

Statistical Methods for Discrete Response, Time Series, and Panel Data (W271): Lab 2

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Instructions (Please Read Carefully):

- Submit by the due date. **Late submissions will not be accepted**
- No page limit, but be reasonable
- Do not modify fontsize, margin or line-spacing settings
- One student from each group should submit the lab to their student github repo by the deadline
- Submit two files:
 1. A pdf file that details your answers. Include all R code used to produce the answers
 2. The R markdown (Rmd) file used to produce the pdf file

The assignment will not be graded unless **both** files are submitted

- Name your files to include all group members names. For example, if the students' names are Stan Cartman and Kenny Kyle, name your files as follows:
 - StanCartman_KennyKyle_Lab2.Rmd
 - StanCartman_KennyKyle_Lab2.pdf
- Although it sounds obvious, please write your name on page 1 of your pdf and Rmd files
- All answers should include a detailed narrative; make sure that your audience can easily follow the logic of your analysis. All steps used in modelling must be clearly shown and explained; do not simply 'output dump' the results of code without explanation
- If you use libraries and functions for statistical modeling that we have not covered in this course, you must provide an explanation of why such libraries and functions are used and reference the library documentation
- For mathematical formulae, type them in your R markdown file. Do not e.g. write them on a piece of paper, snap a photo, and use the image file
- Incorrectly following submission instructions results in deduction of grades
- Students are expected to act with regard to UC Berkeley Academic Integrity.

The Keeling Curve

In the 1950s, the geochemist Charles David Keeling observed a seasonal pattern in the amount of carbon dioxide present in air samples collected over the course of several years. He attributed this pattern to varying rates of photosynthesis throughout the year, caused by differences in land area and vegetation cover between the Earth's northern and southern hemispheres.

In 1958 Keeling began continuous monitoring of atmospheric carbon dioxide concentrations from the Mauna Loa Observatory in Hawaii. He soon observed a trend increase carbon dioxide levels in addition to the seasonal cycle, attributable to growth in global rates of fossil fuel combustion. Measurement of this trend at Mauna Loa has continued to the present.

The `co2` data set in R's `datasets` package (automatically loaded with base R) is a monthly time series of atmospheric carbon dioxide concentrations measured in ppm (parts per million) at the Mauna Loa Observatory from 1959 to 1997. The curve graphed by this data is known as the 'Keeling Curve'.

Part 1 (3 points)

Conduct a comprehensive Exploratory Data Analysis on the `co2` series. This should include (without being limited to) a thorough investigation of the trend, seasonal and irregular elements.

```
opts_chunk$set(tidy.opts = list(width.cutoff = 60), tidy = TRUE,
               warning = FALSE, message = FALSE)

str(co2)

## Time-Series [1:468] from 1959 to 1998: 315 316 316 318 318 ...

summary(co2)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    313.2   323.5   335.2   337.1   350.3   366.8

co2.decompose = decompose(co2)
co2.diff = diff(co2, differences = 1)
co2.seasdiff = diff(co2, lag = 12)
co2.bothdiff = diff(co2.diff, lag = 12)

co2.deseasoned = co2 - co2.decompose$seasonal
co2.detrended = co2 - co2.decompose$trend

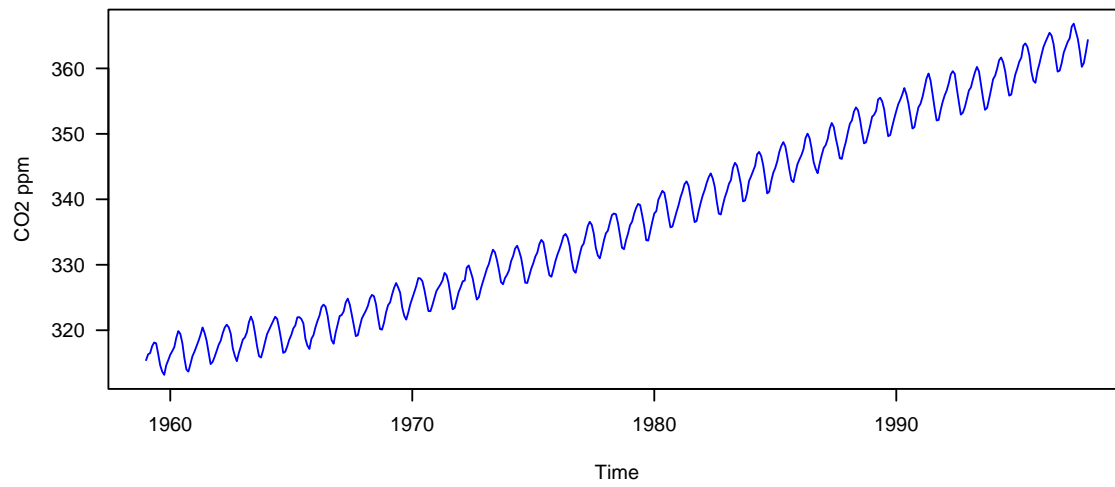
par(mfrow = c(3, 1))

plot(co2, ylab = expression("CO2 ppm"), col = "blue", las = 1)
title(main = "Figure1: Monthly Mean CO2 Variation")

boxplot(co2 ~ cycle(co2), main = "Boxplot of CO2 (ppm) by month")

plot(co2.deseasoned, main = expression("Figure2: Presence of CO2 in air after removing season"),
     xlab = "year", ylab = expression("CO2 ppm"))
```

Figure1: Monthly Mean CO2 Variation



Boxplot of CO2 (ppm) by month

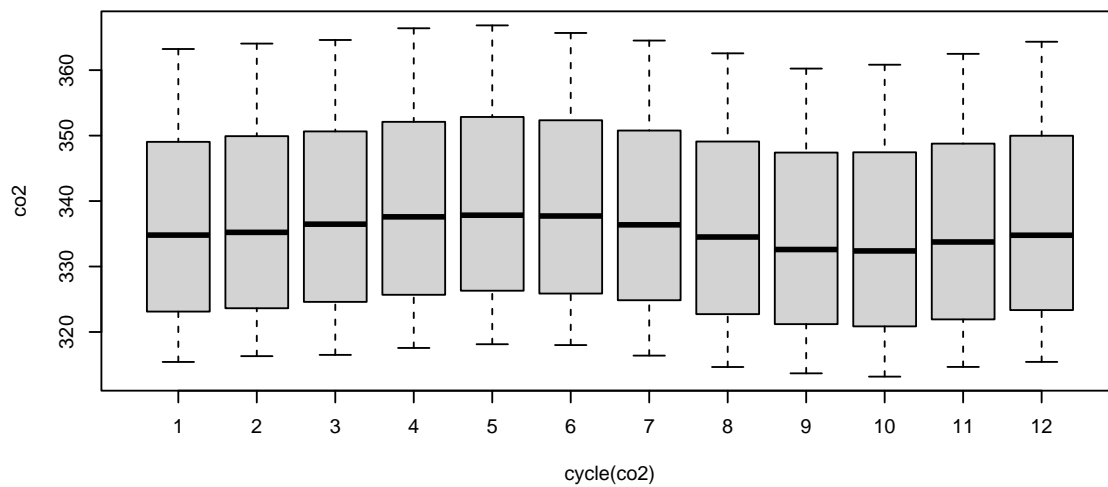
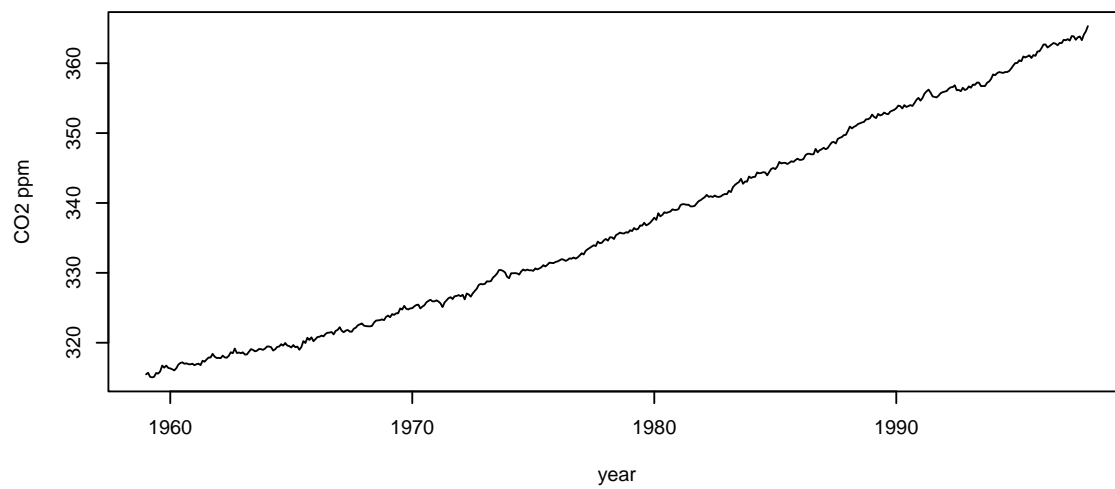


Figure2: Presence of CO2 in air after removing season



```

plot(co2.detrended, main = expression("Figure3: Presence of CO2 in air after removing trend"),
     xlab = "year", ylab = expression("CO2 ppm"), col = "red",
     las = 1)

abline(h = 0)

plot(co2.diff, main = expression("Figure4: Presence of CO2 in air after differencing"),
     xlab = "year", ylab = expression("CO2 ppm"), col = "red",
     las = 1)

abline(h = 0)

plot(co2.seasdiff, main = expression("Figure5: Presence of CO2 in air after seasonal differencing"),
     xlab = "year", ylab = expression("CO2 ppm"), col = "red",
     las = 1)
abline(h = 0)

```

Figure3: Presence of CO2 in air after removing trend

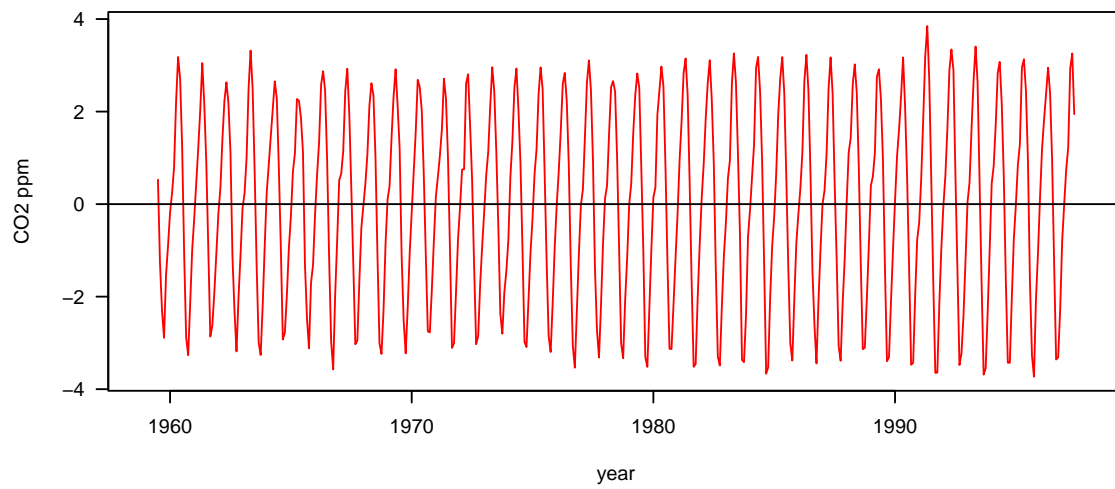


Figure4: Presence of CO2 in air after differencing

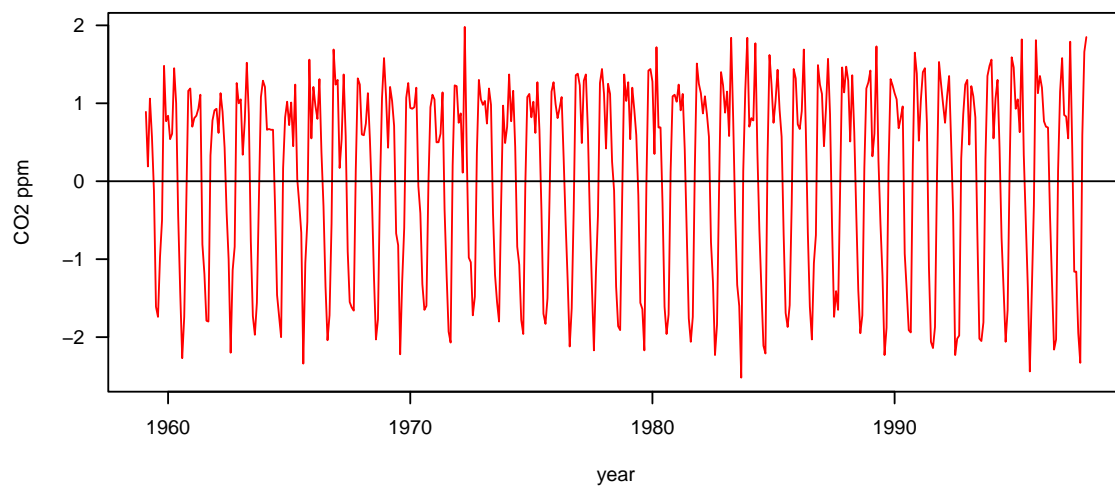
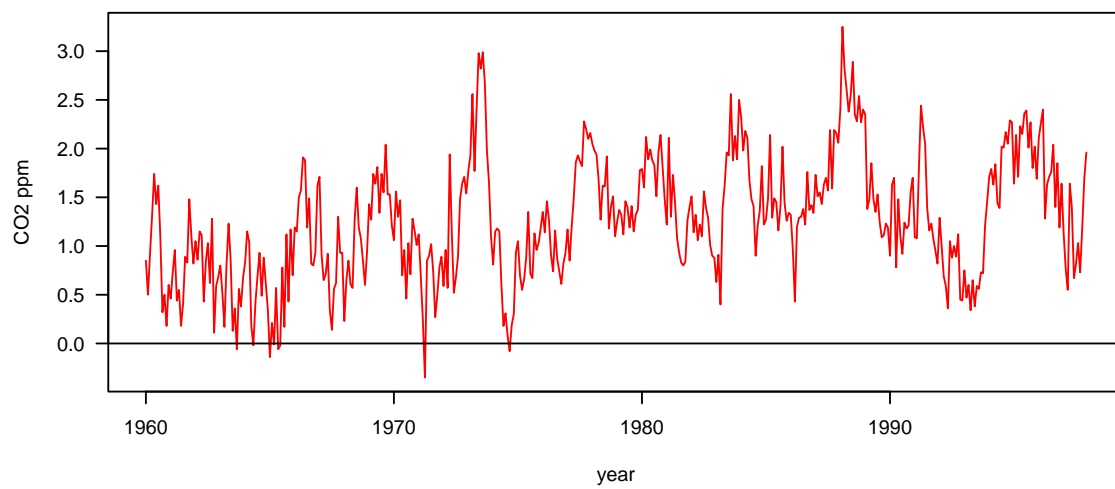
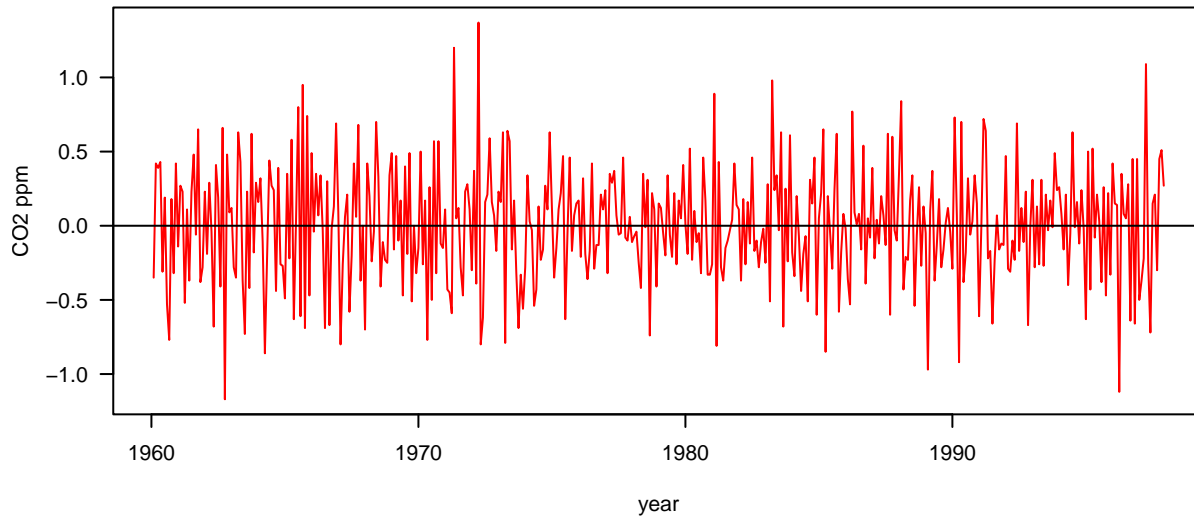


Figure5: Presence of CO2 in air after seasonal differencing



```
plot(co2.bothdiff, main = expression("Figure6: Presence of CO2 in air non-seasonal and seasonal"),
     xlab = "year", ylab = expression("CO2 ppm"), col = "red",
     las = 1)
abline(h = 0)
```

Figure6: Presence of CO2 in air non-seasonal and seasonal differencing



Data provided has CO2 presence in the air (parts per million) in monthly time series format from 1959 to 1998.

