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Dynamic Multi-Objective Recommendation Via Discrete Soft Actor-Critic

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ABSTRACT

Modern recommender systems often need to optimize multiple conflicting objectives, such as accuracy, diversity, and novelty. This paper proposes a novel approach, Dynamic Multi-Objective Recommendation via Discrete Soft Actor-Critic (DMOR-DSAC), to address this challenge. DMOR-DSAC employs a reinforcement learning framework with a discrete action space, utilizing the Soft Actor-Critic algorithm to learn a policy that dynamically balances these objectives. Experimental results on benchmark datasets demonstrate the effectiveness of DMOR-DSAC in achieving superior multi-objective performance compared to existing methods.

KEYWORDS

Multi-objective recommendation, reinforcement learning, Soft Actor-Critic, discrete action space, dynamic weighting, recommender systems.

INTRODUCTION

Recommender systems have become indispensable tools for helping users discover relevant items in various domains, including e-commerce, online media, and social networks [1]. Traditional recommender systems primarily focused on optimizing a single objective, such as prediction accuracy, which measures how well the system predicts user preferences [17, 19]. However, in real-world scenarios, recommender systems often need to satisfy multiple, potentially conflicting objectives [4, 28, 49].

For example, a news recommendation system may aim to:

- Maximize user engagement: Recommending articles that users are likely to click on and read.
- Promote diversity: Recommending a variety of articles from different sources and topics to broaden users' perspectives.
- Enhance novelty: Recommending new or less-known articles to help users discover fresh content.

Similarly, an e-commerce recommender system might seek to balance:

- Maximize sales: Recommending products that users are likely to purchase.
- Increase user satisfaction: Recommending products that align with users' long-term interests.
- Ensure fairness: Avoiding biased recommendations that disproportionately favor certain products or sellers.

Multi-objective recommendation presents significant challenges. Different objectives may require different modeling approaches, and optimizing one objective may negatively impact others. Furthermore, user preferences and the importance of different objectives can vary

dynamically over time and across different users [48, 50].

Reinforcement learning (RL) has emerged as a promising framework for addressing the challenges of multi-objective recommendation [1, 6, 13]. RL enables the recommender system to interact with users in a dynamic environment, learn from their feedback, and adapt its recommendation strategy over time. By formulating the recommendation process as a Markov decision process (MDP), RL can optimize long-term rewards that reflect multiple objectives.

However, applying RL to multi-objective recommendation also faces challenges. Many RL algorithms are designed for continuous action spaces, which are not always suitable for recommendation scenarios where the system typically selects from a discrete set of items. Furthermore, effectively balancing multiple objectives in RL requires careful design of the reward function and the learning algorithm.

This paper proposes a novel approach, Dynamic Multi-Objective Recommendation via Discrete Soft Actor-Critic (DMOR-DSAC), to address these challenges. Our approach utilizes the Soft Actor-Critic (SAC) algorithm [15, 16], which is known for its sample efficiency and stable learning, adapted for discrete action spaces [8, 11]. DMOR-DSAC dynamically balances multiple recommendation objectives by learning a stochastic policy that maximizes a weighted sum of rewards, where the weights adapt based on the user's current state and feedback. This dynamic balancing enables the system to provide personalized recommendations that effectively cater to the user's evolving needs and preferences.

METHODS

The proposed DMOR-DSAC method formulates the multi-objective recommendation problem as a Markov Decision Process (MDP) and employs a modified Soft Actor-Critic (SAC) algorithm designed for discrete action spaces. The key components are described below:

1. MDP Formulation:

State: The state (s_t) represents the user's situation at a specific time (t). It includes all the information relevant to making a recommendation, such as their past interactions with the system, demographic details, and the context of their current session. The document also mentions that features from knowledge graphs can be used to represent items.

Action: The action (a_t) is the set of items that the recommender system chooses to present to the user at time (t). The key point here is that the action space is discrete, meaning the system selects from a finite set of possible item combinations.

Reward: The reward (r_t) is a set of values that quantify how well the recommendation system is achieving each of its objectives. Instead of a single reward value, there's a vector of 'K' rewards, where each value corresponds to a different objective (e.g., accuracy, diversity, novelty). These rewards are normalized to have a common scale.

Transition: The transition function defines how the user's state changes as a result of the system's recommendation and the user's response to it. In simpler terms, it determines how the user's preferences and context evolve over time as they interact with the recommender system.

2. Dynamic Multi-Objective Reward:

* To balance multiple objectives, we define a dynamic weighted sum of the individual rewards:

Weighted Sum of Rewards: The overall reward (R_t) is calculated as a weighted sum of individual rewards (r_k,t) for each objective (k). The weight (w_k,t) determines the contribution of each individual reward to the total reward.

Dynamic Weights: The key idea is that these weights (w_k,t) are not constant. They change dynamically based on two factors: the user's current state (s_t) and their past feedback history (h_t-1).

Neural Network Function: A neural network function (f) is used to predict the optimal weights. This function takes the user's state and feedback history as input and outputs the weight distribution.

Adaptation to User Preferences: This dynamic weighting mechanism allows the system to adapt to the user's changing preferences and priorities. For example, if a user has shown a preference for diverse recommendations in the past, the system can increase the weight for the diversity objective in the future.

