Fine-Grained Session Recommendations in E-commerce using Deep Reinforcement Learning

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ABSTRACT
Sustaining users’ interest and keeping them engaged in the platform is very important for the success of an e-commerce business. A session encompasses different activities of a user between logging into the platform and logging out or making a purchase. User activities in a session can be classified into two groups: Known Intent and Unknown intent. Known intent activity pertains to the session where the intent of a user to browse/purchase a specific product can be easily captured. Whereas in unknown intent activity, the intent of the user is not known. For example, consider the scenario where a user enters the session to casually browse the products over the platform, similar to the window shopping experience in the offline setting. While recommending similar products is essential in the former, accurately understanding the intent and recommending interesting products is essential in the latter setting in order to retain a user. In this work, we focus primarily on the unknown intent setting where our objective is to recommend a sequence of products to a user in a session to sustain their interest, keep them engaged and possibly drive them towards purchase. We formulate this problem in the framework of the Markov Decision Process (MDP), a popular mathematical framework for sequential decision making and solve it using Deep Reinforcement Learning (DRL) techniques. However, training the next product recommendation is difficult in the RL paradigm due to large variance in browse/purchase behavior of the users. Therefore, we break the problem down into predicting various product attributes, where a pattern/trend can be identified and exploited to build accurate models. We show that the DRL agent provides better performance compared to a greedy strategy.

CCS CONCEPTS
• Computing methodologies → Sequential decision making
  Reinforcement learning

KEYWORDS
Sequential Recommendation, Reinforcement Learning, Session Intent Prediction

1 INTRODUCTION
An e-commerce platform provides a promising alternative to the traditional retail business where users can browse, compare, make purchases and get delivery from the comfort of their homes. This setting has become even more popular recently due to the pandemic, where contactless purchase and delivery was preferred over the traditional shopping experience. This increased digital footprint of users on the platform led to an exponential growth of customer data like browsing history, purchase history, session activity, etc. From the e-commerce business point of view, it is paramount to make optimal use of this data not only to increase the profits of the business but also to improve the customer experience by recommending appropriate items.

Session recommendation is an essential subproblem in the recommendation system where the objective is to recommend the items to the users primarily based on the user’s activity thus far in the session. It differs from the traditional recommendation systems that use the user’s historical browse/purchase interactions data. On the contrary, each session is treated independently in session recommendation problems. This is due to the difficulty in learning the dependencies between the different sessions of the user. Moreover, the sessions might not be correlated, and the user’s prior history (before the session starts) is not always available for cold start cases. Although appealing due to its simplicity, this paradigm is challenging to solve due to the inherent heterogeneity in the users’ activities across the platform and varying goals associated with it. To understand this, consider the following example: In the off-line shopping scenario, a sequence of items is suggested to the customers by the sales executive based on the explicit feedback provided by the customer. It is imperative that the executive suggests the items to sustain the customers’ interest and ultimately drive them towards a purchase. Each item that is suggested has an
The previous products are considered for recommending products at instant $k + 1$. First, the attributes of the products $(A, B, C)$ are extracted. Next, these attributes are then fed to the RL agents to generate the next attribute recommendations. Finally, the attribute recommendations are combined to obtain the products to be recommended at instant $k + 1$ (fourth in this example).

immediate impact (i.e., customers might either like and continue exploring it or exit the store) and also influences the future actions of the customers (i.e., making a purchase). Emulating this in the online scenario requires capturing this dynamic nature of the problem and balancing short-term and long-term goals. This motivates us to formulate it in the framework of the Markov Decision Process (MDP) [3, 24]. We define a session as a sequence of events of a user until it leads to one of the following (a) purchase (b) user exits the session. This work aims to optimally recommend a sequence of products that could potentially lead to a purchase event.

Reinforcement Learning (RL) [31] is a popular model-free paradigm for solving an MDP problem. Here, we train an agent to make optimal decisions based only on the trajectories of the environment. When the number of states and actions in the environment is very high, one resorts to function approximation architectures. RL algorithms combined with neural network architectures, i.e., Deep RL, have achieved a lot of success in recent times [21, 22]. In this work, we train a Deep RL agent to recommend a sequence of products in a session. It is important to note that the traditional RL setup where agents learn by exploring different actions is not a favorable setting for our problem due to a large number of products in the e-commerce space. Hence, we train the algorithm under an off-policy setting using the users’ historical session data. The dataset considered in this work is compiled from the click-stream data of users on the Myntra e-commerce platform, one of the largest fashion e-commerce in India.

