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Deep Learning for Cross-Domain Recommendation with Spatial-Channel Attention

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Abstract:

With the advancement of information technology, recommendation systems have become essential for enhancing user experience and improving information retrieval efficiency. Traditional recommendation methods perform well in single-domain scenarios but face challenges in cross-domain tasks, including data sparsity, user interest drift, and feature heterogeneity. To address these issues, this study proposes a cross-domain recommendation algorithm based on an improved Spatial-Channel Attention Mechanism (SCAM). By integrating spatial and channel attention, the method effectively captures user interest patterns across domains and optimizes cross-domain feature fusion. Additionally, this study examines the impact of different item feature inputs and model parameters (e.g., embedding size and attention heads) on recommendation performance. Experimental results demonstrate that the proposed method outperforms existing approaches across multiple evaluation metrics (HR@10, NDCG@10, Precision@10, and Recall@10) and exhibits strong generalization ability. Future research can further optimize the model architecture by incorporating graph neural networks and reinforcement learning to enhance the intelligence of recommendation systems.

Keywords:

Cross-domain recommendation, spatial channel attention mechanism, deep learning, user interest modeling

1. Introduction

In recent years, with the rapid development of information technology, recommendation systems have been widely applied in various fields, including e-commerce, social media, online education, and intelligent content distribution. As the volume of users and the demand for personalized recommendations continue to grow, effectively extracting deep features from data to improve recommendation accuracy and user satisfaction has become a core research challenge [1]. Traditional collaborative filtering and content-based recommendation methods have alleviated the issue of information overload to some extent. However, they still face significant limitations in addressing data sparsity, cold start problems, and user interest modeling. The introduction of deep learning has brought new opportunities to recommendation systems. Among them, the attention mechanism has gained widespread adoption due to its ability to capture key user behavior features and dynamically model interest preferences. However, most existing attention mechanisms rely on single-domain data distributions, making it difficult to capture cross-domain information effectively [2]. As a result, recommendation systems struggle to meet diverse user demands. Therefore, improving attention mechanisms to enhance user preference modeling in cross-domain recommendation scenarios is a critical research direction.

Cross-domain recommendation (CDR) has gained increasing attention in recent years. Its core idea is to leverage user behavior in one domain (such as music or movies) to enhance recommendations in another

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domain (such as books or travel). This approach not only mitigates data sparsity in a single domain but also uncovers users' latent interests, improving recommendation comprehensiveness and accuracy. However, due to significant differences in data distributions across domains, user behavior patterns and preferences may exhibit heterogeneity and domain shifts, making it difficult to directly transfer traditional recommendation algorithms. Therefore, efficiently mining cross-domain correlations, learning user behavior patterns in different domains, and sharing meaningful representations across domains are key to achieving high-quality cross-domain recommendations.

The spatial-channel attention mechanism (SCAM) is a deep learning method that captures both local features and global relationships. It has been widely applied in fields such as computer vision and natural language processing. Compared to traditional attention mechanisms, SCAM not only dynamically adjusts the weights of input features but also effectively integrates spatial and channel information, enhancing the model's ability to represent complex data. In recommendation systems, user interests are often multi-faceted and influenced by factors such as time, environment, and social relationships. A single feature dimension is insufficient to fully characterize user behavior. Therefore, introducing SCAM into cross-domain recommendation tasks is expected to enhance the model's ability to capture user interests, thereby improving recommendation accuracy and personalization [3].

This study proposes an improved spatial-channel attention mechanism for cross-domain recommendation to enhance the model's ability to integrate information across domains. The proposed method optimizes attention computation, enabling the model to better identify and capture user interest features in different domains while reducing interference from irrelevant information. Additionally, by incorporating a cross-domain feature interaction mechanism, the study effectively models shared patterns across domains, improving the model's generalization ability in sparse data scenarios. This research not only enhances the overall performance of recommendation systems but also provides a novel solution for the development of cross-domain recommendation systems. Optimizing recommendation systems is crucial for improving user experience and advancing intelligent information services. As personalized recommendation demands continue to grow, traditional single-domain recommendation methods struggle to meet users' diverse interests. Cross-domain recommendation has become an essential trend in the future development of recommendation systems. By integrating cross-domain features with spatial-channel attention mechanisms, this study aims to overcome existing limitations and improve recommendation accuracy and adaptability. The research findings can be applied to various fields, including e-commerce, online education, and content recommendation, providing theoretical support and technical guidance for building more intelligent and efficient recommendation systems [4].

