

Applied Statistics

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Chapter 1

Introduction

Welcome to Applied Statistics with R!

1.1 About This Book

This book was originally (and currently) designed for use with STAT 420, Methods of Applied Statistics, at the University of Illinois at Urbana-Champaign. It may certainly be used elsewhere, but you may find references to “this course” which is STAT 420.

This book is under active development. When possible, it would be best to always access the text online to be sure you are using the most up-to-date version. (Also the html version provides the most features such as changing text size, font, and colors.) If you are in need of a local copy, a pdf version is continuously maintained at http://daviddalpiaz.github.io/appliedstats/applied_statistics.pdf.

Since this book is under active development you may encounter errors ranging from typos to broken code to poorly explained topics. If you do, please let us know! Simply send an email and we’ll make the changes ASAP. Or, if you know RMarkdown and are familiar with GitHub, make a pull request and fix an issue yourself!

This text uses MathJax to render mathematical notation for the web. Occasionally but rarely a JavaScript error will prevent MathJax from rendering correctly. (And you will see the “code” instead of the expected mathematical equations.) From experience, this is almost always fixed by simply refreshing the page. You’ll also notice that if you right-click any equation you can obtain the MathML Code (for copying into Microsoft Word) or the TeX command used to generate the equation.

$$a^2 + b^2 = c^2$$

1.2 Conventions

R code will be typeset using a **monospace** font which is syntax highlighted.

```
a = 3
b = 4
sqrt(a ^ 2 + b ^ 2)
```

R output lines, which would appear in the console will begin with **##**. They will generally not be syntax highlighted.

[1] 5

1.3 Acknowledgements

- Alex Stepanov
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Chapter 2

Introduction to R

“Measuring programming progress by lines of code is like measuring aircraft building progress by weight.”

- **Bill Gates**

R is both a programming language and software environment for statistical computing, which is *free* and *open-source*. To get started, you will need to install two pieces of software:

- R, the actual programming language, which can be installed from <http://cran.r-project.org/>
 - Chose your operating system, and select the most recent version. (As of writing, 3.3.0.)
- RStudio, an excellent IDE for working with R, which can be obtained from <http://www.rstudio.com/> (Note, you must have R installed to use RStudio. RStudio is simply a way to interact with R.)

R’s popularity is on the rise, and everyday it becomes a better tool for statistical analysis. It even generated this book! (A skill you will learn in this course.) There are many good resources for learning R. They are not necessary for this course, but you may find them useful if you would like a deeper understanding of R:

- Try R from Code School.
 - An interactive introduction to the basics of R. Could be very useful for getting up to speed on R’s syntax.
- Quick-R by Robert Kabacoff.
 - A good reference for R basics.
- R Tutorial by Chi Yau.
 - A combination reference and tutorial for R basics.
- The Art of R Programming by Norman Matloff.
 - Gentle introduction to the programming side of R. (Whereas we will focus more on the data analysis side.) A free electronic version is available through the Illinois library.
- Advanced R by Hadley Wickham.
 - From the author of several extremely popular R packages. Good follow-up to The Art of R Programming. (And more up-to-date material.)
- The R Inferno by Patrick Burns.

- Likens learning the tricks of R to descending through the levels of hell. Very advanced material, but may be important if R becomes a part of your everyday toolkit.
- R Markdown from RStudio.
 - Reference materials for RMarkdown.

RStudio has a large number of useful keyboard shortcuts. A list of these can be found using a keyboard shortcut, the keyboard shortcut to rule them all:

- On Windows: `Option + Shift + K`
- On Mac: `Alt + Shift + K`

The RStudio team has developed a number of “cheatsheets” for working with both R and RStudio which can be found [here](#) or from the help menu inside of RStudio. This one for Base R in particular will summarize many of the concepts in this document.

2.1 Basic Calculations

To get started, we’ll use R like a simple calculator. Note, in R the `#` symbol is used for comments. Lines which begin with two, `##` will indicate output.

- Addition, Subtraction, Multiplication and Division

```
3 + 2
```

```
## [1] 5
```

```
3 - 2
```

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

```
3 * 2
```

```
## [1] 6
```

```
3 / 2
```

```
## [1] 1.5
```

- Exponents

```
3 ^ 2
```

```
## [1] 9
```

```
2 ^ (-3)
```

```
## [1] 0.125
```



```
100 ^ (1 / 2)
```

```
## [1] 10
```

```
sqrt(1 / 2)
```

```
## [1] 0.7071068
```

```
exp(1)
```

```
## [1] 2.718282
```

- Mathematical Constants

```
pi
```

```
## [1] 3.141593
```

```
exp(1)
```

```
## [1] 2.718282
```

- Logarithms

```
log(10) # natural log
```

```
## [1] 2.302585
```

```
log10(1000) # base 10 log
```

```
## [1] 3
```

```
log2(8) # base 2 log
```

```
## [1] 3
```

```
log(16, base = 4) # base 4 log
```

```
## [1] 2
```

- Trigonometry

```
sin(pi / 2)
```

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

```
cos(0)
```

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

2.2 Getting Help

In using R as a calculator, we have seen a number of functions. `sqrt()`, `exp()`, `log()` and `sin()` are all R functions. To get documentation about a function in R, simply put a question mark in front of the function name and RStudio will display the documentation, for example:

```
?log  
?sin  
?paste  
?lm
```

Frequently one of the most difficult things to do when learning R is asking for help. First, you need to decide to ask for help, then you need to know how to ask for help. Your very first line of defense should be to Google your error message or a short description of your issue. (The ability to solve problems using this method is quickly becoming an extremely valuable skill.) If that fails, and it eventually will, you should ask for help. There are a number of things you should include when emailing an instructor, or posting to a help website such as <http://stats.stackexchange.com/>.

- Describe what you expect the code to do.
- State the end goal you are trying to achieve. (Sometimes what you expect the code to do, is not what you want to actually do.)
- The full text of any errors you have received.
- Provide enough code to recreate the error. Often for the purpose of this course, you could simply email your entire `.R` or `.Rmd` file.
- Sometimes it is also helpful to include a screenshot of your entire RStudio window when the error occurs.

If you follow these steps, you will get your issue resolved much quicker, and possibly learn more in the process.

2.3 Installing Packages

TODO: ...

2.4 Data Types

R has a number of basic data *types*.

- Numeric
 - Also known as Double. The default type when dealing with numbers.
 - Examples: 1, 1.0, 42.5.
- Integer

- Examples: 1, 2, 42
- Complex
 - Example: $4 + 2i$
- Logical
 - Two possible values: `TRUE` and `FALSE`.
 - You can also use `T` and `F`, but this is *not* recommended.
 - `NA` is also considered logical.
- Character
 - Examples: `"a"`, `"Statistics"`, `"1 plus 2."`

R also has a number of basic data *structures*. Data structures can be either homogeneous (contain only a single data type) or heterogeneous. (Contain more than one data type.)

Dimension	Homogeneous	Heterogeneous
1	Vector	List
2	Matrix	Data Frame
3+	Array	

We will discuss both vectors and matrices in this chapter. Discussion of lists and data frames will be saved for the following chapter when we encounter them during data analysis.

2.5 Vectors

Many operations in R make heavy use of vectors. Vectors in R are indexed starting at 1. That is what the `[1]` in the output is indicating, that the first element of the row being displayed is the first element of the vector. Larger vectors will start additional rows with `[*]` where `*` is the index of the first element of the row.

Possibly the most common way to create a vector in R is using the `c()` function, which is short for combine. As the name suggests, it combines a list of numbers separated by commas.

```
c(1, 3, 5, 7, 8, 9)
```

```
## [1] 1 3 5 7 8 9
```

Here R simply outputs this vector. If we would like to store this vector in a **variable** we can do so with the **assignment** operator `=`. In this case the variable `x` now holds the vector we just created, and we can access the vector by typing `x`.

```
x = c(1, 3, 5, 7, 8, 9)
x
```

```
## [1] 1 3 5 7 8 9
```

As an aside, there is a long history of the assignment operator in R. For simplicity we will use `=`, but know that often you will see `<=` as the assignment operator. The pros and cons of these two are well beyond the scope of this book, but know that for our purposes you will have no issue if you simply use `=`.

