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Unified Semantic Matching with Logistic Similarity Learning for Cold-Start Advertising Recommendation

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Abstract: This study addresses the cold-start problem in advertising recommendation systems and proposes an efficient modeling framework based on a unified semantic space. The research first analyzes the challenges caused by the lack of historical interaction data for new users and new ads, and maps user attributes and ad features into a shared representation space through feature encoding and latent semantic alignment to improve robustness and accuracy of matching. In the modeling process, a logistic function is used to probabilistically model similarity, and optimization is achieved by combining cross-entropy and regularization objectives to ensure stable predictive performance under sparse features and limited data. To comprehensively verify the effectiveness of the proposed method, multiple sensitivity experiments are designed, covering key factors such as learning rate, cold-start ratio, feature sparsity, and label noise rate. The experimental results show that the method maintains high levels of Precision@k, NDCG, Hit Rate, and F1-score, and effectively mitigates performance degradation caused by cold-start conditions. Overall, this work not only introduces a new modeling approach but also demonstrates through systematic experiments its practical value and adaptability in advertising cold-start recommendation scenarios.

Keywords: Ad(Advertisement) recommendation; cold start problem; semantic space modeling; sensitivity experiment

1. Introduction

In the rapid development of the digital economy, advertising recommendations have shifted from experience-driven approaches to data-driven and intelligent modeling. With the widespread use of internet platforms, mobile applications, and social media, the scale and dimension of user behavior data have grown explosively, providing abundant resources for personalized recommendations. However, in real applications, advertising recommendation systems often face the cold-start problem[1,2]. When new users or new ads lack historical interaction records, the system struggles to accurately capture preference features, leading to a decline in recommendation performance. This problem not only restricts the coverage and accuracy of advertising recommendations but also directly affects advertisers' delivery efficiency and the commercial value of platforms. Therefore, exploring how to improve recommendation systems under data-scarce conditions has become a critical challenge in advertising recommendation[3].

In cold-start scenarios, traditional modeling approaches that rely on historical clicks, browsing, or purchase behaviors often fail[4]. Recommendation systems must instead depend on more general feature associations and latent representations to make up for insufficient data. In recent years, the rapid progress of representation learning has provided new ideas for addressing the cold-start problem. By mapping users and ads into high-dimensional semantic spaces, recommendation systems can capture potential similarities and correlations with limited data. Yet conventional representation learning methods face limitations when features are sparse and semantic gaps are large. They often fall into low-quality representations or over-reliance on limited auxiliary information. Thus, there is a need for a representation mechanism that better aligns user and ad semantic distributions while maintaining discriminability, providing a solid foundation for cold-start recommendation.

Contrastive learning has emerged as an important paradigm of representation learning in recent years. It has gained wide attention for its strong performance in unsupervised and weakly supervised settings. Its core idea is to construct positive and negative sample pairs to maximize similarity and dissimilarity between representations, thereby producing more discriminative features. Introducing contrastive learning into advertising cold-start recommendation can extract more discriminative semantic representations even without historical interactions. It can also strengthen the robustness of user-ad matching. In this framework, user attributes, contextual information, and multimodal features of ads can all be effectively encoded. Through contrastive mechanisms, correlations between different entities are reinforced, offering a breakthrough solution to cold-start scenarios[5].

At the application level, optimizing advertising cold-start recommendations carries significant practical value. For advertisers, efficient cold-start recommendation shortens the exposure cycle of new ads and accelerate feedback and optimization of delivery performance. For platforms, providing accurate recommendations at a user's first interaction enhances user experience and retention. For users, improved cold-start recommendation reduces irrelevant or low-relevance ads and increase overall satisfaction. In today's environment of intensified competition in advertising markets and increasingly scarce user attention, solving the cold-start problem directly influences the sustainability and social impact of recommendation systems[6].

