

STT 3850 : Week 2

Spring 2024

Appalachian State University

Section 1

Outline for the week

By the end of the week:

- Control Structures in R
- Quarto
- Data Visualization

Section 2

Control Structures in R

Control Structures in R

R executes statements/commands sequentially. If you want to control the flow of statement execution, you need to use **control structures**.

- The basic component of most control structures is the **conditional statement**.
- A conditional statement is an R statement that is evaluated as either TRUE or FALSE. They use relational operators such as
 - == for testing equality of R objects,
 - != for testing if two R objects are not equal, <, >, <= and >=.

As an example, look at the following R commands:

Conditional Statement

```
x <- c(1, 2, 3) # creates a vector named x
y <- c(1, 2, 4)
x == y
```

```
[1] TRUE TRUE FALSE
```

- The result of executing the last command is a vector containing the logical values TRUE, TRUE and FALSE since the only elements of the vectors `x` and `y` that are not equal are the 3rd elements.

Similarly,

```
x != y
```

```
[1] FALSE FALSE TRUE
```

Conditional Statement and Logical Operators

- Conditional statements can be combined using logical operators `&`, `|` and `!`.
 - The operator `&` means AND.
 - The operator `|` means OR
 - and the operator `!` means NOT.

As an example of the use of `&`, the following will yield TRUE since both conditions are TRUE.

```
(x[1] == y[1]) & (x[2] == y[2])
```

```
[1] TRUE
```

On the other hand,

```
(x[1] == y[1]) & (x[3] == y[3])
```

```
[1] FALSE
```

Conditional Statement and Logical Operators

However, the following will yield TRUE since at least one condition is TRUE. That is, the | operator will yield TRUE if at least one of the conditions is TRUE.

```
(x[1] == y[1]) | (x[3] == y[3])
```

```
[1] TRUE
```

To negate the truth value of the above statement, use !:

```
!((x[1] == y[1]) | (x[3] == y[3]))
```

```
[1] FALSE
```

Note the use of parentheses.

Conditional Statement and Logical Operators

To see the effect of parentheses, let's remove the parentheses in the previous statement.

```
!(x[3] == y[3]) | (x[1]==y[1])
```

```
[1] TRUE
```

A control structure that uses conditional statement(s) is the **if statement** and its variant **if else** and **if else if**.

- The if statement will perform an R command or a series of R commands only if the conditional statement is TRUE.

Lets see an example.

If Statement

The following will display the value of the sum of the first two elements of the vector `x` since the conditional statement is TRUE.

```
if (x[1] == y[1]){  
  sumx <- x[1] + x[2]  
  sumx  
}
```

```
[1] 3
```

Similarly, the following code will not display anything since the conditional statement is FALSE and hence R will not execute the R statements within the square brackets.

```
if (x[1] != y[1]){  
  sumy <- y[1] + y[2]  
  sumy  
}
```

If Statement

Note that the syntax of an if statement is as follows

- if (conditional statement) {R statements}
 - brackets are optional if there is only one R statement
- If you want R to perform either a series of R statements
 - (say A) when the conditional statement is TRUE or
 - another series of R statements (say B) when the conditional statement is FALSE
 - use the **if else** structure which is as follows:
- if (condition) {R statements A }else{ R statements B }

If Else Statement

As an example, the following will display the sum of the elements of `x` since the conditional statement is TRUE:

```
if (x[1] == y[1]){  
  sumx <- sum(x)  
  sumx  
} else {  
  sumy <- sum(y)  
  sumy  
}
```

```
[1] 6
```

If Else Statement

On the other hand, the following will display the sum of the elements of `y` since the conditional statement is `FALSE`:

```
if (x[1] != y[1]){  
  sumx <- sum(x)  
  sumx  
} else {  
  sumy <- sum(y)  
  sumy  
}
```

```
[1] 7
```

If Else If Statement

The other variant of the if statement is the **if else if** structure which has the following syntax:

- `if (condition 1) {R statements A } else if (condition 2) {R statement B } else if (condition 3) {R statement C } else { R statement D}`
- You can have more than 3 conditions to test so the structure could be longer.

If Else If Statement

As an example, the following code will display the sum of the elements of `y` since the 1st condition is FALSE and 2nd condition is TRUE. It will not evaluate the 3rd condition.

```
if (x[1] != y[1]){
  sumx <- sum(x)
  sumx
} else if (x[2] == y[2]) {
  sumy <- sum(y)
  sumy
} else if (x[3] != y[3]) {
  prodx <- x[1]*x[2]*x[3]
  prodx
} else {
  prody <- y[1]*y[2]*y[3]
  prody
}
```

[1] 7

If Else If Statement

On the other hand, the following will display the product of the elements of y (the content of the object prody) since the 3 conditions are FALSE:

```
if (x[1]!=y[1]){
  sumx <- sum(x)
  sumx
} else if (x[2]!=y[2]) {
  sumy <- sum(y)
  sumy
} else if (x[3]==y[3]) {
  prodx <- x[1]*x[2]*x[3]
  prodx
} else {
  prody <- y[1]*y[2]*y[3]
  prody
}
```

[1] 8

For Loop Statement

The for loop is one of the most useful control structures in R. Its syntax is as follows

- `for (index variable in sequence) {R statements}`

The index variable is usually a dummy integer variable (can have any name) but *i*, *j*, *k*, etc are often used. For example, the following code will display the text "HELLO" five times.

```
for (i in 1:5){  
  print("HELLO")  
}
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

For Loop Statement

Similarly, the following code will do the same thing:

```
for (j in 6:10){  
  print("HELLO")  
}
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

```
[1] "HELLO"
```

The for loop is useful when you want to repeat a command and you know exactly how many times you want the command repeated.

For Loop Statement

- The following code will display the contents of the vector z in reverse order.
 - Note that the first statement creates a vector of length 10.
 - Without the `reverse.z <- numeric(10)` command, R will display an error message saying object `reverse.z` not found.

```
reverse.z <- numeric(10)
z <- 1:10
for (k in 1:10){
  reverse.z[k] <- z[10 -k + 1]
}
reverse.z
```

```
[1] 10  9  8  7  6  5  4  3  2  1
```

Section 3

Quarto

Quarto provides an easy way to produce rich, fully-documented, reproducible analyses.