From Figure1: The time series plot of the mean of co2 presence in the air indicates a clear trend and seasonal effect. We also observe that the variance is constant over time, which suggests no need for transformation.

From Figure2: We see a clear upward trend in the mean of the presence of Co2 in the air

From Figure3: Co2 presence in the air after removing the trend component from the time series indicates the persistent yearly seasonal effect.

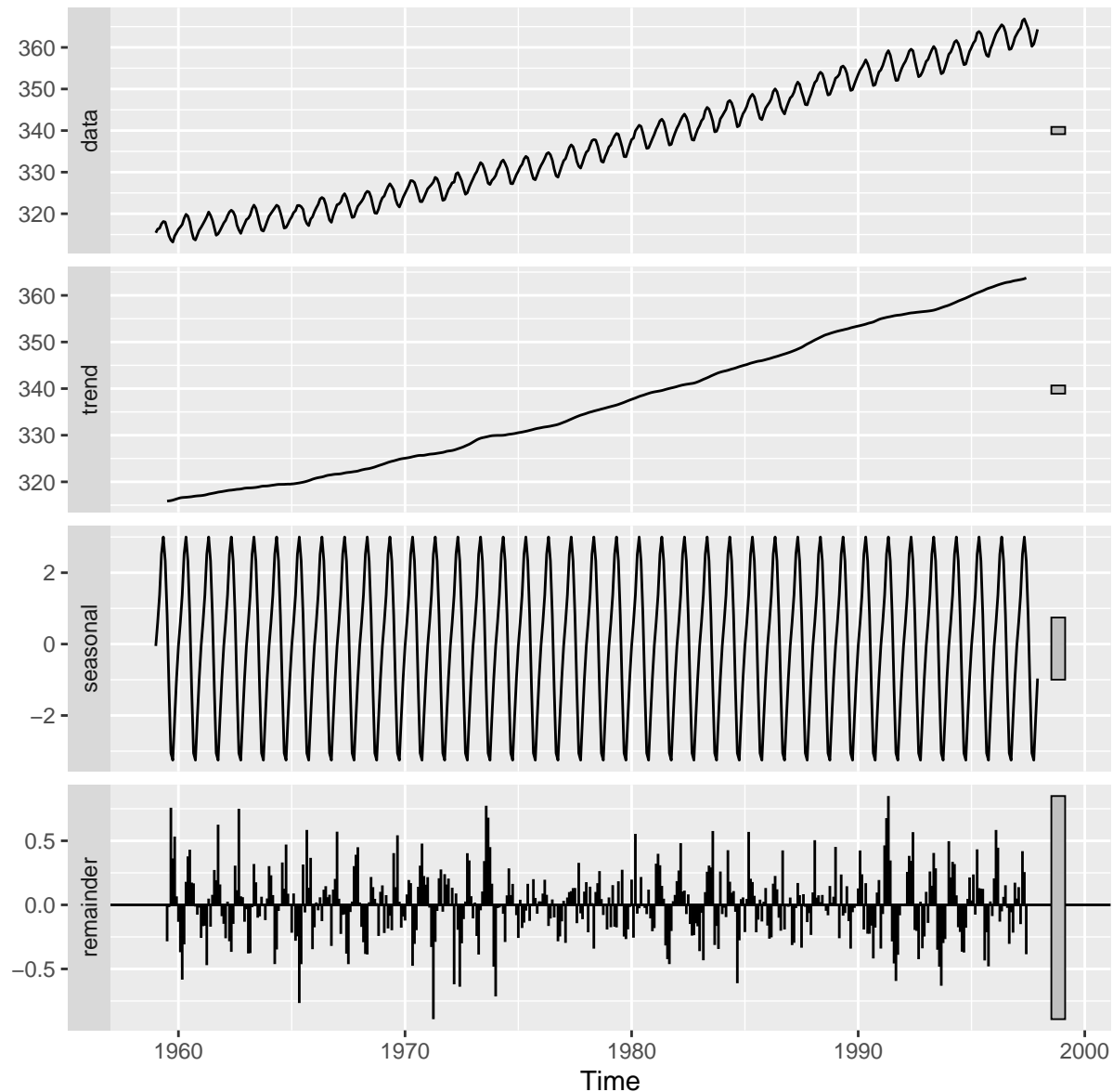
From Figure4: Trend is abstracted after taking the 2-period difference of the time series. It suggests we use ARIMA with integration/difference of 2

From Figure5: Seasonality absent after applying difference of 12 lags for the season. We still see trends present.

From Figure6: Seasonality and trend are absent after difference at two lags and 12 lags for the season. It is much closer to white noise series with non-constant variance. It suggests a possible need of Seasonal adjustment for the ARIMA model

```
autoplot(co2.decompose, main = "Decomposition of CO2 Time Series")
```

Decomposition of CO2 Time Series



```
plot.acf.alldata = acf(co2, plot = FALSE)
plot.pacf.alldata = pacf(co2, plot = FALSE)

plot.acf.deseasoned = acf(co2.deseasoned, plot = FALSE)
plot.pacf.deseasoned = pacf(co2.deseasoned, plot = FALSE)

plot.acf.detrended = acf(window(co2.detrended, start = c(1960),
                                end = c(1996)), plot = FALSE)
plot.pacf.detrended = pacf(window(co2.detrended, start = c(1960),
                                end = c(1996)), plot = FALSE)

plot.acf.residual = acf(window(co2.decompose$random, start = c(1960),
                                end = c(1996)), plot = FALSE)
```



```

plot.pacf.residual = pacf(window(co2.decompose$random, start = c(1960),
                                end = c(1996)), plot = FALSE)

plot.acf.diff = acf(co2.diff, plot = FALSE)
plot.pacf.diff = pacf(co2.diff, plot = FALSE)

plot.acf.seasdiff = acf(co2.seasdiff, plot = FALSE)
plot.pacf.seasdiff = pacf(co2.seasdiff, plot = FALSE)

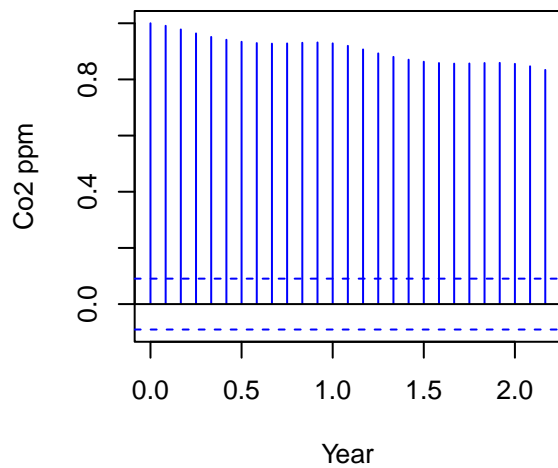
plot.acf.bothdiff = acf(co2.bothdiff, plot = FALSE)
plot.pacf.bothdiff = pacf(co2.bothdiff, plot = FALSE)

par(mfrow = c(2, 2))
plot(plot.acf.alldata, main = "ACF - CO2 Presence in air \n 1959 - 1997",
     xlab = "Year", ylab = "Co2 ppm", col = "blue", cex.main = 0.5)
plot(plot.pacf.alldata, main = "PACF - CO2 Presence in air \n 1959 - 1997",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)

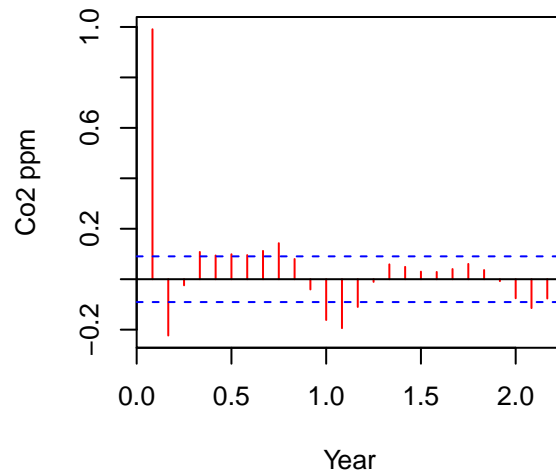
plot(plot.acf.deseasoned, main = "ACF - CO2 Presence in air- \n deseasoned (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.deseasoned, main = "PACF CO2 Presence in air- \n deseasoned (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)

```

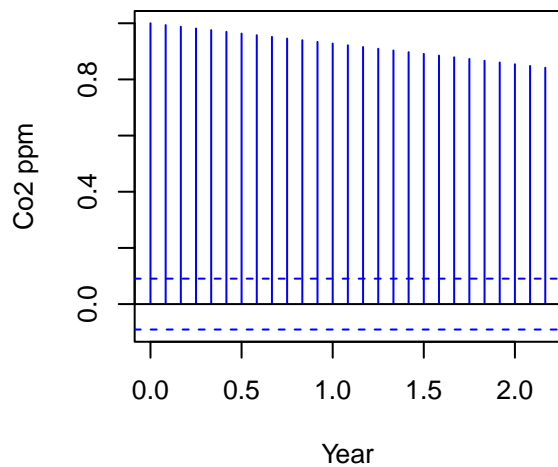
**ACF – CO2 Presence in air
1959 – 1997**



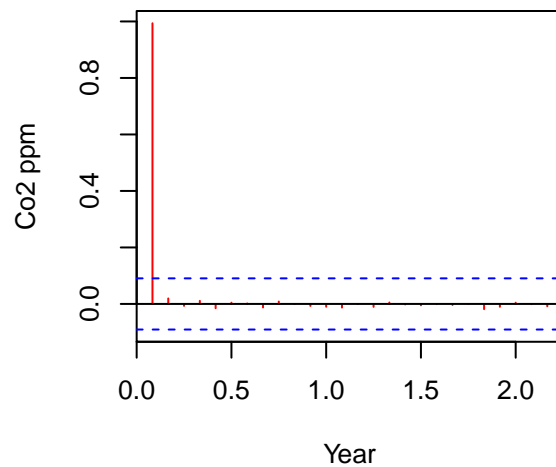
**PACF – CO2 Presence in air
1959 – 1997**



**ACF – CO2 Presence in air–
deseasoned (1959 – 1997)**

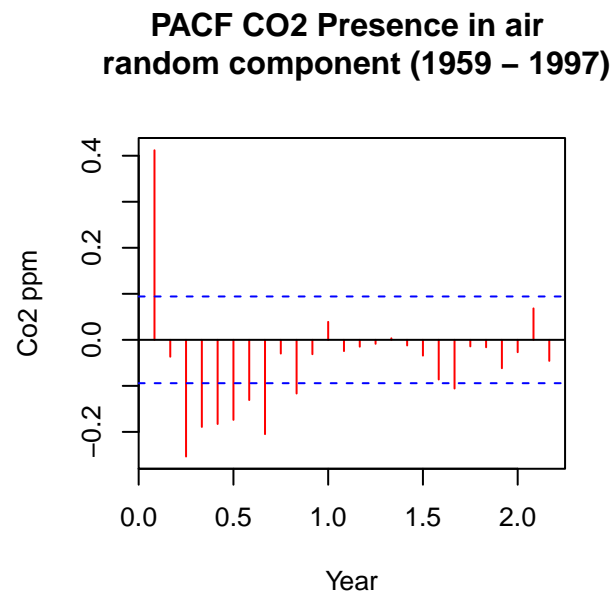
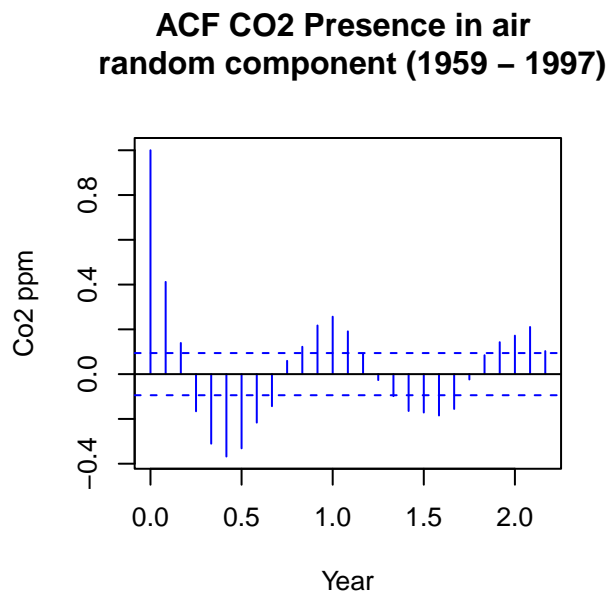
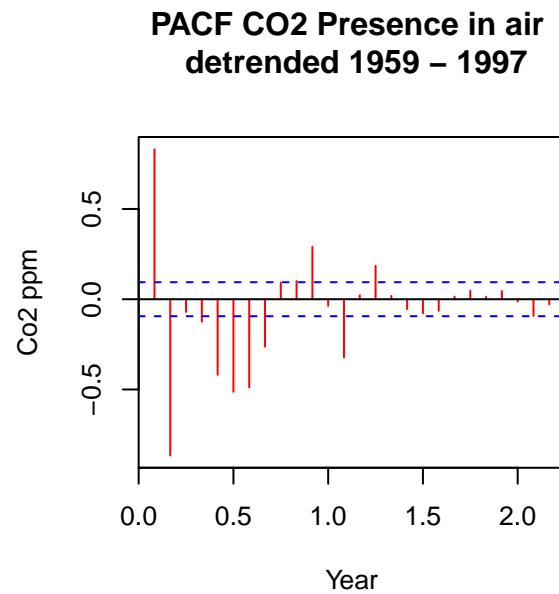
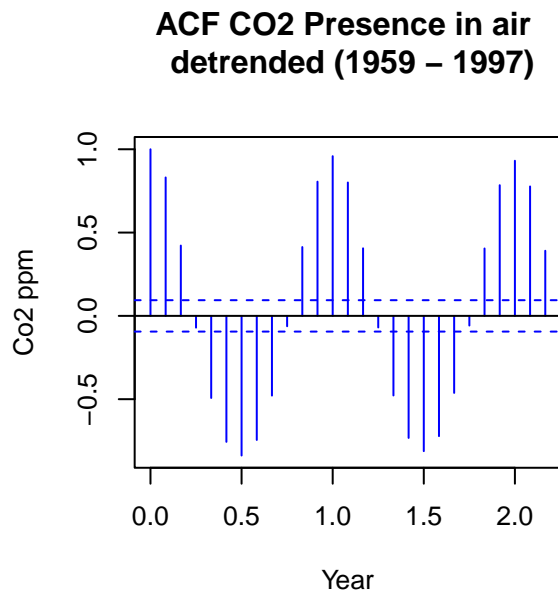