2. Related work

The development of recommendation systems has evolved from rule-based methods to machine learning models and then to deep learning-driven intelligent recommendations. Early recommendation methods mainly included collaborative filtering (CF) and content-based recommendation. CF utilizes a user-item interaction matrix for recommendations but suffers from data sparsity and cold start issues. Content-based methods match items with user preferences by analyzing item features but struggle to handle diverse interests effectively [5]. With the advancement of deep learning, neural network models have been introduced into recommendation systems. Methods based on convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can extract deep features from user behavior history. However, most of these methods focus on single-domain data. They still face challenges in multi-domain data fusion and cross-domain recommendation, making it difficult to fully leverage users' comprehensive interest information.

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Research on cross-domain recommendation mainly focuses on feature transfer and joint learning. Feature transfer methods improve recommendation performance by sharing user or item representations across domains. For example, matrix factorization-based methods enable cross-domain recommendations by sharing latent user vectors. Deep learning methods employ adversarial learning and self-attention mechanisms to achieve efficient cross-domain information fusion. For instance, cross-domain recommendation models based on variational autoencoders (VAEs) can effectively model users' latent interest distributions. Graph neural networks (GNNs) enhance user-item relationship modeling by leveraging cross-domain interaction information. However, existing methods still face challenges in handling cross-domain feature heterogeneity. Developing an efficient cross-domain feature fusion mechanism remains a key research focus [6].

The application of attention mechanisms in recommendation systems has made significant progress. In cross-domain recommendation tasks, they can effectively capture user preference patterns. The spatial-channel attention mechanism (SCAM) has achieved promising results in computer vision and natural language processing by simultaneously modeling spatial and channel information. Recently, it has also been introduced into recommendation system research. Some studies use channel attention to enhance weight allocation across different feature dimensions, optimizing recommendation performance [7]. However, most existing attention mechanisms are designed for single-domain optimization and lack adaptability to cross-domain recommendation. Based on this, this study proposes an improved spatial-channel attention mechanism to enhance information fusion in cross-domain recommendation tasks, improving model generalization and recommendation accuracy.

3. Method

In this study, we proposed a recommendation algorithm based on a cross-domain improved spatial channel attention mechanism to enhance the model's ability in multi-domain data fusion and user preference modeling. The architecture of the spatial channel attention mechanism used in this paper is shown in Figure 1.

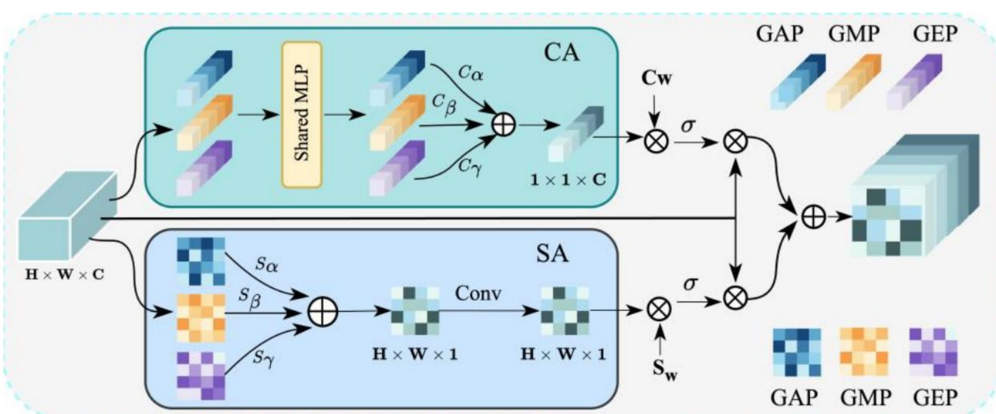

Figure 1. Architecture diagram of cross-domain improved spatial channel attention mechanism

Assume that the recommendation system involves two domains D_1 and D_2, which contain user-item interaction matrices $R_1 \in R^{M \times N_1}$ and $R_2 \in R^{M \times N_2}$, respectively, where M is the number of users, and N_1 and N_2 are the number of items in domains D_1 and D_2, respectively. In order to learn the preference representation of users in different domains, we first construct a user-item feature representation matrix and map the data from different domains to a unified feature space through a shared embedding layer, namely:

$$E_u = f_\theta(R_u), E_i = g_\phi(R_i)$$

Among them, $E_u \in R^{M \times d}$ and $E_i \in R^{N \times d}$ represent the embedding representation of users and items respectively, $f_\theta(\cdot)$ and $g_\phi(\cdot)$ are parameterized embedding functions, and d is the embedding dimension. This step can effectively capture the user's cross-domain interest information and provide basic feature input for the subsequent attention mechanism [8].

