A Duet Recommendation Algorithm Based on Jointly Local and Global Representation Learning

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ABSTRACT
Knowledge graph (KG), as the side information, is widely utilized to learn the semantic representations of item/user for recommendation system. The traditional recommendation algorithms usually just depend on user-item interactions, but ignore the inherent web information describing the item/user, which could be formulated by the knowledge graph embedding (KGE) methods to significantly improve applications’ performance. In this paper, we propose a knowledge-aware-based recommendation algorithm to capture the local and global representation learning from heterogeneous information. Specifically, the local model and global model can naturally depict the inner patterns in the content-based heterogeneous information and interactive behaviors among the users and items. Based on the method that local and global representations are learned jointly by graph convolutional networks with attention mechanism, the final recommendation probability is calculated by a fully-connected neural network. Extensive experiments are conducted on two real-world datasets to verify the proposed algorithm’s validation. The evaluation results indicate that the proposed algorithm surpasses state-of-arts by 10.0%, 5.1%, 2.5% and 1.8% in metrics of MAE, RMSE, AUC and F1-score at least, respectively. The significant improvements reveal the capacity of our proposal to recommend user/item effectively.

1 INTRODUCTION

With the rapid development of Internet technology, the amount of online information has increased sharply, about 88,555 GB of Internet traffic per second¹. The massive data would confuse the users to identify useful information and make the right choice. This is the so-called problem of information overload. To tackle this challenge, recommendation systems have become a vital and indispensable tool to solve this problem.

Prior Works and Limitations. The recommendation system attracts intensive research interest and derives broad applications [1, 6, 21, 25, 29]. Conventional collaborative filtering (CF) methods [1, 3, 7, 20, 26], as one classical algorithm, aim to provide personalized recommendation for users based on the user-item historical interaction data. However, CF-based methods usually suffer from the sparsity and the cold-start problem [31] due to the fact that most active users just have interacted with a small number of items. To solve these problems, the latest studies [8, 27, 31, 33] try to combine different types of side information in the recommendation process, such as social networks, item descriptions, and knowledge graphs.

To integrate such side information, the basic idea is to treat them as auxiliary information corresponding to users/items and characterize both users and items by latent features. Thus, a supervised model takes user-feature and item-feature vectors as input to predict the recommendation results. Many effective approaches fall into this idea, such as factorization machine (FM) [24], singular value decomposition (SVD) [18], collective matrix factorization (CMF) [28] and neural factorization machine (NFM) [11], etc.

Recently, with the development of the semantic web, knowledge graphs (KGs) [5, 30, 39] have been applied in recommendation system research as a novel side information source. It combines various types of entities and relations related to user/item into a unified global relation space. Many works [34, 36, 40, 42] leverages the rich semantic relation among entities in KGs, which helps to provide different perspectives to infer potential connections in user-user, item-item, or user-item. For example, KGAT [36] captures semantic relations by exploring the high-order connections in KGs. IntentGC [42] proposes a framework to predict users’ preferences by capturing heterogeneous auxiliary relationships in a recommendation.

Although promising, there are still several limitations in previous studies. First, most works only utilize the flat features but ignore the various semantic information in KGs, which can help to infer potential user/item relationships from different views [31]. Second, most works only utilize the semantic structure information of KGs while ignoring other important information, such as

¹https://hostingfacts.com/internet-facts-stats/
item descriptions. Third, previous studies lack interpretability for modeling various kinds of information.

Figure 1: Illustration of side information classification: local information (e.g., social networks and item descriptions) and global information (e.g., heterogeneous relations with external entities)

Motivations and Relations. Considering their different characteristics, the side information is divided into two types, local information and global information. As shown in Fig. 1, local information, such as social networks and item descriptions, is the explicit information in user/item itself or between users or items in the local representation space; The global information, including the heterogeneous information in external KGs, is the semantic information between users/items and external entities in KGs in the global representation space. For local information, similar users/items often share similar description information or in the same social network. And for global information, similar items often have similar semantic relations with external entities in KGs. Capturing different sense of the recommendation from different perspectives, the combination of these two kinds of information is more favorable for achieving better performance. We can distinguish two components that may impact a user’s preference: an explicit effect from local information and a semantic effect from global information.

