Music Recommendation System | **Capstone Project II: Milestone Report I**

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Problem:

Recommendation systems are vitals features for companies such as Amazon, Netflix and Google. The underlying goal of the recommendation system is to personalize content and to present the most relevant items to the company's audience. This creates a better user experience while also driving incremental revenue.In this project I will build a recommendation system for users to discover new music.

For my recommendation system I will use a combination of collaborative filtering and classification.The approach will begin with matrix factorization of the user listen count data.Then the latent factors found will join the spotify audio data as additional features. Finally, classification will be performed to provide the final song recommendation.

Client:

My client is any music streaming company such as Spotify. The client will be able to use this data-driven product feature to enable users to more easily discover songs that they are likely to enjoy. The same approach could also work for other types of recommendation systems such as movies, as long as there is metadata such as the Spotify audio features. This feature will ultimately benefit the company because it will enhance user experience and keep users engaged.

Data:

The first part of my dataset comes from the [Million Song Dataset] which contains two files: triplet_file and metadata_file. The triplet_file of 2,000,000 rows contains user_id, song_id and listen count. The metadata_file of 1,000,000 rows of songs contains song_id, title, release_by (release date) and artist_name. I then merged the two datasets by song_id, bringing the count of unique songs from 1,000,000 to 10,000 songs.

The next part of the dataset was called from the [Spotify Web API]. To do this I used an open source tool ([playlist-converter.net]) which can convert a list of songs into a Spotify playlist. I exported a CSV of the 10,000 song names from our previous dataset and created Spotify playlists of around 7,000 of the same songs. The other 3,000 songs were not found in the Spotify search. Using the Spotify API, I extracted the artist name, song title, and spotify ID of the tracks of these playlists. I then merged this data set with our previous dataset by song title and artist.

The last part of the dataset are audio features also called from the Spotify API. The audio features were extracted using the unique spotify ID's of our dataset and then were added in as additional columns. Below is a description of these audio features.

KEY	VALUE DESCRIPTION
duration_ms	The duration of the track in milliseconds.
key	The estimated overall key of the track.
mode	Mode indicates the modality of a track. Major is represented by 1 and minor is 0.
time_signature	The time signature is a notational convention to specify how many beats are in each bar.
acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic.
danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity.
energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity.
instrumentalness	Predicts whether a track contains no vocals.
liveness	Detects the presence of an audience in the recording.
loudness	The overall loudness of a track in decibels (dB).
speechiness	Speechiness detects the presence of spoken words in a track.
valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track.
tempo	The overall estimated tempo of a track in beats per minute (BPM).

