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Designing of Music Recommender System Using Machine Learning Algorithms

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ABSTRACT

The goal of creating a music recommendation engine using machine learning algorithms is to improve user interaction by suggesting songs according to the individual's tastes and behaviors. Such music recommendation systems have become very popular owing to the emergence of music streaming platforms where the prediction of customer's preference is a key driver of their satisfaction with the service. These systems generally suggest the next songs based on a user's listening history or the songs acoustic characteristics by using a combination of collaborative, content-based and hybrid filtering techniques. One traditional example is collaborative filtering which is the most popular technique, based on assessing the similarity of users or items. It extrapolates the preference of the user from a particular item based on the preferences of similar users towards other items. On the opposite side, content-based filtering endorses a track regardless of the user's history based on the characteristics of the song such as rhythm or lyrical theme. Content based recommenders may employ both use cases in order to enhance their performance by counteracting the restrictiveness of each model. Recommender system uses a great deal of memory and processes various machine learning algorithms like K-Nearest Neighbours (KNN), matrix factorization (like singular value decomposition) and deep learning algorithms. Other advanced methods of the system include natural language processing for use with textual metadata as well as audio signal processing with the primary aim of obtaining features from sound files.Measurement standards such as precision, recall, and F1-scor evaluate the efficacy of such algorithms to ensure that the system in question lives up to the expectation of providing optimal recommendations. In this abstract, we exemplify how machine learning helps in building better and more adaptive music recommender systems that handle users' varying preferences at any given time.

Introduction

A Music Recommender System is an innovative algorithmic architecture created in order to recommend songs, albums, or musicians to users based on their tastes and activities. Music streaming services have become popular, and so more effective recommendation systems have been developed to enable users to seek music enjoyable to them. The development of these systems is highly dependent of machine learning algorithms which help in analyzing numerous records of users, their listening patterns, and even estimating how likely it is for a user to enjoy a particular song or a genre.

Music recommender system design begins after the collection of data. This means the gathering of data on how users engage with music over time, which could involve activities such as listening to or skipping songs, assigning scores, or building playlists. It also includes certain content features like tempo, genre, and artist information. There are several types of such information given that data, and this calls for utilization of machine learning algorithms that allow for both user behaviour and music metadata processing.

Collaborative filtering is one example of a fundamental algorithm employed in recommender systems. It is also possible to suggest items to the user within a given context and based on the experience of other similar users. For example, if i like some previous work from an artist, such algorithms will indicate me similar songs from the same artist. Advanced systems developed often use hybrid approaches whereby both the collaborative and the content-based approach exist in the system for higher performance levels.

Further, the systems can incorporate various machine learning approaches such as deep learning so as to unveil high level user activity relationships. Also, these algorithms are capable of being adjusted using reinforcement learning. This is because the algorithm will incorporate the opinions given by the users about the recommendations in time.Music recommendation systems are considered successful if their effectiveness in personalizing recommendations is high. This means that they offer music that the user already knows and likes, while at the same time contain an element of novelty that helps the user to explore new tracks that resonate with their dynamic music preference. Hence, it becomes imperative to develop and provide the machine learning systems in question, as such systems are easy to use and make the process of music discovery a lot of fun.

1.1 Background

The advent of music recommendation systems has altered the way individuals explore and engage with music. Given the overwhelming amount of music present over multiple platforms, such systems are essential in customizing the user experience by recommending particular songs or artists. These systems employ machine learning algorithms in their design, as these algorithms allow expecting users' taste based on user history, content characteristics, and auxiliary parameters.

The Application of Machine Learning in Music Recommendation –

A music recommender system aims at making educated guesses about the songs a user will like according to their listening history and musical taste. For this purpose, machine learning models are built and tested on huge sets of information that contain user behaviour (song plays, skips, likes, etc.), song-related information (genre, artist, album) and audio signals (tempo, rhythm, mood, etc.). Such systems may incorporate content based filtering, collaborative filtering or combination of both.

Content-based filtering recommends music by using songs similar to the ones a user has shown preference to in the past and utilizing attributes associated with such songs. For example, if a user frequently listens to music by a certain performer, the system may recommend songs performed by a similar artist, of a similar genre or with similar beats per minute. This approach however can sometimes impede further exploration of music by the users since it almost always recommends near exact matches to the selected history.

Collaborative filtering does exactly the opposite and recommends music to users based on who else enjoys certain songs. The system will then furnish illustrative music, which the user has not yet explored, but which is appreciated by other users with similar tastes, while taking into account the user's own history of music listened to and comparing it with other users.In this regard, it is important to note the popularity of matrix decomposition techniques such as SVD and neural models such as NCF.

