Commercial Building Energy Consumption modeling

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Part 1 - Data Ingestion

- Files required:
  - Part1.py
  - Finland_addresses_area.csv
  - Finland_masked.csv
- Place the files in the directory of Part1.py.
- Access to the files is done using the getwd in os package. Hence no hardcoding of filepaths.

  path=os.getcwd()

  st=pd.read_csv(os.path.join(path, 'Finland_masked.csv'))   for example.

Filter 'elect' and 'Dist_Heating' and place it in a dataframe.

```
st=pd.read_csv(os.path.join(path, 'Finland_masked.csv'))
df1= pd.read_csv(os.path.join(path, 'Finland_addresses_area.csv'))
st1=(st.loc[st['type'] == 'elect'])
st2=(st.loc[st['type'] == 'Dist_Heating'])
frames = [st1, st2]
result = pd.concat(frames)
result=pd.DataFrame(result)
```

Derive date, DayofWeek, month and other fields. Holiday is scraped from http://www.timeanddate.com/holidays/finland/2013

```
res=requests.get('http://www.timeanddate.com/holidays/finland/2013')
res.raise_for_status()
noScratchsoup=bs4.BeautifulSoup(res.text, 'html.parser')
div=noScratchsoup.select('th.nw')
a=[]
for tag in div:
    source_code=str(tag)
    soup=bs4.BeautifulSoup(source_code,'html.parser')
    tempString=soup.th.string
    key=datetime.strptime(tempString[4:]+'/'+tempString[0:3]+'/'+'2013','%d/%b/%Y')
    a.append(key)
```

```
frameset= [nobuildingname, withbuildingname]
result=pd.concat(frameset)
df=pd.DataFrame(result)
df1=df1.rename(columns = {'building':'vac'})
df=pd.merge(df1,df,on='vac')
df['area/sq meter'] = df['Consumption']/df['area_floor _m.sqr']
df['date']=pd.to_datetime(df['date'], format="%Y%m%d")
df['DayOfWeek']=pd.DatetimeIndex(df['date']).dayofweek
df['month']=pd.DatetimeIndex(df['date']).month
df['WeekDay']=[0 if (x == 0 or x == 6) else 1 for x in pd.DatetimeIndex(df['date']).weekday]
listValues=[0,1,2,3,4,22,23]
df['BaseHourFlag']=[True if (x in listValues) else False for x in df['hour']]
df['Holiday']=[True if (x in a) else False for x in df['date']]
df=df.rename(columns = {'vac':'Building Number','\t address':'address','hour':'Hour','area_floor _m.sqr':'Area(m_sq)','meternumb':'Mete
```

We are gathering the weather data by going through three steps –

1. **Getting geocode – Latitude, Longitude from googleapis API**
2. **Getting the nearby airport code using wunderground API**
3. **Processing a loop for whole year on wunderground airport csv files**

We read the 'Finland_addresses_area.csv' file and keep data in an address list. Maps.googleapis API takes an input of address, where each address will be send by address list.

```
    time.sleep(62)
url = "https://maps.googleapis.com/maps/api/geocode/json?address={address}"
url = url.format(address=address)
```

Next, the json response will be feed as input to wunderground API.

```
nearest_airport = "http://api.wunderground.com/api/2a9107686ea85180/geolookup/q/{lat},{longi}.json"
nearest_airport = nearest_airport.format(lat=json_data["results"][0]["geometry"]["location"]["lat"],
                                         longi=json_data["results"][0]["geometry"]["location"]["lng"])
```

This returns a json, where we gather the airport 'ICAO' code. Since, there are several addresses which have same airport code, we have designed a dictionary which keep tracks of all the data. Airport Code serves as the key and the list of addresses are served as values.

```
icao = airport_json_data["location"]["nearby_weather_stations"]["airport"]["station"][1]["icao"]
address_location_dict[icao] = address_location_dict.get(icao, []) + [address]
```

Using Pandas DataFrame, we created the column headers. Now, we are keeping a loop on year 2013, which will fetch the data from comma separated URL of wunderground.

```
for location_icao in address_location_dict:
    start_date = "2013-01-01"  # desired starting date
    end_date = "2013-12-31"  # desired ending date
    start = parser.parse(start_date)
    end = parser.parse(end_date)
    dates = list(
        rrule.rrule(rrule.DAILY, dtstart=start, until=end))  # generating the dates between starting and ending date
```

```
for d in dates:

    url = "https://www.wunderground.com/history/airport/{icao}/{y}/{m}/{dd}/DailyHistory.html??format=1&format=1"
    url = url.format(icao=location_icao, y=d.year, m=d.month, dd=d.day)
```

```
def timeinhours(tim):
    tim = tim.split(' ')
    if (tim[1] == 'PM'):
        if (int(tim[0].split(':')[0]) == 12):
            return 12
        else:
            return 12 + int(tim[0].split(':')[0])
    else:
        if (tim[0].split(':')[0].strip() == '12'):
            return 0
        else:
            return tim[0].split(':')[0].strip()
```

We need to merge the created dataframe with Finland_masked.csv file. Since one of the criteria for group by will be date, above function will create the exact same date format as we already have in Finland_masked.csv file. This will make the merger easy.

We are using BeautifulSoup to scrap the wunderground csv file and append the total data into a continuous dataframe. After the data is scraped, we are performing basic data cleanup on the columns.

```
dframe['TemperatureF'] = dframe['TemperatureF'].replace([''],np.nan)
dframe['Conditions'].astype(basestring)
dframe['Gust SpeedMPH'] = dframe['Gust SpeedMPH'].replace(['-'], '0')
dframe['Humidity'] = dframe['Humidity'].replace([''],'0')
dframe['PrecipitationIn'] = dframe['PrecipitationIn'].replace(['', 'N/A'], 'N/A')
```

We found that few of rows are blank, or have ‘-‘ or have N/A values. We have replaced the missing values with the appropriate desired values on the columns. We have performed data Cleanup and finding outliers further in the process.

At this point, we will merge the building data and the weather data that is received from scrapping the csv webpage. We have used pandas to merge and remove the duplicates from the code. We have removed the outliers which were either very high or very low.

```
dfMerge['Date']=pd.to_datetime(dfMerge['Date'], format="%Y%m%d")
dfMerge['VisibilityMPH'].replace([-9999],[0],inplace=True)
dfMerge['Wind Direction']=dfMerge['Wind Direction'].astype(str)
dfMerge['Wind Direction'].replace([''],['N/A'],inplace=True)
dfMerge['Conditions']=dfMerge['Conditions'].astype(str)
dfMerge['Conditions'].replace([''],['N/A'],inplace=True)
dfMerge.drop(['TimeEET','DateUTC','PrecipitationIn'],inplace=True,axis=1)
grouped=dfMerge.groupby(['AirportCode','Date','Hour'],as_index=False)
df3=grouped.mean()
df4=grouped.agg({'Wind Direction':lambda x:','.join(x),
                 'Conditions': lambda x: ','.join(x)})
df3['Wind Direction']=df4['Wind Direction']
df3['Conditions']=df4['Conditions']
df = pd.merge(df3, df, on=['AirportCode','Date','Hour'], how='right')
df=df.rename(columns = {'Dew PointF':'Dew_PointF','Sea Level PressureIn':'Sea_Level_PressureIn','Gust Speed
df.to_csv(path+'Final.csv', index=False)
```

Part 2 - Data wrangling and cleaning

We take the input generated from Part1, and consider the rows with BaseHourFlag(0,1,2,3,4,22,23) is equal to TRUE. Take the mean of the dataset by grouping on BuildingId, Consuption_Type, Meter_Number, WeekDay, Month, Holiday. Compute the Base_Hour_Class. If the KWH consumption is greater than the Base_Hour_Usage.

```
#install.packages("dplyr")
library(dplyr)
library(plyr)
setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
consolidate <- read.csv("Final.csv", header=TRUE)
baseHourFrame<-filter(consolidate, BaseHourFlag == "TRUE")
agg<-aggregate(KWH ~ BuildingID+Consumption_Type+Meter_Number+WeekDay+Month+Holiday,data=baseHourFr
agg<-filter(agg, Holiday == "FALSE")
agg<-filter(agg,WeekDay=="1")
agg <- subset(agg, select = -c(Holiday,WeekDay) )
final<-merge(x = consolidate, y = agg, by = c("BuildingID","Consumption_Type","Meter_Number","Montl
names(final)[names(final)=="KWH.x"] <- "KWH"
names(final)[names(final)=="KWH.y"] <- "Base_Hour_Usage"
final$KWH<-as.numeric(final$KWH)
final$Base_Hour_Usage<-as.numeric(final$Base_Hour_Usage)
final$Base_Hour_Class<-ifelse(final$KWH>final$Base_Hour_Usage, "High", "Low")
```

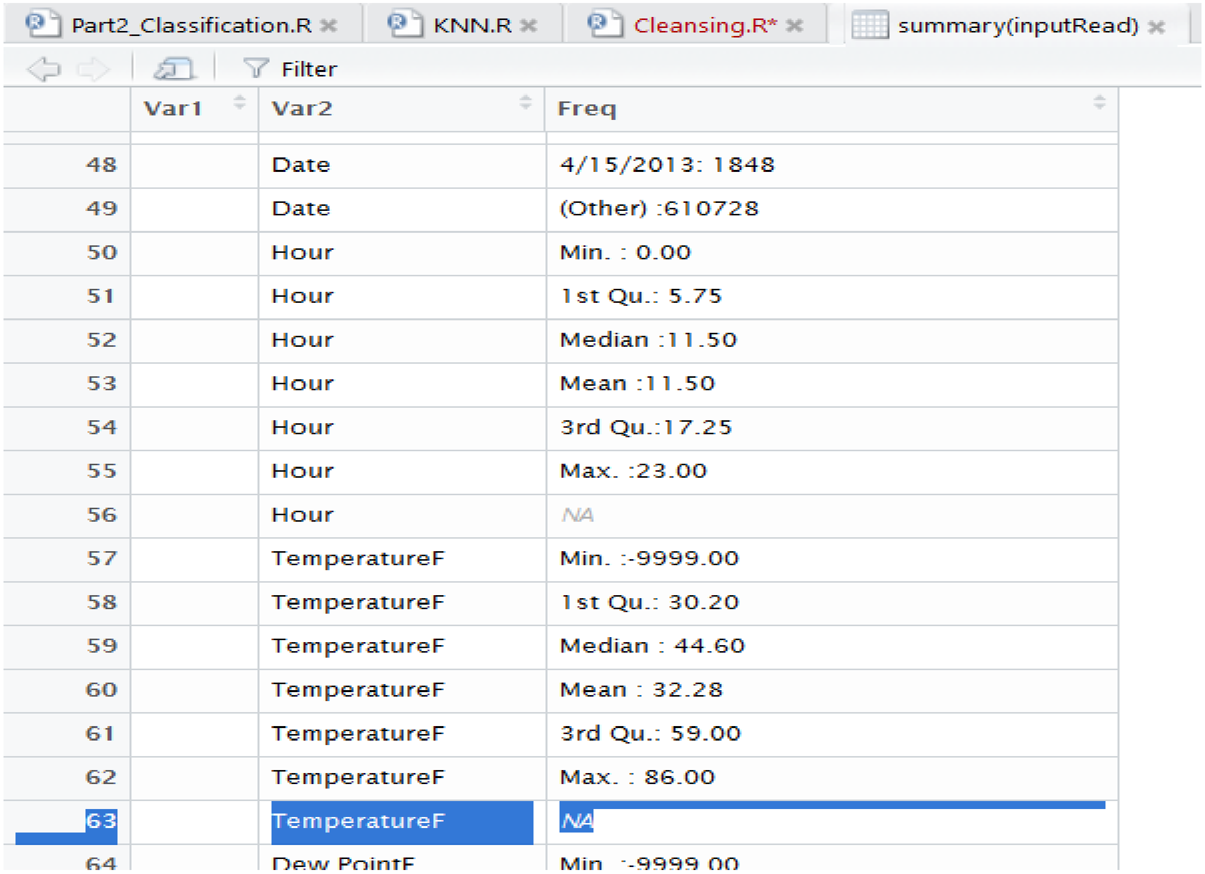
We are Cleaning up the NA and removing the outliers from the dataset. We are using zoo package to cleanse the unwanted data.