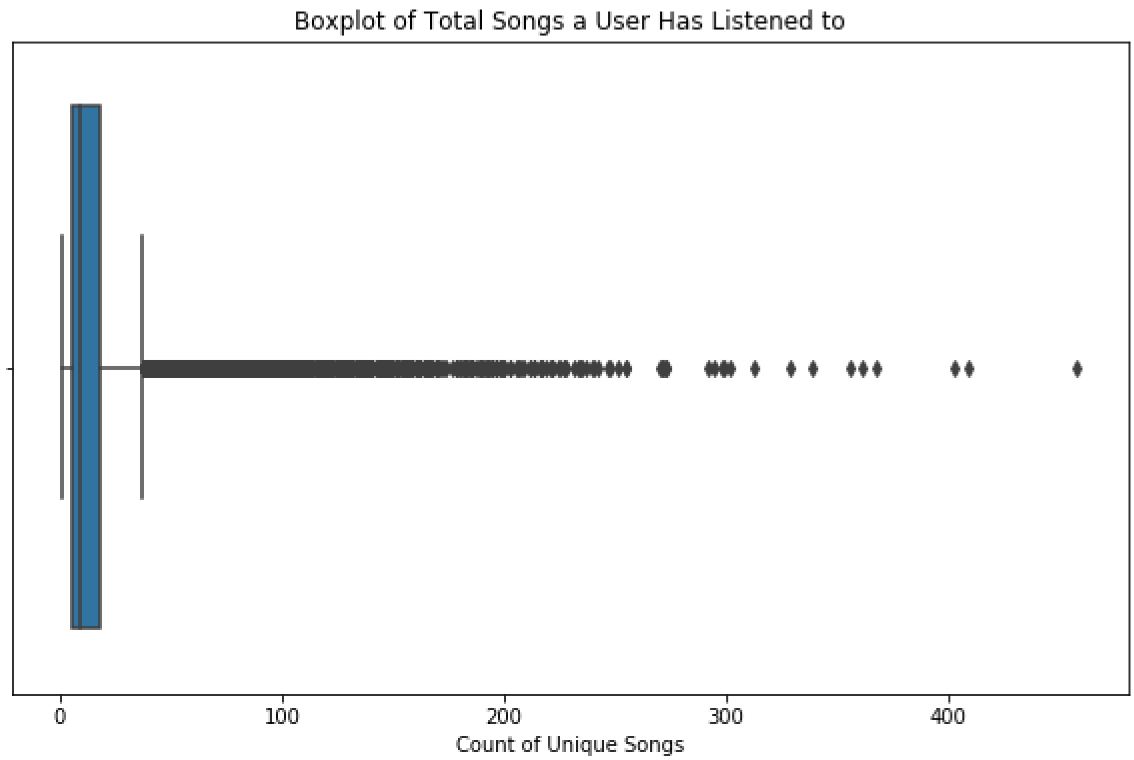
Exploratory Data Analysis:

We will explore the dataset consisting of user's listening activity. In this EDA we explore the dataset without the Spotify audio features. The purpose of this analysis is to understand the users listening behavior and see if there are any outliers that may skew our recommendations or make our dataset invalid. There are four particular areas we will explore:

- How many different songs does a user actually listen to?
- How many times is each song listened to?
- How many unique users listen to each song?

How many different songs does a user actually listen to?

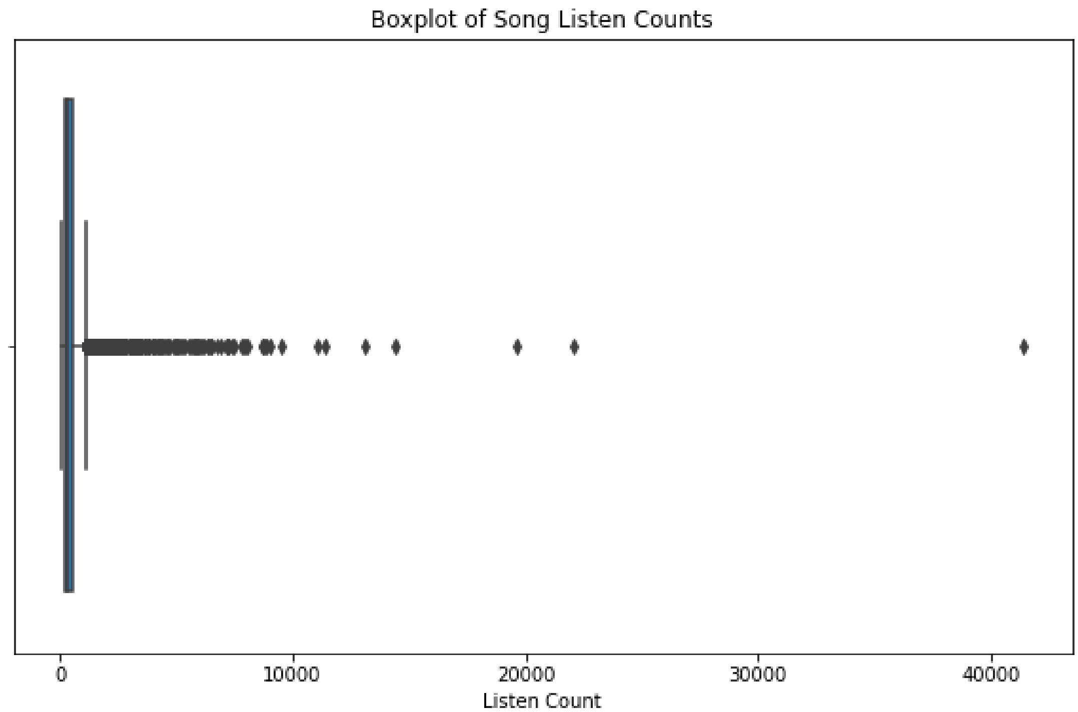
First we explore the distribution of how many different songs each user listens to. The purpose of this is to make sure that our data makes sense with real life user listening habits and to also make sure the data is valid enough to train our recommendation machine.