- It allows users to share a single file containing
 - all of the comments,
 - R code, and
 - metadata needed to reproduce the analysis from beginning to end.
- Quarto allows you to
 - combine chunks of R code with Markdown text and produce a nicely formatted HTML, PDF, or Word file,
 - without having to know any HTML or LaTeX code or fuss with getting the formatting just right in a Microsoft Word DOCX file.

I think you'll be pleasantly surprised at how easy it is to write a Quarto document once you get the hang of it.

Create New Quarto File

To open/create a new (Quarto) file, click on the little green plus on the upper left hand and select Quarto Document; see Figure 1.

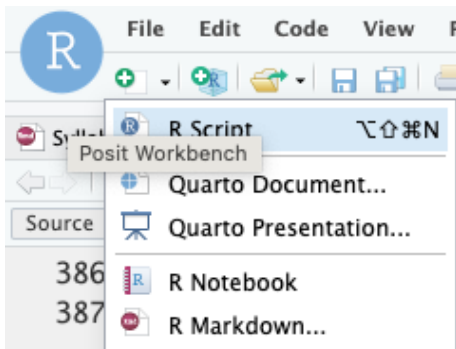


Figure 1: How to open a *.qmd file

Create New Quarto File

Let's make some changes to the Quarto file you just opened

- First, change the title of the lab at the top to “Getting to Know RStudio.”
- Second, add an author line, and insert your name. You need quotation marks!
- Third, name and save the file as **first_quarto.qmd**.

After editing the file you **Render** to your desired output format (HTML, PDF, or Word file).

The Components of a Quarto File: YAML

The top part of the file is called the YAML header.

- YAML is a recursive acronym that stands for “YAML Ain’t Markup Language”
- YAML is defined on its official website at <http://yaml.org> as: a human friendly data serialization standard for all programming languages.
- The YAML header stores the metadata needed for the document.
- You can see an example of a YAML header from our `first_quarto.qmd` file below.

```
1 | ---
2 | title: "Getting to Know RStudio"
3 | author: "Alan T. Arnholt"
4 | format: html
5 | editor: visual
6 | ---
7 |
```


The Components of a Quarto File: Headers

You can create many different sized headers by simply adding one or more # in front of the text you'd like to denote the header.

```
# Top level header
## Second level header
### Third level header
#### Fourth level header
```

- Now let us change the last header (Running Code) in our `first_quarto.qmd` file to `###`.

The Components of Quarto File: Emphasis

- We can add italics by surrounding the word by
 - a single underscore or
 - a single asterisk.
- As we saw in our `first_quarto.qmd` file we can bold a word by surrounding the word by
 - two underscores or
 - two asterisks.
- Now let us italicize the first time weave appears in our `first_quarto.qmd`.

The Components of a Quarto File: Links

- To add a link to a URL,
 - you simply enclose the text you'd like displayed in the resulting HTML file inside [] and
 - then the link itself inside () right next to each other with no space in between.

The Components of a Quarto File: Lists

- To create an unordered list, use – in front of each item.
- We can also create ordered list by using numbers, letters or roman numerals.
- Create the following in our `first_quarto.qmd` file.
 - Create a new second level header with the name “Ordered Lists”.
 - Under the “Ordered Lists” header, create a sub-list using letters (i, ii).
 - Under the “Ordered Lists” header, create a sub-list using numbers (1, 2).

The Components of a Quarto File: Equations

- If you'd like nice mathematical formulas in your document, you can add them between **two dollar signs**.
- Now let us do the following in our `first_quarto.qmd` file.
 - Add another second level header: Equations
 - Type: $y = mx + b$

The Components of a Quarto File: Inline R code

- We've seen that we can add R code and have that run in an R chunk of code enclosed by three backticks.
- However, what if we wanted to include the results of a simple calculation directly in the text of our document? Quarto can do that as well:
- Now let us do the following in our **'first_quarto.qmd'** file.
 - Under the Equations header
 - Type: Multiplying 7 by 14 gives us the result 98 (using inline R code).

The Components of a Quarto File: Chunk Options

You can set many options on a chunk by chunk basis. The most common R chunk options are `echo`, `eval`, and `include`. By default, all three of these options are set to `TRUE`,

- `echo` dictates whether the code that produces the result should be printed before the corresponding R output.
- `eval` specifies whether the code should be evaluated or just displayed without its output.
- `include` specifies whether the code AND its output should be included in the resulting rendered document. If it is set to `FALSE` the code is run, but neither the code or its output are included in the resulting document.

The Components of a Quarto File: Chunk Options

- Do the following in your **'first_quarto.qmd'** document.
 - Create a second level header named “Code Chunks” at the end of your document.
 - Create an R code chunk and set `echo = FALSE`.
 - Inside the code chunk type `5 + 15 > 19`.

- Near the top of your editor window sits one of the more useful tools for writing documents:
 - The spell-check button.
 - The spell-check button is the green check-mark with “ABC” above it.
- Before you submit a document or share it with someone else, please spell check your document!
- Spell check your **‘first_quarto.qmd** document. Did you have an typos?

Section 4

Data Visualization

We begin the development of your data science toolbox with **data visualization**.

- By visualizing data, we gain valuable insights we couldn't initially obtain from just looking at the raw data values.
- At their most basic, graphics/plots/charts (we use these terms interchangeably) provide a nice way to explore the patterns in data, such as
 - the presence of outliers,
 - distributions of individual variables, and
 - relationships between groups of variables.
- Graphics are designed to emphasize the findings and insights you want your audience to understand.

Needed packages

Let's load all the packages needed for this chapter. You need to install them if you haven't already.

```
library(nycflights13)  
library(ggplot2)  
library(moderndiver)
```

The grammar of graphics

We start with a discussion of a theoretical framework for data visualization known as “**the grammar of graphics.**”

- This framework serves as the foundation for the `ggplot2` package which we'll use extensively in this class.
- Think of how we construct and form sentences in English by combining different elements, like nouns, verbs, articles, subjects, objects, etc.
 - We can't just combine these elements in any arbitrary order;
 - we must do so following a set of rules known as a linguistic grammar.
- Similarly to a linguistic grammar, “the grammar of graphics” defines a set of rules for constructing statistical graphics by combining different types of layers.

