Investigating Key Factors Contributing to Track Popularity

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Abstract

Understanding music and track popularity is important not only for the artists who create and perform music but also for the audience. This project is to help the reader to understand music's popularity by making analysis on different factors such as time, genre, and artists. The team first defines the important factors that could have impacts on the popularity of the music based on different related works, to cover multiple aspects of popularity. Then, the analysis of each factor is conducted with real-world recorded and text data to deeply understand the characteristics of music popularity and determine the factors that contribute to the popularity of the music. The team utilizes different methods throughout the analysis such as exploratory data analysis, hypothesis testing, and regression models for defining the factors that affect popularity. In particular, the team focuses on the relatively crucial features of the music such as genres, time, and artists through modeling and testing. The results show that certain genres are indeed more popular than others. In addition, energy, loudness, instrumentalness, and tempo of a song are also factors that can contribute to the popularity. The team also concludes that besides these factors found by the team, there could be other potential factors such as audience opinions, different country, and even society can have impacts on the people's likes of the music. Therefore, future analysis on more factors with more data will be conducted utilizing different models to understand the music popularity more thoroughly.

Keywords

Popular music, music preference, genre, exploratory analysis, rap, rock, hypothesis testing, linear regression

Introduction & Background

We have witnessed the dramatic development of society and technology. As life gets busy, entertainment is even more crucial for us to reduce pressure. And the easiest way to get some entertainment or relaxation is through music. By listening to different music and tracks, it is effective and efficient for us to relax and prepare for everyday life. Nowadays, music plays a very common and popular part in our daily life. We may listen to various tracks with many different styles every day. Throughout the years, the music industry has also evolved with different styles. Some tracks have always been popular for many years while others only survived for a relatively short period. In order to understand this phenomenon, many related works were conducted. One article written by Asai, explored the hit chart period of Japanese popular music in 1990 and in 2004, using the survival model, and examined the factors involved in producing a hit. They found that the fame of the artist was part of the reason that contributed to the hits chart period. In addition, the music's survival period was shorter in 2004 than in 1990 (Asai,2008). This means that time could also be the factor that affects popularity. Another related work was conducted by Knobloch-Westerwick, in which the authors concluded that songs with different messages in different genres, such as rap and rock, could lead to the popularity difference (Knobloch-Westerwick, 2008).

Therefore, based on the research of the related works, we found that genres, time, and artists are the major possible factors that could contribute to the popularity of the tracks and songs. Therefore, the team would like to go deeper and make further analyses utilizing different methods, such as hypothesis testing to compare two different genres and years to figure out which genres have more popularity and whether the popularity is increased throughout the years. In addition, in order to provide a more detailed answer in helping the reader understand the factors that impact the popularity of the tracks, the team makes a deeper analysis concerning the artists by conducting their characteristics such as loudness, energy, and others to determine which factors contribute to the music popularity.

Based on this description above, in order to achieve the objective of finding out the factors such as genres, time, and artist that contribute the music popularity, the team first seeks to establish a broad baseline of data science questions that includes and focuses on three major analysis:

- *Is the popularity of rap music greater than that of rock music?*
- *What are the differences of the track compared in different years?*
- *Which characteristics of an artist have an impact on the popularity of the track?*

By utilizing and focusing on these baseline questions, the team will conduct testings and models to answer the questions respectively to derive new insight about the factors that affect the popularity. For the first question, the team aims to find if the rap genre music has more popularity based on the paper written by Knobloch-Westerwick. As mentioned. For the second question, the goal is to understand what the effect of the characteristic and time can have on the popularity of the songs. By answering these two questions, the team can also provide further understandings based on the two articles found and conduct regression methods to thoroughly analyze the factors that contribute to the popularity of the songs. After the tests and models, the team will also look for different sources in order to help us define further factors for popularity that the team might overlook and conduct further analysis utilizing different models in the future to improve the models and even provide ideas for making predictions on the popularity of the songs.

In conclusion, this project aims to find the factors that determine the popularity of the songs by utilizing different statistical methods and models such as exploratory analysis, hypothesis testing, and regressions to effectively answer the topic questions to obtain new insights and make further implementations in the future.

Data

Data Gathering

Before conducting the analysis and the models, the team performed data gathering in order to gather the necessary data information regarding the musics and popularities for the later processes. The key sources consist of the datasets utilizing spotify and Kaggle. The team has found two different datasets.

The first dataset is found by utilizing Spotify API. Through available packages such as Rspotify and spotifyr, which are R wrappers for pulling track audio features and other information from Spotify's Web API in bulk. The key information about this dataset consists of the characteristics of the songs for the artists; the tracks information such as id and song names; and the date of the released song. The key columns are shown below as table 1,which can give the reader general information about the dataset which the team will utilize in different analyses.

Key Columns	danceability	album_release_year	loudness	valence	tempo
speechiness	energy	instrumentalness	liveness	acousticness	song_name

Table 1: Key columns of the dataset 1 using Spotify API

However, as we can see, the first dataset lacks two key elements that the team will focus on which are the genres and popularity. Therefore, further datasets must be gathered and included. Therefore, the second dataset is also gathered based on the Spotify source for track data. This dataset was originally obtained from Spotify using the spotifyr package. The dataset for this project can be downloaded via the GitHub link which is provided in the reference section. For this dataset, the key difference between the first one and the second one is that the second dataset consists of more information regarding the genres such as rap, rock, and metal as well as the corresponding popularity which is recorded as integer from 0 to 100 with 100 being the most popular. In addition to the genre and popularity columns, other columns are similar to the first dataset which consist of the characteristics of the artists and the corresponding time and name.

Key Columns	artist	popularity	year	genre	subgenre
song_name	danceability	energy	key	loudness	mode
speechiness	acousticness	instrumantalness	liveness	valence	tempo

Table 2: Key columns of the dataset 2 from Spotify

Based on the dataset information with the key columns shown above as table 2, the team has successfully gathered the necessary information to further our analysis through different models. However, before performing further analysis, a basic understanding and definition for each column should be explained briefly, which are included as table 3 shown below.

popularity	As an integer 0 to 100 with 100 being the most popular.
genre	The type or style of the track.
subgenre	One of several categories within a particular genre.
danceability	A measure of how suitable a track is for dancing.
energy	A measure of intensity and activity.
speechiness	The presence of spoken words in a track.
loudness	The quality or strength of a sound in db.
acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic.
instrumantalness	A measure for predicting whether a track contains no vocals.
liveness	The presence of an audience in the recording.
tempo	The speed or pace from the average beat duration.
valence	A measure for describing the musical positiveness conveyed by a track.

Table 3: Explanations of the dataset factors

Data Cleaning

After the gathering process, in order to utilize the data with different models and improve effectiveness. Cleaning processes such as checking empty values, checking duplicates, and removing unnecessary columns are crucial for effectiveness and efficiency.
During cleaning, the team found no missing values, and each value in the dataset is meaningful with corresponding recorded values in numeric or text. However, when the team checked for duplicates, the team found that a song can have multiple genres, as shown below in figure 0.

loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	time_signature	genre	song_name
-7.668	1	0.293	0.2170	0.0000	0.166	0.591	147.988	4	Dark Trap	Venom
-6.856	1	0.181	0.0332	0.0163	0.657	0.392	144.946	4	Dark Trap	Venom
-7.668	1	0.293	0.2170	0.0000	0.166	0.591	147.988	4	Underground Rap	Venom
-6.856	1	0.181	0.0332	0.0163	0.657	0.392	144.946	4	Underground Rap	Venom
-6.856	1	0.181	0.0332	0.0163	0.657	0.392	144.946	4	Trap Metal	Venom
-7.668	1	0.293	0.2170	0.0000	0.166	0.591	147.988	4	Trap Metal	Venom

Figure 0: The duplicate rows for a song

Since the objective and the three data science questions focus on the factors such as genres, if the team keeps the duplicates, the multiple genres for the same song will cause misleading results in the later process. Therefore, the team chooses to remove the duplicate. In addition, for this cleaning step, removing the duplicate genres will not affect the integrity or make it imbalanced because the recorded values for other columns remain the same for each song, as shown in figure 0. Therefore, the team removed the duplicate such that it can not mess with our model analysis in the later process which starts with the Exploratory Data Analysis.

Statistical Analysis & Models Results

Exploratory Data Analysis

In this section, we will do some exploratory analysis for the Spotify data we gathered in the previous sections and try to have a general idea about the data set. As we mentioned before, the data collected included the audio feature and the feature relative to the tracks, so the visual exploration of the data also split into genre exploration and audio feature exploration.

First is genre exploration. We are trying to determine the relationship between different music genres and their popularity scores. As we can see from the chart, Spotify has categorized all of its music tracks into six main genres, EDM, Latin, Pop, R&B, Rap, and Rock, each with four subgenres, making it a total of 24 genres that are able to accurately describe the type of music each track belongs to.

EDM	Big room, Eclectrohouse, pop EDM, progressive electro house
Latin	Latin hip hop, Latin pop, reggaeton, tropical
Pop	Dance-pop, electropop, indie poptimism, post-teen pop
R&B	Hip pop, neo-soul, new jack swing, urban contemporary
Rap	Gangster rap, hip hop, southern hip pop, trap
Rock	Albumrock, classic rock, hard rock, permanent wave

Table 4: Genres from Spotify

To figure out the relationship between genres and popularity, we decided to group the tracks by their genres and subgenres, then rank the average popularity score by genres. As a result, we can see that the most popular main genre is Pop and the least popular genre is EDM, which does correlate with our daily experience since Pop music is more "mainstream" compared to genres like EDM, which are mainly by certain fans. And among all 24 subgenres, post-teen pop is the most popular, with an average of about 57 popularity scores which is nearly double the popularity of the last place, progressive electro house music. Thus, if an artist wants to increase their chances of producing a popular song or big hits, they should choose the pop genre specifically in the post-teen pop category.

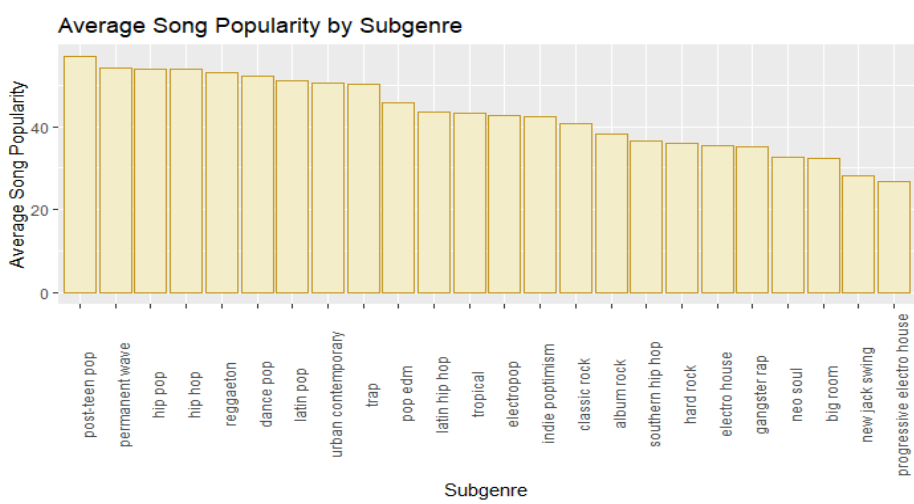

Figure 1: The Average Song Popularity by Subgenre

Nonetheless, to check if the differences in average popularity scores for the music genres are significant. I used Tukey's multiple comparisons of the means test to do this. The results of this test show that for every genre pairing besides rock and r&b, there is a **significant difference** in the average popularity score.

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = popularity ~ genre, data = spotify)

$genre
                  diff        lwr        upr     p adj
latin-edm   12.2113019 10.8822333 13.5403705 0.0000000
pop-edm     12.9113438 11.6055353 14.2171522 0.0000000
r&b-edm      6.3900052  5.0794252  7.7005852 0.0000000
rap-edm      8.4045025  7.1128079  9.6961971 0.0000000
rock-edm     6.8948113  5.5511883  8.2384343 0.0000000
pop-latin    0.7000419 -0.6584696  2.0585534 0.6845195
r&b-latin   -5.8212967 -7.1843952 -4.4581981 0.0000000
rap-latin   -3.8067994 -5.1517501 -2.4618486 0.0000000
rock-latin  -5.3164905 -6.7113885 -3.9215925 0.0000000
r&b-pop     -6.5213386 -7.8617677 -5.1809095 0.0000000
rap-pop     -4.5068413 -5.8288114 -3.1848712 0.0000000
rock-pop    -6.0165325 -7.3892862 -4.6437787 0.0000000
rap-r&b      2.0144973  0.6878138  3.3411809 0.0002188
rock-r&b     0.5048061 -0.8724873  1.8820995 0.9028530
rock-rap    -1.5096912 -2.8690263 -0.1503561 0.0193464
```

Figure 2: Tukey's test for significance of genre and popularity

Besides the genre, we have also performed EDA based on the audio features and the artists, trying to explore other trends in the dataset before diving into a more complex analysis. The team ran a correlation matrix between the audio features such as liveness, tempo, and liveness to compare their relativeness to popularity scores. Although the correlation coefficient does not suggest a strong correlation between these audio features and the popularity of the track, we will test this assumption with linear regression in the later section.

The exploration of the artist and their track's popularity is also interesting. In order to better classify the track's popularity, I have divided the popularity scores (0-100) into three categories, popular(score > 66), moderate (33 <= scores <=66), and not popular (score< 33). When ranking the artist by the number of popular songs they have, Calvin Harris, Ed Sheeran, and Martin Garrix take the top three places. However, the ranks change dramatically when including the number of not popular tracks into the account and ranking them by the ratio of popular songs. In this ranking, DJ Kalid was crowned with a 49% of popular ratio, significantly ahead of all other artists. Young Thug and Ed Sheeran ranked second and third place, respectively, with a nearly 30% popularity ratio.

Hypothesis Testing

Based on the exploratory data analysis, the team discovered that there is a significant difference in average popularity scores by comparing the genres of the music. Therefore, the team plans to make an analysis of the effects of top genres such as pop, rap, and rock on the popularity of the tracks by utilizing hypothesis tests. In addition, the related works found by the team indicate that the time factor can also be a great factor that affects the popularity of the track. Therefore, the team conducted three hypothesis tests concerning the genre and time factor to help understand the music popularity better for further modeling.

Hypothesis testing is an effective way to determine the relations or differences between numerical measures with multiple groups. A null and alternative hypothesis should be established in hypothesis testing to solve a problem. Then, based on the question and hypothesis, a suitable testing method will be chosen, such as t-tests, chi-square tests, and others, to effectively perform the testing to get the visualization and the result. In this section, the results of the testing consist of the p-value, which is a statistical measurement used to validate a hypothesis against observed data, that is calculated from the hypothesis test; the conclusion by comparing the p-value and the significant level; and the confidence interval that represents the probability that a population parameter will fall between a set of values. Throughout the hypothesis testing, the team followed the following steps:

- Define a data science question to answer.
- Create Null and Alternative hypotheses.
- Perform the corresponding suitable test on the hypothesis
- Conclude on the results based on the 95% significance level
- Repeat and confirm the results using bootstrap testing
- Conclude on the results

Hypothesis Testing I

Based on the conclusion from above, there is a difference between the popularity of rap and pop music. However, the team also wishes to know if rap music can be more popular than other genres, such as rock music. In order to further analyze the effects that genre can have on music popularity, another hypothesis test is conducted to determine the answer to the following question: Is the population mean of the popularity of rap music greater than that of rock music?

Based on the data science question, the corresponding null and alternative hypothesis are also created:

- H0: The mean popularity of rap music is the same as the mean popularity of rock music.
- Ha: The mean popularity of rap music is higher than the mean popularity of rock music.

Since the problem consists of evaluating if a sample is greater than or less than a range of values, a two-tailed test is also suitable for this question. By conducting the two-tailed t-test, the results of the p-value and the 95% confidence interval are calculated as follows:

```
        Welch Two Sample t-test

data:  ur_pop and dt_pop
t = 3.2267, df = 10232, p-value = 0.0006281
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.7400385       Inf
sample estimates:
mean of x mean of y
 43.23803  41.72834
```

Figure 3: Welch Two Sample T-test

As the results are shown, we can see that the p-value is relatively small compared to the 95% significance level. This means that we should reject the null hypothesis since we have sufficient evidence that the alternative hypothesis is true, which shows the mean popularity of rap music is higher than the mean popularity of rock music. In addition, the 95% confidence interval shows that we are 95% confident that a population mean of popularity will fall between a set of values from 0.74 to infinity. And the sample estimates also indicate that the mean popularity of rap music is higher than the mean popularity of rock music.

Then based on the results conducted by utilizing the t-test, the team also performed a bootstrap test to verify the results. The bootstrap test is also a statistical test that uses sampling methods for the dataset to simulate the results. This process allows the team to calculate standard errors and construct confidence intervals to verify the results and make the conclusion more compelling. By utilizing the bootstrap hypothesis testing with the same data science question, the results of the bootstrap hypothesis 95% confidence interval is from 0.59 to 2.43, which is shown as the blue lines in the following histogram visualization.

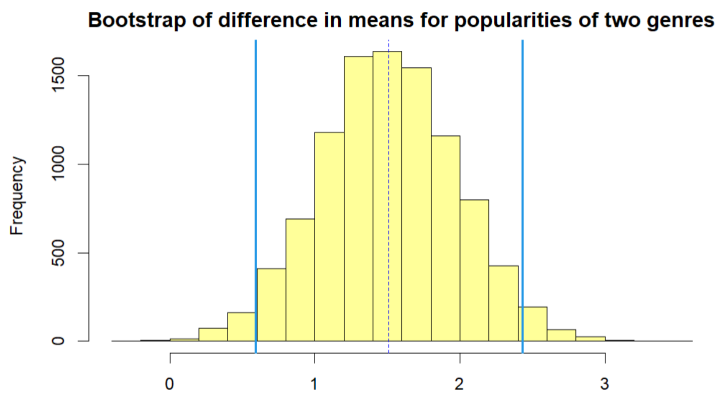

Figure 4: The Bootstrap test of the hypothesis

As shown in the figure above, we can certainly see that the interval is greater than 0. In other words, 0 does not include in the confidence interval of the bootstrap testing. This means that the mean popularity of rap music is not the same as the mean popularity of rock music. Therefore, we also reject the null hypothesis and conclude that rap music's mean popularity is higher than rock music's.

Hypothesis Testing II

From the daily observations, some music genres do dominate the front rank of the listener's music charts, such as pop music. There are many reasons for this phenomenon, such as the fact that these pop music are sung by favorite singers. Hence, with this complex relationship, whether the popularity of music is related to the genre of music itself needs to be studied. In the previous hypothesis test, the relationship between the average popularity of rock music and of rap music has been addressed. However, the general relationship between the genres and the popularity cannot be explained by a test between two specific genres of music.

In the second hypothesis test, whether the popularity is related to the genre will be examined. Before implementing the test method, categorizing the popularity into three different groups - high,medium,low - will be helpful in understanding the relationship. Based on the 0 to 100 popularity score rules on spotify, three categories can be presented as:

- High : the popularity score is greater than and equal to 66.
- Medium : the popularity score is between 33 to 66.
- Low : the popularity score is lower than and equal to 33.

The two-way table is generated to show the frequency of songs in the group of genre and popularity. From the table, it is clear to find that only 613 EDM musics are in the high popularity group, and among the six categories, POP music has the largest number of high popularity scores.

	edm	latin	pop	r&b	rap	rock
High	613	1378	1603	1096	921	1000
Low	2733	1343	1533	2043	1654	1748
Medium	2697	2432	2371	2292	3168	2203

Table 5: Two-way Table of Observed value in groups of Popularity and Genre

In statistics, Chi-squared test is commonly used in testing the independence of two variables. If two variables are independent, it means there is no relationship between two factors. Based on the question of whether the popularity is related to the genre, the null hypothesis (H0) can be set as the popularity and the genre is independent, and then correspondingly, the alternative hypothesis (Ha) will be the popularity and the genre is dependent.In this case, the specific hypotheses are:

- H0: There is no relationship between the popularity and the genre of music.
- Ha: There is a relationship between the popularity and the genre of music.

```
        Pearson's Chi-squared test

data:  t1
X-squared = 1270.6, df = 10, p-value < 2.2e-16
```

Figure 5 : Pearson’s Chi-squared Test Result

From the Chi-squared test output, the p-value is less than the significance level of 5%, which means the rejection of null hypothesis. In this context, rejecting the null hypothesis for the Chi-square test of independence means there is a significant relationship between the popularity and the genre of music. In this way, the genre of music and the popularity of music are dependent on each other.

Hypothesis Testing III

After the comparison between genres, music style change is also an important factor to determine the popularity. Music style change represents audiences' taste change over the year. The tastes of the public caused different years to have different styles of songs. Valence will be the main factor to compare the music style change since Valence is the most representative factor to determine the song's attitude. It mainly describes the song's positiveness, the song with high score represents it will sound happier and more cheerful. Otherwise, the song will sound like a sorrowful or even depressed melody.

Hence the third hypothesis mainly focuses on music style change between two ranges of years. Here comes the data science question: Did music style change significantly from 1999-2010 compared to 2010-2020?
Based on the data science question, the corresponding null and alternative hypothesis are also created:

- H0: The average Valence of songs in 1999-2010 is higher than songs in 2011-2022.
- Ha: The average Valence of songs in 1999-2010 is lower than songs in 2011-2022.

For data preprocessing, the dataset needs to be binned by album released column year. It is combined into two categories which are 1999-2010 and 2011-2022. Here is the distribution of songs in each range of years.

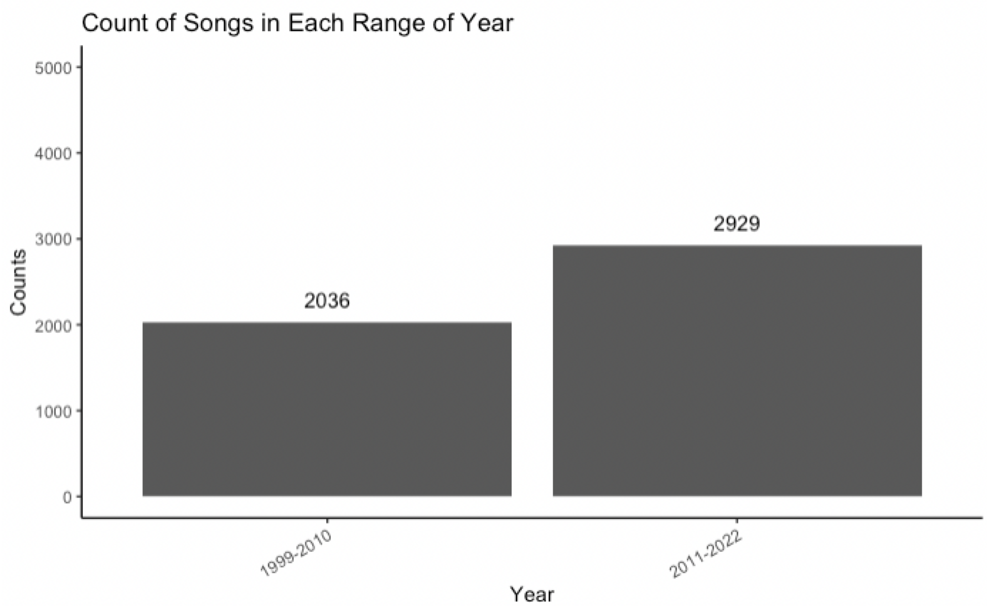

Figure 6: Counts of Songs in Each Range of Year

Welch two sample t-test is a useful tool to determine whether a sample is greater than or less than a range of values. In the Welch two sample t-test, the p-value is 1 which is larger than 0.05. So the null hypothesis cannot be rejected. The first conclusion can be generated from a welch two sample t-test: The average Valence of songs in 1999-2010 is higher than songs in 2011-2022.

```
        Welch Two Sample t-test

data:  Year2010 and Year2022
t = 9.9977, df = 4084.5, p-value = 1
alternative hypothesis: true difference in means is less than 0
95 percent confidence interval:
       -Inf 0.07579864
sample estimates:
mean of x mean of y
0.4736412 0.4085535
```

Figure 7: Welch Two Sample T-Test Output

In order to make a proof to determine whether the conclusion brought from t-test is true, the bootstrap test will calculate the main difference between year 1999-2010 to 2011-2022. Here comes out the result, the 95% confidence interval is between -0.559 to 0.662 which contains zero. So this further proves the conclusion generated from t-test. The null hypothesis cannot be rejected, the average Valence of songs in 1999-2010 is higher than songs in 2011-2022.

```
##    2.5%  97.5%
## -0.559  0.662
```

Figure 8: The 95% Confidence Interval of Bootstrap Sampling

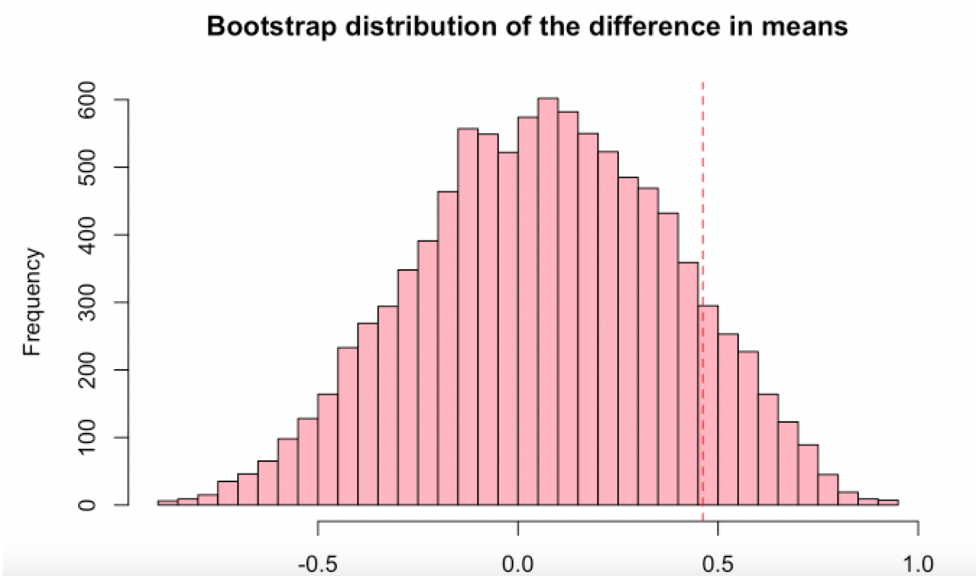

Figure 10: Bootstrapping Distribution of the Difference in Means

Within the conclusion generated above, the music tends to be less positive as time flies. As the audiences' tastes change, the trends of popularity of songs also tends to alter. Popular tastes are always important factors of the determination of popularity.

Regression

In this section, the main task is to answer the data science question: are the variables that contribute to predicting "Popularity" of the songs the same among different genres? This paper tests whether the factors influencing the popularity of different genres are consistent by comparing Pop music and EDM respectively. Here, the tool used is linear regression in the R and results are drawn from the significant variables given by the output of linear regression.

The first linear regression models containing all possible predictors of "Popularity" were done for each of the two different genres. Based on the output of the first model, we get some significant and insignificant variables. Significant variables are those that have a real contribution in the linear regression equation, while insignificant variables have no real contribution and should be excluded. Here, the variables that are significant for Pop music are danceability, energy, loudness, speechiness and instrumentalness respectively, and those that are significant for EDM music are energy, loudness, acousticness and instrumentalness, respectively. Preliminary results have shown that Pop and EDM have different impact contributors.

All insignificant variables were removed and a second linear regression equation was launched with all remaining significant variables. Variables that were significant in the first model remained significant in the second model.

Next, the third model is used to check the interactions. The approach is to check the effect of cross terms on "Popularity" by choosing all variables in the second model to be squared for Pop and EDM, respectively. The result is that for Pop music, the significant cross terms in the third model are energy&loudness and loudness&instrumentalness, respectively; for EDM, the significant cross terms are energy&instrumentalness, energy&tempo, loudness&acousticness, loudness&tempo and acousticness&tempo, respectively.

With the three models above, the data science question posed at the beginning of this section could be easily answered. The answers are, of course, different.

Finally, to compare the strengths and weaknesses of the models, we present tables to compare the RMSE, R square, F-statistics, adjusted R square and RSE. See the tables below.

	RMSE	R square	F-statistics	Adjusted R square	RSE
Model1	24.44	0.078	30.28	0.068	24.21
Model2	24.43	0.079	47.11	0.068	24.21

Model3	21.35	0.102	55.95	0.08	24.01

Table 6: Model evaluation of Pop music

	RMSE	R square	F-statistics	Adjusted R square	RSE
Model1	22.03	0.113	42.69	0.087	22.08
Model2	22.04	0.112	66.94	0.087	22.07
Model3	22.07	0.109	43.54	0.088	22.05

Table 7: Model evaluation of EDM music

It is clear that the third model with heavily filtered variables is the optimal model for both genres.

Conclusion

Based on the related works and the team analysis and modeling, we discovered and proved that the genres and the time play a crucial role in impacting the popularity of the tracks. Throughout the analysis, the team also discovered that not all the songs of a popular artist could be popular. This shows that artists themselves are not a strong factor that can contribute to the track's popularity. In addition, based on the testing, the team presented and found a fact that certain genres, such as rap music, which can pull emotions out of its audience, tend to be more popular than other genre of music. The possible reason the team believes is that the emotions in these music styles are real, authentic, and often based on actual events in the rapper's life. Because of their rawness, this music often touches a nerve or plucks a heartstring in listeners, whereas other genres of music may not. Which caused these types of music to become popular. In addition, the team also found that throughout the years, the valence of the songs tends to decrease, which means that there is more and more musical negativeness that is conveyed by a track, leading to impacts on popularity over time. Based on this, the team can only conclude that the time can affect the track popularity because of the changing of the valence but fail to determine whether they have positive or negative correlations.

Therefore, in order to thoroughly analyze the factors that affect popularity, the team conducted different regressions with multiple factors. Throughout the process, the team evaluated all possible factors and then filtered the important factors for further regressions. By repeating the step, the team succeeded in discovering some major factors of a song that contribute to its popularity: Energy, Loudness, Instrumentalness, and Tempo. However, based on the results, the team found that only loudness among these four factors has a positive correlation to popularity.

This means that more loudness in a track can attract more audience while other factors, such as instrumentalness should be as small as possible to make a track popular.

The possible reason behind this is that the audience prefers strong emotions, either in the song's strength or the true emotions of the music, which can also be related to the conclusion of genre testing from above. And based on the word maps shown in the above figure, the relatively popular ones all contain strong emotions.

After the project analysis and results, the team also realized that there must be more factors that could impact the tracks' popularity. For instance, the team found that in the past, people preferred positive emotions more, but as time went on, the audience’s preference seemed to change. There could be many external factors, such as historical events, global changes, economic, or even political factors, that might also contribute to the audience preference, resulting in changes in popularity. Therefore, the team wishes to continue the research and analysis by finding more datasets to make the model more effective. For instance, the team can look for datasets concerning people's opinions on music throughout the years, the evolution of music history throughout human history, and preferences in different countries. By combining these different possible factors, the team hopes to make the analysis more effective so that it might help us understand music popularity better and even predict its future.

Throughout the project analysis, the team utilized different statistical analysis methods and models, such as exploratory data analysis, hypothesis tests, and regression models, to vividly and thoroughly evaluate the track datasets gathered. Based on the results, the team concluded that the genre of the music, the time changing, the energy, the loudness, the instrumentalness, and the tempo of the track are the major factors that affect the songs' popularity. However, the team also concluded that further analysis with many different datasets, which consist of indirect to the music and external factors such as history changes, audience opinions, and different countries, should also be included in the analysis in the future to make us understand the music popularity better and answer our question: ‘What are the factors that contribute to the music popularity’ with more effective and compelling answers.

References

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Appendix i

Github $ drive link to the codes and outputs:

https://github.com/zy236yuz5/ANLY511-Project_Report_Codes
https://drive.google.com/drive/folders/1xOJ3IehQtmSQCBaNDqJmTCPJ15kNJ-8t?usp=sharing

Appendix ii

The pdf of the code outputs

Combined_Codes

Zonghong Yu, Yicheng Guo, Yilin Yang, Huiting Song, Shiyu Wang

2022-12-12

