Capstone Project 1: Milestone Report

Springboard 2020

Joseph Tran

Problem Statement

Recommender systems are ubiquitous in modern society. Users interact with them on a daily basis, and they influence our lives and behavior by introducing us to content or items we may have previously been unaware of. In that sense, they serve to enrich our experience. In a business context, recommender systems are sophisticated marketing tools used to generate revenue for the business. By generating unique and novel recommendations to users, businesses can expose customers to a larger portfolio of items they offer, increasing time spent in an app and in turn, revenue.

Recommender systems are especially useful with content streaming applications. Users are constantly searching for new content to consume in an ocean of choices. Whether it be tv shows, movies, or music, recommender systems provide a way to narrow down the selection of choices that are most relevant to them. There are several types of recommendation systems, and combinations of those systems. However, this project will focus on model-based collaborative filtering with matrix factorization in the context of recommending new music to users.

Collaborative Filtering

The basic idea behind collaborative filtering is that the history of interactions between users and items can be used to make recommendations. In a simplified example, we can look at two users and five songs. If user 1 has positively interacted with all five songs, and user 2 has positively interacted with all but 1 song, we can then use the similar listening habits of each user to recommend the unheard song to user 2. In model based collaborative filtering this is done by creating a user/item matrix and performing some form of dimensionality reduction. The key idea is that users who agreed in the past will generally agree in the future.

Matrix Factorization

In many cases there are thousands of unique users and items in a set of data, and individual users will most likely only interact with a few items. This leads to a user/item matrix that is incredibly sparse. The goal of matrix factorization is to reduce the sparsity by decomposing the sparse matrix into components, and then reconstructing the matrix by calculating the dot product between user and item features. This results in user vectors which have values corresponding to all the songs. These user vectors can then be sorted and ranked to serve recommendations to songs that have previously not been listened to.

Data: #nowplaying-RS dataset

The dataset chosen was the #nowplaying-RS dataset and was published in Jan. 2020. It was constructed by scraping song and hashtag information from Twitter with the intention of creating a dataset capable of context and content aware recommendation systems, and was created by Eva Zangerle from the University of Innsbruck Austria. The #nowplaying-RS dataset is composed of three separate files: a listening event dataset that includes user id's, track id's, hashtag, and timestamp that contains roughly 17 million listening events. A sentiment file that contains sentiment scores for the hashtags. Lastly, the dataset also includes a file containing various information about context and content. Mainly, it includes the Spotify music attributes obtained from the Spotify API.

The main object required for a non-negative matrix factorization algorithm is the user-item matrix. This can be obtained solely from the listening event file. However, the three files will be merged so all information is contained in one dataframe. Merging the files will also help to reduce observations and thus, reduce the sparsity of the user-item matrix.

Data Wrangling

The data wrangling report encompasses information about the dataset used for the project of building a music recommendation system, and the steps taken to prepare the data for a machine learning model.

The main object required for a non-negative matrix factorization algorithm is the user-item matrix. This can be obtained solely from the listening event file. However, the three files will be merged so all information is contained in one dataframe. Merging the files will also help to reduce observations and thus, reduce the sparsity of the user-item matrix.

The main file is the listening event file that contains user id's, track id's, hashtags, and timestamps. I chose to work with this file first as it contains the information needed to create the user/item matrix necessary for a matrix factorization model. The data was inspected by calling some of the dataframe attributes and was found to have 138,223 unique users and 344,536 unique songs, with a shape of (17560113,4). Inspection of the head reveals identical rows. This was identified by looking at the 'created_at' column and seeing matching timestamps. These duplicate rows were generated from a 'one to many' relationship with a listening event and hashtags. The duplicate rows will be preserved until the datasets are merged. It is advantageous to save all the corresponding hashtags associated with a listening event. Dropping the duplicate rows at this time would discard relevant hashtags. Next, null values were removed as there was only a single null value in the hashtag column.