Components of the grammar

In short, the grammar tells us that

A statistical graphic is a mapping of data variables to aesthetic attributes of geometric objects.

Specifically, we can break a graphic into the following three essential components:

- 1 data: the dataset containing the variables of interest.
- 2 geom: the geometric object in question. This refers to the type of object we can observe in a plot. For example: points, lines, and bars.
- 3 aes: aesthetic attributes of the geometric object. For example, x/y position, color, shape, and size. Aesthetic attributes are mapped to variables in the dataset.

There are other components of the grammar of graphics we can control as well. In this class, we'll keep things simple and only work with these two additional components:

- `faceting` breaks up a plot into several plots split by the values of another variable
- `position` adjustments for barplots.

Five named graphs - the 5NG

We will only focus on five different types of graphics, each with a commonly given name. - We term these “five named graphs” or in abbreviated form, the 5NG:

- 1 scatterplots
 - 2 linegraphs
 - 3 histograms
 - 4 boxplots
 - 5 barplots
- We'll also present some variations of these plots
 - Note that:
 - certain plots are only appropriate for categorical variables,
 - while others are only appropriate for numerical variables.

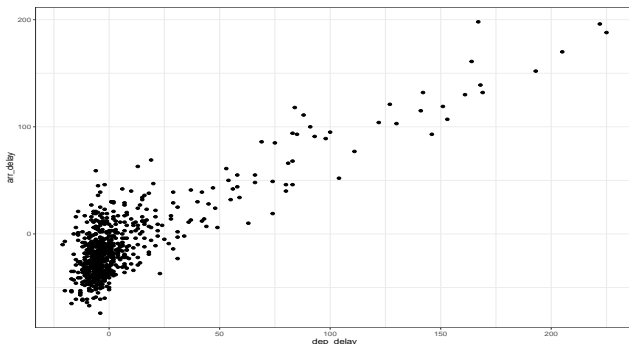
5NG#1: Scatterplots

The simplest of the 5NG are **scatterplots**, also called bivariate plots. They allow you to visualize the relationship between two **numerical** variables.

- Let's view them through the lens of the grammar of graphics we presented earlier.
- Specifically, we will visualize the relationship between the following two numerical variables in the `alaska_flights` data frame included in the `moderndive` package:
 - 1 `dep_delay`: departure delay on the horizontal "x" axis and
 - 2 `arr_delay`: arrival delay on the vertical "y" axis

Scatterplots via `geom_point`

```
ggplot(data = alaska_flights, mapping = aes(x = dep_delay, y = arr_delay)) +  
  geom_point() +  
  theme_bw()
```

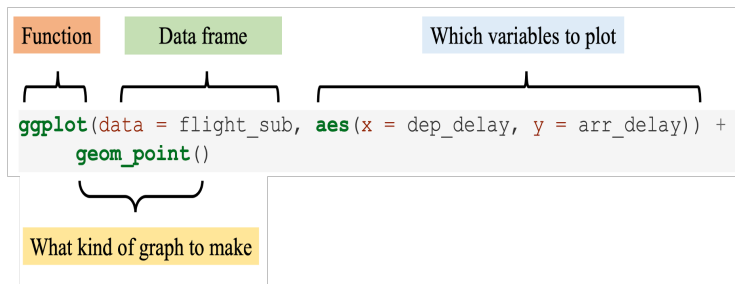


We observe that a **positive** relationship exists between `arr_delay` and `dep_delay`: as departure delays increase, arrival delays tend to also increase.

Scatterplots via `geom_point`

- Within the `ggplot()` function, we specify two of the components of the grammar of graphics as arguments (i.e., inputs):
 - 1 The data as the `alaska_flights` data frame via `data = alaska_flights`.
 - 2 The aesthetic mapping by setting `mapping = aes(x = dep_delay, y = arr_delay)`.
- We then add a layer to the `ggplot()` function call using the `+` sign.
 - The added layer in question specifies the third component of the grammar: the geometric object.
 - In this case, the geometric object is set to be points by specifying `geom_point()`.

Scatterplots via `geom_point`



Note that the + sign comes at the end of lines, and not at the beginning. You'll get an error in R if you put it at the beginning of a line.

Overplotting

From the scatterplot from the `alaska_flights`, the large mass of points near $(0,0)$, can cause some confusion since it is hard to tell the true number of points that are plotted.

- This is the result of a phenomenon called **overplotting**.
 - This corresponds to points being plotted on top of each other over and over again.
 - When this occurs, it is difficult to know the number of points being plotted.
- There are two methods to address the issue of overplotting. Either by
 - Adjusting the transparency of the points or
 - adding a little random “jitter”, or random “nudges”, to each of the points.

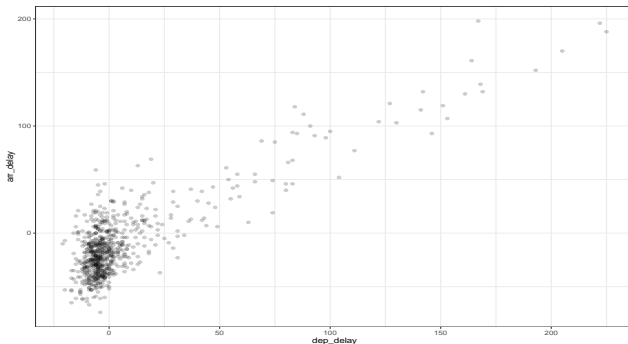
Method 1: Changing the transparency

- Change the transparency/opacity of the points by setting the `alpha` argument in `geom_point()`.
- We can change the `alpha` argument to be any value between 0 and 1,
 - where 0 sets the points to be 100% transparent and
 - 1 sets the points to be 100% opaque.
- By default, `alpha` is set to 1. In other words, if we don't explicitly set an `alpha` value, R will use `alpha = 1`.

Note how the following code is identical to the earlier code that created the scatterplot with overplotting, but with `alpha = 0.2` added to the `geom_point()` function.

