MUSIC POPULARITY PREDICTION

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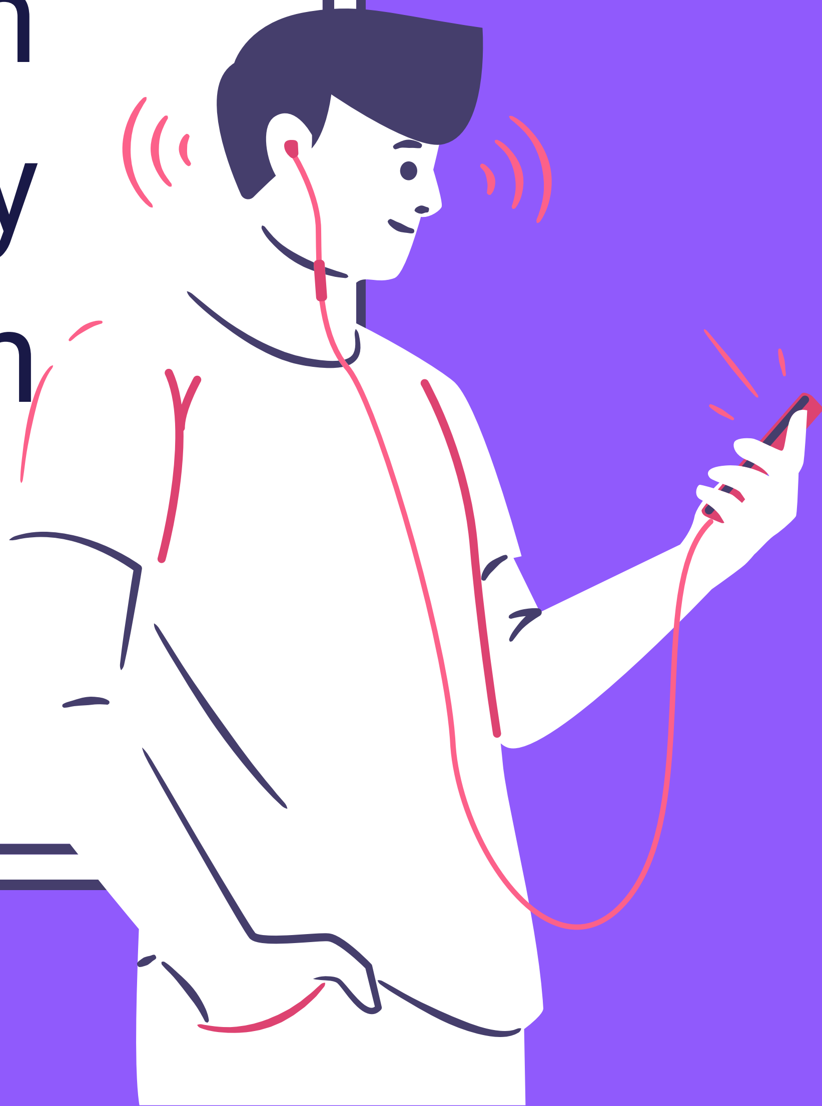
OVERVIEW

Why certain songs are popular?

What makes them popular amongst millions of other songs?

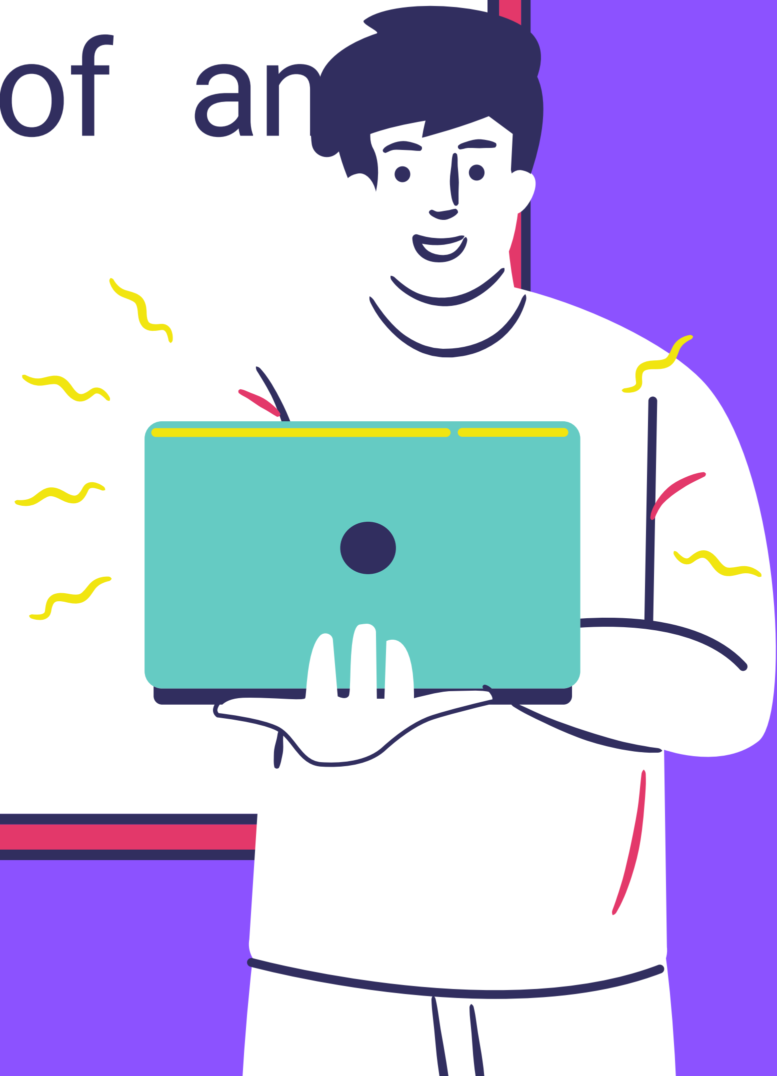
- We should know that there are some specific attributes of a song that makes them popular.

- With our analysis we are trying ascertain the factors responsible for the popularity of the songs by uncovering the trends in the data.



- Our goal here is to determine if a song makes its place in the top 40% even before the release.

- Music companies can be highly benefitted by this model in predicting the popularity of an upcoming song.



BUSINESS UNDERSTANDING

Porter’s Five Forces framework

- **Bargaining Power of Suppliers - (High)**

A music service is nothing without actual music to play, as there are four major music labels that hold monopoly on most music. Artists and their catalog of music are highly distinct in customer's mind, so the supplier has the higher power of bargaining.

- **Bargaining Power of Customers - (Low)**

Buyers are negotiating the digital music market as individuals rather than large groups. As a result, individual buyers/consumers have very little power over the music providers.

