

# Intro to R

Data Cleaning

## Recap on summarization

- `summary(x)`: quantile information
- `summarize`: creates a summary table of columns of interest
- `count(variable)`: how many of each unique value do you have
- `group_by()`: changes all subsequent functions
  - combine with `summarize()` to get statistics per group
- `plot()` and `hist()` are great for a **quick snapshot** of the data

[Cheatsheet](#)

## Recap on data classes

- tibbles show column classes!
- `as.CLASS_NAME(x)` can be used to change the class of an object `x`
- `class()` can test what class an object is
- Logic class objects only have **TRUE** or **False** (without quotes)
- Two kinds of numeric subclasses - integer (whole numbers) and double (fractional values)
- Character class values need quotes
- Factors are a special character class that has levels
- matrix has columns and rows but is all one data class
- lists can contain multiples of any other class of data including lists!
- The `lubridate` package is helpful for dates and times

[Cheatsheet](#)

## Data Cleaning

In general, data cleaning is a process of investigating your data for inaccuracies, or recoding it in a way that makes it more manageable.

**MOST IMPORTANT RULE - LOOK AT YOUR DATA!**

# 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 divide a positive number (or negative number) by 0.

# 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 NAs? (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(jhur)
bike <- read_bike()
bike %>% count(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
airqual <- tibble(airquality)
airqual
```

```
# A tibble: 153 × 6
  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     NA      NA  14.3    56     5     5
6     28      NA  14.9    66     5     6
7     23     299   8.6    65     5     7
8     19      99  13.8    59     5     8
9      8      19  20.1    61     5     9
10    NA     194   8.6    69     5    10
# ... with 143 more rows
```

## **naniar: pct\_complete()**

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

```
pct_complete(airqual)
```

```
[1] 95.20697
```

Or for a particular variable:

```
airqual %>% 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.

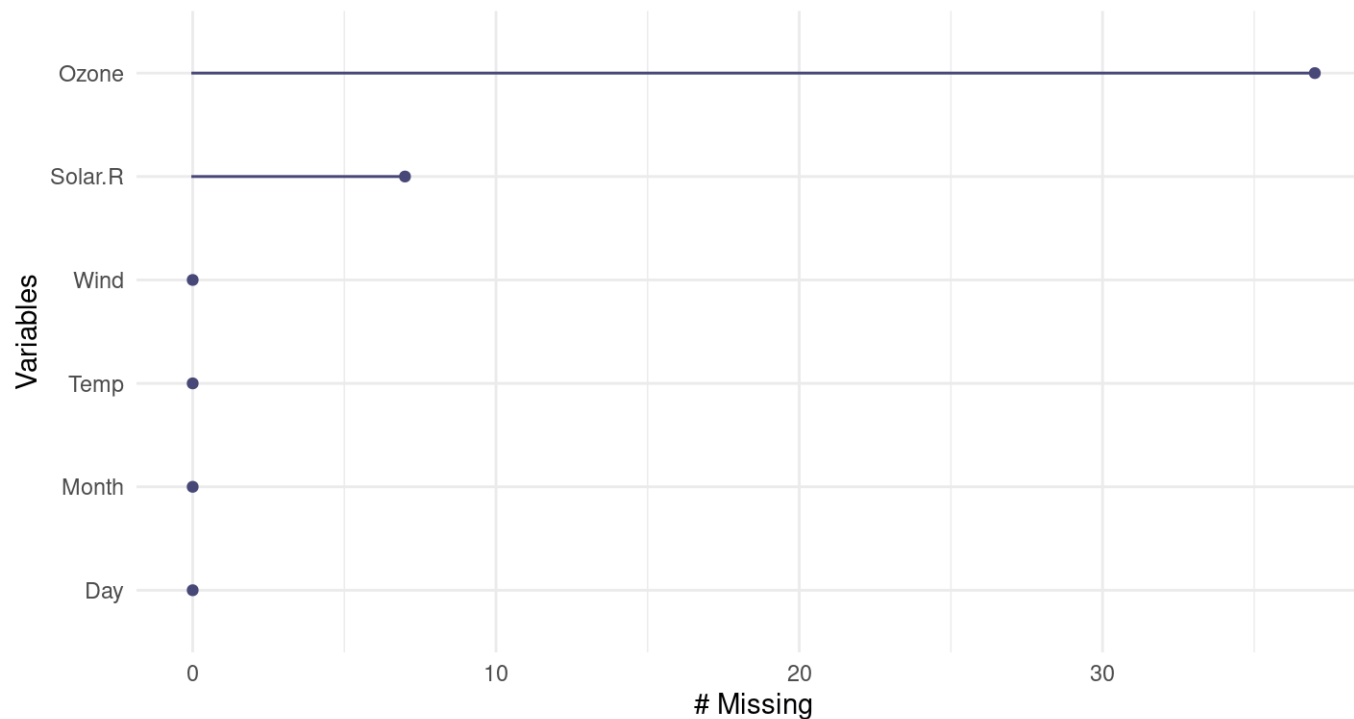
```
miss_var_summary(airqual)
```

```
# 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
```