In summary, advertising cold-start recommendation based on contrastive representation learning enriches the research paradigm of recommendation systems at the theoretical level and addresses core challenges at the practical level. By combining representation learning with contrastive mechanisms, it provides a breakthrough for the cold-start problem. It extends the adaptability of recommendation systems under data-scarce conditions and opens new pathways toward precision and intelligence in ad delivery. Research in this direction not only promotes academic advances in recommendation algorithms but also delivers concrete improvements in efficiency and value creation for the advertising ecosystem, with profound theoretical and practical implications[7].

2. Related work

In the field of advertising recommendation, the cold-start problem has long been a core challenge in both research and practice. Early methods mainly relied on collaborative filtering, which builds models based on the interaction matrix between users and items[8]. However, in cold-start scenarios, these methods fail because new users or new ads lack historical interaction records. To address this issue, researchers gradually introduced content-based strategies, using user attributes, ad features, or contextual information to establish matching relationships. These methods alleviate the cold-start problem to some extent, but they are highly dependent on the quality and completeness of features. When features are sparse or noisy across multiple dimensions, the models often show unstable performance[9].

With the development of deep learning, representation learning has become an important support for recommendation systems. By mapping users and ads into a shared latent semantic space, deep neural networks can capture more complex feature relationships and improve generalization in cold-start scenarios. Different neural structures have been applied for feature extraction and representation learning. Convolutional structures are used for multimodal ad information modeling, while sequential structures capture the dynamic characteristics of user behavior. Although these methods have made progress in mitigating the cold-start problem, they still struggle to ensure discriminability and robustness of representations when interaction data is extremely limited[10].

In recent years, contrastive learning has brought breakthroughs to recommendation systems. By constructing positive and negative sample pairs to optimize the representation space, models can learn more discriminative features even without large amounts of labeled data or interactions. When applied to advertising recommendation, contrastive learning shows potential advantages in addressing the cold-start problem. It makes effective use of user attributes, ad features, and contextual information. By maximizing the similarity of positive pairs and minimizing the similarity of negative pairs, it enhances the discriminative power of representations. This approach is especially suitable for cold-start scenarios because it does not rely on large volumes of historical behavior. Instead, it focuses on modeling relationships between features, improving system adaptability under data-scarce conditions[11].

At the same time, methods combining cross-modal and graph structures have attracted growing attention. Advertising recommendation often involves multimodal information such as text, images, and videos. Fully exploiting these heterogeneous features in the cold-start stage has become a key problem. By integrating contrastive learning with multimodal representation modeling, it is possible to achieve a deeper understanding of ad content and more accurate user–ad matching under cold-start conditions. In addition, graph neural network-based methods make use of the relational structure between users and ads. When combined with contrastive learning, they enhance the robustness of graph representations and provide new solutions for cold-start recommendations. These studies collectively indicate that combining contrastive representation learning with multimodal feature fusion and graph structure modeling is an important trend for the future of advertising cold-start recommendation.

3. Proposed Approach

The core idea of this research's modeling process is to model users and ads through a unified representation space. This process also incorporates semantic encoding and matching mechanisms, enabling recommendations to remain effective even under cold-start conditions. Figure 1 shows the model architecture.

