SUPER-Rec: SUrrounding Position-Enhanced Representation for Recommendation

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Abstract—Collaborative filtering problems are commonly solved based on matrix completion techniques which recover the missing values of user-item interaction matrices. In a matrix, the rating position specifically represents the user given and the item rated. Previous matrix completion techniques tend to neglect the position of each element (user, item and ratings) in the matrix but mainly focus on semantic similarity between users and items to predict the missing value in a matrix. This paper proposes a novel position-enhanced user/item representation training model for recommendation, SUPER-Rec. We first capture the rating position in the matrix using the relative positional rating encoding and store the position-enhanced rating information and its user-item relationship to the fixed dimension of embedding that is not affected by the matrix size. Then, we apply the trained position-enhanced user and item representations to the simplest traditional machine learning models to highlight the pure novelty of our representation learning model. We contribute the first formal introduction and quantitative analysis of position-enhanced item representation in the recommendation domain and produce a principled discussion about our SUPER-Rec to the outperformed performance of typical collaborative filtering recommendation tasks with both explicit and implicit feedback.

Index Terms—Matrix completion, Position-enhanced item representation, Collaborative filtering recommendation

I. INTRODUCTION

Recommender systems aim to filter useful information and contents of user’s potential interests and provide users with the most attractive and relevant items in the era of big data and thus have achieved significant success in social media and e-commerce. Among different recommendation approaches, Collaborative Filtering (CF) methods aim to discover the similarities in the user’s past behaviour and make predictions to the user based on a similar preference with other users. To achieve the goal of CF, a Matrix Completion (MC) is one of the most common formulations that uses a user-item rating matrix where rows and columns represent users and items, and predicts user’s interactions (ratings or actions) in items corresponding to filling in the missing entries [2], [3].

Existing MC-based recommendation models generally factorise the user-item rating matrix into latent features; most models produce two classes of embeddings for users and items, respectively, and apply the dot product between two user/item embedding vectors to predict the unknown ratings or actions [16], [31], [33], [36]. There are different types of user/item embedding-based models, such as graph-based [1], [34], feature-based [7], [22], inductive-based [32] embeddings.

However, those research missed one of the fundamental points in the MC-based recommendation models. We would like to remind that a user-item matrix consists of rows and columns representing users and items, and predicting users’ interest in items corresponds to filling in the specific point of missing entries. The specific point can be presented based on the position of its rows and columns in each matrix. With this in mind, the following question arises: Can we generate item/user embedding that captures the location/position of each entry in the matrix? Such question remains unexplored in this research area so far. To answer this, we first need to consider the best way to capture and apply the location/position information in the matrix. Generally, there are two position encoding types, absolute position and relative position, that we can apply to the user-item matrix with rows and columns. The absolute position would encode the absolute location of a rating entry within the matrix, specific row and column. It is straightforward and clear to index the position of each rating entry. However, If we use the absolute position of users, items, and ratings, there is a significant computation/memory issue and inefficient when the dataset is large and sparse. Another approach is to encode the position of a rating entry relative to surrounding neighbour items and its entry. Inspired by the relative position encoding in the Word2Vec [19], assigning the relative positions of the target items and surrounding neighbour items into different groups (incl. left neighbour item, target item, right neighbour item) by conducting the sliding window [1]. The relative position approach would produce relatively lower dimension embedding so it would not grow with the user/item size, and the embeddings are more computationally efficient.

In this research, we propose a new position-enhanced user/item representation model for recommender systems called SUPER-Rec, which covers the essential matrix information, and the position/location of the entry. Our proposed SUPER-Rec learns item representations based on item’s interactions with its surrounding neighbour items, without

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1The example of the proposed relative position encoding can be found in Figure [1] It shows the step-by-step procedure of encoding and training.
user’s behavioural interactions with items. SUPER-Rec recommendation consists of 3 main stages: The first stage, User-Item Matrix Positioning, defines the position-fixed surrounding item context and forms the training corpus for SUPER-Rec. Then, SUPER-Rec Training is conducted training a decoupled SUPER-Rec item representation utilising the fixed surrounding item position correlated with user feedback taste. The final stage, Matrix Completion with SUPER-Rec, conducts the recommendation based on the trained SUPER-Rec item representation and its derived user representation.

The major contributions of this research paper are summarised as follows:

1) We introduce a new position-enhanced user/item representation for the recommendation that leverages the positions and ratings of surrounding neighbour items.
2) We propose a stand-alone and generally applicable position-enhanced user/item embedding model that can produce the outstanding rating prediction result on most recommendation benchmark datasets (e.g. high or low density; small or large user/item/rating size; explicit or implicit user’s action).
3) The proposed SUPER-Rec achieves the best RMSE/MAE/NDCG/AUC results by a large margin compared with various state-of-the-art matrix completion models on eight(8) widely used recommendation benchmark datasets. The pretrained SUPER-Rec embedding for each dataset will be released to the public and let researchers/developers use it as an input embedding for their deeper and complex recommendation model.

Note that our SUPER-Rec is the stand-alone and generally applicable representation so it can flexibly incorporate with various off-the-shelf models (e.g. Traditional Machine Learning, RNN-, CNN-, GNN-, or Attention-based).