```
df <- read.csv("genres_v2.csv",stringsAsFactors=FALSE)
head(df)
```

```
##   danceability energy key loudness mode speechiness acousticness
## 1        0.831  0.814   2   -7.364    1      0.4200       0.0598
## 2        0.719  0.493   8   -7.230    1      0.0794       0.4010
## 3        0.850  0.893   5   -4.783    1      0.0623       0.0138
## 4        0.476  0.781   0   -4.710    1      0.1030       0.0237
## 5        0.798  0.624   2   -7.668    1      0.2930       0.2170
## 6        0.721  0.568   0  -11.295    1      0.4140       0.0452
##   instrumentalness liveness valence   tempo           type
## 1         1.34e-02   0.0556  0.3890 156.985 audio_features
## 2         0.00e+00   0.1180  0.1240 115.080 audio_features
## 3         4.14e-06   0.3720  0.0391 218.050 audio_features
## 4         0.00e+00   0.1140  0.1750 186.948 audio_features
## 5         0.00e+00   0.1660  0.5910 147.988 audio_features
## 6         2.12e-01   0.1280  0.1090 144.915 audio_features
##                       id                                  uri
## 1 2Vc6NJ9PW9gD9q343XFRKx spotify:track:2Vc6NJ9PW9gD9q343XFRKx
## 2 7pgJBLVz5VmnL7uGHmRj6p spotify:track:7pgJBLVz5VmnL7uGHmRj6p
## 3 0vSWgAlfpye0WCGeNmuNhy spotify:track:0vSWgAlfpye0WCGeNmuNhy
## 4 0VSXnJqQkwuH2ei1nOQ1nu spotify:track:0VSXnJqQkwuH2ei1nOQ1nu
## 5 4jCeguq9rMTlbMmPHuO7S3 spotify:track:4jCeguq9rMTlbMmPHuO7S3
## 6 6fsypiJHyWmeINsOLC1cos spotify:track:6fsypiJHyWmeINsOLC1cos
##                                                 track_href
## 1 https://api.spotify.com/v1/tracks/2Vc6NJ9PW9gD9q343XFRKx
## 2 https://api.spotify.com/v1/tracks/7pgJBLVz5VmnL7uGHmRj6p
## 3 https://api.spotify.com/v1/tracks/0vSWgAlfpye0WCGeNmuNhy
## 4 https://api.spotify.com/v1/tracks/0VSXnJqQkwuH2ei1nOQ1nu
## 5 https://api.spotify.com/v1/tracks/4jCeguq9rMTlbMmPHuO7S3
## 6 https://api.spotify.com/v1/tracks/6fsypiJHyWmeINsOLC1cos
##                                                         analysis_url duration_ms
## 1 https://api.spotify.com/v1/audio-analysis/2Vc6NJ9PW9gD9q343XFRKx      124539
## 2 https://api.spotify.com/v1/audio-analysis/7pgJBLVz5VmnL7uGHmRj6p      224427
## 3 https://api.spotify.com/v1/audio-analysis/0vSWgAlfpye0WCGeNmuNhy       98821
## 4 https://api.spotify.com/v1/audio-analysis/0VSXnJqQkwuH2ei1nOQ1nu      123661
## 5 https://api.spotify.com/v1/audio-analysis/4jCeguq9rMTlbMmPHuO7S3      123298
## 6 https://api.spotify.com/v1/audio-analysis/6fsypiJHyWmeINsOLC1cos      112511
##   time_signature     genre                                    song_name
## 1              4 Dark Trap                          Mercury: Retrograde
## 2              4 Dark Trap                                    Pathology
## 3              4 Dark Trap                                     Symbiote
## 4              3 Dark Trap ProductOfDrugs (Prod. The Virus and Antidote)
## 5              4 Dark Trap                                        Venom
## 6              4 Dark Trap                                      Gatteka
##   Unnamed..0 title
## 1         NA
## 2         NA
## 3         NA
## 4         NA
## 5         NA
## 6         NA
```

```
names(df)
```

```
##  [1] "danceability"     "energy"           "key"              "loudness"
##  [5] "mode"             "speechiness"      "acousticness"     "instrumentalness"
##  [9] "liveness"         "valence"          "tempo"            "type"
## [13] "id"               "uri"              "track_href"       "analysis_url"
## [17] "duration_ms"      "time_signature"   "genre"            "song_name"
## [21] "Unnamed..0"       "title"
```

```
df = subset(df, select = -c(uri, id, track_href, Unnamed..0, duration_ms, analysis_url, title, t
ype) )
```

```
head(df)
```

```
##   danceability energy key loudness mode speechiness acousticness
## 1        0.831  0.814   2   -7.364    1      0.4200       0.0598
## 2        0.719  0.493   8   -7.230    1      0.0794       0.4010
## 3        0.850  0.893   5   -4.783    1      0.0623       0.0138
## 4        0.476  0.781   0   -4.710    1      0.1030       0.0237
## 5        0.798  0.624   2   -7.668    1      0.2930       0.2170
## 6        0.721  0.568   0  -11.295    1      0.4140       0.0452
##   instrumentalness liveness valence   tempo time_signature     genre
## 1         1.34e-02   0.0556  0.3890 156.985              4 Dark Trap
## 2         0.00e+00   0.1180  0.1240 115.080              4 Dark Trap
## 3         4.14e-06   0.3720  0.0391 218.050              4 Dark Trap
## 4         0.00e+00   0.1140  0.1750 186.948              3 Dark Trap
## 5         0.00e+00   0.1660  0.5910 147.988              4 Dark Trap
## 6         2.12e-01   0.1280  0.1090 144.915              4 Dark Trap
##                                      song_name
## 1                           Mercury: Retrograde
## 2                                     Pathology
## 3                                      Symbiote
## 4 ProductOfDrugs (Prod. The Virus and Antidote)
## 5                                         Venom
## 6                                       Gatteka
```

```
df_dup = df[duplicated(df$song_name), ]
head(df_dup)
```

```
##     danceability energy key loudness mode speechiness acousticness
## 81         0.909  0.573   5   -6.856    1      0.1810      0.03320
## 294        0.756  0.746   1   -6.397    1      0.1420      0.23600
## 426        0.705  0.648   4  -10.467    0      0.1410      0.00476
## 489        0.675  0.628   4   -6.165    0      0.0838      0.00997
## 580        0.945  0.587   2   -5.104    1      0.2710      0.25300
## 669        0.733  0.513   6   -5.068    0      0.0389      0.55900
##     instrumentalness liveness valence   tempo time_signature     genre
## 81          1.63e-02   0.6570  0.3920 144.946              4 Dark Trap
## 294         0.00e+00   0.0999  0.0793 207.956              4 Dark Trap
## 426         5.95e-04   0.3730  0.3980 130.037              4 Dark Trap
## 489         0.00e+00   0.0868  0.5110 179.992              4 Dark Trap
## 580         1.01e-06   0.2640  0.5090 131.969              4 Dark Trap
## 669         1.48e-05   0.1740  0.5640 159.944              4 Dark Trap
##                song_name
## 81                 Venom
## 294      Story: No Title
## 426             No Teeth
## 489 Make It Through Fall
## 580               Killer
## 669            Nightmare
```

```
dup <- df[df$song_name == "Venom",]
```

```
df = df[!duplicated(df$song_name), ]
```

```
head(df)
```

```
##   danceability energy key loudness mode speechiness acousticness
## 1        0.831  0.814   2   -7.364    1      0.4200       0.0598
## 2        0.719  0.493   8   -7.230    1      0.0794       0.4010
## 3        0.850  0.893   5   -4.783    1      0.0623       0.0138
## 4        0.476  0.781   0   -4.710    1      0.1030       0.0237
## 5        0.798  0.624   2   -7.668    1      0.2930       0.2170
## 6        0.721  0.568   0  -11.295    1      0.4140       0.0452
##   instrumentalness liveness valence   tempo time_signature     genre
## 1         1.34e-02   0.0556  0.3890 156.985              4 Dark Trap
## 2         0.00e+00   0.1180  0.1240 115.080              4 Dark Trap
## 3         4.14e-06   0.3720  0.0391 218.050              4 Dark Trap
## 4         0.00e+00   0.1140  0.1750 186.948              3 Dark Trap
## 5         0.00e+00   0.1660  0.5910 147.988              4 Dark Trap
## 6         2.12e-01   0.1280  0.1090 144.915              4 Dark Trap
##                                          song_name
## 1                              Mercury: Retrograde
## 2                                        Pathology
## 3                                         Symbiote
## 4 ProductOfDrugs (Prod. The Virus and Antidote)
## 5                                            Venom
## 6                                          Gatteka
```

```
sum(duplicated(df$song_name))
```

```
## [1] 0
```

```
library(tidyverse) #for data cleaning and manipulation
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.2 ──
## ✓ ggplot2 3.3.6     ✓ purrr   0.3.4
## ✓ tibble  3.1.8     ✓ dplyr   1.0.9
## ✓ tidyr   1.2.0     ✓ stringr 1.4.0
## ✓ readr   2.1.2     ✓ forcats 0.5.1
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✕ dplyr::filter() masks stats::filter()
## ✕ dplyr::lag()    masks stats::lag()
```

```
#library(rccdates) #for converting date variables
library(wordcloud) #for creating word cloud visualizations
```

```
## Loading required package: RColorBrewer
```

```
library(ggplot2) #for data visualizations
library(tm) #used for text mining
```

```
## Loading required package: NLP
##
## Attaching package: 'NLP'
##
## The following object is masked from 'package:ggplot2':
##
##     annotate
```

```
library(RColorBrewer) #color schemes for plots
library(SnowballC) #for text stemming
library(corrplot) #for correlation matrix visualization
```

```
## Warning: package 'corrplot' was built under R version 4.2.2
```

```
## corrplot 0.92 loaded
```

```
spotify <- readr::read_csv('https://raw.githubusercontent.com/rfordatascience/tidytuesday/maste
r/data/2020/2020-01-21/spotify_songs.csv')
```

```
## Rows: 32833 Columns: 23
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr (10): track_id, track_name, track_artist, track_album_id, track_album_na...
## dbl (13): track_popularity, danceability, energy, key, loudness, mode, speec...
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
write.csv(spotify, "spotify.csv")
```

```
#removing columns 1,5,6,8,& 9
spotify <- spotify[,-c(1,5,6,8,9)]
#separating track_album_release_date
spotify <- spotify%>%separate(track_album_release_date,c("release_year", "release_month", "relea
se_day"), sep="-")
```

```
## Warning: Expected 3 pieces. Missing pieces filled with `NA` in 1886 rows [152,
## 750, 751, 752, 754, 756, 760, 766, 769, 780, 783, 786, 787, 788, 789, 790, 794,
## 799, 805, 806, ...].
```

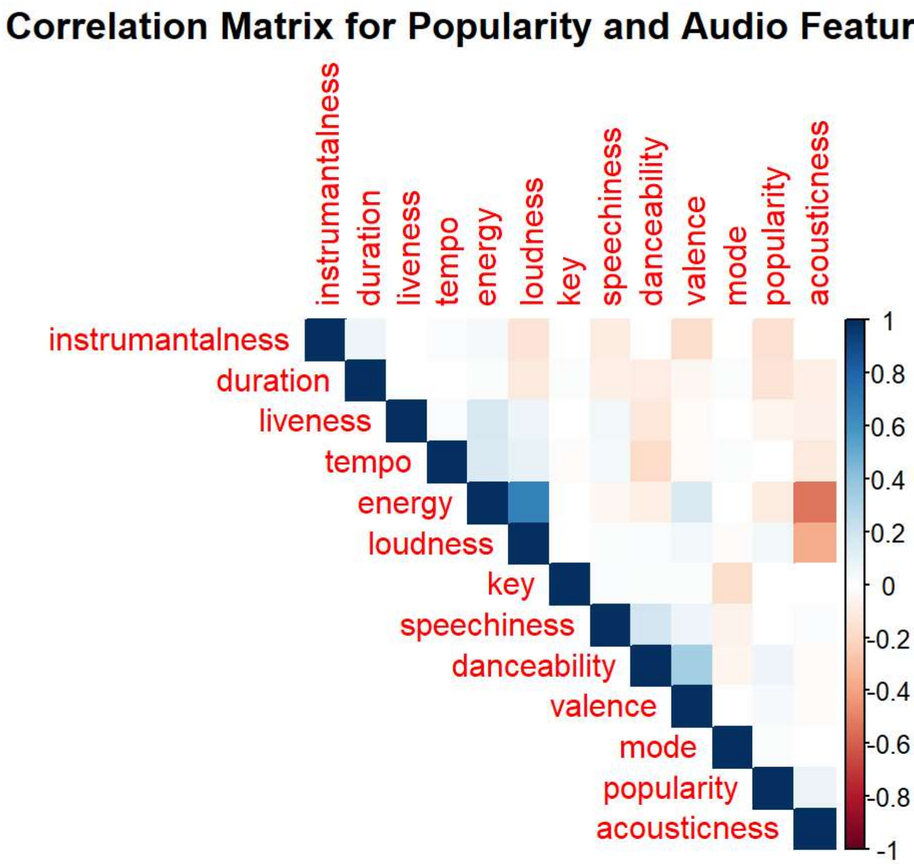
```
#deleting release_month and release_day
spotify <- spotify[,-c(5,6)]

#changing year to a factor
spotify$release_year <- as.factor(spotify$release_year)

#changing genre to a factor
spotify$playlist_genre <- as.factor(spotify$playlist_genre)

#changing subgenre to a factor
spotify$playlist_subgenre <- as.factor(spotify$playlist_subgenre)

#simplifying variable names
names(spotify) <- c("name", "artist", "popularity", "year", "genre", "subgenre", "danceability",
"energy", "key", "loudness", "mode", "speechiness", "acousticness", "instrumantalness", "livenes
s", "valence", "tempo", "duration")
```

```
spotify = na.omit(spotify)
sum(is.na(spotify))
```

```
## [1] 0
```

```
write.csv(spotify, "spotify_cleaned.csv")
```

```
spotify %>%
  select(popularity, danceability, energy, key, loudness, mode, speechiness, acousticness, instr
umantalness, liveness, valence, tempo, duration) %>%
  cor() %>%
  corrplot(method = 'color', order = 'hclust',  type = 'upper',
           diag = TRUE, main = 'Correlation Matrix for Popularity and Audio Features',
           mar = c(2,2,2,2))
```




```
title2 <- Corpus(VectorSource(spotify$name))
# Convert the text to lower case
title2 <- tm_map(title2, content_transformer(tolower))
```

```
## Warning in tm_map.SimpleCorpus(title2, content_transformer(tolower)):
## transformation drops documents
```

```
# Remove numbers
title2 <- tm_map(title2, removeNumbers)
```

```
## Warning in tm_map.SimpleCorpus(title2, removeNumbers): transformation drops
## documents
```

```
# Remove english common stopwords
title2 <- tm_map(title2, removeWords, stopwords("english"))
```

```
## Warning in tm_map.SimpleCorpus(title2, removeWords, stopwords("english")):
## transformation drops documents
```