Frequently you may wish to create a vector based on a sequence of numbers. The quickest and easiest way to do this is with the `:` operator, which creates a sequence of integers between two specified integers.

```
(y = 1:100)
```

```
## [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15
## [16] 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
## [31] 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45
## [46] 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60
## [61] 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75
## [76] 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90
## [91] 91 92 93 94 95 96 97 98 99 100
```

Here we see R labeling the rows after the first since this is a large vector. Also, we see that by putting parentheses around the assignment, R both stores the vector in a variable called `y` and automatically outputs `y` to the console.

If we want to create a sequence that isn't limited to integers and increasing by 1 at a time, we can use the `seq()` function.

```
seq(from = 1.5, to = 4.2, by = 0.1)
```

```
## [1] 1.5 1.6 1.7 1.8 1.9 2.0 2.1 2.2 2.3 2.4 2.5 2.6 2.7 2.8 2.9
## [16] 3.0 3.1 3.2 3.3 3.4 3.5 3.6 3.7 3.8 3.9 4.0 4.1 4.2
```

TODO: function and arguments, etc. where to put?

```
seq(1.5, 4.2, 0.1)
```

```
## [1] 1.5 1.6 1.7 1.8 1.9 2.0 2.1 2.2 2.3 2.4 2.5 2.6 2.7 2.8 2.9
## [16] 3.0 3.1 3.2 3.3 3.4 3.5 3.6 3.7 3.8 3.9 4.0 4.1 4.2
```

TODO: add `rep`

```
rep(0.5, times = 10)
```

```
## [1] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
```

```
rep(x, 3)
```

```
## [1] 1 3 5 7 8 9 1 3 5 7 8 9 1 3 5 7 8 9
```

TODO: Accessing elements

```
x
```

```
## [1] 1 3 5 7 8 9
```

```
x[3]
```

```
## [1] 5
```

```
x[1:3]
```

```
## [1] 1 3 5
```

```
x[-2]
```

```
## [1] 1 5 7 8 9
```

```
x[c(1,3,4)]
```

```
## [1] 1 5 7
```

One of the biggest strengths of R is its use of vectorized operations. (Frequently the lack of understanding of this concept leads to a belief that R is *slow*. R is not the fastest language, but it has a reputation for being slower than it really is.)

```
x = 1:10
x + 1
```

```
## [1] 2 3 4 5 6 7 8 9 10 11
```

```
2 * x
```

```
## [1] 2 4 6 8 10 12 14 16 18 20
```

```
2 ^ x
```

```
## [1] 2 4 8 16 32 64 128 256 512 1024
```

```
sqrt(x)
```

```
## [1] 1.000000 1.414214 1.732051 2.000000 2.236068 2.449490
## [7] 2.645751 2.828427 3.000000 3.162278
```

```
log(x)
```

```
## [1] 0.0000000 0.6931472 1.0986123 1.3862944 1.6094379 1.7917595
## [7] 1.9459101 2.0794415 2.1972246 2.3025851
```

We see that when a function like `log()` is called on a vector `x`, a vector is returned which has applied the function to each element of the vector `x`.

TODO: length (no scalar, just a vector of length 1)

TODO: Basic stat functions. Mean. SD. Etc.

```
y
```

```
##   [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15
##  [16] 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
##  [31] 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45
##  [46] 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60
##  [61] 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75
##  [76] 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90
##  [91] 91 92 93 94 95 96 97 98 99 100
```

```
mean(y)
```

```
## [1] 50.5
```

```
median(y)
```

```
## [1] 50.5
```

```
var(y)
```

```
## [1] 841.6667
```

```
sd(y)
```

```
## [1] 29.01149
```

```
IQR(y)
```

```
## [1] 49.5
```

```
min(y)
```

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

```
max(y)
```

```
## [1] 100
```

```
range(y)
```

```
## [1]  1 100
```

2.6 Matrix Calculations

R can also be used for matrix calculations. Matrices can be created using the `matrix` function.

TODO: matrix all same “data” type. “order matters”. has rows and columns

By default the `matrix` function reorders a vector into columns, but we can also tell R to use rows instead.

```
x = 1:9
x
```

```
## [1] 1 2 3 4 5 6 7 8 9
```

```
X = matrix(x, nrow = 3, ncol = 3)
X
```

```
##      [,1] [,2] [,3]
## [1,]    1    4    7
## [2,]    2    5    8
## [3,]    3    6    9
```

```
Y = matrix(x, nrow = 3, ncol = 3, byrow = TRUE)
Y
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
## [3,]    7    8    9
```

```
Z = matrix(0, 2, 4)
Z
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    0    0    0    0
## [2,]    0    0    0    0
```

```
X
```

```
##      [,1] [,2] [,3]
## [1,]    1    4    7
## [2,]    2    5    8
## [3,]    3    6    9
```

```
X[1, 2]
```

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

```
X[1, ]
```

```
## [1] 1 4 7
```

```
X[, 2]
```

```
## [1] 4 5 6
```

```
X[2, c(1, 3)]
```

```
## [1] 2 8
```

Matrices can also be created by combining vectors as columns, using `cbind` or combining vectors as rows using `rbind`.

```
x = 1:9
rev(x)
```

```
## [1] 9 8 7 6 5 4 3 2 1
```

```
rep(1, 9)
```

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

```
cbind(x, rev(x), rep(1, 9))
```

```
##      x
## [1,] 1 9 1
## [2,] 2 8 1
## [3,] 3 7 1
## [4,] 4 6 1
## [5,] 5 5 1
## [6,] 6 4 1
## [7,] 7 3 1
## [8,] 8 2 1
## [9,] 9 1 1
```

```
rbind(x, rev(x), rep(1, 9))
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9]
## x      1    2    3    4    5    6    7    8    9
##      9    8    7    6    5    4    3    2    1
##      1    1    1    1    1    1    1    1    1
```

R can then be used to perform matrix calculations.

```
x = 1:9
y = 9:1
X = matrix(x, 3, 3)
Y = matrix(y, 3, 3)
X
```

```
##      [,1] [,2] [,3]
## [1,]    1    4    7
## [2,]    2    5    8
## [3,]    3    6    9
```



```
Y
```

```
##      [,1] [,2] [,3]
## [1,]    9    6    3
## [2,]    8    5    2
## [3,]    7    4    1
```

TODO: byrow

```
X + Y
```

```
##      [,1] [,2] [,3]
## [1,]   10   10   10
## [2,]   10   10   10
## [3,]   10   10   10
```

```
X - Y
```

```
##      [,1] [,2] [,3]
## [1,]   -8   -2    4
## [2,]   -6    0    6
## [3,]   -4    2    8
```

```
X * Y
```

```
##      [,1] [,2] [,3]
## [1,]    9   24   21
## [2,]   16   25   16
## [3,]   21   24    9
```

```
X / Y
```

```
##      [,1] [,2] [,3]
## [1,] 0.1111111 0.6666667 2.3333333
## [2,] 0.2500000 1.0000000 4.0000000
## [3,] 0.4285714 1.5000000 9.0000000
```

