

# FML final project

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```
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'  
  
## The following objects are masked from 'package:stats':  
##  
##   filter, lag  
  
## The following objects are masked from 'package:base':  
##  
##   intersect, setdiff, setequal, union
```

```
library(ISLR)  
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.3.2 --  
  
## v ggplot2 3.3.6      v purrr  0.3.4  
## v tibble  3.1.8      v stringr 1.4.1  
## v tidyr   1.2.1      v forcats 0.5.2  
## v readr   2.1.2  
## -- Conflicts ----- tidyverse_conflicts() --  
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag()    masks stats::lag()
```

```
library(NbClust)  
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

*loading the file*

```
rawdata=read.csv("C:/Users/kurra/Downloads/fuel_receipts_costs_eia923 (3).csv")
```

*replacing empty values with 0*

```
data1 = rawdata                                # Duplicate data frame
data1[data1 == ""] <- 0                        # Replace blank by 0
View(data1)                                    # Print updated data frame
```

*omitting NA values*

```
data2= na.omit(data1)
```

*considering 12000 data as a sample*

```
set.seed(1234)
data3= sample_n(data2, 12000)
view(data3)
```

*splitting the data into training and test data*

```
library(caret)
```

```
## Loading required package: lattice
```

```
##
```

```
## Attaching package: 'caret'
```

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

```
##
```

```
## lift
```

```
set.seed(3456)
Split_data= createDataPartition(data3$rowid, p = .75, list = FALSE, times = 1)

train_data=data3[Split_data,]
test_data=data3[-Split_data,]

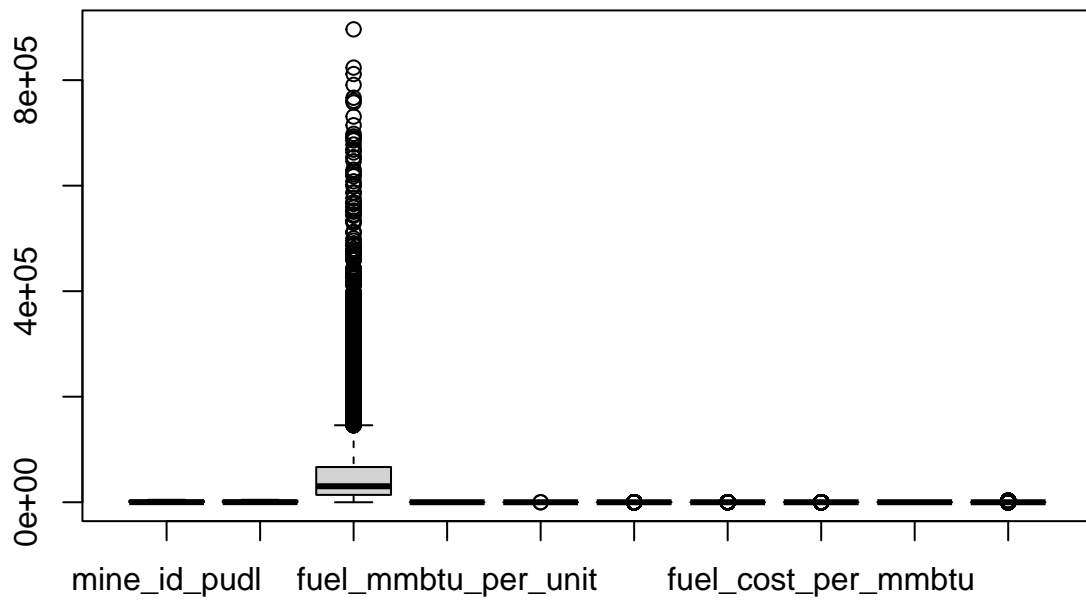
View(train_data)
View(test_data)
```

*looking at the data distribution*

```
library(corrplot)
```

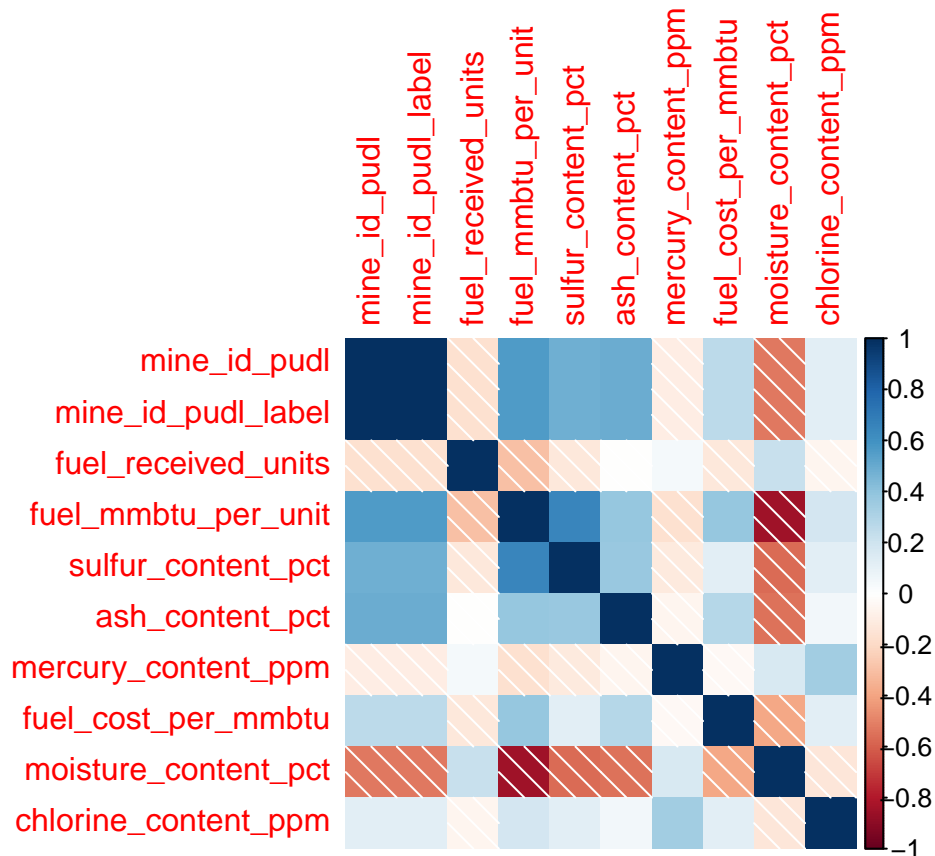
```
## corrplot 0.92 loaded
```

```
boxplot(train_data[, c(12,13,15,16,17,18,19,20,27,28)])
```



*#some variables had big ranges and outliers*

```
corrplot(cor(train_data[, c(12,13,15,16,17,18,19,20,27,28)]), method= "shade")
```



*#plotting correlation between different variables, sulfur content and heat produced shows a showing pos*

- Building the clustering model\*

*#1- Use Kmeans clustering to identify clusters*

*#Normalizing variables related to purchases process using z-score*  
`ncol(Split_data)`

`## [1] 1`

`fuel_cost_normalized =scale(train_data[, c(12,13,15,16,17,18,19,20,27,28)])`  
`head(fuel_cost_normalized)`

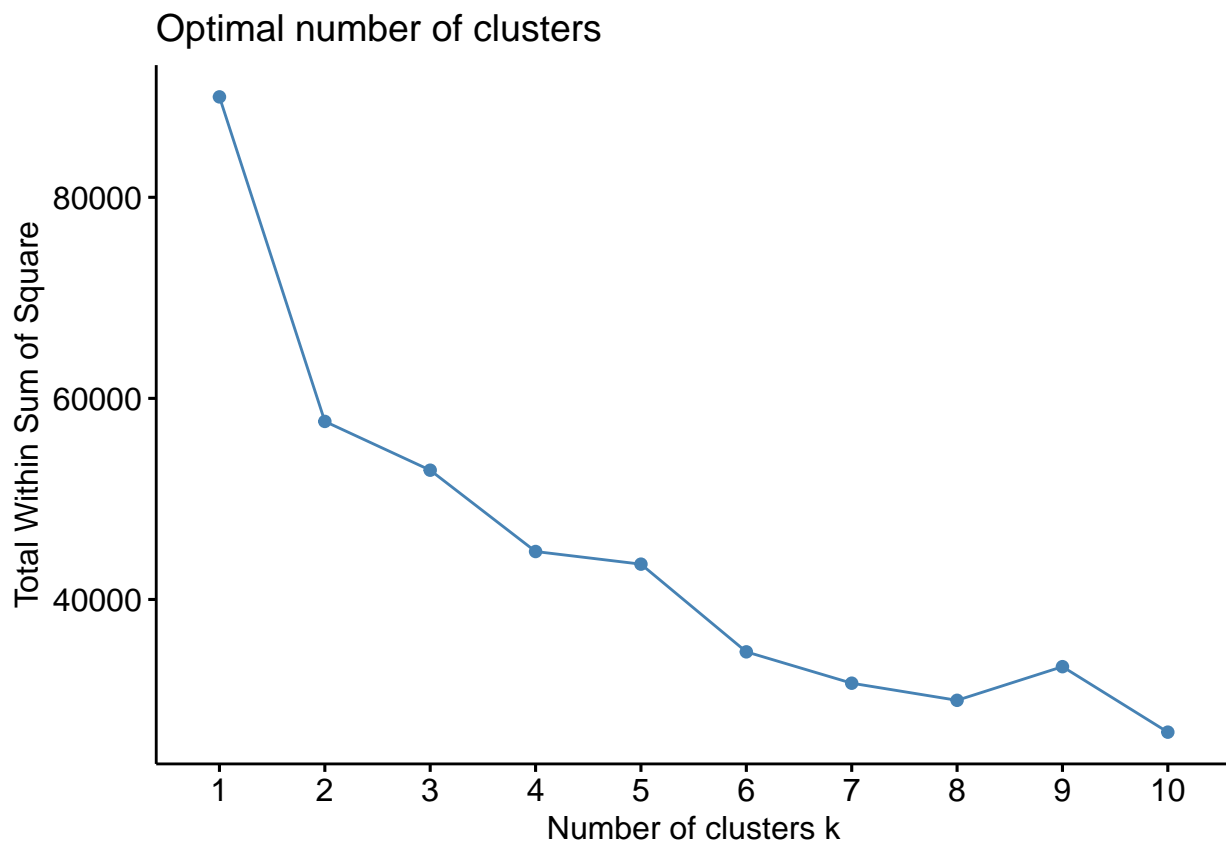
```
##      mine_id_pudl mine_id_pudl_label fuel_received_units fuel_mmbtu_per_unit
## 2      -0.7950106      -0.7950106      -0.12490814      -0.8577856
## 3      -0.6688621      -0.6688621      -0.23050958       0.4666931
## 4       0.5062120       0.5062120       2.23237205       1.0616200
## 5      -0.7956414      -0.7956414      -0.68252118      -0.9855359
## 6      -0.7943799      -0.7943799      -0.51817634      -0.7689905
## 10     -0.6688621      -0.6688621       0.07892807       0.4391952
##      sulfur_content_pct ash_content_pct mercury_content_ppm fuel_cost_per_mmbtu
## 2      -0.7609267      -0.6760496      -0.4168514      -0.54895324
## 3       1.5269385       0.2009245      -0.4168514      -0.33032647
```

```
## 4      1.9481700      0.4135243      -0.4168514      0.04480362
## 5      -0.8435211     -0.8886494      1.3054379     -0.83328752
## 6      -0.8352617     -0.5963247     -0.4168514      0.10334303
## 10     1.5351980      0.1743495     -0.4168514     -0.16187633
##      moisture_content_pct chlorine_content_ppm
## 2      1.0019118      -0.1816172
## 3      -0.2794774      -0.1816172
## 4      -0.8188595      -0.1816172
## 5      1.1246283      -0.1816172
## 6      0.7992868      -0.1816172
## 10     -0.2547438      -0.1816172
```

```
View(fuel_cost_normalized)
```