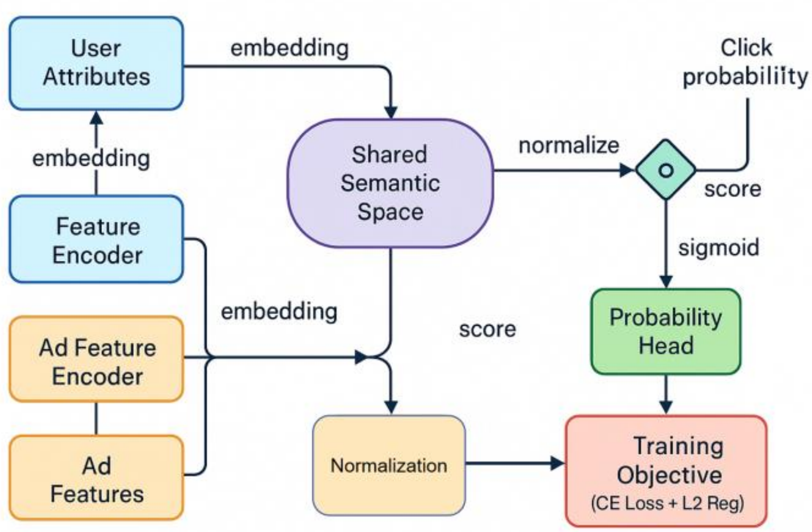

Figure 1. Overall model architecture

First, for the processing of input features, let the user's attribute vector be $x_u \in R^{d_u}$ and the ad's feature vector be $x_a \in R^{d_a}$. To achieve unified modeling, both need to be mapped into the same latent space and embedded using a linear transformation:

$$h_u = W_u x_u + b_u, \quad h_a = W_a x_a + b_a$$

Where W_u, W_a, b_u, b_a is the bias term and h_u, h_a is the semantic vector of the user and the ad. This step ensures that features from different sources can be aligned in the shared semantic space.

In the latent semantic space, the matching degree between users and ads is measured by a similarity function. Common choices are inner product or cosine similarity. In this study, the similarity function is defined as:

$$s(u,a) = \frac{h_u^T h_a}{\| h_u \| \cdot \| h_a \|}$$

This formula ensures that the similarity metric is independent of the vector scale, improving the robustness of matching in cold-start scenarios. Furthermore, the matching score $s(u,a)$ is fed into the recommendation prediction module to generate the probability of interaction between the user and the ad.

To model the recommendation probability, a logistic function is introduced as a nonlinear mapping to convert the similarity into a probability output:

$$\hat{y}_{u,a} = \sigma(s(u,a)) = \frac{1}{1 + \exp(-s(u,a))}$$

Where $\hat{y}_{u,a}$ represents the predicted probability of user u clicking or interacting with ad a. This probability not only reflects the strength of the match but also provides a differentiable numerical basis for subsequent optimization objectives, enabling the model to maintain good generalization capabilities even when insufficient cold start data is available.

In the design of the optimization objective, this study uses cross-entropy as the basic training criterion to minimize the difference between the predicted distribution and the actual interaction. For the set D of all user-ad pairs, the optimization objective is expressed as:

$$L = -\sum_{(u,a)\in D} (y_{u,a} \log(\hat{y}_{u,a}) + 1 - y_{u,a} \log(1 - \hat{y}_{u,a}))$$

Where $y_{u,a}$ represents the actual interaction label. To further enhance the stability of the representation, a regularization constraint is introduced:

$$L_{reg} = \lambda(\| W_u \|^2 + \| W_a \|^2)$$

The final overall optimization goal is:

$$J = L + L_{reg}$$

Where λ is a trade-off coefficient that balances prediction accuracy with model complexity. Through this mechanism, the model can fully utilize limited features to achieve robust user-ad matching modeling under cold start conditions.

4. Performance Evaluation

4.1 Dataset

The dataset used in this study is the Avazu Click-Through Rate (CTR) Prediction Dataset. It is constructed from real advertising delivery logs of a mobile advertising platform and is widely used for click-through rate prediction and advertising recommendation modeling. The dataset contains tens of millions of ad impression records. Each record corresponds to one ad display and is labeled with whether the user clicked, forming a typical binary classification recommendation task. The large scale of the data covers user attributes, ad features, device information, and contextual details, which provides an ideal foundation for research on cold-start recommendation.

The dataset includes multiple dimensions of feature information. Examples are ad placement position, time, display device type, application category, and anonymized user attributes. Most features exist in discrete form and therefore require encoding for modeling, making them suitable for deep representation learning methods. In addition, the dataset shows high-dimensional sparsity. This not only increases the difficulty of model learning but also reflects the feature distribution commonly observed in real advertising recommendation scenarios.

