DSCI353-353m-453: Class w06a-p2-ggplot2-graphs-2

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6.1.2.1 ggplot2 Graphics

- Whenever we analyze data, the first thing we should do is look at it.
  - For each variable,
    * what are the most common values?
    * How much variability is present?
    * Are there any unusual observations?
  - R provides a wealth of functions for visualizing data. Lets look at graphs that help is understand
    * a single categorical or continuous variable.

This topic includes

- Visualizing the distribution of a variable
- Comparing the distribution of a variable across two or more groups

In both cases, the variable

- can be continuous (for example, car mileage as miles per gallon)
  - or categorical (for example, treatment outcome as none, some, or marked).
- Later we'll explore graphs that display
  - more complex relationships among variables.

Here we'll explore

- bar charts,
- pie charts,
- tree maps,
- histograms,
- kernel density plots,
- box plots,
- violin plots,
- and dot plots.

Some of these may be familiar to you,

- whereas others (such as tree charts or violin plots) may be new to you.

The goal, as always, is

- to understand your data better
- and to communicate this understanding to others.

6.1.2.2 Bar Charts

- In these examples, you'll plot the outcome of a study
  - investigating a new treatment for rheumatoid arthritis.
- The data are contained in the Arthritis data frame
  - distributed with the `vcd` package.
- Note that the vcd package isn't needed to create bar charts.
  - You're installing it to gain access to the Arthritis dataset.

In the Arthritis study, the variable `Improved`

- records the patient outcomes for individuals receiving a placebo or drug:

```
data(Arthritis, package = "vcd")
table(Arthritis$Improved)
```

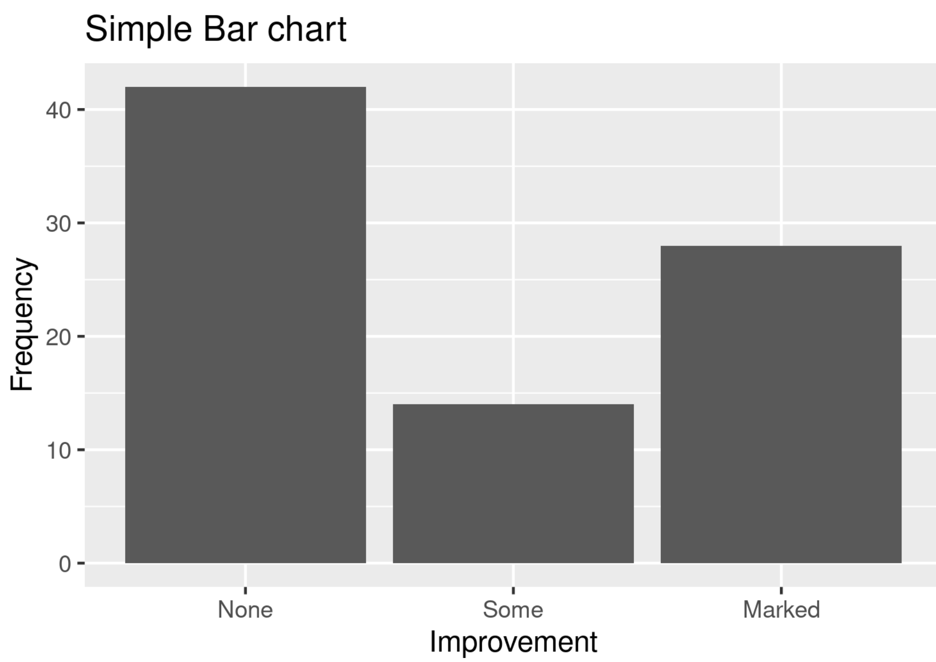
```
##
##   None   Some Marked
##     42     14     28
```

Here, you see that

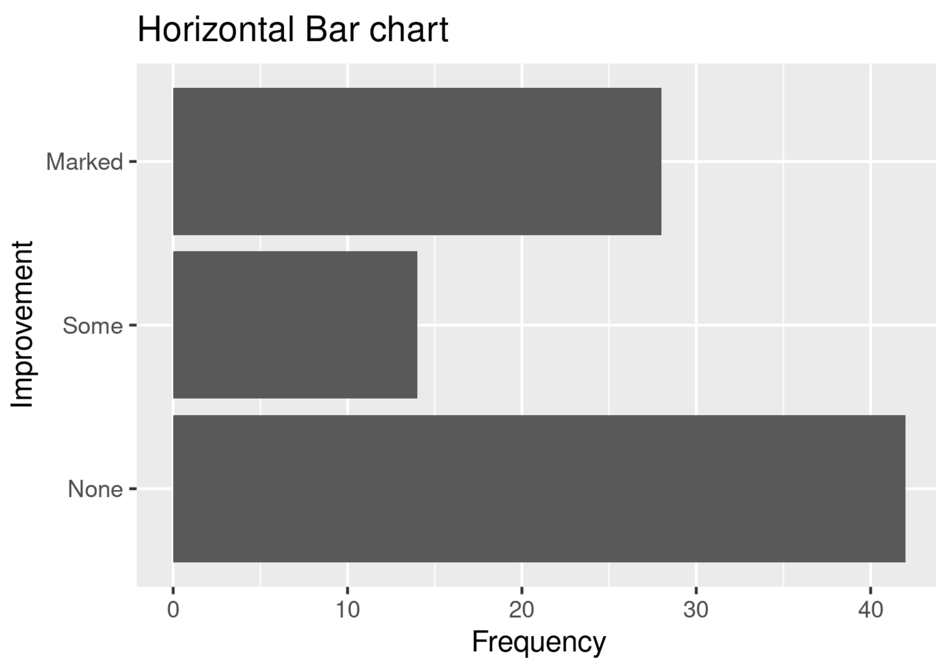
- 28 patients showed marked improvement,
- 14 showed some improvement,
- and 42 showed no improvement.

You can graph these counts using a vertical or horizontal bar chart.

```
library(ggplot2)
data(Arthritis, package = "vcd")
ggplot(Arthritis, aes(x = Improved)) + geom_bar() +
  labs(title = "Simple Bar chart",
       x = "Improvement",
       y = "Frequency")
```




```
ggplot(Arthritis, aes(x = Improved)) + geom_bar() +
  labs(title = "Horizontal Bar chart",
       x = "Improvement",
       y = "Frequency") +
  coord_flip()
```



6.1.2.2.1 Stacked, grouped and filled bar charts

- The central question in the Arthritis study is
  - "How does the level of improvement
    - vary between the placebo and treated conditions?".

The table() function can used

- to generate a cross-tabulation of the variables.

```
table(Arthritis$Improved, Arthritis$Treatment)
```

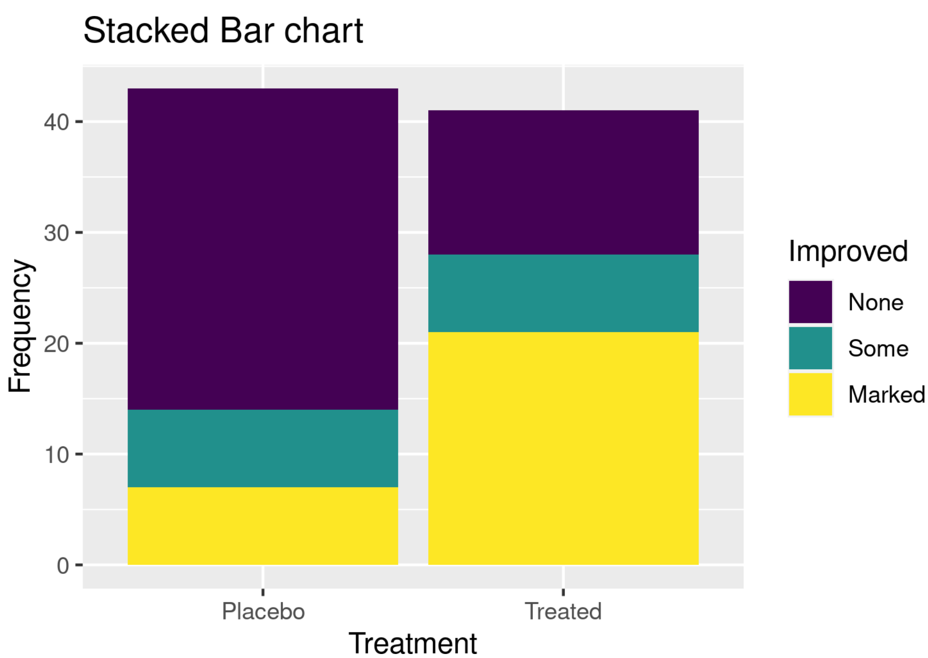
```
##
##            Placebo Treated
##   None          29      13
##   Some           7       7
##   Marked         7      21
```

While the tabulation is helpful,

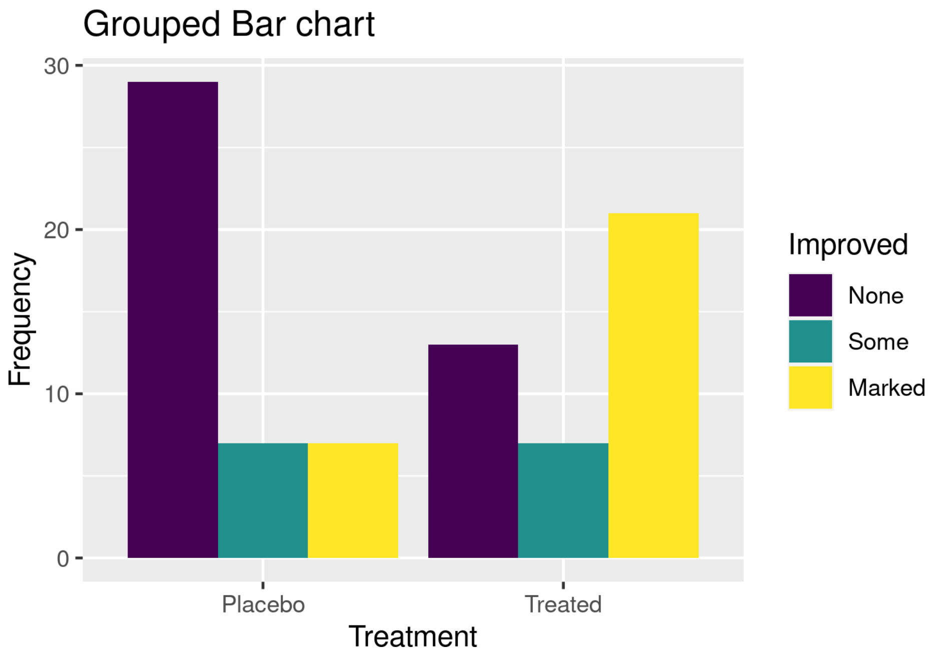
- the results are easier to grasp with a bar chart.
- The relationship between two categorical variables can be plotted
  - using stacked, grouped, or filled bar charts.

