Data Visualization with R

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Contents

Prerequisites and Preparations

To get the most out of this workshop you should have:

- a **basic knowledge** of R and/or be familiar with the topics covered in the Introduction to R.
- have a recent version of R and RStudio installed.
- have installed the `tidyverse` package.

Recommended:

- Create a new RStudio project `R-data-viz` in a new folder `R-data-viz` and download both CSV files into a subdirectory called `data`:
  - Download `MS_stops.csv` from here: https://github.com/cengel/R-data-viz/raw/master/data/MS_stops.csv
  - Download `MS_county_stops.csv` from here: https://github.com/cengel/R-data-viz/raw/master/data/MS_county_stops.csv
  - If you have your working directory set to `R-data-viz` which contains a folder called `data` you can copy, paste, and run the following lines in R:

```
download.file("https://github.com/cengel/R-data-viz/raw/master/data/MS_stops.csv",
              "data/MS_stops.csv")

download.file("https://github.com/cengel/R-data-viz/raw/master/data/MS_stops_by_county.csv",
              "data/MS_stops_by_county.csv")
```

- Open up a new R Script file `R-data-viz.R` for the code you'll create during the workshop.

References

Chang, W. (2012): R Graphics Cookbook. Stanford only online access

Healy, K (2019): Data visualization : a practical introduction. Searchworks

Murrell, P. (2012): R Graphics, 2nd ed. Stanford only online access

Rahlf, T (2017): Data Visualisation with R. http://www.springer.com/us/book/9783319497501

Wickham, H. (2016): ggplot2: Elegant Graphics for Data Analysis. 2nd ed. http://link.springer.com/book/10.1007/978-3-319-24277-4

Acknowledgements

Part of the materials for this tutorial are adapted from http://datacarpentry.org and http://softwarecarpentry.org.

Data sample taken from https://openpolicing.stanford.edu/

Chapter 1

Data Visualization with `ggplot2`

Learning Objectives

- Bind a data frame to a plot
- Select variables to be plotted and variables to define the presentation such as size, shape, color, transparency, etc. by defining aesthetics (`aes`)
- Add a graphical representation of the data in the plot (points, lines, bars) adding "geoms" layers
- Produce univariate plots, barplots and histograms, area plots, boxplots, and line plots, using ggplot.
- Produce bivariate plots, like scatter plots, hex plots, stacked bars, and bivariate line charts using ggplot.
- Modify the aesthetics for the entire plot as well as for individual "geoms" layers
- Modify plot elements (labels, text, scale, orientation)
- Group observations by a factor variable
- Break up plot into multiple panels (facetting)
- Apply ggplot themes and create and apply customized themes
- Save a plot created by ggplot as an image

1.1 What is `ggplot2`

There are three main plotting systems in R, the base plotting system, the lattice package, and the ggplot2 package.

Here we will introduce the `ggplot2` package, which has recently soared in popularity. `ggplot` allows you to create graphs for univariate and multivariate numerical and categorical data in a straightforward manner. It also allows for easy grouping and conditioning. It can generate complex plots create high quality graphics for publication.

`ggplot` is built on Leland Wilkinson's The Grammar of Graphics, the idea that any plot can be expressed from the same set of components:

- a data set,
- a coordinate system,
- and a set of geoms–the visual representation of data points.

The key to understanding `ggplot` is thinking about a figure in layers. This idea may be familiar to you if you have used image editing programs like Photoshop, Illustrator, or Inkscape.

`ggplot2` provides a programmatic interface for specifying what variables to plot, how they are displayed, and what the general visual properties are, so we only need minimal changes if the underlying data change or if we decide to change from a bar plot to a scatterplot. This helps in creating plots quickly with minimal amounts of adjustments and tweaking.

`ggplot` generally likes data in the 'long' format: i.e., a column for every dimension, and a row for every observation. Well structured data will save you lots of time when making figures with ggplot.

1.2 Plotting with ggplot2

We start by loading the required package. Note that **`ggplot2`** is part of the collection of the **`tidyverse`** packages.

```
library(ggplot2)
```

Next we load the data into R:

```
stops_county <- read.csv('data/MS_stops_by_county.csv')
```

These data are a small subset extracted from the openpolicing.stanford.edu dataset and contain traffic stops by police aggregated for each county in Missisippi. Let's take a look at the data.

```
head(stops_county)
str(stops_county)
```

The table contains two variables which represent for each county, and for both white and black, the ratio of drivers stopped out of the total population over 18: `pct_black_stopped` and `pct_white_stopped`. In order to see if there is any 'bias' we can plot the two values against each other and see if they line up at a 45 degree angle.

`ggplot` graphics are built step by step by adding new elements (layers) using the `+` sign.

To build a `ggplot` we need to:

- bind the plot to a specific data frame using the `data` argument

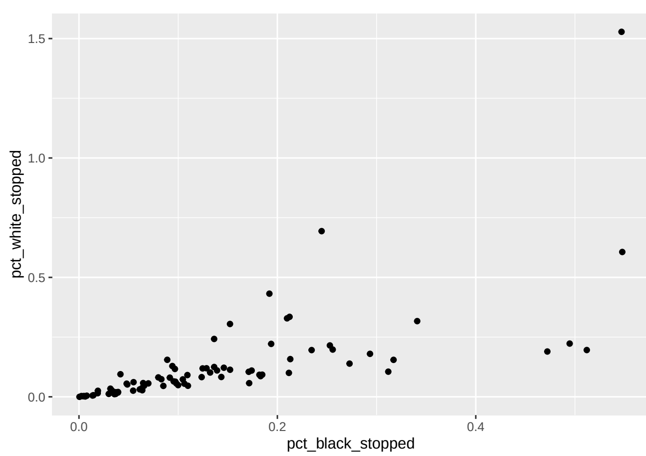
```
ggplot(data = stops_county)
```

- define aesthetics (`aes`), by selecting the variables to be plotted and the variables to define the presentation such as plotting size, shape color, etc.

```
ggplot(data = stops_county, aes(x = pct_black_stopped, y = pct_white_stopped))
```

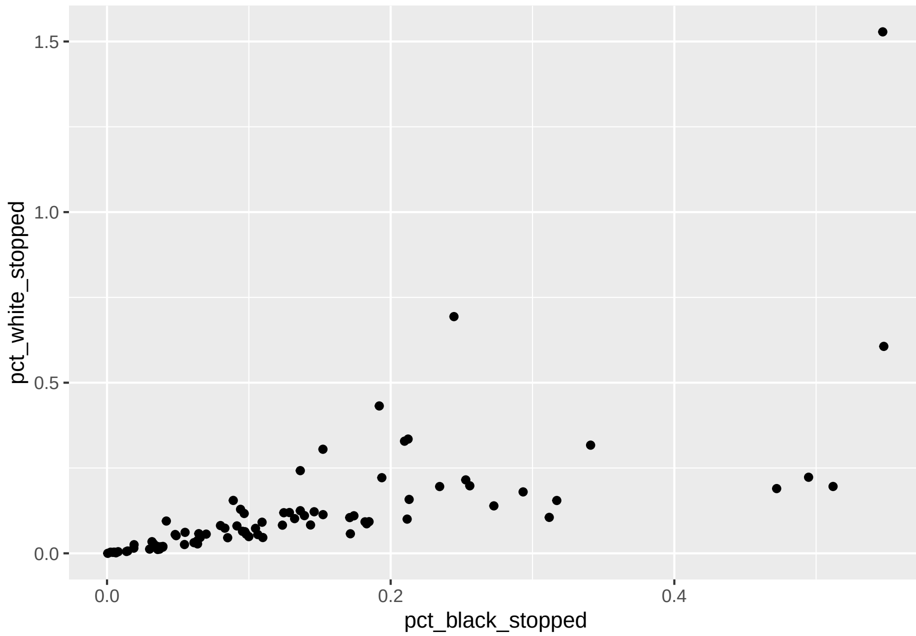
- add "geoms" – a graphical representation of the data in the plot (points, lines, bars). To add a geom to the plot use `+` operator

```
ggplot(data = stops_county, aes(x = pct_black_stopped, y = pct_white_stopped)) +
  geom_point()
```



The `+` in the `ggplot2` package is particularly useful because it allows you to modify existing `ggplot` objects. This means you can easily set up plot "templates" and conveniently explore different types of plots, so the above plot can also be generated with code like this:

```
# Assign plot to a variable
MS_plot <- ggplot(data = stops_county, aes(x = pct_black_stopped, y = pct_white_stopped))

# Draw the plot
MS_plot + geom_point()
```



Notes:

- Any parameters you set in the `ggplot()` function can be seen by any geom layers that you add (i.e., these are universal plot settings). This includes the x and y axis you set up in `aes()`.
- Any parameters you set in a `geom_*()` function are treated independently of (and possibly override) the settings defined globally in the `ggplot()` function.
- Geoms are plotted in the order they are added after each `+`, that means geoms last added will display on top of prior geoms.
- The `+` sign used to add layers **must be placed at the end of each line** containing a layer. If, instead, the `+` sign is added in the line before the other layer, `ggplot2` will not add the new layer and will return an error message.

```
# this is the correct syntax for adding layers
MS_plot +
  geom_point()

# this will not add the new layer and will return an error message
MS_plot
  + geom_point()
```

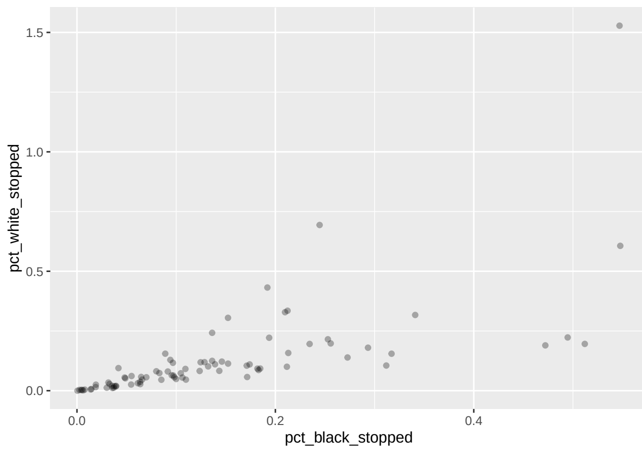
To learn more about `ggplot` after the workshop, you may want to check out this cheatsheet about `ggplot`.

1.3 Building your plots iteratively

Building plots with ggplot can be of great help when you engage in exploratory data analysis. It is typically an iterative process, where you go back and forth between your data and their graphical representation, which helps you in the process of getting to know your data better.

