Capstone Project: Music Recommendation System

Final Report

Executive summary

Key takeaways

Recommendation is an important field strongly related to the web business which has been actively researched in the past ten years, when electronic web sites including music streaming platforms started their activity. Recommender systems in music streaming platforms as Spotify learn from the users' history and proactively suggest new selections to users by predicting user preferences. They help to filter millions of songs and make personalized recommendations to users. Hence this project proposes potential recommendation systems for music platform.

The challenge of music recommender system is to create a system that can continually navigate attractive new music which understands the users' preferences. This requires that the music personalized recommender system should effectively reflect the personal preferences. One of the benefits of recommender engines is enabling users to discover new artists, albums or songs and to increase user interaction. In order to accomplish this, we will perform a complete analysis of music recommendation problem, by providing clear highlights about the recommendation techniques used in many systems which implement recommendation engines through diverse mathematical models. The following project consisted of the following main stages:

1. Beginning stage that includes problem identification.
2. Analyzing dataset.
3. Data cleaning, selection and preparation.
4. Modeling recommender systems.
5. Designing, implementing and evaluating the music recommender system application.

Key next steps

So, the suggested model for our problem will be an optimized user-based collaborative filtering method based on F-1 score metric. It further can be improved by considering more possibilities for the hyperparameters in our model. Another potential good model is content-based recommender technique, since it involved more deep information about the songs. It is recommended that the stakeholders consider these into account in building more personalized better recommender systems.

Problem and evolution summary

What problem was being solved?

Music is one of the popular types of today's entertainment in the digital century and can be considered as an integral part of our life. Listening and getting access to different genres and styles of music is not hard in this digital era. Rapid development of technology and internet have made it possible for humanity to access different music streaming platforms easily. The number of songs available may even exceed the listening capacity of single individual. Hence it may be sometimes difficult and time consuming for people to choose the relevant ones from millions of songs. Therefore, it is very crucial to create and manage recommendation systems that will automatically suggest the suitable songs for users. Today we have several audio streaming platforms available for people. One of the most widely used one is Spotify. It includes different features to use for recommender systems such as artist name, release, year, album name and so on. The discussed analysis and models will help to create an efficient way to manage the content that consists of millions of songs and help the customers by providing quality recommendations.

Final proposed solution design

Several recommender systems were applied and investigated as part of the solution design. We have implemented various algorithms to try to build an effective recommender system. We firstly implemented popularity-based model which was quite simple and trivial. Collaborative filtering algorithms which predicted taste of a user by considering similarities between users or (and) songs. We have also implemented cluster-based recommendation technique that helped us to identify groups of users with similar tastes. Lastly, we have implemented content-based models and matrix factorization-based models, based on latent features.

Below is the comparison table of different methods based on F-1 score metric. Each of the methods mentioned above were improved by optimizing hyperparameters in that model technique.

	User-based	Optimized User-based	Item-based	Optimized item-based
F-1 Score (%)	50.4	52.5	39.7	50.6
	SVD method	Optimized SVD	Cluster-based	Optimized cluster-based
F-1 Score (%)	49.8	50.2	47.2	46.5

Why is this a 'valid' solution that is likely to solve the problem?

The final proposed solution is optimized user-based collaborative filtering technique. The key points that were used in identifying the proposed solution are mathematical metrics such as RMSE and F-1 score. Mainly F-1 score played the crucial part since F-1 score can be considered as the average of other metrics like precision and recall. Where precision is the fraction of recommended song that are relevant in top 10 predictions and recall is the fraction of relevant songs that are recommended to the user in top 10 predictions. Generally, collaborative filtering method has a strong predictive power among recommendation systems. It does not require any song information, rather considers user and item preferences. People usually tend to get the recommendations from someone that share similar tastes. So, user-based collaborative filtering engine would be suitable for our problem.

Our proposed solution design would impact the problem or business itself to increase user interaction and the number of play counts of songs as well as number of songs that the user may consider.

