Lab2 - Introduction to data

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Contents

1 Analysis

Load required packages.

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

Load *nycflights* data.

```
data("nycflights")
```

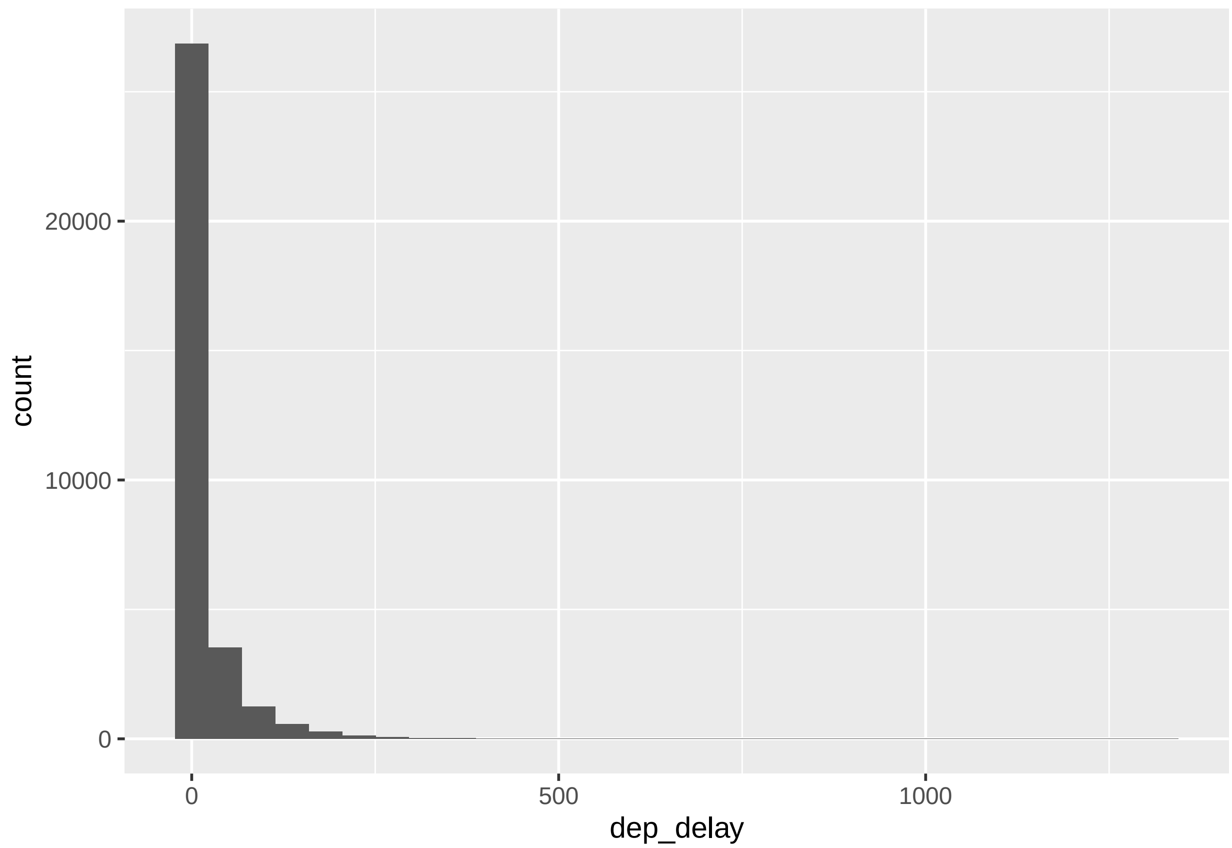
1.1 Departure delays

1.1.1 Exercise 1

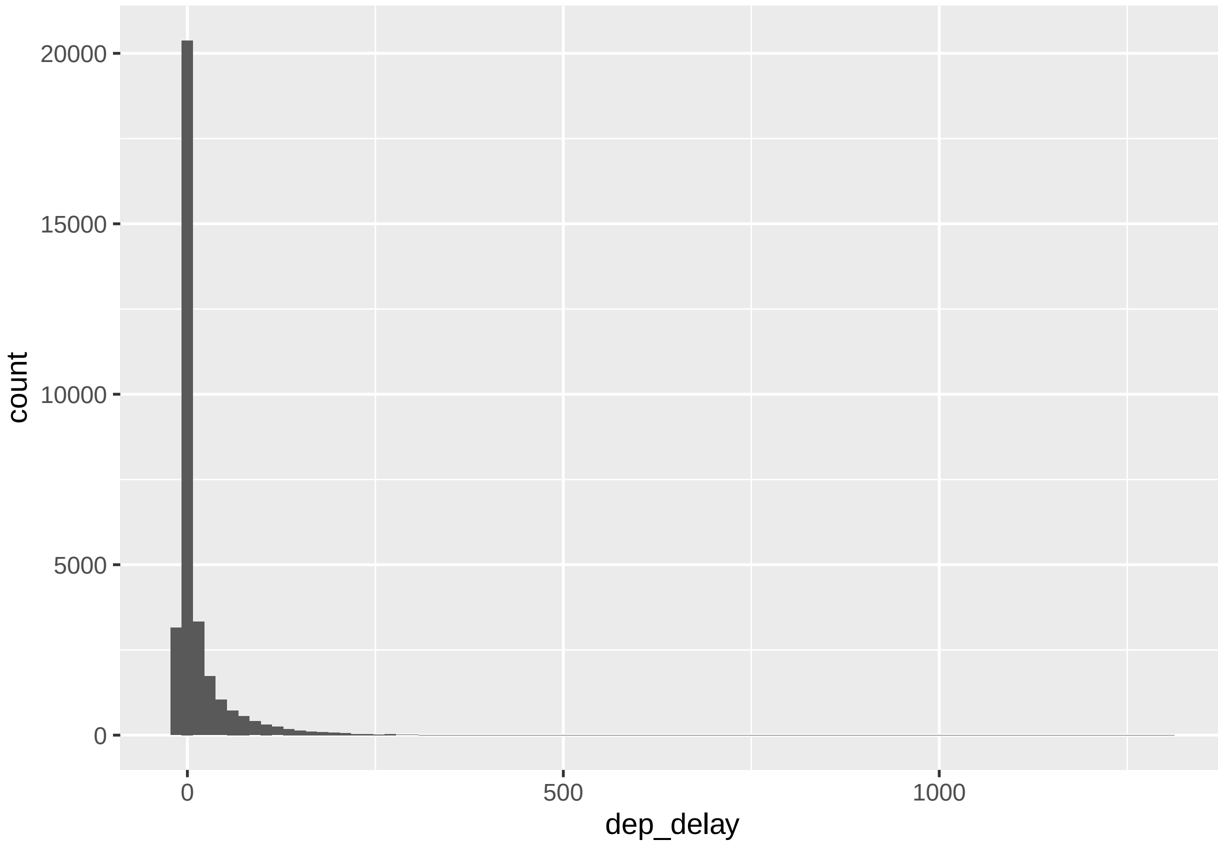
Look carefully at these three histograms. How do they compare? Are features revealed in one that are obscured in another?

