

# Tochi Okorie Dissertation

```
chooseCRANmirror(graphics=FALSE, ind=1)
knitr::opts_chunk$set(echo = TRUE)
```

## Dissertation

*Tochi Okorie* Carbon footprints of digital systems

```
pkgs <- c("moments", "ggplot2", "dplyr", "tidyr", "tidyverse")
install.packages(pkgs, repos = "http://cran.us.r-project.org")
```

```
## Installing packages into 'C:/Users/tochi/Documents/R/win-library/4.0'
## (as 'lib' is unspecified)
```

```
## package 'moments' successfully unpacked and MD5 sums checked
## package 'ggplot2' successfully unpacked and MD5 sums checked
## package 'dplyr' successfully unpacked and MD5 sums checked
```

```
## Warning: cannot remove prior installation of package 'dplyr'
```

```
## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying C:
## \Users\tochi\Documents\R\win-library\4.0\00LOCK\dplyr\libs\x64\dplyr.dll to C:
## \Users\tochi\Documents\R\win-library\4.0\dplyr\libs\x64\dplyr.dll: Permission
## denied
```

```
## Warning: restored 'dplyr'
```

```
## package 'tidyr' successfully unpacked and MD5 sums checked
```

```
## Warning: cannot remove prior installation of package 'tidyr'
```

```
## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying C:
## \Users\tochi\Documents\R\win-library\4.0\00LOCK\tidyr\libs\x64\tidyr.dll to C:
## \Users\tochi\Documents\R\win-library\4.0\tidyr\libs\x64\tidyr.dll: Permission
## denied
```

```
## Warning: restored 'tidyr'
```

```
## package 'tidyverse' successfully unpacked and MD5 sums checked
##
```

```
## The downloaded binary packages are in
```

```
## C:\Users\tochi\AppData\Local\Temp\RtmpQRXTPB\downloaded_packages
```

```
tinytex::install_tinytex()
```

```
## tlmgr conf auxtrees add "C:/PROGRA~1/R/R-40~1.2/share/texmf"
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.0.5
```

```
install.packages("rlang")
```

```
## Installing package into 'C:/Users/tochi/Documents/R/win-library/4.0'  
## (as 'lib' is unspecified)
```

```
## package 'rlang' successfully unpacked and MD5 sums checked
```

```
## Warning: cannot remove prior installation of package 'rlang'
```

```
## Warning in file.copy(savedcopy, lib, recursive = TRUE): problem copying C:  
## \Users\tochi\Documents\R\win-library\4.0\00LOCK\rlang\libs\x64\rlang.dll to C:  
## \Users\tochi\Documents\R\win-library\4.0\rlang\libs\x64\rlang.dll: Permission  
## denied
```

```
## Warning: restored 'rlang'
```

```
##
```

```
## The downloaded binary packages are in
```

```
## C:\Users\tochi\AppData\Local\Temp\RtmpQRXTPB\downloaded_packages
```

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.0.5
```

```
## -- Attaching packages ----- tidyverse 1.3.1 --
```

```
## v tibble 3.1.4    v dplyr  1.0.7  
## v tidyr  1.1.3    v stringr 1.4.0  
## v readr  1.4.0    v forcats 0.5.1  
## v purrr  0.3.4
```

```
## Warning: package 'tibble' was built under R version 4.0.5
```

```
## Warning: package 'tidyr' was built under R version 4.0.5
```

```
## Warning: package 'readr' was built under R version 4.0.3
```

```
## Warning: package 'purrr' was built under R version 4.0.3
```

```
## Warning: package 'dplyr' was built under R version 4.0.5
```

```
## Warning: package 'forcats' was built under R version 4.0.5

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
```

```
install.packages("lmtest", repos = "http://cran.us.r-project.org")
```

```
## Installing package into 'C:/Users/tochi/Documents/R/win-library/4.0'
## (as 'lib' is unspecified)
```

```
## package 'lmtest' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
## C:\Users\tochi\AppData\Local\Temp\RtmpQRXTPB\downloaded_packages
```

Load the merged carbon footprint data into my notebook.

```
cf_data <- read.csv("C:/Users/tochi/Desktop/carbonfootprint_data.csv")
```

## EXPLORATORY DATA ANALYSIS

Explore the data numerically and graphically. Confirm the variables that are categorical and numerical/continuous and that R has read them in #appropriately

```
# inspect the dataset
str(cf_data)
```

```
## 'data.frame': 99 obs. of 8 variables:
## $ WEIGHT_OF_CO2_per_time_visited.grams.: num 1.69 1.48 0.68 1.3 11.87 ...
## $ GREEN_HOSTING : int 0 0 0 0 0 0 0 0 0 0 ...
## $ WEIGHT_OF_CARBON.In_grams_yearly. : int 203340 177620 82180 155760 237750 135900 94990 287140
## $ Energy.Kwh. : int 428 374 173 328 2999 316 200 667 1677 444 ...
## $ Score.percentage. : num 0.3 0.35 0.39 0.32 0.39 0.38 0.46 0.32 0.43 0.21 ...
## $ Google_page_insights : int 84 73 79 67 31 88 84 45 53 37 ...
## $ HTTP_REQUEST : int 369 242 105 115 224 102 85 300 130 121 ...
## $ FINDABILITY.Mozrank. : num 9.2 8.4 6.5 5.3 5.5 5.7 5 7.4 5.5 7.7 ...
```

```
# get a summary report
summary(cf_data)
```

```
## WEIGHT_OF_CO2_per_time_visited.grams. GREEN_HOSTING
## Min. : 0.170 Min. :0.0000
## 1st Qu.: 1.330 1st Qu.:0.0000
## Median : 2.040 Median :0.0000
## Mean : 2.584 Mean :0.1414
## 3rd Qu.: 3.070 3rd Qu.:0.0000
## Max. :12.810 Max. :1.0000
## WEIGHT_OF_CARBON.In_grams_yearly. Energy.Kwh. Score.percentage.
## Min. : 20560 Min. : 43.0 Min. :0.2000
## 1st Qu.:159265 1st Qu.: 344.5 1st Qu.:0.3550
```

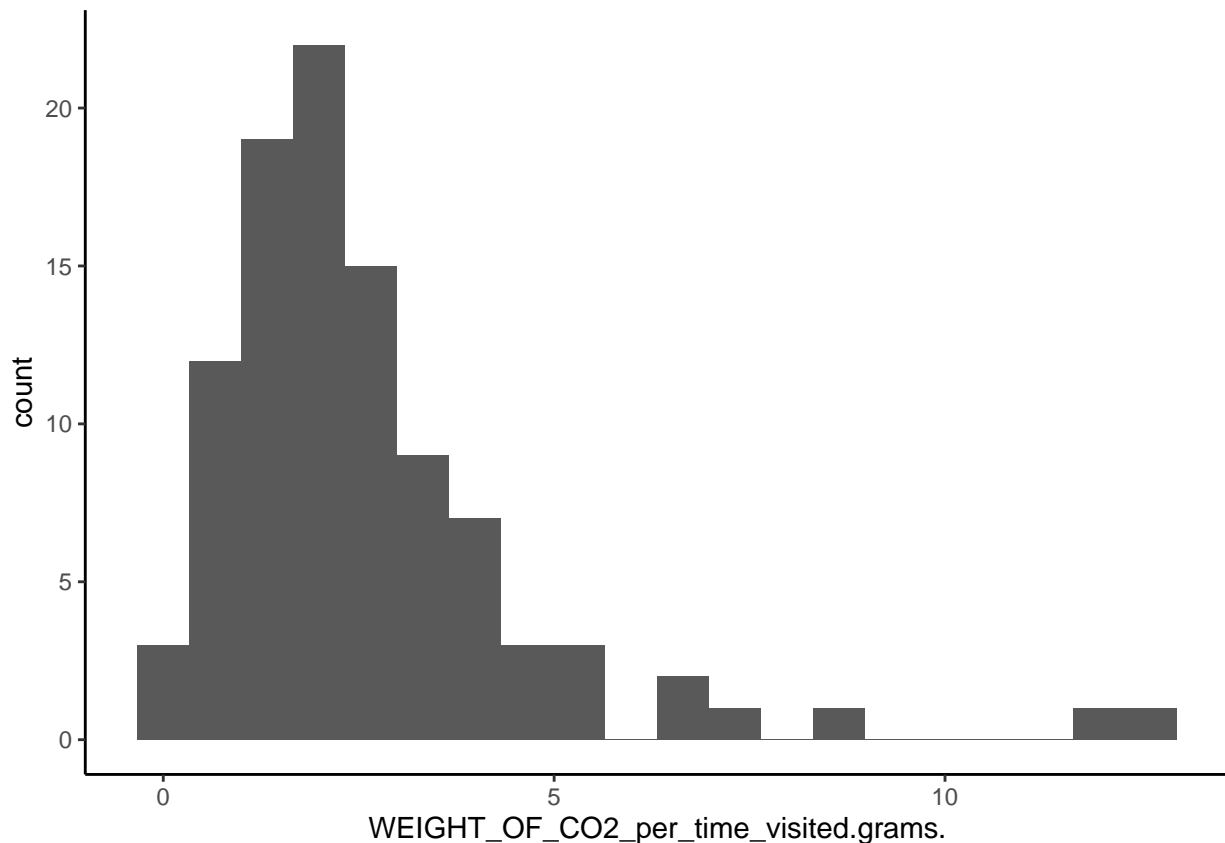
```
## Median :237750          Median : 518.0   Median :0.4100
## Mean   :259377          Mean   : 661.4   Mean   :0.4058
## 3rd Qu.:329275          3rd Qu.: 776.0   3rd Qu.:0.4550
## Max.   :635360          Max.   :3236.0   Max.   :0.7000
## Google_page_insights HTTP_REQUEST FINDABILITY.Mozrank.
## Min.    : 14.00        Min.    : 20.0   Min.    :1.300
## 1st Qu.: 52.50        1st Qu.: 85.0   1st Qu.:5.200
## Median : 71.00        Median :128.0   Median :6.000
## Mean    : 66.18        Mean    :153.8   Mean    :5.944
## 3rd Qu.: 84.00        3rd Qu.:200.0   3rd Qu.:6.800
## Max.    :132.00        Max.    :535.0   Max.    :9.200
```

The variable “Greenhosting” should be a categorical variable (actually binary as it only has two levels). R has read it in as numerical so this can be fixed by making it into a Factor.

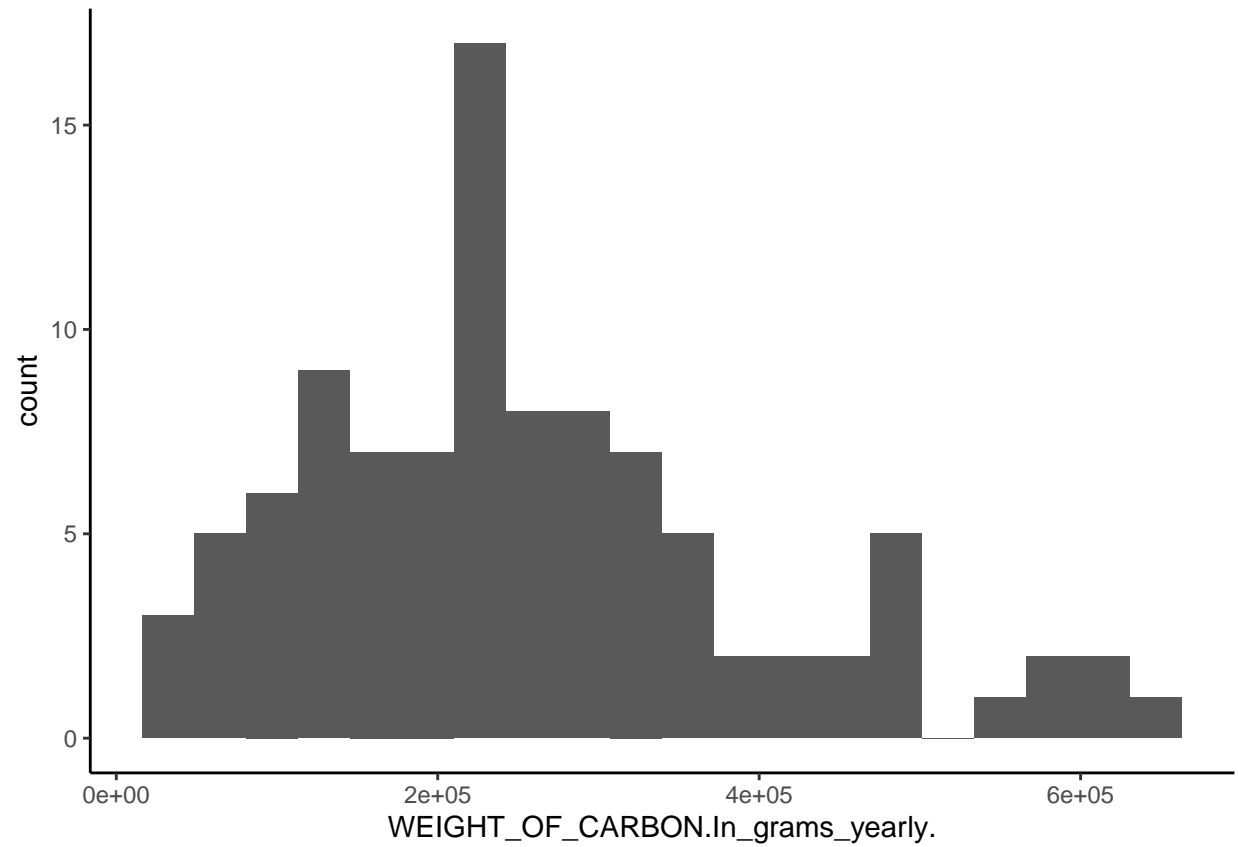
```
#cf_data$GREEN_HOSTING<-as.factor(cf_data$GREEN_HOSTING)
```

Then i look at the distribution of the variables:

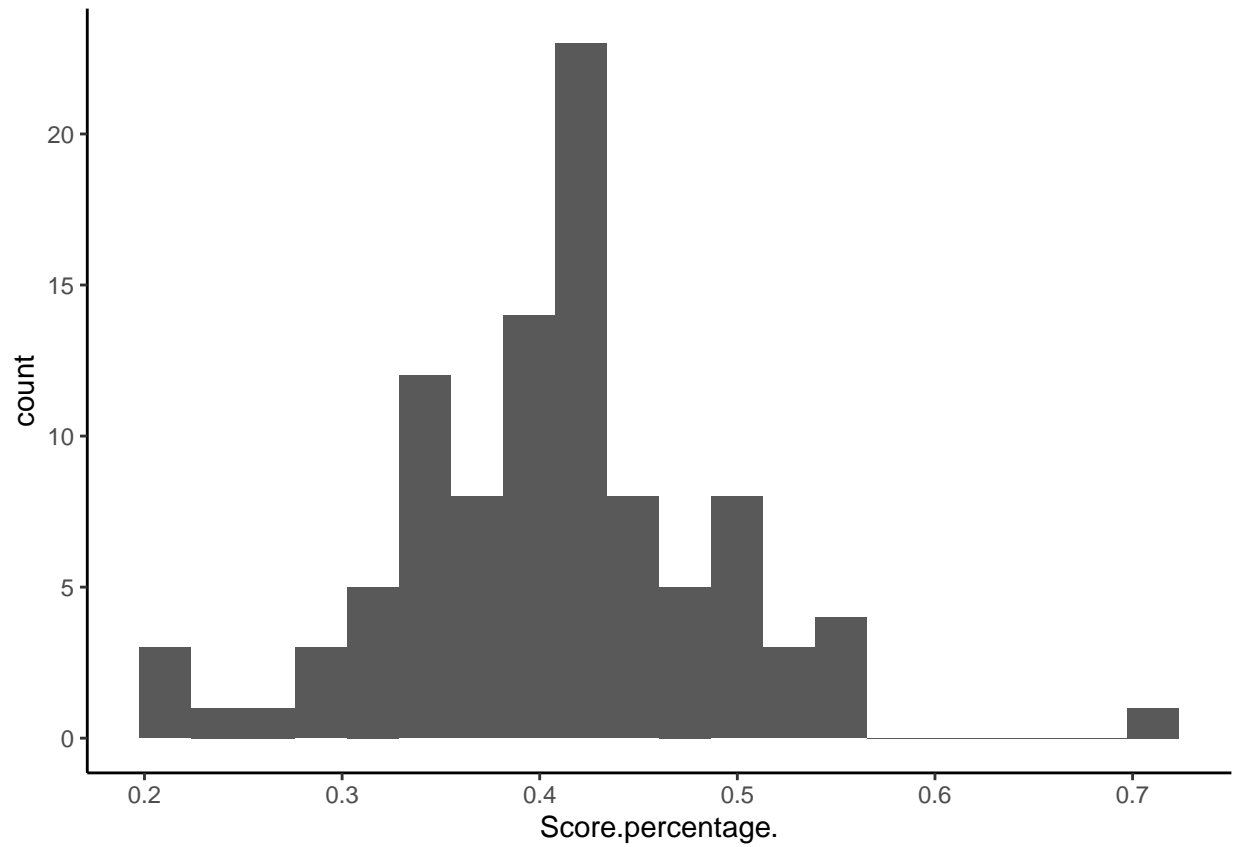
```
ggplot(data = cf_data, aes(x=WEIGHT_OF_CO2_per_time_visited.grams.)) + geom_histogram(bins = 20) + theme
```



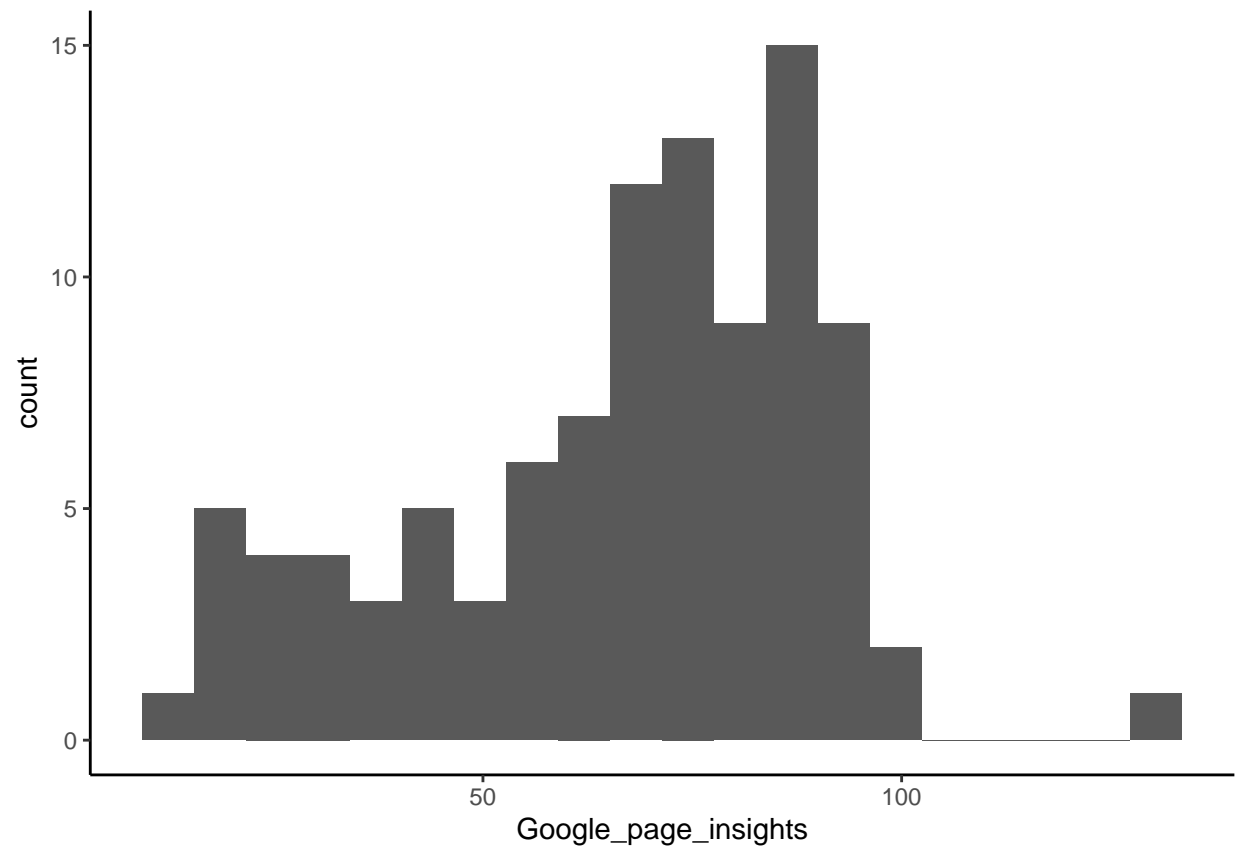
```
ggplot(data = cf_data, aes(x=WEIGHT_OF_CARBON.In_grams_yearly.
)) + geom_histogram(bins = 20) + theme_classic()
```



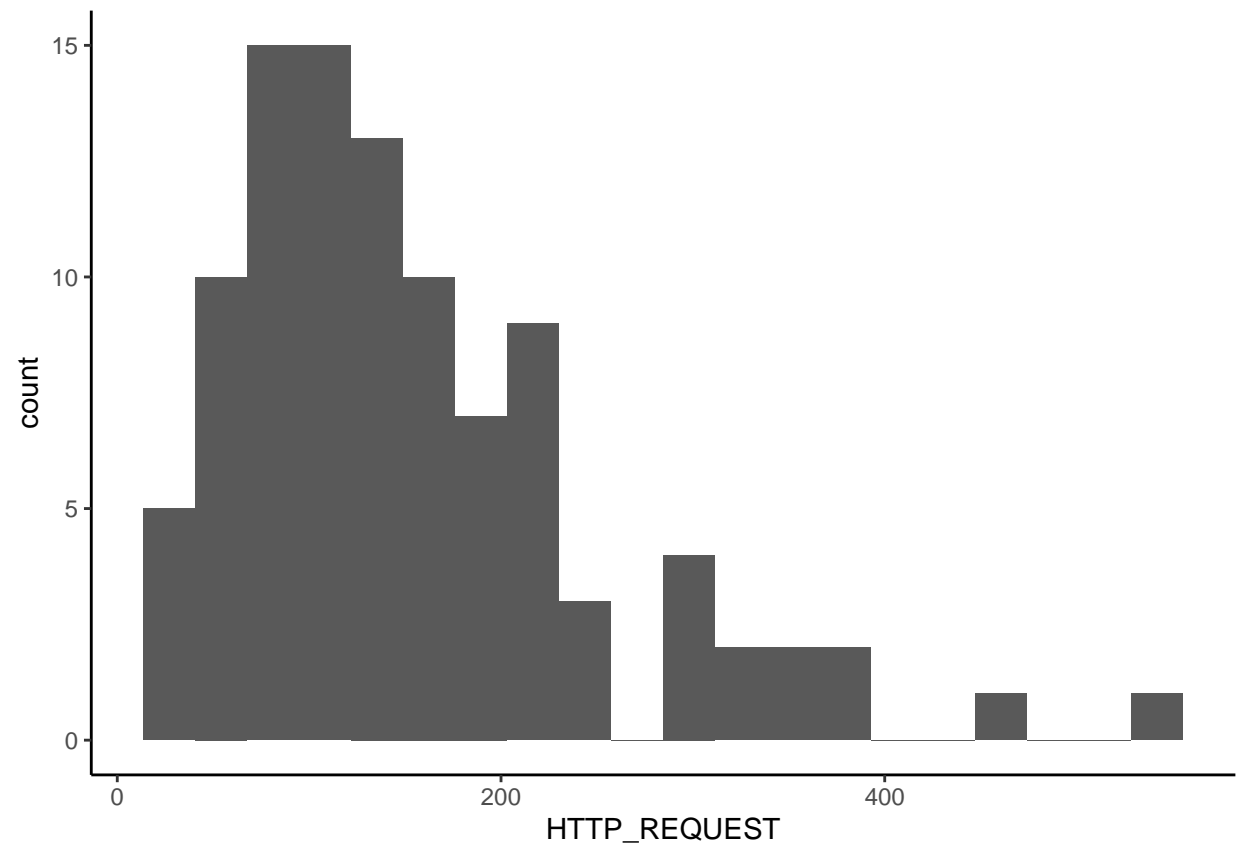
```
ggplot(data = cf_data, aes(x=Score.percentage.)) + geom_histogram(bins = 20) + theme_classic()
```



