Gumble Softmax For User Behavior Modeling

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ABSTRACT

Recently, sequential recommendation systems are important in solving the information overload in many online services. Current methods in sequential recommendation focus on learning a fixed number of representations for each user at any time, with a single representation or multi-interest representations for the user. However, when a user is exploring items on an e-commerce recommendation system, the number of this user's interests may change overtime (e.g. increase/reduce one interest), affected by the user's evolving self needs. Moreover, different users may have various number of interests. In this paper, we argue that it is meaningful to explore a personalized dynamic number of user interests, and learn a dynamic group of user interest representations accordingly. We propose a Reinforced sequential model with dynamic number of interest representations for recommendation systems (RDRSR). Specifically, RDRSR is composed of a dynamic interest discriminator (DID) module and a dynamic interest allocator (DIA) module. The DIA module explores the number of a user’s interests by learning the overall sequential characteristics with bi-directional self-attention and Gumble-Softmax. The DIA module allocates the historical clicked items into a group of sub-sequences and constructs user’s dynamic interest representations. We formalize the allocation problem in the form of Markov Decision Process (MDP), and sample an action from policy $\pi$ for each item to determine which sub-sequence it belongs to. Additionally, experiments on the real-world datasets demonstrates our model’s effectiveness.

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1 INTRODUCTION

With the development of Internet technologies, recommender systems have been widely applied to many online services such as e-commerce, advertising, social media, and etc. Recommender systems serve to alleviate the information overload problem and enhance user experiences. Traditional recommender systems mostly focus on promoting generalized user interests, such as collaborative filtering [22, 23]. In recent years, more and more researchers study the sequential recommendation problem to capture the dynamic user behaviors, which assumes that a user’s information need changes over the time [19].

The existing sequential recommendation solutions represent a user as a fixed number of representations, including a single representation or multiple representations. For the single representation recommendation, only one user embedding representation is generated for the next-item prediction. Early solutions usually adapted the Markov Chain [19] which assumes that the next-item prediction is closely related to the previous item [20]. With the breakthrough of deep learning in many areas (e.g. computer vision and natural language processing) [36], sequential neural networks such as recurrent neural network [9, 17] and Transformer [29] have been adopted to the sequential recommendation tasks. These sequential neural networks can characterize the sequential item interactions and learn informative representations for user behaviors [14]. Additional context information can also be considered to enhance the performance of neural sequential recommendation [10, 37]. For multi-representation recommendation approaches, a user is assumed to have multiple interests and these interests jointly affect the user’s next item selection. From the empirical analysis, a user usually interacts with several types of items that are conceptually different over time. For example, zhang [37] identifies that the items in a user’s recent behaviors belong to different categories on Taobao dataset. Various approaches have been adopted to model the multiple interests from the user’s historical behaviors, including Capsule routing network [21] and multi-head self-attention [33]. The temporal information in the sequence can also be considered to enhance the recommendation
A's interest changes from one to three. Therefore, modeling a fixed item prediction to form multi interests through average-pooling method for the next leverages the DIA to allocate the click into different sub-sequence DID to learn the user's dynamic interest number over the time and sequential recommendation. The exploration of user interest number improves the performance in the dynamic number of interest in sequential recommendation. The DIA determines which sub-sequence it belongs to. Here each sub-sequence represents a group of items that are related to each other. The DIA allocates the click to the corresponding sub-sequence based on the user's dynamic interest number. Furthermore, we design Dynamic Interest Allocator (DIA) to allocate the user’s click sequence into a dynamic group of interest sub-sequences, where DIA formalizes the allocation process in the form of Markov Decision Process (MDP) and sample the action for each item to determine which sub-sequence it belongs to. Here each sub-sequence forms a user’s interest representation with average-pooling method. As for the next-item prediction, we input the candidate item into the policy \( \pi \) to decide which sub-sequence it belongs to and use the corresponding user interest representation to calculate the compatibility between the sub-sequence and candidate item for prediction.

To summarize, the main contributions of this paper are:

- We conducted experiments on several real datasets with several public benchmarks to verify the effectiveness of the model. We analyze the DID module and DIA module to validate the proposed RDRSR model through ablation study.

2 RELATED WORK

Before introducing the details of the proposed model, in this section, we introduce the related literature about recommendation systems, including general model, sequential model, multi-interest recommendation systems and attention mechanism we used in the paper.

