Data Cleaning

Data Wrangling in R

Dealing with Missing Data

Missing data types

One of the most important aspects of data cleaning is missing values.

Types of “missing” data:

- `NA` - general missing data
- `NaN` - stands for “**N**ot **a N**umber”, happens when you do 0/0.
- `Inf` and `-Inf` - Infinity, happens when you take a positive number (or negative number) by 0.

Missing Data with Logicals

Logical operations return `NA` for `NA` values. Think about it, the data could be `> 2` or not we don't know, so `R` says there is no `TRUE` or `FALSE`, so that is missing:

```
x = c(0, NA, 2, 3, 4)
x > 2
```

```
[1] FALSE    NA FALSE  TRUE  TRUE
```

Missing Data with Operations

Similarly with logicals, operations/arithmetic with `NA` will result in `NA`s:

```
x + 2
```

```
[1]  2 NA  4  5  6
```

```
x * 2
```

```
[1]  0 NA  4  6  8
```

Missing Data Issues

Recall that mathematical operations with `NA` often result in `NA`s.

```
sum(c(1,2,3,NA))
```

```
[1] NA
```

```
mean(c(1,2,3,NA))
```

```
[1] NA
```

```
median(c(1,2,3,NA))
```

```
[1] NA
```

Missing Data Issues

Also true when we combine mathematical operations and logicals. Recall that `TRUE` is evaluated as 1 and `FALSE` is evaluated as 0.

```
x <- c(TRUE, TRUE, TRUE, TRUE, FALSE, NA)
sum(x)
```

```
[1] NA
```

```
sum(x, na.rm = TRUE)
```

```
[1] 4
```

Finding Missing data

- `is.na` - looks for `NAN` and `NA`
- `is.nan`- looks for `NAN`
- `is.infinite` - looks for Inf or -Inf

```
test <- c(0,NA, -1)
test/0
```

```
[1]  NaN   NA -Inf
```

```
test <- test/0
is.na(test)
```

```
[1]  TRUE  TRUE FALSE
```

```
is.nan(test)
```

```
[1]  TRUE FALSE FALSE
```

```
is.infinite(test)
```

```
[1] FALSE FALSE  TRUE
```

Useful checking functions

Do we have any `NA`s? (`any` can help)

```
A <- c(1, 2, 3, NA)
B <- c(1, 2, 3, 4)
any(is.na(A)) # are there any NAs - YES/TRUE
```

```
[1] TRUE
```

```
any(is.na(B)) # are there any NAs- NO/FALSE
```

```
[1] FALSE
```

Useful checking functions

Are all the values `NA`? (`all` can help)

```
A <- c(1, 2, 3, NA)
B <- c(1, 2, 3, 4)
all(is.na(A)) # are there any NAs - YES/TRUE
```

```
[1] FALSE
```

```
all(is.na(B)) # are there any NAs- NO/FALSE
```

```
[1] FALSE
```

Finding `NA` values with `count()`

Check the values for your variables, are they what you expect?

`count()` is a great option because it gives you:

1. The unique values
2. The amount of these values

Check if rare values make sense.

```
library(readr)
bike <-read_csv("https://sisbid.github.io/Data-Wrangling/labs/Bike_Lanes.csv")
count(bike, subType)
```

```
# A tibble: 4 × 2
  subType      n
  <chr>    <int>
1 STCLN        1
2 STRALY       3
3 STRPRD    1623
4 <NA>         4
```

`naniar`

Sometimes you need to look at lots of data though… the `naniar` package is a good option.

```
#install.packages("naniar")
library(naniar)
```

Air quality data

The `airquality` dataset comes with R about air quality in New York in 1973.

```
?airquality # use this to find out more about the data
```

naniar: `pct_complete()`

This can tell you if there are missing values in the dataset.

```
pct_complete(airquality)
```

```
[1] 95.20697
```

Or for a particular variable:

```
airquality %>% select(Ozone) %>%
pct_complete()
```

```
[1] 75.81699
```

naniar: `miss_var_summary()`

To get the percent missing (and counts) for each variable as a table, use this function.

```
miss_var_summary(airquality)
```

```
# A tibble: 6 × 3
  variable n_miss pct_miss
  <chr>     <int>    <dbl>
1 Ozone        37    24.2
2 Solar.R       7     4.58
3 Wind          0     0
4 Temp          0     0
5 Month         0     0
6 Day           0     0
```

