```
Data_clust = props
#scaling the data and finding generalized euclidean distance
scale_data = scale(Data_clust)
scale_data
```

```
##            Energy Dancebility   Loudness     Valence Acoustiveness
##   [1,]  1.15021860  0.18804631  0.8986926  1.23159462    0.22115398
##   [2,]  1.40011168  0.79630428  0.2877298  0.51918924    0.46134664
##   [3,]  0.83785224  0.87233653  1.4332851  0.83086660   -0.21119281
##   [4,]  1.33763841  0.41614305  0.8986926  0.83086660   -0.69157813
##   [5,]  0.83785224 -0.04005043  0.2877298 -0.41584281   -0.59550107
##   [6,]  0.96279878  0.64423979  0.2877298  0.07393588   -0.49942401
##   [7,]  0.46301261  0.79630428  0.8986926  1.32064529   -0.69157813
##   [8,]  0.33806606 -0.95243739 -0.3232331 -0.63846949   -0.35530841
##   [9,] -2.09839153 -1.25656638 -1.4687884 -1.70707755    2.86327326
##  [10,]  0.08817298  1.10043327  0.8986926  0.38561324   -0.06707721
##  [11,]  1.02527205 -0.19211492  0.8986926 -0.23774147   -0.54746254
##  [12,]  0.77537897 -0.19211492  0.2877298 -0.19321613    0.89369343
##  [13,]  0.71290569  0.94836877  0.2877298  0.47466391    0.17311545
##  [14,]  0.77537897  1.40456225 -0.3232331  0.83086660   -0.64353960
##  [15,]  0.83785224 -1.56069536 -1.4687884  1.14254395   -0.64353960
##  [16,]  0.27559279  1.02440102 -0.3232331 -0.86109617    0.26919251
##  [17,] -0.59903301  0.56820754  0.8986926  1.36517063   -0.45138547
##  [18,]  0.65043242  1.32853001 -1.4687884 -0.37131748   -0.35530841
##  [19,]  0.58795915 -0.11608268 -0.8578255 -0.68299483   -0.69157813
##  [20,] -0.59903301  1.40456225  0.8986926  1.05349328   -0.64353960
##  [21,] -0.47408647  1.17646551 -0.8578255 -0.54941882   -0.69157813
##  [22,] -0.16172011 -1.56069536  0.2877298 -0.32679214   -0.64353960
##  [23,] -0.16172011  0.64423979  0.2877298  0.96444260   -0.69157813
##  [24,]  0.65043242  0.41614305  0.2877298  0.91991727   -0.69157813
##  [25,]  1.52505822 -0.87640514  0.8986926  0.56371458    0.55742371
##  [26,]  0.77537897 -1.25656638 -0.3232331  0.96444260   -0.69157813
##  [27,]  1.21269187 -0.26814717  0.2877298  1.58779731   -0.59550107
##  [28,]  1.46258495  0.03598182  1.4332851  0.91991727   -0.59550107
##  [29,]  0.58795915  0.56820754  0.2877298  0.29656256   -0.59550107
##  [30,]  0.27559279  1.10043327  0.8986926 -0.54941882   -0.69157813
##  [31,]  0.02569971  0.41614305  2.0442479  1.18706928   -0.45138547
##  [32,]  1.15021860  0.26407856  0.8986926  1.36517063   -0.64353960
##  [33,]  0.83785224  0.79630428  1.4332851 -0.01511479   -0.30726988
##  [34,] -1.16129245 -0.34417942 -0.8578255 -0.50489348    0.17311545
##  [35,]  0.71290569 -1.10450188  0.2877298  0.11846122    0.07703838
##  [36,] -0.47408647  