Introduction to data

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.

```r
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:

```r
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

```r
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:

```r
?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.

```r
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:

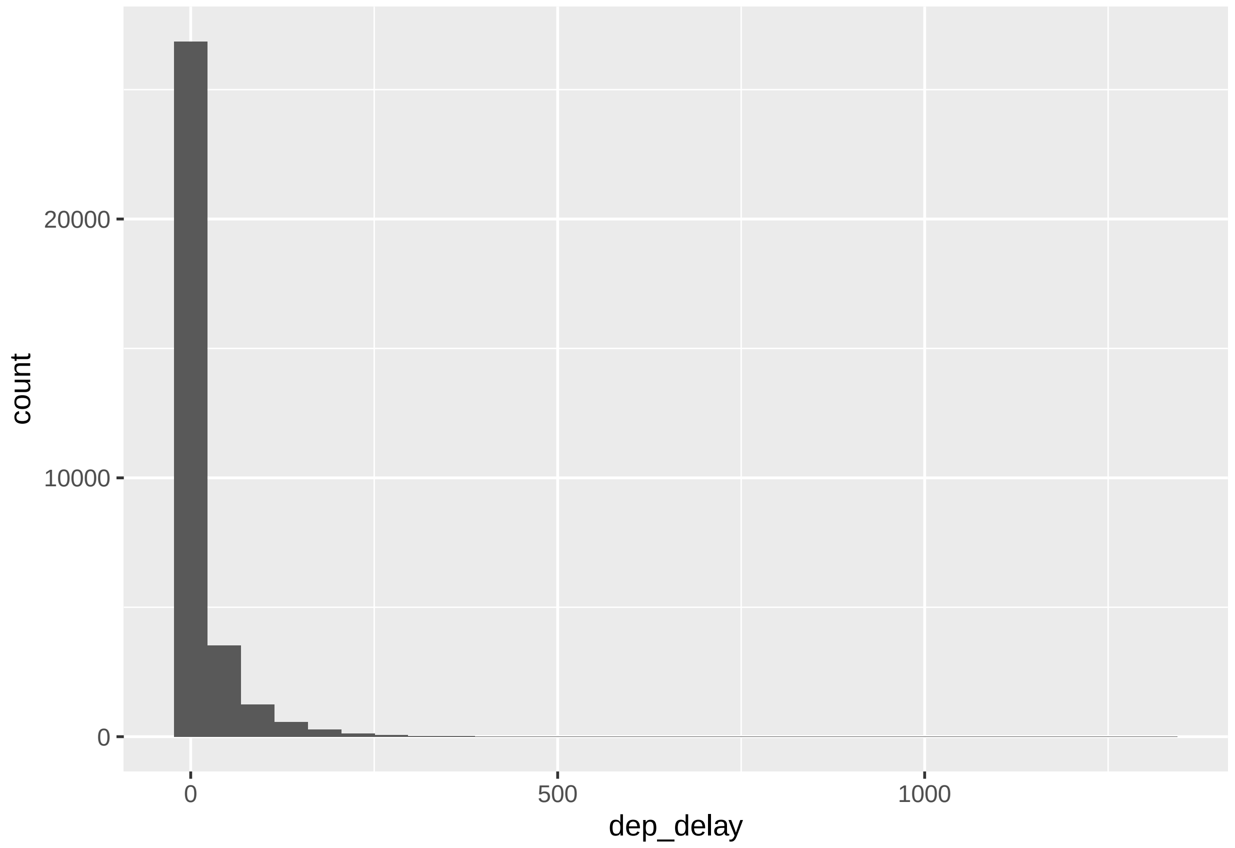
- How delayed were flights that were headed to Los Angeles?
- How do departure delays vary by month?
- Which of the three major NYC airports has the best on time percentage for departing flights?

Analysis

Departure delays

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

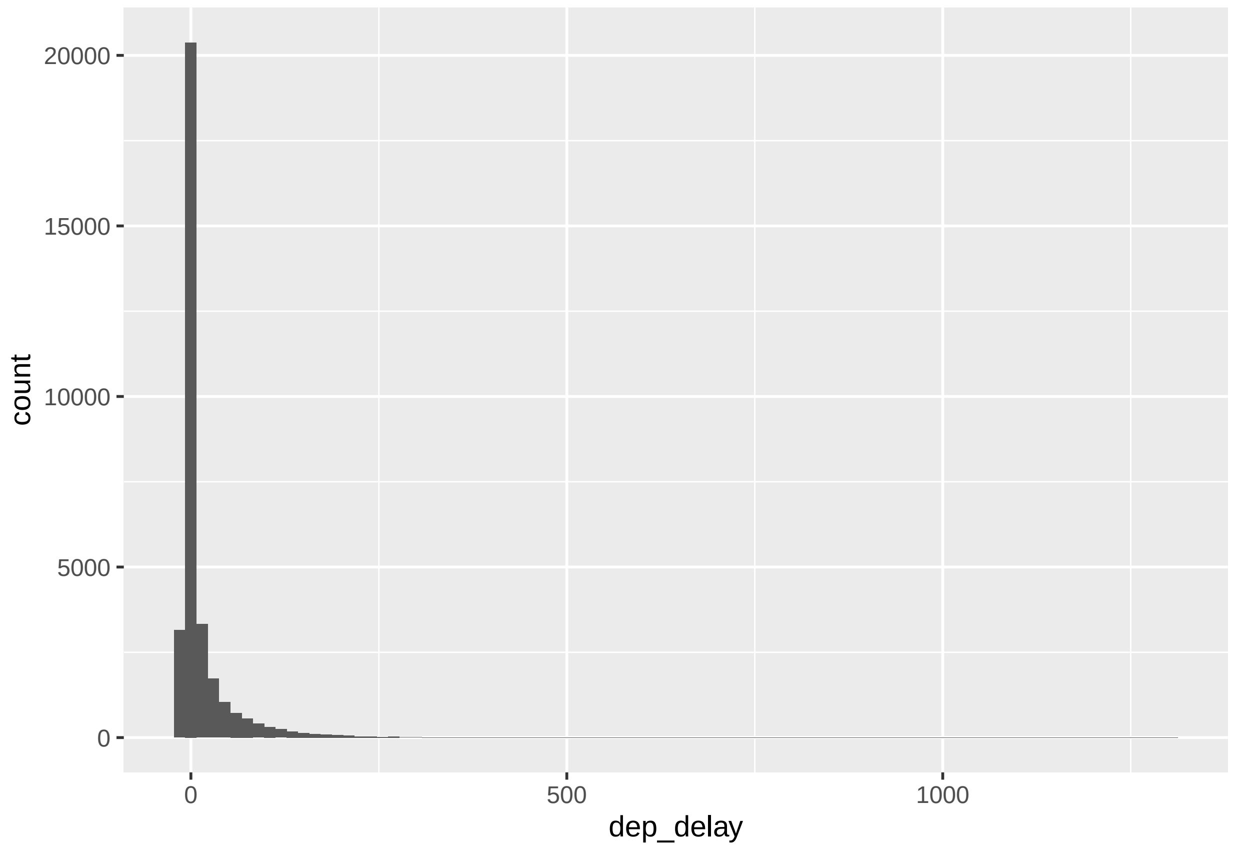
```
