Analysis of the top 200 Spotify songs (2017-2021)

Cervini Stella Mattia Simone Montalbano Daniel

What makes a hit song

This essay was written by Cervini Stella, Mattia Simone and Montalbano Daniel. The goal of this project is to analyse the characteristics of the top Spotify songs (between 2017-2021 in global) and eventually discover the common properties that made these songs so popular in the first place.

1. Data

The dataset used for project was retrieved from Kaggle.

```
raw_dataset <- read.csv("../Dataset/spotify.csv", header = TRUE, sep = ";")
```

It contains the Spotify Global weekly top 200 songs between 2017-2021.

```
dim(raw_dataset)
```

```
## [1] 74660    40
```

This dataset consists of a total of 74.661 rows and 40 columns, each row representing a track and each column containing a different variable that describes the entity. Here we have the totality of the material needed for the analysis.

```
str(raw_dataset, vec.len = 2, strict.width = "cut")
```

```
## 'data.frame':    74660 obs. of  40 variables:
##  $ track_id          : chr  "5aAx2yezTd8zXrkmtKl66Z" "5aAx2yezTd8zXrkmtKl66Z" ..
##  $ track_name        : chr  "Starboy" "Starboy" ...
##  $ track_popularity  : int  0 0 84 84 75 ...
##  $ track_number      : int  1 1 1 1 1 ...
##  $ album_id          : chr  "09fggMHib4YkOtwQNXEBII" "09fggMHib4YkOtwQNXEBII" ..
##  $ album_name        : chr  "Starboy" "Starboy" ...
##  $ album_img         : chr  "https://i.scdn.co/image/ab67616d0000b2730c8599cb"..
##  $ album_type        : chr  "album" "album" ...
##  $ album_label       : chr  "Universal Music Group" "Universal Music Group" ...
##  $ album_track_number: int  1 1 1 1 1 ...
##  $ album_popularity  : int  0 0 71 71 62 ...
##  $ artist_num        : int  2 2 2 2 3 ...
##  $ artist_names      : chr  "The Weeknd, Daft Punk" "The Weeknd, Daft Punk" ...
##  $ artist_id         : chr  "1Xyo4u8uXC1ZmMpatF05PJ" "4tZwfgrHOc3mvqYlEYSvVi" ..
##  $ artist_name       : chr  "The Weeknd" "Daft Punk" ...
##  $ artist_img        : chr  "https://i.scdn.co/image/ab6761610000e5ebb5f9e282"..
```

```
##  $ artist_followers  : int  51215861 8953122 19562506 18598273 4943046 ...
##  $ artist_popularity : int  94 81 81 84 76 ...
##  $ artist_genres     : chr  "canadian contemporary r&b, canadian pop, pop" "e"..
##  $ rank              : int  1 1 2 2 3 ...
##  $ week              : chr  "1/6/2017" "1/6/2017" ...
##  $ collab            : chr  "True" "True" ...
##  $ explicit          : chr  "True" "True" ...
##  $ release_date      : chr  "2016-11-25" "2016-11-25" ...
##  $ danceability      : num  0.681 0.681 0.748 0.748 0.72 ...
##  $ energy            : num  0.594 0.594 0.524 0.524 0.763 ...
##  $ key               : int  7 7 8 8 9 ...
##  $ mode              : int  1 1 1 1 0 ...
##  $ time_signature    : int  4 4 4 4 4 ...
##  $ loudness          : num  -7.03 -7.03 ...
##  $ speechiness       : num  0.282 0.282 0.0338 0.0338 0.0523 ...
##  $ acousticness      : num  0.165 0.165 0.414 0.414 0.406 ...
##  $ instrumentalness  : num  3.49e-06 3.49e-06 0.00 0.00 0.00 ...
##  $ liveness          : num  0.134 0.134 0.111 0.111 0.18 ...
##  $ valence           : num  0.535 0.535 0.661 0.661 0.742 ...
##  $ tempo             : num  186 186 ...
##  $ duration          : int  230453 230453 244960 244960 251088 ...
##  $ pivot             : int  0 1 0 1 0 ...
##  $ streams           : int  25734078 25734078 23519705 23519705 21216399 ...
##  $ track_index       : int  1 1 2 2 3 ...
```

For example, in the datset we can find the information necessary for Spotify to uniquely identify the song (*track_id*, *album_id*,*artist_id*, ...), the metrics generated by Spotify to evaluate the performances of the song/artist/album (*rank*, *artist_popularity*, ...), the musical characteristics of the song, such as danceability or tempo and also some time references, which include the end date of the week the track was in the charts and the release date.
While inspecting the dataset, we noticed that a large number of rows was duplicated, due to the fact that a song stayed in the charts for more weeks. Furthermore, if a tune had two or more authors, it appeared in the dataset one time for each of them.
For instance, we can run the following test:

```
redundancy_test <- raw_dataset[raw_dataset$track_id == "5aAx2yezTd8zXrkmtKl66Z",
    ]
dim(redundancy_test)
```

```
## [1] 132  40
```

These facts result in a superfluous amount of data, making the information set complicated to work with.

Clean data In order to perform our analysis, we modified the dataset, obtaining a new table based on our needs. We wanted to clean the data, so that the new dataset consists only of 200 unique songs per week, eliminating the redundant rows. In addition to that, we considered only the columns holding the information referred to the musical specifications of the songs, adding other variables whenever necessary. The query applied on the original data is the following:

```
dataset <- raw_dataset %>%
    select(track_id, artist_num, danceability, energy, loudness,
        speechiness, acousticness, liveness, valence, tempo,
```

```r
        artist_popularity, rank, streams, key, mode) %>%
    group_by(track_id) %>%
    mutate(n_weeks = n()/artist_num, art_popularity = mean(artist_popularity)/100,
        best_rank = min(rank), max_streams = max(streams)) %>%
    distinct(track_id, .keep_all = TRUE) %>%
    ungroup() %>%
    select(!c(track_id, artist_popularity, rank, streams))

write.csv(dataset, "../Dataset/clean_spotify.csv", row.names = FALSE)

clean_Spotify_200 <- read.csv("../Dataset/clean_spotify.csv",
    header = TRUE, sep = ",")
```

```r
dim(clean_Spotify_200)
```

```
## [1] 4247   15
```

```r
clean_Spotify_200 <- clean_Spotify_200 %>%
    mutate(key = factor(key), mode = factor(mode))
str(clean_Spotify_200, vec.len = 5, strict.width = "cut")
```

```
## 'data.frame':    4247 obs. of  15 variables:
##  $ artist_num    : int  2 2 3 2 2 2 1 1 1 2 2 3 ...
##  $ danceability  : num  0.681 0.748 0.72 0.476 0.735 0.783 0.928 0.358 0.818 0..
##  $ energy        : num  0.594 0.524 0.763 0.718 0.451 0.623 0.481 0.557 0.803 ..
##  $ loudness      : num  -7.03 -5.6 -4.07 -5.31 -8.37 -6.13 ...
##  $ speechiness   : num  0.282 0.0338 0.0523 0.0576 0.0585 0.08 0.287 0.059 0.0..
##  $ acousticness  : num  0.165 0.414 0.406 0.0784 0.0631 0.338 0.105 0.695 0.03..
##  $ liveness      : num  0.134 0.111 0.18 0.122 0.325 0.0975 0.176 0.0902 0.153..
##  $ valence       : num  0.535 0.661 0.742 0.142 0.0862 0.447 0.613 0.494 0.632..
##  $ tempo         : num  186 95 102 200 118 100 ...
##  $ key           : Factor w/ 12 levels "0","1","2","3",..: 8 9 10 9 1 8 10 11 ..
##  $ mode          : Factor w/ 2 levels "0","1": 2 2 1 2 2 2 1 2 2 1 2 2 ...
##  $ n_weeks       : int  66 160 53 44 64 27 36 218 48 59 25 76 ...
##  $ art_popularity: num  0.875 0.819 0.78 0.845 0.88 0.875 ...
##  $ best_rank     : int  1 2 3 4 2 6 7 7 9 9 11 12 ...
##  $ max_streams   : int  25734078 23519705 22844114 19852704 30752312 18411654 ..
```

The new dataset contains the essential data for the analysis and all the variables are already in a correct data type with respect to the data they represent. It consists of 4247 rows and 13 column, therefore it appears less complicated to work with, but still complete.
Original columns/variables:

- **artist_num:** number of artists in the track;
- **danceability:** how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable;
- **energy:** measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity;
- **loudness:** overall loudness of a track in decibels (dB). Values typically range between -60 and 0 db;
- **speechiness:** detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value;

- **acousticness:** confidence measure from 0.0 to 1.0 of whether the track is acoustic, where 1.0 represents high confidence the track is acoustic;
- **liveness:** presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live;
- **valence:** measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track;
- **tempo:** overall estimated tempo of a track in beats per minute (BPM);
- **key:** key the track is in. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C#/Db, 2 = D, and so on. If no key was detected, the value is -1;
- **mode:** modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.