Note that `X * Y` is not matrix multiplication. It is element by element multiplication. (Same for `X / Y`). Instead, matrix multiplication uses `%*%`. `t()` gives the transpose of a matrix, and `solve()` returns the inverse of a matrix.

```
X %*% Y
```

```
##      [,1] [,2] [,3]
## [1,]   90   54   18
## [2,]  114   69   24
## [3,]  138   84   30
```

```
t(X)
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
## [3,]    7    8    9
```

```
Z = matrix(c(9, 2, -3, 2, 4, -2, -3, -2, 16), 3, byrow = T)
Z
```

```
##      [,1] [,2] [,3]
## [1,]    9    2   -3
## [2,]    2    4   -2
## [3,]   -3   -2   16
```

```
solve(Z)
```

```
##      [,1]      [,2]      [,3]
## [1,] 0.12931034 -0.05603448 0.01724138
## [2,] -0.05603448 0.29094828 0.02586207
## [3,] 0.01724138 0.02586207 0.06896552
```

```
X = matrix(1:6, 2, 3)
X
```

```
##      [,1] [,2] [,3]
## [1,]    1    3    5
## [2,]    2    4    6
```

```
dim(X)
```

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

```
rowSums(X)
```

```
## [1]  9 12
```

```
colSums(X)
```

```
## [1]  3  7 11
```

```
rowMeans(X)
```

```
## [1] 3 4
```

```
colMeans(X)
```

```
## [1] 1.5 3.5 5.5
```

```
diag(Z)
```

```
## [1]  9  4 16
```

```
diag(1:5)
```

```
##      [,1] [,2] [,3] [,4] [,5]
## [1,]    1    0    0    0    0
## [2,]    0    2    0    0    0
## [3,]    0    0    3    0    0
## [4,]    0    0    0    4    0
## [5,]    0    0    0    0    5
```

```
diag(5)
```

```
##      [,1] [,2] [,3] [,4] [,5]
## [1,]    1    0    0    0    0
## [2,]    0    1    0    0    0
## [3,]    0    0    1    0    0
## [4,]    0    0    0    1    0
## [5,]    0    0    0    0    1
```

2.7 Distributions

When working with different statistical distributions, we often want to make probabilistic statements based on the distribution.

We typically want to know one of four things:

- The density (pdf) value at a particular value of x .
- The distribution (cdf) value at a particular value of x .
- The quantile x value corresponding to a particular probability.
- A random value from a particular distribution.

This used to be done with statistical tables printed in the back of textbooks. Now, R has functions for obtaining density, distribution, quantile and random values.

The general naming structure of the relevant R functions is:

- **dname** calculates density (pdf) value at input x .
- **pname** calculates distribution (cdf) value at input x .
- **qname** calculates quantile x value at input probability.
- **rname** generates a random value from a particular distribution.

Note that **name** represents the name of the given distribution.

For example, to calculate the value of the pdf for a $N(2, 25)$ for $x = 3$, use:

```
dnorm(3, mean = 2, sd = 5)
```

```
## [1] 0.07820854
```

Or, to calculate the value of the cdf for a $N(2, 25)$ for $x = 3$, use:

```
pnorm(3, mean = 2, sd = 5)
```

```
## [1] 0.5792597
```

Or, to calculate the quantile for probability 0.975, use:

```
qnorm(0.975, mean = 2, sd = 5)
```

```
## [1] 11.79982
```

Lastly, to generate a random sample of size $n = 10$, use:

```
rnorm(10, mean = 2, sd = 5)
```

```
## [1] -7.16049474 13.99363806 -5.08833990  8.37823938  3.60697787
## [6]  7.88064109  0.08600241 -4.57264994  0.12905622  4.76183463
```

These functions exist for many other distributions, including but not limited to:

Command	Distribution
*binom	Binomial
*t	t
*pois	Poisson
*f	F
*chisq	Chi-Squared

Where ***** can be **d**, **p**, **q**, and **r**. Each distribution will have its own set of parameters which need to be passed to the functions as arguments. For example, `pbinom()` would not have arguments for `mean` and `sd`, since those are not parameters of the distribution. Instead a binomial distribution is usually parameterized by n and p , however R chooses to call them something else. To find the names that R uses we would use `?pbinom` and see that R instead calls the arguments `size` and `prob`. For example:

```
pbinom(5, size = 10, prob = 0.75)
```

```
## [1] 0.07812691
```

2.8 Programming Basics

2.8.1 Logical Operators

Operator	Summary
<code>x < y</code>	x less than y
<code>x > y</code>	x greater than y
<code>x <= y</code>	x less than or equal to y
<code>x >= y</code>	x greater than or equal to y
<code>x == y</code>	x equal to y
<code>x != y</code>	x not equal to y
<code>!x</code>	not x
<code>x y</code>	x or y
<code>x & y</code>	x and y

In R, logical operators are vectorized.

```
heights = c(110, 120, 115, 136, 205, 156, 175)
weights = c(64, 67, 62, 60, 77, 70, 66)
heights < 121
```

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

```
heights < 121 | heights == 156
```

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

```
weights[heights > 150]
```

```
## [1] 77 70 66
```

Be careful when comparing vectors that you are comparing vectors of the same length.

```
a = 1:10
b = 2:4
a < b
```

```
## Warning in a < b: longer object length is not a multiple of
## shorter object length
```

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

What happened here? R still performed the operation, but it also gives us a warning. (To perform the operation automatically made `b` longer by repeating `b` as needed.)

In R, the if/else syntax is:

```
if (...) {
  some R code
} else {
  more R code
}
```

For example,

```
x = 1
y = 3
if (x > y) {
  z = x * y
  print("x is larger than y")
} else {
  z = x + 5 * y
  print("x is less than or equal to y")
}
```

```
## [1] "x is less than or equal to y"
```

```
z
```

```
## [1] 16
```

TODO: ifelse

Now a for loop example,

```
x = 11:15
for (i in 1:5) {
  x[i] = x[i] * 2
}
```

```
x
```

```
## [1] 22 24 26 28 30
```

Note that this for loop is very normal in many programming languages, but not in R. In R we would not use a loop, instead we would simply use a vectorized operation:

```
x = 11:15
x = x * 2
x
```

```
## [1] 22 24 26 28 30
```

Lastly, we can write our own functions in R. For example,

```
standardize = function(x) {
  m = mean(x)
  std = sd(x)
  result = (x - m) / std
  result
}

x = rnorm(10, 2, 25)
standardize(x)
```

```
## [1] -0.88527686 0.62673245 -1.87751106 0.02472152 -0.34752032
## [6] -0.43271225 0.32336355 0.86629704 1.76925185 -0.06734593
```

TODO: function with arguments, control flow, if based return, how return works. compare these two?

```
get_sd = function(x, biased = FALSE) {
  n = length(x)
  if (biased) {
    std = sqrt((1 / n) * sum((x - mean(x)) ^ 2))
  } else {
    std = sqrt((1 / (n - 1)) * sum((x - mean(x)) ^ 2))
  }
  std
}
```

```
get_sd = function(x, biased = FALSE) {
  n = length(x) - 1 * biased
  sqrt((1 / n) * sum((x - mean(x)) ^ 2))
}
```

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

2.9 Hypothesis Tests in R

2.9.1 One Sample t-Test: Review

Suppose $x_i \sim N(\mu, \sigma^2)$ and we want to test $H_0 : \mu = \mu_0$ versus $H_1 : \mu \neq \mu_0$.

Assuming σ is unknown, use the one-sample Student's t test statistic:

$$T = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \sim t_{n-1}$$

where $\bar{x} = \frac{\sum_{i=1}^n x_i}{n}$ and $s = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}}$

A $100(1 - \alpha)\%$ CI for μ is given by

$$\bar{x} \pm t_{n-1}^{(\alpha/2)} \frac{s}{\sqrt{n}}$$

where $t_{n-1}^{(\alpha/2)}$ is the critical value such that $P(T > t_{n-1}^{(\alpha/2)}) = \alpha/2$ for $n - 1$ degrees of freedom.