1.25249776  0.2877298  1.23159462   -0.30726988
##  [37,] -1.84849844 -2.70117906  0.2877298 -2.01875491    3.29562005
##  [38,]  1.27516514  0.03598182  0.8986926  1.18706928   -0.64353960
##  [39,]  1.27516514  0.56820754 -0.3232331  1.40969596   -0.59550107
##  [40,]  0.65043242 -1.10450188  0.2877298 -1.17277352   -0.54746254
##  [41,]  0.90032551 -1.02846964  0.8986926  0.87539193    1.56623288
##  [42,] -1.84849844  0.49217530 -0.8578255 -1.88517890   -0.49942401
```

```r
dist_data = dist(scale_data,method ="euclidean")
dist_data
```

```
##              1         2         3         4         5
6
## 2    1.1708603
## 3    1.0950441 1.4777231
## 4    1.0396236 1.3957361 0.9871463
## 5    1.9758168 1.7340233 1.9613067 1.5474784
## 6    1.5735058 1.1557236 1.4268700 1.0842858 0.8561418
## 7    1.2973973 1.7952709 0.9501200 1.0720896 2.0586139
1.4957918
## 8    2.6986748 2.5625013 2.9739973 2.5762930 1.2501068
1.9599070
## 9    5.8191003 5.5013338 6.1212162 6.2679625 5.1785328
5.5271193
## 10   1.6610697 1.5760798 1.0577599 1.6179212 1.7769528
1.2768809
## 11   1.7058294 1.7553897 1.6458957 1.2768097 0.6823146
1.0844898
## 12   1.7722014 1.4358651 2.1722743 2.1497024 1.5146912
1.6573357
## 13   1.3106717 0.7618631 1.2681730 1.3861479 1.5415439
0.8762610
## 14   2.0054416 1.5657141 1.8866496 1.6698857 2.0051624
1.2570622
## 15   3.0848438 3.2505821 3.8243615 3.1403969 2.7979625
3.0208276
## 16   2.7091003 1.9057695 2.5530616 2.6032363 1.6638551
1.5668780
## 17   1.9169130 2.4434909 1.6691603 2.0290375 2.4496267
2.1184829
## 18   3.1712918 2.3217594 3.1829679 2.9099815 2.2479256
1.9672828
## 19   2.8271397 2.3619527 2.9683587 2.4944770 1.2087702
1.6250413
## 20   2.3063407 2.4992173 1.6941602 2.1862157 2.5857449
2.0906904
## 21   3.2719695 2.7277458 3.0329562 2.9750598 2.1308366
2.0213101
## 22   2.8859696 3.1513845 3.1238091 2.8056591 1.8225651
2.5115003
## 23   1.7908158 1.9974805 1.6161939 1.6404945 1.8389716
1.4472277
## 24   1.2670093 1.4820122 1.3394908 0.9238277 1.4271386
0.9498466
```

```
## 25   1.3537735  1.7883113  2.1161947  1.8267958  1.9580054
2.0877219
## 26   2.1505727  2.5505550  2.8053697  2.1505900  1.9420371
2.2025874
## 27   1.1743495  1.8512248  1.8639050  1.1997146  2.0511233
1.7877091
## 28   1.0819213  1.7809548  1.1159763  0.6805029  1.8688563
1.6300234
## 29   1.5411503  1.3704414  1.3785542  1.1194328  0.9695080
0.4528566
## 30   2.3669620  2.0497491  1.6703026  1.8711980  1.4202773
1.2161967
## 31   1.7558928  2.5294328  1.1939651  1.7938933  2.5579595
2.2927958
## 32   0.8782474  1.6295535  1.1071333  0.5882502  1.9333027
1.4969906
## 33   1.6083705  1.5826196  0.8548077  1.2423668  1.5018144
1.1814760
