Practice Session: Coding, Stats, and R Basics

CSUCI Datathon – Southern California Consortium for Data Science

2025-04-26

0. Installing and Loading R Packages

```r
install.packages("tidyverse")
library(tidyverse)
```

1. Basics

In this section, you will learn the basics of `R`.

To follow along, you should type the code that appears in each box to ensure you are getting the intended result.

1. When you encounter a "**Challenge**", this is a task you should solve with your group using critical thinking.

2. In this first part, whenever you see a box of code, you should also type out that code and run it to verify the output. We all need to learn the basics.
3. When we get to part 2 (*Data Frames*), it is okay to focus more on the challenges and read code and the output. However, you should still type out any code that feels "brand new." Physically typing out the code helps more than you might think.

Don't be afraid to ask for help at any point during the datathon! Raise your hand and a volunteer will come help right away.

1.1 `R` is a calculator

What is $2 + 2$? `R` can do this for us in three different ways.

Method 1

Input `2+2` into the **console** and press `ENTER` to obtain `4`.

```
2+2
```

```
[1] 4
```

Method 2

Try doing it from the script by following these steps:

1. Input `2+2` into the **script** file.
2. Pressing `CTRL+ENTER`. *(`CMD+ENTER` on a mac.)*

Now, look at the console and you will notice that the code "gets run" in the console.

Method 3

- Go back to the line for `2+2` in the script file, and click the `RUN` button.

Using Comments

Lines that start with a # are called *comments* and is not run. They are useful for making notes to yourself or to explain complex code.

Type each of these two lines into the script file and run them one-by-one.

```
# Multiply 2 by 3 and then add 7
2*3 + 7
```

```
[1] 13
```

You do not need to type out the comments in this next example, but you should read them and run the code.

```
# Calculate the average of four numbers.
# First, we sum the numbers using parentheses, then divide by the count.
(2 + 7 + 3 + 2) / 4
```

```
[1] 3.5
```

In what follows, you do not necessarily need to type out all of the comments. However, it is considered "good coding practice" to add comments to your code. *(Can you think of a couple of reasons as to why?)*

1.2 Workflow Tips

- Think of the `script` as a whiteboard. You can adjust it as you need to.

- The `console` can be used to run quick commands directly

What if the `7` is instead a `9`?

Instead of typing out this code, go back and adjust `(2 + 7 + 3 + 2) / 4)` in the script. Then use `CTRL + ENTER` to run it.

```
(2 + 9 + 3 + 2) / 4
```

```
[1] 4
```

You can also *recycle* commands with the console:

- Click anywhere in the console, and press the `up arrow` on the keyboard. Keep pressing it and cycle through to see the commands you have ran.
- Click on the `"History"` tab in the upper right as another way to see previous commands. (*Make sure to click back to `"Environment"`…we will be using it soon*)
- You can highlight multiple lines of code and run them at once. Right now, highlight all of your code and run it. Your resulting console should give output like this:

```
2+2
```

```
[1] 4
```

```
# Multiply 2 by 3 and then add 7
2*3 + 7
```

```
[1] 13
```

```
# Calculate the average of four numbers.
# First, we sum the numbers using parentheses, then divide by the count.
(2 + 9 + 3 + 2) / 4
```

```
[1] 4
```

White Space

- White space (empty lines) do not affect code. It is encouraged to make code more readable.
- Instead a script with no spaces, something like this is preferable:

```
2+2

# Multiply 2 by 3 and then add 7
2*3 + 7

# Calculate the average of four numbers.
# First, we sum the numbers using parentheses, then divide by the count.
(2 + 9 + 3 + 2) / 4
```

1.2 Using Functions

`R` includes functions for other types of math

```
# using a function: rounding numbers
round(3.14)
```

```
[1] 3
```

An *argument* is an *input* to a function. Functions can take in many arguments:

```
# using a function with more arguments
round(3.14, digits = 1)
```

```
[1] 3.1
```

Note on `R` Syntax

Here are three ways to do the same thing. Can you see why this happens?

```
# Method 1
round(3.14, digits = 1)
```

```
[1] 3.1
```

```
# Method 2
round(3.14,
      digits = 1)
```

```
[1] 3.1
```

```
# Method 3
round(3.14,
```

```
      digits = 1
)
```

```
[1] 3.1
```

`R` reads from left to right, line by line. If it does not see the end of a statement, then it will keep going onto the next line.

Challenge 1

What do you think this code will produce? Predict the answer yourself before running it.

```
100 +
  30 +
  7
```

Syntax Warning

```
# Correct syntax
round(3.14,
  digits = 1)

# Incorrect syntax: This will cause an error because the statement is not complete without ")"
round(3.14,
  digits = 1

# Incorrect syntax: This will cause an error because R is case sensitive.
Round(3.14,
  digits = 1)
```

1.3 Assigning Objects

```
# assigning value to an object
weight_kg <- 55
```

Now, look in the upper right and you will see `weight_kg` in the `environment`. This means we can use it in various ways:

```
# recall object
weight_kg
```

```
[1] 55
```

```
# multiply an object (convert kg to lb)
2.2 * weight_kg
```

```
[1] 121
```

```
# assign converted weight in lbs
weight_lb <- 2.2 * weight_kg
```

```
# reassign new value to an object
weight_kg <- 100
```

After running the last code, notice that `weight_kg` changed in the environment panel.

CAUTION:

Reminder: `R` is case sensitive. So it will treat `weight_kg`, `Weight_kg`, and `WEIGHT_kg` differently. (*Try running the command `Weight_kg`. What error does it produce?*)

1.4 Vectors

In `R`, a **vector** can be thought of as a list *(usually of numbers)*.

```
# assign vector
ages <- c(16, 18, 20, 22, 24)

# recall vector
ages
```

```
[1] 16 18 20 22 24
```

All sorts of functions can be applied to vectors:

```
# how many things are in object?
length(ages)
```

```
[1] 5
```

```
# average the ages to obtain the mean: (16 + 18 + 20 + 22 + 24) / 5
mean(ages)  # this is faster than typing out (16 + 18 + 20 + 22 + 24) / 5
```

```
[1] 20
```

```
# smallest and largest ages
range(ages)
```

```
[1] 16 24
```

```
# what are the ages if everyone becomes 5 years older?
ages + 5
```

```
[1] 21 23 25 27 29
```

```
# what are the ages if everyone is two times as old as they are now?
ages * 2
```

```
[1] 32 36 40 44 48
```

Vectors of Words

Words need to be put in quotation marks.

```
# vector of foods
foods <- c("pizza", "spaghetti", "steak")
```

```r
foods
```

```
[1] "pizza"     "spaghetti" "steak"
```

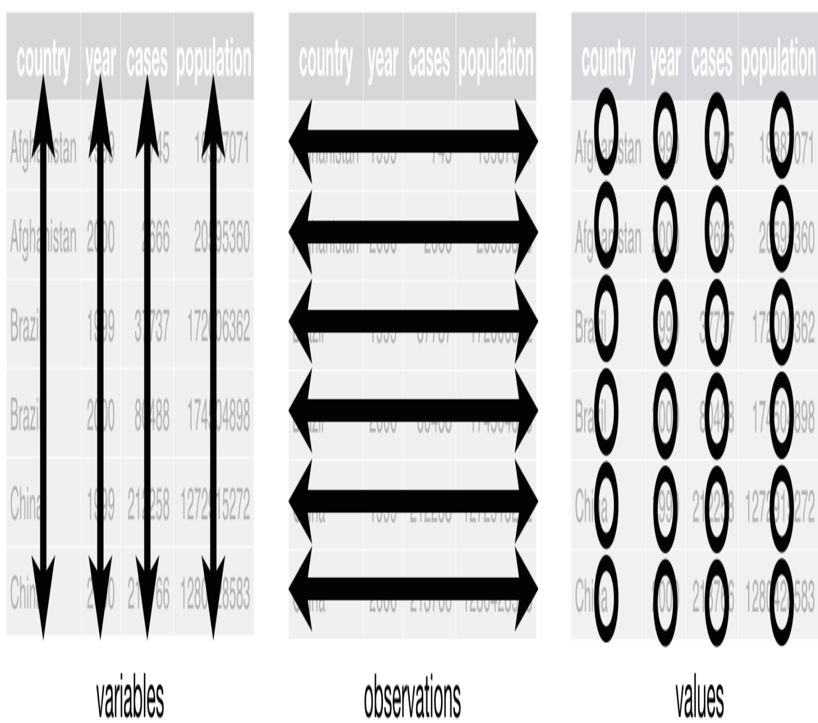
```r
# It doesn't make sense to take an average of the foods.
# NA means "Not Available"
mean(foods)
```

```
[1] NA
```

2. Data Frames and Statistics Basics

A **data frame** is like a spreadsheet. They can

1. be created from scratch like we did with `ages` (using the `data.frame(...)` command)
2. imported from a *package* (or, exist in *base `R`*)
3. be imported *(excel spreadsheets can be imported!)*



Libraries

`libraries` are separate functions functions someone else wrote that are not built into R. They need to be installed ahead of time, but we have done that for you.

Now, load the package `ggplot2`. This code needs to be run **once** per `R` session.

```
# Load package.  Gives access to plotting tools and loads "mpg".
library(ggplot2)

# Insert mpg into environment
data(mpg)
```

2.1 Data Frame Functions (`mpg`)

In `mpg`,

- each row corresponds to an *observation* (in this case, a car)
- each column corresponds to a *variable* car characteristic
- each cell has a value

Here are some things you can use to understand a data frame better:

```
# get the variable  names
names(mpg)
```

```
 [1] "manufacturer" "model"        "displ"        "year"         "cyl"
 [6] "trans"        "drv"          "cty"          "hwy"          "fl"
[11] "class"
```

```
# get the number of observations and variables.  dim means dimension
dim(mpg)
```

```
[1] 234  11
```

```
# display the first 10 observations of the dataframe
head(mpg, 10)
```

```
# A tibble: 10 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~
```

```
# access a certain variable with a "$"
mpg$hwy  # highway mpg
```

```
  [1] 29 29 31 30 26 26 27 26 25 28 27 25 25 25 25 24 25 23 20 15 20 17 17 26 23
 [26] 26 25 24 19 14 15 17 27 30 26 29 26 24 24 22 22 24 24 17 22 21 23 23 19 18
 [51] 17 17 19 19 12 17 15 17 17 12 17 16 18 15 16 12 17 17 16 12 15 16 17 15 17
 [76] 17 18 17 19 17 19 19 17 17 17 16 16 17 15 17 26 25 26 24 21 22 23 22 20 33
[101] 32 32 29 32 34 36 36 29 26 27 30 31 26 26 28 26 29 28 27 24 24 24 22 19 20
[126] 17 12 19 18 14 15 18 18 15 17 16 18 17 19 19 17 29 27 31 32 27 26 26 25 25
[151] 17 17 20 18 26 26 27 28 25 25 24 27 25 26 23 26 26 26 26 25 27 25 27 20 20
[176] 19 17 20 17 29 27 31 31 26 26 28 27 29 31 31 26 26 27 30 33 35 37 35 15 18
[201] 20 20 22 17 19 18 20 29 26 29 29 24 44 29 26 29 29 29 29 23 24 44 41 29 26
[226] 28 29 29 29 28 29 26 26 26
```

```r
# average highway mpg of cars in the dataset
mean(mpg$hwy)
```

```
[1] 23.44017
```

```r
# view the data frame like an excel spreadsheet
View(mpg)
```

You can also use the environment instead of typing `View(...)`. Do this now by clicking on `mpg` in the environment tab.

Challenge 2:

Find the average city miles per gallon for a car in the dataset and compare it to the average highway miles per gallon. Does the result surprise you?

