Analyzing users' music listening habits and the effects of track number on song popularity

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Overview

Spotify, founded in Sweden, is a commercial music streaming service that provides podcasts, music, and videos from record labels and media producers from around the world. As of 2016, it provides over 20 million songs and has over 75 million active users. It also provides an extensive Web API, making it a prime candidate for analyzing music listeners' behavior and its effects on song popularity.

In this project, our group proposed, investigated, and tested two hypotheses about the Spotify data-set, as well as building a personalized Music Recommendation app. To do this, we wrote several programs in JavaScript (using Node.js) and Python (using SciPy and NumPy), making a variety of calls to the Spotify API to get samplings of artists, albums, songs, and user playlists.

Hypotheses:

Music hypothesis: Does track number influence the popularity of a song relative to an album's mean popularity?

User hypothesis: As a user's "hipster score" increases, will the user listen to a higher number of genres per artist?

Music Results

With a confidence interval of 95% (alpha: 0.05), this allowed us to reject the null hypothesis for all track numbers (except 5), and say that each track numbers stdevs varied from the assumed random value of zero. Then, to verify that there was a downward slope in popularity as track number increased, we drew a regression line through the scatterplot of all tracks (Figure 2), and in a t-test against the null hypothesis that the slope of this line was 0, we got a p-value of 0.0 (confidence interval of 99.9999%). Although we see that our regression line only has an R2: 0.146, this p-value allows us to reject the null hypothesis, and say with confidence that the track number of a song influences its popularity relative to the mean popularity of the album.

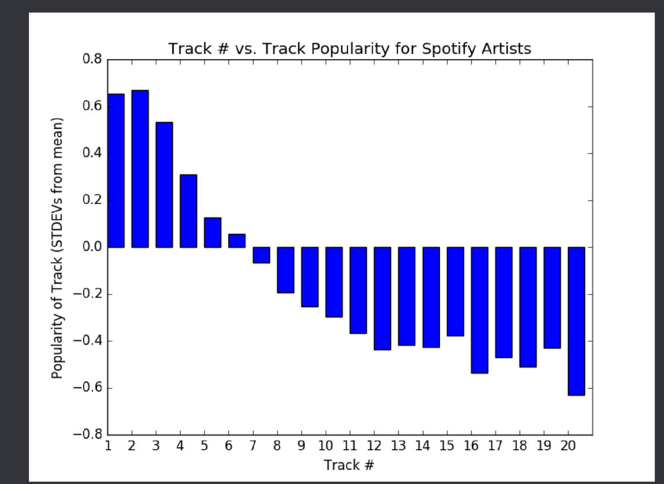


Figure 1: Comparison of track number to mean standard deviation of track popularity from album mean. Note the quasi-linear downward trend.

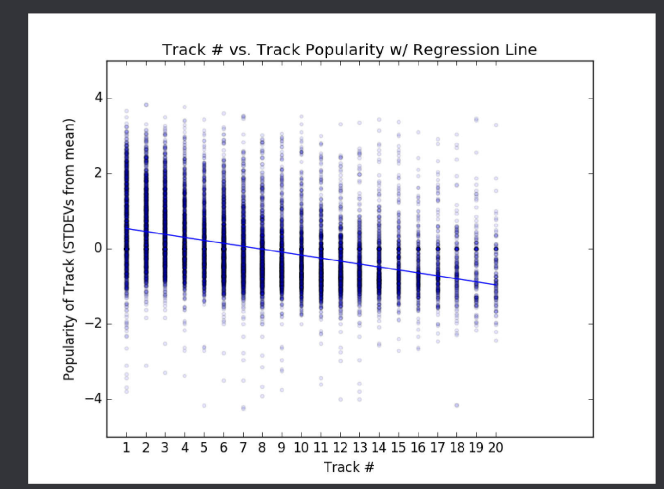


Figure 2: Distribution of track popularities for each track number, showing downward-sloping regression line of popularity with respect to track number.
slope: -0.0787, intercept: 0.6134, r-squared: 0.1468, stderr: 0.00169

User Results

Hipster scores converged toward 50 because each artist the user listened to could be considered as a random selection of popularity, the mean of which would approach the overall mean, according to the Law of Large Numbers. Next, we tested the hypothesis that as the number of artists increased, so would the number of genres (Figure 5).

