Assignments

This page will contain all the assignments you submit for the class.

Assignment 1

Collaborators: Theodora Athanitis and Halle Wasser

Problem 1

Install the datasets package on the console below using `install.packages("datasets")`. Now load the library.

```
# install.packages('datasets')
library(datasets)
```

Answer: Installed!

Load the USArrests dataset and rename it `dat`. Note that this dataset comes with R, in the package datasets, so there's no need to load data from your computer. Why is it useful to rename the dataset?

```
dat <- USArrests
```

Answer: Renaming data sets ensures that you do not edit any of your original data on accident, and it is also easier to type.

Problem 2

Use this command to make the state names into a new variable called State.

```
dat$state <- tolower(rownames(USArrests))
```

This dataset has the state names as row names, so we just want to make them into a new variable. We also make them all lower case, because that will help us draw a map later - the map function requires the states to be lower case.

List the variables contained in the dataset `USArrests`.

```
names(dat)
```

```
## [1] "Murder"   "Assault"  "UrbanPop" "Rape"     "state"
```

Answer: The variables are Murder, Assault, Urban Population, and Rape, in addition to the new variable that we just created, state.

Problem 3

What type of variable (from the DVB chapter) is `Murder`?

Answer: Murder is a quantitative variable according to the DVB chapter because we are measuring the amount of murder arrests per 100,000.

What R Type of variable is it?

```
class(dat$Murder)
```

```
## [1] "numeric"
```

Answer: In R, the data points in the Murder column are numeric variables according to the class() function.

Problem 4

What information is contained in this data set, in general? What do the numbers mean?

```
head(dat)
```

```
##            Murder Assault UrbanPop Rape      state
## Alabama      13.2     236       58 21.2    alabama
## Alaska       10.0     263       48 44.5     alaska
## Arizona       8.1     294       80 31.0    arizona
## Arkansas      8.8     190       50 19.5   arkansas
## California    9.0     276       91 40.6 california
## Colorado      7.9     204       78 38.7   colorado
```

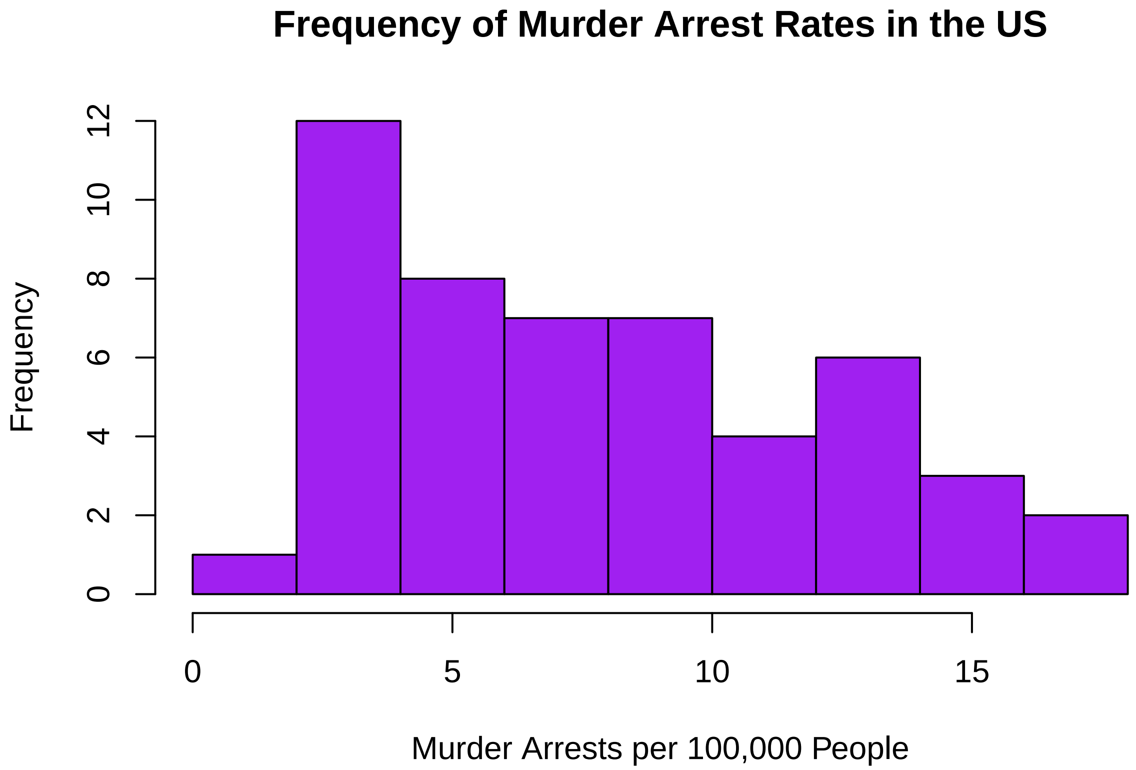
```
`?`(USArrests)
```

Answer: Generally, this data set contains rates for specific crime arrests per 100,000 people collected by D.R. McNeil, as well as percentages of urban population per state in 1973. The numbers in the Murder, Assault, and Rape columns are equivalent to the calculated arrest rates for Murder, Assault, and Rape. The Urban Population numbers are the percentages of the population in each state that live in an urban area.

Problem 5

Draw a histogram of `Murder` with proper labels and title.

```
hist(dat$Murder, xlab = "Murder Arrests per 100,000 People",
    main = "Frequency of Murder Arrest Rates in the US", col = "purple")
```



Problem 6

Please summarize `Murder` quantitatively. What are its mean and median? What is the difference between mean and median? What is a quartile, and why do you think R gives you the 1st Qu. and 3rd Qu.?

```
summary(dat$Murder)
```

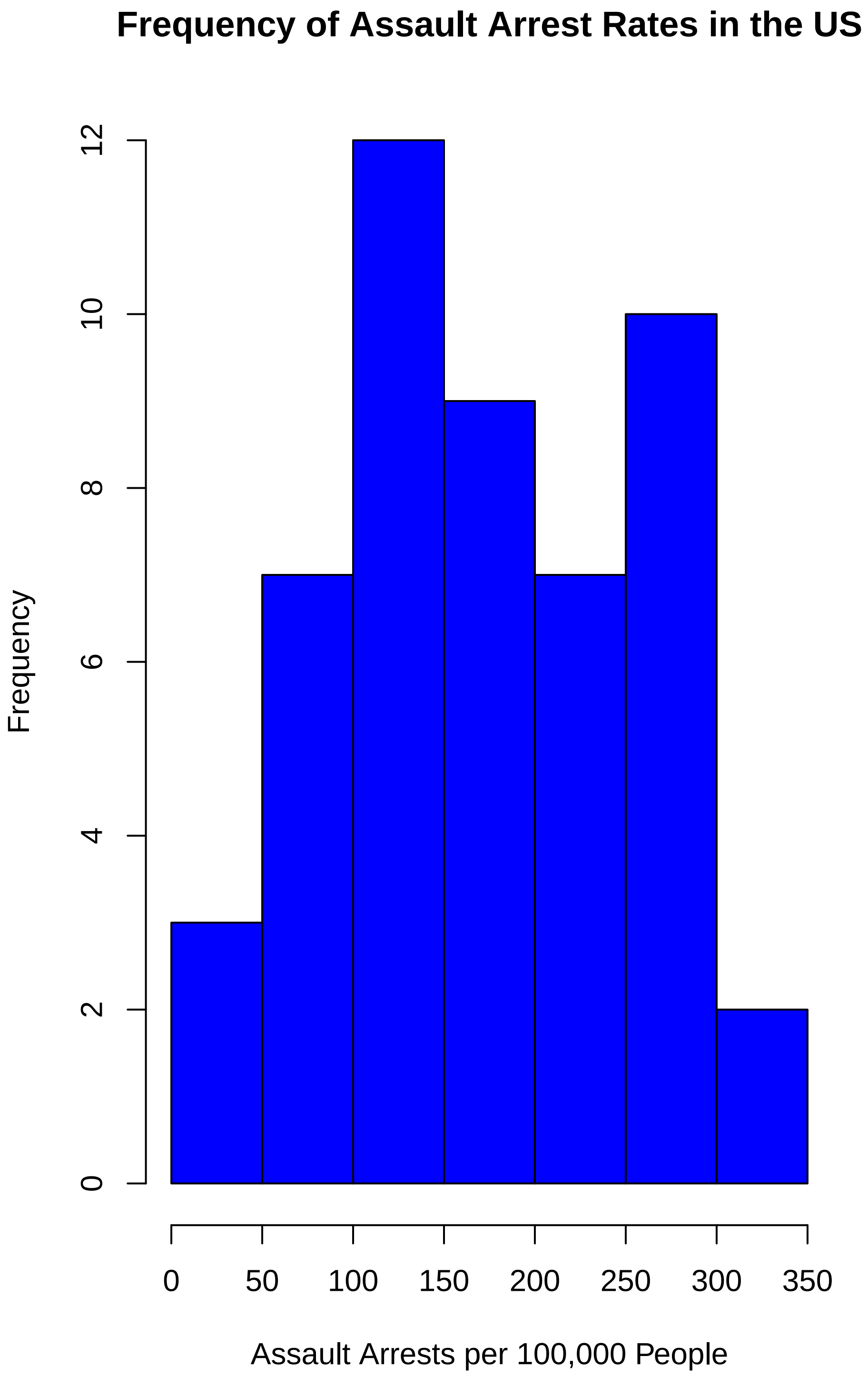
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.800   4.075   7.250   7.788  11.250  17.400
```

Answer: The mean is 7.788. The median is 7.250. Q1 is 4.075 and Q3 is 11.250. The minimum value is .800 and the maximum value is 17.400. Mean and median are both measures of center; however, the mean is the average value of a data set, which is calculated by adding all of the values and dividing by the number of total data points, and the mean is calculated by finding the middle value when the data set is arranged in order. A quartile is essentially the same as a median, but with 25% and 75% of the data, rather than 50%. This means that 25% of the data in a data set is below the 1st quartile, 50% is below the second quartile (the median), and 75% is below the 3rd quartile. R gives you quartiles in order to help visualize the data and see if it is distributed symmetrically, and only gives you quartiles 1 and 3 because the median is the 2nd quartile.

Problem 7

Repeat the same steps you followed for `Murder`, for the variables `Assault` and `Rape`. Now plot all three histograms together. You can do this by using the command `par(mfrow=c(3,1))` and then plotting each of the three.

```
hist(dat$Assault, xlab = "Assault Arrests per 100,000 People",
    main = "Frequency of Assault Arrest Rates in the US", col = "Blue")
```

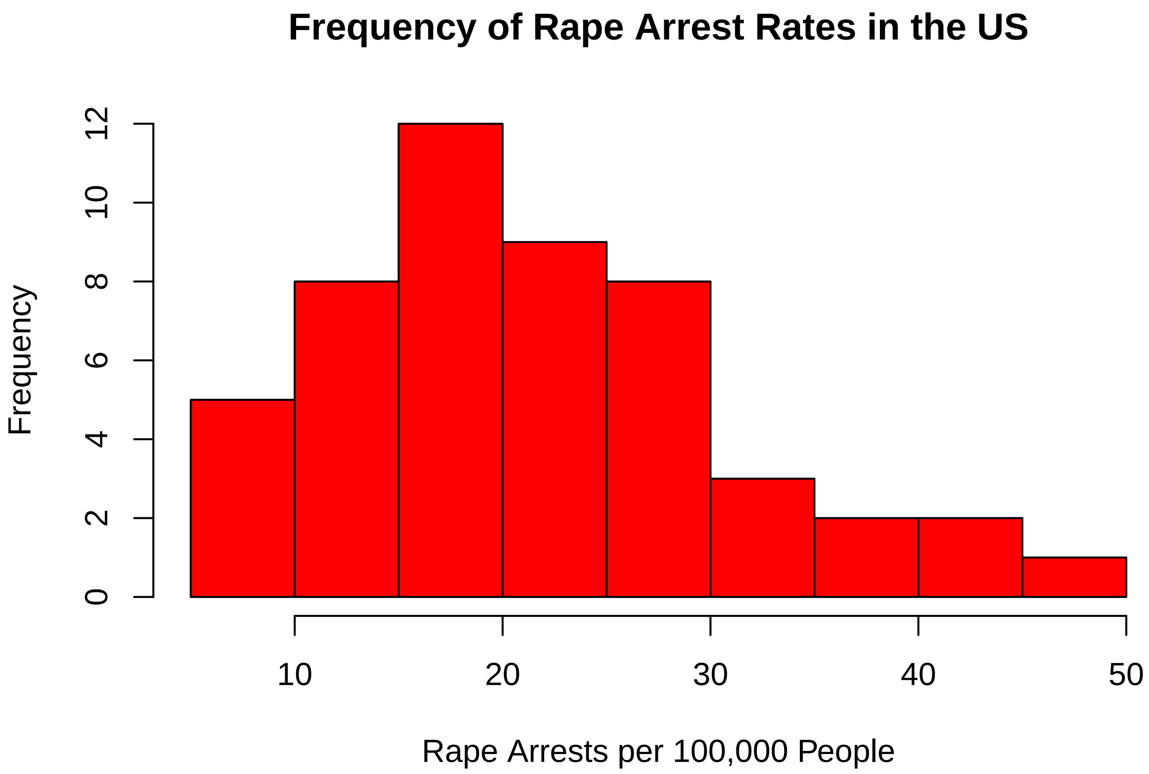


```
summary(dat$Assault)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    45.0   109.0   159.0   170.8   249.0   337.0
```

Answer: The mean is 170.8. The median is 159.0. Q1 is 109.0 and Q3 is 249.0. The minimum value is 45.0 and the maximum value is 337.0.

```
hist(dat$Rape, xlab = "Rape Arrests per 100,000 People", main = "Frequency of Rape Arrest Rates in the
    col = "Red")
```

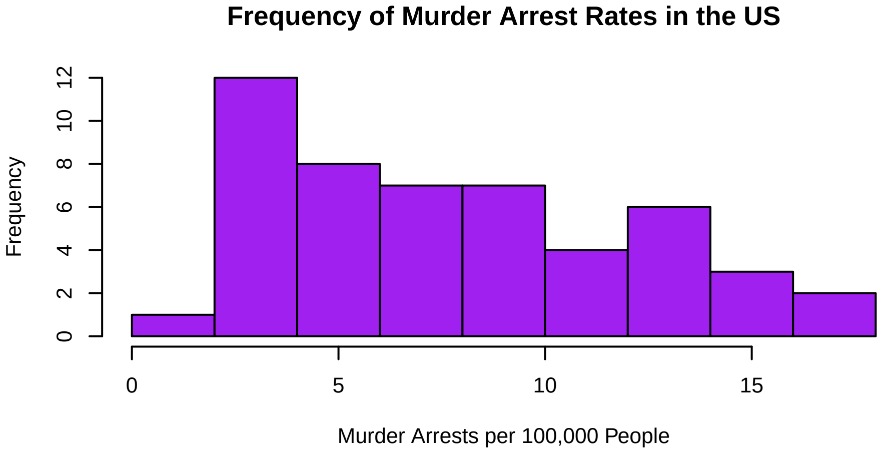


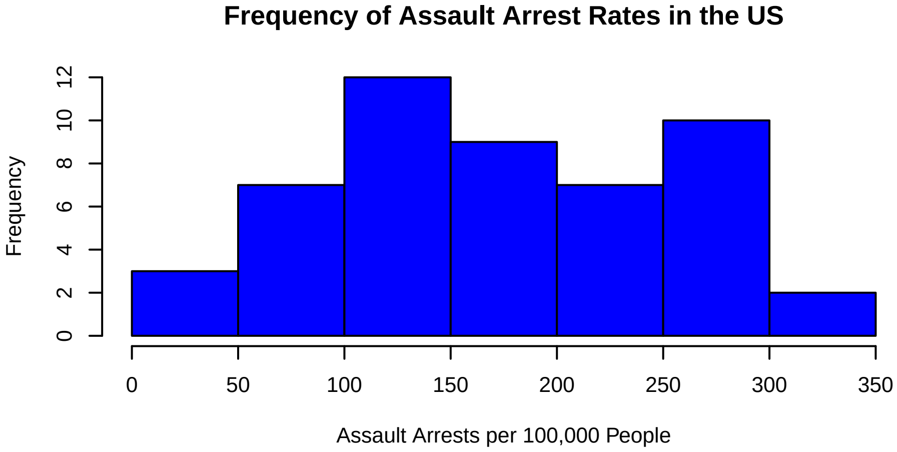
```
summary(dat$Rape)
```

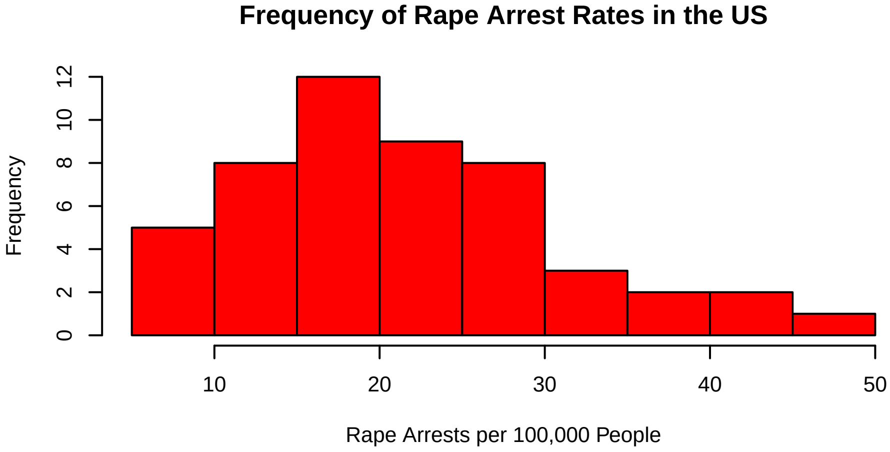
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##    7.30   15.07   20.10   21.23   26.18   46.00
```

Answer: The mean is 21.23. The median is 20.10. Q1 is 15.07 and Q3 is 26.18. The minimum value is 7.30 and the maximum value is 46.00.

```
par(mfrow = c(3, 1))
hist(dat$Murder, xlab = "Murder Arrests per 100,000 People",
    main = "Frequency of Murder Arrest Rates in the US", col = "purple")
hist(dat$Assault, xlab = "Assault Arrests per 100,000 People",
    main = "Frequency of Assault Arrest Rates in the US", col = "Blue")
hist(dat$Rape, xlab = "Rape Arrests per 100,000 People", main = "Frequency of Rape Arrest Rates in the U
    col = "Red")
```







What does the command par do, in your own words (you can look this up by asking R `?par`)?

Answer: The 'par' command sets parameters for graphs, changes how they are displayed, and allows us to tell R to compare additional variables within the data set. 'mfrow' puts things in an array, and the parameters of (1,3) tell it to display them stacked on top of each other, rather than side by side or otherwise.

What can you learn from plotting the histograms together?

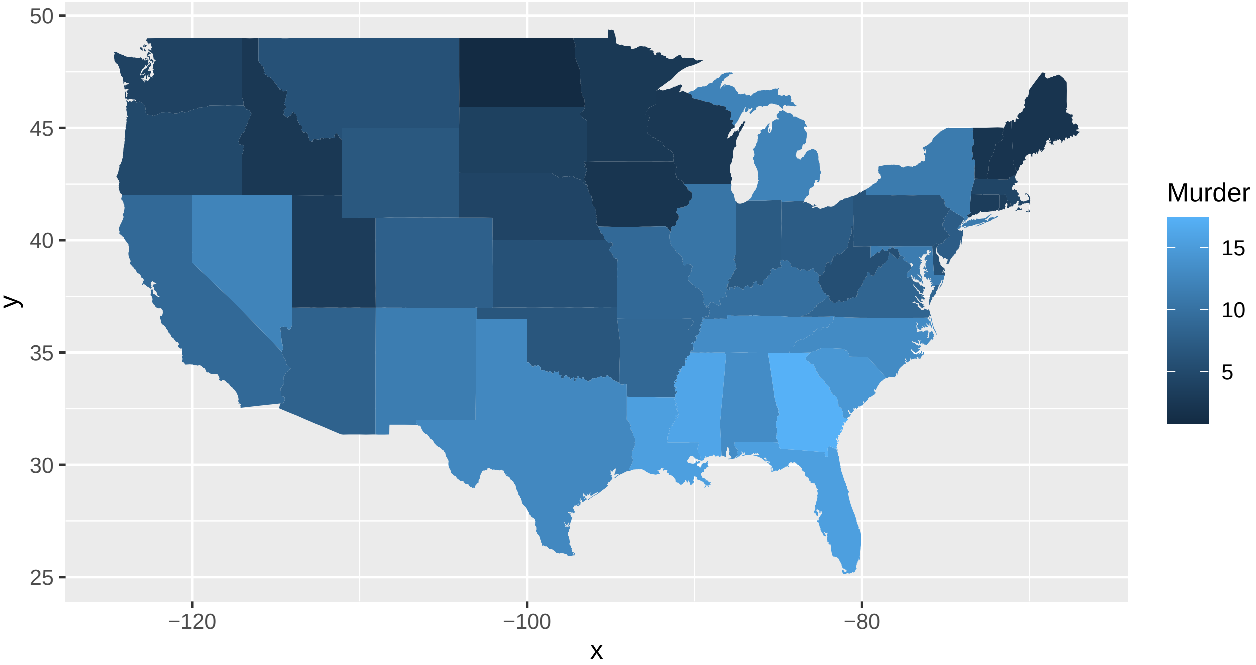
Answer: We can learn that assault arrest rates per 100,000 people are far higher than the arrest rates for *murder and rape by comparing the x axis of all three histograms. Additionally, while the frequency of arrest rates for rape and murder skew relatively right and are unimodal, the frequency of assault arrest rates is bimodal. Comparing and plotting them together can generally help us visually compare distributions overall.*

Problem 8

In the console below (not in text), type `install.packages("maps")` and press Enter, and then type `install.packages("ggplot2")` and press Enter. This will install the packages so you can load the libraries.

Run this code:

```
# install.packages('maps') install.packages('ggplot2')
library("maps")
library("ggplot2")

ggplot(dat, aes(map_id = state, fill = Murder)) + geom_map(map = map_data("state")) +
    expand_limits(x = map_data("state")$long, y = map_data("state")$lat)
```



What does this code do? Explain what each line is doing.

Answer:

```
# install.packages('maps')
#- This line installs a package that allows for map-drawing based on state names provided within the da
# install.packages('ggplot2')
#- This line installs a package that makes improves the data visualization so that the map is easier to
# library('maps')
#- This line tells R where to find the package to help draw the map
# library('ggplot2')
#- This line tells R where to find the package to help draw the map
# ggplot(dat, aes(map_id=state, fill=Murder)) +
# geom_map(map=map_data('state')) +
# expand_limits(x=map_data('state')$long,
# y=map_data('state')$lat)
#- This line tells R to use ggplot and to take information from dat variable 'state', and then to draw
```

Assignment 2

Collaborators: Theodora Athanitis

Problem 1

Instructions: Copy your code, paste it into a Word document, and turn it into Canvas. You can turn in a .docx or .pdf file. Show any EDA (graphical or non-graphical) you have used to come to this conclusion.

Problem 1: Load data

Set your working directory to the folder where you downloaded the data.

```
setwd("/Users/toriborlase/Desktop/University of Pennsylvania/Fall 2021/CRIM 250/Tori-Borlase-Crim-250")
```

Read the data

```
dat <- read.csv(file = "dat.nsduh.small.1.csv")
```

What are the dimensions of the dataset?

```
dim(dat)
```

```
## [1] 171   7
```

Answer: 171 by 7. 171 rows and 7 columns.

Problem 2: Variables

Describe the variables in the dataset.

```
names(dat)
```

```
## [1] "mjage"     "cigage"    "iralcage"  "age2"      "sexatract" "speakengl"
## [7] "irsex"
```

Answer: The variables in the dataset are mjage, cigage, iralcage, age2, sexatract, speakengl, and irsex. According to the code book, these correspond to how old someone was when they first tried marijuana or hashish, how old someone was when they started smoking cigarettes every day, how old someone was when they first tried alcohol, the final age that someone was determined to be at the time of taking the survey (which was asked multiple times as a consistency check), which statement about sexual orientation best described the respondent's feelings, how well they speak English, and imputation revised gender.

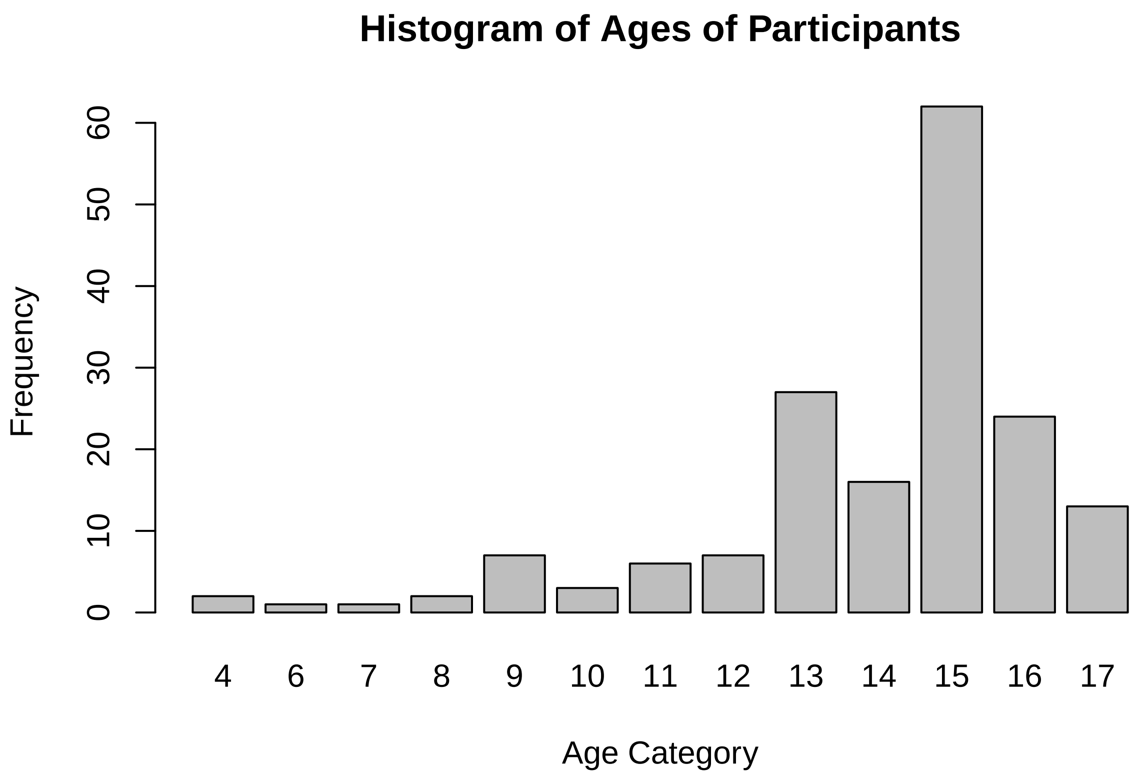
What is this dataset about? Who collected the data, what kind of sample is it, and what was the purpose of generating the data?

Answer: This dataset is from the 2019 National Survey on Drug Use and Health (NSDUH). Individuals within the Center for Behavioral Health Statistics and Quality collected this data in order to measure the "prevalence and correlates of substance use and mental health issues" in the US. This was a stratified random sample, as they collected data in all 50 states for civilian and non-institutionalized populations.

Problem 3: Age and gender

What is the age distribution of the sample like? Make sure you read the codebook to know what the variable values mean.

```
counts <- table(dat$age2)
barplot(counts, main = "Histogram of Ages of Participants", xlab = "Age Category",
    ylab = "Frequency")
```



Answer: The age distribution of this sample is skewed left. However, because the numbers within the data set are not actual ages, but rather a range of ages or individual ages that are coded as numbers 1 through 17, we cannot base our true age distribution off of the numbers that form the labels of the histogram. While it appears that the Final Edited Age is skewed left, this may just be because the upper coded ages contain wider ranges of ages, and the lower coded ages contain only one or two ages.

Do you think this age distribution representative of the US population? Why or why not?

Answer: No, I do not believe this age distribution is representative of the US population. According to Census data, and other population pyramids that display the distribution of population, there are many more younger people than are represented in this graph, as well as many individuals outside of the scope of the study, such as those under 12, etc. Even though (as I mentioned before) there are multiple ages within certain categories, this data shows many more older individuals compared to teenagers and those in their early twenties, and Census data shows large numbers of those populations.

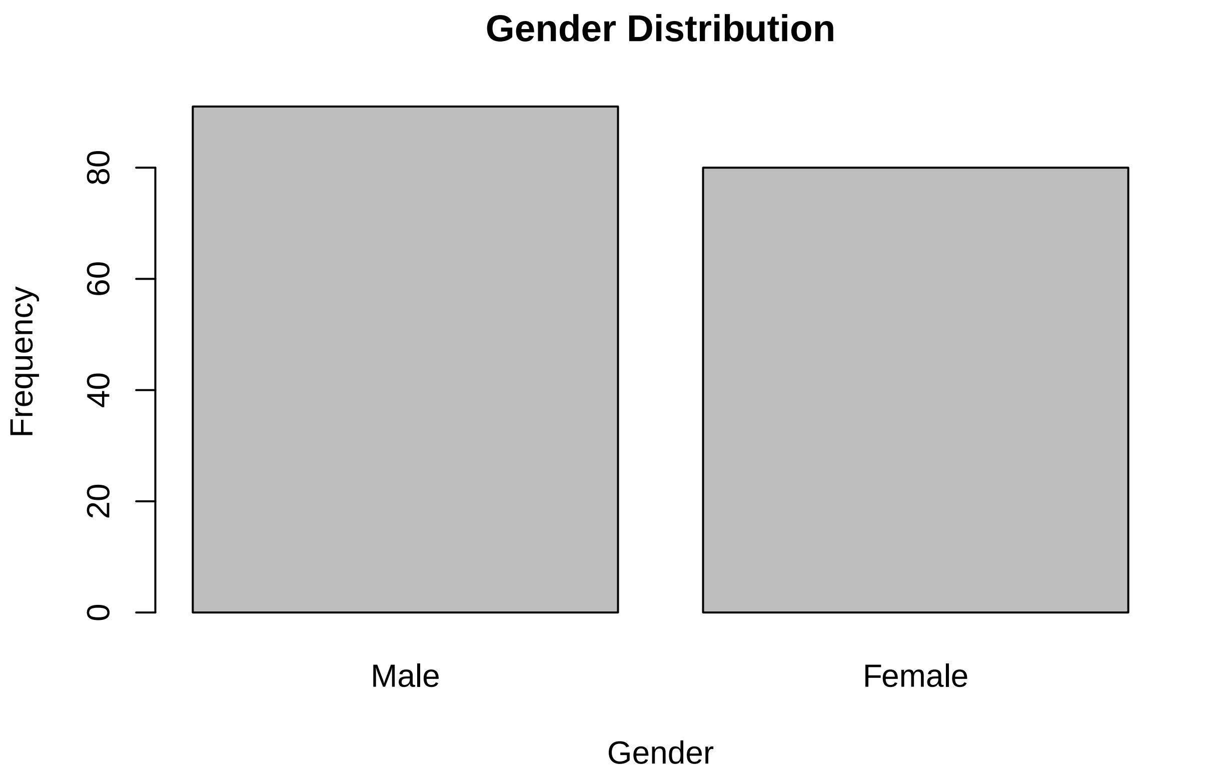
Is the sample balanced in terms of gender? If not, are there more females or males?

```
table(dat$irsex)
```

```
##
##  1  2
## 91 80
```

1 (Male) 2 (Female) 91 80

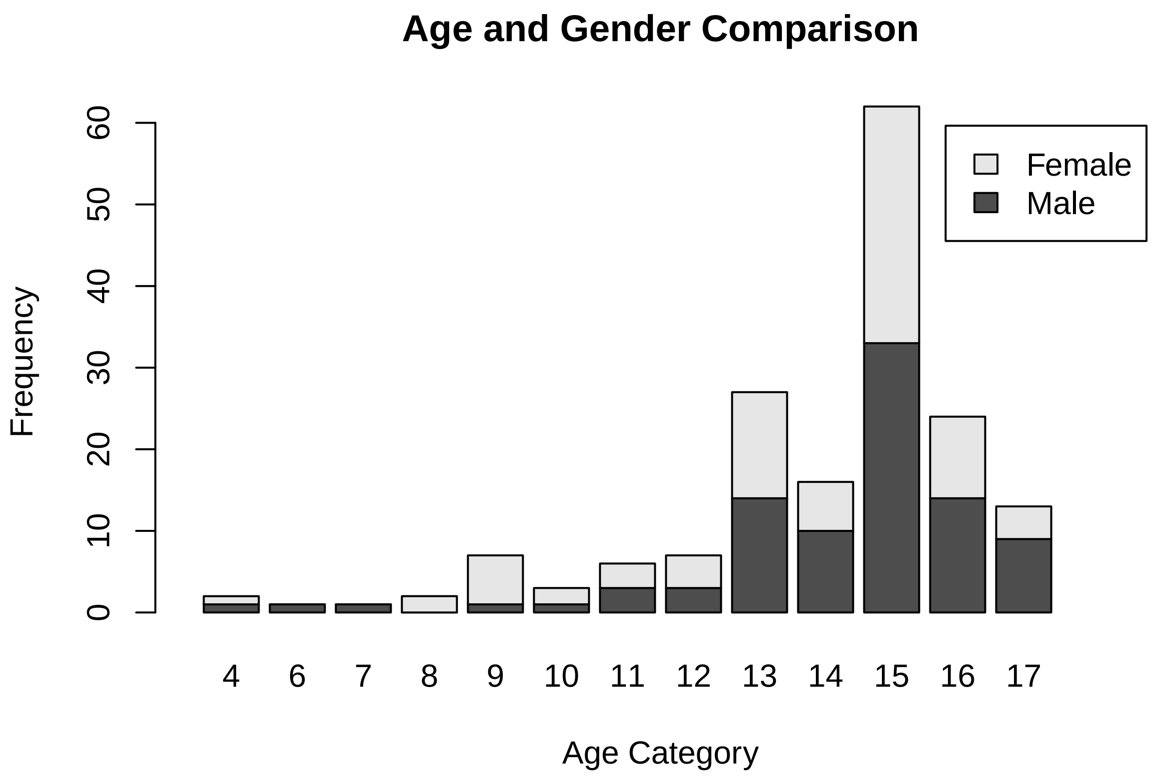
```
counts <- table(dat$irsex)
barplot(counts, main = "Gender Distribution", xlab = "Gender",
    ylab = "Frequency", names = c("Male", "Female"))
```



Answer: The sample is not gender balanced, as there are more males (91) than females (80). Using a bar chart clearly demonstrates this disparity.

Use this code to draw a stacked bar plot to view the relationship between sex and age. What can you conclude from this plot?

```
tab.agesex <- table(dat$irsex, dat$age2)
barplot(tab.agesex, main = "Age and Gender Comparison", xlab = "Age Category",
    ylab = "Frequency", legend.text = c("Male", "Female"), xlim = c(0,
        17), beside = FALSE)  # Stacked bars (default)
```

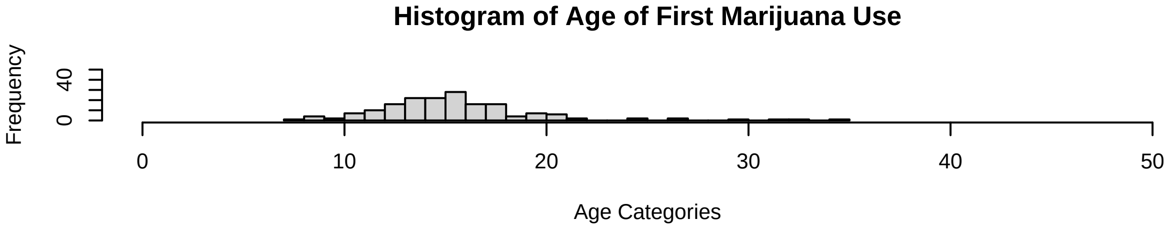


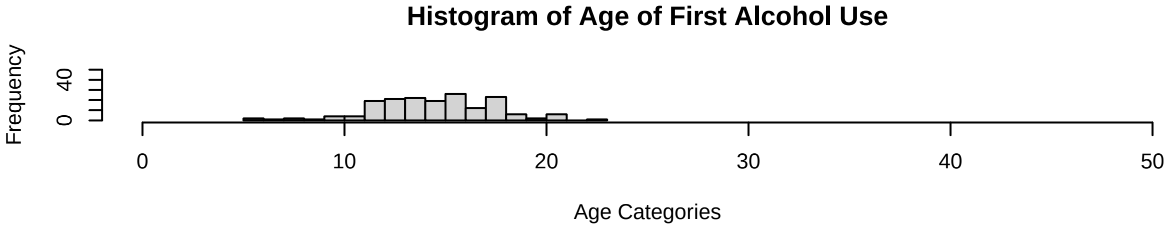
Answer: We can conclude from this plot that for most age categories, there were more males than females. However, for age categories 8, 9, 13, and 15, there appear to be more females or the same number of males and females.

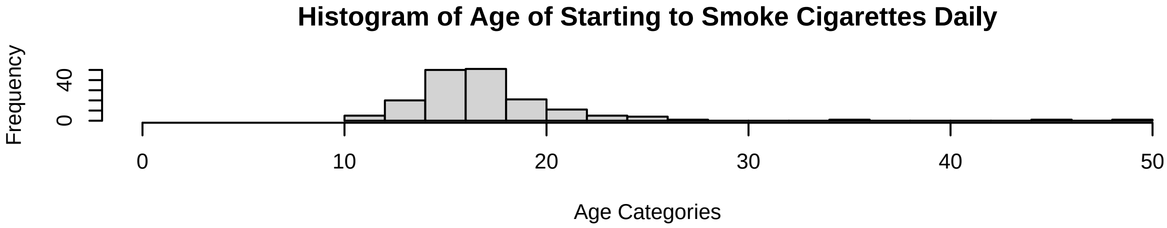
Problem 4: Substance use

For which of the three substances included in the data set (marijuana, alcohol, and cigarettes) do individuals tend to use the substance earlier?

```
par(mfrow = c(3, 1))
hist(dat$mjage, main = "Histogram of Age of First Marijuana Use",
    xlab = "Age Categories", ylab = "Frequency", xlim = c(0,
        50), ylim = c(0, 50), breaks = 20)
hist(dat$iralcage, main = "Histogram of Age of First Alcohol Use",
    xlab = "Age Categories", ylab = "Frequency", xlim = c(0,
        50), ylim = c(0, 50), breaks = 20)
hist(dat$cigage, main = "Histogram of Age of Starting to Smoke Cigarettes Daily",
    xlab = "Age Categories", ylab = "Frequency", xlim = c(0,
        50), ylim = c(0, 50), breaks = 20)
```





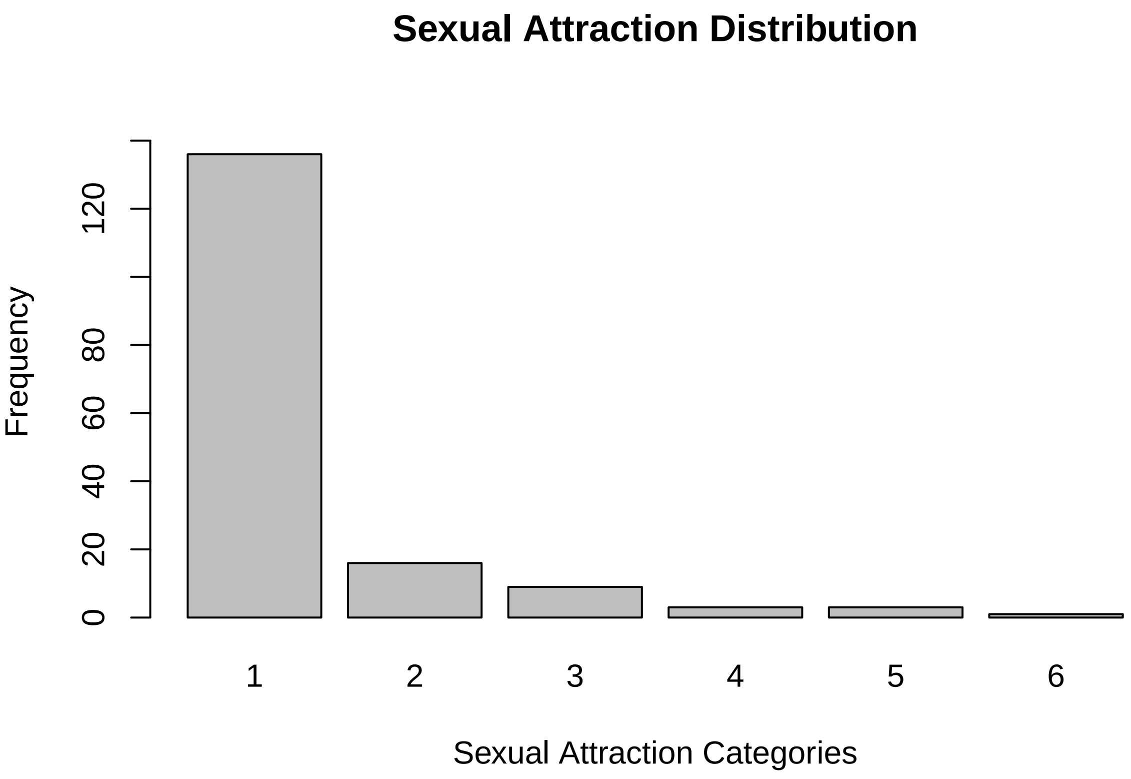


Individuals tend to use alcohol earlier, as seen on the histograms.

Problem 5: Sexual attraction

What does the distribution of sexual attraction look like? Is this what you expected?