```
# Remove punctuations
title2 <- tm_map(title2, removePunctuation)
```

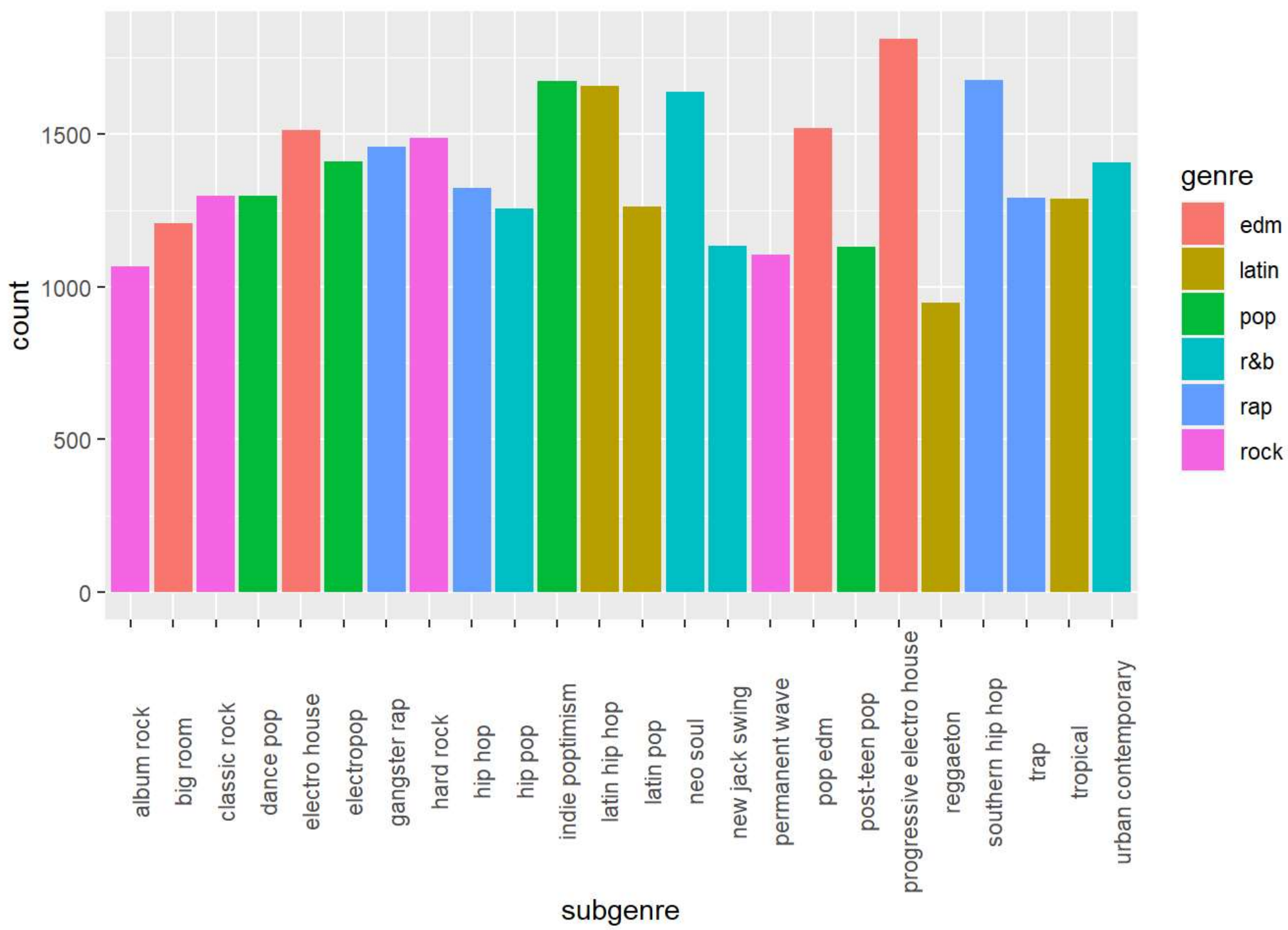
```
## Warning in tm_map.SimpleCorpus(title2, removePunctuation): transformation drops
## documents
```

```
# Remove other data specific stop words
title2 <- tm_map(title2, removeWords, c("feat","edit", "version", "radio", "remix", "remastere
d", "mix","like", "original", "remaster"))
```

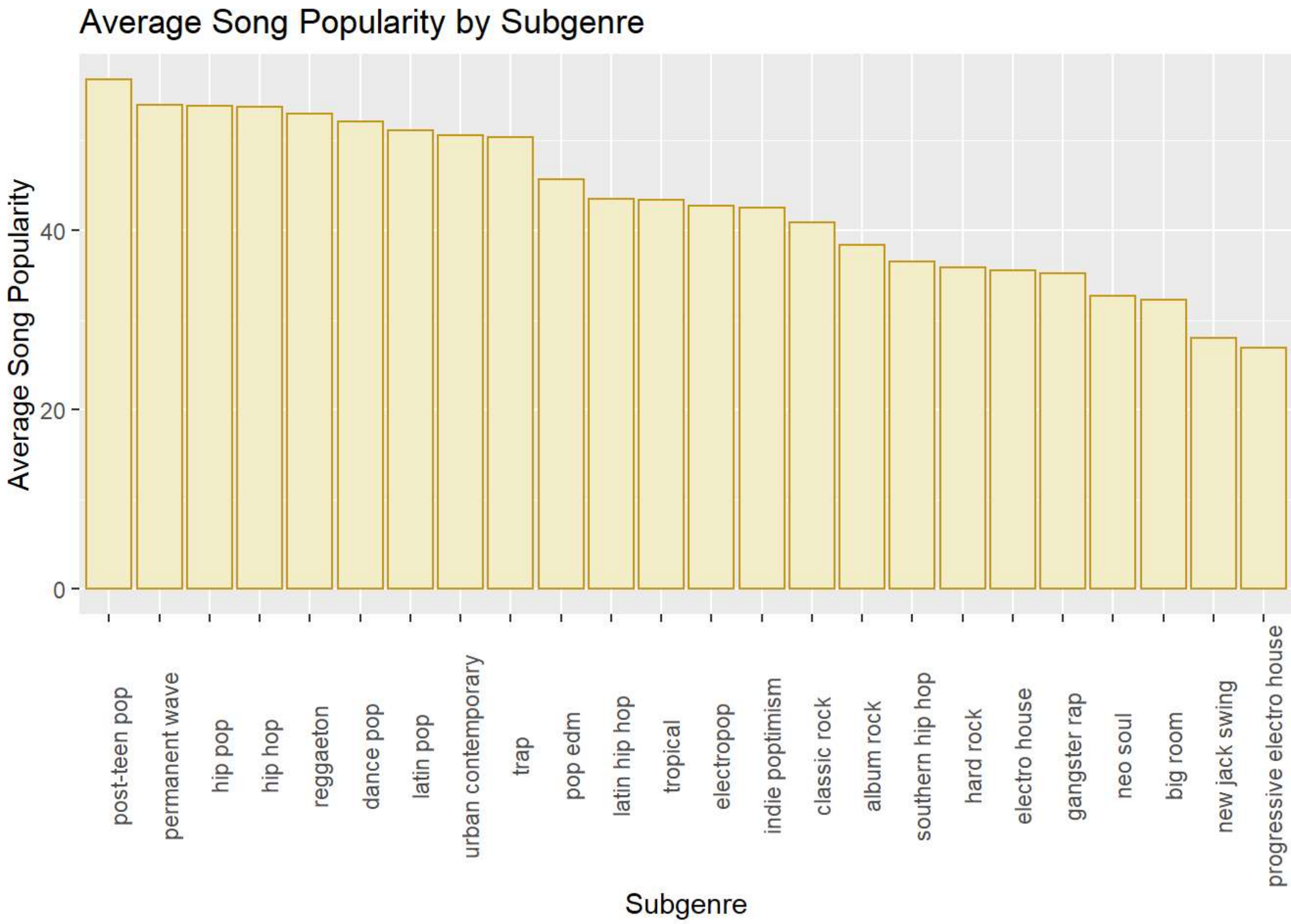
```
## Warning in tm_map.SimpleCorpus(title2, removeWords, c("feat", "edit",
## "version", : transformation drops documents
```

```
title2_dtm <- DocumentTermMatrix(title2)
title2_freq <- colSums(as.matrix(title2_dtm))
freq2 <- sort(colSums(as.matrix(title2_dtm)), decreasing=TRUE)
title2_wf <- data.frame(word=names(title2_freq), freq=title2_freq)

#create word cloud
set.seed(1234)
wordcloud(words = title2_wf$word, freq = title2_wf$freq, min.freq =1,
          max.words=200, random.order=FALSE, rot.per=0.35,
          colors=brewer.pal(8, "Dark2"))
```

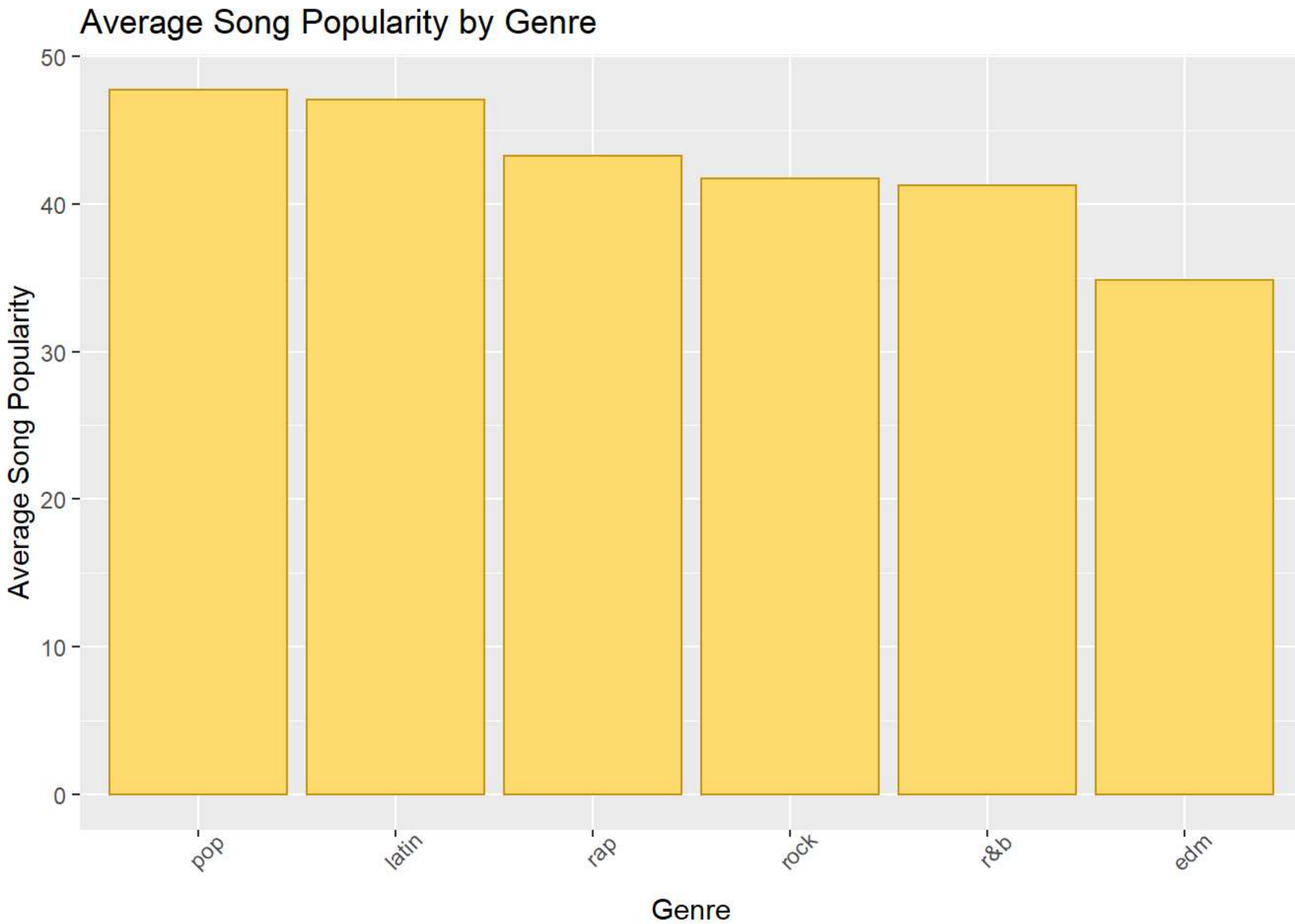
```
ggplot(data = spotify, aes(x = subgenre, fill = genre)) +
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90))
```




```
spotify %>% group_by(subgenre) %>%
  summarize(average_popularity=mean(popularity)) %>%
  ggplot(aes(x=reorder(subgenre,-average_popularity), y=average_popularity))+
  geom_col(fill = "#F4EDCA", color = "#C4961A")+
  theme(axis.text.x = element_text(angle = 90))+
  ggtitle("Average Song Popularity by Subgenre")+
  labs(y="Average Song Popularity", x = "Subgenre")
```




```
spotify %>% group_by(genre) %>%
  summarize(average_popularity=mean(popularity)) %>%
  ggplot(aes(x=reorder(genre,-average_popularity), y=average_popularity))+
  geom_col(fill = "#FFDB6D", color = "#C4961A")+
  theme(axis.text.x = element_text(angle = 45))+
  ggtitle("Average Song Popularity by Genre")+
  labs(y="Average Song Popularity", x = "Genre")
```




```
# Compute the analysis of variance
res.aov <- aov(popularity ~ genre, data = spotify)
# Tukey's multiple comparison of means
TukeyHSD(res.aov)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = popularity ~ genre, data = spotify)
##
## $genre
##                  diff        lwr        upr     p adj
## latin-edm  12.2113019 10.8822333 13.5403705 0.0000000
## pop-edm    12.9113438 11.6055353 14.2171522 0.0000000
## r&b-edm     6.3900052  5.0794252  7.7005852 0.0000000
## rap-edm     8.4045025  7.1128079  9.6961971 0.0000000
## rock-edm    6.8948113  5.5511883  8.2384343 0.0000000
## pop-latin   0.7000419 -0.6584696  2.0585534 0.6845195
## r&b-latin  -5.8212967 -7.1843952 -4.4581981 0.0000000
## rap-latin  -3.8067994 -5.1517501 -2.4618486 0.0000000
## rock-latin -5.3164905 -6.7113885 -3.9215925 0.0000000
## r&b-pop    -6.5213386 -7.8617677 -5.1809095 0.0000000
## rap-pop    -4.5068413 -5.8288114 -3.1848712 0.0000000
## rock-pop   -6.0165325 -7.3892862 -4.6437787 0.0000000
## rap-r&b     2.0144973  0.6878138  3.3411809 0.0002188
## rock-r&b    0.5048061 -0.8724873  1.8820995 0.9028530
## rock-rap   -1.5096912 -2.8690263 -0.1503561 0.0193464
```

```
spotify$popular_level<-rep(0, nrow(spotify))

spotify <- within(spotify, {

  popular_level[popularity>=66] <- "very_popular"
  popular_level[popularity>=33 & popularity< 66] <- "Moderate"
  popular_level[popularity <= 33] <- "not_popular"
} )
```

```
popular_table <- spotify %>%
  group_by(artist) %>%

  summarize(total_popular=sum(popular_level == "very_popular"),
            total_not_popular=sum(popular_level == "not_popular"),
            moderate = sum(popular_level == "Moderate"),
            popularity_ratio=ifelse(
              total_not_popular>0,total_popular/total_not_popular,total_popular)) %>%

  top_n(10,total_popular) %>%
  select(artist, total_popular,moderate,total_not_popular, popularity_ratio) %>%
  arrange(desc(total_popular))

popular_table
```

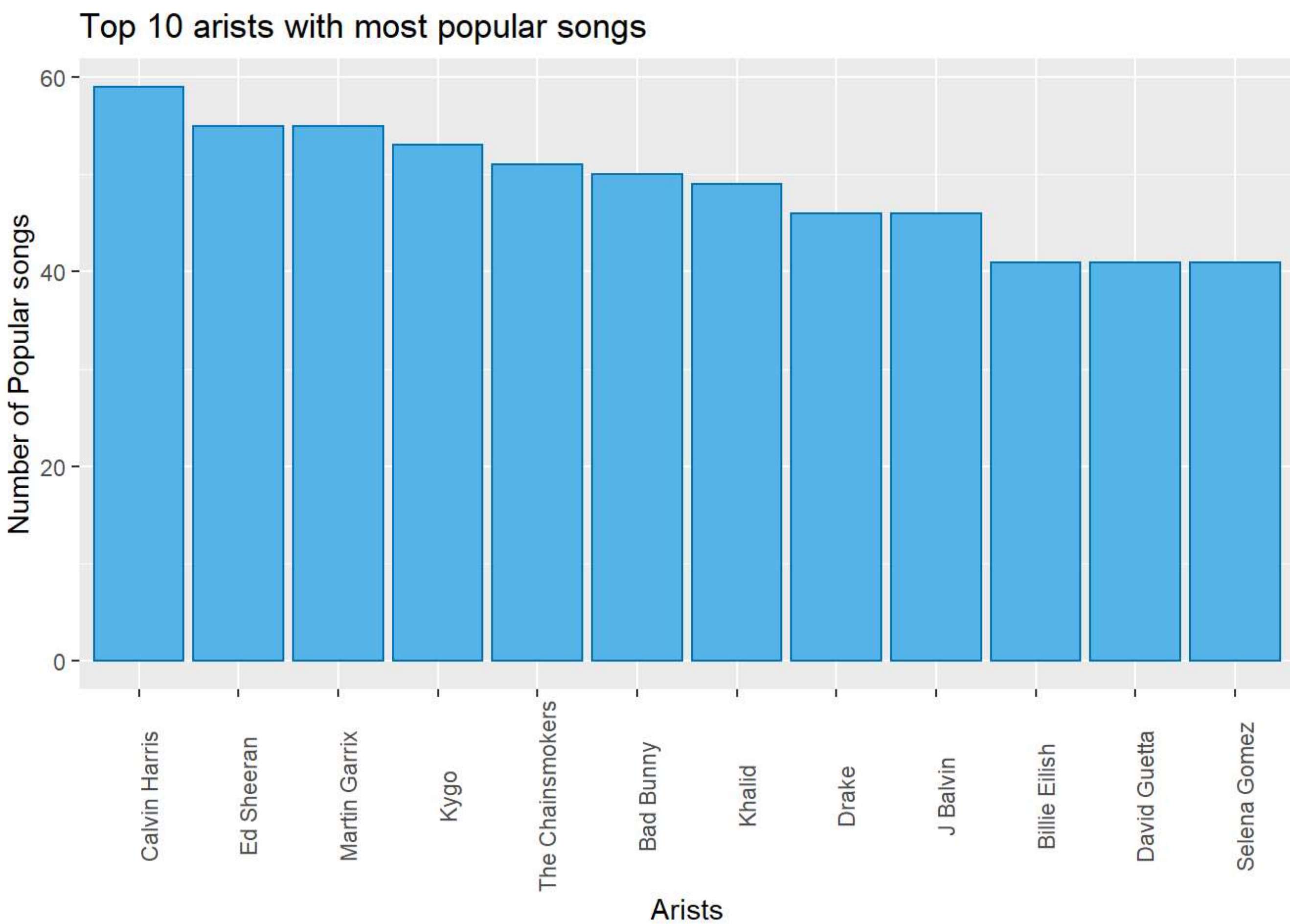
```
## # A tibble: 12 × 5
##    artist          total_popular moderate total_not_popular popularity_ratio
##    <chr>                   <int>    <int>             <int>            <dbl>
##  1 Calvin Harris              59       20                12             4.92
##  2 Ed Sheeran                 55       12                 2            27.5
##  3 Martin Garrix              55       63                43             1.28
##  4 Kygo                       53       23                 7             7.57
##  5 The Chainsmokers           51       57                15             3.4
##  6 Bad Bunny                  50        1                10             5
##  7 Khalid                     49        8                 0            49
##  8 Drake                      46       13                41             1.12
##  9 J Balvin                   46       10                16             2.88
## 10 Billie Eilish              41        0                 2            20.5
## 11 David Guetta               41       49                20             2.05
## 12 Selena Gomez               41        7                 4            10.2
```