- **Threat of New Entrants - (Low)**

It's low for well established music industries and it's notoriously hard for newcomers to break into the industry

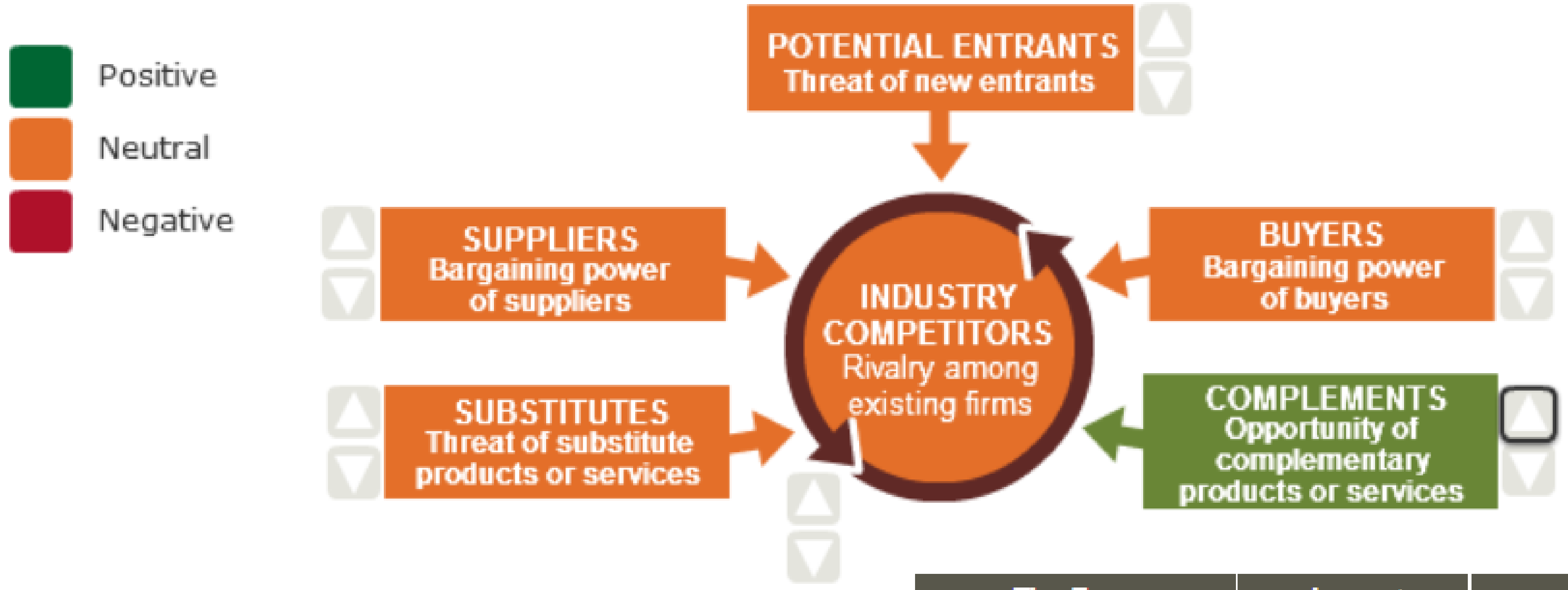
- **Availability of Substitute Products - (High)**

A person can consume music many ways—with a number of them free. So much choice makes it difficult for digital music providers to drive profit margins higher.

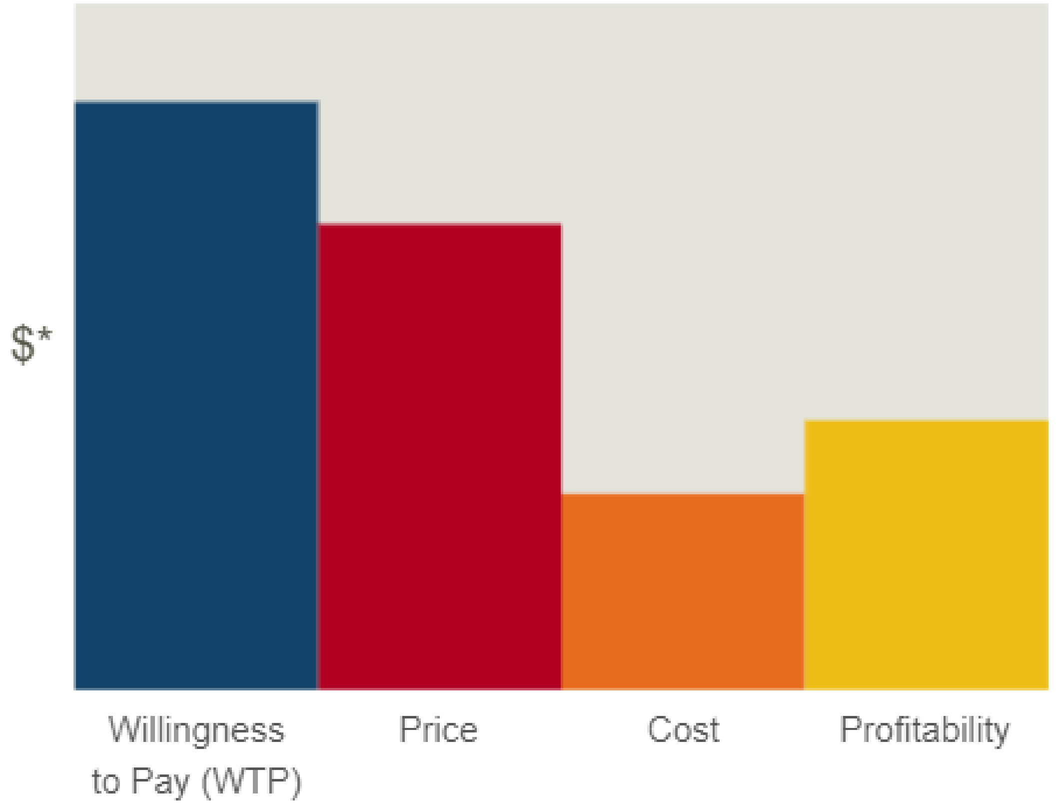
- **Intensity of Competitive Rivalry in the Industry - (High)**

The user experience of consuming music can vary with each provider. Since there is no clear leader(s) in the digital music market, companies are fighting hard to secure customer loyalty.

Porter's Forces Framework



* Dollar of WTP or Cost per Dollar of Capital Employed



The Force		Impact		Root Causes	
IF threat of entry	↑				
IF threat of entry	↓	profitability	↑	*because*	WTP ↑ Prices ↑ Costs ↓
IF supplier power	↑	profitability	↓	*because*	Costs ↑
IF supplier power	↓				
IF buyer power	↑				
IF buyer power	↓	profitability	↑	*because*	Prices ↑
IF substitutes	↑	profitability	↓	*because*	WTP ↓ Prices ↓
IF substitutes	↓				
IF rivalry	↑				
IF rivalry	↓				
IF complements	↑	profitability	↑	*because*	WTP ↑ Prices ↑
IF complements	↓				

Sources

SONY ENTERTAINENT

Target Firm - Sony Entertainment

- American entertainment company established in 2012.
- Headquarters is located at New York, 18000 employees.