*#Finding the optimal k number using both Elbow method and Silhouette*

```
fviz_nbclust(fuel_cost_normalized, kmeans, method = "wss")
```



```
#elbow method
wss<- kmeans(fuel_cost_normalized, centers= 2, nstart= 25)
View(wss)
```

```
## Error in as.data.frame.default(x): cannot coerce class '"kmeans"' to a data.frame
```

```
wss$size # cluster 1 is large size.
```

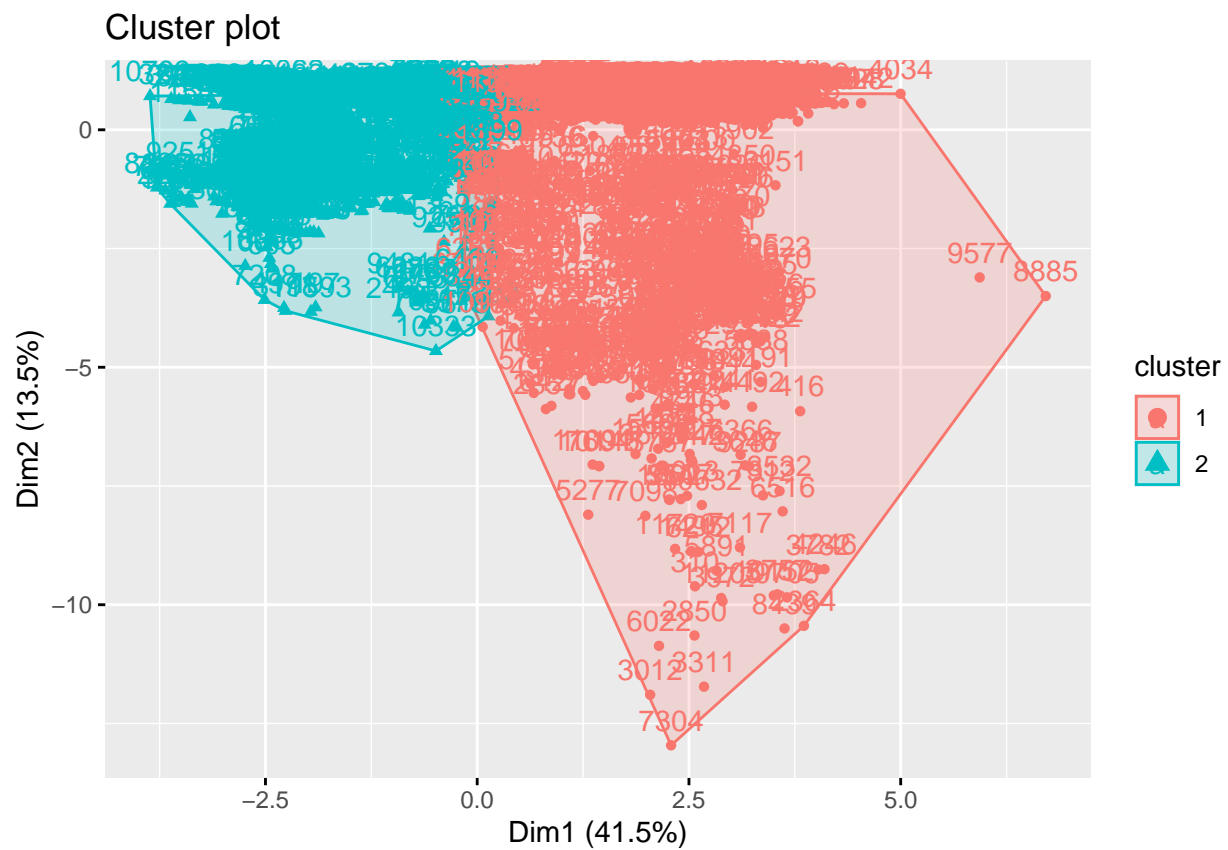
```
## [1] 4614 4386
```

```
wss$withinss#cluster 2 has least within cluster sum of squares
```

```
## [1] 39003.89 18704.74
```

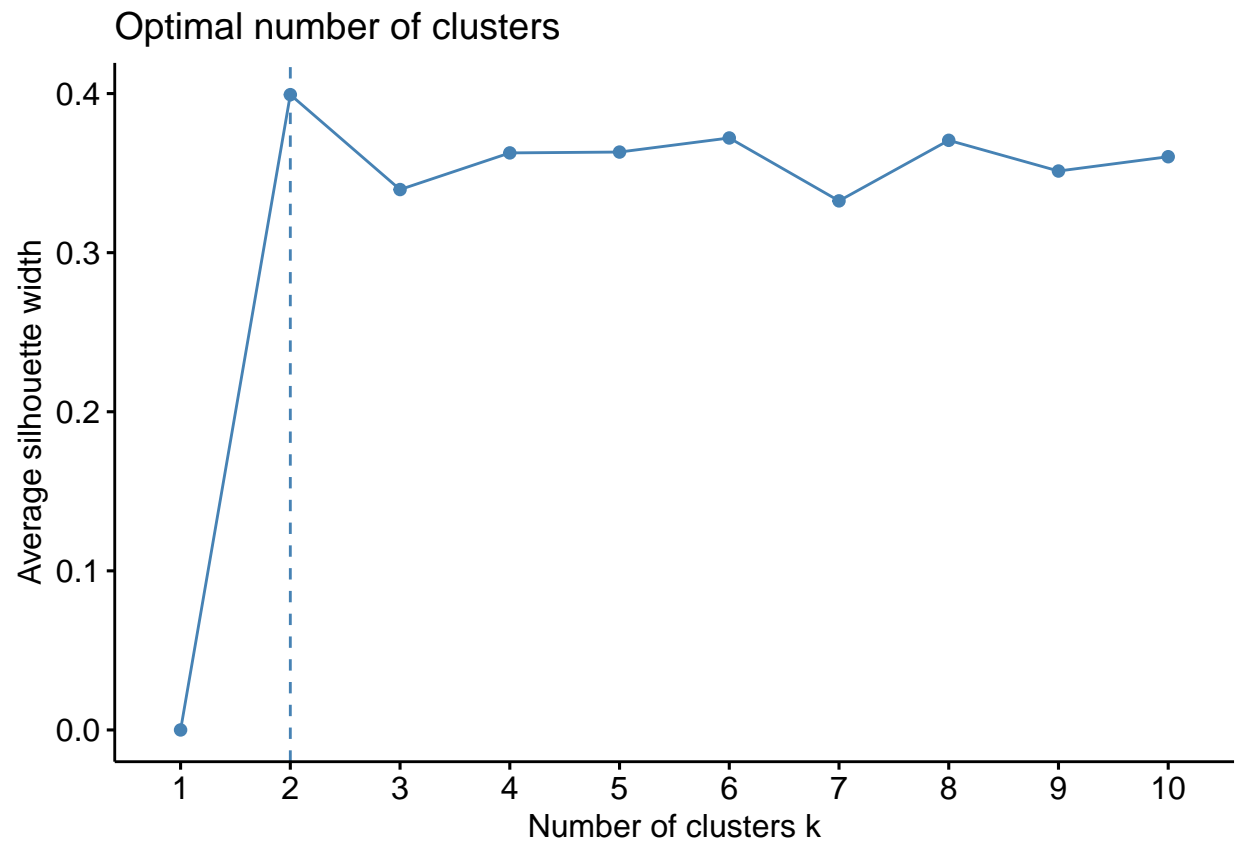
```
#plotting clusters
```

```
fviz_cluster(wss, data = fuel_cost_normalized )
```