## 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(airqual)
```



# Missing Data Issues

Recall that mathematical operations with **NA** often result in **NAs**.

```
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

This is also true for logical data. 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
```

## **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.

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

```
# A tibble: 2 × 6
```

	Ozone	Solar.R	Wind	Temp	Month	Day
	<int>	<int>	<dbl>	<int>	<int>	<int>
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.

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

```
# A tibble: 39 × 6
   Ozone Solar.R Wind Temp Month Day
  <int>   <int> <dbl> <int> <int> <int>
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     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
# ... with 29 more rows
```

## 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(airqual)
```

```
[1] 153    6
```

```
airqual %>% drop_na(Ozone)
```

```
# A tibble: 116 × 6
   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    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
# ... with 106 more rows
```

## 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.

```
airqual %>% drop_na()
```

```
# A tibble: 111 × 6
   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
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
# ... with 101 more rows
```

## Drop columns with any missing values

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

```
miss_var_which(airqual) # 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)

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

```
# A tibble: 153 × 4
  Wind Temp Month Day
  <dbl> <int> <int> <int>
1  7.4   67     5     1
2    8   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
# ... with 143 more rows
```



## Change a value to be NA

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

```
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

# Lab Part 1

[Class Website](#)  
[Lab](#)

# Recoding Variables

## Example of Recoding

```
set.seed(124)
data_diet <- tibble(Diet = rep(c("A", "B", "B"),
                              times = 4),
                   Gender = c("Male",
                              "m",
                              "Other",
                              "F",
                              "Female",
                              "M",
                              "f",
                              "O",
                              "Man",
                              "f",
                              "F",
                              "O"),
                   weight_start = sample(100:250, size = 12),
                   weight_change = sample(-10:20, size = 12))
```

Say we have some data about samples in a diet study:

```
data_diet
```

```
# A tibble: 12 × 4
  Diet Gender Weight_start Weight_change
<chr> <chr>      <int>      <int>
1 A     Male      164        16
2 B     m        104        -4
3 B     Other     233        -7
4 A     F         173         1
5 B     Female     242         9
6 B     M         190         6
7 A     f         119        -5
8 B     O         121         0
9 B     Man        229        -1
10 A    f         125        -3
11 B    F         129        13
12 B    O         222        15
```

# Oh dear...

This needs lots of recoding.

```
data_diet %>%  
  count(Gender)
```

```
# A tibble: 9 × 2  
  Gender      n  
  <chr>   <int>  
1 f         2  
2 F         2  
3 Female    1  
4 m         1  
5 M         1  
6 Male      1  
7 Man       1  
8 O         2  
9 Other     1
```

## dp1yr can help!

Using Excel to find all of the different ways gender has been coded, could be hectic! In dp1yr you can use the recode function.

(need mutate for data frames/tibbles!)

```
# General Format - this is not code!
```

```
{data_input} %>%
```

```
  mutate({variable_to_fix} = recode({Variable_fixing}, {old_value} = {new_value},  
                                     {another_old_value} = {new_value}))
```

## recode() function

Need quotes for new values! Tolerates quotes for old values.

```
data_diet %>%  
  mutate(Gender = recode(Gender, M = "Male",  
                           m = "Male",  
                           Man = "Male",  
                           O = "Other",  
                           f = "Female",  
                           F = "Female")) %>%  
  count(Gender, Diet)
```



## recode()

```
data_diet %>%  
  mutate(Gender = recode(Gender, M = "Male",  
                           m = "Male",  
                           Man = "Male",  
                           O = "Other",  
                           f = "Female",  
                           F = "Female")) %>%  
  count(Gender)
```

```
# A tibble: 3 × 2  
  Gender      n  
  <chr>   <int>  
1 Female     5  
2 Male       4  
3 Other      3
```

## Or you can use `case_when()`

The `case_when()` function of `dplyr` can help us to do this as well.

