Exercise C

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Exercise C

```
## loading all the R workspace data

load("C:/AppliedDataScienceAndStatistics/Applied-Data-Science-and-Statistics/Term1/Applica
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load("C:/AppliedDataScienceAndStatistics/Applied-Data-Science-and-Statistics/Term1/Applica
dataCharacteristics = read_csv("C:/AppliedDataScienceAndStatistics/Applied-Data-Science-an
```
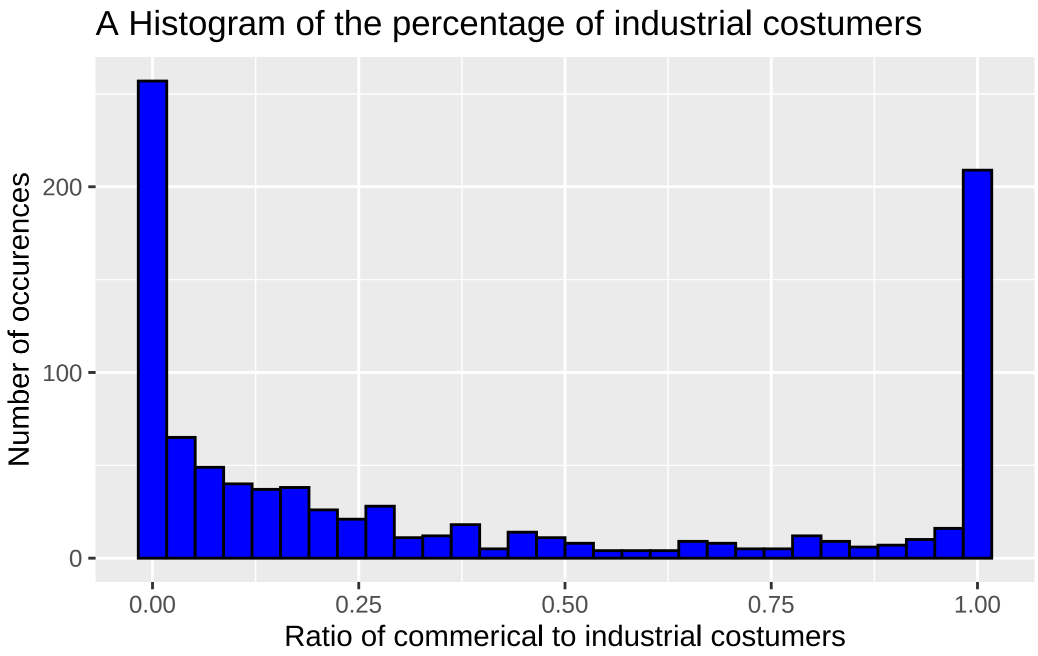

Exercise C 1.i

```r
summary(dataCharacteristics)
```

```
 SUBSTATION_NUMBER TRANSFORMER_TYPE   TOTAL_CUSTOMERS Transformer_RATING
 Min.   :511016    Length:948         Min.   :  0.0   Min.   :   0.0
 1st Qu.:521516    Class :character   1st Qu.:  3.0   1st Qu.: 200.0
 Median :532653    Mode  :character   Median : 67.5   Median : 315.0
 Mean   :534344                       Mean   :104.3   Mean   : 389.1
 3rd Qu.:552386                       3rd Qu.:179.2   3rd Qu.: 500.0
 Max.   :564512                       Max.   :569.0   Max.   :1000.0
 Percentage_IC     LV_FEEDER_COUNT  GRID_REFERENCE
 Min.   :0.00000   Min.   : 0.000   Length:948
 1st Qu.:0.01048   1st Qu.: 1.000   Class :character
 Median :0.17849   Median : 3.000   Mode  :character
 Mean   :0.37982   Mean   : 2.762
 3rd Qu.:0.90271   3rd Qu.: 4.000
 Max.   :1.00000   Max.   :16.000
```

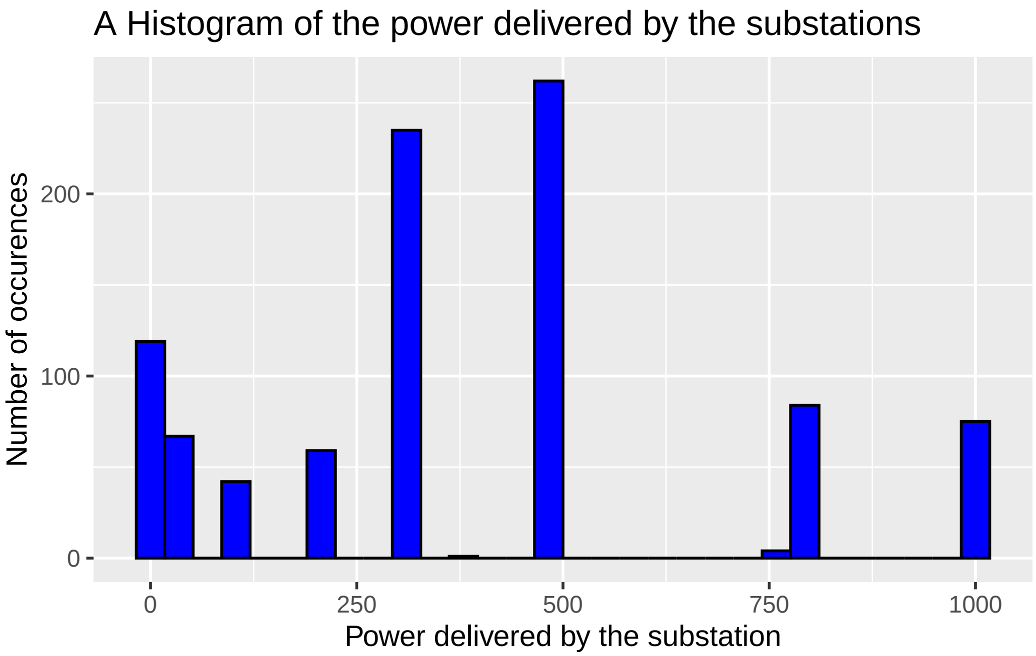
To visualise the distributions of the percentage of industrial and commercial costumer, transformer ratings and transformer types We will plot a histogram of each of these variables

```r
ggplot(dataCharacteristics, aes(Percentage_IC)) + geom_histogram(bins = 30,
    fill = "blue", color = "black") + ggtitle("A Histogram of the percentage of industrial
    xlab("Ratio of commerical to industrial costumers") + ylab("Number of occurences")
```



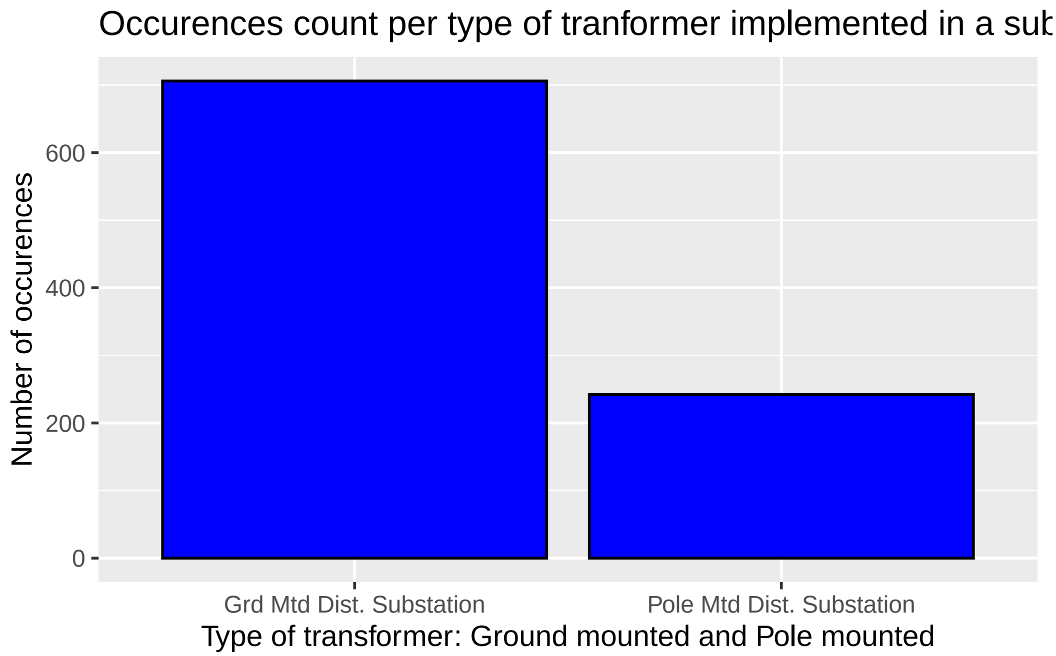
The histogram here the number of occurrences cluster around fully commercial costumers and fully industrial costumers where both these values have a much higher number of occurrences than any other percentage ratio of costumers. As the number of industrial costumers increase, the number of occurrences slowly decreases until it reach it's lowest near the 50 percentile, barely increasing again around the 80 percentile until reaching another high peak on 100% industrial costumers, following what it seems to be a very steep u-shaped distribution also called u-quadratic distribution.

```
ggplot(dataCharacteristics, aes(Transformer_RATING)) + geom_histogram(bins = 30,
    fill = "blue", color = "black") + ggtitle("A Histogram of the power delivered by the s
    xlab("Power delivered by the substation") + ylab("Number of occurences")
```



As we can see in the histogram above the amount of power being delivered to the substations is the highest around 500 and second highest around 300. It is also evident that there is a large gap around amounts of power being delivered to the substation. We can also see that with the exception to 0 or near 0 power delivered and two other values that can possible be outliers the number of occurrences increase as we get closer to 500 power delivered by the substations, following what would resemble a normal distribution.

```
ggplot(dataCharacteristics, aes(TRANSFORMER_TYPE)) + geom_bar(fill = "blue",
    color = "black") + ggtitle("Occurences count per type of tranformer implemented in a s
    xlab("Type of transformer: Ground mounted and Pole mounted") + ylab("Number of occuren
```



As we can see the number of ground mounted substations is almost 3 times bigger than the pole mounted substations.

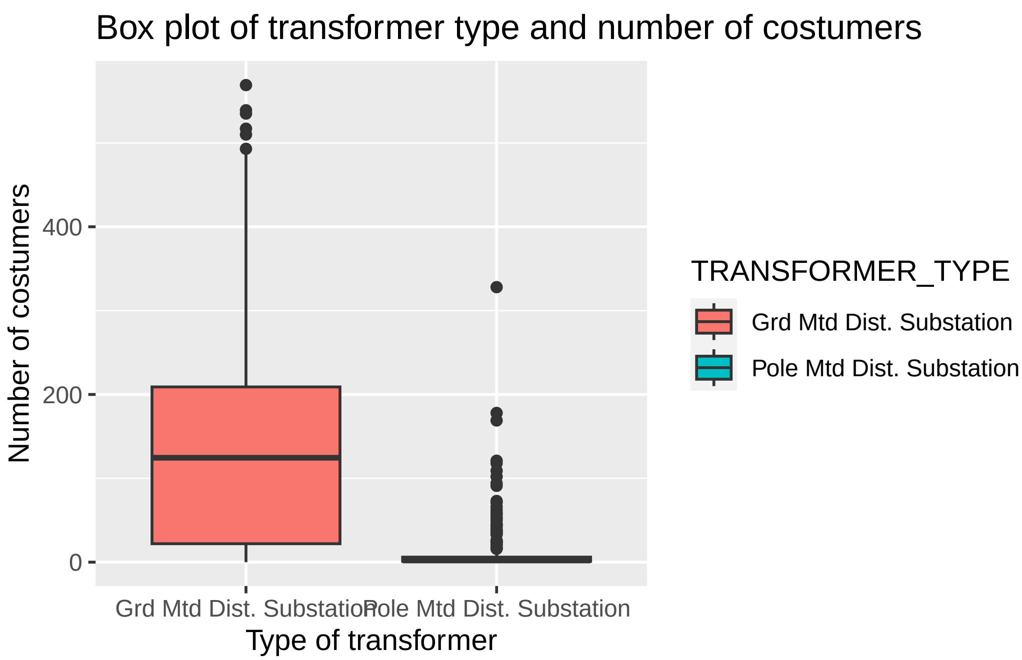
Exercise C 1.ii

There are several ways to describe the relationships between different characteristics:

- Correlation: This measures the strength and direction of the relationship between two variables. A positive correlation means that as one variable increases, the other variable also increases. A negative correlation means that as one variable increases, the other variable decreases.
- Regression: This is a statistical method used to find the relationship between a dependent variable and one or more independent variables. It can be used to predict the value of the dependent variable based on the values of the independent variables.
- Clustering: This is a method used to group similar observations together based on their characteristics. Clustering can be used to identify patterns or relationships in the data.
- Dimensionality reduction: This is a technique used to reduce the number of variables in a dataset while preserving as much information as possible. This can be useful for visualizing and understanding relationships between variables.
- Visualization: This is a way of representing data graphically, such as with charts, plots, and maps. Visualization can help to identify patterns and relationships in the data.