The next file that was worked on was the sentiment values dataset. The file contains sentiment scores from four popular sentiment dictionaries; AFFIN, Opinion Lexicon, SentiStrength, and Sentiment Hashtag Lexicon. Scores were only assigned to unique hashtags that were scored by at least one of the sentiment dictionaries. In addition to the score, minimum, maximum, sum, and average scores for the four dictionaries are included. Of the four dictionaries used, scores were only assigned to 5290 of the 32208 unique hashtags in the main file. Upon inspecting the head of this dataset, it was found that columns were mis-aligned and nested in a hierarchical index under the column name 'hashtag.' After inspection it was found that the first four columns did not have column names and somehow got thrown into the multi index. To fix this, column names were created with the dictionary name abbreviation and score, indicating that the column is the score generated from the dictionary. The new column names are assigned to the column in the order the dictionaries appear in the dataset. The multi-index column name 'hashtag' is renamed to 'ss_score' indicating the score for the sentiment dictionary. Afterwards, the new column names are assigned to the different levels of the multi-index, and the index is reset to create a standard range index. This is verified by calling type on the index. The only information that is desired is the hashtag, sentiment score, and average. Some of the sentiment scores have null values so the average score column is retained to impute those missing values row-wise, rather than imputing the mean or some other transformation column-wise. A key-error was produced on the first attempt to drop the columns. Upon inspection, it was found that many of the field names contained leading white spaces. The columns are renamed to a standard form and then dropped from the dataset. When checking the null values of the resulting dataframe, it was found that the score columns for each dictionary contained 1423 null values. Instead of taking the mean of the column and imputing, the average score for each dictionary is imputed row-wise from the corresponding average score column. After the imputation, the null values are put into a bar chart and it is found that the ol_score resulted in the least amount of null values. This column is selected for our data and the remaining column dropped, afterwhich the null values are dropped from the data. The resulting data frame consists only of the 'hashtag' and 'ol_score' columns, with all null values dropped from 'ol_score,' leaving 4831 unique hashtags, and their score from the Opinion Lexicon sentiment dictionary.

The last file to be worked on was the context/content file containing Spotify attributes and other contextual information. The columns: 'coordinates','id','place','geo','entities','time_zone' are dropped as they are not necessary for our model. The ‘tweet_lang’ and ‘lang’ columns will also be dropped, but first the dataset is filtered based on English. Once the filtering has been done these two columns are also dropped.

The next data wrangling process was to merge the three datasets. First, the listening event dataset is merged with the sentiment dataset with an inner join on ‘hashtag.’ This merged dataset is called ‘temp_df.’ Finally, all three sets are combined by merging the content/context dataset with temp_df with an inner join on 'track_id','created_at','user_id.’

With all the data in a single frame we can now preserve the hashtags and drop the duplicated rows. This is achieved by creating a dictionary to store the hashtags associated with a listening event. The values are added to the dataframe by mapping the dictionary keys to the user_id and track_id in the dataframe. After the new column containing the hashtags is added to the dataframe, the duplicate rows are dropped.

This is the point in the data wrangling process that we filter the track_id’s so that each track appears no less than 10 times. A temporary data frame is built from a value_count operation that limits the track count to be at least 10. The track_id count dataframe is then joined to the main dataframe on the track_id column, returning the track_id’s with 10 or more plays. Lastly, the user_id, artist_id and track_id are assigned category codes for sequential ordering.

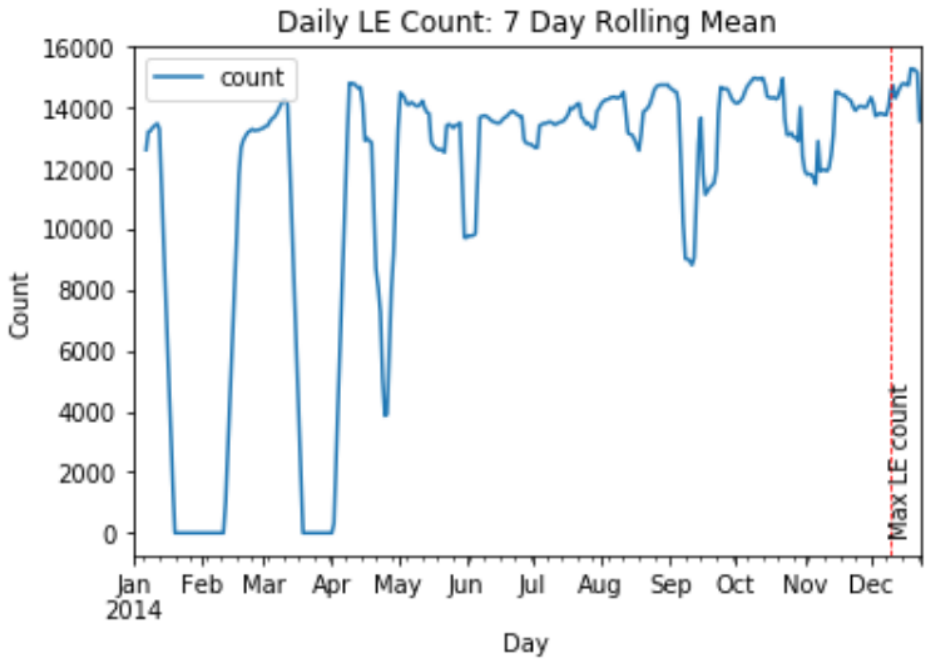
Overall, the length of the final dataset is reduced from 17.6 million listening events to 4.4 million, and contains columns from all three files in the dataset. The final dataframe is saved as a csv titled ‘NPRS_FINAL.csv.’