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

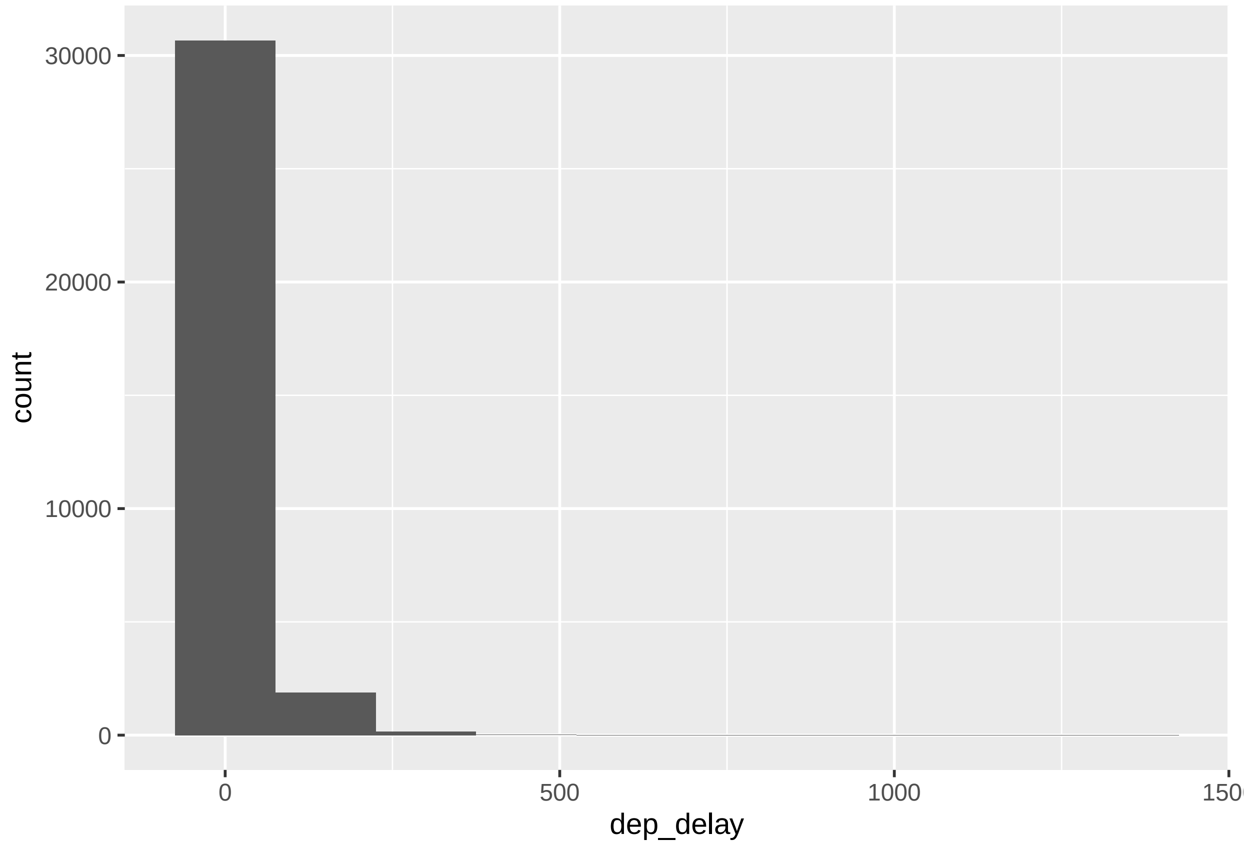
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




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




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



The *binwidth* parameter of *geom_histogrm* function has an impact on the *granualarity* (level of detail) of the resulting plot. First plot has (default) *binwidth=30*. The second plot, has *binwidth=15* and shows the fine-grained details of the underlying observations. The third plot has large bins, *binwidth=150*, and masks the underlying details.

Compared to smaller bins, larger bins mask details of variations in the underlying observations.

1.1.2 Exercise 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?

Let's filter the observations for flights to SFO in February. There were *68* flights departing for SFO in February.