Training a deep RL agent to recommend the products directly is not practical due to heterogeneity (in terms of different attributes) in the users’ browsing history. There are two problems associated with this training paradigm. First, the number of products is huge (which constitutes the action space). Second, there might not be a definite trend that can be learned from this data, making the training very unstable. For example, consider a scenario where two users browse products in a sequence that is similar in every regard (like product type, color) except a specific attribute ‘brand.’ Say the session of the former user ends up in a purchase, whereas the latter is a non-purchase session. The effectiveness of RL training lies in the generalization of actions and hence the sessions of such nature will lead to unstable learning. To mitigate this problem, we propose a divide-and-conquer approach where multiple RL agents will be trained to recommend various attributes of the products, and these recommendations will be combined at the end to generate product recommendations. This is illustrated in Figure 1. First, attributes of the products (like color, product type, and brand) are extracted. These attributes are then sent as inputs to independent DRL models to obtain the recommendations for attributes in the next time instant. Finally, the products that match the attributes are presented as final recommendations to the user.

The overall contributions of the paper are as follows:

- We mathematically formulate the problem of User Session recommendation in the framework of MDP.
- We propose a Deep Q-Learning based model to predict the next products within a user session while optimizing for purchase intent.
- We compare the proposed model with a similarity-based baseline model to showcase our proposed approach’s efficacy.

### 2 RELATED WORK

Recommendation systems deal with building algorithms for recommending products to the user to meet various objectives like user personalization, increased engagement rate, and improving business goals. The idea here is to accurately predict users’ interest and recommend products that meet their expectations. Recommendation systems finds its applications in various domains like news recommendation [16, 17, 19, 39, 42], movie recommendation [2, 26, 30, 35] etc. The importance of recommendation systems is even more pronounced in the e-commerce business, where the buying and selling of products are performed virtually online. Therefore, it is imperative from the business point of view to recommend relevant and specific products to the users to sustain their interest over a long period. As a result, a lot of research has been dedicated to build good recommendation systems [33] in recent times to solve problems like Click-Through-Rate (CTR) prediction [7, 14, 40, 41], intent and purchase prediction [6, 13, 37] etc.

Deep Learning is a popular class of machine learning algorithms that uses artificial neural networks to learn and derive required patterns from the input data. We will now discuss some popular deep learning techniques proposed in the literature for solving the recommendation problem. In [34], two deep learning algorithms based on the collaborative filtering technique have been proposed to handle cold-start problems. In [8], a deep learning model has been deployed to simulate the interaction between item and user by feeding the pre-trained representations of item and user as input to
the model. In [18], Recurrent Neural Networks (RNNs) have been deployed to generate recommendations from user reviews.

However, these techniques do not efficiently capture the dynamic nature of the recommendation problem. Reinforcement Learning (RL) models have the capability to handle the dynamic nature by maximizing the expected long-run objective and hence is the right paradigm for this problem. In [36], a self-supervised RL algorithm, where the output of the RL has been used as a regularizer for self-supervised learning, has been proposed. In [23], a recommender system based on a deep RL algorithm has been proposed. In [1, 5], a detailed survey on the application of RL to the recommendation systems along with potential future directions has been provided.

We now discuss the literature on the session recommendation problem. Session recommendation models have received a lot of attention in recent years. In [12, 27], RNN based models are proposed to solve the session recommendation. In [29], context information is included in the modeling of RNN and proposes a new class of Contextual RNNs. The RNN-based model is further improved by [11] where a novel loss function is used that results in improved performance. [15] studies the attention mechanism that selects the most salient information for session recommendation and proposes Neural Attention Recommendation Machine (NARM) to solve this problem. In [4], the authors have studied the impact of incorporating dwell times in the structure of RNNs and showed improved performance over standard RNN-based recommendations. In [25], hierarchical RNNs have been proposed to improve the quality of recommendations.

