HW1

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1-1

```
library(tidyverse)
```

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

```
## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.0.3     v dplyr   1.0.0
## v tidyr   1.1.0     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

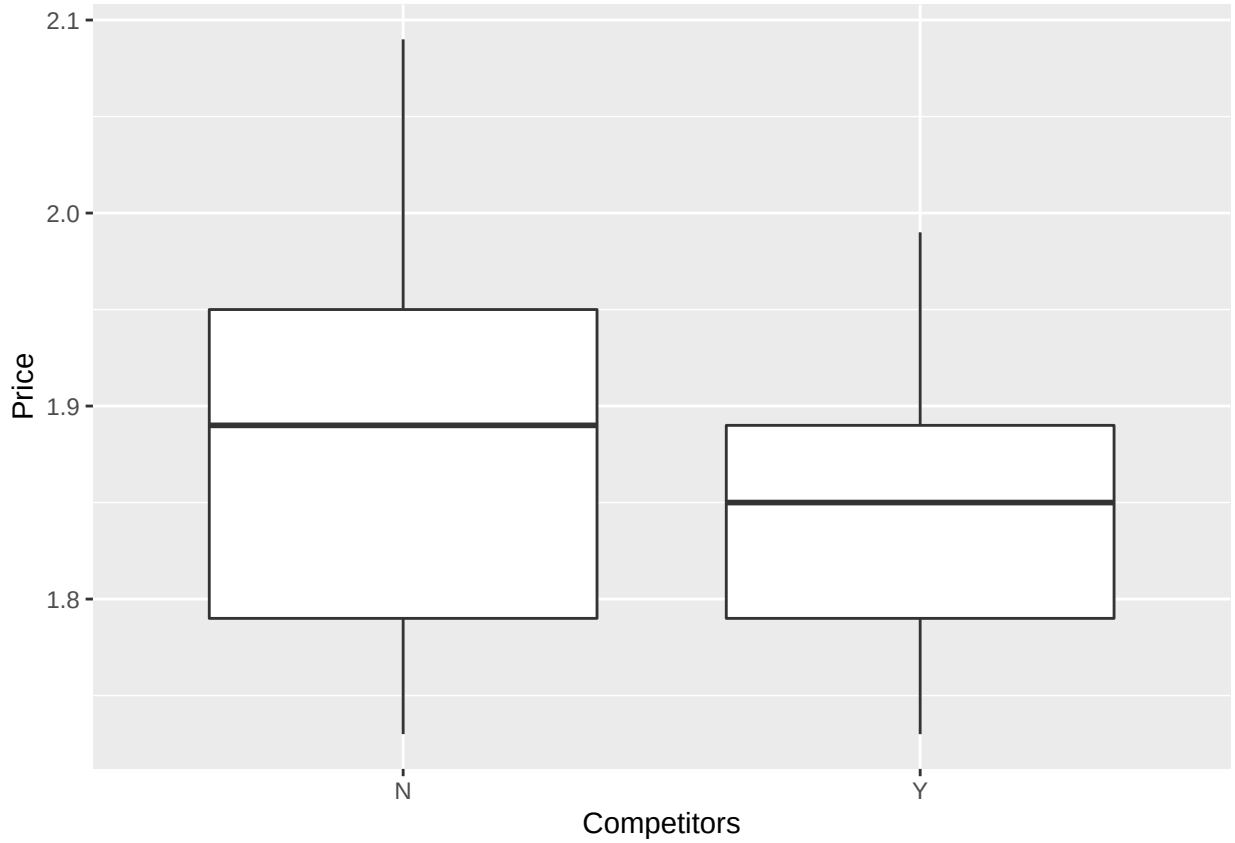
```
## -- Conflicts ------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(ggplot2)

GasPrices = read.csv('C:/Users/CHOI/Desktop/GasPrices.csv')
```

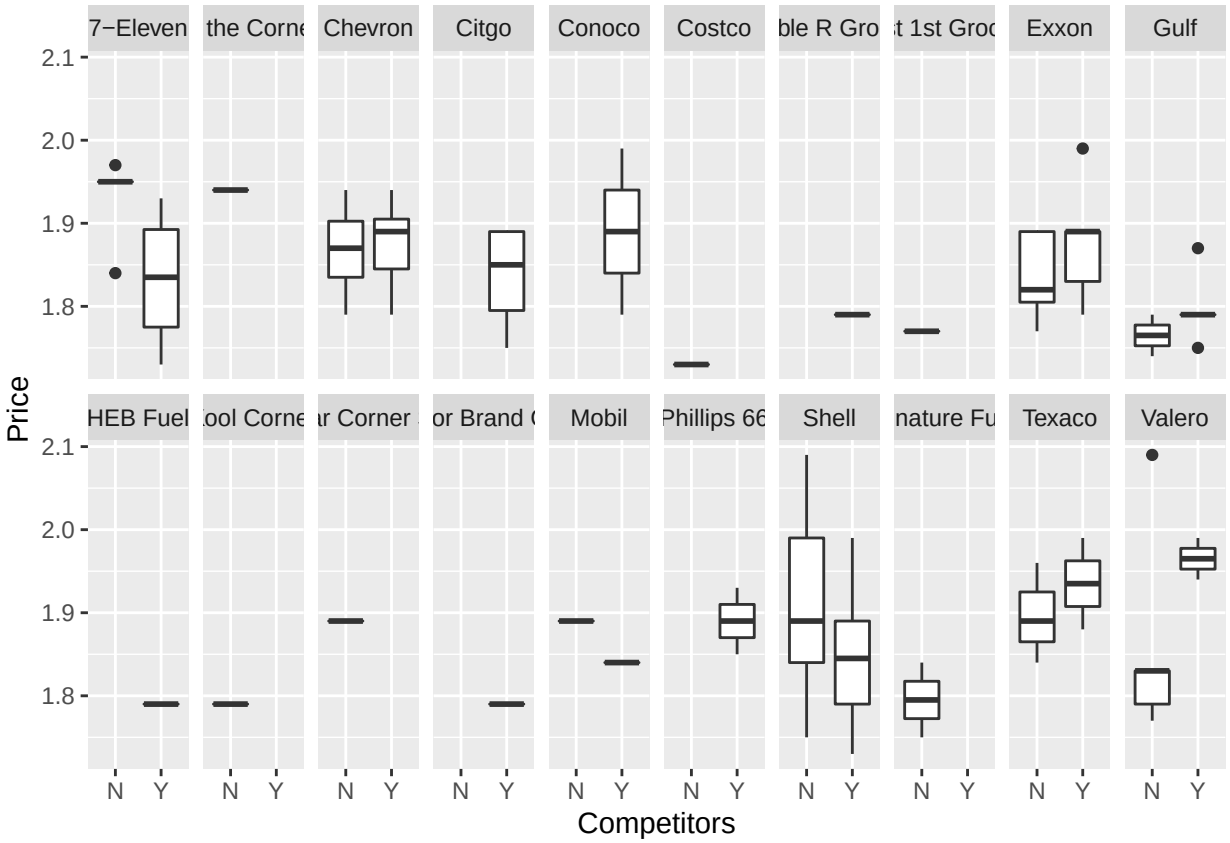
A. Competition & Price

```
ggplot(data=GasPrices) +
  geom_boxplot(aes(x = Competitors, y=Price))
```



The bar plot above shows the gas price of gas providers which have competitors is lower than the price of the providers which do not have competitors.

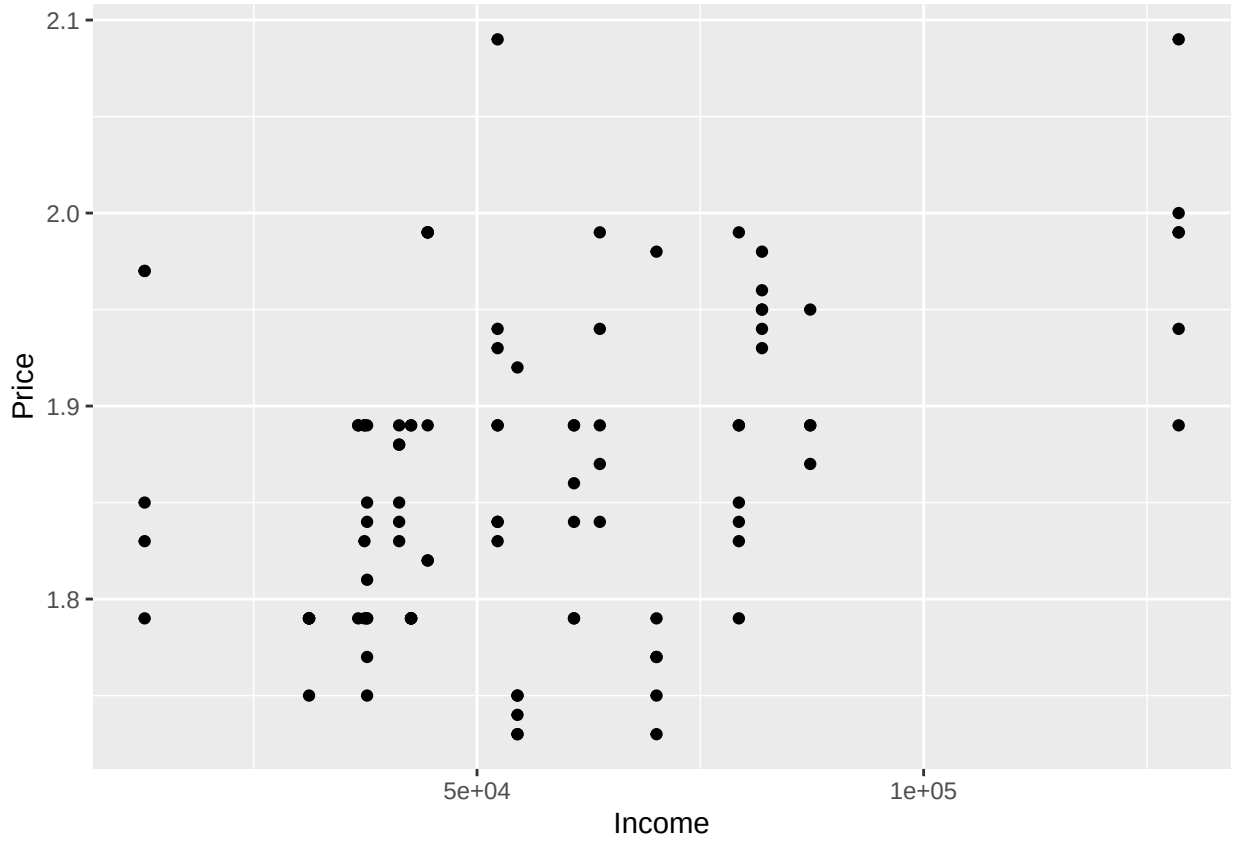
```
ggplot(data=GasPrices) +
  geom_boxplot(aes(x = Competitors, y=Price)) +
  facet_wrap(~Name, nrow=2)
```



However, it would be hard to generalize the relation between the price and the existence of competitors for all providers. Only three providers shows lower price when they have competitors than without-competitors cases among the eight eligible cases out of twenty, whose with-competitor prices and without-competitors prices can be compared.

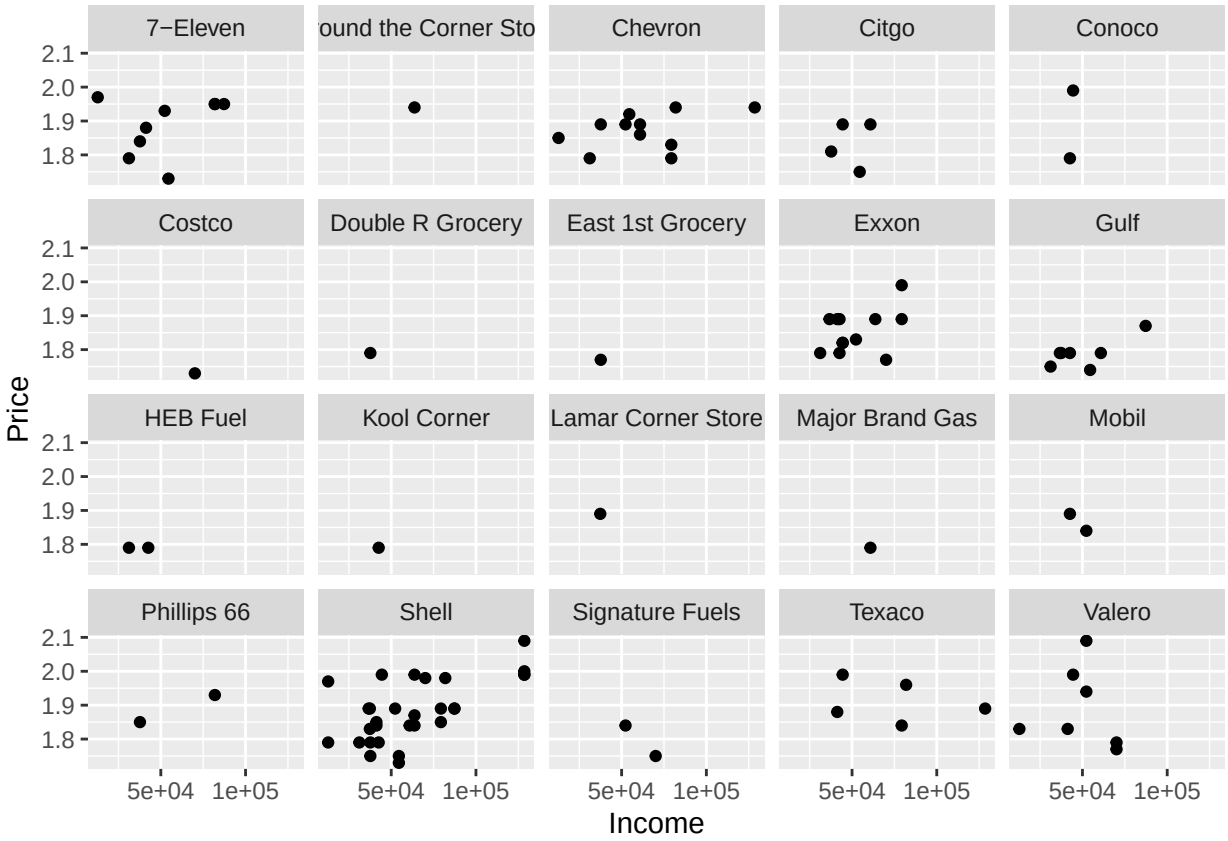
B. Income & Price

```
ggplot(data=GasPrices) +
  geom_point(mapping = aes(x=Income, y=Price))
```



We can see upward shape of dots in this graph, which means the gas prices and income of the area where the gas station is located have a positive relation.