ggplot(data = nycflights, aes(x = dep_delay)) +
  geom_histogram()
```



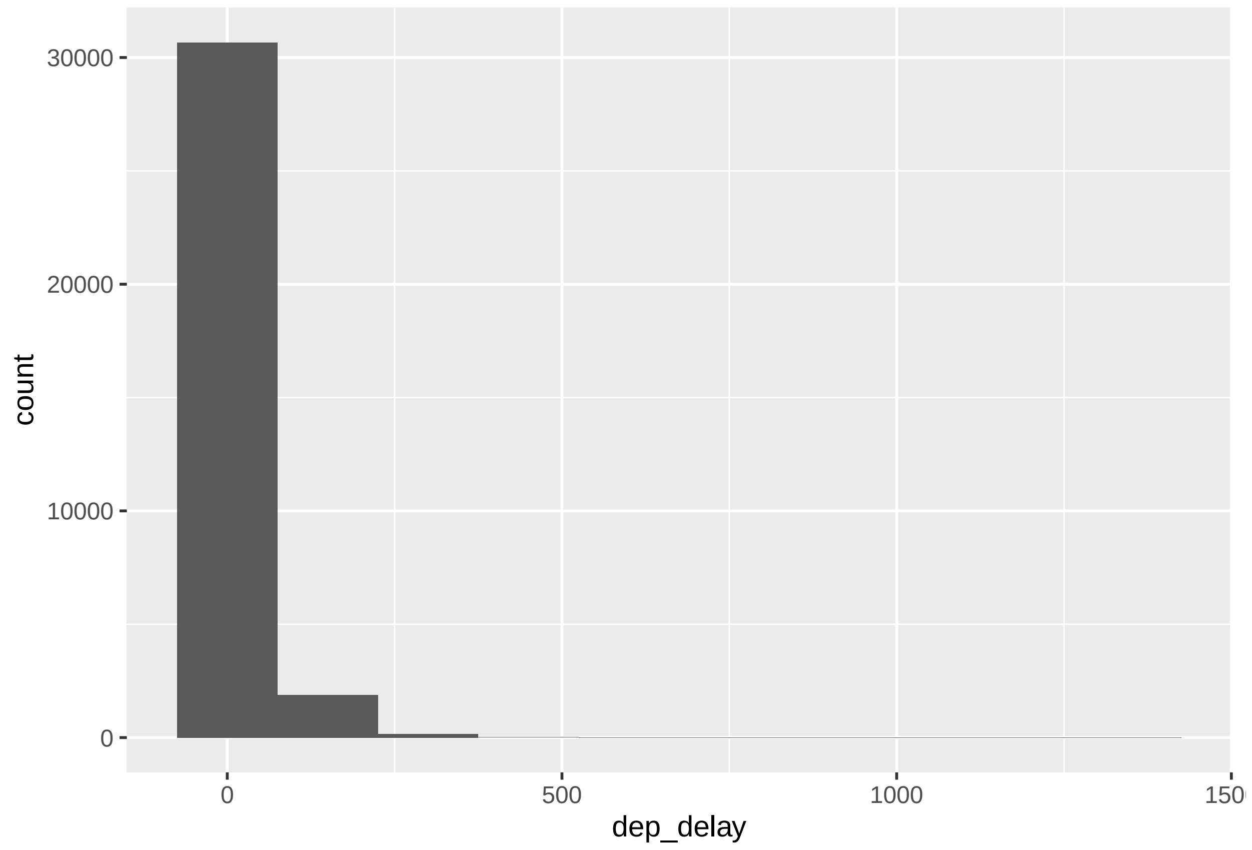
This function says to plot the `dep_delay` variable from the `nycflights` data frame on the x-axis. It also defines a `geom` (short for geometric object), which describes the type of plot you will produce.

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)
```



