

# ML Final Project

## Loading the necessary Libraries for project

```
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(caret)

## Loading required package: ggplot2

## Loading required package: lattice

library(missForest)

## Warning: package 'missForest' was built under R version 4.2.2

library(corrplot)

## corrplot 0.92 loaded

library(factoextra)

## Warning: package 'factoextra' was built under R version 4.2.2

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

library(cluster)

## Warning: package 'cluster' was built under R version 4.2.2
```

## Reading the CSV File

```
# reading file
Fuel_Receipts_Costs_Data=read.csv("C:/Users/Pavan
Chaitanya/Downloads/fuel_receipts_costs_eia923 (1).csv")

# head part of file
head(Fuel_Receipts_Costs_Data,5)
```

##	rowid	plant_id_eia	report_date	contract_type_code	contract_expiration_date
## 1	1	3	2008-01-01	C	2008-04-01
## 2	2	3	2008-01-01	C	2008-04-01
## 3	3	3	2008-01-01	C	
## 4	4	7	2008-01-01	C	2015-12-01
## 5	5	7	2008-01-01	S	2008-11-01

##	energy_source_code	fuel_type_code_pudl	fuel_group_code	mine_id_pudl
## 1	BIT	coal	coal	0
## 2	BIT	coal	coal	0
## 3	NG	gas	natural_gas	NA
## 4	BIT	coal	coal	1
## 5	BIT	coal	coal	2

##	supplier_name	fuel_received_units	fuel_mmbtu_per_unit
## 1	interocean coal	259412	23.100
## 2	interocean coal	52241	22.800
## 3	bay gas pipeline	2783619	1.039
## 4	alabama coal	25397	24.610
## 5	d & e mining	764	24.446

##	ash_content_pct	mercury_content_ppm	fuel_cost_per_mmbtu
## 1	5.4	NA	2.135
## 2	5.7	NA	2.115
## 3	0.0	NA	8.631
## 4	14.7	NA	2.776
## 5	15.5	NA	3.381

##	primary_transportation_mode_code	secondary_transportation_mode_code
## 1	RV	
## 2	RV	
## 3	PL	
## 4	TR	
## 5	TR	

##	natural_gas_transport_code	natural_gas_delivery_contract_type_code
## 1	firm	
## 2	firm	
## 3	firm	
## 4	firm	
## 5	firm	

##	moisture_content_pct	chlorine_content_ppm	data_maturity
## 1	NA	NA	final
## 2	NA	NA	final

## 3	NA	NA	final
## 4	NA	NA	final
## 5	NA	NA	final

*#Checiking NA's*

```
colMeans(is.na(Fuel_Receipts_Costs_Data))
```

```
##                                rowid
plant_id_eia
##                                0.0000000
0.0000000
##                                report_date
contract_type_code
##                                0.0000000
0.0000000
##                                contract_expiration_date
energy_source_code
##                                0.0000000
0.0000000
##                                fuel_type_code_pudl
fuel_group_code
##                                0.0000000
0.0000000
##                                mine_id_pudl
supplier_name
##                                0.6440512
0.0000000
##                                fuel_received_units
fuel_mmbtu_per_unit
##                                0.0000000
0.0000000
##                                sulfur_content_pct
ash_content_pct
##                                0.0000000
0.0000000
##                                mercury_content_ppm
fuel_cost_per_mmbtu
##                                0.4756797
0.3290363
##                                primary_transportation_mode_code
secondary_transportation_mode_code
##                                0.0000000
0.0000000
##                                natural_gas_transport_code
natural_gas_delivery_contract_type_code
##                                0.0000000
0.0000000
##                                moisture_content_pct
chlorine_content_ppm
##                                0.8488641
```

```
0.8488641
##                               data_maturity
##                               0.0000000
```

## Data Cleaning and Removing the Unnecessary Columns that are present in dataset

*# Randomly Assigning the seed value*

```
set.seed(2875)
```

*#checking the NA Values*

```
Fuel_Receipts_Costs_Data[Fuel_Receipts_Costs_Data==""] = NA
```