```
ggplot(data=GasPrices) +
  geom_point(mapping = aes(x=Income, y=Price)) +
  facet_wrap(~Name, nrow=4)
```



On the graph of each company, several companies such as 7-Eleven, Exxon, of Shell represent these positive relation obviously. On the contrary, we can see that some companies like Costco sticks to one-price polices.

C. Price of Shell vs Other sellers

```
GasPrices = GasPrices %>%
  mutate(class = ifelse(Name == 'Shell', 'Shell', 'others'))

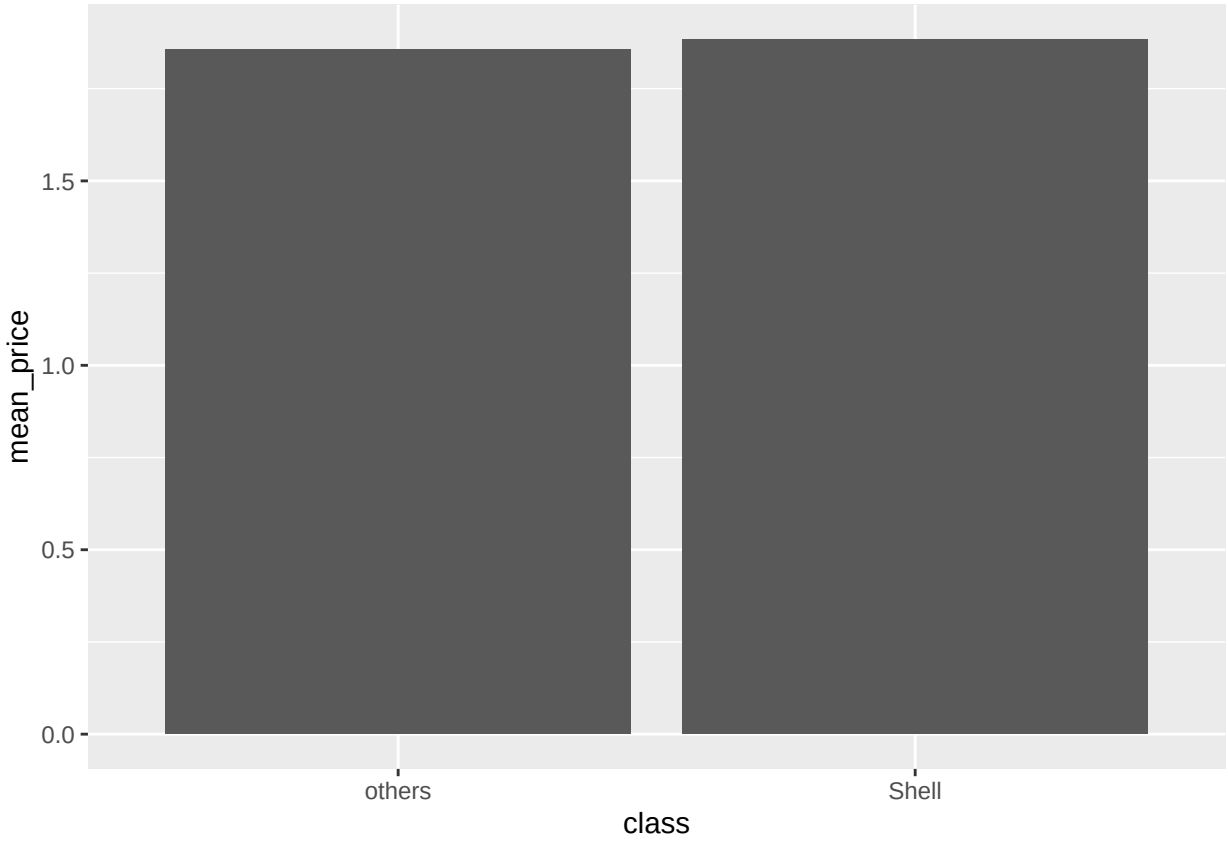
d1 = GasPrices %>%
  group_by(class) %>%
  summarise(mean_price = mean(Price))
```

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

```
d1
```

```
## # A tibble: 2 x 2
##   class  mean_price
##   <chr>       <dbl>
## 1 others       1.86
## 2 Shell        1.88
```

```
ggplot(data=d1) +
  geom_col(mapping=aes(x=class, y=mean_price), position = 'dodge')
```



The average gas price of Shell($1.88) is a little bit higher than that of other providers($1.86).

```
d2 = GasPrices %>%
  group_by(Name) %>%
  summarise(mean_price = mean(Price))
```

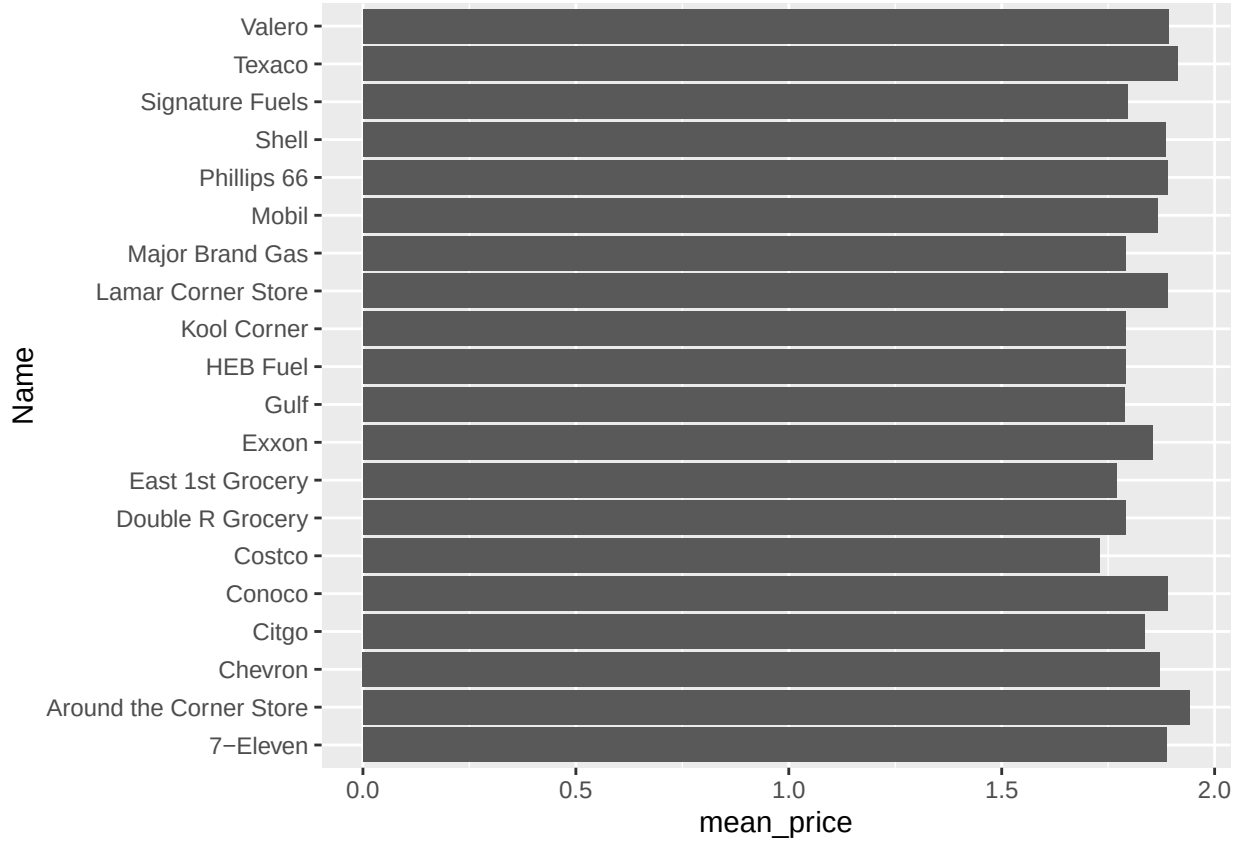
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
d2
```

```
## # A tibble: 20 x 2
##    Name                    mean_price
##    <chr>                        <dbl>
##  1 7-Eleven                      1.89
##  2 Around the Corner Store       1.94
##  3 Chevron                       1.87
##  4 Citgo                         1.84
##  5 Conoco                        1.89
##  6 Costco                        1.73
##  7 Double R Grocery              1.79
##  8 East 1st Grocery              1.77
##  9 Exxon                         1.86
## 10 Gulf                          1.79
## 11 HEB Fuel                      1.79
## 12 Kool Corner                   1.79
## 13 Lamar Corner Store            1.89
## 14 Major Brand Gas               1.79
## 15 Mobil                         1.86
```

```
## 16 Phillips 66                  1.89
## 17 Shell                        1.88
## 18 Signature Fuels              1.80
## 19 Texaco                       1.91
## 20 Valero                       1.89
```

```
ggplot(data=d2) +
  geom_col(mapping=aes(x=mean_price, y=Name), position = 'dodge')
```

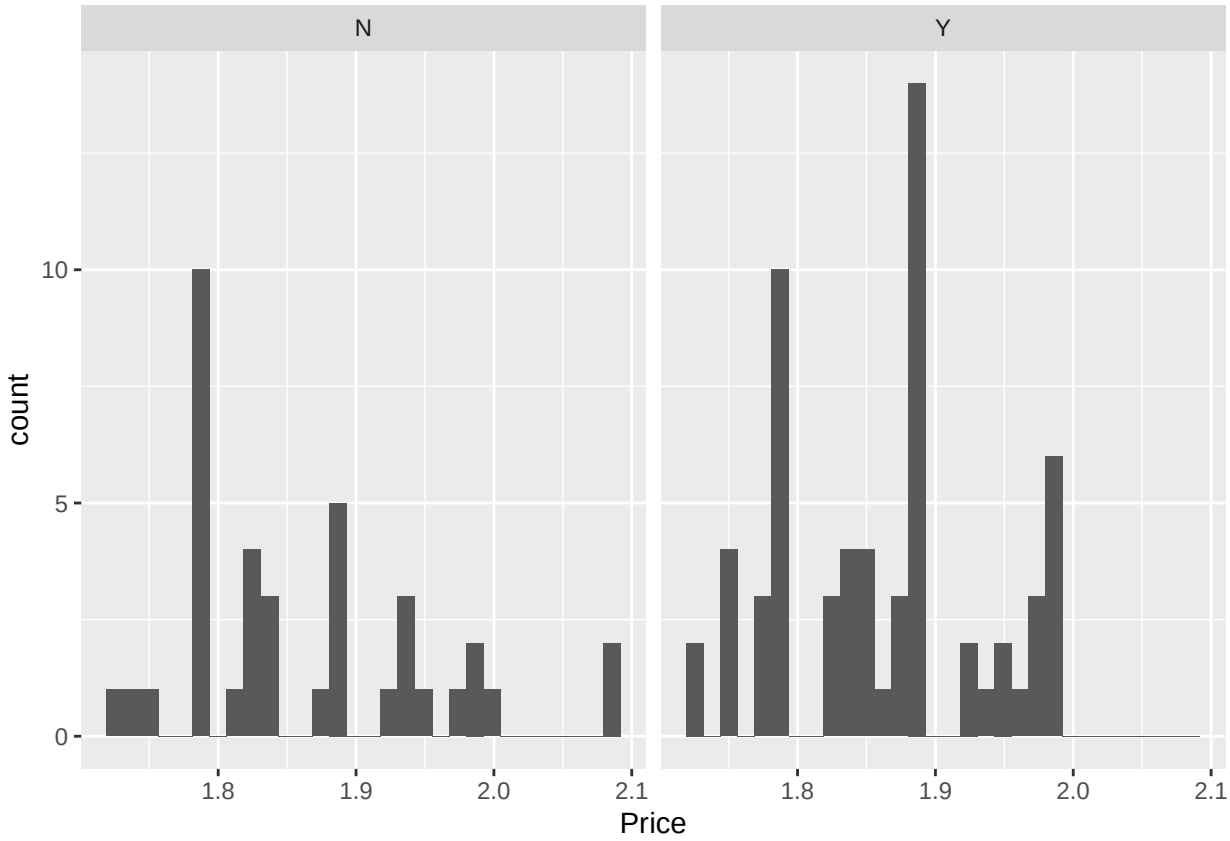


The 12 out of 19 providers have lower average gas prices than that of Shell.