We have already have resorted to visualization of the distributions on the previous question so now I will be visualising and correlation each of the variables against each other.

```
## variables to compare: transformer type, number of customers, rating,
## percentage of I&C customers and number of feeders these are:
## TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

## lets start with transformer type comparison against all other
## variable the first one will be comparing it with total customers

ggplot(data = dataCharacteristics, aes(x = TRANSFORMER_TYPE, y = TOTAL_CUSTOMERS,
    fill = TRANSFORMER_TYPE)) + geom_boxplot() + ggtitle("Box plot of transformer type and
    xlab("Type of transformer") + ylab("Number of costumers")
```



As we can clearly observe the type of transformer is a strong indicator of the number of costumers as pole mounted substations values from the minimum third quantile values equal or approximate to zero comparing to ground mounted substations, these already have a number of costumers superior to 0 on the first quartile and the entire interquartile range holds values only present on the top quartile of the pole mounted substations.

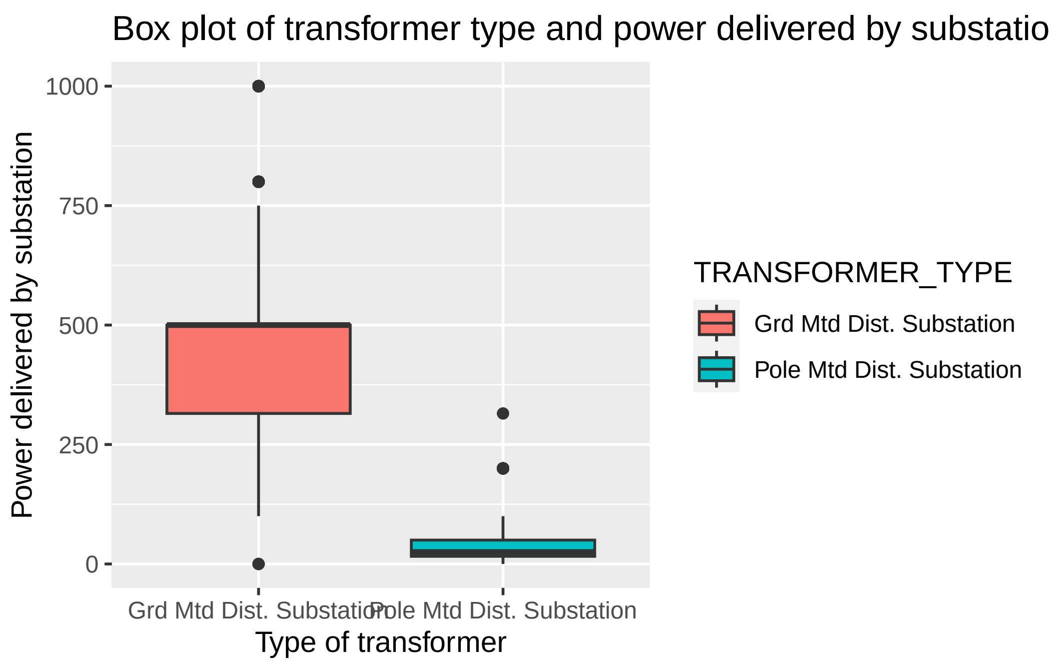
```r
modelTransTypeNCostumer = lm(TOTAL_CUSTOMERS ~ TRANSFORMER_TYPE, data = dataCharacteristic

summary(modelTransTypeNCostumer)
```

```
Call:
lm(formula = TOTAL_CUSTOMERS ~ TRANSFORMER_TYPE, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max 
-135.78  -72.03  -10.63   49.22  433.22 

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                                135.778      3.854   35.23   <2e-16
TRANSFORMER_TYPEPole Mtd Dist. Substation -123.150      7.629  -16.14   <2e-16
                                             
(Intercept)                               ***
TRANSFORMER_TYPEPole Mtd Dist. Substation ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 102.4 on 946 degrees of freedom
Multiple R-squared:  0.216, Adjusted R-squared:  0.2151 
F-statistic: 260.6 on 1 and 946 DF,  p-value: < 2.2e-16
```

As we can see from the summary of the linear model, a substation being pole mounted largely decreases the number of costumers in such substation. It is also important to notice the the multiple R-squared and adjusted R-squared values as they signify that the type of transformer mounted only explains explains 21% of the variation in the number of costumers.

Now we will proceed to analyse the comparison of transformer type and transformer rating.

```r
ggplot(data = dataCharacteristics, aes(x = TRANSFORMER_TYPE, y = Transformer_RATING,
    fill = TRANSFORMER_TYPE)) + geom_boxplot() + ggtitle("Box plot of transformer type and
    xlab("Type of transformer") + ylab("Power delivered by substation")
```



We can observe again that the type of transformer is a strong indicator of the power delivered by the substation, as with exception of 2 outliers the pole mounted entire range of power delivered is smaller then the first quartile of power delivered by ground mounted substations. As such it is clear how impactful are the type of transformer in the power delivered to the substations.

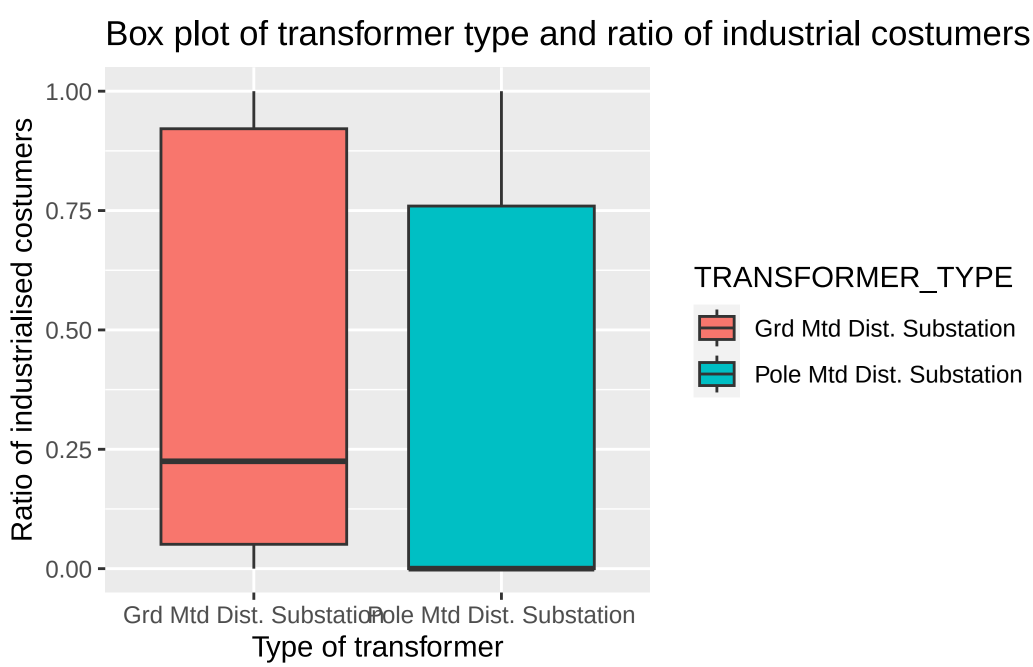
```
modelTransTypePowerDelivery = lm(Transformer_RATING ~ TRANSFORMER_TYPE, data = dataCharact

summary(modelTransTypePowerDelivery)
```

```
Call:
lm(formula = Transformer_RATING ~ TRANSFORMER_TYPE, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max 
-505.16 -190.16   -5.16   -0.60  494.84 

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                                505.156      7.826   64.55   <2e-16
TRANSFORMER_TYPEPole Mtd Dist. Substation -454.555     15.490  -29.34   <2e-16
```

```
(Intercept)                                  ***
TRANSFORMER_TYPEPole Mtd Dist. Substation ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 208 on 946 degrees of freedom
Multiple R-squared:  0.4765,	Adjusted R-squared:  0.476
F-statistic: 861.1 on 1 and 946 DF,  p-value: < 2.2e-16
```

As we can see from the summary of the model the type of transformer has a massive impact determining the amount of energy supplied to the substation and as observed from the R-squared value the type of mounted substation can explain almost half of the variation in power supplied to the substations

```r
ggplot(data = dataCharacteristics, aes(x = TRANSFORMER_TYPE, y = Percentage_IC,
    fill = TRANSFORMER_TYPE)) + geom_boxplot() + ggtitle("Box plot of transformer type and
    xlab("Type of transformer") + ylab("Ratio of industrialised costumers")
```



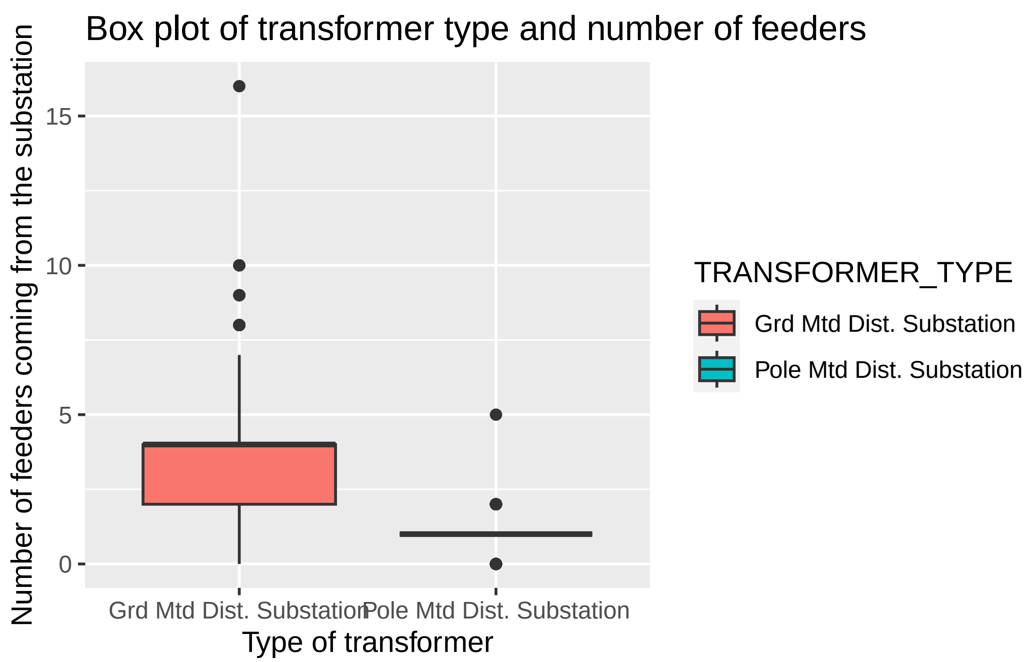
In the bar graph we can see that half of the pole mounted substation have only business costumers and therefore no industrial costumers. We can also observe that pole mounted substations have in general considerably bigger ratio of business costumers has more pole mounted substations 3rd quartile is approximately 15% lower on industrial costumers ratio than the ground mounted 3rd quartile. It should also be noted that the 1st quartile of the ground mounted substations is above 0 meaning the large majority of ground mounted substations have some degree of industrial costumers.

```
modelTransTypeRatioIndustrialCostumers = lm(Percentage_IC ~ TRANSFORMER_TYPE,
    data = dataCharacteristics)

summary(modelTransTypeRatioIndustrialCostumers)
```

```
Call:
lm(formula = Percentage_IC ~ TRANSFORMER_TYPE, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.4096 -0.3128 -0.2194  0.5057  0.7071 

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                                0.40961    0.01521  26.932  < 2e-16
TRANSFORMER_TYPEPole Mtd Dist. Substation -0.11672    0.03010  -3.878 0.000113
                                             
(Intercept)                               ***
TRANSFORMER_TYPEPole Mtd Dist. Substation ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4041 on 946 degrees of freedom
Multiple R-squared:  0.01565,   Adjusted R-squared:  0.0146 
F-statistic: 15.04 on 1 and 946 DF,  p-value: 0.0001128
```

As we can see from the summary of our model having a pole mounted substation as opposed to a ground mounted substation decreases the number the expected percentage of industrial costumers by approximately 11.7%. As observed by the R-squared value the type of transformer is capable of 40% of the variation of ratio of industrial costumers meaning we can really in our model to some degree but we shouldn't overly rely on it.

```
ggplot(data = dataCharacteristics, aes(x = TRANSFORMER_TYPE, y = LV_FEEDER_COUNT,
    fill = TRANSFORMER_TYPE)) + geom_boxplot() + ggtitle("Box plot of transformer type and
    xlab("Type of transformer") + ylab("Number of feeders coming from the substation")
```



The most apparent difference between ground mounted and pole mounted substations is how the 1st and 3rd quartile coincide on only 1 feeder for the pole mounted substations with no apparent whiskers with only 3 values marked as outliers, meaning almost all pole mounted substations have the same number of feeders. Ground mounted substations not only can have a considerably higher number of feeders, as the first quartile of the box is over the 3rd quartile of the pole mounted substations, the approximatly 75% of ground mounted substations have at least double the amount of feeders than pole mounted substations.