## 34   3.4248215  3.2102358  3.5577558  3.5270457  2.4495045
2.7547025
```

```
(kmeans5 <- kmeans(scale_data,5,nstart = 20))
```

```
## K-means clustering with 5 clusters of sizes 66, 129, 45, 192, 166
## 
## Cluster means:
##       Energy Dancebility   Loudness    Valence Acoustiveness
## 1 -0.9047734  -0.6644365 -0.9052677 -1.2982540   -0.01394369
## 2 -0.4978166   0.8104498 -0.5973375  0.2371954   -0.18884931
## 3 -2.0692373  -1.1247771 -1.3482929 -1.0233663    2.83978775
## 4  0.6780899   0.5175194  0.6759457  0.9062350   -0.27324258
## 5  0.5232278  -0.6593010  0.4078061 -0.4389102   -0.30148210
## 
## Clustering vector:
##   [1] 4 4 4 4 5 4 4 5 3 4 5 5 4 4 5 2 4 2 5 4 2 5 4 4 5 5 4 4 4 4 4 4 4 1
5
##  [36] 2 3 4 4 5 5 1 5 4 3 4 4 4 5 4 1 3 4 5 4 4 4 4 1 4 4 5 1 5 5 5 4 4 2
1
##  [71] 4 4 4 5 4 5 4 2 2 4 5 4 5 4 4 5 3 5 4 4 4 4 4 3 5 3 2 2 4 5 4 4 2 5
4
## [106] 1 4 4 2 2 4 5 2 4 2 4 4 4 4 5 4 2 2 4 2 5 5 4 4 5 4 5 5 4 4 4 5 5 5
1
## [141] 2 5 5 2 5 2 1 5 2 5 2 4 5 5 5 5 2 5 4 5 2 4 4 4 4 1 1 2 1 4 2 2 4 4
5
## [176] 5 2 4 5 5 1 2 5 5 3 5 2 5 4 5 3 5 5 4 5 4 4 5 5 4 2 5 2 5 4 1 4 5 3
3
## [211] 4 4 4 4 1 5 4 4 1 4 2 2 5 5 5 2 5 5 2 2 2 1 5 2 4 2 4 2 4 1 4 4 5 1
5
```

```
## [246] 4 5 3 1 4 5 1 5 3 1 2 4 4 3 1 2 2 5 2 2 2 3 1 3 2 3 4 5 3 1 1 2 2 2
4
## [281] 2 3 5 5 5 5 5 4 5 2 5 2 1 4 2 4 5 4 5 4 5 4 4 5 5 4 4 5 5 5 4 1 5 5
4
## [316] 4 5 5 4 4 4 4 2 4 1 5 3 3 2 5 4 2 5 4 4 4 1 5 1 5 1 5 1 5 1 4 5 4 1
3
## [351] 5 4 4 4 5 4 3 4 2 1 3 4 5 1 5 5 3 1 2 4 2 5 1 2 2 2 2 1 2 4 2 5 2 2
5
## [386] 2 4 2 5 4 1 1 5 2 3 5 5 4 1 5 5 4 5 5 5 5 5 3 5 4 5 5 5 2 4 4 1 4 3
1
## [421] 3 2 5 5 4 4 4 3 4 5 1 2 3 5 2 2 4 2 4 2 2 5 2 5 2 5 2 2 2 5 2 4 1 4
4
## [456] 3 4 4 1 1 5 4 4 2 5 2 3 5 3 2 2 1 2 5 4 4 4 2 4 5 2 1 4 4 2 5 4 2 1
5
## [491] 4 1 4 4 3 4 2 2 4 5 3 4 5 4 2 4 2 4 2 2 2 5 1 2 5 5 4 5 2 3 4 2 4 3
4
## [526] 1 4 4 2 5 2 1 2 3 2 5 2 5 1 4 1 2 2 2 1 2 2 5 5 5 2 1 4 1 3 3 5 4 2
2
## [561] 5 1 2 2 5 2 4 3 3 3 2 5 2 3 4 5 4 2 2 2 4 5 4 2 4 1 4 2 5 1 4 4 4 1
2
## [596] 5 5 1
## 
## Within cluster sum of squares by cluster:
## [1] 162.1891 267.8626 208.7179 297.5688 292.4047
##  (between_SS / total_SS =  58.8 %)
## 
## Available components:
## 
## [1] "cluster"      "centers"      "totss"        "withinss"    
## [5] "tot.withinss" "betweenss"    "size"         "iter"        
## [9] "ifault"
```

```
kmeans5
```

```
## K-means clustering with 5 clusters of sizes 66, 129, 45, 192, 166
## 
## Cluster means:
##       Energy Dancebility   Loudness    Valence Acoustiveness
## 1 -0.9047734  -0.6644365 -0.9052677 -1.2982540   -0.01394369
## 2 -0.4978166   0.8104498 -0.5973375  0.2371954   -0.18884931
## 3 -2.0692373  -1.1247771 -1.3482929 -1.0233663    2.83978775
## 4  0.6780899   0.5175194  0.6759457  0.9062350   -0.27324258
## 5  0.5232278  -0.6593010  0.4078061 -0.4389102   -0.30148210
## 
## Clustering vector:
##   [1] 4 4 4 4 5 4 4 5 3 4 5 5 4 4 5 2 4 2 5 4 2 5 4 4 5 5 4 4 4 4 4 4 4 1
5