```
ggplot(data = cf_data, aes(x=Google_page_insights)) + geom_histogram(bins = 20) + theme_classic()
```

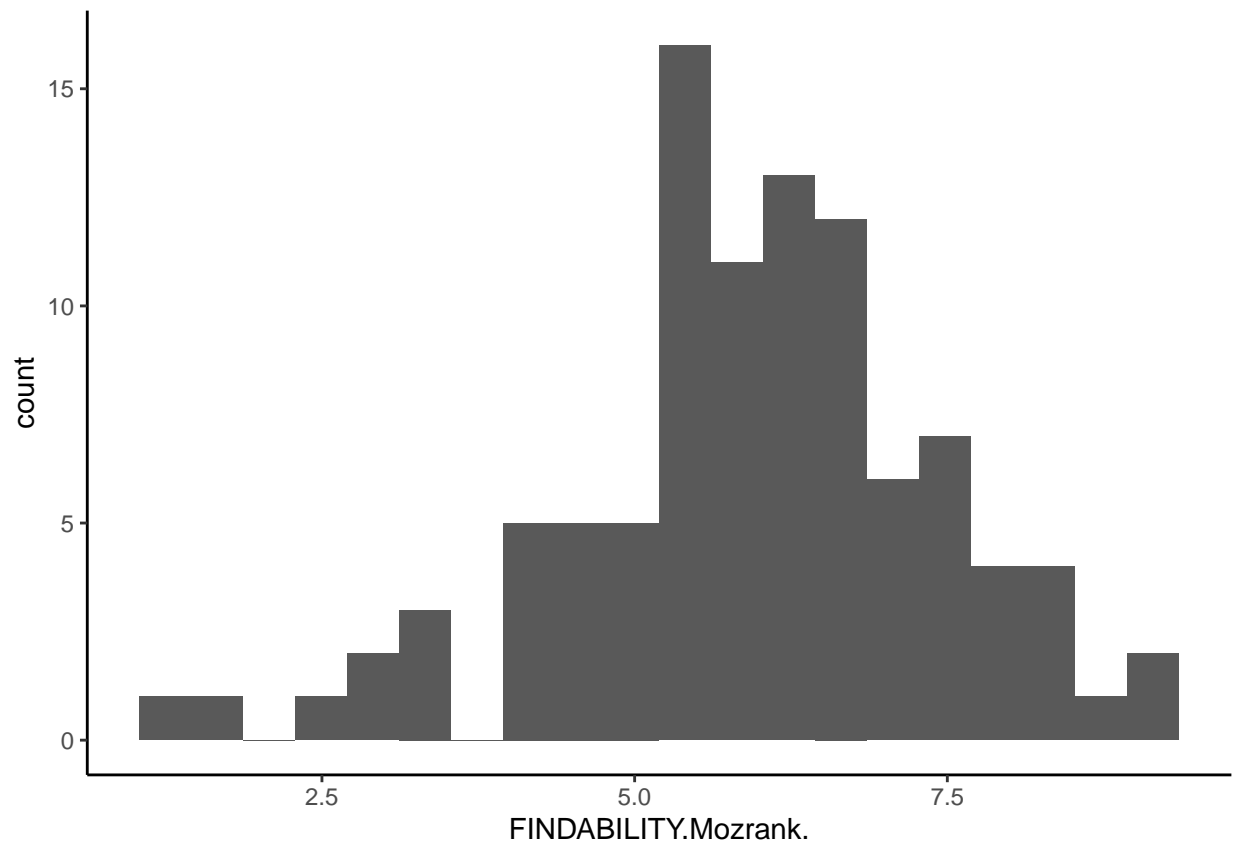