**PACF CO2 Presence in air–
deseasoned (1959 – 1997)**



```
plot(plot.acf.detrended, main = "ACF CO2 Presence in air \n detrended (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.detrended, main = "PACF CO2 Presence in air \n detrended 1959 - 1997",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)

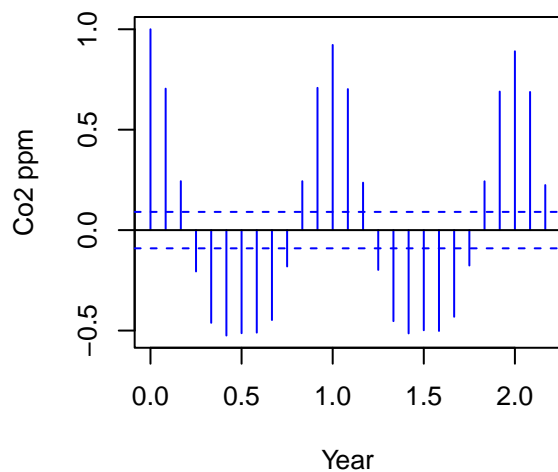
plot(plot.acf.residual, main = "ACF CO2 Presence in air \n random component (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.residual, main = "PACF CO2 Presence in air \n random component (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)
```



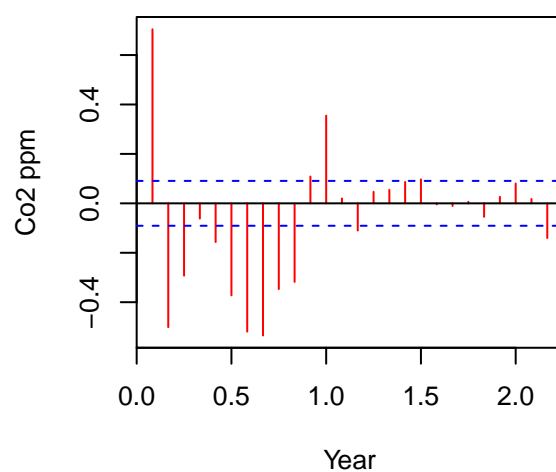
```
plot(plot.acf.diff, main = "ACF CO2 Presence in air \n AR diff (2nd Order)(1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.diff, main = "PACF CO2 Presence in air \n AR differencing (2nd Order)(1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)

plot(plot.acf.seasondiff, main = "ACF CO2 Presence in air \n seasonal diff (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.seasondiff, main = "PACF CO2 Presence in air \n season difference (1959 - 1997)",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)
```

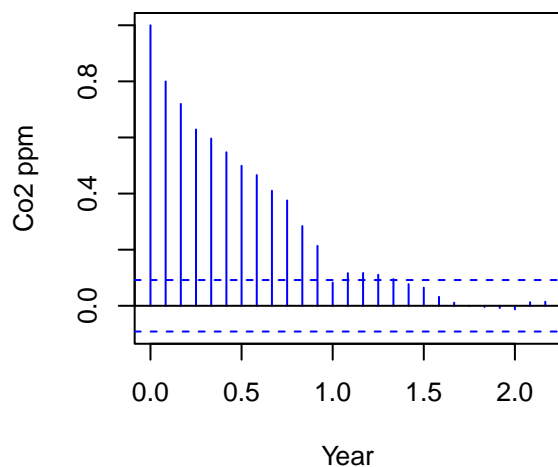
ACF CO2 Presence in air
AR diff (2nd Order)(1959 – 1997)



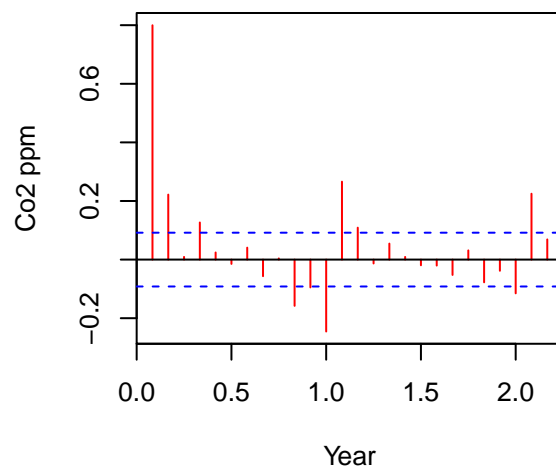
PACF CO2 Presence in air
AR differencing (2nd Order)(1959 – 1997)



ACF CO2 Presence in air
seasonal diff (1959 – 1997)

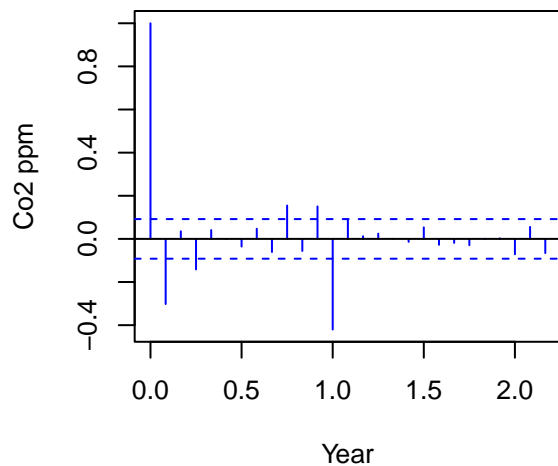


PACF CO2 Presence in air
season difference (1959 – 1997)

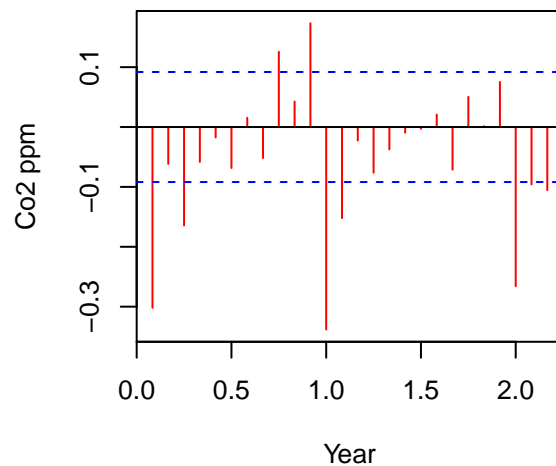


```
plot(plot.acf.bothdiff, main = "ACF CO2 Presence in air \n AR and seasonal differences",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
plot(plot.pacf.bothdiff, main = "PACF CO2 Presence in air \n AR and seasonal differences",
     xlab = "Year", ylab = "Co2 ppm", col = "red", cex.main = 0.5)
```

**ACF CO2 Presence in air
AR and seasonal differences**



**PACF CO2 Presence in air
AR and seasonal differences**



Decomposition graph confirms the findings from EDA, trend and seasonality are present in the time series.

Above ACF and PACF graph shows for different adjustments of time series: 1) original series 2) de-seasoned 3) de-trended 4) random component of time series 5) Two period differenced for trend 5) Two period difference and seasonal differenced time series. Few observations from above graphs

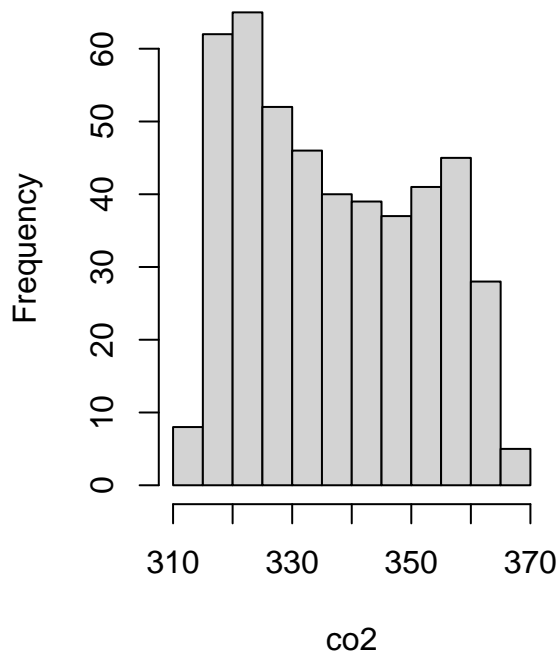
* PACF graph shows autocorrelation dying off at second lag after de-seasoned. This suggests to use only 1st order Auto regressive model. This also suggests removing seasonality is important

* ACF graph shows clear seasonal effect after removing trend

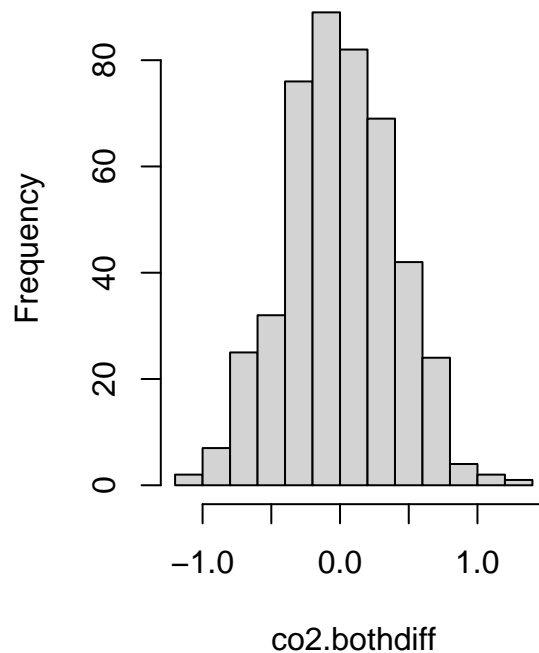
* ACF graph after performing auto regressive (AR) and seasonal differences looks closer to white noise ACF graph. This confirms the need for seasonal and Integrated treatment for our model

```
par(mfrow = c(1, 2))
hist(co2, main = "Histogram: CO2 Presence in air \n 1959 - 1997")
hist(co2.bothdiff, main = "Histogram: CO2 Presence in air\n after AR and seasonal difference")
```

**Histogram: CO2 Presence in air
1959 – 1997**



**Histogram: CO2 Presence in air
after AR and seasonal differenc**



Histogram after applying seasonal and regressive difference looks close to Gaussian distribution.

Part 2 (3 points)

Fit a linear time trend model to the `co2` series, and examine the characteristics of the residuals. Compare this to a higher-order polynomial time trend model. Discuss whether a logarithmic transformation of the data would be appropriate. Fit a polynomial time trend model that incorporates seasonal dummy variables, and use this model to generate forecasts up to the present.

Linear Time Trend Model

```
# First fit a linear time trend model
par(mfrow = c(3, 1))
co2.ts.lm.linear = lm(co2 ~ time(co2))
summary(co2.ts.lm.linear)

##
## Call:
## lm(formula = co2 ~ time(co2))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.0399 -1.9476 -0.0017  1.9113  6.5149
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.250e+03  2.127e+01  -105.8   <2e-16 ***
```

```

## time(co2)      1.308e+00  1.075e-02  121.6    <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.618 on 466 degrees of freedom
## Multiple R-squared:  0.9695, Adjusted R-squared:  0.9694
## F-statistic: 1.479e+04 on 1 and 466 DF,  p-value: < 2.2e-16

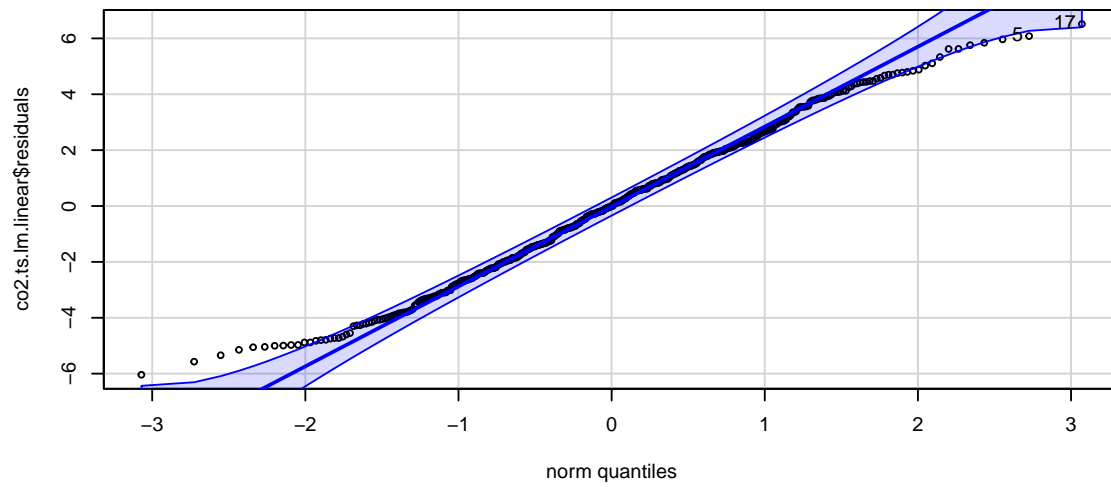
qqPlot(co2.ts.lm.linear$residuals, main = expression("Linear Model co2 ~ time(co2) "))

## [1] 17  5

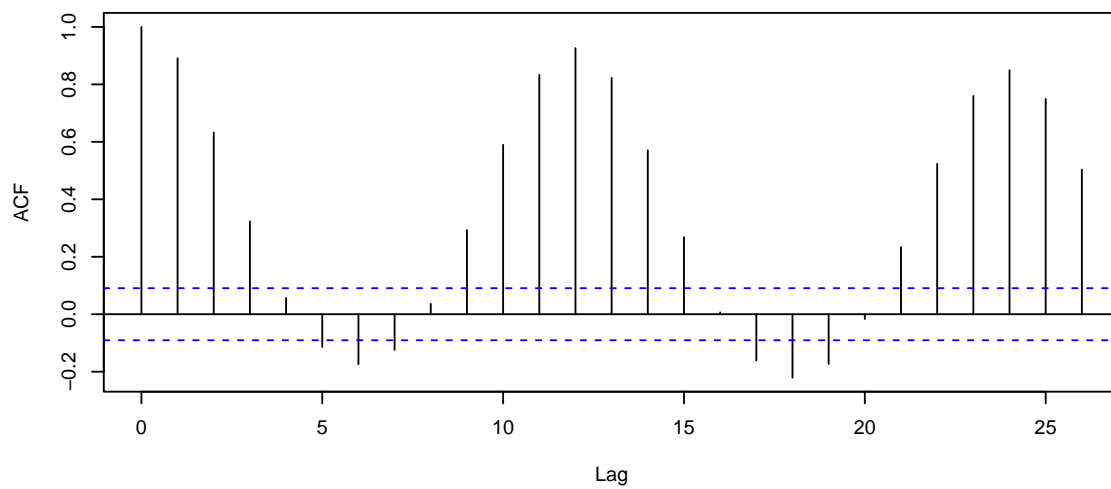
plt.acf = acf(co2.ts.lm.linear$residuals, plot = FALSE)
plt.pacf = pacf(co2.ts.lm.linear$residuals, plot = FALSE)
plot(plt.acf, main = expression("ACF - Linear Model co2 ~ time(co2) "))
plot(plt.pacf, main = expression("PACF - Linear Model co2 ~ time(co2) "))

```

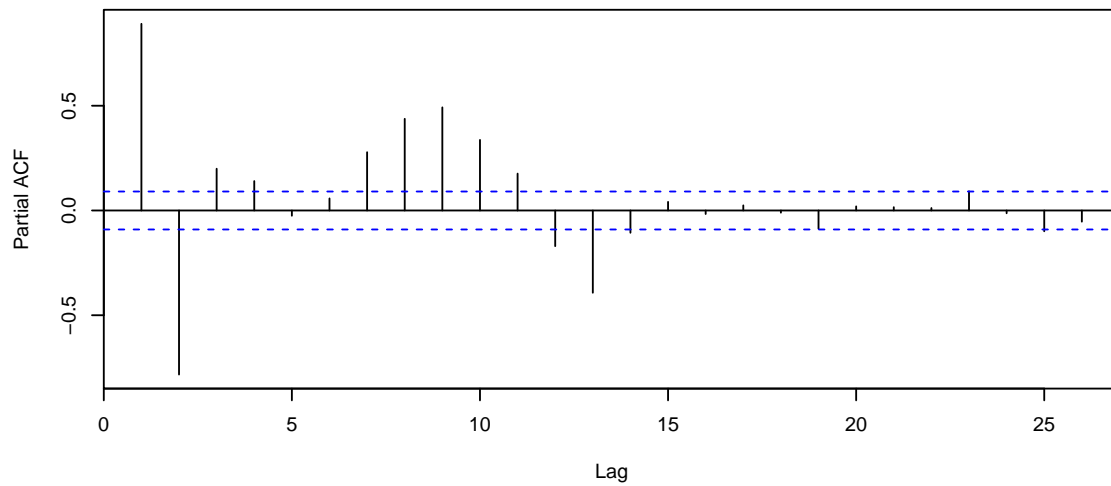
Linear Model $\text{co2} \sim \text{time}(\text{co2})$



ACF – Linear Model $\text{co2} \sim \text{time}(\text{co2})$



PACF – Linear Model $\text{co2} \sim \text{time}(\text{co2})$




```
Box.test(co2.ts.lm.linear$residuals, type = "Ljung-Box")
```

```
##
## Box-Ljung test
##
## data:  co2.ts.lm.linear$residuals
## X-squared = 373.94, df = 1, p-value < 2.2e-16
```

Because the variance around the trend line appeared constant, we chose not to take the log of the values of our time series observations.