2.2 Data Frame Filtering with `subset` (`mpg`)

```r
# Filtering cars with highway mileage greater than 30
subset(mpg, hwy > 30)

# Filtering cars that are rear wheel drive
subset(mpg, drv == "r")
```

```r
# Average hwy mpg of minivans
minivans <- subset(mpg, class == "minivan")
mean(minivans$hwy)
```

```
[1] 22.36364
```

2.3 Statistics Primer

Variable Types

There are two main types of variables

- **Numerical** *(or quantitative)*: Typically numbers; makes sense to add and average them.
- **Categorical** (*or factor, or qualitative*): Typically things that have names; does not make sense to add or average them.

```r
# engine size (displacement) is a numeric variable.
mean(mpg$displ)  # average of engine sizes
```

```
[1] 3.471795
```

```r
sum(mpg$displ)  # sum of engine sizes
```

```
[1] 812.4
```

```r
# class, or "type" of car is a categorical variable
mean(mpg$class)  # this will return an error
```

```
[1] NA
```

```r
unique(mpg$class)  # gives the unique elements of car type ("levels" or "categories")
```

```
[1] "compact"    "midsize"    "suv"        "2seater"    "minivan"
[6] "pickup"     "subcompact"
```

Challenge 3:

1. Give another numerical variable in `mpg`, and report its average.
2. Give another categorical variable in `mpg`, and report its possible categories.

TECHNICAL NOTE 1:

(Feel free to run the code in the helper script and skip this part)

When doing statistics, categorical variables should be stored as *factor* variables, which tells `R` that the words are more than just words and will be used for statistics. The `Levels` are the possible categories.

```r
# foods, as a character
foods
```

```
[1] "pizza"     "spaghetti" "steak"
```

```r
# foods, as a factor
factor(foods)
```

```
[1] pizza     spaghetti steak
Levels: pizza spaghetti steak
```

Categorical variables are usually already factor variables in `R`, but depending on how the data is imported, they may need to be converted. We need to do this with `mpg`.

```r
# Approach 1: tedious but straightforward
# repeat this for each categorical variable
mpg$manufacturer <- as.factor(mpg$manufacturer)
# ...


# Approach 2: does it automatically, but the code is very complicated.
# You can find this code in the helper script so you do not have to type it by hand.
mpg[sapply(mpg, is.character)] <- lapply(mpg[sapply(mpg, is.character)],
                                           as.factor)
```

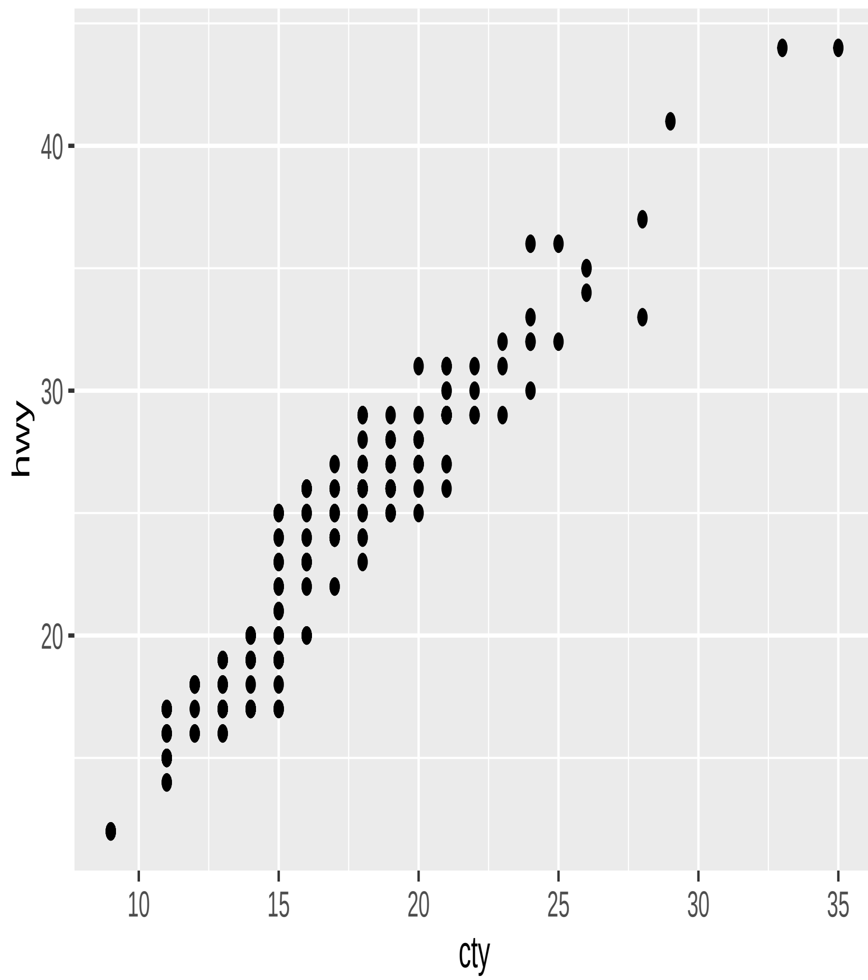
3. Plots and Summary Statistics

3.1 Basic Plots

Scatterplots

Scatterplots illustrate a relationship between two numeric variables.

```
# Most common syntax
ggplot(mpg) +
  geom_point(aes(x = cty, y = hwy))
```



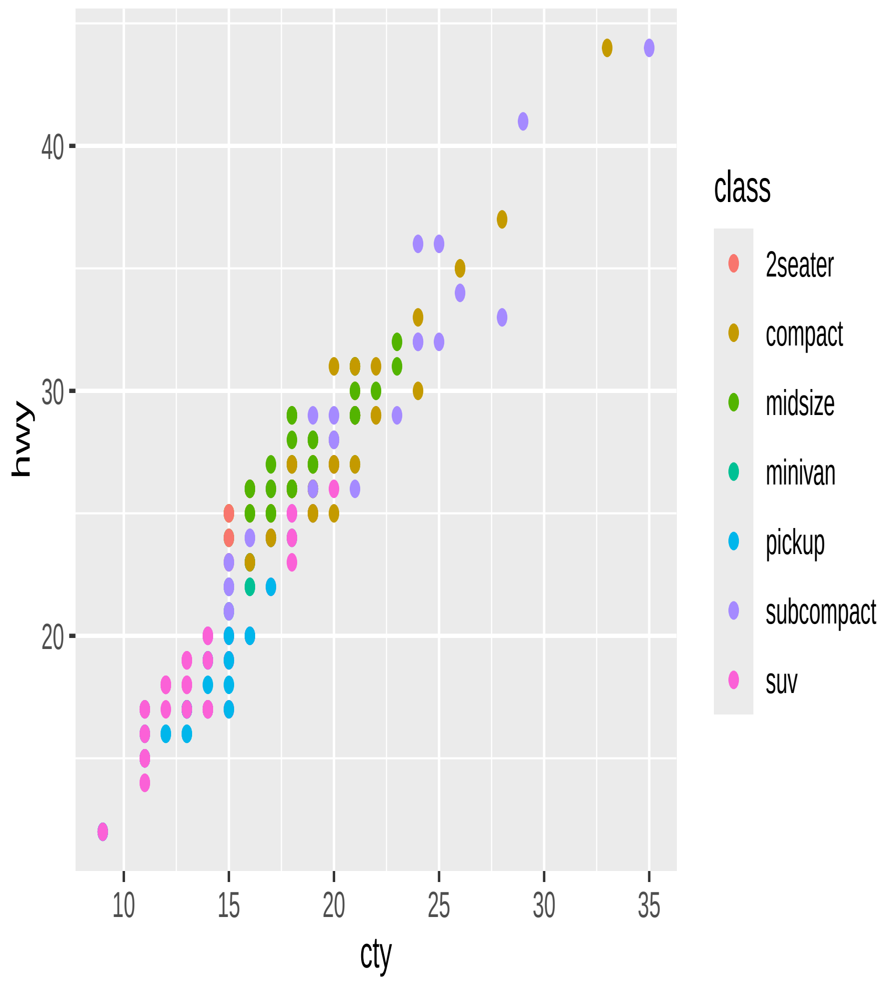

```
# Alternative syntax, can be too long (examples later)
ggplot(mpg) + geom_point(aes(x=cty, y = hwy))


# Syntax to illustrate each part
ggplot(mpg) +              # We want to plot "mpg"
  geom_point(              # Make a "point" plot (scatterplot)
    aes(x=cty, y = hwy)    # Aesthetically, cty is on x-axis, hwy is on y-axis
  )
```

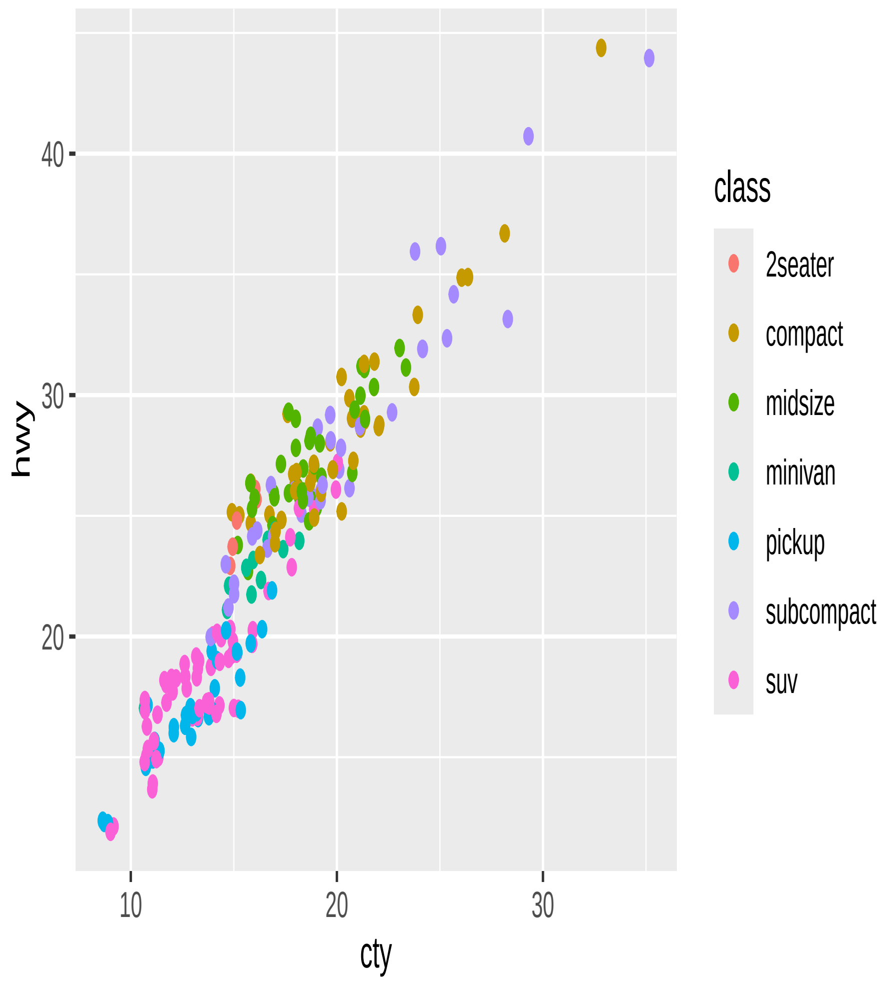
`aes(...)` tells the plot what **aesthetics** you want it to have. Some examples of things to specify:

- `x`: variable to put on x-axis
- `y`: variable to put on y-axis
- `col`: if you want to add color according to a certain variable
- `size`: if you want to change the

