



**ALVAREZ**

College of Business

The University of Texas at San Antonio

# Introduction to Programming in R

**Module 4:**  
Data Wrangling  
Part 1

# Learning Objectives

- Importing and exporting using *readr*
- Tibbles
- Filtering rows using *dplyr*
- Sorting using *dplyr*
- Selecting columns using *dplyr*
- Computing and concatenating new columns using *dplyr*
- Grouping using *dplyr*

# Data Importing

- The *tidyverse* package has a *readr* package (much faster than Base R importing functions, such as *read.csv()*, and produces tibbles (next).
- Readr uses the following importing functions.

Function	
<code>read_csv()</code>	Comma delimited files
<code>read_csv2()</code>	Semicolon delimited files
<code>read_tsv()</code>	Tab delimited files
<code>read_delim()</code>	Any delimited files
<code>read_fwf()</code>	Fixed-width files
<code>read_log</code>	Apache style log files

- We will use `read_csv()`: most popular and the syntax is similar across all of them.
- 1<sup>st</sup> argument is the pathname (location) of the file including the filename.

# Properties of *read\_csv()*

- By default, the first line of the imported data will be the column names (i.e. the variable names).
- You can change this behavior by using argument *skip* = ). For e.g. if the first 2 lines were unnecessary header data, use *skip* = 2.
- If the data does not have column names, then use argument *col\_names* = *FALSE*. Then column names will be *X1*, *X2*, ..., *Xn*.
- Otherwise, you can specify your own column names by providing *col\_names* = *c()*.
- For missing values, that maybe stored as a . or empty space, use argument *na* = "." or *na* = " ".
- This set of information will help you import most csv files, especially clean ones.
  - With more messy data with lots of missing values and mixed data types, we need to understand parsing a file.

# Examples

- Before you can load, we need to check what is our working folder.
    - Use *getwd()*, *setwd()*, and *read\_csv()*
  - Read in *hmda\_2017\_tx\_all\_06.csv*.
  - Check the data type of each variable.
1. Load the historical state populations file: *introductory\_state\_example.csv*
    - Make sure the columns are named appropriately.
  2. Load the historical college information file: *college\_history.csv*.
    - Caution the *original\_name* column has missing values with different inputs.

# How does *readr* work?

- Without going into too much detail – we need to understand how readr automatically guesses each type of variable, and how to overwrite it, if needed.
- Readr reads the first 1000 rows of a column, and then guesses the data type based on some rules.
- Uses `guess_parser()` and `parse_guess()`.

```
> guess_parser(c("TRUE", "FALSE", ""))  
[1] "logical"  
> parse_guess(c("TRUE", "FALSE", ""))  
[1] TRUE FALSE  NA
```
- You can have issues if you're dealing with large files.
  - First 1000 rows might be special cases. For e.g. first 1000 rows are integer with numeric next.
  - First 1000 rows may be missing.
- Let's see an e.g. read in the file `challenge.csv`.
  - Again make sure either the data is in the working directory or provide the pathname.

# How does *read\_csv()* work?

```
> read_csv(readr_example("Challenge.csv"))
```

```
Parsed with column specification:
```

```
cols(  
  x = col_double(),  
  y = col_logical()  
)
```

```
Warning: 1000 parsing failures.
```

row	col	expected	actual
file			
1001	y	1/0/T/F/TRUE/FALSE	2015-01-16 '/Library/Frameworks/R.framework/Versions/3.4/Resources/library/readr/extdata/Challenge.csv'
1002	y	1/0/T/F/TRUE/FALSE	2018-05-18 '/Library/Frameworks/R.framework/Versions/3.4/Resources/library/readr/extdata/Challenge.csv'
1003	y	1/0/T/F/TRUE/FALSE	2015-09-05 '/Library/Frameworks/R.framework/Versions/3.4/Resources/library/readr/extdata/Challenge.csv'
1004	y	1/0/T/F/TRUE/FALSE	2012-11-28 '/Library/Frameworks/R.framework/Versions/3.4/Resources/library/readr/extdata/Challenge.csv'
1005	y	1/0/T/F/TRUE/FALSE	2020-01-13 '/Library/Frameworks/R.framework/Versions/3.4/Resources/library/readr/extdata/Challenge.csv'

```
.....
```

```
.....
```

```
See problems(...) for more details.
```

```
# A tibble: 2,000 x 2
```

	x	y
	<dbl>	<lgl>
1	404	NA
2	4172	NA
3	3004	NA
4	787	NA
5	37	NA
6	2332	NA
7	2489	NA

- Based on the first 1000 rows (NAs), *readr* is expecting logicals. Remember NAs get stored as logicals. But after 1000 rows it's dates.

