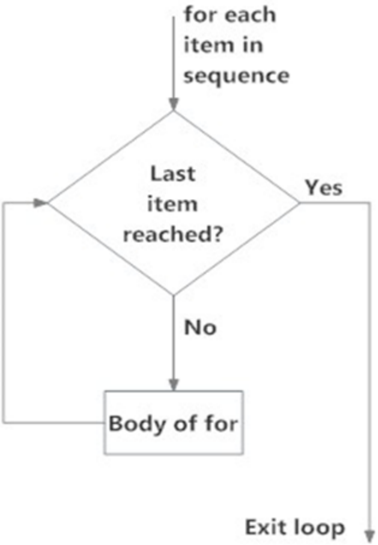
Module 2

March 9, 2018

Day 2

Recap Last Week



For-loops: Warm Up Exercise

- Cubing every number from 1 to 8 and print the results

```
for(num in      ){
    print(      **3)
}
```

Recap Last Week - In-Class Exercise

- Like we did last class, let's convert this vector of substrings into a single string. Make sure to use meaningful variable names in your code. (Hint: Use the paste function.)

```
string_vec <- c("Economics", "is", "the", "best",
    "subject!")

## initialize the variable

for (item in string_vec) {
    ## code to be executed
}
```

Goals for Today

Economics - Question of the Day

- How does the sale price of residential property change based on various factors?

What things will affect the property value?

Goals for Today

- Determinants of property values
  - Size of house (square footage)
  - Size of property
  - Higher floors vs lower floors
  - Quality of local schools
  - Number of bedrooms and bathrooms
  - Neighborhood location (metro, restaurants, library)

Goals for Today

Programming - R

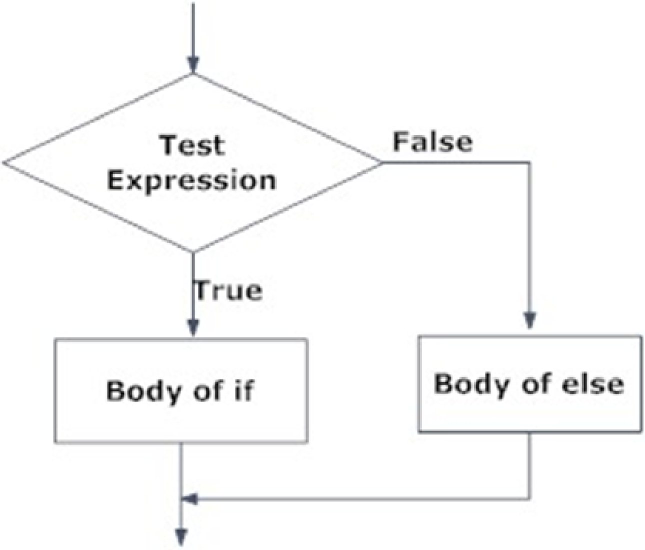
- Reviewing for-loops and if/else Statements
- Introduction to stringr
- Combining data using `bindrows`, `%in%`, and `join` functions
- Cleaning data
- Effective graphics for data visualization

If/Else Statements: Introduction

- We have previously used `ifelse()` to make decisions about recoding our variables with `mutate`
- If/else statements work in a similar way
- In R, a basic if/else statement takes the following form:

```
if(logical argument){
  ## code to be executed
} else{
  ## code to be executed
}
```

If/Else Statements: Example



Evens and Odds Example

- We will use the modulo operator (%%) to characterize numbers as even or odd
- %% returns the remainder after division of the first argument by the second argument

```
# %% is the modulus operator We are finding the
# remainder!
4%%1
## [1] 0
10%%4
## [1] 2
3%%2
## [1] 1
testNum <- 12
if (testNum%%2 == 0) {
    print(paste(testNum, "is EVEN"))
} else {
    # If the remainder after division by 2 is not 0
    # then it must be odd (right..?)
    print(paste(testNum, "is ODD"))
}
## [1] "12 is EVEN"
```

If/Else Statements Combined with For-Loops

- Let's characterize and record the numbers from 1 to 10 as even or odd

```
evens <- numeric()
odds <- numeric()

for (i in seq(1, 10, by = 1)) {
    if (i%%2 == 0) {
        # %% is the modulus operator --- we are finding
        # the remainder!
        evens <- c(evens, i)
    } else {
        odds <- c(odds, i)
    }
}

evens
```

```
## [1]  2  4  6  8 10
```

```
odds
```