Computed/added columns:

- **n_weeks:** total number of weeks that a song stayed in chart. It is calculated by dividing the occurrence count of a track by the artists that compose it:

```
n_weeks = n()/artist_num
```

- **art_popularity:** mean of the *artist_popularity* that compose a same track normalized between 0 and 1. It is necessary in order to eliminate the duplicates rows due to the precence of more that one composer.

```
art_popularity = mean(artist_popularity)/100
```

- **best_rank:** best position a song reached in the charts. It is obtained as

```
best_rank = min(rank)
```

- **max_streams:** total number of streams thata song reaches at its peak, computed as

```
max_streams = max(streams)
```

It interesting to notice that the dataset do not contain any missing values.

```
length(unique(complete.cases(clean_Spotify_200))) == 1
```

```
## [1] TRUE
```

Now that we have gathered all the information we needed in a clean and consistent dataset, we can start the analysis.

Significant columns to analyze First of all, we chose the columns that seems actually useful to our descriptive statistics analysis. We've used the **summary** function to understand which columns are the most interesting to analyse deeply.
We thought that *max_streams* and *n_weeks* columns are the most important and relevant to determine the entire performance of a song in the charts. Then, we chose the columns that could in some way explain the reasons behind the success of a tune: *danceability*, *energy*, *tempo*, *key* and *mode*. We made a distinction between quantitative and qualitative variables and then we computed their most important indices, expecting that they could help us understand the information the data enclose. For example, we analyzed them through mean, median, quantile, variance, standard deviation, range of variation and interquantile range.

2. Descriptive statistics

- ***Quantitative:*** danceability, energy, tempo, n_weeks and max_streams
- ***Qualitative:*** key, mode

Frequency: absolute and relative In order to compute the absolute and relative frequency of the quantitative continuous variables, we used the functions **nclass.Sturges** and **nclass.FD** to find to optimal number of intervals for every distribution. We did not apply these methods on *key* and *mode* since they are qualitative variables.

```
nclass.Sturges(clean_Spotify_200$n_weeks)
```

```
## [1] 14
```

```
nclass.FD(clean_Spotify_200$n_weeks)
```

```
## [1] 160
```

We noticed that the nclass.FD function returned always a larger number of ranges. To simplify, we chose to use the results of the function nclass.Sturges. Below are shown all the absolute and relative frequency, including cumulative frequencies, for all the variables.

- **n_weeks**

```
n_weeks_class <- cut(clean_Spotify_200$n_weeks,
    breaks = nclass.Sturges(clean_Spotify_200$n_weeks))
n_weeks_abs_freq <- table(n_weeks_class)
n_weeks_rel_freq <- round(n_weeks_abs_freq/sum(n_weeks_abs_freq),
    4)
n_weeks_summary <- cbind(n_weeks_abs_freq,
    cumsum(n_weeks_abs_freq), n_weeks_rel_freq,
    cumsum(n_weeks_rel_freq))
colnames(n_weeks_summary) <- c("Absolute",
    "Cum. absolute", "Relative", "Cum. relative")
n_weeks_summary
```

```
##               Absolute Cum. absolute Relative Cum. relative
## (0.783,16.5]     3442          3442   0.8105        0.8105
## (16.5,32]         483          3925   0.1137        0.9242
## (32,47.5]         163          4088   0.0384        0.9626
## (47.5,63]          64          4152   0.0151        0.9777
## (63,78.5]          45          4197   0.0106        0.9883
## (78.5,94]          17          4214   0.0040        0.9923
## (94,110]           11          4225   0.0026        0.9949
## (110,125]           7          4232   0.0016        0.9965
## (125,140]           5          4237   0.0012        0.9977
## (140,156]           2          4239   0.0005        0.9982
## (156,172]           3          4242   0.0007        0.9989
## (172,187]           0          4242   0.0000        0.9989
## (187,202]           2          4244   0.0005        0.9994
## (202,218]           3          4247   0.0007        1.0001
```

- **danceability**

```
##               Absolute Cum. absolute Relative Cum. relative
## (0.149,0.209]        3             3   0.0007        0.0007
## (0.209,0.269]       14            17   0.0033        0.0040
## (0.269,0.328]       44            61   0.0104        0.0144
## (0.328,0.387]       72           133   0.0170        0.0314
## (0.387,0.446]      107           240   0.0252        0.0566
## (0.446,0.506]      218           458   0.0513        0.1079
## (0.506,0.565]      314           772   0.0739        0.1818
## (0.565,0.624]      460          1232   0.1083        0.2901
## (0.624,0.684]      648          1880   0.1526        0.4427
## (0.684,0.743]      707          2587   0.1665        0.6092
## (0.743,0.802]      760          3347   0.1789        0.7881
## (0.802,0.861]      497          3844   0.1170        0.9051
## (0.861,0.921]      307          4151   0.0723        0.9774
## (0.921,0.981]       96          4247   0.0226        1.0000
```

- **energy**

```
##                 Absolute Cum. absolute Relative Cum. relative
## (0.0269,0.0958]        9             9    0.002         0.002
## (0.0958,0.164]        21            30    0.005         0.007
## (0.164,0.231]         39            69    0.009         0.016
## (0.231,0.299]         72           141    0.017         0.033
## (0.299,0.367]        115           256    0.027         0.060
## (0.367,0.435]        230           486    0.054         0.114
## (0.435,0.503]        337           823    0.079         0.193
## (0.503,0.571]        521          1344    0.123         0.316
## (0.571,0.639]        673          2017    0.158         0.474
## (0.639,0.707]        694          2711    0.163         0.637
## (0.707,0.774]        641          3352    0.151         0.788
## (0.774,0.842]        518          3870    0.122         0.910
## (0.842,0.91]         289          4159    0.068         0.978
## (0.91,0.979]          88          4247    0.021         0.999
```

- **tempo**

```
##             Absolute Cum. absolute Relative Cum. relative
## (46.6,58.5]        3             3    0.001         0.001
## (58.5,70.3]       27            30    0.006         0.007
## (70.3,82.2]      277           307    0.065         0.072
## (82.2,94]        476           783    0.112         0.184
## (94,106]         785          1568    0.185         0.369
## (106,118]        420          1988    0.099         0.468
## (118,129]        626          2614    0.147         0.615
## (129,141]        504          3118    0.119         0.734
## (141,153]        417          3535    0.098         0.832
## (153,165]        256          3791    0.060         0.892
## (165,177]        264          4055    0.062         0.954
## (177,188]        134          4189    0.032         0.986
## (188,200]         36          4225    0.008         0.994
## (200,212]         22          4247    0.005         0.999
```

- **max_streams**

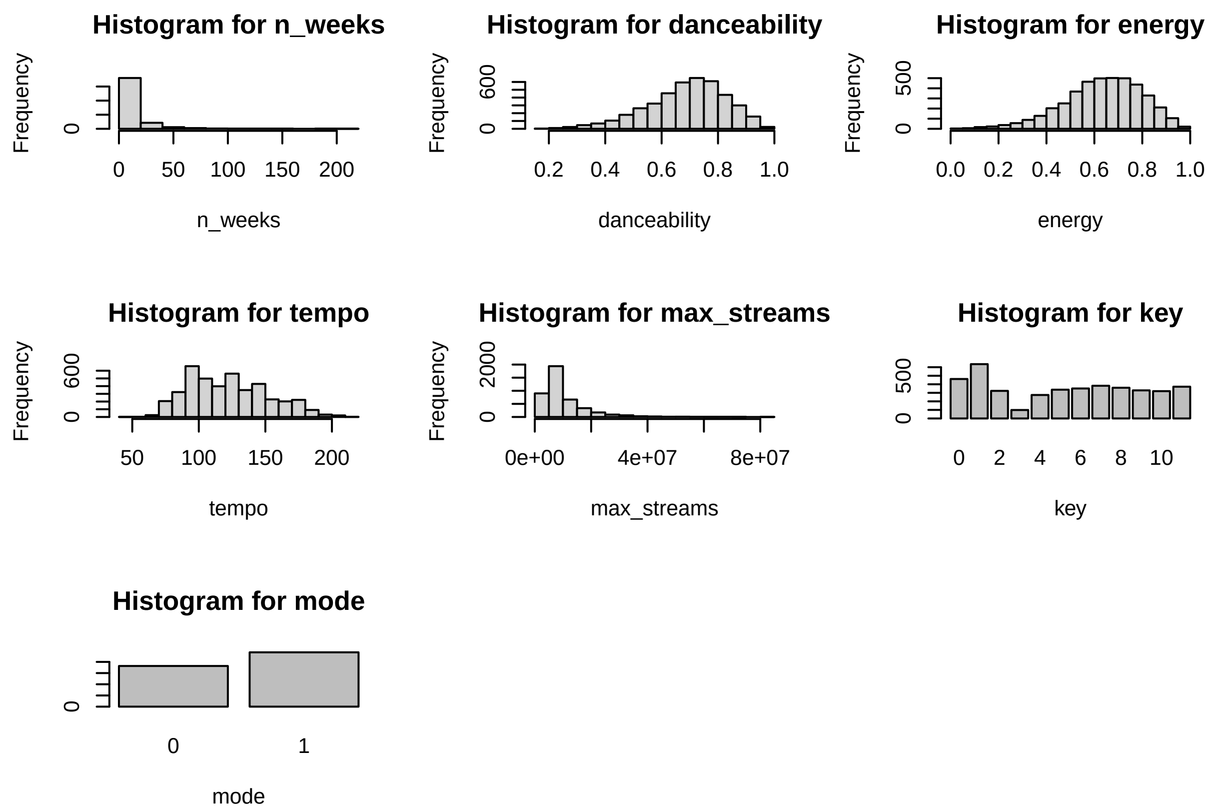
```
##                       Absolute Cum. absolute Relative Cum. relative
## (2.45e+06,8.11e+06]     2432          2432   0.5726        0.5726
## (8.11e+06,1.37e+07]      949          3381   0.2235        0.7961
## (1.37e+07,1.93e+07]      424          3805   0.0998        0.8959
## (1.93e+07,2.49e+07]      205          4010   0.0483        0.9442
## (2.49e+07,3.05e+07]      106          4116   0.0250        0.9692
## (3.05e+07,3.61e+07]       59          4175   0.0139        0.9831
## (3.61e+07,4.16e+07]       33          4208   0.0078        0.9909
## (4.16e+07,4.72e+07]       13          4221   0.0031        0.9940
## (4.72e+07,5.28e+07]        9          4230   0.0021        0.9961
## (5.28e+07,5.84e+07]        9          4239   0.0021        0.9982
## (5.84e+07,6.4e+07]         2          4241   0.0005        0.9987
## (6.4e+07,6.96e+07]         4          4245   0.0009        0.9996
## (6.96e+07,7.52e+07]        1          4246   0.0002        0.9998
## (7.52e+07,8.08e+07]        1          4247   0.0002        1.0000
```

