SonoBat Analysis v4 - 2022

ANLY-705-50-A-2023 Spring

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load libraries

```
library(tidyverse)
library(readxl)
library(ggplot2)
library(dplyr)
library(cluster)
library(factoextra)
library(FactoMineR)
library(datasets)
library(corrplot)
library(reshape)
# Modeling packages
library(tidymodels)
library(earth) # for fitting MARS models
library(caret) # for automating the tuning process
library(randomForest)
```

load the 2022 dataset

```
df22 <- read.delim("SierraLeone2022113.txt")
```

EDA

```
# Sub dataset of highly correlated variables
df22_sub <- subset(df22, select = c('Fc','FreqMaxPwr','StartF','EndF','LowFreq',
                                    'HiFreq','FreqKnee','FFwd5dB','FFwd15dB','FFwd20dB'))
head(df22_sub)
```

```
##         Fc FreqMaxPwr   StartF     EndF  LowFreq   HiFreq FreqKnee  FFwd5dB
## 1 30.09062   30.69036 31.75588 29.76242 29.66113 31.75588 30.40580 31.14302
## 2 30.47646   31.32279 31.81982 30.55663 30.19313 32.04760 30.39610 31.54788
## 3 30.12007   30.23859 32.11109 30.24524 29.89022 32.11109 30.59488 31.22807
## 4 30.41762   30.41394 31.65980 30.17061 30.17061 31.66190 30.50557 31.35421
```

```
## 5 30.89197   31.07854 32.88805 30.90555 30.74737 32.88805 32.23373 32.03769
## 6 29.93181   30.28021 31.55084 30.47441 29.91662 31.70977 30.55992 31.07320
##   FFwd15dB FFwd20dB
## 1 31.43476 31.58063
## 2 31.81580 31.94976
## 3 31.50877 31.64912
## 4 31.71051 31.88866
## 5 32.33922 32.48999
## 6 31.41022 31.54502
```

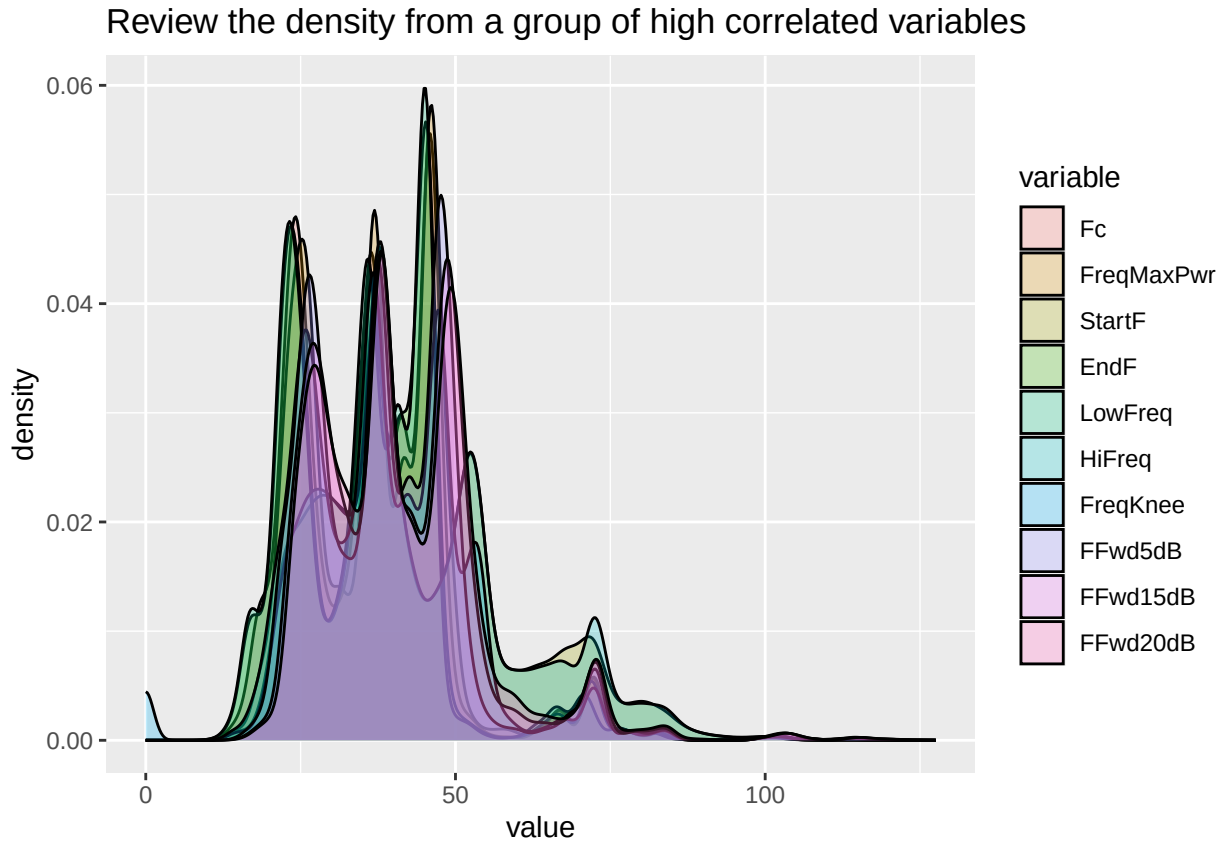
```
# convert from wide format to long format
data_sub <- melt(df22_sub)
```

```
## Using  as id variables
```

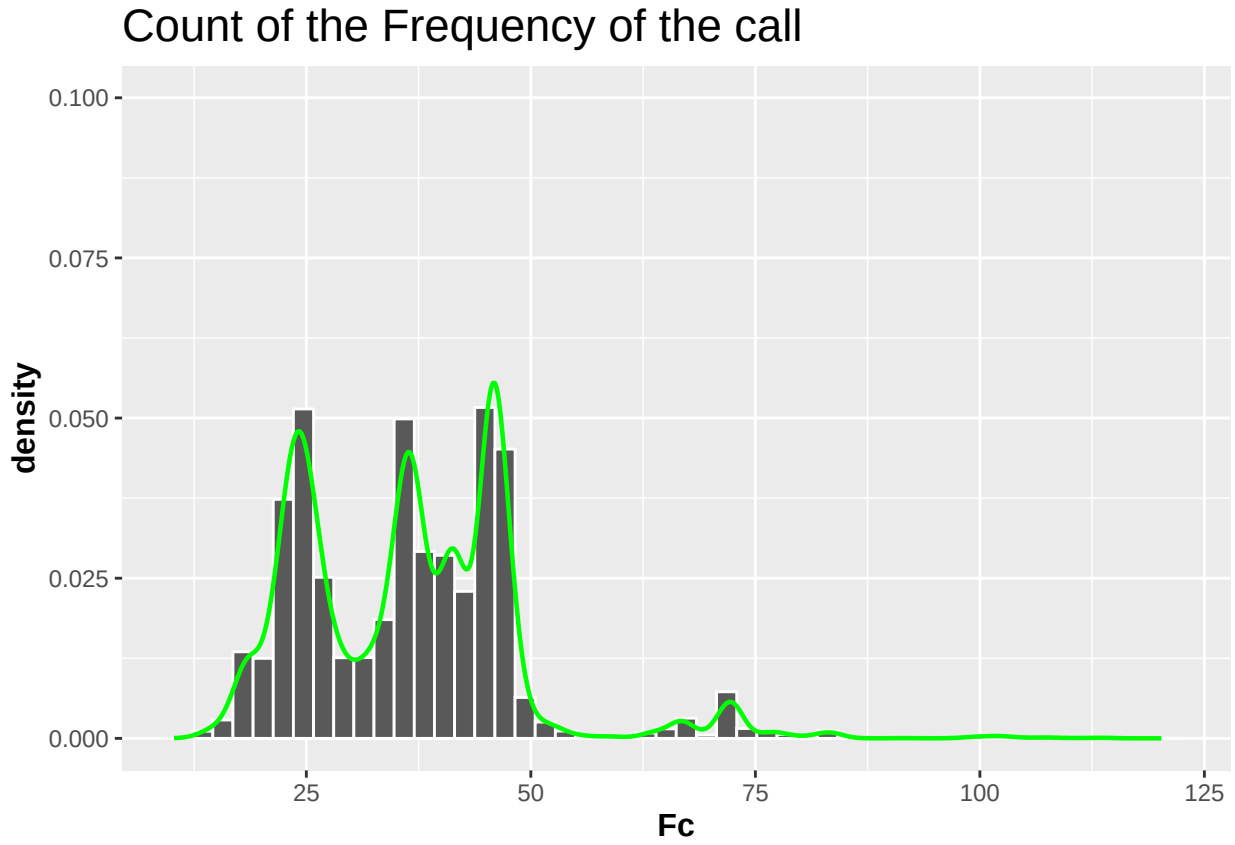
```
# view first six rows
head(data_sub)
```

```
##   variable    value
## 1       Fc 30.09062
## 2       Fc 30.47646
## 3       Fc 30.12007
## 4       Fc 30.41762
## 5       Fc 30.89197
## 6       Fc 29.93181
```

```
# create overlaying density plots
ggplot(data_sub, aes(x=value, fill=variable)) +
  geom_density(alpha=.25) +
  ggtitle("Review the density from a group of high correlated variables")
```




```
# exploring features of SonoBat dataset
tidymodels_prefer()
ggplot(df22, aes(x = Fc)) +
  geom_histogram(aes(y = ..density..), bins = 50, col = "white") +
  geom_line(stat = "density", color="green", size=0.8) +
  ylim(0,0.1) +
  ggtitle("Count of the Frequency of the call") +
  theme(title=element_text(color = "black", size = 14),
        axis.title=element_text(size=12,face="bold"))
```



