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Optimization Strategies in Consumer Choice Behavior for Personalized Recommendation Systems Based on Deep Reinforcement Learning

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ABSTRACT

In domains such as e-commerce and media recommendations, personalized recommendation systems effectively alleviate the issue of information overload. However, existing systems still face challenges in multimodal data processing, data sparsity, and dynamic changes in user preferences. This paper proposes a Hierarchical Generative Reinforcement Learning Recommendation Optimization framework (HG-RLRO) that addresses these issues by integrating multimodal data, Generative Adversarial Networks (GAN), Inverse Reinforcement Learning (IRL), and Hierarchical Temporal Difference Learning (HTD). HG-RLRO employs a multi-agent architecture to handle textual and image data and utilizes GAN to generate simulated user behavior data to mitigate data sparsity. IRL dynamically infers user preferences across multiple time scales.

KEYWORDS

Personalized Recommendation Systems, Multimodal Data Fusion, Generative Adversarial Networks (GAN), Inverse Reinforcement Learning (IRL), Dynamic User Preference Modeling

INTRODUCTION

Personalized recommendation systems are widely applied in domains such as e-commerce, media recommendations, and online advertising (Ko et al., 2022), effectively alleviating information overload and helping users quickly find content that matches their interests. However, current recommendation systems still face significant challenges in handling multimodal data, data sparsity, and the dynamic nature of user preferences (Wang et al., 2020). Existing research mainly focuses on employing deep learning, reinforcement learning, and graph neural networks (Khilji et al., 2023). However, these approaches tend to focus on single-modal data or consider only short-term user preferences (Deldjoo et al., 2024), which limits their ability to integrate multimodal data and balance long- and short-term preferences effectively (Liu et al., 2023).

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Multimodal data integration has emerged as a crucial focus in modern recommendation systems, as it enables a richer representation of user interests by combining diverse data sources such as text, images, and audio (Mu & Wu, 2023). However, the inherent heterogeneity of multimodal data poses significant challenges (Rahate et al., 2022). For instance, textual data emphasize semantic relationships, whereas visual data capture spatial patterns, leading to disparities in feature representation and fusion (Zou et al., 2025). Existing methods often rely on static fusion techniques, such as weighted averaging, which inadequately capture the complementary nature of different modalities (Jeong et al., 2024). Furthermore, the high computational cost of processing multimodal features can limit scalability, especially when handling complex interactions between data types (Yan et al., 2022).

Data sparsity remains a fundamental issue, particularly in cold-start scenarios involving new users or items with limited interaction histories (Kumar et al., 2023). While some approaches employ generative models such as variational autoencoders or generative adversarial networks (GANs) to synthesize user behavior data (Chen et al., 2022), these methods often fail to fully leverage the potential of multimodal features, and the generated data may lack diversity or authenticity. Moreover, most existing systems inadequately address the dynamic nature of user preferences, which evolve over time due to changes in user needs, external influences, or contextual factors. Current solutions tend to either emphasize short-term preferences at the expense of long-term trends or struggle to balance these two aspects effectively (Ramisa et al., 2024).

To address these limitations, this paper proposes hierarchical generative reinforcement learning recommendation optimization (HG-RLRO). The framework integrates multimodal data processing, GANs, inverse reinforcement learning (IRL), and hierarchical temporal difference (HTD) learning to offer a comprehensive solution. The primary contributions of this study include:

1. **A novel approach to multimodal data fusion and dynamic preference modeling:** The HG-RLRO framework utilizes a multi-agent system to independently process textual and visual data, enabling the effective integration of complementary features. This approach significantly enhances recommendation accuracy and diversity compared to traditional fusion methods.
2. **An innovative solution to address data sparsity:** By incorporating GAN, HG-RLRO generates high-quality synthetic user behavior data, enriching training datasets and improving system robustness in sparse data environments. This contribution is particularly impactful in addressing cold-start challenges for new users or items.
3. **Dynamic adaptation to evolving user preferences:** Using IRL, the framework dynamically infers latent user preferences from behavior data and adapts recommendation strategies across multiple time scales. Combined with HTD, HG-RLRO effectively balances long-term and short-term preferences, ensuring stability and responsiveness in dynamic environments.
4. **Comprehensive experimental validation:** The proposed framework is thoroughly evaluated using multimodal datasets, demonstrating superior performance in precision, recall, diversity, and novelty compared to state-of-the-art models.

This study introduces significant advancements in recommendation systems by addressing critical challenges in multimodal data integration, data sparsity, and dynamic preference modeling. By combining these innovations, HG-RLRO demonstrates superior performance in providing personalized, diverse, and adaptive recommendations, with potential applications across a wide range of domains.

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