Introduction to data

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Some define statistics as the field that focuses on turning information into knowledge. The first step in that process is to summarize and describe the raw information – the data. In this lab we explore flights, specifically a random sample of domestic flights that departed from the three major New York City airports in 2013. We will generate simple graphical and numerical summaries of data on these flights and explore delay times. Since this is a large data set, along the way you'll also learn the indispensable skills of data processing and subsetting.

Getting started

Load packages

In this lab, we will explore and visualize the data using the **tidyverse** suite of packages. The data can be found in the companion package for OpenIntro labs, **openintro**.

Let's load the packages.

```
library(tidyverse)
library(openintro)
```

The data

The Bureau of Transportation Statistics (BTS) is a statistical agency that is a part of the Research and Innovative Technology Administration (RITA). As its name implies, BTS collects and makes transportation data available, such as the flights data we will be working with in this lab.

First, we'll view the `nycflights` data frame. Type the following in your console to load the data:

```
data(nycflights)
```

The data set `nycflights` that shows up in your workspace is a *data matrix*, with each row representing an *observation* and each column representing a *variable*. R calls this data format a **data frame**, which is a term that will be used throughout the labs. For this data set, each *observation* is a single flight.

To view the names of the variables, type the command

```
names(nycflights)
```

```
##  [1] "year"      "month"     "day"       "dep_time"  "dep_delay" "arr_time"
##  [7] "arr_delay" "carrier"   "tailnum"   "flight"    "origin"    "dest"
## [13] "air_time"  "distance"  "hour"      "minute"
```

This returns the names of the variables in this data frame. The **codebook** (description of the variables) can be accessed by pulling up the help file:

```
?nycflights
```

One of the variables refers to the carrier (i.e. airline) of the flight, which is coded according to the following system.

- `carrier`: Two letter carrier abbreviation.
  - `9E`: Endeavor Air Inc.
  - `AA`: American Airlines Inc.
  - `AS`: Alaska Airlines Inc.
  - `B6`: JetBlue Airways
  - `DL`: Delta Air Lines Inc.
  - `EV`: ExpressJet Airlines Inc.
  - `F9`: Frontier Airlines Inc.
  - `FL`: AirTran Airways Corporation
  - `HA`: Hawaiian Airlines Inc.
  - `MQ`: Envoy Air
  - `OO`: SkyWest Airlines Inc.
  - `UA`: United Air Lines Inc.
  - `US`: US Airways Inc.
  - `VX`: Virgin America
  - `WN`: Southwest Airlines Co.
  - `YV`: Mesa Airlines Inc.

Remember that you can use `glimpse` to take a quick peek at your data to understand its contents better.

```
glimpse(nycflights)
```

```
## Rows: 32,735
## Columns: 16
## $ year      <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, ~
## $ month     <int> 6, 5, 12, 5, 7, 1, 12, 8, 9, 4, 6, 11, 4, 3, 10, 1, 2, 8, 10~
## $ day       <int> 30, 7, 8, 14, 21, 1, 9, 13, 26, 30, 17, 22, 26, 25, 21, 23, ~
## $ dep_time  <int> 940, 1657, 859, 1841, 1102, 1817, 1259, 1920, 725, 1323, 940~
## $ dep_delay <dbl> 15, -3, -1, -4, -3, -3, 14, 85, -10, 62, 5, 5, -2, 115, -4, ~
## $ arr_time  <int> 1216, 2104, 1238, 2122, 1230, 2008, 1617, 2032, 1027, 1549, ~
## $ arr_delay <dbl> -4, 10, 11, -34, -8, 3, 22, 71, -8, 60, -4, -2, 22, 91, -6, ~
## $ carrier   <chr> "VX", "DL", "DL", "DL", "9E", "AA", "WN", "B6", "AA", "EV", ~
## $ tailnum   <chr> "N626VA", "N3760C", "N712TW", "N914DL", "N823AY", "N3AXAA", ~
## $ flight    <int> 407, 329, 422, 2391, 3652, 353, 1428, 1407, 2279, 4162, 20, ~
## $ origin    <chr> "JFK", "JFK", "JFK", "JFK", "LGA", "LGA", "EWR", "JFK", "LGA~
## $ dest      <chr> "LAX", "SJU", "LAX", "TPA", "ORF", "ORD", "HOU", "IAD", "MIA~
## $ air_time  <dbl> 313, 216, 376, 135, 50, 138, 240, 48, 148, 110, 50, 161, 87,~
## $ distance  <dbl> 2475, 1598, 2475, 1005, 296, 733, 1411, 228, 1096, 820, 264,~
## $ hour      <dbl> 9, 16, 8, 18, 11, 18, 12, 19, 7, 13, 9, 13, 8, 20, 12, 20, 6~
## $ minute    <dbl> 40, 57, 59, 41, 2, 17, 59, 20, 25, 23, 40, 20, 9, 54, 17, 24~
```

The `nycflights` data frame is a massive trove of information. Let's think about some questions we might want to answer with these data:

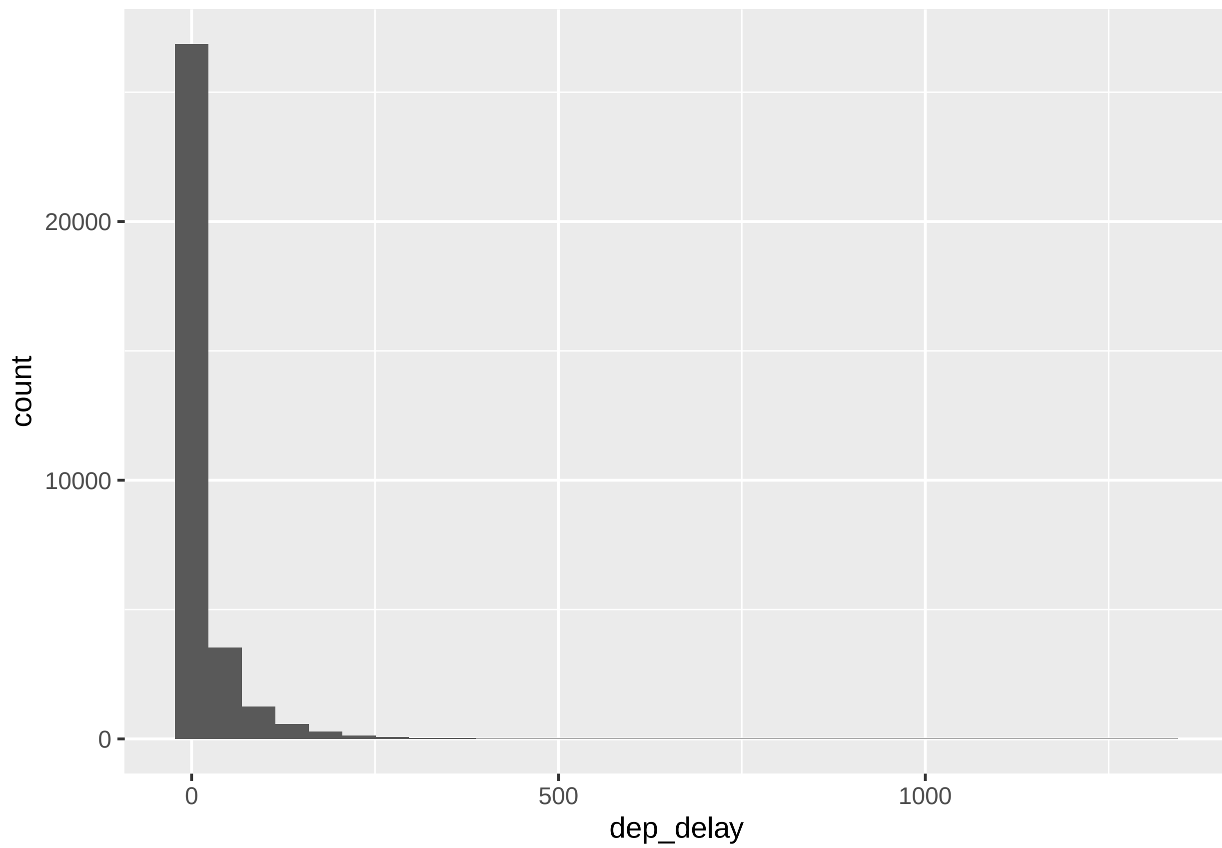
- How delayed were flights that were headed to Los Angeles?
- How do departure delays vary by month?
- Which of the three major NYC airports has the best on time percentage for departing flights?

Analysis

Departure delays

Let's start by examining the distribution of departure delays of all flights with a histogram.

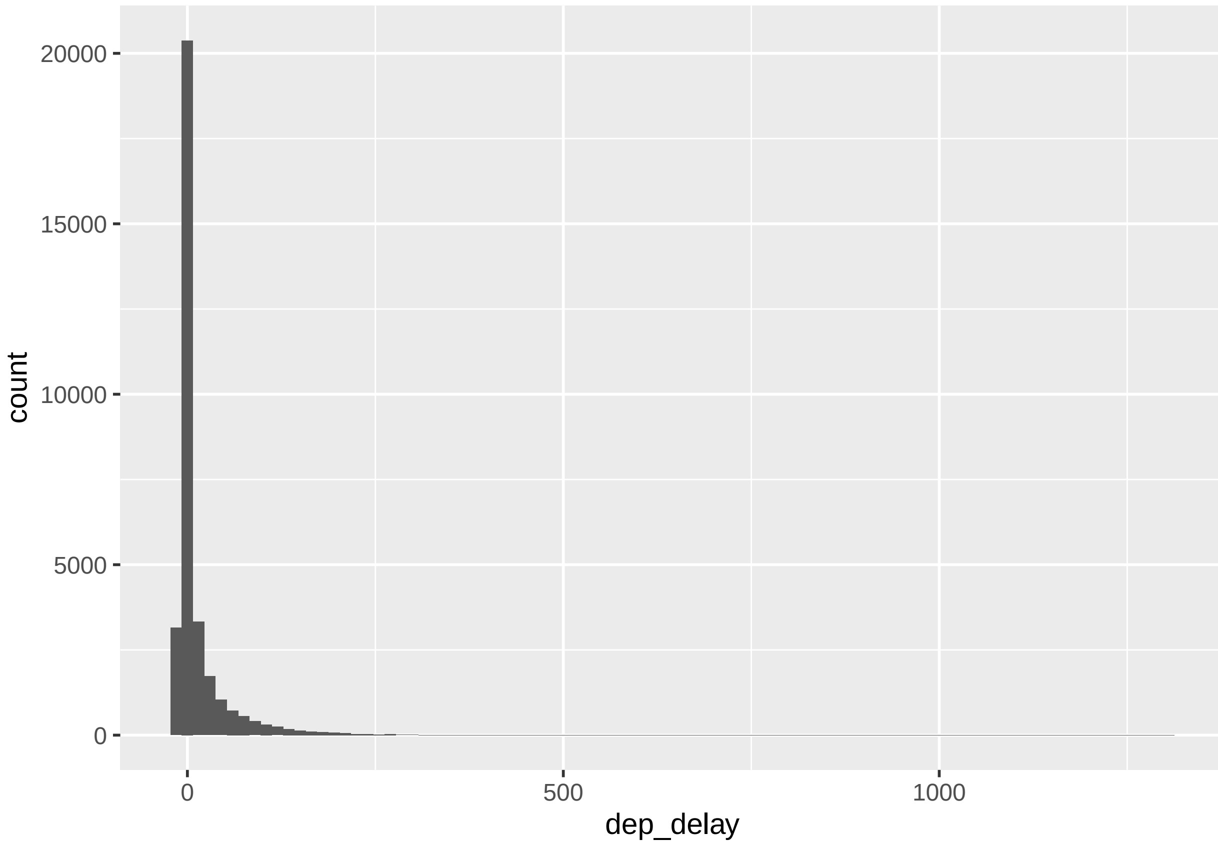
```
ggplot(data = nycflights, aes(x = dep_delay)) +
  geom_histogram()
```