D. stoplights' effects on Price

```
ggplot(data = GasPrices) +
  geom_histogram(aes(x=Price)) +
  facet_wrap(~ Stoplight)
```

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



Gas stations nearby stoplights generally have higher gas prices. Prices of gas stations without stoplight nearby(the left graph) are concentrated around 1.8, while gas stations near stoplight have a lot of prices around 1.8~1.9.

E. The effect of Highway access on Price

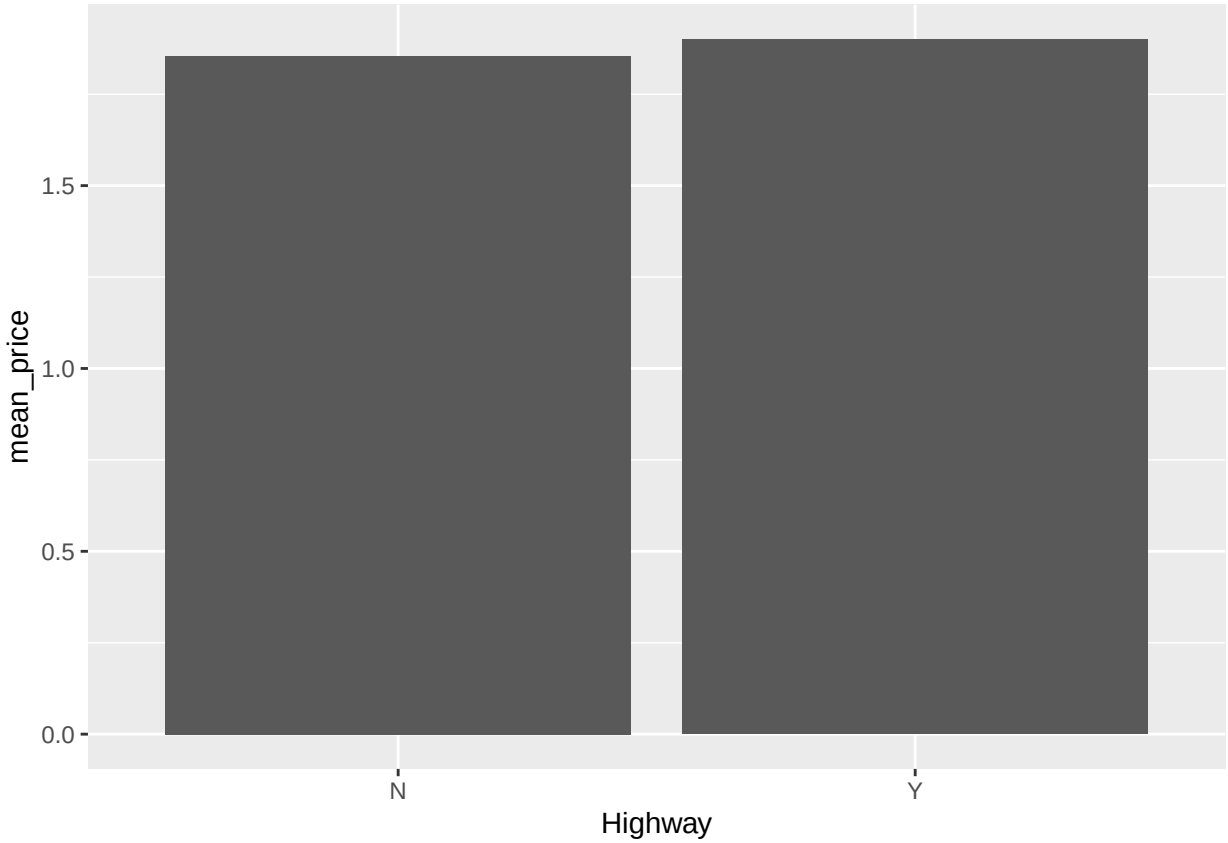
```
d3 = GasPrices %>%
  group_by(Highway) %>%
  summarise(mean_price = mean(Price))
```

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

```
d3
```

```
## # A tibble: 2 x 2
##   Highway mean_price
##   <chr>        <dbl>
## 1 N             1.85
## 2 Y             1.9
```

```
ggplot(data=d3) +
  geom_col(mapping = aes(x=Highway, y=mean_price))
```



Gas stations which is accessible to highways tend to set gas prices higher than gas stations which is far from highways.

```
d4 = GasPrices %>%
  group_by(Highway, Name) %>%
  summarize(mean_price = mean(Price))
```

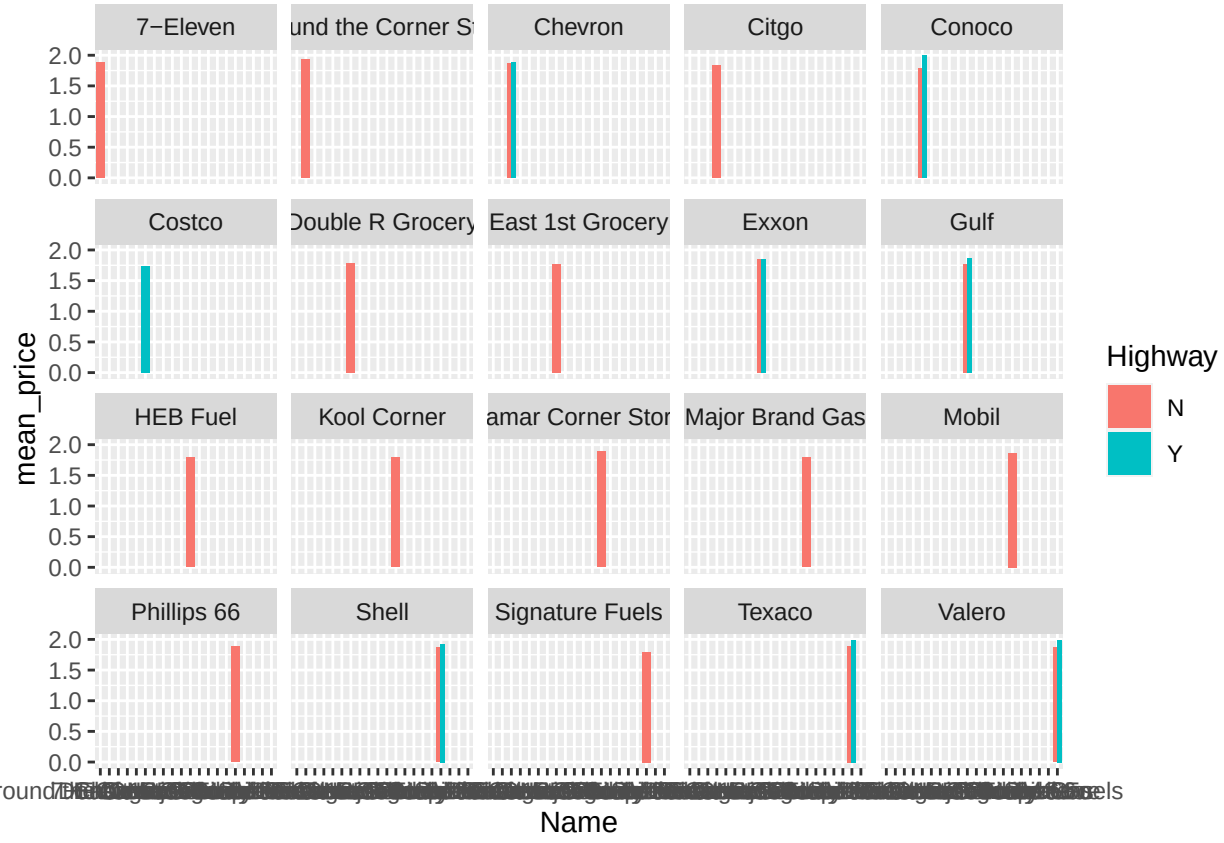
```
## `summarise()` regrouping output by 'Highway' (override with `.groups` argument)
```

```
d4
```

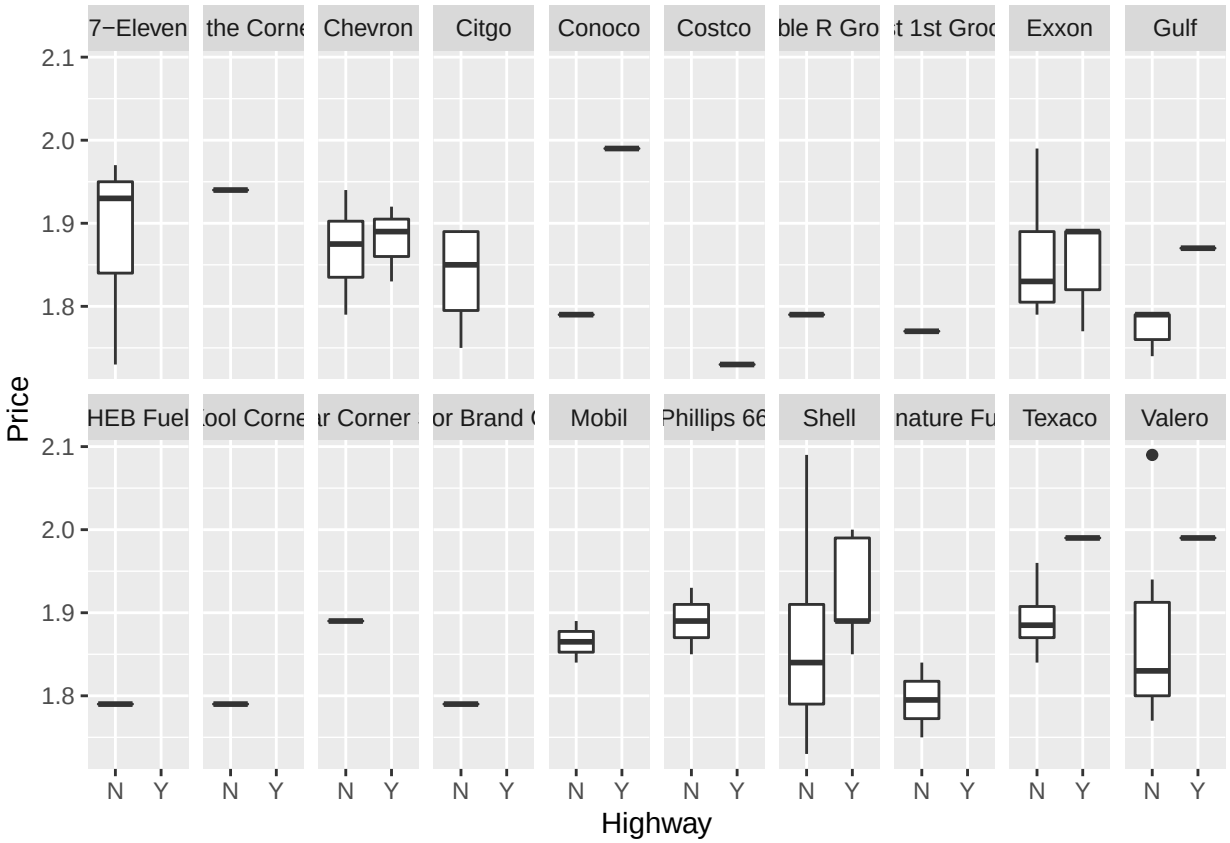
```
## # A tibble: 27 x 3
## # Groups:   Highway [2]
##    Highway Name                    mean_price
##    <chr>   <chr>                        <dbl>
##  1 N       7-Eleven                      1.89
##  2 N       Around the Corner Store       1.94
##  3 N       Chevron                       1.87
##  4 N       Citgo                         1.84
##  5 N       Conoco                        1.79
##  6 N       Double R Grocery              1.79
##  7 N       East 1st Grocery              1.77
##  8 N       Exxon                         1.86
##  9 N       Gulf                          1.78
## 10 N       HEB Fuel                      1.79
## # ... with 17 more rows
```

```
ggplot(data = d4) +
  geom_col(mapping = aes(x = Name,y = mean_price,
```

```
                          fill=Highway), position = 'dodge') +
  facet_wrap(~Name, nrow=4)
```




```
ggplot(data=GasPrices) +
  geom_boxplot(aes(x = Highway, y=Price)) +
  facet_wrap(~Name, nrow=2)
```



These plots show that companies usually set higher gas price for the gas stations which are highway accessible.