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

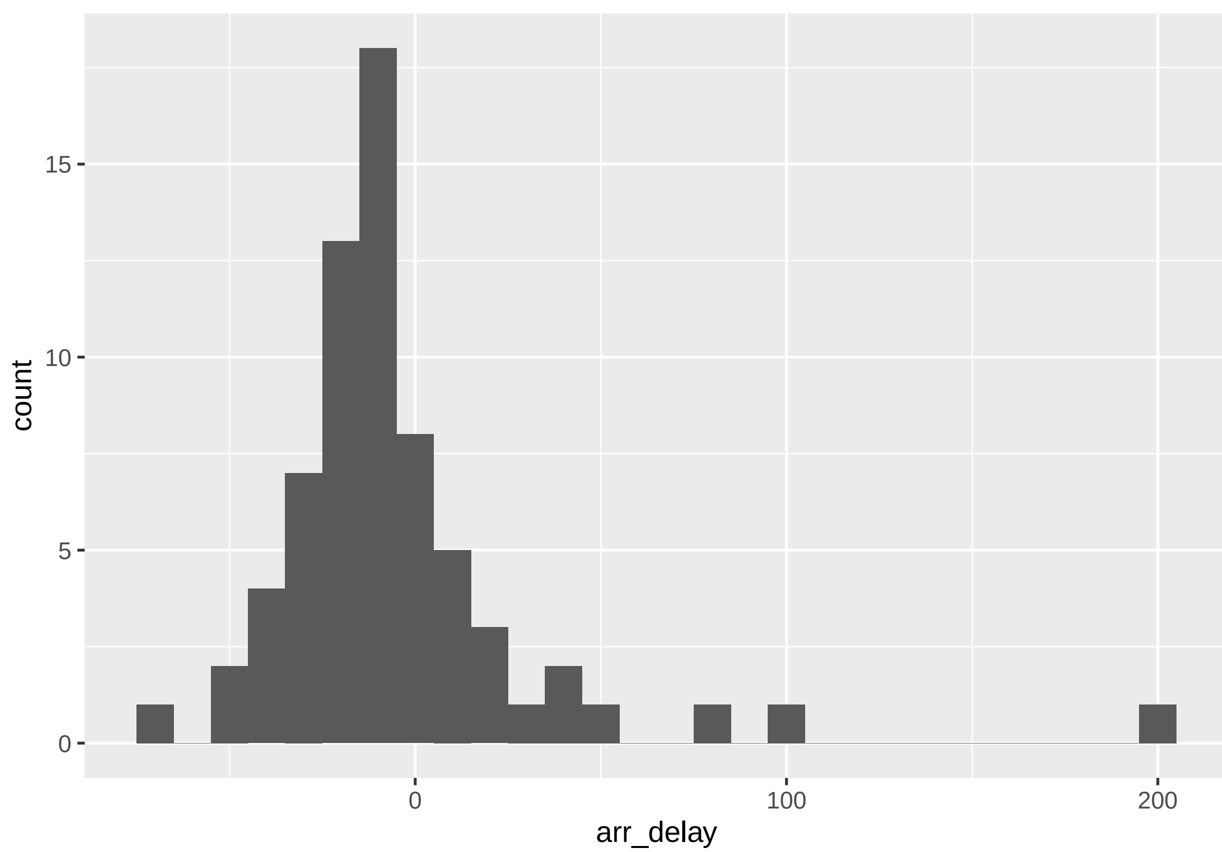
```
## $ arr_time  <int> 1903, 1008, 1313, 2239, 1644, 1737, 1352, 2122, 1412, 1039, ~
## $ arr_delay <dbl> 48, 38, -28, -6, -21, -13, -10, 2, -13, -6, 2, -5, -30, -22,~
## $ carrier   <chr> "DL", "UA", "DL", "UA", "UA", "UA", "B6", "AA", "UA", "DL", ~
## $ tailnum   <chr> "N711ZX", "N502UA", "N717TW", "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~
```

1.1.3 Exercise 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.

Let's plot the arrival delay of flights to SFO. We will use a fine-grained *binwidth = 5* because there are relatively few observations (68) and we want to see detailed shape of the distribution.

```r
ggplot(data = sfo_feb_flights, aes(x = arr_delay)) +
  geom_histogram(binwidth = 10)
```



The arrival delay for SFO bound flights is skewed with a long right tail. Due to the skeweness, *mean* is not a good measure of central tendency. The *median* is a better measure. For the same reason, the spread in the data is captured better with *IQR* compared to *standard deviation*. The *min* and *max* are appropriate measures of range.

To verify our visual observation, lets compute summary stats. The *median=-11*, *IQR=23.25*, *min=-66*, *max=196*. This is in line with the visual observations about outliers.

```
sfo_feb_flights %>%
    summarise(
              irq_dd = IQR(arr_delay),
              median_dd = median(arr_delay),
              min_dd = min(arr_delay),
              max_dd = max(arr_delay)
             )
```

```
## # A tibble: 1 x 4
##   irq_dd median_dd min_dd max_dd
##    <dbl>     <dbl>  <dbl>  <dbl>
## 1   23.2       -11    -66    196
```

1.1.4 Exercise 4

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

DL and UA are *tied* for the most variable delays because their IRQs are tied for the highest at *22.0* (with VX a close third). This suggests that both carriers exhibit the greatest variation in arrival delays for the middle *50%* of their respective observations.

```
sfo_feb_flights %>%
    group_by(carrier) %>%
    summarise(
              iqr_dd = IQR(arr_delay),
              median_dd = median(arr_delay),
              min_dd = min(arr_delay),
              max_dd = max(arr_delay),
              spread_dd = max_dd - min_dd) %>%
    arrange(desc(iqr_dd))
```

```
## # A tibble: 5 x 6
##   carrier iqr_dd median_dd min_dd max_dd spread_dd
##   <chr>    <dbl>     <dbl>  <dbl>  <dbl>     <dbl>
## 1 DL        22       -15      -48     48        96
## 2 UA        22       -10      -35    196       231
## 3 VX        21.2     -22.5    -66     99       165
## 4 AA        17.5       5      -26     76       102
## 5 B6        12.2     -10.5    -18     11        29
```

1.2 Departure delays by month

1.2.1 Exercise 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?

Mean:
Pro: It tells you what is the average departure delay over the whole data set.
Con: It can get skewed by outliers in the observations.

