Music Streaming Song Recommender

Increasing Audio Streaming User Retention via Music Recommendation System

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Dev10 Data Science & Engineering Capstone

October 5, 2022

Introduction

Upon beginning our Capstone Project, team Land'o'datalakes was first interested in exploring recommender models. We found it interesting that when you make, or even think about making an online purchase, stores like Amazon already know items to cross-sell with your potential purchase. If you put a lawn chair in your cart, how does Amazon decide to tell you "here are some other lawn chairs you might like more" or "don't you need these cool sunglasses, too?". We also considered creating a recommender model to be an interesting and feasible challenge. While we hadn't ever created machine learning models geared to recommendations before, we knew that with some smart application of previously learned subjects and research we could make a successful attempt at them.

Then, the group extended the question to "what other things are recommended to us online?". Music quickly became the topic of the group's conversation. Online music streaming is the main method of music distribution, and such platforms use recommenders all the time (Curry, 2022). Spotify has Autoplay which, when you reach the end of an album, playlist, or selection of songs, automatically plays similar songs so the music never stops. Spotify also gives users a Discover Weekly, revealing new music personalized to what the user was listening to last week. Apple Music has Replay, where it selects the user's favorite songs. How and why do they do that?

Our research on audio streaming services made us consider these questions:

- Who are the people who use audio streaming services?
- How might we build a database that allows us to make recommendations based on music?
- How would songs trend over time in this database?
- What trends or patterns are there in the user metrics of our application?
- How does our database compare to actual music streaming services?
- Are recommendation models important to user retention on a music platform?

With these exploratory questions in mind, we dove in. This report documents how team Land'o'datalakes created their own song recommenders like those on music streaming platforms, such as Spotify. In this report we first introduce the data sources we used to answer our questions and create our song recommender app and then briefly describe our ETL processing of that data. Next, in the Analysis section, we share our conclusions to our questions about music streaming via analysis of these datasets. Then, based on the conclusions from our analysis, we created two recommender systems which are both described in the Machine Learning section. Lastly, the Data Dashboard section presents our data dashboard and how it summarizes what we have discovered and our recommender models in a user friendly interface.

Data Sources

Three datasets pertaining to music streaming and United States demographics are used to create a narrative of music streaming in the United States.

Current Population Survey: Computer and Internet Use Supplement 2019

Current Population Survey: Computer and Internet Use Supplement 2019 (United States Census Bureau, 2020) from the United States Census Bureau illustrated the demographic characteristics of households in the United States that, among other things, stream music.

Spotify Dataset 1921-2020, 600k+ Tracks

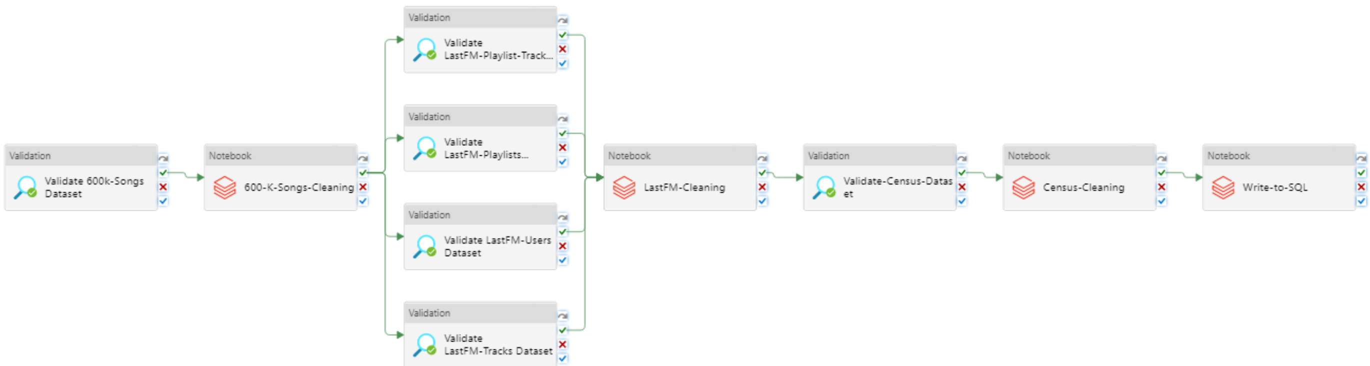
The first large dataset we used for the data streaming and machine learning of this project was "Spotify Dataset 1921-2020, 600k+ Tracks" (Eren Ay, 2021) which was used for the attributes it presents on individual songs. This data set was used to make a content recommender based on an individual song's attributes, like popularity or danceability.

Streamable Playlists with User Data

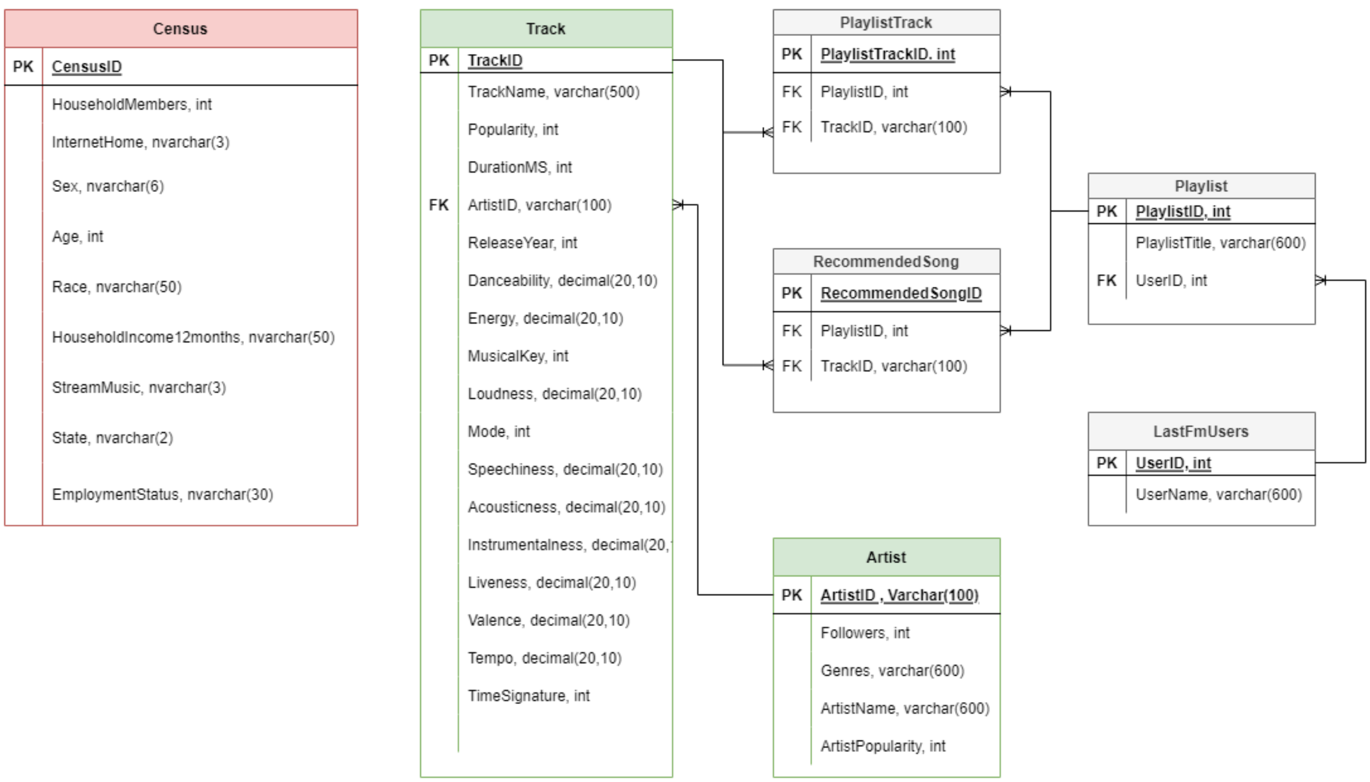
The second large data set we used was the Streamable Playlists with User Data (Boland, n.d.) dataset. From it we were able to collect music streaming users' playlists. This revealed how users like to group songs, which we used to create a collaborative recommender model.

