Assignment 1

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```
library(tidyverse)
## -- Attaching packages -----
## v ggplot2 3.3.2
                      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)
library(scales)
##
## Attaching package: 'scales'
## The following object is masked from 'package:purrr':
##
##
       discard
## The following object is masked from 'package:readr':
##
##
       col_factor
library(FNN)
library(class)
##
## Attaching package: 'class'
## The following objects are masked from 'package:FNN':
##
##
      knn, knn.cv
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':

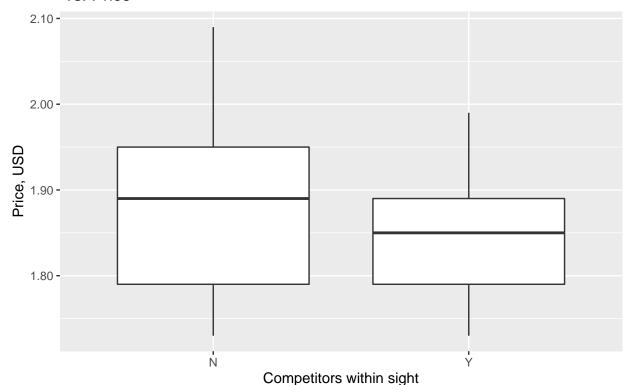
##
## accumulate, when

GasPrices <- read.csv("/Volumes/G-DRIVE mobile USB-C/GasPrices.csv")
bikeshare <- read.csv("/Volumes/G-DRIVE mobile USB-C/bikeshare.csv")
ABIA <- read.csv("/Volumes/G-DRIVE mobile USB-C/ABIA.csv")
sclass <- read.csv("/Volumes/G-DRIVE mobile USB-C/sclass.csv")</pre>
```

Data Visualization: gas prices

A) Gas stations charge more if they lack direct competition in sight (boxplot).

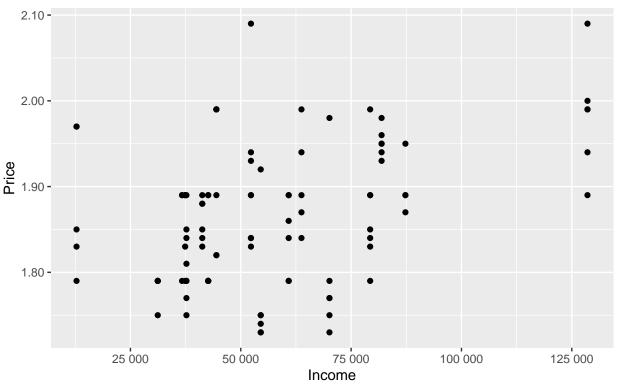
Direct Competition within sight vs. Price



B) The richer the area, the higher the gas price (scatter plot).

ggplot(data=GasPrices)+geom_point(mapping=aes(x=Income,y=Price))+scale_y_continuous(labels=scales::numb

Median Household Income within the zip code vs. Gas Price

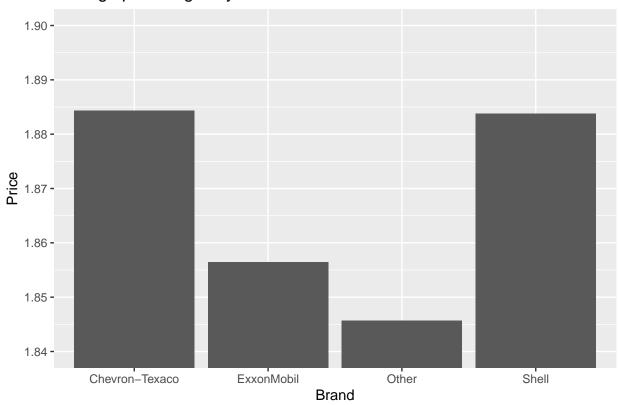


C) Shell charges more than other brands (bar plot).

ggplot(data=GasPrices,aes(x=Brand,y=Price))+geom_bar(stat="summary",fun.y="mean")+scale_y_continuous(la

- ## Warning: Ignoring unknown parameters: fun.y
- ## No summary function supplied, defaulting to `mean_se()`

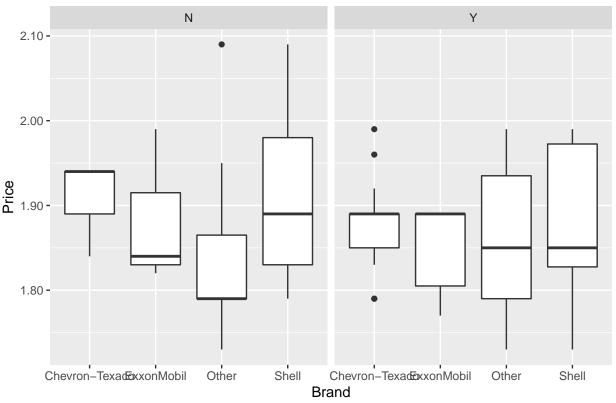
Average price of gas by brand



D) Gas stations at stoplights charge more (faceted histogram).

 $\verb|ggplot(data=GasPrices)+geom_boxplot(aes(x=Brand,y=Price))+facet_wrap(~Stoplight)+ggtitle("Average price))|$

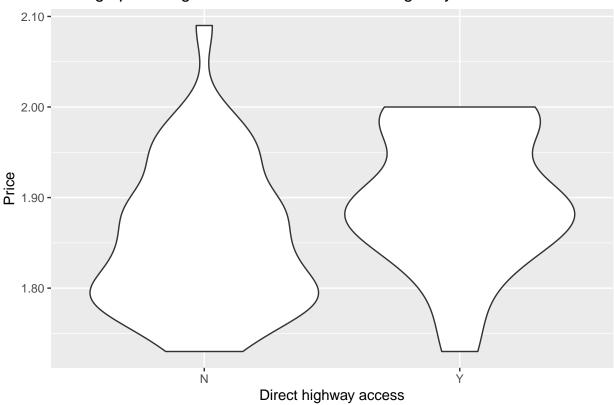
Average price of gas by brand, at stoplights and not at stoplights



E) Gas stations with direct highway access charge more (your choice of plot).

 $\verb|ggplot(data=GasPrices)+geom_violin(aes(x=factor(Highway),y=Price))+scale_y_continuous(labels=scales::number of the property of the propert$

Average price of gas with and without direct highway access



Data visualization: a bike share network

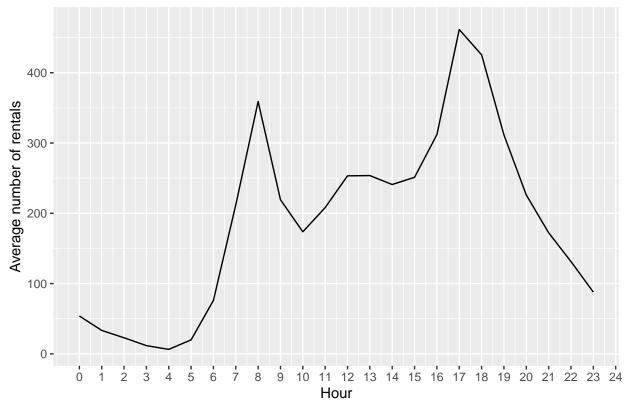
```
Plot A: a line graph showing average bike rentals versus hour of the day.

