Assignment 8: Time Series Analysis

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OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on time series analysis.

Directions

1. Change "Student Name" on line 3 (above) with your name.
2. Work through the steps, **creating code and output** that fulfill each instruction.
3. Be sure to **answer the questions** in this assignment document.
4. When you have completed the assignment, **Knit** the text and code into a single PDF file.
5. After Knitting, submit the completed exercise (PDF file) to the dropbox in Sakai. Add your last name into the file name (e.g., "Salk_A06_GLMs_Week1.Rmd") prior to submission.

The completed exercise is due on Tuesday, March 3 at 1:00 pm.

Set up

1. Set up your session:

- Check your working directory
- Load the tidyverse, lubridate, zoo, and trend packages
- Set your ggplot theme
- Import the ten datasets from the Ozone_TimeSeries folder in the Raw data folder. These contain ozone concentrations at Garinger High School in North Carolina from 2010-2019 (the EPA air database only allows downloads for one year at a time). Call these GaringerOzone201*, with the star filled in with the appropriate year in each of ten cases.

```
getwd()
```

```
## [1] "C:/Timwork/ENV872/Environmental_Data_Analytics_2020/Assignments"
```

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 3.5.3
## Warning: package 'ggplot2' was built under R version 3.5.3
## Warning: package 'purrr' was built under R version 3.5.3
## Warning: package 'dplyr' was built under R version 3.5.3
## Warning: package 'forcats' was built under R version 3.5.3
```

