

HW1

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1-1

```
library(tidyverse)
```

```
## -- Attaching packages -----
```

```
## 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 -----
```

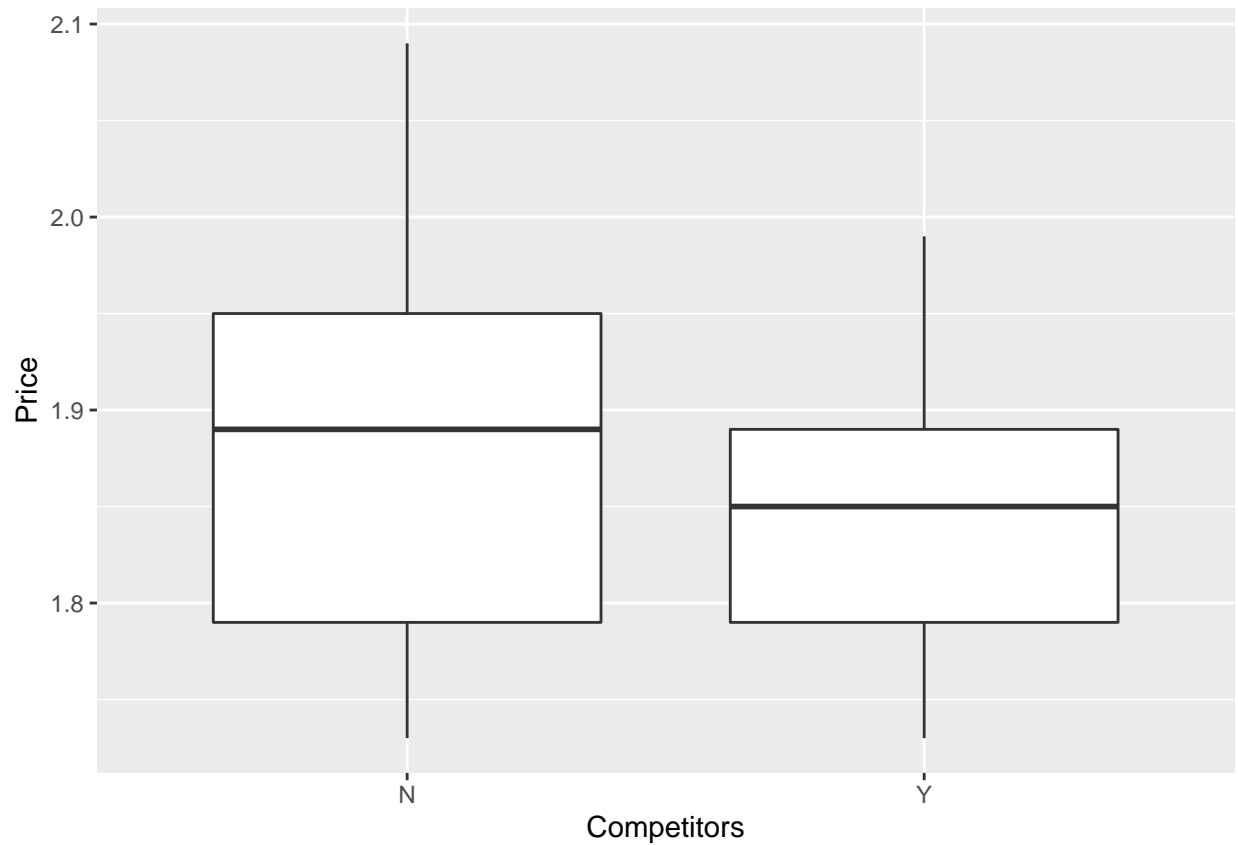
```
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag()     masks stats::lag()
```

```
library(ggplot2)
```

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

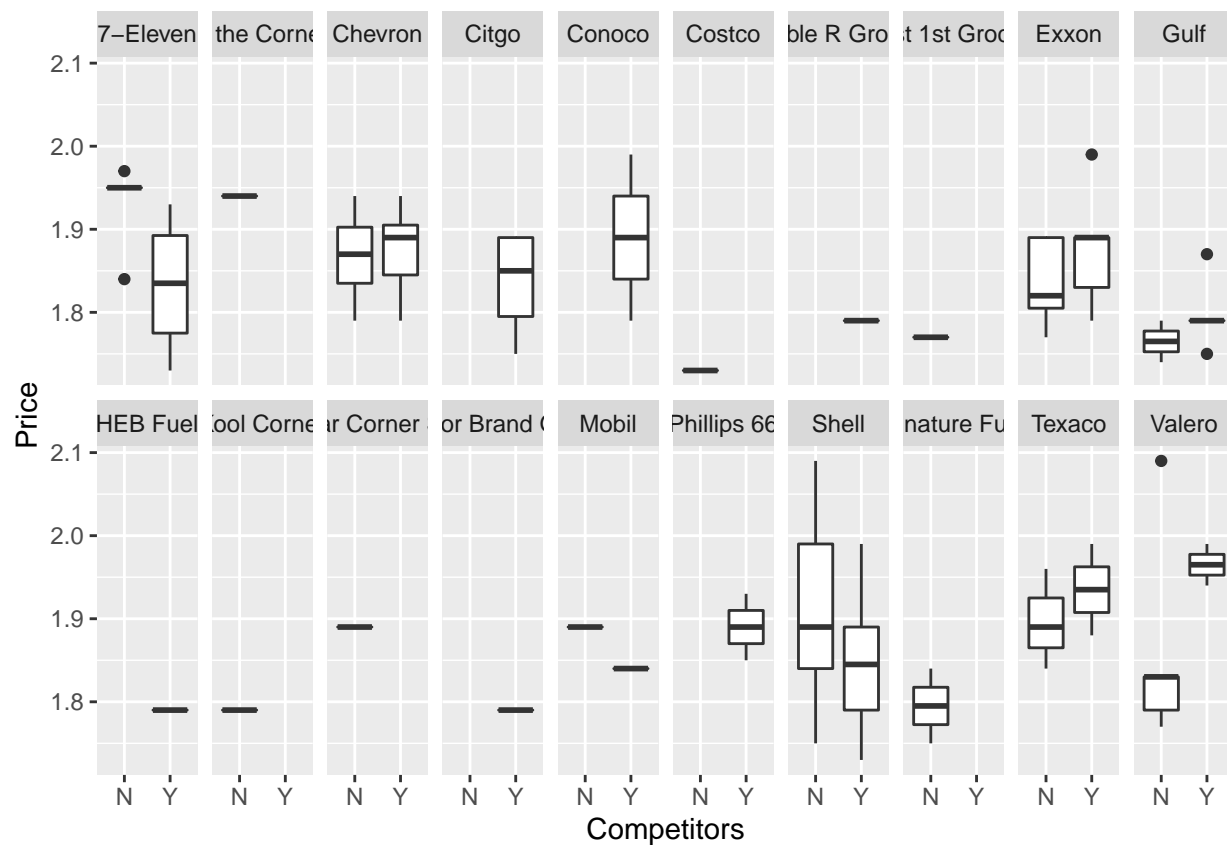
A. Competition & Price

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



The box 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.

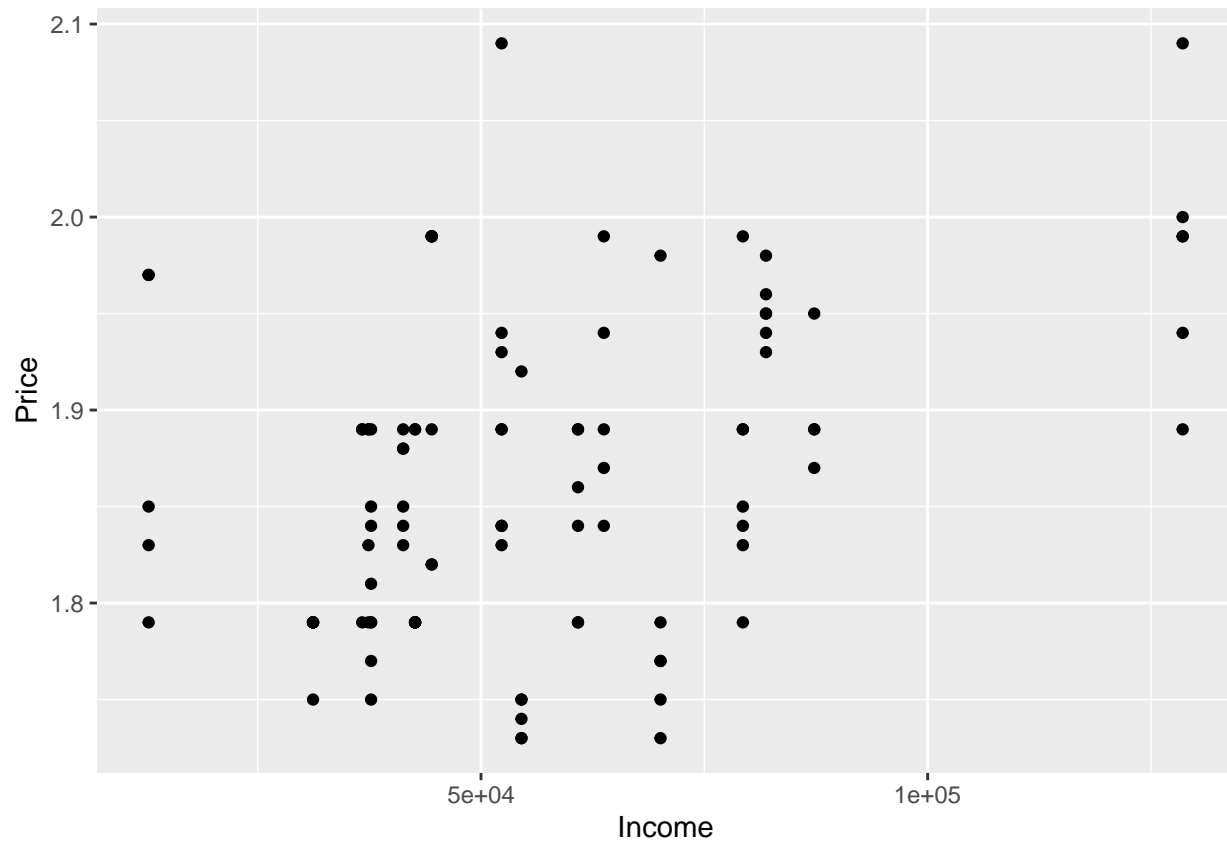
```
ggplot(data=GasPrices) +  
  geom_boxplot(aes(x = Competitors, y=Price)) +  
  facet_wrap(~Name, nrow=2)
```



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-copetitors prices can be compared.

