Predicting Song Popularity

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***Abstract*—This project aims to predict the popularity of songs by analysing acoustic features such as tempo, duration, mode, loudness, key; artist information such as location and popularity; and metadata such as release title and year. The codebase for the project is located at `https://github.com/inSam/SoundScorer221`**

I. Introduction

The goal of this project is to predict the popularity of a song by analyzing its audio features and metadata. Such a tool would be valuable for record labels, streaming services, and average consumers; it would also help the research community understand what acoustic features are currently popular with the public. In this progress report, we would like to expand on (1) our overall strategy for dataset and feature extraction (2) details about our regression algorithms (3) next steps we plan to take to finish up our project.

II. Methods

A. Dataset

Our dataset comprises 7,473 songs extracted from the Spotify API, which provides acoustic features, author information, song metadata, and a popularity score. Spotify's popularity score ranges from 0 (least popular) to 100 (most popular), and is determined as a function of number of plays on Spotify and the recency of those plays.

We pulled these songs from Spotify's 1,000 top albums released in 2018, which gives us a range of songs across popularity, genre and acoustic features. In addition, limiting our analysis to songs released in 2018 partially controls for the effect of age on popularity.

We further made sure to eliminate all duplicate songs from our dataset, as some songs are cross-listed on multiple albums. This should prevent our score from being artificially inflated, as it would be if some songs appeared on both our training and test set. We use an 85/15/15 train/dev/test split throughout the paper. In this progress milestone, as we are prototyping models without tuning hyperparameters, we report evaluation metrics on our development set.

Note to the reader: Our original sampling of songs, described in the project proposal, turned out to be highly imbalanced, skewing heavily towards popular songs over unpopular songs. To remedy this, we changed our data sample from the top 10,000 songs to all songs from the top 1,000 albums. This results in a much more balanced dataset. We've re-run our original baseline tests on our new dataset, and we report these figures throughout the paper. Since our data is more evenly spread from 0 to 100, this results in a higher MSE than on our previous dataset.

B. Concrete Example

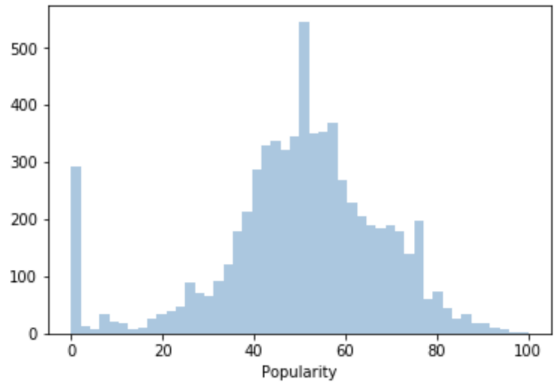
For each song in our dataset, we model its features as extracted from the Spotify and Echo Nest APIs. Here's a sample representation for the song *Never Gonna Give You Up*:

$$
\begin{aligned}
&"TRAXLZU12903D05F94" : \{ \\
&\qquad "features" : \{ \\
&\qquad artist\_name : RickAstley \\
&\qquad loudness : -7.75 \\
&\qquad tempo : 113.359 \\
&\qquad duration : 211.69587 \\
&\qquad mode : 1 \\
&\qquad energy : 48.149 \\
&\qquad previewurl : p.scdn.co/mp3/99 \\
&\quad ...\}, \\
&\quad \}
\end{aligned}
$$

We format songs' feature dictionaries as Pandas dataframes for consumption, then input the song dataframes into the models described below. Our desired output is simply the Spotify popularity rating. Although a song's popularity fluctuates over time, we predict only the current popularity rating.

C. Data Exploration

Below, we've plotted the distribution of song popularity in our dataset.



Our dataset appears approximately normally distributed around mean 50. Also of note, there is a significant spike of highly unpopular songs with score 0. These unpopular songs likely comprise a "long tail" of music on Spotify which users rarely listen to.

As a gut check that Spotify's popularity rating is sensible, we also printed out the most popular songs in our dataset. The five most popular songs in our dataset are:

- 'Promises (with Sam Smith)', 95
- 'SICKO MODE', 96
- 'Without Me', 96
- 'Happier', 98
- 'Taki Taki (with Selena Gomez, Ozuna Cardi B)', 100

These popularity scores make sense to us. All the kids listen to Cardi B. Hopefully they make sense to you.

D. Feature Selection

We extract three broad categories of features for use in our regression models. The first are low-level audio features, such as song duration and time signature, extracted from Spotify's Audio Analysis feature. The second are high-level audio features such as "danceability" and "valence", extracted from audio files using The Echo Nest API. The third are metadata for each song, such as artist information.

