend model (Figure 5) and saw that there was good normality in the QQ plot with a minor Gaussian tail. The Residuals vs Fitted plot shows that the residuals are somewhat scattered around the zero line with significant trends at certain peaks.

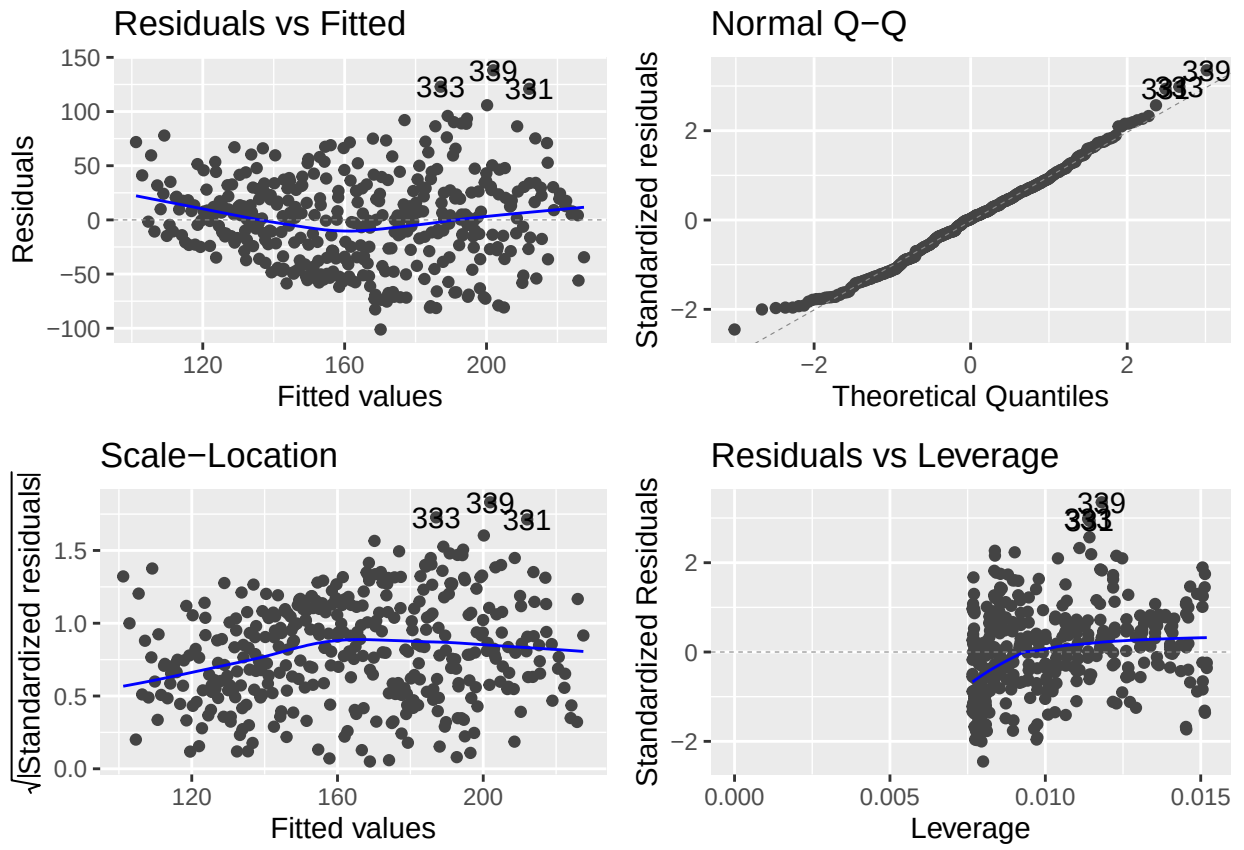
```
#creating the seasonality model
time.no2<-c(1:(length(no2.ts)))

no2.trend.seasonal <- lm(no2.ts ~ time.no2 + sin(2*pi*time.no2/7) +
                           cos(2*pi*time.no2/7))
summary(no2.trend.seasonal)
```

```
##
## Call:
## lm(formula = no2.ts ~ time.no2 + sin(2 * pi * time.no2/7) + cos(2 *
##     pi * time.no2/7))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -101.153  -28.634    0.959   26.687  138.096
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              116.17036    4.19832  27.671  < 2e-16 ***
## time.no2                   0.24817    0.01856  13.370  < 2e-16 ***
## sin(2 * pi * time.no2/7)  15.36453    2.95925   5.192 3.37e-07 ***
## cos(2 * pi * time.no2/7)   5.61983    2.96659   1.894   0.0589 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41.43 on 387 degrees of freedom
## Multiple R-squared:  0.3491, Adjusted R-squared:  0.344
## F-statistic: 69.17 on 3 and 387 DF,  p-value: < 2.2e-16
```

```
#Figure 4:
graph.seasonal.no2 <- ggplot(dailyAQ, aes(x=Group.1,y=NO2.GT.)) + geom_line() +
  geom_line(aes(x=Group.1,y=no2.trend.seasonal$fitted.values),color="red",
            width=6, height=6) +
  xlab("") + ylab("Figure 4: NO2 Seasonality Graph")
```

```
## Warning: Ignoring unknown parameters: width, height
```

```
#Figure 5:
autoplot(no2.trend.seasonal, labels.id = NULL,width=6, height=6)
```



(b) Here, we are discovering and modeling any trends. First, we started by creating a time variable using only data points in no2. Then, we built a model that predicts the time series of no2 based on the newly created time variable. Based on the model diagnostics, the model is significant with a p-value of less than 2.2e-16. The coefficient for the time variable is 0.25646, which means that for every 1 increase in unit of time, there is a 0.25646 increase in NO2 levels. The time term is also statistically significant indicating that there is a relationship between duration and NO2 levels. Based on the graph (Figure 6), the trend line shows that there is a positive linear relationship between time and NO2 levels. The graph also seems to show that time series is has additive seasonal changes.

We also ran diagnostics for the plot (Figure 7). The QQ plot shows a good fit of normality with no Gaussian tails. The Residuals vs Fitted plot shows that the residuals are somewhat scattered around the zero line which indicates that the assumption that the relationship is somewhat linear is reasonable. The residuals vs fitted plot also shows several outliers, particularly obvervations 339,331,and 333. The scale-location plot indicates a small lack of fit as shown by the non-horizontal trend line. This could mean that there are other predictors that could explain the variance in the dataset, or that the outliers are skewing the data.

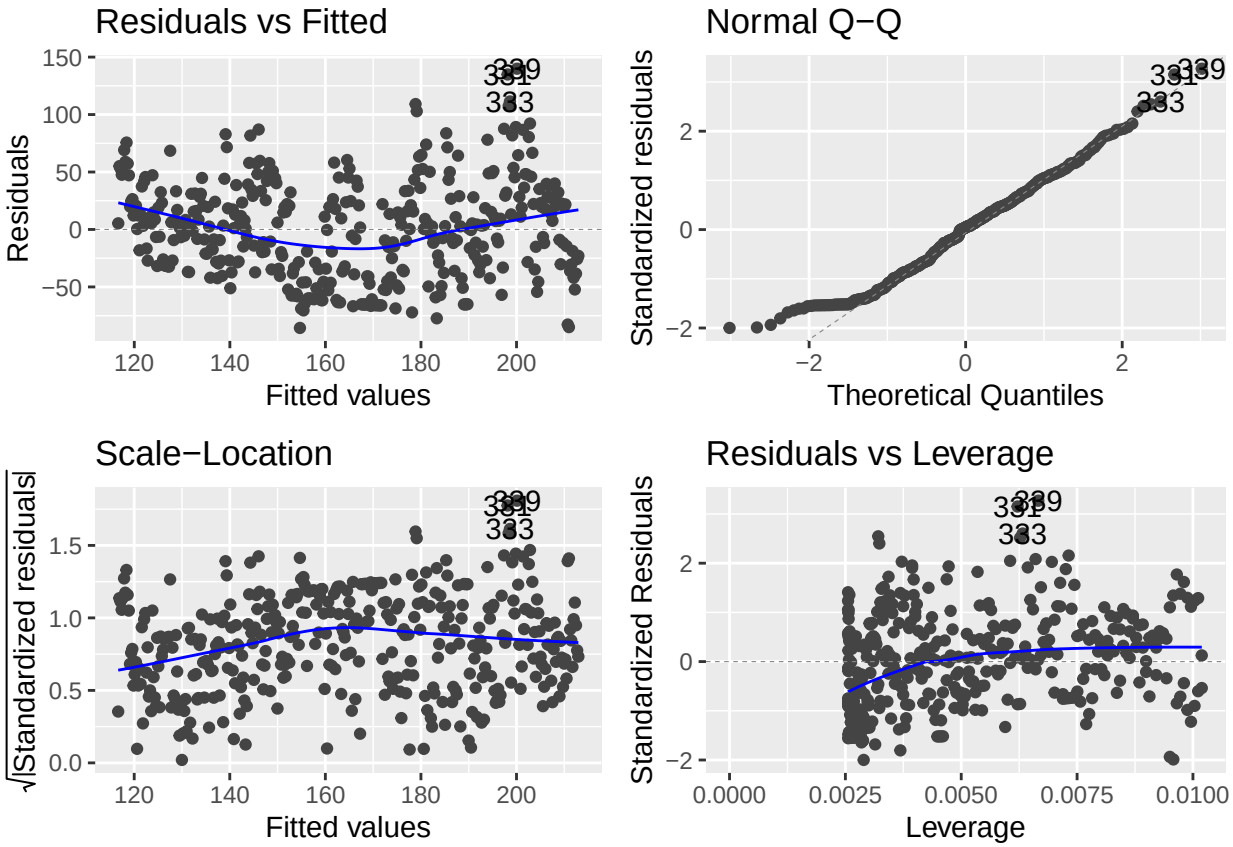
```r
#New model called no2.trend which predicts no2.ts based on the time variable
no2.trend <- lm(no2.ts[time.no2] ~ time.no2)
summary(no2.trend)
```

```
##
## Call:
## lm(formula = no2.ts[time.no2] ~ time.no2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -85.674 -34.168   1.771  28.437 139.893
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 116.40204    4.34936   26.76   <2e-16 ***
## time.no2      0.24692    0.01923   12.84   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 42.92 on 389 degrees of freedom
## Multiple R-squared:  0.2977, Adjusted R-squared:  0.2959
## F-statistic: 164.9 on 1 and 389 DF,  p-value: < 2.2e-16
```

```r
#Figure 6:
graph.trend.no2 <- ggplot(dailyAQ, aes(x=Group.1,y=NO2.GT.)) + geom_line() + stat_smooth(method="lm",co
  ylab("Figure 6: Trend Graph of NO2")
```

```
## Warning: Ignoring unknown parameters: width, height
```

```r
#Figure 7:
autoplot(no2.trend, labels.id = NULL,width=6, height=6)
```



In addition to the trend model, we also built a trendseason model which models trend while accounting for weekly seasonality. In order to do this, we built dummy variables modeling each day of the week in relation to the dates in our dataset. We then built a linear regression model using both time and the dummy variables as explanatory variables and the time series as the response variable. We found that the model is significant with a p-value of 2.2e-16. The time variable is also significant with a coefficient of 0.25749 indicating that for every 1 increase in time, there is a 0.25749 increase in NO2 levels. In terms of the dummy variables, we found that only Saturday and Sunday are statistically significant with coefficients of -26.67938 and -39.97451, respectively. This indicates that the likelihood of NO2 levels being impacted by the day of week, specifically on Saturdays and Sundays, may not be due to random chance. Figure 8 shows the trend+seasonality of the time series data.

