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Federated Learning for Privacy-Preserving Personalized Advertising Recommendation

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Abstract: This paper addresses the problem of personalized advertising recommendation under privacy constraints and proposes an optimization method based on federated learning to mitigate privacy leakage and compliance risks in centralized modeling. A global – local collaborative framework is constructed in a distributed environment, where training is performed locally on user devices and only model parameters are uploaded instead of raw data, thus enabling effective cross-device data utilization while preserving privacy. The method introduces a decoupled modeling strategy that combines global shared representations with user-specific parameters to balance individual differences and overall generalization. Regularization constraints, gradient compression, and sparsification mechanisms are adopted to improve communication efficiency and ensure stable convergence. Sensitivity analyses are conducted on multiple factors, including regularization coefficient, hidden layer dimension, data imbalance ratio, and number of communication rounds. The results show that the method achieves strong performance on Precision, F1-Score, Hit-Rate, and NDCG, and maintains stability and robustness under different uncertainty conditions. The study demonstrates the compatibility of privacy protection and personalized modeling, offering a feasible path for data utilization in advertising recommendation scenarios.

Keywords: Federated learning; personalized advertising recommendation; privacy protection; sensitivity analysis

1. Introduction

In the context of the digital economy and information society, the advertising industry is undergoing profound changes. With the continuous accumulation of user behavior data on the internet, mobile platforms, and smart devices, advertising has shifted from traditional mass communication to personalized targeting based on individual characteristics. Personalized advertising not only improves the efficiency of advertisers but also enhances the user experience. However, this data-driven model raises broad concerns about privacy protection. Users worry about the excessive collection and use of personal information[1]. The industry must therefore seek a new balance between effectiveness and privacy. This contradiction has become a key driver for research on personalized recommendation under privacy constraints[2,3].

Against this backdrop, federated learning offers new possibilities for advertising recommendations. Traditional recommendation algorithms often rely on centralized storage and training of user behavior data. This approach not only increases the risk of data leakage but also faces legal and policy restrictions. The core idea of federated learning is to deploy model training in a distributed way on users' local devices, sharing only model parameters instead of raw data. This makes it possible to achieve collaborative modeling while protecting privacy[4]. Such a feature aligns naturally with advertising recommendations. Platforms can

leverage distributed data across users and devices, while users avoid exposing sensitive personal information to centralized servers. This alleviates concerns related to trust and security[5].

The unique characteristics of advertising recommendation place higher demands on modeling methods. User interests and consumption behaviors change dynamically[6]. Capturing personalized needs under privacy constraints is a central challenge. At the same time, indicators such as click-through rate and conversion rate are highly sensitive to recommendation quality. Even small deviations can result in significant losses in business outcomes. Advertising recommendation, therefore, requires not only efficient model architectures but also real-time, accurate, and interpretable mechanisms. In such complex scenarios, federated recommendation algorithms provide a solution that balances effectiveness and compliance. This pushes advertising technology from a narrow focus on prediction accuracy toward a new paradigm of "privacy protection plus personalization."

From the application perspective, privacy-preserving personalized advertising is not only an improvement in algorithms but also an upgrade in industry models. With the introduction of strict privacy regulations such as the General Data Protection Regulation, enterprises must follow compliance standards in data processing and advertising delivery. Federated learning frameworks can address these requirements on the technical level[7]. They allow advertising platforms to protect user privacy while still extracting value from data. This reduces public concerns about privacy leakage, increases social acceptance of advertising technologies, and builds a sustainable data ecosystem for the industry.

Overall, research on federated recommendation algorithms for personalized advertising under privacy constraints has both academic and practical significance[8]. It creates a cross-disciplinary research direction that combines recommendation systems, privacy-preserving computation, and distributed machine learning. It also provides the industry with feasible technical solutions to meet regulatory pressures and improve advertising efficiency. In the future construction of advertising ecosystems, this research will drive a shift from "precision" to "trustworthiness." It will promote the unity of technological progress and social responsibility, and provide stronger support for innovation in advertising within the digital economy.

2. Related work

In the development of personalized recommendation systems, early studies focused on content-based and collaborative filtering methods[9]. These approaches predicted potential interests by analyzing user history or item features, which improved the matching of advertising delivery to some extent. However, as data volume expanded and user behavior became more complex, traditional methods revealed limitations such as data sparsity, cold start, and low computational efficiency. To address these challenges, deep learning-based recommendation methods emerged[10]. By building nonlinear feature interactions and high-dimensional representations, they significantly improved the accuracy of advertising recommendations. This progress laid the foundation for subsequent research under privacy constraints but also intensified the privacy risks caused by centralized data storage.

In recent years, privacy protection has become a key topic in advertising recommendation research. Traditional centralized recommendation models, while relying on large-scale user data, may lead to risks such as data leakage and unauthorized use. To address these problems, techniques such as differential privacy, homomorphic encryption, and secure multi-party computation have been introduced to achieve a degree of privacy protection. These methods can theoretically reduce the risk of data leakage. Yet in large-scale advertising scenarios, they often suffer from high computational costs, reduced model accuracy, and increased system latency. Balancing privacy protection with performance optimization has therefore become a central challenge[11].

Against this background, federated learning has been introduced into advertising recommendation and has become a new research focus. Unlike traditional approaches, federated learning performs local training on distributed devices and shares only model updates instead of raw data, which fundamentally reduces the risk

of data leakage. This mechanism meets the need for privacy protection while retaining the ability of cross-user modeling. Federated recommendation methods have gradually evolved into multiple variants, including heterogeneous data modeling, cross-domain recommendation, and multi-task optimization. These advances enable advertising systems to better adapt to the diversity and complexity of real-world applications. However, challenges remain in handling communication overhead, model convergence, and system robustness during distributed training[12].