*#Converting the mean values to the percentage*

```
Filtering_NA =
```

```
Fuel_Receipts_Costs_Data[, (colMeans(is.na(Fuel_Receipts_Costs_Data))*100)<50]
```

*#Sampling the 2 % of the data*

```
Creating_Two_data_Partition =
```

```
createDataPartition(Filtering_NA$plant_id_eia,p=0.02,list = FALSE)
```

```
Creating_Two_data_Partition1 = Filtering_NA[Creating_Two_data_Partition,]
```

*# Printing the 2% data*

```
head(Creating_Two_data_Partition1,10)
```

```
##      rowid plant_id_eia report_date contract_type_code energy_source_code
## 120    120         130  2008-01-01                C          BIT
## 125    125         136  2008-01-01                C          BIT
## 142    142         160  2008-01-01                C          SUB
## 219    219         525  2008-01-01                C          BIT
## 275    275         535  2008-01-01                S           NG
## 309    309         564  2008-01-01                C          BIT
## 351    351         619  2008-01-01                C           NG
## 389    389         666  2008-01-01                S           NG
## 486    486         876  2008-01-01               NC          SUB
## 619    619        1077  2008-01-01                C          PC
##      fuel_type_code pudl fuel_group_code      supplier_name
## 120             coal      coal             arch
## 125             coal      coal      alliance coal
## 142             coal      coal             rio tinto
## 219             coal      coal      peabody coal
## 275             gas      natural_gas      suncor energy
## 309             coal      coal             icg
## 351             gas      natural_gas florida gas transmission
## 389             gas      natural_gas florida gas transmission
## 486             coal      coal             rio tinto
## 619             coal petroleum_coke      petcoke
##      fuel_received_units fuel_mmbtu_per_unit sulfur_content_pct
## ash_content_pct
## 120             21769             24.700             0.79
```