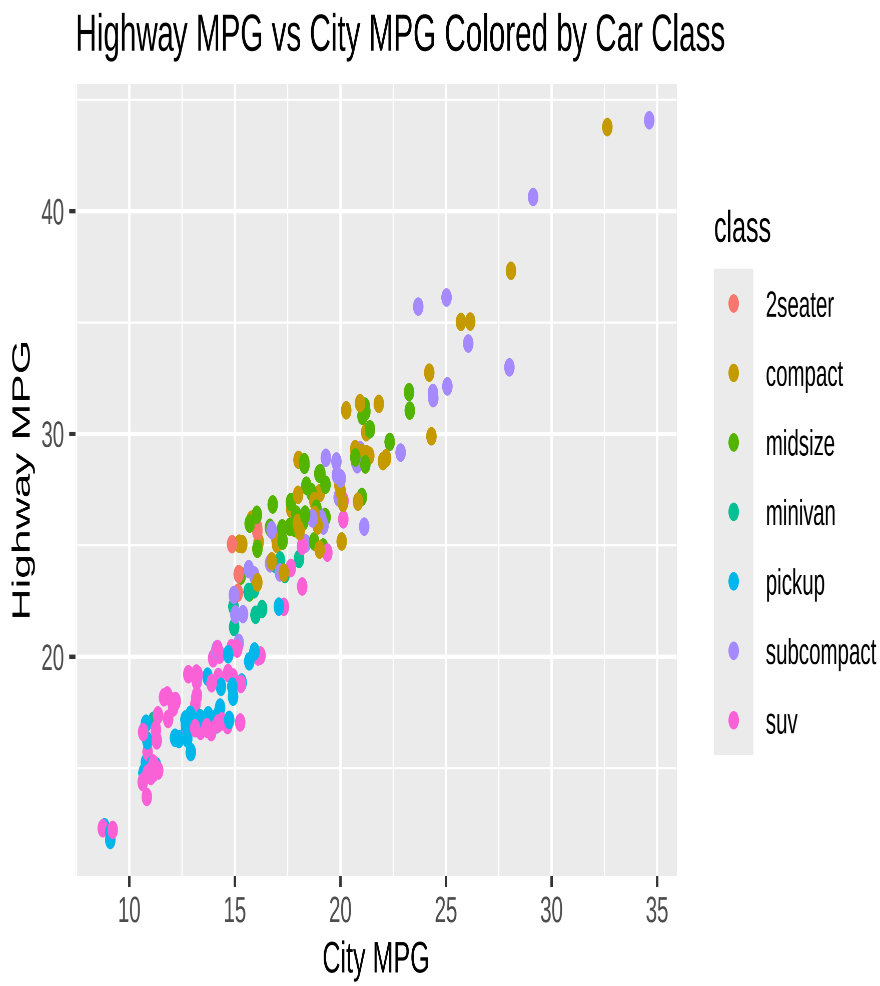
```
# Colored by car type
ggplot(mpg) +
  geom_point(aes(x = cty, y = hwy, col = class))
```




```r
# Adding jitter is useful when data might overlap.
ggplot(mpg) +
  geom_jitter(aes(x = cty, y = hwy, col = class))
```




```
# You can also add labels
ggplot(mpg) +
  geom_jitter(aes(x = cty, y = hwy, col = class)) +
  xlab("City MPG") +
  ylab("Highway MPG") +
  ggtitle("Highway MPG vs City MPG Colored by Car Class")
```



CAUTION:

Use `geom_point` unless the data is overlapping (common when the numeric values are forced to be whole numbers). Only use `jitter` when needed *(otherwise the data is slightly misrepresented)*.

Challenge 4:

Answer a couple of questions based on the plot just created.

- What pattern do you notice between city and highway MPG? In particular, suppose that you know a car has a relatively high city MPG. What is likely about its highway MPG?
- What class of cars tend to have the lowest MPG (in general)?
- What class of cars tend to have the highest MPG (in general)?

3.2 Five Number Summaries

A five number summary (and mean) helps summarize numeric variables. It is best motivated by looking at the data a certain way. Let's represent each mpg as a point on a plot.

```r
summary(mpg$hwy)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  12.00   18.00   24.00   23.44   27.00   44.00 
```

- The **minimum** (`Min.`) highway mpg is 12. This represents the lowest data point in the dataset.
- The **maximum** (`Max.`) highway mpg is 44. This is the highest value observed in the dataset.
- The **mean** (`Mean`) highway mpg is 23.44. This is indicated by the arrow on the plot and can be thought of as the *center of balance*.
  - If the red arrow was moved to the left, then the right side would tip over. If it was moved to the right, then the left side would tip over.
- The **median** (`Median`, 24), **first quartile** (`1st Qu.`, 18) **third quartile** (`3rd Qu.`, 27) divide the data into **quarters** (or, fourths).
  - The circles are the smallest.
  - The triangles are the next smallest.
  - The squares are the next.
  - The plus's are next *(so, they are the largest quarter of the data!)*

Another way to think about it:

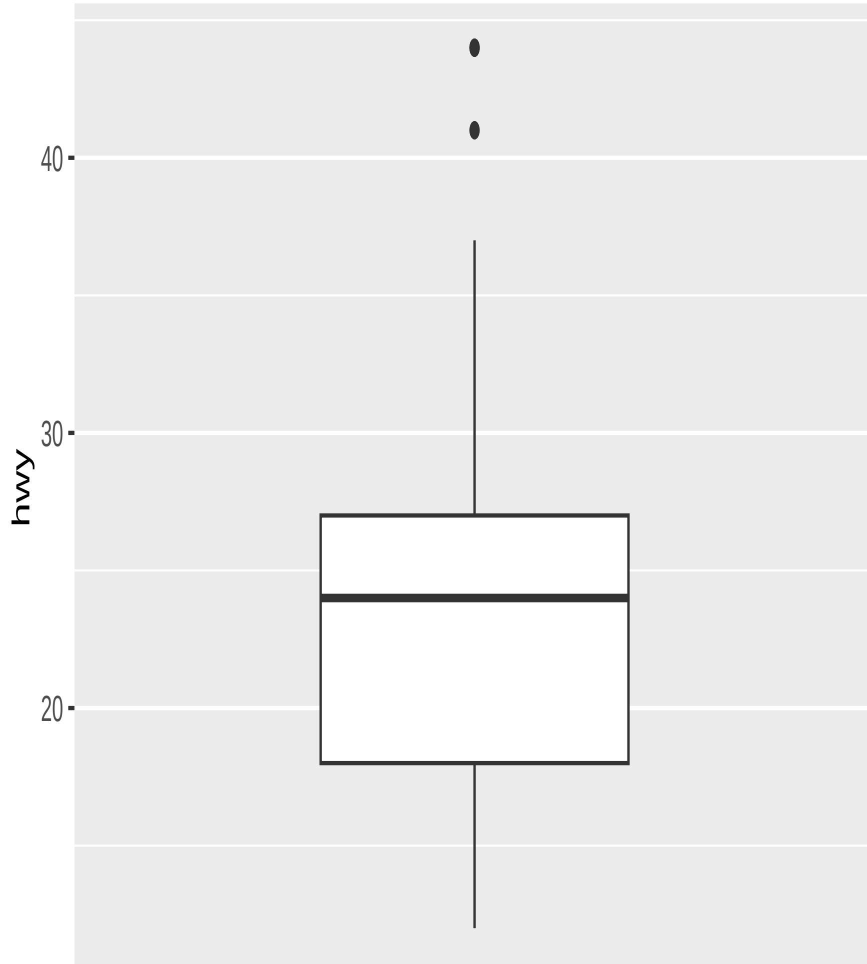
- 25% of the data is at or below `1st Qu.`
- 50% of the data is at or below `Median` *(so, half of the data is at or below the median, and the other half is above.)*
- 75% of the data is at or below `3rd Qu.`

(*Note: the five number summary is `Min`, `1st Qu.`, `Median`, `3rd Qu.`, and `Max`. The mean is not considered as part of the "five number summary".*)

Boxplot

The five number summary is also expressed as a boxplot:

```r
# Single Boxplot
ggplot(mpg) +
  geom_boxplot(aes(y = hwy)) +   # boxplot with y axis as highway mpg
  scale_x_discrete()             # optional, but makes it look better
```

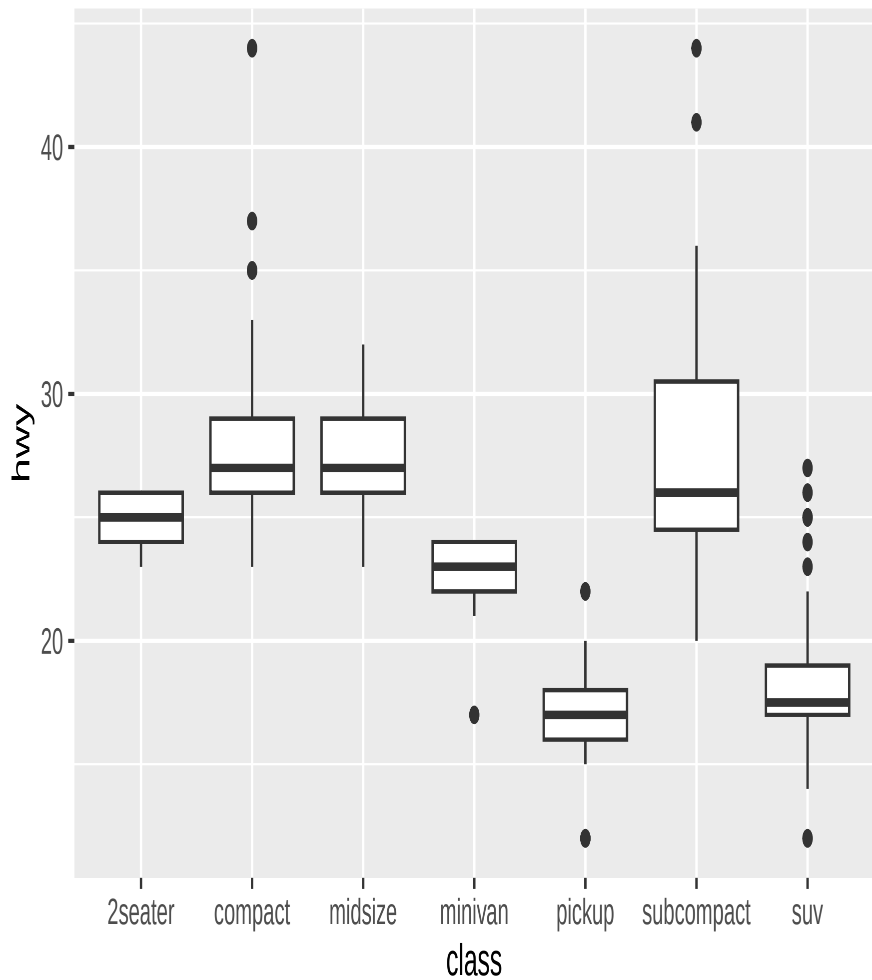


Look at the y-axis (`hwy`) and note that it matches the five number summary.

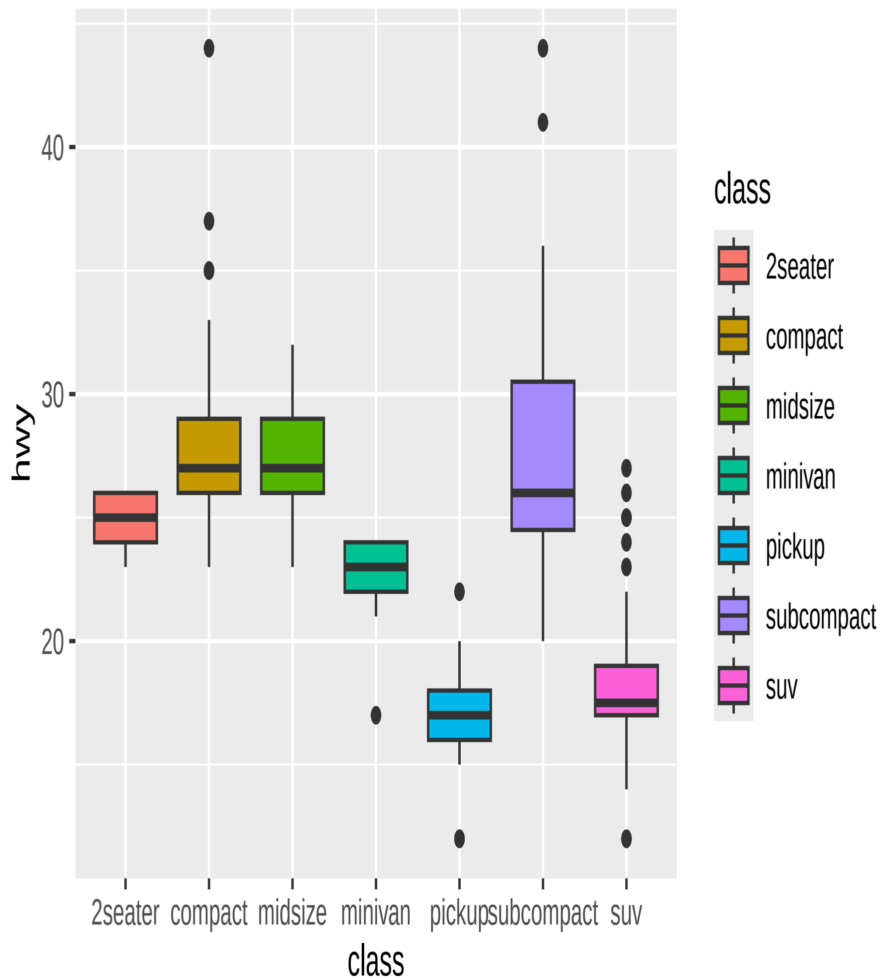
The dots represent **outliers** and are extreme values.