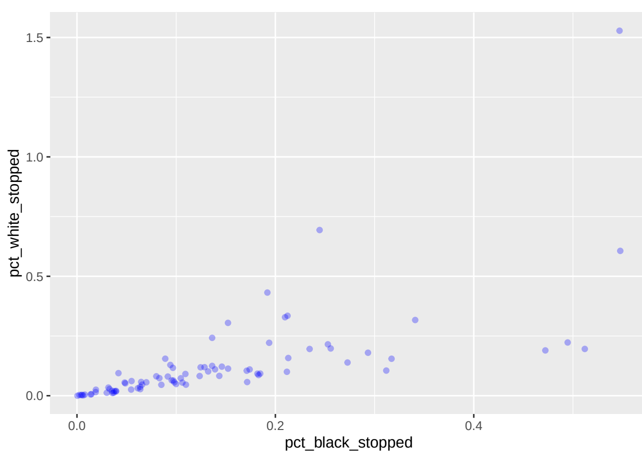
We can start modifying this plot to extract more information from it. For instance, we can add transparency (`alpha`) to avoid overplotting:

```
MS_plot +
  geom_point(alpha = 0.3)
```



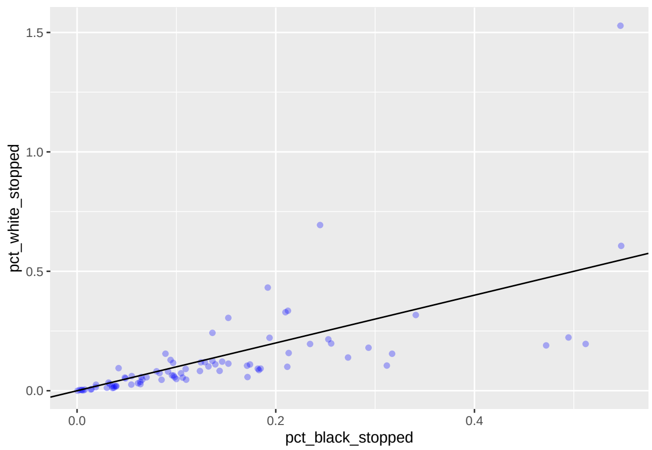
We can also add a color for all the points:

```
MS_plot +
  geom_point(alpha = 0.3, color= "blue")
```



We can add another layer to the plot with `+`:

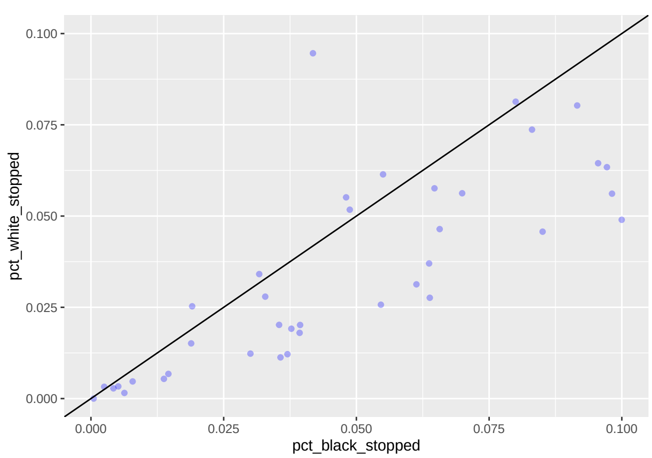
```r
MS_plot +
  geom_point(alpha = 0.3, color= "blue") +
  geom_abline(intercept = 0)
```



If we wanted to "zoom" into the plot, we could filter to a smaller range of values before passing them to ggplot, but we can also tell ggplot to only plot the x and y values for certain ranges. For this we use `scale_x_continuous` and `scale_y_continuous`. You will receive a message from ggplot telling you how many rows it has removed from the plot.

```r
MS_plot +
  geom_point(alpha = 0.3, color= "blue") +
  geom_abline(intercept = 0) +
  scale_x_continuous(limits = c(0, 0.1)) +
  scale_y_continuous(limits = c(0, 0.1))
```

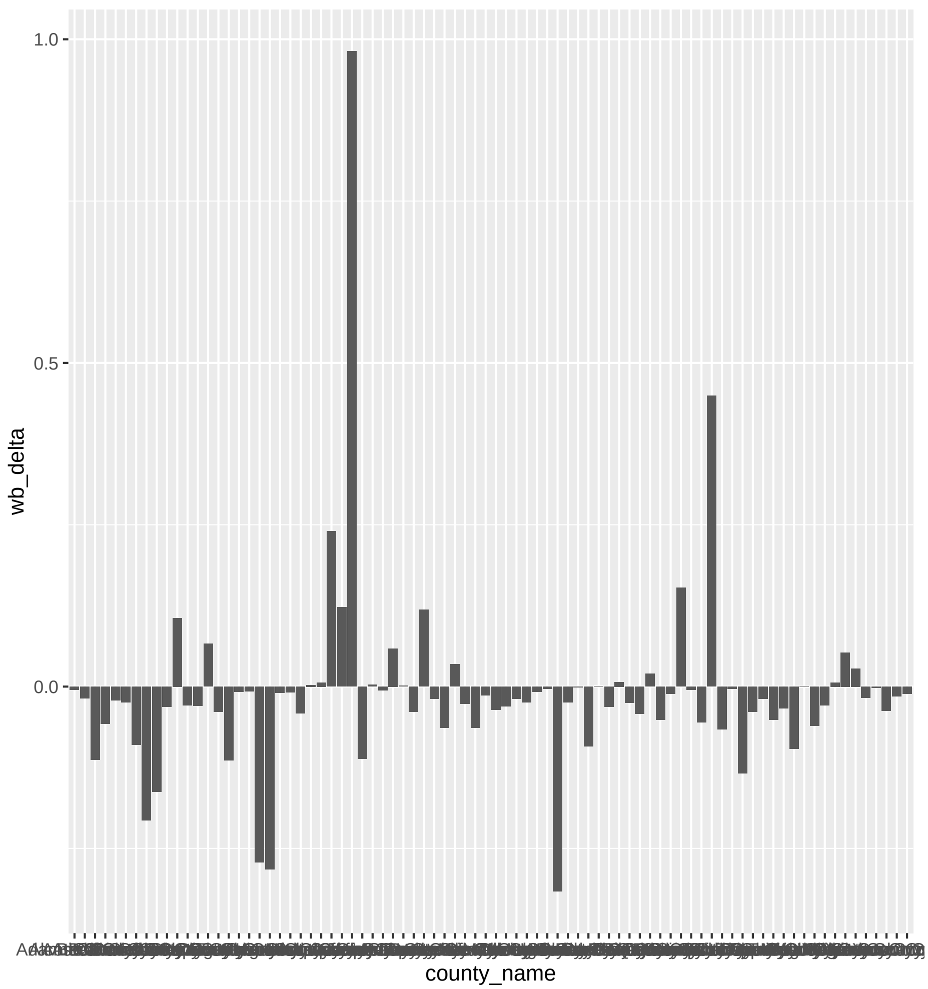
```
#> Warning: Removed 44 rows containing missing values (geom_point).
```



> Challenge
>
> Modify the plot above to display different color for both points and abline, and show a different range of data. How might you change the size of the dots?

Let us now use the `wb_delta` variable (where I have subtracted `pct_black_stopped` from `pct_white_stopped`) to indicate bias for each of the MS counties. We can use a geom called `geom_col`, where heights of the bars represent values in the data, like so:

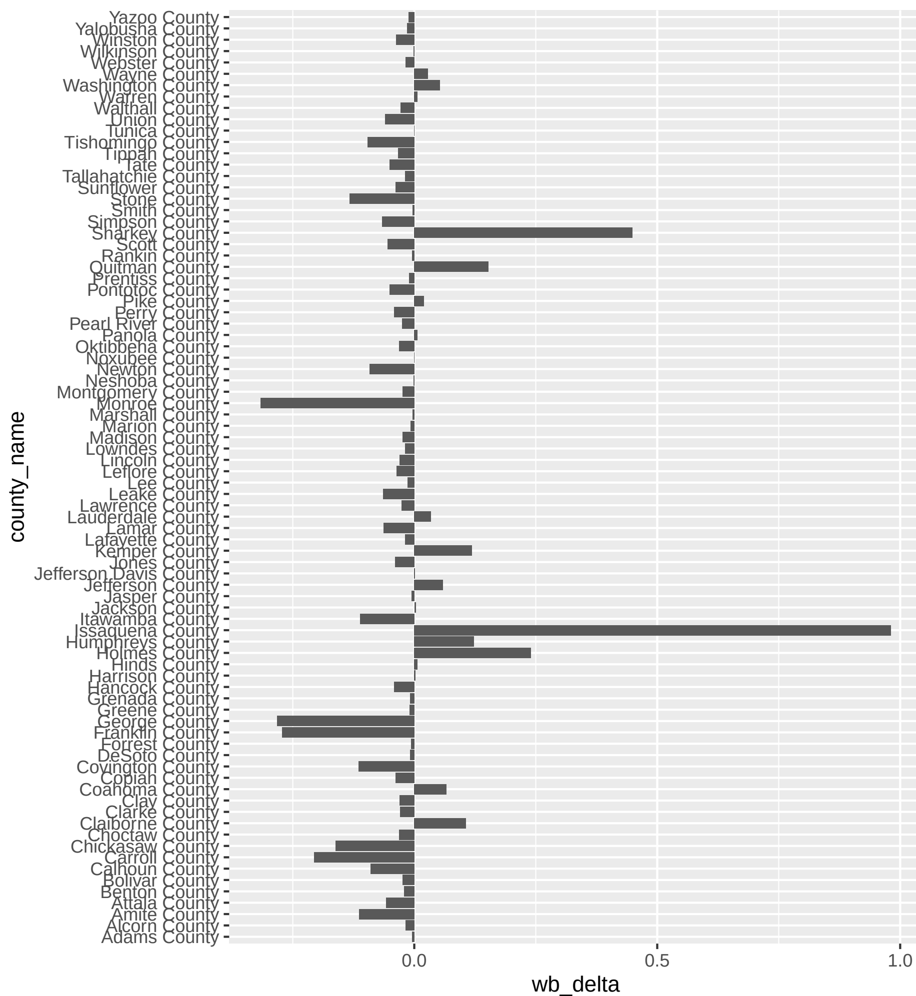
```
ggplot(stops_county, aes(x = county_name, y = wb_delta)) +
  geom_col()
```



This is not very readable, so we will make some changes.