#A Stacked bar chart #B Grouped bar chart #C Filled bar chart

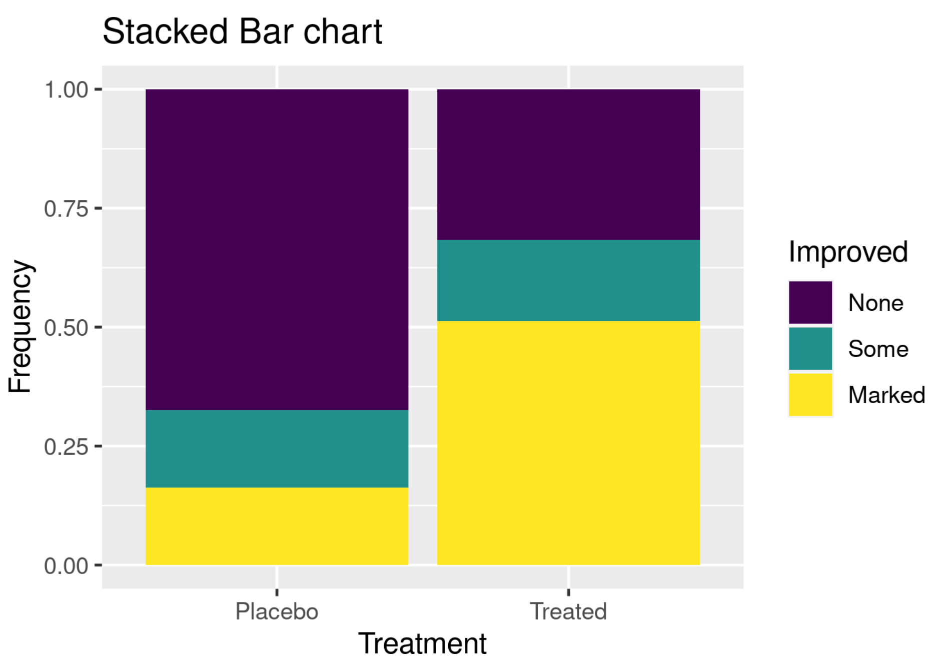
```
ggplot(Arthritis, aes(x = Treatment, fill = Improved)) +      #A
  geom_bar(position = "stack") +
  labs(title = "Stacked Bar chart",
       x = "Treatment",
       y = "Frequency")
```




```
ggplot(Arthritis, aes(x = Treatment, fill = Improved)) +      #B
  geom_bar(position = "dodge") +
  labs(title = "Grouped Bar chart",
       x = "Treatment",
       y = "Frequency")
```




```
ggplot(Arthritis, aes(x = Treatment, fill = Improved)) +      #C
  geom_bar(position = "fill") +
  labs(title = "Stacked Bar chart",
       x = "Treatment",
       y = "Frequency")
```



In the stacked bar chart,

- each segment represents the frequency or proportion of cases
  - within in a given Treatment (Placebo, Treated)
  - and Improvement (None, Some, Marked) level combination.
- The segments are stacked separately for each Treatment level.
- The grouped bar chart

    - places the segments representing Improvement
        * side by side within each Treatment level.
- The filled bar chart is a stacked bar chart
    - rescaled so that the height of each bar is 1
    - and the segment heights represent proportions.
- Filled bar charts are particularly useful
    - for comparing the proportions of one categorical variable
    - over the levels of another categorical variable.
    - For example, the filled bar chart
        * clearly displays the larger percentage of treated patients
        * with marked improvement
        * compared with patients receiving a placebo.

6.1.2.2.2 Mean bar charts

- Bar plots needn't be based on counts or frequencies.
    - You can create bar charts that represent
        * means, medians, percents, standard deviations, and so forth
        * by summarizing the data with an appropriate statistic
        * and passing the results to ggplot2.

In the following graph, we'll plot

- the mean illiteracy rate for regions of the United States in 1970.
- The built-in R dataset state.x77 has the illiteracy rates by state,
    - and the dataset state.region has the region names for each state.

#1 Generate means by region #2 Plot means in a sorted bar chart

```
states <- data.frame(state.region, state.x77)

library(dplyr)
```

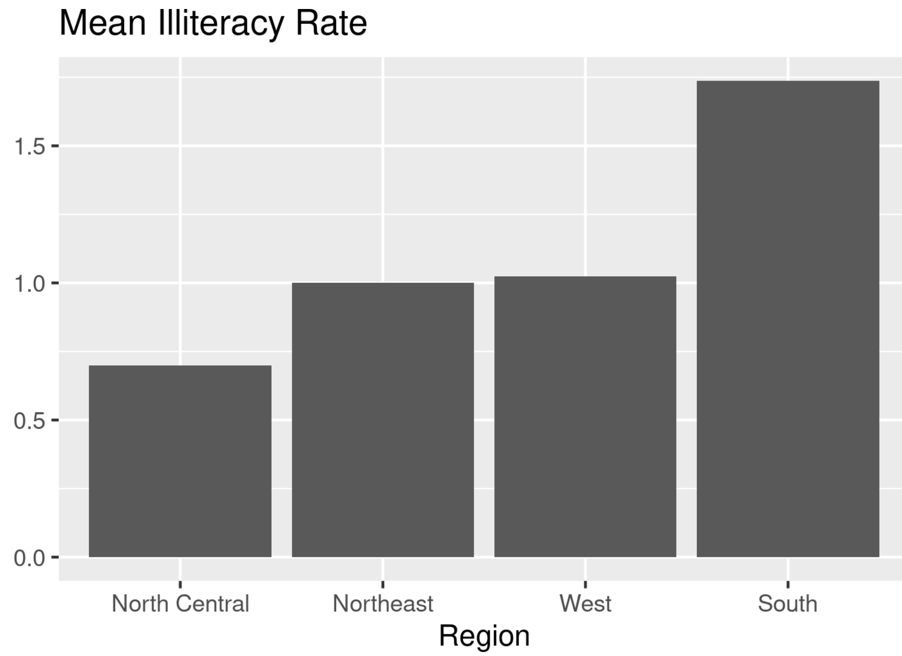
```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
plotdata <- states %>%     #1
  group_by(state.region) %>%
  summarize(mean = mean(Illiteracy))
plotdata
```

```
## # A tibble: 4 x 2
##   state.region   mean
##   <fct>         <dbl>
## 1 Northeast      1
## 2 South          1.74
## 3 North Central  0.7
## 4 West           1.02
```

```
ggplot(plotdata, aes(x = reorder(state.region, mean), y = mean)) +      #2
  geom_bar(stat = "identity") +
```

```
  labs(x = "Region",
       y = "",
       title = "Mean Illiteracy Rate")
```



When plotting summary statistics such as means,

- it's good practice to indicate the variability of the estimates involved.
- One measure of variability
  - is the standard error of the statistic
- an estimate of the expected variation of the statistic
  - across hypothetical repeated samples.

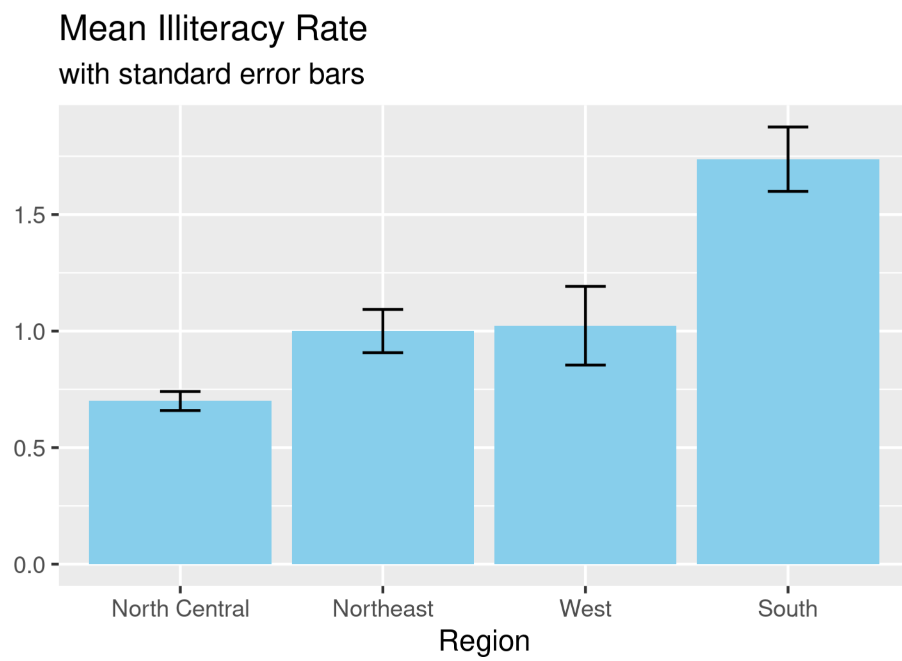
#1 Generate means and standard errors by region #2 Plot means in a sorted bar chart #3 Add error bars

```
plotdata <- states %>%     #1
  group_by(state.region) %>%
  summarize(
    n = n(),
    mean = mean(Illiteracy),
    se = sd(Illiteracy) / sqrt(n)
  )

plotdata
```

```
## # A tibble: 4 x 4
##   state.region      n  mean     se
##   <fct>         <int> <dbl>  <dbl>
## 1 Northeast         9  1    0.0928
## 2 South            16  1.74 0.138
## 3 North Central    12  0.7  0.0408
## 4 West             13  1.02 0.169
```

```
ggplot(plotdata, aes(x = reorder(state.region, mean), y = mean)) +     #2
  geom_bar(stat = "identity", fill = "skyblue") +
  geom_errorbar(aes(ymin = mean - se, ymax = mean + se), width = 0.2) +     #3
```

```
  labs(
    x = "Region",
    y = "",
    title = "Mean Illiteracy Rate",
    subtitle = "with standard error bars"
  )
```



The means and standard errors are calculated for each region #1.

- The bars are then plotted in order of increasing illiteracy.
- The color is changed from a default dark grey
  - to a lighter shade (sky blue)
  - so that error bars to be added in the next step will stand out #2.
- Finally, the error bars are plotted #3.
  - The width option in the `geom_errorbar()` function
  - controls the horizontal width of the error bars and is purely aesthetic
    * it has no statistical meaning.

In addition to displaying the mean illiteracy rates,

- we can see that the mean for the North Central region
  - is the most reliable (least variability)
- and the West region is least reliable
  - (largest variability).