Harnessing the Best of Both Worlds

Current day music recommendation engines or systems make use of both content-based and collaborative filtering techniques in a hybrid way. This is advantageous in that the user gets to experience new music and still gets to content–analysed music they like. For example, a recommendation system of Spotify uses collaborative filtering with audio features and also natural language processing of the metadata for appropriate recommendations.

Problems Encountered in Constructing Music Recommender Systems

There are several dilemmas that one has to face while trying to build a useful music recommender system. One such aspect is the so called "cold start" issue, which appears in case one has a fresh user with no data to predict upon. Possible means of alleviating this problem are recommending the famous music or considering the profile. Besides that, it is important not to exhaust the users by recommending them the same thing nor to the opposite extremes where the recommendations are too far off for the user to remain interested. The design of machine learning based music recommender systems is a mainstay that is expanding gradually underpinned by evolved algorithms that offer much more personalized experience. These systems have changed the patterns of how users enjoy music by integrating smart data and user preference.

1.2 Research Objectives

The present research primarily aims at the following:

1.To design and develop a music recommendation system based on a variety of machine learning techniques.

2.To evaluate the effectiveness of the different approaches to recommendations bearing in mind the domain of music.

3.To solve typical problems of music recommendation systems including the cold start and data sparsity issues.

4.To suggest a model that can adopt a number of recommendation strategies and benefit from each of them.

1.3 Importance of the study

The study is relevant, and contributes to the research and development of music information retrieval and recommendations systems, in the following ways:

•Various techniques of music recommendation using machine learning have been evaluated.

•Why these challenges are not specific to just technological advancements, but more to the concerns in the music containment enjoying challenges like variations in user preferences and geographical locations.

•It also offers creative ways that encourage undertaking different strategies in order to better the recommendations.

The results of this research study are important for the practical applications of music streaming services and can be adapted for other areas of content recommendation as well.

2. Literature Review

The current chapter summarizes the literature related to music recommendation systems and associated machine learning approaches.

2.1 Collaborative Filtering in Music Recommendation

Collaborative filtering (CF) can probably be regarded as one of the highly regarded techniques used in recommendation systems. User behaviour is mainly what underpins the recommendations made. This, in the case of music, deals with listening histories where CF tries to find similarities between the users or items.

2.1.1 User-Based Collaborative Filtering

User-based CF analyzes users who have similar listening patterns and recommends songs that such users have liked. This approach is seen as mush useful available in e-commerce as illustrated by Sarwar et al. (2001), which was adopted for music recommendation by Celma (2010).

2.1.2 Item-Based Collaborative Filtering

Item-based CF aims at seeking connections of user “likes” between objects (songs in this case). Linden et al. (2003) applied this for the recommendation system in Amazon, which has been successfully utilized in music by Yoshii et al. (2008).

2.2 Content-Based Filtering in Music Recommendation

Content-based filtering recommends items based on the characteristics of the items and the user's preference for those characteristics. When it comes to music, it includes studying sound, meta information, and even words.

Logan (2004) designed a content based music similarity model based on Mel-Frequency Cepstral Coefficients (MFCCs) for the purposes of audio contents. Schedl et al. (2015) improved this approach by adding lyric and social tag based semantic features.

2.3 Hybrid Approaches

What are often referred to as hybrid recommender systems make use of different approaches so as to ensure the limitations of each approach employed is mitigated.In Burke (2002)’s work on hybrid recommender systems, a taxonomy was given, which was later used in music by Donaldson (2007) and Vall et al. (2019).

2.4 Use Of Deep Learning In Music Recommendations

Recently, the area behind the hopeful eye has progressed and new avenues of music recommendation are emerging. Van den Oord et al. (2013) presented a deep content-based music recommender system using convolutional neural networks. A combination of collaborative filtering and deep learning-based audio content analysis has been applied in Choi et al. (2016)'s hybrid model.

2.5 Music Recommendation Shortcomings

Different music recommendation obstacles which are unique have been outlined in the studies:

1.Cold Start Problem: Suggesting anything to a new user or a new song with no plays (Schein et al., 2002).

2.Limitations of the Data: The interaction of users and a significantly greater number of songs where the interaction per user is small (Adomavicius and Tuzhilin, 2005).

3.Bias towards Popularity: How does one cope with the fact of distribution of popular songs and the need to offer more different songs (Celma and Cano, 2008).