After fitting a linear model of time, we performed several checks to assess model fit. As seen above, the plot of the residuals against the normal distribution shows skewing in the tails, suggesting that the linear model residuals are not normally distributed.

The ACF and PACF plots do not resemble those of white noise, suggesting poor model fit, and show evidence of autocorrelation in the residuals. This latter finding is supported by the results of the Ljung-Box test, which has a small p-value (< 0.05) - meaning that we fail to reject the null hypothesis that the residuals are correlated.

Seasonal Time-Trend Model

```
# Add seasonal dummy to data.frame
co2.df = data.frame(ppm = c(co2), time = c(time(co2)))
co2.df$season = as.factor(cycle(co2))

par(mfrow = c(3, 1))
co2.ts.lm.stt = lm(ppm ~ time + I(time(co2)^2) + season, data = co2.df)
summary(co2.ts.lm.stt)
```

```
##
## Call:
## lm(formula = ppm ~ time + I(time(co2)^2) + season, data = co2.df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.99478 -0.54468 -0.06017  0.47265  1.95480
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.771e+04  1.156e+03  41.289 < 2e-16 ***
## time         -4.920e+01  1.168e+00 -42.120 < 2e-16 ***
## I(time(co2)^2) 1.277e-02  2.952e-04  43.242 < 2e-16 ***
## season2        6.642e-01  1.640e-01   4.051 5.99e-05 ***
## season3        1.407e+00  1.640e-01   8.582 < 2e-16 ***
## season4        2.538e+00  1.640e-01  15.480 < 2e-16 ***
## season5        3.017e+00  1.640e-01  18.400 < 2e-16 ***
## season6        2.354e+00  1.640e-01  14.357 < 2e-16 ***
## season7        8.331e-01  1.640e-01   5.081 5.50e-07 ***
```

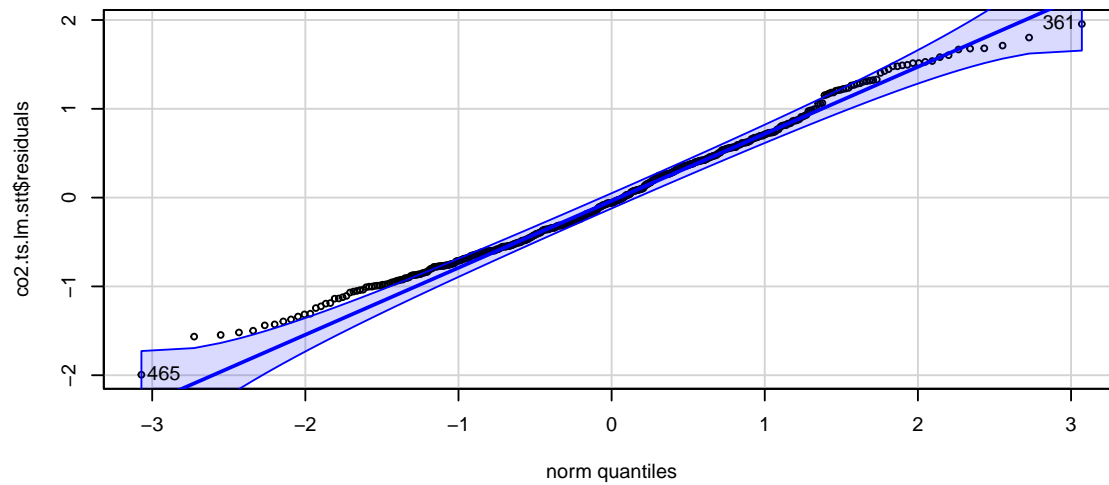
```

## season8      -1.235e+00  1.640e-01  -7.531  2.75e-13 ***
## season9      -3.059e+00  1.640e-01 -18.659  < 2e-16 ***
## season10     -3.243e+00  1.640e-01 -19.777  < 2e-16 ***
## season11     -2.054e+00  1.640e-01 -12.526  < 2e-16 ***
## season12     -9.374e-01  1.640e-01  -5.717  1.97e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.724 on 454 degrees of freedom
## Multiple R-squared:  0.9977, Adjusted R-squared:  0.9977
## F-statistic: 1.531e+04 on 13 and 454 DF,  p-value: < 2.2e-16
qqPlot(co2.ts.lm.stt$residuals, main = expression("Quadratic Time Trend Model with 12 Seasonal

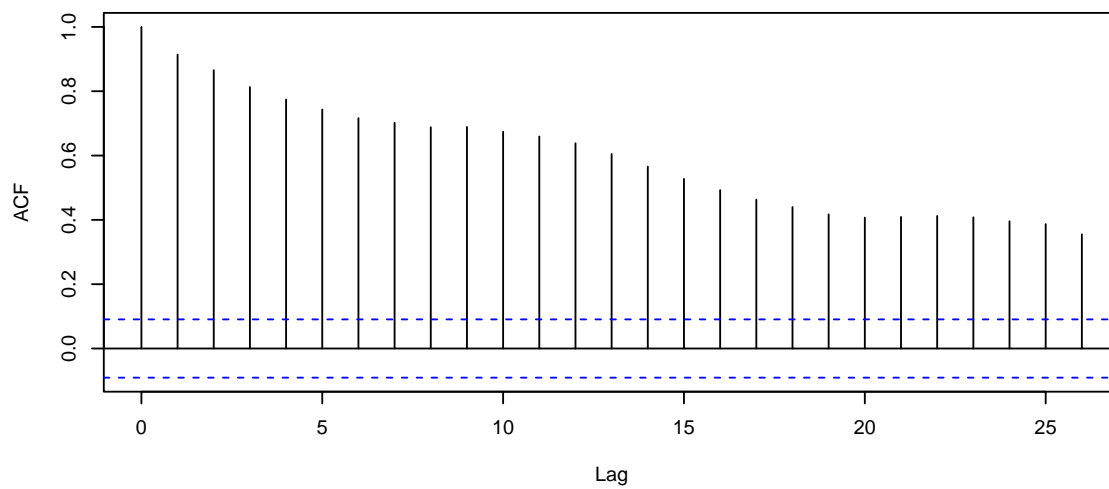
## [1] 465 361
plt.acf = acf(co2.ts.lm.stt$residuals, plot = FALSE)
plt.pacf = pacf(co2.ts.lm.stt$residuals, plot = FALSE)
plot(plt.acf, main = expression("ACF - Quadratic Time Trend Model with 12 Seasonal Components"),
plot(plt.pacf, main = expression("PACF - Quadratic Time Trend Model with 12 Seasonal Components"))

```

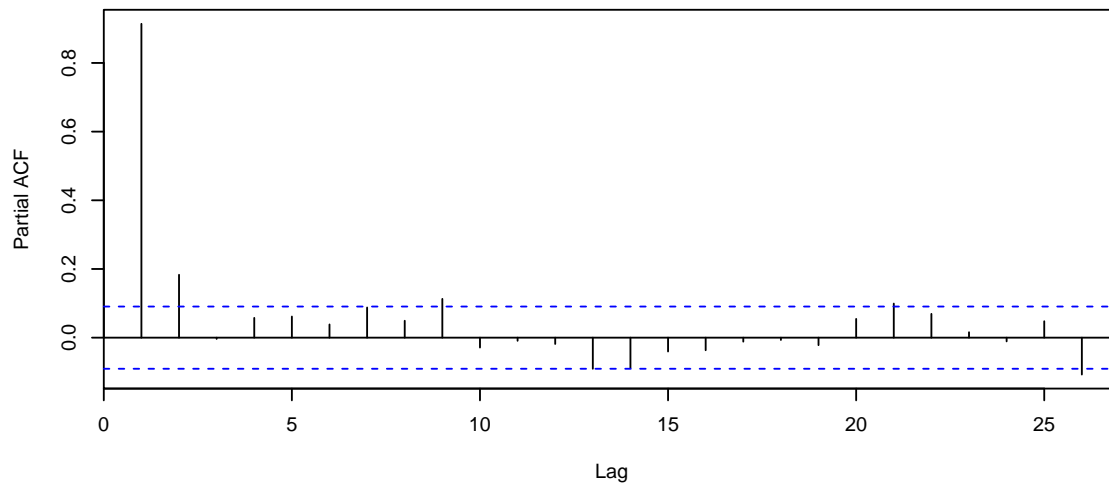
Quadratic Time Trend Model with 12 Seasonal Components



ACF – Quadratic Time Trend Model with 12 Seasonal Components



PACF – Quadratic Time Trend Model with 12 Seasonal Components



```
Box.test(co2.ts.lm.stt$residuals, type = "Ljung-Box")
```

```
##  
## Box-Ljung test  
##  
## data: co2.ts.lm.stt$residuals  
## X-squared = 393.48, df = 1, p-value < 2.2e-16
```

Based upon residual plots, the quadratic model with time and seasonal dummy variables appears to be a better fit. The residual tails are less skewed away from the qqline in the plot against the normal distribution. However, the ACF plot of the residuals, like those of the time linear model, show a trend not captured by our model - the majority of autocorrelations are significant and there is a gradual decay in values over the lags. The PACF shows fewer significant autocorrelations. Again, we find that the model fails the Ljung-Box test, indicating correlation in the residuals.

Despite these inadequacies, the model predictions in the short term do not appear unreasonable, as seen in our forecast plot.

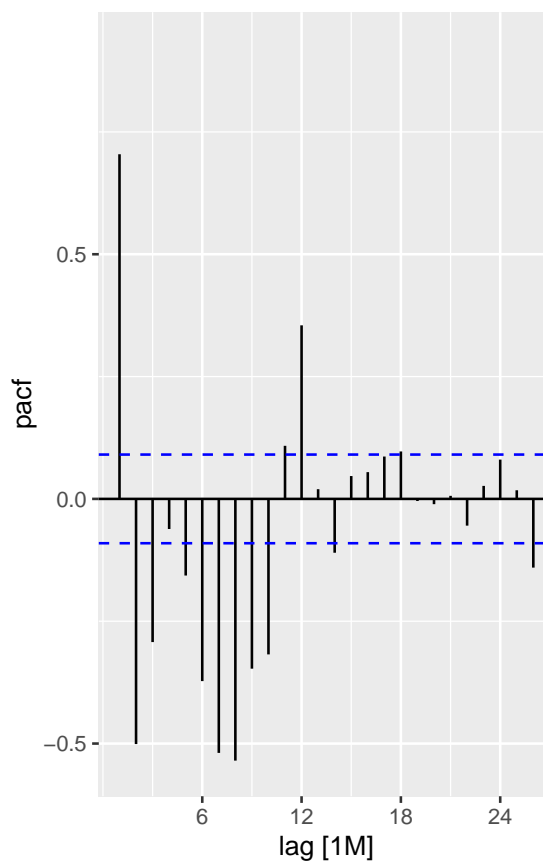
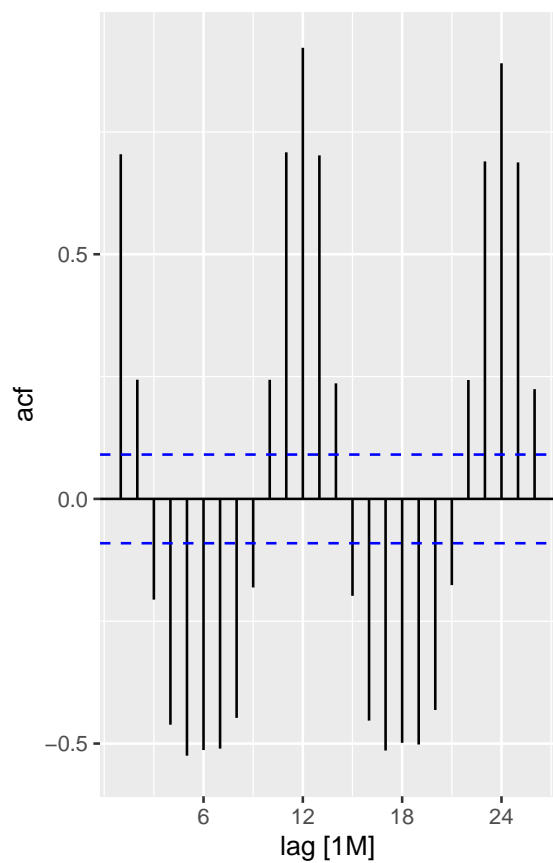
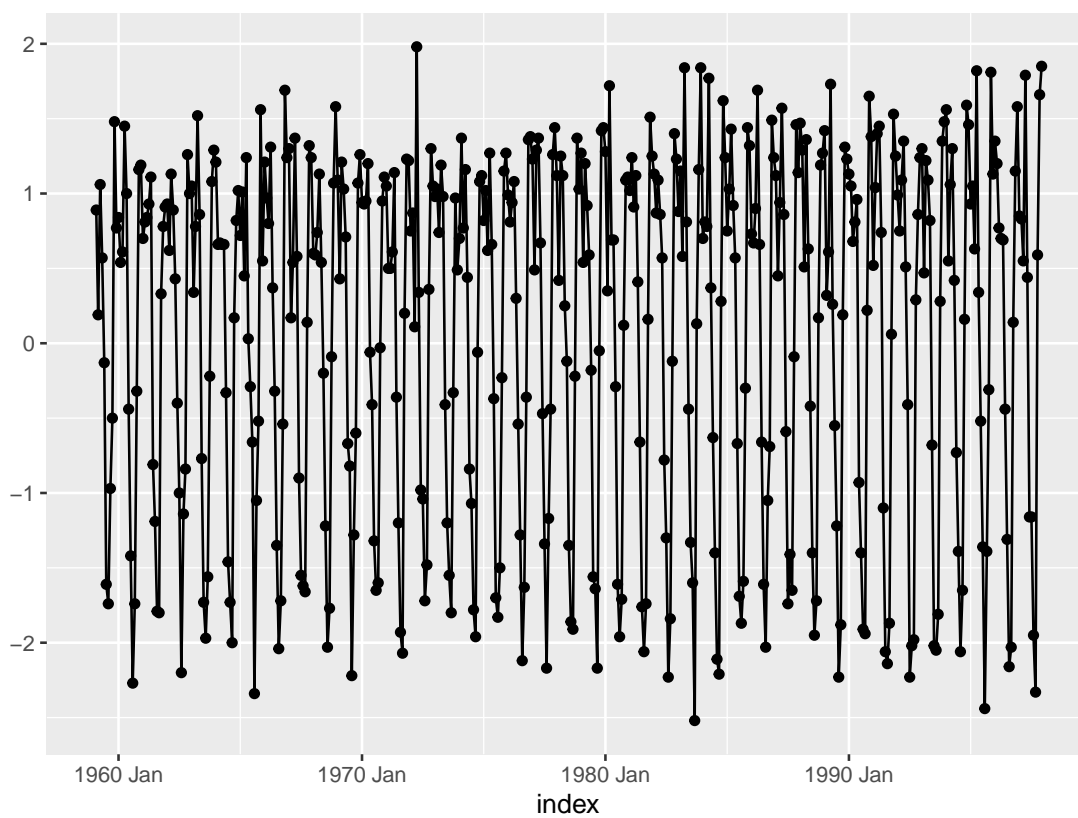
Part 3 (4 points)

Following all appropriate steps, choose an ARIMA model to fit to this co2 series. Discuss the characteristics of your model and how you selected between alternative ARIMA specifications. Use your model to generate forecasts to the present.

