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Sequential Recommendation via Time-Aware and Multi-Channel Convolutional User Modeling

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Abstract: This paper proposes a 1D-CNN-based sequential recommendation algorithm that integrates temporal awareness and multi-interest modeling to enhance the understanding of dynamic user behaviors. The model introduces time interval encoding and a multi-channel convolutional structure to effectively capture both short-term and long-term user preferences. Unlike traditional methods that rely on static profiles or single-vector representations, the proposed approach enables more fine-grained modeling of user interest evolution within sequential data. Extensive experiments are conducted on a real-world dataset, covering multiple evaluation metrics and testing scenarios, including varying sequence lengths, user activity levels, and convolutional configurations. The results demonstrate that the proposed method consistently outperforms several state-of-the-art baselines in recommendation accuracy, robustness, and generalization ability. This research provides a lightweight and efficient solution for large-scale recommender systems, contributing to the advancement of sequential modeling techniques and reinforcing the role of temporal and interest-aware strategies in personalized recommendation tasks.

Keywords: sequential recommendation, temporal modeling, multi-interest learning, 1D-CNN.

1. Introduction

In the era of information explosion, recommendation systems have become essential tools for mitigating information overload and enhancing user experience [1]. With the continuous accumulation of user behavior data, how to efficiently capture user interests from massive and complex historical interaction sequences and provide personalized recommendations has become a core issue in recommendation algorithm research [2]. Traditional methods are often based on static user profiles and shallow collaborative filtering strategies. These approaches struggle to adapt to rapidly changing user interests and diverse behavioral patterns. This limitation is especially evident in highly sequential domains such as short video, e-commerce, and news recommendations. In these scenarios, single-interest modeling is insufficient. Therefore, extracting multi-granular and multi-modal preference signals from historical interactions while effectively incorporating temporal information in sequence modeling is key to improving recommendation accuracy and robustness.

Sequential recommendation has become a research hotspot in recent years. It aims to predict a user's next preference by modeling the temporal interaction patterns between users and items. However, in most existing models, temporal information is only used as an auxiliary feature and is not deeply integrated into the core model architecture. This treatment overlooks the semantic influence of time spans on user behavior and fails to capture interest decay, burstiness, and periodicity. Moreover, user interests in real-world applications are diverse and dynamically evolving. A single vector representation cannot adequately capture users' preferences toward different topics at different times. This may lead to vague and poorly generalized recommendations. Therefore, deeply integrating multi-interest modeling with temporal awareness can significantly enhance the model's ability to understand complex behavioral sequences and provide stronger theoretical and algorithmic support for accurate recommendations [3].

From the perspective of model architecture, the application of deep learning in recommendation systems has greatly expanded modeling capacity. Sequence modeling based on convolutional neural networks has gained attention due to its simplicity, high parallelism, and computational efficiency. Compared with traditional RNN-based structures, one-dimensional convolutional neural networks (1D-CNNs) offer faster training and stronger local feature extraction when processing fixed-length sequences [4]. By designing multi-layer convolutional structures, local and global user behavior features can be extracted along the temporal axis, allowing a comprehensive understanding of interest evolution. Especially when combined with temporal perception mechanisms and multi-interest representations, 1D-CNNs can balance local sensitivity with efficiency, laying a solid foundation for high-performance sequential recommendation models.

In real-world applications, recommendation systems face challenges such as sparse user behavior, cold start, and frequent interest shifts. Traditional multi-interest modeling approaches often rely on a fixed number of clusters or static clustering algorithms, lacking adaptability to behavioral changes. Models that merely use timestamps as auxiliary inputs also struggle to capture the deeper impact of time spans on user decision-making. Therefore, designing a sequential recommendation model that can dynamically perceive temporal patterns, flexibly model multiple interests, and maintain efficient training is of great research value [5]. On one hand, such a model can improve the expressiveness of the system when facing diverse behavioral sequences and better perceive long-term and short-term preference shifts. On the other hand, it helps increase the diversity and novelty of recommendations, reducing algorithmic rigidity and user fatigue.