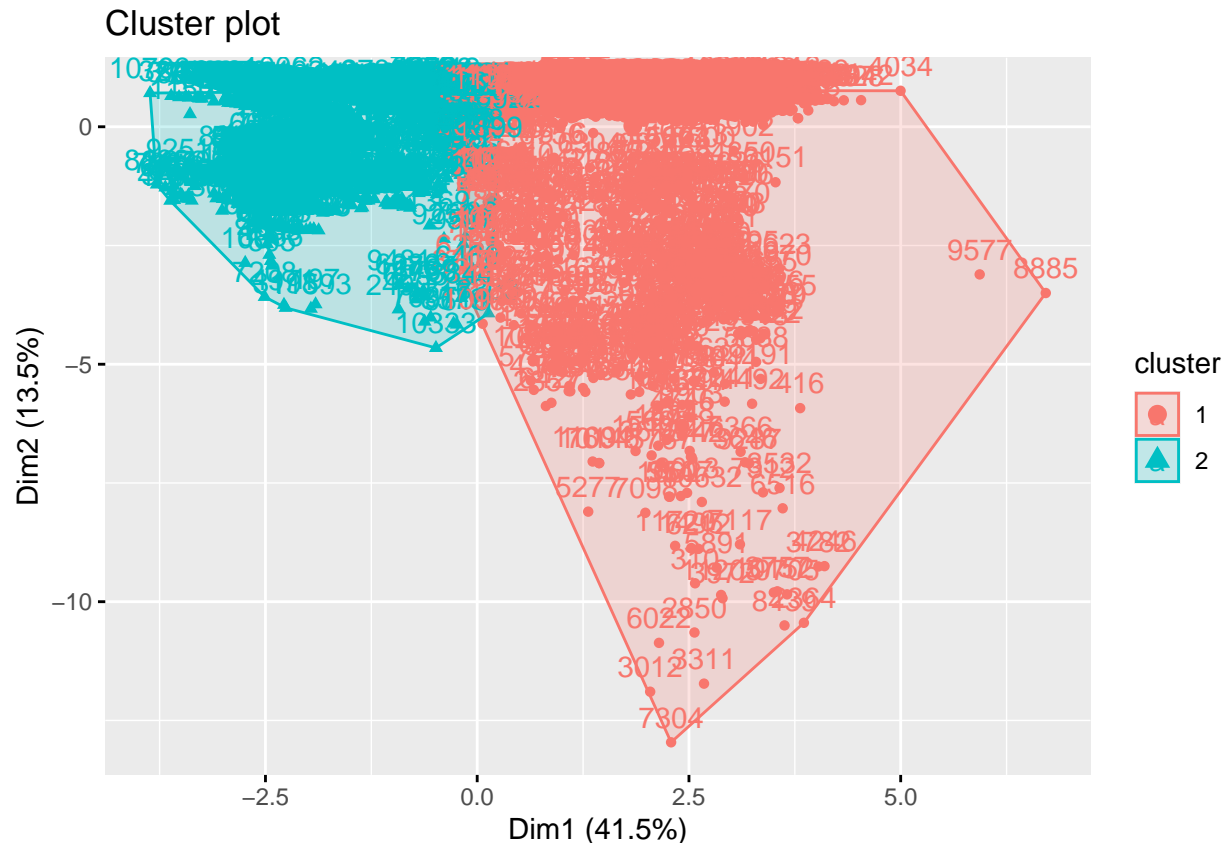


```
#silhouette method
```

```
fviz_nbclust(fuel_cost_normalized, kmeans, method = "silhouette")
```



```
silhouette=kmeans(fuel_cost_normalized,centers=2,nstart=25)  
fviz_cluster( silhouette, data = fuel_cost_normalized)
```



```
#Running cluster centroids to better understand the characteristics of each cluster
df = as.data.frame(t(wss$centers)) %>% rename(Cluster1 = 1, Cluster2 = 2)

df1 = as.data.frame(t(silhouette$centers)) %>% rename(Cluster1 = 1, Cluster2 = 2)
```

#Summary: Cluster 1 is the largest cluster with size of 4357 , has the highest amount of fuel received units and moisture content. Cluster 2 has the highest amount of heat produced with less fuel received units, and has 2 nd highest amount of ash and 1 st highest sulfur content To summarize, Cluster 1 is better in terms of ecologically and economically as it uses less ash and sulfur content with least fuel cost per heat produced and also cluster 2 is better in terms of heat produced.

```
#library(cluster) #clusplot(fuel_cost_normalized, wss_kmeans$cluster, main='2D representation of the
Cluster solution',color=TRUE,shade=TRUE,labels=2,lines=0)
```

**\*\*Binding the cluster assignment to the original data frame for analysis,creating dataframe to combine**

```
```r
clusters_wss <- wss$cluster
clusters_silhouette <- silhouette$cluster
fuel_model1 <- cbind(train_data,clusters_wss)
fuel_model2 <- cbind(train_data,clusters_silhouette)

fuel_model2=fuel_model2[,c(12,13,15,16,17,18,19,20,27,28,31)]
View(fuel_model2)
```



```
library(dplyr)
```

```
#mean value of the clusters to know the distribution  
mean_data=fuel_model2 %>% group_by(clusters_silhouette)%>% summarize(mean)
```

```
## Error in 'summarize()':  
## ! Problem while computing '..1 = mean'.  
## x '..1' must be a vector, not a function.  
## i The error occurred in group 1: clusters_silhouette = 1.
```

```
View(mean_data)
```

```
## Error in as.data.frame(x): object 'mean_data' not found
```

*plotting the clusters for different variables*

*tells that as fuel cost is not much affected by sulfur content*

```
library(ggplot2)
```

```
ggplot(fuel_model1) + aes(x = sulfur_content_pct, y = fuel_cost_per_mmbtu) + geom_point(shape =  
"circle", size = 1.5, colour = "#112446") + theme_minimal()
```

*similarly ash content has least effect on fuel price,as ash content increases fuel has less variance.*

```
library(ggplot2)
```

```
ggplot(fuel_model1) + aes(x = fuel_cost_per_mmbtu, y = ash_content_pct) + geom_point(shape =  
"circle", size = 1.5, colour = "#112446") + theme_minimal()
```

*#here we can observe that most of fuel type used from clusters is coal*

```
library(ggplot2)
```

```
ggplot(fuel_model1) + aes(x = clusters_wss, fill = fuel_group_code) + geom_histogram(bins = 16L) +  
scale_fill_hue(direction = 1) + theme_minimal()
```

*#from this we can conclude that fuel cost is most affected in cluster 3 and cluster 1 where the fuel cost is least affected in cluster 2 it uses chlorine content*

```
library(ggplot2)
```

```
ggplot(fuel_model1) + aes(x = fuel_cost_per_mmbtu, y = clusters_wss) + geom_point(shape = "circle",  
size = 1.5, colour = "#112446") + theme_minimal()
```

*#using multiple linear regression for predidcting data*

```
library(dplyr)  
library(caret)  
fuel_cost_normalized_testdata =scale(test_data[, c(12,13,15,16,17,18,19,20,27,28)])  
head(fuel_cost_normalized_testdata)
```

```
##      mine_id_pudl mine_id_pudl_label fuel_received_units fuel_mmbtu_per_unit  
## 1      -0.8127306      -0.8127306          0.6146180      -0.8998426  
## 7       0.5325952       0.5325952          0.1698876       0.8677333  
## 8      -0.7452770      -0.7452770         -0.3182440      -1.0471406  
## 9      -0.7452770      -0.7452770         -0.1803898      -1.1205007  
## 19     -0.8114815     -0.8114815          0.3249425      -0.9287245  
## 22     -0.8008638     -0.8008638          2.9602995      -1.2065690
```

```
##      sulfur_content_pct ash_content_pct mercury_content_ppm fuel_cost_per_mmbtu
## 1          -0.8812028      -0.88788993      -0.4313577      -0.43811004
## 7           1.1724519      -0.05403387      -0.4313577      -1.28201472
## 8          -0.8066750      -0.69168850      -0.4313577      -0.66352698
## 9          -0.8149559      -0.61811297       2.4656045       0.24800278
## 19         -0.8315176      -0.64263815      -0.4313577       0.14938287
## 22         -0.7238664      -0.81431439      -0.4313577       0.09866406
##      moisture_content_pct chlorine_content_ppm
## 1           1.0499901      -0.1917533
## 7          -0.5648093      -0.1917533
## 8           1.2135872      -0.1917533
## 9           1.2540053      -0.1917533
## 19          0.9431709      -0.1917533
## 22          1.3252182      -0.1917533
```

```
View(fuel_cost_normalized_testdata)
```

```
#Developing linear regression model using train data
```

```
model= lm(fuel_cost_per_mmbtu~fuel_cost_normalized_testdata , data=test_data)
```

```
summary(model)
```

```
## Warning in summary.lm(model): essentially perfect fit: summary may be unreliable
```

```
##
```

```
## Call:
```

```
## lm(formula = fuel_cost_per_mmbtu ~ fuel_cost_normalized_testdata,
```

```
##      data = test_data)
```

```
##
```

```
## Residuals:
```

```
##      Min      1Q      Median      3Q      Max
```

```
## -4.477e-14 -7.700e-17  2.000e-18  5.800e-17  8.205e-14
```

```
##
```

```
## Coefficients: (1 not defined because of singularities)
```

```
##              Estimate Std. Error
```

```
## (Intercept)      2.261e+00  3.302e-17
```

```
## fuel_cost_normalized_testdatamine_id_pudl -9.210e-17  4.459e-17
```

```
## fuel_cost_normalized_testdatamine_id_pudl_label      NA      NA
```

```
## fuel_cost_normalized_testdatafuel_received_units  1.729e-18  3.455e-17
```

```
## fuel_cost_normalized_testdatafuel_mmbtu_per_unit  1.003e-15  7.642e-17
```

```
## fuel_cost_normalized_testdatasulfur_content_pct -4.132e-16  4.642e-17
```

```
## fuel_cost_normalized_testdataash_content_pct -8.053e-17  4.371e-17
```

```
## fuel_cost_normalized_testdatamercury_content_ppm  2.217e-16  3.700e-17
```

```
## fuel_cost_normalized_testdatafuel_cost_per_mmbtu  7.098e-01  4.048e-17
```

```
## fuel_cost_normalized_testdatamoisture_content_pct  4.323e-18  6.982e-17
```

```
## fuel_cost_normalized_testdatachlorine_content_ppm -1.798e-17  3.719e-17
```

```
##              t value Pr(>|t|)
```

```
## (Intercept)      6.848e+16 < 2e-16 ***
```

```
## fuel_cost_normalized_testdatamine_id_pudl -2.066e+00  0.0389 *
```

```
## fuel_cost_normalized_testdatamine_id_pudl_label      NA      NA
```

```
## fuel_cost_normalized_testdatafuel_received_units  5.000e-02  0.9601
```

```
## fuel_cost_normalized_testdatafuel_mmbtu_per_unit  1.312e+01 < 2e-16 ***
```

```
## fuel_cost_normalized_testdatasulfur_content_pct -8.901e+00 < 2e-16 ***
```

