Contents

1. Clustering (k-means)

K-Means is a clustering approach that belogs to the class of unsupervised statistical learning methods. The general idea of a clustering algorithm is to partition a given dataset into distinct, exclusive clusters so that the data points in each group are quite similar to each other.

Let's read our building records as one large dataset of around 6 million and try to find cluster's.

1) Reading the csv and removing features which we would not use and will not make sense in the clustering

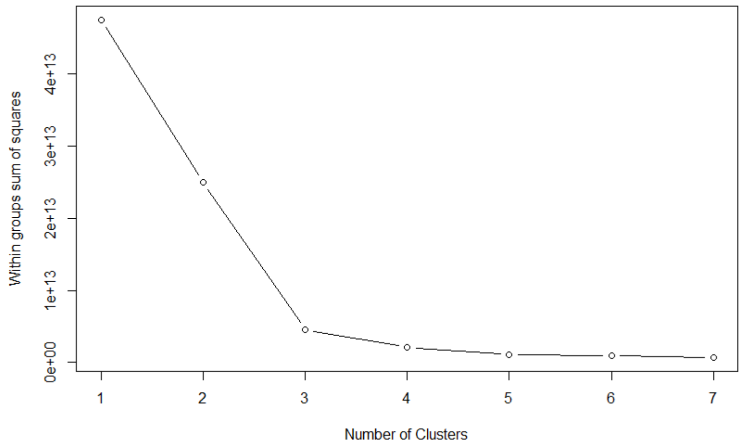
```
csv <- read.csv("finland_allBuilding_allWeather.csv",stringsAsFactors = FALSE)

require(dplyr)
mergeData <- csv %>%
  select(-c(X,date,
            vac,BuildingID,
            meternumb,type,Consumption,City, Wind_Direction,Conditions))
```

2) Converting the features to appropriate data type

```
## Converting non numeric features to numeric
mergeData$hour <- as.numeric(mergeData$hour)
mergeData$consumption.Kwh.sqm <- as.numeric(mergeData$consumption.Kwh.sqm)
mergeData$month <- as.numeric(mergeData$month)
mergeData$Day.of.Week <-  as.numeric(mergeData$Day.of.Week)
mergeData$weekday <-  as.numeric(mergeData$weekday)
mergeData$Holiday <- as.numeric(mergeData$Holiday)
mergeData$Base_Hour_Class <- as.factor(mergeData$Base_Hour_Class)
```

3) A plot of the within groups sum of squares by number of clusters extracted can help determine the appropriate number of clusters. We will use bend graph function to check within groups sum of squares by number of clusters and deciding the optimal number of clusters

```
wssplot <- function(data, nc=15, seed=1234){
  wss <- (nrow(data)-1)*sum(apply(data,2,var))
  for (i in 2:nc){
    set.seed(seed)
    wss[i] <- sum(kmeans(data, centers=i)$withinss)}
  plot(1:nc, wss, type="b", xlab="Number of Clusters",
       ylab="Within groups sum of squares")}

wssplot(mergeData[,-10],nc=7)
```



4) From the graph we can see that, within groups sum of squares is not improving after K =3
5) Using k=3, Let's use the **kmeans** function from R base stats package. Removing Base_Hour_Class from the feature list. Hence mergedata[,-10]

```
## Using k=3 as seen from the Bend graph
k.means.fit <- kmeans(mergeData[,-10],3)
```