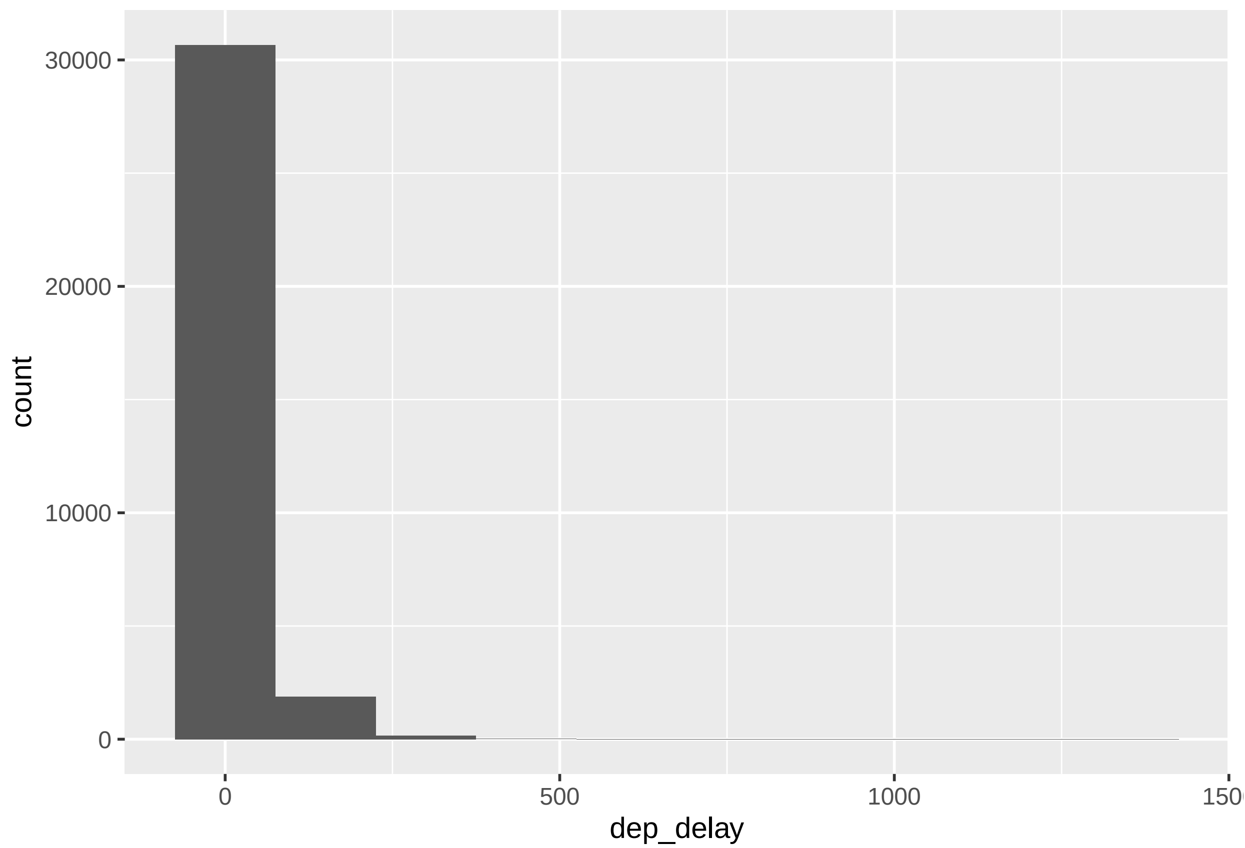
This function says to plot the `dep_delay` variable from the `nycflights` data frame on the x-axis. It also defines a `geom` (short for geometric object), which describes the type of plot you will produce.

Histograms are generally a very good way to see the shape of a single distribution of numerical data, but that shape can change depending on how the data is split between the different bins. You can easily define the binwidth you want to use:

```
ggplot(data = nycflights, aes(x = dep_delay)) +
  geom_histogram(binwidth = 15)
```




```r
ggplot(data = nycflights, aes(x = dep_delay)) +
  geom_histogram(binwidth = 150)
```