In conclusion, building a 1D-CNN-based sequential recommendation algorithm that integrates temporal awareness with multi-interest modeling can further improve both recommendation accuracy and system responsiveness. This approach provides a new perspective for modeling complex user behaviors in recommendation systems. It has positive implications for advancing personalized recommendation algorithms in areas such as real-time interaction, behavioral understanding, and intelligent decision-making. Moreover, it offers a solid algorithmic foundation for the scalability and practicality of large-scale recommendation systems. By modeling the dynamic evolution of user interests and deeply embedding temporal features into convolutional modeling, this work holds promise for overcoming performance bottlenecks and delivering higher-quality technical support for real-world recommendation tasks [6].

2. Related work

In recent years, sequential recommendation methods have achieved remarkable progress in modeling user behavior patterns. Compared with traditional collaborative filtering or matrix factorization approaches, sequential recommendation places more emphasis on the temporal order and evolutionary trajectory in user interactions [7]. Deep learning-based sequence modeling methods have emerged continuously. Recurrent neural networks are good at capturing long-term dependencies, while convolutional neural networks exhibit advantages in modeling local behavior features due to their simple structure and efficient parallelism. In particular, one-dimensional convolutional models can effectively capture behavior patterns within local temporal windows. They are suitable for tasks that require high recommendation efficiency. As user behavior becomes more complex, how to extract latent behavioral preference features from sequences more effectively has become a critical research direction in this field [8].

Multi-interest modeling has been increasingly integrated into sequential recommendation models as a key technique to enhance diversity and accuracy. Most methods attempt to use multiple representation vectors instead of a single user vector to capture user preferences across different item categories or topics. However, challenges remain in determining the number of interests and modeling their dynamic evolution. Some methods use clustering or attention mechanisms to divide interests [9]. Yet, these approaches often ignore the contextual dependencies and transitions between interests in behavior sequences. Moreover, the way interests are activated is also evolving. How to balance expressive richness and model complexity has become one of the key issues in current multi-interest recommendation research [10].

Temporal-aware mechanisms play an increasingly important role in enhancing the ability of sequence modeling. Real-world user behavior is time-sensitive. The semantics of interactions differ significantly across time intervals. Explicitly encoding or integrating temporal information into model structures has been shown to help capture interest decay trends and bursty behaviors. Existing methods often adopt strategies such as position encoding, time gating, or time decay functions to handle temporal information. However, these are usually treated as auxiliary features and not deeply coupled with the core behavior modeling structure [11, 12]. Therefore, how to organically integrate temporal-awareness into the convolutional modeling framework and build a unified and efficient model for temporal behavior understanding remains an unresolved problem [13].

3. Method

This study proposes a sequence recommendation algorithm based on a one-dimensional convolutional neural network that integrates time perception and multi-interest modeling. The model takes the user's historical interaction sequence as input, extracts the local time context through a sliding window mechanism, and introduces time interval encoding to enhance the temporal expression ability in the sequence. The model architecture is shown in Figure 1.