Major Products/ Service lines :

- Sony Pictures Entertainment(7.097 billion USD)
- Sony Music Group(8.86 billion USD)

Geographic Footprints:

- United States of America
- Latin America and the Caribbean
- Europe
- Singapore
- Japan

SWOT Analysis

Strength

- High Market Share
- Strong Brand Awareness
- Social Media Marketing

Weakness

- Bad and Low Quality music production
- Lousy investments on newly signed artists

Opportunities

- AI and ML has notched some notable wins in the field of music in line of popularity prediction.

Threat

- Wrong selection of an album released may result badly to the company
- Piracy

DATA ANALYSIS AND UNDERSTANDING

- Dataset - Spotify Data. https://developer.spotify.com/
- Dataset Source - Spotify.
- It has 34080 records and 23 columns.
- There are 24128 unique tracks with 10379 artists.
- 23 attributes for each song, 12 of them numerical.
- Time Period - 1956 - 2022.
- Target Variable - POPULARITY.

ATTRIBUTE	DESCRIPTION
Acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic.
Danceability	Danceability ranges from 0.0 - 1.0 and describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity.
duration_ms	Duration of the track in ms
energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy.
instrumentalness	Predicts whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context. Values ranges from 0 - 1
key	The estimated overall key of the track. Values ranges from 0 - 11
liveness	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live.

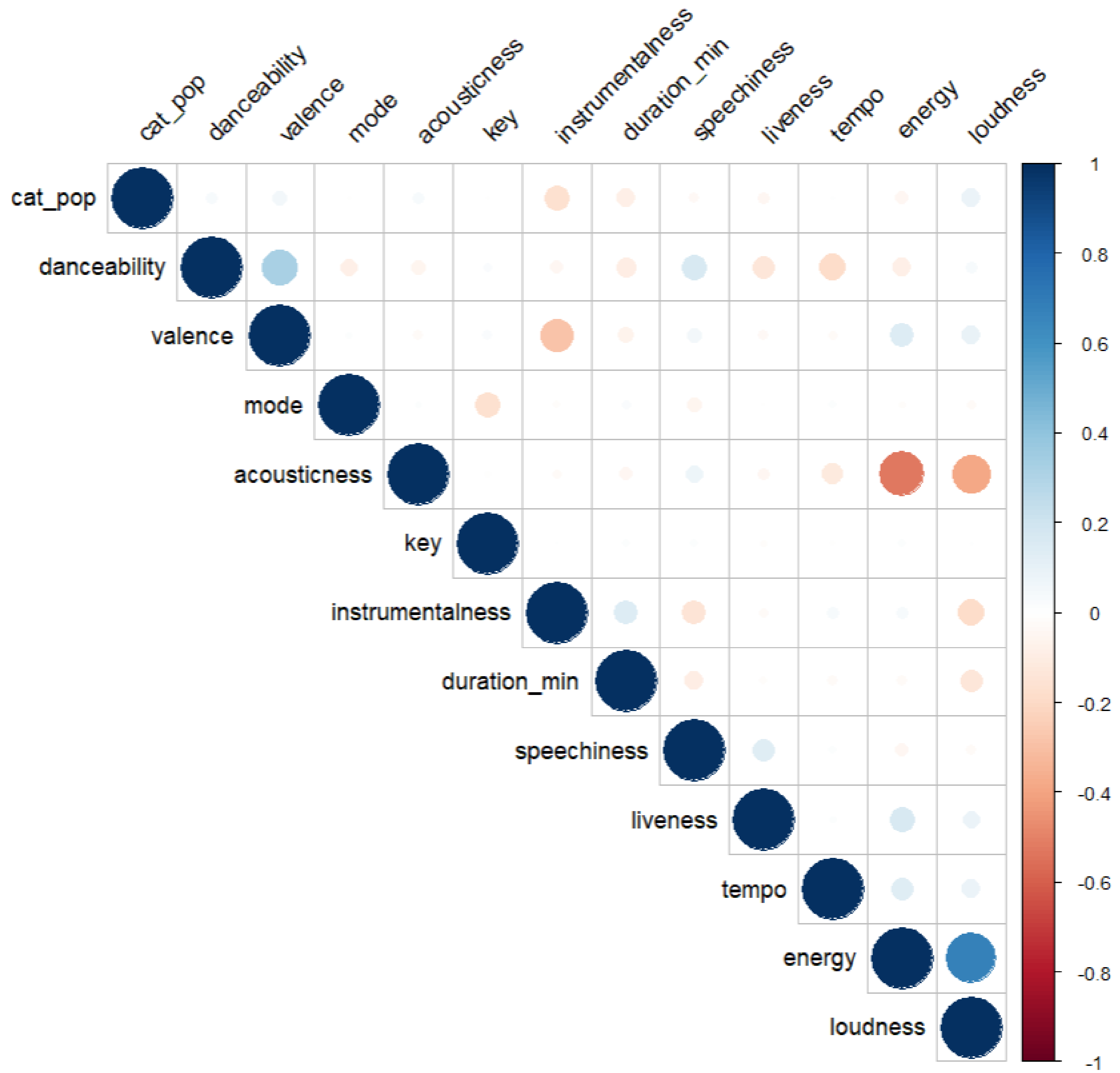
ATTRIBUTE	DESCRIPTION
loudness	The overall loudness of a track in decibels (dB). Values ranges from -60 - 0db.
mode	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived.
speechiness	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value.
tempo	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