Using View(Summary(inputRead)) we identy the rows with NA.

	Var1	Var2	Freq
47		Date	4/14/2013: 1848
48		Date	4/15/2013: 1848
49		Date	(Other) :610728
50		Hour	Min. : 0.00
51		Hour	1st Qu.: 5.75
52		Hour	Median :11.50
53		Hour	Mean :11.50
54		Hour	3rd Qu.:17.25
55		Hour	Max. :23.00
56		Hour	NA
57		TemperatureF	Min. :-9999.0
58		TemperatureF	1st Qu.: 30.2
59		TemperatureF	Median : 44.6
60		TemperatureF	Mean : 32.3
61		TemperatureF	3rd Qu.: 59.0
62		TemperatureF	Max. : 86.0
63		TemperatureF	NA's :7624
64		Dew.PointF	Min. :-9999.00
65		Dew.PointF	1st Qu.: 26.60
66		Dew.PointF	Median : 39.20
67		Dew.PointF	Mean : 25.93
68		Dew.PointF	3rd Qu.: 51.80

Here we see that the Temperature has lot of NA's. We fill in the NA's with the approx function in the zoo package.

```
library(zoo)

inputRead$TemperatureF[is.na(inputRead$TemperatureF)] <-na.approx(inputRead$TemperatureF)
```


Part2_Classification.R KNN.R Cleansing.R* summary(inputRead)
Filter

	Var1	Var2	Freq
48		Date	4/15/2013: 1848
49		Date	(Other) :610728
50		Hour	Min. : 0.00
51		Hour	1st Qu.: 5.75
52		Hour	Median :11.50
53		Hour	Mean :11.50
54		Hour	3rd Qu.:17.25
55		Hour	Max. :23.00
56		Hour	NA
57		TemperatureF	Min. :-9999.00
58		TemperatureF	1st Qu.: 30.20
59		TemperatureF	Median : 44.60
60		TemperatureF	Mean : 32.28
61		TemperatureF	3rd Qu.: 59.00
62		TemperatureF	Max. : 86.00
63		TemperatureF	NA
64		Dew PointF	Min. :-9999.00

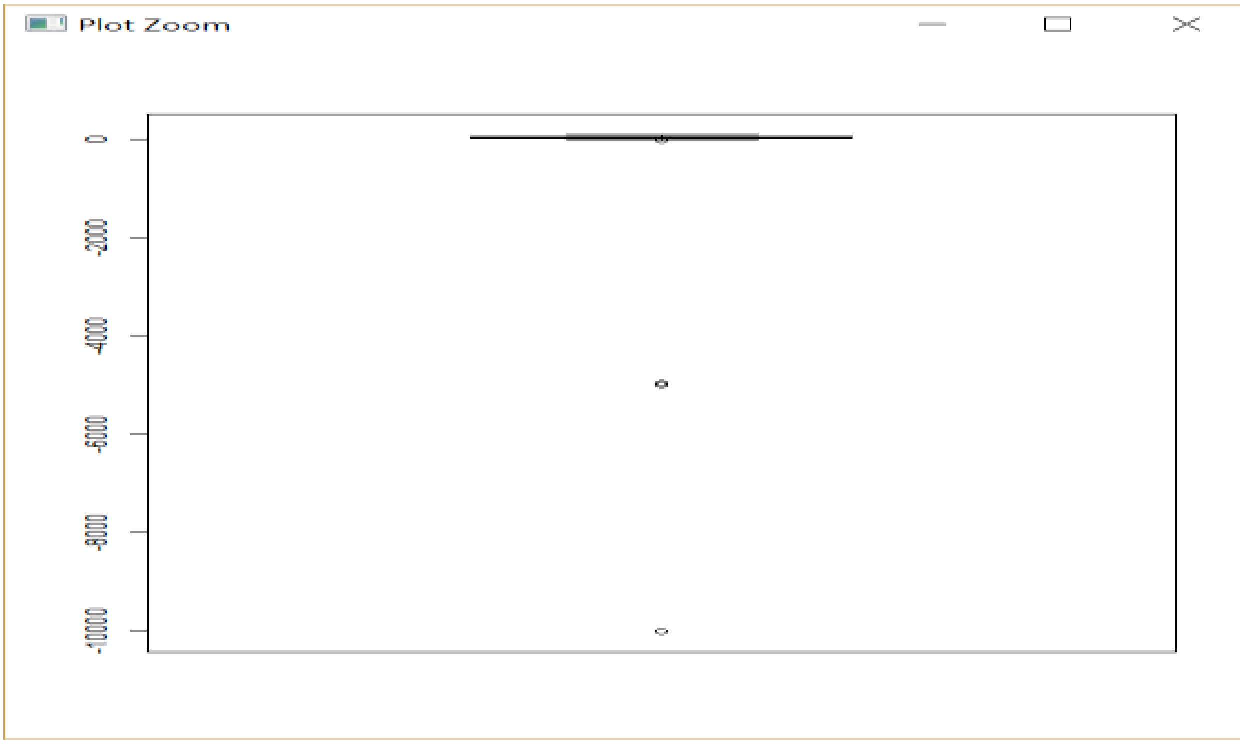
We follow the above steps to fill out na's with approximations for all the other fields.

Outliers detection.

We perform boxplot on individual fields to identy outliers.

boxplot(inputRead$TemperatureF)

We detect the outliers, which are deviating or lie far away in the boxplot. And eliminate them. In the below screenshot we see that the temperature has outliers.

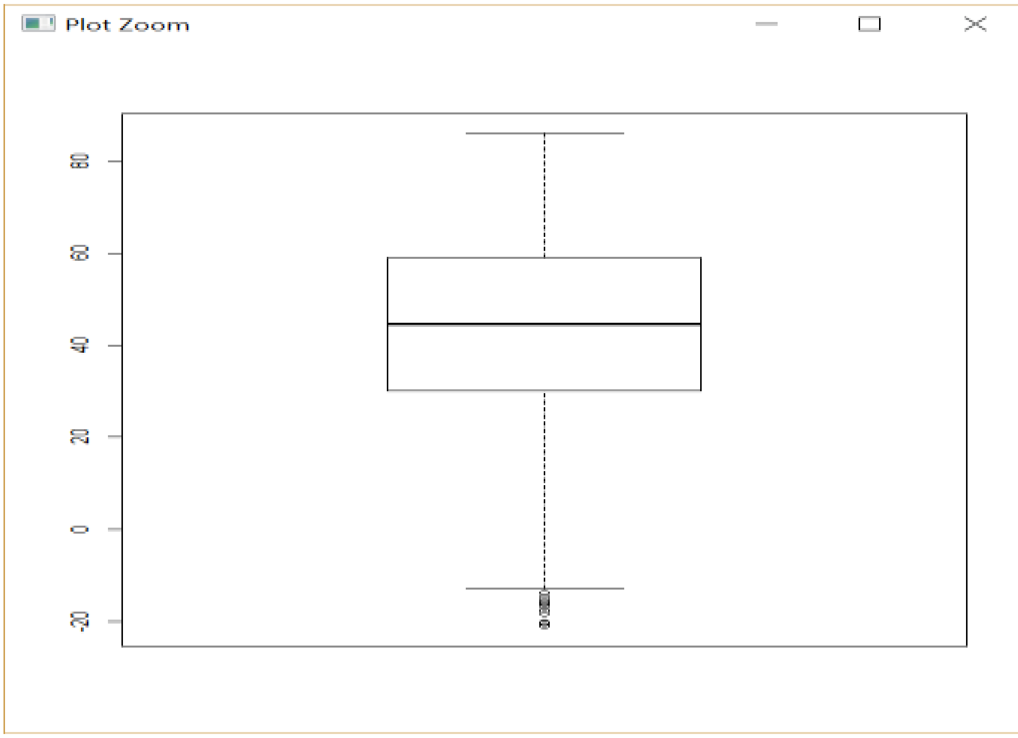


We filter out the rows with Values below -1000, to get the below box blot

inputRead[inputRead$TemperatureF < -1000,]

out <- which(inputRead$TemperatureF < -1000, arr.ind=TRUE)

inputRead <- inputRead[-out,]



3. PREDECTION

1. In this step, we first take the dataset and group it by BuildingID and Meter Number to get 78 distinct datasets. We first take the data from the cleansed csv file and store it in inputRead. We then subset the data based on the model selection step where we chose certain features to be used for prediction. We store this subset of data in df2.

Then, we split this df2 dataset into 78 different parts by grouping the data by BuildingID and Meter Number.

```r
library(tidyr)
library(grid)
library(MASS)
library(neuralnet)
library(FNN)

#Setting the working directory-

setwd("/home/sankalp/Documents/ADS/ads_midterm/Data")

#Reading the input data
inputRead <- read.csv("Cleansed.csv")
names(inputRead)

#Selecting only the selected features
df2 <- subset(inputRead, select = c(KWH,Hour,TemperatureF,Area,DayOfWeek,Month,BaseHourFlag,BuildingID,Meter_Number))

#Grouping the dataset by BuildingID and Meter_Number to get 78 different models
df<-split(df2, with(df2, interaction(BuildingID,Meter_Number)), drop = TRUE)
```

2. We apply regression for the 78 models in our dataset “df”.

```r
for (i in 1:78){
	dataset<- df[[i]]
	names(dataset)
	read_size <- floor(0.80 * nrow(dataset))
	set.seed(80)
	train_data_ind <- sample(seq_len(nrow(dataset)), size = read_size)
	train_data <- dataset[train_data_ind, ]
	test_data <- dataset[-train_data_ind, ]
	train_data[train_data==0]<-0.000001
	test_data[test_data==0]<- 0.000001
	varnames <- c("Hour", "TemperatureF", "Area", "DayOfWeek","Month","BaseHourFlag")
	modelfits <- vector(length(varnames), mode = "list")
	names(modelfits) <- varnames
	names(train_data)
	modelfits[[i]]<- lm(KWH~Hour+TemperatureF+Area+DayOfWeek+Month,data = train_data)
	summary(modelfits[[i]])
	library(forecast)
	pred = predict(modelfits[[i]], test_data)
	accuracy_pred=accuracy(pred, test_data$KWH)
	x <- list(accuracy_pred)
	print(x)
	 summary(modelfits[[i]])
}
```

```
Console ~/Documents/ADS/ads_midterm/Data/
[1271] 0.200000000 0.190909091 0.190909091 0.154545455 0.190909091 0.163636364 0.163636364 0.154545455 0.181818182 0.200000000
[1281] 0.227272727 0.218181818 0.227272727 0.200000000 0.227272727 0.209090909 0.181818182 0.218181818 0.209090909 0.236363636
[1291] 0.200000000 0.218181818 0.254545455 0.254545455 0.218181818 0.181818182 0.227272727
> head(test_data$KWH)
[1] 0.227272727 0.245454545 0.245454545 0.218181818 0.209090909 0.236363636
```

