Final Project

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Results

Packages I will be using throughout the project

```
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.2 ──
## ✔ ggplot2 3.3.6      ✔ purrr   0.3.4
## ✔ tibble  3.1.8      ✔ dplyr   1.0.10
## ✔ tidyr   1.2.1      ✔ stringr 1.4.1
## ✔ readr   2.1.3      ✔ forcats 0.5.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
```

```
library(ggplot2)
```

As you can see the `tidyverse` library contains other libraries such as `tibble`, `ggplot` and `dplyr` which I will be using throughout.

I will introduce more as I go on.

This project is made up of 3 components:

- Analysis
- R Packages
- Functions/Programming

Analysis | R Packages | Functions/Programming | Citations

Context:

The Spotify dataset provides insight into users data about which songs people listen to, and not just the popularity of tracks, but also features of the tracks they have in their library is recorded in their database.

For further reading: https://github.com/rfordatascience/tidytuesday/blob/master/data/2020/2020-01-21/readme.md (https://github.com/rfordatascience/tidytuesday/blob/master/data/2020/2020-01-21/readme.md)

```
#reading my csv file from local machine
df <- read.csv("spotify_songs.csv", header = T)

#A glimpse at the dataset
df[1:5,1:19]
```

```
##                track_id                                                    track_name
## 1 6f807x0ima9a1j3VPbc7VN I Don't Care (with Justin Bieber) - Loud Luxury Remix
## 2 0r7CVbZTWZgbTCYdfa2P31                       Memories - Dillon Francis Remix
## 3 1z1Hg7Vb0AhHDiEmnDE79l                       All the Time - Don Diablo Remix
## 4 75FpbthrwQmzHlBJLuGdC7                     Call You Mine - Keanu Silva Remix
## 5 1e8PAfcKUYoKkxPhrHqw4x               Someone You Loved - Future Humans Remix
##       track_artist track_popularity          track_album_id
## 1       Ed Sheeran               66 2oCs0DGTsRO98Gh5ZSl2Cx
## 2         Maroon 5               67 63rPSO264uRjW1X5E6cWv6
## 3     Zara Larsson               70 1HoSmj2eLcsrR0vE9gThr4
## 4 The Chainsmokers               60 1nqYsOef1yKKuGOVchbsk6
## 5    Lewis Capaldi               69 7m7vv9wlQ4i0LFuJiE2zsQ
##                                          track_album_name
## 1 I Don't Care (with Justin Bieber) [Loud Luxury Remix]
## 2                      Memories (Dillon Francis Remix)
## 3                      All the Time (Don Diablo Remix)
## 4                          Call You Mine - The Remixes
## 5              Someone You Loved (Future Humans Remix)
##   track_album_release_date playlist_name            playlist_id playlist_genre
## 1               14/06/2019     Pop Remix 37i9dQZF1DXcZDD7cfEKhW            pop
## 2               13/12/2019     Pop Remix 37i9dQZF1DXcZDD7cfEKhW            pop
## 3               05/07/2019     Pop Remix 37i9dQZF1DXcZDD7cfEKhW            pop
## 4               19/07/2019     Pop Remix 37i9dQZF1DXcZDD7cfEKhW            pop
## 5               05/03/2019     Pop Remix 37i9dQZF1DXcZDD7cfEKhW            pop
##   playlist_subgenre danceability energy key loudness mode speechiness
## 1         dance pop        0.748  0.916   6   -2.634    1      0.0583
## 2         dance pop        0.726  0.815  11   -4.969    1      0.0373
## 3         dance pop        0.675  0.931   1   -3.432    0      0.0742
## 4         dance pop        0.718  0.930   7   -3.778    1      0.1020
## 5         dance pop        0.650  0.833   1   -4.672    1      0.0359
##   acousticness instrumentalness
## 1       0.1020         0.00e+00
## 2       0.0724         4.21e-03
## 3       0.0794         2.33e-05
## 4       0.0287         9.43e-06
## 5       0.0803         0.00e+00
```

Now we will look at the structure of the data set. We will see it is a data frame with 32,828 observations and 23 variables

```
str(df)
```

```
## 'data.frame':    32833 obs. of  23 variables:
##  $ track_id                : chr  "6f807x0ima9a1j3VPbc7VN" "0r7CVbZTWZgbTCYdfa2P31" "1z1Hg7V
b0AhHDiEmnDE79l" "75FpbthrwQmzHlBJLuGdC7" ...
##  $ track_name              : chr  "I Don't Care (with Justin Bieber) - Loud Luxury Remix" "M
emories - Dillon Francis Remix" "All the Time - Don Diablo Remix" "Call You Mine - Keanu Silva
Remix" ...
##  $ track_artist            : chr  "Ed Sheeran" "Maroon 5" "Zara Larsson" "The Chainsmokers"
...
##  $ track_popularity        : int  66 67 70 60 69 67 62 69 68 67 ...
##  $ track_album_id          : chr  "2oCs0DGTsRO98Gh5ZSl2Cx" "63rPSO264uRjW1X5E6cWv6" "1HoSmj2
eLcsrR0vE9gThr4" "1nqYsOef1yKKuGOVchbsk6" ...
##  $ track_album_name        : chr  "I Don't Care (with Justin Bieber) [Loud Luxury Remix]" "M
emories (Dillon Francis Remix)" "All the Time (Don Diablo Remix)" "Call You Mine - The Remixes"
...
##  $ track_album_release_date: chr  "14/06/2019" "13/12/2019" "05/07/2019" "19/07/2019" ...
##  $ playlist_name           : chr  "Pop Remix" "Pop Remix" "Pop Remix" "Pop Remix" ...
##  $ playlist_id             : chr  "37i9dQZF1DXcZDD7cfEKhW" "37i9dQZF1DXcZDD7cfEKhW" "37i9dQZ
F1DXcZDD7cfEKhW" "37i9dQZF1DXcZDD7cfEKhW" ...
##  $ playlist_genre          : chr  "pop" "pop" "pop" "pop" ...
##  $ playlist_subgenre       : chr  "dance pop" "dance pop" "dance pop" "dance pop" ...
##  $ danceability            : num  0.748 0.726 0.675 0.718 0.65 0.675 0.449 0.542 0.594 0.642
...
##  $ energy                  : num  0.916 0.815 0.931 0.93 0.833 0.919 0.856 0.903 0.935 0.818
...
##  $ key                     : int  6 11 1 7 1 8 5 4 8 2 ...
##  $ loudness                : num  -2.63 -4.97 -3.43 -3.78 -4.67 ...
##  $ mode                    : int  1 1 0 1 1 1 0 0 1 1 ...
##  $ speechiness             : num  0.0583 0.0373 0.0742 0.102 0.0359 0.127 0.0623 0.0434 0.05
65 0.032 ...
##  $ acousticness            : num  0.102 0.0724 0.0794 0.0287 0.0803 0.0799 0.187 0.0335 0.02
49 0.0567 ...
##  $ instrumentalness        : num  0.00 4.21e-03 2.33e-05 9.43e-06 0.00 0.00 0.00 4.83e-06 3.
97e-06 0.00 ...
##  $ liveness                : num  0.0653 0.357 0.11 0.204 0.0833 0.143 0.176 0.111 0.637 0.0
919 ...
##  $ valence                 : num  0.518 0.693 0.613 0.277 0.725 0.585 0.152 0.367 0.366 0.59
...
##  $ tempo                   : num  122 100 124 122 124 ...
##  $ duration_ms             : int  194754 162600 176616 169093 189052 163049 187675 207619 19
3187 253040 ...
```

Attributes:

I will explain the variables for this dataset to give some context

- **track_id**: Song ID
- **track_name**: Song Namw
- **track_artist**: Song Artist
- **track_popularity**: Song popularity (rating 0-100)
- **track_album_id**: Album ID
- **track_album_name**: Song album name
- **track_album_name**: Song album name
- **track_album_release_date**: Date the album was released

- **playlist_name**: Name of playlist
- **playlist_id**: Playlist ID
- **playlist_genre**: Playlist genre
- **playlist_subgenre**: Playlist subgenre
- **danceability**: Danceability describes how suitable a track is for dancing. 0.0 being least danceable 1.0 being most danceable
- **energy**: Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy.
- **key**: The estimated overall key of the track.
- **loudness**: The overall loudness of a track in decibels (dB). Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db.
- **mode**: Mode indicates the 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.
- **speechiness**: 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. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
- **acousticness**: A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
- **instrumentalness**: Predicts whether a track contains no vocals.The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0. The distribution of values for this feature look like this:
- **liveness**: Detects the 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**: A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).
- **tempo**: The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
- **duration_ms**: The duration of the track in milliseconds.