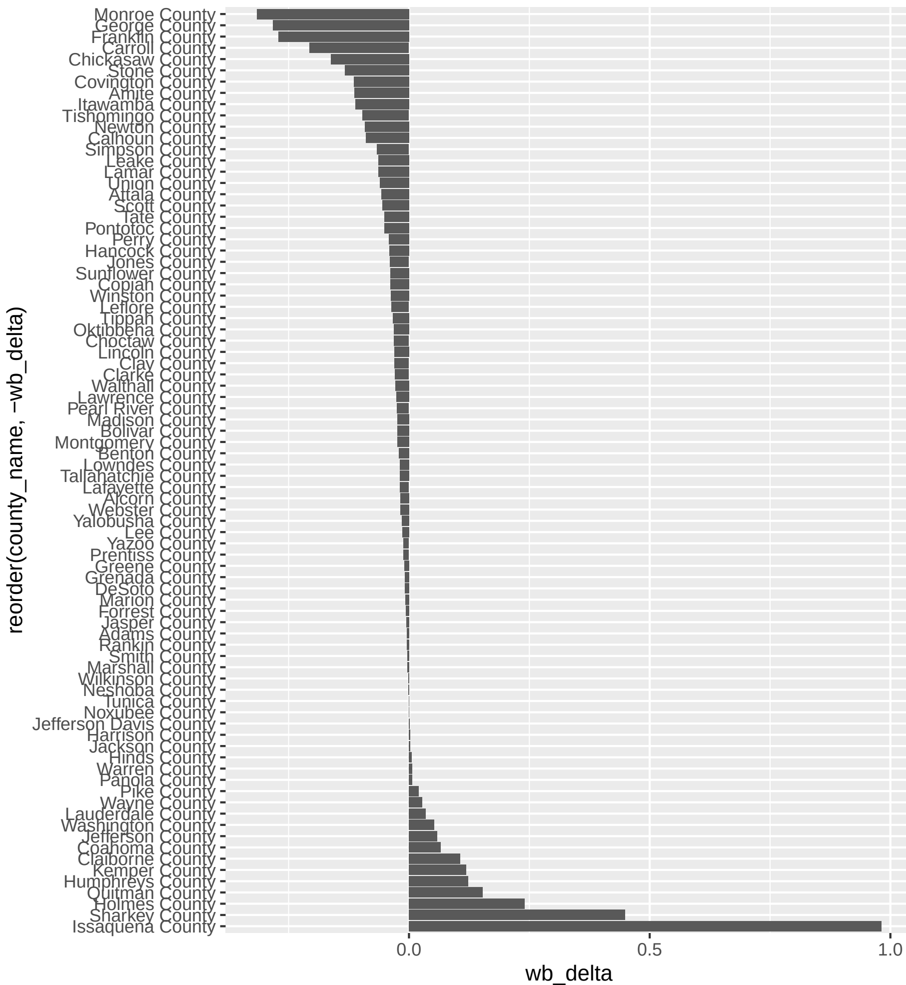
1. We use coord_flip() to switch the x and y axes and be able to read the county names better:

```r
ggplot(stops_county, aes(x = county_name, y = wb_delta)) +
  geom_col() +
  coord_flip()
```



2. We order the counties (x axis) by the delta values plotted on the y axis. From lowest (=black bias) to highest value (=white bias).

```r
ggplot(stops_county, aes(x = reorder(county_name, -wb_delta), y = wb_delta)) +
  geom_col() +
  coord_flip()
```



We can still improve this, but will leave it for now.

1.4 Univariate distributions

For this section we will use the other dataset provided.

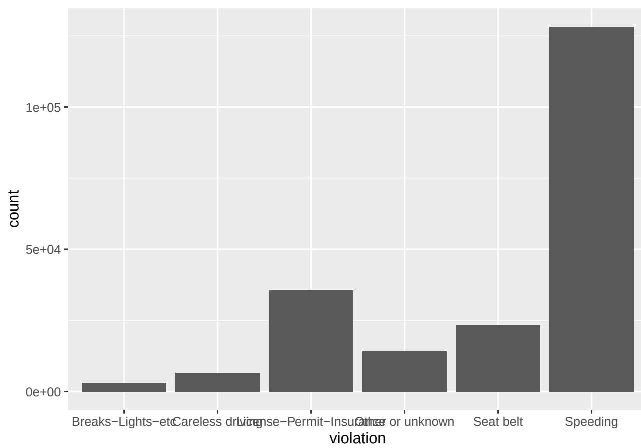
```r
stops <- read.csv('data/MS_stops.csv')
```

It contains one entry for each traffic stop in Mississippi between 2013 and 2016.

```r
str(stops)
```

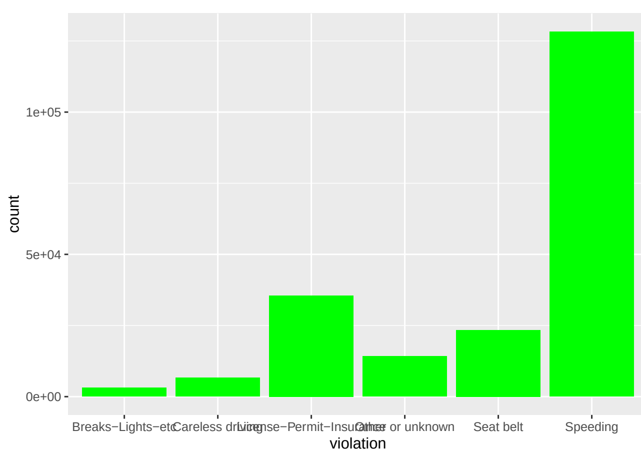
For distributions of discrete variables we use `geom_bar`. It makes the height of the bar proportional to the number of cases in each group and counts the number of cases at each x position. If we wanted to see how many traffic violations we have of each type could say:

```
ggplot(stops, aes(violation)) +
  geom_bar()
```



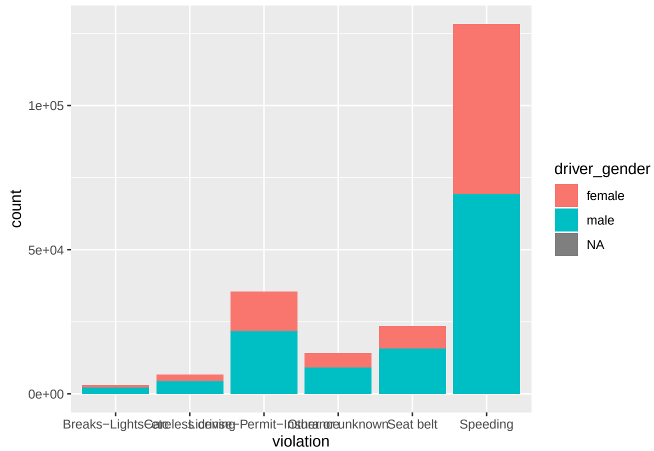
We could color the bars, but instead of `color` we use `fill`. (What happens when you use `color`?)

```
ggplot(stops, aes(violation)) +
  geom_bar(fill = "green")
```



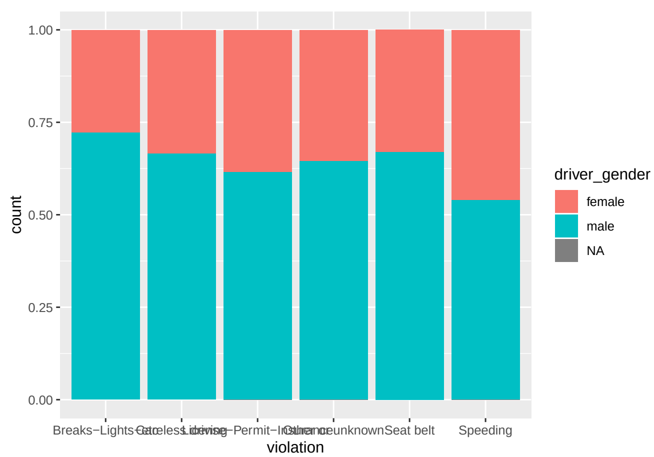
Instead of coloring everything the same we could also color by another category, say gender. For this we have to set the parameter within the `aes()` function, which takes care of mapping the values to different colors:

```
ggplot(stops, aes(violation)) +
  geom_bar(aes(fill = driver_gender))
```



If we wanted to see the proportions within each category we can tell ggplot to stretch the bars between 0 and 1, we can set the position parameter to 'fill':

```
ggplot(stops, aes(violation)) +
  geom_bar(aes(fill = driver_gender), position = "fill")
```



> Challenge
>
> Make a barplot that shows for each race the proportion of stops for male and female drivers. How could you get rid of the NAs?

To map a numerical continuous variable we use `geom_histogram`.

> Challenge
>
> Plot a histogram that shows the distribution of drivers age. Bonus: Add a vertical line for the mean age of the driver. Hint: there is a geom for this!

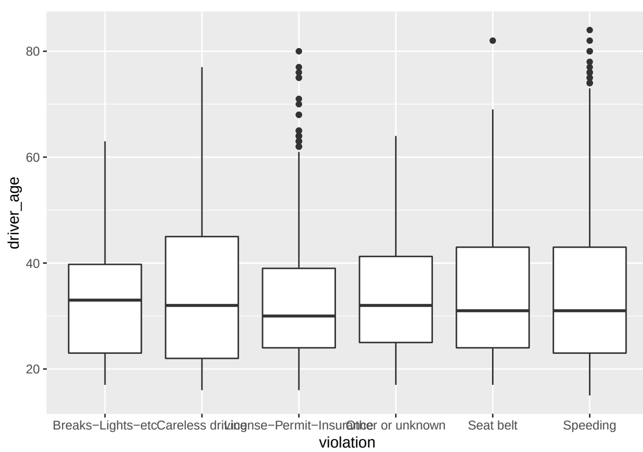
1.5 Boxplot

For this segment let's extract and work with the stops for Chickasaw County only.

```
library(dplyr)
Chickasaw_stops <- filter(stops, county_name == "Chickasaw County")
```