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

In-Class Exercise: If/Else Statements

- Given the following grade, use an if/else statement to determine if the student passed or failed
  - **(A passing grade is greater than or equal to 60)**

```
student_grade <- 71
```

Return a correct statement that the student passed or failed

```
if(              ){
  print("     ")
} else {
  print("     ")
}
```

Else-if statements: Introduction

- We aren't limited to choosing between two conditions
- Similar to `case_when()`, else-if lets us make multiple decisions
  - provides us with even more flexibility
- Checks each condition one by one
  - check the first condition, if false then it moves on to the the next one
- **Else catches everything that does not meet the previous criteria** so be careful when coding or deciding what to include

Else-if statements: Example

- Here's an example of assigning survey numerical responses to genders.

```r
response_list <- c(0, 1, 2, 2, 0, 1, 2, 1, 0, 2,
    2, 1, 1, 1, 2, 1, 0)
female <- 0
male <- 0
other <- 0

for (person in response_list) {
    if (person == 1) {
        male <- male + 1
    } else if (person == 2) {
        female <- female + 1
    } else {
        other <- other + 1
    }
}
survey_genders <- data.frame(male, female, other)
survey_genders
```

```
##   male female other
## 1    7      6     4
```

Else-if statements: Assigning Grades - In-Class Exercise

- You've been given a list of test scores that you want to categorize into letter grades
- Use if else statements to assign letters to the numeric grades
  - A 90 - 100, B 80 - 89, C 70 - 79, D 60 - 69, F $<$ 60

```r
test_scores <- c(85,55,100,67,73,92,94,99,87,89.3)

# Initialize our vector
letter_grades <-

for(grade in test_scores){
  if(   >= 90){
    letter_grades <- paste(letter_grades,"A")
  } else if(   ) {
    letter_grades <-    (             ,"B")
  } else if
    letter_grades <-
    else if

  } else {
    letter_grades <- paste(       "F")
  }
}
letter_grades
```

Reading in Data: Introduction

- Before we can access our datasets we need to help R find them
- We can create a vector of all the files in our data folder using the `list.files` function
- **What sorts of files are in the folder?**

```
## create a vector of dataset names
temp_files <- list.files("./Data/")
temp_files
```

```
##  [1] "location_redfin_01.csv" "location_redfin_02.csv"
##  [3] "location_redfin_03.csv" "location_redfin_04.csv"
##  [5] "location_redfin_05.csv" "location_redfin_06.csv"
##  [7] "location_redfin_07.csv" "location_redfin_08.csv"
##  [9] "Metro_lat_lon.xlsx"     "property_redfin_01.csv"
## [11] "property_redfin_02.csv" "property_redfin_03.csv"
## [13] "property_redfin_04.csv" "property_redfin_05.csv"
## [15] "property_redfin_06.csv" "property_redfin_07.csv"
## [17] "property_redfin_08.csv"
```

Reading in Data: Introduction

- We need to be able to access these files, we'll need to tell R to look in the folder 'Data'
  - Therefore, we should append 'data' onto the title using `paste0`

```
files <- paste0("./Data/", temp_files)
files
```

```
##  [1] "./Data/location_redfin_01.csv" "./Data/location_redfin_02.csv"
##  [3] "./Data/location_redfin_03.csv" "./Data/location_redfin_04.csv"
##  [5] "./Data/location_redfin_05.csv" "./Data/location_redfin_06.csv"
##  [7] "./Data/location_redfin_07.csv" "./Data/location_redfin_08.csv"
##  [9] "./Data/Metro_lat_lon.xlsx"     "./Data/property_redfin_01.csv"
## [11] "./Data/property_redfin_02.csv" "./Data/property_redfin_03.csv"
## [13] "./Data/property_redfin_04.csv" "./Data/property_redfin_05.csv"
## [15] "./Data/property_redfin_06.csv" "./Data/property_redfin_07.csv"
## [17] "./Data/property_redfin_08.csv"
```

- Now that we know the names of the files with the datasets, we need to decide which datasets are useful and which go together
- **What are the two major categories of files?**
- **How can we combine these files most effectively?**