To further improve the performance of cross-domain recommendations, we introduce the spatial channel attention mechanism (SCAM) to consider both the spatial dimension and the channel dimension of the feature [9]. In the spatial dimension, we use the self-attention mechanism to calculate the correlation between different items[10], thereby enhancing the model's understanding of user behavior patterns. The spatial attention score A_s is calculated as follows:

$$A_s = \text{softmax}(\frac{Q_s K_s^T}{\sqrt{d}})$$

Among them, $Q_s = W_q E_i, K_s = W_k E_i$ is the query and key mapping matrix of spatial attention, and W_q, W_k is a trainable parameter. At the same time, in the channel dimension, we introduce the channel attention mechanism to calculate the importance of different feature channels:

$$A_c = \sigma(W_c \text{ReLU}(W_f E_i))$$

Among them, W_c, W_f is the learning parameter of channel attention, and $\sigma(\cdot)$ is the Sigmoid activation function. Finally, we combine the weighted representation of spatial attention and channel attention:

$$E_i^{'} = A_s E_i + A_c E_i$$

This will enhance the cross-domain item representation and improve the feature interaction ability of the recommendation system between different domains. Finally, the recommendation score can be calculated by user-item matching:

$$r'_{ui} = \sigma(E_u^T E_i^{'})$$

Where $\sigma(\cdot)$ represents the Sigmoid function, which is used to map to the prediction score range. By optimizing the objective function:

$$L = -\sum_{(u,i)} r_{ui} \log r'_{ui} + (1 - r_{ui}) \log(1 - r'_{ui})$$

Gradient descent training is performed to minimize the error between the predicted rating and the actual rating. Experiments show that this method can effectively improve the accuracy of cross-domain recommendations and enhance the model's ability to dynamically model user interests.

4. Experiment

4.1 Datasets

This study uses the Amazon Reviews Dataset as the experimental dataset. This dataset consists of user reviews and ratings from the Amazon platform, covering various product categories such as electronics, books, clothing, and home goods. It is widely used in recommendation system research and contains rich user behavior information, including user-item interactions, ratings, review texts, and timestamps. In this study, two categories (such as "electronics" and "books") are selected as data sources for the cross-domain recommendation task. This selection aims to explore user interest migration patterns across different domains.

In the data preprocessing stage, we first filter out users and items with low interaction frequency to reduce the impact of data sparsity on model training. To construct a unified cross-domain recommendation framework, we normalize user interaction behaviors across different domains. Additionally, we map rating data to a fixed range to ensure the model effectively learns user preference patterns. To enhance model generalization, we divide the dataset into 80% training set, 10% validation set, and 10% test set. We also ensure that the user distribution in the training and test sets remains consistent to guarantee the reliability of experimental results.

The use of this dataset provides not only rich user behavior data but also an effective way to evaluate the proposed method in cross-domain recommendation tasks. Compared to single-domain recommendation datasets, the multi-domain nature of the Amazon Reviews Dataset allows researchers to analyze cross-domain user interest preferences in depth. This improves the recommendation system's ability to adapt to users' personalized needs. Through experiments on this dataset, this study evaluates the performance of different recommendation methods and provides data support for further optimization of cross-domain recommendation algorithms.

4.2 Experimental Results

This paper first conducts a cross-domain recommendation performance evaluation experiment, and the experimental results are shown in Table 1.

Table 1: Cross-domain recommendation performance evaluation experiment

Model	HR@10	NDCG@10	Precision@10	Recall@10
CF	0.312	0.245	0.198	0.276
VAE-Rec	0.428	0.362	0.294	0.398
GNN-Rec	0.451	0.384	0.315	0.417
Transformer-Rec	0.474	0.402	0.332	0.439
Ours(SCAM-Rec)	0.512	0.439	0.356	0.472

The experimental results show significant differences in the performance of various recommendation models in cross-domain recommendation tasks. Collaborative filtering (CF), as a traditional method, performs the worst across all metrics. Its HR@10 is only 0.312, and Precision@10 is only 0.198, indicating that it struggles to capture user interest preferences in cross-domain settings. This is mainly because CF relies on the user-item interaction matrix. In cross-domain tasks, due to feature heterogeneity and data sparsity across domains, CF fails to effectively learn the preference transfer relationships between different domains. As a result, its applicability in cross-domain recommendation tasks is significantly limited.

