ECO 395 Exercise1

Areeya Aksornpan, Zayd Abdalla

2/8/2021

R Markdown

##1) Data visualization: gas prices

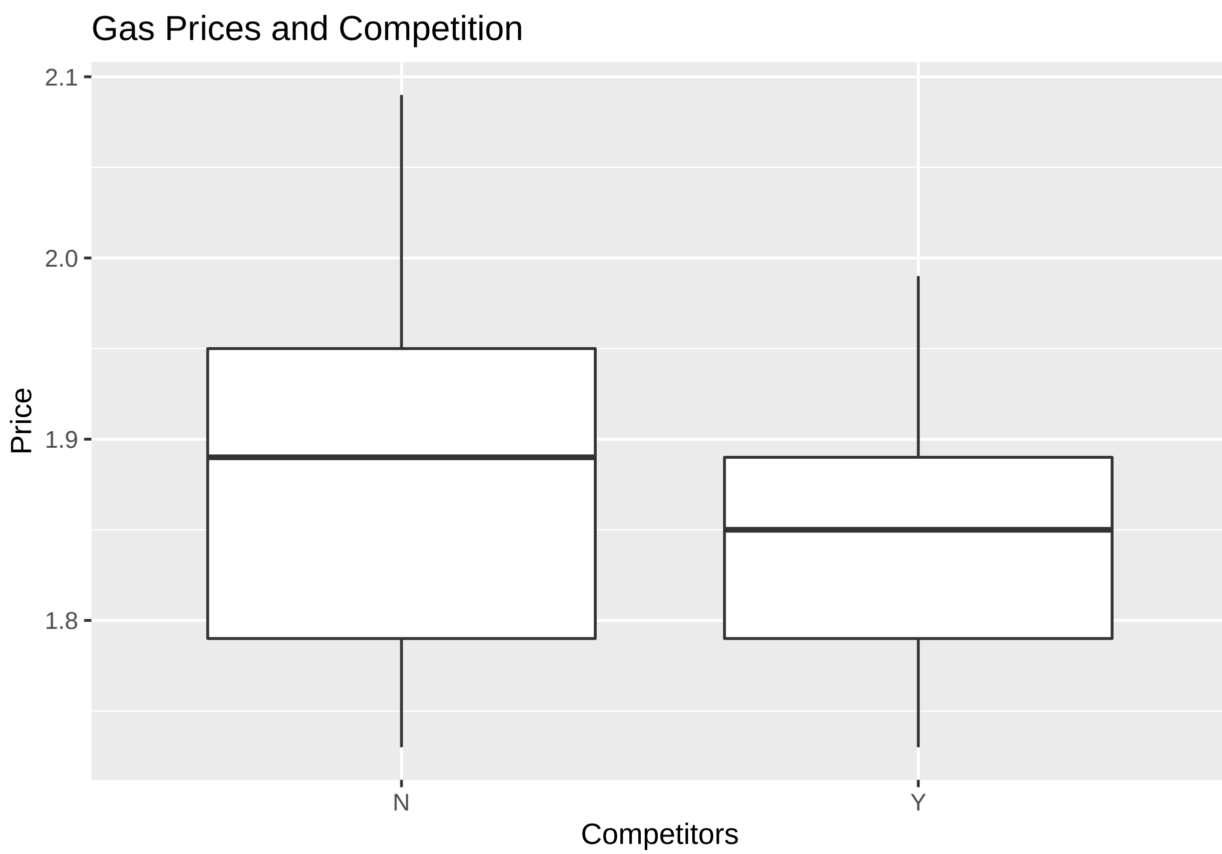
```
library(ggplot2)
library(tidyverse)
```

```
## -- Attaching packages ------------------------------ tidyverse 1.3.0 --
```

```
## v tibble  3.0.3     v dplyr   1.0.1
## v tidyr   1.1.1     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
## v purrr   0.3.4
```

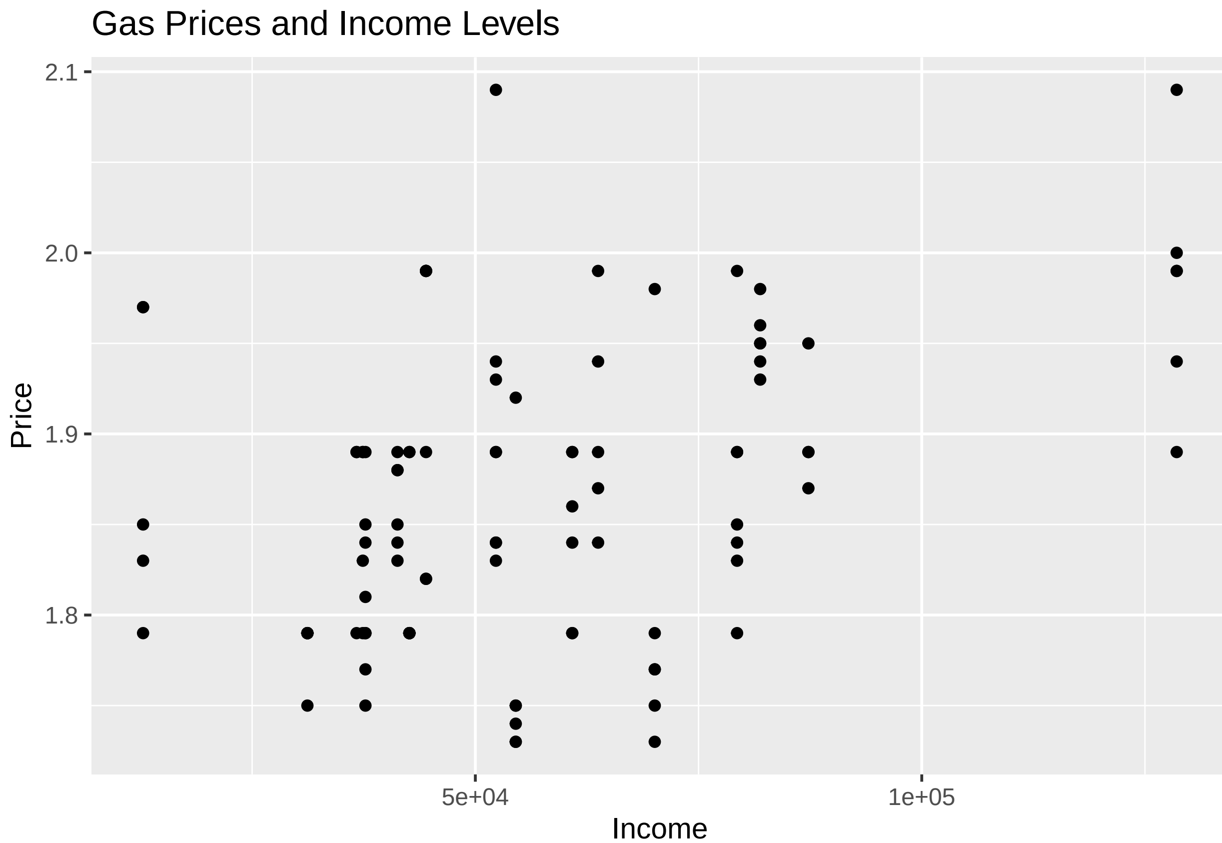
```
## -- Conflicts --------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
GasPrices = read.csv('~/Desktop/GasPrices.csv')
##A
ggplot(GasPrices, aes(x=Competitors, y=Price)) + geom_boxplot() + ggtitle("Gas Prices and Competition")
```



