Chapter 02: First steps

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Setup

This chapter focuses on getting familiar with the basic recipes to create graphics using ggplot2.

```
# Load libraries
library(tidyverse)
library(kableExtra)
library(patchwork)

# Set ggplot2 theme
my_theme <- theme(
  panel.grid = element_blank(),
  panel.background = element_rect(fill = "white", color = "black")
)
```

Fuel economy data exercises

1) *List five functions that you could use to get more information about the* `mpg` *dataset.*

If you wanted more general information about the `mpg` dataset (e.g., descriptions of the underlying data, or where to find more detailed information or the source), you could use `?`, `??`, or `help()`. If you wanted to get a quick summary of the data and see the distribution of each variable, you could use the `summary()` function.

There are a few additional functions that you could use, some of which are described at the following page: https://www.r-project.org/help.html. There is no such vignette for the `mpg` dataset, but `browseVignettes()` or `vignette()` can be used to find tutorials for selected packages. Additionally, if you really don't know the name of the package you are interested in and don't want to consult Google, you could use the `apropos()` function to identify the object or function in the R environment using regular expression pattern matching.

2) *How can you find out what other datasets are included with ggplot2?*

To find which datasets are included in ggplot2 (or any other package you are interested in), use the command `data(package = "<package_name>")`. For example, using `data(package = "ggplot2")`, we can see that there are datasets not only on fuel economy (`mpg`), but others on diamond prices and characteristics (`diamonds`), seal movements (`seals`), and housing sales in Texas (`txhousing`).

Table 1: Fuel economy (distance traveled with one US gallon) and fuel consumption (liters consumed per 100 kiometers.

manufacturer	model	year	cty	hwy	cty_lpkm	hwy_lpkm
audi	a4	1999	18	29	13.07	8.11
audi	a4	1999	21	29	11.20	8.11
audi	a4	2008	20	31	11.76	7.59
audi	a4	2008	21	30	11.20	7.84
audi	a4	1999	16	26	14.70	9.05
audi	a4	1999	18	26	13.07	9.05

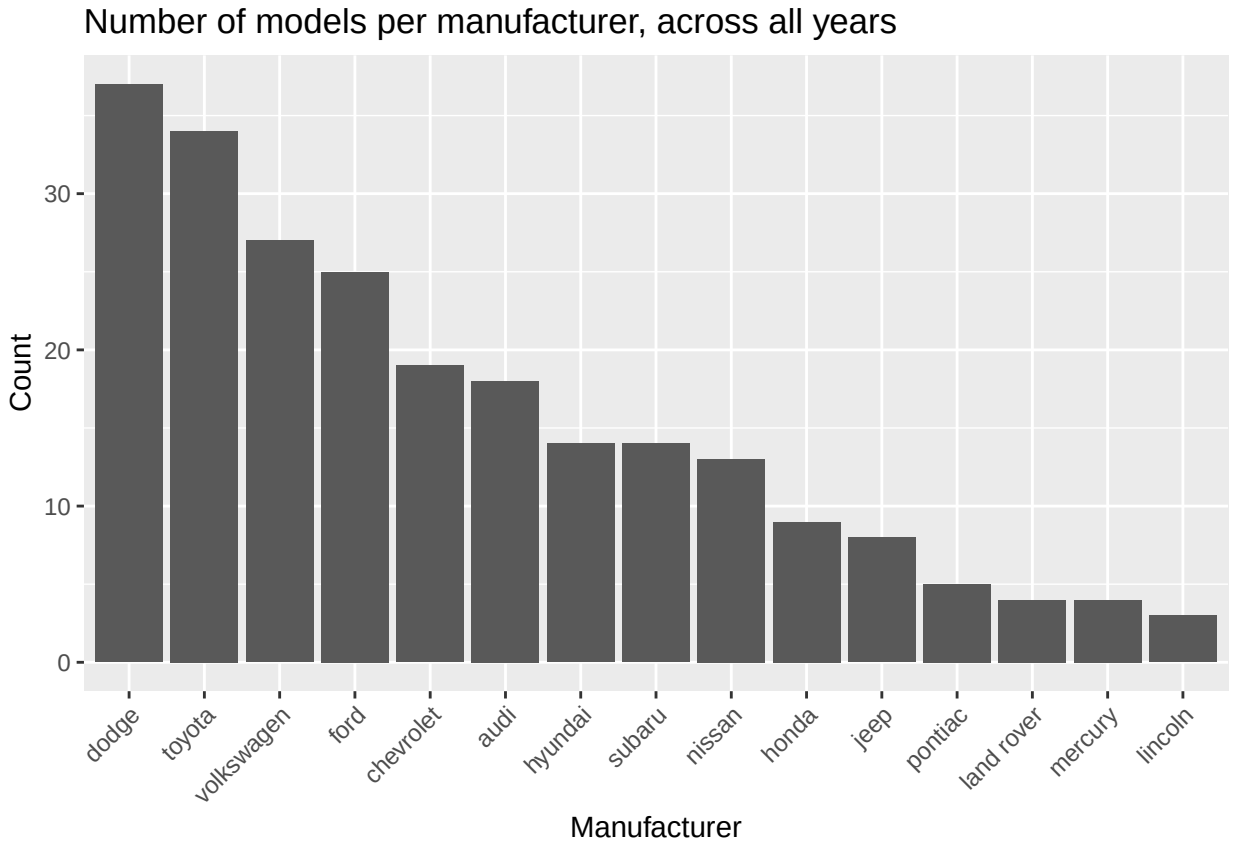
3) *Apart from the US, most countries use fuel consumption (fuel consumed over fixed distance) rather than fuel economy (distance traveled with a fixed amount of fuel). How could you convert the* `cty` *and* `hwy` *into the European standard of l/100km?*