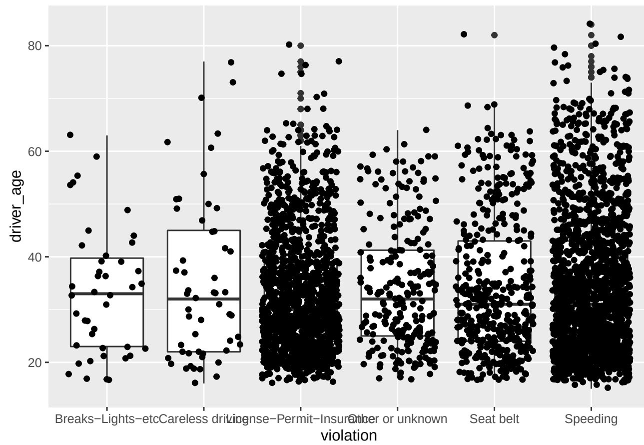
We can use boxplots to visualize the distribution of driver age within each violation:

```
ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
    geom_boxplot()
```



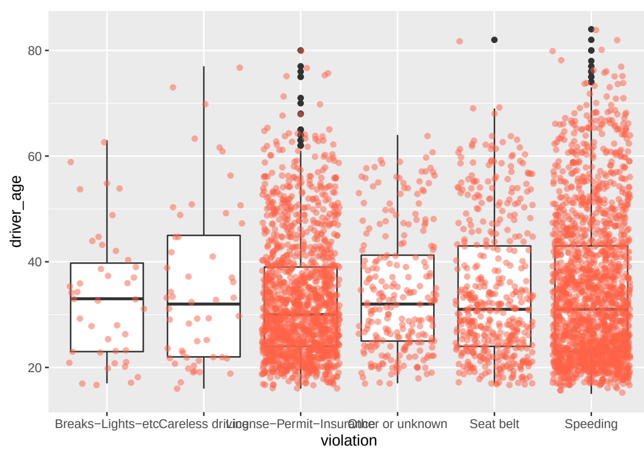
By adding points to boxplot, we can have a better idea of the number of measurements and of their distribution.

```
ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
    geom_boxplot() +
    geom_jitter()
```



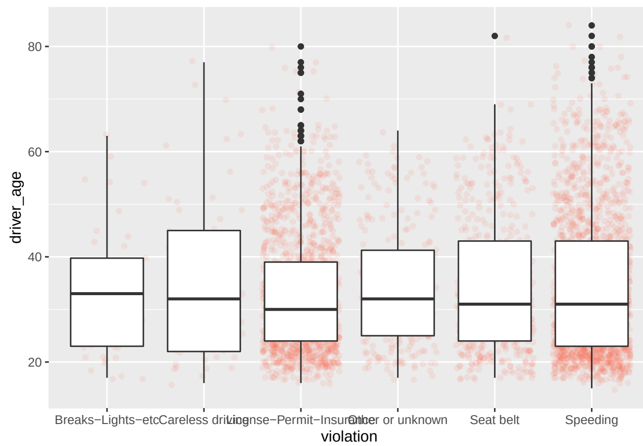
That looks quite messy. Let's clean it up by using the `alpha` parameter to make the dots more transparent and also change their color:

```
ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
    geom_boxplot() +
    geom_jitter(alpha = 0.5, color = "tomato")
```



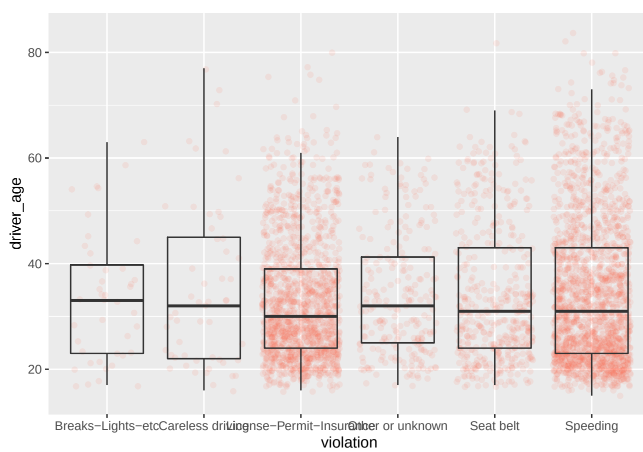
Notice how the boxplot layer is behind the jitter layer. We will change the plotting order to keep the boxplot visible.

```
ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
    geom_jitter(alpha = 0.1, color = "tomato") +
    geom_boxplot()
```



And finally we will change the transparency of the box plot so it does not cover the points:

```
ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
    geom_jitter(alpha = 0.1, color = "tomato") +
    geom_boxplot(alpha = 0)
```



Boxplots are useful summaries, but hide the *shape* of the distribution. For example, if there is a bimodal distribution, it would not be observed with a boxplot. An alternative to the boxplot is the violin plot (sometimes known as a beanplot), where the shape (of the density of points) is drawn.

> Challenge
>
> - Replace the box plot of the last graph with a violin plot.
> - So far, we've looked at the distribution of age within violations Create a new plot to explore the distribution of age for another categorical variable.

1.6 Plotting time series data

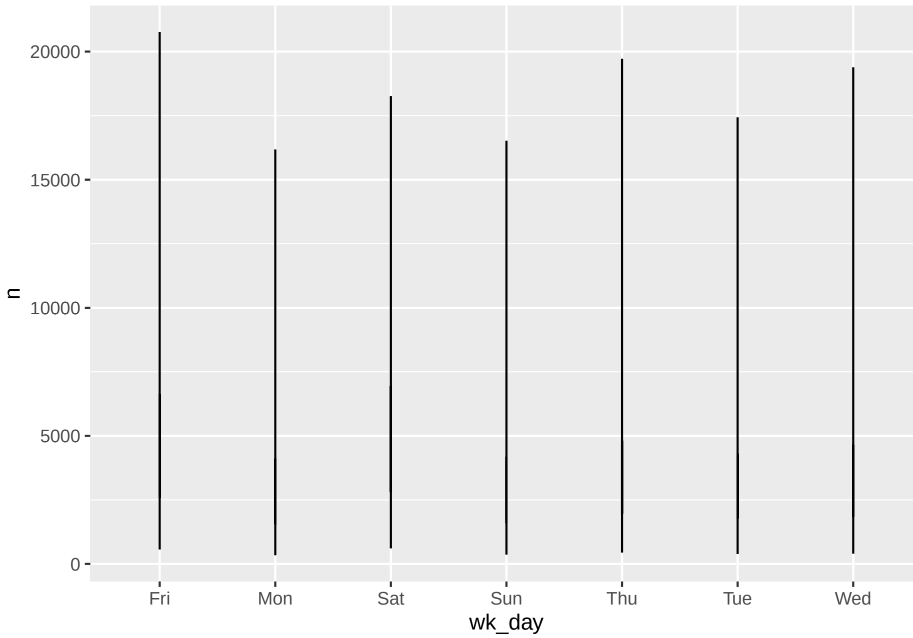
To demonstrate time series data we will count the number of violations for each day of the week. First we will create a table `wd_violations`.

```
wd_violations <- stops %>%
  # group by weekday and violations:
  group_by(wk_day, violation) %>%
  # count occurrences:
  tally()

head(wd_violations)
```

```
#> # A tibble: 6 x 3
#> # Groups:   wk_day [1]
#>   wk_day violation                     n
#>   <fct>  <fct>                     <int>
#> 1 Fri    Breaks-Lights-etc           564
#> 2 Fri    Careless driving           1150
#> 3 Fri    License-Permit-Insurance   6603
#> 4 Fri    Other or unknown           2603
#> 5 Fri    Seat belt                  3948
#> 6 Fri    Speeding                  20767
```

Time series data can be visualized as a line plot (with – you guessed it! – `geom_line()`) mapping the days to the x axis and counts to the y axis:

```
ggplot(wd_violations, aes(x = wk_day, y = n)) +
  geom_line()
```

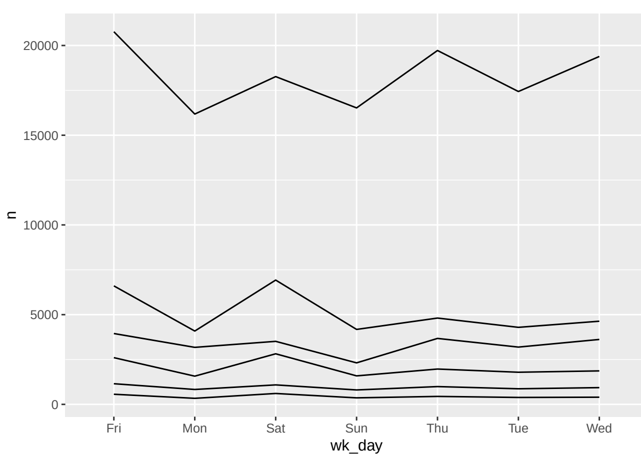


Oops.

Unfortunately, there are a couple of problems with this plot.

Firstly, because we plotted data for all the violations together, ggplot displays the **range of all values** for each day in a vertial line. We need to tell ggplot to draw **a line for each violation**. We do this by modifying the aesthetic function to include an instruction to to group by violation: `group = violation`.

```r
ggplot(wd_violations, aes(x = wk_day, y = n, group = violation)) +
  geom_line()
```



Secondly, the weekdays are out of order. When we read the table with `read.csv` R determined that `wk_day` was a factor and assigned levels in alphabetical order.

```
class(stops$wk_day)
```

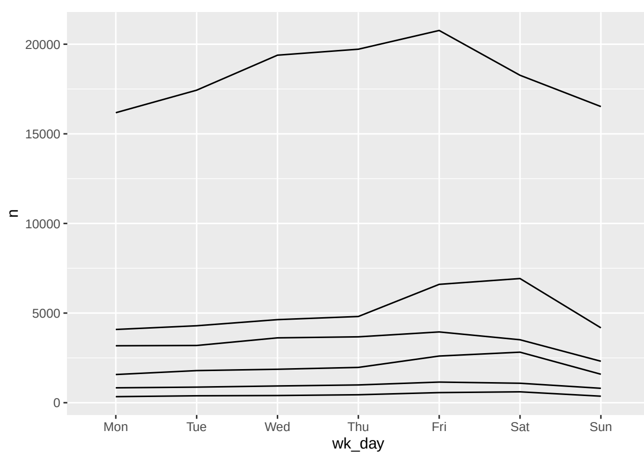
```
#> [1] "factor"
```

```
levels(stops$wk_day)
```

```
#> [1] "Fri" "Mon" "Sat" "Sun" "Thu" "Tue" "Wed"
```