Regression summary-

Now we apply KNN algorithm to the datasets.

```
Neuralnets.R  modelSelection.R  knn.R  randomforest.R  part2-Prediction.R*  fullmod
Source on Save                                                    Run
df<-split(df2, with(df2, interaction(BuildingID,meter_Number)), drop = TRUE)

##########################################################

#Regression on 78 models
for (i in 1:78){
  dataset<- df[[i]]
  names(dataset)
  read_size <- floor(0.80 * nrow(dataset))
  set.seed(80)
  train_data_ind <- sample(seq_len(nrow(dataset)), size = read_size)
  train_data <- dataset[train_data_ind, ]
56:1  (Top Level)
```

```
Console ~/Documents/ADS/ads_midterm/Data/
                          ME            RMSE             MAE          MPE         MAPE
Test set -0.000003206457912 0.001382827064 0.001177420924 -1898.483395 1922.845466

[[1]]
                       ME           RMSE             MAE          MPE        MAPE
Test set 0.0001879128689 0.01019031315 0.007845020265 -55955.75532 56002.83524

[[1]]
                         ME            RMSE             MAE         MPE        MAPE
Test set 0.000001061415797 0.006942194467 0.006093543904 -41957.9802 41988.2539

[[1]]
                       ME            RMSE             MAE          MPE         MAPE
Test set 0.0002035741474 0.006690560266 0.005507107696 -135021.9747 142347.6216

[[1]]
                         ME             RMSE              MAE          MPE         MAPE
Test set 0.00001918888911 0.0002000565812 0.0001379060994 -3773.153066 6545.283984

[[1]]
                          ME             RMSE              MAE         MPE          MAPE
Test set -0.000002771611598 0.0001519357691 0.0001268547632 -156.417131 179.2585142

[[1]]
```

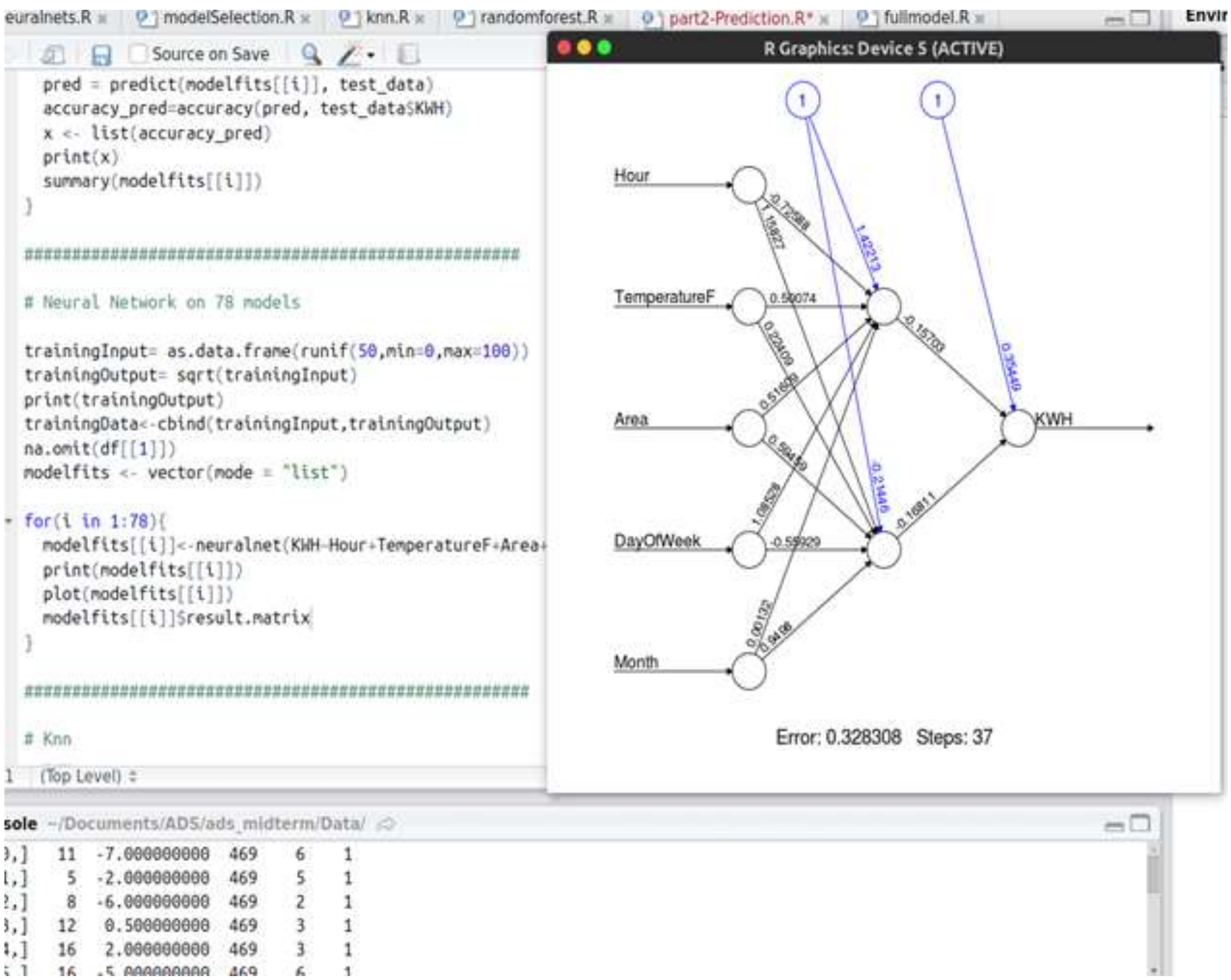
Prediction by KNN :

```
Console ~/Documents/ADS/ads_midterm/Data/
[1443] 0.010878011000 0.054908055000 0.016576016667 0.014763015000 0.011655011667 0.009842009667 0.015799016000
[1450] 0.052836053000 0.037814037667 0.015281015333 0.015540015667 0.057757057667 0.011655012000
Prediction:
   [1] 0.067750677667 0.045167118667 0.049683830333 0.090334237000 0.049683830333 0.063233965667 0.081300813000
   [8] 0.081300813000 0.040650407000 0.036133695000 0.103884372667 0.049683830333 0.076784101333 0.058717254000
  [15] 0.112917796000 0.076784101333 0.099367660667 0.081300813333 0.054200542000 0.045167118667 0.090334237000
  [22] 0.099367660667 0.085817525000 0.063233966000 0.081300813333 0.126467931667 0.054200542000 0.036133695000
  [29] 0.063233966000 0.040650407000 0.054200542000 0.108401084333 0.040650406667 0.085817525000 0.121951219667
  [36] 0.036133695000 0.090334237000 0.045167118667 0.054200542000 0.108401084000 0.090334237000 0.063233966000
  [43] 0.121951220000 0.045167118667 0.090334237000 0.067750677667 0.126467931667 0.049683830333 0.054200542000
  [50] 0.045167118667 0.054200542000 0.058717254000 0.040650406667 0.049683830333 0.103884372333 0.054200542000
  [57] 0.076784101333 0.085817525000 0.072267389667 0.054200542000 0.094850948667 0.099367660667 0.121951220000
  [64] 0.063233966000 0.049683830333 0.054200542000 0.103884372667 0.058717254000 0.045167118667 0.045167118667
  [71] 0.049683830333 0.072267389667 0.072267389667 0.067750677667 0.045167118667 0.076784101333 0.045167118667
  [78] 0.112917796000 0.117434508000 0.076784101333 0.054200542000 0.054200542333 0.076784101333 0.094850949000
  [85] 0.045167118667 0.049683830333 0.072267389667 0.072267389667 0.054200542000 0.072267389667 0.094850949000
  [92] 0.126467931667 0.049683830333 0.117434508000 0.090334237000 0.045167118667 0.081300813000 0.054200542000
  [99] 0.081300813000 0.072267389667 0.112917796000 0.058717254000 0.045167118667 0.045167118667 0.063233966000
 [106] 0.018066847667 0.022583559333 0.027100271000 0.031616983000 0.049683830333 0.027100271000 0.049683830333
 [113] 0.018066847667 0.027100271000 0.031616983000 0.022583559333 0.027100271000 0.040650407000 0.031616983000
 [120] 0.063233966000 0.045167118667 0.031616983000 0.067750678000 0.067750678000 0.049683830333 0.018066847667
 [127] 0.031616983000 0.049683830333 0.027100271333 0.022583559333 0.013550136000 0.054200542333 0.049683830333
 [134] 0.013550136000 0.045167118667 0.036133695000 0.036133694667 0.058717254333 0.018066847667 0.067750678000
 [141] 0.036133695000 0.018066847667 0.067750678000 0.031616983000 0.027100271333 0.040650406667 0.045167118667
```

Finally, we apply neural network on our dataset

```
 modelfits[[i]]<-
neuralnet(KWH~Hour+TemperatureF+Area+DayOfWeek+Month,data=df[[i]],hidden=2,threshol
d=0.01)
 print(modelfits[[i]])
 plot(modelfits[[i]])
 modelfits[[i]]$result.matrix
```

We run this code in for loop for each model.



3. We apply Regression, KNN and neural network on the entire datasets

When we apply regression on the full dataset, we get the following summary-

```
Console ~/Documents/ADS/ads_midterm/Data/
                         MPE                    MAPE
Test set 0.000000000005832253551 0.000000000005832253551
> summary(modelfit)

Call:
lm(formula = KWH ~ Hour + TemperatureF + Area + DayOfWeek + Month,
    data = train_data)

Residuals:
                         Min                          1Q                      Median                          3Q
-0.00000000000000000042168761 -0.0000000000000000000005029  0.0000000000000000000008702  0.0000000000000000000022008
                         Max
 0.0000000000000000000055137

Coefficients: (1 not defined because of singularities)
                              Estimate                    Std. Error             t value
(Intercept)   0.00000099999999999994023892533  0.000000000000000000000242413782 412517800335574.50000
Hour          0.00000000000000000000015517992  0.000000000000000000000011442937            1.35612
TemperatureF -0.00000000000000000000009952212  0.000000000000000000000009537823           -1.04345
Area                                        NA                              NA                  NA
DayOfWeek    -0.00000000000000000000060870534  0.000000000000000000000039245123           -1.55103
Month         0.00000000000000000000035335108  0.000000000000000000000026162770            1.35059
                         Pr(>|t|)
(Intercept)  < 0.0000000000000002 ***
Hour                     0.17512
TemperatureF             0.29679
Area                          NA
DayOfWeek                0.12095
Month                    0.17688
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0000000000000000000005758744 on 5369 degrees of freedom
Multiple R-squared:  0.5000096, Adjusted R-squared:  0.4996371
F-statistic: 1342.302 on 4 and 5369 DF,  p-value: < 0.00000000000000022204
```

By applying all the algorithms on our entire dataset, we get a sense of which model is supposed to perform better based on the RMSE, MAPE, MSE.

RMSE, MAPE, MSE for all models-

1. Regression-

RMSE- 0.1374464
MAE- 0.137446
MAPE- 124232.1

2. KNN-

RMSE- 0.032355
MAE- 0.53440
MAPE- Inf

3. Neural Network-

RMSE- 0.503944
MAE- 0.342290
MAPE- Inf

After observing the RMSE values of the models, we choose KNN as our model.