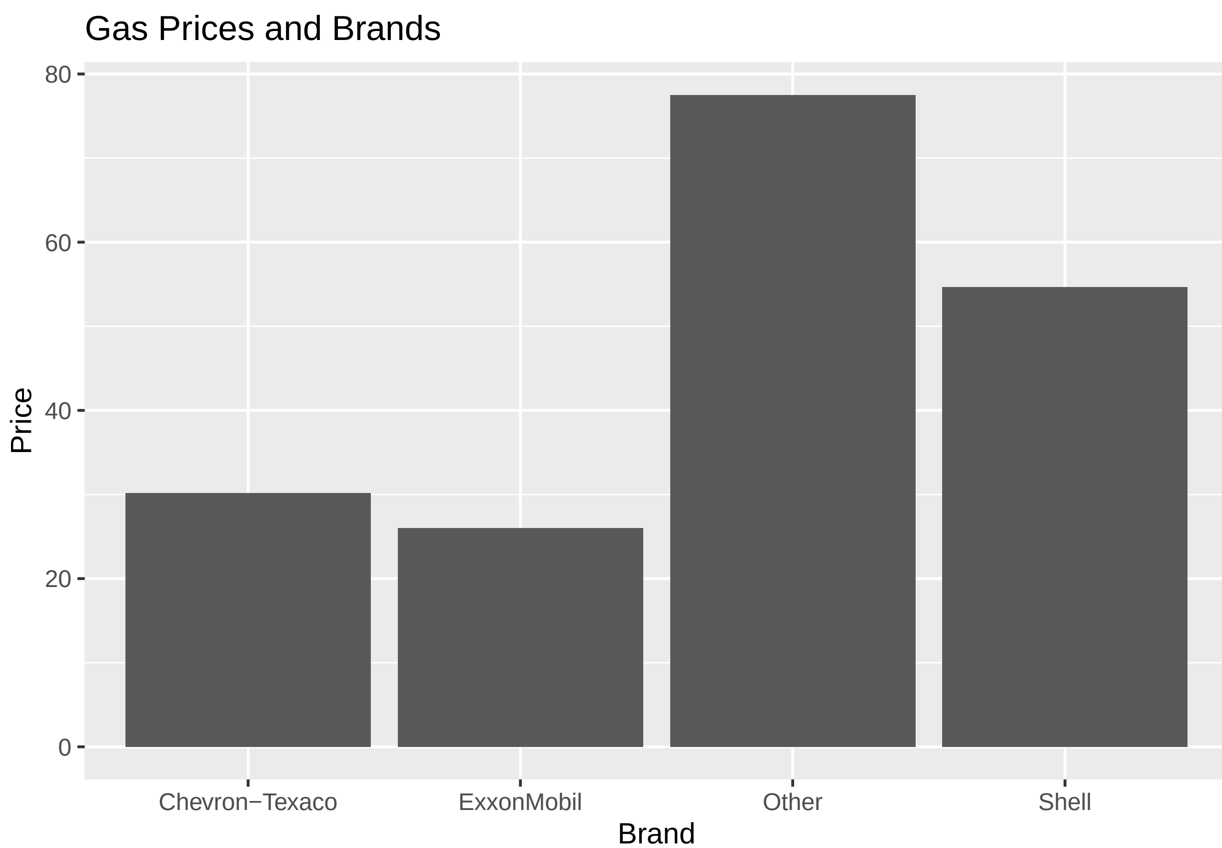
This theory that gas stations charge more if they lack direct competition in sight seems plausible. The boxplot with no competition has a higher median price and its right whisker extends to higher price levels than the plot of gas stations with competition.

```
##B
ggplot(GasPrices, aes(x=Income, y=Price)) + geom_point() + ggtitle("Gas Prices and Income Levels")
```



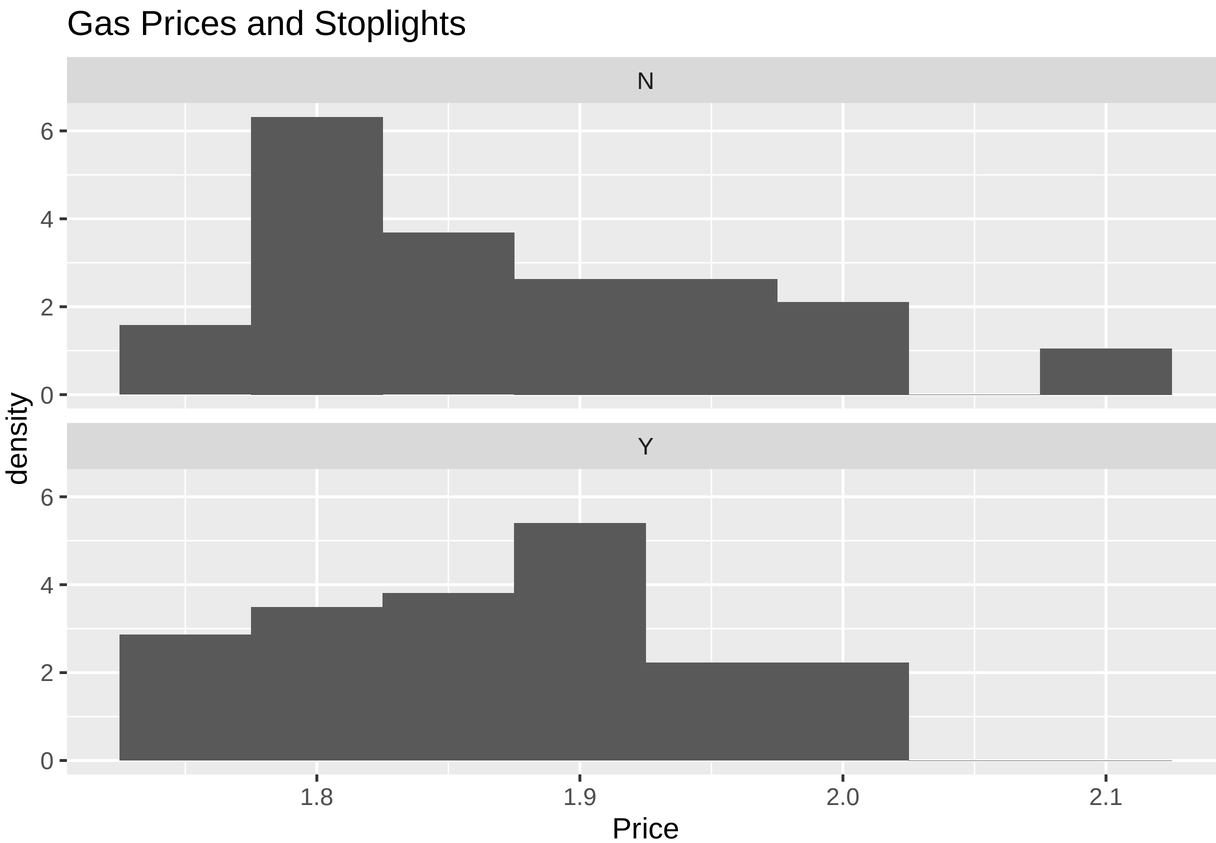
This theory that the richer the area, the higher the gas price seems generally plausible. The scatterplot shows that as income levels increase, the prices trend to higher levels.

```
##C
ggplot(GasPrices, aes(x=Brand, y=Price)) + geom_col() + ggtitle("Gas Prices and Brands")
```



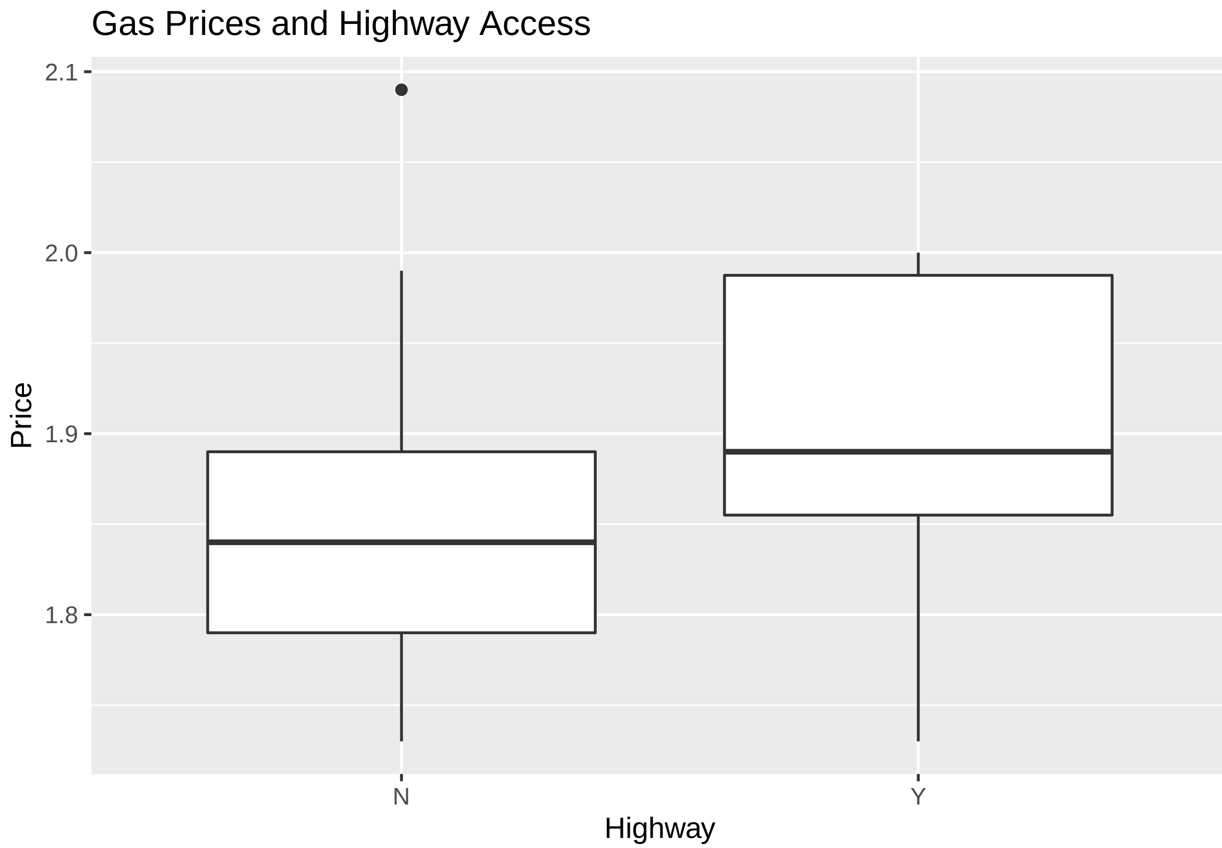
Although it is claimed that Shell charges more than other brands, this bar plot shows that the theory is only partly supported by the data. Shell's price is higher than Chevron-Texaco and Exxon Mobil, but there are other brands that sell gas in a higher price compare to Shell.

```
##D
ggplot(GasPrices) +
  geom_histogram(aes(x=Price, after_stat(density)), binwidth = 0.05) +
  facet_wrap(~Stoplight, nrow = 2) + ggtitle("Gas Prices and Stoplights")
```