ggplot(data=bikeshare)+geom_line(aes(hr,total),stat="summary",fun.y="mean")+scale_x_continuous(breaks=0)

## Warning: Ignoring unknown parameters: fun.y

## No summary function supplied, defaulting to `mean_se()`
```

Average bike rentals by hour of the day



Plot B: a faceted line graph showing average bike rentals versus hour of the day, faceted according to whether it is a working day.

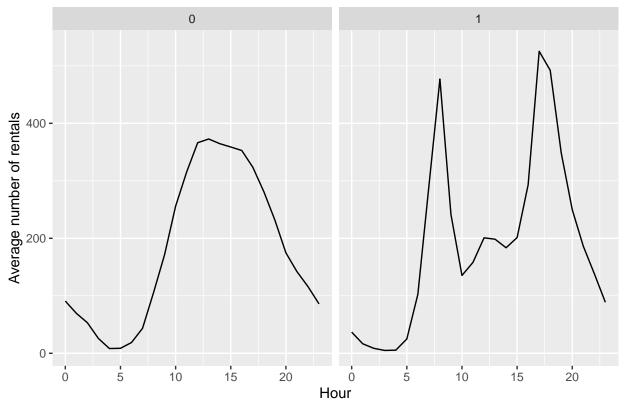
 $\verb|ggplot(data=bikeshare)+geom_line(aes(hr,total), \verb|stat="summary",fun.y="mean")+facet_wrap(~workingday)+ggt|\\$