- **key**

```
##    Absolute Cum. absolute   Relative Cum. relative
## 0       462           462 0.10878267     0.1087827
## 1       636          1098 0.14975277     0.2585354
## 2       323          1421 0.07605368     0.3345891
## 3        99          1520 0.02331057     0.3578997
## 4       275          1795 0.06475159     0.4226513
## 5       337          2132 0.07935013     0.5020014
## 6       351          2483 0.08264657     0.5846480
## 7       383          2866 0.09018130     0.6748293
## 8       360          3226 0.08476572     0.7595950
## 9       329          3555 0.07746645     0.8370615
## 10      320          3875 0.07534730     0.9124088
## 11      372          4247 0.08759124     1.0000000
```

- **mode**

```
##   Absolute Cum. absolute  Relative Cum. relative
## 0     1818          1818 0.4280669     0.4280669
## 1     2429          4247 0.5719331     1.0000000
```



By looking at the histogram of the variable *n_weeks*, we can say that most of the songs stayed in the charts only for a few weeks, while it is less common that a tune stays in top for longer periods of time.
We know that *danceability* is a measure of how danceable a track is. The histogram seems to tell us that the more a song in danceable, more are the chances that the song reaches the top 200. On the other side, the highest values are less dense, suggesting that very rhythmical songs are not too popular.
The frequency distribution of the variable *energy* seems similar to the one just described. Therefore, for a song to be in the top chart is important to not be too energetic or chaotic. Recalling that *tempo* refers to the BPM of a song, here we can observe that the values are not condensed around a single value, like *danceability* and *energy*, but they are more spread
Regarding *max_strams*, we notice that, as seen for the variable *n_weeks*, the majority of the values is in the lower intervals of the distribution. For example, the first interval contains the 57% of the whole distribution. This could mean that is more complex for a song to stay in chats for longer and therefore have more streams. For what concernes the variable *key*, we notice that there is a peak in the first intervals. In fact, the 33% of the songs is composed in key DO or RE, while others pitches are not so popular. Lastly, by looking at the histogram for *mode*, we can notice that most of the song are composed in Major modality.

Empirical Cumulative Distribution Function:

- **danceability**

```
ecdf(clean_Spotify_200$danceability)
```

```
## Empirical CDF
## Call: ecdf(clean_Spotify_200$danceability)
##  x[1:646] =   0.15,  0.153,  0.184,  ...,  0.974,   0.98
```

- **energy**

```
## Empirical CDF
## Call: ecdf(clean_Spotify_200$energy)
##  x[1:750] = 0.0279, 0.0316,  0.054,  ...,  0.974,  0.978
```

- **tempo**

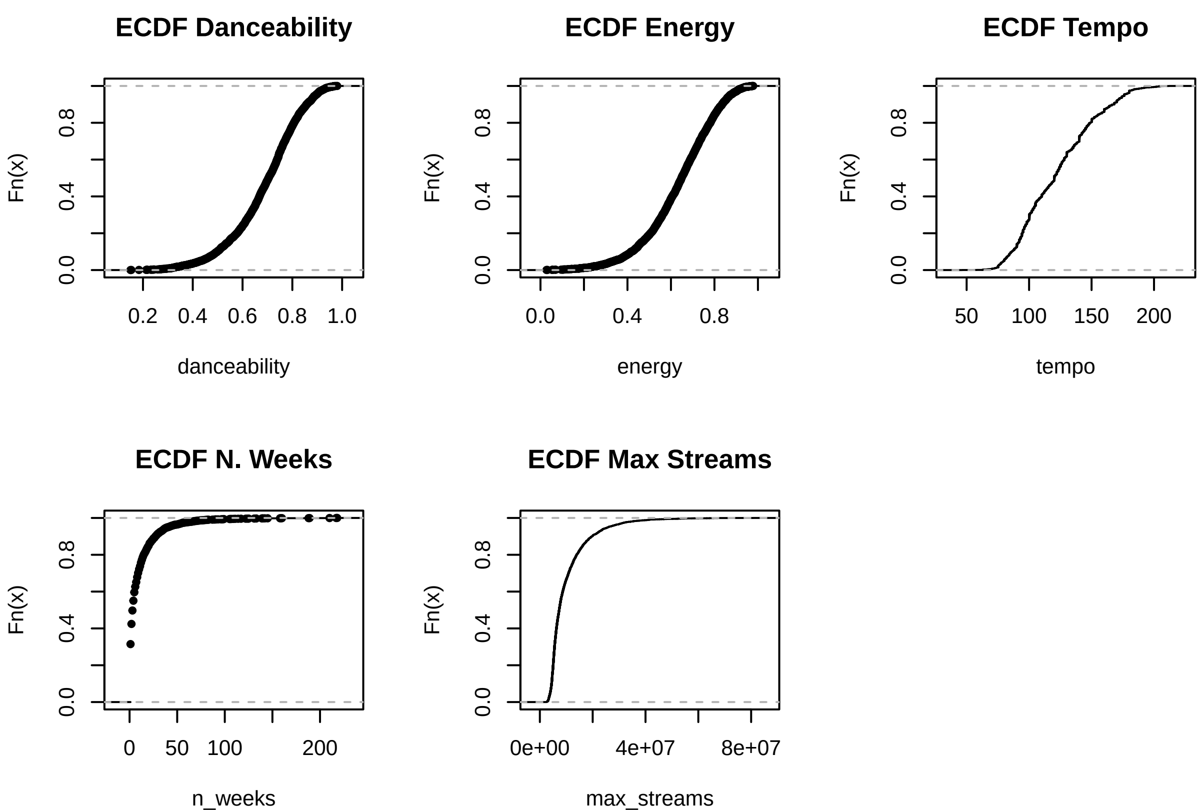
```
## Empirical CDF
## Call: ecdf(clean_Spotify_200$tempo)
##  x[1:3635] = 46.718, 54.747, 57.967,  ..., 211.84, 212.12
```

- **n_weeks**

```
## Empirical CDF
## Call: ecdf(clean_Spotify_200$n_weeks)
##  x[1:115] =      1,      2,      3,  ...,    217,    218
```

- **max_streams**

```
## Empirical CDF
## Call: ecdf(clean_Spotify_200$max_streams)
##  x[1:4247] = 2.5252e+06, 2.542e+06, 2.5805e+06,  ..., 7.1468e+07, 8.0764e+07
```



By computing the Empirical Cumulative Distribution Function plots, we can confirm what discovered with the histograms.
Regarding *danceability*, *energy* and *tempo* variables, we can notice that their distributions are more dense in the center of the distribution. The frequency of *n_weeks* and *max_streams* variables, instead, is mostly distributed in the lowest intervals. We can explain the behavior of these two distributions pointing out that most songs stay in top charts only for few weeks and it is when they obtain the highest number of streams. That is also the reason *n_weeks* distributions is more concentrated in the lower intervals.

Mean, median and quartiles In this section, we computed the measures of central tendency for the quantitative variables.

```
##                     Min        Mean         Max
## n_weeks            1.00       10.41      218.00
## max_streams  2525159.00 10119015.49 80764045.00
## danceability       0.15        0.69        0.98
## energy             0.03        0.64        0.98
## tempo             46.72      122.25      212.12
```

By observing the table above, we can acknowledge a few features. For example, *n_weeks* tell us that a song stays in the charts for an average of 11 weeks, reaching more that 10 millions streams. The most popular song in the dataset stayed in the top positions for 218 week, being listened more than 80 million times. For what concernes *danceability* and *energy*, knowing that they both range from 0 to 1, we can observe that they never touch the maximum value, but their mean is slightly higher than the perfect half of their interval (0.5). The mean of the variable *tempo* tells us that the most popular songs has an overall tempo of 122 BPM.

```
##                 1st Qu.     Median     3rd Qu.
## n_weeks            1.00       4.00       12.00
## max_streams  5195188.00 7223124.00 12185103.00
## danceability       0.61       0.70        0.79
## energy             0.54       0.65        0.76
## tempo             97.96     120.01      142.98
```

This second table complete the information above. The median tell us which is the central value of the distributions, while the first and the third quartile mark, respectively, where the 25% and 75% of the distribution is. For example, we can observe that the 25% of the *danceability* values is lower that 0.61 and the 75% is lower than 0.79.
We can understand better this aspect by examine the boxplots displayed below.