##This theory that gas stations at stoplights charge more seems plausible. The bulk of gas stations near stoplights charge a price of roughly $1.9 whereas the gas stations not near stoplights charge a price of roughly $1.8.

```
##E
ggplot(GasPrices, aes(x=Highway, y=Price)) + geom_boxplot() + ggtitle("Gas Prices and Highway Access")
```



The boxplot illustrates the theory that gas stations with direct highway access charge more. The average price increases when there is direct highway access to the gas station. The minimum price increases from below $1.8 to approximately $1.85 and the maximum price increases from nearly $1.9 to close to $2.0. ##2) Data visualization: a bike share network

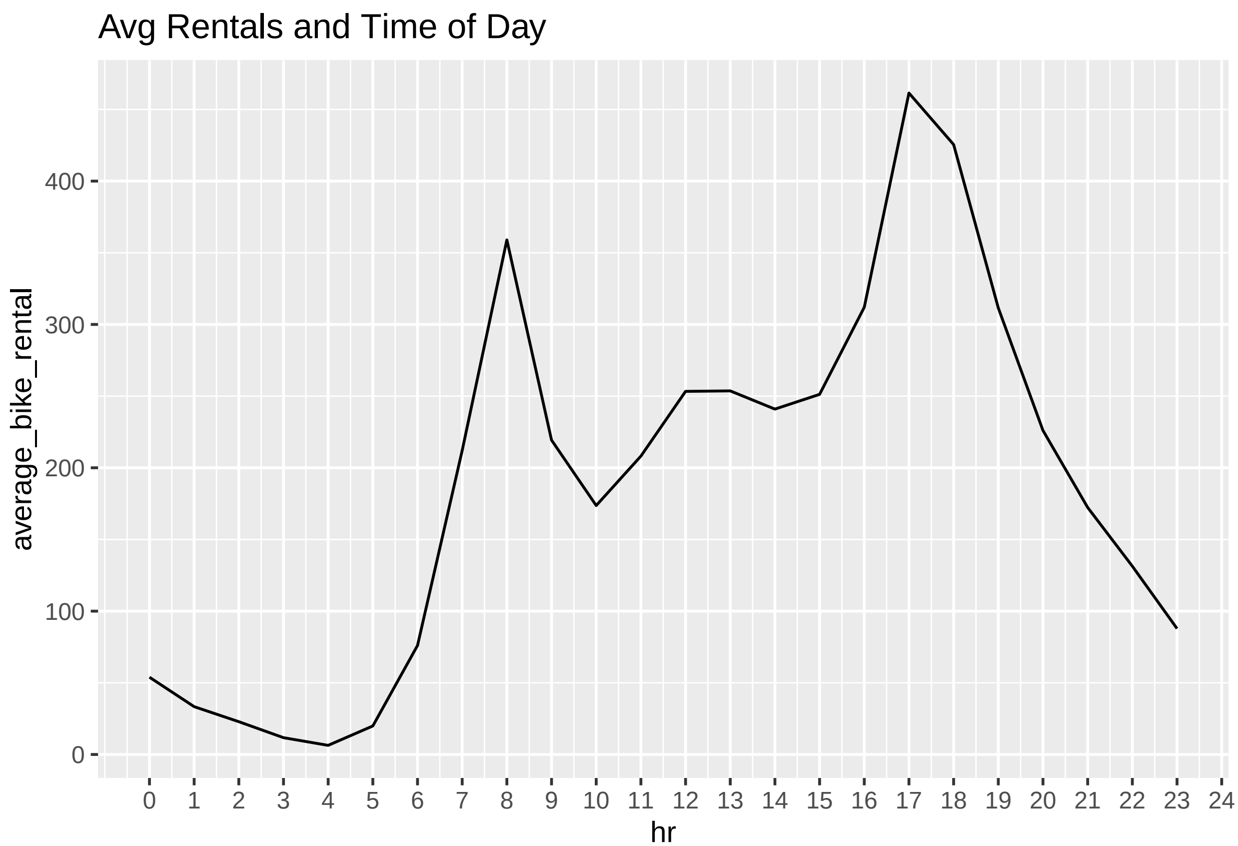
```r
library(ggplot2)
library(tidyverse)
bikeshare = read.csv('~/Desktop/bikeshare.csv')
head(bikeshare)
```

```
##   instant     dteday season yr mnth hr holiday weekday workingday weathersit
## 1       1 2011-01-01      1  0    1  0       0       6          0          1
## 2       2 2011-01-01      1  0    1  1       0       6          0          1
## 3       3 2011-01-01      1  0    1  2       0       6          0          1
## 4       4 2011-01-01      1  0    1  3       0       6          0          1
## 5       5 2011-01-01      1  0    1  4       0       6          0          1
## 6       6 2011-01-01      1  0    1  5       0       6          0          2
##   temp total
## 1 0.24    16
## 2 0.22    40
## 3 0.22    32
## 4 0.24    13
## 5 0.24     1
## 6 0.24     1
```

```
##Plot A: a line graph showing average bike rentals (total) versus hour of the day (hr).
#Average bike rentals
bikerent_total1 = bikeshare %>%
  group_by(hr) %>%
  summarize(average_bike_rental = mean(total))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
#Plot the result over time in a line graph
ggplot(bikerent_total1) +
  geom_line(aes(x=hr, y=average_bike_rental)) + scale_x_continuous(breaks = 0:24) + ggtitle("Avg Rentals
```



##The x-axis is the hour which bikers rent bicycles and the y-axis is the average number of total bike rentals in that hour, including both casual and registered users. ##The main takeaway is that bicycle renters appear to prefer renting bicycles typically around 8am and 5pm, which is before and after common working hours. There is also a slight increase from 10am to 12pm, which is when workers could have their lunch breaks. This finding may also imply the idea that people tend to leave their house around 5am and return home around 6pm.

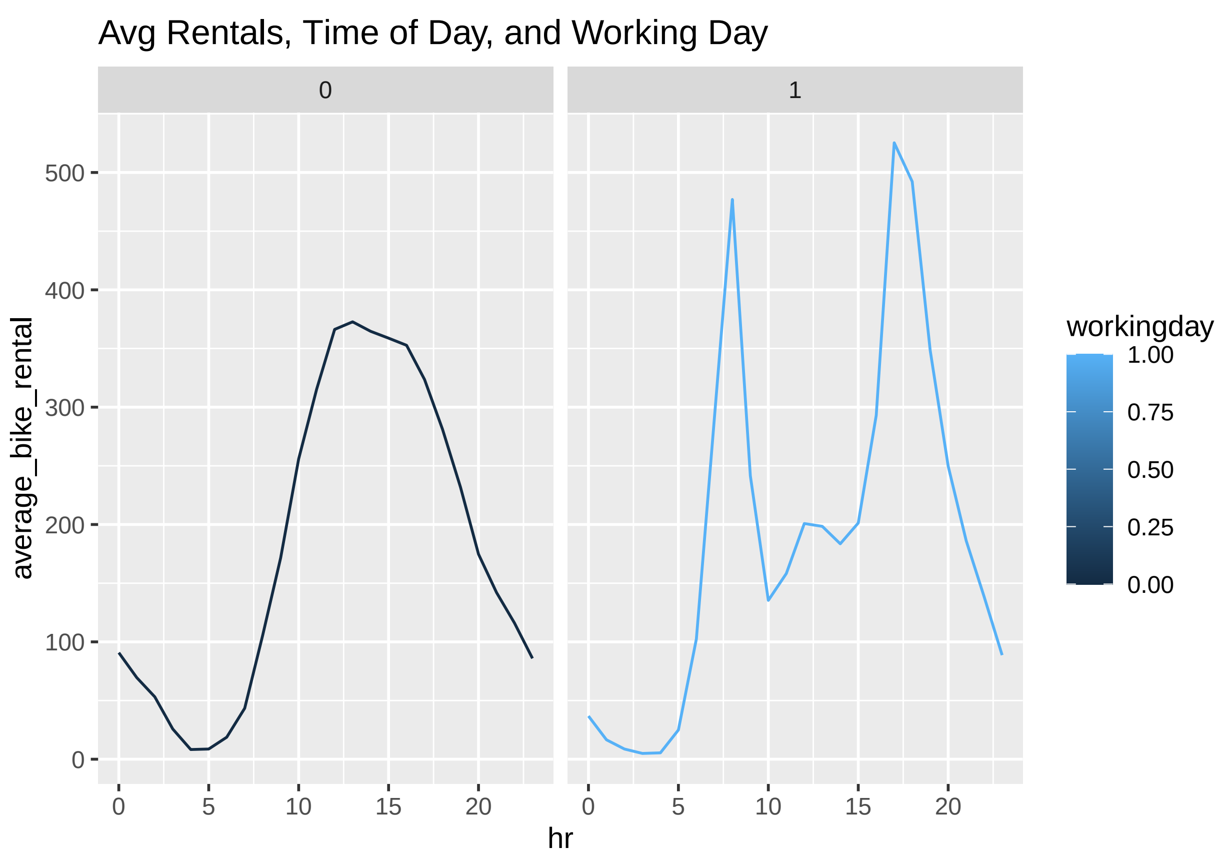
```
##Plot B: a faceted line graph showing average bike rentals versus hour of the day, faceted according t
bikerent_total2 = bikeshare %>%
  group_by(hr, workingday) %>%
  summarize(average_bike_rental = mean(total))
```

```
## `summarise()` regrouping output by 'hr' (override with `.groups` argument)
```

```r
head(bikerent_total2, 30)
```

```
## # A tibble: 30 x 3
## # Groups:   hr [15]
##       hr workingday average_bike_rental
##    <int>      <int>               <dbl>
##  1     0          0               90.8
##  2     0          1               36.8
##  3     1          0               69.5
##  4     1          1               16.6
##  5     2          0               53.2
##  6     2          1                8.68
##  7     3          0               25.8
##  8     3          1                4.94
##  9     4          0                8.26
## 10     4          1                5.43
## # ... with 20 more rows
```

```r
ggplot(bikerent_total2) +
  geom_line(aes(x=hr, y=average_bike_rental, color=workingday)) +
  facet_wrap(~workingday) + ggtitle("Avg Rentals, Time of Day, and Working Day")
```