```
## Warning: Ignoring unknown parameters: fun.y
```

^{##} No summary function supplied, defaulting to `mean_se()`

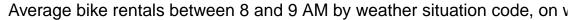
^{##} No summary function supplied, defaulting to `mean_se()`

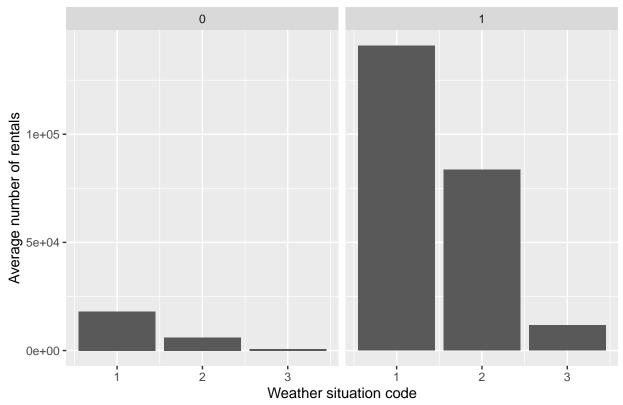
Average bike rentals by hour of the day, split between working and non-wo



Plot C: a faceted bar plot showing average ridership during the 8 AM hour by weather situation code, faceted according to whether it is a working day or not.

bikeshare %>%
filter(hr=="8") %>% ggplot()+geom_bar(aes(x=weathersit,y=total),stat="identity")+facet_wrap(~workingd)





Data visualization: flights at ABIA

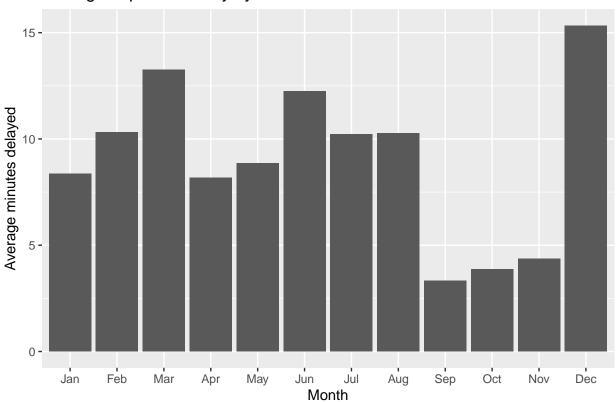
I would like to examine the difference in flight delays between different months, times of day, and carriers. With this information I could choose which month to travel, what time I should try to book my flight for, and which carrier to book my flight with, if my goal is to avoid all kinds of delays.

```
ggplot(data=ABIA,aes(x=factor(Month),y=DepDelay))+geom_bar(stat="summary",fun.y="mean")+scale_x_discret
## Warning: Ignoring unknown parameters: fun.y
```

No summary function supplied, defaulting to `mean_se()`

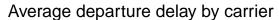
Warning: Removed 1413 rows containing non-finite values (stat_summary).

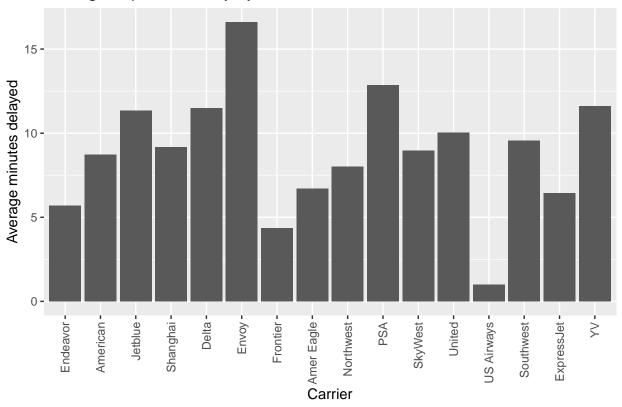
Average departure delay by month



Next, I will see which carriers have the shortest and longest average departure delays.

- ## Warning: Ignoring unknown parameters: fun.y
- ## Warning: Removed 1413 rows containing non-finite values (stat_summary).
- ## No summary function supplied, defaulting to `mean_se()`





K-nearest neighbors

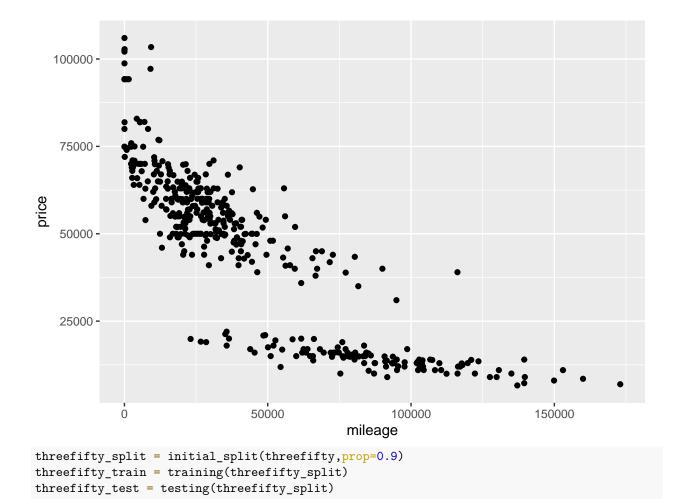
Splitting the 350 AMG data and the 63 AMG data.