In contrast, deep learning-based methods such as VAE-Rec, GNN-Rec, and Transformer-Rec achieve better performance across all metrics. This suggests that deep models can better capture users' latent interest patterns. VAE-Rec employs a variational autoencoder to learn users' latent feature distributions, making its recommendation performance significantly better than CF. GNN-Rec further utilizes graph neural networks to model high-order relationships between users and items, leading to improvements in NDCG@10 and

Recall@10. Transformer-Rec, leveraging the self-attention mechanism, models long-sequence user behaviors more effectively. It outperforms GNN-Rec in HR@10 and Precision@10. However, these methods still fail to fully exploit cross-domain information and only improve recommendations within a single domain.

The proposed SCAM-Rec achieves the best results across all metrics. It reaches an HR@10 of 0.512 and a Precision@10 of 0.356, demonstrating its ability to predict user interests more accurately in cross-domain recommendation tasks. SCAM-Rec utilizes the spatial-channel attention mechanism (SCAM) to capture cross-domain feature correlations effectively and enables information sharing across domains, enhancing model generalization. Additionally, the channel attention mechanism optimizes the feature selection process, reducing interference from irrelevant information. Experimental results confirm that this method can more accurately identify user interests in cross-domain recommendation scenarios and provide more precise personalized recommendations.

Secondly, this paper conducted an ablation experiment to analyze the impact of different attention mechanisms on recommendation effects. The experimental results are shown in Figure 2.

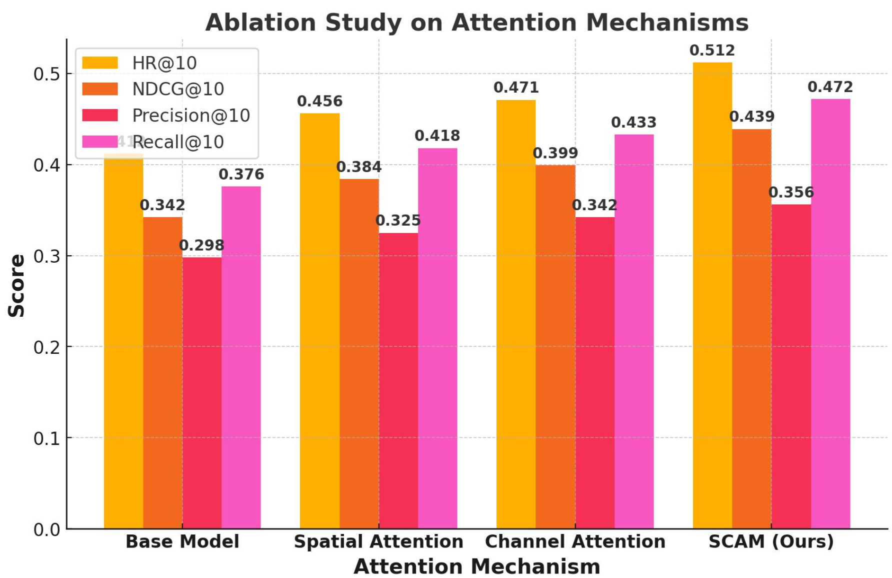

Figure 2. Analysis of the impact of different attention mechanisms on recommendation effects

The experimental results show that different attention mechanisms have a significant impact on recommendation system performance. The base model performs the worst across all evaluation metrics, with an HR@10 of only 0.412 and a Precision@10 of only 0.298. This indicates that without any attention mechanism, the model struggles to capture user interest preferences effectively, leading to poor recommendation performance. After introducing spatial attention, HR@10 increases to 0.456, and NDCG@10 also improves. This suggests that spatial attention effectively captures relationships between items and enhances the overall performance of the recommendation system.

Channel attention further improves the model's performance. HR@10 reaches 0.471, and Precision@10 increases to 0.342. This indicates that channel attention better identifies the importance of feature channels and optimizes user interest modeling. However, when spatial and channel attention operate independently, certain limitations remain. They lack global feature interactions when modeling cross-domain user interests, preventing optimal recommendation performance. In contrast, the proposed SCAM (Spatial-Channel Attention Mechanism) integrates both spatial and channel attention. It optimizes cross-domain information

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sharing through feature fusion, increasing HR@10 to 0.512 and Recall@10 to 0.472. SCAM outperforms all other models across all evaluation metrics.