2.9.2 One Sample t-Test: Example

A store sells “16-ounce” boxes of *Captain Crisp* cereal. A random sample of 9 boxes was taken and weighed. The results were

15.5 16.2 16.1 15.8 15.6 16.0 15.8 15.9 16.2

ounces. Assume the weight of cereal in a box is normally distributed.

a) Compute the sample mean \bar{x} and the sample standard deviation s .

$$\begin{aligned}\bar{x} &= \frac{1}{n} \sum_{i=1}^n x_i = (1/9)(15.5 + \cdots + 16.2) = (1/9)(143.1) = \mathbf{15.9} \\ s^2 &= \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_i^2 - n\bar{x}^2 \right] \\ &= (1/8) [2275.79 - 9(15.9^2)] = (1/8)(0.5) = 0.0625 \\ s &= \sqrt{0.0625} = \mathbf{0.25}\end{aligned}$$

```
x = c(15.5, 16.2, 16.1, 15.8, 15.6, 16.0, 15.8, 15.9, 16.2)
mean(x)
```

```
## [1] 15.9
```

```
sd(x)
```

```
## [1] 0.25
```

b) Construct a 95% confidence interval for the overall average weight of boxes of *Captain Crisp* cereal.

$t_{n-1}^{(\alpha/2)} = t_8^{(0.025)} = 2.306$, so the 95% CI for the average weight of a cereal box is:

$$15.9 \pm 2.306 \sqrt{\frac{0.0625}{9}} = [15.708, 16.092]$$

Or, in R:

```
t.test(x, alternative = c("two.sided"), conf.level = 0.95)
```

```
##
## One Sample t-test
##
## data: x
## t = 190.8, df = 8, p-value = 6.372e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## 15.70783 16.09217
## sample estimates:
## mean of x
## 15.9
```


Or if we only wanted to display the interval:

```
tt = t.test(x, alternative = c("two.sided"), conf.level = 0.95)
tt$conf.int
```

```
## [1] 15.70783 16.09217
## attr(,"conf.level")
## [1] 0.95
```

Or, we could calculate it “by hand” in R.

```
qt(0.975, 8)
```

```
## [1] 2.306004
```

```
c(mean(x) - qt(0.975, 8) * sd(x) / sqrt(9),
   mean(x) + qt(0.975, 8) * sd(x) / sqrt(9))
```

```
## [1] 15.70783 16.09217
```

c) The company that makes *Captain Crisp* cereal claims that the average weight of its box is at least 16 ounces. Use a 0.05 level of significance to test the company’s claim. What is the p-value of this test?

To test $H_0 : \mu \geq 16$ versus $H_1 : \mu < 16$, the test statistic is

$$T = \frac{15.9 - 16}{\sqrt{0.0625/9}} = -1.2$$

We know that $T \sim t_8$, so the rejection reject is $T < -t_{n-1}^{(\alpha)} = -t_8^{(0.05)} = -1.860$.

Therefore, we **do NOT reject the null hypothesis** at the $\alpha = .05$ level. We could have also bounded the p-value of the test using the t table.

```
t.test(x, mu = 16, alternative = c("less"), conf.level = 0.95)
```

```
##
## One Sample t-test
##
## data: x
## t = -1.2, df = 8, p-value = 0.1322
## alternative hypothesis: true mean is less than 16
## 95 percent confidence interval:
##      -Inf 16.05496
## sample estimates:
## mean of x
##      15.9
```

2.9.3 Two Sample t-Test: Review

Suppose $x_i \sim N(\mu_x, \sigma^2)$ and $y_i \sim N(\mu_y, \sigma^2)$.

Want to test $H_0 : \mu_x - \mu_y = \mu_0$ versus $H_1 : \mu_x - \mu_y \neq \mu_0$.

Assuming σ is unknown, use the two-sample Student's t test statistic:

$$T = \frac{(\bar{x} - \bar{y}) - \mu_0}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}} \sim t_{n+m-2}$$

where $\bar{x} = \frac{\sum_{i=1}^n x_i}{n}$, $\bar{y} = \frac{\sum_{i=1}^m y_i}{m}$, and $s_p^2 = \frac{(n-1)s_1^2 + (m-1)s_2^2}{n+m-2}$

A $100(1 - \alpha)\%$ CI for $\mu_x - \mu_y$ is given by

$$(\bar{x} - \bar{y}) \pm t_{n+m-2}^{(\alpha/2)} \left(s_p \sqrt{\frac{1}{n} + \frac{1}{m}} \right)$$

where $t_{n+m-2}^{(\alpha/2)}$ is critical t_{n+m-2} value such that $P(T > t_{n+m-2}^{(\alpha/2)}) = \alpha/2$.

2.9.4 Two Sample t-Test: Example

Assume that the distributions of X and Y are $N(\mu_1, \sigma^2)$ and $N(\mu_2, \sigma^2)$, respectively. Given the $n = 6$ observations of X ,

70, 82, 78, 74, 94, 82

and the $m = 8$ observations of Y ,

64, 72, 60, 76, 72, 80, 84, 68

find the p-value for the test $H_0 : \mu_1 = \mu_2$ versus $H_1 : \mu_1 > \mu_2$.

First, note that the sample means and variances are given by

$$\begin{aligned} \bar{x} &= (1/6) \sum_{i=1}^6 x_i = (1/6)480 = 80 \\ \bar{y} &= (1/8) \sum_{i=1}^8 y_i = (1/8)576 = 72 \\ s_x^2 &= (1/5) \sum_{i=1}^6 (x_i - \bar{x})^2 = (1/5)344 = 68.8 \\ s_y^2 &= (1/7) \sum_{i=1}^8 (y_i - \bar{y})^2 = (1/7)448 = 64 \end{aligned}$$

which implies that the pooled variance estimate is given by

$$\begin{aligned} s_p^2 &= \frac{(n-1)s_x^2 + (m-1)s_y^2}{n+m-2} \\ &= \frac{344 + 448}{12} \\ &= 66 \end{aligned}$$

Thus, the relevant t test statistic is given by

$$\begin{aligned} T &= \frac{(\bar{x} - \bar{y}) - \mu_0}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}} \\ &= \frac{(80 - 72) - 0}{\sqrt{66} \sqrt{\frac{1}{6} + \frac{1}{8}}} \\ &= 1.82337 \end{aligned}$$

Note that $T \sim t_{12}$, so

$$0.025 < p\text{-value} < 0.05$$

since

$$t_{12}^{(0.025)} = 1.782 < 1.82337 < t_{12}^{(0.05)} = 2.179.$$

```
x = c(70, 82, 78, 74, 94, 82)
y = c(64, 72, 60, 76, 72, 80, 84, 68)
t.test(x, y, alternative = c("greater"), var.equal = TRUE)

##
## Two Sample t-test
##
## data: x and y
## t = 1.8234, df = 12, p-value = 0.04662
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.1802451      Inf
## sample estimates:
## mean of x mean of y
##      80      72
```

Or, performing the calculations by hand in R:

```
sPooled2 = ((6 - 1) * var(x) + (8 - 1) * var(y)) / (6 + 8 - 2)
sPooled2

## [1] 66

test_stat = (mean(x) - mean(y)) / sqrt(sPooled2 * (1 / 6 + 1 / 8))
test_stat

## [1] 1.823369

1 - pt(test_stat, 6 + 8 - 2)

## [1] 0.04661961
```

2.10 Simulation in R

2.10.1 Paired Differences

Consider the model:

$$\begin{aligned} X_{11}, X_{12}, \dots, X_{1n} &\sim N(\mu_1, \sigma^2) \\ X_{21}, X_{22}, \dots, X_{2n} &\sim N(\mu_2, \sigma^2) \end{aligned}$$

Assume that $\mu_1 = 6$, $\mu_2 = 5$, $\sigma^2 = 4$ and $n = 25$.

Let $\bar{X}_1 = \frac{1}{n} \sum_{i=1}^n X_{1i}$, $\bar{X}_2 = \frac{1}{n} \sum_{i=1}^n X_{2i}$ and $D = \bar{X}_1 - \bar{X}_2$.