```
threefifty <- sclass[sclass$trim=="350",]
sixtyfive <- sclass[sclass$trim=="65 AMG",]</pre>
```

350 AMG

Splitting the data into a training and a testing set

ggplot(data=threefifty)+geom_point(mapping=aes(x=mileage,y=price))



Running K-nearest-neighbors, from K=2 to K=25

```
knn2 = knnreg(price~mileage, data=threefifty_train, k=2)
knn3 = knnreg(price~mileage, data=threefifty_train, k=3)
knn4 = knnreg(price~mileage, data=threefifty_train, k=4)
knn5 = knnreg(price~mileage, data=threefifty_train, k=5)
knn6 = knnreg(price~mileage, data=threefifty_train, k=6)
knn7 = knnreg(price~mileage, data=threefifty train, k=7)
knn8 = knnreg(price~mileage, data=threefifty_train, k=8)
knn9 = knnreg(price~mileage, data=threefifty train, k=9)
knn10 = knnreg(price~mileage, data=threefifty_train, k=10)
knn11 = knnreg(price~mileage, data=threefifty_train, k=11)
knn12 = knnreg(price~mileage, data=threefifty_train, k=12)
knn13 = knnreg(price~mileage, data=threefifty train, k=13)
knn14 = knnreg(price~mileage, data=threefifty_train, k=14)
knn15 = knnreg(price~mileage, data=threefifty_train, k=15)
knn16 = knnreg(price~mileage, data=threefifty_train, k=16)
knn17 = knnreg(price~mileage,data=threefifty_train,k=17)
knn18 = knnreg(price~mileage, data=threefifty_train, k=18)
knn19 = knnreg(price~mileage, data=threefifty_train, k=19)
knn20 = knnreg(price~mileage, data=threefifty_train, k=20)
```

```
knn21 = knnreg(price~mileage,data=threefifty_train,k=21)
knn22 = knnreg(price~mileage,data=threefifty_train,k=22)
knn23 = knnreg(price~mileage,data=threefifty_train,k=23)
knn24 = knnreg(price~mileage,data=threefifty_train,k=24)
knn25 = knnreg(price~mileage,data=threefifty_train,k=25)
```

Calculating the out-of-sample root mean-squared error (RMSE) for each value of k

```
rmse2 = rmse(knn2,threefifty_test)
rmse3 = rmse(knn3,threefifty_test)
rmse4 = rmse(knn4,threefifty test)
rmse5 = rmse(knn5,threefifty_test)
rmse6 = rmse(knn6,threefifty test)
rmse7 = rmse(knn7,threefifty_test)
rmse8 = rmse(knn8,threefifty_test)
rmse9 = rmse(knn9,threefifty test)
rmse10 = rmse(knn10,threefifty test)
rmse11 = rmse(knn11,threefifty_test)
rmse12 = rmse(knn12,threefifty_test)
rmse13 = rmse(knn13,threefifty_test)
rmse14 = rmse(knn14,threefifty_test)
rmse15 = rmse(knn15,threefifty_test)
rmse16 = rmse(knn16,threefifty_test)
rmse17 = rmse(knn17,threefifty_test)
rmse18 = rmse(knn18,threefifty_test)
rmse19 = rmse(knn19,threefifty_test)
rmse20 = rmse(knn20,threefifty_test)
rmse21 = rmse(knn21,threefifty test)
rmse22 = rmse(knn22,threefifty_test)
rmse23 = rmse(knn23,threefifty test)
rmse24 = rmse(knn24,threefifty_test)
rmse25 = rmse(knn25,threefifty_test)
```

Plotting RMSE versus K