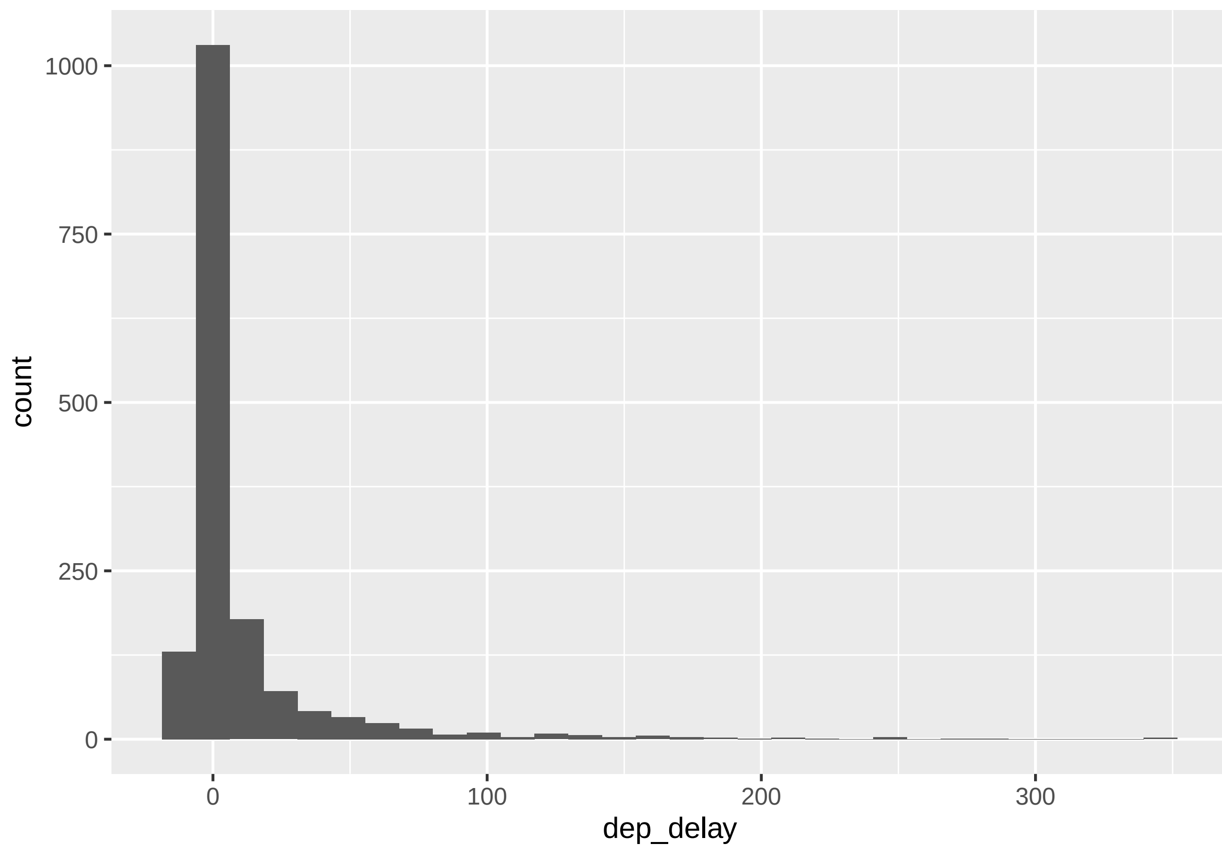


1. Look carefully at these three histograms. How do they compare? Are features revealed in one that are obscured in another?

- ***All three histograms are showing the same data, departure delays and count. The first chart, has a max value closer to 3,000 and there's 6-7 visible bins. The second chart has a max value a little over 2,000 and there's 14-15 visible bins. The last chart has a count a bit more than 3,000 and has 3-4 visible bins. For each chart the bandwidth size differs from 30, 15 to 150. Each bandwidth shows us the data very differently but the second histogram is the less obscure and a more accurate representation of the data.***

If you want to visualize only on delays of flights headed to Los Angeles, you need to first `filter` the data for flights with that destination (`dest == "LAX"`) and then make a histogram of the departure delays of only those flights.

```
lax_flights <- nycflights %>%
  filter(dest == "LAX")
ggplot(data = lax_flights, aes(x = dep_delay)) +
  geom_histogram()
```



Let's decipher these two commands (OK, so it might look like four lines, but the first two physical lines of code are actually part of the same command. It's common to add a break to a new line after `%>%` to help readability).

- Command 1: Take the `nycflights` data frame, `filter` for flights headed to LAX, and save the result as a new data frame called `lax_flights`.
  - `==` means "if it's equal to".
  - `LAX` is in quotation marks since it is a character string.
- Command 2: Basically the same `ggplot` call from earlier for making a histogram, except that it uses the smaller data frame for flights headed to LAX instead of all flights.

Logical operators: Filtering for certain observations (e.g. flights from a particular airport) is often of interest in data frames where we might want to examine observations with certain characteristics separately from the rest of the data. To do so, you can use the `filter` function and a series of **logical operators**. The most commonly used logical operators for data analysis are as follows:

- `==` means "equal to"
- `!=` means "not equal to"
- `>` or `<` means "greater than" or "less than"
- `>=` or `<=` means "greater than or equal to" or "less than or equal to"

You can also obtain numerical summaries for these flights:

```
lax_flights %>%
  summarise(mean_dd   = mean(dep_delay),
            median_dd = median(dep_delay),
            n         = n())
```

```
## # A tibble: 1 x 3
##   mean_dd median_dd     n
##     <dbl>     <dbl> <int>
## 1    9.78        -1  1583
```

Note that in the `summarise` function you created a list of three different numerical summaries that you were interested in. The names of these elements are user defined, like `mean_dd`, `median_dd`, `n`, and you can customize these names as you like (just don't use spaces in your names). Calculating these summary statistics also requires that you know the function calls. Note that `n()` reports the sample size.

Summary statistics: Some useful function calls for summary statistics for a single numerical variable are as follows:

- `mean`
- `median`
- `sd`
- `var`
- `IQR`
- `min`
- `max`

Note that each of these functions takes a single vector as an argument and returns a single value.

You can also filter based on multiple criteria. Suppose you are interested in flights headed to San Francisco (SFO) in February:

```
sfo_feb_flights <- nycflights %>%
  filter(dest == "SFO", month == 2)
```

Note that you can separate the conditions using commas if you want flights that are both headed to SFO **and** in February. If you are interested in either flights headed to SFO **or** in February, you can use the `|` instead of the comma.

2. Create a new data frame that includes flights headed to SFO in February, and save this data frame as `sfo_feb_flights`. How many flights meet these criteria?