II. RELATED WORK

User/item-based Collaborative Filtering (CF) has achieved great success in the field of recommendation systems, with the essence of modeling the user-item interaction based on the partially observed interaction matrix. Especially, item-side observation is shown to convey rich information for user modeling and recommendation prediction. Some existing recommendation approaches demonstrate similar intention of ours in terms of addressing item feature modeling. For instance, early works such as SLIM and FISM learn the latent item factors via decomposing the interaction matrix with a trainable coefficient matrix and an item-item similarity matrix respectively for top-N recommendation. Besides, there are many Auto-encoder (AE)-based recommender systems that learn the item embedding in the low-dimensional hidden space as a latent variable, and reconstruct it in output space to predict the item’s ratings from users. In order to reinforce the item feature modeling, GLocal-K further proposes convolutional global kernel to the AE-based matrix completion framework that effectively captures the characteristics of each item.

A recent success has been made in exploiting both latent factor and word embedding models for item representation learning in the recommender systems. On the one hand, there are some approaches, such as CoFactor, RME, CDIE, CRML that implicitly factorize the item-context co-occurrence matrix composed of the Pointwise Mutual Information (PMI) of the respective item and context pairs shifted by a global constant, which is proved to be equivalent to applying skip-gram model with negative sampling for modeling the latent item embedding. However, those item representations are integrated into the matrix completion model and thus is limited to the specific model architecture. On the other hand, several works apply the Word2Vec model for learning item embeddings directly with the semantically ordered item sequence, which can be decoupled as a separate embedding like our SUPER-Rec. Nevertheless, same to the other approaches above, the item representation learning is contextualized in an inconsistent manner since the defined item-context varies among users due to their historical interaction with items, e.g. or/and the context is sequentialized based on time/session series. None of them utilize the original fixed position information from the user-item interaction matrix as in our SUPER-Rec for enhancing the item feature representation, which is of great importance since the interaction matrix for completion is composed of rows and columns that naturally entails a fixed context pattern for modeling item-item correlations.

Especially, many of the aforementioned approaches utilize the item representations to form an effective user representation accordingly, which resolves the limitation of user-specific embeddings. For instance, FISM combines the rated items from the latent item representation of users to compute user embedding. Those AE-based models such as AutoRec infer the user rating vectors based on the latent item embeddings modeled in the hidden space. LatentTrajectory uses Word2Vec model to learn the item representation contextualized by sequentially ordered items in the user trajectory. The user representation is then modeled based on the mean of the translations needed to move from one item to the next one in the trajectory. RRLC also applies Word2Vec model and learns the item representation from an timely ordered sequence of interacted items of the user, which is then used to represent the users based on their nearest neighbours measured by the similarity of item representations. Similar to these works, we will utilize our SUPER-Rec item representation to form the user representation and demonstrate its effectiveness together with the SUPER-Rec.

There are also some existing works that integrate graph-based user/item representation learning for recommender systems. GCMC and IGMC conduct the matrix completion for recommendation in a way of link prediction on a bipartite user-item interaction graph, during which the item node representation is learned via graph convolution that aggregates the graph structural information of the user-item connections.

2Note it uses a simple Neural Network as a rating prediction classifier.
in the graph. SpectralCF [35] applies the similar approach with spectral convolution operation. RM-GCNN [21] decomposes the row(user)- and column(item)-graphs from the user-item interaction matrix and employs the multi-graph convolutions to extract local stationary features, based on which a RNN is used to diffuse the score values for matrix reconstruction. All of those graph-based item representation is modeled based on how its surrounding positioned items are liked by the interaction with users, which varies from item to item. This is an essential difference in comparison with our SUPER-Rec that exerts the fixed positions in the original user-item interaction matrix for item representation modeling.

III. SUPER-Rec

Data for recommendation tasks are generally composed of a set of users and items, and the feedback that users give to items. It is normally stored as a user-item interaction matrix \( D \in \mathbb{R}^{M \times N} \) where each row \( i \in M \) and each column \( j \in N \) correspond to the \( i \)-th user and the \( j \)-th item while their indexed value represents the corresponding feedback \( D_{i,j} \) that the \( i \)-th user gives to the \( j \)-th item, which can be either explicit feedback such as movie rating ranging from 1-5, or implicit feedback such as the user click behavior denoted as 0 or 1. For each user at the row of the user-item matrix \( D \), each item can be uniquely identified by its fixed position at the column shared among all users, and user’s taste is indicated by the given feedback for the item. We propose a surrounding position-enhanced feature representation for recommendation systems, SUPER-Rec, which utilizes only the user-item interaction matrix \( D \) for capturing the latent item features by learning to model user’s taste over an item based on how its surrounding positioned items are liked by the user. Figure 1 articulates the three main stages for SUPER-Rec recommendation: 1) User-item Positioning, 2) SUPER-Rec Training, and 3) Matrix Completion with SUPER-Rec. We describe each stage in details as follows.

A. User-item Matrix Positioning

To begin with, we first define the target items with their surrounding neighbours so as to prepare the training corpus for SUPER-Rec. As is shown in the first stage in Figure 1, we reformulate the aforementioned user-item interaction matrix \( D \in \mathbb{R}^{M \times N} \) as \( D \in \mathbb{R}^{N \times M} \) for better illustration, where each row \( j \in N \) represents the item and each column \( i \in M \) indicates the user. We regard each item with feedback available in \( D \) as one of the target items. Assume that a target item is positioned at the row \( j \) in \( D \) and is given a feedback \( D_{j,i} \) from user \( i \), being either explicit or implicit. Then, we define the scope of surrounding neighbour items based on the bilateral context of the target item as \( \{ j + k \mid k \in \{ K \cup -K \} \} \), where \( K \in \{ 1, 2, ..., K \} \) and \( K \) is the window size that indicates the single-side length of the context. Likewise, the corresponding item feedback from user \( i \) in this surrounding context can be represented as \( \{ D_{j+k,i} \mid k \in \{ K \cup -K \} \} \). We set \( k \) to \( -K \leq k < N-j \) to constrain the surroundings in the scope of \( D \). The example demonstrated in Figure 1 takes the target item at row \( j = 2 \) for user \( i = 1 \) as with position index of 1 and feedback of 1, indicating the explicit feedback ranging from level 1-5. With window size \( K = 1 \), the bilateral surrounding context can be defined as item neighbours with position index of \( j - 1 = 0 \) and \( j + 1 = 2 \) while their corresponding item feedback would be 1 and 5. By this way, we can form the training corpus \( C \) for SUPER-Rec, consisting of each target item with its surrounding neighbour items. During the training, we will utilize these position-aware neighbour items and their feedback of user taste as the condition for inferring the identity(position) and feedback of the target item.