1) Spotify Audio Analysis: The most low-level audio features are those provided by Spotify's Audio Analysis feature. This provides both concrete song features, such as duration and average volume, as well as estimated features like the song's key and tempo. The audio analysis also provides more high-level analysis by subdividing the song into sections (i.e. Chorus, Bridge, Verse) and further subdividing sections into segments.

Spotify is somewhat slow to deliver audio analysis statistics, as making a call to audio analysis requires Spotify to parse each song. We plan to make these API calls in our future feature extractors.

2) The Echo Nest: We then add seven high-level audio features extracted by The Echo Nest API, which is integrated into the Spotify API. The Echo Nest uses proprietary audio analysis algorithms to extract high-level features from audio files. The seven features we used are "acousticness", "danceability", "energy", "loudness", "speechiness", "tempo", "valence". These audio features are extracted directly from the audio files of each song. The Echo Nest's algorithms are propietary, and we are unable to access how they extracted these features, but we use them in all experiments described below.

3) Artist Metadata: We plan to further utilize song and artist metadata such as an artist's past releases, genre, and length of career. Spotify's API yields metrics for an artist's genre and current number of followers. We may also use the powerful feature of Spotify artist popularity; however, Spotify computes this feature using the popularity of an artist's individual songs, so this may not be suitable. [**Question**: Is it fair to use the current popularity of an artist to predict the popularity of one of their songs?]

E. Data Split

After extracting these features for each song in our dataset, we converted our list of songs and features into a Pandas dataframe for consumption by scikit-learn models, split our data according to a 85/15/15 train/dev/test split, and trained the models described below.

F. Support Vector Regression

As our first algorithm, we chose to to leverage non-linear Support Vector Regression (SVR). SVR applies hinge loss and non-linear kernels to regression problems, performing regressions on a dataset and generating non-linear contours. We feed our baseline features and additional features into our SVR, with results reported below.

G. Random Forest

For our second classical algorithm, we will train a Random Forest Regressor on our features. Random Forest Regressors are extremely similar to Random Forest Classifiers, also using a forest of decision trees. In our case, the Random Forest classifier should give us a reasonably strong and interpretable model for use on our features.

III. Initial Evaluation

Our initial evaluations involve running our models on our dataset with the basic features described above.

A. Linear Regression (Baseline)

For our baseline, we trained a simple linear regression model on our dataset. Solely using the seven features from The Echo Nest, our linear regression model achieved a mean squared error of 279.62.

Worth noting in this linear regression baseline are the learned coefficient weights, which provide a crude approximation for the importance of each factor. The factor most strongly predictive of popularity is 'danceability', with a weight of 21.10. The factor most strongly predictive of unpopularity is 'valence', with a weight of -9.75.

B. SVR

As described above, we then trained a Support Vector Regression model on our dataset. Our SVR used a radial basis function (rbf) kernel, with regularization parameter $C = 1.0$. With these settings and our basic features, we achieve a mean squared error of 295.72, which is slightly worse performance than our linear regression baseline. In the future, we plan to experiment with various kernels and hyperparameter configurations to optimize the SVR model.

C. Random Forest Regression

We then trained a Random Forest Regression model on our dataset, using a forest with 100 trees and leaving all other hyperparameters as scikit-learn defaults. This resulted in a mean squared error of 250.41, somewhat better than either the SVR or linear regression models.

D. Gradient Boosting Decision Trees

We also trained a Gradient Boosting decision tree model, packaged in scikit-learn's GradientBoostingRegressor model. As in our random forest, we used 100 trees. This yielded a mean squared error of 252.27, similar to Random Forest.

IV. Next Steps

A. Data Processing

We would like to extract more songs from the Spotify database to bolster our dataset. This should be straightforward to do, by increasing the number of albums we draw songs from, though calls to the API our rather slow. Garnering a larger dataset should also allow us to properly split our dataset into train, dev and test sets, which will allow us to tune the hyperparameters for our models.

B. Improve Features

As mentioned at the beginning, we will soon incorporate low-level audio features from Spotify's "Audio Analysis" tool, as well as artist metadata from the Spotify API. We will also explore more features from the Spotify database such as song age, location, audio sections, and signature.

We may further try to construct more advanced features from historical data such as musical trends. Using Spotify's provided links to song previews, we may be able to extract more advanced features from the audio recordings of each song. This step will involve a lot more feature tuning and experimentation.

C. Improve Models

For our existing models, we will tune hyperparameters via grid search on our development set to improve performance.

For future models, we will try to tackle this problem by using further ensemble models to derive meaning from our features. In particular, neural networks may be able to extract more meaningful features from the audio tracks of each song.

V. Challenges

One challenge is to consider the effects of time on the popularity on the song. We may be able to tackle this by simply adding the age of the song as a additional feature.

Another challenge is that there is plenty of noise that influences a song's popularity, beyond its mere auditory features. While we have assumed a 100% success rate with our Oracle, this may be unrealistic to achieve with a classifier.

References

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