Find $P(0 < D < 2)$.

$$D = \bar{X}_1 - \bar{X}_2 \sim N\left(\mu_1 - \mu_2, \frac{\sigma^2}{n} + \frac{\sigma^2}{n}\right) = N\left(6 - 5, \frac{4}{25} + \frac{4}{25}\right)$$

So,

$$D \sim N(1, 0.32)$$

Thus,

$$P(0 < D < 2) = P(-1.77 < Z < 1.77) = 0.9616 - 0.0384 = 0.9232.$$

```
z = 1 / sqrt(0.32)
pnorm(z) - pnorm(-z)
```

```
## [1] 0.9229001
```

Empirical distribution of D

Generate $S = 1000$ datasets for each of group 1 and group 2. For each of the $s = 1 : 1000$ datasets, compute $d_s = \bar{x}_{1s} - \bar{x}_{2s}$. Make a histogram for the 1000 values of d . What is the proportion of values of d (among the 1000 values of d generated) that are between 0 and 2?

```
set.seed(42)
sample_size = 25
mu1 = 6
mu2 = 5
std = 2

samples = 10000
count = 0
differences = rep(0, samples)

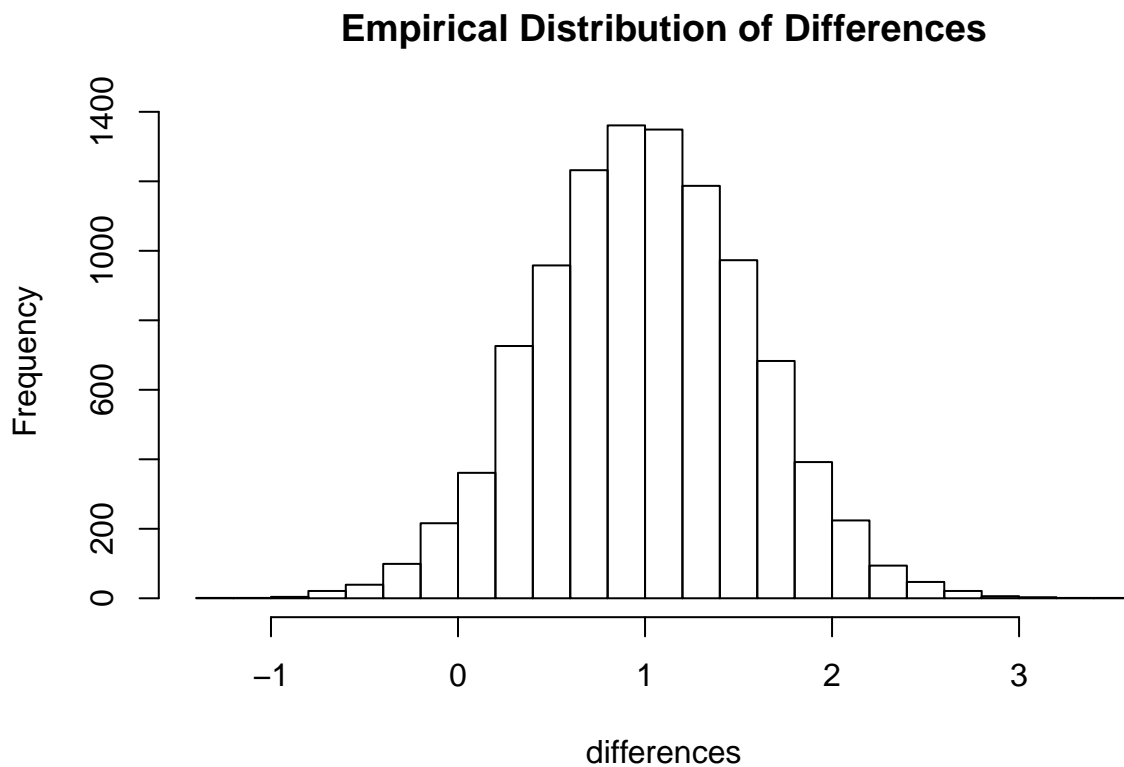
for (i in 1:samples) {
  x1 = rnorm(sample_size, mu1, std)
```

```
x2 = rnorm(sample_size, mu2, std)
differences[i] = mean(x1) - mean(x2)
}

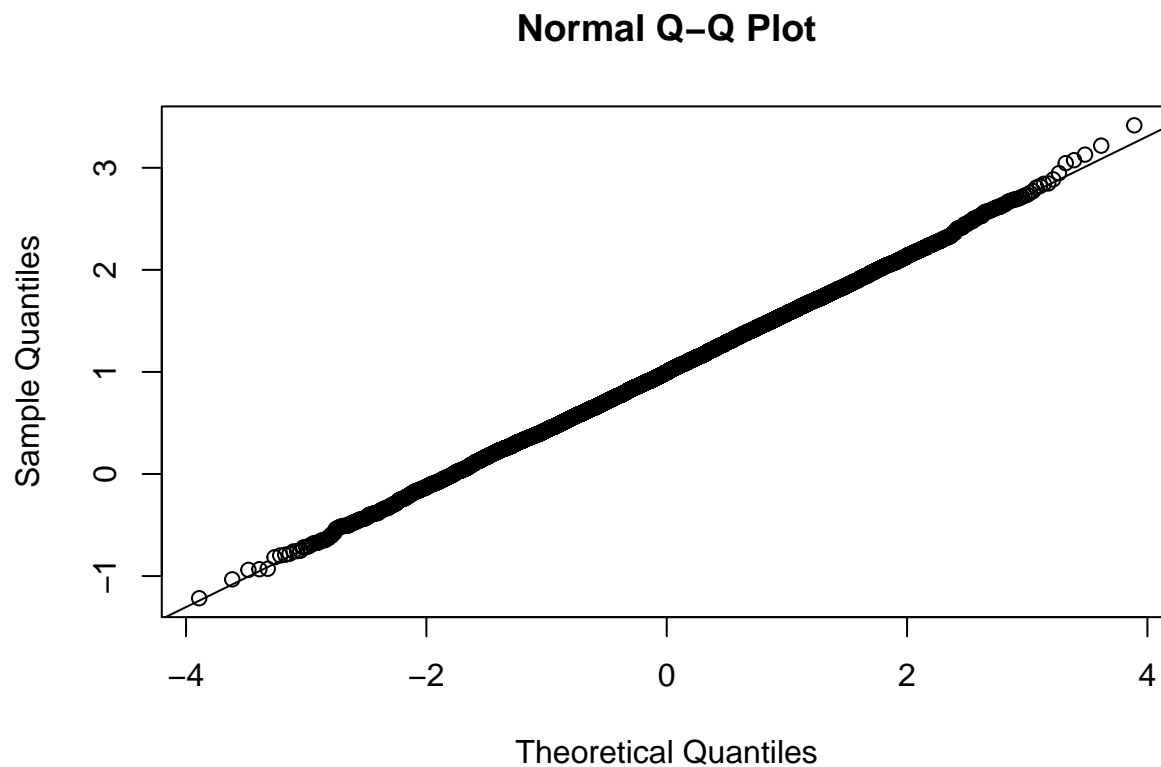
mean(0 < differences & differences < 2)
```

```
## [1] 0.9222
```

```
hist(differences, breaks = 20, main = "Empirical Distribution of Differences")
```



```
qqnorm(differences)
qqline(differences)
```



