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Temporal-Aware Neural Networks for Balancing Dynamic Preferences and Long-Term Interests in Recommendation Systems

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Recommendation systems face the challenge of balancing dynamic short-term preferences with stable long-term interests to deliver personalized and timely recommendations. Traditional methods often treat these aspects separately, leading to suboptimal integration and limited adaptability to evolving user behavior. This paper introduces Temporal-Aware Neural Networks (TANR), a novel framework that leverages a time-aware Transformer architecture to dynamically balance short-term and long-term user preferences. The proposed model incorporates a time decay mechanism within the attention layer to adjust the influence of recent and historical interactions, ensuring a balanced representation of user behavior. Additionally, TANR employs a hybrid training framework combining offline pre-training with online incremental updates, enabling real-time adaptation to user behavior shifts. Extensive experiments on the MovieLens-1M and MIND datasets demonstrate that TANR outperforms state-of-the-art models in both short-term engagement metrics (*e.g.*, Hit Rate, NDCG) and long-term user retention. The results highlight the effectiveness of TANR in capturing temporal dynamics and improving recommendation accuracy, offering a robust solution for modern recommendation systems.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning approaches → Neural networks

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Keywords: temporal-aware recommendation, dynamic preferences, long-term interests, transformer, online learning

1. Introduction

In recent years, recommendation systems have evolved significantly with the advancement of deep learning techniques [1–3]. Traditional methods, such as collaborative filtering and matrix factorization, have been increasingly replaced by neural network-based approaches, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and more recently, Transformer architectures. These methods have demonstrated remarkable success in capturing complex user-item interactions and improving recommendation accuracy [4–5]. However, as user behavior becomes more dynamic and diverse, the need for models that can adapt to both short-term preferences and long-term interests has become increasingly critical.

One of the most pressing challenges in modern recommendation systems is the ability to balance short-term dynamic preferences with long-term stable interests. Short-term preferences, such as recent clicks or searches, often reflect immediate user needs but can be highly volatile and sparse. On the other hand, long-term interests, such as consistent preferences for specific genres or categories, provide a stable signal but may fail to capture sudden shifts in user behavior. Striking a balance between these two aspects is essential for delivering personalized and timely recommendations while maintaining user satisfaction over time.

Several approaches have been proposed to address the challenge of balancing short-term and long-term preferences [5–7]. For instance, hybrid models like Wide & Deep networks combine immediate user actions with historical behavior patterns. Sequential models leverage user interaction sequences to capture temporal dynamics. Additionally, reinforcement learning-based methods have been explored to dynamically adjust recommendation strategies based on real-time feedback. While these methods have shown promise, they often struggle to effectively integrate the temporal nature of user behavior into a unified framework.

In recent years, temporal-aware recommendation systems have garnered significant attention in the field of personalized recommendations. With the increasing volume of user behavior data, effectively modeling temporal information to enhance recommendation quality has become a key research focus. Graph Neural Networks (GNNs) have demonstrated outstanding performance in user behavior modeling. Peng *et al.* (2025) proposed the TagRec method, which utilizes temporal-aware graph contrastive learning to improve the accuracy of sequential recommendations [8]. Tang *et al.* (2025) further introduced a temporal collaboration-aware mechanism to optimize the graph co-evolution learning framework, making it more suitable for dynamic recommendation scenarios [9]. Additionally, Chen *et al.* (2024) integrated temporal information and session data to enhance recommendation performance using GNNs [10], while Shen *et al.* (2023) proposed a multi-interest graph neural network approach to more accurately capture users' dynamic interests [11]. Contrastive learning, which has gained popularity in recent years, has also been applied in temporal-aware recommendations. For instance, Chen *et al.* (2024) introduced a multi-behavior collaborative contrastive learning method to improve the robustness of sequential recommendations [12]. Meanwhile, Xuan and Li (2023) investigated a temporal-aware multi-behavior contrastive learning recommendation model, further enhancing recommendation accuracy [13]. Gao *et al.* (2024) proposed a temporal privacy-preserving model that ensures the security of social recommendations while maintaining high recommendation quality [14]. In terms of traditional approaches, Ying *et al.* (2017) developed a temporal-aware POI recommendation system based on context-aware tensor decomposition and weighted HITS algorithms [15], while Chen and Zhang (2023) optimized personalized POI recommendations using grey relational analysis [16]. Deep learning has also played a significant role in temporal-aware recommendation applications. For example, Wang *et al.* (2022) leveraged the self-attention mechanism of Transformers to enhance music recommendation quality [17], while Chu *et al.* (2024) explored methods to improve the temporal awareness of large language models (LLMs) to support cross-domain recommendation tasks [18]. Despite the progress made in this field in recent years, challenges remain, such as data sparsity, multi-level temporal modeling, privacy protection, and cross-domain recommendation. Future research can further explore ways to enhance recommendation quality while simultaneously addressing privacy and fairness concerns, promoting the continued development of temporal-aware recommendation systems.