Exploratory Data Analysis

Descriptive Statistics

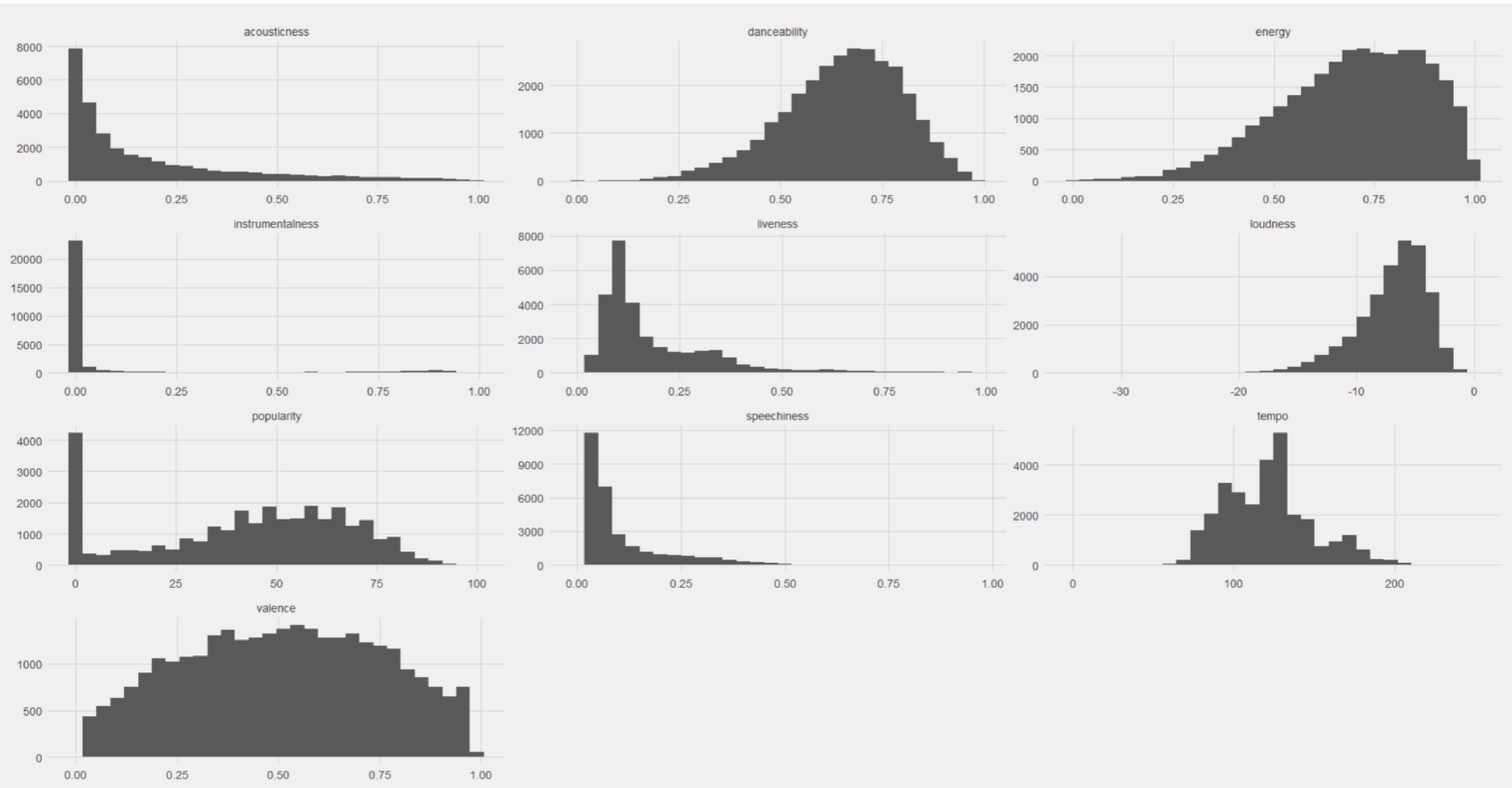
	mean	median	sd	variance	min	max	count	miss.val
popularity	42.97342865	47.0000000	25.2138004	635.73572962	0.00000000	100.00000	29656	0
danceability	0.65261971	0.6670000	0.1459697	0.02130715	0.00000000	0.98800	29656	0
energy	0.69440247	0.7150000	0.1796107	0.03226001	0.00251000	1.00000	29656	0
key	5.33136633	6.0000000	3.5926388	12.90705321	0.00000000	11.00000	29656	0
loudness	-6.94016057	-6.3630000	3.0443399	9.26800542	-34.11400000	0.00000	29656	0
mode	0.57519558	1.0000000	0.4943216	0.24435386	0.00000000	1.00000	29656	0
speechiness	0.10918757	0.0598000	0.1136165	0.01290870	0.00000000	0.96700	29656	0
acousticness	0.17659792	0.0788000	0.2209015	0.04879749	0.00000132	0.99600	29656	0
instrumentalness	0.09907276	0.0000192	0.2446509	0.05985407	0.00000000	0.99500	29656	0
liveness	0.19061995	0.1280000	0.1535439	0.02357573	0.01140000	0.99200	29656	0
valence	0.51086714	0.5155000	0.2423133	0.05871572	0.00000000	0.99000	29656	0
tempo	121.39733669	122.0210000	27.1897991	739.28517578	0.00000000	249.43800	29656	0
duration_min	3.79708943	3.6069083	1.1912893	1.41917018	0.40488333	45.70093	29656	0
Bin_pop	0.28678851	0.0000000	0.4522696	0.20454776	0.00000000	1.00000	29656	0

Correlation Matrics



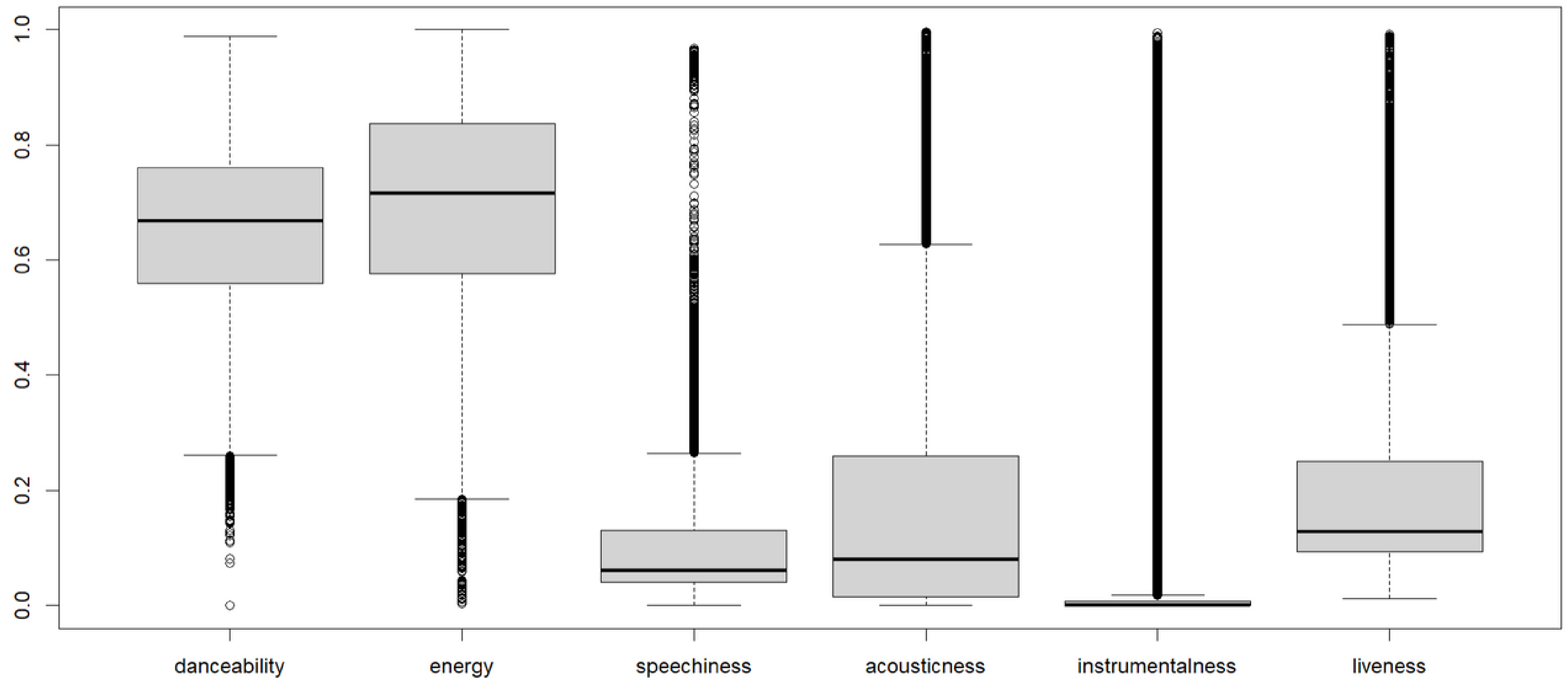
- We can see that there is a strong linear relationship between energy and loudness.
- Inverse linear relationship between acousticness and energy
- Inverse linear relationship between acousticness and loudness