##  [36] 2 3 4 4 5 5 1 5 4 3 4 4 4 5 4 1 3 4 5 4 4 4 4 1 4 4 5 1 5 5 5 4 4 2
1
##  [71] 4 4 4 5 4 5 4 2 2 4 5 4 5 4 4 5 3 5 4 4 4 4 4 3 5 3 2 2 4 5 4 4 2 5
```

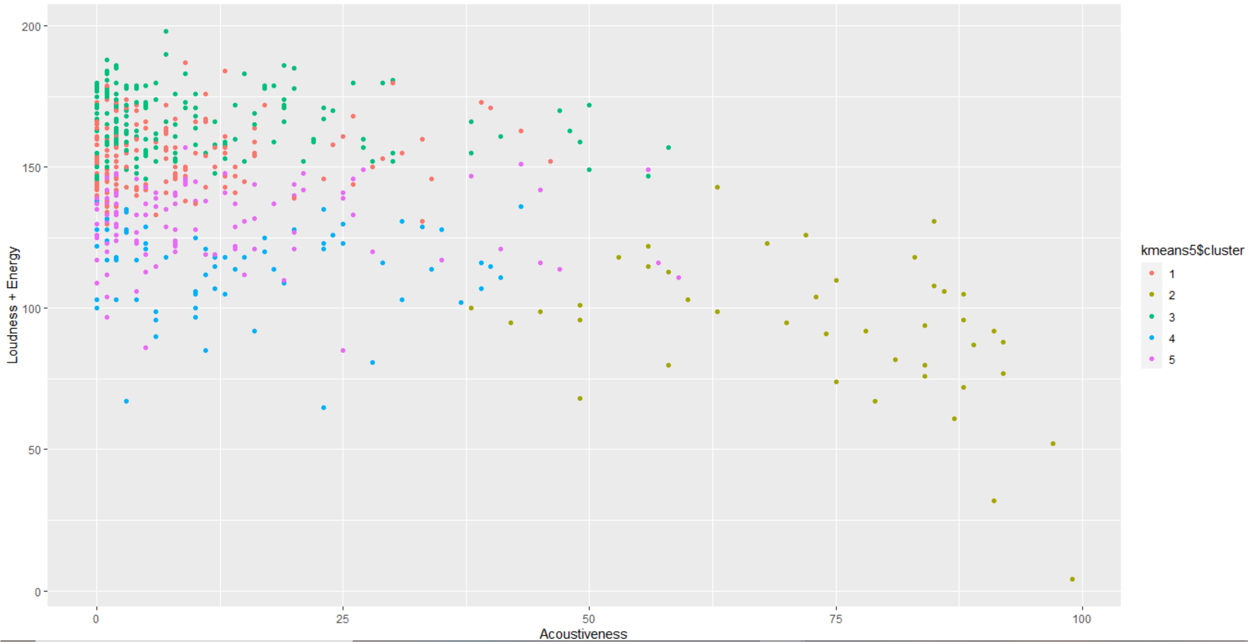
```
4
## [106] 1 4 4 2 2 4 5 2 4 2 4 4 4 4 5 4 2 2 4 2 5 5 4 4 5 4 5 5 4 4 4 5 5 5
1
## [141] 2 5 5 2 5 2 1 5 2 5 2 4 5 5 5 5 2 5 4 5 2 4 4 4 4 1 1 2 1 4 2 2 4 4
5
## [176] 5 2 4 5 5 1 2 5 5 3 5 2 5 4 5 3 5 5 4 5 4 4 5 5 4 2 5 2 5 4 1 4 5 3
3
## [211] 4 4 4 4 1 5 4 4 1 4 2 2 5 5 5 2 5 5 2 2 2 1 5 2 4 2 4 2 4 1 4 4 5 1
5
## [246] 4 5 3 1 4 5 1 5 3 1 2 4 4 3 1 2 2 5 2 2 2 3 1 3 2 3 4 5 3 1 1 2 2 2
4
## [281] 2 3 5 5 5 5 5 4 5 2 5 2 1 4 2 4 5 4 5 4 5 4 4 5 5 4 4 5 5 5 4 1 5 5
4
## [316] 4 5 5 4 4 4 4 2 4 1 5 3 3 2 5 4 2 5 4 4 4 1 5 1 5 1 5 1 5 1 4 5 4 1
3
## [351] 5 4 4 4 5 4 3 4 2 1 3 4 5 1 5 5 3 1 2 4 2 5 1 2 2 2 2 1 2 4 2 5 2 2
5
## [386] 2 4 2 5 4 1 1 5 2 3 5 5 4 1 5 5 4 5 5 5 5 5 3 5 4 5 5 5 2 4 4 1 4 3
1
## [421] 3 2 5 5 4 4 4 3 4 5 1 2 3 5 2 2 4 2 4 2 2 5 2 5 2 5 2 2 2 5 2 4 1 4
4
## [456] 3 4 4 1 1 5 4 4 2 5 2 3 5 3 2 2 1 2 5 4 4 4 2 4 5 2 1 4 4 2 5 4 2 1
5
## [491] 4 1 4 4 3 4 2 2 4 5 3 4 5 4 2 4 2 4 2 2 2 5 1 2 5 5 4 5 2 3 4 2 4 3
4
## [526] 1 4 4 2 5 2 1 2 3 2 5 2 5 1 4 1 2 2 2 1 2 2 5 5 5 2 1 4 1 3 3 5 4 2
2
## [561] 5 1 2 2 5 2 4 3 3 3 2 5 2 3 4 5 4 2 2 2 4 5 4 2 4 1 4 2 5 1 4 4 4 1
2
## [596] 5 5 1
## 
## Within cluster sum of squares by cluster:
## [1] 162.1891 267.8626 208.7179 297.5688 292.4047
##  (between_SS / total_SS =  58.8 %)
## 
## Available components:
## 
## [1] "cluster"      "centers"      "totss"        "withinss"    
## [5] "tot.withinss" "betweenss"    "size"         "iter"        
## [9] "ifault"
```

```
kmeans5$centers
```

```
##       Energy Dancebility   Loudness    Valence Acoustiveness
## 1 -0.9047734  -0.6644365 -0.9052677 -1.2982540   -0.01394369
## 2 -0.4978166   0.8104498 -0.5973375  0.2371954   -0.18884931
## 3 -2.0692373  -1.1247771 -1.3482929 -1.0233663    2.83978775
## 4  0.6780899   0.5175194  0.6759457  0.9062350   -0.27324258
## 5  0.5232278  -0.6593010  0.4078061 -0.4389102   -0.30148210
```

```
kmeans5$cluster <- as.factor(kmeans5$cluster)
```

```
ggplot(Data_clust, aes(Acoustiveness,Loudness+Energy,color =
kmeans5$cluster)) + geom_point()
```




```
#To validate our assumption we took the help of the nbclust function t find
optimal no. of clusters
nb_clust = NbClust(Data_num, distance="euclidean", method = 'kmeans')
```

```
## *** : The Hubert index is a graphical method of determining the number of
clusters.