Recent research in personalized recommendation systems has focused on modeling dynamic user preferences, which evolve over time due to various factors. Approaches like dynamic graph neural networks (DGNNs), time-aware neural networks, and attention mechanisms have been proposed to better capture these changes. DGNNs, such as dynamic graph convolutional networks and heterogeneous graph networks, improve recommendation accuracy by modeling dynamic interactions between users and content [19–21]. Time-aware models like LSTMs and attention mechanisms capture long-term and short-term preferences, while dynamic memory networks enhance historical behavior modeling [20, 23, 24]. Attention-based methods, including deep collaborative filtering and hypergraph attention networks, improve personalized recommendations and information diffusion prediction [26, 27]. Additionally, federated learning and reinforcement learning have been applied to efficiently model dynamic preferences while preserving privacy and optimizing content selection [25, 28]. Despite progress, challenges remain, such as balancing long-term and short-term preferences and improving model scalability, with future research focusing on self-supervised learning and federated learning to enhance performance [30].

Despite their advancements, existing methods face several limitations. First, many models treat short-term and long-term preferences as separate components, leading to suboptimal integration and potential conflicts. Second, the temporal dynamics of user behavior are often oversimplified, with limited consideration of time decay effects or the evolving nature of interests. Third, the scalability and efficiency of these models in real-world applications, particularly in online learning scenarios, remain a significant challenge. These limitations highlight the need for a more sophisticated and unified approach to balancing dynamic preferences and long-term interests.

In this paper, we propose a novel framework, Temporal-Aware Neural Networks (TANN) for Balancing Dynamic Preferences and Long-Term Interests in Recommendation Systems. Our approach leverages a time-aware Transformer architecture to seamlessly integrate short-term and long-term user behavior signals. By incorporating a time decay mechanism into the attention mechanism, the model dynamically adjusts the influence of historical and recent interactions, ensuring a balanced representation of user preferences. Furthermore, we introduce an online learning framework with incremental updates to enable real-time adaptation to evolving user behavior.

The TANR framework introduces three key innovations to address the challenge of balancing dynamic short-term preferences and stable long-term interests in recommendation systems. First, TANR leverages a time-aware Transformer architecture that incorporates a time decay mechanism within the attention layer, dynamically adjusting the influence of historical and recent user interactions based on temporal intervals. This allows the model to better capture the evolving nature of user behavior, ensuring a balanced representation of both short-term and long-term preferences. Second, TANR employs a hybrid training framework that combines offline pre-training with online incremental updates. The offline phase captures long-term interest patterns from historical data, while the online phase uses a sliding window strategy to fine-tune the model in real-time, enabling rapid adaptation to shifting user behaviors. Additionally, Elastic Weight Consolidation (EWC) is integrated to prevent catastrophic forgetting during online updates. Third, TANR enhances the multi-head attention mechanism with a logarithmic time decay function, which outperforms linear and exponential decay in modeling the impact of time intervals on user behavior. This combination allows the model to simultaneously capture global and local dependencies in user interaction sequences, improving both recommendation accuracy and diversity. Experimental results on the MovieLens-1M and MIND datasets demonstrate that TANR significantly outperforms state-of-the-art baselines in metrics such as Hit Rate, NDCG, and MRR, particularly excelling in capturing short-term user interests and ensuring timely recommendations.

The paper is structured as follows: Section 1 outlines the challenges of balancing short-term preferences and long-term interests in recommendation systems, emphasizing the limitations of existing methods and the need for temporal-aware solutions. Section 2 details the proposed TANR framework, including the time-aware Transformer architecture, the time decay mechanism integrated into the attention layer, and the hybrid training framework that combines offline pre-training with online incremental updates. Section 3 presents experimental evaluations on the MovieLens-1M and MIND datasets, demonstrating TANR's superior performance over state-of-the-art models in metrics such as Hit Rate, NDCG, and MRR. This section also includes ablation studies to validate the contributions of key components like the time decay factor and logarithmic decay function. Section 4 analyzes the advantages of TANR in capturing temporal dynamics and improving recommendation accuracy, while also addressing its limitations and potential areas for improvement. Finally, Section 5 summarizes the key contributions of TANR, highlights its effectiveness in balancing short-term and long-term user interests, and suggests future research directions, such as adaptive decay functions and computational efficiency optimizations.

2. Methodology

2.1. Overall Framework

This paper proposes a recommendation system framework that dynamically balances real-time user needs and historical preferences, aiming to achieve precise and adaptive personalized recommendations through an end-to-end learning mechanism. The framework takes user behavior sequences as input, which include user-content interaction identifiers, timestamps, and contextual features (such as interaction types and device information). The input data is first transformed into implicit representations that the model can process through embedding and encoding layers. The content embedding module maps discrete interaction identifiers into dense vectors, capturing the semantic information of the content. The temporal encoding module generates time-aware vectors by combining periodic patterns and temporal decay trends. Contextual features are mapped into low-dimensional vectors through fully connected layers and added to content embeddings and temporal encodings to form comprehensive behavior representations.

In the time-aware attention layer, the model dynamically adjusts the importance weights of behaviors at different timestamps based on a multi-head self-attention mechanism. By introducing a learnable time decay factor, this layer adaptively assigns higher weights to recent behaviors while suppressing the influence of historical behaviors. The corrected attention scores are normalized using the Softmax function, generating time-sensitive aggregated behavior representations that provide high-quality sequence encodings for downstream recommendation tasks.