Median:
Pro: Not impacted by outliers in observations, tell you that half of the time departure will be less than (greater than) than the median.
Con: Does not give a sense of how the data is distributed. For example, the median departure delay of a hypothetical dataset with an odd number of observations *[-60, -30, -20, 30, 500, 1000, 2000]*, is *30*. It conveys no information about the spread or range.

1.3 On time departure rates for NYC airports

1.3.1 Exercise 6

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

Let's compute on-time departures, assuming a flight that leaves up to 5 minutes after scheduled departure is considered on time.

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

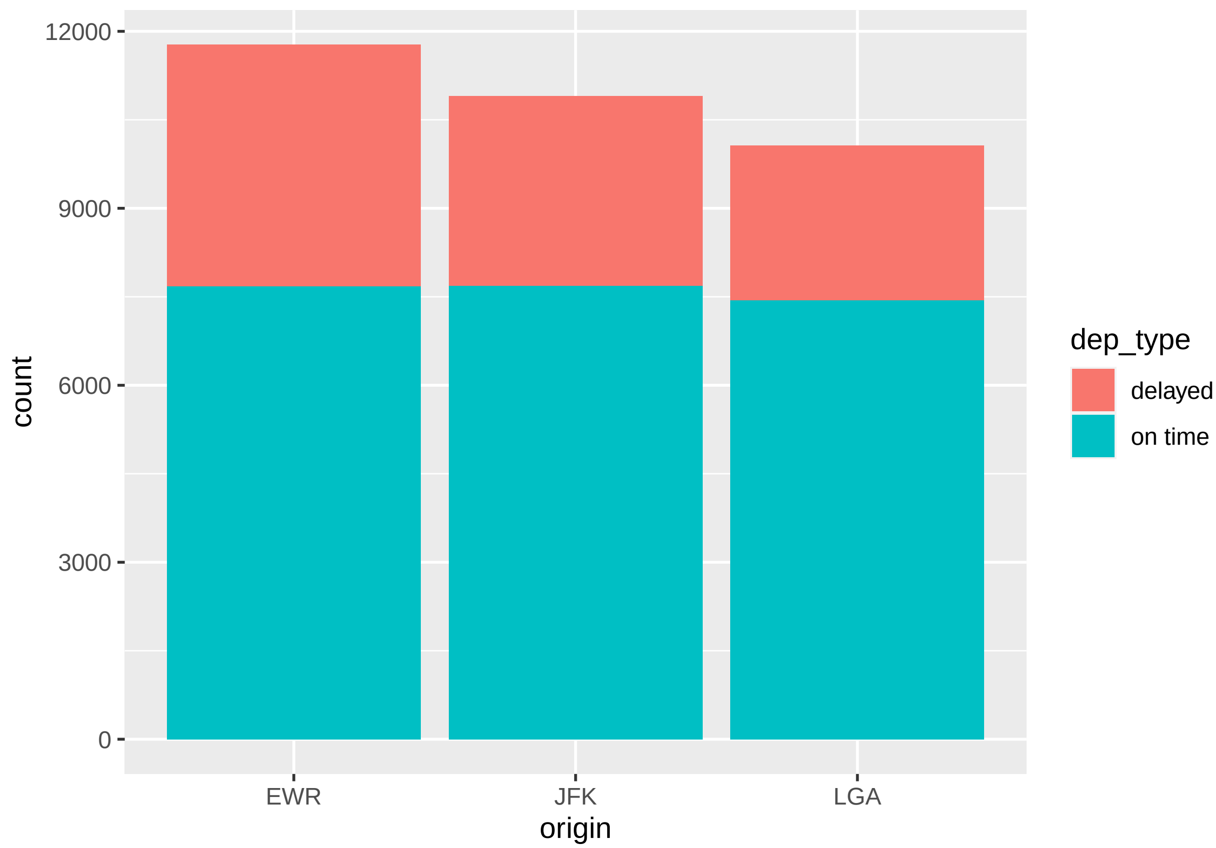
Now compute on-time departure percentage for all airports. Based on these on-time departure percentages, I would prefer flying out of NYC airports in following order of preference (first to last): LGA, JFK, EWR.

```
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          0.739
## 2 JFK          0.705
## 3 EWR          0.652
```

A picture is worth a thousand words and a quick visual inspection shows that LGA indeed has best proportion of flights leaving on time.