During the data wrangling process attempts we made to pull song metadata from Spotify API. The presence of the content features alerted me to the fact that these features were pulled from Spotify, and suggested I could use the track_id to pull the extra data. However, after spending several hours learning to connect to the Spotify API, I learned that the track_id and song_id were not Spotify labels, but hashed values intended to protect private information. Thus, I was not able to pull any metadata for the tracks. I reached out to the authors of the dataset, but they were unwilling to provide the hash keys.

Data Story

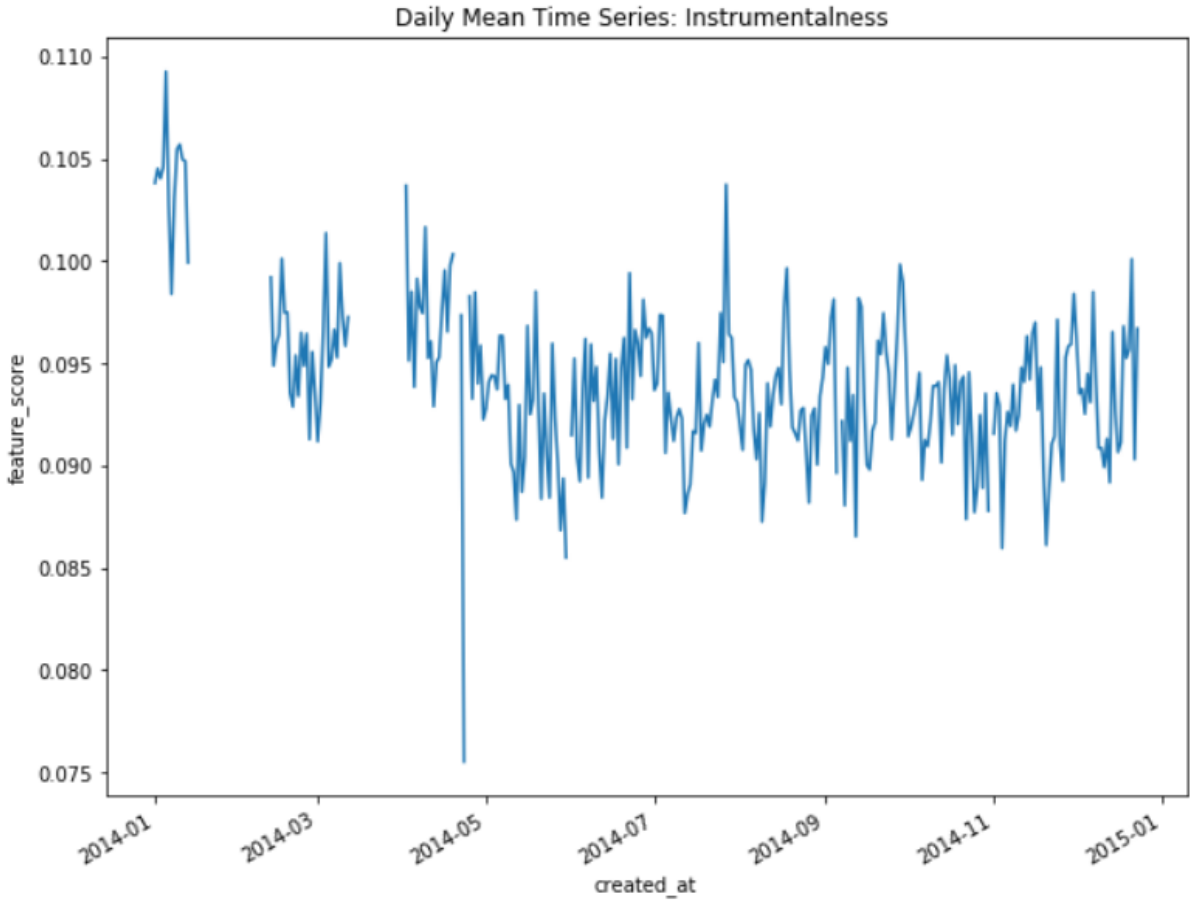
Since the only object necessary for a basic matrix factorization algorithm is the user-item matrix, it is difficult to weave a story with only that information. However, the final dataset from the data wrangling process contained numeric content features that we can plot as time series to look at the behavior over time. In addition, there is the categorical information we can plot and look at to find descriptive characteristics.