```
k <- c(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25)
rmse <- c(rmse2,rmse3,rmse4,rmse5,rmse6,rmse7,rmse8,rmse9,rmse10,rmse11,rmse12,rmse13,rmse14,rmse15,rms
errors <- data.frame(k,rmse)
errors</pre>
```

```
##
       k
## 1
       2 11947.43
## 2
       3 12445.49
## 3
       4 12375.27
## 4
       5 11131.40
## 5
       6 10646.19
## 6
       7 10111.60
## 7
       8 10235.23
## 8
      9 10331.56
## 9 10 10357.92
## 10 11 10089.25
## 11 12 10160.32
## 12 13 10112.53
```

```
## 13 14 10064.03

## 14 15 10134.03

## 15 16 10339.22

## 16 17 10462.43

## 17 18 10374.28

## 18 19 10438.77

## 19 20 10491.47

## 20 21 10634.54

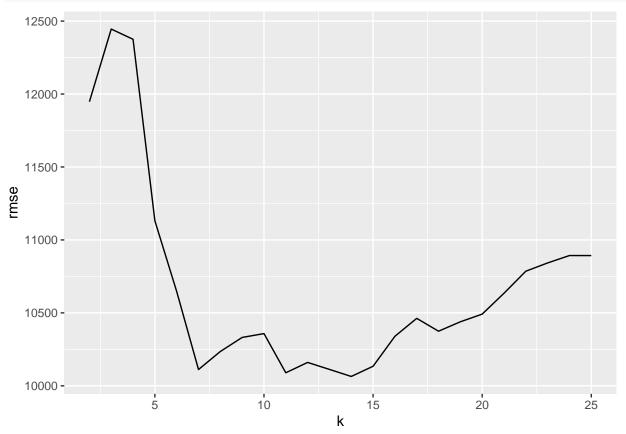
## 21 22 10785.66

## 22 23 10842.32

## 23 24 10892.94

## 24 25 10892.73
```

ggplot(data=errors)+geom_line(aes(k,rmse))

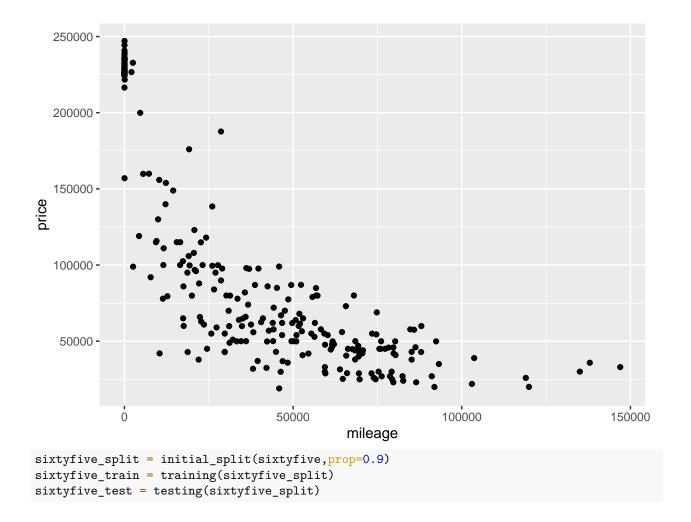


It looks like the optimal value of K is 19.

65 AMG

```
Splitting the data into a training and a testing set
```

```
ggplot(data=sixtyfive)+geom_point(mapping=aes(x=mileage,y=price))
```



Running K-nearest-neighbors, from K=2 to K=100

```
knn2 = knnreg(price~mileage,data=sixtyfive_train,k=2)
knn3 = knnreg(price~mileage,data=sixtyfive_train,k=3)
knn4 = knnreg(price~mileage, data=sixtyfive_train, k=4)
knn5 = knnreg(price~mileage, data=sixtyfive_train, k=5)
knn6 = knnreg(price~mileage,data=sixtyfive_train,k=6)
knn7 = knnreg(price~mileage,data=sixtyfive_train,k=7)
knn8 = knnreg(price~mileage, data=sixtyfive_train, k=8)
knn9 = knnreg(price~mileage,data=sixtyfive_train,k=9)
knn10 = knnreg(price~mileage, data=sixtyfive_train, k=10)
knn11 = knnreg(price~mileage,data=sixtyfive_train,k=11)
knn12 = knnreg(price~mileage,data=sixtyfive_train,k=12)
knn13 = knnreg(price~mileage, data=sixtyfive_train, k=13)
knn14 = knnreg(price~mileage, data=sixtyfive train, k=14)
knn15 = knnreg(price~mileage,data=sixtyfive_train,k=15)
knn16 = knnreg(price~mileage, data=sixtyfive train, k=16)
knn17 = knnreg(price~mileage,data=sixtyfive_train,k=17)
knn18 = knnreg(price~mileage, data=sixtyfive_train, k=18)
knn19 = knnreg(price~mileage,data=sixtyfive_train,k=19)
knn20 = knnreg(price~mileage, data=sixtyfive_train, k=20)
knn21 = knnreg(price~mileage,data=sixtyfive_train,k=21)
knn22 = knnreg(price~mileage, data=sixtyfive_train, k=22)
```