10.50			
## 125	56274	23.376	2.88
7.10			
## 142	13105	20.764	0.40
5.00			
## 219	115560	22.512	0.50
10.20			
## 275	7	1.000	0.00
0.00			
## 309	11096	22.190	1.18
11.10			
## 351	732643	1.026	0.00
0.00			
## 389	48274	1.054	0.00
0.00			
## 486	31664	17.530	0.29
6.20			
## 619	3380	28.000	5.80
0.54			
##	mercury_content_ppm	fuel_cost_per_mmbtu	
primary_transportation_mode_code			
## 120	NA	2.300	
RR			
## 125	NA	2.201	
RR			
## 142	NA	1.661	
RR			
## 219	NA	1.431	
RR			
## 275	NA	9.703	
<NA>			
## 309	NA	2.761	
RR			
## 351	NA	9.386	
<NA>			
## 389	NA	10.715	
<NA>			
## 486	NA	NA	
RR			
## 619	NA	1.944	
TR			
##	natural_gas_transport_code	data_maturity	
## 120	<NA>	final	
## 125	<NA>	final	
## 142	<NA>	final	
## 219	<NA>	final	
## 275	firm	final	
## 309	<NA>	final	
## 351	firm	final	
## 389	interruptible	final	

```
## 486          <NA>          final
## 619          <NA>          final
```

```
colMeans(is.na(Creating_Two_data_Partition1))*100
```

```
##          rowid          plant_id_eia
##          0.00000000          0.00000000
##          report_date          contract_type_code
##          0.00000000          0.04107451
##          energy_source_code          fuel_type_code_pudl
##          0.00000000          0.00000000
##          fuel_group_code          supplier_name
##          0.00000000          0.00000000
##          fuel_received_units          fuel_mmbtu_per_unit
##          0.00000000          0.00000000
##          sulfur_content_pct          ash_content_pct
##          0.00000000          0.00000000
##          mercury_content_ppm          fuel_cost_per_mmbtu
##          47.96681180          32.81853282
## primary_transportation_mode_code          natural_gas_transport_code
##          9.79216298          43.76899696
##          data_maturity
##          0.00000000
```

```
#converting the date to date format
```

```
Creating_Two_data_Partition1$report_date <-
as.Date(Creating_Two_data_Partition1$report_date)
```

```
Creating_Two_data_Partition1$report_date <-
as.numeric(format(Creating_Two_data_Partition1$report_date, "%Y"))
```

```
# removing the unnecessary COLUMNS
```

```
Creating_Two_data_Partition1=Creating_Two_data_Partition1[, -c(6,8,17)]
```

```
# Printing the data data frame after removing unnecessary columns
```

```
head(Creating_Two_data_Partition1,10)
```

```
##          rowid plant_id_eia report_date contract_type_code energy_source_code
## 120      120      130      2008          C          BIT
## 125      125      136      2008          C          BIT
## 142      142      160      2008          C          SUB
## 219      219      525      2008          C          BIT
## 275      275      535      2008          S          NG
## 309      309      564      2008          C          BIT
## 351      351      619      2008          C          NG
## 389      389      666      2008          S          NG
## 486      486      876      2008          NC          SUB
## 619      619     1077      2008          C          PC
##          fuel_group_code fuel_received_units fuel_mmbtu_per_unit
##          sulfur_content_pct
```

```

## 120      coal      21769      24.700
0.79
## 125      coal      56274      23.376
2.88
## 142      coal      13105      20.764
0.40
## 219      coal      115560     22.512
0.50
## 275      natural_gas      7      1.000
0.00
## 309      coal      11096      22.190
1.18
## 351      natural_gas      732643     1.026
0.00
## 389      natural_gas      48274      1.054
0.00
## 486      coal      31664      17.530
0.29
## 619      petroleum_coke      3380      28.000
5.80
##      ash_content_pct mercury_content_ppm fuel_cost_per_mmbtu
## 120      10.50      NA      2.300
## 125      7.10      NA      2.201
## 142      5.00      NA      1.661
## 219      10.20     NA      1.431
## 275      0.00      NA      9.703
## 309      11.10     NA      2.761
## 351      0.00      NA      9.386
## 389      0.00      NA     10.715
## 486      6.20      NA      NA
## 619      0.54      NA      1.944
##      primary_transportation_mode_code natural_gas_transport_code
## 120      RR      <NA>
## 125      RR      <NA>
## 142      RR      <NA>
## 219      RR      <NA>
## 275      <NA>      firm
## 309      RR      <NA>
## 351      <NA>      firm
## 389      <NA>      interruptible
## 486      RR      <NA>
## 619      TR      <NA>

```

## Data Imputation

```

# Converting the variables of char to factor type for data imputaion
Creating_Two_data_Partition1$report_date =
as.factor(Creating_Two_data_Partition1$report_date)

```

```

Creating_Two_data_Partition1$contract_type_code =
as.factor(Creating_Two_data_Partition1$contract_type_code)

Creating_Two_data_Partition1$energy_source_code =
as.factor(Creating_Two_data_Partition1$energy_source_code)

Creating_Two_data_Partition1$fuel_group_code =
as.factor(Creating_Two_data_Partition1$fuel_group_code)

Creating_Two_data_Partition1$primary_transportation_mode_code =
as.factor(Creating_Two_data_Partition1$primary_transportation_mode_code)

Creating_Two_data_Partition1$natural_gas_transport_code =
as.factor(Creating_Two_data_Partition1$natural_gas_transport_code)