`miss_case_summary` which rows have missing data in order

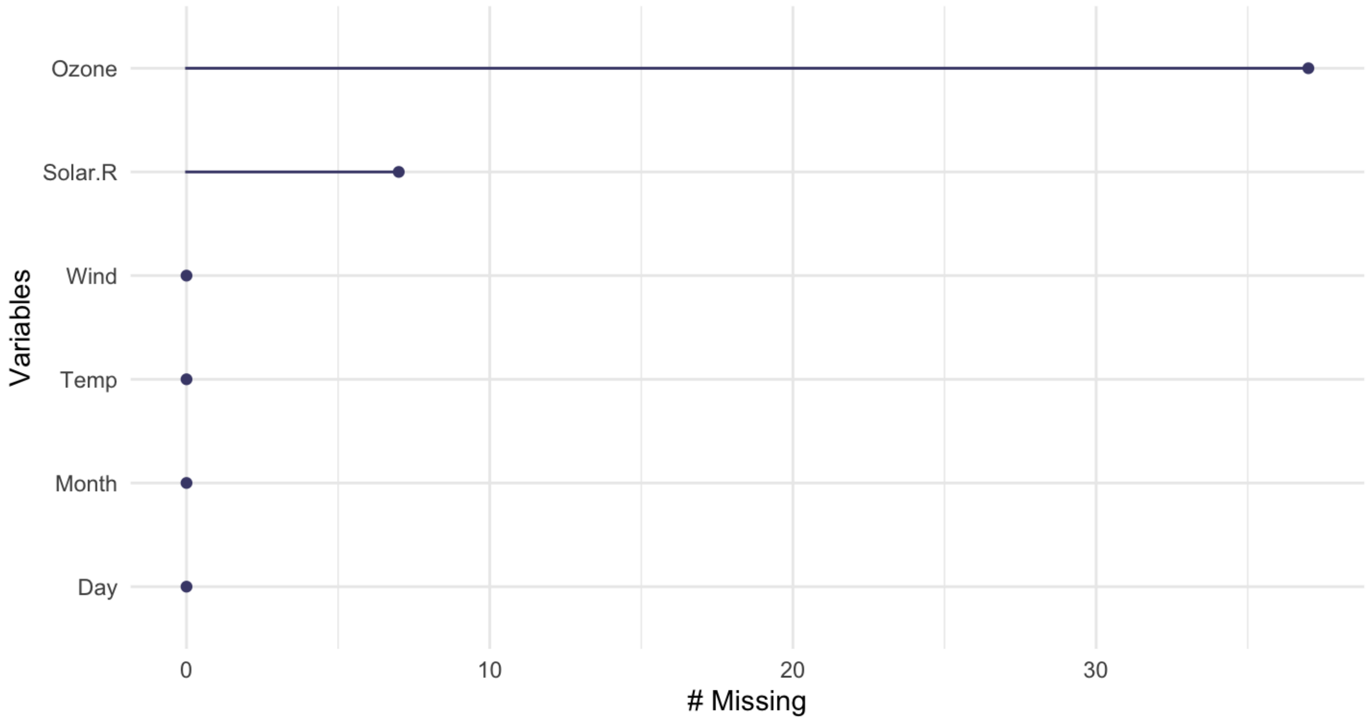
```
miss_case_summary(airquality)
```

```
# A tibble: 153 × 3
    case n_miss pct_miss
   <int>  <int>    <dbl>
 1     5      2     33.3
 2    27      2     33.3
 3     6      1     16.7
 4    10      1     16.7
 5    11      1     16.7
 6    25      1     16.7
 7    26      1     16.7
 8    32      1     16.7
 9    33      1     16.7
10    34      1     16.7
# ℹ 143 more rows
```

naniar plots

The `gg_miss_var()` function creates a nice plot about the number of missing values for each variable, (need a data frame).

```
gg_miss_var(airquality)
```



filter() and missing data

Be **careful** with missing data using subsetting!

`filter()` removes missing values by default. Because R can't tell for sure if an `NA` value meets the condition. To keep them need to add `is.na()` conditional.

Think about if this is OK or not - it depends on your data!

filter() and missing data

What if NA values represent values that are so low it is undetectable?