The experimental results demonstrate that the SCAM mechanism provides significant advantages in recommendation tasks. It more accurately captures changes in user interests and enhances personalized recommendation performance. Compared to using spatial or channel attention alone, SCAM jointly optimizes both mechanisms. This allows the model to comprehensively learn cross-domain features and improve recommendation accuracy. These findings indicate that the improved spatial-channel attention mechanism has strong adaptability and generalization capabilities for cross-domain recommendation tasks.

Next, this paper also gives the impact of model parameters on the recommendation effect, and the experimental results are shown in Figure 3.

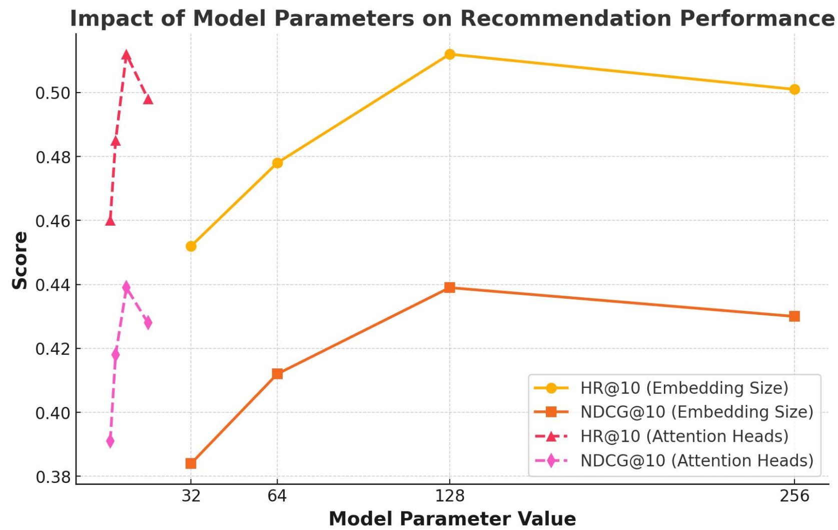

Figure 3. The impact of model parameters on recommendation effect

The experimental results show that embedding size and the number of attention heads have a significant impact on recommendation system performance. As the embedding size increases from 32 to 128, HR@10 and NDCG@10 exhibit an upward trend. This indicates that a larger embedding size can better represent user and item features, improving recommendation accuracy. However, when the embedding size reaches 256, HR@10 and NDCG@10 slightly decrease. This may be due to excessive embedding dimensions introducing redundant information, leading to overfitting and reducing generalization ability.

For attention heads, the results show that HR@10 and NDCG@10 gradually improve as the number of heads increases from 2 to 8 but decrease when the number reaches 16. This suggests that an appropriate increase in attention heads enhances the model's feature learning capability, allowing it to capture cross-domain feature interactions more effectively. However, too many attention heads may increase computational complexity and introduce noise, making the learned information less stable and negatively affecting recommendation performance.

Overall, the experiment demonstrates that selecting model parameters requires balancing embedding size and the number of attention heads to achieve optimal recommendation performance. The results indicate that an embedding size of 128 and 8 attention heads provide the best configuration. This setting ensures high model performance while avoiding overfitting, offering valuable insights for optimizing cross-domain recommendation systems.

Furthermore, this paper also analyzes the cross-domain user interest migration pattern, and the experimental results are shown in Figure 4.