1-2

```
library(tidyverse)
library(ggplot2)

bikeshare = read.csv('C:/Users/CHOI/Desktop/bikeshare.csv')
```

plot A

```
bikeshare_a = bikeshare %>%
  group_by(hr) %>%
  summarise(average_rental=mean(total))
```

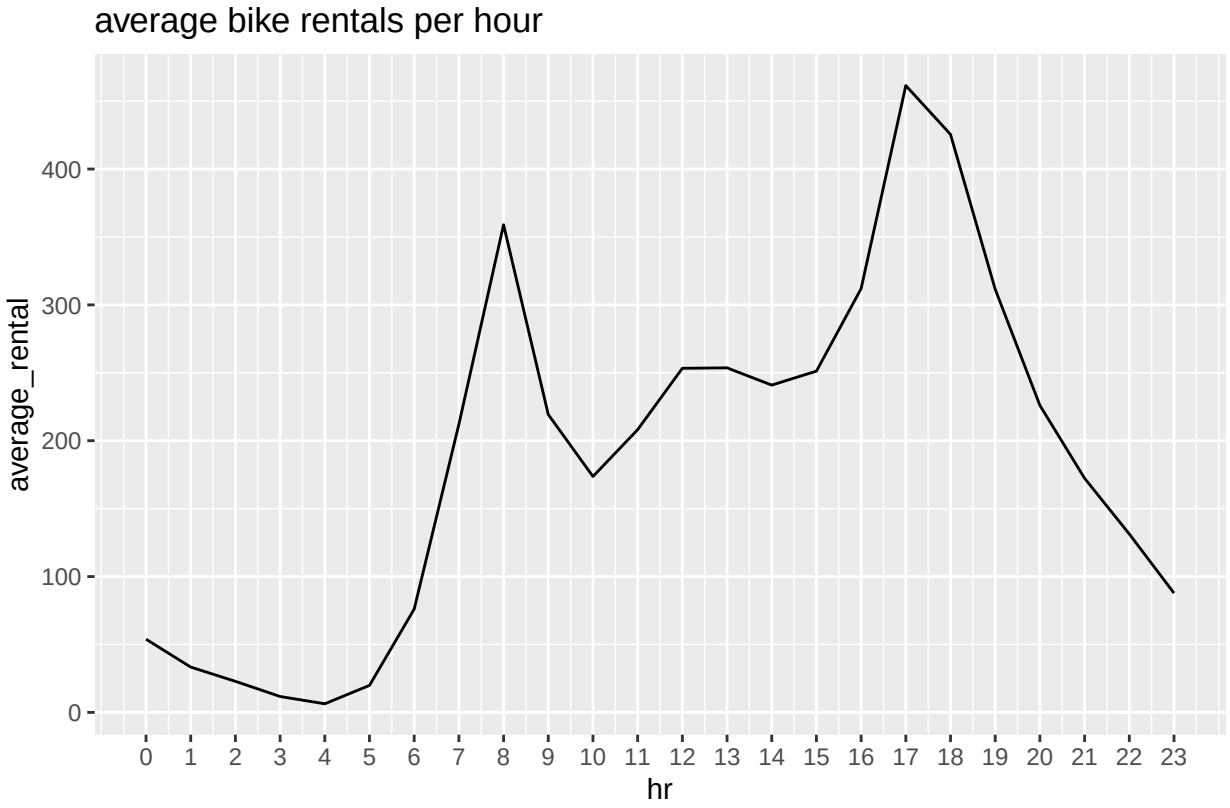
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
head(bikeshare_a)
```

```
## # A tibble: 6 x 2
##      hr average_rental
##   <int>          <dbl>
## 1     0           53.9
## 2     1           33.4
## 3     2           22.9
## 4     3           11.7
```

```
## 5     4           6.35
## 6     5          19.9
```

```
ggplot(data=bikeshare_a) +
  geom_line(aes(x=hr, y=average_rental)) +
  scale_x_continuous(breaks=0:23) +
  labs(title="average bike rentals per hour", caption="Most used during rush hour(8:00, 17:00)")
```



plot B

```
bikeshare_b = bikeshare %>%
  mutate(work = ifelse(workingday==1, "working", "dayoff")) %>%
  group_by(hr, work) %>%
  summarise(average_rental=mean(total))
```

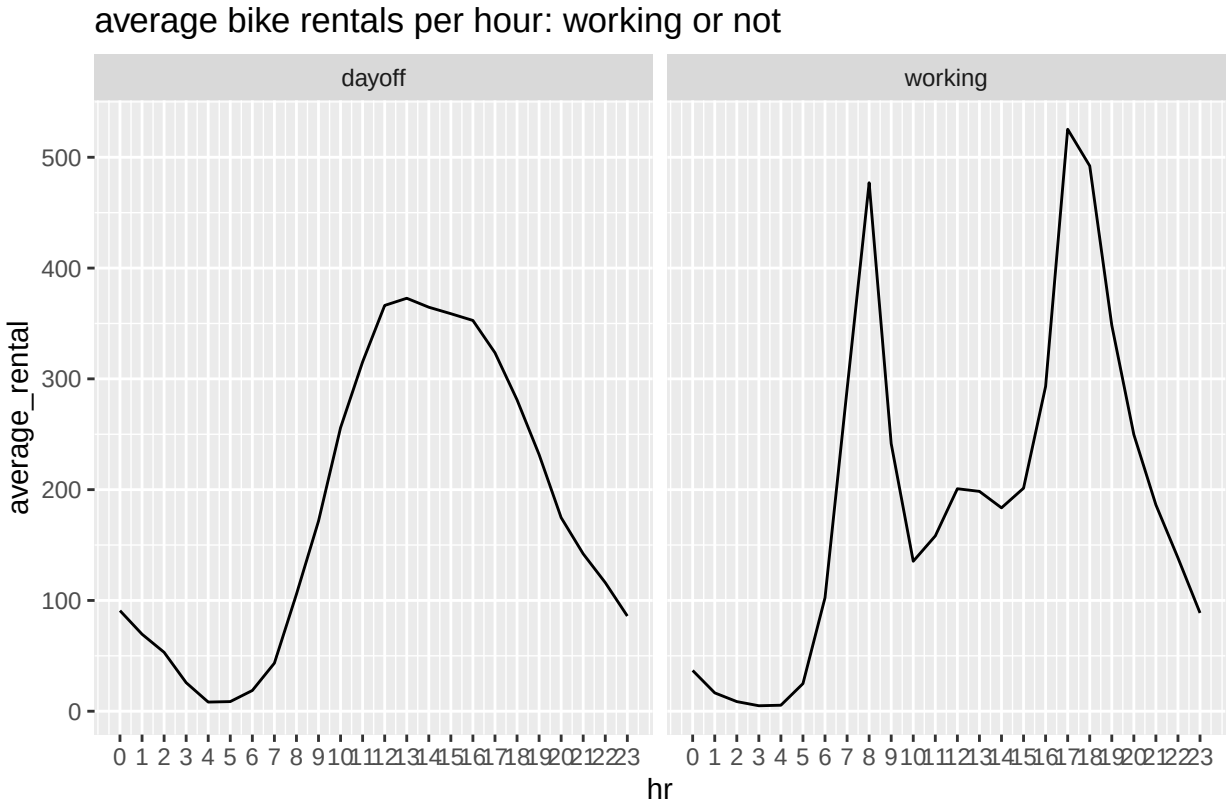
```
## `summarise()` regrouping output by 'hr' (override with `.groups` argument)
```

```
head(bikeshare_b)
```

```
## # A tibble: 6 x 3
## # Groups:   hr [3]
##      hr work    average_rental
##   <int> <chr>            <dbl>
## 1     0 dayoff            90.8
## 2     0 working           36.8
## 3     1 dayoff            69.5
## 4     1 working           16.6
```

```
## 5     2 dayoff           53.2
## 6     2 working           8.68
```

```
ggplot(data=bikeshare_b) +
  geom_line(aes(x=hr, y=average_rental)) + facet_wrap(~work) +
  scale_x_continuous(breaks=0:23) +
  labs(title="average bike rentals per hour: working or not",
       caption="In working day, most used during rush hour(8:00, 17:00). But in day off, most used in a
```

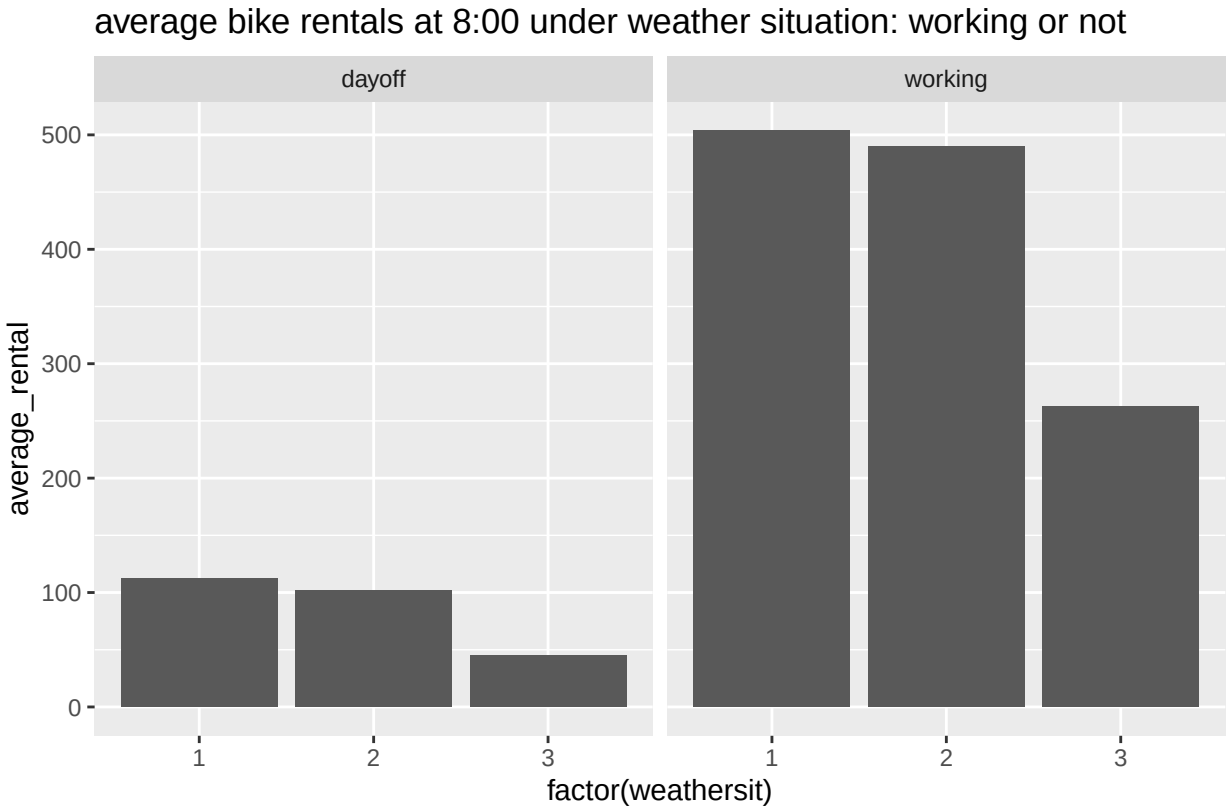


plot C

```
bikeshare_c = bikeshare %>%
  filter(hr==8) %>%
  mutate(work = ifelse(workingday==1, "working", "dayoff")) %>%
  group_by(weathersit, work) %>%
  summarise(average_rental=mean(total))
```

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

```
ggplot(data=bikeshare_c) +
  geom_col(aes(x=factor(weathersit), y=average_rental)) +
  facet_wrap(~work) +
  labs(title="average bike rentals at 8:00 under weather situation: working or not",
       caption="The difference in rental depending on the weather is 'working-day' greater than 'day-of
```



The difference in rental depending on the weather is 'working−day' greater than 'day−off'

1-3

```
library(tidyverse)
library(ggplot2)