We also ran diagnostics for the plot (Figure 9). The QQ plot shows a good fit of normality with a very minor Gaussian tail. The Residuals vs Fitted plot shows that the residuals are somewhat scattered around the zero line which indicates that the assumption that the relationship is somewhat linear is reasonable. The residuals vs fitted plot also shows several outliers, particularly observations 339,331,and 333. The scale-location plot indicates a small lack of fit as shown by the non-horizontal trend line. This could mean that there are other predictors that could explain the variance in the dataset, or that the outliers are skewing the data.

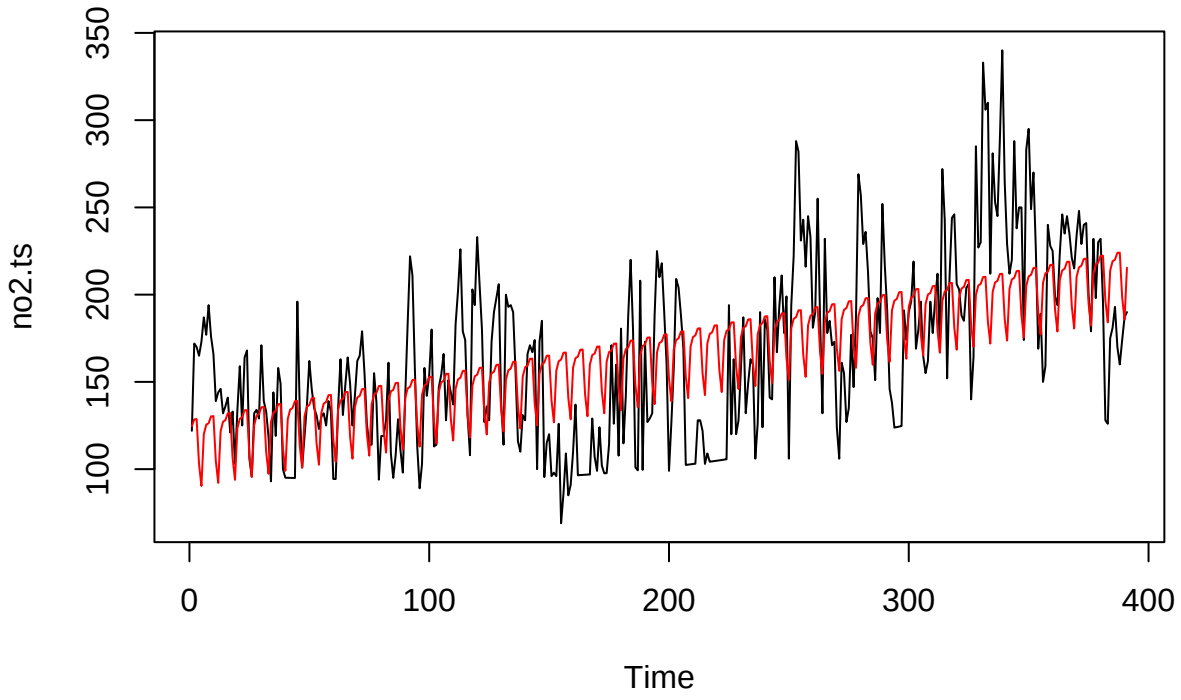
```
#Model the seasonality for no2 data set using dummy variables. Use day of the week as the interval.

no2.day <- time.no2 %% 7
no2.day <-as.factor(time.no2 %% 7)
fulltime = c(1:length(no2.ts))



Day <- rep(NA, length(no2.ts))
```

```r
Day[which((fulltime %% 7)    == 1)] <- "W"
Day[which((fulltime %% 7)    == 2)] <- "Th"
Day[which((fulltime %% 7)    == 3)] <- "Fri"
Day[which((fulltime %% 7)    == 4)] <- "Sat"
Day[which((fulltime %% 7)    == 5)] <- "Sun"
Day[which((fulltime %% 7)    == 6)] <- "M"
Day[which((fulltime %% 7)    == 0)] <- "T"
Day <- as.factor(Day)

#building a trendseason model
no2.trendseason<-lm(no2.ts[time.no2]~time.no2+Day[time.no2])


#Is no2.trendseason significant?
summary(no2.trendseason)
```

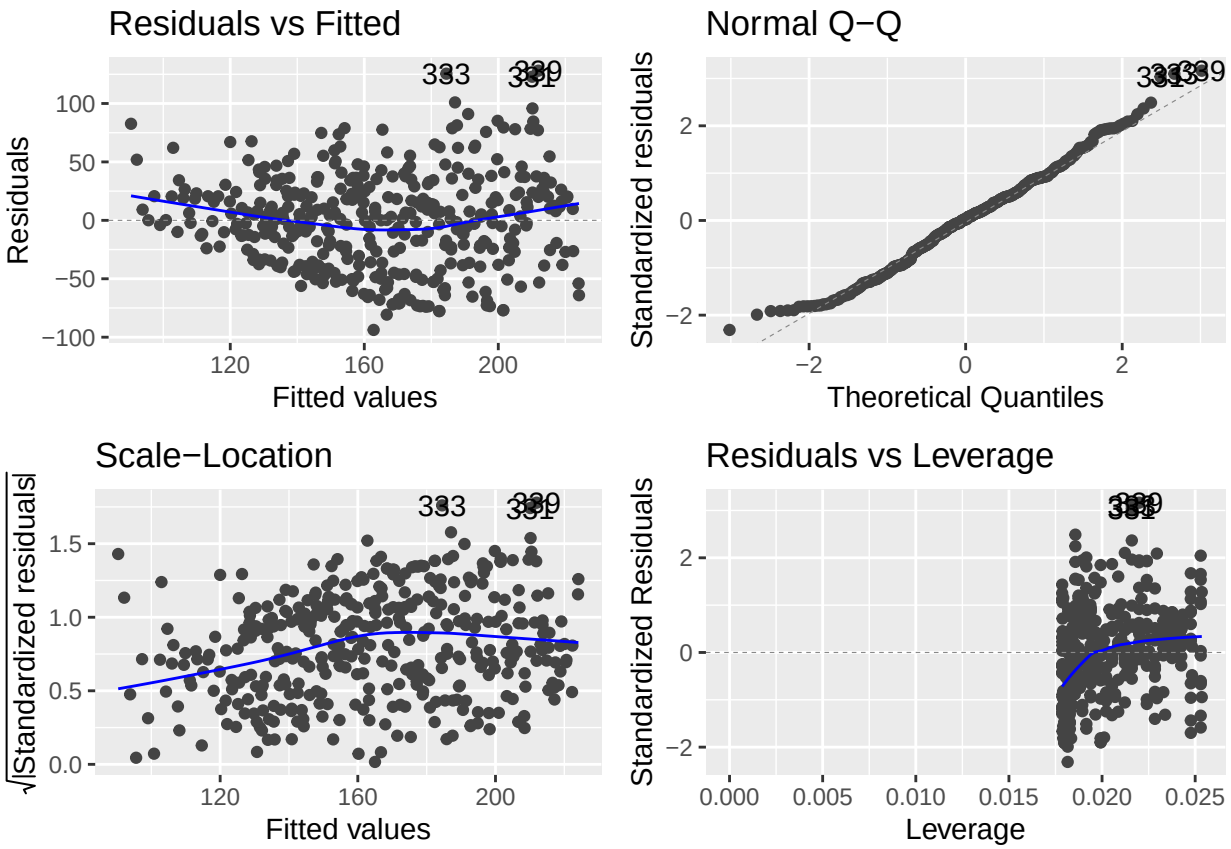
```
##
## Call:
## lm(formula = no2.ts[time.no2] ~ time.no2 + Day[time.no2])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -93.791 -27.894   1.166  24.649 128.062
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      127.90546    6.53950  19.559  < 2e-16 ***
## time.no2           0.24788    0.01834  13.517  < 2e-16 ***
## Day[time.no2]M    -9.39653    7.73463  -1.215 0.225166
## Day[time.no2]Sat -25.94796    7.73446  -3.355 0.000873 ***
## Day[time.no2]Sun -38.76853    7.73452  -5.012 8.23e-07 ***
## Day[time.no2]T    -4.20795    7.76952  -0.542 0.588411
## Day[time.no2]Th    0.14057    7.73446   0.018 0.985509
## Day[time.no2]W    -3.53620    7.73452  -0.457 0.647789
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 40.93 on 383 degrees of freedom
## Multiple R-squared:  0.3712, Adjusted R-squared:  0.3597
## F-statistic:  32.3 on 7 and 383 DF,  p-value: < 2.2e-16
```

```r
# Figure 8:
plot(no2.ts, main = "Figure 8: Plot of Trend+Season Model for NO2 Values")
lines(ts(no2.trendseason$fitted.values),col="red")
```

Figure 8: Plot of Trend+Season Model for NO2 Values

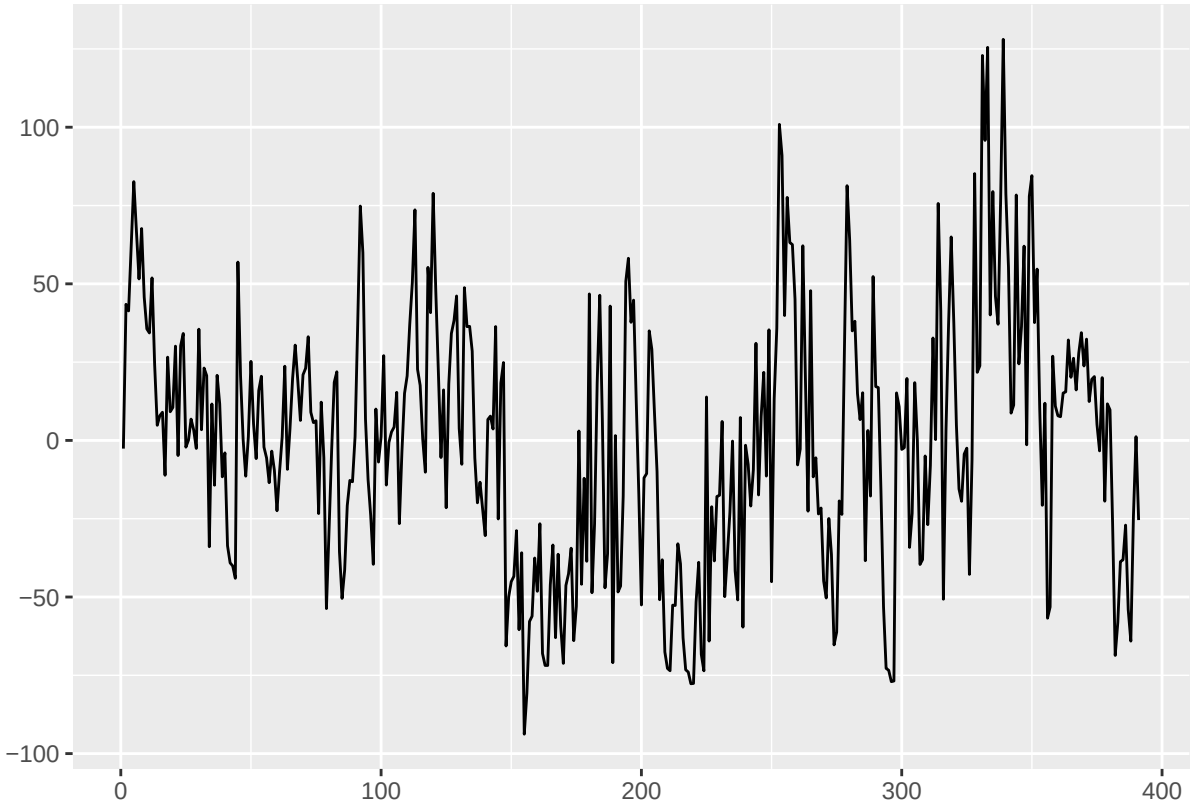



```
#Figure 9:
autoplot(no2.trendseason, labels.id = NULL,width=6, height=6)
```