To achieve stable modeling of long-term interests and dynamic adaptation to short-term preferences, the framework adopts a hybrid training strategy. In the offline training phase, the model parameters are optimized using the full historical data, learning long-term interest patterns through cross-entropy loss and regularization constraints. Elastic weight consolidation techniques are employed to prevent catastrophic forgetting during subsequent online learning. In the online learning phase, real-time data is processed using a sliding window strategy, and a subset of parameters is incrementally updated to ensure the model can quickly adapt to the latest user behaviors. The loss function additionally incorporates temporal consistency constraints to ensure smooth transitions in behavior representations and avoid abrupt changes caused by short-term noise.

2.2. User-Content Interaction Data Processing

The model receives preprocessed user behavior sequences as input, structured as $\mathcal{S}_u = \{(i_1, t_1, \mathbf{c}_1), (i_2, t_2, \mathbf{c}_2), ..., (i_n, t_n, \mathbf{c}_n)\}$, where i_k represents the interaction identifier (*e.g.*, product ID or video ID) between the user and the k-th content, t_k is the normalized timestamp (expressed as the number of days relative to the current time), and $\mathbf{c}_k$ is a vector containing contextual features such as interaction type and device information. Through embedding layers, temporal encoding, and contextual feature fusion, the model transforms the raw input into a time-aware sequence representation.

First, the content embedding layer maps discrete content IDs into dense vectors $\mathbf{e}_k \in \mathbb{R}^d$, wher the content embedding matrix $\mathbf{E}_{\text{item}} \in \mathbb{R}^{N\times d}$ contains semantic representations of all content items. The temporal encoding module combines an improved sinusoidal positional encoding w_i a linear projection layer to generate time-aware vectors $\mathbf{t}_k$. The sinusoidal encoding captures periodic patterns (*e.g.*, daily active hours of users) using sin and cos functions, while the linear projection layer models temporal decay trends (*e.g.*, the importance of recent behaviors decreases as days pass). Contextual features $\mathbf{c}_k$ are mapped into low-dimensional vectors $\mathbf{c}'_k$ through a fully connected layer and added to the content embeddings and temporal encoding to obtain the comprehensive representation of each behavior: $\mathbf{h}_k = \mathbf{e}_k + \mathbf{t}_k + c'_k$.

To further enhance sequence modeling capabilities, the model introduces relative positional encoding and interaction type gating mechanisms. Relative positional encoding calculates the time interval Δt_{ij} between behaviors to generate positional bias vectors $\mathbf{p}_{ij}$, which are used to adjust interaction weights in the attention mechanism. Interaction type gating, based on the interaction type (*e.g.*, click, purchase) in the contextual features, generates gating weights g_k through a Sigmoid function, dynamically adjusting the contribution of different interaction behaviors (*e.g.*, purchase behaviors may have a more long-term impact than click behaviors).

For handling variable-length sequences, the model adopts dynamic padding and hierarchical aggregation strategies. For sequences shorter than the maximum length $L_{\max}$, zero vectors are used for padding, and binary masks are generated to identify valid positions. For excessively long sequences, they are segmented by time windows, with each segment processed independently and aggregated at the segment level. The final outputs are the behavior-level representation matrix $\mathbf{H}' \in \mathbb{R}^{L_{\max}\times d}$ and the relative positional encoding matrix $\mathbf{P} \in \mathbb{R}^{L_{\max}\times L_{\max}\times d}$, which serve as inputs to the time-aware attention module.

2.3. Time-Aware Attention Mechanism

The time-aware attention mechanism dynamically adjusts the importance weights of behaviors at different timestamps in user interaction sequences through a time decay factor, balancing short-term dynamic preferences and long-term stable interests. Given the implicit representation matrix of the behavior sequence $\mathbf{H} \in \mathbb{R}^{n\times d}$, where n is the sequence length and d is the embedding dimension, the query (Q), key (K), and value (V) matrices are generated via linear transformations:

$$\mathbf{Q} = \mathbf{HW}^{\mathrm{Q}},\ \mathbf{K} = \mathbf{HW}^{\mathrm{K}},\ \mathbf{V} = \mathbf{HW}^{\mathrm{V}}, \qquad (1)$$

where $\mathbf{W}^{\mathrm{Q}}, \mathbf{W}^{\mathrm{K}}, \mathbf{W}^{\mathrm{V}} \in \mathbb{R}^{d\times d}$ are learnable parameters. The attention score matrix $\mathbf{A} \in \mathbb{R}^{n\times n}$ is computed using the scaled dot-product:

$$\mathbf{A} = \frac{\mathbf{QK}^T}{\sqrt{d}}. \qquad (2)$$

To incorporate temporal decay, a time decay factor is introduced. For any two behaviors i and j, the time interval $\Delta t_{ij} = |t_i - t_j|$ is weighted by a learnable decay coefficient γ, generating a correction term:

$$\text{Time-Decay}_{ij} = -\gamma \cdot \log(1 + \Delta t_{ij}), \qquad (3)$$

where $\gamma > 0$ controls the decay intensity, and $\log(1 + \Delta t_{ij})$ smooths the impact of time intervals. The corrected attention score is defined as:

$$\mathbf{A}_{ij} = \frac{\mathbf{Q}_i\mathbf{K}_j^T}{\sqrt{d}} + \text{Time-Decay}_{ij}. \qquad (4)$$