- ***68 flights meet this criteria.***

```
#Create new data frame to show flights headed to SFO in February
sfo_feb_flights <- nycflights %>%
  filter(dest == "SFO", month == 2)
count(sfo_feb_flights)
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1    68
```

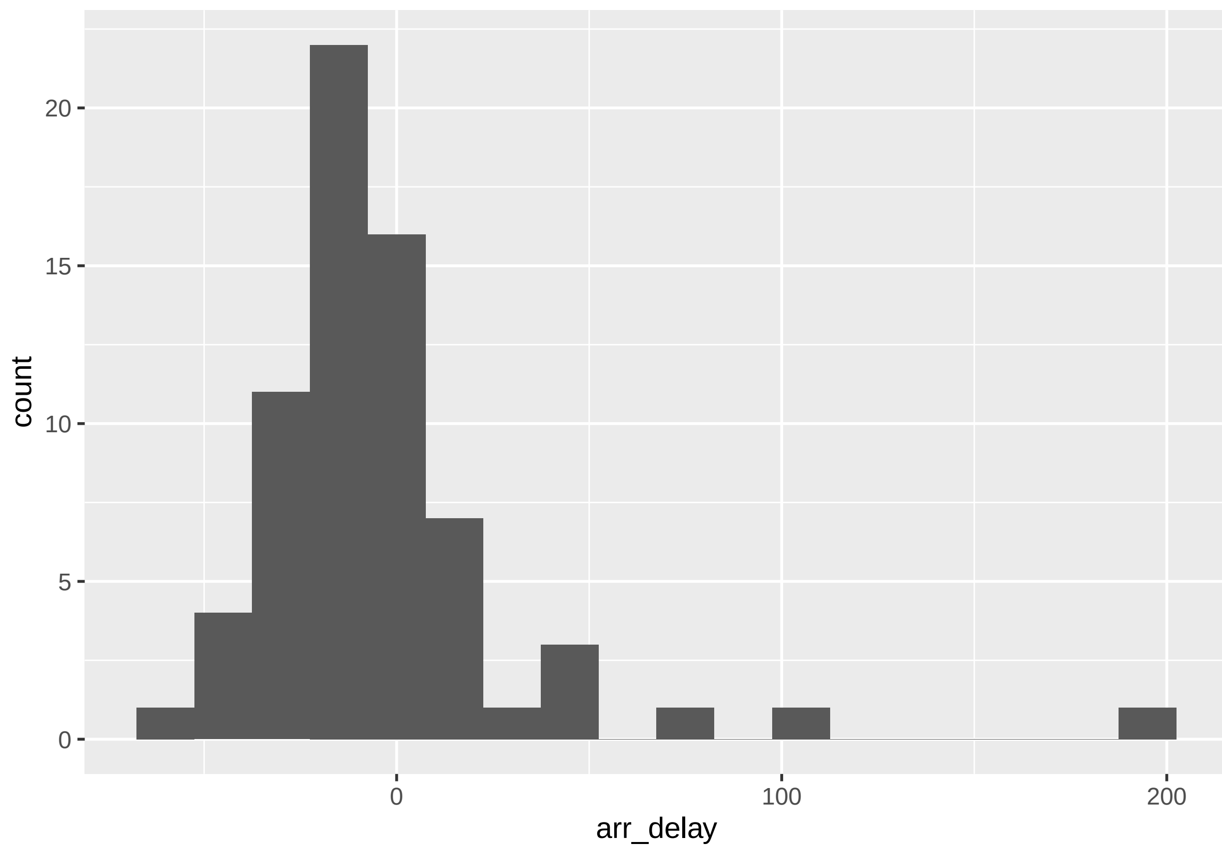
```r
glimpse(sfo_feb_flights)
```

```
## Rows: 68
## Columns: 16
## $ year      <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, ~
## $ month     <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
## $ day       <int> 18, 3, 15, 18, 24, 25, 7, 15, 13, 8, 11, 13, 25, 20, 12, 27,~
## $ dep_time  <int> 1527, 613, 955, 1928, 1340, 1415, 1032, 1805, 1056, 656, 191~
## $ dep_delay <dbl> 57, 14, -5, 15, 2, -10, 1, 20, -4, -4, 40, -2, -1, -6, -7, 2~
## $ arr_time  <int> 1903, 1008, 1313, 2239, 1644, 1737, 1352, 2122, 1412, 1039, ~
## $ arr_delay <dbl> 48, 38, -28, -6, -21, -13, -10, 2, -13, -6, 2, -5, -30, -22,~
## $ carrier   <chr> "DL", "UA", "DL", "UA", "UA", "UA", "B6", "AA", "UA", "DL", ~
## $ tailnum   <chr> "N711ZX", "N502UA", "N717TW", "N24212", "N76269", "N532UA", ~
## $ flight    <int> 1322, 691, 1765, 1214, 1111, 394, 641, 177, 642, 1865, 272, ~
## $ origin    <chr> "JFK", "JFK", "JFK", "EWR", "EWR", "JFK", "JFK", "JFK", "JFK~
## $ dest      <chr> "SFO", "SFO", "SFO", "SFO", "SFO", "SFO", "SFO", "SFO", "SFO~
## $ air_time  <dbl> 358, 367, 338, 353, 341, 355, 359, 338, 347, 361, 332, 351, ~
## $ distance  <dbl> 2586, 2586, 2586, 2565, 2565, 2586, 2586, 2586, 2586, 2586, ~
## $ hour      <dbl> 15, 6, 9, 19, 13, 14, 10, 18, 10, 6, 19, 8, 10, 18, 7, 17, 1~
## $ minute    <dbl> 27, 13, 55, 28, 40, 15, 32, 5, 56, 56, 10, 33, 48, 49, 23, 2~
```

3. Describe the distribution of the **arrival** delays of these flights using a histogram and appropriate summary statistics. **Hint:** The summary statistics you use should depend on the shape of the distribution.