4. Classification

Classification:

Logistic Regression:

In logistic Regression classification we make use of the library(caret).
We take the cleansed data, and find out the percentage of High, Low values for

table(inputRead$Base_Hour_Class)/nrow(inputRead)

Divide the train and test data, as below

```
smp_size=floor(0.54*nrow(inputRead))

set.seed(123)

train_ind<-sample(seq_len(nrow(inputRead)),size=smp_size)

train<-inputRead[train_ind,]

test<-inputRead[-train_ind,]
```

We fit the logistic Regression model using the below code:

```
fit<-
glm(Base_Hour_Class~BuildingID+Consumption_Type+Meter_Number+Month+Hou
r+TemperatureF+Dew_PointF+Humidity+Sea_Level_PressureIn+WindDirDegrees
+KWH+DayOfWeek+WeekDay,data=train,family=binomial(link="logit"))
```

Generated the Confusion Matrix and write to the CSV file using

```
cm<-confusionMatrix(test$Base_Hour_Class,pred)

tocsv <- data.frame(cbind(t(cm$overall),t(cm$byClass)))

write.csv(tocsv,file="LogisticRegression_ConfusionMatrix.csv",row.name
s=FALSE)
```

We generate the ROC curve by

```
prediction<-prediction(test$predictions,test$Base_Hour_Class)

performance<-performance(prediction,measure="tpr",x.measure="fpr")

plot(performance,main="ROC Curve",xlab="1-
Specificity",ylab="Sensitivity")
```

LogisticRegression_Prediction.csv,LogisticRegression_ConfusionMatrix.csv were generated.

KNN Algorithm:

KNN alogrithm works on normalized and numerical data. Hence the columns chosen were numeric.

```
normalize <- function(x) {
  return ((x - min(x)) / (max(x) - min(x))) }


inputReadNumeric <- subset(inputRead,
select=c('TemperatureF','Dew_PointF','Humidity','Sea_Level_PressureIn'
,'VisibilityMPH','WindDirDegrees','KWH','WeekDay','DayOfWeek','Base_Ho
ur_Class'))

inputReadNormalized <-
as.data.frame(lapply(inputReadNumeric[,c('TemperatureF','Dew_PointF','
Humidity','Sea_Level_PressureIn','VisibilityMPH','WindDirDegrees','KWH
','WeekDay','DayOfWeek')], normalize))
```

Use library(class) to fit the KNN training algorithm as below,80 was chosen since it is the square root of the number of rows that were present the dataset.

```
m1<-knn(train=train,test=test,cl=train_target,k=80)
```

Random Forest:

We create the train and test dataset that are created as mentioned above and We fit the data for Random Forest using

rforest <- randomForest(concatVal, train, ntree=100,importance=T)

We consider 'TemperatureF','Dew_PointF','Humidity','Sea_Level_PressureIn','VisibilityMPH','WindDirDegrees','KWH','WeekDay','DayOfWeek','Base_Hour_Class' numeric values since random forest works best with Random Forest.

RandomForest_Predictions.csv, RF_ConfusionMatrix.csv were the output files generated.

Neural Network:

We use the nnet package to perform Neural Network Classification. We normalize the input data using the normalize function, and we consider only the numeric data 'TemperatureF','Dew_PointF','Humidity','Sea_Level_PressureIn','VisibilityMPH','WindDirDegrees','KWH','WeekDay','DayOfWeek','Base_Hour_Class.

We split the data into train and test data. We try to fit the neural network algorithm using he below

neuNet = nnet(train[,-10], ideal[train_ind,], size=10, softmax=TRUE)

Calculate the confusion matrix using the below code

confusionMatrix(test$predictions,test$Base_Hour_Class)

We get the accuracy of 0.73 with neural networks

2) Running 78 Models

Random Network:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
2	0.916048	0.831418	0.906369	0.925025	0.531696	0	1	0.921053	0.910366	0.921053	0.910366	0.921053	0.921053	0.921053	0.531696	0.48972	0.531696	0.915709243
3	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
4	0.95047	0.856082	0.943224	0.957038	0.778766	########	0.886114	0.886338	0.968689	0.889401	0.967742	0.889401	0.886338	0.887867	0.221234	0.196088	0.220472	0.927513194
5	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
6	0.95353	0.904354	0.946484	0.959892	0.580498	0	0.038469	0.935835	0.966317	0.952557	0.954212	0.952557	0.935835	0.944122	0.419502	0.392585	0.412138	0.951076031
7	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
8	0.964204	0.91859	0.957921	0.969786	0.675298	0	0.312216	0.949961	0.971053	0.940402	0.975822	0.940402	0.949961	0.945158	0.324702	0.308454	0.328002	0.960506769
9	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
10	1	1	0.998984	1	0.963892	1.13E-58	NA	1	1	1	1	1	1	1	0.963892	0.963892	0.963892	1
11	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
12	0.96775	0.922304	0.961747	0.973045	0.70772	0	0.286954	0.950478	0.974883	0.939863	0.979452	0.939863	0.950478	0.94514	0.29228	0.277806	0.295582	0.962680616
13	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
14	0.9446	0.861628	0.936988	0.951542	0.717916	########	0.005489	0.882883	0.96885	0.917603	0.954656	0.917603	0.882883	0.899908	0.282084	0.249047	0.27141	0.92586622
15	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
16	0.939787	0.864048	0.931896	0.947016	0.675305	0	0.001821	0.926448	0.9462	0.892238	0.963971	0.892238	0.926448	0.909021	0.324695	0.300813	0.337144	0.936323862
17	Accuracy	Kappa	AccuracyL	AccuracyU	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.Accuracy
18	0.968973	0.929	0.963065	0.974168	0.681587	0	0.005007	0.964058	0.971269	0.940031	0.983006	0.940031	0.964058	0.951893	0.318413	0.306968	0.326551	0.967663082

We ran the random network, on 78 models, which is the combination of Building ID and MeterNumber, We see that the accuracy for most models are in the range of 0.95 and above. Hence we conclude that Random Network gives us the best predictions. We perform the same steps that were done on the entire set of data.

KNN:

We perform the same steps that were done on the entire data set, but here we split the data into different datasets using the below

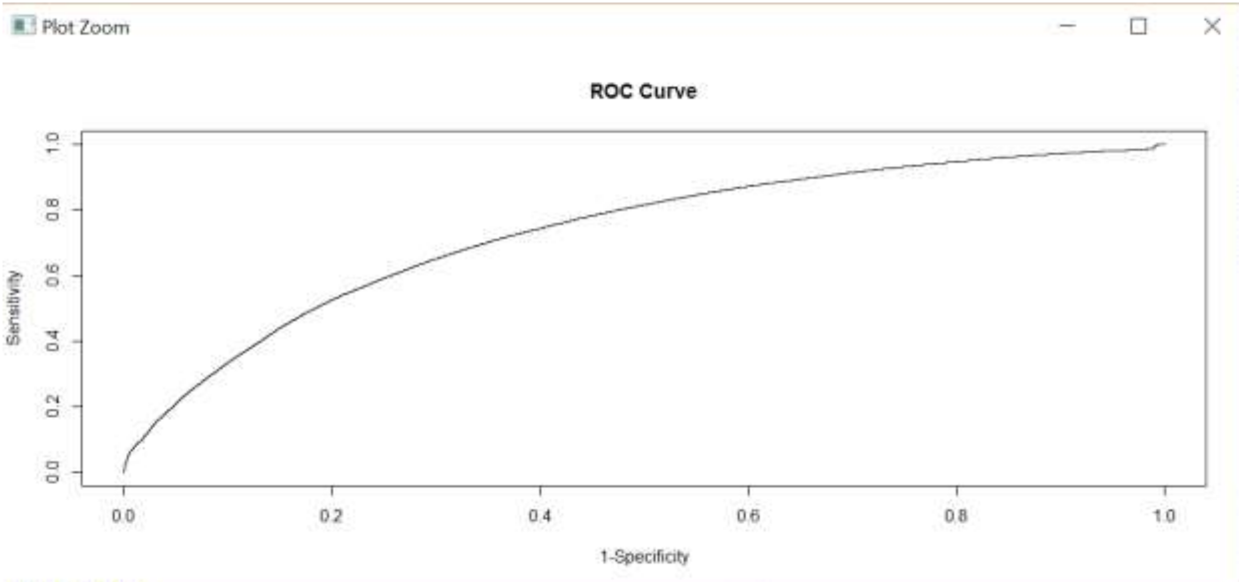
inputDateRead_Group <- split(dataRead, with(dataRead, interaction(BuildingID,Meter_Number)), drop = TRUE)

Below is the generated confusion matrix written to a file.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.698951	0.393212	0.675966	0.721213	0.556447	4.08E-32	0.113108	0.685675	0.709534	0.65298	0.73903	0.65298	0.685675	0.668928	0.443553	0.304133	0.465762	0.697604	5198_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.797586	0.236552	0.778396	0.815815	0.921009	1	3.98E-41	0.812984	0.618056	0.961268	0.220844	0.961268	0.812984	0.880929	0.921009	0.748766	0.778936	0.71552	5199_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.582556	0.085313	0.559527	0.605319	0.811849	1	2.85E-57	0.593919	0.533528	0.846006	0.233418	0.846006	0.593919	0.697896	0.811849	0.482172	0.56994	0.563723	5286_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.787281	0.493992	0.767772	0.805861	0.722039	1.01E-10	9.26E-05	0.823083	0.69428	0.874899	0.601709	0.874899	0.823083	0.8482	0.722039	0.594298	0.679276	0.758681	5290_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.98869	0.816779	0.982395	0.993178	0.97381	1.52E-05	3.64E-05	1	0.988386	0.698413	1	0.698413	1	0.82243	0.02619	0.02619	0.0375	0.994193	5304_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.789358	0.421988	0.769907	0.807873	0.808557	0.981832	2.10E-16	0.81479	0.681948	0.915396	0.465753	0.915396	0.81479	0.862168	0.808557	0.658804	0.719693	0.748369	5306_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.779363	0.400974	0.759606	0.798217	0.794731	0.949876	1.24E-10	0.816298	0.636364	0.896813	0.472222	0.896813	0.816298	0.854664	0.794731	0.648738	0.723381	0.726331	5308_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.767289	0.419594	0.74719	0.786523	0.766191	0.468858	1.90E-12	0.795845	0.673709	0.8888	0.501748	0.8888	0.795845	0.839758	0.766191	0.609769	0.686059	0.734777	5310_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID
0.778144	0.434281	0.758346	0.797042	0.79352	0.949562	4.14E-23	0.791003	0.728723	0.918072	0.475694	0.918072	0.791003	0.849814	0.79352	0.627677	0.68369	0.759863	5311_1
Accuracy	Kappa	AccuracyL	AccuracyL	AccuracyN	AccuracyP	Mcnemarl	Sensitivity	Specificity	Pos.Pred.\	Neg.Pred.'	Precision	Recall	F1	Prevalenc	Detection.	Detection.	Balanced.	BID_MID

The accuracy generated by different models is in the range of 0.70 and 0.80.

