Uniformity

CLEANING DATA IN R

Maggie Matsui
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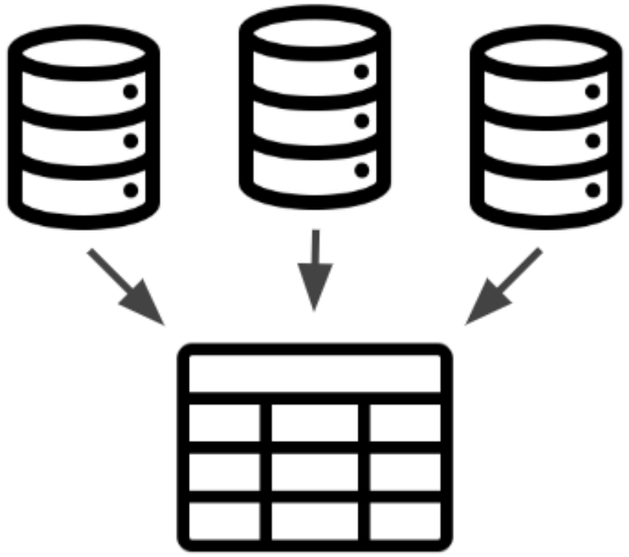
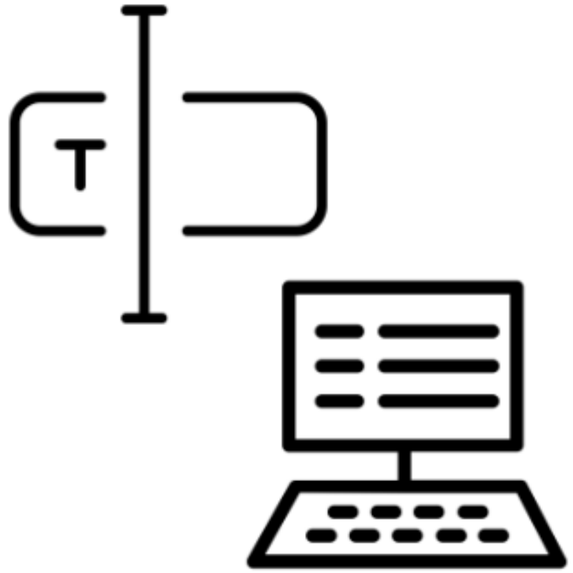
Uniformity

- Different units or formats
  - **Temperature:** `°C` vs. `°F`
  - **Weight:** `kg` vs. `g` vs. `lb`
  - **Money:** USD `$` vs. GBP `£` vs. JPY `¥`
  - **Date:** `DD-MM-YYYY` vs. `MM-DD-YYYY` vs. `YYYY-MM-DD`

Where do uniformity issues come from?