- ***The distribution is right skewed multi-modal. For the summary statistics the median and IQR are the best representation of the data since it'll show the middle number and the outliers.***

```r
#Create a histogram for arrival delays
ggplot(data = sfo_feb_flights, aes(x = arr_delay)) +
  geom_histogram(binwidth = 15)
```




```
#Summarize data to show arrival delays
summary(sfo_feb_flights$arr_delay)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -66.00  -21.25  -11.00   -4.50    2.00  196.00
```

```
IQR(sfo_feb_flights$arr_delay)
```

```
## [1] 23.25
```

Another useful technique is quickly calculating summary statistics for various groups in your data frame. For example, we can modify the above command using the `group_by` function to get the same summary stats for each origin airport:

```
sfo_feb_flights %>%
  group_by(origin) %>%
  summarise(median_dd = median(dep_delay), iqr_dd = IQR(dep_delay), n_flights = n())
```

```
## # A tibble: 2 x 4
##   origin median_dd iqr_dd n_flights
##   <chr>      <dbl>  <dbl>     <int>
## 1 EWR          0.5   5.75         8
## 2 JFK         -2.5  15.2         60
```

Here, we first grouped the data by `origin` and then calculated the summary statistics.

4. Calculate the median and interquartile range for `arr_delays` of flights in in the `sfo_feb_flights` data frame, grouped by carrier. Which carrier has the most variable arrival delays?

- ***Based on the IQR the carriers with the most variable arrival delays are DL and UA with the highest IQR values of 22 each.***

```
#Summarize arr_delay group by carrier
sfo_feb_flights %>%
  group_by(carrier) %>%
  summarise(median_dd = median(arr_delay), iqr_dd = IQR(arr_delay), n_flights = n())
```

```
## # A tibble: 5 x 4
##   carrier median_dd iqr_dd n_flights
##   <chr>       <dbl>  <dbl>     <int>
## 1 AA            5     17.5        10
## 2 B6          -10.5   12.2         6
## 3 DL          -15     22          19
## 4 UA          -10     22          21
## 5 VX          -22.5   21.2        12
```

Departure delays by month

Which month would you expect to have the highest average delay departing from an NYC airport? * ***I expect December and the start summer vacation, July, to be the months with the highest delays departing from NYC airports. In December, many people are looking to go away and escape the snow or visit family. In July, all the students are out from school and families are trying to enjoy the summer before going back to school.***

Let's think about how you could answer this question:

- First, calculate monthly averages for departure delays. With the new language you are learning, you could
  - `group_by` months, then
  - `summarise` mean departure delays.
- Then, you could to `arrange` these average delays in `desc`ending order

```
nycflights %>%
  group_by(month) %>%
  summarise(mean_dd = mean(dep_delay)) %>%
  arrange(desc(mean_dd))
```

```
## # A tibble: 12 x 2
##    month mean_dd
##    <int>   <dbl>
##  1     7    20.8
##  2     6    20.4
##  3    12    17.4
##  4     4    14.6
##  5     3    13.5
```

```
## 6      5   13.3
## 7      8   12.6
## 8      2   10.7
## 9      1   10.2
## 10     9    6.87
## 11    11    6.10
## 12    10    5.88
```

5. Suppose you really dislike departure delays and you want to schedule your travel in a month that minimizes your potential departure delay leaving NYC. One option is to choose the month with the lowest mean departure delay. Another option is to choose the month with the lowest median departure delay. What are the pros and cons of these two choices?

- ***Pros for choosing mean: it accounts for the whole data set therefore, being a great representation of what the data looks like.***
- ***Cons for choosing mean: if there's many outliers this can skew the mean and not give a 100% representation of the data set.***
- ***Pros for choosing median: accounts for the middle number of the data set.***
- ***Cons for choosing median: it only accounts for the middle number in the data set, there's no account on outliers or any other part of the data set that would be beneficial to decision making.***

On time departure rate for NYC airports

Suppose you will be flying out of NYC and want to know which of the three major NYC airports has the best on time departure rate of departing flights. Also supposed that for you, a flight that is delayed for less than 5 minutes is basically "on time."" You consider any flight delayed for 5 minutes of more to be "delayed".

In order to determine which airport has the best on time departure rate, you can

- first classify each flight as "on time" or "delayed",
- then group flights by origin airport,
- then calculate on time departure rates for each origin airport,
- and finally arrange the airports in descending order for on time departure percentage.

Let's start with classifying each flight as "on time" or "delayed" by creating a new variable with the `mutate` function.

```
nycflights <- nycflights %>%
  mutate(dep_type = ifelse(dep_delay < 5, "on time", "delayed"))
```

The first argument in the `mutate` function is the name of the new variable we want to create, in this case `dep_type`. Then if `dep_delay < 5`, we classify the flight as `"on time"` and `"delayed"` if not, i.e. if the flight is delayed for 5 or more minutes.

Note that we are also overwriting the `nycflights` data frame with the new version of this data frame that includes the new `dep_type` variable.

We can handle all of the remaining steps in one code chunk:

```
nycflights %>%
  group_by(origin) %>%
  summarise(ot_dep_rate = sum(dep_type == "on time") / n()) %>%
  arrange(desc(ot_dep_rate))
```