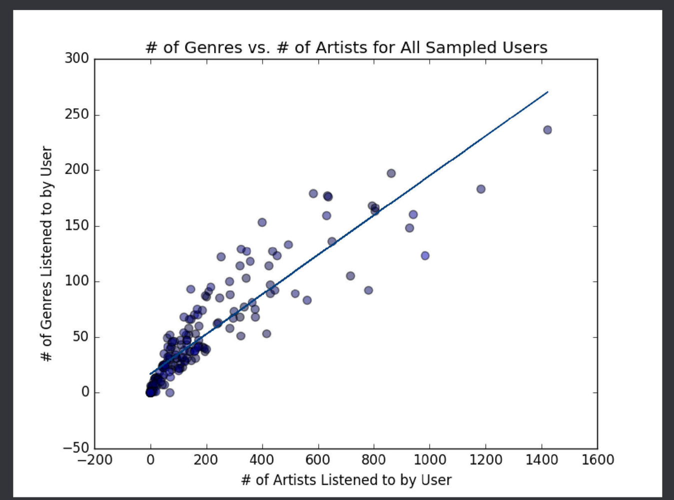


Figure 5: Comparison of track number to mean standard deviation of track popularity from album mean. Note the quasi-linear downward trend. The r-squared value is 0.807.

Here we saw a clear correlation, with an R2: 0.807. Knowing this, we decided to divide our count of genres by the number of artists listened to by the user, result in Figure 6. Here we reached our final conclusion: since our regression line for this chart has a p-value of 0.718, and a correlation score of 0.028, there is no statistically significant correlation between hipster score and number of genres per artist, so we do not reject the null hypothesis.

