Exercise 1

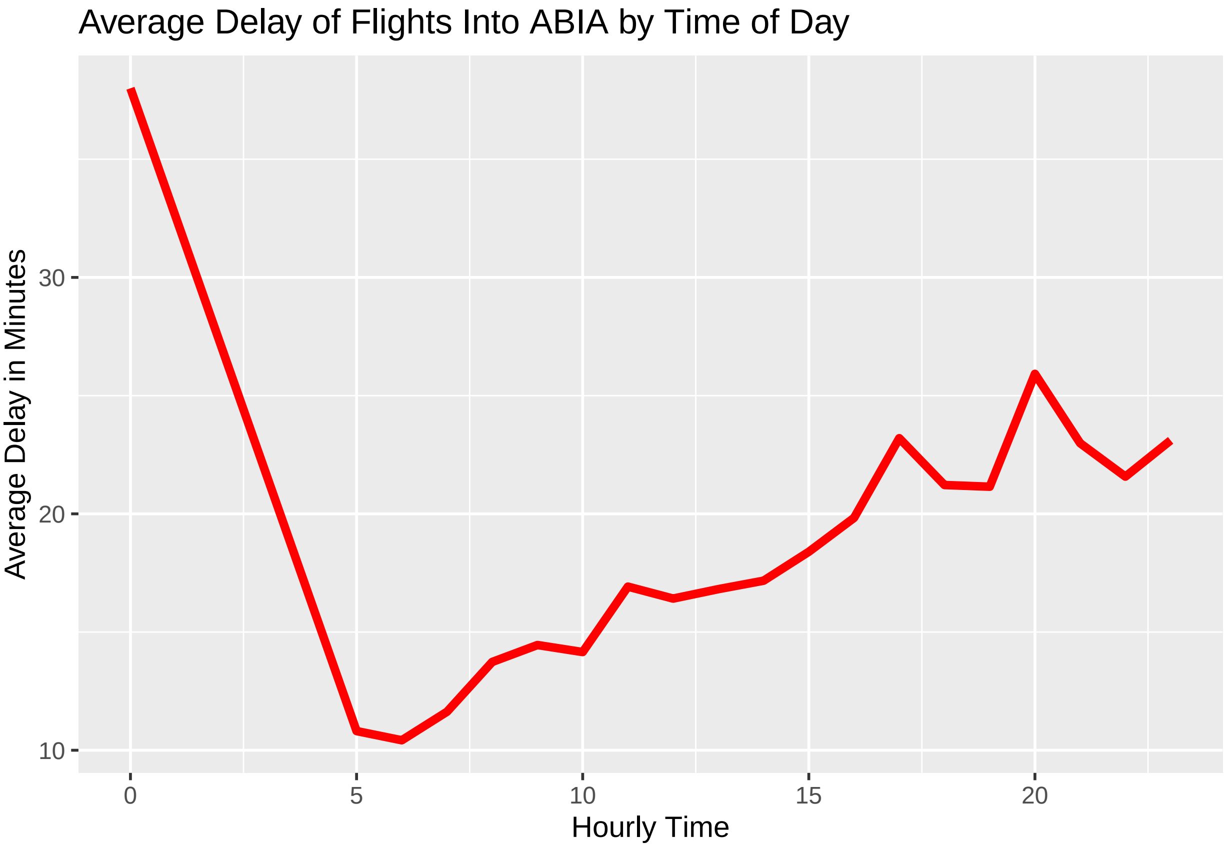
Jack Cunningham, Ali Fazl, and Ken Noddings