```
## fuel_cost_normalized_testdataash_content_pct -1.842e+00  0.0655 .
```

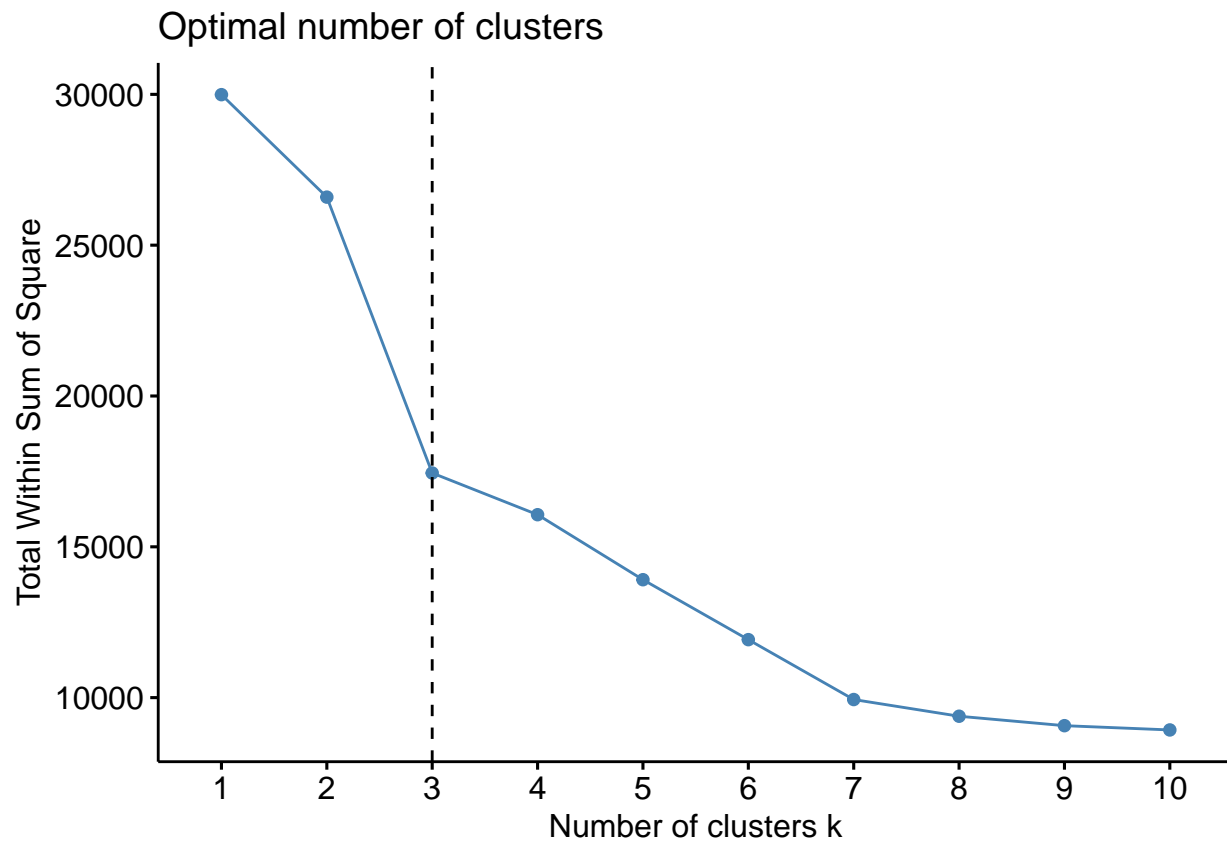
```
## fuel_cost_normalized_testdatamercury_content_ppm 5.991e+00 2.33e-09 ***
## fuel_cost_normalized_testdatafuel_cost_per_mmbtu 1.753e+16 < 2e-16 ***
## fuel_cost_normalized_testdatamoisture_content_pct 6.200e-02 0.9506
## fuel_cost_normalized_testdatachlorine_content_ppm -4.840e-01 0.6288
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.808e-15 on 2990 degrees of freedom
## Multiple R-squared: 1, Adjusted R-squared: 1
## F-statistic: 5.133e+31 on 9 and 2990 DF, p-value: < 2.2e-16
```

```
#Eliminating all the columns with p value greater than 5%( NULL hypothesis).Dependent variables with p
new_data=fuel_cost_normalized_testdata[,c(1,4,5,7,8)]
model1= lm(fuel_cost_per_mmbtu~new_data , data=test_data)
summary(model1)
```

```
## Warning in summary.lm(model1): essentially perfect fit: summary may be
## unreliable
```

```
##
## Call:
## lm(formula = fuel_cost_per_mmbtu ~ new_data, data = test_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.497e-14 -6.700e-17 -1.500e-17  4.100e-17  1.006e-13
##
## Coefficients:
##              Estimate Std. Error    t value Pr(>|t|)
## (Intercept)      2.261e+00  3.723e-17  6.073e+16 < 2e-16 ***
## new_datamine_id_pudl -2.882e-16  4.672e-17 -6.170e+00 7.75e-10 ***
## new_datafuel_mmbtu_per_unit -1.428e-15  6.092e-17 -2.345e+01 < 2e-16 ***
## new_data sulfur_content_pct  4.691e-16  5.128e-17  9.147e+00 < 2e-16 ***
## new_datamercury_content_ppm -1.395e-16  3.778e-17 -3.693e+00 0.000226 ***
## new_datafuel_cost_per_mmbtu  7.098e-01  4.448e-17  1.596e+16 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.039e-15 on 2994 degrees of freedom
## Multiple R-squared: 1, Adjusted R-squared: 1
## F-statistic: 7.267e+31 on 5 and 2994 DF, p-value: < 2.2e-16
```

```
#clusters for test data
fviz_nbclust(fuel_cost_normalized_testdata, kmeans, method = "wss") +
geom_vline(xintercept = 3, linetype = 2)
```



```
wss_kmeans_testdata= kmeans(fuel_cost_normalized_testdata, centers= 2, nstart= 25)
View(wss_kmeans_testdata)
```

```
## Error in as.data.frame.default(x): cannot coerce class '"kmeans"' to a data.frame
```

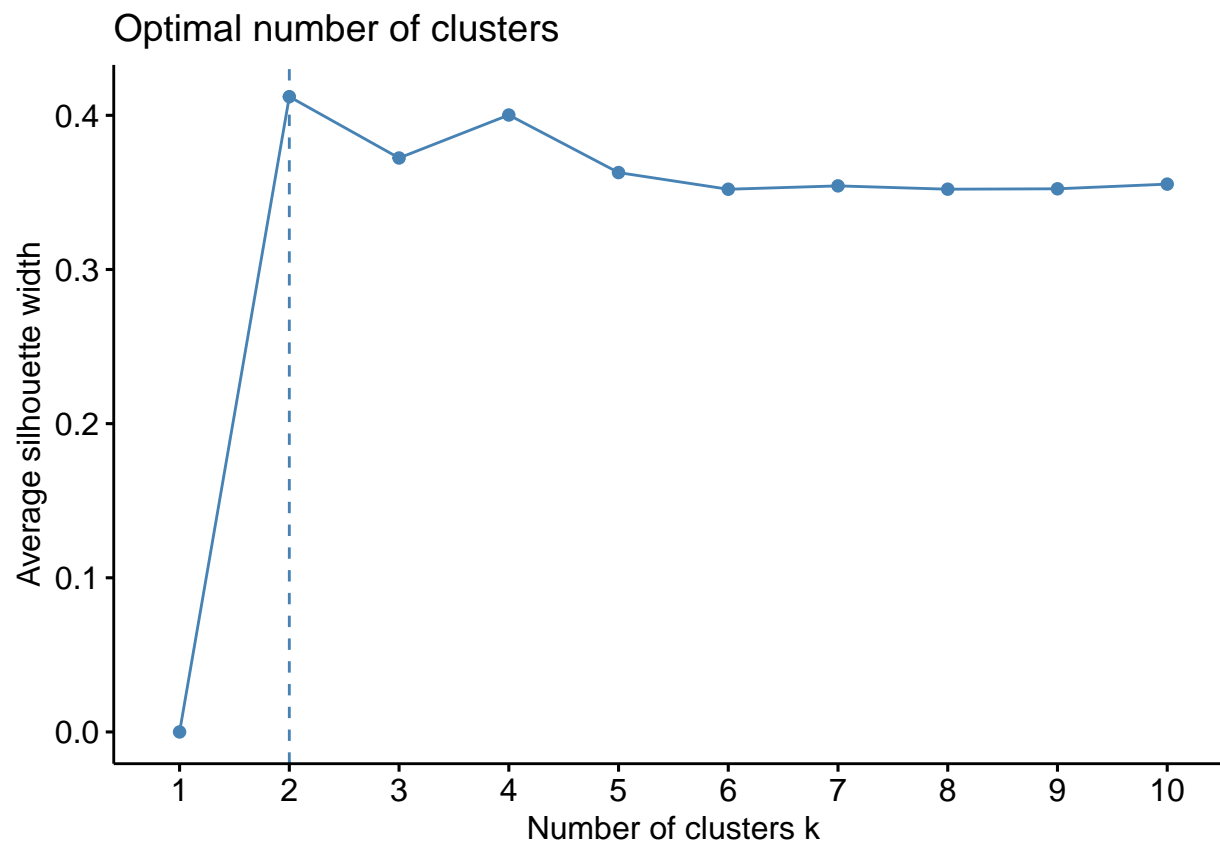
```
wss_kmeans_testdata$size # cluster 1 has high
```

```
## [1] 1426 1574
```

```
wss_kmeans_testdata$withinss#cluster 2 has least within cluster sum of squares
```

```
## [1] 6019.101 12893.421
```

```
fviz_nbclust(fuel_cost_normalized_testdata, kmeans, method = "silhouette")
```



```
silhouette_kmeans=kmeans(fuel_cost_normalized_testdata,centers=2,nstart=25)
silhouette_kmeans
```