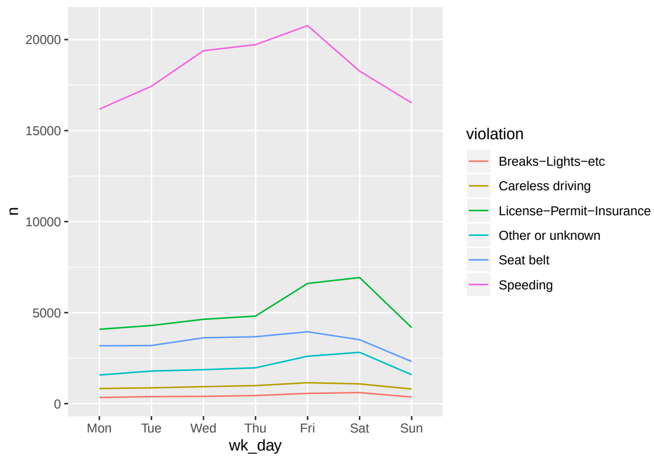
We can reorder the levels, recreate the summary table and plot again.

```
stops$wk_day <- factor(stops$wk_day,
                       levels=c("Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun"))

wd_violations <- stops %>%
  group_by(wk_day, violation) %>%
  tally()

ggplot(wd_violations, aes(x = wk_day, y = n, group = violation)) +
  geom_line()
```



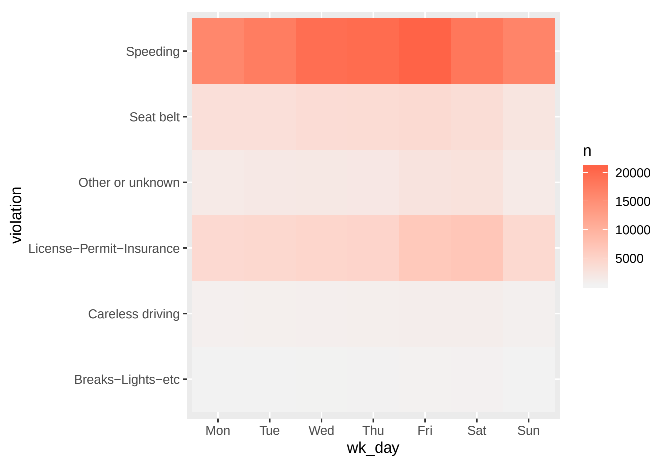
We will be able to distinguish violations in the plot if we add colors. (If the variable is numeric `color` groups automatically.)

```
ggplot(wd_violations, aes(x = wk_day, y = n, group = violation, color = violation)) +
  geom_line()
```



If you have a lot of data (like for example a term document matrix) you may want to plot your data as a heatmap. There is no specific heatmap plotting function in ggplot2, but combining `geom_tile` with a smooth gradient fill (`scale_fill_gradient`) does the job very well. For our weekday example it would look like this:

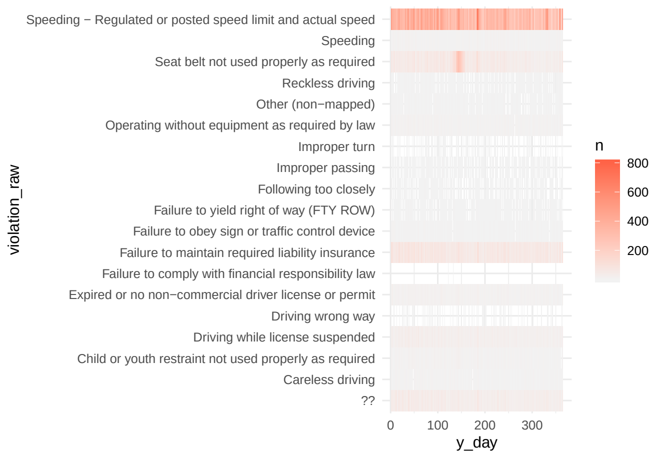
```
ggplot(wd_violations, aes(x = wk_day, y = violation)) +
     geom_tile(aes(fill=n)) +
     scale_fill_gradient(low="grey95", high = "tomato")
```



The code below show a more extensive example that maps raw violations against day of the year.

```
stops %>%
  group_by(y_day, violation_raw) %>%
  tally() %>%
  ggplot(aes(y_day, violation_raw)) +
```

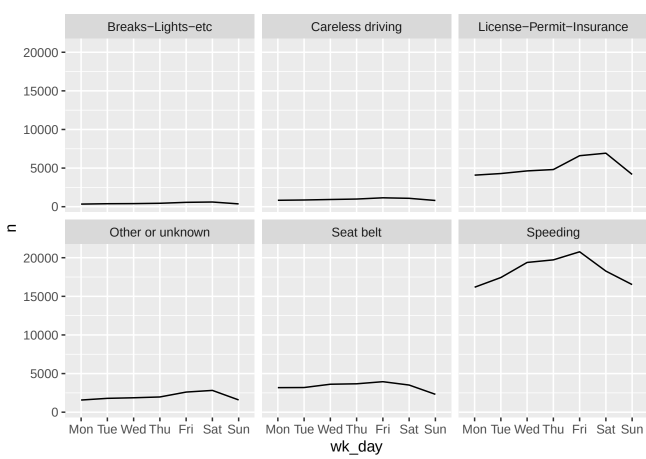
```r
    geom_tile(aes(fill=n)) +
    scale_fill_gradient(low="grey95", high = "tomato") +
    theme_minimal() # (more about this below)
```



1.7 Faceting

`ggplot` implements a special technique called *faceting* that allows to split one plot into multiple plots based on a factor included in the dataset. We will use it to make a time series plot for each violation:

```r
ggplot(wd_violations, aes(x = wk_day, y = n, group = violation)) +
    geom_line() +
    facet_wrap(~ violation)
```



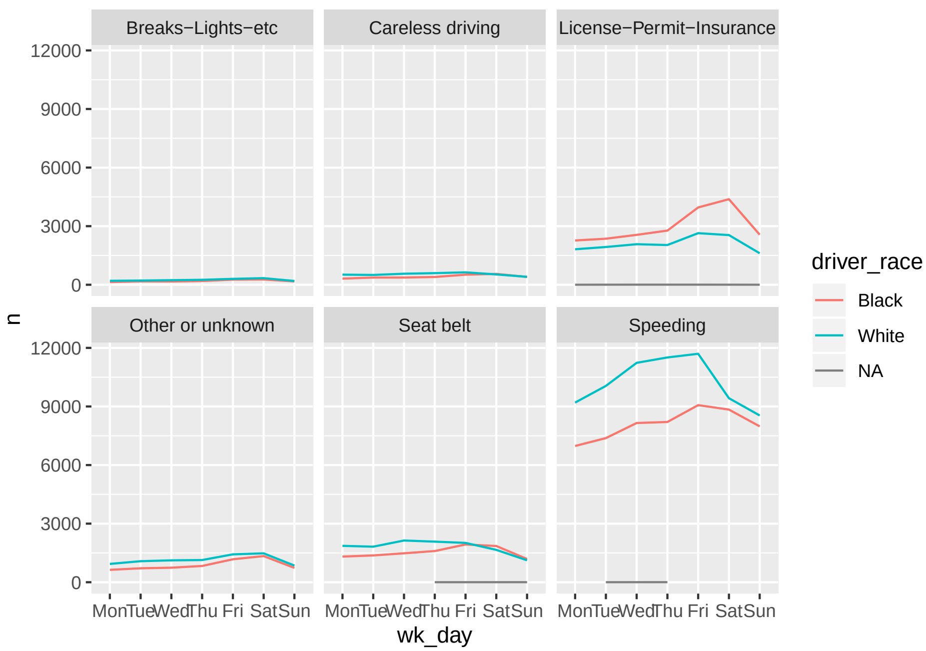
Now we would like to split the line in each plot by the race of the driver. To do that we need to create a different data frame with the counts grouped not only by `wk_day` and `violation`, but also `driver_race`.

```
wd_viol_race <- stops %>%
  group_by(wk_day, violation, driver_race) %>%
  tally()
```

```
#> Warning: Factor `driver_race` contains implicit NA, consider using
#> `forcats::fct_explicit_na`
```

We then make the faceted plot by splitting further by race using `color` and `group` (within a single plot):

```
ggplot(wd_viol_race, aes(x = wk_day, y = n, color = driver_race, group = driver_race))
  geom_line() +
  facet_wrap(~ violation)
```



Note that there is an alternative, the `facet_grid` geometry, which allows you to explicitly specify how you want your plots to be arranged via formula notation (`rows ~ columns`; a `.` can be used as a placeholder that indicates only one row or column).

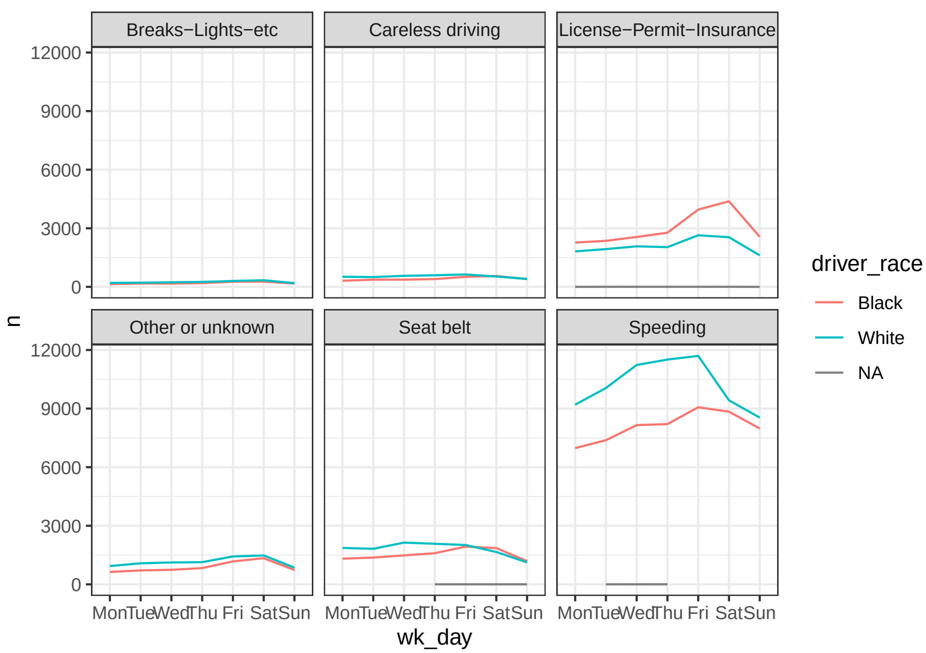
> Challenge
>
> Use what you just learned to create a plot that depicts the change of the average age of drivers through the week for each driver race. First create a data frame `wd_viol_age`, grouped by weekday, race, and violation and calculate the mean age per grouop. Hint: Instead

of tally use `summarize(avg_age = mean(driver_age))` to calculate the mean driver age. Now split your plot so we can see one plot for each violation type. How would you go about visualizing both lines and points on the plot?

