Frank Pasqualini

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STAT 1223

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Spotify Music Library Regression Analysis

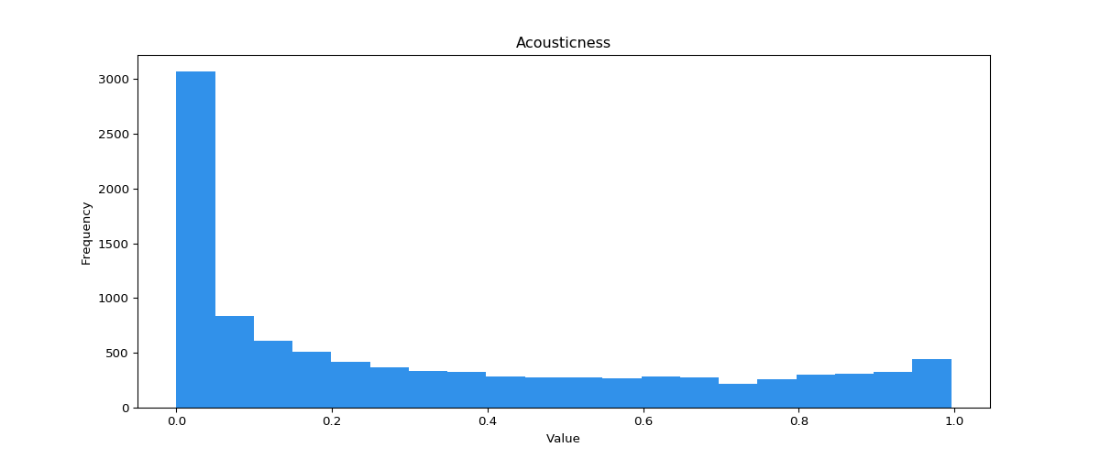
ABSTRACT

In this study we will look at the relationship between a user’s enjoyment of a song and various attributes of the song, such as its tempo and loudness. We will attempt to build a regression model to predict songs that a user might enjoy, and we will also analyze the differences between songs a user saves to their library and the amount of times they listen to that song. There will end up being no strong correlation between any of the predictors and the response, and only minimal differences between songs in the library and songs in the play history.

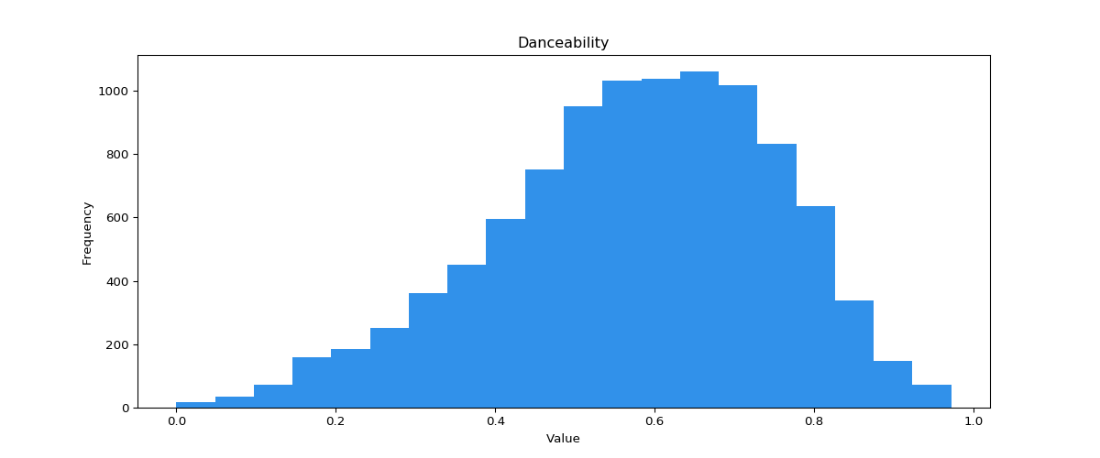
This study was conducted to build a multivariate regression model relating multiple attributes of a musical track on Spotify to a specific user’s musical preferences. The response variable was play count, the amount of times that the user has listened to that song. We believe that a play count is a good estimate of how much a user likes a track, because if they like the track more they will listen to it more. We thought results would be particularly interesting if the study was successful because it could be turned into a generalized tool that a user could insert the data from their own music library into. The resulting regression model could be then used on a per-individual basis to find songs that are likely to be enjoyed by the listener, by giving recommendations for songs that would maximize the response variable based on the predictors. This was a case study based off of the Spotify and Last.fm accounts of Frank Pasqualini.

For this study, we performed the regression on the music library of Frank Pasqualini, using data from his Spotify and Last.fm accounts. At the time of gathering the data to be used in the study, Frank had 5,774 tracks saved to his Spotify library and 37,933 scrobbles saved to his Last.fm account from 1,342 artists. A scrobble is a recorded instance of a track being played. Frank has been tracking his scrobbles using Last.fm since December of 2017, and those scrobbles were tracked directly by linking his Last.fm account to his Spotify account, so the data should be mostly valid even though the predictors were collected from a different source than the response. We used 15 potential predictor variables, which are as follows: duration\_ms, explicit, popularity, mode, acousticness, danceability, energy, instrumentalness, liveness, loudness, speechiness, valence, tempo, release\_date, and album\_popularity. These were retrieved for each track using Spotify’s Web API.

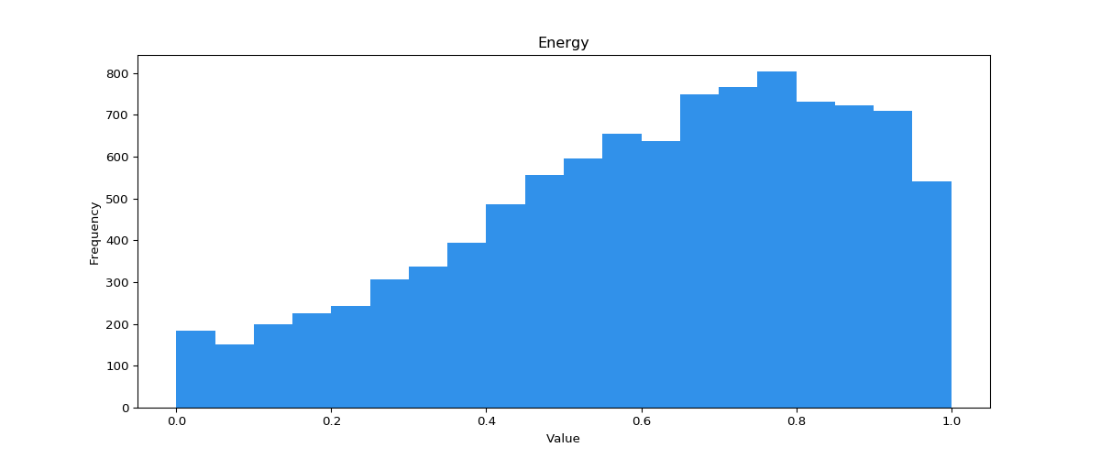
Almost all the variables we used in our model were retrieved from the “Get Audio Features for a Track” Spotify API call. The documentation for this API call gives in depth descriptions about what each of these values represent, as well as providing the distributions that we have included below, but we will provide a general description of each of them. Some of the more basic variables were taken directly from the track object returned from the API call. Duration\_ms is a measurement of the length of the track in milliseconds. Explicit is a categorical variable that tells whether the track has been marked to contain vulgar language. Popularity is an integer value between 0 and 100 that is a calculated by one of Spotify’s algorithms based on total plays and how recent those plays are. Mode is another categorical variable with 0 representing if the track is in a minor key for the majority of the track and 1 if the track is in a major key for the majority of the track. Acousticness is a confidence measure of whether the track is acoustic. It has the distribution featured in the following figure:



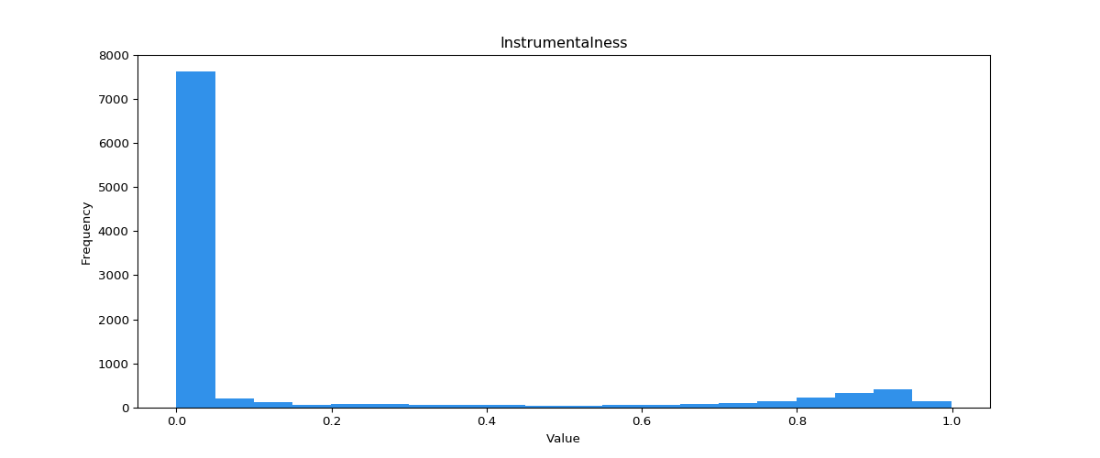
Danceability is an estimate of how well suited a track is for dancing to based on many attributes such as tempo, stability, and regularity, and has the distribution shown in following figure:



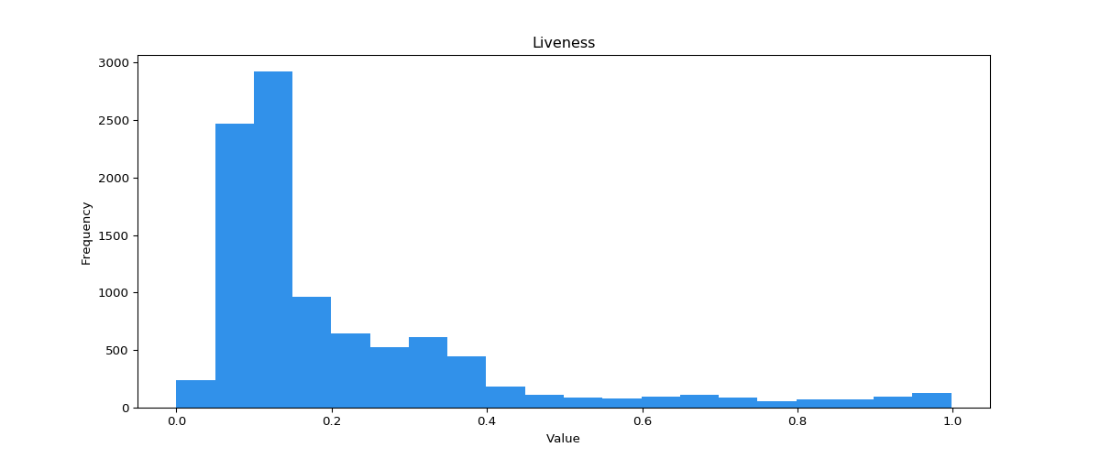
Since danceability is in part based on tempo, we hypothesized that there would likely be high covariance between these two variables. Energy is an estimate of the intensity of the track based on attributes such as entropy, timbre, and loudness, and has the distribution featured in the following figure:



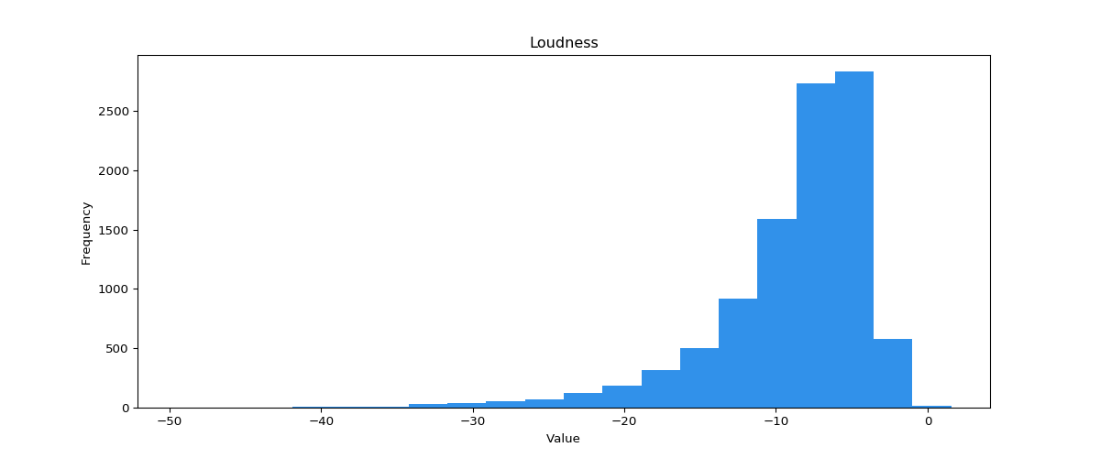
Since energy is in part based on loudness, we hypothesized that there would likely be high covariance between these two variables. Instrumentalness is a confidence measure of whether the track contains no vocals and has a very skewed distribution represented by the following figure:



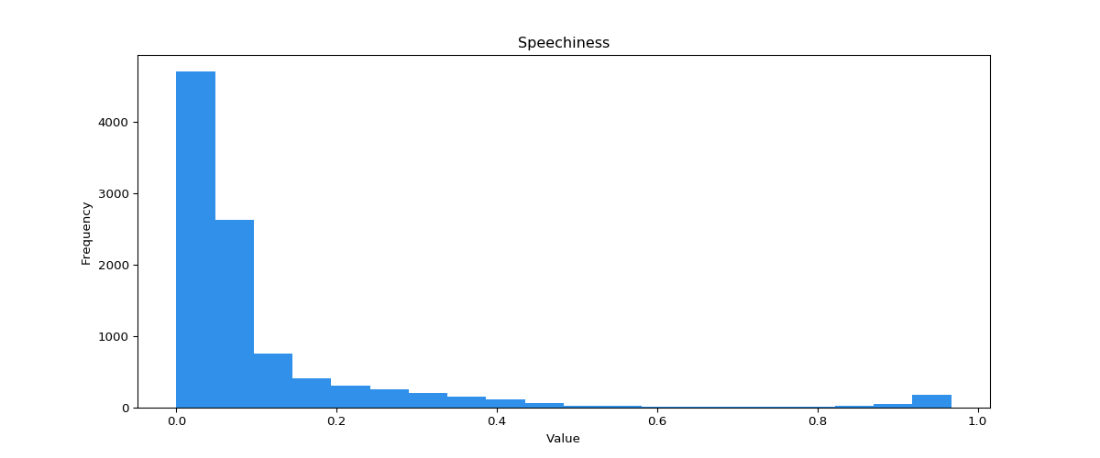
Liveness is a confidence measure of whether there is a live audience in the recording and has the distribution in the following figure:



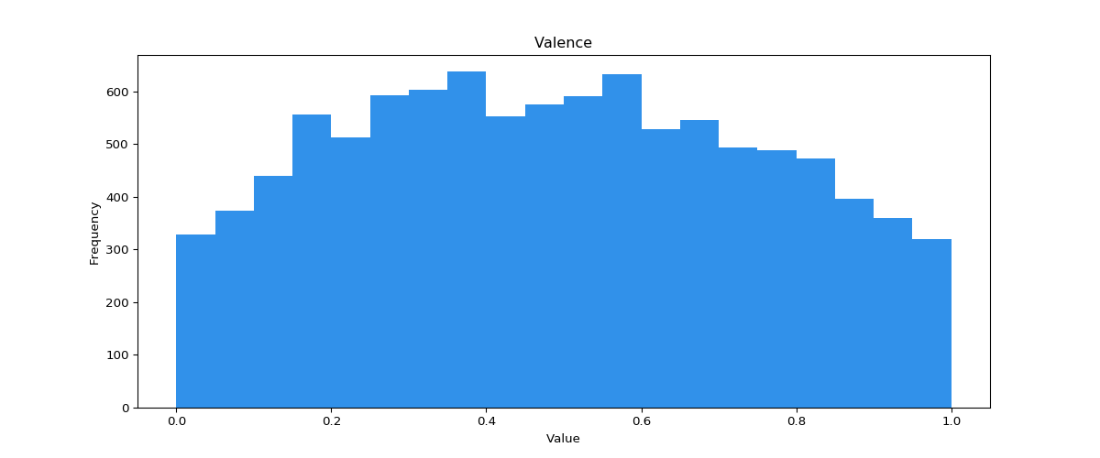
Loudness is the measure of the average decibel value of the track and has the distribution in the following figure:



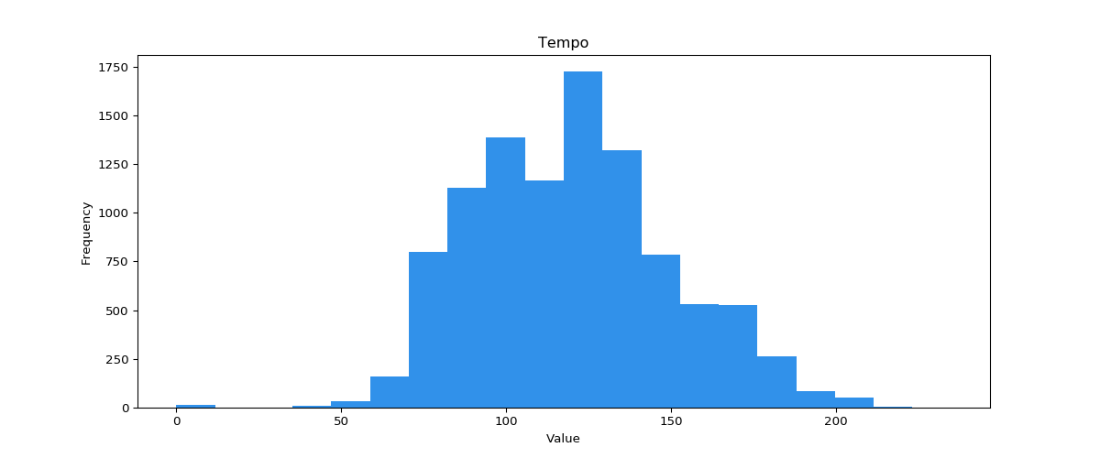
Speechiness represents the exclusivity of speech in the track, and high values are almost entirely speech while low values contain little speech but possibly sung words. It has the distribution featured in the following figure:



Valence is a measure of the “happiness” of a song and has the distribution in the following figure:



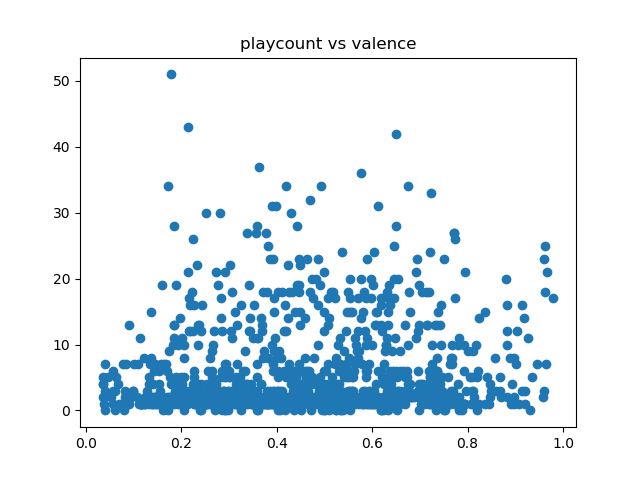
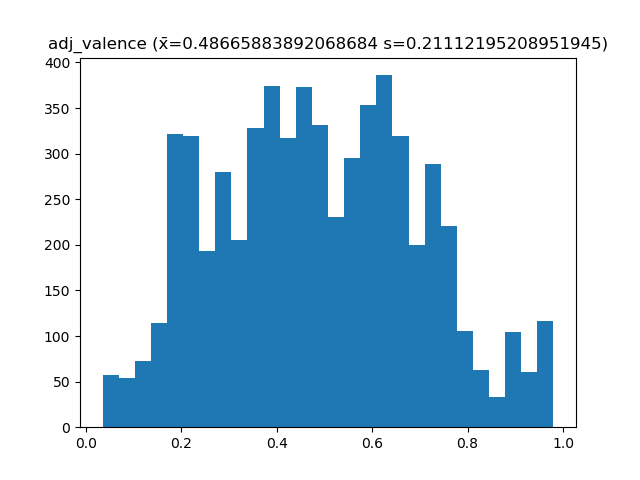
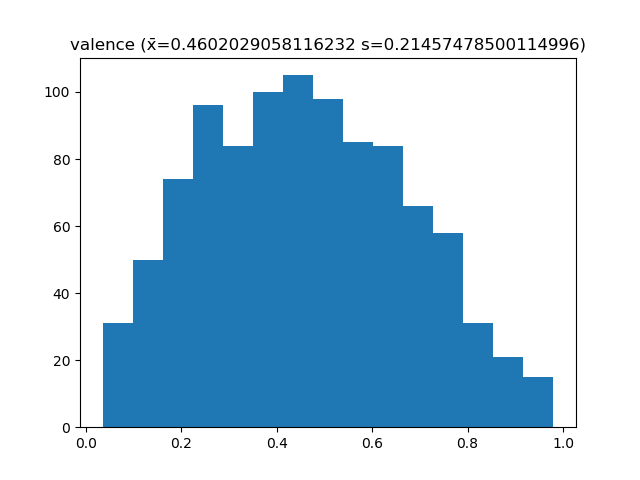
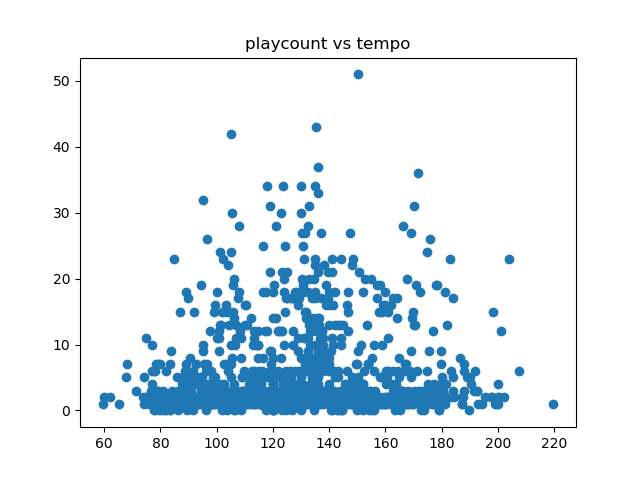
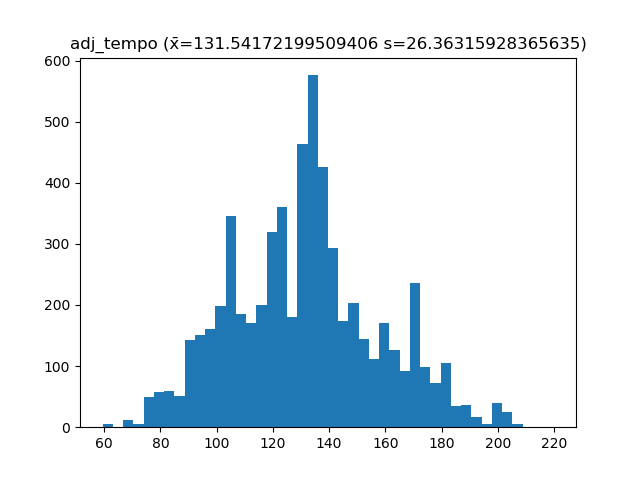
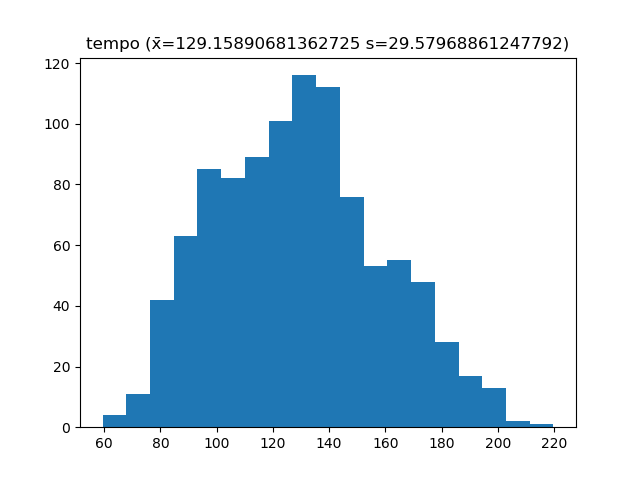
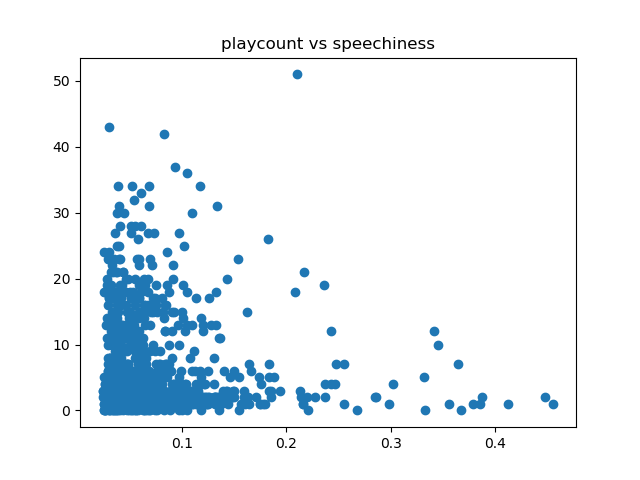
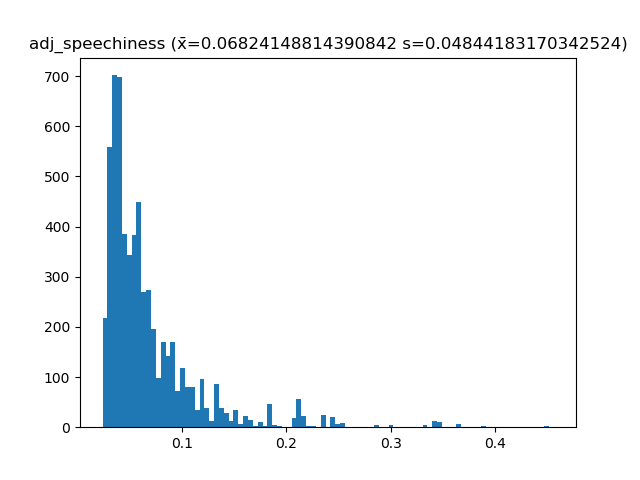
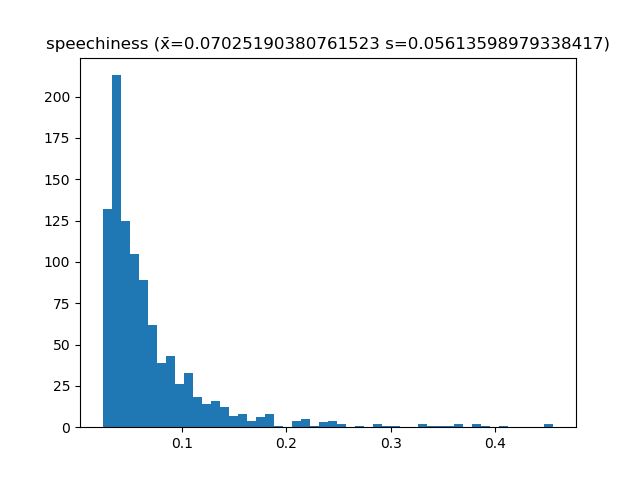
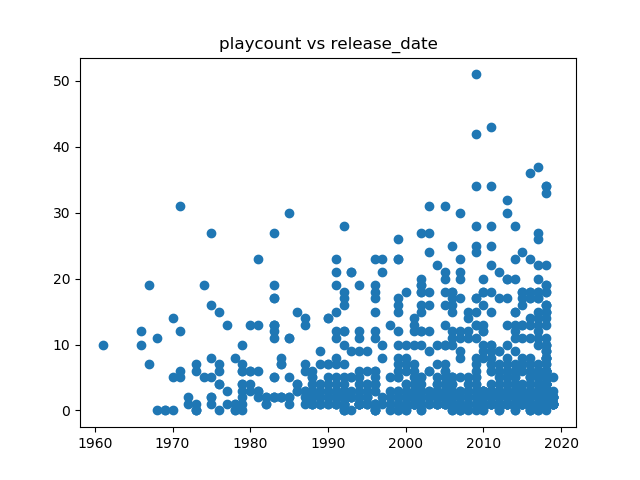
