In the realm of online recommendation systems, the Combinatorial Recommender (CR) system stands out for its unique approach. It presents users with a list of items on a result page, where user behavior is simultaneously influenced by contextual information and the items listed. Formulated as a combinatorial optimization problem, the objective of the CR system is to maximize the recommendation reward across the entire list of items. Despite the significant potential of CR systems, developing a practical and efficient model remains substantial challenges. These challenges stem from the dynamic nature of online environments and the pressing need for personalized recommendations. To tackle these challenges, we decompose the overarching problem into two sub-problems: list generation and list evaluation. We propose novel and pragmatic model architectures for each sub-problem aiming to concurrently enhance both effectiveness and efficiency. To further adapt the CR system to online scenarios, we integrate a bootstrap algorithm into an actor-critic reinforcement framework. This innovative approach called JD Recommender System (JDRec) is designed to continuously refine the recommendation mode through sustained user interaction, ensuring the system's adaptability and relevance. The proposed JDRec framework, tested through rigorous offline and online experiments, has shown promising results. It has been successfully deployed in online JD recommendation systems, yielding a notable improvement in click-through rate by 2.6% and augmenting the total value of the platform by 5.03%. Besides, we release the large scale dataset used in our work to facilitate further research.

1 INTRODUCTION

Recommender systems play a core role in e-commerce by effectively mining user preferences, whose core task is ranking the relevant items and presenting the result to users. Learning-to-rank refers to a series of methods that attempt to solve ranking problems with machine learning algorithms. Based on different designs of model formulation and loss functions, existing learning-to-rank methods can be categorized into four groups: point-wise [6], pair-wise [4], list-wise [2, 3], set-wise [7]. Most of the learning-to-rank methods are based on the probability ranking principle with an assumption that an item’s attractiveness to a user remains constant regardless of what surrounding items are. This kind of method ignores inter-item relationship and local context information which are proved to be important for understanding user behaviors in online systems [5, 11].

There are two main context-aware ranking approaches: point-wise methods enhanced with contextual information, list-wise optimization via slate reranking. Contextual point-wise methods, like Deep Determinantal Point Process [13] and the Deep List-Wise Context Model [1], incorporate local contextual data and generate item lists using greedy algorithms. This kind of method takes the diversity of the lists into accounts, but ignores other user experience factors (e.g. category importance and correlation). On the other hand, slate reranking methods [8, 10, 12] utilize global list-wise
optimization for better recommendations. Slate reranking methods try to present combinatorial recommendation from a global perspective instead of point-wise value estimation and sorting along with rule-based diversity control. There remains two challenges in slate reranking methods: how to generate superior candidate lists, and how to evaluate these lists to select the best one.

The principle of reinforcement learning - try, evaluation, feedback and improvement - is ideal for solving the slate reranking problem. The generator-critic framework belonging to the actor-critic reinforcement method [9] is proposed in industrial recommender system to solve the slate reranking problem. These approaches align with the actor-critic reinforcement method and seek to optimize both the list generation and the list evaluation. They propose RNN-based generators and attention-based evaluators. While transformative, this generator-critic framework presents the following challenges: (1) high time cost of RNN-based generators. (2) prediction bias of the list evaluator. (3) initiating the list generator before deploying it online presents a significant challenge.

In this work, we propose JDRec framework with a novel model structure for the list generator to reduce the cost of time online, and use a bootstrap approach to solve the initialization problem.

2 METHODOLOGY

The combinatorial recommendation problem can be formulated as follows: given a set of candidate items denoted as $I = \{I_1, I_2, \ldots, I_n\}$ and a specific user profile denoted as $U$, the objective is to find an optimal sequence $\{A\} = \{I_{a_1}, I_{a_2}, \ldots, I_{a_l}\}$, where $I_{a_i} \in I \ (1 \leq i \leq l)$. This optimized sequence $\{A\}$ is then presented to the user. Subsequently, the user provides feedback, represented as $r(U, A)$. The objective is to maximize the expected overall utility or benefit of sequence $A$, denoted as $E \{r(U, A)\}$. Typically, $E_X[]$ represents the expectation over variable $X$, and $E[\cdot]$ represents the expectation over repeated experiments.

JDRec framework (shown in Figure 1) is a variation of the actor-critic reinforcement learning framework tailored for recommender systems, which consists of a list generator and a list evaluator.

The goal of the list generator is to model a mapping from candidate set to a list generation policy probability matrix. The structure of the proposed set-to-list generator is shown in Figure 2. The existing generator-critic methods tend to model list generation procedure as a recurrent generation paradigm, which has a high time cost online. Our proposed list generator takes as input a candidate item set, which is permutation invariant. The target of the list generator is to generate a probability distribution in the list generation procedure, which will be then used to sample several candidate item lists. The output of the set-to-list generator is a $(L + 1) \times N$ 2D matrix $M$, where $N$ represents the size of candidate set and $L$ represents the length of the generated candidate list. Table 1 shows an example of the list generator’s output. We propose the Softmax2D cross entropy loss for the list generator which is actually a mixture of two sub-tasks, comprising of id selection for each position and rank classification for each candidate item.

The goal of the list evaluator is to predict click-through rate for each item in the list. The model structure of the proposed list evaluator is shown in Figure 3. The list evaluator takes as input a sequence of items with user interactive features in user sessions, point-wise prediction results and other additional information of items. The output of the list evaluator is the overall click-through rate of the list. The training procedure of the list evaluator can be formulated as follows. Given an item list $\{A\} = \{I_{a_1}, I_{a_2}, \ldots, I_{a_l}\}$ and its exposure label $\{L_e\} = \{L_{c,a_1}, L_{c,a_2}, \ldots, L_{c,a_l}\}$ and click label $\{L_c\} = \{L_{c,a_1}, L_{c,a_2}, \ldots, L_{c,a_l}\}$, where $L_{c,a_i} \in \{0, 1\}$ and $L_{c,a_i} \in \{0, 1\}$ and 1 means exposure or click respectively. The objective of the list evaluator is to estimate CTR of the candidate lists. So we use the sigmoid cross entropy loss as the loss function and ignore the loss computation on those unexposed items.

3 EXPERIMENTAL RESULTS

Table 1: An example of the list generator’s output ($L=4$, $N=6$)

|  | 1       | 2       | 3       | 4       | 5       | 6       |
|---|---------|---------|---------|---------|---------|---------|
| 1 | 0.9     | 0.1     | 0       | 0       | 0       | 0       |
| 2 | 0.05    | 0.8     | 0.15    | 0       | 0       | 0       |
| 3 | 0.05    | 0.1     | 0.7     | 0.15    | 0       | 0       |
| 4 | 0       | 0       | 0.15    | 0.85    | 0       | 0       |
| Not in | 0 | 0 | 0 | 1 | 1 |

Table 2: A/B Test Results

|                        | click-through rate | total value |
|------------------------|--------------------|-------------|
| Evaluator (21st May)   | +2.16%             | +3.68%      |
| Generator (9th Dec)    | +0.44%             | +1.35%      |

We conducted online evaluation of our JDRec framework, including A/B tests for 2 main steps. The A/B test results are shown in Table 2, where total value means synthetical value brought by user clicks (e.g., order and income). As shown in Table 2, the JDRec framework brings immediate gains for online recommendation, ensuring a seamless release process for the proposed JDRec framework.
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