Towards Dynamic User Intention in Sequential Recommendation

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ABSTRACT

User intention is an important factor to be considered for recommender systems. Different from inherent user preference addressed in traditional recommendation algorithms, which is generally static and consistent, user intention always changes dynamically in different contexts. Recent studies (represented by sequential recommendation) begin to focus on predicting what users want beyond what users like, which can better capture dynamic user intention and have attracted a surge of interest. However, user intention modeling is non-trivial because it is generally influenced by various factors, such as repeat consumption behavior, item relation, temporal dynamics, etc. To better capture dynamic user intention in sequential recommendation, we plan to investigate the influential factors and construct corresponding models to improve the performance. We also want to develop an adaptive way to model temporal evolutions of the effects caused by different factors. Based on the above investigations, we further plan to integrate these factors to deal with extremely long history sequences, where long-term user preference and short-term user demand should be carefully balanced.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Sequential Recommendation, User Intention, Temporal Dynamics

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1 MOTIVATION AND RESEARCH QUESTIONS

It is essential for recommender systems to understand the underlying intent of users since the intention is assumed to be the immediate antecedent of interactions. In real-world scenarios, user intention generally evolves with time dynamically, which depends on not only long-term user preference but also short-term user demand. Sequential recommendation aims to predict a user's next action based on recent interactions, which can better capture dynamic user intention and gains growing interests recently. However, current sequential recommendation algorithms mainly focus on the representation of the history sequence. Many other factors also have impacts on user intention, such as repeat consumption, item relation, etc. This motivates our first research question:

- **RQ1**: *What are the influential factors accounting for dynamic user intention in different recommendation scenarios?*

Due to the complex patterns in user interaction sequences, it is challenging to incorporate various factors to build a holistic recommendation model. For example, when considering repeat consumption behavior, the algorithm should determine whether it is time to recommend a previously interacted item or present a new choice (exploration and exploitation). This leads to our second research question:

- **RQ2**: *How can we introduce these factors to better capture user intention and improve recommendation performance?*

Besides, different factors' impacts on user intention evolve dynamically with time. And the temporal evolution may vary dramatically across scenarios and factors. For instance, temporal patterns of repeat consumption can be divergent for e-commerce and music listening. Even though in the same scenario of e-commerce, users tend to consume complements in a short term, while substitutes are usually consumed when the lifetime of the previous one runs out. To address this issue, we propose our third research question:

- **RQ3**: *How to model the temporal dynamics of different factors' impacts on user intention in an adaptive way?*

Based on the above investigations, we further plan to integrate these factors to deal with extremely long history sequences, which brings more noises because interactions can be driven by either long-term user preference or short-term user demand. We hope the discovered influential factors will help the model to focus on relevant historical interactions when making recommendations. Therefore, the fourth research question is proposed as:

- **RQ4**: *How to model extremely long history sequences and fuse effects of long-term user preference and short-term user demand?*

2 PROGRESS AND FUTURE PLAN

2.1 Influential Factors on User Intention

Regarding **RQ1** and **RQ2**, we respectively investigate the dynamic impacts of repeat consumption and different item relations and propose corresponding models to enhance recommendation.

2.1.1 Repeat Consumption [2]. To uncover temporal patterns of repeat consumption behavior, we first look into the distribution

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of inter-consumption gaps (time interval between consumptions for the same item) in different real-world datasets. Besides the 1) short-term effect (recency) revealed in previous work, we find repeat consumptions for some items demonstrate obvious 2) lifetime effect. Users tend to repurchase items when the lifetime of the previous one runs out, and different items usually have different lifetimes. Therefore, we propose to combine Collaborative Filter (CF) and Hawkes Process (HP) to explicitly model short-term and life-time effects caused by previous consumptions: $\lambda^{u,i}(t) = \lambda_0^{u,i} + \alpha_i \sum_{(t',i')\in S_t^u} I(i'=i)\gamma_i(t-t')$. Here $\lambda^{u,i}(t)$ is the intensity function in HP, whose value will be utilized as the dynamic ranking score at time t. The kernel function $\gamma_i(t-t')$ controls how the repurchasing intention drifts with time. We use Exponential and Gaussian mixture distribution with item-specific parameters to cultivate short-term and life-time effects, respectively.