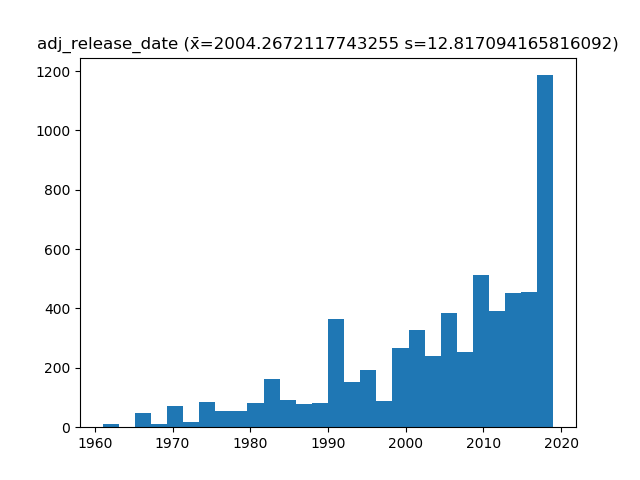
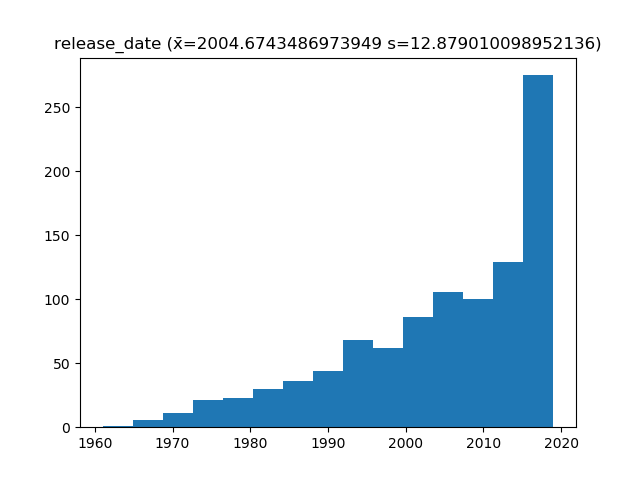
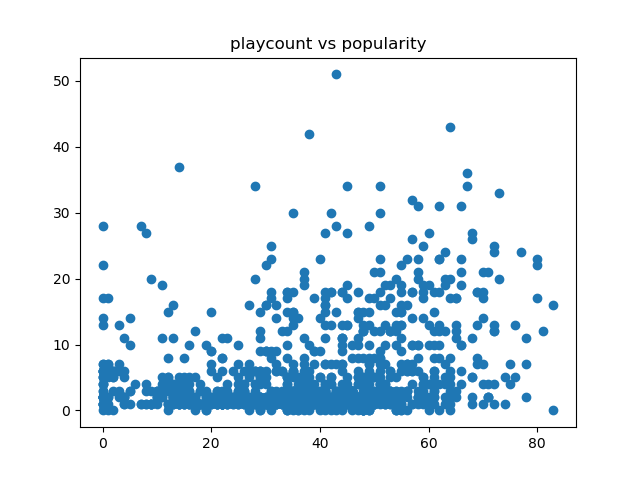
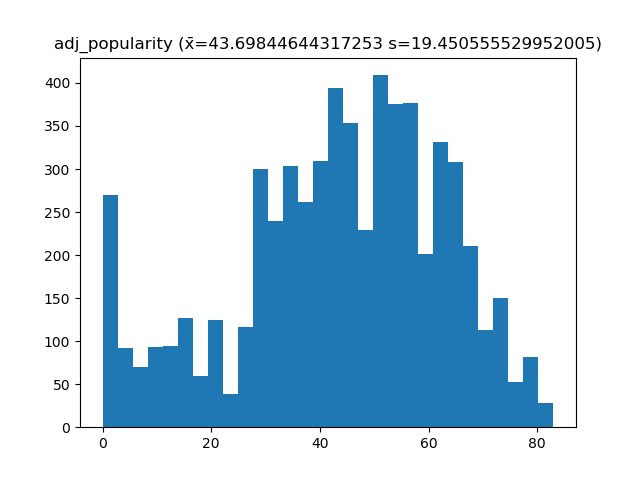
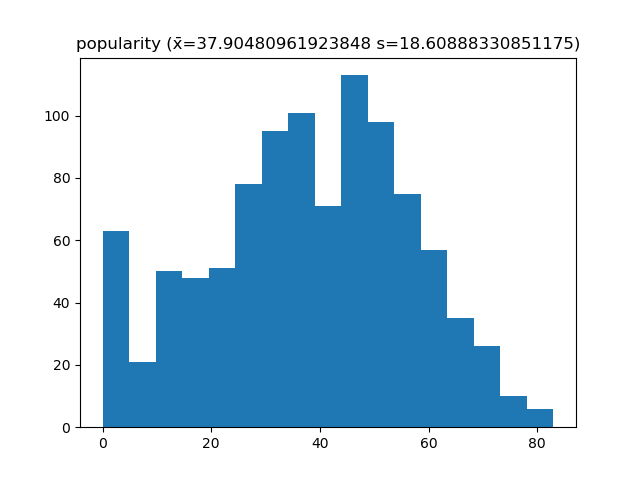
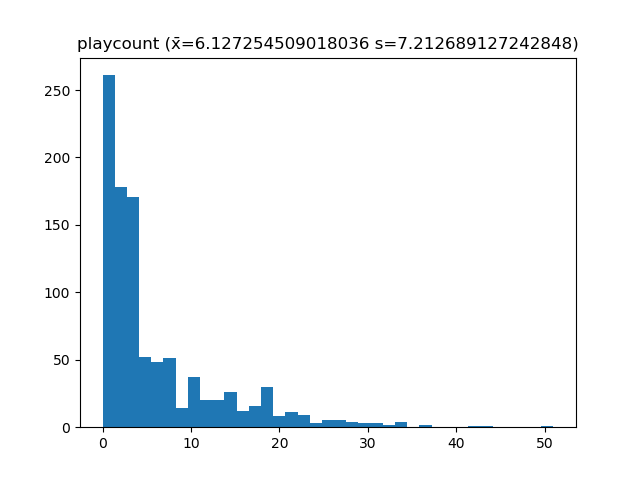
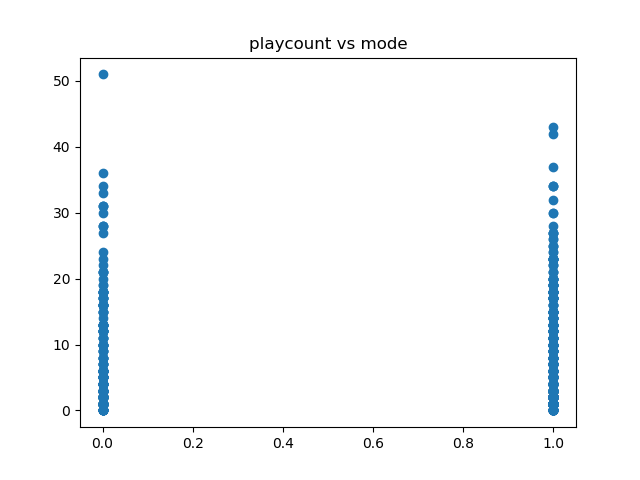
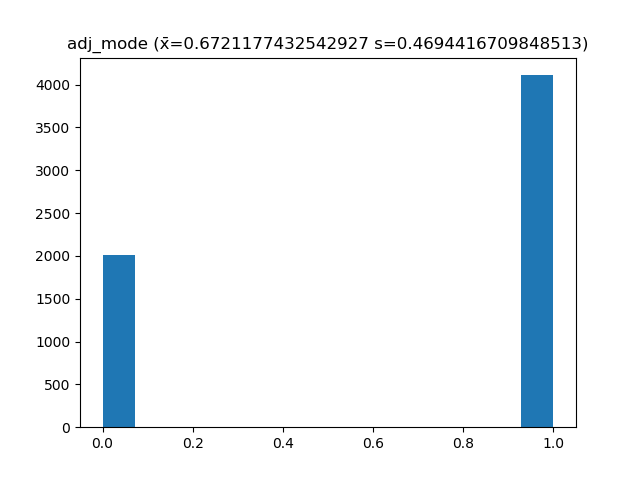
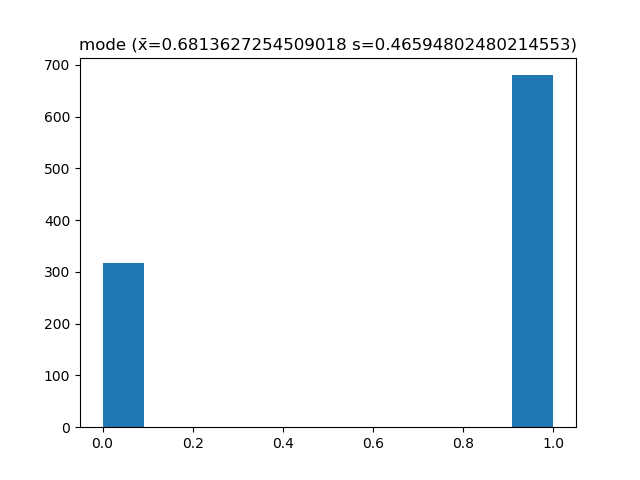
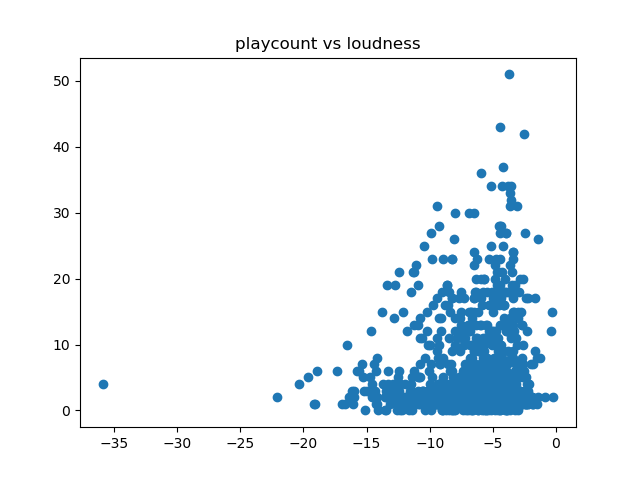
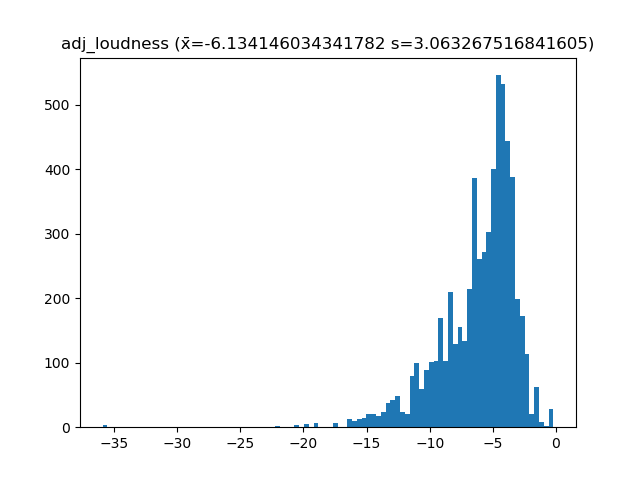
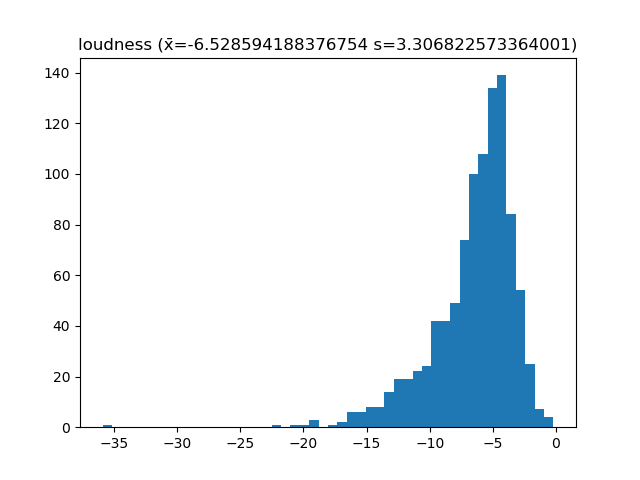
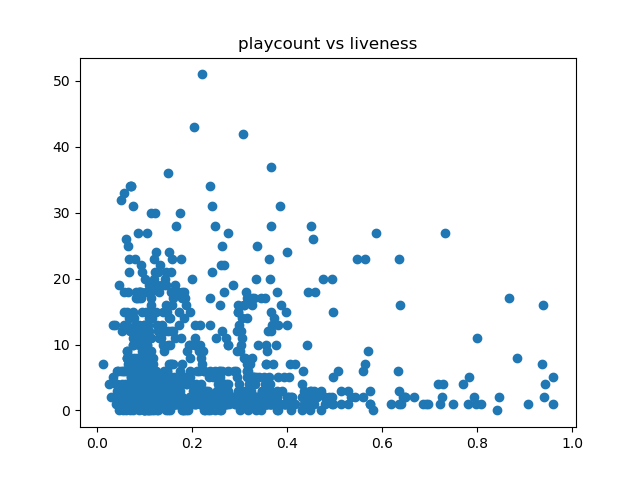
