MH3511 Data Analysis with Computer
Group Project

Numbers in Spotify and YouTube: Views, Likes and Streams

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Abstract:

The way that people listen to music has changed drastically in this digital age. Streaming giants like Spotify have become many users' go-to platforms for instant music gratification due to their large libraries of music. However, YouTube, a platform that is traditionally known for its video streaming popularity, has notably become a significant factor in music discovery and consumption, especially in the form of music videos. This intriguing dynamic poses a question to determine if there is a correlation between a song's performance on YouTube and its performance on Spotify. By measuring statistics from an artist's top songs, we aim to find any relationship between these two popularity measurements.

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1. Introduction

Music has seen a significant shift in recent times from old record DVDs to now digital music being streamed on multiple platforms such as Spotify and YouTube. Spotify, primarily being an audio and media service provider, provides more than 602 million users with millions of songs from creators all over the world. On the other hand, YouTube, an American online video-sharing and social media platform offers a broad range of content including music videos. This poses an interesting question if there is a correlation between a song's streams on Spotify with its corresponding YouTube music video.

In our project, a dataset containing the statistics for the Top 10 songs of various Spotify artists and their respective YouTube music videos as of 7th February 2023. Based on this dataset, we aim to answer the following questions around artists' songs:

1. Does the views of YouTube music videos have a correlation to the number of streams on Spotify? (JH)
2. Do songs on Spotify without music videos on Youtube gain as much popularity as those with music videos? (Oscar)
3. Does a song's Spotify streams depend on the Tempo of the song? (Zane)
4. Is there a single song characteristic that is more important in affecting the streams of the song? (Iain)

This report will cover the data descriptions and analysis using R language. For each of our research objectives, we performed statistical analysis and concluded the most appropriate approach, together with explanations and elaborations.

2. Data Description and Variable Selection

The dataset, titled "Spotify and Youtube", is obtained from the online community of data scientists and machine learning engineers, Kaggle. The original CSV titled "Spotify_Youtube.csv" consists of 20718 songs and 26 variables for each song.

Before proceeding to data analysis, we first performed a preliminary data cleaning to ensure that:

- There are no NULL values for each of the columns pertaining to Spotify:
- …

After all the preparation, 20718 observations (songs) with 17 variables are retained for analysis:

1. Artist
2. Album_type
3. Danceability
4. Energy
5. Key (explain with ref to kaggle dataset, each number correspond to 1 key)
6. Loudness
7. Speechiness
8. Acousticness
9. Valence

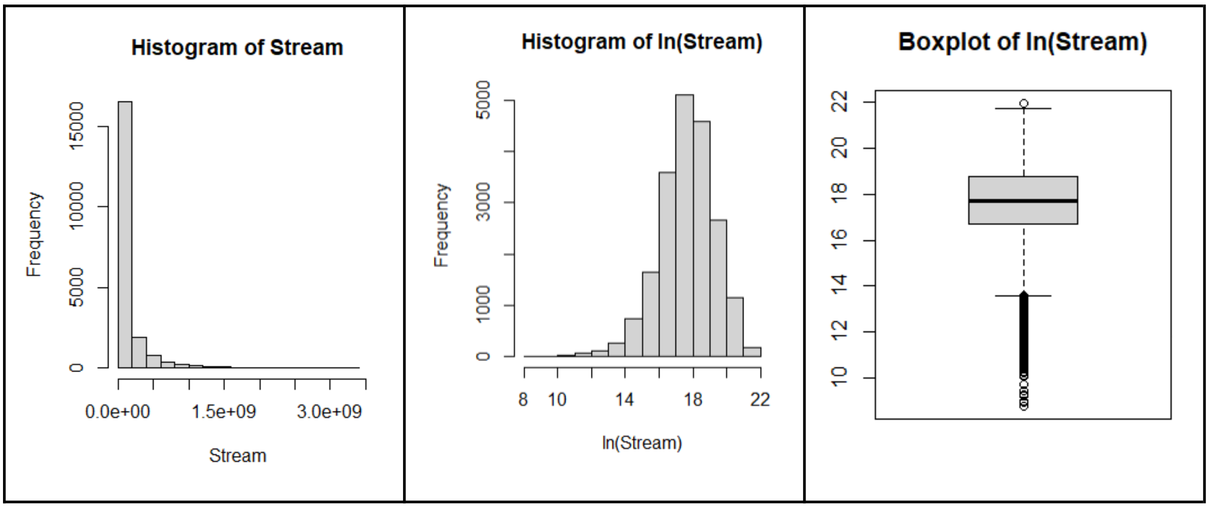
10. Tempo
11. Duration_ms
12. Views
13. Likes
14. Comments
15. Licensed
16. official_video
17. Stream

3. Description and Cleaning of Dataset

In this section, we shall look into the data in more detail. Each variable is investigated individually to look for possible outliers, and/or to perform a transformation to avoid highly skewed data.

3.1. Summary statistics for the main variable of interest, *Stream*

The following plots show the overall distribution of the variable *Stream.*

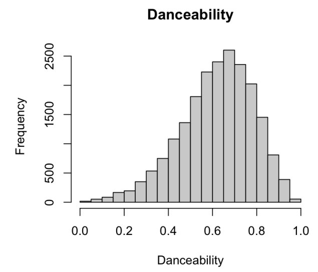


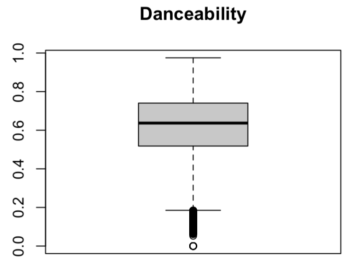
It appears that the variable Stream is highly skewed, hence we apply a log-transformation (base *e*) to the variable. The log-transformed data appears to have some outlying values at the left tail.

3.2. Summary statistics for other variables

The histogram, the boxplot, the transformation applied and the outliers removed from the variables are tabulated in the following subsections.

