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SONG RECOMMENDATIONS SYSTEM

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Abstract: A music recommendation system was developed that can learn users' preferences. The system can classify a wide range of stored music using automatic music content analyses. Users can opt for music according to their mood, using such words as "bright", "exciting", "quiet", and "sad". Building a music recommendation system is one of the information retrieval tasks. This research is devoted to a content-based music recommender system. The main peculiarity of our work is that the developed recommender system is based on the acoustic similarity of musical compositions. Two approaches to building a content-based music recommender system are considered in this paper. The first is a quite common approach that uses acoustic features analysis. The second approach includes deep learning and computer vision methods applications aimed at improving the results of the recommender system.

Keywords: Numpy, Pandas, Cosine Similarity, Count Vectorizer

I. INTRODUCTION

With the explosion of networks in the past decades, the internet has become the major source of retrieving multimedia information such as video, books, and music, etc. People have considered that music is an important aspect of their lives and they listen to music, an activity they engage infrequently. People sometimes feel it is difficult to choose from millions of songs. With commercial music streaming services which can be accessed from mobile devices, the availability of digital music currently is abundant compared to the previous era. Music service providers needan efficient way to manage songs and help their customers to discover music by giving quality recommendations.

A music recommender system is a system that learns from the user's past listening history and recommends songs which they would probably like to hear in the future. By using a music recommender system, the music provider can predict and then offer the appropriate songs to their users based on the characteristics of the music that has been heard previously. Sorting out all this digital music is very time-consuming and causes information fatigue. Therefore, it is very useful to develop a music recommender system that can search in the music libraries automatically and suggest suitable songs to users. Thus, there is a strong need for a good recommendation system.

Recommendation Systems are everywhere and pretty standard all over the web. Currently, there are many music streaming services, like Pandora, Spotify, etc., which are working on building high-precision commercial music recommendation systems. Amazon, Netflix, and many such companies are using Recommendation Systems. Music recommendation is a very difficult problem as we have to structure music in a way that we recommend the favorite songs to users which is never a definite prediction. In this project, we have designed, implemented, and analyzed a song recommendation system. The one we are going to build is pretty common to what Spotify or Youtube Music uses but much more straightforward

II. METHODOLOGY

Deep learning is developed with the research on the cognitive and thinking process of the human brain nervous system in biology. Because of the strong nonlinear fitting ability of deep neural networks and good results in many fields, more and more scholars apply deep learning to the extraction of music audio features. In deep learning, processors are used to replace neurons in the human brain. To build the link between the lower layer of features and the higher layer of things, each layer of processors gets the features extracted by the upper layer of processors and extracts additional features for the next layer of processors.

At present, the recommendation based on deep learning overcomes the obstacles of a traditional linear model, thus significantly improving the recommendation quality. Deep learning can effectively capture the nonlinear relationship between users and items and obtain the vector representation of users or items by vectorization or coding. In the general

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training process, the process of deep learning is usually divided into supervised learning and unsupervised learning. The recommendation engine contains a recommendation algorithm and a recommendation rationale that will construct a link between the user characteristics and the things to be suggested to propose the target items of interest to users based on the established link. The recommendation engine comprehensively calculates the information of the user's education, age, label, and gene description of the item to be recommended and then combines the user's preference for the item: depending on the item itself, it may include the user's rating of the item, the user's click record, etc. and finally form the recommendation result.

The operating systems used will be Windows 7 & above.
The programming language used is Python.
XAMPP server
4GB RAM or higher
100 GB ROM or higher

III. LITERATURE SURVEY

Pasquale Lops, Marco American state Gemmis, and Giovanni Semeraro, 2010 [1] in their paper Content-based Recommender Systems: State of the Art and Trends discusses the most problems associated with the illustration of things, ranging from easy techniques for representing structured information to a lot of complicated techniques returning from {the information|the knowledge|the information} Retrieval analysis space for unstructured data.

This work is split into three components. The primary half presents the essential ideas of content-based recommender systems, a high-level design, and their main blessings and disadvantages. The second half is a review of the state of the art of systems adopted in many application domains by describing each classical and advanced technique for representing things and user profiles. The foremost widely adopted techniques for learning user profiles also are conferred. The last half discusses trends and future analysis which could lead towards the ensuing generation of systems, by describing the role of User Generated Content as how taking under consideration evolving vocabularies, and also the challenge of feeding users with lucky recommendations, that's to mention amazingly fascinating things that they could not have otherwise discovered.

Hybrid Recommender Systems

Robin Burke, in his survey Hybrid Recommender Systems: Survey and Experiments, explains numerous recommendation techniques. These techniques show the complementary benefits and downsides. It compares the assorted techniques and shows that techniques area unit higher supported the analysis metrics. This reality has provided an incentive for analysis in hybrid recommender systems that mix techniques for improved performance. It proposes numerous hybrid approaches which may be accustomed recommendation systems supported the appliance for higher accuracy and results.