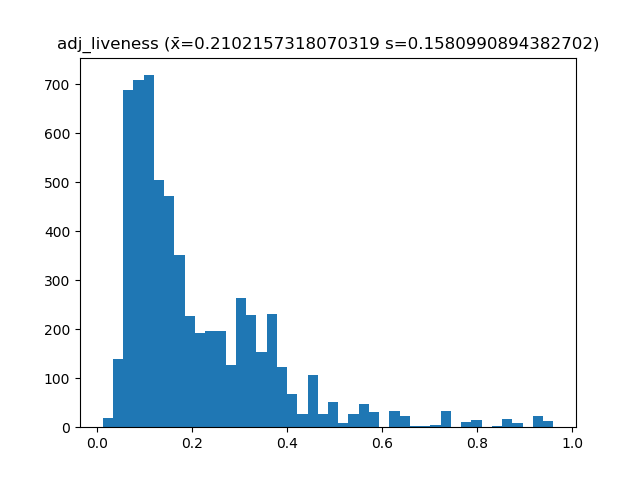
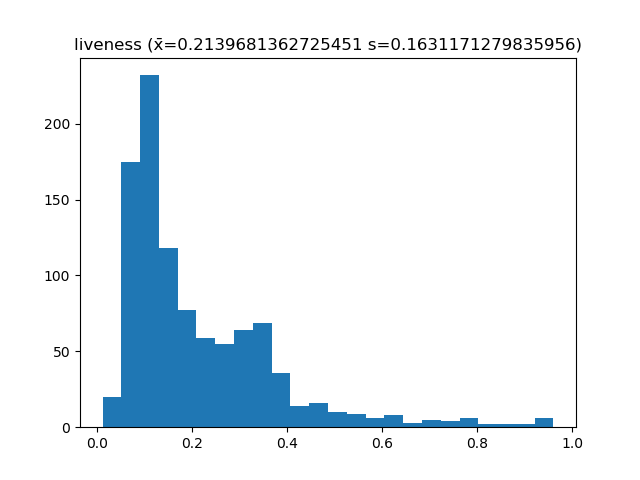
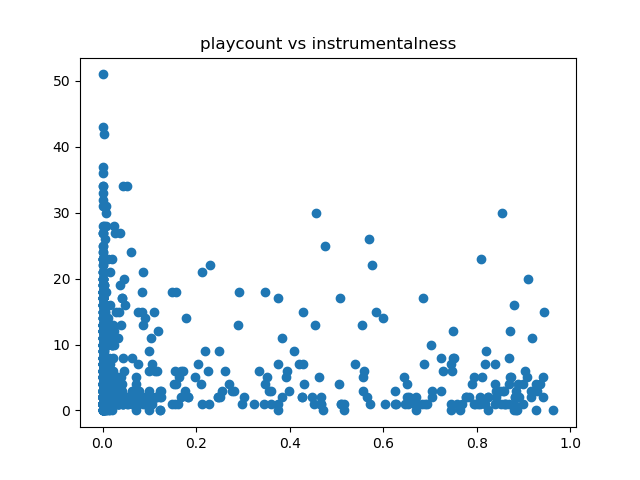
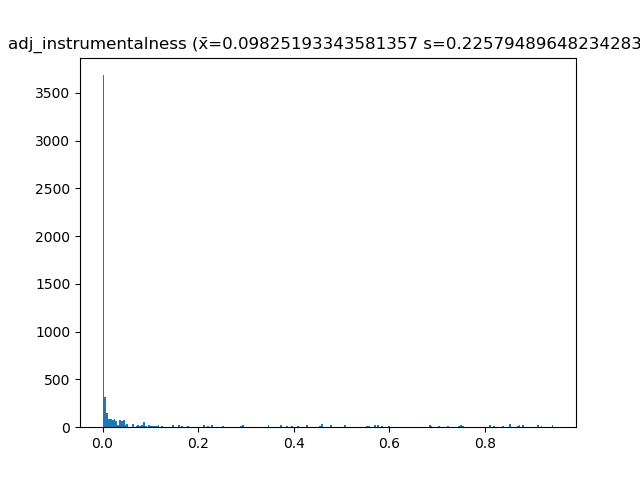
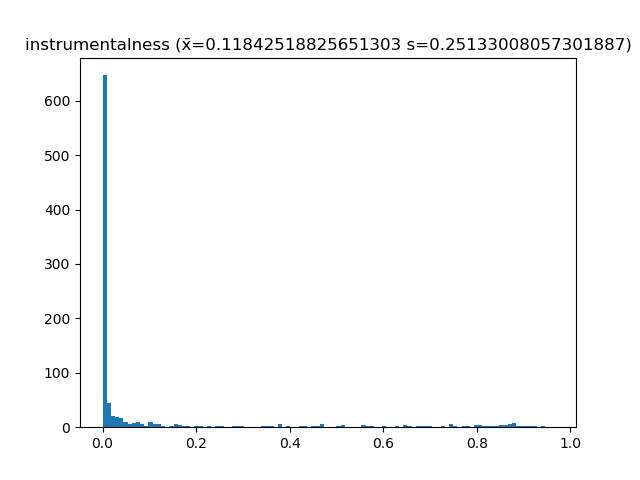
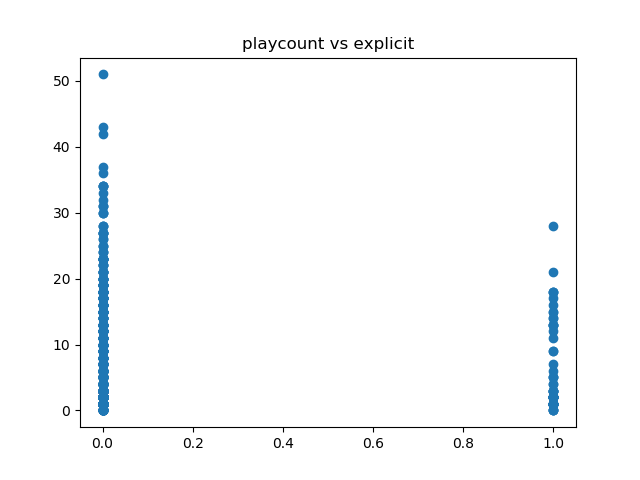
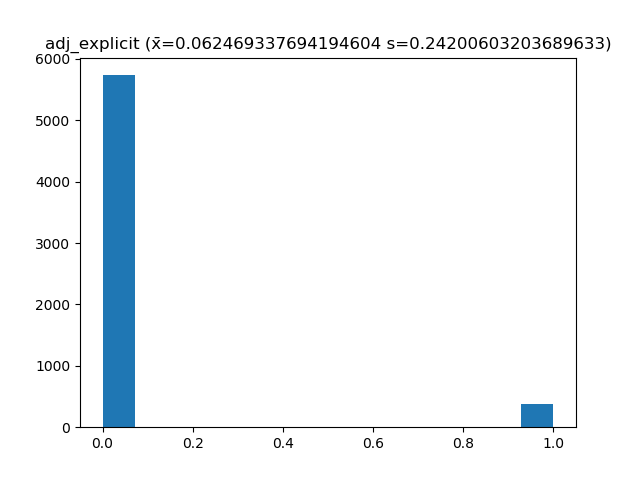
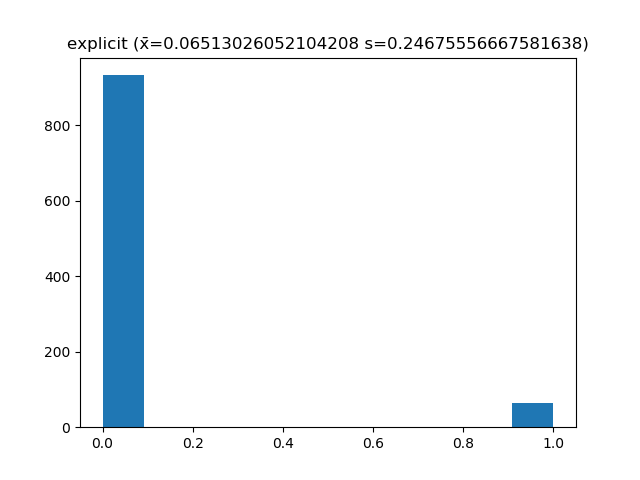
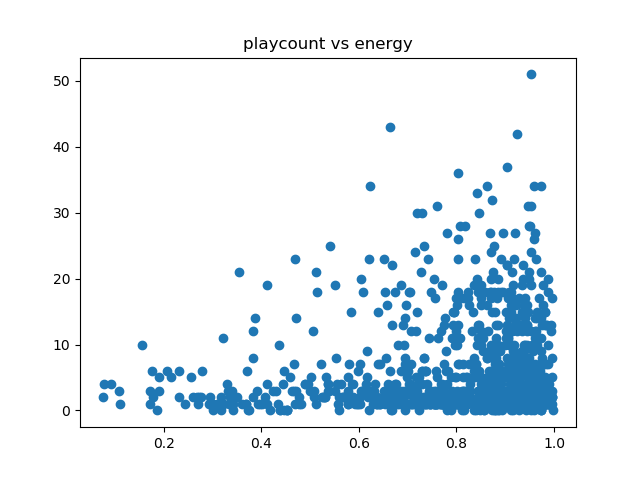
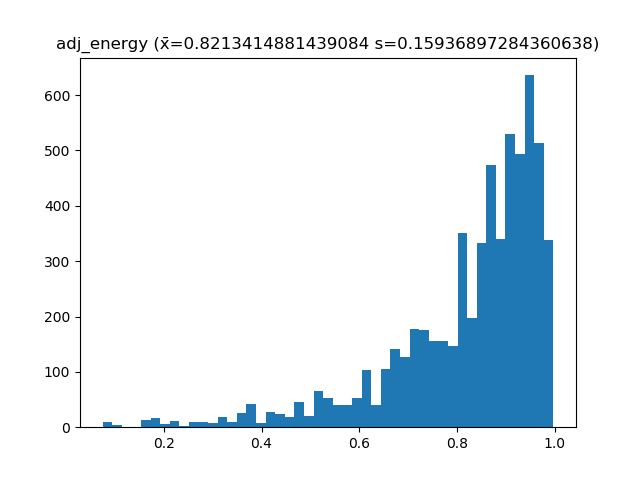
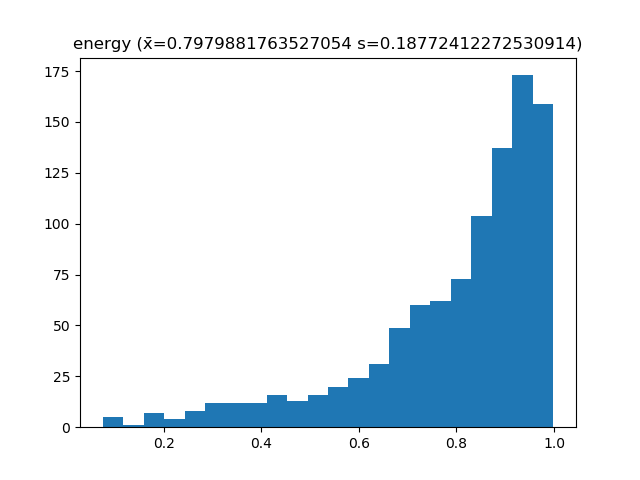
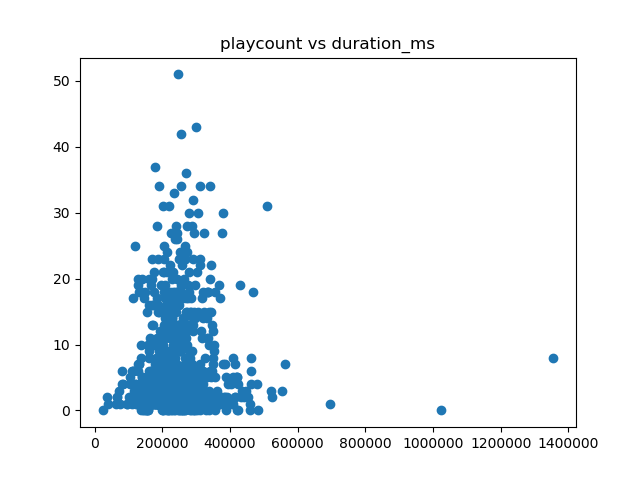
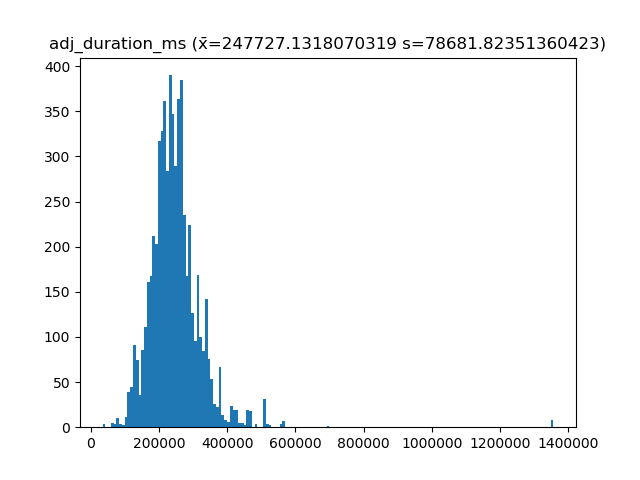