2.10.2 Distribution of a Sample Mean

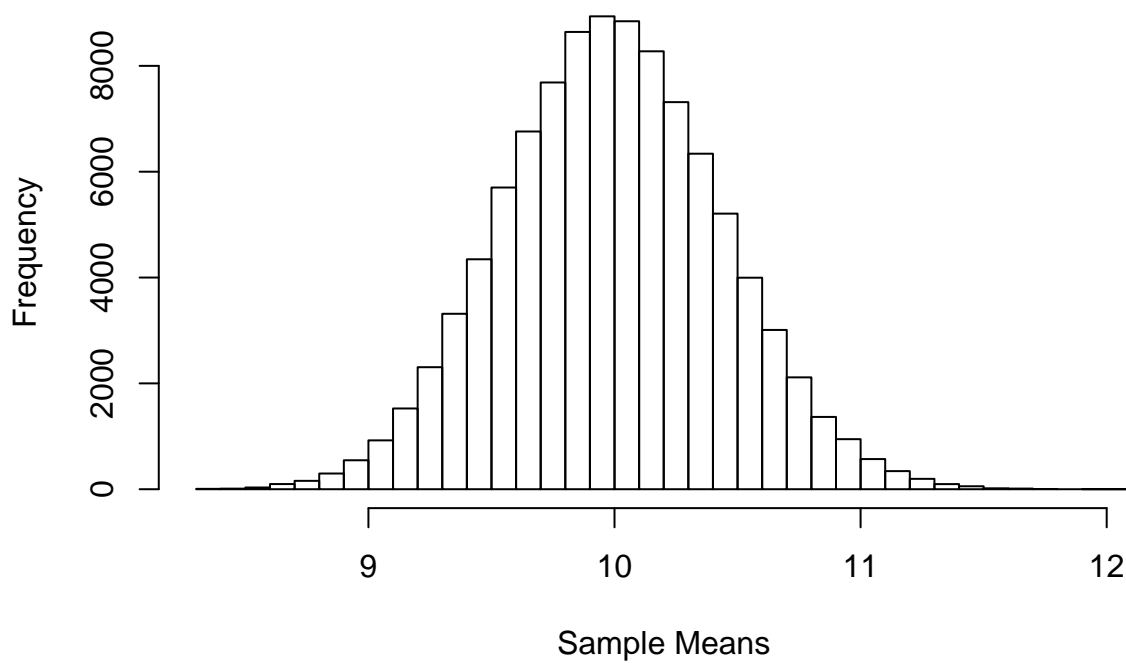
TODO: Move in front of paired?

```
set.seed(42)
sample_size = 50
mu = 10
samples = 100000
x_bar = rep(0, samples)

for(i in 1:samples){
  x_bar[i] = mean(rpois(sample_size, lambda = mu))
}

x_bar_hist = hist(x_bar, breaks = 50,
                  main = "Histogram of Sample Means",
                  xlab = "Sample Means")
```

Histogram of Sample Means



```
c(mean(x_bar), mu)
```

```
## [1] 10.00009 10.00000
```

```
c(sd(x_bar), sqrt(mu) / sqrt(sample_size))
```

```
## [1] 0.4454965 0.4472136
```

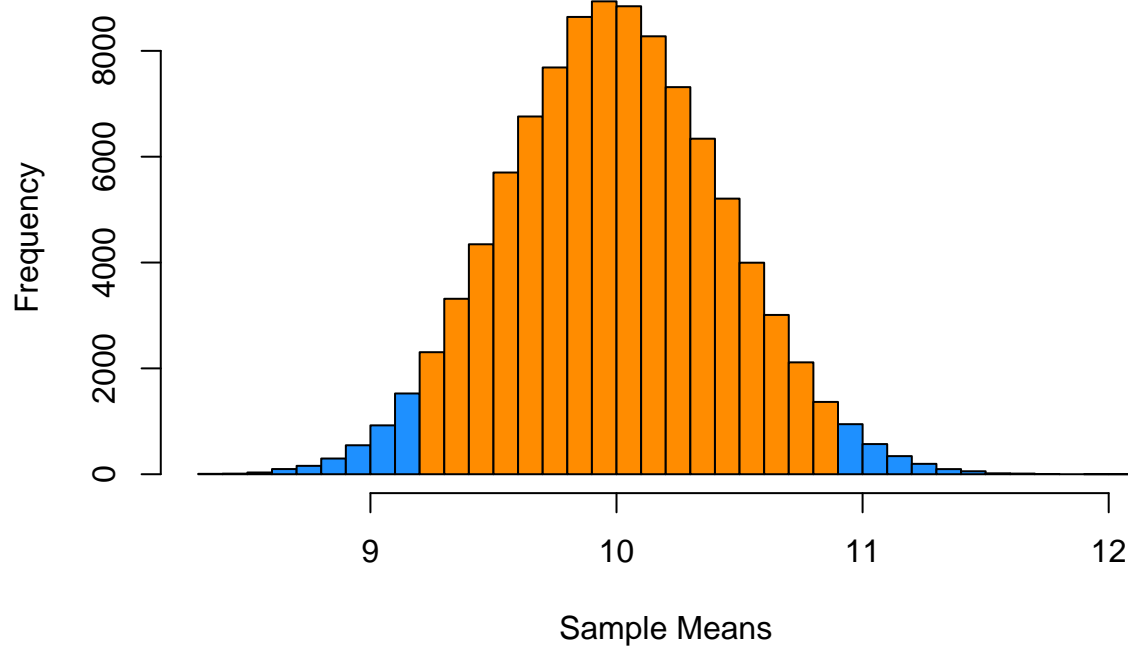
```
mean(x_bar > mu - 2 * sqrt(mu) / sqrt(sample_size) &
     x_bar < mu + 2 * sqrt(mu) / sqrt(sample_size))
```

```
## [1] 0.95459
```

```
shading = ifelse(x_bar_hist$breaks > mu - 2 * sqrt(mu) / sqrt(sample_size) &
                 x_bar_hist$breaks < mu + 2 * sqrt(mu) / sqrt(sample_size),
                 "darkorange", "dodgerblue")
```

```
x_bar_hist = hist(x_bar, breaks = 50, col = shading,
                 main = "Histogram of Sample Means, Two Standard Deviations",
                 xlab = "Sample Means")
```

Histogram of Sample Means, Two Standard Deviations



Chapter 3

Simple Linear Regression

“All models are wrong, but some are useful.”

- **George E. P. Box**

Suppose you are the owner of the *Momma Leona's Pizza*, a restaurant chain located near several college campuses. You currently own 10 stores and have data on the size of the student population as well as quarterly sales for each. Your data is summarized in the table below.

Restaurant	Student Population	Quarterly Sales
1	2	58
2	6	105
3	8	88
4	8	118
5	12	117
6	16	137
7	20	157
8	20	169
9	22	149
10	26	202

Here,

- Restaurant, i
- Student Population, x_i , in 1000s
- Quarterly Sales, y_i , in \$1000s

```
momma_leona <- data.frame(students = c(2, 6, 8, 8, 12, 16, 20, 20, 22, 26),  
                           sales = c(58, 105, 88, 118, 117, 137, 157, 169, 149, 202))
```

We have previously seen vectors and matrices for storing data as we introduced R. We will now introduce a **data frame** which will be the most common way that we store and interact with data in this course.

list of vectors observations and variables order “doesn’t matter” (unlike a matrix)

```
names(momma_leona)
```

```
## [1] "students" "sales"
```

```
momma_leona$sales
```

```
## [1] 58 105 88 118 117 137 157 169 149 202
```

```
momma_leona$students
```

```
## [1] 2 6 8 8 12 16 20 20 22 26
```

```
dim(momma_leona)
```

```
## [1] 10 2
```

```
nrow(momma_leona)
```

```
## [1] 10
```

```
ncol(momma_leona)
```

```
## [1] 2
```