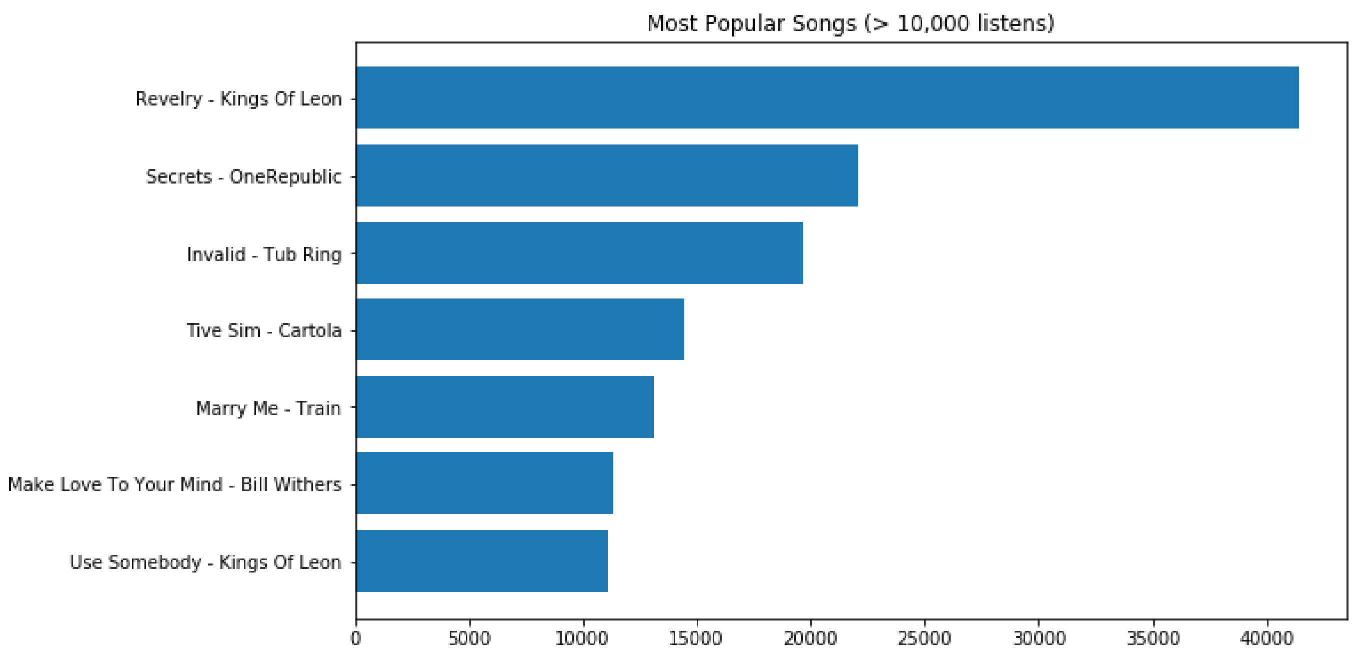
It does appear that there are quite a few outliers in regards to the amount of songs a user listens to. However, since we are building a recommendation system, outliers are treated differently as it is valid data of human activity. In this case, what we are concerned about is having a dataset that would not allow us to train a recommendation system. In our data, only 3357 out of 74,904 users only listened to one song (5%) so we can conclude that our data is valid for our model.

How many times is each song listened to?