This plot shows us that the data are right-skewed, there are much smaller numbers than the large count in Fc.

```
# Exploring the 2022 dataset
head(df22)
```

```
##                                                                 Path
## 1 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
## 2 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
## 3 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
## 4 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
## 5 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
## 6 E:\\SierraLeone\\AcousticData\\5-2022\\KBH-1_20220507_191026.wav
##                  Filename TimeInFile PrecedingIntrvl CallsPerSec CallDuration
## 1 KBH-1_20220507_191026.wav       1339             174    5.571619     13.73850
## 2 KBH-1_20220507_191026.wav        691             172    5.571619     14.95602
## 3 KBH-1_20220507_191026.wav       1514             176    5.571619     14.27390
## 4 KBH-1_20220507_191026.wav       2346             171    5.571619     11.26184
## 5 KBH-1_20220507_191026.wav       1645             130    5.571619     13.28864
## 6 KBH-1_20220507_191026.wav       2519             175    5.571619     14.87257
##         Fc   HiFreq  LowFreq  Bndwdth FreqMaxPwr PrcntMaxAmpDur TimeFromMaxToFc
## 1 30.09062 31.75588 29.66113 2.094757   30.69036       52.51447        5.839990
## 2 30.47646 32.04760 30.19313 1.854476   31.32279       38.19162        8.302497
## 3 30.12007 32.11109 29.89022 2.220872   30.23859       80.33998        2.617597
## 4 30.41762 31.66190 30.17061 1.491294   30.41394       92.87591       -0.047009
## 5 30.89197 32.88805 30.74737 2.140684   31.07854       74.30500        2.896576
```

```
## 6 29.93181 31.70977 29.91662 1.793147   30.28021       75.74210        2.900367
##   FreqKnee PrcntKneeDur   StartF     EndF DominantSlope SlopeAtFc StartSlope
## 1 30.40580     69.79122 31.75588 29.76242      0.102458  0.374462  -0.397281
## 2 30.39610     91.02874 31.81982 30.55663      0.125534  0.087964  -0.110441
## 3 30.59488     58.76594 32.11109 30.24524      0.105369  0.070998  -0.848749
## 4 30.50557     67.62201 31.65980 30.17061      0.056590  0.054453  -0.083356
## 5 32.23373     12.73800 32.88805 30.90555      0.148622  0.093604  -0.147918
## 6 30.55992     45.68915 31.55084 30.47441      0.102887  0.197388  -0.120748
##    EndSlope SteepestSlope LowestSlope TotalSlope HiFtoKnSlope KneeToFcSlope
## 1  0.079700      0.402521    0.012330   0.121189     0.120307      0.160323
## 2 -0.240827      0.299449    0.002555   0.127720     0.131206      0.204417
## 3  0.274263      0.474276    0.003707   0.129362     0.129874      0.105438
## 4 -0.336729      0.370681    0.000328   0.121868     0.126511      0.060584
## 5  0.470184      0.502855    0.002062   0.148062     0.451635      0.130891
## 6  0.384728      0.398594    0.001158   0.119814     0.151485      0.081653
##   CummNmlzdSlp HiFtoFcExpAmp HiFtoFcDmp KnToFcExpAmp KnToFcDmp HiFtoKnExpAmp
## 1     0.132652      0.238721   0.144117     0.066988  0.463974      0.195406
## 2     0.143118      0.212305   0.149537     0.021113  1.278390      0.260004
## 3     0.136665      0.233137   0.143647     0.029836  0.495926      0.185551
## 4     0.114130      0.184034   0.184496     0.041912  0.427134      0.253072
## 5     0.154234      0.171928   0.192721     0.168279  0.196062      0.157423
## 6     0.132191      0.209137   0.157434     0.161267  0.186608      0.204758
##   HiFtoKnDmp FreqLedge LedgeDuration LdgToFcSlp KnToFcDur UpprKnFreq
## 1   0.193069  29.81975      0.919608   0.425551  3.466423   31.47637
## 2   0.142817  30.39610      0.400169   0.204417  0.400169   31.90886
## 3   0.233254  30.00565      0.471639   0.233301  5.697055   31.52909
## 4   0.200184  30.38093      0.540605   0.091026  2.797044   31.33969
## 5   0.951423  30.85924      0.164799   0.248427 11.077992   32.38654
## 6   0.273281  30.03805      0.565925   0.238914  7.370012   31.45446
##   HiFtoUpprKnSlp HiFtoUpprKnAmp HiFtoUpprKnExp HiFtoKnAmp HiFtoKnExp HiFtoFcAmp
## 1       0.311719       32.55108      -0.009859   31.82506  -0.003891   31.83766
## 2       0.223328       32.66302      -0.006978   32.32240  -0.004222   32.29787
## 3       0.500066       33.33506      -0.015739   32.03484  -0.004175   32.03505
## 4       0.357447       33.58187      -0.011336   32.20854  -0.004072   32.17363
## 5       0.446222       34.23316      -0.013637   34.25621  -0.013858   32.97719
## 6       0.339414       32.87662      -0.010728   32.06753  -0.004877   31.85910
##   HiFtoFcExp UpprKnToKnAmp UpprKnToKnExp KnToFcAmp KnToFcExp LdgToFcAmp
## 1  -0.003944      32.47378     -0.005367  32.45210 -0.005322   24.13833
## 2  -0.004114      28.56538      0.004035  27.35948  0.006704   27.35948
## 3  -0.004206      31.59220     -0.003193  31.71317 -0.003492   26.53478
## 4  -0.003946      31.42564     -0.002259  31.30889 -0.001991   29.06128
## 5  -0.004699      32.93767     -0.004843  32.77774 -0.004168   27.26371
## 6  -0.003919      31.17619     -0.002245  31.33902 -0.002699   34.21957
##   LdgToFcExp  FreqCtr FBak32dB FFwd32dB FBak20dB FFwd20dB FBak15dB FFwd15dB
## 1   0.014223 30.71671 29.68433 32.01823 30.04900 31.58063 30.19487 31.43476
## 2   0.006704 30.94288 29.87336 32.28467 30.27525 31.94976 30.47619 31.81580
## 3   0.007740 30.77138 29.68421 32.42105 30.03509 31.64912 30.17544 31.50877
## 4   0.002993 30.89845 15.23173 34.38274 30.10717 31.88866 30.28532 31.71051
## 5   0.008046 31.45177 30.53004 32.94228 30.83157 32.48999 30.98233 32.33922
## 6  -0.007970 30.53643 29.52291 32.01685 29.92733 31.54502 30.06214 31.41022
##    FBak5dB  FFwd5dB  Bndw32dB Bndw20dB Bndw15dB  Bndw5dB DurOf32dB DurOf20dB
## 1 30.48661 31.14302  2.333903 1.531624 1.239886 0.656410  0.282956 11.287954
## 2 30.81109 31.54788  2.411303 1.674516 1.339613 0.736787  0.023539 12.413966
## 3 30.45614 31.22807  2.736842 1.614035 1.333333 0.771930  0.023582 11.399816
```

```
## 4 30.64161 31.35421 19.151009 1.781489 1.425191 0.712596  0.026143  0.026143
## 5 31.28386 32.03769  2.412250 1.658422 1.356890 0.753828  0.023543 10.629694
## 6 30.33175 31.07320  2.493944 1.617694 1.348078 0.741443  0.023580 11.598096
##   DurOf15dB DurOf5dB Amp1stQrtl Amp2ndQrtl Amp3rdQrtl Amp4thQrtl Amp1stMean
## 1 10.039495 6.086671  130.28833  17281.554  16891.655   12801.14   0.929226
## 2 10.391252 5.523897  124.37214  20350.936  18764.732   14174.52   0.903128
## 3 10.009441 6.015063  106.51411  13988.481  19669.105   19252.03   0.829289
## 4  0.379221 5.993666   86.20392   5960.607   7991.483   16983.38   0.762675
## 5  9.405933 5.195669  124.12725  17704.742  18487.054   17101.47   0.896930
## 6 11.032982 5.008191  132.08999  16954.333  18765.954   16800.62   0.903175
##   Amp2ndMean Amp3rdMean Amp4thMean LnExpA_StartAmp LnExpB_StartAmp
## 1   0.968364   0.964800   0.899538       -0.005587       -0.290485
## 2   0.973312   0.972437   0.903134        0.011588       -0.223018
## 3   0.898427   0.960601   0.952779        0.016248       -0.760481
## 4   0.764390   0.813589   0.921102        0.013607       -1.331607
## 5   0.946568   0.957132   0.949112        0.008725       -0.468741
## 6   0.924924   0.936323   0.897257        0.033862       -1.229953
##   AmpStartLn60ExpC LnExpA_EndAmp LnExpB_EndAmp AmpEndLn60ExpC AmpK.start
## 1         4.094345      0.001690     -0.200338       4.094345   5.595655
## 2         4.094345      0.019821     -0.511712       4.094345   3.833285
## 3         4.094345      0.005645     -0.276453       4.094345  21.828047
## 4         4.094345     -0.111835     -0.234212       4.094345  77.365796
## 5         4.094345     -0.015154     -0.148069       4.094345  12.172568
## 6         4.094345     -0.045308     -0.094687       4.094345  17.920305
##   AmpK.end AmpKurtosis   AmpSkew AmpVariance AmpMoment AmpGausR2  PreFc250
## 1 3.223241   13.382612 -2.801709    0.002822  0.002817  0.512548  0.268184
## 2 6.884980    8.804000 -2.316084    0.004054  0.004048  0.658756 -0.114148
## 3 3.086202    5.570938 -1.234727    0.004108  0.004101  0.813091 -0.229106
## 4 1.667381    3.249620  0.901986    0.005819  0.005806  0.542832  0.022880
## 5 2.221442   12.565960 -2.539664    0.001987  0.001984  0.528395  0.105247
## 6 1.264784   10.781834 -2.395888    0.004145  0.004139  0.291348 -0.211283
##    PreFc500 PreFc1000 PreFc250Residue PreFc500Residue PreFc1000Residue
## 1  0.504507  0.363335        1.35e-04       0.0002860         0.001719
## 2  0.267900  0.293707        7.23e-05       0.0006100         0.000711
## 3  0.265423  0.297202        2.36e-05       0.0013060         0.001049
## 4  0.088360  0.002960        3.46e-06       0.0000192         0.000207
## 5 -0.013381  0.147683        6.07e-05       0.0002530         0.000945
## 6 -0.242640 -0.069328        2.31e-05       0.0000158         0.001027
##   PreFc3000 PreFc3000Residue KneeToFcResidue Kn.FcCurviness meanKn.FcCurviness
## 1 -0.172370         0.010882        0.009812     -0.0030160          -2.08e-05
## 2  0.261109         0.000770        0.000621     -0.0096980          -6.47e-04
## 3 -0.071040         0.007726        0.005156      0.0054630           2.28e-05
## 4 -0.058375         0.001021        0.001075     -0.0000751          -6.42e-07
## 5 -0.117347         0.004350        0.003345      0.0071160           1.52e-05
## 6 -0.111972         0.003669        0.002871      0.0053300           1.71e-05
##   Kn.FcCurvinessTrndSlp  Quality HiFminusStartF FcMinusEndF RelPwr2ndTo1st
## 1            -5.910e-05 0.609682       0.000000    0.328197       0.254055
## 2            -3.044e-03 0.741729       0.227784   -0.080171       0.205209
## 3            -1.270e-05 0.713494       0.000000   -0.125175       0.112483
## 4            -4.950e-06 0.672488       0.002100    0.247011       0.149517
## 5             3.270e-06 0.644394       0.000000   -0.013580       0.220801
## 6             8.250e-06 0.692571       0.158924   -0.542607       0.288667
##   RelPwr3rdTo1st ParentDir    NextDirUp Filter Preemphasis MinAccpQuality
## 1              0    May-22 AcousticData  5 kHz      medium            0.8
```

```
## 2              0    May-22 AcousticData  5 kHz      medium            0.8
## 3              0    May-22 AcousticData  5 kHz      medium            0.8
## 4              0    May-22 AcousticData  5 kHz      medium            0.8
## 5              0    May-22 AcousticData  5 kHz      medium            0.8
## 6              0    May-22 AcousticData  5 kHz      medium            0.8
##   MaxSegLngth Max.CallsConsidered
## 1     0.5 sec                  32
## 2     0.5 sec                  32
## 3     0.5 sec                  32
## 4     0.5 sec                  32
## 5     0.5 sec                  32
## 6     0.5 sec                  32
```

```
# str(df_2022)
# summary(df_2022)
```