ETL

Our data sources contain playlist information for Spotify users and also the characteristics of over six hundred thousand tracks on Spotify. We also used an API call of computer and internet use from the US Census Bureau to identify the demographics of individuals who stream music. As illustrated in the diagram below, these three datasets were all extracted and transformed before finally being loaded into a SQL database.



To load the data into the SQL database, we used the following ERD diagram as a reference to the column names and datatypes. The data was loaded using Apache Spark within Azure Databricks.



For full documentation of our extract-transform-load (ETL) process, please refer to our RepeatableETLReport.pdf, available on the GitHub corresponding to this project.

Analysis

The database created in our ETL process was then used to answer our exploratory questions and create visualizations to illustrate these answers.

<u>What population uses audio streaming platforms?</u>

We wanted to find out if there is a specific group of people in the United States that is more likely to use music streaming services. Who are they? Where do they live? What are they like? Following is our investigation of our target market.

How much of the U.S. population does this segment represent?

After performing the necessary ETL on the US Census Bureau data from our API call, we were able to dive deeper into our analysis and discover what demographics contain our target market.

In order to figure out what segment of the US population uses audio streaming services, it is important to analyze each demographic category and find the specific groups with the most individuals that stream music. We began our search by looking into the sex demographic to see if one was more prevalent than the other.

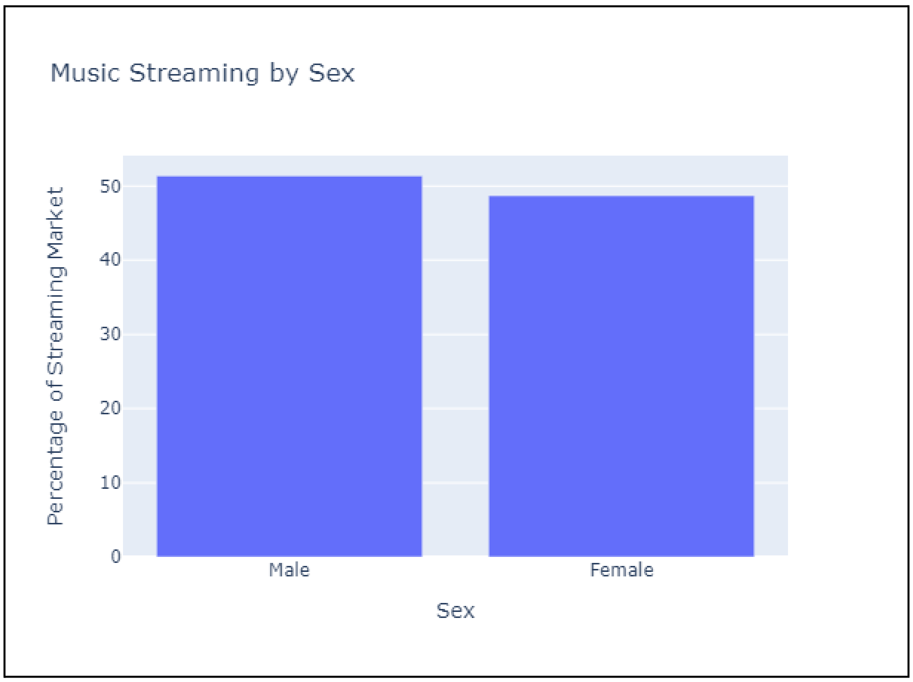


Figure 1. Percentage of the streaming market based on sex.

As seen in Figure 1, both males and females seem to occupy around half of the music streaming market each. This means that there is no set sex that dominates over the other one in the music streaming market. From this we can see that the sex of an individual would not be an important factor for our target market.

Next, we decided to look into the ages of individuals and see if there were any ages that stood out. From this information we can identify what age or ages consist of the greatest portion of the streaming market

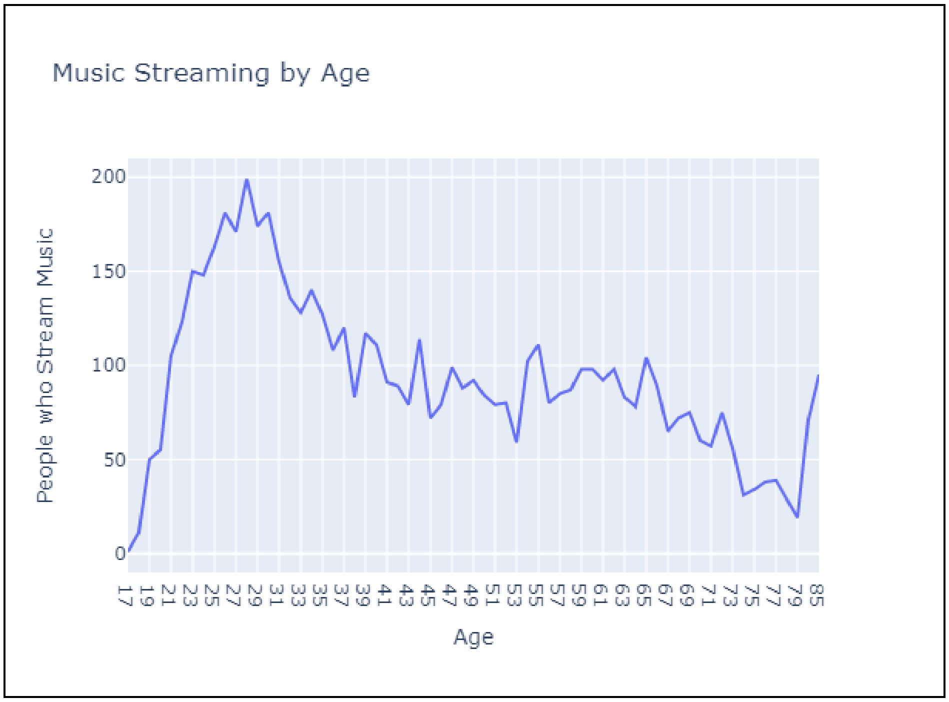


Figure 2. Number of people who stream music based on their age.

Looking at figure 2 we can see that the age with the most amount of people that stream music is 28. Also, from the range of people aged 23-30, the number of people who stream music is the greatest. After 30, there begins a steady decrease in the number of people who stream music until 40 where the number of people who stream music begins to stabilize. Our target population would include those individuals aged 23-30 since this is the range at which the greatest number of individuals are located. Since audio streaming is a relatively newer concept than previous ways of obtaining music, the younger adult population would be more attracted to the moderness.

Another category in which we decided to look further into was income level by household. This information allowed us to see if the number of people streaming music could be related to how much money they were making.

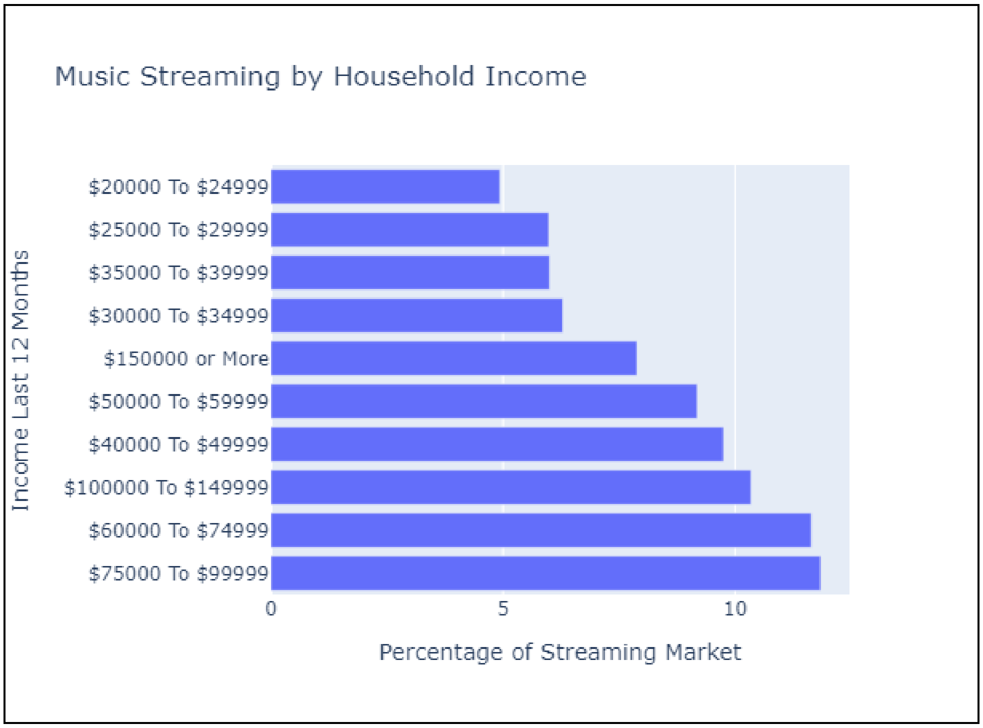


Figure 3. Percent of people who stream music based on their household income (Top 10).