IV. PROPOSED SYSTEM

This research focuses on determining the most effective DM technique with the highest precision between the different classification techniques to be used. In addition, finding the effect of the train/test data ratio on the accuracy of the prediction.

The detailed working of the subunits is as follows:

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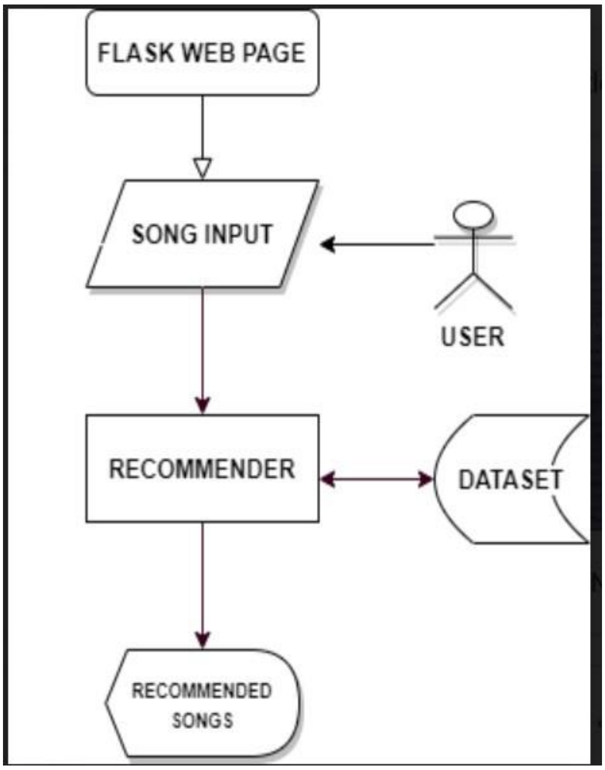

Data collection unit: The real dataset is used for the research. We have taken music data which contains 2000 records and 15 fields, including categorical and numeric features. Each record in the music data set represents single musical information, and each field in the record represents a feature of that.

- Image preprocessing unit: After the process of data collection is finished, the process of preparing the data is performed. It is important to refine this data so that it can be suitable for the models and generate better results. The data of Spotify had various attributes which were not relevant, i.e., was not giving any useful information, like Title, Artist, Top Genre, Energy, BPM, Liveness, etc.; hence these attributes are removed in this phase.

- Feature Selection: Feature selection is one of the main concepts of DM and Machine Learning. Where it is a process of selecting necessary useful variables in a dataset to improve the results of machine learning and make it more accurate, there are a lot of columns in the predictor variable. So, the correlation coefficient is calculated to see which of them are important and this are then used for training methods. From there, we get the top factors that affect performance.

- Test and Train Dataset: Separating data into test datasets and training datasets is an important part of evaluating data mining models as it minimizes the effects of data inconsistency and better understands the characteristics of the model. The test data set contains all the required data for data prediction, and the training data set contains all irrelevant data. We have split the dataset into variable ratios to study the estimation of Prediction.

V. METHODOLOGY, TECHNIQUE, AND ALGORITHM

Most of the music information prediction is carried out in a specific range, and the research of the method is based on the music feature extraction extracted from the music signal itself. During the development of this field, a large number of feature vectors have been explored to better express the musical characteristics of the music itself. The selection and extraction of these features are the basis of music information prediction. In the task of music classification, the model needs to extract the features that reflect the overall characteristics of music, so that it can be better applied in the recommendation task. Therefore, we mainly focus on the task of music classification. Feature extraction is carried out for items in the recommended field, and the feature information extracted by different elements is different. For example, documents, posts, and short messages are mainly divided into words, and the weight of keywords in the whole text is calculated. Music, fitness, and books are the main features of extracting labels and classification.

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Music is a kind of tuned audio. The changing pattern of pitch is called pitch, and different music has different tones. If the same person sings the same phrase, the pitch frequency will alter with varied music, such as the singing environment, emotional state, physical condition, and so on. These contents may be overlooked while recording music data, yet they are a significant factor for individuals when selecting music; hence pitch frequency conveys critical music data. The item we wish to promote is music, and the audio content of music is the most essential component in determining whether or not consumers will like it; thus the processing of audio characteristics is crucial.

VI. CONCLUSION

Music has gradually become an inseparable and important part of people's lives. With the rapid development of the network digital music industry, music recommendation system has become the focus of major music websites. The quality of content recommended by users directly affects the user experience. It can be said that the quality of music recommendation systems is related to the operation of music websites to a certain extent, and designers have paid the research on this aspect more and more attention. Deep learning has achieved great success in many fields, such as computer vision, speech recognition, and natural language processing. Because deep learning can provide end-to-end learning and is good at dealing with complex tasks, academia, and industry have been applying deep learning to more fields. The research value and importance of data recommendation technology and the music recommendation sector are examined in this work. In the realm of data recommendation, it summarises the application and development status of music recommendation technology and deep learning.

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