Lab 05 - Data Wrangling

Learning goals

- Use the `merge()` function to join two datasets.
- Deal with missings and impute data.
- Identify relevant observations using `quantile()`.
- Practice your GitHub skills.

Lab description

For this lab we will be dealing with the meteorological dataset `met`. In this case, we will use `data.table` to answer some questions regarding the `met` dataset, while at the same time practice your Git+GitHub skills for this project.

This markdown document should be rendered using `github_document` document.

Part 1: Setup a Git project and the GitHub repository

1. Go to wherever you are planning to store the data on your computer, and create a folder for this project

2. In that folder, save this template as "README.Rmd". This will be the markdown file where all the magic will happen.

3. Go to your GitHub account and create a new repository of the same name that your local folder has, e.g., "JSC370-labs".

4. Initialize the Git project, add the "README.Rmd" file, and make your first commit.

5. Add the repo you just created on GitHub.com to the list of remotes, and push your commit to origin while setting the upstream.

Most of the steps can be done using command line:

```
# Step 1
cd ~/Documents
mkdir JSC370-labs
cd JSC370-labs

# Step 2
wget https://raw.githubusercontent.com/JSC370/jsc370-2023/main/labs/lab05/lab05-wrangling-gam.Rmd
mv lab05-wrangling-gam.Rmd README.Rmd
# if wget is not available,
curl https://raw.githubusercontent.com/JSC370/jsc370-2023/main/labs/lab05/lab05-wrangling-gam.Rmd --outp
```

```
# Step 3
# Happens on github

# Step 4
git init
git add README.Rmd
git commit -m "First commit"

# Step 5
git remote add origin git@github.com:[username]/JSC370-labs
git push -u origin master
```

You can also complete the steps in R (replace with your paths/username when needed)

```r
# Step 1
setwd("~/Documents")
dir.create("JSC370-labs")
setwd("JSC370-labs")

# Step 2
download.file(
  "https://raw.githubusercontent.com/JSC370/jsc370-2023/main/labs/lab05/lab05-wrangling-gam.Rmd",
  destfile = "README.Rmd"
  )

# Step 3: Happens on Github

# Step 4
system("git init && git add README.Rmd")
system('git commit -m "First commit"')

# Step 5
system("git remote add origin git@github.com:[username]/JSC370-labs")
system("git push -u origin master")
```

Once you are done setting up the project, you can now start working with the MET data.

Setup in R

1. Load the `data.table` (and the `dtplyr` and `dplyr` packages if you plan to work with those).

```r
library(data.table)
library(dtplyr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:data.table':
##
##     between, first, last
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag

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

```
library(ggplot2)
library(mgcv)
```

```
## Loading required package: nlme

##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##     collapse

## This is mgcv 1.8-41. For overview type 'help("mgcv-package")'.
```

```
library(leaflet)
```

2. Load the met data from https://github.com/JSC370/jsc370-2023/blob/main/labs/lab03/met_all.gz or (Use https://raw.githubusercontent.com/JSC370/jsc370-2023/main/labs/lab03/met_all.gz to download programmatically), and also the station data. For the latter, you can use the code we used during lecture to pre-process the stations data:

```
fn <- "https://raw.githubusercontent.com/JSC370/jsc370-2023/main/labs/lab03/met_all.gz"
if (!file.exists("met_all.gz"))
  download.file(fn, destfile = "met_all.gz")
met <- data.table::fread("met_all.gz")

head(met)
```

```
##    USAFID  WBAN year month day hour min  lat      lon elev wind.dir wind.dir.qc
## 1: 690150 93121 2019     8   1    0  56 34.3 -116.166  696      220           5
## 2: 690150 93121 2019     8   1    1  56 34.3 -116.166  696      230           5
## 3: 690150 93121 2019     8   1    2  56 34.3 -116.166  696      230           5
## 4: 690150 93121 2019     8   1    3  56 34.3 -116.166  696      210           5
## 5: 690150 93121 2019     8   1    4  56 34.3 -116.166  696      120           5
## 6: 690150 93121 2019     8   1    5  56 34.3 -116.166  696       NA           9
##    wind.type.code wind.sp wind.sp.qc ceiling.ht ceiling.ht.qc ceiling.ht.method
## 1:              N     5.7          5      22000             5                 9
## 2:              N     8.2          5      22000             5                 9
## 3:              N     6.7          5      22000             5                 9
## 4:              N     5.1          5      22000             5                 9
## 5:              N     2.1          5      22000             5                 9
## 6:              C     0.0          5      22000             5                 9
##    sky.cond vis.dist vis.dist.qc vis.var vis.var.qc temp temp.qc dew.point
```