```
knitr::kable(popular_table, align = "lccc", format="markdown",col.names = c('Artist', 'Popula
r','Moderate', ' Not popular', 'popularity ratio'), caption="Top 10 Artists by Number of Popular
Songs")
```

Top 10 Artists by Number of Popular Songs

Artist	Popular	Moderate	Not popular	popularity ratio
Calvin Harris	59	20	12	4.916667
Ed Sheeran	55	12	2	27.500000
Martin Garrix	55	63	43	1.279070
Kygo	53	23	7	7.571429
The Chainsmokers	51	57	15	3.400000
Bad Bunny	50	1	10	5.000000
Khalid	49	8	0	49.000000
Drake	46	13	41	1.121951
J Balvin	46	10	16	2.875000
Billie Eilish	41	0	2	20.500000
David Guetta	41	49	20	2.050000
Selena Gomez	41	7	4	10.250000

```
ggplot(popular_table,
       aes(x=reorder(artist, -total_popular), y=total_popular)) + geom_bar(stat = "identity",fil
l = "#56B4E9", color = "#0072B2")+
  theme(axis.text.x = element_text(angle = 90))+
  ggtitle("Top 10 arists with most popular songs")+
  labs(y="Number of Popular songs", x = "Arists")
```

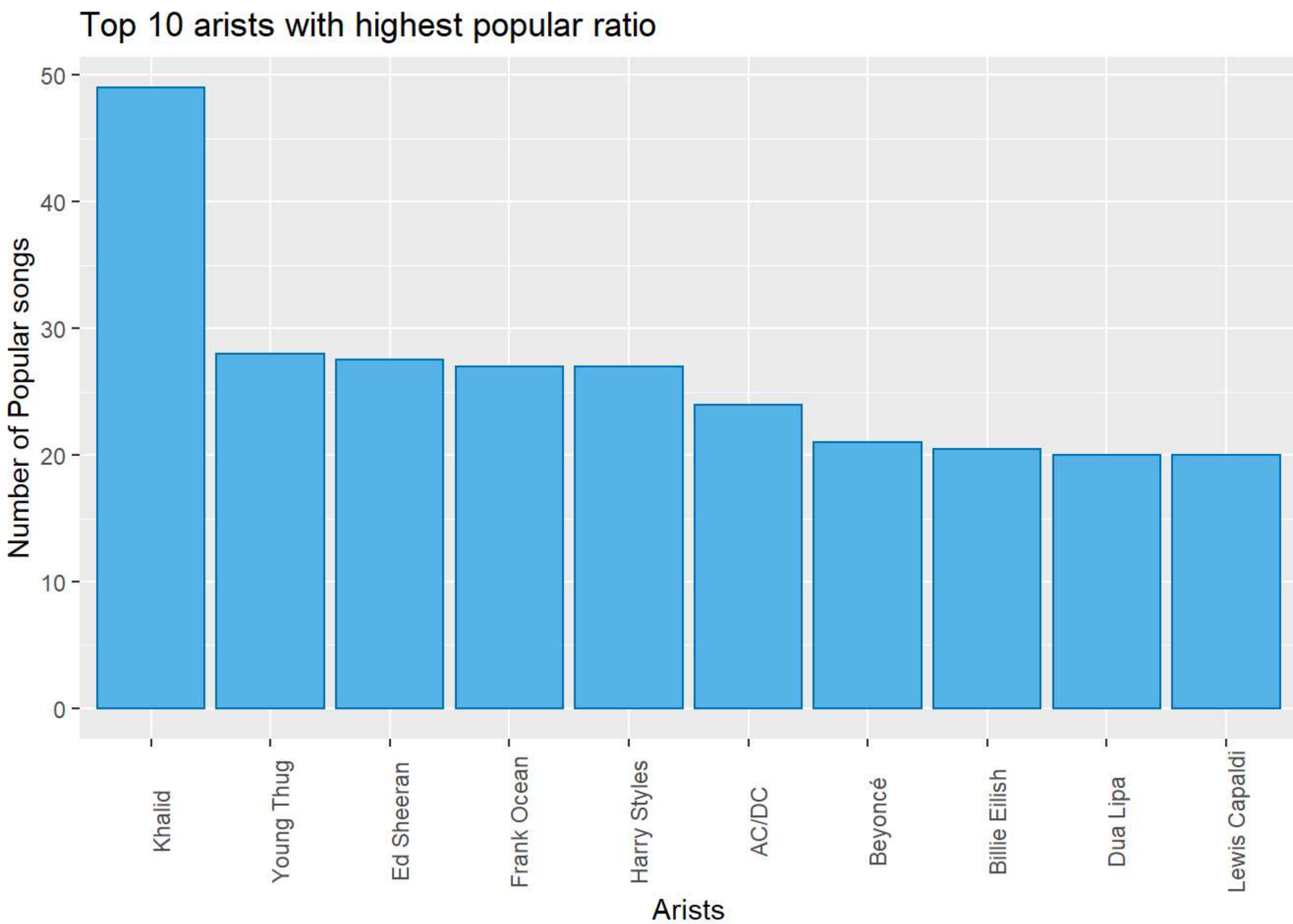



```
ratio_table <- spotify %>%
  group_by(artist) %>%

  summarize(total_popular=sum(popular_level == "very_popular"),
            total_not_popular=sum(popular_level == "not_popular"),
            moderate = sum(popular_level == "Moderate"),
            popularity_ratio=ifelse(
              total_not_popular>0,total_popular/total_not_popular,total_popular)) %>%

  top_n(10,popularity_ratio) %>%
  select(artist, total_popular,moderate,total_not_popular, popularity_ratio) %>%
  arrange(desc(popularity_ratio))


knitr::kable(ratio_table, align = "lccc", format="markdown",col.names = c('Artist', 'Popular','M
oderate', ' Not popular', 'Popular ratio'), caption="Top 10 Artists by Popular Ratio")
```

Top 10 Artists by Popular Ratio

Artist	Popular	Moderate	Not popular	Popular ratio
Khalid	49	8	0	49.0
Young Thug	28	15	1	28.0
Ed Sheeran	55	12	2	27.5
Frank Ocean	27	13	1	27.0
Harry Styles	27	0	0	27.0
AC/DC	24	4	0	24.0
Beyoncé	21	4	0	21.0
Billie Eilish	41	0	2	20.5
Dua Lipa	20	8	1	20.0
Lewis Capaldi	20	1	0	20.0

```
ggplot(ratio_table,
       aes(x=reorder(artist, -popularity_ratio), y=popularity_ratio)) + geom_bar(stat = "identit
y",fill = "#56B4E9", color = "#0072B2")+
  theme(axis.text.x = element_text(angle = 90))+
  ggtitle("Top 10 arists with highest popular ratio")+
  labs(y="Number of Popular songs", x = "Arists")
```




```
# parse out the keywords from the pipe-delimited string and determine keyword frequency
parse_key <- data.frame(table(unlist(strsplit(as.character(spotify$artist), split = "|",
                                              fixed = TRUE))))
# list the 20 most frequent keywords
head(parse_key[order(parse_key$Freq, decreasing = TRUE), ], 10)
```

```
##                           Var1 Freq
## 6165             Martin Garrix  161
## 7735                     Queen  136
## 9351          The Chainsmokers  123
## 2284              David Guetta  110
## 2634                  Don Omar  102
## 2683                     Drake  100
## 2487 Dimitri Vegas & Like Mike   93
## 1492             Calvin Harris   91
## 3873                  Hardwell   84
## 5290                      Kygo   83
```

```
# Packages
library(tidyverse)
library(plotly)
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

```
library(ggplot2)
library(boot)
```

Write your Null and Alternative Hypothesis.

```
df <- read.csv("spotify_cleaned.csv",stringsAsFactors=FALSE)
head(df)
```

```
##   X                                                  name           artist
## 1 1 I Don't Care (with Justin Bieber) - Loud Luxury Remix       Ed Sheeran
## 2 2                        Memories - Dillon Francis Remix         Maroon 5
## 3 3                        All the Time - Don Diablo Remix     Zara Larsson
## 4 4                      Call You Mine - Keanu Silva Remix The Chainsmokers
## 5 5                Someone You Loved - Future Humans Remix    Lewis Capaldi
## 6 6     Beautiful People (feat. Khalid) - Jack Wins Remix       Ed Sheeran
##   popularity year genre  subgenre danceability energy key loudness mode
## 1         66 2019   pop dance pop        0.748  0.916   6   -2.634    1
## 2         67 2019   pop dance pop        0.726  0.815  11   -4.969    1
## 3         70 2019   pop dance pop        0.675  0.931   1   -3.432    0
## 4         60 2019   pop dance pop        0.718  0.930   7   -3.778    1
## 5         69 2019   pop dance pop        0.650  0.833   1   -4.672    1
## 6         67 2019   pop dance pop        0.675  0.919   8   -5.385    1
##   speechiness acousticness instrumantalness liveness valence   tempo duration
## 1      0.0583       0.1020         0.00e+00   0.0653   0.518 122.036   194754
## 2      0.0373       0.0724         4.21e-03   0.3570   0.693  99.972   162600
## 3      0.0742       0.0794         2.33e-05   0.1100   0.613 124.008   176616
## 4      0.1020       0.0287         9.43e-06   0.2040   0.277 121.956   169093
## 5      0.0359       0.0803         0.00e+00   0.0833   0.725 123.976   189052
## 6      0.1270       0.0799         0.00e+00   0.1430   0.585 124.982   163049
```

```
# My Data Science Question:
# Is the population mean of popularity of rock music greater than that of rap music?


# Hypothesis:
# H0: The mean popularity of rock music is the same as the mean popularity of rap music
# Ha: The mean popularity of rock music is higher than the mean popularity of rap music
```

Do a t-test (if your Data science question is about population averages. If your question is about comparing proportions then use a Z-test), and write your conclusion at 5% significance level.

```
# Since my question is to compare average, therefore, I use t-test for my hypothesis:

dt_pop <- df$popularity[df$genre == "rock"]


ur_pop <- df$popularity[df$genre == "rap"]




# Since the hypothesis is to compare energy of KC and AG,  alternative is higher, use greater in
t-test.
t.test(ur_pop, dt_pop, alt="greater",conf.level = 0.95)  #at 5% significance level.
```

```
##
##  Welch Two Sample t-test
##
## data:  ur_pop and dt_pop
## t = 3.2267, df = 10232, p-value = 0.0006281
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.7400385       Inf
## sample estimates:
## mean of x mean of y
##  43.23803  41.72834
```

```
# Conclusion:
# Based on the t-test, we can see that the p-value is less than 0.05 which is the 5% significanc
e level.
# Therefore, we reject the Null hypothesis at this significant level.
# We can conclude that we have enough evidence to prove that the mean energy of Kelly Clarkson i
s not the same as the mean energy of Ariana Grande. In fact, we can say that the mean energy of
Kelly Clarkson is larger than the mean energy of Ariana Grande

# this conclusion also aligns with my EDA analysis, that the mean energy of Kelly Clarkson is la
rger than the mean energy of Ariana Grande
```

Do a bootstrap test(here you will be using bootstrap sampling and 95% bootstrap percentile interval) to answer the same question and write your conclusion at 5% significance level.

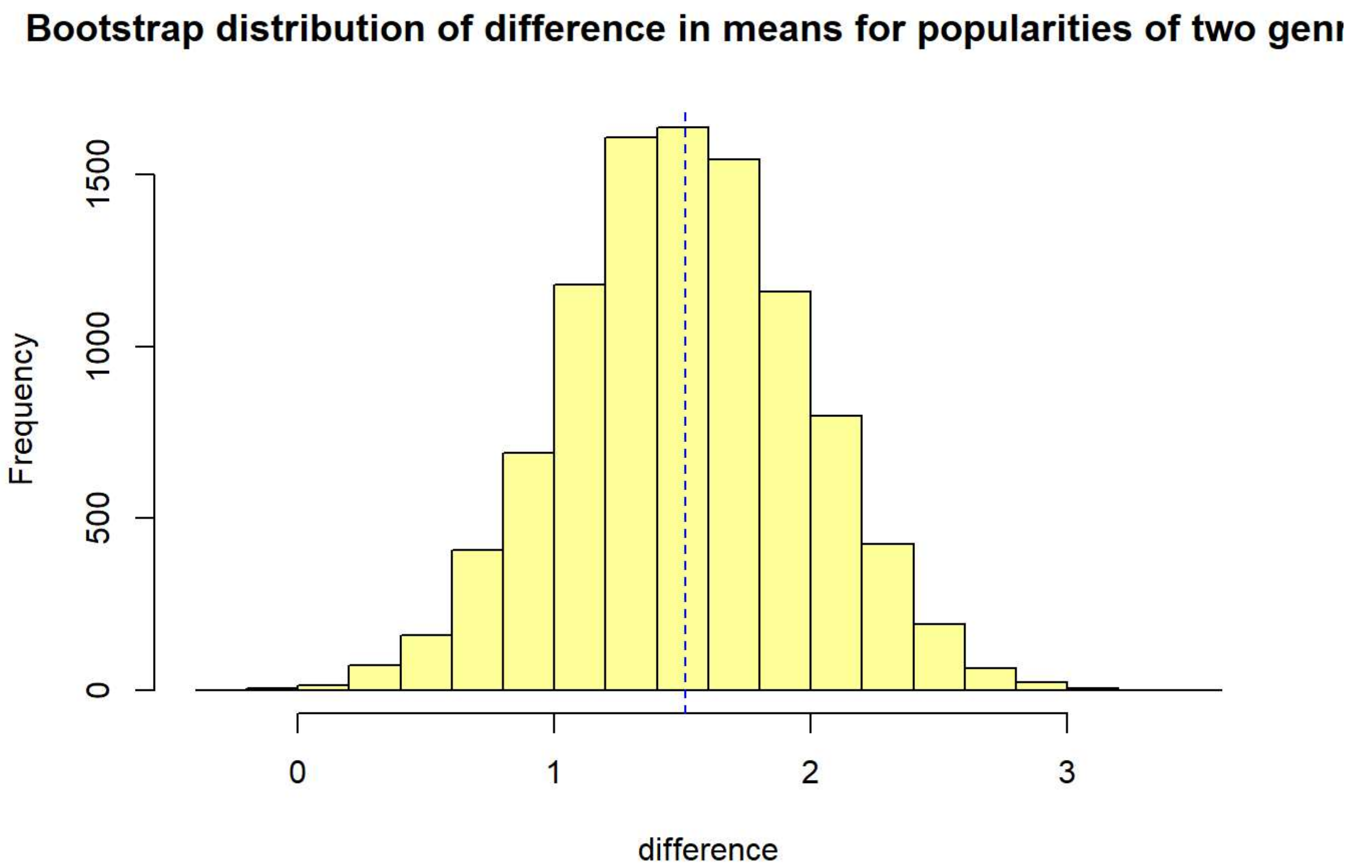
```
# Use bootstrap

set.seed(2)
difference <- rep(NA,10000)
boot_ratio <- rep(NA, 10000)

for (j in 1:10000){
  boot_dt <- mean(sample(dt_pop, length(dt_pop), replace = T))
  boot_ur <- mean(sample(ur_pop, length(ur_pop), replace = T))
  difference[j] <- boot_ur - boot_dt   #the difference
  boot_ratio[j] <- boot_ur / boot_dt # The ratio
}

mean(difference) #bootstrap mean difference
```

```
## [1] 1.509232
```

