STAT111 R Bootcamp

Roodmap

- ▶ What is R?
- Basics and fundmaentals
- Data exploration exercises and OHs

What is R?

- Open-source language for statistical computing and graphics
- Ranked 12th TIOBE index.
- Built for things statisticians care about:
 - Vectors and matrices
 - Linear/non-linear modeling
 - Statistical tests
 - Visualization and more!
- Highly extensible because of packages (and you can write your own, too!)

R and Stat 111

- Do not worry if you have no coding experience!
- Goal of this workshop is to build comfort looking things up and solving your own problems in R
- Homeworks may involve computation on real/synthetic data to demonstrate inference in practice
 - Other languages are also allowed (e.g. Python)
- ▶ At OH, Course staff will primarily provide conceptual support with computational problems, NOT debugging code

RStudio

- An integrated development environment (IDE) to organize your code, data, plots, files, and more.
- ► You can even type your homeworks using RMarkdown!

R Resources

- DataCamp, whose Chief Data Scientist was a Harvard stat concentrator
- R for Data Science, the free online book by Grolemund and Wickham.
- Google and Stackoverflow

Language Fundamentals

- Functions and documentation
- Variables and data types
- ▶ Vectors, matrices, data frames
- ► Loops, conditionals, vectorization
- Plotting

Not covered but worth reading: Factors, lists, pipes, apply() function

Functions and Documentation

► Functions take inputs ("arguments") and return an output

```
sum(110, 111, 211)
```

```
## [1] 432
```

* Sometimes, arguments are optional or carry a default value. * **Exercise**: Look up rnorm() and generate 10 i.i.d. N(5, 1) data points. What do pnorm(), dnorm() and qnorm() do? (Hint: Use ?rnorm to read documentation)

Functions and Documentation

?rnorm

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```
rnorm(n = 10, mean = 5, sd = 1)

## [1] 3.501596 6.604848 2.839507 5.854525 4.315099 5.285335 6.159325

## [8] 4.143381 4.706517 3.972850

pnorm(0.5)

## [1] 0.6914625

dnorm(0.5)
```

Writing Your Own Functions

```
SayHello <- function(name = "world"){
  # This is a comment
  # Use ?cat to see what cat do
  # function will "return" or output the value of the last line
  # also can use "return()"
  cat("hello", name)
}
SayHello()</pre>
```

hello world

```
SayHello("Joe and Susan")
```

hello Joe and Susan

Variables

- ▶ Often store values in "buckets" called variables.
 - Represent values without having to retype them
 - Update a variable if the value changes

Assign or update using "<-"

"=" also works

[1] 1.630184

```
m_{11} < -2.56
y <- rnorm(1, mean = mu)
pnorm(y, mean = mu)
## [1] 0.1762332
# update
mu <- mu + 1
pnorm(y, mean = mu)
## [1] 0.02681482
print(y)
```

Basic Data Types

- ▶ Values in R are generally one of the following types:
 - ► Logical: TRUE, FALSE
 - ▶ Integer: 110, 111
 - ▶ Decimal: 3.14
 - ► Complex: 3+2i
 - Character: "joe", "susan"
- ▶ Use class() to check a value's type.

Basic Data Types

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Complex: 3+2i
Character: "joe", "susan"

- Use class() to check a value's type.
- Careful not all data types play well together!

```
# This won't work

# "hello" + 1

# This is okay

1 + 3+2i + 2.72
```

```
# This is okay, too; logicals are coerced into 1's and 0's
4 + TRUE + FALSE
```

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

[1] 6.72+2i

Useful Operators for Numerics

- Operators
 - ▶ Basic operations: +, -, *, /
 - Exponents: ^
 - ► Modulo: %%
 - ► Comparisons: <, <=, >, >=, ==, !=
 - Other functions: exp(), log(), sin(), cos()
- **Exercise**: Predict results for the following computations:

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```
110 < 111
exp(log(-1))
4 + 12 / 6 %% 3
```

Useful Operators for Numerics

Operators

[1] Inf

- Basic operations: +, -, *, /
- Exponents: ^
- ▶ Modulo: %%; Quotient: %/%
- ► Comparisons: <, <=, >, >=, ==, !=
- Other functions: exp(), log(), sin(), cos()
- **Exercise**: Predict results for the following computations:

```
110 < 111

## [1] TRUE

exp(log(-1))

## Warning in log(-1): NaNs produced

## [1] NaN

4 + 12 / 6 %% 3
```