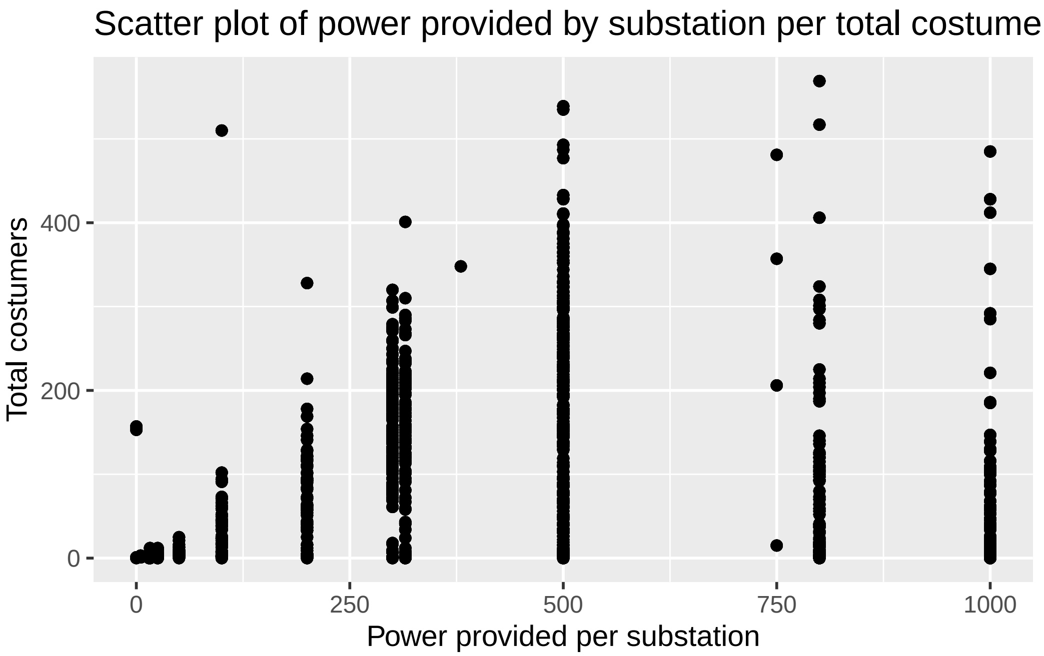
```
modelTransTypeFeederCount = lm(LV_FEEDER_COUNT ~ TRANSFORMER_TYPE, data = dataCharacterist

summary(modelTransTypeFeederCount)
```

```
Call:
lm(formula = LV_FEEDER_COUNT ~ TRANSFORMER_TYPE, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.3555 -0.3555 -0.0289  0.6445 12.6445 

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                3.35552    0.06035   55.60   <2e-16
```

```
TRANSFORMER_TYPEPole Mtd Dist. Substation -2.32660    0.11945  -19.48   <2e-16

(Intercept)                               ***
TRANSFORMER_TYPEPole Mtd Dist. Substation ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.604 on 946 degrees of freedom
Multiple R-squared:  0.2862,    Adjusted R-squared:  0.2855
F-statistic: 379.4 on 1 and 946 DF,  p-value: < 2.2e-16
```

Immediately we can see that the type of transformer isn't the best indicator of feeder count as the R-squared value is only 0,286 meaning it will only account for 28,6% of the variation on the number of feeders. It should still be noted that a pole mounted substation estimated value is very approximate to 1.

```r
## these are: TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

ggplot(data = dataCharacteristics, aes(y = TOTAL_CUSTOMERS, x = Transformer_RATING)) +
    geom_point() + #geom_smooth(method = 'lm', se = FALSE) + geom_point()
    geom_point() + #geom_smooth(method = 'lm', se = FALSE) + +
    geom_point() + #geom_smooth(method = 'lm', se = FALSE) + #geom_smooth(method
    geom_point() + #geom_smooth(method = 'lm', se = FALSE) + = 'lm', se
    geom_point() + #geom_smooth(method = 'lm', se = FALSE) + = FALSE) +
ggtitle("Scatter plot of power provided by substation per total costumers") +
    xlab("Power provided per substation") + ylab("Total costumers")
```



The relationship between power provided and total costumers seem to follow a normal distribution without noticeable skewness.

```
modelPowerNcostumers = lm(Transformer_RATING ~ TOTAL_CUSTOMERS, data = dataCharacteristics

summary(modelPowerNcostumers)
```

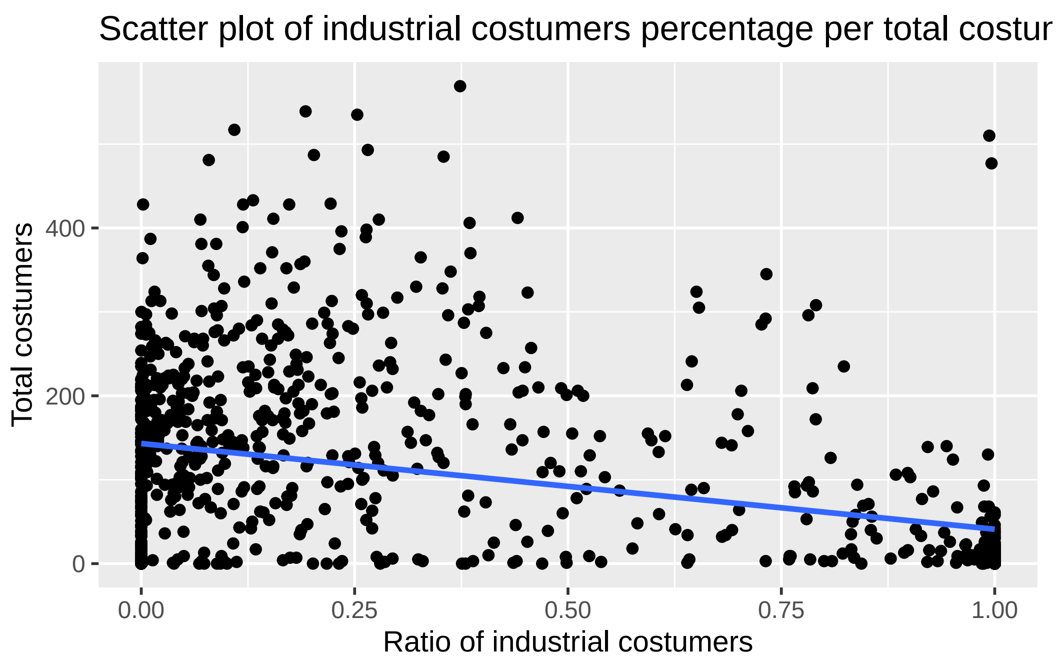
```
Call:
lm(formula = Transformer_RATING ~ TOTAL_CUSTOMERS, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max
-525.15 -207.89  -76.78  141.43  671.59

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     328.41083   12.22831  26.857  < 2e-16 ***
TOTAL_CUSTOMERS   0.58183    0.07855   7.407 2.85e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 279.4 on 946 degrees of freedom
```

```
Multiple R-squared:  0.05482,   Adjusted R-squared:  0.05382
F-statistic: 54.87 on 1 and 946 DF,  p-value: 2.85e-13
```

As we can see from the R-squared the relationship between total customers and power provided per substation being only approximately 5% means these two variables can barely explain the variation between each other. This could mean that the independent variable in the model is not relevant, or that there are other factors that are not included in the model that are affecting the dependent variable.

```r
## these are: TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

ggplot(data = dataCharacteristics, aes(y = TOTAL_CUSTOMERS, x = Percentage_IC)) +
    geom_point() + geom_smooth(method = "lm", se = FALSE) + ggtitle("Scatter plot of indus
    xlab("Ratio of industrial costumers") + ylab("Total costumers")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



As we can see from the scatter plot we can see too values with a very high concentration of occurrences around fully business costumers and fully industrial costumers. Around the 0% industrial costumers marks is where the largest concentration of total costumers per substation are located and we can see a clear decreasing trend on the number of total costumers as the percentage of industrial costumers increase. However there does not seem to be any other clear trend between the high concentration of occurrences between none and exclusively industrial costumers.

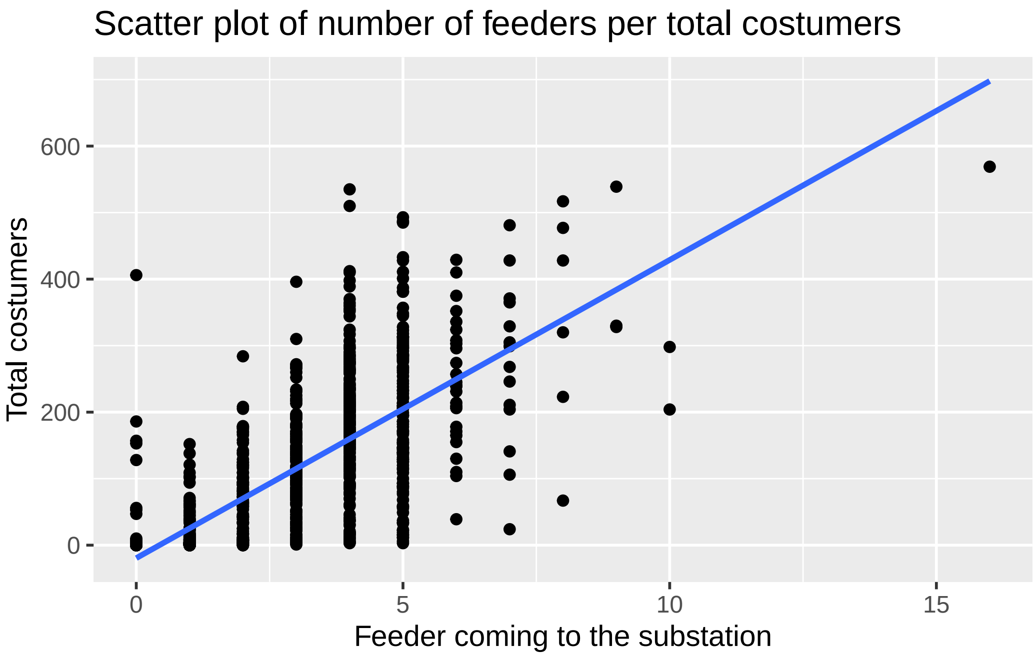
```
modelRatioIndustrialNcostumers = lm(TOTAL_CUSTOMERS ~ Percentage_IC, data = dataCharacteri

summary(modelRatioIndustrialNcostumers)
```

```
Call:
lm(formula = TOTAL_CUSTOMERS ~ Percentage_IC, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max
-143.14  -55.85  -29.98   54.91  468.37

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    143.143      4.795   29.85   <2e-16 ***
Percentage_IC -102.161      8.614  -11.86   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 107.9 on 946 degrees of freedom
Multiple R-squared:  0.1294,    Adjusted R-squared:  0.1285
F-statistic: 140.7 on 1 and 946 DF,  p-value: < 2.2e-16
```

First thing to note is that how big of a difference is the number of total costumers for a fully industrial costumer substation compared to the intersect, so a fully business substation. Second thing to note is our quite low R-squared values of 12,9% meaning our model capability of explaining the number of costumers of one substation through the percentage of industrial costumers is incredibly small as these two variables are not linearly correlated enough to explain a significant proportion of the variation in the dependent variable.