```
## K-means clustering with 2 clusters of sizes 1426, 1574
##
## Cluster means:
##   mine_id_pudl mine_id_pudl_label fuel_received_units fuel_mmbtu_per_unit
## 1   -0.7429850      -0.7429850         0.2884592      -0.9252107
## 2    0.6731236       0.6731236        -0.2613360       0.8382150
##   sulfur_content_pct ash_content_pct mercury_content_ppm fuel_cost_per_mmbtu
## 1    -0.7819428     -0.6222200         0.1468565      -0.4921554
## 2     0.7084183      0.5637139        -0.1330479       0.4458790
##   moisture_content_pct chlorine_content_ppm
## 1      0.8574555      -0.1866602
## 2     -0.7768307       0.1691090
##
## Clustering vector:
##    1    7    8    9   19   22   25   27   31   35   37   42   46
##    1    2    1    1    1    1    1    2    1    1    1    2    1
##   50   52   56   58   61   62   63   65   68   71   75   76   77
##    1    2    2    1    1    2    1    2    1    1    1    1    2
##   82   88   90   92   93   97  100  103  109  111  114  116  127
##    1    1    2    2    2    1    1    1    2    1    1    1    2
##  128  131  134  136  138  141  147  152  153  157  160  164  166
##    2    2    2    1    1    1    2    2    2    1    2    2    1
```

##	168	170	173	175	179	184	189	190	192	198	205	206	207
##	1	2	1	2	1	1	1	2	1	1	1	1	1
##	213	215	216	223	229	231	232	234	235	243	248	249	254
##	1	1	2	2	2	1	2	2	2	1	2	1	1
##	255	258	260	261	265	266	267	270	271	273	274	277	278
##	1	2	1	2	2	1	1	2	1	2	2	2	2
##	284	292	293	294	298	299	302	304	309	311	316	317	319
##	2	1	1	2	2	2	2	1	1	1	2	1	2
##	326	331	334	337	339	344	347	349	350	353	359	363	364
##	2	1	2	2	1	1	1	1	1	2	2	2	2
##	365	368	371	372	374	377	381	384	386	387	388	391	392
##	1	1	2	2	1	1	2	1	1	1	2	2	2
##	399	412	414	422	423	425	429	439	440	441	452	456	460
##	2	1	1	1	1	1	1	2	2	2	1	1	1
##	461	463	464	468	469	470	471	475	485	490	492	511	514
##	1	2	2	2	2	2	1	1	2	1	2	2	1
##	515	521	523	533	534	538	548	559	560	561	562	567	571
##	1	2	2	1	2	2	2	2	2	2	2	1	1
##	574	575	579	583	589	590	595	598	603	606	609	616	625
##	2	2	2	2	1	1	1	2	1	2	1	1	1
##	626	629	631	641	644	650	653	656	664	666	668	679	682
##	1	2	1	1	2	1	1	2	1	1	1	1	2
##	683	684	689	690	691	692	693	694	696	700	709	713	726
##	2	2	2	1	2	1	2	1	2	1	2	2	2
##	728	734	740	756	764	767	768	772	783	787	788	792	793
##	2	2	2	1	1	2	1	2	2	1	2	2	2
##	797	800	801	805	813	814	817	822	823	829	833	835	837
##	2	1	2	2	2	2	2	1	1	1	1	1	2
##	838	843	849	851	853	855	861	867	876	881	884	885	887
##	2	2	1	2	2	1	2	1	2	2	2	2	2
##	888	898	903	914	915	918	919	920	921	927	929	930	940
##	2	1	2	2	1	2	2	2	1	2	2	1	1
##	941	942	945	961	962	978	982	989	990	991	995	996	1006
##	2	2	2	2	1	2	2	2	2	1	2	2	1
##	1010	1014	1025	1031	1032	1033	1036	1043	1047	1049	1050	1059	1069
##	1	2	2	2	2	2	1	2	2	1	1	1	1
##	1074	1081	1085	1088	1093	1096	1098	1099	1103	1108	1116	1117	1122
##	2	1	1	1	1	1	1	1	2	2	1	1	2
##	1124	1132	1134	1146	1149	1161	1163	1168	1171	1173	1176	1180	1181
##	2	2	1	2	2	2	2	1	2	1	1	2	1
##	1182	1192	1193	1195	1213	1214	1216	1224	1235	1240	1241	1242	1250
##	1	2	1	2	1	1	2	2	1	2	1	2	2
##	1252	1257	1258	1269	1276	1277	1281	1282	1285	1286	1287	1291	1294
##	2	2	1	1	2	2	1	2	2	1	1	1	1
##	1306	1307	1315	1316	1319	1323	1330	1331	1332	1334	1336	1341	1345
##	2	1	2	2	1	2	2	2	1	2	1	1	2
##	1348	1358	1363	1365	1368	1374	1376	1379	1384	1393	1399	1406	1409
##	2	2	2	1	1	1	1	2	2	1	1	2	1
##	1413	1415	1418	1421	1423	1425	1427	1430	1433	1434	1439	1441	1442
##	2	2	1	1	2	1	2	1	1	1	2	2	1
##	1446	1447	1448	1449	1450	1473	1475	1489	1490	1494	1496	1497	1513
##	1	1	2	2	2	2	2	1	2	1	1	1	2
##	1517	1520	1525	1528	1531	1532	1534	1536	1539	1547	1551	1557	1558
##	2	1	2	1	1	2	1	2	2	2	2	1	1

##	1561	1566	1568	1570	1571	1572	1585	1590	1593	1595	1596	1603	1608
##	1	2	2	2	2	2	1	1	1	2	2	2	2
##	1611	1619	1620	1625	1627	1628	1629	1632	1637	1639	1647	1648	1649
##	1	2	1	2	2	2	2	1	1	1	1	2	1
##	1656	1663	1664	1674	1677	1678	1681	1684	1686	1688	1690	1692	1702
##	2	1	1	1	1	2	1	1	2	1	2	2	2
##	1703	1712	1720	1725	1726	1738	1743	1745	1747	1749	1755	1764	1767
##	1	2	1	2	2	1	1	1	2	2	1	2	2
##	1770	1773	1776	1779	1782	1784	1785	1790	1795	1796	1800	1801	1805
##	2	2	1	2	2	1	1	2	1	2	2	2	2
##	1809	1811	1815	1824	1832	1835	1842	1844	1857	1859	1863	1864	1872
##	1	1	1	2	2	2	1	2	2	2	2	2	1
##	1876	1881	1883	1885	1888	1895	1910	1911	1912	1914	1915	1924	1941
##	2	2	1	2	1	1	2	1	1	2	1	2	1
##	1944	1945	1952	1955	1956	1959	1965	1979	1981	1983	1987	1990	1996
##	1	2	1	2	2	1	2	2	1	2	1	2	1
##	1997	1999	2000	2001	2003	2008	2012	2017	2018	2020	2021	2025	2026
##	2	2	1	2	1	1	2	2	2	2	2	1	2
##	2027	2033	2036	2039	2041	2048	2051	2068	2071	2075	2076	2079	2105
##	2	1	1	2	2	1	2	2	2	2	1	2	2
##	2109	2113	2115	2119	2122	2128	2129	2132	2135	2136	2137	2139	2144
##	1	2	1	2	2	1	2	2	1	1	1	1	1
##	2146	2148	2150	2154	2155	2158	2160	2162	2175	2178	2181	2182	2185
##	2	2	1	1	2	1	1	1	1	2	2	1	2
##	2191	2197	2201	2203	2206	2212	2213	2215	2217	2224	2227	2229	2238
##	2	2	1	1	2	2	1	1	1	2	2	2	1
##	2239	2245	2247	2249	2255	2256	2267	2272	2275	2278	2280	2281	2283
##	2	1	2	1	2	2	2	1	2	2	2	1	1
##	2285	2286	2288	2291	2294	2302	2308	2310	2313	2314	2322	2336	2337
##	1	1	2	1	1	1	1	1	1	2	1	2	1
##	2341	2346	2347	2349	2350	2351	2353	2359	2362	2365	2374	2376	2380
##	1	2	2	1	1	1	1	2	2	1	2	1	2
##	2383	2384	2388	2396	2398	2399	2402	2404	2405	2412	2415	2416	2423
##	1	2	2	2	2	2	1	2	1	1	1	1	2
##	2438	2441	2443	2445	2452	2454	2456	2457	2459	2461	2463	2489	2491
##	1	1	1	1	2	2	1	2	2	1	2	1	1
##	2501	2504	2505	2509	2511	2518	2519	2521	2526	2528	2529	2530	2544
##	1	2	2	2	1	1	1	2	1	1	2	1	2
##	2548	2555	2560	2562	2563	2566	2567	2572	2573	2584	2586	2589	2594
##	1	2	1	2	2	2	1	2	1	2	2	2	1
##	2601	2602	2604	2611	2614	2627	2629	2639	2641	2642	2644	2650	2663
##	1	2	2	1	2	2	1	2	2	1	1	1	1
##	2665	2668	2673	2674	2678	2679	2680	2681	2682	2685	2691	2695	2696
##	1	2	2	1	2	2	2	1	1	2	1	2	2
##	2697	2705	2706	2709	2717	2720	2721	2723	2724	2725	2729	2731	2737
##	1	1	2	2	1	2	1	1	2	2	2	2	2
##	2740	2743	2753	2757	2760	2765	2769	2774	2775	2776	2778	2781	2794
##	2	2	2	2	2	2	2	1	2	1	1	1	2
##	2797	2799	2802	2803	2807	2824	2827	2833	2835	2844	2845	2851	2855
##	2	1	2	1	1	2	1	2	1	2	1	1	2
##	2856	2860	2862	2870	2875	2880	2881	2884	2886	2888	2892	2893	2897
##	1	1	2	1	1	1	1	2	1	1	2	1	1
##	2900	2908	2915	2916	2919	2929	2933	2934	2939	2943	2954	2956	2957
##	2	2	1	2	2	2	2	1	1	2	1	1	2

##	2961	2962	2963	2964	2970	2971	2972	2973	2977	2988	2999	3000	3002
##	1	1	1	2	2	1	2	2	1	1	2	2	1
##	3009	3011	3013	3020	3024	3029	3031	3034	3036	3037	3047	3048	3051
##	1	1	1	1	2	1	1	1	2	2	1	2	2
##	3058	3064	3075	3076	3088	3090	3091	3097	3104	3108	3112	3119	3134
##	2	2	2	1	1	1	2	1	2	2	1	2	2
##	3136	3138	3143	3149	3153	3154	3166	3169	3171	3175	3190	3200	3206
##	2	2	2	1	2	2	1	1	1	2	2	2	2
##	3207	3211	3214	3218	3223	3228	3230	3231	3240	3243	3245	3262	3268
##	1	1	2	1	2	2	1	2	2	1	1	1	1
##	3270	3272	3275	3278	3282	3285	3290	3291	3299	3300	3309	3316	3317
##	2	2	1	2	2	1	2	1	1	2	1	2	1
##	3318	3319	3321	3323	3324	3325	3326	3331	3334	3338	3340	3341	3344
##	2	1	1	1	1	2	1	1	2	2	1	2	1
##	3347	3350	3355	3356	3362	3363	3371	3382	3384	3385	3390	3391	3398
##	1	1	2	2	1	1	1	1	2	1	2	1	1
##	3399	3412	3413	3427	3432	3434	3439	3441	3446	3448	3450	3451	3457
##	2	2	1	2	2	1	1	1	1	1	1	2	2
##	3466	3471	3473	3474	3475	3477	3488	3492	3493	3496	3501	3505	3507
##	2	1	2	1	1	1	1	1	2	2	2	1	1
##	3508	3509	3515	3517	3519	3521	3523	3534	3535	3545	3546	3552	3555
##	2	1	1	2	2	1	2	1	2	2	1	2	1
##	3558	3565	3572	3576	3577	3586	3589	3591	3592	3594	3596	3604	3614
##	1	1	1	1	2	1	2	1	1	2	1	1	1
##	3616	3628	3632	3636	3642	3649	3652	3654	3655	3656	3666	3669	3673
##	2	2	1	2	2	2	1	1	1	2	2	2	1
##	3679	3681	3684	