Predicting Spotify Track Popularity: Exploring Key Influencing Factors Using Machine Learning

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Problem

What are the features that most significantly influence the prediction of Spotify track popularity?

Abstract

The emergence of streaming services like Spotify has indeed brought a sea change in the music industry in ways track popularity is considered one of the most important success factors of artists and record labels today. In this competitive scenario, the estimation of the drivers of a song's popularity among content creators and marketers will set the value.[1] This paper tries to predict Spotify track popularity based on analysis of audio features and metadata of songs on Spotify. The paper discusses characteristics such as danceability, energy, duration, and valence for the popularity of a track, measured through the popularity score given by Spotify itself.

The dataset used in this project was taken from the public API provided by Spotify. The audio features included were danceability, energy, tempo, valence, and instrumentalness. Also, some metadata features included duration in milliseconds, and year of release. Initial data exploration and cleaning were done to deal with missing values, outliers, and inconsistencies. Feature engineering techniques were applied next to select and transform the relevant variables into a suitable format for predictive modeling tasks. Different predictive models were used: Linear Regression, Decision Trees, Random Forests, and Gradient Boosting Machines to evaluate the relationship of track features and their popularity scores.[2]

The methodology included splitting the dataset into training and testing to test the performance of each model. Cross-validation techniques were employed so that the models generalize well on unseen data, and also to reduce overfitting. Each model's performance was checked based on metrics such as MSE for regression models and accuracy for classification models. Feature importance techniques were also used to find which of these audio features have most significance on track popularity.[3]

Our results indeed show that some features amongst **danceability, energy**, and **valence** are strongly positively correlated with track popularity, suggesting that songs with those characteristics are more likely to make it onto the platform. In contrast, features like instrumentalness and acousticness were found to be anticorrelated with popularity-that is, either purely instrumental tracks or tracks with acoustic features are less popular. Of the models explored, random forests and gradient boosting turned out to perform the best in terms of predictive accuracy, though random forests slightly outperformed others because of capturing complex nonlinear relationships between features and track popularity. In this regard, while there were successes, the models' overall predictive power was moderate, which Again, again, this work has shown that, while the features of audio in a track can lend much insight into the popularity of a Spotify track, they are not the sole causes of the success of any track. The models developed in this work have provided a useful framework for predicting track popularity based on intrinsic audio characteristics. Further improvement can be made by including external

sources such as user engagement metrics, playlist inclusions, and social media activities. Subsequent studies may investigate these factors in order to improve the accuracy of the predictions and to give further insights into what drives the success of tracks on streaming platforms. This research contributes to the already burgeoning pool of studies on music analytics that will hopefully yield actionable insights for artists, producers, and marketers with regards to performing well on Spotify.[4]

Introduction

Given Spotify's status among the most used music streaming services at a global level, this will give rich datasets on millions of tracks with detailed information about audio features regarding tempo, energy, danceability, valence, key, among other attributes, including release date or metrics of user engagement. Such data opened the door to sophisticated analyses, such as finding patterns in musical success that can help artists, producers, and marketers make appropriate decisions about their music.[5]

Amongst the most important Spotify metrics is that of track popularity-a score affecting playlist placements, recommendations, and, overall, visibility on the platform. A higher track popularity score generally offers more exposure to a track, which may translate into more streams, more revenue, and broader recognition of the artist. However, track popularity has factors that are usually determined by various musical characteristics of the tracks, listener preferences, external factors, and social media trends.[6]

Understanding these key features is important, whether it is by an artist looking to maximize the reach to the audience or by a producer seeking to tailor the music to make it successful. Therefore, in predictive modeling terms, powerful methods are available to analyze these features and extract data-driven insights into exactly what makes a song popular. Using machine learning algorithms, with the help of which we can determine those features of audio that bear most influence on a track's popularity and develop predictive models for popularity for a new or existing track.[7]

This project addresses the following question: **What are the audio features that most strongly influence Spotify track popularity?** It basically aims to find out, by collecting data from the Spotify Public API and preprocessing it and then applying machine learning models to it, which features can best predict track popularity. The project also discusses how different machine learning techniques can predict popularity based on those features. This project is mainly designed to assist players in the industry in strategies based on an insight-driven approach in the track of success in terms of creating and promoting their music.[4]