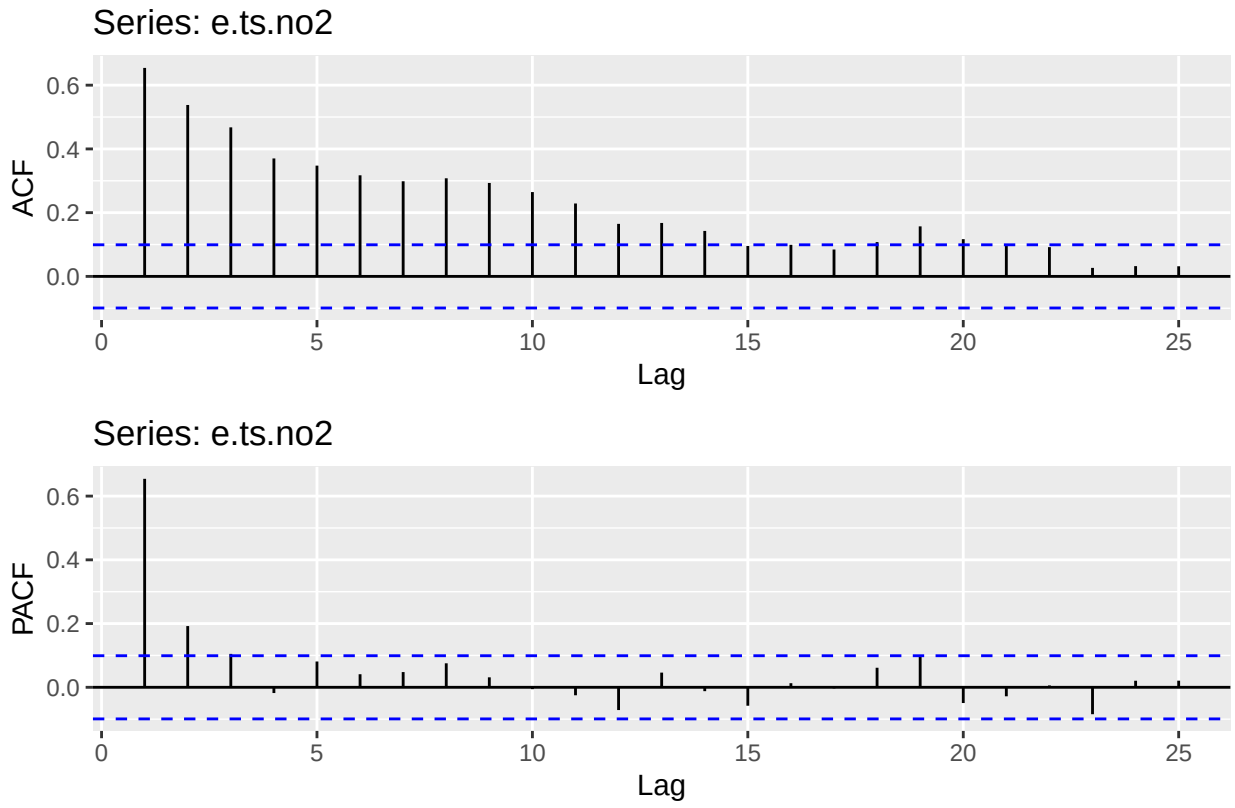
(c) Here, we are looking at autoregressive or moving average components. A weekly stationary time series is one that has a constant mean with autocorrelation as a function of the lag. Because the acf does not have a slow or linear decay, it is clear that it is a stationary time series. Based on the ACF and PACF plot of the residuals from no2.trendseason (Figure 10), the data displays autoregressive components as the ACF shows a sinusoidal decrease. Additionally, the PACF only displays a small number, 2, of lags before it cuts off.

```
# Getting the residuals from no2.trendseason model above and store in e.ts.no2:
e.ts.no2 <- ts(no2.trendseason$residuals)

#Figure 10:
autoplot(e.ts.no2,width=6, height=6)
```




```
#the ACF for the residuals
no2.acf <- ggAcf(e.ts.no2)

#PACF for the residuals
no2.pacf <- ggPacf(e.ts.no2)

# Plot acf and pacf side by side for easier examination
plot <- ggarrange(no2.acf,no2.pacf,nrow=2,ncol=1)
annotate_figure(plot, top = text_grob("Figure 10: ACF and PACF Side by Side"))
```

Figure 10: ACF and PACF Side by Side



(d) We built four different types of models: autoregressive, moving average, autoregressive moving average, and autoregressive integrated moving average. For each model, we decided build two versions: one with the mean and one without the mean. We looked at the AIC values for each and chose the model that had the lower value. After we found our best model for the different types, we decided to compare all four of the chosen ones using AIC, BIC, and the Ljung-Box test. We found that the auto model has the best AIC, the autoregressive model (AR) has the best BIC, and the moving average (MA) and the autoregressive moving average (ARMA) have the best Ljung-Box statistic with p-values above 0.05.

Looking at AIC value is useful for finding the best model for predicting future observations. Based on that, we choose to use an autoregressive integrated moving average model (as defined by our variable no2.auto) going forward. The model has p,d,q values of 3,1,1 respectively. Looking at the residuals vs fitted plot (Figure 11) for our overaggressive integrated moving average model, we can see that the residuals bounce randomly around the zero line and also no one residual stands out. These are characteristics of a well behaved residuals vs fitted plot. The QQ plot for our autoregressive integrated moving average model seems to display decent normality with a slight upper Gaussian tail. Looking at Ljung-Box test (Figure 12), we can see that all of the points have a p-value of above 0.05 which indicates that the residuals are independent. Based on everything above, our autoregressive integrated moving average model is a good fit for the data. Further improvements in the diagnostics can be made by addressing the slight Gaussian tail in the QQ plot.

```r
#AR Model
#ar(1) p=2
no2.ar1 <- arima(e.ts.no2, order=c(2,0,0))

no2.ar1 <- arima(e.ts.no2, order=c(3,0,0), include.mean=FALSE)
#better model compared to first one

#MA Model:
#ma(12) p=0, q=14
no2.ma12 <- arima(e.ts.no2, order=c(0,0,14))

no2.ma12 <- arima(e.ts.no2, order=c(0,0,14), include.mean=FALSE)
#better model compared to first one

#ARMA Model
#arma(1,12) p=2, q=14
no2.arma12 <- arima(e.ts.no2, order=c(2,0,14))

no2.arma12 <- arima(e.ts.no2, order=c(2,0,14), include.mean=FALSE)
#better model compared to first


#ARIMA AUTO:
no2.auto <- auto.arima(e.ts.no2)

no2.auto <- auto.arima(e.ts.no2,approximation=FALSE) #better arima


#AIC comparison
AIC(no2.ar1)
```

```
## [1] 3775.017
```

```r
AIC(no2.ma12)
```

```
## [1] 3786.159
```

```r
AIC(no2.arma12)
```

```
## [1] 3790.275
```

```r
AIC(no2.auto) #best model
```

```
## [1] 3773.473
```

```r
#BIC comparison
BIC(no2.ar1) #best model
```

```
## [1] 3790.892
```

```
BIC(no2.ma12)
```

```
## [1] 3845.69
```

```
BIC(no2.arma12)
```

```
## [1] 3857.743
```

```
BIC(no2.auto)
```

```
## [1] 3785.379
```

```
# assess residuals vs. fitted
model1 = ggplot() + geom_point(aes(x=fitted(no2.ar1),
                                   y=no2.ar1$residuals,width=6, height=6)) +
  ggtitle("AR1")
```

```
## Warning: Ignoring unknown aesthetics: width, height
```

```
model2 = ggplot() + geom_point(aes(x=fitted(no2.ma12),
                                   y=no2.ma12$residuals,width=6, height=6)) +
  ggtitle("MA2")
```

```
## Warning: Ignoring unknown aesthetics: width, height
```

```
model3 = ggplot() + geom_point(aes(x=fitted(no2.arma12),
                                   y=no2.arma12$residuals,width=6, height=6)) +
  ggtitle("ARMA12")
```

```
## Warning: Ignoring unknown aesthetics: width, height
```

```
model4 = ggplot() + geom_point(aes(x=fitted(no2.auto),
                                   y=no2.auto$residuals,width=6, height=6)) +
  ggtitle("Auto")
```

