Final Report - SpotRec
A Spotify Recommendation System

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1. Abstract

Spotify users and music lovers in general need a better user experience of receiving recommended songs. We are building a new recommendation system to provide a more customizable (controlled) and sound-based recommendation result. Our system takes a new and unique approach by implementing a combination of collaborative filtering and content-based filtering algorithms on two different datasets. We will then validate the outcome of our system by evaluating with accuracy metrics and comparing to Spotify's existing system's outputs.

2. Background

Most of the existing open-source solutions are flawed because they typically only use one type of approach. Collaborative filtering only approach causes uneven distribution of data (popular items get more data and less popular data get "drowned out") and the content-based filtering only approach tends to ignore user patterns and social trends. Spotify's current recommendation system is fully automated using historical data, which has no consideration for user input, no way to reset user data and start fresh, and no flexibility to "tweak" algorithm if users are unsatisfied with the recs. We combine both approaches to recommend newly released (still unpopular) music based on existing user patterns as well as musically-similar content. Our solution gives the users the option to input their preferences for how the song is sonically in the form of audio feature sliders on the UI.

3. Datasets

To build the recommendation system, we use two separate datasets:

- Spotify Million Playlists Dataset (MPD)
- 160K Track Dataset (Spotify API)

3.1 Datasets Overview

3.1.1 MPD

Spotify Million Playlists Dataset contains one million playlists created between 2010 and 2017 by Spotify users in the U.S. The dataset is 33GB, and contains 1,000 JSON files, each consisting of 1,000 playlists.

Each playlist contains:

- Playlist meta-data: id, name, description, # of albums, # of artists, # of tracks, # of followers, duration, *etc*.
- Track: url, name, artist, album, duration, the position in the playlist, *etc*.

Playlists	Tracks	Albums	Artists
1000000	2262292	571629	287742

3.1.2 The Spotify Dataset

Collected using the Spotify API, this dataset consists of 169909 songs with release dates between 1921 and 2020.

Each song contains:

- Song Description: Song Artist(s), Track ID, Song Name, Genre, Released Date, Released Year, and Song Popularity
- Audio Features: Acousticness, Danceability, Energy, Duration (ms), Instrumentalness, Valence, Tempo, Liveness, Loudness, Speechiness, Key Mode, Song Key, and Explicit Content.

4. Analysis

4.1 Data Cleaning and EDA

4.1.1 EDA for MPD

Firstly, we used pandas to check for any duplicate playlists or null values in the tracks and found that there are none. Besides the tracks, we care about some metadata of the playlist: number of albums, number of artists, number of tracks, and number of followers. These fields help identify the diversity and the popularity of the playlists.

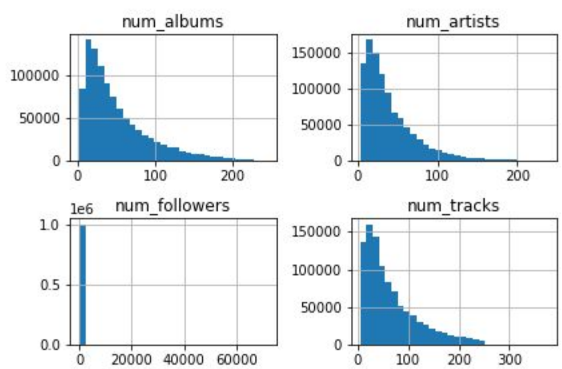


Fig 1: Distributions of Features

From Fig 1, we can see that all these fields have a high peak and a long tail except for the number of followers, suggesting that the dataset is noisy and contains outliers. The following bar plots help us in detecting the quantiles and outliers.

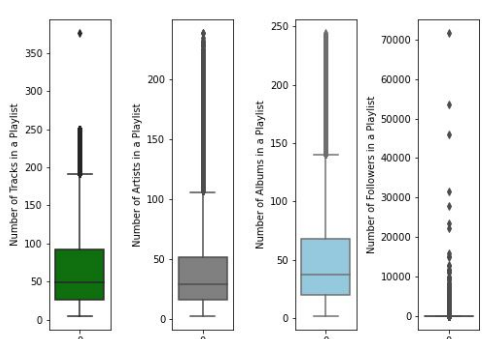


Fig 2: Barplots of Features

Although there are some outliers as shown in the figure above, the "nearest-neighbor" approach for generating recommendations using our system means that the outputs are unaffected by their existence.