```
ggplot(data = cf_data, aes(x=HTTP_REQUEST)) + geom_histogram(bins = 20) + theme_classic()
```



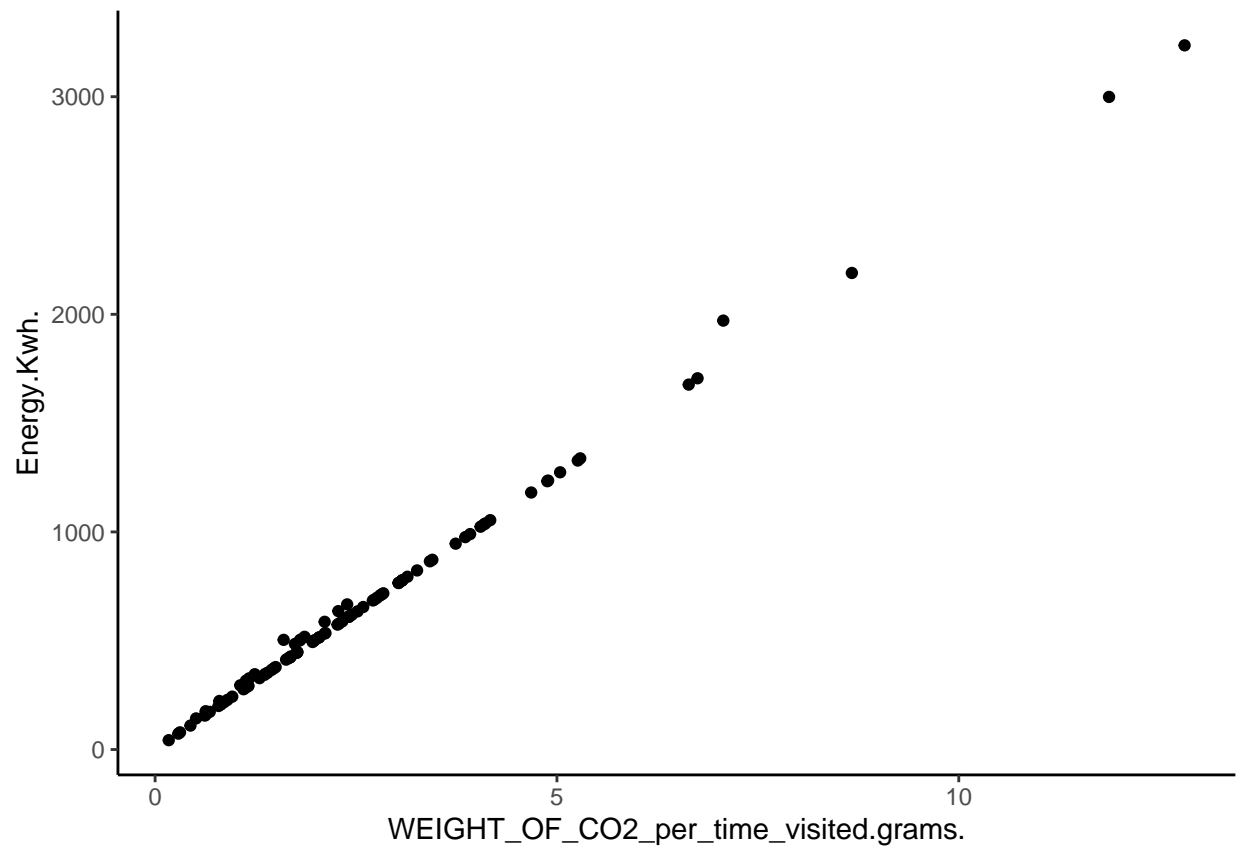
```
ggplot(data = cf_data, aes(x=Findability.Mozrank.)) + geom_histogram(bins = 20) + theme_classic()
```



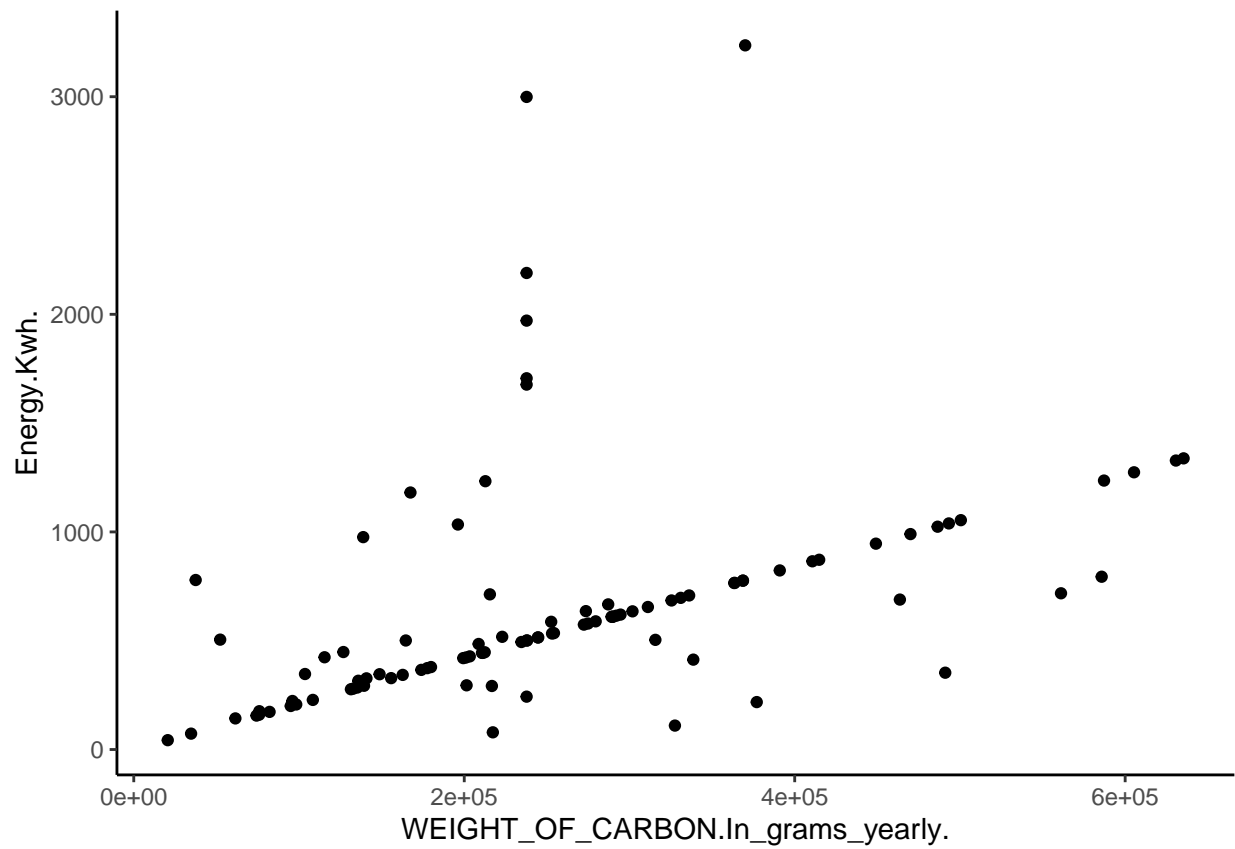


The distribution for Weight per time visited and weight of co2 yearly seems skewed to the left, other variables look generally symmetric. This does not warrant any transformations at this stage.

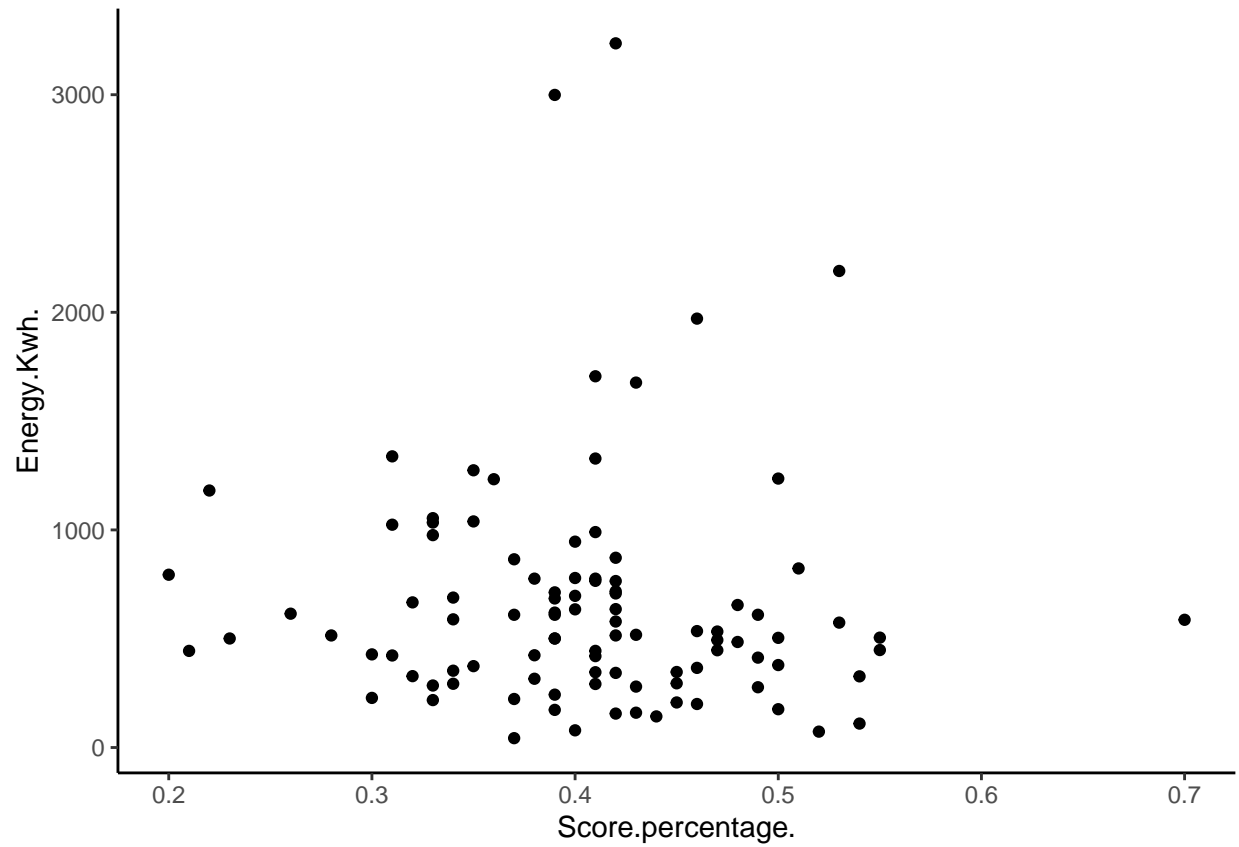
```
ggplot(data = cf_data, aes(x=WEIGHT_OF_CO2_per_time_visited.grams., y=Energy.Kwh.)) + geom_point() + th
```



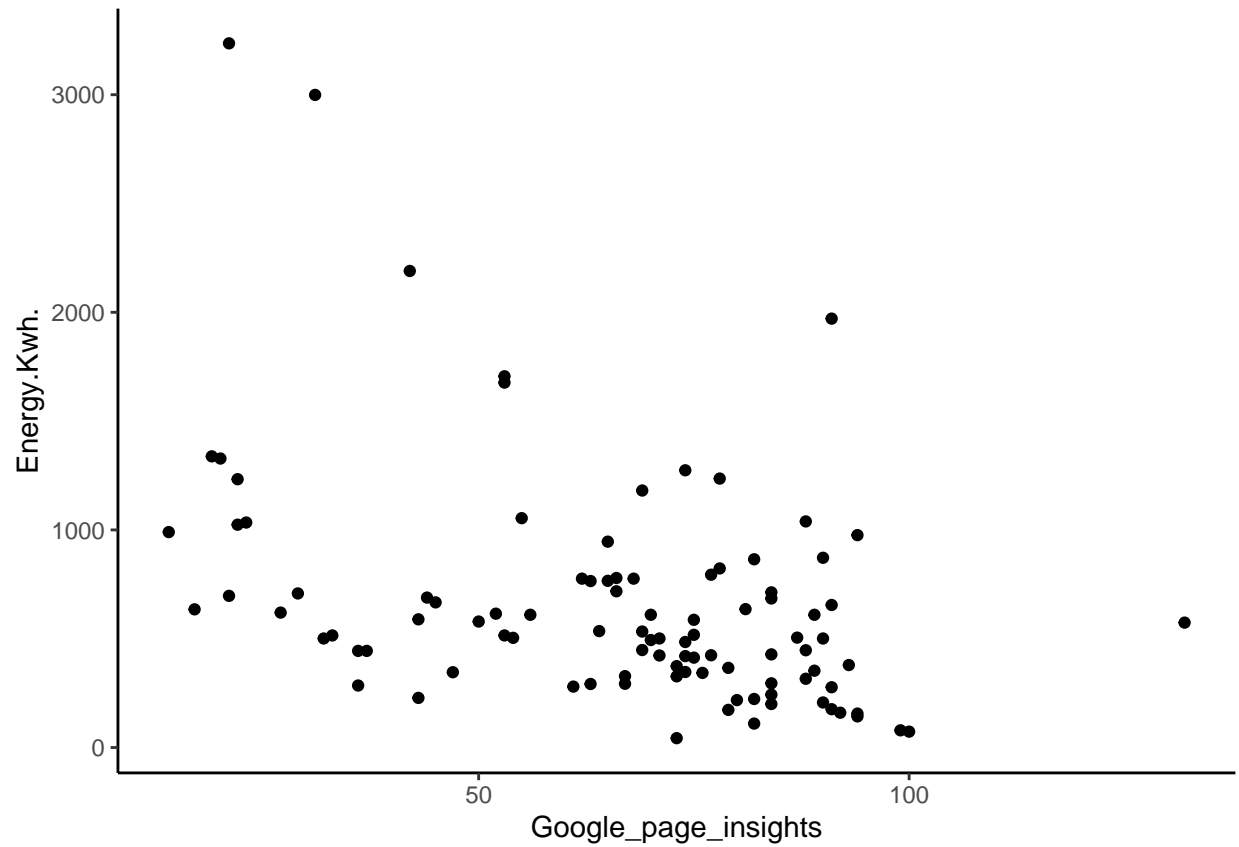
```
ggplot(data = cf_data, aes(x=WEIGHT_OF_CARBN.In_grams_yearly., y=Energy.Kwh.)) + geom_point() + theme_
```



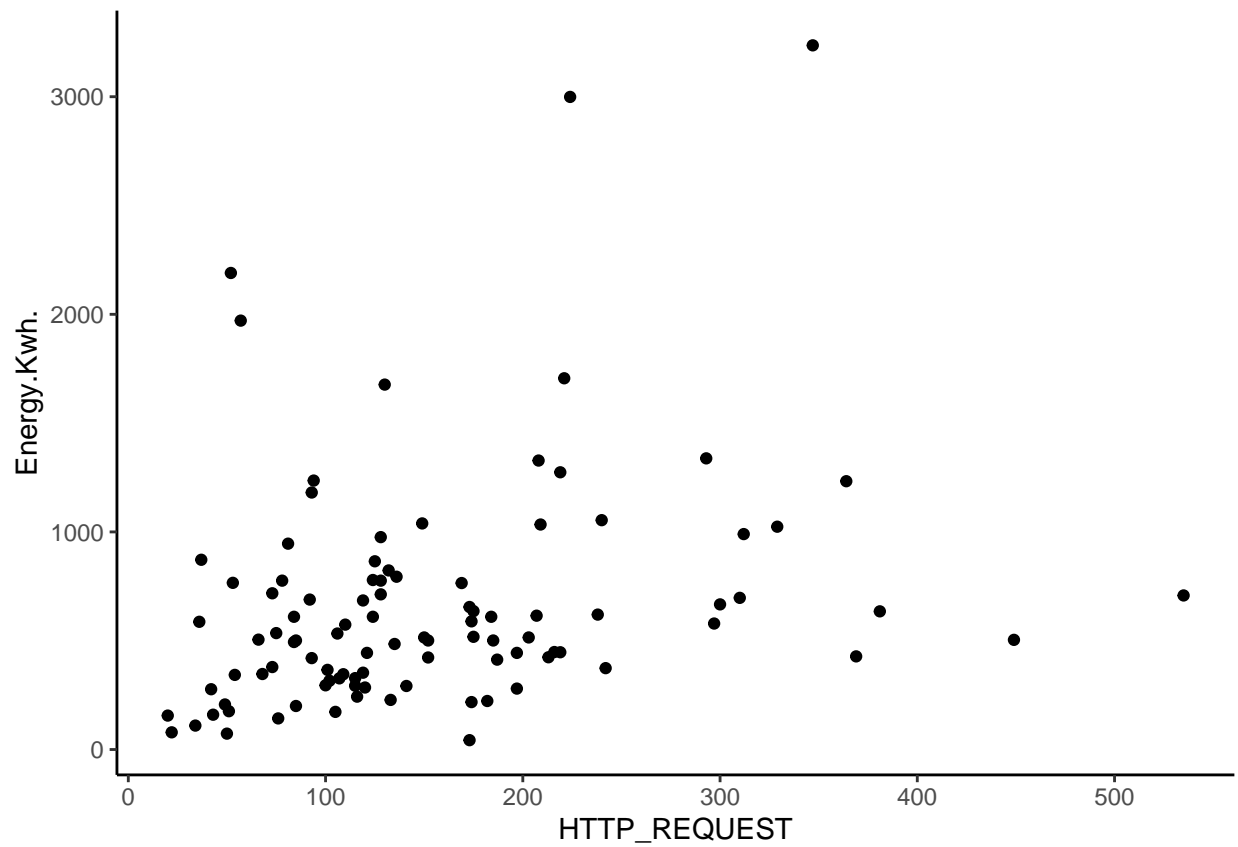
```
ggplot(data = cf_data, aes(x=Score.percentage., y=Energy.Kwh.)) + geom_point() + theme_classic()
```



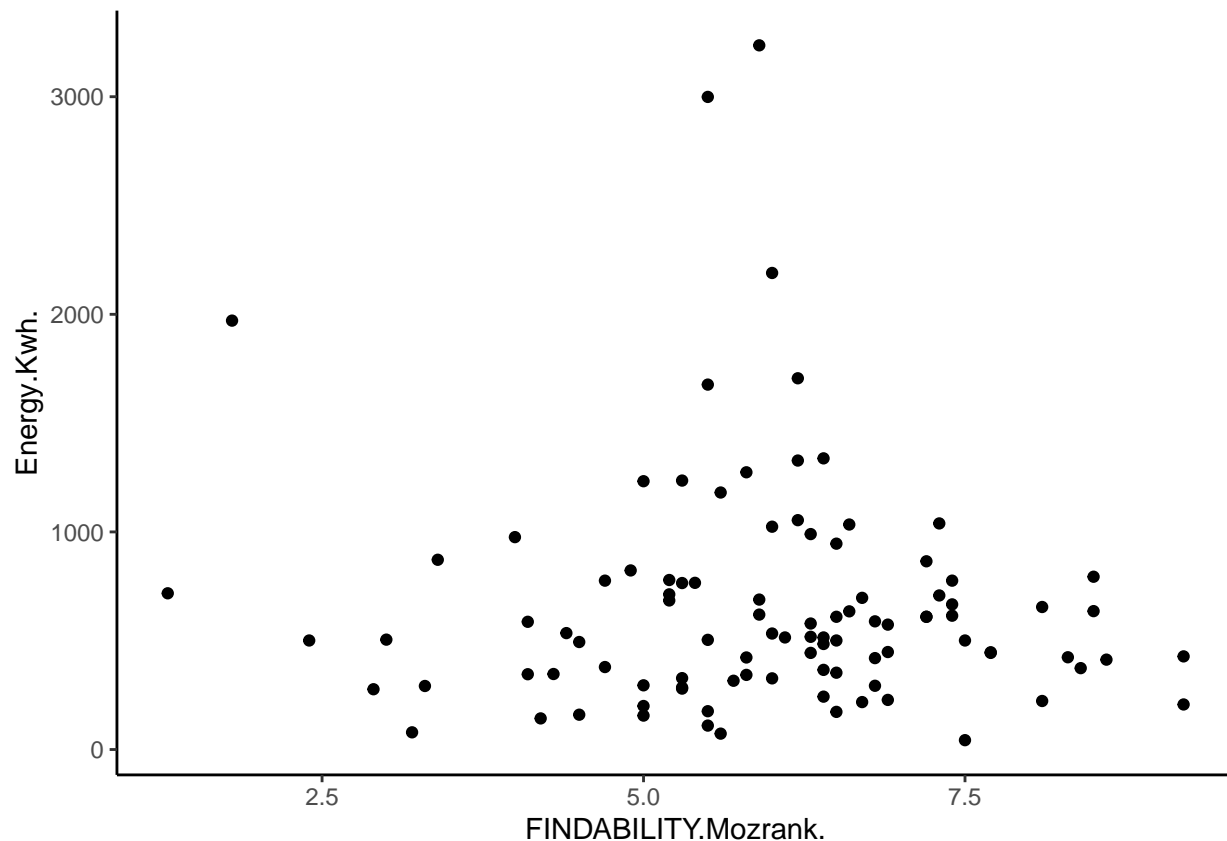
```
ggplot(data = cf_data, aes(x=Google_page_insights, y=Energy.Kwh.)) + geom_point() + theme_classic()
```