SARIMA Model Selection

```
# Find the number of seasonal and non-seasonal differences  
# needed for stationarity 1 non-seasonal difference and 0  
# seasonal differences are required  
unitroot_ndiffs(co2)  
  
## ndiffs  
##      1  
  
unitroot_nsdiffs(co2)  
  
## nsdiffs  
##      0  
  
# Plot the residuals, ACF, and PACF of the  
# first-differenced series The PACF chart has fewer  
# repeated significant spikes at seasonal lags than the ACF  
# does so we'll use it for the seasonal part of the model  
# in our initial estimate The PACF only a seasonal spike at  
# a lag of 12 - (1,0,0) Since we used the PACF for the  
# seasonal part, we'll estimate the non-seasonal with the  
# ACF The first 2 autocorrelations in the ACF are  
# significant, so we'll estimate an MA(2)  
as_tsibble(co2) %>%  
  gg_tsdisplay(difference(value), plot_type = "partial") +  
  labs(title = "Non-Seasonal 1st Difference", y = "")
```

Non-Seasonal 1st Difference



```

# Create an Arima model based upon our observations
co2.sarima = arima(co2, order = c(0, 1, 2), seas = list(order = c(1,
  0, 0), frequency(co2)), method = "CSS")

# Find the AIC of the Arima model, check the residuals, and
# perform Ljung-Box
co2.sarima.aicc <- -2 * co2.sarima$loglik + log(length(co2) +
  1) * (length(co2.sarima$coef))
co2.sarima.aicc

## [1] 413.4629

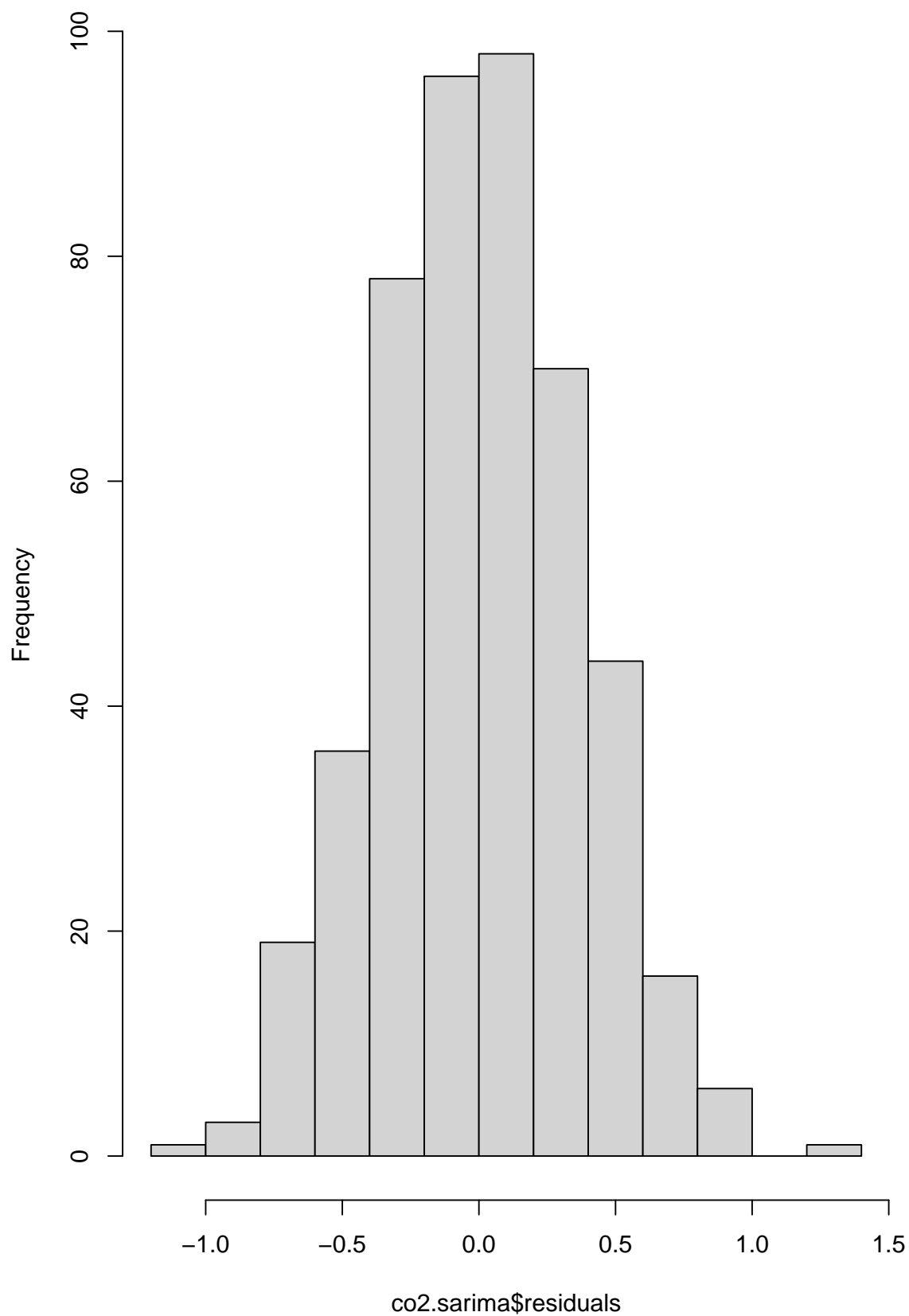
# Look at the estimated coefficients
summary(co2.sarima)

##
## Call:
## arima(x = co2, order = c(0, 1, 2), seasonal = list(order = c(1, 0, 0), frequency(co2)),
##      method = "CSS")
##
## Coefficients:
##          ma1          ma2          sar1
##      -0.3501  -0.0577   0.9804
## s.e.    0.0462   0.0444   0.0108
##
## sigma^2 estimated as 0.1364:  part log likelihood = -197.51
##
## Training set error measures:
##              ME          RMSE          MAE          MPE          MAPE          MASE
## Training set 0.00639654 0.3641826 0.2888305 0.001826364 0.08591893 0.2683615
##              ACF1
## Training set 0.007648558

# The histogram plot looks approximately normal
hist(co2.sarima$residuals, main = "SARIMA (0,1,2) (1,0,0)")

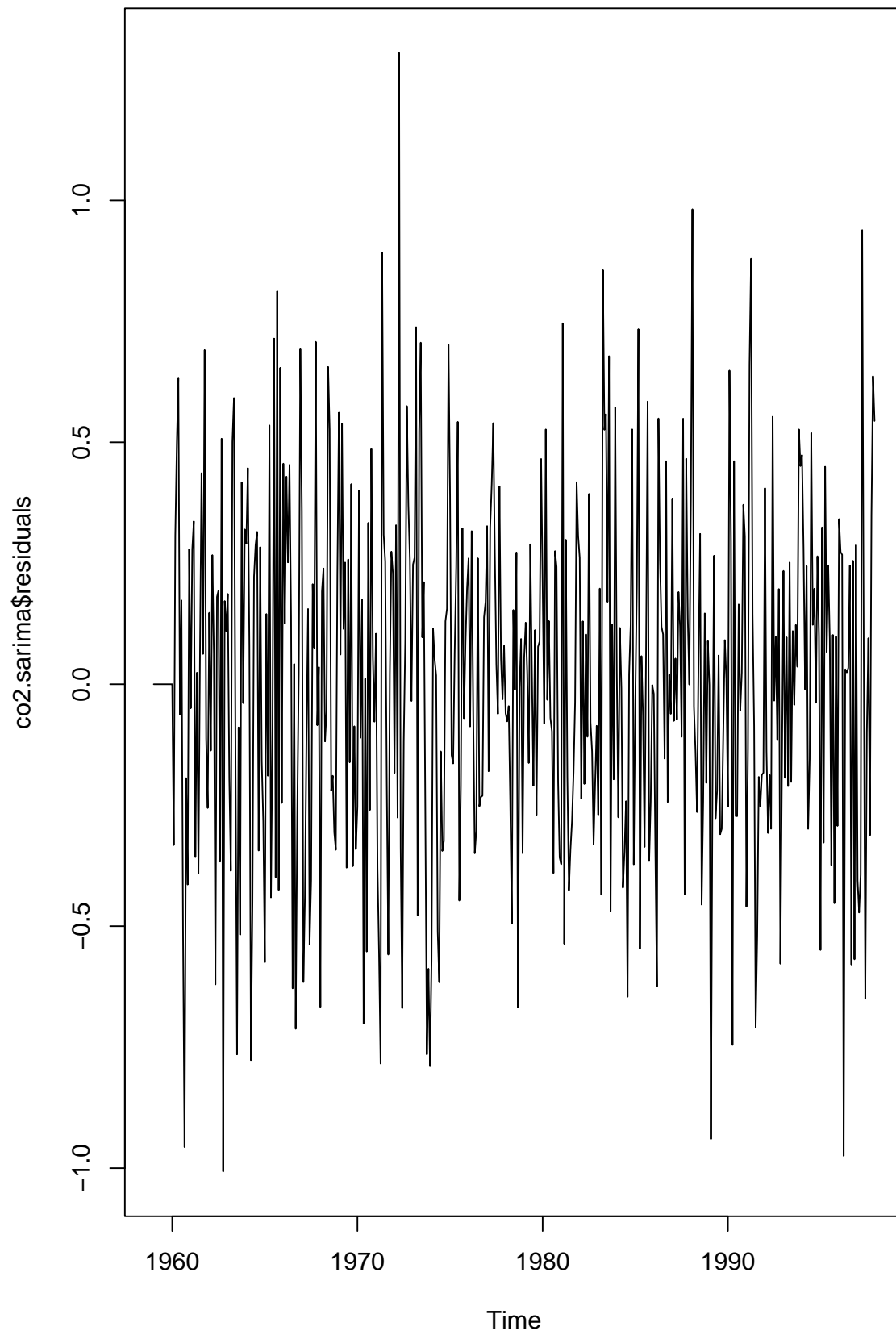
```

SARIMA (0,1,2) (1,0,0)



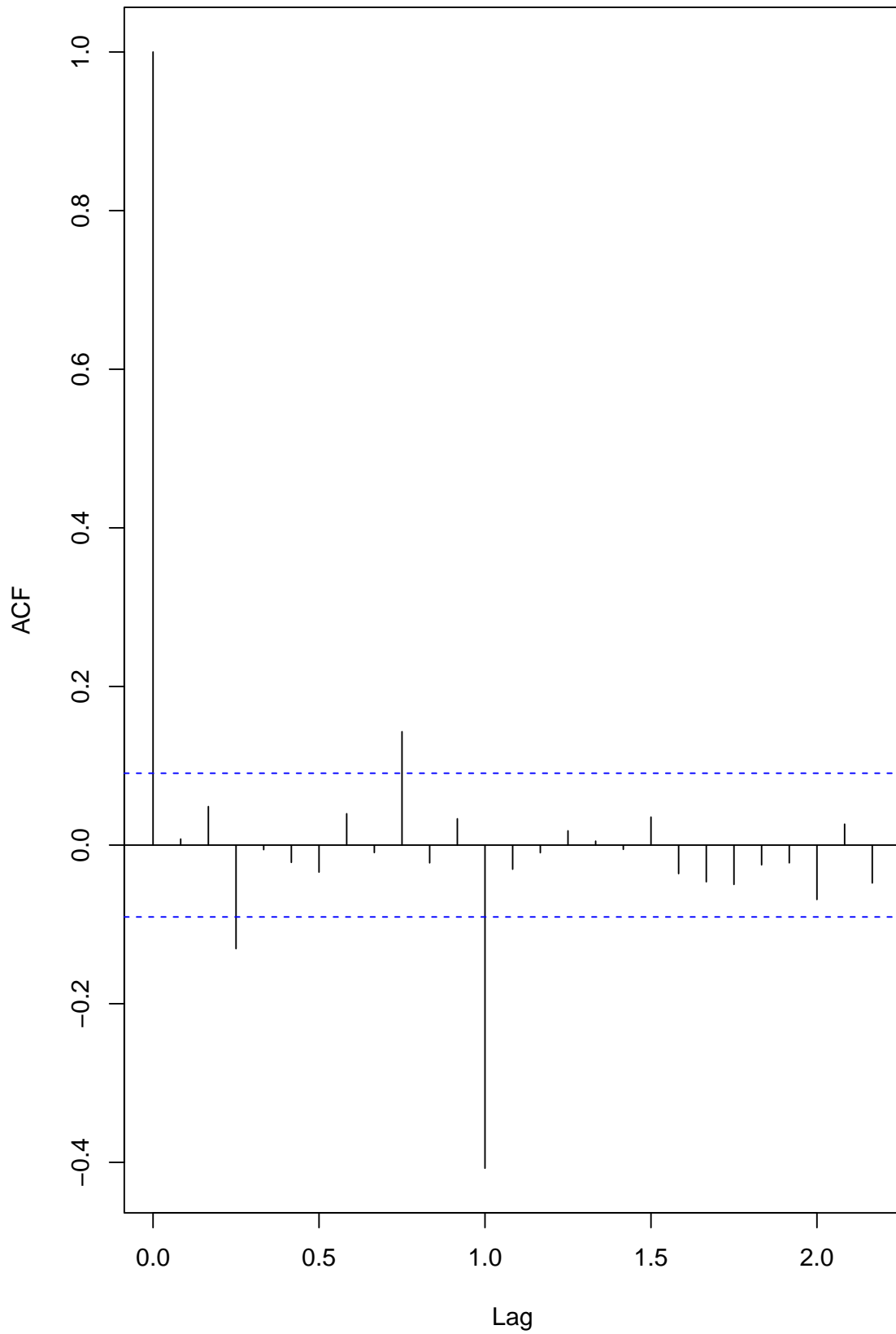
```
# A time series plot of the residuals appears to have a  
# constant mean  
plot(co2.sarima$residuals, main = "SARIMA (0,1,2) (1,0,0)")
```


SARIMA (0,1,2) (1,0,0)