Methodologies and Results. Motivated by the combination of local and global information, we propose a novel recommendation model based on feature representation learning. It is comprised of two independent deep neural networks (DNN) models that formulate users’ preferences using local and global information, respectively. Specifically, we term the two models as the local model and the global model. The local model employs one DNN structure model to embed the textual descriptions of information into explicit local representation for users’ preferences, which aggregates users’ history interaction data attentively. For the global model, we first construct a unified relation graph (URG) by aligning items with entities in unified global representation space. And then, one knowledge graph embedding network [4, 13, 19] is designed to capture the semantic structural information and learn the global semantic representation for users’ preferences. It attentively aggregates adjacent entities’ embeddings that contain various types of features related to items. In the recommendation process, two models are jointly trained as part of a single neural network for a common goal. Such duet architecture possesses two advantages: 1) two DNN models could fully take advantage of both local explicit and global semantic information; 2) two DNN models incorporate different information in the form of KGs from the web information retrieve, which could alleviate cold-start and data sparsity problem. To verify the effectiveness of our model, we conduct experiments on two benchmark datasets from Amazon ~ Book and MovieLens ~ 20M. The results show that the proposed method surpasses the state-of-art 10.0%, 5.1%, 2.5% and 1.8% in metrics of MAE, RMSE, AUC and F1-score at least.

The major contributes in this paper are summarized as follows:

1) To the best of our knowledge, we firstly distinguish the local information and global information notions in view of side information. These different general aspects of side information enable the model to capture more users’ preferences and improve performance significantly.

2) We design a novel duet recommendation architecture, which employs two DNNs coherently learning local and global representations of users/items, respectively. Based on the latent embedding features, we calculate the probability of users’ preference from different angles to alleviate cold start and data sparsity problems, which also enhances the interpretability of our model.

3) We conduct extensive experiments on two datasets from the real-world to verify the validation of the proposed algorithm. The results demonstrate that our algorithm surpasses state-of-arts by 10.0%, 5.1%, 2.5% and 1.8% in metrics of MAE, RMSE, AUC and F1-score at least, respectively, and also reveal the interpretability and parameter influence of our algorithm for modeling user preference.

2 PRELIMINARY

In this section, we first introduce the terminologies and concepts involved in this work, and then explicitly describe our problem formulation.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure2.png}
\caption{A toy example of a KG and description information in movie domain. KG contains movies, actors, genres and directors as entities; categorizing, acting and directing as entity relations. Description information indicates detailed information about movies.}
\end{figure}

2.1 User-Item Feedback

In a general recommendation scenario, the most common data we can get is the user-item historical interaction data (e.g., purchases and clicks). Assume that there are $m$ users and $n$ items, we represent historical data as the user-item interaction matrix $R \in \mathbb{R}^{m \times n}$, which is defined as

$$R_{ij} = \begin{cases} 
1, & \text{if user } i \text{ and item } j \text{ have the interaction;} \\
0, & \text{otherwise.}
\end{cases} \quad (1)$$
where \( R_{ij} = 1 \) indicates an observed interaction between user \( i \) and item \( j \), e.g., users read a book or users click news; otherwise \( R_{ij} = 0 \). It is worth noting that the interactive information reflects the users’ preference most directly.

### 2.2 Knowledge Graph

With the development of the semantic web, the knowledge graph, as an auxiliary data source, has been widely used to improve the quality of the recommendation system. It contains rich real-world entities and relationships to complement information of users and items in the recommendation process. As shown in Fig. 2, movie information can be complemented with its directors, actors, genre, and description provided by the knowledge graph. In this work, we leverage the structural content and textual content in KGs to reach a better recommendation.

For structural content, KG is a heterogeneous graph, which is composed of triple facts as (subject, predicate, object). Formally, it can be defined as \( H = \{(h, r, t) | h, t \in \xi, r \in \mathcal{R}\} \), where each triple indicates that there is a relationship \( r \) from head entity \( h \) to tail entity \( t \). It indicates the information between multiple entities in the knowledge graph’s entity and relation space. For example, \((\text{JayChou}, \text{ActorOf}, \text{Secret})\) describes that Jay Chou acts in the movie Secret. We can extract this kind of information from the graph structure to infer the similarity between item entities, which is useful for the next recommendation process.

For textual content, each entity in KGs may be associated with different kinds of textual content, which indicates the information of the entity itself, such as entity name and entity description. We can utilize it as the auxiliary information for entities to describe them more accurately.

### 2.3 Task Description

Before formulating the recommendation task formally, we present the definition of local information and global information used in this paper.

**Definition 2.1. Local Information:** textual description information corresponding to item/user, which can directly model the similarity between items in local representation space.

**Definition 2.2. Global Information:** semantic structure information in KGs, which can help to infer potential relationships between items and external entities in global representation space.