```
## 1:        N    16093          5       N          5 37.2       5       10.6
## 2:        N    16093          5       N          5 35.6       5       10.6
## 3:        N    16093          5       N          5 34.4       5        7.2
## 4:        N    16093          5       N          5 33.3       5        5.0
## 5:        N    16093          5       N          5 32.8       5        5.0
## 6:        N    16093          5       N          5 31.1       5        5.6
##    dew.point.qc atm.press atm.press.qc       rh
## 1:            5    1009.9            5 19.88127
## 2:            5    1010.3            5 21.76098
## 3:            5    1010.6            5 18.48212
## 4:            5    1011.6            5 16.88862
## 5:            5    1012.7            5 17.38410
## 6:            5    1012.7            5 20.01540
```

```r
# Download the data
stations <- fread("ftp://ftp.ncdc.noaa.gov/pub/data/noaa/isd-history.csv")
stations[, USAF := as.integer(USAF)]
```

```
## Warning in eval(jsub, SDenv, parent.frame()): NAs introduced by coercion
```

```r
# Dealing with NAs and 999999
stations[, USAF   := fifelse(USAF == 999999, NA_integer_, USAF)]
stations[, CTRY   := fifelse(CTRY == "", NA_character_, CTRY)]
stations[, STATE  := fifelse(STATE == "", NA_character_, STATE)]

# Selecting the three relevant columns, and keeping unique records
stations <- unique(stations[, list(USAF, CTRY, STATE)])

# Dropping NAs
stations <- stations[!is.na(USAF)]

# Removing duplicates
stations[, n := 1:.N, by = .(USAF)]
stations <- stations[n == 1,][, n := NULL]
```

3. Merge the data as we did during the lecture.

```r
met <- merge(
# Data
 x = met,
 y = stations,
# List of variables to match
 by.x = "USAFID",
 by.y = "USAF",
# Which obs to keep?
 all.x = TRUE,
 all.y = FALSE
 )

head(met[, list(USAFID, WBAN, STATE)], n = 4)
```

```
##    USAFID  WBAN STATE
```

```
## 1: 690150 93121    CA
## 2: 690150 93121    CA
## 3: 690150 93121    CA
## 4: 690150 93121    CA
```

```
met_lz <- lazy_dt(met, immutable= FALSE)
```

Question 1: Representative station for the US

Across all weather stations, what is the median station in terms of temperature, wind speed, and atmospheric pressure? Look for the three weather stations that best represent continental US using the `quantile()` function. Do these three coincide?

```
# Get the mean statistics for each weather station
met_avg_lz <- met_lz |>
  group_by(USAFID) |>
  summarise(
    across(
      c(temp, wind.sp, atm.press, lat, lon),
      function(x) mean(x, na.rm = TRUE)
    )
  )
```

```
# Find medians of temp, wind.sp, atm.press
met_med_lz <- met_avg_lz |>
  summarise(across(
    2:4,
    function(x) quantile(x, probs = .5, na.rm = TRUE)
  ))
```

```
# Find the weather station whose average statistic is closest to the median.
# temperature
temp_us_id <- met_avg_lz |>
  mutate(d = abs(temp - met_med_lz |> pull(temp))) |>
  arrange(d) |>
  slice(1) |>
  pull(USAFID)

# wind speed
wsp_us_id <- met_avg_lz |>
  mutate(d = abs(wind.sp - met_med_lz |> pull(wind.sp))) |>
  arrange(d) |>
  slice(1) |>
  pull(USAFID)

# atm speed
atm_us_id <- met_avg_lz |>
  mutate(d = abs(atm.press - met_med_lz |> pull(atm.press))) |>
  arrange(d) |>
  slice(1) |>
  pull(USAFID)
```

```r
# Present the results in a table
met_avg_lz_q1 <- met_avg_lz |>
  select(USAFID, lon, lat) |>
  distinct() |>
  filter(USAFID %in% c(temp_us_id, wsp_us_id, atm_us_id))

as.data.table(met_avg_lz_q1)
```

```
##    USAFID       lon     lat
## 1: 720458 -82.63700 37.7510
## 2: 720929 -91.98100 45.5060
## 3: 722238 -85.66667 31.3499
```

```r
as.data.table(met_med_lz)
```

```
##        temp  wind.sp atm.press
## 1: 23.68406 2.461838  1014.691
```

Answer: From the table above, we can see median temperature, wind speed and atm. The other table shows the weather stations whose average is the closest to one of these three medians. The three weather stations are different, so they do not coincide.

Knit the document, commit your changes, and save it on GitHub. Don't forget to add `README.md` to the tree, the first time you render it.

Question 2: Representative station per state

Just like the previous question, you are asked to identify what is the most representative, the median, station per state. This time, instead of looking at one variable at a time, look at the euclidean distance. If multiple stations show in the median, select the one located at the lowest latitude.