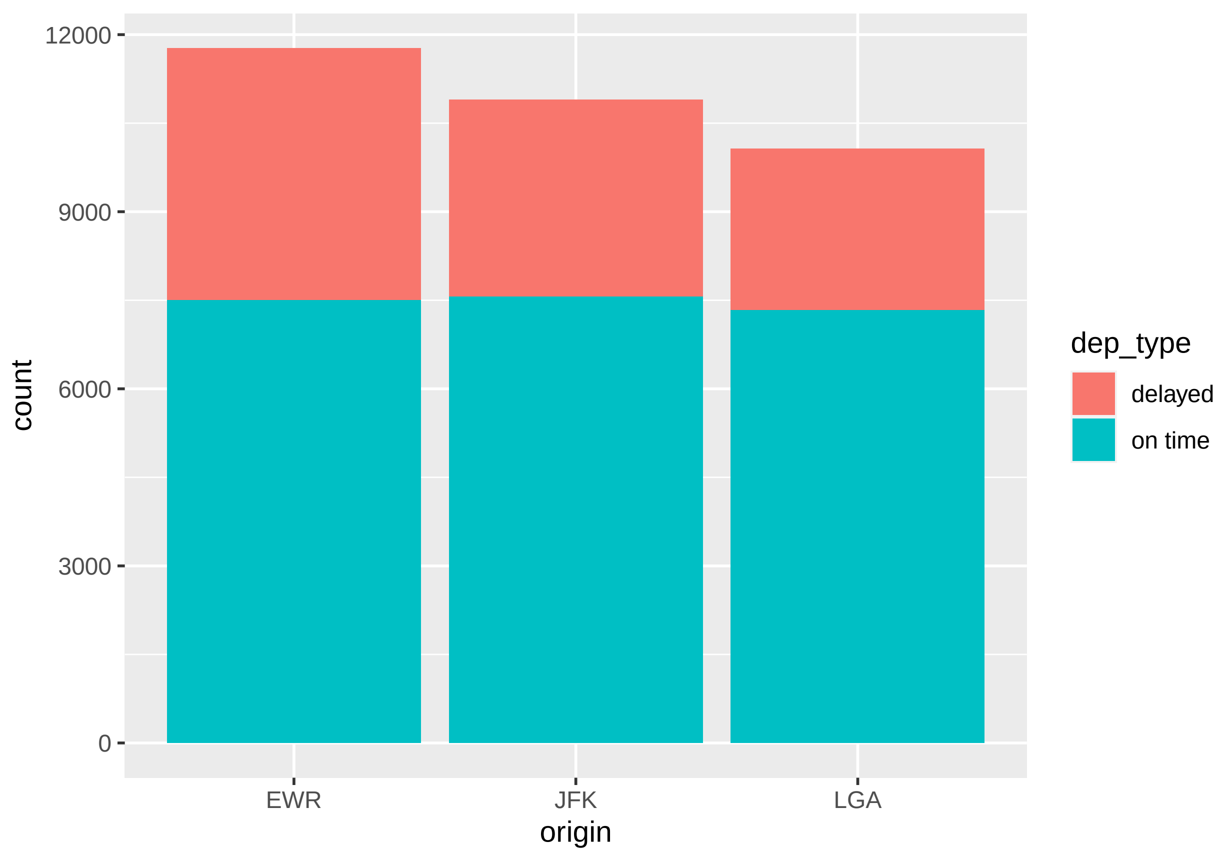
```
## # A tibble: 3 x 2
##   origin ot_dep_rate
##   <chr>        <dbl>
## 1 LGA          0.728
## 2 JFK          0.694
## 3 EWR          0.637
```

6. If you were selecting an airport simply based on on time departure percentage, which NYC airport would you choose to fly out of?

- ***I would fly out from LGA because it has the lowest delays percentage on departures.***

You can also visualize the distribution of on on time departure rate across the three airports using a segmented bar plot.

```r
ggplot(data = nycflights, aes(x = origin, fill = dep_type)) +
  geom_bar()
```



More Practice

7. Mutate the data frame so that it includes a new variable that contains the average speed, `avg_speed` traveled by the plane for each flight (in mph). **Hint:** Average speed can be calculated as distance divided by number of hours of travel, and note that `air_time` is given in minutes.

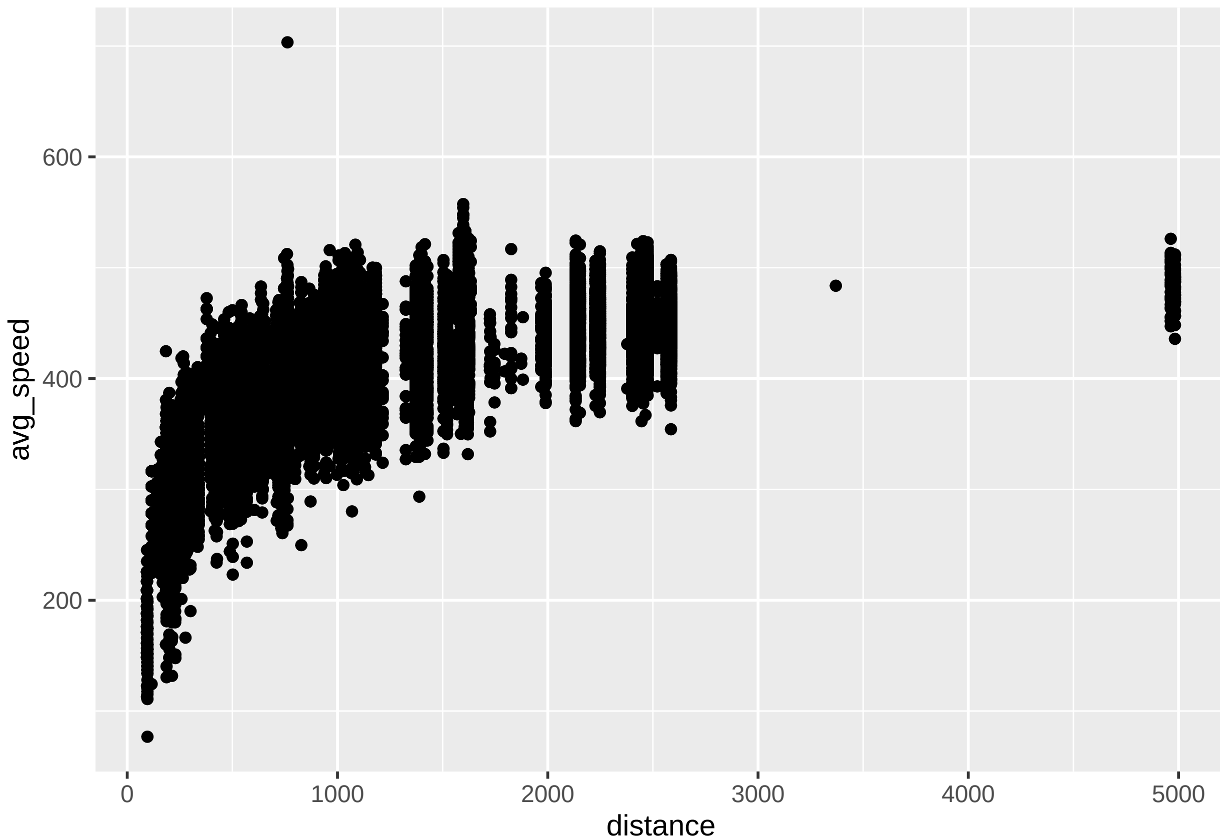
```r
# Mutate data frame
nycflights <- nycflights %>%
  mutate(avg_speed = distance / (air_time / 60))
nycflights
```

```
## # A tibble: 32,735 x 18
##     year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##    <int> <int> <int>    <int>     <dbl>    <int>     <dbl> <chr>   <chr>
##  1  2013     6    30      940        15     1216        -4 VX      N626VA
##  2  2013     5     7     1657        -3     2104        10 DL      N3760C
##  3  2013    12     8      859        -1     1238        11 DL      N712TW
##  4  2013     5    14     1841        -4     2122       -34 DL      N914DL
##  5  2013     7    21     1102        -3     1230        -8 9E      N823AY
##  6  2013     1     1     1817        -3     2008         3 AA      N3AXAA
##  7  2013    12     9     1259        14     1617        22 WN      N218WN
##  8  2013     8    13     1920        85     2032        71 B6      N284JB
##  9  2013     9    26      725       -10     1027        -8 AA      N3FSAA
## 10  2013     4    30     1323        62     1549        60 EV      N12163
## # ... with 32,725 more rows, and 9 more variables: flight <int>, origin <chr>,
## #   dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   dep_type <chr>, avg_speed <dbl>
```