As shown in Fig. 1, social network and item description can be seen as the local information, but KGs are taken as the global information to mining the potential relationships among users and items.

Based on the global and local information, the recommendation problem to be addressed in this paper can be defined as follows:

Given a heterogeneous graph \( G \) with structural content \( G \), textual content \( D \), and user-item interaction matrix \( R \) as input, the global information \( G \) and local information \( D, R \) are embedded into the numeral vector by the proposed joint models, respectively. The output is the probability \( P_{um} \) of user \( u \) being interested in item \( m \), which is calculated through the multi-layer neural networks based on the embedding features.

### 3 Overview

In this section, we clarify the proposed model detailedly, whose framework is illustrated in Fig. 3. To better understand, we first introduce the knowledge complement linkage process, which can extract local and global entity information from KGs. Then, we present the local and global models respectively, which are designed for processing different information. And during this process, we show the attention mechanism used in these two sub-models. Finally, we describe the jointly training process of the local and global models.

#### 3.1 Knowledge Complement Linkage

Fig. 4 shows the process of knowledge complement from external KGs. We firstly utilize entity linking technology to extract the entities in items, which is represented by its textual content (e.g., item titles). Then, we disambiguate these extracted entities to the correct entity in a knowledge graph. Each predefined entity is associated with external semantics in a knowledge graph, e.g., descriptions, types, and relations. Note that these semantics can be roughly divided into two categories: one is the local information associated with entities themselves, and the other is the global information related to other entities in KGs. Specifically, the extracted description information is taken as the local information, and the constructed sub-graphs for the identified entities with completed relational links are taken as the global information. By thoroughly analyzing the characteristic of the adopted data, we respectively design the local and the global model to effectively utilize the complement information for item recommendation.

#### 3.2 Local Model

The local model is designed to utilize the local information from KGs based on patterns of content-based recommendation. As shown in Fig. 3, it includes three main components: the knowledge enhanced embedding (KEE), the history-based attention network (HAN), and the prediction calculation. Next, we will introduce these three components in detail.

**Knowledge Enhanced Embedded (KEE)** is used to associate each item title with its local description information and encode each item into its latent space representation. We define the title \( W_t \) of the item \( i \), which is composed of sequences of words. KEE first utilizes an embedding layer to map each word \( w_{i,j} \) in item title \( W_t \) to its embedding \( \hat{w}_{i,j} \).

\[
W_t = \{w_{i,1}, w_{i,2}, \ldots, w_{i,n}\} \xrightarrow{\text{embedding}} \{\hat{w}_{i,1}, \hat{w}_{i,2}, \ldots, \hat{w}_{i,n}\}.
\]

we use description \( D_t \) for item \( i \) as the local information, which is also consists of sequences of words. In the same way, we can embed each word \( d_{i,j} \) in description \( D_t \) to its embedding \( \hat{d}_{i,j} \).

\[
D_t = \{d_{i,1}, d_{i,2}, \ldots, d_{i,m}\} \xrightarrow{\text{embedding}} \{\hat{d}_{i,1}, \hat{d}_{i,2}, \ldots, \hat{d}_{i,m}\}.
\]

Specifically, Given the embedding of each word, a straightforward way to compute the sequences’ embedding is to take the mean value of them, i.e.,

\[
\tilde{D}_t = \text{mean}(\hat{d}_{i,1}, \hat{d}_{i,2}, \ldots, \hat{d}_{i,m}).
\]
Figure 3: The duet architecture is composed of the local and global model. The local sub-model takes user-item history interactions, the title and description information of corresponding items as input, whereas the global sub-model learning embedding of users and items from the unified relation graph. Then the parameters of both models are jointly optimized during training.

However, we consider this simple strategy has the following limitations: 1) Taking average of each word’s embedding gives each word the same weight, but in fact, they are of different importance; 2) the local information between words in a sentence can not be captured, which may be effective in some situations; 3) the mean strategy does not consider the order of words in the sentence, which may confuse the meaning of the sentence.

Being aware of the above limitations, as shown in Fig. 5, KEE uses a CNN model to process the word sequence. It composes the word embeddings using filters, and the maximum value of each dimension is obtained through max-pooling to generate the sentence embedding, which is defined as

$$F_q = W_1 \hat{w}_{p,p+h}, \quad s = \max(F_1, \ldots, F_q, \ldots, F_{n-h})$$

where $W_1$ and $h$ are weights and filter size of the CNN.