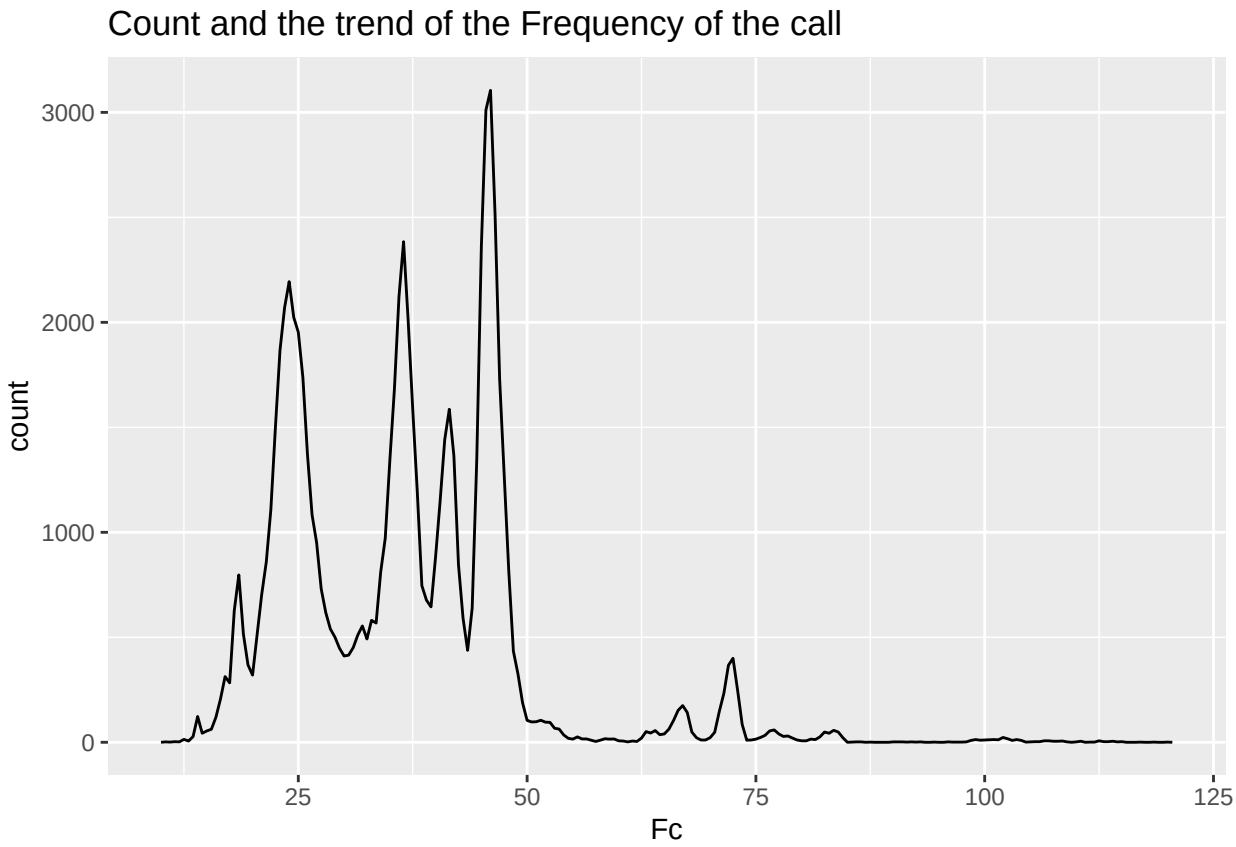
```
# Remove NA values
df22 <- na.omit(df22)
```

```
# convert characters into factor in case we have it in the dataset
df22 <- read.delim("SierraLeone2022113.txt") |>
mutate(across(where(is_character), as_factor))
#print(df22)
#summary(df22)
```

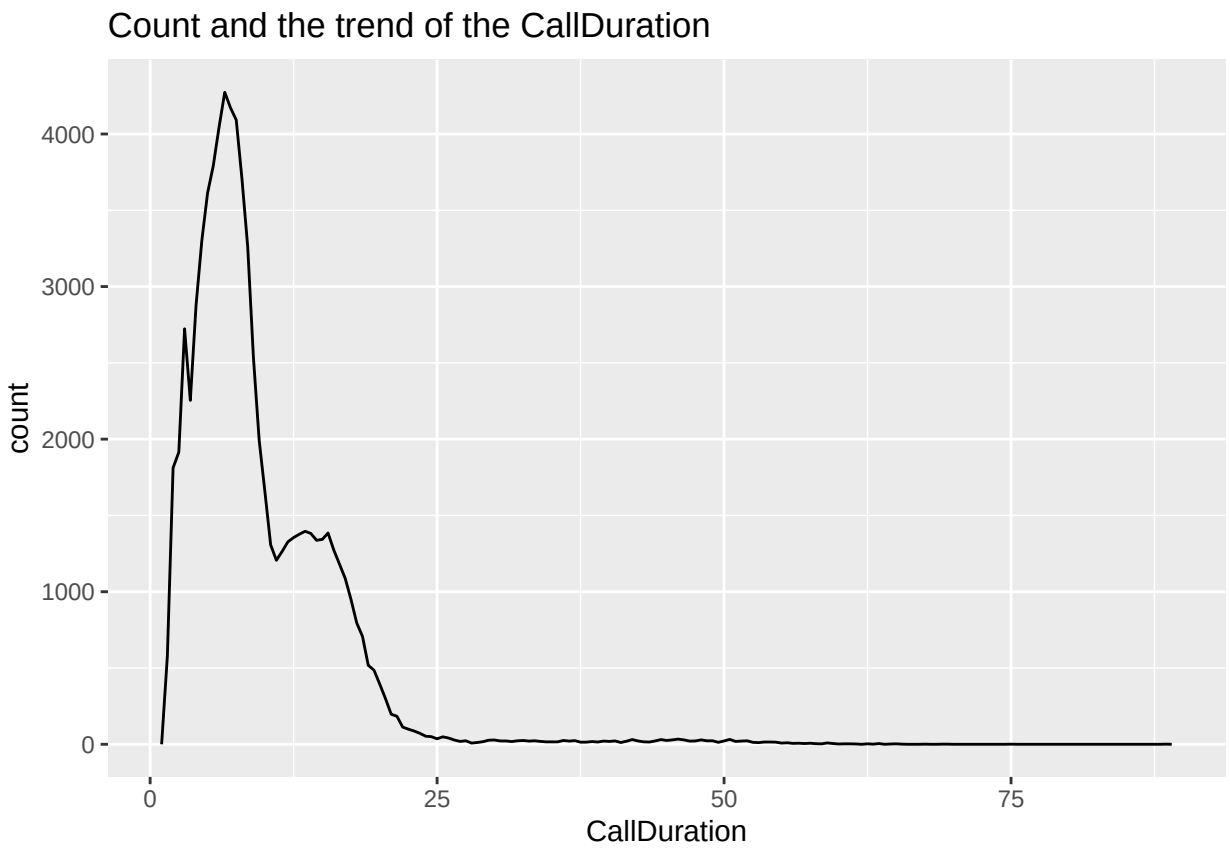
```
# remove those attributes have zero variance and character cols
df22_new <- df22[, !(names(df22) %in% c("AmpStartLn60ExpC","AmpEndLn60ExpC","NextDirUp",
                                        "Preemphasis","MinAccpQuality","MaxSegLngth",
                                        "Max.CallsConsidered","Path","Filename",
                                        "ParentDir","Filter"))]
dim(df22_new)
```

```
## [1] 77207   102
```

```
# exploring features of SonoBat dataset
tidymodels_prefer()
ggplot(df22, aes(x = Fc, colour = HiFreq)) +
  geom_freqpoly(binwidth = 0.5) +
  ggtitle("Count and the trend of the Frequency of the call")
```

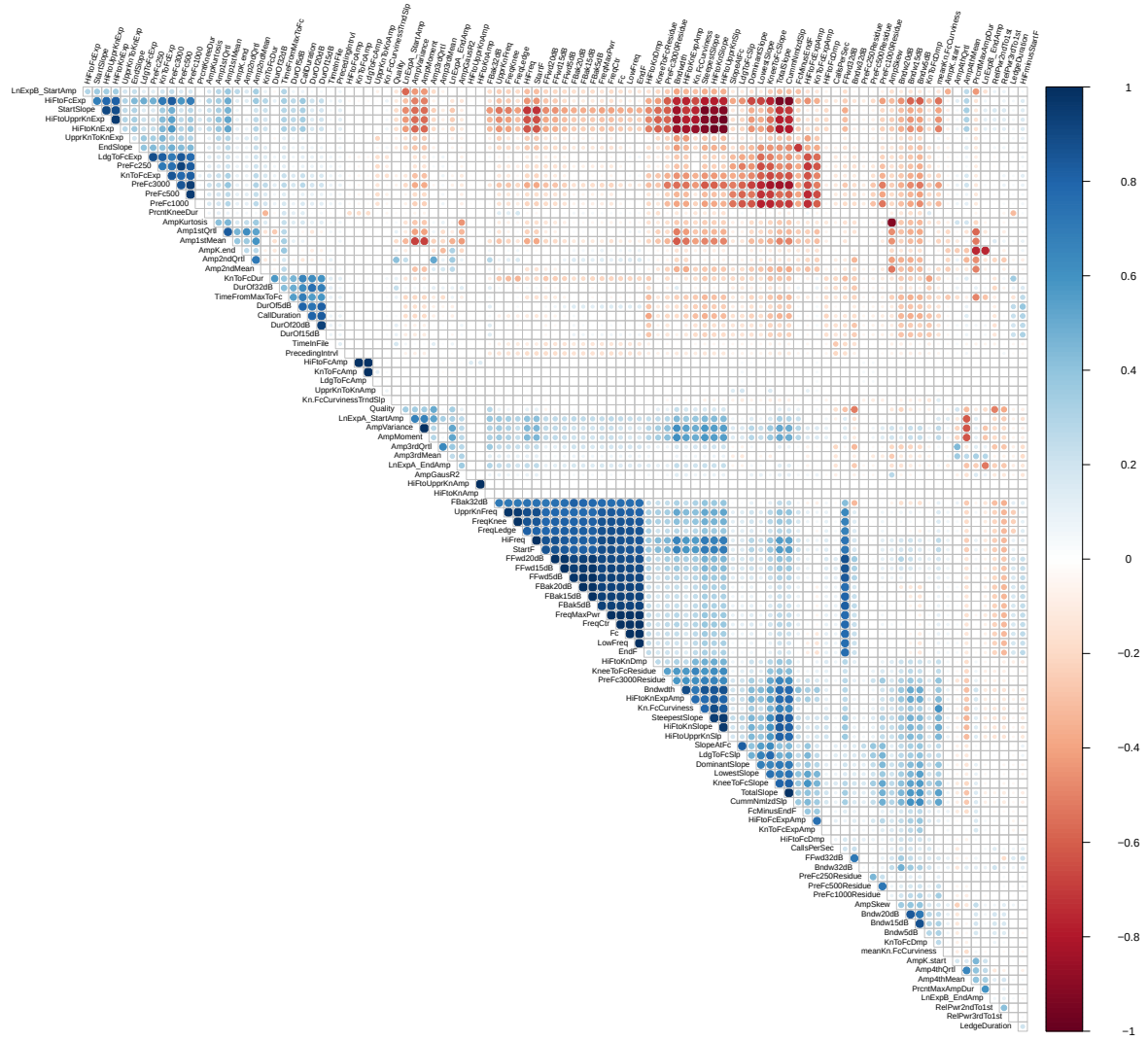



```
ggplot(df22, aes(x = CallDuration, colour = HiFreq)) +
  geom_freqpoly(binwidth = 0.5) +
  ggtitle("Count and the trend of the CallDuration")
```



