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Collaborative Filtering based Hybrid Music Recommendation System

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***Abstract*--** Even though people are nowadays listening all types of songs, still algorithms are struggling in many fields. With less historic figures, how does the system know the listeners like a new artist or a new song? And, how do you know which songs to suggest to new users? In this perspective, the proposed research work aims to assess the likelihood that a user will listen to the song repeatedly after the first apparent listening experience begins in the time frame. If the user has a recurring auditory occurrence within a month following the first apparent listening event, its goal is 1 and otherwise 0 identified. The approaches like collaborative filtering, content-based filtering, singular value decomposition (SVD) and factorization machines (FM) are also used. At last, the proposed system is hybridized by using SVD and FM.

Keywords*-- *Collaborative Filtering; Content Based Filtering; Singular Value Decomposition; Factorization Machine; Hybridization.

I. INTRODUCTION

Automated song recommendation gets become more important in current times, as most of the music is now sold and consumed digitally. In recent years, the music industry has increasingly moved toward digital delivery across online music store up and running customer services such as Google Play, Grooveshark, Spotify and iTunes, [1, 2].

Hybrid recommenders combine recommendation procedures to improve the overall accuracy of assessments and reduce specific policy problems. To end this, hybrid recommendations in many applications combine social and content-based recommendations into one of many configurations [3, 4].

II. METHODOLOGY

A. Dataset Exploration

The original dataset contained 7,377,418 observations, where each observation corresponds to the first apparent auditory event for each particular user's song pair [5].

For our training Models, the data is filtered by selecting users with at least 1000 songs and 500 events. 75% of the filtered dataset is trained and tested the remaining 25%. This results in a training set of 869,783 observations and a testing set of 289,928 observations. The metadata of the songs are also examined. The features will be useful in content based and FM model.

B. Collaborative Filtering

Interaction methods recommend music pieces to the user by looking at how the other person has evaluated them. For instance, think there is a discriminating user who loves piece A. But several others love A and B, B will be suggested by the customer. This method is commonly used in e-commerce applications (for example, the iTunes music store and Amazon.com), and has been shown to be successful [5].

Collaborative system is classified into two categories:

1. User Based Collaborative Filtering (UBCF):

Well, UBCF utilizes that reasoning and suggests objects by discovering like consumers to the dynamic consumer (towards whom the suggested music are aimed) [6] shown in figure 1. A particular purpose of it is the consumer-based Nearest Neighbour algorithm.

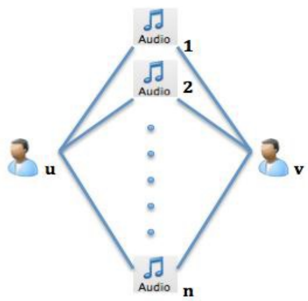

Fig. 1 User based collaborative filtering

2. Item Based Collaborative Filtering (IBCF):

The Item-item collaborative filtering, or item-based collaborative filtering, is a filtering technique that is used for recommendation system and the base being similarity between the items which is calculated using people's ratings of those items [7] shown in figure 2.

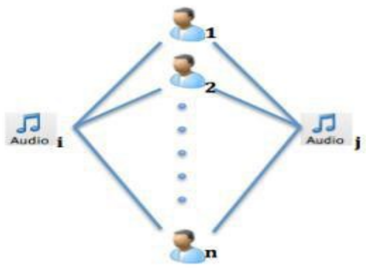

Fig. 2 Example of Item based collaborative filtering

These are basically built on item based and user based collaborative filter models by using the Recommender lab package so as to take this as a baseline for the future models. The Important parameters for the model are:

"User-Based Collaborative Filter Accuracy was: 0.6743".

"Item-Based Collaborative Filter Accuracy was: 0.7073".

C. *Factorization Machines*

First, the factorization machine is explored. At the core, a factorization machine allows us to model feature-rich datasets by including higher order interactions weighted by the inner product of latent vectors [8, 9].