1.8 ggplot2 themes

ggplot2 comes with several other themes which can be useful to quickly change the look of your visualization, for example `theme_bw()` changes the plot background to white:

```
ggplot(wd_viol_race, aes(x = wk_day, y = n, color = driver_race, group = driver_race)) +
  geom_line() +
  facet_wrap(~ violation) +
  theme_bw()
```



The complete list of themes is available at http://docs.ggplot2.org/current/ggtheme.html. `theme_minimal()` and `theme_light()` are popular, and `theme_void()` can be useful as a starting point to create a new hand-crafted theme.

The ggthemes package provides a wide variety of options (including an Excel 2003 theme). The **ggplot2** extensions website provides a list of packages that extend the capabilities of **ggplot2**, including additional themes.

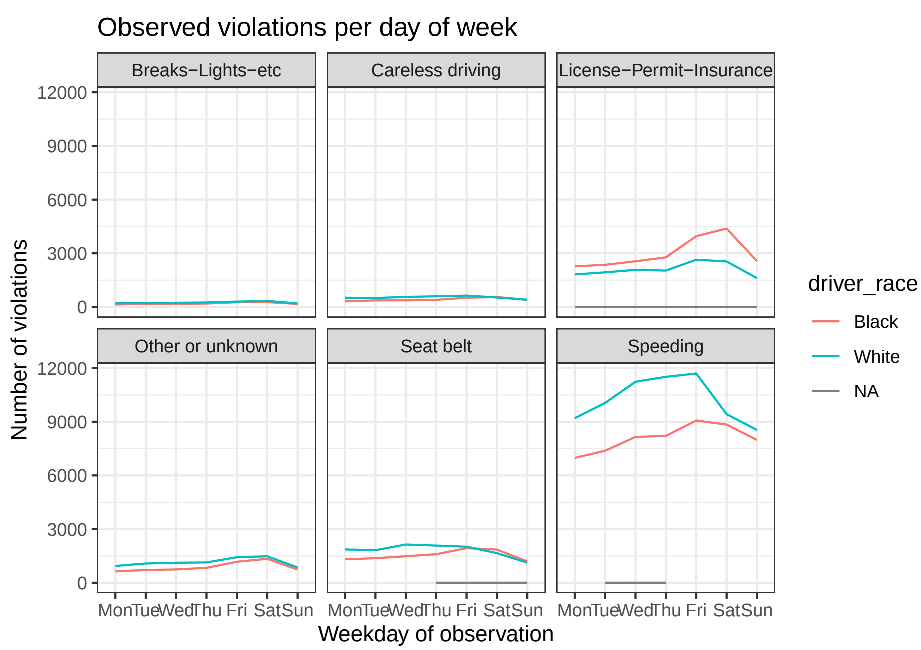
1.9 Customization

There are endless possibilities to customize details of your plot, particularly when you are ready for publication or presentation. Let's look into just a few examples. Before we do that we will assign our plot above to a variable.

```
stops_facet_plot <- ggplot(wd_viol_race, aes(x = wk_day, y = n, color = driver_race, g
  geom_line() +
  facet_wrap(~ violation)
```

Now, let's change names of axes to something more informative than 'wk_day' and 'n' and add a title to the figure:

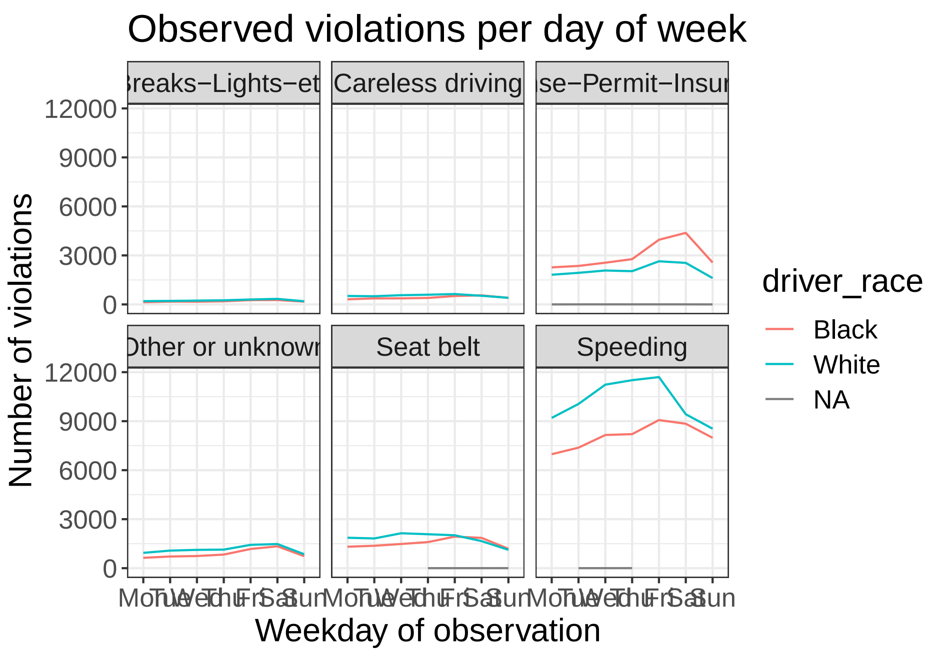
```
stops_facet_plot +
  labs(title = 'Observed violations per day of week',
         x = 'Weekday of observation',
         y = 'Number of violations') +
  theme_bw()
```



The axes have more informative names, but their readability can be improved by increasing the font size:

```
stops_facet_plot +
  labs(title = 'Observed violations per day of week',
         x = 'Weekday of observation',
         y = 'Number of violations') +
  theme_bw() +
```

```
  theme(text = element_text(size=16))
```

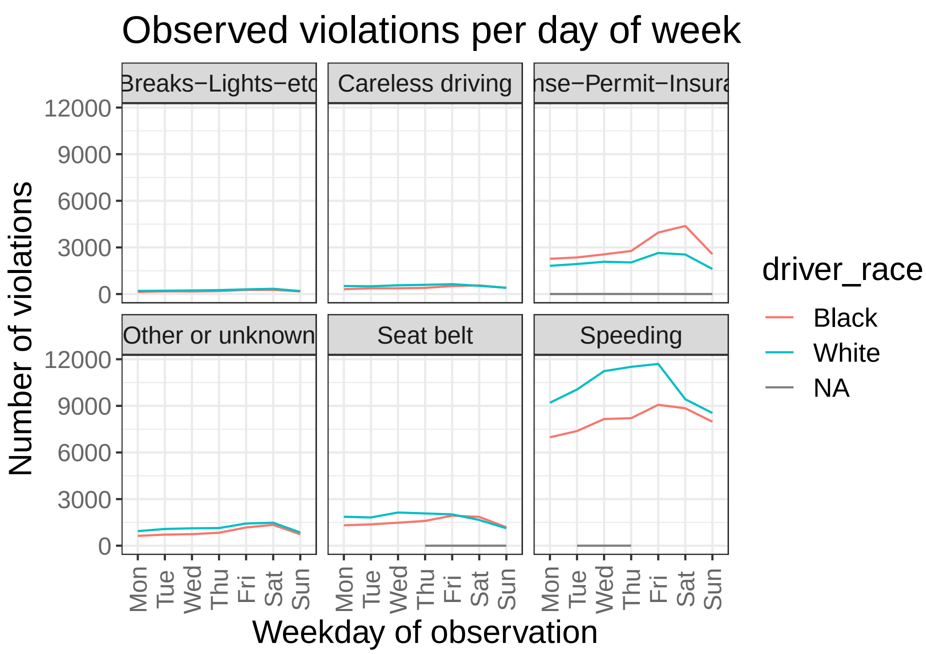


That bumps up all the text sizes, so let's manipulate them individually.

For the x-axis we will make the text smaller and adjust the labels vertically and horizontally so they don't overlap. You can use a 90 degree angle, or experiment to find the appropriate angle for diagonally oriented labels.

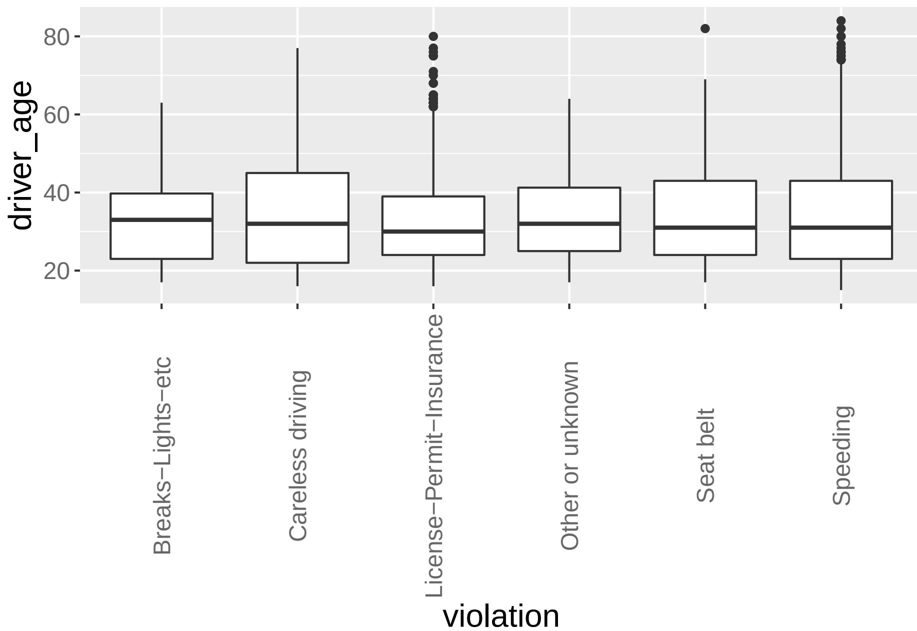
For the titles of the subplots we also reduce the size back to 12 pixels.

```
stops_facet_plot +
  labs(title = 'Observed violations per day of week',
         x = 'Weekday of observation',
         y = 'Number of violations') +
  theme_bw() +
  theme(axis.text.x = element_text(colour="grey40", size=12, angle=90, hjust=.5, vjust=.5),
        axis.text.y = element_text(colour="grey40", size=12),
        strip.text = element_text(size=12),
        text = element_text(size=16))
```



If you like the changes you created better than the default theme, you can save them as an object and apply it to other plots you may create:

```
my_grey_theme <- theme(axis.text.x = element_text(colour="grey40", size=12, angle=90,
                       axis.text.y = element_text(colour="grey40", size=12), text=element_t

ggplot(data = Chickasaw_stops, aes(x = violation, y = driver_age)) +
  geom_boxplot() +
  my_grey_theme
```



Note that it is also possible to change the fonts of your plots. If you are on Windows, you may have to install the **extrafont** package, and follow the instructions included in the README for this package.