Multiple data sources



Data entry errors

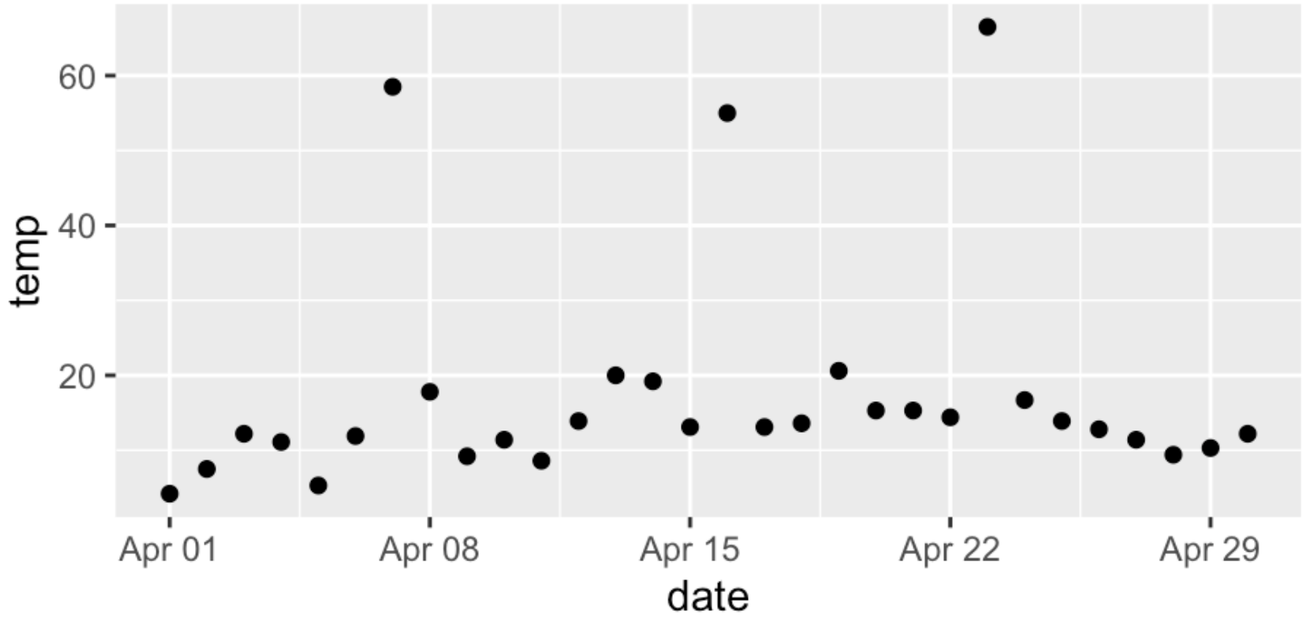
Finding uniformity issues

```
head(nyc_temps)
```

```
         date temp
1  2019-04-01  4.2
2  2019-04-02  7.5
3  2019-04-03 12.2
4  2019-04-04 11.1
5  2019-04-05 41.5
6  2019-04-06 11.9
```

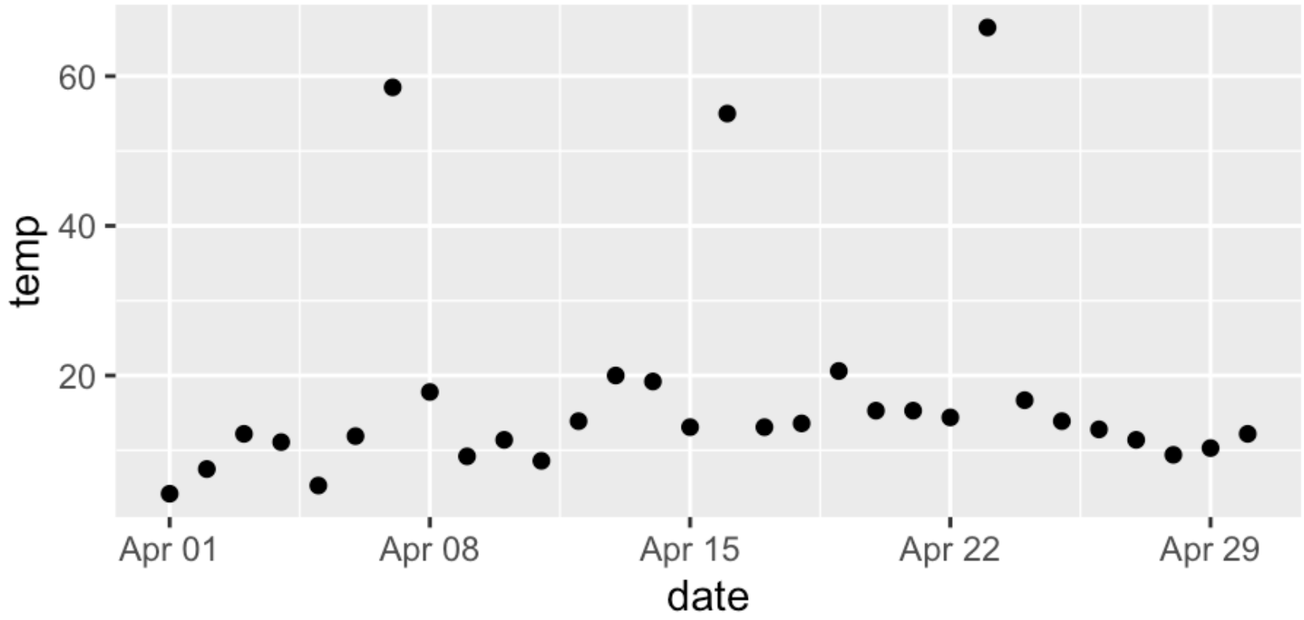
Finding uniformity issues

```
library(ggplot2)
ggplot(nyc_temps, aes(x = date, y = temp)) +
  geom_point()
```



