Deep Content-User Embedding Model for Music Recommendation

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ABSTRACT
Recently deep learning based recommendation systems have been actively explored to solve the cold-start problem using a hybrid approach. However, the majority of previous studies proposed a hybrid model where collaborative filtering and content-based filtering modules are independently trained. The end-to-end approach that takes different modality data as input and jointly trains the model can provide better optimization but it has not been fully explored yet. In this work, we propose deep content-user embedding model, a simple and intuitive architecture that combines the user-item interaction and music audio content. We evaluate the model on music recommendation and music auto-tagging tasks. The results show that the proposed model significantly outperforms the previous work. We also discuss various directions to improve the proposed model further.

CCS CONCEPTS
•Information systems → Recommender systems; •Computing methodologies → Neural networks;

KEYWORDS
music recommendation, cold-start problem, deep content-user embedding model

ACM Reference format:
Jongpil Lee, Kyungyun Lee, Jiyoung Park, Jangyeon Park, and Juhan Nam. 2016. Deep Content-User Embedding Model for Music Recommendation. In Proceedings of DLRS 2018, Vancouver, Canada, October 6, 2018, 5 pages. DOI: 10.1145/nmnnmn.nmnnnn

1 INTRODUCTION
Music recommendation has gained more attention in recent years as accessibility to music has dramatically increased by music streaming services and recommending songs that satisfy users’ taste has become essential in the services. Music recommendation is also an important feature of AI speakers that are widely spreading recently. However, building a successful music recommendation system still remains as a challenging problem, because of the semantic gap between user context and music content [2].

Common approaches to solve the music recommendation problem can be broadly divided into Collaborative Filtering (CF) and Content-Based Filtering (CBF) [2, 18]. The CF approach, which utilizes user listening counts or song ratings, is an effective solution, but it suffers from the cold-start problem especially for new items. On the other hand, the CBF approach, which directly uses the content information (e.g. tag or audio), can solve the item cold-start problem, but it is difficult to exploit common consumption patterns from users or song popularity.

To address this problem, hybrid approaches, which incorporate different modalities (e.g. user and content data) into one system, have been explored. A prominent approach is deep content-based music recommendation model proposed by Oord et al., in which the CBF model is trained to predict the item latent factor obtained from the CF model [17, 19]. This was further extended to take not only audio content, but also artist biographies [15]. On the contrary, the CF model can also be trained to match up with the pre-trained CBF model [13]. However, these hybrid approaches still have a problem in that the learning stages of the CF and CBF models are separated, which can yield a sub-optimal solution.

To bridge this gap, hybrid approaches, which incorporate different modalities (e.g. user and content data) into one system, have been explored. A prominent approach is deep content-based music recommendation model proposed by Oord et al., in which the CBF model is trained to predict the item latent factor obtained from the CF model [17, 19]. This was further extended to take not only audio content, but also artist biographies [15]. On the contrary, the CF model can also be trained to match up with the pre-trained CBF model [13]. However, these hybrid approaches still have a problem in that the learning stages of the CF and CBF models are separated, which can yield a sub-optimal solution.

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Meanwhile, Deep Learning (DL) based recommendation systems have been actively investigated in recent years due to the success of DL in many application domains [9, 21]. Especially, Neural Collaborative Filtering (NCF) introduced the general framework to conduct CF using deep learning techniques [8]. The overall architecture is
as follows: For each user-item interaction, the user and item indexes are injected to each side of user and item embedding layer. Then, the user and item features are combined (this can be done using element-wise product or simple concatenation) and used to predict its interaction score with several layers of MLP. Another interesting approach is Deep Structured Semantic Model (DSSM) [5, 11]. The architecture of DSSM is more similar to the matrix factorization-based CF than the NCF, because the objective of the model is directly calculated from the similarity score of the user and item’s high-level latent factors. This has the benefit of directly utilizing the latent factors for the user or item similarity-based search or filtering.

In this work, we introduce deep content-user embedding music recommendation model, a hybrid DL-based music recommender model, which utilizes user-item interaction and song audio together in an end-to-end manner to solve the item cold-start problem. We evaluate the model for music recommendation and music auto-tagging tasks. The results show that the proposed model outperforms the baseline [19] for both tasks. The advantage of the proposed model lies in the architecture and objective function, which provide a simple and intuitive way to handle the domain gap between the user-item interactions and unstructured audio data.

First, a huge number of users may lead to a computational burden when the raw user one-hot vector is utilized with the fully-connected layer in the first layer on the user side. To overcome this problem, the DSSM [11] used n-gram based word hashing technique to reduce the vocabulary size in the first layer of their application. In [4], they used a similar hashing technique, but using a preference vector instead. On the other hand, a lookup-table style embedding layer has been introduced in training word representations [14]. This method has an advantage of saving the computational cost by updating only the selected user’s embedding, while keeping the diversity of the user’s taste profile. Therefore, we use the lookup-table style embedding layer for the first layer on the user side.