ABIA = read.csv('C:/Users/CHOI/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
```

Which day of a week is the worst departure/arrival(long delay) in Austin?

Departure Delay

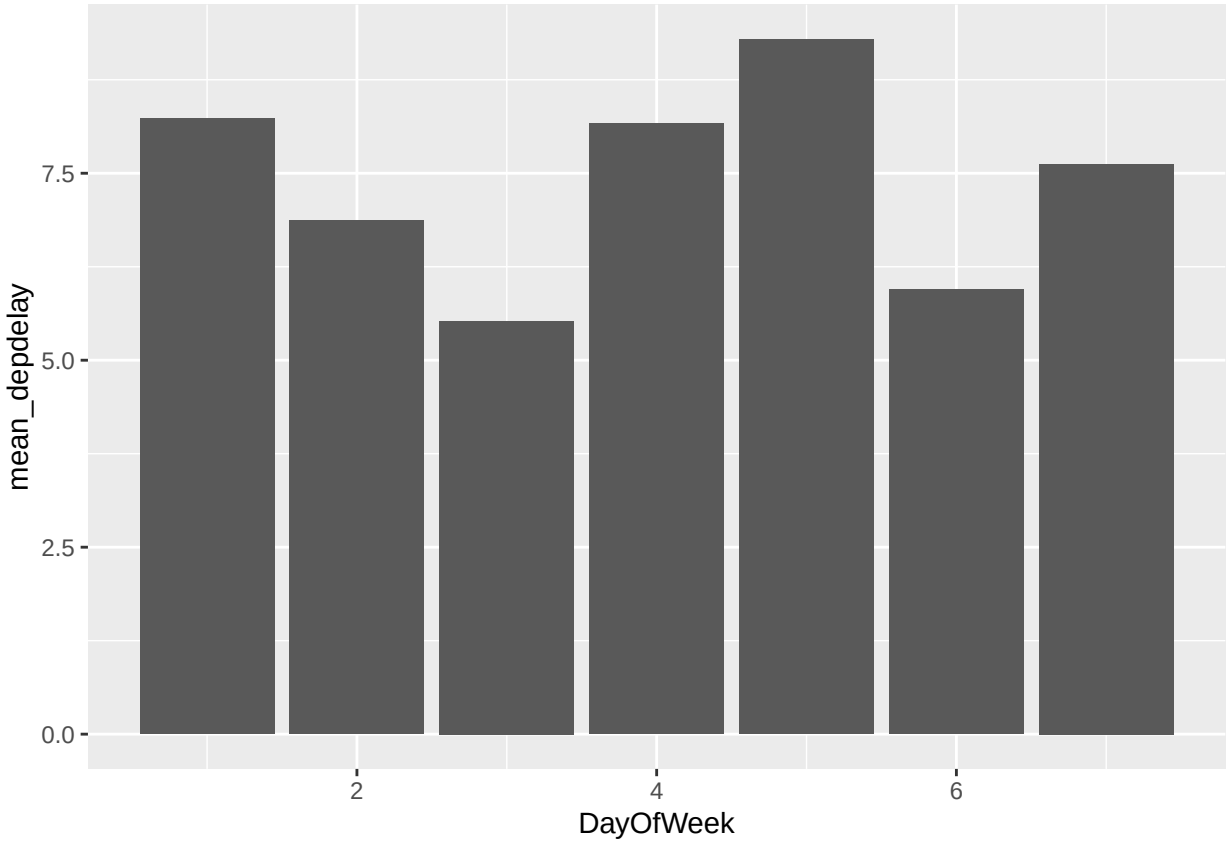
```
d1 = ABIA %>%
  filter(Origin == 'AUS') %>%
  filter(!is.na(DepDelay)) %>%
  group_by(DayOfWeek) %>%
  summarise(mean_depdelay = mean(DepDelay))
```

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

```
d1
```

```
## # A tibble: 7 x 2
##   DayOfWeek mean_depdelay
##       <int>         <dbl>
## 1         1          8.23
## 2         2          6.87
## 3         3          5.53
## 4         4          8.17
## 5         5          9.29
## 6         6          5.94
## 7         7          7.62
```

```
ggplot(data=d1) +
  geom_col(aes(x=DayOfWeek, y=mean_depdelay), position = 'dodge')
```



If you leave from Austin by airplane, Wednesday is the best choice, which you can minimize your departure delay, the average departure delay is around 5 minutes, while Friday gives the longest delay.

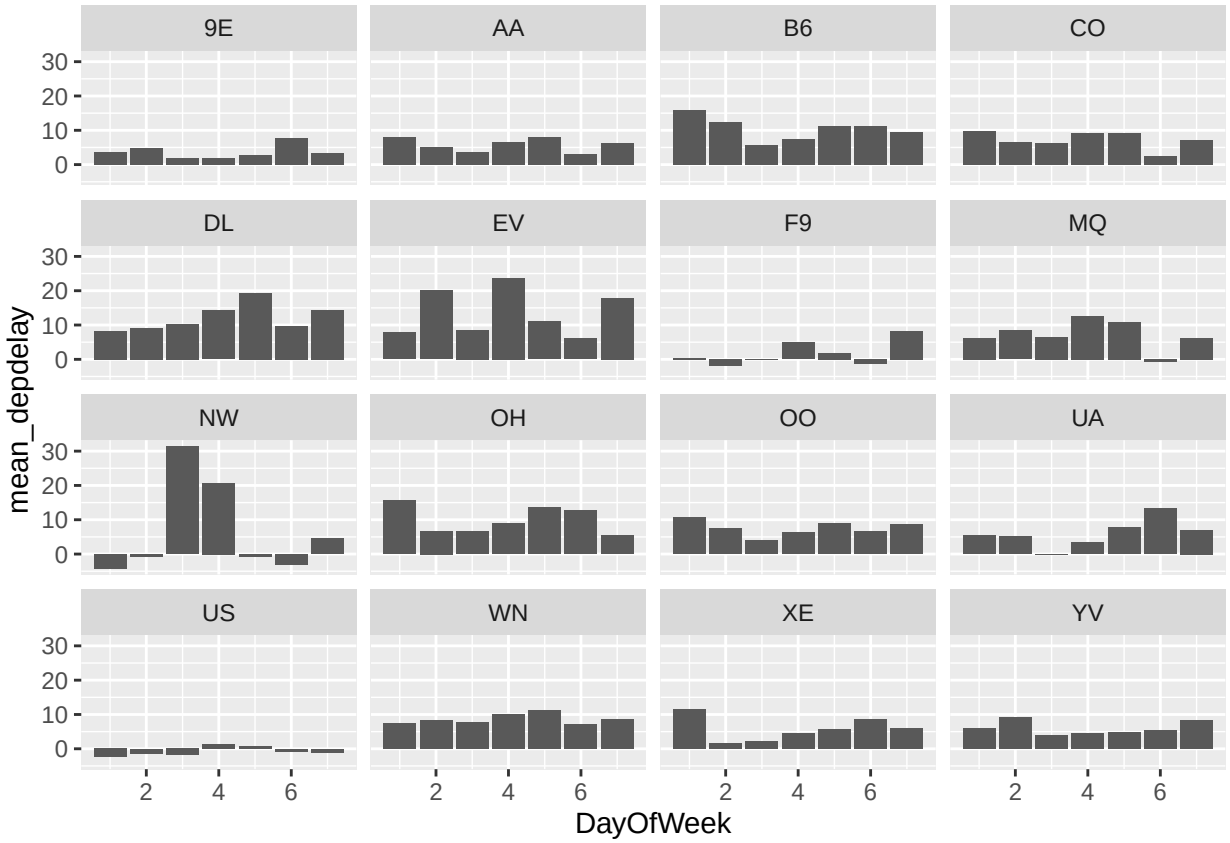
```
d2 = ABIA %>%
  filter(Origin == 'AUS') %>%
  filter(!is.na(DepDelay)) %>%
  group_by(DayOfWeek, UniqueCarrier) %>%
  summarise(mean_depdelay = mean(DepDelay))
```

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

```
d2
```

```
## # A tibble: 112 x 3
## # Groups:   DayOfWeek [7]
##    DayOfWeek UniqueCarrier mean_depdelay
##        <int> <chr>                 <dbl>
##  1         1 9E                    3.55
##  2         1 AA                    8.04
##  3         1 B6                   15.9
##  4         1 CO                    9.78
##  5         1 DL                    8.23
##  6         1 EV                    7.78
##  7         1 F9                    0.487
##  8         1 MQ                    6.12
##  9         1 NW                   -4.17
## 10         1 OH                   15.7
## # ... with 102 more rows
```

```
ggplot(data=d2) +
  geom_col(aes(x=DayOfWeek, y=mean_depdelay), position = 'dodge') +
  facet_wrap(~UniqueCarrier)
```



However, each airline has different delay pattern by day of week. So, if you plan airline trip, you might need to consider which day of week is best and worst for your airline.

Arrival Delay

```
d3 = ABIA %>%
  filter(Dest=='AUS') %>%
  filter(!is.na(ArrDelay)) %>%
  group_by(DayOfWeek) %>%
  summarise(mean_ArrDelay = mean(ArrDelay))
```

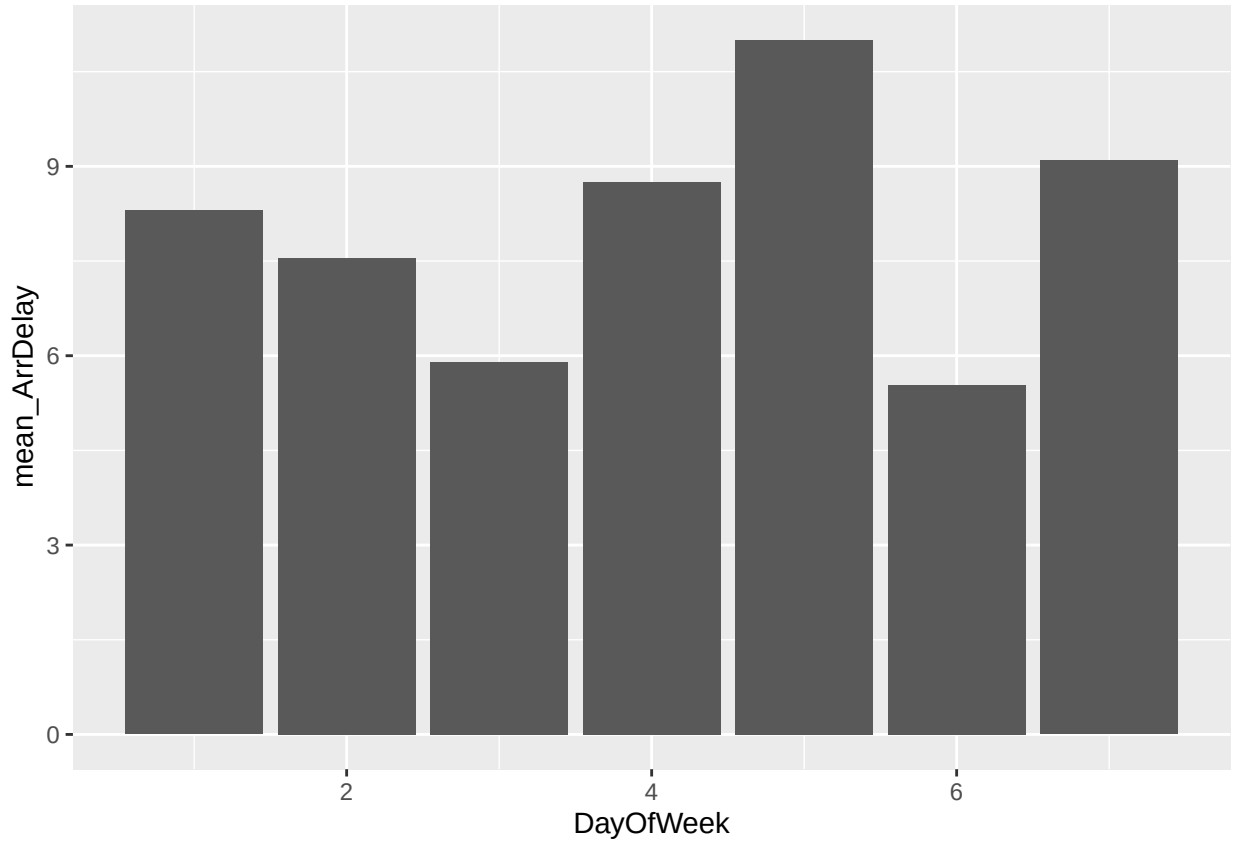
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
d3
```

```
## # A tibble: 7 x 2
##   DayOfWeek mean_ArrDelay
##       <int>         <dbl>
## 1         1          8.30
## 2         2          7.54
## 3         3          5.90
## 4         4          8.75
## 5         5         11.0
## 6         6          5.54
```

```
## 7         7          9.09
```

```
ggplot(data=d3) +
  geom_col(aes(x=DayOfWeek, y=mean_ArrDelay), position = 'dodge')
```