The first plot is a tabulation of total listening events per day. A vertical marking the day with the highest song count is plotted for reference. The plot has a lot of dips in song count over the year 2014 time period. It is hypothesized that the dip in song count is due to the web scraper breaking, being fixed, and collecting information again. I apply a 7 day rolling average to the data for smoothing in the next plot.



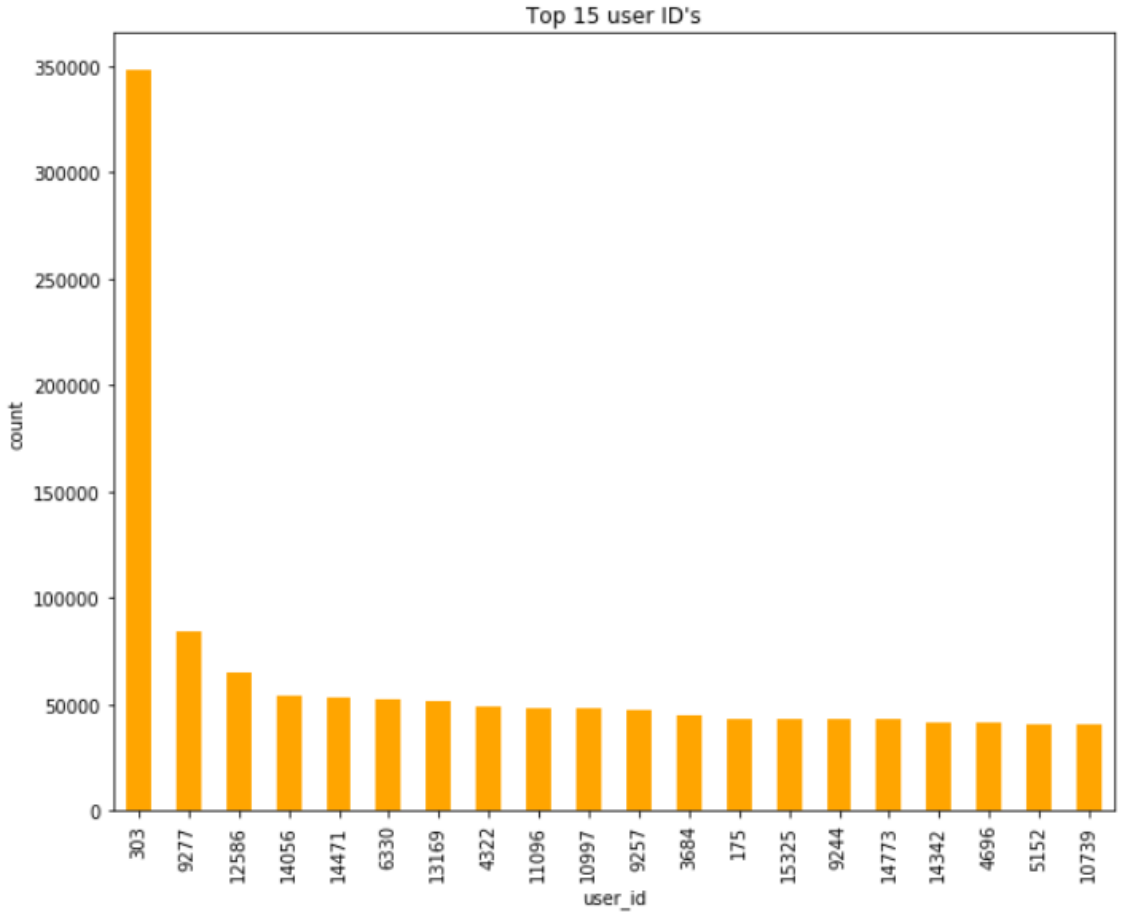
The next eight plots in the notebook are time series plots for the daily average value of the feature plotted over the time period. The indication is that the population listens to popular music. I would expect to see features such as ‘instrumentalness’ to have low values, as a value closer to 1 indicates a track with no vocals. This would mean genres like classical or jazz, that are not popular. I expect that the mean daily value for this feature is low. The rest of the plots