```
ggplot(data = cf_data, aes(x=HTTP_REQUEST, y=Energy.Kwh.)) + geom_point() + theme_classic()
```



```
ggplot(data = cf_data, aes(x=HTTP_REQUEST, y=Energy.Kwh.)) + geom_point() + theme_classic()
```



```
#ggplot(cf_data, aes(x=GREEN_HOSTING, y=Energy.Kwh.)) + geom_boxplot()
```

The first two graphs appear to have a linear relationship while the others have no specific pattern just clusters at different regions of the graphs. The collection of scatter plots do not show that most of the variables is clearly linear, but some show a linear trend.

## UNSUPERVISED LEARNING

Using unsupervised learning method Principal component analysis:

```
# perform PCA on the cf_data dataset
# note: variables are centered and scaled before analysis
pc_cf_data <- prcomp(cf_data, center = T, scale. = T)

# inspect the attributes of the PCA object returned by prcomp
attributes(pc_cf_data)
```

```
## $names
## [1] "sdev"      "rotation" "center"   "scale"    "x"
##
## $class
## [1] "prcomp"
```

Visual analysis of PCA results{#Visual\_analysis\_PCA}

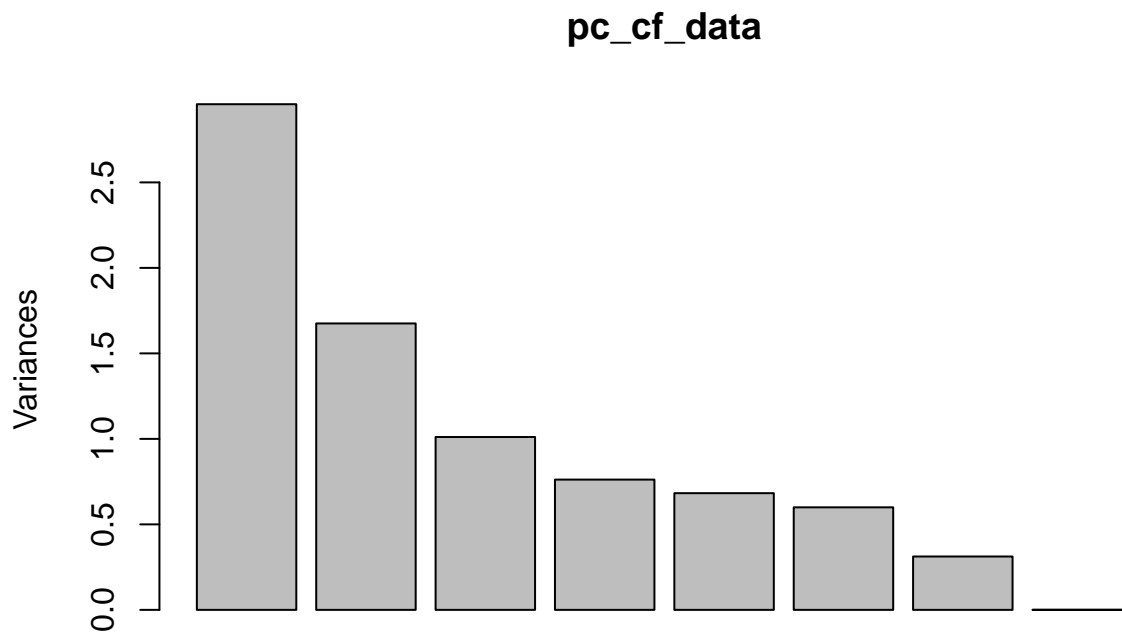
```
# calculate the proportion of explained variance (PEV) from the std values
pc_cf_data_var <- pc_cf_data$sdev^2
pc_cf_data_var
```

```
## [1] 2.9573122077 1.6751336598 1.0109269287 0.7618205353 0.6825166481
## [6] 0.5997164209 0.3120470302 0.0005265694
```

```
pc_cf_data_PEV <- pc_cf_data_var / sum(pc_cf_data_var)
pc_cf_data_PEV
```

```
## [1] 3.696640e-01 2.093917e-01 1.263659e-01 9.522757e-02 8.531458e-02
## [6] 7.496455e-02 3.900588e-02 6.582117e-05
```

```
# plot the variance per PC
# note: this can be done using the plot function on the prcomp object
plot(pc_cf_data)
```



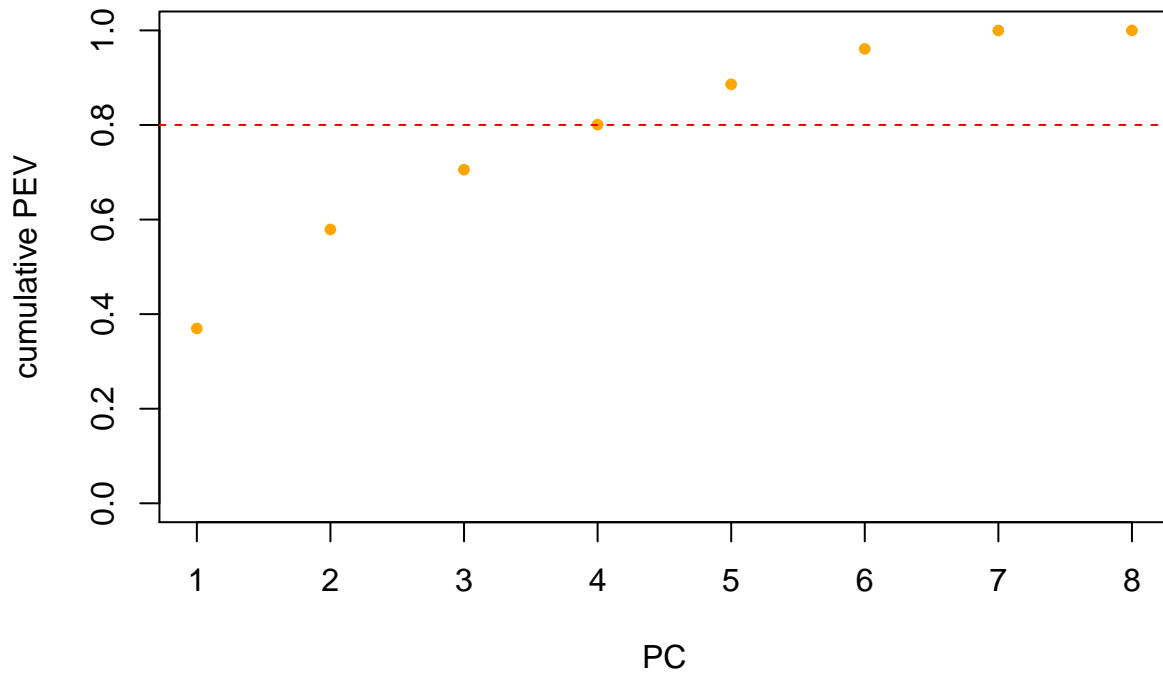
```
# plot the cumulative value of PEV for increasing number of additional PCs
# note: add an 80% threshold line to inform the feature extraction
# according to the plot the first 3 PCs should be selected
opar <- par()
plot(
  cumsum(pc_cf_data_PEV),
```



```

ylim = c(0,1),
xlab = 'PC',
ylab = 'cumulative PEV',
pch = 20,
col = 'orange'
)
abline(h = 0.8, col = 'red', lty = 'dashed')

```



```
par(opar)
```

```

## Warning in par(opar): graphical parameter "cin" cannot be set
## Warning in par(opar): graphical parameter "cra" cannot be set
## Warning in par(opar): graphical parameter "csi" cannot be set
## Warning in par(opar): graphical parameter "cxy" cannot be set
## Warning in par(opar): graphical parameter "din" cannot be set
## Warning in par(opar): graphical parameter "page" cannot be set

```

```

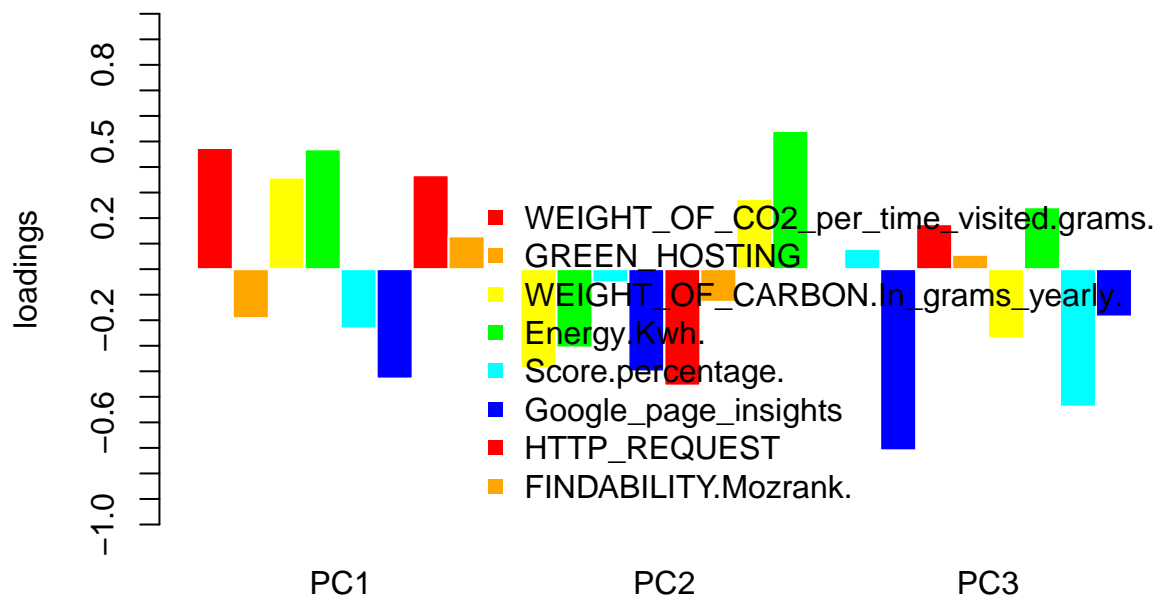
# get and inspect the loadings for each PC
# note: loadings are reported as a rotation matrix (see lecture)
pc_cf_data_loadings <- pc_cf_data$rotation
pc_cf_data_loadings

##              PC1              PC2              PC3
## WEIGHT_OF_CO2_per_time_visited.grams.  0.4744627 -0.38746110  0.07880132
## GREEN_HOSTING                        -0.1917415 -0.30694039 -0.70953223
## WEIGHT_OF CARBON.In_grams_yearly.     0.3585778 -0.05105031  0.17611563
## Energy.Kwh.                          0.4691568 -0.40073313  0.05620290
## Score.percentage.                    -0.2323316 -0.45613952 -0.27038104
## Google_page_insights                 -0.4284734 -0.12777996  0.24233669
## HTTP_REQUEST                         0.3678387  0.27439925 -0.53847275
## FINDABILITY.Mozrank.                 0.1286915  0.54109370 -0.18545350
##              PC4              PC5              PC6
## WEIGHT_OF_CO2_per_time_visited.grams. -0.079024523 -0.25790963  0.2073403
## GREEN_HOSTING                        0.001864303  0.33171482  0.4926299
## WEIGHT_OF CARBON.In_grams_yearly.    -0.448130912  0.77700440 -0.1730194
## Energy.Kwh.                         -0.076297527 -0.24849905  0.2215836
## Score.percentage.                   -0.394022017 -0.24591625 -0.6410974
## Google_page_insights                -0.506770179 -0.04838973  0.2805702
## HTTP_REQUEST                        0.012101806 -0.03958291 -0.2896077
## FINDABILITY.Mozrank.                -0.612285232 -0.30590377  0.2483803
##              PC7              PC8
## WEIGHT_OF_CO2_per_time_visited.grams.  0.03119490  0.708395417
## GREEN_HOSTING                       -0.11142938  0.021164163
## WEIGHT_OF CARBON.In_grams_yearly.    -0.05747769 -0.001608466
## Energy.Kwh.                         0.04328174 -0.705407983
## Score.percentage.                   -0.19523774 -0.001048991
## Google_page_insights                 0.63517229  0.005891237
## HTTP_REQUEST                        0.64328225  0.006992389
## FINDABILITY.Mozrank.                -0.35504889 -0.006348386