The arrival delay is also the longest on Friday like the departure delay in Austin.

```
d4 = ABIA %>%
  filter(Dest=='AUS') %>%
  filter(!is.na(ArrDelay)) %>%
  group_by(DayOfWeek, UniqueCarrier) %>%
  summarise(mean_ArrDelay = mean(ArrDelay))
```

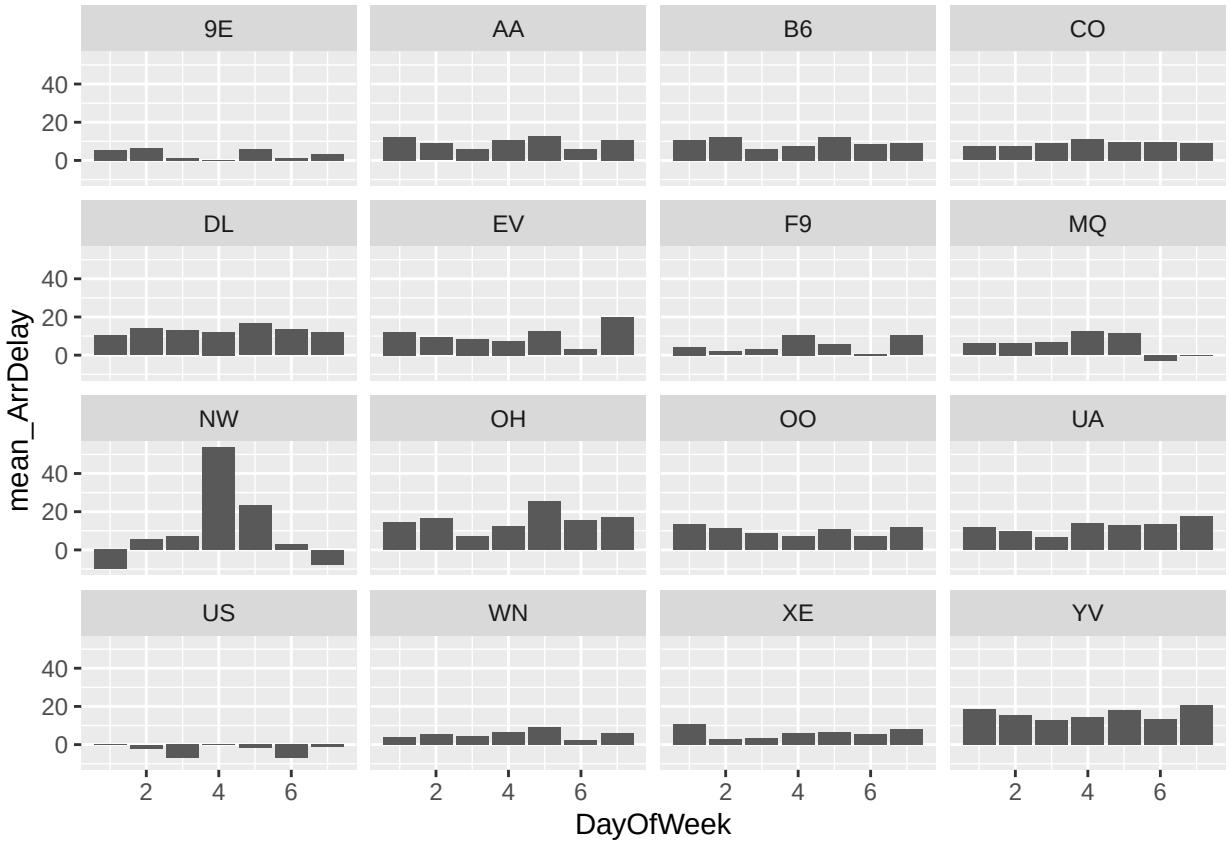
```
## `summarise()` regrouping output by 'DayOfWeek' (override with `.groups` argument)
```

```
d4
```

```
## # A tibble: 112 x 3
## # Groups:   DayOfWeek [7]
##    DayOfWeek UniqueCarrier mean_ArrDelay
##        <int> <chr>                 <dbl>
##  1         1 9E                     5.48
##  2         1 AA                    12.3
##  3         1 B6                    10.9
##  4         1 CO                     7.29
##  5         1 DL                    10.4
##  6         1 EV                    12.1
##  7         1 F9                     4.26
##  8         1 MQ                     6.09
```

```
##  9         1 NW                    -10
## 10         1 OH                     14.4
## # ... with 102 more rows
```

```
ggplot(data=d4) +
  geom_col(aes(x=DayOfWeek, y=mean_ArrDelay), position = 'dodge') +
  facet_wrap(~UniqueCarrier)
```



Each airline has different shape of arrival delay by day of week. The interesting thing is NW airline shows high peak in departure and arrival delay in the middle of week, while US airline has very low, and stable delay.

1-4

```
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('C:/Users/CHOI/Desktop/sclass.csv')
```

To separate data set and make training/testing set

```
sclass %>%
  filter(trim=="350" | trim=="65 AMG")  %>%
  select(trim, mileage, price)
```

```
##       trim mileage  price
## 1      350   21929  55994
## 2      350   17770  60900
## 3      350   29108  54995
## 4      350   35004  59988
## 5      350   66689  37995
## 6      350   19567  59977
## 7      350   10616  69900
## 8      350    2578  68960
## 9      350   23677  61001
## 10     350   28384  58992
## 11     350   21388  69900
## 12  65 AMG     106 235375
## 13  65 AMG      11 226465
## 14     350   87100   9995
## 15  65 AMG   74461  24995
## 16     350   26183  49990
## 17     350   32800  53999
## 18     350   55683  62997
## 19     350   29044  61900
## 20     350   61676  35900
## 21     350  117683  12900
## 22  65 AMG   73415  54981
## 23  65 AMG   17335 102500
## 24     350   29468  40999
## 25  65 AMG       7 230860
## 26     350   35642  21995
## 27  65 AMG   48398  35888
## 28  65 AMG   61500  45981
## 29  65 AMG   49515  49982
## 30  65 AMG   70692  43990
## 31  65 AMG       5 216510
## 32     350    7342  53900
## 33     350   22751  56991
## 34     350    2384  75900
```

```
## 35      350   21874  58975
## 36      350    5404  81895
## 37      350   12414  64900
## 38      350   15435  68950
## 39      350   41075  53981
## 40      350   11862  76878
## 41      350   31300  53000
## 42   65 AMG      50 226115
## 43   65 AMG      89 221750
## 44      350   68221  16980
## 45      350   52003  17998
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## 48   65 AMG   79795  41995
## 49   65 AMG   55730  78992
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## 51      350   21185  51495
## 52      350   32290  48789
## 53      350   38310  47994
## 54      350   40755  46995
## 55   65 AMG       7 244325
## 56   65 AMG      43 224625
## 57   65 AMG   31048  59888
## 58   65 AMG   11632 110995
## 59   65 AMG   31321  79888
## 60      350   31782  52999
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## 62   65 AMG      11 235365
## 63      350   62028  15991
## 64   65 AMG   45200  85000
## 65   65 AMG   85142  37900
## 66   65 AMG   48579  77444
## 67      350   33720  42999
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## 69   65 AMG      10 227715
## 70   65 AMG      12 227685
## 71   65 AMG      10 236125
## 72      350   76146  14950
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## 78      350    9300 103410
## 79      350   19266  62995
## 80   65 AMG      18 240825
## 81      350   80511  15991
## 82   65 AMG   51670  59995
## 83   65 AMG   49735  61900
## 84   65 AMG   52045  61491
## 85   65 AMG   28626  89888
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## 87      350    7000  82000
## 88      350   29996  61995
```