To convert the fuel economy variables `cty` and `mpg` into fuel consumption by the European standard of l/100km, we can simply create a new variable `lpkm` by dividing the mpg estimate by the conversion factor 235.21.

```
# Convert miles per gallon to liters per 100 kilometers
mpg %>%
  mutate(cty_lpkm = round(235.21 / cty, 2),
         hwy_lpkm = round(235.21 / hwy, 2)) %>%
  dplyr::select(manufacturer, model, year, cty, hwy, cty_lpkm, hwy_lpkm) %>%
  head() %>%
  kbl(caption = "Fuel economy (distance traveled with one US gallon) and fuel consumption (liters consu
  kable_classic_2(full_width = FALSE)
```

4) *Which manufacturer has the most models in this dataset? Which model has the most variations? Does your answer change if you remove the redundant specification of drive train (e.g., "pathfinder 4wd", "a4 quattro") from the model name?*

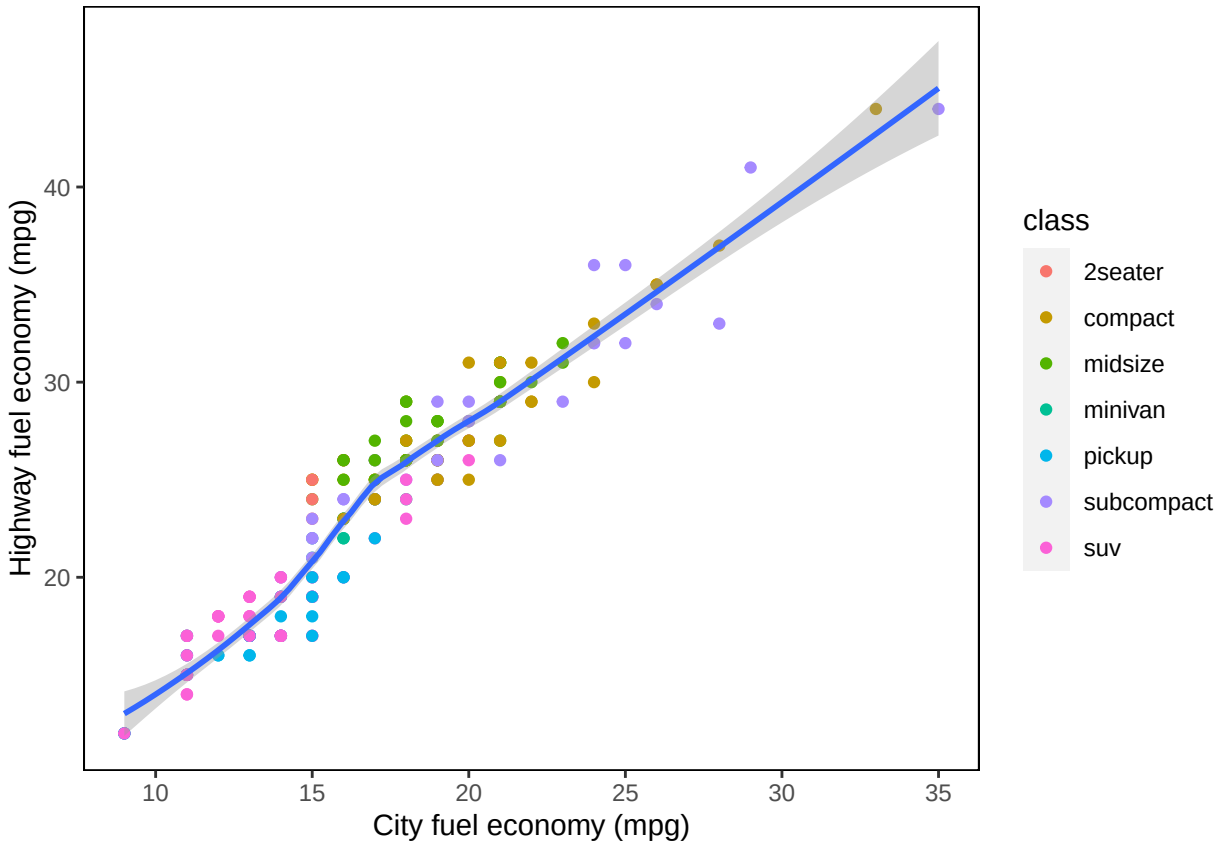
Dodge has the most models in the dataset (37; see visualization below), and the Dodge caravan 2wd has the most variations (11). Interestingly, the number doesn't change if we remove the redundant information (e.g., "quattro" or "4wd"), likely because manufacturers don't want to use the same model name as competitors.



Aesthetic attributes exercises

1) *How would you describe the relationship between* `cty` *and* `hwy`*? Do you have any concerns about drawing conclusions for that plot?*

First, let's generate the plot of the two variables.