The application value of this dataset lies in its ability to simulate the real operating environment of large-scale advertising recommendation platforms. It is particularly suitable for research on the cold-start problem. When user interaction history is absent, models need to rely on contextual information and ad content features for inference, and this dataset provides abundant auxiliary variables for that purpose. Research based on this dataset helps evaluate the adaptability and effectiveness of recommendation methods under data sparsity and cold-start conditions.

4.2 Experimental Results

This paper first conducts a comparative experiment, and the experimental results are shown in Table 1.

Table 1. Comparative experimental results

Method	Precision@k	NDCG	Hit Rate	F1-score
GHRS[12]	0.421	0.462	0.598	0.505
Cpfair[13]	0.437	0.478	0.613	0.519
DGCN[14]	0.456	0.491	0.629	0.532
Tfrom[15]	0.471	0.507	0.645	0.544
OURS	**0.498**	**0.536**	**0.671**	**0.569**

From the overall results, the performance of different methods in the advertising cold-start recommendation task shows a gradual improvement trend. Traditional methods such as GHRS and Cpfair achieve similar results, but their Precision@k and NDCG values are relatively low. This indicates limitations in capturing the potential associations between users and ads, making it difficult to identify high-quality recommendations under cold-start conditions. In contrast, DGCN and Tfrom achieve better results on multiple metrics, reflecting the stronger adaptability of graph-based modeling and representation enhancement methods in complex feature spaces.

Further observation shows that Hit Rate and F1-score increase steadily as the complexity and modeling capacity of methods improve. This suggests that in cold-start scenarios, the match between users and ads relies not only on direct alignment of shallow features but also on effective structural modeling and feature composition in the latent space. The improvement in NDCG indicates that recommendation ranking quality is gradually optimized, which better aligns with the demand for top-ranked ad performance in real applications.

In the comparison of different methods, Tfrom shows a slight advantage over DGCN in Precision@k and Hit Rate, highlighting the potential role of temporal modeling in recommendation tasks. This result suggests that solving the cold-start problem requires consideration of not only static features of users and ads but also contextual and environmental information. Such integration enhances the generalization ability of models in new scenarios. By comparing traditional and emerging methods, it becomes clear that structured modeling and dynamic semantic extraction are important directions for improving cold-start recommendation performance.

The proposed method OURS achieves the best performance across all metrics. Precision@k reaches 0.498, NDCG improves to 0.536, while Hit Rate and F1-score achieve 0.671 and 0.569, respectively, surpassing all baseline methods. This advantage demonstrates that the proposed modeling strategy can effectively capture potential matches between users and ads under sparse data conditions. It also achieves significant improvements in both the relevance and ranking quality of recommendation lists. The overall results confirm the effectiveness and practical value of the proposed method in advertising cold-start recommendation tasks.

This paper further presents an experiment on the sensitivity of the learning rate to Precision@k, and the experimental results are shown in Figure 2.