- So if you store this as a variable, all the date information will be lost, and only NAs will be stored.
- You can see this by `view(challenge)` and scrolling down.

# How does *read\_csv()* work? (cont.)

```
> read_csv(
+   readr_example("challenge.csv"),
+   col_types = cols(
+     x = col_number(),
+     y = col_date()
+   )
+ )
# A tibble: 2,000 x 2
      x y
  <dbl> <date>
1   404 NA
2  4172 NA
3  3004 NA
4   787 NA
5    37 NA
6  2332 NA
7  2489 NA
8  1449 NA
9  3665 NA
10 3863 NA
# ... with 1,990 more rows
```

- You can add argument *col\_types* to *read\_csv()* if you already know.
- Here, *col\_double()* (numeric) & *col\_date()* works.

```
> read_csv(readr_example("Challenge.csv"), guess_max = 1001)
Parsed with column specification:
cols(
  x = col_double(),
  y = col_date(format = "")
)
# A tibble: 2,000 x 2
      x y
  <dbl> <date>
1   404 NA
2  4172 NA
3  3004 NA
4   787 NA
5    37 NA
6  2332 NA
7  2489 NA
8  1449 NA
9  3665 NA
10 3863 NA
# ... with 1,990 more rows
```

- You can also use *guess\_max* = as an argument.
- Here, if you used *guess\_max* = 1001, it'd work.



# Data Exporting

- You can use `write_csv()` (comma) and `write_tsv()` (tab).
- Save the tidy `college_hist` data to `college_history.csv` file.
- However, these functions do not save data types. So when you read it in again, you'll have to go through parsing again.
  - This is bad for intermediate data manipulations and storing.

For e.g. do `write_csv(challenge, "test_challenge.csv")`, then `read_csv("test_challenge.csv")`.

- For intermediate storing, use `write_rds()` and `read_rds()`. This keeps the data type information.

For e.g. do Try `write_rds(challenge, "test_challenge.rds")`, then `read_rds("test_challenge.rds")`.

# Tibble

- Very much like a data frame, a bit more modernized.
- Load built-in data frame mtcars.
  - `data("mtcars")` and `head(mtcars)`
- Since we have a data frame, we can coerce it using `as_tibble(mtcars)`

```
> as_tibble(mtcars)
# A tibble: 32 x 11
   mpg   cyl  disp    hp  drat    wt   qsec    vs  am  gear  carb
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1    21     6   160   110   3.9   2.62  16.5     0     1     4     4
2    21     6   160   110   3.9   2.88  17.0     0     1     4     4
3   22.8     4   108    93   3.85   2.32  18.6     1     1     4     1
4   21.4     6   258   110   3.08   3.22  19.4     1     0     3     1
5   18.7     8   360   175   3.15   3.44  17.0     0     0     3     2
6   18.1     6   225   105   2.76   3.46  20.2     1     0     3     1
7   14.3     8   360   245   3.21   3.57  15.8     0     0     3     4
8   24.4     4   147.    62   3.69   3.19  20.0     1     0     4     2
9   22.8     4   141.    95   3.92   3.15  22.9     1     0     4     2
10  19.2     6   168.   123   3.92   3.44  18.3     1     0     4     4
# ... with 22 more rows
```

## Advantages:

- ✓ Does not convert strings to factors!
- ✓ Tibble column names are more flexible.
- ✓ A single value variable will be auto-replicated to match size of longest variable.
- ✓ Can create variables that depend on existing variables in the tibble.