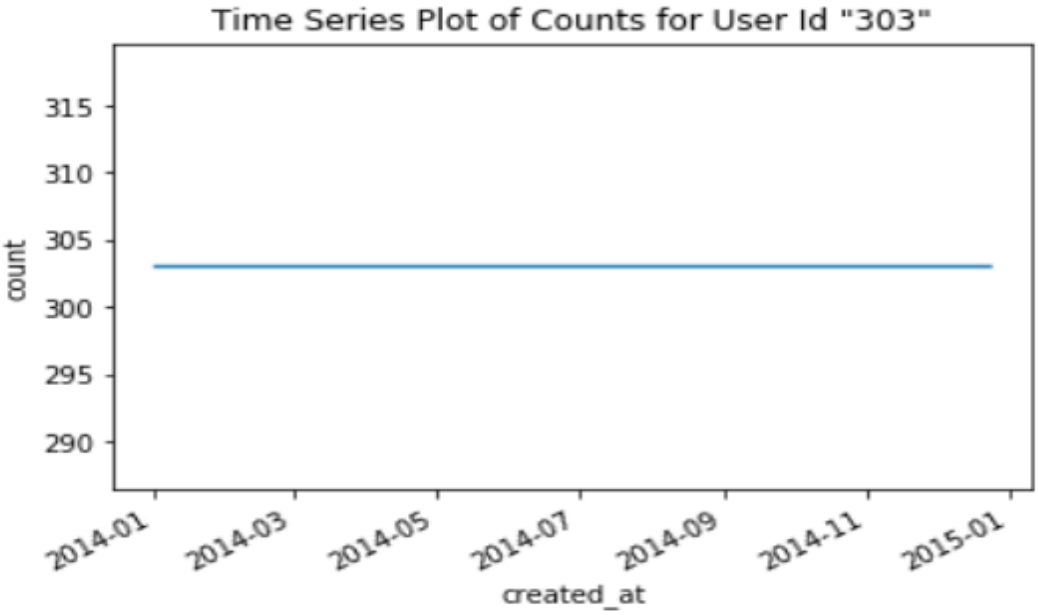
for the Spotify features follow this logic and suggest what one may think about the listening habits of the masses: on the whole, there is no tendency to radical listening habits. The series plot for the daily mean ‘instrumentalness’ score is shown below.



In addition to the content features, bar plots are made for the user_id, track_id, artist_id, and hashtag combinations. For the matrix factorization model, the user_id and track_id represent the most relevant information as these are the values in the user item matrix.
I expected these charts to be boring and not reveal anything interesting, but I was mistaken. Plotting the counts for each user it was revealed that one user, user ‘303’ was not an actual user, but some time of bot. Looking more closely at the user revealed that the time series plot of LE’s generated by the ‘user’ was flat throughout the time period with around 303 LE’s recorded per day. In addition, there are no breaks in the data from when the scraper was not working. This is in contradiction to all the other time series plots. The user being assigned a code of '303' and the count per day of the user being 303 is a weird coincidence as the user code was generated from the hashed user ID. Being that a bot was discovered, this ‘user’ will

be removed prior to constructing the user-item matrix. The bar chart for most active users and time series plot for user ‘303’ are shown below.