```
## these are: TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

ggplot(data = dataCharacteristics, aes(y = TOTAL_CUSTOMERS, x = LV_FEEDER_COUNT)) +
    geom_point() + geom_smooth(method = "lm", se = FALSE) + ggtitle("Scatter plot of numbe
    xlab("Feeder coming to the substation") + ylab("Total costumers")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



As we can clearly see as the number of feeders increase so does the number of costumers, following a very sharp increase in the first 5 feeders and a gradual increase in the remaining number of feeders.

```
modelNFeederslNcostumers = lm(TOTAL_CUSTOMERS ~ LV_FEEDER_COUNT, data = dataCharacteristic

summary(modelNFeederslNcostumers)
```

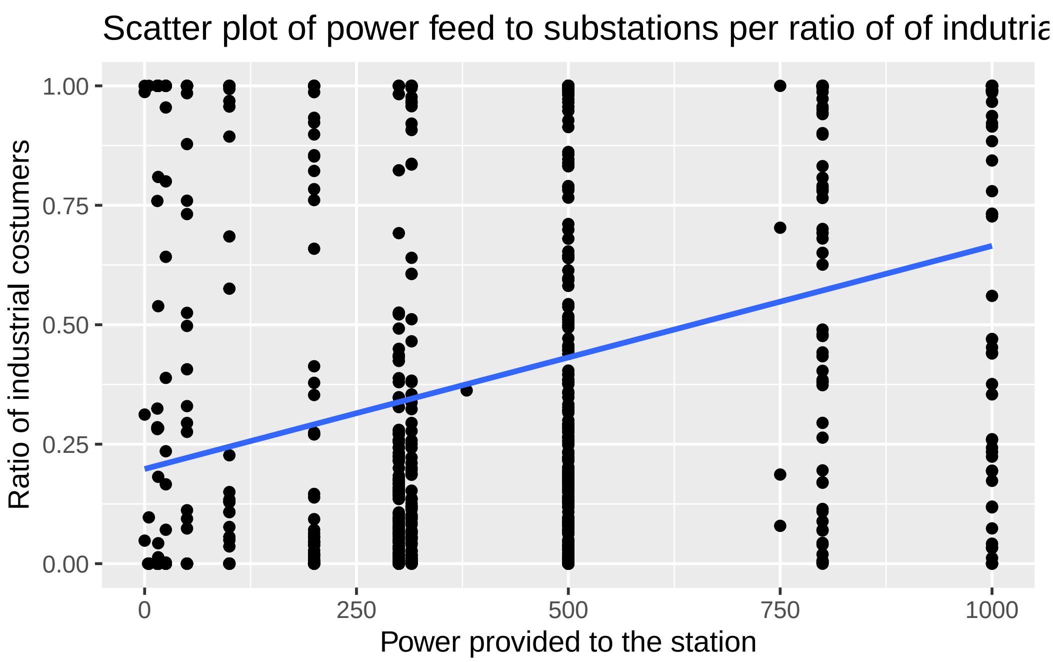
```
Call:
lm(formula = TOTAL_CUSTOMERS ~ LV_FEEDER_COUNT, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max
-272.17  -25.37  -18.77   32.35  425.46

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      -19.458      4.495  -4.328 1.66e-05 ***
LV_FEEDER_COUNT   44.828      1.342  33.405  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 78.34 on 946 degrees of freedom
Multiple R-squared:  0.5412,    Adjusted R-squared:  0.5407
F-statistic:  1116 on 1 and 946 DF,  p-value: < 2.2e-16
```

While just one singular linear model will not be as precise for the first 5 feeders, this model alone can explain more than half of the variation of the number of costumers of each substation.

```
## these are: TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

ggplot(data = dataCharacteristics, aes(x = Transformer_RATING, y = Percentage_IC)) +
    geom_point() + geom_smooth(method = "lm", se = FALSE) + ggtitle("Scatter plot of power
    xlab("Power provided to the station") + ylab("Ratio of industrial costumers")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



From this graph we can see that substation with a bigger percentage of business costumers are more likely to provide less power than substations with a bigger industrial costumers base.

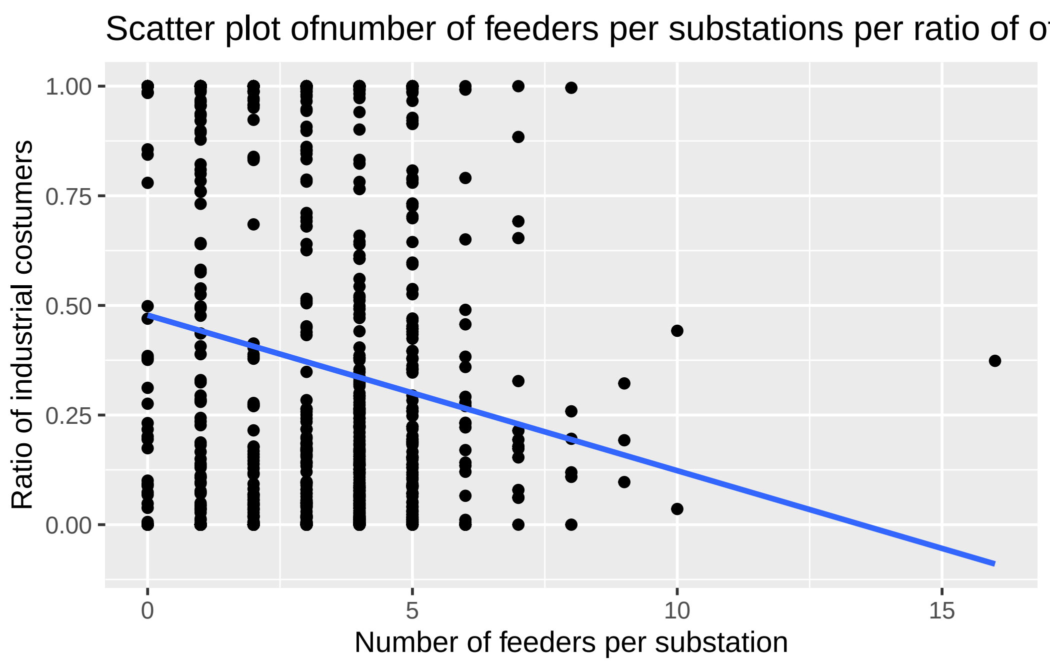
```r
modelNFeederslNcostumers = lm(Percentage_IC ~ Transformer_RATING, data = dataCharacteristi

summary(modelNFeederslNcostumers)
```

```
Call:
lm(formula = Percentage_IC ~ Transformer_RATING, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6650 -0.2875 -0.1988  0.3350  0.8019 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        0.1981319  0.0210372   9.418   <2e-16 ***
Transformer_RATING 0.0004669  0.0000435  10.733   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3846 on 946 degrees of freedom
Multiple R-squared:  0.1086,    Adjusted R-squared:  0.1076 
F-statistic: 115.2 on 1 and 946 DF,  p-value: < 2.2e-16
```

As we can see from the model, the power provided to the substations does explain approximately 11% of the changes in percentage of industrial costumer per substation which is a extremely low level of explanatory power. Therefore we should not really on the power provided to substation to predict the ratio industrial costumers.

```r
## these are: TRANSFORMER_TYPE, TOTAL_CUSTOMERS , Transformer_RATING ,
## Percentage_IC and LV_FEEDER_COUNT

ggplot(data = dataCharacteristics, aes(x = LV_FEEDER_COUNT, y = Percentage_IC)) +
    geom_point() + geom_smooth(method = "lm", se = FALSE) + ggtitle("Scatter plot ofnumber
    xlab("Number of feeders per substation") + ylab("Ratio of industrial costumers")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



From the plot we can see that there is a tendency for the ratio of industrials costumers to decrease as the number of feeder increases per substation. It appears that the jump from when there are no feeders to the fist feeder might be an actual increase on the ratio industrial costumers but it is not going to be properly represented with a singular linear model.

```
modelNFeederslNcostumers = lm(Percentage_IC ~ LV_FEEDER_COUNT, data = dataCharacteristics)

summary(modelNFeederslNcostumers)
```

```
Call:
lm(formula = Percentage_IC ~ LV_FEEDER_COUNT, data = dataCharacteristics)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4777 -0.3359 -0.1623  0.5073  0.8022

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.477744   0.023051  20.726  < 2e-16 ***
LV_FEEDER_COUNT -0.035460   0.006881  -5.153 3.12e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.4017 on 946 degrees of freedom
Multiple R-squared:  0.02731,	Adjusted R-squared:  0.02628 
F-statistic: 26.56 on 1 and 946 DF,  p-value: 3.117e-07
```

As we can see form the minuscule Multiple R-squared value this model simply is not an adequate and cannot bring any meaningful correlation between these two variables.

Exercise C 2.i

```r
## as data from 0:00 to 7:50

tenMinuteMaximum = January_2013[, -c(1:2)]

## first we need to the maximum power output of the day i

maxVal = 0
January_2013$max = 0


for (i in 1:nrow(tenMinuteMaximum)) {

    ## the apply() function is used with the MARGIN parameter set to 1,
    ## which applies the function to all rows of the dataframe. Inside
    ## the function, we are checking if the row name is not equal to
    ## substation as the substation number is also bigger than the
    ## power measured in the interval of 10 mins

    maxVal = apply(tenMinuteMaximum[i, ], 1, max)

    # tenMinuteMaximum

    January_2013$max[i] = maxVal


}

January_2013[, 3:146] = January_2013[, 3:146]/January_2013$max


January_2013
```

```
# A tibble: 15,095 x 147
   Date       Substation `00:00` `00:10` `00:20` `00:30` `00:40` `00:50` `01:00`
   <date>          <int>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 2013-01-03     511016   0.597   0.603   0.614   0.611   0.576   0.555   0.565
 2 2013-01-03     511029   0.624   0.723   0.754   0.644   0.802   0.835   0.843
 3 2013-01-03     511030   0.701   0.654   0.645   0.627   0.603   0.636   0.633
 4 2013-01-03     511033   0.297   0.285   0.288   0.293   0.295   0.298   0.299
 5 2013-01-03     511034   0.557   0.549   0.557   0.534   0.536   0.530   0.517
 6 2013-01-03     511035   0.524   0.591   0.586   0.547   0.523   0.490   0.479
 7 2013-01-03     511079   0.427   0.361   0.364   0.321   0.330   0.307   0.299
 8 2013-01-03     511150   0.137   0.140   0.132   0.133   0.136   0.137   0.141
 9 2013-01-03     511151   0.223   0.181   0.194   0.236   0.228   0.214   0.183
10 2013-01-03     511188   0.257   0.244   0.243   0.233   0.235   0.220   0.249
# ... with 15,085 more rows, and 138 more variables: `01:10` <dbl>,
#   `01:20` <dbl>, `01:30` <dbl>, `01:40` <dbl>, `01:50` <dbl>, `02:00` <dbl>,
#   `02:10` <dbl>, `02:20` <dbl>, `02:30` <dbl>, `02:40` <dbl>, `02:50` <dbl>,
#   `03:00` <dbl>, `03:10` <dbl>, `03:20` <dbl>, `03:30` <dbl>, `03:40` <dbl>,
#   `03:50` <dbl>, `04:00` <dbl>, `04:10` <dbl>, `04:20` <dbl>, `04:30` <dbl>,
#   `04:40` <dbl>, `04:50` <dbl>, `05:00` <dbl>, `05:10` <dbl>, `05:20` <dbl>,
#   `05:30` <dbl>, `05:40` <dbl>, `05:50` <dbl>, `06:00` <dbl>, ...
```

Exercise C 2.ii

```
## group by substation and get the mean of each time interval 0:00,
## 0:10, 0:20 etc.

January_2013Grouped = January_2013 %>%
    group_by(Substation) %>%
    summarise_all(mean)

January_2013Grouped = January_2013Grouped[, -c(2)]

January_2013Grouped
```

