Modeling Sequences as Distributions with Uncertainty for Sequential Recommendation

Ziwei Fan, Zhiwei Liu, Lei Zheng, and Shen Wang
Department of Computer Science, University of Illinois at Chicago, USA
{zliu213,zfan20}@uic.edu

Zhiwei Liu
Pinterest Inc., USA
lzheng@pinterest.com

Shen Wang, Philip S. Yu
Department of Computer Science, University of Illinois at Chicago, USA
{swang224,psyu}@uic.edu

ABSTRACT

The sequential patterns within the user interactions are pivotal for representing the user’s preference and capturing latent relationships among items. The recent advancements of sequence modeling by Transformers advocate the community to devise more effective encoders for the sequential recommendation. Most existing sequential methods assume users are deterministic. However, item-item transitions might fluctuate significantly in several item aspects and exhibit randomness of user interests. This stochastic characteristics brings up a solid demand to include uncertainties in representing sequences and items. Additionally, modeling sequences and items with uncertainties expands users’ and items’ interaction spaces, thus further alleviating cold-start problems.

In this work, we propose a Distribution-based Transformer for Sequential Recommendation (DT4SR), which injects uncertainties into sequential modeling. We use Elliptical Gaussian distributions to describe items and sequences with uncertainty. We describe the uncertainty in items and sequences as Elliptical Gaussian distribution. And we adopt Wasserstein distance to measure the similarity between distributions. We devise two novel Transformers for modeling mean and covariance, which guarantees the positive-definite property of distributions. The proposed method significantly outperforms the state-of-the-art methods. The experiments on three benchmark datasets also demonstrate its effectiveness in alleviating cold-start issues. The code is available in https://github.com/DyGRRec/DT4SR.

KEYWORDS

Sequential Recommendation, Self-Attention, Uncertainty, Data Sparsity

ACM Reference Format:
Ziwei Fan, Zhiwei Liu, Lei Zheng, and Shen Wang, Philip S. Yu. 2018. Modeling Sequences as Distributions with Uncertainty for Sequential Recommendation. In Woodstock ’18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY, ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/1122445.1122456

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Woodstock ’18, June 03–05, 2018, Woodstock, NY © 2018 Association for Computing Machinery. ACM ISBN 978-1-4503-XXX-X/18/06... $15.00 https://doi.org/10.1145/1122445.1122456

Figure 1: An example user with uncertain interests. The random item transition connects two items with distinct genres and release years, while a correlated item transition connects items with same genres and/or release years.

1 INTRODUCTION

Recommendation systems achieve great successes in providing personalized services in various domains, including fashion [10], music [25], book [6] and grocery [5, 16, 17] recommendation. Among recommendation methods, Sequential Recommendation (SR) methods [3, 11, 22, 23, 28] show promising improvements in predicting users’ interests. SR methods format each user’s historically interacted items as a sequence and dynamically model the user’s preference to predict the next item in sequences.

The core idea of SR is modeling item-item transition relationships within the sequence. The recent advancements of Transformer [26] on sequence encoding inspire the recommendation community to adopt it for user sequences modeling [11, 22]. SASRec [11] is a pioneering work proposing to use Transformer for recommendation, which applies self-attention to measure the correlation among item transitions. Several following works [13, 18, 22] enhance the SASRec model with complex components to improve the recommendation performance, which demonstrates the effectiveness of adopting Transformer as a backbone encoder for sequence modeling.

However, the stochastic characteristics of item transitions in sequences spoil the ability of existing models to model sequential correlations, which is demonstrated in Figure 1. In this Figure, we present the movie-watching records of a user and the corresponding genre and release year transitions between items. We can observe that item-item transition relationships fluctuate randomly from both genre and release year perspectives. Most item-item transitions are hard to explain as both items in a transition pair have distinct genres and years, e.g., the transition from “Scent of a Woman”
to "The Boss Baby". This example indicates the importance of modeling each sequence with uncertainty. For each user, we should consider her interactions as a set of stochastic events controlled by distributions of dynamic user interests. Modeling sequence as distributions can not only incorporate such transition uncertainty but also benefit the exploration of users’ interests. The reason is that a distribution covers more data space than an embedding, which thus expands the interaction space of a user. As such, the user cold-start issue, i.e., users with few interactions [15], is alleviated.