What to do?

- There's no one best option. ***It depends on your dataset!***
- Do your research to understand where your data comes from



- Data from Apr 7, 16, and 23 is from an external source that measured temps in °F

Unit conversion

$$C = (F - 32) \times \frac{5}{9}$$

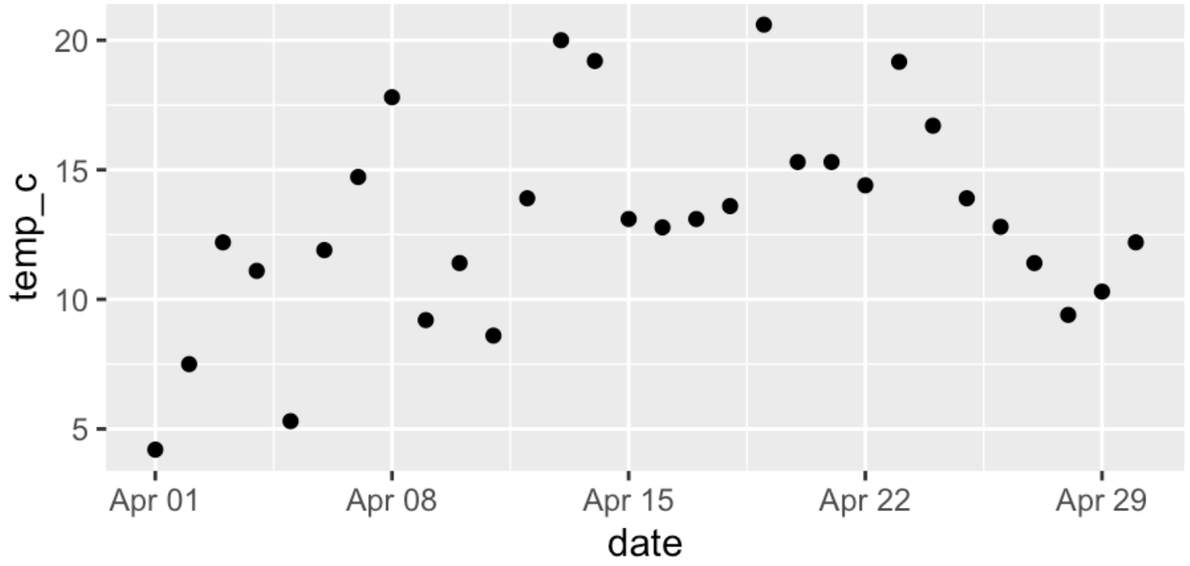
`ifelse(condition, value_if_true, value_if_false)`

```
nyc_temps %>%
  mutate(temp_c = ifelse(temp > 50, (temp - 32) * 5 / 9, temp))
```

```
         date temp   temp_c
1  2019-04-01  4.2  4.20000
...
7  2019-04-07 58.5 14.72222
...
```

Unit conversion

```
nyc_temps %>%
  mutate(temp_c = ifelse(temp > 50, (temp - 32) * 5 / 9, temp)) %>%
  ggplot(aes(x = date, y = temp_c)) +
    geom_point()
```