Through the above process, we can firstly get the title embedding $\tilde{W}_i$ and description embedding $\tilde{D}_i$ for item $i$, then combine them as

$$\tilde{s} = H(\tilde{W}_i \sqcup \tilde{D}_i).$$

Following the characteristic that the user’s interest changes with different items, we propose a History-based Attention Network (HAN) to model the different rating impacts of history item $i$ on the candidate item $m$. It consists of a two-layer DNN $N$ with attention mechanism, and the softmax function is used for calculating the

Figure 4: The process of knowledge complement linkage for each item, including entity linking, disambiguating entities and extracting two different information from external KGs.
normalized weight $a_{im}$, which is formalized as

$$s^u_i = KEE(W^u_i, D^u) \quad i = 1, 2, \ldots, n,$$

$$s_m = KEE(W^m_m, D^m),$$

$$a^u_{im} = N(s^u_i, \bar{s}_m),$$

$$= W_1^2 \sigma(W_1 [s^u_i \cup \bar{s}_m] + b_1) + b_2,$$

$$a^m_{im} = \frac{\exp(a^m_{im})}{\sum_{j \in R(u)} \exp(a^m_{jm})},$$

where the $a^u_{im}$ indicates the impact weight between the historical item $i$ and the candidate item $m$ for user $u$.

Based on the HAN’s outputs, the local embedding of user $u$ with respect to the candidate item $m$ can thus be calculated as the weighted sum of his historical items $KEE$ embedding,

$$\hat{e}^u_u = \sum_{k=1}^{n} a_{ku} \hat{e}^u_k,$$

In local model, we can finally get the user $u$’s local embedding $\hat{e}^u_u$ and the candidate item $m$’s local embedding $\bar{s}_m$. The probability of user $u$ clicking item $m$ is predicted by

$$p'(u, m) = \mathcal{F}(\hat{e}^u_u, \bar{s}_m),$$

where $\mathcal{F}$ is the function for calculating the probability based on the local learning representation, such as multiple-layers perceptron (MLP).

3.3 Global Model

The global model is designed to capture the global information in item knowledge from KGs. As shown in Fig. 3, its framework consists of four main components: the unified relational graph construction, the knowledge graph embedding, the knowledge-aware attention network, and the prediction method.

Unified Relation Graph contains global information in user behaviors and item knowledge, which is organized in the form of KGs. In this work, we reorganize the user-item feedback as the bipartite graph $G$, which is defined as $\{(u, r_{ui}, i) | u \in \mathcal{U}, i \in \mathcal{T} \}$, where $\mathcal{U}$ and $\mathcal{T}$ represent the user and item sets respectively, and $r_{ui} = 1$ indicates an interaction between user $u$ and item $i$.

Then, we define one user behavior as $(u, \text{Interact}, i)$ and merge it with items’ knowledge graph, where Interact is an additional heterogeneous relation. In this way, we can get a unified relation graph $H = \{(h, r, t) | h \in \xi, r \in \mathcal{R} \}$, where $\xi = \xi \cup \mathcal{U}$ is the entity set, $\mathcal{R}' = \mathcal{R} \cup \{\text{Interaction}\}$ is the relation set, $h$, $t$, and $r$ are entities and $r$ is the relation.

Knowledge Graph Embedding is an effective way to model the graph structure data and learn dense low-dimensional vector representations of entities and relations in a graph that preserves the graph structure information. In this work, we employ a widely used translation-based method TransR [19], which introduces a projection matrix for each relation to map entity embeddings to the corresponding relation space. For each triple $(h, r, t)$ in the graph, we define that $\hat{e}_h, \hat{e}_r \in \mathbb{R}^d$, $\bar{e}_r \in \mathbb{R}^k$ and $M_r \in \mathbb{R}^{k \times d}$ for the embeddings of entities $h$, $r$, relation $r$ and the projection matrix for relation $r$ respectively. The embedding is learned by optimizing the translation principle $\hat{e}_h + \bar{e}_r \approx \hat{e}_t$, where $\hat{e}_h = \hat{e}_h M_r$, and $\hat{e}_t = \bar{e}_t M_r$ are the mapping representations of $\hat{e}_h$ and $\hat{e}_t$ in the relation $r$’s space. Then, the plausibility score for triple $(h, r, t)$ is defined as,

$$g_r(h, t) = ||\hat{e}_h + \bar{e}_r - \hat{e}_t||^2_2.$$  \hfill (6)

A lower score of $g_r(h, t)$ represents that the triplet is more likely to be a valid one; otherwise, it’s a broken one. To encourage the discrimination between them, we use the following margin-based ranking loss for training,

$$L_{KG} = \sum_{(h, r, t) \in \mathbb{G}} \max(0, g_r(h, t) + \gamma - g_r(h', t')),$$  \hfill (7)

where $\gamma$ is the margin, and $\mathbb{G} = \{(h, h', r, t, t')(h, r, t) \in \mathbb{G}, (h', r, t') \notin \mathbb{G}\}$. In this way, we can learn the representation of entities and relations in the graph on the granularity of triples with the node and connection information.