2.1 General recommendation

The main methods in traditional recommendation system is extracting users’ general tastes from their historical behaviors to make recommendation. Typical methods include Collaborative Filtering [22, 38], Matrix Factorization [15] and Factorization Machines. Collaborative Filtering method is based on the similarity of users [38] or the similarity of items [22] for recommendation. But it is a non-trivial work to quickly and accurately find the similar users or items. Matrix Factorization (MF) [15] as one of the most popular technique in recommendation system, map users and items into joint latent space and estimate user-item scores through the inner product between their embedding vectors. Factorization Machines (FM) [19] methods consider all the variable interaction information which not only improve the recommendation results but also achieve good results even when the data is sparse. With the success of deep learning in computer vision and natural language processing [36], more and more efforts has been done to apply deep learning to the recommendation system [34]. He [7, 7, 8] makes a great success, NCF [7] uses multi-layer perceptions to replace the inner product operation in MF for interaction estimation. [7, 8] use deep learning to obtain higher-order interactive expressions of interaction with a fast calculation trick. These deep learning based methods achieve good performance. Moreover, several attempts also tried to apply graph neural networks [6, 13, 26].

2.2 Sequential recommendation

In relevant literature, many sequential recommendation models have been proposed to leverage user historical records in a sequential manner to capture the user’s preference for the next item. By integrating the good performance of matrix factorization and the sequential pattern of Markov chains, factorized personalized Markov chains (FPMC) [20] embeds the sequential information between adjacent clicked items into the final prediction for recommendation, and later the hierarchical representation model (HRM) [30] simultaneously consider the sequence behaviors and user preferences. Though they make progress in sequential recommendation, these methods only model the local sequential patterns between every two adjacent clicked item [35]. To model longer sequential behaviors, [9] first adopted recurrent neural network to model the long sequence pattern for recommendation. RNN care too much about the sequence pattern which could be disturbed by the noise in the click sequence while neglect the user’s main intent, [17, 18] not only consider the sequence pattern in the sequence and also explore the user’s main purpose through the attention mechanism. Later, [14] consider the importance of each item and other items in the click sequence achieve great
progress in many real datasets [24] with unsupervised learning to
learn the hidden relationships between items and make a difference.

2.3 Multi-Interest recommendation systems
The main difference between multi-interest recommendation and single
embedding recommendation is that multi interest recommendation
does multi vectors to represent the user while only one vector
in other methods. The classic method [3, 16] use a capsule routing
based method to extract the user’s multi interest. [33] explore user’s
with multi-head self-attentive, where the multi-head number as the
multi-interest number through sum-pooling method. [4] consider
the time interval to extract the multi interest and [27] infer a sparse set
of concepts for each user from the large concept as its multi interest.
Those methods have achieved good performance in recommenda-
tion, but non of them consider the different interest number between
different users at different time and the dynamic user interest number
over time.

2.4 Attention
The originality of attention mechanism is in computer vision [2, 25]
to make the target object get more weight, but its great success in various fields in artificial intelligence comes only in recent years
with the development of deep learning. It first come to the center of
the stage is in machine translation [1, 29] and is rather useful and
efficient in real-world application tasks. It is also been successfully
applied in recommendation applications [32] which learns the im-
portance of each feature interaction from data via a neural attention
network. What’s more, [14, 24] use the different relationships be-
tween items in the clicked sequence to capture both the long-term semantics and short-term semantics make a difference.

3 OUR MODEL
In this section, before going into the details of our proposed model.
We first describe the problem statement in our work. And then
we will give an overview of the proposed Learning Reinforced
Dynamic Representations for Sequential Recommendation (RDRSR)
framework (as shown Figure 2), which consists two main modules
DID and DIA for dynamic interest number detector and user behavior
allocation.

3.1 Problem definition
The key claim of sequential recommendation is that the current
user preference should be related with the historical behaviors.
Formally, suppose we have a user set \( U = \{u_1, u_2, ..., u_n\} \), an item set
\( I = \{i_1, i_2, ..., i_m\} \), and \( n \) and \( m \) are the numbers of users and items
in the sequential recommendation task. Unlike general recommenda-
tion, which only captures the correlation between a user and an
item without considering the order of the click sequence. We use
\( C = \{x_1, x_2, ..., x_t, x_{t+1}\} \) to denote a sequence of items in chronological
order that a user has interacted, and the \( x_t \) in \( I \). The goal of sequential
recommendation is to predict the next item \( x_{t+1} \) depending on
the previous click sequence \( \{x_1, x_2, ..., x_t\} \).