```

#### *# Computing the Data Imputation*

```
Genertated_Data = missForest(Creating_Two_data_Partition1)
```

#### *#Taking only the ximp data frame*

```
Imputed = Genertated_Data$ximp
```

#### *#Printing the data frame after computation of the missing values*

```
head(Imputed,10)
```

```

##      rowid plant_id_eia report_date contract_type_code energy_source_code
## 120      120          130         2008                C              BIT
## 125      125          136         2008                C              BIT
## 142      142          160         2008                C              SUB
## 219      219          525         2008                C              BIT
## 275      275          535         2008                S              NG
## 309      309          564         2008                C              BIT
## 351      351          619         2008                C              NG
## 389      389          666         2008                S              NG
## 486      486          876         2008               NC              SUB
## 619      619         1077         2008                C              PC
##      fuel_group_code fuel_received_units fuel_mmbtu_per_unit
sulfur_content_pct
## 120          coal          21769          24.700
0.79
## 125          coal          56274          23.376
2.88
## 142          coal          13105          20.764
0.40
## 219          coal          115560          22.512
0.50
## 275    natural_gas              7          1.000
0.00
## 309          coal          11096          22.190
1.18

```



```

## 351      natural_gas              732643          1.026
0.00
## 389      natural_gas              48274          1.054
0.00
## 486          coal              31664          17.530
0.29
## 619  petroleum_coke              3380          28.000
5.80
##      ash_content_pct mercury_content_ppm fuel_cost_per_mmbtu
## 120          10.50      1.655000e-02      2.300000
## 125          7.10      1.318733e-02      2.201000
## 142          5.00      2.240737e-02      1.661000
## 219          10.20      1.781000e-02      1.431000
## 275          0.00     -2.234844e-16      9.703000
## 309          11.10      1.932000e-02      2.761000
## 351          0.00     -2.314121e-16      9.386000
## 389          0.00     -2.581269e-16     10.715000
## 486          6.20      1.446737e-02      1.634491
## 619          0.54      1.980333e-02      1.944000
##      primary_transportation_mode_code natural_gas_transport_code
## 120                      RR                      firm
## 125                      RR                      firm
## 142                      RR                      firm
## 219                      RR                      firm
## 275                      PL                      firm
## 309                      RR                      firm
## 351                      PL                      firm
## 389                      PL          interruptible
## 486                      RR                      firm
## 619                      TR                      firm

```

## Partitioning the 2 % data into 75 % training data.

```
Data_Partition = createDataPartition(Imputed$plant_id_eia,p=0.75,list = FALSE)
```

```
Data_Partition_Trained = Imputed[Data_Partition,]
```

```
Data_Partition_Tested = Imputed[-Data_Partition,]
```

## As data has Outliers we are making sure that the outlier are removed.

```

# For the fuel received units performing the quartile ranges and IQR
Quartiled_data = quantile(Data_Partition_Trained$fuel_received_units,
probs=c(.25, .75), na.rm = FALSE)
Data_Partition_Quartiled = IQR(Data_Partition_Trained$fuel_received_units)

```

```
Fuelunits_Lower = Quartiled_data[1] - 1.5*Data_Partition_Quartiled
```

```

Fuelunits_Upper = Quartiled_data[2] + 1.5*Data_Partition_Quartiled

Data_With_No_Outliers = subset(Data_Partition_Trained,
Data_Partition_Trained$fuel_received_units > Fuelunits_Lower &
Data_Partition_Trained$fuel_received_units < Fuelunits_Upper)

# For the fuel cost per mmbtu performing the quartile ranges and IQR
Range_of_Fuel = quantile(Data_With_No_Outliers$fuel_cost_per_mmbtu,
probs=c(.25, .75), na.rm = FALSE)
Fuelcost_IQR <- IQR(Data_With_No_Outliers$fuel_cost_per_mmbtu)

Fuelcost_Lower = Range_of_Fuel[1] - 1.5*Fuelcost_IQR
Fuelcost_Upper = Range_of_Fuel[2] + 1.5*Fuelcost_IQR

No_Outlier_Data = subset(Data_With_No_Outliers,
Data_With_No_Outliers$fuel_cost_per_mmbtu > Fuelcost_Lower &
Data_With_No_Outliers$fuel_cost_per_mmbtu < Fuelcost_Upper)