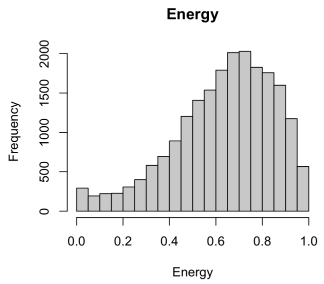
3.2.1 Danceability

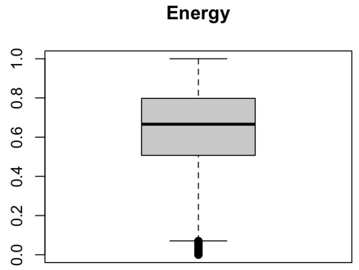




- 2 missing values of *Danceability* are removed

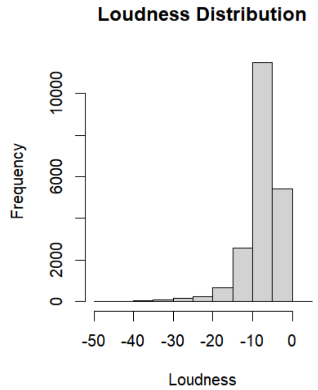
3.2.2 Energy

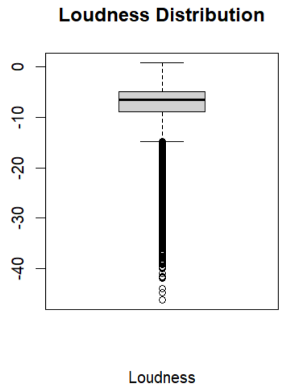




- 2 missing values of *Energy* are removed

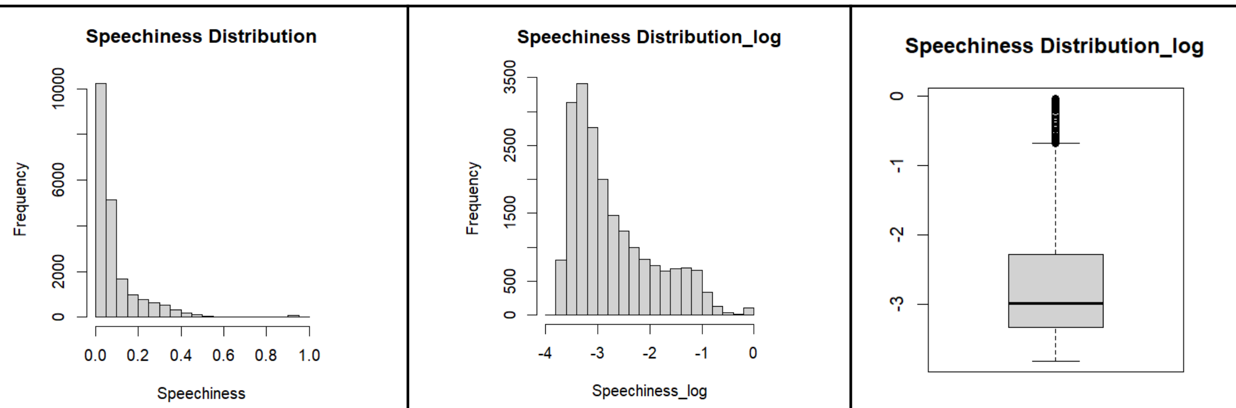
3.2.3 Loudness





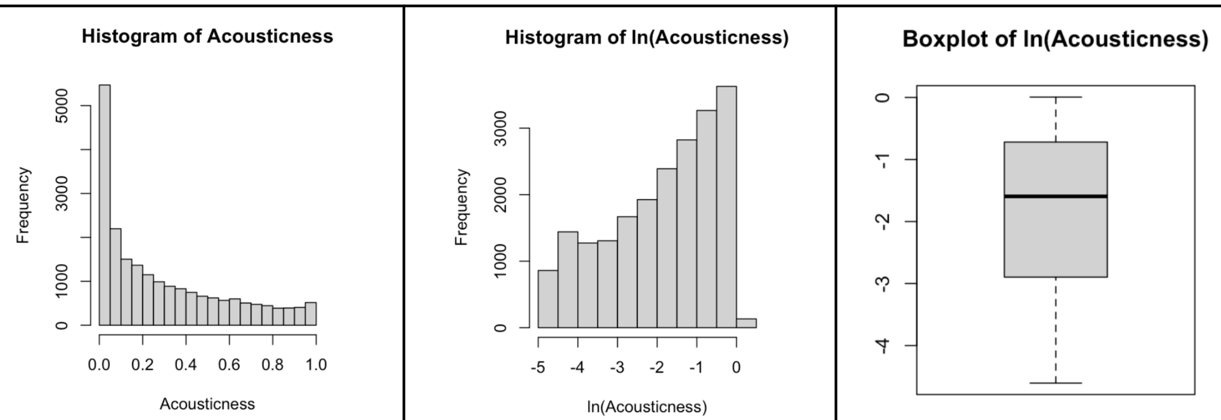
- 2 missing values of *Loudness* are removed

3.2.4 Speechiness



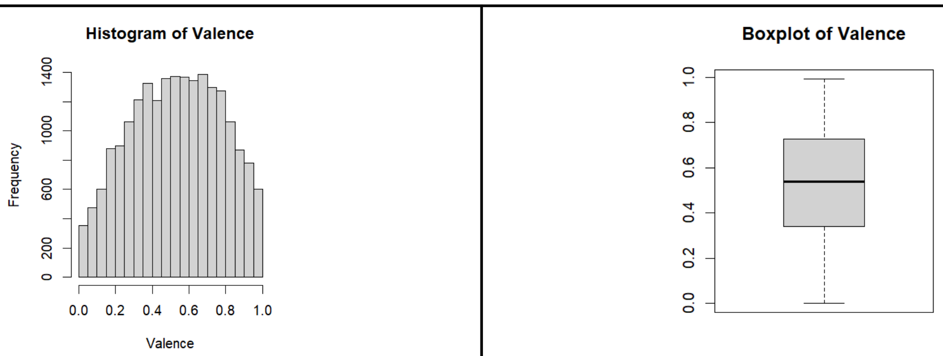
- The log-transformation (base *e*) is applied
- 2 missing values of *Speechiness* are removed

3.2.5 Acousticness



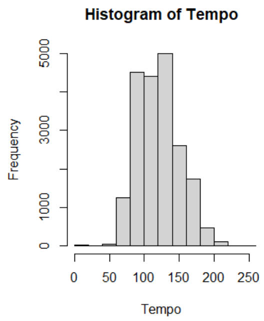
- The log-transfomation (base *e*) is applied
- 2 missing values of *Acousticness* are removed

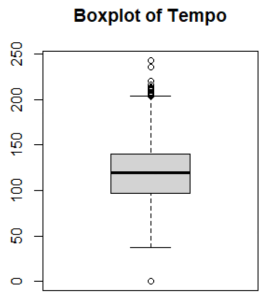
3.2.6 Valence



- 2 missing values of *Valence* are removed

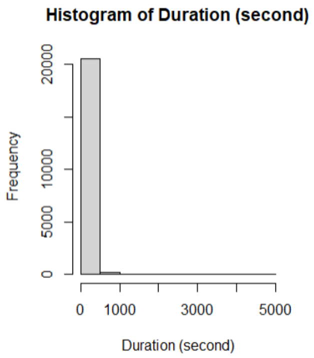
3.2.7 Tempo

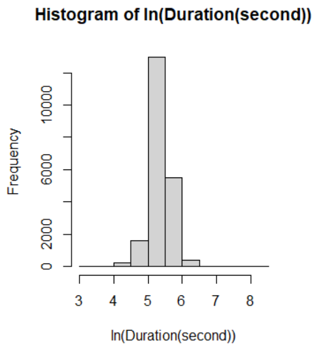


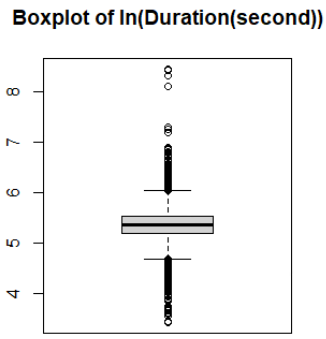


- 2 missing values of *Tempo* are removed

3.2.8 Duration(second)

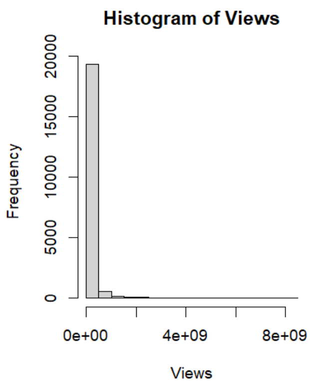


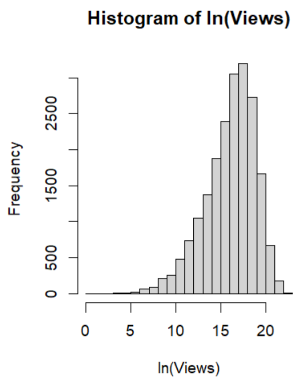


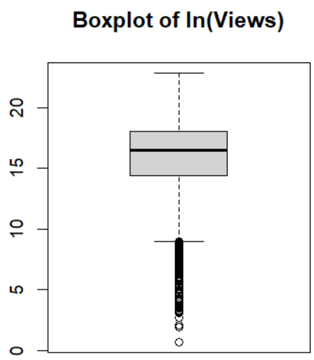


- The log-transfomation (base *e*) is applied
- 2 missing values of *Duration* are removed

3.2.9 Views

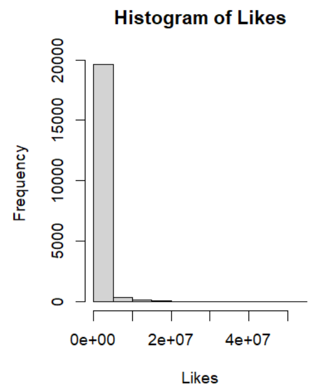


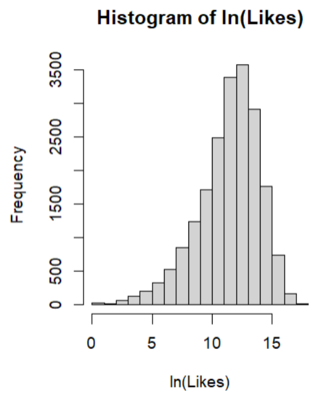


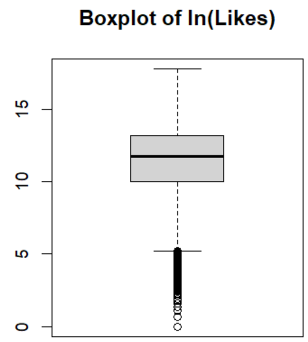


- The log-transformation (base e) is applied
- 569 missing values of *Views* are removed