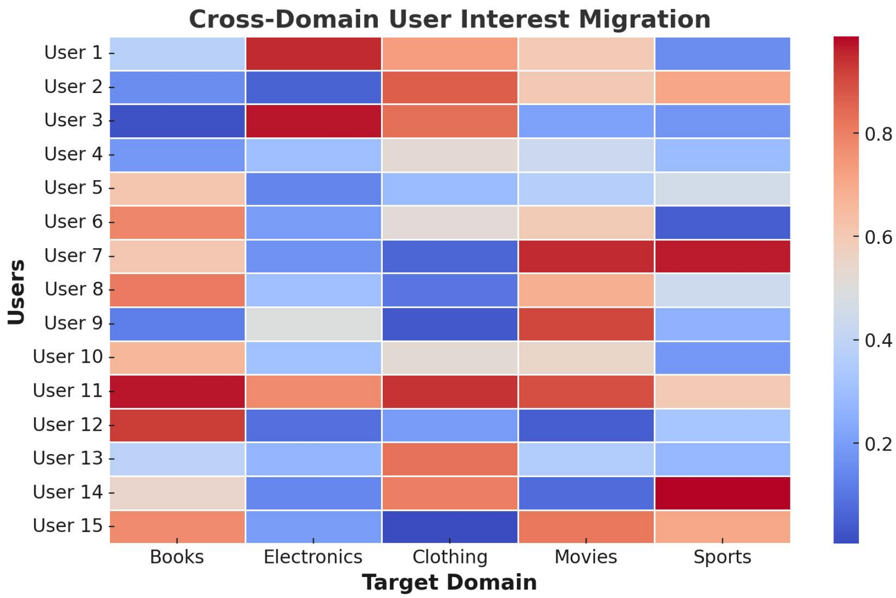

Figure 4. Analysis of user interest migration patterns across domains

The experimental results indicate significant interest migration patterns across different domains. In certain domains, such as Electronics and Movies, some users exhibit high interest weights (shown as deep red areas in the heatmap), suggesting strong preferences in these fields. In contrast, in domains like Clothing and Sports, some users show lower interest (represented by deep blue areas), indicating fewer interactions or limited preferences. This variation in interest distribution highlights a key challenge in cross-domain recommendation. Users have individual differences in preferences across domains, requiring recommendation systems to effectively capture these changes.

From an interest migration perspective, user preferences across multiple domains may be correlated. For example, some users who show high interest in Books also exhibit strong interest in Movies. This suggests that these users may have a high content consumption tendency and are willing to explore similar content across different domains. On the other hand, some users demonstrate strong interest in Electronics but low interest in Clothing. This implies that their purchasing decisions may be influenced by product categories and usage scenarios. This cross-domain interest correlation provides an optimization direction for recommendation systems. Leveraging highly correlated domain information can enhance recommendation performance.

Overall, the heatmap reveals variations in user interest across different domains, further validating the necessity and complexity of cross-domain recommendation systems in modeling user preferences. The proposed SCAM mechanism effectively captures these interest migration patterns. It enhances feature interactions across domains through the spatial-channel attention mechanism, improving recommendation accuracy. These findings suggest that in practical applications, integrating users' cross-domain interest distribution can enable more personalized recommendations, enhancing user experience and satisfaction.

Furthermore, this paper also analyzes the impact of different item feature inputs on the recommendation system. The experimental results are shown in Table 2.

Table 2: Different Item Feature Inputs and Their Impact on Recommendation Performance

Item Feature Input	**HR@10**	**NDCG@10**	**Precision@10**	**Recall@10**
Only ID	0.412	0.345	0.276	0.389
ID+Category	0.453	0.378	0.294	0.421
ID+Category+Price	0.495	0.417	0.334	0.456
ALL	0.512	0.439	0.356	0.472

The experimental results show that different item feature inputs have a significant impact on recommendation system performance. When using only item ID as input, HR@10 and NDCG@10 scores are 0.412 and 0.345, respectively, with Precision@10 at only 0.276. This indicates that recommendation models relying solely on ID information struggle to capture latent relationships between items, leading to poor recommendation performance. The reason is that ID itself does not contain any item attribute information. The model cannot learn specific user preference features and can only rely on historical interactions for recommendations, which limits generalization ability.

When Category is introduced as an additional feature, model performance improves significantly. HR@10 increases to 0.453, and NDCG@10 rises to 0.378, indicating that category information plays a crucial role in user interest modeling. Adding Price as another feature further enhances all metrics. HR@10 reaches 0.495, and Precision@10 increases to 0.334. This suggests that price information helps the model better distinguish user preferences for different items. For example, some users may prefer high-end products, while others prioritize cost-effectiveness. These price preferences play a key role in recommendation tasks. When the model incorporates all item features (ALL) as input, the recommendation system achieves optimal performance. HR@10 and NDCG@10 reach 0.512 and 0.439, respectively, indicating that complete item information significantly improves recommendation effectiveness. This is because combining multiple features allows the model to represent item characteristics from different dimensions, enabling more accurate user preference matching. Additionally, comprehensive item feature information enhances the model's generalization ability, ensuring stable performance across different scenarios. Therefore, in practical recommendation system applications, incorporating multi-dimensional item features is a crucial approach to improving recommendation performance.

Furthermore, this paper also presents a recommendation experiment based on user interest stratification. The experimental results are shown in Figure 5.