6.1.2.2.3 Tweaking Bar Charts

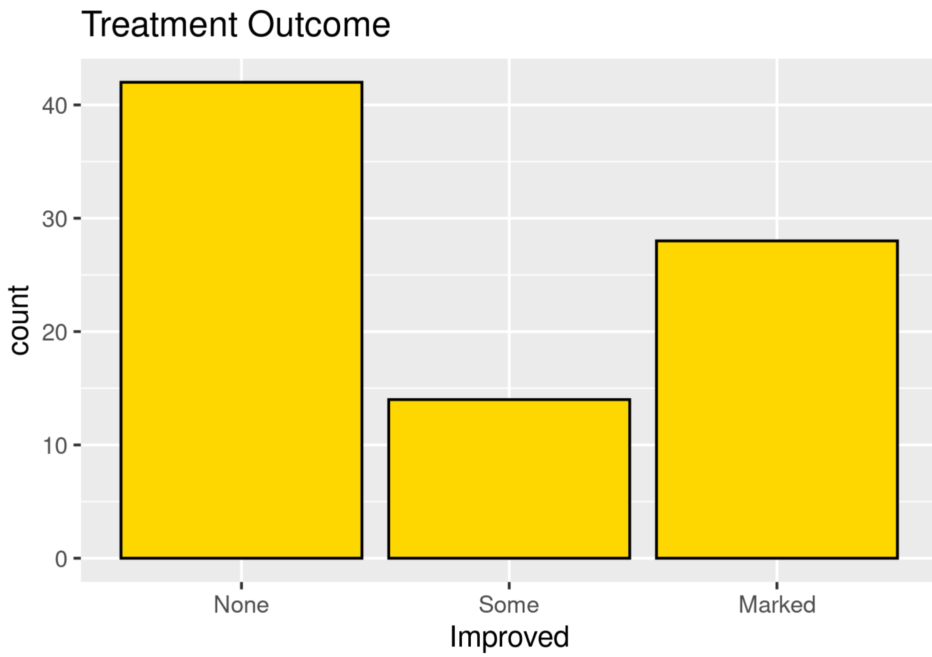
- There are several ways to tweak the appearance of a bar chart.
  - The most common are customizing the bar colors and labels.

Fill vs. Color

- In general, ggplot2 uses **fill**
  - to specify the color of geometric objects that have area
  - (such as bars, pie slices, boxes),
- and the term **color** when referring to

    - the color of geometric objects without area
    - (such as lines, points, and borders).

```
data(Arthritis, package = "vcd")
ggplot(Arthritis, aes(x = Improved)) +
  geom_bar(fill = "gold", color = "black") +
  labs(title = "Treatment Outcome")
```



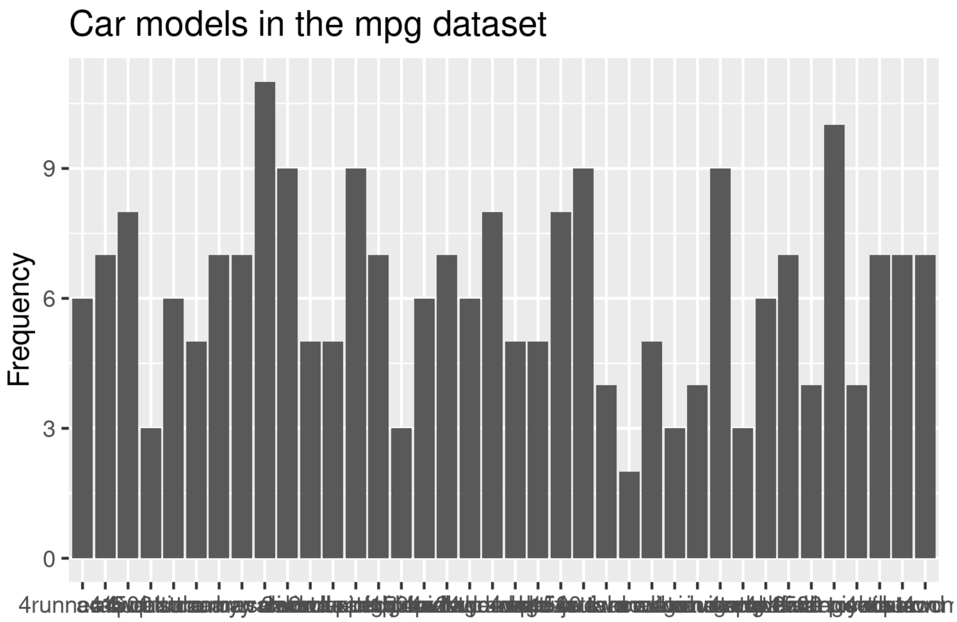
Here, bar fill colors are mapped to the levels of the variable Improved.

- The `scale_fill_manual()` function specifies
    - red for None,
    - grey for Some,
    - and gold for Marked improvement.

6.1.2.2.4 Bar Chart Labels

- When there are many bars or long labels,
    - bar chart labels tend to overlap and become unreadable.
    - Consider the following example.
    - The dataset mpg in the ggplot2 package
        * describes fuel economy data from for 38 popular car models
            · in 1999 and 2008.
        * Each model has several configurations
            · (transmission type, number of cylinders, etc.).

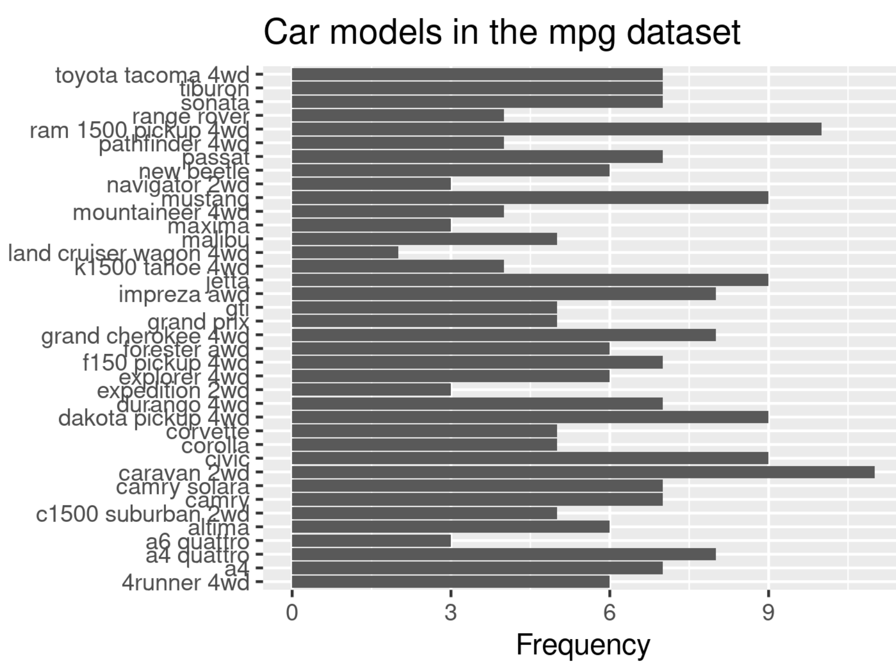
```
ggplot(mpg, aes(x = model)) +
  geom_bar() +
  labs(title = "Car models in the mpg dataset",
       y = "Frequency", x = "")
```



Two simple tweaks will make the labels readable.

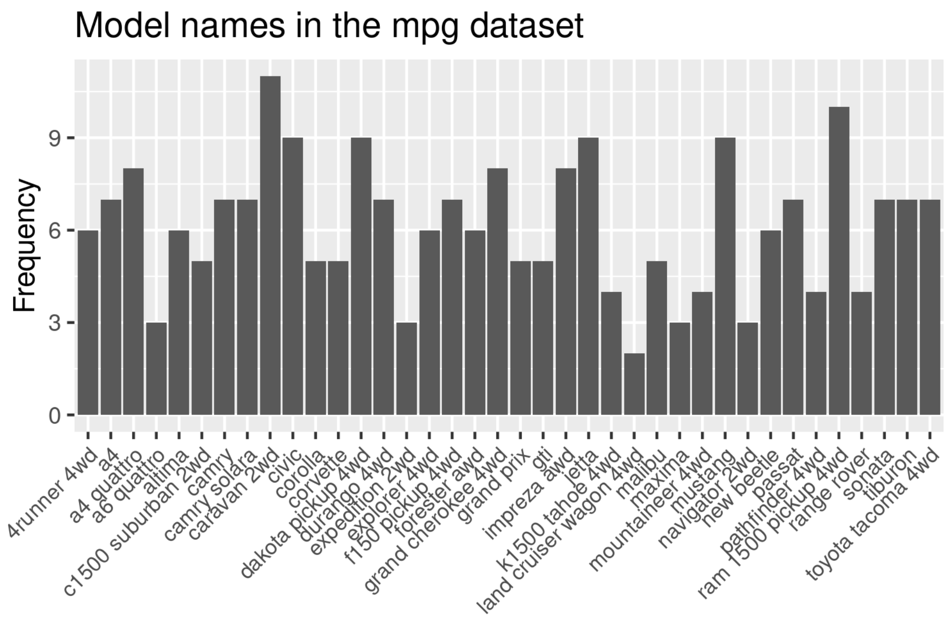
- First, we can plot the data as a horizontal bar chart.
- Second, we can angle the label text and use a smaller font.

```
ggplot(mpg, aes(x = model)) +
  geom_bar() +
  labs(title = "Car models in the mpg dataset",
       y = "Frequency", x = "") +
  coord_flip()
```




```
ggplot(mpg, aes(x = model)) +
  geom_bar() +
  labs(title = "Model names in the mpg dataset",
       y = "Frequency", x = "") +
```

```r
  theme(axis.text.x = element_text(
    angle = 45,
    hjust = 1,
    size = 8
  ))
```



6.1.2.3 Pie Charts (Something I don't use)

- Pie charts are ubiquitous in the business world,
  - but they're denigrated by most statisticians,
    - including the authors of the R documentation.
  - They recommend bar or dot plots over pie charts
    - because people are able to judge length more accurately than volume.
  - Perhaps for this reason, the pie chart options in R
    - are severely limited
    - when compared with other statistical platforms.