Method 1: Changing the transparency

```
ggplot(data = alaska_flights, mapping = aes(x = dep_delay, y = arr_delay)) +  
  geom_point(alpha = 0.2) +  
  theme_bw()
```



Now areas with a high-degree of overplotting are darker, whereas areas with a lower degree are less dark.

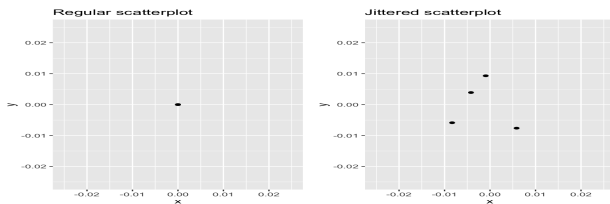
Method 2: Jittering the points

The second way of addressing overplotting is by **jittering** all the points.

- This means giving each point a small “nudge” in a random direction.
 - You can think of “jittering” as shaking the points around a bit on the plot.

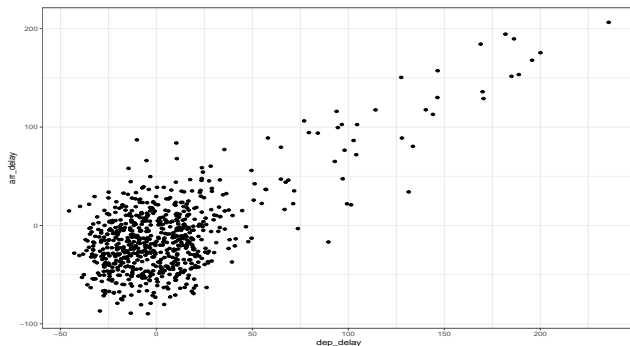
Method 2: Jittering the points

- Example: Say we have a data frame with 4 identical rows of x and y values: $(0,0)$, $(0,0)$, $(0,0)$, and $(0,0)$
 - scatterplot of these 4 points (on the left)
 - and its jittered counterpart (on the right)



Method 2: Jittering the points

```
ggplot(data = alaska_flights, mapping = aes(x = dep_delay, y = arr_delay)) +  
  geom_jitter(width = 30, height = 30) +  
  theme_bw()
```



Which method was better?

- Keep in mind, that jittering is strictly a visualization tool; the original values saved in the data frame remain unchanged.

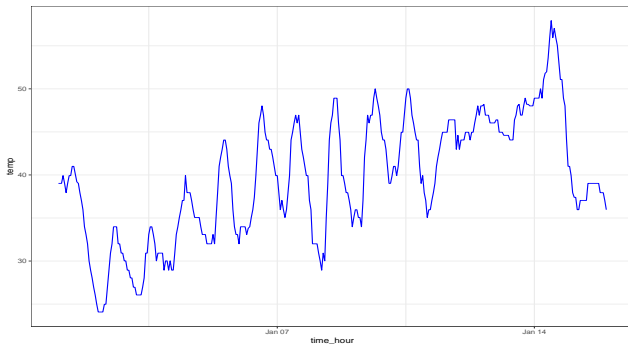
5NG#2: Linegraphs

- Linegraphs show the relationship between two numerical variables when the variable on the x-axis, also called the explanatory variable, is of a **sequential nature**. In other words, there is an inherent ordering to the variable.
- The most common examples of linegraphs have some notion of time on the x-axis: hours, days, weeks, years, etc.
 - Since time is sequential, we connect consecutive observations of the variable on the y-axis with a **line**.
 - Linegraphs that have some notion of time on the x-axis are also called **time series plots**.

Lets explore the `early_january_weather` data frame included in the `moderndive` package, which contains hourly weather observations.

Linegraphs via geom_line

```
ggplot(data = early_january_weather,  
       mapping = aes(x = time_hour, y = temp)) +  
  geom_line(color = "blue") +  
  theme_bw()
```



We observe an upward trend and seasonality.

5NG#3: Histograms

Let's consider the `temp` variable in the `weather` data frame from the `nycflights13` package.

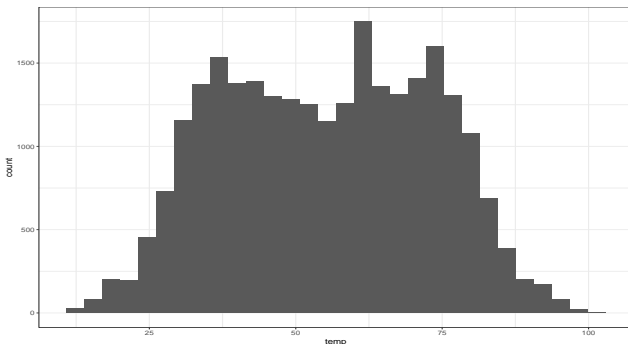
- Here, we only care about how the values of `temp` distribute. In other words:
 - 1 What are the smallest and largest values?
 - 2 What is the “center” or “most typical” value?
 - 3 How do the values spread out?
 - 4 What are frequent and infrequent values?

One way to do that is by producing a **histogram**. A histogram is a plot that visualizes the distribution of a numerical value as follows:

- 1 We first cut up the x-axis into a series of **bins**, where each bin represents a range of values.
- 2 For each bin, we count the number of observations that fall in the range corresponding to that bin.
- 3 Then for each bin, we draw a bar whose height marks the corresponding count.

Histograms via `geom_histogram`

```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram() +  
  theme_bw()
```



- Note that:

- The y-aesthetic of a histogram, the count of the observations in each bin, gets computed for you automatically.
- The histogram was constructed using `bins = 30` (Default value).

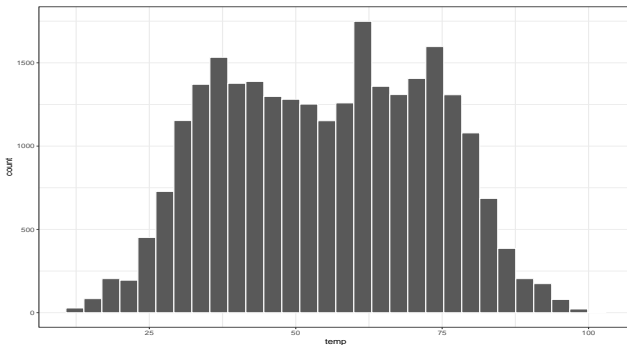
Histograms via `geom_histogram`

Now let's unpack the resulting histogram

- Observe that values less than $25^{\circ}F$ as well as values above $80^{\circ}F$ are rather rare.
- However, because of the large number of bins, it's hard to get a sense for which range of temperatures is spanned by each bin
 - let's add white vertical borders demarcating the bins by adding a `color = "white"` argument to `geom_histogram()`.