# plot the loadings for the first three PCs as a barplot
# note: two vectors for colours and labels are created for convenience
# for details on the other parameters see the help for barplot and legend
opar <- par()
colvector = c('red', 'orange', 'yellow', 'green', 'cyan', 'blue')
labvector = c('PC1', 'PC2', 'PC3')
barplot(
  pc_cf_data_loadings[,c(1:3)],
  beside = T,
  yaxt = 'n',
  names.arg = labvector,
  col = colvector,
  ylim = c(-1,1),
  border = 'white',
  ylab = 'loadings'
)
axis(2, seq(-1,1,0.1))
legend(
  'bottomright',
  bty = 'n',

```

```
col = colvector,
pch = 15,
row.names(pc_cf_data_loadings)
)
```



```
par(opar)
```

```
## Warning in par(opar): graphical parameter "cin" cannot be set
```

```
## Warning in par(opar): graphical parameter "cra" cannot be set
```

```
## Warning in par(opar): graphical parameter "csi" cannot be set
```

```
## Warning in par(opar): graphical parameter "cxy" cannot be set
```

```
## Warning in par(opar): graphical parameter "din" cannot be set
```

```
## Warning in par(opar): graphical parameter "page" cannot be set
```

```
# generate a biplot for each pair of important PCs (and show them on the same page)
```

```
# note: the option choices is used to select the PCs - default is 1:2
```

```
opar = par()
```

```
par(mfrow = c(2,2))
```

```

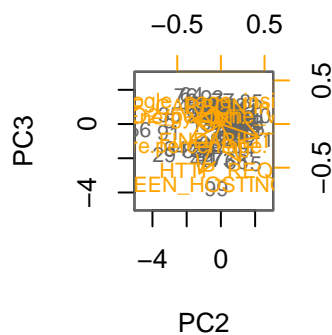
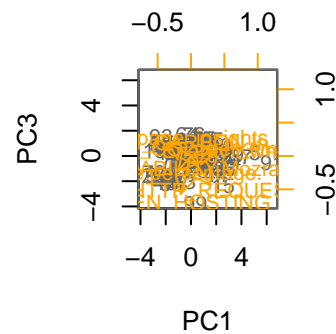
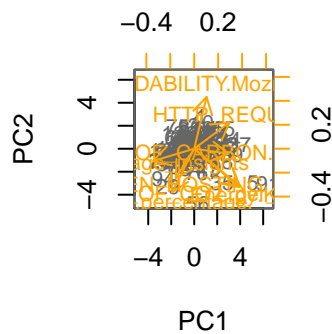
biplot(
  pc_cf_data,
  scale = 0,
  col = c('grey40','orange')
)
biplot(
  pc_cf_data,
  choices = c(1,3),
  scale = 0,
  col = c('grey40','orange')
)
biplot(
  pc_cf_data,
  choices = c(2,3),
  scale = 0,
  col = c('grey40','orange')
)
par(opar)

```

```

## Warning in par(opar): graphical parameter "cin" cannot be set
## Warning in par(opar): graphical parameter "cra" cannot be set
## Warning in par(opar): graphical parameter "csi" cannot be set
## Warning in par(opar): graphical parameter "cxy" cannot be set
## Warning in par(opar): graphical parameter "din" cannot be set
## Warning in par(opar): graphical parameter "page" cannot be set

```



```
# the space of the first three PCs is better explored interactively...
# ...using a function from the pca3d package
# first install pca3d
if(require(pca3d) == FALSE){
  install.packages('pca3d')
}
```

```
## Loading required package: pca3d
```

```
## Warning: package 'pca3d' was built under R version 4.0.5
```

```
# then plot and explore the data by rotating/zoom with the mouse
pca3d::pca3d(pc_cf_data, show.labels = T)
```

```
## [1] 0.12860729 0.09499318 0.07505453
## Creating new device
```

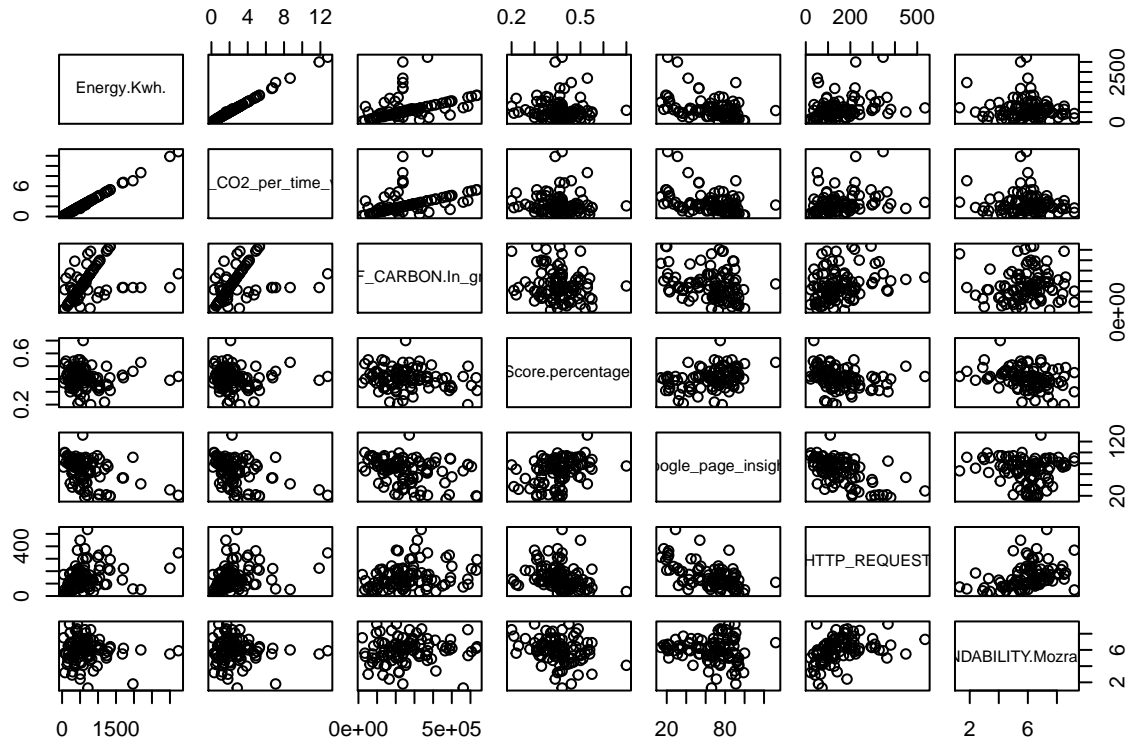
```
# and save a snapshot of the view in png format
pca3d::snapshotPCA3d('pc_cf_data_3D.png')
```

From the Principal component analysis we have the line drawn through the 4th PC which means that's how much we have explained variance up to 4 variables.

Using pearson correlation coefficient, Focusing only on the continuous explanatory variables - check their correlations with the Energy. I want to do this only for the continuous variables, so can look to remove the

column that is binary from this plot. (This is done so that the pairs plot is legible and that we can run a corr function on the resulting dataframe)

```
cf_data.cont<-subset(cf_data, select=c("Energy.Kwh.", "WEIGHT_OF_CO2_per_time_visited.grams.", "WEIGHT_OF_CARBON.In_grams_yearly."),
pairs(cf_data.cont))
```



```
cor(cf_data.cont)
```

```
## Energy.Kwh. 1.00000000
## WEIGHT_OF_CO2_per_time_visited.grams. 0.99890976
## WEIGHT_OF_CARBON.In_grams_yearly. 0.41227795
## Score.percentage. -0.05473021
## Google_page_insights -0.41141346
## HTTP_REQUEST 0.27177211
## FINDABILITY.Mozrank. -0.07952552
## WEIGHT_OF_CO2_per_time_visited.grams.
## Energy.Kwh. 0.99890976
## WEIGHT_OF_CO2_per_time_visited.grams. 1.00000000
## WEIGHT_OF_CARBON.In_grams_yearly. 0.41842680
## Score.percentage. -0.06608393
## Google_page_insights -0.41886559
## HTTP_REQUEST 0.27162477
## FINDABILITY.Mozrank. -0.06726358
## WEIGHT_OF_CARBON.In_grams_yearly.
```

```
## Energy.Kwh. 0.41227795
## WEIGHT_OF_CO2_per_time_visited.grams. 0.41842680
## WEIGHT_OF CARBON.In_grams_yearly. 1.00000000
## Score.percentage. -0.18137499
## Google_page_insights -0.29344960
## HTTP_REQUEST 0.26412030
## FINDABILITY.Mozrank. 0.08457789
##
## Score.percentage. Google_page_insights
## Energy.Kwh. -0.05473021 -0.4114135
## WEIGHT_OF_CO2_per_time_visited.grams. -0.06608393 -0.4188656
## WEIGHT_OF CARBON.In_grams_yearly. -0.18137499 -0.2934496
## Score.percentage. 1.00000000 0.3394626
## Google_page_insights 0.33946265 1.00000000
## HTTP_REQUEST -0.24004944 -0.5813457
## FINDABILITY.Mozrank. -0.28990679 -0.1064145
##
## HTTP_REQUEST FINDABILITY.Mozrank.
## Energy.Kwh. 0.2717721 -0.07952552
## WEIGHT_OF_CO2_per_time_visited.grams. 0.2716248 -0.06726358
## WEIGHT_OF CARBON.In_grams_yearly. 0.2641203 0.08457789
## Score.percentage. -0.2400494 -0.28990679
## Google_page_insights -0.5813457 -0.10641454
## HTTP_REQUEST 1.0000000 0.37787145
## FINDABILITY.Mozrank. 0.3778715 1.00000000
```

Correlation of the coefficients have been discovered. There do not seem to be any obvious multi collinearity (highly correlated explanatory variables) except the relationship between energy and weight of CO2 per time visited and a few of the plots above point to potential for a linear relationships, therefore at this stage I am not going to explore any transformations.

## MACHINE LEARNING (SUPERVISED LEARNING)

Using the continuous explanatory variables decide on a maximal model for Energy and run it.

```
cf_data.lm<-lm(cf_data$Energy.Kwh.~cf_data$WEIGHT_OF_CO2_per_time_visited.grams.+cf_data$WEIGHT_OF_CARBON.In_grams_yearly.+cf_data$Score.percentage.+cf_data$Google_page_insights+cf_data$HTTP_REQUEST+cf_data$FINDABILITY.Mozrank.)
summary(cf_data.lm)
```

```
##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##     cf_data$WEIGHT_OF_CARBON.In_grams_yearly. + cf_data$Score.percentage. +
##     cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -26.072 -12.571  -4.503   3.106  148.971
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    -5.532e+00  2.059e+01  -0.269
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams.  2.538e+02  1.344e+00 188.843
## cf_data$WEIGHT_OF_CARBON.In_grams_yearly.    -1.823e-05  1.889e-05  -0.965
## cf_data$Score.percentage.      3.984e+01  3.284e+01   1.213
## cf_data$Google_page_insights    2.588e-01  1.377e-01   1.879
```

```
## cf_data$HTTP_REQUEST      8.076e-02  3.309e-02  2.440
## cf_data$FINDABILITY.Mozrank. -5.057e+00  1.798e+00 -2.813
##                               Pr(>|t|)
## (Intercept)                0.78877
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. < 2e-16 ***
## cf_data$WEIGHT_OF CARBON.In_grams_yearly.      0.33716
## cf_data$Score.percentage.      0.22809
## cf_data$Google_page_insights      0.06341 .
## cf_data$HTTP_REQUEST            0.01659 *
## cf_data$FINDABILITY.Mozrank.      0.00601 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.51 on 92 degrees of freedom
## Multiple R-squared:  0.9982, Adjusted R-squared:  0.9981
## F-statistic: 8408 on 6 and 92 DF,  p-value: < 2.2e-16
```

I got a negative intercept and a almost seemingly over fitted model with an Rsquared of 99%. it is possible to start with a model that has interactions, all interactions could be used or a Tree approach can help understand if the relationship between an explanatory variable and the target variable is different based on the value (or range) of the explanatory variable.

So i introduced a step function to get the minimal adequate model. Use a model selection approach to achieve a minimal adequate mode

```
step(cf_data.lm)
```

```
## Start:  AIC=631.94
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##      cf_data$WEIGHT_OF CARBON.In_grams_yearly. + cf_data$Score.percentage. +
##      cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.
##
##                               Df Sum of Sq      RSS      AIC
## - cf_data$WEIGHT_OF CARBON.In_grams_yearly.      1      515    51378  630.93
## - cf_data$Score.percentage.                      1      814    51677  631.51
## <none>                                           50863  631.94
## - cf_data$Google_page_insights                   1     1952    52815  633.66
## - cf_data$HTTP_REQUEST                           1     3293    54156  636.15
## - cf_data$FINDABILITY.Mozrank.                   1     4374    55237  638.10
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams.  1 19716025 19766888 1220.24
##
## Step:  AIC=630.93
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##      cf_data$Score.percentage. + cf_data$Google_page_insights +
##      cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.
##
##                               Df Sum of Sq      RSS      AIC
## - cf_data$Score.percentage.                      1      975    52353  630.79
## <none>                                           51378  630.93
## - cf_data$Google_page_insights                   1     2018    53396  632.75
## - cf_data$HTTP_REQUEST                           1     3097    54475  634.73
## - cf_data$FINDABILITY.Mozrank.                   1     4484    55862  637.22
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams.  1 22393724 22445102 1230.81
##
```



```
## Step: AIC=630.79
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##     cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.
##
##                                     Df Sum of Sq      RSS      AIC
## <none>                                     52353  630.79
## - cf_data$Google_page_insights             1      3229   55583  634.72
## - cf_data$HTTP_REQUEST                     1      3287   55641  634.82
## - cf_data$FINDABILITY.Mozrank.             1       6061   58415  639.64
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 1 22472695 22525048 1229.17

##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##     cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.)
##
## Coefficients:
##                                     (Intercept)
##                                     7.10635
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams.
##                                     253.45616
##           cf_data$Google_page_insights
##                                     0.31753
##           cf_data$HTTP_REQUEST
##                                     0.08029
##           cf_data$FINDABILITY.Mozrank.
##                                     -5.74259
```

My minimal adequate model has been achieved. Once I have the minimal adequate model, explain its findings and test its residuals

```
mam.lm<-lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. + cf_data$Google_page_insights +
  cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.)