# Tibble (cont.)

- You can also manually create a tibble using *tibble()*.
- Here, *b* is a singleton. It's replicated to match size of other variables.
- Also, *c* depends on *a*, so once *a* is entered, *c* gets auto-populated.

```
> tibble(`$$` = c("USD", "AUD", "PES", "Yen"), `.1` = 20)
```

```
# A tibble: 4 x 2
```

```
  `$$`    `.1`  
  <chr> <dbl>  
1 USD      20  
2 AUD      20  
3 PES      20  
4 Yen      20
```

- You can also name variables in tibble that would be invalid outside of the tidyverse package.
- You must put such names inside single quotes ` `.

```
> tibble(a = c(1:10), b = "x", c = 4*a)
```

```
# A tibble: 10 x 3
```

```
      a b      c  
  <int> <chr> <dbl>  
1     1 x      4  
2     2 x      8  
3     3 x     12  
4     4 x     16  
5     5 x     20  
6     6 x     24  
7     7 x     28  
8     8 x     32  
9     9 x     36  
10    10 x     40
```

# Tibble (cont..)

- Another way to manually enter a tibble is using *tribble()*. Stands for transposed tibble.
- The tilde ~ denotes the name of the variables.

## Differences with data.frame:

- Printing and subsetting.
  - Object stored as a data frame will print the whole thing. But as a tibble, only print the first 10 obs, by default.
  - Let's try with the built-in dataset *Iris*. Do *data("iris")*.
  - It is stored as a data frame. Do *print(iris)*
  - Then do *tib\_iris = as\_tibble(iris)* and *print(tib\_iris)*.

```
> tribble(~a, ~b, ~c,  
+         1, "x", 4,  
+         2, "x", 8,  
+         3, "x", 12)  
# A tibble: 3 x 3  
      a b      c  
  <dbl> <chr> <dbl>  
1     1 x      4  
2     2 x      8  
3     3 x     12
```

# Tibble (cont...)

- When printing, it does not overwhelm your console.
- Only shows the number of variables that fit on screen.
- Tibbles also show the type of data stored in each variable, like *str()*.
- It also shows the remaining number of obs, after the first 10.
  - You can modify the number to show, using *n =* argument inside the print function.
- When subsetting using *\$* or *[[ ]]*, data frame & tibble provides a *NULL* if you have an error, but tibble also provides a “*unknown*” warning.

```
> print(tib_iris)
# A tibble: 150 x 5
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
      <dbl>         <dbl>         <dbl>         <dbl> <fct>
1         5.1           3.5           1.4           0.2 setosa
2         4.9           3           1.4           0.2 setosa
3         4.7           3.2           1.3           0.2 setosa
4         4.6           3.1           1.5           0.2 setosa
5          5           3.6           1.4           0.2 setosa
6         5.4           3.9           1.7           0.4 setosa
7         4.6           3.4           1.4           0.3 setosa
8          5           3.4           1.5           0.2 setosa
9         4.4           2.9           1.4           0.2 setosa
10        4.9           3.1           1.5           0.1 setosa
# ... with 140 more rows
```

```
> iris$special
NULL
> tib_iris$special
NULL
Warning message:
Unknown or uninitialised column: 'special'.
```

# Transformations

- Using dplyr package.
  - Can pick observations based on values: *filter()*
  - Reorder observations/rows: *arrange()*
  - Extract variables using names: *select()*
  - Create a new variable using functions on existing ones: *mutate()*
  - Collapse multiple observations to a single summary: *summarize()*
- You can also use *group\_by()* to use the above functions on the entire data or on results of each other.
- With the above functions, the first argument is the data, and the following argument state what to do with variables.
- Result is a tibble (data frame).

# *filter()*

- You can subset a tibble based on values of observations.
- Let's use built-in data mtcars. Do data("mtcars").
- You want to see the cars that have 1 carburetor and 4 gears:

```
> filter(mtcars, carb==1, gear==4)
```

	mpg	cyl	dis	hp	drat	wt	qsec	vs	am	gear	carb
1	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
2	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
3	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
4	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1

- Note that if you want to save this output, you'll have to use <-
- R will either assign or print the result of the expression.
- To do both, wrap the expression in parenthesis ( ).
- For evaluating a criteria do not use a single =, as that is for assigning.
  - Here I used == for testing the criteria. You can also use >, >=, <, <=, !=, or between().

