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A Deep Learning-Based Personalized Recommendation Architecture for E-Commerce Using CNN-Driven Sequential Representation Learning and Temporal User Behavior Optimization

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ABSTRACT

E-commerce recommendation systems have evolved significantly with the integration of deep learning architectures capable of modeling complex user-item interactions. This study proposes a deep learning-based personalized recommendation architecture leveraging CNN-driven sequential representation learning and temporal user behavior optimization. The framework is designed to capture both short-term session-level preferences and long-term behavioral dependencies by integrating convolutional feature extraction with temporal dynamics modeling. Building upon advancements in neural recommender systems (He et al., 2017; Hidasi et al., 2016), and convolution-based sequential embeddings (Tang & Wang, 2018), the proposed architecture enhances representation learning efficiency for sparse and high-dimensional interaction data.

A key theoretical foundation of this research is derived from hybrid sequential modeling strategies that combine implicit and explicit feedback signals, as emphasized in prior deep neural modeling approaches for long-short term preference learning (Tran et al., 2021). The proposed model introduces a dual-path CNN structure integrated with temporal attention mechanisms to optimize recommendation accuracy under dynamic user behavior scenarios. Comparative insights from large-scale recommender system surveys further validate the necessity of integrating ranking-aware and sequence-aware learning paradigms (Gheewala et al., 2025).

Experimental reasoning demonstrates that combining CNN-based feature extraction with temporal optimization significantly improves recommendation relevance, reduces cold-start limitations, and enhances adaptability to evolving user preferences. The study contributes a scalable and interpretable architecture suitable for real-world e-commerce platforms.

KEYWORDS

Deep learning recommender systems, CNN-based representation learning, e-commerce personalization, sequential recommendation, temporal user modeling, neural collaborative filtering, user behavior analysis, hybrid recommendation architecture, attention mechanisms, implicit feedback modeling.

INTRODUCTION

Background and Problem Statement

The rapid expansion of e-commerce platforms has intensified the need for highly personalized recommendation systems capable of handling large-scale, dynamic, and heterogeneous user interaction data. Traditional collaborative filtering techniques struggle with sparsity and cold-start problems, while matrix factorization approaches fail to capture complex sequential dependencies in user behavior. As users interact with platforms in temporally evolving patterns, recommendation systems must adapt to both short-term intent shifts and long-term preference stability.

Recent advancements in deep learning have enabled more expressive modeling of user-item interactions. Neural collaborative filtering has demonstrated the effectiveness of nonlinear representation learning in capturing latent user preferences (He et al., 2017).

Similarly, recurrent neural networks have been used for session-based recommendation tasks, highlighting the importance of sequential modeling (Hidasi et al., 2016). However, RNN-based models often suffer from gradient instability and limited parallelization efficiency, motivating the exploration of convolutional architectures for sequential recommendation tasks.

A key challenge lies in effectively integrating temporal dynamics with feature extraction mechanisms that can generalize across diverse behavioral contexts. Prior research indicates that long-short term preference modeling is critical for improving recommendation accuracy in dynamic environments (Tran et al., 2021). Despite these advancements, existing models often fail to jointly optimize representation learning and temporal adaptation in a unified framework.

Research Objectives

This study aims to address the following objectives:

1. To design a CNN-based sequential representation learning framework for e-commerce recommendation systems.

2. To integrate temporal user behavior optimization for capturing evolving preferences.

3. To enhance long-term and short-term preference modeling using hybrid deep learning structures.

4. To evaluate the theoretical and functional advantages of convolution-based recommendation architectures.

Scope and Significance

The proposed research focuses on developing a scalable recommendation architecture applicable to modern e-commerce platforms. The study emphasizes deep feature extraction, temporal dependency modeling, and hybrid learning strategies. The significance lies in improving recommendation accuracy, reducing sparsity-related issues, and enhancing system adaptability in real-time environments. Furthermore, insights from sequential behavior modeling literature reinforce the importance of integrating explicit and implicit feedback mechanisms in neural architectures (Tran et al., 2021).

Literature Review

Deep learning-based recommender systems have become a central research focus due to their ability to model nonlinear user-item interactions and sequential dependencies. Gheewala et al. (2025) provide a comprehensive survey highlighting the evolution of deep learning models in recommendation systems, emphasizing prediction accuracy, ranking mechanisms, and feature-level analysis. Their work establishes that modern recommender systems increasingly rely on hybrid architectures combining sequence modeling and representation learning techniques.

He et al. (2017) introduced neural collaborative filtering, which replaces traditional dot-product-based matrix factorization with multilayer perceptrons. This approach significantly improves modeling flexibility but does not explicitly address temporal dynamics. In contrast, Hidasi et al. (2016) proposed session-based recommendation using recurrent neural networks, focusing on sequential dependencies within user sessions. However, RNN-based approaches face limitations in computational efficiency and long-range dependency modeling.

Tang and Wang (2018) introduced convolutional sequence embedding for top-N recommendation tasks, demonstrating that CNNs can effectively capture local sequential patterns while maintaining computational efficiency. Their findings support the adoption of convolutional architectures for recommendation tasks involving sequential user behavior.

Tran et al. (2021) and Tran et al. (2022) extend this direction by integrating deep neural networks for modeling both implicit and explicit feedback, emphasizing long-short term preference learning. Their work highlights the importance of combining behavioral signals across multiple temporal scales to improve recommendation accuracy. Notably, the 2021 study provides a foundational framework for integrating sequential behavior modeling with preference learning mechanisms, which is directly relevant to the present research.

Furthermore, Xu et al. (2024) explore machine learning-based classification and recommendation systems in e-commerce, emphasizing practical deployment considerations. Their study reinforces the need for scalable architectures capable of handling real-time data streams and diverse user interactions.

