Intro To dplyr

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Contents

Chapter 1

R Data Structures

There are a number of data structures in R such as **vectors, lists, matricies** and **arrays** but the the premier data structure in R is known as 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.

1.1 The Mighty Data Frame

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
```

Figure 1.1:

```
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
```

1.2 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
```

1.3 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.

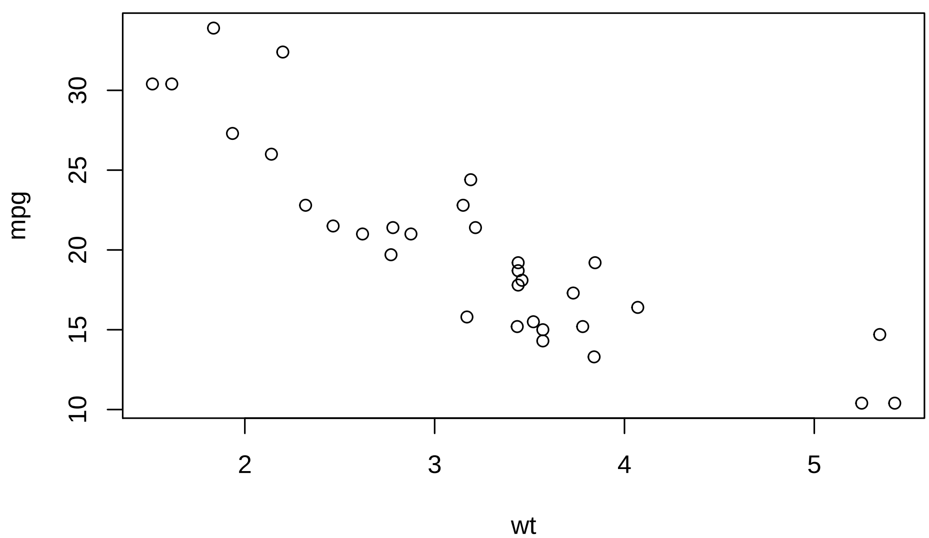
```
data(mtcars)
mtcars
```

```
##                      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
```

```r
# 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
```

```r
# 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 ?

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

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

Find all rows that correspond to cars with 4 cylinders

```r
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.

```r
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

```r
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:

```r
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

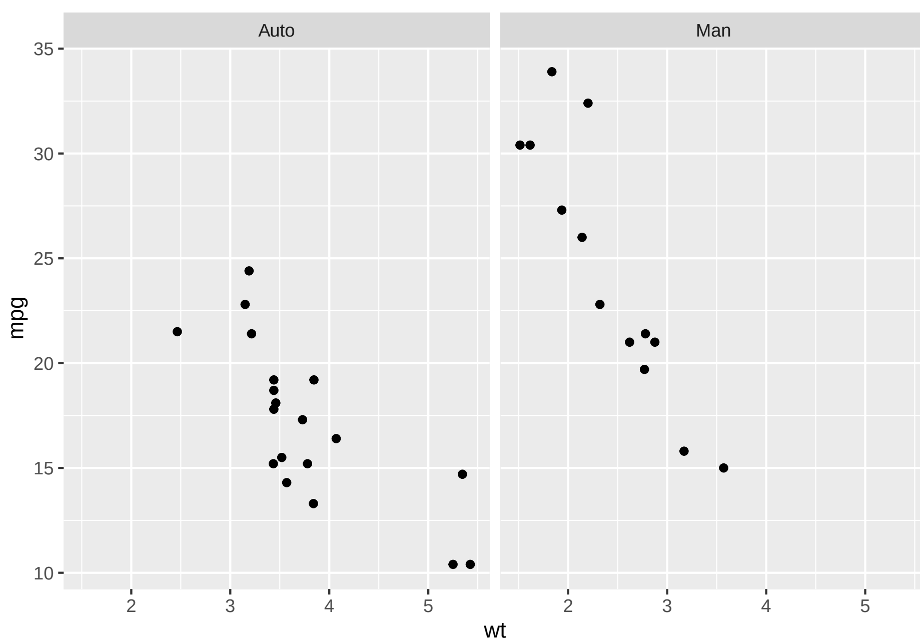
```
mtcars$am <- factor(mtcars$am,
                     levels = c(0,1),
                     labels = c("Auto","Man") )
```

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 Creating Data Frames From 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/SUPPORT

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

Literature

Here is a review of existing methods.

Chapter 4

Methods

We describe our methods in this chapter.

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