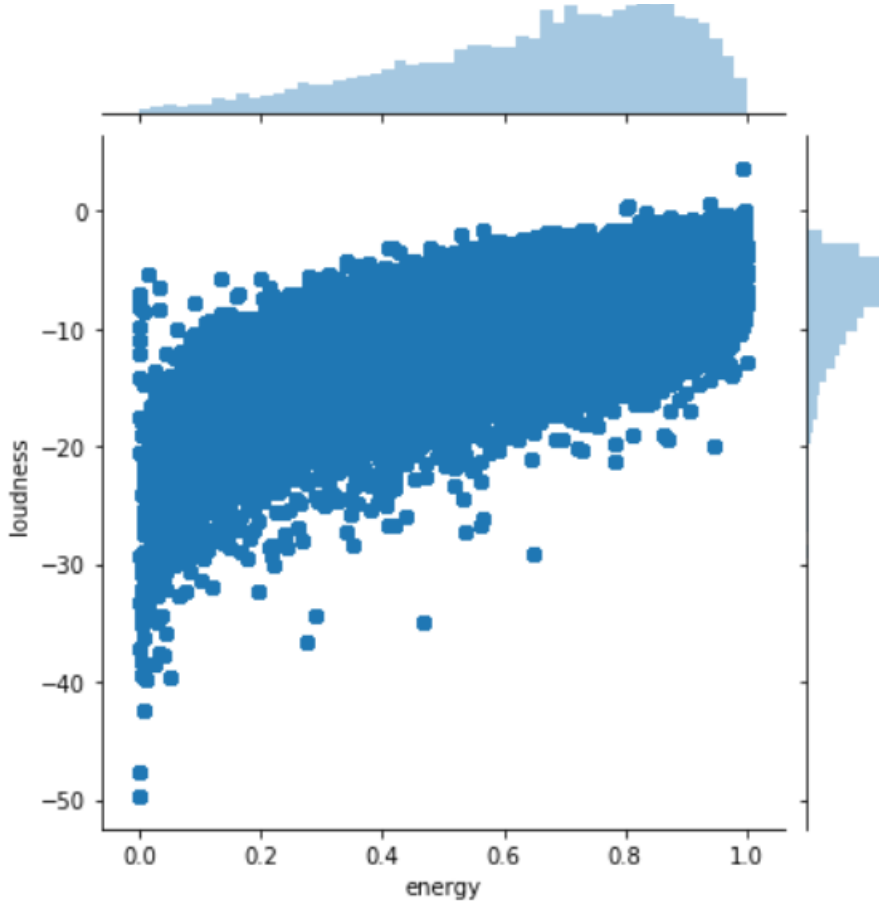




The artist ID bar plot revealed that the artist with the most occurrences was artist ‘7582.’ This artist appeared more than 55,000 times, with a unique song count of 79 different songs. It would be interesting to see who this is, but it is not possible with the data presented.

The bar plot of the hashtag combinations show that the single hashtag ‘nowplaying’ occurs, by itself, way more than any other hashtag. The single hashtag of now playing is removed to view the next highest count of hashtag combinations. Many of these combinations also include ‘nowplaying’ with another hashtag. The hashtag combinations show that the majority of the time users are listening to some type of rock related music, whether it be punk, classic, doommetal, or rockmusic.

Lastly, some correlation plots are made for selected content features that would intuitively seem correlated: energy/loudness, energy/danceability, energy,valence, and speechiness/instrumentalness. Of the plots generated, only one showed some type of correlation which was energy/loudness. This makes sense as loudness is proportional to energy. The correlation seems to be vaguely linear as both features increase in value. This plot is shown below.