Moda ang Gini Index For our qualitative variables, we computed the moda and the Gini index, using our own functions.

Moda Function:

```r
moda <- function(x) {
    abs_freq <- table(x)
    abs_freq[which.max(abs_freq)]
}
```

Gini index function:

```r
gini <- function(x) {
    rel_freq <- table(x)/length(x)
    1 - sum(rel_freq^2)
}
```

Column *key* Here we compute the value of the two indices for the variable *key*.

```r
moda(clean_Spotify_200$key)
```

```
##   1
## 636
```

```r
gini(clean_Spotify_200$key)
```

```
## [1] 0.9074248
```

As discovered above, level 1 is the most frequent. Also, the Gini index is 0.9074248. We know that if we consider maximum diversity, the Gini index is

$$\frac{k-1}{k}$$

where k is the number of different levels of the variable. In this case we have

```r
(12 - 1)/12
```

```
## [1] 0.9166667
```

so we can assert that the variable *key* has maximum diversity.
We can confirm this conclusion computing the normalized Gini index, that is

```r
12/(12 - 1) * gini(clean_Spotify_200$key)
```

```
## [1] 0.989918
```

Since this value in very close to 1, we can assure what declared above.

Column *mode* Here we compute the value of the two indices for the variable *mode*.

```r
moda(clean_Spotify_200$mode)
```

```
##    1
## 2429
```

```r
gini(clean_Spotify_200$mode)
```

```
## [1] 0.4896512
```

The moda supports what we noticed in the histogram regarding this variable. On the other hand, we have that the Gini index is equal to 0.4896512. Computing maximum diversity and the normalized Gini index, we know that

```r
(2 - 1)/2
```

```
## [1] 0.5
```

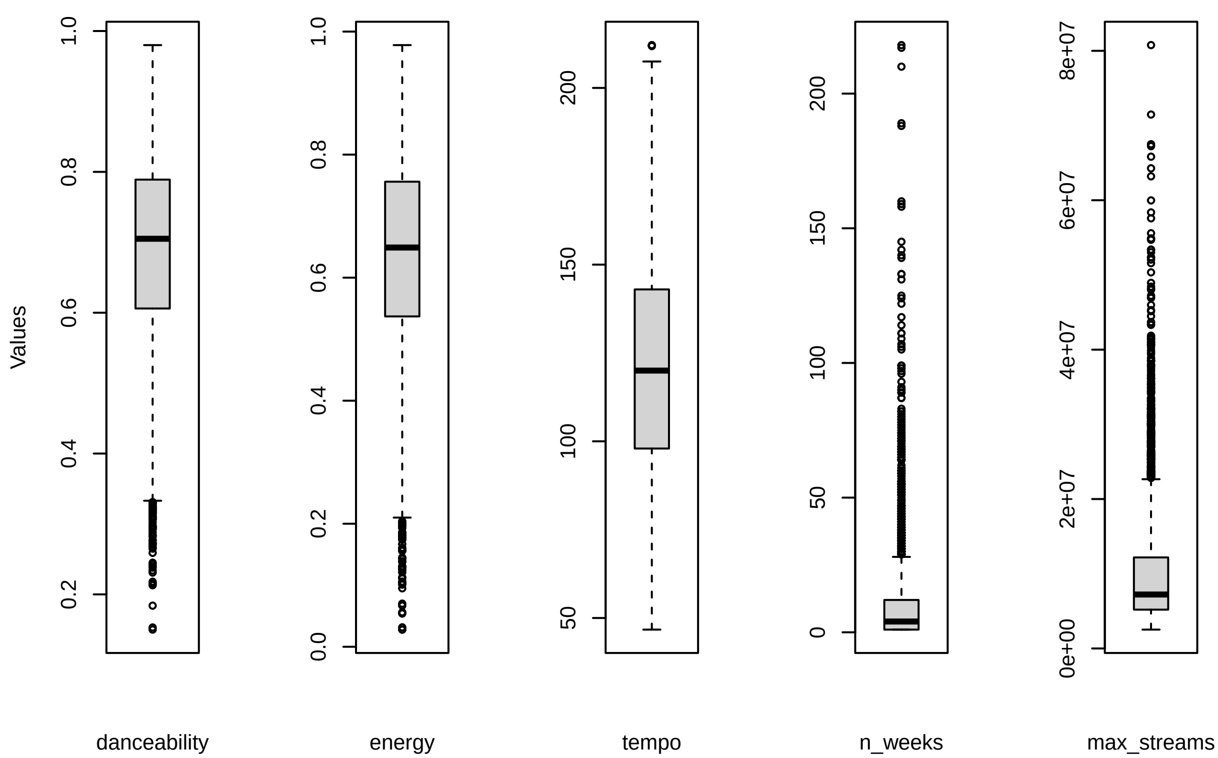
```r
2/(2 - 1) * gini(clean_Spotify_200$mode)
```

```
## [1] 0.9793025
```

Also in this case we have maximum diversity.

Boxplots To summarize what we have just computed and comprehend better the distributions of the data, we can plot side by side all the boxplot of the variables.

```r
par(mfrow = c(1, 5))
boxplot(clean_Spotify_200$danceability, xlab = "danceability", ylab = "Values")
boxplot(clean_Spotify_200$energy, xlab = "energy")
boxplot(clean_Spotify_200$tempo, xlab = "tempo")
boxplot(clean_Spotify_200$n_weeks, xlab = "n_weeks")
boxplot(clean_Spotify_200$max_streams, xlab = "max_streams")
```



In this way we can put emphasis on the different scales of the data and try to discover the first relations between the variables. As we can see, *danceability* and *energy* have similar values of mean, median, quartiles and variance. This could be due to the fact that the two variables are on the same scale and have similar

distributions. We can notice that all the distributions, aside from the variable *tempo*, have a lot of outliers. This means that many values are numerically distant from the rest of the data and do not fell well inside the overall pattern of the data.
This phenomenon concernes *n_weeks* and *max_streams* the most. The presence of outliers could be motivated by the reasons exposed above: a lot of tracks does not reach a top position in the charts and, the ones that does, are treated as odd observations.

Variance, standard deviation and other variance measures Here we compute and then discuss the variability of the data.

VAR, SD and IQR In this section, we compute and comment the indices regarding the variability of the data, that are *variance*, *standard deviation*, *range of variation*, *interquatile range* and *MAD*.
We created our own **interquantile_range** function to calculate the difference between the first and the third quartile:

```
interquartile_range <- function(x) {
    diff(quantile(x, probs = c(0.25, 0.75)))
}
```

The table below contains all the indicators listed previously.

```
##                   Variance Standar deviation         Diff Interq. Range
## Danceability 1.939673e-02      1.392722e-01 8.300000e-01          0.183
## Energy       2.635241e-02      1.623343e-01 9.501000e-01          0.219
## Tempo        8.956246e+02      2.992699e+01 1.653990e+02         45.026
## Weeks        3.141774e+02      1.772505e+01 2.170000e+02         11.000
## Streams      6.318015e+13      7.948594e+06 7.823889e+07    6989915.000
##                        MAD
## Danceability 1.334340e-01
## Energy       1.630860e-01
## Tempo        3.398267e+01
## Weeks        4.447800e+00
## Streams      3.738484e+06
```

By examining the table, it is not so clear how variable are the data. Therefore, in order to understand better the variability of the data, we computed the coefficient of variation.

Coefficient of variation Here we compute the coefficient of variation, implementing our own function.

```
cv <- function(x) {
    return(sd(x)/mean(x))
}
cv_column <- rbind(cv(clean_Spotify_200$danceability),
    cv(clean_Spotify_200$energy), cv(clean_Spotify_200$tempo),
    cv(clean_Spotify_200$n_weeks), cv(clean_Spotify_200$max_streams))
row.names(cv_column) <- c("Danceability", "Energy",
    "Tempo", "N. Weeks", "Max Streams")
colnames(cv_column) <- c("Coefficient of Variation")
cv_column
```

```
##              Coefficient of Variation
## Danceability                0.2021610
## Energy                      0.2553384
## Tempo                       0.2448082
## N. Weeks                    1.7031287
## Max Streams                 0.7855106
```

The coefficient of variation is useful because is dimensionless, that is independent of the unit in which the measurement was taken, and allow to compare data sets with different units or widely different means.
cv is the ratio between the standard deviation and the mean, so the higher the coefficient of variation, the higher the standard deviation relative to the mean. In this case, we can point out that *n_week* is the most volatile variable of all the columns.

Skewness Skewness is a measure of the symmetry of the frequency distribution, compared to a standard normal distribution. A negative skewness indicates that the distribution is skewed towards the left while a positive skewness would indicate the that a distribution is right skewed. These features tells us that the data is asymmetric.

```
sk_column <- rbind(skewness(clean_Spotify_200$danceability),
    skewness(clean_Spotify_200$energy), skewness(clean_Spotify_200$tempo),
    skewness(clean_Spotify_200$n_weeks), skewness(clean_Spotify_200$max_streams))
row.names(sk_column) <- c("Danceability", "Energy",
    "Tempo", "N. Weeks", "Max Streams")
colnames(sk_column) <- c("Skewness")
sk_column
```

```
##                Skewness
## Danceability -0.5856732
## Energy       -0.5436471
## Tempo         0.4105994
## N. Weeks      4.4121723
## Max Streams   2.6977251
```

The variables *danceability* and *energy* has a negative value as the result of the computation of the skewness index. Therefore, it indicates that the tail is left-sided. That confirms also that the mean is lower than the median.
On the other hand, *tempo*, *n_weeks* and *max_streams* has a positive value of skewness, so it means that the tail is towards the right-side. We can also notice that *n_weeks* has the highest index, emphasizing, as seen before, that the vast majority of the values are in the lower part of the distribution.