The negative sign ensures that larger time intervals reduce attention weights. To maintain numerical stability, the Softmax function is applied after subtracting the maximum value of each row:

$$\mathbf{A}' = \text{Softmax}(\mathbf{A} - \max(\mathbf{A})). \qquad (5)$$

The final output is computed as:

$$\mathbf{Z} = \mathbf{A}'\mathbf{V}. \qquad (6)$$

The mechanism is extended to a multi-head form to enhance model expressiveness. The Q, K, and V matrices are split into h heads along the embedding dimension. Each head independently computes time-aware attention:

$$\text{head}_k = \text{Softmax}\left(\frac{Q_k\mathbf{K}_k^T}{\sqrt{d/h}} + \text{Time-Decay}^{(k)}\right)\mathbf{V}_k, \qquad (7)$$

where $\mathbf{Q}_k, \mathbf{K}_k, \mathbf{V}_k \in \mathbb{R}^{n\times(d/h)}$ correspond to the k-th head. The outputs of all heads are concatenated and linearly projected:

$$\mathbf{Z} = \text{Concat}(\text{head}_1, ..., \text{head}_h)\, \mathbf{W}^O, \qquad (8)$$

with $\mathbf{W}^O \in \mathbb{R}^{d\times d}$ as the output projection matrix.

The revised mechanism ensures that recent behaviors (small Δt_{ij}) receive higher weights due to smaller negative corrections, while historical behaviors (large Δt_{ij}) are assigned lower weights. The learnable parameter γ is constrained to be non-negative through initialization or activation functions (*e.g.*, Softplus) to prevent reverse decay effects.

2.4. Offline Training and Online Learning

To achieve stability in modeling long-term user interests and dynamic adaptation to short-term preferences, we propose a hybrid training framework combining offline pre-training and online incremental learning. The offline phase leverages historical behavioral data to capture long-term interest patterns, while the online phase fine-tunes the model with real-time data to adapt to short-term preference shifts. The detailed design is as follows:

Offline Training: Using the full historical dataset $\mathcal{D}_{\text{offline}} = \{\mathcal{S}_u, y_u\}$ (where y_u denotes the user's true interaction labels), the model is pre-trained by minimizing the cross-entropy loss:

$$L_{\text{offline}} = \frac{1}{|D_{\text{offline}}|} \sum_{u,t} \text{BCE}\left(y_{u,t}, \hat{y}_{u,t}\right) + \lambda_{\text{reg}} \|\theta\|_2^2 . \quad (9)$$

Where BCE is the cross-entropy loss, $\hat{y}_{u,t}$ is the model's predicted probability for user u at timestep t_r and λ_{reg} controls the strength of $L2$ regularization. To prevent catastrophic forgetting during subsequent online learning, Elastic Weight Consolidation (EWC) constraints are applied to critical parameters θ_{key} (*e.g.*, time decay coefficient γ and attention projection matrices) after offline training:

$$L_{\text{EWC}} = \sum_i \frac{\alpha}{2} F_i \left(\theta_i - \theta_{\text{offline},i}\right)^2, \quad (10)$$

where F_i represents the diagonal elements of the Fisher information matrix, quantifying the importance of parameter θ_i, and α is a trade-off coefficient.

Online Learning: When new user behavior data $\mathcal{D}_{\text{online}} = \{\mathcal{S}_u^{\text{new}}\}$ arrives, the model is incrementally updated using a sliding window strategy (window size T_{window}). The online loss function is defined as:

$$L_{\text{online}} = \mathcal{L}_{\text{ce}} + \mathcal{L}_{\text{EWC}} + \beta \mathcal{L}_{\text{temporal}}, \quad (11)$$

where $\mathcal{L}_{\text{ce}}$ is the online cross-entropy loss, and $\mathcal{L}_{\text{temporal}}$ enforces temporal consistency to ensure smoothness in behavior representations across adjacent time windows:

$$L_{\text{temporal}} = \frac{1}{T_{\text{window}}} \sum_{t=1}^{T_{\text{window}}} \left\|H_t - H_{t-1}\right\|_2^2 . \quad (12)$$

During online updates, only a subset of parameters (*e.g.*, attention heads and time decay coefficients) are fine-tuned, while others remain frozen to improve efficiency. The update rule is:

$$\theta_{\text{online}} \leftarrow \theta_{\text{offline}} - \eta \nabla_\theta \mathcal{L}_{\text{online}}, \quad (13)$$

where η is the online learning rate, typically much smaller than the offline rate.

Hybrid Inference: During online serving, the model combines offline pre-trained weights and online fine-tuned parameters to generate recommendations. For cold-start users (with behavior count $n_u < N_{\min}$), the system defaults to the offline model to ensure stability. For active users, long-term and short-term signals are dynamically fused:

$$\hat{y}_u = \left(1 - w_u\right) \cdot \hat{y}_{\text{offline},u} + w_u \cdot \hat{y}_{\text{online},u}, \quad (14)$$

where $w_u \in [0, 1]$ is a user activity weight dynamically computed based on behavior frequency and recency.

3. Results

3.1. Dataset and Experimental Implementation

To validate the effectiveness of the proposed framework, we conducted experiments on two widely used content recommendation datasets: MovieLens-1M and MIND. The MovieLens-1M dataset contains 1 million movie ratings from 6,000 users on 4,000 movies, along with rich metadata such as movie genres, release years, and user-provided tags. The MIND (Microsoft News Recommendation) dataset is a large-scale news recommendation dataset that includes user click behaviors, news articles with rich textual content, and temporal information. MIND provides diverse user interaction behaviors and temporal dynamics, making it suitable for modeling temporal patterns and user preference evolution in content recommendation tasks. Both datasets include timestamps for each interaction, facilitating the modeling of temporal patterns and user preference evolution.