Histograms via `geom_histogram`

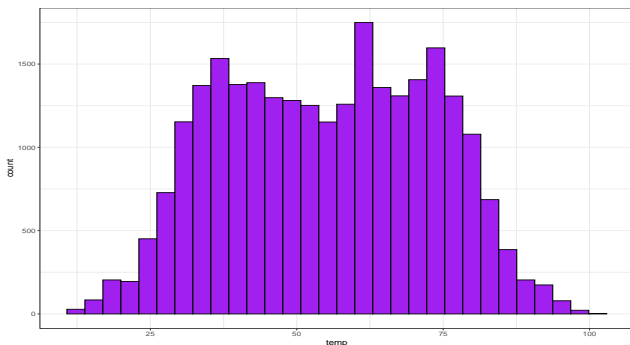
```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(color = "white") +  
  theme_bw()
```



- We now have an easier time associating ranges of temperatures to each of the bins.
- We can also vary the color of the bars by setting the `fill` argument.

Histograms via geom_histogram

```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(color = "black", fill = "purple") +  
  theme_bw()
```



- Run `colors()` to see all 657 possible choice of colors in R!
- Note that in the 50-75°F range there appear to be roughly 8 bins. Thus each bin has width 25 divided by 8 or 3.125°F.

Adjusting the bins

Method 1: By adjusting the number of bins via the `bins` argument to `geom_histogram()`.

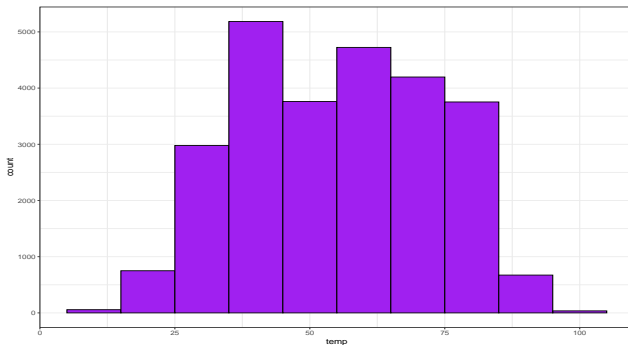
```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(bins = 40, color = "black", fill = "purple") +  
  theme_bw()
```



Adjusting the bins

Method 2: By adjusting the width of the bins via the `binwidth` argument to `geom_histogram()`

```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(binwidth = 10, color = "black", fill = "purple") +  
  theme_bw()
```



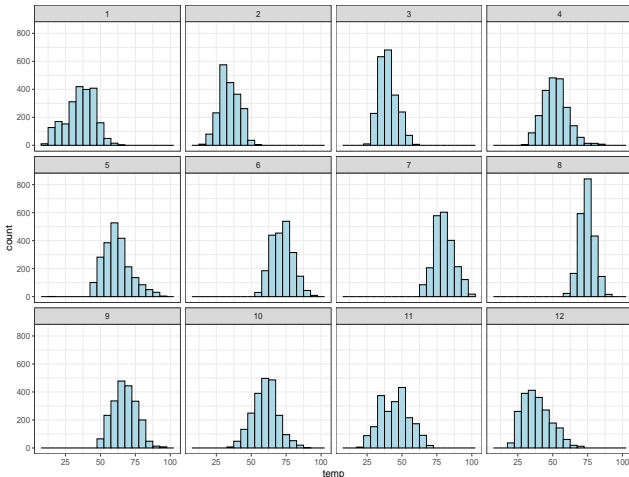
Before continuing with the next of the 5NG, let's briefly introduce a new concept called **faceting**.

- Faceting is used when we'd like to split a particular visualization by the values of another variable.
- This will create multiple copies of the same type of plot with matching x and y axes, but whose content will differ.

Example: lets Looking at how the histogram of hourly **temperature** recordings at the three NYC airports we saw earlier differed in each **month**.

Facets

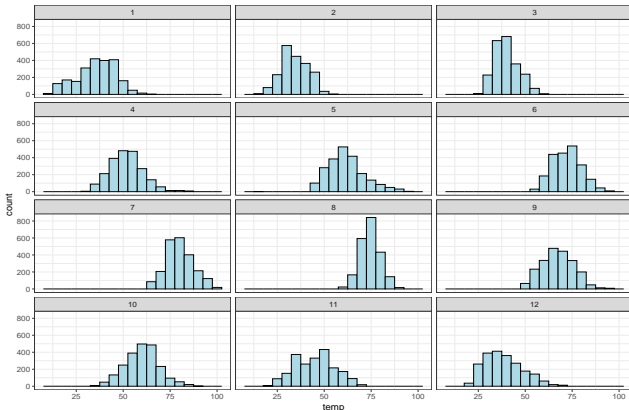
```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(binwidth = 5, color = "black", fill = "lightblue") +  
  facet_wrap(vars(month)) +  
  theme_bw()
```



Facets

We can also specify the number of rows and columns in the grid by using the `nrow` and `ncol` arguments inside of `facet_wrap()`.

```
ggplot(data = weather, mapping = aes(x = temp)) +  
  geom_histogram(binwidth = 5, color = "black", fill = "lightblue") +  
  facet_wrap(vars(month), nrow = 4) +  
  theme_bw()
```



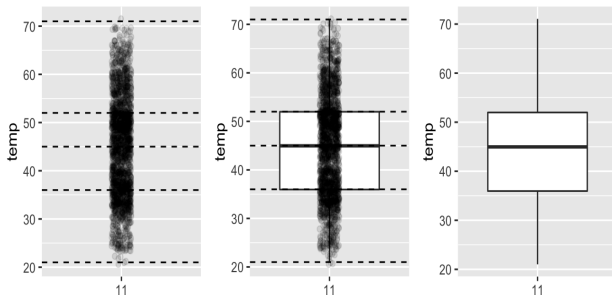
5NG#4: Boxplots

Another type of visualization that can be used to compare the distribution of a numerical variable split by the values of another variable is a **side-by-side boxplot**.