Kurtosis Kurtosis is a measure of the "tailedness" of the frequency distribution. A negative value for this index indicates a thin tailed distribution. That means that the values of the data are distributed closer to the median than we would expect for a standard normal distribution, while a positive kurtosis value indicates we are dealing with a heavier tailed distribution, where extreme outcomes are more common.

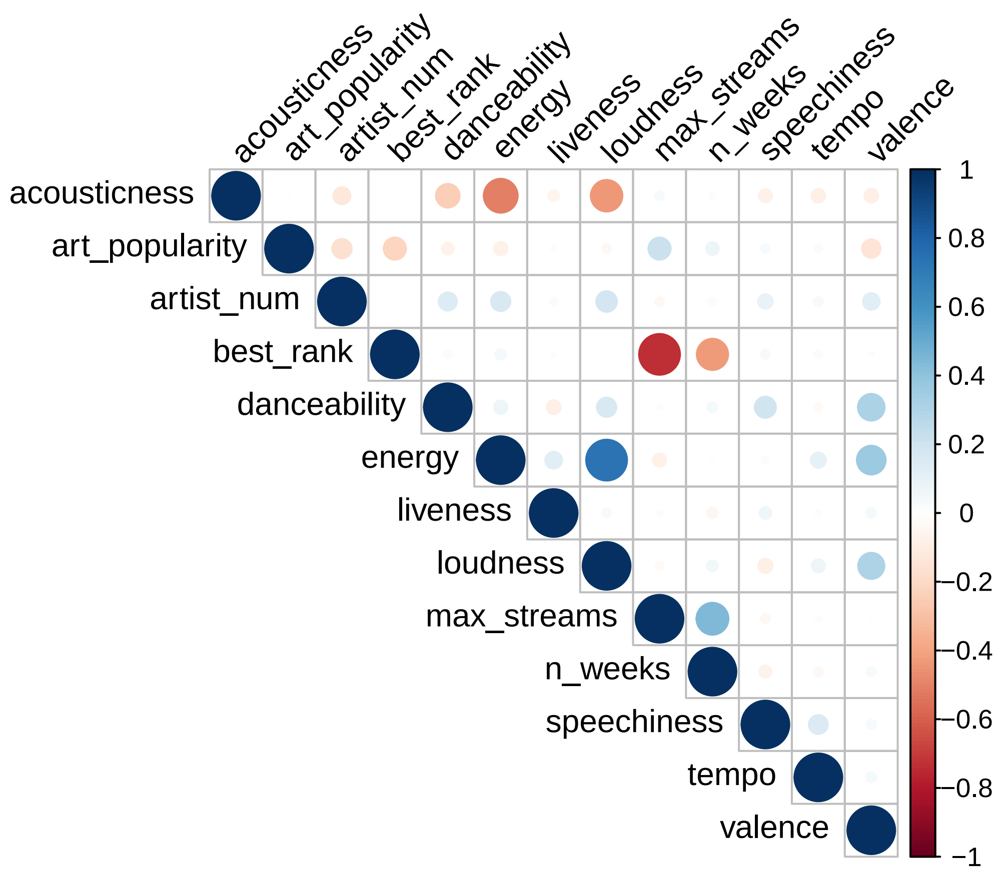
```
k_column <- rbind(kurtosis(clean_Spotify_200$danceability),
    kurtosis(clean_Spotify_200$energy), kurtosis(clean_Spotify_200$tempo),
    kurtosis(clean_Spotify_200$n_weeks), kurtosis(clean_Spotify_200$max_streams))
row.names(k_column) <- c("Danceability", "Energy",
    "Tempo", "N. Weeks", "Max Streams")
colnames(k_column) <- c("Kurtosis")
k_column
```

```
##                 Kurtosis
## Danceability  3.185286
## Energy        3.197617
## Tempo         2.399680
## N. Weeks     32.949550
## Max Streams  13.489061
```

All the variables have a positive value as result of computation of Kurtosis. An higher value of Kurtosis indicates a more pointed distribution.

Relationship between variable Let's start with a global view of all the relationship between all variables in the dataset:

```
corrplot(cor(clean_Spotify_200 %>%
    select(!c(key, mode))), type = "upper", order = "alphabet",
    tl.col = "black", tl.srt = 45)
```

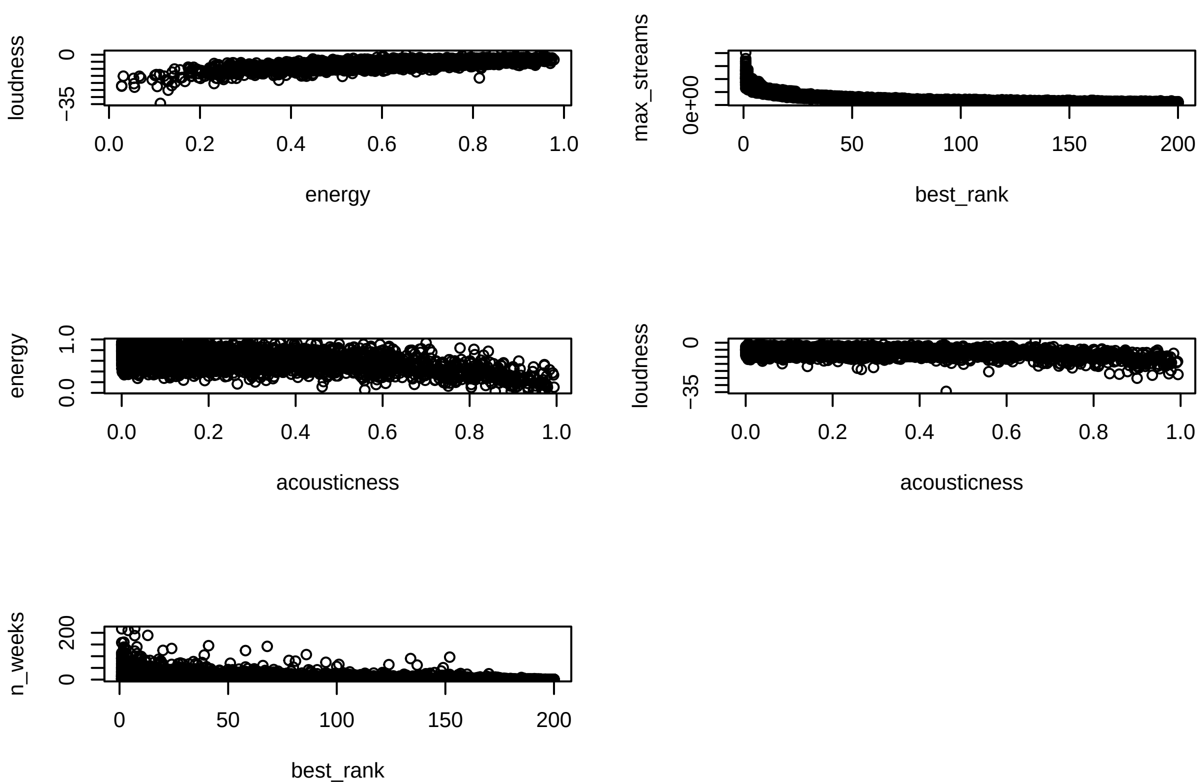


Looking at the table above, one can immediately see that the most important relationships are those between the following variables:

- energy and loudness
- best_rank and max_streams
- acousticness and energy

- acousticness and loudness
- best_rank and n_weeks

```
par(mfrow = c(3, 2))
plot(clean_Spotify_200$energy, clean_Spotify_200$loudness,
    xlab = "energy", ylab = "loudness")
plot(clean_Spotify_200$best_rank, clean_Spotify_200$max_streams,
    xlab = "best_rank", ylab = "max_streams")
plot(clean_Spotify_200$acousticness, clean_Spotify_200$energy,
    xlab = "acousticness", ylab = "energy")
plot(clean_Spotify_200$acousticness, clean_Spotify_200$loudness,
    xlab = "acousticness", ylab = "loudness")
plot(clean_Spotify_200$best_rank, clean_Spotify_200$n_weeks,
    xlab = "best_rank", ylab = "n_weeks")
```



Covariance An indicator measuring the strength of the linear relationship between two variables is the **covariance**:

- **Positive covariance** indicates that two variables tend to move in the same direction;
- **Negative covariance** reveals that two variables tend to move in inverse directions;
- **Zero covariance** indicates that two variables do not have a linear relationship.

```r
cov(clean_Spotify_200$energy, clean_Spotify_200$loudness)
```

```
## [1] 0.2978995
```

The covariance is at his maximum when

$$cov(x, y) = sd(x) * sd(y)$$

and it's at his minimun when

$$cov(x, y) = -sd(x) * sd(y)$$

```r
sd(clean_Spotify_200$energy) * sd(clean_Spotify_200$loudness)
```

```
## [1] 0.4070951
```

So in this case the covariance isn't at his minimun and it isn't at his maximum.