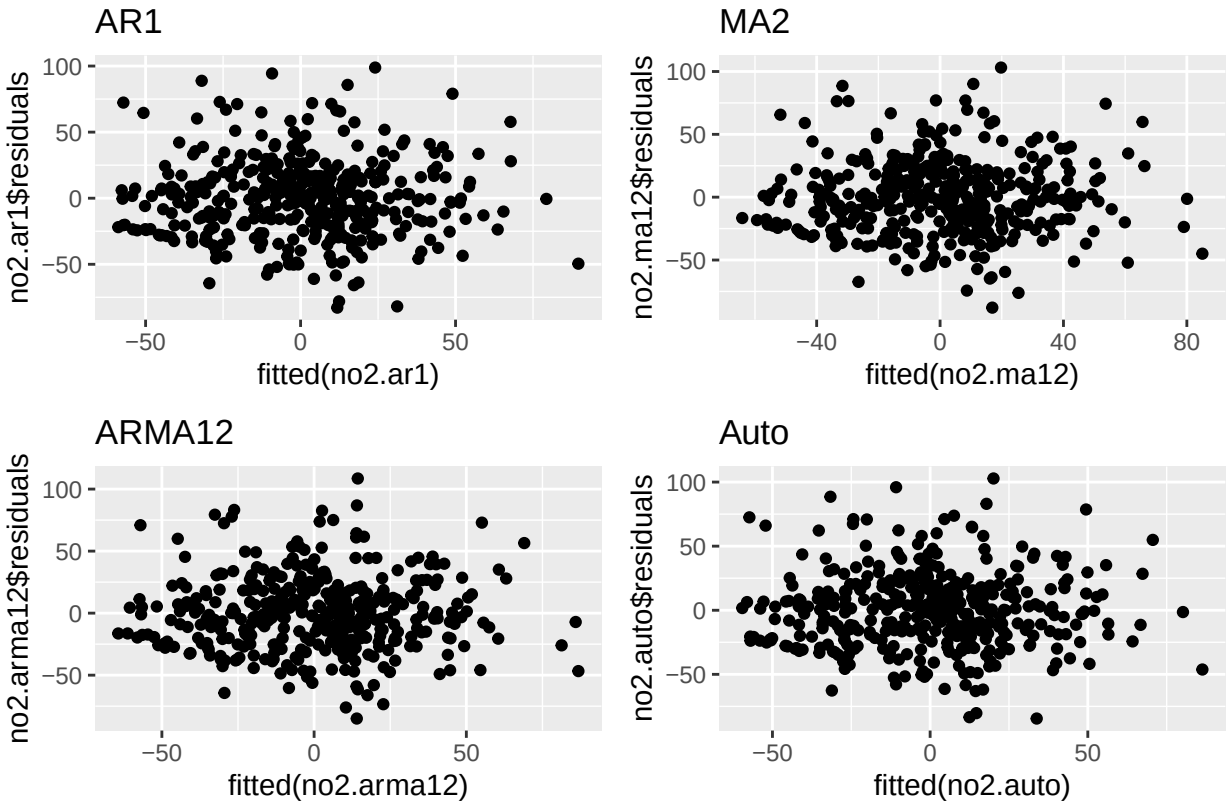
```
## Warning: Ignoring unknown aesthetics: width, height
```

```
best_model_plot <- ggarrange(model1, model2, model3, model4, ncol=2, nrow=2)
```

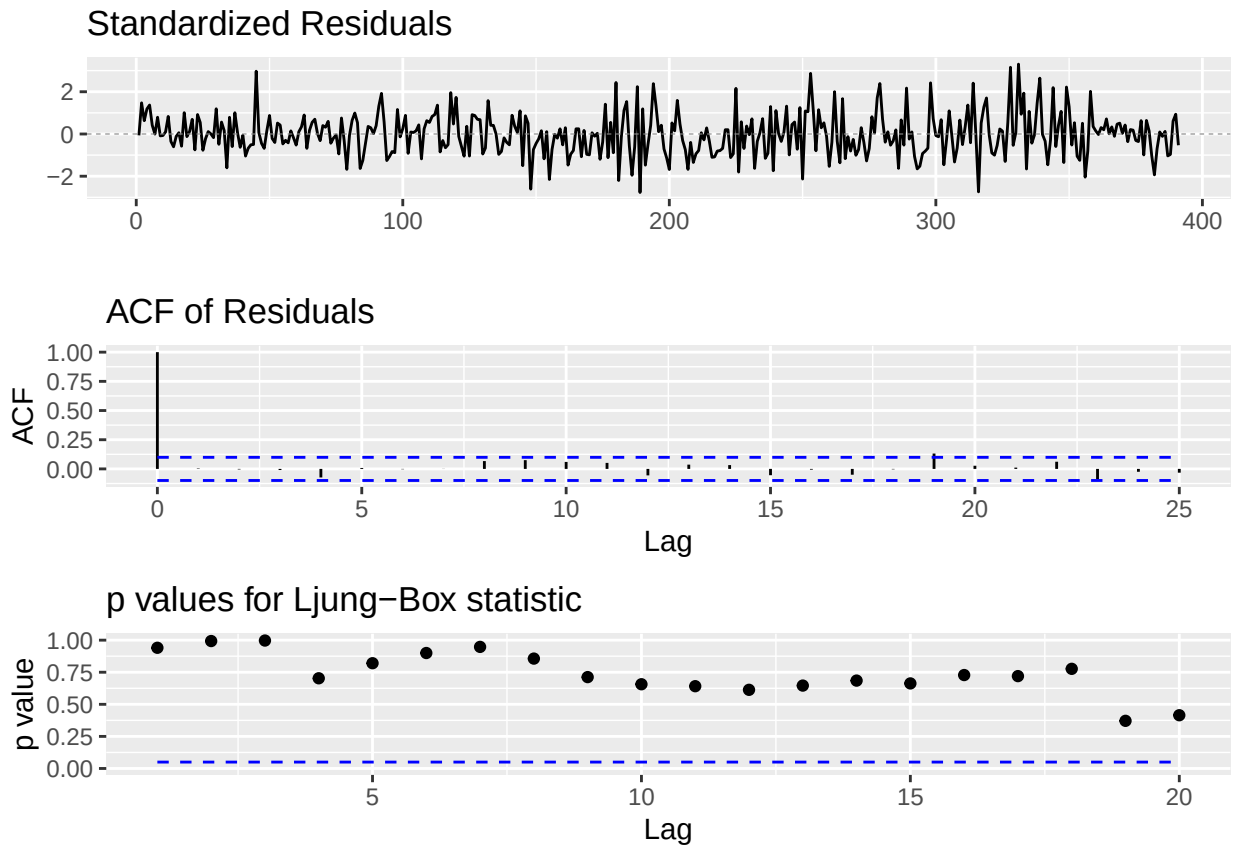
```
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
```

```
annotate_figure(best_model_plot, top =
                  text_grob("Figure 11: Residuals of Chosen Models"))
```

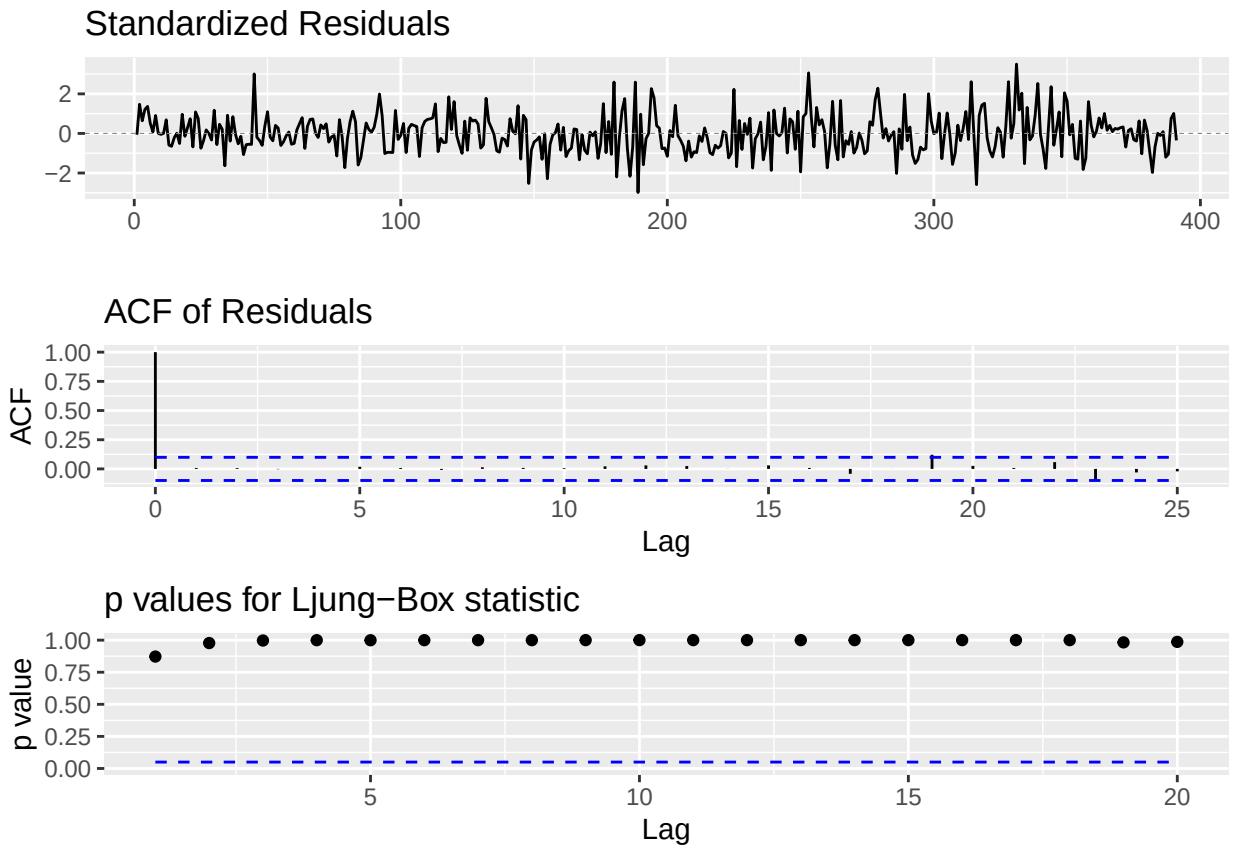
Figure 11: Residuals of Chosen Models



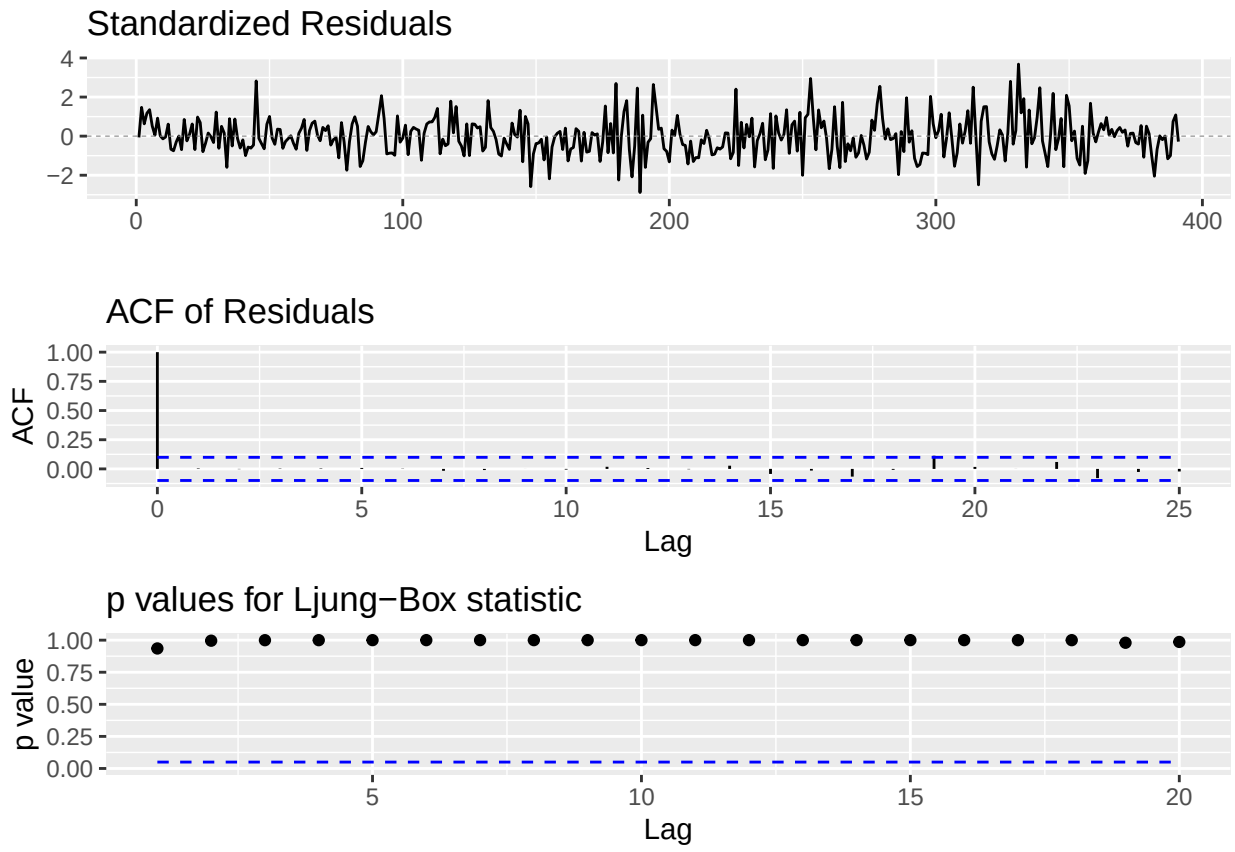

```
#QQ Plots
ggtsdiag(no2.ar1,gof.lag=20)
```