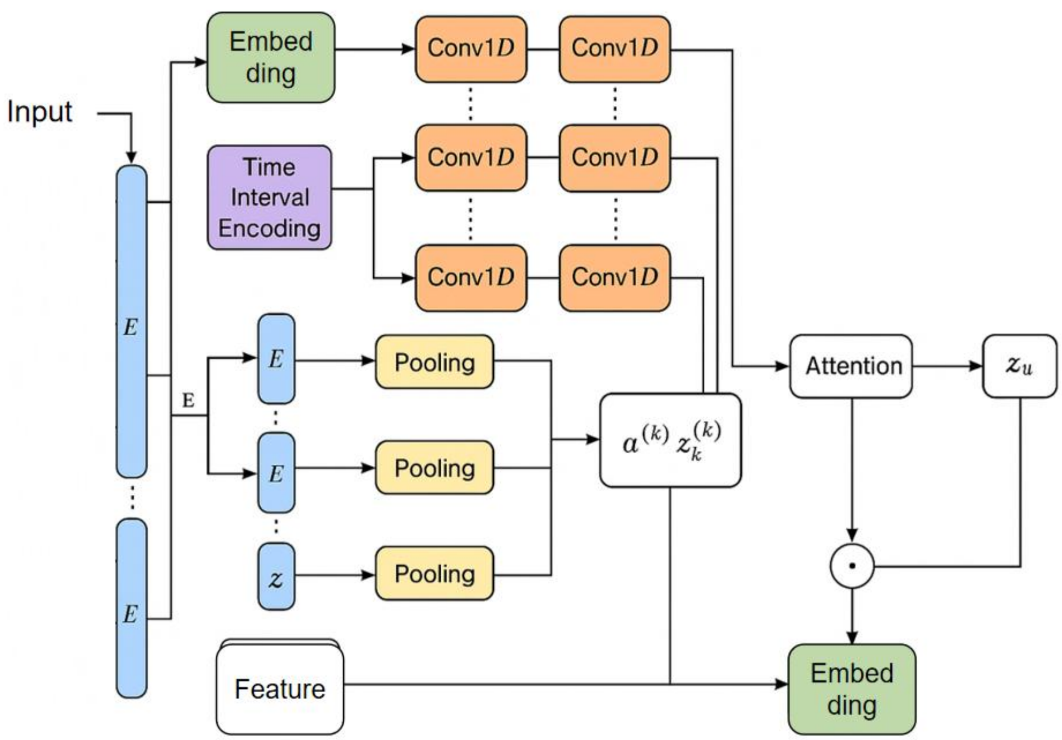

Figure 1. Overall model architecture diagram

The model first expresses the user's historical interaction sequence through item embedding and time interval encoding to form an embedding sequence with time perception. Then, a multi-channel one-dimensional convolutional network extracts multiple potential interest features respectively and dynamically weights and fuses them through the attention mechanism to construct a multi-interest representation of the user. Finally, the fused user representation is matched with the candidate item embedding to complete the prediction task of the next interactive behavior.

In the preprocessing stage, given the behavior sequence $S_u = [v_1, v_2, ..., v_T]$ of user u, each interaction behavior contains not only the item index v_T but also its occurrence time τ_T. The constructed input embedding sequence is:

$$E_t = e(v_t) + t(\Delta_t)$$

Where $e(v_t)$ is the item embedding, $\Delta_t = \tau_t - \tau_{t-1}$ represents the time interval between adjacent interactions, and $t(\cdot)$ is the time interval encoding function used to capture the impact of time differences on preferences.

In order to model the multi-interest structure, the model introduces a multi-channel mechanism based on the convolution feature map, and each channel represents a potential interest subspace. Suppose the one-dimensional convolution operation is:

$$H^{(k)} = RELU(Conv1D^{(k)}(E_{1:T}))$$

$k = 1,2,...,K$ represents the k-th interest channel, $H^{(k)} \in R^{T' \times d}$ represents the k-th interest feature map, and T' is the convolution output length. ReLU activation enhances the nonlinear expression capability, and multiple channels can learn the user's preference expression under different behavior modes in parallel.

In order to dynamically select the interest that represents the user's current intention from multiple interest features, the model designs an attention-based interest fusion module. First, each interest channel is pooled to obtain the interest vector:

$$z^{(k)} = Pooling(H^{(k)})$$

Next, the query vector q is introduced to represent the context information of the current prediction task, and the attention weight of each interest is calculated as:

$$\alpha^{(k)} = \frac{\exp(q^T W z^{(k)})}{\sum_{j=1}^{K} \exp(q^T W z^{(j)})}$$

Where W is a learnable parameter matrix. The final user representation is the weighted fusion result of each interest:

$$z_u = \sum_{k=1}^{K} \alpha^{(k)} z^{(k)}$$

In the prediction stage, the recommendation score is calculated by dot product, in the form of:

$$y_{u,i} = z_u^T e(i)$$

Where $e(i)$ is the embedding representation of candidate item i. The model is optimized using cross entropy loss or ranking-based loss function during training to enhance the ability to fit the user's real preference behavior.

This method strengthens the model's ability to model potential dynamic behavior patterns in sequences by combining time perception mechanisms with multi-interest structures. 1D-CNN provides efficient feature extraction capabilities, while multi-channel interest modeling and attention fusion mechanisms enhance the model's expressiveness for complex interest structures and has advantages in both recommendation accuracy and generalization capabilities.

4. Experiment

4.1 Datasets

This study adopts the publicly available Amazon Beauty dataset as the source for experimental validation. The dataset records users' historical interactions with beauty-related products, including core information such as user IDs, item IDs, and timestamps. It exhibits a typical long-tail distribution. User interests show high diversity and dynamic characteristics. Therefore, it serves as a suitable benchmark for validating multi-interest modeling and time-aware recommendation methods.