Vectors

[1] 4 2 5

Like in math, a 1d collection of elements of the same type.

```
# Create a vector
my_vector <- vector("numeric", length = 3)</pre>
my_vector
## [1] 0 0 0
# my vector <- numeric(length = 3)</pre>
# Combine vectors
c(my\_vector, -7, 32)
## [1] 0 0 0 -7 32
# Vector arithmetic
my_vector + 1
## [1] 1 1 1
my_vector + c(4, 2, 5)
```

Vectors: Naming and Accessing Elements

```
enrollment <- c(586, 328, 51)
# Give elements names
names(enrollment) <- c("Stat 110", "Stat 111", "Stat 211")</pre>
# Access Stat 111 enrollment in a few different ways
enrollment[2]; enrollment["Stat 111"];
## Stat 111
##
        328
## Stat 111
##
        328
enrollment[c(FALSE, TRUE, FALSE)]
## Stat 111
        328
##
```

Exercise: How would you get the enrollment of Stat 110 AND Stat 111?

Vectors: Naming and Accessing Elements

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enrollment[2]; enrollment["Stat 111"];
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##
        328
## Stat 111
##
        328
enrollment[c(FALSE, TRUE, FALSE)]
## Stat 111
        328
##
Exercise: How would you get the enrollment of Stat 110 AND Stat 111?
enrollment[c(1, 2)]
## Stat 110 Stat 111
      586
              328
enrollment[c("Stat 110", "Stat 111")]
```

Vectors: Useful Functions

```
# The colon operator or seq() function yield sequences.
my vector <- 1:10
my other vector \leftarrow seq(1, 10, by = 2)
# Other useful functions
mean(my_vector)
## [1] 5.5
var(my_vector)
## [1] 9.166667
summary(my_vector)
     Min. 1st Qu. Median Mean 3rd Qu. Max.
##
##
     1.00 3.25 5.50
                             5.50
                                     7.75 10.00
table(my_vector)
## my_vector
```

Matrices

▶ Like in math, a 2d collection of elements of the same type.

```
# Create a matrix
my_matrix <- matrix(1:6, nrow = 2, ncol = 3, byrow = TRUE)
# Matrix arithmetic
my_matrix * 2

## [,1] [,2] [,3]
## [1,] 2 4 6
## [2,] 8 10 12

# Matrix multiplication and transpose
my_matrix %*% t(my_matrix)</pre>
```

```
## [,1] [,2]
## [1,] 14 32
## [2,] 32 77
```

Matrices

Exercise: Try my_matrix * my_matrix ?

Matrices

```
Exercise: Try my_matrix * my_matrix ?
```

```
my_matrix * my_matrix
```

Create a matrix

```
## [,1] [,2] [,3]
## [1,] 1 4 9
## [2,] 16 25 36
```

Matrices: Naming and Accessing Elements

```
enrollment = matrix(c(586, 620, 328, 355, 51, 44), nrow = 2)
rownames(enrollment) = c("2018", "2019")
colnames(enrollment) = c("Stat 110", "Stat 111", "Stat 211")
enrollment
```

```
## Stat 110 Stat 111 Stat 211
## 2018 586 328 51
## 2019 620 355 44
```

* Predict the following

```
enrollment[1, 2]
enrollment["2020", "Stat 110"]
enrollment[2, ]
```

Matrices: Useful Functions

```
# Merge matrices together; also see rbind()
enrollment = cbind(enrollment, "Stat 139" = c(152, 175))
```

```
# You can guess what these do
dim(); nrow(); ncol()
rowSums(); colSums()
```

Matrices: Useful Functions

```
# Merge matrices together; also see rbind()
enrollment = cbind(enrollment, "Stat 139" = c(152, 175))

# You can guess what these do
dim(enrollment); nrow(enrollment); ncol(enrollment)
rowSums(enrollment); colSums(enrollment)
```

Data Frames

Like matrices, but columns can be of different types.

