Assignment 4: Data Wrangling (Spring 2025)

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OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on Data Wrangling

Directions

1. Rename this file `<FirstLast>_A04_DataWrangling.Rmd` (replacing `<FirstLast>` with your first and last name).
2. Change "Student Name" on line 3 (above) with your name.
3. Work through the steps, **creating code and output** that fulfill each instruction.
4. Be sure to **answer the questions** in this assignment document.
5. When you have completed the assignment, **Knit** the text and code into a single PDF file.
6. Ensure that code in code chunks does not extend off the page in the PDF.

Set up your session

1a. Load the `tidyverse`, `lubridate`, and `here` packages into your session.

1b. Check your working directory.

1c. Read in all four raw data files associated with the EPA Air dataset, being sure to set string columns to be read in a factors. See the README file for the EPA air datasets for more information (especially if you have not worked with air quality data previously).

2. Add the appropriate code to reveal the dimensions of the four datasets.

```
#1a: I'm loading the packages into my session
library(tidyverse)
library(lubridate)
library(here)

#1b: Now I'm checking the working directory
getwd()
```

```
## [1] "/home/guest/R/EDA_Spring2025"
```

```
#1c: Now I'm reading in all data
EPAair_O3_NC2018_raw <- read.csv(here("./Data/Raw/EPAair_O3_NC2018_raw.csv"),
stringsAsFactors = TRUE)

EPAair_O3_NC2019_raw <- read.csv(here("./Data/Raw/EPAair_O3_NC2019_raw.csv"),
```

```
stringsAsFactors = TRUE)

EPAair_PM25_NC2018_raw <- read.csv(here
("./Data/Raw/EPAair_PM25_NC2018_raw.csv"), stringsAsFactors = TRUE)

EPAair_PM25_NC2019_raw <- read.csv(here
("./Data/Raw/EPAair_PM25_NC2019_raw.csv"), stringsAsFactors = TRUE)

#2: Now, I'm calculating the dimension of the datasets

dim(EPAair_O3_NC2018_raw)
```

```
## [1] 9737   20
```

```
dim(EPAair_O3_NC2019_raw)
```

```
## [1] 10592    20
```

```
dim(EPAair_PM25_NC2018_raw)
```

```
## [1] 8983   20
```

```
dim(EPAair_PM25_NC2019_raw)
```

```
## [1] 8581   20
```

> All four datasets should have the same number of columns but unique record counts (rows). Do your datasets follow this pattern?

#Answer:Yes, all of the datasets have 20 columns but different rows.

Wrangle individual datasets to create processed files.

3. Change the Date columns to be date objects.
4. Select the following columns: Date, DAILY_AQI_VALUE, Site.Name, AQS_PARAMETER_DESC, COUNTY, SITE_LATITUDE, SITE_LONGITUDE
5. For the PM2.5 datasets, fill all cells in AQS_PARAMETER_DESC with "PM2.5" (all cells in this column should be identical).
6. Save all four processed datasets in the Processed folder. Use the same file names as the raw files but replace "raw" with "processed".

```
#3 I change the data columns to be date objects
EPAair_O3_NC2018_raw$Date <- lubridate::mdy(EPAair_O3_NC2018_raw$Date)

EPAair_O3_NC2019_raw$Date <- lubridate::mdy(EPAair_O3_NC2019_raw$Date)

EPAair_PM25_NC2018_raw$Date <- lubridate::mdy(EPAair_PM25_NC2018_raw$Date)
```

```
EPAair_PM25_NC2019_raw$Date <- lubridate::mdy(EPAair_PM25_NC2019_raw$Date)


#4 Now, I'm selecting required columns

selected_columns <- c("Date", "DAILY_AQI_VALUE", "Site.Name",
  "AQS_PARAMETER_DESC", "COUNTY", "SITE_LATITUDE", "SITE_LONGITUDE")

EPAair_O3_NC2018_processed <- EPAair_O3_NC2018_raw %>%
  select(all_of(selected_columns))

EPAair_O3_NC2019_processed <- EPAair_O3_NC2019_raw %>%
  select(all_of(selected_columns))

EPAair_PM25_NC2018_processed <- EPAair_PM25_NC2018_raw %>%
  select(all_of(selected_columns))

EPAair_PM25_NC2019_processed <- EPAair_PM25_NC2019_raw %>%
  select(all_of(selected_columns))

#5 Filling the cells AQS_PARAMETER_DESC with "PM2.5"

EPAair_PM25_NC2018_processed$AQS_PARAMETER_DESC <- "PM2.5"
EPAair_PM25_NC2019_processed$AQS_PARAMETER_DESC <- "PM2.5"

#6 saving the processed datasets

write.csv(EPAair_O3_NC2018_processed,
here("./Data/Processed/EPAair_O3_NC2018_processed.csv"), row.names = FALSE)

write.csv(EPAair_O3_NC2019_processed,
here("./Data/Processed/EPAair_O3_NC2019_processed.csv"), row.names = FALSE)

write.csv(EPAair_PM25_NC2018_processed,
here("./Data/Processed/EPAair_PM25_NC2018_processed.csv"), row.names = FALSE)

write.csv(EPAair_PM25_NC2019_processed,
here("./Data/Processed/EPAair_PM25_NC2019_processed.csv"), row.names = FALSE)
```

Combine datasets

7. Combine the four datasets with `rbind`. Make sure your column names are identical prior to running this code.

8. Wrangle your new dataset with a pipe function (%>%) so that it fills the following conditions:

- Include only sites that the four data frames have in common:

"Linville Falls", "Durham Armory", "Leggett", "Hattie Avenue",
"Clemmons Middle", "Mendenhall School", "Frying Pan Mountain", "West Johnston Co.", "Garinger High School", "Castle Hayne", "Pitt Agri. Center", "Bryson City", "Millbrook School"

(the function `intersect` can figure out common factor levels - but it will include sites with missing site information, which you don't want...)