summary(mam.lm)
```

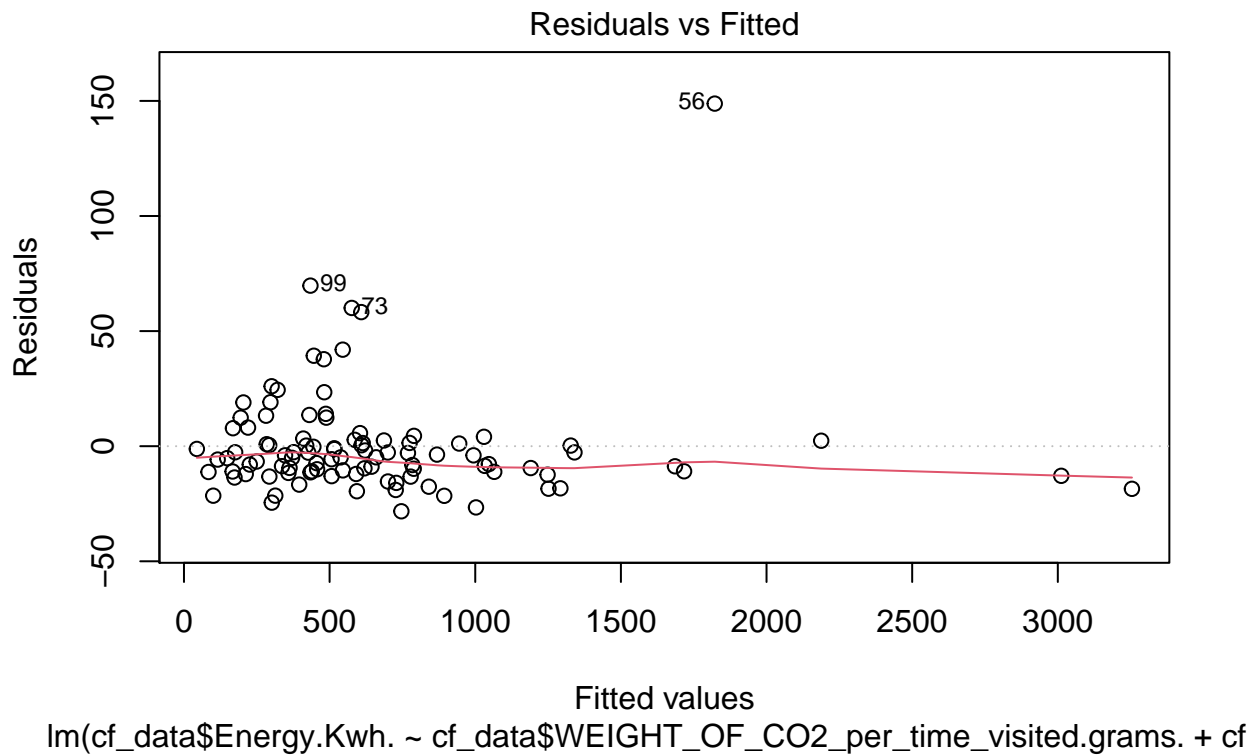
```
##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##     cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank.)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -28.275 -11.286  -4.864   2.427 148.823
##
## Coefficients:
##                                     Estimate Std. Error t value
## (Intercept)                        7.10635    15.42750   0.461
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 253.45616     1.26178 200.872
## cf_data$Google_page_insights           0.31753     0.13187   2.408
## cf_data$HTTP_REQUEST                   0.08029     0.03305   2.429
## cf_data$FINDABILITY.Mozrank.          -5.74259     1.74073  -3.299
##                                     Pr(>|t|)
```

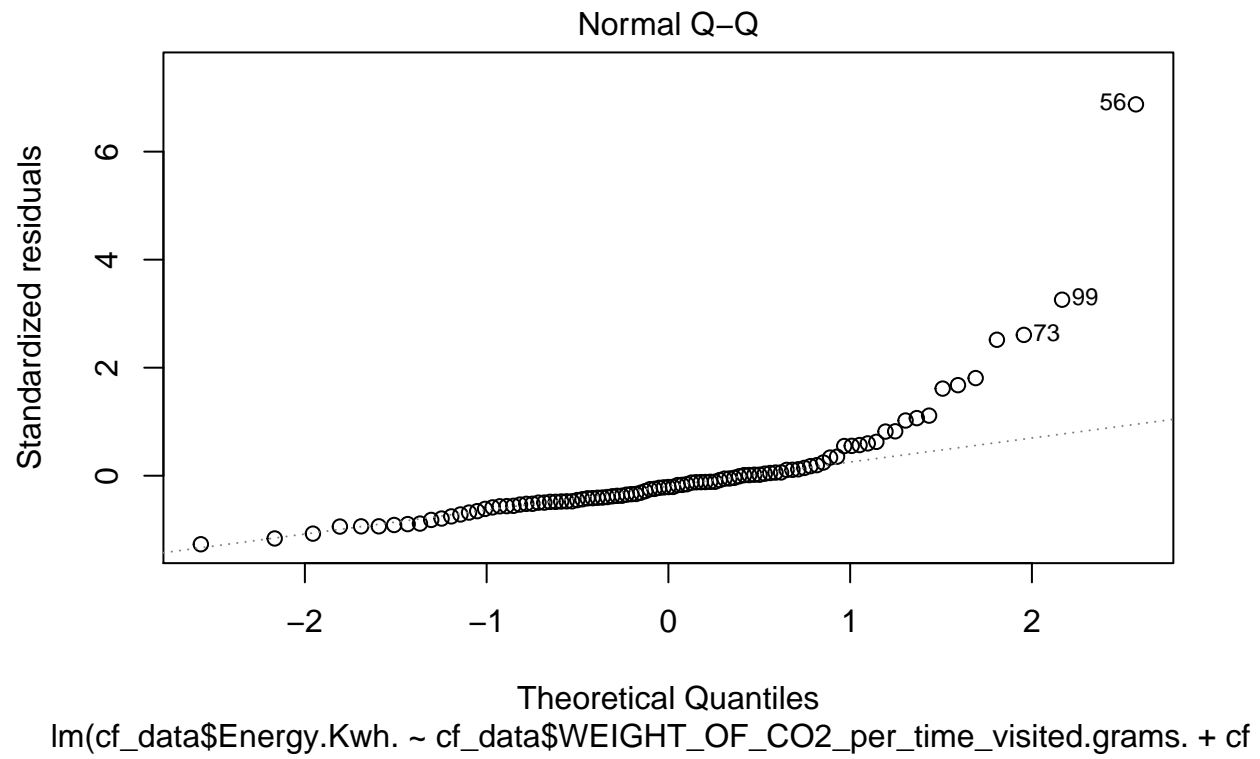
```
## (Intercept)                                0.64613
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. < 2e-16 ***
## cf_data$Google_page_insights                0.01799 *
## cf_data$HTTP_REQUEST                        0.01702 *
## cf_data$FINDABILITY.Mozrank.                0.00137 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.6 on 94 degrees of freedom
## Multiple R-squared:  0.9981, Adjusted R-squared:  0.998
## F-statistic: 1.252e+04 on 4 and 94 DF,  p-value: < 2.2e-16
```

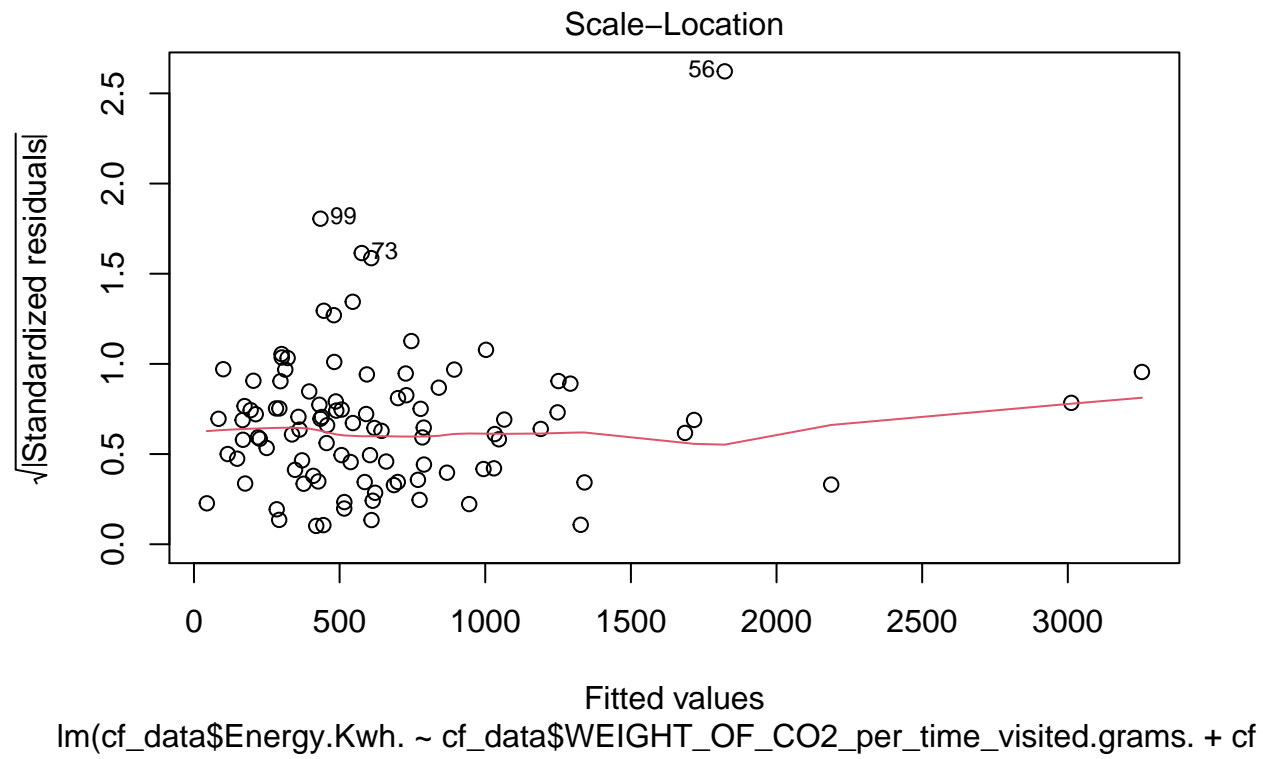
This model has acceptable goodness of fit, all the coefficients are significant (so there is no need to simplify further),  $r^2$  is too high and the F statistic is significant.

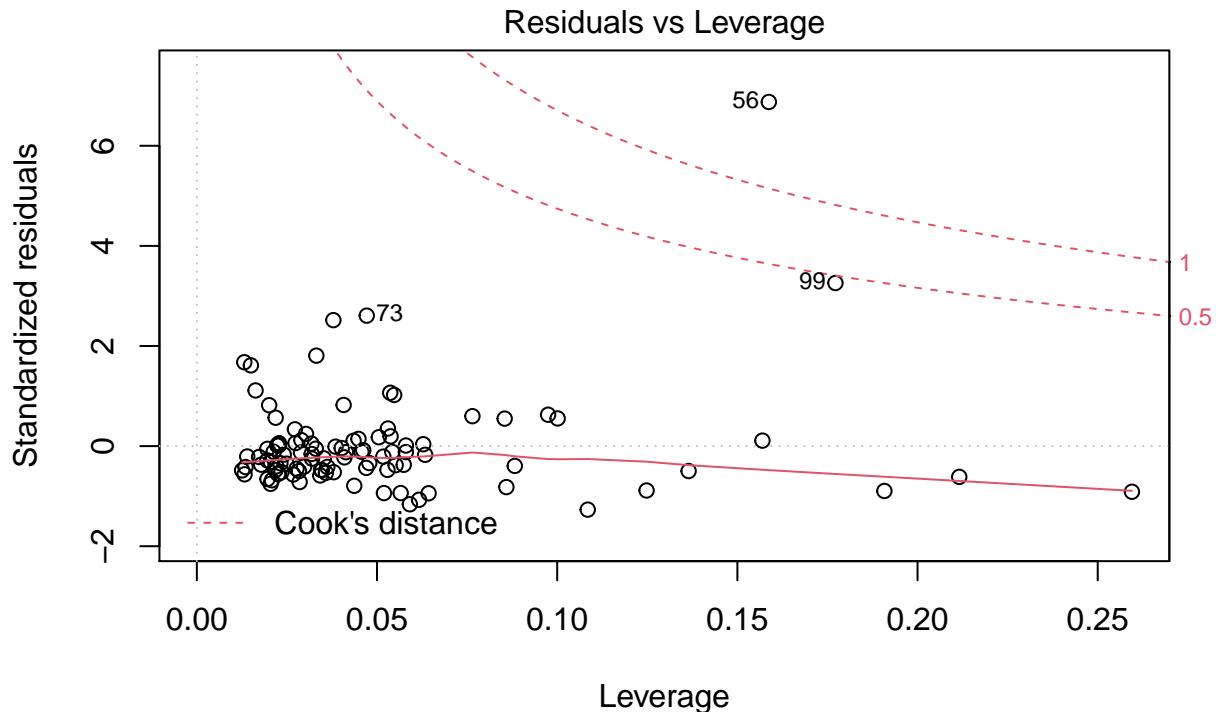
Next the residuals should be scrutinised:

```
plot(mam.lm)
```









`lm(cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. + cf`

In this case the residuals look ok, the variance is quite steady in the first plot - considering the data size. QQ plot also looks aligned.

Now i want to model the relationship between the energy and the explanatory variables (including the ones that are not continuous).

```
model.all.lm<-lm(cf_data$Energy.Kwh.~cf_data$WEIGHT_OF_CO2_per_time_visited.grams.+cf_data$WEIGHT_OF_CAR
summary(model.all.lm)
```

```
##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##     cf_data$WEIGHT_OF_CARBON.In_grams_yearly. + cf_data$Score.percentage. +
##     cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
##     cf_data$GREEN_HOSTING)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -40.340  -5.330  -0.914   2.727  117.132
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)      1.739e+00  1.581e+01   0.110
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams.  2.544e+02  1.033e+00 246.344
## cf_data$WEIGHT_OF_CARBON.In_grams_yearly.    -7.655e-06  1.454e-05  -0.526
```

```
## cf_data$Score.percentage. -9.299e+00 2.589e+01 -0.359
## cf_data$Google_page_insights 1.827e-01 1.060e-01 1.724
## cf_data$HTTP_REQUEST 5.494e-02 2.556e-02 2.149
## cf_data$FINDABILITY.Mozrank. -3.210e+00 1.397e+00 -2.298
## cf_data$GREEN_HOSTING 4.565e+01 5.636e+00 8.099
## Pr(>|t|)
## (Intercept) 0.9126
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. < 2e-16 ***
## cf_data$WEIGHT_OF CARBON.In_grams_yearly. 0.5999
## cf_data$Score.percentage. 0.7203
## cf_data$Google_page_insights 0.0881 .
## cf_data$HTTP_REQUEST 0.0343 *
## cf_data$FINDABILITY.Mozrank. 0.0239 *
## cf_data$GREEN_HOSTING 2.39e-12 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.02 on 91 degrees of freedom
## Multiple R-squared: 0.9989, Adjusted R-squared: 0.9989
## F-statistic: 1.228e+04 on 7 and 91 DF, p-value: < 2.2e-16
```

The  $R^2$  is looking same but lets see what a step process would achieve in terms of simplifying the model:

```
step(model.all.lm)
```

```
## Start: AIC=580.2
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##   cf_data$WEIGHT_OF CARBON.In_grams_yearly. + cf_data$Score.percentage. +
##   cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
##   cf_data$GREEN_HOSTING
##
##           Df Sum of Sq    RSS    AIC
## - cf_data$Score.percentage. 1      42  29600  578.34
## - cf_data$WEIGHT_OF CARBON.In_grams_yearly. 1      90  29648  578.50
## <none>                                29558  580.20
## - cf_data$Google_page_insights 1     965  30523  581.38
## - cf_data$HTTP_REQUEST 1    1500  31058  583.10
## - cf_data$FINDABILITY.Mozrank. 1    1715  31273  583.78
## - cf_data$GREEN_HOSTING 1   21305  50863  631.94
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 1 19711502 19741060 1222.11
##
## Step: AIC=578.34
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##   cf_data$WEIGHT_OF CARBON.In_grams_yearly. + cf_data$Google_page_insights +
##   cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. + cf_data$GREEN_HOSTING
##
##           Df Sum of Sq    RSS    AIC
## - cf_data$WEIGHT_OF CARBON.In_grams_yearly. 1      80  29680  576.61
## <none>                                29600  578.34
## - cf_data$Google_page_insights 1     926  30526  579.39
## - cf_data$HTTP_REQUEST 1    1487  31087  581.19
## - cf_data$FINDABILITY.Mozrank. 1    1677  31278  581.80
## - cf_data$GREEN_HOSTING 1   22077  51677  631.51
```

```
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 1 19911421 19941021 1221.10
##
## Step: AIC=576.61
## cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
## cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
## cf_data$GREEN_HOSTING
##
##
## Df Sum of Sq RSS AIC
## <none> 29680 576.61
## - cf_data$Google_page_insights 1 955 30635 577.74
## - cf_data$HTTP_REQUEST 1 1436 31116 579.29
## - cf_data$FINDABILITY.Mozrank. 1 1708 31389 580.15
## - cf_data$GREEN_HOSTING 1 22673 52353 630.79
## - cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 1 22416995 22446675 1230.82

##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
## cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
## cf_data$GREEN_HOSTING)
##
## Coefficients:
## (Intercept)
## -3.19522
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams.
## 254.18927
## cf_data$Google_page_insights
## 0.17514
## cf_data$HTTP_REQUEST
## 0.05349
## cf_data$FINDABILITY.Mozrank.
## -3.13167
## cf_data$GREEN_HOSTING
## 45.48271
```

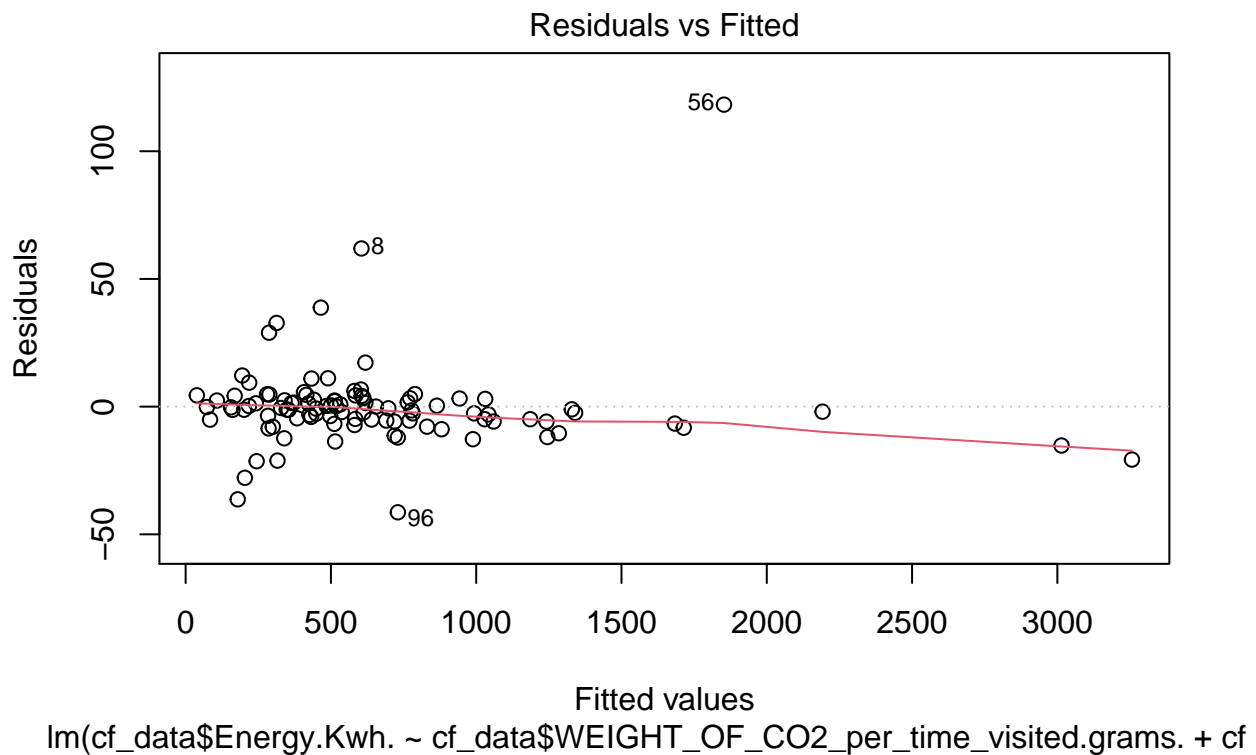
It is evident Greenhosting has an effect on this model so i would explore it further. The binary variable I added as part of the explanatory variables does add much and this is confirmed as the step process proposes a model that does include it as an explanatory variable.

```
all.mam.lm<-lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. + cf_data$GREEN_HOSTING)
summary(all.mam.lm)
```

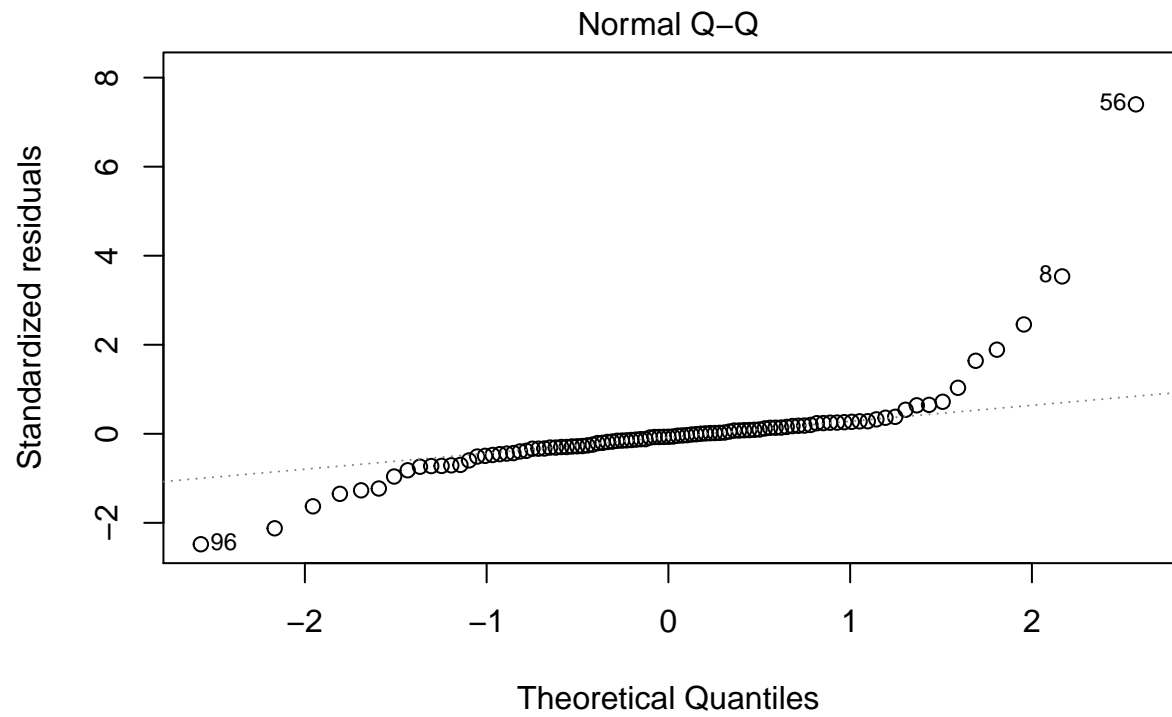
```
##
## Call:
## lm(formula = cf_data$Energy.Kwh. ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
## cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
## cf_data$GREEN_HOSTING)
##
## Residuals:
## Min 1Q Median 3Q Max
## -41.374 -5.650 -1.175 2.866 118.245
##
```