```
# Create a data frame
my_df <- data.frame("Dept" = c("Stat", "CS", "Gov"),</pre>
 "Enrollment" = c(177, 244, 221))
# More commonly, open a file
my_df <- read.table("filename")</pre>
my_df <- read.csv("filename")</pre>
# Preview data
head(my_df); tail(my_df);
##
    Dept Enrollment
## 1 Stat
           177
## 2 CS 244
## 3 Gov 221
    Dept Enrollment
##
## 1 Stat
            177
## 2 CS 244
## 3 Gov 221
# View(my_df); str(mu_df)
```

Data Frames

```
my_df
```

```
## Dept Enrollment
## 1 Stat 177
## 2 CS 244
## 3 Gov 221
```

Predict the following:

```
subset(my_df, Enrollment > 200)
my_df[nrow(my_df):1, ]
my_df[sample(nrow(my_df)), ]
```

Data Frames

```
my_df
```

3

```
## Dept Enrollment
## 1 Stat 177
## 2 CS 244
## 3 Gov 221
```

Predict the following:

```
subset(my_df, Enrollment > 200)
my_df[nrow(my_df):1, ]
my_df[sample(nrow(my_df)), ]

## Dept Enrollment
## 2 CS 244
```

```
## Dept Enrollment
## 3 Gov 221
## 2 CS 244
## 1 Stat 177
```

221

Gov

Conditionals: If ... Then ... Else ...

[1] "You got a negative number!"

```
x <- rnorm(1)
x

## [1] -0.1625652

if (x > 0) {
    print("You got a positive number!")
} else {
    print("You got a negative number!")
}
```

Loops: Repeat Chunks of Code

For loops vs while loops

```
total <- 0
for (i in 1:10) {
    total <- total + i
print(total)
## [1] 55
total <- 0
i <- 1
while (i <= 10) {
   total <- total + i
   i <- i + 1
print(total)
```

```
## [1] 55
```

Loops vs. Vectorization

- Vectoriztion:
 - Avoid loops/conditionals
 - Vectorized functions that apply an operation to an entire vector and return a vector.
 - Cleaner and computationally faster!
 - See the apply() function for more!

```
sum(1:10)
## [1] 55
enrollment
       Stat 110 Stat 111 Stat 211 Stat 139
##
            586
                     328
                              51
                                      152
## 2018
       620
## 2019
                    355
                        44
                                      175
apply(enrollment, 2, mean)
  Stat 110 Stat 111 Stat 211 Stat 139
     603.0
              341.5
                       47.5
                               163.5
```

Visualization: Plotting with ggplot2

- R has built-in plotting called base graphics, which follows a "pen-and-paper" model
- ggplot2 is more modular, layering elements individually
- ► Google: "ggglot2 cheatsheet""
- ▶ Highly recommended: Chapter 3 of R for Data Science
- Install ggplot2 package

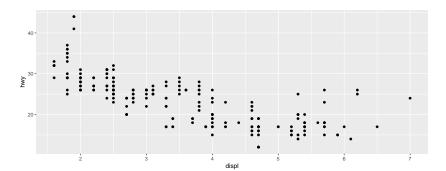
```
install.packages("ggplot2")
library(ggplot2)
```

ggplot2: The Grammar of Graphics

graphic <- ggplot(data = <DATA>) +

```
<GEOM_FUNCTION>(mapping = aes(<MAPPINGS>))
# Try explore "mgp" data first
?mgp
str(mpg)
```

```
# scatterplot: engine displacement vs. highway miles per gallon
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy))
```

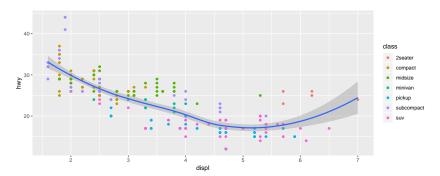


ggplot2: The Grammar of Graphics

- Layer geoms together
- Mappings can be specified globally or locally

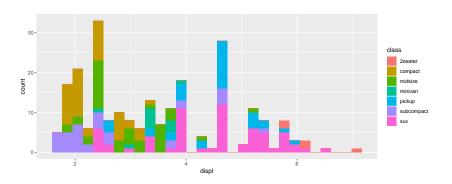
```
# Then add a color aesthetic for class.
# Other aesthetics you can try include shape, size, and alpha.
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
geom_point(mapping = aes(color = class)) +
geom_smooth()
```

$geom_smooth()$ using method = 'loess' and formula 'y ~ x'



ggplot2: The Grammar of Graphics

```
# histogram
ggplot(data = mpg, mapping = aes(x = displ, fill = class)) +
geom_histogram()
```



look up geom_histogram, adjust binwidth, boundary...

Exercises and Data Exploration

- Logs of all Bluebikes trips in December 2018
- https://canvas.harvard.edu/files/7228708/
- Attempt the exercises on the handout and ask a TF if you need help!