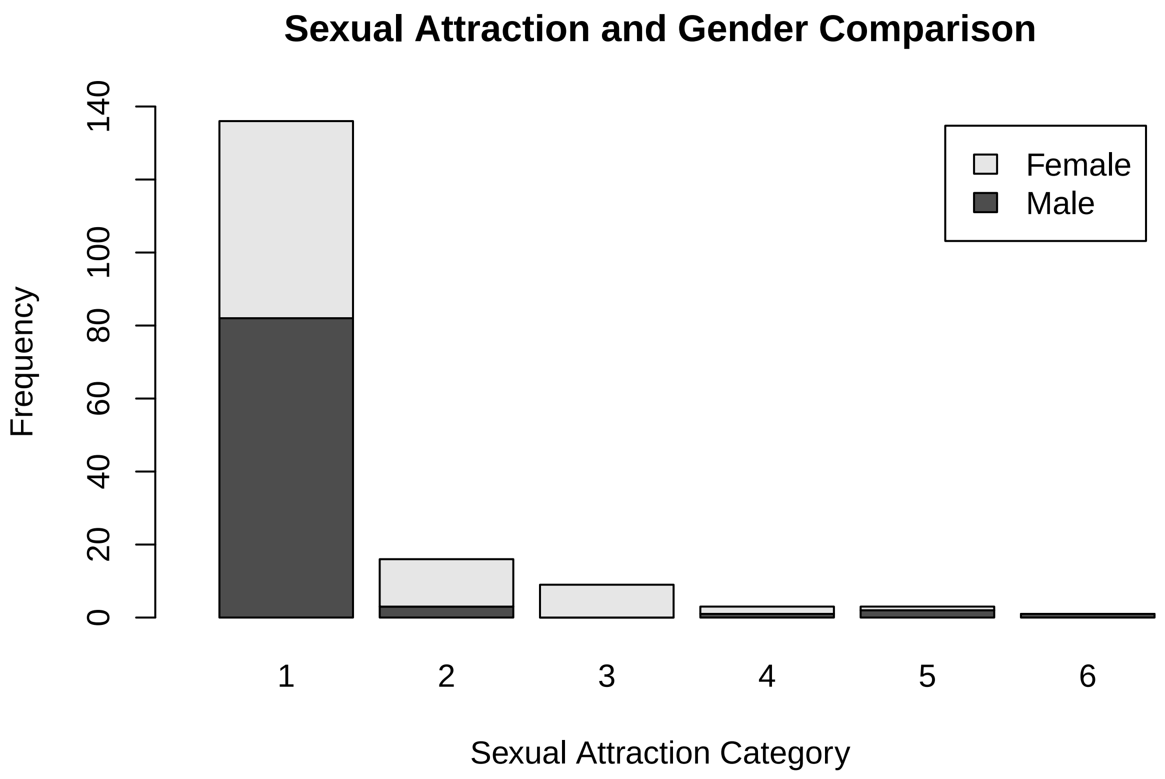
```r
dat1 <- dat[dat$sexatract != 99, ]
counts1 <- table(dat1$sexatract)
barplot(counts1, main = "Sexual Attraction Distribution", xlab = "Sexual Attraction Categories",
    ylab = "Frequency", ylim = c(0, 150))
```



Answer: The distribution of sexual attraction is skewed right, which is what I expected, as most people identify as only being attracted to the opposite sex, with fewer people identifying as being attracted to the same sex in any way. This is what I expected because I believe that LGBT+ populations are still a relatively small minority within the US compared to those who are only attracted to the opposite sex.

What is the distribution of sexual attraction by gender?

```r
dat1 <- dat[dat$sexatract != 99, ]
tab.sexor <- table(dat1$irsex, dat1$sexatract)
barplot(tab.sexor, main = "Sexual Attraction and Gender Comparison",
    xlab = "Sexual Attraction Category", ylab = "Frequency",
    legend.text = c("Male", "Female"), xlim = c(0, 7), ylim = c(0,
        140), beside = FALSE)  # Stacked bars (default)
```

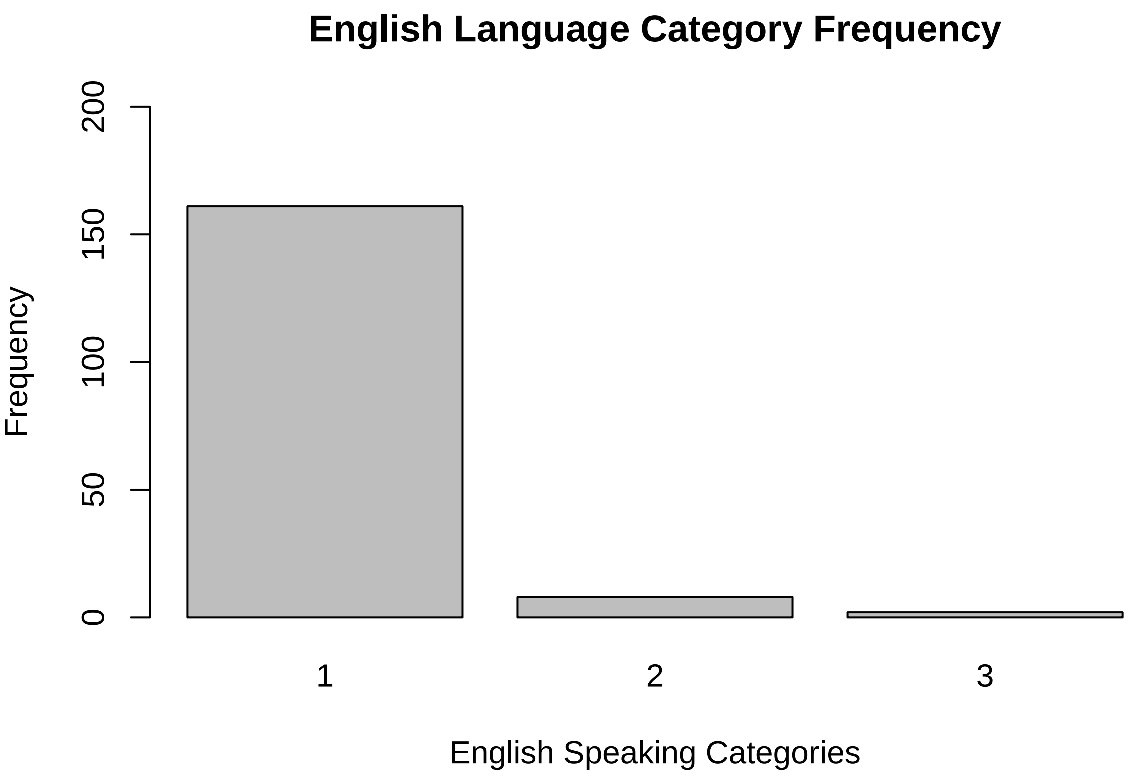


The distribution by gender is also skewed right, but there are more females that identify with statements about being attracted to the same sex in some way, and more males that identify with statements about being attracted to the opposite sex, as can be seen in the stacked bar chart.

Problem 6: English speaking

What does the distribution of English speaking look like in the sample? Is this what you might expect for a random sample of the US population?

```r
counts2 <- table(dat$speakengl)
barplot(counts2, main = "English Language Category Frequency",
    xlab = "English Speaking Categories", ylab = "Frequency",
    ylim = c(0, 200))
```



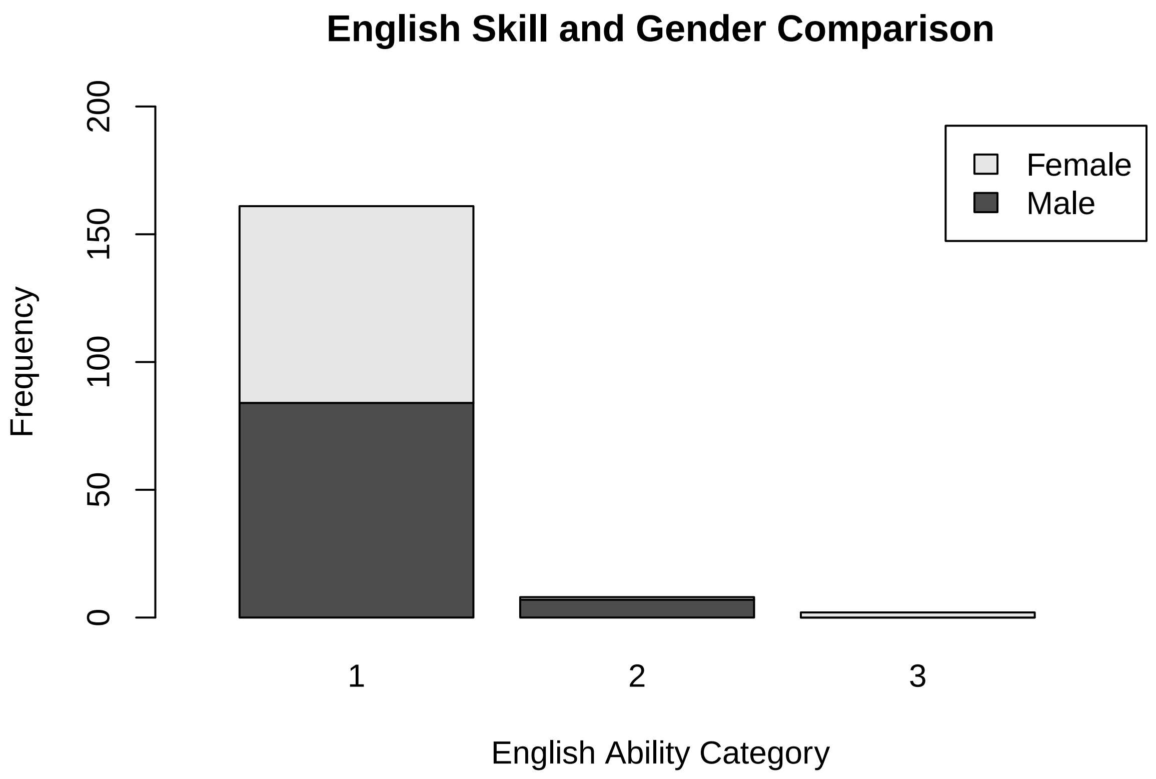
This distribution is also skewed right, with most individuals responding that they speak English very well, and less than 50 individuals total saying that the speak English well or not well, and nobody saying they did not speak English at all. This is similar to the distribution that I would expect in the United States because even though the US has no official language, most people need to speak some English in order to work and live here. However, there are probably more people in the US that speak no English at all, but they just were not able to participate in the survey because it was conducted in English.

Are there more English speaker females or males?

```
table(dat$irsex, dat$speakengl)
```

```
##
##       1  2  3
##    1 84  7  0
##    2 77  1  2
```

```
tab.sexor <- table(dat$irsex, dat$speakengl)
barplot(tab.sexor, main = "English Skill and Gender Comparison",
    xlab = "English Ability Category", ylab = "Frequency", legend.text = c("Male",
        "Female"), xlim = c(0, 4), ylim = c(0, 200), beside = FALSE)  # Stacked bars (default)
```



There are more male English speakers than female English speakers, but that might also be due to the fact that there are more males than females within the data set to begin with.

Exam 1

Instructions

a. Create a folder in your computer (a good place would be under Crim 250, Exams).
b. Download the dataset from the Canvas website (fatal-police-shootings-data.csv) onto that folder, and save your Exam 1.Rmd file in the same folder.
c. Download the README.md file. This is the codebook.
d. Load the data into an R data frame.

```
setwd("/Users/toriborlase/Desktop/University of Pennsylvania/Fall 2021/CRIM 250/Tori-Borlase-Crim-250")
dat <- read.csv(file = "fatal-police-shootings-data.csv")
```

Problem 1 (10 points)

a. Describe the dataset. This is the source: https://github.com/washingtonpost/data-police-shootings . Write two sentences (max.) about this.

This dataset was collected by the Washington Post and contains records of every fatal shooting by a police officer in the U.S. since January 1, 2015. The data includes names, dates, manner of death, if that individual was armed, their age, gender, race, location, as well as other general factors, and an ID number of each individual who was victimized according to the criteria established by the Washington Post.

b. How many observations are there in the data frame?

```
dim(dat)
```

```
## [1] 6594   17
```

There are 6594 observations in the data set, as well as 17 variables.

c. Look at the names of the variables in the data frame. Describe what "body_camera", "flee", and "armed" represent, according to the codebook. Again, only write one sentence (max) per variable.

```
names(dat)
```

```
##  [1] "id"                      "name"
##  [3] "date"                    "manner_of_death"
##  [5] "armed"                   "age"
##  [7] "gender"                  "race"
##  [9] "city"                    "state"
## [11] "signs_of_mental_illness" "threat_level"
## [13] "flee"                    "body_camera"
## [15] "longitude"               "latitude"
## [17] "is_geocoding_exact"
```

The variable "body_camera" represents that news reports have indicated an officer was wearing a body camera and it may have recorded some portion of the incident. The variable "flee" represents if news reports have indicated the victim was moving away from officers, as well as if they were fleeing by car or by foot, or otherwise. The variable "armed" indicates that the victim was armed with some sort of implement that a police officer believed could inflict harm, as well as detailing what that implement was.

d. What are three weapons that you are surprised to find in the "armed" variable? Make a table of the values in "armed" to see the options.

```
table(dat$armed)
```

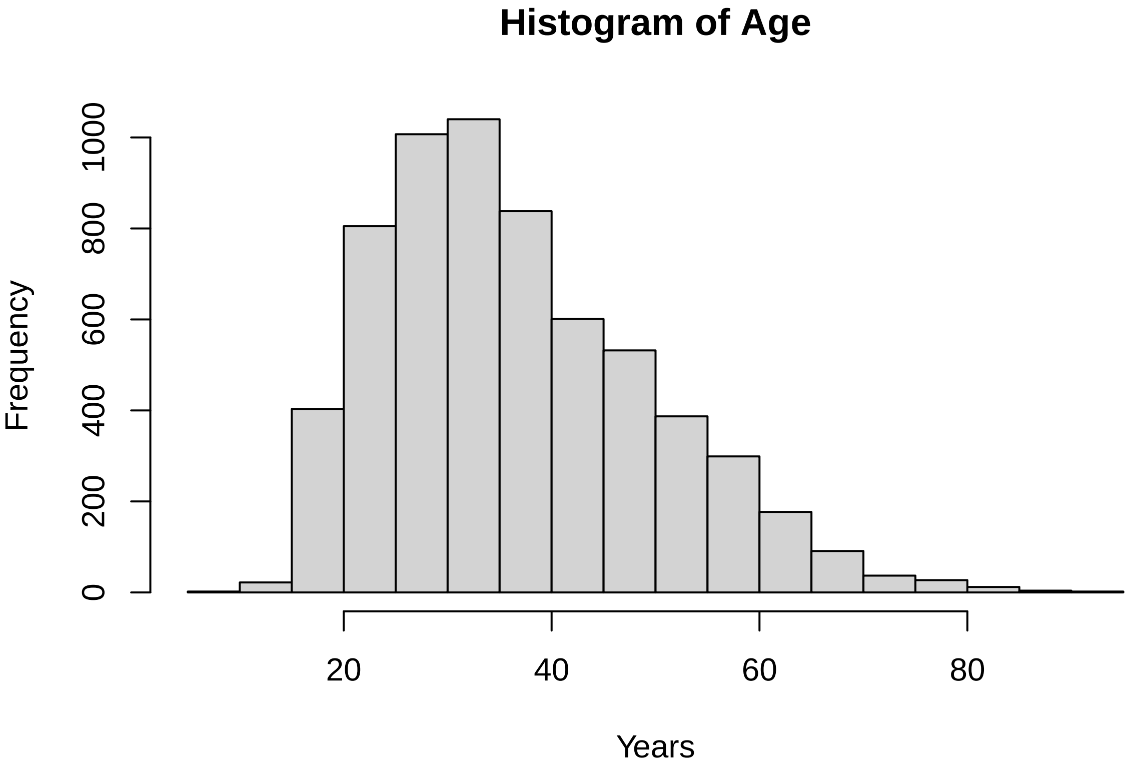
```
## 
##                                                     air conditioner 
##                              207                                  1 
##                       air pistol                     Airsoft pistol 
##                                1                                  3 
##                               ax                           barstool 
##                               24                                  1 
##                     baseball bat            baseball bat and bottle 
##                               20                                  1 
## baseball bat and fireplace poker             baseball bat and knife 
##                                1                                  1 
##                            baton                             BB gun 
##                                6                                 15 
##               BB gun and vehicle                       bean-bag gun 
##                                1                                  1 
##                      beer bottle                         binoculars 
##                                3                                  1 
##                     blunt object                             bottle 
##                                5                                  1 
##                    bow and arrow                         box cutter 
##                                1                                 13 
##                            brick                car, knife and mace 
##                                2                                  1 
##                          carjack                              chain 
##                                1                                  3 
##                        chain saw                           chainsaw 
##                                2                                  1 
##                            chair                 claimed to be armed
##                                4                                1
##               contractor's level                   cordless drill
##                                1                                1
##                         crossbow                          crowbar
##                                9                                5
##                        fireworks                         flagpole
##                                1                                1
##                       flashlight                      garden tool
##                                2                                2
##                      glass shard                          grenade
##                                4                                1
##                              gun                      gun and car
##                             3798                               12
##                    gun and knife                  gun and machete
##                               22                                3
##                    gun and sword                  gun and vehicle
##                                1                               17
##              guns and explosives                           hammer
##                                3                               18
##                       hand torch                          hatchet
##                                1                               14
##                  hatchet and gun                         ice pick
##                                2                                1
##                incendiary device                            knife
##                                2                              955
##                knife and vehicle                 lawn mower blade
##                                1                                2
##                          machete                  machete and gun
##                               51                                1
##                     meat cleaver                  metal hand tool
##                                6                                2
##                     metal object                       metal pipe
##                                5                               16
##                       metal pole                       metal rake
##                                4                                1
##                      metal stick                       microphone
##                                3                                1
##                       motorcycle                         nail gun
##                                1                                1
##                              oar                       pellet gun
##                                1                                3
##                              pen                     pepper spray
##                                1                                2
##                         pick-axe                    piece of wood
##                                4                                7
##                             pipe                        pitchfork
##                                7                                2
##                             pole                   pole and knife
##                                3                                2
##                  railroad spikes                             rock
##                                1                                7
##                    samurai sword                         scissors
##                                4                                9
##                      screwdriver                     sharp object
##                          16                           14
##                      shovel                        spear
##                           7                            2
##                     stapler         straight edge razor
##                           1                            5
##                       sword                        Taser
##                          23                           34
##                   tire iron                   toy weapon
##                           4                          226
##                     unarmed                 undetermined
##                         421                          188
##              unknown weapon                      vehicle
##                          82                          213
##             vehicle and gun         vehicle and machete
##                           8                            1
##               walking stick                   wasp spray
##                           1                            1
##                      wrench
##                           1
```

Even though only one was reported, I was surprised to see a bean-bag gun because I have no idea what that is (but it sounds interesting). I was also surprised by the spear and railroad spike reports, especially because those weapons seem very difficult to obtain in the 21st Century.

Problem 2 (10 points)

a. Describe the age distribution of the sample. Is this what you would expect to see?

```
counts <- table(dat$age)
hist(dat$age, main = "Histogram of Age", xlab = "Years", ylab = "Frequency")
```



The sample of ages is skewed right, with the highest frequency of reported age being between 20 and 40 years. I would expect to see this distribution because I expect most people that the police find threatening (and would have used force against) would have to be an age where they would be physically capable of injuring an officer or other people.

b. To understand the center of the age distribution, would you use a mean or a median, and why? Find the one you picked.

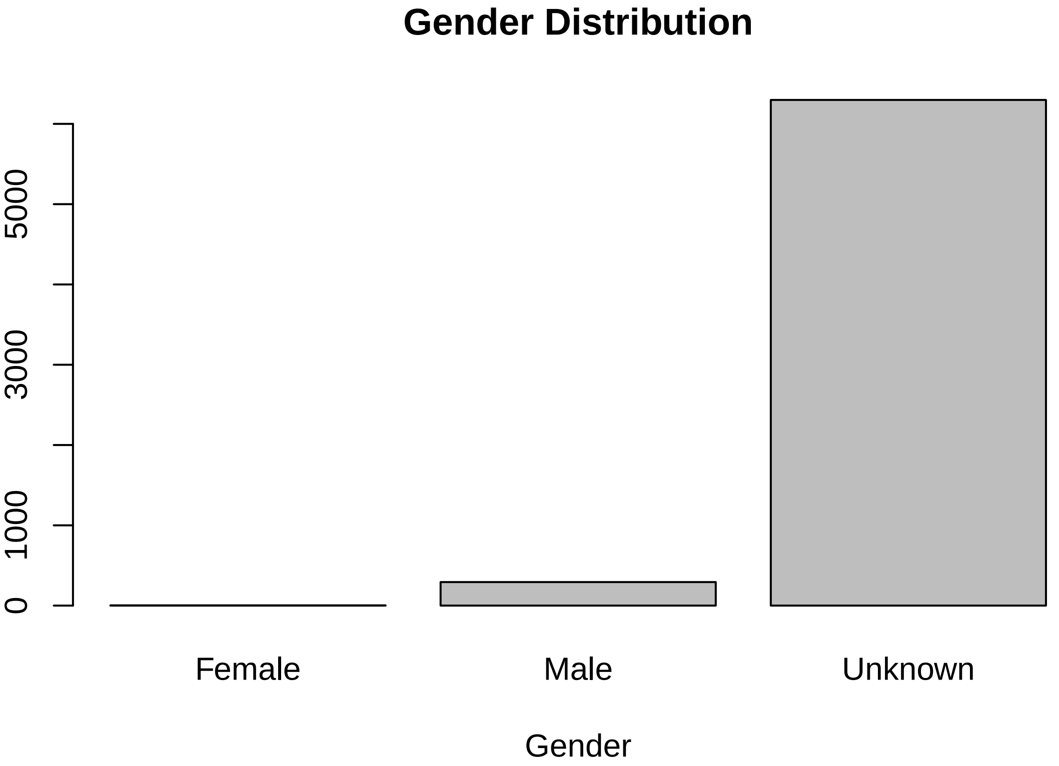
```
summary(dat$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    6.00   27.00   35.00   37.12   45.00   91.00     308 
```

Because our data is skewed, I would use a median to understand the center of the distribution, as a mean may be impacted by the data points that are on the right-hand side of the graph in a way that makes it seem like the center of the data is higher. This is demonstrated by our summary, where we can see that the median is 35.00, and the mean is 37.12. In this case, the median age is 35.00.

c. Describe the gender distribution of the sample. Do you find this surprising?

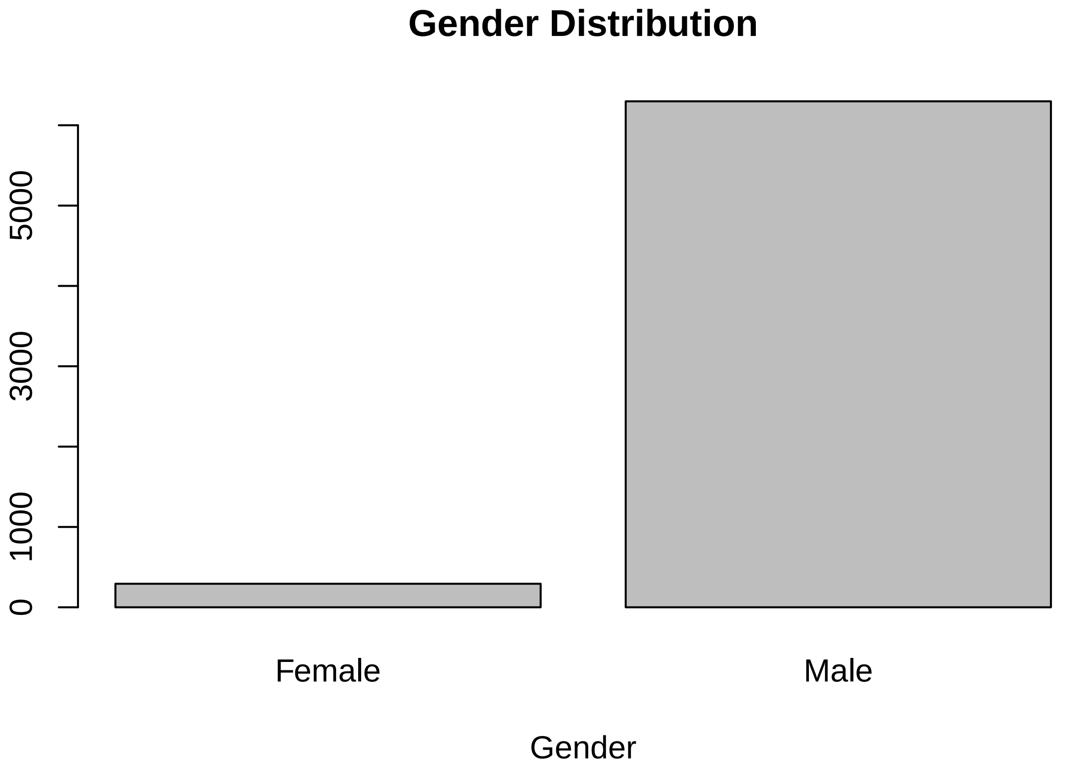
```
counts <- table(dat$gender)
barplot(counts, main = "Gender Distribution", xlab = "Gender",
    names = c("Female", "Male", "Unknown"))
```



```
table(dat$gender)
```

```
## 
##         F    M 
##    3  293 6298 
```

```
dat1 <- dat[dat$gender != "", ]
counts1 <- table(dat1$gender)
barplot(counts1, main = "Gender Distribution", xlab = "Gender",
    names = c("Female", "Male"))
```



It is clear from the first bar plot that most genders of individuals are unknown. However, if we remove the individuals with unknown gender, we can see that most victims were male. This is not surprising, as to my knowledge most people who are victims of homicide in general are male, and police are also more likely to perceive males as threatening, which may mean they are more likely to use force against them.

Problem 3 (10 points)

a. How many police officers had a body camera, according to news reports? What proportion is this of all the incidents in the data? Are you surprised that it is so high or low?

```
table(dat$body_camera)
```

```
##
## False  True
##  5684   910
```

910 police had a body camera according to the news reports, and 5684 did not. Out of all incidents (6594), that would mean that only 13.8 percent of police had a body camera. I am not surprised that this is low, as body cameras are expensive, and also are only more recently becoming common. Given that this data collection started in 2015, it may just be the case that most police districts do not mandate body cameras or do not have the funding to provide body cameras to all of their police officers.

b. In how many of the incidents was the victim fleeing? What proportion is this of the total number of incidents in the data? Is this what you would expect?

```
table(dat$flee)
```

```
##
##                     Car        Foot Not fleeing       Other
##         491        1058         845        3952         248
```

Because people were identified as fleeing both on foot and in a car, we can add 1058 and 845 to get a total number of incidents where the victim was fleeing: 1903. While only 3952 people were marked as not fleeing, there are unknown values, as well as values marked "Other" that we cannot determine if they were fleeing or not. So, the true number of people fleeing might be more than 1903, but we cannot tell what the other individuals did. The proportion of those who fled compared to overall reports (aka including the "Other" reports, not just compared to those who did not flee) is 28.9 percent. This is a bit higher than I was expecting, because normally, I associate police shootings with police officers claiming self-defense. However, almost 30% of people were fleeing the police officer at the time of the shooting, which seems like a very high number to me since police tend to claim that the victim was being aggressive and approaching them in a threatening way. However, it might make sense if police are trained to shoot individuals who are fleeing from a crime, but I don't have any knowledge of if police officers are trained to shoot in those situations.

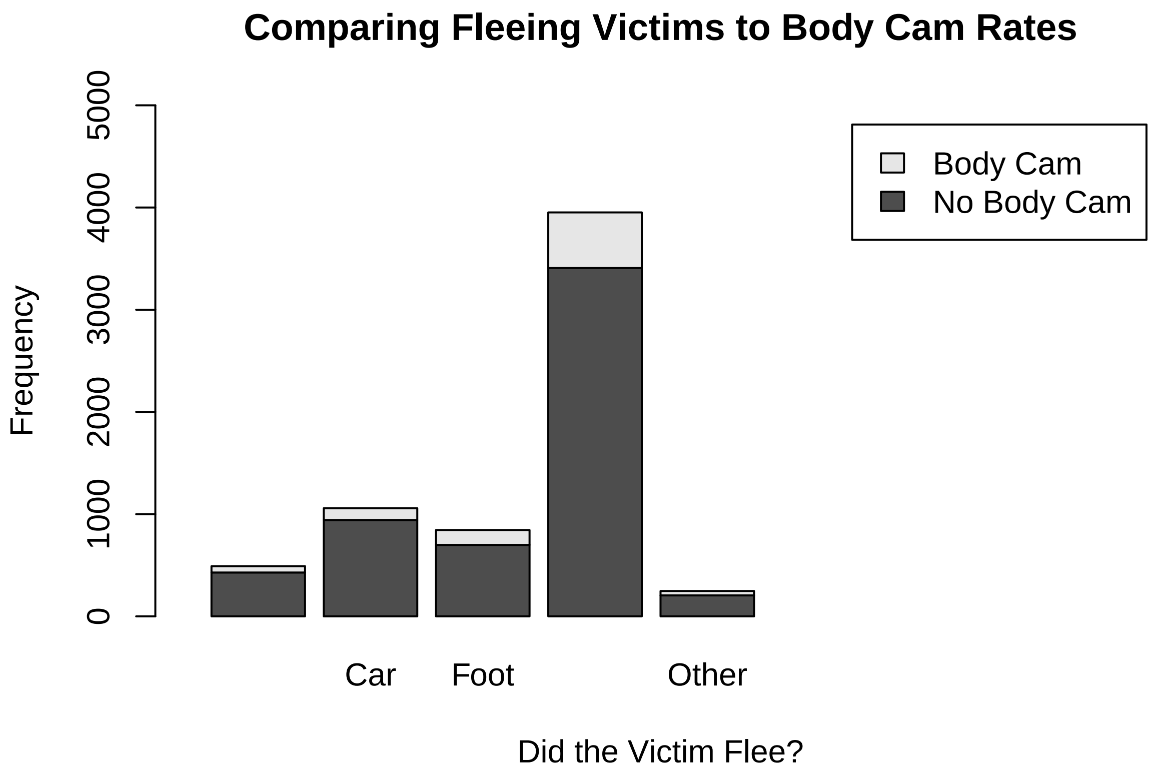
Problem 4 (10 points) - Answer only one of these (a or b).

a. Describe the relationship between the variables "body camera" and "flee" using a stacked barplot. What can you conclude from this relationship?

Hint 1: The categories along the x-axis are the options for "flee", each bar contains information about whether the police officer had a body camera (vertically), and the height along the y-axis shows the frequency of that category).

Hint 2: Also, if you are unsure about the syntax for barplot, run ?barplot in R and see some examples at the bottom of the documentation. This is usually a good way to look up the syntax of R code. You can also Google it.

```
tab.sexor <- table(dat$body_camera, dat$flee)
barplot(tab.sexor, main = "Comparing Fleeing Victims to Body Cam Rates",
    xlab = "Did the Victim Flee?", ylab = "Frequency", legend.text = c("No Body Cam",
        "Body Cam"), xlim = c(0, 10), ylim = c(0, 5000), beside = FALSE)
```



First, it is important to note that there were many incidents of police shootings where we are unsure if the victim fled or not, and those columns without a label or labeled "Other" are reflecting those incidents. Even *though the "other" column might represent people who fled in a different way than by car or by foot, the codebook does not specify, so I will just consider those values to have unknown significance. Even though it is very clear that most police officers did not have body cameras, it looks like there is a higher level of body cameras involved in incidents where people don't flee as compared to the incidents when people do flee (i.e. by car or by foot). We could conclude many things from this observation, one of which being that police are more likely to accurately report that the victim was not fleeing if there was video evidence. However, it may also be the case that in situations where police have to chase people who are fleeing, they are not wearing body cameras. Overall, I hesitate to conclude anything about the direct relationship between these variables, but I can say that it looks apparent that there was a higher rate of body cameras among the police officers that shot people who were not fleeing.*

b. Describe the relationship between age and race by using a boxplot. What can you conclude from this relationship?

Hint 1: The categories along the x-axis are the race categories and the height along the y-axis is age.

Hint 2: Also, if you are unsure about the syntax for boxplot, run ?boxplot in R and see some examples at the bottom of the documentation. This is usually a good way to look up the syntax of R code. You can also Google it.

N/A.

Extra credit (10 points)

a. What does this code tell us?

```
mydates <- as.Date(dat$date)
head(mydates)
(mydates[length(mydates)] - mydates[1])
`?`(length)
```

This code tells us a few things. The first line tells r not to evaluate this r chunk, which is helpful especially as this extra credit question is not involving the data that we are currently using for our other problems. The second line tells us to make a new data frame called mydates, and to interpret values from the date column in dat as calendar dates rather than normal character representations. The third line tells r to read the first few entries of the data frame mydates. The fourth line tells r to set the length of mydates to a certain value.

b. On Friday, a new report was published that was described as follows by The Guardian: "More than half of US police killings are mislabelled or not reported, study finds." Without reading this article now (due to limited time), why do you think police killings might be mislabeled or underreported?

The dataset we were given was only measuring the number and types of police killings that were both shootings as well as reported in the news. Because the Washington Post data that we used was only based on news reports, it is likely that there are many police killings that are not published in the news. Therefore, because it may be hard to access police reports in order to get a more complete idea of the incidents that happen, police killings may be underreported. Additionally, police shootings may be mislabeled because oftentimes police are the only people who have a complete record of what occured at a scene, and police are probably unwilling to accurately report what happened in order to avoid punitive measures. Especialy given that so many people do not have body cameras, police may be lying about what happened in order to avoid losing their job or other criminal implications.

c. Regarding missing values in problem 4, do you see any? If so, do you think that's all that's missing from the data?

For problem 4 I selected a barplot of flee and body-cameras. There were a bunch of missing values in the flee category, their flee status could have been in a way other than by car or by foot, and there were also people who simply did not have any value entered in the flee category. It is unlikley that that's all that is missing from the data - because this data was collected from news articles, and not all news reporters are mandated to report on every single variable that the researchers were tracking, I am sure that there were other missing *values. There were also unknown genders that we had to remove from the data set earlier in another problem, which indicates that there is absolutely more missing data in this set. Despite this fact, it is still good to collect this type of data so that we can analyze it.*

Assignment 3

Collaborators: Theodora Athanitis.

```
knitr::opts_chunk$set(echo = TRUE)
```

This assignment is due on Canvas on Wednesday 10/27/2021 before class, at 10:15 am. Include the name of anyone with whom you collaborated at the top of the assignment.

Submit your responses as either an HTML file or a PDF file on Canvas. Also, please upload it to your website.

Save the file (found on Canvas) crime_simple.txt to the same folder as this file (your Rmd file for Assignment 3).

Load the data.

```
library(readr)
library(knitr)
dat.crime <- read_delim("crime_simple.txt", delim = "\t")
```

```
## Rows: 47 Columns: 14
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## dbl (14): R, Age, S, Ed, Ex0, Ex1, LF, M, N, NW, U1, U2, W, X
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

This is a dataset from a textbook by Brian S. Everitt about crime in the US in 1960. The data originates from the Uniform Crime Report of the FBI and other government sources. The data for 47 states of the USA are given.

Here is the codebook:

R: Crime rate: # of offenses reported to police per million population

Age: The number of males of age 14-24 per 1000 population

S: Indicator variable for Southern states (0 = No, 1 = Yes)

Ed: Mean of years of schooling x 10 for persons of age 25 or older

Ex0: 1960 per capita expenditure on police by state and local government

Ex1: 1959 per capita expenditure on police by state and local government

LF: Labor force participation rate per 1000 civilian urban males age 14-24

M: The number of males per 1000 females

N: State population size in hundred thousands

NW: The number of non-whites per 1000 population

U1: Unemployment rate of urban males per 1000 of age 14-24

U2: Unemployment rate of urban males per 1000 of age 35-39

W: Median value of transferable goods and assets or family income in tens of $

X: The number of families per 1000 earning below 1/2 the median income

We are interested in checking whether the reported crime rate (# of offenses reported to police per million population) and the average education (mean number of years of schooling for persons of age 25 or older) are related.

1.

How many observations are there in the dataset? To what does each observation correspond?

```
dim(dat.crime)
```

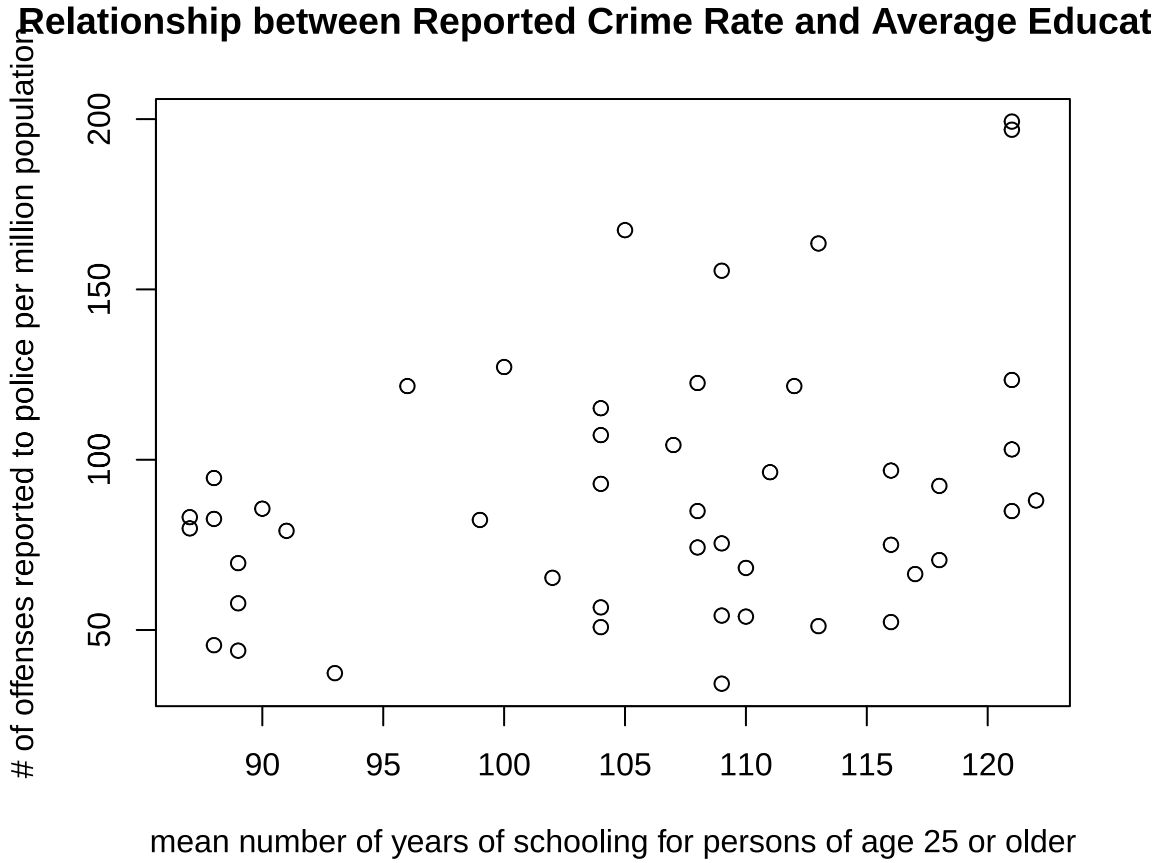
```
## [1] 47 14
```

There are 47 observations in the dataset. Each observation corresponds with a state in the US.

2.

Draw a scatterplot of the two variables. Calculate the correlation between the two variables. Can you come up with an explanation for this relationship?

```
library(readr)
library(knitr)
plot(dat.crime$Ed, dat.crime$R, main = "Relationship between Reported Crime Rate and Average Education"
    xlab = "mean number of years of schooling for persons of age 25 or older",
    ylab = "# of offenses reported to police per million population")
```



```
cor(dat.crime$Ed, dat.crime$R)
```

```
## [1] 0.3228349
```

The correlation between these two variables is 0.3228349. This makes sense because there seems to be little relationship in the scatter plot between the two variables.

3.

Regress reported crime rate (y) on average education (x) and call this linear model `crime.lm` and write the summary of the regression by using this code, which makes it look a little nicer `{r, eval=FALSE} kable(summary(crime.lm)$coef, digits = 2)`.

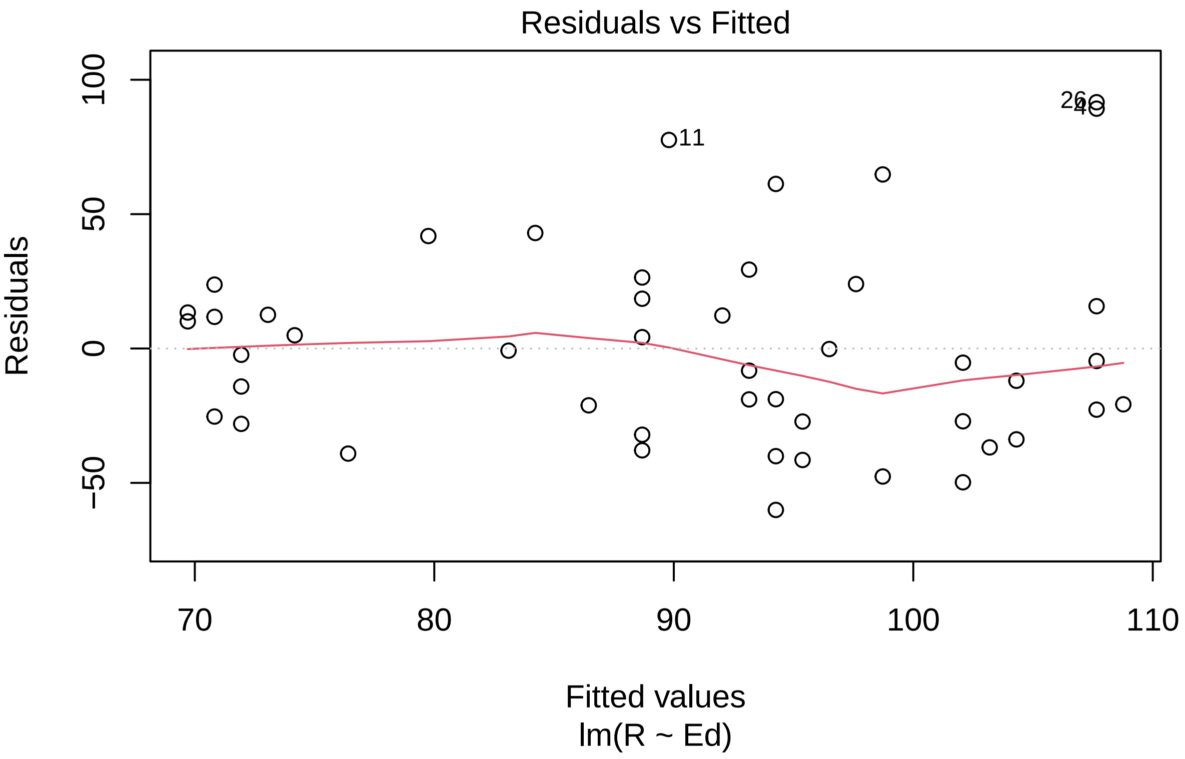
```
# Remember to remove eval=FALSE above!

crime.lm <- lm(formula = R ~ Ed, data = dat.crime)
kable(summary(crime.lm)$coef, digits = 2)
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-27.40	51.81	-0.53	0.60
Ed	1.12	0.49	2.29	0.03

4.