2023-01-30

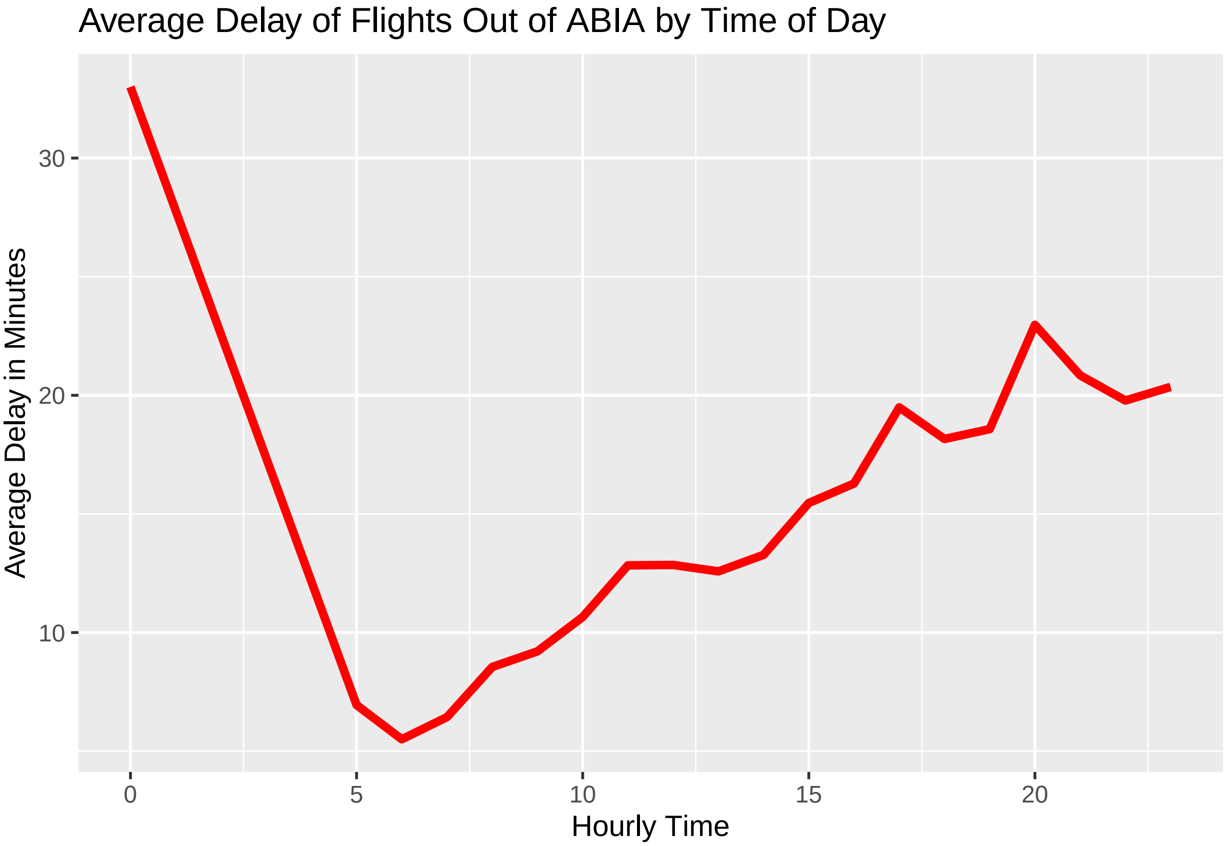
Exercise 1: Data visualization - flights at ABIA

Your task is to create a figure, or set of related figures, that tell an interesting story about flights into and out of Austin. You should annotate your figure(s), of course, but strive to make them as easy to understand as possible at a quick glance.

```
## # A tibble: 6 x 2
##   hourly_time AvgArrDel
##         <dbl>     <dbl>
## 1           6      10.4
## 2           5      10.8
## 3           7      11.6
## 4           8      13.7
## 5          10      14.2
## 6           9      14.5
```

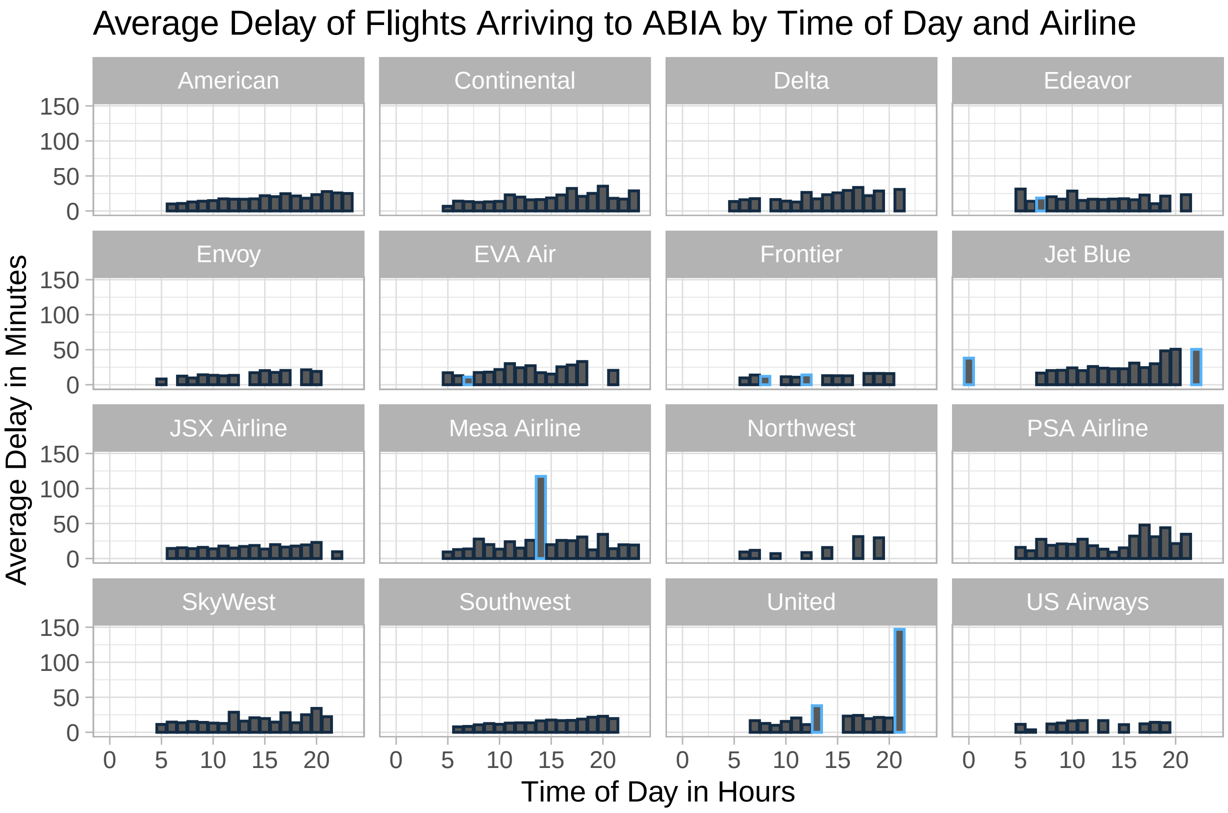


```
## # A tibble: 6 x 2
##   hourly_time AvgDepDel
##         <dbl>     <dbl>
## 1           6      5.50
## 2           7      6.44
## 3           5      6.95
## 4           8      8.55
## 5           9      9.21
## 6          10     10.7
```