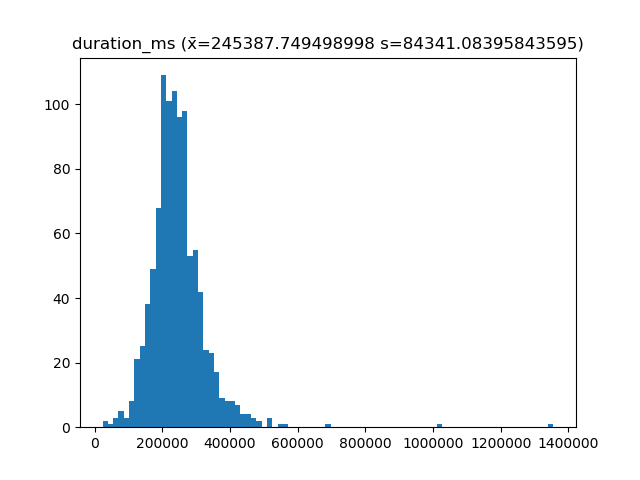
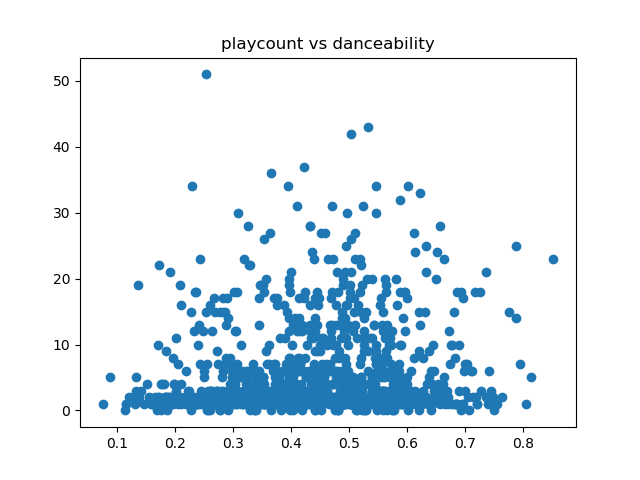
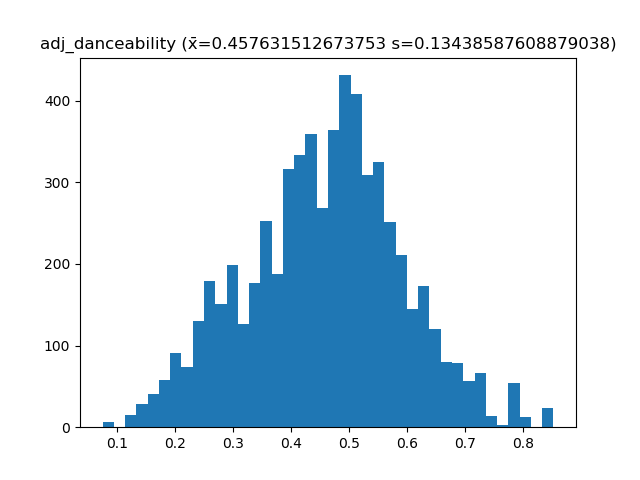
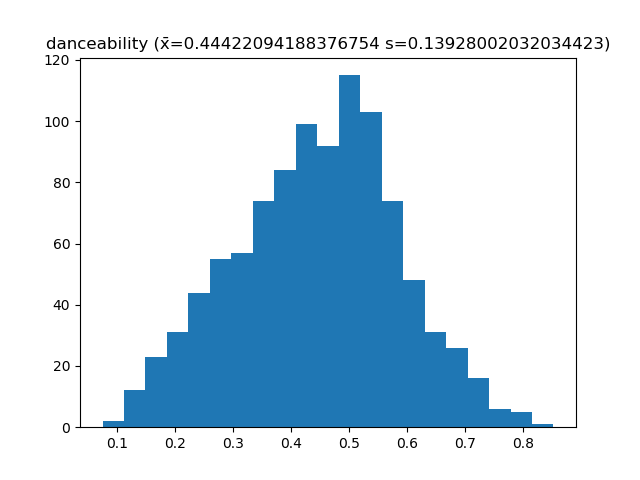
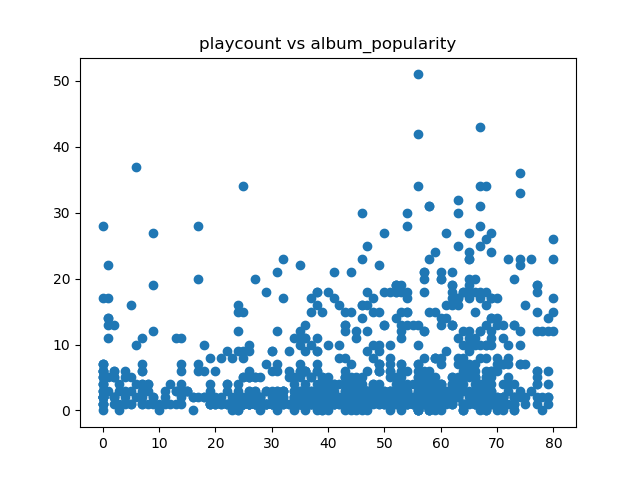
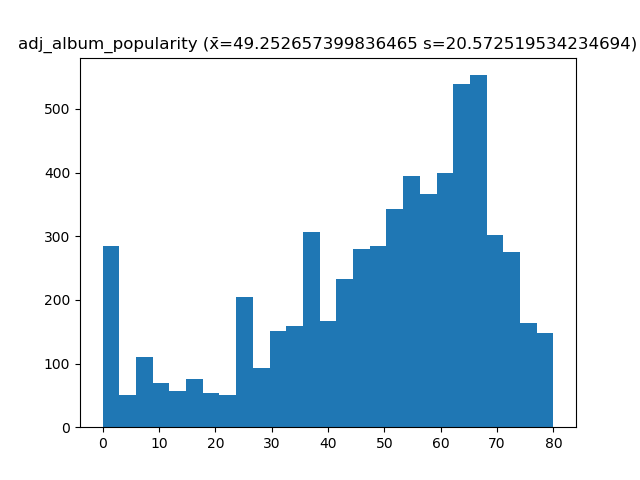
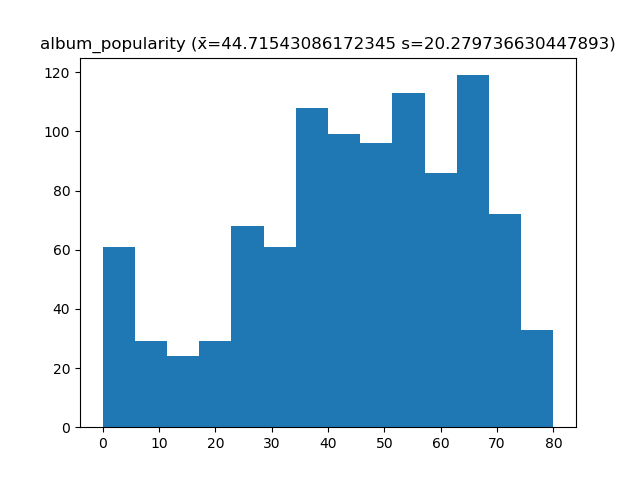
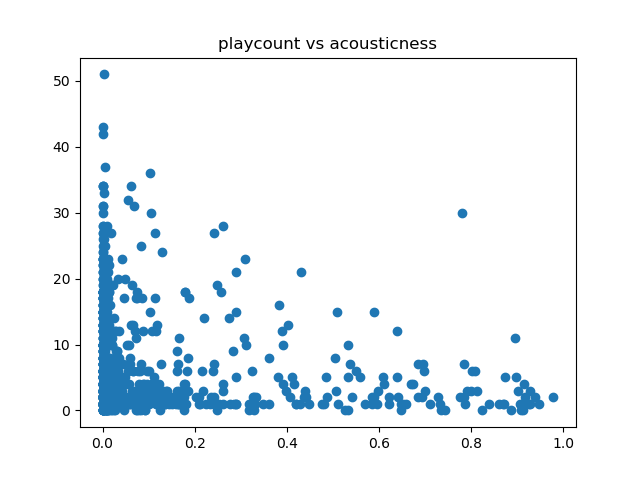
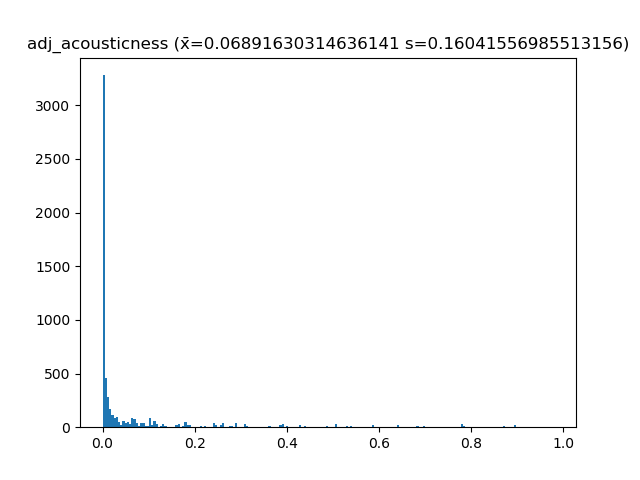
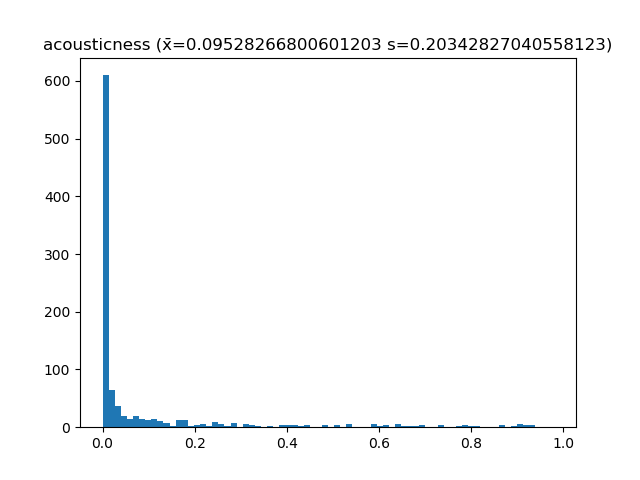
Tempo is the estimated average beats per minute of the track and has the distribution in the following figure:



Release\_date is the value for the year the album the song was featured on was released. Finally, album\_popularity is similar to popularity, but instead of being the popularity of the individual song, it is the popularity of the album as a whole.

The data for this study was collected with a Python script which can be found in the file “Data Scraper.py” on this project’s GitHub page. The script parsed the entire Spotify library of Frank Pasqualini and got the audio features for a random sample of 1000 songs. This was done with the help of the Spotipy python package, which simplifies the Spotify API calls to be easily used in python scripts, but due to some limitations of the package a lot of work had to be done collecting the results in a useable form. The Spotipy package can only gather tracks fifty at a time, so we had to write the script to gather fifty songs, then jump down the list of the songs and gather fifty more in a loop until less than fifty songs were returned, which would be the end of the list. We then had to interpret the results from this data collection into a usable data structure with the variables we needed. The script used Frank’s Last.fm account to get the play count by submitting a GET HTTP request with the title and artist for each track gathered in the sample, and one of the functions in Spotipy to gather the rest of the audio features. Finally, the script took all of the variables we had collected and placed them into an easy to use data structure and exported the entirety of the structure to a file to be analyzed by a different script. We picked 1000 as our sample size because it is a large enough sample size that we thought the results would be significant, but not so big that the analysis would take too long to run. Unfortunately, this sample was slightly biased towards songs with higher play counts and popularity, because the user was more likely to have added songs to their Spotify library if they had heard the song multiple times before, which is familiarity bias. This sample also did not return a full 1000 songs, because the data was gathered from two different sources and it was not possible to correctly link every song. Fortunately, only two songs from the 1000 song sample were left out, so the sample still has a strong 998 members.

