Data Cleaning

Recap on summarization

- `summary(x)`: quantile information
- `summarize`: creates a summary table of columns of interest
  - combine with `across()` to programmatically select columns
- `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
- Logic class objects only have `TRUE` or `False` (without quotes)
- The repeat `rep()` and `seq()` functions help you create vectors with `to` and `from` arguments (and others)
- `sample()` makes random vectors. Can be used for integers or double depending on what it is sampling from.
- 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

- `any` will be `TRUE` if ANY are true
  - `any(is.na(x))` - do we have any `NA`'s in `x`?

```
A = c(1, 2, 4, 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
```

Fining 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.

The `pct_complete()` function shows the percentage that is complete for a given data object.

```
#install.packages("naniar")
library(naniar)
x = c(0, NA, 2, 3, 4, -0.5, 0.2)
pct_complete(x)
```

```
[1] 85.71429
```

```
test
```

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

```
pct_complete(test) # doesn't count infinite values as missing
```

```
[1] 33.33333
```

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()`

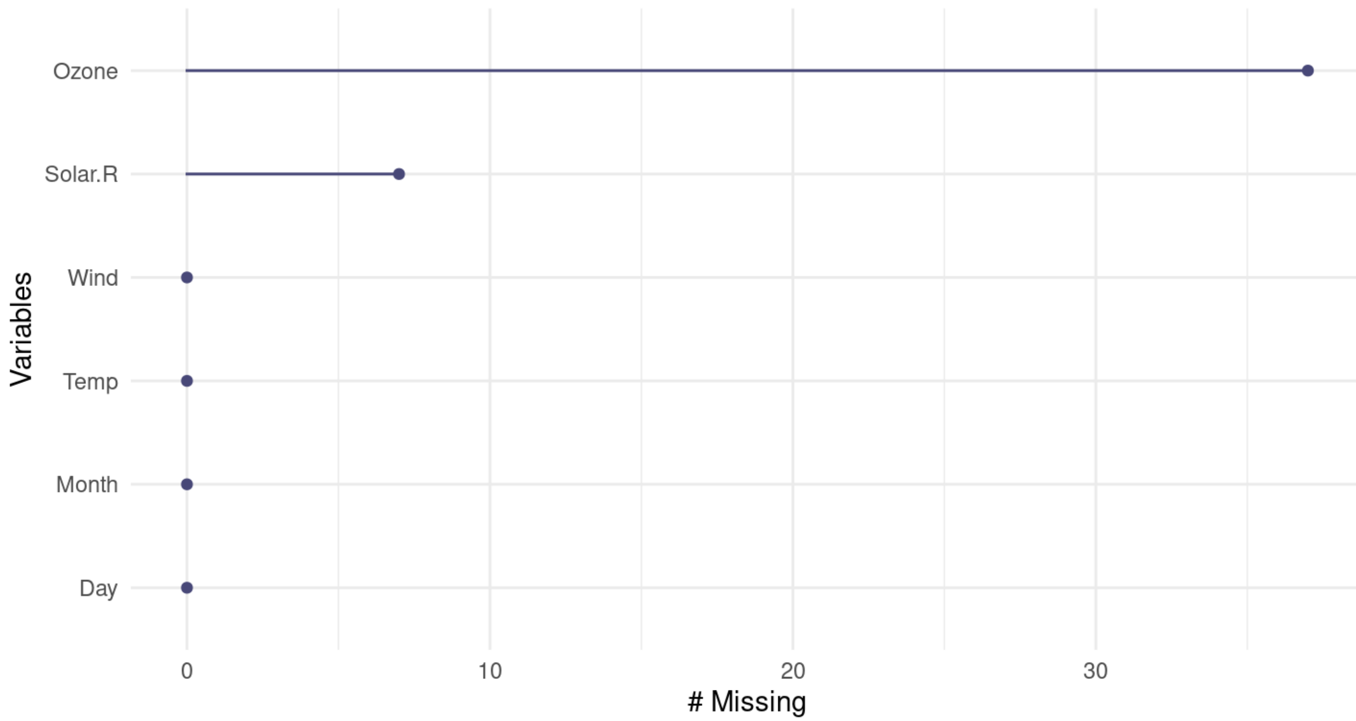
```
pct_complete(airquality)
```

```
[1] 95.20697
```

naniar plots

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

```
gg_miss_var(airqual)
```



Missing Data Issues

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

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

```
[1] NA
```

```
mean(c(2,4,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.

filter() and missing data

```
df
```

```
# A tibble: 6 × 2
    Dog   Cat
  <dbl> <dbl>
1     0    NA
2    NA     8
3     2     6
4     3    NA
5     1     2
6     1    NA
```

```
df %>% filter(Dog < 3)
```

```
# A tibble: 4 × 2
    Dog   Cat
  <dbl> <dbl>
1     0    NA
2     2     6
3     1     2
4     1    NA
```

filter() and missing data

```
df %>% filter(Dog < 3 | is.na(Dog))
```

```
# A tibble: 5 × 2
    Dog   Cat
  <dbl> <dbl>
1     0    NA
2    NA     8
3     2     6
4     1     2
5     1    NA
```

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

A function from the `tidyr` package.