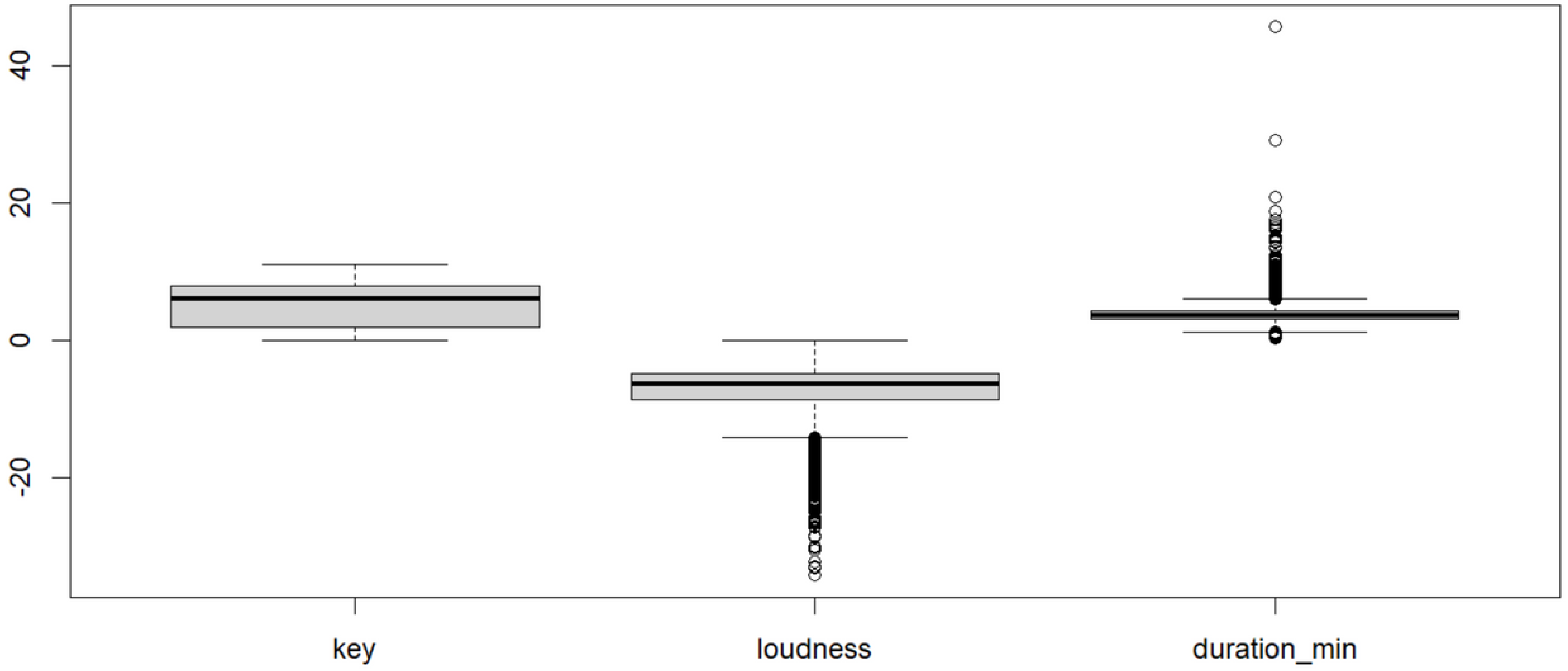
Feature Distribution



- Most of the songs are not acoustic.
- Most of the songs are not recorded during live concert as liveness distribution is close to 0.
- Songs are pretty fast as the mean of the temp is ~ 120.