Introduction to str_detect()

- `str_detect()` is a function in the tidyverse package that can tell whether a string contains a certain word or phrase. The function returns:
  - `TRUE` if the word you're looking for is in the string
  - `FALSE` if the word you're looking for is *not* in the string

```r
str_detect("property_redfin_01.csv", "property")
```

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

```r
str_detect("location_redfin_01.csv", "property")
```

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

```r
str_detect(c("property_redfin_01.csv", "location_redfin_01.csv"),
    "location")
```

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

Using str_detect

- Using what we've learned about `str_detect`, let's create a vector that only includes location files.

```
files[str_detect(files, "location")]
```

```
## [1] "./Data/location_redfin_01.csv" "./Data/location_redfin_02.csv"
## [3] "./Data/location_redfin_03.csv" "./Data/location_redfin_04.csv"
## [5] "./Data/location_redfin_05.csv" "./Data/location_redfin_06.csv"
## [7] "./Data/location_redfin_07.csv" "./Data/location_redfin_08.csv"
```

Building our Dataset - In-Class Exercise

- You will need to use for-loops and if-else statements to create two datasets, one dataset that includes all the 'location' data and one dataset that includes all the 'property' data.
  - Initialize two data frames to store all your new data: one data frame for the 'property data' and one for the 'location data'
  - Create a for-loop that cycles through each csv in the folder and checks if it is a 'location' or 'property file'.
  - If it's a property file, add (bind) the csv's data onto your property data frame
  - If it's a location file, bind it into your location_data data frame. **Hint(check out what the `bind_rows` function does.)**

```
property_data <- data_frame() # initialize empty data frame for the property data
 <- data_frame() # initialize empty data frame for the location data
for(file in        ){
    # You only want to have property data in the first dataset
    if(str_detect(     ,"property")){
         <- read_csv(   )
        property_data <- bind_rows(property_data, )
    }
  # Now let's combine location data into a different dataset
  else if(str_detect(      , "location")){
    }
}
```

Overview of the Data

- Let's take a look at the variables in our two dataframes - property data and location data
- **What does the property data do? What does the location data do?**
- The good news is that we have much of the data we need, the bad news is that the data is split between location information and price information
- **What piece of information is available in both datasets?**
- We want to combine these two datasets around that common piece of information

Comparing our Datasets

- Harnessing the power of the %in% function

```
vec1 <- c("green", "yellow", "dog", "teal", "violet",
    "beige", "cat", "red", "horse", "orange")
vec2 <- c("yellow", "red", "blue", "purple", "green",
    "orange")
# What does the %in% function show us?
vec1 %in% vec2
```

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

```
# Where are the words that overlap across
# vectors?  Where are the words in vector 1 that
# appear in vector 2?
which(vec1 %in% vec2)
```

```
## [1]  1  2  8 10
```

```
# How do we return the names of the elements that
# appear in both vectors?
vec1[vec1 %in% vec2]
```

```
## [1] "green"  "yellow" "red"    "orange"
```

Where to Combine the Data

- Using our %in% function, let's find what variable(s) occur(s) in **both** our property and location datasets.
- We'll save the result as 'overlap', which is a variable we can use for our next step.

```
property_names <- names(property_data)
location_names <- names(location_data)

# What variable exists in both datasets?
property_names %in% location_names
```

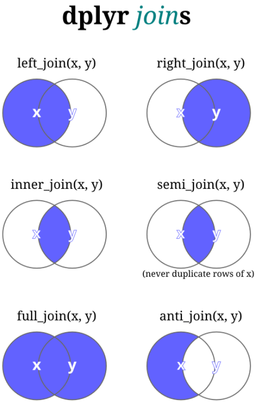
```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [12] FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE
```

```
overlap <- property_names[property_names %in% location_names]
overlap
```

```
## [1] "URL"
```

“Joining” the Data: Introduction

- Our URL column exists in both of the dataframes!
- We only want houses that exist in both datasets
- We call combining data frames “joining.” Below are types of joins:
- Which type of joining combines our dataframes so we only have properties with both location and property information?