So as an outcome, the important features are estimated even in highly sparse data! Factorization machine consists of the following parameters shown in figure 3 that must be learned (where n is the number of features in dataset and k being the dimensionality of latent features):

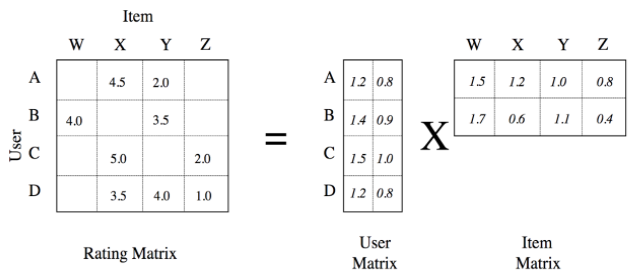

Fig. 3 Example of factorization machine

1. *Tuning Hyper parameters*:

The accuracy has been taken to be number of the targeted value that the model correctly predicts divided by total number of targeted values in the left out data. The error rate being (1 – Accuracy).

The results of our cross-validation parameters tuning are taken into consideration by plotting the mean error rate across the fold as a function of k. The parameter k is chosen along with the lowest average error rate across the three folds, or equivalently the highest average accuracy.

2. *Factorization Machine Model*

- From the above part parameter tuning, it has determined that with k = 25, latent dimensions give us the highest accuracy. Along with that, an initialized standard deviation of 0.1 leads to the quickest error rate convergence.
- So, it is required to set the hyper parameters to these values for the final model. Here, final factorization Machine model is trained and then the same model is used to generate predictions for testing the dataset.
- At the last, the proposed model is evaluated according to the metrics error, accuracy precision, and recall. It has been started by writing one generic evaluation function, which will be used to compare the how the different models are performing. Then the recently made function is called over the output probabilities of FM model.
- After that it is recognized that the accuracy of approx 0.7482 is quite higher than the item-item based filtering (i.e 0.71) and user- user based filtering (0.67). It also indicates the coverage of our model built is precisely good, since not only a targeted value of 1 is predicted for the most famous songs and most addictive or active users. Still, our prediction accuracy can be affected by the popularity of the given song.

D. *Content Based Recommender*

The Content-based techniques suggest musical fragments on the basis of the user's favourites in term of their songs-based features. This projects in very sizable range of singers; i.e., several pieces are being suggested still once they had not been ranked [11, 12].

Content based methods are actually devised to utilize scenario wherein the objects could be explained with the factual sets of features and the working of content-based recommender systemshown below in figure 4.

But, such techniques have important problems regarding the precision of suggestions because possible similarity in their substance is only one of several reasons describing customer inclinations. In supplement, it is hard to add customer favourites with musical substance by utilizing a real databank where the majority of the customers deliver fewer ranking grade to the songs.

Content-based systems are significantly utilized in those circumstances in which a substantial total of characteristic knowledge is actually presented at hand otherwise not. In this case, structured-data is obtained in the form of artists' genres, composer, lyricist, song length and their corresponding language.

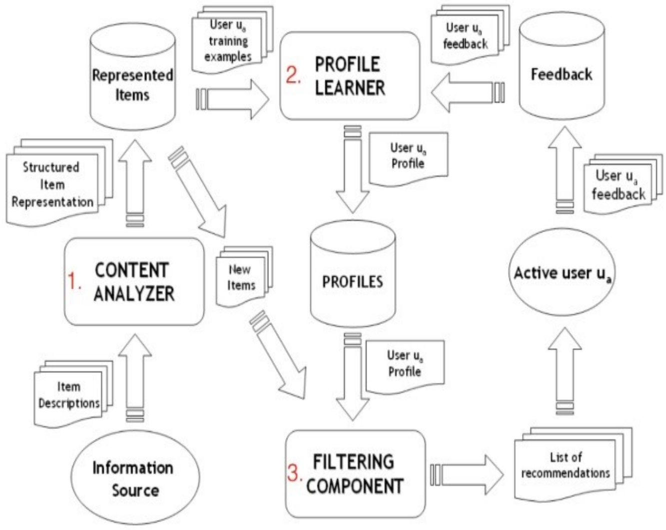

Fig. 4 Content based recommender model

1. Pre-processing And Feature Extraction:

In feature mining stage, the explanations of the several objects are being obtained. However, this is likely make use of any type of interpretation, such as a multidimensional information interpretation, as being the extremely common method.

We are going to generate one hot encoded vector for the items that will be represented in feature space.