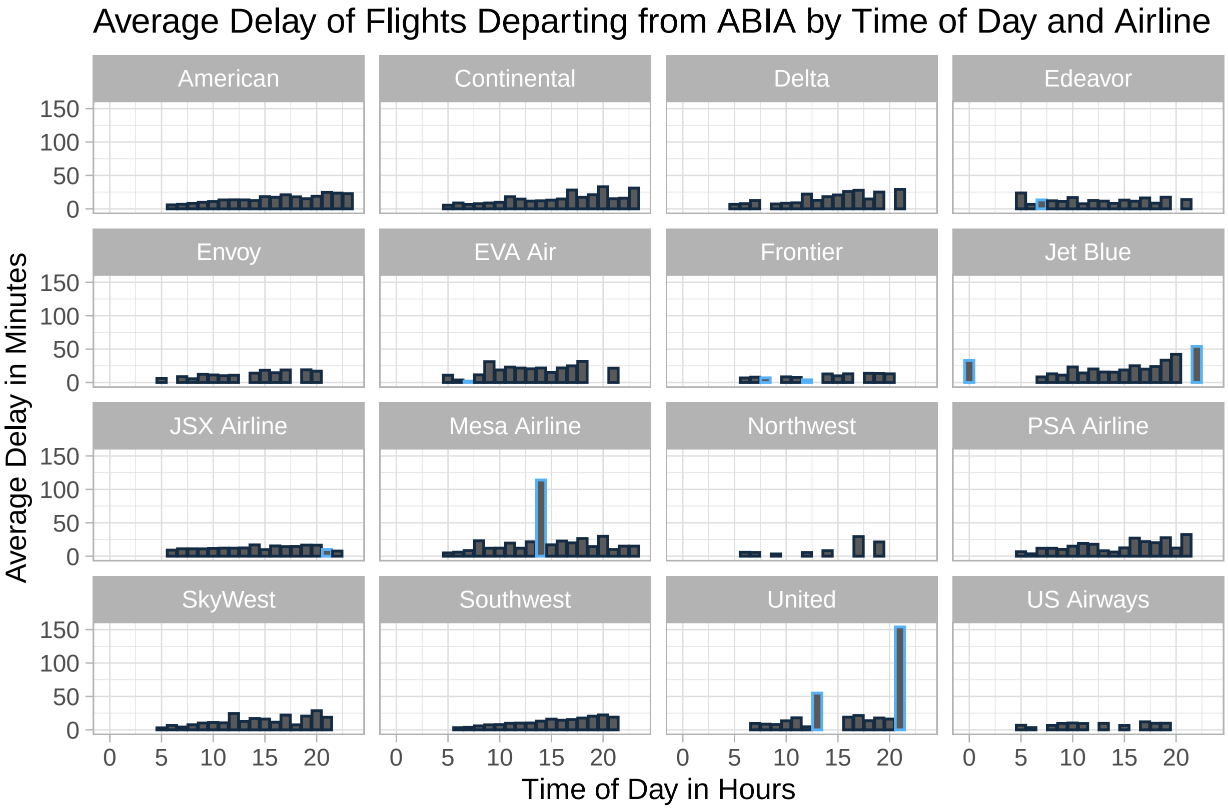
Here we show the average delays for both arriving flights into ABIA and departing flights from ABIA, plotted by hour of the day. It is best to both arrive at and depart from ABIA in the 6:00 AM hour for the smallest delays; in general, mornings see small delays for both incoming and departing flights relative to evenings. The 8:00 PM hour sees both the largest departure delays from ABIA and arrival delays into ABIA. In general, arrival delays are higher than departure delays across hours.

```
## `summarise()` has grouped output by 'UniqueCarrier'. You can override using the
## `.groups` argument.
```



Columns outlined in blue represent averages calculated from less than four data points.

```
## `summarise()` has grouped output by 'UniqueCarrier'. You can override using the
## `.groups` argument.
```



Columns outlined in blue represent averages calculated from less than four data points.