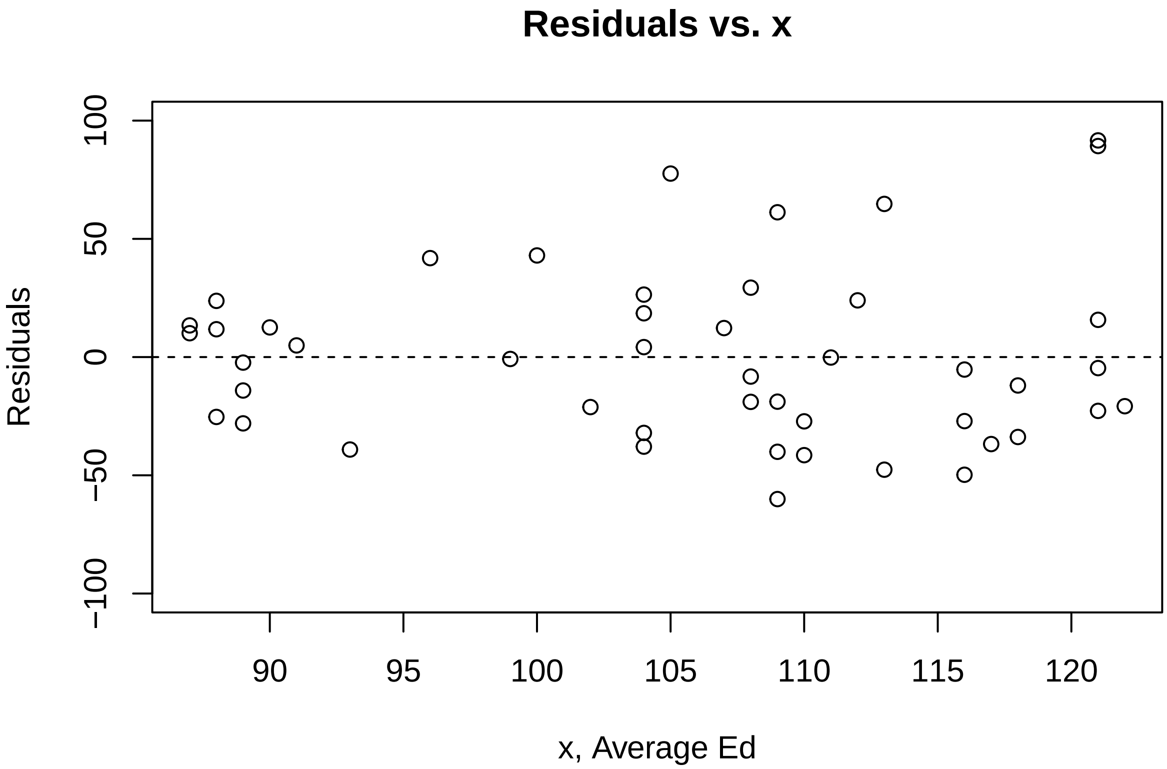
Are the four assumptions of linear regression satisfied? To answer this, draw the relevant plots. (Write a maximum of one sentence per assumption.)

```
plot(crime.lm, which = 1)
```



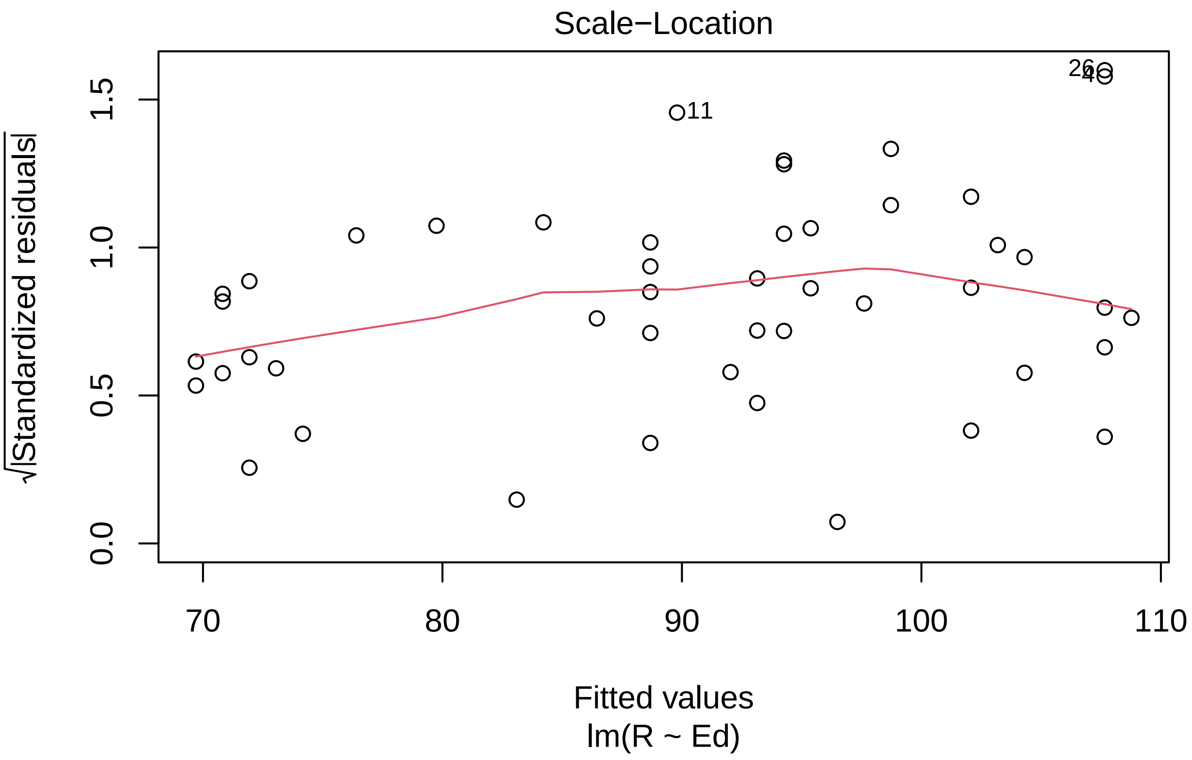
Assumption 1: Linearity. This assumption is satisfied because the line representing average value of the residuals at each value of fitted value looks relatively flat.

```
plot(dat.crime$Ed, crime.lm$residuals, ylim = c(-100, 100), main = "Residuals vs. x",
    xlab = "x, Average Ed", ylab = "Residuals")
abline(h = 0, lty = "dashed")
```



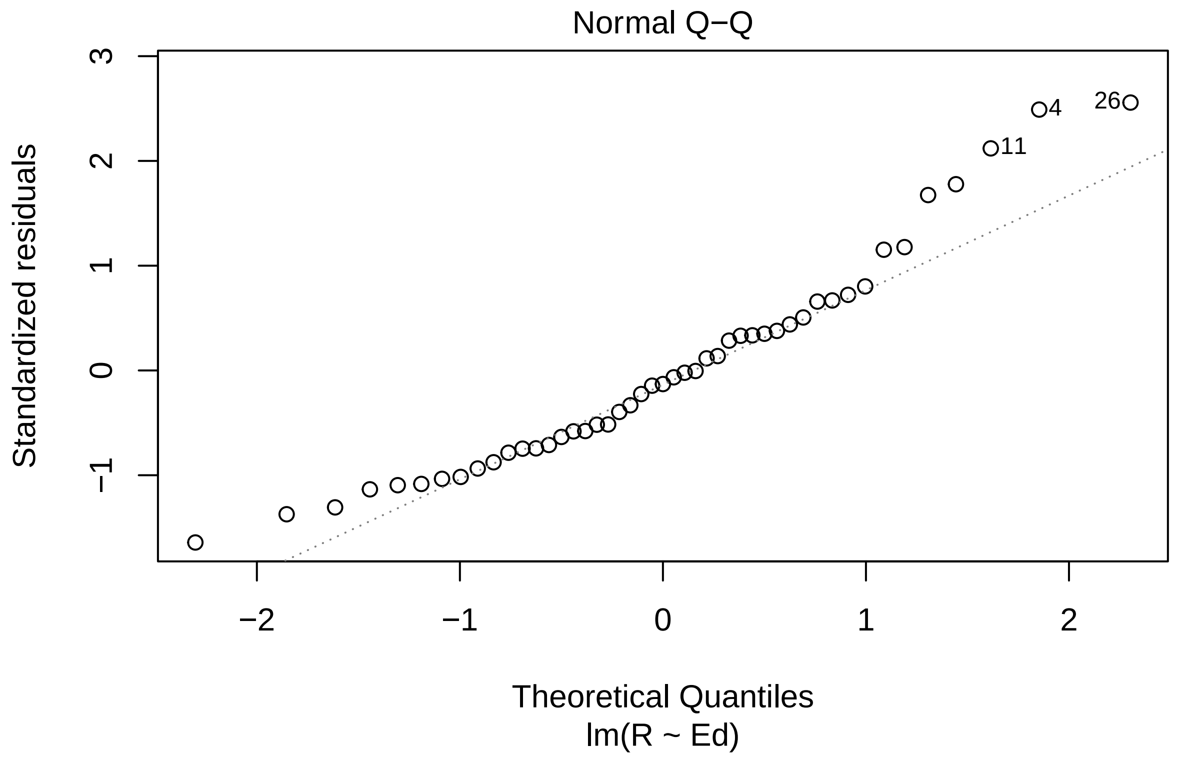
Assumption 2: Independence. While there is no way to check this is true, based on our plots, this assumption is satisfied because there is no apparent patterns in the residuals plot.

```
plot(crime.lm, which = 3)
```



Assumption 3: Homoscedasticity. There appears to be no patterns in variability of x and y, and the scale-location plot above appears to have a relatively flat line.

```
plot(crime.lm, which = 2)
```



Assumption 4: Normal Population. The values in the top right and the shape of the QQ plot show that it may

have a light tail, or may be smaller than usual for a normal distribution.

5.

Is the relationship between reported crime and average education statistically significant? Report the estimated coefficient of the slope, the standard error, and the p-value. What does it mean for the relationship to be statistically significant?

```
summary(crime.lm)
```

```
##
## Call:
## lm(formula = R ~ Ed, data = dat.crime)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -60.061 -27.125  -4.654  17.133  91.646
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -27.3967    51.8104  -0.529   0.5996
## Ed            1.1161     0.4878   2.288   0.0269 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 37.01 on 45 degrees of freedom
## Multiple R-squared:  0.1042, Adjusted R-squared:  0.08432
## F-statistic: 5.236 on 1 and 45 DF,  p-value: 0.02688
```

The estimated coefficient of slope is 1.1161. The Standard Error is 0.4878. The p-value is 0.0269. However, because of the QQ plot results, this significance result may be too strong compared to reality, so we should be cautious when saying that the relationship is statistically significant even though the p-value is less than .05. A relationship is statistically significant when the result is very unlikely to be due to chance; in this case, having these results is relatively unlikely if there is no correlation between R and Ed.

6.

How are reported crime and average education related? In other words, for every unit increase in average education, how does reported crime rate change (per million) per state?

For every unit increase in average education, reported crime rate increases by 1.1161 (per million) per state.

7.

Can you conclude that if individuals were to receive more education, then crime will be reported more often? Why or why not?

No. Just because these variables are correlated does not prove that one of them causes the other to occur. There may be causation in the reverse way, where crime being reported more often causes individuals to recieve more education, or there may be a third variable or condition that is causing both of them to change.

Assignment 4

3

```
# library(tidyverse)
```

This chunk loads a bunch of different packages, including ggplot, that help make data look nicer, as well as helping access the datasets, help pages, and functions related to ggplot.

```
# install.packages('tidyverse') library(tidyverse)
```

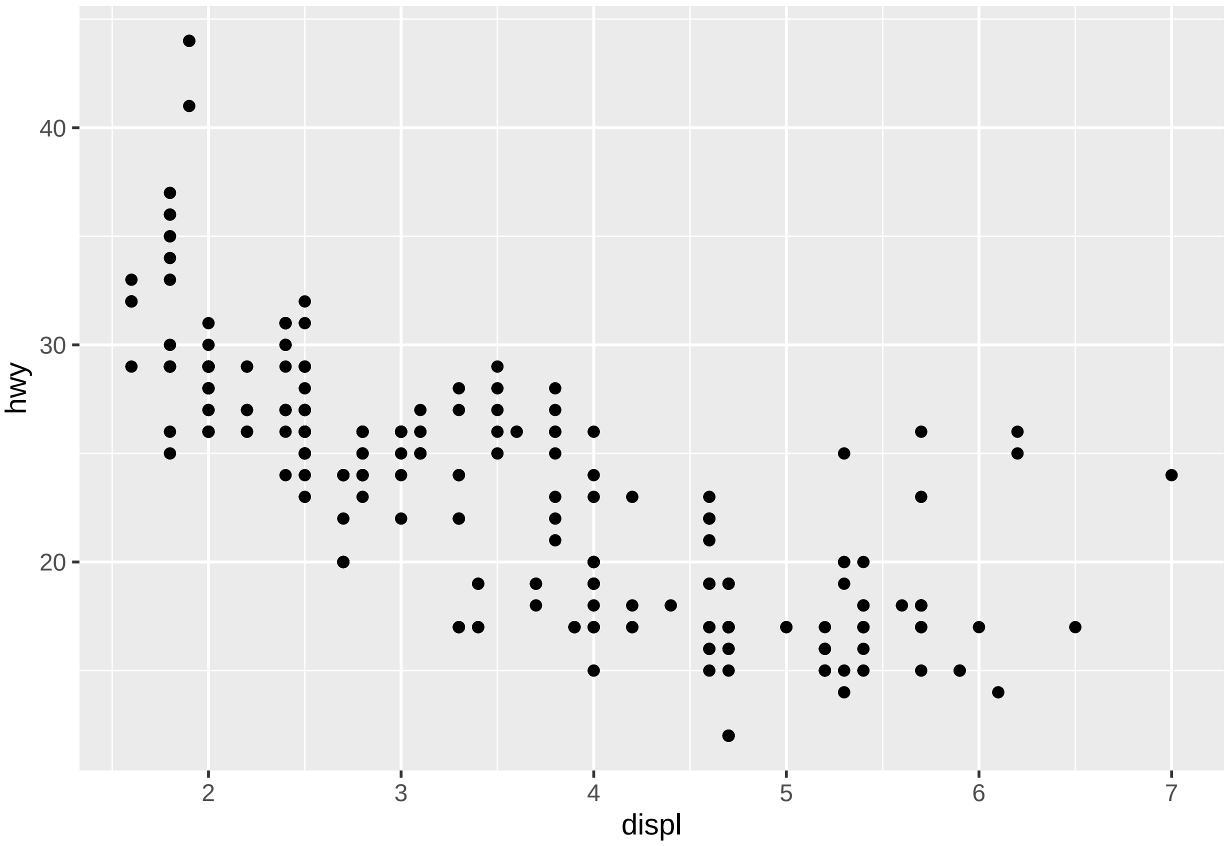
This chunk installs the tidyverse package which is what is described in the previous chunk.

```
mpg
```

```
## # A tibble: 234 x 11
##    manufacturer model      displ  year   cyl trans drv     cty   hwy fl    class
##    <chr>        <chr>      <dbl> <int> <int> <chr> <chr> <int> <int> <chr> <chr>
##  1 audi         a4           1.8  1999     4 auto~ f        18    29 p     comp~
##  2 audi         a4           1.8  1999     4 manu~ f        21    29 p     comp~
##  3 audi         a4           2    2008     4 manu~ f        20    31 p     comp~
##  4 audi         a4           2    2008     4 auto~ f        21    30 p     comp~
##  5 audi         a4           2.8  1999     6 auto~ f        16    26 p     comp~
##  6 audi         a4           2.8  1999     6 manu~ f        18    26 p     comp~
##  7 audi         a4           3.1  2008     6 auto~ f        18    27 p     comp~
##  8 audi         a4 quattro   1.8  1999     4 manu~ 4        18    26 p     comp~
##  9 audi         a4 quattro   1.8  1999     4 auto~ 4        16    25 p     comp~
## 10 audi         a4 quattro   2    2008     4 manu~ 4        20    28 p     comp~
## # ... with 224 more rows
```

This chunk is a sample dataframe from ggplot2, which contains observations collected by the US Environmental Protection Agency on 38 models of car.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy))
```

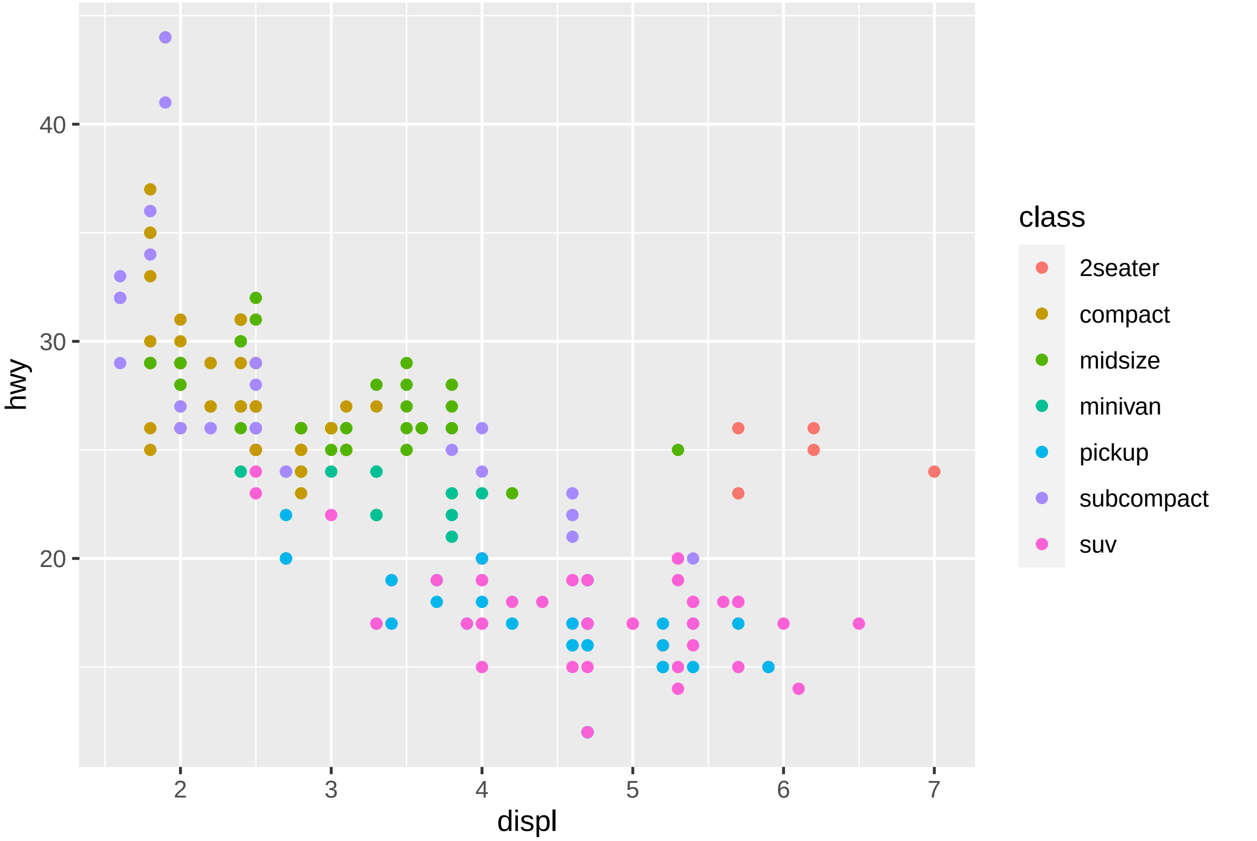


This chunk plots mpg, and puts displ on the x-axis and hwy on the y-axis.

```
# ggplot(data = <DATA>) + <GEOM_FUNCTION>(mapping =
# aes(<MAPPINGS>))
```

This chunk serves as a template for any future mapping that we do with ggplot. To make a plot, we would replace the bracketed sections in the code below with a dataset, a geom function, or a collection of mappings

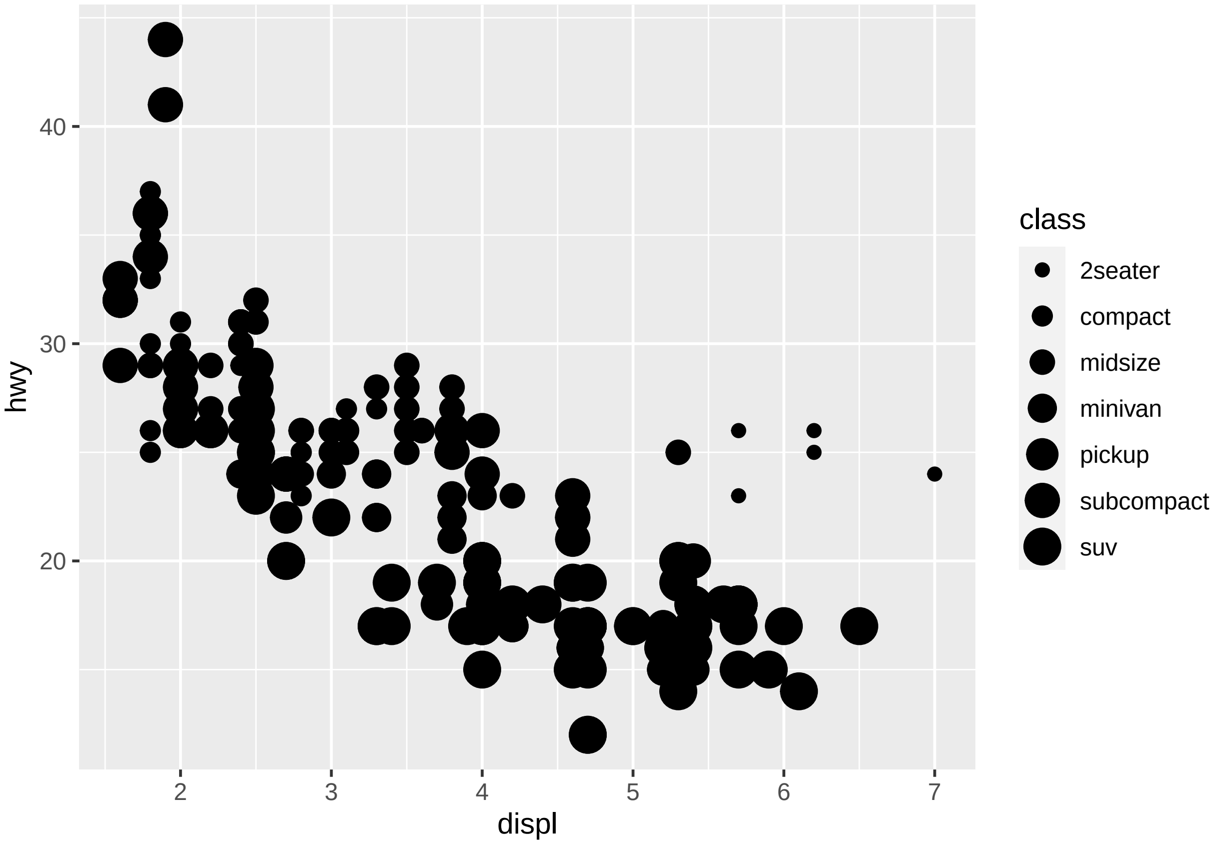
```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy,
    color = class))
```



This is an example of the template in use. In this case, by using the aesthetics feature of ggplot, we are allowing the car class to be displayed by color. The process of assigning a unique aesthetic is known as scaling.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy,
    size = class))
```

```
## Warning: Using size for a discrete variable is not advised.
```

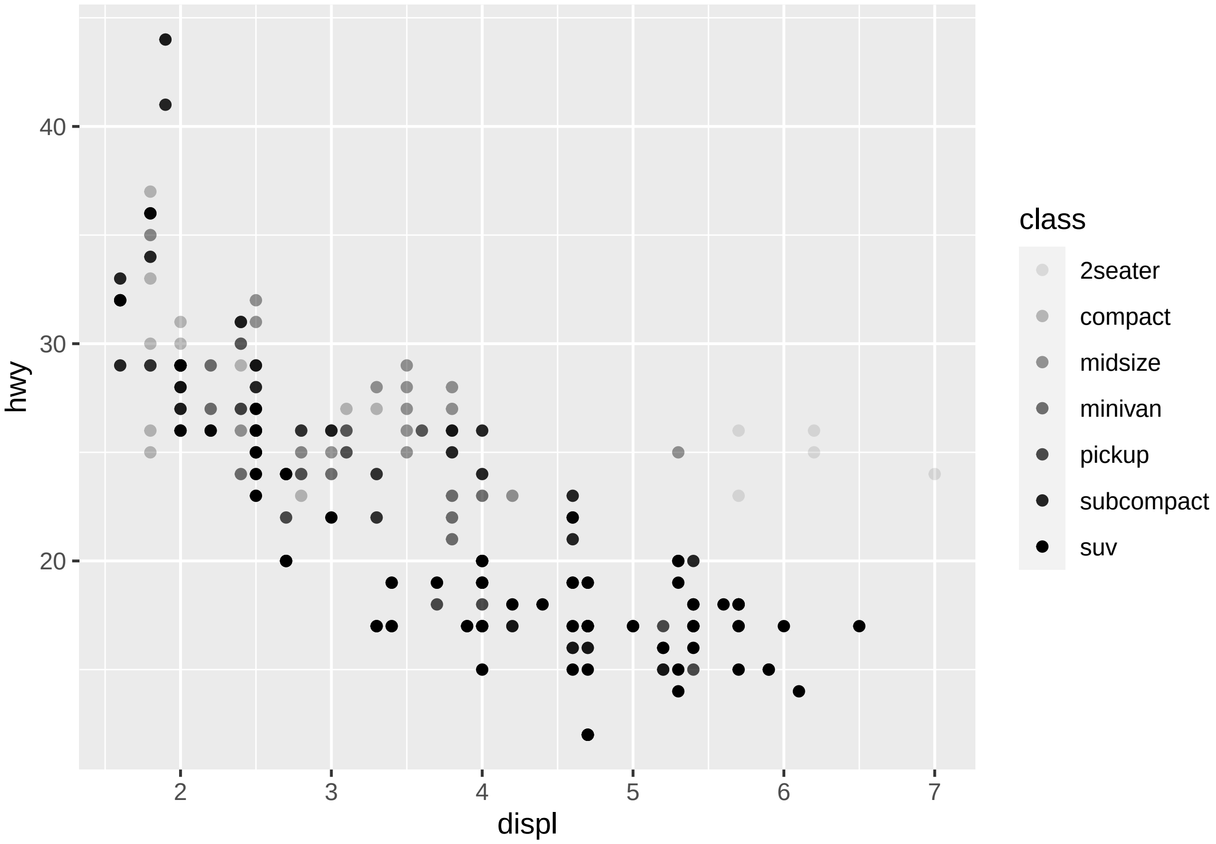


```
# > Warning: Using size for a discrete variable is not
# advised.
```

This is an example of using aesthetics in a non-advisable way. In contrast with the example above, where color is used to mark the class of the car, size is used instead, prodiucing a very confusing output, especially given that "class" is a discrete variable.

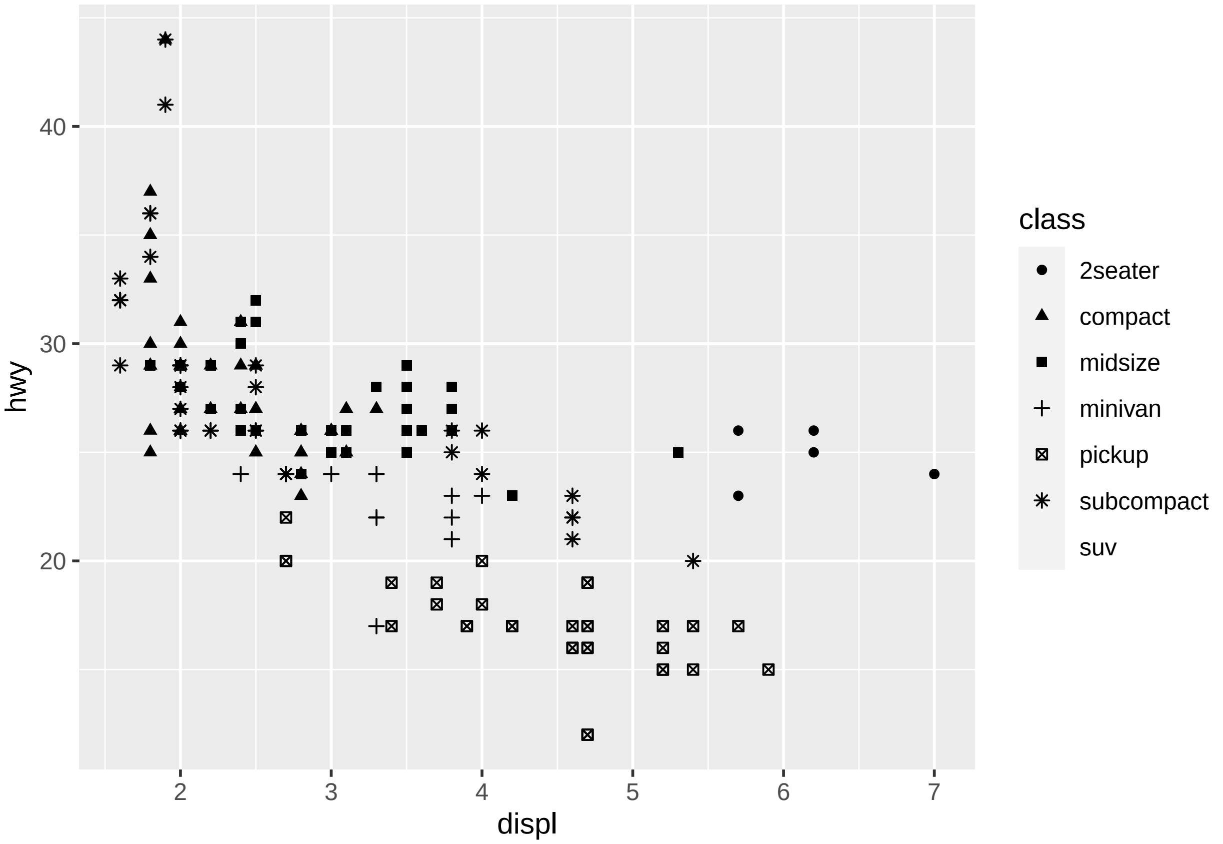
```
# Left
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy,
    alpha = class))
```

```
## Warning: Using alpha for a discrete variable is not advised.
```



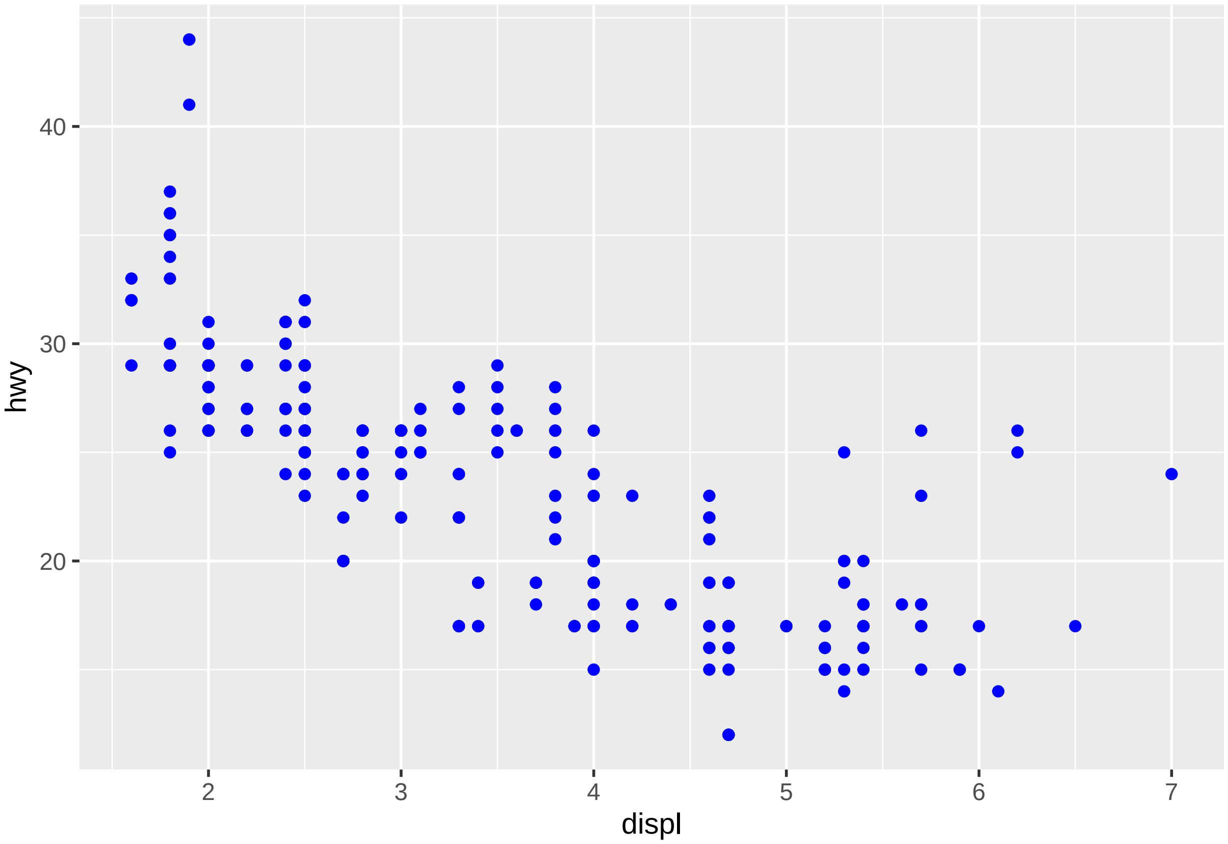
```
# Right
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy,
    shape = class))
```

```
## Warning: The shape palette can deal with a maximum of 6 discrete values because
## more than 6 becomes difficult to discriminate; you have 7. Consider
## specifying shapes manually if you must have them.

## Warning: Removed 62 rows containing missing values (geom_point).
```



This is yet another example of mapping aesthetics with GGplot. The first one maps class to the alpha aesthetic, which controls the transparency of the points, and the second one maps class to the shape aesthetic, which controls the shape of the points.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy),
    color = "blue")
```

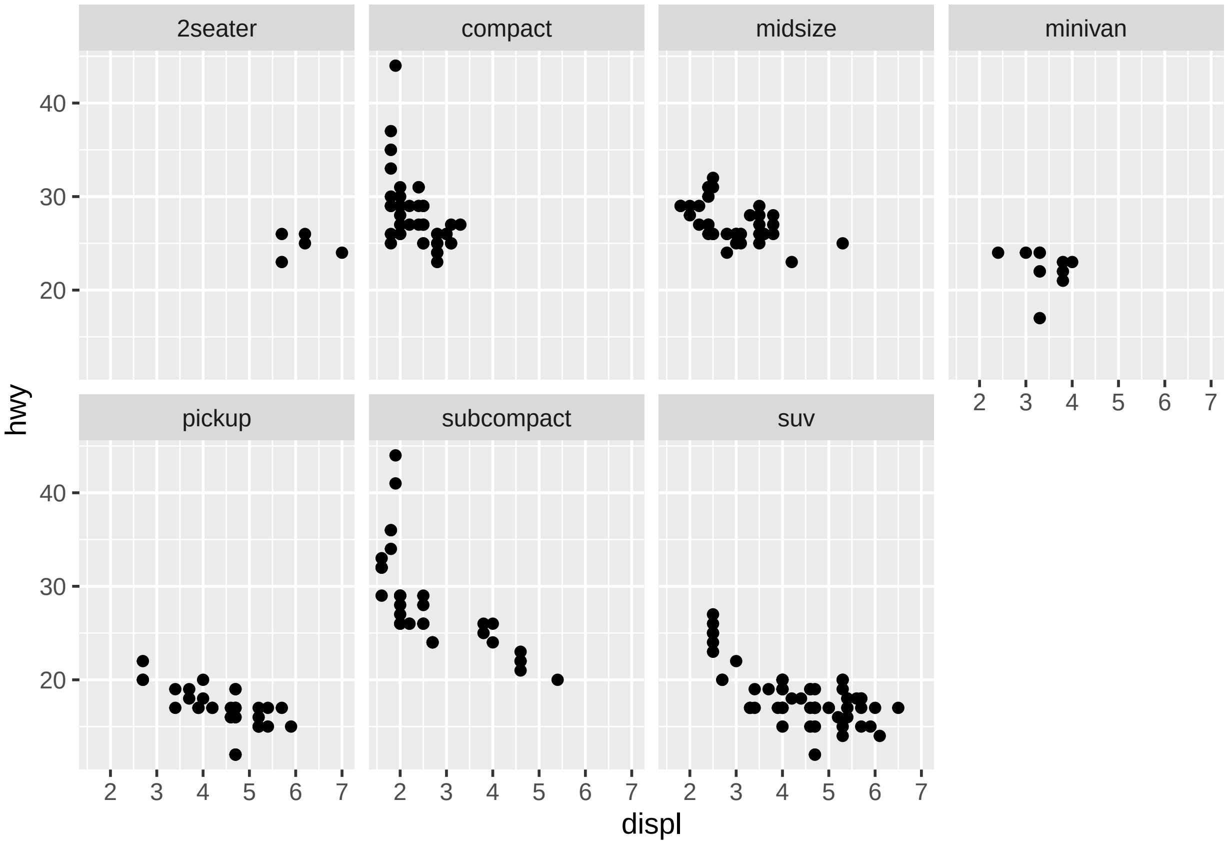


While we can use the aesthetics feature to convey information about different variables, we can also just change colors and shapes normally. The information within the aes function tells ggplot to use color, shape, size, etc. to give information about the data. Here, the instruction for color = blue is outside the aes function, allowing it to apply to all data points.

```
# ggplot(data = mpg)
#+ geom_point(mapping = aes(x = displ, y = hwy))
```

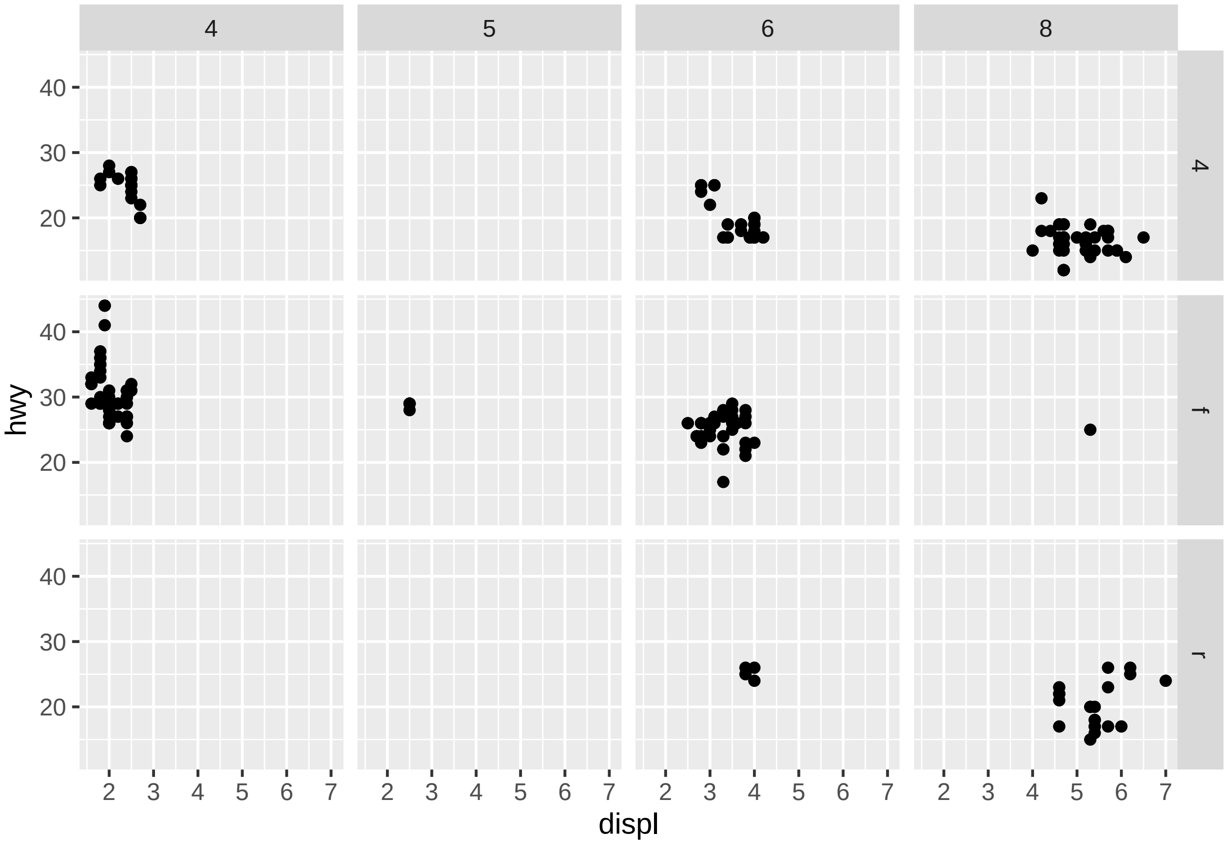
This is an example of a mistake in ggplot. The + needs to come at the end of the first line, rather than at the beginning of the second line.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    facet_wrap(~class, nrow = 2)
```