In the experimental implementation, we preprocess the datasets by filtering out users and items with fewer than 10 interactions to ensure data quality. The interaction sequences are split into training, validation, and test sets based on timestamps, ensuring that the training data precedes the validation and test data. This temporal splitting simulates real-world scenarios where the model is trained on historical data and evaluated on future interactions.

We implemented the proposed framework using PyTorch and optimized it with the Adam optimizer. The model was trained on a single NVIDIA RTX2080 with a batch size of 64 and an initial learning rate of 0.001. Early stopping was applied based on validation performance to prevent overfitting. For online learning, we simulated real-time data streams by sequentially feeding new interaction data and incrementally updating parameters.

To comprehensively evaluate the model's performance, the following metrics were adopted:

1. Hit Rate (HR@K): Measures the proportion of test cases where the ground-truth item appears in the top-K recommendations;
2. Normalized Discounted Cumulative Gain (NDCG@K): Evaluates the ranking quality of the top-K recommendations, assigning higher weights to items ranked closer to the top;
3. Mean Reciprocal Rank (MRR): Computes the average reciprocal rank of the ground-truth item across all test cases.

3.2. Experimental Results

This paper comprehensively evaluates the proposed framework, Time-Aware Neural Recommender (TANR), on two widely used datasets, MovieLens-1M and MIND, and compares its performance against several state-of-the-art baseline models. The baseline models include Long Short-Term Memory (LSTM), Gated Recurrent Unit for Recommendation (GRU4Rec), Self-Attentive Sequential Recommendation (SASRec), Time Interval-Aware Self-Attention Sequential Recommendation (TiSASRec), and Dual-LSTM. Each of these models represents a distinct approach to sequential recommendation, and their inclusion allows for a thorough comparison of TANR's performance in capturing temporal dynamics and user preferences.

Long Short-Term Memory (LSTM): LSTM is a classic sequential model that processes user interaction sequences by maintaining a hidden state that captures temporal dependencies over time. It is widely used in recommendation systems for its ability to model long-term dependencies in sequential data. In this study, the LSTM model is implemented with a hidden layer size of 128 and trained using the Adam optimizer with a learning rate of 0.001. Despite its effectiveness in capturing sequential patterns, LSTM struggles to explicitly model the time intervals between interactions, which limits its ability to adapt to dynamic user preferences.

Gated Recurrent Unit for Recommendation (GRU4Rec): GRU4Rec is a variant of recurrent neural networks (RNNs) that simplifies the architecture of LSTM by using gating mechanisms to control information flow. It is specifically designed for session-based recommendations and is known for its efficiency in handling short-term user interactions. The GRU4Rec model in this experiment uses a hidden layer size of 128 and is trained with a learning rate of 0.001. While GRU4Rec performs well in capturing short-term patterns, it lacks mechanisms to explicitly incorporate time interval information, which is crucial for modeling evolving user interests.

Self-Attentive Sequential Recommendation (SASRec): SASRec is a Transformer-based model that leverages self-attention mechanisms to capture complex dependencies in user interaction sequences. It processes sequences by computing attention scores between all pairs of interactions, enabling it to model both local and global patterns. The SASRec model in this study uses 2 attention layers with 4 attention heads and a hidden dimension of 128. It is trained with a learning rate of 0.001. Although SASRec excels in capturing sequential dependencies, it does not explicitly account for the time intervals between interactions, which limits its ability to model temporal dynamics effectively.

Time Interval-Aware Self-Attention Sequential Recommendation (TiSASRec): TiSASRec extends SASRec by incorporating time interval information into the self-attention mechanism. It introduces time-aware attention scores that adjust the influence of interactions based on their temporal proximity. The TiSASRec model in this experiment uses 2 attention layers, 4 attention heads, and a hidden dimension of 128. It is trained with a learning rate of 0.001. While TiSASRec improves upon SASRec by considering time intervals, its time-aware mechanism is relatively simplistic and may not fully capture the nuanced temporal patterns in user behavior.

Dual-LSTM: Dual-LSTM is a hybrid model that employs two LSTM networks to separately model short-term and long-term user preferences. The short-term LSTM focuses on recent interactions, while the long-term LSTM captures historical behavior patterns. The Dual-LSTM model in this study uses a hidden layer size of 128 for both LSTMs and is trained with a learning rate of 0.001. Although Dual-LSTM attempts to balance short-term and long-term preferences, its separate modeling approach may lead to suboptimal integration of temporal dynamics.

Table 1. Results on MovieLens-1M dataset.

Model	**HR@5**	**NDCG@5**	**MRR**	**HR@10**	**NDCG@10**	**HR@20**	**NDCG@20**
LSTM	0.6326	0.4741	0.4216	0.7624	0.5163	0.8618	0.5416
GRU4Rec	0.6453	0.4862	0.4335	0.7778	0.5294	0.8732	0.5541
SASRec	0.6729	0.5127	0.4572	0.8036	0.5598	0.8925	0.5833
TiSASRec	0.6842	0.5283	0.4681	0.8164	0.5736	0.9037	0.5972
Dual-LSTM	0.6738	0.5184	0.4619	0.8071	0.5629	0.8954	0.5867
TANR (Ours)	0.6985	0.5436	0.4823	0.8291	0.5914	0.9179	0.6128

Table 2. Results on MIND dataset.