```r
# Find the median station per state
met_avg_by_state_lz <- met_lz |>
  group_by(STATE) |>
  summarise(
    across(
      c(temp, wind.sp, atm.press, lat, lon),
      function(x) mean(x, na.rm = TRUE)
    )
  )


# Summarise the mean by USAFID (i.e. by weather stations)
met_avg_by_USAFID <- met |>
  group_by(USAFID) |>
  summarise(
    across(
      c(temp, wind.sp, atm.press, lat, lon),
      function(x) mean(x, na.rm = TRUE)
    )
  )
```

```r
# Add State to met_by_USAFID
met_avg_by_USAFID <- merge(
 x = met_avg_by_USAFID,
 y = stations,
 by.x = "USAFID",
 by.y = "USAF",
 all.x = TRUE,
 all.y = FALSE
 )


# Further merge the median statistics by state to the average statistics by USAFID
met_avg_by_USAFID <- merge(
  x = met_avg_by_USAFID,
  y = met_avg_by_state_lz,
  by.x = "STATE",
  by.y = "STATE",
  all.x = TRUE,
  all.y = FALSE
)

# Now each row have the average statistics for each weather stations, and the median statistics for the
# met_avg_by_USAFID

# We can now calculate the Euclidean distance between each weather station's mean and their states' med
met_avg_by_USAFID <- met_avg_by_USAFID |>
  mutate(d = (temp.x - temp.y)^2 + (wind.sp.x - wind.sp.y)^2 + (atm.press.x - atm.press.y)^2)

# Show the results.
met_avg_by_USAFID <- met_avg_by_USAFID |>
  group_by(STATE) |>
  slice(which.min(d))

met_avg_by_USAFID
```

```
## # A tibble: 46 x 14
## # Groups:   STATE [46]
##    STATE USAFID temp.x wind.~1 atm.p~2 lat.x  lon.x CTRY  temp.y wind.~3 atm.p~4
##    <chr>  <int>  <dbl>   <dbl>   <dbl> <dbl>  <dbl> <chr>  <dbl>   <dbl>   <dbl>
##  1 AL    722285   25.3    1.45   1016.  34.0  -86.1 US      26.2    1.57   1016.
##  2 AR    723407   25.9    2.21   1015.  35.8  -90.6 US      26.2    1.84   1015.
##  3 AZ    722745   30.3    3.31   1010.  32.2 -111.  US      28.8    2.98   1011.
##  4 CA    722977   22.3    2.36   1013.  33.7 -118.  US      22.4    2.61   1013.
##  5 CO    724676   18.9    3.22   1014.  39.2 -107.  US      19.5    3.08   1014.
##  6 CT    725087   22.6    2.13   1015.  41.7  -72.7 US      22.3    2.19   1015.
##  7 DE    724180   24.6    2.75   1015.  39.7  -75.6 US      24.6    2.76   1015.
##  8 FL    722210   27.7    2.53   1015.  30.5  -86.5 US      27.5    2.50   1015.
##  9 GA    723160   26.6    1.68   1015.  31.5  -82.5 US      26.5    1.51   1015.
## 10 IA    725480   21.4    2.76   1015.  42.6  -92.4 US      21.3    2.57   1015.
## # ... with 36 more rows, 3 more variables: lat.y <dbl>, lon.y <dbl>, d <dbl>,
## #   and abbreviated variable names 1: wind.sp.x, 2: atm.press.x, 3: wind.sp.y,
## #   4: atm.press.y
```

From the table above, it shows the weather station ID (USAFID) which has the most similar statistics to the median of each state. The suffix "dot x" (.x) for the statistics is the statistics of the representing weather station, while the suffix "dot y" (.y) is the statistics for the each of the states.

Knit the doc and save it on GitHub.

Question 3: In the middle?

For each state, identify what is the station that is closest to the mid-point of the state. Combining these with the stations you identified in the previous question, use `leaflet()` to visualize all ~100 points in the same figure, applying different colors for those identified in this question.