Knowledge-aware Attention Network is used to aggregate the embedding representation non-linearly. Differently, for the target entity $h$, we define $N(h)$ to donate the set of neighbor entities directly connected to $h$, termed ego-network [22]. To capture the semantic information contained in the first-order connectivity structure of entity $h$, we compute neighbor representation $\bar{e}_N(h)$ by combining latent factors in $h$’s ego-network with a localized convolution [17]:

$$\bar{e}_N(h) = \sigma(W_3 \cdot \{\sum_{i \in N(h)} \pi_{hi} \hat{e}_i\} + b)$$  \hfill (8)

where $\sigma$ is the non-linear activation function and $\pi_{hi}$ represents the combination coefficient between entity $h$ and $i$.

In order to take the different contributions of neighbor entities to the target entity into consideration, we design a knowledge-aware attention mechanism to compute $\pi_{hi}$, which characterizes the contribution degree. We achieve it with a two-layer neural network, the input to this network is the entity $h$’s embedding $\bar{e}_h$ and the neighbor entity $i$’s embedding $\hat{e}_i$. The attention weight can be formally computed as:

$$\pi^a_{hi} = W^T_4 \cdot \sigma(W^3_5 \cdot (\hat{e}_h \cup \hat{e}_i) + b_1) + b_2$$  \hfill (9)

Hereafter, we obtain the final attention weights by normalizing the above scores with the Softmax function:

$$\pi_{hi} = \frac{\exp(\pi^a_{hi})}{\sum_{j \in N(h)} \exp(\pi^a_{hj})}$$  \hfill (10)

In the combination process, the final attention weights can be regarded as an effective signal for suggesting which neighbor entities should be given more attention to capture the semantic information among them, by which the interpretability of the recommendation process is enhanced.

The final step is to aggregate the target entity embedding $\bar{e}_h$, and its neighbor embedding $\bar{e}_N(h)$ as a single vector of entity $h$. We implement this operation with concat aggregator [9], which concatenates two embeddings before applying a nonlinear transformation:

$$\bar{e}_h = \text{LeakyRelu}(W_6 (\bar{e}_h \cup \bar{e}_N(h)))$$  \hfill (11)

where $W_6$ and LeakyRelu are the weight and the activation function of a neural network, respectively.
Through the above steps, we can get the user $u$’s global embedding $\mathbf{e}_u$ and the candidate item $m$’s global embedding $\mathbf{e}_m$, which contain the global semantic information in KGs.

In the global model, the probability of user $u$ clicking item $m$ is predicted by

$$
p_f^g(u, m) = \mathcal{F}(\mathbf{e}_u^g, \mathbf{e}_m^g),
$$

where $\mathcal{F}$ is the function to calculate the probability based on the learning representation, such as multiple-layers perceptron (MLP).

### 3.4 Prediction

We obtain the local and global probability from the two different models, which capture the local information of the user/item itself and the global semantic information between the user/item and the external KGs. The final probability of user $u$ clicking item $m$ is computed by combining these two special probabilities,

$$
p_f(u, m) = nn(p_f^l(u, m), p_f^g(u, m)),
$$

where $nn(\cdot)$ can be a fully-connected layer and choose a sigmoid activation function.

### 3.5 Training

For modeling user preference, the recommendation task is required to compute the predicted probability for implicit feedback. Thus, we adopt the loss function of cross-entropy formulated as,

$$
Loss = - \sum_{(u, m)} R_{um} \log p_f(u, m) + (1 - R_{um}) \log (1 - p_f(u, m)),
$$

where $R_{um}$ is the assignment of the interaction matrix $R$ for user $u$ and item $m$. It’s a pointwise loss. Meanwhile, other pairwise loss functions can also be used, and we will leave them for future research.

To optimize the loss function, we adopt the mini-batch Adam [16] in our implementation. Because Adam is a widely used optimizer, which is able to adaptively control the learning rate, w.r.t. the absolute value of gradients.