3.2 Embedding Layer
We create an item embedding matrix \( \mathbf{E}_{item} \in \mathbb{R}^{d \times I} \) and an user
embedding matrix \( \mathbf{E}_{user} \in \mathbb{R}^{d \times I} \), where \( d \) is the latent dimension
and \( n \) and \( m \) are the number of user and item. We retrieve the click
item in the click sequence \( C = \{x_1, x_2, ..., x_t\} \) with a latent vector in the
item embedding embedding and get the item sequence embedding
\( \mathbf{E}_t = \{e_1, e_2, ..., e_t\} \) and the corresponding user embedding \( \mathbf{e}_u \), where
t is the click sequence length and we process the datasets like [14].
Furthermore, we incorporate a learnable position encoding matrix
\( \mathbf{P} \in \mathbb{R}^{d \times d} \) to enhance the input representations. In this way, the
input representations \( \mathbf{E} \in \mathbb{R}^{d \times d} \) for the generator can be obtained by
summing two embedding matrices: \( \mathbf{E} = \mathbf{E}_t + \mathbf{P} \).

3.3 Dynamic Interest Discriminator
As mentioned before, the user’s dynamic interest number is evolving
and changing by the time, a new click item would indicate user get
one more interest or reduce a interest due to he may get what he
want. DID aims to find the user dynamic interest number with the
user’s current click sequence. First, we stack multiple bi-directional
architecture self-attention [29] block based on the embedding layer.
With the bi-directional architecture self-attention block, interest
relevant items in the click sequence are clustering more close and
get a more informative item representation.

Self-Attention From the formula, the attention layer calculates
a weighted sum of all values, where the weight between query and
value, which could cluster those items belong to the same interest
and effectively finds the dynamic interest number.

\[
Attention(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d}})V
\]  

(1)

And the scale factor \( \sqrt{d} \) is to avoid overly large values of the inner
product when the dimension is very high.

We take \( E \) as input, convert it to three matrices through linear
projections, and feed them into an attention layer:

\[
S = Attention(EW^Q, EW^K, EW^V)
\]  

(2)

where the projections matrices \( W^Q \), \( W^K \), \( W^V \in \mathbb{R}^{d \times d} \). The projections
make the model more flexible.

Feed Forward Network Though the attention calculation is able to aggregate previous items’ embeddings with corresponding
weights, it is still a linear model. In order to enforce the model with
non-linearity and to get more high-order interaction information, we apply a two-layer feed-forward network to all \( S_i \).

\[
F_i = FFN(S_i) = \text{ReLU}(S_i W^1 + b^1) W^2 + b^2
\]  

(3)

where \( W^1, W^2 \) are \( d \times d \) matrices and \( b^1, b^2 \) are \( d \)-dimensional vec-
tors.

In order to get the user’s dynamic interest number, we set an
attention mechanism with the \( F \) and \( e_u \) to get the united user general
purpose representation.

\[
a_i = \text{Softmax}((F_i W_f + e_u W_u) W_f + b)
\]  

(4)

\[
f = W_k \left( \sum_{i=1}^{t} a_i F_i \right)
\]  

(5)

where \( f \) is a k-dimensional vector represent the probability of each possible
interest number, \( W_k \) is a \( d \times k \) matrix and \( k \) is the max dynamic
interest number set in our model.
We employ the Gumble Softmax [11] sampling method to produce the user dynamic interest number. DID(Dynamic Interest Discriminator) draws z from a categorical distribution with class probabilities $f = \{f_1, f_2, ..., f_k\}$.

$$h = \text{argmax}_i \left[ g_i + \log f_i \right]$$  \hspace{1cm} (6)

where $h$ is current generated dynamic interest number and $\{g_1, g_2, ..., g_k\}$ are sample drawn from Gumble(0,1) distributions. In practice, we sample the Gumble(0,1) distribution using inverse transform sampling by drawing $u$ from a uniform distribution. What’s more, those added new Gumble distribution as the noise changes the probability distributions and give other original non-max alternative interest number chance to be chosen, which improve the exploration of the user interest number and make our model more solid.

$$g = -\log(-\log(u))$$  \hspace{1cm} (7)

where $u$ is sampling from Uniform(0,1).