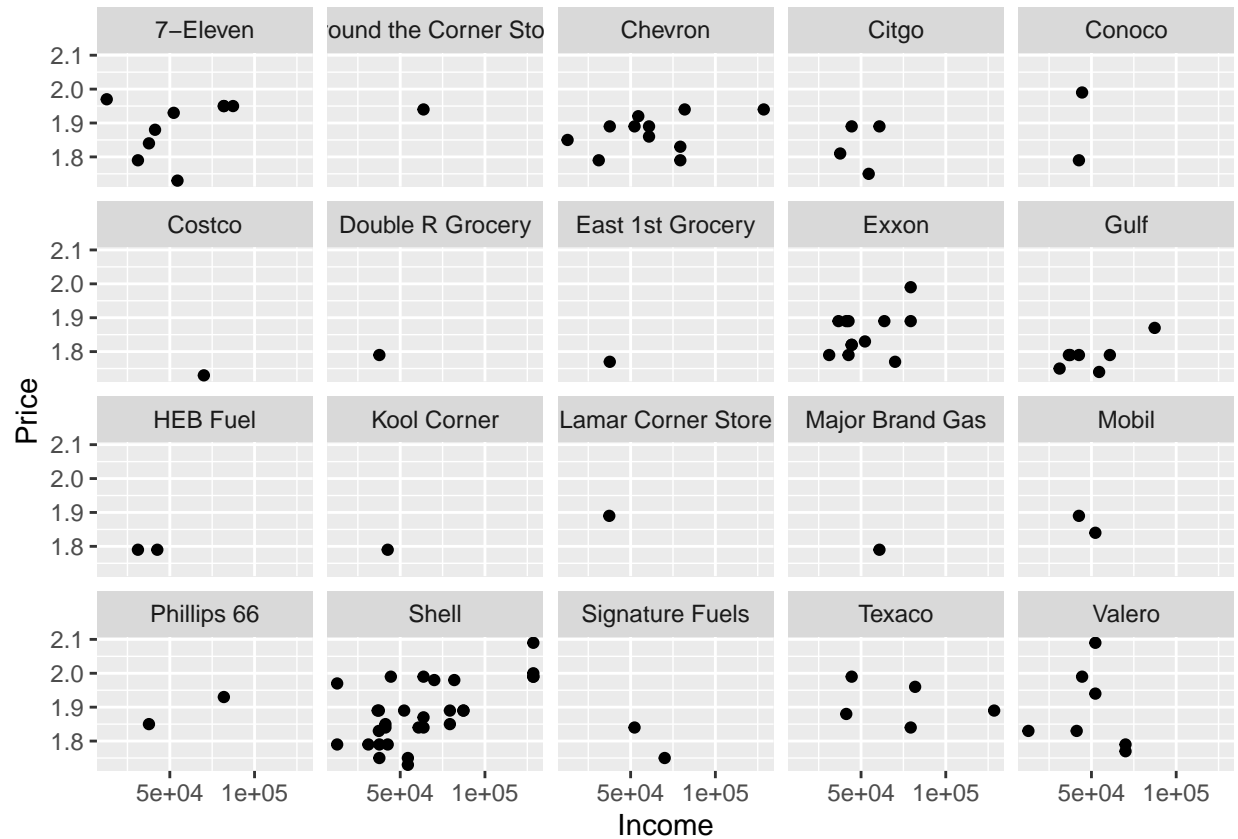
B. Income & Price

```
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 policies.

C. Price of Shell vs Other sellers

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

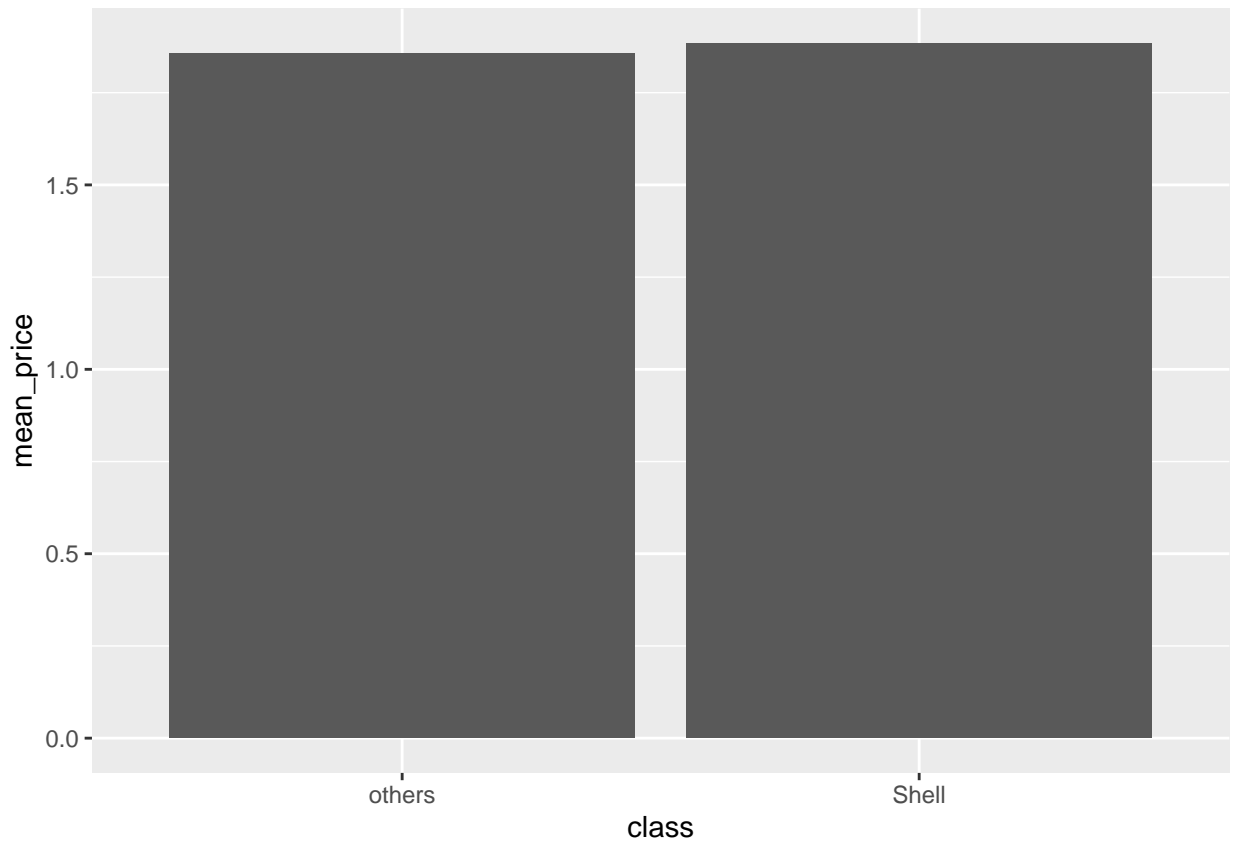
d1 = GasPrices %>%
  group_by(class) %>%
  summarise(mean_price = mean(Price))

## `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))
```