Collaborative filtering often suffers from the "cold start" problem. Therefore, it is always good to know popular tracks/artists/albums when users provide little information about their playlists. Here we generated the top 10 frequent tracks/artists/albums showed up in the million playlists:

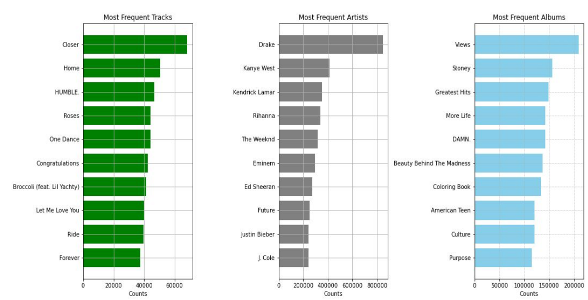


Fig 3: Frequent Items

4.1.2 EDA for Spotify Dataset

Our initial analysis on the 160k tracks and their features shows that there are no missing or null values in the dataset.

In the cases where users wish to see a global recommendation before inputting a song or playlist, we look at the "popularity" feature to recommend songs that are most popular. Here are the top five most popular songs and their popularity scores:

Song	Popularity
Blinding Lights	100
ROCKSTAR (feat. Roddy Ricch)	99
death bed (coffee for your head)	97
THE SCOTTS	96
Toosie Slide	95

We use different similarity metrics that are affected by the feature values' range. So to prepare this data, we normalize many of the features using Sklearn's MinMaxScalar.

For content-based filtering, we mostly care about the audio features and some of the song's information, such as popularity and year released. Three of these features (explicit, mode, and key) are discrete features (binary or integer), while the other 12 are continuous floats.

Histograms of these 15 normalized features are shown below in Figure 4.

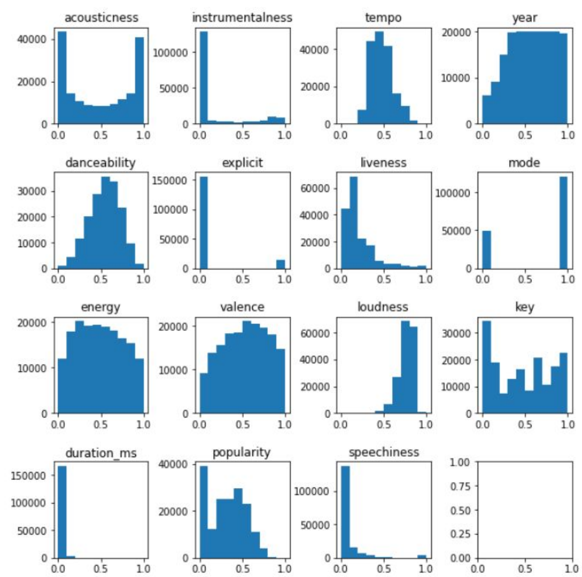


Fig 4: Histogram of Normalized Audio Features

From Fig 4, we see that several fields have skewed distributions, such as duration_ms, because there exist outliers with extreme values while the rest have a much lower average. However, since we are mainly using similarity measures that are based on distance or cosine, the outliers (farther) are not as important to resolve as abnormally high variance in the data. To account for this "bias"/noise, we performed further statistical analysis and calculated the coefficient of variation for each column and the standard error of the mean. The results showed that "explicit" had a much higher coefficient of variance at ~3.25. As a result, we decided to discard the column to remove noise.

5. Recommendation Algorithms

5.1 Collaborative Filtering

Firstly, we processed MPD to a utility matrix to perform user-user collaborative filtering. In this case, the user is the playlist, and the item is the track. The Jaccard similarity is calculated to measure the distance between playlists. However, due to the number of playlists and the number of unique tracks, we used MinHash and Locality Sensitive Hashing to approximate nearest neighbors of playlists. After finding the top-k nearest neighbors, we computed the real Jaccard Similarity to exclude false positives. To increase the recall rate, we would find $3k$ nearest neighbors when we need to obtain k true nearest neighbors. The following plot shows the predicted Jaccard similarity and real value after finding 10 neighbor playlists of a query input on about $\frac{1}{10}$ of the entire dataset.