Boxplot separated by categorical variable

```
# Separate hwy by vehicle class
ggplot(mpg) +
  geom_boxplot(aes(y = hwy, x = class))
```




```
# Add color (fill in the boxplot)
ggplot(mpg) +
  geom_boxplot(aes(y = hwy, x = class, fill = class))
```



3.3 Summarizing an entire dataset

`summary(mpg)` gives some summary statistics for each column of the data frame `mpg`.

- Numeric variables: five number summary and mean
- Categorical variables: reports the *count* or *frequency* of occurrences of each type

```
# Basic summary of each column
summary(mpg)
```

```
    manufacturer                 model         displ            year     
 dodge      :37    caravan 2wd         : 11   Min.   :1.600   Min.   :1999  
 toyota     :34    ram 1500 pickup 4wd: 10   1st Qu.:2.400   1st Qu.:1999  
 volkswagen:27    civic               :  9   Median :3.300   Median :2004  
 ford       :25    dakota pickup 4wd   :  9   Mean   :3.472   Mean   :2004  
 chevrolet :19    jetta               :  9   3rd Qu.:4.600   3rd Qu.:2008  
 audi       :18    mustang             :  9   Max.   :7.000   Max.   :2008  
 (Other)    :74    (Other)             :177                                
      cyl              trans      drv           cty             hwy       
 Min.   :4.000   auto(l4)   :83   4:103   Min.   : 9.00   Min.   :12.00  
```

```
 1st Qu.:4.000   manual(m5):58   f:106   1st Qu.:14.00   1st Qu.:18.00  
 Median :6.000   auto(l5)  :39   r: 25   Median :17.00   Median :24.00  
 Mean   :5.889   manual(m6):19           Mean   :16.86   Mean   :23.44  
 3rd Qu.:8.000   auto(s6)  :16           3rd Qu.:19.00   3rd Qu.:27.00  
 Max.   :8.000   auto(l6)  : 6           Max.   :35.00   Max.   :44.00  
                 (Other)   :13                                          
 fl             class   
 c:  1   2seater   : 5  
 d:  5   compact   :47  
 e:  8   midsize   :41  
 p: 52   minivan   :11  
 r:168   pickup    :33  
         subcompact:35  
         suv       :62  
```

For example, there are 62 SUV's in the dataset and 11 minivans, and the average city mpg is 16.86.

```
# Summary statistics for minivans.
#   Remember we defined "minivans" earlier?  Look in your environment!
summary(minivans)
```

```
 manufacturer          model               displl             year     
 Length:11          Length:11          Min.   :2.400   Min.   :1999  
 Class :character   Class :character   1st Qu.:3.300   1st Qu.:1999  
 Mode  :character   Mode  :character   Median :3.300   Median :1999  
                                       Mean   :3.391   Mean   :2003  
                                       3rd Qu.:3.800   3rd Qu.:2008  
                                       Max.   :4.000   Max.   :2008  
      cyl           trans               drv                 cty       
 Min.   :4.000   Length:11          Length:11          Min.   :11.00  
 1st Qu.:6.000   Class :character   Class :character   1st Qu.:15.50  
 Median :6.000   Mode  :character   Mode  :character   Median :16.00  
 Mean   :5.818                                         Mean   :15.82  
 3rd Qu.:6.000                                         3rd Qu.:17.00  
 Max.   :6.000                                         Max.   :18.00  
      hwy             fl               class          
 Min.   :17.00   Length:11          Length:11          
 1st Qu.:22.00   Class :character   Class :character   
 Median :23.00   Mode  :character   Mode  :character   
 Mean   :22.36                                         
 3rd Qu.:24.00                                         
 Max.   :24.00                                         
```

Other Summary Statistics

```
# Table of counts separated by two categorical variables
table(mpg$class, mpg$drv)
```

```
             
               4  f  r
  2seater      0  0  5
  compact     12 35  0
```

```
midsize     3 38  0
minivan     0 11  0
pickup     33  0  0
subcompact  4 22  9
suv        51  0 11
```

For example, there are 12 compacts with 4 wheel drive, and all minivans (11) have front wheel drive.

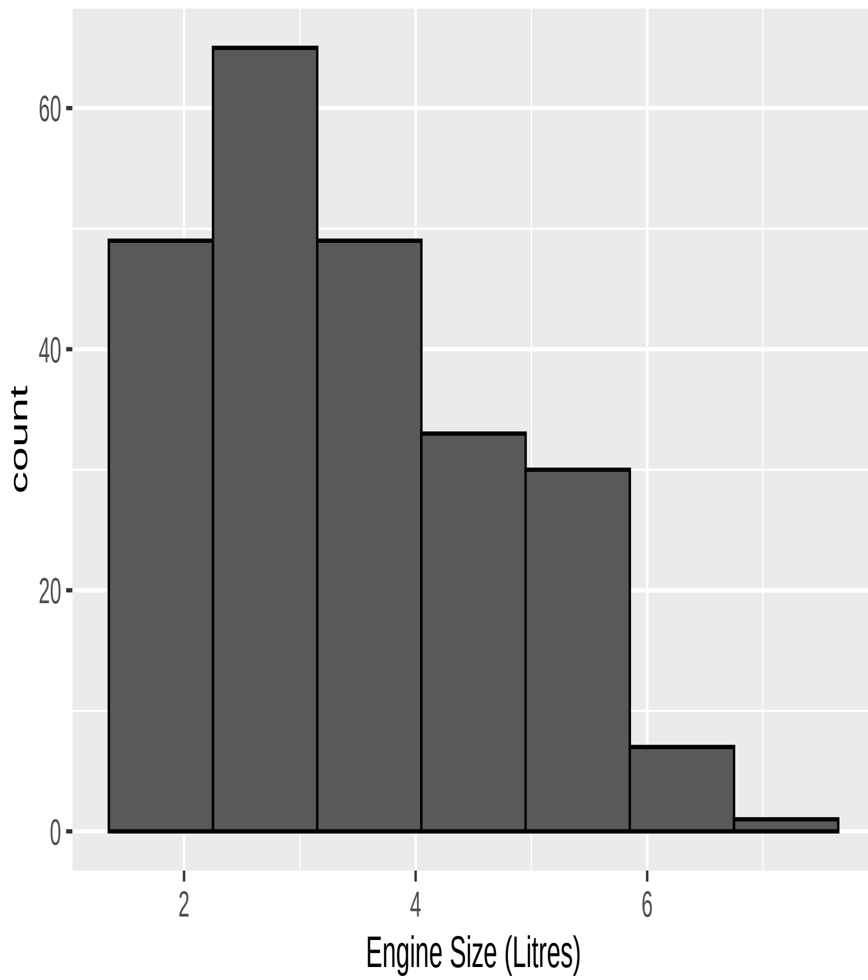
3.4 Other Plotting Tools

Histograms

Histograms are useful for numeric variables that can take **decimal values** *(decimal valued variables are called "continuous". Whole number valued are called "discrete").*

They "bin" the data into ranges.

```
# Using 7 bins
ggplot(mpg) +
  geom_histogram(aes(x = displ), bins = 7, col = "black") +
  xlab("Engine Size (Litres)")
```



So there are roughly…

- 49 engines with a size between (approximately) 1.4 to 2.3, (first "bin" or rectangle)
- 65 engines with a size between (approximately) 2.3 to 3.2, (first "bin" or rectangle)
- 49 engines with a size between (approximately) 3.2 to 4.1, (first "bin" or rectangle)

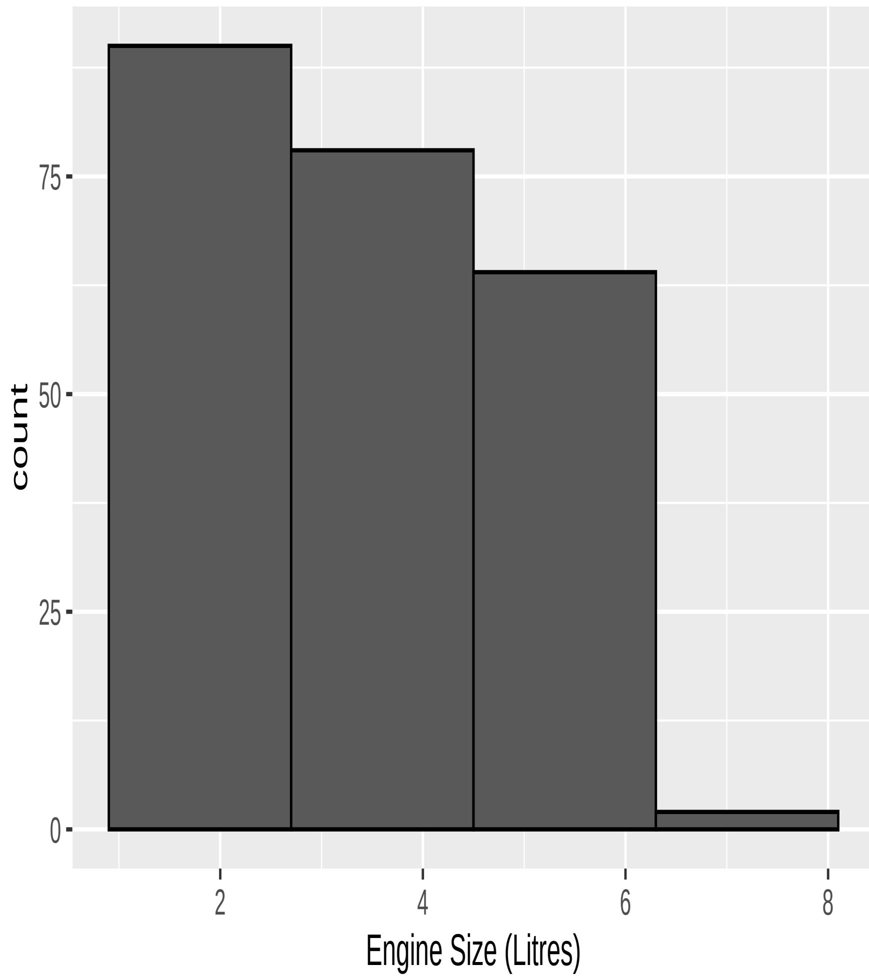
and so forth.

Histograms are helpful to describe the **general shape** (a **visual summary**) of a numeric variable. So we can see that the number of engines with large sizes are very small, and that number decreases very quickly. The majority of engines are around the 1 to 4 litre range.

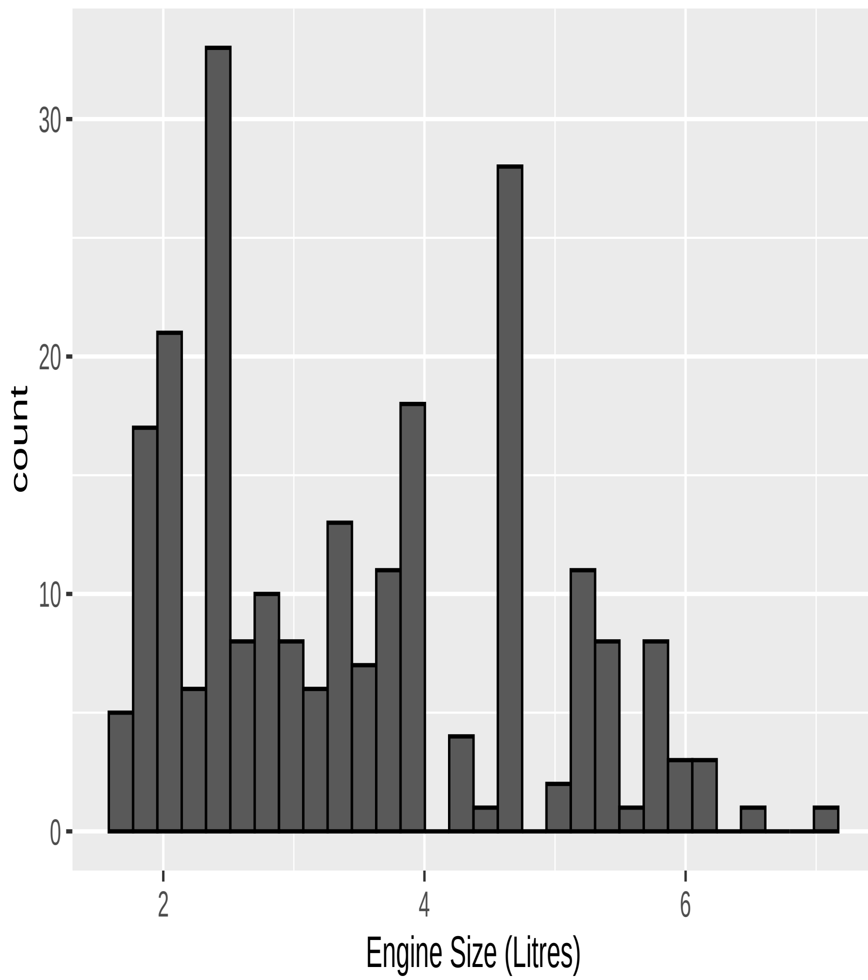
You can change the number of bins that get used, but it will change the way the results are displayed.