[The issue with Pie Charts]

6.1.2.4 Tree Maps

- An alternative to a pie chart is a tree map.
  - A tree map displays the distribution of a categorical variable
    - using rectangles that are proportional to variable levels.
  - Unlike pie charts, tree maps
    - can handle categorical variables with many levels.
  - We'll use the `treemapify` package

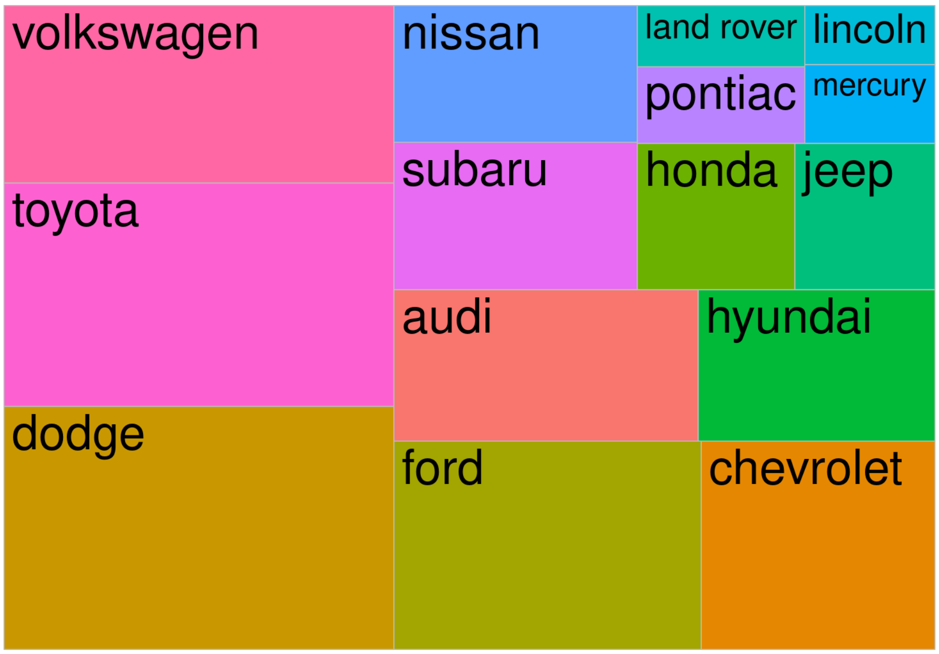
We'll start by creating a tree map

- displaying the distribution of car manufacturers in the mpg data frame.

#1 Summarize the data #2 Create the tree map

```r
library(ggplot2)
library(dplyr)
```

```r
library(treemapify)

plotdata <- mpg %>% count(manufacturer)      #1

ggplot(plotdata,      #2
       aes(fill = manufacturer,
           area = n,
           label = manufacturer)) +
  geom_treemap() +
  geom_treemap_text() +
  theme(legend.position = "none")
```



First we calculate the frequency counts

- for each level the manufacturer variable #1.
- This information is passed to ggplot2
  - to create the graph #2.
- In the `aes()` function,
  - fill refers to the categorical variable,
  - area is the count for level,
  - and label is the option variable used to label the cells.
- The `geom_treemap()` function
  - creates the tree map
  - and the `geom_tree_text()` function adds the labels to each cell.
- The `theme()` function is used to suppress the legend,
  - which is redundant here, since each cell is labeled.

In the next example, a second variable is added drivetrain.

- The number of cars by manufacturer is plotted
  - for front-wheel, rear-wheel, and four-wheel drives.

#1 Compute cell counts #2 Provide better labels for drivetrains #3 Create tree map

```
plotdata <- mpg %>%      #1
  count(manufacturer, drv)
plotdata$drv <- factor(
  #2
  plotdata$drv,
  #3
  levels = c("4", "f", "r"),
  labels = c("4-wheel", "front-wheel", "rear")
)

ggplot(plotdata,
       aes(
         fill = manufacturer,
         area = n,
         label = manufacturer,
         subgroup = drv
       )) +
  geom_treemap() +
  geom_treemap_subgroup_border() +
  geom_treemap_subgroup_text(
    place = "middle",
    colour = "black",
    alpha = 0.5,
    grow = FALSE
  ) +
  geom_treemap_text(colour = "white",
                    place = "centre",
                    grow = FALSE) +
  theme(legend.position = "none")
```

6.1.2.5 Histograms

- Histograms display the distribution of a continuous variable

- by dividing the range of scores
  - into a specified number of bins on the x-axis
  - and displaying the frequency of scores in each bin on the y-axis.

`ggplot(data, aes(x = contvar)) + geom_histogram()`

You can create histograms using `geom_histogram`

- where data is a data frame
- and contvar is a continuous variable.

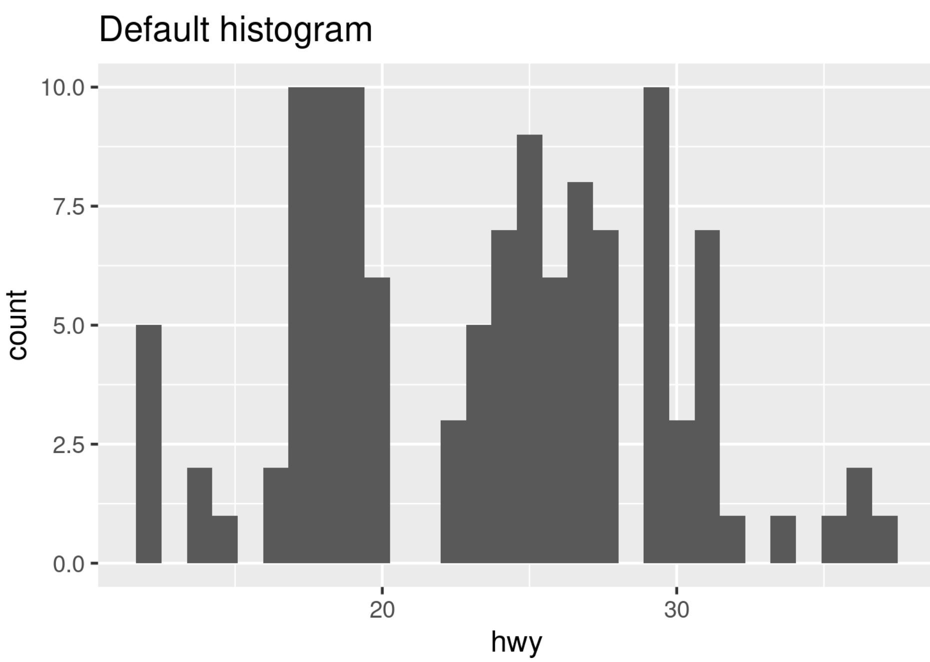
Using the mpg data set in the ggplot package,

- we'll examine the distribution of city miles per gallon (cty)
  - for 117 automobile configurations in 2008.

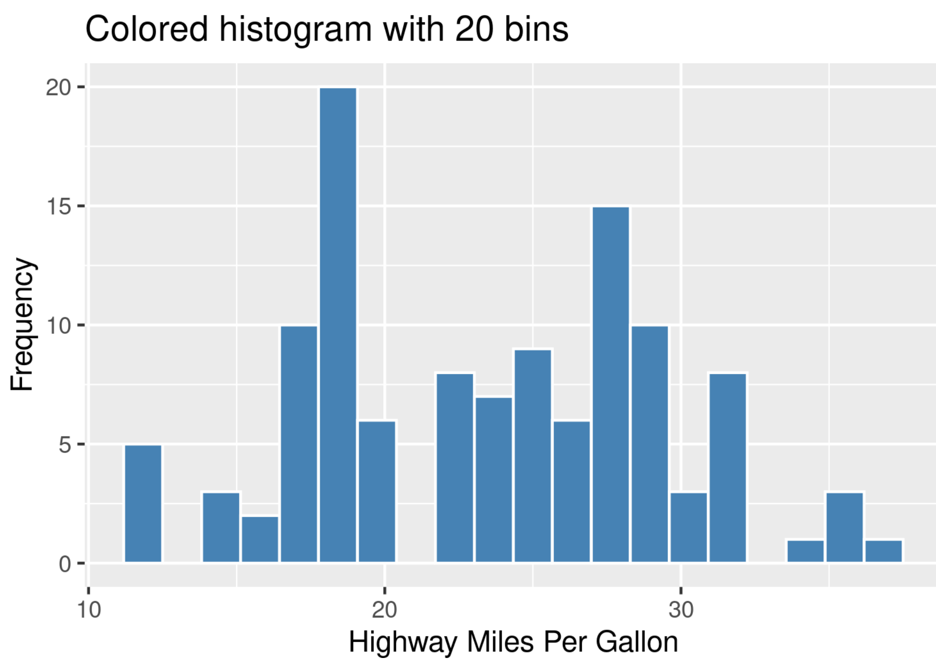
#1 Simple histogram #2 Colored histogram with 20 bins #3 Histogram with percentages #4 Histogram with density curve

```
library(ggplot2)
library(scales)

data(mpg)
cars2008 <- mpg[mpg$year == 2008, ]

ggplot(cars2008, aes(x = hwy)) +       #1
  geom_histogram() +
  labs(title = "Default histogram")
```

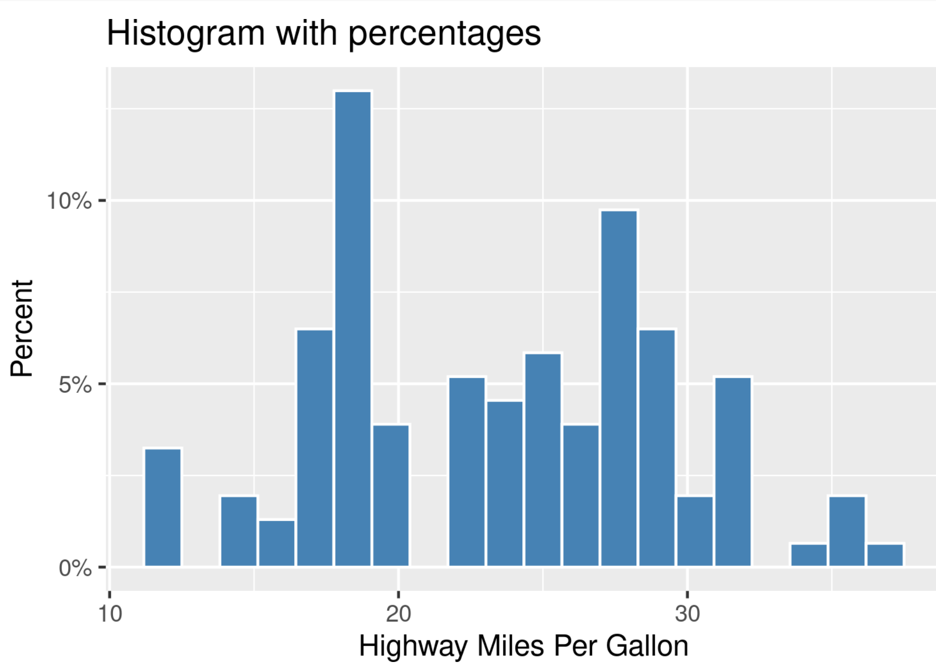
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(cars2008, aes(x = hwy)) +
  geom_histogram(bins = 20, color = "white", fill = "steelblue") +      #2
  labs(title = "Colored histogram with 20 bins",
       x = "Highway Miles Per Gallon",
       y = "Frequency")
```

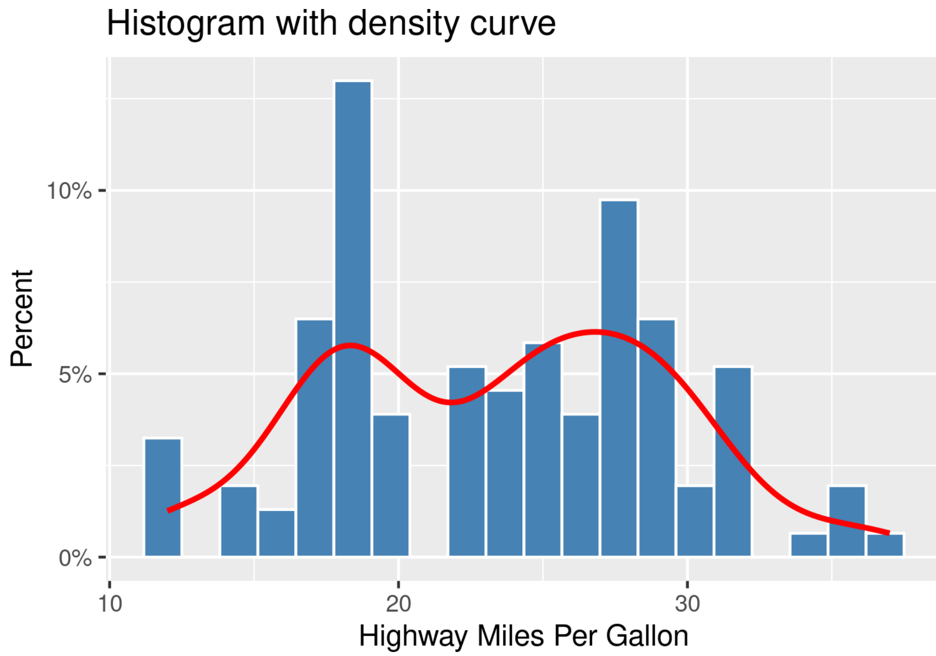