##The x-axis is the hour which bikers rent bicycles and the y-axis is the average number of total bike rentals in that hour, including both casual and registered users. ##The left graph is the average bike rentals versus hour of weekend or holiday. Bicycle renters prefer to rent bicycles mostly around noon. It seems plausible to assume that renters started leaving the house around 6am and return home around 1pm. ##The right graph is the average bike rentals versus hour of workingday. Bicycle renters prefer to rent bicycles mostly around 8am and 5pm, which is before and after working hours.This suggests that most renters started leaving the house around 5am and went back home around 6pm.

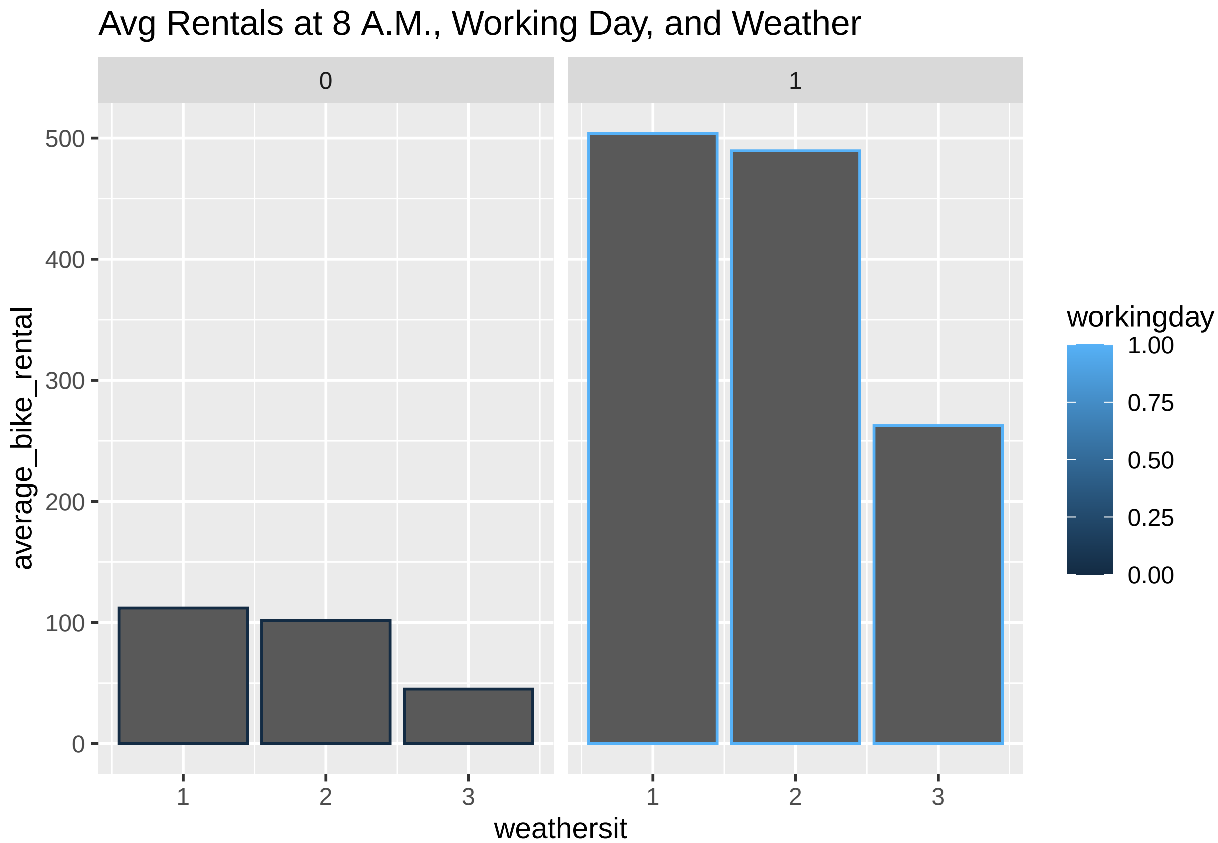
```
##Plot C: a faceted bar plot showing average ridership during the 8 AM hour by weather situation code (
bikerent_total3 = bikeshare %>%
  filter(hr==8) %>%
  group_by(weathersit, workingday) %>%
  summarise(average_bike_rental = mean(total))
```

```
## `summarise()` regrouping output by 'weathersit' (override with `.groups` argument)
```

```
head(bikerent_total3, 30)
```

```
## # A tibble: 6 x 3
## # Groups:   weathersit [3]
##   weathersit workingday average_bike_rental
##        <int>      <int>               <dbl>
## 1          1          0               112.
## 2          1          1               504.
## 3          2          0               102.
## 4          2          1               489.
## 5          3          0                45.1
## 6          3          1               263.
```

```
ggplot(bikerent_total3) +
  geom_col(aes(x=weathersit, y=average_bike_rental, color=workingday)) +
  facet_wrap(~workingday) + ggtitle("Avg Rentals at 8 A.M., Working Day, and Weather")
```



##The y-axis is average ridership at 8 A.M. and the x-axis is the weather situation, which is sorted as follows: ##1: Clear, Few clouds, Partly cloudy, Partly cloudy ##2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist ##3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds ##4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog ##The left graph is the average bike rentals versus weather situation on weekends or holidays, while the right graph is the average bike rentals versus weather situation on workdays. ##Numbers of bike rentals on both graphs decreased as the weather situation worsened. When there is light snow, light rain with scattered clouds or thunderstorm (3), the numbers of average bike rentals lessened by half. When it is mist(2), the number of average bike rental does not decrease much compare to when it is clear or cloudy (1). Since the weather condition lessens the number of bike rentals, we could expect a fewer number of bike rentals on a snowy or rainy day. ##3) Data visualization: flights at ABIA

```
library(ggplot2)
library(tidyverse)
ABIA = read.csv('~/Desktop/ABIA.csv')
head(ABIA)
```

```
##   Year Month DayofMonth DayOfWeek DepTime CRSDepTime ArrTime CRSArrTime
## 1 2008     1          1         2     120       1935     309       2130
## 2 2008     1          1         2     555        600     826        835
## 3 2008     1          1         2     600        600     728        729
## 4 2008     1          1         2     601        605     727        750
## 5 2008     1          1         2     601        600     654        700
## 6 2008     1          1         2     636        645     934        932
##   UniqueCarrier FlightNum TailNum ActualElapsedTime CRSElapsedTime AirTime
## 1            9E      5746  84129E               109            115      88
## 2            AA      1614  N438AA               151            155     133
```

```
## 3            YV      2883  N922FJ              148            149      125
## 4            9E      5743  89189E               86            105       70
## 5            AA      1157  N4XAAA               53             60       38
## 6            NW      1674   N967N              178            167      145
##   ArrDelay DepDelay Origin Dest Distance TaxiIn TaxiOut Cancelled
## 1      339      345    MEM  AUS      559      3      18         0
## 2       -9       -5    AUS  ORD      978      7      11         0
## 3       -1        0    AUS  PHX      872      7      16         0
## 4      -23       -4    AUS  MEM      559      4      12         0
## 5       -6        1    AUS  DFW      190      5      10         0
## 6        2       -9    AUS  MSP     1042     11      22         0
##   CancellationCode Diverted CarrierDelay WeatherDelay NASDelay SecurityDelay
## 1                         0          339            0        0             0
## 2                         0           NA           NA       NA            NA
## 3                         0           NA           NA       NA            NA
## 4                         0           NA           NA       NA            NA
## 5                         0           NA           NA       NA            NA
## 6                         0           NA           NA       NA            NA
##   LateAircraftDelay
## 1                 0
## 2                NA
## 3                NA
## 4                NA
## 5                NA
## 6                NA
```

```
##What is the best time of year to fly to minimize delays, and does this change by destination?
ABIA_DepDelay1 = ABIA %>%
  group_by(Month) %>%
  summarize(ABIA_total1 = mean(na.omit(DepDelay)))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
Desination = c('AUS', 'DFW', 'IAH', 'PHX', 'DEN')
ABIA_DepDelay2 = ABIA %>%
  filter(Dest %in% Desination) %>%
  group_by(Month, Dest) %>%
  summarize(ABIA_total2 = mean(na.omit(DepDelay)))
```