Second, the method of combining the user and item factors can be varied. There are broadly two types of combining methods: feature fusion and pair-wise similarity calculation. The feature fusion method can be further divided into element-wise multiplication [4] and concatenation [15]. After the features are combined, fully-connected layers are often added to make a binary prediction. In this work, we explore the pair-wise similarity calculation following [11]. This is because the pair-wise calculation is more similar to the matrix factorization method that can provide high-level user and item factors. This can also be applied to the user and item similarity calculation or filtering. The relevance score calculation between the user feature vector and the item feature vector is another issue that we should consider. In our preliminary experiments, we compared cosine similarity score and dot product. The cosine similarity
method was more effective in the proposed model. Thus, the relevance score between the user feature vector and the item feature vector is defined as the following cosine similarity score:

\[ R(U, I) = \cos(y_U, y_I) = \frac{y_U^T y_I}{|y_U| |y_I|} \]  

where \( y_U \) and \( y_I \) are the feature vectors of the user and item, respectively.

Third, the choice of loss function and training strategy is also important. We apply the negative sampling technique over the pairwise similarity score function following [11]. Therefore, for each user-item interaction, the model takes one listened song and several non-listened songs as the input on the item side. Then, the loss is calculated using the relevance scores obtained from the user feature vector and the item feature vectors. We tested two loss functions: One is the softmax function with categorical cross-entropy loss to maximize the positive relationships and the other is the max-margin hinge loss to set margins between positive and negative examples [7]. In our preliminary experiments, the proposed relevance score with negative sampling technique was successfully trained only with the max-margin loss function between the two objectives, which is defined as follows:

\[ \text{loss}(U, I) = \sum_{I} \max[0, \Delta - R(U, I^+) + R(U, I^-)] \]  

where \( \Delta \) is the margin, \( I^+ \) and \( I^- \) denote positive example and negative examples, respectively. We also grid-searched the number of negative samples and the margin, and settled on the number of negative samples as 20 and the margin value \( \Delta \) as 0.2. The settings of the audio model and the training strategy are mostly adopted from [16]. We note that the user play counts have been binarized in this work, following [8]. In other words, when the user-item interaction occurs at least once, we treat them as a positive case, otherwise negative. We leave the more advanced loss function, which can take into account the raw implicit feedback data, as our future work.

Once the model is trained, the prediction of the user’s preference on the non-listened song is simply calculated through the relevance score function of the user and item feature vectors, which is extracted from the user’s index and the item’s audio, respectively.

3 EXPERIMENTAL SETTINGS

In this section, we describe the model setup and training details.

3.1 Model Setup

The proposed model consists of two networks, user model and audio model, as depicted in Figure 1. The user model is constructed using an embedding layer and fully-connected layers. The audio model is configured using one-dimensional convolution layers, sliding over only temporal dimension. Mel-spectrogram is used as an input to the audio model and the model parameters are shared across all positive and negative samples. The audio model is composed of 5 convolution and max pooling layers. For both user and audio model, rectified linear unit (ReLU) activation layers are used after every layer except for the feature vector layer.

3.2 Dataset

The proposed model was evaluated in a similar settings to that in [19]. We use the Million Song Dataset (MSD) [1] along with two associated datasets, Echo Nest Taste Profile Subset and Last.fm dataset. The Echo Nest Taste Profile Subset provides play count data for over 380,000 songs and one million users. The Last.fm dataset offers tags for over 500,000 songs. We validate the model with two tasks, music recommendation and music auto-tagging. In the recommendation experiments, we use a subset of the Echo Nest Taste Profile Subset, which contains the most frequently listened 10000 songs and the most active 20000 users. In the auto-tagging experiments, we first filter the song list and tag list to have at least one of the 50 most-used tags. Then, we leave 6903 songs that are present in both the recommendation song subset and the tagging song list. In both tasks, we randomly split the song lists into train/valid/test sets at a proportion of 70%/10%/20%. We use AUC (Area Under Receiver Operating Characteristic) as a primary evaluation metric for the both tasks.

3.3 Training Details

For the audio preprocessing, we compute the spectrogram using 1024 samples for FFT with a Hanning window, 512 samples for hop size and 22050 Hz as sampling rate. We then convert it to mel-spectrogram with 128 bins along with a log magnitude compression. We choose 3 seconds as a context window of the audio model input following previous work [16]. Out of the several seconds audio, we randomly extract the context size audio and put them into the network as a single example. The input normalization is performed by dividing standard deviation after subtracting mean value across the training data. We optimize the loss using stochastic gradient descent with 0.9 Nesterov momentum with 1e6 learning rate decay. Our system is implemented in Python 2.7, Keras 2.1.1 and Tensorflow-gpu 1.4.0 for the back-end of Keras [3]. We use NVIDIA Tesla M40 GPU machines for training our models.

4 EVALUATION

In this section, we explain the baseline model and the evaluation methods.