3) RoC Curve for Logistic Regression



- **Confustion Matric for Logistic Regression**

```
> confusionMatrix(test$Base_Hour_Class,pred)
Confusion Matrix and Statistics

          Reference
Prediction  High   Low
      High 18445 55677
      Low  37707 25976

               Accuracy : 0.3223
                 95% CI : (0.3199, 0.3248)
    No Information Rate : 0.5925
    P-Value [Acc > NIR] : 1

                  Kappa : -0.3366
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.3285
            Specificity : 0.3181
```

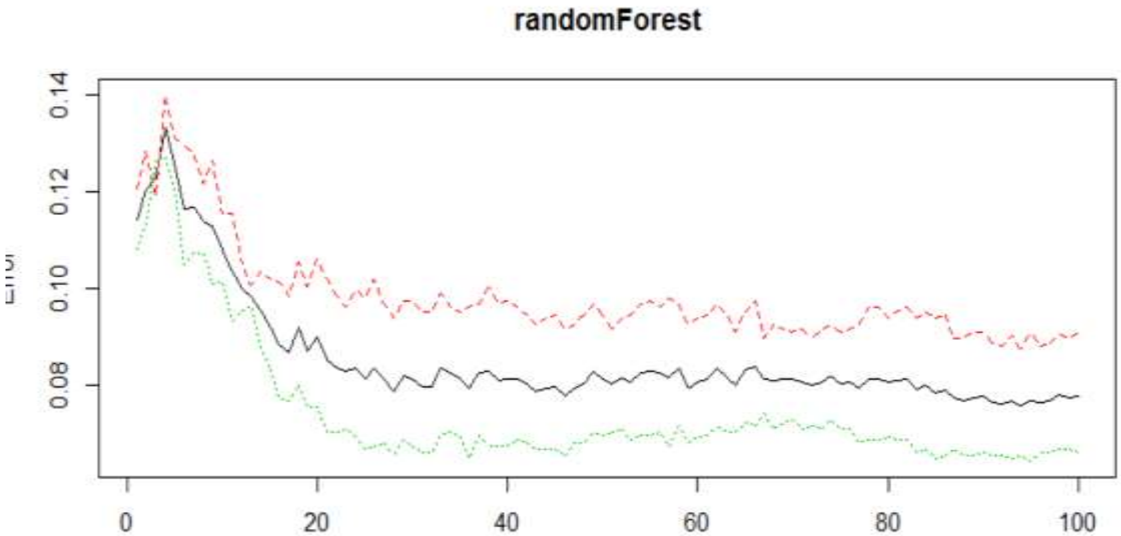
- **Confusion Matrix for KNN Algorithm**

```
> confusionMatrix(test_target,m1)
Confusion Matrix and Statistics

          Reference
Prediction High  Low
      High 1337  961
      Low   713 1852

               Accuracy : 0.6558
                 95% CI : (0.6422, 0.6691)
    No Information Rate : 0.5784
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3056
 Mcnemar's Test P-Value : 1.57e-09

            Sensitivity : 0.6522
            Specificity : 0.6584
         Pos Pred Value : 0.5818
         Neg Pred Value : 0.7220
             Prevalence : 0.4216
         Detection Rate : 0.2749
   Detection Prevalence : 0.4725
      Balanced Accuracy : 0.6553

       'Positive' Class : High
```

- **Confusion Matrix for Random Forest**

```
Confusion Matrix and Statistics

          Reference
Prediction High  Low
      High 1493  147
      Low   147 1715

               Accuracy : 0.916
                 95% CI : (0.9064, 0.925)
    No Information Rate : 0.5317
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.8314
 Mcnemar's Test P-Value : 1

            Sensitivity : 0.9211
            Specificity : 0.9104
         Pos Pred Value : 0.9211
         Neg Pred Value : 0.9104
             Prevalence : 0.5317
         Detection Rate : 0.4897
   Detection Prevalence : 0.5317
      Balanced Accuracy : 0.9157

       'Positive' Class : Low
```

- **ROC graph for Random Forest**



- **Confusion Matrix of Neural Network**

```
> confusionMatrix(test$predictions,test$Base_Hour_Class)
Confusion Matrix and Statistics

          Reference
Prediction  High   Low
      High 58978 22702
      Low  15144 40981

               Accuracy : 0.7254
                 95% CI : (0.723, 0.7277)
    No Information Rate : 0.5379
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.4429
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.7957
            Specificity : 0.6435
         Pos Pred Value : 0.7221
         Neg Pred Value : 0.7302
             Prevalence : 0.5379
         Detection Rate : 0.4280
   Detection Prevalence : 0.5927
      Balanced Accuracy : 0.7196

       'Positive' Class : High
```

-
-

4) Going by the Confusion Matrix the predictions given by the randomForest were found to be more accurate than the other models.

Random Forest gives the high accuracy of 0.916 as compared to 0.65 and 0.32 given by KNN and Logistic Regression respectively.

5. CLUSTERING

We created a Json file , from where we can change the configuration of the clustering. It has three option, to choose the cluster, name the distance_measure and the nstart.

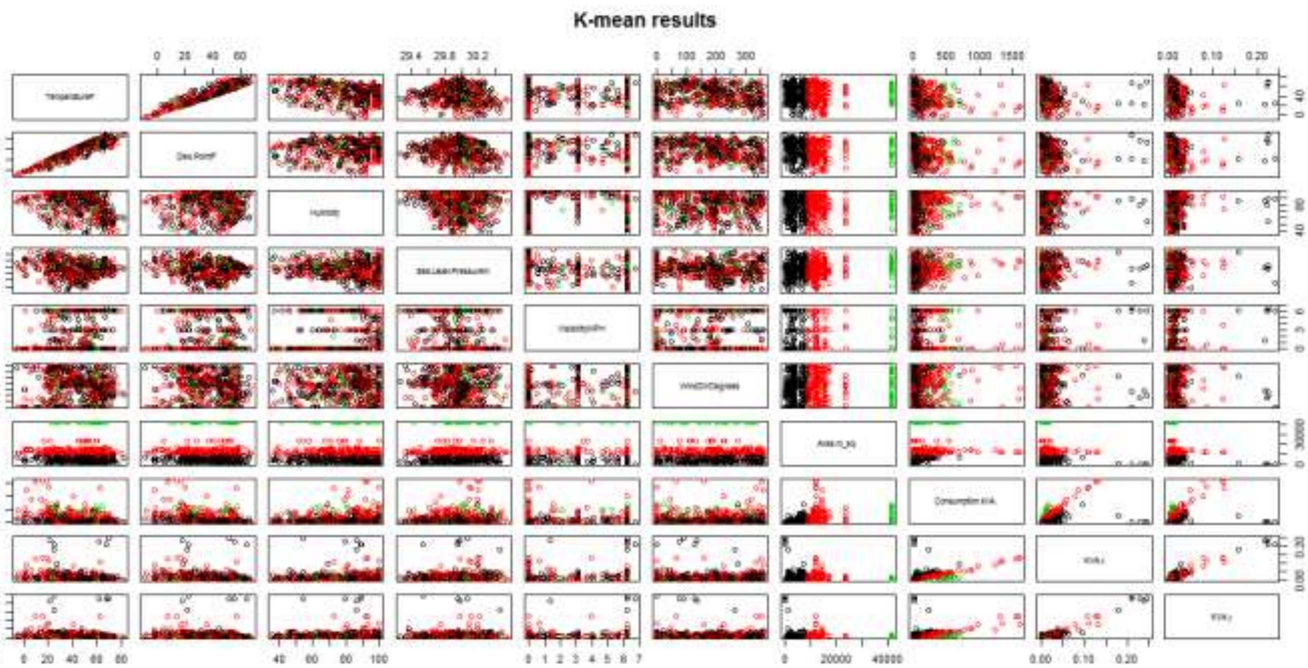
```
{
    "Clusters": "3",
    "Distance_Measure":"Euclidean",
    "nstart" : "10"
}
```

Code snippet

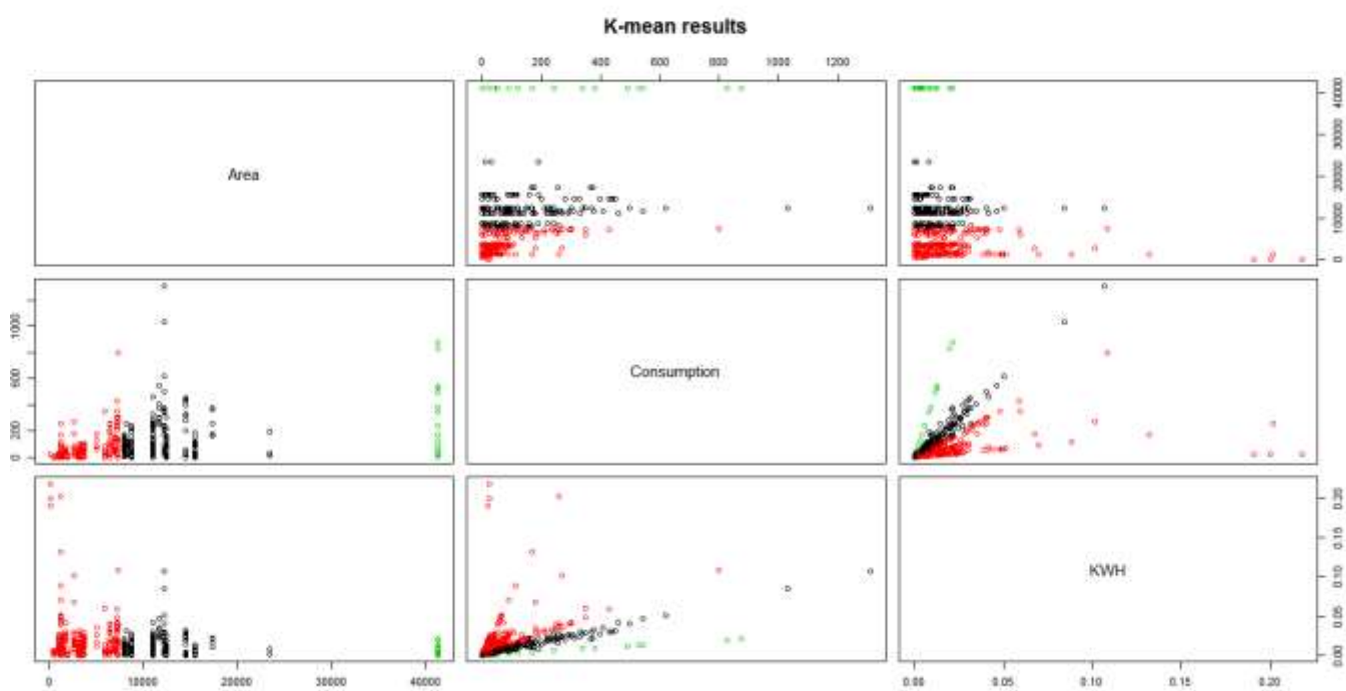
```
### Reading the configuration from json file.
if(json_data$Distance_Measure == 'Euclidean'){
  km.out <- kmeans(inputRead,as.numeric(json_data$Clusters),nstart = as.numeric(json_data$nstart))

} else if (json_data$Distance_Measure == 'manhattan' || json_data$Distance_Measure == 'correlation'){

  km.out <- kmeans(inputRead,as.numeric(json_data$Clusters),iter.max = 1000,nstart=as.numeric(json_data$r
```

K-Means

The data is huge and it has large number of rows. If we apply the k-means on total rows, it's is difficult to understand the clustering. We deployed the graph for 10 columns. Below are the results ::



Hence, We decided to proceed only with three values, which are related to the building more directly. We choose area, consumption, KWH. Below are the cluster plot ::