3686	3687	3692	3693	3694	3695	3703	3710	3712	3713
##	2	2	2	1	1	1	2	2	2	2	1	2	1
##	3718	3720	3726	3728	3735	3742	3747	3752	3758	3768	3770	3771	3772
##	1	2	2	2	1	2	2	1	2	1	2	1	1
##	3773	3775	3776	3777	3781	3783	3784	3787	3790	3791	3796	3803	3805
##	2	1	1	2	2	2	2	1	1	2	2	1	2
##	3811	3814	3816	3829	3834	3835	3839	3845	3854	3857	3860	3863	3869
##	2	2	1	1	2	1	2	2	1	1	2	1	1
##	3870	3874	3877	3878	3885	3886	3888	3890	3897	3905	3907	3914	3919
##	1	2	1	2	2	1	1	1	1	1	1	2	2
##	3924	3926	3932	3933	3938	3941	3944	3951	3953	3954	3956	3958	3975
##	2	2	2	2	2	1	1	2	1	1	2	2	1
##	3980	3987	3988	3994	3997	4005	4008	4010	4013	4014	4017	4019	4022
##	1	2	1	1	2	2	1	2	2	1	2	2	1
##	4023	4027	4037	4038	4042	4044	4055	4056	4057	4059	4063	4068	4069
##	1	2	2	1	1	1	2	1	1	1	1	2	1
##	4072	4074	4079	4084	4085	4087	4088	4089	4091	4092	4093	4099	4109
##	2	1	1	1	2	2	2	2	1	2	1	1	2
##	4111	4128	4130	4134	4140	4141	4149	4152	4154	4156	4160	4161	4165
##	1	1	2	2	2	2	2	2	2	1	2	1	2
##	4166	4174	4175	4176	4177	4180	4189	4195	4201	4202	4205	4215	4222
##	2	1	1	2	1	1	2	2	1	2	2	2	2
##	4225	4229	4231	4237	4247	4248	4259	4263	4269	4271	4273	4276	4280
##	2	1	2	2	1	2	2	2	2	2	2	2	1
##	4284	4303	4308	4309	4320	4328	4334	4337	4340	4343	4346	4351	4352
##	1	1	2	2	2	2	2	2	2	2	2	1	2
##	4353	4354	4356	4357	4358	4362	4367	4368	4376	4381	4384	4386	4387
##	1	2	1	1	2	2	1	1	1	2	1	2	1



##	4392	4399	4405	4425	4426	4427	4431	4432	4434	4438	4457	4462	4466
##	1	2	1	1	1	1	2	2	2	1	2	1	1
##	4468	4469	4475	4480	4483	4488	4491	4499	4501	4504	4512	4514	4519
##	1	1	1	2	2	1	2	1	2	1	1	1	1
##	4526	4530	4535	4538	4543	4544	4547	4548	4550	4552	4553	4559	4561
##	2	2	2	2	1	1	1	2	1	2	1	1	2
##	4562	4573	4576	4580	4589	4590	4592	4596	4613	4615	4616	4619	4625
##	2	1	1	2	1	2	2	2	1	1	2	2	1
##	4630	4632	4633	4652	4654	4655	4656	4660	4661	4669	4670	4674	4679
##	2	1	1	1	2	2	2	2	1	1	2	2	1
##	4681	4687	4688	4697	4699	4700	4703	4707	4708	4713	4714	4718	4719
##	1	1	2	2	2	1	2	2	2	1	2	1	1
##	4720	4724	4725	4735	4748	4752	4755	4759	4764	4767	4771	4779	4781
##	2	1	1	2	1	2	2	2	2	1	2	1	1
##	4782	4787	4790	4794	4796	4810	4817	4820	4821	4825	4827	4829	4842
##	1	2	2	2	2	2	1	2	1	1	1	1	1
##	4843	4851	4858	4862	4864	4865	4866	4869	4875	4877	4890	4892	4903
##	2	2	2	1	1	1	2	2	2	1	1	2	1
##	4912	4936	4939	4940	4944	4947	4959	4966	4969	4981	4987	4988	4992
##	2	1	2	1	2	1	1	2	1	1	2	1	2
##	4995	4996	5000	5007	5011	5014	5015	5021	5023	5024	5025	5029	5030
##	2	2	1	2	1	1	1	2	1	1	2	1	1
##	5032	5046	5049	5054	5055	5059	5060	5065	5066	5068	5069	5074	5075
##	1	2	1	1	1	2	2	1	1	1	2	1	2
##	5077	5080	5084	5091	5092	5097	5099	5107	5109	5111	5115	5117	5121
##	2	1	1	2	1	1	2	1	1	2	1	2	1
##	5123	5125	5135	5139	5140	5141	5142	5143	5145	5151	5160	5161	5168
##	1	1	2	1	2	1	2	1	1	1	2	1	1
##	5171	5172	5188	5198	5201	5215	5216	5228	5230	5232	5236	5241	5265
##	2	2	2	1	2	1	2	1	1	1	1	1	1
##	5269	5278	5282	5288	5299	5302	5305	5309	5315	5320	5325	5326	5332
##	2	1	1	1	1	2	2	2	1	2	2	2	1
##	5333	5337	5338	5339	5344	5346	5350	5351	5356	5367	5371	5378	5383
##	1	1	1	1	2	2	1	2	1	1	2	1	2
##	5389	5394	5399	5402	5404	5406	5416	5423	5427	5429	5446	5449	5452
##	1	1	1	1	1	2	1	1	1	1	2	1	2
##	5467	5471	5479	5481	5500	5502	5505	5507	5509	5513	5517	5523	5526
##	1	2	1	1	2	1	2	2	1	1	2	1	2
##	5531	5536	5540	5543	5547	5552	5558	5561	5562	5565	5566	5567	5570
##	1	1	1	1	2	1	1	2	1	2	1	1	2
##	5572	5573	5575	5580	5583	5584	5586	5589	5590	5592	5596	5597	5602
##	2	2	1	1	1	1	2	1	2	2	2	2	1
##	5606	5607	5610	5611	5612	5614	5616	5617	5619	5623	5626	5640	5644
##	1	1	2	1	2	2	2	2	1	2	2	1	2
##	5645	5646	5649	5651	5657	5660	5662	5670	5672	5674	5675	5676	5678
##	2	2	2	2	1	1	2	1	1	2	2	2	1
##	5680	5682	5683	5684	5685	5690	5703	5707	5716	5719	5720	5721	5722
##	1	2	1	2	2	2	1	1	2	2	2	1	2
##	5728	5729	5730	5733	5735	5736	5737	5739	5741	5742	5754	5756	5757
##	2	2	1	2	2	2	1	1	1	1	1	2	2
##	5759	5763	5774	5778	5780	5782	5783	5784	5788	5789	5796	5804	5807
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##	5808	5810	5811	5813	5817	5820	5828	5830	5832	5835	5847	5850	5853
##	1	1	2	2	2	1	1	1	1	2	1	2	2

##	5855	5857	5862	5864	5865	5867	5868	5876	5877	5882	5885	5890	5895
##	2	1	1	2	1	1	1	1	2	2	2	2	1
##	5896	5903	5906	5909	5913	5919	5923	5931	5935	5936	5941	5949	5954
##	2	1	2	2	1	2	1	2	2	2	2	2	2
##	5967	5970	5972	5974	5975	5980	5988	5990	5991	5992	5998	5999	6003
##	2	1	1	2	1	1	2	1	1	1	2	2	1
##	6012	6013	6014	6015	6019	6020	6025	6027	6039	6042	6045	6047	6050
##	2	2	1	2	1	2	1	1	1	2	1	1	1
##	6051	6057	6063	6066	6067	6076	6078	6087	6093	6097	6100	6102	6104
##	2	2	1	1	1	2	2	2	1	1	1	1	2
##	6106	6110	6117	6121	6127	6141	6142	6144	6153	6161	6162	6163	6173
##	2	1	1	1	1	2	1	1	2	2	2	1	2
##	6179	6182	6184	6187	6188	6190	6201	6202	6203	6209	6213	6220	6233
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##	6236	6238	6242	6244	6246	6252	6258	6263	6271	6277	6280	6281	6286
##	1	1	2	2	2	2	1	2	2	1	2	2	2
##	6301	6309	6314	6316	6326	6334	6337	6338	6342	6347	6350	6352	6355
##	1	1	1	1	1	2	1	1	2	2	1	1	1
##	6357	6359	6361	6362	6377	6383	6390	6391	6392	6401	6405	6406	6407
##	1	1	2	2	2	1	1	1	2	2	2	1	2
##	6409	6421	6425	6426	6429	6434	6437	6442	6445	6448	6451	6455	6457
##	1	2	1	2	2	2	2	1	2	2	2	1	1
##	6462	6464	6467	6480	6488	6491	6492	6493	6495	6496	6498	6507	6508
##	1	1	1	2	1	2	2	1	2	1	2	1	1
##	6510	6526	6532	6533	6538	6539	6542	6544	6546	6557	6559	6560	6567
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##	6568	6569	6571	6579	6588	6593	6598	6599	6608	6609	6610	6613	6614
##	1	2	1	1	1	1	1	2	2	2	2	1	1
##	6616	6617	6618	6624	6627	6629	6631	6645	6648	6661	6674	6677	6679
##	2	2	1	2	1	2	1	2	2	1	1	2	2
##	6680	6683	6685	6687	6690	6691	6694	6695	6698	6702	6703	6704	6712
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##	6721	6723	6732	6748	6754	6759	6760	6763	6767	6772	6774	6775	6778
##	1	2	2	2	2	2	1	2	1	1	1	1	1
##	6783	6785	6786	6787	6790	6795	6796	6803	6811	6816	6820	6821	6822
##	2	2	2	1	2	1	1	2	2	2	2	2	1
##	6827	6829	6830	6842	6844	6852	6867	6876	6878	6880	6886	6889	6896
##	1	1	2	2	2	2	1	2	2	2	2	2	1
##	6899	6901	6906	6910	6916	6927	6928	6936	6937	6940	6942	6945	6952
##	2	1	1	1	2	1	1	2	2	2	2	1	2
##	6956	6959	6961	6962	6970	6979	6985	6989	6993	6994	6996	6999	7002
##	2	1	2	1	1	1	1	2	2	2	1	2	2
##	7003	7008	7009	7016	7017	7018	7020	7027	7034	7038	7043	7047	7064
##	1	2	2	2	2	1	2	1	1	1	2	1	1
##	7066	7069	7078	7080	7082	7086	7093	7105	7110	7115	7126	7131	7134
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##	7140	7143	7151	7153	7160	7165	7168	7170	7171	7172	7173	7177	7178
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##	7182	7186	7195	7196	7202	7204	7210	7213	7218	7220	7222	7229	7233
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##	7236	7239	7241	7242	7244	7245	7247	7248	7253	7255	7256	7265	7269