Visualize correlations between attributes

```
# visualize the correlation in the new dataset
corrMatrix <- stats::cor(df22_new[,1:ncol(df22_new)])
corrplot(corrMatrix,
         order = "hclust", # order for labels, can be "original"
         type = "upper", # matrix: full, upper, lower
         diag = F, # remove diagonal
         tl.cex = 0.6, # font size
         tl.srt = 75, # label angel
         tl.col = "black",addrect = 8)
```

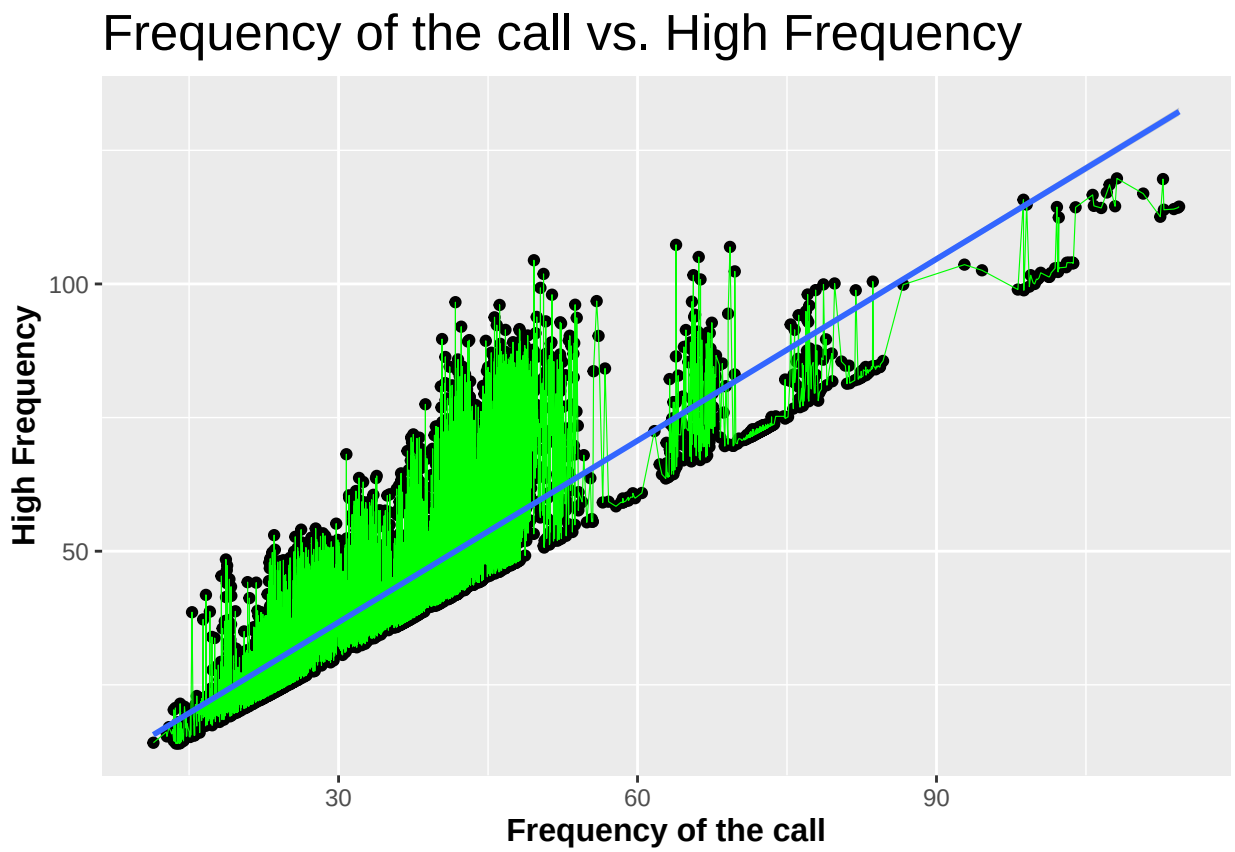


SPLIT THE DATA

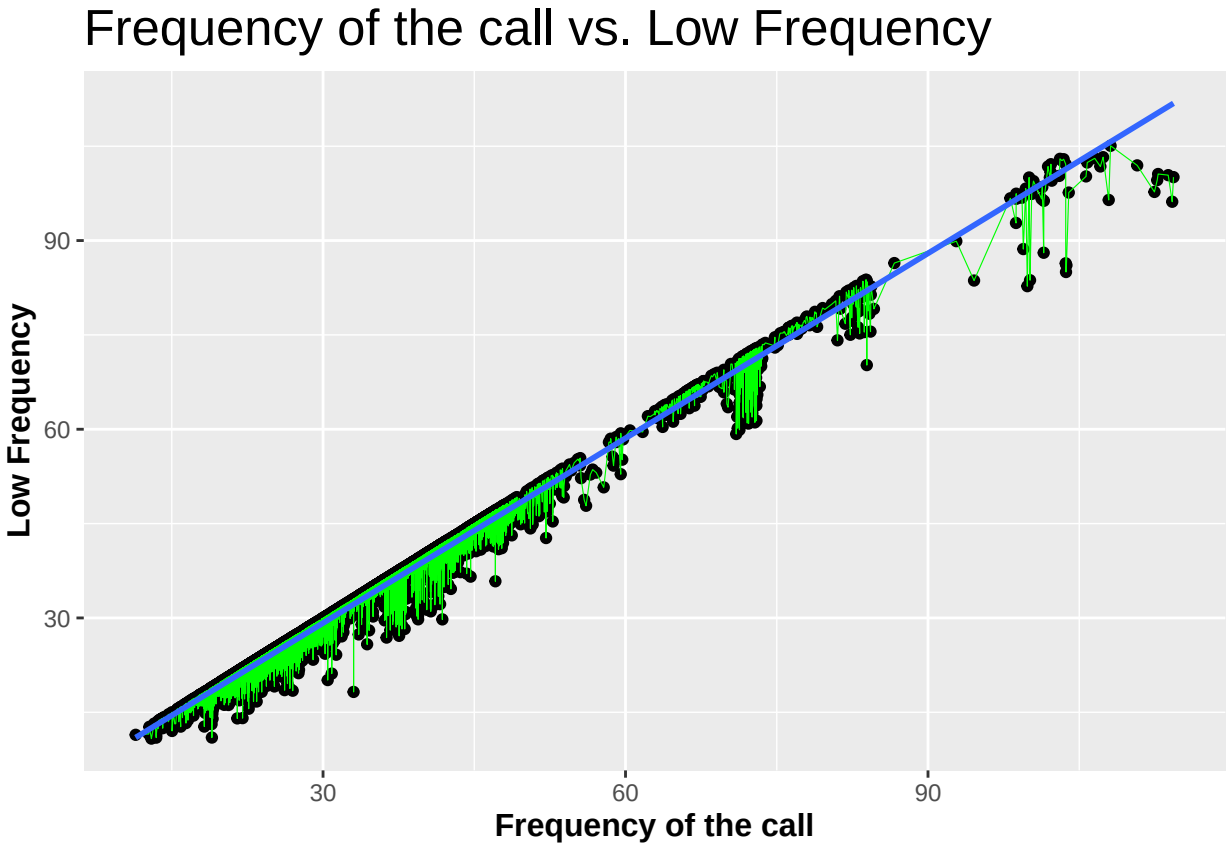
```
# Split the data into training and testing sets
set.seed(123)
train_idx <- sample(nrow(df22_new), 0.8 * nrow(df22_new))
train_data <- df22_new[train_idx, ]
test_data <- df22_new[-train_idx, ]
```

```
ggplot(test_data, aes(x = Fc, y = HiFreq)) +  # create ggplot object with data and aesthetics
  #geom_jitter() + ggtitle("Frequency of the call vs. High Frequency") +
  geom_point() + ggtitle("Frequency of the call vs. High Frequency") + # add points to the plot
  geom_line(data = test_data, colour = "green", size = 0.2) +
```

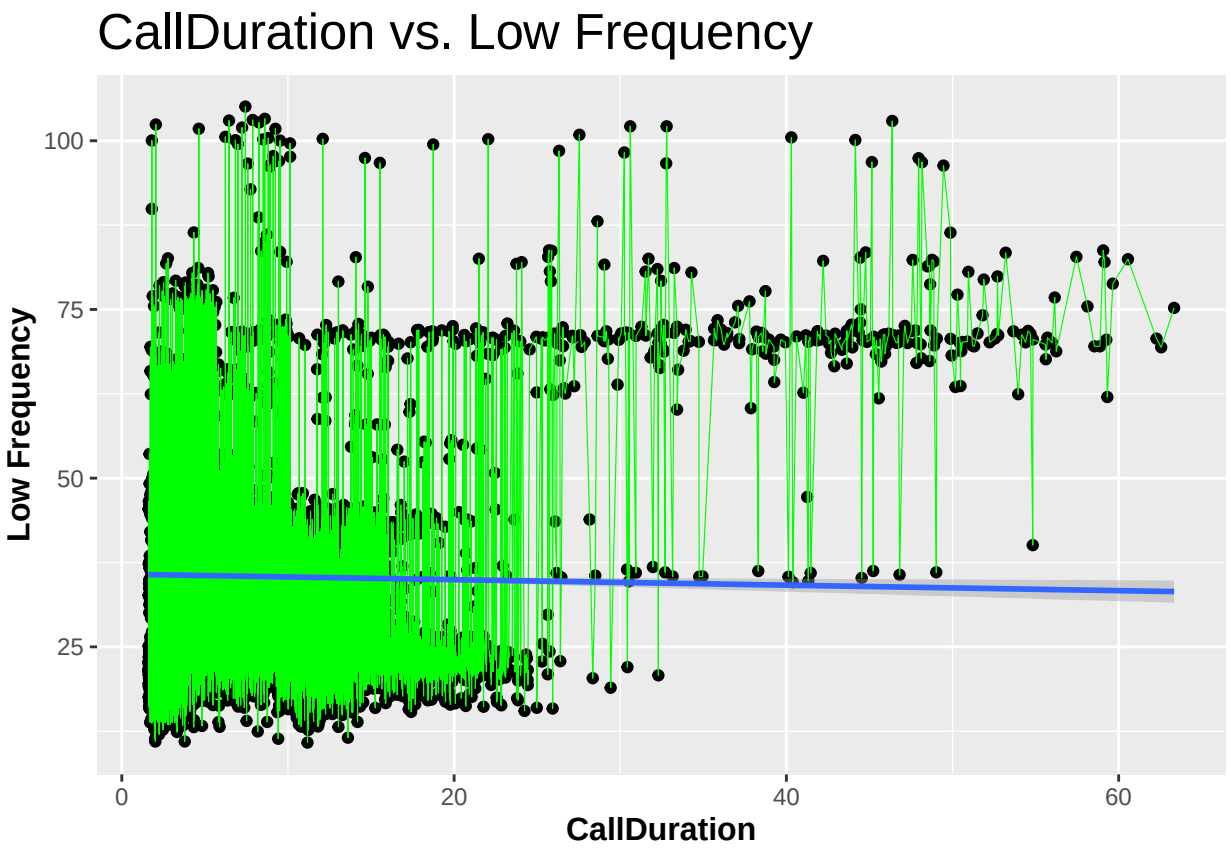
```
  xlab("Frequency of the call") + ylab("High Frequency") +
  geom_smooth(method = "lm") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 16),
        axis.title=element_text(size=12,face="bold"))
```