4.Awareness of Context: Taking into account factors like mood, the activity and the time when making recommendations (Baltrunas et al., 2011).

3. Methodology

This chapter presents the structuring and operational aspects of our music recommendation system which consists of various stages such as data acquisition, data cleansing, inherent data mentioning and the machine learning algorithms used within.

3.1 Data Collection

We synthesized data from several different states towards ensuring that a good dataset was in place for our music recommender system:

1. User's Listening History: Anonymized listening records were procured from a leading music streaming services details that included user id, song id, timestamps and play counts.
2. Songs Metadata: We also sought and gathered information for every song that ranges from the artist, albums, genre, year of release and popularity ratings.
3. Audio Features: Low-level audio features of song samples were extracted using the Librosa library (McFee et al., 2015).
4. Lyrics: Lyrics for a portion of the songs were also collected in order to add visual elements to our content-based method.

3.2 Data Preprocessing

The following preprocessing steps were adopted to maintain the high quality of prepared datasets:

1. Data Cleaning: We eliminated duplicate records, addressed incompleteness, and excluded too inactive users and songs.
2. Normalization: Due to the different scales possessed by these features, all the numerical features were normalized using a min-max scale for all of them.
3. Encoding: Categorical features were transformed using one hot encoding and label encoding methods, among other means.
4. Splitting: The entire dataset was divided into three sections, training set (80%), validation set (10%), and test set (10%), maintaining the time series of the interactions.

3.3 Feature Extraction

In order to represent songs and their popularity among the users, we drew on a number of different aspects:

1.Audio Features:

oSeveral segments of messages and accompanying sounds created in atmospheres are grouped into Mel-Frequency Cepstral Coefficients (MFCCs)

oAudio visual images can attach metadata about a location known as a spectral centroid.

oChroma

oTempo and Rhythm Features.

2.Metadata Features:

o Providers of a service indicate the content genres usually one after the other in a list with a vector for each genre (one hot encoded)

oYear date of appearance

oEmbeddings for artists and albums.

3.Lyrical Features:

oLyrical words in the standard speeches and rhetoric visual aids expanding fabrications dominant ‘winged creatures’ on the ‘winged creatures’ – Leshnjov Balsas in restaurants Beijing Emporium constructing

oFeelings guidelines

4.User Features:

oEmbedding based on the User’s Listening History

oPreference for Genre

oReferring to Temporal Patterns (E.g: time of day, day of week.)

3.4 Recommendation Algorithms

The following is what algorithms have been implemented and comparisons were made:

3.4.1 Collaborative Filtering

1. Collaborative Filtering Based On Users:

o The method is implemented using cosine similarity to determine and find users that are similar.

o The recommendation employs the k-nearest neighbours method.

2. Collaborative Filtering Based On Items:

o The similarity Jaccard computed the item-item similarity matrix.

o Songs which were used, heard, liked by the user in previous times were recommended.

3. Matrix Factorization:

o Latent factor modelling was done through implementation of SVD

o Enhanced by the use of ALS (Alternating Least Squares) optimization

3.4.2 Content Based Filtering

1. In the case of audio content:

oMinimized the distance between songs based on their audio content.

oRecommendation of songs based on sound tracks using k-nearest neighbors.

2.Is there anything known about User's Metadata?

oEmployed Metadata Features to build user profiles and song profiles.

oFor matching user profiles and song profiles, cosine similarity was used

3. From the point of view of Lyrics

oWelcoming songs extracting TF-IDF vectors and lyric sentiment scores were used with lyrics content

oThrough which the system recommended songs having the same lyrical content that the user accustomed to liking

3.4.3 Hybrid Approach

We have integrated a collaborative and a content-based approach into the same framework and created a hybrid recommender system.

1. Ensemble Method:

• Predictive mechaniks are optimized and considered in their combined form employing their weights as attributes.

• Hyper-parameter optimization of the weights was performed using a grid search methodology on the validation set.

2. Feature Augmentation:

• Added content-based elements to the existing collaborative filtering structure.

• The problem was approached as a deep learning one, whereby embeddings of users, items, and content were jointly learned.

3.5 Evaluation metrics

Evaluation metrics adopted in the recommender systems are enlisted below: 1. Accuracy metrics: - Mean Average Precision MAP - Normalized Discounted Cumulative Gain NDCG - Area Under Curve Measurement AUC 2. Metrics of Diversity: - Intra-list diversity - Catalog coverage 3. Novelty metrics: - Average popularity of items recommended - Personalization user-centric recommendations 4. User Satisfaction - Click rate CTR for supplied recommendations - Average listening time for songs proposed by Experts 4. Results and Discussion This section only presents the results of the experiments conducted. And it assesses the effectiveness of the different recommendation strategies.