3.2.10 Likes

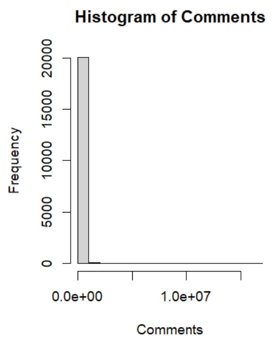


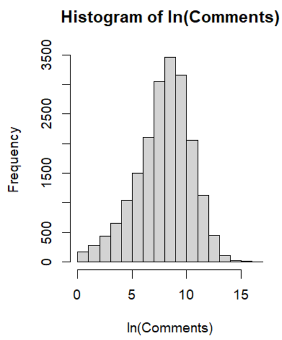


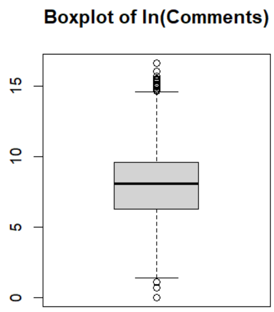


- The log-transformation (base e) is applied
- 569 missing values of *Likes* are removed

3.2.11 Comments

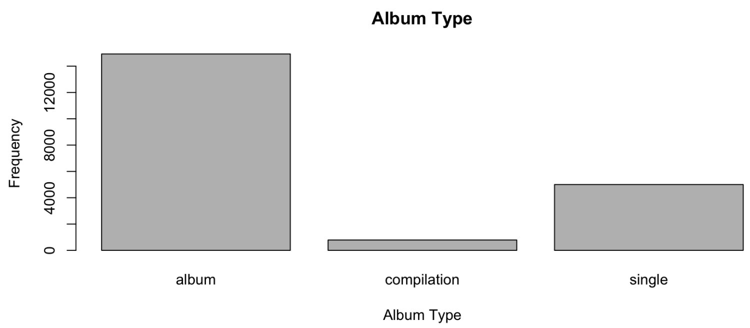






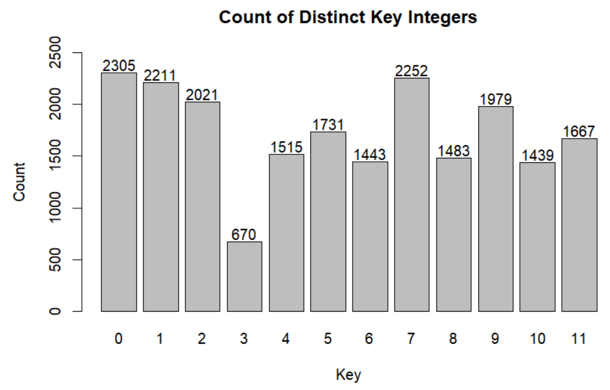
- The log-transformation (base e) is applied
- 569 missing values of *Comments* are removed

3.2.12 Album_type



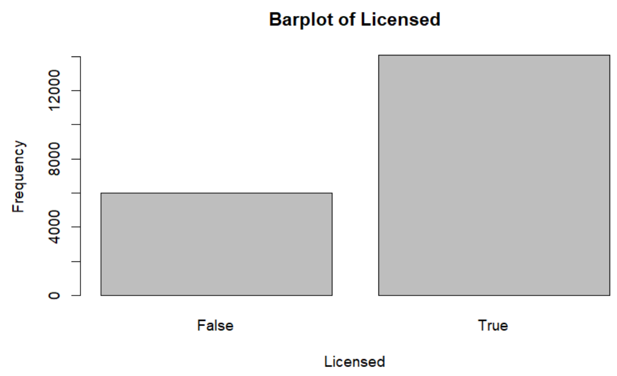
- No data cleaning is performed

3.2.13 Key



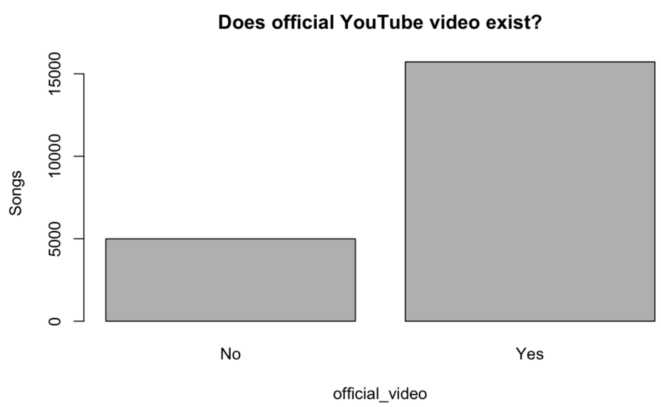
- 2 missing values of *Key* are removed

3.2.14 Licensed



- 569 missing values of *Licensed* are removed

3.2.15 official_video



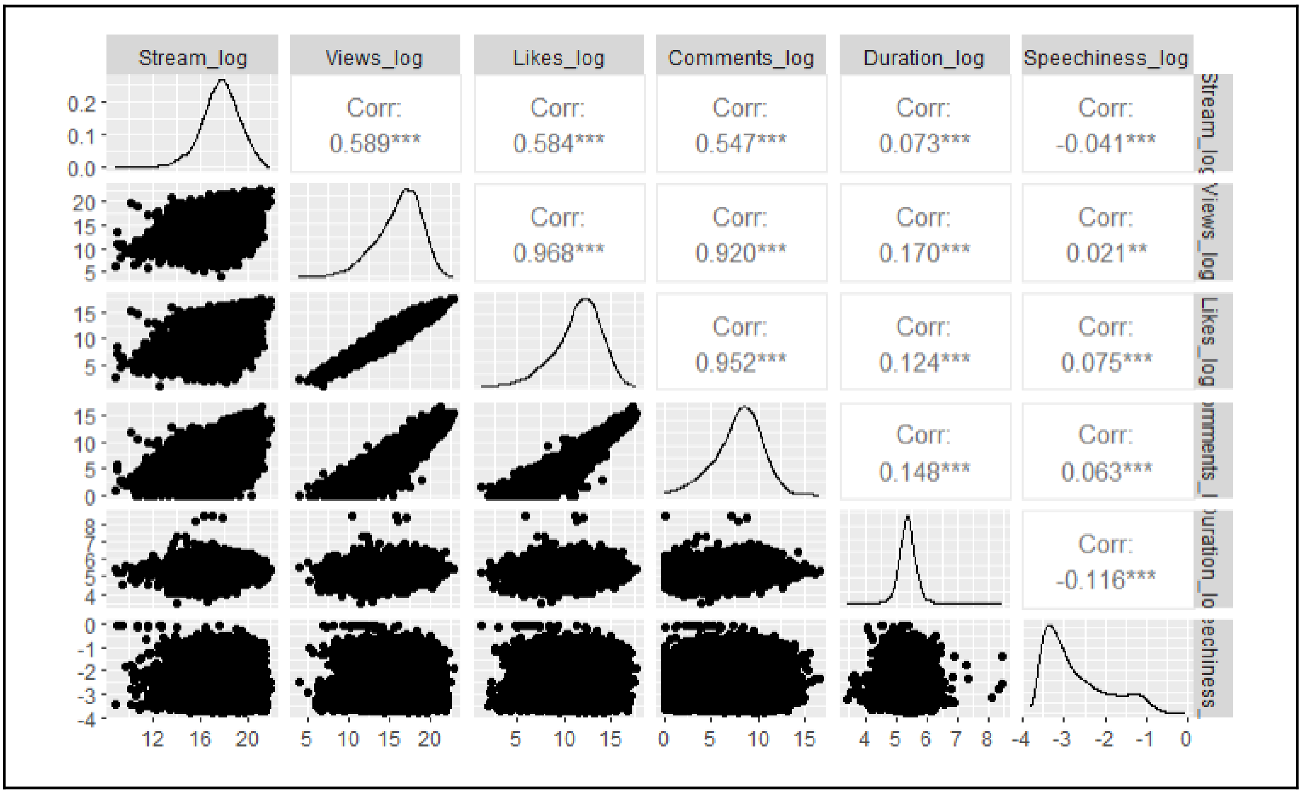
- 2 missing values of *official_video* are removed

4. Statistical Analysis

4.1 Correlations between ln(*Stream*) and other Continuous Variables

Scatter plots and correlation coefficients are useful in studying the possible linear relationships between a song's stream count and other variables.