Correlation coefficient To state whether the covariance is small or large, we must therefore compare it with the product of the mean squared deviations: as a result, covariance is usually presented directly in its normalized form, called **pearson correlation coefficient**.

```r
cor(clean_Spotify_200$energy, clean_Spotify_200$loudness)
```

```
## [1] 0.7317687
```

```r
energy_loudness <- cbind(cov(clean_Spotify_200$energy,
    clean_Spotify_200$loudness), cor(clean_Spotify_200$energy,
    clean_Spotify_200$loudness))
best_rank_max_streams <- cbind(cov(clean_Spotify_200$best_rank,
    clean_Spotify_200$max_streams), cor(clean_Spotify_200$best_rank,
    clean_Spotify_200$max_streams))
acousticness_energy <- cbind(cov(clean_Spotify_200$acousticness,
    clean_Spotify_200$energy), cor(clean_Spotify_200$acousticness,
    clean_Spotify_200$energy))
acousticness_loudness <- cbind(cov(clean_Spotify_200$acousticness,
    clean_Spotify_200$loudness), cor(clean_Spotify_200$acousticness,
    clean_Spotify_200$loudness))
best_rank_n_weeks <- cbind(cov(clean_Spotify_200$acousticness,
    clean_Spotify_200$energy), cor(clean_Spotify_200$acousticness,
    clean_Spotify_200$energy))

cov_cor <- rbind(energy_loudness, best_rank_max_streams,
    acousticness_energy, acousticness_loudness, best_rank_n_weeks)
colnames(cov_cor) <- c("Covariance", "Correlation")
row.names(cov_cor) <- c("energy-loudness", "best_rank-max_streams",
    "acousticness-energy", "acousticness-loudness",
    "best_rank-n_weeks")
cov_cor <- round(cov_cor, 3)
cov_cor
```

Results

```
##                          Covariance Correlation
## energy-loudness        2.980000e-01       0.732
## best_rank-max_streams -3.419704e+08      -0.731
## acousticness-energy   -1.900000e-02      -0.504
## acousticness-loudness -2.590000e-01      -0.436
## best_rank-n_weeks     -1.900000e-02      -0.504
```

Analysing the plots and the correlation ratio, there are no very strong relationships, but someone can be used with a simple linear regression to make some predictions.

3. Regression

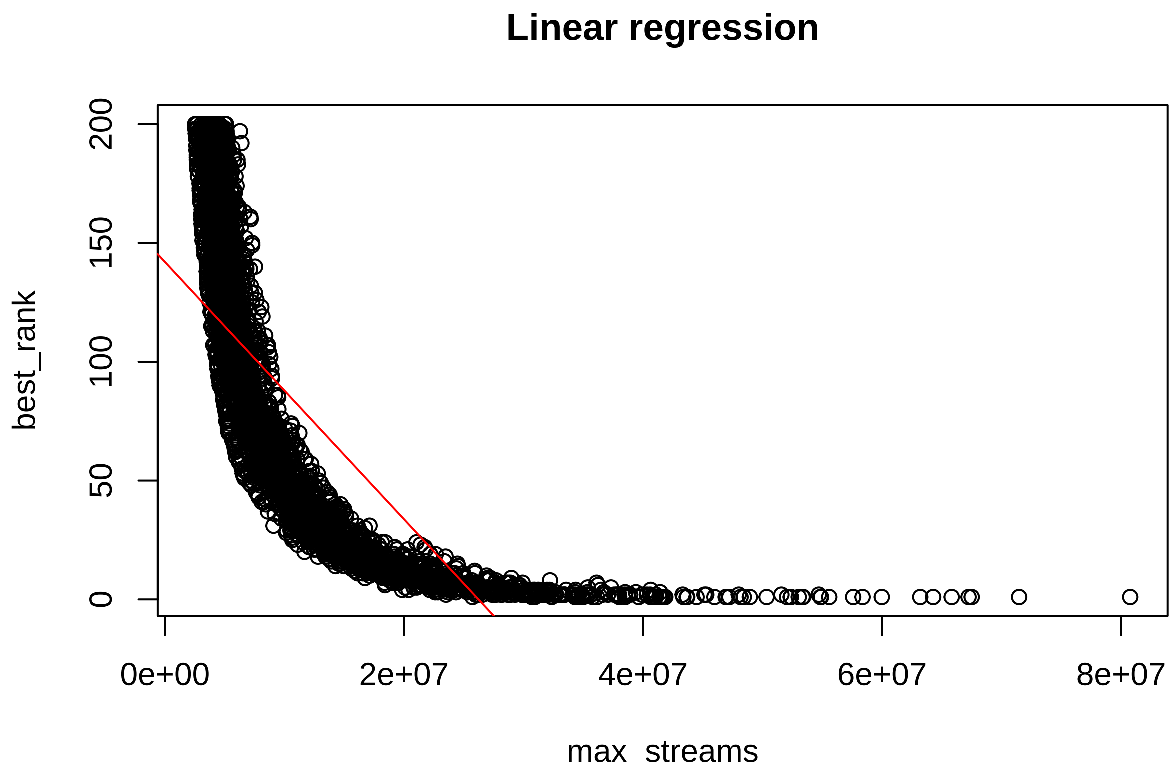
Simple linear regression We can use a simple linear regression to make some prediction about the best rank given the number of streams, equations:

$$y_i = \beta_0 + \beta_1 x_i$$

Where:

- y_i is the response variable best_rank
- x_i is the predictor variable max_streams
- β_i are the regression coefficients

```r
first_model = lm(best_rank ~ max_streams, data = clean_Spotify_200)
plot(x = clean_Spotify_200$max_streams, y = clean_Spotify_200$best_rank,
    main = "Linear regression", xlab = "max_streams",
    ylab = "best_rank")
abline(first_model, col = "red")
```



Looking at the plot, we realise that a linear model is too simple to represent the data.

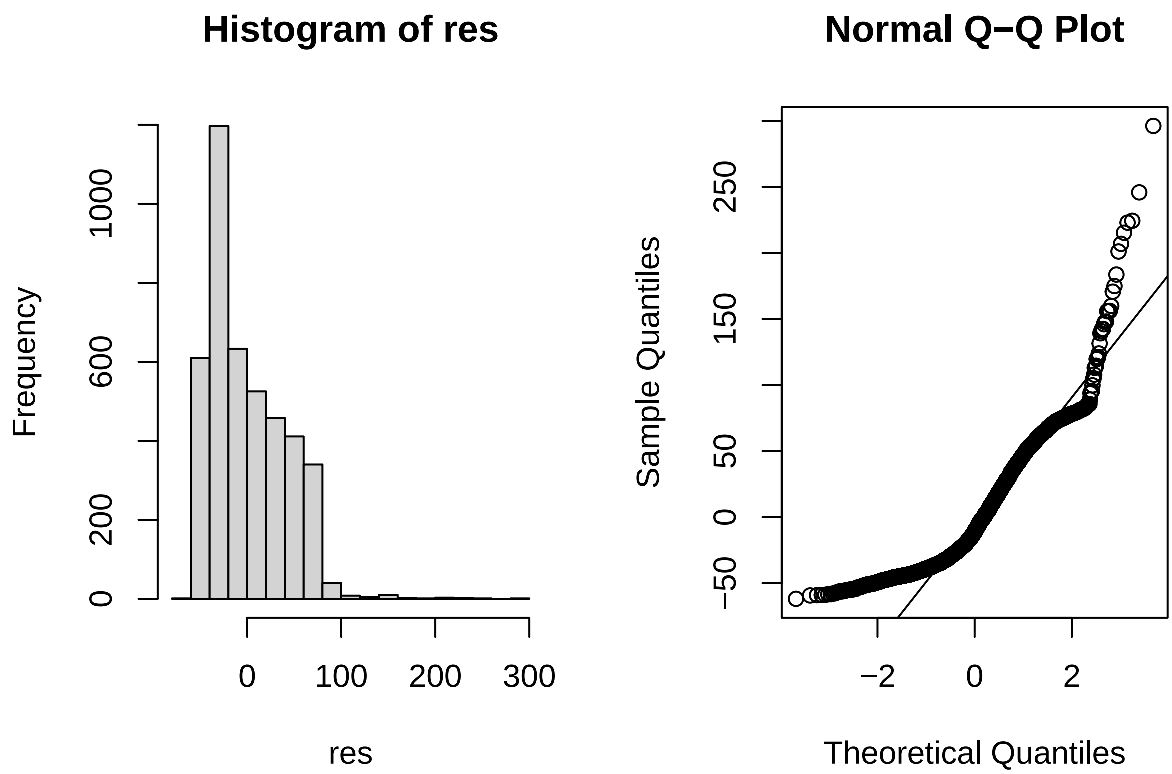
```
summary(first_model)
```

```
##
## Call:
## lm(formula = best_rank ~ max_streams, data = clean_Spotify_200)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -61.82 -33.94 -11.20  28.89 296.15
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.420e+02  9.989e-01  142.15   <2e-16 ***
## max_streams -5.413e-06  7.763e-08  -69.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 40.21 on 4245 degrees of freedom
## Multiple R-squared:  0.5338, Adjusted R-squared:  0.5337
## F-statistic:  4861 on 1 and 4245 DF,  p-value: < 2.2e-16
```

This is demonstrated by the low value of R-squared (0.5338): it means that only 53% of the variation in the output variable is explained by the input variables.