Filter will drop them from the data.

```
airquality %>% filter(Ozone < 5)
```

```
  Ozone Solar.R Wind Temp Month Day
1     1       8  9.7   59     5  21
2     4      25  9.7   61     5  23
```

filter() and missing data

`is.na()` can help us keep them.

```
airquality %>% filter(Ozone < 5 | is.na(Ozone))
```

```
   Ozone Solar.R Wind Temp Month Day
1     NA      NA 14.3   56     5   5
2     NA     194  8.6   69     5  10
3      1       8  9.7   59     5  21
4      4      25  9.7   61     5  23
5     NA      66 16.6   57     5  25
6     NA     266 14.9   58     5  26
7     NA      NA  8.0   57     5  27
8     NA     286  8.6   78     6   1
9     NA     287  9.7   74     6   2
10    NA     242 16.1   67     6   3
11    NA     186  9.2   84     6   4
12    NA     220  8.6   85     6   5
13    NA     264 14.3   79     6   6
14    NA     273  6.9   87     6   8
15    NA     259 10.9   93     6  11
16    NA     250  9.2   92     6  12
17    NA     332 13.8   80     6  14
18    NA     322 11.5   79     6  15
19    NA     150  6.3   77     6  21
20    NA      59  1.7   76     6  22
21    NA      91  4.6   76     6  23
22    NA     250  6.3   76     6  24
23    NA     135  8.0   75     6  25
```

To remove **rows** with **`NA`** values for a **variable** use **`drop_na()`**

A function from the `tidyr` package. (Need a data frame to start!)

Disclaimer: Don't do this unless you have thought about if dropping `NA` values makes sense based on knowing what these values mean in your data.

```
dim(airquality)
```

```
[1] 153   6
```

```
airquality %>% drop_na(Ozone)
```

```
    Ozone Solar.R Wind Temp Month Day
1      41     190  7.4   67     5   1
2      36     118  8.0   72     5   2
3      12     149 12.6   74     5   3
4      18     313 11.5   62     5   4
5      28      NA 14.9   66     5   6
6      23     299  8.6   65     5   7
7      19      99 13.8   59     5   8
8       8      19 20.1   61     5   9
9       7      NA  6.9   74     5  11
10     16     256  9.7   69     5  12
11     11     290  9.2   66     5  13
12     14     274 10.9   68     5  14
13     18      65 13.2   58     5  15
14     14     334 11.5   64     5  16
15     34     307 12.0   66     5  17
```

To remove rows with `NA` values for a **data frame** use `drop_na()`

This function of the `tidyr` package drops rows with **any** missing data in **any** column when used on a df.

```
airquality %>% drop_na()
```

```
    Ozone Solar.R Wind Temp Month Day
1      41     190  7.4   67     5   1
2      36     118  8.0   72     5   2
3      12     149 12.6   74     5   3
4      18     313 11.5   62     5   4
5      23     299  8.6   65     5   7
6      19      99 13.8   59     5   8
7       8      19 20.1   61     5   9
8      16     256  9.7   69     5  12
9      11     290  9.2   66     5  13
10     14     274 10.9   68     5  14
11     18      65 13.2   58     5  15
12     14     334 11.5   64     5  16
13     34     307 12.0   66     5  17
14      6      78 18.4   57     5  18
15     30     322 11.5   68     5  19
16     11      44  9.7   62     5  20
17      1       8  9.7   59     5  21
18     11     320 16.6   73     5  22
19      4      25  9.7   61     5  23
20     32      92 12.0   61     5  24
21     23      13 12.0   67     5  28
22     45     252 14.9   81     5  29
```

Drop **columns** with any missing values

Use the `miss_var_which()` function from `naniar`

```
miss_var_which(airquality) # which columns have missing values
```

```
[1] "Ozone"   "Solar.R"
```

Drop **columns** with any missing values

`miss_var_which` and function from `naniar` (need a data frame)

```
airquality %>% select(!miss_var_which(airquality))
```

```
    Wind Temp Month Day
1    7.4   67     5   1
2    8.0   72     5   2
3   12.6   74     5   3
4   11.5   62     5   4
5   14.3   56     5   5
6   14.9   66     5   6
7    8.6   65     5   7
8   13.8   59     5   8
9   20.1   61     5   9
10   8.6   69     5  10
11   6.9   74     5  11
12   9.7   69     5  12
13   9.2   66     5  13
14  10.9   68     5  14
15  13.2   58     5  15
16  11.5   64     5  16
17  12.0   66     5  17
18  18.4   57     5  18
19  11.5   68     5  19
20   9.7   62     5  20
21   9.7   59     5  21
22  16.6   73     5  22
23   9.7   61     5  23
```