RL has also been used for session recommendation in [28, 32]. However, they do not make use of function approximation networks leading to state and action space explosions. In [38], Deep RL techniques have been utilized to solve the session recommendation problem. However, these do not exploit the recurrent nature between the states in the session. In our work, we use Deep Recurrent Q-Network (DRQN) [10] to tackle the session recommendation problem. As our approach does not require prior history or user information, it can also be used in cold-start recommendation problems. Moreover, as the agent is trained at the attribute-level, the recommendations can be analyzed to understand the user’s affinities towards these attributes. The closest work to ours is [43] where an RL algorithm has been proposed to optimize for the long-term engagement in feed streaming recommendations. Our work differs from [43] in the following ways:

- [43] considers the problem of a sequence of recommendations in feed streaming data. In contrast, our model deals with recommending products (that are computed as a function of attributes) in a session.
- The reward structure in [43] is aimed at improving the long-term engagement while our reward function optimizes for a purchase.
- The information about the user is also part of the state space in the MDP proposed by [43] whereas our models treat each session independently and do not take into consideration the user data.

3 MODEL

We model the session recommendation problem in the framework of Markov Decision Process (MDP). An MDP is characterized by the tuple $< S, A, P, R, γ >$. Here $S$ denotes the state space, $A$ denotes the action space, $P$ denotes the probability transition matrix, $R$ is the single-stage reward function and $0 ≤ γ < 1$ is the discount factor.

In the following, we describe the MDP model for recommending a sequence of attributes.

- **State Space:** This constitutes the necessary and sufficient information to make a decision. In our problem of recommending a sequence of attributes, the information of the previous $k$ attributes browsed by the user becomes the state space. This information of the attributes is captured in the form of embeddings, which are obtained by training language models like Word2Vec [20].
- **Action Space:** This constitutes the possible actions that can be taken at each step in a session. In our problem, the set of all attributes is the action space.
- **Reward Function:** Based on the action $a$ chosen in a given state $s$, we obtain an immediate reward $R(s, a)$ from the environment. In our problem formulation, we formulate the reward structure as follows
  1. At every intermediate step of a session, the normalized dwell time (i.e., time spent by the user browsing the product) is considered to be the reward.
  2. If the session has ended in a purchase, the reward is set to +10.
  3. If the session has not ended in a purchase, the reward is set to 0.

This reward structure motivates the RL agent to recommend attributes that maximize not only the user’s immediate interest (captured in the form of the dwell time) but also those that ultimately lead to a purchase. An important point to note here is that the rewards are not stationary, i.e., $R(s, a)$ for a fixed state, and action $(s, a)$ changes over time. Therefore, we treat the reward as a random variable, which, as we explain later, is efficiently handled in the RL paradigm.

- **Probability Transition Matrix:** Based on the action $a$ chosen in a given state $s$, the system transitions to a new state which is sampled from the distribution $P(.|s, a)$. In our problem, the next state is the next $k$ attributes on the rolling window basis.

The objective of the RL agent is to find an optimal policy $π^∗ : S → A$, which is a mapping from state space to action space. It represents the optimal action that needs to be taken in any given state. To compute this optimal policy $π^∗$, the first step is to compute the $Q$-value function that satisfies the following Bellman equation:

$$Q(s, a) = E \left[ R(s, a) + γ \max_{b} Q(s', b) \right], \forall (s, a) ∈ (S × A),$$

(1)

where $E[.]$ is the expectation over the next state $s’$ and reward function $r$. Intuitively, $Q(s, a)$ specifies the score (combination of immediate and future rewards) that is obtained when action $a$ is taken in state $s$. Hence, the optimal policy can be obtained from
Q-value as follows:
\[
\pi^*(s) = \arg \max_a Q(s, a), \forall s \in S.
\] (2)

In order to solve (1) and obtain the optimal policy as in (2), we make use of the popular RL algorithm Deep Q-learning Network (DQN) that makes use of neural networks. This algorithm can handle continuous state spaces and hence is a right fit for our problem. In DQN, the Q-values are approximated as follows:
\[
Q(s, a) \approx f(s, a, \theta), \forall (s, a) \in (S \times A),
\] (3)
where \( f \) is a non-linear function of state \( s \), action \( a \) and \( \theta \) is the parameter of the neural network. These parameters are trained by minimizing the loss function at each iteration \( i \), given by \([21]\):
\[
L_i(\theta_i) = E_{(s,a) \sim \rho(.)} \left[ (y_i - f(s,a,\theta_i))^2 \right],
\] (4)
where \( \rho(.) \) is the distribution from where states and actions are sampled and
\[
y_i = E_{s' \sim \rho(.)} \left[ R(s,a) + \gamma \max_b f(s',b,\theta_{i-1}) \right].
\] (5)