4.1 Task1 : Music Recommendation

To validate the effectiveness of the proposed model, we reproduce the deep content-based music recommendation model [19] and compared them with our model. They used Weighted Matrix Factorization (WMF) algorithm for CF [10] and we implement it with the Implicit python library [6]. For predicting latent factors from the corresponding audio, we use the same audio model as the audio side of the proposed model. We perform the evaluation by reconstructing the user-item matrices using the item latent factor obtained from WMF and also using the predicted latent factor from the corresponding audio. We term the former as WMF and the latter as WMF+Regresssion. Similarly, we reconstruct the user-item matrix using the relevance score between the user and item feature vector in our work. Finally, we calculate the AUC scores for each user and averaged them. We also report popularity-based recommendation result as a baseline of the recommendation performance. This
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modality.

Table 1: Music recommendation results.

| Type       | Models                                   | AUC   |
|------------|------------------------------------------|-------|
| –          | Popularity                               | 0.7059|
| CF         | WMF                                      | 0.9302|
| Hybrid     | WMF+Regression [19]                      | 0.6967|
| Hybrid     | Deep Content-User Embedding Model        | 0.7914|

Table 2: Music auto-tagging results.

| Type  | Models                                      | AUC   |
|-------|---------------------------------------------|-------|
| CF    | WMF                                         | 0.8683|
| Hybrid| WMF+Regression [19]                         | 0.7876|
| Hybrid| Deep Content-User Embedding Model           | 0.8450|

means that it recommends the same songs to all users based on the
total number of songs played.

4.2 Task2 : Music Auto-Tagging
To verify the proposed end-to-end architecture and the feature
vector’s usefulness, we also conduct music auto-tagging task in
a transfer learning setting. The item factor, predicted item factor
and item feature vector from the WMF, WMF+Regression and Deep
Content-User Embedding Model is used as a feature vector of a song.
We then trained a 2-layer MLP on top of the feature to predict the
tags.

5 RESULTS
In this section, we examine the proposed model and compare them
to the reproduced results of [19].

5.1 Task1 : Music Recommendation
Table 1 shows the recommendation results. We can first find that
the reproduced result of the WMF+Regression is in a similar perform-
ance level to the original work (0.70987). However, the score is
comparable to the popularity-based recommendation result. Sec-
ond, the result of the proposed model shows significantly better
performance than it. The performance gain is seen to be from the
dead-to-end optimization architecture of the proposed model. Third,
we can see that there still exists a large difference between the WMF
and the proposed model. To examine the bottleneck of the proposed
model, we tested another model that has the same architecture as
the proposed model on the user side, but audio model. In this model,
the item side is constructed with the same architecture as the user
side so the model takes user and item indexes rather than user and
audio. This comparison showed 0.7832 score, which is close to the
proposed model. We analyze this result as follows. Bridging the gap
between user-item interaction and unstructured audio data can be
solved using a proper deep learning based recommender system.
Also, it seems that the choice of loss function and learning strategy
affects the model performance rather than the choice of the input
modality.

5.2 Task2 : Music Auto-Tagging
From the Table 2, we can also find that the reproduced result of WMF
is close to the previous work (0.86703). In the music auto-tagging
task, the performance gap between the proposed model and WMF
seems to be small and the proposed model largely outperforms the
WMF+Regression. We believe that this result is obtained from the
advantages of the proposed end-to-end architecture.

6 CONCLUSION AND FUTURE WORK
In this work, we presented the deep content-user embedding model
to simultaneously learn the user-item interaction and unstructured
audio data in an end-to-end fashion. The proposed model consists
of the user and item sides, each of which takes user index and
multiple audio as input, respectively. The model architecture and
learning strategy are designed to preserve the advantage of the
conventional matrix factorization based recommendation approach.
The embedding layer in the user side enables the computational
cost to be reduced. The item side takes audio directly to solve
the item cold-start problem. The model is verified in the music
recommendation and music auto-tagging tasks. The results showed
that the proposed model is highly more effective than the deep
content-based music recommendation model. When comparing the
results to the conventional matrix factorization method which has
the cold-start problem, there is still a room to improve. However, we
believe that the proposed model shows a good direction to utilize
deep learning techniques to solve the recommendation problems.

For future work, we will thoroughly investigate the following
issues. First, various loss function and learning strategy should be
explored. As introduced in Section 2, there exist many choices in
constructing the architecture. For example, the way of conducting
negative sampling can be varied depending on the choices of the
loss function (pair-wise vs point-wise loss) and it can significantly
affect the model performance. Second, we used binarized implicit
feedback data in this work, which may affect the learning property
of the model. Raw implicit feedback data can have more informa-
tion about users’ music consumption pattern or song popularity
information. Third, the evaluation metric should be diversified to
measure different aspects of the architecture. For example, AUC
score and precision at K may have different trends if raw implicit
feedback can be utilized to train the model due to its popularity
bias property. Fourth, more advanced audio models such as [12]
can be applied to the item side of the proposed model. Lastly,
the model can be extended to have a multi-view architecture [5]. This
method allows interaction between different domains (e.g. user-
item interactions, audio, artist bibliographies and album images),
which can make the feature representation richer.

ACKNOWLEDGMENTS
This work was supported by Basic Science Research Program through
the National Research Foundation of Korea funded by the Ministry
of Science, ICT & Future Planning (2015R1C1A1A02036962) and by
NAVER Corp.
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