##                 In the plot of Hubert index, we seek a significant knee
that corresponds to a
##                 significant increase of the value of the measure i.e the
significant peak in Hubert
##                 index second differences plot.
##
```

```
## *** : The D index is a graphical method of determining the number of
clusters.
##                 In the plot of D index, we seek a significant knee (the
significant peak in Dindex
##                 second differences plot) that corresponds to a significant
increase of the value of
```

```
##                   the measure.
##
## *******************************************************************
## * Among all indices:
## * 9 proposed 2 as the best number of clusters
## * 2 proposed 3 as the best number of clusters
## * 8 proposed 4 as the best number of clusters
## * 1 proposed 6 as the best number of clusters
## * 1 proposed 8 as the best number of clusters
## * 2 proposed 10 as the best number of clusters
## * 1 proposed 15 as the best number of clusters
##
##                      ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is  2
##
##
## *******************************************************************
```

```
nb_clust
```

```
## $All.index
##        KL       CH Hartigan     CCC    Scott      Marriot      TrCovW
## 2   5.3459 179.3297  75.3766 56.1026 3829.165 8.603133e+41 58272462097
## 3   0.2856 138.4604  87.0761 33.8910 4201.822 1.038003e+42 45365031712
## 4   2.0534 134.6145  55.1959 32.1655 4777.885 7.042283e+41 33253803097
## 5   0.6527 123.9324  61.3638 32.2060 5076.744 6.675573e+41 29563036522
## 6   2.8979 121.4731  35.0111 32.6460 5306.351 6.547867e+41 21226652533
## 7   0.9009 112.8585  33.2984 32.0953 5480.079 6.665369e+41 17811320916
## 8   1.0121 106.7621  30.9208 31.8175 5660.363 6.439886e+41 15201455326
## 9   2.1497 102.0046  21.9362 31.6813 5836.477 6.071298e+41 13152384646
## 10 7.9626  96.3211  14.9572 31.2358 6007.672 5.629462e+41 12004628169
## 11 0.0811  90.2362  22.6243 30.5508 6126.232 5.586612e+41 11916052845
## 12 2.2671  87.1027  16.1458 30.4657 6300.023 4.971763e+41 10549607032
## 13 0.4526  83.2472  20.5650 30.1151 6404.077 4.903047e+41 10032125808
## 14 1.4850  80.9882  16.6940 30.1285 6558.340 4.393420e+41  9387626937
## 15 1.0567  78.4110  15.7136 29.9979 6657.297 4.274277e+41  8757460252
##       TraceW Friedman   Rubin Cindex     DB Silhouette   Duda  Pseudot2
## 2  1589169.3 301.3525 33.8525 0.2470 1.7153     0.2742 1.5463 -131.0656
## 3  1410750.6 333.0064 38.1338 0.2471 2.0069     0.1433 1.9614 -231.3512
## 4  1230649.5 331.1899 43.7146 0.2889 1.5045     0.2257 1.2040  -39.1414
## 5  1126017.2 333.4215 47.7766 0.2889 1.6756     0.1538 1.1054  -17.0646
## 6  1020423.6 372.2858 52.7206 0.2798 1.5559     0.1669 1.5912  -66.8810
## 7   963445.0 396.5807 55.8385 0.2713 1.6256     0.1477 1.4828  -51.4444
## 8   912057.5 448.2672 58.9846 0.3287 1.6067     0.1489 1.4769  -61.6751
## 9   866638.6 455.5597 62.0758 0.3207 1.6153     0.1461 1.4585  -39.2941
## 10  835521.2 464.2882 64.3877 0.3493 1.6406     0.1463 1.7726  -51.8654
## 11  814794.9 478.6988 66.0256 0.3227 1.5870     0.1432 1.7556  -60.2545
## 12  784556.4 482.9828 68.5704 0.3339 1.6456     0.1419 1.4011  -38.9332
## 13  763519.4 502.1824 70.4596 0.3313 1.6750     0.1357 1.5328  -33.0229
```