“Joining” the Data: In Practice

```
joined_data <- inner_join(property_data, location_data,
    by = overlap)

names(joined_data)
```

```
##  [1] "SALE.TYPE"                    "SOLD.DATE"
##  [3] "PROPERTY.TYPE"                "PRICE"
##  [5] "BEDS"                         "BATHS"
##  [7] "SQUARE.FEET"                  "LOT.SIZE"
##  [9] "YEAR.BUILT"                   "HOA.MONTH"
## [11] "STATUS"                       "NEXT.OPEN.HOUSE.START.TIME"
## [13] "NEXT.OPEN.HOUSE.END.TIME"     "URL"
## [15] "SOURCE"                       "MLS."
## [17] "FAVORITE"                     "INTERESTED"
## [19] "LIST.DATE"                    "ADDRESS"
## [21] "ZIP_CODE"                     "LAT_LON"
## [23] "CITY_STATE"                   "LOCATION"
```

"Joining" the Data: Additional Notes

- Success! Now we have one dataset with all of our housing data
- Note - It is also possible to perform a `join` where the columns we are matching in each table do not have the same name using the 'by' argument: by = c("name1" = "name2").
- Similarly, it is also possible to `join` based on multiple columns: by = c(column1, column2, etc. . .)

Examining the Data

- Now we can examine the data to check for any problems.
- **What are some problems you see in terms of usability for this data?**

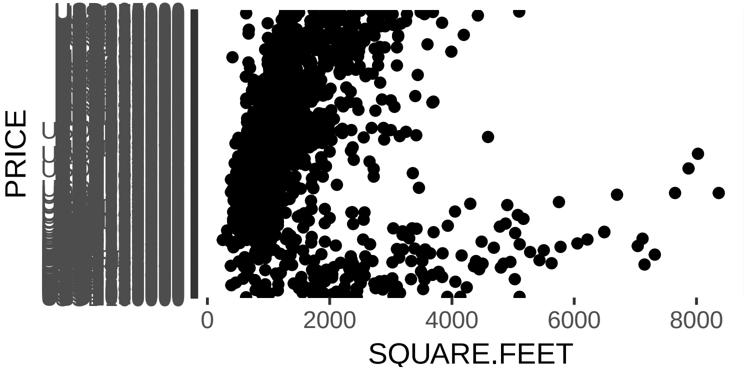
Examining the Data: Potential Problems

- price column - USD in front of the numbers
- propertytype column - has “propertytype” in front of every observation
- city_state column - state is inconsistent (va, VA, Virginia) and unwanted states
- lat_lon column - & in the middle of the string
- zip_code column - extra zeros
- sold.dates, list.date columns - dates are not consistent

Cleaning the Data: Why We Do It

- If we try to make a plot without cleaning up our data. . . it doesn't work too well

```
## Warning: Removed 13 rows containing missing values (geom
```



Cleaning the Data: Price Column

- Let's start by looking at our price data more closely

```
head(joined_data$PRICE)
```

```
## [1] "USD280000" "USD405000" "USD510000" "USD395000" "USD339900" "USD415000"
```

- There's a USD in front of each number of the column
- What class of variable is the price column?

Cleaning the Data: Price Column

- How can we fix this problem for a character variable? What type of method could we use?

Cleaning the Data: Price Column

- One way we could eliminate the USD is by replacing the USD with nothing, “” (this would be the same as removing it).
- Try using the str_replace function to modify the string “USD40000” to be “40000”

```
str_replace("USD40000", "USD", "")
```

```
## [1] "40000"
```

Cleaning the Data: Price Column

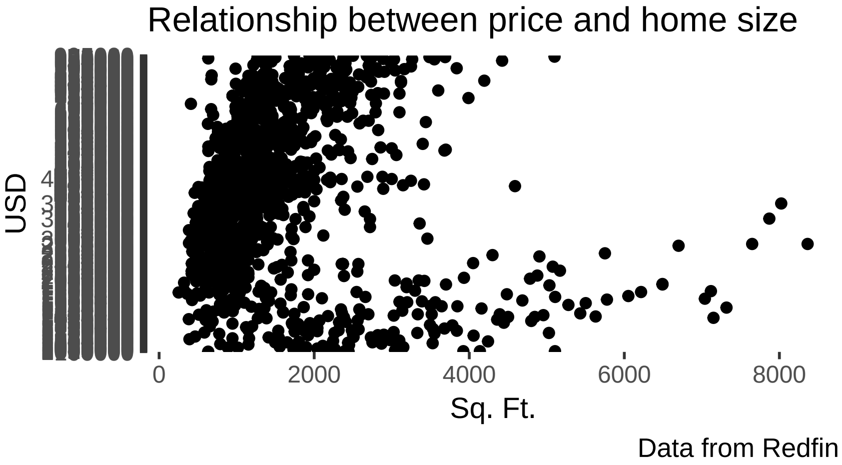
- Let's mutate the price column to remove "USD" from the character string

```
joined_data <- joined_data %>% mutate(PRICE = str_replace(PRICE,
    "USD", ""))
head(joined_data$PRICE)
```