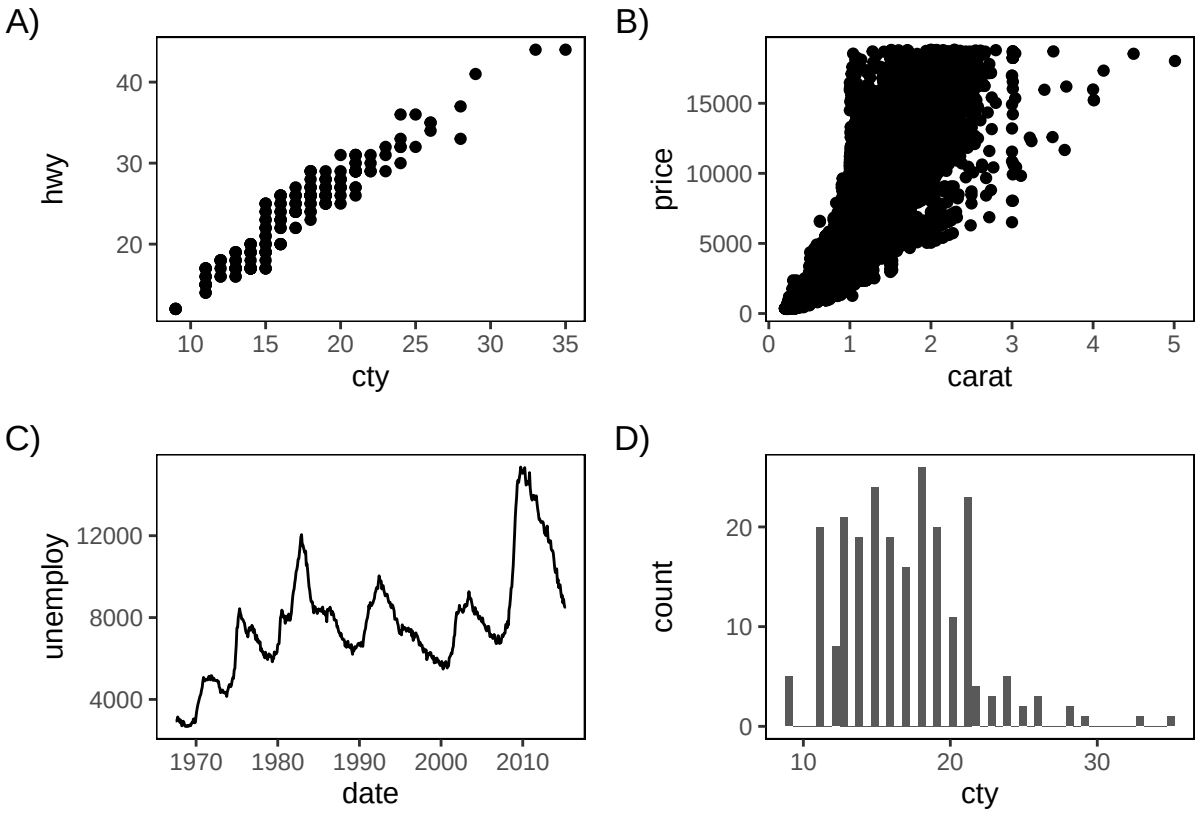
From the plot above, we can see that in general, the highway fuel economy increases as the city fuel economy increases. However, by mapping `class` to the color aesthetic, we can see that there are differences within each vehicle class that likely have to do with other features of the vehicles, like the year, perhaps.

2) *What does `ggplot(mpg, aes(model, manufacturer)) + geom_point()` show? Is it useful? How could you modify the data to make it more informative?*

In general, the plot produced from the code `ggplot(mpg, aes(model, manufacturer)) + geom_point()` is not very useful because it only shows us the manufacturer for each car model in the dataset in the same way we would view the data in a table. To modify the data and make it more informative for visualization, we could create a plot to show the total number of vehicles for each manufacturer using a bar chart, for example.

3) *Describe the data, aesthetic mappings and layers used for each of the following plots. You'll need to guess a little because you haven't see all the datasets and functions yet, but use your common sense! See if you can predict what the plot will look like before running the code.*