- Some sites have multiple measurements per day. Use the split-apply-combine strategy to generate daily means: group by date, site name, AQS parameter, and county. Take the mean of the AQI value, latitude, and longitude.
- Add columns for "Month" and "Year" by parsing your "Date" column (hint: `lubridate` package)
- Hint: the dimensions of this dataset should be 14,752 x 9.

9. Spread your datasets such that AQI values for ozone and PM2.5 are in separate columns. Each location on a specific date should now occupy only one row.
10. Call up the dimensions of your new tidy dataset.
11. Save your processed dataset with the following file name: "EPAair_O3_PM25_NC1819_Processed.csv"

```
#7 I'm combining the datasets
combined_data <- bind_rows(
  EPAair_O3_NC2018_processed,
  EPAair_O3_NC2019_processed,
  EPAair_PM25_NC2018_processed,
  EPAair_PM25_NC2019_processed
)

#8 I'm defining the list of common sites.

common_sites <- c("Linville Falls", "Durham Armory", "Leggett", "Hattie Avenue",
                  "Clemmons Middle", "Mendenhall School", "Frying Pan Mountain",
                  "West Johnston Co.", "Garinger High School", "Castle Hayne",
                  "Pitt Agri. Center", "Bryson City", "Millbrook School")

# Now I'm wrangling the combined data
Wrangled_data <- combined_data %>%
  filter(Site.Name %in% c( "Linville Falls", "Durham Armory", "Leggett",
"Hattie Avenue", "Clemmons Middle", "Mendenhall School", "Frying Pan Mountain",
"West Johnston Co.", "Garinger High School", "Castle Hayne", "Pitt Agri.
Center", "Bryson City", "Millbrook School")) %>%
  group_by(Date, Site.Name, AQS_PARAMETER_DESC, COUNTY) %>%
  summarize( mean_AQI = mean(DAILY_AQI_VALUE), SITE_LATITUDE =
               mean(SITE_LATITUDE), SITE_LONGITUDE = mean(SITE_LONGITUDE) ) %>%
  mutate( year=year(Date),
          month = month(Date))
```

```
## `summarise()` has grouped output by 'Date', 'Site.Name', 'AQS_PARAMETER_DESC'.
## You can override using the `.groups` argument.
```

```
#9 Spreading the datasets
final_tidy_data <- Wrangled_data %>%
  pivot_wider(
    names_from = AQS_PARAMETER_DESC,
    values_from = mean_AQI)

#10 checking the dimension of the dataset
dim(final_tidy_data)
```

```
## [1] 8279    9
```

```
#11 saving the processed data
write.csv(final_tidy_data,
          here("./Data/Processed/EPAair_O3_PM25_NC1819_Processed.csv"),
          row.names = FALSE)
```

Generate summary tables

12. Use the split-apply-combine strategy to generate a summary data frame. Data should be grouped by site, month, and year. Generate the mean AQI values for ozone and PM2.5 for each group. Then, add a pipe to remove instances where mean **ozone** values are not available (use the function `drop_na` in your pipe). It's ok to have missing mean PM2.5 values in this result.

13. Call up the dimensions of the summary dataset.

```
#12 I group data  by site, month, and year, also calculated mean AQI for
#ozone and PM2.5
summary_data <- final_tidy_data %>%
  group_by(Site.Name,month,year) %>%
  summarize(
    mean_Ozone = mean(Ozone),
    mean_PM25 = mean(PM2.5)
    ) %>%

  #na.omit(mean_Ozone)

drop_na(mean_Ozone)
```

```
## `summarise()` has grouped output by 'Site.Name', 'month'. You can override
## using the `.groups` argument.
```

```
#13
dim(summary_data)
```

```
## [1] 171   5
```

14. Why did we use the function `drop_na` rather than `na.omit`? Hint: replace `drop_na` with `na.omit` in part 12 and observe what happens with the dimensions of the summary date frame.

    Answer: We use drop_na instead of na.omit because drop_na allows us to remove rows with missing values only in specific columns, preserving useful data in other columns. In contrast, na.omit eliminates any row containing at least one missing value across all columns, which can drastically reduce the dataset size and potentially discard valuable information. This selective approach helps retain a more comprehensive and informative dataset for analysis, particularly when some missing values are in non-essential columns.I have also replaced drop_na with na.omit and the dimesnion has changed from 8976 9 to 101 5, which means na.omit has reduced the dataset size significantly.However, when I use the drop_na, it is going to be 182 5. I also found that with having omit.na, the knit option does not work.