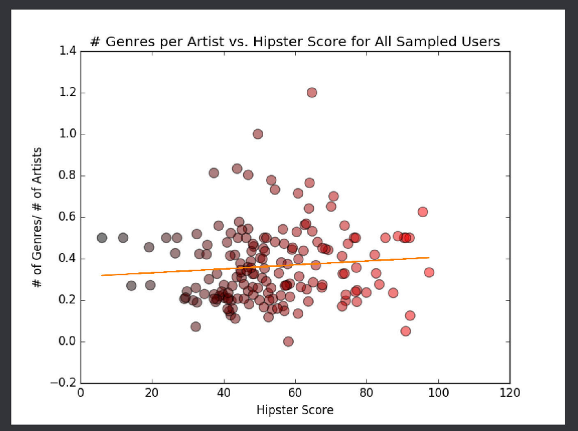
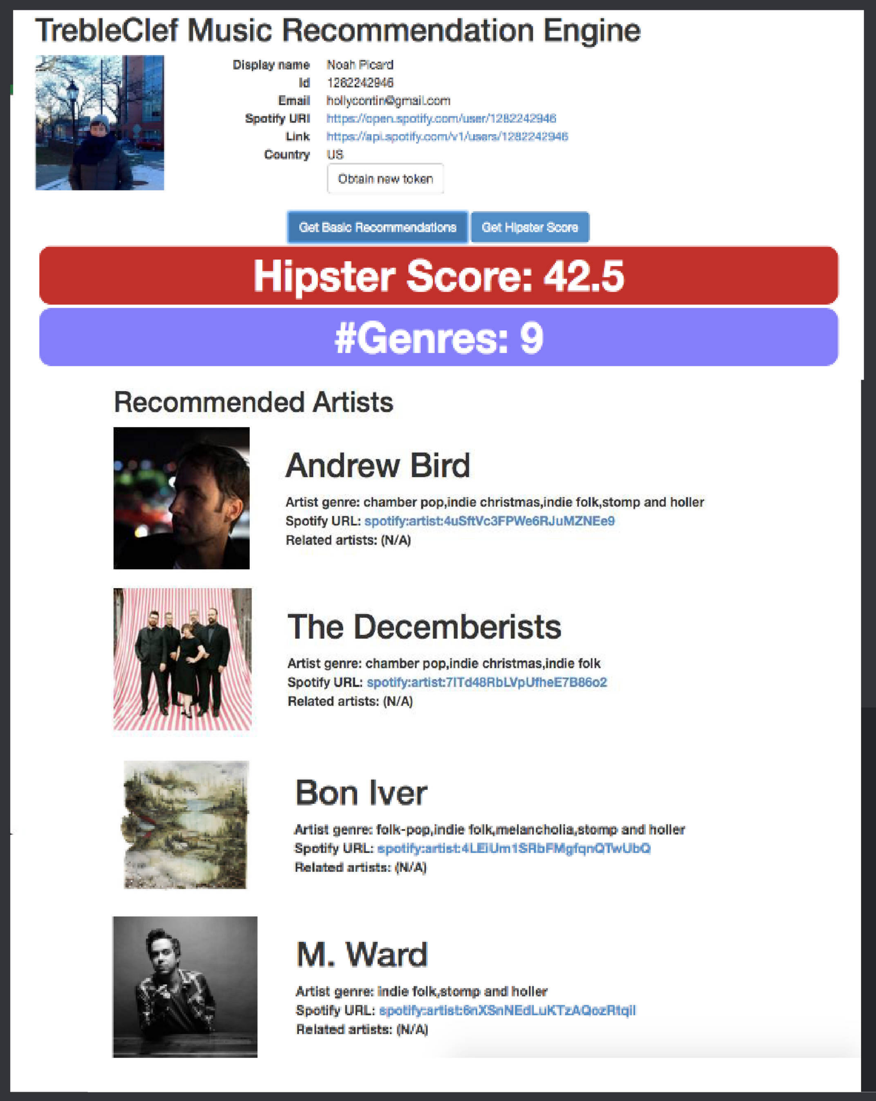


Figure 6: Comparison of track number to mean standard deviation of track popularity from album mean. Note the quasi-linear downward trend.

Our App

We created an artist recommendation app that takes a users' top artists, finds all related artists to those top artists and returns the top 5 artists with the highest related artist count. In addition, it tells you your hipster score, which is based on your aggregate artist popularity and the number of genres you listen to.



Data Set

For the User-Centric testing, for each user, the information we used consists of:

User's Hipster Score -(100 - mean(popularities of all tracks in user playlists)),
- Mean: 53.55, StDev: 17.28

Count of Genres of all Artists
- Mean: 53.74, StDev: 49.34

Number of Artists listened to
- Mean: 206.66, StDev: 248.92

For the Music-Centric testing, for each track we kept track of the:

Track Number in Album
- Mean: 7.79, StDev: 4.78

Track Popularity Score
- Mean: 38.86, StDev: 17.18

Artist Popularity Score
- Mean: 72.35, StDev: 6.76

Music Methodology

We gathered track numbers and popularity scores for the 100 albums produced top-ranked artists and compiled dictionary mapping album ids to a list of its tracks with their respective track numbers and track popularities. Creating a bar chart for the mean stdev for the track from the mean popularity for each album, we saw a curve similar to our final resulting graph (Figure 1), with high values for the first few track and a clear downward trend

track #	stdev	mean	samples	t-statistic
0	0.653	1.136	986	18.059
1	0.671	0.971	940	21.196
2	0.533	0.943	937	17.317
3	0.311	0.925	937	10.308
4	0.127	0.854	929	4.538
5	0.056	0.891	922	1.919
6	-0.067	0.883	880	-2.257
7	0.194	0.85	856	-6.68
8	-0.255	0.83	841	-8.907
9	-0.297	0.825	815	-10.283
10	-0.367	0.812	734	-12.258
11	-0.435	0.774	618	-13.977
12	-0.415	0.817	502	-11.385
13	-0.425	0.818	421	-10.67
14	-0.379	0.882	352	-8.036
15	-0.537	0.766	294	-12.016
16	0.469	0.876	224	-8.005
17	-0.508	0.949	180	-7.187
18	-0.429	0.983	147	-5.284
19	-0.628	0.833	125	-8.426