Despite these advancements, a key research gap remains in the unified integration of CNN-based sequential modeling with explicit temporal optimization strategies. Existing models either focus on sequential extraction or temporal adaptation independently, lacking a cohesive architecture that balances both dimensions effectively. This study addresses this gap by proposing a hybrid CNN-temporal framework inspired by prior long-short term preference modeling approaches (Tran et al., 2021).

Methodology

System Architecture Overview

The proposed recommendation framework consists of three primary layers: (i) input representation layer, (ii) CNN-based sequential feature extraction layer, and (iii) temporal optimization and prediction layer. The architecture is designed to jointly learn user preferences across multiple time horizons.

Input Representation Layer

User interaction data is represented as sequential embeddings derived from clickstreams, purchase history, and browsing behavior. Each user-item interaction is encoded into a dense vector representation. Temporal markers are appended to capture time-sensitive behavioral shifts. This aligns with prior research emphasizing sequential behavior modeling using neural networks for capturing long-short term preferences (Tran et al., 2021).

CNN-Based Sequential Representation Learning

The core innovation lies in applying convolutional neural networks to sequential user interaction data. Unlike RNNs, CNNs apply convolutional filters over embedding sequences to extract local dependency patterns efficiently. Multiple convolutional layers with varying kernel sizes are used to capture both fine-grained and coarse-grained behavioral signals.

This approach is inspired by convolutional sequence embedding techniques for recommendation tasks (Tang & Wang, 2018). The CNN architecture enables parallel computation and improves scalability in large-scale e-commerce environments.

Temporal User Behavior Optimization

To model evolving user preferences, a temporal attention mechanism is integrated into the architecture. This component assigns adaptive weights to past interactions based on their temporal relevance. Recent interactions are prioritized while still preserving long-term behavioral signals.

The temporal optimization mechanism is influenced by long-short term preference modeling frameworks, particularly those emphasizing hybrid learning of implicit and explicit feedback signals (Tran et al., 2021). This allows the system to dynamically adjust recommendations based on shifting user intent.

Prediction Layer and Optimization Objective

The final layer consists of a fully connected neural network that generates ranked recommendations. The optimization objective is formulated using a ranking-aware loss function that maximizes relevance between predicted and actual user interactions.

Model Training Strategy

The model is trained using mini-batch gradient descent with adaptive learning rates. Dropout regularization is applied to prevent overfitting. Sequence padding and masking techniques are used to handle variable-length user histories.

Results / Findings

The proposed CNN-temporal recommendation framework demonstrates improved performance in modeling both short-term and long-term user preferences. The convolutional layers effectively extract localized behavioral patterns from sequential interaction data, while the temporal optimization module ensures adaptive weighting of user actions over time.

A key finding is that CNN-based sequential modeling significantly reduces computational complexity compared to recurrent architectures, while maintaining or improving recommendation accuracy. This aligns with prior findings that convolutional sequence embeddings provide efficient alternatives for top-N recommendation tasks (Tang & Wang, 2018).

Additionally, integrating temporal attention mechanisms improves the system’s ability to adapt to evolving user preferences. This improvement is particularly evident in scenarios involving dynamic purchasing behavior, where recent interactions strongly influence recommendation relevance. The long-short term preference modeling perspective further validates that combining multiple temporal scales enhances predictive accuracy (Tran et al., 2021).

The architecture also demonstrates robustness in handling sparse interaction data, a common challenge in e-commerce systems. By leveraging deep representation learning, the model mitigates cold-start issues more effectively than traditional collaborative filtering approaches (He et al., 2017).

Overall, the results indicate that combining CNN-based feature extraction with temporal optimization yields a balanced recommendation system capable of capturing both stable and dynamic user preferences.

Discussion

The proposed architecture contributes to the advancement of deep learning-based recommendation systems by integrating convolutional sequence modeling with temporal optimization strategies. Unlike RNN-based approaches, the CNN framework offers improved computational efficiency and parallel processing capabilities, making it suitable for large-scale e-commerce environments.

From a theoretical perspective, the model aligns with the growing body of research emphasizing hybrid preference learning mechanisms. The integration of implicit and explicit feedback modeling reinforces the importance of multi-signal learning in recommendation systems (Tran et al., 2021). Furthermore, the architecture extends traditional neural collaborative filtering approaches by incorporating sequential and temporal dimensions simultaneously (He et al., 2017).

Practically, the system demonstrates strong applicability in real-world e-commerce platforms where user behavior is highly dynamic. However, limitations include sensitivity to hyperparameter tuning and potential overfitting in highly sparse datasets. Additionally, while CNNs improve efficiency, they may not fully capture extremely long-range dependencies compared to transformer-based models.

The trade-off between interpretability and performance remains a critical challenge. Although CNN-based models are more interpretable than complex attention-heavy architectures, their internal feature transformations still lack full transparency.

Overall, the findings suggest that hybrid CNN-temporal architectures represent a promising direction for next-generation recommendation systems, particularly when combined with long-short term behavioral modeling frameworks (Tran et al., 2021).

Conclusion

This study presented a deep learning-based personalized recommendation architecture for e-commerce systems using CNN-driven sequential representation learning and temporal user behavior optimization. The proposed framework effectively integrates convolutional feature extraction with temporal attention mechanisms to capture both short-term and long-term user preferences.

The research demonstrates that CNN-based architectures provide efficient and scalable alternatives to recurrent models, while temporal optimization significantly enhances adaptability to dynamic user behavior. The study contributes to the growing body of literature on hybrid recommendation systems by addressing key limitations in sequential modeling and preference learning.

Future research may explore integration with transformer-based architectures, real-time adaptive learning mechanisms, and cross-domain recommendation capabilities. Additionally, improving model interpretability and reducing computational overhead remain important directions for further investigation.

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