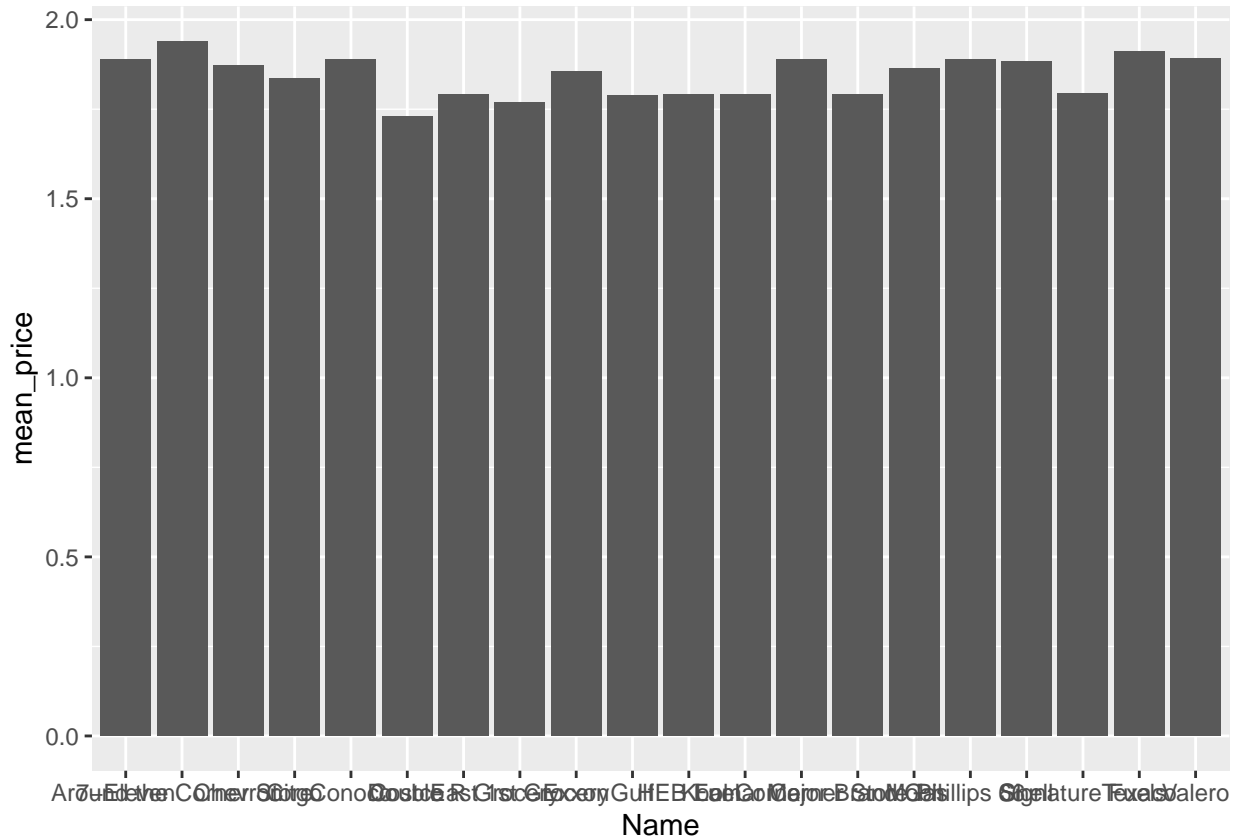
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
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=Name, y=mean_price), position = 'dodge')
```

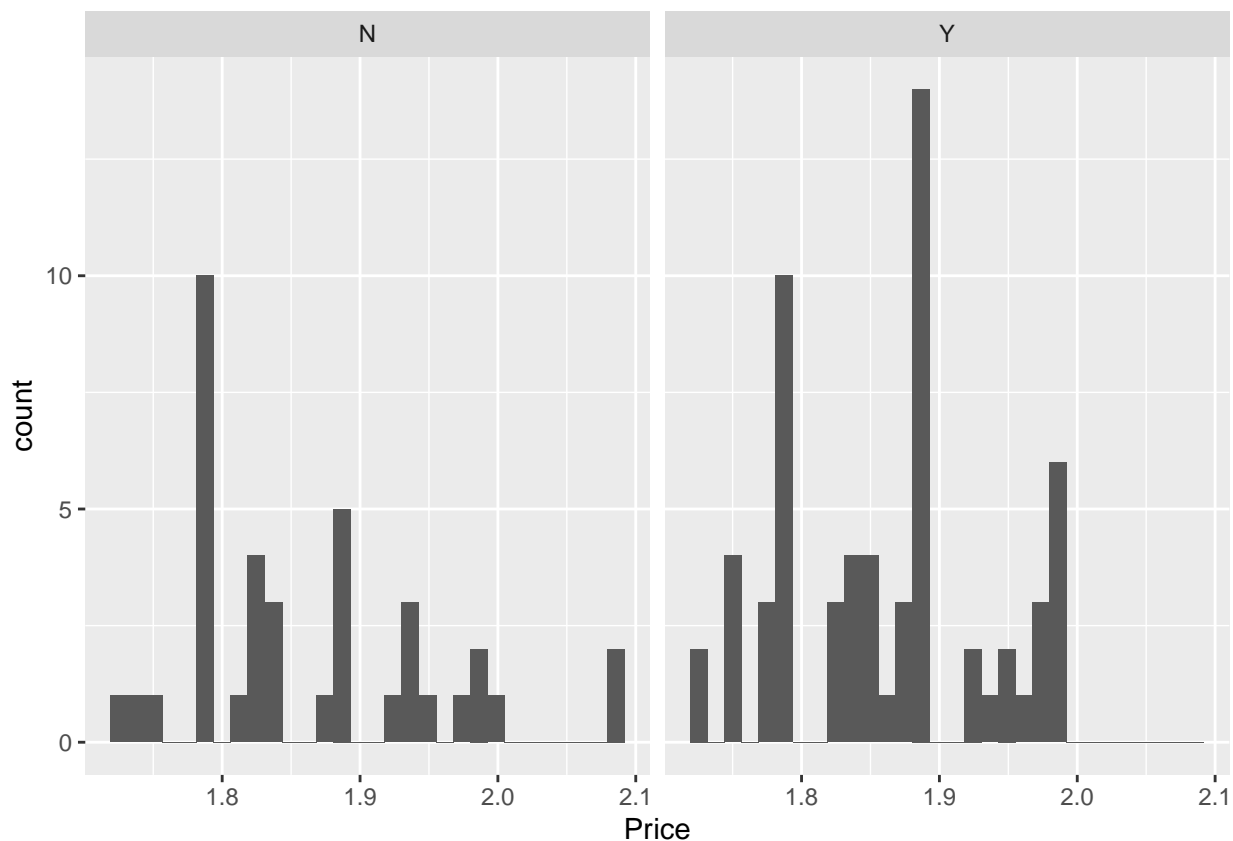


The 12 out of 19 providers have lower average gas prices than that of Shell.

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

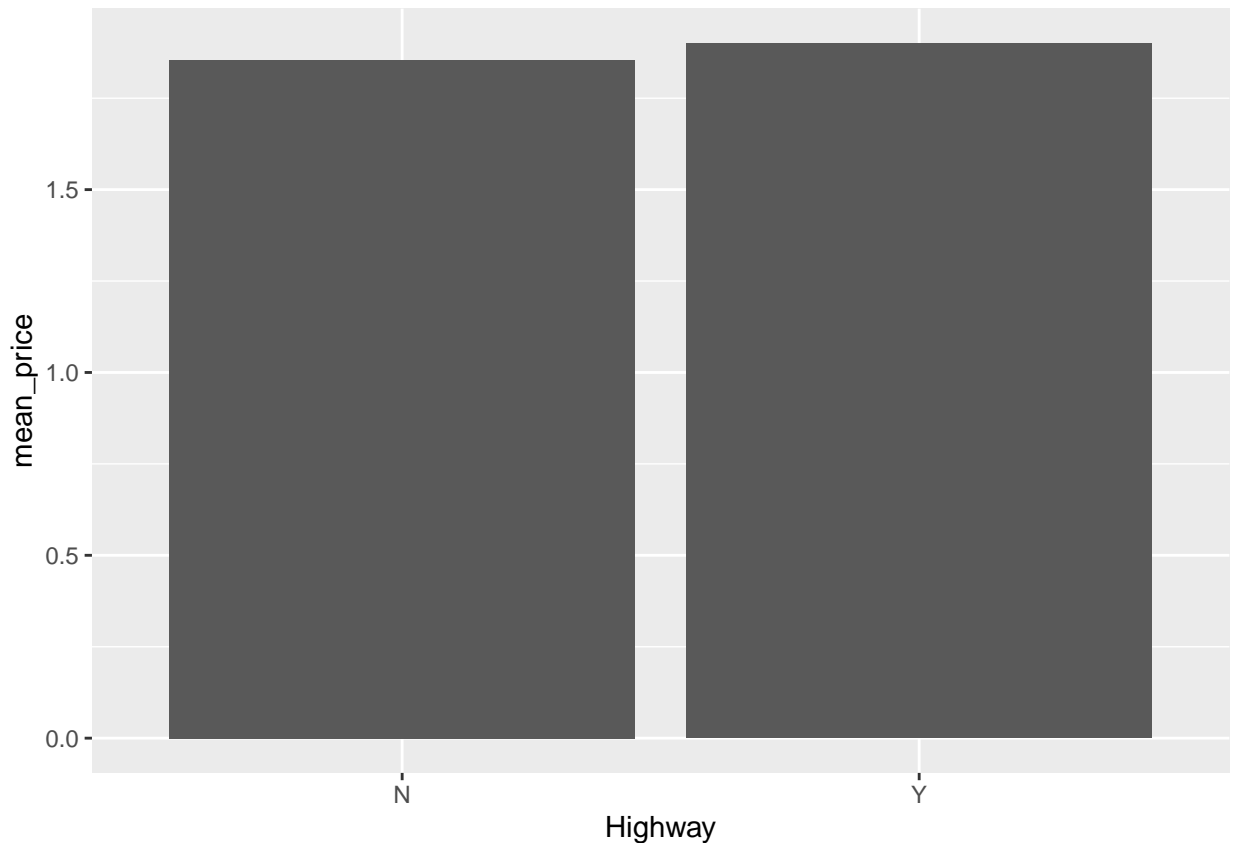
```
d3 = GasPrices %>%
  group_by(Highway) %>%
  summarise(mean_price = mean(Price))
```

```
## `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))
```

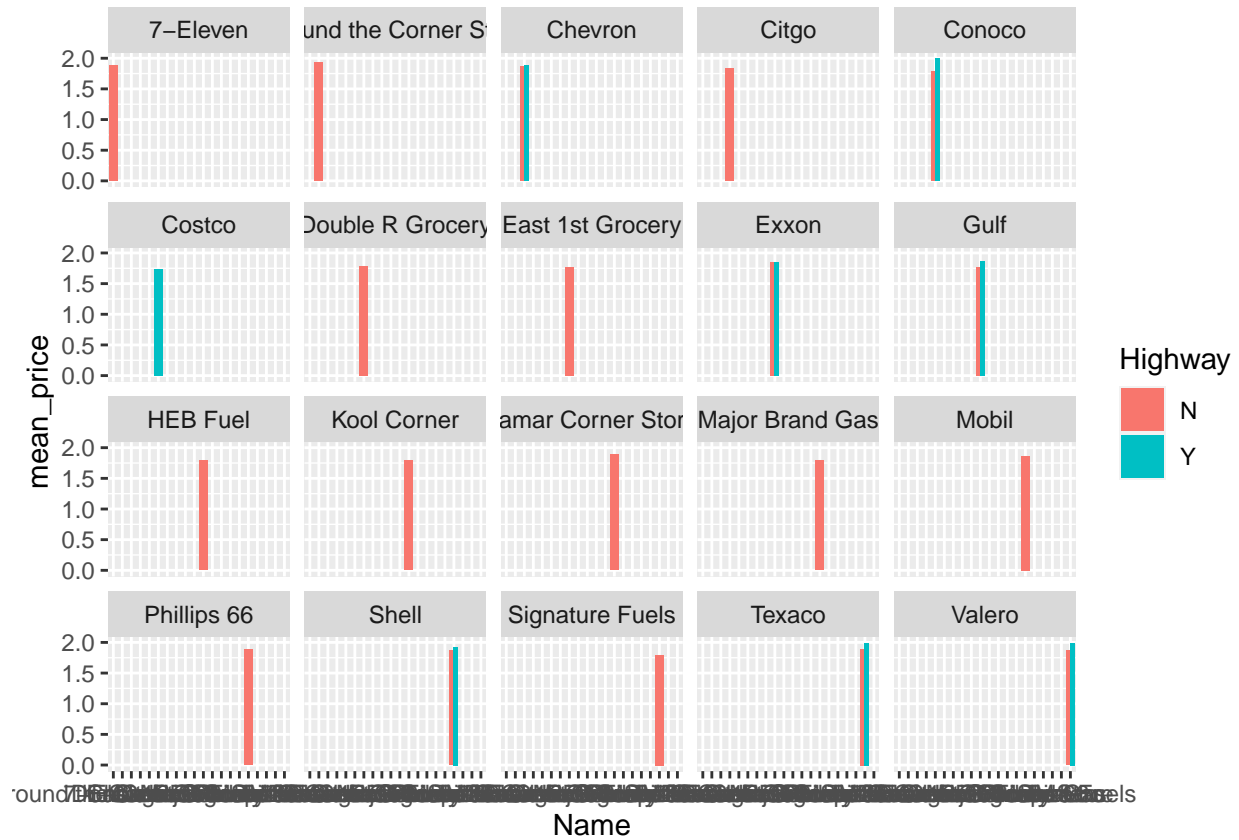
```
## `summarise()` regrouping output by 'Highway' (override with `.groups` argument)
```