```
## 14  737590.3 501.5172 72.9366 0.3247 1.6600     0.1398 1.6691  -56.5250
## 15  717091.8 531.6740 75.0215 0.3290 1.6721     0.1335 1.3933  -30.2022
##      Beale Ratkowsky      Ball Ptbiserial    Frey McClain   Dunn Hubert
## 2  -1.8555    0.2332 794584.67     0.4533  2.7603  0.4451 0.0644      0
## 3  -2.5674    0.2395 470250.21     0.3573 -0.8841  1.2506 0.0364      0
## 4  -0.8889    0.2677 307662.36     0.4985  2.7917  0.9745 0.0715      0
## 5  -0.5008    0.2590 225203.45     0.3802 -0.1707  2.1328 0.0662      0
## 6  -1.9515    0.2473 170070.59     0.4107  0.9709  2.1215 0.0503      0
## 7  -1.7079    0.2323 137635.00     0.3757  0.0659  2.8381 0.0491      0
## 8  -1.6933    0.2199 114007.18     0.3813  0.8241  2.9375 0.0751      0
## 9  -1.6448    0.2120  96293.18     0.3530 -0.0418  3.6926 0.0609      0
## 10 -2.2795    0.2067  83552.12     0.3598  0.5527  3.7059 0.0881      0
## 11 -2.2515    0.1983  74072.27     0.3483  0.2852  4.1047 0.0633      0
## 12 -1.4973    0.1968  65379.70     0.3392  1.4791  4.6196 0.0691      0
## 13 -1.8158    0.1907  58732.26     0.3165  0.0595  5.4192 0.0629      0
## 14 -2.0909    0.1883  52685.02     0.3184  0.6919  5.5541 0.0646      0
## 15 -1.4711    0.1826  47806.12     0.3043  0.3738  6.2122 0.0691      0
##    SDindex  Dindex   SDbw
## 2   0.0986 47.6936 1.2421
## 3   0.1068 44.9709 1.3984
## 4   0.0875 42.5334 0.9640
## 5   0.0946 40.3459 0.7546
## 6   0.1013 38.8089 0.6189
## 7   0.1040 37.5770 0.5528
## 8   0.1015 36.8551 0.5283
## 9   0.1014 35.8684 0.4874
## 10  0.0960 35.2885 0.4696
## 11  0.1065 34.9389 0.4637
## 12  0.1043 34.1707 0.4421
## 13  0.1068 33.6281 0.4212
## 14  0.1069 33.1544 0.4140
## 15  0.1112 32.6511 0.3936
##
## $All.CriticalValues
##    CritValue_Duda CritValue_PseudoT2 Fvalue_Beale
## 2          0.8009            92.2383            1
## 3          0.7777           134.8898            1
## 4          0.7899            61.4499            1
## 5          0.8034            43.8029            1
## 6          0.8009            44.7518            1
## 7          0.7894            42.1538            1
## 8          0.7869            51.7315            1
## 9          0.7695            37.4437            1
## 10         0.7664            36.2680            1
## 11         0.7680            42.2963            1
## 12         0.7664            41.4491            1
## 13         0.7578            30.3618            1
## 14         0.7476            47.6112            1
## 15         0.7429            37.0307            1
##
```

```