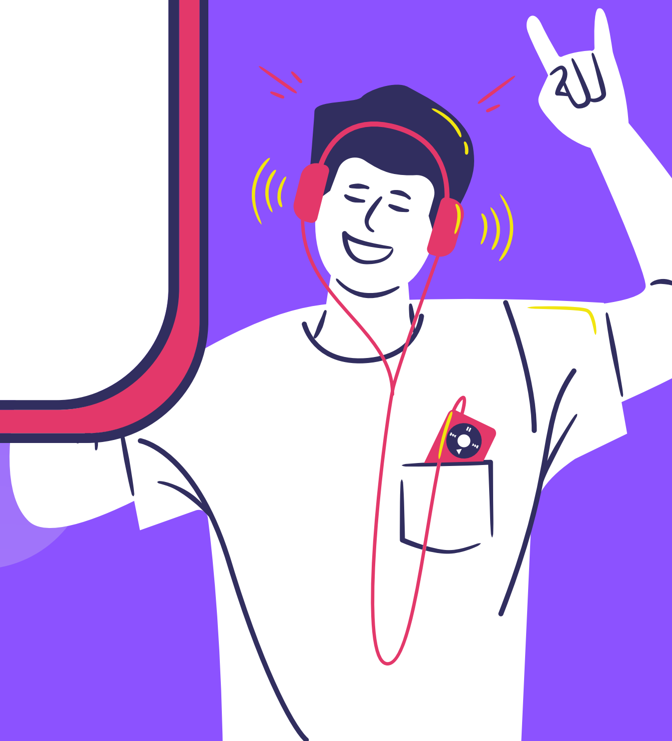
Box Plots of the Independent Variables





Data Modeling

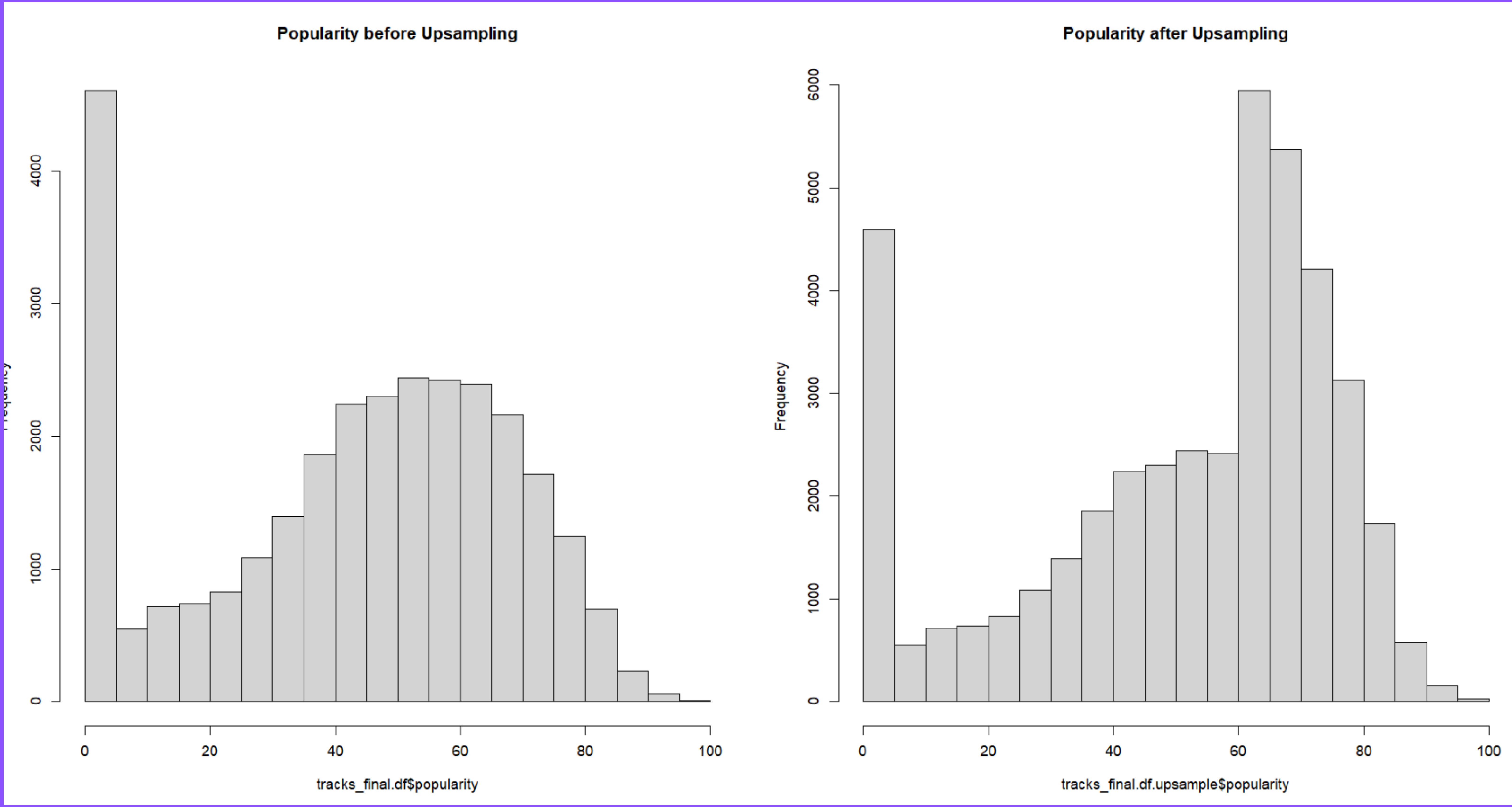
- The goal of our project is to predict the popularity of the song.
- The target variable in our analysis is popularity and it's value ranges from 0 - 100.
- For the purpose of our analysis we have categorised the popularity into binary values 0 and 1 with the threshold value of 60.
- With this analysis one can determine if a song lies in the top 40% of the songs.



Data Transformations

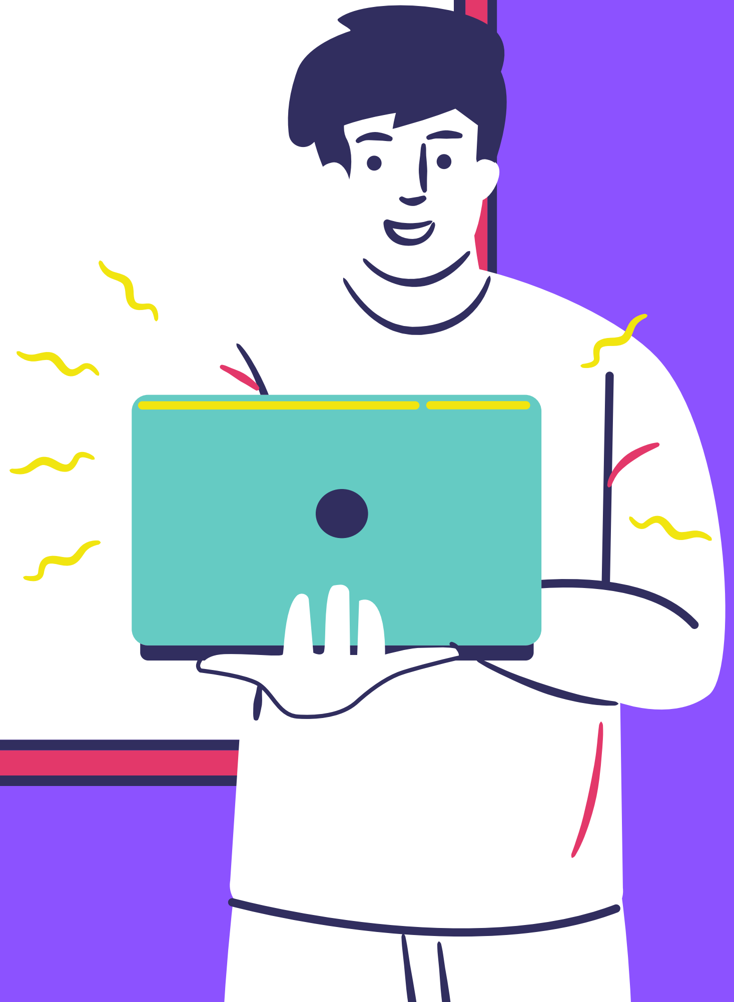
- Removed unnecessary columns such as track.album.id, track.album.name, playlist_name, playlist_id.
- Renamed few columns for easy understanding.
- Eliminated the duplicate records using id.
- Removed NA's present in artist and track.name columns.
- Loudness values > 0 is set to 0.
- Converted duration_ms into minutes.
- Categorised the popularity into binary values 0 and 1 with the threshold value of 60.
- Factorized artist and genre.
- Upsampled our data to create a balance between 0's and 1's.