Table 1: t-statistic of track numbers vs popularity

We continued by gathering the most recent albums from the top 1000 artists , and created graphs for the total of 12640 tracks. For each track number, we took the gaussian formed by the track popularities of tracks with that track number, and performed a two-tailed t-test against the null hypothesis that they had a mean of exactly 0 stdevs from the album mean, giving us the t-statistics visible in Table 1.

User Methodology

We collected 370 user ids, and acquired each user's playlists. We then found the average popularity of the playlist's songs, and the number of genres the user listened to. Using this, we created the distribution in Figure 3. Trying to form a linear correlation was clearly infeasible (when t-testing the slope against a null hypothesis of 0, p-value: 0.308), but the distribution's bell curve shape led us to wonder if there was a third factor influencing this dataset: the number of artists the user listened to. To check this, we plotted hipster score vs number of artists (Figure 4), and found that as the number of artists listened to increased, the users' hipster scores fell toward the mean of 50.

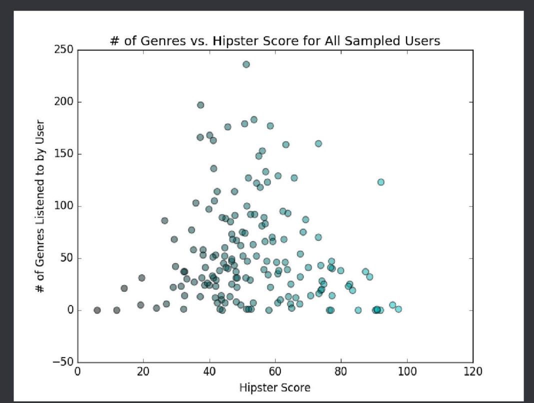


Figure 3: Comparison of number of genres and hipster scores. Note the bell curve shape but no linear correlation.

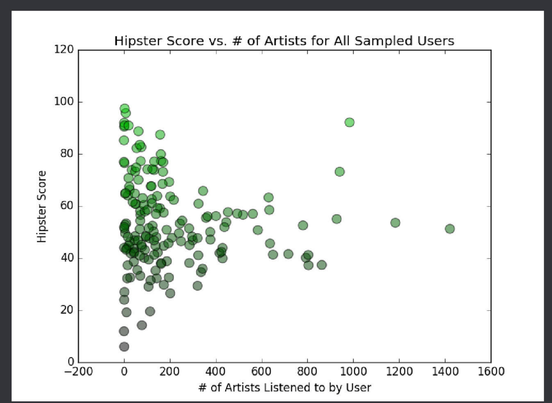
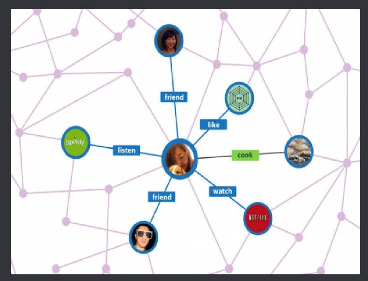


Figure 4: Comparison of hipster score and number of artists listened to. Note the hipster score converges toward 50.

Challenges

Originally we had planned to incorporate a more social aspect into our investigations by using the Facebook Graph API. However, complications with permissions for friends and other users led us to abandon this idea.



Since API calls were occuring asynchronously, we had to work with JavaScript promises to track of all our calls and their status, waiting until each one was finished.

We also had some trouble working with the Spotify API when the server would start rejecting requests once the number hit a certain limit. This required delaying our requests using JavaScript's setTimeout() and minimizing the number of calls we made.