Intro To dplyr

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2020-01-25

Contents

Chapter 1

R Data Structures

There are a number of data structures in R such as **vectors, lists** qnd **matrices**. The **vector** structure winds up being helpful in understanding how to work with data frames.

1.1 Vectors

It is a container for a series of related data of the same type: height measurements of students, whether a group of people smoke or not, their blood pressure. The only rule here is that a vector can contain only one data type at a time.

```
names  <- c("P1","P2","P3","P4","P5")
temp   <- c(98.2,101.3,97.2,100.2,98.5)
pulse  <- c(66,72,83,85,90)
gender <- c("M","F","M","M","F")
```

To access elements, or ranges of elements, within a vector involves using the "bracket" notation:

```
# Get the first element of temp
temp[1]
```

```
## [1] 98.2
```

```
# Get elements 3,4, and 5 from pulse
pulse[3:5]
```

```
## [1] 83 85 90
```

We can also use logical expressions to find elements that satisfy some condition. This is a very powerful capability in R.

```
temp < 98
```

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

Whoa. What was that ? Well we get back a T/F logical vector that tells us what elements satisfy the specified condition. We can then use this info to get the elements of interest.

```
temp[temp < 98]
```

```
## [1] 97.2
```

Working with individual vectors is fine but a more general way of working with them is in data frames which provides more fleibility:

```
(my_df <- data.frame(names,temp,pulse,gender))
```

```
##   names  temp pulse gender
## 1    P1  98.2    66      M
## 2    P2 101.3    72      F
## 3    P3  97.2    83      M
## 4    P4 100.2    85      M
## 5    P5  98.5    90      F
```

Looking at each column, we see that they are the vectors we were just working with. If we need to access them from the data frame it's easy.

```
# Get the temp column
my_df$temp
```

```
## [1]  98.2 101.3  97.2 100.2  98.5
```

```
# What's the mean of the temp column
mean(my_df$temp)
```

```
## [1] 99.08
```

1.2 Data Frames

But we are getting ahead of ourselves. Just know that the **premier data structure** in R is the **data.frame**. This structure can be described as follows:

- A data frame is a special type of list that contains data in a format that allows for easier manipulation, reshaping, and open-ended analysis
- Data frames are tightly coupled collections of variables. It is one of the more important constructs you will encounter when using R so learn all you can about it
- A data frame is an analogue to the Excel spreadsheet but is much more flexible for storing, manipulating, and analyzing data
- Data frames can be constructed from existing vectors, lists, or matrices. Many times they are created by reading in comma delimited files, (CSV files), using the read.table command

Once you become accustomed to working with data frames, R becomes so much easier to use. In fact, it could be well argued tht UNTIL you wrap your head around the data frame concept then you cannot be productive in R. This is mostly true, in my experience.

R comes with with a variety of built-in data sets that are very useful for getting used to data sets and how to manipulate them.

```
AirPassengers            Monthly Airline Passenger Numbers 1949-1960
BJsales                  Sales Data with Leading Indicator
BOD                      Biochemical Oxygen Demand
CO2                      Carbon Dioxide Uptake in Grass Plants
ChickWeight              Weight versus age of chicks on different diets
DNase                    Elisa assay of DNase
Formaldehyde             Determination of Formaldehyde
HairEyeColor             Hair and Eye Color of Statistics Students
Harman23.cor             Harman Example 2.3
```

```
Harman74.cor          Harman Example 7.4
Indometh              Pharmacokinetics of Indomethacin
InsectSprays          Effectiveness of Insect Sprays
JohnsonJohnson        Quarterly Earnings per Johnson & Johnson Share
LakeHuron             Level of Lake Huron 1875-1972
LifeCycleSavings      Intercountry Life-Cycle Savings Data
Loblolly              Growth of Loblolly pine trees
Nile                  Flow of the River Nile
Orange                Growth of Orange Trees
OrchardSprays         Potency of Orchard Sprays
PlantGrowth           Results from an Experiment on Plant Growth
Puromycin             Reaction Velocity of an Enzymatic Reaction
Theoph                Pharmacokinetics of Theophylline
```

1.3 A Reference Data Frame

We will use a well-known data frame, at least in R circles, called **mtcars** which is part of any default installation of R. It is a simple data set relating to, well, automobiles. This data frame has the distinction of being the most (ab)used data frame in R education.

```
The data was extracted from the 1974 Motor Trend US
magazine, and comprises fuel consumption and 10 aspects
of automobile design and performance for 32 automobiles
(1973-74 models).

A data frame with 32 observations on 11 (numeric)
variables.

[, 1]   mpg Miles/(US) gallon
[, 2]   cyl Number of cylinders
[, 3]   disp    Displacement (cu.in.)
[, 4]   hp  Gross horsepower
[, 5]   drat    Rear axle ratio
[, 6]   wt  Weight (1000 lbs)
[, 7]   qsec    1/4 mile time
[, 8]   vs  Engine (0 = V-shaped, 1 = straight)
[, 9]   am  Transmission (0 = automatic, 1 = manual)
[,10]   gear    Number of forward gears
[,11]   carb    Number of carburetors
```

1.4 Relation to dplyr

What you will discover is that the **dplyr** package, which itself is part of the much larger **tidyverse** package set , extends upon the idea of the basic R data frame in a way that some feel is superior. It depends on your point of view though the **tidyverse** has a lot of what I call a philosophic consistency in it which makes it **very** useful once you get some concepts in mind.

While you could start exclusively with **dplyr** and the **tidyverse** the world is still full of older code. Plus, many of the advantages of **dplyr** only become quite apparent when compared to the "older way" of doing things. So my recommendation is to know how to deal with data frames in base R while also spending time to learn the **dplyr** way of doing things.

Chapter 2

Digging In

Data frames look like an Excel Spreadsheet. The rows are observations and the columns are variables or "features" that represent some measurement or character-based description of a given observation. When viewed from the row point of view, the data can be heterogenous. When viewed as a column, the data is homogenous.

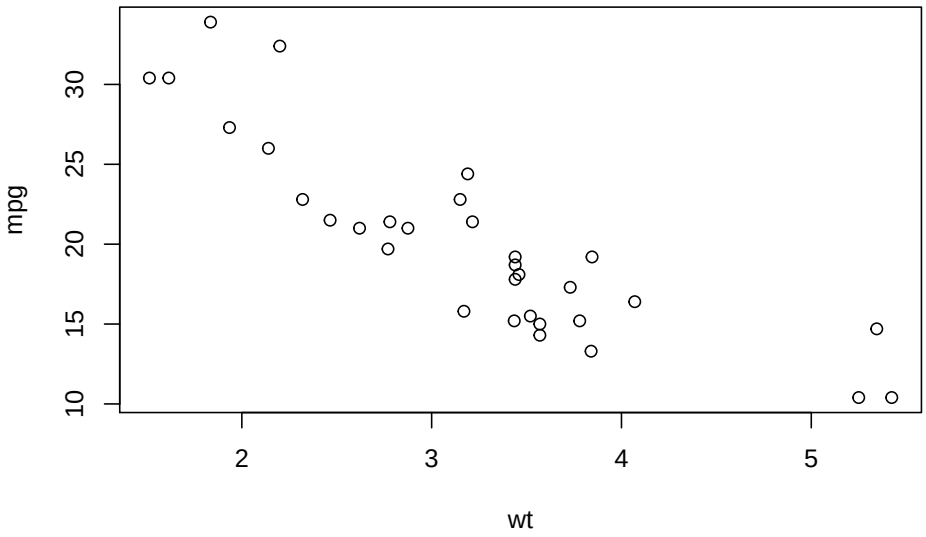
```
data(mtcars)
mtcars
```

```
##                     mpg cyl  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
## Hornet Sportabout  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## Valiant            18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## Duster 360         14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## Merc 240D          24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230           22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Merc 280           19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
## Merc 280C          17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## Merc 450SE         16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
## Merc 450SL         17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## Merc 450SLC        15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4  8 460.0 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial  14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## Fiat 128           32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic        30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla     33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
```

```
## Toyota Corona       21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
## Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## Fiat X1-9           27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2       26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa        30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## Ferrari Dino        19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## Volvo 142E          21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

We can do this with this data such as make plots or create models:

```
plot(mpg ~ wt, data=mtcars)
```



Let's create a regression model. It doesn't take long to realize that most functions in R will use a data frame as input. This means that you will spend a lot of time working with data frames to get them into shape for use with modeling and visualization tools. In fact you will spend most of your time **importing, transforming, and cleaning**.

```
(mylm <- lm(mpg ~ ., data = mtcars))
```

```
##
## Call:
## lm(formula = mpg ~ ., data = mtcars)
##
## Coefficients:
```

```
## (Intercept)          cyl         disp           hp         drat
##    12.30337     -0.11144      0.01334     -0.02148      0.78711
##          wt         qsec           vs           am         gear
##    -3.71530      0.82104      0.31776      2.52023      0.65541
##        carb
##    -0.19942
```

There are some useful functions that help you understand the structure of a data frame. One of the most important ones is called the **str()** function which is short hand for **structure**.

2.1 Structure

```
str(mtcars)
```

```
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
##  $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
##  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

This gives you some idea about the number of rows and columns of the data frame along with a description of the variable types and their values. I use this function frequently. Other functions that will help you include the following.