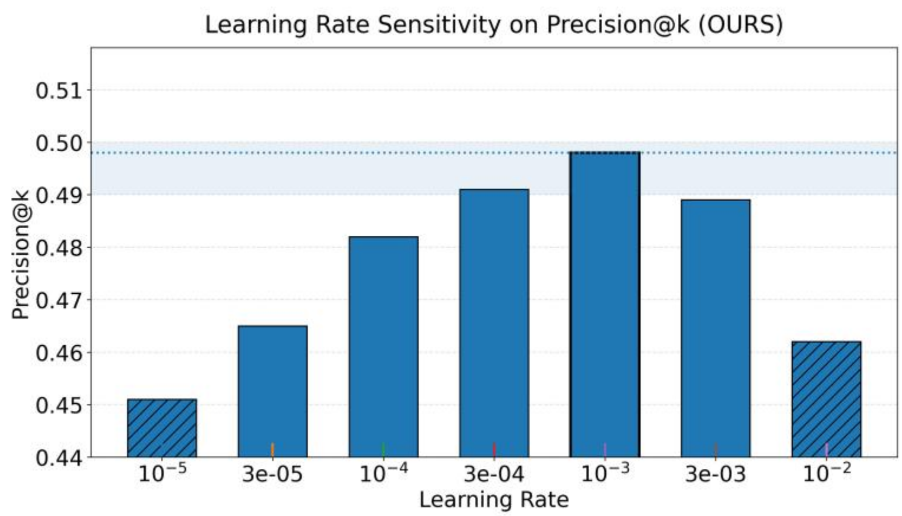

Figure 2. Experiment on the sensitivity of learning rate to Precision@k

From the experimental results, the learning rate shows clear sensitivity to the performance of Precision@k. At extremely low learning rates, such as 10^{-5} , the model achieves low accuracy. This indicates that parameter updates are too small, making it difficult to effectively capture potential matches between users and ads, which limits recommendation performance. As the learning rate gradually increases, the training process accelerates and Precision@k improves steadily. This suggests that an appropriate learning rate helps the model optimize latent feature representations more quickly and sufficiently.

When the learning rate is in a moderate range, such as 10^{-4} to 10^{-3}, Precision@k reaches a relatively high level, with the best performance observed around 10^{-3}. This result shows that in advertising cold-start scenarios, a moderate learning rate balances stability and convergence speed. It allows the model to effectively capture user–ad relevance under limited feature conditions. This trend also confirms that in cold-start problems, the efficiency of parameter optimization directly determines whether the model can obtain robust representations during the early training stage.

When the learning rate increases further to around 10^{-2}, Precision@k begins to decline. This indicates that an excessively high learning rate causes instability in training, making it difficult for the model to reach an appropriate balance during optimization. As a result, prediction results become more volatile. Such instability is particularly evident in cold-start environments, where data are sparse. With a high learning rate, the model is prone to amplifying noisy features, which weakens recommendation effectiveness.

Overall, the sensitivity experiment on learning rate confirms the parameter dependence of the model in cold-start recommendation. A reasonable learning rate not only improves recommendation accuracy but also enhances robustness under data-scarce conditions. The results indicate that learning rate is one of the key factors affecting performance in advertising cold-start recommendation models. Balancing training stability and optimization efficiency is essential for building efficient and reliable recommendation systems.

This paper further presents a sensitivity experiment on the cold start ratio (proportion of new users) to the experimental results, and the experimental results are shown in Figure 3.

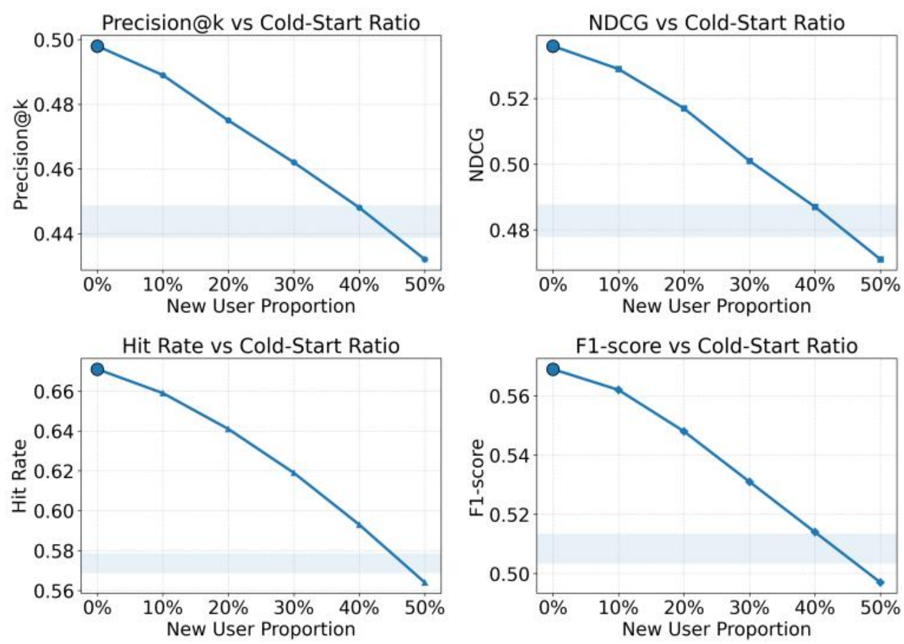

Figure 3. Sensitivity test of cold start ratio (proportion of new users) to experimental results