- A **boxplot** is constructed from the information provided in the **five-number summary** of a numerical variable.
- Let's see an example of a boxplot using hourly temperature recordings for the month of November.
 - Minimum: 21°F
 - First quartile (25th percentile): 36°F
 - Median (second quartile, 50th percentile): 45°F
 - Third quartile (75th percentile): 52°F
 - Maximum: 71°F

5NG#4: Boxplots

- From the figure below:
 - In the leftmost plot let's mark these 5 values with dashed horizontal lines on top of the 2141 points(observations).
 - In the middle plot, let's add the boxplot.
 - In the rightmost plot, let's remove the points and the dashed horizontal lines for clarity's sake.



5NG#4: Boxplots

From the Boxplot:

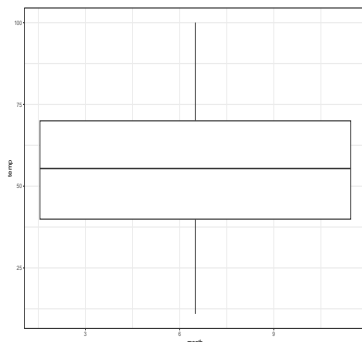
- 25% of observations were below 36°F .
- 25% of observations were between 36°F and 45°F and 50% of observations were below 45°F .
- 25% of observations were between 45°F and 52°F and 75% of observations were below 52°F .
- 25% of observations were above 52°F .
- The middle 50% of points lie within the interquartile range (IQR) between the first and third quartile. IQR for this example is $52 - 36 = 16^{\circ}\text{F}$.

From the Boxplot:

- The whiskers stick out from either end of the box all the way to the **minimum**(21°F) and **maximum** observed temperatures (71°F).
 - However, the whiskers extend no more than $1.5 \times \text{IQR}$ from either end of the box.
 - Any observed values outside this range get marked with points called **outliers**.

Boxplots via `geom_boxplot`: Invalid specification

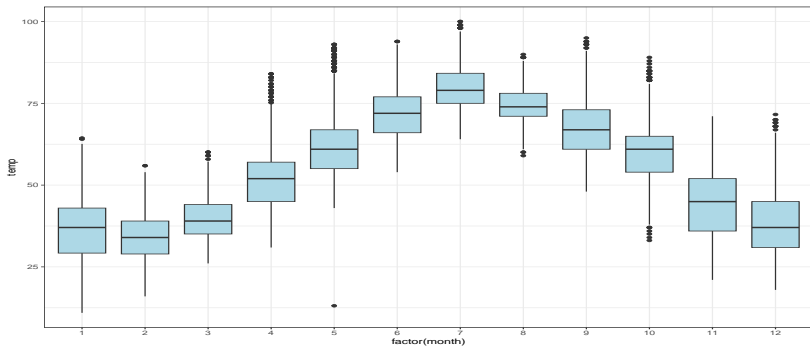
```
ggplot(data = weather, mapping = aes(x = month, y = temp)) +  
  geom_boxplot() +  
  theme_bw()
```



- Observe that this plot does not provide information about temperature separated by month.
 - Boxplots, require a categorical variable to be mapped to the x-position aesthetic. But the `month` variable is numerical variable.

Boxplots via geom_boxplot

```
ggplot(data = weather, mapping = aes(x = factor(month), y = temp)) +  
  geom_boxplot(fill = "lightblue") +  
  theme_bw()
```



Thus the 12 separate boxplots are shown “side-by-side.”

5NG#5: Barplots

- Both histograms and boxplots are tools to visualize the distribution of numerical variables.
- Another commonly desired task is to visualize the distribution of a categorical variable.
 - we are simply counting different categories within a categorical variable, also known as the levels of the categorical variable
- Often the best way to visualize these different counts, also known as **frequencies**, is with **barplots** (also called barcharts).

5NG#5: Barplots

- One complication, however, is how your data is represented.
 - Is the categorical variable of interest “pre-counted” or not?
- For example, run the following code that manually creates two data frames representing a collection of fruit: 3 apples and 2 oranges.

```
library(dplyr)
fruits <- tibble(
  fruit = c("apple", "apple", "orange", "apple", "orange")
)
fruits_counted <- tibble(
  fruit = c("apple", "orange"),
  number = c(3, 2)
)
```

5NG#5: Barplots

```
fruits

# A tibble: 5 x 1
  fruit
  <chr>
1 apple
2 apple
3 orange
4 apple
5 orange

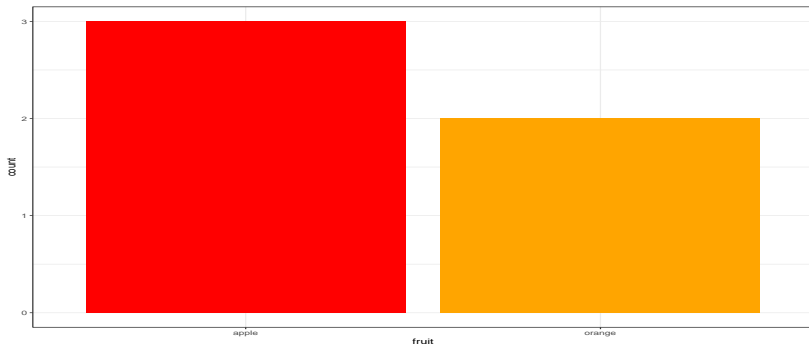
fruits_counted
```

```
# A tibble: 2 x 2
  fruit number
  <chr>   <dbl>
1 apple     3
2 orange     2
```

Depending on how your categorical data is represented, you'll need to add a different geometric layer type to your `ggplot()` to create a barplot.