Here we will investigate the correlation of *log(Stream)* with *log(Views), log(Likes), log(Comments), log(Duration(second)), log(Speechiness).*

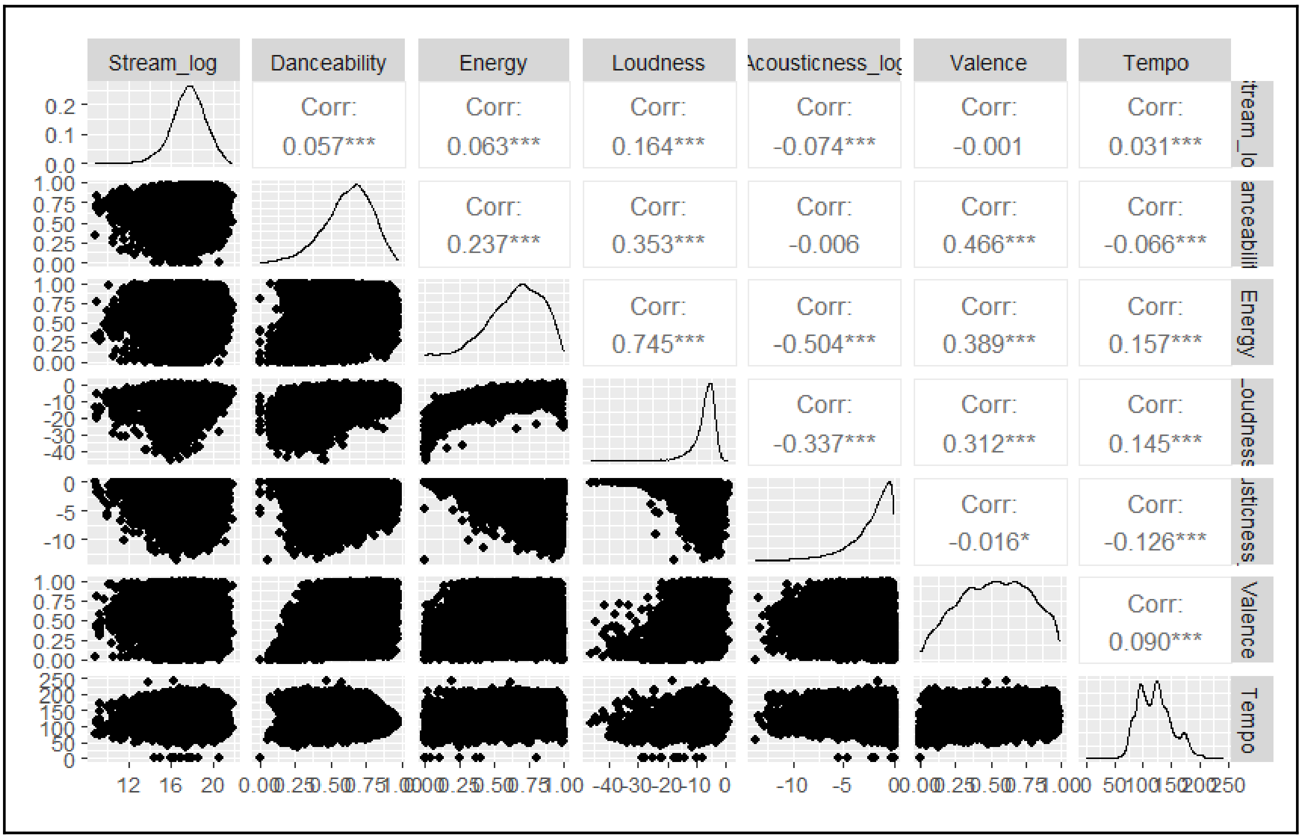


From the plots, it appears that *log(Stream)* is more correlated with *log(Views), log(Comments)* and *log(Likes)* than other variables.

Among the variables, there are a few interesting observations from this tabulation:

- *log(Views)* and *log(Likes)* are highly positively correlated (= 0.968)
- *log(Views)* and *log(Comments)* are highly positively correlated (= 0.920)
- *log(Likes)* and *log(Comments)* are highly positively correlated (= 0.952)

Next, we investigated the correlation of *log(Stream)* with, *Danceability, Energy, Loudness, log(Acousticness), Valence, Tempo.*



From the plots, it appears that *log(Stream)* has a weak correlation with each audio feature, which is expected as there are many different factors influencing the likeability of the song, thus affecting its stream numbers.

Among the variables, there are a few interesting observations from this tabulation:

- *Loudness* and *Energy* are highly correlated (= 0.745)
- *Loudness* and *log(Acousticness)* are inversely correlated (= -0.504)
- *Danceability* and *Valence* are correlated (= 0.466)

4.2 Statistical Tests

4.2.1 YouTube Views vs Spotify Streams

In this section, we try to answer the question "Do songs tend to accumulate more Views on YouTube compared to Streams on Spotify?"

Since the size of the dataset is large (>30), we can assume CLT. The mean of Views and Streams is normally distributed.
Hence, we will perform a pairwise t-test to investigate the two hypotheses:

$$H_0: \mu_1 = \mu_2 \quad \textit{against} \quad H_1: \mu_1 > \mu_2$$

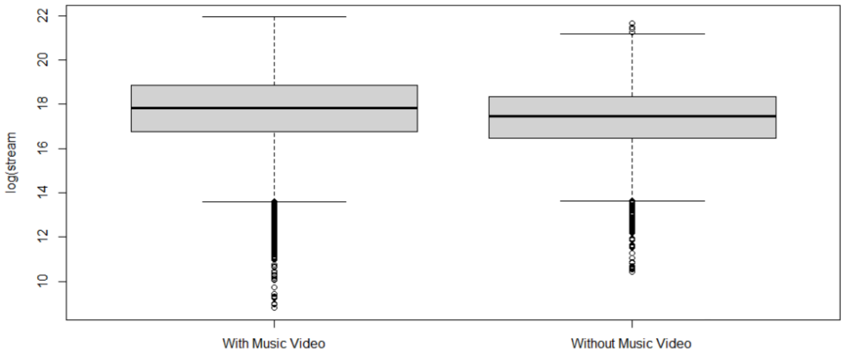
```
        Paired t-test

data:  clean_data$log_Stream and clean_data$log_Views
t = 98.315, df = 19531, p-value < 2.2e-16
alternative hypothesis: true mean difference is greater than 0
95 percent confidence interval:
 1.53182      Inf
sample estimates:
mean difference
       1.557885
```

The p-value obtained is less than 2.2e-16, with $\alpha = 0.05$, we reject H_0 in favour H_1 of as there is enough evidence to conclude that the mean of Stream is larger than mean of Views

4.2.2 Relation between Streams and Music Video

In this section, we try to answer the question "Do songs on Spotify without music videos on YouTube gain as much popularity as those with music videos?"

A Welch two-sample t-test will be conducted to determine whether the log(Stream) is different for songs with or without music videos. The following plot illustrates the distribution of log(Stream) grouped by music video.



Looking at the boxplot, we see that both groups seem to be normally distributed. Hence, the one-tailed Welch two-sample t-test is appropriate for testing:

$$H_0: \mu_1 = \mu_2 \quad against \quad H_1: \mu_1 > \mu_2$$

We first performed an F-test to check if the variance of log(Stream) of the 2 groups is equal or not and concluded that variances are not equal according to the result shown below.

```
        F test to compare two variances

data:  official_video$log_Stream and non_official_video$log_Stream
F = 1.1215, num df = 15244, denom df = 4286, p-value = 3.573e-06
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 1.068678 1.176187
sample estimates:
ratio of variances
          1.121511
```

We then conducted a one-tailed t-test assuming variance to be not equal.

```
        Welch Two Sample t-test

data:  official_video$log_Stream and non_official_video$log_Stream
t = 14.785, df = 7214, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.3605478       Inf
sample estimates:
mean of x mean of y
 17.73451  17.32882
```

The p-value obtained is 2.2e-16. Therefore, we rejected H_0 at α = 0.05. Thus, we can conclude that songs on Spotify with music videos are more popular than songs without.

4.2.3 Relation between Streams and Tempo

In this section, we try to answer the question "Does a song's Spotify streams depend on the Tempo of the song?".

A Pearson's product-moment correlation test is conducted to check if log(Stream) depends on Tempo, we then test:

$$H_0: \rho = 0 \quad against \quad H_1: \rho \neq 0$$

Where ρ is the correlation coefficient between log(Stream) and Tempo.

The correlation test is conducted with the following results:

```
        Pearson's product-moment correlation

data:  data$log_Stream and data$Tempo
t = 4.1966, df = 19530, p-value = 2.722e-05
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.01599804 0.04402128
sample estimates:
       cor
0.03001556
```

The p-value obtained is 2.722e-05. Therefore, we rejected H_0 at α = 0.05. Thus, we can conclude that $\rho \neq 0$, and that log(Stream) and Tempo are correlated.