The argmax operation in Eq. (6) is non-differentiable, but we can resort to the Gumbel Softmax distribution, which adopts softmax as a continuous relaxation to argmax in order to alleviate the non-differentiable problem used in Eq. (11)(12).

$$z_i = \frac{\exp((\log f_i + g_i)/T)}{\sum_{j=1}^k \exp((\log f_j + g_j)/T)} \text{ for } i = 1, 2, ..., k$$  \hspace{1cm} (8)

where $T$ is a temperature parameter to control the discreteness of the output vector $z$, which is set 10 in our model. Now, we get the probability $z$ for each dynamic interest number. During the forward pass, we sample the dynamic interest number $h$ using Eq. (6) for the click item sequence. As for the backward pass, we are able to estimating the gradients of the discrete samples by computing the gradients of the continuous softmax relaxation $z$ in Eq. (8).

### 3.4 Dynamic Interest Allocator

After the user’s dynamic interest number $h$ generated in Eq. (6) and more informative representation $F$ in Eq. (3) of item vector found in DID, DIA split the click sequence into different sub-sequences, where each sub-sequence represents a user’s interest and we use average-pooling method to get the user’s interest representation of those sub-sequence. DIA formalizes the allocation click sequence problem in the form of Markov Decision Process(MDP), and sample action form policy $\pi$ for each item to determine which sub-sequence it belongs to. Item representation $F$ with the bi-directional architecture self-attentive, our policy $\pi$ can foresee future sequential information when making a decision, which could offer insightful clues to determine item-level relevance without direct supervision signals. We consider an episodic RL approach to allocate the click sequence $C_i\{x_1, x_2, ..., x_t\}$ into $h$ sub-sequence $S_{seq}\{sub_1, sub_2, ..., sub_h\}$ and each sub-sequence represent a user interest representation.

**Episode RL** We see the allocation sequence split as an episode RL approach. At each time $T$, the process is in some state $s^T \in S$. According to the state $s^T$, the agent performs an action $a^T_i$ modeled...
by a policy $\pi(a_t^T \mid s^T)$. The action space is $a \in \{a_1, a_2, ..., a_h\}$, where $a_t^T$ is that at time $T$, the item $T$ belongs to sub-sequence $a_t$. The following is the policy $\pi$.

$$\pi(a_t^T \mid s^T) = \text{Softmax}(\text{ReLU}(s^T W_{p1} + b_{p1}))W_{p2} + b_{p2}$$  \hspace{1cm} (9)

where $\pi(a_t^T \mid s^T)$ is the discrete probability distribution that item $T$ belongs to sub-sequence $a_t$ and $W_{p1}$ is a d x $d_t$ matrix and $W_{p2}$ is a $d_t$ x h matrix.

**State Transition** We give each sub-sequence an initial multi interest representation at time $0$ $P^0 = \{p_1^0, p_2^0, ..., p_h^0\}$ where each $p_i$ is a d-dimension vector and initialize with the corresponding user embedding $e_u$. At time $T$, we put the $s^T$ into the policy $\pi$ to get the action $a_t^T$ (the sub-sequence $a_t$ item $T$ belongs to). Then we use our well-designed pooling method to update the corresponding interest representation embedding with the new added item $T$, where the representation of item $T$ is $F_T$.

$$p_{t+1}^T = \text{average – Pooling}(p_t^T, F_T) \hspace{1cm} (10)$$

In reality, there are complex relationships between the user’s click sequence, like point level, union level with or without skip[28]. For accurately capturing those relationships, we use a well-designed attention mechanism to define the state transition, which explore the relationships between the new click item and the generated subsequence with a weighted sum $p_t, F_{t+1}$ in Eq. (3) and dynamic interest number distribution probability information $z$ in Eq. (8) through a Neural Networks to get the $s_{t+1}$

$$s_{t+1} = \text{concat}(\sum_{j=1}^{h} \alpha_j p_j^T, F_{T+1}, z)W^0 \hspace{1cm} (11)$$

$$\alpha_j = \frac{\exp((p_t^T \cdot F_{t+1}))}{\sum_{j=1}^{h} \exp((p_t^T \cdot F_{t+1}))} \hspace{1cm} (12)$$

where $W^0$ is a $2x3d$ matrix and $(\cdot)$ represent the inner product.