The first thing we did with the data we collected was generate histograms for every variable using matplotlib, in addition to every variable adjusted for playcount. To adjust for playcount, we took every value in the list and added it to the adjusted list multiple times, one for each play. The histograms of the non-adjusted variables represent the songs in Frank’s library, and the histograms of the adjusted variables represent the instances of songs that Frank has listened to. We also generated scatter plots of playcount vs all of the other variables. All of these graphs are pictured below:

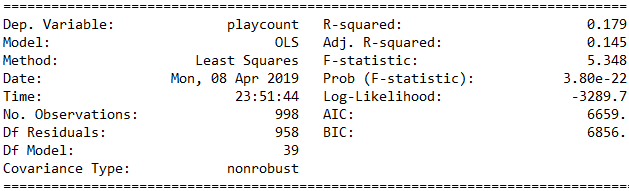
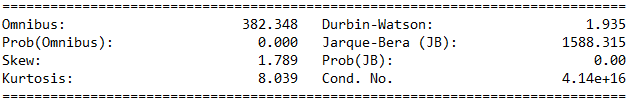


One thing we noticed immediately is that some adjusted distributions, such as tempo and release\_date, have a similar shape to the non-adjusted distributions but with more pronounced extremes. The non-adjusted distributions also seemed to be more extreme versions of the distributions provided by Spotify. Spotify’s distributions did not come with any information regarding means or stand deviations, and we decided that measuring the pixel height of the bars provided to estimate the values was too prone to error and time consuming. We did however run a difference of mean tests for every distribution against its adjusted counterpart, and got the following results:

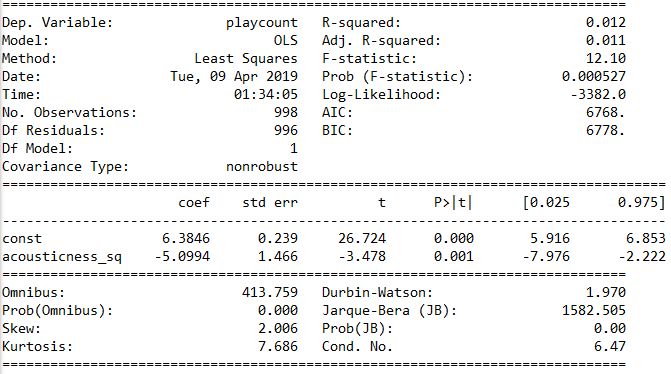


With 997 degrees of freedom at α=.05, the T-score for significance is approximately +/- 1.962. The variables that we could reject the null hypothesis of not having a different mean once playcount was accounted for were popularity, acousticness, danceability, energy, instrumentalness, loudness, valence, tempo, and album\_popularity, with popularity having the most significant difference. The other variables we failed to reject. For the variables we did reject, we had significant evidence to believe that the means of the values for total songs listened to was different than the means of songs saved to the library. This seemed to suggest that, for example, songs in the library with a higher popularity value were listened to more often than songs in the library with a lower popularity.

Another observation was that most of the scatter plots looked like they would not support regression, as most of the points were evenly spread around the low values of the y axis. To see if regression was worth looking into at all, we created a third-degree polynomial model with all two-variable interaction terms. The summarized results are below:

The full results including all 823 variables and their coefficients, standard errors, t scores, and more are available in the GitHub Repository under the Documentation folder in the file “Full Regression Results.txt” and all of the graphs displayed earlier are also available in the Documentation folder in the subfolder Graphs. The overall results were not promising, because even the likely very overfit model could only account for 17.9% of the variance. The most promising variables were acousticness\_sq with a t-score of 2.595, tempo with a t-score of 1.308, album\_popularity\_cu with a t-score of 1.183, and a few interaction terms with a t-score of over 1. Not a single term passed a T-test at α=.05 for the test of overall regression, and only acousticness\_sq passed a T-test at α=.10, but just barely. The regression run with just acousticness\_sq is shown below:



These results are significant, but account for very little of the overall variance. It is likely that some of the variables could benefit from a non-polynomial model, but since time and resources for this study were limited, we decided not to explore further transformations for the small chance of slight improvement.

We were able to conclude that some variables have higher proportional playcounts compared to their values in the library, but not all of them. We were not able to prove that any variables have any proportional playcount difference compared to the global average due to not having the correct data supplied by Spotify. We were also not able to build a valid regression model to estimate playcount with the variables we could obtain. We can think of a few possible sources of error. The variable playcount not a perfect estimate of user enjoyment of a song because it is possible for a user to have discovered a track recently that is one of their favorites, but due to not having known about it for a long period of time the play count would be low. The reverse is also true, where a user could have a song that they think is okay but not one of their favorites, but since it has been in their library for years, they have listened to it more times. It is also very likely that there are more attributes about songs that could be found from other sources to fill in the missing variance. There is a chance that, given more time, we could find transformations that fit the data better than the general cubic model we used. It is also entirely possible that music cannot be quantified in the same way as other, more concrete concepts such as salary or GPA. Overall, no useful conclusions were drawn from this study that would allow us to accomplish our goal of creating a model to find songs that it is likely a user would enjoy. If this study were to be continued or revised in the future, we would recommend spending more time trying to find the correct transformations and attempting to find more potential sources of variance.

Through gathering data from Spotify of 998 songs and their attributes, we attempted and failed to build a regression model that was significant. We did manage to find some significant differences between mean values of tracks in the library and tracks in the play history, but this was of no use to the model. Our original goal of creating a generalized tool to analyze a user’s library and find suggested songs will not be met unless further research is done into this study.

Works Cited

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Pasqualini, Frank J. “Spotify-Regression-Analysis-Data-Scraper.” GitHub, github.com/Frank-Pasqualini/Spotify-Regression-Analysis-Data-Scraper/.