```

## Choosing and Normalising the selected variables

```

All_Numeric_Variables=No_Outlier_Data[,c(7,8,9,10,11,12)]
head(All_Numeric_Variables,12)

```

	fuel_received_units	fuel_mmbtu_per_unit	sulfur_content_pct
ash_content_pct			
## 120	21769	24.700	0.79
10.50			
## 125	56274	23.376	2.88
7.10			
## 219	115560	22.512	0.50
10.20			
## 309	11096	22.190	1.18
11.10			
## 389	48274	1.054	0.00
0.00			
## 486	31664	17.530	0.29
6.20			
## 619	3380	28.000	5.80
0.54			
## 685	10905	22.082	3.96
16.20			
## 709	40051	1.011	0.00
0.00			
## 737	20400	24.790	0.98
10.30			
## 747	17889	24.006	1.54
12.70			
## 796	33756	1.025	0.00
0.00			

```
##      mercury_content_ppm fuel_cost_per_mmbtu
## 120      1.655000e-02      2.300000
## 125      1.318733e-02      2.201000
## 219      1.781000e-02      1.431000
## 309      1.932000e-02      2.761000
## 389     -2.581269e-16     10.715000
## 486      1.446737e-02      1.634491
## 619      1.980333e-02      1.944000
## 685      1.850000e-02      1.765000
## 709     -2.546574e-16      8.329000
## 737      1.080000e-02      2.182000
## 747      1.134091e-02      2.425000
## 796     -2.361653e-16      8.633000
```

```
Scaled_Data = scale(All_Numeric_Variables)
head(Scaled_Data,12)
```

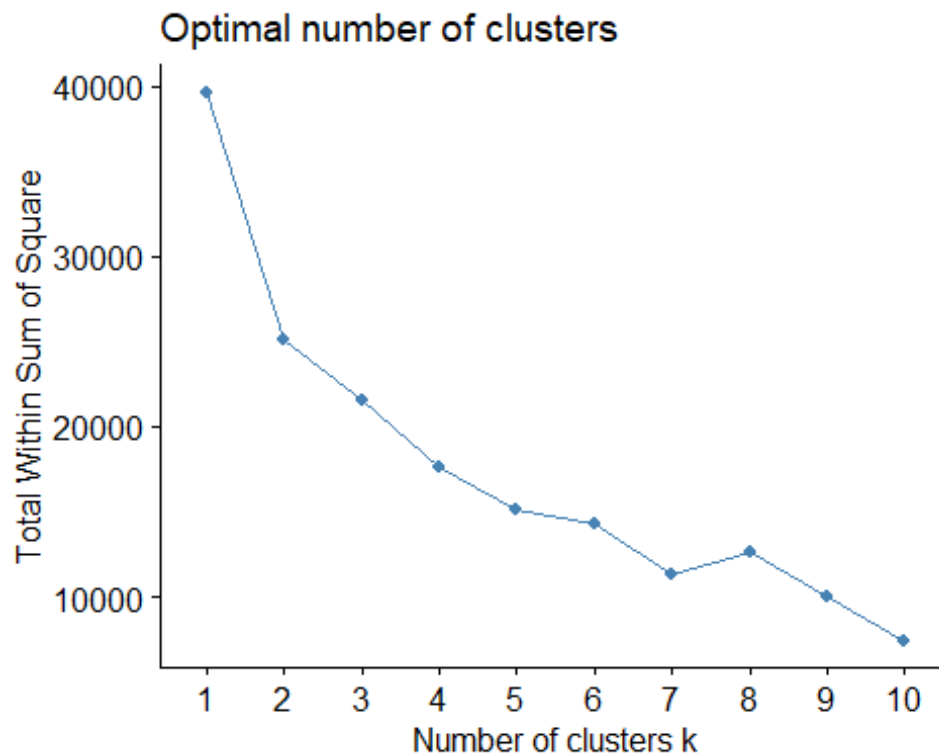
```
##      fuel_received_units fuel_mmbtu_per_unit sulfur_content_pct
ash_content_pct
## 120      -0.343145722      1.3206695      0.1248810
0.8434456
## 125      0.294744214      1.1942800      2.0336736
0.3548104
## 219      1.390757626      1.1118022     -0.1399754
0.8003308
## 309     -0.540456237      1.0810639      0.4810672
0.9296754
## 389      0.146849141     -0.9365870     -0.5966243      -
0.6655750
## 486     -0.160218004      0.6362185     -0.3317679
0.2254658
## 619     -0.683101034      1.6356888      4.7005035      -
0.5879682
## 685     -0.543987231      1.0707542      3.0200354
1.6626283
## 709     -0.005168507     -0.9406918     -0.5966243      -
0.6655750
## 737     -0.368454267      1.3292610      0.2984076
0.8147024
## 747     -0.414874833      1.2544200      0.8098545
1.1596214
## 796     -0.121543443     -0.9393554     -0.5966243      -
0.6655750
##      mercury_content_ppm fuel_cost_per_mmbtu
## 120      0.076866008     -0.6919802
## 125     -0.007240504     -0.7397989
## 219      0.108380938     -1.1117215
## 309      0.146148830     -0.4693096
## 389     -0.337080099      3.3726032
## 486      0.024775636     -1.0134318
```

```
## 619      0.158237891      -0.8639341
## 685      0.125639114      -0.9503940
## 709     -0.337080099       2.2201259
## 737     -0.066952126      -0.7489762
## 747     -0.053422989      -0.6316032
## 796     -0.337080099       2.3669629
```

