Karaoke Song Predictor

Steve Burke *sfburke@stanford.edu*

Problem Statement

The success of any Karaoke outing is highly dependent on the choice of songs throughout the event. Whether at a public bar or in a private karaoke room, if care is not taken to ensure quality songs are chosen, attendees may end up sitting in the back of the room, bored, and wondering why they even showed up.

The Karaoke Song Predictor assists users in evaluating whether a song is likely to be a hit at a karaoke event. The predictor takes as input an individual song along with a set of known data about the song, and outputs a binary prediction of success. In the future, this predictor could make use of more complex predictive models, or acquire the data points on a song automatically, rather than requiring manual data entry by the user.

Data

The dataset included 75 individual songs and associated data, as well as binary good/bad labels. Each song's data consisted of:

- **Song Title**
- **Artist**
- **Duration**
- **Release Year**
- **Genre**
- **Tempo**
- **Key**
- **Singer: Male / Female / Duet**
- **Music Video Views on YouTube**
- **Number of Listens on Spotify**
- **US Billboard Hot 100: highest rank**

The songs and binary labels (Good/Bad) for the data were chosen based on an online article [1] for best karaoke songs, a Spotify playlist [2] of best karaoke songs, and were supplemented and modified by the extensive experience of the author.

Implementation

I implemented a feature extraction function to take the known information about each song in the dataset and extract features for a linear predictor. The extracted features consisted of:

- Artist → this is its own feature
- Duration (seconds): 100 – 200; 200 – 300; > 300
- Release Year: 1950s; 1960s; 1970s; 1980s; 1990s; 2000s; 2010s
- Genre → this is its own feature
- Tempo (bpm) < 75; 75-100; 100-110; 110-120; 120-130; >130
- Key → this is its own feature
- Singer: Male / Female / Duet → this is its own feature
- Music Video Views on YouTube (Millions): < 100; 100-250; 250–500; 500–1000; > 1000
- Number of listens on Spotify (Millions): < 100; 100-250; 250-500; 500-1000; > 1000
- US Billboard Hot 100 Highest Rank: 1-3; 3-5; 5-10; 10-20; >20

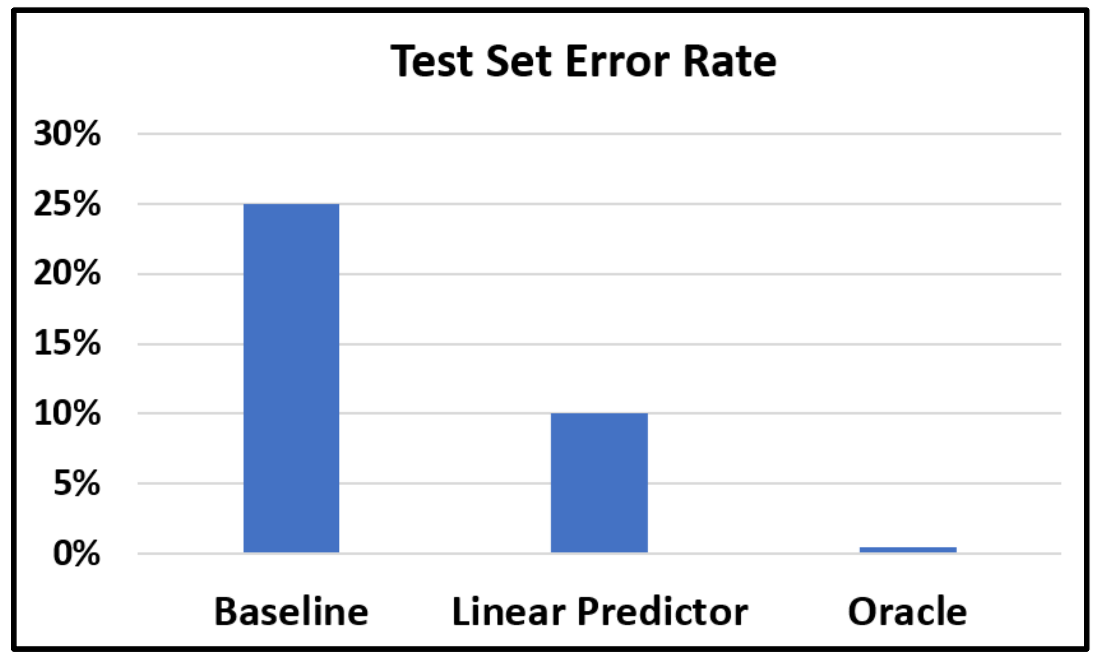
I trained a linear predictor based on these extracted features, by using stochastic gradient descent and a hinge loss over the 50 songs in the training dataset, over 5 epochs with a step size of 0.02.

$$\text{Loss}_{\text{hinge}}(x, y, \mathbf{w}) = \max\{1 - (\mathbf{w} \cdot \phi(x))y, 0\}$$

$$\mathbf{w} \leftarrow \mathbf{w} - \eta \nabla_{\mathbf{w}} \text{Loss}(x, y, \mathbf{w})$$

Results

The plot below compares the performance of the linear predictor to an oracle (human) predictor as well as a baseline which set a simple good / bad threshold at a duration of 200 seconds. The data below is reported for a test set of 20 songs.



Discussion

By examining the weights vector of the linear predictor after 5 epochs, I found that some of the most positive factors leading to a "Good" song prediction were:

- **Artist: Beyoncé**
- **Tempo: 75-100 bpm**
- **Duration: 100-200 seconds**
- **1960s**
- **Music Video Views: 250-500 Million**

Some of the strongest features leading to a "Bad" prediction were:

- **Artist: Male**
- **Tempo: < 75 bpm**
- **Duration: > 300 seconds**
- **1990s**
- **Music Video Views: < 100 Million**

Many of these make intuitive sense – songs that are more popular, shorter, or with high tempo are more likely to be good karaoke songs. But others, including the negatively weighted Male artist feature, would likely be improved with a larger sample size of training data.

Future Directions

Future directions include optimizing the linear predictor by increasing the size of the training dataset, as well as by modifying the resolution of various feature categories (tempo, views, duration, etc.).

Alternative models for reducing classification error could include: nearest neighbors, clustering, or neural networks. In general, the application of this type of predictor would benefit from an automated way of downloading the input information associated with each song.

References

[1] Harris, Sophie; Timeout Editors. *The Best Karaoke Songs Ever*. Timeout Magazine, 1 Oct. 2018, https://www.timeout.com/newyork/music/the-50-best-karaoke-songs-ever. Accessed 16 Nov 2019

[2] Parkinson, Brie. *Best Karaoke Songs*. Spotify.com. Accessed 16 Nov 2019.