B. SUPER-Rec Training

In order to learn the SUPER-Rec representation for items using the prepared corpus \( C \), we first define an item position embedding matrix \( P \) and a feedback embedding matrix \( V \), where \( P = (p_1, ..., p_N) \in \mathbb{R}^{N \times d} \) and \( V = (v_1, ..., v_F) \in \mathbb{R}^{F \times d} \). Each embedding vector \( p \) or \( v \) uniquely corresponds to a specific item or feedback type. \( N \) and \( F \) refer to the total number of items and feedback types, e.g. \( F = 5 \) for 1-5 ranged user rating and \( F = 2 \) for the binary user interaction data such as user clicks, whereas \( d \) denotes the embedding dimension. We then define two transformation operators \( f(\cdot) \)
and \( g(\cdot) \) that learn to transform the combined position and feedback embedding of a surrounding neighbour item into both item space \( E \in \mathbb{R}^N \) and feedback space \( T \in \mathbb{R}^F \) so as to predict the position and feedback of the target item accordingly. Concretely, the transformation process is shown in Eq.\((1)\) and \((2)\). Given an target item \( j \) with a surrounding neighbour item \( j + k \) for user \( i \), we first concatenate (\( \oplus \)) the position embedding vector \( p_{j+k} \) and the feedback embedding vector \( v_{D_{j+k},i} \) of the surrounding neighbour item. Then, we project the concatenated embedding (\( \in \mathbb{R}^{2d} \)) into the item space and feedback space via multiplying with the learnable weight matrices \( W \in \mathbb{R}^{2d \times N} \) and \( Q \in \mathbb{R}^{2d \times F} \) respectively, resulting in the two projected vectors for target item position and feedback prediction. An illustrative example of predicting the target item prediction proceeds, the item position embedding matrix \( V \in \mathbb{R}^{F \times d} \) ← Feedback embedding matrix
\( W \in \mathbb{R}^{2d \times N} \), \( Q \in \mathbb{R}^{2d \times F} \) ← Two transformation weight matrices
\( \sigma_p \) space using Eq.\((1)\).

The second objective is to minimize the feedback prediction loss \( L_{p} \) for predicting each target item position as \( j^{'} \) against the ground truth position \( j \), given the user \( i \). As is indicated in Eq.\((3)\), it calculates the summed cross-entropy loss over predictions of all the surrounding neighbour items \( j+k \). Here \( \sigma_j(\cdot) \) is the negative-log softmax probability of the predicted target item position being the ground truth \( j \) based on the information of surrounding neighbour item \( j+k \), as is derived in Eq.\((4)\). \( \epsilon \) is used to avoid the Log-0 problem.

\[
L_p(j' = j | i) = \sum_{k \in \{K \cup -K\}} \sigma_j(f(j+k, i)) \tag{3}
\]

\[
\sigma_j(f(j+k, i)) = -\log \left( \frac{\exp(f_j(j+k, i))}{\sum_{a \in N} \exp(f_a(j+k, i)) + \epsilon} \right) \tag{4}
\]

The second objective is to minimize the feedback prediction loss \( L_v \), which is calculated in a similar way but is instead based on the feedback predictions of the target item, as is shown in Eq.\((5)\) for loss calculation and Eq.\((6)\) for deriving the negative-log softmax probability of the predicted feedback being the ground truth target item feedback \( r \).

\[
L_v(D'_{j,i} = r) = \sum_{k \in \{K \cup -K\}} \sigma_r(g(j+k, i)) \tag{5}
\]

\[
\sigma_r(g(j+k, i)) = -\log \left( \frac{\exp(g_r(j+k, i))}{\sum_{b \in F} \exp(g_b(j+k, i)) + \epsilon} \right) \tag{6}
\]

We jointly optimise these two objectives based on their weighted sum. As is denoted in Eq.\((7)\) for our joint loss \( \mathcal{L} \).

\[
\mathcal{L} = (1 - \alpha) \cdot L_p(j' = j | i) + \alpha \cdot L_v(D'_{j,i} = r) \tag{7}
\]