Some questions I asked myself before this:

- What kind of distributions are the musical variables?
- Who is the most popular artist?
- Is there more positvity in major modes?
- What year was the most popular between 2010 - 2020?
- Can Post Malone be considered a rapper under these variables?

Data Cleaning:

Before I answer some of these questions the data needs to be cleaned. I will lay out each variable that I will be changing anything I don’t mention I have left as is.

```
#Changing my dataset into a tibble for easier manipulation and make full use of dplyr and ggplo
ts

df <- as_tibble(df)
```

id

The original data set never had an `id` variable so I decided to add one in to give a number to each row

```
# Create a column with numbers 1:32833 (no. of rows)
# and append it to the data set before the track column
# which is originally the first column



df %>%
  mutate(id = c(1:32833),.before = track_id) -> df

#Taking the first 4 rows and 3 columns to check if id was appended
df[1:4,1:3]
```

```
## # A tibble: 4 × 3
##      id track_id               track_name
##   <int> <chr>                  <chr>
## 1     1 6f807x0ima9a1j3VPbc7VN I Don't Care (with Justin Bieber) - Loud Luxury …
## 2     2 0r7CVbZTWZgbTCYdfa2P31 Memories - Dillon Francis Remix
## 3     3 1z1Hg7Vb0AhHDiEmnDE79l All the Time - Don Diablo Remix
## 4     4 75FpbthrwQmzHlBJLuGdC7 Call You Mine - Keanu Silva Remix
```

track_id

We won't need the `track_id` for each track because we now have the `id` variable so we will drop this variable

```
#selecting the data frame and minusing the variable uri
df <- select(df,-track_id)
```

track_album_id

Same as above we won't need `track_album_id`

```
#selecting the data frame and minusing the variable uri
df <- select(df,-track_album_id)
```

track_album_release year

The release year is in YYYY-MM-DD. To make the analysis easier I will turn this variable into YYYY

```
#Set of functions to deal with dates in an easier way
library(lubridate)
```

```
## Loading required package: timechange
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
# use a for loop to go through each value
for (i in 1:length(df$track_album_release_date)){
  # check if the value is a date in the DD/MM/YYYY format
  if (grepl("^[0-9]{4}$", df$track_album_release_date[i])) {
  #Adding a 01-01 to release years that just have YYYY so I can use the lubridate functions wit
hout getting NA's
    df$track_album_release_date[i] <- paste("01","01",df$track_album_release_date[i], sep =
"/")
  }
}



# Convert the dates to Date objects
dates <- as.Date(df$track_album_release_date, format = "%d/%m/%Y")

# Extract the year from the Date objects
df$track_album_release_date <- format(dates, "%Y")

#Turning years into factor variables
df$track_album_release_date <- factor(df$track_album_release_date)

#Analysing structure
str(df$track_album_release_date)
```

```
##  Factor w/ 63 levels "1957","1958",..: 62 62 62 62 62 62 62 62 62 62 ...
```

playlist_id

```
#selecting the data frame and minusing the variable uri
df <- select(df,-playlist_id)
```

mode

mode is a categorical variable so we will let `0 = Minor` and `1 = Major` how ever when we look at the structure again R will set `0` to `1` and `1` to `2` with `1 = Minor` and `2 = Major`

```
#Setting the variable mode as a factor with categories major and minor
df$mode <- factor(df$mode, labels = c("Minor", "Major"))
str(df$mode)
```

```
##  Factor w/ 2 levels "Minor","Major": 2 2 1 2 2 2 1 1 2 2 ...
```

playlist_genre

`playlist_genre` can be categorised into factors which I will do

```
#Used to eliminate or delete the duplicate values or the rows present in the vector
unique(df$playlist_genre)
```

```
## [1] "pop"   "rap"   "rock"  "latin" "r&b"   "edm"
```

```
#Categorising playlist_genre variable
df$playlist_genre <- factor(df$playlist_genre, labels = c("pop","rap","rock","latin","r&b","ed
m"))
str(df$playlist_genre)
```

```
##  Factor w/ 6 levels "pop","rap","rock",..: 3 3 3 3 3 3 3 3 3 3 ...
```

playlist_subgenre

`playlist_subgenre` can be categorised into factors which I will do

```
unique(df$playlist_subgenre)
```

```
##  [1] "dance pop"                 "post-teen pop"
##  [3] "electropop"                "indie poptimism"
##  [5] "hip hop"                   "southern hip hop"
##  [7] "gangster rap"              "trap"
##  [9] "album rock"                "classic rock"
## [11] "permanent wave"            "hard rock"
## [13] "tropical"                  "latin pop"
## [15] "reggaeton"                 "latin hip hop"
## [17] "urban contemporary"        "hip pop"
## [19] "new jack swing"            "neo soul"
## [21] "electro house"             "big room"
## [23] "pop edm"                   "progressive electro house"
```

```
#Categorising playlist_subgenre variable
df$playlist_subgenre <- factor(df$playlist_subgenre)
str(df$playlist_genre)
```

```
##  Factor w/ 6 levels "pop","rap","rock",..: 3 3 3 3 3 3 3 3 3 3 ...
```

key

I will remove key as I am not educated enough in music do perform any analysis in terms of keys and scales etc…

```
#minusing the key variable
df <- select(df,-key)
```

tempo

We will change the tempo name to BPM as it is measured in ‘Beats per Minute’ (BPM)

```
df %>%
  #Appending the name 'BPM' to the variable 'tempo'
  rename("BPM" = "tempo") -> df
```

duration_ms

The song duration is in milliseconds we will change this to minutes and seconds, it is easier to read and that is the usual convention in music apps. We will also change the variable name from `duration_ms` to `duration(secs)`

```
#Convert input in any one of character, integer, numeric, factor, or ordered type into 'POSIXct' (or 'Date') objects
library(anytime)

# as. POSIXct stores both a date and time with an associated time zone. The default time zone selected, is the time zone that my computer is set to
as.POSIXct(Sys.Date()) + df$duration_ms/ 1000
df$duration_ms  <- format( as.POSIXct(Sys.Date()) +
                            df$`duration_ms`  /1000,"%M:%S")

#Changing the name of the column
df <- rename(df, "duration(secs)" = "duration_ms")
```

The times are now in MM:SS

```
#Glimpse of variable in MM:SS and mod 60
head(df$`duration(secs)`,10)
```

```
##  [1] "03:14" "02:42" "02:56" "02:49" "03:09" "02:43" "03:07" "03:27" "03:13"
## [10] "04:13"
```