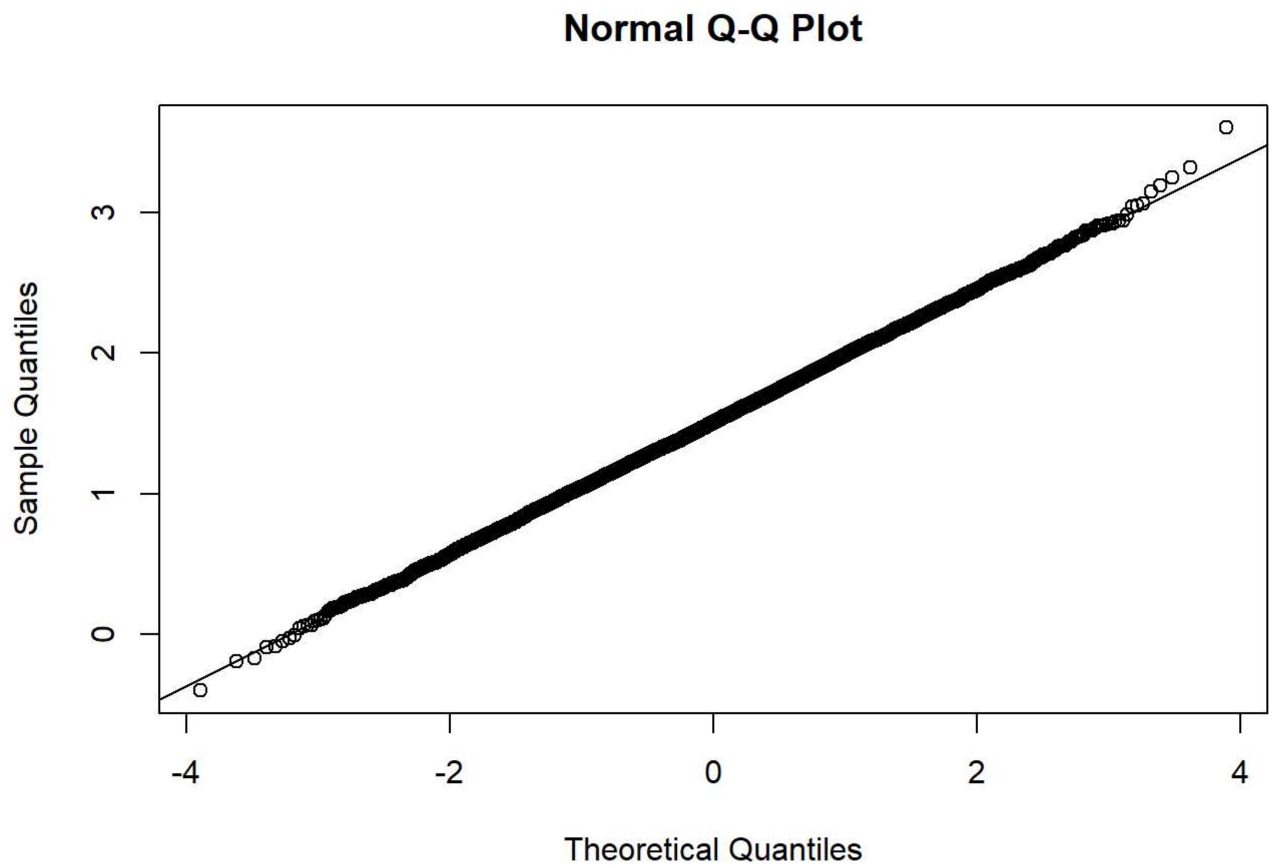
```
mean(boot_ratio) #bootstrap mean rAtio
```

```
## [1] 1.036242
```

```
hist(difference, main = "Bootstrap distribution of difference in means for popularities of two g
enres",col = '#FFFF99')
abline(v = mean(ur_pop) - mean(dt_pop), col = "blue", lty = 2)
```



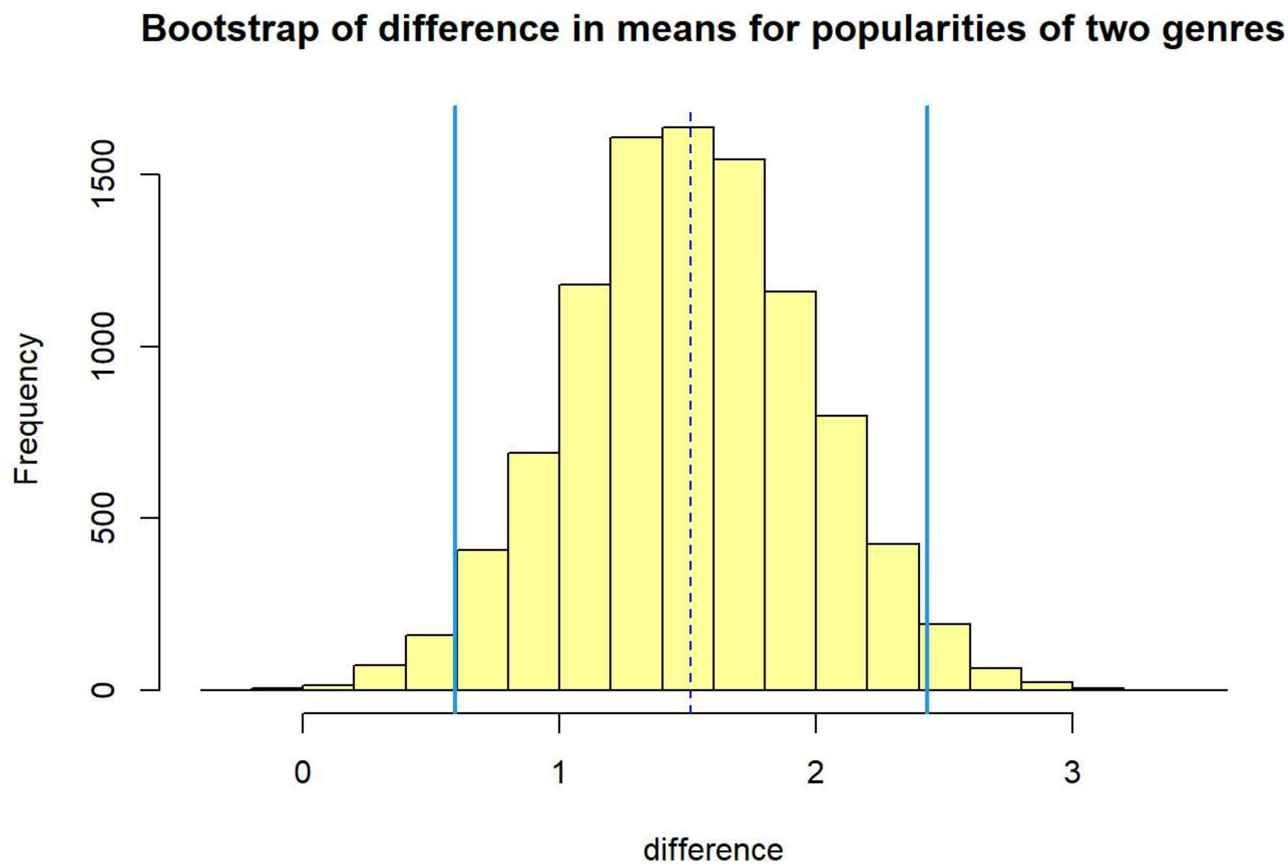

```
qqnorm(difference)
qqline(difference)
```




```
# 95% CI
CI <- quantile(difference, c(0.025, 0.975))
CI
```

```
##      2.5%     97.5%
## 0.5916207 2.4320700
```

```
hist(difference, main = "Bootstrap of difference in means for popularities of two genres",col =
'#FFFF99')
abline(v = mean(ur_pop) - mean(dt_pop), col = "blue", lty = 2)
abline(v = CI, col = 4, lwd = 2)
```



Import the cleaned dataset

```
df <- read.csv("spotify_cleaned.csv")
head(df,5)
```

```
##   X                                                 name            artist
## 1 1 I Don't Care (with Justin Bieber) - Loud Luxury Remix       Ed Sheeran
## 2 2                         Memories - Dillon Francis Remix         Maroon 5
## 3 3                         All the Time - Don Diablo Remix     Zara Larsson
## 4 4                       Call You Mine - Keanu Silva Remix The Chainsmokers
## 5 5                  Someone You Loved - Future Humans Remix    Lewis Capaldi
##   popularity year genre  subgenre danceability energy key loudness mode
## 1         66 2019   pop dance pop        0.748  0.916   6   -2.634    1
## 2         67 2019   pop dance pop        0.726  0.815  11   -4.969    1
## 3         70 2019   pop dance pop        0.675  0.931   1   -3.432    0
## 4         60 2019   pop dance pop        0.718  0.930   7   -3.778    1
## 5         69 2019   pop dance pop        0.650  0.833   1   -4.672    1
##   speechiness acousticness instrumantalness liveness valence   tempo duration
## 1      0.0583       0.1020         0.00e+00   0.0653   0.518 122.036   194754
## 2      0.0373       0.0724         4.21e-03   0.3570   0.693  99.972   162600
## 3      0.0742       0.0794         2.33e-05   0.1100   0.613 124.008   176616
## 4      0.1020       0.0287         9.43e-06   0.2040   0.277 121.956   169093
## 5      0.0359       0.0803         0.00e+00   0.0833   0.725 123.976   189052
```

From the daily observations, some music genres do dominate the front rank of the listener's music charts, such as pop music. There are many reasons for this phenomenon, such as the fact that these pop music are sung by favorite singers. Hence, with this complex relationship, whether the popularity of music is related to the genre of music itself needs to be studied. In the previous hypothesis test, the relationship between the average populative of rock music and of rap music has been addressed. However, the general relationship between the genres and the popularity cannot be explained by a test between two specific genres of musics.

In the second hypothsis test, whether the popularity is related to the genre will be examinated. Before implementing the test method, categorizing the popularity into three different groups - high,medium,low - will be helpful in understanding the relationship. Based on the 0 to 100 popularity score rules on spotify, three categories can be presented as: - High: popularity >= 66 - medium: 33 > popularity > 66 - low: popularity <= 33

The two-way table is generated to show the frequency of songs in the group of genre and popularity.

```
df$popularity <- as.factor(ifelse(df$popularity>=66, 'High',
                     ifelse(df$popularity<66 & df$popularity>33, 'Medium','Low')))
```

```
library(knitr)
t1 = table(df$popularity,df$genre)
kable(t1,align = "lccrr")
```

	edm	latin	pop	r&b	rap	rock
High	613	1378	1603	1096	921	1000
Low	2733	1343	1533	2043	1654	1748
Medium	2697	2432	2371	2292	3168	2203

In statistics, Chi-square test is commonly used in testing the independence of two variables. If two variables are independent, it means there is no relationship between two factors. Based on the question of whether the popularity is related to the genre, the null hypothesis (H0) can be set as the popularity and the genre is independent, and then correspondingly, the alternative hypothesis (Ha) will be the popularity and the genre is dependent.In this case, the specific hypotheses are:

- H0: There is no relationship between the popularity and the genre of musics.
- Ha: There is relationship between the popularity and the genre of musics.

```
t2 <- chisq.test(t1)
t2
```

```
##
##  Pearson's Chi-squared test
##
## data:  t1
## X-squared = 1270.6, df = 10, p-value < 2.2e-16
```

```
chisq.test(t1)$expected
```

```
##
##              edm    latin      pop      r&b      rap      rock
##   High   1216.957 1037.726 1109.016 1093.711 1156.542  997.0471
##   Low    2034.828 1735.143 1854.343 1828.752 1933.810 1667.1242
##   Medium 2791.215 2380.131 2543.641 2508.537 2652.647 2286.8287
```

From the output, the p-value is less than the significance level of 5%, which means the rejection of null hypothesis. In this context, rejecting the null hypothesis for the Chi-square test of independence means there is a significant relationship between the popularity and the genre of musics.

Load the required dataset

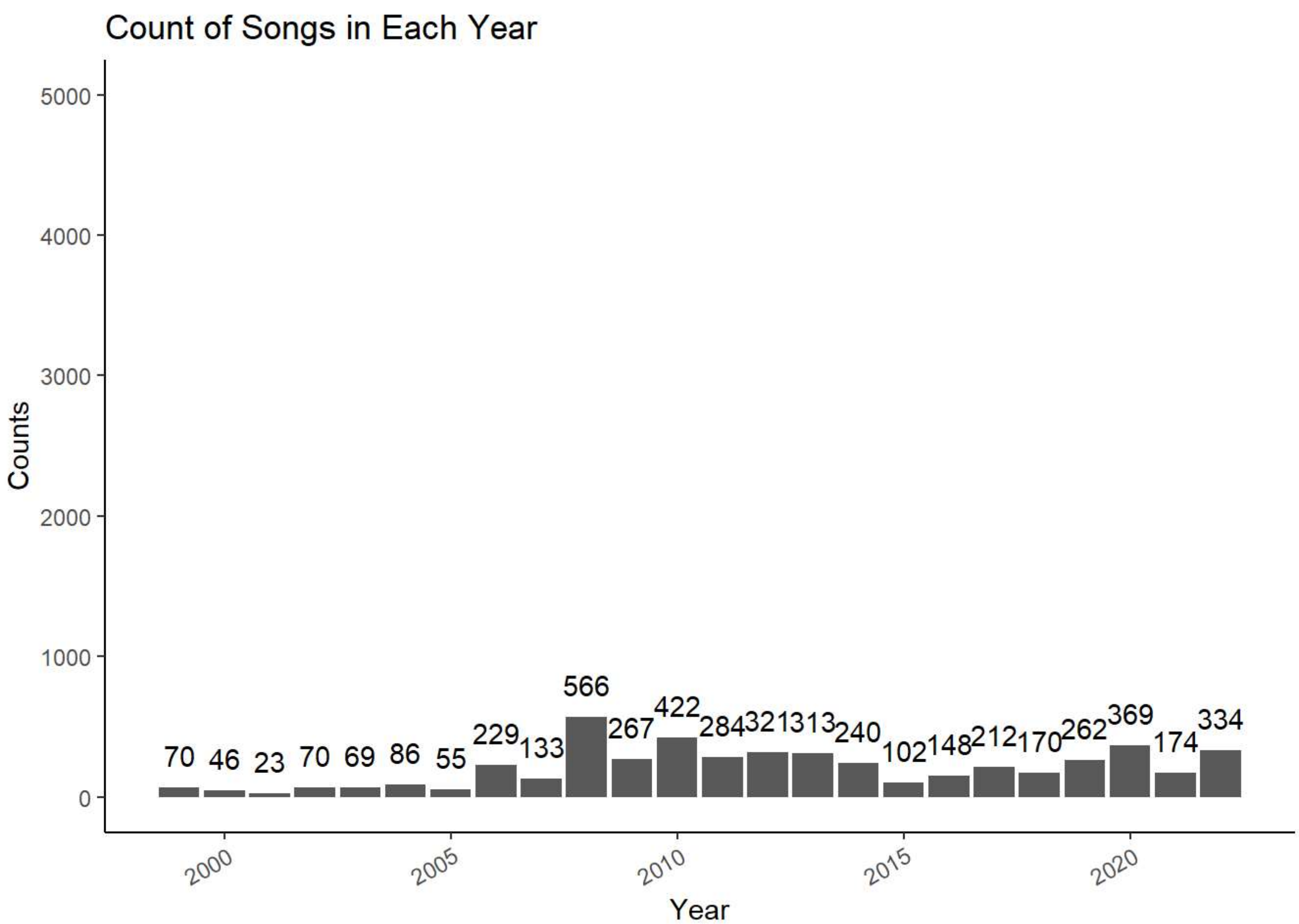
```
artists <- read.csv("./Tracks_Artists.csv")
head(artists)
```

```
##   X  artist_name Valence danceability energy loudness speechiness acousticness
## 1 1 Taylor Swift  0.0984        0.735  0.444  -10.519      0.0684       0.2040
## 2 2 Taylor Swift  0.0382        0.658  0.378   -8.300      0.0379       0.0593
## 3 3 Taylor Swift  0.5190        0.638  0.634   -6.582      0.0457       0.1330
## 4 4 Taylor Swift  0.1540        0.659  0.323  -13.425      0.0436       0.7350
## 5 5 Taylor Swift  0.3760        0.694  0.380  -10.307      0.0614       0.4160
## 6 6 Taylor Swift  0.2300        0.636  0.377  -11.721      0.0708       0.7100
##   liveness   tempo                             track_name
## 1   0.1700  97.038                          Lavender Haze
## 2   0.0976 108.034                                 Maroon
## 3   0.1520  96.953                              Anti-Hero
## 4   0.1160 110.007 Snow On The Beach (feat. Lana Del Rey)
## 5   0.1260 120.044               You're On Your Own, Kid
## 6   0.1150 139.966                          Midnight Rain
##               album_name album_release_year
## 1 Midnights (3am Edition)               2022
## 2 Midnights (3am Edition)               2022
## 3 Midnights (3am Edition)               2022
## 4 Midnights (3am Edition)               2022
## 5 Midnights (3am Edition)               2022
## 6 Midnights (3am Edition)               2022
```

```
summary(artists$album_release_year)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1999    2008    2012    2013    2018    2022
```