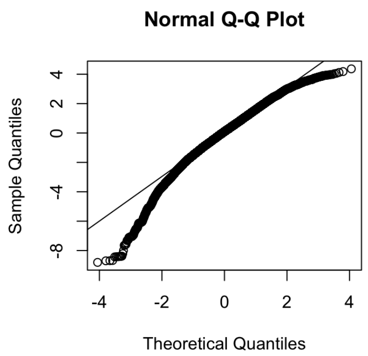
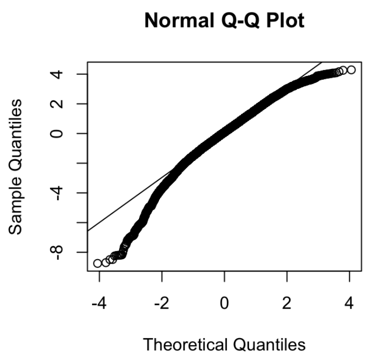
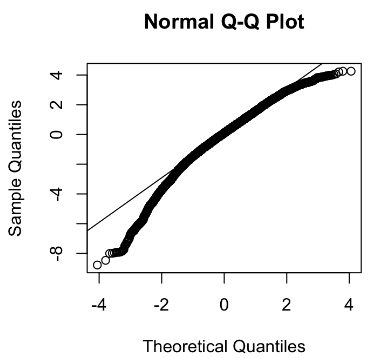
4.2.4 The single most important song characteristic that is affecting streams

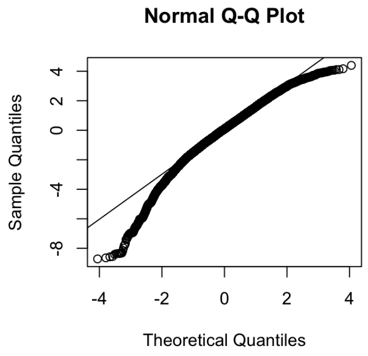
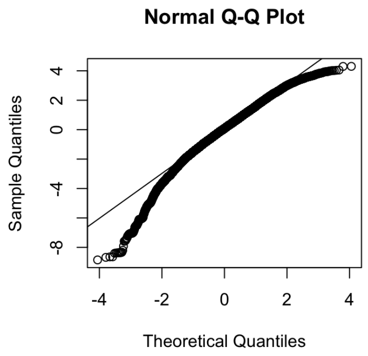
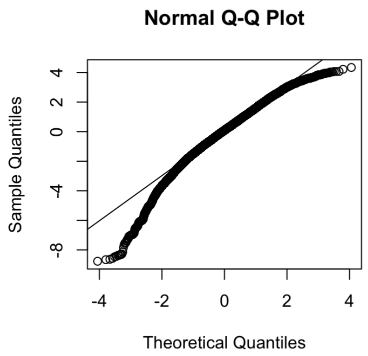
In this section, we try to answer the question "Is there a single song characteristic that is more important in affecting the streams of the song?" We now will perform a single linear regression analysis to determine which of the 5 musical characteristics could be used to model log(stream) linearly.

$$log(Stream) = \beta_0 + \beta_1 * X + \varepsilon$$

where X could be any one of Danceability, Energy, Loudness, log(Accounsticness), Valence or Tempo. The summary of the analysis is listed in the table below.

By comparing the R-squared and the residual plot, Loudness is determined to be the single most important song characteristic to model the log(Stream) using a simple linear model.

Variable (X)	Fitted Model, with Y being log(Stream)	p-value	R-squared	QQ-plot of residuals
Danceability	$\hat{Y} = 17.29 + 0.569X$	4.587e-16	0.003270	
Energy	$\hat{Y} = 17.33 + 0.4885X$	1.966e-19	0.004028	
Loudness	$\hat{Y} = 18.09 + 0.05841X$	6.834e-122	0.02700	

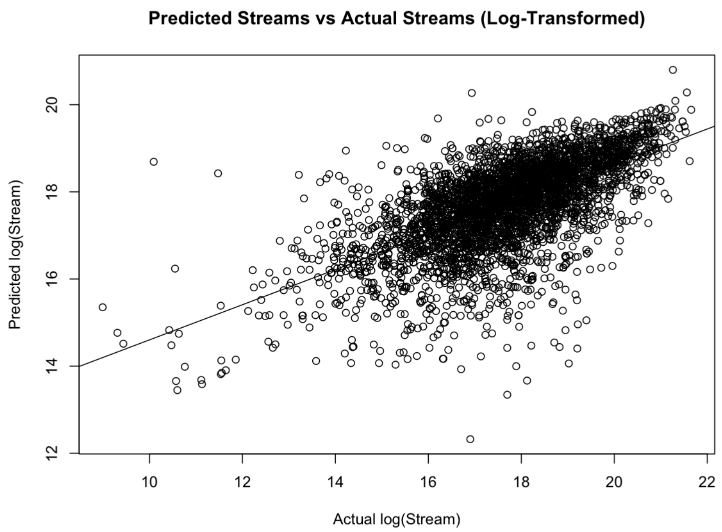
log(Acousticness)	$\hat{Y} = 17.51 - 0.06003X$	1.130e-25	0.005433	
Valence	$\hat{Y} = 17.64 - 0.004937X$	0.9169	5.405e-07	
Tempo	$\hat{Y} = 17.43 + 0.001724$	1.101e-05	0.0009593	

4.3 Multiple Linear Regression

Recognising the plethora of variables affecting Streams, we will build a Multi-Linear Regression (MLR) model (See Appendix). From our initial MLR model, we have identified variables that were more significant ($p<0.05$) in predicting the value of $log(Stream)$ and used them to construct a less erroneous model *(RMSE of 1.26)* with its respective coefficients. The model is as follows:

$$log(Stream) = 13.94 - 0.54(Energy) + 0.02(Loudness) - 0.16(log(Speechiness)) \\ - 0.05(log(Acousticness)) - 0.17(Valence) - 0.15(log(Duration)) \\ + 0.10(log(Views)) + 0.38(log(Likes)) - 0.05(log(Comments)) \\ - 0.30(Album\_type) - 0.64(official\_video) + \varepsilon$$

```
> # Predict results of the test set using our trained model
> test$predicted_log_Stream = predict(linreg_significant,test)
>
> # Plot Actual and Predicted log(Streams)
> plot(test$log_Stream,test$predicted_log_Stream,xlab = "Actual log(Stream)", ylab = "Predicted log(Stream)", main = "Predi
cted Streams vs Actual Streams (Log-Transformed)")
>
> # Plot a best fit line
> abline(lm(test$predicted_log_Stream~test$log_Stream))
```




```
> # Calculate residuals
> residuals <- test$log_Stream - test$predicted_log_Stream
>
> # Square the residuals
> squared_residuals <- residuals^2
>
> # Calculate mean squared residuals
> mean_squared_residuals <- mean(squared_residuals)
>
> # Calculate RMSE
> rmse <- sqrt(mean_squared_residuals)
>
> print(rmse)
[1] 1.263613
```

5. Conclusion and Discussion

In the realm of audio entertainment, the intersection of music and video content has become a pivotal arena for attracting audiences and generating revenue. The Spotify and YouTube dataset, offering insights as recent as February 2023, presents a rich tapestry of information that underscores the dynamic characteristics of songs and the music industry. As the music and video streaming platforms continue to evolve, understanding the factors influencing viewership, engagement, and content performance is crucial for stakeholders seeking to adapt and thrive in this competitive landscape. In this report, we delve into the analysis of the Spotify YouTube dataset, aiming to shed light on key aspects related to music streams, music video views, and the evolving digital media ecosystem.

We conclude that:

- Songs tend to have a higher number of Views on YouTube than Streams on Spotify
- Songs on Spotify with music videos are more popular than songs without
- The number of Spotify streams of a song depends on its tempo

Additionally, we found that although loudness had the highest significance in affecting a song's Spotify streams, it is still considerably weak and does not fully represent the most important audio feature that can accurately model a song's streams. As such, we conclude that each audio feature alone does not have a significant impact on the number of streams of a song. The true factor could be a combination of audio features, semantic meaning, social media trends and artist fanbase.

Although the results are intriguing, it must be noted that this report is only based on the top 10 songs of each artist. By focusing on the top 10 songs of each artist, we may have missed out on a broader understanding of each artist's discography or the overall music landscape. Additionally, the top 10 songs may not be representative of an artist's entire body of work. A wider analysis will still be required to fully understand the factors affecting a song's popularity.