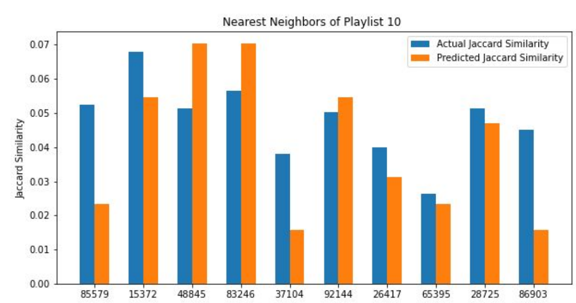


Fig 5: Jaccard Similarity of "Neighbors"

We also build a LSH for item-item CF, but decide not to use it because of the curse of dimensionality.

5.2 Content-based Filtering

In order to find songs that are similar to the user's input song, we initially utilized four similarity metrics: Cosine Similarity, Inner

Product, Pearson Correlation, and Euclidean Distance. Since the milestone, we've also added Spearman Correlation and Manhattan Distance as two additional metrics. For each similarity, we find the top-*k* similar items to the input song, using the 14 features shown above in Figure 4 (excluding "explicit").

For input handling, we want to solve the "cold start problem" mentioned earlier and still output recommendations even if the input does not exist within our dataset. In order to get the audio features for these new songs, we use the python library *Spotipy* to gain access to Spotify's Web API. Our system can take an input of a list of song titles and artists and retrieve the best match from Spotify library with our own client ID.

pid	
617759	['spotify:track:5WMTu6y1QGqVS6EjL4Xf6R',
693227	['spotify:track:5vYA1mW9g2Coh1HUFUSmlb',
906065	['spotify:track:6zL0Cqwxzh2AFxIAS6TExD',
828507	['spotify:track:4g3Ax56IslQkI6XVfYKVc5',
869730	['spotify:track:7mGxOZo8doES0s78zvCdwr',

To output a coalesced ranked list using the separate metrics, we combine the scores of 6 separate metrics into a single final ranking by averaging them. While test running the combined algorithm, we noticed Pearson and Spearman were noticeably slower than other metrics and became the performance bottlenecks. To fix this, we implemented K-Means clustering to narrow down the size of the dataset that we apply the similarity algorithm to by splitting it into 8 clusters (default value) and choosing the one that the input belongs to, according to the model.

In implementing the audio feature sliders that differentiate our project from Spotify's current recommendation system, we want to incorporate a user input to specify custom weights for features. In formulating the code and approach, we found two interpretations:

1. Users choose which columns are more important or less important for them (*e.g. "I want recommendations that, most importantly, have the same level of acousticness as my input song/playlist."*).
2. Users choose which columns they want to change or modify from input (*e.g. "I want recommendations that resemble my input BUT an acoustic version with less speechiness."*).

For the users, we believe that both of these interpretations are meaningful. As a result, we implemented both and decided that it can serve as two modes / options for the users in the intended user interface. For the first, we used the following formula to apply input weights to the similarity metrics:

$$\frac{\sum_i w_i u_i v_i}{\sqrt{\sum_i w_i u_i^2}\sqrt{\sum_i w_i v_i^2}}$$

For the second, we simply translate the input scale of 0-10 on the UI to a value between 0 and 1 and replace the specified column with that value, since our dataset is normalized.

5.3 Combining Both Methods

In order to combine both methods, we assign a weight to the recommendations of the content based system and another weight to the recommendations of the collaborative filtering system. The weights determine how much of an influence each system has on the final output and should sum up to one. We then multiply these weights to the similarity score of each recommendation. The final output will be songs whose scaled similarity score is the highest:

$$\bar{r} = \alpha r_{CF} + (1-\alpha) r_{CON}$$

To determine the weights, we evaluate using R-precision on a custom-created test set and find the best performing distribution.