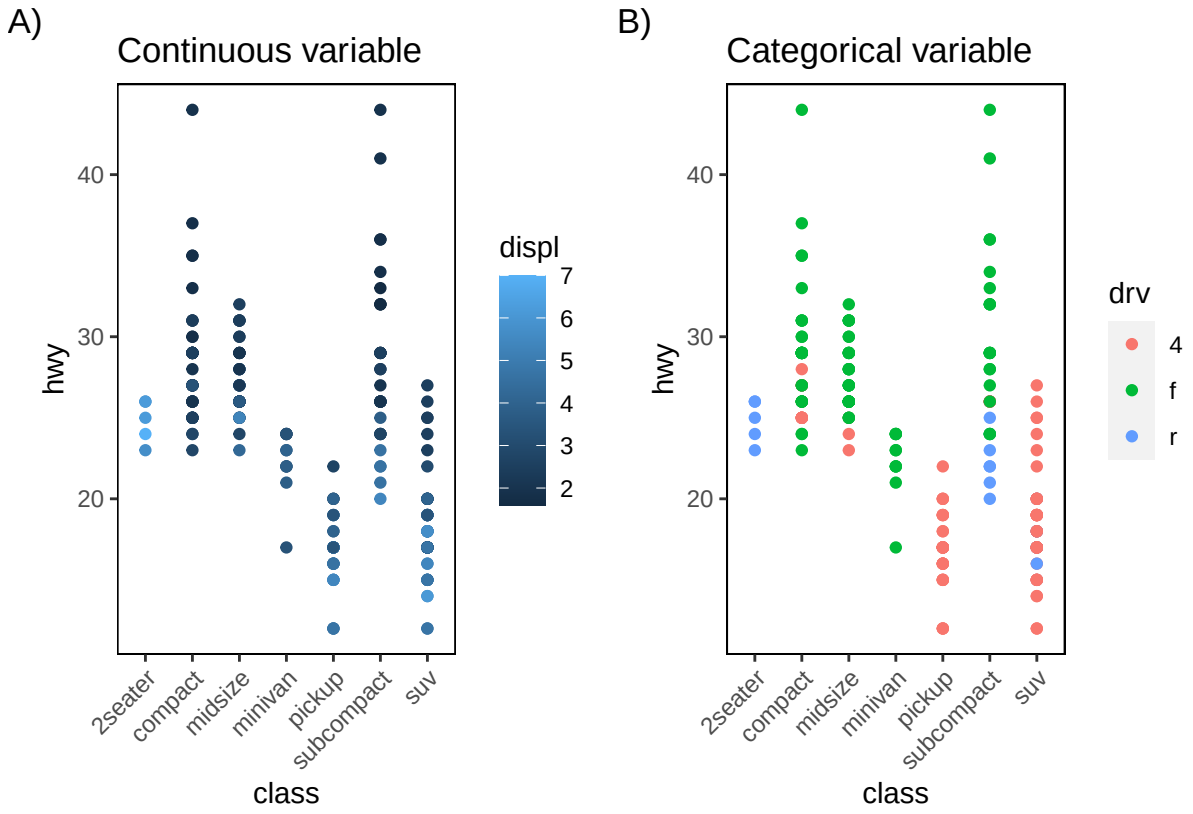
The first plot is identical to one of the plots we generated previously, except there is no variable mapped to the color aesthetic. The second plot shows the distribution diamond prices as a function of the number of carats. The third plot is a time series line plot of the number of unemployed Americans over time, starting in 1970 and extending until