It is more flexible and powerful.

(need `mutate` here too!)

## Or you can use `case_when()`

Need quotes for conditions and new values!

```
data_diet %>%  
  mutate(Gender = case_when(Gender == "M" ~ "Male",  
                             Gender == "m" ~ "Male",  
                             Gender == "Man" ~ "Male",  
                             Gender == "O" ~ "Other",  
                             Gender == "f" ~ "Female",  
                             Gender == "F" ~ "Female")) %>%  
  count(Gender)
```

```
# A tibble: 4 × 2  
  Gender      n  
  <chr>  <int>  
1 Female      4  
2 Male        3  
3 Other        2  
4 <NA>         3
```

# What happened?

```
data_diet %>%  
  mutate(Gender = case_when(Gender == "M" ~ "Male",  
                             Gender == "m" ~ "Male",  
                             Gender == "Man" ~ "Male",  
                             Gender == "O" ~ "Other",  
                             Gender == "f" ~ "Female",  
                             Gender == "F" ~ "Female"))
```

```
# A tibble: 12 × 4
```

	Diet	Gender	Weight_start	Weight_change
	<chr>	<chr>	<int>	<int>
1	A	<NA>	164	16
2	B	Male	104	-4
3	B	<NA>	233	-7
4	A	Female	173	1
5	B	<NA>	242	9
6	B	Male	190	6
7	A	Female	119	-5
8	B	Other	121	0
9	B	Male	229	-1
10	A	Female	125	-3
11	B	Female	129	13
12	B	Other	222	15

# Original data

data\_diet

```
# A tibble: 12 × 4
  Diet Gender Weight_start Weight_change
<chr> <chr>      <int>      <int>
1 A     Male      164        16
2 B     m        104        -4
3 B     Other     233        -7
4 A     F         173         1
5 B     Female     242         9
6 B     M         190         6
7 A     f         119        -5
8 B     O         121         0
9 B     Man        229        -1
10 A    f         125        -3
11 B    F         129        13
12 B    O         222        15
```

## case\_when() drops unspecified values

Note that automatically values not reassigned explicitly by case\_when() will be NA unless otherwise specified.

```
# General Format - this is not code!  
{data_input} %>%  
  mutate({variable_to_fix} = case_when({Variable_fixing}  
    /some condition/ ~ {value_for_con},  
    TRUE ~ {value_for_not_meeting_condition}))
```

{value\_for\_not\_meeting\_condition} could be something new or it can be the original values of the column

## case\_when with TRUE ~ original variable name

```
data_diet %>%  
  mutate(Gender = case_when(Gender == "M" ~ "Male",  
                             Gender == "m" ~ "Male",  
                             Gender == "Man" ~ "Male",  
                             Gender == "O" ~ "Other",  
                             Gender == "f" ~ "Female",  
                             Gender == "F" ~ "Female",  
                             TRUE ~ Gender)) %>%  
  count(Gender)
```

```
# A tibble: 3 × 2  
  Gender      n  
  <chr>  <int>  
1 Female      5  
2 Male        4  
3 Other       3
```

## More complicated case\_when()

```
data_diet %>%  
  mutate(Gender = case_when(  
    Gender %in% c("M", "male", "Man", "m", "Male") ~ "Male",  
    Gender %in% c("F", "Female", "f", "female") ~ "Female",  
    Gender %in% c("O", "Other") ~ "Other"))
```

# A tibble: 12 × 4

	Diet	Gender	Weight_start	Weight_change
	<chr>	<chr>	<int>	<int>
1	A	Male	164	16
2	B	Male	104	-4
3	B	Other	233	-7
4	A	Female	173	1
5	B	Female	242	9
6	B	Male	190	6
7	A	Female	119	-5
8	B	Other	121	0
9	B	Male	229	-1
10	A	Female	125	-3
11	B	Female	129	13
12	B	Other	222	15



## Another reason for `case_when()`

`case_when` can do very sophisticated comparisons

```
data_diet <- data_diet %>%  
  mutate(Effect = case_when(Weight_change > 0 ~ "Increase",  
                             Weight_change == 0 ~ "Same",  
                             Weight_change < 0 ~ "Decrease"))  
  
head(data_diet)
```