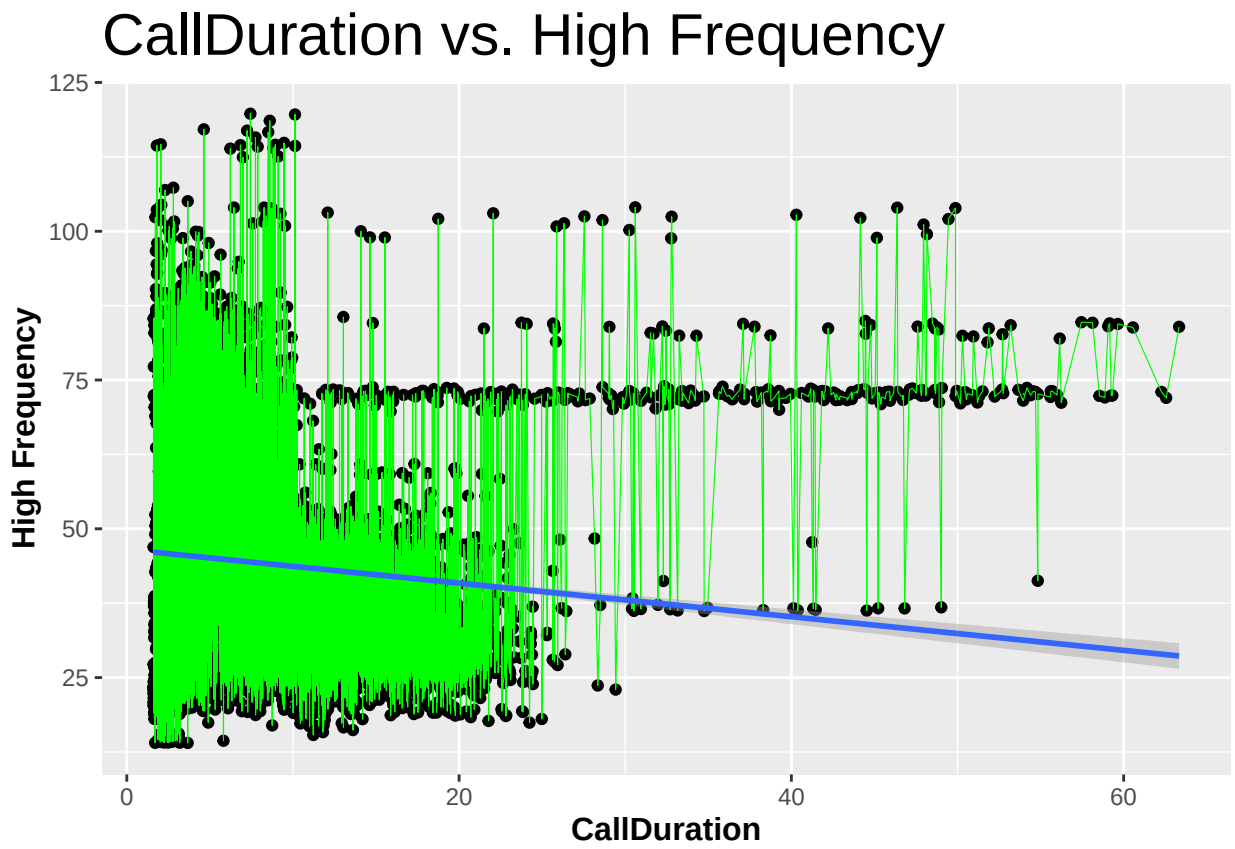

```
ggplot(test_data, aes(x = Fc, y = LowFreq)) +  # create ggplot object with data and aesthetics
  #geom_jitter() + ggtitle("Frequency of the call vs. Low Frequency") +
  geom_point() + ggtitle("Frequency of the call vs. Low Frequency") + # add points to the plot
  geom_line(data = test_data, colour = "green", size = 0.2) +
  xlab("Frequency of the call") + ylab("Low Frequency") +
  geom_smooth(method = "lm") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 16),
        axis.title=element_text(size=12,face="bold"))
```




```
ggplot(test_data, aes(x = CallDuration, y = LowFreq)) +  # create ggplot object with data and aesthetic
  geom_point() + ggtitle("CallDuration vs. Low Frequency") + # add points to the plot
  geom_line(data = test_data, colour = "green", size = 0.2) +
  xlab("CallDuration") + ylab("Low Frequency") +
  geom_smooth(method = "lm") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 16),
        axis.title=element_text(size=12,face="bold"))
```




```
ggplot(test_data, aes(x = CallDuration, y = HiFreq)) +  # create ggplot object with data and aesthetics
  geom_point() + ggtitle("CallDuration vs. High Frequency") + # add points to the plot
  geom_line(data = test_data, colour = "green", size = 0.2) +
  xlab("CallDuration") + ylab("High Frequency") +
  geom_smooth(method = "lm") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 18),
        axis.title=element_text(size=12,face="bold"))
```




```
# Train the random forest model
rf_model <- randomForest(Fc ~ ., data = train_data, ntree = 10)
# use 10 trees to grow in the forest
```

```
print(rf_model)
```

```
##
## Call:
##  randomForest(formula = Fc ~ ., data = train_data, ntree = 10)
##                Type of random forest: regression
##                      Number of trees: 10
## No. of variables tried at each split: 33
##
##           Mean of squared residuals: 0.1462736
##                     % Var explained: 99.91
```

The mean of squared residuals is 0.1462736 and % Var explained is 99.92. This suggests that the model is performing well in terms of predicting the target variable Fc, as it has a low mean squared error and high variance explained.

Note: - The mean of squared residuals: This is a measure of the average distance between the predicted and actual values of the target variable (in this case, Fc) squared. A lower value indicates better performance.

- % Var explained: This is the percentage of variance in the target variable that is explained by the model. A higher value indicates better performance.

```r
# Evaluate the model
predictions <- predict(rf_model, newdata = test_data)
#predictions
```

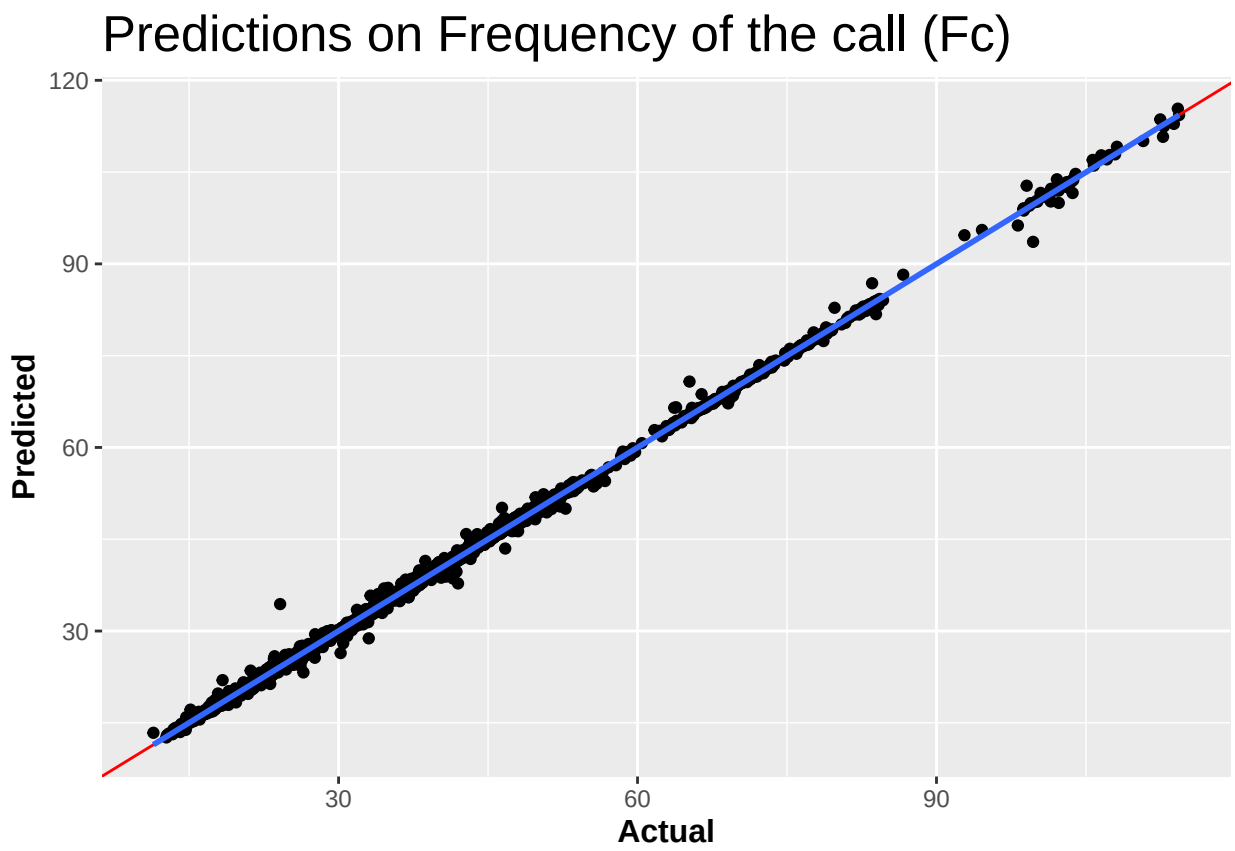
```r
summary(predictions)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   12.61   25.44   36.38   36.34   44.85  115.37
```

```r
# Evaluate the model performance using confusion matrix
#conf_mat <- caret::confusionMatrix(predictions, test_data$Fc)
#print(conf_mat)
```

we are using ggplot2 to create a scatter plot of the actual vs. predicted values on the testing set. We are also adding a diagonal dashed line to represent perfect predictions.