## *filter() (cont.)*

- Boolean operations:

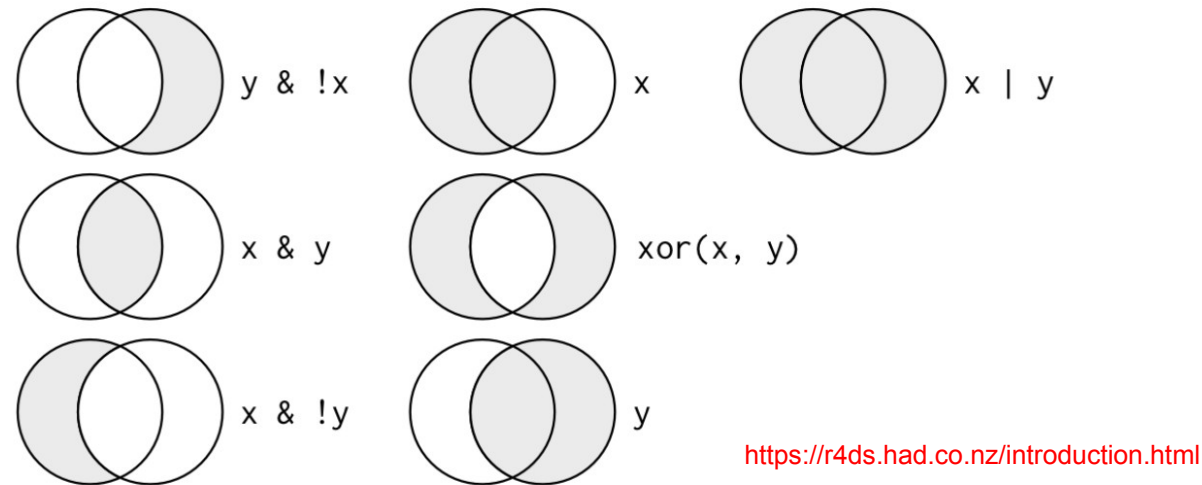


Figure 5.1: Complete set of boolean operations.  $x$  is the left-hand circle,  $y$  is the right-hand circle, and the shaded region show which parts each operator selects.

- Find all cars with either 6 cylinders or 5 gears: `filter(mtcars, cyl==6 | gear==5)`
- Find all cars with with 6 cylinders and 5 gears: `filter(mtcars, cyl==6 & gear==5)`
- Find all cars with mileage between 20 and 25mpg: `mtcars[between(mtcars$mpg, 20, 25),]`



# arrange()

- Change the order of rows – sorting.
- Provide column name(s). If you provide more than one, after the first, each columns is used to break ties when sorting.
  - E.g. Sort cars by cylinder, then gears, then carburetor.
- Use *desc()* to reorder in descending order.
  - E.g. Same sort as above, but with gears in descending order.
- If you have NAs, they will be sorted and put at the bottom.

```
> arrange(mtcars, cyl, gear, carb)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
1	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
2	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
4	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
5	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
6	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
7	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
8	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
9	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2
10	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2

```
> arrange(mtcars, cyl, desc(gear), carb)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
1	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
2	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
3	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
4	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
5	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
6	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
7	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
8	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
9	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
10	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

## Examples (cont.)

1. Find the colleges in our college history data that have a “Secular” sponsorship.
2. Order them from most recent to oldest.
  - Is there any college in this list that had a different original name.
  - Retrieve that name, without looking at the data.
3. Find all the states in 1840 and order them in decreasing population size.
4. Print the top 5.

Extra: Using the Texas data, find the largest population where the median family income is >75K.