6. Recommendation Outputs

6.1 Collaborative Filtering

Currently, users can input a list of song names or playlist ID existing in the MP dataset, and the collaborative filtering would return a top-k songs output to the user based on the output of the LSH. Here, k is a hypermeter that the user defines.

```
Playlist 10 have songs:
 ['Fix You', 'Tiny Dancer', 'Chasing Cars', 'Say Something', 'Iris', '100
Years', 'Drops of Jupiter', 'Hallelujah', 'Slow Dancing in a Burning Roo
m', 'Breathe Me', 'Rather Be (feat. Jess Glynne)', 'For the First Time',
'This Dance', 'Find A Way (feat. Emmanuel Jal)', 'Sign of the Times', 'St
op And Stare', "I'll Be", 'Calling All Angels', 'Too Much To Ask', 'This
Town', 'With Or Without You', 'She Will Be Loved - Radio Mix', "You're Be
autiful", 'Fields Of Gold', 'Paper Houses', 'Praying', 'Perfect', 'Shoo
p', 'Push It', 'Whatta Man', 'Jump', 'Bust A Move', "U Can't Touch This",
"It's Tricky", 'Insane in the Brain', 'Brass Monkey', 'Wannabe - Radio Ed
it', 'The Way You Make Me Feel - 2012 Remaster', "Don't Stop 'Til You Get
Enough - Single Version", "Wanna Be Startin' Somethin'", 'Man in the Mirr
or - 2012 Remaster', 'Beat It - Single Version', 'Barbie Girl', 'My Prero
gative', 'Macarena', 'Blue (Da Ba Dee) - Video Edit', 'What Is Love', 'Ne
ver Gonna Give You Up', 'Wake Me up Before You Go-Go', 'Take On Me', "Sta
yin' Alive", 'Dancing Queen', 'Mamma Mia', 'Fernando', 'Oh, Pretty Woma
n', "These Boots Are Made For Walkin'", 'Feeling Good', 'The Tide Is Hig
h', "Don't Stop Believin'", 'I Melt With You', "Friday I'm In Love", 'The
Safety Dance', 'You Spin Me Round (Like a Record)', 'Down Under', 'Afric
a', 'My Sharona', 'Ballroom Blitz', 'Love Shack', 'Whip It', 'Tainted Lov
e', 'Heartbreaker', 'Your Love']


We can recommend the follwing songs:
 ['pick up the phone', 'iSpy (feat. Lil Yachty)', 'Congratulations', 'Bou
nce Back', 'HUMBLE.']
```

6.2 Content-based filtering

Here is a sample of output recommendations using our content-based filtering, without user-specified weights:

```
Input Song: baby
Input Artists: ['justin bieber']
Input Weights: {'acousticness': 1, 'energy': 1, 'popularity': 1}

Recommendations:
1. One More Night
   by ['Maroon 5']
   Similarity score: 0.9413
2. I Just Wanna Shine
   by ['Fitz and The Tantrums']
   Similarity score: 0.9366
3. Everything Black
   by ['Unlike Pluto', 'Mike Taylor']
   Similarity score: 0.9362
4. Leave Em Alone (Layton Greene, Lil Baby feat. City Girls, PnB Rock)
   by ['Quality Control', 'Layton Greene', 'Lil Baby', 'City Girls', 'PnB Rock']
   Similarity score: 0.9355
5. Hide The Wine
   by ['Carly Pearce']
   Similarity score: 0.9345
```

We then can change the weights to change which audio features are taken more into consideration and to produce unique, user controlled recommendation (interpretation 1 is shown):

```
Input Song: baby
Input Artists: ['justin bieber']
Input Weights: {'acousticness': 1, 'energy': 7, 'popularity': 10}

Recommendations:
1. Everything Black
   by ['Unlike Pluto', 'Mike Taylor']
   Similarity score: 0.9458
2. Airplanes (feat. Hayley Williams)
   by ['B.o.B', 'Hayley Williams']
   Similarity score: 0.9455
3. My Way
   by ['Calvin Harris']
   Similarity score: 0.9411
4. Dance with Me (feat. Thomas Rhett & Young Thug)
   by ['Diplo', 'Thomas Rhett', 'Young Thug']
   Similarity score: 0.9399
5. One More Night
   by ['Maroon 5']
   Similarity score: 0.9396
```

6.3 Combined

In terms of a joint system that has a joint dataset and is capable of outputting live, combined recommendations, the size of the MPD dataset (~30GB) made it infeasible to host online, so we kept the datasets separate and proceeded to combined the two outputs manually as described in the following section for evaluating the combined recs (content-based/collaborative).