## $Best.nc
##                      KL       CH Hartigan     CCC    Scott      Marriot
## Number_clusters 10.0000   2.0000   4.0000  2.0000   4.0000 4.000000e+00
## Value_Index      7.9626 179.3297  31.8802 56.1026 576.0629 2.971041e+41
##                      TrCovW   TraceW Friedman  Rubin Cindex     DB
## Number_clusters           3     4.00   8.0000  6.000  2.000 4.0000
## Value_Index     12907430385 75468.95  51.6865 -1.826  0.247 1.5045
##                 Silhouette   Duda  PseudoT2   Beale Ratkowsky     Ball
## Number_clusters     2.0000 2.0000    2.0000  2.0000    4.0000      3.0
## Value_Index         0.2742 1.5463 -131.0656 -1.8555    0.2677 324334.5
##                 PtBiserial   Frey McClain    Dunn Hubert SDindex Dindex
## Number_clusters     4.0000 2.0000  2.0000 10.0000      0  4.0000      0
## Value_Index         0.4985 2.7603  0.4451  0.0881      0  0.0875      0
##                    SDbw
## Number_clusters 15.0000
## Value_Index      0.3936
##
## $Best.partition
##   [1] 2 1 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1
1
##  [36] 2 1 2 1 1 2 1 1 2 1 2 2 2 1 2 1 1 2 2 2 2 2 1 2 2 2 1 1 2 1 1 2 2 1
2
##  [71] 1 1 2 2 2 1 2 2 2 2 1 2 2 2 2 1 1 2 2 2 1 2 2 1 1 1 2 2 2 1 2 2 2 1
2
## [106] 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
1
## [141] 1 2 2 2 2 2 1 2 1 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 1 1 2 2 2 1 1 2 2
2
## [176] 2 2 2 2 2 1 1 2 2 1 1 1 2 2 2 1 2 1 2 1 2 2 2 2 2 2 1 1 2 2 2 1 2 1 1
2
## [211] 2 2 2 2 2 1 2 2 1 2 2 2 1 1 1 2 1 2 2 2 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2
1
## [246] 2 2 1 1 2 2 2 2 1 1 1 2 2 2 1 2 1 2 2 2 1 1 1 1 1 1 2 2 2 1 1 2 2 2
2
## [281] 2 1 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
2
## [316] 2 1 2 2 2 2 2 2 2 1 2 2 2 1 1 2 2 1 2 2 2 1 2 1 2 1 2 1 2 2 2 2 2 2 1
1
## [351] 1 2 2 2 2 2 1 2 1 1 1 2 2 2 1 2 2 2 1 2 2 2 1 2 2 1 2 1 2 2 2 2 1 2
2
## [386] 2 2 2 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 1 2 1
1
## [421] 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 1 1 2
1
## [456] 1 2 2 1 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2
2
## [491] 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 1
2
## [526] 1 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 1 1 2 2 2
1
```

```
## [561] 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2
2
## [596] 1 2 2
```

```
# for 2 clusters
(kmeans2 <- kmeans(scale_data,2,nstart = 10))
```

```
## K-means clustering with 2 clusters of sizes 110, 488
##
## Cluster means:
##       Energy Dancebility  Loudness    Valence Acoustiveness
## 1 -1.4855855  -0.7070606 -1.240372 -1.0258399     1.3138122
## 2  0.3348656   0.1593784  0.279592  0.2312344    -0.2961462
##
## Clustering vector:
##   [1] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
2
##  [36] 2 1 2 2 2 2 1 2 2 1 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
1
##  [71] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2
2
## [106] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2
## [141] 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2
2
## [176] 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1
1
## [211] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 2 2 2
2
## [246] 2 2 1 2 2 2 1 2 1 2 2 2 2 1 1 1 1 2 1 2 1 1 1 1 2 1 2 2 1 1 1 1 2 2
2
## [281] 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
2
## [316] 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 2 2 1
1
## [351] 2 2 2 2 2 2 1 2 2 1 1 2 2 1 2 2 1 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
2
## [386] 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1
1
## [421] 1 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
2