Date uniformity

```
nyc_temps
```

```
                date temp_c
1         2019-11-23   5.12
2           01/15/19  -0.67
3    April 24, 2019  17.46
4           08/30/19  26.46
5  October 3, 2019  14.63
6         2019-03-17   3.47
```

Date string	Date format
`"2019-11-23"`	`"%Y-%m-%d"`
`"01/15/19"`	`"%m/%d/%y"`
`"April 24, 2019"`	`"%B %d, %Y"`

`?strptime` in R console

Parsing multiple formats

```
library(lubridate)
parse_date_time(nyc_temps$date,
                orders = c("%Y-%m-%d", "%m/%d/%y", "%B %d, %Y"))
```

```
"2019-11-23 UTC" "2019-01-15 UTC" "2019-04-24 UTC" "2019-08-30 UTC"
"2019-10-03 UTC" "2019-03-17 UTC"
```

```
parse_date_time("Monday, January 3",
                orders = c("%Y-%m-%d", "%m/%d/%y", "%B %d, %Y"))
```

```
NA
```

Ambiguous dates

Is 02/04/2019 in February or April?

- Depends on your data!

Options include:

- Treat as missing
- If your data comes from multiple sources, infer based on source
- Infer based on other data in the dataset

Let's practice!

CLEANING DATA IN R

Cross field validation

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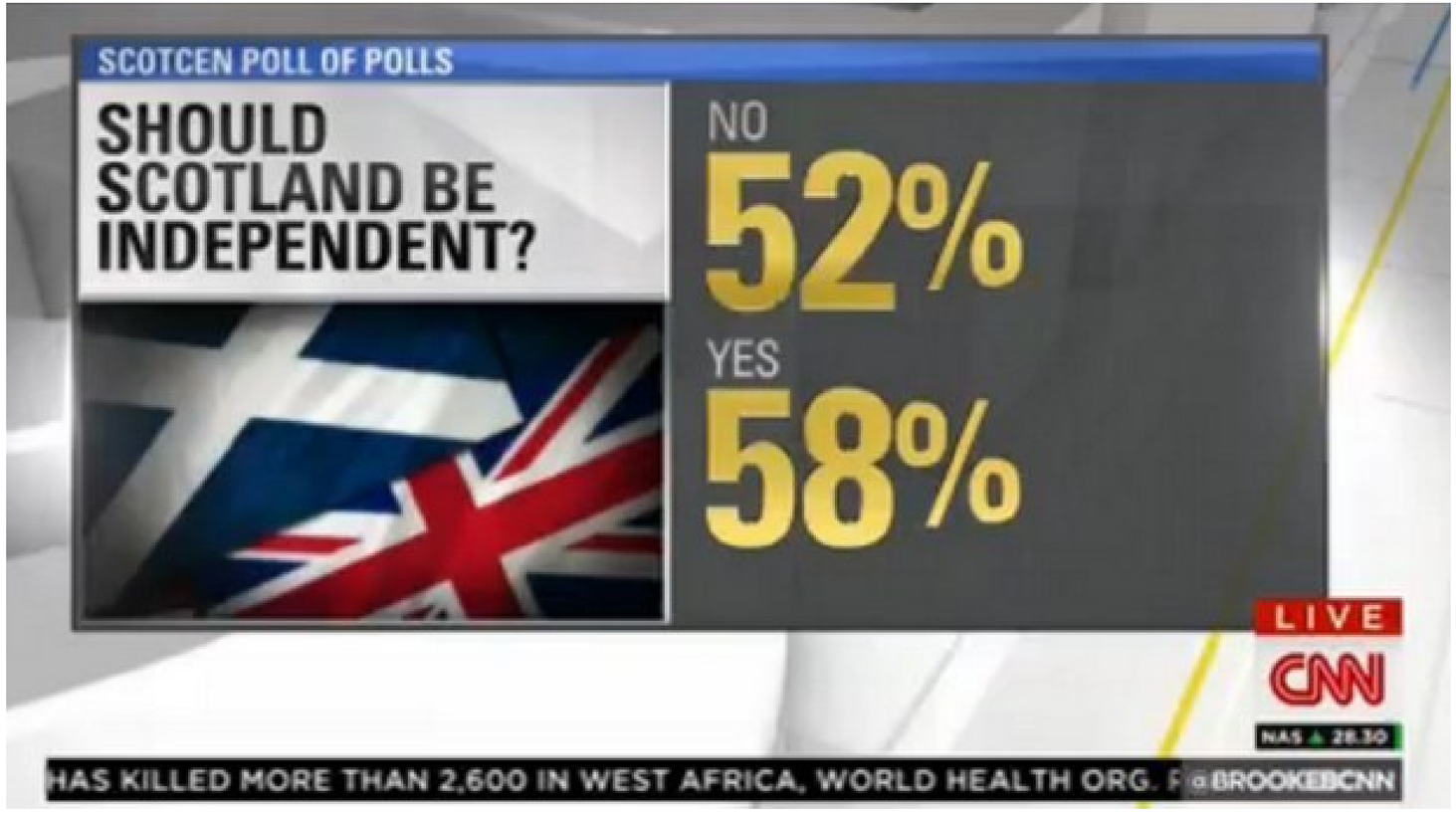
What is cross field validation?