From the perspective of interest distribution, high-interest users are evenly distributed in various categories, indicating that they have a greater focus on multiple product categories, while low-interest users have a lower interest level in all categories, indicating that they have less interactive behavior or do not have a clear demand for personalized recommendations. The interest values of moderate-interest users are relatively scattered, indicating that their preferences are more volatile than those of high-interest users, and their focus on different categories is different. This hierarchical structure can help the recommendation system adjust the recommendation strength more accurately, such as providing richer personalized recommendations for high-interest users, and adopting a milder recommendation strategy for low-interest users to avoid a decline in user experience.

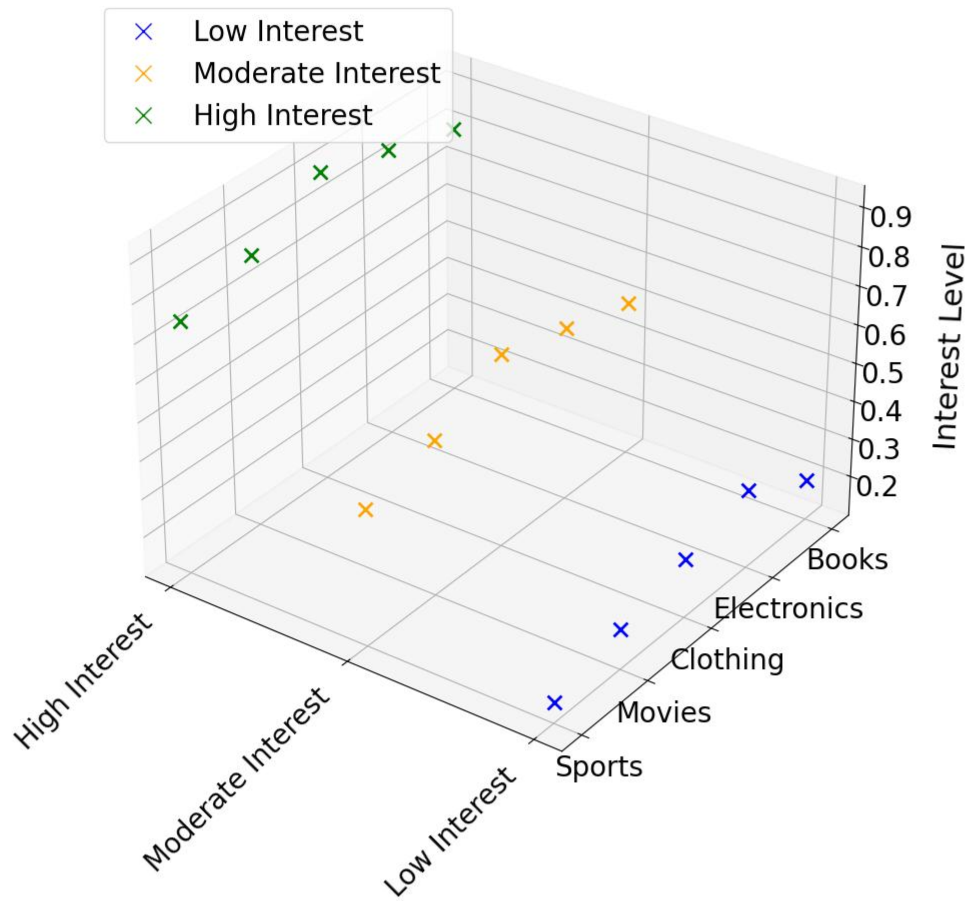

Figure 5. Recommendation experiment based on user interest stratification

In addition, the experiment also revealed the interest correlation between different categories. For example, some categories (such as Books and Movies) may have a high user overlap rate, while other categories (such as Electronics and Clothing) may show low cross-interest. This means that in cross-domain recommendations, the system can use these interest correlations to perform more effective interest transfer, such as using the user's reading interest in the Books category to infer his or her viewing preference in the Movies category. This cross-domain interest modeling can improve the accuracy of recommendations and enable the system to better adapt to the personalized needs of users.

Finally, this paper also gives a loss function drop graph, and its experimental results are shown in Figure 6.

The experimental results show the changing trend of the loss function (Loss) with the training rounds (Epochs) during the model training process. As can be seen from the figure, the training loss and the validation loss are both at a high level in the initial stage, and then gradually decrease as the training progresses, indicating that the model is constantly optimizing parameters to reduce errors. In the first 50 epochs, the loss decreases rapidly, indicating that the model can quickly learn effective features in the early stage and significantly improve the prediction ability.