2.2 Meta Information

```
# how many rows
nrow(mtcars)
```

```
## [1] 32
```

```
# how many columns
ncol(mtcars)
```

```
## [1] 11
```

```
# Column names
names(mtcars)
```

```
##  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
## [11] "carb"
```

2.3 Printing

Some data frames, such as mtcars, don't have many rows but others might have hundreds, thousands or even more than that ! Imagine trying to view one of those data frames. It is for this reason that the **head()** and **tail()** functions exist.

```
head(mtcars,5) # First 5 rows
```

```
##                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
```

```
tail(mtcars,3) # Last 3 rows
```

```
##                mpg cyl disp  hp drat   wt qsec vs am gear carb
## Ferrari Dino  19.7   6  145 175 3.62 2.77 15.5  0  1    5    6
## Maserati Bora 15.0   8  301 335 3.54 3.57 14.6  0  1    5    8
## Volvo 142E    21.4   4  121 109 4.11 2.78 18.6  1  1    4    2
```

2.4 Accessing Rows And Columns

There are various ways to select, remove, or exclude rows and columns of a data frame. We use the **bracket** notation to do this. This is very powerful. Keep in mind that data frames have rows and columns so it would make sense that you need a way to specify what rows and columns you want to access.

```
mtcars[1,]     # First row, all columns
```

```
##           mpg cyl disp  hp drat   wt  qsec vs am gear carb
## Mazda RX4  21   6  160 110  3.9 2.62 16.46  0  1    4    4
```

```
mtcars[1:3,]   # First three rows, all columns
```

```
##                mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4     21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag 21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
```

```
## Datsun 710    22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
```

```
# All rows, and first 4 columns
mtcars[,1:4]
```

```
##                      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
## Duster 360          14.3   8 360.0 245
## Merc 240D           24.4   4 146.7  62
## Merc 230            22.8   4 140.8  95
## Merc 280            19.2   6 167.6 123
## Merc 280C           17.8   6 167.6 123
## Merc 450SE          16.4   8 275.8 180
## Merc 450SL          17.3   8 275.8 180
## Merc 450SLC         15.2   8 275.8 180
## Cadillac Fleetwood  10.4   8 472.0 205
## Lincoln Continental 10.4   8 460.0 215
## Chrysler Imperial   14.7   8 440.0 230
## Fiat 128            32.4   4  78.7  66
## Honda Civic         30.4   4  75.7  52
## Toyota Corolla      33.9   4  71.1  65
## Toyota Corona       21.5   4 120.1  97
## Dodge Challenger    15.5   8 318.0 150
## AMC Javelin         15.2   8 304.0 150
## Camaro Z28          13.3   8 350.0 245
## Pontiac Firebird    19.2   8 400.0 175
## Fiat X1-9           27.3   4  79.0  66
## Porsche 914-2       26.0   4 120.3  91
## Lotus Europa        30.4   4  95.1 113
## Ford Pantera L      15.8   8 351.0 264
## Ferrari Dino        19.7   6 145.0 175
## Maserati Bora       15.0   8 301.0 335
## Volvo 142E          21.4   4 121.0 109
```

```
# Rows 1-5 and columns 1,2 and 8-10
mtcars[1:4,c(1:2,8:10)]
```

```
##                 mpg cyl vs am gear
## Mazda RX4      21.0   6  0  1    4
## Mazda RX4 Wag  21.0   6  0  1    4
## Datsun 710     22.8   4  1  1    4
## Hornet 4 Drive 21.4   6  1  0    3
```

```
# Rows 1-5 and columns 1,2 and 8-10
mtcars[1:4,c(1:2,8:10)]
```

```
##                 mpg cyl vs am gear
## Mazda RX4      21.0   6  0  1    4
## Mazda RX4 Wag  21.0   6  0  1    4
## Datsun 710     22.8   4  1  1    4
## Hornet 4 Drive 21.4   6  1  0    3
```

```
# Rows 1-5 and columns by name
mtcars[1:4,c("mpg","wt","drat")]
```

```
##                 mpg    wt drat
## Mazda RX4      21.0 2.620 3.90
## Mazda RX4 Wag  21.0 2.875 3.90
## Datsun 710     22.8 2.320 3.85
## Hornet 4 Drive 21.4 3.215 3.08
```

2.5 Interrogation

Many times you will wish to find rows that satisfy certain conditions. For example, what rows have an mpg > 11 and at wt < 2.0 ? We use the bracket notation to help us. We can pass logical conditions into the brackets. Note the following:

```
mtcars$mpg > 11 & mtcars$wt < 2.0
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [12] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE FALSE FALSE
## [23] FALSE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE FALSE FALSE
```

There are 32 elements in this logical vector each with a value of either TRUE or FALSE. When passed into the row index of the bracket notation, it will print that row if the corresponding value is TRUE. If FALSE, the row will not be printed.

```
mtcars[mtcars$mpg > 11 & mtcars$wt < 2.0,]
```

```
##                 mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Honda Civic    30.4   4 75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla 33.9   4 71.1  65 4.22 1.835 19.90  1  1    4    1
## Fiat X1-9      27.3   4 79.0  66 4.08 1.935 18.90  1  1    4    1
## Lotus Europa   30.4   4 95.1 113 3.77 1.513 16.90  1  1    5    2
```

What if we just want to know how many cars satisfy this condition ?

```
nrow(mtcars[mtcars$mpg > 11 & mtcars$wt < 2.0,])
```

```
## [1] 4
```

Find all rows that correspond to cars with 4 cylinders

```
mtcars[mtcars$cyl == 4,]
```

```
##                 mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## Datsun 710     22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## Merc 240D      24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230       22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Fiat 128       32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic    30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona  21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Fiat X1-9      27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2  26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa   30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Volvo 142E     21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

We can even use other R functions in the bracket notation. Extract all rows whose MPG value exceeds the mean MPG for the entire data frame.

```
mtcars[mtcars$mpg > mean(mtcars$mpg),]
```

```
##                 mpg cyl  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
## Merc 240D      24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230       22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Fiat 128       32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic    30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona  21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Fiat X1-9      27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2  26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa   30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Volvo 142E     21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

Now find the cars for which the MPG exceeds the 75% percentile value for MPG

```
mtcars[mtcars$mpg > quantile(mtcars$mpg)[4],]
```

```
##                 mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## Merc 240D      24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Fiat 128       32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
```

```
## Honda Civic    30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Fiat X1-9      27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2  26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa   30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
```

2.6 Missing values

This is big deal. Most "real" data has rows that do not contain values for all columns. This is the so called "missing value" problem. Here is an example. The following code will read in a version of the mtcars data frame that has some missing values:

```
url <- "https://raw.githubusercontent.com/steviep42/utilities/master/data/mtcars_na.csv
(mtcars_na <- read.csv(url, stringsAsFactors = FALSE))
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## 2  21.0   6 160.0 110 3.90    NA 17.02  0  1    4    4
## 3  22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## 4  21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## 5  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## 6  18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## 7  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## 8  24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## 9  22.8   4 140.8  95 3.92    NA 22.90  1  0    4    2
## 10 19.2   6 167.6 123 3.92 3.440 18.30  1  0    4   NA
## 11 17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## 12 16.4   8 275.8 180 3.07 4.070 17.40  0  0    3   NA
## 13 17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## 14 15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## 15 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## 16 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
## 17 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## 18 32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## 19 30.4   4  75.7  52 4.93 1.615 18.52  1  1    4   NA
## 20 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4   NA
## 21 21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## 22 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## 23 15.2   8 304.0 150 3.15    NA 17.30  0  0    3   NA
## 24 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## 25 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## 26 27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## 27 26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## 28 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5   NA
```

```
## 29 15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## 30 19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## 31 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## 32 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

If you look, you can see the missing values "NA" present in certain columns. This is R's way of indicating what is missing. There are functions that can help you find these. This is important because, for example, if you wanted to find the average value of a column, say the **wt** column then there will be a problem as it contains a missing value:

```
mean(mtcars_na$wt)
```

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

We have to tell the function to remove missing values from consideration.

```
mean(mtcars$wt, na.rm=TRUE)
```

```
## [1] 3.21725
```

A more general approach would involve the following functions.

```
complete.cases(mtcars_na)
```

```
##  [1]  TRUE FALSE  TRUE  TRUE  TRUE  TRUE  TRUE  TRUE FALSE FALSE  TRUE
## [12] FALSE  TRUE  TRUE  TRUE  TRUE  TRUE  TRUE FALSE FALSE  TRUE  TRUE
## [23] FALSE  TRUE  TRUE  TRUE  TRUE FALSE  TRUE  TRUE  TRUE  TRUE
```

```
# How many rows in the df do not contain any NAs ?
sum(complete.cases(mtcars_na))
```

```
## [1] 24
```

```
# How many rows in the df do contain at least one NA ?
sum(!complete.cases(mtcars_na))
```

```
## [1] 8
```

How would we find those rows and print them ?