- Cross field validation = a sanity check
- *Does this value make sense based on other values?*



[1] https://www.buzzfeednews.com/article/katienotopoulos/graphs-that-lied-to-us

Credit card data

```
head(credit_cards)
```

```
  date_opened dining_cb groceries_cb  gas_cb total_cb acct_age
1  2018-07-05     26.08         83.43   78.90   188.41        1
2  2016-01-23   1309.33          4.46 1072.25  2386.04        4
3  2016-03-25    205.84        119.20  800.62  1125.66        4
4  2018-06-20     14.00         16.37   18.41    48.78        1
5  2017-02-08     98.50        283.68  281.70   788.33        3
6  2014-11-18    889.28       2626.34 2973.62  6489.24        5
```

Validating numbers

```
credit_cards %>%
  select(dining_cb:total_cb)
```

```
   dining_cb groceries_cb  gas_cb total_cb
1      26.08         83.43   78.90   188.41
2    1309.33          4.46 1072.25  2386.04
3     205.84        119.20  800.62  1125.66
4      14.00         16.37   18.41    48.78
5      98.50        283.68  281.70   788.33
6     889.28       2626.34 2973.62  6489.24
```

Validating numbers

```
credit_cards %>%
  mutate(theoretical_total = dining_cb + groceries_cb + gas_cb) %>%
  filter(theoretical_total != total_cb) %>%
  select(dining_cb:theoretical_total)
```

```
  dining_cb groceries_cb  gas_cb total_cb theoretical_total
1     98.50        283.68  281.70   788.33            663.88
2   3387.53        363.85 2706.42  4502.94           6457.80
```

Validating date and age

```
credit_cards %>%
  select(date_opened, acct_age)
```

```
   date_opened acct_age
1   2018-07-05        1
2   2016-01-23        4
3   2016-03-25        4
4   2018-06-20        1
5   2017-02-08        3
6   2014-11-18        5
```

Calculating age

```
library(lubridate)
date_difference <- as.Date("2015-09-04") %--% today()
date_difference
```

```
2015-09-04 UTC--2020-03-09 UTC
```

```
as.numeric(date_difference, "years")
```

```
4.511978
```

```
floor(as.numeric(date_difference, "years"))
```

```
4
```

Validating age

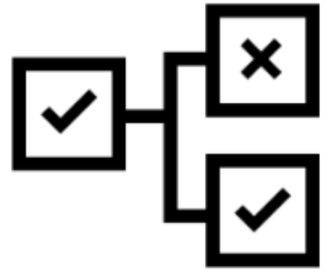
```
credit_cards %>%
  mutate(theor_age = floor(as.numeric(date_opened %--% today(), "years"))) %>%
  filter(theor_age != acct_age)
```

```
  date_opened acct_age dining_cb groceries_cb  gas_cb total_cb theor_age
1  2016-03-25        4    814.34       471.58 3167.41  4453.33         3
2  2018-03-06        3    238.48       186.05  213.84   638.37         2
```

What next?