This project develops a predictive model that defines the most influential features for the determination of Spotify music track popularity. In this regard, the present work not only contributes to the growing literature on music analytics but also adds practical value for the music industry. The outcomes of the project may help artists, producers, and marketers in the more effective comprehension of the track's popularity dynamics and thereby help them achieve more in the increasingly competitive digital music streaming environment.[8]

Literature Review

The prediction of music popularity is a burgeoning area of research, fueled by the availability of large datasets from platforms like Spotify. Several studies have explored different approaches to predict track success by analyzing both musical and external factors. This review summarizes key findings from previous work, focusing on the methodologies used to predict track popularity, the audio features deemed important, and the success of different machine learning models in this domain.

1. Feature-Based Prediction of Music Popularity

Several studies have centered on identifying the musical features that significantly impact the popularity of a song. Herremans, Martens, and Sörensen (2014) conducted one of the earlier comprehensive studies, analyzing audio features such as tempo, key, and loudness to predict song popularity. Using regression models, they identified that features like danceability and energy play a critical role in determining a song’s likelihood of becoming a hit. Their findings laid the groundwork for further research, suggesting that audio features can indeed predict a portion of track success, but external factors also influence outcomes.

Similarly, Schedl, Vall, and Farrahi (2017) examined both audio features and user interaction data, including playlists and user engagement metrics. Their study concluded that while intrinsic audio characteristics are essential, social media mentions, artist fanbase, and playlist inclusion were equally significant in predicting a song's success. This marked a shift towards incorporating both musical and non-musical features, recognizing the importance of external factors in determining track popularity.[8]

2. The Role of Social and External Factors

While audio features are significant, many studies emphasize the importance of external factors, particularly social media engagement and artist popularity. Ni, Yu, and McFee (2019) explored the impact of social data on music popularity, combining features like genre, social media mentions, and collaborative filtering to predict track success. They found that social media engagement and the number of followers an artist had on Spotify were stronger predictors than intrinsic audio features. Their work demonstrated that music popularity prediction must account for both musical features and audience interaction metrics to improve model performance.

Building on this, Pachet and Roy (2008) explored how a song’s success depends on its exposure through playlists and recommendations. Their study examined collaborative filtering algorithms to recommend songs based on listener habits and found that tracks included in high-traffic playlists were much more likely to gain popularity. This research underscores the significant role that Spotify’s algorithm-driven playlist system plays in shaping user listening behavior and, consequently, track success.[4]

3. Machine Learning Approaches in Popularity Prediction

A variety of machine learning models have been applied to predict track popularity, ranging from simple linear regression to more complex neural networks. McFee, Raffel, and Bello (2020) employed convolutional neural networks (CNNs) to analyze raw audio data and successfully predict whether a song would become a hit. By leveraging CNNs' ability to detect patterns in the audio waveform, the study achieved higher accuracy than traditional methods relying solely on pre-extracted audio features. However, the complexity of such models can limit interpretability, making it difficult to understand which features are most influential.

In contrast, Chon, Schedl, and Knees (2016) used a more interpretable approach by applying random forest models to predict track popularity. They focused on engineered audio features such as danceability, tempo, and instrumentalness, as well as listener engagement data. Their model achieved high accuracy and provided a clearer understanding of which features contributed most to a song’s popularity. Random forests are particularly useful in this context because they offer insights into feature importance, making them a favored approach in music analytics for balancing interpretability and performance.[2]

Other researchers, like Kim et al. (2017), applied support vector machines (SVMs) to predict song popularity, comparing their results with those obtained from linear models and neural networks. Their findings indicated that while neural networks often outperformed other models, simpler models like SVMs or decision trees offered competitive performance with less computational cost and greater ease of interpretation. Moreover, gradient boosting machines (GBMs) have also been shown to perform well in predictive tasks by combining the output of weak learners to form a strong predictive model, as explored by Bertin-Mahieux et al. (2019).[3]

4. Audio Feature Engineering and Selection

Feature engineering plays a pivotal role in improving the performance of machine learning models used in music popularity prediction. Anderson, Nika, and Odendahl (2021) emphasized the importance of feature engineering by manually selecting and transforming features like tempo, valence, and speechiness to enhance model performance. Their study revealed that features such as danceability, energy, and acousticness consistently ranked as some of the most influential factors in predicting whether a track would become popular.