```
## Coefficients:
##
##              Estimate Std. Error t value
## (Intercept)      -3.19522    11.74211  -0.272
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 254.18927    0.95910 265.030
## cf_data$Google_page_insights      0.17514    0.10124   1.730
## cf_data$HTTP_REQUEST      0.05349    0.02522   2.121
## cf_data$FINDABILITY.Mozrank.    -3.13167    1.35362  -2.314
## cf_data$GREEN_HOSTING      45.48271    5.39617   8.429
##
##              Pr(>|t|)
## (Intercept)      0.7861
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. < 2e-16 ***
## cf_data$Google_page_insights      0.0870 .
## cf_data$HTTP_REQUEST      0.0366 *
## cf_data$FINDABILITY.Mozrank.    0.0229 *
## cf_data$GREEN_HOSTING      4.28e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.86 on 93 degrees of freedom
## Multiple R-squared:  0.9989, Adjusted R-squared:  0.9989
## F-statistic: 1.749e+04 on 5 and 93 DF,  p-value: < 2.2e-16
```

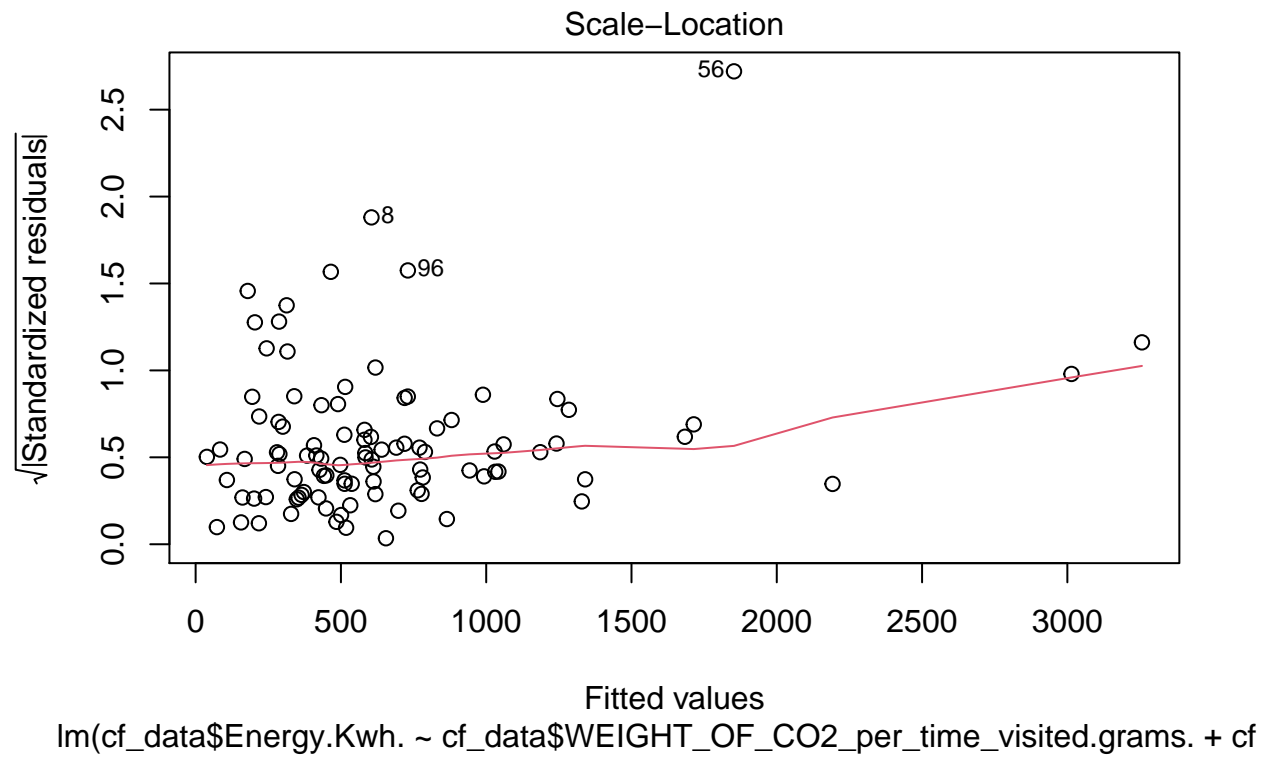
```
plot(all.mam.lm)
```

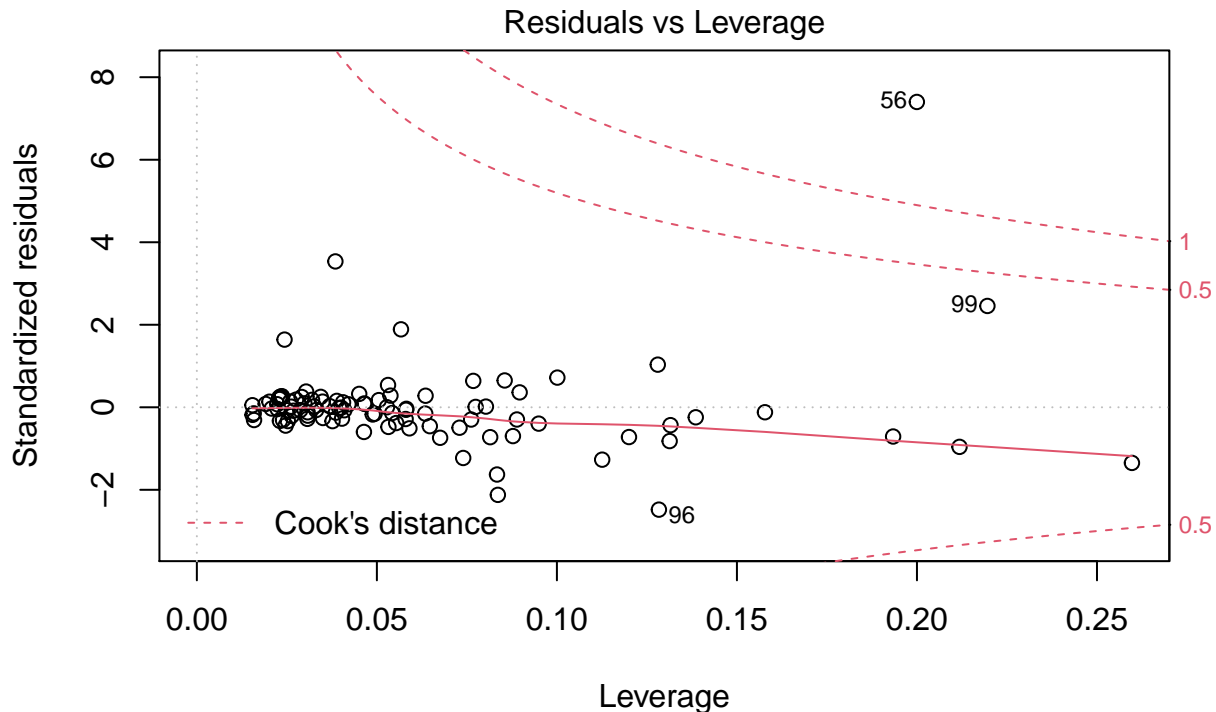






$\ln(\text{cf\_data}\$Energy.Kwh. \sim \text{cf\_data}\$WEIGHT\_OF\_CO2\_per\_time\_visited.grams. + \text{cf\_data}\$$





$\text{lm}(\text{cf\_data}\$Energy.Kwh. \sim \text{cf\_data}\$WEIGHT\_OF\_CO2\_per\_time\_visited.grams. + \text{cf\_data}\$Google\_page\_insights + \text{cf\_data}\$HTTP\_REQUEST + \text{cf\_data}\$FINDABILITY.Mozrank. + \text{cf\_data}\$GREEN\_HOSTING)$

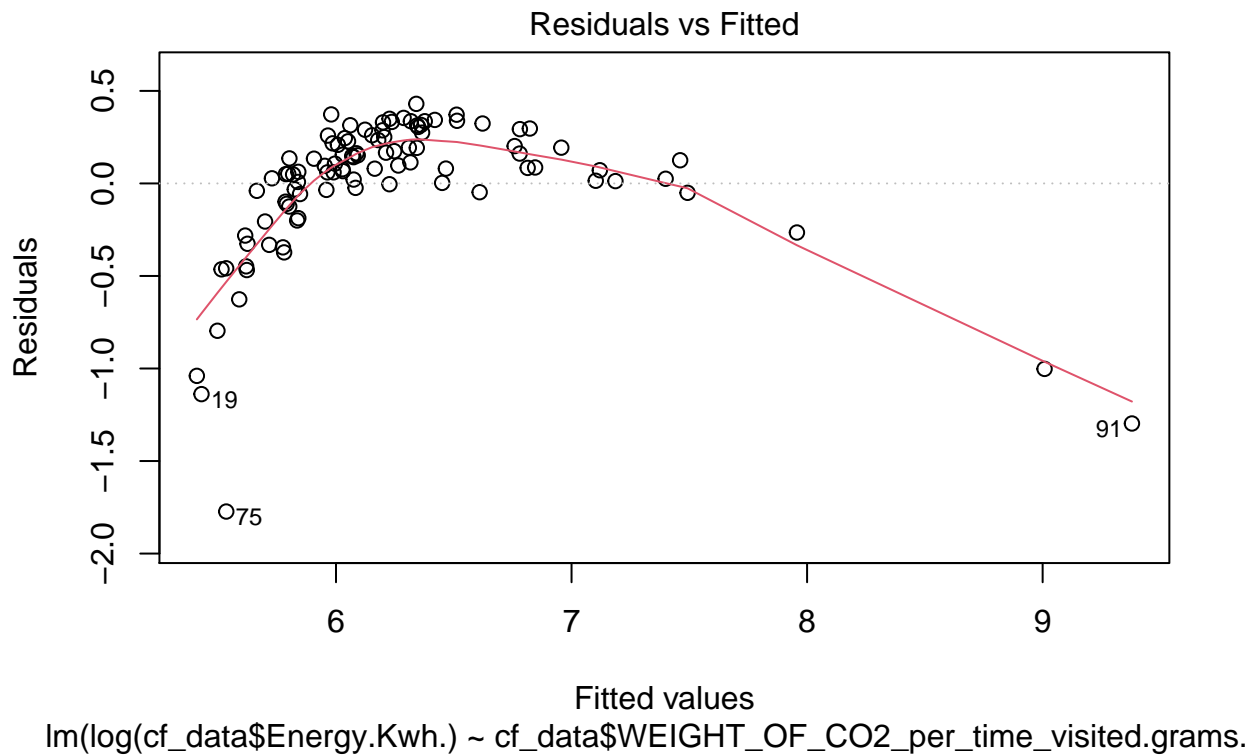
Now i have to optimise the model to reduce the chances of error. I would use the log transformation method to do this.

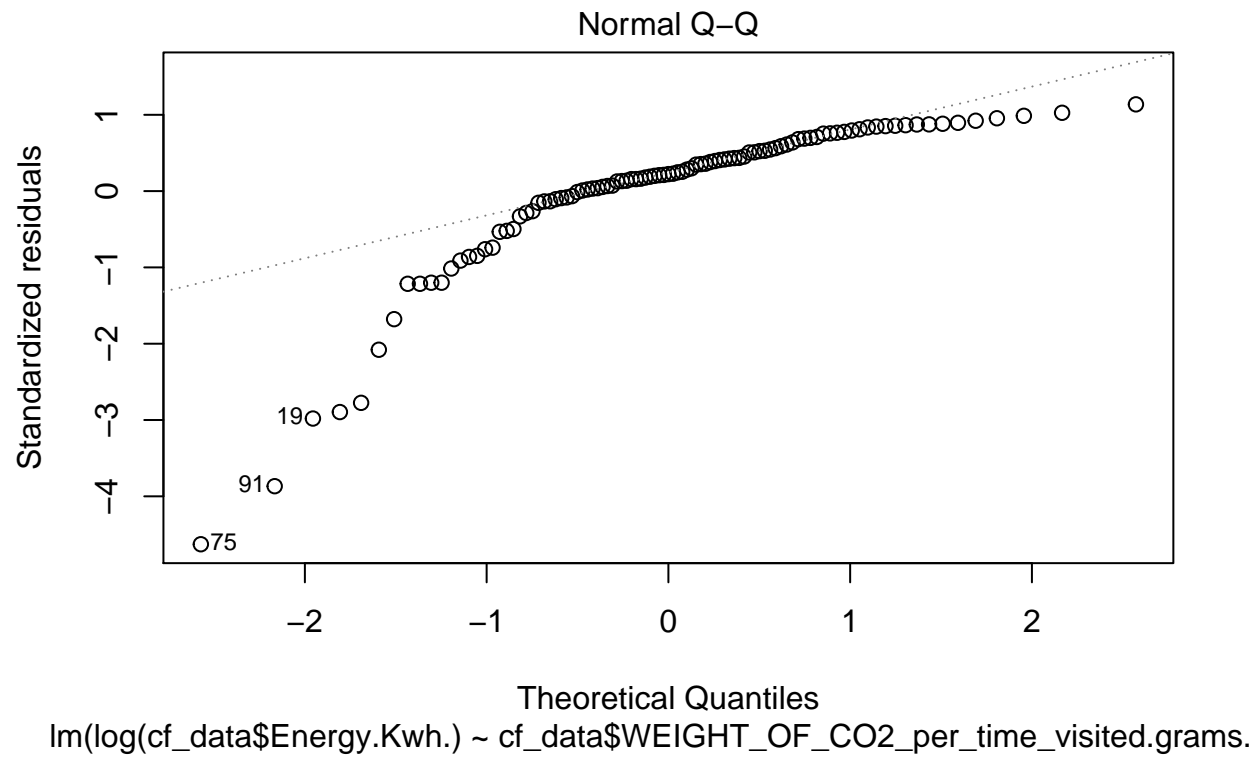
```
optimised_mam.lm<-lm(formula = log(cf_data$Energy.Kwh.) ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams.
summary(optimised_mam.lm)
```

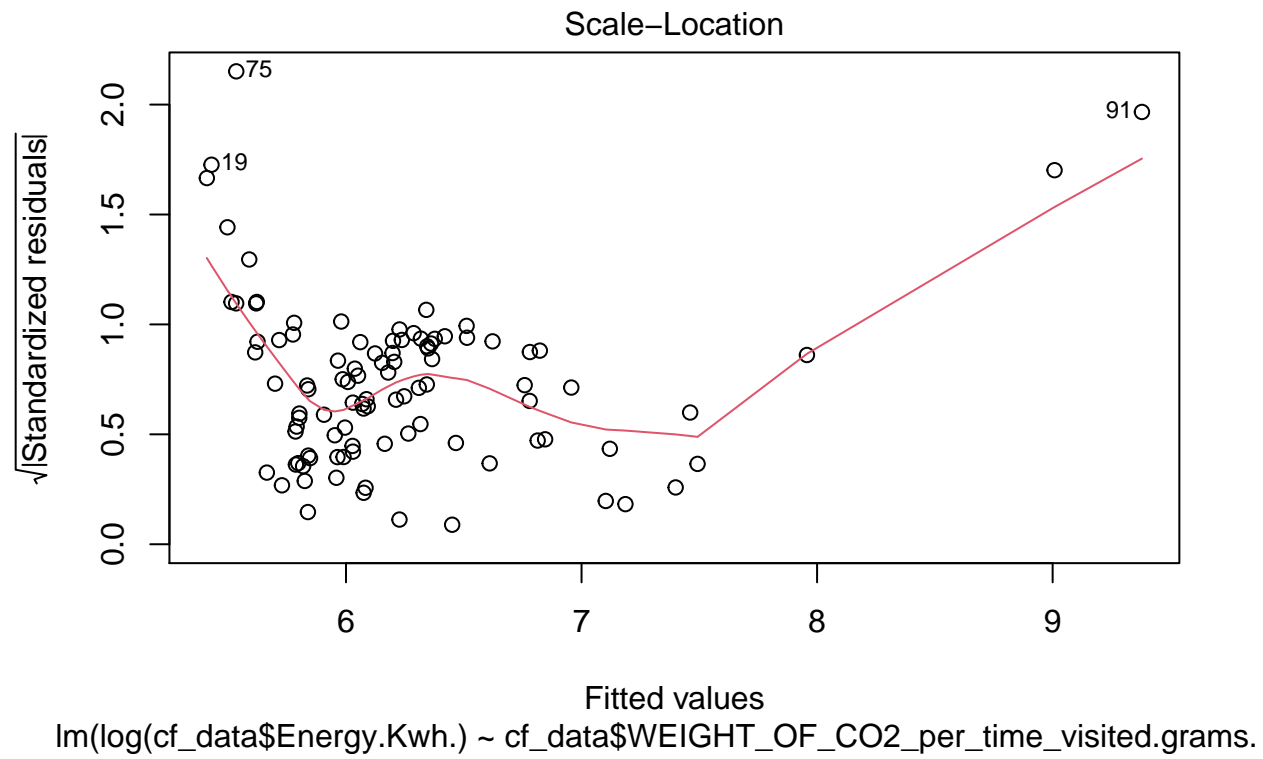
```
##
## Call:
## lm(formula = log(cf_data$Energy.Kwh.) ~ cf_data$WEIGHT_OF_CO2_per_time_visited.grams. +
##   cf_data$Google_page_insights + cf_data$HTTP_REQUEST + cf_data$FINDABILITY.Mozrank. +
##   cf_data$GREEN_HOSTING)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77286 -0.04904  0.08396  0.23954  0.42997
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.4872534   0.2562362  21.415  <.0001
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams.  0.2877573   0.0209294  13.749  <.0001
## cf_data$Google_page_insights -0.0019596   0.0022093  -0.887  0.375
## cf_data$HTTP_REQUEST    0.0006451   0.0005503   1.172  0.243
## cf_data$FINDABILITY.Mozrank.  0.0039111   0.0295387   0.132  0.895
## cf_data$GREEN_HOSTING    0.0739018   0.1177552   0.628  0.531
##
```

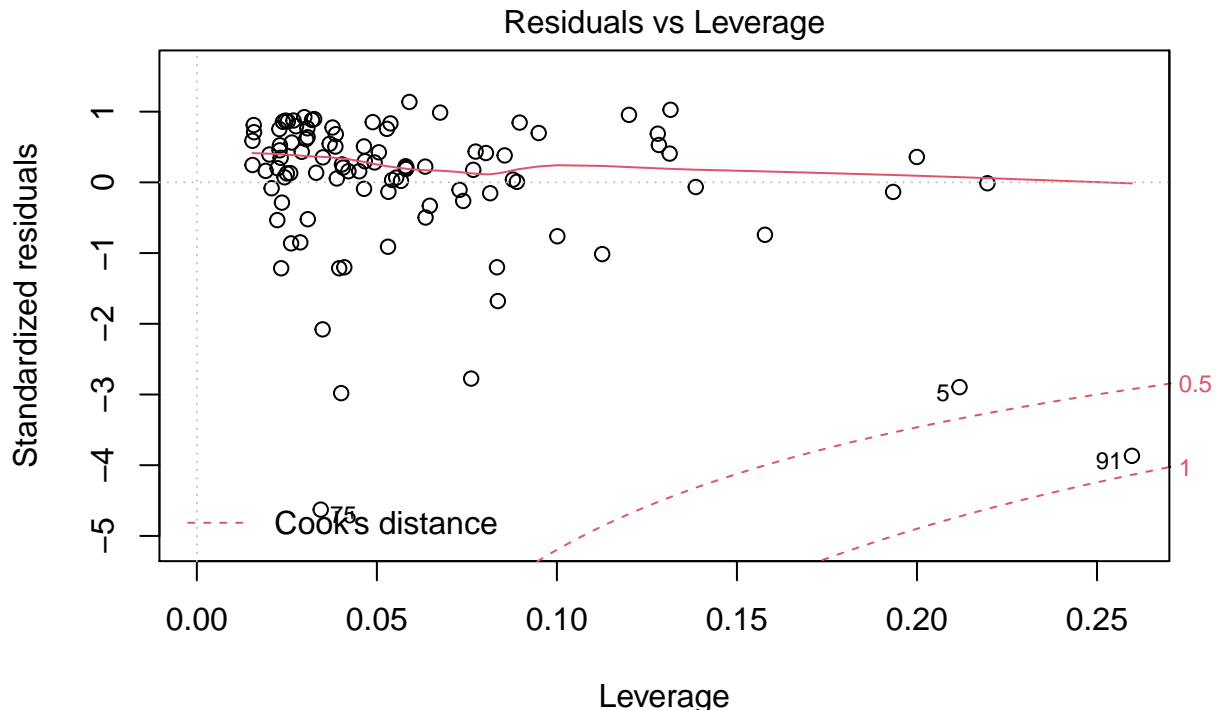
```
## (Intercept) <2e-16 ***
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. <2e-16 ***
## cf_data$Google_page_insights 0.377
## cf_data$HTTP_REQUEST 0.244
## cf_data$FINDABILITY.Mozrank. 0.895
## cf_data$GREEN_HOSTING 0.532
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3898 on 93 degrees of freedom
## Multiple R-squared:  0.7429, Adjusted R-squared:  0.7291
## F-statistic: 53.75 on 5 and 93 DF,  p-value: < 2.2e-16
```

```
plot(optimised_mam.lm)
```









$\text{lm}(\log(\text{cf\_data}\$Energy.Kwh.) \sim \text{cf\_data}\$WEIGHT\_OF\_CO2\_per\_time\_visited.grams.$

Now it is evident from my result this model is very significant owing from the value of its Adjusted Rsquared which is 73% and its F-statistic.

Now i move on to calculate my Confidence Interval and Sigma (residual standard error)

*#Calculating the sigma*

```
sigma(optimised_mam.lm)/mean(cf_data$Energy.Kwh.)
```

```
## [1] 0.0005894417
```

*#calculating the confidence interval*

```
confint(optimised_mam.lm)
```

```
##                                2.5 %    97.5 %
## (Intercept)                   4.978419016 5.996087724
## cf_data$WEIGHT_OF_CO2_per_time_visited.grams. 0.246195696 0.329318894
## cf_data$Google_page_insights -0.006346765 0.002427558
## cf_data$HTTP_REQUEST          -0.000447737 0.001738000
## cf_data$FINDABILITY.Mozrank.  -0.054746855 0.062569088
## cf_data$GREEN_HOSTING         -0.159936662 0.307740277
```

I am 97.5% confident my mean is between 4.978 and 5.996. I also do have a good value of sigma which is 0.00059.

From the values gotten from my model, this model can be used to predict the energy produced by other variables that make up the carbon footprint of companies.