Now lets look at our data again

```
str(df)
```

```
## tibble [32,833 × 20] (S3: tbl_df/tbl/data.frame)
##  $ id                      : int [1:32833] 1 2 3 4 5 6 7 8 9 10 ...
##  $ track_name              : chr [1:32833] "I Don't Care (with Justin Bieber) - Loud Luxury Remix" "Memories - Dillon Francis Remix" "All the Time - Don Diablo Remix" "Call You Mine - Keanu Silva Remix" ...
##  $ track_artist            : chr [1:32833] "Ed Sheeran" "Maroon 5" "Zara Larsson" "The Chainsmokers" ...
##  $ track_popularity        : int [1:32833] 66 67 70 60 69 67 62 69 68 67 ...
##  $ track_album_name        : chr [1:32833] "I Don't Care (with Justin Bieber) [Loud Luxury Remix]" "Memories (Dillon Francis Remix)" "All the Time (Don Diablo Remix)" "Call You Mine - The Remixes" ...
##  $ track_album_release_date: Factor w/ 63 levels "1957","1958",..: 62 62 62 62 62 62 62 62 62 62 ...
##  $ playlist_name           : chr [1:32833] "Pop Remix" "Pop Remix" "Pop Remix" "Pop Remix" ...
##  $ playlist_genre          : Factor w/ 6 levels "pop","rap","rock",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ playlist_subgenre       : Factor w/ 24 levels "album rock","big room",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ danceability            : num [1:32833] 0.748 0.726 0.675 0.718 0.65 0.675 0.449 0.542 0.594 0.642 ...
##  $ energy                  : num [1:32833] 0.916 0.815 0.931 0.93 0.833 0.919 0.856 0.903 0.935 0.818 ...
##  $ loudness                : num [1:32833] -2.63 -4.97 -3.43 -3.78 -4.67 ...
##  $ mode                    : Factor w/ 2 levels "Minor","Major": 2 2 1 2 2 2 1 1 2 2 ...
##  $ speechiness             : num [1:32833] 0.0583 0.0373 0.0742 0.102 0.0359 0.127 0.0623 0.0434 0.0565 0.032 ...
##  $ acousticness            : num [1:32833] 0.102 0.0724 0.0794 0.0287 0.0803 0.0799 0.187 0.0335 0.0249 0.0567 ...
##  $ instrumentalness        : num [1:32833] 0.00 4.21e-03 2.33e-05 9.43e-06 0.00 0.00 0.00 4.83e-06 3.97e-06 0.00 ...
##  $ liveness                : num [1:32833] 0.0653 0.357 0.11 0.204 0.0833 0.143 0.176 0.111 0.637 0.0919 ...
##  $ valence                 : num [1:32833] 0.518 0.693 0.613 0.277 0.725 0.585 0.152 0.367 0.366 0.59 ...
##  $ BPM                     : num [1:32833] 122 100 124 122 124 ...
##  $ duration(secs)          : chr [1:32833] "03:14" "02:42" "02:56" "02:49" ...
```

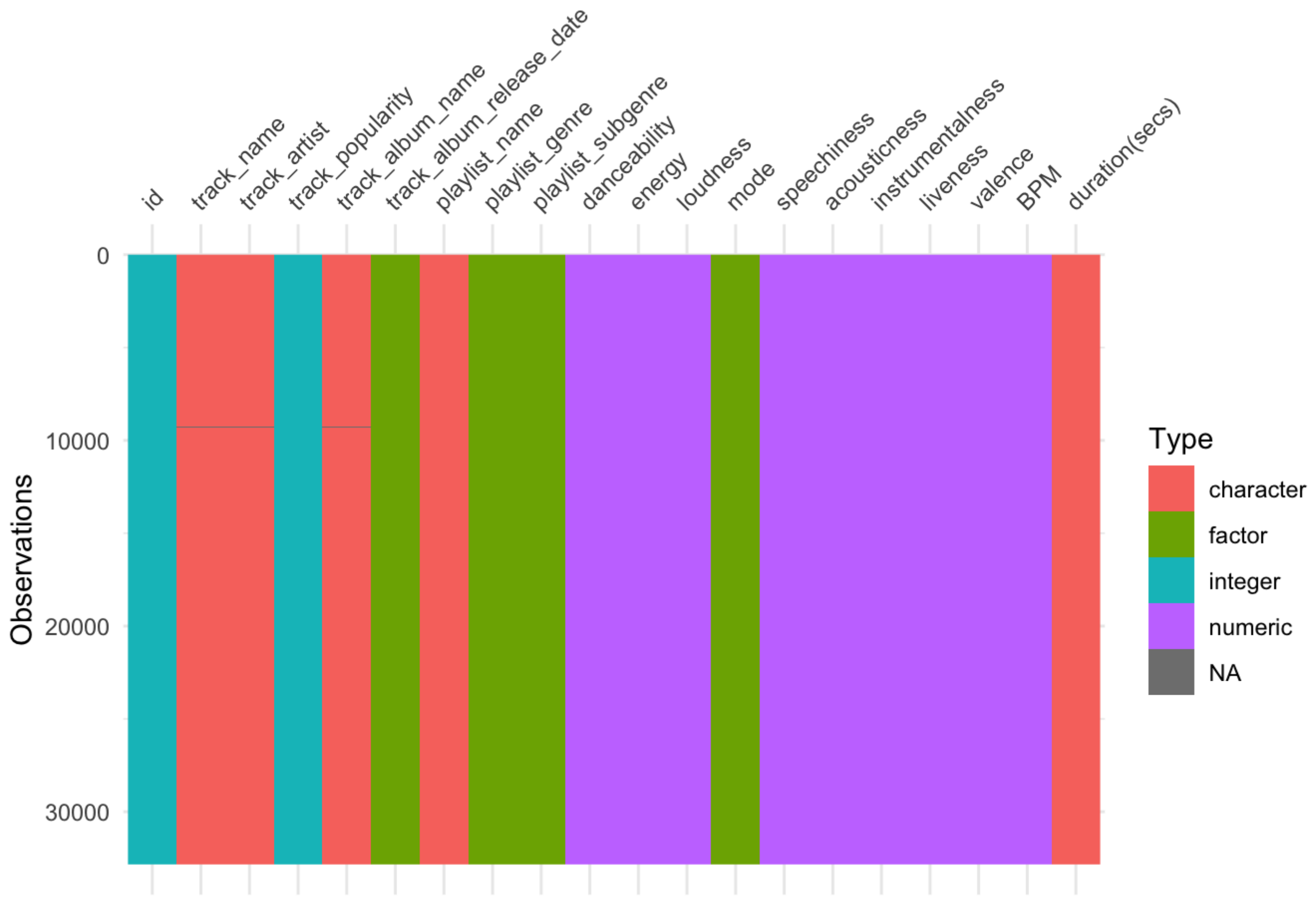
We now have a tibble with 32,828 observations and this time only 20 variables

We can graph this structure too

```
#The visdat package provides visualisations of an entire dataframe at once
library(visdat)
```

```
visdat::vis_dat(df,sort_type = FALSE)
```

```
## Warning: `gather_()` was deprecated in tidyr 1.2.0.
## Please use `gather()` instead.
```