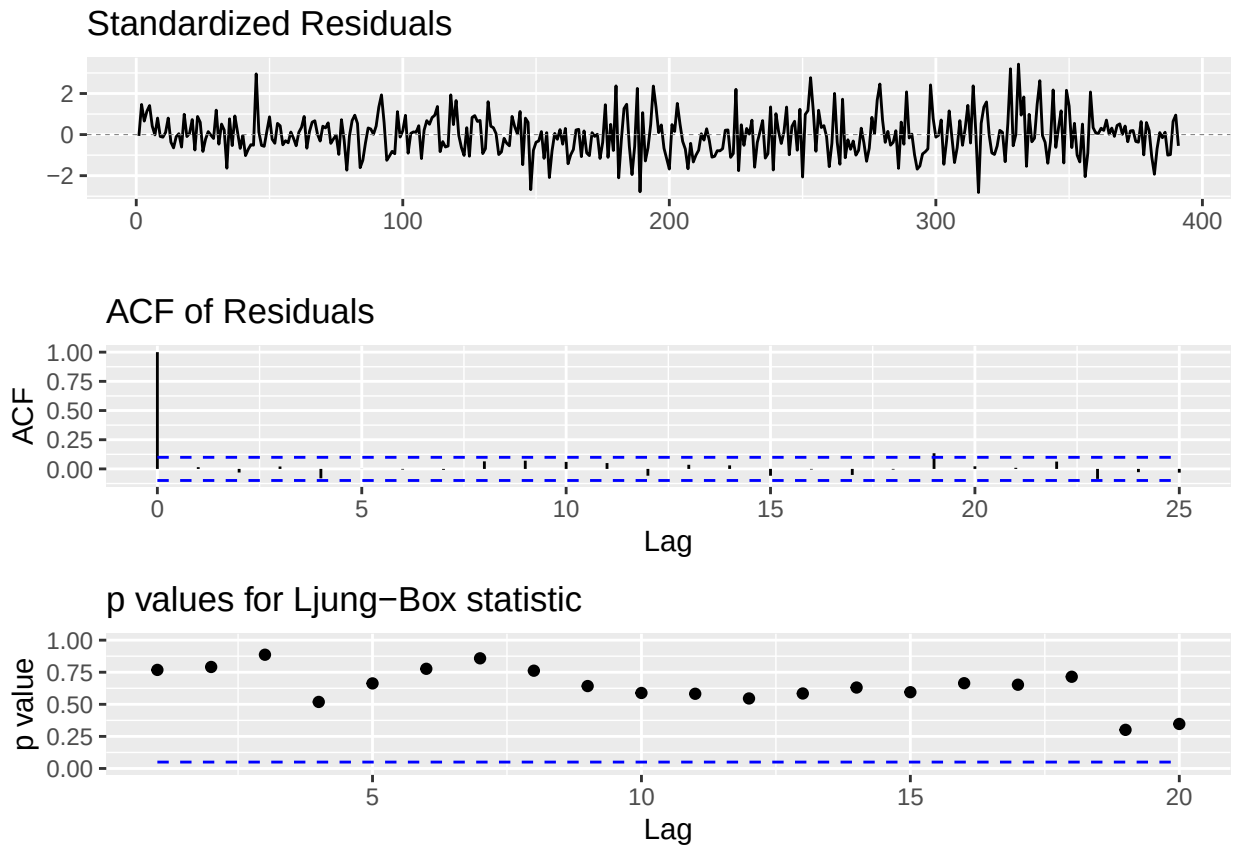

```
ggtsdiag(no2.ma12,gof.lag=20) #better box test
```




```
ggtsdiag(no2.arma12,gof.lag=20) #better box test
```




```
ggtsdiag(no2.auto,gof.lag=20)
```

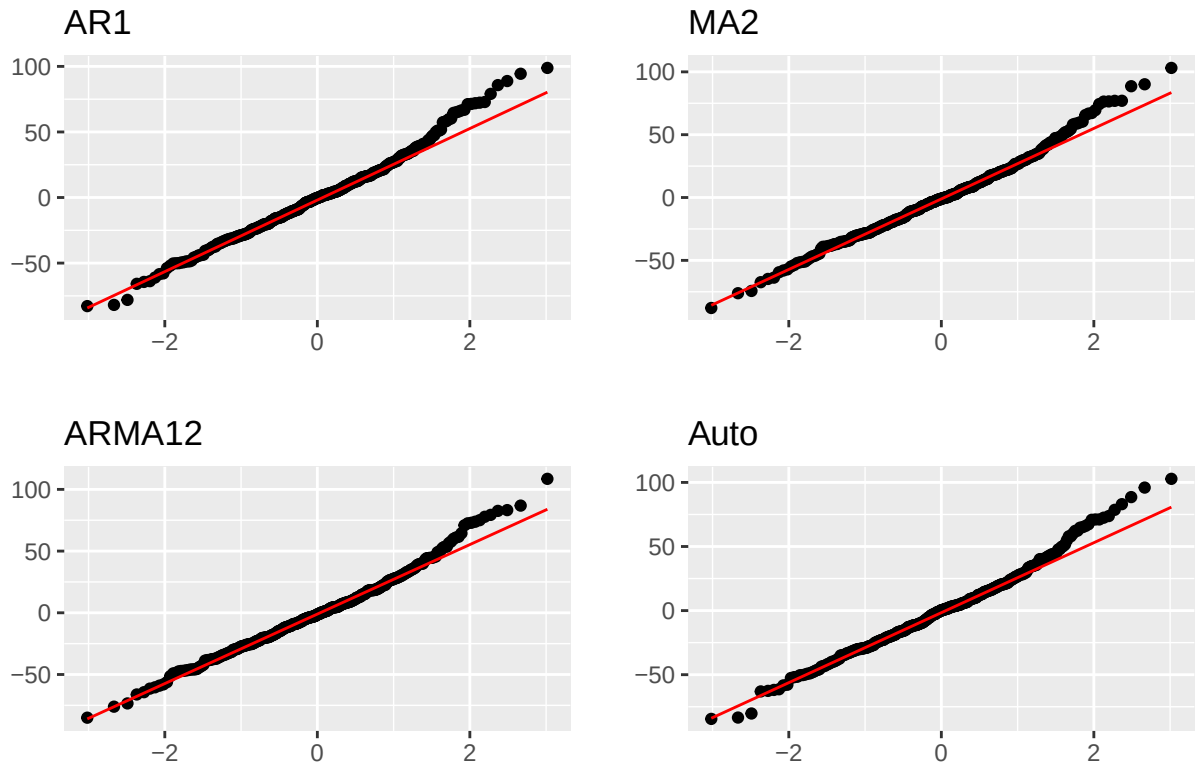



```
# assess normality of residuals
model1 = qplot(sample=no2.ar1$residuals) + stat_qq_line(color="red") +
  ggtitle("AR1")
model2 = qplot(sample=no2.ma12$residuals) + stat_qq_line(color="red") +
  ggtitle("MA2")
model3 = qplot(sample=no2.arma12$residuals) + stat_qq_line(color="red") +
  ggtitle("ARMA12")
model4 = qplot(sample=no2.auto$residuals) + stat_qq_line(color="red") +
  ggtitle("Auto")

plot2 <- ggarrange(model1, model2, model3, model4, ncol=2, nrow=2)
```

```
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
## Don't know how to automatically pick scale for object of type ts. Defaulting to continuous.
```

```
annotate_figure(plot2, top = text_grob("Figure 12: Normality of Chosen Models"))
```

Figure 12: Normality of Chosen Models



(e) Here, we forecasted the next 7 days of NO2 concentrations using our chosen autoregressive integrated moving average model. We created a new time variable for the next 7 days of the dataset. We then made a dataframe which sets time to be the next 7 days and only looks at the last 7 values of our NO2 time series dataset. We then predicted the next 7 days using our trendseason model and forecasted using our autoregressive integrated moving average model.

Our mean square error for the model was 36023.04 which is relatively high indicating that our model was not very accurate at predicting the last 7 days of NO2 observations. Moreover, plotting the predicted and actual values (Figure 13), we can see a significant gap in the values further reinforcing our point.