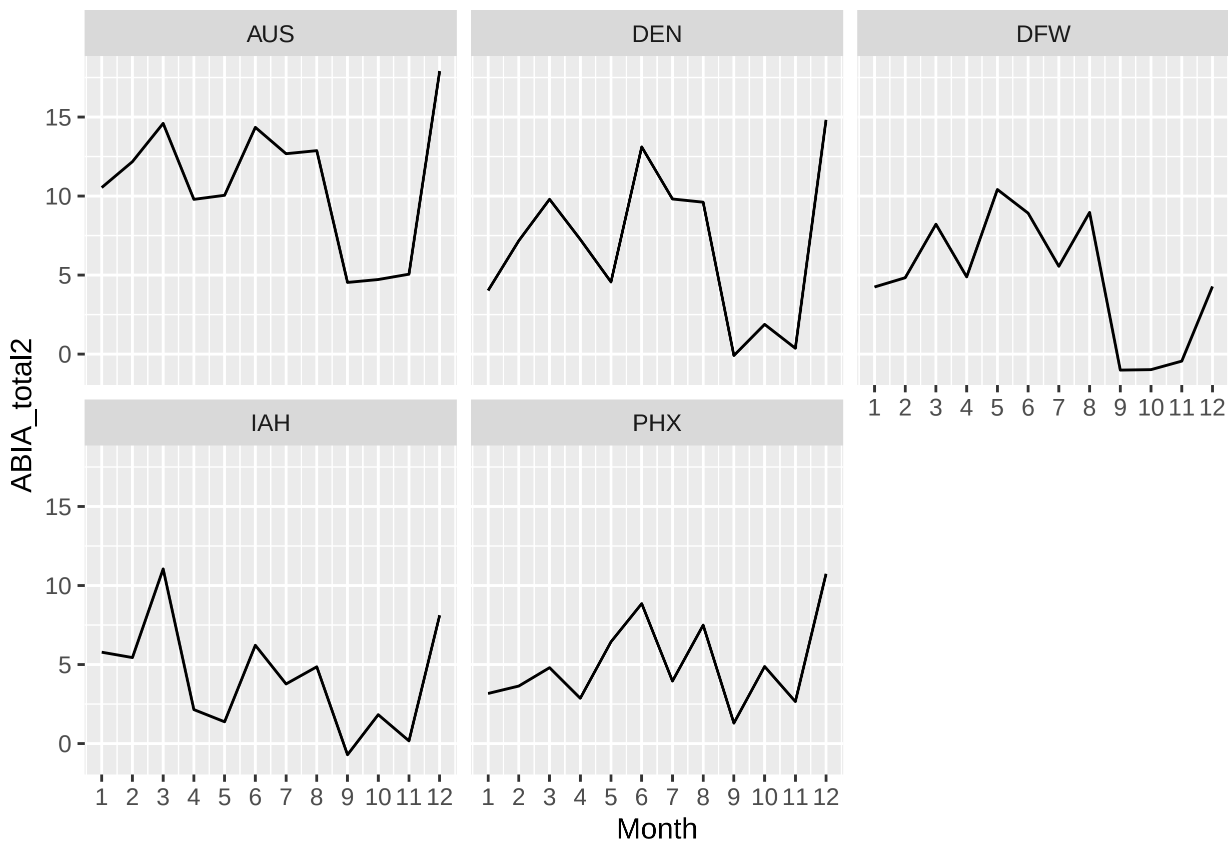
```
## `summarise()` regrouping output by 'Month' (override with `.groups` argument)
```

```
head(ABIA_DepDelay1, 100)
```

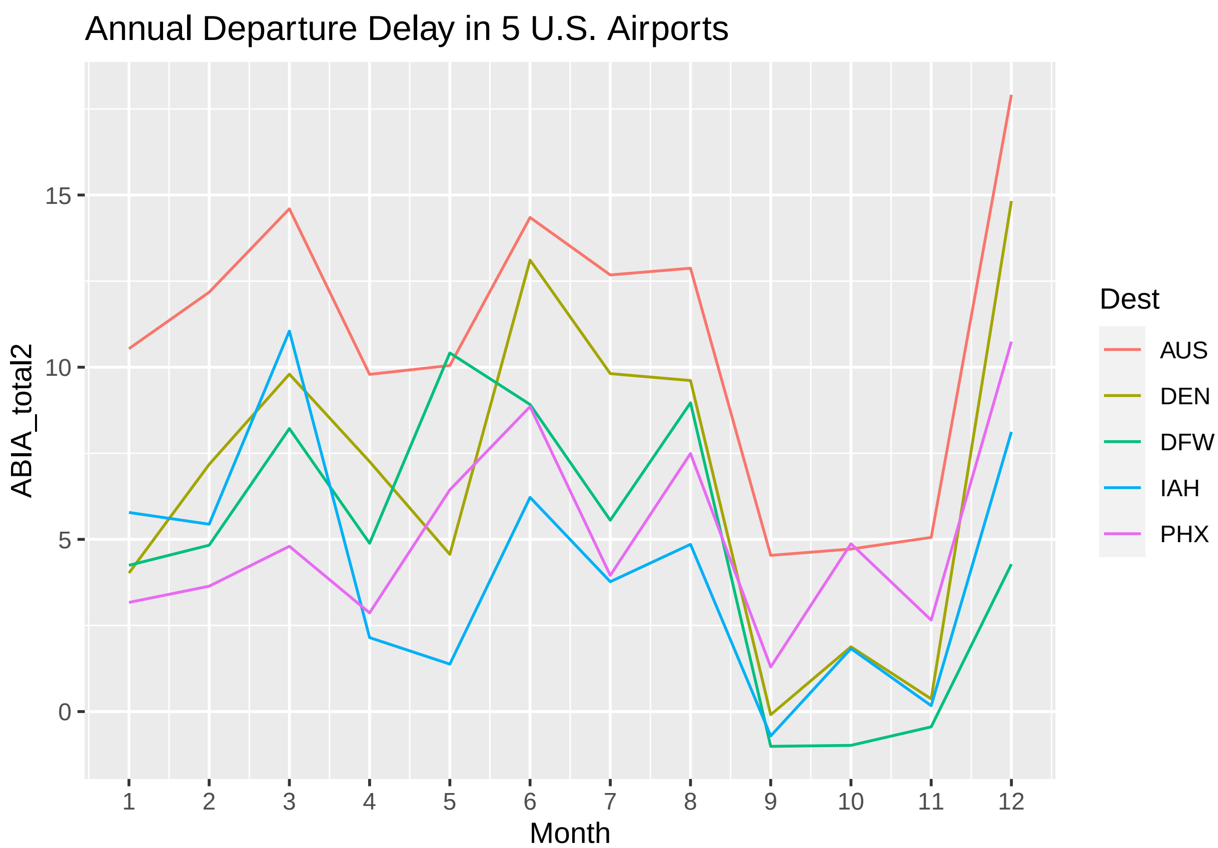
```
## # A tibble: 12 x 2
##    Month ABIA_total1
##    <int>       <dbl>
##  1     1        8.37
##  2     2       10.3
##  3     3       13.3
##  4     4        8.17
##  5     5        8.85
##  6     6       12.2
```

```
## 7     7        10.2
## 8     8        10.3
## 9     9         3.33
## 10   10         3.88
## 11   11         4.36
## 12   12        15.3
```

```
ggplot(ABIA_DepDelay2) +
  geom_line(aes(x=Month, y=ABIA_total2)) +
  facet_wrap(~Dest) +
  scale_x_continuous(breaks = 1:12)
```




```
ggplot(ABIA_DepDelay2) +
  geom_line(aes(x=Month, y=ABIA_total2, color=Dest)) +
  scale_x_continuous(breaks = 1:12) + ggtitle("Annual Departure Delay in 5 U.S. Airports")
```