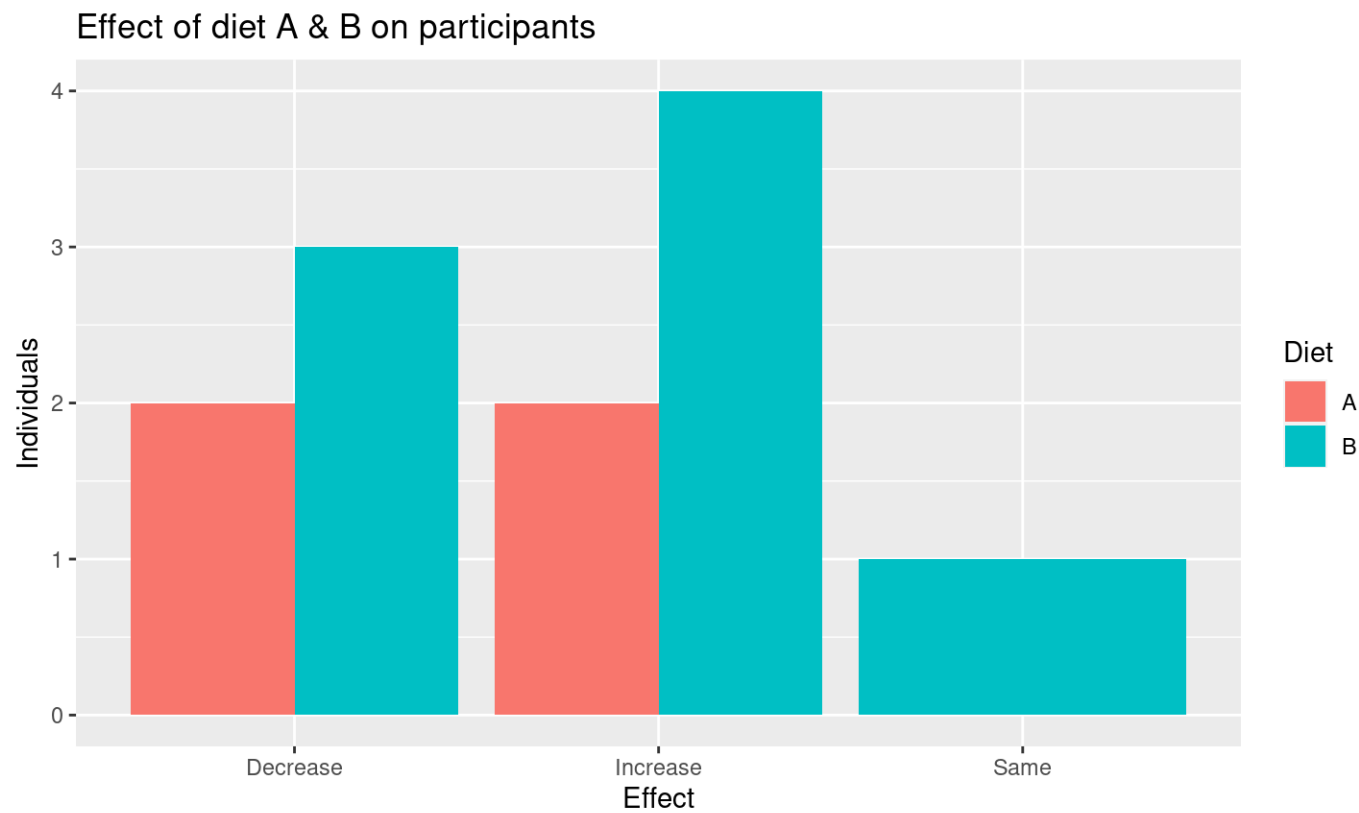
```
# A tibble: 6 × 5  
  Diet Gender Weight_start Weight_change Effect  
  <chr> <chr>      <int>      <int> <chr>  
1 A     Male        164         16 Increase  
2 B     m           104         -4 Decrease  
3 B     Other        233         -7 Decrease  
4 A     F            173          1 Increase  
5 B     Female        242          9 Increase  
6 B     M            190          6 Increase
```

## Now it is easier to see what is happening

```
data_diet %>%  
  count(Diet, Effect)
```

```
# A tibble: 5 × 3  
  Diet Effect      n  
  <chr> <chr>   <int>  
1 A     Decrease 2  
2 A     Increase 2  
3 B     Decrease 3  
4 B     Increase 4  
5 B     Same      1
```

# Taking a look at the data



# Working with strings

# Strings in R

- R can do much more than find exact matches for a whole string!