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## 90     350   10721  62988
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## 93  65 AMG   15512 114998
## 94     350   25685  61900
## 95     350   38239  51312
## 96     350   20868  44999
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## 100 65 AMG      10 226115
## 101 65 AMG       8 224765
## 102 65 AMG      16 228325
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## 104 65 AMG   86472  22994
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## 106    350   24501  66900
## 107    350   29648  69994
## 108    350   59439  39995
## 109    350    1514  94230
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## 111 65 AMG      13 235475
## 112    350   77159  16995
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## 114 65 AMG   61560  47888
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## 116    350   31158  62995
## 117 65 AMG    4685 199900
## 118    350  102919  13895
## 119    350   52670  19495
## 120    350   93400  12995
## 121 65 AMG   50942  49900
## 122 65 AMG   22662 114889
## 123 65 AMG    9982 129995
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## 125    350   22634  62995
## 126    350   18516  51950
## 127    350   41913  49888
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## 134 65 AMG       4 226710
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## 136    350   95011  13998
## 137 65 AMG   24482  44992
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## 139 65 AMG    2563  98888
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## 141    350   12018  69500
## 142    350   21596  59991
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## 155 65 AMG       8 226965
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## 157 65 AMG   79713  45888
## 158 65 AMG   40527  62498
## 159    350   19259  59881
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## 164 65 AMG   76271  26900
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## 166 65 AMG      27 227360
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## 176    350   31810  51295
## 177    350   33917  49888
## 178    350   18046  51990
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## 182 65 AMG   32115  50999
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## 184 65 AMG   68444  49999
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## 192 65 AMG   18741  42888
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## 194 65 AMG   20000  79900
## 195 65 AMG   18667  95000
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## 247    350   63347  15999
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## 250 65 AMG   75973  44950
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## 268 65 AMG       8 237935
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## 274 65 AMG   69966  43998
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## 303    350   71963  15977
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## 310    350   83649  12989
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## 315    350    2325  74899
## 316    350   27214  59995
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## 318 65 AMG       6 224975
## 319 65 AMG   64734  25247
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## 322 65 AMG   17570  59994
## 323 65 AMG   52340  86991
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## 325 65 AMG   39721  97699
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## 328    350   29755  53999
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## 330    350   18540  64900
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## 332 65 AMG      10 230985
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## 337    350   29715  55990
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## 339    350   58662  19795
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## 347    350   16928  55881
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## 358    350       6 102460
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## 365    350   34008  57995
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## 367    350   85214  10800
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## 370 65 AMG   26561  83950
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## 374    350   27300  53991
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## 376    350   57773  40999
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## 382    350   31825  48955
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## 384 65 AMG       5 228825
## 385 65 AMG   29712  42990
## 386 65 AMG   69415  39950
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## 395 65 AMG   91102  26980
## 396 65 AMG   50761  63895
## 397    350   34271  58991
## 398    350    4308  82910
## 399    350   14515  59988
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## 404 65 AMG      17 226465
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## 411 65 AMG   57242  79888
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## 427    350   26733  54990
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## 432 65 AMG      14 229870
## 433 65 AMG       8 226135
## 434 65 AMG       7 226620
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## 457 65 AMG      18 228935
## 458 65 AMG       9 226625
## 459    350   35681  17995
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## 466    350      10 106010
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## 477 65 AMG   58243  57800
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## 487    350   74439  17500
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## 490 65 AMG   75341  29981
## 491 65 AMG   20834  96777
## 492    350   20033  47000
## 493    350   16877  49995
## 494    350    5864  69991
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## 520    350    2714  65995
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## 533    350   94087  12988
## 534 65 AMG   36123  97995
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## 550    350   16474  58985
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## 580 65 AMG      10 229810
## 581 65 AMG       9 226465
## 582 65 AMG       8 224351
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## 585 65 AMG   82636  24000
## 586    350   12741  66990
## 587    350    5508  81991
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## 594    350   22020  67988
## 595    350   15211  69900
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## 621 65 AMG      22 225975
## 622 65 AMG       5 224625
## 623 65 AMG      36 234215
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## 633 65 AMG   80256  49888
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## 637    350   38956  52995
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## 639    350  116385  11990
## 640 65 AMG   52596  56490
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## 642    350   14588  63500
## 643    350   18126  49994
## 644    350   27079  58881
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## 655    350   29846  61995
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## 667 65 AMG      16 236020
## 668 65 AMG      10 226485
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## 670 65 AMG   44210  57750
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## 682    350   90756  14900
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## 683    350   97724  11995
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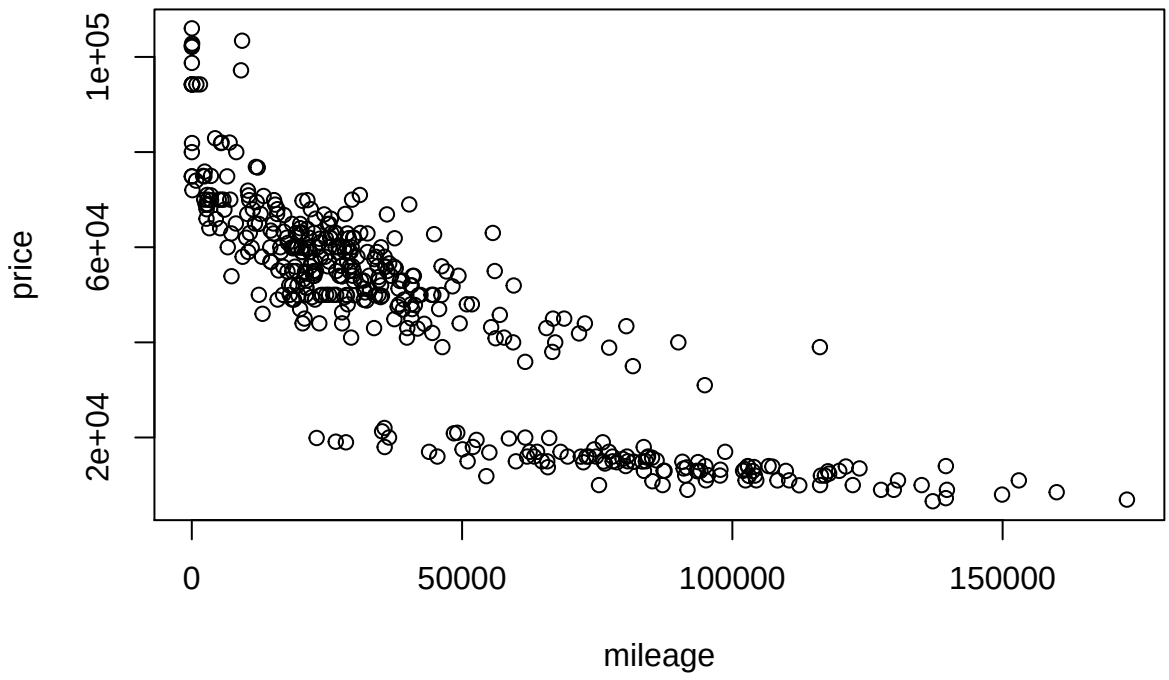
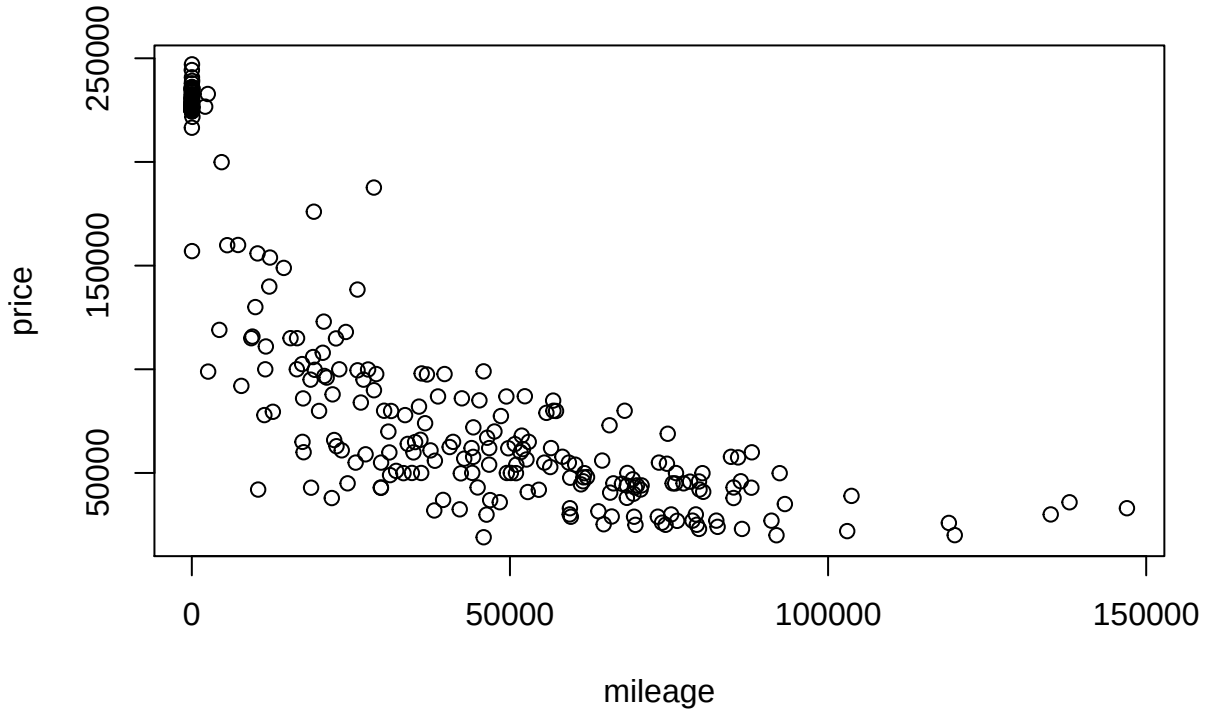
## 692 65 AMG      25 229135
## 693 65 AMG      11 226465
## 694    350   49112  20995
## 695    350   59950  14990
## 696    350    8227  79990
## 697    350   20485  69759
## 698    350   80386  43400
## 699    350   14554  56995
## 700    350   28391  66990
## 701    350   35200  21290
## 702    350   87291  12994
## 703    350   87458  12995
## 704    350   20056  64000
## 705    350   27730  53900
## 706    350   29143  58990
## 707    350   29583  59995
## 708 65 AMG      10 226465
```

```r
s3 = subset(sclass, trim=="350")
s6 = subset(sclass, trim=="65 AMG")

plot(price ~ mileage, data = s3)
```




```
plot(price ~ mileage, data = s6)
```




```
s3_split = initial_split(s3, prop=0.8)
s3_train = training(s3_split)
s3_test = testing(s3_split)

s6_split = initial_split(s6, prop=0.8)
s6_train = training(s6_split)
s6_test = testing(s6_split)
```

350 trim of sclass

k=2,5,10,15,20,25,50,100

```
s3_knn2 = knnreg(price ~ mileage, data=s3_train, k=2)
s3_knn5 = knnreg(price ~ mileage, data=s3_train, k=5)
s3_knn10 = knnreg(price ~ mileage, data=s3_train, k=10)
s3_knn15 = knnreg(price ~ mileage, data=s3_train, k=15)
s3_knn20 = knnreg(price ~ mileage, data=s3_train, k=20)
s3_knn25 = knnreg(price ~ mileage, data=s3_train, k=25)
s3_knn50 = knnreg(price ~ mileage, data=s3_train, k=50)
s3_knn100 = knnreg(price ~ mileage, data=s3_train, k=100)

s3_test = s3_test %>%
  mutate(price_pred = predict(s3_knn2, s3_test)) %>%
  mutate(price_pred = predict(s3_knn5, s3_test)) %>%
  mutate(price_pred = predict(s3_knn10, s3_test)) %>%
  mutate(price_pred = predict(s3_knn15, s3_test)) %>%
```

```
  mutate(price_pred = predict(s3_knn20, s3_test)) %>%
  mutate(price_pred = predict(s3_knn25, s3_test)) %>%
  mutate(price_pred = predict(s3_knn50, s3_test)) %>%
  mutate(price_pred = predict(s3_knn100, s3_test))
```

Calculating RMSE

```
modelr::rmse(s3_knn2, s3_test)
```

```
## [1] 12029.8
```

```
modelr::rmse(s3_knn5, s3_test)
```

```
## [1] 9819.399
```

```
modelr::rmse(s3_knn10, s3_test)
```

```
## [1] 9047.477
```

```
modelr::rmse(s3_knn15, s3_test)
```

```
## [1] 8871.22
```

```
modelr::rmse(s3_knn20, s3_test)
```

```
## [1] 9340.975
```

```
modelr::rmse(s3_knn25, s3_test)
```

```
## [1] 9578.985
```

```
modelr::rmse(s3_knn50, s3_test)
```

```
## [1] 10201.22
```

```
modelr::rmse(s3_knn100, s3_test)
```

```
## [1] 12181.37
```

When k=15, RMSE minimized

65 AMG trim of sclass

k=2,5,10,15,20,25,50,100

```
s6_knn2 = knnreg(price ~ mileage, data=s6_train, k=2)
s6_knn5 = knnreg(price ~ mileage, data=s6_train, k=5)
s6_knn10 = knnreg(price ~ mileage, data=s6_train, k=10)
s6_knn15 = knnreg(price ~ mileage, data=s6_train, k=15)
s6_knn20 = knnreg(price ~ mileage, data=s6_train, k=20)
s6_knn25 = knnreg(price ~ mileage, data=s6_train, k=25)
s6_knn50 = knnreg(price ~ mileage, data=s6_train, k=50)
s6_knn100 = knnreg(price ~ mileage, data=s6_train, k=100)

s6_test = s6_test %>%
  mutate(price_pred = predict(s6_knn2, s6_test)) %>%
  mutate(price_pred = predict(s6_knn5, s6_test)) %>%
  mutate(price_pred = predict(s6_knn10, s6_test)) %>%
  mutate(price_pred = predict(s6_knn15, s6_test)) %>%
```

```
  mutate(price_pred = predict(s6_knn20, s6_test)) %>%
  mutate(price_pred = predict(s6_knn25, s6_test)) %>%
  mutate(price_pred = predict(s6_knn50, s6_test)) %>%
  mutate(price_pred = predict(s6_knn100, s6_test))
```

Calculating RMSE

```
modelr::rmse(s6_knn2, s6_test)
```

```
## [1] 27794.96
```

```
modelr::rmse(s6_knn5, s6_test)
```

```
## [1] 23037.39
```

```
modelr::rmse(s6_knn10, s6_test)
```

```
## [1] 22976.64
```

```
modelr::rmse(s6_knn15, s6_test)
```

```
## [1] 22716.98
```

```
modelr::rmse(s6_knn20, s6_test)
```

```
## [1] 22699.01
```

```
modelr::rmse(s6_knn25, s6_test)
```

```
## [1] 22773.9
```

```
modelr::rmse(s6_knn50, s6_test)
```

```
## [1] 29639.08
```

```
modelr::rmse(s6_knn100, s6_test)
```

```
## [1] 39280.94
```

When k=20, RMSE minimized

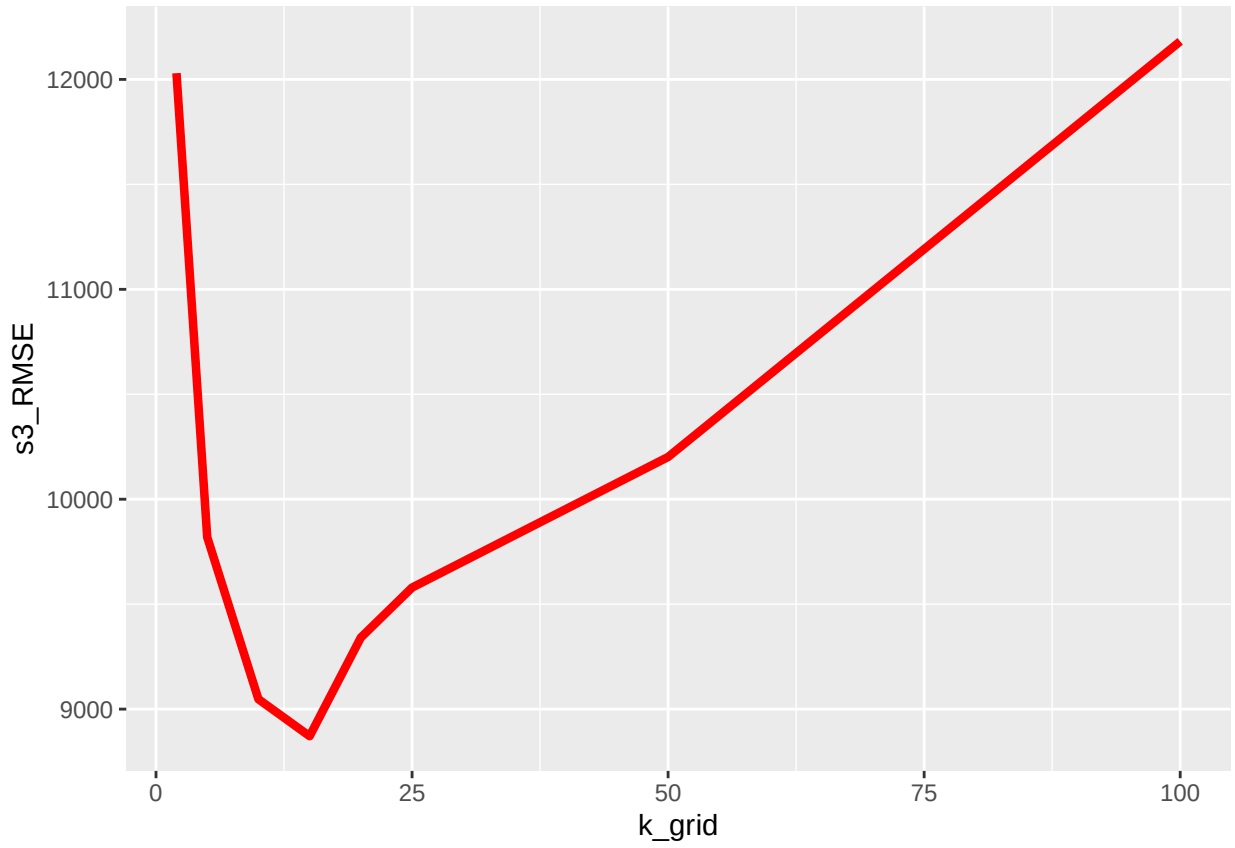
K vs RMSE

350 trim of sclass