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

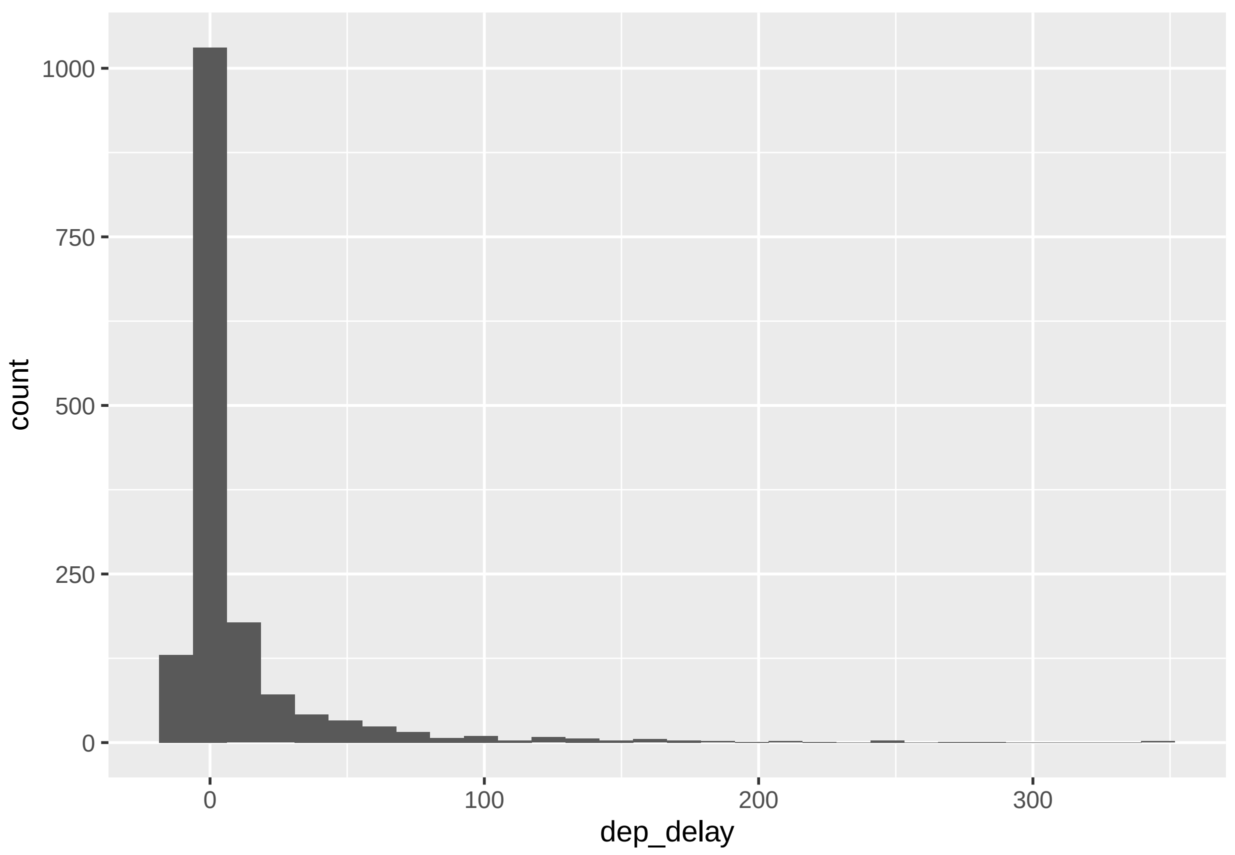


1. Look carefully at these three histograms. How do they compare? Are features revealed in one that are obscured in another?

Insert your answer here Looking at the original histogram width the default binwidth, it seems to how an overall trend downwards. Meaning, that the longer the delay the lower the odds of it happening is. However, by narrowing the binwidth in the second histogram we can an interesting stat. We can now see that the beginning of the graph is actually much lower than than the next bin and slightly lower than the third. This actually makes a lot of sense since the first bin represents early departures, the second represents on-time departures and only after that do nthe bins represent delays. The benefit of narrowing the bins this way is being able to see how much of that first bin in the first histogram was on-time flights versus delayed flights. That specific subset can very important in analyzing this data. Another benefit is being able to see how much of that first bin was early departures and how that compares to delays (we can see it is the third most likely outcome). A big drawback of this binwidth is how little we can