After creating your plot, you can save it out to a file in your prefered format. You can change the dimension (and resolution) of your plot by adjusting the appropriate arguments (`width`, `height` and `dpi`):

```
my_plot <- stops_facet_plot +
  labs(title = 'Observed violations per day of week',
         x = 'Weekday of observation',
         y = 'Number of violations') +
  theme_bw() +
  theme(axis.text.x = element_text(colour="grey40", size=12, angle=90, hjust=.5, vjust=.5),
        axis.text.y = element_text(colour="grey40", size=12),
        strip.text = element_text(size=14),
        text = element_text(size=16))

ggsave("name_of_file.png", my_plot, width=15, height=10)
```

Note: The parameters `width` and `height` also determine the font size in the saved plot.

> Challenge
>
> Improve one of the plots you generated or create a beautiful graph of your own and save it to your desktop. Use the RStudio `ggplot2` cheat sheet for inspiration.

Here are some ideas: * See if you can change the thickness of the lines. * Can you find a way to change the name of the legend? What about its labels? * Try using a different color palette (see http://www.cookbook-r.com/Graphs/Colors_(ggplot2)/).

Chapter 2

Interactive graphs

Learning Objectives

- Be aware of R interactive graphing capabilities and options
- Know some graphing packages that are based on htmlwidgets
- Create a simple interactive plot
- Understand the basic structure of a `shiny` app

2.1 `htmlwidgets`

JavaScript is probably the most widely used scripting languages to create interactive webpages (html). The `htmlwidgets` package provides a framework to bind R commands to various existing, interactive JavaScript libraries, including those that greate data graphs. The interactive components ("widgets") created using the framework can be:

- used at the R console for data analysis just like conventional R plots (via RStudio Viewer).
- seamlessly embedded within R Markdown documents and Shiny web applications.
- saved as standalone web pages for ad-hoc sharing via email, Dropbox, etc.

While you can certainly develop yor own widget, there are a number of widgets already available, that you can install and that make creating interacive visualizations much easier. In fact, the packages used for the examples in section **??** are all based on htmlwidgets.

For a complete list check out the htmlwidgets gallery.

The `htmlwidgets` framework ensures that the graphics are rendered locally. By default they either run in your web browser or in the R Studio viewer. If you use R Markdown, the html pages rendered contain the full JavaScript code, so you can also also deploy them to a standard webserver (like github pages).

2.2 plotly

We will start with a widget called `plotly`. `plotly` binds R commands to the JavaScript plotly.js graphing library. The R package allows you to easily translate `ggplot2` graphics to an interactive web-based version.

First we install and load the package.

```
install.packages(plotly) # if you haven't installed the package
library(plotly)
```

Let us go back to our initial scatterplot.

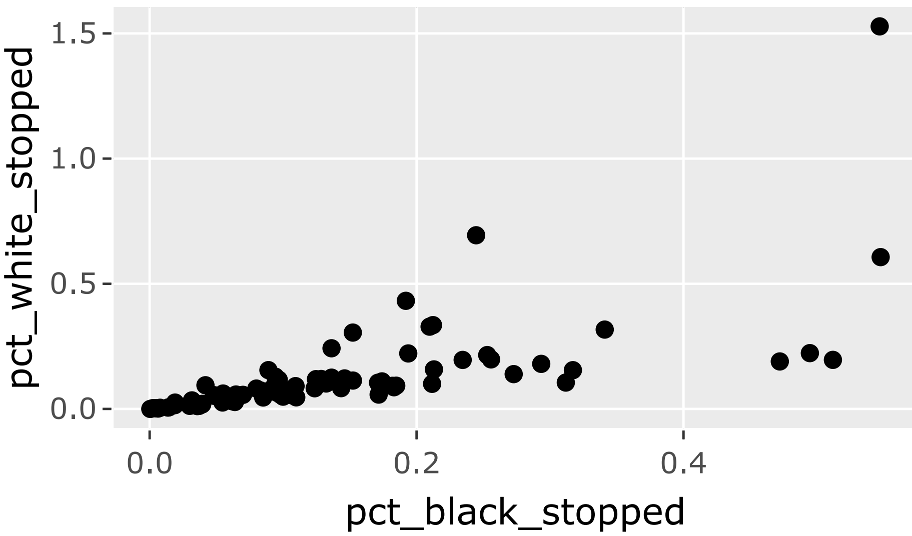
```
ggplot(data = stops_county, aes(x = pct_black_stopped, y = pct_white_stopped)) +
  geom_point()
```

To turn this into an interactive graph with `plotly`, we create a ggplot object by assigning it to a variable:

```
p <- ggplot(data = stops_county, aes(x = pct_black_stopped, y = pct_white_stopped)) +
  geom_point()
```

We can then pass that object to the `ggplotly` function (the dev. version of ggplot2 has a `ggplotly()` function, but this works):

```
ggplotly(p)
```



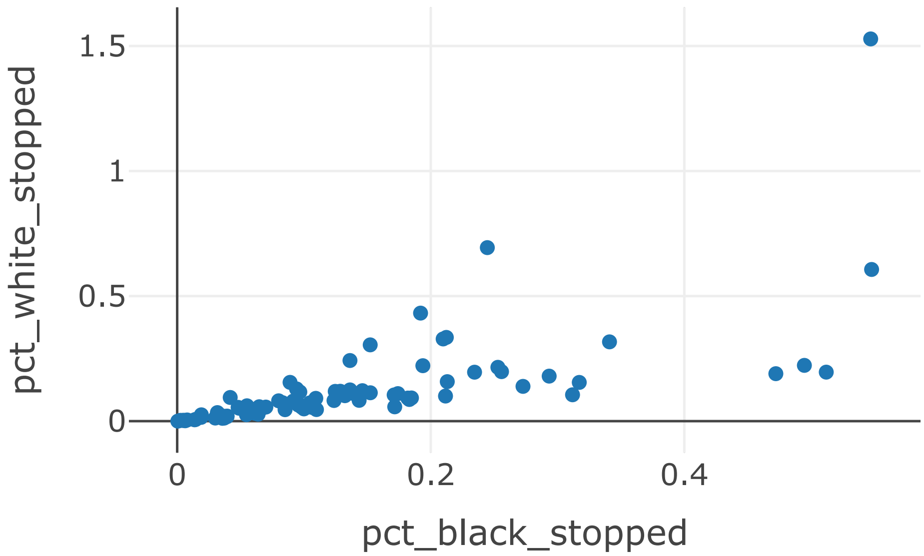
This is really all that is to it.

ALternatively, it is possible to forgo ggplot and using the `plot_ly` function to create your graph from scratch. For our example that would be:

```
plot_ly(stops_county, x = ~pct_black_stopped, y = ~pct_white_stopped)
```

```
#> No trace type specified:
#>   Based on info supplied, a 'scatter' trace seems appropriate.
#>   Read more about this trace type -> https://plot.ly/r/reference/#scatter
```

```
#> No scatter mode specifed:
#>   Setting the mode to markers
#>   Read more about this attribute -> https://plot.ly/r/reference/#scatter-mode
```



> Challenge
>
> Go back to the box plot we created earlier using the Chickasaw_stops: `ggplot(Chickasaw_stops, aes(x = violation, y = driver_age)) + geom_boxplot()` Create an interactive version of it, using both approaches, `ggplotly` and `plot_ly`.

The full documentation of all the arguments `plot_ly` can take is here: https://plot.ly/r/reference/

2.3 shiny

`htmlwidgets` are very powerful, but if you require more customization and flexibility, particularly with regard to user input, you may want to look into `shiny`. Because it executes acutal R code, which web browsers cannot execute, `shiny` requires its own server.

There are verious ways in which a shiny application can be run. We will use an example run it from the

R Commandline.

Rmarkdown: To call Shiny code from an R Markdown document, add runtime: shiny to the header shiny server: either run your own, or host it at ShinyApps.io

Building shiny apps deserves its own workshop, so here - to give you a teaser - I have provided only a very simple example. We will re-use our barchart from earlier where we plotted the proportional amount of traffic violations for each gender:

```
ggplot(stops, aes(violation)) +
        geom_bar(aes(fill = driver_gender), position = "fill")
```

We want to create a plot where we can choose which county we'd like to display this bar chart for.

I have prepared the code for this, which you can run like this:

1. Install and load the `shiny` package (`install.packages(shiny)`).
2. In your `R-data-viz` folder create a new folder called `shinyapps`.
3. Download `app.R` into that folder:

```
download.file("https://raw.githubusercontent.com/cengel/R-data-viz/master/shinyapp/app.R", "shiny
```

4. In your R console:

```
library(shiny)
runApp("./shinyapp/")
```

Let us now go over the code in the `app.R` script.

We define two functions and call them `ui` (for user interface, which we present to the user and receive input) and `server` (where the input is used and the magic happens).

This is what happens in the `ui` function:

Using some of the layout functions shiny comes with we define a panel with a sidebar, where the input is received the main panel, where the plot is going to be displahyed. We also assign the plot a name (`violationsPlot`) that we will reuse later. Lastly we add some text to help users understand what this graph about.

A very important function is `selectInput`, where we define the choices that the user has (the county names in the table) and also define the name of the variable that will hold the input from the user: `county`.

The `server` is where input and output are processed. In this example we really only render the plot. You see that the name for our plot (`violationsPlot`) appears attached to the `output` variable. You can also detect our ggplot code from earlier, with the only difference that we use the input county value `input$county` to filter the data frame before we send them to ggplot to plot.