- Use too few bins, and the data gets "over-summarized".
- Use too many bins, and the results are too fine. It is hard to come up with general conclusions of the data.

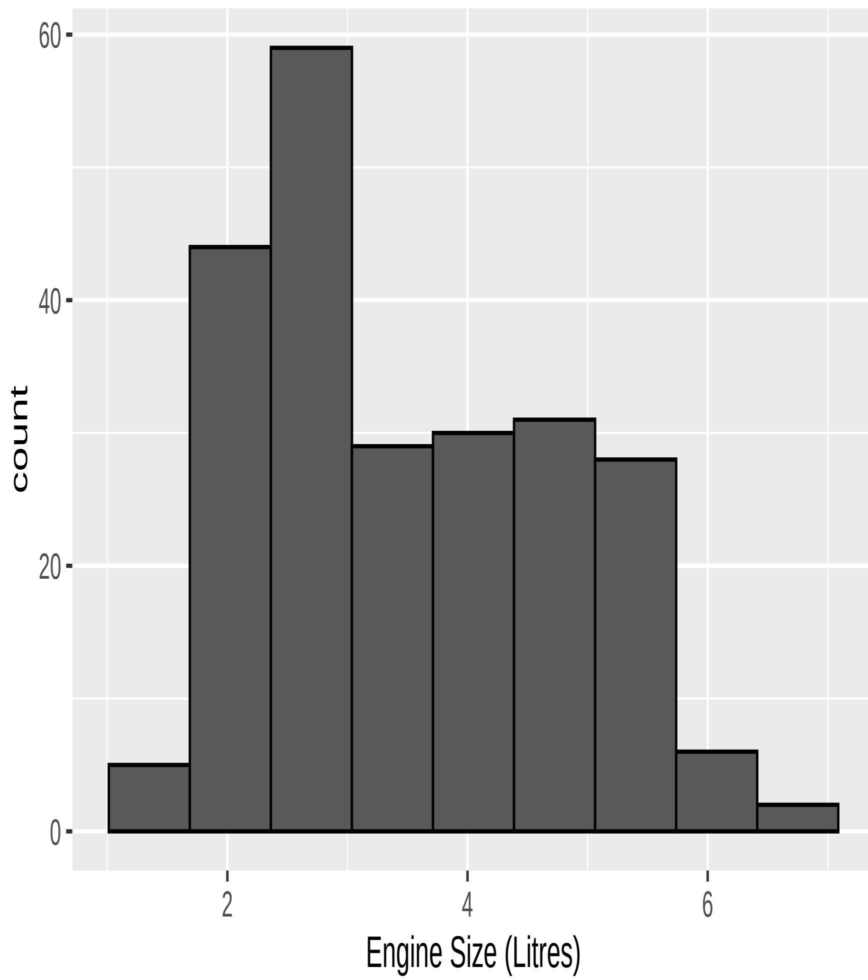
```
# 4 bins, over-summarized
ggplot(mpg) +
  geom_histogram(aes(x = displ), bins = 4, col = "black") +
  xlab("Engine Size (Litres)")
```




```
# 30 bins, does not give good summary
ggplot(mpg) +
  geom_histogram(aes(x = displ), bins = 30, col = "black") +
  xlab("Engine Size (Litres)")
```




```
# 9 bins, does a pretty good job
ggplot(mpg) +
  geom_histogram(aes(x = displ), bins = 9, col = "black") +
  xlab("Engine Size (Litres)")
```

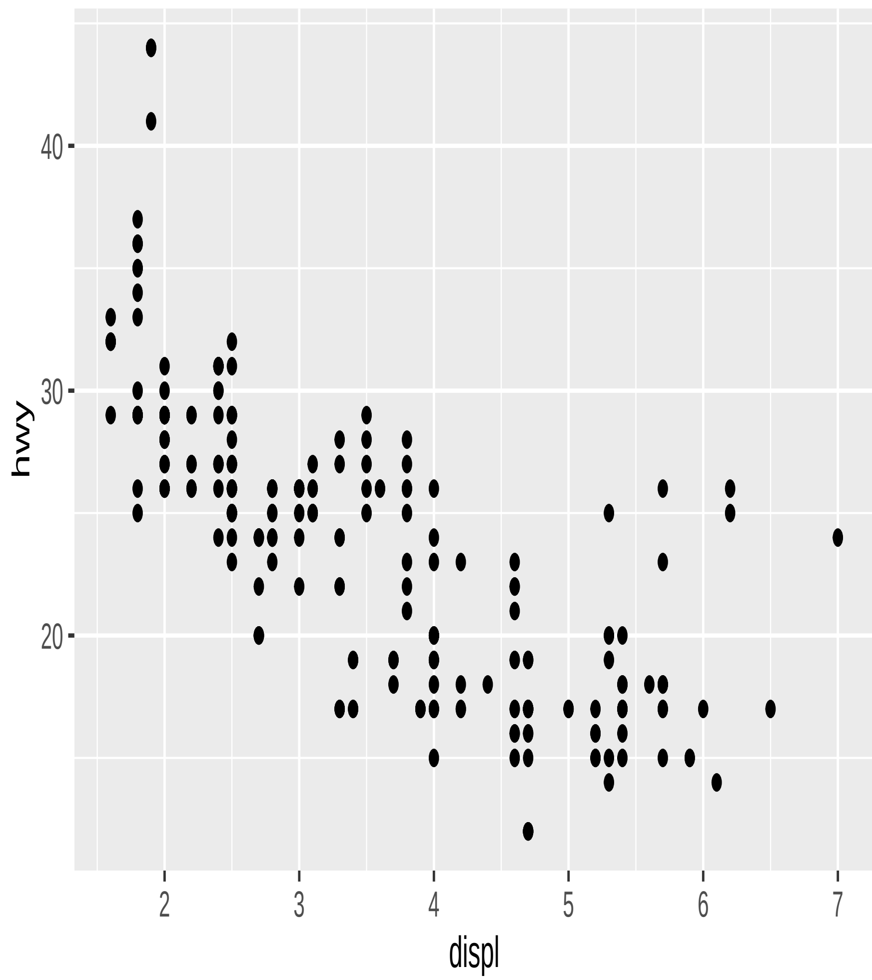


Here we can see the data **"tails off"** to the right, and the majority is around 2 and 3 size engines.

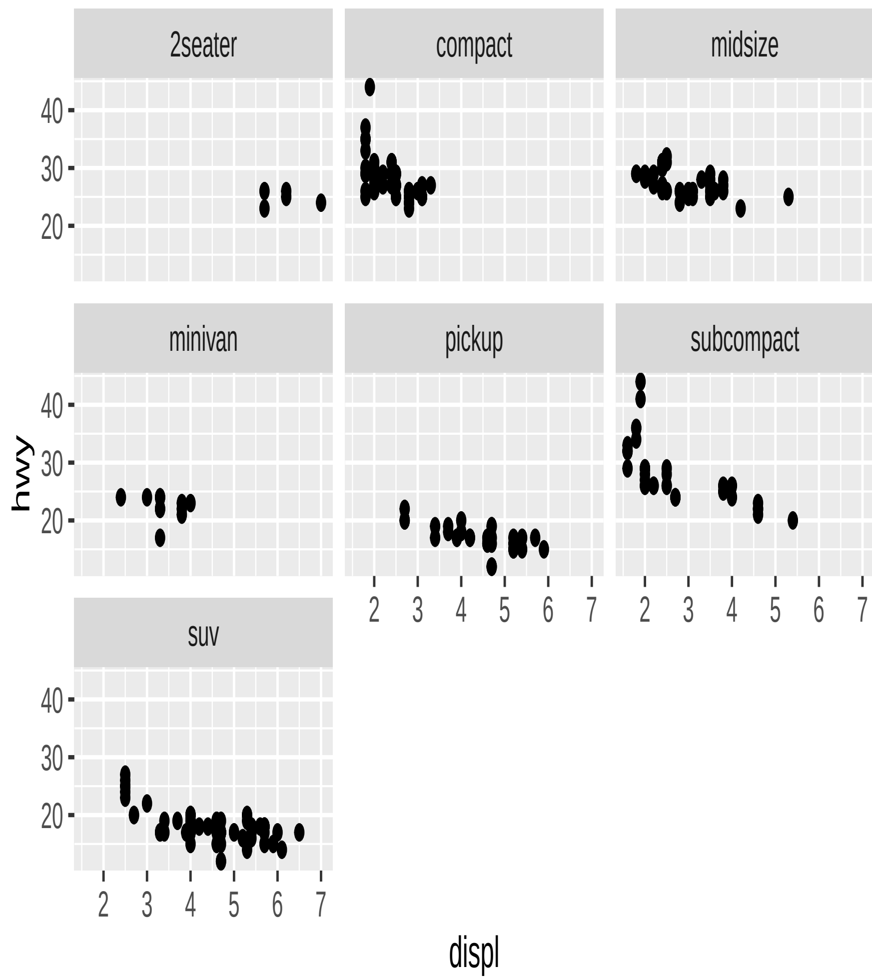
Faceting

Faceting is useful to display plots broken up by categorical variables.

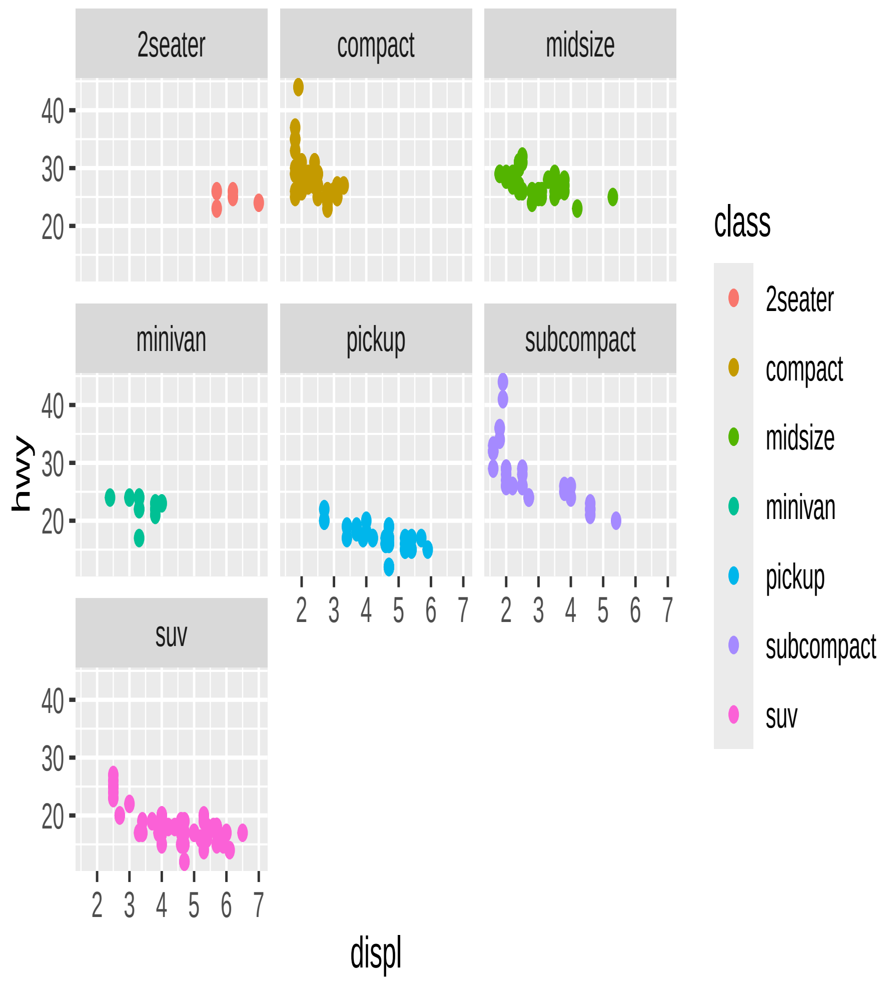
```
# No Facet
ggplot(mpg) + geom_point(aes(x = displ, y = hwy))
```




```
# Facet by type
ggplot(mpg) +
  geom_point(aes(x = displ, y = hwy)) +
  facet_wrap(~class)
```