3. Discrete Soft Actor-Critic (DSAC):

Adaptation of SAC for Discrete Action Spaces: The text mentions that the SAC algorithm, which is originally designed for continuous action spaces, is modified to work with discrete action spaces, where the recommender system selects from a finite set of items.

Maximizing Expected Reward and Entropy: SAC aims to find a policy that not only maximizes the expected reward (i.e., how well the recommendations achieve the objectives) but also the entropy of the policy. Entropy measures the randomness or diversity of the policy. By maximizing entropy, SAC encourages exploration and prevents the model from getting stuck in suboptimal solutions.

Actor-Critic Architecture: SAC uses an actor-critic architecture, which consists of two main components:

• Actor: The actor network learns a stochastic policy, which is a probability distribution over the possible actions (i.e., which items to recommend). The policy determines the likelihood of recommending each set of items.

• Critic: The critic network learns two Q-functions. Q-functions estimate the expected future reward for taking a specific action in a given state. Having two Q-functions helps to improve the stability and accuracy of the learning process.

Iterative Updates: The SAC algorithm updates the actor and critic networks iteratively. The critic updates its Q-functions to become more accurate in estimating future rewards. The actor updates its policy to maximize the soft Q-function (which is the minimum of the two Q-functions) plus the entropy of the policy. This update rule encourages the actor to choose actions that lead to high rewards while also maintaining a degree of randomness.

Deep Neural Networks (DNNs): The actor, critic, and reward weighting function are implemented using deep neural networks (DNNs), such as multi-layer perceptrons (MLPs). These networks are trained using stochastic gradient descent and techniques like batch normalization to improve the learning process.

4. Training and Inference:

Training: The model is trained offline, meaning it learns from a pre-existing dataset of user interaction history. During training, the user feedback within this dataset is used to calculate the reward values for each recommendation objective (e.g., accuracy, diversity, novelty).

Inference: This is the process of generating recommendations for real users. It happens online, meaning the system makes recommendations in real-time as users interact with it. The process involves these steps:

1. The system observes the user's current state (e.g., their browsing history, current context).

2. It calculates the dynamic weights for each objective using the learned function f. This function determines the importance of each objective based on the user's state.

3. The actor network generates a probability distribution over possible item recommendations. This distribution indicates how likely the system is to recommend each set of items.

4. The system recommends the items with the highest probabilities to the user.

RESULTS

The DMOR-DSAC method was evaluated on benchmark datasets for multi-objective recommendation. The datasets were adapted to simulate the dynamic user behavior and multi-objective rewards. The key findings are summarized below:

• DMOR-DSAC achieved superior performance compared to baseline methods that optimize a single objective or use a fixed weighting of multiple objectives.

• The dynamic weighting of objectives allowed the model to adapt to different user preferences and contexts, leading to improved overall user satisfaction.

• The incorporation of entropy regularization in the SAC algorithm encouraged exploration and helped the model discover better recommendation strategies.

• The results show that DMOR-DSAC is effective in balancing conflicting objectives, such as accuracy and diversity, providing a more balanced and comprehensive recommendation experience.

• DMOR-DSAC demonstrated robust performance across different datasets and evaluation metrics.

DISCUSSION

The results demonstrate the effectiveness of the proposed DMOR-DSAC approach for dynamic multi-objective recommendation. By employing a discrete SAC algorithm with dynamically weighted rewards, the system can effectively learn policies that balance multiple conflicting objectives.

The key advantages of DMOR-DSAC are:

• Dynamic Objective Balancing: The dynamic weighting of objectives allows the system to adapt to the user's evolving preferences and contextual factors. This provides a more personalized and relevant recommendation experience. Previous methods have used fixed weights [25, 26, 27, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 41, 42, 43, 44, 45, 46, 47, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63], which lack this adaptability.

• Effective Exploration: The entropy regularization in the SAC algorithm encourages exploration of the action space, which is crucial for discovering effective recommendation policies, especially in complex multi-objective scenarios. "Never give up" exploration strategies are relevant here [3].

• Sample Efficiency: SAC is known for its relatively high sample efficiency, which is important for real-world recommender systems where collecting large amounts of user interaction data can be costly.

However, several aspects warrant further investigation:

- Offline vs. Online Learning: This paper focuses on offline training. Exploring online learning strategies, where the model continuously learns from user interactions, could further improve its performance and adaptability.

- Long-Term User Satisfaction: The current reward function primarily focuses on short-term user feedback. Incorporating long-term user satisfaction metrics would be valuable for building more sustainable and user-centric recommender systems.

- Explainability: Developing techniques to explain the multi-objective trade-offs and the reasons behind the recommendations would enhance user trust and transparency [4, 41].

- Scalability: Addressing the scalability of DMOR-DSAC to handle very large item catalogs and user bases is an important area for future research.

CONCLUSION

This paper presented a novel approach, Dynamic Multi-Objective Recommendation via Discrete Soft Actor-Critic (DMOR-DSAC), for addressing the challenges of multi-objective recommendation. By adapting the Soft Actor-Critic algorithm to discrete action spaces and incorporating dynamically weighted rewards, DMOR-DSAC effectively learns policies that balance multiple recommendation objectives. Experimental results demonstrate the superiority of DMOR-DSAC compared to existing methods. This work contributes to the advancement of multi-objective recommender systems and offers a promising direction for future research in this area.

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