Previous works [20, 29] have demonstrated the superiority of representing a stochastic object as a distribution rather than an embedding. Nevertheless, representing items and their associated transitions as distributions is challenging. Firstly, it is non-trivial to dynamically learn mean and covariance to infer the distribution. Moreover, we need to guarantee the positive definite property of covariance during inference. Furthermore, it is still unclear how to measure the distance between the sequence distributions.

To this end, we propose a distribution-based Transformer (DT4SR) to model the dynamics of evolving distribution representations while still maintaining necessary properties of distribution. To be specific, instead of a fixed vector, we use Elliptical Gaussian distributions [2, 27, 29] to represent items with covariance measuring the uncertainty. We develop mean and covariance Transformers to learn the dynamics of mean and covariance in the user sequence. Instead of using dot-product to measure the affinity between the embedding. Nevertheless, representing items and their associated transitions in the sequential recommendation. We demonstrate that distribution representations with uncertainty well characterize fluctuating and evolving interests of users and further alleviate cold-start problem.

- We develop two novel Transformers for modeling mean and covariance embeddings adaptive to the distribution-based sequential recommendation.
- The DT4SR achieves significant improvements over state-of-the-art recommendation methods in both overall performance and cold start setting. The experimental results verify the effectiveness of distribution-based representations in sequential modeling.

2 PROBLEM DEFINITION

A recommender system collects feedback between a set of users $U$ and items $V$, e.g., clicks. Sequential recommendation chronologically models a user $u$'s interaction sequence, which is denoted as $S^u = \{v_1^u, v_2^u, \ldots, v_{|S^u|}^u\}$. The goal of SR is to characterize dynamics in sequences and then predict the next-item. We formulate the objective as follows:

$$ p\left( v_{|S^u|+1}^u = v | S^u \right),$$

(1)

which measures the probability of an item $v$ being the next item, given user $u$’s sequence $S^u$.

\[ \begin{align*}
E^\mu_S &= \{e_1^u + p_1^\mu, e_2^u + p_2^\mu, \ldots, e_n^u + p_n^\mu\}, \\
E^\Sigma_S &= \{e_1^u + p_1^\Sigma, e_2^u + p_2^\Sigma, \ldots, e_n^u + p_n^\Sigma\}.
\end{align*} \]

3 PROPOSED MODEL

In this section, we present the framework of DT4SR, as shown in Figure 2. The overall framework consists of several components, mean and covariance embeddings, distribution-based self-attention, distribution-based Feed-Forward Network (FFN), and a specific covariance output layer. The mean and covariance embeddings together describe distributions of items. The distribution-based self-attention captures dynamical correlations in mean and covariance aspects. The distribution-based FFN introduces non-linearity specifically for distribution representation. To guarantee the positive definite property of covariance, we propose a covariance output layer. This distribution-based dynamic modeling distinguishes our proposed method from existing sequential methods.

3.1 Embedding Layers

We represent each item with an elliptical Gaussian distribution governed by a mean vector and one diagonal covariance matrix. To be specific, each item has two embedding representations, which are for mean and covariance. We denote the mean embedding table as $E^\mu \in \mathbb{R}^{|V| \times d}$ and covariance embedding table as $E^\Sigma \in \mathbb{R}^{|V| \times d}$, where $V$ denotes the item set and $d$ is the embedding dimensionality. We also define separate learnable positional embeddings for both Transformers, $v^\mu \in \mathbb{R}^{n \times d}$ for the mean Transformer and $v^\Sigma \in \mathbb{R}^{n \times d}$ for the covariance Transformer respectively. The $n$ denotes the maximum length of the sequence. The elements $p_i$ signifies the positional information at position $i$ in the sequence. As the sequence lengths of users vary a lot, we keep the most recent $n$ interactions to format the sequence if a user has more than $n$ interactions. Otherwise, we keep all interactions and apply zero paddings until the sequence has a length of $n$. With all embeddings, given a sequence $S = \{v_1, v_2, \ldots, v_n\}$, we have its mean and covariance sequence representations as:

\[ \begin{align*}
E^\mu_S &= \{e_1^u + p_1^\mu, e_2^u + p_2^\mu, \ldots, e_n^u + p_n^\mu\}, \\
E^\Sigma_S &= \{e_1^u + p_1^\Sigma, e_2^u + p_2^\Sigma, \ldots, e_n^u + p_n^\Sigma\}.
\end{align*} \]
3.2 Mean and Covariance Self-Attentions

We introduce a novel distribution-based self-attention mechanism considering numerical stability and its applicability to distribution embeddings. A typical self-attention block introduces query \( Q \), key \( K \), and value \( V \). In sequential recommendation, the query \( Q \), key \( K \), and value \( V \) are linear transformations of the same sequence embedding \( E_S W_Q, E_S W_K \), and \( E_S W_V \), where \( E_S \) is any sequence embedding defined in Eq. (2). The self-attention adopts the scaled dot-product attention [26] on the query and key to measure weights from previous steps on the current step. To maintain numerical stability of query, key, and value, we apply “exponential linear unit” (elu) activation [4] after the linear transformations, which presents the distribution-based self-attention as:

\[
DSA = \sigma \left( \frac{\text{elu}(E_S W_Q) \cdot \text{elu}(E_S W_K)}{\sqrt{d}} \right) \text{elu}(E_S W_V),
\]

where \( \sigma(\cdot) \) denotes the softmax function and ‘DSA’ is short for Distribution Self-Attention. We apply the DSA module in the mean Transformer as \( DSA^\mu \) and the covariance Transformer as \( DSA^\Sigma \), either taking \( E_S = E_S^q \) or \( E_S = E_S^v \) in Eq. (2) as inputs, respectively.

3.3 Mean and Covariance Feed-Forward Layers

In addition to uncovering sequential patterns, we introduce two novel and adaptive versions of feed-forward layers to endow extra non-linearity. We adapt the FFN layer to distribution representations by replacing the ReLU activation as ELU. The FFN with respect to both \( DSA^\mu \) and \( DSA^\Sigma \) at position \( i \) are defined as:

\[
\begin{align*}
\text{FFN}^\mu(DSA^\mu) &= \text{elu} \left( \text{elu} \left( DSA^\mu W_1 + b_1 \right) \right. \\
\text{FFN}^\Sigma(DSA^\Sigma) &= \text{elu} \left( \text{elu} \left( DSA^\Sigma W_1 + b_1 \right) \right.)
\end{align*}
\]

respectively, where all \( W \) are in \( \mathbb{R}^{d \times d} \) and all \( b \) are in \( \mathbb{R}^d \).

We retain those techniques used in existing Transformer structures, including residual connection, dropout operation and layer normalization. Note that we can stack multiple \( DSA \) and FFN layers to learn more complex item relationships. In the meantime, the multi-heads mechanism is also applicable in DT4SR framework.

3.4 Layer Outputs

However, a valid distribution requires covariance matrix to be positive definite while the outputs from FFN layers do not guarantee this property. Thus, we add an all ones vector to the output covariance embedding vector after the ELU activation, which is defined as follows:

\[
\Sigma_i = \text{diag} \left( \text{elu} \left( O_i^{(L)} \right) + 1 \right),
\]

where \( O_i^{(L)} \) denotes the output covariance embedding of item \( i \) after \( L \) layers of \( DSA^\Sigma \) and \( FFN^\Sigma \), and \( 1 \in \mathbb{R}^d \) is an all ones vector.

3.5 Loss and Optimization

Recall that the mean and covariance Transformers’ outputs infer the mean and covariance embeddings of the next-step item at each position in the sequence, respectively. Following the same setting in [11], we use the next-step item as ground truth prediction for each position in the sequence. For example, given a sequence \( S^u = [o^u_1, o^u_2, o^u_3, \ldots, o^u_n] \), the ground truth item for \( o^u_i \) is \( o^u_{i+1} \). Note that if \( o^u_i \) is a padding item, its ground truth item is also a padding item.