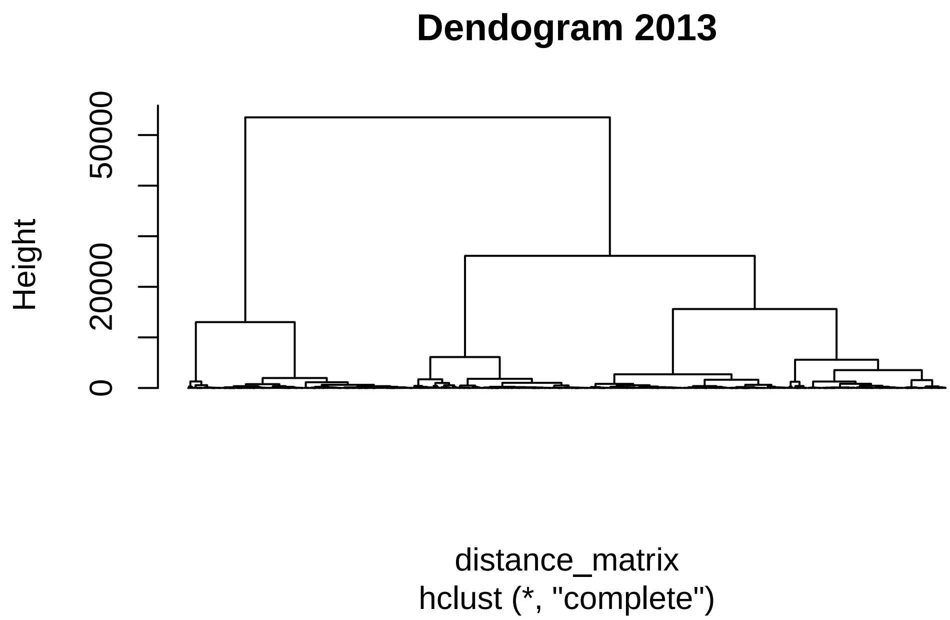
```
# A tibble: 535 x 146
   Substation `00:00` `00:10` `00:20` `00:30` `00:40` `00:50` `01:00` `01:10`
        <int>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1     511016   0.622   0.625   0.610   0.599   0.590   0.578   0.566   0.553
 2     511029   0.568   0.642   0.675   0.702   0.762   0.749   0.734   0.716
 3     511030   0.607   0.588   0.566   0.546   0.531   0.523   0.515   0.503
 4     511033   0.309   0.298   0.309   0.306   0.302   0.302   0.306   0.300
```

```
 5     511034   0.526   0.521   0.510   0.509   0.501   0.492   0.484   0.484
 6     511035   0.527   0.548   0.531   0.509   0.503   0.492   0.476   0.470
 7     511079   0.419   0.396   0.380   0.363   0.351   0.339   0.333   0.333
 8     511150   0.208   0.203   0.200   0.199   0.208   0.201   0.203   0.203
 9     511151   0.306   0.305   0.305   0.298   0.293   0.309   0.303   0.302
10     511188   0.340   0.338   0.341   0.341   0.336   0.340   0.345   0.346
# ... with 525 more rows, and 137 more variables: `01:20` <dbl>, `01:30` <dbl>,
#   `01:40` <dbl>, `01:50` <dbl>, `02:00` <dbl>, `02:10` <dbl>, `02:20` <dbl>,
#   `02:30` <dbl>, `02:40` <dbl>, `02:50` <dbl>, `03:00` <dbl>, `03:10` <dbl>,
#   `03:20` <dbl>, `03:30` <dbl>, `03:40` <dbl>, `03:50` <dbl>, `04:00` <dbl>,
#   `04:10` <dbl>, `04:20` <dbl>, `04:30` <dbl>, `04:40` <dbl>, `04:50` <dbl>,
#   `05:00` <dbl>, `05:10` <dbl>, `05:20` <dbl>, `05:30` <dbl>, `05:40` <dbl>,
#   `05:50` <dbl>, `06:00` <dbl>, `06:10` <dbl>, `06:20` <dbl>, ...
```

Exercise C 2.iii

Manhattan distance (also known as L1 distance) is a measure of the absolute differences between the coordinates of two points in a multi-dimensional space.

```r
## TODO REMOVE THE LAST ONE
January_2013Grouped = January_2013Grouped[, -c(146)]

distance_matrix <- dist(January_2013Grouped, method = "manhattan")

cluster = hclust(distance_matrix)

# plot(cluster, xlab='', sub='')

plot(cluster, main = "Dendogram 2013", labels = FALSE, hang = -1)
```



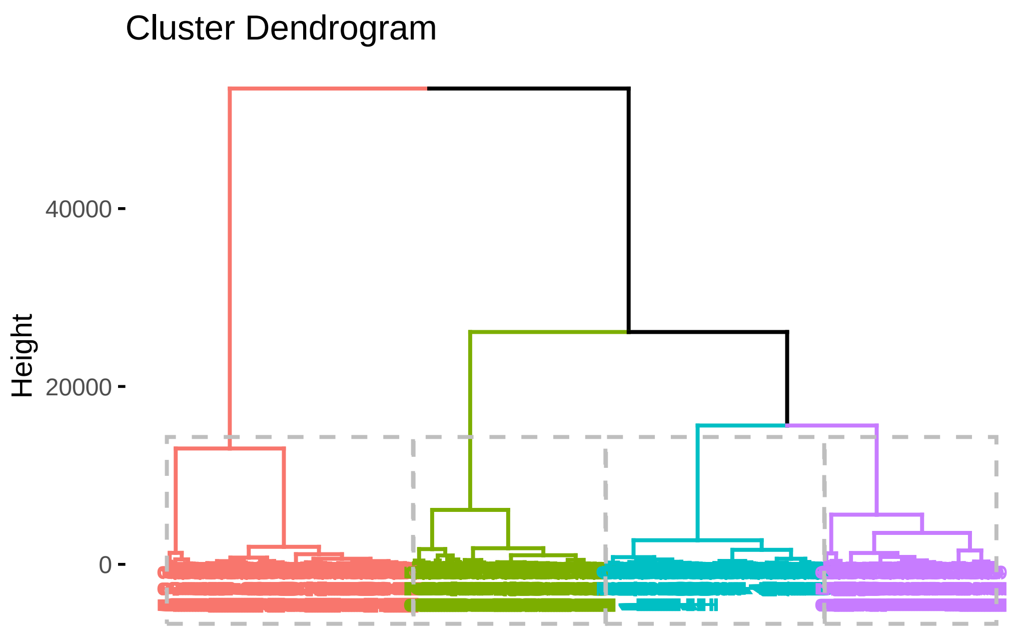
Exercise C 2.iv

Using the visualization method to decide the number of clusters we can observe from the dendrogram the natural breaks, where it branches into multiple clusters and we will be deciding if they should be a new cluster by comparing the height difference of the breaks. The initial data set is first divided into 2 with one of the subdivision containing most of the occurrences. Comparing the height between the second division of leafs and any possible further down divisions we can see that there is still a significant height difference. So we can go down a level and reaching the 3 divisions, into 3 clusters. If we further analyse any other branches with the same heigh as the 3 previous clusters we can see there is still 1 more with similar height on the very left side, making it possible to have 4 clusters without decreasing the height difference between branches. However if we want to make any further divisions we can see that there will be significantly smaller heights for any other possible clusters, meaning we would be sacrificing the similarity or distance between the clusters that are joined at this point.

```
## here we can see the the dendogram with the proper clusters already
## cut has mentioned above, using the factoextra library
fviz_dend(cluster, k = 4, rect = TRUE, show_labels = TRUE)
```

```
Warning: The `<scale>` argument of `guides()` cannot be `FALSE`. Use "none" instead as
of ggplot2 3.3.4.
```

```
i The deprecated feature was likely used in the factoextra package.
  Please report the issue at <https://github.com/kassambara/factoextra/issues>.
```



Exercise C 2.v

```r
# cut the dendrogram into 4 clusters
groups <- cutree(cluster, k = 4)

# find number of observations in each cluster
table(groups)
```

```
groups
  1   2   3   4
141 111 124 159
```

```r
table2013 = table(groups)


## now I will have to get an average of the entire cluster to plot
```

```
January_2013GroupedCluster = cbind(January_2013Grouped, cluster = groups)

## we will have to convert it to factor

January_2013GroupedCluster$cluster = as.factor(January_2013GroupedCluster$cluster)
```

```
## now we will be grouping by cluster to be able to have the average of
## each time interval

January_2013GroupedClusterAverage = January_2013GroupedCluster %>%
    group_by(cluster) %>%
    summarise_all(mean)


## we got to transform this into vertical data so we can have a colum
## of time and the power percent to plot

January_2013GroupedClusterAverageVertical = transpose(January_2013GroupedClusterAverage)


# Change colnames of all columns
colnames(January_2013GroupedClusterAverageVertical) <- c("Cluster1", "Cluster2",
    "Cluster3", "Cluster4")

## we will also be dropping the first row as we no longer need the
## cluster variables and these will interfere with the plotting
January_2013GroupedClusterAverageVertical = January_2013GroupedClusterAverageVertical[-1,
    ]

## we will also be dropping the last row as we no longer need the max
## values and these will interfere with the plotting as well

January_2013GroupedClusterAverageVertical = January_2013GroupedClusterAverageVertical[-nro
    ]
```

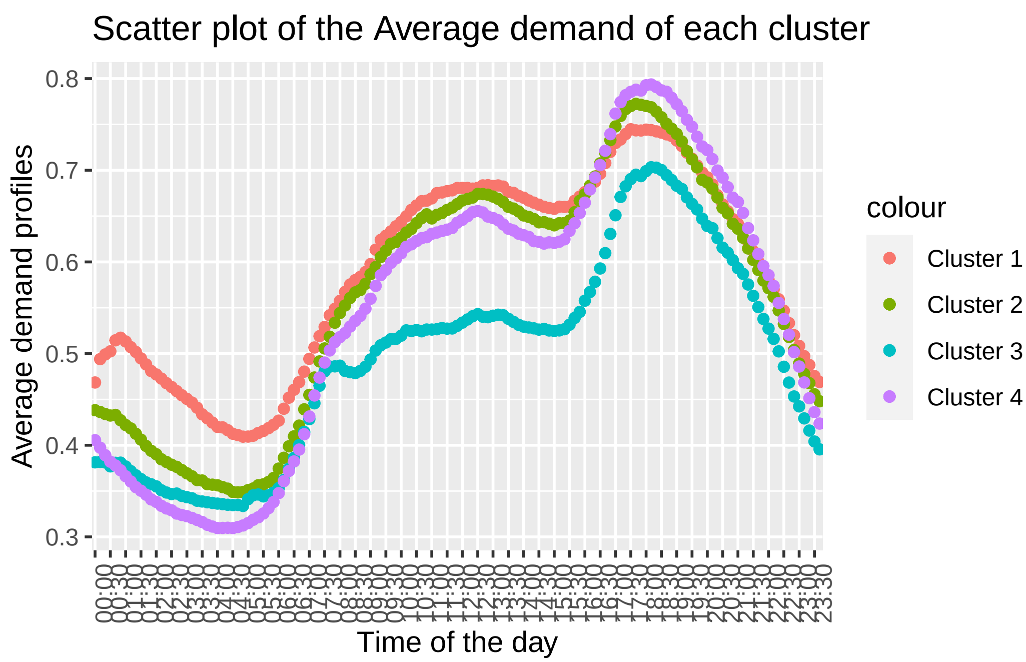
```
time_interval <- seq(from = as.numeric(as.POSIXlt("0000", format = "%H%M")),
    to = as.numeric(as.POSIXlt("2340", format = "%H%M")), by = 10 * 60)
time_interval <- format(as.POSIXlt(time_interval, origin = "1970-01-01"),
    format = "%H:%M")
```

```r
January_2013GroupedClusterAverageVertical$timeIntervals = time_interval

str(January_2013GroupedClusterAverageVertical)
```

```
'data.frame':   143 obs. of  5 variables:
 $ Cluster1     : chr  "0.468467247588763" "0.493925891135066" "0.499048837449598" "0.502442
 $ Cluster2     : chr  "0.4382325402407" "0.436303506379899" "0.43405936134153" "0.432404498
 $ Cluster3     : chr  "0.381342297712971" "0.381807705603982" "0.381193795730681" "0.376947
 $ Cluster4     : chr  "0.405499884129606" "0.397328827163718" "0.389122525987762" "0.382044
 $ timeIntervals: chr  "00:00" "00:10" "00:20" "00:30" ...
```

```r
## it seems we will have to convert the values of the clusters to float

January_2013GroupedClusterAverageVertical$Cluster1 = as.double(January_2013GroupedClusterA
January_2013GroupedClusterAverageVertical$Cluster2 = as.double(January_2013GroupedClusterA
January_2013GroupedClusterAverageVertical$Cluster3 = as.double(January_2013GroupedClusterA
January_2013GroupedClusterAverageVertical$Cluster4 = as.double(January_2013GroupedClusterA
```

```r
ggplot() + geom_point(data = January_2013GroupedClusterAverageVertical, aes(x = timeInterv
    y = Cluster1, color = "Cluster 1")) + geom_point(data = January_2013GroupedClusterAver
    aes(x = timeIntervals, y = Cluster2, color = "Cluster 2")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster3, color = "Cluster 3")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster4, color = "Cluster 4")) + ggtitle("Scatter plot of
    xlab("Time of the day") + ylab("Average demand profiles") + theme(axis.text.x = elemen
    scale_x_discrete(breaks = c("00:00", "01:00", "02:00", "03:00", "04:00",
        "05:00", "06:00", "07:00", "08:00", "09:00", "10:00", "11:00", "12:00",
        "13:00", "14:00", "15:00", "16:00", "17:00", "18:00", "19:00", "20:00",
        "21:00", "22:00", "23:00", "00:30", "01:30", "02:30", "03:30", "04:30",
        "05:30", "06:30", "07:30", "08:30", "09:30", "10:30", "11:30", "12:30",
        "13:30", "14:30", "15:30", "16:30", "17:30", "18:30", "19:30", "20:30",
        "21:30", "22:30", "23:30"))
```