#All these five airports commonly have the least amount of delays in September and the most amount of delays in December, which refers that the destination does not affect the departure time and its' delay. It's possible that the weather is a major factor in delay. It could alternatively be the air traffic in December since it is the peak time of the high season. ##4) K-nearest neighbors

```
library(tidyverse)
library(ggplot2)
library(rsample)
library(caret)
```

```
## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(modelr)
library(parallel)
library(foreach)
```

```
##
## Attaching package: 'foreach'
```

```
## The following objects are masked from 'package:purrr':
##
##     accumulate, when
```

```
sclass = read.csv('~/Desktop/sclass.csv')
##350
model350 = sclass %>%
  filter(trim %in% '350')
#1.Split the data into a training and a testing set.

sclass350_split =  initial_split(model350, prop=0.9)
sclass350_train = training(sclass350_split)
sclass350_test  = testing(sclass350_split)
#2.Run K-nearest-neighbors, for many different values of K, starting at K=2 and going as high as you ne
K_folds = 5
model350 = model350 %>%
  mutate(fold_id = rep(1:K_folds, length=nrow(model350)) %>% sample)
head(model350)
```

```
##    id trim subTrim condition isOneOwner mileage year  color displacement   fuel
## 1 282  350    unsp       CPO          f   21929 2012  Black        3.0 L Diesel
## 2 284  350    unsp       CPO          f   17770 2012 Silver        3.0 L Diesel
## 3 285  350    unsp      Used          f   29108 2012  Black        3.0 L Diesel
## 4 288  350    unsp       CPO          f   35004 2013  White        3.0 L Diesel
## 5 289  350    unsp      Used          t   66689 2012  Black        3.0 L Diesel
## 6 290  350    unsp       CPO          f   19567 2012  Black        3.0 L Diesel
##   state region   soundSystem wheelType wheelSize featureCount price fold_id
## 1    MA    New          unsp      unsp      unsp           82 55994       2
## 2    IL    ENC       Premium     Alloy      unsp           72 60900       3
## 3    VA    SoA          unsp      unsp      unsp            5 54995       1
## 4    NH    New Harman Kardon      unsp      unsp           83 59988       3
## 5    NJ    Mid Harman Kardon     Alloy      unsp           79 37995       2
## 6    LA    WSC       Premium     Alloy      unsp           76 59977       3
```

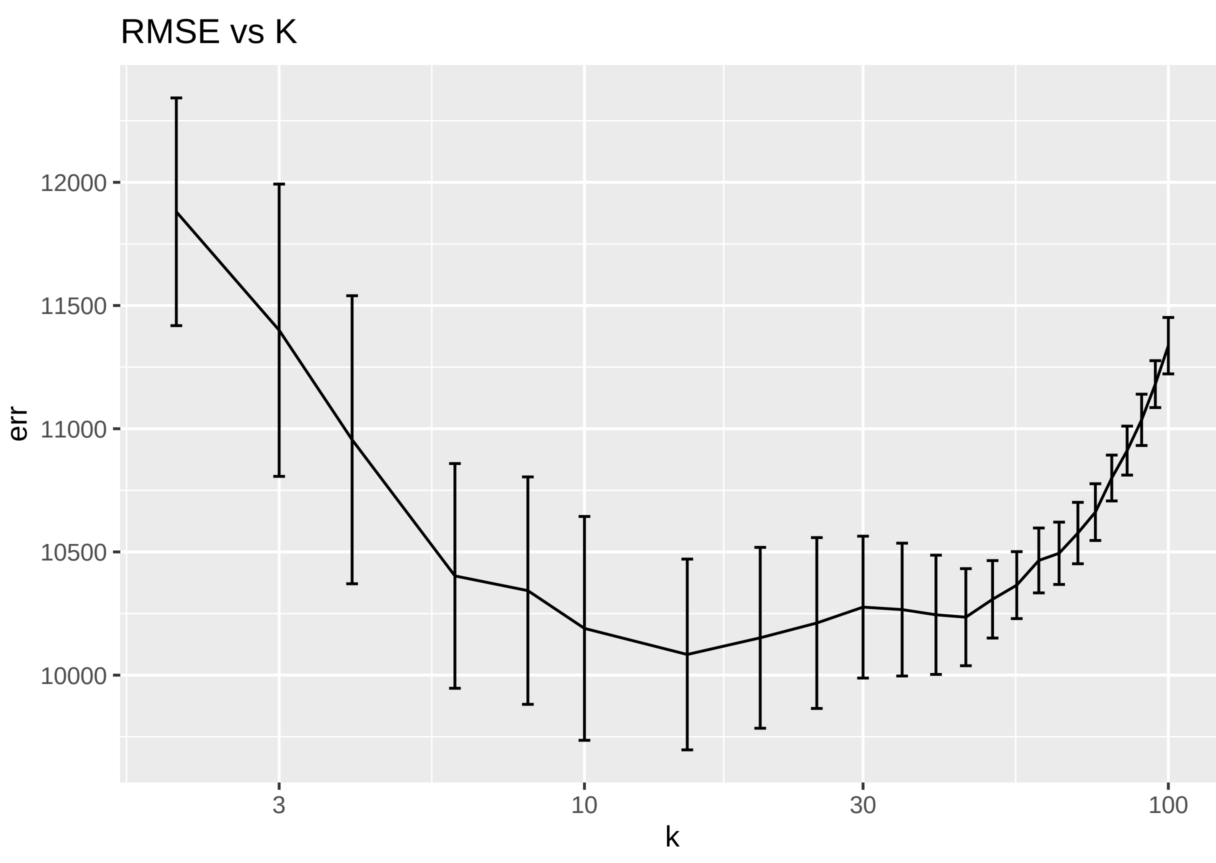
```
#3.Calculate the out-of-sample root mean-squared error (RMSE) for each value of K.
rmse_cv = foreach(fold = 1:K_folds, .combine='c') %do% {
  knn100 = knnreg(price ~ mileage,
                  data=filter(model350, fold_id != fold), k=100)
  modelr::rmse(knn100, data=filter(model350, fold_id == fold))
}
k_grid = c(2, 3, 4, 6, 8, 10, 15, 20, 25, 30, 35, 40, 45,
           50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100)
model350_folds = crossv_kfold(model350, k=K_folds)
cv_grid = foreach(k = k_grid, .combine='rbind') %dopar% {
  models = map(model350_folds$train, ~ knnreg(price ~ mileage, k=k, data = ., use.all=FALSE))
  errs = map2_dbl(models, model350_folds$test, modelr::rmse)
  c(k=k, err = mean(errs), std_err = sd(errs)/sqrt(K_folds))
} %>% as.data.frame
```

```
## Warning: executing %dopar% sequentially: no parallel backend registered
```

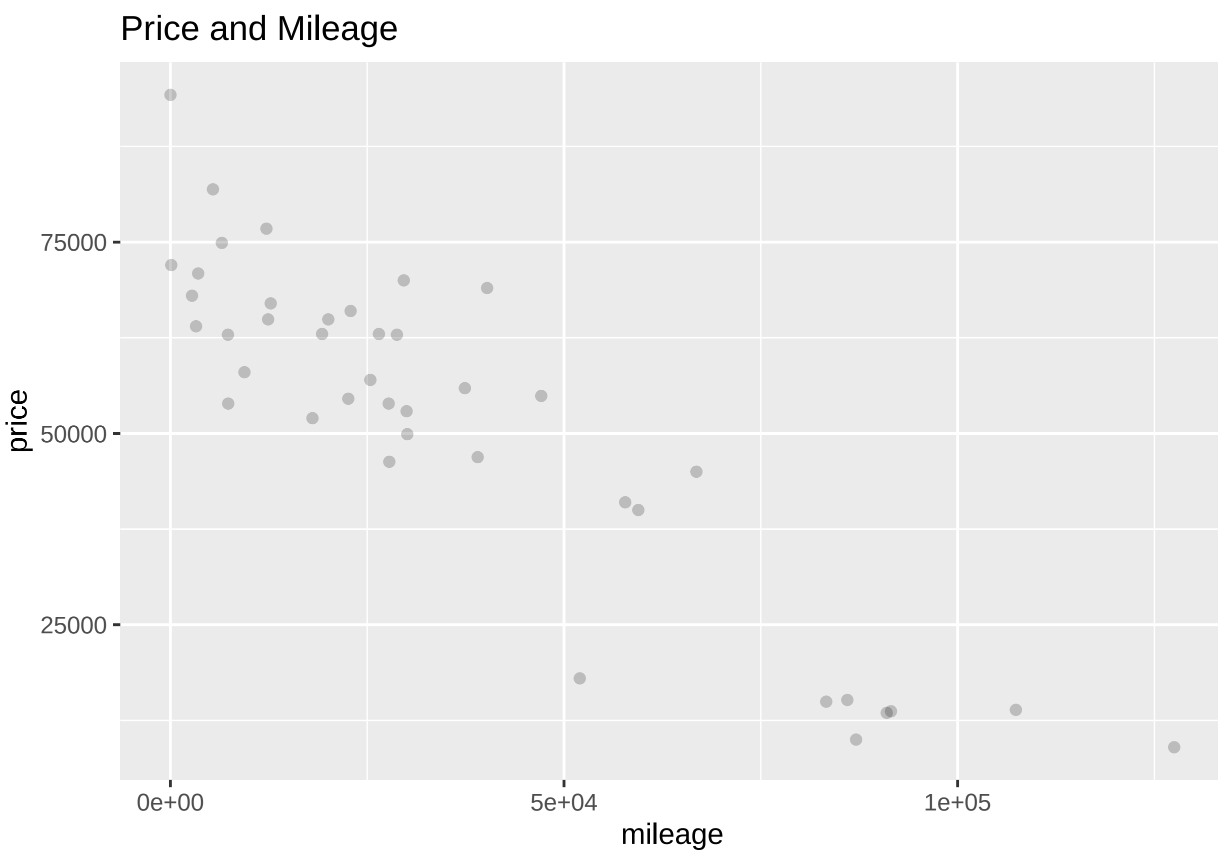
```r
head(cv_grid)
```

```
##             k      err  std_err
## result.1  2 11880.40 462.1131
## result.2  3 11399.72 593.1166
## result.3  4 10955.29 584.4623
## result.4  6 10402.66 455.9885
## result.5  8 10342.94 461.5398
## result.6 10 10189.69 454.2263
```