```
d4
```

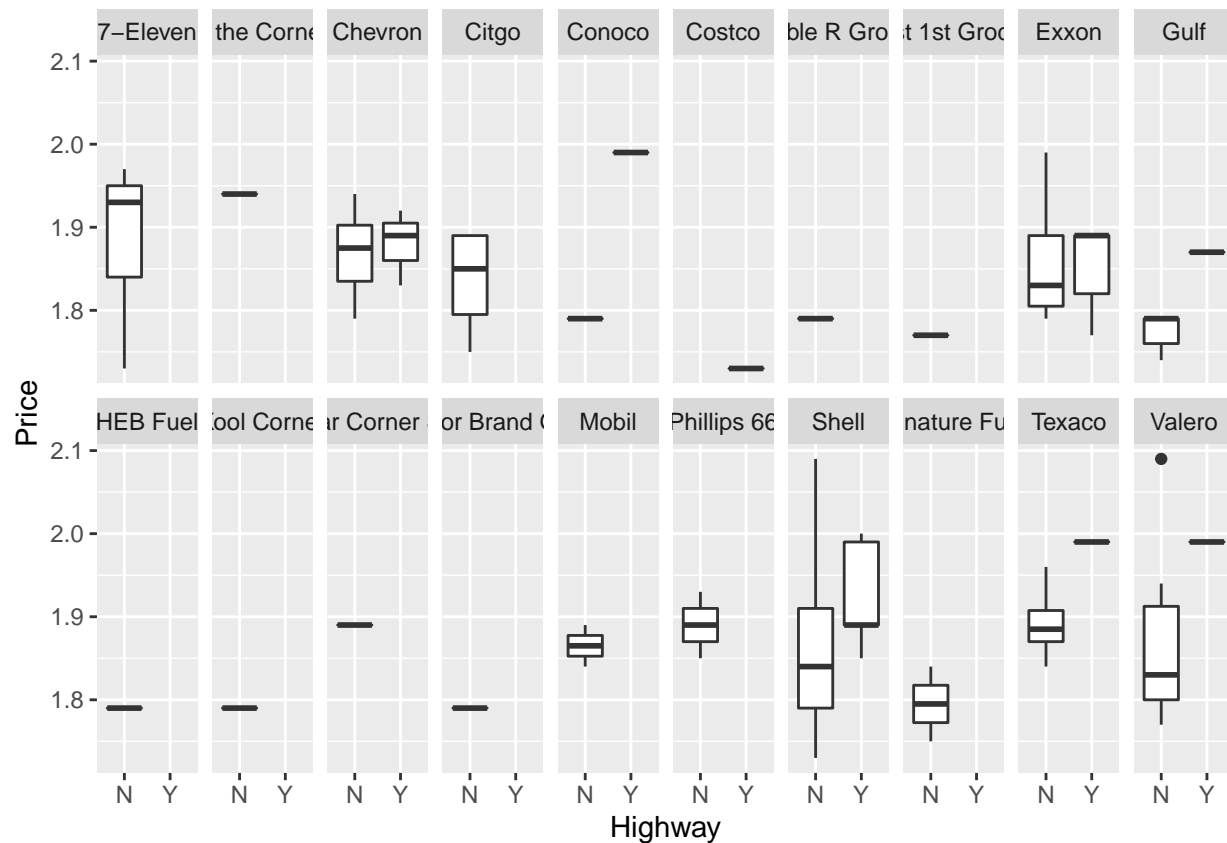
```
## # A tibble: 27 x 3
## # Groups:   Highway [2]
##   Highway Name          mean_price
##   <chr>    <chr>          <dbl>
## 1 N       7-Eleven             1.89
## 2 N       Around the Corner Store 1.94
## 3 N       Chevron              1.87
## 4 N       Citgo                1.84
## 5 N       Conoco               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))
```

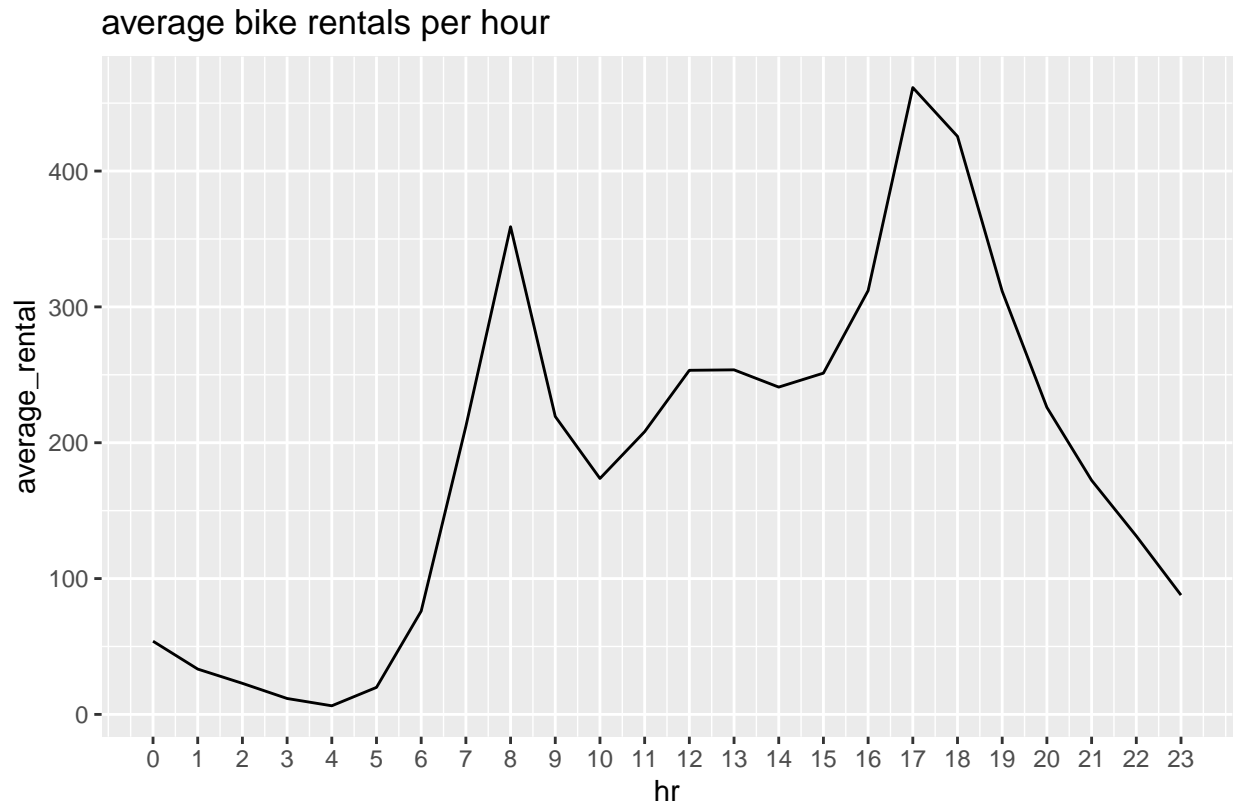
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
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)")
```



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))
```

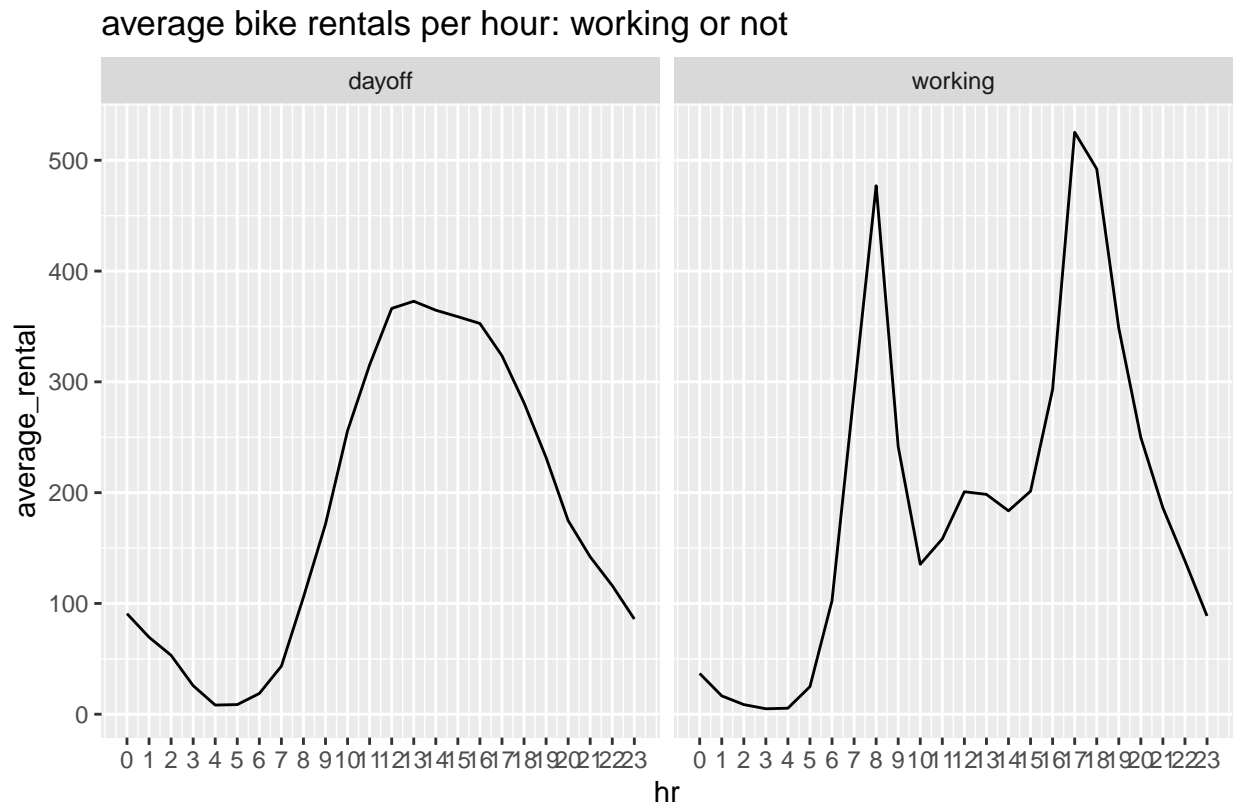
```
## `summarise()` regrouping output by 'hr' (override with `.groups` argument)
```