### Algorithm 1 SUPER-Rec training algorithm

**Input:** \( \{j, i\} \leftarrow \{\text{target item, given user}\} \)

**Output:** \( \mathcal{L} \leftarrow \text{Joint cross-entropy loss for the } j^{\text{th}} \text{ target item} \)

1. Define \( P \in \mathbb{R}^{N \times d} \leftarrow \text{Item position embedding matrix} \)
2. Initialize \( L_p = 0, L_v = 0, \alpha \in (0, 1) \)
3. \( r \leftarrow D_{j,i} \)
4. for \( k \in \{-K, -K + 1, ..., -1, 1, 2, ..., K\} \) do
5. if \( -j \leq k < N - j \) then
6. A surrounding neighbour item is out of range of item position, so skip the below statements and continue for-loop.
7. end if
8. Calculate \( f(j+k, i) \) for the projected vector in item space using Eq.\((1)\).
9. Calculate \( \sigma_j(f(j+k, i)) \) for the log softmax probability of the predicted target item position using Eq.\((4)\).
10. \( L_p \leftarrow L_p + \sigma_j(f(j+k, i)) \) (refer to Eq.\((3)\))
11. Calculate \( g(j+k, i) \) for the projected vector in feedback space using Eq.\((2)\)
12. Calculate \( \sigma_r(g(j+k, i)) \) for the log softmax probability of the predicted target item feedback using Eq.\((6)\).
13. \( L_v \leftarrow L_v + \sigma_r(g(j+k, i)) \) (refer to Eq.\((5)\))
14. end for
15. \( \mathcal{L} \leftarrow (1 - \alpha) \cdot L_p + \alpha \cdot L_v \)
16. return \( \mathcal{L} \)

**C. Matrix Completion with SUPER-Rec**

The trained SUPER-Rec representation \( \tilde{p}_j, j \in N \) for items captures the position-enhanced latent item features correlated to users’ tastes. Based on it, we can further construct user embedding vectors \( z_i, i \in M \). The intuition here is that
the unique preference of a user for providing the feedback to items can be inferred via their historical feedback-giving patterns over all their interacted items represented by SUPER-Rec. Concretely, as is demonstrated in the third stage in Figure 1 for a user $i$, we first weigh each item $j$ based on the feedback $D_{j,i}$ given by this user and calculate the weighted average of all their interacted items represented by SUPER-Rec accordingly. In case of the aforementioned implicit feedback, we directly calculate the average of all the interacted items, i.e. $D_{j,i} = 1$. It is worth to note that here we do not use original feedback types, e.g. 1-5, but instead their power-raised values as the weights for the summation so that more preferred items would result in much higher weight and thus the user’s preference can be better emphasized. In addition, since we are not to recommend only the most favourable items to users but instead to model how users react to all items that they did not give feedback yet, we adopt users’ historical feedback from all items no matter the feedback is positive or not.

With the SUPER-Rec based item and user representations, our end goal of recommendation is to predict all the unobserved item feedback in the user-item interaction matrix via matrix factorisation (MF). In order to demonstrate that our SUPER-Rec item representation and its derived user representation alone can exert superior feature representation power that leads to excellent recommendation performance in any neural network model, we apply it to a matrix factorisation model with only simple neural network structure: Feed-Forward Neural Networks-based MF (NNMF), which adopts a multi-layer perceptron. As is denoted in Eq.(8) for the NNMF model $h(\cdot)$, given user-item pair $(i, j)$, it first conducts an element-wise product ($\odot$) between the item representation $\tilde{p}_j$ and the user representation $z_i$ to derive the user-item relation representation, which is then concatenated ($\|\|$) with $\tilde{p}_j$ and $z_i$. Followed by [5], we then employ a three-layer neural network with relu activation denoted as $nn$. We conduct a log softmax layer $\sigma$ over the output of $h(\cdot)$ as in Eq.(9), where $\sigma_r$ represents the negative-log probability of the predicted feedback being $r \in F$.

$$h(j, i; \theta) = nn[\tilde{p}_j \| \tilde{p}_j \odot z_i \| z_i]$$ \hspace{1cm} (8)

$$\sigma_r(h(j, i; \theta)) = -\log \left( \frac{\exp(h_r(j, i; \theta))}{\sum_{b \in F} \exp(h_b(j, i; \theta))} + \epsilon \right)$$ \hspace{1cm} (9)

Our final loss function $L_{MF}$ for training is formulated in Eq. (10), in which we adopt $I[\cdot]$ to calculate the loss from feedback prediction being the ground truth $D_{j,i}$, the value of which equals to 1 only when $r$ equals to the ground truth feedback $D_{j,i}$ and 0 otherwise. The matrix $\Omega \in \{0, 1\}^{N \times M}$ serves as a mask for unobserved item feedback so that ones occur when only for items with available feedback in the original interaction matrix while zeros refer to unobserved item feedback. Hence, the training optimisation will only be conducted over observed feedback in the interaction matrix, updating all the trainable parameters $\theta$, including $\Omega \in \{0, 1\}^{N \times M}$ and the trained item position embedding matrix $P$, while considering L2 regularisation for $\{\omega_l \mid l = 1, 2, 3\} \cup \{\tilde{p}_j \mid j \in N\}$. $\lambda$ is a scaling factor for the two regularization items. We train the model based on the loss $L_{MF}$ with the training set while selecting the best model based on the validation set.

$$L_{MF} = \sum_{j, i : \Omega_{j,i} = 1} \sum_{r \in F} I[D_{j,i} = r] \cdot \sigma_r(h(j, i; \theta)) + \frac{1}{2} \lambda \cdot \left( \sum_{l=1, 2, 3} \|\omega_l\|^2 + \sum_{j \in N} \|\tilde{p}_j\|^2 \right)$$ \hspace{1cm} (10)

The trained SUPER-Rec with NNMF empowers the inductive inference for any user $i$, either being an existing one or a new one, provided with all the historical rated feedback over the $N$ items. As is shown in Eq.(11), to infer an unobserved feedback over an item $t \in N$ for a user $i$, we apply the softmax over the output of the trained SUPER-Rec with NNMF (parameterized with $\theta$, denoting the trained parameters in $\theta$), which derives the probability distribution over each feedback candidate $r \in F$, being either implicit or explicit. We then use the weighted sum (expected value) $D'_{t,i}$ as our final predicted feedback for recommendation.