tell about the second half of the histogram. We can't see how they compare to one another or even how many total bins there are. Expanding the binwidth allows us to have them all combined into one bin and gain a more accurate picture of the total information.

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.

```r
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:

```r
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:

```r
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?

Insert your answer here

```r
#The code to create and save the data frame was already writen
glimpse(sfo_feb_flights)
```

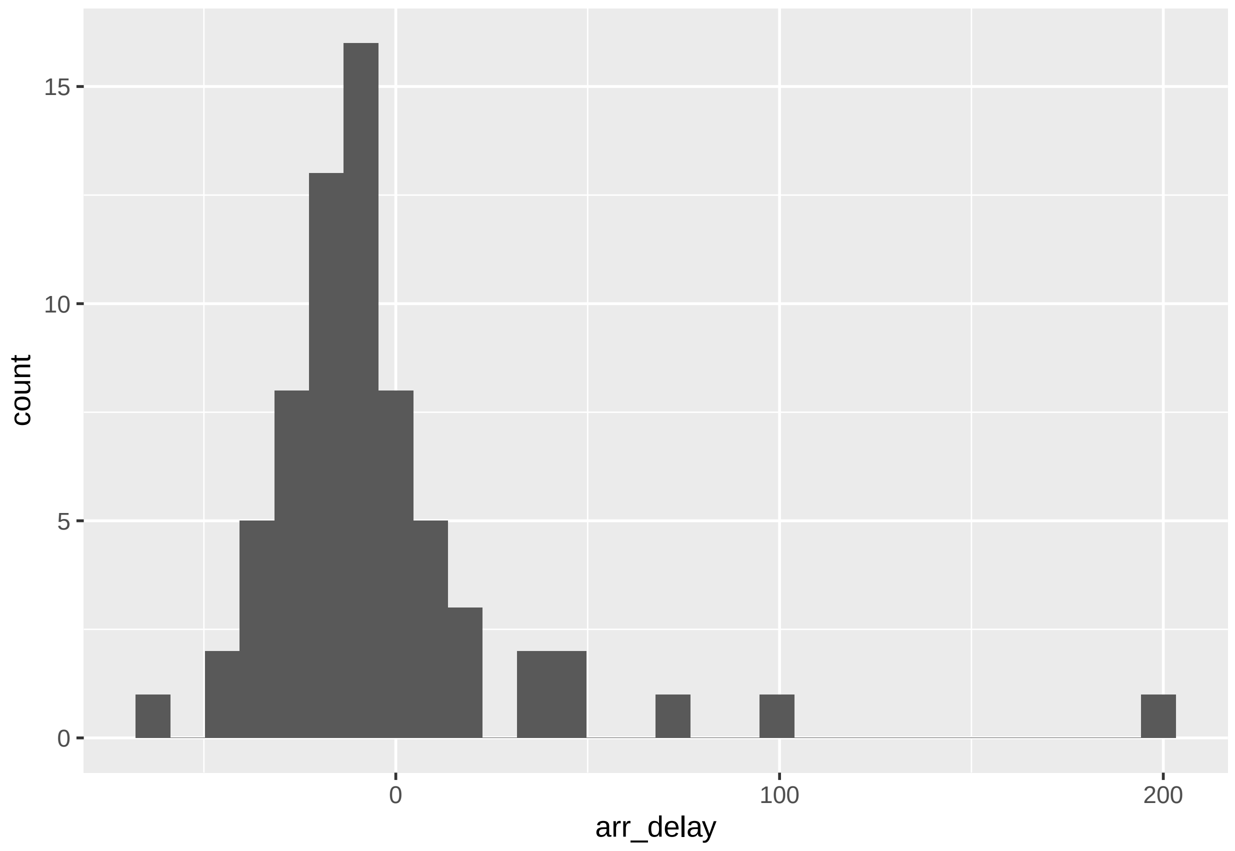
```
## Rows: 68
## Columns: 16
## $ year      <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, ~
## $ month     <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
## $ day       <int> 18, 3, 15, 18, 24, 25, 7, 15, 13, 8, 11, 13, 25, 20, 12, 27,~
## $ dep_time  <int> 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~
```

By using the glimpse() function, we can see there are 68 rows included in the dataframe. Since the rows represent flights, we know there were 68 flights from NYC to SFO in February.

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.

Insert your answer here