```
mtcars_na[complete.cases(mtcars_na),]
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## 3  22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## 4  21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## 5  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## 6  18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## 7  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## 8  24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## 11 17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
```

```
## 13 17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## 14 15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## 15 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## 16 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
## 17 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## 18 32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## 21 21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## 22 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## 24 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## 25 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## 26 27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## 27 26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## 29 15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## 30 19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## 31 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## 32 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

And here are the ones that do contain missing values:

```
mtcars_na[!complete.cases(mtcars_na),]
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 2  21.0   6 160.0 110 3.90    NA 17.02  0  1    4    4
## 9  22.8   4 140.8  95 3.92    NA 22.90  1  0    4    2
## 10 19.2   6 167.6 123 3.92 3.440 18.30  1  0    4   NA
## 12 16.4   8 275.8 180 3.07 4.070 17.40  0  0    3   NA
## 19 30.4   4  75.7  52 4.93 1.615 18.52  1  1    4   NA
## 20 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4   NA
## 23 15.2   8 304.0 150 3.15    NA 17.30  0  0    3   NA
## 28 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5   NA
```

One quick way to omit rows with missing values is:

```
na.omit(mtcars_na)
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## 3  22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## 4  21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## 5  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## 6  18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## 7  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## 8  24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## 11 17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## 13 17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## 14 15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## 15 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## 16 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
```

```
## 17 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## 18 32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## 21 21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## 22 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## 24 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## 25 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## 26 27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## 27 26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## 29 15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## 30 19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## 31 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## 32 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

2.7 Continuous vs Factors

One **recipe** that I use frequently is given below. This tells me how many unqiue values are assumed by each column which then helps to identify continuous quantities and categories. If a column assumes only a small number of unique values then perhaps it should be classified as a factor. Don't let the code here scare you. If you are new to R and don't yet understand what is going on then just use this as a "recipe" for now.

```
sapply(mtcars, function(x) length(unique(x)))
```

```
##  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
##   25    3   27   22   22   29   30    2    2    3    6
```

So it looks to me, for example, that **cyl, vs, am, gear, and carb** are actually categories rather than measured quantities. If you look at the help page for mtcars you will see that **am** is a 0 or 1 which corresponds to, respectively, a car with an automatic transmission (0) or a manual transmission (1). If you use the **summarize** function it will treat this variable as a numeric, continuous quantity.

Is it actually possible to have a transmission value of 0.4062 ?

```
summary(mtcars$am)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.4062  1.0000  1.0000
```

I might then use some code to transform this into factors so that when they are used with various modeling functions they will be recognized as such. For example, if we summarize the data frame right now, we will see the following

```
summary(mtcars$am)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

```
##  0.0000  0.0000  0.0000  0.4062  1.0000  1.0000
```

Let's turn **am** into a factor

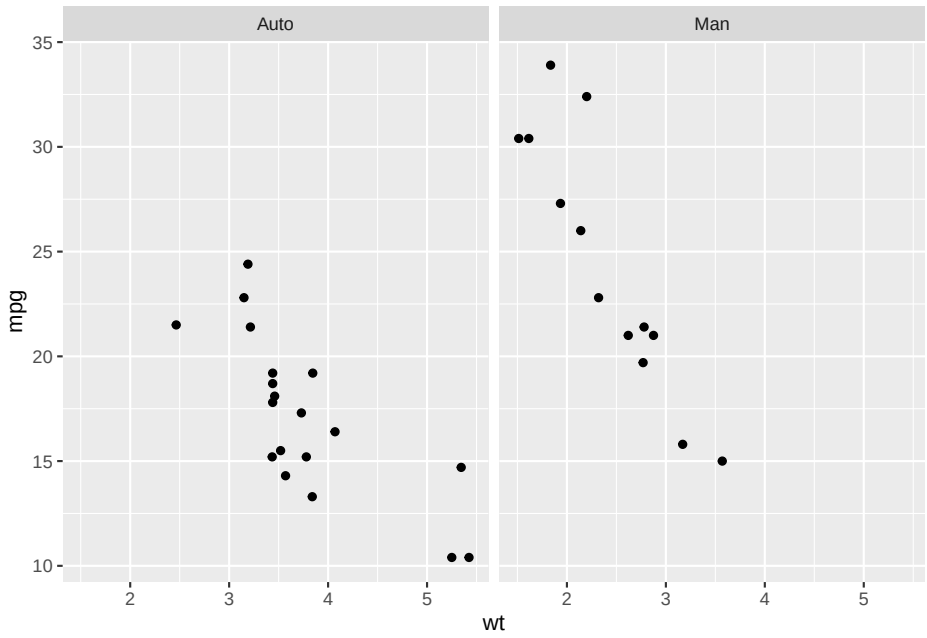
```
mtcars$am <- factor(mtcars$am,
                    levels = c(0,1),
                    labels = c("Auto","Man") )
```

Now the summary will make more sense. This is also useful because graphics packages such as ggplot2 will know how to handle factors.

```
summary(mtcars$am)
```

```
## Auto  Man
##   19   13
```

```
ggplot(mtcars,aes(x=wt,y=mpg)) +
  geom_point() +
  facet_wrap(~am)
```



2.8 Sorting data

Sorting rows in a data fram is a common activity. However, in Base R this is called "ordering" because of the function used to "order" the data. Let's say we want to sort or "order" the mtcars data frame such that the row with the

lowest mpg value is listed first and the row with the highest mpg value is listed last. First, look at the **order** function's output. What are those numbers ?

```
order(mtcars$mpg)
```

```
##  [1] 15 16 24  7 17 31 14 23 22 29 12 13 11  6  5 10 25 30  1  2  4 32 21
## [24]  3  9  8 27 26 19 28 18 20
```

Oh, so they are row numbers corresponding to rows in mtcars. Row 15 has the car with the lowest mpg. Row 16 corresponds to the car with the next lowest mpg and so on. So we can use this information to order our dataframe accordingly:

```
mtcars[order(mtcars$mpg),]
```

```
##                      mpg cyl  disp  hp drat    wt  qsec vs   am gear carb
## Cadillac Fleetwood  10.4   8 472.0 205 2.93 5.250 17.98  0 Auto    3    4
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0 Auto    3    4
## Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0 Auto    3    4
## Duster 360          14.3   8 360.0 245 3.21 3.570 15.84  0 Auto    3    4
## Chrysler Imperial   14.7   8 440.0 230 3.23 5.345 17.42  0 Auto    3    4
## Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  Man    5    8
## Merc 450SLC         15.2   8 275.8 180 3.07 3.780 18.00  0 Auto    3    3
## AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0 Auto    3    2
## Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0 Auto    3    2
## Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  Man    5    4
## Merc 450SE          16.4   8 275.8 180 3.07 4.070 17.40  0 Auto    3    3
## Merc 450SL          17.3   8 275.8 180 3.07 3.730 17.60  0 Auto    3    3
## Merc 280C           17.8   6 167.6 123 3.92 3.440 18.90  1 Auto    4    4
## Valiant             18.1   6 225.0 105 2.76 3.460 20.22  1 Auto    3    1
## Hornet Sportabout   18.7   8 360.0 175 3.15 3.440 17.02  0 Auto    3    2
## Merc 280            19.2   6 167.6 123 3.92 3.440 18.30  1 Auto    4    4
## Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0 Auto    3    2
## Ferrari Dino        19.7   6 145.0 175 3.62 2.770 15.50  0  Man    5    6
## Mazda RX4           21.0   6 160.0 110 3.90 2.620 16.46  0  Man    4    4
## Mazda RX4 Wag       21.0   6 160.0 110 3.90 2.875 17.02  0  Man    4    4
## Hornet 4 Drive      21.4   6 258.0 110 3.08 3.215 19.44  1 Auto    3    1
## Volvo 142E          21.4   4 121.0 109 4.11 2.780 18.60  1  Man    4    2
## Toyota Corona       21.5   4 120.1  97 3.70 2.465 20.01  1 Auto    3    1
## Datsun 710          22.8   4 108.0  93 3.85 2.320 18.61  1  Man    4    1
## Merc 230            22.8   4 140.8  95 3.92 3.150 22.90  1 Auto    4    2
## Merc 240D           24.4   4 146.7  62 3.69 3.190 20.00  1 Auto    4    2
## Porsche 914-2       26.0   4 120.3  91 4.43 2.140 16.70  0  Man    5    2
## Fiat X1-9           27.3   4  79.0  66 4.08 1.935 18.90  1  Man    4    1
## Honda Civic         30.4   4  75.7  52 4.93 1.615 18.52  1  Man    4    2
## Lotus Europa        30.4   4  95.1 113 3.77 1.513 16.90  1  Man    5    2
## Fiat 128            32.4   4  78.7  66 4.08 2.200 19.47  1  Man    4    1
```

```
## Toyota Corolla      33.9   4  71.1  65 4.22 1.835 19.90  1  Man    4    1
```