$$D'_{t,i} = \sum_{r \in F} r \cdot \frac{\exp(h_r(t, i; \theta))}{\sum_{b \in F} \exp(h_b(t, i; \theta))}$$ \hspace{1cm} (11)

IV. Evaluation Setup

A. Datasets

We conducted experiments on eight widely-used recommendation benchmark datasets with both explicit and implicit feedback, MovieLens-100K (ML-100K) [20], MovieLens-1M (ML-1M) [20], MovieLens-10M (ML-10M) [9], Douban [17], Flixster [11], YahooMusic [4], and two implicit feedback, Amazon-Books and Amazon-Beauty [9, 13]. Note that the first six datasets contain users’ explicit ratings on items, and the latter two datasets provide users’ implicit feedback on items, indicating users’ actions (clicked or not-clicked).

We directly adopt the canonical u1 train/test splits as in [21, 24] for ML-100K and randomly split the dataset into 0.9/0.1 train/test set for ML-1M and ML-10M, followed by [22]. For Douban, Flixster and YahooMusic, we use the preprocessed train/test splits provided by [21]. For the two Amazon datasets, we use the last ten interactions of each user as the test set and keep the rest as the train set, followed by the IDCF [32]. The raw Amazon datasets are very large and sparse, so IDCF [32] filtered out infrequent items and users with less than five interactions. We leave out 10% of the training data as the validation set for early stopping in training. The statistics of datasets are summarised in Table I.

3We tested 5, 10, 20% of the training data as the validation set, but there is no significant difference.
TABLE I: Statistics of six explicit datasets and two implicit datasets used in the experiments. Note that explicit feedbacks are represented with the specific ratings in different ranges (e.g. 1-5, 1-100) and implicit feedbacks are based on the user’s action (Clicked or Not-Clicked).

| Feedback | Dataset         | #Users | #Items | #Ratings | Density | Rating types                  |
|----------|-----------------|--------|--------|----------|---------|-------------------------------|
| Explicit | ML-100K         | 943    | 1,682  | 100,000  | 6.30%   | 1, 2, 3, 4, 5                |
|          | ML-1M           | 6,040  | 3,706  | 1,000,020| 4.47%   | 1, 2, 3, 4, 5                |
|          | ML-10M          | 71,567 | 10,681 | 10,000,054| 1.30%   | 0.5, 1, 1.5, ..., 5          |
|          | Ddouban         | 3,000  | 3,000  | 136,891  | 1.52%   | 1, 2, 3, 4, 5                |
|          | Flixster        | 3,000  | 3,000  | 26,173   | 0.29%   | 0.5, 1, 1.5, ..., 5          |
|          | YahooMusic      | 3,000  | 3,000  | 5,335    | 0.06%   | 1, 2, 3, ..., 100            |
| Implicit | Amazon-Books    | 52,643 | 91,599 | 2,911,466| 0.06%   | Clicked/Not-Clicked          |
|          | Amazon-Beauty   | 2,944  | 57,289 | 82,904   | 0.04%   | Clicked/Not-Clicked          |

B. Baselines

We compare our novel position-enhanced embedding learning model, SUPER-Rec, with the following six(6) baseline models for explicit datasets. We first include models with graph-based user/item embeddings, GC-MC and IGMC. GC-MC [1] is a graph-based matrix completion framework that extracts user/item embeddings using a GNN and reconstructs the rating links via a bilinear decoder. IGMC [34] is also a graph-based model but extracts 1-hop enclosing subgraphs of user-item pairs and uses a GNN to encode the subgraph-based item embeddings. In addition, feature-based user/item embedding models, SparseFC and GLocal-K, are selected to compare. SparseFC [22] is a user/item-based autoencoder (AE) model, which feeds a high-dimensional user-item matrix, projects it into a low-dimensional latent feature space, and then reconstructs its entries to predict unknown ratings. This model regularises the weight matrices of hidden layers by projecting them into a low-dimensional space using support kernel matrices. GLocal-K [7] is an item-based AE architecture model, which takes a user-item interaction matrix as input and extracts item embeddings from each row vector of item ratings in the user-item matrix. Moreover, it proposes to apply two types of kernels in two training stages to improve the feature extraction performance: 1) pre-training the AE model using local kernelised weight matrices, and 2) fine-tuning the pre-trained model with the rating matrix, produced via convolution with global kernels. Finally, the inductive user/item embedding learning model, IDCF, is also considered as baseline. IDCF [32] proposes an inductive collaborative filtering framework, which is comprised of the two-stage training process: 1) pre-training a matrix factorisation model to obtain pre-trained user embeddings, which are further leveraged as metadata to inductively compute new users’ embeddings, and 2) learning the user graph with message-passing layers based on the pre-trained meta embeddings to generalise to compute inductive representations for new users. Note that IDCF has two variants; one (IDCF-NN) adopts multi-layer perceptron as a prediction model, and another (IDCF-GC) applies graph convolution networks.

For the implicit feedback dataset, we applied four(4) baseline models, two variants of IDCF as above, and two item-based CF models with item embeddings. FISM [12] proposes an item-item similarity matrix-based top-N recommendation framework, which learns the matrix as a product of low-rank latent factor matrices and estimates the ratings based on the dot product between the aggregated latent vector of the items that have been rated by a user (user embedding) and unrated item latent vector from different factor matrices. MultVAE [16] proposes a variational autoencoder-based collaborative filtering framework, which adopts multinomial conditional likelihood on the generative model (decoder) for modelling user-item implicit feedback data, and makes predictions by sorting all the items based on the predicted multinomial probability.