NA Values

It would make sense to remove rows with any `NA` values in them

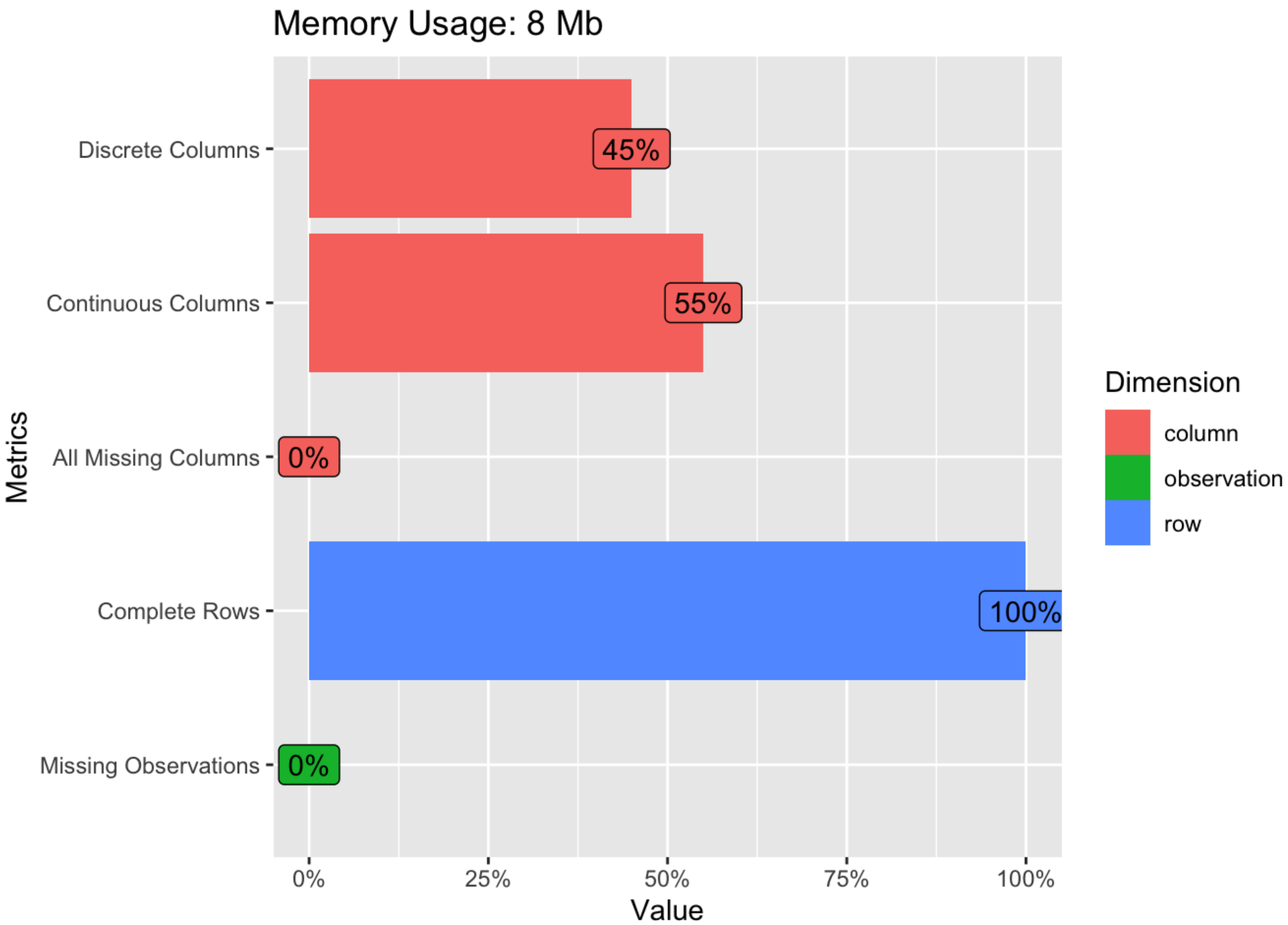
```
df <- print(df[complete.cases(df), ] )
```

```
## # A tibble: 32,797 × 20
##       id track…¹ track…² track…³ track…⁴ track…⁵ playl…⁶ playl…⁷ playl…⁸ dance…⁹
##    <int> <chr>   <chr>     <int> <chr>   <fct>   <chr>   <fct>   <fct>     <dbl>
##  1     1 I Don'… Ed She…      66 I Don'… 2019    Pop Re… rock    dance …   0.748
##  2     2 Memori… Maroon…      67 Memori… 2019    Pop Re… rock    dance …   0.726
##  3     3 All th… Zara L…      70 All th… 2019    Pop Re… rock    dance …   0.675
##  4     4 Call Y… The Ch…      60 Call Y… 2019    Pop Re… rock    dance …   0.718
##  5     5 Someon… Lewis …      69 Someon… 2019    Pop Re… rock    dance …   0.65
##  6     6 Beauti… Ed She…      67 Beauti… 2019    Pop Re… rock    dance …   0.675
##  7     7 Never … Katy P…      62 Never … 2019    Pop Re… rock    dance …   0.449
##  8     8 Post M… Sam Fe…      69 Post M… 2019    Pop Re… rock    dance …   0.542
##  9     9 Tough … Avicii       68 Tough … 2019    Pop Re… rock    dance …   0.594
## 10    10 If I C… Shawn …      67 If I C… 2019    Pop Re… rock    dance …   0.642
## # … with 32,787 more rows, 10 more variables: energy <dbl>, loudness <dbl>,
## #   mode <fct>, speechiness <dbl>, acousticness <dbl>, instrumentalness <dbl>,
## #   liveness <dbl>, valence <dbl>, BPM <dbl>, `duration(secs)` <chr>, and
## #   abbreviated variable names ¹track_name, ²track_artist, ³track_popularity,
## #   ⁴track_album_name, ⁵track_album_release_date, ⁶playlist_name,
## #   ⁷playlist_genre, ⁸playlist_subgenre, ⁹danceability
```

Data Exploration:

A useful thing to look at which we didn't talk too much about in the course was memory consumption. This is quite a big data set so memory consumption would be something worth keeping an eye on

```r
#automate data exploration and treatment
library(DataExplorer)
plot_intro(df)
```



The total memory usage is 8Mb with the rows taking up the most amount of memory.

This can also show if you have any missing data. If we did completed rows would not be 100% and discrete and continuous columns both add to give 100%. Missing columns and observations is also 0%

Now we will look at answering some of my questions previously.

I wanted to find mean of song duration

```
#Converting times into seconds for easier calculation
toSeconds <- function(x){

  #stop if the input is not a string in H:M:S
  if (!is.character(x)) stop("x must be a character string of the form H:M:S")
  #If x is <= 0 we return the input as you can have negative or 0 time
  if (length(x)<=0)return(x)

  #The function knows that if you put 1 digit in it is seconds
  # 2 digits is minutes:seconds
  # 3 digits is houra:minutes:seconds
  unlist(lapply(x, function(i){
    i <- as.numeric(strsplit(i,':',fixed=TRUE)[[1]])

    if (length(i) == 3) #Hours
      i[1]*3600 + i[2]*60 + i[3]

    else if (length(i) == 2) #Mins
      i[1]*60 + i[2]

    else if (length(i) == 1) #Seconds
      i[1]
  }
  )
  )
}


#dividing and rounding seconds by 60 to get minutes and seconds
mean(toSeconds(df$`duration(secs)`)) / 60
```

```
## [1] 3.755009
```

As we can see the mean for song duration is 3 minutes and 76 seconds. We can run this in a function called `timecon` which will convert the duration to minutes and seconds if the seconds are greater than 60

```
timecon <- function(x){

  # seperating the whole number and decimal to get the decimal part
  l <- x - floor(x)

  #If the decimal part is <= 60 we return the number as is because the seconds are still betwee
n 1 and 60 so no conversion needed
  if (l <= 0.6){return(x)}

  #Otherwise we multiply the decimal part by 100 and divide by 60 adding on the while number
  else {(round((x - floor(x)) * 100,0) / 60) + floor(x)}

}


round(timecon(3.76),2)
```

```
## [1] 4.27
```

The actual mean is 4 minutes and 27 seconds.

I wanted to look at some information about the dataset's genres

```
df %>%
  count(genre = playlist_genre) -> gencount

gencount %>%
   arrange(desc(n), gencount) %>%
    rename(count = n) -> gencount
```

```
knitr::kable(gencount, col.names = gsub("", "", names(gencount)))
```

genre	count
pop	6043
r&b	5742
rock	5505
latin	5427
rap	5153
edm	4927

Unsurprisingly, pop has the most songs in the dataset followed by r&b, rock, latin, rap and finally edm. How about subgenres?