April 2015. Finally, the fourth plot shows the distribution of city fuel economy (mpg) for all vehicle models and manufacturers.



Faceting exercises

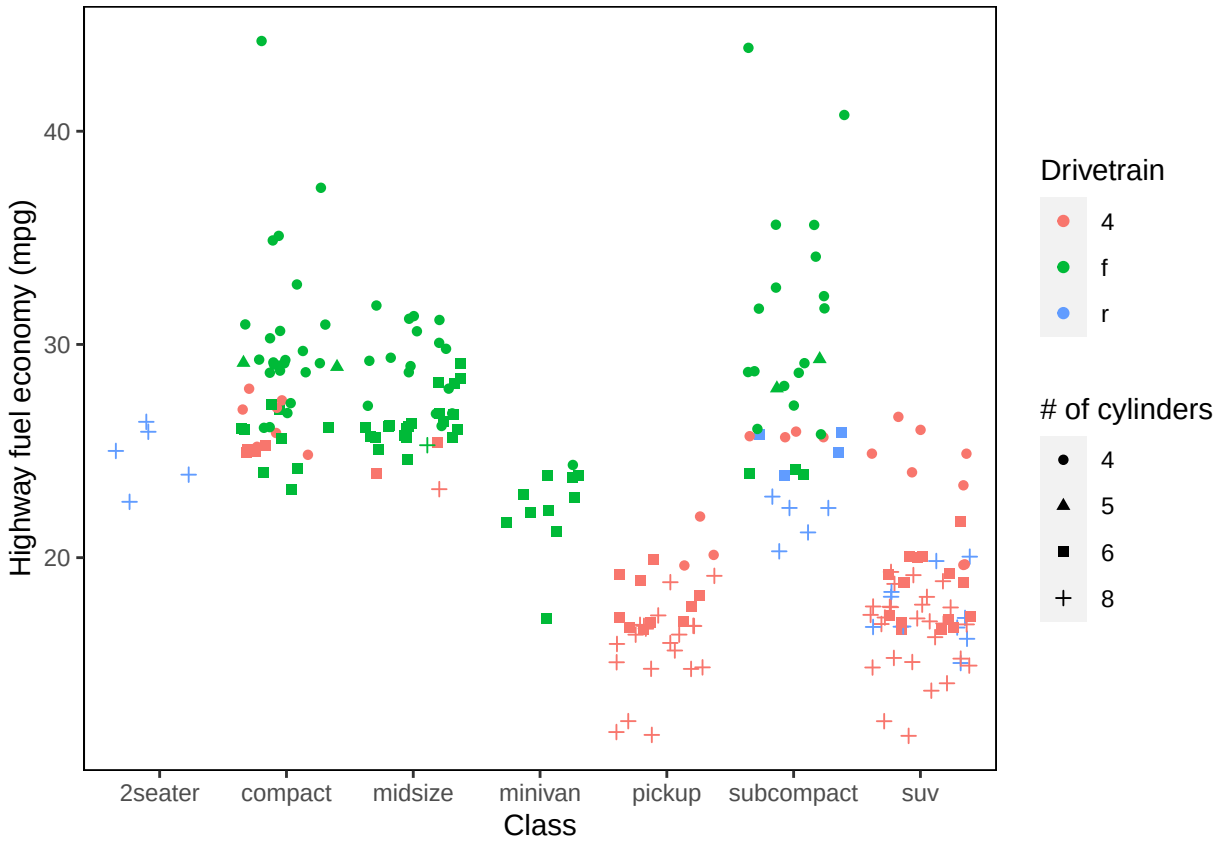
1) *Experiment with the color, shape, and size aesthetics. What happens when you map them to continuous values? What about categorical values? What happens when you use more than one aesthetic in a plot?*