Distribution of Popularity(target variable)



K Nearest Neighbours

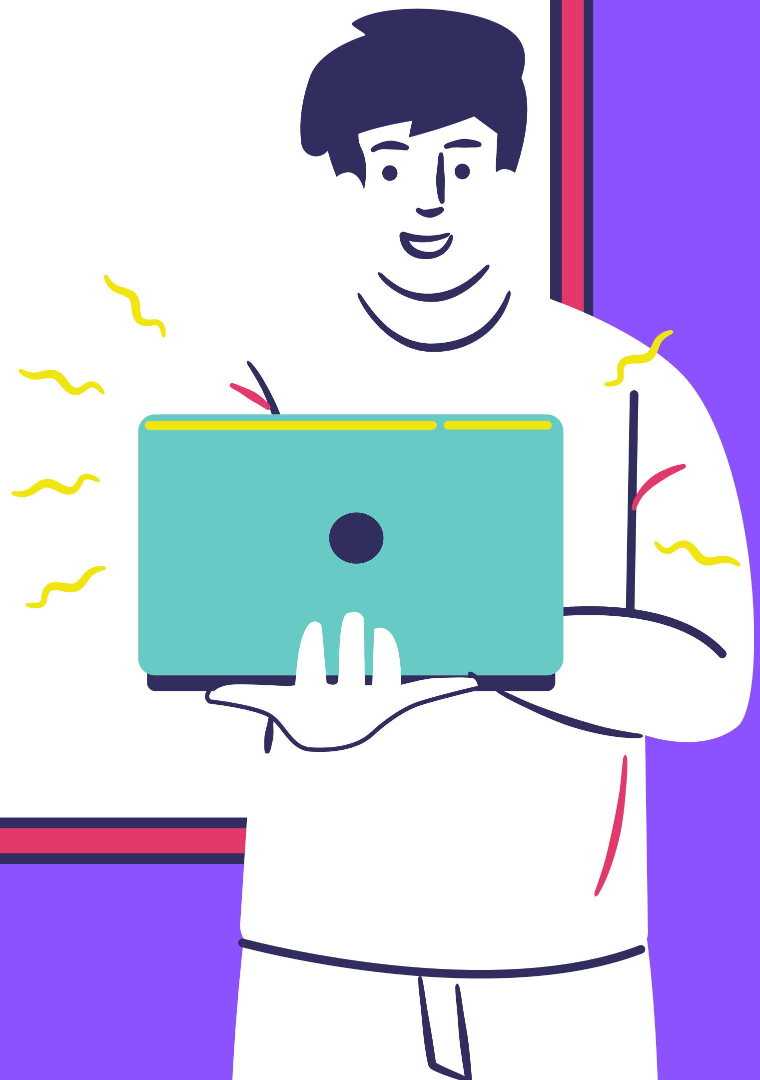
- The model has the highest accuracy of 79.97% when k = 1.
- Type 1 error - 13.4%
- Type 2 error - 28.14%
- Hence we can conclude that we are 79.97% sure that the target song will be in top 40% of the songs.



```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 7432 2389
         1 1000 6100

               Accuracy : 0.7997
                 95% CI : (0.7936, 0.8057)
    No Information Rate : 0.5017
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5996

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.8814
            Specificity : 0.7186
         Pos Pred Value : 0.7567
         Neg Pred Value : 0.8592
             Prevalence : 0.4983
         Detection Rate : 0.4392
   Detection Prevalence : 0.5804
      Balanced Accuracy : 0.8000

       'Positive' Class : 0
```

Decision Tress

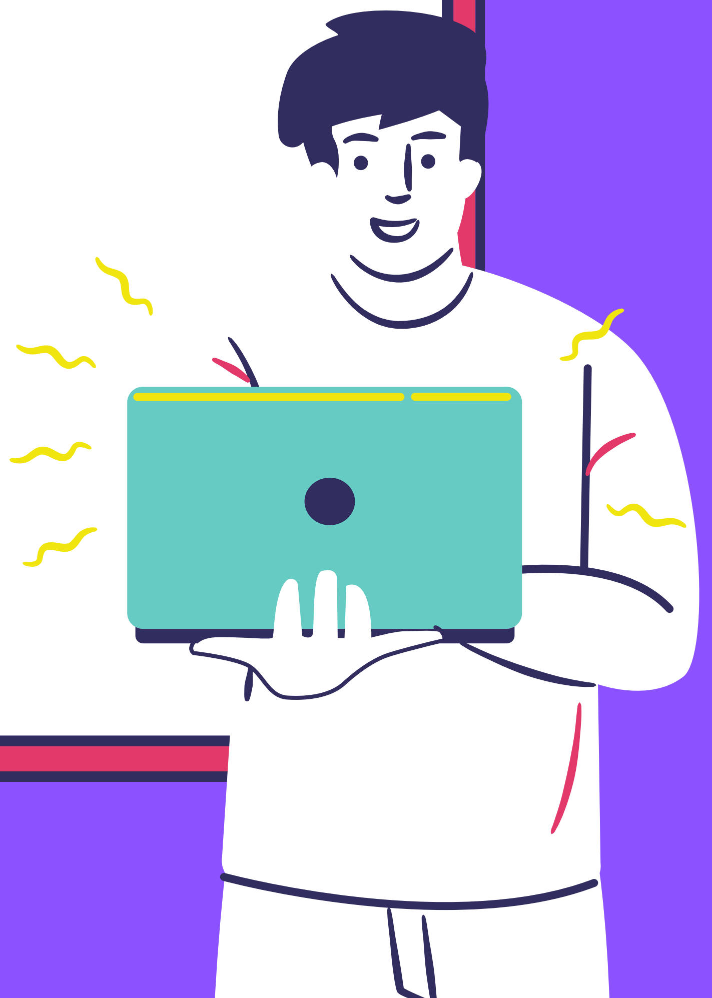
- This model has an accuracy of 77.14%.
- To reduce the complexity of the decision trees we have used pruning technique and reduced the size of the tree.
- CP - 0.00167
- Best Split - 10
- Type 1 error - 9.7%
- Type 2 error - 35.8%



```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 7609 3045
         1  823 5444

               Accuracy : 0.7714
                 95% CI : (0.765, 0.7777)
    No Information Rate : 0.5017
    P-Value [Acc > NIR] : < 0.0000000000000022

                  Kappa : 0.5432

 Mcnemar's Test P-Value : < 0.0000000000000022

            Sensitivity : 0.9024
            Specificity : 0.6413
         Pos Pred Value : 0.7142
         Neg Pred Value : 0.8687
             Prevalence : 0.4983
         Detection Rate : 0.4497
   Detection Prevalence : 0.6296
      Balanced Accuracy : 0.7718

       'Positive' Class : 0
```