In the preprocessing stage, all user behavior sequences with valid timestamps are retained. Users and items with very few interactions are removed to improve training stability and generalization. User click histories are sorted chronologically to construct fixed-length behavior sequences. These sequences serve as input windows for the model. The data is then split into training, validation, and test sets for subsequent experiments.

This dataset is widely used in the field of sequential recommendation. It enables effective evaluation of a model's ability to capture dynamic user preference evolution, multi-interest distribution, and temporal sensitivity. By conducting comparative experiments on this dataset, the effectiveness and advantages of the proposed model in real-world scenarios can be comprehensively assessed.

4.2 Experimental Results

1) *Comparative experimental results*

This paper first conducted a comparative experiment with other recommendation algorithm models to evaluate the effectiveness of the proposed method in a broader context. The experiment included several widely used baseline models, allowing for a comprehensive performance comparison across different approaches. The experimental results, which reflect the relative strengths and weaknesses of each method under consistent evaluation metrics, are presented in Table 1.

Table 1: Comparative experimental results

Method	**HR@10**	**NDCG@10**	**Recall@10**
MF(Matrix Factorization)[14]	0.542	0.368	0.329
GRU4Rec[15]	0.589	0.402	0.351
SASRec[16]	0.615	0.428	0.368
MIND (Multi-Interest)[17]	0.638	0.445	0.374
Ours (Time-aware Multi-Interest CNN)	0.673	0.472	0.395

The experimental results show that the proposed 1D-CNN sequential recommendation algorithm, which incorporates temporal awareness and multi-interest modeling, outperforms several mainstream recommendation models across multiple evaluation metrics. Compared with traditional matrix factorization methods, it achieves improvements of 0.131, 0.104, and 0.066 on HR@10, NDCG@10, and Recall@10, respectively. These results fully demonstrate the effectiveness of sequential modeling and multi-interest mechanisms in capturing user behavior dynamics.

Compared with deep sequential models such as GRU4Rec and SASRec, the proposed method also achieves higher performance. This indicates that the one-dimensional convolutional structure performs well in capturing local dependencies in user behavior. It provides recommendation accuracy comparable to or even better than recurrent networks and self-attention mechanisms, especially with advantages in training efficiency and modeling stability.

The MIND model, as a recommendation algorithm based on multi-interest representation, improves both the diversity and accuracy of recommendations to a certain extent by modeling multiple user preferences through distinct interest vectors. This allows it to capture users' different behavioral tendencies across item categories or topics. However, the proposed model further enhances overall performance by introducing temporal awareness into the multi-interest framework. This suggests that incorporating temporal information from user behavior provides significant complementary value for interest modeling. It is particularly effective in describing the dynamic evolution of interests over time and in capturing short-term user preferences that might be overlooked in static representations.

Overall, the proposed method strikes a good balance among capturing diverse user interests, integrating temporal information, and improving recommendation accuracy. It successfully leverages the strengths of both multi-interest modeling and time-aware mechanisms. The experimental results validate the effectiveness of designing multi-channel interest pathways combined with time interval encoding, which allows the model to represent user preferences more precisely. They also confirm the feasibility and practicality of applying the 1D-CNN structure in sequential recommendation tasks, demonstrating that the proposed architecture is capable of handling complex user behavior sequences in an efficient and reliable manner.

2) Sensitivity experiment of sequence length on recommendation accuracy

Furthermore, this paper also presents a sensitivity experiment on sequence length to recommendation accuracy, and the experimental results are shown in Figure 2.