Dropping Data

Set to missing and impute



Apply rules from domain knowledge

Let's practice!

CLEANING DATA IN R

Completeness

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What is missing data?

Occurs when no data value is stored for a variable in an observation

Can be represented as `NA`, `nan`, `0`, `99`, `.` ...

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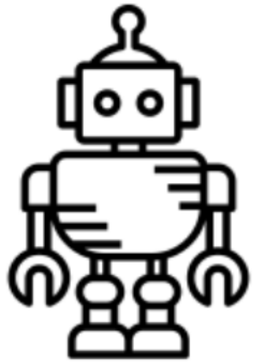

Technical error

What is missing data?

Occurs when no data value is stored for a variable in an observation

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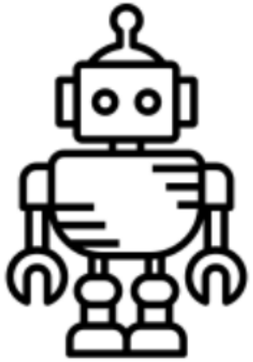


Technical error

Human error

Air quality

```
head(airquality)
```

```
   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     NA      NA 14.3   56     5   5
6     28      NA 14.9   66     5   6
```

Air quality

```
head(airquality)
```

```
   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     NA      NA 14.3   56     5   5
6     28      NA 14.9   66     5   6
```

Finding missing values

```
is.na(airquality)
```

```
      Ozone Solar.R  Wind  Temp Month   Day
[1,] FALSE   FALSE FALSE FALSE FALSE FALSE
[2,] FALSE   FALSE FALSE FALSE FALSE FALSE
[3,] FALSE   FALSE FALSE FALSE FALSE FALSE
[4,] FALSE   FALSE FALSE FALSE FALSE FALSE
[5,]  TRUE    TRUE FALSE FALSE FALSE FALSE
[6,] FALSE    TRUE FALSE FALSE FALSE FALSE
```