```
ggplot(cars2008, aes(x = hwy, y = ..density..)) +
  geom_histogram(bins = 20, color = "white", fill = "steelblue") +      #3
  scale_y_continuous(labels = scales::percent) +
  labs(title = "Histogram with percentages",
       y = "Percent",
       x = "Highway Miles Per Gallon")
```




```
ggplot(cars2008, aes(x = hwy, y = ..density..)) +
  geom_histogram(bins = 20, color = "white", fill = "steelblue") +      #4
  scale_y_continuous(labels = scales::percent) +
  geom_density(color = "red", size = 1) +
  labs(title = "Histogram with density curve",
```

```
       y = "Percent" ,
       x = "Highway Miles Per Gallon")
```



The first histogram #1

- demonstrates the default plot when no options are specified.
  - In this case, 30 bins are created.
- For the second histogram #2,
  - 20 bins, a steel blue fill, and a white border color are specified.
  - In addition, more informative labels have been added.
- The number of bins can strongly influence the appearance of the histogram.
- It is a good idea to experiment with the bins value
  - until you find one that captures the distribution well.
  - With 20 bins, it appears that there are two peaks to the distribution
    - one around 13 mpg
    - and one around 20.5 mpg.
- The third histogram #3 plots the data as percents rather than frequencies.
  - This is accomplished by assigning
    - the built-in variable `density` to the y axis.
  - The scales package is used to format the y-axis as percents.
  - The fourth histogram #4 is similar to the previous plot,
    - but adds a density curve.
    - The density curve is a kernel density estimate
    - and is described in the next section.
  - It provides a smoother description of the distribution of scores.
  - The geom_density() function is used
    - to plot the kernel curve in a red color
    - and a width that's slightly larger the default thickness for lines.
  - The density curve also suggests a bimodal distribution (two peaks).

6.1.2.6 Kernel density plots

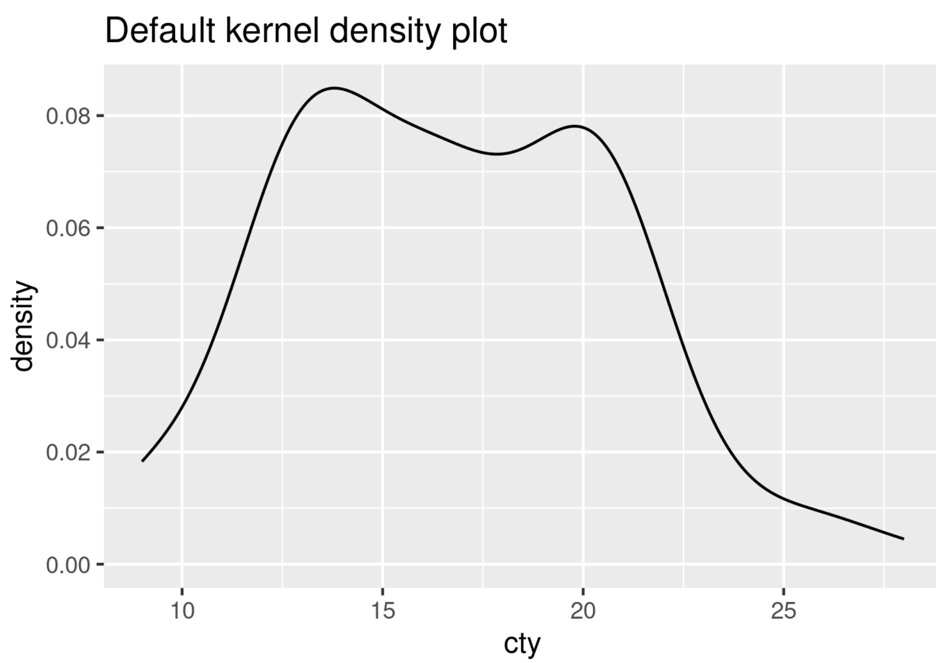
- Technically, kernel density estimation
  - is a nonparametric method for estimating

    * the probability density function of a random variable.

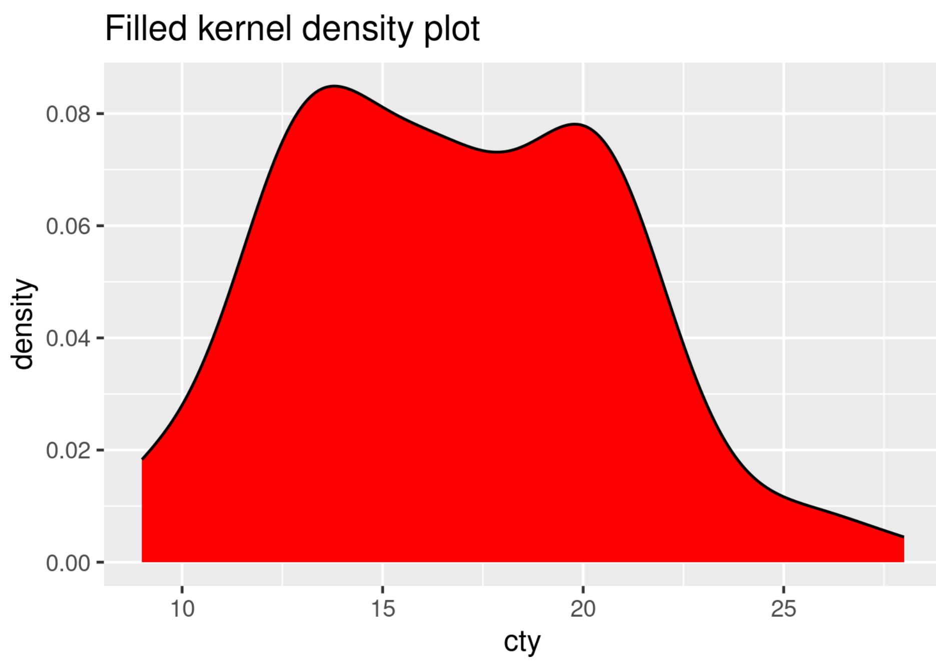
- Basically, we're trying to draw a smoothed histogram,
  - where the area under the curve equals one.
- Although the mathematics are beyond the scope now,
  - density plots can be an effective way
    * to view the distribution of a continuous variable.
- The format for a density plot is
  - `ggplot(data, aes(x = contvar)) + geom_density()`
    * where data is a data frame
    * and contvar is a continuous variable.

#1 Default density plot #2 Filled density plot #3 Print default bandwidth #4 Density plot with smaller bandwidth

```
data(mpg, package = "ggplot2")
cars2008 <- mpg[mpg$year == 2008,]

ggplot(cars2008, aes(x = cty)) +      #1
  geom_density() +
  labs(title = "Default kernel density plot")
```



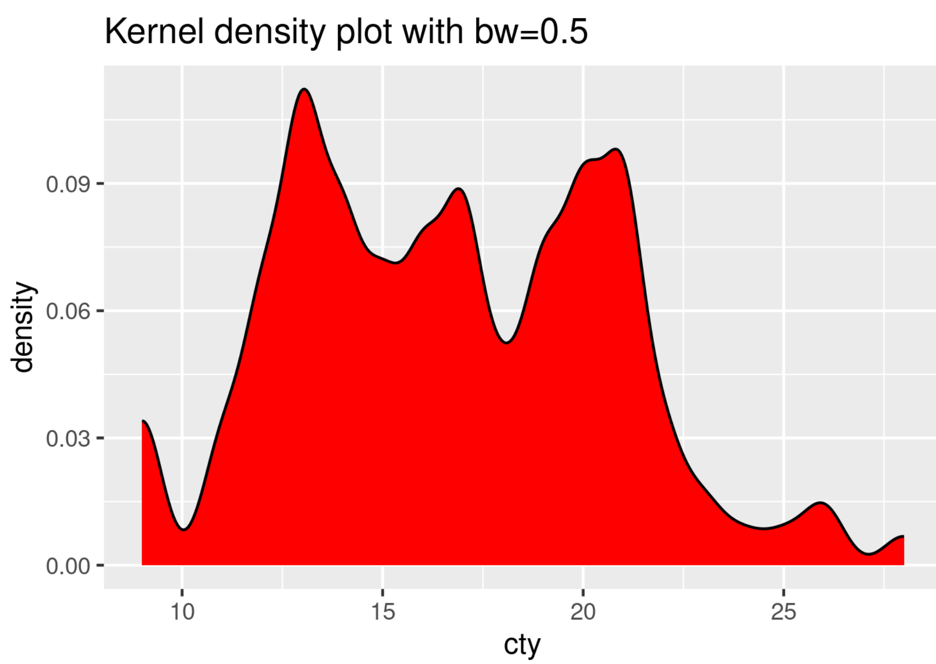

```
ggplot(cars2008, aes(x = cty)) +      #2
  geom_density(fill = "red") +
  labs(title = "Filled kernel density plot")
```




