Capstone Project: Music Recommendation Systems

Final Report

Executive Summary

In this project we tested different models and came to the conclusion to propose three different techniques in the form of a hybrid model for song recommendation, attacking and solving with these models the different possible problems that may arise. These three models proposed are the Popularity-Based, the optimized User-User Similarity-Based Collaborative Filtering and the Content Based Recommendations Systems. The models were trained with music ranging from 1969 to 2010, the more variety of music the better, as nowadays people like to listen to music from different eras. Within our models there are certain limitations, for example, the number of features in which the artist-sourced metadata can be enriched with more information, as well as analyzing different types of user interactions such as playlist adds, shares, skips, listening sessions length, etc. Stakeholders are encouraged to consider these variables to improve the performance of the models for more accurate recommendations, as well as the analysis of song lyrics and people's opinions on the Internet to obtain an overall classification of the song.

Problem Summary

Listening to music impacts people in different ways and exerts a powerful influence on them. Music can boost memory, build task endurance, lighten your mood, reduce anxiety and depression, stave off fatigue, improve the response to pain, and help work out more effectively. These are just some of the advantages of listening to music. But why would listening to music be a problem?
With the development and advancement of new technologies, people have become more efficient with the activities they perform on a daily basis due to the fact that they have to perform more activities. This is why they have less and less time to invest in the search and consumption of good content such as music. Many people today perform their activities listening to music, this is why the main objective of this project is **developing a model to recommend songs to the users in a more precise way** within the various music platforms keeping them in long listening sessions while performing their daily activities.

Solution design

A number of recommendations systems models and techniques were built as part of the solution design proposed. Some of the models built include the Rank-Based recommendation system, the Similarity-Based Collaborative Filtering and Matrix Factorization, Cluster Based and Content Based recommendation system. The final proposed solution is a kind of hybrid recommendation system that encompasses three models which are the **Rank-Based recommendation system** which is going to help us with the cold start problem when a new user joins the platform. The **User-User Collaborative Filtering with Hyperparameter Tuning** which is going to help our model to filter data from user interactions to make personalized recommendations for users with similar preferences. Finally, the Content-Based Recommendation System which is going to help us classify items with specific keywords, learning what the user likes, looks up those terms, and then recommends similar things. Also, this model is going to help us on cold start but for new artists that would like to start a music career on the platform.

Table 1 shows the comparison performance between the different models that were built. To measure the performance of each model we take into account the F_1 score and then the RMSE. In the case of the F_1 score the closer to 1, the better and in the RMSE the lower the better, but for this project our priority is the F_1 score. The table shows the best model, which has the highest F_1 score and the second lowest RMSE (0.525 and 1.0521).

Technique	Model	RMSE	F_1 Score
Collaborative Filtering	User-User Baseline Model	1.0878	0.504
	Optimized User-User Model	**1.0521**	**0.525**
	Item-Item Baseline Model	1.0394	0.397
	Optimized Item-Item Model	1.0328	0.506
	Matrix Factorization Baseline Model	1.0252	0.498
	Optimized Matrix Factorization Model	1.0141	0.502

Cluster Based	Cluster Based Baseline Model	1.0487	0.472
	Optimized Cluster Based Model	1.0654	0.465

Table 1: Performance of the different models built in terms of RMSE and F_1 score.

Why do we focus on the F_1 score? The goal of the F1 score is to combine the precision and recall metrics into a single metric. In summary, the F_1 score is the harmonic mean of precision and recall. We want to take into account both precision and recall to be optimized because for business purposes we would like to minimize the losses in the fraction of recommended items that are relevant and the fraction of relevant items that are recommended to the user.

Analysis and Key Insights

To draw accurate conclusions about the selected recommendation models, we tested these models to predict song recommendations and play counts of certain users on certain songs. The Rank-Based Recommendation System model was tested by recommending the top 10 songs of the database with a minimum interaction of 200, ordering the output by the average play count of each song and the interaction with the sum of the play counts. **Table 2** shows the output of a list of recommended songs with the specific configuration.

<table>
<tr><th>Top 10 songs</th><th>200 minimum interactions</th></tr>
<tr><td colspan="2">1. Victoria (LP Version)
2. The Big Gundown
3. Brave The Elements
4. Greece 2000
5. Secrets
6. Transparency
7. Video Killed The Radio Star
8. Sehr kosmisch
9. Luvstruck
10. You're The One</td></tr>
</table>

Table 2: Top 10 recommended songs and 200 min interactions with Rank-Based.

The optimized User-User Collaborative Filtering Model was tested by predicting the play count value with a user that has already listened to the song and the same user, but with a song that he/she has not listened to before. **Table 3** shows the prediction made with the user with user_id = 6958 and a song with song_id = 1671 he/she has listened to. With this model we got an estimated play_count value of 1.96 which is very close to the real value that is 2.

User_id	6958
Song_id	1671
Real value	2
Estimated value	1.96

Table 3: The estimated play_count value of a user that has listened to the song.

Table 4 shows the predicted play_count value of the same user with user_id = 6958, but with a song with song_id = 3232 that the user has not listened to before. We got an estimated play_count value of 1.45. In this case the optimized model would not classify this song as relevant because we have a threshold of 1.5. Hence, this song will not be recommended to this user.

User_id	6958
Song_id	3232
Real value	None
Estimated value	1.45

Table 4: The estimated play_count value of a user that has not listened to the song.

Finally, to test the model we create a function in which we recommend the number of songs we want based on the user of our choice along with the estimated value of our play_count variable (See appendix 1).