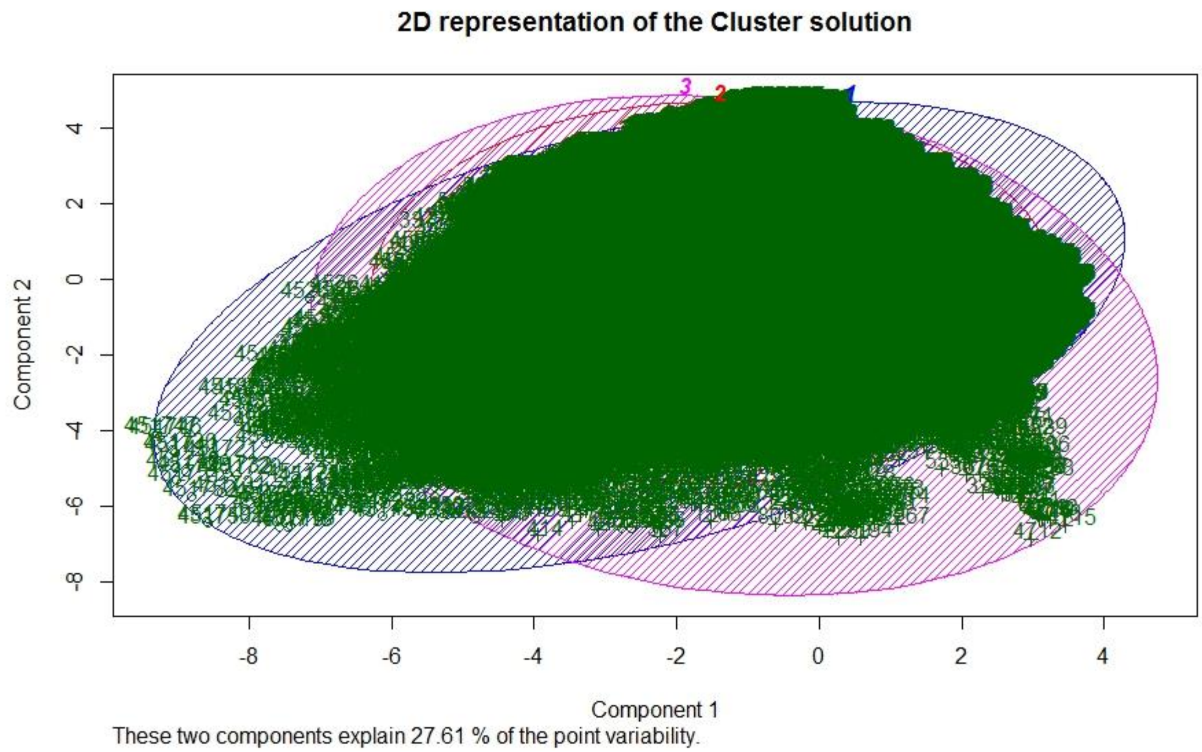
6) We can see the Within cluster sum of squares by cluster percentage of 90.5% which suggests good variance in between cluster

```
Within cluster sum of squares by cluster:
[1] 1.500202e+09 2.977045e+12 1.524417e+12
 (between_SS / total_SS =  90.5 %)
```

7) Further analyzing the results of our model, we can find out the centers of our clusters according to the feature

```
> k.means.fit$centers
  hour    month Day.of.Week   weekday Base_hour_Flag    Holiday area_floor._m.sqr consumption.Kwh.sqm base_hr_usage TemperatureF Dew_PointF
1 11.5 6.111233    4.005333 0.7137052      0.2916667 0.04689749         11986.321         0.012968686     131.59166     44.16141   37.78187
2 11.5 6.415397    4.003208 0.7145148      0.2916667 0.04570970         41339.000         0.006159809     205.01885     45.64414   39.11011
3 11.5 6.182115    4.005292 0.7135964      0.2916667 0.04677407          3558.796         0.022182093      48.95188     44.27843   37.86958
  Humidity Sea_Level_PressureIn VisibilityMPH Wind_SpeedMPH WindDirDegrees
1 80.61580             29.90159      5.506452      6.453348       177.8844
2 80.27218             29.89641      5.525084      6.512837       178.1044
3 80.52758             29.90055      5.528377      6.507188       178.2768
```

8) We can see good separation in terms of **area_floor, consumption, base_hr_usage**.
9) Plotting the result in 2-D space would give some idea about out cluster. Since the data is huge, we will not able to analyze the cluster's well



10) Plotting against our Base_Hour_Flag, we can see the below result

```
> table(mergeData[,10],k.means.fit$cluster)

          1      2      3
  High 162047  14099 177735
  Low  121465  15829 130641
```