```
# Find the mid-point of each state.

states_mid_pts <- met |>
  group_by(STATE) |>
  summarise(
    across(
      c(lat, lon),
      function(x) mean(x, na.rm = TRUE)
    )
  )

as.data.table(states_mid_pts)
```

```
##     STATE      lat        lon
##  1:    AL 32.75554  -86.65318
##  2:    AR 35.18904  -92.68849
##  3:    AZ 33.91659 -111.54154
##  4:    CA 36.50457 -120.03186
##  5:    CO 39.12441 -105.69753
##  6:    CT 41.48119  -72.71733
##  7:    DE 39.15950  -75.47708
##  8:    FL 28.33518  -82.39921
##  9:    GA 32.56718  -83.33168
## 10:    IA 41.85552  -93.49382
## 11:    ID 45.02638 -115.17229
## 12:    IL 40.22512  -88.81862
## 13:    IN 40.51988  -86.33665
## 14:    KS 38.32236  -97.96264
## 15:    KY 37.50187  -85.11900
## 16:    LA 30.51183  -91.71927
## 17:    MA 42.03785  -70.99897
## 18:    MD 39.06089  -76.82664
## 19:    ME 44.60213  -69.57403
## 20:    MI 43.41830  -84.69928
## 21:    MN 45.23699  -94.31785
## 22:    MO 38.28066  -92.75603
## 23:    MS 33.05395  -89.77502
## 24:    MT 45.81591 -108.98264
## 25:    NC 35.55578  -79.17800
## 26:    ND 47.75992 -100.08523
## 27:    NE 41.26627  -98.59109
## 28:    NH 43.54523  -71.55302
```

```
## 29:    NJ 40.31345  -74.47269
## 30:    NM 34.30261 -105.89839
## 31:    NV 38.68753 -117.21082
## 32:    NY 42.40904  -75.50851
## 33:    OH 40.40494  -82.94026
## 34:    OK 35.55121  -97.15465
## 35:    OR 43.31317 -122.79527
## 36:    PA 40.62764  -77.62156
## 37:    RI 41.62342  -71.49612
## 38:    SC 33.92152  -80.79047
## 39:    SD 44.22241  -99.86385
## 40:    TN 35.70926  -86.55706
## 41:    TX 31.12371  -98.01178
## 42:    UT 39.38740 -112.33426
## 43:    VA 37.54765  -78.21585
## 44:    VT 44.35726  -72.58793
## 45:    WA 47.41976 -122.56157
## 46:    WI 44.46353  -89.93145
## 47:    WV 38.72488  -80.58560
## 48:    WY 42.72014 -108.18546
##     STATE      lat        lon
```

```r
# Find the lat and lon for each station
met_lat_lon <- met |>
  group_by(USAFID) |>
  summarise(
    across(
      c(lat, lon),
      function(x) median(x)
    )
  )

# Add State to met_by_USAFID
met_lat_lon <- merge(
 x = met_lat_lon,
 y = stations,
 by.x = "USAFID",
 by.y = "USAF",
 all.x = TRUE,
 all.y = FALSE
 )

# Further merge the with states_mid_pts so we can compare the mid point and the location later.
met_lat_lon <- merge(
  x = met_lat_lon,
  y = states_mid_pts,
  by.x = "STATE",
  by.y = "STATE",
  all.x = TRUE,
  all.y = FALSE
)

# Find the weather stations closest to the midpoint of their respective states.
met_lat_lon <- met_lat_lon |>
```

```r
  mutate(d = abs(lat.x - lat.y) + abs(lon.x - lon.y))

met_lat_lon <- met_lat_lon |>
  group_by(STATE) |>
  slice(which.min(d))

met_lat_lon[1:4]
```

```
## # A tibble: 48 x 4
## # Groups:   STATE [48]
##    STATE USAFID lat.x  lon.x
##    <chr>  <int> <dbl>  <dbl>
##  1 AL    722300  33.2  -86.8
##  2 AR    723429  35.3  -93.1
##  3 AZ    723745  34.3 -111.
##  4 CA    723890  36.8 -120.
##  5 CO    726396  39.0 -106.
##  6 CT    725027  41.5  -72.8
##  7 DE    724088  39.1  -75.5
##  8 FL    722014  28.5  -82.5
##  9 GA    722175  32.6  -83.6
## 10 IA    725466  41.7  -93.6
## # ... with 38 more rows
```