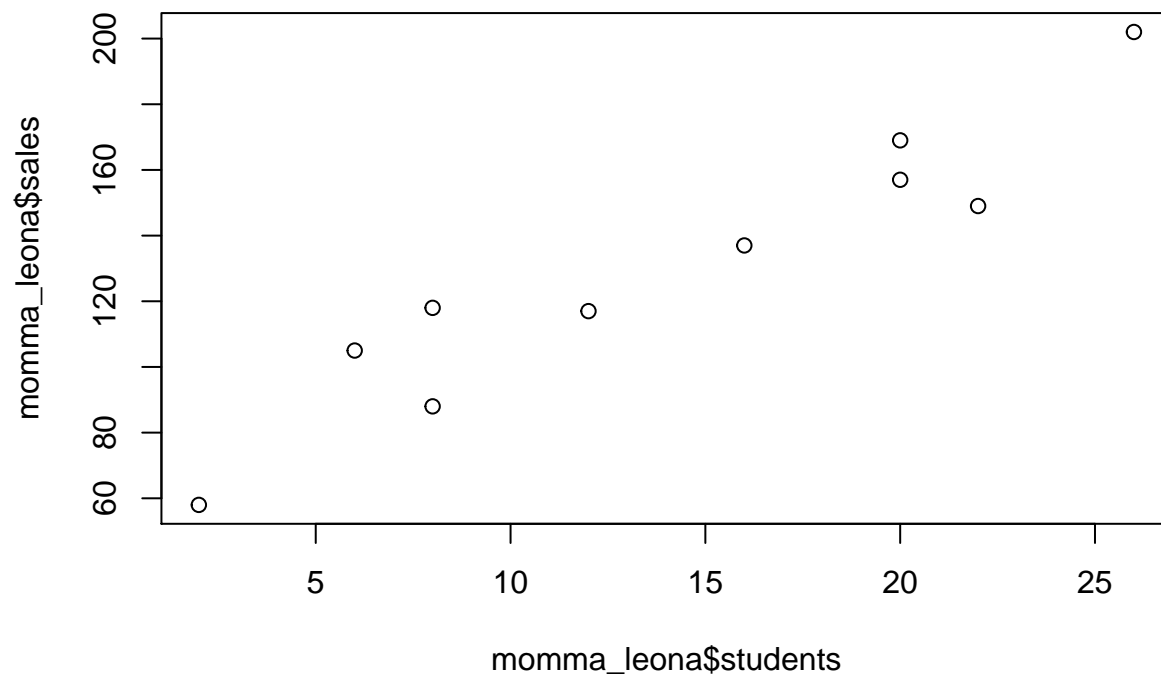
```
str(momma_leona)
```

```
## 'data.frame': 10 obs. of 2 variables:  
## $ students: num 2 6 8 8 12 16 20 20 22 26  
## $ sales : num 58 105 88 118 117 137 157 169 149 202
```

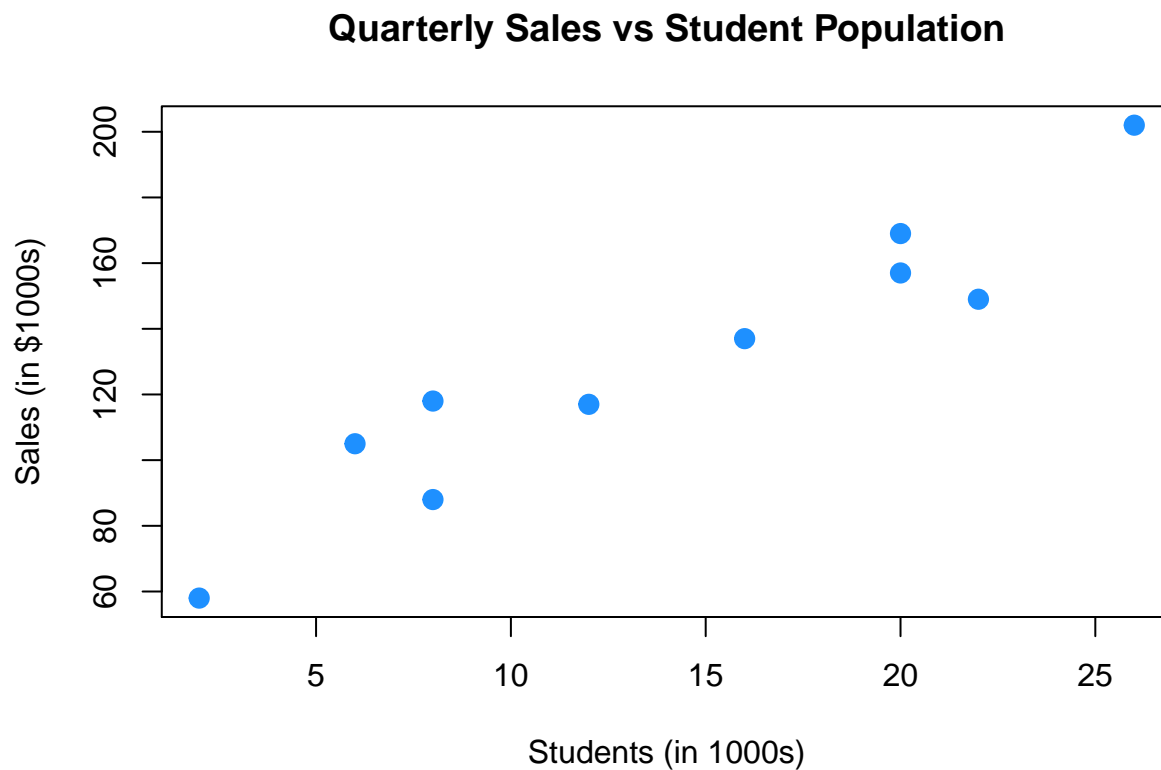
data is csv here

TODO: import into R/RStudio

```
plot(momma_leona$students, momma_leona$sales)
```



```
plot(momma_leona$students, momma_leona$sales,
     xlab = "Students (in 1000s)",
     ylab = "Sales (in $1000s)",
     main = "Quarterly Sales vs Student Population",
     pch = 20,
     cex = 2,
     col = "dodgerblue")
```



response, outcome predictor, explanatory

note about “independent”

How can you use this data to:

- Explain relationship
 - Significant?
 - Which *variables* (word?) are most important? (Say, a variable for public/private)
- Predict

One tool will do both, LINEAR REGRESSION

3.1 History

3.2 Model

$$y = f(x) + \epsilon$$

$$y = \beta_0 + \beta_1 x + \epsilon$$

PARAMETERS

DATA = PREDICTION + ERRORS = SIGNAL + NOISE = MODEL + ERROR

Unexplained:

- missing variables
- measurement error

3.3 What is the Best Line?

Goldilocks

- Underfitting (Just using \bar{y})
- Just right (SLR)
- Overfitting (Connect the dots)

TODO: picture with lines. one for overall mean. one for LS?

$$\operatorname{argmin}_{\beta_0, \beta_1} \max |y_i - (\beta_0 + \beta_1 x_i)|$$

$$\operatorname{argmin}_{\beta_0, \beta_1} \sum_{i=1}^n |y_i - (\beta_0 + \beta_1 x_i)|$$

$$\operatorname{argmin}_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2$$

historical, easy math

3.4 Least Squares Approach

Function to minimize.

$$f(\beta_0, \beta_1) = \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2 = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

Take derivatives.

$$\frac{df}{d\beta_0} = -2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)$$

$$\frac{df}{d\beta_1} = -2 \sum_{i=1}^n (x_i)(y_i - \beta_0 - \beta_1 x_i)$$

Set equal to zero.

$$\sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) = 0$$

$$\sum_{i=1}^n (x_i)(y_i - \beta_0 - \beta_1 x_i) = 0$$

Rearrange, **normal equations**.

$$\sum_{i=1}^n y_i = n\beta_0 + \beta_1 \sum_{i=1}^n x_i$$

$$\sum_{i=1}^n x_i y_i = \beta_0 \sum_{i=1}^n x_i + \beta_1 \sum_{i=1}^n x_i^2$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i - \frac{(\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n}}{\sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n x_i)^2}{n}} = \frac{SXY}{SXX}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

$$SXY = \sum_{i=1}^n x_i y_i - \frac{(\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$SXX = \sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n x_i)^2}{n} = \sum_{i=1}^n (x_i - \bar{x})^2$$