Here is a sample output with combined:

```
Artist: Taylor Swift
Input Song: ['willow']

Recommendations:
1. None Of Your Concern (feat. Big Sean)
   Similarity score: 0.9839
2. None Of Your Concern
   Similarity score: 0.9796
3. Comfortable
   Similarity score: 0.9792
```

7. Evaluation

7.1 Quantitative Evaluation

7.1.1 Metrics

In this project, we primarily use R-precision as the main metric, along with Precision@10, Precision@25 and Precision@50. R-precision reflects how many correct songs are retrieved within the first n songs (n equals to the length of the real playlist):

$$R - precision = \frac{|G \cap R_{:|G|}|}{|G|}$$

7.1.2 Train - Val Split

Among the 1 million playlists, we take 50k of them as the validation dataset and the rest of them are used to create the training datasets. In the validation playlists, we leave some tracks as input and the rest are hidden ground truth.

We have following scenarios:

- 0 tracks (empty playlists)
- First 10 tracks
- First 25 tracks
- First 50 tracks
- First 100 tracks

7.1.3 Evaluation Results

Prior to combining the two algorithms, we first evaluated the collaborative filtering on the validation dataset.

To do so, we first performed hyperparameter tuning to find out the best number of nearest neighbors for each query in the sets that we created, as described in the previous section.

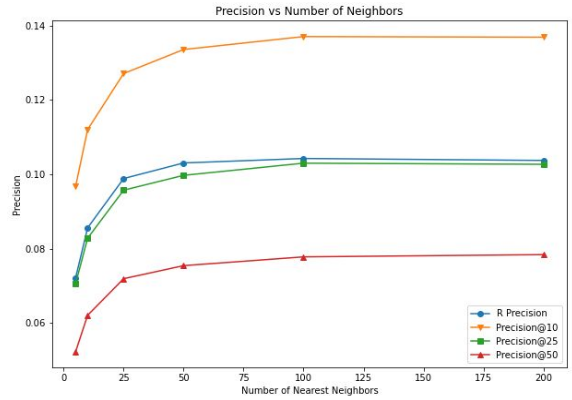


Fig 6: Effect of Number of Nearest Neighbors on Precision

From the figure above, we choose 100 as the number of nearest neighbors. To be specific, for each playlist, we query 300 possible nearest playlists (to decrease false positive) and find 100 nearest playlists among them.

We then evaluate the combined algorithms. The combined predictions are calculated by using the weighted average as previously discussed. We did a grid search to find the weight to combine two algorithms.

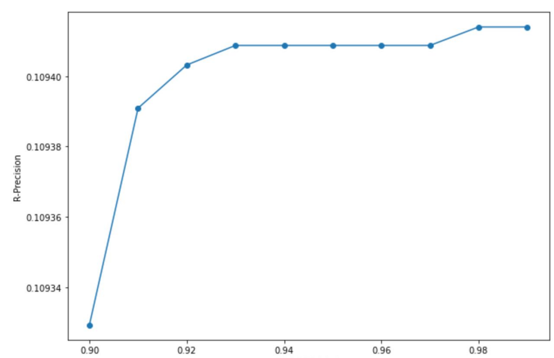
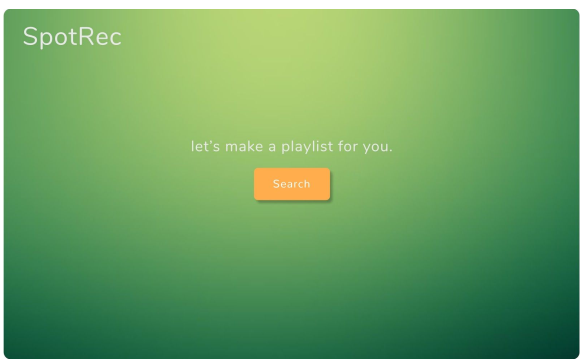