```
library(lubridate)
```

```
## Warning: package 'lubridate' was built under R version 3.5.3
```

```
library(zoo)
```

```
## Warning: package 'zoo' was built under R version 3.5.3
```

```
library(trend)
```

```
## Warning: package 'trend' was built under R version 3.5.3
```

```r
# Set theme
mytheme <- theme_classic(base_size = 12) +
  theme(axis.text = element_text(color = "black"),
        legend.position = "top")
theme_set(mytheme)
# Import Ozone_data
Garingerzone2010 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2010_raw.csv")
Garingerzone2011 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2011_raw.csv")
Garingerzone2012 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2012_raw.csv")
Garingerzone2013 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2013_raw.csv")
Garingerzone2014 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2014_raw.csv")
Garingerzone2015 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2015_raw.csv")
Garingerzone2016 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2016_raw.csv")
Garingerzone2017 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2017_raw.csv")
Garingerzone2018 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2018_raw.csv")
Garingerzone2019 <- read.csv("../Data/Raw/Ozone_TimeSeries/EPAair_O3_GaringerNC2019_raw.csv")
```

Wrangle

2. Combine your ten datasets into one dataset called GaringerOzone. Think about whether you should use a join or a row bind.
3. Set your date column as a date class.
4. Wrangle your dataset so that it only contains the columns Date, Daily.Max.8.hour.Ozone.Concentration, and DAILY_AQI_VALUE.
5. Notice there are a few days in each year that are missing ozone concentrations. We want to generate a daily dataset, so we will need to fill in any missing days with NA. Create a new data frame that contains a sequence of dates from 2010-01-01 to 2019-12-13 (hint: `as.data.frame(seq())`). Call this new data frame Days. Rename the column name in Days to "Date".
6. Use a `left_join` to comine the data frames. Specify the correct order of data frames within this function so that the final dimensions are 3652 rows and 3 columns. Call your combined data frame GaringerOzone.

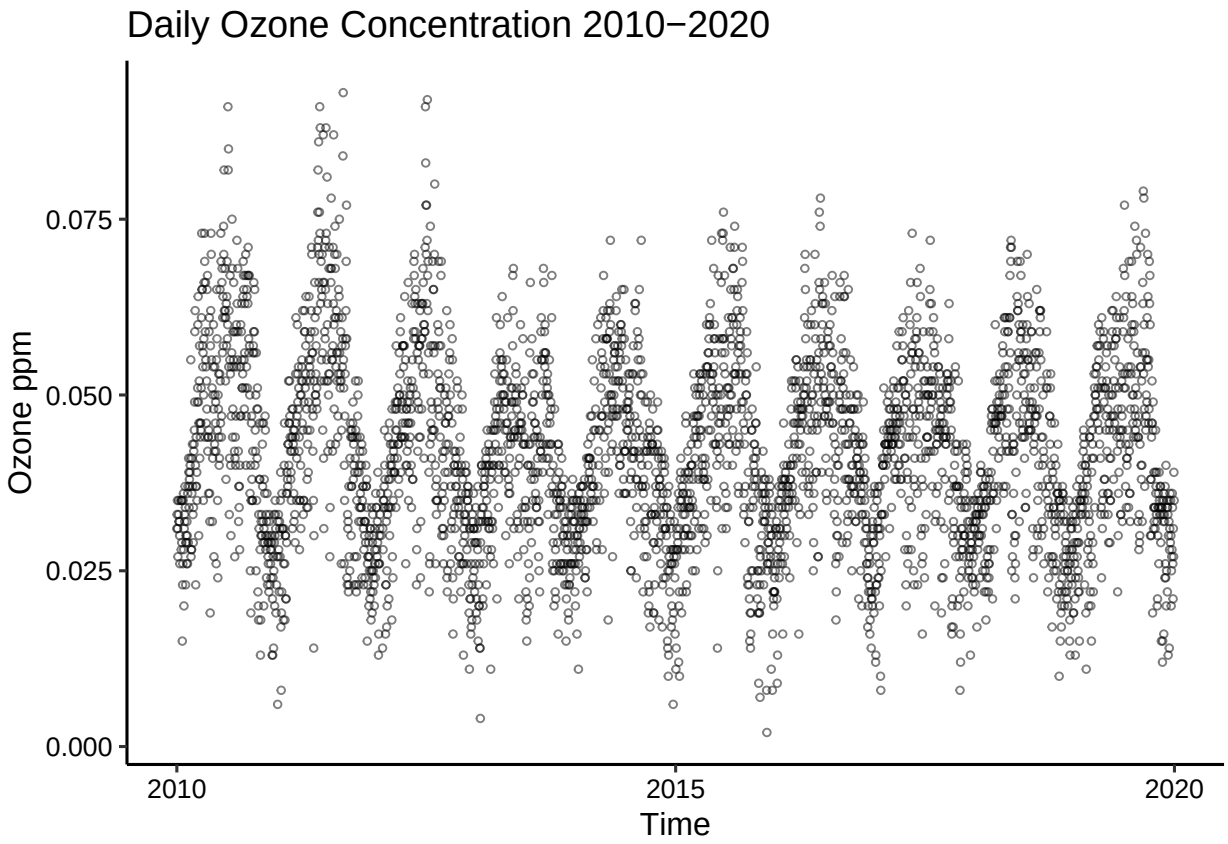
```r
# 2
GaringerOzone <- rbind(Garingerzone2010,Garingerzone2011,Garingerzone2012,Garingerzone2013,Garingerzone
# 3
GaringerOzone$Date <- as.Date(GaringerOzone$Date, format="%m/%d/%Y")
# 4
my.GaringerOzone <- GaringerOzone[,c("Date", "Daily.Max.8.hour.Ozone.Concentration", "DAILY_AQI_VALUE")]

# 5
Days <- as.data.frame(seq(c(ISOdate(2010,1,1)),c(ISOdate(2019,12,31)), by = "day"))
names(Days) <- c("Date")
# 6 Use a `left_join` to comine the data frames. Specify the correct order of data frames within this f

Days$Date <- as.Date(Days$Date, format ="%Y%m%d")
GaringerOzone <- left_join(Days,my.GaringerOzone, by = "Date")
```

Visualize

7. Create a ggplot depicting ozone concentrations over time. In this case, we will plot actual concentrations in ppm, not AQI values. Format your axes accordingly.