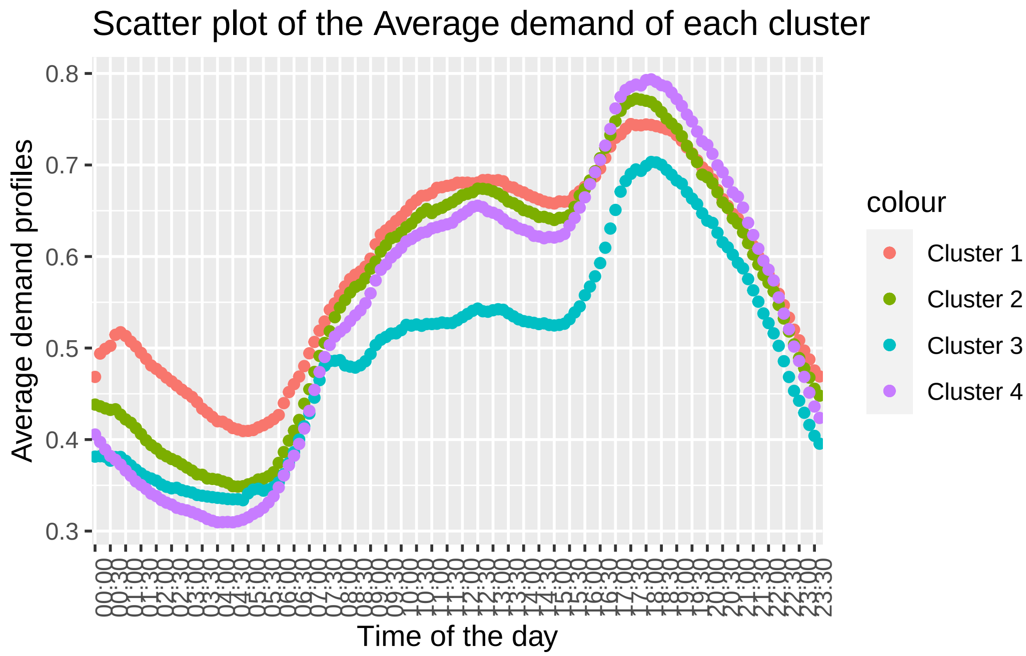
Exercise C 2.vi

```
January_2013Weekdays = January_2013 %>%
    group_by(Substation) %>%
    summarise_all(mean)
January_2013Weekdays = cbind(January_2013Weekdays, cluster = groups)

## Now we got to check which days are week days and which days are
## weekends

January_2013Weekdays$isWeekDay = 1

for (i in 1:nrow(January_2013Weekdays)) {
    if (weekdays(January_2013Weekdays$Date[i]) == "Saturday") {
        January_2013Weekdays$isWeekDay[i] = 0
    }
    if (weekdays(January_2013Weekdays$Date[i]) == "Sunday") {
        January_2013Weekdays$isWeekDay[i] = 0
    }
}
```

```
## then I will group by weekday and substation? TODO figure out


January_2013WeekdaysGrouped = January_2013Weekdays %>%
    group_by(isWeekDay, Substation) %>%
    summarise_all(mean)
```

Exercise C 2.vii

```
ggplot() + geom_point(data = January_2013GroupedClusterAverageVertical, aes(x = timeInterv
    y = Cluster1, color = "Cluster 1")) + geom_point(data = January_2013GroupedClusterAver
    aes(x = timeIntervals, y = Cluster2, color = "Cluster 2")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster3, color = "Cluster 3")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster4, color = "Cluster 4")) + ggtitle("Scatter plot of
    xlab("Time of the day") + ylab("Average demand profiles") + theme(axis.text.x = elemen
    scale_x_discrete(breaks = c("00:00", "01:00", "02:00", "03:00", "04:00",
        "05:00", "06:00", "07:00", "08:00", "09:00", "10:00", "11:00", "12:00",
        "13:00", "14:00", "15:00", "16:00", "17:00", "18:00", "19:00", "20:00",
        "21:00", "22:00", "23:00", "00:30", "01:30", "02:30", "03:30", "04:30",
        "05:30", "06:30", "07:30", "08:30", "09:30", "10:30", "11:30", "12:30",
        "13:30", "14:30", "15:30", "16:30", "17:30", "18:30", "19:30", "20:30",
        "21:30", "22:30", "23:30"))
```




```r
table(groups)
```

```
groups
  1   2   3   4 
141 111 124 159 
```

There are several ways to compare the characteristics data for each of the clusters in R. Firstly we will be comparing characteristics through the visualization of the graph and table of clusters.

As we can see from the tables all of the cluster have a very similarly distributed number of values, with cluster 2 and 3 having slightly less than cluster 1 and 4.

As the cluster 3 is also obviously the one that runs with the lowest average demand during the day, running significantly lower in power demand than the other clusters. A possible explanation for this lower level of power demand and high level of substations is that this cluster could be representing a majority of business serving substations, that usually have less power in comparison the industries. A high level of business costumers would also help explaining the significantly less power usage during the night as business are less likely to have nocturnal working hours than industries. Another possible explanation would be that this cluster has a large amount of pole mounted substations as these also didn't have a large percentage of industrial costumers and the power delivered was significantly lower than its ground counterpart. Therefore I believe we should give cluster 3 the name of poleMounted_business.

Cluster 1 seems to be the one to have on average the approximately power demand as it has a very significantly higher power demand after midnight, that although its lead is reduced during the early morning hours it is maintained until approximately 16:30. After its decrease in demand around 18:00 it maintains demand power levels similar to cluster 2 and 4. Such high power demand could be attributed to high power demand, highly industrialised substations, as it is more likely for an industry to have high power demand outside of working hours, due to the constant production and manufacturing of some industries compared to businesses. It is also possible that the majority of these substations are ground mounted has these were the ones to register significantly higher power levels. Therefore I suggest the name of groundMounted_industries

Next we analyse cluster 4 visualization, this cluster is the one with the least power demand between midnight and the early hours of the morning where power consumption begin to increase. Due to this, this cluster is the one to have the biggest increase in power demand during the day falling shortly behind cluster 1 and 3. It is in the later part of the afternoon that this cluster achieves its last demand increasing surpassing both cluster 1 and 3, becoming the one with the highest percentage of power demand until 21:00. Such high level of power demand during the evening and low power consumption during the early hours of the day could potentially be attribute to business that provide services such as food or entertainment that are highly sought after during the middle of the day and after working hours. Therefore I suggest referring to this cluster as the goodsServices_business

Lastly cluster 2 who seems to be a a mixture of some of the characteristics of the other clusters, as this cluster never becomes the biggest or lowest power consumer, always maintaining itself as an average of these other clusters. Therefore i suggest naming this cluster as averageCharacteristics.

We can use the tapply() function to calculate summary statistics (e.g mean, median, standard deviation) for each cluster. Summary statistics such as mean, median, and standard deviation are important to compare each cluster because they provide a quantitative measure of the central tendency and spread of the characteristic variable within each cluster. The mean is a measure of central tendency that represents the average value of the characteristic variable within a cluster. It is useful to compare the mean value of the characteristic variable across different clusters to see if there are any significant differences. The median is another measure of central tendency that represents the middle value of the characteristic variable within a cluster when the data is sorted. It is useful to compare the median value of the characteristic variable across different clusters to see if there are any significant differences. The standard deviation is a measure of spread that represents the amount of variation or dispersion of the characteristic variable within a cluster. It is useful to compare the standard deviation of the characteristic variable across different clusters to see if there are any significant differences. By comparing these statistics across clusters, we can gain insights into the underlying structure of the data and identify patterns or trends that might not be immediately apparent from visual inspection.

```r
## we will know get the summary for each cluster
Cluster1_summary <- January_2013GroupedClusterAverageVertical %>%
    summarize(mean = mean(Cluster1), median = median(Cluster1), sd = sd(Cluster1))

Cluster2_summary <- January_2013GroupedClusterAverageVertical %>%
    summarize(mean = mean(Cluster2), median = median(Cluster2), sd = sd(Cluster2))

Cluster3_summary <- January_2013GroupedClusterAverageVertical %>%
    summarize(mean = mean(Cluster3), median = median(Cluster3), sd = sd(Cluster3))

Cluster4_summary <- January_2013GroupedClusterAverageVertical %>%
    summarize(mean = mean(Cluster4), median = median(Cluster4), sd = sd(Cluster4))


Cluster1_summary
```

```
       mean    median        sd
1 0.5899623 0.6240561 0.1072105
```

```r
Cluster2_summary
```

```
       mean    median       sd
1 0.5635166 0.6122495 0.134687
```

```r
Cluster3_summary
```

```
      mean    median        sd
1 0.495339 0.5243339 0.1106274
```

```r
Cluster4_summary
```

```
       mean    median        sd
1 0.5483276 0.6038117 0.1549162
```

As we can observe by the summary statistics cluster 3 has significantly less power demand than the other clusters being 5% of the second lower power consuming cluster, cluster 4, with the highest power consuming cluster being cluster 1. It is also notorious that cluster 1 is the one the lowest standard deviation, meaning this is the cluster whose substations are the most similar to each other. In comparison cluster 4 has almost 50% higher standard deviation meaning that the substations in cluster 4 are that much less similar to each other than the ones from cluster 1. Since clustering is done based on the similarity of the occurences this could indicate that if the number of clusters increased, cluster 4 would be the one to be most likely branched.