# The **stringr** package

The `stringr` package:

- Modifying or finding **part** or all of a character string
- We will not cover `grep` or `gsub` - base R functions
  - are used on forums for answers
- Almost all functions start with `str_*`

## **stringr**

`str_detect`, and `str_replace` search for matches to argument pattern within each element of a **character vector** (not data frame or tibble!).

- `str_detect` - returns TRUE if pattern is found
- `str_replace` - replaces pattern with replacement

## str\_detect()

The `string` argument specifies what to check

The `pattern` argument specifies what to check for (case sensitive)

```
Effect <- pull(data_diet) %>% head(n = 6)  
Effect
```

```
[1] "Increase" "Decrease" "Decrease" "Increase" "Increase" "Increase"
```

```
str_detect(string = Effect, pattern = "d")
```

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

```
str_detect(string = Effect, pattern = "D")
```

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



## **str\_replace()**

The `string` argument specifies what to check

The `pattern` argument specifies what to check for

The `replacement` argument specifies what to replace the pattern with

```
str_replace(string = Effect, pattern = "D", replacement = "d")
```

```
[1] "Increase" "decrease" "decrease" "Increase" "Increase" "Increase"
```

**str\_replace()** only replaces the first instance of the pattern in each value

str\_replace\_all() can be used to replace all instances within each value

```
str_replace(string = Effect, pattern = "e", replacement = "E")
```

```
[1] "IncrEase" "DEcrease" "DEcrease" "IncrEase" "IncrEase" "IncrEase"
```

```
str_replace_all(string = Effect, pattern = "e", replacement = "E")
```

```
[1] "IncrEasE" "DEcrEasE" "DEcrEasE" "IncrEasE" "IncrEasE" "IncrEasE"
```

## Subsetting part of a string

`str_sub()` allows you to subset part of a string

The `string` argument specifies what strings to work with

The `start` argument specifies position of where to start

The `end` argument specifies position of where to end

```
str_sub(string = Effect, start = 1, end = 3)
```

```
[1] "Inc" "Dec" "Dec" "Inc" "Inc" "Inc"
```

## filter and stringr functions

```
head(data_diet, n = 4)
```

```
# A tibble: 4 × 5
  Diet Gender Weight_start Weight_change Effect
<chr> <chr>      <int>         <int> <chr>
1 A    Male      164           16 Increase
2 B    m        104           -4 Decrease
3 B    Other     233           -7 Decrease
4 A    F        173            1 Increase
```

```
data_diet %>%
  filter(str_detect(string = Gender,
                    pattern = "M"))
```

```
# A tibble: 3 × 5
  Diet Gender Weight_start Weight_change Effect
<chr> <chr>      <int>         <int> <chr>
1 A    Male      164           16 Increase
2 B    M        190            6 Increase
3 B    Man      229           -1 Decrease
```

## OK back to our original problem

```
count(data_diet, Gender)
```

```
# A tibble: 9 × 2
```

	Gender	n
	<chr>	<int>
1	f	2
2	F	2
3	Female	1
4	m	1
5	M	1
6	Male	1
7	Man	1
8	O	2
9	Other	1

## Recode was nice but what if miss something?

```
data_diet %>%  
  mutate(Gender = recode(Gender, M = "Male",  
                           m = "Male",  
                           Man = "Male",  
                           O = "Other",  
                           f = "Female",  
                           F = "Female")) %>%  
  count(Gender, Diet)
```

## **case\_when()** was an improvement

But we still might miss a strange value

```
data_diet %>%  
  mutate(Gender = case_when(  
    Gender %in% c("M", "male", "Man", "m", "Male") ~ "Male",  
    Gender %in% c("F", "Female", "f", "female") ~ "Female",  
    Gender %in% c("O", "Other") ~ "Other"))
```

## case\_when() improved with stringr

^ indicates the beginning of a character string \$ indicates the end

```
data_diet %>%  
  mutate(Gender = case_when(  
    str_detect(string = Gender, pattern = "^m|^M") ~ "Male",  
    str_detect(string = Gender, pattern = "^f|^F") ~ "Female",  
    str_detect(string = Gender, pattern = "^o|^O") ~ "Other")) %>%  
  count(Gender)
```

```
# A tibble: 3 × 2  
  Gender      n  
  <chr>  <int>  
1 Female      5  
2 Male        4  
3 Other       3
```

This is a more robust solution! It will catch typos as long as first letter is correct.



That's better!