Even we use a hard allocate, but some information from other sub-sequence is transitioning into the dynamic interest representation when we define the state transition, which makes our model more solid.

**Reward Setting** After the allocation process, we get the multi interests representation at time $1$ $P^1 = \{p_1^1, p_2^1, ..., p_h^1\}$. With the generated dynamic multi interests, here comes to the question that which interest representation is related to the target item. To confirm the target interest, we use the target item $p_{target}^T$ to get the current state $s^{T+1}$ through formulas Eq.(11)(12) and put it into the policy net $\pi(a_t^T \mid s^{T+1})$ set in Eq. (9) to sample action for getting the subsequence $p_{target}^T$ the target item belongs to. Here we leverage a Sampled Softmax technique [5, 12] to calculate reward where the relationship $p_{target}^T$ with the target item and other candidate item will be considered.

$$R_c = \frac{\exp((p_{target}^T \cdot e_{target}))}{\sum_{i=1}^{h} \exp(p_{target}^T \cdot e_i)} \hspace{1cm} (13)$$

$o$ is the sample item number in the dataset. Through $R_c$ consider other items when calculate the reward, it doesn’t use other generated multi interests which means that only when our target interest selection is correct, the reward is the optimal result. In order to promote the policy $\pi$ to choose the right action, we employ a baseline in the reward function which use the average scores of all generated multi interests, defined as:

$$R_{baseline} = \frac{\sum_{j=1}^{h} \exp((p_j^T \cdot e_i))}{h}$$  \hspace{1cm} (14)

with the baseline reward setting, and the advantage of selected dynamic interest representation reward setting is as below:

$$R_{advantage} = R_c - R_{baseline} \hspace{1cm} (15)$$

In order to enforce the learned dynamic multi interests representation orthogonally. Specific, we denote the $R_{orthogonal}$ as the mean of the absolute value of the inner product between all different generated dynamic interest representations $p_i^T$ in $P^t$.

$$R_{orthogonal} = -\frac{\sum_{i=1}^{h} \sum_{j=1}^{h} |p_i^T \cdot p_j^T|}{h(h-1)}$$  \hspace{1cm} (16)

where $\cdot$ represents the absolute value of inner product between $p_i^T$ and $p_j^T$ in $P^t$. Combine the two reward above, the final reward function of our model is:

$$R_s = R_{advantage} + \lambda_0 \cdot R_{orthogonal} \hspace{1cm} (17)$$

where $\lambda_0$ is the trade-off parameter to balance the two rewards, which is set 0.001 in our experiments.

### 3.5 Model optimization

We treat the allocation task as a RL problem and apply the classic policy gradient to learn the model parameters. Specifically, the corresponding probability of generating $p^T_\text{target}$ sub-sequence is $P(\text{sub})$ which is calculated as follows:

$$P(\text{sub}) = \prod_{T=1}^{t} \pi(a_t^T \mid s^T, \theta) = P(s^{T+1} \mid s^T, a_t^T, \theta) = \prod_{T=1}^{t} \pi(a_t^T \mid s^T, \theta) \hspace{1cm} (18)$$

The $P^T_\text{target}$ is then used for the dynamic interest selection for target item $\pi(a_t^T \mid s^{T+1})$ in Reward Setting. Thus, the probability of the generated sample action sequence is as followed:

$$P(s) = P(\text{sub}) \cdot \pi(a_t^T \mid s^{T+1}) \hspace{1cm} (19)$$

Formally, the objective of the policy network is to maximize the expected reward at the final prediction.

$$J(\theta) = E[R_s | \theta] = \sum_{s \in C} R_s \cdot P(s) \hspace{1cm} (20)$$

where $R_s$ is defined in Eq.(17) and its gradient will be detached in the training process, $C$ is all the generated action sequence of target sub-sequence and $\theta$ is the parameters of the model including the parameters of DIA and DID. The gradient of the objective function
\( \nabla_\theta \mathcal{J}(\theta) \) regard to the model parameters \( \theta \) can derived as:

\[
\nabla_\theta \mathcal{J}(\theta) = \nabla_\theta \sum_{s \in C} R_s \times \mathcal{P}(s) \\
= \sum_{s \in C} \nabla_\theta R_s \times \mathcal{P}(s) \\
= \sum_{s \in C} \mathcal{P}(s) \times R_s \times \nabla_\theta \log(\mathcal{P}(s)) \\
= \sum_{s \in C} \sum_{t=1}^{t+1} \mathcal{P}(s) R_s \times \nabla_\theta \log(\pi(a_t^s | s, \theta)) \\
= E_{s \in C} \left[ \sum_{t=1}^{t+1} R_s \times \nabla_\theta \log(\pi(a_t^s | s, \theta)) \right]
\]