When you map a continuous variable to an aesthetic like color, for example, a continuous color scale is used. In contrast, when you map a categorical variable to the same aesthetic, the discrete color scale is used. To demonstrate, I've plotted the vehicle class (`class`) and the highway fuel economy (`hwy`) with the engine displacement (`displ`) variable mapped to the color aesthetic in one plot and the drive train (`drv`) mapped to the same aesthetic in another.



When you map more than one variable to an aesthetic in a plot, the legend populates to display how the aesthetic maps back to the original data. For example, we can map the `drv` variable to the color aesthetic and the number of cylinders (`cyl`) to the shape aesthetic to see the relationship between `class` and `hwy`.

```
mpg %>%
  ggplot(aes(class, hwy)) +
  geom_jitter(aes(color = drv, shape = as.factor(cyl))) +
  my_theme +
  scale_shape_discrete("# of cylinders") +
  scale_color_discrete("Drivetrain") +
  labs(x = "Class",
       y = "Highway fuel economy (mpg)")
```



2) *What happens if you map a continuous variable to shape? Why? What happens if you map* `trans` *to shape? Why?*

If you try to map a continuous variable, like `displ`, to a shape, ggplot2 will throw an error because shapes are used for distinguishing distinct classes of categorical data. In other words, there is no continuous scale to apply to various shapes for continuous data. If you try to map `trans` to shape, technically the variable is categorical, but there are too many shapes to accurately discern (ggplot2 will only map data to 6 distinct shapes). When the plot becomes overly complicated, it becomes difficult to interpret and alternative strategies are needed.

3) *How is drive train related to fuel economy? How is drive train related to engine size and class?*