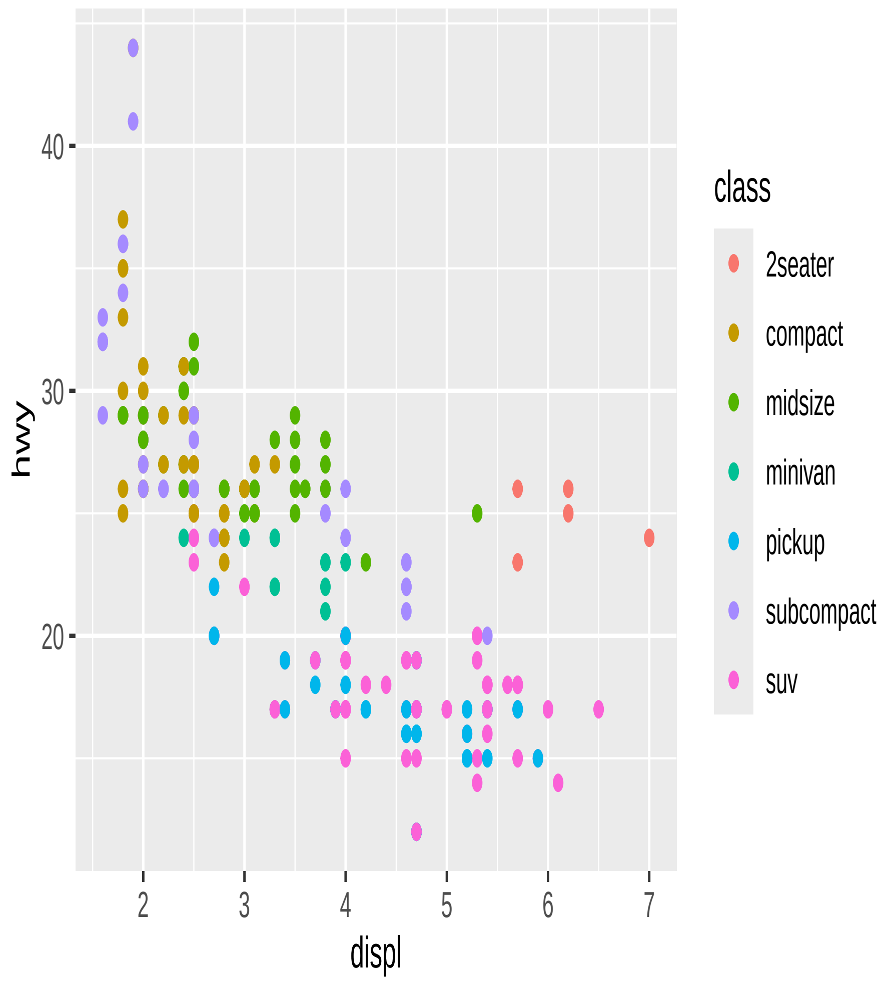



```
# Add color
ggplot(mpg) +
  geom_point(aes(x = displ, y = hwy, color = class)) +
  facet_wrap(~class)
```



You can also add color without faceting, but it can be hard to tell what is going on when there are many categories.

```
ggplot(mpg) +
  geom_point(aes(x = displ, y = hwy, col = class))
```



Dot Plots

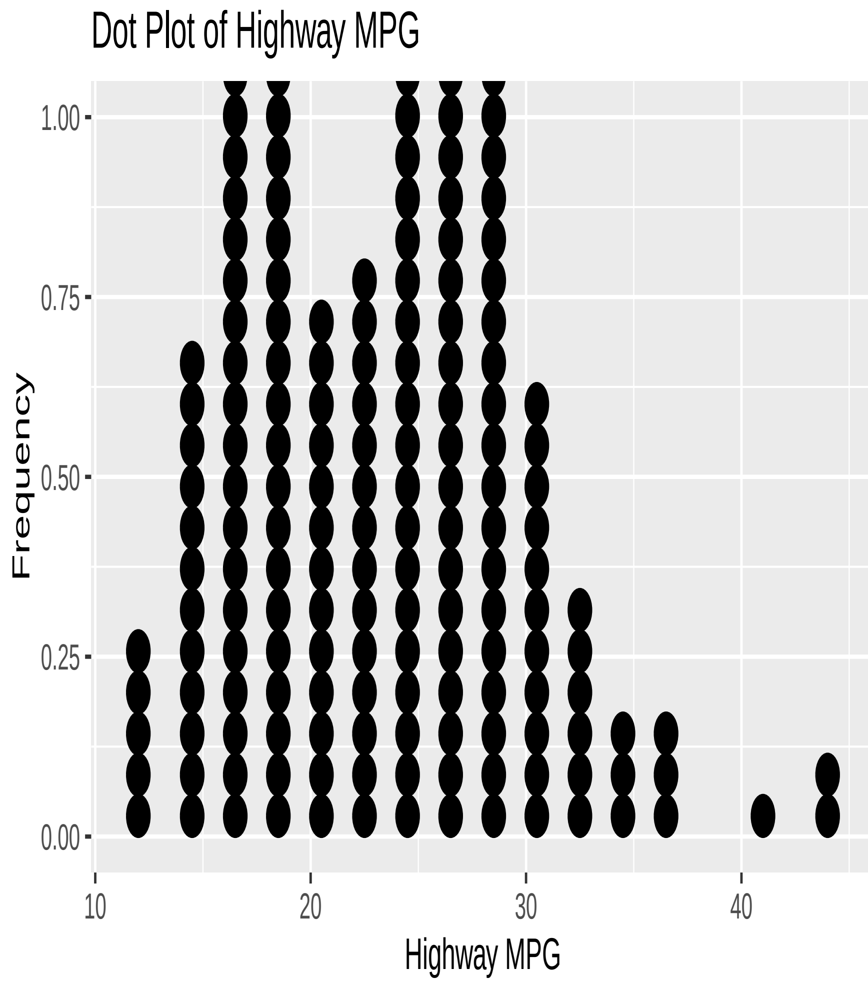
A **dot plot** is a simple way to display data using dots along a number line. Each dot represents one occurrence of a value in a data set. Dot plots are especially useful for small to moderate-sized data sets and give a clear visual of the distribution, frequency, and possible clusters or outliers in the data.

Key Features:

- Each dot represents a data point.
- Values are placed along a horizontal axis.
- Stacked dots indicate multiple occurrences of the same value.
- Good for comparing small groups or identifying patterns.

Dot plots are often used in statistics and education for easy interpretation of numerical data.

```
ggplot(mpg) +
  geom_dotplot(aes(hwy)) +
  labs(title = "Dot Plot of Highway MPG",
       x = "Highway MPG",
       y = "Frequency")
```



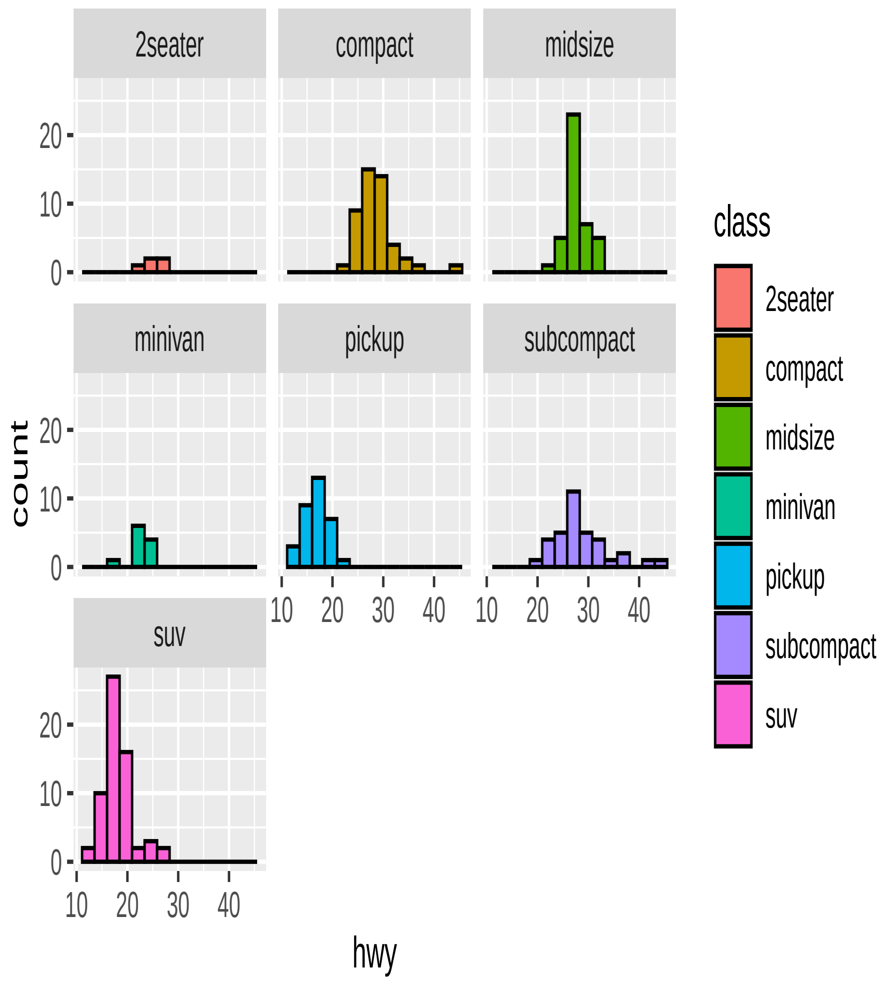
Challenge 5

Use the faceted scatterplot to determine what classes of cars have the best highway mpg. What can we say about the engine sizes of those cars?

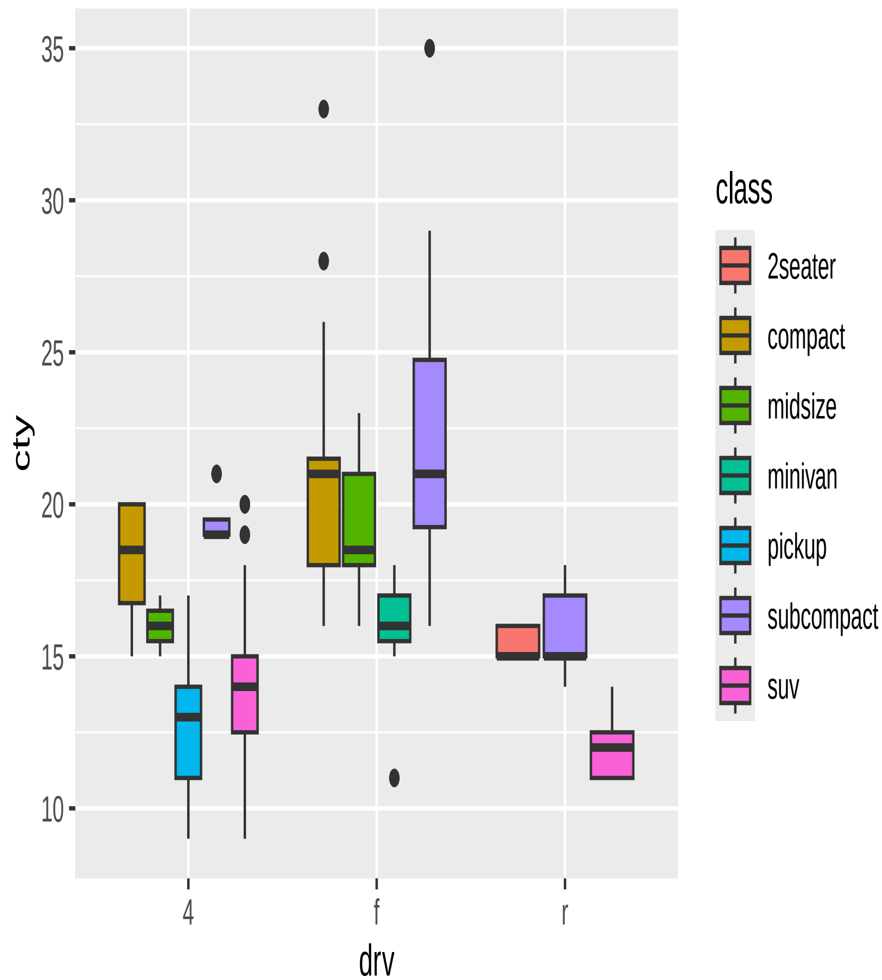
Now, try to answer the same question with the last scatterplot made (with color but without faceting). (*It should be a harder question to answer…*)

Some additional examples

```
ggplot(mpg) +
  geom_histogram(aes(x = hwy, fill = class), color = "black", bins = 14) +
  facet_wrap(~class)
```




```
# This is a good proof of concept, but produces some boxplots with too small
#   of sample sizes to get a good summary of.
ggplot(mpg) +
  geom_boxplot(aes(y = cty, x = drv, fill = class))
```



3.5 Frequencies Proportions

What Are Frequencies?