```
p.ozone <- ggplot(GaringerOzone,
                  aes(Date,Daily.Max.8.hour.Ozone.Concentration))+                    geom_point(size=
                  labs(x="Time", y= "Ozone ppm",
                  title = "Daily Ozone Concentration 2010-2020")
print(p.ozone)
```

```
## Warning: Removed 63 rows containing missing values (geom_point).
```



Time Series Analysis

Study question: Have ozone concentrations changed over the 2010s at this station?

8. Use a linear interpolation to fill in missing daily data for ozone concentration. Why didn't we use a piecewise constant or spline interpolation?

   Answer: As we glimpse the data, we find no data as same as the neighbor day, so the Piecewise constant method is not applicable. The graph of ozone concentration shows the trends of data could be linked with a straight line, then we can choose the linear method, not "spline" which is much complicated.

9. Create a new data frame called GaringerOzone.monthly that contains aggregated data: mean ozone concentrations for each month. In your pipe, you will need to first add columns for year and month to form the groupings. In a separate line of code, create a new Date column with each month-year combination being set as the first day of the month (this is for graphing purposes only)

10. Generate a time series called GaringerOzone.monthly.ts, with a monthly frequency that specifies the correct start and end dates.

11. Run a time series analysis. In this case the seasonal Mann-Kendall is most appropriate; why is this?

    Answer: Because the concentrations of ozone are significant seasonal and we use the mean concentrations of the month which are reduced temporal autocorrelation so seasonal Mann-Kendall is the most appropriate choice.

12. To figure out the slope of the trend, run the function `sea.sens.slope` on the time series dataset.

13. Create a plot depicting mean monthly ozone concentrations over time, with both a geom_point and a geom_line layer. No need to add a line for the seasonal Sen's slope; this is difficult to apply to a graph with time as the x axis. Edit your axis labels accordingly.

```
# 8
GaringerOzone$Daily.Max.8.hour.Ozone.Concentration<- na.approx(GaringerOzone$Daily.Max.8.hour.Ozone.Con

# 9
GaringerOzone.monthly <- GaringerOzone %>%
  mutate(Year = year(Date),
         Month = month(Date)) %>%
  group_by(Year, Month) %>%
  summarise(Concentration = mean(Daily.Max.8.hour.Ozone.Concentration))

GaringerOzone.monthly$Date <-      as.Date(paste(GaringerOzone.monthly$Year, GaringerOzone.monthly$Mont

# 10
GaringerOzone.monthly.ts <- ts(GaringerOzone.monthly$Concentration,
                   frequency = 12,
                  start = c(2010, 1, 1), end = c(2019, 12, 1))