##	2	2	2	2	2	1	1	1	2	1	2	2	1
##	7275	7281	7285	7289	7293	7303	7314	7317	7323	7327	7330	7331	7333
##	2	2	1	1	2	1	2	1	2	2	2	1	1

##	7335	7340	7342	7344	7345	7348	7350	7356	7357	7359	7369	7375	7387
##	2	1	2	1	1	2	1	2	1	2	2	2	2
##	7392	7402	7412	7418	7422	7424	7428	7429	7433	7434	7436	7447	7450
##	2	2	1	2	1	1	2	2	2	1	2	2	2
##	7451	7453	7455	7456	7465	7466	7467	7469	7473	7475	7480	7483	7484
##	1	2	1	1	2	2	1	1	1	1	1	1	2
##	7485	7488	7489	7500	7508	7510	7511	7515	7522	7525	7530	7531	7533
##	2	1	1	1	2	1	2	1	1	1	1	2	1
##	7534	7535	7536	7538	7539	7554	7555	7559	7560	7564	7570	7575	7583
##	2	1	2	1	2	2	1	2	2	2	2	2	2
##	7584	7585	7586	7616	7618	7622	7625	7627	7631	7634	7644	7646	7648
##	2	2	1	2	1	2	1	2	1	1	2	2	1
##	7650	7655	7663	7669	7677	7678	7679	7680	7685	7689	7691	7696	7702
##	2	2	1	1	2	2	2	1	1	1	2	2	2
##	7705	7707	7709	7710	7715	7727	7732	7734	7735	7739	7740	7742	7747
##	1	2	1	2	1	2	2	1	1	1	1	2	2
##	7753	7754	7755	7758	7763	7764	7770	7778	7782	7788	7789	7792	7793
##	2	1	2	2	1	2	2	1	1	2	1	2	2
##	7798	7800	7804	7805	7817	7818	7822	7825	7828	7829	7832	7842	7845
##	2	2	2	2	1	2	1	1	1	2	2	2	2
##	7852	7855	7858	7868	7875	7877	7894	7905	7907	7908	7910	7912	7917
##	1	2	2	2	1	1	2	2	1	2	2	2	2
##	7927	7929	7935	7936	7937	7938	7944	7947	7953	7961	7962	7970	7975
##	1	2	2	1	1	2	1	1	1	2	1	1	2
##	7982	7992	7993	7997	7999	8011	8012	8018	8020	8021	8025	8026	8027
##	2	1	1	2	1	1	1	2	2	2	2	2	1
##	8034	8045	8047	8051	8058	8060	8063	8071	8073	8078	8082	8083	8087
##	2	2	1	1	2	1	2	2	1	1	1	2	2
##	8088	8090	8092	8096	8097	8099	8100	8101	8102	8104	8105	8107	8108
##	1	2	2	2	1	2	2	1	1	2	1	2	1
##	8109	8112	8117	8119	8127	8134	8141	8142	8146	8150	8153	8158	8160
##	1	2	2	1	2	1	2	2	1	2	2	2	2
##	8178	8179	8180	8182	8185	8188	8190	8191	8192	8193	8194	8200	8203
##	1	1	1	1	2	2	2	2	1	2	2	2	2
##	8207	8209	8215	8216	8218	8229	8232	8238	8239	8250	8255	8267	8276
##	2	2	1	2	1	2	1	2	2	2	2	1	2
##	8279	8280	8282	8283	8291	8292	8295	8297	8300	8304	8307	8308	8309
##	2	1	2	2	2	1	1	2	2	1	1	2	2
##	8310	8317	8318	8325	8333	8341	8342	8343	8345	8347	8358	8359	8364
##	2	2	2	2	2	1	1	2	1	2	1	1	1
##	8365	8368	8370	8371	8378	8383	8384	8386	8387	8390	8391	8396	8398
##	1	2	2	1	1	2	2	1	1	1	1	2	1
##	8400	8403	8405	8418	8419	8420	8425	8426	8428	8429	8434	8436	8438
##	2	1	2	1	2	2	2	1	1	2	1	1	2
##	8441	8446	8451	8453	8459	8462	8469	8475	8476	8480	8488	8489	8493
##	1	1	2	2	1	1	2	1	1	1	2	1	2
##	8495	8497	8511	8517	8526	8527	8534	8535	8542	8546	8563	8569	8577
##	2	1	1	2	1	1	1	1	1	2	1	2	1
##	8579	8580	8587	8590	8595	8596	8598	8599	8601	8606	8615	8618	8621
##	1	1	1	1	1	2	1	1	1	2	2	2	1
##	8622	8632	8642	8643	8649	8651	8653	8658	8661	8674	8675	8677	8683
##	2	1	2	2	2	1	1	2	2	1	2	2	1
##	8686	8689	8692	8695	8701	8702	8709	8712	8719	8725	8732	8733	8735
##	2	2	2	2	1	2	2	2	1	1	1	1	2

##	8738	8740	8741	8745	8748	8750	8756	8765	8766	8772	8774	8779	8785
##	1	1	1	1	2	1	1	1	2	2	2	2	1
##	8786	8787	8790	8796	8799	8804	8806	8811	8816	8819	8822	8824	8835
##	2	1	2	1	2	1	1	2	1	2	1	2	2
##	8836	8849	8853	8857	8869	8870	8879	8884	8886	8889	8894	8899	8901
##	2	1	1	2	1	1	1	2	1	2	2	2	1
##	8908	8913	8915	8917	8920	8921	8923	8930	8932	8934	8937	8938	8947
##	2	2	2	2	2	1	1	2	1	2	1	1	2
##	8955	8957	8960	8968	8972	8977	8979	8981	8992	8997	9004	9005	9008
##	1	1	2	2	2	1	1	2	2	2	2	2	1
##	9009	9011	9032	9033	9037	9044	9046	9047	9050	9066	9073	9077	9079
##	1	2	2	1	1	2	1	2	2	1	2	2	2
##	9082	9088	9095	9099	9105	9108	9109	9114	9116	9121	9123	9124	9125
##	1	1	1	2	1	2	2	2	2	2	1	2	2
##	9126	9129	9133	9135	9143	9145	9146	9147	9150	9154	9166	9171	9172
##	1	2	1	1	2	2	2	2	2	1	2	1	2
##	9176	9182	9192	9200	9201	9202	9207	9211	9216	9221	9225	9232	9233
##	1	1	1	1	2	2	2	1	2	2	1	2	1
##	9237	9245	9254	9257	9259	9265	9275	9276	9282	9284	9286	9291	9298
##	1	2	2	1	1	2	1	2	2	2	2	2	2
##	9307	9309	9310	9315	9316	9317	9321	9322	9327	9328	9332	9347	9348
##	2	2	2	2	1	1	2	2	1	2	2	1	1
##	9350	9351	9355	9358	9360	9364	9366	9378	9380	9391	9397	9408	9421
##	1	1	1	2	2	2	1	1	1	2	1	1	1
##	9425	9428	9431	9432	9439	9441	9445	9447	9450	9452	9460	9467	9475
##	1	2	2	2	1	1	1	1	1	1	2	2	1
##	9482	9486	9498	9502	9512	9515	9521	9533	9536	9539	9545	9546	9552
##	2	2	2	1	2	1	2	2	2	2	2	1	1
##	9554	9556	9564	9567	9569	9574	9575	9576	9580	9586	9594	9595	9605
##	1	2	1	1	2	2	2	2	1	1	1	1	1
##	9612	9613	9615	9617	9618	9625	9626	9628	9629	9634	9635	9636	9638
##	2	1	1	1	2	2	1	1	2	1	2	1	2
##	9640	9647	9649	9657	9658	9662	9687	9694	9697	9698	9700	9703	9704
##	2	1	2	2	1	2	1	2	1	2	1	2	1
##	9706	9710	9711	9714	9718	9720	9722	9723	9724	9725	9727	9731	9733
##	1	2	1	1	1	2	2	1	1	1	2	1	2
##	9734	9747	9748	9750	9752	9760	9767	9768	9770	9773	9785	9793	9794
##	2	2	2	2	2	1	2	1	2	2	1	1	2
##	9795	9808	9814	9815	9816	9817	9821	9827	9830	9832	9837	9838	9843
##	1	2	2	1	2	2	2	2	1	2	2	2	2
##	9847	9853	9855	9859	9861	9864	9866	9867	9869	9870	9871	9873	9874
##	2	1	1	1	2	2	2	1	1	2	2	1	2
##	9881	9883	9885	9886	9894	9895	9897	9901	9905	9910	9914	9916	9919
##	2	2	2	1	2	1	2	2	2	1	2	1	2
##	9920	9923	9925	9927	9938	9943	9945	9946	9947	9949	9952	9955	9961
##	2	1	1	2	2	2	2	2	1	2	2	1	2
##	9963	9975	9983	9985	9986	9987	9994	9996	9998	10000	10002	10009	10010
##	1	2	1	1	2	2	1	1	1	2	2	2	2
##	10012	10016	10017	10018	10020	10029	10034	10038	10039	10044	10047	10048	10056
##	1	2	2	2	1	1	1	2	2	2	1	1	1
##	10064	10069	10073	10079	10080	10081	10082	10086	10087	10089	10092	10099	10108
##	2	1	2	1	1	2	2	1	2	1	2	2	2
##	10118	10120	10123	10125	10126	10129	10132	10134	10135	10137	10139	10140	10141
##	2	2	2	1	1	2	2	1	1	2	2	2	2

##	10151	10153	10156	10161	10165	10169	10179	10184	10185	10191	10192	10193	10194
##	2	2	2	2	1	2	2	1	1	2	1	2	2
##	10197	10209	10215	10217	10227	10231	10232	10233	10234	10240	10242	10245	10256
##	1	2	1	2	1	2	2	1	2	2	1	2	2
##	10261	10270	10274	10276	10277	10278	10283	10285	10292	10293	10294	10297	10298
##	2	2	2	1	1	2	2	2	1	1	2	2	2
##	10315	10316	10319	10323	10327	10328	10336	10342	10347	10353	10355	10357	10358
##	1	2	1	1	1	1	1	1	2	2	1	2	2
##	10369	10372	10373	10374	10376	10390	10392	10393	10396	10405	10407	10408	10409
##	1	2	1	2	1	1	1	2	1	2	2	2	1
##	10411	10414	10421	10424	10425	10426	10449	10451	10456	10468	10470	10471	10473
##	2	1	2	1	1	1	1	2	2	1	1	2	1
##	10474	10479	10482	10483	10489	10498	10503	10505	10506	10513	10514	10519	10520
##	2	1	2	1	2	2	1	1	2	2	1	2	2
##	10521	10547	10553	10560	10561	10569	10570	10572	10575	10577	10584	10585	10587
##	2	1	1	1	1	1	1	1	2	2	2	1	1
##	10588	10593	10594	10599	10605	10612	10622	10623	10624	10625	10626	10633	10640
##	2	1	1	2	2	2	2	1	1	2	1	2	2
##	10641	10646	10647	10648	10649	10653	10656	10658	10659	10661	10664	10666	10670
##	2	2	1	1	2	2	1	2	2	1	2	2	2
##	10672	10673	10677	10678	10686	10687	10691	10693	10696	10701	10702	10705	10708
##	2	1	1	2	1	1	1	1	1	1	1	1	1
##	10716	10720	10726	10728	10732	10736	10738	10740	10742	10744	10745	10746	10751
##	1	1	2	1	2	2	2	1	2	2	2	2	2
##	10756	10761	10763	10766	10772	10773	10774	10775	10783	10784	10794	10796	10804
##	1	2	2	1	2	2	1	1	1	2	1	2	2
##	10808	10810	10814	10816	10826	10831	10833	10838	10840	10845	10846	10847	10851
##	1	1	1	2	1	1	1	1	1	1	2	1	2
##	10856	10857	10866	10868	10870	10872	10878	10880	10889	10891	10895	10898	10906
##	2	2	2	1	2	1	1	2	2	1	2	1	1
##	10910	10914	10924	10926	10927	10928	10930	10931	10934	10935	10936	10947	10948
##	2	1	2	2	2	1	1	2	1	2	2	2	2
##	10956	10965	10966	10969	10970	10976	10979	10981	10989	10994	10995	10998	11000
##	1	1	1	2	1	1	2	1	1	1	1	2	1
##	11005	11006	11007	11012	11015	11024	11025	11029	11031	11035	11041	11062	11065
##	1	2	2	2	1	1	2	1	2	2	1	2	2
##	11067	11072	11074	11078	11079	11085	11088	11090	11092	11094	11095	11097	11100
##	2	2	2	2	2	1	2	1	2	2	1	2	2
##	11109	11111	11114	11115	11117	11121	11123	11125	11126	11127	11134	11135	11140
##	1	1	2	1	2	1	1	1	2	2	2	2	1
##	11142	11143	11144	11153	11155	11157	11161	11168	11169	11173	11175	11178	11179
##	2	2	2	1	2	2	1	2	1	2	2	2	2
##	11187	11191	11200	11204	11206	11208	11210	11220	11224	11228	11231	11234	11236
##	2	2	1	1	2	2	2	1	1	2	1	2	2
##	11237	11248	11249	11250	11251	11254	11255	11257	11260	11262	11263	11264	11268
##	1	2	2	2	2	2	2	2	2	1	1	1	2
##	11271	11275	11279	11281	11282	11290	11303	11305	11306	11309	11311	11313	11317
##	1	2	2	1	2	2	1	1	2	1	2	1	1
##	11322	11327	11329	11332	11340	11343	11344	11346	11347	11348	11351	11355	11357
##	2	1	2	2	2	1	2	2	2	1	2	2	2
##	11358	11360	11361	11364	11371	11373	11374	11377	11378	11379	11386	11387	11390
##	2	1	2	2	2	2	2	2	2	1	2	2	1
##	11391	11394	11395	11401	11402	11407	11422	11425	11427	11430	11434	11438	11443
##	1	1	2	2	2	1	1	2	2	2	1	1	1