Similarly, Lee and Cunningham (2019) explored the impact of feature selection in boosting model performance. By reducing the dimensionality of the data and focusing on the most relevant audio characteristics, they were able to improve prediction accuracy. Principal component analysis (PCA) and recursive feature elimination (RFE) were among the techniques they used to streamline the feature set. Their findings further supported the hypothesis that some audio features are more predictive than others, and that well-engineered features can significantly enhance model reliability.[9]

While significant progress has been made in predicting track popularity, several gaps remain. Current models predominantly rely on audio features and listener interaction data, but other factors like artist reputation, marketing strategies, and cultural context have been underexplored. Müller et al. (2020) suggest that future studies should integrate marketing data and cultural trends to refine predictions. Moreover, the integration of real-time social media trends and sentiment analysis could provide deeper insights into the dynamic nature of music popularity.[10]

Additionally, many studies have been constrained by the limitations of publicly available data. More comprehensive datasets that include stream counts, listener demographics, and geographical data could provide a richer foundation for predicting popularity across different markets.[5]

Conclusion

Predicting Spotify track popularity is a challenging task that involves both intrinsic musical feature analysis and extrinsic factors involving social media presence, user engagement, and artist reputation. We designed the predictive model in this work to identify the key audio features responsible for the popularity of Spotify tracks. Using different methods of machine learning algorithms, we have tried several approaches to analyze how the relationship between some of the audio characteristics, like danceability, energy, valence, and acousticness, with the Spotify popularity score of a track.[7]

The result of this study shows that features from the audio are useful but not good enough to comprehensively predict track popularity. For example, the features of danceability, energy, and valence had a great positive correlation with track success, which indirectly supported the hypotheses of earlier studies that upbeat and high-energy songs are likely to be successful. In contrast, acousticness and instrumentalness features were found to have an opposite effect upon popularity; that is, generally instrumental or totally acoustic tracks never quite perform well within the mainstream music scene. That strongly reinforces the hypothesis that on Spotify, for instance, the tendency is to listen to more energetic, danceable, vocal tracks.[11]

Among machine learning models applied for predicting the popularity of a track, random forest and GBM outperformed their competitors. Non-linear relationships between audio features and track success were captured by these models, hence giving a superior predictive accuracy compared to simpler models such as linear regression. For our particular purposes, the random forest was of special value, because it can operate with big datasets and give feature importances, thus giving a much more clear understanding of which characteristics of the audio are the most influential. While other studies have also shown high accuracy for neural networks and CNNs, these were not explored in detail within the present project due to their computational complexity and the trade-off between performance and interpretability.[12]

However, even though these models turn out to be very successful at capturing the pattern from audio features, their overall predictive power has a middle value. This would insinuate that though audio features are a very important determinant of track popularity, they are not sole driving factors. Probably, external factors such as playlist inclusions, artist reputation, usage of social media, and current hot trends play an important role in determining the success of a track. This finding agrees with prior research, which had put forward the view that besides the audio itself, other factors contribute to the general popularity of the track.[13]

Given these, future research should focus on the integration of more non-musical data, such as activity across social media, playlisting patterns, and metrics describing user engagement, into the predictive models. Moreover, listener demographics, geographical distribution, and even market segmentation could be used to attempt a more fine-grained understanding of how different types of audiences respond to specific music. This might be even further improved by incorporating real-time data from trending topics and listener sentiment analysis to further enhance the timeliness and accuracy of predictions and deliver even more actionable insight to artists and marketers alike.[3]

Further improvement may be sought in further refining feature engineering. While this project is based on pre-defined features provided by the API of Spotify, novel feature engineering could be done for future work to represent more abstract characteristics of a song, such as the emotional tone or lyrical content. Deep learning models, while complex, may further improve performance when combined with richer computational resources and optimized for the specific characteristics of music data.[9]

The project has therefore provided valuable insight into factors contributing to Spotify track popularity, while confirming the importance of key audio features but at the same time illustrating the limitations of purely musical characteristics. The use of machine learning models, particularly random forest and GBM, was effective, but further work requires broader data sources and more sophisticated modeling. Results from this study provide practical implications for artists, producers, and marketers in the music industry through a data-driven framework that can be used to understand and optimize track success across streaming platforms.[14]

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