To invert the sense of the order use the **rev** function. We'll also use the head function to list only the first 5 rows of the result. Note that in base R, using composite functions is welcomed although you will find out that this is not a value in the tidyverse. For math people, using a composite function is natural which, in large part, is why R embraced that approach early on.

```
head(mtcars[rev(order(mtcars$mpg)),])
```

```
##                 mpg cyl  disp  hp drat    wt  qsec vs  am gear carb
## Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1 Man    4    1
## Fiat 128       32.4   4  78.7  66 4.08 2.200 19.47  1 Man    4    1
## Lotus Europa   30.4   4  95.1 113 3.77 1.513 16.90  1 Man    5    2
## Honda Civic    30.4   4  75.7  52 4.93 1.615 18.52  1 Man    4    2
## Fiat X1-9      27.3   4  79.0  66 4.08 1.935 18.90  1 Man    4    1
## Porsche 914-2  26.0   4 120.3  91 4.43 2.140 16.70  0 Man    5    2
```

2.9 Reading CSV Files

Many times data will be read in from a comma delimited file exported from Excel. These are known as Comma Separated Value files - generally abbreviated as **CSV**. The file can be read from a local drive or even from the Web as long as you know the URL associated with the file. In this example, there is a file on the Internet relating to some testing data involving students and various subjects.

```
url <- "https://raw.githubusercontent.com/pittardsp/bios545r_spring_2018/master/SUPPOR

data1 <- read.csv(url,header=T,sep=",")

head(data1)
```

```
##    id female race ses schtyp prog read write math science socst
## 1  70      0    4   1      1    1   57    52   41      47    57
## 2 121      1    4   2      1    3   68    59   53      63    61
## 3  86      0    4   3      1    1   44    33   54      58    31
## 4 141      0    4   3      1    3   63    44   47      53    56
## 5 172      0    4   2      1    2   47    52   57      53    61
## 6 113      0    4   2      1    2   44    52   51      63    61
```

Chapter 3

The tidyverse

The **dplyr** package is part of the larger **tidyverse** package set which has expanded considerably in recent years and continues to grow in size and utility such that many people never learn the "older way" of doing things in R. But we've already been through that in the previous section. The tidyverse has the following packages. The descriptions have been lifted from the tidyverse home page.

ggplot2 - ggplot2 is a system for declaratively creating graphics, based on The Grammar of Graphics. You provide the data, tell ggplot2 how to map variables to aesthetics, what graphical primitives to use, and it takes care of the details.

dplyr - dplyr provides a grammar of data manipulation, providing a consistent set of verbs that solve the most common data manipulation challenges.

tidyr - tidyr provides a set of functions that help you get to tidy data. Tidy data is data with a consistent form: in brief, every variable goes in a column, and every column is a variable.

readr - readr provides a fast and friendly way to read rectangular data (like csv, tsv, and fwf). It is designed to flexibly parse many types of data found in the wild, while still cleanly failing when data unexpectedly changes.

tibble - tibble is a modern re-imagining of the data frame, keeping what time has proven to be effective, and throwing out what it has not. Tibbles are data.frames that are lazy and surly: they do less and complain more forcing you to confront problems earlier, typically leading to cleaner, more expressive code.

stringr - stringr provides a cohesive set of functions designed to make working with strings as easy as possible. It is built on top of stringi, which uses the ICU C library to provide fast, correct implementations of common string manipulations.

lubdriate - Date-time data can be frustrating to work with in R. R commands for date-times are generally unintuitive and change depending on the type of date-time object being used. Moreover, the methods we use with date-times must be robust to time zones, leap days, daylight savings times, and other time related quirks. Lubridate makes it easier to do the things R does with date-times and possible to do the things R does not.

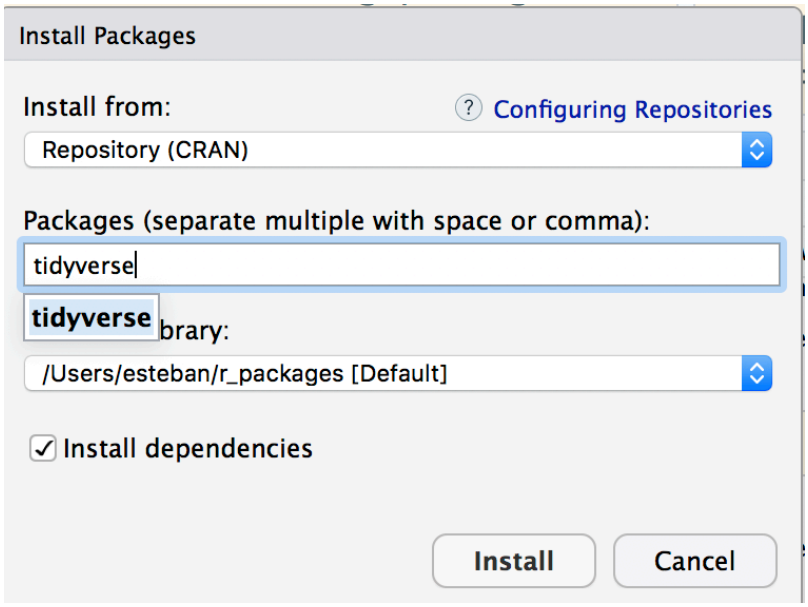
3.1 Installing

You will probably use a number of functions from several of these packages so it's best to go ahead and install the entire **tidyverse** in one go. To install it, do one of the following:

1) At the R Console from within RStudio, type:

```
install.packages("tidyverse")
```

2) Use the Tools -> Install Packages menu item in RStudio:



After you have installed the package you may load it by doing:

```
suppressMessages(library(tidyverse))
```

Note that the **cheatsheet** for **dplyr** can be found here

Data Transformation with dplyr : : CHEAT SHEET

3.2 dplyr Basics

dplyr is a grammar of data manipulation, providing a consistent set of verbs that help you solve the most common data manipulation challenges. In fact if you were paying attention during the opening section on data frames you will have noticed that most of the activities we performed related to the following activires. In dplyr-speak there are the **verbs** that help us get work done.

```
mutate() - adds new variables that are functions of existing variables
select() - picks variables based on their names.
filter() - picks cases based on their values.
summarise() - reduces multiple values down to a single summary.
arrange() - changes the ordering of the rows.
```

3.3 First Steps

Note that this material references "Becoming a data ninja with dplyr" as well as this dplyr tutorial

We'll go back to the basics here by using a very small data frame which will make it clear how the various **dplyr** verbs actually work:

```
df <- data.frame(id = 1:5,
                 gender = c("MALE","MALE","FEMALE","MALE","FEMALE"),
                 age = c(70,76,60,64,68))
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

3.3.1 filter()

The **filter()** function allows us to sift through the data frame to find rows that satisfy some logical condition. (With the older approach we would be using the bracket notation). The following example allows is to find only the observations relating to a declared gender of **female**.

```
filter(df,gender == "FEMALE")
```

```
##   id gender age
## 1  3 FEMALE  60
## 2  5 FEMALE  68
```

```
# Given this data frame, the following is equivalent

filter(df, gender != "MALE")
```

```
##   id gender age
## 1  3 FEMALE  60
## 2  5 FEMALE  68
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE
3	FEMALE	60
5	FEMALE	68

So, now find only the **ids** that relate to rows 1,3, or 5. This is a highly specialized search but it is helpful to show that you can use a wide variety of logical constructs.

```
filter(df, id %in% c(1,3,5))
```

```
##   id gender age
## 1  1   MALE  70
## 2  3 FEMALE  60
## 3  5 FEMALE  68
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE
1	MALE	70
3	FEMALE	60
5	FEMALE	68

3.3.2 mutate()

Mutate is used to add or remove columns in a data frame. Let's create a new column in the data frame that contains the mean value of the age column.

```
mutate(df,meanage = mean(age))
```

```
##   id gender age meanage
## 1  1   MALE  70    67.6
## 2  2   MALE  76    67.6
## 3  3 FEMALE  60    67.6
## 4  4   MALE  64    67.6
## 5  5 FEMALE  68    67.6
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE	MEANWT
1	MALE	70	67.6
2	MALE	76	67.6
3	FEMALE	60	67.6
4	MALE	64	67.6
5	FEMALE	68	67.6

Next we will create a new column designed to tell us if a given observation has an age that is greater than or equal to the average age. Specifically, create a variable called **old_young** and assign a value of "Y" if the observed age for that row is above the mean age and a value of "N" if it is not.

```
mutate(df,old_young=ifelse(df$age>=mean(df$age),"Y","N"))
```

```
##   id gender age old_young
## 1  1   MALE  70         Y
## 2  2   MALE  76         Y
## 3  3 FEMALE  60         N
## 4  4   MALE  64         N
## 5  5 FEMALE  68         Y
```

One way we could use something like this is in making a plot where the observations exhibiting an age value above the mean are plotted in a certain color and those below the mean are in another color.