Let's pick the top 10

```
df %>%
  count(playlist_subgenre) -> subcount

subcount %>%
   arrange(desc(n), subcount) %>%
  rename(count = n) -> subcount
```

```
knitr::kable(head(subcount, 10), col.names = gsub("", "", names(subcount)))
```

playlist_subgenre	count
progressive electro house	1809
southern hip hop	1673
indie poptimism	1672
latin hip hop	1655
neo soul	1636
pop edm	1517
electro house	1511
hard rock	1482
gangster rap	1456
electropop	1406

It is interesting that edm is the lowest of the genres but progressive electro house is the highest of the subgenres. Which indicates most of edm's subgenres fall under progressive electro house.

Personally, I like live music even listening to it on recording. I want to see what percentage of is above 0.8 (In the music attributes it is stated anything greater than 0.8 is normally live)

```
df %>%
  count(liveness >= 0.8) %>%
  rename(count = n) -> livecount

livecount$count[2] / length(df$liveness)
```

```
## [1] 0.0100619
```

Only 1% of tracks have 0.8 and over for the amount of liveness. In other words only 1% of tracks are live.

Who has the highest BPM?

```
df %>%
  filter(BPM == max(BPM)) -> highbpm

highbpm %>%
  select(track_name, track_artist, BPM) -> highbpm

knitr::kable(head(highbpm, 10), col.names = gsub("", "", names(highbpm)))
```

track_name	track_artist	BPM
Dope's Gotta Hold On Me (feat. Ese Rich Roc)	Spanish F.L.Y.	239.44

"Dope's gotta hold on me by Spanish F.L.Y" has the highest BPM with a result of 239.44

Who has the lowest danceability?

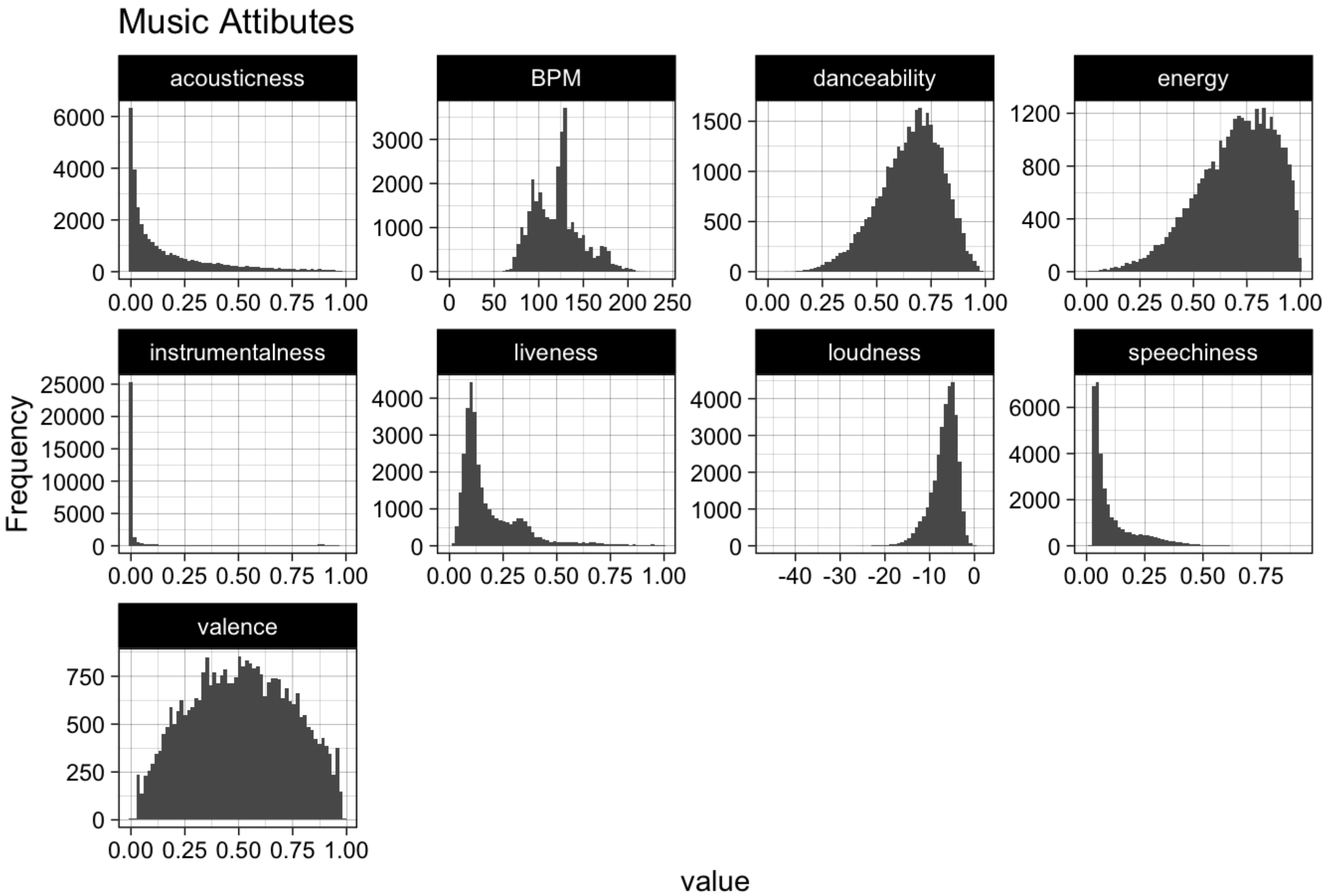
```
df %>%
  filter(danceability == min(danceability)) -> lowdnce

lowdnce %>%
  select(track_name, track_artist, danceability) -> lowdnce

knitr::kable(head(lowdnce, 10), col.names = gsub("", "", names(lowdnce)))
```

track_name	track_artist	danceability
Hi, How're You Doin'?	DREAMS COME TRUE	0

It is "Hi, How're You Doin" by "DREAMS COME TRUE" with 0

Next, we can graph all the music attributes and look at them at a glimpse

```r
library(ggthemes)
#I am also using the Data Explorer library here too but I have called it previously
plot_histogram(
  df[,10:20], #Only variables 10 - 20
  geom_histogram_args = list(bins = 60L),
  scale_x = "continuous",
  title = 'Music Attibutes',
  ggtheme = theme_linedraw(),
  theme_config = list(),
  nrow = 4L,
  ncol = 4L,
  parallel = T
)
```