The distribution of residuals has a median of -11.20 with a minimum and maximum of -61.82 and 296.15, the 75% of the residuals is between -33.94 and 28.89: not a good result.

```r
res <- resid(first_model)
par(mfrow = c(1, 2))
hist(res)
qqnorm(res)
qqline(res)
```



A histogram and a Q-Q plot help determine whether or not the generated residuals follow a normal distribution: in this case, the distribution is not normal.

Polynomial regression We then tried to use a more complex polynomial regression model:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \beta_4 x_i^4 + \beta_5 x_i^5$$

Where:

- y_i is the response variable best_rank
- x_i is the predictor variable max_streams
- β_i are the regression coefficients

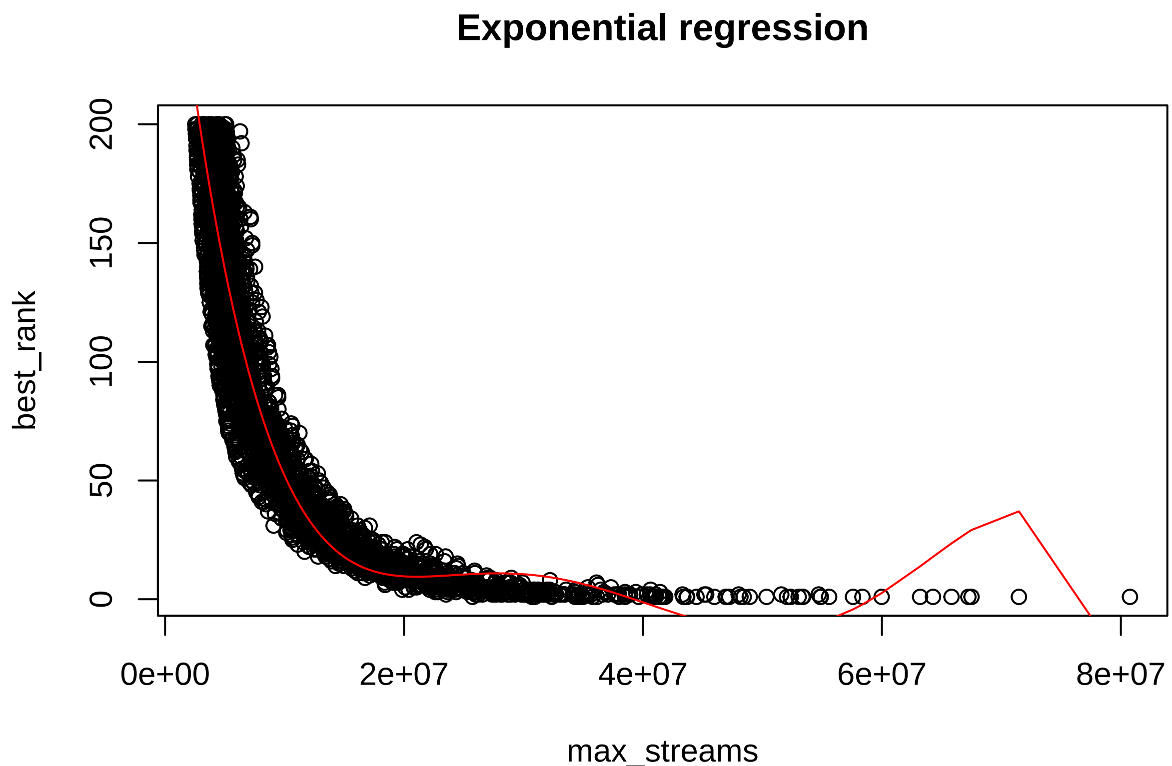
```r
second_model = lm(best_rank ~ poly(max_streams, 5), data = clean_Spotify_200)
summary(second_model)
```

```
##
## Call:
## lm(formula = best_rank ~ poly(max_streams, 5), data = clean_Spotify_200)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -61.091 -10.247  -0.633   9.317  87.079
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             87.2204     0.3075  283.65   <2e-16 ***
## poly(max_streams, 5)1 -2803.4201    20.0387 -139.90   <2e-16 ***
## poly(max_streams, 5)2  1784.3327    20.0387   89.04   <2e-16 ***
## poly(max_streams, 5)3 -1164.1427    20.0387  -58.09   <2e-16 ***
## poly(max_streams, 5)4   695.6781    20.0387   34.72   <2e-16 ***
## poly(max_streams, 5)5  -369.9682    20.0387  -18.46   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.04 on 4241 degrees of freedom
## Multiple R-squared:  0.8843, Adjusted R-squared:  0.8842
## F-statistic:  6484 on 5 and 4241 DF,  p-value: < 2.2e-16
```

The regression function is:

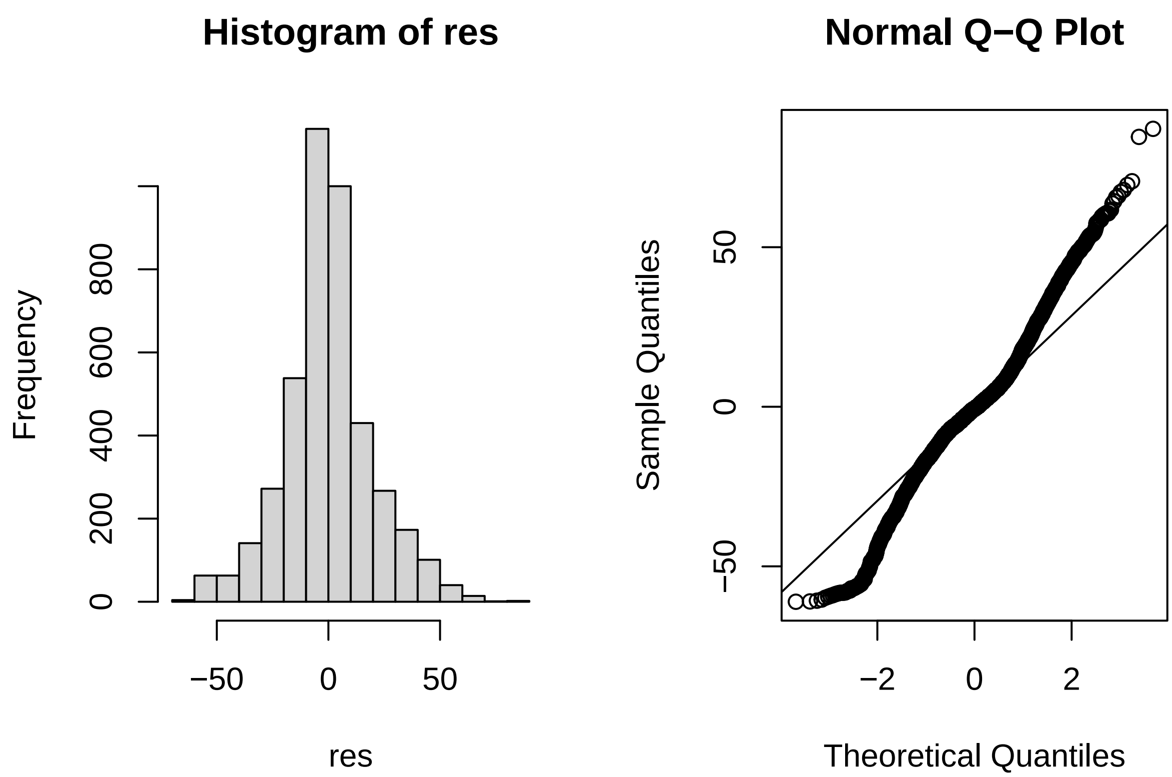
$$y_i = 87.2204 - 2803.4201x_i + 1784.3327x_i^2 - 1164.1427x_i^3 + 695.6781x_i^4 - 369.9682x_i^5$$

```r
plot(x = clean_Spotify_200$max_streams, y = clean_Spotify_200$best_rank,
    main = "Exponential regression", xlab = "max_streams",
    ylab = "best_rank")
lines(sort(clean_Spotify_200$max_streams),
    fitted(second_model)[order(clean_Spotify_200$max_streams)],
    col = "red", type = "l")
```



In this case we have obtained a R-squared value of 0.8843: it means 88.4% of the variation in the output variable is explained by the input variables.

The distribution of the residuals has a median of -0.633 with a minimum and maximum of -61.091 and 87.079, the 75% of the residuals is between -10.247 and 9.317: a good result.



The histogram and the Q-Q plot show that the distribution of residuals is quite normal around 0, but there are anomalies at the extremes.