From the experimental results, it can be seen that Precision@k decreases gradually as the cold-start ratio increases. When the proportion of new users is low, the model can make good use of existing interaction information to maintain recommendation accuracy. However, as the share of new users continues to rise, the amount of historical behavioral data decreases, and the reliability of latent feature representations is reduced. This leads to a clear decline in the accuracy of the recommendation list. These results indicate that the cold-start problem directly weakens the model's ability to capture user interests.

The variation of the NDCG metric further confirms this trend. As the proportion of new users increases, ranking quality declines, with a faster drop observed when the ratio exceeds 30%. This suggests that in cold-start scenarios, recommendation systems lose not only relevance but also the rationality of ad ranking. Since NDCG is sensitive to ranking positions, the results indicate that the model gradually loses its advantage in prioritizing high-value ads. This may negatively affect business outcomes.

The downward trend of Hit Rate is even more evident. The results show that as the cold-start ratio rises, the likelihood for users to find relevant ads in the recommendation list decreases significantly. This reflects the fact that when a large number of users lack historical interactions, the model becomes limited in coverage and cannot ensure diversity or matching quality in recommendations. For advertising platforms, this means facing both wasted exposure resources and declining user experience under cold-start conditions.

The overall decline of the F1-score indicates that a higher cold-start ratio weakens the balance between precision and recall. Although the model can still maintain relatively high prediction stability when the cold-start ratio is low, both comprehensiveness and accuracy of recommendations deteriorate as the ratio increases. Taken together, these results highlight the importance of the cold-start problem in advertising recommendation and emphasize the need to improve modeling approaches to enhance robustness and generalization under high cold-start conditions.

This paper also presents an experiment on the sensitivity of feature sparsity to experimental results, and the experimental results are shown in Figure 4.