## K-Means Clustering

*#wss*

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



*# We feel that k=2 is best.*

```
wss_k2 = kmeans(Scaled_Data, centers=2, nstart=50)
```

```
wss_group=wss_k2$cluster
```

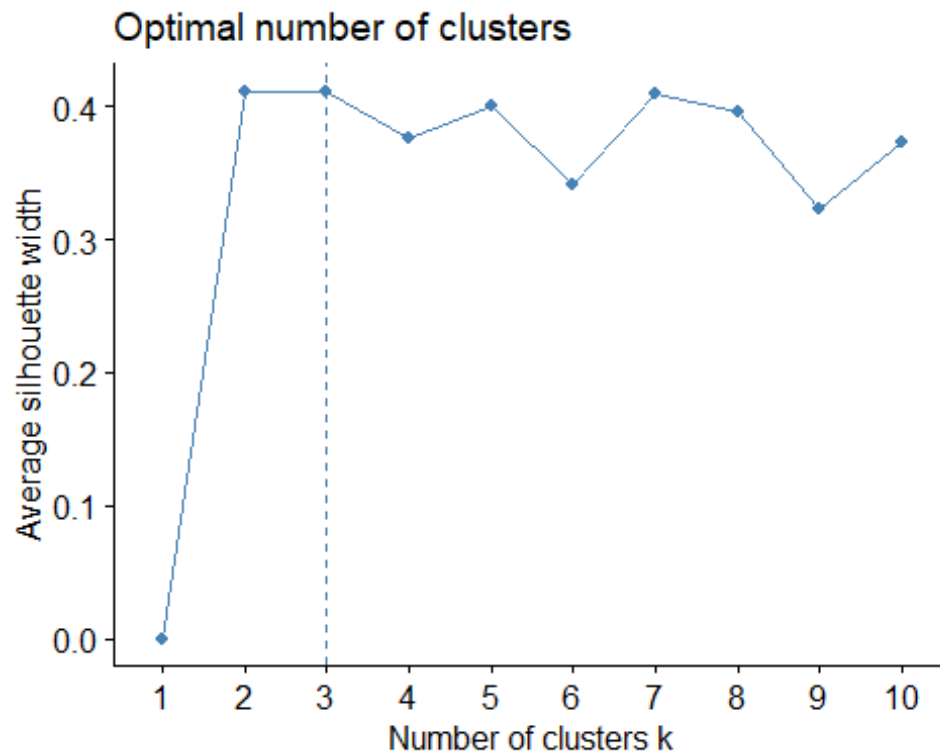
```
wss_k2$withinss
```

```
## [1] 8364.451 16771.092
```

```
wss_k2$tot.withinss
```

```
## [1] 25135.54
```