Cleaning the Data: A Second Attempt at Plotting

- Let's redo the plot!

```
## Warning: Removed 13 rows containing missing values (geom
```



Cleaning the Data: Reclassifying Columns and Removing N/As - In-Class Exercise

- We still have a problem, we forgot to convert our PRICE column to be class numeric!
- We also currently have a warning about missing values – what should we do about those?
- You should:
  - Convert the price column to be numeric
  - Remove any missing values from the price and square feet columns
  - Then replot and see how it looks

Cleaning the Data: Reclassifying Columns and Removing N/As - In-Class Exercise

```
joined_data <- joined_data %>% filter(!is.na(), !is.na()) %>%
    mutate(PRICE = as.numeric())

# Now make the plot
joined_data %>% ggplot(aes(x = , y = )) + geom_point() +
    # Note that the scale_y_continuous makes sure we
# don't get expotentials!
scale_y_continuous("USD", labels = dollar) + labs(title = "Price vs. Home Size"
    y = , x = , caption = "Data from Redfin")
```

- What is the relationship between Sq Ft and home price?

Understanding the Data: Property Type and Price

- What about the relationship between property type (apt, single family house, condo, etc.) and price?
- Let's produce a table and a bar plot of the average price per square foot by property type.

Cleaning the Data: Property Type - In-Class Exercise

- Let's clean the property type column
- Check out the PROPERTY.TYPE column and use `str_replace` to fix it

```
joined_data <-          %>%
    mutate(PROPERTY.TYPE = str_replace(            ,
    "propertytype:",   ))
```

Understanding the Data: Property Price/Sq Ft Table

- Let's create a table of average price per square foot by property type

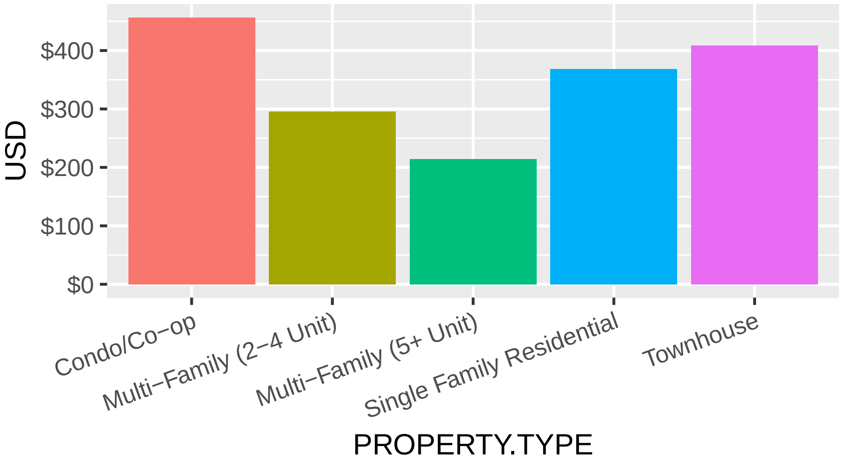
```r
type_price <- joined_data %>% group_by(PROPERTY.TYPE) %>%
    summarise(price = mean(PRICE/SQUARE.FEET, na.rm = T))

type_price
```

```
## # A tibble: 5 x 2
##               PROPERTY.TYPE    price
##                       <chr>    <dbl>
## 1               Condo/Co-op 456.6841
## 2   Multi-Family (2-4 Unit) 295.3326
## 3    Multi-Family (5+ Unit) 214.7378
## 4 Single Family Residential 368.6735
## 5                 Townhouse 408.2464
```

Understanding the Data: Property Price/Sq Ft Graph

- Now let's check out a graph. This is obviously not a production-quality graph, just something for our reference.
- How are the colors defined in the graph?