## [456] 1 2 2 1 2 1 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
2
## [491] 2 1 2 2 1 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 1
2
## [526] 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2
2
## [561] 2 2 2 2 2 2 2 1 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 2
2
## [596] 2 2 1
```

```
##
## Within cluster sum of squares by cluster:
## [1]  648.3949 1389.8219
##  (between_SS / total_SS =  31.7 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"
## [5] "tot.withinss" "betweenss"    "size"         "iter"
## [9] "ifault"
```

```
kmeans2
```

```
## K-means clustering with 2 clusters of sizes 110, 488
##
## Cluster means:
##       Energy Dancebility  Loudness    Valence Acoustiveness
## 1 -1.4855855  -0.7070606 -1.240372 -1.0258399     1.3138122
## 2  0.3348656   0.1593784  0.279592  0.2312344    -0.2961462
##
## Clustering vector:
##   [1] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
2
##  [36] 2 1 2 2 2 2 1 2 2 1 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
1
##  [71] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2
2
## [106] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2
## [141] 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2
2
## [176] 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1
1
## [211] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 2 2 2
2
## [246] 2 2 1 2 2 2 1 2 1 2 2 2 2 1 1 1 1 2 1 2 1 1 1 1 2 1 2 2 1 1 1 1 2 2
2
## [281] 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
2
## [316] 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 2 2 1
1
## [351] 2 2 2 2 2 2 1 2 2 1 1 2 2 1 2 2 1 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
2
## [386] 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1
1
## [421] 1 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
2
## [456] 1 2 2 1 2 1 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
2
## [491] 2 1 2 2 1 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 1
```

```
2
## [526] 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2
2
## [561] 2 2 2 2 2 2 2 1 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 2
2
## [596] 2 2 1
##
## Within cluster sum of squares by cluster:
## [1]  648.3949 1389.8219
##  (between_SS / total_SS =  31.7 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"
## [5] "tot.withinss" "betweenss"    "size"         "iter"
## [9] "ifault"
```

```
kmeans2$cluster <- as.factor(kmeans2$cluster)
```

```
kmeans2$centers
```

```
##       Energy Dancebility  Loudness    Valence Acoustiveness
## 1 -1.4855855  -0.7070606 -1.240372 -1.0258399     1.3138122
## 2  0.3348656   0.1593784  0.279592  0.2312344    -0.2961462
```

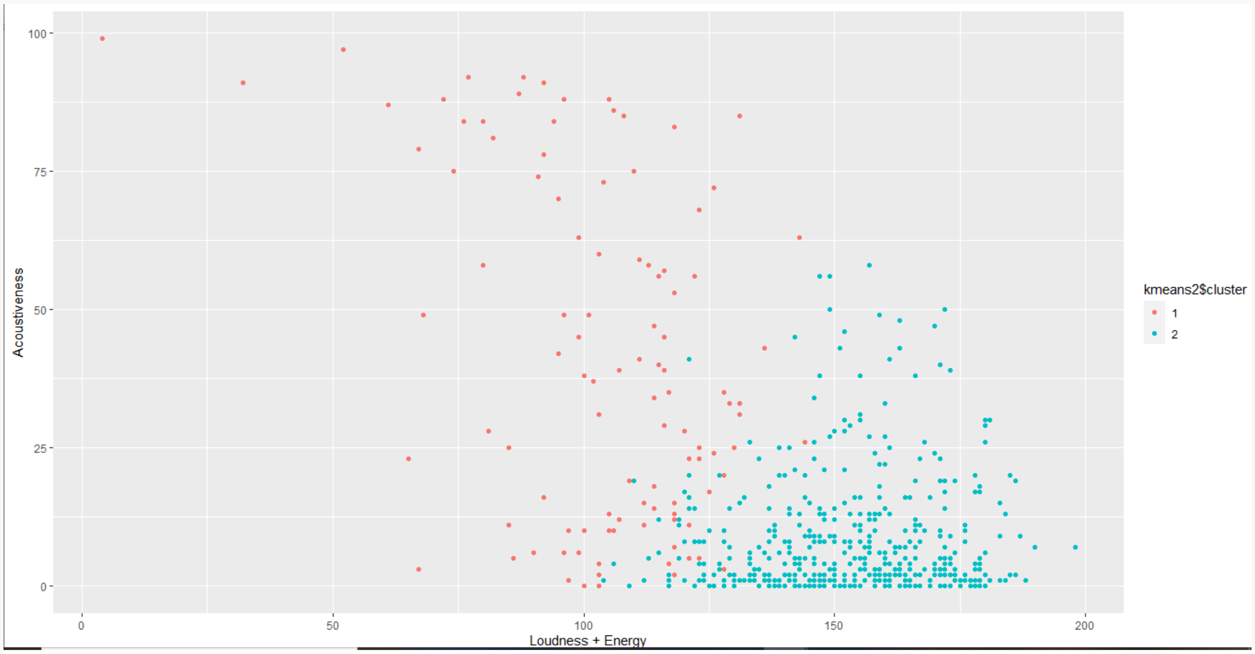
```
kmeans2$withinss
```

```
## [1]  648.3949 1389.8219
```

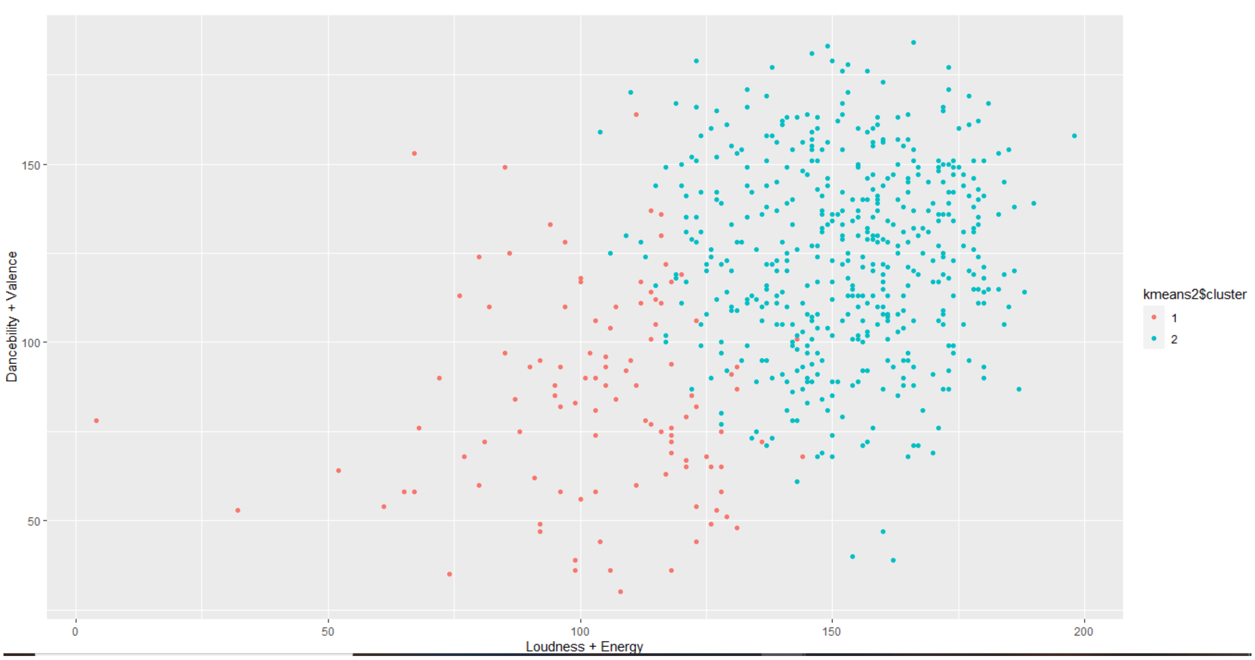
```
kmeans2$size
```

```
## [1] 110 488
```

```r
ggplot(Data_clust, aes(Loudness+Energy,Acoustiveness,color =
kmeans2$cluster)) + geom_point()
```




```r
ggplot(Data_clust, aes(Loudness+Energy,Dancebility+Valence,color =
kmeans2$cluster)) + geom_point()
```



```
ggplot(Data_clust, aes(Acoustiveness,Dancebility+Valence,color =
kmeans2$cluster)) + geom_point()
```