```
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 afternoon")
```



In working day, most used during rush hour(8:00, 17:00). But in day off, most used in afternoon

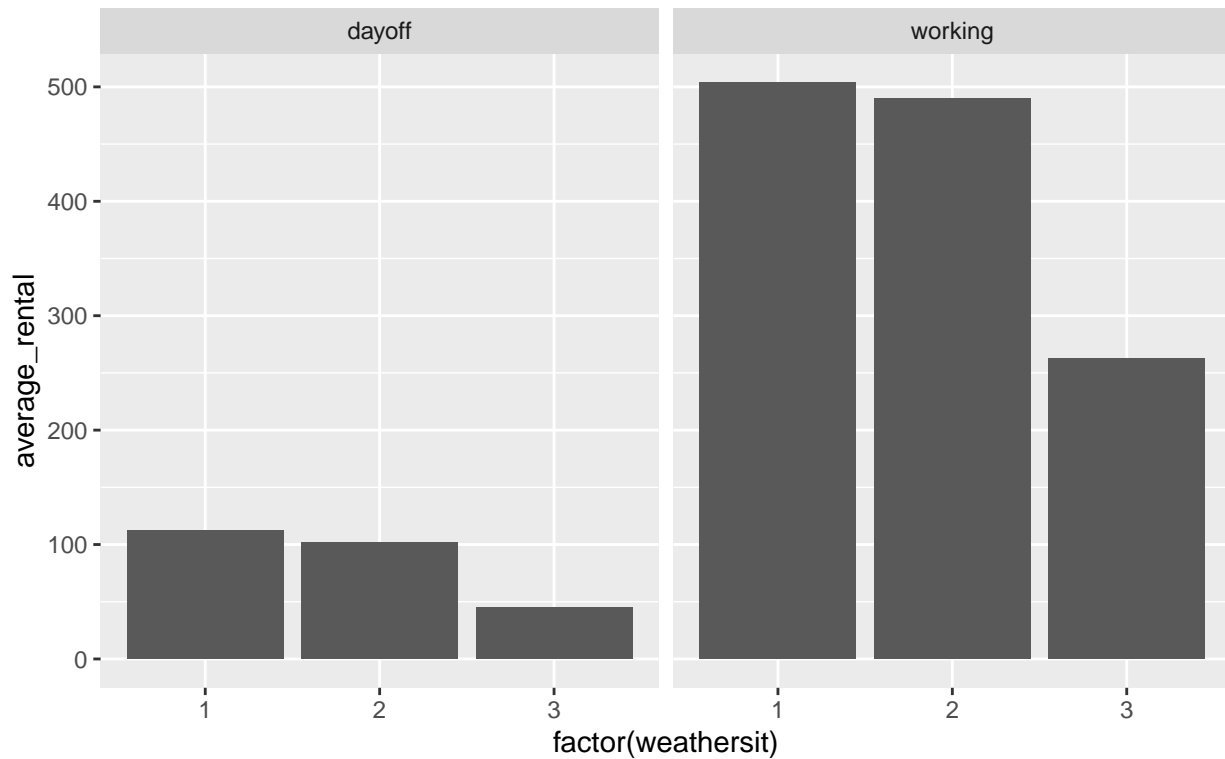
plot C

```
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-")
```

average bike rentals at 8:00 under weather situation: working or not



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?

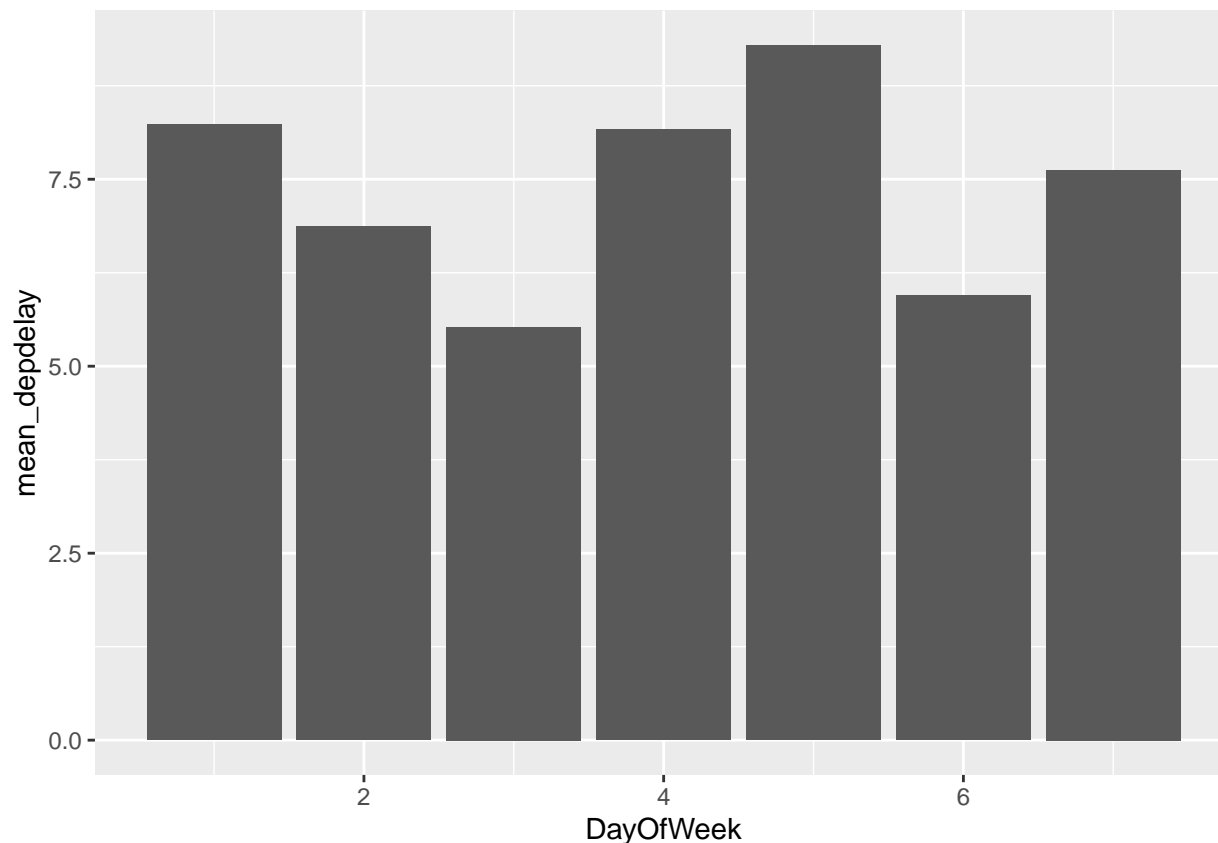
Departure Delay

```
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))
```

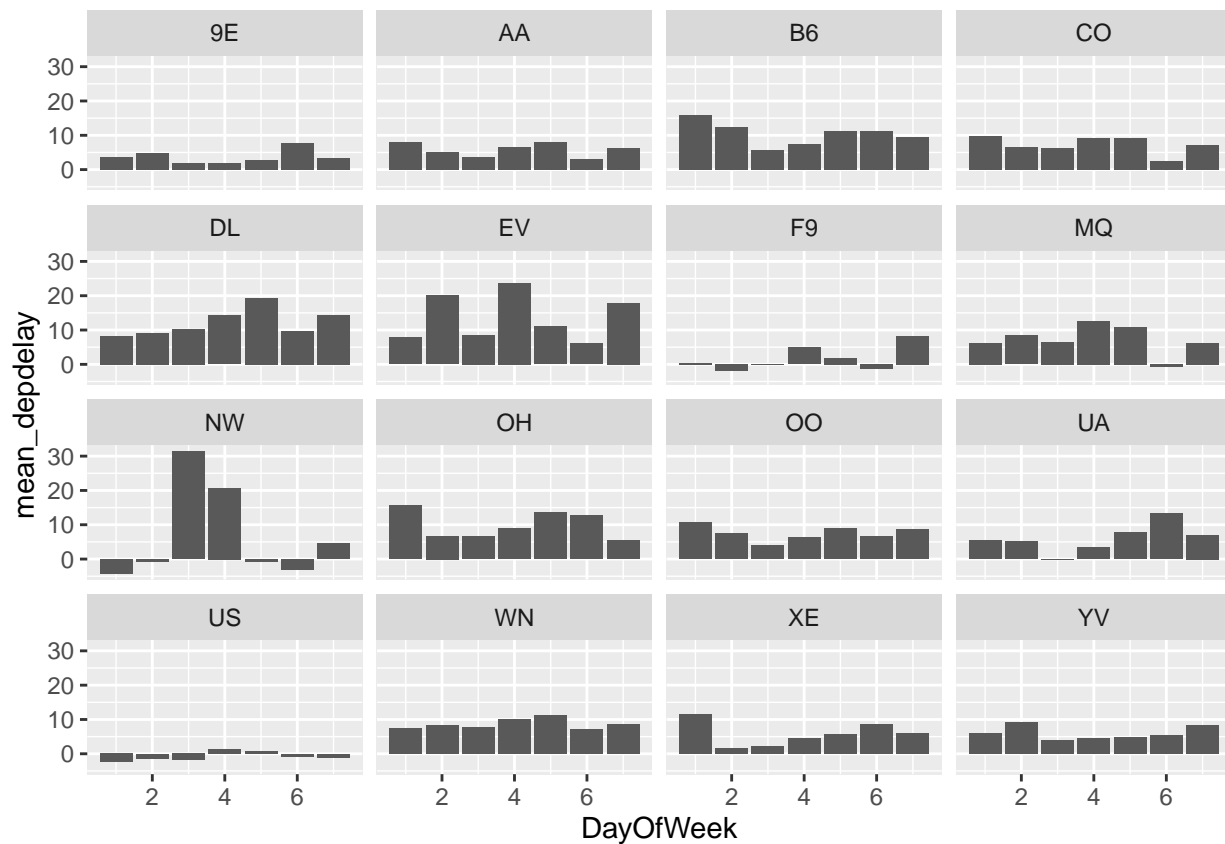
```
## `summarise()` regrouping output by 'DayOfWeek' (override with `.groups` argument)
```