11) We can say from this interpretation is that, the Base_Hour_Flag is missing a cluster of records. It should be **High, Low** and maybe **Neutral (for the consumption which is equal to the base_hour_usage)**

2. Clustering (hierarchical clustering)

1) K-means clustering requires us to specify the number of clusters, and finding the optimal number of clusters can often be hard**. Hierarchical clustering** is an alternative approach which builds a hierarchy from the bottom-up, and doesn't require us to specify the number of clusters beforehand.
2) Hierarchical methods use a distance matrix as an input for the clustering algorithm. The choice of an appropriate metric will influence the shape of the clusters, as some elements may be close to one another according to one distance and farther away according to another
3) We can use hclust for this. hclust requires us to provide the data in the form of a distance matrix. We can do this by using dist. By default, **the complete linkage method is used.**
4) Now since the data is huge, we will first transpose our data to a data matrix, and calculate the distance matrix

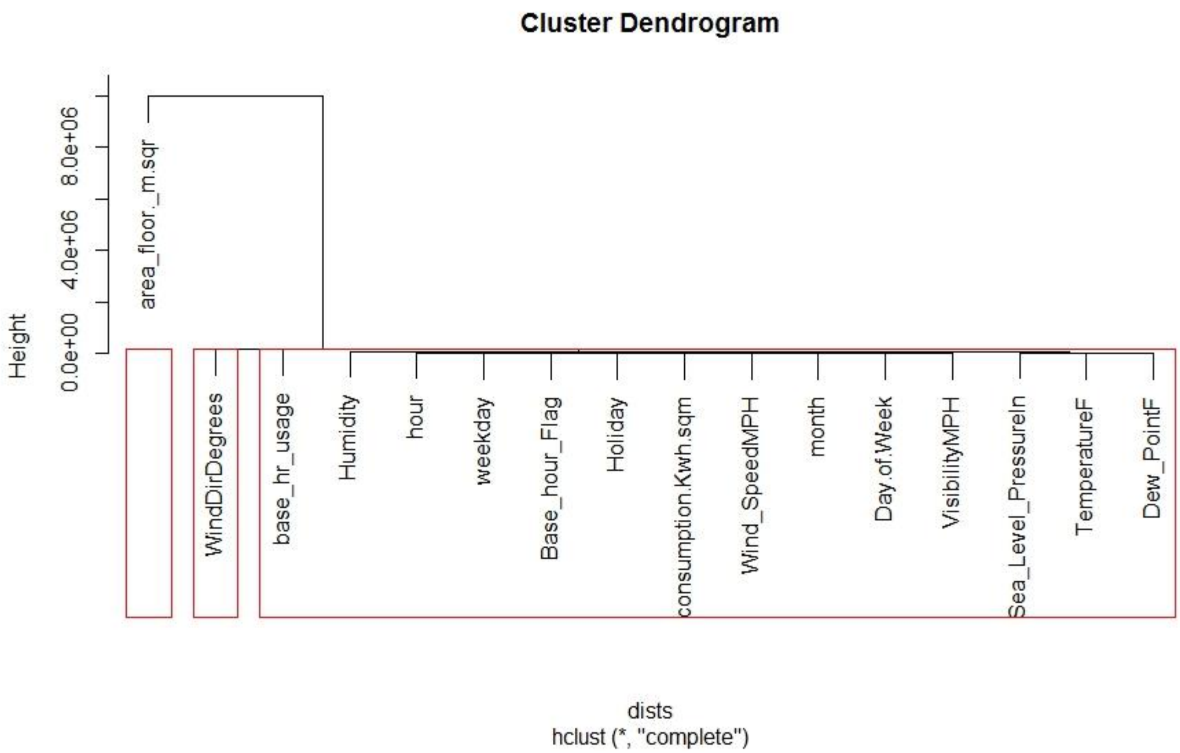
```
# Create transposed data matrix
data.matrix.t <- t(as.matrix(mergeData[,-10]))

# Create distance matrix
dists <- dist(data.matrix.t)
```