C. Evaluation Metrics

For datasets with explicit feedback, the goal is to predict user’s ratings on items, i.e. estimate the missing values in a user-item rating matrix. We use the prediction accuracy metrics, including RMSE (Root Mean Square Error) and MAE (Mean Absolute Error), which mainly focus on comparing the actual and predicted ratings. MAE presents a holistic view of the recommendation prediction without any bias of extrema in error terms, while RMSE disproportionately penalises large errors and is affected by outliers or bad predictions. Both metrics measure whether the predicted value is close to the actual value but do not account for the order of predictions. We apply the Normalised Discounted Cumulative Gain (NDCG), an average score that measures the consistency between the ranking of predicted ratings and the ground truth for each user. Datasets with implicit feedback aim to predict whether a user interacts with an item. Since the dataset is very sparse and has positive instances only, we uniformly sample five items as negative samples for each clicked item followed by [52] and adopt AUC and NDCG to measure the global and personalised ranking accuracy, respectively. AUC measures the global consistency between the ranking of all the predicted user-item interactions and the ground truth, which ranks all the 1’s before 0’s.

D. Implementation Details

For all benchmark datasets, we used the window size of 1, which included the very next item on the left and right sides as neighbours in the context. Adam optimiser and early stopping technique with a patience parameter of 5 were used for training optimisation. We empirically applied the learning rate of 1e-4 for ML-1M, 1e-2 for Amazon-Books and 1e-3 for all the other datasets. The batch size was set in proportion to the data size: 500 for YahooMusic, 5,000 for Amazon-Books, 10,000 for ML-10M and 1,000 for all the other datasets. We searched for the optimal embedding dimension in every size of 100, starting from 100 for the explicit rating-based datasets. For Amazon-Books and Amazon-Beauty, we tried dimensions within [200, 500, 1000] and [200, 500, 1000, 2000, 4000]. We found that the data with a higher density (or lower sparsity) requires a deeper search to find the optimal embedding dimension. We restricted the number of interactions of users to 100 for ML-10M and Amazon-Books due to the limitation of computational and
memory resources. We trained the MF model using the Adam optimiser and the L2 regularisation technique. We searched for the optimal regularisation parameter within [0.1, 0.3, 0.5, 1.0, 3.0, 5.0] for all datasets. The learning rate was empirically selected as 1e-5 for ML-100K, ML-1M and Amazon-Beauty, and 1e-4 for all the other datasets. The batch size was set to 500 for YahooMusic, 5,000 for Amazon-Books and 1,000 for all the other datasets.

V. RESULT

A. Performance Comparison on Explicit Datasets

Table II presents the prediction results for test ratings on five explicit rating-based datasets including ML-100K, ML-1M, Douban, Flixster, and YahooMusic. Our model with the proposed position-enhanced item/user embedding representation SUPER-Rec significantly outperforms all baselines on all five datasets by a large margin. Note that we applied a simple neural network as a rating prediction model. The overall result proves that our SUPER-Rec performed exceptionally better than all types of item embedding models when looking toward rating accuracy (MAE), focusing on the importance of the bad rating prediction (RMSE) and how good the ordering is (NDCG). More specifically, our SUPER-Rec rapidly outperforms Glocal-K, with 0.168/0.144/0.084, 0.231/0.232/0.067, 0.101/0.101/0.055 improvement of RMSE/MAE/NDCG on three explicit datasets ML-100K, ML-1M, and Douban, which has the rating 1,2,3,4,5. With datasets with a larger rating range, Flixster and YahooMusic, our model SUPER-Rec improves 0.045/0.051/0.058 and 2.0/1.6/0.042 compared to the second-best models, IGMC and IDCF, in RMSE/MAE/NDCG. The result validates the robustness of the position-enhanced item/user representation learning approach and its efficacy for recommendation in various rating ranges of user-item data.

The implication is that our proposed position-enhanced user/item representation has a great potential to predict the user’s ratings of the specific position (row/column) in the user-item matrix.

B. Impact of Embedding Dimension

We now take a more in-depth look into the optimal dimension size of the surrounding neighbours’ position-enhanced representation from the user-item matrix on all the six explicit datasets. This evaluation aims to check what dimension size would be the smallest vector space but better represent the surrounding position information with user/item ratings.

As shown in Figure 2, the testing performance varies depending on different datasets as the dimension of feature representation changes, which implies that different data nature may entail a different amount of latent feature needed for conducting the recommendation, and thus leads to different optimal dimension size for embedding representation. With this in mind, we could find a strong correlation between the rating density of each dataset and the optimal dimension size to represent the position-enhanced item/user representation. Specifically, ML-100K and ML-1M have relatively higher rating densities of 6.30% and 4.47%, and produce a better performance as the dimension size increases; The best performance for ML-100K and ML-1M are at dimensions 2000 and 1600, respectively. In contrast, the three sparser datasets, Douban, Flixster, and YahooMusic, display an opposite overall pattern and reach their performance peak at smaller dimensions, such as 100 or 200. This trend implies that rich rating data would require the position-enhanced representation with more neighbour position and rating information, but the sparse rating data conveys relatively less neighbour information and its rating pattern.

The result validates the robustness of the position-enhanced item/user representation learning approach and its efficacy for recommendation in various rating ranges of user-item data.