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



```
# Silhouette shows that k=3 is best.
Sil_k3 = kmeans(Scaled_Data, centers=3, nstart=50)
Silhouette_group=Sil_k3$cluster
Sil_k3$withinss

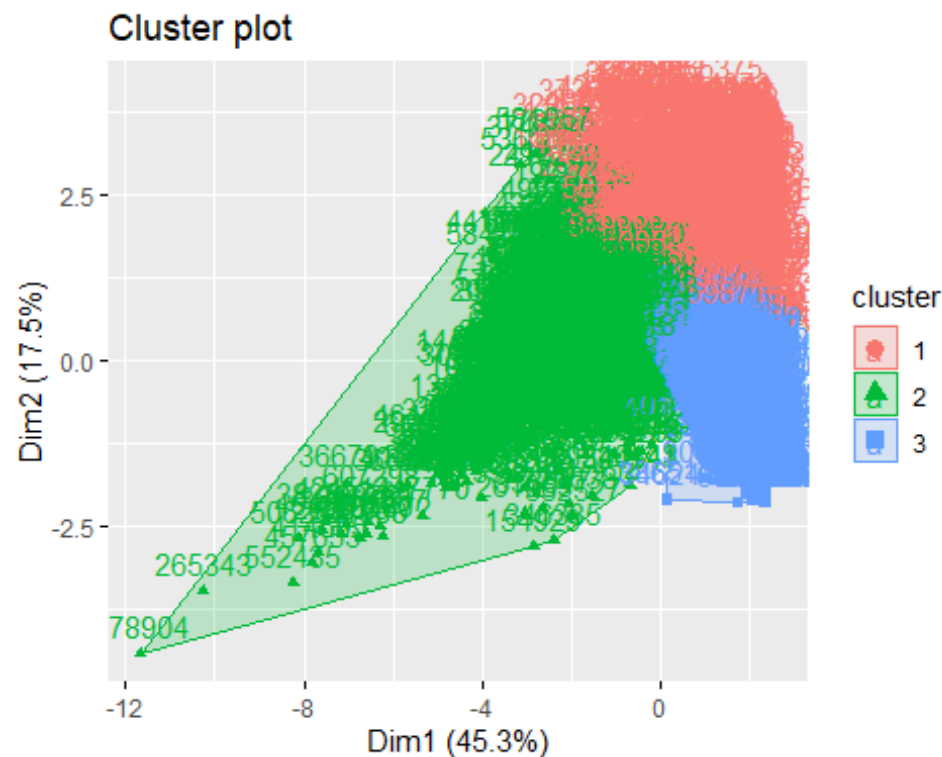
## [1] 1916.686 15046.584 4047.306

Sil_k3$tot.withinss

## [1] 21010.58

# By comparing the both methods and by finding the withiness we have come to
# an idea that k=3 is the best k for our project.
# ie Sil_k3$tot.withinss is less than that of Wss_k2$tot.withinss
# 2101.58 is less than 25135.54

fviz_cluster(Sil_k3, data=Scaled_Data)
```