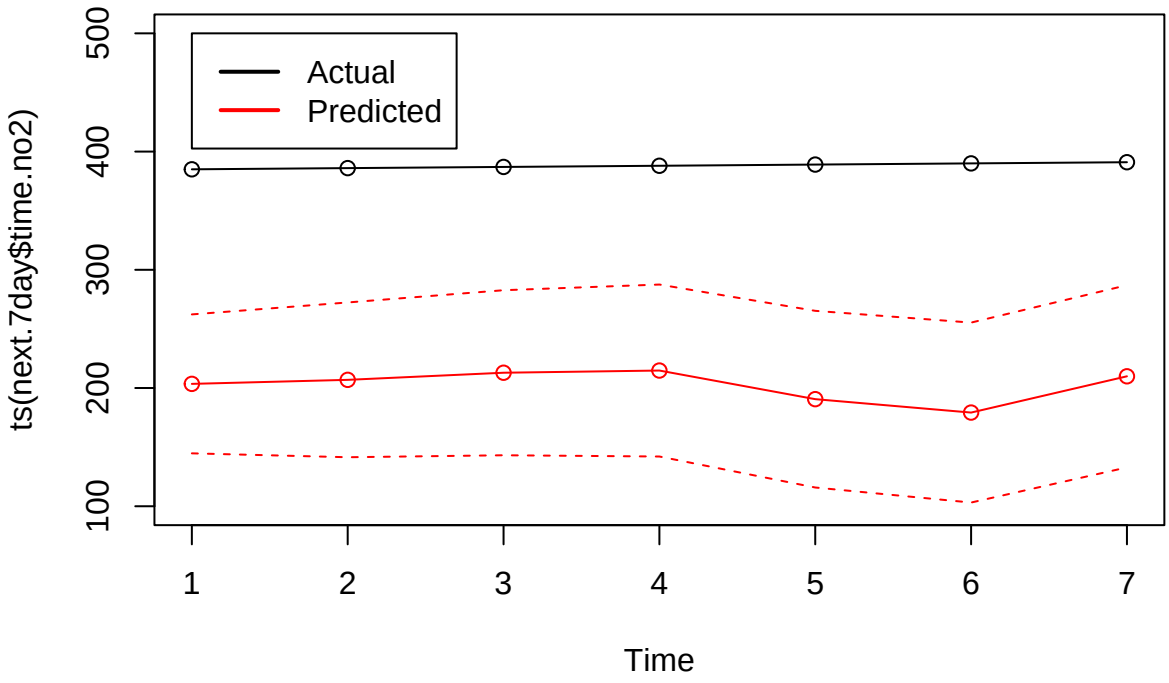
```
#a next 7 day time variable and dataframe
next.7day.time <- c((length(time.no2)-6):(length(time.no2)))

next.7day <- data.frame(time.no2 = next.7day.time, no2.ts[next.7day.time]) #7day for no2 full

# Prediction for the next 7days by no2.trendseason and forecast by no2.auto
no2.predict <- predict(no2.trendseason, newdata=next.7day)

no2.forecast <- forecast(no2.auto, h=7)
next.7day.prediction <- no2.predict + no2.forecast$mean


# MSE:
mean((next.7day.prediction-next.7day$time.no2)^2)
```

```
## [1] 34557.78
```

```r
#Figure 13:
plot(ts(next.7day$time.no2),type='o',ylim=c(100,500),width=6, height=6)
```

```
## Warning in plot.window(xlim, ylim, log, ...): "width" is not a graphical
## parameter

## Warning in plot.window(xlim, ylim, log, ...): "height" is not a graphical
## parameter

## Warning in title(main = main, xlab = xlab, ylab = ylab, ...): "width" is not a
## graphical parameter

## Warning in title(main = main, xlab = xlab, ylab = ylab, ...): "height" is not a
## graphical parameter

## Warning in axis(1, ...): "width" is not a graphical parameter

## Warning in axis(1, ...): "height" is not a graphical parameter

## Warning in axis(2, ...): "width" is not a graphical parameter

## Warning in axis(2, ...): "height" is not a graphical parameter

## Warning in box(...): "width" is not a graphical parameter

## Warning in box(...): "height" is not a graphical parameter
```

```r
lines(ts(next.7day.prediction),col='red',type='o')
lines(1:7, no2.predict + no2.forecast$lower[,2], col = "red", lty = "dashed")
lines(1:7, no2.predict + no2.forecast$upper[,2], col = "red", lty = "dashed")
legend(1,500, legend = c("Actual", "Predicted"), lwd = 2,
       col = c("black", "red"))
```

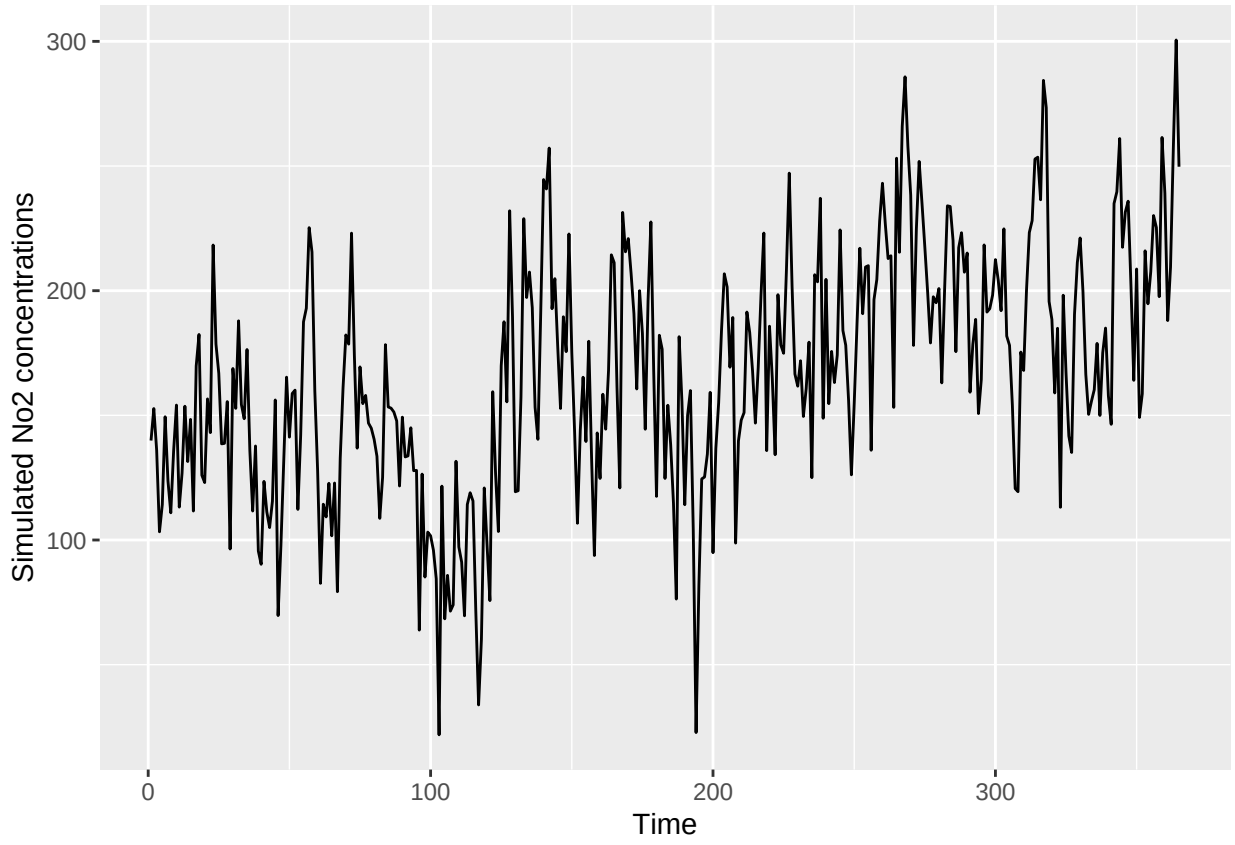


Question 2

(a) Here, we are setting the seed to 1 to begin our simulation. We simulated a model for a year of NO2 predictions using the auto regressive components, moving average components, and standard deviation components of our chosen autoregressive integrated moving average model. We then made a time variable that spanned an entire year and a whole data frame with time as the next year values. We then predicted the next year values using our trend season model. We combined the predicted next year NO2 values and the simulated autoregressive, moving average, and standard deviation components. Lastly, we converted the simulated dataset into a time series. The plot of the new simulated time series model looks similar to the observed time series model as seen in Figure 14.

```
#setting the seed
set.seed(1)

#simulation of residuals
auto.sim <- arima.sim(n=365, list(ar=c(no2.auto$coef[1],0),
                                  ma=c(no2.auto$coef[2])),
                      sd=sqrt(no2.auto$sigma2))
```

```r
# next year time variable and dataframe
next.yr.time <- c(1:365)
next.yr <- data.frame(time.no2 = next.yr.time)

next.yr.predictions <- predict(no2.trendseason, newdata=next.yr)

no2.sim <- next.yr.predictions + auto.sim

no2.sim.ts <- ts(no2.sim)


#Figure 14
autoplot(no2.sim.ts,xlab="Time",ylab="Simulated No2 concentrations",
         width=6, height=6)
```



(b) Here, we started by creating a time variable which spans the length of a year. Then, we created a Day variable to create dummy variables to account for the weekly seasonality in the data. The contrasts of the Day variable shows that the base case is Friday. Lastly, we created a trend season model using our simulated time series data as our response variable, and the time and Day dummy variables as explanatory variables. The model is significant with a p-value of less than 2.2e-16. The time variable is also significant with a coefficient of 0.24602 indicating that for every 1 increase in time, there is a 0.24602 increase in NO2 levels. In terms of the dummy variables, we found that Monday, Saturday,and Sunday are statistically significant with coefficients of -15.99891, -31.89066, and -38.74804, respectively. This indicates that the likelihood of NO2 levels being impacted by the day of week, specifically on Saturdays, Sundays, and Mondays may not be due to random chance.

We also calculated percentage difference of the time coefficient between our observed trendseason model and our original trendseason model and found that there is a ~4.45% absolute difference.

```
#Model the seasonality for simulated dataset

time.sim <- c(1:length(next.yr.predictions))


Day.sim <- rep(NA, length(time.sim))
Day.sim[which((time.sim %% 7)    == 1)] <- "W"
Day.sim[which((time.sim %% 7)    == 2)] <- "Th"
Day.sim[which((time.sim %% 7)    == 3)] <- "Fri"
Day.sim[which((time.sim %% 7)    == 4)] <- "Sat"
Day.sim[which((time.sim %% 7)    == 5)] <- "Sun"
Day.sim[which((time.sim %% 7)    == 6)] <- "M"
Day.sim[which((time.sim %% 7)    == 0)] <- "T"
Day.sim <- as.factor(Day.sim)


#Trend season model of simulation
no2.trendseason.sim<-lm(no2.sim.ts~time.sim + Day.sim)

summary(no2.trendseason.sim)
```

```
##
## Call:
## lm(formula = no2.sim.ts ~ time.sim + Day.sim)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -120.294  -24.907    0.866   24.137   89.080
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 133.4296     6.3263  21.091  < 2e-16 ***
## time.sim      0.2411     0.0190  12.689  < 2e-16 ***
## Day.simM    -12.9412     7.5007  -1.725  0.08534 .
## Day.simSat  -24.2375     7.5005  -3.231  0.00135 **
```

```
## Day.simSun  -37.1315     7.5006  -4.950 1.14e-06 ***
## Day.simT      0.9409     7.5009   0.125  0.90025
## Day.simTh     3.4393     7.5005   0.459  0.64684
## Day.simW    -10.9686     7.4651  -1.469  0.14263
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 38.25 on 357 degrees of freedom
## Multiple R-squared:  0.368,  Adjusted R-squared:  0.3556
## F-statistic: 29.69 on 7 and 357 DF,  p-value: < 2.2e-16
```

```
#percent difference of time

pct.diff <- ((no2.trendseason.sim$coefficients[2]-
                no2.trendseason$coefficients[2])/
               no2.trendseason$coefficients[2])*100
pct.diff
```

