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Neural Collaborative For Music Recommendation System

To cite this article: Abba Suganda Girsang *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1071** 012021

Neural Collaborative For Music Recommendation System

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Abstract. In music there are various types of genres and every person has their own choice of the type of music they want to hear. Recommendation system is an important feature in an application, especially with the large number of choices for a particular item. With a good recommendation system, users will be helped by the suggestions given and can improve the user experience of the application. It is better provided by using collaborative filtering (CF) approach by recommending products related to one's preferences history. However, CF approach still lacking in integrating complex users data. Therefore, hybrid technique could be the solution to polish the CF approach. Combining neural network and CF also called NCF thought to be better than CF alone. This study focuses on collaborative filtering approach combined with neural network or called neural collaborative filtering. In this study, we use 20,000 users, 6,000 songs, and 470,000 transaction ratings then predict the score using CF and NCF approach. The aim of this study is to differentiate recommendation systems with the use of CF alone and NCF. Through this research, it was found that NCF is better than user-based collaborative filtering in gather those playlist they really want to hear, but requires more time to build it.

1. Introduction

Information related to entertainment is one of the most sought after things in various digital information media. Content that shares information in the form of music is very easy to obtain. Referring to these things, of course, digital content has become one of the important needs to be provided in the form of attractive information with various methods. Generally, digital music content providers will take advantage of user behavior data when exploring the digital world via the internet. Currently, millions of song catalogs have been distributed on the internet and can be accessed easily by users.

On average, each digital-based song content has a duration of around 3 minutes, so it can be concluded that with that duration to complete 1 million digital music content it will take approximately 5 years. The increase in the amount of digital music content every month results in an unstructured amount of song catalog data and makes it difficult for users to choose the songs they want to listen to. To make it easier for users to optimize the music catalog that has been subscribed to a large number, a music recommendation-based system is needed that allows users to be able to manage a catalog of digital music content according to their needs. One of the method recommendation is collaborative filtering. Collaborative screening recommendation techniques began to emerge in the decade of the 90's mainly due to the increasing number of web and the vast amount of information available through it. These techniques are domain independent and use information from multiple users to determine similarities between items. In collaborative filtering, the most popular technique is matrix factorization (MF), but it is still lacking in capturing the complex structure of user interaction data. Therefore, the need of combining another technique is required to give a better outcome [1]. Currently, hybrid techniques are the ones most extensively implemented in recommender systems in an attempt to address the limitation of CF approach [2], [3]. One of which is by combining with neural networks for learning the interaction function from data [1]. This study focuses on collaborative filtering approach combined with neural network or called neural collaborative filtering (NCF). This study aims to enhance the collaborative

2. Related Work

Collaborative recommendation system relied on two different types of input, of which are explicit feedback and implicit feedback. In the explicit feedback, data obtained from input by users regarding their interest in products. However, it is not always available. Therefore, we need the implicit feedback by observing user behavior. Some examples of implicit feedback are mouse click, number of times a video or music played, etc. Note to the implicit feedback, it has no negative feedback, it is inherently noisy, the numerical value indicates confidence, and its evaluation requires appropriate measures [4].

The basic needs to create a neighbourhood method in CF recommendation system consist of identifying similar users based on their preferences, then select k nearest neighbour based on users similarity [1], [5], [6]. The top k nearest neighbour then gives a good quality of recommendation. The other and most popular method is matrix factorization (MF) that reflects users and items using latent vector [7]. Another research showed that processing the data with a neighbourhood method using KNN algorithm gives better error result as well as good to predict similarities between the pair of song given the attributes [2], [6].

However, each technique had its own weakness, therefore combining techniques could give a promising future in providing better service. Currently, hybrid techniques are the ones most extensively implemented in recommender systems in an attempt to address the limitation of CF approach [2], [3].

3. Methodology

Neural collaborative filtering approaches combine general matrix factorization with neural network matrix factorization as shown Figure 1. Each transactions are extracted into two matrices / part named user vector, and item vector. The user vector and item vector are then represented into generalized matrix factorization (GMF). In other hand, two vectors user and item are concatenated into multi layer perceptron (MLP). , then we create four dense layers and each layer using dropout with rate 0.25. Each dense layer is using ReLu activation function. Next, we concatenate general matrix factorization with the output of the neural network layer. Finally, the output layer is using ReLu activation function as we want to predict the music rating. The formulation of neural collaborative filtering as shown in Eq.(1), Eq(2), Eq(3) [1]

$$GMF = p_u \cdot q_i \tag{1}$$

$$\mathrm{MLP} = \alpha_L\left(\mathrm{W}_L^T\left(\alpha_{L\text{-}1}\left(\ldots\alpha_2\left(\mathrm{W}_L^T\begin{bmatrix}p_u\\ q_i\end{bmatrix}+\mathrm{b}_2\right)..\right)\right)+\mathrm{b}_L\right) \tag{2}$$

$$y_{ui} = \sigma\left(h^T\begin{bmatrix}GMF\\ MLP\end{bmatrix}\right) \tag{3}$$

Where p_u denotes user embedding and q_i denotes item embedding. The training model is linear regression and the loss function is mean square error (MSE). Parameters are batch size = 64, epochs = 10, learning rate = 0.001, and use ADAM optimizer.

Data used in this study consist of users, music, and the total number of times the music was played. There are over 20,000 users, 6,105 music, and 470,759 records of music played. We need to normalize the number of times the music is played c_{ui} due to different habits each user is likely listening to music. The normalize value then considered as rating r_{ui} – the rating from user *u* for item *I* as shown Eq. (4):

$$r_{ui}=\frac{c_{ui}}{Max(c_u)}\times 100 \quad (4)$$

Rating value is then stored in the database and used for suggesting music content to each user. It is ranging from 0-100.