Model	**nDCG@5**	**nDCG@10**	**MRR**
LSTM	0.3128	0.3712	0.2931
GRU4Rec	0.3241	0.3836	0.3058
SASRec	0.3397	0.4015	0.3243
TiSASRec	0.348	0.415	0.3357
Dual-LSTM	0.3412	0.4078	0.3294
TANR (Ours)	0.3525	0.4273	0.3589

The Time-Aware Neural Recommender (TANR) proposed in this paper demonstrates outstanding performance on both the MovieLens-1M and MIND datasets, significantly outperforming all baseline models. On the MovieLens-1M dataset, TANR achieves the best results across all evaluation metrics. Specifically, TANR's HR@5 reaches 0.6985, significantly higher than LSTM (0.6326) and GRU4Rec (0.6453), particularly excelling in capturing users' short-term interests. In terms of NDCG@5, TANR's score of 0.5436 also surpasses TiSASRec (0.5283) and SASRec (0.5127), highlighting its advantage in recommendation accuracy. Additionally, TANR performs best in metrics such as MRR, HR@10, HR@20, NDCG@10, and NDCG@20, further validating its ability to capture temporal information in user behavior sequences.

On the MIND dataset, TANR also delivers excellent performance, particularly in the nDCG@10 and MRR metrics. TANR achieves an nDCG@5 of 0.3525, slightly higher than TiSASRec (0.348) and SASRec (0.3397), while its nDCG@10 score of 0.4273 significantly outperforms TiSASRec (0.415) and SASRec (0.4015), demonstrating its strength in recommendation diversity. Moreover, TANR's MRR of 0.3589 is approximately 2.3 and 3.5 percentage points higher than TiSASRec (0.3357) and SASRec (0.3243), respectively, further proving its effectiveness in capturing users' long-term interests.

Compared to baseline models, TANR significantly outperforms traditional LSTM and GRU4Rec models, indicating that the integration of time-aware mechanisms and neural recommendation frameworks can better capture temporal information in user behavior sequences. At the same time, TANR surpasses SASRec and TiSASRec in most metrics, showcasing its advantages in handling time interval information and modeling changes in user interests. Furthermore, TANR outperforms Dual-LSTM in almost all metrics, further validating the effectiveness of its time-aware mechanism. Overall, by incorporating time-aware mechanisms, TANR can better capture temporal information in user behavior sequences, thereby significantly outperforming existing baseline models in recommendation accuracy, diversity, and user interest modeling.

3.3. Ablation Experiments

To validate the effectiveness of key components in 2.3 Time-Aware Attention Mechanism, we designed ablation experiments focusing on the contributions of the time decay factor, time decay function, and the overall time-aware attention mechanism. The time decay factor dynamically adjusts behavior weights by incorporating time interval information to capture users' short-term interests. The time decay function (logarithmic decay, linear decay, exponential decay) models the impact of time intervals on the importance of behaviors. The overall time-aware attention mechanism combines the time decay factor with a multi-head attention mechanism to capture complex dependencies in user behavior sequences. By progressively removing or replacing these components, we can evaluate their specific contributions to model performance.

In Table 3 and Table 4 are the detailed results of the experiments.

From the experimental results, it can be observed that after removing the time decay factor, the model's HR@5 on the MovieLens-1M dataset drops from 0.6985 to 0.6121, NDCG@5 drops from 0.5436 to 0.4587, and MRR drops from 0.4823 to 0.4012. On the MIND dataset, nDCG@5 drops from 0.3525 to 0.2821, nDCG@10 drops from 0.4273 to 0.3412, and MRR drops from 0.3589 to 0.2812. This indicates that the time decay factor plays a crucial role in capturing users' short-term interests and recommendation timeliness, and its removal significantly degrades model performance.

When replacing the time decay function, logarithmic decay outperforms linear and exponential decay. On the MovieLens-1M dataset, using linear decay results in HR@5 of 0.6243, NDCG@5 of 0.4691, and MRR of 0.4098; using exponential decay results in HR@5 of 0.6202, NDCG@5 of 0.4656, and MRR of 0.4071. On the MIND dataset, linear decay achieves nDCG@5 of 0.2908, nDCG@10 of 0.3523, and MRR of 0.2898; exponential decay achieves nDCG@5 of 0.2887, nDCG@10 of 0.3491, and MRR of 0.2872. Logarithmic decay performs better than other decay functions, demonstrating its effectiveness in capturing both long-term and short-term patterns in user behavior.

Table 3. Ablation results on the MovieLens-1M dataset.

Experiment Setup	HR@5	NDCG@5	MRR	HR@10	NDCG@10
Full TANR (Logarithmic Decay)	0.6985	0.5436	0.4823	0.8291	0.5914
Remove Time Decay Factor	0.6121	0.4587	0.4012	0.7412	0.4923
Replace with Linear Decay	0.6243	0.4691	0.4098	0.7524	0.5032
Replace with Exponential Decay	0.6202	0.4656	0.4071	0.7487	0.4998
Remove Time-Aware Attention	0.5823	0.4321	0.3787	0.7121	0.4712

Table 4. Ablation results on the MIND dataset.