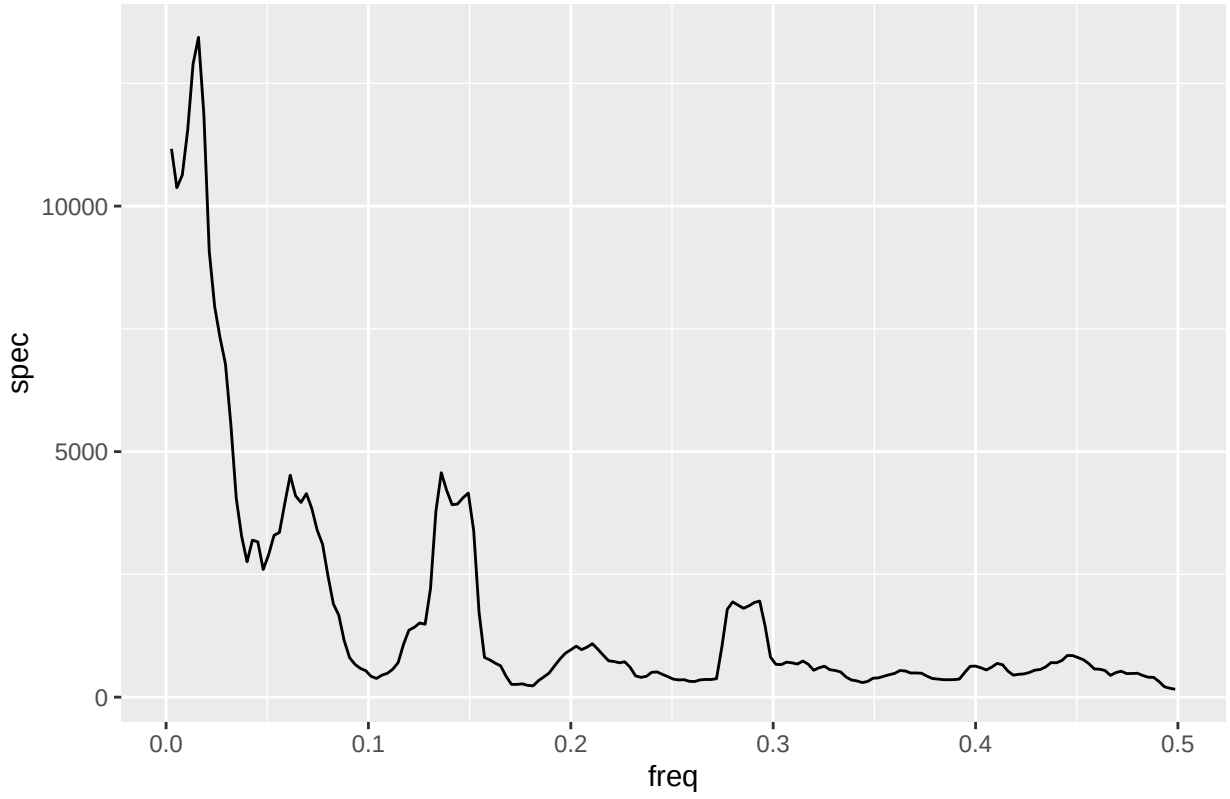
```
##  time.sim
## -2.734943
```

(c) Looking at the periodogram of the original time series, the most notable features are a large peak towards the beginning of the plot, the second largest peak around 0.15 freq, and a mini peak right before 0.3 freq. After the first large peak, all other peaks are considerably smaller and the data reaches a bit of plateau towards the end. Visually, the periodogram of the simulation has a higher quantity of noticeable peaks that are also much higher and sharper and does not emulate the plateau near the end of the graph. However, it does show a significant peak around 0.5 freq, similar to the original time series data, and another before 0.3 freq.

```
#periodogram for simulation
pg.sim <- spec.pgram(no2.sim.ts,spans=9,demean=T,log='no', plot=F)

spec.sim <- data.frame(freq=pg.sim$freq, spec=pg.sim$spec)
ggplot(spec.sim) + geom_line(aes(x=freq,y=spec),width=6, height=6) +
  ggtitle("Figure 15: Smooth Periodogram of Simulated No2")
```

```
## Warning: Ignoring unknown parameters: width, height
```

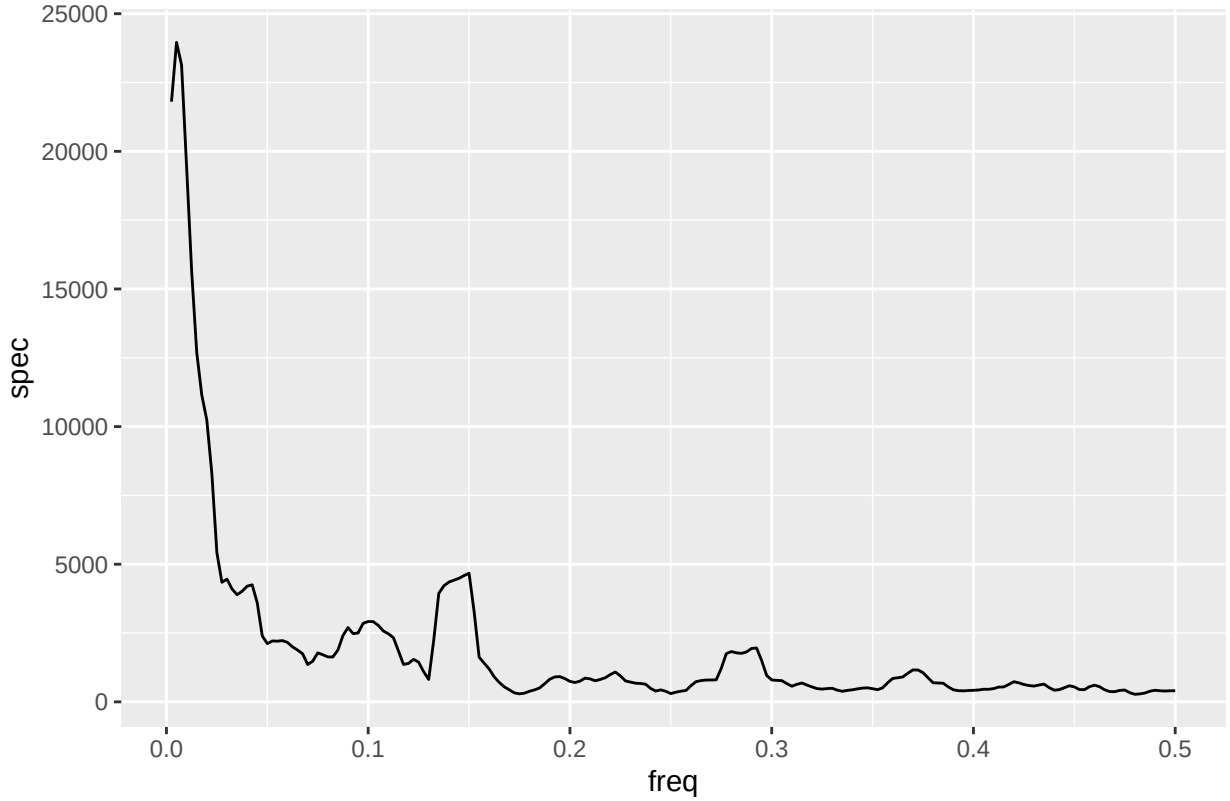
Figure 15: Smooth Periodogram of Simulated No2




```
#periodogram for observations
pg.no2 <- spec.pgram(no2.ts,spans=9,demean=T,log='no',plot=F)

spec.no2 <- data.frame(freq=pg.no2$freq, spec=pg.no2$spec)
ggplot(spec.no2) + geom_line(aes(x=freq,y=spec),width=6, height=6) +
  ggtitle("Figure 16: Smooth Periodogram of Observed No2")
```

```
## Warning: Ignoring unknown parameters: width, height
```

Figure 16: Smooth Periodogram of Observed No2



(d) Based on our calculations, the mean of the observed time series dataset is 164.80, while the predicted dataset mean is 163.38, resulting in a -0.086% difference. Thus, the prediction's estimation of mean is relatively accurate. As for the variance, the observed data's variance is 2616.039, while the simulated dataset's variance is 2076.232; the percent difference between the observed and simulated variance is -20.63%, meaning the model was less accurate at reproducing the variance of the original dataset. This is a weak point in our model that we would continue to dissect and address in future iterations of analysis.

```
#mean of observed
mean.no2 <- mean(no2.ts)
#mean of simulated
mean.sim <- mean(no2.sim.ts)
#variance of observed
var.no2 <- var(no2.ts)
#variace of simulated
var.sim <- var(no2.sim.ts)

mean.no2
```

```
## [1] 164.7976
```

```
mean.sim
```

```
## [1] 165.9962
```

```
var.no2
```

```
## [1] 2616.039
```

```
var.sim
```

```
## [1] 2269.759
```

```
#pct diffs between means
(mean.sim-mean.no2)/(mean.no2)*100
```

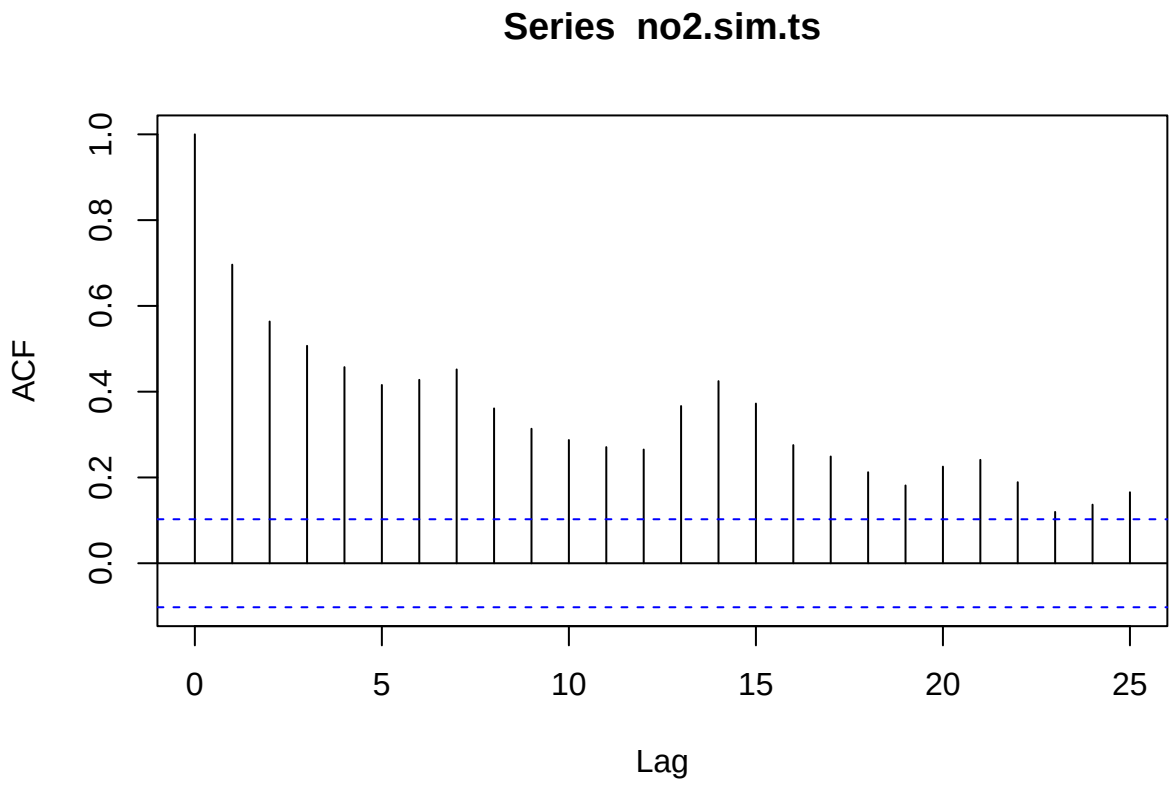
```
## [1] 0.7273139
```

```
#pct diffs between vars
((var.sim-var.no2)/var.no2)*100
```