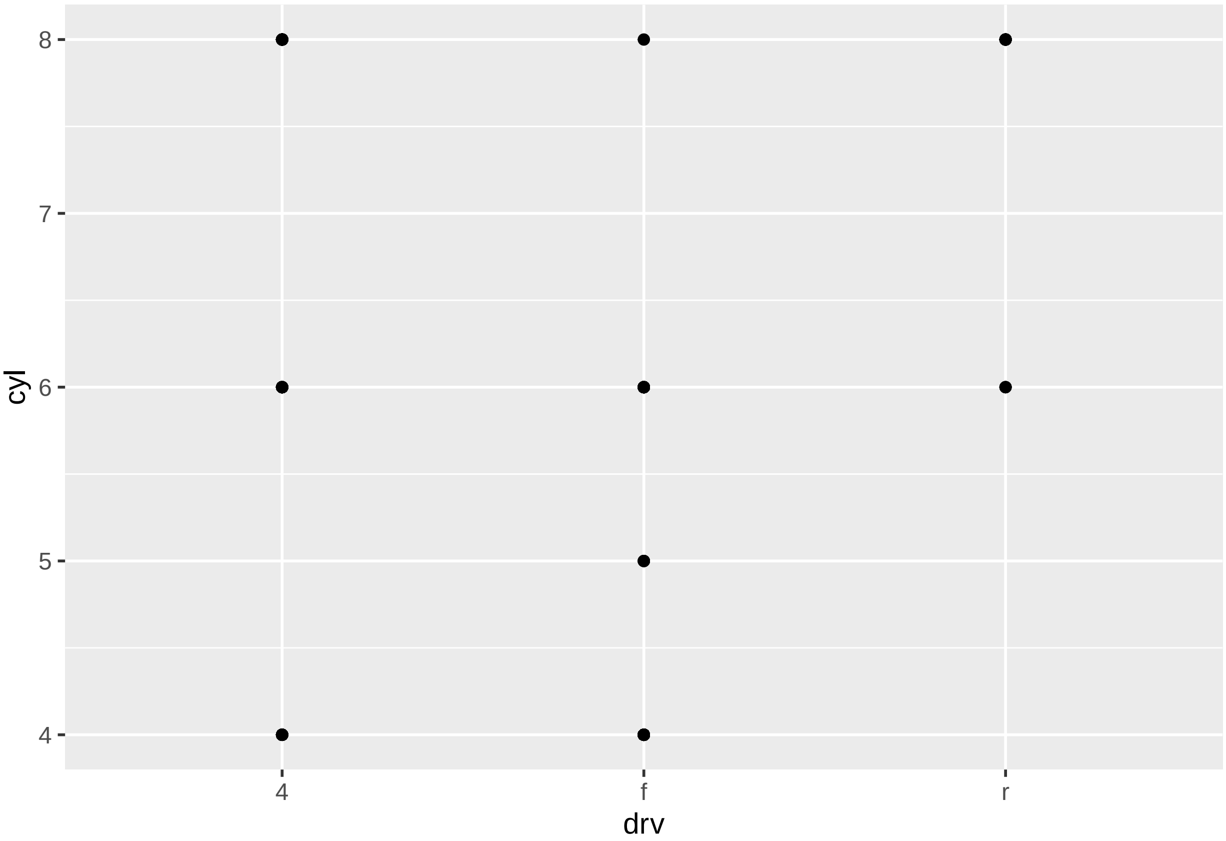
In order to split our data into separate categories, we can use the facet function in ggplot, allowing you to plot different categories of data. This code tells ggplot to plot mpg with displ and hwy, but to split it up into different graphs based on one variable (class), and to have these graphs in 2 different rows.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    facet_grid(drv ~ cyl)
```



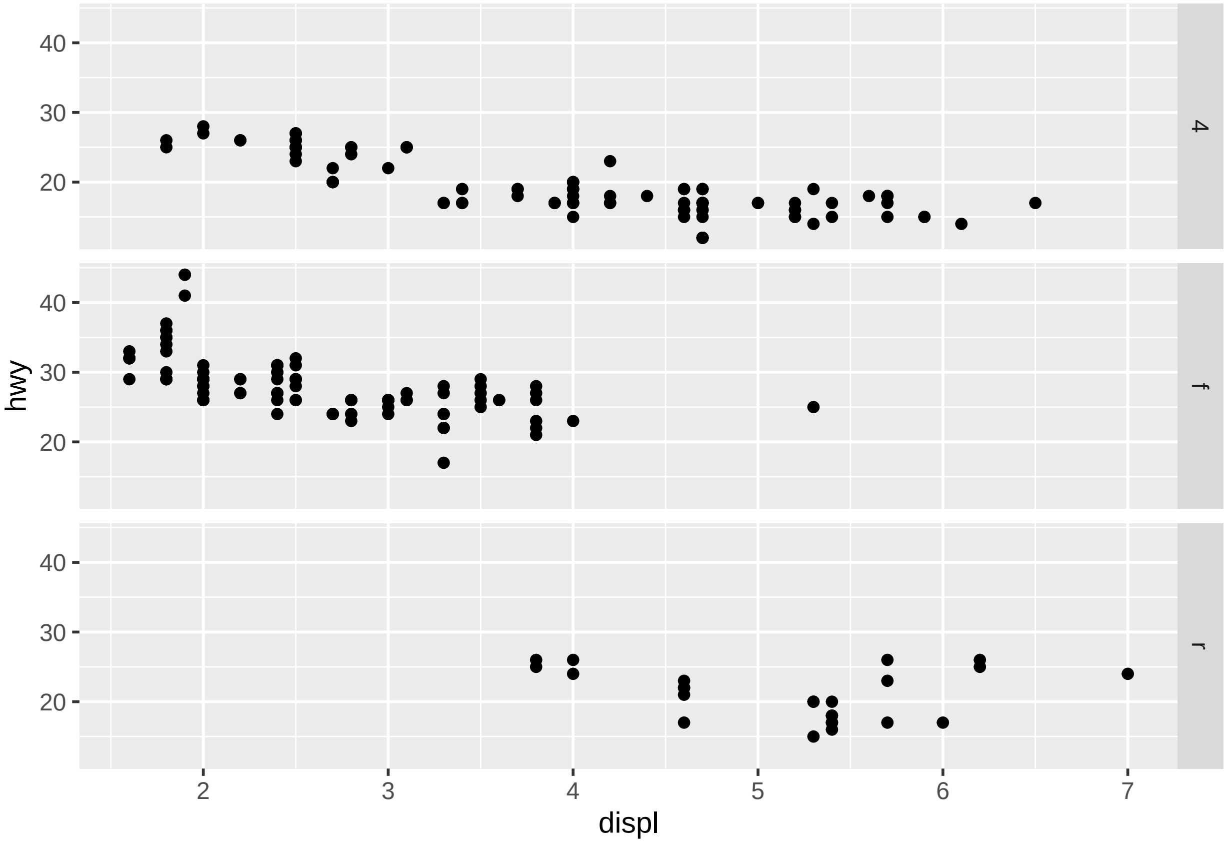
This code tells ggplot to split the data visualization up based on two different variables. Just like the first facet function, this facet_grid will display data based on variables, but allows there to be a plot of two different variables that devide the data up between displays. This creates a grid, hence, facet_grid. The formula should contain two variable names separated by a ~

```
ggplot(data = mpg) + geom_point(mapping = aes(x = drv, y = cyl))
```

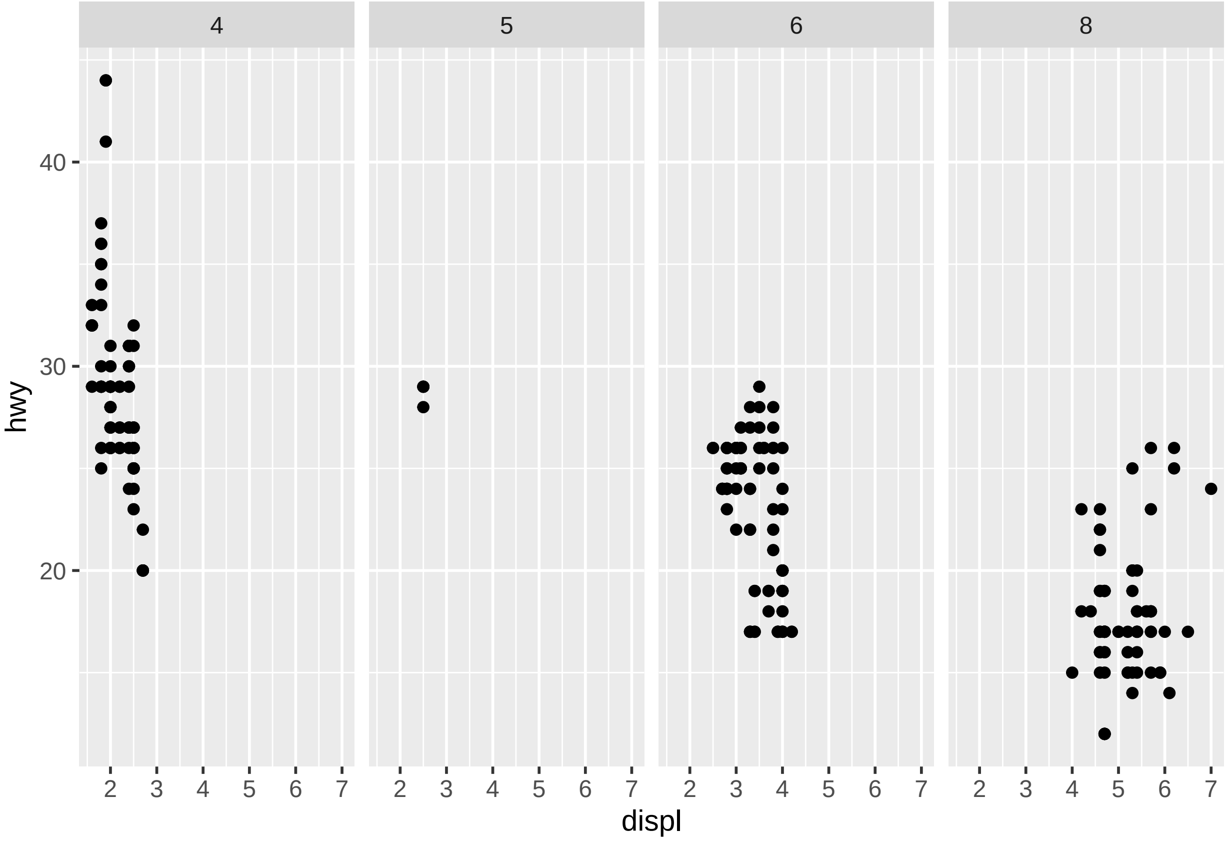


This code tells ggplot to create a scatterplot to display the relationship between drv and cyl.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    facet_grid(drv ~ .)
```

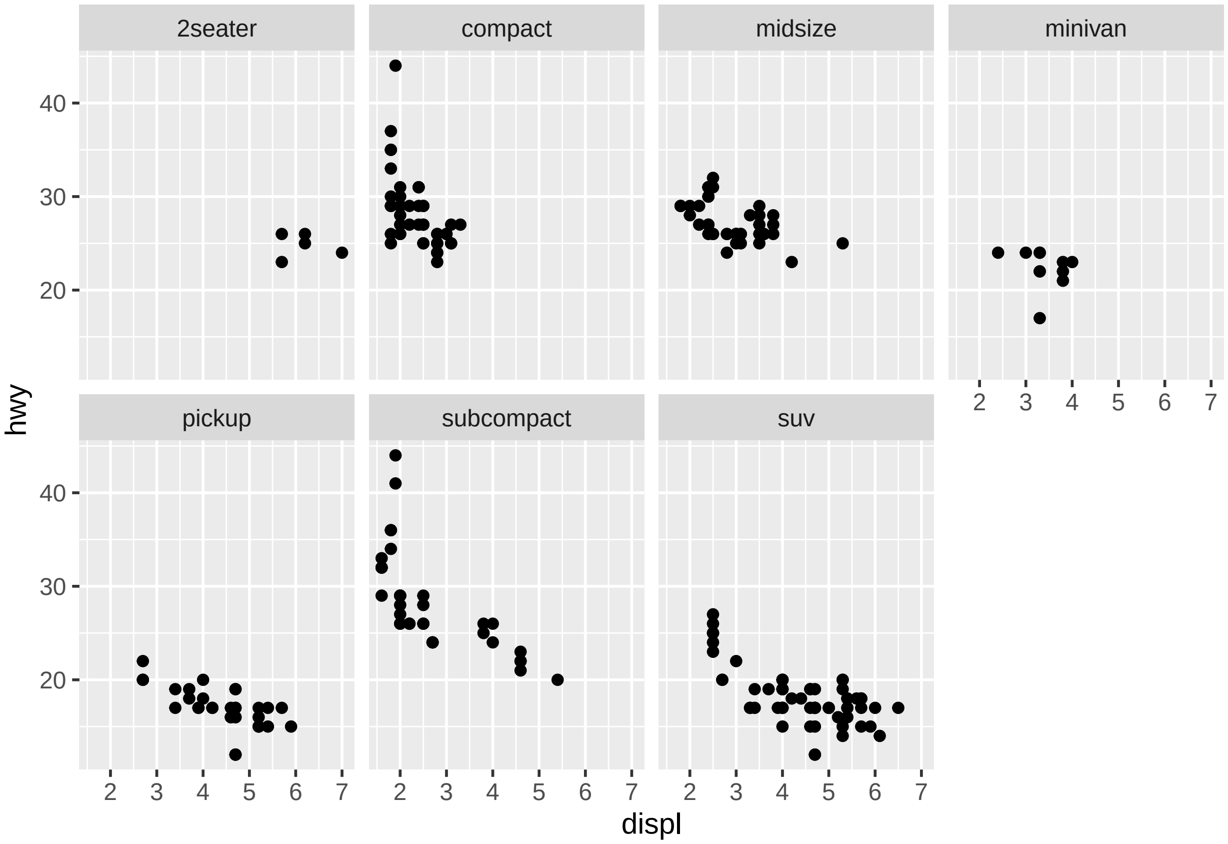


```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    facet_grid(. ~ cyl)
```



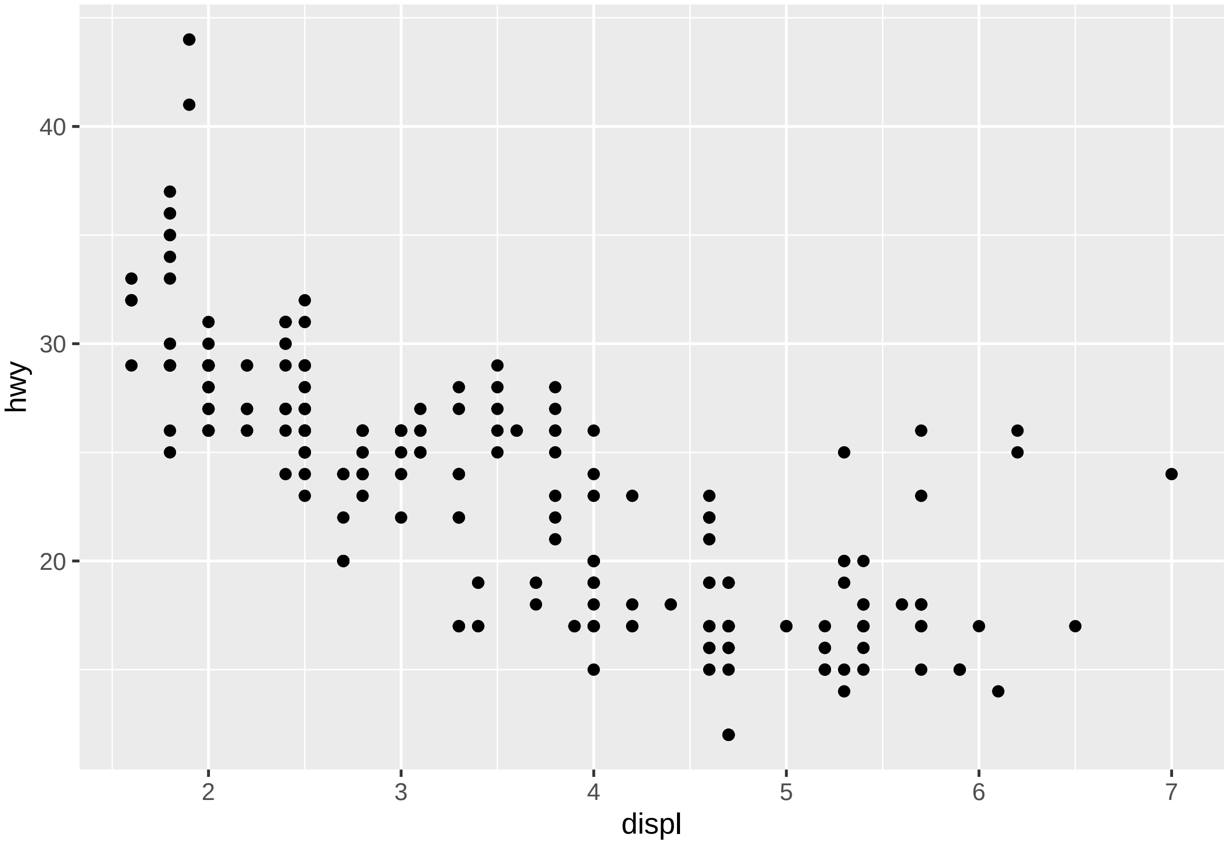
These two code chunks demonstrate how to create facets specifically within rows and columns. Making a grid, and having the "." as one of the variables, allows ggplot to make a 1xn or nx1 grid displaying the facets.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    facet_wrap(~class, nrow = 2)
```



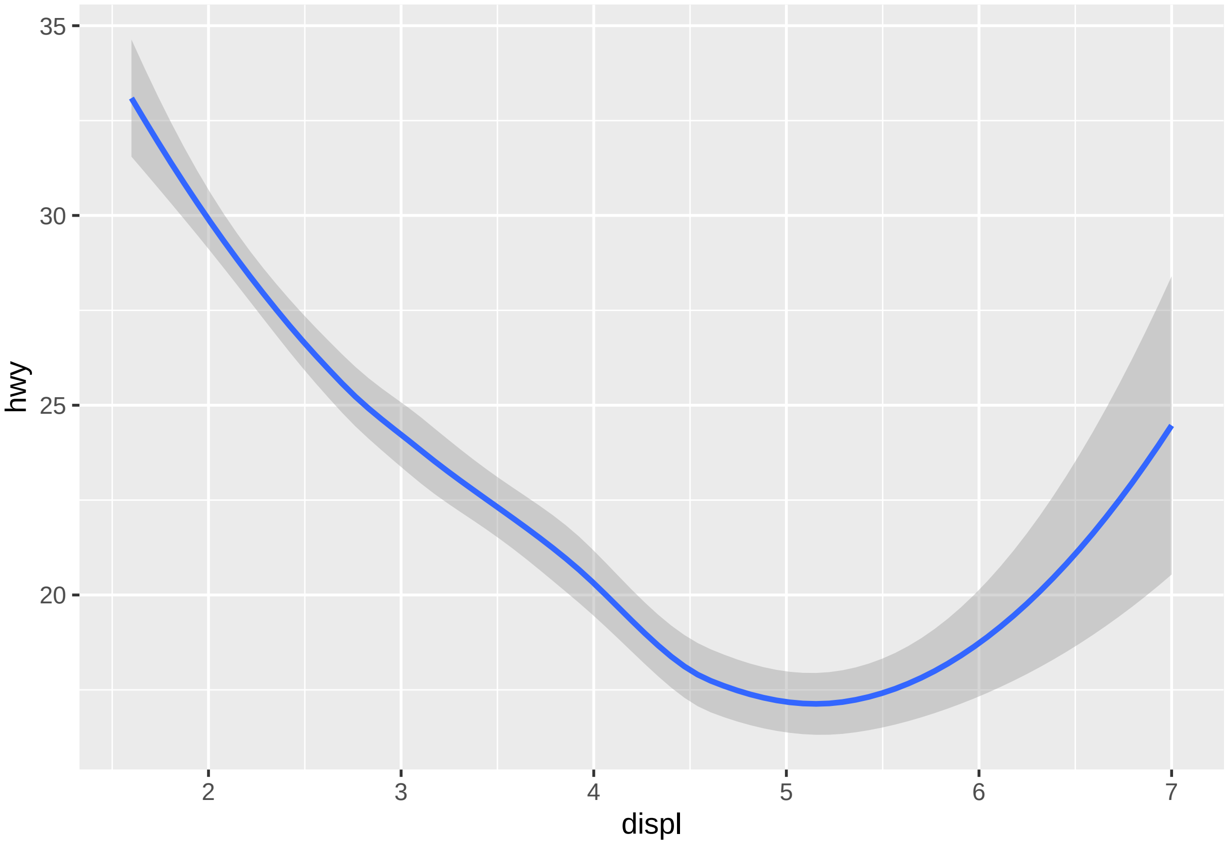
This code makes the class of car into the facet that ggplot will devide up the data based on. This mapping could be a better option compared to color aesthetic matching because it helps more clearly delineate patterns within car class, and with larger data sets, would avoid colors looking very similar to one another. It is just a more effective way of organizing.

```
# left
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy))
```



```
# right
ggplot(data = mpg) + geom_smooth(mapping = aes(x = displ, y = hwy))
```

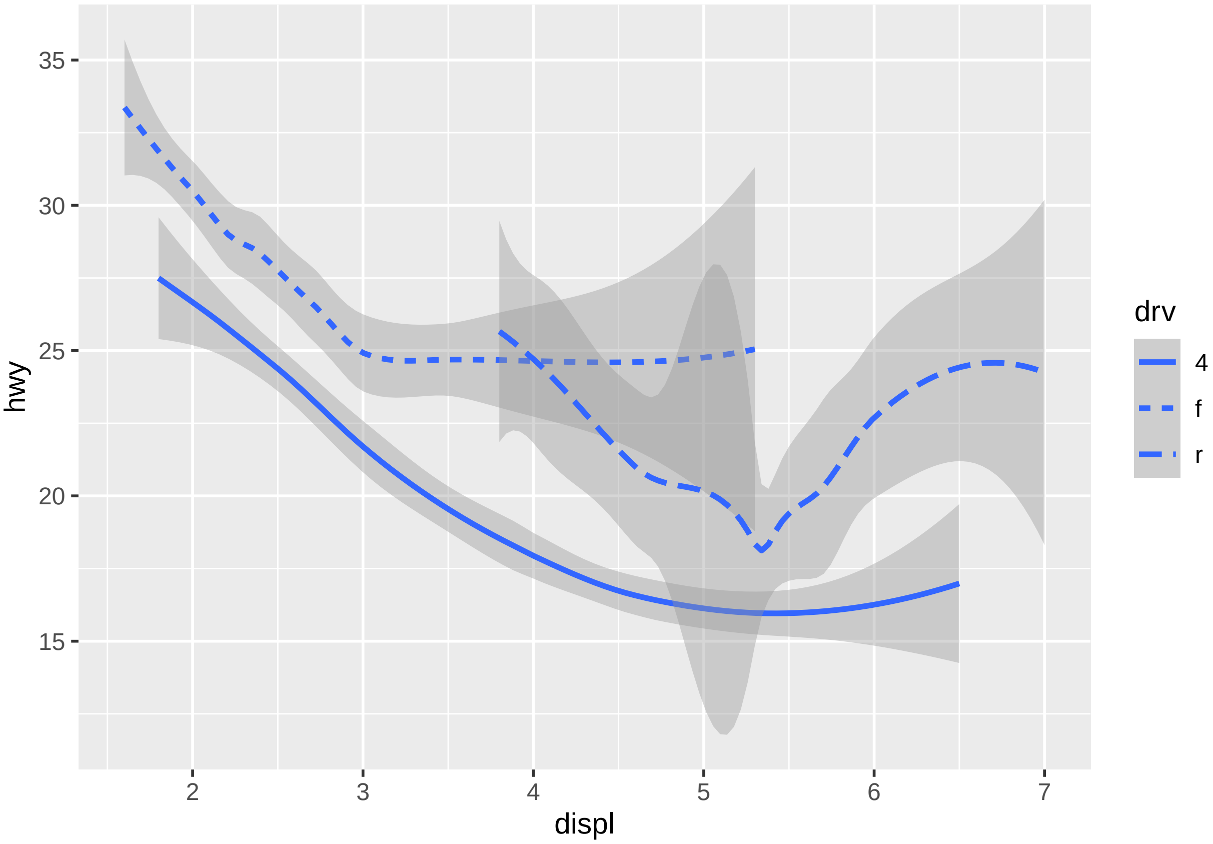
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



The first example is an example of code that maps a scatterplot with ggplot. The mapping instruction of geom_point tells ggplot to make a scatterplot. In the second example, that instruction is changed to geom_smooth, which makes a smooth line fitted to the data. They still both rely on x and y as their variables, but display the data in different ways.

```
ggplot(data = mpg) + geom_smooth(mapping = aes(x = displ, y = hwy,
    linetype = drv))
```

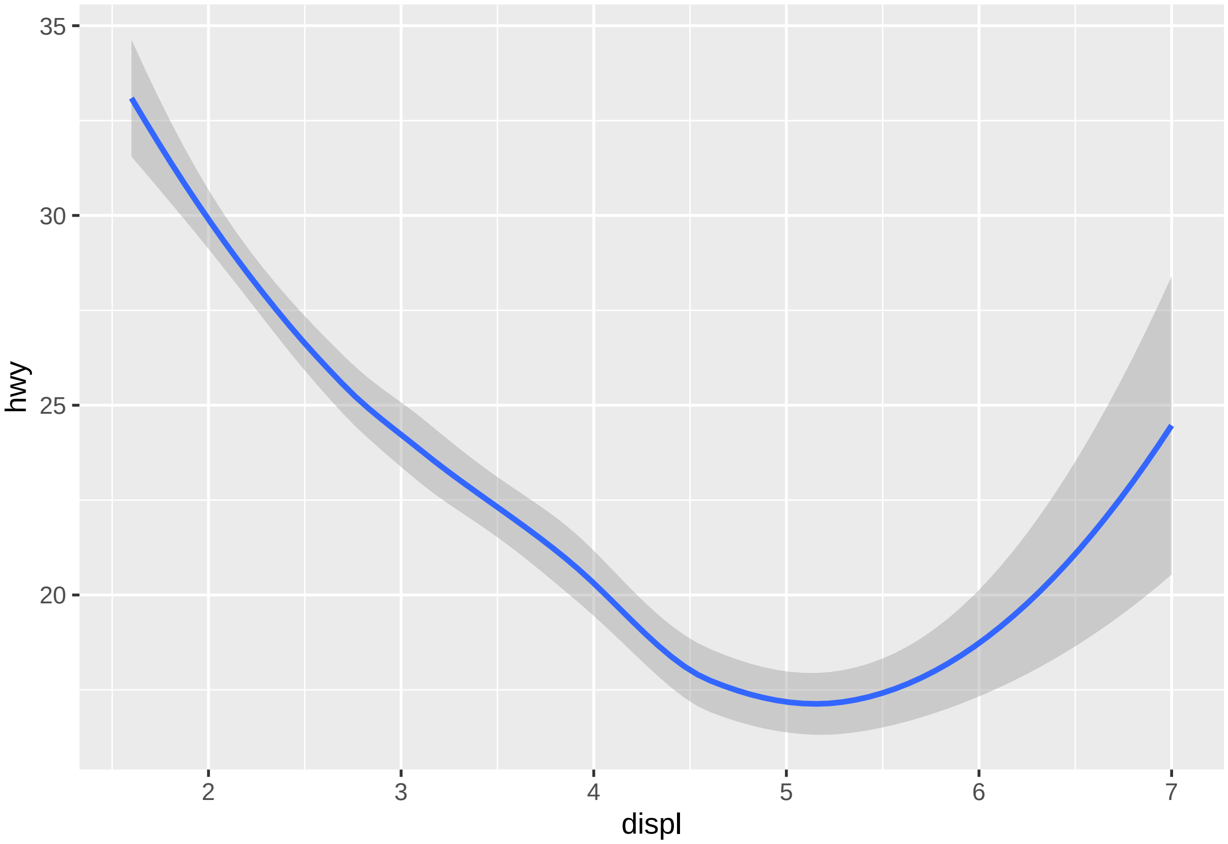
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



This code is an example of how to correctly use aesthetics mapping for smooth line displays. If you wanted to change the shape of the points in the scatterpolot, you would set the shape within the aesthetics argument. However, within the geom_smooth function, you need to set the linetype, rather than trying to set the shape. This will draw a different line, with a different linetype, for each unique value of the variable given, here being drv.

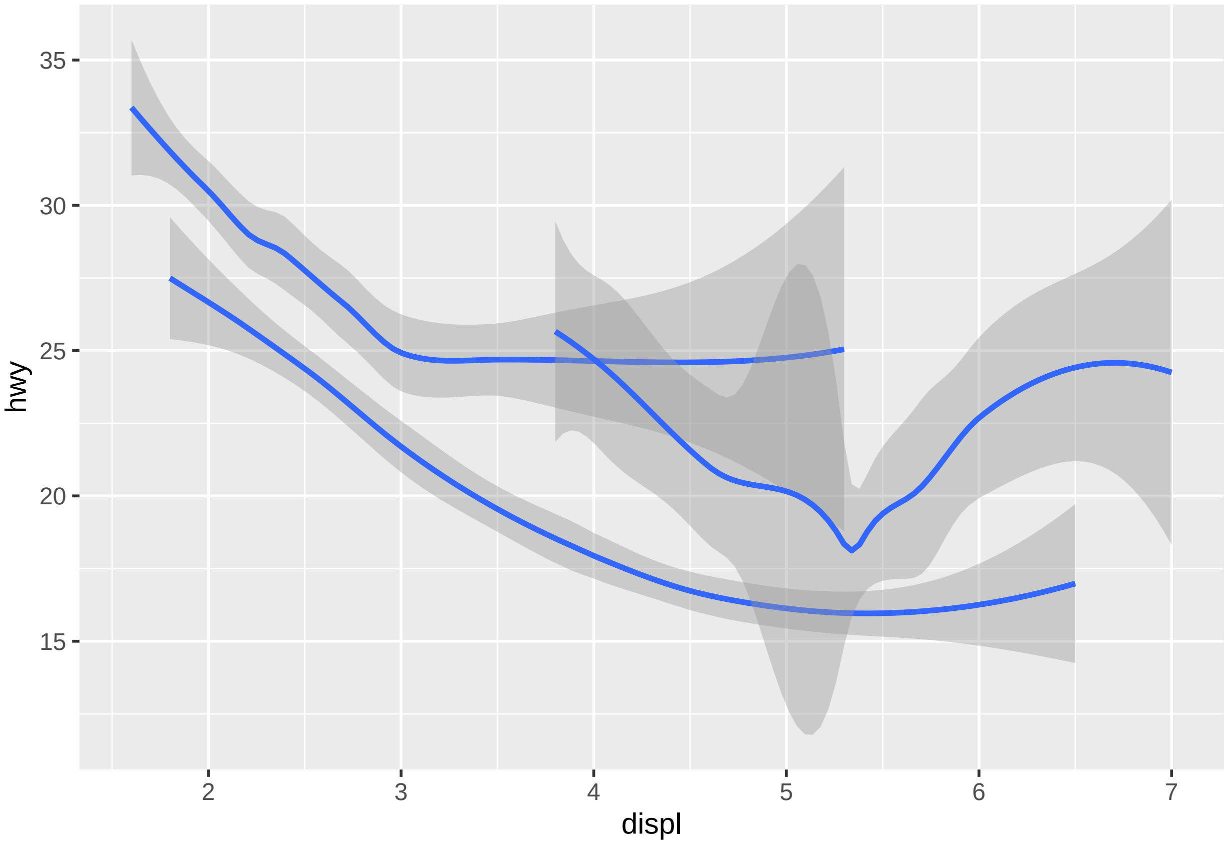
```
ggplot(data = mpg) + geom_smooth(mapping = aes(x = displ, y = hwy))
```

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



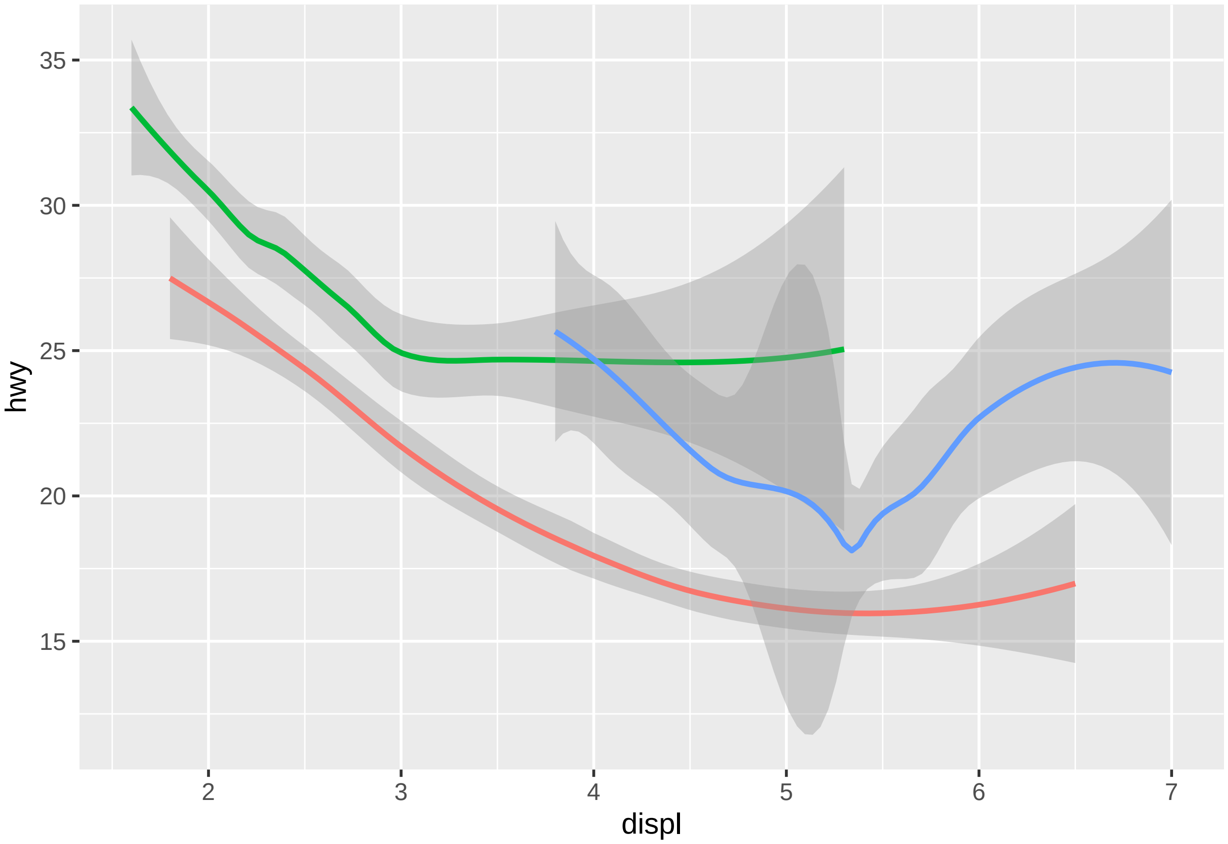
```
ggplot(data = mpg) + geom_smooth(mapping = aes(x = displ, y = hwy,
    group = drv))
```

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



```
ggplot(data = mpg) + geom_smooth(mapping = aes(x = displ, y = hwy,
    color = drv), show.legend = FALSE)
```

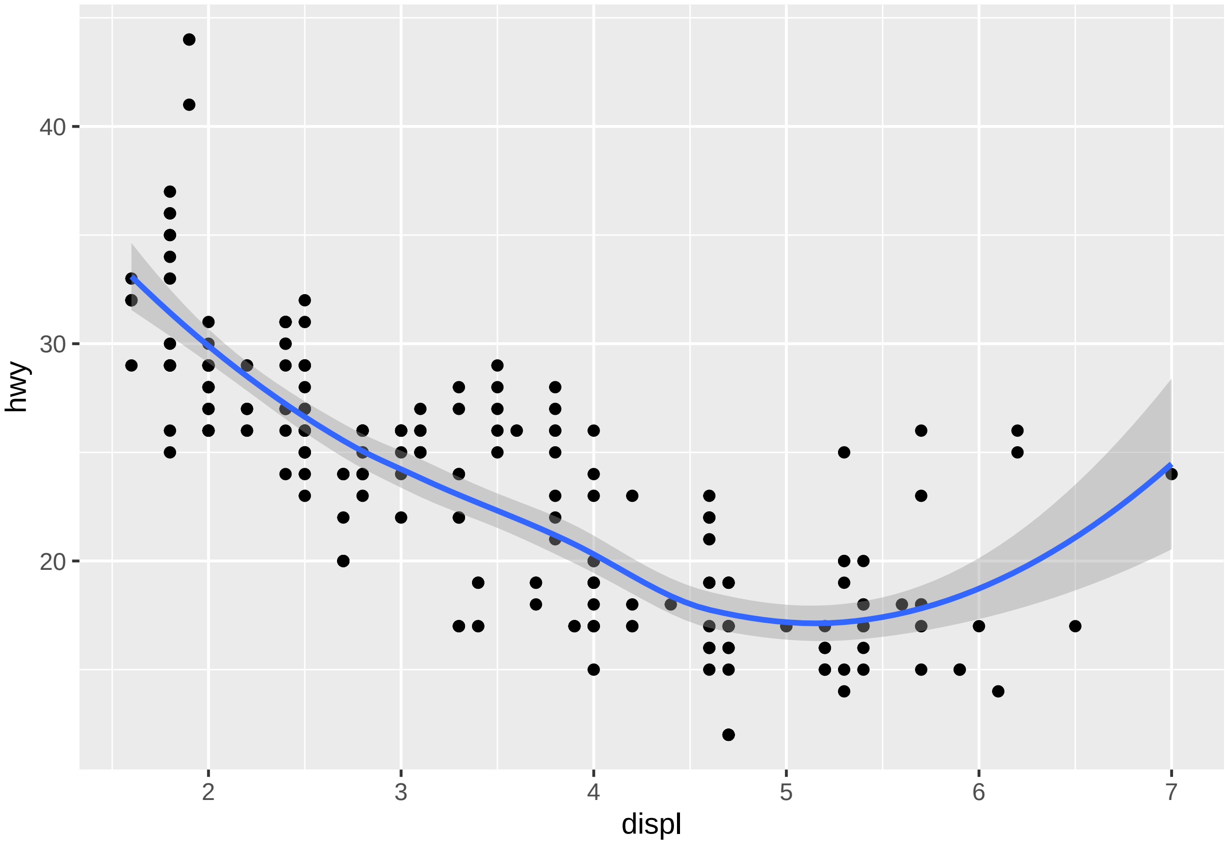
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Here, there are three different plots. The first one just plots a smoothed line of x and y, the second plots smoothed lines of x and y for each aspect of the drv variable, and the third one makes each line based on the drv variable a different color. In order to do the second version, you use the grouping command within aesthetics, and the third one, you use the color command.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy)) +
    geom_smooth(mapping = aes(x = displ, y = hwy))
```

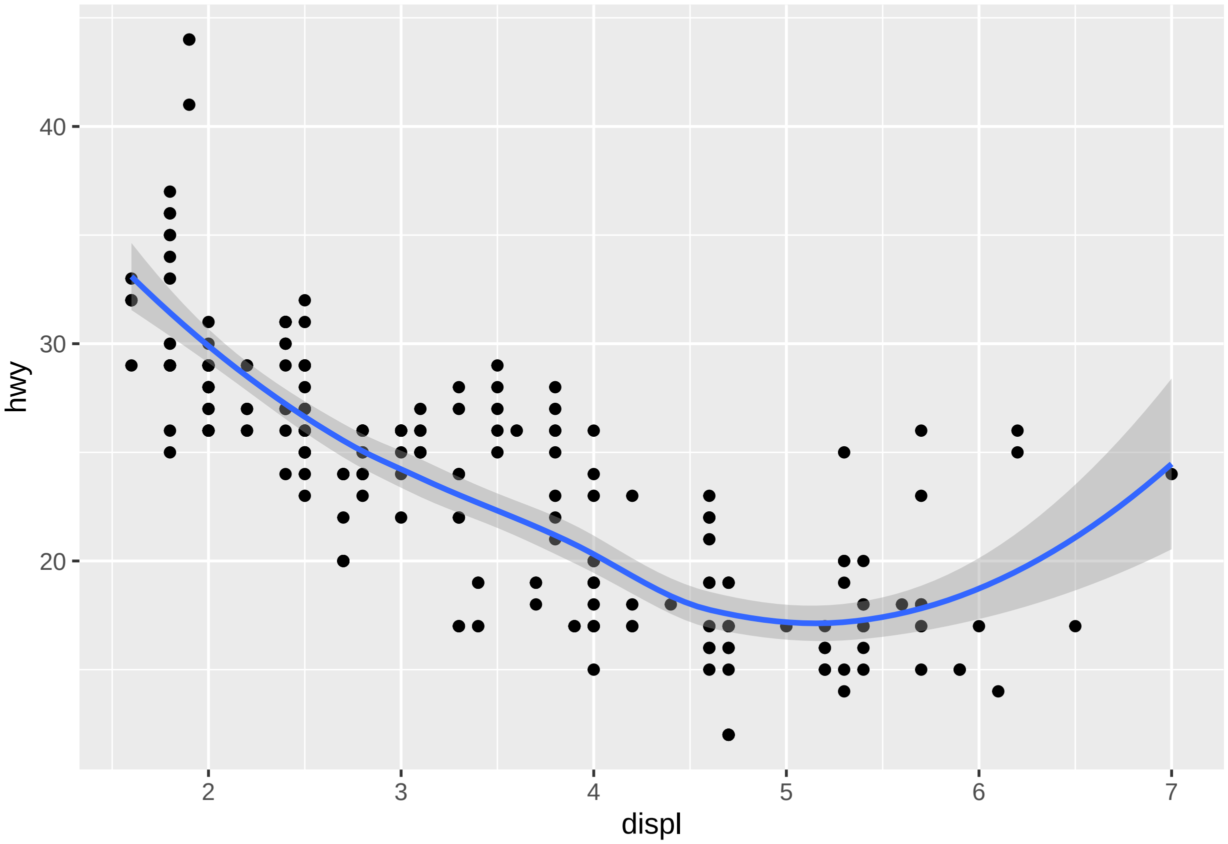
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



By adding an additional line to this code, it tells ggplot to plot two geoms on the same plot. It is important to remember to add the + sign at the end of the first and second lines, rather than at the beginning of the line below. This is just plotting the scatterplot on top of the smoothed line plot.

```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) + geom_point() +
    geom_smooth()
```

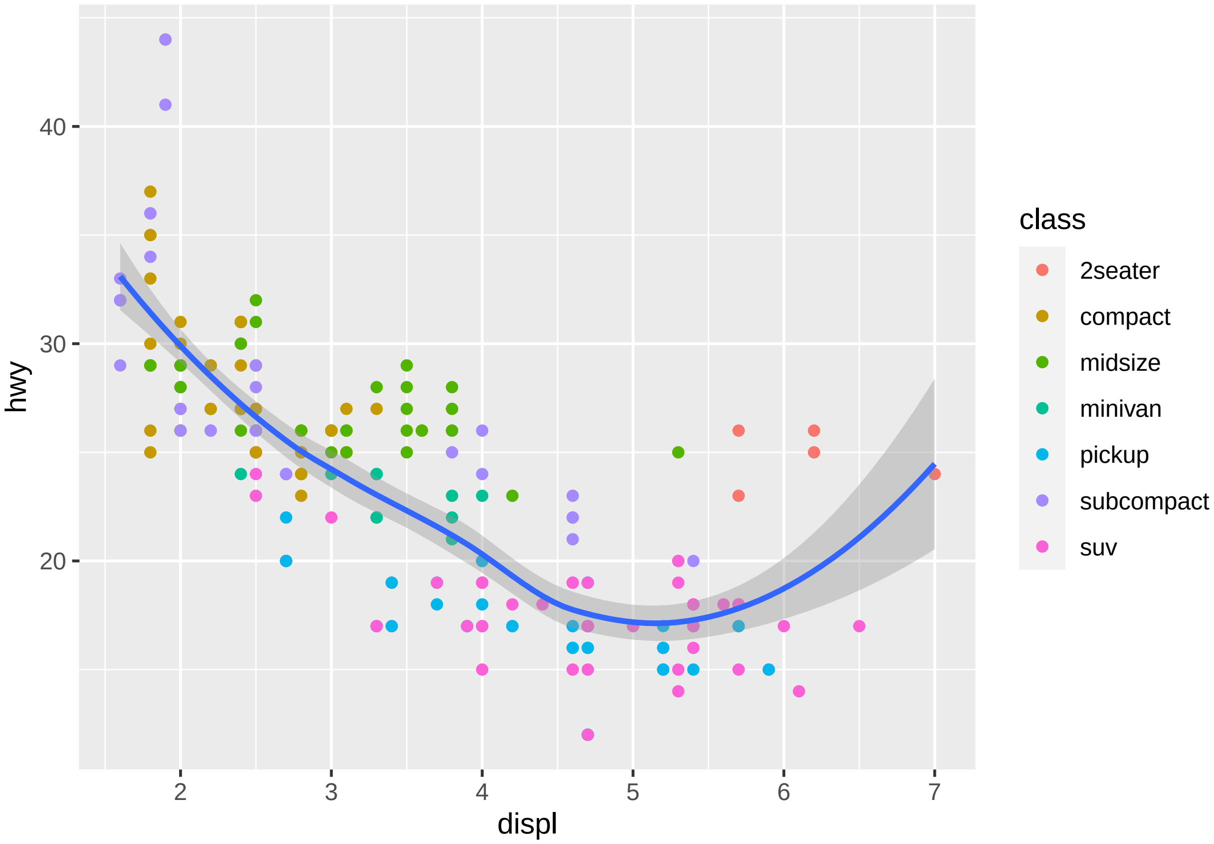
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



This chunk is a more user-friendly way of doing the same thing in the last chunk. By adding the mapping and aesthetics instructions in the first line, we can automatically apply them to the second and third lines, which helps in case you want to copy the code and change the x or y axis - you would only have to change one line, rather than 2

```
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'
```



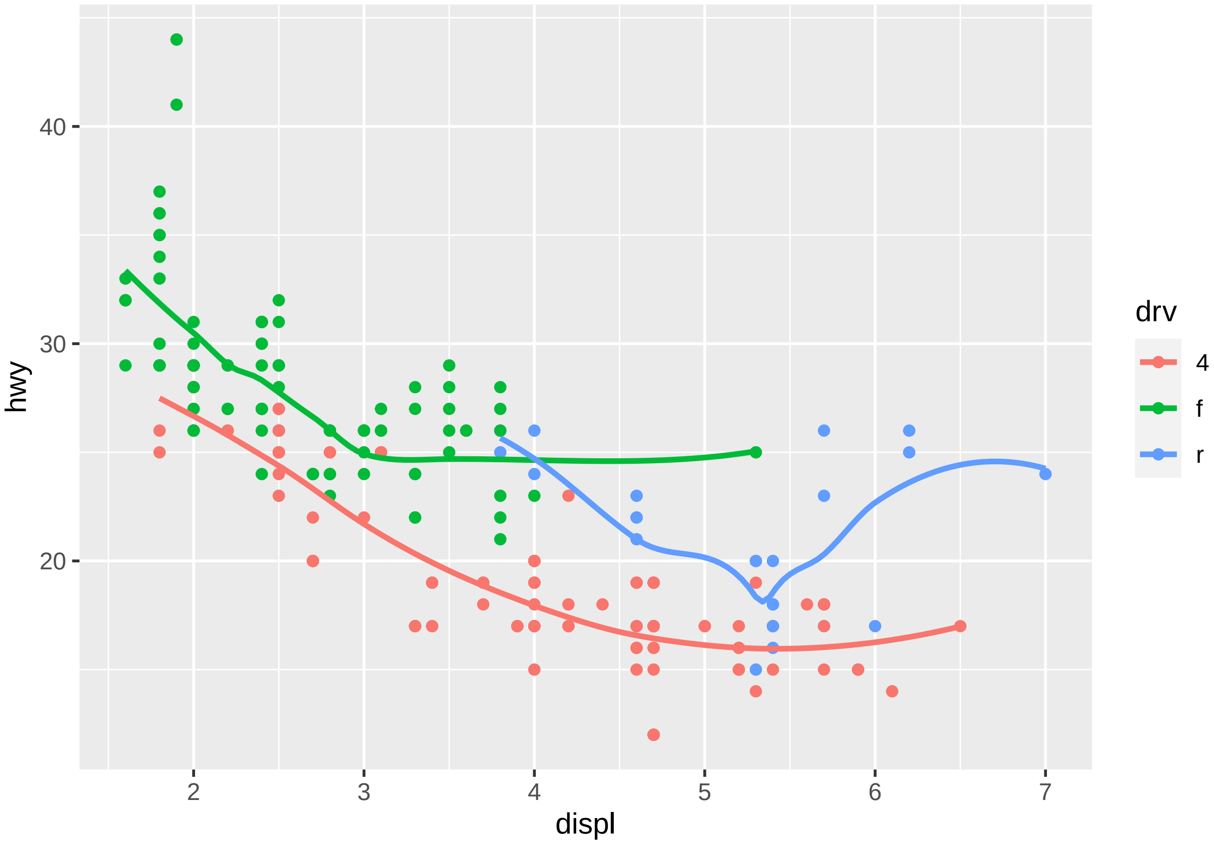
If you want to map different aesthetics for differnt layers, we can still use the more user-friendly format, but this time, we can just add specifications in the second line if we want it to do something different from the rest of the aesthetic mapping, in this case, mapping the car class with color, but the smoothed line without.

```
# ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) +
# geom_point(mapping = aes(color = class)) +
# geom_smooth(data = filter(mpg, class == 'subcompact'), se
# = #FALSE)
```

Just like the case where we wanted to apply different aesthetics to the different layers of the ggplot, we can also apply different data within the lines which overrrides the instructions from the first line. The new, third line tells ggplot to add a smooth line, but only from data that is from the subcompact class of cars, which is determined using a filter function.