```r
# Create 1 table for Q1, Q2, Q3
# Q1
met_avg_lz_q1 <- as.data.table(met_avg_lz_q1)
met_avg_lz_q1$type <- 'Closest Temp/Wind.sp/Atm.press'

# Q2
met_avg_by_USAFID <- met_avg_by_USAFID[c("USAFID", "lat.x", "lon.x")]
colnames(met_avg_by_USAFID) <- c('USAFID', 'lat', 'lon')
# Add a label
met_avg_by_USAFID$type <- 'Closest Euclidean'

# Q3
met_lat_lon <- met_lat_lon[c('USAFID', 'lat.x', 'lon.x')]
colnames(met_lat_lon) <- c('USAFID', 'lat', 'lon')
# Add a label
met_lat_lon$type <- 'Mid-Point'

# Join the dataset
q3_points <- rbind(as.data.table(met_avg_lz_q1), as.data.table(met_avg_by_USAFID), as.data.table(met_la

# Divide the points from Q1 to Q3 into three colors.
pal <- colorFactor(
  palette = c('red', 'green', 'blue'),
  domain = q3_points$type
)

# Draw the map
leaflet(q3_points) %>%
  addProviderTiles('OpenStreetMap') |>
```

```
  addCircles(lat = ~lat, lng = ~lon, color = ~pal(type),
             label = ~type,
             opacity = 1, fillOpacity = 1, radius = 500) |>
  addLegend(position = 'topleft', values = ~type, pal=pal)
```

The map above shows dots of three colors. The blue dots show the weather stations which are the closest to the center of their state, among other stations in the same state; the red dot show the weather stations who have the most similar average temperature, wind speed and atm pressure to the average of their state; finally, the green dot shows the weather stations concerned in Q1, the ones which best represent continental US in terms of temperature, wind speed and atmospheric pressure.

Knit the doc and save it on GitHub.

Question 4: Means of means

Using the `quantile()` function, generate a summary table that shows the number of states included, average temperature, wind-speed, and atmospheric pressure by the variable "average temperature level," which you'll need to create.

Start by computing the states' average temperature. Use that measurement to classify them according to the following criteria:

- low: temp < 20
- Mid: temp >= 20 and temp < 25
- High: temp >= 25

```
# Find the median station per state
met_avg_temp_by_state_lz <- met_lz |>
  group_by(STATE) |>
  summarise(
    across(
      c(temp, wind.sp, atm.press),
      function(x) mean(x, na.rm = TRUE)
    )
  )

# Make a new variable.
met_avg_temp_by_state_lz <-
  met_avg_temp_by_state_lz |> mutate(avg_temp := ifelse(temp < 20, 'low', ifelse(temp < 25, 'Mid', 'Hig
```

Once you are done with that, you can compute the following:

- Number of entries (records),
- Number of NA entries,
- Number of stations,
- Number of states included, and
- Mean temperature, wind-speed, and atmospheric pressure.

All by the levels described before.

```r
# Merge the data created above with the whole dataset
met_avg_lz_w_state <- merge(
 x = met_avg_lz,
 y = stations,
 by.x = "USAFID",
 by.y = "USAF",
 all.x = TRUE,
 all.y = FALSE
 )

# Merge again with the summary table above.
met_avg_lz_w_state <- merge(
 x = met_avg_lz_w_state,
 y = met_avg_temp_by_state_lz,
 by.x = "STATE",
 by.y = "STATE",
 all.x = TRUE,
 all.y = FALSE
 )

q4_result <- met_avg_lz_w_state |>
  group_by(avg_temp) |>
  summarise(no_of_states = n_distinct(STATE), no_of_stations = n_distinct(USAFID), no_of_na = sum(is.na