# 11
GaringerOzone.trend <- smk.test(GaringerOzone.monthly.ts)
summary(GaringerOzone.trend)
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data: GaringerOzone.monthly.ts
## alternative hypothesis: two.sided
##
## Statistics for individual seasons
##
## H0
##                      S varS    tau      z Pr(>|z|)
## Season 1:   S = 0   15  125  0.333  1.252  0.21050
## Season 2:   S = 0   -1  125 -0.022  0.000  1.00000
## Season 3:   S = 0   -4  124 -0.090 -0.269  0.78762
## Season 4:   S = 0  -17  125 -0.378 -1.431  0.15241
## Season 5:   S = 0  -15  125 -0.333 -1.252  0.21050
## Season 6:   S = 0  -17  125 -0.378 -1.431  0.15241
## Season 7:   S = 0  -11  125 -0.244 -0.894  0.37109
## Season 8:   S = 0   -7  125 -0.156 -0.537  0.59151
## Season 9:   S = 0   -5  125 -0.111 -0.358  0.72051
## Season 10:   S = 0 -13  125 -0.289 -1.073  0.28313
## Season 11:   S = 0 -13  125 -0.289 -1.073  0.28313
## Season 12:   S = 0  11  125  0.244  0.894  0.37109
## ---
```

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

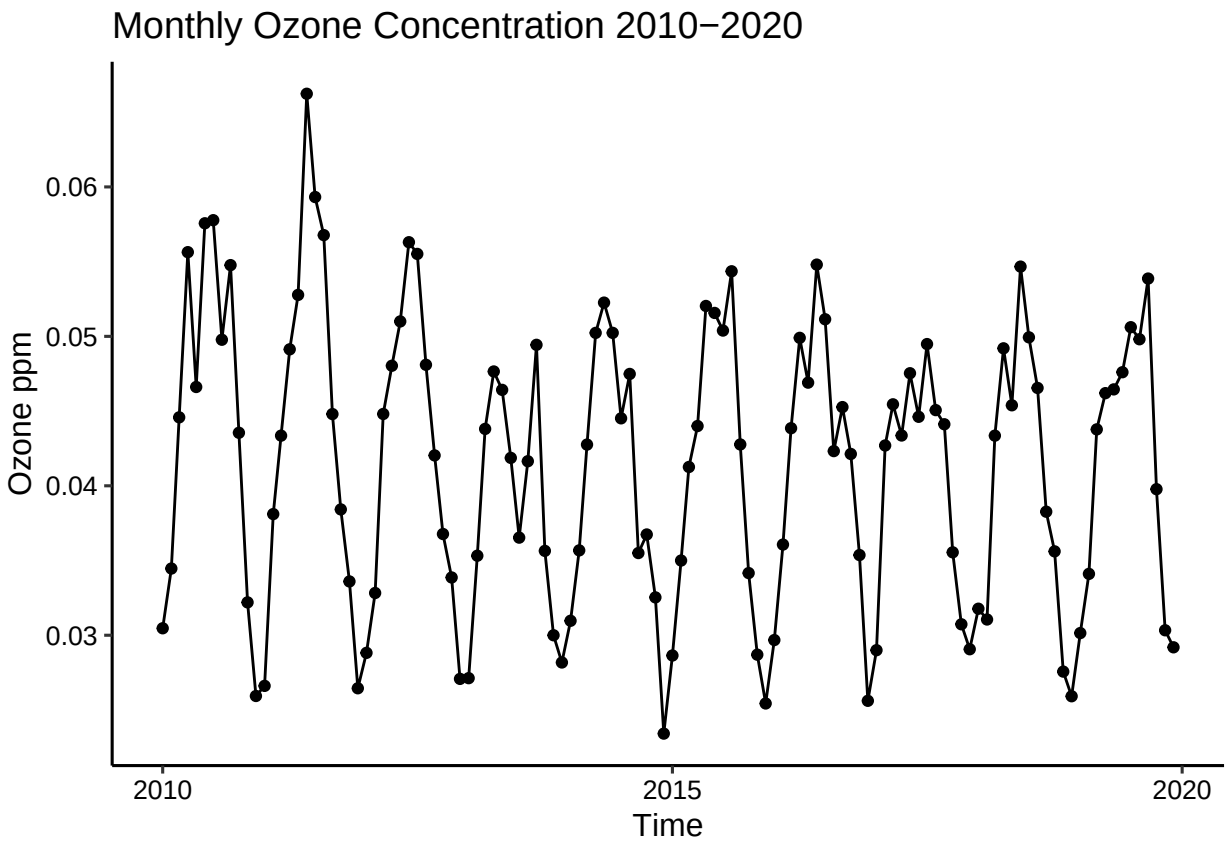
```
GaringerOzone.trend
```

```
##
##  Seasonal Mann-Kendall trend test (Hirsch-Slack test)
##
## data:  GaringerOzone.monthly.ts
## z = -1.963, p-value = 0.04965
## alternative hypothesis: true S is not equal to 0
## sample estimates:
##    S varS
##  -77 1499
```

```
# 12
sea.sens.slope(GaringerOzone.monthly.ts)
```

```
## [1] -0.0002044163
```

```
# 13

GaringerOzone.month <-
ggplot(GaringerOzone.monthly, aes(x = Date, y = Concentration)) +
  geom_point() +
  geom_line() +
  labs(x="Time", y= "Ozone ppm",
                 title = "Monthly Ozone Concentration 2010-2020")
print(GaringerOzone.month)
```



14. To accompany your graph, summarize your results in context of the research question. Include output from the statistical test in parentheses at the end of your sentence. Feel free to use multiple sentences in your interpretation.

    Answer: The graph shows the monthly average concentrations of ozone in 2019 is lower than in 2010 at Garinger. The whole trend of the change is not very obvious. the statistics result indicates that there is a little decreasing trend from 2010 to now(sea.sens.slope=-0.0002).