```
knn23 = knnreg(price~mileage,data=sixtyfive_train,k=23)
knn24 = knnreg(price~mileage,data=sixtyfive_train,k=24)
knn25 = knnreg(price~mileage,data=sixtyfive_train,k=25)
```

Calculating the out-of-sample root mean-squared error (RMSE) for each value of k

```
rmse2 = rmse(knn2,sixtyfive_test)
rmse3 = rmse(knn3,sixtyfive_test)
rmse4 = rmse(knn4,sixtyfive_test)
rmse5 = rmse(knn5,sixtyfive_test)
rmse6 = rmse(knn6,sixtyfive test)
rmse7 = rmse(knn7,sixtyfive_test)
rmse8 = rmse(knn8,sixtyfive test)
rmse9 = rmse(knn9,sixtyfive_test)
rmse10 = rmse(knn10,sixtyfive_test)
rmse11 = rmse(knn11,sixtyfive test)
rmse12 = rmse(knn12,sixtyfive test)
rmse13 = rmse(knn13,sixtyfive_test)
rmse14 = rmse(knn14,sixtyfive_test)
rmse15 = rmse(knn15,sixtyfive_test)
rmse16 = rmse(knn16,sixtyfive_test)
rmse17 = rmse(knn17,sixtyfive_test)
rmse18 = rmse(knn18,sixtyfive_test)
rmse19 = rmse(knn19,sixtyfive_test)
rmse20 = rmse(knn20,sixtyfive_test)
rmse21 = rmse(knn21,sixtyfive_test)
rmse22 = rmse(knn22,sixtyfive_test)
rmse23 = rmse(knn23,sixtyfive test)
rmse24 = rmse(knn24,sixtyfive_test)
rmse25 = rmse(knn25,sixtyfive_test)
```

Plotting RMSE versus K

```
k <- c(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25)
rmse <- c(rmse2,rmse3,rmse4,rmse5,rmse6,rmse7,rmse8,rmse9,rmse10,rmse11,rmse12,rmse13,rmse14,rmse15,rms
errors <- data.frame(k,rmse)
errors</pre>
```

```
##
       k
             rmse
     2 24802.65
## 1
## 2
      3 23503.90
## 3
       4 23035.34
## 4
       5 22571.96
## 5
       6 22961.14
## 6
       7 23024.52
## 7
       8 22832.63
## 8
       9 22886.96
## 9 10 22054.04
## 10 11 21811.97
## 11 12 21887.11
## 12 13 21689.23
## 13 14 21465.36
## 14 15 21640.36
```

```
## 15 16 21839.45

## 16 17 22048.61

## 17 18 22176.57

## 18 19 22263.75

## 19 20 22501.73

## 20 21 22406.36

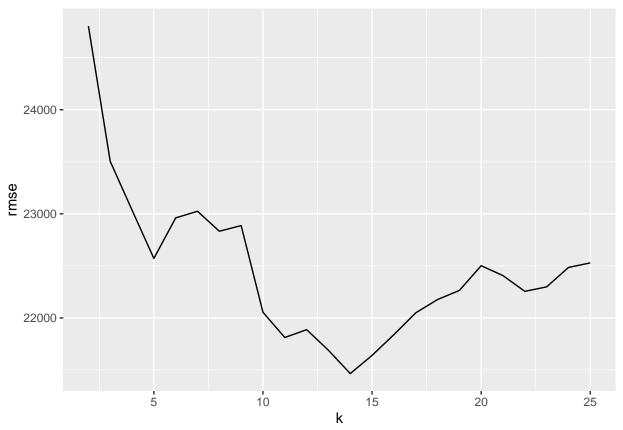
## 21 22 22255.23

## 22 23 22298.31

## 23 24 22484.97

## 24 25 22528.73
```

ggplot(data=errors)+geom_line(aes(k,rmse))



It looks like the optimal value of K is 12.