# We also need to count number of total entries
total_lz <- met

state_avg_temp <- met_avg_temp_by_state_lz |> select('STATE', 'avg_temp')

total_lz <- merge(
  x = total_lz,
  y = state_avg_temp,
  by.x = 'STATE',
  by.y = 'STATE',
  all.x = TRUE,
  all.y = FALSE
)

count_by_avg_temp <- total_lz |>
  group_by(avg_temp) |>
  summarise(count = n())


q4_result <-
  merge(
  x = q4_result,
  y = count_by_avg_temp,
  by.x = 'avg_temp',
  by.y = 'avg_temp'
)

q4_result
```

```
##   avg_temp no_of_states no_of_stations no_of_na mean_temp mean_wind.sp
## 1     High           12            555      264  27.81202     2.608408
## 2      low           11            259      141  19.22394     2.767630
## 3      Mid           25            781      309  22.57768     2.495189
##   mean_atm.press   count
## 1       1013.733  811126
## 2       1014.365  430794
## 3       1014.380 1135423
```

The table above shows the summary statistics of the weather stations in the US, grouped by whether the temperature of the states they stations are in have a high, mid or low average. The summary contains the number of states and stations for each group, as well as the number of NAs, and mean temperature, wind speed and atm. pressure for the states.

Knit the document, commit your changes, and push them to GitHub.

Question 5: Advanced Regression

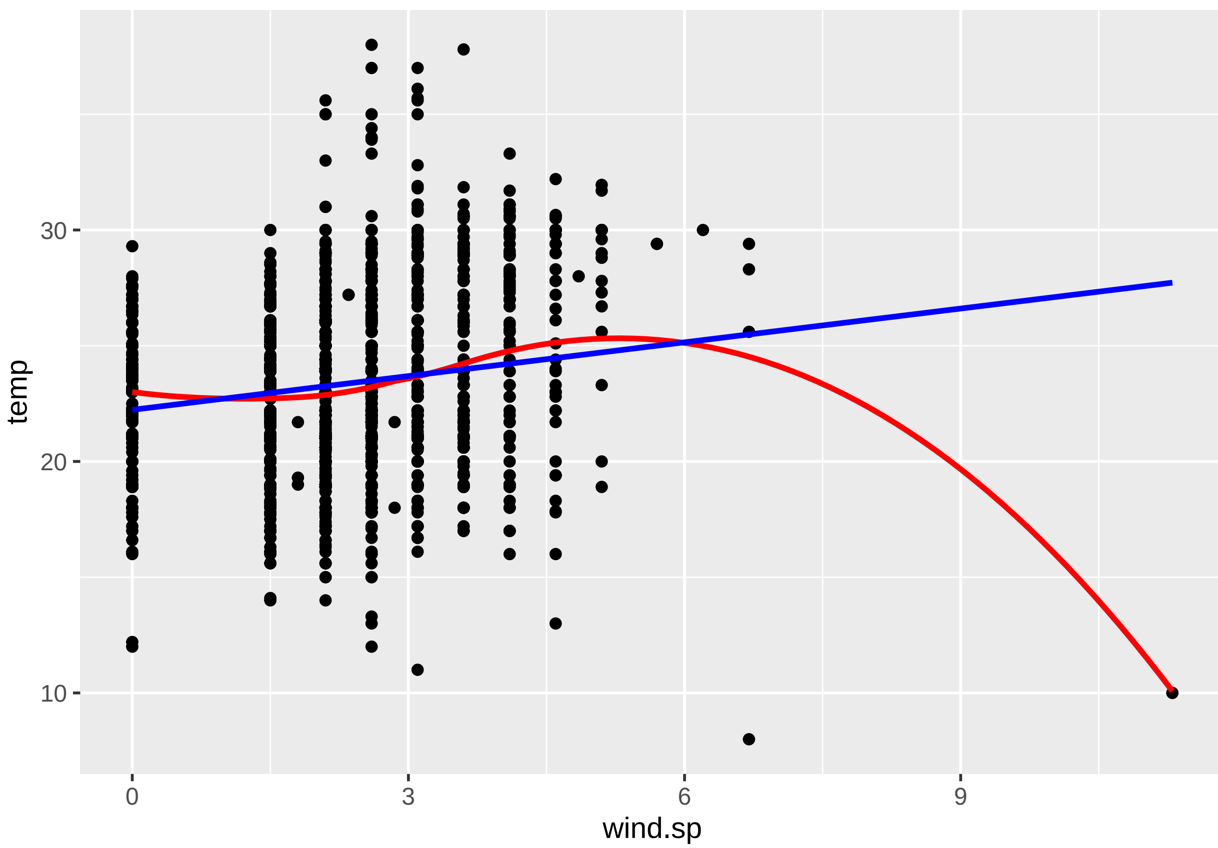
Let's practice running regression models with smooth functions on X. We need the `mgcv` package and `gam()` function to do this.

- using your data with the median values per station, examine the association between median temperature (y) and median wind speed (x). Create a scatterplot of the two variables using ggplot2. Add both a linear regression line and a smooth line.