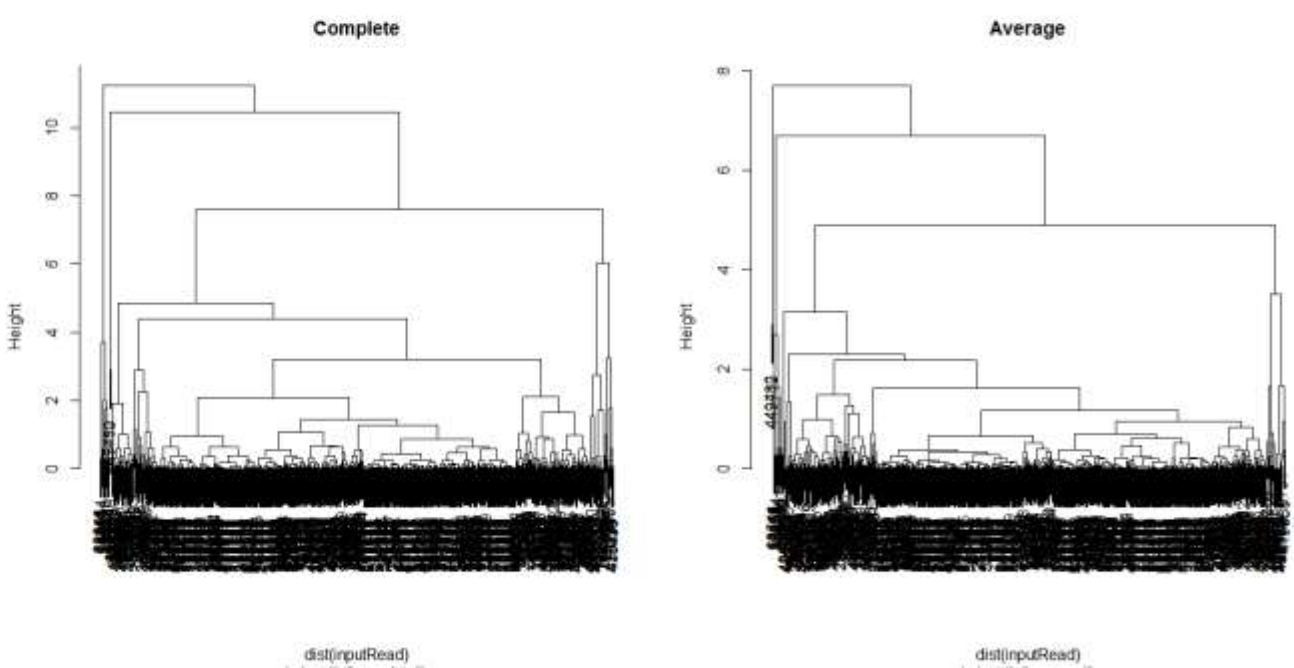


We can observe that mostly all the clusters are separated from each other and there is very less overlapping.

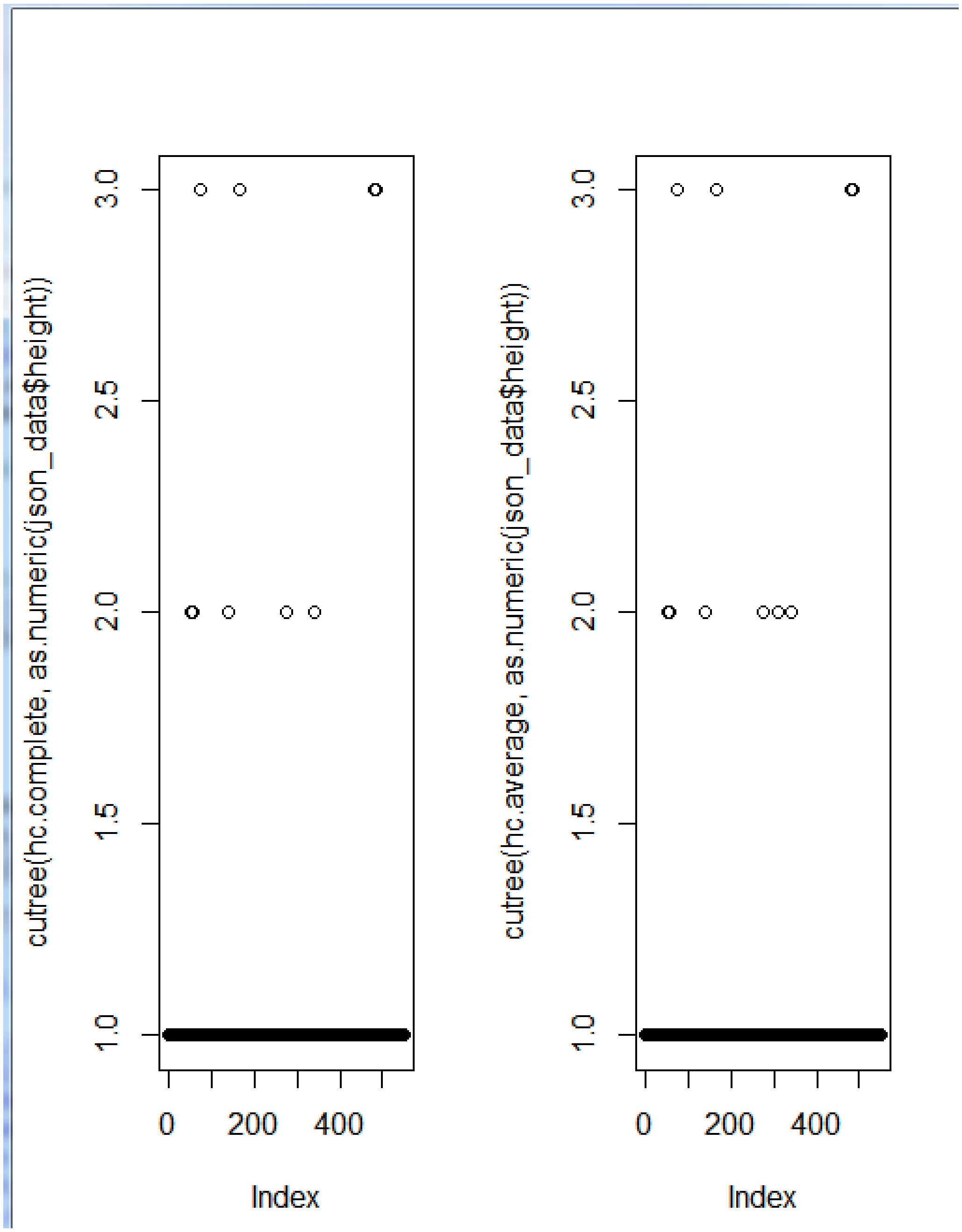
Hierarchical clustering

In case of Hierarchical clustering, we don't provide the cluster size. we can get the number of clusters by cutting Dendrogram at any point.

```
######## Hierarchical clustering########

inputRead <- read.csv("Cleansed.csv")
sample_data <- sample(1:nrow(inputRead),round(0.001*nrow(inputRead)))
kmeansdata <- inputRead[sample_data,]
#inputRead=scale(kmeansdata[, c(8,9,10,11,12,15,20,21,22,27)]) #Scaling the data
inputRead=scale(kmeansdata[, c(19,20,21)]) #Scaling the data
hc.complete=hclust(dist(inputRead),method="complete") # Complete linkage type
hc.average=hclust(dist(inputRead),method="average")  # Average linkage type

par(mfrow=c(1,2)) #Plotting in a matrix form
plot(hc.complete,main='Complete')
plot(hc.average,main='Average')

# cutting the graph to see the different number of clusters
plot(cutree(hc.complete,3))
plot(cutree(hc.average,3))
```



Now, we cut the graph to see the different number of clusters at a point. We choose the height as 3. Below is the plot after treecut-



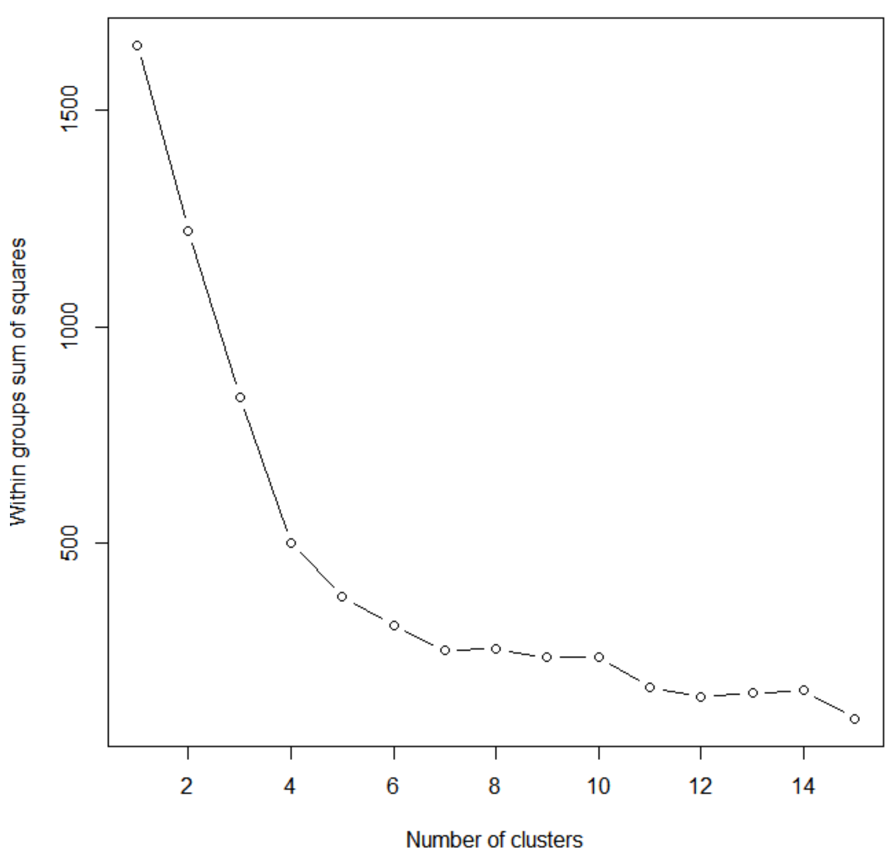
We find that when the tree is cut by height of 3, we can three set of data on the plot. One lying around 1.0, another at 2.0 and few at top 3.0.

Bend Graph

Bend graph is used to find the optimal value of k. k is the number of cluster to be used.

```
### Bend Graph

sample_data <- sample(1:nrow(inputRead),round(0.001*nrow(inputRead)))
kmeansdata <- inputRead[sample_data,]
nrows(kmeansdata)
inputRead=scale(kmeansdata[, c(19,20,21)]) #Scaling the data
wss <- (nrow(inputRead)-1)*sum(apply(inputRead,2,var))
for(i in 2:15){
  wss[i] <- sum(kmeans(inputRead,centers = i)$withinss)
}
plot(2:15,wss,type="l")
plot(1:15, wss,type="b",xlab = "Number of clusters", ylab="Within groups sum of squares")
```

Plot



Going through the graph plot, take the number of cluster where the slope is more. we see that till cluster , there is a steep slope. After cluster 4, there is change in plotting. From cluster 4-5, 5-6, 6-7, we have the decreasing slope. From cluster 8, we can see the slope is not increasing effectively. Since, we see that from cluster 4 – 5, is a change in trend and we see an effective curse, we take the value of k as 5.