```r
ggplot(data = sfo_feb_flights, aes(x =arr_delay)) +
  geom_histogram()
```



```
sfo_feb_flights %>%
  summarise(mean_dd   = mean(arr_delay),
            median_dd = median(arr_delay),
            IQR = IQR(arr_delay),
            n = n())
```

```
## # A tibble: 1 x 4
##   mean_dd median_dd   IQR     n
##     <dbl>     <dbl> <dbl> <int>
## 1    -4.5       -11  23.2    68
```

By creating the histogram first, we can see the overall distribution of the data. We can see that while most of the datapoints are bunched up in one area there are some very small datapoints further out. This is highlighted the most by the last bin. That large of an outlier can really distort the mean, variance and standard deviation of the entire dataset. For that reason, we would probably be best off focusing on the median and IQR. Using the the summarise() function, we can see some relevant summary statistics showing that the median is -11 and the IGR is 23.2. (I included the mean because I think that it is always useful and, unless proven to be a mistake, data should never be completely discarded).

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?

Insert your answer here

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

```
## # A tibble: 5 x 4
##   carrier median_dd iqr_dd n_flights
##   <chr>       <dbl>  <dbl>     <int>
## 1 AA           13     32.8        10
## 2 VX           -3.5   16.8        12
## 3 UA           -2     13          21
## 4 DL           -3      6.5        19
## 5 B6           -2      3.5         6
```

By printing the above summary, we can easily see that American Airlines (AA) has an IQR of 32.8. This is the highest IQR by far of these airlines and illustrates how much the delay time could vary. However, it is worth noting, that AA only flew 10 flights in the selected dataframe and thus has a smaller sample size than some of the other carriers.

Departure delays by month

Which month would you expect to have the highest average delay departing from an NYC airport?

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?

Insert your answer here

Basing your choice of which month to travel on the median maximizes the chance of being in the desired group. You would have a 50% chance of being delayed the median amount or less. However, that doesn't factor in the length of the delays at all. If the distribution of the delays is uneven, for example, if half of the delays are under 10 minutes and the other half range all the way up to 12 hours, then there is a very significant chance of being delayed a lot more than ten minutes. If you use the mean to decide which airport to use, then the total length of the delays are factored in to the equation. In the above example, this would tell you a more accurate time you might be delayed assuming you do end up being delayed. However, one extreme outlier can heavily distort the mean and make you make the wrong decision.

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:

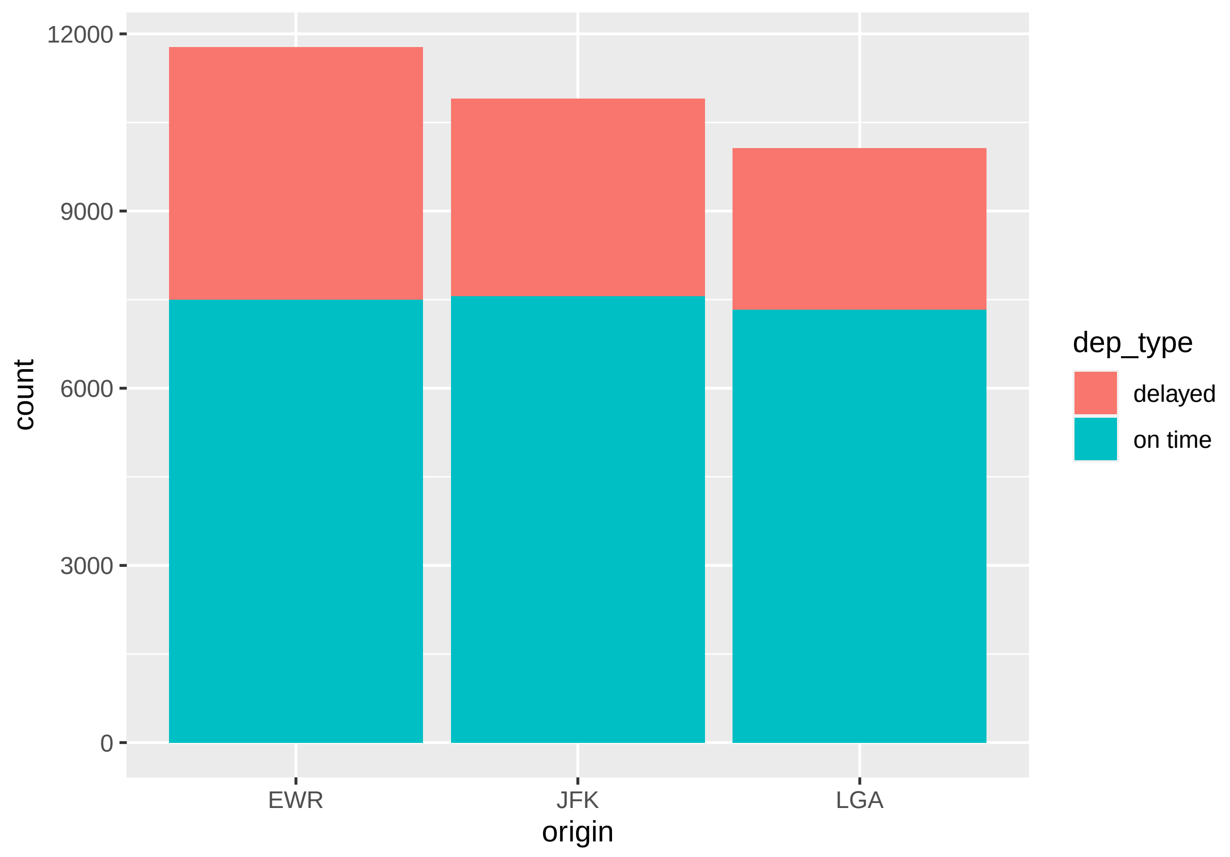
```
nycflights %>%
  group_by(origin) %>%
  summarise(ot_dep_rate = sum(dep_type == "on time") / n()) %>%
  arrange(desc(ot_dep_rate))
```

```
## # 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?

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

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



Insert your answer here

Based on the above information, we see LGA has an on-time departure rate of 0.728. This is the highest of the three NYC airports and would therefor be the best choice for someone who only cares about his chances of getting delayed or not. This does not factor in carrier or length of the delay.

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.