Experiment Setup	nDCG@5	nDCG@10	MRR
Full TANR (Logarithmic Decay)	0.3525	0.4273	0.3589
Remove Time Decay Factor	0.2821	0.3412	0.2812
Replace with Linear Decay	0.2908	0.3523	0.2898
Replace with Exponential Decay	0.2887	0.3491	0.2872
Remove Time-Aware Attention	0.2614	0.3221	0.2621

After completely removing the time-aware attention mechanism, model performance further declines. On the MovieLens-1M dataset, HR@5 drops to 0.5823, NDCG@5 drops to 0.4321, and MRR drops to 0.3787. On the MIND dataset, nDCG@5 drops to 0.2614, nDCG@10 drops to 0.3221, and MRR drops to 0.2621. This indicates that the time-aware attention mechanism significantly contributes to the overall model performance, and its removal leads to a notable decline in the model's ability to capture temporal information in user behavior sequences and recommendation accuracy.

4. Discussion

The TANR proposed in this paper demonstrates outstanding performance on both the MovieLens-1M and MIND datasets, significantly outperforming all baseline models. This superior performance can be attributed to its innovative design, which effectively addresses the limitations of existing approaches in capturing temporal dynamics and balancing short-term preferences with long-term interests. By comparing TANR with baseline models, we can analyze its advantages from a theoretical perspective, highlighting how its unique mechanisms contribute to improved recommendation accuracy, diversity, and user interest modeling.

First, compared to traditional sequential recommendation models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit for Recommendation (GRU4Rec), TANR introduces a time-aware mechanism that better captures temporal information in user behavior sequences. Traditional models like LSTM and GRU4Rec primarily rely on the order of interactions within sequences, treating user behavior as a static sequence of events. While these models are effective in capturing sequential patterns, they often neglect the impact of time intervals between interactions, which are critical for understanding how user interests evolve over time. For example, a user's recent interactions may carry more weight than older ones, but traditional models fail to account for this temporal decay effect. TANR addresses this limitation by dynamically adjusting behavior weights through a learnable time decay factor. This factor assigns higher importance to recent interactions while gradually reducing the influence of older ones, enabling the model to more accurately reflect changes in users' short-term interests. As a result, TANR improves the timeliness and accuracy of recommendations, ensuring that users receive suggestions that align with their current preferences.

Second, compared to attention-based models such as Self-Attentive Sequential Recommendation (SASRec) and Time Interval-Aware Self-Attention Sequential Recommendation (TiSASRec), TANR combines the time decay factor with a multi-head attention mechanism to more effectively capture complex dependencies in user behavior sequences. While SASRec and TiSASRec also incorporate attention mechanisms to model interactions, their approaches to handling time interval information are relatively simplistic. SASRec, for instance, focuses solely on the sequential order of interactions without explicitly considering time intervals, while TiSASRec introduces a basic time-aware mechanism that lacks the flexibility to adapt to diverse user behavior patterns. In contrast, TANR introduces a logarithmic decay function, which provides a more nuanced representation of how time intervals influence behavior importance. Logarithmic decay is particularly effective because it smoothly balances the impact of both recent and historical interactions, avoiding the abrupt changes associated with linear or exponential decay functions. This allows TANR to better capture dynamic changes in user interests, such as sudden shifts in preferences or recurring patterns over time. Additionally, TANR's multi-head attention mechanism enhances its expressive power by enabling the model to simultaneously capture global dependencies (*e.g.*, long-term interests) and local dependencies (*e.g.*, short-term preferences) within user behavior sequences. This dual capability ensures that TANR can provide recommendations that are both contextually relevant and aligned with users' evolving interests.

Through comparisons with baseline models, we conclude that TANR, by introducing a time-aware mechanism, significantly outperforms existing approaches in capturing temporal information in user behavior sequences. Its ability to dynamically adjust behavior weights based on time intervals, combined with the expressive power of multi-head attention, enables TANR to achieve superior performance in recommendation accuracy, diversity, and user interest modeling. These advantages are particularly evident in scenarios where user behavior exhibits rapid changes or complex temporal patterns, such as in news recommendation or e-commerce platforms.

Next, through ablation experiments, we further validate the effectiveness of key components in TANR, providing empirical evidence for their contributions to the model's performance. First, removing the time decay factor leads to a significant decline in model performance across all evaluation metrics. This observation underscores the critical role of the time decay factor in capturing users' short-term interests and ensuring the timeliness of recommendations. By dynamically adjusting behavior weights, the time decay factor allows TANR to prioritize recent interactions, which are often more reflective of users' current preferences. This capability is particularly important in dynamic environments where user interests can shift rapidly, such as in trending news or seasonal product recommendations. Without the time decay factor, the model loses its ability to adapt to these changes, resulting in less accurate and less timely recommendations.

Second, when replacing the time decay function with alternative formulations, such as linear or exponential decay, the model's performance deteriorates. Logarithmic decay consistently outperforms these alternatives, demonstrating its effectiveness in balancing long-term and short-term patterns in user behavior. Linear decay, which assumes a constant rate of decay over time, fails to capture the nuanced relationship between time intervals and behavior importance. Exponential decay, on the other hand, tends to overemphasize recent interactions while neglecting historical ones, leading to an imbalance in the model's representation of user interests. Logarithmic decay, with its smooth and gradual reduction in influence, strikes an optimal balance between these extremes, enabling TANR to more effectively capture dynamic changes in user interests. This finding highlights the importance of carefully designing the time decay function to ensure that it aligns with the temporal characteristics of user behavior.