Understanding the Data: Data Challenges

- City/state is another variable that might impact home sale price... Why?

```r
unique(joined_data$CITY_STATE)
```

```
##  [1] "Arlington, va"           "Alexandria, va"
##  [3] "Arlington, VA"           "Falls Church, va"
##  [5] "Arlington, Virginia"     "Mclean, Virginia"
##  [7] "Chevy Chase, MD"         "Bethesda, MD"
##  [9] "Glen Echo, MD"           "Kensington, MD"
## [11] "Washington, DC"          "Washington, Michigan"
## [13] "Oxon Hill, MD"           "Silver Spring, MD"
## [15] "Washington, COLORADO"    "Capitol Heights, MD"
## [17] "Takoma Park, MD"         "Alexandria, VA"
## [19] "Fairmount Heights, MD"
```

- What issues do we have with the city_state variable?

Cleaning the Data: String Split

- We can use the `str_split_fixed` function to alter our string (or vector of strings) using a ‘pattern’
- The function returns the peices of the string after splitting based on your ‘pattern’, which could be a word, symbol, or number of characters.

```
# We have three arguments, what do they do?
strings <- str_split_fixed("United States of America",
    "of", n = 2)
strings
```

```
##      [,1]             [,2]
## [1,] "United States " " America"
```

```
class(strings)
```

```
## [1] "matrix"
```

Cleaning the Data: String Split

- We told R to split into two pieces (n = 2), so we got two columns in return.
- If we want to get back to individual elements, we can subset the matrix using brackets.

```
strings[1, 1]  # first row, first column
```

```
## [1] "United States "
```

```
strings[1, 2]  # first row, second column
```

```
## [1] " America"
```

Cleaning the Data: String Split

- Let's test it out with something closer to our actual use case.
- Note that we're splitting along the comma and a space, which will remove both!

```r
str_split_fixed("Arlington, Virginia", ", ", n = 2)
```

```
##      [,1]        [,2]
## [1,] "Arlington" "Virginia"
```

Cleaning the Data: String Split - In-Class Exercise

- Use what we just learned to mutate the city_state column and create separate city and state columns.

```
joined_data <-       %>%
    mutate(CITY = str_split_fixed(CITY_STATE,   )[1, 1],
           STATE =     (       )[1, 2])

joined_data %>% select(CITY_STATE, CITY, STATE) %>% head
```

Cleaning the Data: State Data

- We're not done yet. Let's take another look at the state column and see what types of responses exist

```
unique(joined_data$STATE)
```

```
## [1] "va"       "VA"       "Virginia" "MD"       "DC"       "Michigan"
## [7] "COLORADO"
```

* What do you think we need to do to further clean this column?

Cleaning the Data: Capitalizing States

- The function `str_to_upper` will convert all lower case letter to upper case ones

```
str_to_upper("va")
```

```
## [1] "VA"
```

- We'll use this function to mutate the state column to upper case

```
joined_data <- joined_data %>% mutate(STATE = str_to_upper(STATE))

unique(joined_data$STATE)
```

```
## [1] "VA"       "VIRGINIA" "MD"       "DC"       "MICHIGAN" "COLORADO"
```

Cleaning the Data: Abbreviating States - In-Class Exercise

- Now we want to change "VIRGINIA" to "VA" in the column to make the label consistent
- We've already used this function! Go back and find the function you need to make that change

```
joined_data <- joined_data %>%
    mutate(STATE =            (     , "VIRGINIA",    ))
```

Cleaning the Data: Removing Additional States

- The last thing we need to do is toss out the rows with MICHIGAN and COLORADO since we only want DMV data
- Use the `%in%` function to filter only rows with VA, DC, or MD in them.

```
joined_data <- joined_data %>% filter(STATE %in%
    c("VA", "DC", "MD"))

unique(joined_data$STATE)
## [1] "VA" "MD" "DC"
```