### 4 EXPERIMENTS

In this section, we conduct experiments to comprehensively evaluate our proposed model, and the results answer the following research questions:

- **Q1:** How does our duet architecture model perform compared with the local and global models separately?
- **Q2:** How does our duet architecture model perform compared with state-of-the-art models for recommendation with side information?
- **Q3:** How do the local and global sub-models in proposed architecture impact recommendation performance?

#### 4.1 Dataset Description

We apply our model to two benchmark datasets: Amazon-book and MovieLens, which are public accessible and in different domain.

- **Amazon-book**\(^2\) is a widely used benchmark dataset in product recommendations [10], which contains 22 million ratings from 8 million users across nearly 23 million items. To effectively use it, we extract the 10-core data retaining users and items with at least ten interactions.

- **MovieLens-20M**\(^3\) contains approximately 20 million explicit ratings (ranging from 1 to 5) on the MovieLens website. We also extract the 10-core data in order to ensure data quality.

In order to be consistent with the implicit feedback setting, we transform the two datasets with explicit feedback into implicit feedback where each user-item pair is marked with 1 indicating that the user has rated the item positively. The threshold of a positive rating is 3 for them. Additionally, we need to complete the linkage process between items and entities for each dataset. For Amazon-book and MovieLens, we follow the way in Knowledge Complement Linkage to map items to Freebase entities via entity linking technology, and further incorporate one kind of side information as a refined constraint for accurate linkage (e.g., IMDB ID, entity type, writer name). These items cannot be accurately linked or rejected via the above procedure, and we simply discard them. In particular, for identified entities, we extract their description information as local data and consider the triplets in KGs that are directly related to them as global data. For global data quality, we then filter out infrequent entities expected for entities aligned with items (i.e., lower than 10 in both datasets) and retain the relations appearing in at least 50 triplets. The basic statistics and distributions of two datasets and extracted information is summarized in Table 1 and Fig. 6, respectively. Following other works, we randomly select 80% interactions as the training set, and treat the remaining 20% as the testing set for each dataset.

#### 4.2 Experiment Setup

**4.2.1 Evaluation Metrics.** To evaluate our model in click-through rate (CTR) prediction, we apply the trained model to predict each interaction in the test dataset. We adopt the widely-used evaluation protocols, including AUC (Area Under Curve), MAE (Mean Absolute Error), RMSE (Root-Mean-Square Error), and F1-score to evaluate CTR prediction.

**4.2.2 Baselines.** To demonstrate the effectiveness, we compare the proposed model with the following baselines:

- **SVD** [18] is a classical CF-based model using matrix decomposition and inner product to model user-item interactions.
- **LibFM** [23] is a state-of-the-art feature-based factorization model and widely used in CTR prediction. We concatenate user ID and item ID to feed into LibFM.

\(\text{Table 1: Basic statistics of the datasets.}\)

|                      | Amazon-book | MovieLens-20M |
|----------------------|-------------|---------------|
| **User-Item Feedback** |             |               |
| #Users               | 37,290      | 61,859        |
| #Items               | 18,775      | 17,488        |
| #Interactions        | 553,112     | 9,861,984     |
| **Knowledge Graph**  |             |               |
| #Entities            | 70676       | 67,888        |
| #Relations           | 34          | 55            |
| #Triplets            | 1,557,647   | 1,065,513     |

\(^2\)http://jmcauley.ucsd.edu/data/amazon.

\(^3\)https://grouplens.org/datasets/movielens/
Table 2: Comparative results for Amazon-Book and MovieLens-20M. For MAE, RMSE, the smaller value is better, and vice versa for AUC, F1-score.

| Model       | Amazon-Book | MovieLens-20M |
|-------------|-------------|---------------|
|             | MAE         | RMSE          | AUC   | F1-score | MAE         | RMSE          | AUC   | F1-score |
| SVD [18]    | 0.2350      | 0.3095        | 0.9051 | 0.9007   | 0.3190      | 0.3894        | 0.8391 | 0.8465   |
| LibFM [41]  | 0.2536      | 0.3369        | 0.8932 | 0.9022   | 0.3086      | 0.3892        | 0.8368 | 0.8440   |
| DKN [34]    | 0.2430      | 0.3241        | 0.9087 | 0.9058   | 0.3361      | 0.3743        | 0.8280 | 0.7940   |
| CKE [41]    | 0.2290      | 0.2949        | 0.9204 | 0.9120   | 0.3277      | 0.4024        | 0.8394 | 0.8171   |
| KGCN [35]   | 0.2184      | 0.2751        | 0.9022 | 0.9120   | 0.3892      | 0.8368        | 0.8440 | 0.8171   |