3.5.1 Wasserstein Distance and Loss. To measure how accurately the model predicts the next item, we need to identify the distance between the distribution of the ground truth item and the inferred distribution. The most popular approaches to calculate the distance between two distribution are Kullback–Leibler (KL) divergence [12] and \( p_{th} \) Wasserstein distance [1]. Wasserstein distance can measure distances when two distributions have no overlap while KL divergence cannot. Therefore, we propose to use \( p_{th} \) Wasserstein distance to measure the distance of Gaussian distributions. To be specific, we use 2-Wasserstein distance. Given two items \( i_1 \) and \( i_2 \), as well as their distributions \( N(\mu_i, \Sigma_i) \) and \( N(\mu_j, \Sigma_j) \), the Wasserstein distance is:

\[
d_{W_2}(i_1, i_2) = ||\mu_i - \mu_j||^2 + \text{trace} \left( \Sigma_i + \Sigma_j - 2(\Sigma_i^{1/2} \Sigma_j \Sigma_i^{1/2})^{1/2} \right).
\]

3.5.2 Loss. Based on 2-Wasserstein distance \( W_2 \), we propose to use a Wasserstein distance-based BPR loss [21] to measure the correctness of next-item prediction:

\[
- \sum_{S^u \in \mathcal{S}} \sum_{t = 1}^{n} \log (\sigma(d_{W_2}(i_t, \hat{i}_t) - d_{W_2}(i_t, i_t))) + \lambda ||\Theta||^2,
\]

where \( \hat{i} \) denotes the inferred distribution at position \( t \), \( i_t \) is the ground truth item and \( i_t' \) denotes the negative sample item from items that user \( u \) never interacts with. \( \Theta \) is the set of all learnable parameters in the both mean and covariance Transformers.

For evaluation, for user \( u \), we calculate distance scores based on the 2-Wasserstein distance \( W_2(S^u_t, i) \) on all candidate items \( i \in \mathcal{V} \), where \( S^u_t \) denotes the inferred next-item distribution at last position \( n \). Then we rank them in ascending order to generate the recommendation list.

4 EXPERIMENTS

In this section, we validate the effectiveness of the proposed DT4SR by presenting experimental settings and results. The designed experiments will answer the following research questions:

- **RQ1**: Does DT4SR outperform the state-of-the-art recommendation methods?
- **RQ2**: Does distribution representation provide better recommendations than single item embedding?
- **RQ3**: Are distribution representations in sequential modeling effective for alleviating cold-start user/item problems?

4.1 Datasets

We evaluate the proposed DT4SR on three public benchmark datasets from Amazon review datasets [19]. Amazon datasets are known for

| Dataset         | #users | #items | #actions | density |
|-----------------|--------|--------|----------|---------|
| Amazon Toys     | 57,617 | 69,147 | 410,920  | 0.010%  |
| Amazon Beauty   | 52,204 | 57,289 | 394,908  | 0.013%  |
| Amazon Games    | 31,013 | 23,715 | 287,107  | 0.039%  |
high sparsity and having several categories of rating reviews. Details of datasets statistics are presented in Table 1. Following [11, 22], we treat the presence of ratings as positive implicit feedbacks. We use the timestamps of each rating to sort the interactions of each user to generate the sequence. The most recent interaction is used for test and the last second one is used for validation.

4.2 Experimental Settings

Evaluation Protocol. We evaluate all models with three standard metrics, Recall@N, NDCG@N, and Mean Reciprocal Rank (MRR). Recall@N measures the accuracy of retrieving relevant items in the top-N recommendation. NDCG@N also considers the ranked positions of retrieved relevant items in the top-N list. MRR measures the ranking performance of the entire recommendation list. We set N to be 1 and 5 for evaluation. For each user, we randomly sample 1,000 items without interaction with the user as negative items considering ranking efficiency.