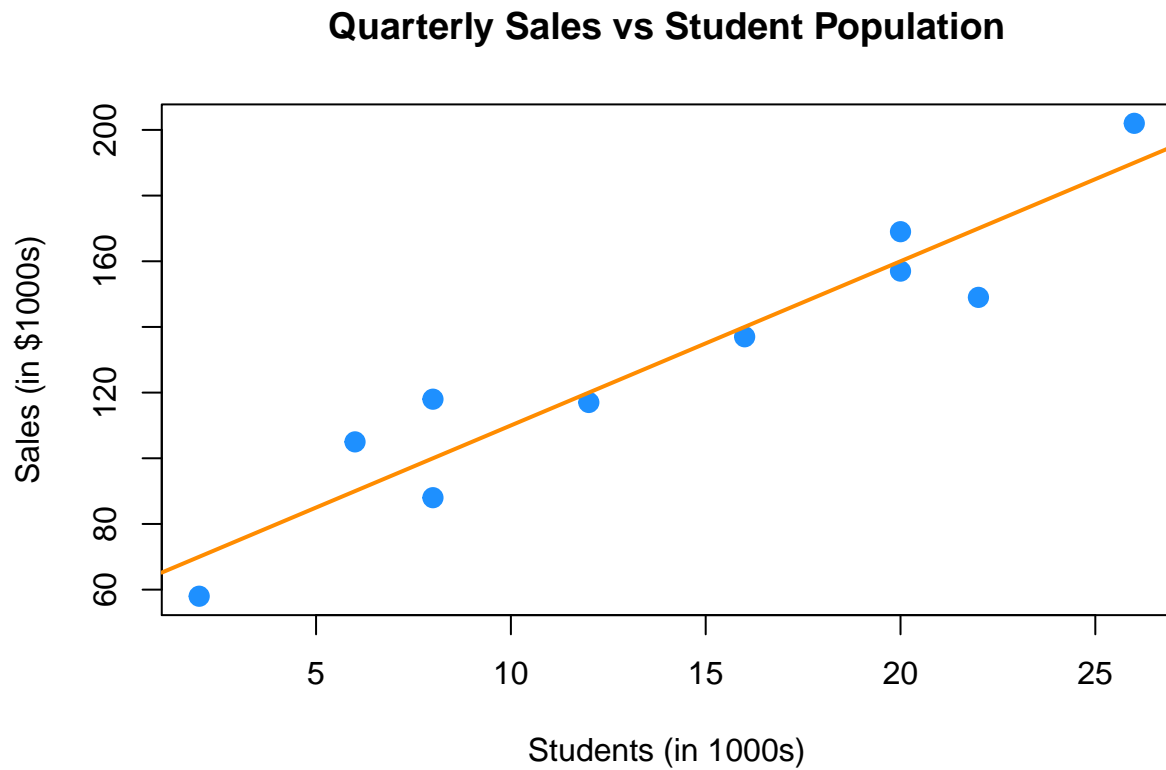
$$SYY = \sum_{i=1}^n y_i^2 - \frac{(\sum_{i=1}^n y_i)^2}{n} = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$\hat{\beta}_1 = \frac{SXY}{SXX} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

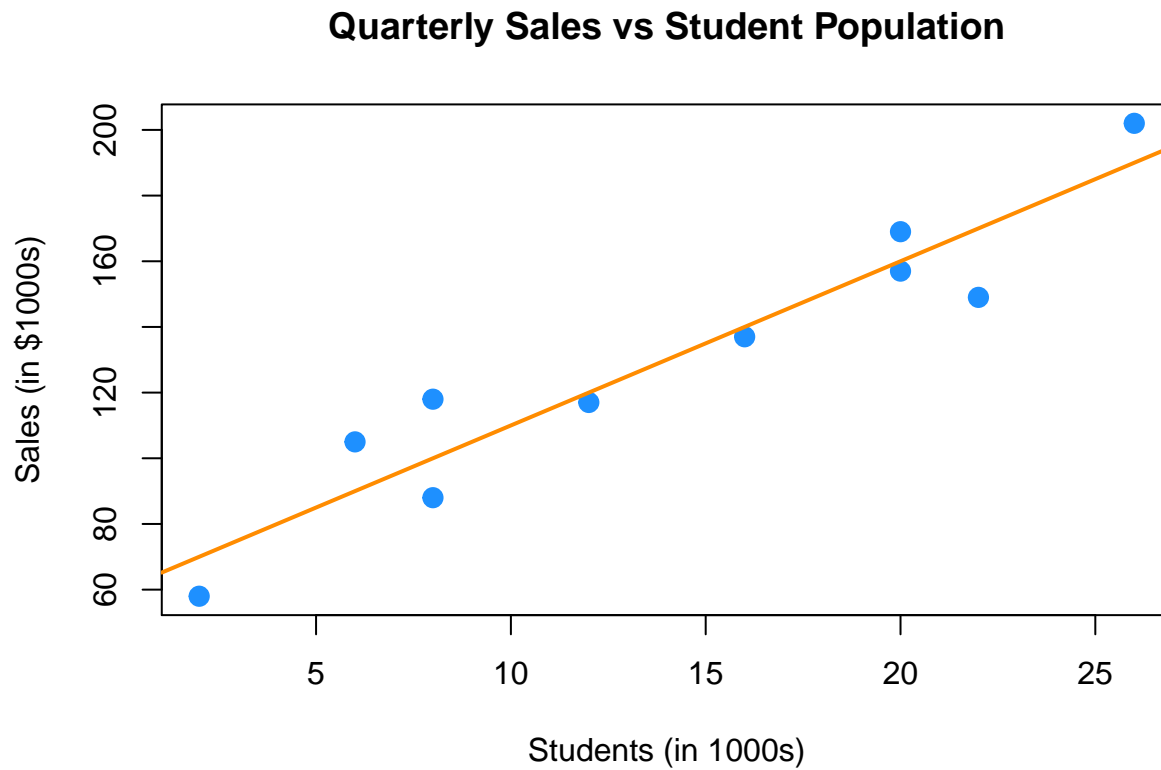
TODO: Fitted line. TODO: variance estimate

```
momma_leona_model = lm(sales ~ students, data = momma_leona)
```

```
plot(momma_leona$students, momma_leona$sales,
     xlab = "Students (in 1000s)",
     ylab = "Sales (in $1000s)",
     main = "Quarterly Sales vs Student Population",
     pch = 20,
     cex = 2,
     col = "dodgerblue")
abline(momma_leona_model, lwd = 2, col = "darkorange")
```



```
plot(sales ~ students, data = momma_leona,  
     xlab = "Students (in 1000s)",  
     ylab = "Sales (in $1000s)",  
     main = "Quarterly Sales vs Student Population",  
     pch = 20,  
     cex = 2,  
     col = "dodgerblue")  
abline(momma_leona_model, lwd = 2, col = "darkorange")
```



TODO: fit in R TODO: extrapolation TODO: interpretation

3.5 Decomposition of Variation

TODO: Residuals

3.6 Coefficient of Determination

R^2

$$\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \sum_{i=1}^n (\hat{y}_i - \bar{y})^2$$

Decomposing variation.

3.7 MLE Approach

$$L(\beta_0, \beta_1, \sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{1}{2} \left(\frac{Y_i - \beta_0 - \beta_1 x_i}{\sigma} \right)^2 \right]$$

Chapter 4

Inference for Simple Linear Regression

“There are three types of lies: lies, damn lies, and statistics.”
- **Benjamin Disraeli**

4.1 Schedule

Introduction to Linear Models

- Week 1: R, Markdown, Simulation, Testing, Probability
- Week 2: SLR
- Week 3: SLR Inference, Matrix Approach
- Week 4: Correlation, MLR

Extending Linear Models

- Week 5: ANOVA and ANCOVA
- Week 6: Diagnostics and Transformations
- Week 7: Model Selection
- Week 8: Time Series

4.2 Ideas

4.3 Misc Notes

- Week 7 is light, and Week 8 is unneeded for undergrads, which gives time to work on projects.
- Project should be released by Week 5.

Bibliography