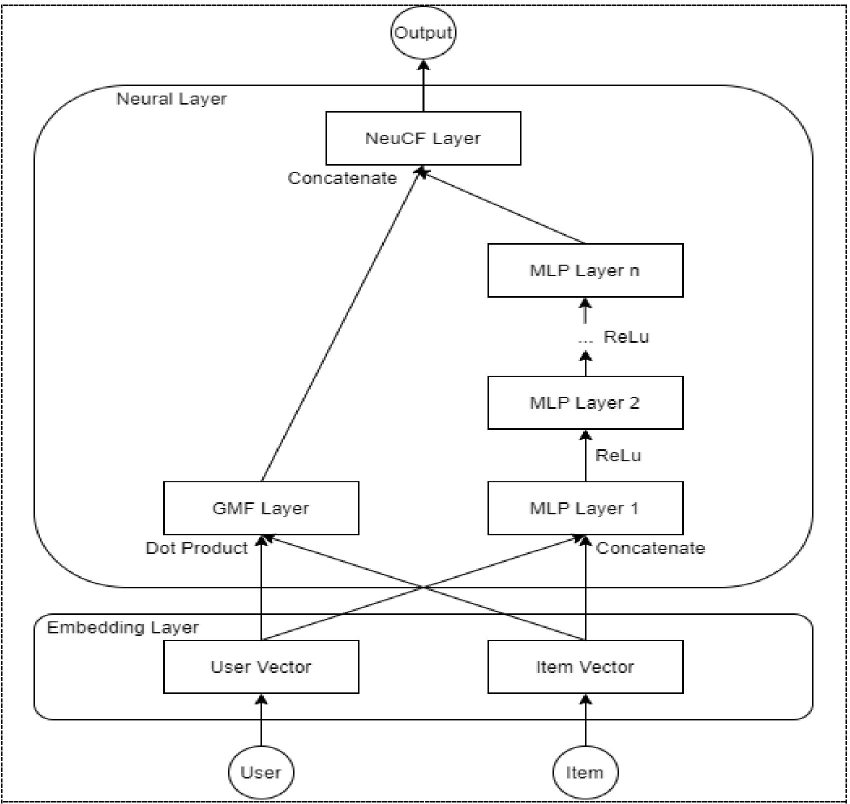

Figure 1. Architecture of Neural Collaborative Filtering.

4. Evaluation

To evaluate and compare our music recommendation systems, we used regression evaluation metrics: mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE). Regression evaluation metrics are used due to the output of the recommendation system is the predicted rating. Thus, it calculates the difference between actual and predicted value of music rating. The formula of each evaluation metrics as shown Eq. (5)- Eq(8)

$$\text{MAE}=\frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{5}$$

$$\text{MAPE}=\frac{\sum_{i=1}^{n}\frac{|y_i - x_i|}{y_i}}{n} \text{ x } 100\% \tag{6}$$

$$\text{MSE}=\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n} \tag{7}$$

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \tag{8}$$

Where y and x denote actual and predicted value respectively.

Based on the methods and steps described in chapter 3, the results of evaluation metrics of collaborative filtering and neural collaborative filtering can be seen in Table 1. From that results, it can be seen that the error from the NCF framework is lower than user-based CF using several methods like MAE, MAPE, MSE, and RMSE.

Table 1. Evaluation Error Results

Method	MAE	MAPE	MSE	RMSE
CF	14.866	66.118	645.786	26.107
NCF	7.933	28.591	246.422	15.697

Table 2 shows several examples of the results of recommendations using collaborative filtering and neural collaborative filtering. It uses 2 users given 7 songs, then the CF recommendation and NCF recommendation predict the rating. The closest prediction to the actual rating is the best. A better predictive score is done by NCF framework with 11/14 score.

Table 2. Evaluation Results

# User	# Song	Actual	CF Score	NCF Score	Winner
1	1	34	43.666	25.124	NCF
	2	13	28.5	10.368	NCF
	3	20	54.75	40.449	NCF
	4	17	13.3	18.745	CF
	5	17	19.66	22.226	CF
	6	3	27	25.456	NCF
	7	6	26.8	25.338	NCF
2	1	5	20.4	17.052	NCF
	2	50	58	51.9	NCF
	3	20	54.75	40.449	NCF
	4	5	13.5	13.961	CF
	5	5	17.666	6.296	NCF
	6	5	23.375	6.747	NCF

7	11	85	34.424	NCF

Based on Table 1 and 2, it showed that NCF framework generates less error and more accurate predicted rating. Unfortunately, matrix factorization's model using NCF needs lots of time to build, yet it predicts ratings more faster if we use the model that was built before than user-based CF.

In the application of music recommendation, the system will perform user-based collaborative filtering calculations, it is different from neural collaborative filtering which only predicts the model that has been built. This gives an advantage in run time because it does not require a long training process, but in real application it must be monitored and provided feedback so that the model still gives the best performance. The comparison of the two frameworks can be seen in Table 1, and Table 2.

5. Conclusion

In this study, we make a comparison between collaborative filtering and neural collaborative filtering on the music dataset. From the comparison, it was found that neural collaborative filtering gave better results than collaborative filtering. This process can increase people's engagement with an application, especially digital online music, because the right recommendations can improve the user experience of an application. The next step of this study is to improve recommendation performance so that existing errors can be reduced and produce better recommendations.

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