Separating and uniting data

## Uniting columns

The `unite()` function can help combine columns

The `col` argument specifies new column name

The `sep` argument specifies what separator to use when combining -default is

"\_" The `remove` argument specifies if you want to drop the old columns

```
diet_comb <- data_diet %>%  
  unite(Diet, Effect, col = "change", remove = TRUE)
```

```
diet_comb
```

```
# A tibble: 12 × 4  
  change      Gender Weight_start Weight_change  
  <chr>      <chr>      <int>         <int>  
1 A_Increase Male      164           16  
2 B_Decrease m        104           -4  
3 B_Decrease Other    233           -7  
4 A_Increase F        173            1  
5 B_Increase Female   242            9  
6 B_Increase M        190            6  
7 A_Decrease f        119           -5  
8 B_Same      0        121            0  
9 B_Decrease Man     229           -1  
10 A_Decrease f        125           -3  
11 B_Increase F        129           13  
12 B_Increase 0        222           15
```

## Separating columns based on a separator

The `separate()` function from `tidyr` can split a column into multiple columns.

The `col` argument specifies what column to work with

The `into` argument specifies names of new columns

The `sep` argument specifies what to separate by

```
diet_comb <- diet_comb %>%  
  separate(col = change, into = c("Diet", "Change"), sep = "_" )  
diet_comb
```

```
# A tibble: 12 × 5
```

	Diet <chr>	Change <chr>	Gender <chr>	Weight_start <int>	Weight_change <int>
1	A	Increase	Male	164	16
2	B	Decrease	m	104	-4
3	B	Decrease	Other	233	-7
4	A	Increase	F	173	1
5	B	Increase	Female	242	9
6	B	Increase	M	190	6
7	A	Decrease	f	119	-5
8	B	Same	0	121	0
9	B	Decrease	Man	229	-1
10	A	Decrease	f	125	-3
11	B	Increase	F	129	13
12	B	Increase	0	222	15

## Summary

- `recode()` and `case_when()` require `mutate()` when working with dataframes/tibbles
- `recode()` can help with simple recoding (not based on condition but **exact** swap) (only need quotes for new values - but it tolerates redundant quotes)
- `case_when()` can recode **entire values** based on **conditions** (need quotes for conditions and new values)
  - remember `case_when()` needs `TRUE ~ variable` to keep values that aren't specified by conditions, otherwise will be NA

## Summary Continued

- `stringr` package has great functions for looking for specific **parts of values** especially `filter()` and `str_detect()` combined
- `stringr` also has other useful string functions like `str_detect()` (finding patterns in a column or vector), `str_subset()` (parsing text), `str_replace()` (replacing the first instance in values), `str_replace_all()` (replacing all instances in each value) and more!
- `separate()` can split columns into additional columns
- `unite()` can combine columns
- `:` can indicate when you want to start and end with columns next to one another

## Lab Part 2

[Class Website](#)  
[Lab](#)



Image by [Gerd Altmann](#) from [Pixabay](#)

Extra Slides



# String Splitting

- `str_split(string, pattern)` - splits strings up - returns list!

```
library(stringr)
x <- c("I really like writing R code")
df <- tibble(x = c("I really", "like writing", "R code programs"))
y <- unlist(str_split(x, " "))
y
```

```
[1] "I"          "really"    "like"     "writing"  "R"         "code"
```

```
length(y)
```

```
[1] 6
```

## A bit on Regular Expressions

- <http://www.regular-expressions.info/reference.html>
- They can use to match a large number of strings in one statement
- `.` matches any single character
- `*` means repeat as many (even if 0) more times the last character
- `?` makes the last thing optional
- `^` matches start of vector `^a` - starts with "a"
- `$` matches end of vector `b$` - ends with "b"

## Let's look at modifiers for `stringr`

`?modifiers`

- `fixed` - match everything exactly
- `ignore_case` is an option to not have to use `tolower`

## Using a fixed expression

One example case is when you want to split on a period ".". In regular expressions . means **ANY** character, so we need to specify that we want R to interpret "." as simply a period.

```
str_split("I.like.strings", ".")
```

```
[[1]]  
[1] "" "" "" "" "" "" "" "" "" "" "" "" "" "" "" ""
```

```
str_split("I.like.strings", fixed("."))
```

```
[[1]]  
[1] "I"      "like"   "strings"
```

```
str_split("I.like.strings", "\\.")
```

```
[[1]]  
[1] "I"      "like"   "strings"
```

