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Billboard prediction using listeners' perspective and audio features from top music platforms

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ABSTRACT

Music has been a form of entertainment for many years. The music industry is constantly putting forth effort to improve the quality of our music. It would be an interesting exercise to predict that the song makes it into top charts from a mathematical perspective. The proposed model in this paper predicts the success of a song based on its audio features and listeners perspective factors that will be of great help to music producers. Violating the features of the song to predict whether the song will be hit before it is released can greatly help producers to increase their profits and reduce the risks, they take in producing songs. The audio features can be processed using machine learning algorithms like Logistic Regression, Support Vector Machines, Random Forest, Naive Bayes Classifier and patterns may be identified in the processed data, which can finally be combined with listeners perspective features to effectively predict hit songs.

Keywords— *Machine Learning, Billboards Charts, Spotify Web API, Audio Features, Supervised learning*

1. INTRODUCTION

Music is a form of art that has existed for centuries. With millions of dollars in revenue each year, the music industry is growing rapidly. Over the past decade, the way people interact with music and sound has changed dramatically. Music is a kind of content that has similar issues and challenges. Sales of digital music have skyrocketed. Paid subscriptions and industry revenue from broadcasting are growing rapidly. Meanwhile, the global music publishing industry has shown resilience in all economic cycles over the past decade. According to the International Confederation of Societies of Authors and Composers (CISAC), the publication of collections (royalties) has increased from € 6.5 billion in 2013 to € 8.5 billion in 2018. business- CISAC collections and non-CISAC publisher revenue estimates from Music & Copyright - cost 11.7 billion by 2020. So, exploring the potential success of a given song based on its acoustic features is an important task in the music industry.

Companies and individuals involved in the production, distribution, and management industries have a keen interest in music. Predicting hot songs can be used in audio source management for online streaming services and music delivery services. For example, it can be used to produce playlists [4], [5] or to recommend a song [6] - [7] which is expected to be popular with the user who often enjoys hit songs. As another example, it may be helpful to use a song that is predicted to be popular in an ad to improve the marketing effect due to the public response to the song.

The task of predicting hit songs is viewed on two fronts [6,7]: an internal perspective which relies solely on (musical) features extracted from the audio and an external perspective, which defines the features of the musical system, for example including social media or market data. In this work, we look at the internal perspective, focusing on the meanings of the sound of the song to predict its success. It can define the expected response to a song from the listener's perspective, by looking at the audio features. The features can be processed using machine learning, and patterns can be seen in used data, which can be used successfully to predict hit songs.

The Billboard Hot 100 Chart remains one of the definitive ways to measure the success of a popular song. This research focuses on Billboard's prediction using listeners perspective and audio features from top musical platform like Spotify. Various musical features will be extracted using Spotify Web API and studied thoroughly to predict a Hit song. The musical features will be further merged with the respective songs and the required dataset can be prepared. We can investigate the final

dataset using machine learning techniques to predict whether or not a song will become a Billboard Hot 100 hit, based on its audio features. Considering the listeners perspective, we will be using the features like Artist popularity based on social media followers, current status artist on billboard's top charts, age - group and music genre. Finally, the machine learning model and listeners perspective model will be combined to predict the weather song will be hit or not hit.

The paper proceeds as Section II consists of Related work. Section III gives a detailed information on the proposed methodology which consists of Data Collection, Data Preprocessing and Model Building using various Machine Learning Algorithms. The paper then concludes in Section IV.

2. RELATED WORK

Rajyashree R, Anmol Anand, Yash Soni, Harshitaa Mahajan [1] proposed a model to analyze metadata and audio analysis features using various machine learning techniques. The work done prior this was mostly considering the intrinsic quality of music piece, psychological factors, public opinion and social factors. This work focused mostly on audio features for better prediction.

The dataset used were Million Song Dataset (MSD) and Musical Instrument Digital Interface (MIDI). Preprocessing included extracting three audio features namely tempo, Mel frequency Cepstral Coefficient, and the consonant element. j Symbolic was used. Apart from above three features other features like artist familiarity ,the language in which the song is produced were studied. Machine learning algorithms like logistic regression, SVM, Naive bayes, Random forest, Neural Network were trained and Neural Network model showed best results.