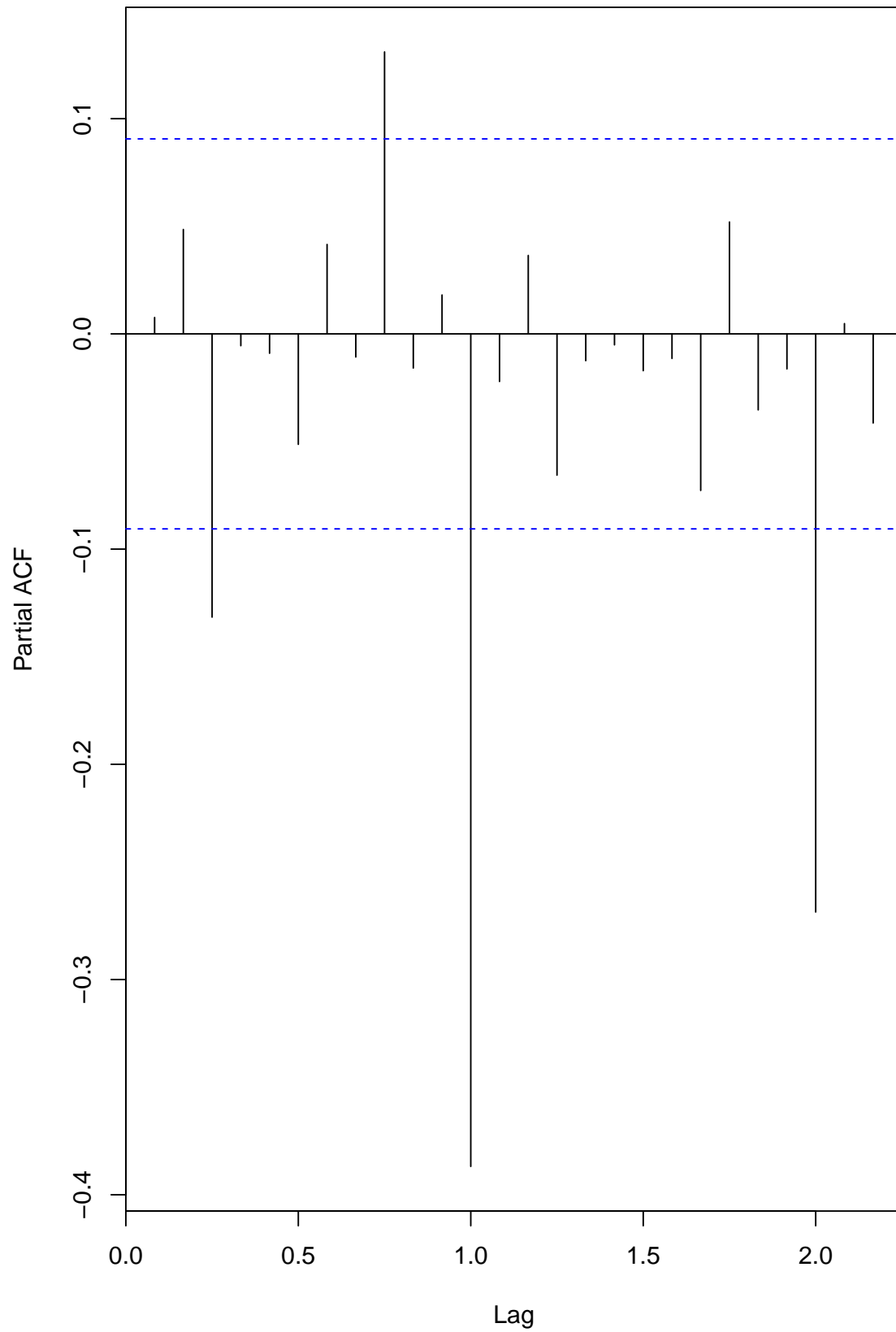
```
plt.acf = acf(co2.sarima$residuals, plot = FALSE)
plt.pacf = pacf(co2.sarima$residuals, plot = FALSE)
# The ACF and PACF plots still have a few significant
# autocorrelations
plot(plt.acf, main = "SARIMA (0,1,2) (1,0,0)")
```

SARIMA (0,1,2) (1,0,0)



```
plot(plt.pacf, main = "SARIMA (0,1,2) (1,0,0)")
```

SARIMA (0,1,2) (1,0,0)



```
# However, the model passes the Ljung-Box test
Box.test(co2.sarima$residuals, type = "Ljung-Box")
```

```
##
## Box-Ljung test
##
## data: co2.sarima$residuals
## X-squared = 0.027554, df = 1, p-value = 0.8682
```

To create our initial model, we first ran unit root tests to check the number of seasonal and non-seasonal differences required for stationarity. These tests returned 1 non-seasonal difference and 0 seasonal differences required, so we used these values as our d and D to estimate our initial Arima model. To obtain p , q , P , and Q , we took a first non-seasonal difference and plotted the ACF, PACF, and differenced values as a time series. The time series plot of the differenced values appeared relatively stationary. The ACF and PACF still showed evidence of autocorrelation. Since the PACF had fewer repeating seasonal lags, we used this plot to estimate the seasonal part of the Arima model. The PACF plot showed a significant autocorrelation at only the first seasonal lag, at 12, so we estimated $(1, 0, 0)$ for the seasonal part of the model. For the non-seasonal part of the Arima model, the ACF showed significant autocorrelation at lags 1 and 2, so we estimated an MA model of order 2, or $(0, 1, 2)$ for the non-seasonal component (with a difference of 1 since we took 1 non-seasonal difference).

The ACF and PACF plots of the residuals of this estimated model $((0, 1, 2)(1, 0, 0)_{12})$ shows several significant autocorrelations (notably at 1 year in the ACF and PACF and at 2 years in the PACF), although the majority of values fall within the confidence interval for white noise values.

The Ljung-Box test shows a p -value > 0.05 , meaning that we reject the null hypothesis that the residuals are auto-correlated.

Since the ACF and PACF plots still showed several strong autocorrelations, we proceeded to iterate over model parameters to see if we could improve the AIC score and create a model with residuals that better approximated white noise.

Model Selection Algorithm

```
get.best.arima <- function(x.ts, maxord = c(1, 1, 1, 1, 1, 1)) {
  best.aic <- 1e+08
  df.results = data.frame()
  n <- length(x.ts)
  for (p in 0:maxord[1]) for (d in 0:maxord[2]) for (q in 0:maxord[3]) for (P in 0:maxord[4])
    fit <- arima(x.ts, order = c(p, d, q), seas = list(order = c(P,
      D, Q), frequency(x.ts)), method = "CSS")
  # consistent AIC
  fit.aicc <- -2 * fit$loglik + (log(n) + 1) * length(fit$coef)
  # regular AIC
  fit.aic <- -2 * fit$loglik + 2 * (length(fit$coef) +
    1)
  # BIC
  fit.bic <- -2 * fit$loglik + log(n) * (length(fit$coef) +
```

```

1)
df <- data.frame(model = paste(p, d, q, P, D, Q), AICc = fit.aicc,
  AIC = fit.aic, BIC = fit.bic)
df.results <- rbind(df.results, df)
}
# list(best.aic, best.fit, best.model)
df.results
}

arima.search <- get.best.arima(co2, maxord = c(2, 2, 2, 2, 2,
2))

```

To find a parsimonious seasonal Arima model that better fit the time series, we looped over values in the range of 0 to 2 for the parameters p, q, P, and Q. We also chose the range of 0 to 2 for the number of seasonal and non-seasonal differences, since differencing beyond order 2 is rarely required.

For the best fit model, we chose to use the model with the lowest AICc, as seen in our table below (using AICc since it penalizes the model fit with increasing parameters and corrects for the bias in predictor selection introduced by AIC). As seen below, the best fitting model is (0, 1, 1)(1, 1, 2).

Table 1: Top 10 Models.

model	AICc	AIC	BIC
0 1 1 1 1 2	193.5103	174.9164	195.6587
0 1 1 2 0 2	196.8432	173.1008	197.9916
0 1 1 1 1 1	197.0927	183.6473	200.2412
1 1 1 1 1 2	197.6924	173.9500	198.8408
0 1 2 1 1 2	199.2472	175.5049	200.3957
1 0 1 1 1 2	199.8742	176.1318	201.0227
1 1 0 1 1 2	201.1810	182.5871	203.3294
1 1 1 1 1 1	201.1950	182.6012	203.3435
1 1 1 2 0 2	201.2614	172.3706	201.4099
0 1 1 2 1 2	201.3117	177.5693	202.4602

```

# Estimate an Arima model with the parameters of the model
# with the lowest AICc found from our parameter search
pdqPDQ <- as.list(unlist(strsplit(best10.arima[1, 1], "[:space:]")))
p <- strtoi(pdqPDQ[[1]])
d <- strtoi(pdqPDQ[[2]])
q <- strtoi(pdqPDQ[[3]])
P <- strtoi(pdqPDQ[[4]])
D <- strtoi(pdqPDQ[[5]])
Q <- strtoi(pdqPDQ[[6]])

# Estimate the model
co2.sarima.2 <- arima(co2, order = c(p, d, q), seasonal = list(order = c(P,

```

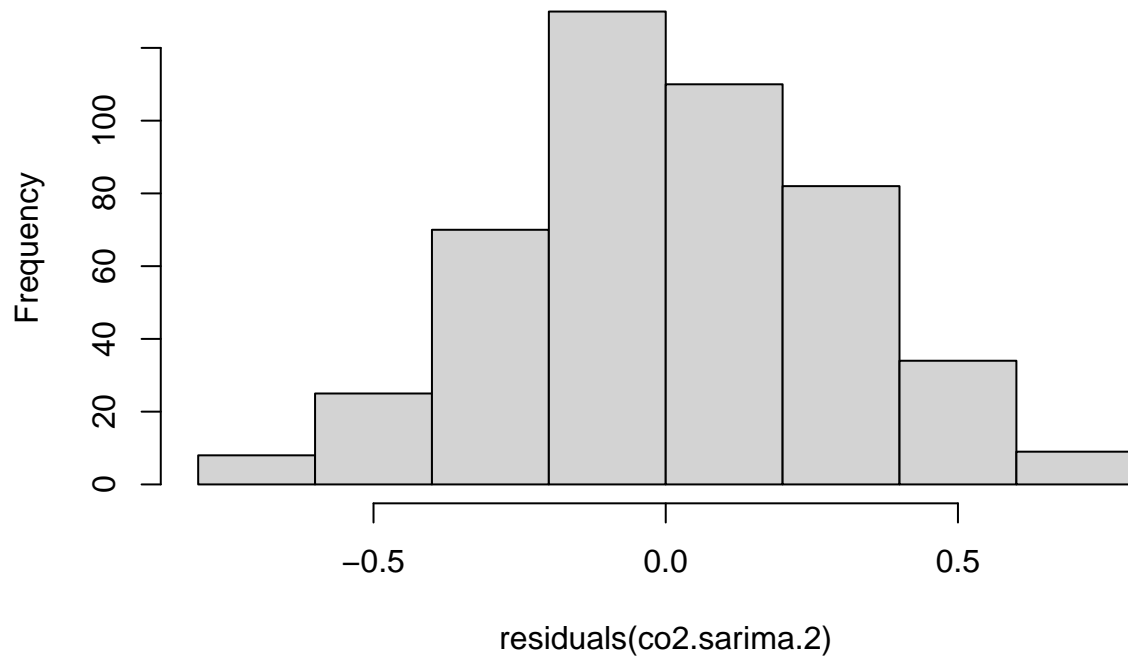
```

D, Q)), method = "CSS")

# Inspect the residual plots and find the estimated AICc
sarima2.aicc <- -2 * co2.sarima.2$loglik + (log(length(co2)) +
1) * length(co2.sarima.2$coef)
hist(residuals(co2.sarima.2))

```

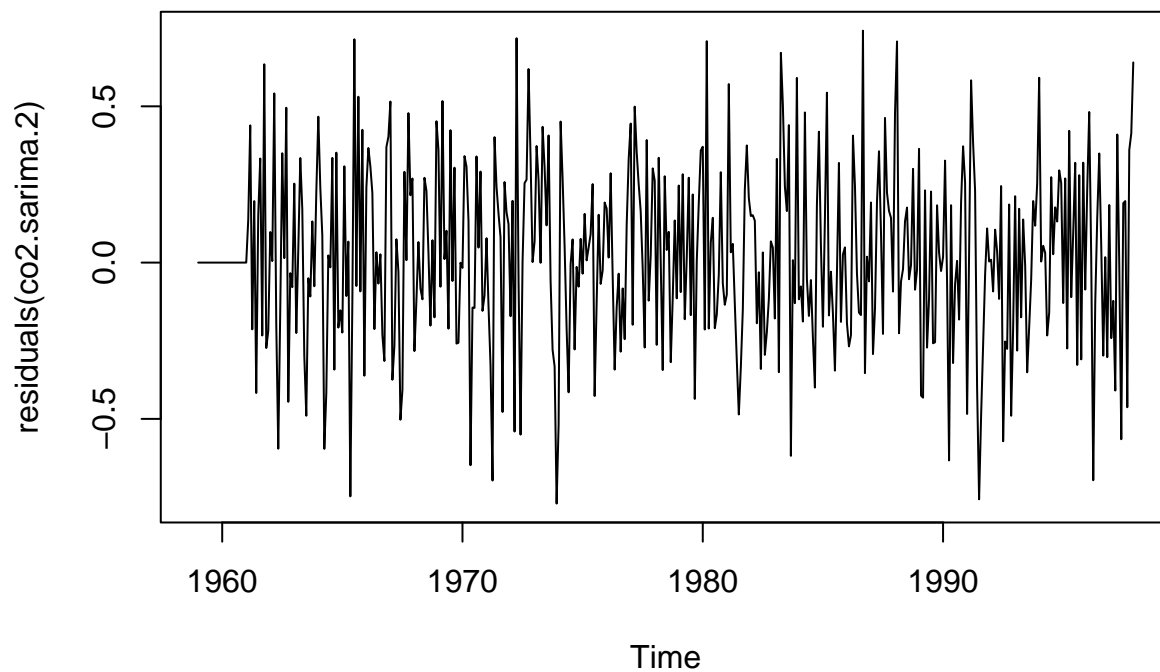
Histogram of residuals(co2.sarima.2)



```

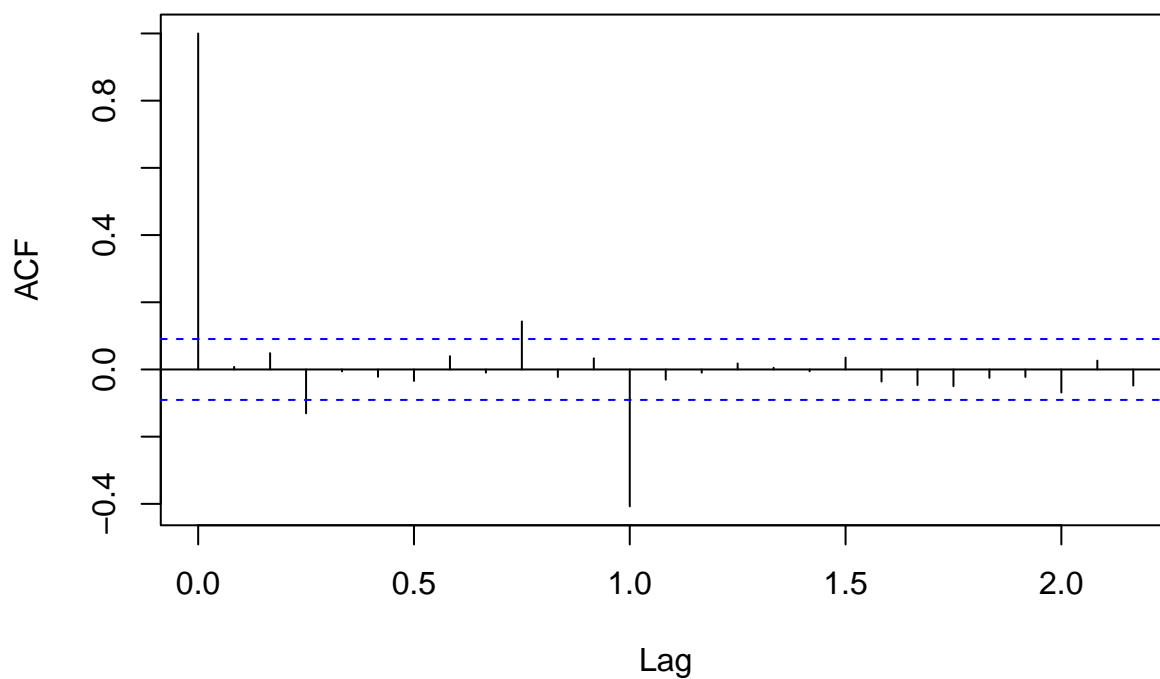
plot(residuals(co2.sarima.2))