```
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))
```

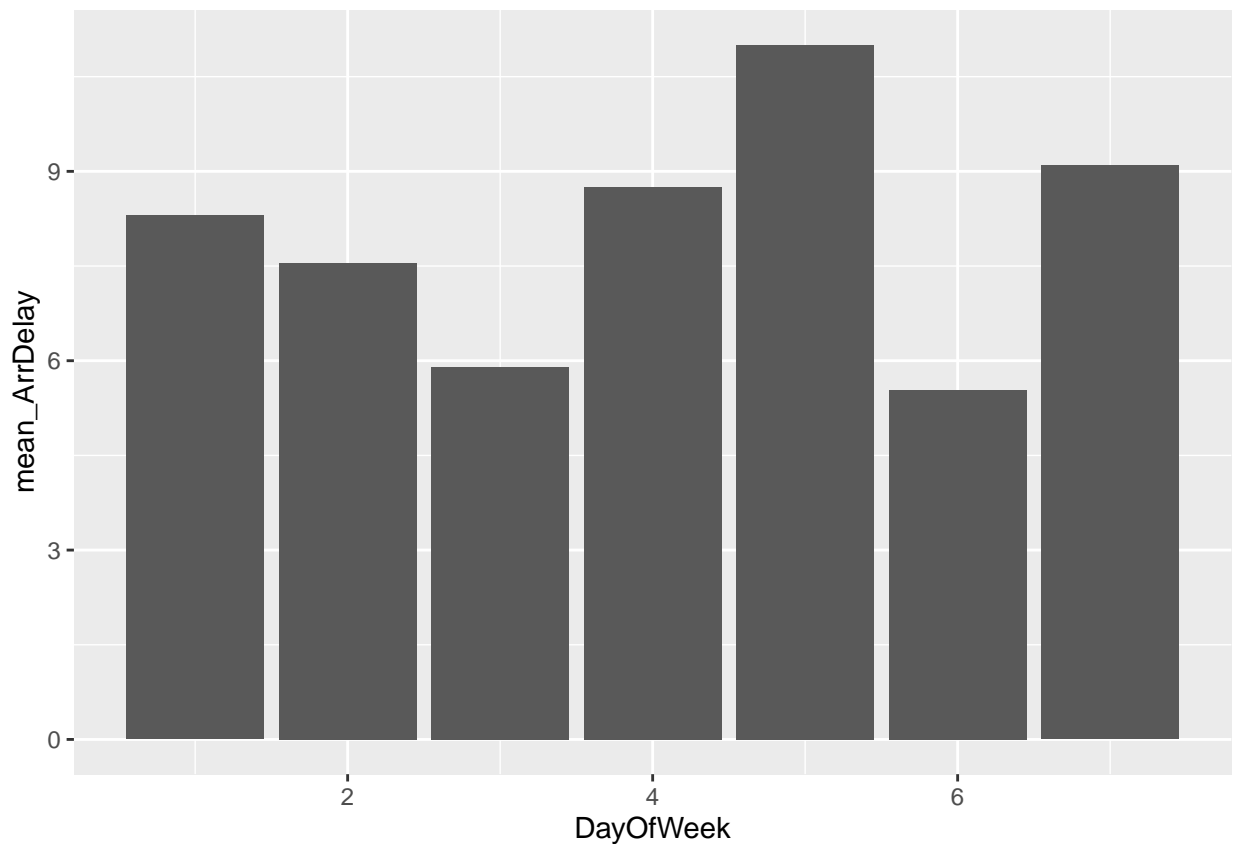
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
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))
```

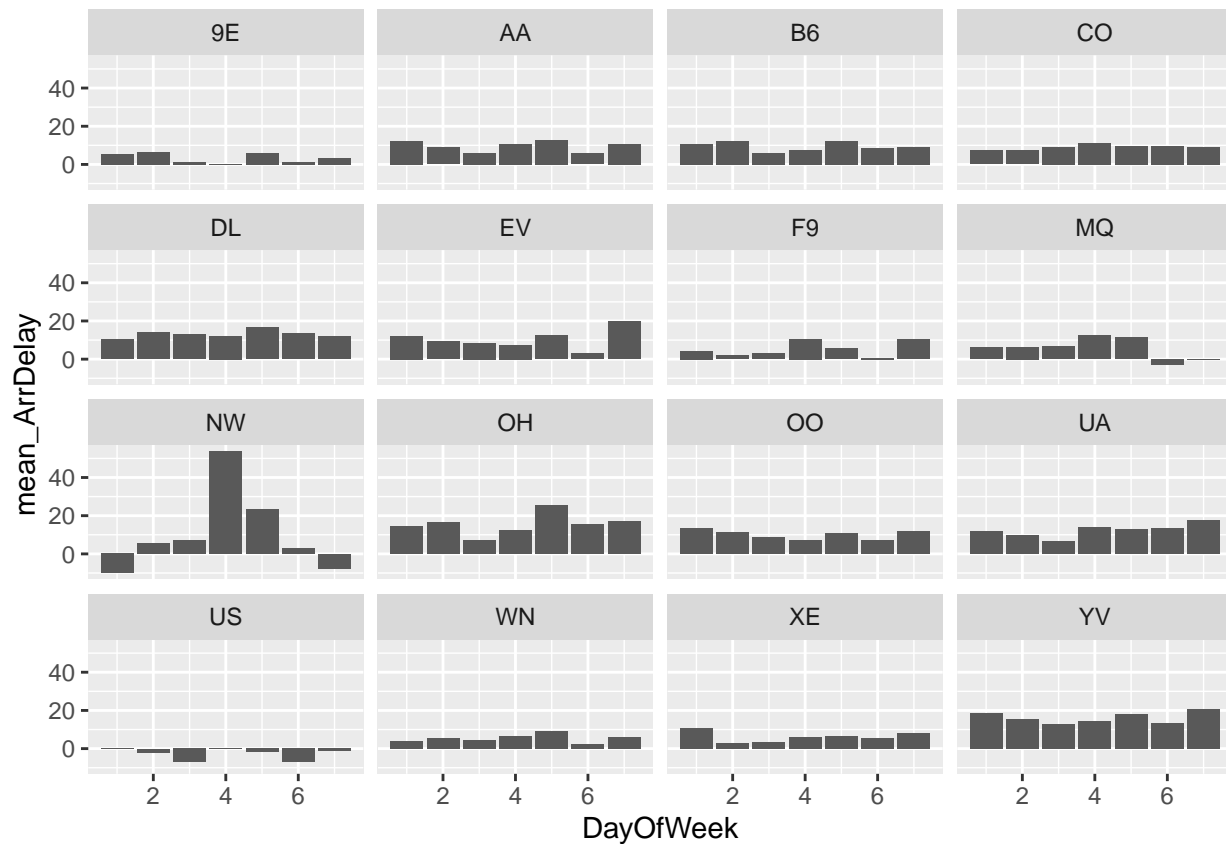
```
## `summarise()` regrouping output by 'DayOfWeek' (override with `.groups` argument)
```

```
d4
```

```
## # A tibble: 112 x 3  
## # Groups:   DayOfWeek [7]  
##   DayOfWeek UniqueCarrier mean_ArrDelay  
##   <int> <chr> <dbl>  
## 1     1 1 9E 5.48  
## 2     1 1 AA 12.3  
## 3     1 1 B6 10.9  
## 4     1 1 CO 7.29  
## 5     1 1 DL 10.4  
## 6     1 1 EV 12.1  
## 7     1 1 F9 4.26  
## 8     1 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
## 46	350	104426	10995
## 47	65 AMG	69652	42982
## 48	65 AMG	79795	41995
## 49	65 AMG	55730	78992
## 50	350	11076	59900
## 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
## 61	350	14	74900
## 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
## 68	65 AMG	17	225681
## 69	65 AMG	10	227715
## 70	65 AMG	12	227685
## 71	65 AMG	10	236125
## 72	350	76146	14950
## 73	65 AMG	52800	40800
## 74	65 AMG	76093	49950
## 75	65 AMG	52951	64999
## 76	65 AMG	49436	86887
## 77	350	18748	59995
## 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
## 86	350	10385	71895
## 87	350	7000	82000
## 88	350	29996	61995

## 89	350	3524	70900
## 90	350	10721	62988
## 91	65 AMG	3	224625
## 92	350	51026	14991
## 93	65 AMG	15512	114998
## 94	350	25685	61900
## 95	350	38239	51312
## 96	350	20868	44999
## 97	350	48230	51777
## 98	350	38503	52900
## 99	65 AMG	20	231325
## 100	65 AMG	10	226115
## 101	65 AMG	8	224765
## 102	65 AMG	16	228325
## 103	350	65757	14993
## 104	65 AMG	86472	22994
## 105	350	32047	50500
## 106	350	24501	66900
## 107	350	29648	69994
## 108	350	59439	39995
## 109	350	1514	94230
## 110	65 AMG	11	225975
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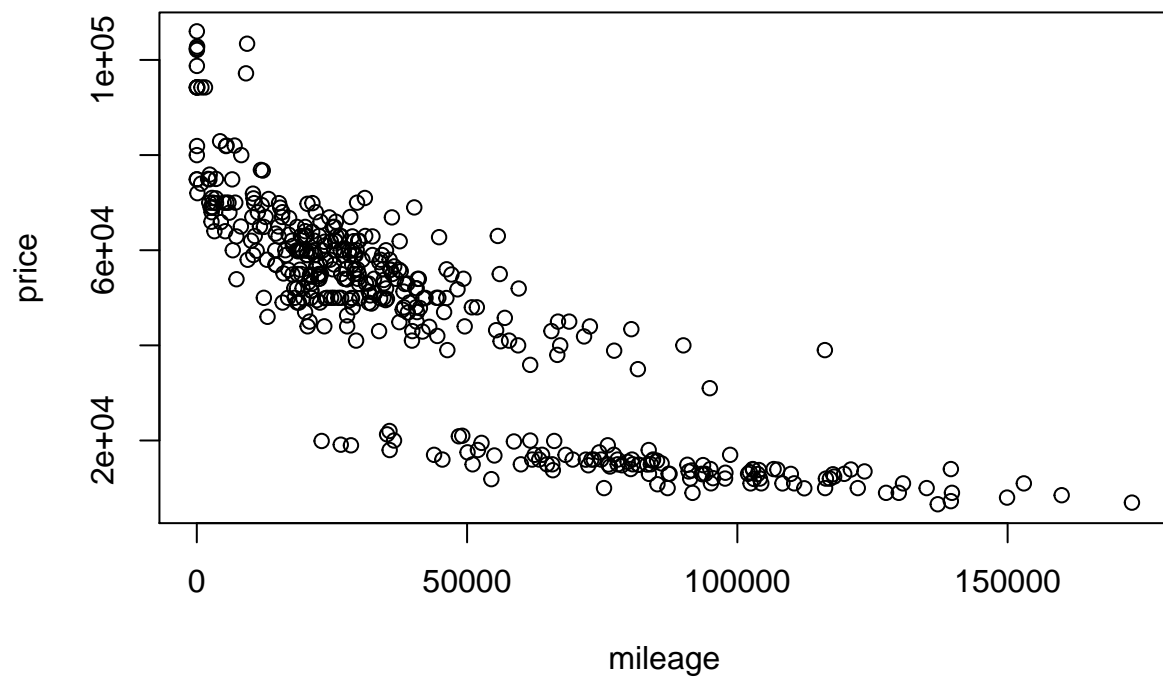
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##	678	65	AMG	26035	138450
##	679		350	34588	53750
##	680	65	AMG	17	232675
##	681		350	97789	13226
##	682		350	90756	14900

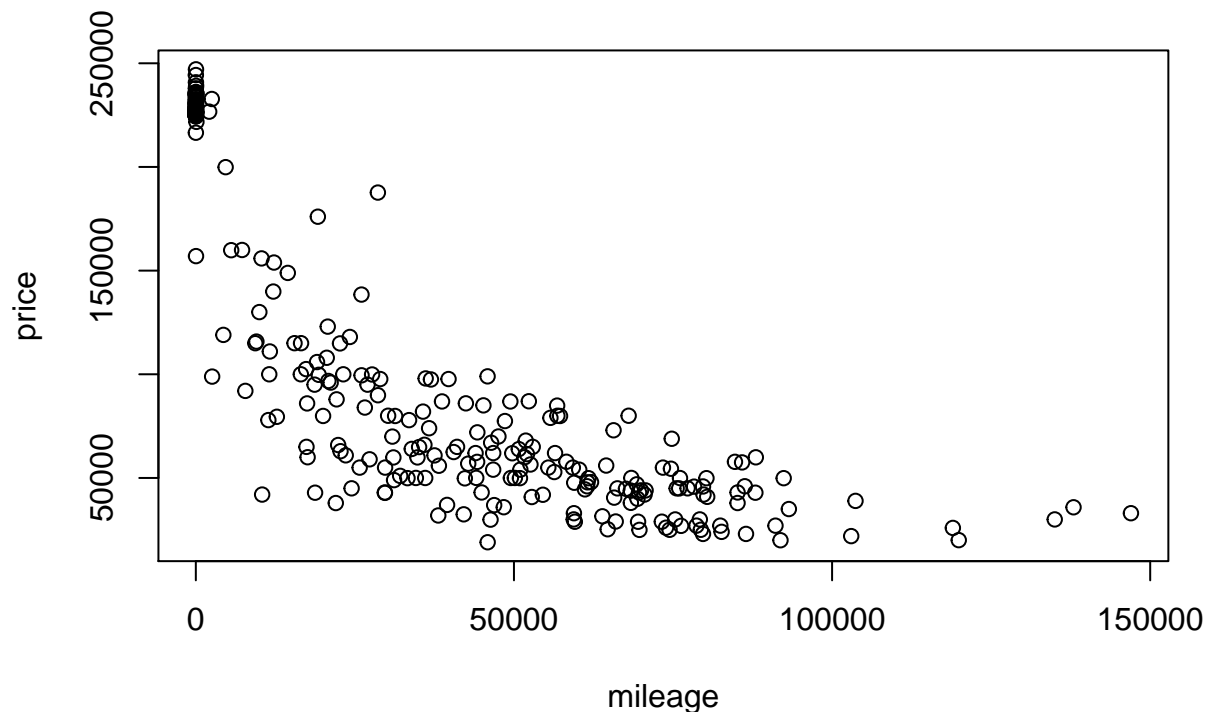