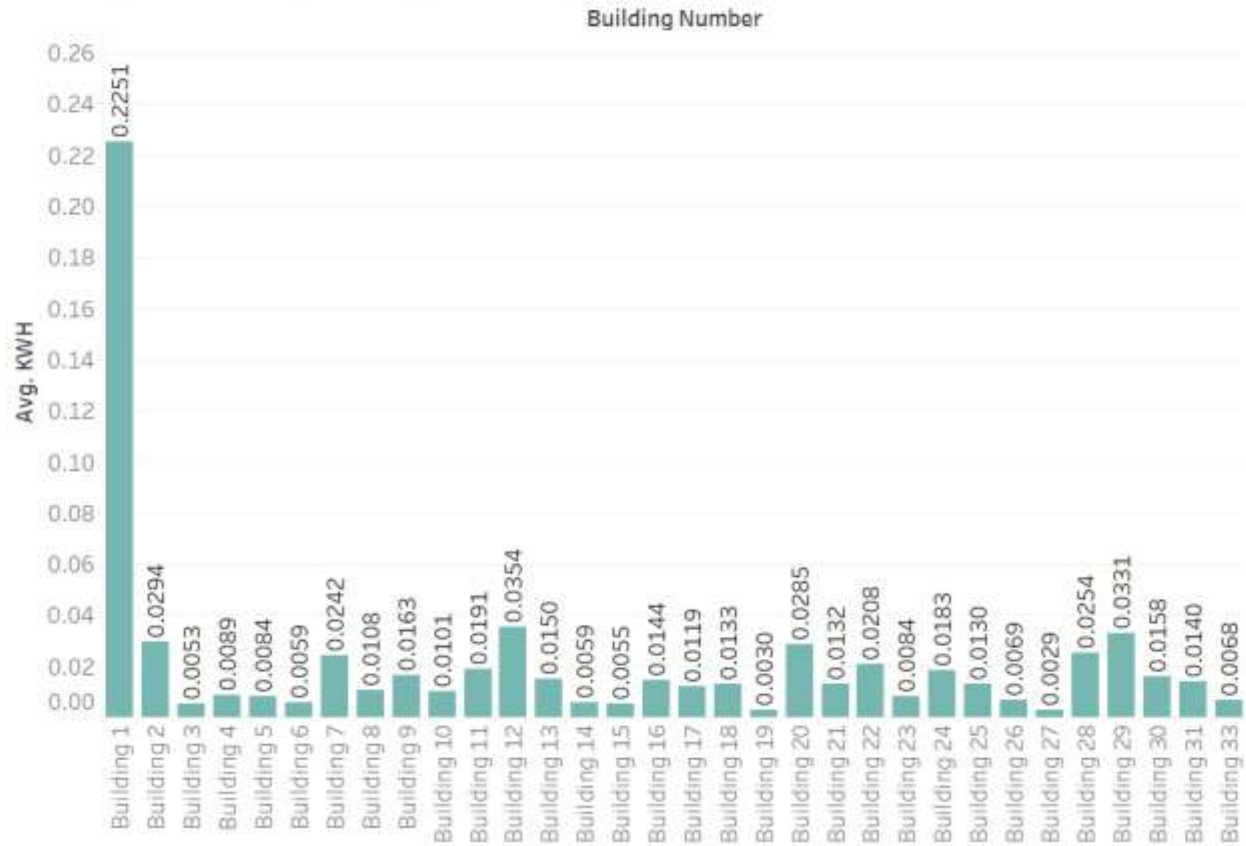
6. Visualization and DashBoard

Part 1: Exploratory data analysis

Dashboard 1

In the below figure, we are finding the relationship between the average KWH consumption, and individual building names. We use KWH as our row, and building names in columns. This consumption is average consumption for each building over the entire course of time.

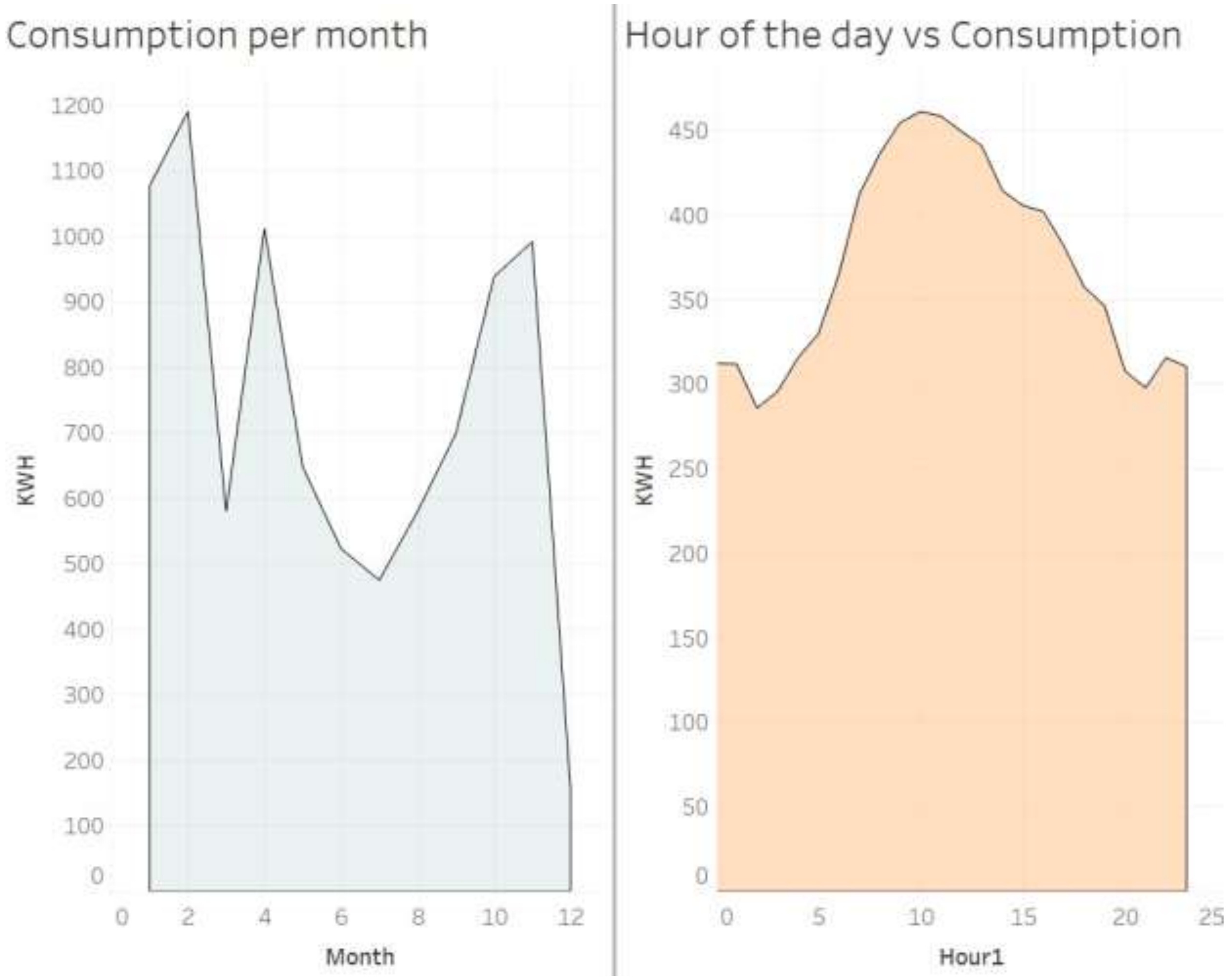
Average consumption by building name



Dashboard 2-

Two important relationship we considered while visualization were average consumption per month, and average consumption for each hour of the day. We have plotted two different graphs, and pitched them together in the same dashboard.

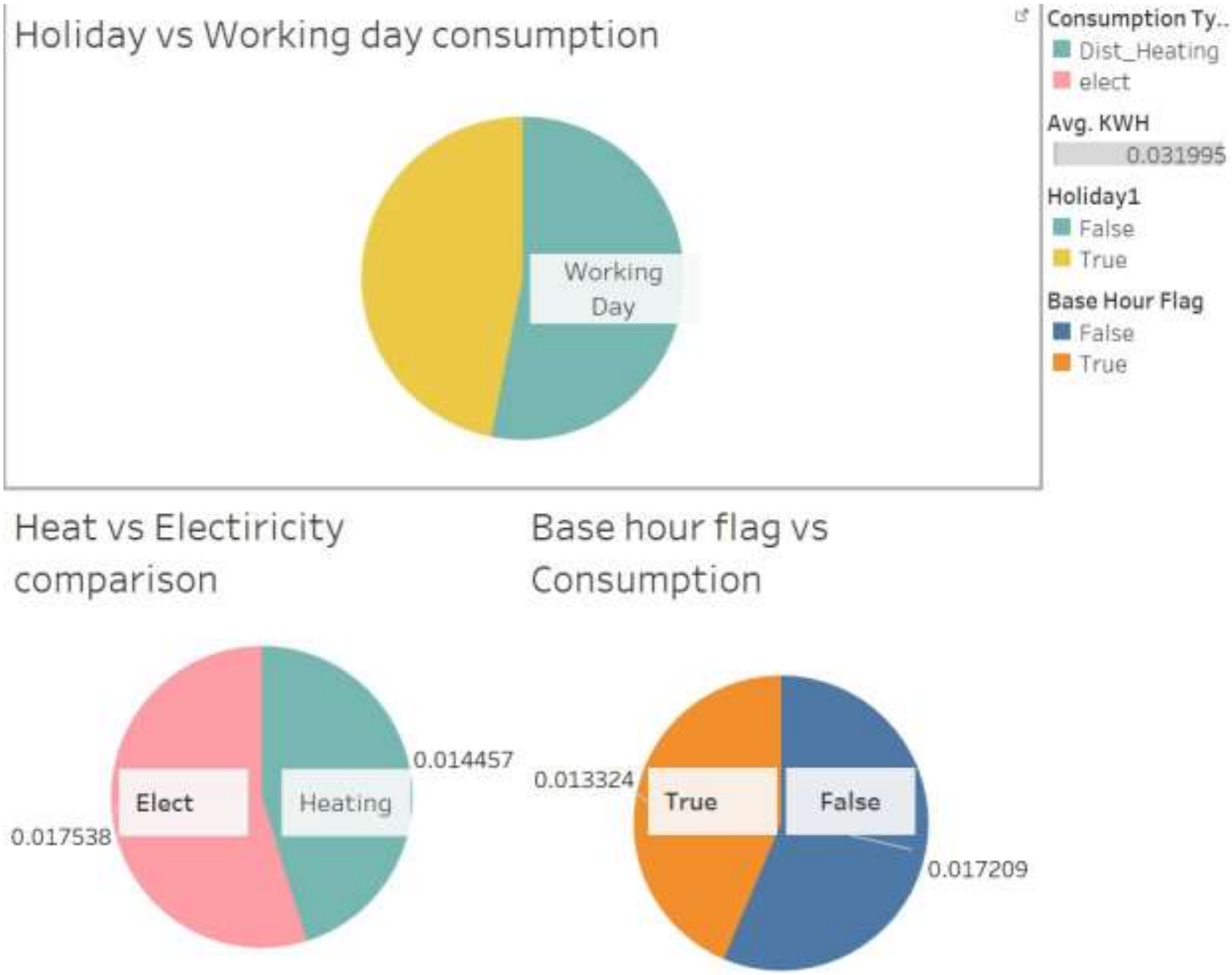
Our findings reveal that the consumption was at its peak during the day, and that the consumption during winter (November to February) was higher as compared to summers.



Dashboard 3-

Now we plot three different pie charts showing the relationships between holiday and working days, heat consumption vs electricity consumption, and relationship between base hour flag and consumption.

Our findings were that the Consumption during holidays was relatively less than working days. We also realized that the electricity consumption was considerably larger than heating consumption.