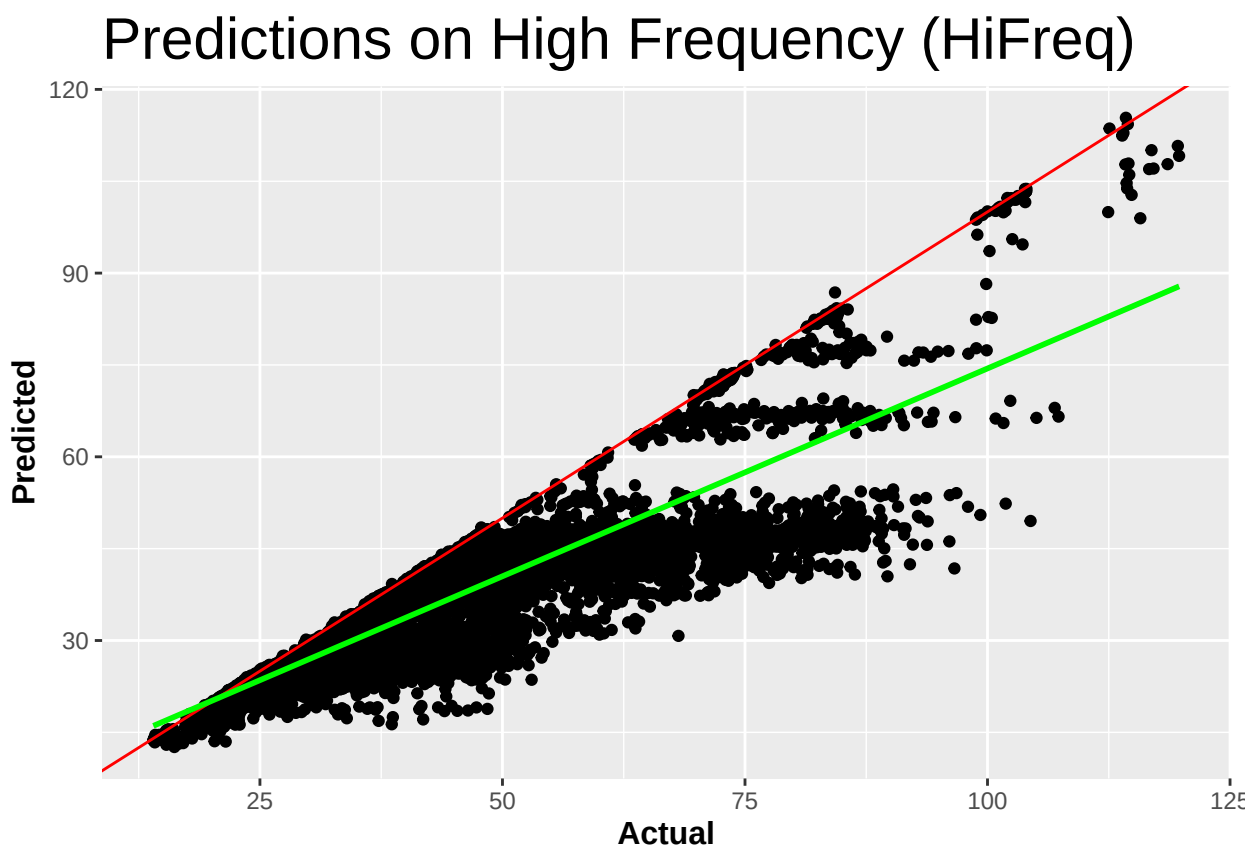
```r
# To predict the trends of Fc with the test data
ggplot(data.frame(Predicted=predictions, Actual=test_data$Fc), aes(x=Actual, y=Predicted)) +
  geom_point() + ggtitle("Predictions on Frequency of the call (Fc)") +
  geom_abline(intercept=0, slope=1, color="red") +
  geom_smooth(method = "lm") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 16),
        axis.title=element_text(size=12,face="bold"))
```



This scatterplot of the predicted values on the y-axis and actual values on the x-axis, with a red line showing

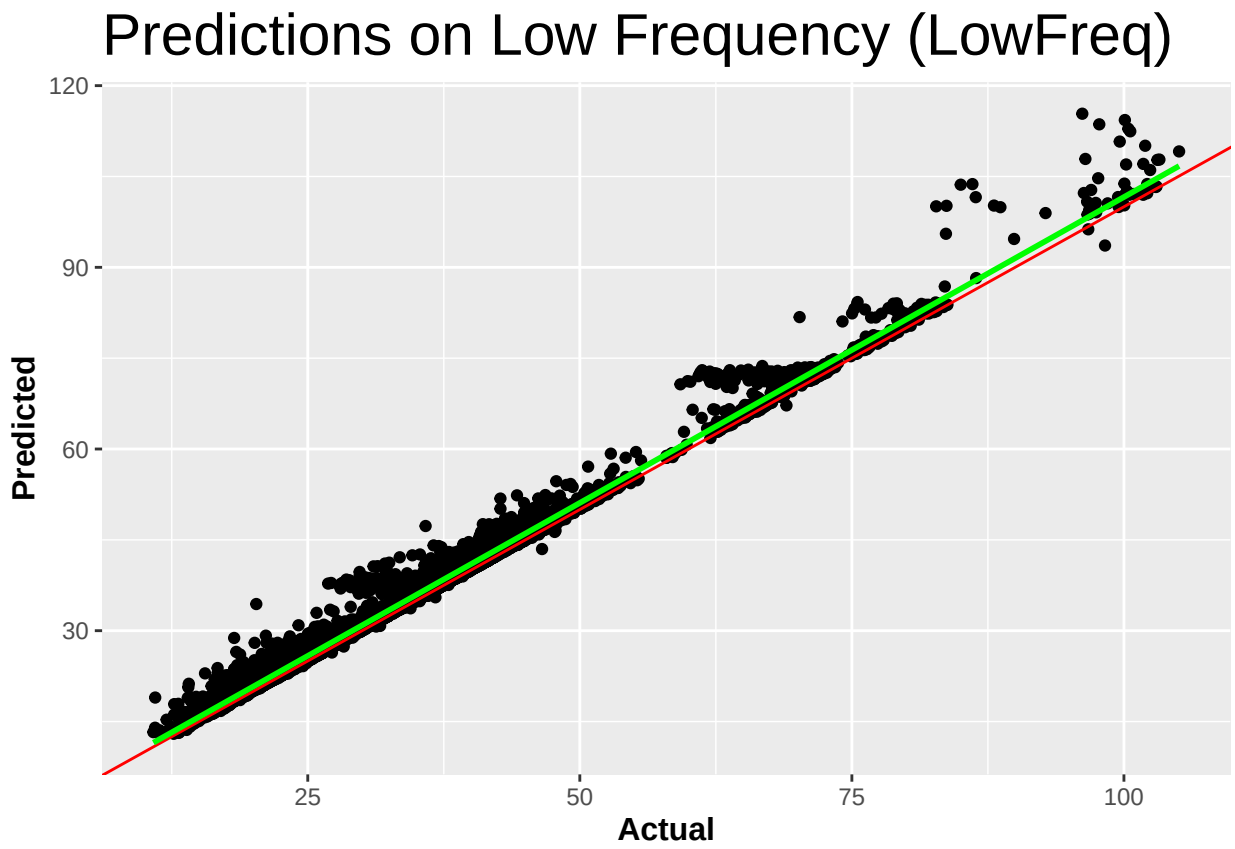
perfect agreement between the two. The result: Fc (Frequency of the call) attribute is perfectly fit in the test data

```
# To predict the trends of HiFreq with the test data
ggplot(data.frame(Predicted=predictions, Actual=test_data$HiFreq), aes(x=Actual, y=Predicted)) +
  geom_point() + ggtitle("Predictions on High Frequency (HiFreq)") +
  geom_abline(intercept=0, slope=1, color="red") +
  geom_smooth(method = "lm", color = "green") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 18),
        axis.title=element_text(size=12,face="bold"))
```



Result: The HiFreq attribute performs lower fit in the test data

```
# To predict the trends of LowFreq with the test data
ggplot(data.frame(Predicted=predictions, Actual=test_data$LowFreq),
       aes(x=Actual, y=Predicted)) +
  geom_point() + ggtitle("Predictions on Low Frequency (LowFreq)") +
  geom_abline(intercept=0, slope=1, color="red") +
  geom_smooth(method = "lm", color = "green") + # add a linear regression line to the plot
  theme(title=element_text(color = "black", size = 18),
        axis.title=element_text(size=12,face="bold"))
```



Result: The LowFreq data trend performs higher fit in the test data

```
predictions <- as.factor(predictions)
actual <- as.factor(test_data$Fc)
```

we are using the predict function to make predictions on the testing set using the trained random forest model. Then, we are using the confusionMatrix function from the caret package to evaluate the performance of the model. This function provides a table of true positive, true negative, false positive, and false negative counts, as well as various performance metrics such as accuracy, sensitivity, and specificity.

```
# Reserved code for re-run to create the confusion matrix
# Get the unique levels of both vectors
pred_levels <- unique(predictions)
actual_levels <- unique(actual)

# Combine the levels and make sure they are the same for both vectors
all_levels <- unique(c(pred_levels, actual_levels))

# Convert both vectors to factors with the same levels
predictions <- factor(predictions, levels = all_levels)
actual <- factor(actual, levels = all_levels)
```

Note: confusionMatrix() is a function in R used to evaluate the performance of a classification model. It takes in two vectors, one with the predicted classes and the other with the actual classes, and produces a confusion matrix that summarizes the results. From the confusion matrix, various performance metrics such as accuracy, precision, recall, and F1 score can be calculated to assess the model's performance. confusion-

Matrix() is particularly useful for multi-class classification problems, where it can handle more than two classes and produce metrics that take into account the imbalances in class distribution.

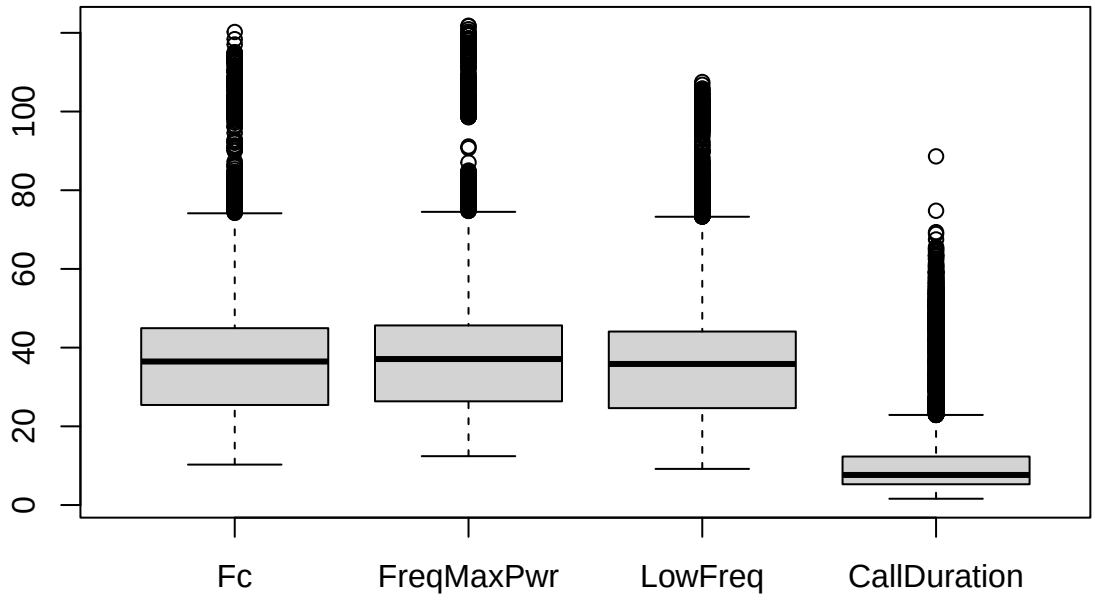
```
# Create confusion matrix
#confusionMatrix(predictions, actual)

# View confusion matrix
#print(cm$table)
```

```
# Check the correlation value between two variables
stats::cor(df22$Fc, df22$FreqMaxPwr)
```

```
## [1] 0.9930315
```

```
df22 |>
  select(Fc, FreqMaxPwr, LowFreq, CallDuration) |>
  boxplot()
```



MODEL SELECTION - MARS

MARS (Multivariate Adaptive Regression Splines) is a type of regression analysis that is designed to be flexible in handling both linear and nonlinear relationships between the response variable and the predictors.

One of the advantages of MARS is that it uses a stepwise approach to build the model, where the algorithm iteratively adds basis functions (splines) and interactions between them, based on their predictive power.

This allows MARS to capture complex relationships between the predictors and the response variable, even in high-dimensional datasets.

Because MARS is built using a stepwise approach that selects only the most relevant predictors and interactions, it has a built-in method for variable selection and regularization. This means that MARS can avoid overfitting the training data, making it less prone to the problem of overfitting that typically arises when using other machine learning models with many parameters.