Here we plot average arrival and departure delays by time of day for each airline flying into and out of ABIA. We noticed some times on some airlines featured outlying average delays, so we isolated low observation counts (<4 data points) for each airline at each hour. The outlying delay times all come from such low observation count flights. This implies possible poor accuracy in calculating delays from those airlines at those times.

Exercise 2: Wrangling the Olympics

A) What is the 95th percentile of heights for female competitors across all Athletics events (i.e., track and field)?

```
## # A tibble: 132 x 2
##    event                                        quant95
##    <chr>                                          <dbl>
##  1 Athletics Women's 1,500 metres                  172
##  2 Athletics Women's 10 kilometres Walk            170
##  3 Athletics Women's 10,000 metres                 168.
##  4 Athletics Women's 100 metres                    180.
##  5 Athletics Women's 100 metres Hurdles            176
##  6 Athletics Women's 20 kilometres Walk            173
##  7 Athletics Women's 200 metres                    180
##  8 Athletics Women's 3,000 metres                  170
##  9 Athletics Women's 3,000 metres Steeplechase     177.
## 10 Athletics Women's 4 x 100 metres Relay          176
## # ... with 122 more rows
```

```
##   quant95
## 1     186
```

The table provides the 95th quantile of height for female competitors within each Athletics event. The 95th quantile of height for female competitors across all Athletics events is 186 cm.

B) Which single women's event had the greatest variability in competitor's heights across the entire history of the Olympics, as measured by the standard deviation?

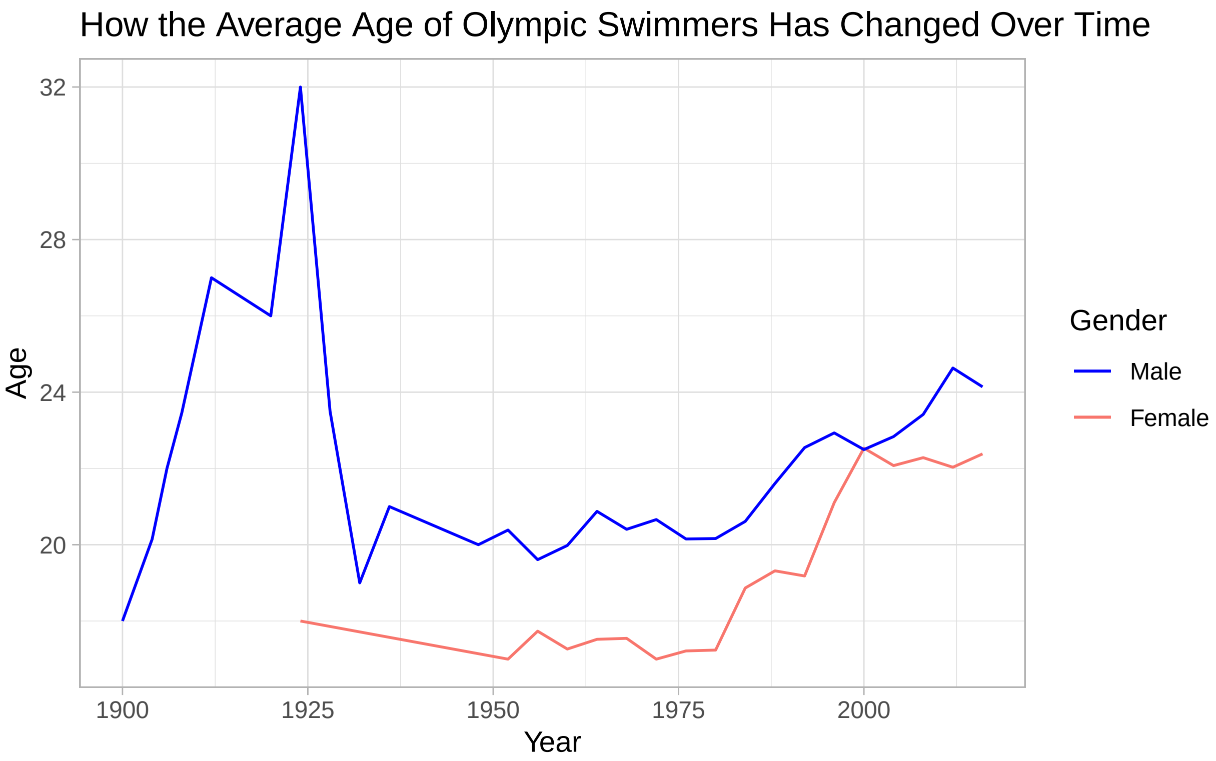
```
## # A tibble: 132 x 2
##    event                                         sd
##    <chr>                                      <dbl>
##  1 Athletics Women's 1,500 metres              5.03
##  2 Athletics Women's 10 kilometres Walk        4.31
##  3 Athletics Women's 10,000 metres             5.41
##  4 Athletics Women's 100 metres                6.29
##  5 Athletics Women's 100 metres Hurdles        4.68
##  6 Athletics Women's 20 kilometres Walk        5.28
##  7 Athletics Women's 200 metres                5.14
##  8 Athletics Women's 3,000 metres              5.48
##  9 Athletics Women's 3,000 metres Steeplechase  6.06
## 10 Athletics Women's 4 x 100 metres Relay      5.57
## # ... with 122 more rows
```

Women's Rowing Coxed Fours was the most variable event, with a standard deviation of 10.87.