Multivariate To predict the bast_rank we can use a multivariate linear regression, consisting of:

- Seven variables (already normalized between 0 and 1)
- Regression coefficients

Defined by the equation:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i}$$

Where:

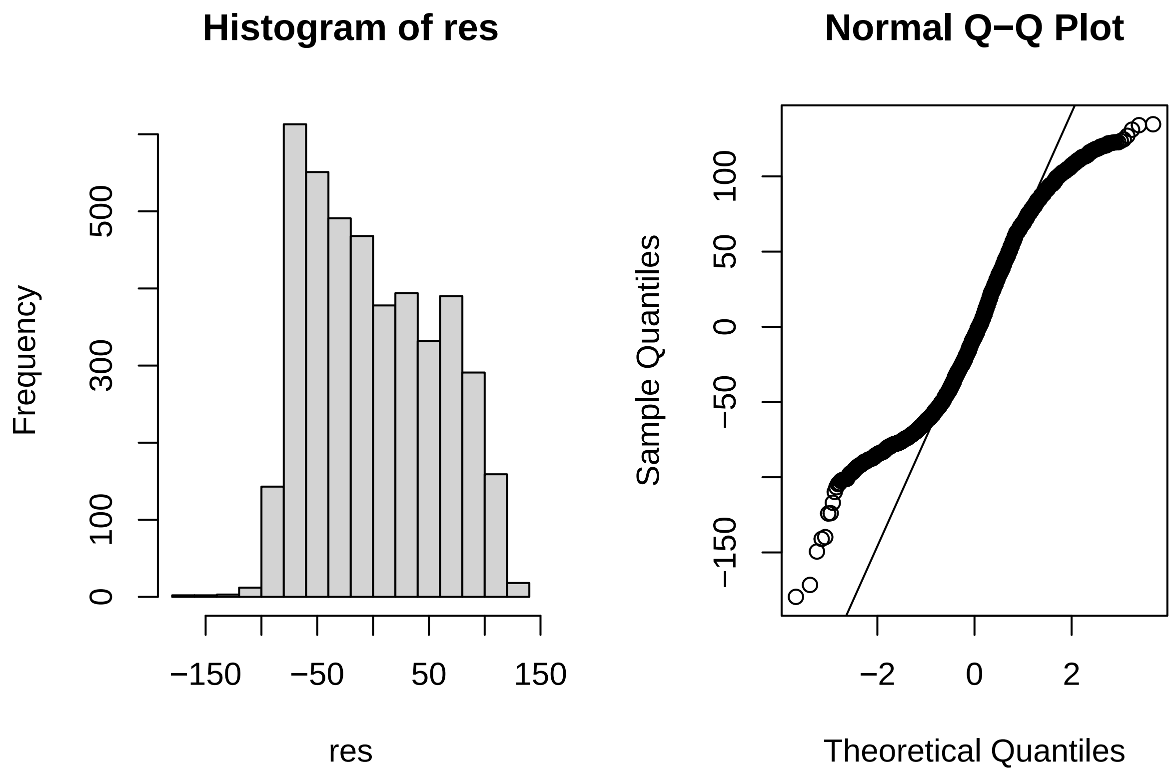
- y_i is the response variable best_rank
- x_{1i} is the danceability variable
- x_{2i} is the energy variable
- x_{3i} is the speechiness variable
- x_{4i} is the acousticness variable
- x_{5i} is the liveness variable

- x_{6i} is the valence variable
- x_{7i} is the art_popularity variable
- β_i are the regression coefficients

```
third_model = lm(best_rank ~ danceability + energy +
    speechiness + acousticness + liveness + valence +
    art_popularity, data = clean_Spotify_200)
summary(third_model)
```

```
##
## Call:
## lm(formula = best_rank ~ danceability + energy + speechiness +
##     acousticness + liveness + valence + art_popularity, data = clean_Spotify_200)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -179.533  -50.319   -7.084   46.920  134.669
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     183.8866    10.0474  18.302  < 2e-16 ***
## danceability    -18.0359     7.1142  -2.535 0.011274 *
## energy           17.9673     6.9375   2.590 0.009634 **
## speechiness      25.5797     7.6685   3.336 0.000858 ***
## acousticness      1.8658     4.5494   0.410 0.681739
## liveness         -0.4393     6.6469  -0.066 0.947310
## valence          -7.3844     4.5872  -1.610 0.107522
## art_popularity -120.5363     8.1908 -14.716  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 57.33 on 4239 degrees of freedom
## Multiple R-squared:  0.05347,    Adjusted R-squared:  0.05191
## F-statistic: 34.21 on 7 and 4239 DF,  p-value: < 2.2e-16
```

Again, a linear model is too simple for the data we have: this is demonstrated by the low value of R square (0.05347) and the distribution of residuals: 75% of that are between -50.319 and 46.920.



The histogram and the Q-Q plot show that the distribution of residuals is not normal.

4. Tests

In this section, we show some example of tests that we conducted on the data. After a few tries, we selected the tests that returned the much significant results that could help us understand the theory behind the tests analysis.
In this first part, we used the *t.test* function on the column *best_rank* to find the confidence interval for its mean at a level of 0.99.

```
t.test(clean_Spotify_200$best_rank, alternative = "two.sided", conf.level = 0.99)
```

```
##
##  One Sample t-test
##
## data:  clean_Spotify_200$best_rank
## t = 96.531, df = 4246, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 99 percent confidence interval:
##  84.89195 89.54883
## sample estimates:
## mean of x
##  87.22039
```

Here, we obtained a p-value equal to $2.2e - 16$, that indeed is significantly smaller that 0.05. This mean that we cannot cannot accept the null hypothesis H_0, that is true mean equal to zero. We must accept the

alternative hypothesis H_1 that state the exact opposite (true mean is not equal to zero). Knowing that the the true mean is 87.22039, we found the confidence interval, that is $84.89195 \leq 87.22039 \leq 89.54883$. This test tells us that, with 99% of confidence, the mean is in this interval.
By using the code below, we tried to make some assumptions on the mean. Knowing that the variable *best_rank* can space between 1 and 200, we presumed that the unknown mean is equal to 90, which is slightly lower that the center of the range for the variable (100th position in the charts).

```
t.test(clean_Spotify_200$best_rank, mu = 90, conf.level = 0.95)
```

```
##
##  One Sample t-test
##
## data:  clean_Spotify_200$best_rank
## t = -3.0763, df = 4246, p-value = 0.002109
## alternative hypothesis: true mean is not equal to 90
## 95 percent confidence interval:
##  85.44896 88.99182
## sample estimates:
## mean of x
##  87.22039
```

```
t.test(clean_Spotify_200$best_rank, mu = 90, alternative = "greater", conf.level = 0.95)
```

```
##
##  One Sample t-test
##
## data:  clean_Spotify_200$best_rank
## t = -3.0763, df = 4246, p-value = 0.9989
## alternative hypothesis: true mean is greater than 90
## 95 percent confidence interval:
##  85.73386      Inf
## sample estimates:
## mean of x
##  87.22039
```

```
t.test(clean_Spotify_200$best_rank, mu = 90, alternative = "less", conf.level = 0.95)
```

```
##
##  One Sample t-test
##
## data:  clean_Spotify_200$best_rank
## t = -3.0763, df = 4246, p-value = 0.001055
## alternative hypothesis: true mean is less than 90
## 95 percent confidence interval:
##      -Inf 88.70693
## sample estimates:
## mean of x
##  87.22039
```

In general, here we reject the null hypothesis is the p-value in lower that 0.05. In the first test, we wanted to discover is the real mean of the variable is 90 and the test returns a p-value equal to 0.002109. Since p is lower than than our threshold, we reject H_0 and accept H_1, which specify that the true mean of the data is

not equal to 90.
The other two tests were applied to locate where the true mean of the data lied, above or below our hypothetical mean of 90. The first inquiry if the true value is *greater* than 90, the second if it is *less*. We obtain a p-value of 0.9989 and 0.001055 respectively. So, in the first case we are accept the null hypothesis while in the second case we H_0 and acknowledge the alternative hypothesis instead. Combined, this two tests reveal that the mean in lower that 90 and included in the interval (85.73386, 88.70693).
This last *t.test*, was utilized to test if the two variables *danceability* and *energy* had the same mean, since they space in the same interval [0, 1] and in the previous section we notice that they have similar distributions.

```
t.test(clean_Spotify_200$danceability, clean_Spotify_200$energy,
    var.equal = FALSE, conf.level = 0.95)
```

```
##
##  Welch Two Sample t-test
##
## data:  clean_Spotify_200$danceability and clean_Spotify_200$energy
## t = 16.196, df = 8300.1, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.04672185 0.05958928
## sample estimates:
## mean of x mean of y
## 0.6889169 0.6357613
```

This test confirms that, even if they are analogous, their means are different and given a p-value equal to $2.2e - 16$, we sure reject the null hypothesis and accept H_1, that states that the true difference in means is not equal to 0.
Afterward, we run the *shapiro.test* function to test if a variable have a normal distribution. In this case, we chose to apply the test on the variable *dancebility* since, by observing its histogram, we noticed that, from all the histograms, it could look more similar to a normally distributed dataset.

```
shapiro.test(clean_Spotify_200$danceability)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  clean_Spotify_200$danceability
## W = 0.97729, p-value < 2.2e-16
```

The test confute our observation. The p-value is lower than 0.05 and therefore we must accept the alternative hypothesis: the values are not normally distributed.

Pearson's Chi-squared test, performed on the contingency table, tests the independence between two variables. If the p-value is higher than 0.05, the null hypothesis can't be rejected.

```
best_rank_chunks <- cut(clean_Spotify_200$best_rank,
    breaks = nclass.Sturges(clean_Spotify_200$best_rank))
chisq_table <- table(best_rank_chunks, clean_Spotify_200$key)
chisq.test(chisq_table)
```

```
##
##  Pearson's Chi-squared test
```

```
##
## data:  chisq_table
## X-squared = 160.08, df = 143, p-value = 0.1559
```

We used the *chisq.test* function to analyze the independency of two variables. We computed the p-value using the of the contingency table based on the *best_rank* and *key* variables. We obtained a p-value of 0.1559 that is grater than 0.05, so the hypothesis H_0 can be accepted and we can state that the *best_rank* and *key* variables are independent.