Therefore, MARS may not necessarily need a separate train/test split, as it automatically selects the best predictors and interactions during the modeling process. However, it is still recommended to use some form of cross-validation or resampling technique to validate the model's performance and ensure that it is generalizable to new data.

```
# fit a basic MARS model - Multivariate Adaptive Regression Splines
mars1 <- earth(
  Fc ~ ., data = df22_new
)
summary(mars1)
```

```
## Call: earth(formula=Fc~., data=df22_new)
##
##                              coefficients
## (Intercept)                    101.191645
## h(12.062-Bndwdth)                0.084999
## h(Bndwdth-12.062)               -0.033662
## h(-0.364327-HiFtoFcExpAmp)       0.732087
## h(HiFtoFcExpAmp- -0.364327)     -1.490753
## h(101.002-FreqCtr)              -1.010274
## h(FreqCtr-101.002)               1.085139
##
## Selected 7 of 7 terms, and 3 of 101 predictors
## Termination condition: RSq changed by less than 0.001 at 7 terms
## Importance: FreqCtr, HiFtoFcExpAmp, Bndwdth, TimeInFile-unused, ...
## Number of terms at each degree of interaction: 1 6 (additive model)
## GCV 0.2868884    RSS 22142.33    GRSq 0.9981652    RSq 0.9981658
```

The earth function fits a multivariate adaptive regression spline (MARS) model to the data, which can capture nonlinear relationships and interactions between variables. In this case, the model appears to have selected seven terms to include in the final model, out of a total of 101 predictors.

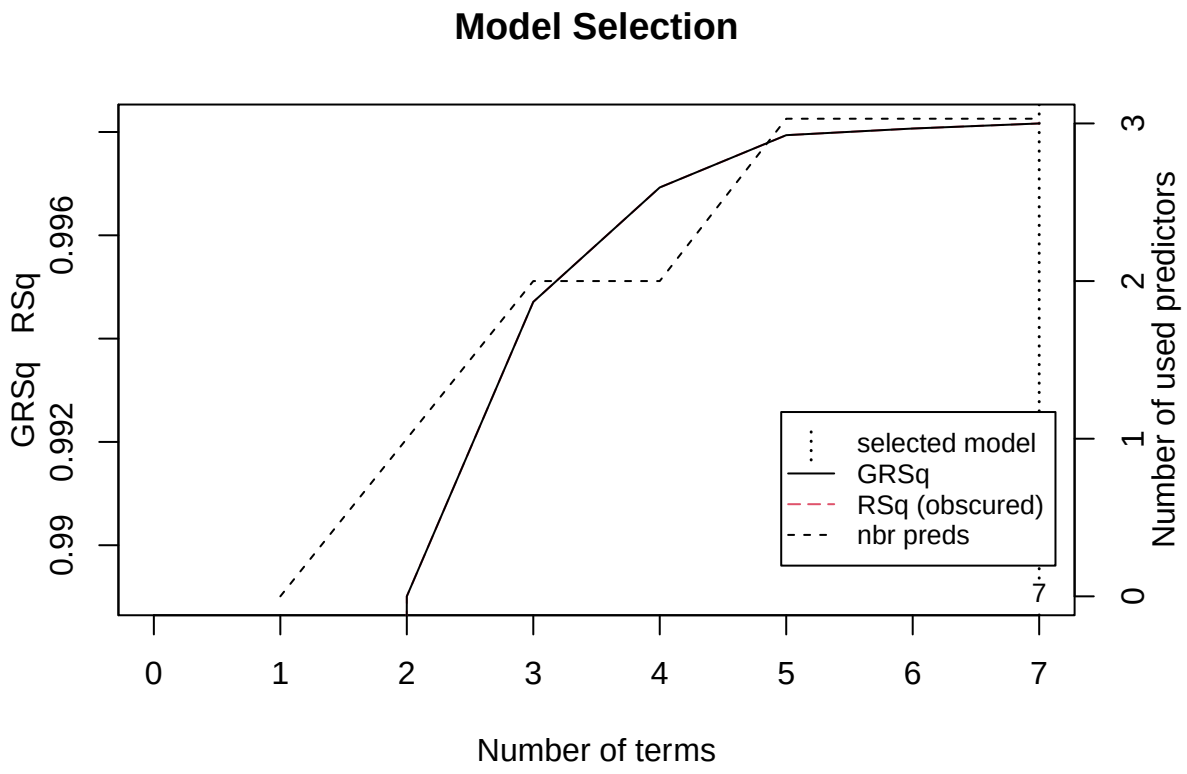
The "Selected 7 of 7 terms, and 3 of 101 predictors" line indicates that the model has used only seven of the seven terms that were available in the formula you specified (i.e., all variables except for the response variable Fc). This suggests that some of the terms may have been redundant or not useful for predicting Fc.

The "Termination condition" line shows that the model stopped adding terms once the maximum R-squared value was reached, indicating that the model has a good fit to the data. The "Importance" line shows which predictors were most important in the model, with the FreqCtr, HiFtoFcExpAmp, Bndwdth, and TimeInFile variables apparently not contributing much to the fit.

- GCV = 0.2868884: Generalized Cross-Validation (GCV) score for the final model, where 0 is the minimum value and lower values indicate better models.
- RSS = 22142.33: Residual Sum of Squares (RSS) for the final model, which measures the total difference between the predicted and actual values of the response variable. A lower RSS score indicates a better fit of the model.
- GRSq = 0.9981652: Generalized R-Squared (GRSq) for the final model, which is a measure of how well the model fits the data, where 1 is the maximum value and higher values indicate better models.

- RSq = 0.9981658: R-Squared (RSq) for the final model, which is a similar measure of how well the model fits the data as GRSq. A higher R-squared score indicates a better fit of the model.

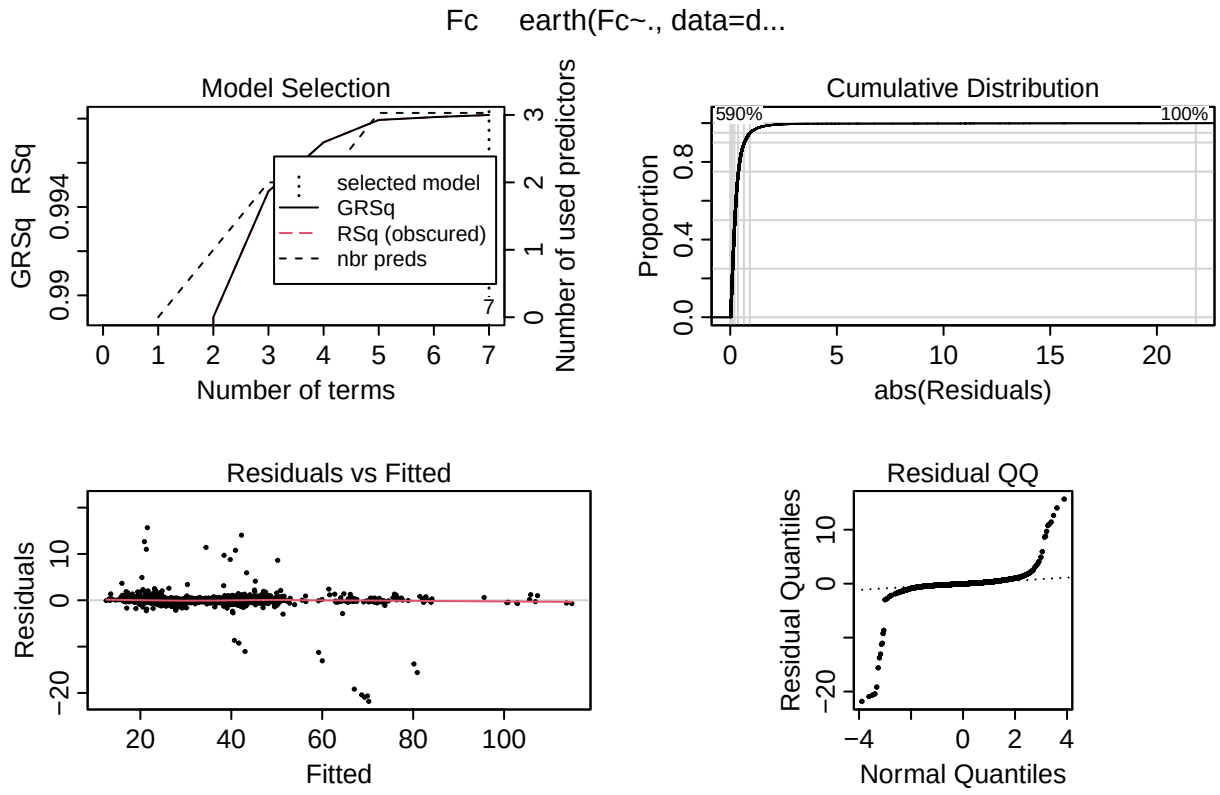
```
plot(mars1, which = 1)
```



The plot method for MARS model objects provide useful performance and residual plots. This model selection plot that graphs the GCV R^2 (left-hand y-axis and solid black line) based on the number of terms retained in the model (x-axis) which are constructed from a certain number of original predictors (right_hand y-axis). The vertical dashed line at 7 tells us the optimal number of non-intercept terms retained where marginal increases in GCV R^2 are less than 0.001.

For this model, 6 non-intercept terms were retained which are based on 3 predictors. Any additional terms retained in the model, over and above these 6, result in less than 0.001 improvement in the GCV R^2.

```
# Other views in plot of model MARS1
plot(mars1)
```