```

## 11446 11447 11448 11450 11455 11458 11459 11460 11462 11463 11468 11474 11478
##      2      2      2      2      1      2      2      1      2      2      1      2      1
## 11481 11483 11485 11486 11498 11500 11502 11509 11512 11515 11516 11523 11531
##      2      2      1      2      1      2      2      1      2      1      2      1      2
## 11539 11540 11542 11546 11548 11550 11558 11559 11570 11580 11585 11586 11587
##      2      1      1      2      1      1      1      1      1      1      2      1      2
## 11592 11594 11595 11599 11605 11629 11636 11641 11645 11651 11654 11657 11665
##      2      2      2      2      2      2      1      1      1      1      2      2      2
## 11666 11667 11669 11670 11674 11677 11687 11688 11689 11692 11698 11699 11701
##      2      2      2      2      2      2      2      1      1      2      1      2      2
## 11702 11705 11709 11713 11714 11716 11721 11723 11731 11735 11737 11740 11745
##      1      1      1      1      1      2      2      2      2      1      1      1      2
## 11746 11754 11760 11763 11766 11770 11771 11774 11796 11802 11810 11813 11821
##      2      2      1      2      1      2      2      1      1      1      2      2      2
## 11827 11832 11833 11834 11835 11839 11841 11842 11844 11847 11849 11851 11853
##      2      2      2      2      2      1      1      2      2      1      1      2      1
## 11854 11856 11857 11859 11863 11865 11868 11870 11875 11878 11885 11889 11892
##      2      2      1      2      1      2      1      1      2      1      2      1      1
## 11893 11900 11911 11920 11939 11940 11941 11944 11952 11963 11965 11966 11968
##      1      1      1      2      1      1      2      1      1      2      2      2      1
## 11969 11972 11976 11981 11982 11988 11994 11997 11999 12000
##      2      1      2      1      2      2      2      1      2      2
##
## Within cluster sum of squares by cluster:
## [1] 6019.101 12893.421
## (between_SS / total_SS = 36.9 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"

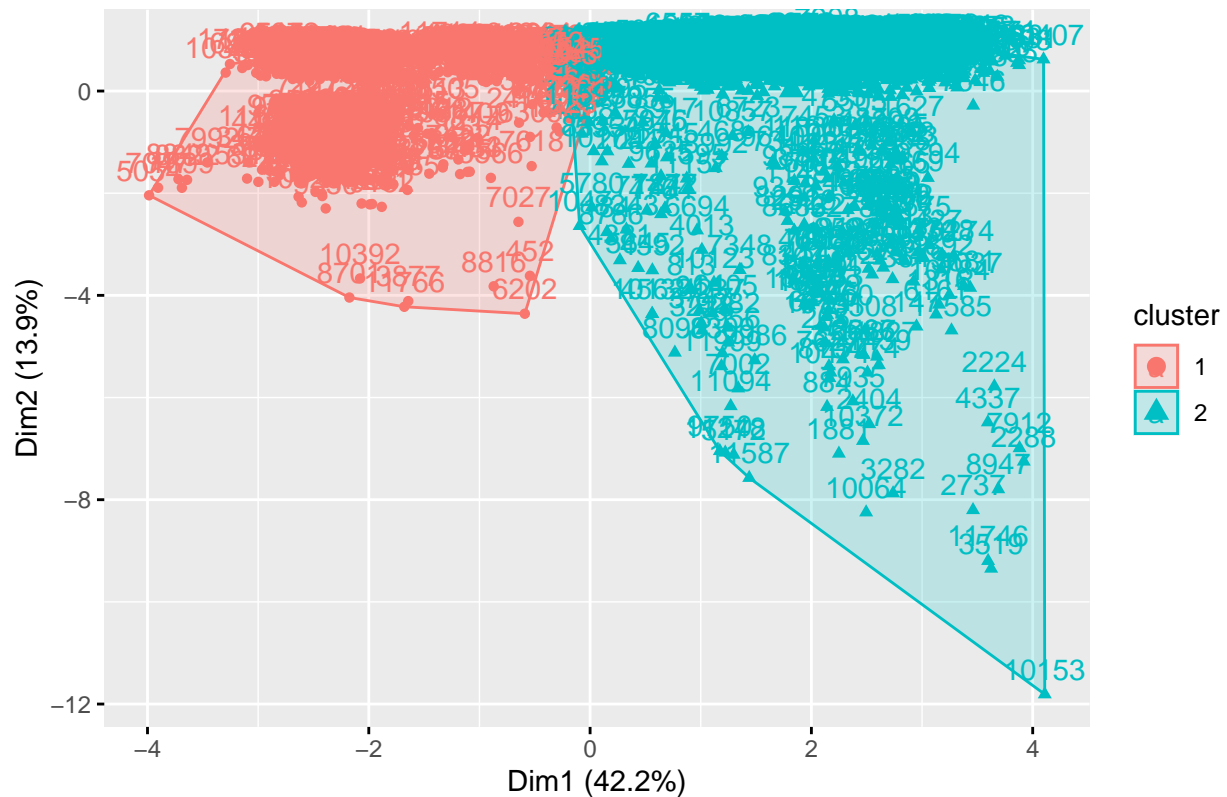
```

```

#plotting cluster
fviz_cluster(wss_kmeans_testdata, data = fuel_cost_normalized_testdata )

```

Cluster plot



```
varImp(model1, scale = FALSE)
```

```
## Warning in summary.lm(object): essentially perfect fit: summary may be
## unreliable
```

```
##                                Overall
## new_datamine_id_pudl          6.169941e+00
## new_datafuel_mmbtu_per_unit    2.344597e+01
## new_datasulfur_content_pct     9.147009e+00
## new_datamercury_content_ppm    3.692552e+00
## new_datafuel_cost_per_mmbtu    1.595915e+16
```

```
value_To_Predict<-model1[c(1,4,5,7,8)]
```

```
Prob<-predict(model1, data = value_To_Predict, type = "response")
Pred_data<-ifelse(Prob>0.3,"yes","no")
```

```
head(Pred_data)
```

```
##      1      7      8      9     19     22
## "yes" "yes" "yes" "yes" "yes" "yes"
```