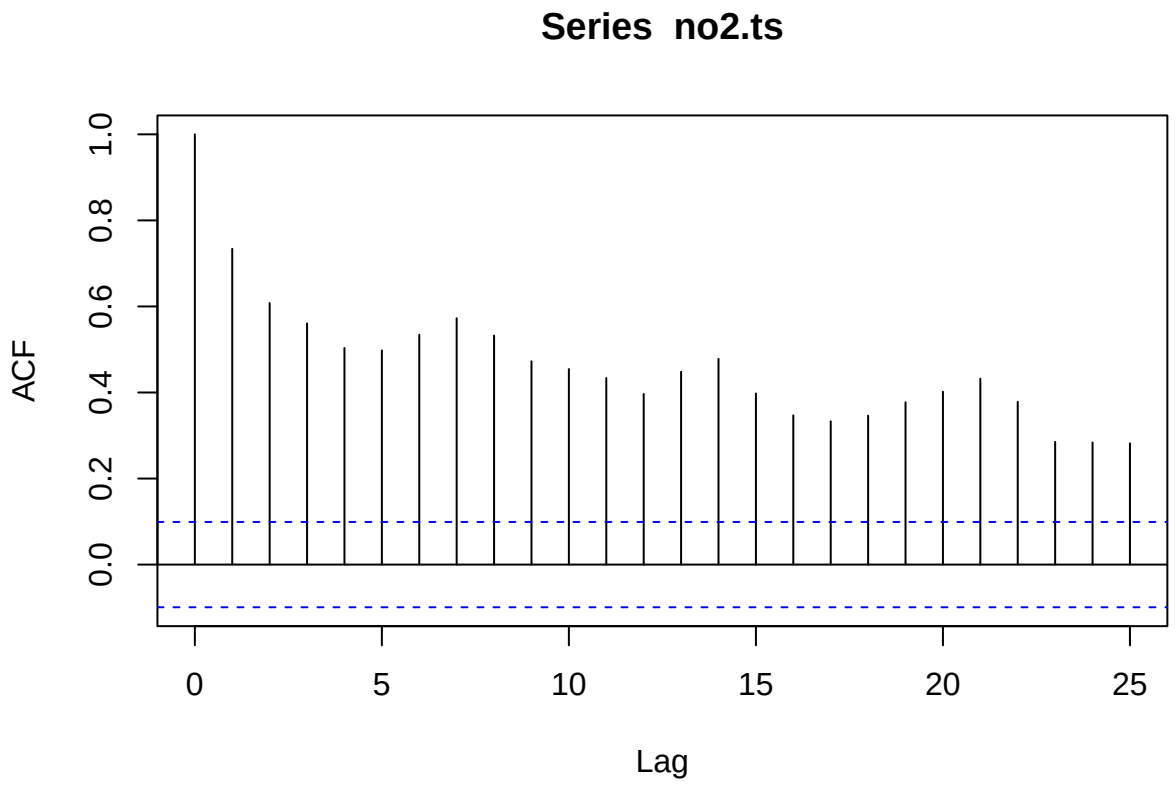
```
## [1] -13.23678
```

(e) The ACF of the observed dataset displays a sinusoidal decay pattern with a peak every 7 days. The ACF of the simulated data somewhat displays this pattern with peaks occurring every 7 days that have a greater amplitude than those in the observed dataset. The PACF of the observed dataset has roughly 6 significant lags around 2,3,5,6,7 and become insignificant around lag 8, whereas the PACF of the simulated dataset has roughly 3 significant lags around 6,7,13 (which is beyond 8). Thus, the simulation was only able to reproduce some components of the autocorrelation of the ovserved values, but requires improvement in other areas. In future work, we would look further into exploring the autoregressive and moving average components of our data to produce more accurate results.

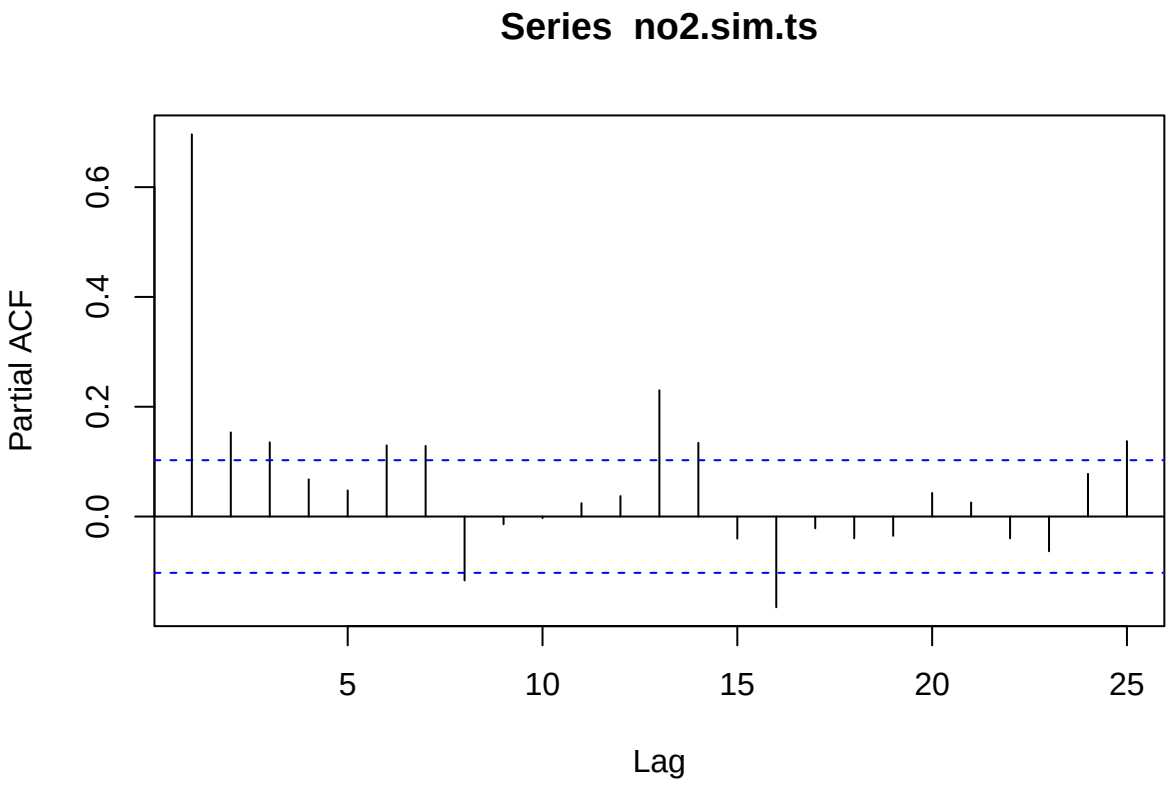
```
#acf of simulation
acf.sim <- acf(no2.sim.ts)
```



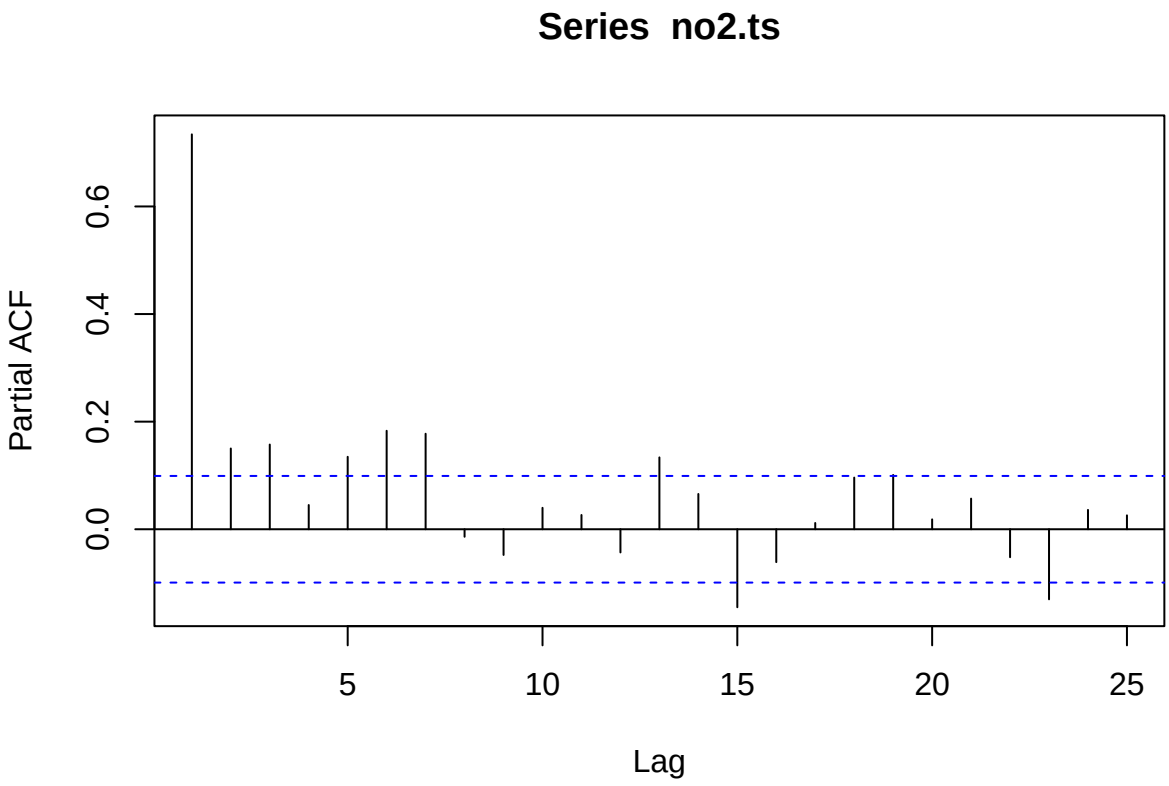

```
#acf of obsverations
acf.obs <- acf(no2.ts)
```




```
#pacf of simulation
pacf.sim <- pacf(no2.sim.ts)
```




```
#pacf of obsverations
pacf.obs <- pacf(no2.ts)
```



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.