# *select()*

- Quickly select a subset of variable from the full data frame.
- After the data, subsequent arguments are the variable to select.
  - E.g. For the cars data, only extract mileage, cylinders, horsepower, and transmission data for the cars.
- You can also select a range of columns using colon (:) operator.
  - E.g. If you only want to extract the first 4 columns of mtcars.
- Or if you want to exclude columns use –
  - E.g. Get all columns except the first 4.

```
> select(mtcars, mpg, cyl, hp, am)
```

	mpg	cyl	hp	am
Mazda RX4	21.0	6	110	1
Mazda RX4 Wag	21.0	6	110	1
Datsun 710	22.8	4	93	1
Hornet 4 Drive	21.4	6	110	0
Hornet Sportabout	18.7	8	175	0
Valiant	18.1	6	105	0

```
> select(mtcars, mpg:hp)
```

	mpg	cyl	disp	hp
Mazda RX4	21.0	6	160.0	110
Mazda RX4 Wag	21.0	6	160.0	110
Datsun 710	22.8	4	108.0	93
Hornet 4 Drive	21.4	6	258.0	110
Hornet Sportabout	18.7	8	360.0	175
Valiant	18.1	6	225.0	105

```
> select(mtcars, -c(mpg:hp))
```

	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	3.90	2.875	17.02	0	1	4	4
Datsun 710	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	3.15	3.440	17.02	0	0	3	2

# *select() (cont.)*

Built-in functions within *select()*:

- *starts\_with("abc")* will find variables that start with abc.
- *ends\_with("xyz")* will find variables that end with xyz.
- *contains("ijk")* will find variables that contain ijk in exact order.
- And others...

You can also rename columns (variables) using *rename()*

Suppose you want to reorder variables and move some to the front, use *everything()*.

- E.g. Move gears and cylinders to the front:  
*select(mtcars, gear, cyl, everything())*

```
> select(mtcars, starts_with("mp"))
```

	mpg
Mazda RX4	21.0
Mazda RX4 Wag	21.0
Datsun 710	22.8
Hornet 4 Drive	21.4
Hornet Sportabout	18.7

```
> select(mtcars, contains("se"))
```

	qsec
Mazda RX4	16.46
Mazda RX4 Wag	17.02
Datsun 710	18.61
Hornet 4 Drive	19.44
Hornet Sportabout	17.02

```
> rename(mtcars, cylind = cyl)
```

	mpg	cylind	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1

# *mutate()*

- Add new columns to the end using functions on existing columns.
- For example, when we look at mileage of a car, we also look at number of cylinders.
- So, we can create a new variable,  $\text{MileagePerCylinder} = \text{mpg} / \text{cyl}$

```
> mutate(mtcars, MileagePerCylinder = mpg/cyl)
```

	mpg	cyl	disp	hp	drat	wt	asec	vs	am	gear	carb	MileagePerCylinder
1	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4	3.500000
2	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4	3.500000
3	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1	5.700000
4	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1	3.566667
5	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2	2.337500
6	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1	3.016667
7	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4	1.787500
8	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2	6.100000

- Something in the middle: High mpg and many cylinders.
- You can also right away create new columns based on the one you just created.
- If you only want the new variables, use *transmute()*.

```
> transmute(mtcars, MileagePerCylinder = mpg/cyl)
```

	MileagePerCylinder
1	3.500000
2	3.500000
3	5.700000

# Other functions for *mutate()*

- Arithmetic operations  $+$ ,  $-$ ,  $/$ ,  $*$ ,  $^$  all work. Vector inputs are expected. If you enter a singleton, it will be replicated.
- You can also use  $\%/\%$  for integer division and  $\%\%$  for the remainder.
- $\log()$ ,  $\log2()$ , and  $\log10()$  all help when data ranges across multiple orders of magnitude. Logs can convert multiplicative to additive:  $\log a + \log b = \log (a*b)$
- $\text{lead}()$  (leading) and  $\text{lag}()$  (lagging) is very handy when studying temporal trends.

```
> a = c(1:10)
> lag(a)
[1] NA 1 2 3 4 5 6 7 8 9
> lead(a)
[1] 2 3 4 5 6 7 8 9 10 NA
```

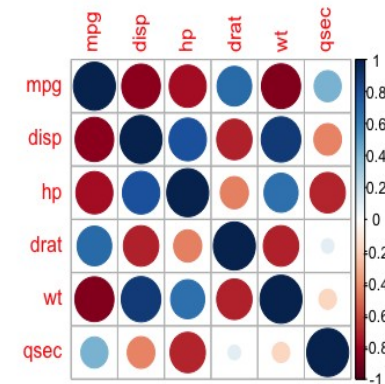
- Cumulative and rolling functions:  $\text{cumsum}()$  (sum),  $\text{cumprod}()$  (product),  $\text{cumin}()$  (minimum),  $\text{cummax}()$  (maximum), and  $\text{cummean}()$  (mean)

```
> cumprod(a)
[1] 1 2 6 24 120 720 5040 40320 362880 3628800
> cummin(a)
[1] 1 1 1 1 1 1 1 1 1 1
> cummean(a)
[1] 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5
> cummax(a)
[1] 1 2 3 4 5 6 7 8 9 10
> cumsum(a)
[1] 1 3 6 10 15 21 28 36 45 55
```

# Examples (cont..)

Install package and load *corrplot*.