Looking at Figure 3 we observed that households making more money seemed more likely to stream music than households that were making less. We can see that households making $75000 - $99999, $60000 - $74999, and $100000 - $149999 make up the top three household income levels that stream music. Combining these levels of income we can see that they make up around a third of the total audio streaming market. Households which made $40000 - $59999 account for a little under 20% of our streaming market as well. From this information we will include the middle class and upper middle class in our target audience.

Next, we decided to look into the audio streaming market for each state. This information allowed us to see where our target market is located geographically.

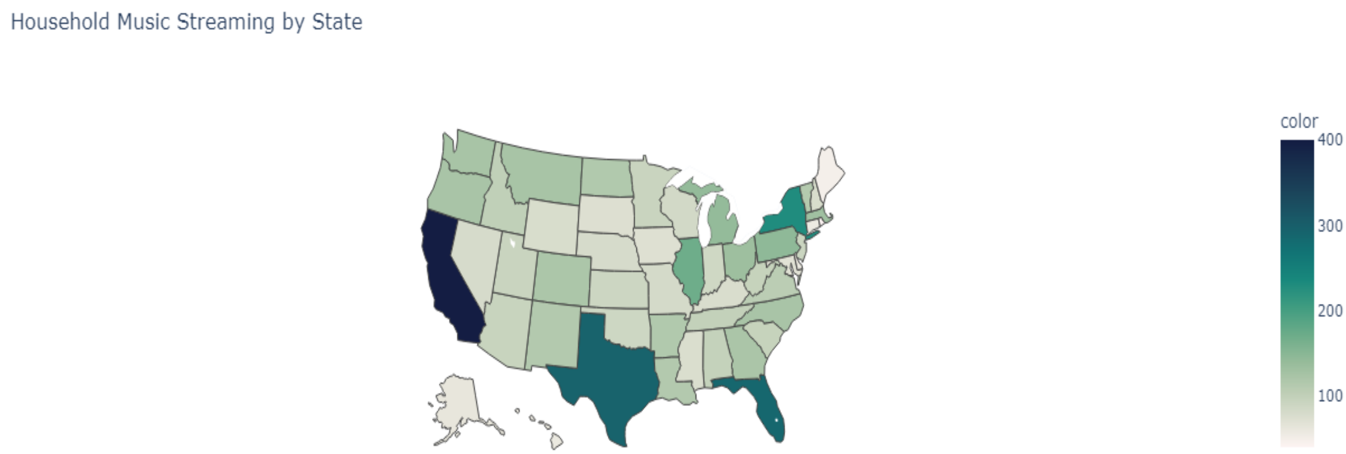


Figure 4. Number of households who stream music by state.

From Figure 4 we can see that the number of households that stream music is largest in states with higher populations. States like California, Texas, Florida, New York, and Illinois would be ideal states to factor into our target market. Large cities in these states make for more specific areas in which we will target.

Finally, we wanted to look into the race demographic. From this information we were able to see how each race compared when it came to music streaming.

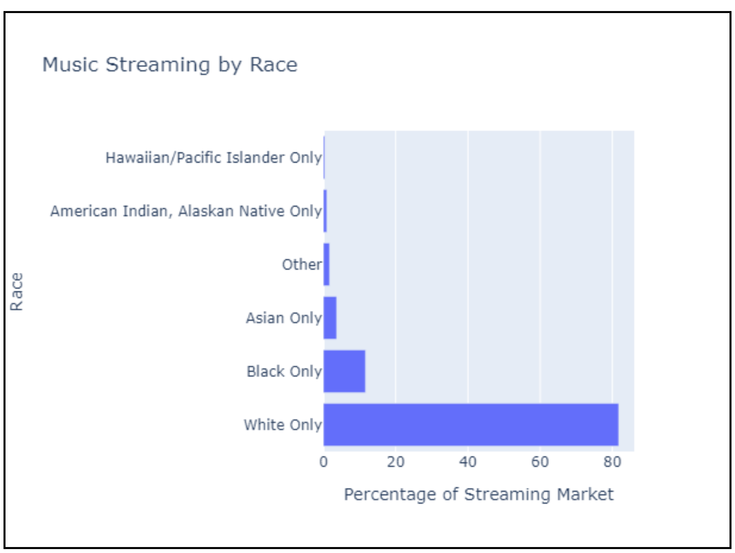


Figure 5. Percentage of people who stream music based on their race.

From Figure 5, we can see that the majority of people who stream music is white only. White people account for around 80% of the total streaming market. Since the United States as a whole has a majority of white people, this demographic seems accurate. We will include white individuals into our target market as they show an overwhelming amount of dominance in the audio streaming market.

What important characteristics of this target population might be difficult to explain with only demographic data?

Previously, Spotify had focused its marketing efforts on Millennials. Now, due to recent world events, Spotify's focus is turning to Gen Z. Gen Zs "look to audio to provide the opportunity to curate the stories they want to tell about themselves" as well as interact with artists. Gen Zs are invested in their playlist as a reflection of themselves, which would indicate they would like to stay in a relationship with a music streaming service. Additionally, Gen Zs "make discovery part of their daily routine." (*Gen Z Be Heard*, 2022) Meaning discovering fresh content, like with our recommenders, is important to keep Gen Zs engaged.

Where should music streaming services deploy their marketing campaigns based on who their target users are?

Based on what we discovered in the US Census Bureau's quantitative data, the largest users or music streaming services are young, white, and located in more densely populated states.

<u>The young factor</u>

Based on the findings from Spotify (*Gen Z Be Heard*, 2022) (*Q&A With Spotify's Marion Boeri*, 2022) Gen Z is a large and growing segment of the target market. These users like to be engaged with the artists, such as on social media. Gen Z is very computer literate and freely engages in social media platforms which may be a good placement for marketing to this segment. Furthermore, "47% of American Zs said they've joined a digital community, such as a Subreddit or Discord, for fans of a particular creator." (Spotify, n.d.) Digital communities like Subreddit or Discord should be investigated as marketing opportunites.

<u>How do songs in our library trend?</u>

The exploration of how the songs in our database trended by release year began by exploring how popular they are. Spotify uses an algorithm to calculate popularity based on the total number of plays a track has had and how recent those plays were. In Figure 6, there is a trend where the newer songs are also rated as more popular. This makes sense, because a newer song would most likely have more plays. There is an interesting spike around the 1950's where the popularity randomly spikes upwards. When taking a deeper dive into some of the songs released around that time frame, you get songs like "I can't quit you baby" by Led Zeppelin, "Little Red Rooster" by the Rolling Stones, and "Perhaps, perhaps, perhaps" by Doris Day. These were top hits back in the 1950's. It could be the case that users that listen to older songs would listen to the more popular hits. This would potentially lead to a greater probability of listening to the same song among different users, therefore, increasing its popularity.