Optimisation algorithms like stochastic gradient descent could be applied to iteratively improve the parameters \( \theta \) of the neural network. Here, the gradient function is obtained by differentiating (4) with respect to parameters \( \theta \) given by \([21]\):
\[
\nabla_{\theta_i} L_i(\theta_i) = E_{(s,a) \sim \rho(.)} \left[ \left( R(s,a) + \gamma \max_b f(s', b, \theta_{i-1}) - f(s,a,\theta_i) \right) \nabla_\theta f(s,a,\theta_i) \right].
\] (6)

As described above, the embeddings of previous \( k \) attributes constitute the state which is fed as input to the RL algorithm. The following are some of the possible options to obtain the input state:

- Concatenation of all \( k \) previous embeddings. In this representation, the input scales quadratically with \( k \), hence not an optimal choice.
- Average of \( k \) embeddings. Here, all the \( k \) embeddings are given equal weight and hence might not be an optimal choice in practical settings.
- Weighted average of \( k \) embeddings. This enables one to give different weights to different embeddings, for example, higher weight to recent attributes.

Even though the weighted average of \( k \) embeddings input representation looks appealing, it fails to capture the dependence among the attributes. The relation between the attributes might form a crucial form of the state space that aids in optimal decision-making. While optimising for long-term reward, it is very important to capture the sequential relationship and hence we rely on LSTM rather than average and weighted average. This motivates us to make use of the architecture shown in Figure 2, similar to the Deep Recurrent Q-Network (DRQN). The pseudo-code of our proposed algorithm is described in Algorithm 1. The algorithm is trained on the session data where each session is of form \( s_i = \{a_n, d_n\}_{n=0}^{N_i} \) where \( a_n \) is the attribute of the product that was browsed by the user, \( d_n \) is the dwell time, at instant \( n \) and \( N_i \) is the number of steps in the session \( i \). In each step of a session, the embeddings of the previous \( k \) attributes are processed through an LSTM to obtain a representation of the state. Subsequently, the state is passed through a series of dense layers to obtain Q-values. Finally, the parameters of the neural network are updated by performing stochastic gradient descent on loss function \( L(\theta) \), which is shown in eq.(4).

Algorithm 1 DRQN- Recommendation

1. Input: Session Data \( S = \{s_i\}_{i=0}^\infty \), where each session \( s_i = \{a_n, d_n\}_{n=0}^{N_i} \).
2. Input: \( k \) \leftarrow Number of previous steps considered as state.
3. Input: Function \( E(\cdot) \) : Maps attributes to embeddings.
4. Input: \( \alpha \) \leftarrow Step-size.
5. Initialize the parameters of the neural network \( \theta \).
6. for \( i = 0, \ldots, \infty \) do
7. for \( n = k, \ldots, N_i \) do
8. State \( s = \text{LSTM}(E(a_{n-k}),E(a_{n-k+1}),\ldots,E(a_{n-1})) \)
9. Action \( a = a_n \).
10. Reward \( r = d_n \).
11. Next State \( s' = (E(a_{n-k+1}),\ldots,E(a_n)) \)
12. if \( n = N_i \) then
13. \( y_n = \begin{cases} 10, & \text{if session ended in a purchase} \\ 0, & \text{otherwise} \end{cases} \)
14. else \( y_n = r + \gamma \max_b f(s', b, \theta) \).
15. \( \theta \leftarrow \theta + \alpha \nabla \theta L_i(\theta) \).

4 EXPERIMENTS AND RESULTS

In this section, we discuss the experiments and results of the proposed algorithm. We train our proposed algorithm to recommend...
In the future, we would like to extend the training of the DRL algorithm to recommend multiple attributes and develop an end-to-end model. Also, we would like to develop other novel comparison metrics that can efficiently capture the behavior of the RL agent. Performing A/B test and observe the metrics like average purchase, RPU (Revenue Per User), Average CTR etc is also a part of our future work. Moreover, applying off-policy Actor-Critic algorithms [9] for this problem would be an interesting future direction.

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