We compare the performance of our proposed method with other models involving repeat consumption on four datasets with different recommendation scenarios. Results suggest that our proposed method outperforms existing solutions, and the item-specific parameters in the kernel function are highly explainable, reflecting different items' characteristics.

2.1.2 *Item Relations [1].*

Users always incline to consume related items in real life, such as complements and substitutes. Understanding the effects of different item relations will greatly boost the modeling of user intention. Actually, repeat consumption can be seen as a special relation between items themselves, whose impacts only involve a single item; while general item relations will influence other items if the relation holds for the item pair.

Unlike existing works that only encode the semantics of item relations into embeddings in a static way, we further focus on the temporal evolution of different relations' effects. Specifically, we find when the target item serves as a complement of some items in history, it will more likely to be consumed when the time gap is short; while in the case of substitutes, the effects can change from short-term negative to long-term positive. As a result, we propose to give the target item a knowledge-aware and time-aware embedding to capture its dynamic meanings in different contexts. We first learn a KG embedding task with TransE to get basic item and relation embeddings. Then we derive relational embeddings for each item as the representation when it plays the corresponding role in the context. Together with the basic item embedding, all these embeddings for the target item will be dynamically integrated according to whether there are relational items in history and the time intervals. We design temporal kernel function for each relation type to control the temporal evolution of its effects. Finally, the dynamic embedding of the target item can be leveraged by any embedding-based algorithms to generate the ranking score.

We test our method on representative categories of the Amazon dataset, which includes relations between items besides interaction data. Experiments show that the proposed method is superior to previous work introducing item relations. Ablation study demonstrates either the KG embedding task and the dynamic integration plays an important role.

2.2 Temporal Dynamics (RQ3)

Notice that although we have taken time intervals into consideration in our previous studies, they both need predefined temporal

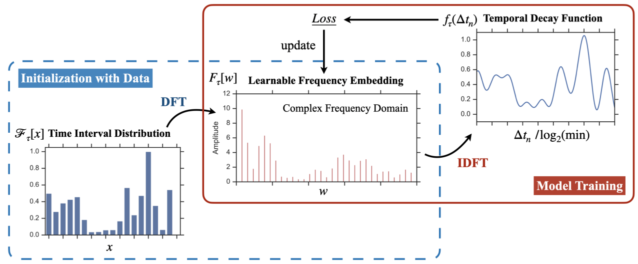

Figure 1: Illustration of the DFT-based method to estimate the temporal decay function.

kernel functions. This hinders them from directly being applied to other scenarios without prior knowledge. As a result, we try to find an adaptive way to model temporal effects of different factors. This is an ongoing work and the key insight is mapping the continuous temporal decay function to the frequency domain, which becomes discrete and can be seen as an embedding. Then given any input time interval, we can get corresponding decay through Inverse Discrete Fourier Transform (IDFT). And the frequency embedding can be updated according to the final loss function. Besides, if we have prior knowledge of time gaps in data, we can initialize the frequency embedding with the DFT result of the distribution. We hope this can provide a general approach to model continuous temporal effects in neural networks, which still needs further validation.

2.3 Long History Sequence (RQ4)

In sequential recommendation, many studies have uncovered that model performance will not always benefit from the increase of history length when it exceeds a threshold. Extremely long history sequences may include interactions driven by either long-term user preference or short-term user demand, which brings more noises to the model. To tackle the problem of long history sequence, we have two immature future directions. On the one hand, we can combine the influential factors investigated above to help the model pay attention to selected sub-sequences that are the most relevant to the current recommendation. On the other hand, inspired by contrastive learning, we plan to construct similar sequences through methods such as partial permutation. Then we can first train a contrastive learning task to enhance the history representation module.

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