The very last line of the script binds the two together as a shiny app.

```
library(shiny)
library(ggplot2)
library(dplyr)

# uncomment this if you need to reload the stops table
```

```
# stops <- read.csv('https://github.com/cengel/R-data-viz/raw/master/data/MS_stops.csv

## UI
# Use a fluid Bootstrap layout
ui <- fluidPage(

  # Give the page a title
  titlePanel("Missisippi Violations by County"),

  # Generate a row with a sidebar
  sidebarLayout(

    # Define the sidebar with one input
    sidebarPanel(
      selectInput("county", "County:",
                  choices=unique(stops$county_name)),
      hr(),
      helpText("Data from Stanford Openpolicing Project.")
    ),

    # Create a spot for the barplot
    mainPanel(
      plotOutput("violationsPlot")
    )

  )
)

## Server

# Define a server for the Shiny app
server <- function(input, output) {

  # Fill in the spot we created for a plot
  output$violationsPlot <- renderPlot({

    stops %>%
      filter(county_name == input$county) %>%
      ggplot(aes(violation)) +
        geom_bar(aes(fill = driver_gender), position = "fill")
  })
}

shinyApp(ui, server)
```

There are numerous examples of shiny apps of different complexity, for example here: http://shiny.rstudio.com/gallery/

Chapter 3

Domain specific graphs

Learning Objectives

- Be aware of specialized graph packages and know where to look for them
- Understand the basic structure of iheatmapr, tmap, and visNetwork examples
- Modify parameters of provided graph examples

`ggplot` can get you a long way, but if you need to do a particular, more complex graph it is worth checking if there might be an R package for that. Typically it would do one type of visualization and do that really well. Below are a few examples.

3.1 Heatmaps (e.g. `iheatmapr`)

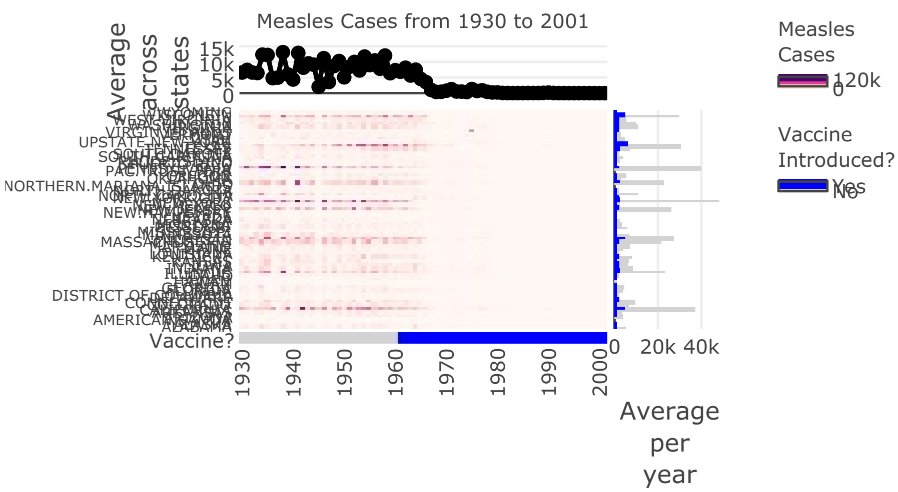
The **`iheatmapr`** package specializes in creating interactive heatmaps, that range from standard heatmaps to relatively complex ones, that can be built up iteratively. It uses the plotly for interactivity.

The example below is taken from https://ropensci.github.io/iheatmapr/index.html.

The data mapped are from a matrix that contains the yearly number of measles cases from 1930-2001 for US states.

```
library(iheatmapr)
data(measles, package = "iheatmapr")

main_heatmap(measles, name = "Measles<br>Cases", x_categorical = FALSE,
```

```
           layout = list(font = list(size = 8))) %>%
  add_col_groups(ifelse(1930:2001 < 1961,"No","Yes"),
                side = "bottom", name = "Vaccine<br>Introduced?",
                title = "Vaccine?",
                colors = c("lightgray","blue")) %>%
  add_col_labels(ticktext = seq(1930,2000,10),font = list(size = 8)) %>%
  add_row_labels(size = 0.3,font = list(size = 6)) %>%
  add_col_summary(layout = list(title = "Average<br>across<br>states"),
                yname = "summary")  %>%
  add_col_title("Measles Cases from 1930 to 2001", side= "top") %>%
  add_row_summary(groups = TRUE,
                type = "bar",
                layout = list(title = "Average<br>per<br>year",
                              font = list(size = 8)))
```



Note that **iheatmapr** has a Bioconductor dependency, so if you receive a message `package 'S4Vectors' is not available` do this:

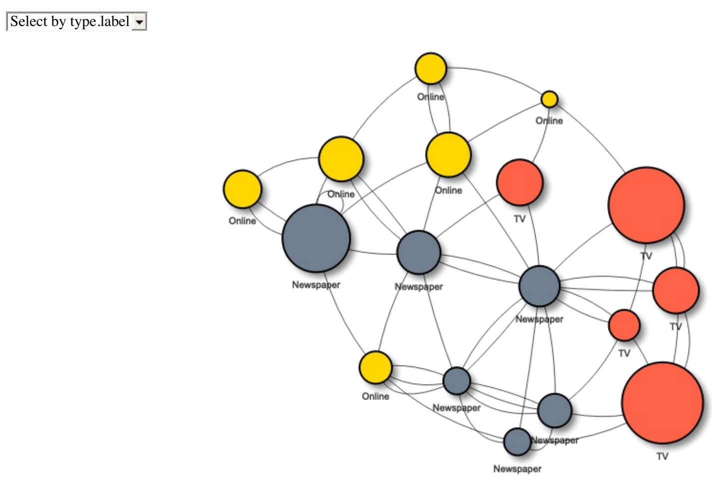
```
if (!requireNamespace("BiocManager", quietly = TRUE))
    install.packages("BiocManager")

BiocManager::install("S4Vectors")
```

(More info here.)

3.2 Networks (e.g. visNetwork)

visNetwork is an R interface to the 'vis.js' JavaScript library, a package to visualize networks in an interactive fashion. It takes a table of nodes (vertices) and a table of edges (links) as inputs. The example below is taken from Katherine Ognyanova's tutorial and represents a network of hyperlinks and mentions among various news sources.

```
library('visNetwork')
nodes <- read.csv("https://github.com/cengel/R-data-viz/raw/master/demo-data/network/Dataset1-Med
links <- read.csv("https://github.com/cengel/R-data-viz/raw/master/demo-data/network/Dataset1-Med
nodes$shape <- "dot"
nodes$shadow <- TRUE # Nodes will drop shadow
nodes$title <- nodes$media # Text on click
nodes$label <- nodes$type.label # Node label
nodes$size <- nodes$audience.size # Node size
nodes$borderWidth <- 2 # Node border width

nodes$color.background <- c("slategrey", "tomato", "gold")[nodes$media.type]
nodes$color.border <- "black"
nodes$color.highlight.background <- "orange"
nodes$color.highlight.border <- "darkred"

visNetwork(nodes, links) %>%
  visOptions(highlightNearest = TRUE,
             selectedBy = "type.label")
```



3.3 Maps (e.g. `tmap`)

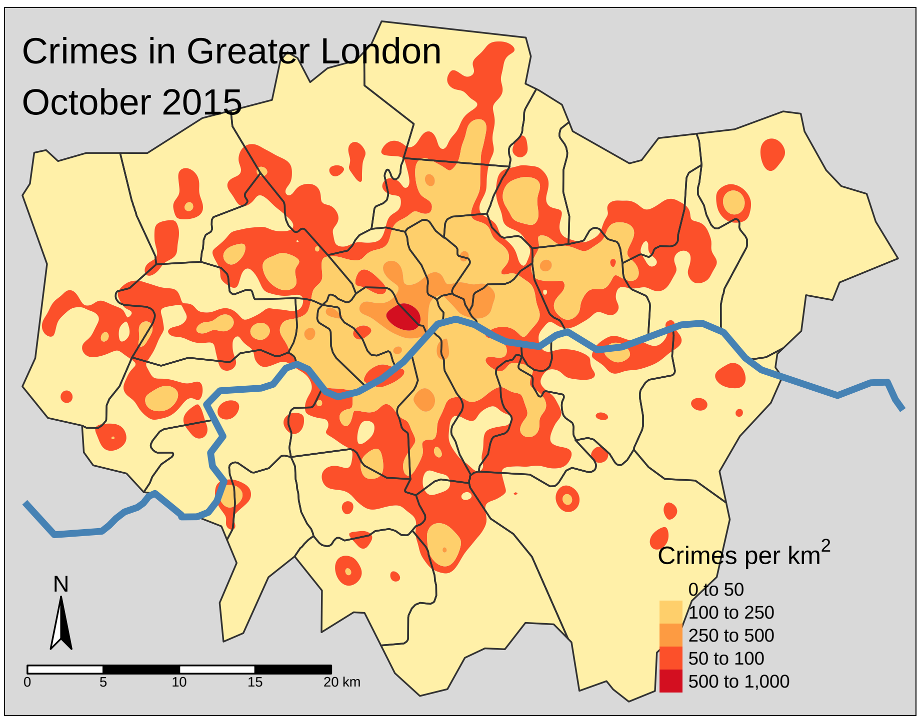
The **`tmap`** package is designed to visualize spatial data distributions in geographic space, so called "thematic maps". The example is adapted from mtennekes and shows a map of crimes registered during October 2015. We combine several layers, one with the outline of London, one with the river Thames, and one with the actual crime densities.

For this demo we first need to download the data. If you have your working directory set to `R-data-viz` and it contains a folder called `data`, this will download and extract the map data into a subfolder of your `data` folder, called `map`:

```
download.file("https://github.com/cengel/R-data-viz/raw/master/demo-data/map.zip",
              "data/map.zip")
unzip("data/map.zip", exdir="data")
```

Now, here is the map.

```
#> Warning in tm_style_gray(title = "Crimes in Greater London\nOctober
#> 2015"): tm_style_gray is deprecated as of tmap version 2.0. Please use
#> tm_style("gray", ...) instead
```




```
library(tmap)
library(tmaptools)
suppressPackageStartupMessages(library(sf))

london <- st_read("data/map", "London", quiet = TRUE)
crime_densities <- st_read("data/map", "Crimes", quiet = TRUE)
thames <- st_read("data/map", "Thames", quiet = TRUE)

tm_shape(crime_densities) +
```

```
  tm_fill(col = "level", palette = "YlOrRd",
    title = expression("Crimes per " * km^2)) +
tm_shape(london) + tm_borders() +
tm_shape(thames) + tm_lines(col = "steelblue", lwd = 4) +
tm_compass(position = c("left", "bottom")) +
tm_scale_bar(position = c("left", "bottom")) +
tm_style_gray(title = "Crimes in Greater London\nOctober 2015")
```

Good starting places to look for additional examples and packages are the R Graph Gallery: https://www.r-graph-gallery.com/all-graphs/ and the CRAN Task View: https://CRAN.R-project.org/view=Graphics.