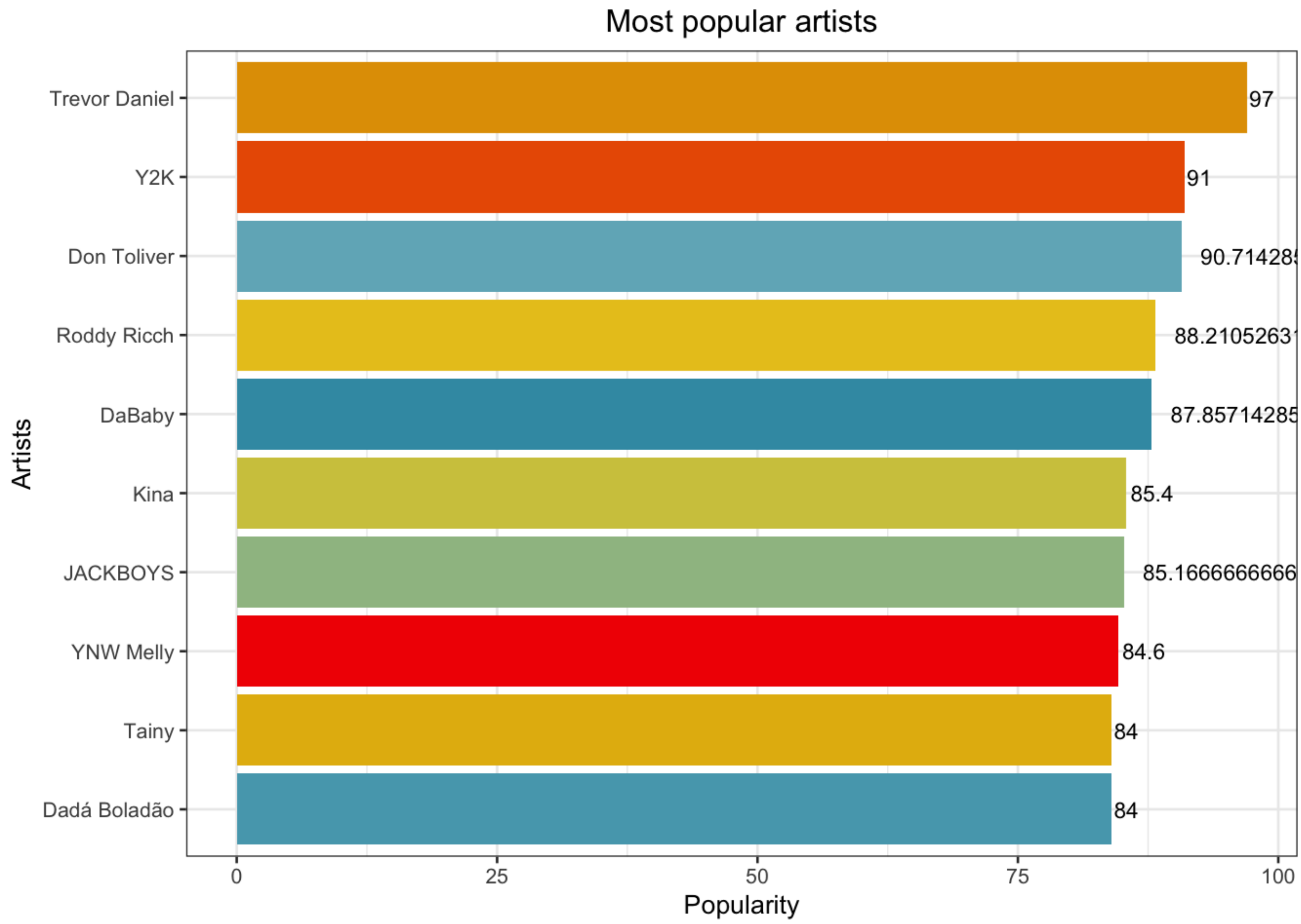


From the graphs we can say:

- Acousticness is rightly skewed
- Valence is normally distributed
- Speechiness in songs are not as popular, people prefer less words
- High energy songs are popular
- Most songs have a loudness between 6-10 dBs

Next I thought it would be interesting to look at the most popular artists in terms of average popularity

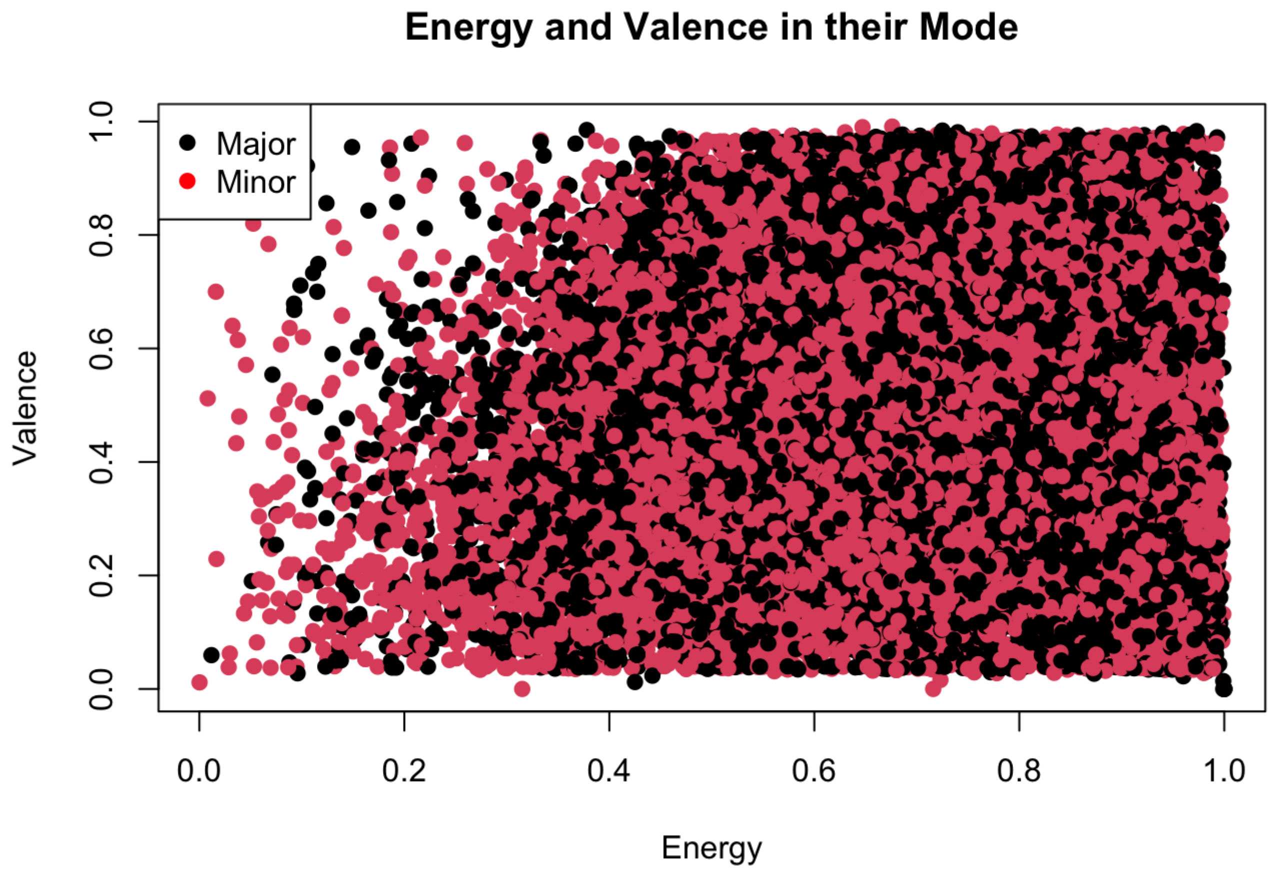
```r
#Subset of artists with the amount of songs they have in the dataset
df %>%
  count(track_artist) -> artcount

#Grouping by artist and adding up their total popularity in a new column
df %>%
  group_by(track_artist) %>%
  summarise(Total_Popularity = sum(track_popularity)) -> pop

# Adding the number of tracks we original got to our new subset
pop %>%
  mutate(No_of_tracks = artcount$n) -> pop

# a new column averaging the popularity dividing total popularity by amount of songs
pop %>%
  mutate(average_popularity = Total_Popularity / No_of_tracks) -> popavg



library(wesanderson) #Color pallette package
col2 = c(wes_palette('Zissou1', 10, type = "continuous")) #Setting up a gradual color pallette

popavg %>%
  top_n(10, average_popularity) %>% #Top 10 in average popularity
  ggplot(aes(x = reorder(track_artist,+ average_popularity), y = average_popularity)) + #settin
g up axes
  geom_bar(stat = 'identity', fill = col2) + #Using color pallette
  coord_flip() + #Flipping the axes so the names of artists arent at the bottom
  theme_bw(base_size=10) +
  labs(y="Popularity", x="Artists") +
  ggtitle("Most popular artists") +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_text(aes(label = average_popularity), hjust=-0.1, size=3) #Adjusting position
```



On average the top artists are quite close with a range from 84 - 97 but Trevor Daniels takes the lead by a good bit.

I thought I would look at major and minor modes. In music people say major modes sound more positive while minor modes tend to be more sad. I decided to take the modes and plot them against valence which is how positive a song is and energy.