```
bw.nrd0(cars2008$cty)      #3
```

```
## [1] 1.408399
```

```
ggplot(cars2008, aes(x = cty)) +       #4
  geom_density(fill = "red", bw = .5) +
  labs(title = "Kernel density plot with bw=0.5")
```



The default kernel density plot is given first #1.

- In the second example #2, the area under the curve is fill with red.
- The smoothness of the curve is controlled with a bandwidth parameter,
  - which is calculated from the data being plotted.
  - The code `bw.nrd0(cars2008$cty)` displays this value (1.408) #3.

- Using a larger bandwidth will give a smoother curve with less details.
    - A smaller value will give a more squiggly curve.
- The third example uses a smaller bandwidth (`bw=`),
    - allowing us to see more detail #4.
- As with the bins parameter for histograms,
    - it is a good idea to try several bandwidth values
    - to see which value helps you visualize the data most effectively.

Kernel density plots can be used to compare groups.

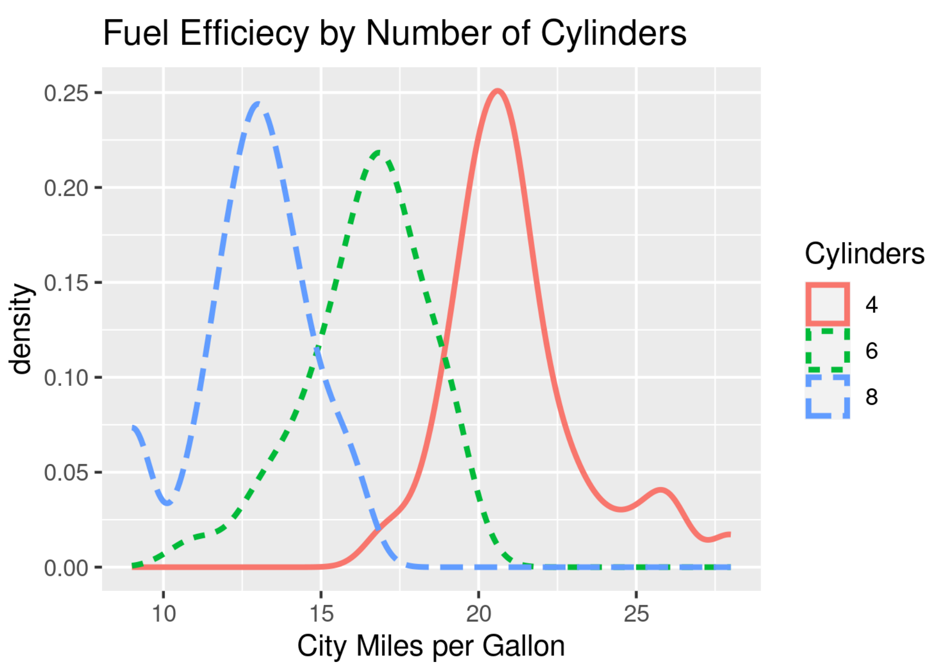
- This is a highly underutilized approach,
    - probably due to a general lack of easily accessible software.

For this example, we'll compare the 2008 city gas mileage estimates

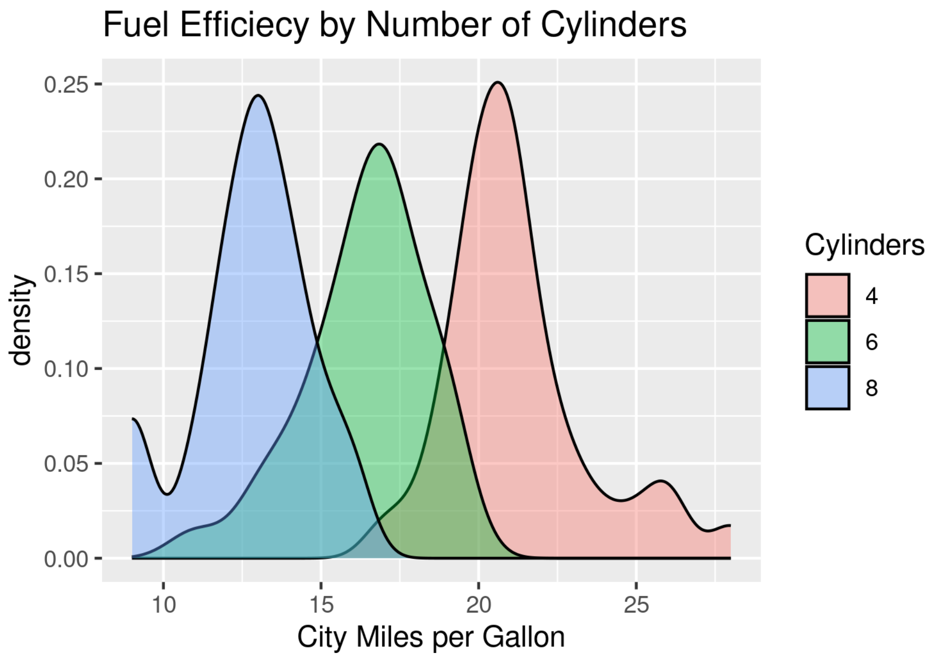
- for 4-, 6-, and 8- cylinder cars.
- There are only a handful of cars with 5 cylinders
    - so we will drop them from the analyses.

#1 Prepare the data #2 Plots the density curves #3 Plot filled density curves

```
data(mpg, package = "ggplot2")      #1
cars2008 <- mpg[mpg$year == 2008 & mpg$cyl != 5,]
cars2008$Cylinders <- factor(cars2008$cyl)

ggplot(cars2008, aes(
  #2
  x = cty,
  color = Cylinders,
  linetype = Cylinders
)) +
  geom_density(size = 1)  +
  labs(title = "Fuel Efficiecy by Number of Cylinders",
       x = "City Miles per Gallon")
```



```
ggplot(cars2008, aes(x = cty, fill = Cylinders)) +      #3
  geom_density(alpha = .4) +
  labs(title = "Fuel Efficiecy by Number of Cylinders",
       x = "City Miles per Gallon")
```



First, a fresh copy of the data is loaded

- and 2008 data for cars with 4, 6, or 8 cylinders are retained #1.
- The number of cylinders (cyl) is saved as a categorical factor (Cylinders).
- The transformation is required
  - because ggplot2 expects the grouping variable to be categorical
  - (and cyl is stored as a continuous variable).
- A kernel density curve is plotted for each level of the Cylinders variable #2.
  - Both the color (red, green, blue)
  - and line type (solid, dotted, dashed)
  - are mapped to the number of cylinders.
- Finally, the same plot is produced with filled curves #3.
  - Transparency is added ($\alpha = 0.4$),
    - since the filled curves overlap
    - and we want to be able to see each one.

Overlapping kernel density plots

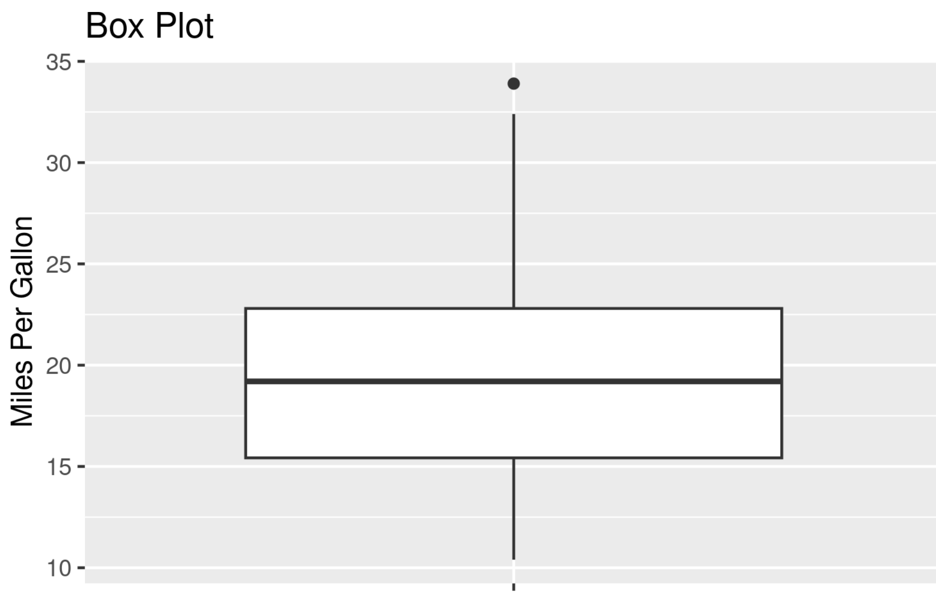
- can be a powerful way to compare groups of observations
  - on an outcome variable.
- Here you can see both the shapes of the distributions
  - and the amount of overlap between groups.

6.1.2.7 Box Plots

- A box-and-whiskers plot describes
  - the distribution of a continuous variable
    - by plotting its five-number summary:
      - the minimum,
      - lower quartile (25th percentile),

        - median (50th percentile),
        - upper quartile (75th percentile),
        - and maximum.
    - It can also display observations
        * that **may be outliers* (values outside the range of $\pm 1.5 \cdot IQR$,
            - where IQR is the interquartile range
            - defined as the upper quartile minus the lower quartile).

```
ggplot(mtcars, aes(x = "", y = mpg)) +
  geom_boxplot() +
  labs(y = "Miles Per Gallon", x = "", title = "Box Plot")
```