C) How has the average age of Olympic swimmers changed over time? Does the trend look different for male swimmers relative to female swimmers? Create a data frame that can allow you to visualize these trends over time, then plot the data with a line graph with separate lines for male and female competitors. Give the plot an informative caption answering the two questions just posed.

```
## `summarise()` has grouped output by 'sex'. You can override using the `.groups`
## argument.
```

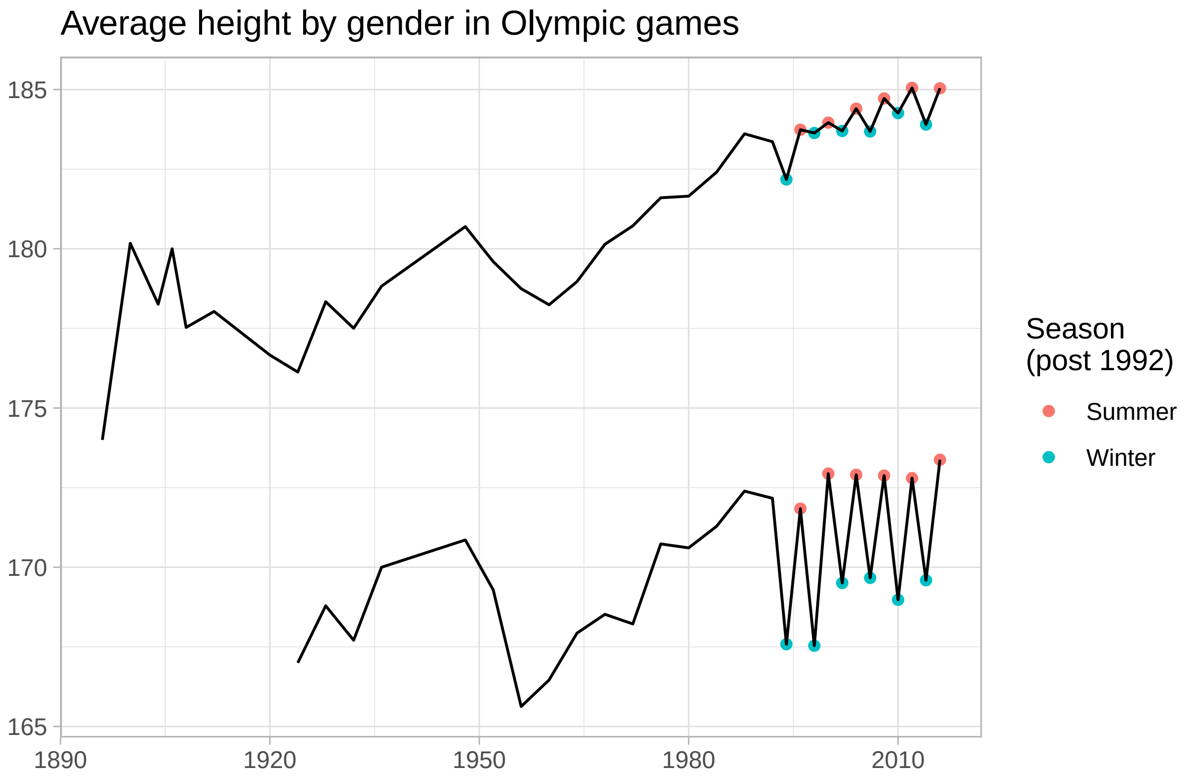
```
## # A tibble: 6 x 3
##   sex    year  mean
##   <chr> <int> <dbl>
## 1 F      1924  18
## 2 F      1952  17
## 3 F      1956  17.7
## 4 F      1960  17.3
## 5 F      1964  17.5
## 6 F      1968  17.5
```



How the Average Age of Olympic Swimmers Has Changed Over Time

While average ages in the early Olympics were quite chaotic, in more recent years from 1928 onwards, Olympic swimmers ages have been steadily increasing on average. This trend is roughly the same between both male and female swimmers.

```
## `summarise()` has grouped output by 'sex'. You can override using the `.groups`
## argument.
```