2. KNN classification Model:

The nearest neighbour classifier is one of the easiest classification technique, and this can be applied in a fairly clear-cut way. We constructed a model for every user based on his ratings for the items. Content based recommender systems can be taken as a classification problem for each and every user [13].

The in general accuracy for all neighbours which are included in the content based model comes out to be 0.6880569. From here we can bring it to a close that increasing the number of KNN neighbours will increase the accuracy in KNN – content based recommendation system.

We compared the content based model with the collaborative filtering models and saw that this performed better and outperformed the user-based collaborative filtering technique, however, the number of neighbours in the KNN model were actually restricted to 32.

E. Singular Value Decomposition (SVD)

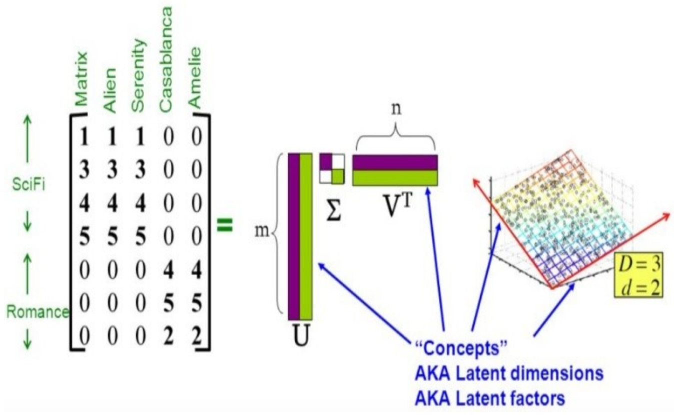

Fig. 5 Singular value decomposition approach

The SVD algorithm is a matrix factorization procedure to reduce the number of unnecessary parameters into the dataset, the working of this model is shown in figure 5. For a large M×N user-item ratings matrix A of rank r, SVD model sort of maps both the users and items to a joint latent factor space of k singular values by decomposing the rating matrix and decreasing its space dimensions from r to k. The latent factor space efforts to describe the rankings by describing the items and the users on issues automatically deduced from the user response.

1. Proposed Model

First of all, we will change the provided data into a M×N ratings matrix with all songs and users so that each element 'r' represents if user u is going to listen to the song 'I' again or not. For a missing user-song pair, we will replace it with NA. We will also replace the identified values in original test data with 'NA', so that we can make our prediction. A little later, we will be comparing model predictions with real values in model evaluation.

Then we divide the matrix in training and testing with a train proportion of 0.8.

Then, we started training our models with the train matrix. For choosing the optimal parameter later, we used 5 distinguished k values.

2. Tuning Parameters:

We tested our SVD model using different number of latent factors (k=5, 8, 10, 20, 40) and also compared their training RMSE for choosing the most favourable one. Naturally, more latent factors will output more accurate results, but we also taken into account both the training and prediction time, which varies considerably with dissimilar k values.

From RSME and the prediction accuracy we have got, we can see that larger value of k will not improve the model notably. Thus, we choose the optimal value of k to be 10.

The final accuracy for SVD approximation with k = 10 is 0.71.

F. *Hybridisation*

Traditional recommendation system methods like content-based, knowledge-based filtering and collaborative filtering, each of them has their unique strong points and weaknesses. As an illustration, collaborative filtering undergoes from cold start problems and sparsity, while content-based approach suffers from narrowness, and also requires lots of description. On the other hand, a hybrid technique be able to utilize a method to get projections someplace the other one fails, following in a stronger recommendation Scheme.

- In proposed work, we took a novel way to ensemble the outputs from Factorization Machines and SVD to design a deep neural network based recommendation System and observed that it increases the accuracy of our predictions.
- The scores from the SVD and Factorization Machines are noted and we treat it as one of a classification problem to obtain the hybrid recommendations for songs.
- We build the hybrid recommender on the testing data part of the original data. We further split the original testing data into new training and testing set to make our model.

1. *Parameter Tuning*

We train our deep learning model on various net sizes and the decay rate to come with the best feature set.

2. *Accuracy*

We judged the obtained accuracy against the factorization machine output and SVD output and saw that there is slight increase into the accuracy for the neural net hybrid recommendation system. We will further discuss our results in the next section.