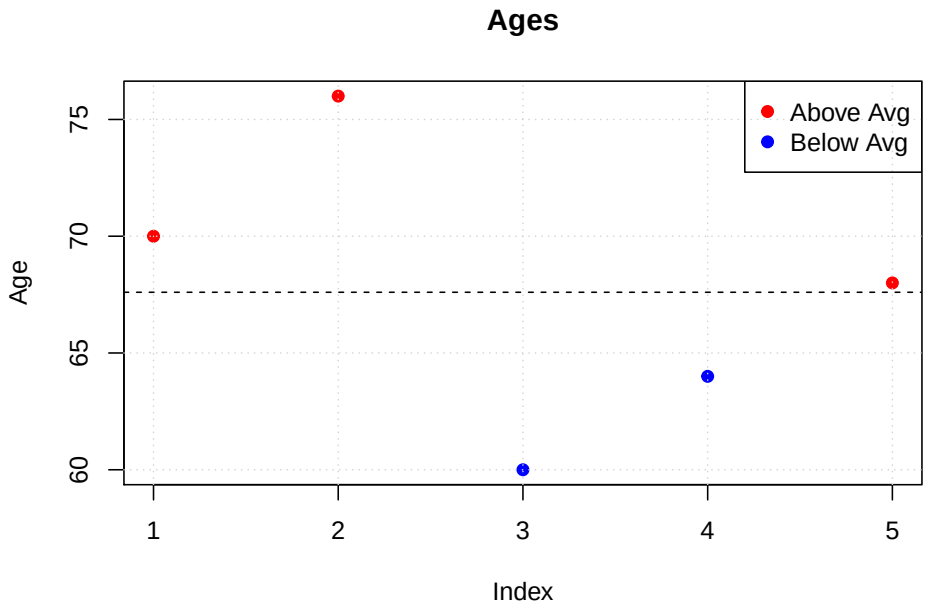
```
tmp <- mutate(df, color = ifelse(age > mean(age),"red","blue"))

plot(tmp$age,col=tmp$color, type="p",
     pch=19,main="Ages",ylab="Age")

grid()

abline(h=mean(tmp$age),lty=2)

legend("topright",
       c("Above Avg","Below Avg"),col=c("red","blue"),pch=19)
```



3.3.3 arrange()

Use arrange for sorting the data frame by one or more columns. When using the basic data frame structure from R we had to use the **order()** function to help us generate a vector that has the row numbers of the data frame that correpsond to the desired order of display (lowest to highest, etc).

Let's sort the data frame **dff** by age from oldest to youngest. First we'll use the older approach. While this will work, it is not exactly very intuitive.

```
df[rev(order(df$age)),]
```

```
##   id gender age
## 2  2   MALE  76
## 1  1   MALE  70
## 5  5 FEMALE  68
## 4  4   MALE  64
## 3  3 FEMALE  60
```

dplyr makes this process more simple - at least in my opinion

```
arrange(df,desc(age))
```

```
##   id gender age
## 1  2   MALE  76
## 2  1   MALE  70
## 3  5 FEMALE  68
```

```
## 4  4   MALE  64
## 5  3 FEMALE  60
```

Next, let's sort **df** by gender (alphabetically) and then by age from olderst to youngest. The rows relating to a gender of **female** are going to be listed first because, alphabetically speaking, the letter "F" comes before the letter "M". Then within those categories we have the ages sorted from oldest to youngest.

```
arrange(df, gender,desc(age))
```

```
##   id gender age
## 1  5 FEMALE  68
## 2  3 FEMALE  60
## 3  2   MALE  76
## 4  1   MALE  70
## 5  4   MALE  64
```

If we used the older approach it would look like the following. Ugh !

```
df[order(df$gender,-df$age),]
```

```
##   id gender age
## 5  5 FEMALE  68
## 3  3 FEMALE  60
## 2  2   MALE  76
## 1  1   MALE  70
## 4  4   MALE  64
```

3.3.4 select()

The select() functions allows us to select one or more columns from a data frame.

```
# Reorder the columns
select(df,gender,id,age)
```

```
##   gender id age
## 1   MALE  1  70
## 2   MALE  2  76
## 3 FEMALE  3  60
## 4   MALE  4  64
## 5 FEMALE  5  68
```

```
# Select all but the age column
select(df,-age)
```

```
##   id gender
## 1  1   MALE
## 2  2   MALE
## 3  3 FEMALE
```

```
## 4  4   MALE
## 5  5 FEMALE
```

```
# Can use the ":" operator to select a range
select(df,id:age)
```

```
##   id gender age
## 1  1   MALE  70
## 2  2   MALE  76
## 3  3 FEMALE  60
## 4  4   MALE  64
## 5  5 FEMALE  68
```

The select() function provides the ability to select by "regular expressions"" or numeric patterns:

```
# Select all columns that start with an "a"
select(df,starts_with("a"))
```

```
##   age
## 1  70
## 2  76
## 3  60
## 4  64
## 5  68
```

```
names(mtcars)
```

```
##  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
## [11] "carb"
```

```
# Get only columns that start with "c"

select(mtcars,starts_with("c"))
```

```
##                     cyl carb
## Mazda RX4             6    4
## Mazda RX4 Wag         6    4
## Datsun 710            4    1
## Hornet 4 Drive        6    1
## Hornet Sportabout     8    2
## Valiant               6    1
## Duster 360            8    4
## Merc 240D             4    2
## Merc 230              4    2
## Merc 280              6    4
## Merc 280C             6    4
## Merc 450SE            8    3
## Merc 450SL            8    3
```

```
## Merc 450SLC           8    3
## Cadillac Fleetwood    8    4
## Lincoln Continental   8    4
## Chrysler Imperial     8    4
## Fiat 128              4    1
## Honda Civic           4    2
## Toyota Corolla        4    1
## Toyota Corona         4    1
## Dodge Challenger      8    2
## AMC Javelin           8    2
## Camaro Z28            8    4
## Pontiac Firebird      8    2
## Fiat X1-9             4    1
## Porsche 914-2         4    2
## Lotus Europa          4    2
## Ford Pantera L        8    4
## Ferrari Dino          6    6
## Maserati Bora         8    8
## Volvo 142E            4    2
```

This example is more realistic in that data frames can have a large number of columns named according to some convention. For example, the measurements on a patient might not be labelled specifically - they might have a common prefix such as "m_" followed by some sequential number (or not).

```
testdf <- expand.grid(m_1=seq(60,70,10),
                      age=c(25,32),
                      m_2=seq(50,60,10),
                      m_3=seq(60,70,10))
```

```
testdf
```

```
##    m_1 age m_2 m_3
## 1   60  25  50  60
## 2   70  25  50  60
## 3   60  32  50  60
## 4   70  32  50  60
## 5   60  25  60  60
## 6   70  25  60  60
## 7   60  32  60  60
## 8   70  32  60  60
## 9   60  25  50  70
## 10  70  25  50  70
## 11  60  32  50  70
## 12  70  32  50  70
## 13  60  25  60  70
## 14  70  25  60  70
```

```
## 15  60  32  60  70
## 16  70  32  60  70
```

Find all the columns that include a "_" character

```
select(testdf,matches("_"))
```

```
##    m_1 m_2 m_3
## 1   60  50  60
## 2   70  50  60
## 3   60  50  60
## 4   70  50  60
## 5   60  60  60
## 6   70  60  60
## 7   60  60  60
## 8   70  60  60
## 9   60  50  70
## 10  70  50  70
## 11  60  50  70
## 12  70  50  70
## 13  60  60  70
## 14  70  60  70
## 15  60  60  70
## 16  70  60  70
```

This will select columns beginning with "m_" but only those with a suffx of 1 or 2.

```
select(testdf,num_range("m_",1:2))
```

```
##    m_1 m_2
## 1   60  50
## 2   70  50
## 3   60  50
## 4   70  50
## 5   60  60
## 6   70  60
## 7   60  60
## 8   70  60
## 9   60  50
## 10  70  50
## 11  60  50
## 12  70  50
## 13  60  60
## 14  70  60
## 15  60  60
## 16  70  60
```

3.3.5 group_by()

The **group_by()** function let's you organize a data frame by some factor or grouping variable. This a very powerful function that is typically used in conjunction with a function called **summarize**. Here is what it looks like by itself. It's somewhat underwhelming. It does seem to create table of some kind but it doesn't do much else.

```
df
```

```
##   id gender age
## 1  1   MALE  70
## 2  2   MALE  76
## 3  3 FEMALE  60
## 4  4   MALE  64
## 5  5 FEMALE  68
```

```
# Hmm. the following doesn't do anything - or so it seems

group_by(df)
```

```
## # A tibble: 5 x 3
##      id gender   age
##   <int> <fct>  <dbl>
## 1     1 MALE      70
## 2     2 MALE      76
## 3     3 FEMALE    60
## 4     4 MALE      64
## 5     5 FEMALE    68
```

So as mentioned, the **group_by** function is usually paired with the **summarize** function. Ah. so what this does is to first group the data frame by the **gender** column and then it **counts** the number of occurrences therein. So this is a form of aggregation.

```
summarize(group_by(df,gender),total=n())
```

```
## # A tibble: 2 x 2
##   gender total
##   <fct>  <int>
## 1 FEMALE     2
## 2 MALE       3
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

GENDER	TOTAL
FEMALE	2
MALE	3

Let's group the data frame by gender and then compute the average age for each group.