Next we look at the number of times each song is listened to by users. We want to see if there are any outliers so that our analysis is not skewed when recommending songs. For example, we wouldn't want a song to be recommended to users only because it's listen count is considerably higher than all other songs.



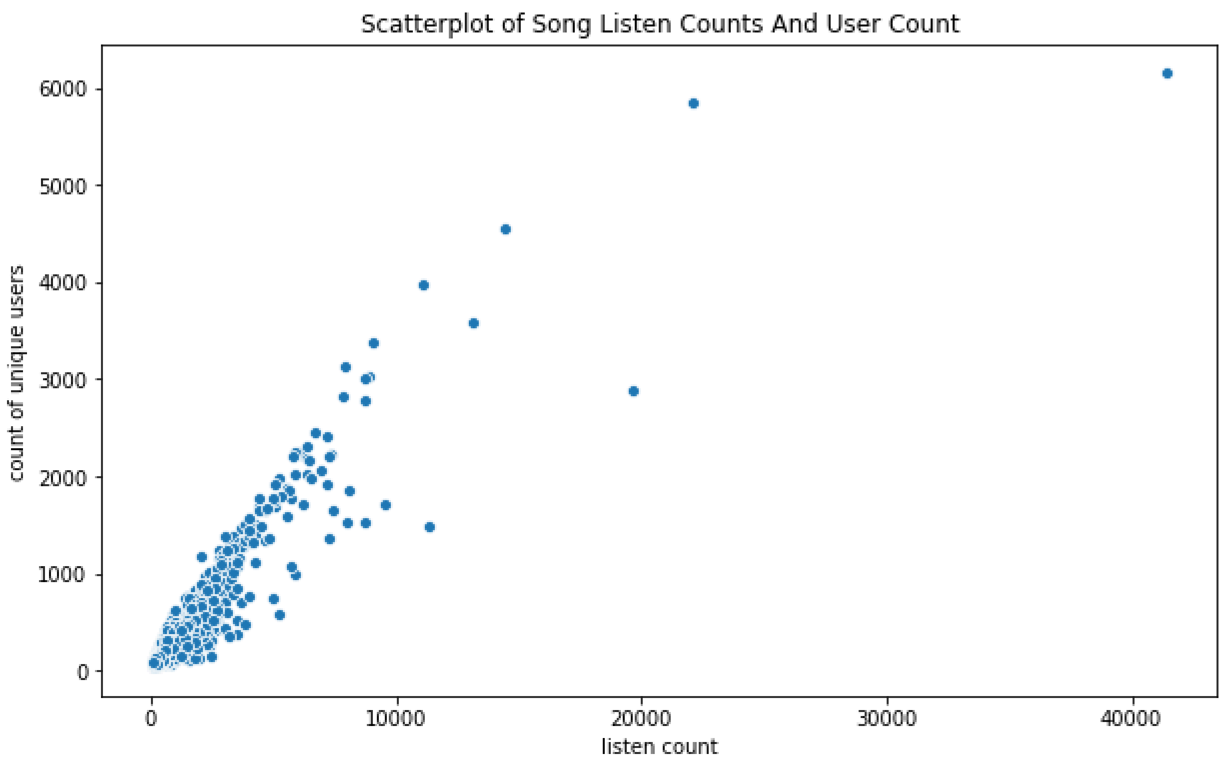
From the boxplot you can see that there are a few songs with very high listen counts. Below is a closer look at the songs with a listen count greater than 10,000.



These songs would be considered outliers, however we do not want to remove them from our data. But we do want to keep these songs in mind during our modeling stage so that they will not be recommended to users solely due to their popularity.

How many unique users listen to each song?

Next we looked at the distribution of the number of unique users that listen to each song. We explored this to see if the songs with high listen counts were caused by certain users listening to these songs an extreme amount of times as this could potentially skew our data.



The scatterplot shows that there is a relationship between number of listens and number of users. With the exception of a couple of outliers, the number of users that listen to a song increases as the number of listens increases. This tells us that the listen count of our popular songs is not skewed by a few users with extreme listen counts.