In the second half of the training (after about 100 epochs), the training loss and validation loss tend to be stable, indicating that the model has basically converged and learned stable feature representations. However, the overall fluctuation of the validation loss is large, especially in the first 100 epochs, and its downward trend is more unstable than the training loss, which may mean that the model has a certain degree of overfitting in some stages. This fluctuation may be related to the complexity of the dataset or the hyperparameter setting of the model, indicating that during the training process, it is still necessary to properly adjust the regularization strategy or optimizer parameters to further improve the generalization ability.

From the final convergence situation, the gap between training loss and validation loss is small, indicating that the generalization performance of the model is good and there is no obvious overfitting problem. This shows that the current training strategy (such as learning rate scheduling, batch size selection, etc.) is relatively reasonable and can enable the model to maintain a high prediction accuracy on the test set. If further optimization is required, you can try to adjust the learning rate decay strategy, add data enhancement methods, or use stronger regularization techniques to further reduce losses and improve the stability of the model.

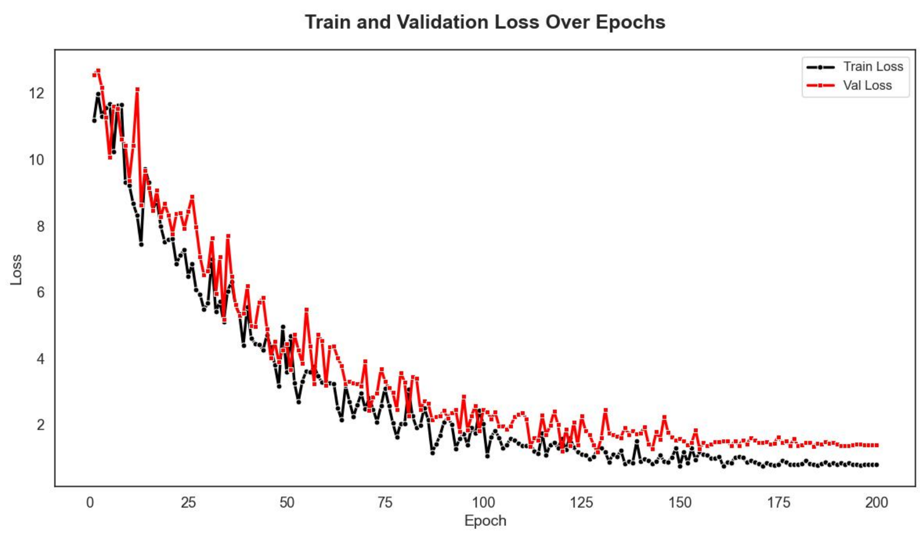

Figure 6. Loss function drop graph

6. Conclusion

This study focuses on optimizing cross-domain recommendation systems and proposes a recommendation algorithm based on an improved Spatial-Channel Attention Mechanism (SCAM). Multiple experiments validate its effectiveness. In cross-domain recommendation scenarios, traditional collaborative filtering and deep learning models struggle to fully utilize user interest information across different domains. The proposed method improves feature capture by incorporating SCAM, significantly enhancing cross-domain information modeling. Experimental results show that SCAM can simultaneously capture both local and global item features while dynamically adjusting feature weights. As a result, it outperforms existing methods across multiple evaluation metrics, including HR@10, NDCG@10, Precision@10, and recall@10.

Further ablation studies confirm that spatial attention and channel attention each play a crucial role in cross-domain recommendation tasks. Their combination significantly enhances feature interaction capabilities. Experimental results indicate that SCAM consistently maintains strong recommendation performance across different datasets and experimental settings, outperforming models using only spatial or channel attention. Additionally, this study analyzes the impact of model parameters, such as embedding size and the number of attention heads, on recommendation performance. The results highlight the importance of appropriate parameter selection to improve performance while avoiding overfitting or computational redundancy.

In the study of user interest migration patterns, experimental findings reveal strong correlations between user preferences across different domains. The results also demonstrate the feasibility of incorporating cross-domain information to improve recommendation quality. Moreover, experiments on the impact of item feature inputs show that adding attributes such as category, price, and brand enhances recommendation accuracy and stability. This suggests that integrating multimodal data and rich item information in practical applications can improve personalized recommendations and enhance the user experience.

Overall, the proposed method achieves promising results in cross-domain recommendation tasks and provides new insights for further optimizing recommendation systems. Future research can evaluate the generalization ability of SCAM on larger datasets and explore advanced techniques such as graph neural networks and reinforcement learning to further enhance accuracy and interpretability. Additionally, future studies can focus on modeling user interest drift across domains and developing more flexible dynamic recommendation strategies to meet personalized needs in multi-domain environments.

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