```
summarize(group_by(df,gender),av_age=mean(age))
```

```
## # A tibble: 2 x 2
##   gender av_age
##   <fct>   <dbl>
## 1 FEMALE     64
## 2 MALE       70
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

GENDER	AV_AGE
FEMALE	64
MALE	70

Let's group by gender and then compute the total number of observations in each gender group and then compute the mean age.

```
summarize(group_by(df,gender),av_age=mean(age),total=n())
```

```
## # A tibble: 2 x 3
##   gender av_age total
##   <fct>   <dbl> <int>
## 1 FEMALE     64     2
## 2 MALE       70     3
```

Chapter 4

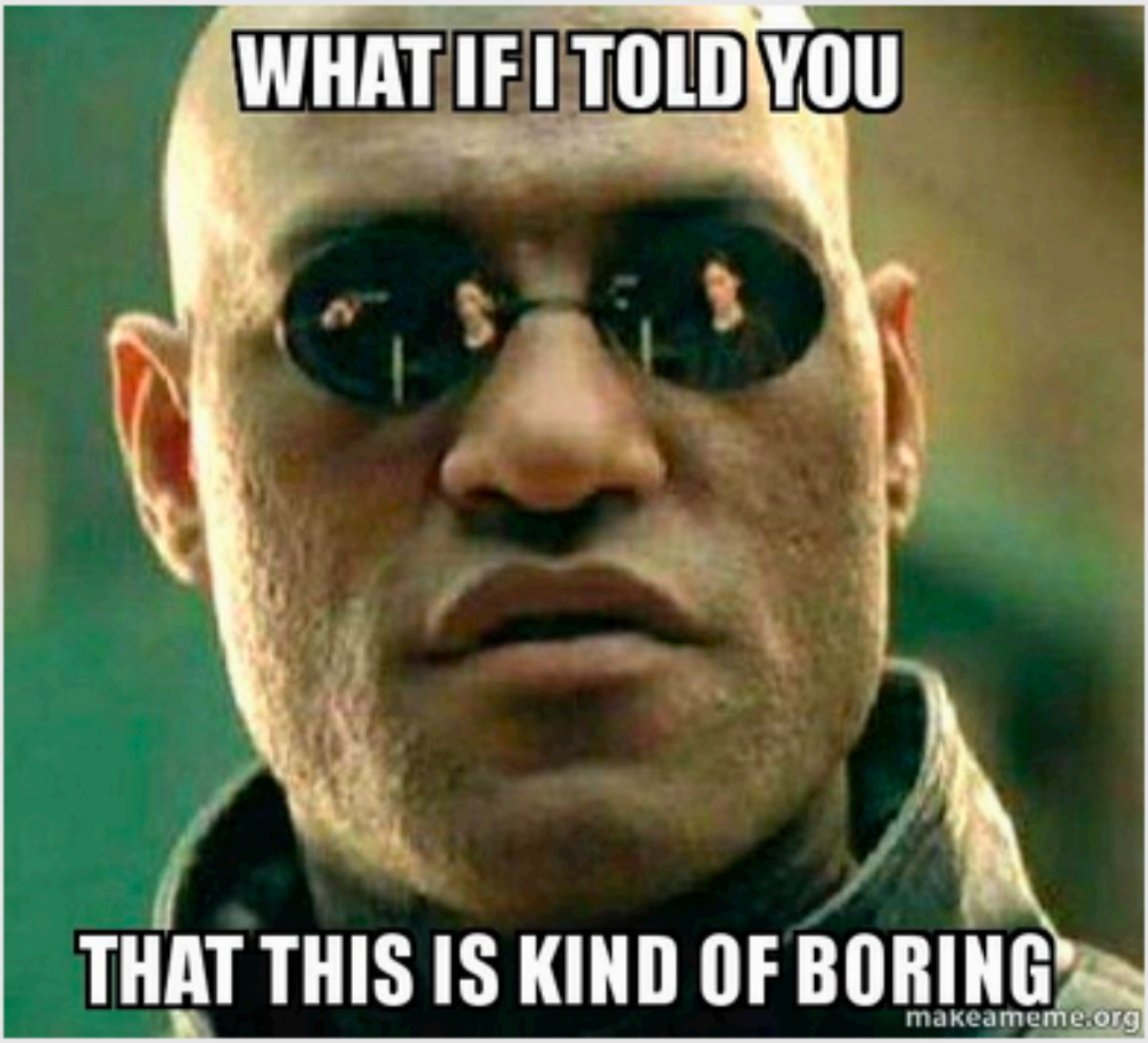
Split Apply Combine

This pattern of using **group_by()** followed by **summarize()** is called **Split Apply Combine**. The idea is that we

1) Split up the data frame by gender group
2) Then for each group, apply the average function
3) Then combine the average results for each group

```
summarize(group_by(df,gender),av_age=mean(age))
```

```
## # A tibble: 2 x 2
##   gender av_age
##   <fct>   <dbl>
## 1 FEMALE     64
## 2 MALE       70
```



4.1 What Are Pipes ?

Before moving forward let us consider the "pipe" operator that is included with the dplyr - well actually **magrittr** package. This is used to make it possible to "pipe" the results of one command into another command and so on.

The inspiration for this comes from the UNIX/LINUX operating system where pipes are used all the time. So in effect using "pipes" is nothing new in the world of research computation.

```
$ cat /etc/passwd | awk -F ":" '{print $1}' | sort | grep -v "#" | grep -v "_"
daemon
nobody
root
```

Warning: Once you get used to pipes it is hard to go back to not using them.

Let's use the mtcars data frame to illustrate the basics of the piping mechanism as used by dplyr. Here we will select the **mpg** and **am** column from mtcars and view the top 5 rows.

```
head(select(mtcars, mpg, am))
```

```
##                   mpg   am
## Mazda RX4         21.0  Man
## Mazda RX4 Wag     21.0  Man
## Datsun 710        22.8  Man
## Hornet 4 Drive    21.4 Auto
## Hornet Sportabout 18.7 Auto
## Valiant           18.1 Auto
```

Okay, how would we do this using pipes ? Whoa ! Note that each command is "it's own thing" independently of the pipe character. So the: - output of mtcars goes into the - input of the **select** function whose output goes into the - input of the **head** function

```
mtcars %>% select(mpg, am) %>% head
```

```
##                   mpg   am
## Mazda RX4         21.0  Man
## Mazda RX4 Wag     21.0  Man
## Datsun 710        22.8  Man
## Hornet 4 Drive    21.4 Auto
## Hornet Sportabout 18.7 Auto
## Valiant           18.1 Auto
```

Break this down:

```
mtcars %>% select(mpg, am)
```

```
##                     mpg   am
## Mazda RX4           21.0  Man
## Mazda RX4 Wag       21.0  Man
## Datsun 710          22.8  Man
## Hornet 4 Drive      21.4 Auto
## Hornet Sportabout   18.7 Auto
## Valiant             18.1 Auto
## Duster 360          14.3 Auto
## Merc 240D           24.4 Auto
## Merc 230            22.8 Auto
```

```
## Merc 280            19.2 Auto
## Merc 280C           17.8 Auto
## Merc 450SE          16.4 Auto
## Merc 450SL          17.3 Auto
## Merc 450SLC         15.2 Auto
## Cadillac Fleetwood  10.4 Auto
## Lincoln Continental 10.4 Auto
## Chrysler Imperial   14.7 Auto
## Fiat 128            32.4  Man
## Honda Civic         30.4  Man
## Toyota Corolla      33.9  Man
## Toyota Corona       21.5 Auto
## Dodge Challenger    15.5 Auto
## AMC Javelin         15.2 Auto
## Camaro Z28          13.3 Auto
## Pontiac Firebird    19.2 Auto
## Fiat X1-9           27.3  Man
## Porsche 914-2       26.0  Man
## Lotus Europa        30.4  Man
## Ford Pantera L      15.8  Man
## Ferrari Dino        19.7  Man
## Maserati Bora       15.0  Man
## Volvo 142E          21.4  Man
```

The key to understanding how this works is to **read** this from left to right. It bears repeating that each command is "it's own thing" independently of the pipe character. So the:

```
- output of mtcars goes into the
- input of the **select** function whose output goes into the
- input of the **head** function
```

Let's use our new found knowledge to re-imagine our use of the **group_by** and **summarize** functions that we have been using in **composite** form up unitl now.

4.2 Using Pipes To Do Split-Apply-Combine

```
df %>% group_by(gender) %>% summarize(avg=mean(age))
```

```
## # A tibble: 2 x 2
##   gender   avg
##   <fct>  <dbl>
## 1 FEMALE    64
## 2 MALE      70
```

```
# Same as the following but the pipes don't require you to "commit"
# With the following, you have to know in advance what you want to do

summarize(group_by(df,gender), avg=mean(age))
```

```
## # A tibble: 2 x 2
##   gender   avg
##   <fct>  <dbl>
## 1 FEMALE    64
## 2 MALE      70
```

This approach allows us to build a "pipeline" containing commands. We don't have to commit to a specific sequence of functions. This enables a free-form type of exploration.