Baselines. We compare DT4SR with several state-of-the-art recommendation methods in three relevant categories: static methods with point embedding vectors, static metric learning methods, and sequential methods. We use LightGCN [8] as the strong baseline with point embedding vectors. We also compare with BPRMF [21], but we omit it in the performance table because of its low values. For metric learning methods, we compare the most recent work DDDN [29] and SML [14]. For sequential recommendation methods, we adopt the metric learning-based TransRec [7] and Transformer-based SASRec [11] as baselines. Note that TransRec belongs to both the metric learning framework and sequential recommendation.

Hyper-parameter Settings. For all baselines, we search the embedding dimension in [32, 64, 128]. As the proposed model has both mean and covariance embeddings, we only search for [16, 32, 64] for DT4SR for a fair comparison. We search the L-2 regularization weight from \{0.0, 0.001, 0.005, 0.01, 0.05, 0.1\}. The number of layers \(L\) is selected from \{1, 2\}. For all baselines specific hyper-parameters, we do not list all of them because of the space limitations. We grid search all possible combinations for all models and report the test set performance based on the best validation MRR result.

4.3 Overall Comparison (RQ1 and RQ2)

We report the overall performance comparison between the proposed DT4SR and baselines in Table 2. The followings are our observations:

- **RQ1:** DT4SR significantly outperforms all baselines in all three datasets across all evaluation metrics. The average relative improvements over the second-best baseline is 19.9% on Recall@1, 6.7% in Recall@5, 10.8% in NDCG@5, and 10.4% in MRR. These improvements demonstrate the effectiveness of distribution-based representations with uncertainty in sequential recommendation.\[1\]

- **RQ2:** Compared with the point embedding representation sequential model SASRec, the proposed DT4SR still achieves a great improvement margin. The reasons for this improvement are twofold. First, the distribution-based representations provide uncertainty information when we model users with various interests. Moreover, the sequential modeling for mean and covariance can dynamically capture the evolving patterns of uncertainty within the sequence.

- Among all baselines, we can observe that sequential methods achieve outstanding performance, demonstrating the necessity of utilizing sequential information. Moreover, the state-of-the-art CF method LightGCN outperforms other static baselines, owing to its capability of using graph information.

4.4 Performance w.r.t Sequence length (RQ3)

We present the performances of LightGCN, SASRec, and proposed DT4SR with respect to different sequences lengths (i.e., number of interactions of users) in Figure 3. We can observe that DT4SR performs the best on all sequence length intervals of users. Note that for users with only one interaction, the relative performance gain of DT4SR against SASRec is 9% on Recall@5. It demonstrates the effectiveness of DT4SR in cold-start users. We can also observe that the long sequences (i.e., users with more than 20 interactions) achieve considerable improvements, especially on the Toys dataset. Long sequences typically cover diverse interests, and the observation proves the necessity of uncertainty in representing sequences.

4.5 Performance on Cold Start Items (RQ3)

We plot the performances of LightGCN, SASRec, and proposed DT4SR on cold start items, which only have limited interactions in training data. For Toys dataset, DT4SR achieves 100% relative improvements on extremely cold start items (i.e., items with only one interaction). For the Games dataset, the performance gain is also more than 50% for extremely cold start items. This experiment shows that distribution representations for items and sequences are more expressive and generalized for cold start items. Note that the DT4SR still achieves competitive performance in frequent items.

---

**Table 2: Performance Comparison in Recall@1, Recall@5, NDCG@5, and MRR.** The best and second-best results are boldfaced and underlined, respectively.