```

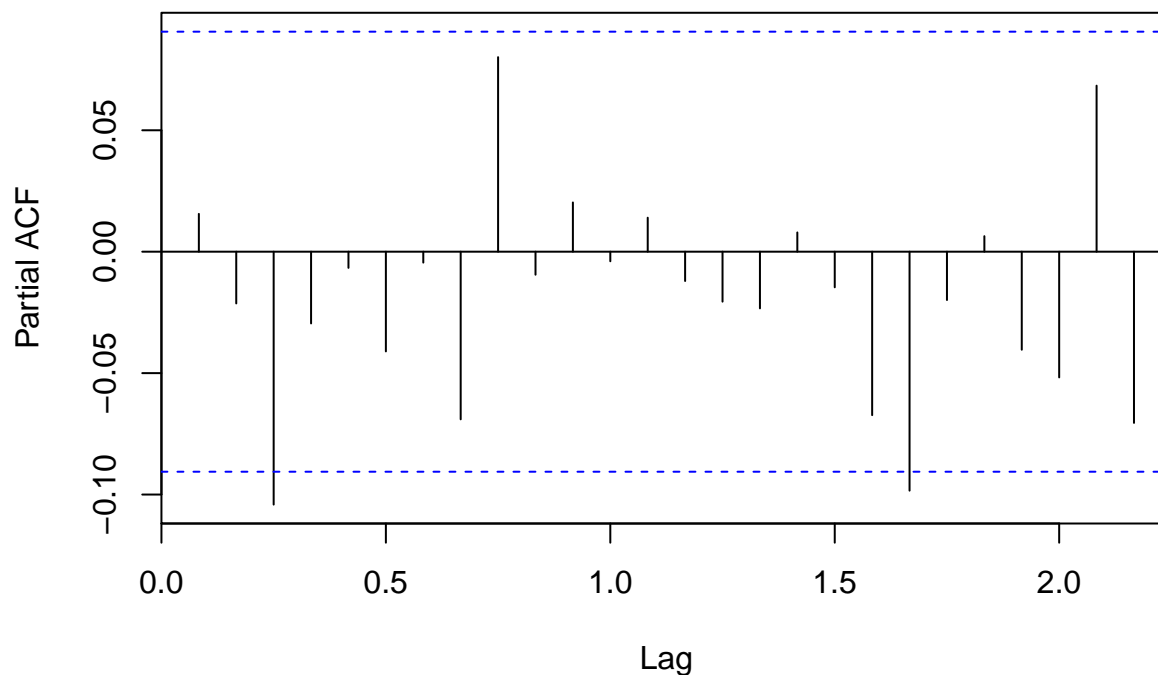
```
acf(co2.sarima$residuals)
```

Series `co2.sarima$residuals`



```
pacf(co2.sarima.2$residuals)
```

Series co2.sarima.2\$residuals



```
sarima2.aicc
```

```
## [1] 193.5103
```

```
Box.test(co2.sarima.2$residuals, type = "Ljung-Box")
```

```
##
```

```
## Box-Ljung test
```

```
##
```

```
## data: co2.sarima.2$residuals
```

```
## X-squared = 0.11422, df = 1, p-value = 0.7354
```

The AICc value is smaller than that of our initial model estimate, and the majority of ACF and PACF values fall within the 95% confidence interval bounds for white noise. In addition, the Ljung-Box test indicates that the data are independently distributed since we fail to reject the null hypothesis.

The histogram of the residuals shows them to be approximately normally distributed and the plot of the residuals as a time series resembles white noise.

Since this model has a lower AICc than our initial estimate, the residuals resemble white noise, and we have not found significant evidence of residual autocorrelation, we proceed with using this model in our forecast.

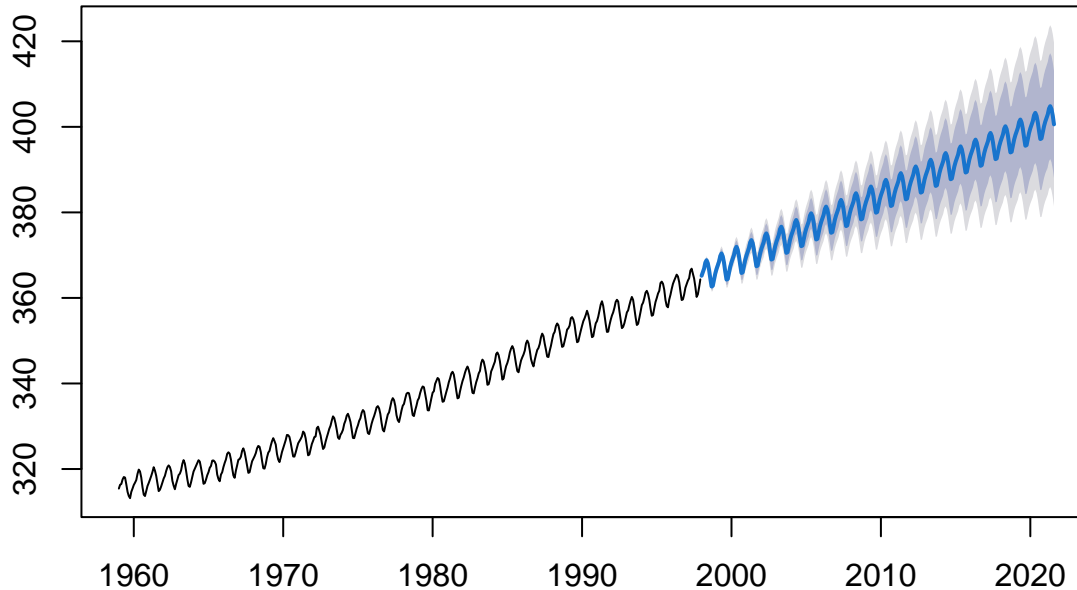
Best Model Forecasts

```
co2.forecast <- forecast(co2.sarima.2, 284)
```

```
co2_forecast_ts <- co2.forecast[4]$mean
```

```
plot(co2.forecast, main = "SARIMA Model - CO2 present in air(ppm) forecasting",
     col.main = "darkgreen")
```

SARIMA Model – CO2 present in air(ppm) forecasting



Part 4 (5 points)

The file `co2_weekly_mlo.txt` contains weekly observations of atmospheric carbon dioxide concentrations measured at the Mauna Loa Observatory from 1974 to 2020, published by the National Oceanic and Atmospheric Administration (NOAA). Convert these data into a suitable time series object, conduct a thorough EDA on the data, addressing the problem of missing observations and comparing the Keeling Curve's development to your predictions from Parts 2 and 3. Use the weekly data to generate a month-average series from 1997 to the present and use this to generate accuracy metrics for the forecasts generated by your models from Parts 2 and 3.

```
co2_weekly <- read.table("co2_weekly_mlo.txt", header = FALSE)
colnames(co2_weekly) <- c("year", "month", "day", "decimal",
  "ppm", "days", "1yr_ago", "10yrs_ago", "since1800")
summary(co2_weekly)
```

```
##      year      month      day      decimal
##  Min.   :1974   Min.    : 1.00   Min.    : 1.00   Min.    :1974
##  1st Qu.:1986   1st Qu.: 4.00   1st Qu.: 8.00   1st Qu.:1986
##  Median :1997   Median : 7.00   Median :16.00   Median :1998
##  Mean   :1997   Mean    : 6.52   Mean    :15.72   Mean    :1998
##  3rd Qu.:2009   3rd Qu.:10.00   3rd Qu.:23.00   3rd Qu.:2010
##  Max.    :2021   Max.    :12.00   Max.    :31.00   Max.    :2021
##      ppm      days      1yr_ago      10yrs_ago
##  Min.   :-1000.0   Min.    :0.000   Min.    : -1000.0   Min.    : -999.99
##  1st Qu.: 347.1   1st Qu.:5.000   1st Qu.: 345.6   1st Qu.: 331.48
##  Median : 365.2   Median :6.000   Median : 363.5   Median : 350.18
```

```
## Mean : 358.3 Mean :5.871 Mean : 328.4 Mean : 59.61
## 3rd Qu.: 388.4 3rd Qu.:7.000 3rd Qu.: 386.2 3rd Qu.: 368.45
## Max. : 420.0 Max. :7.000 Max. : 417.8 Max. : 395.23
## since1800
## Min. : -999.99
## 1st Qu.: 66.95
## Median : 84.55
## Mean : 80.38
## 3rd Qu.: 108.07
## Max. : 136.87
```

```
describe(co2_weekly)
```

```
## co2_weekly
##
## 9 Variables      2458 Observations
## -----
## year
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      48      1      1997      15.71      1976      1979
##      .25      .50      .75      .90      .95
##    1986      1997      2009      2016      2019
##
## lowest : 1974 1975 1976 1977 1978, highest: 2017 2018 2019 2020 2021
## -----
## month
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      12    0.993      6.52      3.965      1      2
##      .25      .50      .75      .90      .95
##      4      7      10      11      12
##
## lowest : 1 2 3 4 5, highest: 8 9 10 11 12
##
## Value      1      2      3      4      5      6      7      8      9      10      11
## Frequency    208    190    208    201    211    205    208    208    202    207    202
## Proportion 0.085 0.077 0.085 0.082 0.086 0.083 0.085 0.085 0.082 0.084 0.082
##
## Value      12
## Frequency    208
## Proportion 0.085
## -----
## day
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      31    0.999      15.72      10.16      2      4
##      .25      .50      .75      .90      .95
##      8      16      23      28      29
##
## lowest : 1 2 3 4 5, highest: 27 28 29 30 31
```

```

## -----
## decimal
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      2458        1      1998      15.71      1977      1979
##      .25      .50      .75      .90      .95
##    1986      1998      2010      2017      2019
##
## lowest : 1974.380 1974.399 1974.418 1974.437 1974.456
## highest: 2021.390 2021.410 2021.429 2021.448 2021.467
## -----
## ppm
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      2148        1      358.3      47.87      332.4      336.1
##      .25      .50      .75      .90      .95
##   347.1     365.2     388.4     404.6     410.6
##
## lowest : -999.99 326.72 326.99 327.07 327.23
## highest: 419.28 419.47 419.53 419.55 420.01
##
## Value      -1000    320    340    360    380    400    420
## Frequency      18     45    638    662    527    435    133
## Proportion 0.007 0.018 0.260 0.269 0.214 0.177 0.054
##
## For the frequency table, variable is rounded to the nearest 20
## -----
## days
##      n missing distinct      Info      Mean      Gmd
##    2458      0          8     0.896     5.871     1.378
##
## lowest : 0 1 2 3 4, highest: 3 4 5 6 7
##
## Value      0      1      2      3      4      5      6      7
## Frequency      18     14     36     101    176     402     648    1063
## Proportion 0.007 0.006 0.015 0.041 0.072 0.164 0.264 0.432
## -----
## 1yr_ago
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0      2097        1      328.4      101.7      330.5      334.4
##      .25      .50      .75      .90      .95
##   345.6     363.5     386.2     402.0     408.2
##
## lowest : -999.99 326.73 326.84 326.98 327.21
## highest: 417.09 417.10 417.21 417.46 417.83
##
## Value      -1000    320    340    360    380    400    420
## Frequency      70     45    638    665    523    436     81
## Proportion 0.028 0.018 0.260 0.271 0.213 0.177 0.033
##

```

```
## For the frequency table, variable is rounded to the nearest 20
## -----
## 10yrs_ago
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0     1644    0.989    59.61    479.1 -1000.0 -1000.0
##      .25     .50     .75     .90     .95
##    331.5    350.2    368.5    382.4    387.0
##
## lowest : -999.99  326.66  327.04  327.10  327.26
## highest:  394.08  394.15  394.43  395.13  395.23
##
## Value      -1000    330    340    350    360    370    380    390    400
## Frequency    541    196    328    343    339    286    248    175     2
## Proportion 0.220 0.080 0.133 0.140 0.138 0.116 0.101 0.071 0.001
##
## For the frequency table, variable is rounded to the nearest 10
## -----
## since1800
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2458      0     2086      1    80.38    43.66    52.11    55.81
##      .25     .50     .75     .90     .95
##    66.95    84.55    108.07    125.10    130.75
##
## lowest : -999.99    49.60    49.65    49.72    49.95
## highest:  136.49    136.61    136.64    136.74    136.87
##
## Value      -1000     50     60     70     80     90    100    110    120    130    140
## Frequency     18    194    326    325    371    270    260    245    200    216     33
## Proportion 0.007 0.079 0.133 0.132 0.151 0.110 0.106 0.100 0.081 0.088 0.013
##
## For the frequency table, variable is rounded to the nearest 10
## -----
```

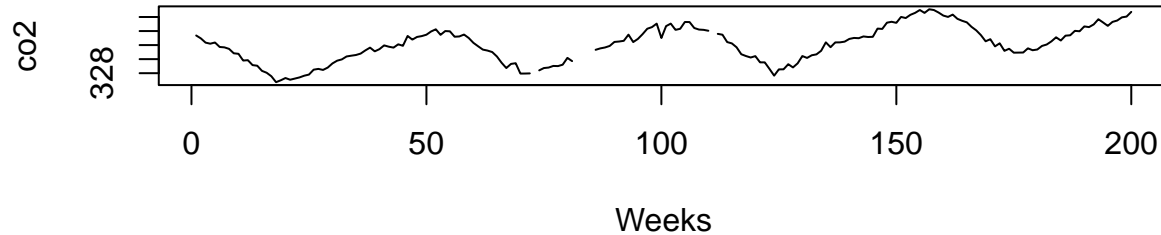
NOAA data provided in the file has 2458 weekly observations from 1974 to 2021 with 10 variables. Variable `ppm` tracks weekly `co2` presence. We will be using `ppm` values for our analysis. It appears that NOAA uses -999 to represent missing values. For `ppm`, there are 18 observations missing. and we have 18 observations that have `ppm` value as a null, we will fill them in before developing time series model.