Change a value to be `NA`

Let's say we think that all 0 values should be `NA`.

```
library(readr)
bike <-read_csv("https://sisbid.github.io/Data-Wrangling/labs/Bike_Lanes.csv")
count(bike, dateInstalled)
```

```
# A tibble: 9 × 2
  dateInstalled     n
          <dbl> <int>
1             0   126
2          2006     2
3          2007   368
4          2008   206
5          2009    86
6          2010   625
7          2011   101
8          2012   107
9          2013    10
```

Change a value to be `NA`

The `na_if()` function of `dplyr` can be helpful for changing all 0 values to `NA`.

```
bike <- bike %>%
  mutate(dateInstalled = na_if(dateInstalled, 0))
count(bike, dateInstalled)
```

```
# A tibble: 9 × 2
  dateInstalled     n
          <dbl> <int>
1          2006     2
2          2007   368
3          2008   206
4          2009    86
5          2010   625
6          2011   101
7          2012   107
8          2013    10
9            NA   126
```

Change `NA` to be a value

The `replace_na()` function (part of the `tidyr` package), can do the opposite of `na_if()`. (note that you must use numeric values as replacement - we will show how to replace with character strings soon)

```
bike %>%
  mutate(dateInstalled = replace_na(dateInstalled, 2005)) %>%
  count(dateInstalled)
```

```
# A tibble: 9 × 2
  dateInstalled     n
          <dbl> <int>
1          2005   126
2          2006     2
3          2007   368
4          2008   206
5          2009    86
6          2010   625
7          2011   101
8          2012   107
9          2013    10
```

Think about `NA`

THINK ABOUT YOUR DATA FIRST!

⚠️ Sometimes removing `NA` values leads to distorted math - be careful!

⚠️ Think about what your `NA` means for your data (are you sure ?).

- Is an `NA` for values so low they could not be reported?
- Or is it if it was too low and also if there was a different issue (like no one reported)?

Think about `NA`

If it is something more like a zero then you might want it included in your data like a zero instead of an `NA`.

Example: - survey reports `NA` if student has never tried cigarettes - survey reports 0 if student has tried cigarettes but did not smoke that week

⚠️ You might want to keep the `NA` values so that you know the original sample size.

Word of caution

⚠️ Calculating percentages will give you a different result depending on your choice to include NA values.!

This is because the denominator changes.

Word of caution - Percentages with `NA`

```
count(bike, dateInstalled) %>% mutate(percent = (n/(sum(n)) *100))
```

```
# A tibble: 9 × 3
  dateInstalled     n percent
          <dbl> <int>   <dbl>
1          2006     2   0.123
2          2007   368  22.6
3          2008   206  12.6
4          2009    86   5.27
5          2010   625  38.3
6          2011   101   6.19
7          2012   107   6.56
8          2013    10   0.613
9            NA   126   7.73
```

Word of caution - Percentages with `NA`

```
bike %>% drop_na(dateInstalled) %>%
  count(dateInstalled) %>% mutate(percent = (n/(sum(n)) *100))
```

```
# A tibble: 8 × 3
  dateInstalled     n percent
          <dbl> <int>   <dbl>
1          2006     2   0.133
2          2007   368  24.5
3          2008   206  13.7
4          2009    86   5.71
5          2010   625  41.5
6          2011   101   6.71
7          2012   107   7.11
8          2013    10   0.664
```

Should you be dividing by the total count with `NA` values included?
It depends on your data and what `NA` might mean.
Pay attention to your data and your `NA` values!

Summary

- `is.na()`,`any(is.na())`, `count()`, and functions from `naniar` like `gg_miss_var()` can help determine if we have `NA` values
- `filter()` automatically removes `NA` values - can't confirm or deny if condition is met (need `| is.na()` to keep them)
- `drop_na()` can help you remove `NA` values from a variable or an entire data frame
- `NA` values can change your calculation results
- think about what `NA` values represent - don't drop them if you shouldn't