Agha Haider Raza, Krishnadas Nanath [2] looks at Apriori parameters of a song to predict the success of a song and tries to answer the question - "Is there any Apriori secret formula to predict hit songs". While previous studies mostly looked into posteriori properties like user perception, social media strategy, promotions, release platforms, and others. This work focused more on the internal factors of the songs. Dataset used was Billboard top charts and Spotify web API to extract features. Features included danceability, energy, loudness, etc. Microsoft Azure was used for sentiment analysis after which a score was calculated which were included in a file consisting of the audio features and the Year of release. Based on the research, Logistic Regression showed the best result with a precision of 52%. This work clearly concludes that using lyrics for the hit prediction of a song cannot be considered since it reduces the accuracy of the model. Their future work focuses on considering artist ranking and fan following which plays a vital role in the success of a song and this can be brought in as Apriori parameters. Another major key feature that is excluded from this research is the genre of the song.

Eva Zangerle, Ramona Huber, Michael Vötter [3] This work takes on the internal perspective, focusing on audio descriptors of a song to predict its success. Other aspects like social media trends and events, psychological issues or social influence are not considered in this work. The study mainly focused on leveraging both low level features as well as high level features. Low level features include Mel-Frequency Cepstral Coefficients, melodic features, temporal features and high-level features like danceability. Low-level features allow for a detailed description of the acoustic characteristics of a song whereas high-level features add to this with abstract concepts such as mood or danceability, resulting in a more comprehensive description of a song.

The architecture trains a wide linear model along with a deep neural network while differentiating two types of features: wide features are basically high-level features that can be regarded as abstract, high-level features whereas deep features which are low-level features in the deep part of the network used to learn dense, lower-dimensional representations of input features. Based on both these features a regression task is performed for predicting hit songs.

3. PROPOSED METHODOLOGY

3.1 Data collection

Song titles are available on the Billboard Hot 100 charts, and this includes hot and low-key songs. The song is classified as a hit when the song appears in the top 20 at the end of each month. Likewise, in unbeatable songs, the process of having the titles be among the top ten songs at the end of each month. Once the initial data is complete, the Spotify Title ID can be collected and edited from the Spotify app. Audio features can be extracted from the Spotify API with the help of an access token provided by the developer to integrate features into the applications. Using the previously available Spotify ID, the API loading parameters that include the Spotify ID and access token can be changed, and the features are stored in CSV files. The audio features along with their data types and description is provided in Fig 1.

Feature	Data Type	Description
Danceability	*Float*	Danceability describes how suitable a track is for dancing based on a combination of musical elements. A value of 0.0 is least danceable, and 1.0 is most danceable.
Energy	*Float*	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity.
Key	*Int*	Predicts whether a track contains no vocals
Loudness	*Float*	The overall loudness of a track in decibels (dB). Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db.
Mode	*Float*	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
Speechiness	*Float*	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording, the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words.
Acoustieness	Float	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
Instrumentaln ess	Float	Predicts whether a track contains no vocals. The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content.
Liveness	Float	Detects the presence of an audience in the recording.
Valence	Float	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track.

Fig 1: Audio Features along with its data type and description

3.2 Data Preprocessing

The hit and not-hit songs titles collected from Billboards Charts are clubbed together. The audio features of every song title as mentioned above are extracted using Spotify Web API . The first step of preparing the final dataset was to combine both the files together. Extra variables need to be added considering the Hit song as '1'
and Non-hit song as '0'. Following steps are considered to preprocess the data:

(a) Finding correlation between musical features using heat maps: A heat map is a data visualization technique that shows the magnitude of a phenomenon as color in two dimensions. The variation in color may be by hue or intensity, giving obvious visual cue. Heat map allows us to find the relevant audio features in the dataset and reduce the number of variables while training the model.

(b) Data Cleaning: Entries with missing values or wrong data are removed from the dataset. Songs of languages other than English are removed from the dataset as well. All the variables are checked, and irrelevant ones are removed, such as Language Indicator, Spotify ID, URI of the song.

(c) Data Transformation: Feature Scaling is a technique to standardize the independent features present in the data in a fixed range. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values. Features like tempo, liveliness, danceability need the feature scaling to be done. Standardization is a very effective technique which re-scales a feature value so that it has distribution of values between 0 and 1. Energy, speechiness, acousticness and few other audio features were standardized.