Therefore, the optimization of the policy network is calculate with a log trick as follow:

\[
\mathcal{L}_{RL} = -\log(\mathcal{P}(s)) \times R_s 
\]

Here we use the standard cross-entropy and a Sampled Softmax technique [5, 12] to calculate the classification loss:

\[
\mathcal{L}_{CE} = -\frac{\exp(p^t_{\text{target}} \cdot \epsilon_{\text{target}})}{\sum_{i=1}^{n} \exp(p^t_{\text{target}} \cdot \epsilon_i)} 
\]

\( \epsilon \) is the same as the negative sample number in reward calculation. Finally, we jointly train the allocation task and classification task with a trade-off parameter \( \beta \):

\[
\mathcal{L} = \mathcal{L}_{CE} + \beta \times \mathcal{L}_{RL}
\]

\( \beta \) control the weight of the \( \mathcal{L}_{RL} \) loss, which is set 1 in our experiments.

### 3.6 Prediction

When we do the prediction, we first scan the user click session and select each action with the maximal probability at policy \( \pi \) Eq. (9) and corresponding state transition Eq. (11)-(12), which can be written as follows:

\[
a_t^\text{max} = \arg\max_{a_t} \pi(a_t^s | s, \theta) 
\]

For each candidate item, we put it into policy net to get which subsequence it belongs to and get its corresponding reward. We then rank all candidate items according to their rewards at Eq. (13) and return the top-\( N \) rewards item as the final recommendations.

## 4 EXPERIMENTS

In this section, we conduct experiments on sequential recommendation to evaluate the performance of our proposed method RDRSR on three benchmark datasets compare with several state-of-the-art baselines. We first briefly introduce the datasets and the state-of-the-art methods, then we conduct experimental analysis on the proposed model and the benchmark models. Specifically, we try to answer the following questions:

- **How effective is the proposed model compared to other state-of-the-art baselines?** Q1
- **What are the effects of the DIA(Dynamic Interest Allocator) and DID(Dynamic Interest Discriminator) modules through ablation studies?** Q2
- **How sensitive are the hyper-parameter the max dynamic interest number \( k \) in proposed model RDRSR?** Q3

### 4.1 Experimental Setup

In this section, we introduce the details of the three experiment datasets, evaluation metrics, and comparing baselines in our experiments.

**Datasets** We perform experiments on three publicly available dataset, including MovieLens, Lastfm and Foursquare. And the relative statistics information of the three datasets are shown in Table 1.

| Dataset | # User | # Item | # Interaction |
|---------|--------|--------|---------------|
| MovieLens | 944 | 1,683 | 100,000 |
| Foursquare | 2,294 | 61,859 | 211,955 |
| Lastfm | 1,860 | 2,824 | 583,933 |

- **ML – 100k** is a dataset about user’s rating score for movies. In experiments, we follow [8] to preprocess the dataset.
- **Foursquare** is a location based social networks datasets which contains check-in, tip and tag data of restaurant venues in NYC collected from Foursquare from 24 October 2011 to 20 February 2012.
- **Lastfm** records the music records of users from Last.fm. In experiments, we only use the click behaviors.

For Foursquare and Movielens datasets, we filter items and users interacted less ten times, and five times in Lastfm datasets. And all datasets are taken Leave-one-out method in [14] to split the datasets into training, validation and testing sets. Specifically, we split the historical sequence for each user into three parts: (1) the most recent action for testing, (2) the second most recent action for validation, and (3) all remaining actions for training. And if the click sequence length is less than \( t \), we repeatedly add a ‘padding’ item to the left until the length is \( t \). Note that during testing, the input sequences contain training actions and the validation actions.

**Baselines** We compare our proposed model RDRSR with the following state-of-the-art sequential recommendation baselines, including single representation methods and multi representation methods.