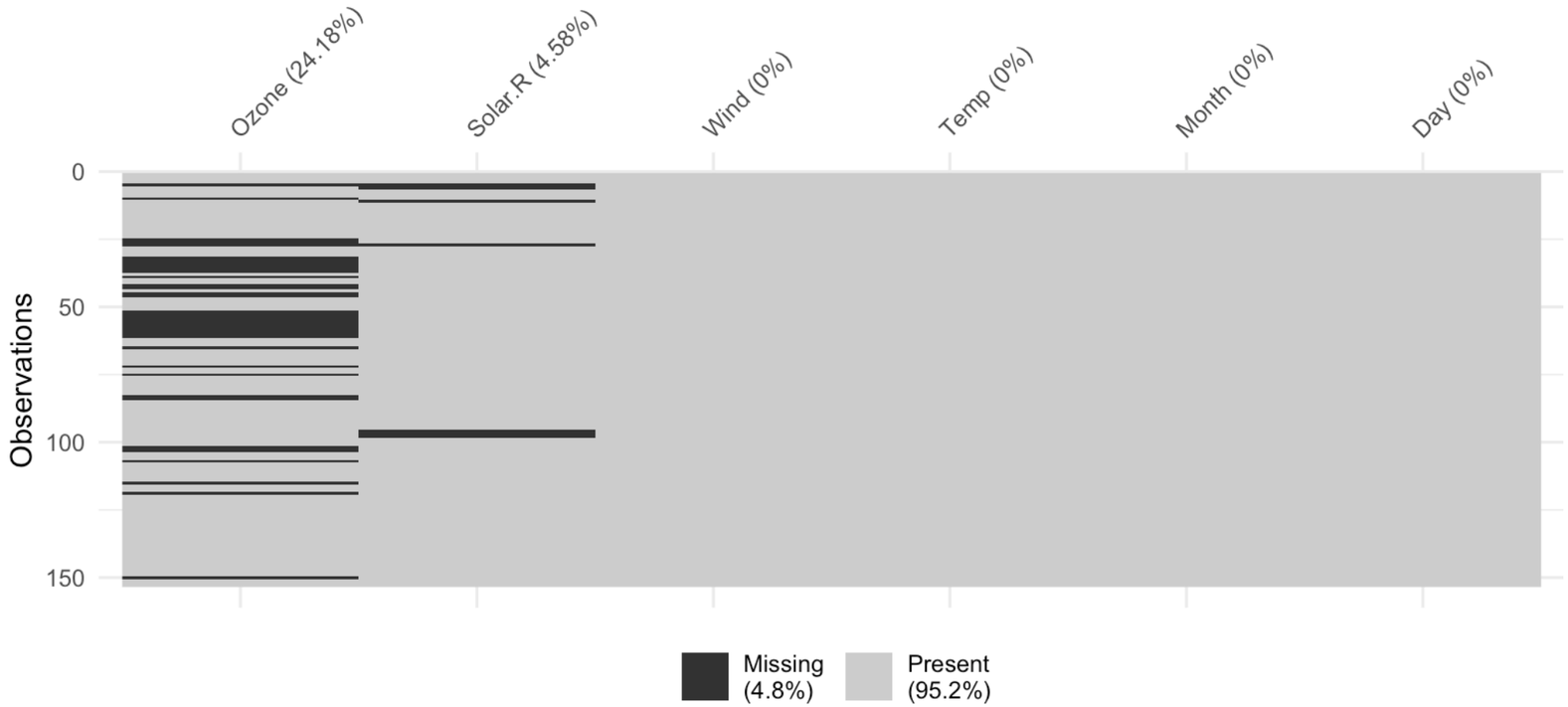
Counting missing values

```
# Count missing vals in entire dataset
sum(is.na(airquality))
```

```
44
```

Visualizing missing values

```
library(visdat)
vis_miss(airquality)
```



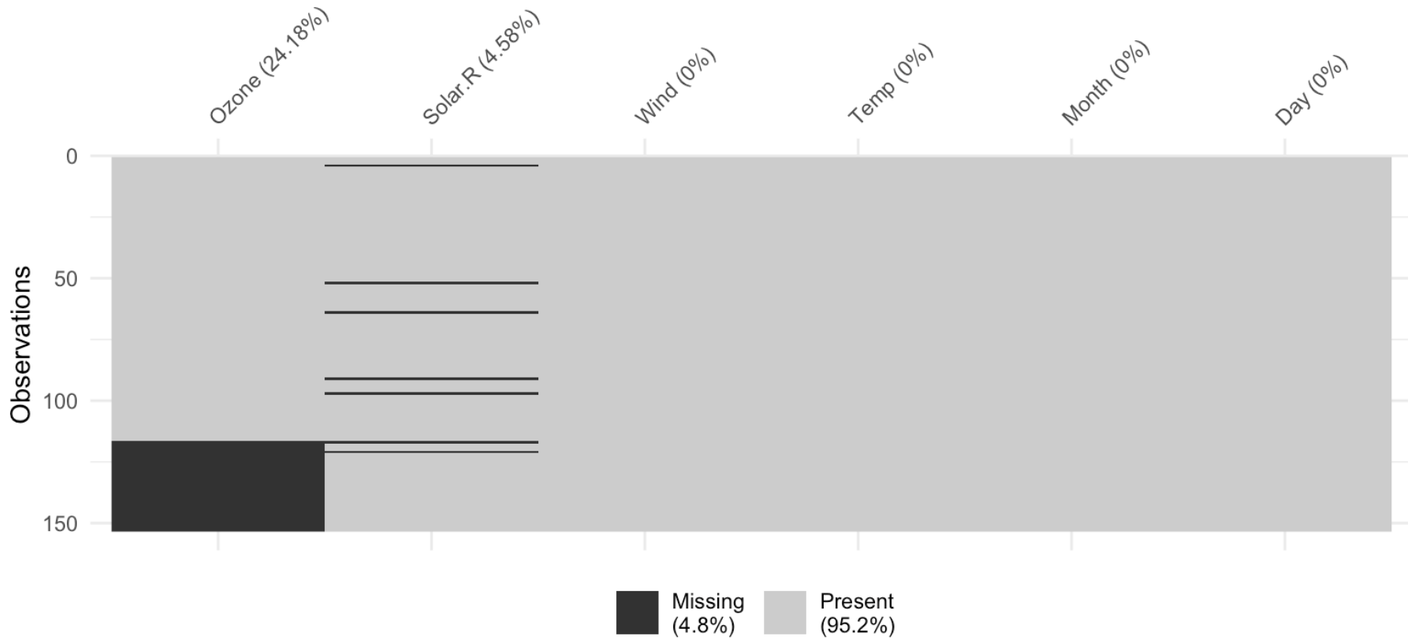
Investigating missingness

```
airquality %>%
  mutate(miss_ozone = is.na(Ozone)) %>%
  group_by(miss_ozone) %>%
  summarize(across(everything(), median, na.rm = TRUE))
```

```
  miss_ozone Ozone Solar.R  Wind  Temp Month   Day
  <lgl>      <dbl>   <int> <dbl> <dbl> <dbl> <dbl>
1 FALSE       31.5     207   9.7    65     7    16
2 TRUE         NA      194   9.7    99     6    15
```