Table II: Overall performance comparison with baseline models on the five explicit datasets. The baseline models are ordered in chronological order from top to bottom. IDCF and GLocal-K were published in 2021.

| Model       | RMSE ↓ | MAE ↓ | NDCG ↑ | RMSE ↓ | MAE ↓ | NDCG ↑ | RMSE ↓ | MAE ↓ | NDCG ↑ | RMSE ↓ | MAE ↓ | NDCG ↑ | RMSE ↓ | MAE ↓ | NDCG ↑ |
|------------|--------|-------|--------|--------|-------|--------|--------|-------|--------|--------|-------|--------|--------|-------|--------|
| SparseFC   | 0.895  | 0.700 | 0.905  | 0.824  | 0.642 | 0.928  | 0.730  | 0.569 | 0.941  | 0.981 | 0.699 | 0.924  | 3.40   | 22.7  | 0.848  |
| GC-MC      | 0.905  | 0.714 | 0.900  | 0.832  | 0.658 | 0.923  | 0.734  | 0.573 | 0.938  | 0.917 | 0.684 | 0.886  | 20.5   | 16.0  | 0.844  |
| IGMC       | 0.905  | 0.741 | 0.899  | 0.857  | 0.784 | 0.903  | 0.721  | 0.591 | 0.939  | 0.872 | 0.697 | 0.927  | 19.1   | 16.3  | 0.865  |
| IDCF-NN    | 0.931  | 0.732 | 0.896  | 0.844  | 0.663 | 0.922  | 0.738  | 0.576 | 0.939  | 0.910 | 0.693 | 0.925  | 21.5   | 16.9  | 0.929  |
| IDCF-GC    | 0.905  | 0.714 | 0.901  | 0.839  | 0.652 | 0.924  | 0.733  | 0.574 | 0.940  | 0.896 | 0.682 | 0.928  | 19.3   | 15.2  | 0.922  |
| GLocal-K   | 0.888  | 0.695 | 0.906  | 0.822  | 0.641 | 0.929  | 0.720  | 0.562 | 0.943  | 0.980 | 0.699 | 0.925  | 33.8   | 22.6  | 0.864  |
| SUPER-Rec  | 0.720  | 0.551 | 0.990  | 0.591  | 0.409 | 0.996  | 0.619  | 0.461 | 0.998  | 0.827 | 0.632 | 0.986  | 17.1   | 13.7  | 0.972  |

As mentioned in Section III, we train SUPER-Rec position-enhanced item representation by using a single surrounding neighbour item as an input and a centre item as a target. In this evaluation, we aim to test input variants of the position-enhanced item representation training, which produces better performance for the optimal regularisation parameter within [0.1, 0.3, 0.5, 1.0, 3.0, 5.0] for all datasets. The learning rate was empirically selected as 1e-5 for ML-100K, ML-1M and Amazon-Beauty, and 1e-4 for all the other datasets. Note that the performance (RMSE & NDCG) of the proposed SUPER-Rec significantly outperforms all baselines on all five datasets by a large margin. More specifically, our SUPER-Rec rapidly outperforms Glocal-K, with 0.168/0.144/0.084, 0.231/0.232/0.067, 0.101/0.101/0.055 improvement of RMSE/MAE/NDCG on three explicit datasets ML-100K, ML-1M, and Douban, which has the rating 1,2,3,4,5. With datasets with a larger rating range, Flixster and YahooMusic, our model SUPER-Rec improves 0.045/0.051/0.058 and 2.0/1.6/0.042 compared to the second-best models, IGMC and IDCF, in RMSE/MAE/NDCG. The result validates the robustness of the position-enhanced item/user representation learning approach and its efficacy for recommendation in various rating ranges of user-item data.
joint learning of position and rating of items. As shown in Table III, Single refers to the training model with a single neighbour item as an input and a centre item as a target, while the Double refers to that with the sum of both left and right neighbour items as an input and a centre item as a target. Those two variant testing would give insight into which input format covers the surrounding neighbour item information for the position-enhanced item embedding training.7

We tested those two variants on the five explicit datasets, shown in Table III. The performance gap between the two variants is extremely small, but the type Single refers to that with the sum of both left and right neighbour items as input and a centre item as a target. This result implies that 1-to-1 neighbour-based training is better than N-to-1 (N=both side, left-right neighbour items).

D. Comparison of Rating Prediction Model Variants

In this evaluation, we would like to validate the robustness of our SUPER-Rec as a standalone position-enhanced item representation for recommendation systems. In Section III we applied a simple neural network as a matrix factorisation model but consider that it is also worth testing with other simple and traditional machine learning classifiers. We compare three machine learning techniques with our SUPER-Rec: k-NN (k-Nearest Neighbour), SVM (Support Vector Machine), and NN (Neural networks) on two explicit datasets, Flixster and YahooMusic, with lower rating density and relatively bad rating prediction performance, as shown in Table IV.

As described in Section III-C, we concatenated 1) item, 2) user, and 3) user-item relation representation and applied this concatenated representation as the input for each classifier. First, we use k-NN based on the k(=5) nearest samples, and it results in relatively worse performance in both evaluation metrics for both datasets, even though it is still competitive and higher than most of the baseline models in Table III. Secondly, SVM classifies from a view of the global training samples, and it achieves better performance than KNN in both datasets. It sometimes slightly outperforms NN in NDCG, achieving 0.987
TABLE V: Performance comparison of RMSE with baseline models on ML-10M.

| Model      | RMSE ↓ |
|------------|--------|
| I-AutoRec  | 0.782  |
| GC-MC [25] | 0.777  |
| SparseFC   | 0.769  |
| MRMA [14]  | 0.763  |
| SUPER-Rec  | 0.651  |

in Flixster and 0.973 in YahooMusic.