**Single representation models** The most common sequential recommendation methods which generates a single embedding representation for the next-item prediction:

- **GRU4Rec** [9] is a pioneering work which first leverages GRU to model user behavior sequences for prediction.
- **Caser** [28] is a recently proposed CNN-based method capturing sequential pattern by applying convolutional operations on the embedding matrix for the most recent items, and achieves state-of-the-art sequential recommendation performance.
- **BERT4Rec** [24] is a recently proposed BERT-based method which achieves state-of-the-art sequential recommendation performance.
- **STAMP** [18] is a neural sequential model by incorporating user short-term memories and preferences.

1https://grouplens.org/datasets/movielens/100k/
2https://sites.google.com/site/yangdingqi/home/foursquare-dataset
3http://millionsongdataset.com/lastfm/
Multi representation model: Sequential recommendation methods that generate multi representation to model user click behavior for the next-item prediction.

- MCPRN [31] is a recent representative work for extracting multiple interests which designs a mixture-channel purpose routing networks with a purpose routing network to detect the purposes of each item and assign them into the corresponding channels to form multi presentations.

Parameter Configuration. For a fair comparison, all baseline methods are implemented in Pytorch and optimized with Adam optimizer with a mini-batch size of 2048. The learning rate is tuned in the ranges of [0.01, 0.001]. We tuned the parameters of comparing methods according to values suggested in original papers and set the embedding size $d$ as 64, and sequence length $t=10$. For our method, it has three crucial hyper-parameters: the trade-off parameter $\lambda_\omega$, $\lambda_\epsilon$ and the max dynamic interest number $k$. We search $k$ from 3, 4, 5, and we set $\lambda_\omega$, $\lambda_\epsilon$ 0.001 and 1. In order to keep the policy consistent in Dynamic Interest Allocator, we put the same user training dataset in a batch to train the model. The configuration of the other two parameters max dynamic interest number $k$ and neg samples $o$ for three datasets are reported in Table 3.

Table 3: The optimal setting of our hyper-parameters for our model. Other parameters like dimension $d$ and learning rate $\gamma$ are set as 64 and 0.001, respectively.

|                | max dynamic interest number $k$ | neg samples $o$ |
|----------------|-------------------------------|-----------------|
| MovieLens      | 4                             | 99              |
| Foursquare     | 3                             | 99              |
| Lastfm         | 3                             | 199             |

Evaluation Metrics. For each user in the test set, we treat all the items that the user has not interacted with as negative items. We use two commonly used evaluation criteria [7]: Hit Rate (HR) and Normalized Discounted Cumulative Gain (NDCG) to evaluate the performance of our model.

4.2 Overall performance (Q1)

Table 1 summarizes the performance of RDRSR and baselines including single-representation and multi-presenation methods on three benchmark datasets. Obviously, RDRSR achieves comparable performance to other the baselines on the evaluation metrics in general. In the baselines of single representation methods, we find that GRU4Rec obtains good performance over other single-representation methods. What’s more, compare single representation methods with multi representation methods, it is obvious that recommendation with multiple presentations (MCPRN, RDRSR) for a user click sequence perform generally better than those with single representation (Caser, GRU4Rec, BERT4Rec ...). Therefore, it is necessary to explore multiple representation to model user’s diverse intents. Moreover, we can observe that the improvement introduced by capturing user’s various intentions is more significant for Movielens and Lastfm datasets due to their density. The users in denser datasets like Movielens and Lastfm tend to exhibit more diverse interests in online activity than rating datasets Movielens, which verifies the necessity of our motivation to model the dynamic interest number in the user behavior and the effectiveness of the DIA module in exploring the user’s dynamic interest number. The improvement of RDRSR over the fixed interest number multi representation method (MCPRN) shows that dynamic interest exploration serves as a better multi-interest extractor than fixed multi interest. Considering the RDRSR and other baselines results, RDRSR consistently outperforms them on three datasets over all evaluation metrics. This can be attributed to two points: 1) The Dynamic Interest Discriminator explores user’s dynamic interest number which takes the advantage of single representation methods when user’s intent is one and multi representation methods when user’s intents are more than one. 2) RMRSR could correctly explore user’s dynamic interest number and generates corresponding dynamic interest representation for next-item prediction while all other methods could be seen as fixed interest number method which are without enough flexibility.