For the last model, Content Based recommendation system, we build a function to recommend similar songs based on a song of our choice. In this case we choose the ‘Learn To Fly’ song from Foo Fighters. **Table 5** shows the relations of the recommended songs we got from our model. The song belongs to Alternative/Rock and Pop Rock genres, and the majority of the recommendations lie in one or both of these genres. Also, the band or the artists that are recommended make music of similar genres. So, we imply that the resulting recommendation system works well.

Song	Artist name	Genres
Learn To Fly	**Foo Fighters**	**Alternative Rock / Pop rock**
Everlong	Foo Fighters	Post-grunge / Alternative Rock / Hard Rock
The Pretender	Foo Fighters	Hard Rock
Nothing Better (Album)	The Postal Service	Alternative Indie / Folk / Rock
From Left To Right	Boom Bip	Dance / Electronic
Lifespan Of A Fly	The Bird and the Bee	Jazz / French Indie / Pop / Dance Electronic / Alternative Indie
Under The Gun	The Killers	Alternative Indie / Rock / Dance Electronic
I Need A Dollar	Aloe Blacc	Soul / Pop
Feel The Love	Cut Copy	Vocal / Easy Listening / Pop
All The Pretty Faces	The Killers	Alternative Indie / Rock
Bones	The Killers	Alternative Indie / Rock

Table 5: Top 10 recommended songs based on the ‘Learn To Fly’ song

Recommendations for Implementation

For the implementation of the final design our main objective is to keep users having long listening sessions through the platform by getting good recommendations of what they want to hear. One approach of the implementation is through the creation of playlists for users with specific music for them. These playlist creations can be based on the recent listening behavior of the user inside the platform and can also depend on the day of the week, month, hour of the day, etc, to recommend more accurate songs to the user.

For the purpose of the quality, quantity and variety of music and genres, stakeholders need to consider feeding and updating the databases with music from different periods up to the most recent years, since in this case we have music up to 2010. Also, to consider all kinds of music genres, languages and cultures so that more users from different parts of the world will be satisfied to use the streaming music platform.

The global music market generates over $19 billion in revenue with music streaming accounting for almost half of that revenue in the last years, with 255 million paid users worldwide (see appendix 2). Within the industry of the music streaming platforms, the most popular way this services make money is by the paid premium subscriptions which give many benefits to the users. Also, some platforms offer a freemium model that generates revenue through advertisers. This is why, having a good music recommendation system as platforms like Spotify and Apple Music have, can be attractive to users to start and keep using a specific platform where they feel comfortable and keep doing their daily activities while listening to music.

Although the final solution encompasses three models in order to attack different possible problems, our model is able to obtain accurate recommendations but not at an optimal level. For further analysis that can be done to improve our model performance and making it more accurate in the content based recommendations as written above, we can add more metadata about the artist and the song, as well for the lyrics of the song, opinions given on internet and analyzing the playlist in which users tend to add some type of music. Also, for the user-user collaborative filtering model it can be improved by analyzing different types of interactions between the user and the song, for example, library saves, playlist adds, shares, skips, listening session lengths and many more.

Bibliography

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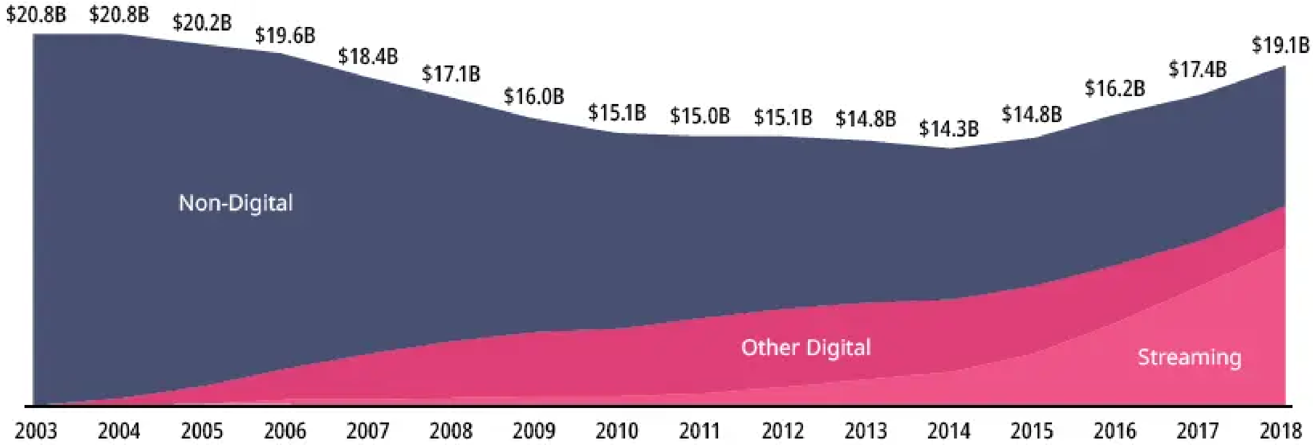
Appendix

Appendix 1: Table of recommended songs to user 6958 using the optimized user-user collaborative filtering model.

song_id	play_freq	predicted_play_count	corrected_play_count
5531	1427	2.55	2.58
317	836	2.52	2.55
4954	338	2.4	2.46
8635	259	2.40	2.46
5943	830	2.39	2.45

Appendix 2: Global Recorded Music Revenues



Source: 2019 Global Music Report