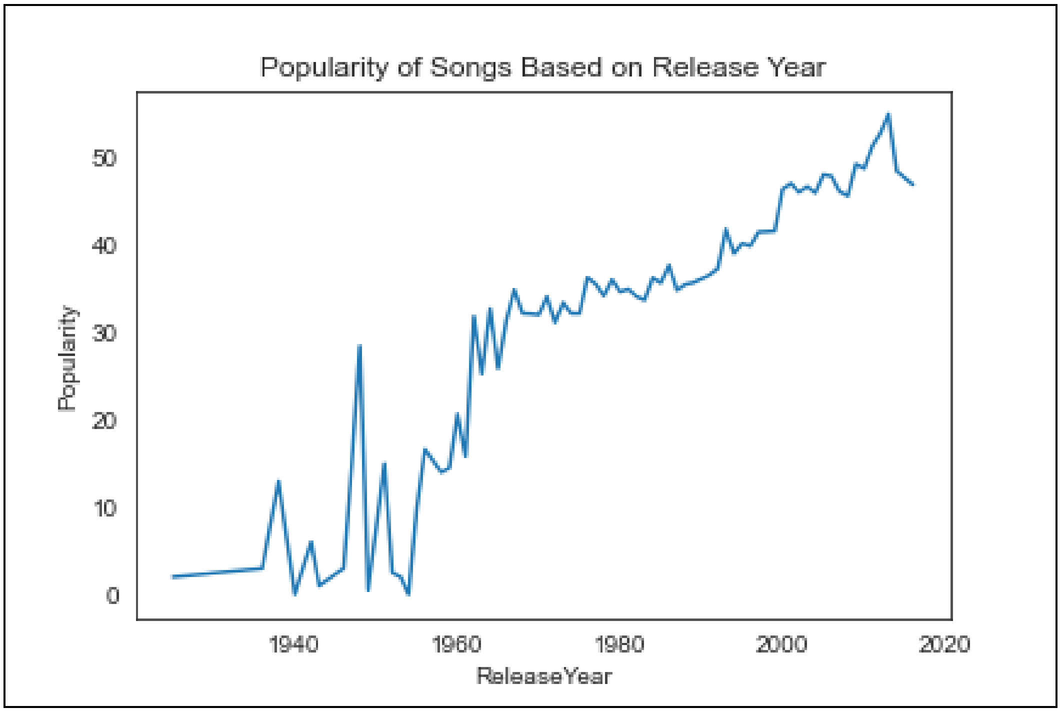


Figure 6. Popularity of Songs based on their release year

Next, we wanted to look at what features correlated with popularity, if any. In the correlation matrix below the only feature with the greatest correlation with popularity was the release year, which again isn't suprising. Interestingly, loudness and energy were not strongly correlated with popularity, even though the popular songs of this day and age seem to be more energetic and loud.

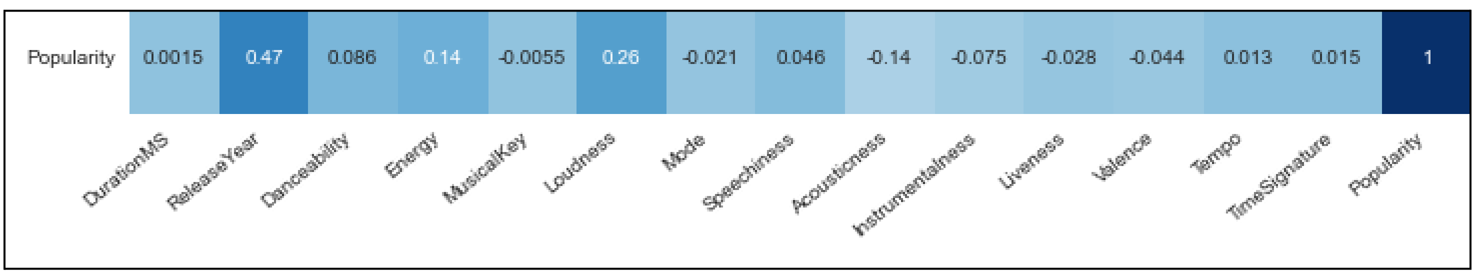


Figure 7. Correlation between popularity and song attributes

This led to us taking a deeper dive into what attributes correlate with Energy. In the correlation matrix below, loudness and Acousticness had correlations of 0.75 and -0.7, respectively. Therefore, a song with more energy would most likely be louder and less acoustic. This relationship makes sense because songs that are more energetic typically feel fast, upbeat, and lively.

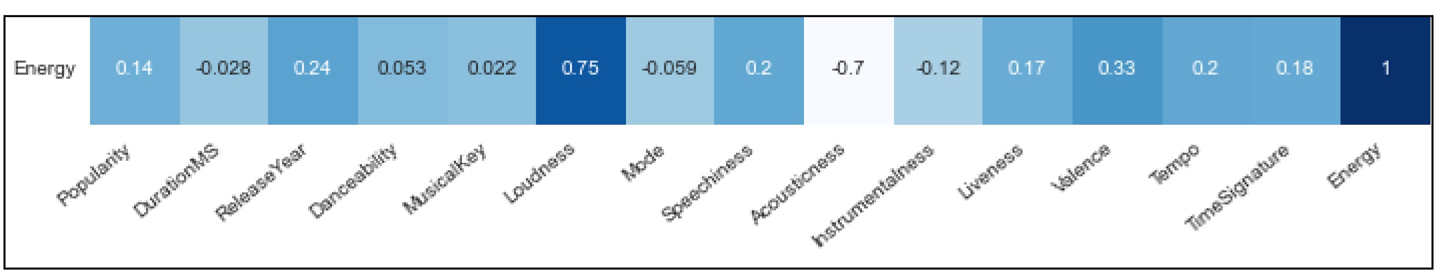


Figure 8. Correlation between energy and other song attributes

However, when we further analyzed the relationship between energy and loudness based on a song's release year, there was a notable difference. In Figure 9 the energy of a song generally increases over release year, even when the loudness remains the same.

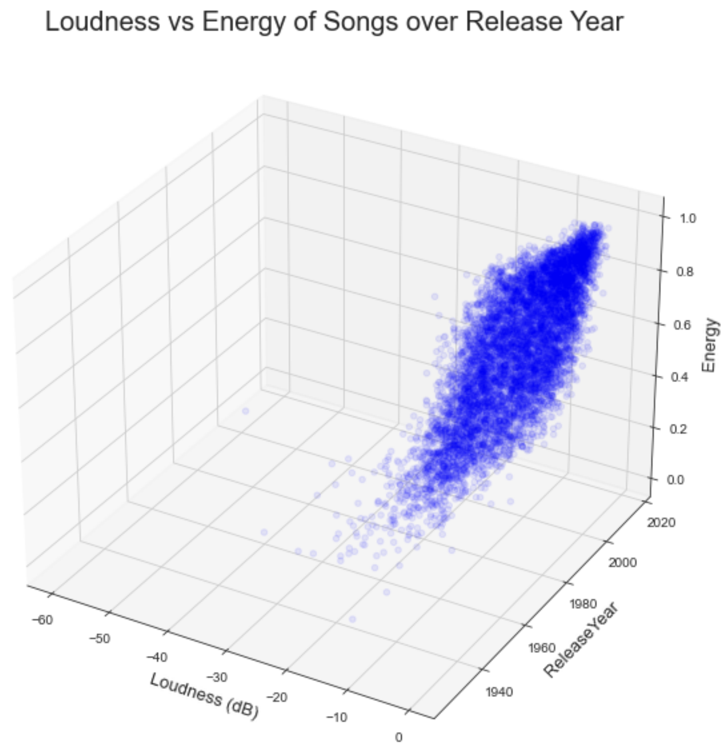


Figure 9. Loudness(dB) and Energy, no unit but ranges from 0-1, of a song based on the release year

This relationship between energy and loudness is most likely more complex than initially thought. According to the spotify website, energy is a perceptual feature that can be characterized by dynamic range, perceived loudness, timbre, onset rate, and general entropy (*Web API Reference*, n.d.). These characteristics could explain why the energy of a song seems to be increasing even when the loudness remains the same. Further analysis of each of those sub features could help explain more of the intricate relationship between the loudness and energy of a song.