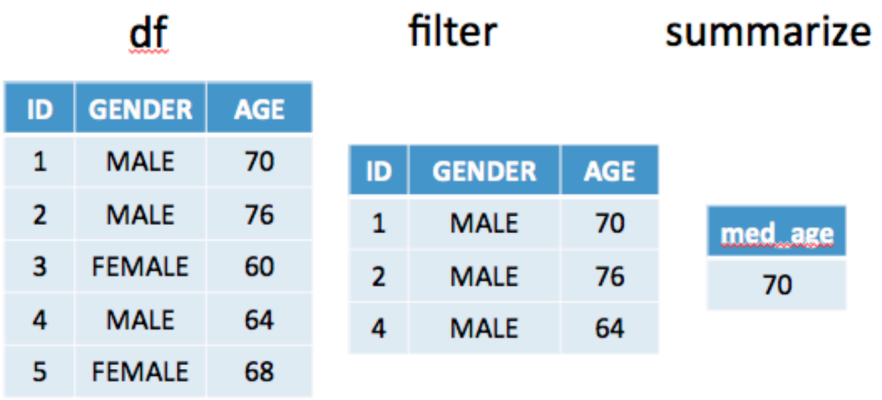
```
df %>%
  group_by(gender) %>%
  summarize(avg=mean(age),total=n())
```

```
## # A tibble: 2 x 3
##   gender   avg total
##   <fct>  <dbl> <int>
## 1 FEMALE    64     2
## 2 MALE      70     3
```

What is the median age of all males ?

```
df %>%
  filter(gender == "MALE") %>%
  summarize(med_age=median(age))
```

```
##   med_age
## 1      70
```



4.2.1 Saving Results

It should be observed that if you want to save the results of some sequence of commands that you will need to use the "<-" operator. Using the previous example we could the following to save our result.

```
results <- df %>%
              filter(gender == "MALE") %>%
              summarize(med_age=median(age))
```

4.3 An Example

Using the built in mtcars dataframe, do the following:

1) **filter** for records where the wt is greater than 3.3 tons.

2) Then, using the **mutate** function to create a column called ab_be (Y or N) that indicates whether that observation's mpg is greater (or not) than the average mpg for the filtered set.

3) Then present the average mpg for each group.

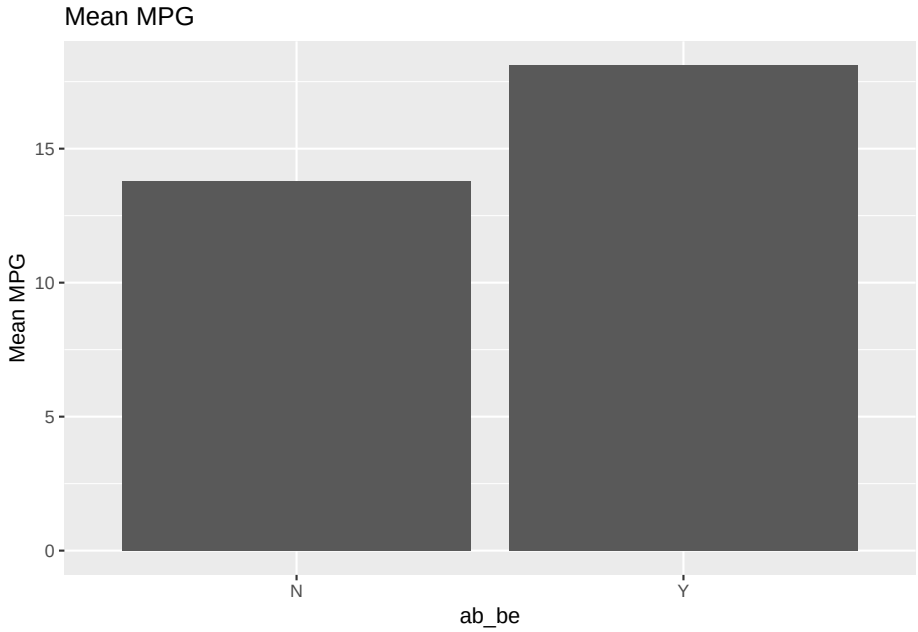
This is easy using pipes and dplyr verbs.

```
mtcars %>% filter(wt > 3.3)  %>%
           mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")) %>%
           group_by(ab_be) %>%
           summarize(mean_mpg=mean(mpg))
```

```
## # A tibble: 2 x 2
##   ab_be mean_mpg
##   <chr>    <dbl>
## 1 N         13.8
## 2 Y         18.1
```

This could be then "piped" into the input of the **ggplot** command to plot a corresponding bar chart. If you don't yet know ggplot then it's okay as this will nudge you in that direction. Both **ggplot** and **dplyr** are part of the **tidyverse** which means that the two packages "talk" to each other well.

```
mtcars %>% filter(wt > 3.3)  %>%
           mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")  ) %>%
           group_by(ab_be) %>% summarize(mean_mpg=mean(mpg)) %>%
           ggplot(aes(x=ab_be,y=mean_mpg)) +
           geom_bar(stat="identity") +
           ggtitle("Mean MPG") + labs(x = "ab_be", y = "Mean MPG")
```



4.4 Working With Flowers

Let's work with the built in **iris** data frame to explore the world of flowers. This is famous (Fisher's or Anderson's) **iris** data set gives the measurements in centimeters of the variables sepal length and width and petal length and width, respectively, for 50 flowers from each of 3 species of iris. The species are Iris setosa, versicolor, and virginica.

I'll use dyplr idioms here as opposed to the typical Base R approach which might involve use of composite functions. First, load up the iris data

```
data(iris)
```

4.4.1 Structure of The Data frame

It's always helpful to look at what types of data you have in a data frame. As you already known, base R has a function called **str** which is useful. The tidyverse equivalent is **glimpse** although the two commands basically provide the same types of information. Personally, I still prefer the "old" **str** function if only because I've been using it for so long.

```
str(iris)
```

```
## 'data.frame':    150 obs. of  5 variables:
```

```
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 .
```

```
glimpse(iris)
```

```
## Observations: 150
## Variables: 5
## $ Sepal.Length <dbl> 5.1, 4.9, 4.7, 4.6, 5.0, 5.4, 4.6, 5.0, 4.4, 4.9,...
## $ Sepal.Width  <dbl> 3.5, 3.0, 3.2, 3.1, 3.6, 3.9, 3.4, 3.4, 2.9, 3.1,...
## $ Petal.Length <dbl> 1.4, 1.4, 1.3, 1.5, 1.4, 1.7, 1.4, 1.5, 1.4, 1.5,...
## $ Petal.Width  <dbl> 0.2, 0.2, 0.2, 0.2, 0.2, 0.4, 0.3, 0.2, 0.2, 0.1,...
## $ Species      <fct> setosa, setosa, setosa, setosa, setosa, setosa, s...
```

4.4.2 More Practice

1) Get all the rows where the Species is "setosa" Sepal.Length is > 4.7 but < 5.0. Use the pipes feature to help you with this.

```
iris %>%
  filter(Sepal.Length > 4.7 & Sepal.Length < 5.0 & Species=="setosa" )
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          4.9         3.0          1.4         0.2  setosa
## 2          4.9         3.1          1.5         0.1  setosa
## 3          4.8         3.4          1.6         0.2  setosa
## 4          4.8         3.0          1.4         0.1  setosa
## 5          4.8         3.4          1.9         0.2  setosa
## 6          4.8         3.1          1.6         0.2  setosa
## 7          4.9         3.1          1.5         0.2  setosa
## 8          4.9         3.6          1.4         0.1  setosa
## 9          4.8         3.0          1.4         0.3  setosa
```

2) Select out only the columns relating Sepal measurements. List only the top five rows:

```
iris %>% select(c(Sepal.Length,Sepal.Width)) %>% head(5)
```

```
##   Sepal.Length Sepal.Width
## 1          5.1         3.5
## 2          4.9         3.0
## 3          4.7         3.2
## 4          4.6         3.1
## 5          5.0         3.6
```

```
# Or use a helper function to process strings

iris %>% select(starts_with("Sepal")) %>% head(5)
```

```
##   Sepal.Length Sepal.Width
## 1          5.1         3.5
## 2          4.9         3.0
## 3          4.7         3.2
## 4          4.6         3.1
## 5          5.0         3.6
```

```
# Or if you know which column numbers you want

iris %>% select(c(1:2)) %>% head(5)
```

```
##   Sepal.Length Sepal.Width
## 1          5.1         3.5
## 2          4.9         3.0
## 3          4.7         3.2
## 4          4.6         3.1
## 5          5.0         3.6
```

3) Sort the data frame by Sepal.Width such that the row with the largest Sepal.Width is listed first. Print only the first 5 rows

```
iris %>% arrange(desc(Sepal.Width)) %>% head(5)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.7         4.4          1.5         0.4  setosa
## 2          5.5         4.2          1.4         0.2  setosa
## 3          5.2         4.1          1.5         0.1  setosa
## 4          5.8         4.0          1.2         0.2  setosa
## 5          5.4         3.9          1.7         0.4  setosa
```