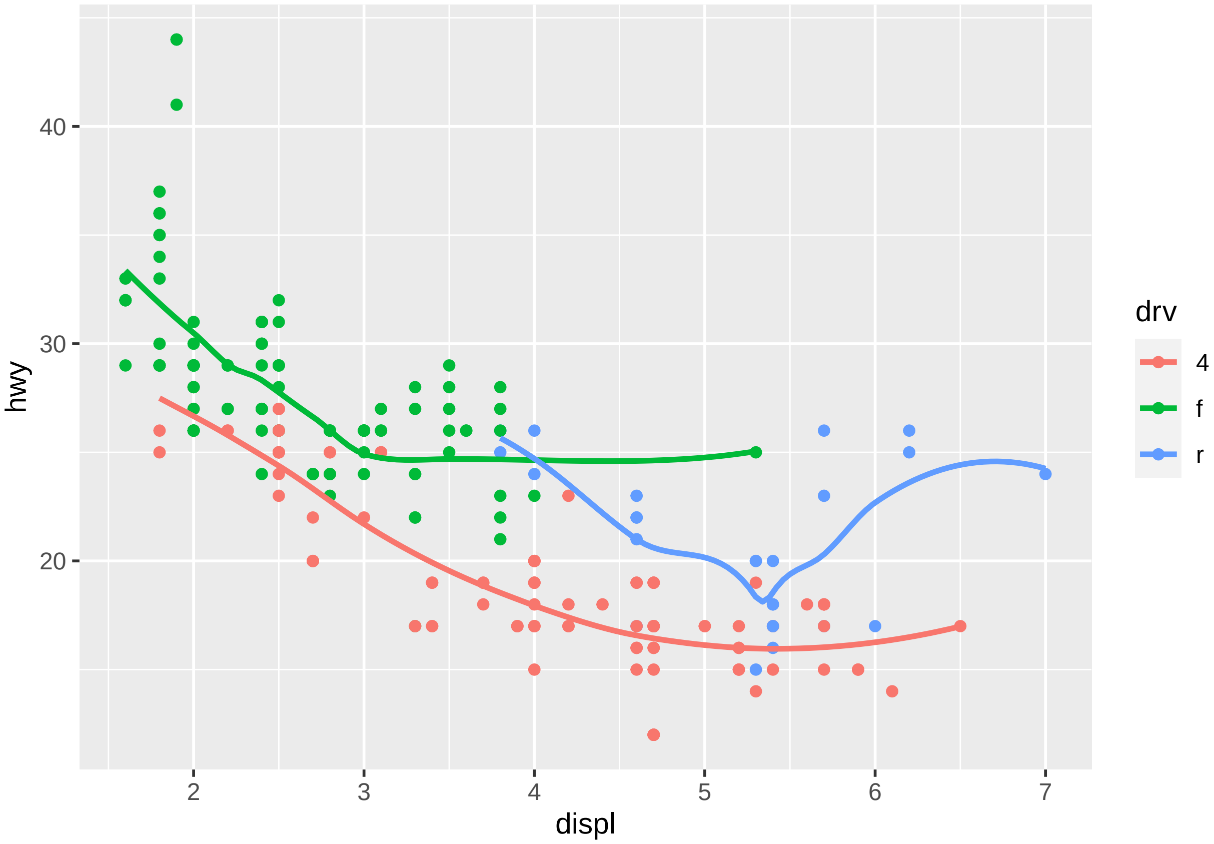
```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color = drv)) +
    geom_point() + geom_smooth(se = FALSE)
```

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



```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color = drv)) +
    geom_point() + geom_smooth(se = FALSE)
```

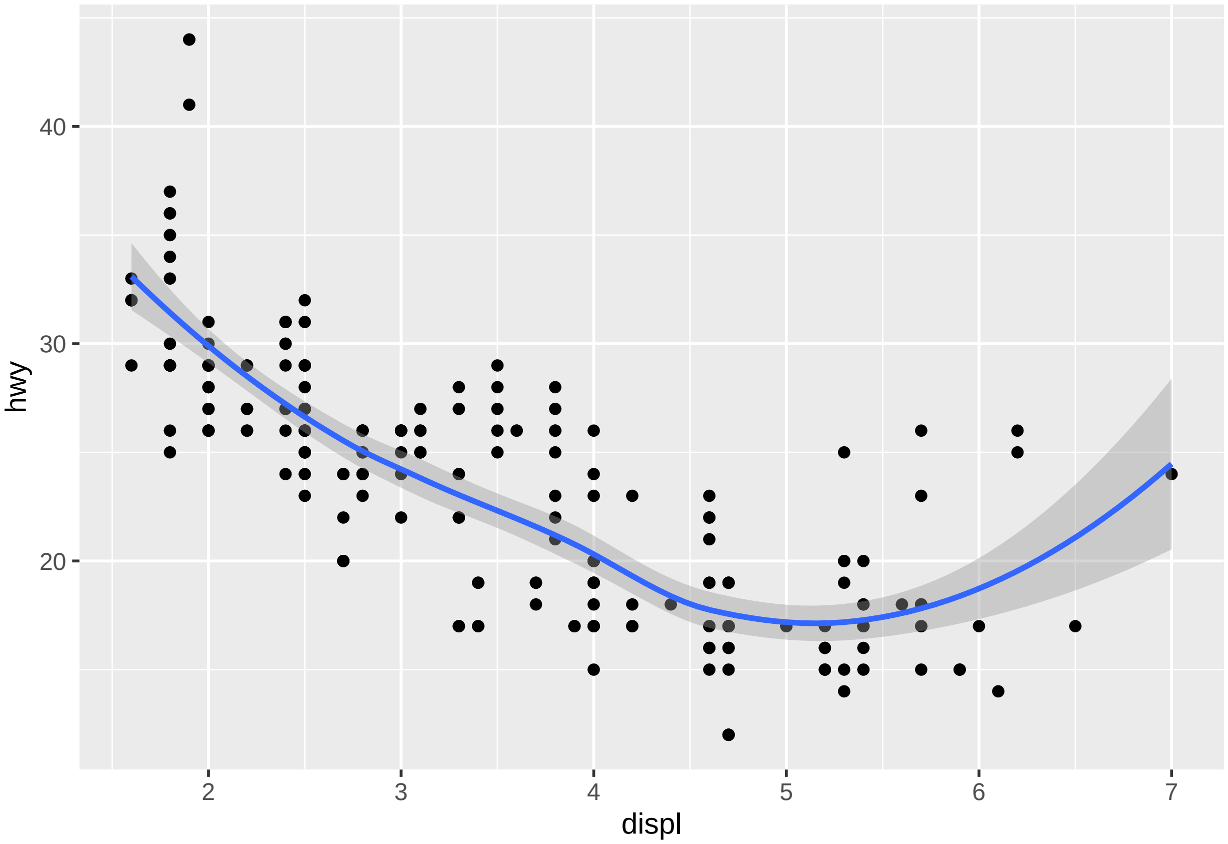
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



This chunk tells ggplot to map displ as x and hwy as y, and to do aesthetics for drv with color. The following lines say that the scatterplot and the smoothed line can use the same aesthetics mapping instructions as the global code, and the se = FALSE just tells ggplot to only display the main line, not the error

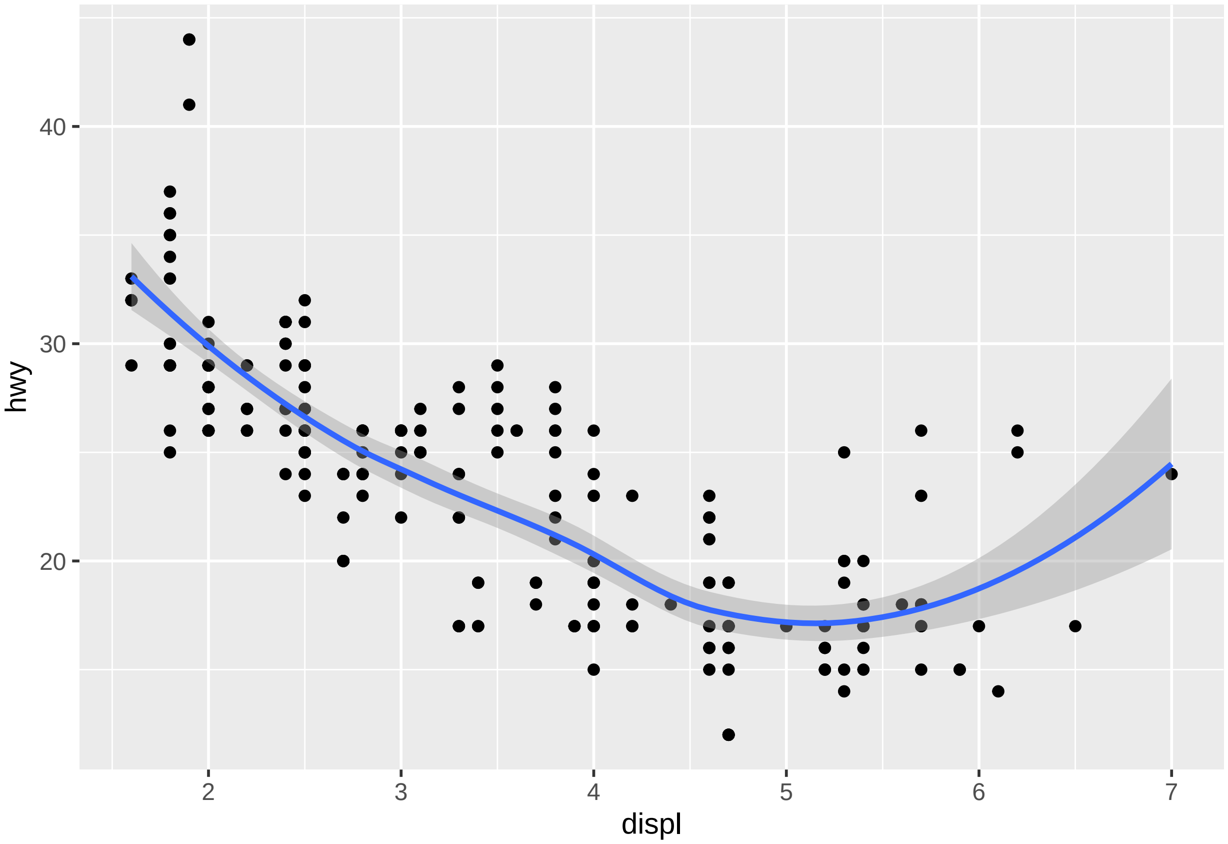
```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy)) + geom_point() +
    geom_smooth()
```

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



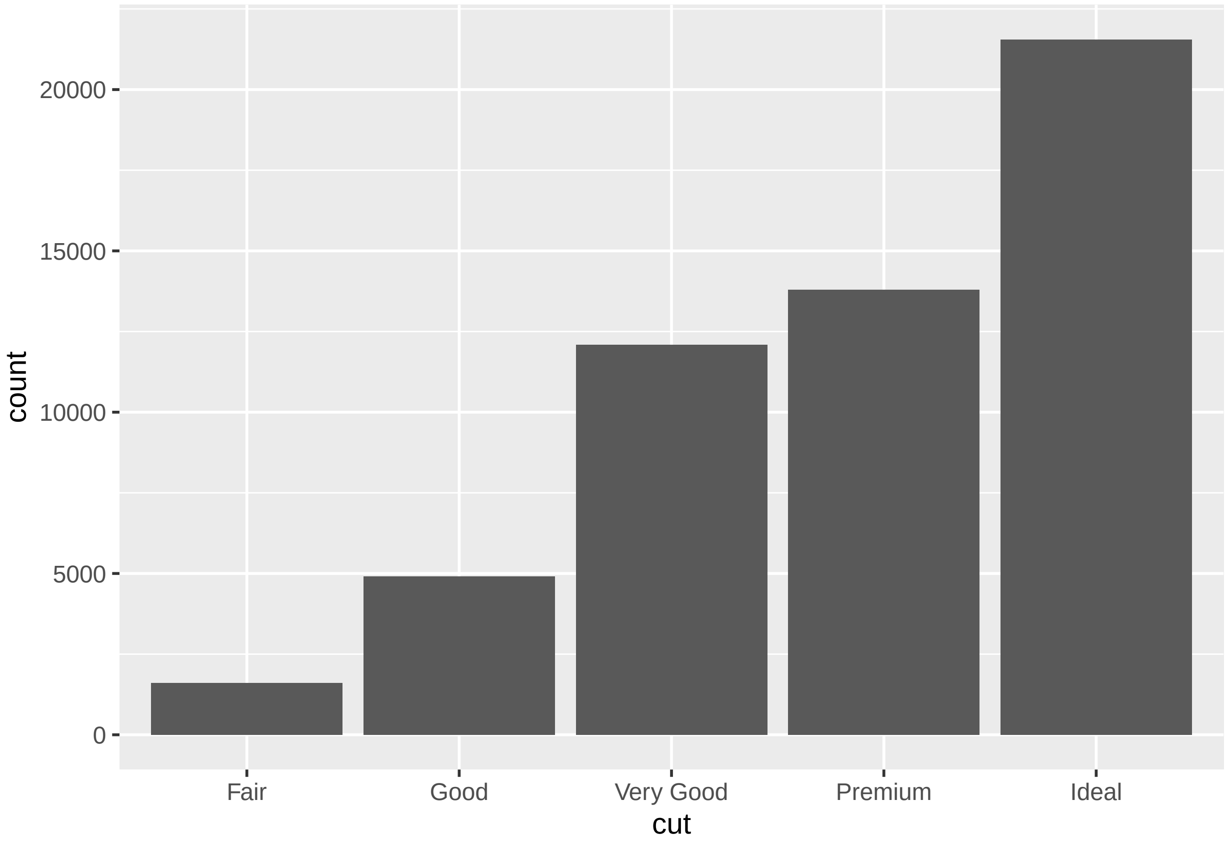
```
ggplot() + geom_point(data = mpg, mapping = aes(x = displ, y = hwy)) +
    geom_smooth(data = mpg, mapping = aes(x = displ, y = hwy))
```

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



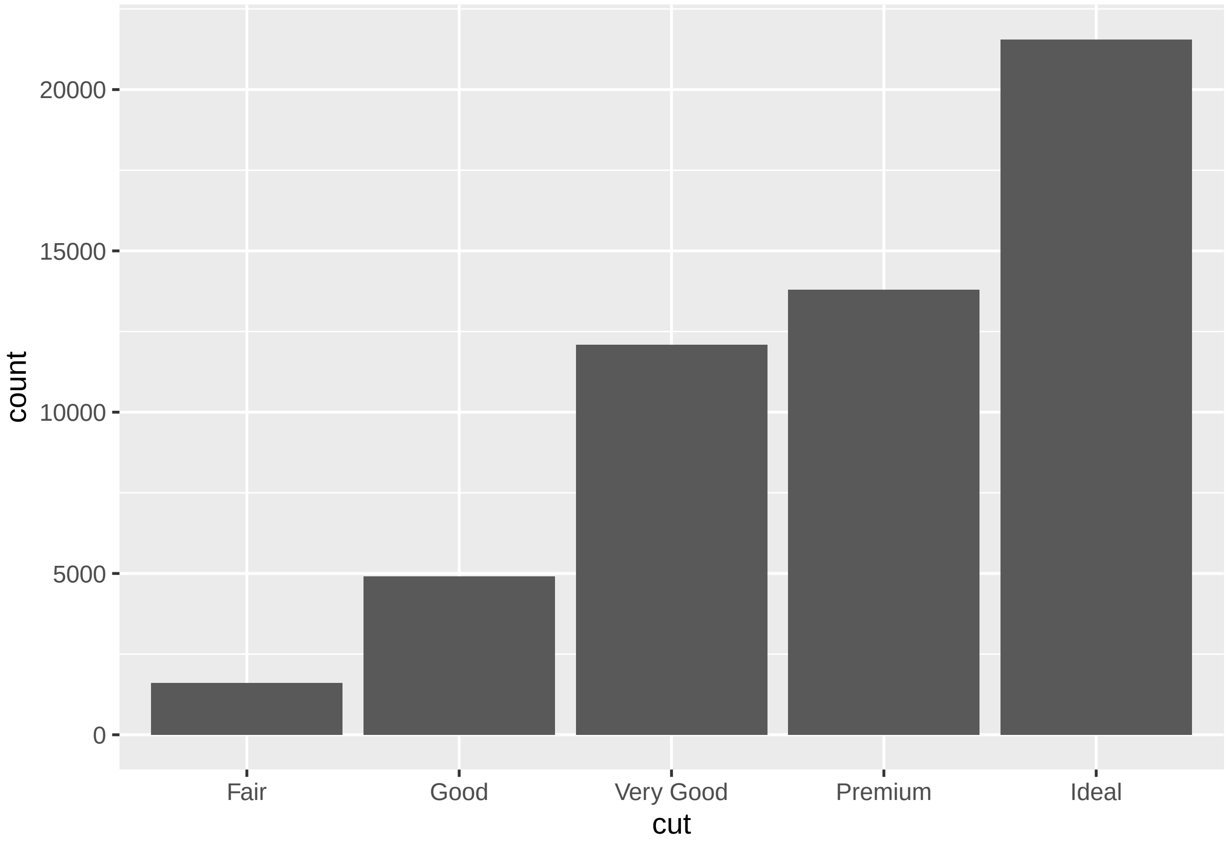
These two graphs are the same - the code may look different, but these are just different versions of the same instructions.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut))
```



This is how to create a bar chart in ggplot. The data is from a new datasource about diamonds, and the aesthetics mapping is telling ggplot to put the cut of the diamond on the x axis, with the count on they y axis

```
ggplot(data = diamonds) + stat_count(mapping = aes(x = cut))
```

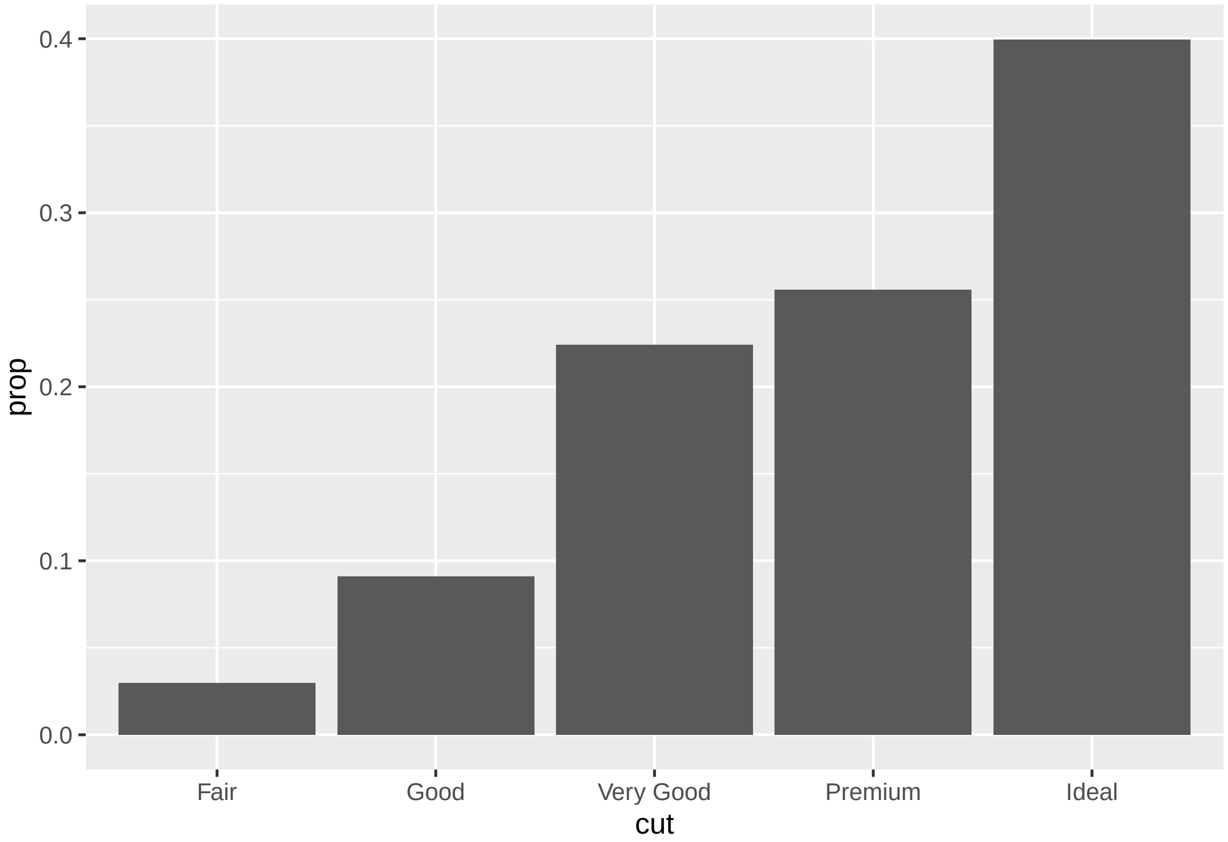


Because ggplot, in order to make a barplot, has to make a table of all of the values for a certian vareuable in a dataset, it is easy to just ask ggplot to make a stat_count representation, which will give you the same output as the geom_bar. This is because they require the same steps to reach their final end goal, which is displaying computed variables i.e. the count of each type of cut.

```
# demo <- tribble( ~cut, ~freq, 'Fair', 1610, 'Good', 4906,
# 'Very Good', 12082, 'Premium', 13791, 'Ideal', 21551 )

# ggplot(data = demo) + geom_bar(mapping = aes(x = cut, y =
# freq), stat = 'identity')
```

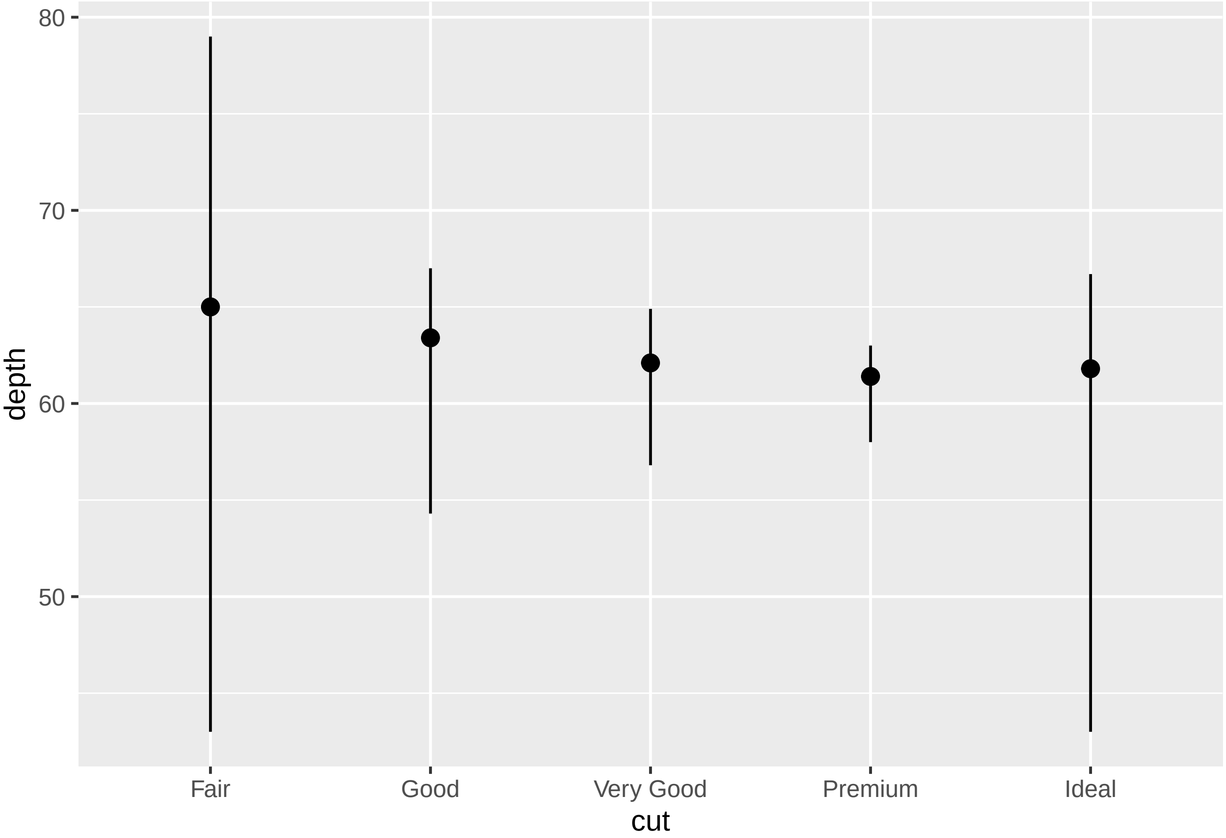
This chunk overrides the default pairing between stat and geom that we had relied on in the previous two chunks. This means that instead of measuring the cut based on the number of times that cut appears, it could be measured by some other factor. In this case, we are using identity.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, y = stat(prop),
    group = 1))
```



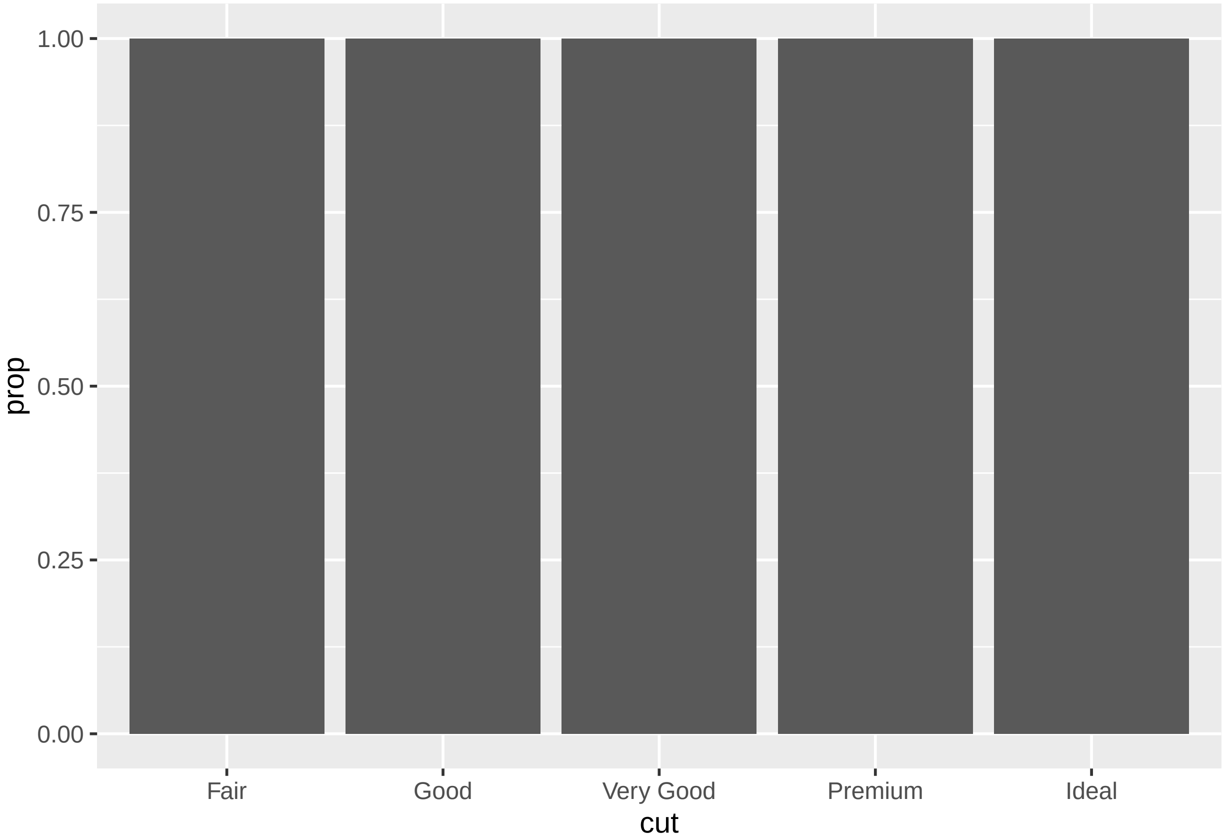
This allows us to display a bar chart of a proportion instead of a count of the number of occurrences of cut.

```
ggplot(data = diamonds) + stat_summary(mapping = aes(x = cut,
    y = depth), fun.min = min, fun.max = max, fun = median)
```

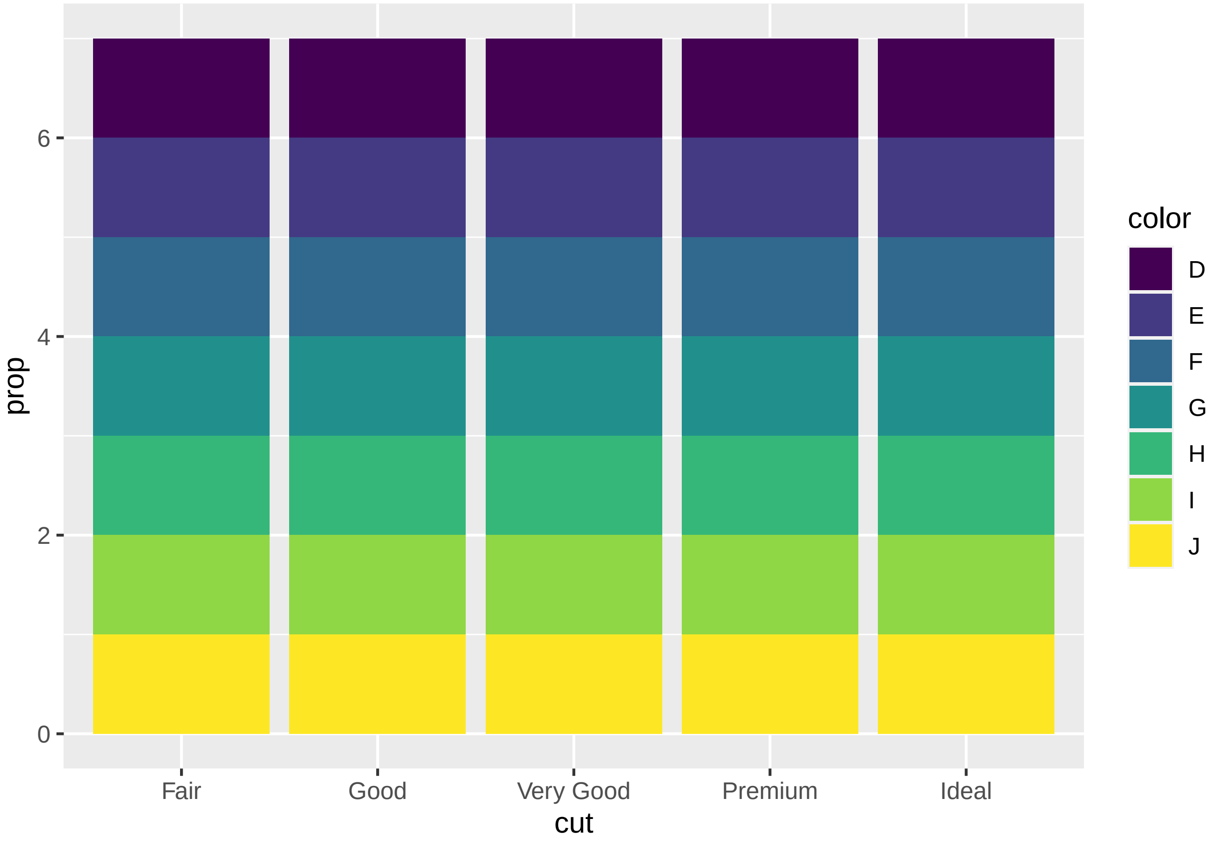


This plot more accurately describes the spread of y values for any variable x, allowing us to see the min, max, and median of all of the groupings.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, y = after_stat(prop)))
```

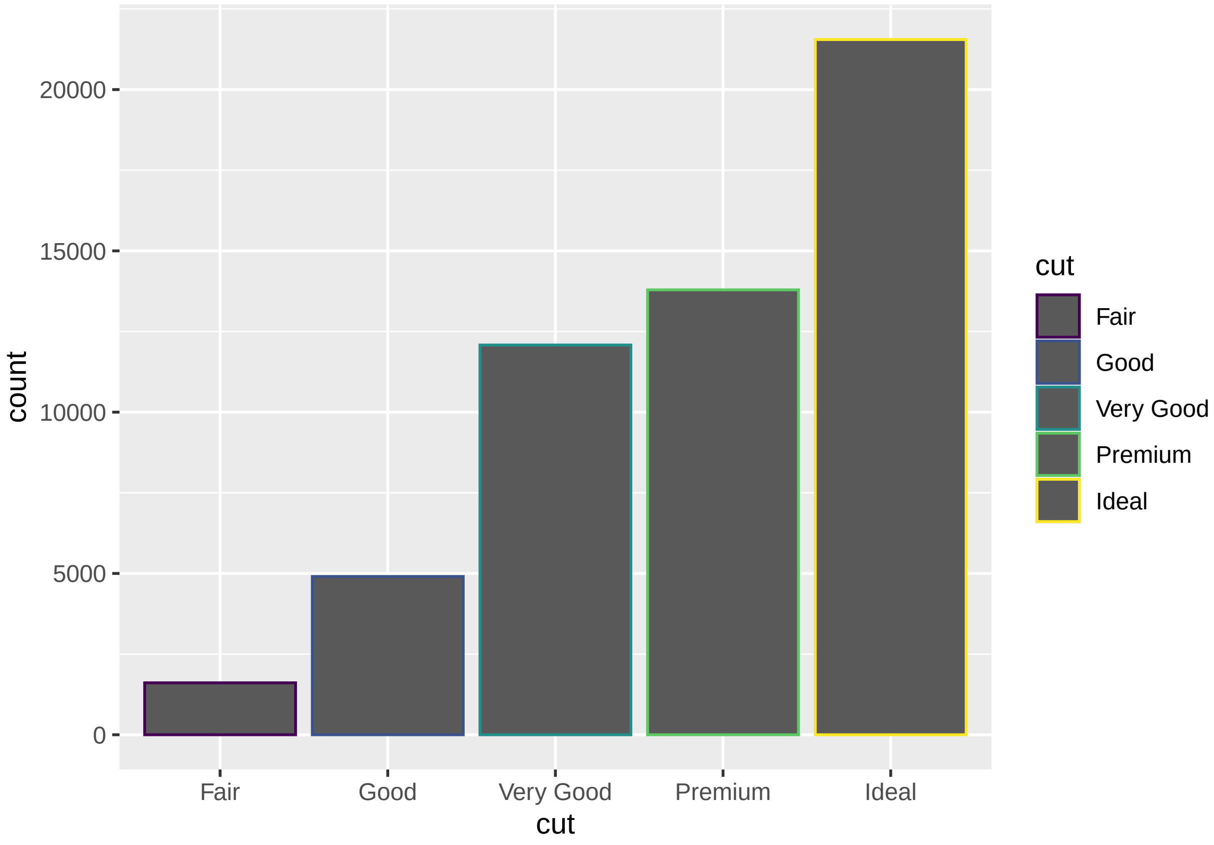


```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, fill = color,
    y = after_stat(prop)))
```

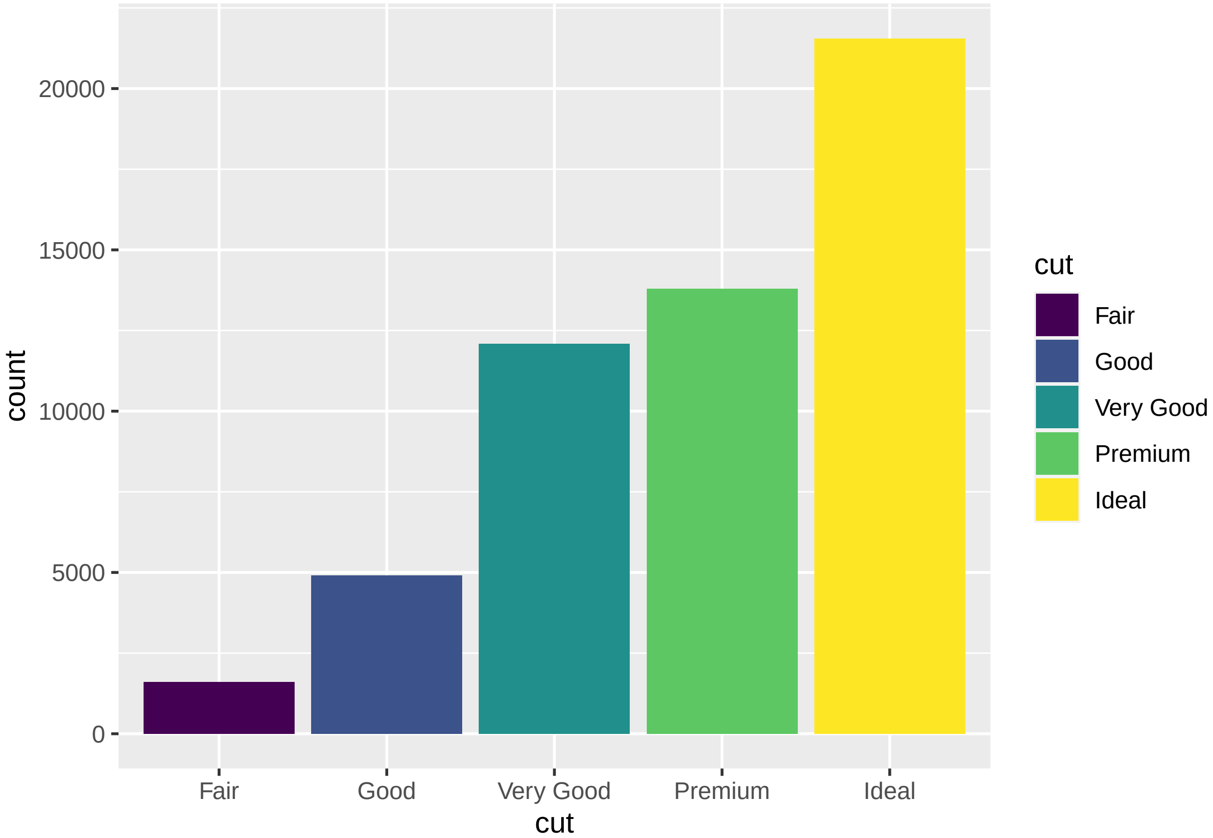


The problem with these two graphs is that it doesn't specify the group, which makes each bar graph full, as it will not correctly display the proportion otherwise.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, colour = cut))
```