Plotting the Data: Price by State

- Let's find out the average prices by state for our dataset

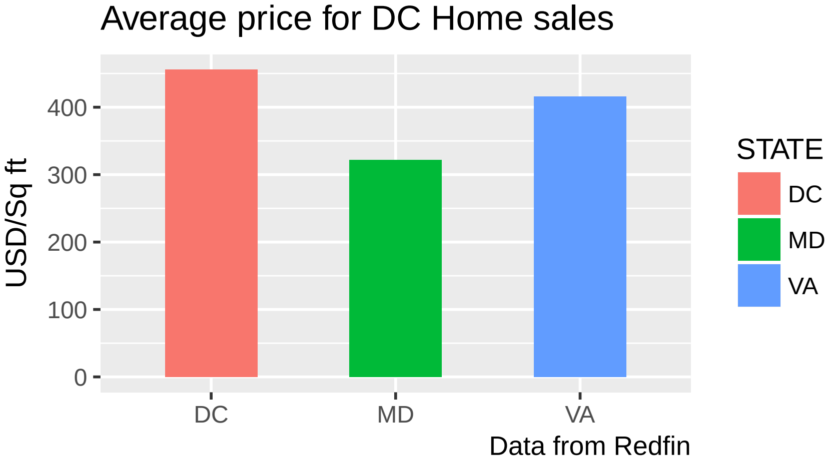
```
state_average <- joined_data %>% group_by(STATE) %>%
    summarise(price = mean(PRICE/SQUARE.FEET, na.rm = T))

state_average_plot <- state_average %>%
    ggplot(aes(x = STATE, y = price, fill = STATE)) +
    geom_bar(stat = "identity", width = 0.5) +
    labs(x = NULL, # What does this do?
         y = "USD/Sq ft",
         title = "Average price for DC Home sales",
         caption = "Data from Redfin")

state_average_plot
```

Plotting the Data: Price by State

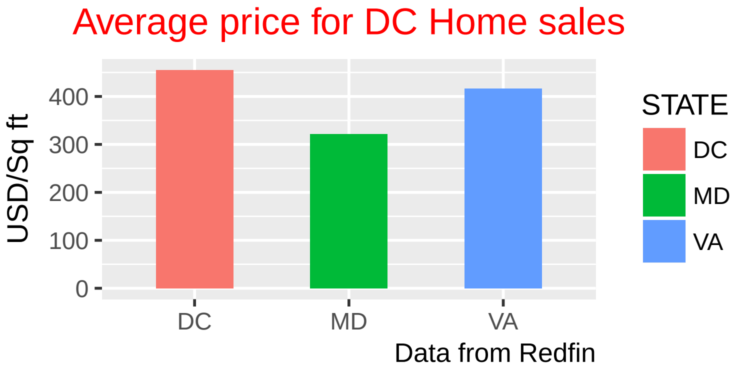
- I want to have a larger plot title and have it centered
- How can we do that? Would we use a data-related dimension or an aesthetic option?



Plotting the Data: Price by State

- We can use the `theme()` function to alter elements of the graph.
- What other textual elements can we alter in this graph?

```
state_average_plot + theme(plot.title = element_text(size = 14,
    hjust = 0.5, color = "Red"))
```



Plotting the Data: Appearance Options

- We can use `element_text` to control any text on our graph, including the title, axis labels, legend, etc. `element_text` allows us to set:
  - font family (Times New Roman, Arial, etc...)
  - font size (10, 12, 14, etc...)
  - font face (bold, italic)
  - color
  - hjust (horizontal adjustment)
  - vjust (vertical adjustment)
  - angle
  - other aspects that impact the display of text.