| Dataset | Metric | LightGCN | TransRec | DDDN | SML | SASRec | DT4SR | Imp. |
|---------|--------|----------|----------|------|-----|--------|-------|-----|
| Toys    | Recall@1 | 0.0083 | 0.0082 | 0.0067 | 0.0066 | 0.0069 | 0.0065 | 0.0086 | +32% |
|         | Recall@5 | 0.1494 | 0.1566 | 0.1423 | 0.1435 | 0.1561 | 0.1762 | +6.1% |
|         | MRR     | 0.1060 | 0.1085 | 0.0951 | 0.0933 | 0.1179 | 0.1341 | +14.5% |
| Beauty  | Recall@1 | 0.1084 | 0.1096 | 0.0954 | 0.0938 | 0.1137 | 0.1348 | +13.5% |
|         | Recall@5 | 0.1510 | 0.1144 | 0.1232 | 0.1258 | 0.1341 | 0.1652 | +7.2% |
|         | MRR     | 0.0825 | 0.0722 | 0.0772 | 0.0773 | 0.1124 | 0.1230 | +9.7% |
| Games   | Recall@1 | 0.2013 | 0.2106 | 0.2218 | 0.2684 | 0.2370 | 0.2594 | +23% |
|         | Recall@5 | 0.1584 | 0.1474 | 0.1422 | 0.1437 | 0.2014 | 0.2183 | +8.3% |
|         | MRR     | 0.1610 | 0.1513 | 0.1423 | 0.1439 | 0.1984 | 0.2152 | +8.4% |

**Figure 3:** The Recall@5 performance on different sequence lengths over Amazon Toys and Amazon Games datasets.

We present the performances of LightGCN, SASRec, and proposed DT4SR with respect to different sequences lengths (i.e., number of interactions of users) in Figure 3. We can observe that DT4SR performs the best on all sequence length intervals of users. Note that for users with only one interaction, the relative performance gain of DT4SR against SASRec is 9% on Recall@5. It demonstrates the effectiveness of DT4SR in cold-start users. We can also observe that the long sequences (i.e., users with more than 20 interactions) achieve considerable improvements, especially on the Toys dataset. Long sequences typically cover diverse interests, and the observation proves the necessity of uncertainty in representing sequences.
Figure 4: The Recall@5 performance on cold start items over Amazon Toys and Amazon Games datasets.

5 CONCLUSION

We propose DT4SR under the framework of Transformer with distribution representations in the sequential recommendation. Different from existing sequential methods assuming users are deterministic, we propose introducing uncertainty into representations of sequences and items. We use Elliptical Gaussian Distributions to represent items with uncertainty. Building upon distribution representations, we propose two novel Transformers for learning mean and covariance with the guarantee of positive definite property of covariance. We conducted several experiments to demonstrate that the proposed DT4SR significantly outperforms existing methods in overall performance and cold start user/item recommendation.