5) Now calculating the cluster

```
# Clustering
hcl <- hclust(dists)
```

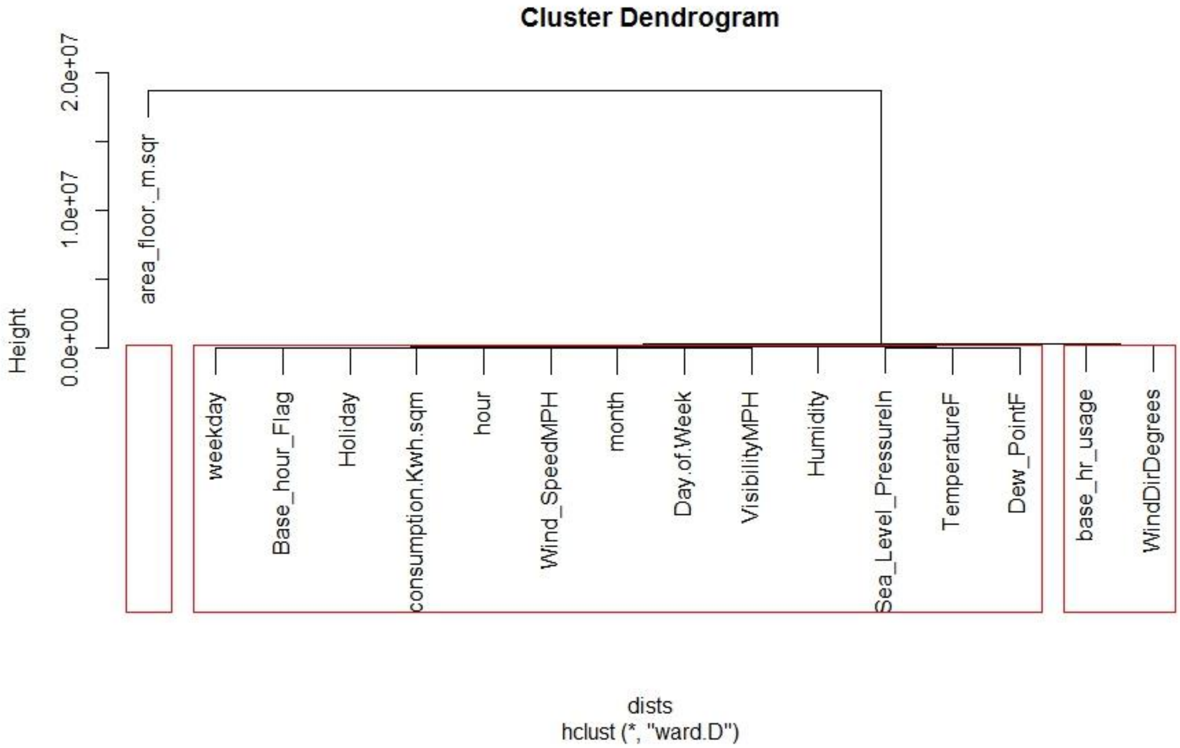
6) We can draw the dendogram and see the results

```
# draw dendogram with red borders around the 3 clusters
rect.hclust(hcl, k=3, border="red")
```



7) From the hierarchical clustering we can see that, 3 clusters are formed. With area_floor again driving the cluster segmentation. WindDirDegrees a major contributor in a cluster and the rest for the third cluster
8) We can also use Ward's minimum variance criterion to minimizes the total within-cluster variance and plot the result

```
#We use the Euclidean distance as an input for the clusterin
H.fit <- hclust(dists, method="ward.D")

#The clustering output can be displayed in a dendrogram
plot(H.fit) # display dendogram
groups <- cutree(H.fit, k=3) # cut tree into 5 clusters

# draw dendogram with red borders around the 5 clusters
rect.hclust(H.fit, k=3, border="red")
```



9) A different clustering group can be analyzed from here. Base_hr_usage now influencing the second cluster and rest remains the same. This is pretty much in alliance with our K-means clustering algorithm