```
k_grid = c(2,5,10,15,20,25,50,100)

s3_RMSE = foreach(k=k_grid, .combine='c') %do% {
  s3_knn_model = knnreg(price~mileage, data=s3_train, k=k)
  modelr::rmse(s3_knn_model, s3_test)}

ggplot() +
  geom_line(aes(x = k_grid, y = s3_RMSE), color='red', size=1.5)
```

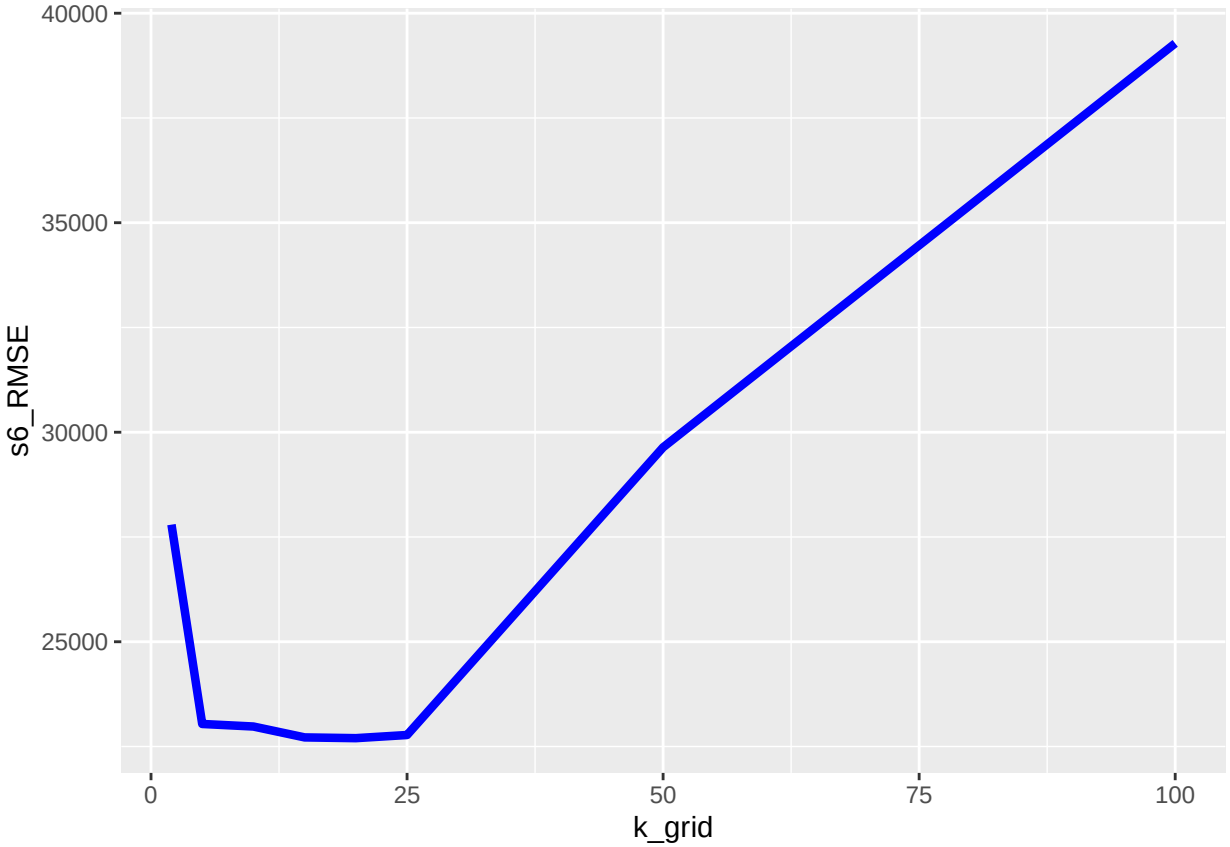


65 AMG trim of sclass

```
k_grid = c(2,5,10,15,20,25,50,100)

s6_RMSE = foreach(k=k_grid, .combine='c') %do% {
  s6_knn_model = knnreg(price~mileage, data=s6_train, k=k)
  modelr::rmse(s6_knn_model, s6_test)}

ggplot() +
  geom_line(aes(x = k_grid, y = s6_RMSE), color='blue', size=1.5)
```



plot 2 models

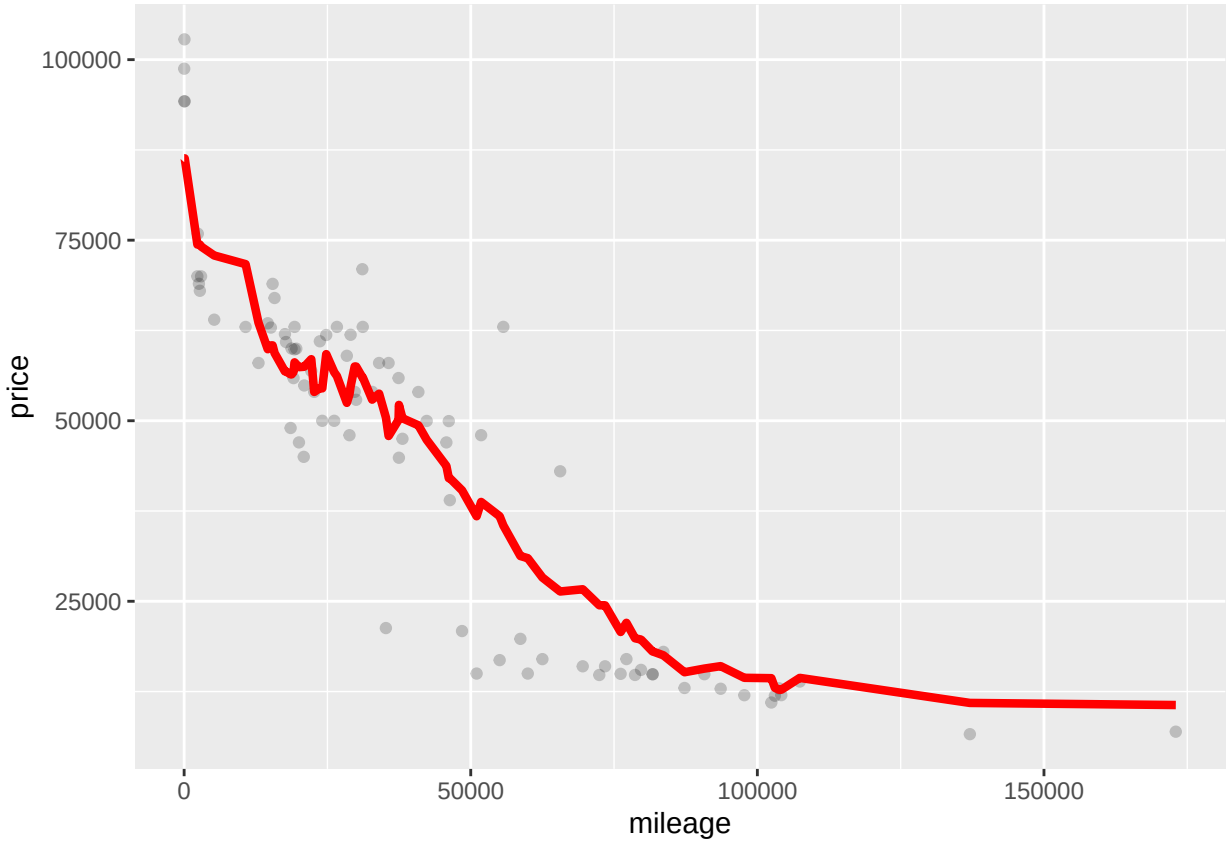
350 trim with K = 15

```
s3_knn15_plot = knnreg(price ~ mileage, data=s3_train, k=15)
s3_test = s3_test %>%
  mutate(price_pred = predict(s3_knn15_plot, s3_test))
modelr::rmse(s3_knn15_plot, s3_test)
```

```
## [1] 8871.22
```

```
s3_plot = ggplot(data = s3_test) +
  geom_point(mapping = aes(x = mileage, y = price), alpha=0.2) +
  geom_line(aes(x = mileage, y = price_pred), color='red', size=1.5)

s3_plot
```



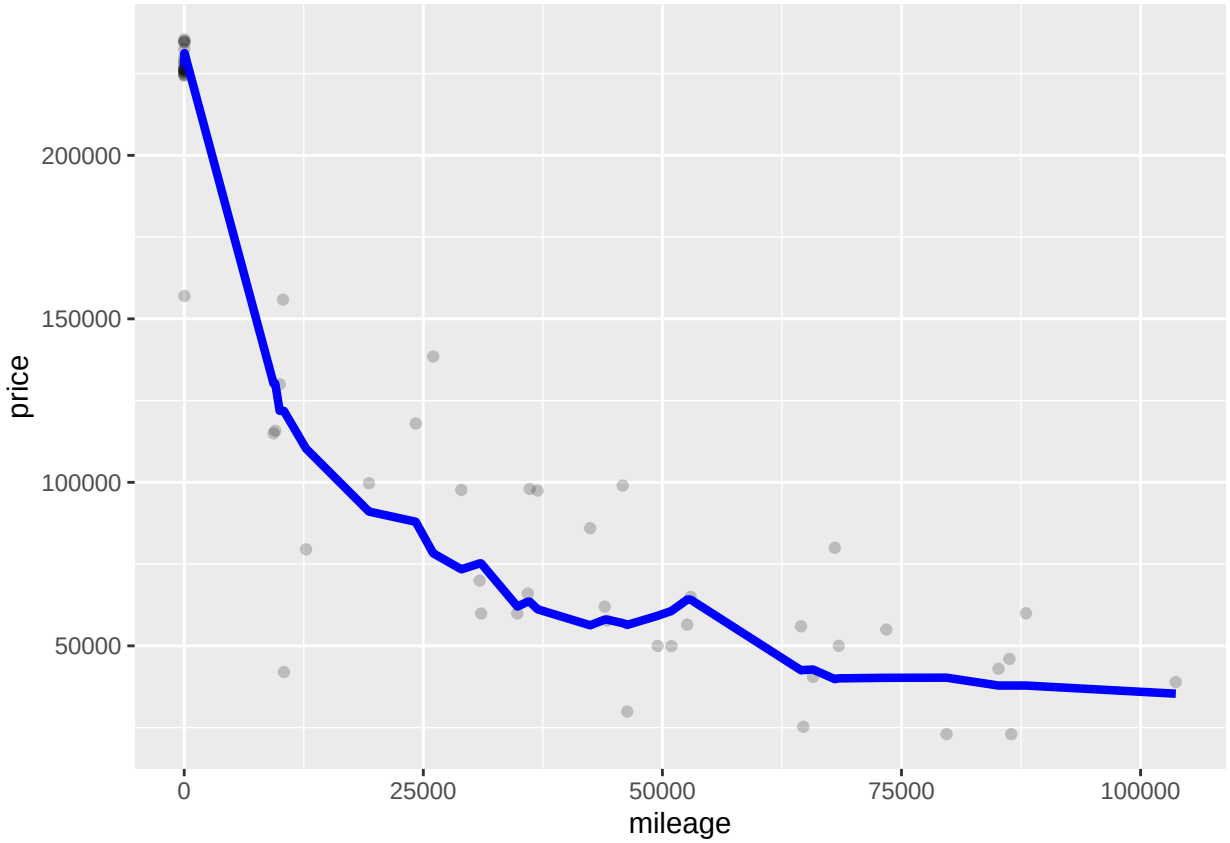
65 AMG trim with K = 20

```
s6_knn20_plot = knnreg(price ~ mileage, data=s6_train, k=20)
s6_test = s6_test %>%
  mutate(price_pred = predict(s6_knn20_plot, s6_test))
modelr::rmse(s6_knn20_plot, s6_test)
```

```
## [1] 22699.01
```

```
s6_plot = ggplot(data = s6_test) +
  geom_point(mapping = aes(x = mileage, y = price), alpha=0.2) +
  geom_line(aes(x = mileage, y = price_pred), color='blue', size=1.5)

s6_plot
```



RMSE of '350 trim' is smaller than '65 AMG Trim' in optimal 'K'. So, '350 trim' yields a larger optimal value of 'K'