Local model 0.2268 0.3058 0.8994 0.9058 0.3277 0.4024 0.8394 0.8171
Global model 0.2177 0.2551 0.9236 0.9058 0.3277 0.4024 0.8394 0.8171
Duet model 0.1934 0.2417 0.9536 0.9536 0.3361 0.9218 0.8836 0.8836

4.3 Comparative Results: Q1

The experiment results for algorithm comparison are shown in Table 2. On both two datasets, the proposed duet model has the best performance in all metrics. Overall, the duet model surpasses others significantly by 10.0%, 5.1%, 2.5% and 1.8% in metrics of MAE, RMSE, AUC, and F1-score at least, respectively. The local model and global model hardly achieve the best performance individually. While, the outperformance of duet model indicates the combination of them is effective and meaningful. There are also some other observations from the experiment results. First, we find that most methods with side information perform better than traditional methods in all situations, which reveals that combining with side information is an effective way to address the fundamental data sparsity problem in the recommendation process. Second, for DKN and KGCN, the reason for their occasionally poor performance may be that they just consider one type of side information, which can’t get multi-aspects information from different data. Third, compared to CKE, it also utilizes various information during the recommendation process but has a poorer performance. The results indicate that the designed embedding method in KEE for the local model and the proposed attention mechanism used in both sub-models according to their distribution. For the global model, we choose TransR [19] to process the unified relation graph and learn entity embeddings. The dimension of entity embeddings is set 50. The Leaky ReLu slope is 0.2. The word embeddings are initialized by the skip-gram embeddings of words trained on the description corpora [38], and we use Adam [16] to train our model by optimizing the loss function.

The hyper-parameter settings for baselines are set as follows: For SVD, we use the unbiased version. The dimension and learning rate for different datasets are set as: $d = 8, \eta = 0.5$ for MovieLens-20M and $d = 8, \eta = 0.1$ for Amazon-Book. For LibFM, the dimension is $(1, 1, 8)$, and the number of training epochs is 50. For KGCN, the dimension of the two datasets are both 50. The training weight for KG part is 0.5 for MovieLens-20M and 0.1 for Amazon-Book. For CKE, the dimension of the two datasets is both 128. The training weight for the KG part is 0.1 for both datasets. The learning rate is the same as in SVD. For DKN, the dimension of both word embeddings and entity embeddings are set as 128. Other hyper-parameters are the same as reported in their original papers or as default in their codes.

4.2.3 Implement Details. The hyper-parameters of the proposed model are configured following popular choices or previous research. For the local model, the dimension of both word embeddings and CNN filters are set to 128. The length of the CNN used to encode description is set to 3, which refers as tri-gram. The descriptions are fetched from Freebase, and the fixed size of words in the description is set 40 for MovieLens-20m and 200 for Amazon-book.
We study the performance variation for our model, such as the with local model and global model. These two kinds of information together provide proof for the hypothesis that the two sub-models can complement each other, and hence a combination of the two is more appropriate.

In order to verify the effectiveness of the combination with local model and global model, we conduct some ablation experiments and the results are shown in Table 2. It reveals that the duet model performs better than the individual local and global models. For better understanding, we randomly select two films with description information for items in the recommendation process.

The sharply rising knowledge graph (KG) provides different perspectives from other side information to capture novel information between both items and users. For example, KGAT [36] explores the high-order connectivity with heterogeneous semantic relations in KGs for the knowledge-aware recommendation. DKN [34] generates embedding for news by combining information from heterogeneous semantic information in sub-KG related to it and multiple embedding of its title and aligned entities. Compared to prior works that mainly utilized one kind of side information, we propose a novel framework to jointly combine the heterogeneous structure information in KGs and textual description for items in the recommendation environment, deep learning techniques have made significant success in recent years. For instance, DeepCoNN [43] enhances the model interpretability and alleviates the data sparsity problem by adopting two parallel CNNs for modeling rich semantic information in user behaviors and item properties from review texts. ConvMF [15] adopts CNNs to capture accurate local contextual information for the rating prediction via word embedding and convolutional kernels, which provides a deeper understanding of description documents.

**Figure 7:** Illustration of the effectiveness of the combination with local model and global model.

**Figure 8:** Parameter sensitivity experiments are effective to capture potential information on the different side information.