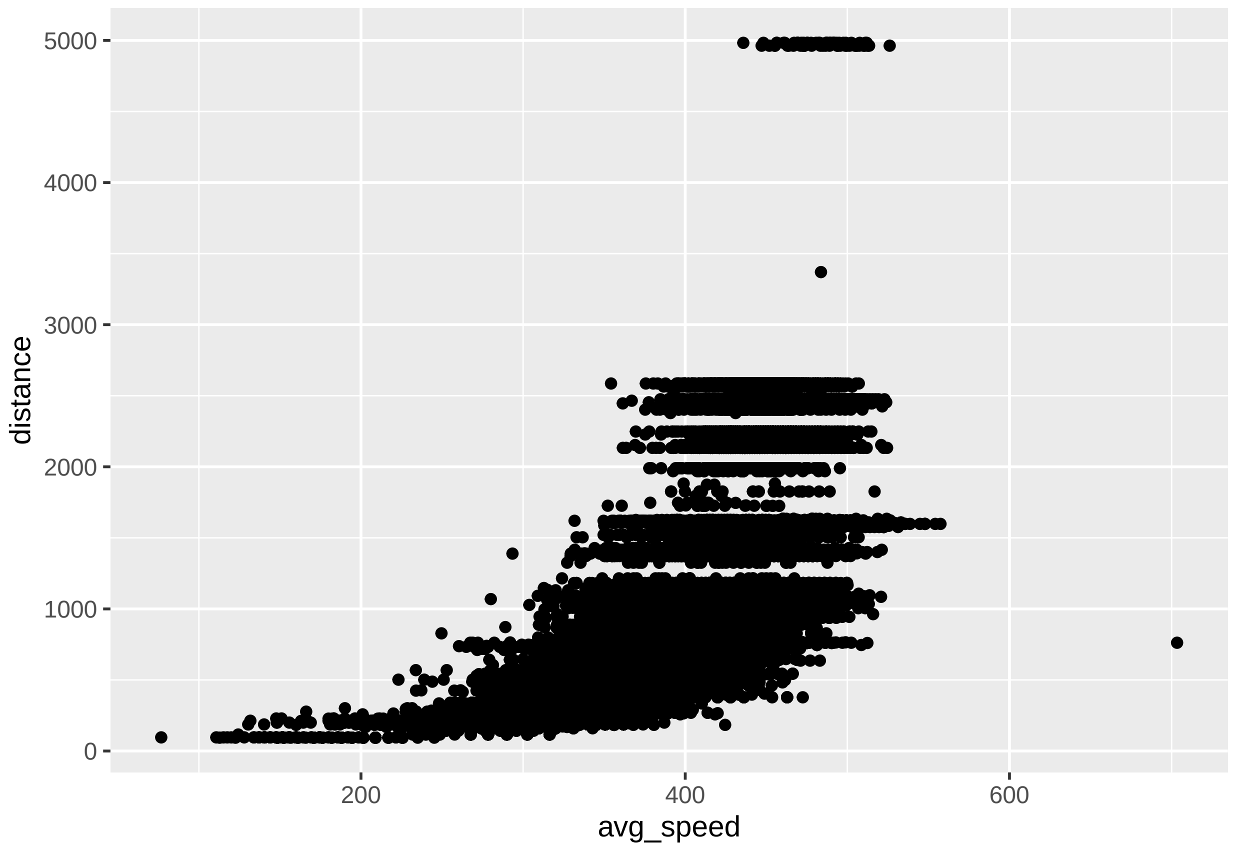
Insert your answer here

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

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

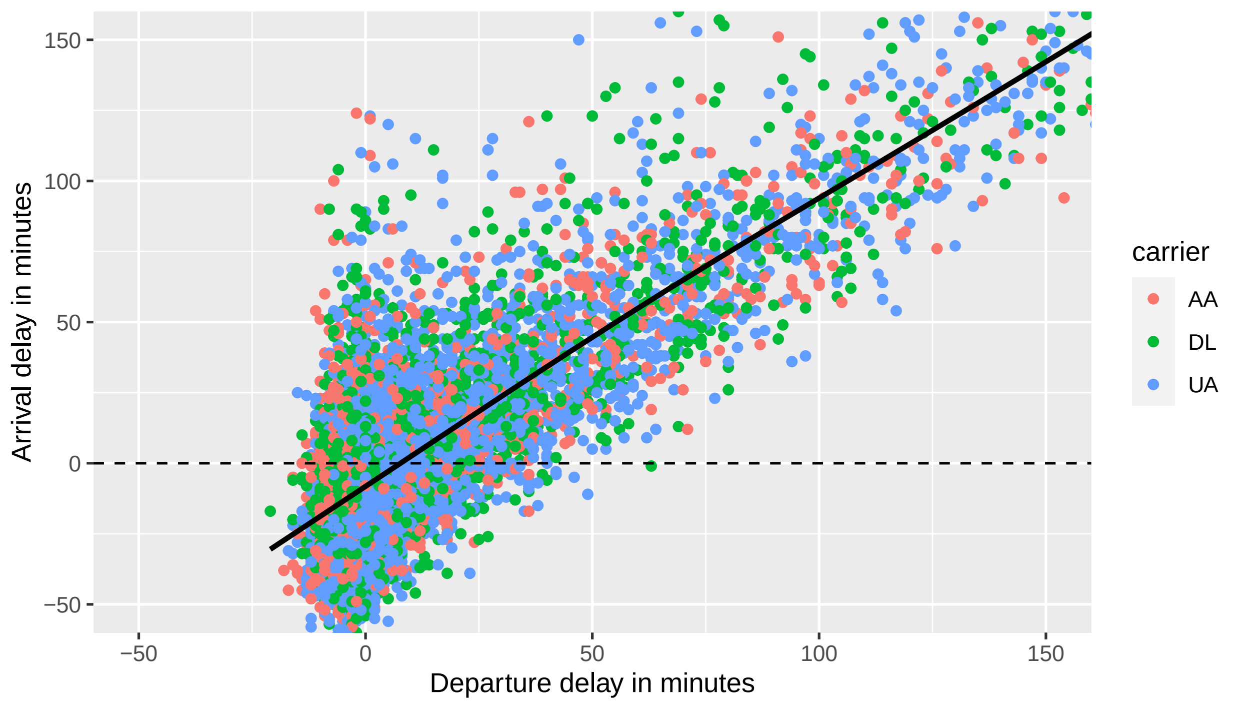
Insert your answer here

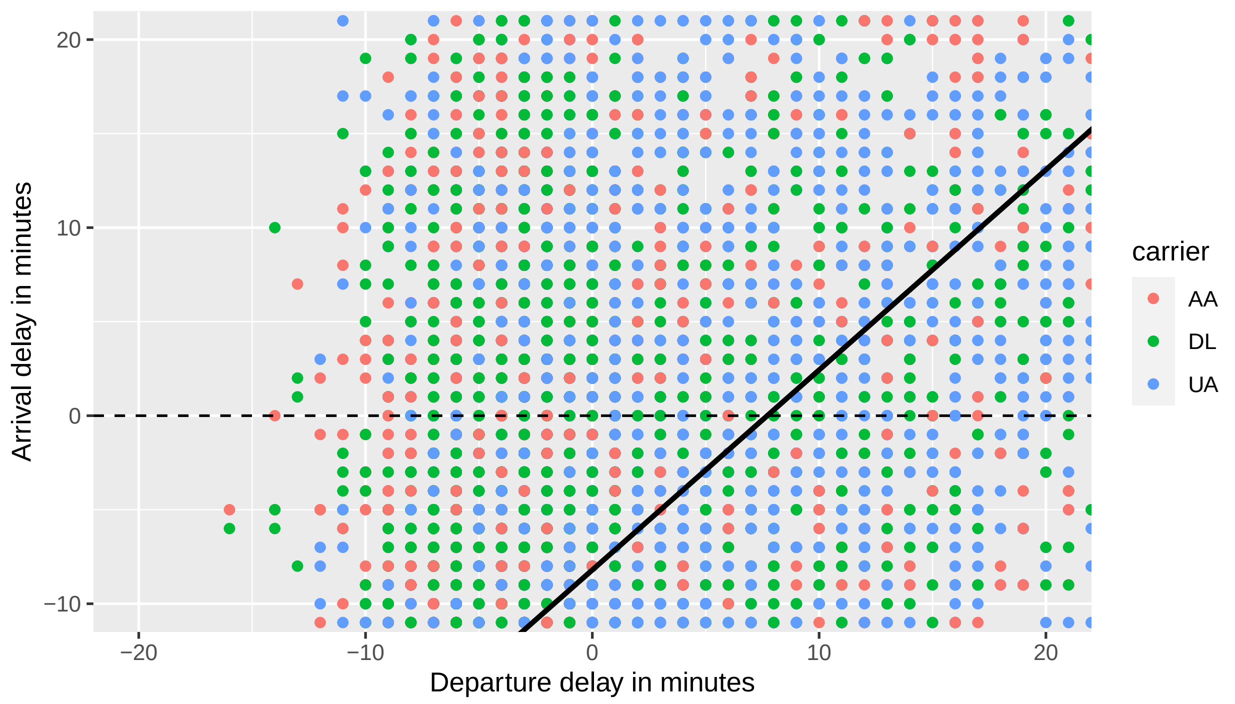
```r
ggplot(data = nycflights, aes(x =avg_speed, y =distance)) +
  geom_point()
```



As we can see in the above scatterplot, there is a distinct correlation between the distance flown and the average speed. The longer the distance flown, the faster the average speed is. This is probably due to the ratio of the beginng and end of the flight, when the plane flies slower, to the total flight duration. The longer the flight is, the less those periods drag down the average speed. It is possible that the median flight speed is the same regardless of flight duration. This is another instance of the pros and cons of using mean versus median.

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.





Insert your answer here

Here I zoomed in to the original plot twice. The first one I zoomed in just enough to isolate the datapoints needed to answer the question. The furthest observed datapoint where someone arrived on time was after a delay of around 65 minutes. This obviously doesn't mean one can **expect** to arrive on time, just that it is **possible**. In the second zoom, we can easily see where the fit line and 0 miute arrival delay overlap. It seems to be at around 9 minutes departure delay. This implies that someone could have a delay of around 9 minutes and still reasonably expect to arrive in time. This doesn't take into account the length of the flight. A shorter flight would have a much harder time making up for any delay as opposed to a longer one.