3.3 Model Building

3.3.1 Machine Learning Model based on audio features: In order to develop a prediction model on audio features of songs to predict success, a range of machine learning algorithms can be used. Being a supervised learning problem

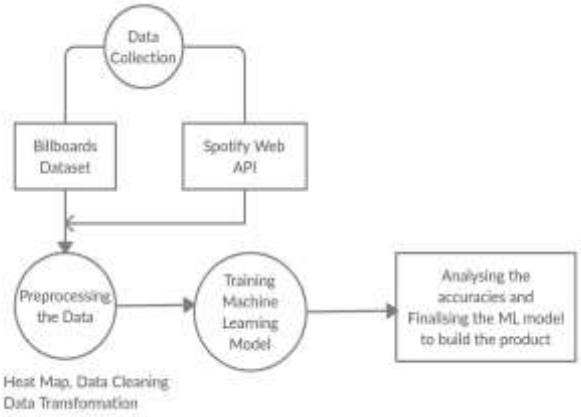

Fig. 2: Machine Learning Model

four algorithms are selected based on their previous application in a similar context - Logistic Regression, Support Vector Machines, Random Forests, and Naïve Bayes classifier. Initially, the dataset will be split into training set dataset and testing set dataset. For solving classification problems and the Literature Survey for this study revealed that Logistic Regression is the most basic and popular amongst machine learning algorithms [19]. The model is based on predicting the probabilities of success using the logistic function. Since the objective here is to predict a song being hit or not, the logistic function of a hit song is used as a dependent variable, and all the parameters of the song, including are independent variables.

$$log\left(\frac{P(HitSong)}{1-P(Hitsong)}\right) = \beta_0 + \sum \beta_i x_i$$

The list of xi can be represented as Song Name + Artist Name + Release + Energy + Danceability + Key + Mode + Speechiness + Acousticness + Instrumentalness + Liveness + Tempo + Score + Loudness + Valence. Along with Logistic Regression the model can also be trained on other three algorithms to check the accuracy and result.

3.3.2 Listener's Perspective Model: In order to develop the model based on the listener's perspective three categories can be considered like Artist Weightage, Audience age group and Music Genre. Artist Weightage will be given the top priority and can be calculated based on artists social media popularity and whether the artist has any current song or album featured in the Billboard's Top Charts. Audience age group will be considered while predicting the output. The research reveals that audience of age group between 18-35 is most active audience. Music genre has many types like hip-hop and rap, romantic, sad, party, dance and electronic, country music, rock music, etc. Music genre plays an important part in prediction of hit song. In this way these three factors will be considered to build the Listener's perspective model which is shown in Fig 3.

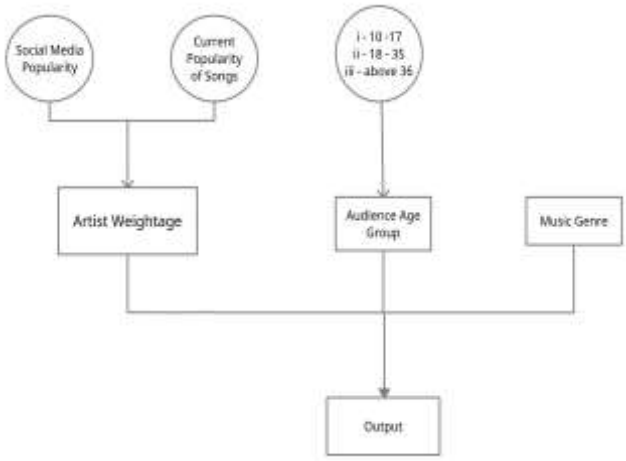

Fig. 3: Listener's Perspective Model

Finally, Machine Learning Model of audio features and the model based on listeners perspective can be combined together to get the prediction of hit or not-hit song.

4. CONCLUSION

Thus, we propose a model that predicts hit music using machine learning algorithms taking into consideration various audio features and also considering the factors based on listeners perspective which plays an important role in determining whether the song will be hit or not. Audio features that are most important for prediction are recognized after undertaking various surveys which results in a better prediction will also help music streaming services to come up with better recommendations and playlist.

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