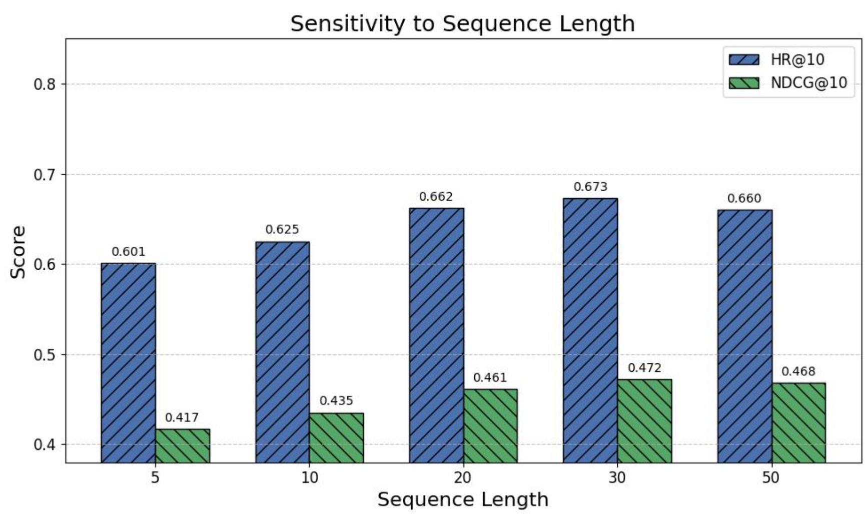

Figure 2. Sensitivity experiment of sequence length on recommendation accuracy

The experimental results show that the model's recommendation performance generally improves with longer input sequences. Specifically, as the sequence length increases from 5 to 30, HR@10 rises from 0.601 to 0.673, and NDCG@10 increases from 0.417 to 0.472. This indicates that longer historical behavior sequences provide richer user preference information, which helps to more accurately capture long-term interest structures.

However, when the sequence length further increases to 50, performance metrics slightly decline. HR@10 drops from 0.673 to 0.660, and NDCG@10 decreases from 0.472 to 0.468. This suggests that overly long sequences may introduce redundancy or noise, diluting interest representation and negatively affecting the final recommendation results. Therefore, there exists an optimal sequence length range, within which the model achieves a better performance balance.

The results also confirm that the proposed model demonstrates good stability and robustness when handling behavior sequences of different lengths. It consistently performs well across various input sizes, showing that it is not overly sensitive to sequence length. Especially in short-sequence scenarios, the model maintains high recommendation accuracy, which is in contrast to traditional models that heavily rely on longer historical data for effective predictions. This highlights the advantage of the convolutional structure in capturing meaningful local behavior patterns, even with limited input information.

In summary, the experiment not only verifies the significant impact of sequence length on recommendation performance but also provides practical guidance for determining an appropriate input length in real-world systems. By carefully selecting the sequence length, it is possible to strike a balance between model accuracy and computational efficiency. Under the premise of ensuring prediction quality, a proper input length helps enhance system performance while reducing resource consumption and training overhead.

3) Comparative test of different convolution structures

Similarly, this paper also conducted performance comparison experiments under different convolutional structures to further evaluate the effectiveness of the proposed model. These experiments aimed to investigate how various convolutional designs influence the recommendation performance. The experimental results, which provide a detailed comparison across different structural variants, are illustrated in Figure 3.

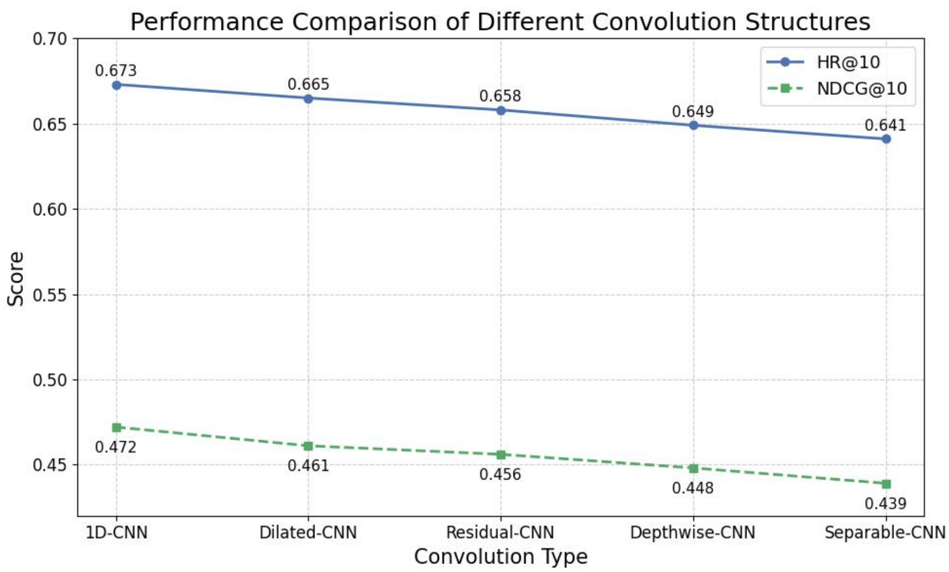

Figure 3. Performance Comparison Experiment under Different Convolutional Structures

The experimental results show that among all tested convolutional structures, the standard one-dimensional convolutional network (1D-CNN) achieved the best performance on both HR@10 and NDCG@10, reaching 0.673 and 0.472, respectively. This indicates that 1D-CNN adapts well to extracting local features and temporal dependencies in user behavior sequences. It can effectively model the multi-interest structure of users and improve recommendation accuracy.