```r
q5_data <- met_lz |>
  group_by(USAFID) |>
    summarise(across(
    c('temp', 'wind.sp'),
    function(x) quantile(x, probs = .5, na.rm = TRUE)
  ))

q5_data |> filter(!is.na(wind.sp) & !is.na(temp)) |> as.data.table() |>
  ggplot(aes(x = wind.sp, y = temp), na.rm) + geom_point() +
  geom_smooth(method='loess', color = 'red', se = FALSE) +
  geom_smooth(method='lm', formula = y ~ x, color='blue', se=FALSE)
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



- fit both a linear model and a spline model (use `gam()` with a cubic regression spline on wind speed). Summarize and plot the results from the models and interpret which model is the best fit and why.

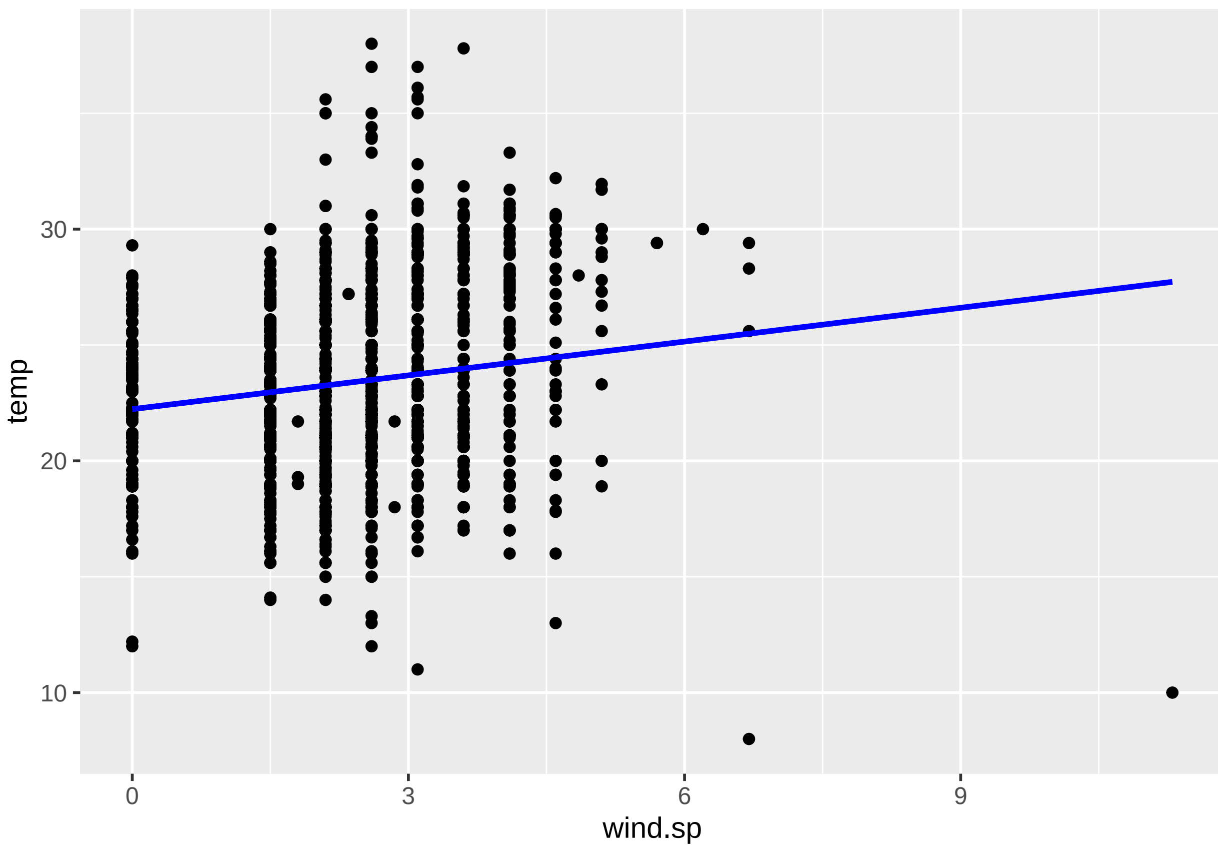
```
q5_data_exploded <- q5_data |> filter(!is.na(wind.sp) & !is.na(temp)) |> as.data.table()

# Linear Model
lm_temp <- lm(temp ~ wind.sp, data=q5_data_exploded)
summary(lm_temp)
```