## Pasting strings with `paste` and `paste0`

Paste can be very useful for joining vectors together:

```
paste("Visit", 1:5, sep = "_")
```

```
[1] "Visit_1" "Visit_2" "Visit_3" "Visit_4" "Visit_5"
```

```
paste("Visit", 1:5, sep = "_", collapse = "_")
```

```
[1] "Visit_1_Visit_2_Visit_3_Visit_4_Visit_5"
```

```
# and paste0 can be even simpler see ?paste0  
paste0("Visit", 1:5) # no space!
```

```
[1] "Visit1" "Visit2" "Visit3" "Visit4" "Visit5"
```

Comparison of **stringr** to base R -  
not covered

# Splitting Strings

# Substringing

stringr

- `str_split(string, pattern)` - splits strings up - returns list!



## Splitting String:

In `stringr`, `str_split` splits a vector on a string into a list

```
library(stringr)
x <- c("I really", "like writing", "R code programs")
y <- str_split(x, pattern = " ") # returns a list
y
```

```
[[1]]
[1] "I"      "really"
```

```
[[2]]
[1] "like"   "writing"
```

```
[[3]]
[1] "R"      "code"   "programs"
```

## 'Find' functions: stringr compared to base R

Base R does not use these functions. Here is a "translator" of the `stringr` function to base R functions

- `str_detect` - similar to `grep1` (return logical)
- `grep(value = FALSE)` is similar to `which(str_detect())`
- `str_subset` - similar to `grep(value = TRUE)` - return value of matched
- `str_replace` - similar to `sub` - replace one time
- `str_replace_all` - similar to `gsub` - replace many times

# Important Comparisons

Base R:

- Argument order is (pattern, x)
- Uses option (fixed = TRUE)

stringr

- Argument order is (string, pattern) aka (x, pattern)
- Uses function fixed(pattern)

some data to work with

```
Sal = read_salaries() # or
```

## Showing difference in `str_extract`

`str_extract` extracts just the matched string

```
ss = str_extract(Sal$Name, "Rawling")
```

Warning: Unknown or uninitialised column: `Name`.

```
head(ss)
```

```
character(0)
```

```
ss[ !is.na(ss)]
```

```
character(0)
```

## Showing difference in `str_extract` and `str_extract_all`

`str_extract_all` extracts all the matched strings

```
head(str_extract(Sal$AgencyID, "\\d"))
```

```
[1] "0" "2" "6" "9" "4" "9"
```

```
head(str_extract_all(Sal$AgencyID, "\\d"), 2)
```

```
[[1]]  
[1] "0" "3" "0" "3" "1"
```

```
[[2]]  
[1] "2" "9" "0" "4" "5"
```

## Using Regular Expressions

- Look for any name that starts with:
  - Payne at the beginning,
  - Leonard and then an S
  - Spence then capital C

```
head(grep("^Payne.*", x = Sal$name, value = TRUE), 3)
```

```
[1] "Payne El,Boaz L"      "Payne El,Jackie"  
[3] "Payne Johnson,Nickole A"
```

```
head(grep("Leonard.?S", x = Sal$name, value = TRUE))
```

```
[1] "Payne,Leonard S"      "Szumlanski,Leonard S"
```

```
head(grep("Spence.*C.*", x = Sal$name, value = TRUE))
```

```
[1] "Spencer,Charles A"  "Spencer,Clarence W" "Spencer,Michael C"
```

## Using Regular Expressions: **stringr**

```
head(str_subset( Sal$name, "^Payne.*"), 3)
```

```
[1] "Payne El, Boaz L"      "Payne El, Jackie"  
[3] "Payne Johnson, Nickole A"
```

```
head(str_subset( Sal$name, "Leonard.?S"))
```

```
[1] "Payne, Leonard S"      "Szumlanski, Leonard S"
```

```
head(str_subset( Sal$name, "Spence.*C.*"))
```

```
[1] "Spencer, Charles A"   "Spencer, Clarence W" "Spencer, Michael C"
```



# Replace

Let's say we wanted to sort the data set by Annual Salary:

```
class(Sal$AnnualSalary)
```

```
[1] "character"
```

```
sort(c("1", "2", "10")) # not sort correctly (order simply ranks the data)
```

```
[1] "1"  "10" "2"
```

```
order(c("1", "2", "10"))
```

```
[1] 1 3 2
```

# Replace

So we must change the annual pay into a numeric:

```
head(Sal$AnnualSalary, 4)
```

```
[1] "$55314.00" "$74000.00" "$64500.00" "$46309.00"
```

```
head(as.numeric(Sal$AnnualSalary), 4)
```

Warning in head(as.numeric(Sal\$AnnualSalary), 4): NAs introduced by coercion

```
[1] NA NA NA NA
```

R didn't like the \$ so it thought turned them all to NA.

sub() and gsub() can do the replacing part in base R.