What are the most popular artists and genres in our library?

We completed an exploratory data analysis to find the most popular artists and genres based on the frequency at which they appeared within our user's playlists. In figure 10, Madonna was the most frequent artist added to user's playlists with a count of 67, The Beach Boys appeared across playlists 52 times, and The Cure was the third most frequent artist with a count of 47. It was surprising to see that the most frequently saved artists were from before the 2000's in terms of when their top songs and albums were recorded.

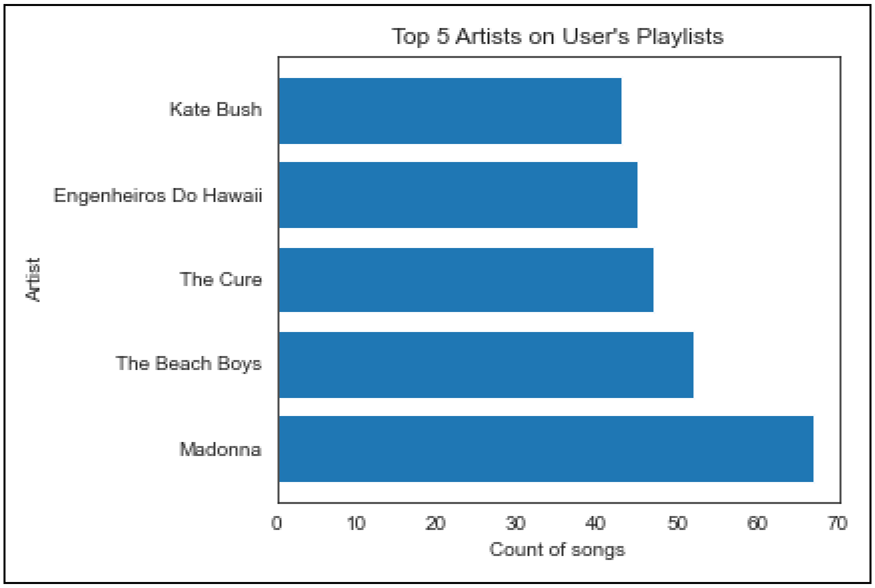


Figure 10. Top 5 artists that appear on all users' playlists

The three most popular genres across all of the user's playlists were album rock, alternative metal, and dance pop shown in figure 11. Album rock is a genre that was created around the 1970's by radio stations that wanted to play albums from artists instead of random singles. (*Album Rock Music Genre Overview*, n.d.) This genre is pretty diverse as it consists of heavy metal to southern blues recorded between 1960-1970. (*Album Rock Music Genre Overview*, n.d.) Alternative metal can be characterized by rhythmic drop-tuned and mid-tempo riffs, as well as melodic and harsh vocal stylings. (*Alternative Metal - Music Genre - Rate Your Music*, n.d.) Lastly the dance pop genre contains songs with catchy melodies and throbbing beats.

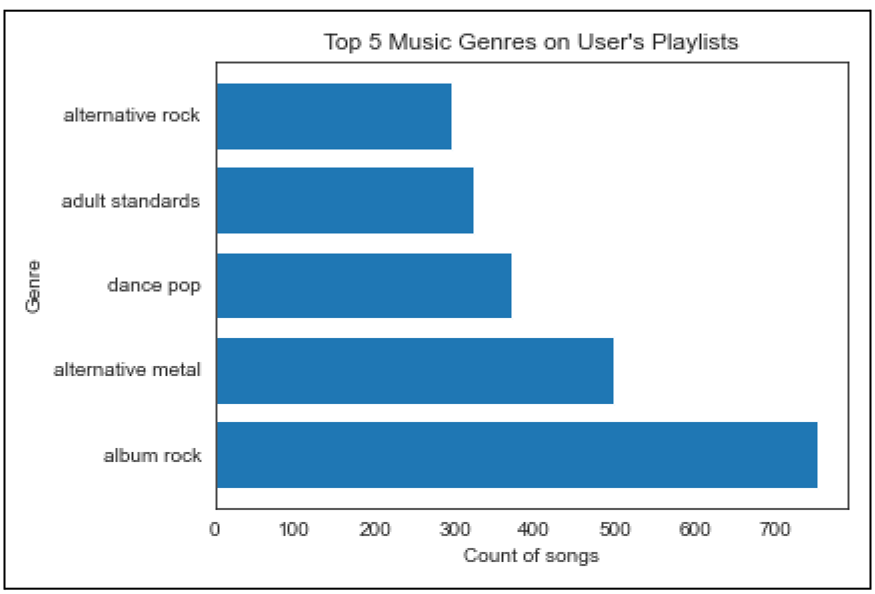


Figure 11. Top 5 genres that appear on all users' playlists

What is the average number of songs on a playlist?

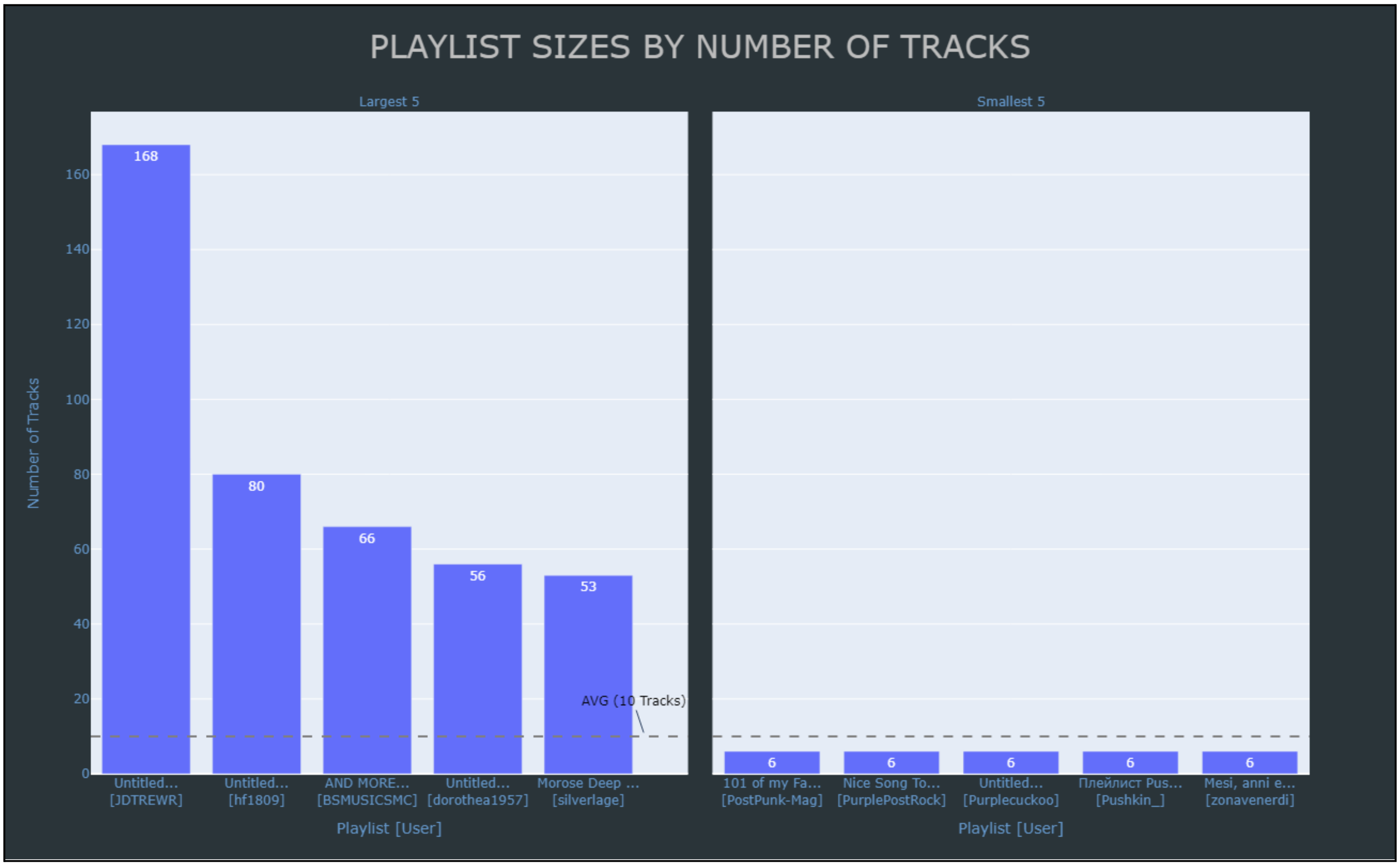


Figure 12. Playlist Sizes by Number of Tracks (Group database)

In our group's database the maximum number of tracks on a playlist is 168 tracks. The minimum number of tracks to a playlist is 6 tracks. However, while there is only one playlist with the maximum number of tracks, there are numerous playlists hitting the minimum number. This is exemplified by our average number of tracks over the database: 10 tracks. Something is bringing this average down.