Frequencies represent the number of times a particular value or category appears in a dataset. They are raw counts and are often used as a starting point for descriptive statistics.

- **Example:**
  In a survey of 100 people, if 60 say "Yes" and 40 say "No", the frequencies are:
  - "Yes" = 60

  - "No" = 40

Frequencies are useful for understanding the **absolute** size or quantity of a group.

What Are Proportions?

Proportions express how large one part is relative to the whole. A proportion is the **frequency of a category divided by the total number of observations**.

- **Formula:**

$$\text{Proportion} = \frac{\text{Frequency}}{\text{Total Count}}$$

- **Example (continued):**
  From the previous example:
  - Proportion of "Yes" = 60 / 100 = 0.6
  - Proportion of "No" = 40 / 100 = 0.4

Proportions can also be converted to **percentages** by multiplying by 100.

Key Differences

Concept	Description	Example
Frequency	Raw count of occurrences	"Yes" = 60
Proportion	Relative frequency (part of the whole)	"Yes" = 0.60
Percentage	Proportion × 100	"Yes" = 60%

Why Use Proportions?

- To compare groups of different sizes
- To visualize data more clearly (e.g., pie charts, bar graphs)
- To interpret survey responses, population data, etc.

In R

You can compute frequencies with `table()` and proportions with `prop.table()`:

```
# Create a frequency table of the 'manufacturer' column in the 'mpg' dataset
manufacturer_table <- table(mpg$manufacturer)
manufacturer_table  # Display the count of cars for each manufacturer
```

```
      audi  chevrolet      dodge       ford      honda    hyundai       jeep 
        18         19         37         25          9         14          8 
land rover    lincoln    mercury     nissan    pontiac     subaru     toyota 
         4          3          4         13          5         14         34 
volkswagen 
        27 
```

This tells you:

- Dodge appears 37 times in the dataset — likely the most represented manufacturer.
- Honda appears only 9 times.
- This gives a sense of which manufacturers are more prevalent in this dataset.

```
# Convert the frequency table to proportions (relative frequencies)
manufacturer_prop <- prop.table(manufacturer_table)
manufacturer_prop  # Display the proportion of cars for each manufacturer
```

```
      audi  chevrolet      dodge       ford      honda    hyundai       jeep
0.07692308 0.08119658 0.15811966 0.10683761 0.03846154 0.05982906 0.03418803
land rover    lincoln    mercury     nissan    pontiac     subaru     toyota
0.01709402 0.01282051 0.01709402 0.05555556 0.02136752 0.05982906 0.14529915
volkswagen
0.11538462
```

This tells you:

- Toyota makes up about 14.5% of all the car entries in the dataset.
- Audi makes up 7.7%.

These are calculated as: `manufacturer count / total number of entries`.

3.6 Bar Plots

What Is a Bar Plot?

A **bar plot** is a type of chart that displays **categorical data** with rectangular bars. The **length or height** of each bar represents the **count** or **value** for that category.

Key Features

- **X-axis**: Categories (e.g., car types, countries, months)
- **Y-axis**: Frequency or value associated with each category
- Note: Both the **X-axis** and **Y-axis** may be reversed.
- Bars can be **vertical** or **horizontal**
- Can be **grouped** or **stacked** to compare sub-categories

When to Use:

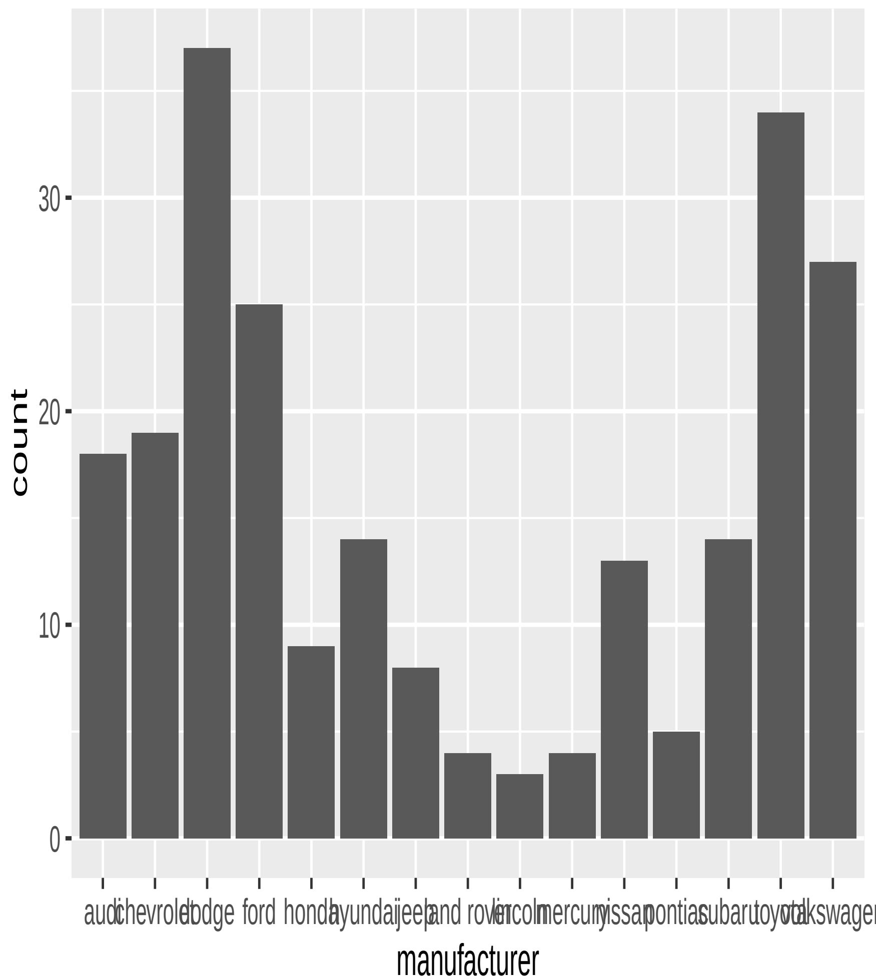
- To compare counts across categories
- To visualize distributions of a single categorical variable
- To show changes across groups or time (with discrete intervals)

Bar plots are easy to read and useful for summarizing and comparing categorical data.

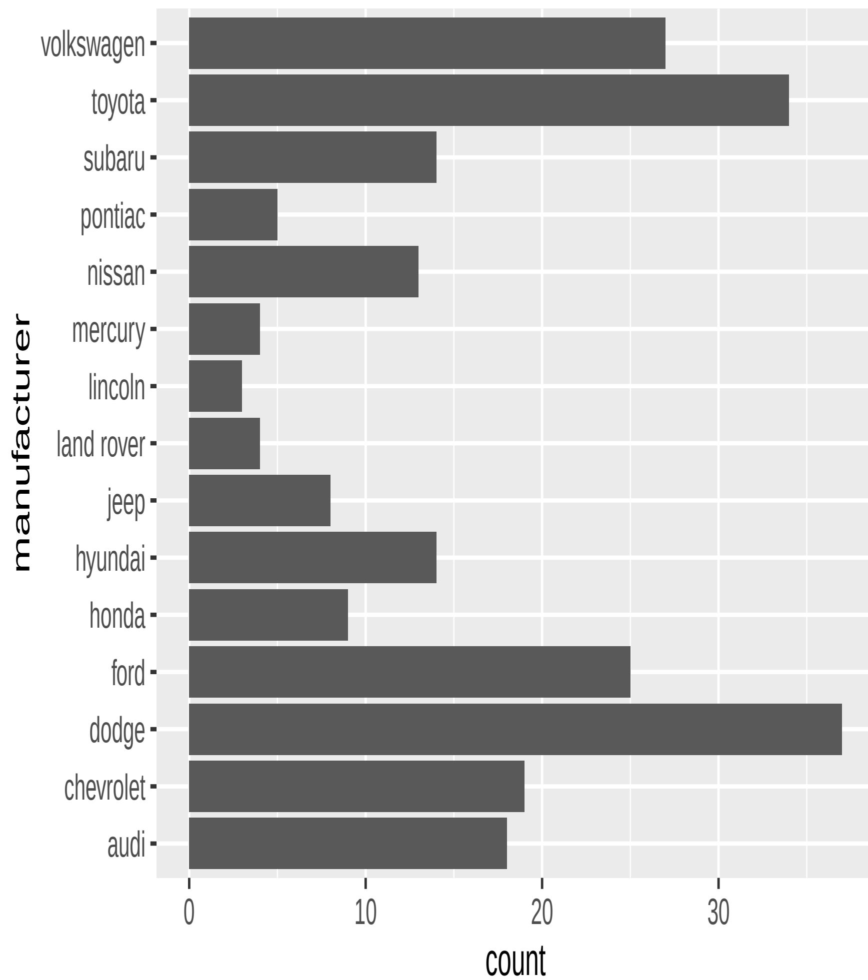
Bar Plots in R

Both of the code chunks below provide 2 different ways to create a bar chart.

```
# Create a bar plot showing the number of vehicles by manufacturer
ggplot(mpg, aes(x = manufacturer)) +  # Set 'manufacturer' on the x-axis (categorical variable)
  geom_bar()                          # Automatically counts observations for each manufacturer and plots
```




```
# Create a horizontal bar chart showing the number of vehicles by manufacturer
ggplot(mpg) +  # Sets 'mpg'
  geom_bar(aes(y = manufacturer))                          # Automatically counts observations for each ma
```



Interpretation of the Bar Plot: Vehicle Count by Manufacturer

This horizontal bar chart displays the **number of vehicle models** per manufacturer in the `mpg` dataset. Each bar represents a car manufacturer, and the **length of the bar reflects how many entries (vehicle models)** that brand has in the dataset.

Key Observations

- **Dodge** has the **most vehicles** in the dataset.
- **Toyota Volkswagen** and **Ford** also have a high number of entries.
- Other well-represented manufacturers include:
  - **Chevrolet**
  - **Audi**
- Manufacturers with the **fewest vehicles** include:
  - **Lincoln**
  - **Mercury**
  - **Pontiac**
  - **Land Rover**

Interpretation

- This plot provides insight into **which brands are most prevalent** in the dataset.
- Manufacturers like **Dodge, Toyota, Ford, and Volkswagen** have a larger presence, indicating either more vehicle lines or more representation in the data source.
- **Smaller bars** indicate fewer models or less coverage in the dataset.

3.7 Contingency Tables

What Is a Contingency Table?

A **contingency table** (also called a **cross-tabulation** or **crosstab**) is a type of table that displays the frequency distribution of variables. It is commonly used to **summarize the relationship between two or more categorical variables**.

Each cell in the table shows the number of observations that fall into the corresponding category combinations.

Why Use Contingency Tables?