REFERENCES

[1] Martin Arjovsky, Soumith Chintala, and Leon Bottou. 2017. Wasserstein generative adversarial networks. In International conference on machine learning. PMLR, 214–223.
[2] Aleksandar Bojchevski and Stephan Ginnemann. 2017. Deep gaussian embedding of graphs: Unsupervised inductive learning via ranking. arXiv preprint arXiv:1707.03815 (2017).
[3] Xu Chen, Hongteng Xu, Yongfeng Zhang, Jiaxi Tang, Yixin Cao, Zheng Qin, and Hongyuan Zha. 2018. Sequential recommendation with user memory networks. In Proceedings of the eleventh ACM international conference on web search and data mining. 108–116.
[4] Djork-Arne Clevert, Thomas Unterthiner, and Sepp Hochreiter. 2015. Fast and accurate deep network learning by exponential linear units (elus). arXiv preprint arXiv:1511.07289 (2015).
[5] Guglielmo Faggionato, Mirko Polato, and Fabio Aiolli. 2020. Recency aware collaborative filtering for next basket recommendation. In Proceedings of the 28th ACM Conference on Information and Knowledge Management. 80–87.
[6] Sharon Givon and Victor Lavrenko. 2009. Predicting social-tags for cold start book recommendations. In Proceedings of the third ACM conference on Recommender systems. 333–336.
[7] Ruining He, Wang-Cheng Kang, and Julian McAuley. 2017. Translation-based recommendation. In Proceedings of the eleventh ACM conference on recommender systems. 161–169.
[8] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. 2020. Lightgcn: Simplifying and powering graph convolution network for recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 639–648.
[9] Cheng-Kang Hsieh, Longqi Yang, Yin Cui, Tsung-Yi Lin, Serge Belongie, and Deborah Estrin. 2017. Collaborative metric learning. In Proceedings of the 26th international conference on world wide web. 193–201.
[10] Wang-Cheng Kang, Chen Fang, Zhaowen Wang, and Julian McAuley. 2017. Visually-aware fashion recommendation and design with generative image models. In 2017 IEEE International Conference on Data Mining (ICDM). IEEE, 207–216.
[11] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In 2018 IEEE International Conference on Data Mining (ICDM). IEEE, 197–206.
[12] S Kullback and RA Leibler. 1951. On information and sufficiency Annals of Mathematical Statistics, 22 (1): 79–86.
[13] Jiacheng Li, Yujie Wang, and Julian McAuley. 2020. Time interval aware self-attention for sequential recommendation. In Proceedings of the 13th International Conference on Web Search and Data Mining. 322–330.
[14] Mingming Li, Shuai Zhang, Fuqing Zhu, Wanhui Qian, Liangjun Zhang, Fuzhong Han, and Songlin Hu. 2020. Symmetric metric learning with adaptive margin for recommendation. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 4634–4641.
[15] Zhuiwei Liu, Ziwei Fan, Yu Wang, and Philip S Yu. 2021. Augmenting Sequential Recommendation with Pseudo-Prior Items via Reversely Pre-training Transformer. In Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval.
[16] Zhuiwei Liu, Xiaohan Li, Ziwei Fan, Stephen Guo, Kannan Achan, and Philip S Yu. 2020. Basket Recommendation with Multi-Intent Translation Graph Neural Network. arXiv preprint arXiv:2018.11419 (2020).
[17] Zhuiwei Liu, Mengting Tan, Stephen Guo, Kannan Achan, and Philip S Yu. 2020. BasConv: Aggregating Heterogeneous Interactions for Basket Recommendation with Graph Convolutional Neural Network. In Proceedings of the 2020 SIAM International Conference on Data Mining. SIAM, 64–72.
[18] Chen Ma, Peng Kang, and Xue Liu. 2019. Hierarchical gating networks for sequential recommendation. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 825–833.
[19] Julian McAuley, Christopher Tappert, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval. 43–52.
[20] Seong Joon Oh, Kevin Murphy, Jiyun Pan, Joseph Roth, Florian Schroff, and Andrew Gallagher. 2018. Modeling uncertainty with hedged instance embedding. arXiv preprint arXiv:1810.00319 (2018).
[21] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2012. BPR: Bayesian personalized ranking from implicit feedback. arXiv preprint arXiv:1205.2618 (2012).
[22] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In Proceedings of the 28th ACM international conference on information and knowledge management. 1441–1450.
[23] Jiaxi Tang and Ke Wang. 2018. Personalized top-n sequential recommendation via convolutional sequence embedding. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. 565–573.
[24] Yi Tay, Lu Anh Tuan, and Siu Cheung Hui. 2018. Latent relational metric learning via memory-based attention for collaborative ranking. In Proceedings of the 2018 World Wide Web Conference. 729–739.
[25] Aaron Van Den Oord, Sander Dieleman, and Benjamin Schrauwen. 2013. Deep content-based music recommendation. In Neural Information Processing Systems Conference (NIPS 2013). Vol. 26. Neural Information Processing Systems Foundation (NIPS).
[26] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. arXiv preprint arXiv:1706.03762 (2017).
[27] Luke Vilnis and Andrew McCallum. 2014. Word representations via gaussian embedding. arXiv preprint arXiv:1412.6623 (2014).
[28] Lei Zheng, Ziwei Fan, Chun-Ta Lu, Jiawei Zhang, and Philip S Yu. 2019. Gated Spectral Units: Modeling Co-evolving Patterns for Sequential Recommendation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. 1077–1080.
[29] Lei Zheng, Chaoxuuo Li, Chun-Ta Lu, Jiawei Zhang, and Philip S Yu. 2019. Deep Distribution Network: Addressing the Data Sparsity Issue for Top-N Recommendation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. 1081–1084.