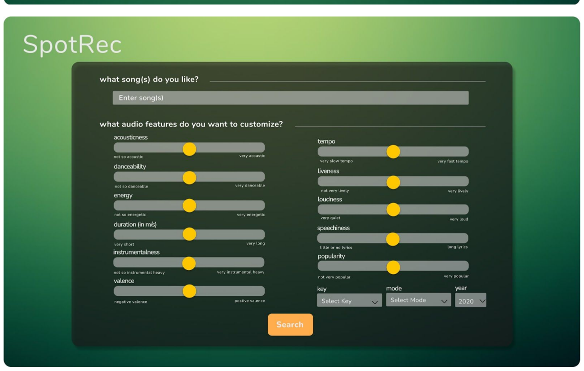
Fig 7: Tradeoff between assigned weights and R-precision

As shown in figure 7, the MPD and Spotify datasets come from different distributions. Thus, adding the content-based filtering will add some random noise and then lower the accuracy. It seems that the best weights to use are those which weigh Collaborative Filtering more heavily.

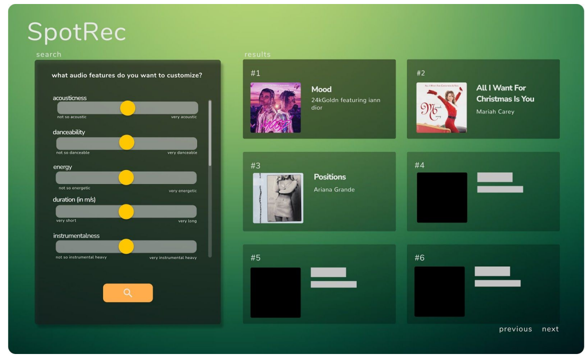
7.2 Qualitative Evaluation

Due to constraints of the MPD dataset’s size (~30GB), we were unable to build and host a fully-functional online platform for the recommendation engine. Thus, to gauge user feedback, we prepared two components that the platform would have consisted of: a user interface and the ranked recommendations. Then, we created a form and planned to survey a number of potential users to ask them to compare the outputs of our system to those of Spotify’s current “Mix Radio. The resulting response would provide us with insight on our project’s realistic value in usage. First, we designed a mockup UI. The inputs are the user's provided song list and user’s preference of different sound feature sliders (shown is of interpretation 2, explained previously). Users can change the sliders to vary the weights on each of the respective audio features.

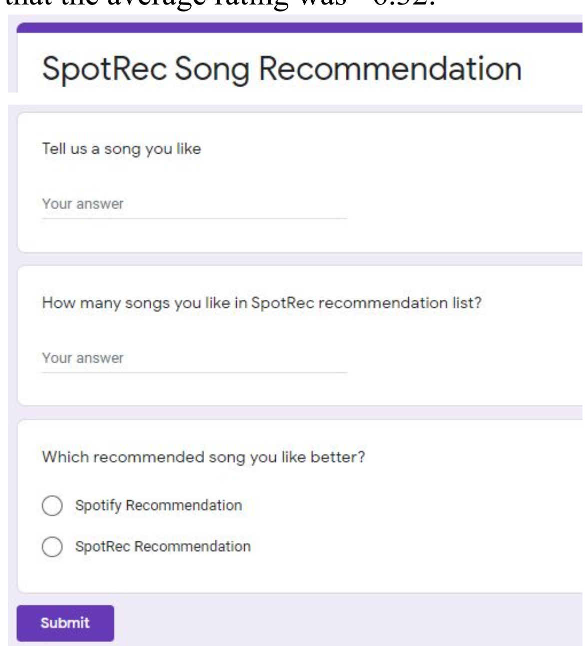




The users will then be shown a list of song recommendations after searching their input song and audio feature weights. The output is a final ranked list of recommended songs.