The truth to our database is that its distribution of tracks per playlist is heavily skewed to the left. This could have been even lower had we not set a floor of at least 5 tracks to the playlists that we used in our database. Our primary reason for doing so was to ensure that we had enough songs in a playlist to build proper recommenders from them.

How does our database compare to actual streaming platforms?

In comparison to a company with an audio streaming platform whose application is already in production and public, our database operates on a far smaller scale. Though we pulled a lot of our data from Spotify, our numbers are proportionately miniscule: In the year 2022, Spotify has "82 million songs" and "11 million artists" (Ruby, 2022). Our database only clocks in at 8349 songs and 3240 artists.

Our database isn't necessarily a representative sample of a music streaming service's catalog. However, the data we used has real-world values, which allows for our recommender models to provide appropriate recommendations. This also means that our database is scalable should we want or need to scale it in the future. Both models can take into account new content, be it new tracks or playlists.

Are recommendation models important to user retention on a music platform?

Music recommenders benefit the music streaming platform in many ways. First, they maximize user engagement. Engagement is important. “For subscription-based platforms like Spotify, higher engagement rates (created by users exploring and adopting new music interests) lead to the earning of more ad-based revenue.” (Dee, 2022). Spotify releases an annual report called Culture Next which says, “Customers will get themselves more engaged in a music streaming service when personalized music recommendations are made to them.” (Spotify Advertising, n.d.) So recommenders are critical to user engagement.

Second, music recommendation systems make music more easily discoverable. If there is a new song out, a content recommender can analyze it, find songs that are similar to it, and then find users that listen to those songs. Culture Next reported “53% of users said they’ve sought more content from more diverse creators in the past year.” (Spotify Advertising, n.d.)It is rewarding when a user discovers a new song or a new-to-them song that appeals to their tastes. When the user has the expectation that the music streaming platform will be presenting them these ‘gifts’ it encourages the user to always come back to see what else they will ‘get.’ (Jena, 2022)

Third, recommenders increase customer satisfaction. The Culture Next report documented, “69% of American Gen Zs feel ‘more centered and generally happier’ when listening to their favorite music on a daily basis.“ (Spotify Advertising, n.d.) When a user signs in and is presented with a playlist completely personalized to them, their desire to listen to music that appeals to them is satisfied versus having to skip undesired songs. “Modern digital music recommendations do what your best friend might have done in the past, they say ‘Hey, listen to this. We know your tastes and feel that you’d be into it.’ And usually, they’re right. That’s because music recommendation functionality is powered by music recommendation algorithms. The algorithms … keep users engaged and continuing to use the app.” (Dee, 2022)

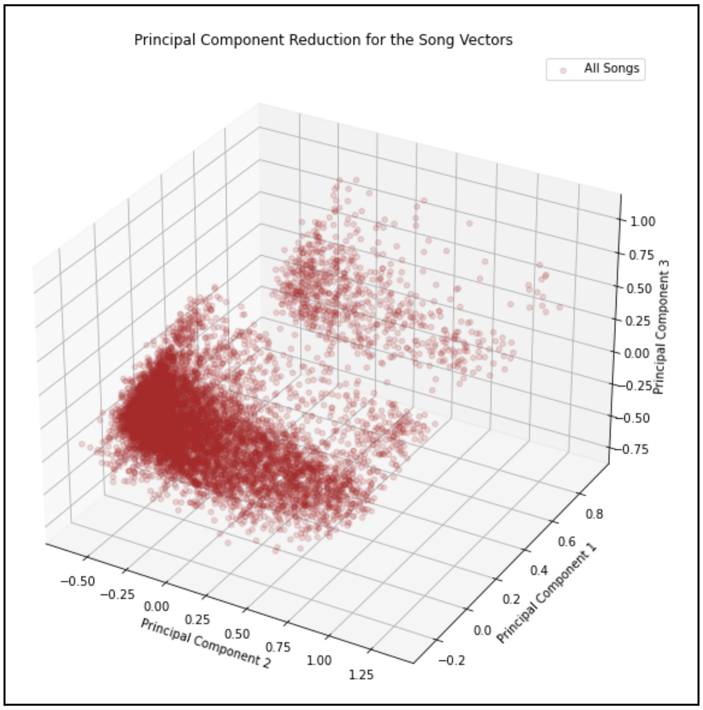
Based on this information, we created our own music recommendation models discussed in the following Machine Learning section.

Machine Learning

To keep users engaged, we created two separate music recommendation models that react to the user’s music choices in real time. This was accomplished with Kafka’s producer and consumer tools in Azure Databricks. The recommenders on our dashboard are unsupervised and use cosine to find similar songs based on different variables.

Content recommender

The content recommender is an unsupervised cosine similarity model we created to recommend songs that are most similar to a user’s selected playlist. This machine learning algorithm works by first converting each song into a vector with 823 dimensions/features. The features include the song’s genre, attributes, popularity, and Release Year. We initially scaled those features using a MinMaxScalar from sklearn and further scaled them based on how sensitive we wanted our model to be for each feature. For example, one of our goals was to make the genre of the song take precedent over the attributes of it. Therefore, we increased our models sensitivity to genre. In our dash interface, when a user selects a playlist, a vector is built based on the sum of the song features. This vector and all of the song vectors are then normalized by dividing by their Euclidean magnitudes. Afterwards, a dot product between the normalized playlist's and each song's unit vector is performed to calculate the cosine similarity. These values range from 0 (no similarity) to 1 (perfectly similar)



and are sorted in descending order. The top 10 songs are selected and shown as recommendations in our dash user interface.

In the figure above, principal component analysis was completed on our song matrix, which allows us to project our data onto a lower dimensional space while preserving as much variance as possible. This gives us some visual insight into some of the patterns and clusterings of our songs within our database.

Collaborative Recommender

The collaborative recommender is an unsupervised cosine distance model we built based on user playlists. When a user searches a song, the model searches for playlists that include that song. The songs that appear most often in playlists that include the user's song are returned as recommendations. For readability to the end user, the cosine of 1 to -1 is converted to pairwise distance of 0 to 1. 0 being the song most similar to the searched song, and 1 being the most dissimilar.

This machine learning algorithm works by first joining datasets to have each row represent a song and a playlist on which it is included. Therefore, a song can be listed more than once if it is on more than one playlist. However, we want to know on which playlist a song is listed, so we create a pivot table with the index being the song, and the columns being playlists. This creates a huge dataframe where if a specific song is on a specific playlist, it will return a 1. Everything else is 0. To make the data more manageable, the pivot table is converted into a sparse matrix. Sparse matrices only show values that exist, so the 1s. From here, we can calculate the cosine distance. This returns a distance matrix, comparing every song with every other song in the dataset.

The distance matrix is an array that starts with a 0, meaning that a specific song is similar to itself. There is a diagonal line of the songs being similar to themselves across the array. From there, we convert the array into a dataframe. A user enters a search for a song, that search term is used to find a matching song/artist. The returned songs are sorted in ascending order, so closest to 0, which is most similar, first.