III. EVALUATION

We built a number of states of the art recommendation systems in this paper, namely Item-Based Collaborative Filtering (IBCF), User based Collaborative Filtering (UBCF), SVD, Factorization Machines, and Content-Based Recommender System.

The following table 1 summarize the accuracies in term of precision of all the models we have built so far.

TABLE 1. Comparison of proposed model with other models

	Model	**Accuracy**
1.	Proposed_Hybrid Model	0.7484048
2.	F.M	0.7482754
3.	Content	0.7112968
4.	SVD	0.7097649
5.	IBCF	0.7072612
6.	UBCF	0.6742836

IV. CONCLUSION

We have also hybridized Factorization Machines and SVD models to better up the whole accuracy of the recommendation system using deep neural networks.

In the content-based recommendation system, we saw that increasing the near neighbours in KNN, also increased the accuracy of model, it's just over SVD performance. However, the total cost of making a content based recommender is much high, as every user has its own model that is built on the basis of features of songs preferred by him.

Factorization machines have very high recall value but lack the precision of some other models. We also observed that the built model performs better over songs that occur quite often in the data, so our future work could involve making the accuracy better on lesser popular songs.

On hybridizing, we could observe that the accuracy improved slightly at cost of recall. The hybrid model has got better precision, but lower recall value as compared to the FM Model.

REFERENCES

[1] McFee, B., BertinMahieux,T., Ellis, D. P., Lanckriet, G. R., "The million song dataset challenge", In Proceedings of the 21st international conference companion on World Wide Web, pp. 909916, April 2012.

[2] Aiolli, F., "A preliminary study on a recommender system for the million songs dataset challenge", Preference Learning: Problems And Applications In AI, 2012.

[3] Koren, Yehuda. "Recommender system utilizing collaborative filtering combining explicit and implicit feedback with both neighborhood and latent factor models." U.S. Patent No. 8,037,080. 11 Oct. 2011.

[4] Cremonesi, Paolo, Yehuda Koren, and Roberto Turrin, "Performance of recommender algorithms on top-n recommendation tasks." Proceedings of the fourth ACM conference on Recommender systems. ACM, 2010.

[5] Szu-Yu Chou, Li-Chia Yang, Yi-Hsuan Yang, and Jyh-Shing Roger Jang, "Conditional preference nets for user and item cold start problems in music recommendation." (ICME 2017) 2017

IEEE International Conference on Multimedia and Expo, pp. 1147–1152, 2017.

[6] Charu C. Aggarwal, «Recommender Systems. The Textbook», pp. 518, 2016.

[7] Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich, Recommender Systems. An Introduction, 2011.

[8] Mohapatra, H., Panda, S., Rath, A., Edalatpanah, S., & Kumar, R., "A tutorial on powershell pipeline and its loopholes", International journal of emerging trends in engineering research, 8(4), pp. 975-982, 2020.

[9] Kumar, R., Edalatpanah, S. A., Jha, S., & Singh, R., "A Pythagorean fuzzy approach to the transportation problem", Complex & intelligent systems, 5(2), 255-263, 2019.

[10] Kumar, R., Edalatpanah, S. A., Jha, S., & Singh, R., "A Pythagorean fuzzy approach to the transportation problem", Complex & intelligent systems, 5(2), pp. 255-263, 2019.

[11] Svetlin Bostandjiev, John Donovan, Tobias Höllerer, "TasteWeights:A Visual Interactive Hybrid Recommender System", ACM/IEEE Computer Science Curricula, 2012.

[12] Royi Ronen, Noam Koenigstein, Elad Ziklik and Nir Nice," Selecting Content-Based Features for Collaborative Filtering Recommenders", ACM/IEEE Computer Science Curricula, 2013.

[13] Mohammad Yahya H. Al-Shamri, Nagi H. Al-Ashwal, "Fuzzy-Weighted Similarity Measures for Memory-Based Collaborative Recommender Systems", Journal of Intelligent Learning Systems and Applications, 2014.

[14] Manoharan, Samuel,"Patient Diet Recommendation System Using K Clique and Deeplearning Classifiers." Journal of Artificial Intelligence 2, no. 02, pp.121-130, 2020.

[15] Smys, S., and C. Vijesh Joe, "Big data business analytics as a strategic asset for healthcare industry." Journal of ISMAC 1, no. 02,pp.92-100,2010.