Investigating missingness

```
airquality %>%
  arrange(Temp) %>%
  vis_miss()
```



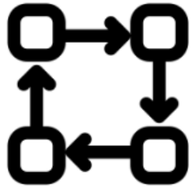
Types of missing data

Missing Completely at Random

(MCAR)

Missing at Random

(MAR)



Missing Not at Random

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Types of missing data

Missing Completely at Random

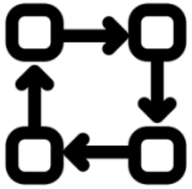
(MCAR)

No systematic relationship between missing data and other values

Data entry errors when inputting data

Missing at Random

(MAR)



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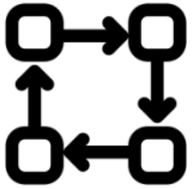
Systematic relationship between missing data and other observed values

Missing ozone data for high temperatures



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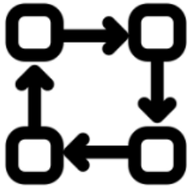

Missing Not at Random

(MNAR)

Systematic relationship between missing data and unobserved values

Missing temperature values for high temperatures

Dealing with missing data

Simple approaches:

1. Drop missing data
2. Impute (fill in) with statistical measures *(mean, median, mode..)* or domain knowledge

More complex approaches:

1. Impute using an algorithmic approach
2. Impute with machine learning models

Learn more in ***Dealing with Missing Data in R***

Dropping missing values

```
airquality %>%
  filter(!is.na(Ozone), !is.na(Solar.R))
```

```
   Ozone Solar.R  Wind  Temp Month   Day
   <int>   <int> <dbl> <int> <int> <int>
 1    41     190   7.4    67     5     1
 2    36     118     8    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
```

Replacing missing values

```
airquality %>%
  mutate(ozone_filled = ifelse(is.na(Ozone), mean(Ozone, na.rm = TRUE), Ozone))
```

```
   Ozone Solar.R  Wind  Temp Month   Day ozone_filled
   <int>   <int> <dbl> <int> <int> <int>         <dbl>
 1    41     190   7.4    67     5     1          41
 2    36     118   8      72     5     2          36
 3    12     149  12.6    74     5     3          12
 4    18     313  11.5    62     5     4          18
 5    NA      NA  14.3    56     5     5          42.1
```

Let's practice!

CLEANING DATA IN R