6. Appendix

```
> # # Installation of packages
> # install.packages("caTools")
> # install.packages("GGally")
> library(caTools)
Warning: package ‘caTools’ was built under R version 4.3.3
> library(tidyr)
Warning: package ‘tidyr’ was built under R version 4.3.3
> library(GGally)
Warning: package ‘GGally’ was built under R version 4.3.3Loading required
package: ggplot2
Warning: package ‘ggplot2’ was built under R version 4.3.3Registered S3 method
overwritten by 'GGally':
  method from
  +.gg   ggplot2
>
> #################### For .Rmd file ####################
> # Data set source:
> data = read.csv("Spotify_Youtube.csv", header = T) # <- uncomment if run on
.Rmd file
>
> #################### For .R file ####################
> # Data set source:
> # data = read.csv("# insert filepath here #", header = T) # <- uncomment if run
on .R file
> # Drop unused columns
> column_to_drop = c("Url_spotify", "Track", "Album", "Uri", "Url_youtube",
"Title", "Channel", "Description")
> data = data[,!(names(data) %in% column_to_drop)]
>
> ########## For .R file ##########
> # check for na in the official_video column, if there is, assign it to "FALSE"
> # data[is.na(data$official_video),]$official_video = "FALSE" #<- uncomment if
run on .R file
>
> ########## For .Rmd file ##########
> # check for empty string in the official_video column, if there is, assign it
to "FALSE"
> data[which(data$official_video == ""),]$official_video = "FALSE" #<- uncomment
if run on .Rmd file
>
> # convert official_video to boolean
> data$official_video = as.logical(data$official_video) # Cast as Boolean
(Logical)
>
> # Acousticness, Instrumentalness, Liveness
> # Since number of NA values is small compared to number of data points, remove
them
> # Instrumentalness, Liveness excluded from analysis
> clean_data = data %>% drop_na(c("Acousticness", "Instrumentalness",
"Liveness"))
>
> # Logit-transform Function to transform values heavily skewed to 0
> logit = function(x) {log(x / (1 - x))}
>
> # Logit-transform Acousticness
> clean_data$log_Acousticness = logit(clean_data$Acousticness)
>
> c("Danceability", "Energy", "Valence", "Tempo", "Duration(second)", "Views",
"Likes", "Comments", "Album_type", "Licensed")
```

```
 [1] "Danceability"     "Energy"            "Valence"           "Tempo"
"Duration(second)"
 [6] "Views"            "Likes"             "Comments"          "Album_type"
"Licensed"
>
> # Key, Loudness, Speech, Valence
> key_row_todrop <- clean_data[is.na(clean_data$Key) | clean_data$Key == -1 ,]
> loudness_row_todrop <- clean_data[is.na(clean_data$Loudness),]
> speech_row_todrop <- clean_data[is.na(clean_data$Speechiness) |
clean_data$Speechiness < 0 | clean_data$Speechiness > 1,]
> valence_row_todrop <- clean_data[is.na(clean_data$Valence) | clean_data$Valence
< 0.0 | clean_data$Valence > 1.0,]
> rows_todrop <- unique(rbind(key_row_todrop$X, loudness_row_todrop$X,
speech_row_todrop$X, valence_row_todrop$X))
> clean_data <- clean_data[!clean_data$X %in% rows_todrop,]
>
> # Logit-transform Speechiness
> clean_data$log_Speechiness = logit(clean_data$Speechiness)
> clean_data = subset(clean_data, !is.infinite(log_Speechiness)) # Remove
infinite
>
> # Views, Likes, Comments, Licensed
> # drop rows in data_sub with null values
> clean_data = clean_data %>% drop_na(c("Views", "Likes", "Comments",
"Licensed"))
>
> # log transform
> clean_data$log_Views = log1p(clean_data$Views)
> clean_data$log_Likes = log1p(clean_data$Likes)
> clean_data$log_Comments = log1p(clean_data$Comments)
> clean_data
>
> # Tempo, Duration_ms
> # Drop NA
> clean_data = clean_data %>% drop_na(c("Tempo", "Duration_ms", "Stream"))
> clean_data
>
> # convert ms to seconds
> clean_data$Duration_s <- clean_data$Duration_ms/1000
>
> # Log-Transform
> clean_data$log_Duration_s = log(clean_data$Duration_s)
>
> # Dependent Variable: Stream
> # Drop all NA in Streams
> clean_data = clean_data %>% drop_na(Stream)
>
> # Normalising Streams (Log-transform)
> clean_data$log_Stream = log(clean_data$Stream)
>
> # Check summary and types of variables
> summary(clean_data)
       X              Artist           Album_type         Danceability
Energy              Key
 Min.   :    0   Length:19532       Length:19532       Min.   :0.0532   Min.
:0.0000203   Min.   : 0.000
 1st Qu.: 5212   Class :character   Class :character   1st Qu.:0.5200   1st
Qu.:0.5090000   1st Qu.: 2.000
 Median :10432   Mode  :character   Mode  :character   Median :0.6390   Median
:0.6660000   Median : 5.000
 Mean   :10408                                         Mean   :0.6216   Mean
:0.6356005   Mean   : 5.294
 3rd Qu.:15624                                         3rd Qu.:0.7420   3rd
Qu.:0.7970000   3rd Qu.: 8.000
```

```
 Max.   :20717                                         Max.   :0.9750   Max.   
:1.0000000   Max.   :11.000  
    Loudness         Speechiness       Acousticness       Instrumentalness     
Liveness     
 Min.   :-46.251   Min.   :0.02200   Min.   :0.0000011   Min.   :0.0000000   Min.   
:0.0145  
 1st Qu.: -8.765   1st Qu.:0.03570   1st Qu.:0.0444000   1st Qu.:0.0000000   1st 
Qu.:0.0940  
 Median : -6.514   Median :0.05070   Median :0.1900000   Median :0.0000023   
Median :0.1250  
 Mean   : -7.621   Mean   :0.09548   Mean   :0.2887929   Mean   :0.0546007   Mean   
:0.1911  
 3rd Qu.: -4.927   3rd Qu.:0.10400   3rd Qu.:0.4700000   3rd Qu.:0.0004253   3rd 
Qu.:0.2340  
 Max.   :  0.920   Max.   :0.96400   Max.   :0.9960000   Max.   :0.9950000   Max.   
:1.0000  
    Valence             Tempo          Duration_ms           Views            
Likes         
 Min.   :0.0000   Min.   : 37.11   Min.   :  30985   Min.   :2.600e+01   Min.   :       
0  
 1st Qu.:0.3390   1st Qu.: 97.00   1st Qu.: 180333   1st Qu.:1.920e+06   1st Qu.:   
22432  
 Median :0.5360   Median :119.97   Median : 213291   Median :1.495e+07   Median :  
128174  
 Mean   :0.5294   Mean   :120.71   Mean   : 224713   Mean   :9.553e+07   Mean   :  
670591  
 3rd Qu.:0.7250   3rd Qu.:139.95   3rd Qu.: 251973   3rd Qu.:7.156e+07   3rd Qu.:  
527366  
 Max.   :0.9930   Max.   :243.37   Max.   :4676058   Max.   :8.080e+09   Max.   
:50788652  
    Comments          Licensed          official_video      Stream          
log_Acousticness  
 Min.   :       0   Length:19532       Mode :logical   Min.   :6.574e+03   Min.   
:-13.7111  
 1st Qu.:     533   Class :character   FALSE:4287      1st Qu.:1.781e+07   1st 
Qu.: -3.0691  
 Median :    3352   Mode  :character   TRUE :15245     Median :4.980e+07   Median 
: -1.4500  
 Mean   :   27886                                      Mean   :1.371e+08   Mean   
: -1.7159  
 3rd Qu.:   14541                                      3rd Qu.:1.391e+08   3rd 
Qu.: -0.1201  
 Max.   :16083138                                      Max.   :3.387e+09   Max.   
:  5.5175  
 log_Speechiness    log_Views         log_Likes       log_Comments       Duration_s      
log_Duration_s 
 Min.   :-3.794   Min.   : 3.296   Min.   : 0.00   Min.   : 0.000   Min.   :   
30.98   Min.   :3.434  
 1st Qu.:-3.296   1st Qu.:14.468   1st Qu.:10.02   1st Qu.: 6.280   1st Qu.:  
180.33   1st Qu.:5.195  
 Median :-2.930   Median :16.520   Median :11.76   Median : 8.117   Median :  
213.29   Median :5.363  
 Mean   :-2.606   Mean   :16.088   Mean   :11.42   Mean   : 7.743   Mean   :  
224.71   Mean   :5.360  
 3rd Qu.:-2.154   3rd Qu.:18.086   3rd Qu.:13.18   3rd Qu.: 9.585   3rd Qu.:  
251.97   3rd Qu.:5.529  
 Max.   : 3.288   Max.   :22.813   Max.   :17.74   Max.   :16.593   Max.   
:4676.06   Max.   :8.450  
   log_Stream    
 Min.   : 8.791  
 1st Qu.:16.695  
 Median :17.723  
 Mean   :17.645  
 3rd Qu.:18.751  
```

```
 Max.   :21.943
> categorical = sapply(clean_data,is.character)
>
> # Convert categorical variables to numeric
> clean_data[ ,categorical] = lapply(clean_data[ ,categorical],function (x)
as.numeric(factor(x)))
> class(clean_data$Licensed)
[1] "numeric"
>
> # Independent Variables
> IV = c("Danceability", "Energy", "Loudness", "log_Speechiness",
"log_Acousticness", "Valence", "Tempo", "log_Duration_s", "log_Views",
"log_Likes", "log_Comments", "Album_type", "Key", "Licensed", "official_video")
> # Plot a Histogram distribution of mean Streams
> par(mfrow = c(1,2))
> hist(clean_data$Stream, xlab = "Streams", ylab = "Number of Songs", main =
"Histogram of Streams")
>
> # Plot a Histogram distribution of ln(Streams)
> par(mfrow = c(1,2))
> hist(clean_data$log_Stream, xlab = "ln(Streams)", ylab = "Number of Songs",
main = "Histogram of ln(Streams)")
>
> # Plot a Boxplot of ln(Streams)
> par(mfrow = c(1,2))
> boxplot(clean_data$log_Stream, xlab = "ln(Streams)", ylab = "Number of Songs",
main = "Boxplot of ln(Streams)")
> # plot histogram for Danceability in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Danceability, main = "Histogram of Danceability", xlab =
"Danceability")
>
> # plot boxplot for Danceability in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Danceability, main = "Boxplot of Danceability")
> # plot histogram for Energy in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Energy, main = "Histogram of Energy", xlab = "Energy")
>
> # plot boxplot for Energy in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Energy, main = "Boxplot of Energy")
> # plot histogram for Loudness in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Loudness, main = "Histogram of Loudness", xlab = "Loudness")
>
> # plot boxplot for Loudness in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Loudness, main = "Boxplot of Loudness")
> # plot histogram for Speechiness in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Speechiness, main = "Histogram of Speechiness", xlab =
"Speechiness")
>
> # plot histogram for log_Speechiness in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$log_Speechiness, main = "Histogram of ln(Speechiness)", xlab =
"ln(Speechiness)")
>
> # plot boxplot for Speechiness in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Speechiness, main = "Boxplot of Speechiness")
> # plot histogram for Acousticness in clean_data
> par(mfrow = c(1,2))
```

```
> hist(clean_data$Acousticness, main = "Histogram of Acousticness", xlab =
"Acousticness")
>
> # plot histogram for logit_Acousticness in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$log_Acousticness, main = "Histogram of logit(Acousticness)",
xlab = "ln(Acousticness)")
>
> # plot boxplot for logit_Acousticness in clean_data
> boxplot(clean_data$log_Acousticness, main = "Boxplot of logit(Acousticness)")
> # plot histogram for Valence in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Valence, main = "Histogram of Valence", xlab = "Valence")
>
> # plot boxplot for Valence in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Valence, main = "Boxplot of Valence")
> # plot histogram for Tempo in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Tempo, main = "Histogram of Tempo", xlab = "Tempo")
>
> # plot boxplot for Tempo in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$Tempo, main = "Boxplot of Tempo")
> # plot histogram for Duration_s in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Duration_s, main = "Histogram of Duration_s", xlab =
"Duration_s")
>
> # plot histogram for log_Duration_s in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$log_Duration_s, main = "Histogram of ln(Duration_s)", xlab =
"ln(Duration_s)")
>
> # plot boxplot for log_Duration_s in clean_data
> par(mfrow = c(1,2))
> boxplot(clean_data$log_Duration_s, main = "Boxplot of ln(Duration_s)")
> # plot histogram for Views in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$Views, main = "Histogram of Views", xlab = "Views")
>
> # plot histogram for log_Views in clean_data
> par(mfrow = c(1,2))
> hist(clean_data$log_Views, main = "Histogram of ln(Views)", xlab = "ln(Views)")
>
> par(mfrow = c(1,2))
> boxplot(clean_data$log_Views, main = "Boxplot of ln(Views)")
> par(mfrow = c(1,2))
> hist(clean_data$Likes, main = "Histogram of Likes", xlab = "Likes")
>
> par(mfrow = c(1,2))
> hist(clean_data$log_Likes, main = "Histogram of ln(Likes)", xlab = "ln(Likes)")
>
> par(mfrow = c(1,2))
> boxplot(clean_data$log_Likes, main = "Boxplot of ln(Likes)")
> par(mfrow = c(1,2))
> hist(clean_data$Comments, main = "Histogram of Comments", xlab = "Comments")
>
> par(mfrow = c(1,2))
> hist(clean_data$log_Comments, main = "Histogram of ln(Comments)", xlab =
"ln(Comments)")
>
> par(mfrow = c(1,2))
> boxplot(clean_data$log_Comments, main = "Boxplot of ln(Comments)")
```