8. Make a scatterplot of `avg_speed` vs. `distance`. Describe the relationship between average speed and distance. **Hint:** Use `geom_point()`.

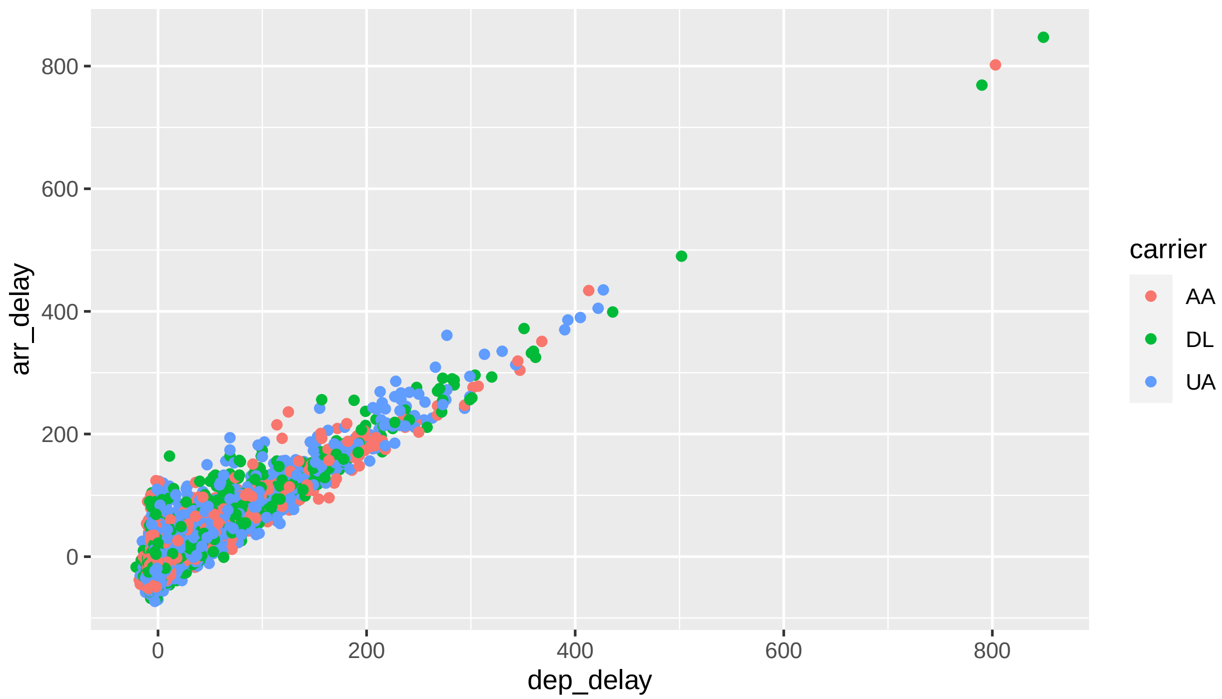
- ***Overall, as the distance increases so does the avg_speed. I do notice that between the ranges of 1000 - 2500, the avg_speed remains consistent with the exception of a few outliers.***

```r
#Scatter plot of avg_speed vs distance
ggplot(data = nycflights, mapping = aes(x = distance, y = avg_speed)) +
        geom_point()
```



9. Replicate the following plot. **Hint:** The data frame plotted only contains flights from American Airlines, Delta Airlines, and United Airlines, and the points are `color`ed by `carrier`. Once you replicate the plot, determine (roughly) what the cutoff point is for departure delays where you can still expect to get to your destination on time.

- ***The first 15-20 mins for any flight you can still expect to arrive to your destination on time. After this time you can see that each carrier has a higher chance of being late.***




```
#Replication of scatterplot
delays_3_carriers <- nycflights %>%
  filter(carrier == "AA" | carrier == "DL" | carrier == "UA" )
ggplot(data = delays_3_carriers, aes(x = dep_delay, y = arr_delay, color = carrier)) +
    geom_point(size=2) +
  xlim(0, 80) +
  ylim(0, 80)
```


arr_delay
dep_delay
0
20
40
60
80
carrier
AA
DL
UA