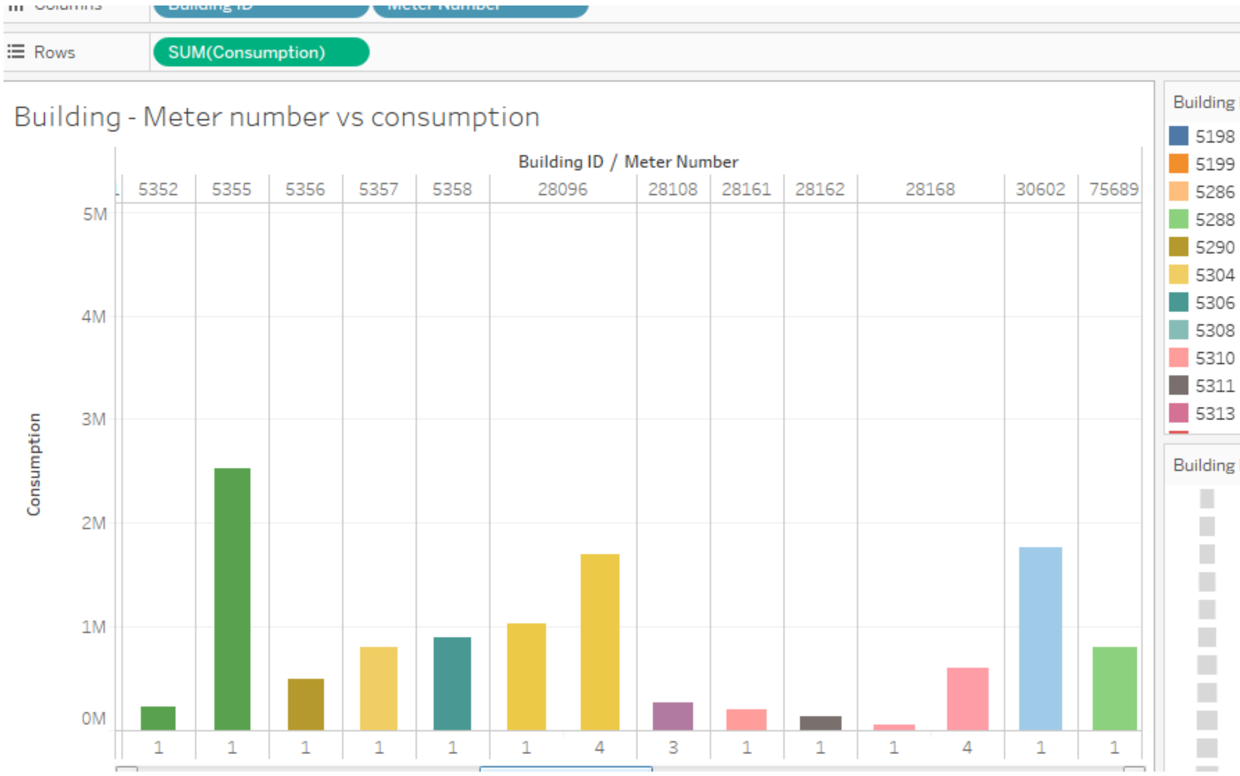


Dashboard 4-

Following is the plotting of polygon graph which represents the consumption by every building in the drop box. The graph also shows a general trend as per the time line, which in this case shows a decreasing trend.

Dashboard 5-

We are merging the data of Building Id and Meter number vs the consumption. The graph can show the building number and the meter number making a unique graph display against consumption.

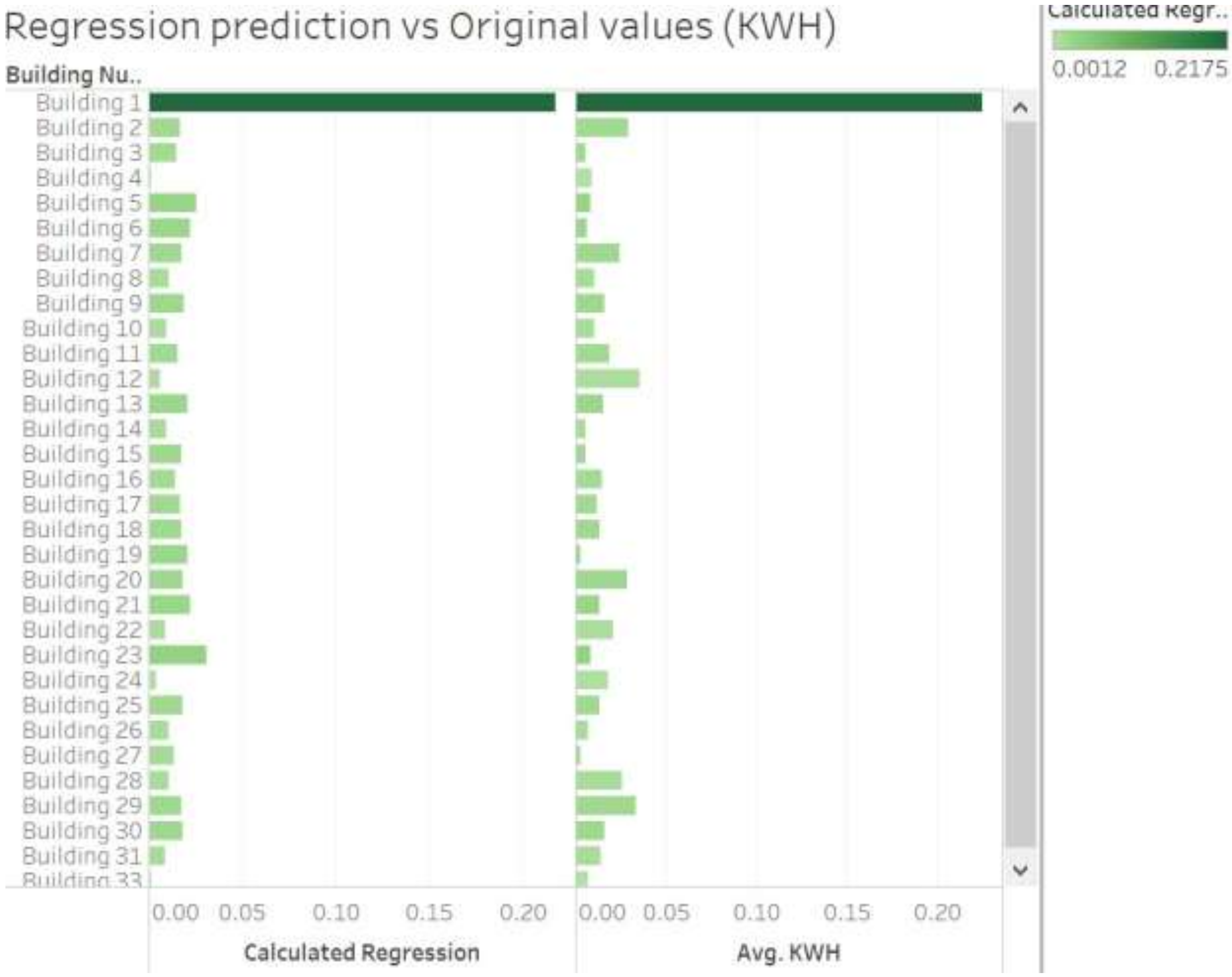


<u>Part 2:</u> Building usage – Electricity and heating

We are displaying the usage per building on electricity and heating computation. The filters are building number and Temperature. The rows are consumption and temperature and the columns are Months. By selecting each building, we can see the dynamic change in data. Each building will display the month, average consumption data and average temperature when hover.

Part 3- Prediction.

After integrating R with Tableau, we write a script for regression and plot two graphs side by side for comparison. We find that although the predicted values are different, but the trend is in agreement with the original consumption graph.

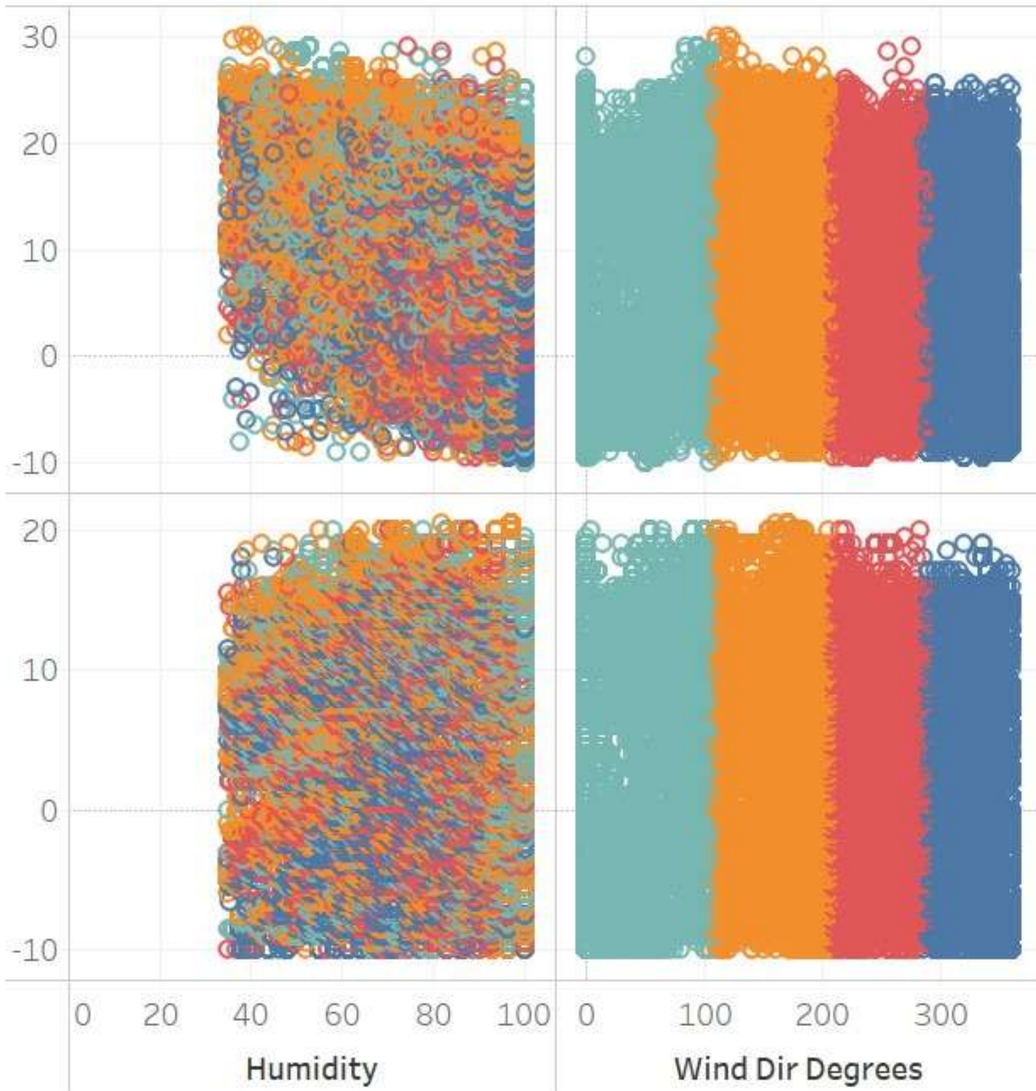


Following is the regression script for R in Tableau-

```
SCRIPT_REAL( "
  kwh <- .arg1
  temperature <- .arg2
  hour <- .arg3
  day_of_week <- .arg4
  month<- .arg5
  area <- .arg6

  fit <- lm(kwh ~ temperature + hour + day_of_week + month + area)

  fit$fitted
"
, AVG( [KWH] ), AVG([Hour1]), AVG([Temperature F]) ,AVG([Day Of Week]), AVG([Month]),
AVG([Area]))
```

3. Clustering

As per our findings in part 2, we have chosen K-means as our algorithm for visualization. In tableau, we have used rserve as our library to connect R to tableau. In the dashboard below, we have contrasted two different graphs, first graphs clusters the KWH values after running our K-means algorithm script in Tableau. In second graph, we have used our original cleansed data for contrasting with the k-means graph.


30
20
10
0
-10
20
10
0
-10
0 20 40 60 80 100
Humidity
0 100 200 300
Wind Dir Degrees