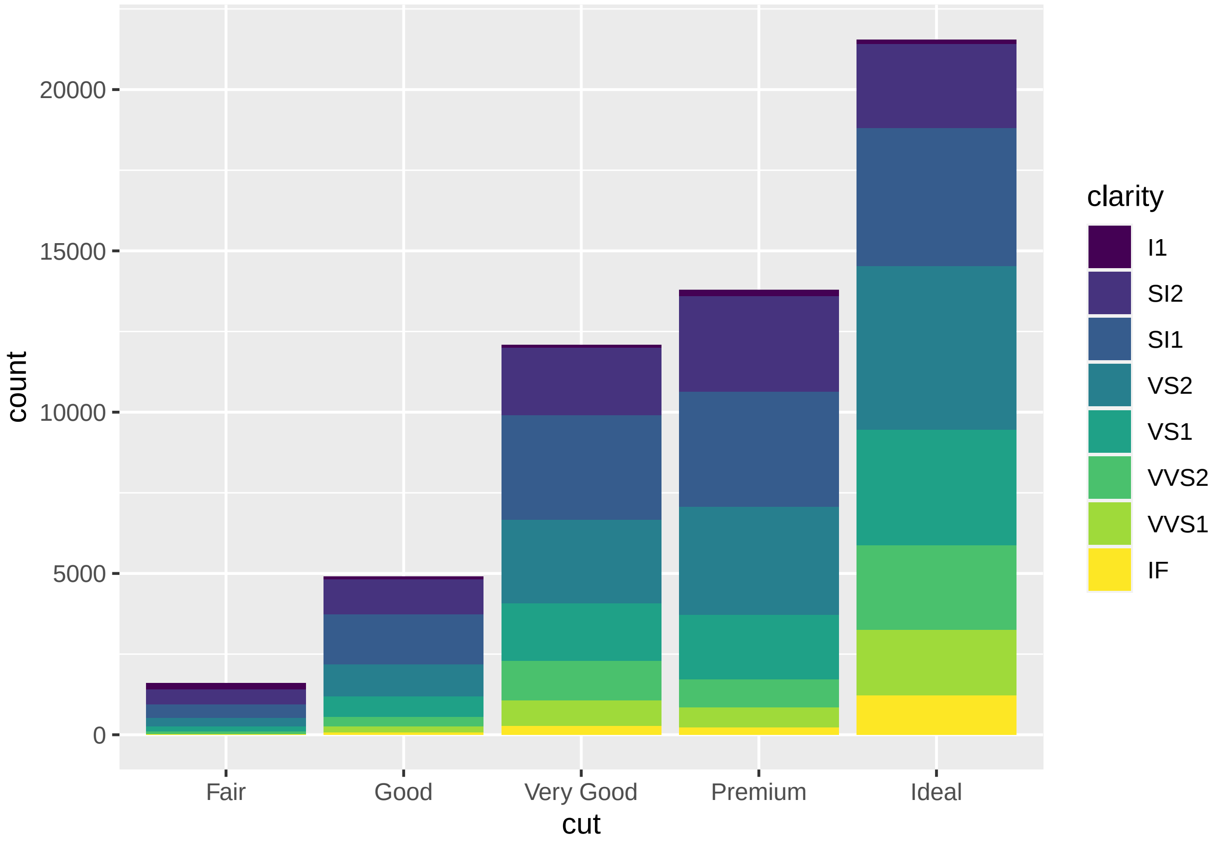


```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, fill = cut))
```



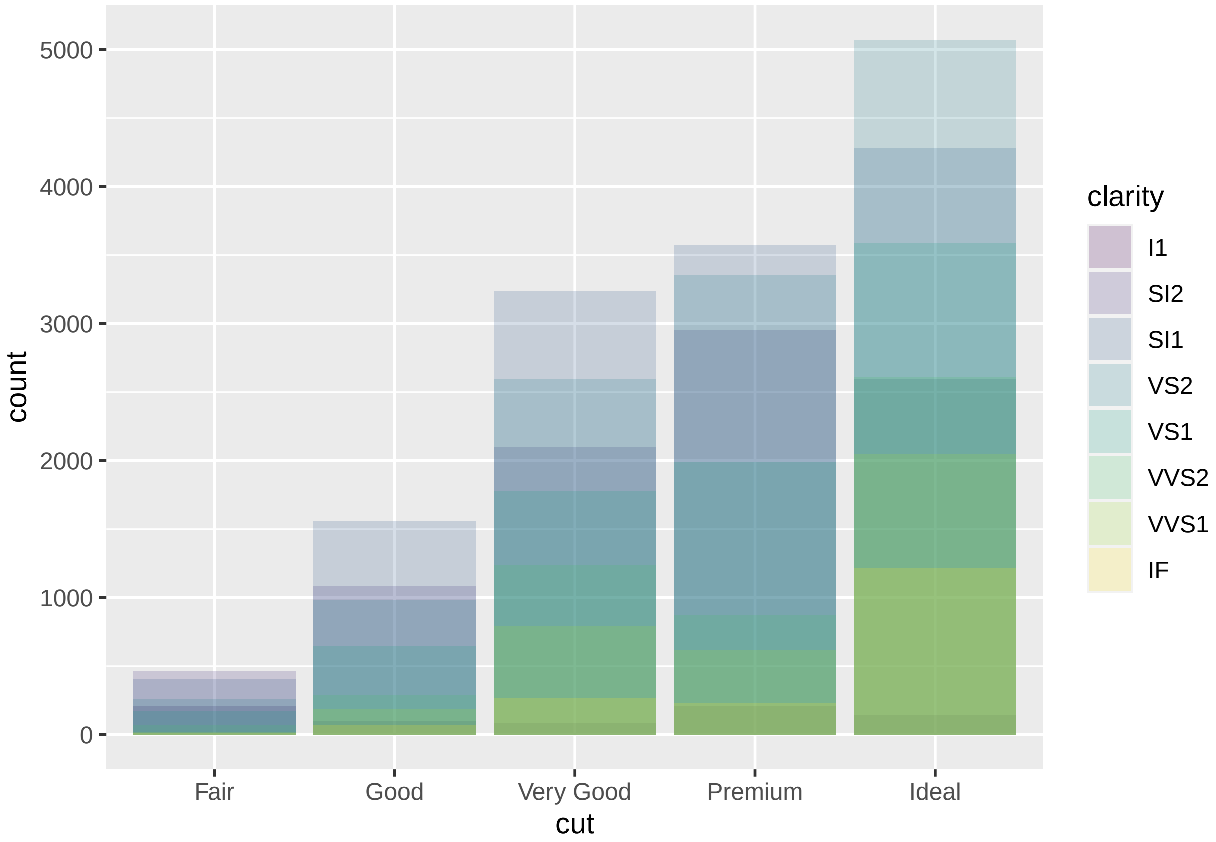
This plot tells ggplot to put cut on the x axis, as well as color based on the variable cut. This means that each different bar will be colored differently, as cit is the same variable for both x and color.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, fill = clarity))
```

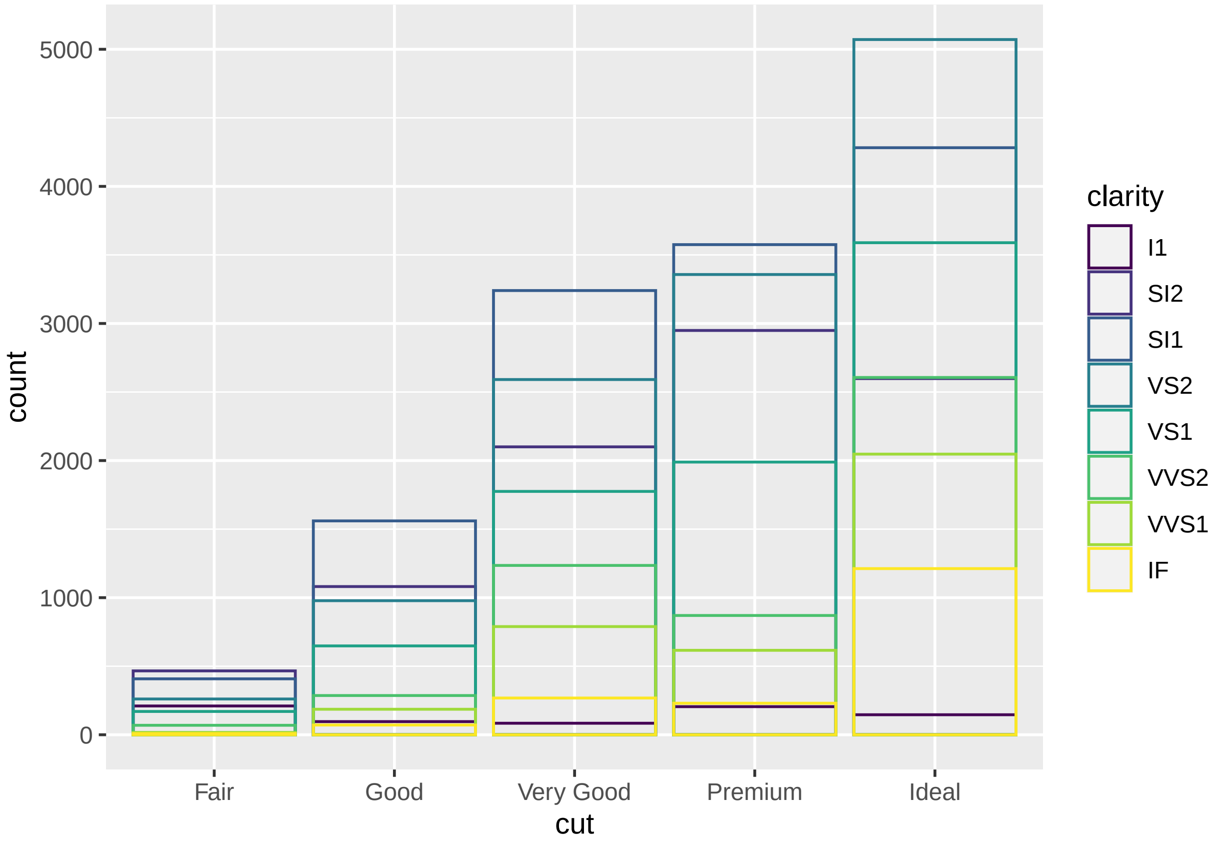


Unlike the example above, we can split the bar graphs between multiple variables. This tells ggplot to put cut on the x axis, but also, to fill each of the cut bars with colors based on the number of any given clarity within that cut, creating a stacked barplot.

```
ggplot(data = diamonds, mapping = aes(x = cut, fill = clarity)) +
    geom_bar(alpha = 1/5, position = "identity")
```

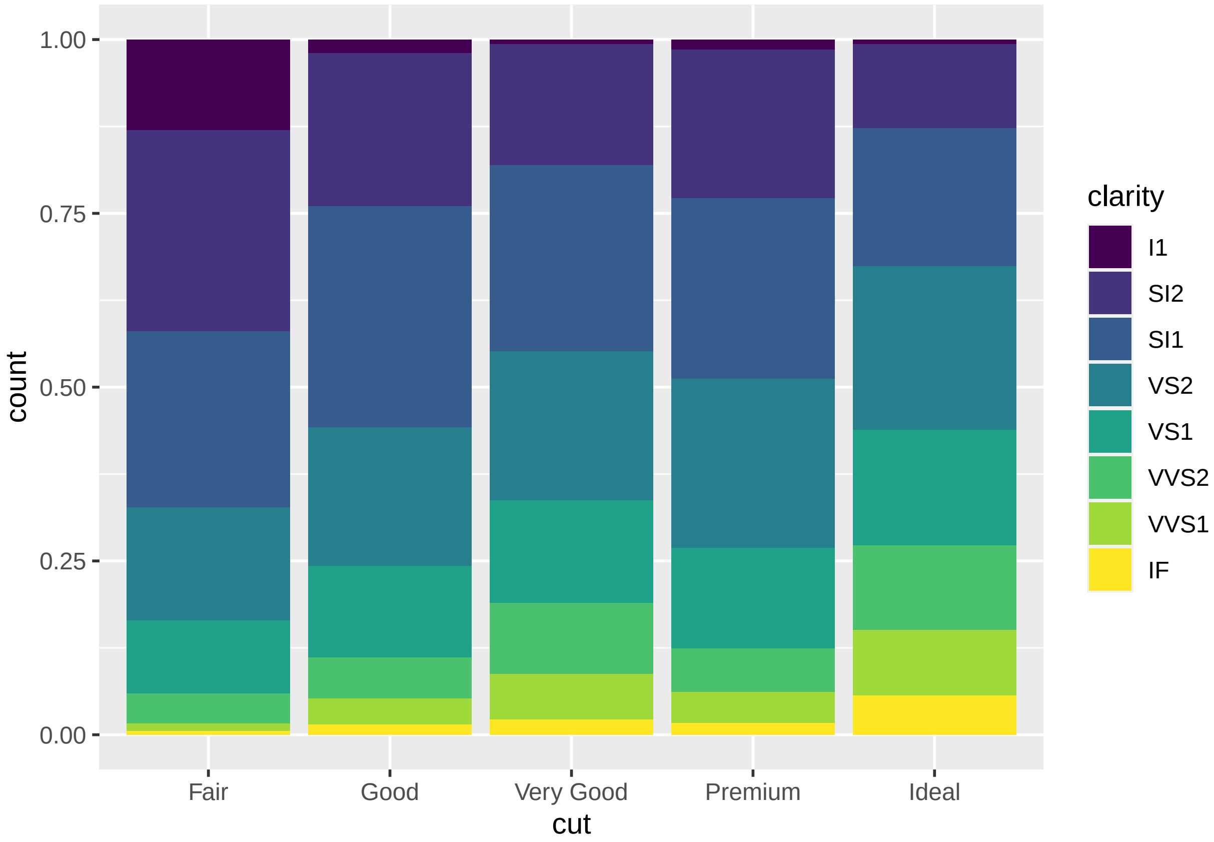


```
ggplot(data = diamonds, mapping = aes(x = cut, colour = clarity)) +
    geom_bar(fill = NA, position = "identity")
```



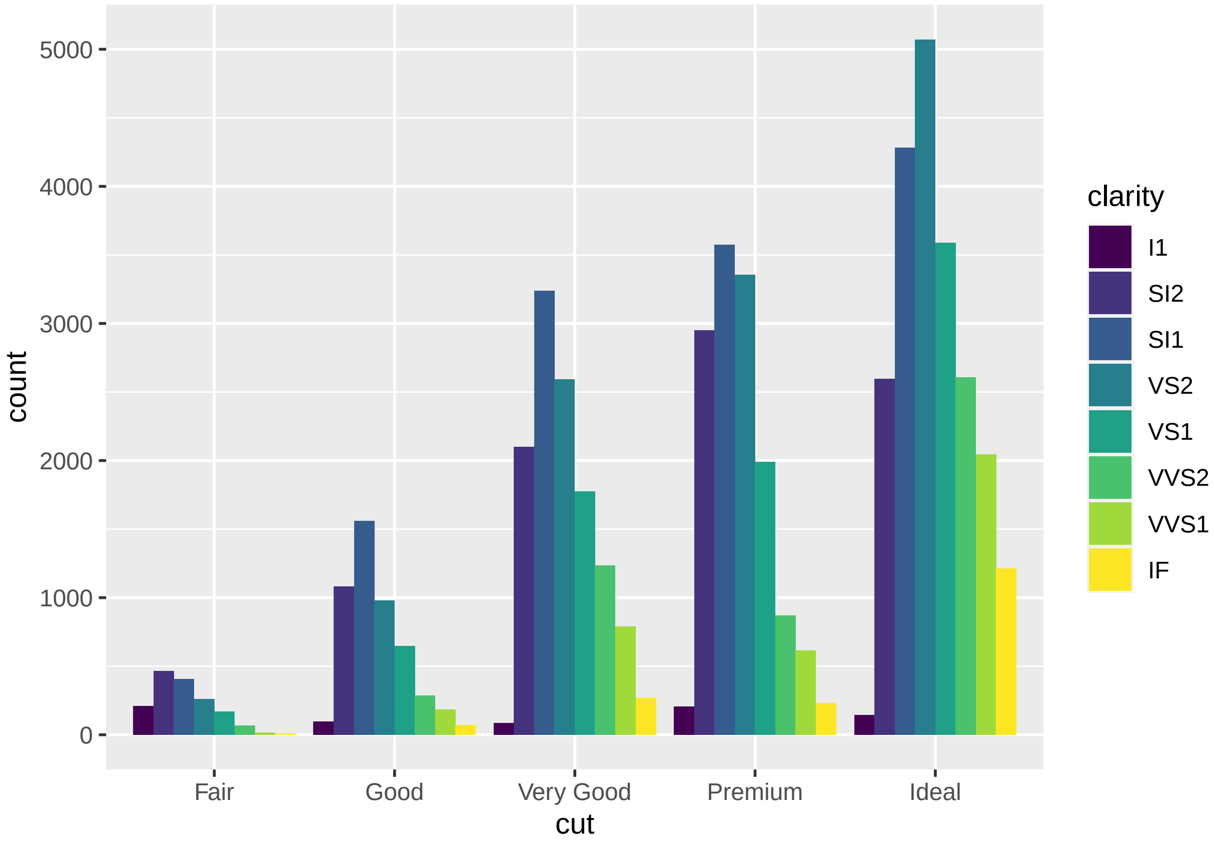
These are the instructions if you do not want the barplots to be stacked, and wish to have each of the clarity types to be displayed on the numerical context of the graph.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, fill = clarity),
    position = "fill")
```



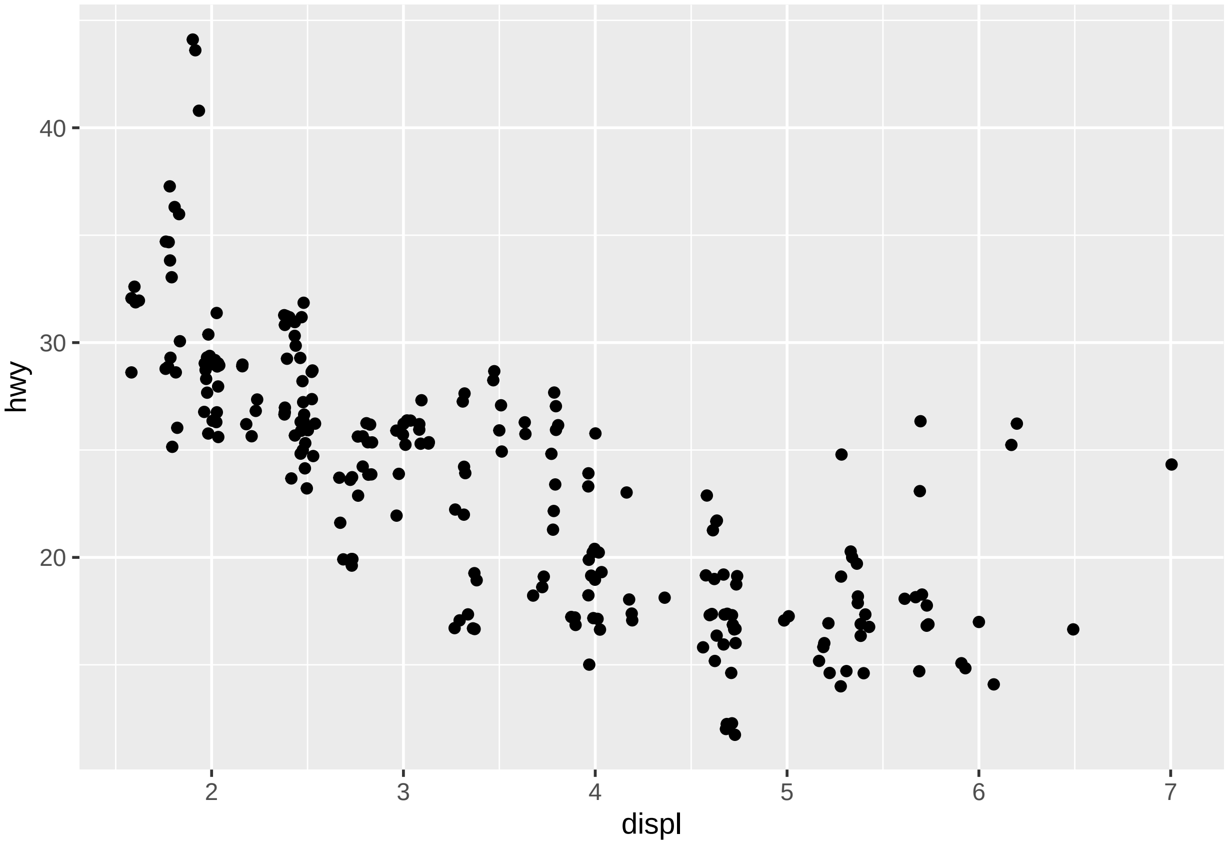
This makes each set of bars the same height in order to ensure that you can compare across subgroups within x, in this case, clarity.

```
ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut, fill = clarity),
    position = "dodge")
```



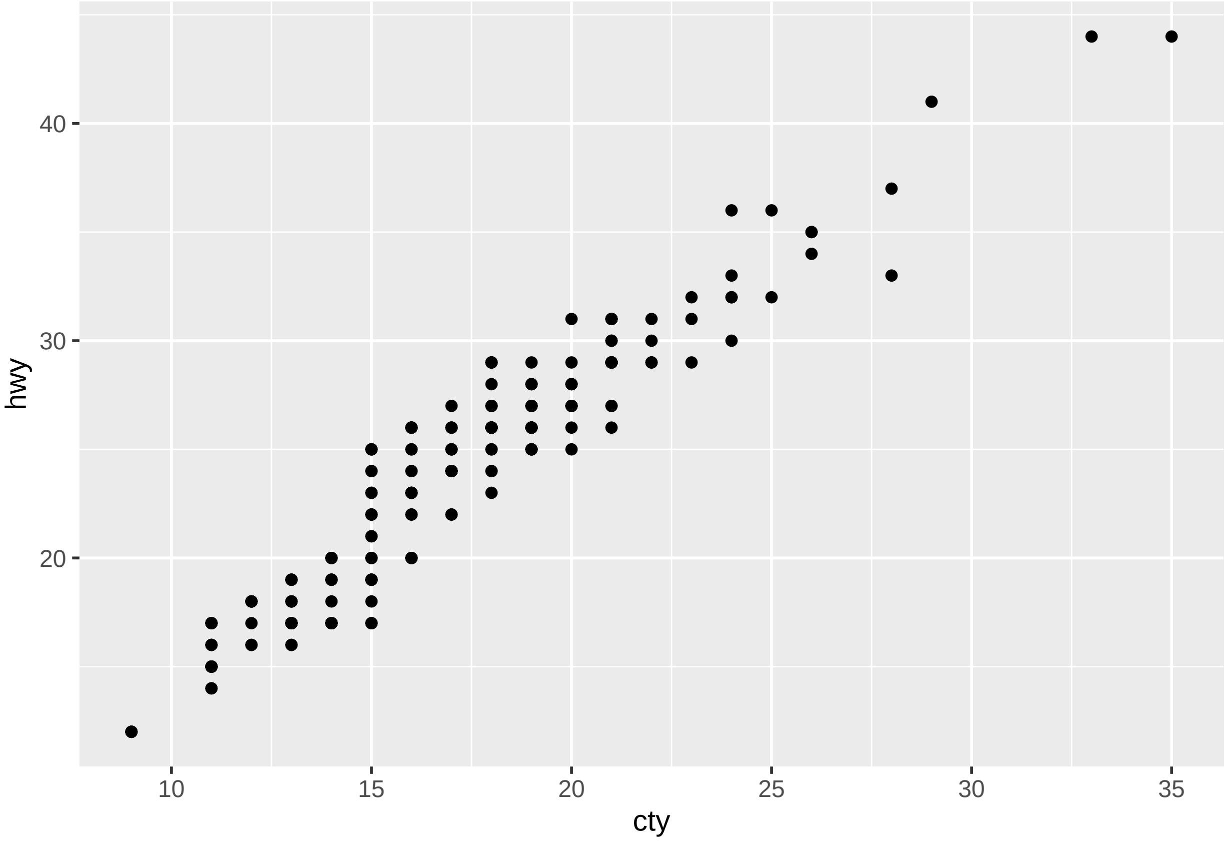
This puts the subvariable analysis in side-by-side bars, which are then grouped based on the initial x variable, in this case, clarity and cut respectively.

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy),
    position = "jitter")
```



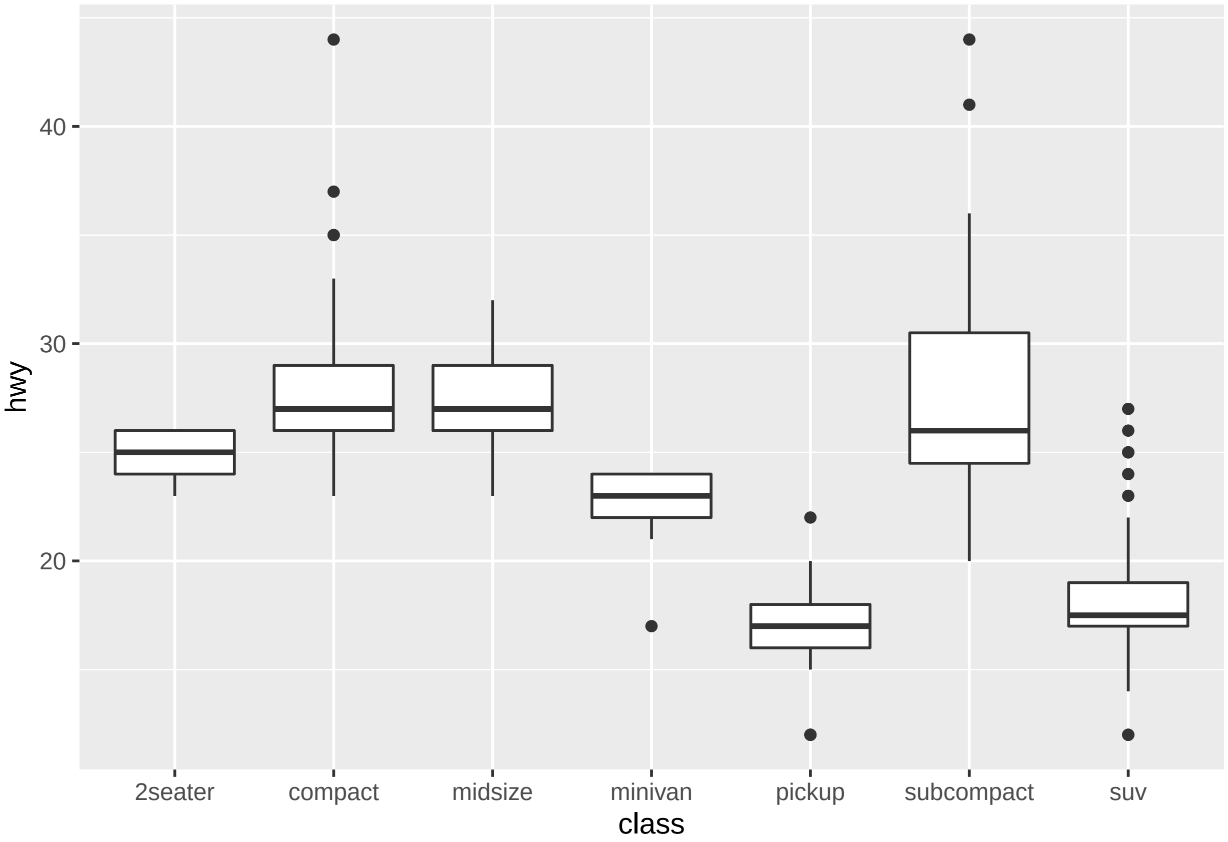
The jitter function adds slight ammounts of random noise to each point in a scatterplot to avoid overplotting.

```
ggplot(data = mpg, mapping = aes(x = cty, y = hwy)) + geom_point()
```

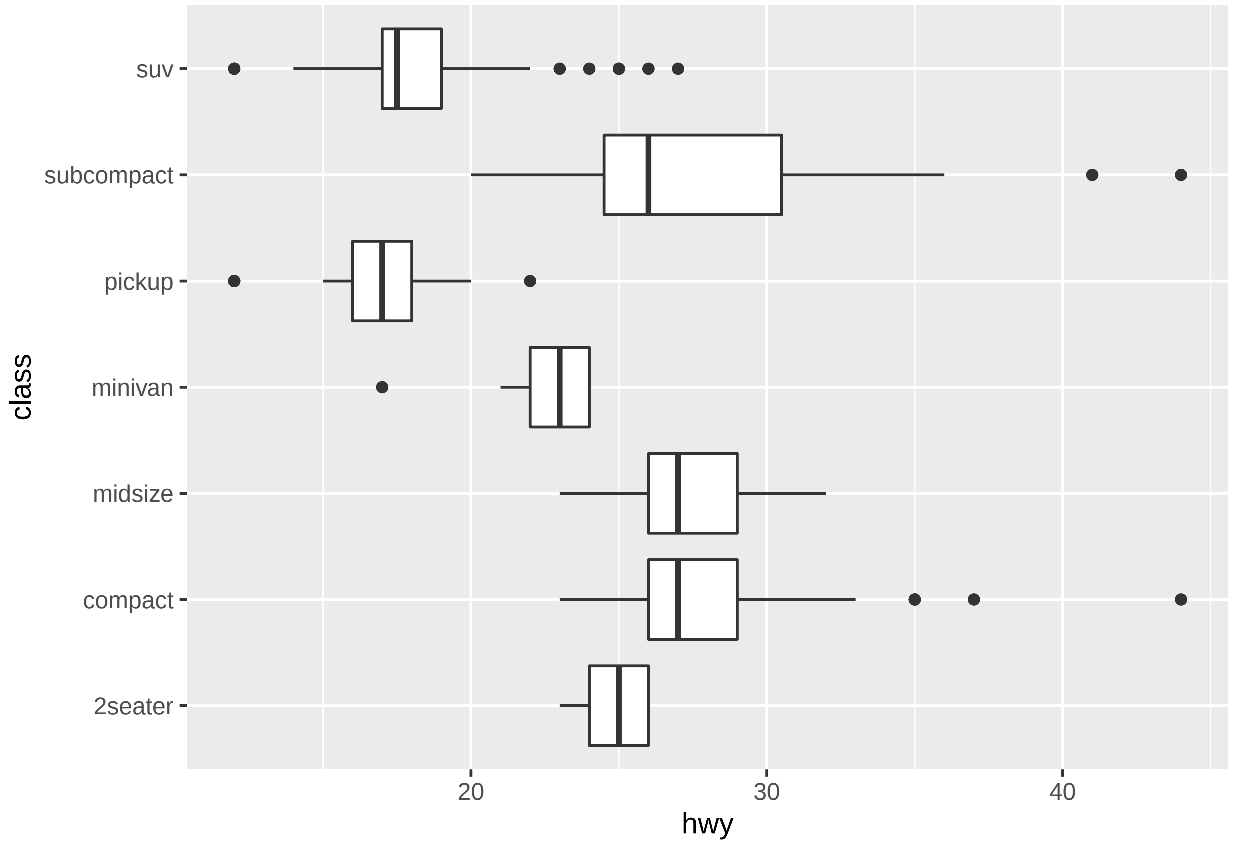


This plot could be improved by adding jitter, which would make it more clear where the data actually is.

```
ggplot(data = mpg, mapping = aes(x = class, y = hwy)) + geom_boxplot()
```

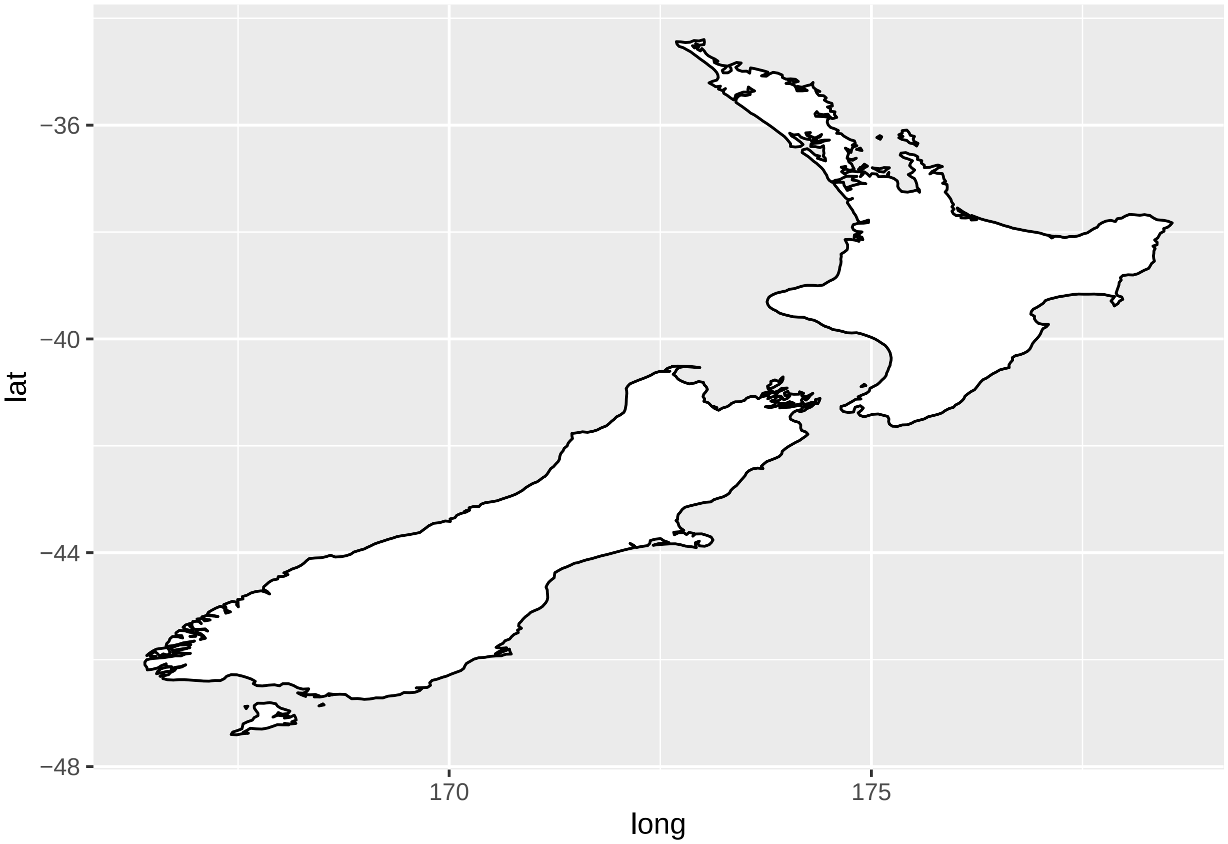


```
ggplot(data = mpg, mapping = aes(x = class, y = hwy)) + geom_boxplot() +
    coord_flip()
```

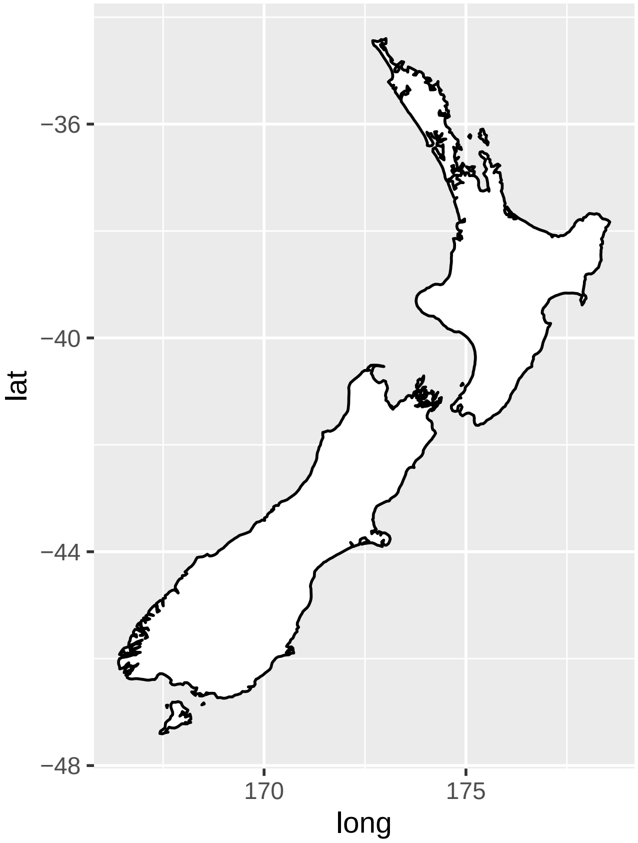


Adding the coordinate flip function at the bottom allows us to flip x and y when displaying data, which helps when there are long labels.

```
nz <- map_data("nz")

ggplot(nz, aes(long, lat, group = group)) + geom_polygon(fill = "white",
    colour = "black")
```

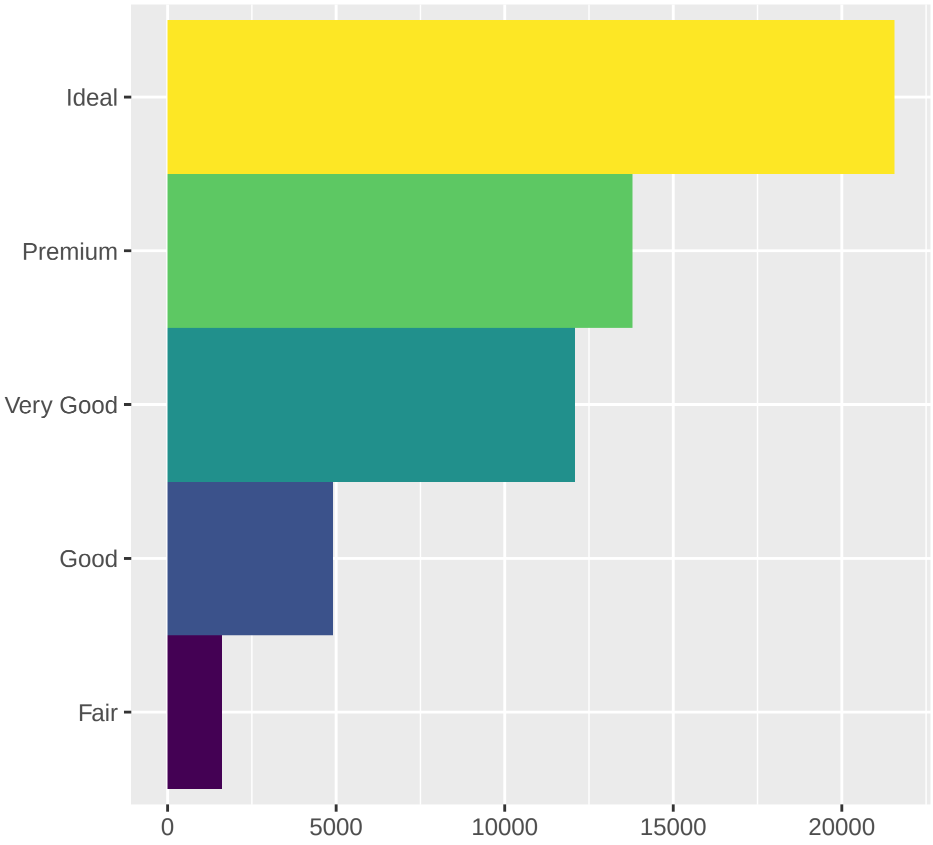


```
ggplot(nz, aes(long, lat, group = group)) + geom_polygon(fill = "white",
    colour = "black") + coord_quickmap()
```

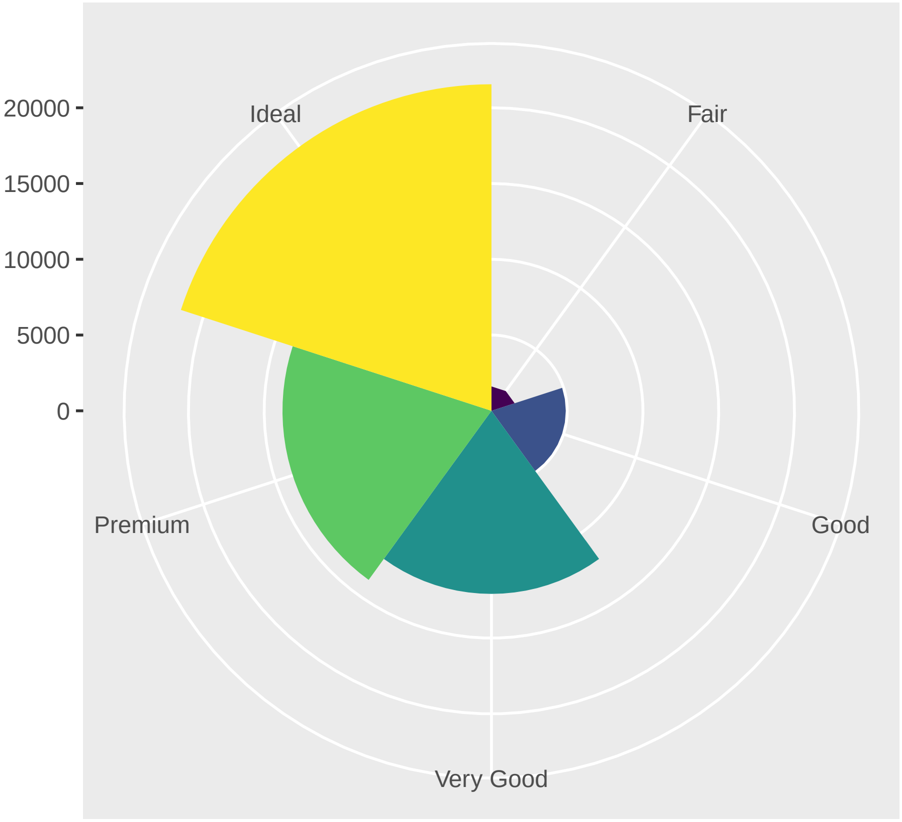


coord_quickmap() sets the correct aspect ratio for maps, which makes them appear more accurate to how they actually appear in real life.

```
bar <- ggplot(data = diamonds) + geom_bar(mapping = aes(x = cut,
    fill = cut), show.legend = FALSE, width = 1) + theme(aspect.ratio = 1) +
    labs(x = NULL, y = NULL)

bar + coord_flip()
```

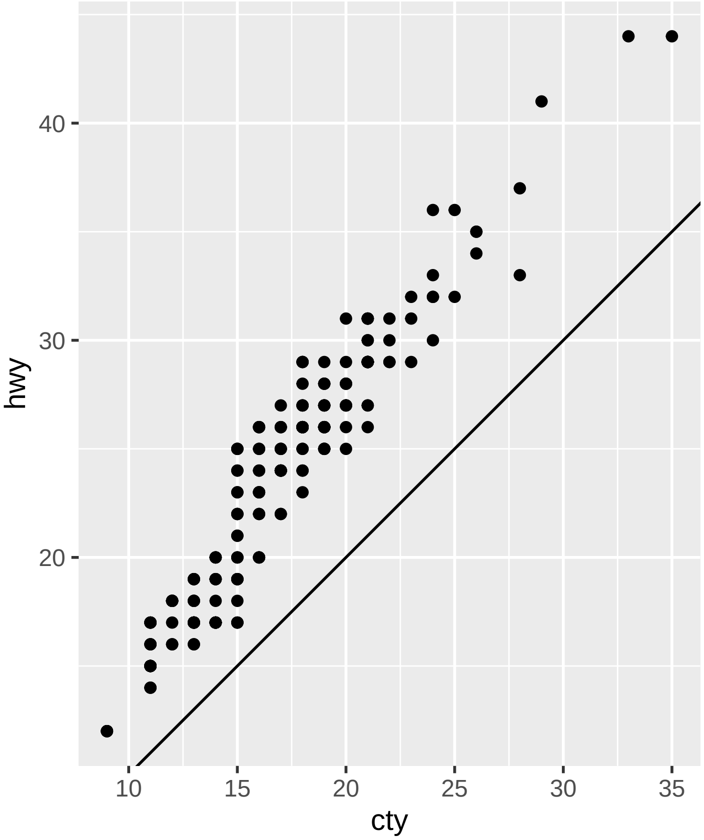


```
bar + coord_polar()
```



This function uses polar coordinates instead of the normal coordinates.