Here we now changing the name of all the clusters to the suggested ones.

```
colnames(January_2013GroupedClusterAverageVertical)[3] = "poleMounted_business"
colnames(January_2013GroupedClusterAverageVertical)[1] = "groundMounted_industries"
colnames(January_2013GroupedClusterAverageVertical)[4] = "goodsServices_business"
colnames(January_2013GroupedClusterAverageVertical)[2] = "averageCharacteristics"
```

Exercise C 3 i

```
load("C:/AppliedDataScienceAndStatistics/Applied-Data-Science-and-Statistics/Term1/Applica
```

```
## is weekend new_substations = new_substations %>%
## group_by(Substation) %>% summarise_all(mean) new_substations =
## cbind(new_substations, cluster = groups)

## Now we got to check which days are week days and which days are
## weekends

## making the opposite to get if its is a weekday or not, it does not
## work with markdown, since it does not render even though it compiles
## new_substations$isWeekDay = !is.weekend(new_substations$Date)

new_substations$isWeekDay = 1
new_substations$Date = as.Date(new_substations$Date, format = "%Y-%m-%d")
for (i in 1:nrow(new_substations)) {
    if (weekdays(new_substations$Date[i]) == "Saturday") {
        new_substations$isWeekDay[i] = 0
    }
    if (weekdays(new_substations$Date[i]) == "Sunday") {
        new_substations$isWeekDay[i] = 0
    }
}
```

```
new_substationsGroupedWeek = new_substations %>%
    group_by(isWeekDay, Substation) %>%
    summarise_all(mean)
```

Exercise C 4

Here we will cluster years 2013 and 2014 to be able to compare how much the number of substations in each cluster change using the function table(groups)

Starting with 2014

```
## as data from 0:00 to 7:50

tenMinuteMaximum = January_2014[, -c(1:2)]

## first we need to the maximum power output of the day i

maxVal = 0
January_2014$max = 0


for (i in 1:nrow(tenMinuteMaximum)) {

    ## the apply() function is used with the MARGIN parameter set to 1,
    ## which applies the function to all rows of the dataframe. Inside
    ## the function, we are checking if the row name is not equal to
    ## substation as the substation number is also bigger than the
    ## power measured in the interval of 10 mins

    maxVal = apply(tenMinuteMaximum[i, ], 1, max)

    # tenMinuteMaximum

    January_2014$max[i] = maxVal


}

January_2014[, 3:146] = January_2014[, 3:146]/January_2014$max
```

```r
January_2014Grouped = January_2014 %>%
    group_by(Substation) %>%
    summarise_all(mean)

January_2014Grouped = January_2014Grouped[, -c(2)]


## REMOVE THE LAST ONE
January_2014Grouped = January_2014Grouped[, -c(146)]

distance_matrix <- dist(January_2014Grouped, method = "manhattan")

cluster = hclust(distance_matrix)

# plot(cluster, xlab='', sub='')

plot(cluster, main = "Dendrogram 2014", labels = FALSE, hang = -1)
```

As we can see the dendrogram is pretty similar to the previous year

```r
## here we can see the the dendogram with the proper clusters already
## cut has mentioned above, using the factoextra library
fviz_dend(cluster, k = 4, rect = TRUE, show_labels = TRUE)
```

```r
# cut the dendrogram into 4 clusters
groups <- cutree(cluster, k = 4)

# find number of observations in each cluster
table(groups)
```

```
groups
  1   2   3   4
141 111 124 159
```

```r
table2014 = table(groups)


## now I will have to get an average of the entire cluster to plot
```

```r
January_2014GroupedCluster = cbind(January_2014Grouped, cluster = groups)

## we will have to convert it to factor

January_2014GroupedCluster$cluster = as.factor(January_2014GroupedCluster$cluster)
```

```r
## now we will be grouping by cluster to be able to have the average of
## each time interval

January_2014GroupedClusterAverage = January_2014GroupedCluster %>%
    group_by(cluster) %>%
    summarise_all(mean)


## we got to transform this into vertical data so we can have a colum
## of time and the power percent to plot

January_2014GroupedClusterAverageVertical = transpose(January_2014GroupedClusterAverage)


# Change colnames of all columns
colnames(January_2014GroupedClusterAverageVertical) <- c("Cluster1", "Cluster2",
    "Cluster3", "Cluster4")

## we will also be dropping the first row as we no longer need the
## cluster variables and these will interfere with the plotting
January_2014GroupedClusterAverageVertical = January_2014GroupedClusterAverageVertical[-1,
    ]

## we will also be dropping the last row as we no longer need the max
## values and these will interfere with the plotting as well

January_2014GroupedClusterAverageVertical = January_2014GroupedClusterAverageVertical[-nro
    ]
```

```r
time_interval <- seq(from = as.numeric(as.POSIXlt("0000", format = "%H%M")),
    to = as.numeric(as.POSIXlt("2340", format = "%H%M")), by = 10 * 60)
time_interval <- format(as.POSIXlt(time_interval, origin = "1970-01-01"),
    format = "%H:%M")
```

```
January_2014GroupedClusterAverageVertical$timeIntervals = time_interval

str(January_2014GroupedClusterAverageVertical)
```

```
'data.frame':   143 obs. of  5 variables:
 $ Cluster1     : chr  "0.468923122763888" "0.487646778905503" "0.491978987945851" "0.494077
 $ Cluster2     : chr  "0.428946424081803" "0.427488267639625" "0.422432925602893" "0.422149
 $ Cluster3     : chr  "0.374846099496887" "0.372873961481572" "0.3717643229765" "0.36633481
 $ Cluster4     : chr  "0.39957974276993" "0.390038502599869" "0.380490884311831" "0.3716652
 $ timeIntervals: chr  "00:00" "00:10" "00:20" "00:30" ...
```

```
## it seems we will have to convert the values of the clusters to float

January_2014GroupedClusterAverageVertical$Cluster1 = as.double(January_2014GroupedClusterA
January_2014GroupedClusterAverageVertical$Cluster2 = as.double(January_2014GroupedClusterA
January_2014GroupedClusterAverageVertical$Cluster3 = as.double(January_2014GroupedClusterA
January_2014GroupedClusterAverageVertical$Cluster4 = as.double(January_2014GroupedClusterA
```

Now that we have year 2014 we just need to do the same again for year 2015

year 2015 version

```
## as data from 0:00 to 7:50

tenMinuteMaximum = January_2015[, -c(1:2)]

## first we need to the maximum power output of the day i

maxVal = 0
January_2015$max = 0


for (i in 1:nrow(tenMinuteMaximum)) {

    ## the apply() function is used with the MARGIN parameter set to 1,
    ## which applies the function to all rows of the dataframe. Inside
    ## the function, we are checking if the row name is not equal to
    ## substation as the substation number is also bigger than the
    ## power measured in the interval of 10 mins
```

```
    maxVal = apply(tenMinuteMaximum[i, ], 1, max)

    # tenMinuteMaximum

    January_2015$max[i] = maxVal


}

January_2015[, 3:146] = January_2015[, 3:146]/January_2015$max


January_2015Grouped = January_2015 %>%
    group_by(Substation) %>%
    summarise_all(mean)

January_2015Grouped = January_2015Grouped[, -c(2)]


## REMOVE THE LAST ONE
January_2015Grouped = January_2015Grouped[, -c(146)]

distance_matrix <- dist(January_2015Grouped, method = "manhattan")

cluster = hclust(distance_matrix)

# plot(cluster, xlab='', sub='')

plot(cluster, main = "Dendrogram 2015", labels = FALSE, hang = -1)
```

As we can see the dendrogram is pretty similar to the previous year

```
## here we can see the the dendogram with the proper clusters already
## cut has mentioned above, using the factoextra library
fviz_dend(cluster, k = 4, rect = TRUE, show_labels = TRUE)
```

```
# cut the dendrogram into 4 clusters
groups <- cutree(cluster, k = 4)

# find number of observations in each cluster
table(groups)
```

```
groups
  1   2   3   4 
141 111 124 159 
```

```r
table2015 = table(groups)


## now I will have to get an average of the entire cluster to plot

January_2015GroupedCluster = cbind(January_2015Grouped, cluster = groups)

## we will have to convert it to factor

January_2015GroupedCluster$cluster = as.factor(January_2015GroupedCluster$cluster)
```

```r
## now we will be grouping by cluster to be able to have the average of
## each time interval

January_2015GroupedClusterAverage = January_2015GroupedCluster %>%
    group_by(cluster) %>%
    summarise_all(mean)


## we got to transform this into vertical data so we can have a colum
## of time and the power percent to plot

January_2015GroupedClusterAverageVertical = transpose(January_2015GroupedClusterAverage)


# Change colnames of all columns
colnames(January_2015GroupedClusterAverageVertical) <- c("Cluster1", "Cluster2",
    "Cluster3", "Cluster4")

## we will also be dropping the first row as we no longer need the
## cluster variables and these will interfere with the plotting
January_2015GroupedClusterAverageVertical = January_2015GroupedClusterAverageVertical[-1,
    ]

## we will also be dropping the last row as we no longer need the max
## values and these will interfere with the plotting as well
```

```r
January_2015GroupedClusterAverageVertical = January_2015GroupedClusterAverageVertical[-nro
    ]
```

```r
time_interval <- seq(from = as.numeric(as.POSIXlt("0000", format = "%H%M")),
    to = as.numeric(as.POSIXlt("2340", format = "%H%M")), by = 10 * 60)
time_interval <- format(as.POSIXlt(time_interval, origin = "1970-01-01"),
    format = "%H:%M")

January_2015GroupedClusterAverageVertical$timeIntervals = time_interval

str(January_2015GroupedClusterAverageVertical)
```

```
'data.frame':   143 obs. of  5 variables:
 $ Cluster1     : chr  "0.474671132868889" "0.491480784073562" "0.495626312113016" "0.493588
 $ Cluster2     : chr  "0.438540575003467" "0.437087658553064" "0.430496204159385" "0.426819
 $ Cluster3     : chr  "0.374377664500345" "0.375667039247904" "0.376140671596003" "0.371943
 $ Cluster4     : chr  "0.400848721662106" "0.391788683848514" "0.379747697679557" "0.372563
 $ timeIntervals: chr  "00:00" "00:10" "00:20" "00:30" ...
```

```r
## it seems we will have to convert the values of the clusters to float

January_2015GroupedClusterAverageVertical$Cluster1 = as.double(January_2015GroupedClusterA
January_2015GroupedClusterAverageVertical$Cluster2 = as.double(January_2015GroupedClusterA
January_2015GroupedClusterAverageVertical$Cluster3 = as.double(January_2015GroupedClusterA
January_2015GroupedClusterAverageVertical$Cluster4 = as.double(January_2015GroupedClusterA
```

Now that we have the 3 years lets start by doing a visual analyses and comparing the 3 graphs of the clusters

Report for this question

This report presents the results of an analysis of power demand clusters by year. The goal of this analysis was to explore whether there were any differences in the membership of clusters between years. Three different clustering methods were used to group the substations into clusters based on their power demand patterns, and the results of these analyses were visualized using graphs.

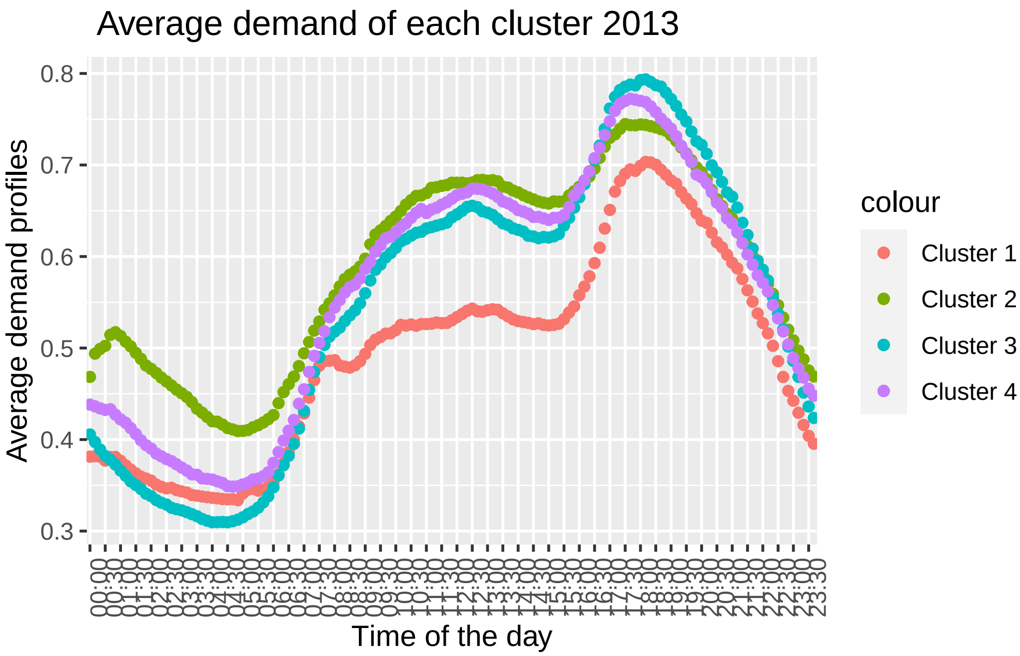
For the initial analysis I have wrangled the data of each year to obtain the average power demand of each 10 minute time interval for the entire day using the maximum value of power for each substation.