 This model only works if users have a song saved to their playlist. if new songs get added to a music streaming platform, it will not be on any playlists, thus will not get recommended. As users add it to their playlists, a correlation will develop and we will be able to see what other songs people like that song listen to. (Jena, 2022)

Data Dashboard

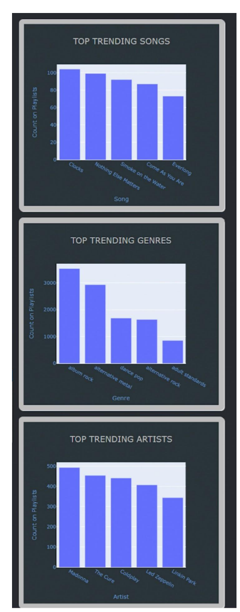
Informed with the answers to the above questions and our recommender models, we created a dashboard to summarize what we learned and present our recommender models to users. Following is a description of our dashboard and its four tabs - User Interface, Target Market, About, and Behind the Scenes.

The Music Streaming Recommender dashboard was created with Plotly's Dash in Python. The visualizations in the dashboard are created with Plotly Express.

<u>User Interface page</u>

The User Interface page is a representation of what the end user would see when they stream music. As we have learned, different kinds of recommenders offering different additional content keep users engaged with a music streaming service longer. User Interface is broken down into two broad sections- Non-Personalized and Personalized and recommenders.

Non-Personalized recommenders



Non-personalized recommendations are more broad music recommendations made to all users. (Dee, 2022) These include the trending figures shown to the right here and also on the right side of our Dashboard's User Interface. These figures quickly show the User the top 5 artists, genres, and songs currently trending on the music streaming platform.

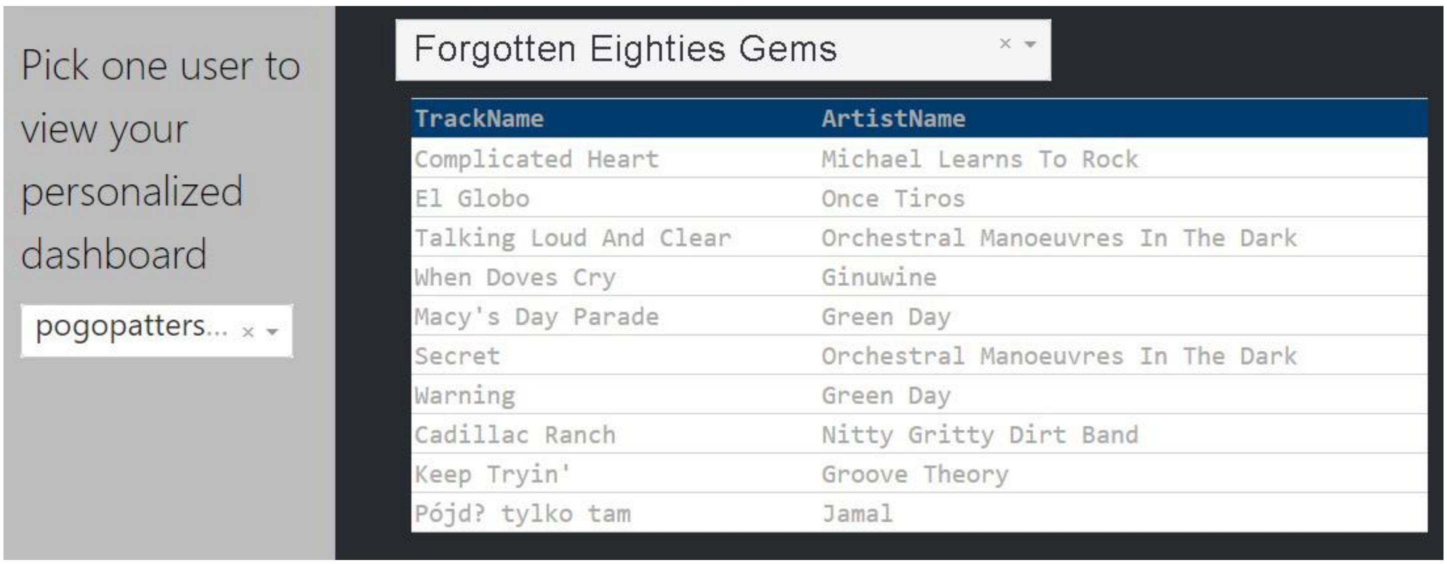
This content, although not personalized to the specific user, does contain songs that are currently popular. This is beneficial for the user because it can lead to discovering new songs, artists, and genres in which they were unaware or had not previously been interested. This is also beneficial to the music streaming platform because they can make these recommendations to someone, such as a new user, of whom they know nothing about.

Personalized recommenders

Personalized recommenders take into account what the user has listened to in the past. (Dee, 2022) Based on this information, there are many methods to provide the user with new content. The two methods we developed are the Content recommender and the Collaborative recommender.

<u>Content recommender</u>

We created our content recommender as a discovery method for our users. A content recommender reviews what songs a user likes, indicated by the fact that the user saved the songs to one of their playlists, and makes recommendations for new songs based on the attributes of the songs in the playlist. Shown in the image of our dashboard below. To receive content recommendations, select a user profile from the menu on the left. Then, select a playlist from the dropdown under “Choose a playlist to get song recommendations in real time!” Based on the selected playlist, the content recommender analyzes the attributes of all the songs on the selected playlist and recommends a list of ten additional songs the user does not have on their playlist but may be interested in appending to their selected playlist.



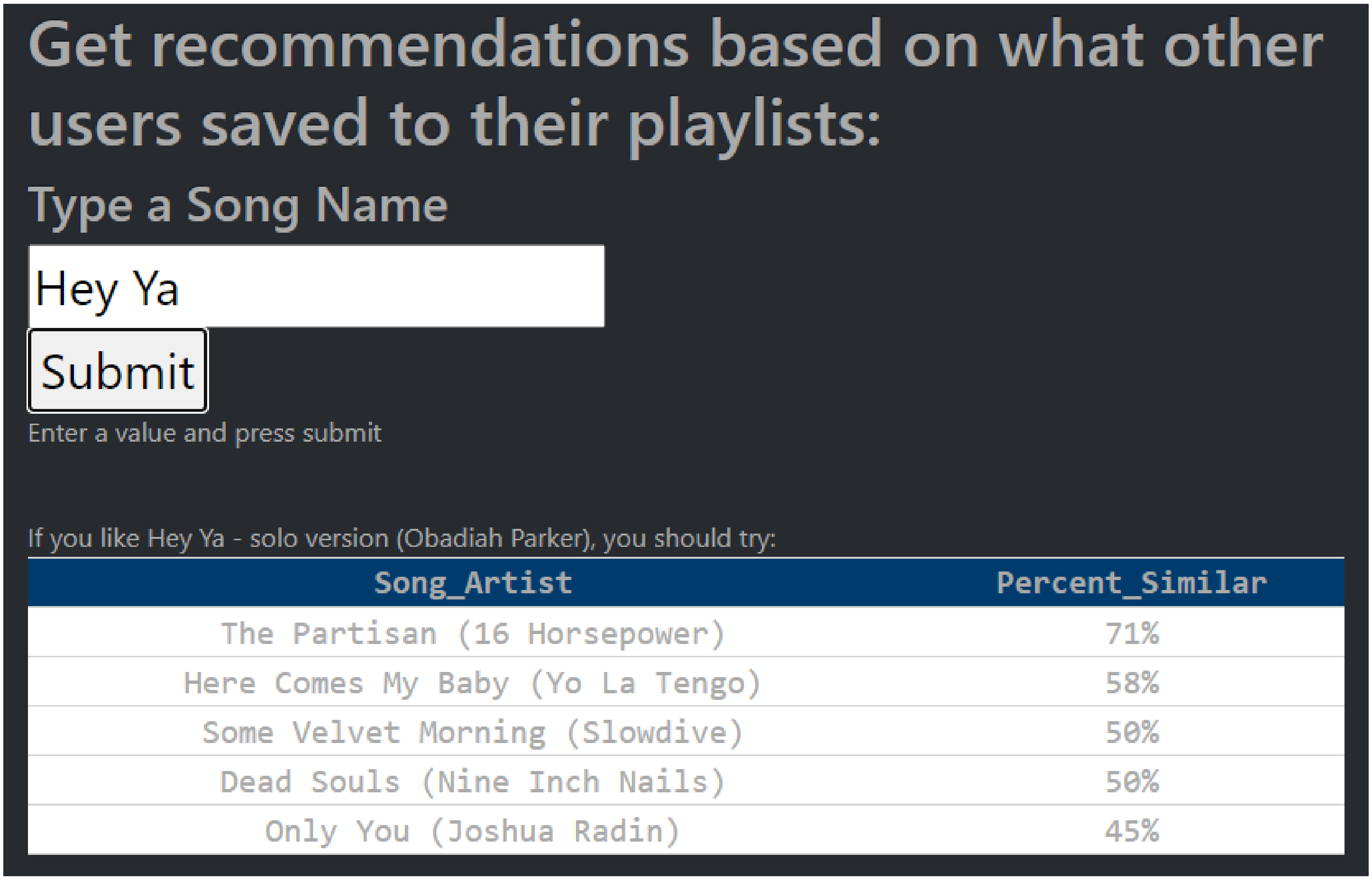
TrackName	ArtistName
Complicated Heart	Michael Learns To Rock
El Globo	Once Tiros
Talking Loud And Clear	Orchestral Manoeuvres In The Dark
When Doves Cry	Ginuwine
Macy's Day Parade	Green Day
Secret	Orchestral Manoeuvres In The Dark
Warning	Green Day
Cadillac Ranch	Nitty Gritty Dirt Band
Keep Tryin'	Groove Theory
Pójd? tylko tam	Jamal