We then created a survey to collect and analyze user’s feedback (as shown below). Following users seeing our UI to get a visual idea of our project and its unique features, we generated output recs based on their submitted inputs with our system and asked users how many songs they like and if, as a whole, they preferred our recommendation output over Spotify’s. We asked 20 people each (100 total) to test our system and fill out the survey. The result showed about 37% of tested users preferred our recommended song list. We also found that users typically liked two of the three songs we recommend and that the number of songs they liked was on average ~1.78. We also asked them to rate the playlist as a whole (1-10 scale, the higher the better). We found that the average rating was ~6.32.



8. Conclusion

8.1 Insights (Quantitative)

The final weights between Content-Based recommendations and Collaborative-Based recommendations provided us with a unique insight into the nature of recommending songs. What we learned was that audio features may not be a key factor that influences whether users will add the track to a playlist. Just because a song is very similar sounding doesn't mean that it is what users want to listen to. It might indicate that the best recommendations are ones that are similar but yet provide different sound variability. In addition, it also shows us that for song recommendations, the opinions and tastes of different users are very useful in providing recommendations for users.

8.2 Insights (Qualitative)

The data we collected through surveying 100 people, though very small in terms of sample size, was qualitative enough to give us insight into the degree of success of our project. The preference towards our system's outputs was expectedly in the minority at 37%, but was more than we had thought. Furthermore, we gathered that participants "liked" or enjoyed the majority of the songs we outputted to them based on their input. Additionally, many participants voiced their appreciation of the ability or at least having the option to customize or have control of the recommendations to some degrees of personal preference. These results identified further work needed to improve the outputs and reconfirmed our system's unique value.

8.3 Final Results

In order to provide a better recommendation system, we took a unique approach in combining Content Based and Collaborative Based filtering. As a result, we were able to build a new recommendation system that is capable of providing a more user-controlled recommendation system through sliders to manually control audio features (importance and value) and through combining the two approaches.

- Link to Deep Note: (CB + CF) https://deepnote.com/project/5f03631c-d4fa-4763-a457-d0212a7a3bc9
- Link to Git Repo: (CF) https://github.com/sh2439/spotify-recommender

8.4 Future Work

For the final combined recommendation, we take both content based and collaborative filtering separately. From our analysis, we found that using the output of the content based system into the input of the collaborative filtering system is useful especially when the input playlist is small.

In addition, instead of combining predictions after the LSH, we can utilize audio features to reduce the dimension of the playlist dataset to improve the speed and the performance. For example, even though the song is not strictly matched, two playlists may also be similar if their songs have similar audio features. Neither algorithms can deal with the "cold start" problem, and our current solution is to recommend top/trending tracks when the input playlist is empty.

As for building a usable product, we hope to create a website with a complete user-facing UI. Users will be able to input songs and adjust sliders that control the weights of each audio feature.

- Link to Figma: https://www.figma.com/proto/f4p6k5zFU2w5SVfYqiB5QF/dsw-project-(spotrec)?node-id=3%3A2&scaling=min-zoom

9. Contributions

Shuo Han

- preprocessed data for MPD
- coded for collaborative filtering
- quantitative eval: CF & combined
- worked on report & video

Edmond Lu

- preprocessed data for 160k Spotify
- coded for content-based (spotipy)
- quantitative eval: CB & combined
- worked on report & video

Alvin Qu

- preprocessed data for 160k Spotify
- worked on content-based (similarity)
- feature analysis, weights, clustering
- worked on report & video

Jungwon Shin

- preprocessed data for MPD
- helped with collaborative filtering
- qualitative eval: created UI design
- worked on report & video

Wei Wang

- preprocessed data for MPD
- helped with collaborative filtering
- qualitative eval: survey & outputs
- worked on report & video

10. References

1. https://www.kaggle.com/yamaerenay/spotify-dataset-19212020-160k-tracks
2. https://www.aicrowd.com/challenges/spotify-million-playlist-dataset-challenge
3. https://link.springer.com/chapter/10.1007/11891321_4
4. https://spotipy.readthedocs.io/en/2.16.1/