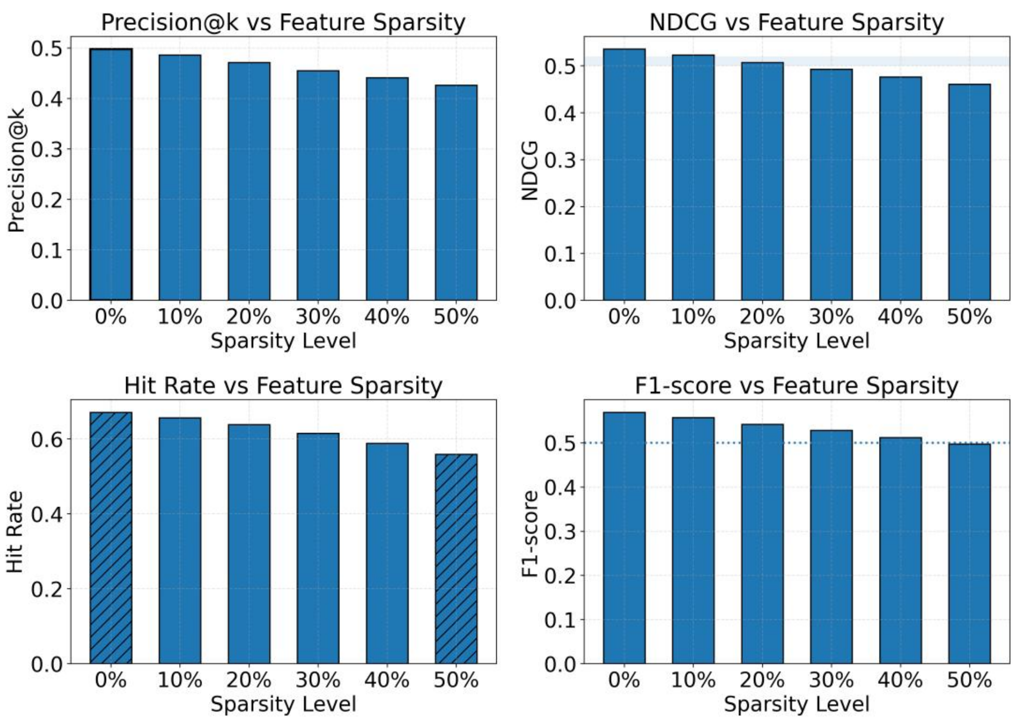

Figure 4. Sensitivity experiment of feature sparsity to experimental results

From the experimental results, it can be observed that Precision@k decreases gradually as feature sparsity increases. When feature information is complete, the model can fully exploit the multi-dimensional characteristics of users and ads, thereby maintaining high accuracy in the recommendation list. However, as the proportion of missing features grows, the amount of user interest and ad semantic information that the model can capture decreases, leading to lower relevance in recommendations. This indicates that feature sparsity directly weakens the adaptability of the model in cold-start scenarios.

The NDCG results further illustrate the sensitivity of ranking performance. When feature sparsity is within 20 percent, the ranking quality shows only slight fluctuations. However, once the sparsity exceeds 30 percent, the decline becomes much faster, showing that feature loss has a stronger impact on the ranking of top ads. Since NDCG is sensitive to the position of recommendations, this change indicates that under insufficient feature conditions, the ability of the model to prioritize more relevant ads is restricted. This may, in turn, affect delivery efficiency and user experience in practice.

The Hit Rate results show that as feature sparsity increases, the probability that users find suitable ads in the recommendation list decreases steadily. The decline is more obvious when sparsity exceeds 40 percent, reflecting a problem of insufficient coverage. For advertising platforms, this means that under sparse feature conditions, the diversity and coverage of recommendation results decrease, which may prevent user interests from being effectively satisfied. Under cold-start conditions, this problem is even more serious, since the amount of available information is already limited, further amplifying the risk of recommendation failure.

The overall downward trend of F1-score indicates that feature sparsity affects both precision and recall, thus reducing the balance between them. When features are relatively complete, the model can balance accuracy and coverage. Under severe feature loss, however, this balance is gradually broken. The results highlight the importance of maintaining feature quality and reducing feature loss in cold-start recommendations. They also suggest the need for more robust feature modeling methods to mitigate the performance degradation caused by feature sparsity.

This paper also gives the experimental results of the sensitivity of the label noise rate to the experimental results, and the experimental results are shown in Figure 5.