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



2 More Practice

2.1 Exercise 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.

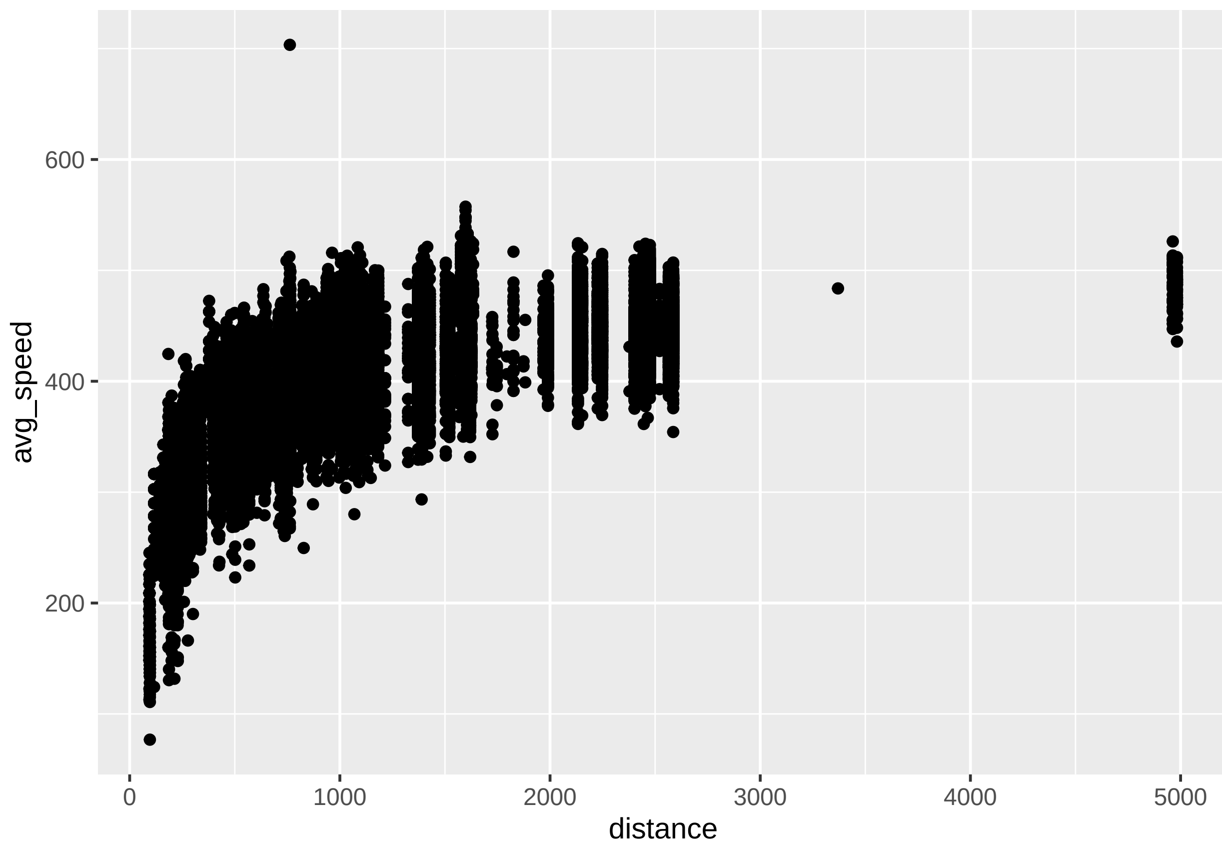
```
nycflights <- nycflights %>%
    mutate(avg_speed = distance / (air_time / 60)) %>%  # Compute avg_speed mph
    arrange(desc(flight))
```

2.2 Exercise 8

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

Average speed is proportional to distance, longer (shorter) distance flights have faster (slower) average speed. However, the increase in average speed with distance tapers off as distance increases. It seems the relationship may be modeled as a *logarithmic* function.

```
nycflights %>%
    ggplot(aes(x = distance, y = avg_speed)) + geom_point()
```