1. Compute a correlation matrix from the mtcars dataset
  - Variables: mileage, displacement, horsepower, rear axle ratio, weight, and 1/4 mi time.
2. Make a correlation matrix plot using *corrplot()*.
3. Add a new indicator variable that is 1 if mpg > 23.
  - Find the mean mpg for these efficient vehicles.



Extra: Using the Texas data, create a new variable  
 $\text{minority population \%} = \text{minority population} * 100 / \text{population}.$

# *summarise() & group\_by()*

- *summarise()* collapses the entire data frame into one row.

```
> summarize(mtcars, avgmpg = mean(mpg), minmpg = min(mpg), maxmpg = max(mpg))
  avgmpg minmpg maxmpg
1 20.09062  10.4   33.9
```

- Not too useful, unless used in conjunction with *group\_by()*.
- Let's see mileage stats of mtcars grouped by cylinders, gears, and carburetors:

```
grp_data = group_by(mtcars, cyl, gear, carb)
```

- Then, we can summarize it

```
> summarise(grp_data, avgmpg = mean(mpg), minmpg = min(mpg), maxmpg = max(mpg))
# A tibble: 12 x 6
# Groups:   cyl, gear [8]
  cyl gear carb avgmpg minmpg maxmpg
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     4     3     1  21.5  21.5  21.5
2     4     4     1  29.1  22.8  33.9
3     4     4     2  24.8  21.4  30.4
4     4     5     2  28.2  26    30.4
5     6     3     1  19.8  18.1  21.4
6     6     4     4  10.2  17.8  21.4
```

- Note: *ungroup()* removes grouping



# *group\_by(), filter() & mutate()*

- Find out the mileage per cylinder of grp\_data with mileage > 27mpg.

```
> filter(grp_data, mpg>27)
# A tibble: 5 x 11
# Groups:   cyl, gear, carb [3]
   mpg   cyl  disp    hp  drat    wt   qsec    vs  am  gear  carb
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  32.4     4  78.7    66  4.08  2.2  19.5     1   1     4     1
2  30.4     4  75.7    52  4.93  1.62  18.5     1   1     4     2
3  33.9     4  71.1    65  4.22  1.84  19.9     1   1     4     1
4  27.3     4   79     66  4.08  1.94  18.9     1   1     4     1
5  30.4     4  95.1   113  3.77  1.51  16.9     1   1     5     2
```

```
> mutate(filter(grp_data, mpg>27), MileagePerCylinder = mpg/cyl)
# A tibble: 5 x 12
# Groups:   cyl, gear, carb [3]
   mpg   cyl  disp    hp  drat    wt   qsec    vs  am  gear  carb MileagePerCylinder
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  32.4     4  78.7    66  4.08  2.2  19.5     1   1     4     1           8.1
2  30.4     4  75.7    52  4.93  1.62  18.5     1   1     4     2           7.6
3  33.9     4  71.1    65  4.22  1.84  19.9     1   1     4     1          8.48
4  27.3     4   79     66  4.08  1.94  18.9     1   1     4     1           6.82
5  30.4     4  95.1   113  3.77  1.51  16.9     1   1     5     2           7.6
```