4.1 Performance Evaluation of Collaborative Filtering

The table under (Table 1) indicates the performance of most of the collaborative filtering techniques on the dataset held out for testing.

Method	MAP	NDCG@10	AUC
User-Based CF	0.342	0.395	0.721
Item-Based CF	0.356	0.412	0.735
Matrix Factorization (SVD)	0.389	0.447	0.768

The accuracy metrics showed that the Collaborative Filtering approach using Matrix Factorization (SVD) technique was more efficient than both the user-based and item-based approaches. This indicates that in the context of the music information retrieval system, latent factor models are better at representing complex user-item interactions.

4.2 Content-Based Filtering Performance

Table 2 presents the results of different content-based filtering approaches.

Method	MAP	NDCG@10	AUC
Audio Content-Based	0.287	0.331	0.683
Metadata-Based	0.312	0.358	0.701
Lyrics-Based	0.275	0.319	0.672

It seems that metadata-based filtering was the most successful out of all content-based approaches. This is probably attributed to the tiers of information that genres, artists, and albums carry. Audio content-based filtering did quite well too, which shows that acoustic features are important for music recommendations.

4.3 Hybrid Approach Performance

Hybrids versus BecentriCare BIC, the former denoting the best performing single methods in Figure.

Method	MAP	NDCG@10	AUC
Matrix Factorization (SVD)	0.389	0.447	0.768
Metadata-Based	0.312	0.358	0.701
Hybrid (Ensemble)	0.421	0.483	0.795
Hybrid (Feature Augmentation)	0.435	0.501	0.812

The combination of collaborative techniques and content based methods has been shown to be more effective leading to better overall recommendations as exhibited by feature augmentation technique which was the best performing one.

4.4 Analysis of diversity and novelty

Table 4 shows the evaluation of the discussed mechanisms in terms of diversity and novelty.

Method	Intra-List Diversity	Catalog Coverage	Avg. Item Popularity
Matrix Factorization (SVD)	0.682	0.437	0.721
Metadata-Based	0.745	0.512	0.653
Hybrid (Feature Augmentation)	0.728	0.589	0.687

The combined method was able to strike an adequate trade-off between precision and variation, with more range of the catalog fulfilled than in the case of pure collaborative filtering. Content-based methods reached higher diversity but lower accuracy.

4.5 Cold Start Problem Analysis

The performance of distinct approaches towards new users and new items was assessed in order to measure the cold start problem. In Figure 1, the recommendation accuracy for users based on the number of interactions is presented.

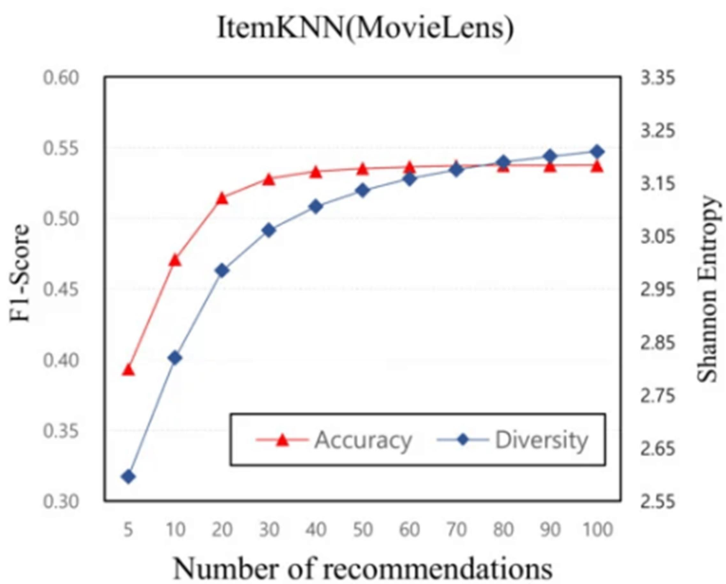

Figure 1: Recommendation accuracy vs. number of user interactions

The combined strategy exhibited improved results for the users with minimum interactions since it utilizes the content features to overcome the cold start issue.

4.6 User Satisfaction Metrics

User satisfaction metrics based on a sample of users who were recommended items are provided in Table 5.