Finally, completely removing the time-aware attention mechanism results in a further decline in model performance, confirming its key role in capturing complex dependencies in user behavior sequences. The time-aware attention mechanism combines the time decay factor with a multi-head attention mechanism, enabling TANR to simultaneously capture global and local dependencies within user behavior sequences. This dual capability is essential for modeling the intricate interplay between short-term preferences and long-term interests, as well as for identifying patterns that span multiple interactions. Without the time-aware attention mechanism, the model loses its ability to integrate temporal information into the recommendation process, leading to a significant reduction in performance. This result underscores the importance of combining temporal modeling with advanced attention mechanisms to achieve state-of-the-art performance in recommendation tasks.

Through ablation experiments, we conclude that the time decay factor is critical for capturing users' short-term interests and ensuring recommendation timeliness; logarithmic decay is more suitable than other decay functions for balancing long-term and short-term patterns in user behavior; and the time-aware attention mechanism significantly contributes to the overall model performance by enabling the integration of temporal information into the recommendation process. These findings provide strong support for the design of TANR and lay a solid foundation for its practical application in recommendation systems.

5. Conclusion

The TANR proposed in this paper introduces a time-aware mechanism that innovatively combines a time decay factor, a logarithmic decay function, and a multi-head attention mechanism, significantly enhancing the ability of recommendation systems to capture temporal information in user behavior sequences. The core novelty of TANR lies in its ability to dynamically adjust behavior weights by incorporating time interval information, thereby better modeling changes in users' short-term and long-term interests. Compared to traditional sequential recommendation models, TANR not only captures the sequential information of user behaviors but also more accurately reflects the impact of time intervals on user interests through the time decay factor and logarithmic decay function. Additionally, TANR's multi-head attention mechanism further enhances the model's expressive power, enabling it to simultaneously capture global and local dependencies in user behavior sequences, thus demonstrating significant advantages in recommendation accuracy, diversity, and user interest modeling. The design of TANR fully considers the temporal characteristics of user behaviors, seamlessly integrating time information into the recommendation process through the time-aware mechanism. This allows the model to more accurately capture dynamic changes in user interests, particularly excelling in handling short-term user behaviors and real-time recommendation tasks.

Experimental results show that TANR significantly outperforms existing baseline models on both the MovieLens-1M and MIND datasets, particularly excelling in capturing users' short-term interests and recommendation timeliness. Through comparisons with baseline models, TANR demonstrates its strong capability in handling time interval information and dynamic changes in user interests. For example, TANR's HR@5 and NDCG@5 on the MovieLens-1M dataset are significantly higher than those of traditional models and attention-based models, indicating its clear advantage in capturing users' short-term interests and recommendation accuracy. On the MIND dataset, TANR's nDCG@10 and MRR also significantly outperform other models, further validating its ability to capture users' long-term interests and recommendation diversity. Ablation experiments further verify the effectiveness of the time decay factor, logarithmic decay function, and time-aware attention mechanism, demonstrating that these components play a critical role in improving model performance. The success of TANR not only proves the importance of time-aware mechanisms in recommendation systems but also provides new insights for future research.

However, despite TANR's outstanding performance in experiments, it still has some limitations. First, the model's modeling of time intervals relies on predefined decay functions (*e.g.*, logarithmic decay), which may not fully adapt to all user behavior patterns. Different users may exhibit significantly different behavior patterns, and a single decay function may not meet the needs of all scenarios. Second, TANR has relatively high computational complexity, especially when processing long sequences, which may affect its efficiency in practical applications. Although the multi-head attention mechanism enhances the model's expressive power, it also introduces additional computational overhead, which could become a bottleneck in large-scale recommendation systems. Furthermore, TANR currently focuses on modeling single-type behavior sequences, and future work could explore how to extend it to multi-modal data (*e.g.*, text, images) and cross-domain recommendation scenarios. For example, in news recommendation or e-commerce recommendation, user behaviors may involve multiple types of data (*e.g.*, clicks, purchases, reviews), and how to effectively integrate such multi-modal data is a direction worth exploring.

Future research directions can be expanded in the following aspects: First, more flexible time interval modeling methods could be explored, such as neural network-based adaptive decay functions, to better adapt to different user behavior patterns. By introducing learnable decay functions, the model could dynamically adjust time decay strategies based on user behavior data, thereby further improving the personalization level of recommendations. Second, the computational efficiency of the model could be further optimized, for example, by introducing sparse attention mechanisms or hierarchical modeling methods to reduce computational complexity. Sparse attention mechanisms could reduce unnecessary computational overhead, while hierarchical modeling methods could improve efficiency by processing long sequences in stages. Additionally, TANR could be combined with other recommendation techniques (*e.g.*, knowledge graphs or reinforcement learning) to further enhance the performance and applicability of recommendation systems. For example, integrating knowledge graphs could provide richer semantic information for recommendation systems, while reinforcement learning could help the model continuously optimize recommendation strategies in dynamic environments. Finally, the application scenarios of TANR could be further expanded, such as in social network recommendations, video recommendations, or ad recommendations, to explore how to leverage time-aware mechanisms to improve recommendation effectiveness.

Conflict of interest

I declare no conflict of interest.

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Data availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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