Based on this evaluation result, our proposed user/item representation SUPER-Rec has an exceptional capability for predicting the rating on a specific position, even with simple traditional machine learning classifiers. It implies a great potential of our SUPER-Rec as an input representation of the deeper and more complicated deep learning-based matrix factorisation models.

E. Large-scale Rating Dataset Analysis

The previous evaluations were mainly conducted on the small or medium-sized rating datasets. In this evaluation, we demonstrate the effectiveness of SUPER-Rec on the larger-scaled and relatively sparse explicit dataset, ML-10M (density of 1.30%), which involves many users (71K), items (10K), and the enormous number of ratings (10M). Note that we compared our performance with the state-of-the-art models in ML-10M with RMSE, shown in Table V. I-AutoRec [25] is an item-based AE model, which represents item embeddings by projecting item-wise rating history into a low-dimensional space. MRMA [14] represents user-item rating representations by a mixture of low-rank matrix approximation (LRMA) models with different ranks (MRMA), which goes beyond the conventional matrix approximation with fixed ranks.

All the baselines achieve the RMSE performance from 0.782 (I-AutoRec [25] in 2015) to 0.763 (MRMA [14] in 2017), and those remain a high RMSE of over 0.76. Surprisingly, SUPER-Rec outperforms them with a significant drop and reaches the lowest RMSE of 0.651. Such results demonstrate the superior power of our SUPER-Rec for well addressing the user/item representation in the large and sparse rating dataset.

F. Performance Comparison on Implicit Datasets

The previous evaluations are based on explicit datasets, mainly focusing on predicting the user’s rating. This evaluation aims to evaluate the item representation capability of our SUPER-Rec in the user’s action prediction with implicit feedback datasets. We evaluate the SUPER-Rec on two implicit feedback datasets, Amazon-Beauty and Amazon-Books, indicating user’s actions (clicked or not-clicked) using AUC and NDCG metrics. Note that both implicit datasets are large and sparse, Amazon-Books (density of 0.06%) and Amazon-Beauty (density of 0.04%).

Surprisingly, as shown in Table VI, our SUPER-Rec hugely outperforms the baselines in both AUC and NDCG, including IDCF-GC with graph convolution, which achieves the best performance among all the baseline models. It produces the best result on both datasets of different sparsity in all metrics, i.e. AUC of 0.959 and 0.997, and NDCG of 0.980 and 0.998 on Amazon-Beauty and Amazon-Books. SUPER-Rec outperforms the second-best model by a large margin (0.168/0.189), especially on Amazon-Beauty, with larger size (50K users and 90K items) and richer user’s action data (3M actions). The results demonstrate the robustness of the proposed representation, not only in the explicit rating nature but also a simple binary implicit action trends.

G. Impact of Sparsity Ratios

While previous evaluation demonstrated the effectiveness of SUPER-Rec on different sparse datasets, we further investigated its efficacy in terms of the sensitivity to the sparsity of the same data source. To conduct this, we gradually decreased the training data ratio from 1.0 (full training data) to 0.2 and compared the test results of the RMSE, MAE and NDCG with three baseline models on ML-1M in Figure 3.

While the three baseline models perform almost similar overall, SUPER-Rec significantly outperforms all three by a large margin for all evaluation metrics at all training ratios. The baseline models show an apparent performance degradation in RMSE, MAE and NDCG as the data gets more sparse, i.e. with a smaller training ratio. On the contrary, SUPER-Rec illustrates a consistent performance with increased sparsity. Similarly, the performance keeps improving in MAE when the training ratio decreases from 1.0 and reaches the best RMSE at 0.4. Even though the performance slightly degrades with the training ratio decreasing to 0.2, it is still better than the training ratio of 1.0, 0.8 or 0.6. On the other hand, SUPER-Rec achieves stable performance in NDCG overall as the data sparsity changes. We can infer that SUPER-Rec is more

TABLE VI: Performance comparison of AUC and NDCG with baseline models on the two implicit feedback datasets.

| Model       | Amazon-Beauty | Amazon-Books |
|-------------|---------------|--------------|
|             | AUC ↑ | NDCG ↑ | AUC ↑ | NDCG ↑ |
| FISM [12]   | 0.613 | 0.678 | 0.792 | 0.752 |
| MultVAE [16] | 0.644 | 0.679 | 0.701 | 0.738 |
| IDCF-NN [32] | 0.774 | 0.750 | 0.920 | 0.939 |
| IDCF-GC [32] | 0.791 | 0.791 | 0.930 | 0.946 |
| SUPER-Rec   | 0.959 | 0.980 | 0.997 | 0.998 |

Fig. 3: Performance comparison with baseline models w.r.t. different sparsity levels on ML-1M.

Note that those baselines generally reported only RMSE in ML-10M so we followed the nature.
robust in recommendation performance and less sensitive to data sparsity than the baseline models. Moreover, SUPER-Rec shows more advantages with sparse datasets, validating its effectiveness in position-enhanced feature representation even with fewer feedback data available.

VI. CONCLUSION

In this paper, we have introduced a position-enhanced user/item representation SUPER-Rec for the recommendation that leverages the positions and ratings of surrounding neighbour items. Our SUPER-Rec significantly outperformed in all RMSE/MAE/NDCG/AUC metrics against state-of-the-art Matrix Completion models on most recommendation benchmark datasets, with high or low density, small or large user/item/rating size, and explicit or implicit user’s action. The pretrained SUPER-Rec embedding for each dataset will be released to the public and let researchers/developers use it as an input embedding for their deeper and complex recommendation model.

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The github will be shared after the paper gets accepted.