EDA Key Findings:

This analysis tells us that we have a valid dataset to begin training our recommendation engine. There are some songs that are 'outliers' in regards to listen count however we will not remove these outliers. We will just keep these songs in mind during the modeling stage and make sure they are not recommended to a lot of users solely due to their popularity.

Recommendation System:

Approach:

We will use a combination of matrix factorization and classification to produce song recommendations for a particular user. We will perform matrix factorization on a subset of our data to extract latent features for our users and songs. Then, we will use these latent factors in conjunction with our audio features to train a classification model. The model will predict classes of a high listen count versus a low listen count of a song. These predictions will then be used to recommend songs to a particular user.

For our model we will randomly split the dataset into three sets. There will be two test data sets and one validation dataset. The first data set will be used to perform matrix factorization to extract user and item latent factors. The second dataset will be used to train our classification model. And lastly, our validation set will be used to evaluate our model.

Matrix Factorization:

Matrix factorization is to find out two matrices such that when you multiply them you will get back the original matrix. Matrix factorization can be used to discover latent features underlying the interactions between two different kinds of entities. The purpose of performing matrix factorization in our project is to extract latent factors of the users and the songs. Below is a matrix of our user-item pairs.

song user_id	& Down - Boys Noize	' Cello Song - Nick Drake	'97 Bonnie & Clyde - Eminem	'Round Midnight - Amy Winehouse	'Round Midnight - Miles Davis	(Antichrist Television Blues) - Arcade Fire	(I Just) Died In Your Arms - Cutting Crew	(If You're Wondering If I Want You To) I Want You To - Weezer	(Nice Dream) - Radiohead	(The Symphony Of) Blase' - Anberlin	...
00003a4459f33b92906be11abe0e93efc423c0ff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
00005c6177188f12fb5e2e82cdbd93e8a3f35e64	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
00030033e3a2f904a48ec1dd53019c9969b6ef1f	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
0007235c769e610e3d339a17818a5708e41008d9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
000a5c8b4d8b2c98f7a205219181d039edcd4506	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

The intuition behind using matrix factorization is that there should be some latent features that determine how many times a user listens to a song. For example, two users would listen to the same song if they both like the genre of the song. Therefore if we can discover these latent features, we can add them as additional features to our dataset since the features associated with the user should match with the features associated with the song.

	user_id	u1	u2	u3	u4	u5	u6	u7
0	00003a4459f33b92906be11abe0e93efc423c0ff	2.292281e-08	8.675921e-06	0.000000	0.000055	0.000029	7.304217e-07	7.148265e-08
1	00005c6177188f12fb5e2e82cdbd93e8a3f35e64	0.000000e+00	0.000000e+00	0.000000	0.000196	0.000159	6.174749e-06	2.112216e-07
2	00030033e3a2f904a48ec1dd53019c9969b6ef1f	0.000000e+00	0.000000e+00	0.000000	0.000000	0.492211	0.000000e+00	0.000000e+00
3	0007235c769e610e3d339a17818a5708e41008d9	4.859820e-08	6.610512e-06	0.000002	0.000011	0.000012	2.942126e-05	1.186700e-05
4	000a5c8b4d8b2c98f7a205219181d039edcd4506	4.055804e-06	9.234415e-07	0.000052	0.000006	0.000018	3.937425e-07	3.131225e-05

	song	s1	s2	s3	s4	s5	s6	s7
0	Lights Of Ayodhya - Yulara	3.736008e-06	0.000069	0.000000e+00	0.000911	0.002214	0.036572	0.000100
1	Ironmasters - The Men They Couldn't Hang	6.799389e-07	0.000016	0.000000e+00	0.000091	0.000303	0.000071	0.000040
2	Chasing Cars - Snow Patrol	2.748346e-07	0.000018	5.600788e-07	0.000085	0.000606	0.000119	0.000012
3	Secrets - OneRepublic	2.552698e-07	0.000004	1.755655e-04	0.000471	0.001095	0.000043	0.000014
4	You'd Be So Nice To Come Home To - Julie London	9.558672e-07	0.000034	5.485172e-06	0.000166	0.000479	0.000121	0.000252

The images above show the values of the latent factors for the user (u) and song (s). These factors will now be used in our classification model. Although we already have some song features from Spotify, the latent factors of the user should help the strength of our recommendation system.