```
## 683      350    97724  11995
## 684 65 AMG    14453 148888
## 685      350    46171  49950
## 686      350    56201  40860
## 687      350    77207  38884
## 688      350    18427  59955
## 689      350    23584  43999
## 690      350    28842  47995
## 691      350     2309  69995
## 692 65 AMG      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
```

```
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] 11485.82
```

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

```
## [1] 10166.73
```

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

```
## [1] 10054.07
```

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

```
## [1] 9993.88
```

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

```
## [1] 9989.683
```

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

```
## [1] 9971.978
```

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

```
## [1] 9876.5
```

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

```
## [1] 10898.11
```

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] 24363.51
```

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

```
## [1] 22762.85
```

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

```
## [1] 22557.7
```

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

```
## [1] 23175.97
```

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

```
## [1] 23384.51
```

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

```
## [1] 24151.82
```

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

```
## [1] 26499.37
```

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

```
## [1] 34639.92
```

When k=20, RMSE minimized

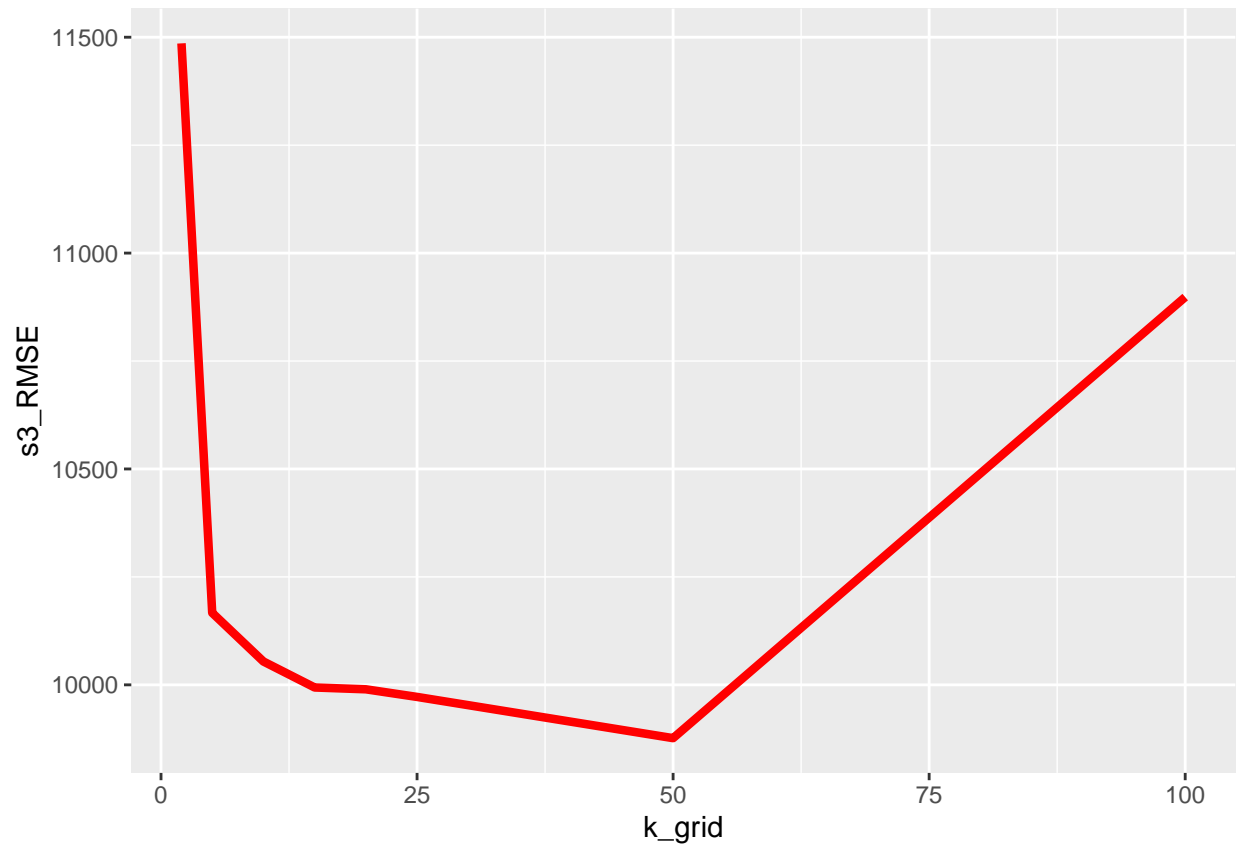
K vs RMSE

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)
```

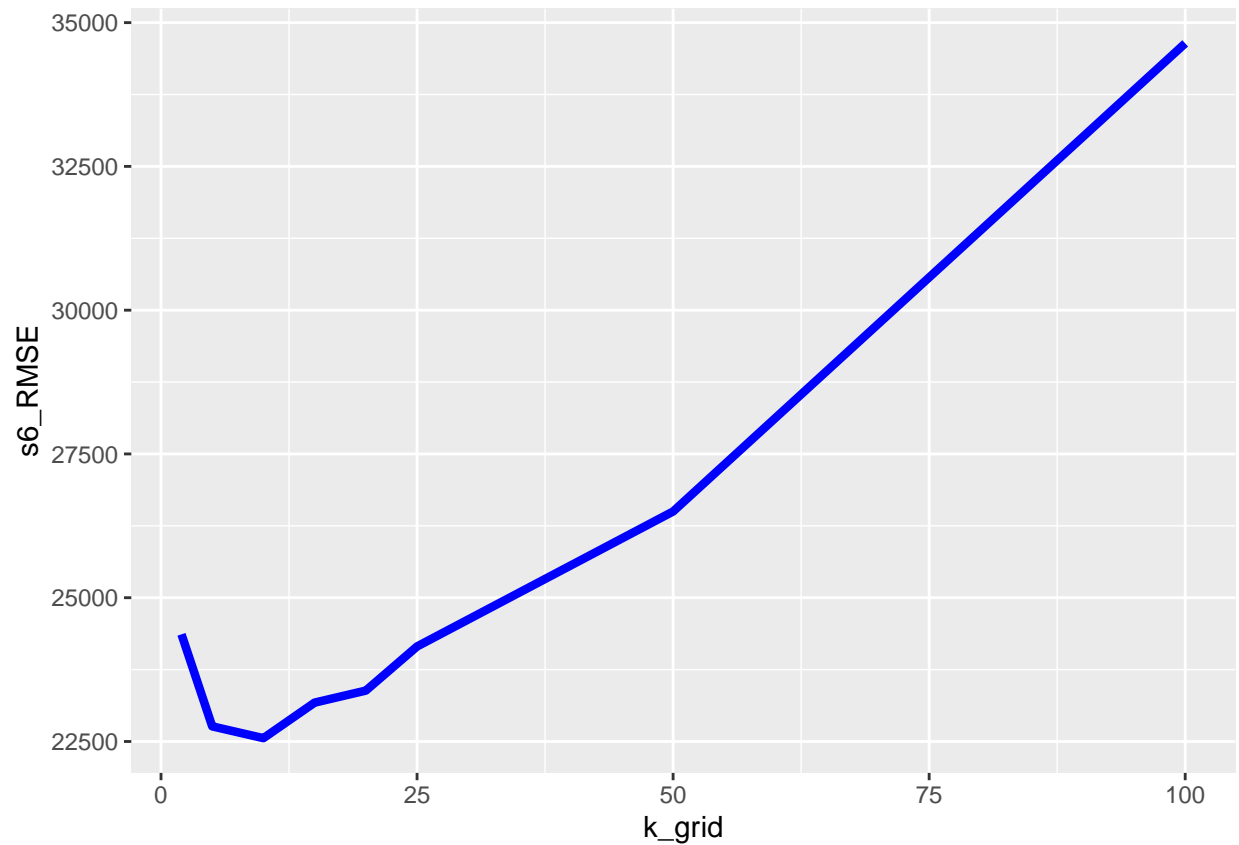


65 AMG trim of sclass

```
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

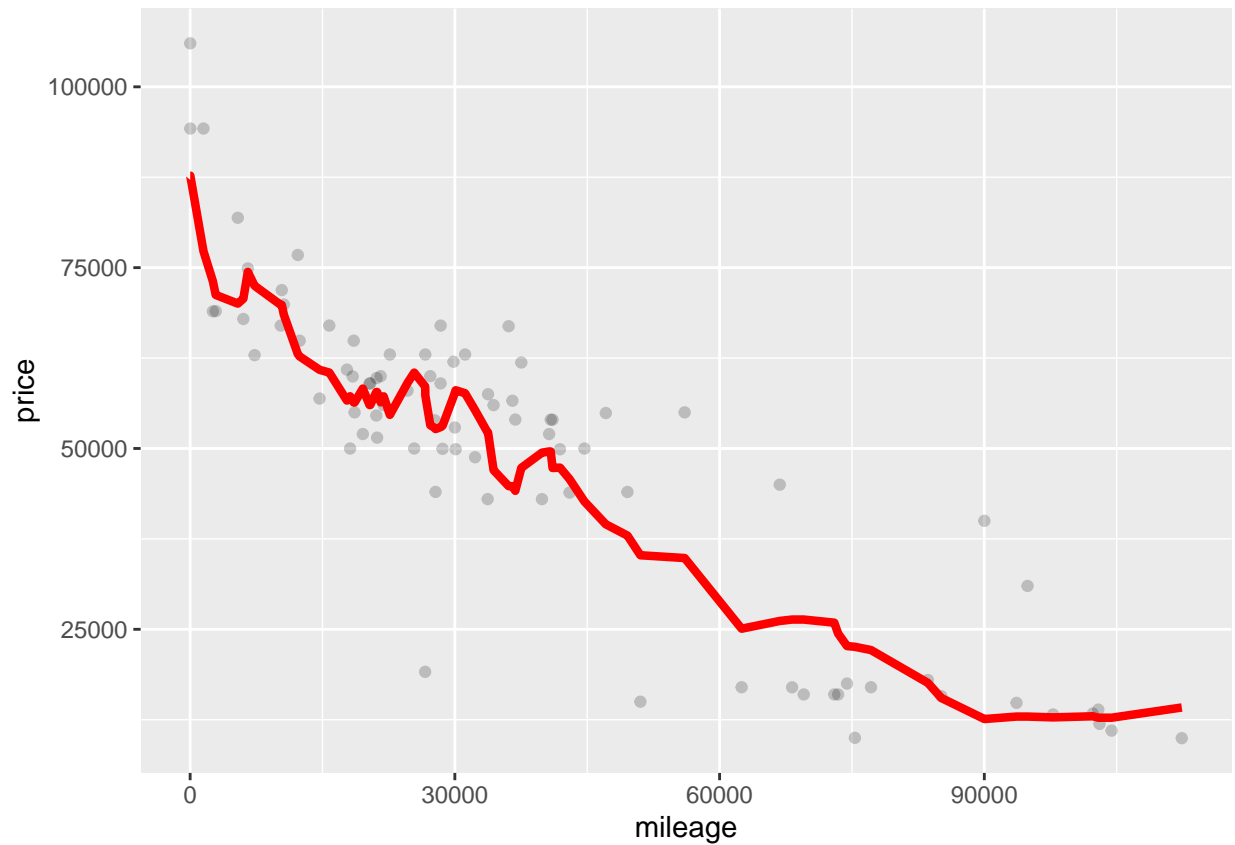
350 trim with K = 15

```
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] 9993.88

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
```



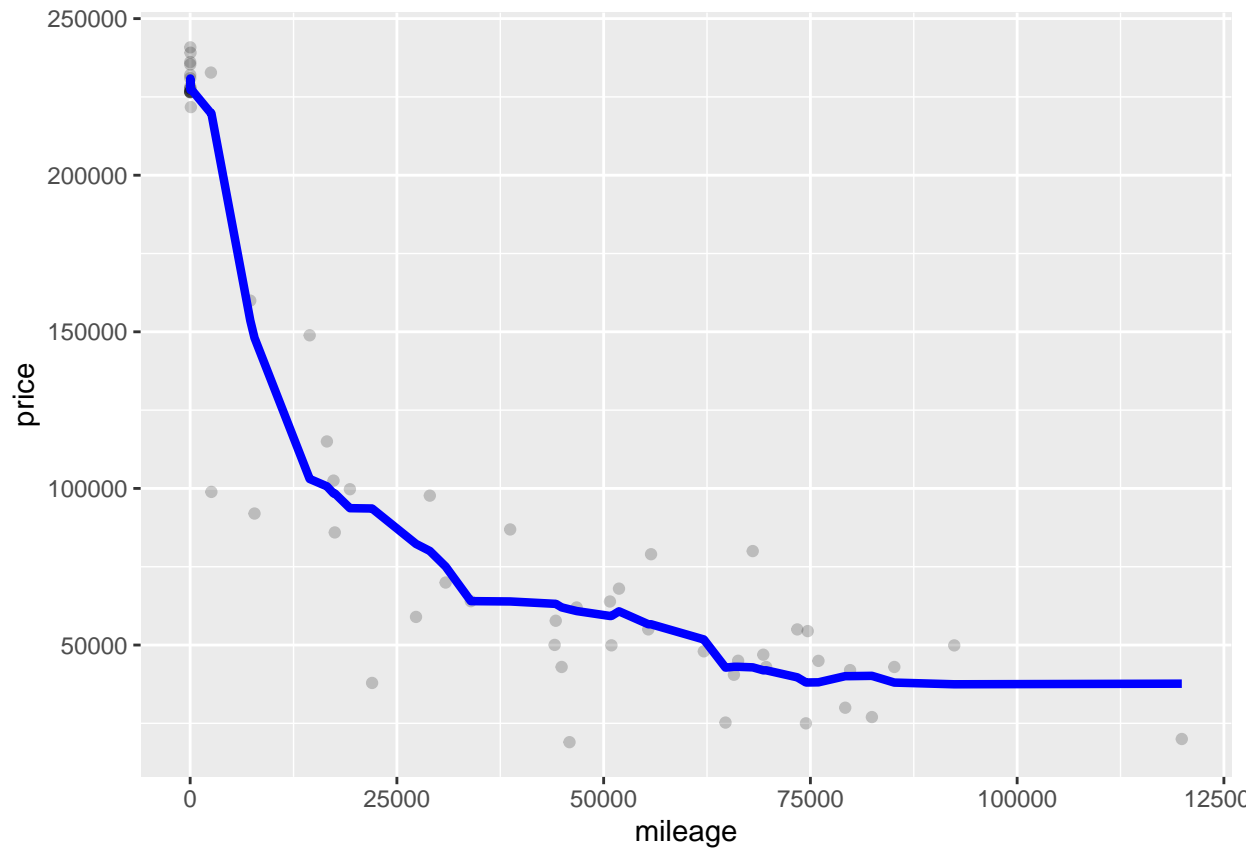
65 AMG trim with K = 20

```
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] 23384.51
```

```
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'