```
df %>% drop_na(Dog)
```

```
# A tibble: 5 × 2
    Dog   Cat
  <dbl> <dbl>
1     0    NA
2     2     6
3     3    NA
4     1     2
5     1    NA
```

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.

```
df %>% drop_na()
```

```
# A tibble: 2 × 2
    Dog   Cat
  <dbl> <dbl>
1     2     6
2     1     2
```

Drop **columns** with any missing values

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

```
df<-df %>% mutate(test =c(1,2,3,4,5,6))
df
```

```
# A tibble: 6 × 3
    Dog   Cat  test
  <dbl> <dbl> <dbl>
1     0    NA     1
2    NA     8     2
3     2     6     3
4     3    NA     4
5     1     2     5
6     1    NA     6
```

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

```
[1] "Dog" "Cat"
```

Drop **columns** with any missing values

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

```
# A tibble: 6 × 1
   test
  <dbl>
1     1
2     2
3     3
4     4
5     5
6     6
```

Removing columns with threshold of percent missing row values

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

```
       Dog   Cat  test
[1,] FALSE  TRUE FALSE
[2,]  TRUE FALSE FALSE
[3,] FALSE FALSE FALSE
```

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

```
      Dog       Cat      test 
0.1666667 0.5000000 0.0000000 
```

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

```
# A tibble: 6 × 2
    Dog  test
  <dbl> <dbl>
1     0     1
2    NA     2
3     2     3
4     3     4
5     1     5
6     1     6
```

Change a value to be `NA`

The `na_if()` function of `dplyr` can be helpful for this. Let's say we think that all 0 values should be `NA`.

```
df %>% head(n = 3)
```

```
# A tibble: 3 × 3
    Dog   Cat  test
  <dbl> <dbl> <dbl>
1     0    NA     1
2    NA     8     2
3     2     6     3
```

```
df %>% mutate(Dog = na_if(Dog, 0))
```

```
# A tibble: 6 × 3
    Dog   Cat  test
  <dbl> <dbl> <dbl>
1    NA    NA     1
2    NA     8     2
3     2     6     3
4     3    NA     4
5     1     2     5
6     1    NA     6
```

Think about `NA`

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 this and also if there was a different issue?

Think about `NA`

If it is something more like a zero then you might want it included in your data like a zero.

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.

```
red_blue
```

```
# A tibble: 3 × 2
  color col_count
  <chr>     <int>
1 blue          3
2 red           3
3 <NA>          3
```

```
red_blue %>% mutate(percent =
                      col_count/sum(pull(red_blue, col_count)))
```

```
# A tibble: 3 × 3
  color col_count percent
  <chr>     <int>   <dbl>
1 blue          3   0.333
2 red           3   0.333
3 <NA>          3   0.333
```

Word of caution

```
red_blue %>% mutate(percent =
                      col_count/sum(pull(drop_na(red_blue), col_count)))
```

```
# A tibble: 3 × 3
  color col_count percent
  <chr>     <int>   <dbl>
1 blue          3     0.5
2 red           3     0.5
3 <NA>          3     0.5
```

Should you be dividing by 9 or 6?
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

Lab Part 1

- Class Website
- Lab

Recoding Variables

Example of Recoding

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            225             3
 2 B     m               105            -3
 3 B     Other           229            18
 4 A     F               110             6
 5 B     Female          159             2
 6 B     M               199            14
 7 A     f               120             5
 8 B     O               201            -9
 9 B     Man             233            -5
10 A     f               108             0
11 B     F               118            12
12 B     O               121             8
```

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
```

`dplyr` can help!

Using Excel to find all of the different ways `gender` has been coded, could be hectic!

In `dplyr` you can use the `recode` function (need `mutate` here too!):

```
# General Format - this is not code!
{data_input} %>%
  mutate({variable_to_fix} = {Variable_fixing}, {old_value} = {new_value},
                                     {another_old_value} = {new_value})
```

```
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, Diet)
```

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

Or you can use `case_when()`

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

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

Note that automatically values not reassigned explicitly by `case_when()` will be `NA` unless otherwise specified.