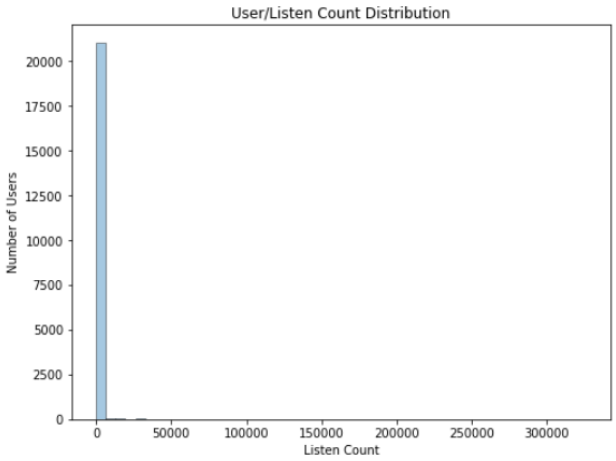


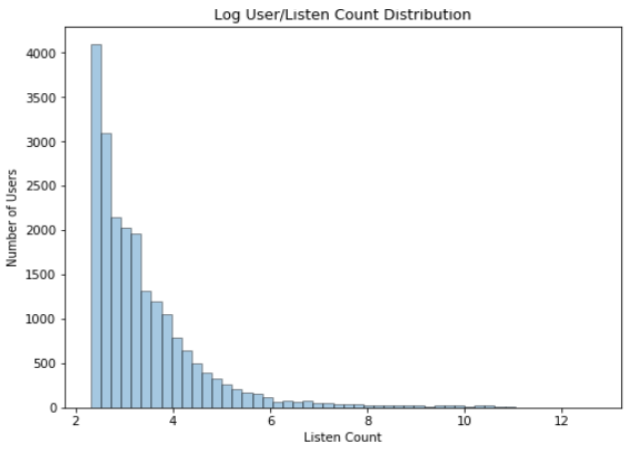
Statistical Analysis

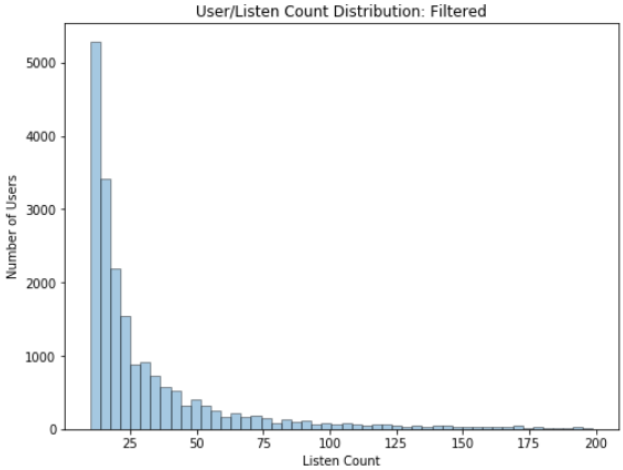
Typically, statistical analysis is performed on the predictor variables to look for relationships, correlations, or test hypotheses one might believe about certain features. This project is different in the sense that to perform model based collaborative filtering only the user/item matrix is required. Being that the only input for the model is user/item interaction data, we can plot the distributions of the count of user events and track plays.

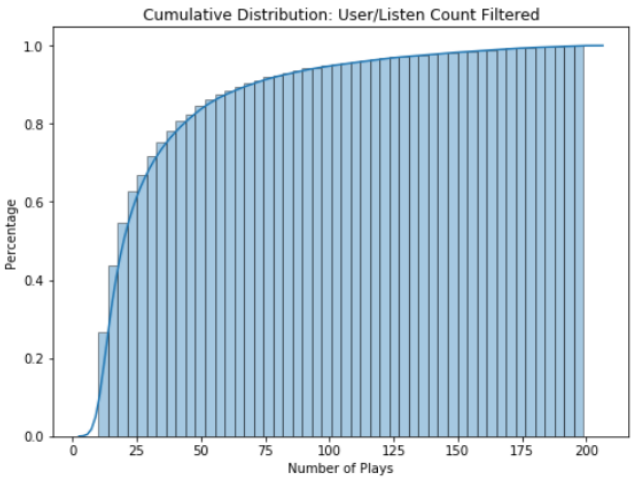
First, we create a column of ones to aggregate in a group-by operation, groupby by user id and track id separately and summing the count column. We now have two data frames representing each user id and how many plays they had, and track id's with play counts.

The initial distribution plot of users and listening events shows a highly right skewed distribution. This is due to a few users who had an unusually high amount of listening events. To reduce the skewness without eliminating these users with high listen counts we can perform a logarithmic transformation. After the transformation we get a clearer view of the data which appears to be exponentially distributed. We can also filter and keep only the users with at most 200 plays. This removes the users with the unusually high song plays, and accounts for 94% of the users in the dataset. What we see after plotting is a distribution that looks similar to the distribution generated from log-transform of the counts. Finally we can plot a cumulative distribution for the filtered data and see that users with between 10 and 15 plays account for roughly 25 percent of the filtered data. Plots are shown below.









We also plot the distribution of play per track. We can see in the first plot that again the data is right skewed. Performing the log transform yields a distribution similar to the user play counts showing a distribution that looks exponential. Again, we can filter the outliers by removing the track id's with play counts over 250. By filtering songs with 250 or less plays, we retain 94% of the data. Doing this yields a distribution similar to that of the log-transformed data. As we can see, there were about 16000 songs with between 15 and 20 plays. Lastly, the cumulative distribution shows that about 80% of the songs in the filtered dataset have 50 or less plays.