Interpretation

```
Silhouette_group = as.data.frame(Silhouette_group)
Sil_bind=cbind(All_Numeric_Variables,Silhouette_group)
Cluster_mean= Sil_bind %>% group_by(Silhouette_group) %>%
summarise_all("mean")
Cluster_mean
```

```
## # A tibble: 3 × 7
##   Silhouette_group fuel_received_units fuel_mm...1 sulfu...2 ash_c...3 mercu...4
##   fuel_...5
##           <int>           <dbl>      <dbl>    <dbl>    <dbl>    <dbl>
## 1             1           161116.    5.23 0.111    1.55    3.45e-3
## 2             2           29500.     21.6 1.42     9.86    2.90e-2
## 3             3           18050.     1.18 0.00413 0.00863 2.13e-5
```

## # ... with abbreviated variable names <sup>1</sup>fuel\_mmbtu\_per\_unit, <sup>2</sup>sulfur\_content\_pct,  
## # <sup>3</sup>ash\_content\_pct, <sup>4</sup>mercury\_content\_ppm, <sup>5</sup>fuel\_cost\_per\_mmbtu

#

# As Sulfer content,ash content,mercury content are Less than 0.001 m they  
can be neglected for intrepretation.

# Cluster 1

#

```
# The power Plants present in this cluster receives fuel of 161115.82 which is high than all the 3 clsuters.  
# Their heat content in the fuel is 5.231477 which is very good wrt to the fuel recieves compared to other 2 clsuters.  
# The fuel cost per mmbtu is also very good(3.704139) wrt to fuel recieved and the heat content.  
# This Cluster is the preferred one to recommend for the Us Government beacuse by looking all the factors like (fuel recieved,heat content,fuel cost per mmbtu).
```

```
# Cluster 2
```

```
#  
# The power Plants present in this cluster receives fuel of 29500.21 which is slightly above the Cluster 3 but not cluster 1.  
# Their heat content in the fuel is very very high of 21.607668 comapared to all the 3 clsuters.  
# The fuel cost per mmbtu is lower(2.635552) than all the 3 clusters formed.  
# This cluster is also not a preferred one to recommend for us Government because of fuel mmbtu per unit.
```

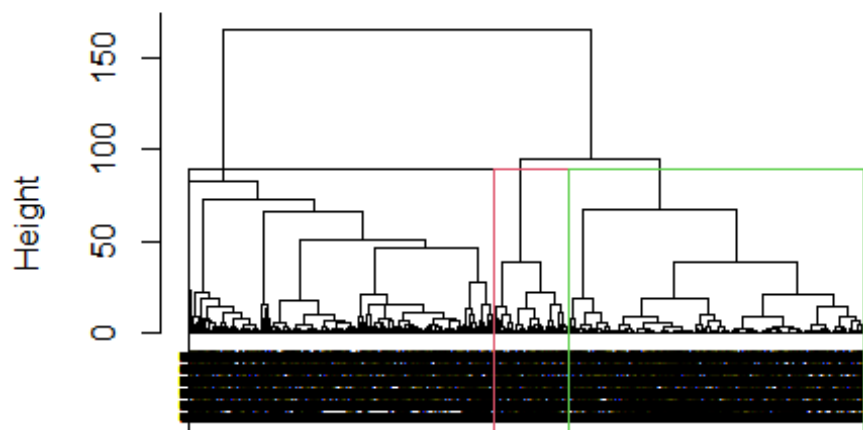
```
# Cluster 3
```

```
#  
# The power plants present in this cluster recieves fuel of 18049.93 which is low compared to other plants.  
# As they are receiving low fuel their heat content in fuel(fuel_mmbtu) is also low (1.183889).  
# The fuel cost per mmbtu is higher (4.889421) than all the 3 clusters formed.  
# This Cluster is not a preferred one to recommend for Us Government because of fuel cost per mmbtu.
```

## Hierarchial Clustering for visualizing the data

```
# Getting distance  
distance= dist(Scaled_Data,method="euclidean")  
# Computing method  
hclust_ward=hclust(distance,method = "ward.D2")  
#plotting  
plot(hclust_ward,cex=0.6,hang=-1);  
rect.hclust(hclust_ward,k=3,border=1:4)
```

## Cluster Dendrogram



distance  
hclust (\*, "ward.D2")