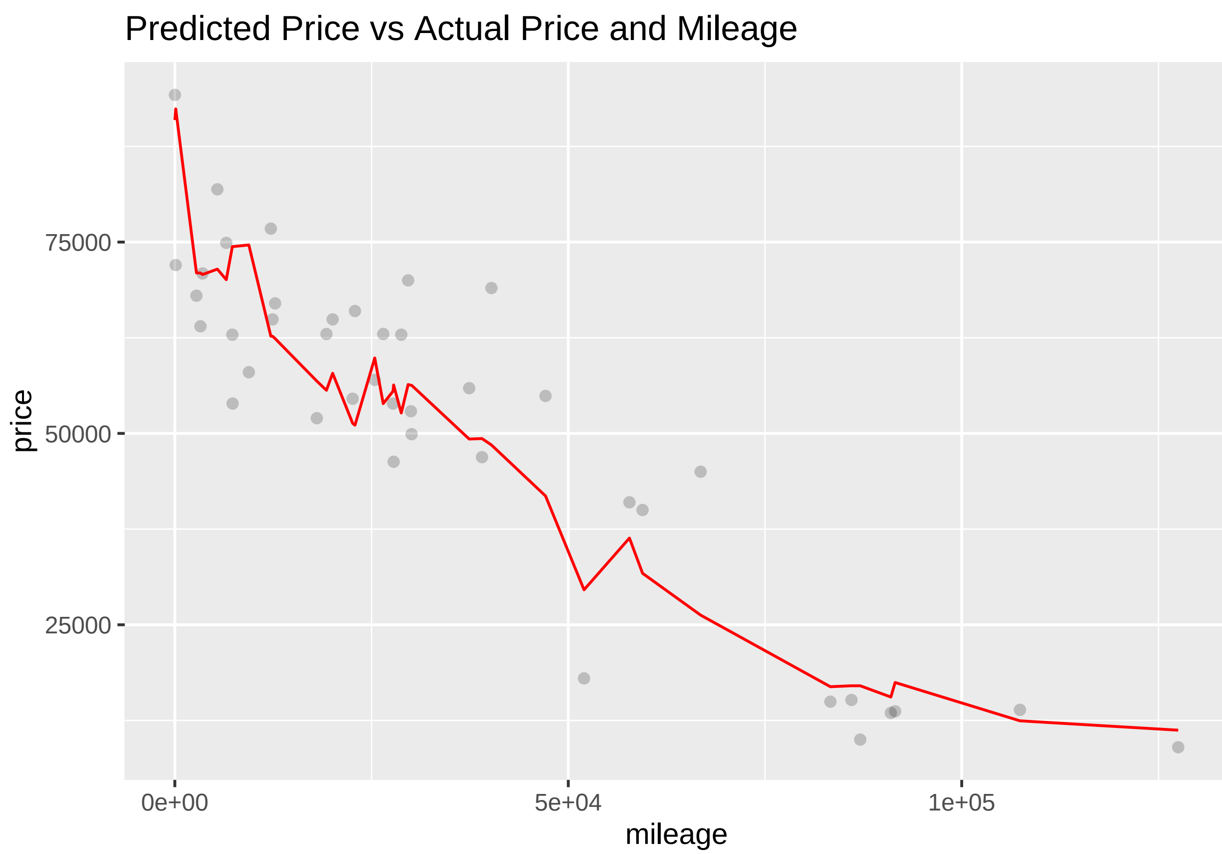
```r
#RMSE versus K plot
ggplot(cv_grid) +
  geom_line(aes(x=k, y=err)) +
  geom_errorbar(aes(x=k, ymin = err-std_err, ymax = err+std_err)) +
  scale_x_log10() + ggtitle("RMSE vs K")
```




```r
#For the optimal value of K (k=10), plot of the fitted model i.e. price prediction vs. mileage
knn10 = knnreg(price ~ mileage, data=sclass350_train, k=10)
sclass350_test = sclass350_test %>%
  mutate(price_pred = predict(knn10, sclass350_test))
p_test = ggplot(data = sclass350_test) +
  geom_point(mapping = aes(x = mileage, y = price), alpha=0.2) + ggtitle("Price and Mileage")
p_test
```



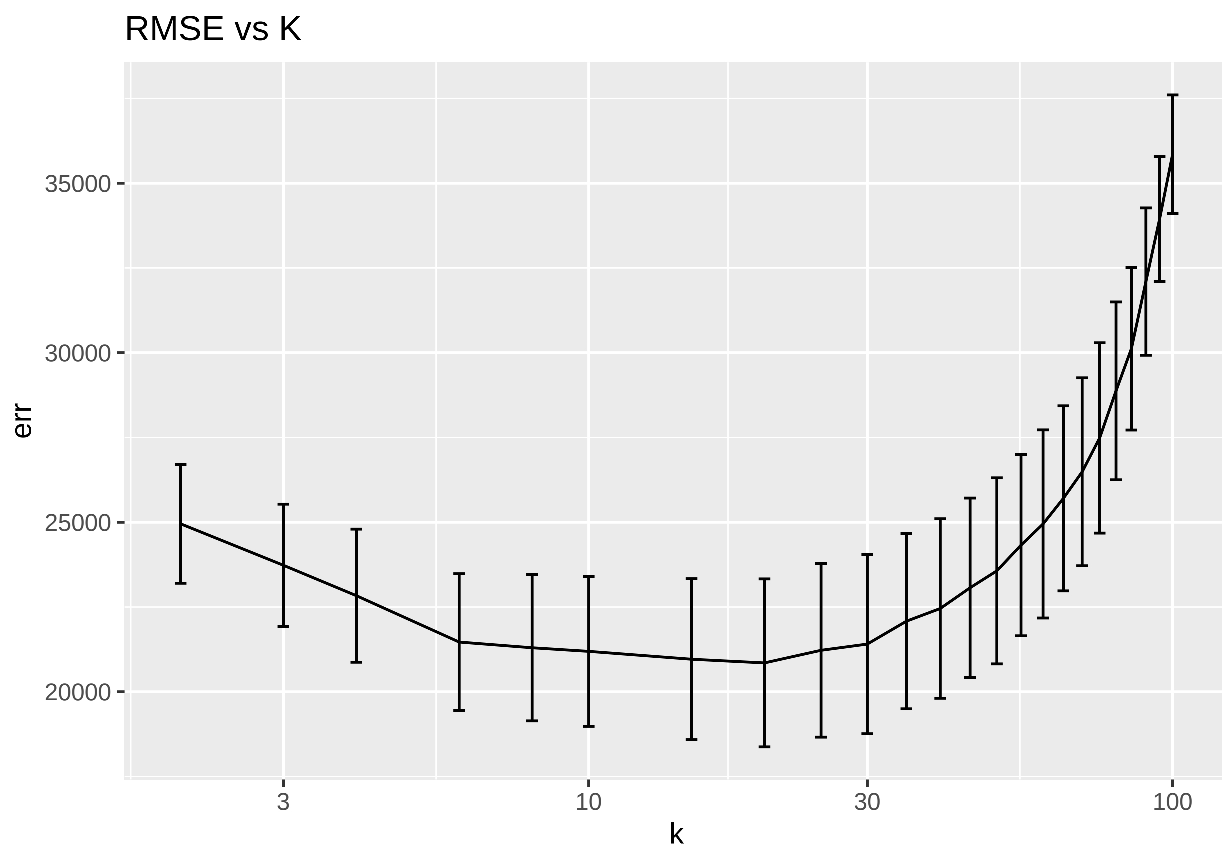

```
p_test + geom_line(aes(x = mileage, y = price_pred), color='red', size=0.5) + ggtitle("Predicted Price v
```