```
boxplot.stats(mtcars$mpg)
```

```
## $stats
## [1] 10.40 15.35 19.20 22.80 33.90
##
## $n
## [1] 32
##
## $conf
## [1] 17.11916 21.28084
##
## $out
## numeric(0)
```

By default, each whisker extends to the most extreme data point,

- which is no more than 1.5 times the interquartile range for the box.
- Values outside this range are depicted as dots.

For example, in this sample of cars,

- the median mpg is 17,
    - 50% of the scores fall between 14 and 19,
    - the smallest value is 9,
    - and the largest value is 35.
- How did I read this so precisely from the graph?

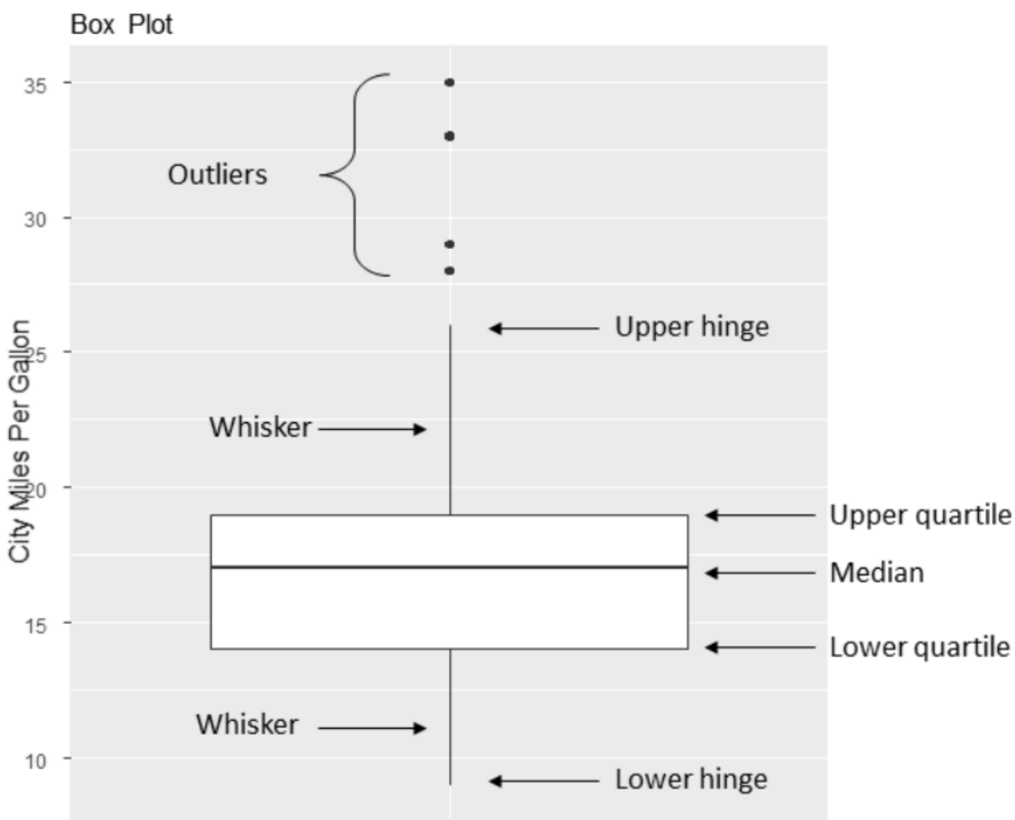


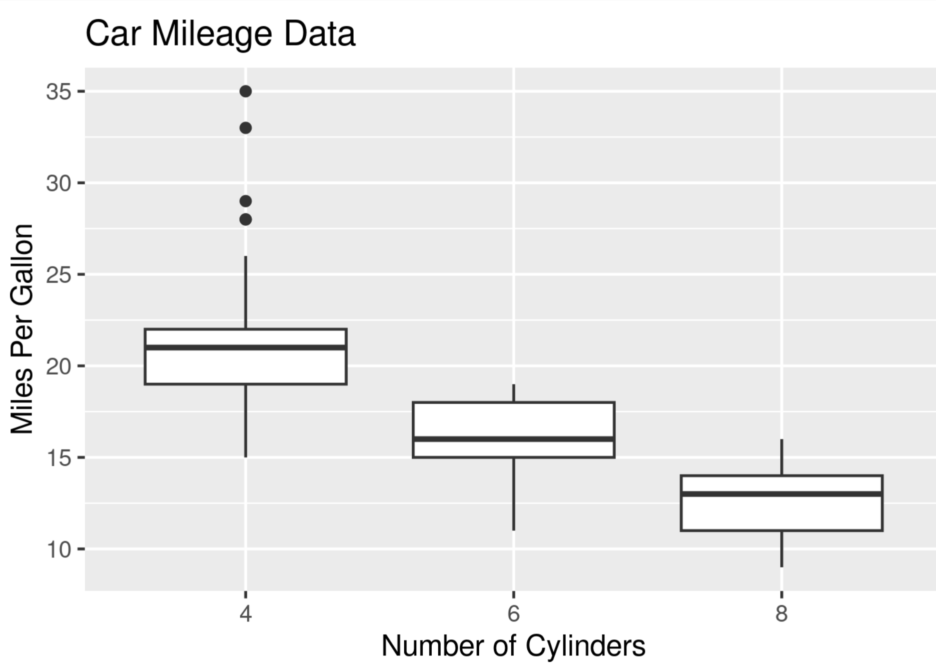
Figure 1: And annotated

    - Issuing `boxplot.stats(mtcars$mpg)`
        - prints the statistics used to build the graph.
- There are four outliers
    - (greater than the upper hinge of 26).
    - These values would be expected to occur
        - less than 1% of the time in a normal distribution.

6.1.2.7.1 Using parallel box plots to compare groups

- Box plots are a useful method of comparing
    - the distribution of a quantitative variable
        - across the levels of a categorical variable.
    - Once again, let's compare city gas mileage for 3-, 6-, and 8-cylinder cars,
        - but this time use both 1999 and 2008 data.
    - Since there are only a few 5-cylinder cars,
        - we will delete them.
    - We'll also convert year and cyl
        - from continuous numeric variables
        - into categorical (grouping) factors.

```
library(ggplot2)
cars <- mpg[mpg$cyl != 5,]
cars$Cylinders <- factor(cars$cyl)
cars$Year <- factor(cars$year)

ggplot(cars, aes(x = Cylinders, y = cty)) +
  geom_boxplot() +
  labs(x = "Number of Cylinders",
       y = "Miles Per Gallon",
       title = "Car Mileage Data")
```



You can see that there's a good

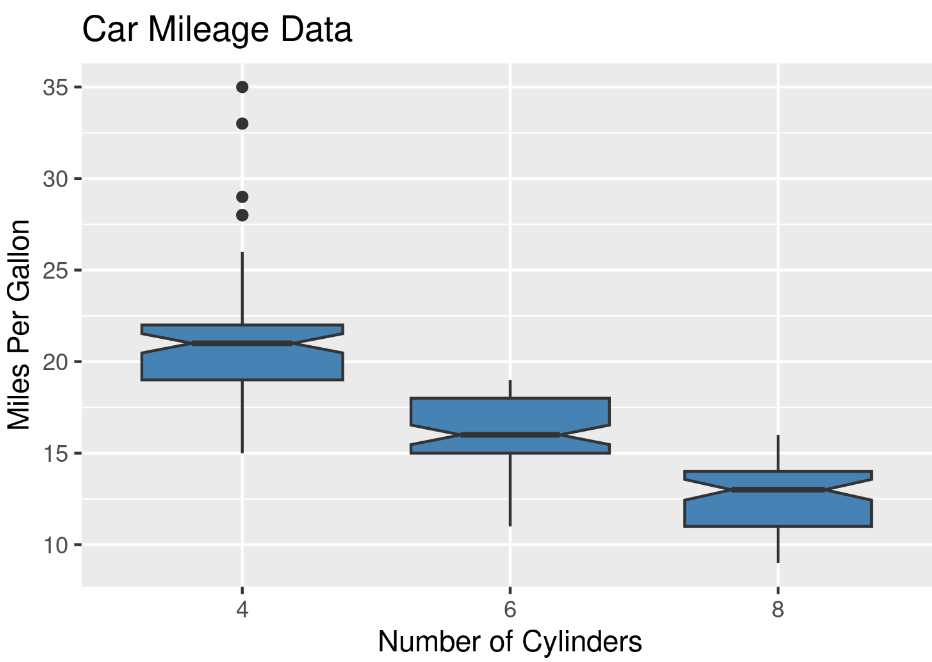
- separation of groups based on gas mileage,

- with fuel efficiency dropping as the number of cylinders increases.
- There are also four outliers
  - (cars with unusually high mileage)
  - in the four-cylinder group.

Box plots are very versatile.

- By adding notch=TRUE,
  - you get notched box plots.
- If two boxes' notches don't overlap,
  - there's strong evidence that their medians differ

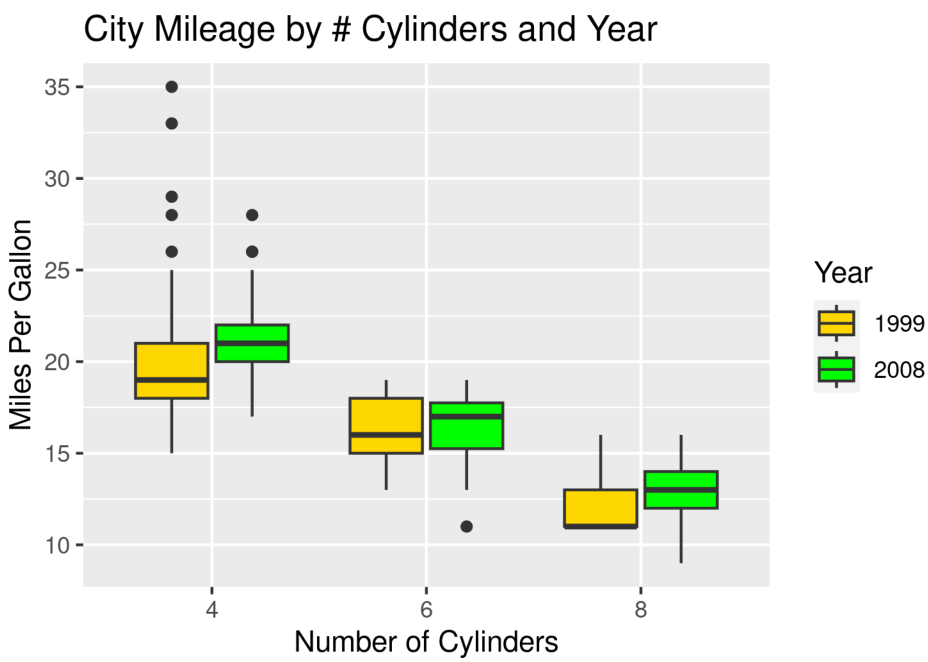
```
ggplot(cars, aes(x = Cylinders, y = cty)) +
  geom_boxplot(notch = TRUE,
               fill = "steelblue",
               varwidth = TRUE) +
  labs(x = "Number of Cylinders",
       y = "Miles Per Gallon",
       title = "Car Mileage Data")
```



The fill option fills the box plots with a red color.

- In a standard box plot,
  - the box width has no meaning.
- Adding `varwidth=TRUE`,
  - draws box widths proportional to the square roots
    - of the number of observations in each group.
- The scale_fill_manual() function has been added
  - in order to customize the fill colors.

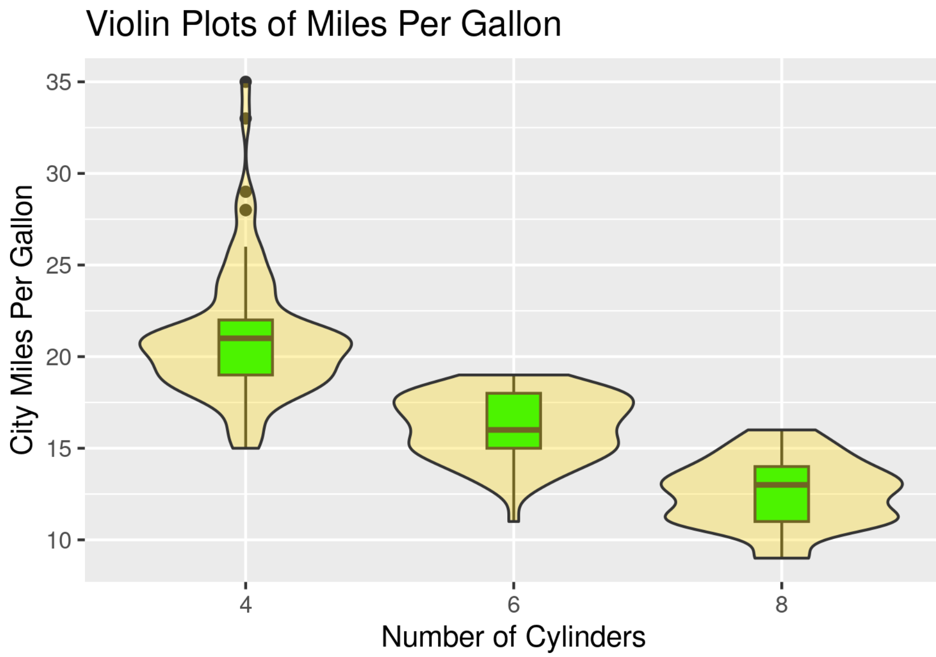
```
ggplot(cars, aes(x = Cylinders, y = cty, fill = Year)) +
  geom_boxplot() +
  labs(x = "Number of Cylinders",
       y = "Miles Per Gallon",
       title = "City Mileage by # Cylinders and Year") +
  scale_fill_manual(values = c("gold", "green"))
```



6.1.2.7.2 Violin Plots

- Before we end our discussion of box plots,
  - it's worth examining a variation called a **violin plot**.
- A violin plot is a combination
  - of a box plot and a kernel density plot.
- You can create one using the `geom_violin()` function.