Exercise 3

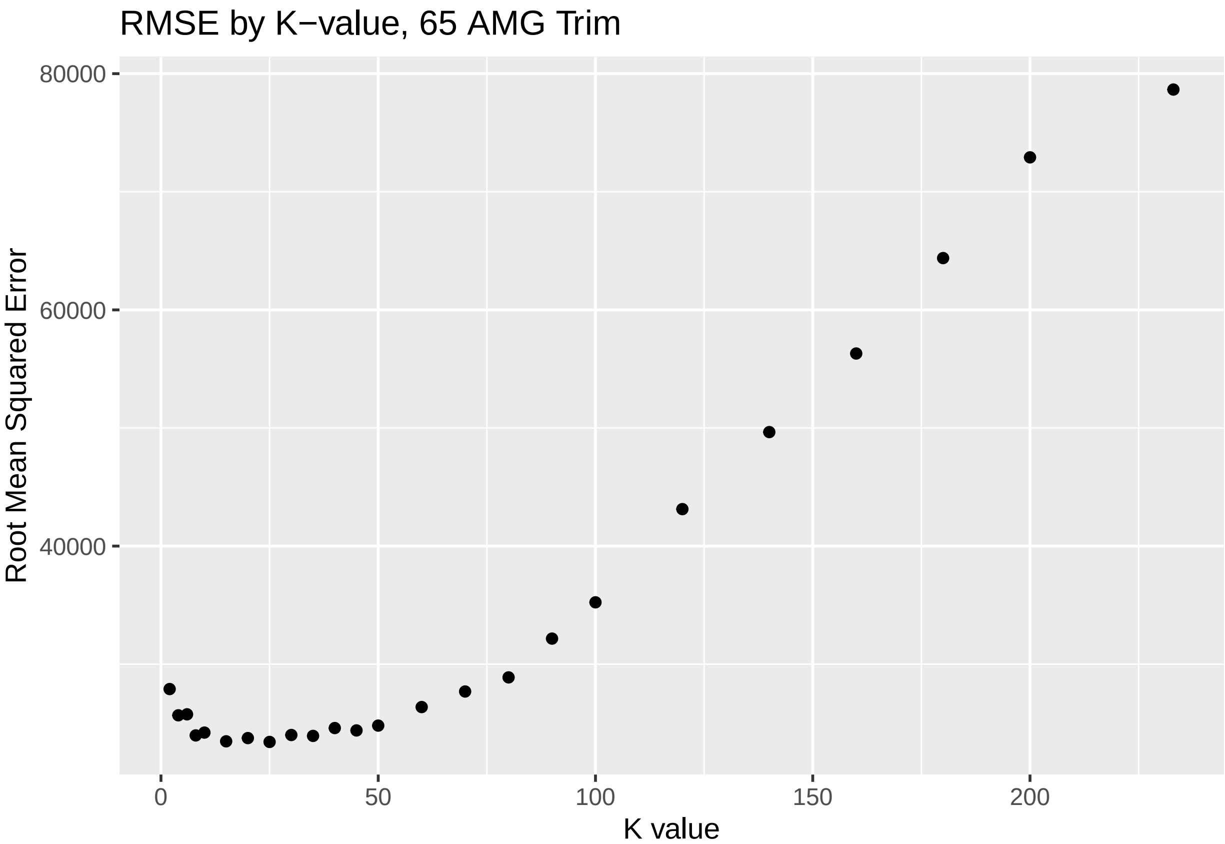
Your goal is to use K-nearest neighbors to build a predictive model for price, given mileage, separately for each of two trim levels: 350 and 65 AMG… That is, you'll be treating the 350's and the 65 AMG's as two separate data sets.

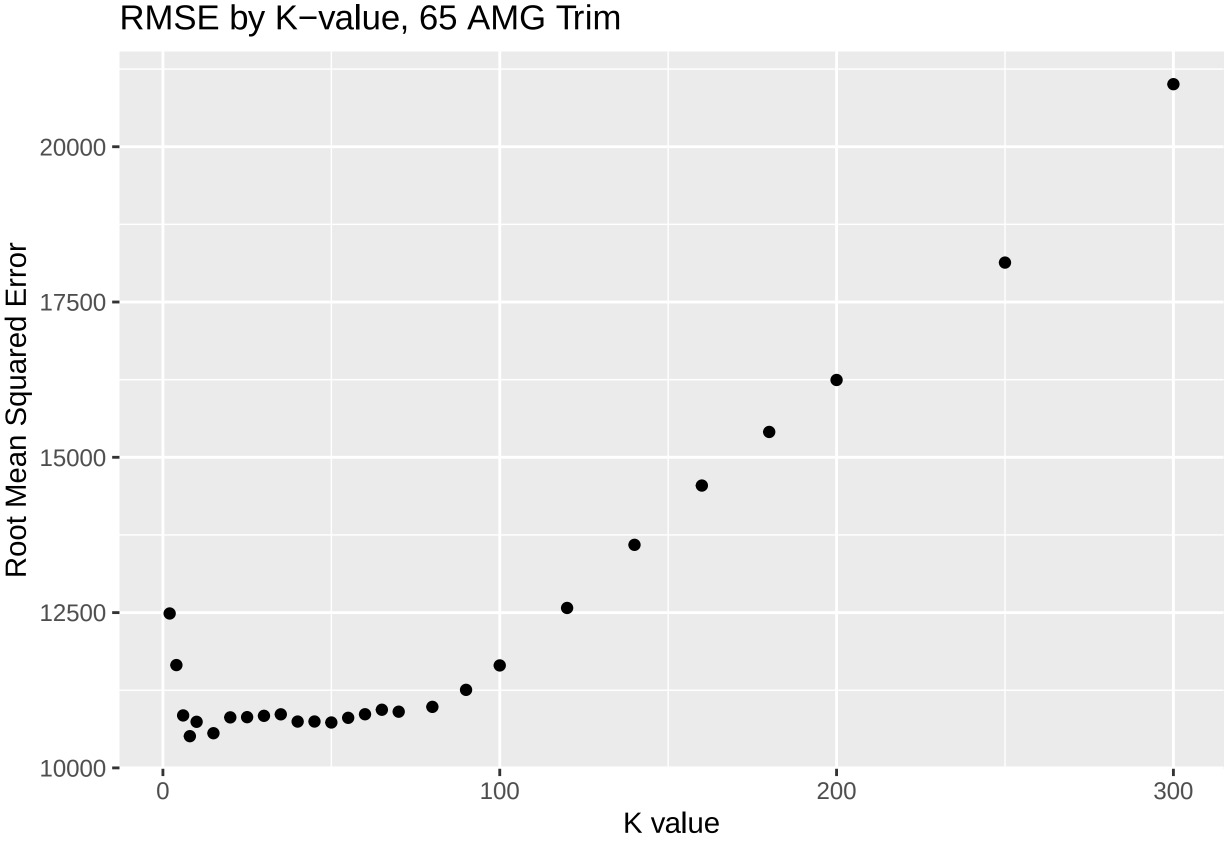
For each of these two trim levels:

1. Split the data into a training and a testing set. 2. Run K-nearest-neighbors, for many different values of K, starting at K=2 and going as high as you need to. For each value of K, fit the model to the training set and make predictions on your test set. 3. Calculate the out-of-sample root mean-squared error (RMSE) for each value of K.

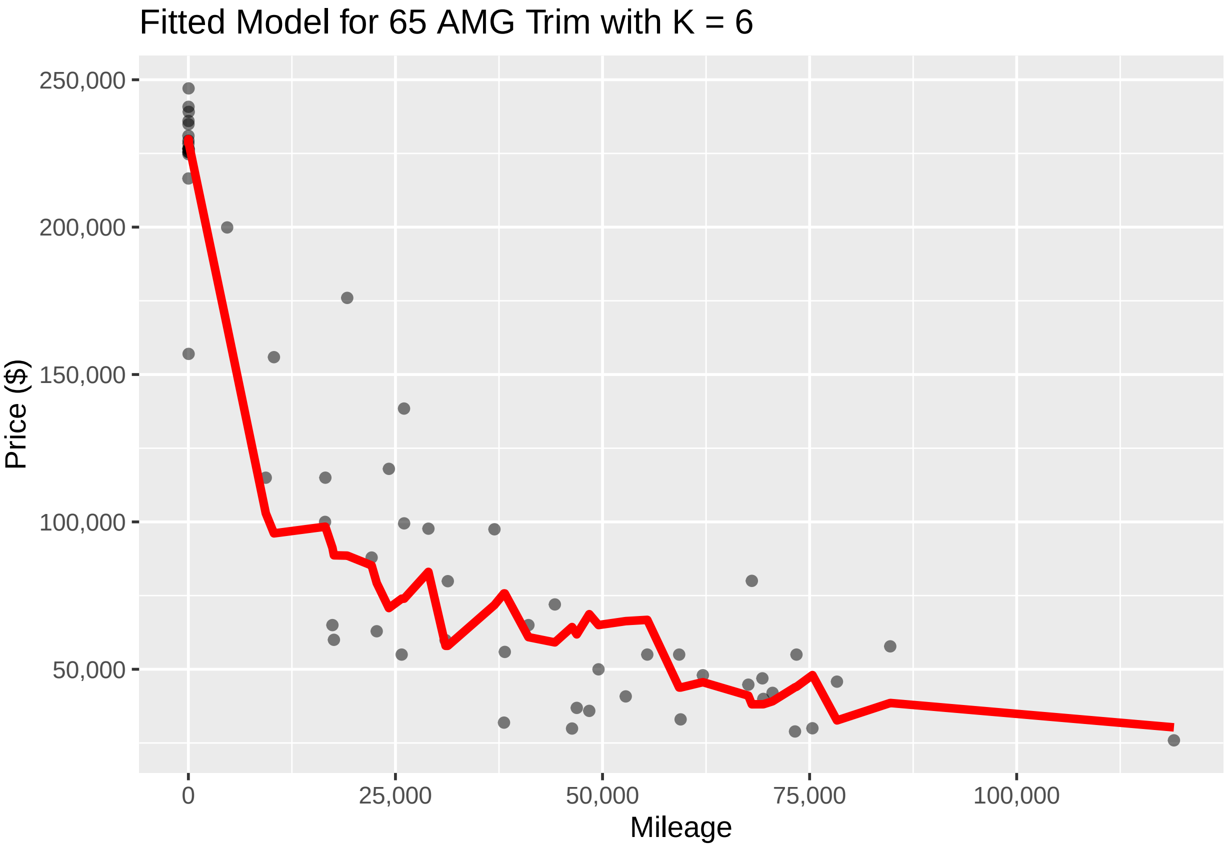
For each trim, make a plot of RMSE versus K, so that we can see where it bottoms out. Then for the optimal value of K, show a plot of the fitted model, i.e. predictions vs. x. (Again, separately for each of the two trim levels.)