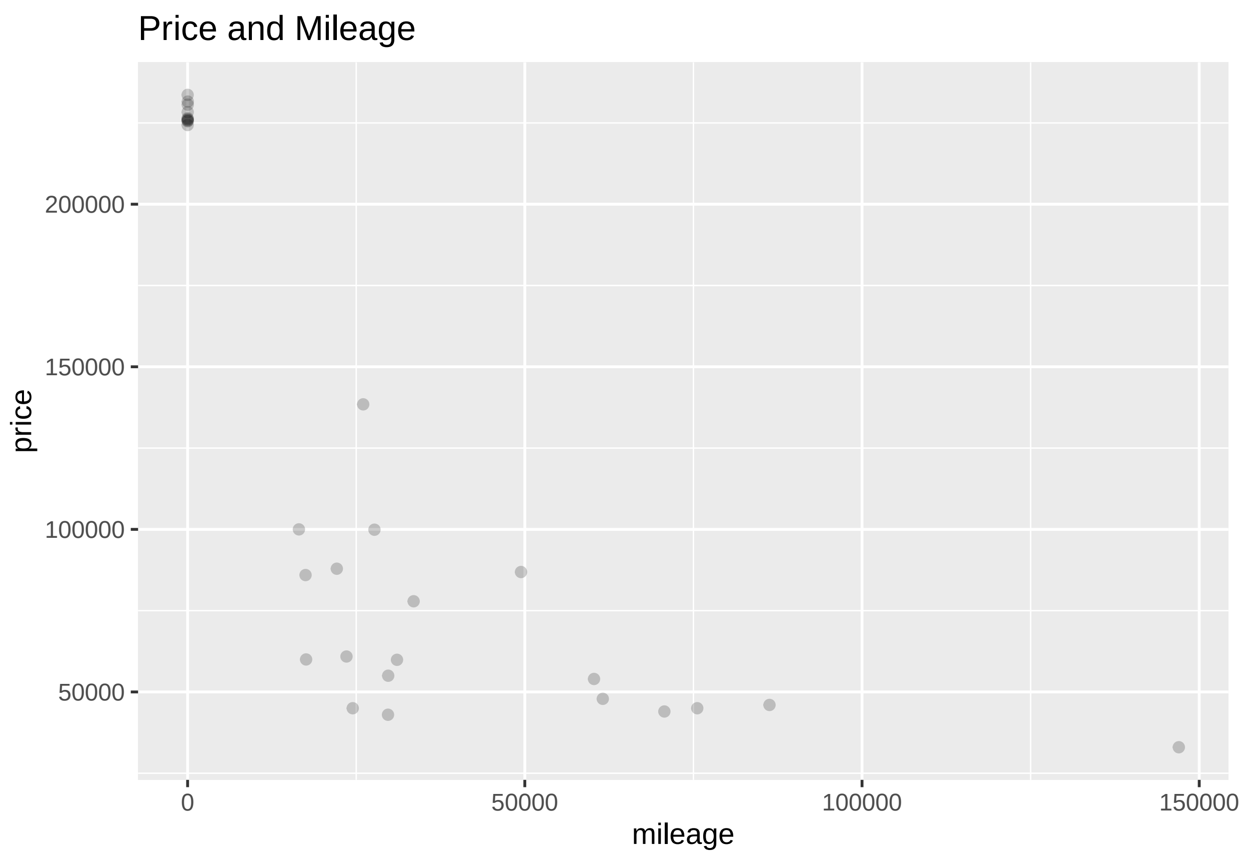

```
##65 AMG
model65AMG = sclass %>%
  filter(trim %in% '65 AMG')
#1.Split the data into a training and a testing set.
sclass65AMG_split =  initial_split(model65AMG, prop=0.9)
sclass65AMG_train = training(sclass65AMG_split)
sclass65AMG_test  = testing(sclass65AMG_split)
#2.Run K-nearest-neighbors, for many different values of K, starting at K=2 and going as high as you ne
K_folds = 5
model65AMG = model65AMG %>%
  mutate(fold_id = rep(1:K_folds, length=nrow(model65AMG)) %>% sample)
#3.Calculate the out-of-sample root mean-squared error (RMSE) for each value of K.
rmse_cv = foreach(fold = 1:K_folds, .combine='c') %do% {
  knn100 = knnreg(price ~ mileage,
                  data=filter(model65AMG, fold_id != fold), k=100)
  modelr::rmse(knn100, data=filter(model350, fold_id == fold))
}
k_grid = c(2, 3, 4, 6, 8, 10, 15, 20, 25, 30, 35, 40, 45,
           50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100)
model65AMG_folds = crossv_kfold(model65AMG, k=K_folds)
cv_grid = foreach(k = k_grid, .combine='rbind') %dopar% {
  models = map(model65AMG_folds$train, ~ knnreg(price ~ mileage, k=k, data = ., use.all=FALSE))
  errs = map2_dbl(models, model65AMG_folds$test, modelr::rmse)
  c(k=k, err = mean(errs), std_err = sd(errs)/sqrt(K_folds))
} %>% as.data.frame
head(cv_grid)
```

```
##            k      err  std_err
## result.1  2 24954.16 1752.469
## result.2  3 23730.93 1802.766
## result.3  4 22834.52 1962.569
## result.4  6 21466.23 2015.247
## result.5  8 21297.82 2156.154
## result.6 10 21192.08 2209.898
```

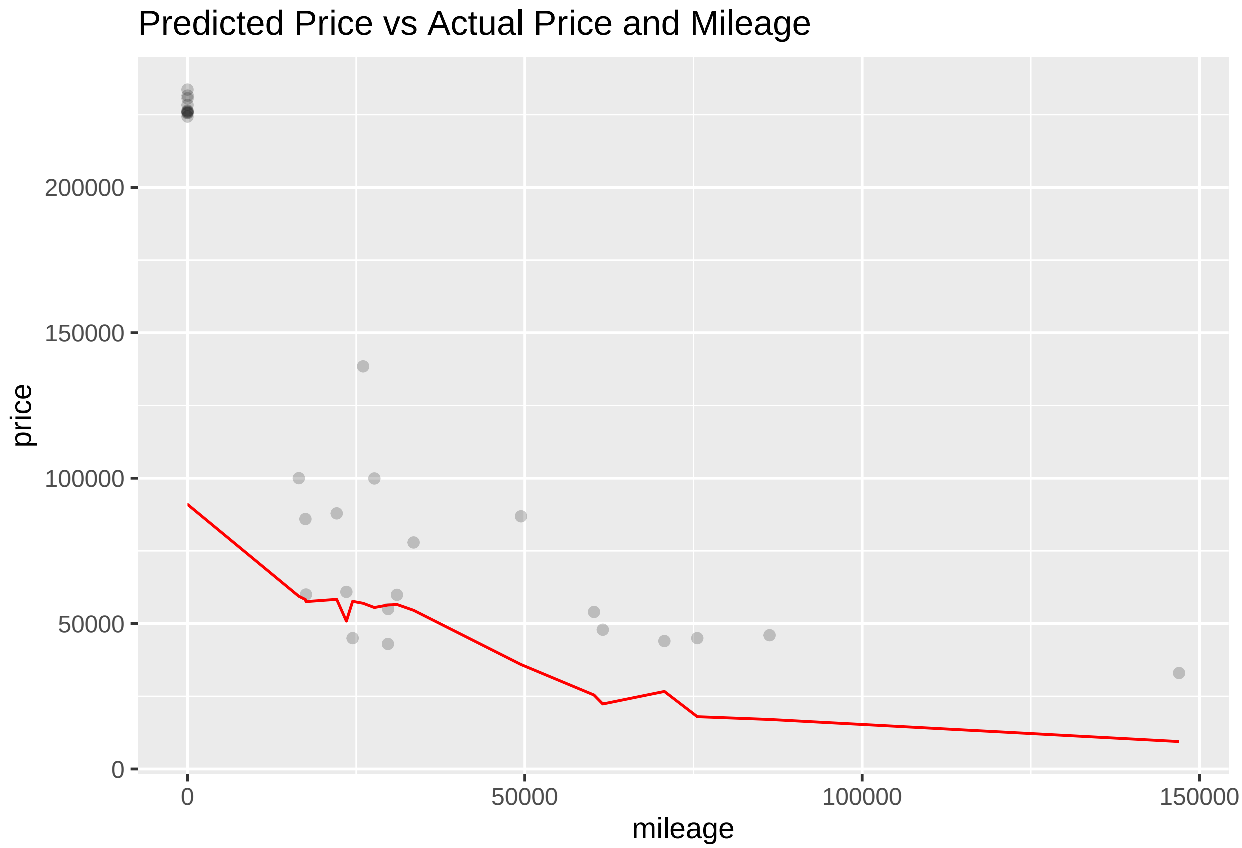
```
#RMSE versus K plot
ggplot(cv_grid) +
  geom_line(aes(x=k, y=err)) +
  geom_errorbar(aes(x=k, ymin = err-std_err, ymax = err+std_err)) +
  scale_x_log10() + ggtitle("RMSE vs K")
```




```
#For the optimal value of K (k=15), plot of the fitted model i.e. price prediction vs. mileage
knn15 = knnreg(price ~ mileage, data=sclass65AMG_train, k=15)
sclass65AMG_test = sclass65AMG_test %>%
  mutate(price_pred = predict(knn10, sclass65AMG_test))
p_test = ggplot(data = sclass65AMG_test) +
  geom_point(mapping = aes(x = mileage, y = price), alpha=0.2) + ggtitle("Price and Mileage")
p_test
```




```
p_test + geom_line(aes(x = mileage, y = price_pred), color='red', size=0.5) + ggtitle("Predicted Price v
```



##The 65 AMG yields a larger optimal value of K. The lowest out-of-sample root mean-squared error of the 65 AMG is lower than the 350. I think this occurs due to the difference in sample sizes since the 65 AMG S-Class has 292 observations whereas the 350 S-class has 416 observations.