Barplots via geom_bar

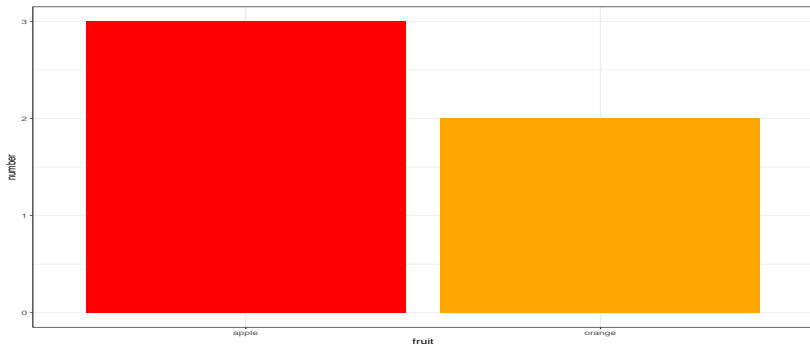
```
ggplot(data = fruits, mapping = aes(x = fruit)) +  
  geom_bar(fill = c("red", "orange")) +  
  theme_bw()
```



When the categorical variable whose distribution you want to visualize is **not pre-counted** in your data frame, we use **geom_bar()**.

Barplots via geom_col

```
ggplot(data = fruits_counted, mapping = aes(x = fruit, y = number)) +  
  geom_col(fill = c("red", "orange")) +  
  theme_bw()
```



When the categorical variable whose distribution you want to visualize is **pre-counted** in your data frame, we use **geom_col()**.

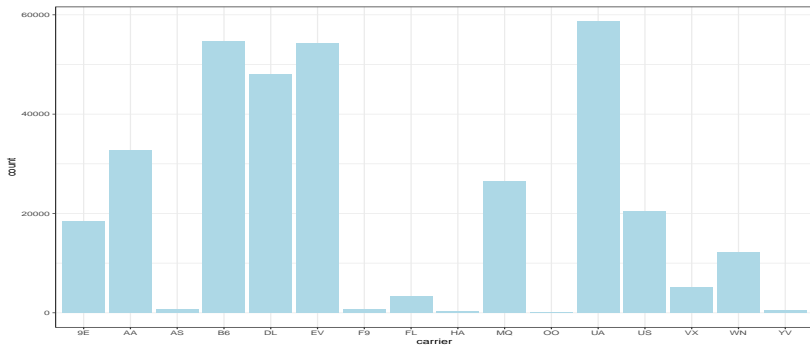
Barplots for flights data

Let's now go back to the `flights` data frame in the `nycflights13` package and visualize the distribution of the categorical variable `carrier`.

- Because the `flights` have **not been pre-counted** by `carrier`, we use `geom_bar()`.

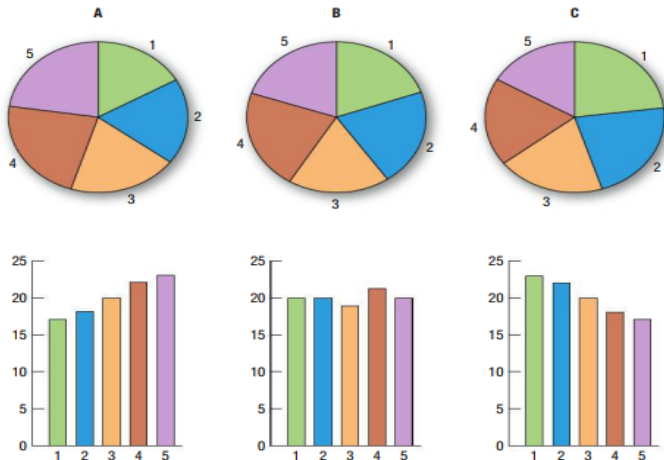
Barplots for flights data

```
ggplot(data = flights, mapping = aes(x = carrier)) +  
  geom_bar(fill = "lightblue") +  
  theme_bw()
```



- One of the most common plots used to visualize the distribution of categorical data is the **pie chart**.
- A pie chart presents each category as a slice of a circle so that each slice has a size that is proportional to the whole in each category.
- While they may seem harmless enough, pie charts actually present a problem in that humans are unable to judge angles well.
 - In other words, it is difficult for us to determine the relative size of one piece of the pie compared to another.
- This makes barplots preferred in certain situations.

Cases Where Barplots are Preferred



It is hard to see the pattern in the pie chart but the bar chart makes it easier to compare frequencies in groups.

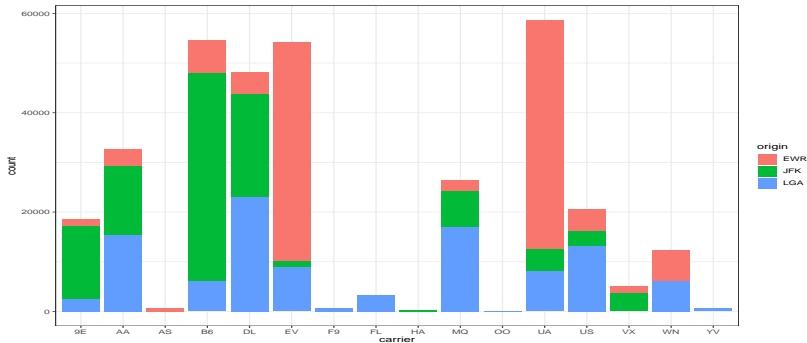
Two categorical variables

- Barplots are a very common way to visualize the frequency of different categories, or levels, of a single categorical variable.
- Another use of barplots is to visualize the joint distribution of **two categorical variables** at the same time.

Let's examine the joint distribution of outgoing domestic flights from NYC by carrier as well as origin.

Two categorical variables: Stacked barplot

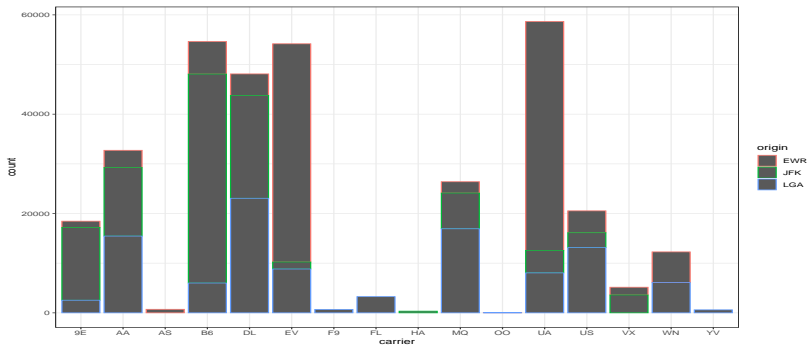
```
ggplot(data = flights, mapping = aes(x = carrier, fill = origin)) +  
  geom_bar() +  
  theme_bw()
```



- This is an example of a **stacked** barplot.
- The `fill` aesthetic corresponds to the color used to fill the bars

Two categorical variables: Stacked barplot

```
ggplot(data = flights, mapping = aes(x = carrier, color = origin)) +  
  geom_bar() +  
  theme_bw()
```



- The `color` aesthetic corresponds to the color of the outline of the bars.