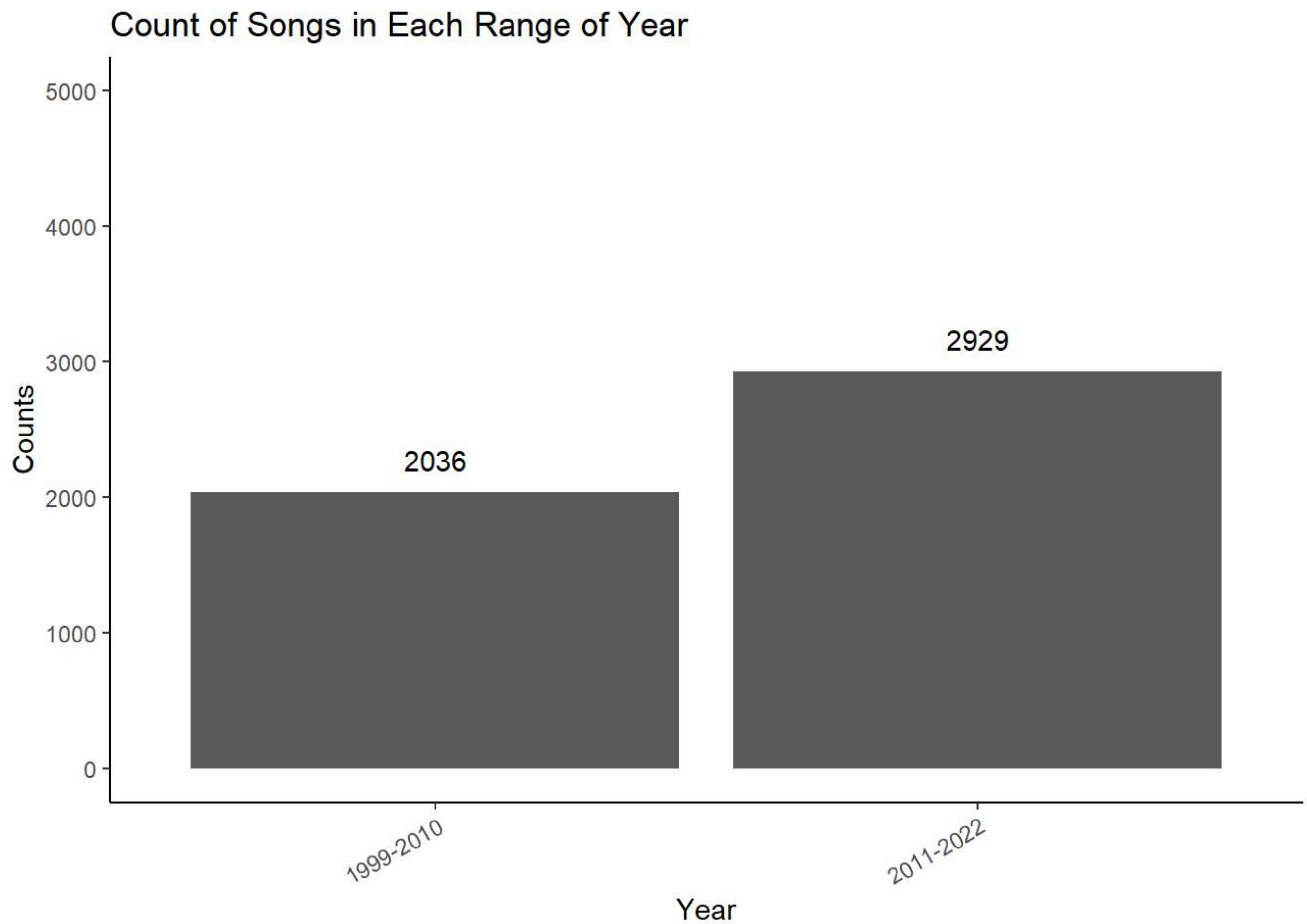
```
library(ggplot2)
ggplot(artists, aes(x=album_release_year)) +
  geom_bar()+
  geom_text(stat='count', aes(label=..count..), vjust=-1)+
  ylim(0,5000)+
  theme_classic()+
  theme(axis.text.x=element_text(angle=30,hjust=1))+
  labs(title="Count of Songs in Each Year",
        x ="Year", y = "Counts")
```




```
artists$year_range <- ifelse(artists$album_release_year < 2011, "1999-2010","2011-2022")
head(artists)
```

```
##   X  artist_name Valence danceability energy loudness speechiness acousticness
## 1 1 Taylor Swift  0.0984        0.735  0.444  -10.519      0.0684       0.2040
## 2 2 Taylor Swift  0.0382        0.658  0.378   -8.300      0.0379       0.0593
## 3 3 Taylor Swift  0.5190        0.638  0.634   -6.582      0.0457       0.1330
## 4 4 Taylor Swift  0.1540        0.659  0.323  -13.425      0.0436       0.7350
## 5 5 Taylor Swift  0.3760        0.694  0.380  -10.307      0.0614       0.4160
## 6 6 Taylor Swift  0.2300        0.636  0.377  -11.721      0.0708       0.7100
##   liveness   tempo                           track_name
## 1   0.1700  97.038                        Lavender Haze
## 2   0.0976 108.034                               Maroon
## 3   0.1520  96.953                            Anti-Hero
## 4   0.1160 110.007 Snow On The Beach (feat. Lana Del Rey)
## 5   0.1260 120.044              You're On Your Own, Kid
## 6   0.1150 139.966                        Midnight Rain
##                album_name album_release_year year_range
## 1 Midnights (3am Edition)               2022  2011-2022
## 2 Midnights (3am Edition)               2022  2011-2022
## 3 Midnights (3am Edition)               2022  2011-2022
## 4 Midnights (3am Edition)               2022  2011-2022
## 5 Midnights (3am Edition)               2022  2011-2022
## 6 Midnights (3am Edition)               2022  2011-2022
```

```
library(ggplot2)
ggplot(artists, aes(x=year_range)) +
  geom_bar()+
  geom_text(stat='count', aes(label=..count..), vjust=-1)+
  ylim(0,5000)+
  theme_classic()+
  theme(axis.text.x=element_text(angle=30,hjust=1))+
  labs(title="Count of Songs in Each Range of Year",
        x ="Year", y = "Counts")
```



Hypothesis 2:

Null Hypothesis: I will make null hypothesis as the average Valence of songs in 1999-2010 is higher than songs in 2011-2011.

Alternative Hypothesis: the average Valence of songs in 1999-2010 is lower than songs in 2011-2011.

```
# group the dataset by Yearrange
Year2010 <- subset(artists, artists$year_range == "1999-2010",select = c("Valence"))
Year2022 <- subset(artists, artists$year_range == "2011-2022",select = c("Valence") )
# t.test
t.test(Year2010,Year2022,alternative = "less")
```

```
##
##  Welch Two Sample t-test
##
## data:  Year2010 and Year2022
## t = 9.9977, df = 4084.5, p-value = 1
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##        -Inf 0.07579864
## sample estimates:
## mean of x mean of y
## 0.4736412 0.4085535
```

```r
set.seed(1)
n1 = length(Year2010)
n2 = length(Year2022)
N <- 10000
diff_mean <- numeric(N)

for (i in 1:N)
{
Year2010.sample <- sample(Year2010$Valence, n1, replace = TRUE)
Year2022.sample <- sample(Year2022$Valence, n2, replace = TRUE)
diff_mean[i] <- mean(Year2010.sample) - mean(Year2022.sample)
}

mean(diff_mean)
```

```
## [1] 0.06635376
```

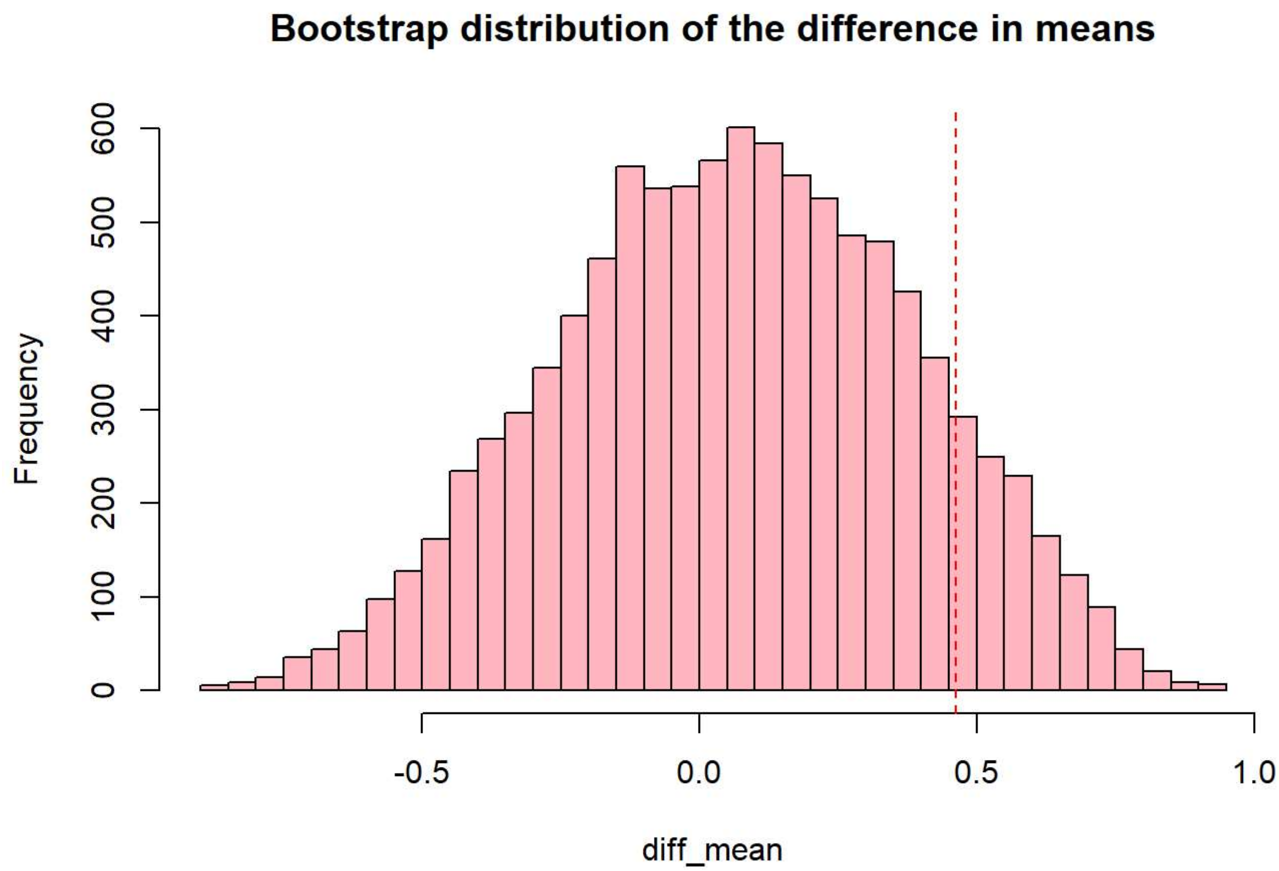
```r
quantile(diff_mean, c(.025, .975))
```

```
##   2.5%  97.5%
## -0.557  0.661
```

```r
mydiff = function(mydf){
  index1 = artists$year_range == "1999-2010"
  index2 = artists$year_range == "2011-2022"
  return(mean(artists$Valence[index1]) - mean(artists$Valence[index2]))
}

mydiff(genre.clean) #actual mean difference from the original sample
```

```
## [1] 0.06508774
```

```r
hist(diff_mean,breaks=50,main = "Bootstrap distribution of the difference in means",col = 'light
pink')
abline(v = mean(Year2010.sample) - mean(Year2022.sample), col = "red", lty = 2)
```




```
data <-  read.csv("spotify_cleaned.csv")
```

Data Science Questions: Are the variables contributing for predicting “popularity” of the songs is same for different genres?

Create a new variable named “Valence_C”.

```
data$Valence_C <- rep(0,nrow(data))

data1 <- within(data, {
  Valence_C[valence>=0.8 & valence<=1] <- "more positive"
  Valence_C[valence>=0.5 & valence<0.8] <- "moderate"
  Valence_C[valence<=0.499] <- "more negative"
})
head(data1)
```

```
##   X                                                    name           artist
## 1 1 I Don't Care (with Justin Bieber) - Loud Luxury Remix       Ed Sheeran
## 2 2                        Memories - Dillon Francis Remix         Maroon 5
## 3 3                        All the Time - Don Diablo Remix     Zara Larsson
## 4 4                      Call You Mine - Keanu Silva Remix The Chainsmokers
## 5 5                Someone You Loved - Future Humans Remix    Lewis Capaldi
## 6 6      Beautiful People (feat. Khalid) - Jack Wins Remix       Ed Sheeran
##   popularity year genre  subgenre danceability energy key loudness mode
## 1         66 2019   pop dance pop        0.748  0.916   6   -2.634    1
## 2         67 2019   pop dance pop        0.726  0.815  11   -4.969    1
## 3         70 2019   pop dance pop        0.675  0.931   1   -3.432    0
## 4         60 2019   pop dance pop        0.718  0.930   7   -3.778    1
## 5         69 2019   pop dance pop        0.650  0.833   1   -4.672    1
## 6         67 2019   pop dance pop        0.675  0.919   8   -5.385    1
##   speechiness acousticness instrumantalness liveness valence   tempo duration
## 1      0.0583       0.1020         0.00e+00   0.0653   0.518 122.036   194754
## 2      0.0373       0.0724         4.21e-03   0.3570   0.693  99.972   162600
## 3      0.0742       0.0794         2.33e-05   0.1100   0.613 124.008   176616
## 4      0.1020       0.0287         9.43e-06   0.2040   0.277 121.956   169093
## 5      0.0359       0.0803         0.00e+00   0.0833   0.725 123.976   189052
## 6      0.1270       0.0799         0.00e+00   0.1430   0.585 124.982   163049
##       Valence_C
## 1      moderate
## 2      moderate
## 3      moderate
## 4 more negative
## 5      moderate
## 6      moderate
```