Impute Missing Values Linearly

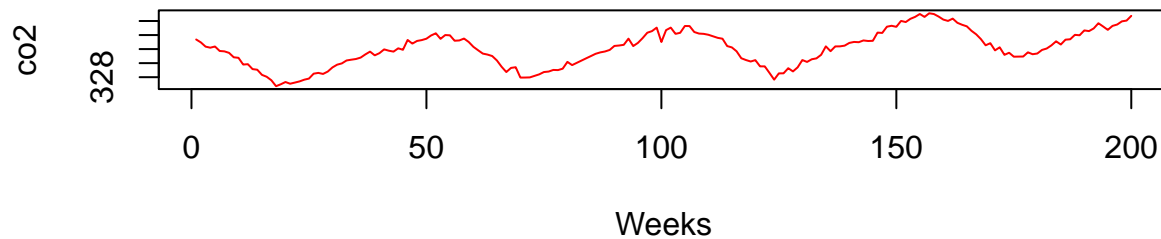
```
co2_weekly <- co2_weekly %>%
  mutate(ppm = ifelse(test = (ppm <= 0), NA, no = ppm))
co2_weekly2 <- data.frame(lapply(co2_weekly, function(X) approxfun(seq_along(X),
  X)(seq_along(X))))
par(mfrow = c(2, 1))
plot(co2_weekly$ppm[1:200], type = "l", xlab = "Weeks", ylab = "co2",
  main = "First 200 Weeks of Raw Data")
```

```
plot(co2_weekly2$ppm[1:200], type = "l", col = "red", xlab = "Weeks",
     ylab = "co2", main = "Linearly Interpolate Missing Values")
```

First 200 Weeks of Raw Data



Linearly Interpolate Missing Values



After careful observation of the data, most of the missing points are spread out across the data set (i.e. we do not need to impute 18 weeks in a row). As a result, we suggest it is reasonable to simply interpolate the missing values linearly. The plot above shows the first 200 weeks of the original data series with missing data and a new time series with missing values imputed.

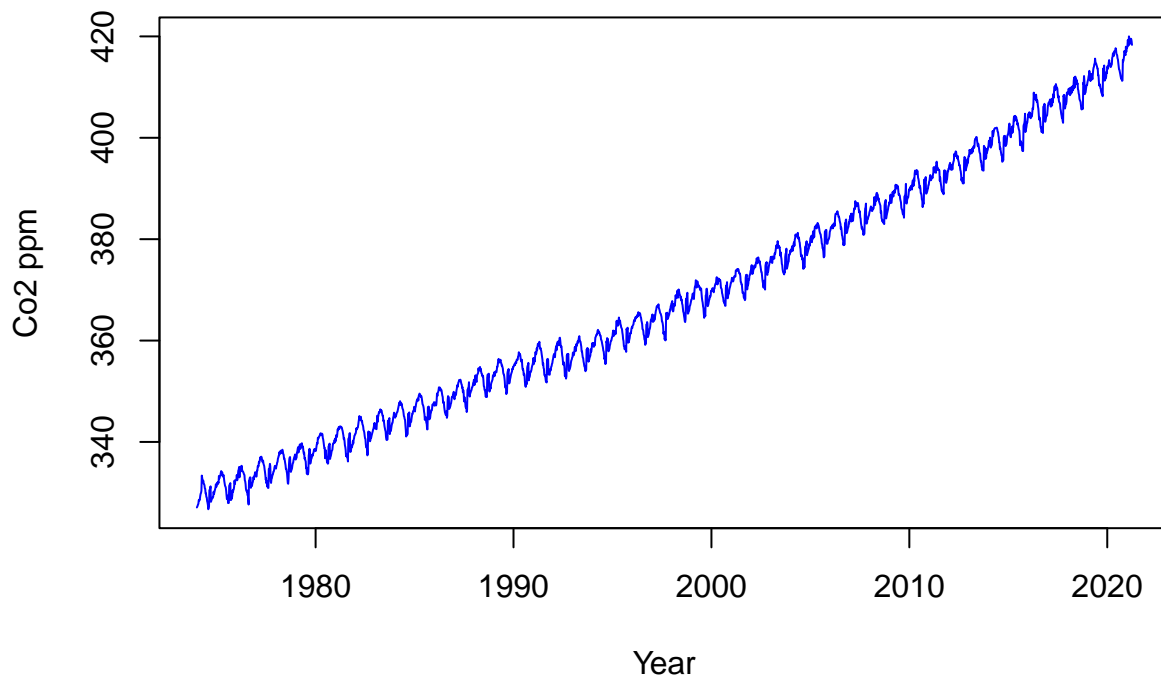
```
# Get monthly averages for replacement after imputing
# missing values
co2_monthly <- co2_weekly2 %>%
  group_by(year, month) %>%
  summarise(ppm_month_avg = mean(ppm))

# join to add monthly averages
co2_merged <- merge(co2_weekly2, co2_monthly, by = c("year",
  "month"))

# Create weekly time series
co2_noaa_weekly_ts <- ts(co2_merged$ppm, start = c(1974), frequency = 52)

# Plot weekly time series
plot(co2_noaa_weekly_ts, main = "Weekly Observations of CO2 (ppm)\n Mauna Loa Observatory 1974",
     xlab = "Year", ylab = "Co2 ppm", col = "blue")
```

Weekly Observations of CO2 (ppm) Mauna Loa Observatory 1974 to 2021



```
# Calculate monthly averages as our forecast is only on  
# monthly basis
```

```
co2_noaa_monthly_df <- co2_merged %>%  
  group_by(year, month) %>%  
  summarise(ppm_month_avg = mean(ppm))  
summary(co2_noaa_monthly_df)
```

```
##      year      month      ppm_month_avg  
## Min.   :1974   Min.   : 1.000   Min.   :327.3  
## 1st Qu.:1986   1st Qu.: 4.000   1st Qu.:347.2  
## Median :1997   Median : 6.000   Median :365.1  
## Mean   :1997   Mean   : 6.496   Mean   :368.2  
## 3rd Qu.:2009   3rd Qu.: 9.000   3rd Qu.:388.1  
## Max.   :2021   Max.   :12.000   Max.   :419.1
```

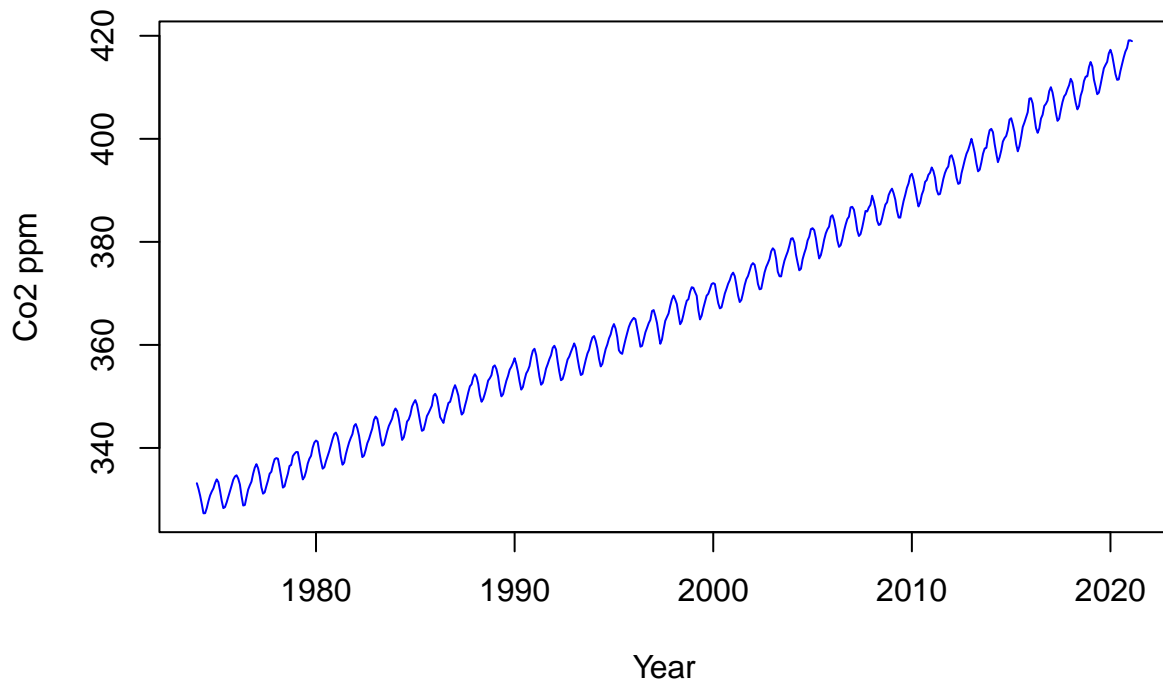
```
# Create monthly ts object (all observations)
```

```
co2_noaa_monthly_ts <- ts(co2_noaa_monthly_df$ppm_month_avg,  
  start = c(1974), frequency = 12)
```

```
# Plot monthly time series
```

```
plot(co2_noaa_monthly_ts, main = "Monthly Observations of CO2 (ppm)\n Mauna Loa Observatory 1974 to 2021",  
  xlab = "Year", ylab = "Co2 ppm", col = "blue")
```


Monthly Observations of CO2 (ppm) Mauna Loa Observatory 1974 to 2021



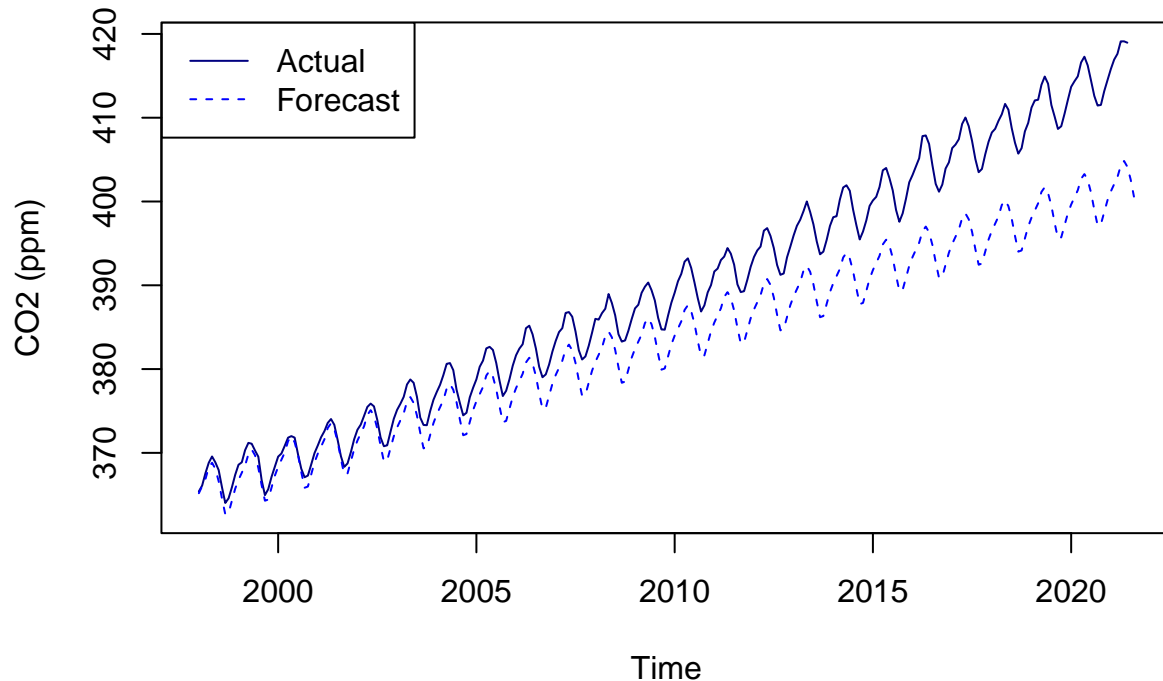
The monthly time series plotted above looks like a smoothed version of the weekly time series.

```
# transforming time series data to dataframe, so that we
# can join
co2_actuals_filtered <- co2_noaa_monthly_df %>%
  filter(year > 1997)

co2_actuals_ts <- ts(co2_actuals_filtered$ppm_month_avg, start = c(1998),
  frequency = 12)

ts.plot(co2_actuals_ts, co2_forecast_ts, lty = 1:2, col = c("navy",
  "blue"), ylab = "CO2 (ppm)", main = "SARIMA(0,1,1,1,1,2) Forecasts vs. Actual Monthly CO2 I
legend("topleft", legend = c("Actual", "Forecast"), col = c("navy",
  "blue"), lty = 1:2)
```

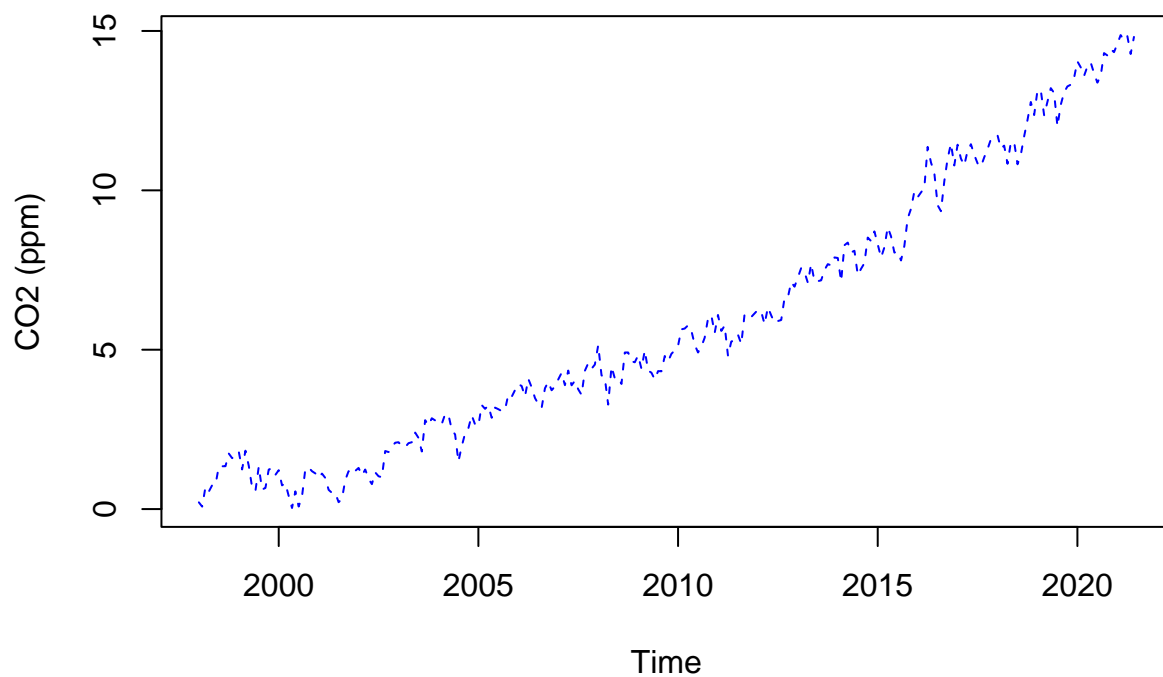
SARIMA(0,1,1,1,1,2) Forecasts vs. Actual Monthly CO2 Levels



```
actuals_fore_diff <- co2_actuals_ts - co2_forecast_ts
```

```
ts.plot(actuals_fore_diff, lty = 2, col = c("blue"), ylab = "CO2 (ppm)",  
main = "Difference between Actual CO2 Levels and Forecasted Levels")
```

Difference between Actual CO2 Levels and Forecasted Levels



The difference between the actual measured CO2 levels from 1998 to present and our forecasts

is stark. It is clear from the plot above that we underestimated the growth of the series over the subsequent 20+ years. Given that our best model's residuals were stationary and resembled white noise, we would conclude that the forecast error was not necessarily due to a model misspecification, but rather a change in the underlying CO₂ generating process. We hypothesize this could be due to the rapid growth of China's economy and other emerging market economies through the 2000s and 2010s¹. This could be the subject of a deeper, causal understanding of what is driving the ever-increasing concentrations of atmospheric CO₂.

Part 5 (5 points)

Split the NOAA series into training and test sets, using the final two years of observations as the test set. Fit an ARIMA model to the series following all appropriate steps, including comparison of how candidate models perform both in-sample and (psuedo-) out-of-sample. Generate predictions for when atmospheric CO₂ is expected to reach 450 parts per million, considering the prediction intervals as well as the point estimate. Generate a prediction for atmospheric CO₂ levels in the year 2100. How confident are you that these will be accurate predictions?

¹<https://climateactiontracker.org/countries/china/>