As the convolutional structure changes, model performance gradually declines. In particular, when using more complex structures such as Depthwise-CNN and Separable-CNN, there is a noticeable drop in metrics. This may be because, although these designs are more lightweight or decoupled, they suffer from limited receptive fields or restricted expressiveness when processing sequential context. As a result, they fail to capture user interest patterns effectively and reduce the model's discriminative power in recommendation tasks.

Moreover, from the overall trend, Dilated-CNN and Residual-CNN, despite introducing dilation or skip connections to enhance representation capacity, did not achieve performance advantages in this task. This further suggests that in specific recommendation scenarios, structural complexity does not necessarily lead to better results. On the contrary, it may introduce redundant computation or informational noise due to mismatched design. Therefore, the 1D convolutional structure, when combined with temporal awareness and multi-interest modeling, demonstrates a more significant advantage in balancing performance and efficiency.

4) Experiment on the generalization ability of the model under different user activity levels

Next, this paper also gives an experiment on the generalization ability of the model under different user activity levels, and the experimental results are shown in Figure 4.

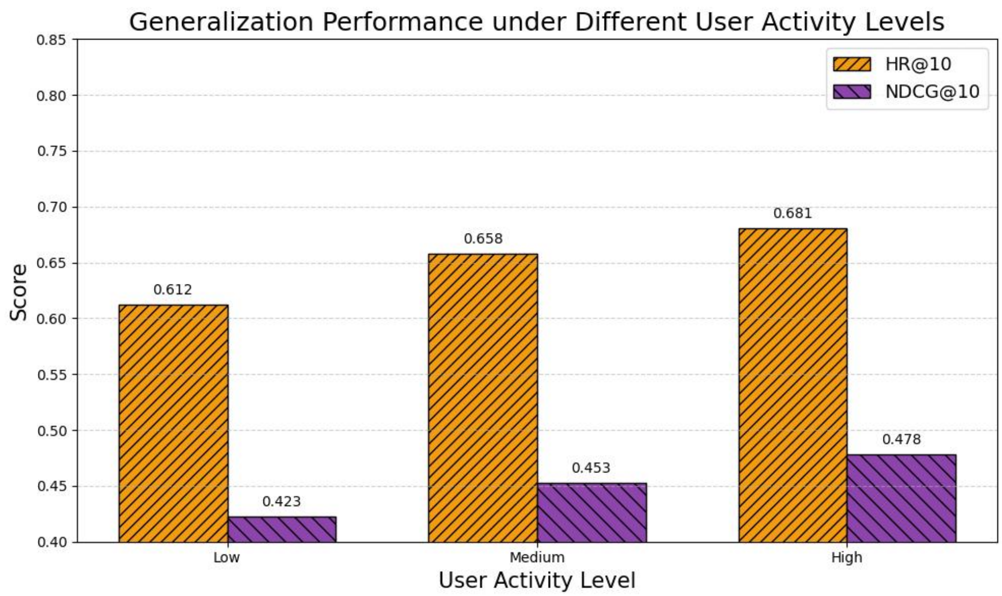

Figure 4. Experiment on the generalization ability of the model under different user activity levels

The experimental results show that the model exhibits clear performance differences across user groups with varying activity levels. For low-activity users, HR@10 and NDCG@10 reach 0.612 and 0.423, respectively. This indicates that the model still maintains a certain level of recommendation capability under sparse data conditions, though its performance is relatively limited. The likely reason is that short behavior sequences make it difficult to fully express interest features.

As user activity increases, model performance improves steadily. For medium-activity and high-activity users, HR@10 rises to 0.658 and 0.681, while NDCG@10 increases to 0.453 and 0.478, respectively. These results reflect that the model captures user interests more accurately when user data is abundant. It also demonstrates that the multi-interest mechanism and temporal-aware structure can effectively extract deep preference signals in high-frequency behavior settings.