Random Forest

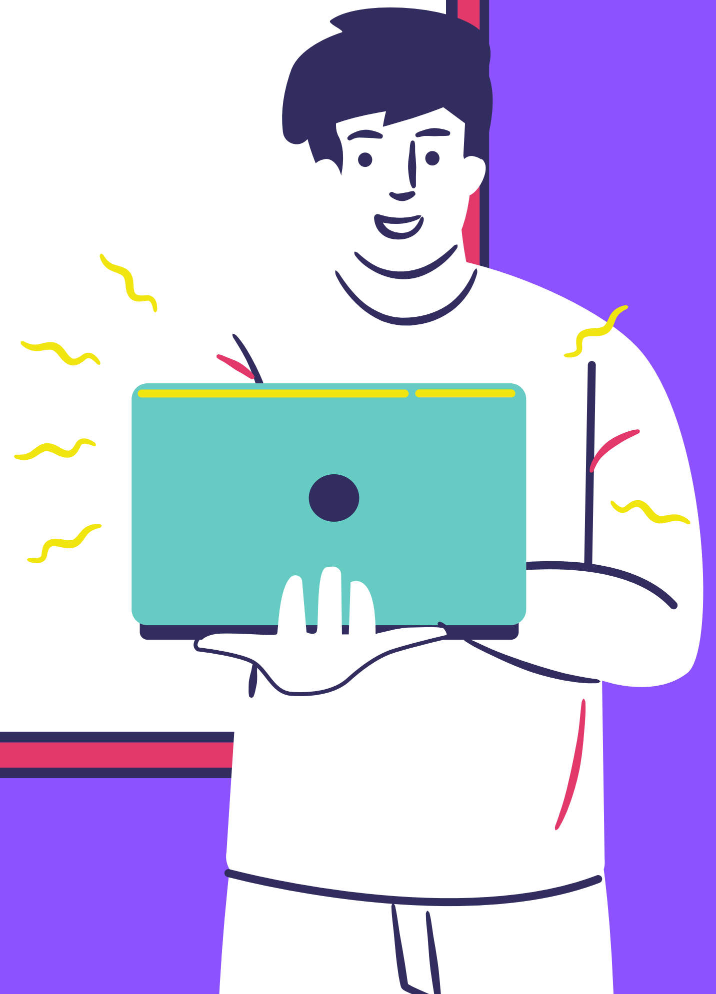
- This model has the accuracy of 59.69%.
- ntree - 1000
- Type 1 error - 2.6%
- Type 2 error - 77.67%



```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 8205 6594
         1  227 1895

               Accuracy : 0.5969
                 95% CI : (0.5895, 0.6043)
    No Information Rate : 0.5017
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.1958

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9731
            Specificity : 0.2232
         Pos Pred Value : 0.5544
         Neg Pred Value : 0.8930
             Prevalence : 0.4983
         Detection Rate : 0.4849
   Detection Prevalence : 0.8746
      Balanced Accuracy : 0.5982

       'Positive' Class : 0
```

Logistic Regression

- This model has the accuracy of 54.1%.
- Threshold value - 0.285.
- Independent Variables used are - danceability, speechiness, valence, duration_min.
- Type 1 error - 46.67%
- Type 2 error - 45.14%



```
Confusion Matrix and Statistics

         FALSE TRUE
  FALSE   4497 3832
  TRUE    3935 4657

               Accuracy : 0.541
                 95% CI : (0.5334, 0.5485)
    No Information Rate : 0.5017
    P-Value [Acc > NIR] : <0.0000000000000002

                  Kappa : 0.0819

 Mcnemar's Test P-Value : 0.2471

            Sensitivity : 0.5333
            Specificity : 0.5486
         Pos Pred Value : 0.5399
         Neg Pred Value : 0.5420
             Prevalence : 0.4983
         Detection Rate : 0.2658
   Detection Prevalence : 0.4922
      Balanced Accuracy : 0.5410

       'Positive' Class : FALSE
```

Summary

Model	Score
K Nearest Neighbours	79.97%
Decision Tree	77.14%
Random Forest	59.69%
Logistic Regression	54.1%

Model Evaluation

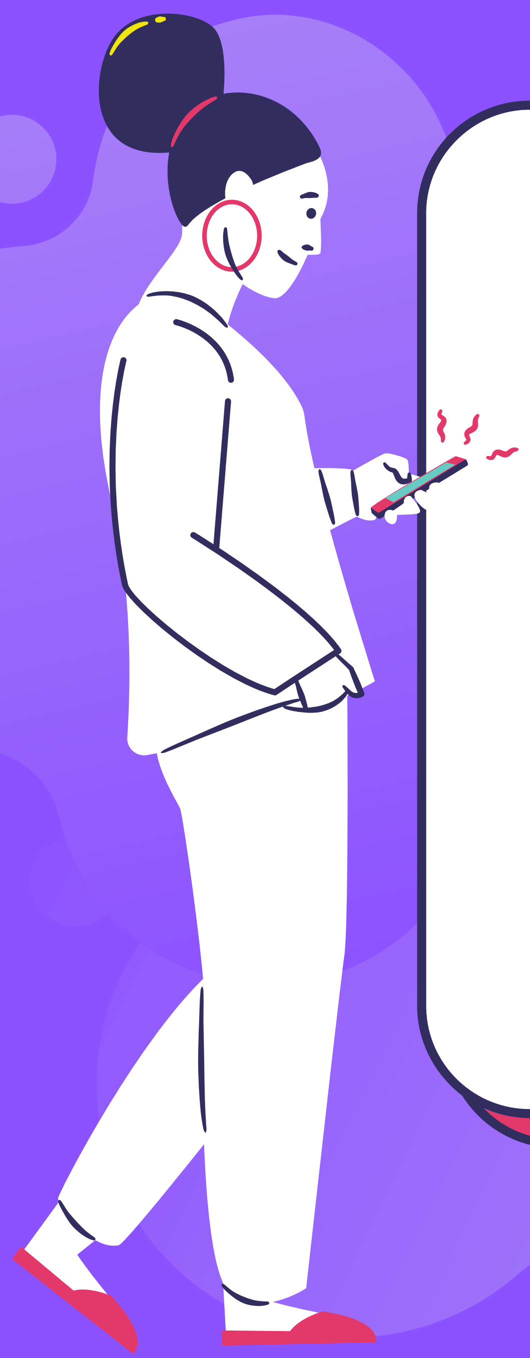
- KNN is the best models with accuracy 79.97% and Type 1 error of 13.4%.

Model limitations

- Currently we have a sample dataset of around 34k records from a metadata of 5M rows. The KNN algorithm doesn't work well with the large dataset.
- KNN is sensitive to outliers and missing values as it works on euclidian distance.
- We can separate the tracks in different types such as Instrumental music, live performed, podcasts which will give us the clustered data and remove the outliers.

Recommendations

Can be used to predict if a song can hit the top 40% when a new artist comes up with a new song to our record label.



Using this model people who work in music industry can craft their musical works to better suit with the market needs.

Music industry can also have the capability to monitor and shape peoples music listening behaviour using this model.

Thank You

Music is the color for the world and everything in it