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```
> # plot bar plot for Album_type in clean_data
> barplot(table(clean_data$Album_type), main = "Barplot of Album_type", xlab =
"Album Type", ylab = "Frequency")
> # plot bar plot for Key in clean_data
> barplot(table(clean_data$Key), main = "Barplot of Distinct Key Integers", xlab
= "Key", ylab = "Count")
> # plot bar plot for Licensed in clean_data
> barplot(table(clean_data$Licensed), main = "Barplot of Licensed", xlab =
"Licensed", ylab = "Frequency")
> # plot bar plot for official_video in clean_data
> barplot(table(clean_data$official_video), main = "Barplot of official_video",
xlab = "Does Official Video Exist?", ylab = "Frequency")
> # First half of the multivariate ggpair plot
> # correlation of log(Stream) with log(Views), log(Likes), log(Comments),
log(Duration(second)), log(Speechiness)
> first_half = clean_data[c("log_Stream", "log_Views", "log_Likes",
"log_Comments", "log_Duration_s", "log_Speechiness")]
> ggpairs(first_half)
>
>
> # Second half of the multivariate ggpair plot
> # correlation of log(Stream) with, Danceability, Energy, Loudness,
log(Acousticness), Valence, Tempo
> second_half = clean_data[c("log_Stream", "Danceability", "Energy", "Loudness",
"log_Acousticness", "Valence", "Tempo")]
> ggpairs(second_half)
> # Perform paired t-test to check if the mean of Stream and Views are equal
> # H0: u1 = u2
> # H1: u1 > u2
> t.test(clean_data$log_Stream, clean_data$log_Views, alternative = "greater",
paired = TRUE)

       Paired t-test

data:  clean_data$log_Stream and clean_data$log_Views
t = 98.315, df = 19531, p-value < 2.2e-16
alternative hypothesis: true mean difference is greater than 0
95 percent confidence interval:
 1.53182     Inf
sample estimates:
mean difference
       1.557885

> # Extract Stream and official_video column from clean_data
> data <- clean_data[,c("log_Stream", "official_video")]
>
> # separate the data into two dataframes group by official_video
> official_video <- data[data$official_video == TRUE,]
> non_official_video <- data[data$official_video == FALSE,]
>
> # Plot boxplot of Stream for official_video and non_official_video
> boxplot(official_video$log_Stream, non_official_video$log_Stream, names =
c("With Music Video", "Without Music Video"), ylab = "log(stream")
>
> # Perform F-test to check if the variance of Stream for official_video and
non_official_video are equal
> var.test(official_video$log_Stream, non_official_video$log_Stream)

       F test to compare two variances

data:  official_video$log_Stream and non_official_video$log_Stream
F = 1.1215, num df = 15244, denom df = 4286, p-value = 3.573e-06
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
```

```
 1.068678 1.176187
sample estimates:
ratio of variances
          1.121511

>
> # Perform t-test to check if the mean of Stream for official_video and
non_official_video are equal, with variance assumed to be not equal
> # H0: u1 = u2
> # H1: u1 > u2
> t.test(official_video$log_Stream, non_official_video$log_Stream, alternative =
"greater", var.equal = FALSE)

	Welch Two Sample t-test

data:  official_video$log_Stream and non_official_video$log_Stream
t = 14.785, df = 7214, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.3605478       Inf
sample estimates:
mean of x mean of y
 17.73451  17.32882

> # Perform Pearson correlation test to check the correlation between log_Stream
and Tempo
> # H0: There is no correlation between log_Stream and Tempo (rho = 0)
> # H1: There is a correlation between log_Stream and Tempo (rho != 0)
> cor.test(clean_data$log_Stream, clean_data$Tempo)

	Pearson's product-moment correlation

data:  clean_data$log_Stream and clean_data$Tempo
t = 4.1966, df = 19530, p-value = 2.722e-05
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.01599804 0.04402128
sample estimates:
       cor
0.03001556