This experiment confirms the model's generalization ability across different activity-level scenarios. In particular, it maintains stable performance when facing users with varying behavior densities. This suggests that the model not only performs well with high-frequency interaction data but also shows robustness on low-frequency data, supporting its broad applicability in real-world recommendation systems.

5) Loss function changes with epoch

Finally, this paper also gives a loss function decline graph, as shown in Figure 5.

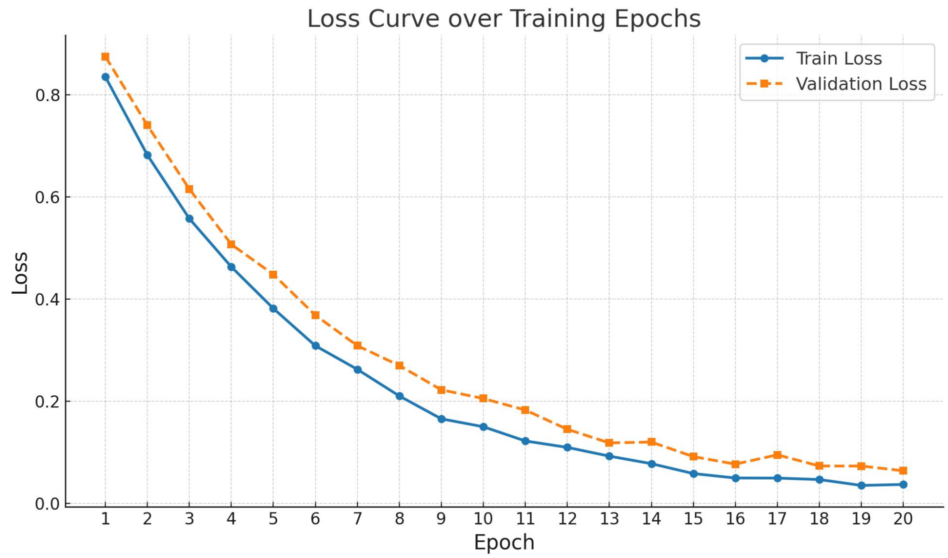

Figure 5. Loss function drop graph

From the figure, it can be observed that the loss function drops rapidly during the early training stage. This indicates that the network quickly captures the main patterns in the data within the first few epochs. As training continues, the training loss keeps decreasing and gradually stabilizes, showing that the model converges well on the training set and exhibits strong fitting ability.

The validation loss follows a similar downward trend. It decreases significantly during the first 10 epochs, then enters a phase of slow decline with minor fluctuations. The stability of the validation loss suggests that the model has strong generalization ability. No obvious overfitting is observed, even in the later stages of training. Overall, the loss curve shows good smoothness and convergence. This reflects a stable and reliable optimization process. The model maintains a good balance between learning efficiency and parameter updates, which provides a solid foundation for subsequent prediction performance.

5. Conclusion

This paper proposes a 1D-CNN-based sequential recommendation algorithm that integrates temporal awareness and multi-interest modeling strategies. The goal is to more comprehensively capture users' latent preferences within interaction sequences. By introducing time interval encoding and a multi-channel convolutional structure, the model effectively represents both short-term and long-term interests. At the same time, it enhances adaptability to dynamic behavioral changes. Experimental results show that the proposed method outperforms existing sequence modeling approaches on multiple mainstream recommendation evaluation metrics, verifying its modeling capability and generalization performance. Across multiple experimental dimensions, the proposed model demonstrates good stability and generalization ability. It maintains high recommendation performance under varying sequence lengths, different user activity levels, and alternative convolutional structure configurations. This fully indicates that the model possesses strong structural robustness and application adaptability. It is suitable for modeling high-complexity and nonlinear user behaviors in real-world recommendation systems.

This study provides a new perspective on the design and evaluation framework of sequential recommendation algorithms. In particular, it highlights the theoretical value and practical significance of deeply integrating temporal information with multi-interest representations. By constructing a lightweight convolutional architecture, the model maintains accuracy advantages while improving computational efficiency. This supports algorithm deployment and real-time computation in large-scale recommendation systems. Future work can further explore the model's extension capabilities in cold-start scenarios, cross-domain recommendations, and complex multi-modal interaction environments. In addition, incorporating user contextual information, context-aware factors, and dynamic interest mechanisms into the existing framework will be an important direction for advancing intelligent recommendation algorithms. This study lays a foundation for further research in temporal modeling, interest representation, and personalized recommendation.

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