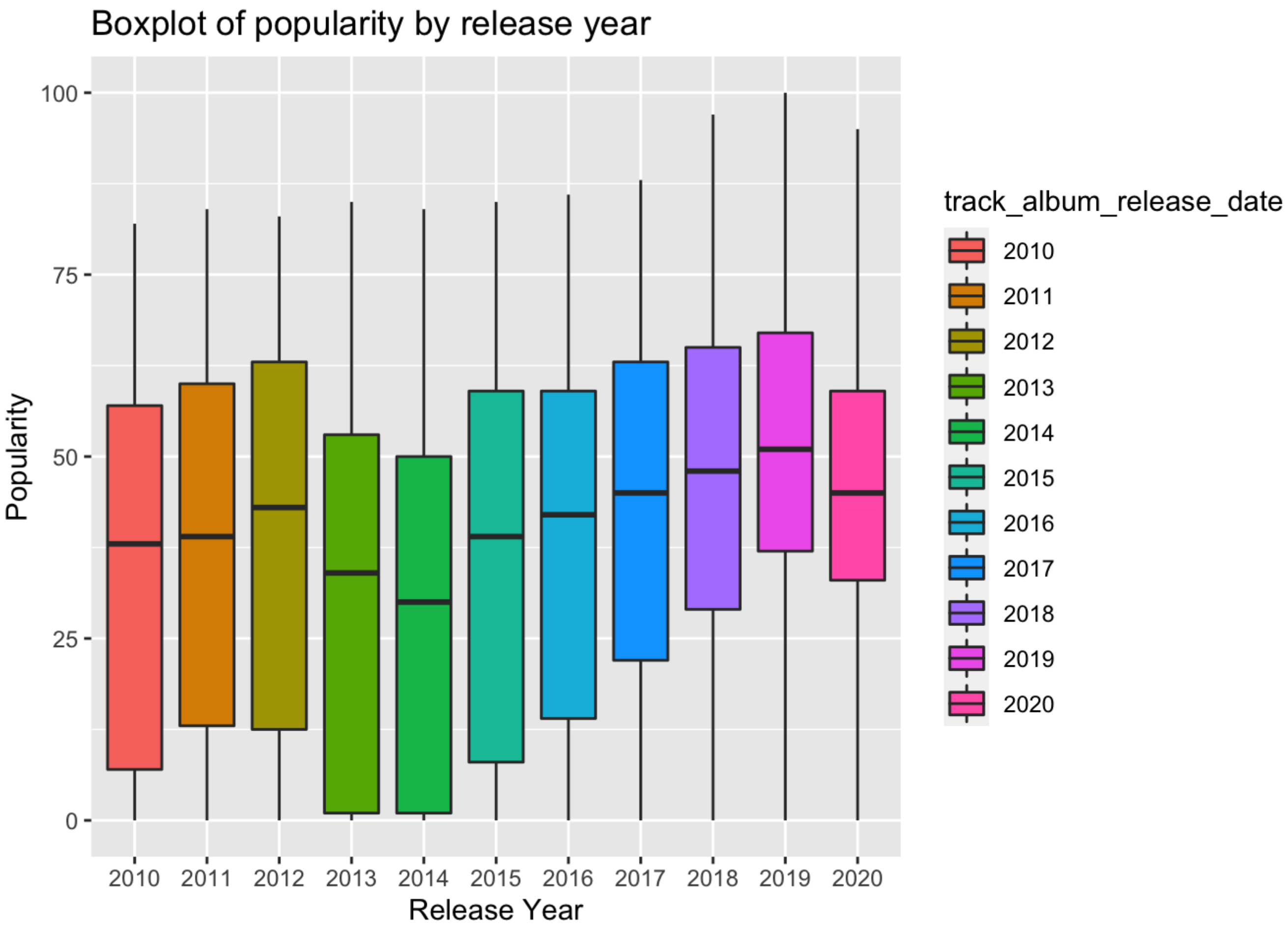
```
plot(x = df$energy, y = df$valence,
     pch = 19,
     col = df$mode,
     xlab = 'Energy',
     ylab = 'Valence',
     main = 'Energy and Valence in their Mode')
legend("topleft",
       legend = c('Major', 'Minor'),
       pch = 19,
       col = c('black', 'red'))
```



Generally it is quite evenly spread I would argue that major does not mean happy and minor does not mean sad. On the left there are some outliers, they are mostly minor with a high valence but just a low energy. This does not necessarily mean the modes determine the positivity of the songs.

I wanted to look at the track popularity with each year between 2010 - 2020, for this I did a boxplot

```
#Picking out release dates with years between 2010 - 2020
OOs <- df %>%
  filter(track_album_release_date %in% c("2010", "2011", "2012", "2013", "2014", "2015", "201
6", "2017", "2018", "2019", "2020"))



#Boxplot
OOs %>%
  ggplot(aes(x = track_album_release_date, y = track_popularity, fill = track_album_release_dat
e)) +
  geom_boxplot() +
  labs(y="Popularity", x="Release Year") +
  ggtitle("Boxplot of popularity by release year")
```



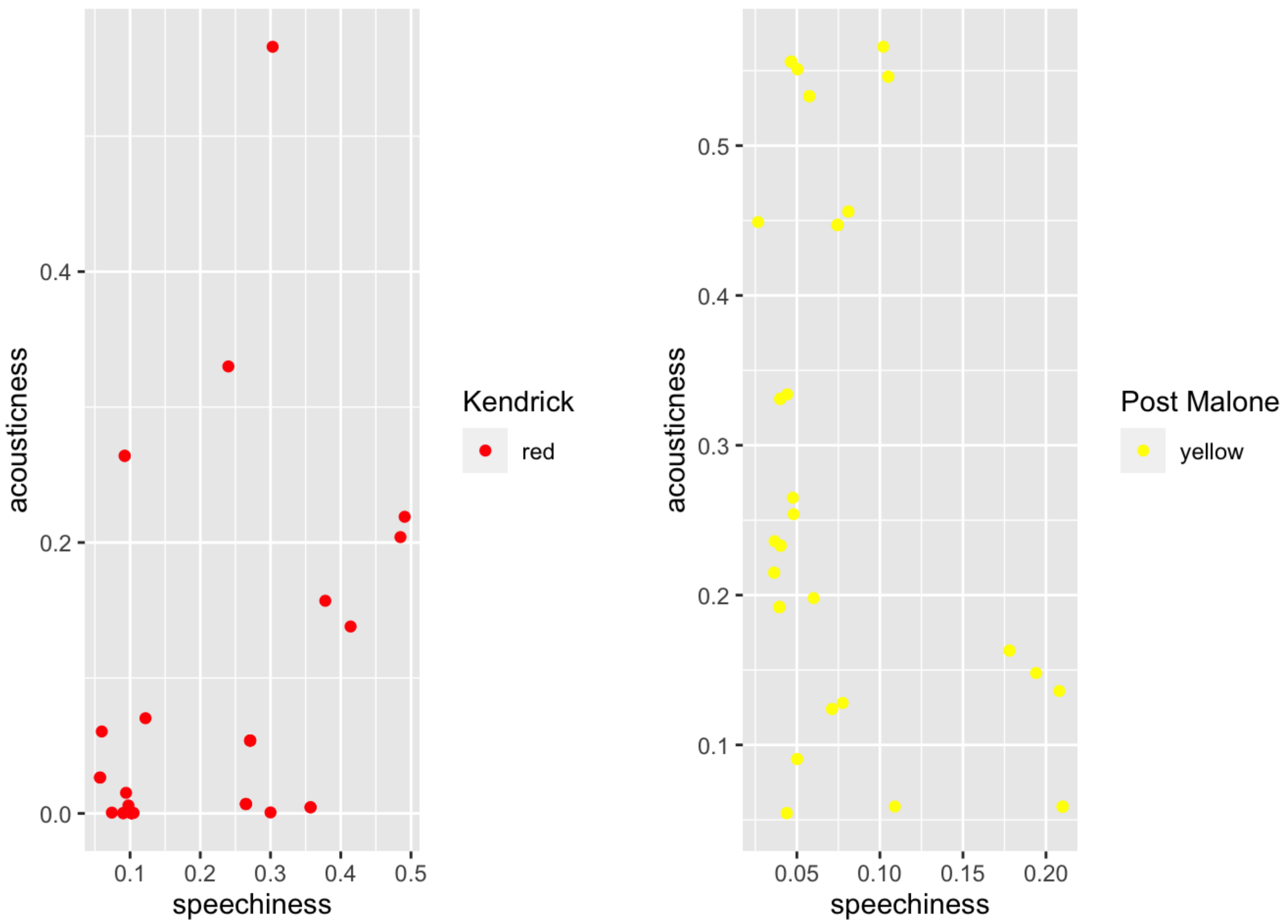
It is close between 2019 and 2012 but judging from the graph 2019 seems to be the most popular year with one of the smallest variances.