In the example content recommender shown above, user pogopatterson has a playlist “Forgotten Eighties Gems.” The content recommender analyzes the songs in the “Forgotten Eighties Gems” and recommends ten songs it predicts pogopatterson might like when listening to said playlist.

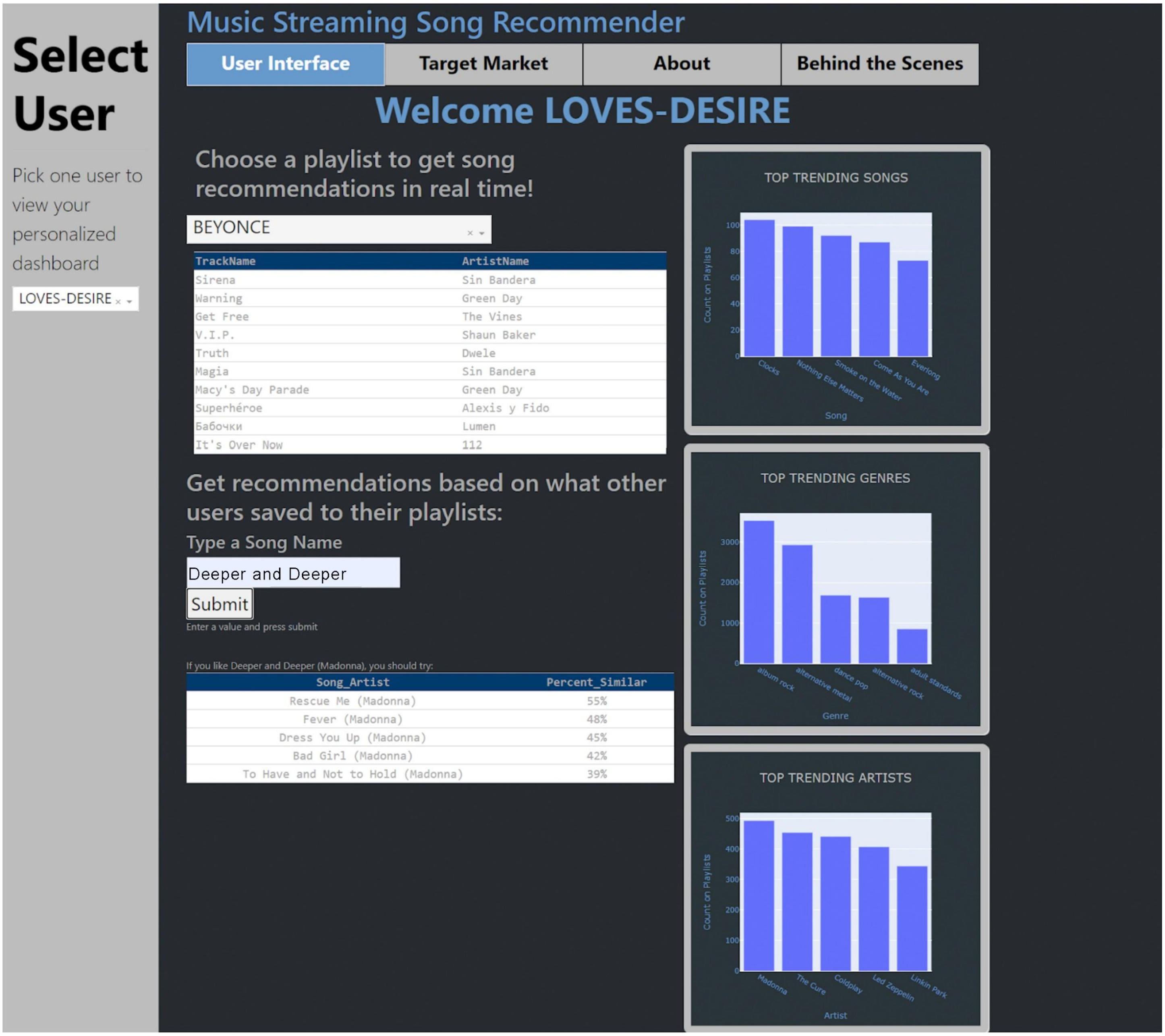
<u>Collaborative Recommender</u>

The collaborative recommender is based on community opinion. It operates under the premise that if a user has a song on a playlist, we assume they like that song. Therefore, if User A’s playlist has songs X, Y, and Z and User B’s playlist has songs X and Y, we assume User B will probably like song Z because other people with similar music tastes like it. In this way, we actively provide users with real time suggestions during their listening session. This “choose your own adventure” environment is engaging for the user and can bring them to new songs that people with similar musical tastes are listening to.

In the example below, the user searched “Hey Ya.” The collaborative recommender searched for that term, found “Hey Ya - solo version (Obadiah Parker)” and then found five songs that commonly appear on playlists that also have “Hey Ya”. The song most similar to “Hey Ya,” meaning the song that most playlists also had was “The Partisan” by 16 Horsepower.



Following is an image of the complete User Interface including non-personalized recommender (right), content recommender (top center), and collaborative recommender (bottom center).



Target Market page

Our Target Market page informs potential investors interested in our recommender models about the target market. It includes some of the visuals presented in the Analysis section of this report to quickly communicate the makeup of the target market.

About page

The About page gives an introduction to team Land'o'datalake and summarizes the layout of the dashboard.

Behind the Scenes page

On the Behind the Scenes page we briefly summarize the metrics of our data and how our recommender machine learning models operate. The Database Metrics section summarizes our database in terms such as total quantities of songs and users. The Machine Learning Models section gives a brief description of the mechanics of our recommender models.

Conclusion

Land'o'datalake's capstone project succeeded in securing data sources concerning characteristics of the music streaming population (United States Census Bureau, 2020), music streaming playlists (Boland, n.d.), and streamed songs and their attributes. (Eren Ay, 2021) We successfully performed ETL on these data sets and were able to answer our exploratory questions. Namely we were able to identify who in the US streams music, as well as attributes of the songs that are streamed such as what is popular and if there are trends in the song characteristics.

As part of this analysis, we uncovered that song recommenders are beneficial for music streaming platforms because they engage users for longer periods of time. (Dee, 2022) With this knowledge we created two unsupervised recommender systems to provide users with additional content. These models are presented to the final user on our dashboard's 'User Interface.'

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