Recommendations for Implementation

What are some key recommendations to implement the solution?

From our experimentation, we have derived several conclusions. The main insight that we discovered is the fact that the model metrics for our results tended to be low, which attributes mainly to the lack of useful features and the fact that our program only recommended constant number of songs for a given user. One of the limitations might be the fact that it is applicable for only short period of time. However, the streaming platform will be adding more songs every day, there is a need to update the system to keep up with changes.

What are the key actions for stakeholders?

For the purpose of creating successful music recommendation engines stakeholders need to consider demographic and personality factors of customers. These factors may include the similarity and diversity of the songs in terms of the theme, artists, mood and genre. Also, some features as age, gender and economic background may have an influence in user's music preference. Although these variables and features were not reflected in our dataset, it might be crucial to include in the future research as they may provide more insights and improved-personalized engines.

What is the expected benefit and/or costs?

The expected benefits of the solution are

- Engaging more users

  User become more engaged when personalized music recommendations are made to them.

- Improving user's experience

  It allows users to be introduced to new songs, artists and be able to acquire completely different taste.

The expected costs of the solution are

- Significant investments required

  It is important to note that good recommendation systems will require a big investment in terms of finance and time as well. It may need several stages until the final release.

- Too many choices

  As was mentioned earlier recommendation engines can be based on different algorithms. Each of the methods will provide different recommendations for customers. However, choosing which of them would be the best for the business is very subtle and crucial challenge. Evaluating each of the methods' pros and cons can be time consuming as well.

What are the key risks and challenges?

- Lack of song history

A lack of song history is a difficult problem for most of our algorithms. In that case it can be solved by recommending a subset of the most popular songs. This scenario also leads to another problem, the near-cold-start problem. If the user has a very small song history, our algorithms may not return an accurate selection of recommended songs.

- Inability to capture changes in user behavior

  Consumers do not stand still and they are constantly behaving and evolving. Staying on top of these changes is a another challenge to consider. A good recommendation engine should be able to identify changes in users' preferences and behavior, and constantly auto generate features and data in real time in order to provide relevant recommendations.

- Issue of "synonyms"

  Our proposed solution collaborative filtering cannot handle fresh songs. They are unable to identify similar items labeled or named differently. Collaborative filtering is unable to discover the latent association between synonyms, so these songs will be treated differently.

What further analysis needs to be done or what other associated problems need to be solved?

There are many different approaches to this problem and we needed to know some algorithms in detail and especially the common models that we have examined in this project. We have faced a lot of problem in dealing with the huge dataset, exploring it and managing it to be able to use it for the project. However, in terms of research, we still have a lot to do to make our models a better. Music recommender system is such a wide, open and complicated field that we can take some initiatives and do a lot more tests in the future. We also have to realize that building a recommender system is not a trivial task. First, large scale dataset makes it difficult in many aspects. Secondly, the data includes huge information and it is difficult to extract relevant features for the song during the exploration. Third, technically speaking, processing such a huge dataset is memory and CPU expensive. In this case, content-based model would be a good option if we would have enough memory and to use the whole data. All these difficulties due to the data and the system make recommendation engines more challenging and also more attractive at the same time.

Even though optimized user-based method had the highest F-1 score among all methods. The value for F-1 score is considered as not good, so model performance is not well. The huge lack of information lead to the bad performance of the methods. We also discussed some of the potential reasons for that and now we will present possible recommendations to overcome those challenges and get more improved models.

- Combining different methods and learning the weights of each method according to the dataset.
- Developing more recommendation algorithms based on different data with assuming more features such as how the user is feeling, social factors and etc.
- Considering user needs comprehensively.
- Automatically extracting the music features by using processing technologies.
- Making necessary adjustments to existent models to achieve personalized recommendations for the needs of different audiences.

In conclusion, the project has attained its goal and can be used to provide more practical significance and great value for the future works.