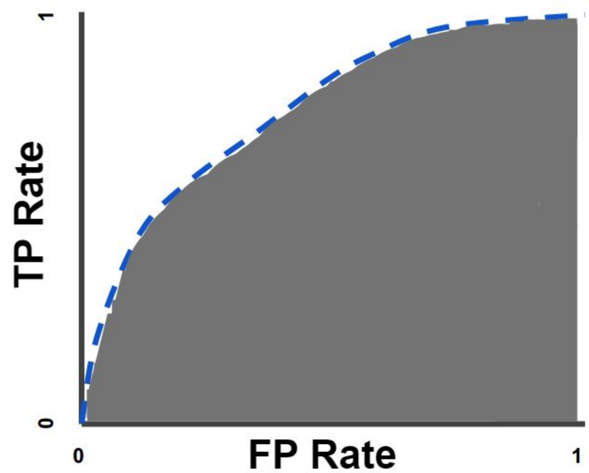
Classification:

After adding on the latent factors found from matrix factorization, we then perform classification on the data set, ignoring the user_id and song_id columns. The column 'listen_count' is transformed into classes of 'one' and 'one_plus'. Since the listen counts are highly skewed we will only perform a binary classification.

Evaluation Metrics:

To evaluate our model we will use ROC AUC score because we have a binary classification with skewed classes. AUC - ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represents measure of separability. It tells how much model is capable of distinguishing between classes.

The image below shows an example of the ROC curve. The shaded area is AUC (Area Under Curve) and the axis’ represent False Positive and True Positive Rates.



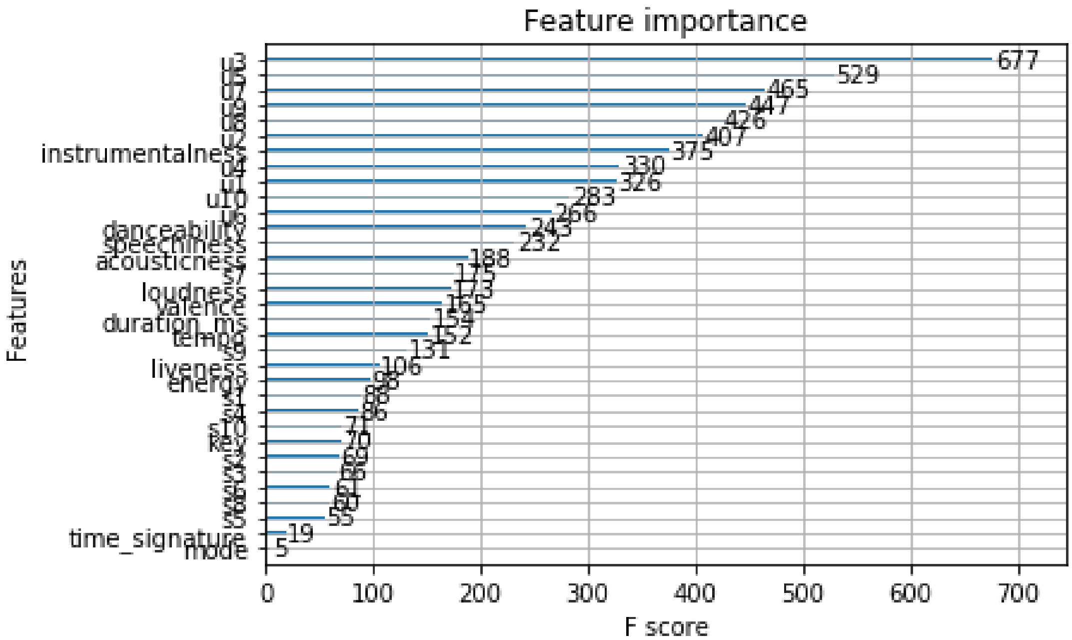
In our case, since we have two classes our baseline AUC is 0.5. If our AUC is 0.5, this tells us our model has no capability of distinguishing between our two classes. We aim to get the AUC of our model as close to 1 as possible.