## Replacing and subbing

Now we can replace the \$ with nothing (used `fixed=TRUE` because \$ means ending):

```
Sal$AnnualSalary <- as.numeric(gsub(pattern = "$", replacement="",  
                                   Sal$AnnualSalary, fixed=TRUE))  
Sal <- Sal[order(Sal$AnnualSalary, decreasing=TRUE), ]  
Sal[1:5, c("name", "AnnualSalary", "JobTitle")]
```

```
# A tibble: 5 × 3
```

	name <chr>	AnnualSalary <dbl>	JobTitle <chr>
1	Mosby, Marilyn J	238772	STATE'S ATTORNEY
2	Batts, Anthony W	211785	Police Commissioner
3	Wen, Leana	200000	Executive Director III
4	Raymond, Henry J	192500	Executive Director III
5	Swift, Michael	187200	CONTRACT SERV SPEC II

## Replacing and subbing: **stringr**

We can do the same thing (with 2 piping operations!) in dplyr

```
dplyr_sal = Sal
dplyr_sal = dplyr_sal %>% mutate(
  AnnualSalary = AnnualSalary %>%
    str_replace(
      fixed("$"),
      "" ) %>%
    as.numeric) %>%
  arrange(desc(AnnualSalary))
check_Sal = Sal
rownames(check_Sal) = NULL
all.equal(check_Sal, dplyr_sal)
```

```
[1] TRUE
```

## Creating Two-way Tables

A two-way table. If you pass in 2 vectors, `table` creates a 2-dimensional table.

```
tab <- table(c(0, 1, 2, 3, 2, 3, 3, 2, 2, 3),  
             c(0, 1, 2, 3, 2, 3, 3, 4, 4, 3),  
             useNA = "always")  
tab
```

	0	1	2	3	4	<NA>
0	1	0	0	0	0	0
1	0	1	0	0	0	0
2	0	0	2	0	2	0
3	0	0	0	4	0	0
<NA>	0	0	0	0	0	0

## Creating Two-way Tables

```
tab_df = tibble(x = c(0, 1, 2, 3, 2, 3, 3, 2, 2, 3),  
                 y = c(0, 1, 2, 3, 2, 3, 3, 4, 4, 3))  
tab_df %>% count(x, y)
```

```
# A tibble: 5 × 3
```

	x	y	n
	<dbl>	<dbl>	<int>
1	0	0	1
2	1	1	1
3	2	2	2
4	2	4	2
5	3	3	4

# Creating Two-way Tables

```
tab_df %>%  
  count(x, y) %>%  
  group_by(x) %>% mutate(pct_x = n / sum(n))
```

```
# A tibble: 5 × 4  
# Groups:   x [4]  
      x     y     n pct_x  
  <dbl> <dbl> <int> <dbl>  
1     0     0     1     1  
2     1     1     1     1  
3     2     2     2    0.5  
4     2     4     2    0.5  
5     3     3     4     1
```

## Creating Two-way Tables

```
library(scales)
tab_df %>%
  count(x, y) %>%
  group_by(x) %>% mutate(pct_x = percent(n / sum(n)))
```

```
# A tibble: 5 × 4
# Groups:   x [4]
      x     y     n pct_x
  <dbl> <dbl> <int> <chr>
1     0     0     1 100%
2     1     1     1 100%
3     2     2     2  50%
4     2     4     2  50%
5     3     3     4 100%
```



# Removing columns with threshold of percent missing values

```
is.na(df) %>% head(n = 3)
```

```
      x  
[1,] FALSE  
[2,] FALSE  
[3,] FALSE
```

```
colMeans(is.na(df))#TRUE and FALSE treated like 0 and 1
```

```
x  
0
```

```
which(colMeans(is.na(df)) < 0.2) #the location of the columns <.2
```

```
x  
1
```

```
df %>% select(which(colMeans(is.na(df)) < 0.2))# remove if over 20% missing
```

```
# A tibble: 3 × 1
```

```
      x  
  <chr>  
1 I really  
2 like writing  
3 R code programs
```