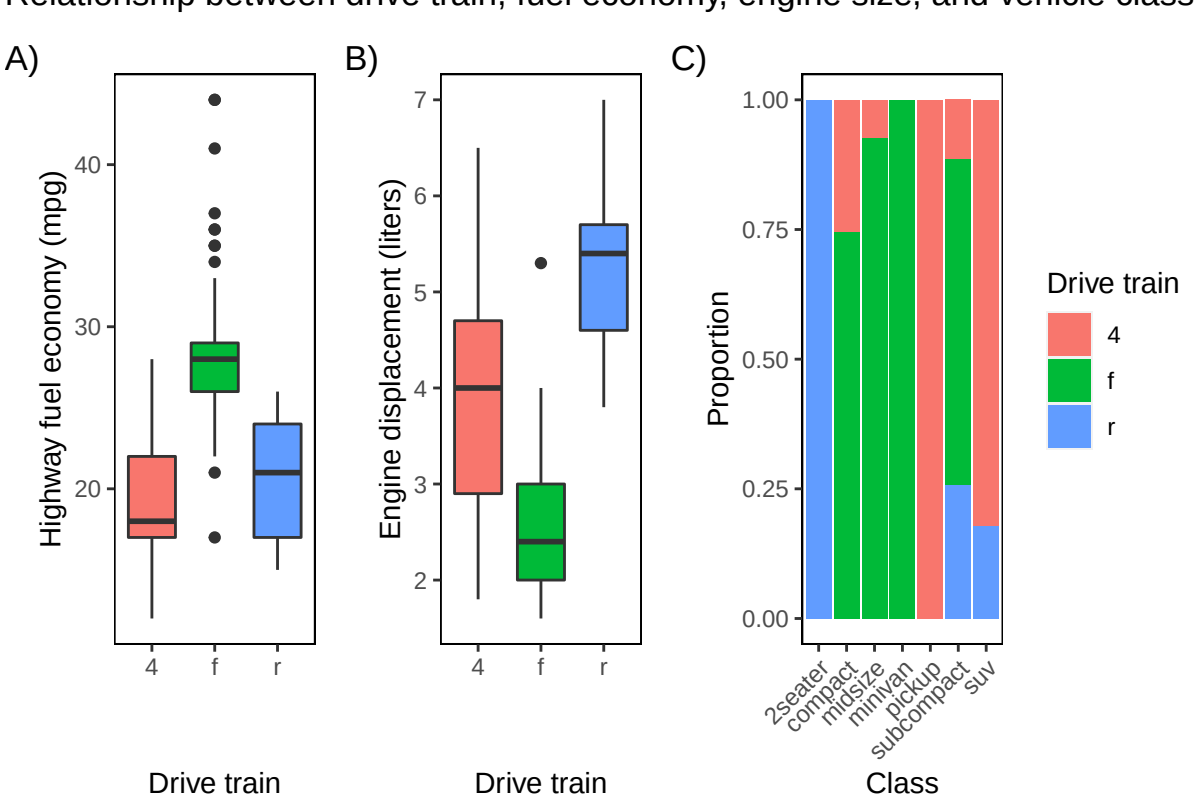
```
a <- mpg %>%
  ggplot(aes(drv, hwy, fill = drv)) +
  geom_boxplot() +
  my_theme +
  labs(x = "Drive train",
       y = "Highway fuel economy (mpg)") +
  theme(legend.position = "none")

b <- mpg %>%
  ggplot(aes(drv, displ, fill = drv)) +
  geom_boxplot() +
  my_theme +
  labs(x = "Drive train",
       y = "Engine displacement (liters)") +
  theme(legend.position = "none")

c <- mpg %>%
```

```
  group_by(class, drv) %>%
  summarise(n = n()) %>%
  group_by(class) %>%
  mutate(total = sum(n),
         proportion = n / total) %>%
  ggplot(aes(class, proportion, fill = drv)) +
  geom_bar(stat = "identity",
           position = "stack") +
  my_theme +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(x = "Class",
       y = "Proportion") +
  scale_fill_discrete("Drive train")

a + b + c +
  plot_layout(guides = "collect") +
  plot_annotation(tag_levels = "A",
                  tag_suffix = ")",
                  title = "Relationship between drive train, fuel economy, engine size, and vehicle clas
```



In plot A), we can see that in general, the front-wheel drive drive train has the best fuel economy, with four-wheel drive having the worst fuel economy. In plot B), we can see that rear-wheel drive vehciles have the largest engines in terms of displacement (liters), with front-wheel drive vehicles having the smallest engines. When we look at plot C), we can see the proportion of the vehicles in each class by drive train. For example, we can see that the 2seater vehicles (e.g. ,corvettes) all have rear-wheel drive trains and since they are more like sports cars, should have the largest engines. In another example, we can see that the pickup trucks in plot C) all have four-wheel drive, and we know that pickups aren't known for exceptional fuel economy. Low

and behold, in plot A) we can see that the four-wheel drive vehicles have the worst highway fuel economy overall (although it's worth noting that a large proportion of SUV's are also four-wheel drive).

Plot geoms exercises