```
ggplot(data = mpg, mapping = aes(x = cty, y = hwy)) + geom_point() +
    geom_abline() + coord_fixed()
```



This fixes the aspect ratio as well as putting a reference line

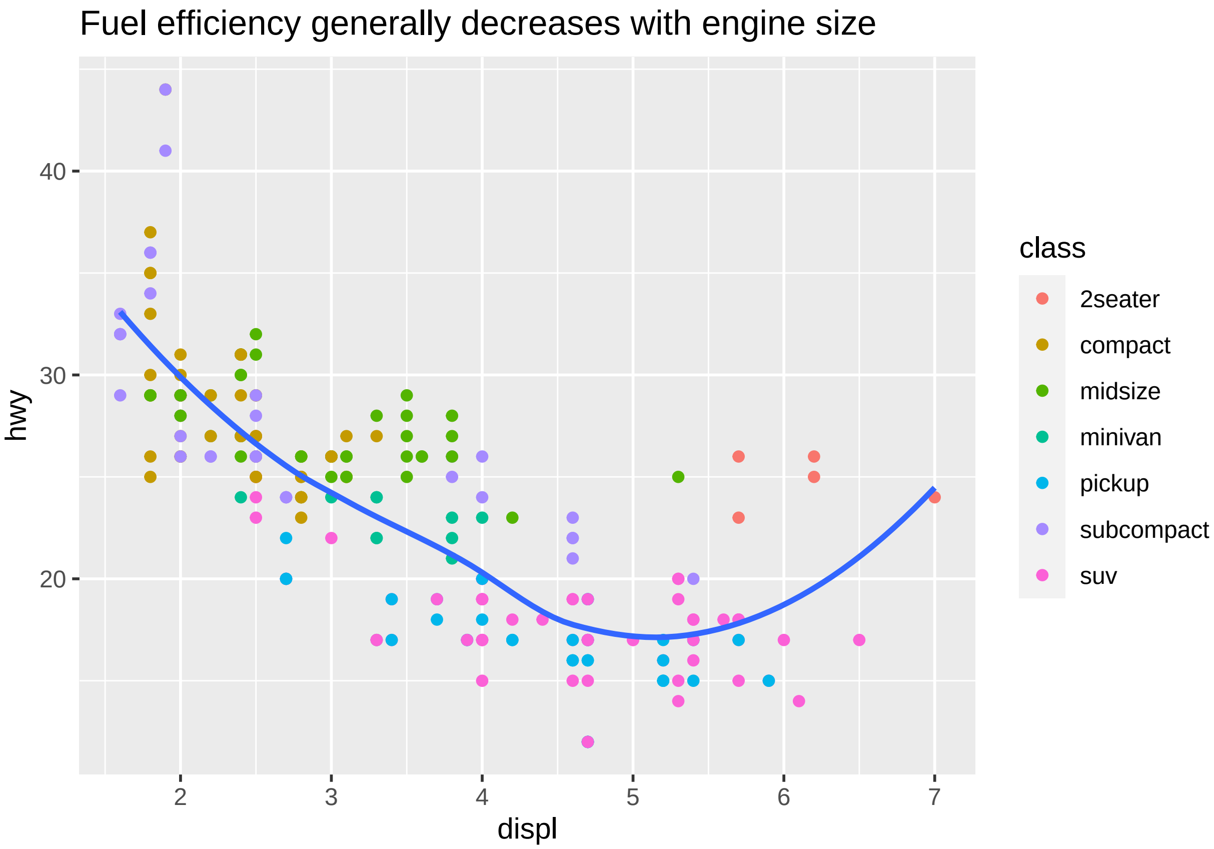
```
# ggplot(data = <DATA>) + <GEOM_FUNCTION>( mapping =
# aes(<MAPPINGS>), stat = <STAT>, position = <POSITION> ) +
# <COORDINATE_FUNCTION> + <FACET_FUNCTION>
```

This is the final code template that we have produced after learning more ggplot functions.

28

```
ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color = class)) +
    geom_smooth(se = FALSE) + labs(title = "Fuel efficiency generally decreases with engine size")
```

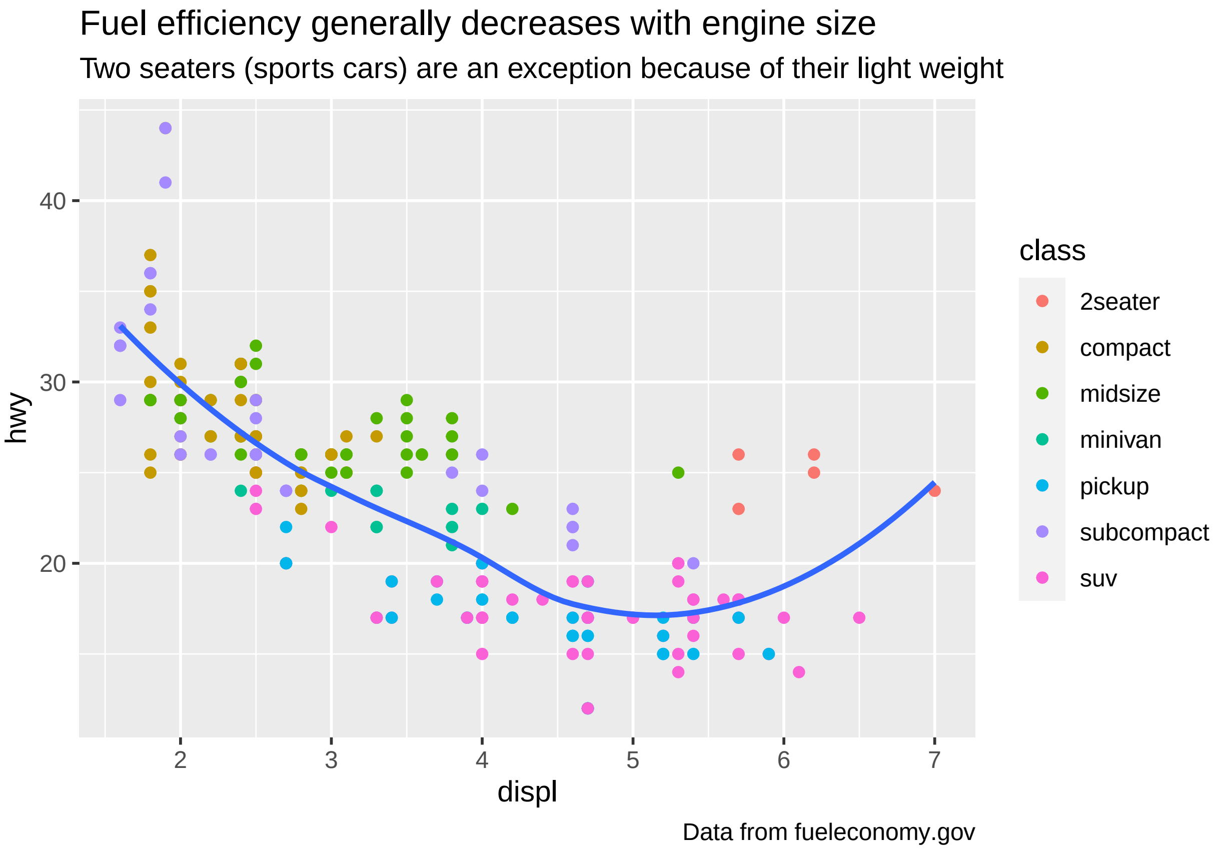
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



This addition adds labels to the plot, specificially in this instance, a title.

```
ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color = class)) +
    geom_smooth(se = FALSE) + labs(title = "Fuel efficiency generally decreases with engine size",
    subtitle = "Two seaters (sports cars) are an exception because of their light weight",
    caption = "Data from fueleconomy.gov")
```

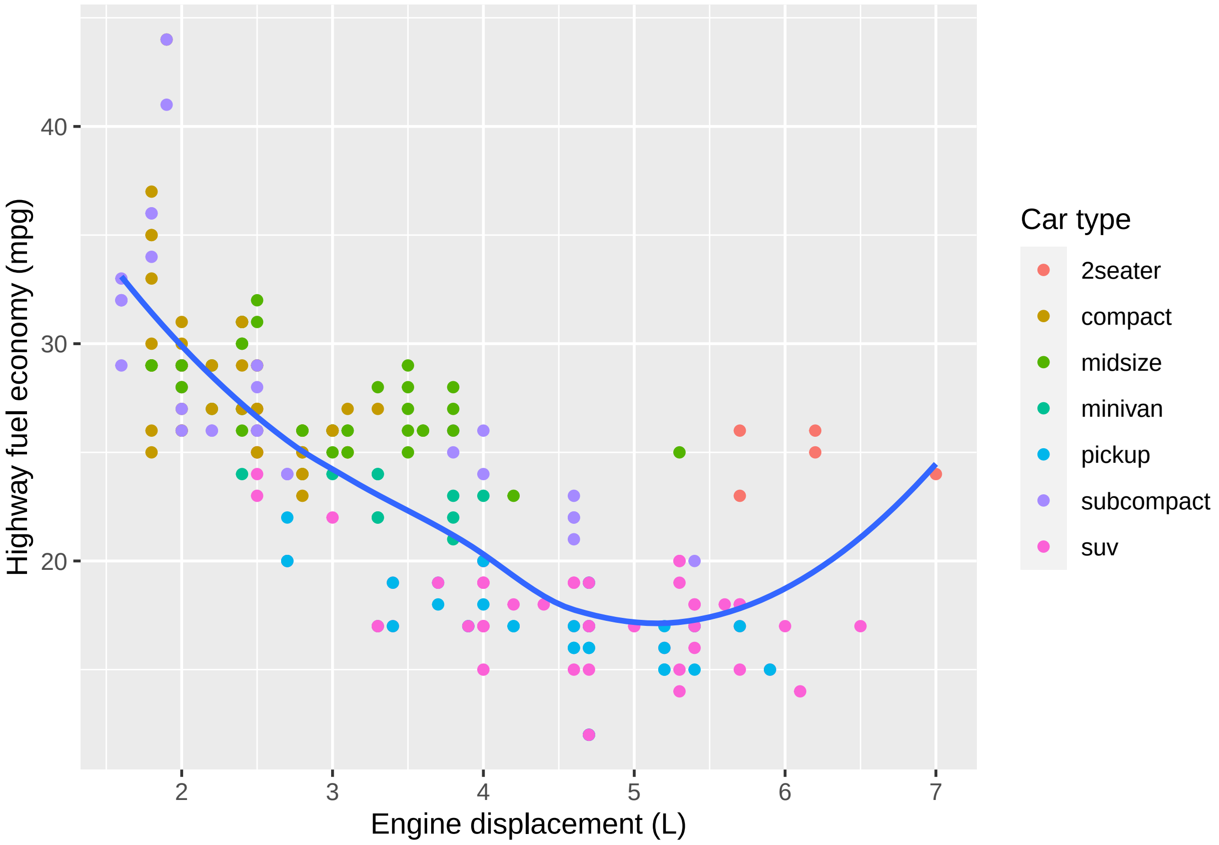
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Here are some examples of more labels that you can add, such as a title, subtitle, and a caption.

```
ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour = class)) +
    geom_smooth(se = FALSE) + labs(x = "Engine displacement (L)",
    y = "Highway fuel economy (mpg)", colour = "Car type")
```

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



This describes how to use the labels command to input x and y axes, as well as how to change the key description. In this instance, because there is a key for the color aesthetics map, we were able to label it.

```
# df <- tibble( x = runif(10), y = runif(10) ) ggplot(df,
# aes(x, y)) + geom_point() + labs( x = quote(sum(x[i] ^ 2,
# i == 1, n)), y = quote(alpha + beta + frac(delta, theta))
# )
```

This chunk is an example of how to use mathematical functions in ggplot as compared to text. In this case, you would switch the word "quote()" with actual quotations, and ggplot would be able to read the function as you had inputted it.

```
# best_in_class <- mpg %>% group_by(class) %>%
# filter(row_number(desc(hwy)) == 1) ggplot(mpg, aes(displ,
# hwy)) + geom_point(aes(colour = class)) +
# geom_text(aes(label = model), data = best_in_class)
```

This chunk demonstrates how to label specific data points within the graph. Specifically, we can look at the best_in_class fearture, and label each car within that category on the larger graph.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour =
# class)) + geom_label(aes(label = model), data =
# best_in_class, nudge_y = 2, alpha = 0.5)
```

As you can observe with the previous graph, some of the labels are hard to read. This can be solved by using geom_label instead of geom_text, as the labeling function adds a small rectangle behidn the text, making it easier to read.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour =
# class)) + geom_point(size = 3, shape = 1, data =
# best_in_class) + ggrepel::geom_label_repel(aes(label =
# model), data = #best_in_class)
```

However, even though we have added rectangles, some of the labels still overlap. If we use ggrepel, the labels will automatically be spaced out from each other.

```
# class_avg <- mpg %>% group_by(class) %>% summarise( displ
# = median(displ), hwy = median(hwy) ) ggplot(mpg,
# aes(displ, hwy, colour = class)) +
# ggrepel::geom_label_repel(aes(label = class), data =
# class_avg, size = 6, label.size = 0, segment.color = NA )
# + geom_point() + theme(legend.position = 'none')
```

In another way to label certain points, you can display class names with this code, and then get rid of the legend by saying legend.position = “none”.

```
# label <- mpg %>% summarise( displ = max(displ), hwy =
# max(hwy), label = 'Increasing engine size is \nrelated to
# decreasing fuel economy.'  )

# ggplot(mpg, aes(displ, hwy)) + geom_point() +
# geom_text(aes(label = label), data = label, vjust =
# 'top', #hjust = 'right')
```

In the case that you only want one label for your graph, but you want the label to be in a specific location, you will need to add another data frame to tell the label where to go. In this case, we can use the summarize function to retrieve the max x and y values, and then to instruct the ggplot to located the new label with those maximum values, putting it in the top right.

```
# label <- tibble( displ = Inf, hwy = Inf, label =
# 'Increasing engine size is \nrelated to decreasing #fuel
# economy.' ) ggplot(mpg, aes(displ, hwy)) + geom_point() +
# geom_text(aes(label = label), data = label, vjust =
# 'top', #hjust = 'right')
```

In the case that you only want one label for your graph, but you want the label to be in a specific location, you will need to add another data frame to tell the label where to go. With the Inf in the code, we can make sure that the labels are precisely aligned with the graph, rather than the data.

```
#'Increasing engine size is related to decreasing fuel economy.' %>%
# stringr::str_wrap(width = 40) %>% writeLines() >
# Increasing engine size is related to > decreasing fuel
# economy.
```

This is just a way to wrap your label so that the lines do not exceed a certain amount.In this case, that amount was 40 characters.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour =
# class))

# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour =
# class)) + scale_x_continuous() + scale_y_continuous() +
# scale_colour_discrete()
```

Because ggplot automatically scales data, if we are looking for the data to be scaled manually, we will need to utilize the functions included here. These specifications can change the color scale, as well as the x and y scale.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point() +
# scale_y_continuous(breaks = seq(15, 40, by = 5))
```

This scale function creates labels, or ticks, every value of 5. This funciton also tells ggplot to start the coount at 15, and keep lableing by 5 up until 40.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point() +
# scale_x_continuous(labels = NULL) +
# scale_y_continuous(labels = NULL)
```

If you want to override the default labeling or scaling, for example, to protect true data values, you can set the scaling to NULL, which will create a plot without x or y numerical labeling.

```
# presidential %>% mutate(id = 33 + row_number()) %>%
# ggplot(aes(start, id)) + geom_point() +
# geom_segment(aes(xend = end, yend = id)) +
# scale_x_date(NULL, breaks = presidential$start,
# date_labels = ''%y')
```

This display marks exactly where observations occur. In this instance, it describes how old US presidents are at the beginning of their term, and the breaks function can demonstrate that there were gaps in time between each start of a presidential term.

```
# base <- ggplot(mpg, aes(displ, hwy)) +
# geom_point(aes(colour = class))

# base + theme(legend.position = 'left') base +
# theme(legend.position = 'top') base +
# theme(legend.position = 'bottom') base +
# theme(legend.position = 'right') # the default
```

This code tells ggplot where to locate the legend, and indicates that it is by default to the right of the plot.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(colour =
# class)) + geom_smooth(se = FALSE) + theme(legend.position
# = 'bottom') + guides(colour = guide_legend(nrow = 1,
# override.aes = list(size = 4))) > `geom_smooth()` using
# method = 'loess' and formula 'y ~ x'
```

If you want more detail for how to control the legend, you can use this chunk of code. For example, controlling the number of rows the legend uses with nrow, and overriding one of the aesthetics to make the points bigger.

```
# ggplot(diamonds, aes(carat, price)) + geom_bin2d()

# ggplot(diamonds, aes(log10(carat), log10(price))) +
# geom_bin2d()

# ggplot(diamonds, aes(carat, price)) + geom_bin2d() +
# scale_x_log10() + scale_y_log10()
```

The final lines of code show how to plot the initial y axis with data that has been transformed. Because we transformed the diamond data, it is now difficult to properly interpret the default labels and scaling for the y axis, so we can also transform the scale of the axes in order to maintain the initial labels.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color =
# drv))

# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color =
# drv)) + scale_colour_brewer(palette = 'Set1')
```

This provides an example of how to change the color pallet of the colors in a plot, specifically to help those with red-green colorblindness.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color =
# drv, shape = drv)) + scale_colour_brewer(palette =
# 'Set1')
```

Another way to make color aesthetics mapping more easily interpreted is to add redundant shapes coding, which could also help if the graphs are eventually printed in black and white.

```
# presidential %>% mutate(id = 33 + row_number()) %>%
# ggplot(aes(start, id, colour = party)) + geom_point() +
# geom_segment(aes(xend = end, yend = id)) +
# scale_colour_manual(values = c(Republican = 'red',
# Democratic = 'blue'))
```

If we have pre-determined colors that we wish to use for certain values, we can pre-set them. In this case, we are able to set red and blue for Republican and Democratic, respectively. This is done using scale_colour_manual()

```
# df <- tibble( x = rnorm(10000), y = rnorm(10000) )
# ggplot(df, aes(x, y)) + geom_hex() + coord_fixed()
# ggplot(df, aes(x, y)) + geom_hex() +
# viridis::scale_fill_viridis() + coord_fixed()
```

Using the viridis scale for color mapping can result in more aesthetically pleasing color schemes.

```
# ggplot(df, aes(x, y)) + geom_hex() +
# scale_colour_gradient(low = 'white', high = 'red') +
# coord_fixed()
```

This code did not overwrite the default because we did not give a new scale. aka: no values = c()

```
# ggplot(mpg, mapping = aes(displ, hwy)) +
# geom_point(aes(color = class)) + geom_smooth() +
# coord_cartesian(xlim = c(5, 7), ylim = c(10, 30))

# mpg %>% filter(displ >= 5, displ <= 7, hwy >= 10, hwy <=
# 30) %>% ggplot(aes(displ, hwy)) + geom_point(aes(color =
# class)) + geom_smooth()
```

In these two plots, we are controlling the plot limits differently. In the first, we are using the coord_cartesian command, which allows us to select x and y limits and effectively zoom in on some of the data. In the second, we are using a filter to display only certain data values. This may result in different looking graphs based on where our data is located.

```
# suv <- mpg %>% filter(class == 'suv') compact <- mpg %>%
# filter(class == 'compact')

# ggplot(suv, aes(displ, hwy, colour = drv)) + geom_point()

# ggplot(compact, aes(displ, hwy, colour = drv)) +
# geom_point()

# x_scale <- scale_x_continuous(limits = range(mpg$displ))
# y_scale <- scale_y_continuous(limits = range(mpg$hwy))
# col_scale <- scale_colour_discrete(limits =
# unique(mpg$drv))

# ggplot(suv, aes(displ, hwy, colour = drv)) + geom_point()
# + x_scale + y_scale + col_scale

# ggplot(compact, aes(displ, hwy, colour = drv)) +
# geom_point() + x_scale + y_scale + col_scale
```

The first set of code demonstrates how the graphs, when compared, can be misleading if they are not scaled on the same axis. Using the x and y and col scales, we can fix this issue, and using the limits of the full data, we can clearly see how they compare.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point(aes(color =
# class)) + geom_smooth(se = FALSE) + theme_bw()
```

In displaying our graphs and charts, we can change the default color schemes and background of the entire thing by using this code. It is also worth mentioning that without any edits, the default will mean a grey background, so if you want to change this in your data, you will have to specify theme_bw() and then denote your desired theme.

```
# ggplot(mpg, aes(displ, hwy)) + geom_point()
# ggsave('my-plot.pdf') > Saving 7 x 4.33 in image
```

These lines describe how to save my plots.

Exam 2

Instructions

a. Create a folder in your computer (a good place would be under Crim 250, Exams).
b. Download the dataset from the Canvas website (sim.data.csv) onto that folder, and save your Exam 2.Rmd file in the same folder.
c. Data description: This dataset provides (simulated) data about 200 police departments in one year. It contains information about the funding received by the department as well as incidents of police brutality. Suppose this dataset (sim.data.csv) was collected by researchers to answer this question: **"Does having more funding in a police department lead to fewer incidents of police brutality?"**
d. Codebook:

- funds: How much funding the police department received in that year in millions of dollars.
- po.brut: How many incidents of police brutality were reported by the department that year.
- po.dept.code: Police department code

Problem 1: EDA (10 points)

Describe the dataset and variables. Perform exploratory data analysis for the two variables of interest: funds and po.brut.

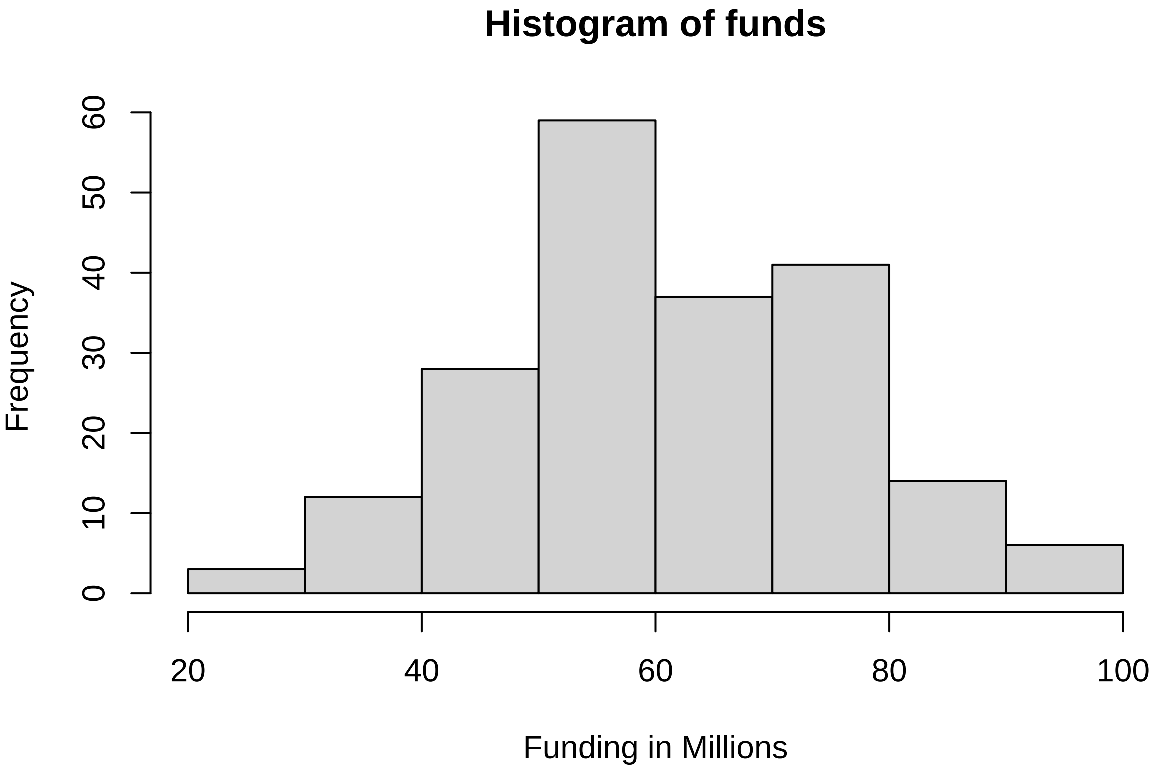
```
dat <- read.csv(file = "sim.data.csv")
names(dat)
```

```
## [1] "po.dept.code" "funds"        "po.brut"
```

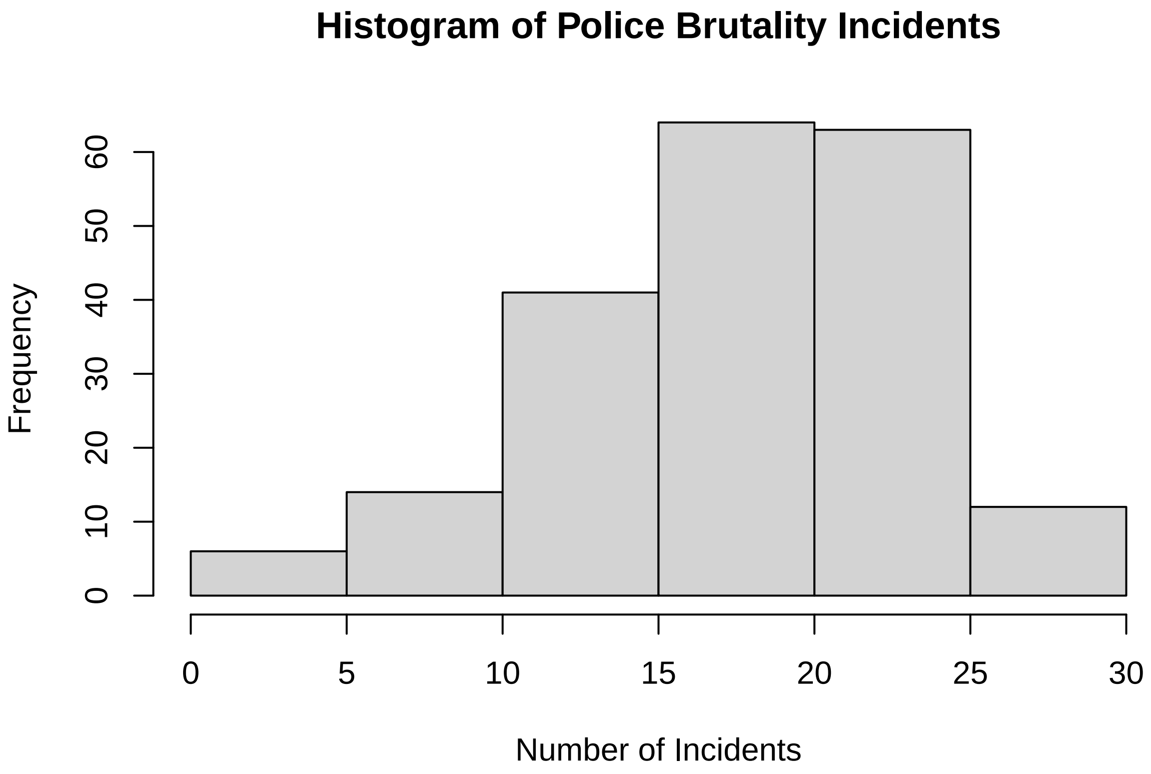
```
summary(dat)
```

```
##   po.dept.code        funds          po.brut
##  Min.   :  1.00   Min.   :21.40   Min.   : 0.00
##  1st Qu.: 50.75   1st Qu.:51.67   1st Qu.:14.00
##  Median :100.50   Median :59.75   Median :19.00
##  Mean   :100.50   Mean   :61.04   Mean   :18.14
##  3rd Qu.:150.25   3rd Qu.:72.17   3rd Qu.:22.00
##  Max.   :200.00   Max.   :99.70   Max.   :29.00
```

```
hist(dat$funds, main = "Histogram of funds", xlab = "Funding in Millions",
    ylab = "Frequency")
```



```
hist(dat$po.brut, main = "Histogram of Police Brutality Incidents",
    xlab = "Number of Incidents", ylab = "Frequency")
```



This dataset contains 200 observations and three variables. The first variable of interest is funds. This variable describes how much funding a police department received in that year in millions of dollars. The median for funds is 59.75. The mean for funds is 61.04. The first and third quartiles are 51.67 and 72.17, respectively. The second variable of interest is po.brut. This variable describes how many incidents of police brutality were reported by a police department that year. The median for po.brut is 19.00. The mean is 18.14. The first and third quartiles are 14.00 and 22.00, respectively.

Problem 2: Linear regression (30 points)

a. Perform a simple linear regression to answer the question of interest. To do this, name your linear model "reg.output" and write the summary of the regression by using "summary(reg.output)".

```
reg.output <- lm(formula = po.brut ~ funds, data = dat)
(summary(reg.output))
```

```
##
## Call:
## lm(formula = po.brut ~ funds, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9433 -0.2233  0.2544  0.5952  1.1803
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 40.543069   0.282503  143.51   <2e-16 ***
## funds       -0.367099   0.004496  -81.64   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

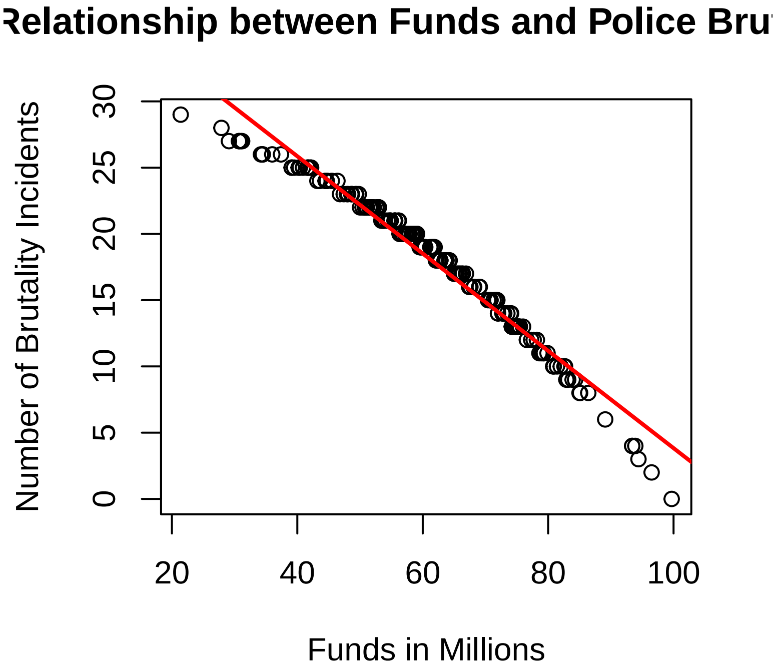
```
## Residual standard error: 0.9464 on 198 degrees of freedom
## Multiple R-squared:  0.9712, Adjusted R-squared:  0.971
## F-statistic:  6666 on 1 and 198 DF,  p-value: < 2.2e-16
```

b. Report the estimated coefficient, standard error, and p-value of the slope. Is the relationship between funds and incidents statistically significant? Explain.

Estimated coefficient: -0.367099. Standard error: 0.004496. P value: approximately 0 (<2e-16). This relationship is statistically significant at the .05 level, as the p-value is lower than the .05 significance level, which means that it is unlikely we will observe a relationship between the funds and brutality due to chance.

c. Draw a scatterplot of po.brut (y-axis) and funds (x-axis). Right below your plot command, use abline to draw the fitted regression line, like this:

```
# Remember to remove eval=FALSE!!
plot(dat$funds, dat$po.brut, main = "Relationship between Funds and Police Brutality",
    xlab = "Funds in Millions", ylab = "Number of Brutality Incidents")
abline(reg.output, col = "red", lwd = 2)
```

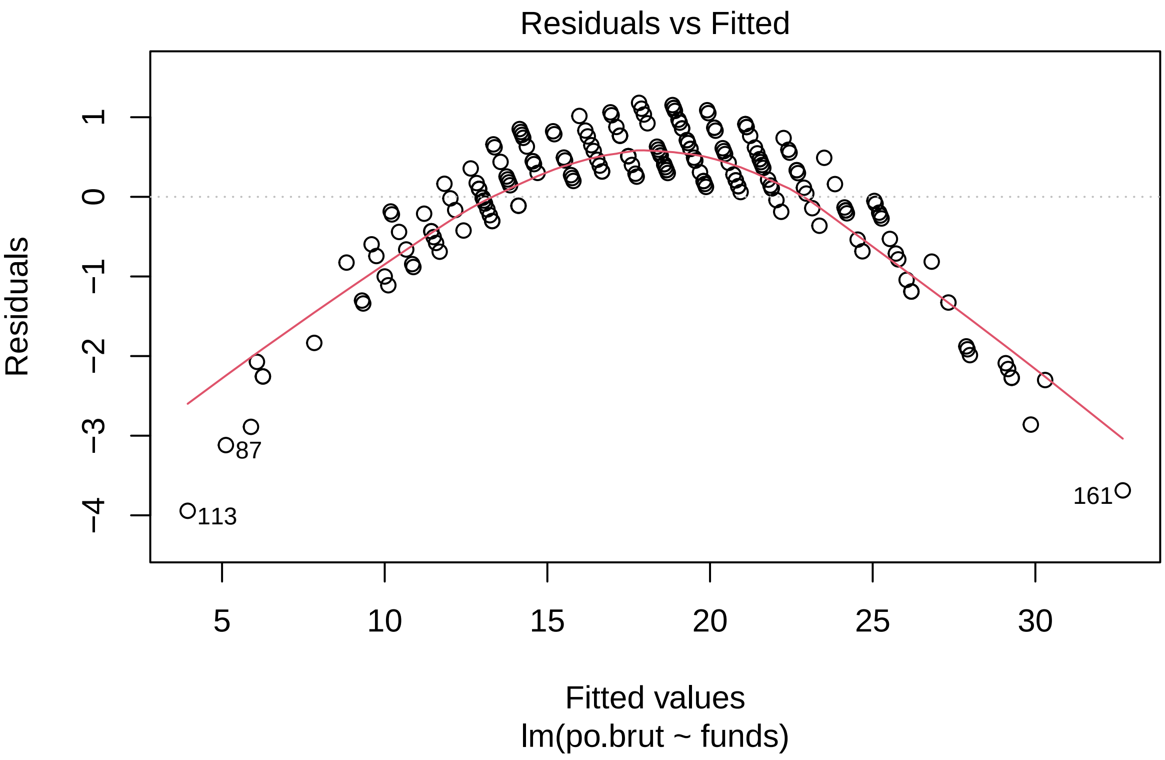


Does the line look like a good fit? Why or why not?

The line does not appear to be a good fit because the data appears to be curved, with the front and end of the data curving away from the line. Because we preform our initial linear regressions with the assumption that the relationship will be linear, we cannot say that this line is a good fit, as the data may have a non-linear relationship.

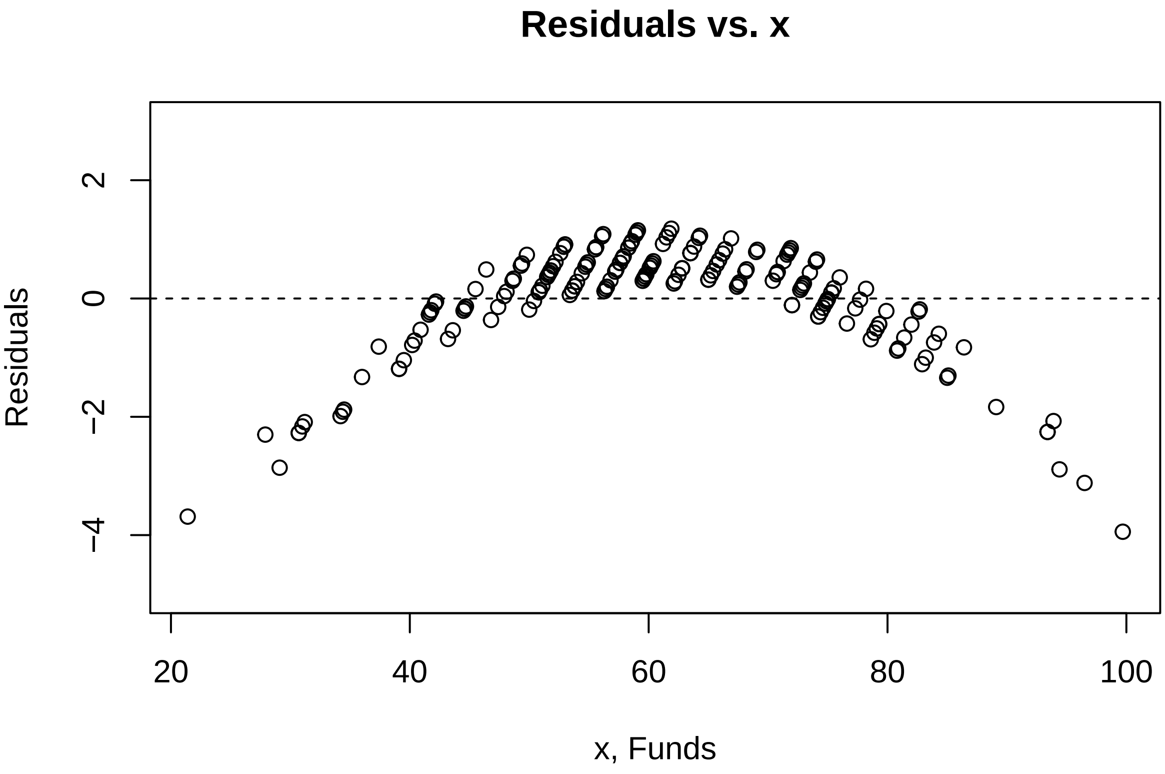
d. Are the four assumptions of linear regression satisfied? To answer this, draw the relevant plots. (Write a maximum of one sentence per assumption.) If not, what might you try to do to improve this (if you had more time)?

```
plot(reg.output, which = 1)
```



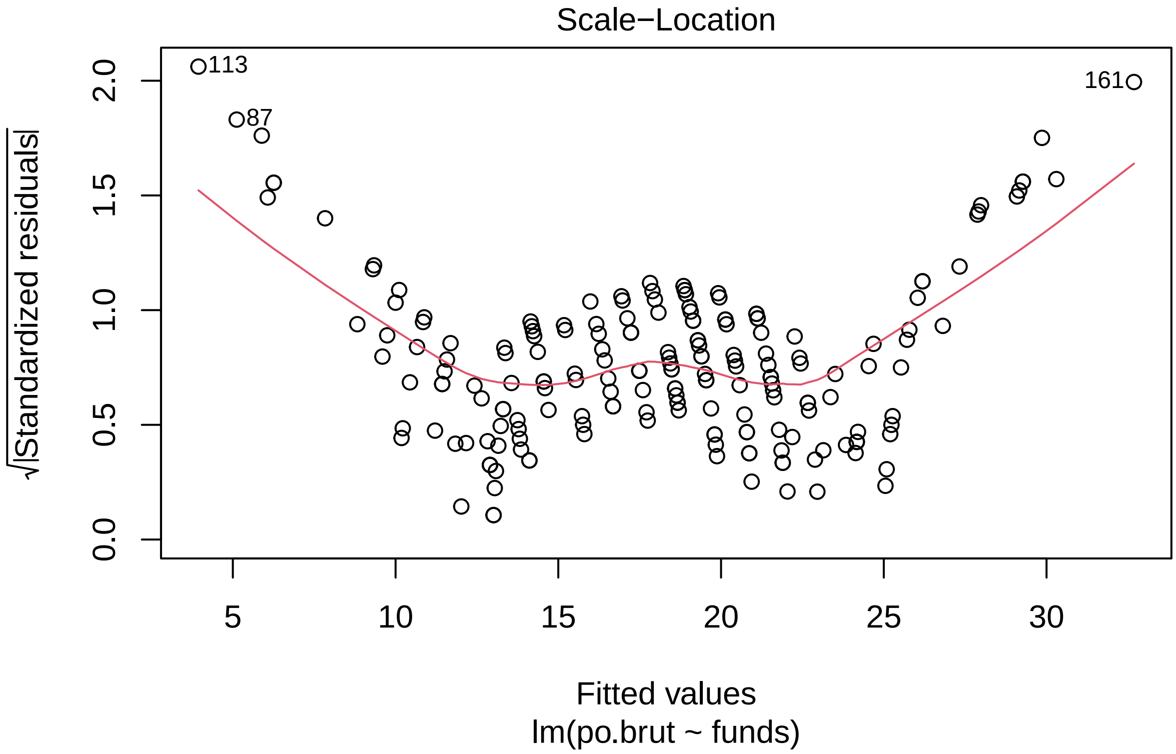
Assumption 1: Linearity. This assumption is not satisfied because the line representing average value of the residuals at each value of fitted value looks relatively curved, and there is an observable non-linear trend.

```
plot(dat$funds, reg.output$residuals, ylim = c(-5, 3), main = "Residuals vs. x",
    xlab = "x, Funds", ylab = "Residuals")
abline(h = 0, lty = "dashed")
```



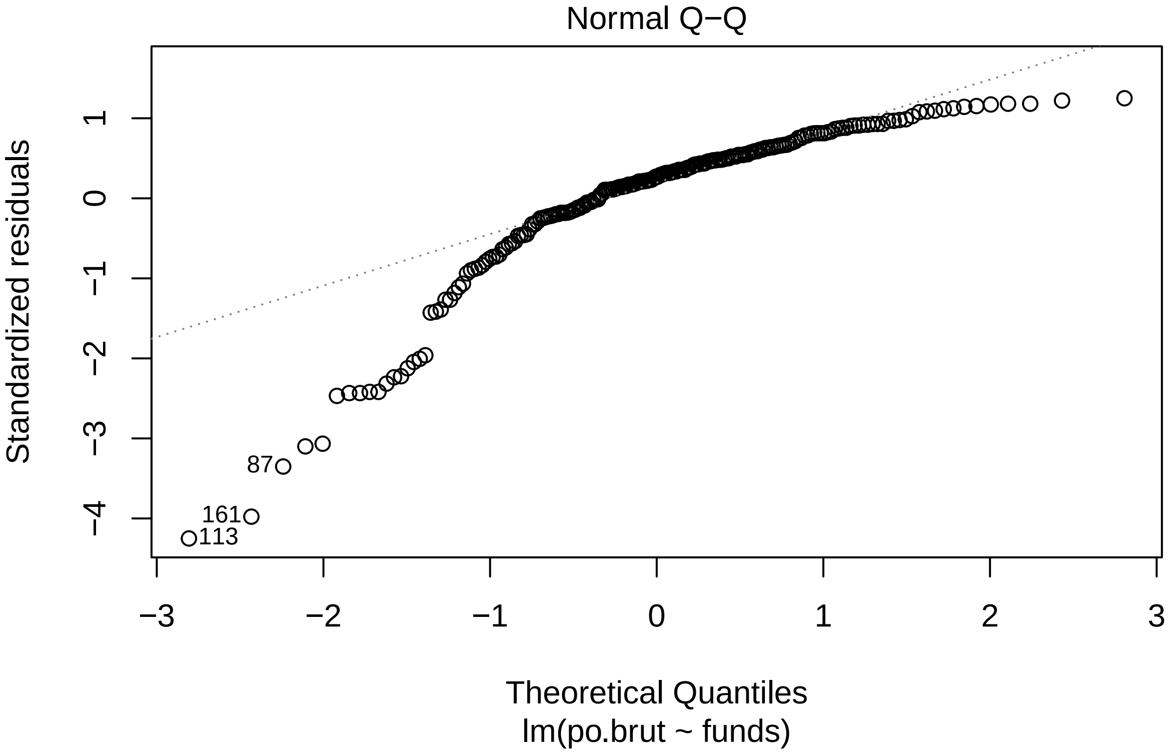
Assumption 2: Independence. Based on our plots, this assumption is not satisfied because there are some apparent patterns in the residuals plot. We can observe what appears to be a curved, consistent shape in the data, almost creating a pattern. While the independence assumption cannot be tested, this plot is a good way to see if there may be a relationship between the two variables that makes them dependent. We should be hesitant to assume that the variables are independent.