In the Rap/Hip-Hop world there are people that dominate. Two of my all time favorites are Kendrick Lamar and Post Malone. Kendrick is considered to be a lyrical genius constantly creating music and winning many awards. Post Malone is similar. Post Malone gets grouped into the Rap/Hip Hop genre all the time however there is a big debate whether he belongs there or not. I thought it would be interesting to compare acousticness, speechiness and BPM between the 'King of Compton' and Post Malone.

```
#Gathering data with the artist being Kendrick
df %>%
  filter(track_artist == 'Kendrick Lamar') -> kendrick

#Gathering data with the artist being Post Malone
df %>%
  filter(track_artist == 'Post Malone') -> posty
```

Now we have each artist's data lets look at their graphs

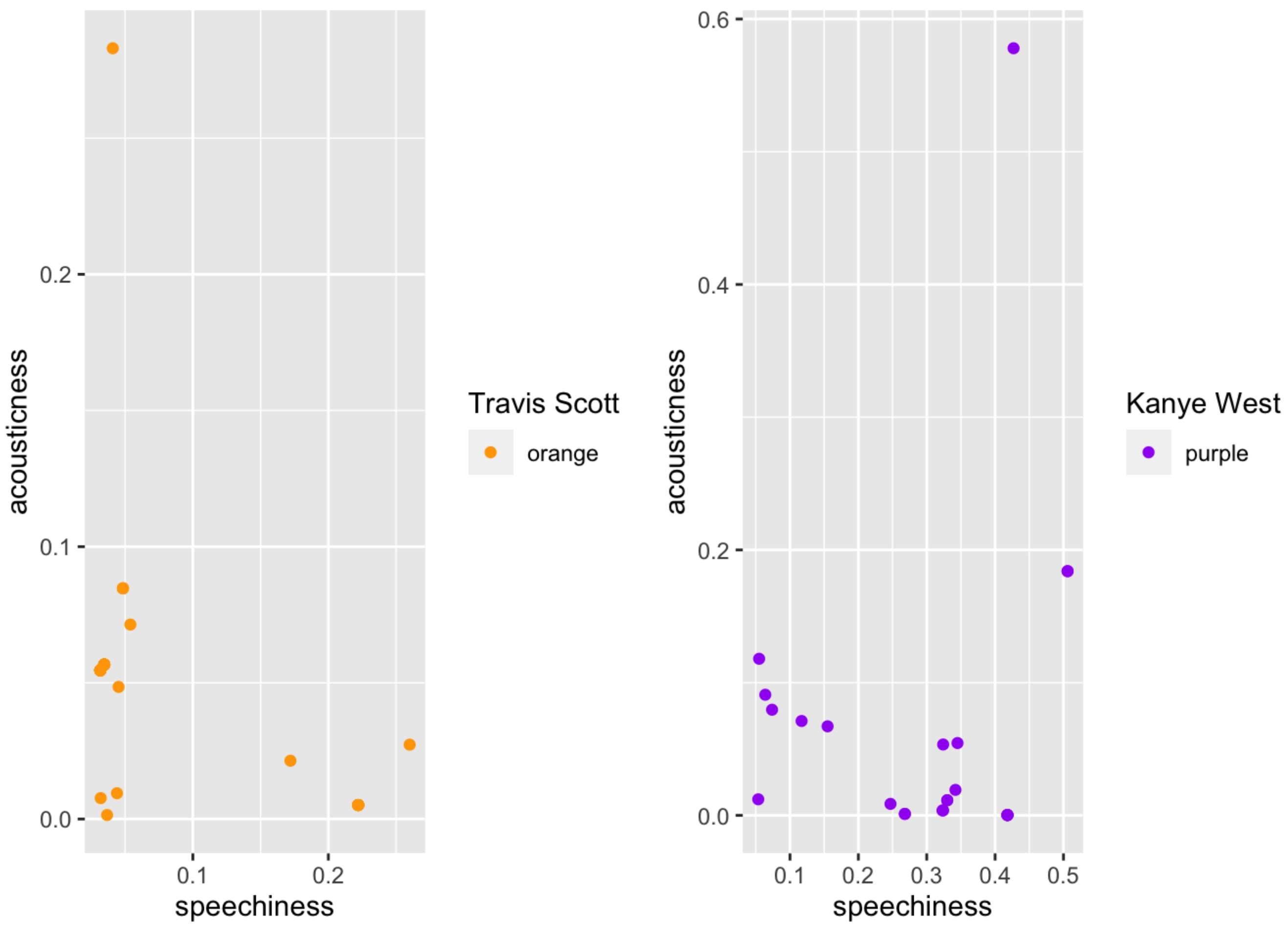
```
#Plotting speechiness against acousticness for Kendrick
kendrick %>%
  ggplot(aes(x = speechiness, y = acousticness)) +
  geom_point(aes(color = 'red')) +
  scale_color_manual(name = "Kendrick", values = 'red') -> kenplot


#Plotting speechiness against acousticness for Post
posty %>%
  ggplot(aes(x = speechiness, y = acousticness)) +
  geom_point(aes(color = "yellow")) +
  scale_color_manual(name = "Post Malone", values = 'yellow') -> postplot




#Displaying the 2 plots against each other
plot_grid(kenplot, postplot, ncol=2,   align = "v", axis = "lr")
```



So from the graphs, we can see Kendrick is more lyrical and Post Malone is more accoustic. Lyrical songs are a characteristic of rap and although rappers can use accoustics in their tracks however it is not as common as rock or pop.

We are only comparing Post Malone to one rapper. Let us look at some more rappers with these characteristics. We will look at Kanye West and Travis Scott, two massive names in rap

```
#Gathering data with the artist being Drake
df %>%
  filter(track_artist == 'Travis Scott') -> travis


travis %>%
  ggplot(aes(x = speechiness, y = acousticness)) +
  geom_point(aes(color = 'orange')) +
  scale_color_manual(name = "Travis Scott", values = 'orange') -> traplot


#Gathering data with the artist being Kanye
df %>%
  filter(track_artist == 'Kanye West') -> kanye

kanye %>%
  ggplot(aes(x = speechiness, y = acousticness)) +
  geom_point(aes(color = 'purple')) +
  scale_color_manual(name = "Kanye West", values = 'purple') -> kanyeplot


plot_grid(traplot, kanyeplot,
          ncol=2,   align = "v", axis = "lr")
```



As you can see these are similar to Kendrick. There is a common trend here one that Post Malone does not follow.

I think it is fair to say based on these graphs Post Malone on paper at least shouldn't be considered a rapper. I think he is more in another genre. I think his accousticness is too much for the rap genre. On a personal note I do agree, I feel Post Malone is very melodic compared to rappers in industry today.

This concludes my analysis of the Spotify dataset. I picked this as I love music and wanted to look at some statistics beyond just popularity or who has the most songs. I think we answered our questions at the beginning plus a few extra in between.