I have use the following clustering methodology for each year:

Clustering Method 1: Utilizing the Manhattan distance function, I have created a distance matrix of the data previously wrangled. Clustering Method 2: Furthermore I have built an hierarchy with my matrix, allowing me cluster my data points based on their similarity with each other and analysing them as such. Clustering Method 3: I have created an dendrogram to visually identify how many significantly distinct groups where in the data and therefore how many should we separate them into, cutting this groups from the initial leaf and creating them as clusters. Clustering Method 4: I have confirmed my initial cluster choice by utilising a second already cut dendrogram to illustrate how my choice of number of cluster would not leave any significant height differences for any future branches, guaranteeing this way that much choice would be optimal compared to any other number of clusters. Clustering Method 5: With the data already distributed through my 4 cluster I did some extra wrangling on the data to be able to plot each cluster power demand throughout the day against each other. These graphs will be shown bellow along with their interpretation.

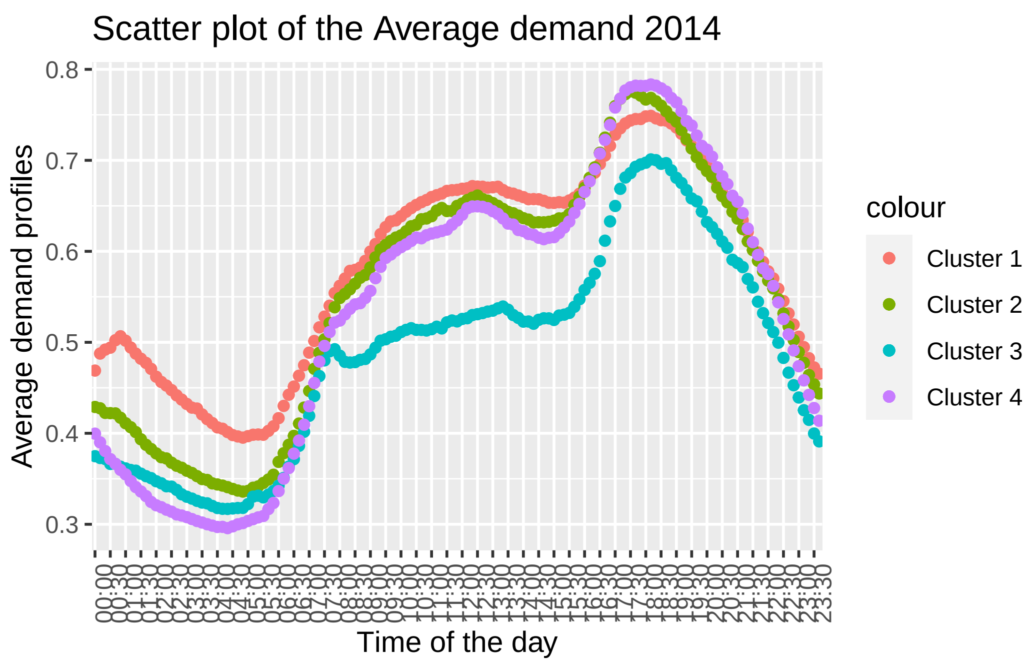
Here we have the graph for 2013

```
# colnames(January_2013GroupedClusterAverageVertical)[3] =
# 'poleMounted_business'
# colnames(January_2013GroupedClusterAverageVertical)[1] =
# 'groundMounted_industries'
# colnames(January_2013GroupedClusterAverageVertical)[4] =
# 'goodsServices_business'
# colnames(January_2013GroupedClusterAverageVertical)[2] =
# 'averageCharacteristics'


ggplot() + geom_point(data = January_2013GroupedClusterAverageVertical, aes(x = timeInterv
    y = poleMounted_business, color = "Cluster 1")) + geom_point(data = January_2013Groupe
    aes(x = timeIntervals, y = groundMounted_industries, color = "Cluster 2")) +
    geom_point(data = January_2013GroupedClusterAverageVertical, aes(x = timeIntervals,
        y = goodsServices_business, color = "Cluster 3")) + geom_point(data = January_2013
    aes(x = timeIntervals, y = averageCharacteristics, color = "Cluster 4")) +
    ggtitle(" Average demand of each cluster 2013") + xlab("Time of the day") +
    ylab("Average demand profiles") + theme(axis.text.x = element_text(angle = 90)) +
    scale_x_discrete(breaks = c("00:00", "01:00", "02:00", "03:00", "04:00",
        "05:00", "06:00", "07:00", "08:00", "09:00", "10:00", "11:00", "12:00",
        "13:00", "14:00", "15:00", "16:00", "17:00", "18:00", "19:00", "20:00",
        "21:00", "22:00", "23:00", "00:30", "01:30", "02:30", "03:30", "04:30",
        "05:30", "06:30", "07:30", "08:30", "09:30", "10:30", "11:30", "12:30",
        "13:30", "14:30", "15:30", "16:30", "17:30", "18:30", "19:30", "20:30",
        "21:30", "22:30", "23:30"))
```



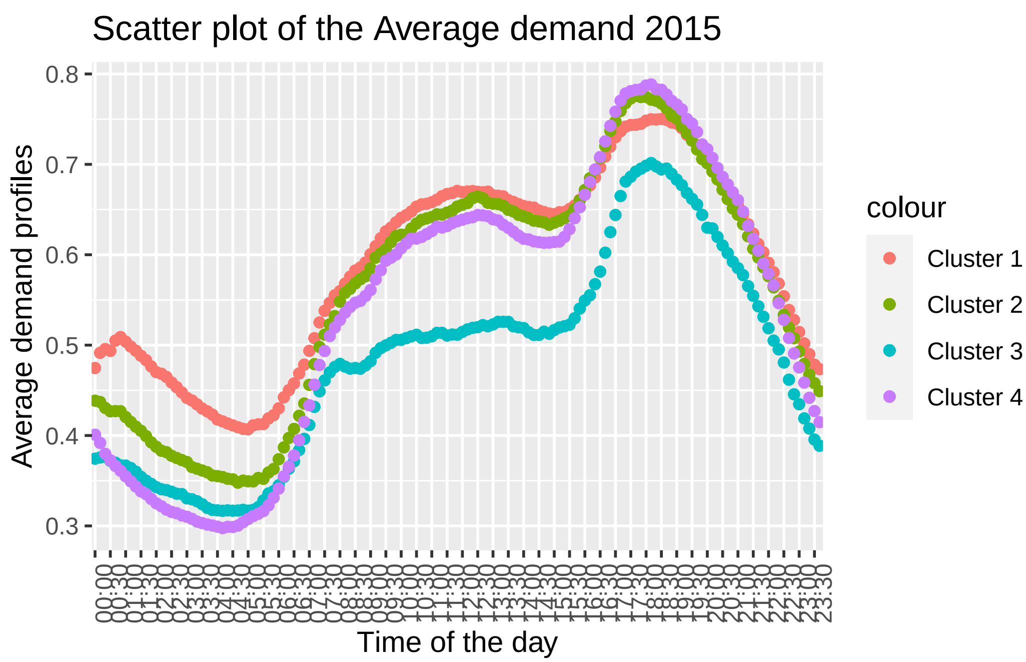
Here we have the graph for 2014

```
ggplot() + geom_point(data = January_2014GroupedClusterAverageVertical, aes(x = timeInterv
    y = Cluster1, color = "Cluster 1")) + geom_point(data = January_2014GroupedClusterAver
    aes(x = timeIntervals, y = Cluster2, color = "Cluster 2")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster3, color = "Cluster 3")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster4, color = "Cluster 4")) + ggtitle("Scatter plot of 
    xlab("Time of the day") + ylab("Average demand profiles") + theme(axis.text.x = elemen
    scale_x_discrete(breaks = c("00:00", "01:00", "02:00", "03:00", "04:00",
        "05:00", "06:00", "07:00", "08:00", "09:00", "10:00", "11:00", "12:00",
        "13:00", "14:00", "15:00", "16:00", "17:00", "18:00", "19:00", "20:00",
        "21:00", "22:00", "23:00", "00:30", "01:30", "02:30", "03:30", "04:30",
        "05:30", "06:30", "07:30", "08:30", "09:30", "10:30", "11:30", "12:30",
        "13:30", "14:30", "15:30", "16:30", "17:30", "18:30", "19:30", "20:30",
        "21:30", "22:30", "23:30"))
```



Here we have the graph for 2015

```
ggplot() + geom_point(data = January_2015GroupedClusterAverageVertical, aes(x = timeInterv
    y = Cluster1, color = "Cluster 1")) + geom_point(data = January_2015GroupedClusterAver
    aes(x = timeIntervals, y = Cluster2, color = "Cluster 2")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster3, color = "Cluster 3")) + geom_point(data = January
    aes(x = timeIntervals, y = Cluster4, color = "Cluster 4")) + ggtitle("Scatter plot of
    xlab("Time of the day") + ylab("Average demand profiles") + theme(axis.text.x = elemen
    scale_x_discrete(breaks = c("00:00", "01:00", "02:00", "03:00", "04:00",
        "05:00", "06:00", "07:00", "08:00", "09:00", "10:00", "11:00", "12:00",
        "13:00", "14:00", "15:00", "16:00", "17:00", "18:00", "19:00", "20:00",
        "21:00", "22:00", "23:00", "00:30", "01:30", "02:30", "03:30", "04:30",
        "05:30", "06:30", "07:30", "08:30", "09:30", "10:30", "11:30", "12:30",
        "13:30", "14:30", "15:30", "16:30", "17:30", "18:30", "19:30", "20:30",
        "21:30", "22:30", "23:30"))
```



Results:

Graph 1: As it can be observed on the first graph The most common feature of all clusters is their peak in energy demand around 17:30 each day and the trough reaches its lowest at approximately 4:30. Besides these common points, cluster 1 has consistently been the cluster with the lowest power demand, which is exacerbated between 7:30 and 16:30 still continuing to be the lowest power demanding cluster through the day. Cluster 2 has also been consistently the one with the highest power demanding cluster during most of the day and with a very significantly higher demand than any other cluster between midnight and 7:00. Lastly cluster 3 has the the lowest power consumption during the night but during the biggest peak of the day it becomes the most power demanding cluster for approximately 3 hours until it crashes back to 3rd most power demanding cluster. Graph 2: The most obvious observation is that in 2014 the previous year main patterns remained the same. However the clusters has now decreases its consumption during the night, with cluster 4 now reaching values below 30% and cluster 1 values bellow 40% on the trough. It seems that these trend has also affected cluster 3 during the peak of energy demand as the maximum demand has decrease by approximately 2,5% while remaining constant on the other clusters during the peak. Lastly cluster 3 had a significant reduction in demand between 7:30 and 15:00, aggravating the difference in power demand with the other clusters. Graph 3: In 2015 there doesn't seem to have been any global change that affected all or the majority of the clusters, in fact this year the results have been considerably more stable then the 2014 ones. Cluster 3 has once again decreased in power between 7:30 and 15:00, aggravating the difference in power demand with the other clusters once again. Cluster 4 has a slight increase around the minor peak in demand at noon. All the other clusters seem to have remaint constant without any noticevae changes in power demand through the day.

Discussion:

Immediately form the graphs we can see that the main patterns of each cluster has been maintained over the years analyses, meaning the substation costumers didn't change significantly enough to cause substations to change in the clusters branching. With significant enough changes it is possible for substations to change their characteristics enough as to become more similar to substations of another cluster.

This can also be observed by the table of number of substations per cluster that the numbers has been kept constant, further confirming that the changes over these 3 years did not affected significantly the power demanded of most of the substations.

```
table2013
```

```
groups
  1   2   3   4 
141 111 124 159 
```

```
table2014
```

```
groups
  1   2   3   4 
141 111 124 159 
```

```
table2015
```

```
groups
  1   2   3   4 
141 111 124 159 
```

Conclusion: This analysis provides an in-depth look at the power demand clusters by year. It has been found that cluster 3 has a tendency to decrease over the years, the peak demand hours is at 17:30 and the trough is at 4:30, furthermore other clusters seem to have remained stable on the last year. These results can be used by power company to make informed decisions about the power demand management.