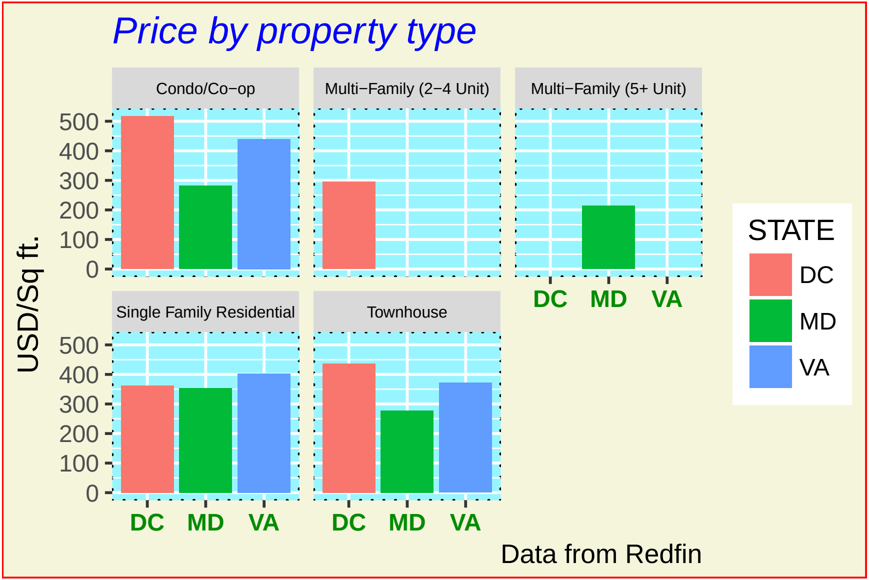
Plotting the Data: Property Type

```
state_proptype <- joined_data %>%
    group_by(PROPERTY.TYPE, STATE) %>%
    summarise(price = mean(PRICE/SQUARE.FEET, na.rm = T))

plot <- state_proptype %>%
    ggplot(aes(x = STATE, y = price, fill = STATE)) +
    geom_bar(stat = "identity") +
    facet_wrap("PROPERTY.TYPE") +
    labs(title = "Price by property type",
         x = NULL,
         y = "USD/Sq ft.",
         caption = "Data from Redfin")

plot + theme(plot.title =
          element_text(face = "italic", size = 14, color = "Blue"),
          axis.text.x = element_text(face = "bold", color = "green4"),
          strip.text.x = element_text(size = 6, color = "black"),
          plot.background = element_rect(fill = "beige", color = "red"),
          panel.background = element_rect(fill = "cadetblue1",
                                          color = "black", linetype = 3))
```

Plotting the Data: Property Type



Understanding the Graphic Appearance

- We used `element_rect()` to adjust rectangular elements of the plot.
- The main plot has a beige background with a red border.
- We used the panel.background option to adjust elements of the area where the data is
- What did the linetype argument do in our panel.background option?

```
plot <- state_proptype %>% ggplot(aes(x = STATE,
    y = price, fill = STATE)) + geom_bar(stat = "identity") +
    facet_wrap("PROPERTY.TYPE") + labs(title = "Price by property type",
    x = NULL, y = "USD/Sq ft.", caption = "Data from Redfin")

plot + theme(plot.title = element_text(face = "italic",
    size = 14, color = "Blue"), axis.text.x = element_text(face = "bold",
    color = "green4"), strip.text.x = element_text(size = 6,
    color = "black"), plot.background = element_rect(fill = "beige",
    color = "red"), panel.background = element_rect(fill = "cadetblue1",
    color = "black", linetype = 3))
```

Understanding the Data: Price per Lot Size

- Perhaps using the price per square foot is not the best method of analysis.
- When a property is sold the surrounding land around the house will likely affect the selling price.
- Let's work on making a plot of price/lot size

Understanding the Data: Price per Lot Size

- We'll start by looking at the head of the data

```
## # A tibble: 6 x 3
##    PRICE SQUARE.FEET LOT.SIZE
##    <dbl>       <int>    <int>
## 1 280000        1055       NA
## 2 405000        1030       NA
## 3 510000        1209       NA
## 4 395000        1135       NA
## 5 339900         930       NA
## 6 415000        1606       NA
```

- We have a lot of NA values. Why is that?

Understanding the Data: Price per Lot Size - In-Class Exercise

- Let's get rid of the `NA` values by replacing them with square footage
- We'll create a new column called Property Size that equals either lot size or square feet
  - Use an `ifelse()` statement in our mutate, where we test whether lot size is `NA`
  - If lot size is `NA`, use square feet. Otherwise, use lot size
- Next we will summarize our data by price per foot of property size.
  - We want to group by property type and state!

```
joined_data <-          %>%
    mutate(PROPERTY.SIZE = ifelse(is.na(       ), SQUARE.FEET,        ))

# Now we can find our average
lot_state_data <- joined_data %>%
    group_by(          ) %>%
    summarise(price = mean(                , na.rm = T))

head(lot_state_data)
```

Understanding the Data: Culminating Exercise

- Make a plot like the one we just did but using our new price/property.size variable with some modifications -
  - **Make your title centered (using hjust) and green**
  - **Make your panel background white with a red border**