4) How many observations are there for each Species group ?

```
iris %>% group_by(Species) %>% count()
```

```
## # A tibble: 3 x 2
## # Groups:   Species [3]
##   Species        n
##   <fct>      <int>
## 1 setosa        50
## 2 versicolor    50
## 3 virginica     50
```

```
# Or

iris %>% group_by(Species) %>% summarize(total=n())
```

```
## # A tibble: 3 x 2
##   Species    total
##   <fct>      <int>
## 1 setosa        50
## 2 versicolor    50
## 3 virginica     50
```

5) Select all columns that do NOT relate to Length. Limit output to 5 rows

```
iris %>% select(-ends_with("Length")) %>% head()
```

```
##   Sepal.Width Petal.Width Species
## 1         3.5         0.2  setosa
## 2         3.0         0.2  setosa
## 3         3.2         0.2  setosa
## 4         3.1         0.2  setosa
## 5         3.6         0.2  setosa
## 6         3.9         0.4  setosa
```

6) Select all columns that do NOT relate to Length or Species. Limit output to 5 rows

```
iris %>% select(-c(ends_with("Length"),"Species")) %>% head()
```

```
##   Sepal.Width Petal.Width
## 1         3.5         0.2
## 2         3.0         0.2
## 3         3.2         0.2
## 4         3.1         0.2
## 5         3.6         0.2
## 6         3.9         0.4
```

```
# Or

iris %>% select(-ends_with("Length")) %>% select(-"Species") %>% head()
```

```
##   Sepal.Width Petal.Width
## 1         3.5         0.2
## 2         3.0         0.2
## 3         3.2         0.2
## 4         3.1         0.2
## 5         3.6         0.2
## 6         3.9         0.4
```

7) Select all columns that do NOT relate to Length or Species. But only for observations where Sepal.Width is > 3.9. There are multiples way to attack this problem.

```
iris %>% filter(Sepal.Width > 3.9) %>%
  select(-ends_with("Length")) %>%
```

```
  select(-"Species")
```

```
##   Sepal.Width Petal.Width
## 1         4.0         0.2
## 2         4.4         0.4
## 3         4.1         0.1
## 4         4.2         0.2
```

```
# Or

iris %>% select(-ends_with("Length")) %>%
  select(-"Species") %>%
  filter(Sepal.Width > 3.9)
```

```
##   Sepal.Width Petal.Width
## 1         4.0         0.2
## 2         4.4         0.4
## 3         4.1         0.1
## 4         4.2         0.2
```

8) Determine the mean, standard deviation, max, and min for Sepal.Length

```
iris %>% summarize(mean=mean(Sepal.Length),
                   sd=sd(Sepal.Length),
                   max=max(Sepal.Length),
                   min=min(Sepal.Length))
```

```
##       mean        sd max min
## 1 5.843333 0.8280661 7.9 4.3
```

9) For each Species type, determine the mean, standard deviation, max, and min for Sepal.Length

```
iris %>% group_by(Species) %>% summarize(mean=mean(Sepal.Length),
                                         sd=sd(Sepal.Length),
                                         max=max(Sepal.Length),
                                         min=min(Sepal.Length))
```

```
## # A tibble: 3 x 5
##   Species     mean    sd   max   min
##   <fct>      <dbl> <dbl> <dbl> <dbl>
## 1 setosa      5.01 0.352   5.8   4.3
## 2 versicolor  5.94 0.516   7     4.9
## 3 virginica   6.59 0.636   7.9   4.9
```

Chapter 5

Your Turn

Now it's time for you to try some exercises on your own. The **ggplot2** package (which is part of the larger **tidyverse** comes with some data sets one of which is called **msleep**. It's easy to load into your workspace:

```
data(msleep)
```

This data set is

> an updated and expanded version of the mammals sleep dataset. Updated sleep times and weights were taken from V. M. Savage and G. B. West. A quantitative, theoretical framework for understanding mammalian sleep. Proceedings of the National Academy of Sciences, 104 (3):1051-1056, 2007

COLUMN NAME	DESCRIPTION
name	common name
genus	taxonomic rank
vore	carnivore, omnivore or herbivore?
order	taxonomic rank
conservation	the conservation status of the mammal
sleep_total	total amount of sleep, in hours
sleep_rem	rem sleep, in hours
sleep_cycle	length of sleep cycle, in hours
awake	amount of time spent awake, in hours
brainwt	brain weight in kilograms
bodywt	body weight in kilograms

You can always get the names of the columns in a data frame using **str** or **names**

```
names(msleep)
```

```
##  [1] "name"         "genus"        "vore"         "order"
##  [5] "conservation" "sleep_total"  "sleep_rem"    "sleep_cycle"
##  [9] "awake"        "brainwt"      "bodywt"
```

```
#

str(msleep)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    83 obs. of  11 variables:
##  $ name        : chr  "Cheetah" "Owl monkey" "Mountain beaver" "Greater short-tailed
##  $ genus       : chr  "Acinonyx" "Aotus" "Aplodontia" "Blarina" ...
##  $ vore        : chr  "carni" "omni" "herbi" "omni" ...
##  $ order       : chr  "Carnivora" "Primates" "Rodentia" "Soricomorpha" ...
##  $ conservation: chr  "lc" NA "nt" "lc" ...
##  $ sleep_total : num  12.1 17 14.4 14.9 4 14.4 8.7 7 10.1 3 ...
##  $ sleep_rem   : num  NA 1.8 2.4 2.3 0.7 2.2 1.4 NA 2.9 NA ...
##  $ sleep_cycle : num  NA NA NA 0.133 0.667 ...
##  $ awake       : num  11.9 7 9.6 9.1 20 9.6 15.3 17 13.9 21 ...
```

```
##  $ brainwt     : num  NA 0.0155 NA 0.00029 0.423 NA NA NA 0.07 0.0982 ...
##  $ bodywt      : num  50 0.48 1.35 0.019 600 ...
```

Not only is this a new data frame for you it also has the added challenge of containing some missing values - those pesky "NAs". In the older approach we used the function **complete.cases** to help us figure out which rows had at least one missin value. We could still use that here although the **dplyr** world has a function called **drop_na()** which could be used but itself or as part of a pipeline.

Here are some questions I want you to answer. Note that the answers are provided so you can check your work. However, the code used to generate the answer is not visible. There is typically more than one way to answer the question.

5.0.0.1 What is the average total sleep time for Omnivores ?

```
## # A tibble: 1 x 1
##    mean
##   <dbl>
## 1  10.9
```

```
## # A tibble: 1 x 2
##   vore   mean
##   <chr> <dbl>
## 1 omni   10.9
```

5.0.0.2 Group the msleep data frame by taxanomic order and then summarize the mean sleep total for each group. Make sure the resulting table is arranged in descending order of the average - from highest sleep_total average to the lowest

```
## # A tibble: 19 x 2
##    order             avg
##    <chr>           <dbl>
##  1 Chiroptera      19.8
##  2 Didelphimorphia 18.7
##  3 Cingulata       17.8
##  4 Afrosoricida    15.6
##  5 Pilosa          14.4
##  6 Rodentia        12.5
##  7 Diprotodontia   12.4
##  8 Soricomorpha    11.1
##  9 Primates        10.5
## 10 Erinaceomorpha  10.2
## 11 Carnivora       10.1
```

```
## 12 Scandentia       8.9
## 13 Monotremata      8.6
## 14 Lagomorpha       8.4
## 15 Hyracoidea       5.67
## 16 Artiodactyla     4.52
## 17 Cetacea          4.5
## 18 Proboscidea      3.6
## 19 Perissodactyla   3.47
```

5.0.0.3 What is the average total sleep time for all vore types ?

```
## # A tibble: 5 x 2
##   vore     mean
##   <chr>   <dbl>
## 1 carni   10.4
## 2 herbi    9.51
## 3 insecti 14.9
## 4 omni    10.9
## 5 <NA>    10.2
```

5.0.0.4 Omitting any rows that contain missing values, what is the average total sleep time for all vore types ? Remember that you will need to use the drop_na function to help you.

```
## # A tibble: 4 x 2
##   vore     mean
##   <chr>   <dbl>
## 1 carni   13.3
## 2 herbi    9.52
## 3 insecti 14.0
## 4 omni    12.2
```

5.0.0.5 Remove all rows that contain a missing value and save the result into a new data table called msleep_na. How many rows does msleep_na contain ?

```
## [1] 20
```

5.0.0.6 Using msleep_na, find the average braintwt for all vores by order. Note that the group_by() function can take multiple arguments.

```
## # A tibble: 12 x 3
```

```
## # Groups:   order [10]
##    order           vore        mean
##    <chr>           <chr>      <dbl>
##  1 Artiodactyla    herbi   0.423
##  2 Artiodactyla    omni    0.18
##  3 Carnivora       carni   0.0478
##  4 Chiroptera      insecti 0.000300
##  5 Cingulata       carni   0.0108
##  6 Didelphimorphia omni    0.0063
##  7 Erinaceomorpha  omni    0.0035
##  8 Lagomorpha      herbi   0.0121
##  9 Perissodactyla  herbi   0.412
## 10 Rodentia        herbi   0.0032
## 11 Soricomorpha    insecti 0.00120
## 12 Soricomorpha    omni    0.000215
```