**4.4 Ablation Research: Q2**

In order to verify the effectiveness of the combination with local model and global model, we conduct some ablation experiments and the results are shown in Table 2. It reveals that the duet model performs better than the individual local and global models. For better understanding, we randomly select two films with description information from review texts. ConvMF [15] adopts CNNs to capture accurate local contextual information for the rating prediction via word embedding and convolutional kernels, which provides a deeper understanding of description documents.

**Table 2:**

| Title               | Description |
|---------------------|-------------|
| Sleeper             | …a tribute to comedians Groucho Marx and Bob Hope… in Sleeper and …featuring Bob Hope… in The Big Broadcast of 1938 is local information, and the mutual connection between comedy and two films is global information. These two kinds of information together provide proof for the recommendation result. This demonstrates that our underlying hypothesis that the two sub-models can complement each other, and hence a combination of the two is more appropriate. |

| Global Information  | |
|---------------------| |
| Comedey             | |
| Sleeper             | |
| film,genre          | |
| film,country        | |
| The Big Broadcast of 1938 |
| USA                 | |
| English             | |

**4.5 Parameter Sensitivity: Q3**

We study the performance variation for our model, such as the length of the description $L$ in the local model, and the dimension of the vector $d$ (word embedding) and $k$ (entity embedding) for local model and global model. We first investigate the influence of the description content length for local model by selecting $L$ from {20, 40, 60, 80} for MovieLens-20m and {100, 150, 200, 250} for Amazon-book. Fig. 8(a) shows that the performance of the proposed model improves with the increase of size of description content within a certain range. The reason is that the more given items’ descriptive information provides a chance to better understand them for model. But excessively increased length will bring many high-frequency common words, which exists in many items’ description content and may mislead the identification process of items. Then, we also explore how the various dimension of word embedding $d$ for local model and dimension of entity embedding $k$ for global model affect model performance by trying all combinations of $d$ and $k$ in {50, 150, 200, 300}. The results are shown in Fig. 8(b), from which we can find that it has the same changing trend as the fixed size of the description information. This is because the longer embedding can carry more useful information of word and entity semantic. But when a certain limitation is reached, the information from the increasing dimensionality will be overwhelmed by noise data, which is confused for recommendation.

**5 RELATED WORKS**

Two lines of researches are highly related work, which are summarized as follows:

**Recommendation with side information.** In order to address the two fundamental issues — data sparsity and cold start issues, multiple research has studied different types of side information (e.g., social networks, user profiles, and item descriptions) for recommendation systems in various domains. For instance, based on the assumption that users share similar preferences with trusted friends in their social network, plenty of trust-aware recommendation algorithms [2, 14, 37] have been proposed. Besides social networks, the side information for users or items helps to deeply understand both item properties and user preferences. Many recommendation algorithms [12, 32] have been proposed by exploiting latent factors in these kinds of side information. The sharply rising knowledge graph (KG) provides different perspectives from other side information to capture novel information between both items and users. For example, KGAT [36] explores the high-order connectivity with heterogeneous semantic relations in KGs for the knowledge-aware recommendation. DKN [34] generates embedding for news by combining information from heterogeneous semantic information in sub-KG related to it and multiple embedding of its title and aligned entities. Compared to prior works that mainly utilized one kind of side information, we propose a novel framework to jointly combine the heterogeneous structure information in KGs and textual description for items in the recommendation process.

**Deep Learning for Recommendation.** Thanks to learning multiple levels of representations and abstractions from raw data in the recommendation environment, deep learning techniques have made significant success in recent years. For instance, DeepCoNN [43] enhances the model interpretability and alleviates the data sparsity problem by adopting two parallel CNNs for modeling rich semantic information in user behaviors and item properties from review texts. ConvMF [15] adopts CNNs to capture accurate local contextual information for the rating prediction via word embedding and convolutional kernels, which provides a deeper understanding of description documents.
Our proposed framework distinguishes itself from the above-mentioned works in the following aspects: 1) considering different characteristics of local and global information, we especially design a novel recommendation model composed of two separate deep learning sub-models combined with attention networks; 2) we design a duet architecture to jointly learning explicit textual knowledge in items’ description and semantic structure information in KGs.

6 CONCLUSION

In this paper, we propose a novel recommendation model, which is composed of two separate deep neural network sub-models. One models users’ preference using a local representation of history items’ descriptions, and another one learns a global representation based on KGs before recommendation. The experiment results demonstrate that the combination of these two sub-models indicates a better performance than the individual sub-models on the recommendation task as well as significant improvements in overall baselines, including both traditional baselines and other recently proposed models based on KGs. Besides, one could extend the proposed model to other information, which provides different perspectives for modeling user preference information.

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