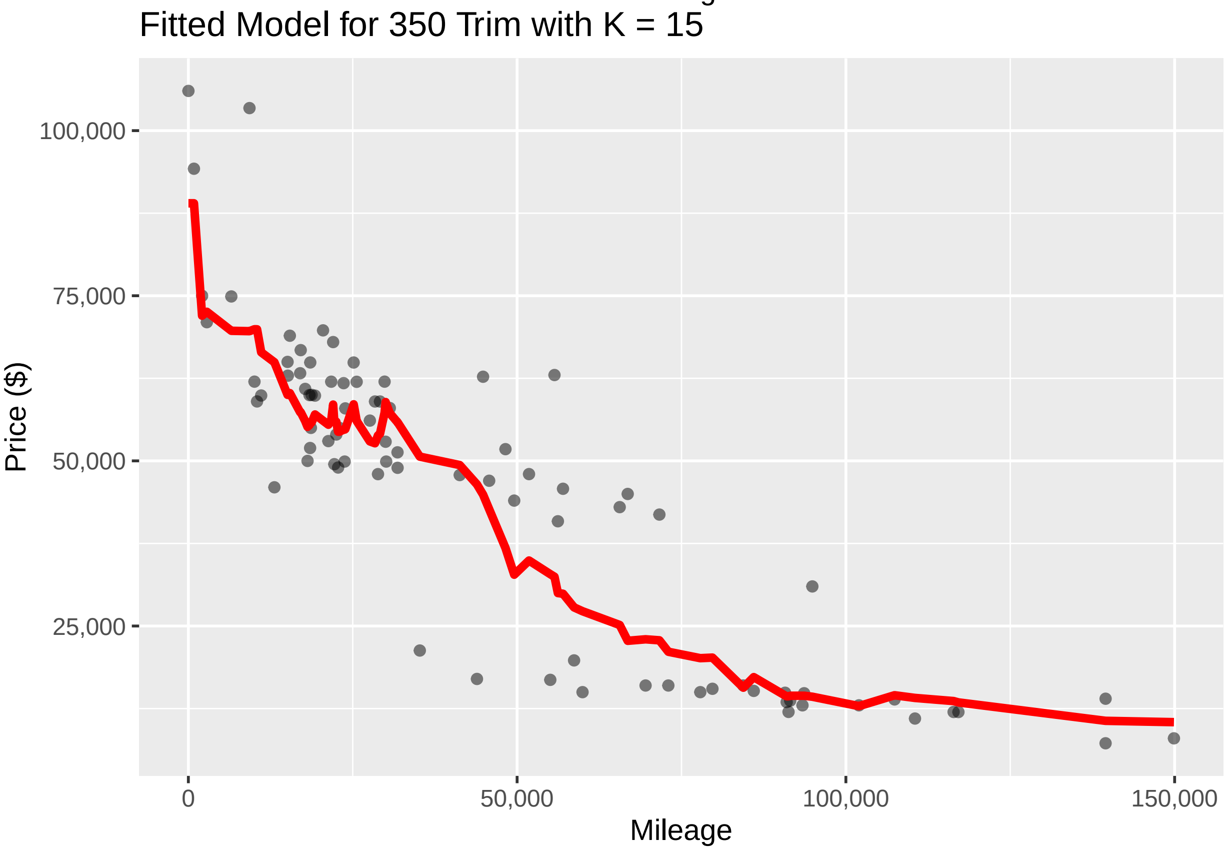
Which trim yields a larger optimal value of K? Why do you think this is?


RMSE by K−value, 65 AMG Trim
Root Mean Squared Error
80000
60000
40000
0
50
100
150
200
K value


RMSE by K−value, 65 AMG Trim
Root Mean Squared Error
20000
17500
15000
12500
10000
0
100
200
300
K value

```
## [1] 10558.18
## [1] 25755.98
```


Fitted Model for 65 AMG Trim with K = 6
Price ($)
250,000
200,000
150,000
100,000
50,000
0
25,000
50,000
75,000
100,000
Mileage


Fitted Model for 350 Trim with K = 15
Price ($)
100,000
75,000
50,000
25,000
0
50,000
100,000
150,000
Mileage

RMSE is minimized for the 350 trim at K = 15.

For the 65 AMG trim, RMSE is minimized at K = 6.

The 350 trim yields a larger optimal value of K. This is likely due to a larger sample size. The dataset contains 417 vehicles with the 350 trim, but only 292 vehicles with the 65 AMG trim. With more data points nearby, we can afford a higher K-value, since the bias is offset by the higher concentration of data points in each "neighborhood."

NOTE: Different values of K were optimal upon repeatedly running different train-test splits for both the 350 and 65 AMG trims. We chose the values of K that most commonly occurred as optimal.