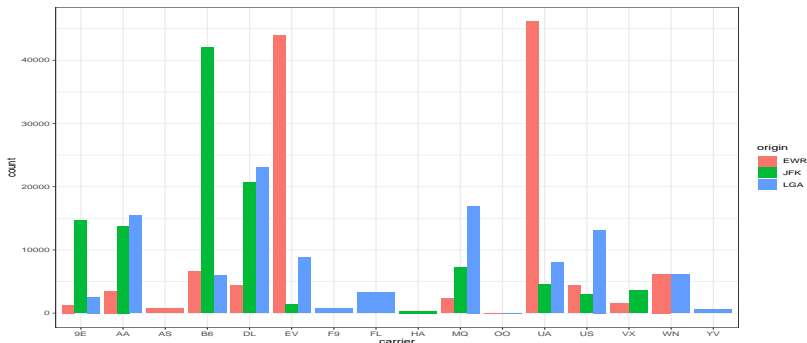
Two categorical variables: side-by-side barplots

While simple to make, in certain aspects it is not ideal.

- For example, it is difficult to compare the heights of the different colors between the bars, corresponding to comparing the number of flights from each origin airport between the carriers.
- An alternative to stacked barplots are **side-by-side barplots**, also known as **dodged barplots**.
- The code to create a side-by-side barplot is identical to the code to create a stacked barplot, but with a `position = "dodge"` argument added to `geom_bar()`.
 - we are overriding the default barplot type, which is a stacked barplot.

Two categorical variables: side-by-side barplots

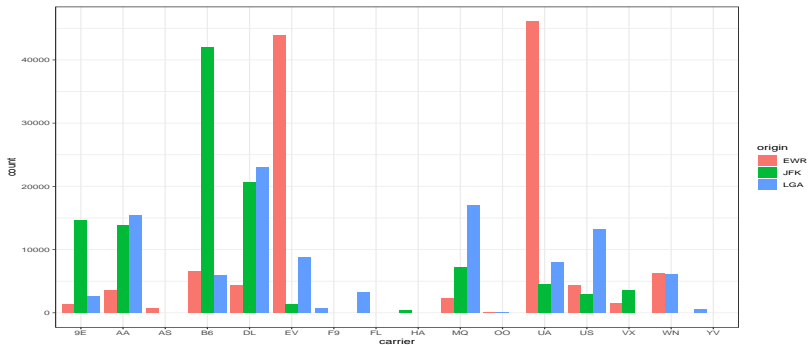
```
ggplot(data = flights, mapping = aes(x = carrier, fill = origin)) +  
  geom_bar(position = "dodge") +  
  theme_bw()
```



- Note the width of the bars for AS, F9, FL, HA and YV is different than the others
- To be the same size in terms of width as the other bars we use a more robust `position_dodge()` function.

Two categorical variables: side-by-side barplots

```
ggplot(data = flights, mapping = aes(x = carrier, fill = origin)) +  
  geom_bar(position = position_dodge(preserve = "single")) +  
  theme_bw()
```

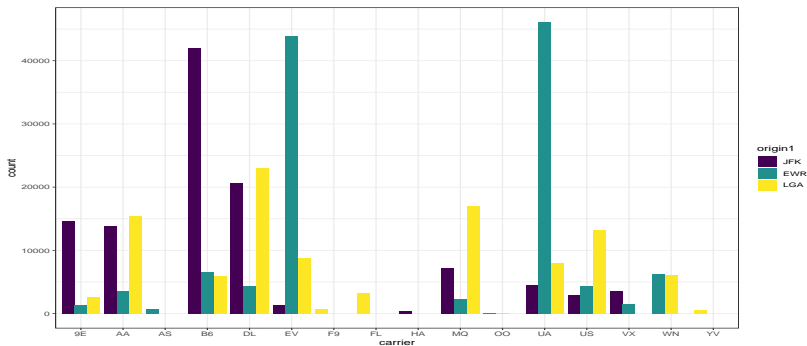


Two categorical variables: side-by-side barplots

Change order:

```
flights1 <- flights
flights1$origin1 <- factor(flights1$origin, ordered = TRUE,
levels = c("JFK", "EWR", "LGA"))

ggplot(data = flights1, mapping = aes(x = carrier, fill = origin1)) +
  geom_bar(position = position_dodge(preserve = "single")) +
  theme_bw()
```



Two categorical variables: faceted barplot

```
ggplot(data = flights, mapping = aes(x = carrier)) +  
  geom_bar(fill = "pink") +  
  facet_wrap(vars(origin), ncol = 1) +  
  theme_bw()
```



Summary table

| | Named graph | Shows | Geometric object | Notes |
|---|-------------|--|--|---|
| 1 | Scatterplot | Relationship between 2 numerical variables | <code>geom_point()</code> | |
| 2 | Linegraph | Relationship between 2 numerical variables | <code>geom_line()</code> | Used when there is a sequential order to x-variable, e.g., time |
| 3 | Histogram | Distribution of 1 numerical variable | <code>geom_histogram()</code> | Facetted histograms show the distribution of 1 numerical variable split by the values of another variable |
| 4 | Boxplot | Distribution of 1 numerical variable split by the values of another variable | <code>geom_boxplot()</code> | To graph without splitting by a categorical variable add <code>x = NULL</code> |
| 5 | Barplot | Distribution of 1 categorical variable | <code>geom_bar()</code> when counts are not pre-counted, <code>geom_col()</code> when counts are pre-counted | Stacked, side-by-side, and facetted barplots show the joint distribution of 2 categorical variables |

Figure 2: Summary of Five Named Graphs