Contingency tables help you:

- Understand the interaction between two categorical variables
- Compute proportions across rows, columns, or the entire table
- Perform statistical tests like the Chi-square test for independence
  - See if the variables are related to each other

Example in R: Using the `mpg` Dataset

We'll create a contingency table of **drive type (`drv`)** by **vehicle class (`class`)** using the `table()`.

```r
# Create a contingency table of drive type (drv) by vehicle class
# This counts how many observations fall into each combination of drv and class
ct <- table(mpg$drv, mpg$class)

# Print the contingency table
ct
```

```
    2seater compact midsize minivan pickup subcompact suv
  4       0      12       3       0     33          4  51
  f       0      35      38      11      0         22   0
  r       5       0       0       0      0          9  11
```

Row and Column Interpretation - drv: Drive type (Row) - f = front-wheel drive - r = rear-wheel drive - 4 = 4-wheel or all-wheel drive - class: Vehicle class (like compact, SUV, etc.) (Column)

Drive Type: `4` (4-Wheel Drive)

- **Most common in**:
  - **SUVs** (51)
  - **Pickups** (33)
- **Also present in**:
  - Compact (12)

- Midsize (3)
  - Subcompact (4)
- **Absent in**:
  - 2seater and Minivan

  4WD is most typical for SUVs and trucks

Drive Type: `f` (Front-Wheel Drive)

- **Most common in**:
  - **Midsize** (38)
  - **Compact** (35)
  - **Subcompact** (22)
- **Also found in**:
  - Minivan (11)
- **Absent in**:
  - SUV, Pickup, 2seater

  FWD is common in passenger vehicles, especially sedans, compacts, and minivans.

Drive Type: `r` (Rear-Wheel Drive)

- **Most common in**:
  - **SUVs** (11)
  - **Subcompact** (9)
  - **2seater** (5)
- **Absent in**:
  - Compact, Midsize, Minivan, Pickup

  RWD is rare overall but more typical in performance cars (e.g., 2seaters) and certain SUVs.

Summary of Key Patterns

Class	Most Common Drive Type
SUV	4WD and RWD
Pickup	4WD only
Minivan	FWD only
Compact	Mostly FWD
Midsize	Mostly FWD
Subcompact	Mix of all types
2seater	Only RWD

- FWD dominates among general passenger cars (compact, midsize, subcompact).
- RWD is least common but associated with performance or specialty vehicles.

What Are Table Proportions?

Table proportions are the relative frequencies calculated from a contingency table. Instead of showing raw counts, proportions express how much each cell contributes to the total — either:

- As a **proportion of the whole table**
- Within each **row** (row-wise)

- Within each **column** (column-wise)

These proportions help you understand distributions and relationships in a more comparable way, especially when counts vary across groups.

Computing Proportions in R

Using the contingency table we already have:

```
ct <- table(mpg$drv, mpg$class)
```

We can abtain the proportions for the entire table with the following code and the `prop.table()` function:

```
prop.table(ct)
```

```
     2seater    compact    midsize    minivan     pickup subcompact
  4 0.00000000 0.05128205 0.01282051 0.00000000 0.14102564 0.01709402
  f 0.00000000 0.14957265 0.16239316 0.04700855 0.00000000 0.09401709
  r 0.02136752 0.00000000 0.00000000 0.00000000 0.00000000 0.03846154

         suv
  4 0.21794872
  f 0.00000000
  r 0.04700855
```

- `drv = 4` (4-Wheel Drive)
  - 21.8% of 4WD vehicles are also SUVs
  - 14.1% are also pickups
  - Smaller proportions in compact (5.1%) and subcompact (1.7%) classes
  - 0% in minivan and 2seater
- `drv = f` (Front-Wheel Drive)
  - 16.2% of FWD vehicles are also midsize cars
  - 15.0% are also compact
  - 9.4% are also subcompacts
  - 4.7% are also minivans
  - 0% in SUV, pickup, and 2seater
- `drv = r` (Rear-Wheel Drive)
  - 4.7% are also SUVs
  - 3.8% are also subcompacts
  - 2.1% are also 2seaters
  - 0% in all other categories

3.8 Stacked Bar Plot

A **stacked bar plot** (or stacked bar chart) is a type of bar graph used to **visualize the composition of categories within groups**.

Instead of placing bars side by side (as in a grouped bar plot), a stacked bar plot **stacks sub-categories on top of one another**, all within a single bar.

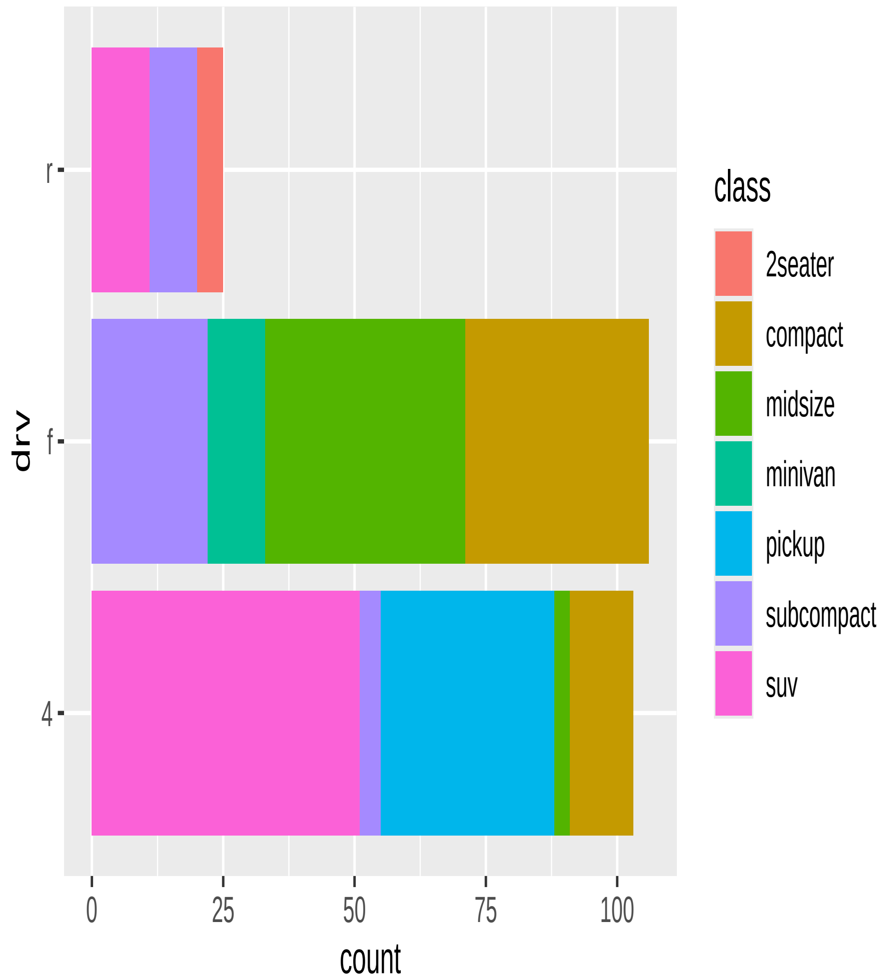
Why Use a Stacked Bar Plot?

A stacked bar plot helps you:

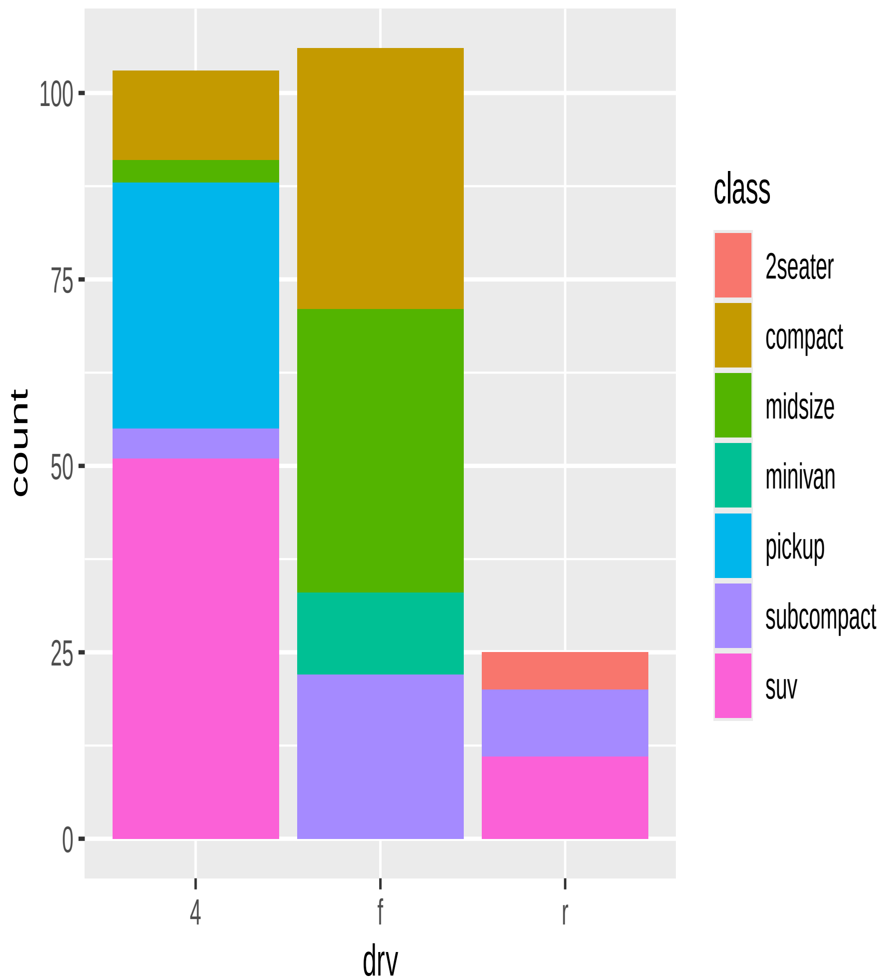
- Compare **totals** across groups (e.g., total sales per region)
- Understand **sub-category composition** within each group (e.g., product types within regions)
- Spot **proportional trends** visually (e.g., increasing share of a category over time)

Stacked Bar Plot in R

```
# Create a stacked bar chart using the mpg dataset
ggplot(mpg) +  # Set 'mpg' as the data set on x-axis and fill bars by 'class'
  geom_bar(aes(y = drv, fill = class))    # Plot counts as bars (defaults to count per group) and sets 'dr
```




```
# Create a stacked bar chart using the mpg dataset
ggplot(mpg) +  # Set 'mpg' as the data set on x-axis and fill bars by 'class'
  geom_bar(aes(drv, fill = class))    # Plot counts as bars (defaults to count per group) and sets 'drv' o
```



Interpretation of Stacked Bar Plot: `drv` by `class` (Most Recent Plot)

This stacked bar chart shows the **count of vehicles** for each **drive type (`drv`)** in the `mpg` dataset, broken down by **vehicle class (`class`)**.

- **x-axis**: Drive type (`drv`)
  - `4` = 4-wheel drive
  - `f` = front-wheel drive
  - `r` = rear-wheel drive
- **y-axis**: Count of vehicles
- **Fill color**: Vehicle class (e.g., SUV, compact, pickup)

Drive Type: `4` (4-Wheel Drive)

- Dominated by:
  - **SUVs**
  - **Pickup trucks**
- Minor presence of:

  - **Subcompacts**
  - **Midsize**
  - **Compacts**
- No **2seaters** or **minivans**

  4WD is commonly used in SUVs and trucks for off-road or utility purposes.

Drive Type: `f` (Front-Wheel Drive)

- Dominated by:
  - **Midsize**
  - **Compact**
  - **Subcompact**
  - **Minivans**
- No presence of:
  - **Pickups**
  - **SUVs**
  - **2seaters**

  FWD is typical for passenger vehicles designed for city or family driving.

Drive Type: `r` (Rear-Wheel Drive)

- Smallest overall count
- Includes:
  - **2seaters**
  - **Subcompacts**
  - **SUVs**
- No **compact**, **midsize**, **pickup**, or **minivan**

  RWD is less common, usually found in performance cars and some SUVs.

Key Takeaway

This stacked bar plot effectively shows how **vehicle classes are distributed across drive types**. It helps identify which types of vehicles are associated with each drivetrain layout.