>  # 4.2.4 The single most important song characteristic that is affecting
streams
>
> # Fit the initial model
> model1 = lm(log_Stream ~ Danceability, data = clean_data)
> model2 = lm(log_Stream ~ Energy, data = clean_data)
> model3 = lm(log_Stream ~ Loudness, data = clean_data)
> model4 = lm(log_Stream ~ log_Acousticness, data = clean_data)
> model5 = lm(log_Stream ~ Valence, data = clean_data)
> model6 = lm(log_Stream ~ Tempo, data = clean_data)
>
> # Extract information for each model (replace "model_name" with actual names)
> models <- list(model1=model1, model2=model2, model3=model3, model4=model4,
model5=model5, model6=model6)
> for (model_name in names(models)) {
+  current_model <- models[[model_name]]
+
+ # Extract coefficients
+ coefficients <- summary(current_model)$coefficients
+
+ # Calculate p-values for coefficients
+ p_values <- summary(current_model)$coefficients[, 4]
+
```

```
+ # Extract p-values from summary
+ # Calculate R-squared
+ r_squared <- summary(current_model)$r.squared
+
+ # Print results
+ cat("Model:", model_name, "\n")
+ cat("Coefficients:\n", coefficients, "\n")
+ cat("P-values:\n", p_values, "\n")
+ cat("R-squared:", r_squared, "\n")
+ cat("\n") }
Model: model1
Coefficients:
 17.29214 0.5684041 0.04599693 0.07153399 375.9413 7.945931 0 2.031313e-15
P-values:
 0 2.031313e-15
R-squared: 0.003222445

Model: model2
Coefficients:
 17.34213 0.4772467 0.03702492 0.0552319 468.3906 8.64078 0 6.006299e-18
P-values:
 0 6.006299e-18
R-squared: 0.003808435

Model: model3
Coefficients:
 18.08952 0.05826348 0.02251264 0.002529009 803.527 23.03807 0 6.780636e-116
P-values:
 0 6.780636e-116
R-squared: 0.02645726

Model: model4
Coefficients:
 17.53788 -0.06270114 0.01411463 0.004572763 1242.532 -13.71187 0 1.357897e-42
P-values:
 0 1.357897e-42
R-squared: 0.009535213

Model: model5
Coefficients:
 17.65065 -0.009794083 0.02808617 0.04815195 628.4463 -0.2033995 0 0.8388249
P-values:
 0 0.8388249
R-squared: 2.118345e-06

Model: model6
Coefficients:
 17.44254 0.001681056 0.04976937 0.0004005796 350.4674 4.196558 0 2.721994e-05
P-values:
 0 2.721994e-05
R-squared: 0.0009009337

>
> # Generate qq-plot of residuals
> qqnorm(model1$residuals)   # model1, Danceability
> qqline(model1$residuals)
>
> qqnorm(model2$residuals)   # model2, Energy
> qqline(model2$residuals)
>
> qqnorm(model3$residuals)   # model3, Loudness
> qqline(model3$residuals)
>
> qqnorm(model4$residuals)   # model4, log_Acousticness
```

```
> qqline(model4$residuals)
>
> qqnorm(model5$residuals)   # model5, Valence
> qqline(model5$residuals)
>
> qqnorm(model6$residuals)   # model6, Tempo
> qqline(model6$residuals)
>
> # Compile into a DF for Regression
> regression_df = clean_data[c(IV,"log_Stream")]
> regression_df
>
> # Splitting the dataset into 80% train, 20% test
> regression_split = sample.split(regression_df$log_Stream,SplitRatio = 0.8)
> train = subset(regression_df, regression_split == TRUE)
> test = subset(regression_df, regression_split == FALSE)
> test
> names(train)
 [1] "Danceability"     "Energy"           "Loudness"         "log_Speechiness"
"log_Acousticness"
 [6] "Valence"          "Tempo"            "log_Duration_s"   "log_Views"
"log_Likes"
[11] "log_Comments"     "Album_type"       "Key"              "Licensed"
"official_video"
[16] "log_Stream"
> # Fit the linear regression model with the test set
> linreg =
lm(log_Stream~Danceability+Energy+Loudness+log_Speechiness+log_Acousticness+Valen
ce+Tempo+log_Duration_s+log_Views+log_Likes+log_Comments+Album_type+Key+Licensed+
official_video, data = train)
> summary(linreg)

Call:
lm(formula = log_Stream ~ Danceability + Energy + Loudness +
    log_Speechiness + log_Acousticness + Valence + Tempo + log_Duration_s +
    log_Views + log_Likes + log_Comments + Album_type + Key +
    Licensed + official_video, data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-8.6205 -0.7858  0.0416  0.8157  7.5030

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)        14.1377315  0.2296235  61.569  < 2e-16 ***
Danceability        0.0320972  0.0780128   0.411 0.680759
Energy             -0.5127604  0.0848483  -6.043 1.54e-09 ***
Loudness            0.0135515  0.0035905   3.774 0.000161 ***
log_Speechiness    -0.1707137  0.0117487 -14.530  < 2e-16 ***
log_Acousticness   -0.0397520  0.0051340  -7.743 1.03e-14 ***
Valence            -0.2059979  0.0519950  -3.962 7.47e-05 ***
Tempo               0.0008183  0.0003543   2.310 0.020907 *
log_Duration_s     -0.1902902  0.0341334  -5.575 2.52e-08 ***
log_Views           0.0910284  0.0163811   5.557 2.79e-08 ***
log_Likes           0.3796117  0.0213736  17.761  < 2e-16 ***
log_Comments       -0.0403999  0.0095581  -4.227 2.38e-05 ***
Album_type         -0.3014763  0.0125360 -24.049  < 2e-16 ***
Key                -0.0063351  0.0028064  -2.257 0.024000 *
Licensed           -0.0751573  0.0381679  -1.969 0.048956 *
official_videoTRUE -0.5581247  0.0431743 -12.927  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.258 on 15609 degrees of freedom
```

```
Multiple R-squared:  0.4173,	Adjusted R-squared:  0.4167 
F-statistic: 745.2 on 15 and 15609 DF,  p-value: < 2.2e-16

> 
> # Only use significant variables in the refined MLR model
> linreg_significant = 
lm(log_Stream~Energy+Loudness+log_Speechiness+log_Acousticness+Valence+log_Durati
on_s+log_Views+log_Likes+log_Comments+Album_type+official_video, data = train)
> summary(linreg_significant)

Call:
lm(formula = log_Stream ~ Energy + Loudness + log_Speechiness + 
    log_Acousticness + Valence + log_Duration_s + log_Views + 
    log_Likes + log_Comments + Album_type + official_video, data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-8.6832 -0.7875  0.0421  0.8149  7.4651 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        14.205102   0.209781  67.714  < 2e-16 ***
Energy             -0.515495   0.083539  -6.171 6.96e-10 ***
Loudness            0.014411   0.003466   4.158 3.22e-05 ***
log_Speechiness    -0.168379   0.011345 -14.842  < 2e-16 ***
log_Acousticness   -0.040360   0.005116  -7.889 3.23e-15 ***
Valence            -0.197706   0.046681  -4.235 2.30e-05 ***
log_Duration_s     -0.196573   0.033988  -5.784 7.45e-09 ***
log_Views           0.088169   0.016308   5.406 6.52e-08 ***
log_Likes           0.381878   0.021284  17.942  < 2e-16 ***
log_Comments       -0.040013   0.009547  -4.191 2.79e-05 ***
Album_type         -0.300045   0.012442 -24.115  < 2e-16 ***
official_videoTRUE -0.625146   0.026926 -23.218  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.258 on 15613 degrees of freedom
Multiple R-squared:  0.4167,	Adjusted R-squared:  0.4163 
F-statistic:  1014 on 11 and 15613 DF,  p-value: < 2.2e-16

> 
> # Predict results of the test set using our trained model
> test$predicted_log_Stream = predict(linreg_significant,test)
> 
> # Plot Actual and Predicted log(Streams)
> plot(test$log_Stream,test$predicted_log_Stream,xlab = "Actual log(Stream)",
ylab = "Predicted log(Stream)", main = "Predicted Streams vs Actual Streams
(Log-Transformed)")
> 
> # Plot a best fit line
> abline(lm(test$predicted_log_Stream~test$log_Stream))
> 
> # Calculate residuals
> residuals <- test$log_Stream - test$predicted_log_Stream
> # Square the residuals
> squared_residuals <- residuals^2
> # Calculate mean squared residuals
> mean_squared_residuals <- mean(squared_residuals)
> # Calculate RMSE
> rmse <- sqrt(mean_squared_residuals)
> 
> print(rmse)
[1] 1.264073
```

7. References

Link to the online dataset:
https://www.kaggle.com/datasets/salvatorerastelli/spotify-and-youtube/data