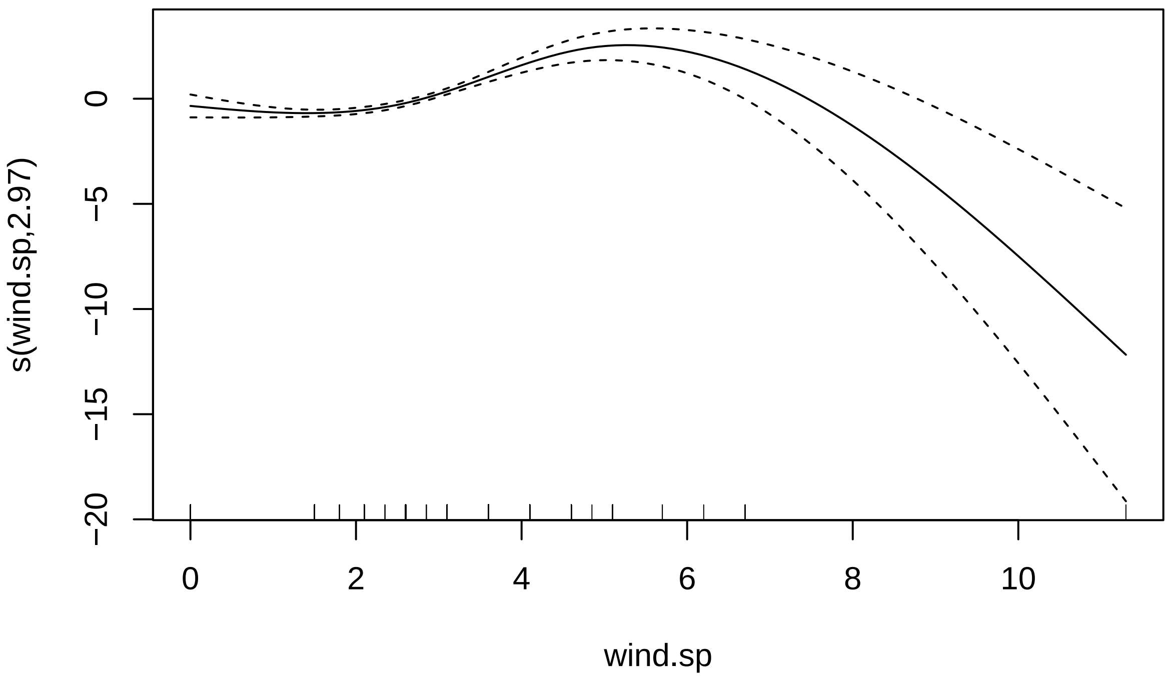
```
##
## Call:
## lm(formula = temp ~ wind.sp, data = q5_data_exploded)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.7243  -2.6518  -0.2309   2.7691  14.5052
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 22.23088    0.21779  102.08  < 2e-16 ***
## wind.sp      0.48614    0.08212    5.92 3.94e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.849 on 1577 degrees of freedom
```

```
## Multiple R-squared:  0.02174,    Adjusted R-squared:  0.02112
## F-statistic: 35.05 on 1 and 1577 DF,  p-value: 3.941e-09
```

```
q5_data_exploded |>
    ggplot(aes(x = wind.sp, y = temp), na.rm=TRUE) + geom_point() +
  geom_smooth(method='lm', formula = y ~ x, color='blue', se=FALSE)
```




```
# Spline model: a cubic regression spline
gam_temp <- gam(temp~s(wind.sp, bs='cr', k=4), data=q5_data_exploded)
plot(gam_temp)
```




```r
summary(gam_temp)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## temp ~ s(wind.sp, bs = "cr", k = 4)
##
## Parametric coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 23.38566    0.09548   244.9   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##              edf Ref.df    F p-value
## s(wind.sp) 2.967  2.999 27.8  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.0489   Deviance explained = 5.07%
## GCV =  14.43  Scale est. = 14.393    n = 1579
```

It is hard to decide which model fits better. On one hand, in the linear regression model, there is a few leverage points with large x values, which are influential on the regression coefficients. This might have made the adjusted R-squared (0.021) lower. On the other hand, the spline model captures the trend of the data points more closely, and this is supported by a higher adjusted R-squared value (0.0489). However, both adjusted R-squared values are quite low, so we should use caution when using either models.