```
cars <- mpg[mpg$cyl != 5, ]
cars$Cylinders <- factor(cars$cyl)

ggplot(cars, aes(x = Cylinders, y = cty)) +
  geom_boxplot(width = 0.2,
               fill = "green") +
  geom_violin(fill = "gold",
              alpha = 0.3) +
  labs(x = "Number of Cylinders",
       y = "City Miles Per Gallon",
       title = "Violin Plots of Miles Per Gallon")
```



The width of the box plots

- are set to 0.2
  - so that they will fit inside the violin plots.
- The violin plots are set with a transparency level of 0.3
  - so that the box plots are still visible.

Violin plots are basically kernel density plots

- superimposed in a mirror-image fashion over box plots.
  - The middle lines are the medians,
  - the black boxes range from the lower to the upper quartile,
  - and the thin black lines represent the whiskers.
  - Dots are outliers.
- The outer shape provides the kernel density plot.
  - Here we can see that the distribution of
    * gas mileage for 8-cylinder cars
  - may be bimodal
    * a fact that is obscured by using box plots alone.

6.1.2.8 Dot Plots

- Dot plots provide a method of plotting
  - a large number of labeled values on a simple horizontal scale.
- You create them with the `dotchart()` function,
  - using the format
  - `ggplot(data, aes(x=contvar, y=catvar)) + geom_point()`

Here's an example using the highway gas mileage

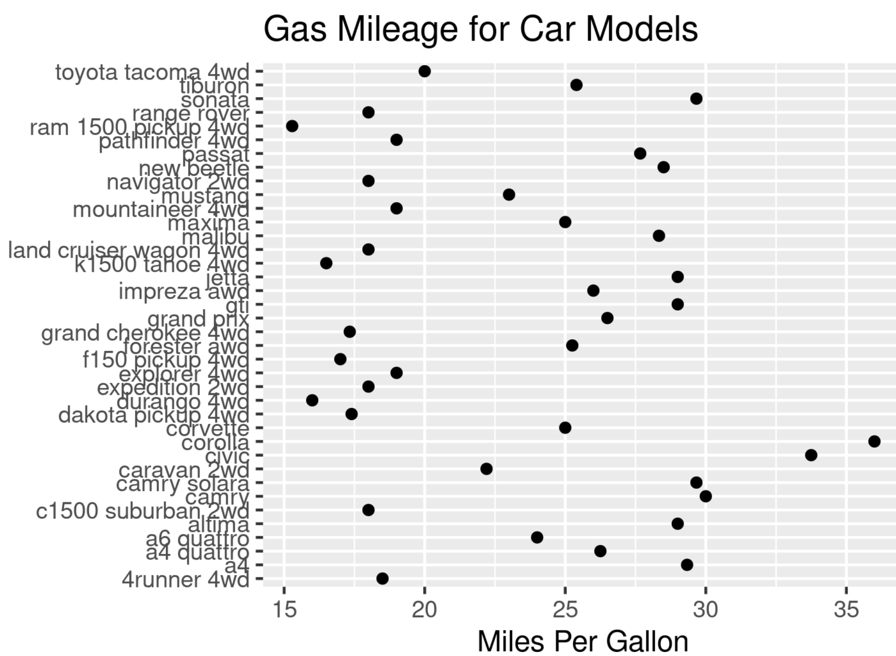
- for the 2008 automobiles in the mpg dataset.
- Highway gas mileage is averaged by car model.

```
plotdata <- mpg %>%
  filter(year == "2008") %>%
  group_by(model) %>%
```

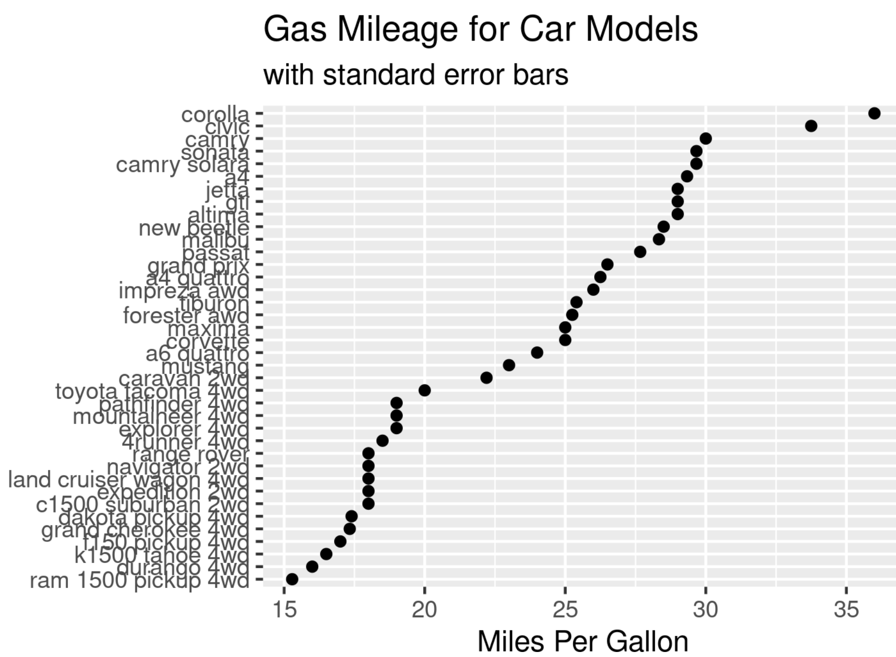
```
  summarize(meanHwy = mean(hwy))
plotdata
```

```
## # A tibble: 38 x 2
##    model               meanHwy
##    <chr>                 <dbl>
##  1 4runner 4wd            18.5
##  2 a4                     29.3
##  3 a4 quattro             26.2
##  4 a6 quattro             24
##  5 altima                 29
##  6 c1500 suburban 2wd     18
##  7 camry                  30
##  8 camry solara           29.7
##  9 caravan 2wd            22.2
## 10 civic                  33.8
## # ... with 28 more rows
```

```
ggplot(plotdata, aes(x = meanHwy, y = model)) +
  geom_point() +
  labs(x = "Miles Per Gallon",
       y = "",
       title = "Gas Mileage for Car Models")
```



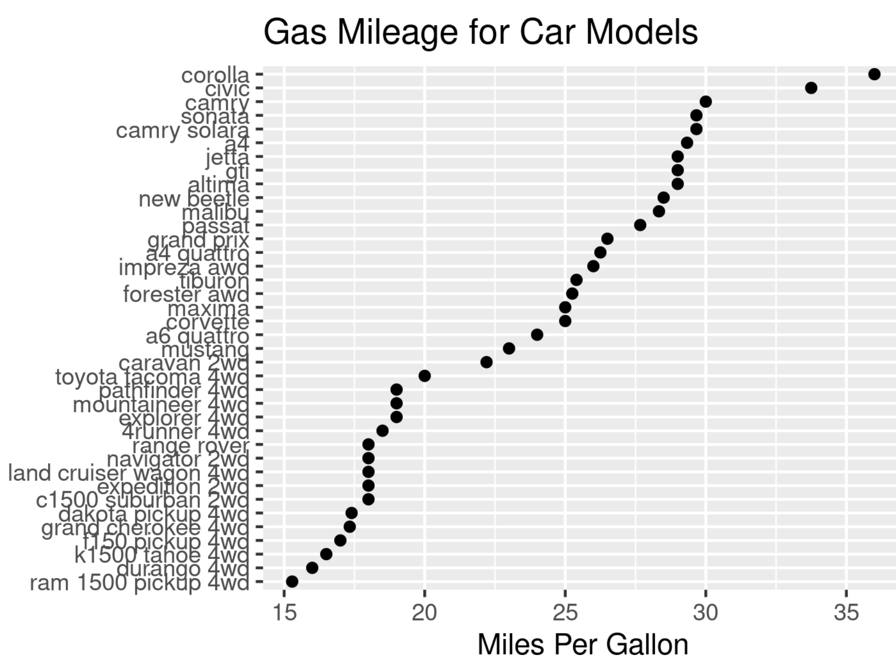

```
ggplot(plotdata, aes(x = meanHwy, y = reorder(model, meanHwy))) +
  geom_point() +
  labs(
    x = "Miles Per Gallon",
    y = "",
    title = "Gas Mileage for Car Models",
    subtitle = "with standard error bars"
  )
```



This graph allows you to see

- the mpg for each car model on the same horizontal axis.
- Dot plots typically become most useful
  - when they're sorted.
- The following code sorts the cars
  - from lowest to highest mileage.

```
ggplot(plotdata, aes(x = meanHwy, y = reorder(model, meanHwy))) +
  geom_point() +
  labs(x = "Miles Per Gallon",
       y = "",
       title = "Gas Mileage for Car Models")
```



You can gain significant insight from the dot plot in this example

- because each point is labeled,
  - the value of each point is inherently meaningful,
  - and the points are arranged in a manner that promotes comparisons.
- But as the number of data points increases,
  - the utility of the dot plot decreases.

6.1.2.9 Summary

- 1. Bar charts (and to a lesser extent pie charts and tree maps)
  - can be used to gain insight into **the distribution of a categorical variable**.
- 2. Stacked, grouped, and filled bar charts
  - can help you understand **how groups differ on a categorical outcome**.
- 3. Histograms, box plots, violin plots, and dot plots
  - can help you **visualize the distribution of continuous variables**.
- 4. Overlapping kernel density plots and parallel box plots
  - can help you **visualize group differences on a continuous outcome variable**.

6.1.2.10 Links

- Robert I. Kabacoff, R in Action, 3rd Edition, Manning Publications 2020