XGBoost:

We first train an XGBoost model on our training set. Without tuning the hyperparameters, the base model gives us an AUC score of 0.6026. After evaluating the feature importance of the model and tuning subsample, colsample_bytree, max_depth, learning_rate and n_estimators, our XGBoost model gives us an AUC score of .657. This AUC tells us that XGBoost has a 66% chance of distinguishing between our two classes of high listen counts and low listen counts.

Feature Importance:

Now that we have extracted these latent factors from matrix factorization. Let’s see how much of an effect these features have on our model. To do this, we use the feature_importances_ feature of our trained XGBoost model.



You can see that the user latent factors have very high ‘importance’ in comparison to our other features. However, our song or item latent factors have low ‘importance’ in compared to our other features. This could be because we already have features of the songs so the additional song latent factors do not add any value.

The user latent factors hold a lot of weight when predicting. This makes sense in relation to our final objective of recommending songs to a user. Of course factors of a user are important when choosing songs to recommend to that user. In this model we dropped the 9 least important features.

Random Forest:

To see if we can increase the models score, we train a Random Forest classifier to be ensembled with our XGBoost model. After training the Random Forest model and increasing the number of trees, the classifier gives us an AUC score of .669. Random Forest has a 67% chance of correctly predicting between our two classes. This score is higher than XGBoost so we then ensemble the two models by averaging their predictions and see if it produces an even higher AUC score.

Ensemble:

To create a final model that uses both our trained XGBoost and Random Forest classifiers, we take an average of the predicted probabilities of the two classes. The averaged probability is then used to predict a class.

This ensembled model gives us an AUC score of .68. This is a .07 increase from our base XGBoost model. This AUC tells us that our model has a 68% chance of correctly distinguishing between our two classes.

Final Recommendation System:

At prediction time, if we want to know if a user will listen to a song we will join the user features and the song features of that song and predict. The function 'get_top_songs', takes in a user id as an argument and recommends five songs by returning the five songs with the highest probability of belonging to our class representing a high listen count.

```
get_top_songs('f1ccb26d0d49490016747f6592e6f7b1e53a9e54')
```

	song_id	song	pred
3067	SOBJYFB12AB018372D	Also Frightened - Animal Collective	0.909438
4239	SOBNAMV12A8C139423	Faces In The Hall - Gym Class Heroes	0.908345
3573	SOKJQGO12AF72ACA9F	Top Down - Swizz Beatz	0.908042
3489	SORWJSF12A8C138AB6	Hello - Evanescence	0.897374
4282	SOWSORU12A8C13D020	Yin Yang - Jarabe De Palo	0.890913

Above shows the recommended songs for user 'f1ccb26d0d49490016747f6592e6f7b1e53a9e54'. Besides AUC score, another way we can evaluate the recommendation system is by seeing if recommended songs are similar to what that user has listened to. Below are the users top 5 listened to songs. How did we do?

	song	listen_count
1323	Sweet home Alabama - Lynyrd Skynyrd	11
989	Woods - Bon Iver	6
1841	Who Can Compare - Foolish Things	6
1196	Lonelily - Damien Rice	4
2459	Over You - Roxy Music	4

Recommendations and Next Steps:

This type of model requires a ton of data. The number of user and item pairs is very large so we are training on a very small subset of the universe of possibilities. More data is necessary for a better score. It is difficult to create a good recommender system with a small amount of data.

Although not big enough, the dataset is still very large. The size of the data affects the quality of hyperparameter tuning of the model. Time and computing power limits our ability to use a grid search method for tuning our hyperparameters. This method would most likely have returned a better final AUC score.