Fit multiple linear regression models separately for different genres.

```
set.seed(12)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'lattice'
```

```
## The following object is masked from 'package:boot':
##
##     melanoma
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(tidyverse)
```

```
pop <- data1[data1$genre=="pop",]
edm <- data1[data1$genre=="edm",]
```

```
names(pop)
```

```
##  [1] "X"                "name"             "artist"           "popularity"
##  [5] "year"             "genre"            "subgenre"         "danceability"
##  [9] "energy"           "key"              "loudness"         "mode"
## [13] "speechiness"      "acousticness"     "instrumantalness" "liveness"
## [17] "valence"          "tempo"            "duration"         "Valence_C"
```

```
training_samples <- pop$popularity %>%
  createDataPartition(p=0.8, list=FALSE)

train <- pop[training_samples, ]
test <- pop[-training_samples, ]
dim(train)
```

```
## [1] 4407   20
```

Fit the FULL linear regression model.

```
fit1 <- lm(popularity ~ danceability + energy + loudness + speechiness + acousticness + instruma
ntalness + liveness + valence + tempo +Valence_C, data = train)
summary(fit1)
```

```
##
## Call:
## lm(formula = popularity ~ danceability + energy + loudness +
##     speechiness + acousticness + instrumantalness + liveness +
##     valence + tempo + Valence_C, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -64.194 -17.056   4.545  19.186  58.333
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             74.966782   4.959693  15.115  < 2e-16 ***
## danceability            14.311075   3.227621   4.434 9.48e-06 ***
## energy                 -33.654892   3.451728  -9.750  < 2e-16 ***
## loudness                 2.548691   0.198625  12.832  < 2e-16 ***
## speechiness             22.378111   5.546528   4.035 5.56e-05 ***
## acousticness             1.132331   2.091348   0.541   0.5882
## instrumantalness       -10.358720   2.168184  -4.778 1.83e-06 ***
## liveness                 0.372393   2.730148   0.136   0.8915
## valence                  4.192508   3.821088   1.097   0.2726
## tempo                    0.002425   0.015471   0.157   0.8754
## Valence_Cmore negative   0.246728   1.379914   0.179   0.8581
## Valence_Cmore positive  -4.052253   1.548440  -2.617   0.0089 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24.18 on 4395 degrees of freedom
## Multiple R-squared:  0.07447,    Adjusted R-squared:  0.07215
## F-statistic: 32.15 on 11 and 4395 DF,  p-value: < 2.2e-16
```

Remove insignificant variables.

```
fit2 <- lm(popularity ~ danceability + energy + loudness + speechiness + instrumantalness + Vale
nce_C, data = train)
summary(fit2)
```

```
##
## Call:
## lm(formula = popularity ~ danceability + energy + loudness +
##     speechiness + instrumantalness + Valence_C, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -64.044 -17.094   4.524  19.181  58.725
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             77.8923     3.9773  19.584  < 2e-16 ***
## danceability            14.7807     3.0557   4.837 1.36e-06 ***
## energy                 -33.8176     3.0221 -11.190  < 2e-16 ***
## loudness                 2.5462     0.1982  12.844  < 2e-16 ***
## speechiness             23.0326     5.4536   4.223 2.46e-05 ***
## instrumantalness       -10.5435     2.1567  -4.889 1.05e-06 ***
## Valence_Cmore negative  -0.9738     0.8297  -1.174   0.2406
## Valence_Cmore positive  -3.0531     1.2655  -2.413   0.0159 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24.18 on 4399 degrees of freedom
## Multiple R-squared:  0.07414,    Adjusted R-squared:  0.07267
## F-statistic: 50.32 on 7 and 4399 DF,  p-value: < 2.2e-16
```

Check interactions.

```
fit12 <- lm(popularity ~ (danceability+energy+loudness+speechiness+instrumantalness)^2, data=tra
in)
summary(fit12)
```

```
##
## Call:
## lm(formula = popularity ~ (danceability + energy + loudness +
##     speechiness + instrumantalness)^2, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -62.687 -16.864   4.522  19.050  53.836
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    103.1230    14.9440   6.901 5.92e-12 ***
## danceability                    -5.9375    22.2770  -0.267 0.789844
## energy                         -72.3426    14.8384  -4.875 1.12e-06 ***
## loudness                         3.8407     0.9789   3.924 8.85e-05 ***
## speechiness                     28.1324    60.8885   0.462 0.644082
## instrumantalness               -70.0682    18.7063  -3.746 0.000182 ***
## danceability:energy             41.5464    21.7212   1.913 0.055850 .
## danceability:loudness            0.3138     1.4425   0.218 0.827802
## danceability:speechiness       -74.1727    42.3132  -1.753 0.079681 .
## danceability:instrumantalness  -1.8488    14.8859  -0.124 0.901163
## energy:loudness                 -1.2025     0.6406  -1.877 0.060553 .
## energy:speechiness              21.8262    47.0904   0.463 0.643032
## energy:instrumantalness         29.7824    13.9461   2.136 0.032772 *
## loudness:speechiness            -4.4678     3.3171  -1.347 0.178077
## loudness:instrumantalness       -4.5224     0.8919  -5.071 4.12e-07 ***
## speechiness:instrumantalness    57.2961    62.7741   0.913 0.361432
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24.09 on 4391 degrees of freedom
## Multiple R-squared:  0.08224,    Adjusted R-squared:  0.0791
## F-statistic: 26.23 on 15 and 4391 DF,  p-value: < 2.2e-16
```

```
fit3 <- lm(popularity~danceability+energy+loudness+speechiness+instrumantalness+energy*loudness+
loudness*instrumantalness,data=train)
summary(fit3)
```

```
##
## Call:
## lm(formula = popularity ~ danceability + energy + loudness +
##     speechiness + instrumantalness + energy * loudness + loudness *
##     instrumantalness, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -62.679 -16.902   4.628  19.004  51.384
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)                85.3323     4.8193  17.706  < 2e-16 ***
## danceability               13.6163     2.8745   4.737 2.24e-06 ***
## energy                    -42.2346     5.2307  -8.074 8.68e-16 ***
## loudness                    3.5558     0.4316   8.239 2.26e-16 ***
## speechiness                23.9101     5.4301   4.403 1.09e-05 ***
## instrumantalness          -36.5057     5.5841  -6.537 6.97e-11 ***
## energy:loudness            -1.1351     0.6160  -1.843   0.0654 .
## loudness:instrumantalness  -3.1077     0.6226  -4.991 6.22e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24.12 on 4399 degrees of freedom
## Multiple R-squared:  0.07821,    Adjusted R-squared:  0.07674
## F-statistic: 53.32 on 7 and 4399 DF,  p-value: < 2.2e-16
```

Make Predictions

```
pred1 <- fit1 %>% predict(test)
p1 = data.frame(
  RMSE=RMSE(pred1,test$popularity),
  R2=R2(pred1,test$popularity)
)

pred2 <- fit2 %>% predict(test)
p2 <- data.frame(
  RMSE=RMSE(pred2,test$popularity),
  R2=R2(pred2,test$popularity)
)

pred3 <- fit3 %>% predict(test)
p3 <- data.frame(
  RMSE=RMSE(pred3,test$popularity),
  R2=R2(pred3,test$popularity)
)
```

```
summary(fit1)$fstatistic[1]
```

```
##   value
## 32.1482
```

```
summary(fit1)$adj.r.squared
```

```
## [1] 0.07215349
```

```
summary(fit1)$sigma #RSE
```

```
## [1] 24.18283
```

```
all=rbind(p1,p2,p3)
all=cbind(all,c(summary(fit1)$fstatistic[1],summary(fit2)$fstatistic[1],summary(fit3)$fstatistic
[1]))
all=cbind(all,c(summary(fit1)$adj.r.squared,summary(fit2)$adj.r.squared,summary(fit3)$adj.r.squa
red))
all=cbind(all,c(summary(fit1)$sigma,summary(fit2)$sigma,summary(fit3)$sigma))

all=cbind(all,c("fit1","fit2","fit3"))
colnames(all)[c(3,4,5,6)]<-c("F stat","Adj R 2","RSE","models")
all
```

```
##       RMSE         R2   F stat    Adj R 2      RSE models
## 1 24.56187 0.06293309 32.14820 0.07215349 24.18283   fit1
## 2 24.56240 0.06287795 50.32470 0.07266956 24.17610   fit2
## 3 24.48017 0.06916223 53.31969 0.07674341 24.12294   fit3
```

It turns out that fit3 is the best model.

Next we check the predictors for genres “EDM” and compared with “Pop”.

```
training_samples <- edm$popularity %>%
  createDataPartition(p=0.8,list = FALSE)

train <- edm[training_samples,]
test <- edm[-training_samples,]
dim(train)
```

```
## [1] 4836   20
```

```
names(train)
```

```
##  [1] "X"                "name"             "artist"           "popularity"
##  [5] "year"             "genre"            "subgenre"         "danceability"
##  [9] "energy"           "key"              "loudness"         "mode"
## [13] "speechiness"      "acousticness"     "instrumantalness" "liveness"
## [17] "valence"          "tempo"            "duration"         "Valence_C"
```

Fit FULL linear regression model for EDM.

```
fit11 <- lm(popularity ~ danceability+energy+loudness+speechiness+acousticness+instrumantalness+
liveness+valence+tempo+Valence_C, data = train)
summary(fit11)
```

```
##
## Call:
## lm(formula = popularity ~ danceability + energy + loudness +
##     speechiness + acousticness + instrumantalness + liveness +
##     valence + tempo + Valence_C, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -60.222 -17.139   1.452  16.119  60.599
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            69.80804    5.19775  13.430  < 2e-16 ***
## danceability           -1.61857    2.98997  -0.541   0.5883
## energy                -22.54855    3.39266  -6.646 3.34e-11 ***
## loudness                1.05649    0.19034   5.551 3.00e-08 ***
## speechiness            -5.85242    4.54543  -1.288   0.1980
## acousticness           18.75716    2.42862   7.723 1.37e-14 ***
## instrumantalness      -11.67195    1.11720 -10.448  < 2e-16 ***
## liveness               -0.50596    1.91175  -0.265   0.7913
## valence                 3.42872    2.88262   1.189   0.2343
## tempo                  -0.06207    0.02144  -2.895   0.0038 **
## Valence_Cmore negative  -3.01397    1.23370  -2.443   0.0146 *
## Valence_Cmore positive  -0.09883    1.62645  -0.061   0.9515
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22 on 4824 degrees of freedom
## Multiple R-squared:  0.09797,    Adjusted R-squared:  0.09592
## F-statistic: 47.63 on 11 and 4824 DF,  p-value: < 2.2e-16
```

Remove insignificant variables.

```
fit22 <- lm(popularity ~ energy+loudness+acousticness+instrumantalness+tempo+Valence_C,data=trai
n)
summary(fit22)
```

```
##
## Call:
## lm(formula = popularity ~ energy + loudness + acousticness +
##     instrumantalness + tempo + Valence_C, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -59.994 -17.040   1.451  16.197  60.350
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            70.63965    4.14229  17.053  < 2e-16 ***
## energy                -22.92205    3.34518  -6.852 8.18e-12 ***
## loudness                1.08253    0.18969   5.707 1.22e-08 ***
## acousticness           18.71702    2.40287   7.789 8.18e-15 ***
## instrumantalness      -11.83083    1.07050 -11.052  < 2e-16 ***
## tempo                  -0.06221    0.02095  -2.969  0.00301 **
## Valence_Cmore negative  -4.03112    0.72655  -5.548 3.04e-08 ***
## Valence_Cmore positive   0.72013    1.45498   0.495  0.62066
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22 on 4828 degrees of freedom
## Multiple R-squared:  0.09733,	Adjusted R-squared:  0.09602
## F-statistic: 74.37 on 7 and 4828 DF,  p-value: < 2.2e-16
```

Check interactions.

```
fit12 <- lm(popularity~(energy+loudness+acousticness+instrumantalness+tempo)^2,data = train)
summary(fit12)
```

```
##
## Call:
## lm(formula = popularity ~ (energy + loudness + acousticness +
##     instrumantalness + tempo)^2, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -61.181 -17.354   1.618  15.903  61.269
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    174.99957   29.15749   6.002 2.09e-09 ***
## energy                        -126.28142   28.83189  -4.380 1.21e-05 ***
## loudness                         5.00799    1.74073   2.877 0.004033 **
## acousticness                   -15.48766   22.37814  -0.692 0.488915
## instrumantalness               -36.98138   14.61259  -2.531 0.011412 *
## tempo                           -0.89089    0.22725  -3.920 8.97e-05 ***
## energy:loudness                  0.02925    0.87817   0.033 0.973426
## energy:acousticness             -4.79823   18.10678  -0.265 0.791023
## energy:instrumantalness         26.52900    9.93878   2.669 0.007628 **
## energy:tempo                     0.79113    0.22253   3.555 0.000381 ***
## loudness:acousticness            1.82139    1.16484   1.564 0.117969
## loudness:instrumantalness       -1.08406    0.51276  -2.114 0.034553 *
## loudness:tempo                  -0.03137    0.01284  -2.443 0.014613 *
## acousticness:instrumantalness    5.23843    9.01513   0.581 0.561220
## acousticness:tempo               0.41017    0.11723   3.499 0.000472 ***
## instrumantalness:tempo          -0.02880    0.08831  -0.326 0.744372
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22.01 on 4820 degrees of freedom
## Multiple R-squared:  0.09745,    Adjusted R-squared:  0.09464
## F-statistic:  34.7 on 15 and 4820 DF,  p-value: < 2.2e-16
```

```
fit33 <- lm(popularity~energy+loudness+acousticness+instrumantalness+tempo+energy*instrumantalne
ss+energy*tempo+loudness*acousticness+loudness*instrumantalness+loudness*tempo+acousticness*temp
o,data = train)
summary(fit33)
```

```
##
## Call:
## lm(formula = popularity ~ energy + loudness + acousticness +
##     instrumantalness + tempo + energy * instrumantalness + energy *
##     tempo + loudness * acousticness + loudness * instrumantalness +
##     loudness * tempo + acousticness * tempo, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -60.852 -17.348   1.649  15.852  61.511
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 173.93172   27.04614   6.431 1.39e-10 ***
## energy                     -124.98282   26.31185  -4.750 2.09e-06 ***
## loudness                      4.94943    1.52289   3.250 0.001162 **
## acousticness                -20.87972   15.32116  -1.363 0.173008
## instrumantalness            -39.70270    9.87629  -4.020 5.91e-05 ***
## tempo                        -0.87870    0.21524  -4.082 4.53e-05 ***
## energy:instrumantalness      25.38726    9.21056   2.756 0.005868 **
## energy:tempo                  0.77807    0.20934   3.717 0.000204 ***
## loudness:acousticness         1.40103    0.64173   2.183 0.029070 *
## loudness:instrumantalness    -1.13734    0.50221  -2.265 0.023578 *
## loudness:tempo               -0.03033    0.01197  -2.535 0.011286 *
## acousticness:tempo            0.41191    0.11624   3.544 0.000399 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22 on 4824 degrees of freedom
## Multiple R-squared:  0.09737,    Adjusted R-squared:  0.09531
## F-statistic: 47.31 on 11 and 4824 DF,  p-value: < 2.2e-16
```

Make predictions

```
pred11 <- fit11 %>% predict(test)
p11=data.frame(
  RMSE=RMSE(pred11,test$popularity),
  R2=R2(pred11,test$popularity)
)

pred22 <- fit22 %>% predict(test)
p22=data.frame(
  RMSE=RMSE(pred22,test$popularity),
  R2=R2(pred22,test$popularity)
)

pred33 <- fit33 %>% predict(test)
p33=data.frame(
  RMSE=RMSE(pred33,test$popularity),
  R2=R2(pred33,test$popularity)
)
```

```
all2=rbind(p11,p22,p33)
all2=cbind(all2,c(summary(fit11)$fstatistic[1],summary(fit22)$fstatistic[1],summary(fit33)$fstat
istic[1]))
all2=cbind(all2,c(summary(fit11)$adj.r.squared,summary(fit22)$adj.r.squared,summary(fit33)$adj.
r.squared))
all2=cbind(all2,c(summary(fit11)$sigma,summary(fit22)$sigma,summary(fit33)$sigma))

all2=cbind(all2,c("fit11","fit22","fit33"))
colnames(all2)[c(3,4,5,6)] <- c("F stat","Adj R 2","RSE","models")
all2
```

```
##       RMSE         R2   F stat    Adj R 2      RSE models
## 1 22.32606 0.07767128 47.63290 0.09591728 21.99751  fit11
## 2 22.32488 0.07775583 74.37116 0.09602481 21.99620  fit22
## 3 22.26614 0.08191485 47.30527 0.09530761 22.00492  fit33
```

It turns out that fit33j is the best model.