```
data_diet %>%
  mutate(Gender = case_when(Gender == "M" ~ "Male"))
```

```
# A tibble: 12 × 4
   Diet  Gender Weight_start Weight_change
   <chr> <chr>         <int>         <int>
 1 A     <NA>            225             3
 2 B     <NA>            105            -3
 3 B     <NA>            229            18
 4 A     <NA>            110             6
 5 B     <NA>            159             2
 6 B     Male            199            14
 7 A     <NA>            120             5
 8 B     <NA>            201            -9
 9 B     <NA>            233            -5
10 A     <NA>            108             0
11 B     <NA>            118            12
12 B     <NA>            121             8
```

Use of **case_when()** without automatic **NA**

```
# 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})
```

Here we use the original values of `Gender` to replace all values of `Gender` that do not meet the condition `== "M"`.

```
data_diet %>%
  mutate(Gender = case_when(Gender == "M" ~ "Male",
                                     TRUE ~ Gender))
```

```
# A tibble: 12 × 4
   Diet  Gender Weight_start Weight_change
   <chr> <chr>         <int>         <int>
 1 A     Male            225             3
 2 B     m               105            -3
 3 B     Other           229            18
 4 A     F               110             6
 5 B     Female          159             2
 6 B     Male            199            14
 7 A     f               120             5
 8 B     O               201            -9
 9 B     Man             233            -5
10 A     f               108             0
11 B     F               118            12
12 B     O               121             8
```

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            225             3
 2 B     Male            105            -3
 3 B     Other           229            18
 4 A     Female          110             6
 5 B     Female          159             2
 6 B     Male            199            14
 7 A     Female          120             5
 8 B     Other           201            -9
 9 B     Male            233            -5
10 A     Female          108             0
11 B     Female          118            12
12 B     Other           121             8
```

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            225             3 Increase
2 B     m               105            -3 Decrease
3 B     Other           229            18 Increase
4 A     F               110             6 Increase
5 B     Female          159             2 Increase
6 B     M               199            14 Increase
```

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

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

```
x<-c("cat", "dog", "mouse")
str_detect(string = x, pattern = "d")
```

```
[1] FALSE  TRUE 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

```
x<-c("cat", "dog", "mouse")
str_replace(string = x, pattern = "d", replacement = "D")
```

```
[1] "cat"   "Dog"   "mouse"
```

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 `start` argument specifies position of where to end

```
x<-c("cat", "dog", "mouse")
str_sub(string = x, start = 1, end = 2)
```

```
[1] "ca" "do" "mo"
```

`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            225             3 Increase
2 B     m               105            -3 Decrease
3 B     Other           229            18 Increase
4 A     F               110             6 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            225             3 Increase
2 B     M               199            14 Increase
3 B     Man             233            -5 Decrease
```

`case_when()` improved with `stringr`

```
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
```

```
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
```

Separating and uniting data

What if our data looked like this?

```
diet_comb
```

```
# A tibble: 4 × 2
  change          n
  <chr>       <int>
1 A_Increase      3
2 A_Same          1
3 B_Decrease      3
4 B_Increase      5
```

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

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

Uniting columns

The `unite()` function can instead help combine columns.
The `col` argument specifies new column name
The `sep` argument specifies what separator to use when combining

```
# A tibble: 4 × 2
     id visit
  <int> <int>
1     1     1
2     2     1
3     3     1
4     4     1
```

```
df_united <- df %>% unite(col = "unique_id", id, visit, sep = "_")
head(df_united, 4)
```

```
# A tibble: 4 × 1
  unique_id
  <chr>
1 1_1
2 2_1
3 3_1
4 4_1
```

Summary

- `recode()` can help with simple recoding (not based on condition but simple swap)
- `case_when()` can recode **entire values** based on conditions
  - remember `case_when()` needs `TRUE ~ varaible` to keep values that aren't specified by conditions, otherwise will be `NA`
- `stringr` package has great functions for looking for specific **parts of values** especially `filter()` and `str_detect()` combined
  - also has other useful string manipulation functions like `str_replace()` and more!
  - `separate()` can split columns into additional columns
  - `unite()` can combine columns

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"
```

!– # Before Cleaning - Subsetting with Brackets –>

–>

–> –> –>

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 `grepl` (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

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

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

```r
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                AnnualSalary JobTitle
  <chr>                      <dbl> <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
```

Website

[Website]

Extra slides

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%
```