In our model, a major novelty is that we want to explore the user’s dynamic interest number and form the corresponding dynamic interest representation. To obtain a better understanding why RDRSR performs better than other models, shown in Figure 3, we further construct a case study on Movielens dataset. Specifically, we present a snapshot of the interaction sequence for a sampled user, which contains seven items, and top-one as the recommendatio result. Here we use different colors to represent the different dynamic interest sub-sequences, which is captured by the DID and DIA modules, and the total number of colors is equal to the user’s dynamic interest number. The first five items are user’s click behavior. In the first line at time $t=6$, the new movie doesn’t not increase the user’s dynamic interest number and the dynamic interest number is still 2. The second line at time $t=6$, the new movie with one more color yellow means that the user’s dynamic interest number is increasing from 2 to 3. Next, the user’s new interest in sci-fi movie is main for the next-item prediction at time $t=7$. The result shows that our model can correctly explore the user’s dynamic interest number and makes better recommendation.
4.3 Ablation study (Q2)

We introduce one variant (RDRSR-F) to validate the effectiveness of the proposed model. Specifically, RDRSR-F shuts down the module Dynamic Interest Discriminator, and the module Dynamic Interest Allocator set a fixed dynamic interest number. We conduct experiments on all three datasets. Table 4 reports the results in terms of NDCG@10. RDRSR-F3 and MCPRN-3 means the fixed interest number is 3 and the max dynamic interest number of RDRSR-3 is 3. Obviously, RDRSR-3 significantly outperforms the variant RDRSR-F3 on all datasets. The substantial difference between RDRSR-F3 and RDRSR-3 shows that the learning dynamic user dynamic interest number in DID module is better than those fixed interest number in RDRSR-F3. And it verifies our motivation to explore the user dynamic interest number in sequential recommendation and the effectiveness of the proposed module DID. What’s more, the improvement of RDRSR-F3 over MCPRN-3 validates that our DIA module is useful to model user’s dynamic interest representations for next-item recommendation.

Table 4: Ablation study. Performance comparison of RDRSR-3 (max dynamic interest number 3), its variant RDRSR-F3 and MCPRN-3 (fixed interest number 3) over three datasets. And all the numbers in the table are percentage numbers with '%' omitted.

| Datasets   | Metric | MCPRN-3 | RDRSR-F3 | RDRSR-3 |
|------------|--------|---------|----------|---------|
| MovieLens  | NDCG@10| 6.32    | 6.30     | 6.60    |
| Foursquare | NDCG@10| 9.73    | 10.10    | 10.50   |
| Lastfm     | NDCG@10| 6.32    | 6.40     | 6.90    |

4.4 Hyperparameter study (Q3)

We also investigate the sensitivity of the max dynamic interest number \(k\) to RDRSR in all three datasets. Figure 4 reports the performance of our model in the metrics of HR and NDCG. In particular, We keep the other parameters in the model consistent with the Q1 settings. From the figure, we can observe that RDRSR obtains the best performance of HR and NDCG when \(k\) equals 3 or 4. With the fixed sequence length \(t\) the result increases with the increase of the max dynamic interest number \(k\), which indicates that the user’s dynamic interest number is multi and bigger max dynamic interest number set in the model may meet the requirements better. RDRSR becomes a single representation method (RDRSR-1) when the max dynamic interest number is 1. The sub-optimal results achieved by RDRSR-1 gives evidences that single representation is not the best solution for sequential recommendation and the necessity of dynamic interest representations. The recommendation performance increases at the beginning, but decreases after reaching a peak due to the complex model structures with bigger max dynamic interest number \(k\), which brings more noise and makes sub-optimal recommendation.

5 CONCLUSION

In this article, we learning a dynamic group of representations for user to improve the performance of the sequential recommender system. In order to achieve this goal, we design DID and DIA to capture the dynamic interest number and form the corresponding dynamic interest representations. What’s more, we conducted a ablation study to explore the effectiveness of DID and DIA modules and verified the effectiveness of RDRSR on several real datasets with SOTA methods. To the best of our knowledge, we are the first to consider the personalized dynamic interest number in sequential recommendation. However, the proposed model also exists shortcomings in computing speed, where we formulate the allocation task in DIA module as a MDP problem which is computing cost and unstable in training. In the future we will consider how to allocate the click sequence in a more effective way.

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