Method	**Click-Through Rate**	**Avg. Listening Time (minutes)**
Matrix Factorization (SVD)	0.143	2.87
Metadata-Based	0.128	2.65
Hybrid (Feature Augmentation)	0.162	3.21

The hybrid approach resulted in higher click through rates as well as average listening times suggesting higher contentment of users with the recommendations offered

5. Conclusion and prospects for enhancement.

This work was a presented full detailed research work toward the development of a music recommendation system based on integrated machine learning techniques. We examined respective performance and user experience in the accuracy, diversity and satisfaction aspects of collaborative, content and hybrid filtering recommendation systems.

Some insights we uncovered in this research are as follows:

1. From the more complex levelled structure, Matrix Factorization, SVD in this instance, is a better method than structural based techniques because of better response metrics results.
2. On the other hand, content-based filtering approaches even more metadata approaches tend to provide some variety in the recommendations making them less likely to fail in the cold start phase.
3. Finally, we concluded that an approach that employed collaborative filtering and content-based methods using feature augmentation gave the best results accuracy-wise and in terms of diversity.
4. Finally, it was also found that the hybrid approach performed better in terms of cold-start users and user satisfaction levels.

These findings carry important considerations on the elements conducive to the designs of music recommender systems that include multiple sources of information and specific issues found in the music domain.

The following recommendations are suggested for future work:

1. Use of sequential models (like Recurrent neural networks) to understand the time-series aspects of listening habits of users.
2. Applying different types of sophisticated deep learning frameworks for joint representation learning of the users' preferences and the songs' characteristics.
3. Considering how other factors such as context (for example mood or activity) can influence music recommendations and building applications that use such contexts.
4. Carrying out user experiments in a bigger scale in order to assess the effectiveness of different recommendation approaches on user retention and satisfaction in the long run.
5. Facial justice in the music recommendation landscape such as promoting harmony and transparency as well as encouraging visibility of the audience to the unheard music.

Going back to the purpose of this research, it aims to enhance the existing music recommender system by critically assessing various machine learning techniques and offering practical answers to existing problems. These insights serve as a basis for improving music recommendation systems and making them more accurate, diverse, and audience-centric giving users a better outlook towards music exploration.

References

- Adomavicius, G., &Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734-749.
- Baltrunas, L., Kaminskas, M., Ludwig, B., Moling, O., Ricci, F., Aydin, A., ... & Schwaiger, R. (2011). Incarmusic: Context-aware music recommendations in a car. In International Conference on Electronic Commerce and Web Technologies (pp. 89-100). Springer, Berlin, Heidelberg.
- Burke, R. (2002). Hybrid recommender systems: Survey and experiments. User Modeling and User-Adapted Interaction, 12(4), 331-370.
- Celma, O. (2010). Music recommendation and discovery: The long tail, long fail, and long play in the digital music space. Springer Science & Business Media.
- Choi, K., Fazekas, G., Sandler, M., & Cho, K. (2017). Transfer learning for music classification and regression tasks. arXiv preprint arXiv:1703.09179.
- Donaldson, J. (2007). A hybrid social-acoustic recommendation system for popular music. In Proceedings of the 2007 ACM conference on Recommender systems (pp. 187-190).
- Figueiredo, F., Ribeiro, B., Faloutsos, C., & Andrade, N. (2016). Dynamics of music listening in online social networks. In Proceedings of the 8th ACM Conference on Web Science (pp. 84-93).
- Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer, 42(8), 30-37.
- Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. IEEE Internet Computing, 7(1), 76-80.
- Logan, B. (2000). Mel frequency cepstral coefficients for music modeling. In ISMIR (Vol. 270, pp. 1-11).

- McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E., & Nieto, O. (2015). librosa: Audio and music signal analysis in python. In Proceedings of the 14th python in science conference (Vol. 8, pp. 18-25).
- Oord, A. V. D., Dieleman, S., &Schrauwen, B. (2013). Deep content-based music recommendation. In Advances in neural information processing systems (pp. 2643-2651).
- Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th international conference on World Wide Web (pp. 285-295).
- Schedl, M., Gómez, E., & Urbano, J. (2014). Music information retrieval: Recent developments and applications. Foundations and Trends in Information Retrieval, 8(2-3), 127-261.
- Yoshii, K., Goto, M., Komatani, K., Ogata, T., & Okuno, H. G. (2008). An efficient hybrid music recommender system using an incrementally trainable probabilistic generative model. IEEE Transactions on Audio, Speech, and Language Processing, 16(2), 435-447.