# Other Useful Functions

- *dplyr* has other useful functions also
  - `sample_n()`: randomly samples *n* rows from a data frame.
    - For e.g. `sample_n(data, 20)` would randomly sample 20 rows from a data frame with more than 20 rows.
  - `sample_frac()`: randomly samples a percentage of rows from the data frame.
    - For e.g. `sample_frac(data, 0.2)` would randomly sample 20% of the rows.
- If we want 5 random observation from the `mtcars` data.

```
> sample_n(mtcars, 5)
  mpg cyl  disp  hp drat   wt  qsec vs am gear carb efficient
1 13.3   8 350.0 245 3.73 3.840 15.41  0  0   3   4           0
2 15.5   8 318.0 150 2.76 3.520 16.87  0  0   3   2           0
3 24.4   4 146.7  62 3.69 3.190 20.00  1  0   4   2           1
4 15.2   8 304.0 150 3.15 3.435 17.30  0  0   3   2           0
5 19.2   6 167.6 123 3.92 3.440 18.30  1  0   4   4           0
```

- `replace` argument forces sampling to occur with or without replacement.

# Other Useful Functions (cont.)

- Sampling functions can be useful when the data is not balanced well.
  - When there are far more observations of a value of a variable than the other values.
  - For e.g. in mtcars there are 15 cars with 3 gears, 12 cars with 4 gears, 5 cars with 5 gears.
  - If this doesn't represent the population well, we can force the sampling to occur within each of these groups.
  - Say we want 9 samples, 3 from each of the gear groups:

```
> by_GEAR <- group_by(mtcars, gear)
> sample_n(by_GEAR, 3)
# A tibble: 9 x 12
# Groups:   gear [3]
   mpg   cyl  disp    hp  drat    wt   qsec    vs  am  gear  carb  efficient
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  10.4     8  460    215     3   5.42  17.8     0     0     3     4         0
2  16.4     8  276    180    3.07  4.07  17.4     0     0     3     3         0
3  14.7     8  440    230    3.23  5.34  17.4     0     0     3     4         0
4  21.0     6  160    110    3.9   2.62  16.5     0     1     4     4         0
5  22.8     4  108     93    3.85  2.32  18.6     1     1     4     1         0
6  30.4     4   75.7    52    4.93  1.62  18.5     1     1     4     2         1
7  26.0     4  120     91    4.43  2.14  16.7     0     1     5     2         1
8  15.0     8  301    335    3.54  3.57  14.6     0     1     5     8         0
9  19.7     6  145    175    3.62  2.77  15.5     0     1     5     6         0
```

# Other Useful Functions (cont..)

- Sometimes the data may need to be recoded.
  - For e.g. male/female stored as logical (1/0).
  - Or student status: freshman, sophomore, junior, senior stored as 1, 2, 3, 4.

- For analysis, we want the values to be descriptive and the class to be correct, so we need to recode it.

- We can use `case_when()` to achieve this.

- Load `data("ChickWeight")` and see `head(ChickWeight)`.
  - There are 4 types of diets – coded as 1 (veges), 2 (fruits), 3 (candy), and 4 (meat).
  - We want to show the actual words instead of the numbers.

```
> mutate(ChickWeight, diet_name = case_when(
+   Diet == 1 ~ "vegetables", Diet == 2 ~ "fruit",
+   Diet == 3 ~ "candy", Diet == 4 ~ "meat"))
# A tibble: 578 x 5
  weight Time Chick Diet diet_name
  <dbl> <dbl> <ord> <fct> <chr>
1     42     0 1     1 vegetables
2     51     2 1     1 vegetables
3     59     4 1     1 vegetables
4     64     6 1     1 vegetables
5     76     8 1     1 vegetables
6     93    10 1     1 vegetables
7    106    12 1     1 vegetables
8    125    14 1     1 vegetables
9    149    16 1     1 vegetables
10   171    18 1     1 vegetables
# ... with 568 more rows
```

# Example

- Install the package *nycflights13* and load it.
  - This dataset contains all 336776 flights that departed from New York City in 2013.
  - The data comes from the US Bureau of Transportation Statistics, and is documented in ?  
*nycflights13*
1. Show all flights on January 1<sup>st</sup>.
  2. Find the flights on January 1<sup>st</sup> flights which had the 5 longest arrival delays.
    - Print the carrier and flight numbers.
  3. Compute 2 new variables and add it onto the flights table
    - $\text{gain} = \text{arrival delay} - \text{departure delay}$
    - $\text{speed} = (\text{distance} / \text{airtime}) * 60$ .
    - Print the top 5 flights (carrier and number) for the best gain in the full flights table.