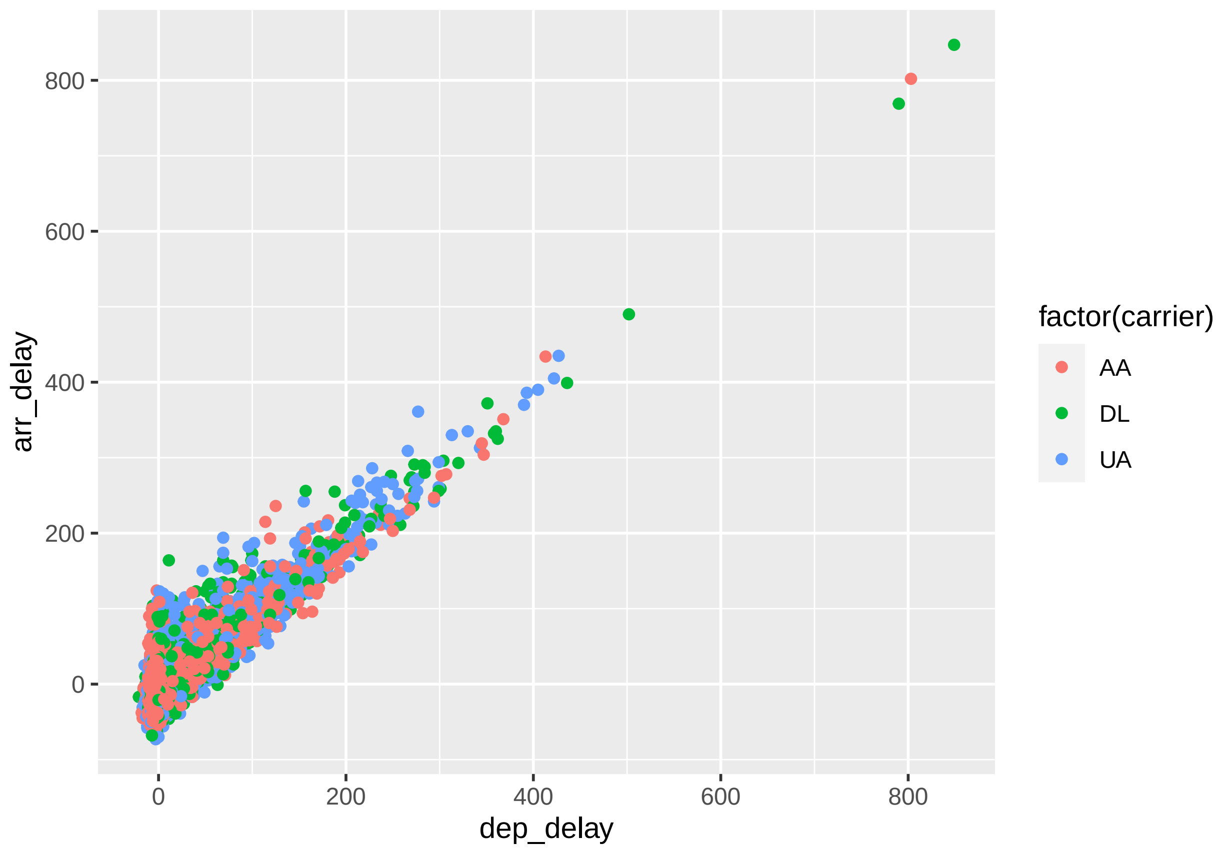
2.3 Exercise 9

Replicate the following plot. Hint: The data frame plotted only contains flights from American Airlines, Delta Airlines, and United Airlines, and the points are colored 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.

From the plot the maximum departure delay, for still getting to the destination on time, is approximately 60 minutes (look at the *horizontal line* where *arr_delay = 0*. Move along the line to the right, until the last point on line).

However, for these 3 airlines, a majority of flights departing exactly on time ($dep\_delay = 0$) nonetheless arrived late ($arr\_delay > 0$). For this data set, flights would have to depart approximately *10* minutes *before* scheduled departure to arrive 'on time'.

```
nycflights %>%
    filter(carrier %in% c('AA', 'DL', 'UA')) %>%
    ggplot(aes(x = dep_delay, y = arr_delay)) + geom_point(aes(color = factor(carrier)))
```



800
600
400
200
0
arr_delay
0
200
400
600
800
dep_delay
factor(carrier)
AA
DL
UA