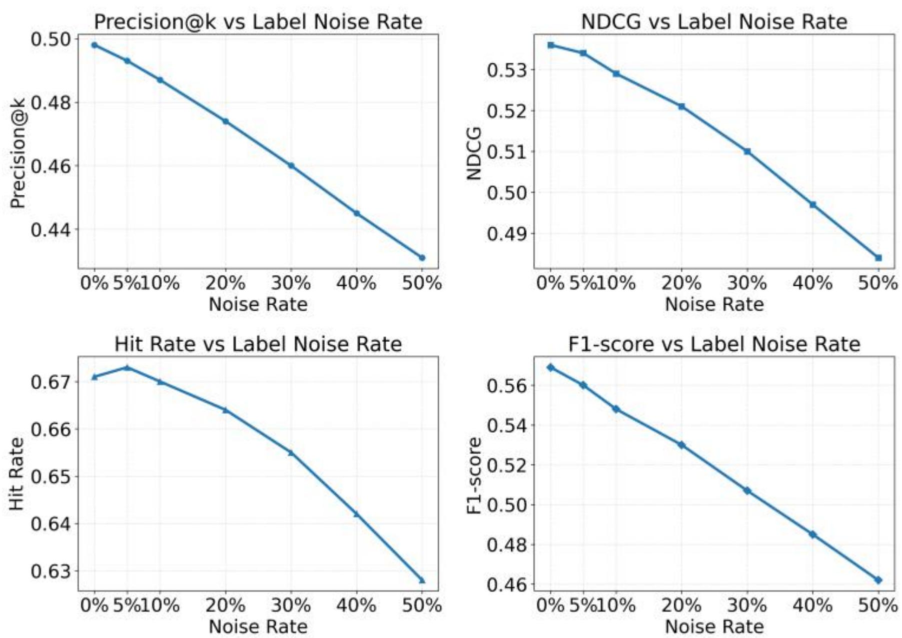

Figure 5. Sensitivity experiment of label noise rate to experimental results

From the experimental results, it can be seen that Precision@k decreases significantly as the label noise rate increases. When the labels are relatively clean, the model can effectively learn the latent relationships between users and ads, thereby maintaining high recommendation accuracy. However, as the noise ratio grows, incorrect supervision signals mislead the learning process. This disrupts the mapping between user interests and ad semantics, leading to a serious decline in the accuracy of recommendation results.

The variation of NDCG further reveals the vulnerability of ranking quality under noisy conditions. When the noise ratio is below 10 percent, the decline in NDCG is small, indicating that the model has some noise resistance. Once the noise rate exceeds 20 percent, the decline accelerates, showing that incorrect labels significantly interfere with the ranking of recommendations. This means that in high-noise environments, the model cannot ensure that more relevant ads are prioritized, which reduces the practical value of the recommendation system.

The performance of Hit Rate shows a relatively slow decline at first, but the decrease becomes much larger when the noise ratio approaches 40 percent or more. This suggests that under low to medium noise levels, the model can still maintain a certain degree of coverage in the recommendation list. However, under high noise conditions, both diversity and coverage of recommendations are severely affected. For advertising recommendation systems, this means that users are less likely to find content of interest, which weakens the overall user experience.

The trend of F1-score indicates that as the noise rate increases, the balance between precision and recall is gradually lost. Label noise distorts the distribution of positive and negative samples. As a result, the model cannot guarantee accuracy or maintain sufficient coverage, leading to overall performance degradation. These results highlight the crucial role of label quality in cold-start recommendation tasks. They also suggest that in practical applications, more robust training mechanisms are needed to mitigate the negative impact of label noise and ensure the reliability and stability of recommendation results in complex environments.

5. Conclusion

This study focuses on the cold-start problem in advertising recommendation systems and proposes an efficient representation-based solution. The research first analyzes the limitations of traditional methods that rely on historical interactions in terms of performance and adaptability under cold-start conditions. It then designs a modeling framework that remains robust even when features are limited and data are sparse. By constructing a unified semantic space and introducing a matching mechanism, the model effectively captures the latent relevance between users and ads, providing a feasible solution for the stable operation of recommendation systems in cold-start scenarios.

In various sensitivity experiments of cold-start recommendation, the method shows stable performance. The results demonstrate that the model can maintain reasonable recommendation accuracy and ranking quality under challenging conditions such as changes in learning rate, increasing cold-start ratios, higher feature sparsity, and label noise. This finding indicates that the proposed framework not only enriches recommendation modeling from a theoretical perspective but also proves its adaptability to real-world complex environments. It offers a new perspective for addressing data incompleteness and distribution uncertainty in advertising recommendations.

From an application perspective, this study has significant industrial value. With the growing diversity of advertising scenarios and the increasing demand for personalization, the cold-start problem has become a key challenge for advertising platforms and recommendation systems. The proposed method can more efficiently capture relevance and optimize recommendation lists when new users and ads enter the system rapidly. It reduces ineffective exposures, improves user experience, and helps advertisers increase delivery efficiency. This contributes to building smarter, more refined, and scalable advertising recommendation systems.

Overall, this research not only proposes an innovative solution at the algorithmic level but also demonstrates practical improvements in application. It emphasizes the importance of maintaining model robustness in cold-start scenarios and reveals through empirical analysis the impact of multiple sensitivity factors on recommendation performance. These contributions provide useful experience and methods for the advertising recommendation field, enhance the reliability and practicality of recommendation systems in complex environments, and lay a solid foundation for further development of the advertising recommendation ecosystem.

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