MARS Model 2 with degree 2

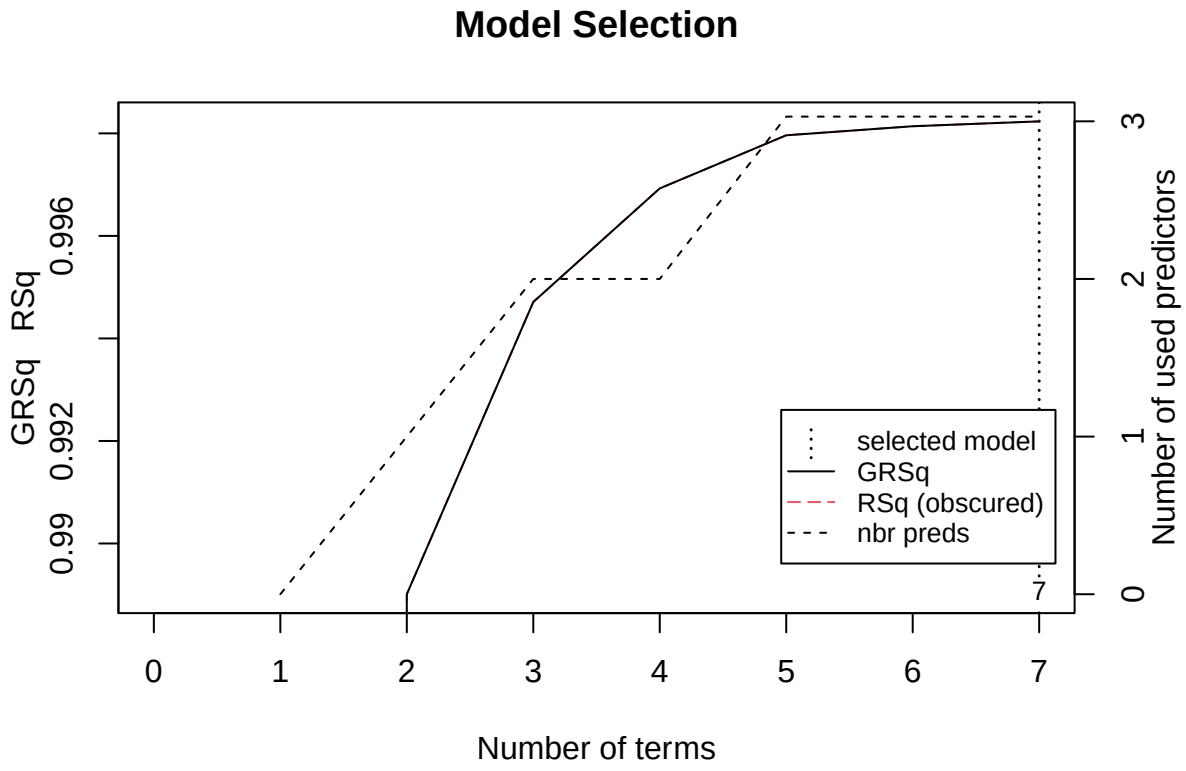
```
# fit a basic MARS model - Multivariate Adaptive Regression Splines
mars2 <- earth(
  Fc ~ ., data = df22_new,
  degree = 2
)
```

```
summary(mars2)
```

```
## Call: earth(formula=Fc~., data=df22_new, degree=2)
##
##                                          coefficients
## (Intercept)                                101.714287
## h(-0.364327-HiFtoFcExpAmp)                   0.723449
## h(HiFtoFcExpAmp- -0.364327)                 -1.482365
## h(101.002-FreqCtr)                          -1.018904
## h(FreqCtr-101.002)                           1.035273
## h(12.2588-Bndwdth) * h(101.002-FreqCtr)      0.001342
## h(Bndwdth-12.2588) * h(101.002-FreqCtr)     -0.000715
##
## Selected 7 of 7 terms, and 3 of 101 predictors
## Termination condition: RSq changed by less than 0.001 at 7 terms
```

```
## Importance: FreqCtr, HiFtoFcExpAmp, Bndwdth, TimeInFile-unused, ...
## Number of terms at each degree of interaction: 1 4 2
## GCV 0.2760953    RSS 21307.66    GRSq 0.9982342    RSq 0.9982349
```

```
plot(mars2, which = 1)
```



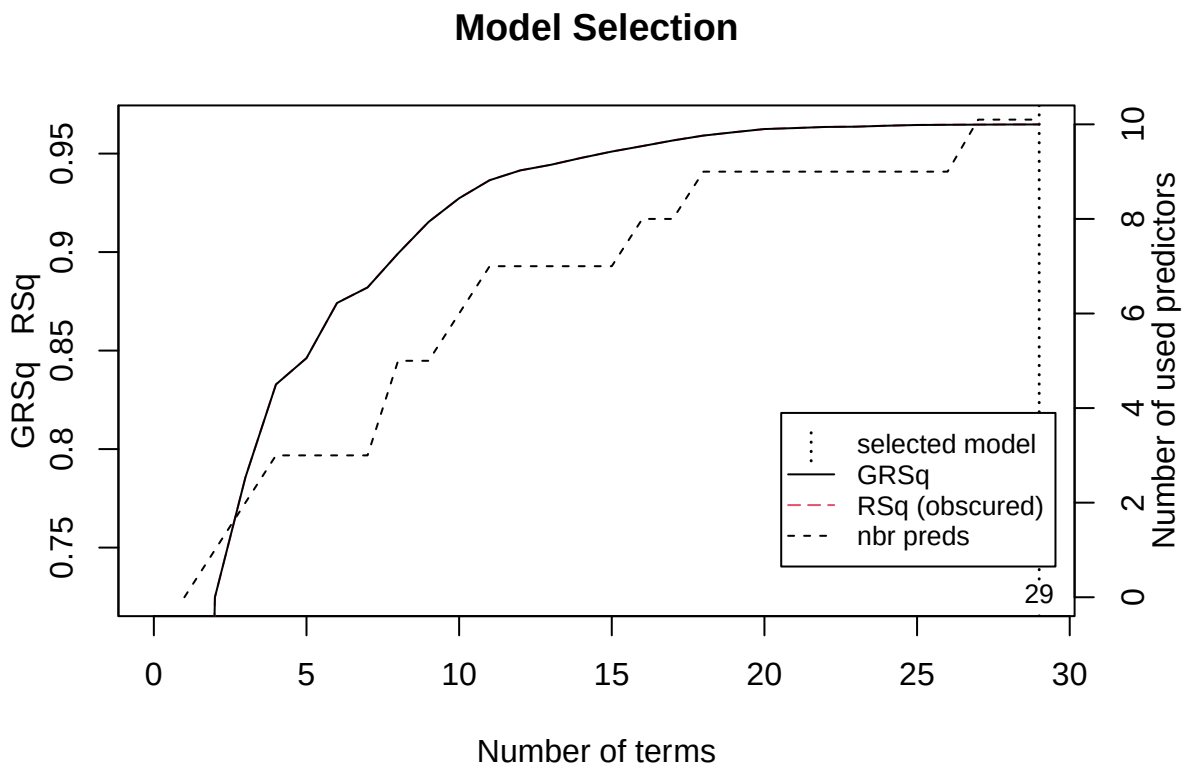
MARS model 3 with CallDuration as a predictor

```
# fit a basic MARS model - Multivariate Adaptive Regression Splines
mars3 <- earth(
  CallDuration ~ ., data = df22_new
)
summary(mars3)
```

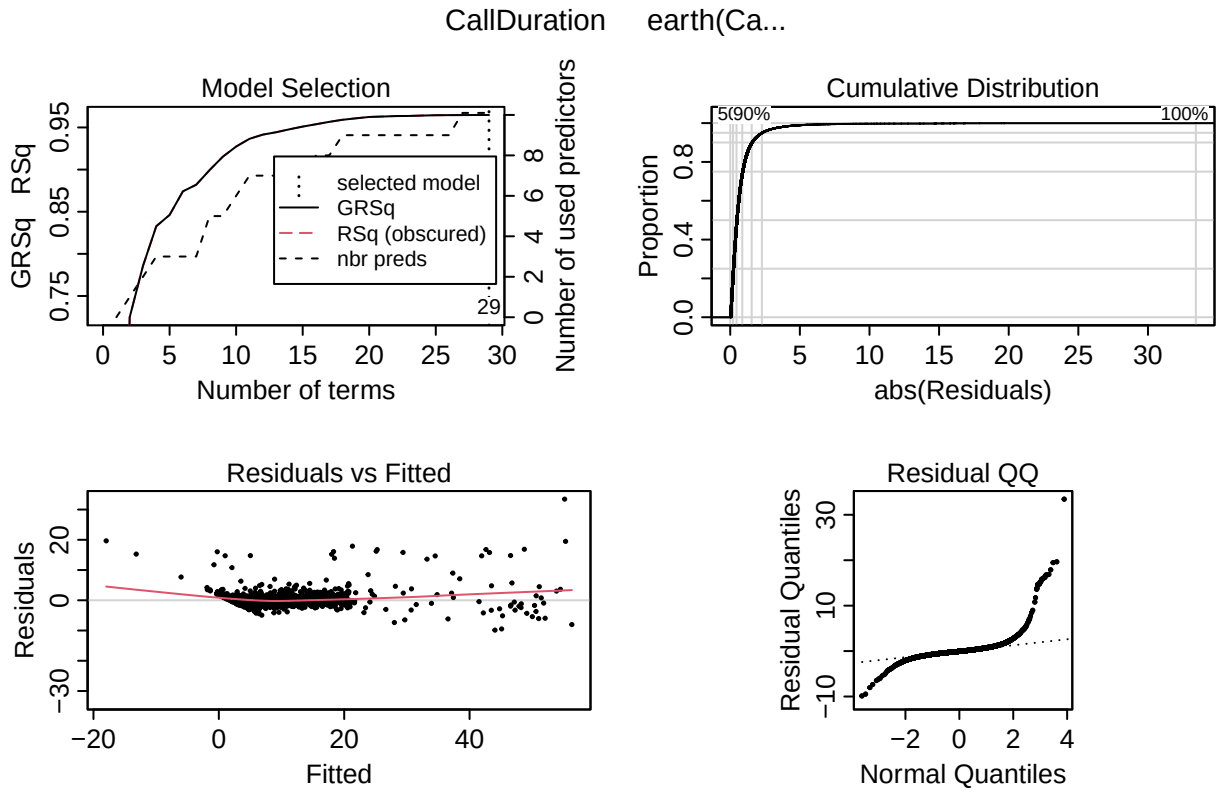
```
## Call: earth(formula=CallDuration~., data=df22_new)
##
##                              coefficients
## (Intercept)                    -58.473564
## h(89.6449-PrcntMaxAmpDur)       -0.056634
## h(PrcntMaxAmpDur-89.6449)       -0.073052
## h(0.072643-TimeFromMaxToFc)      0.320816
## h(TimeFromMaxToFc-0.072643)      0.713869
## h(TimeFromMaxToFc-4.86627)      -0.280562
```

```
## h(TimeFromMaxToFc-16.1513)     -0.321264
## h(22.8773-PrcntKneeDur)        -0.016613
## h(PrcntKneeDur-22.8773)         0.073163
## h(PrcntKneeDur-79.4364)         0.244038
## h(-0.016129-EndSlope)          -0.170821
## h(EndSlope- -0.016129)         -0.151106
## h(0.740731-HiFtoKnDmp)          2.045418
## h(HiFtoKnDmp-0.740731)          0.103476
## h(1.38456-LedgeDuration)        0.179175
## h(LedgeDuration-1.38456)        0.077828
## h(KnToFcDur-1.37676)           -2.056078
## h(4.40175-KnToFcDur)           -3.106349
## h(KnToFcDur-4.40175)            2.875646
## h(KnToFcDur-13.3944)           -0.584730
## h(Bndw5dB-0.294253)            54.915279
## h(Bndw5dB-0.487221)            33.322183
## h(1.13947-Bndw5dB)             89.432982
## h(Bndw5dB-1.13947)            -88.319039
## h(2.61476-DurOf15dB)            0.186994
## h(DurOf15dB-2.61476)            0.174106
## h(FcMinusEndF-0)                1.594257
## h(3.94841-FcMinusEndF)          0.592041
## h(FcMinusEndF-3.94841)         -1.416935
##
## Selected 29 of 29 terms, and 10 of 101 predictors
## Termination condition: RSq changed by less than 0.001 at 29 terms
## Importance: TimeFromMaxToFc, DurOf15dB, PrcntMaxAmpDur, KnToFcDur, Bndw5dB, ...
## Number of terms at each degree of interaction: 1 28 (additive model)
## GCV 1.474584    RSS 113680.2    GRSq 0.9647895    RSq 0.9648405
```

```
plot(mars3, which = 1)
```


Model Selection
GRSq RSq
0.75
0.8
0.85
0.9
0.95
Number of used predictors
0
2
4
6
8
10
selected model
GRSq
RSq (obscured)
nbr preds
29
0
5
10
15
20
25
30
Number of terms

```
plot(mars3)
```


CallDuration earth(Ca...
Model Selection
GRSq RSq
Number of used predictors
Number of terms
selected model
GRSq
RSq (obscured)
nbr preds
29
Cumulative Distribution
Proportion
abs(Residuals)
5(90%
100%
Residuals vs Fitted
Residuals
Fitted
Residual QQ
Residual Quantiles
Normal Quantiles