```
plot(reg.output, which = 3)
```



Assumption 3: Homoscedasticity. There appears to be patterns in variability of x and y, and the scale-location plot above does not result in a flat line, meaning residuals have non-constant variance. Therefore, the assumption that all the errors have the same variance does not appear to be true.

```
plot(reg.output, which = 2)
```



Assumption 4: Normal Population. The values in the QQ plot appear to show a curved trend, which means that the data may have a left skew compared to a normal distribution, so this condition is not satisfied.

In order to "improve" the data, I would attempt to transform the data. Because of the failed assumption tests, it may be necessary to do data transformations in order to properly interpret the relationship between funds and police brutality. This may involve the Box-Cox method, or logging/re-scaling the data in some way. Once I do the necessary transformations, I will interpret the results of that analysis and will be able to more effectively determine the relationship between the two variables of interest.

e. Answer the question of interest based on your analysis.

The question of interest was: Does having more funding in a police department lead to fewer incidents of police brutality? With my current analysis, I would be unable to determine if increasing funding causes fewer incidents of police brutality. Because of the numerous failed assumptions tests in our analysis, it is hard to determine if any apparent slope or relationship is actually a linear relationship, even though our initial plot looked promising. Additionally, even if all of the assumptions were fulfilled, and we eventually had a transformed the data, it would still be inappropriate to answer a causal question with data that only gives insight to correlation. There may be an additional, third factor that influences both of our variables of interest, or the relationship between funding and brutality may be reverse-causal (i.e. police officers receive more funding when they are not under scrutiny after police brutality incidents).

Problem 3: Data ethics (10 points)

Describe the dataset. Considering our lecture on data ethics, what concerns do you have about the dataset? Once you perform your analysis to answer the question of interest using this dataset, what concerns might you have about the results?

The dataset is comprised of the funding and police brutality information about 200 different police departments. Given that for police brutality reports, the departments were the ones reporting the data, rather than an external source collecting information about the departments, there may be cause for concern, as police departments my significantly underreport their brutality incidents in order to avoid scrutiny. Because it is unclear where this data is from, and how it was collected, I would be a bit hesitant to draw any conclusions *about this data, especially given that there are opportunities for sampling bias and the population of police departments that were surveyed may have been sampled in a misleading way (i.e. if the individual collecting the data did not select departments randomly within the population but rather picked police departments that they knew would have certain influence on the data). Additionally, once I have preformed analysis in order to answer the question of interest, I would still be concerned that providing an answer to a causal question based on correlative evidence may lead to unethical policy implications. Because, at the outset, it appeared that the relationship between funding and police brutality had a negative correlation, it might be easy to jump to conclusions and tell policymakers that increasing funding for all police departments can help "solve" the problem of police brutality. However, because we cannot be sure that manipulating funding will cause changes in brutality, and we also cannot be sure that increasing funding will cause a decrease in brutality rather than some other affect (given that the untransformed data fails many of the tests). And, as I said before, there may be a third variable that influences the apparent correlation, or the variables may have a reverse-causal relationship, both of which would mean that the implications of this data could be misleading. Overall, I would have to do more research about the sources of this data, and more analysis before feeling confident.*

Final Project

Investigating the Relationship Between Political Leaning and the Type/Frequency of Criminal Activity on University Campuses Across the United States

Theodora Athanitis, Tori Borlase, Halle Wasser CRIM 250: Statistics for the Social Sciences Dr. Maria Cuellar December 12, 2021

Research Motivation and Question

As college students, the topic of crime on campus is very relevant to us in terms of public safety. Additionally, as all three of us are female students, certain crime types such as those of a violent or sexual nature feel more relevant and concerning. As recent articles in the Daily Pennsylvanian discuss, crime and crime reporting have become more salient to students as classes move back in-person (Perlman, 2021). In light of the return to campus, we feel as though students should be aware of the rates and types of crimes that are most frequent, as well as the factors that impact crime rates on college campuses. Additionally, some studies show that peoples' perceptions of crime differ depending on their political leanings (Gramlich, 2016). Therefore, our research question is as follows: Does the political leaning (Democratic or Republican) of states affect either the crime type or the frequency of criminal activity on the campuses of public universities in that state? Our question and dataset are interesting because we can 1) help students be more aware of crimes that are highly relevant to them and 2) test whether there is a correlation between political beliefs and actual reported crime, or if future research is necessary to determine if the disparities between crime perceptions are due to other factors. With our analysis, we should be able to shed light on our research question as well as help improve our understanding of topics that are particularly relevant to us. Our hypothesis is that, in states with Republican political leanings, crime will be higher because Republican states may place a greater emphasis on policing and dedicate more resources to monitoring crime.

Exploratory Data Analysis

Description of the Dataset

The UCR Table 9 dataset ("Offenses Known to Law Enforcement by State by University and College", 2019) is a voluntary reporting collection composed of 569 observations on 14 variables. The variables in the dataset are: state, university.college, Campus, student.enrollment, violent.crime, murder, rape, robbery, aggravated.assault, property.crime, burglary, larceny.theft, motor.vehicle.theft, and arson (please refer to Appendix A for the codebook), with each observation corresponding to an in-state university or college. It is important to note that these observations were not evenly distributed across states; rather, some states had observations for only one in-state university, while others had observations for more than 5.

Missing Values

Within the dataset, there were many missing values for the “arson” variable. This may be because it is a relatively uncommon crime on college campuses; while some institutions chose to denote a lack of arson with “0”, others may have chosen to simply not report a value. There were four states that were not included in the dataset (namely, Alabama, Idaho, Hawaii, and Oregon) because they either did not release complete 12 month data or they did not release any data at all.

Additional Data

For our analysis, we created several new tables to create our EDA plots and to utilize for our linear regressions. The table used for the majority of our analysis is composed of 46 observations on 13 variables, with each observation representing the states with reported data (omitting Alabama, Idaho, Hawaii, and Oregon). The added variables in these datasets are state.leaning (a binary variable that represents the political affiliation the state had in the 2016 presidential election; 0=democratic and 1= republican) and total (an integer variable that is the summation of all crimes committed in the state; i.e., the sum of all crimes in all participating in-state institutions within a state).

Load the data.

```
library(readr)
library(knitr)
setwd("/Users/toriborlase/Desktop/University of Pennsylvania/Fall 2021/CRIM 250/Tori-Borlase-Crim-250")
dat <- read.csv(file = "FinalProjectData.csv")
dat5 <- read.csv(file = "FinalProjectData5.csv")
```

Breakdown of Political Leaning

Within the UCR Dataset, and of the 46 states that reported data about crime on college campuses, we found that a majority were Republican as determined by the 2016 election results. With 28 Republican states and only 18 Democratic ones, this discrepancy is an important consideration given that our analysis compares the differences in crime rates between these two categories of states on average. This means that a smaller number of states skews the average number of crimes generated during the regression analysis significantly, despite relative consistencies in the number of colleges/populations on average between the two political affiliations. The takeaway of this plot is that there were more Republican states than Democratic states reporting; therefore, we should be cognizant that our conclusions may reflect this disparity.

```
y = data.frame(Political_Leaning = c("Republican", "Democratic"),
    Number = c(28, 18))
colours = c("red", "blue")
w <- c(0.05, 0.05)
barplot(y$Number, width = w, main = "Number of Democratic and Republican
States in the UCR Dataset",
    ylab = "Number of States Represented in the UCR Dataset",
    xlab = "State Political Affiliation", names.arg = y$Political_Leaning,
    col = colours, ylim = c(0, 30))
```

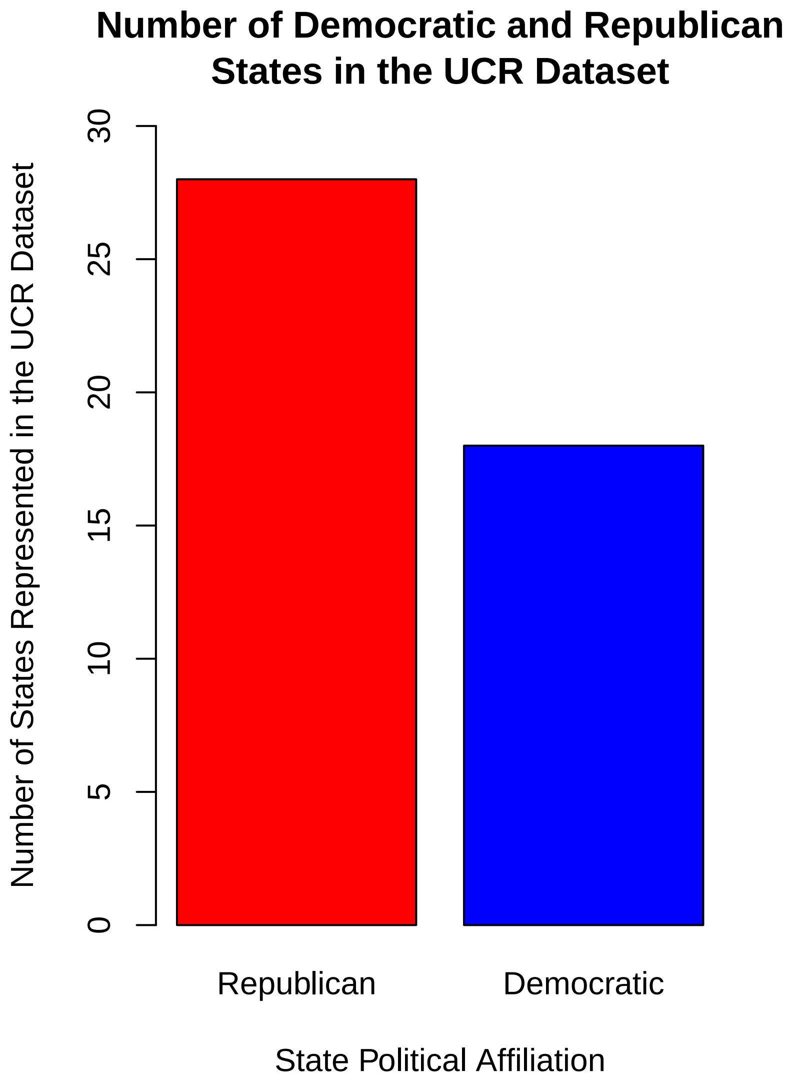


Figure 1. Bar Graph of the Number of Democratic and Republican States in the UCR Table 9 Dataset.

Frequencies of Crime Types

```
The following bar graph shows the frequencies of different types of crimes reported in both Democratic a
```

```
counts5 <- t(as.matrix(dat5[-1]))
counts5
```

```
##    [,1] [,2]  [,3]  [,4] [,5] [,6]  [,7] [,8] [,9] [,10]
## X0 1420  214 47092 22796    2  736 20223 1837   82   646
## X1 1481  211 52346 25404    5  957 22423 2028   58     5
```

```
colnames(counts5) <- dat5$crime_type
colours = c("blue", "red")
barplot(counts5, main = "Frequency of Crime Type by Political Leaning",
    ylab = "Count of Criminal Offenses", xlab = "Crime Type",
    beside = TRUE, col = colours, ylim = c(0, max(counts5) *
        1))

legend("topright", fill = colours, legend = c("Democratic States",
    "Republican States"))
```

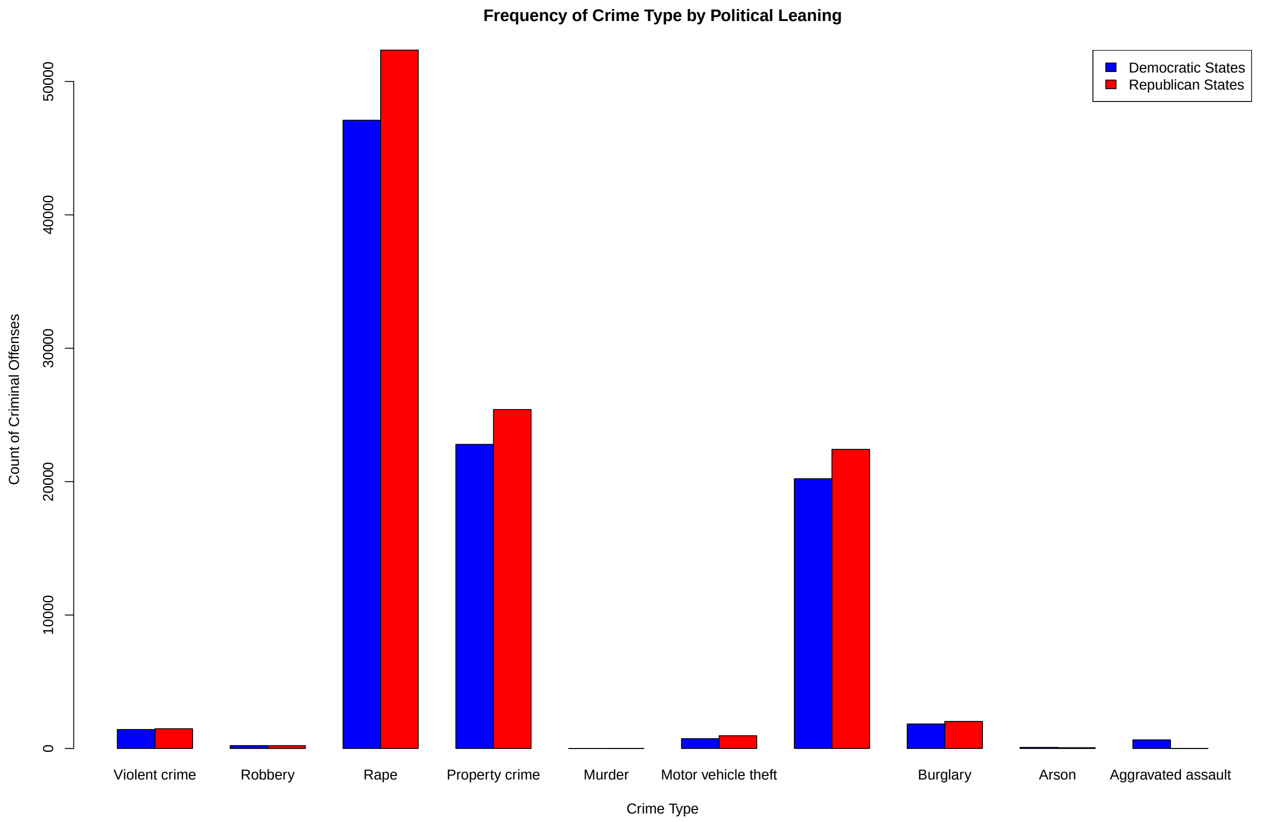


Figure 2. Bar graph of the number and type of crimes at college campuses in Democratic and Republican states.

Modeling the Data

As a preliminary step in assessing the relationship between the total crime variable and the binary state.leaning variable, we first found the correlation between the two variables to be -0.1245639.

```
# Correlation between Crime and Political Affiliation
cor(dat$State.Leaning, dat$Total)
```

```
## [1] -0.1245639
```

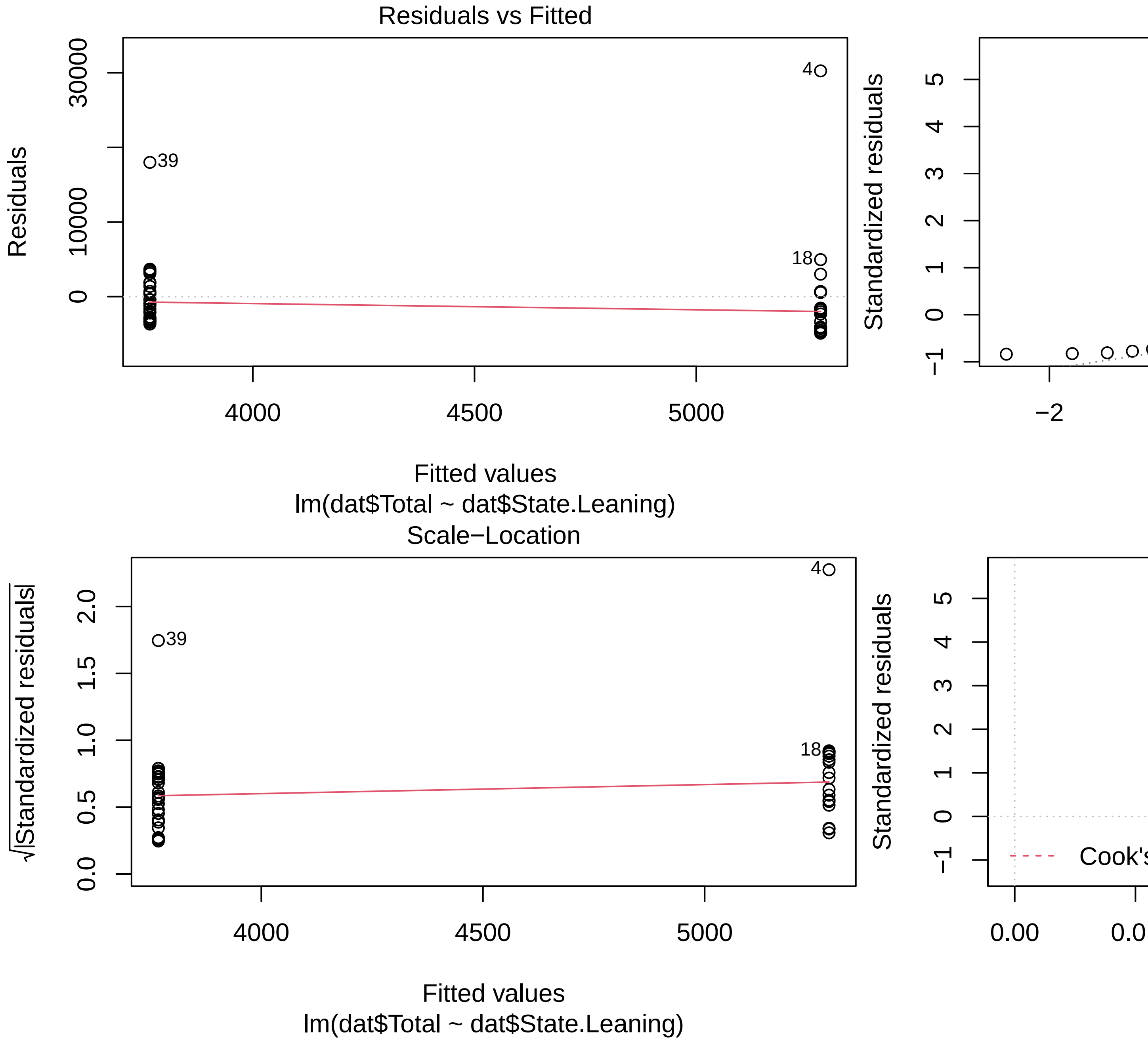
Despite this negative result, we further explored this relationship by regressing total crime on state.leaning. This analysis found that the average number of crimes on college campuses annually is 5280 total crimes Democratic States and 3767 in Republican States. However, we also found that both the equal variance assumption and the normal population assumption were not met, therefore invalidating this model to assess this relationship with the data in its current form (refer to Appendix B for diagnostic plots).

```
# Total Crime Regression
reg.output <- lm(dat$Total ~ dat$State.Leaning, data = dat)
summary(reg.output)
```

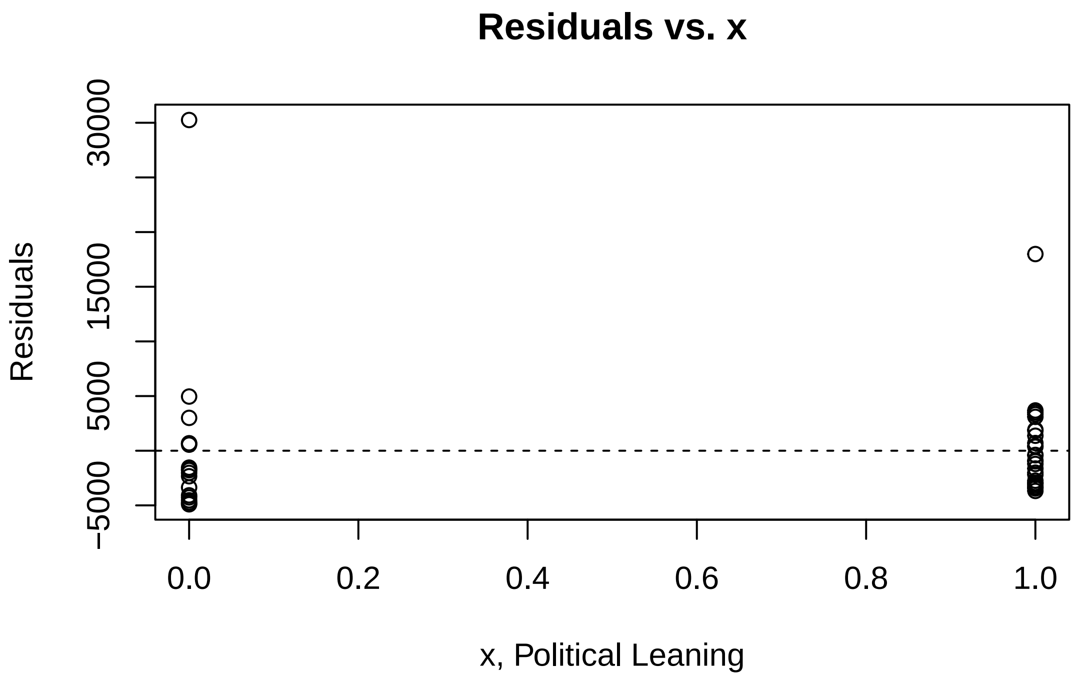
```
##
## Call:
## lm(formula = dat$Total ~ dat$State.Leaning, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4901.4 -3097.1 -1587.2   698.5 30250.6
##
```

```
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)    
## (Intercept)            5280       1417   3.726 0.000551 ***
## dat$State.Leaning     -1513       1816  -0.833 0.409484    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 6012 on 44 degrees of freedom
## Multiple R-squared:  0.01552,    Adjusted R-squared:  -0.006858 
## F-statistic: 0.6935 on 1 and 44 DF,  p-value: 0.4095
```

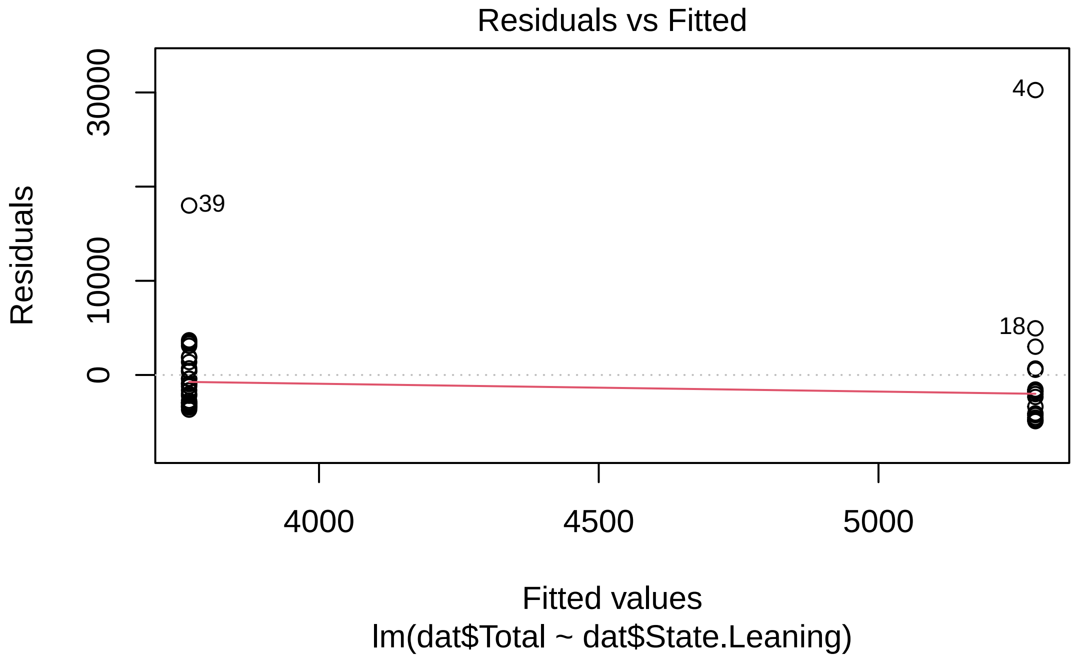
```
plot(reg.output)
```



```r
# Linearity Assumption:
plot(dat$State.Leaning, reg.output$residuals, main = "Residuals vs. x",
    xlab = "x, Political Leaning", ylab = "Residuals")
abline(h = 0, lty = "dashed")
```

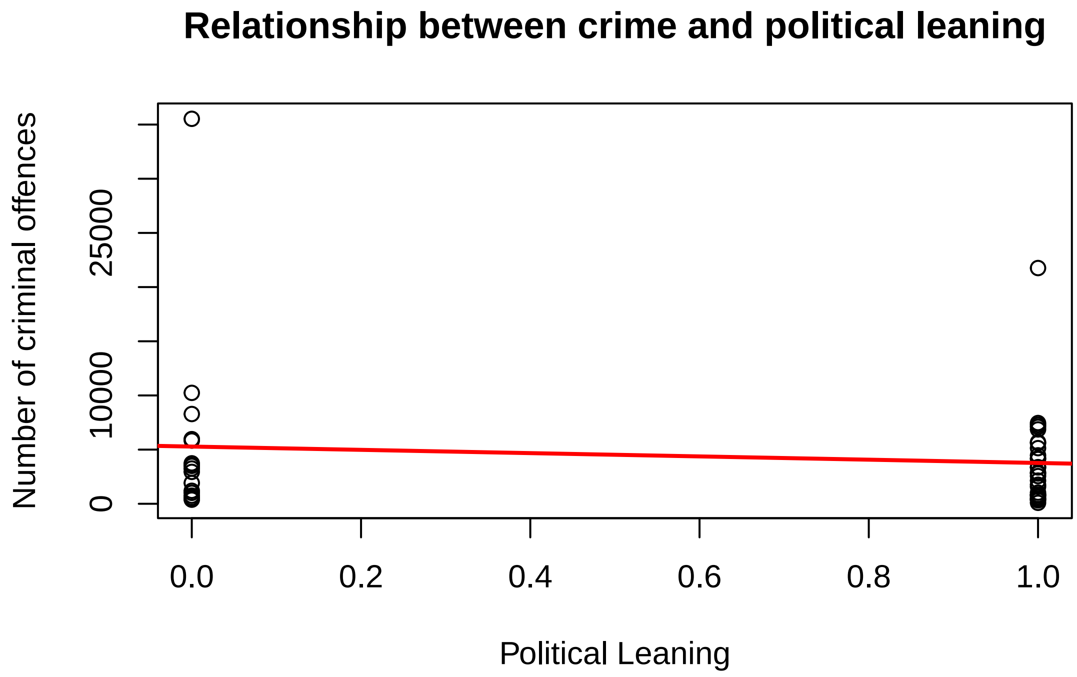


```r
plot(reg.output, which = 1)
```

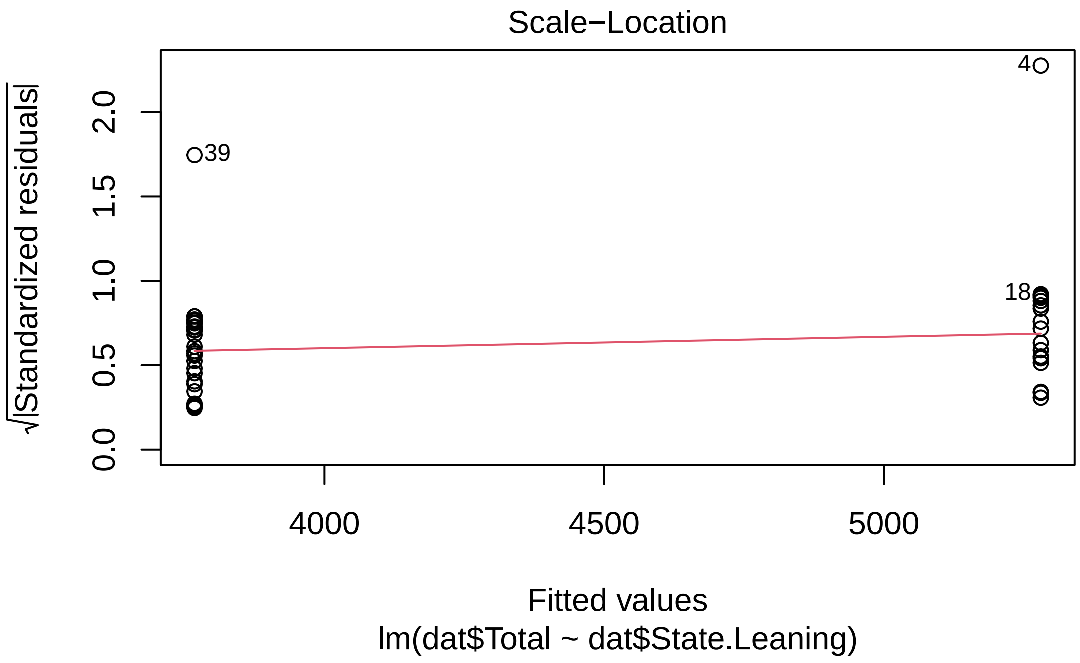


```r
# Independence Assumption: using Residuals vs. x plotted
# above
plot(dat$State.Leaning, dat$Total, main = "Relationship between crime and political leaning",
    xlab = "Political Leaning", ylab = "Number of criminal offences")
```

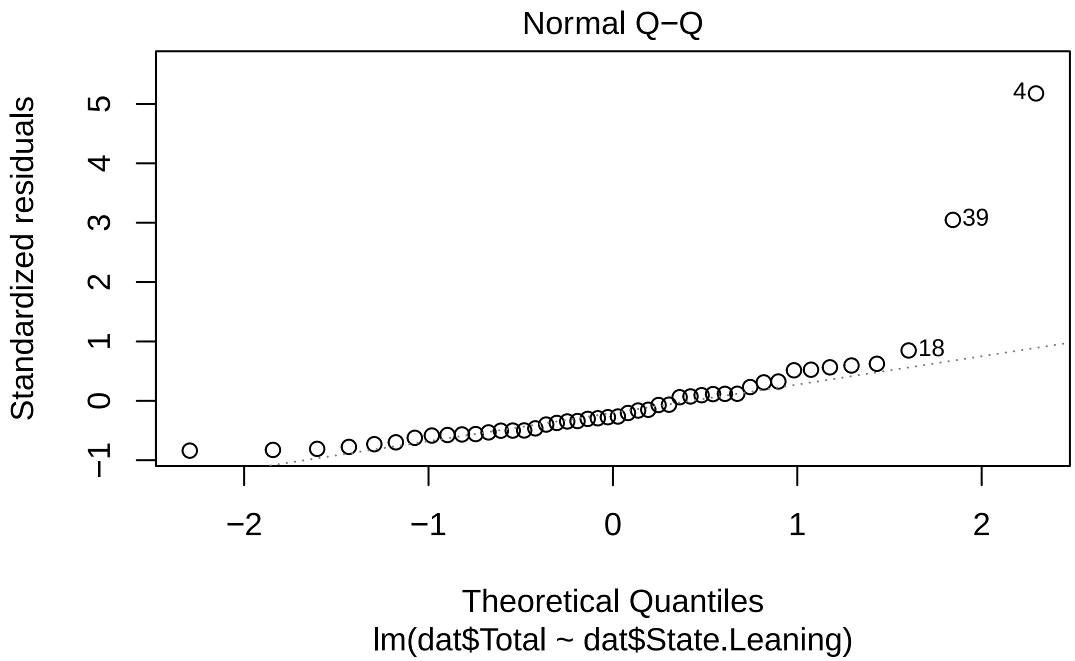
```
abline(reg.output, col = "red", lwd = 2)
```



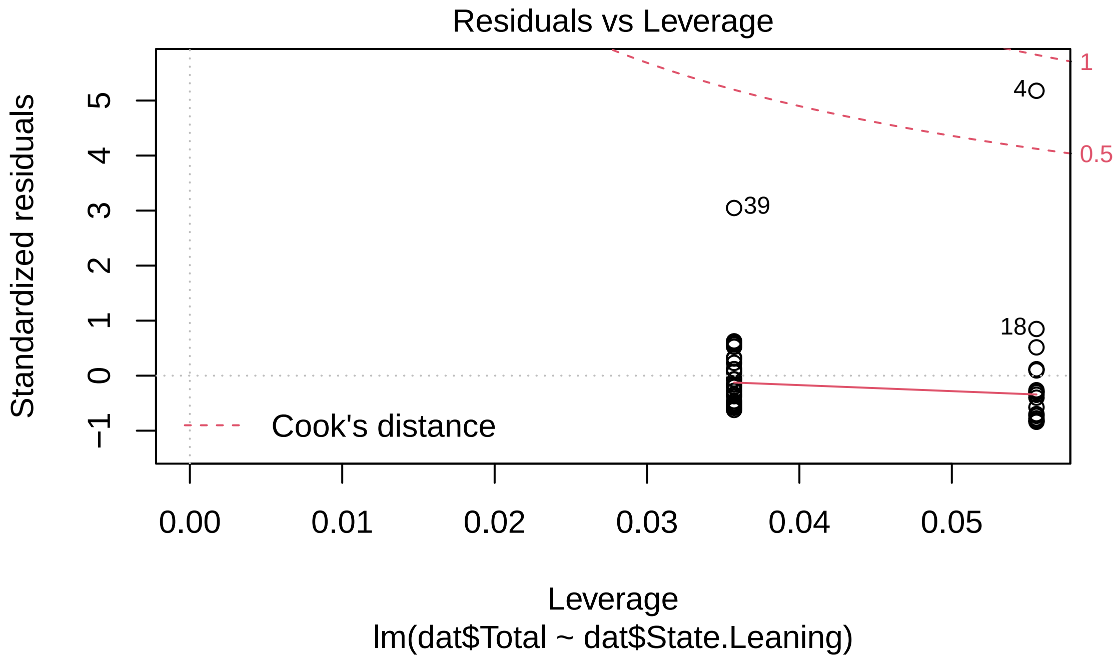
```
# Equal Variance Assumption/ Homoscedasticity:
plot(reg.output, which = 3)
```



```
# Normal Population Assumption:
plot(reg.output, which = 2)
```



```
plot(reg.output, which = 5)
```



Linearity Assumption: This assumption is met. The residuals vs. x plot has a horizontal direction and does have a significant pattern in the data. Furthermore, the residuals vs fitted plot is fairly horizontal and flat, meaning that there is no discernible non-linear trend to the residuals.

Independence Assumption: This assumption is also met for the same reason as the linearity assumption as the residuals vs. x plot has a horizontal direction and does have a significant pattern in the data, as well as because there does not seem to be a time-series component to the data.

Equal Variance Assumption/ Homoscedasticity: This assumption is not met. The scatter plot of crimes vs. political affiliation has no variations with shrinkage in the plot. Additionally, there are significant negative trends, based on the size of the data, shown by the line in the scale-location plot showing that the errors do not have a constant variance.

Normal Population Assumption: This assumption is not met since the q-q plot has significant left skew deviations and is heavy-tailed for the values in this plot.

As these assumptions are not met, normally the next step would be to use the box-cox method to find the best transformation for this data, transform the x variable, and repeat this process. However, as the p-value was so large at 0.4095, demonstrating that this relationship is not statistically significant, we instead concluded that we cannot reject the null hypothesis and instead explored whether or not this relationship existed for a particular crime type variable.

For the rape and violent crime regression it was found that the average number of rapes on college campuses in Democratic states is 2616.2 and 1868.5 in Republican states, and the average number of violent crimes in Democratic states is 78.89 and 52.89 for Republican states. Unfortunately, the two variables that we explored also had significant p-values of 0.4116 and 0.2967, respectively, and we therefore concluded that we cannot reject the null hypothesis for these individual variables either.

```r
# Rape regression
reg.output1 <- lm(dat$Rape ~ dat$State.Leaning, data = dat)
summary(reg.output1)
```

```
##
## Call:
## lm(formula = dat$Rape ~ dat$State.Leaning, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2427.2 -1536.8  -780.4   348.2 14986.8
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2616.2      702.8   3.723 0.000557 ***
## dat$State.Leaning   -746.7      900.8  -0.829 0.411605
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2982 on 44 degrees of freedom
## Multiple R-squared:  0.01538,    Adjusted R-squared:  -0.007001
## F-statistic: 0.6872 on 1 and 44 DF,  p-value: 0.4116
```

```r
# Violent Crime Regression
reg.output2 <- lm(dat$Violent.crime ~ dat$State.Leaning, data = dat)
summary(reg.output2)
```

```
##
## Call:
## lm(formula = dat$Violent.crime ~ dat$State.Leaning, data = dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -77.89 -46.64 -19.39  31.11 417.11
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)          78.89      19.20   4.108 0.000171 ***
## dat$State.Leaning   -26.00      24.62  -1.056 0.296690
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 81.48 on 44 degrees of freedom
## Multiple R-squared:  0.02472,    Adjusted R-squared:  0.002556
## F-statistic: 1.115 on 1 and 44 DF,  p-value: 0.2967
```

While this analysis does not show a relationship between crime frequency on college campuses and the political affiliation of the state in which it is located, this relationship may exist in an indirect fashion and is not represented in this dataset due to other causal factors that we will discuss in the following sections.

Causal Analysis

Causal Factors

As a reminder, our question of interest was if there was a relationship between state political leaning and crime on college campuses. We selected to not conduct a causal analysis given our low p-values in our regression analysis, especially because many other factors could cause crime to increase or decrease, and we are unable to answer a causal question with observational data. There may be other causal mediators that could change crime on college campuses other than a direct effect of the political leanings of the state in which the college is located. As seen in our DAG below, while there may be a direct relationship between our main variables of interest, political affiliations may also impact police funding, social program funding, reporting standards, and open carry laws (to name a few), which may in turn be the true cause of different crimes and their frequencies. The DAG below shows those relationships, and especially given our low p-values, we should be cautious in making any causal assessments for our specific research question.

Figure 3. Directed Acyclic Graph of the relationship between state political party affiliation, crime type and frequency on campus, and other intermediary factors. **Note: DAG is in our final project on Canvas**

Final Discussion

Overall, our regression analysis failed all but two of the assumption tests as well as returning relatively high p-values. We are unable to reject the null hypothesis that political affiliation of states has no impact on the crime type or frequency on college campuses. When analyzing our DAG, it is important to consider which internal nodes have causal effects and the degree to which these nodes influence the potential for a causal relationship. Although our analysis may suggest that there is no causal relationship between our variables of interest, it is clear that the relationship might still exist. In order to reach a conclusion, a discussion of our method's limitations is warranted, as well as future research suggestions to avoid similar issues.

Limitations

Along with the limitations discussed above regarding the incomplete reporting data and the inclusion of more Republican states, there are other key limitations that need to be addressed. Firstly, California and Texas were significant outliers given that they not only had the most in-state institutions voluntarily report but the institutions within these states also had larger student enrollments. Given that our regression analysis results show the number of crimes on average, any state/institution with a larger student enrollment would skew the average for each state, shifting the representative sample of the states within each political affiliation group. Another limitation of our method is that we only utilized 2016 election results to assign political alignment rather than placing the state on a spectrum of the percentage of votes for a certain party. Because of this, the state.leaning variable was binary, which might explain why our linear regression model did not satisfy any of the assumptions. While one might question why we chose to keep this variable as binary, rather than switching to a spectrum before completing our analysis, the existence of swing states would have made it difficult to analyze the results. If states were hovering near 50%, it would be difficult to determine the influence of political affiliation on perceptions of crime and policing.

Future Research Recommendations

Although the results of our analysis suggest that a state's political leaning does not influence the type of frequency of crime on in-state university campuses, this determination is far from sufficient to rule out the possibility of relationship. Based on our study's limitations, it would be beneficial to analyze three different categories of states: (1) Republican stronghold states, (2) Democratic stronghold states, and (3) swing states. This political breakdown, along with a discussion of the changes in crime rates on college campuses within these states for the year directly following an election may better explain the relationship between political affiliation and crime type and frequency of in-state institutions. Another suggestion would be standardizing the data points collected by looking at crime rates per capita and including population and campus size information such that we are able to compare universities of equal student-enrollment. In other words, data points need to be standardized in order to control for confounding variables, such as the environment (urban vs. rural campus, the campus having its own police force, etc.). Lastly, we would suggest utilizing the campus' political leaning, rather than the political leaning of the state where the college is located given that these political leanings may conflict, especially in swing states. These method recommendations lend themselves to better answer the research question of interest.

Concluding Remarks

In conclusion, our data analysis showed that there was no statistically significant correlation between state political leaning and crime types and frequencies on college campuses. Given that our data was observational, we were unable to conduct a proper causal analysis, and we hope that future research in this field can further explore both correlation and causal relationships between our two variables of interest.

References

Federal Bureau of Investigation. (2019). 2019 Crime in the United States: Table 9, Offenses Known to Law Enforcement by State by University and College, 2019. U.S. Department of Justice FBI: UCR. https://ucr.fbi.gov/crime-in-the-u.s/2019/crime-in-the-u.s.-2019/topic-pages/tables/table-9/table-9.xls/view.

Gramlich, J. (2016, November 16). Voters' perceptions of crime continue to conflict with reality. Pew Research Center. https://www.pewresearch.org/fact-tank/2016/11/16/voters-perceptions-of-crime-continue-to-conflict-with-reality/.

Perlman, L. (2021, November 4). 3 crimes, 0 alerts: A look into Penn's crime reporting system. The Daily Pennsylvanian. https://www.thedp.com/article/2021/11/penn-alerts-clery-crimes-reporting-system.

Appendix A

Codebook: Variable Names and Relevant Definitions

```
# state Full name of the state where the college campus is
# located university.college Full name of college or
# university Campus Individual campus name where
# applicable- ex. California State University
# 'Bakersfield', if inapplicable a # value of N/A is
# inputted student.enrollment Integer variable based on
# 2018 United States Department of Education enrollment
# reports that includes both undergraduate and graduate
# populations where applicable
```

The following variables are based on the local definition of the crime in the given jurisdiction- the only exceptions are included below.

```
# violent.crime murder This variable includes both murder
# and non-negligent manslaughter rape This definition is
# based on the 2017 UCR revised defintion of rape that
# removes the variable of 'forcible' from the
# classification robbery aggravated.assault property.crime
# burglary larceny.theft motor.vehicle.theft arson
```