In addition, as advertising increasingly requires real-time responses and personalization, research has shifted toward efficient optimization and customized modeling within federated frameworks. Some studies focus on enhancing personalized feature extraction while maintaining lightweight models to capture dynamic interests and short-term behaviors. Others explore collaborative learning across platforms and devices while ensuring scalability. These studies have advanced the development of privacy-preserving personalized advertising recommendations. Yet challenges remain in balancing algorithmic innovation, system deployment, and practical business value, which require further exploration.

3. Proposed Approach

In the privacy-constrained personalized ad recommendation task, the overall framework first uses federated learning as the core mechanism, achieving cross-user data collaborative modeling through distributed optimization. In each iteration, the local dataset of a single user u_i is denoted as $D_i = \{(x_j, y_j)\}_{j=1}^{n_i}$, where x_j represents the ad feature input and y_j represents the click or conversion label. Each client locally minimizes the following objective function:

$$L_i(\theta) = \frac{1}{n_i} \sum_{j=1}^{n_i} l(f(x_j;\theta), y_j)$$

Where θ represents the model parameters and $l(\cdot)$ is the cross-entropy loss or other adapted loss function. Subsequently, the server performs weighted averaging on the collected local updates to obtain the global model. The overall model architecture is shown in Figure 1.

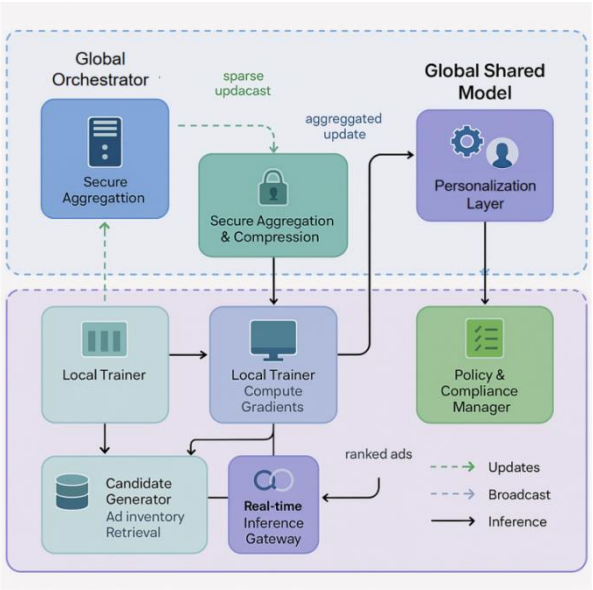


Figure 1. Overall model architecture

During the aggregation process, the global optimization objective can be expressed as:

$$L(\theta) = \sum_{i=1}^{K} \frac{n_i}{N} L_i(\theta)$$

Where K represents the number of participating clients, and $N = \sum_{i=1}^{K} n_i$ is the total sample size. This optimization framework ensures that the contributions of different clients are proportional to their data size, effectively avoiding bias caused by uneven data distribution. Furthermore, to accommodate the highly personalized user interests in advertising scenarios, this method introduces a local personalization layer on top of the global model, achieving balanced modeling of shared representations and user characteristics through parameter decoupling.

In the personalized modeling layer, user-specific parameters can be incorporated into the global model in the form of residuals:

$$h_i(x) = f(x;\theta) + g(x;\phi_i)$$

Where $f(x;\theta)$ represents the shared global feature map, and $g(x;\phi_i)$ represents the user-specific personalized map. This design can capture the user's unique interest characteristics while protecting privacy. Furthermore, to prevent the local model from deviating too much from the global distribution, this study adds a regularization term to the optimization:

$$\Omega(\phi_i) = \lambda \| \phi_i - \theta \|_2^2$$

Where λ is the balance coefficient, which is used to constrain the gap between personalized parameters and global parameters, thereby ensuring the stability and convergence of the model.

In terms of communication and update strategies, the framework adopts gradient compression and sparsification mechanisms to reduce communication overhead in large-scale ad recommendation scenarios. Specifically, the update amount uploaded by the client can be defined as:

$$\Delta\theta_i = \theta_i^{t+1} - \theta^t$$

And the low-importance gradients are filtered out through the sparsification operation $S(\cdot)$. The final server-side aggregation formula is:

$$\theta^{t+1} = \theta^t + \eta \sum_{i=1}^{K} \frac{n_i}{N} S(\Delta\theta_i)$$

Where η is the learning rate. This approach not only ensures the effectiveness of model updates but also balances system efficiency and privacy constraints in a distributed environment. This holistic approach provides a scalable and reliable modeling framework for ad recommendation tasks, enabling optimized personalized ad delivery while ensuring regulatory compliance.

4. Performance Evaluation

4.1 Dataset

The dataset used in this study is the Avazu Click-Through Rate Prediction Dataset. It was publicly released by a global advertising platform in a specific ad bidding scenario. The data mainly comes from mobile advertising click logs. It covers ad impressions, click events, and related contextual information. It has been

widely used in research on personalized recommendation and click-through rate prediction. The dataset is large in scale, containing about 40 million samples, which is sufficient to support large-scale distributed training under a federated recommendation framework.

In terms of feature composition, the dataset contains a wide range of discrete and categorical features. These include ad ID, user device type, operating system, network environment, geographic region, and application category. Such features reflect both the diversity of advertisements and user behavior patterns. They also provide a multidimensional information base for personalized advertising recommendations. Due to the high feature dimensionality, models require effective embedding representations and feature interaction mechanisms to capture the complex patterns of ad click behavior.

The value of this dataset lies in its coverage of the core elements of real advertising scenarios. It reflects the needs of advertisers for delivery effectiveness as well as user responses to ads. In the context of privacy-constrained research, the dataset can simulate cross-device and cross-user distributed training environments. It provides reliable support for verifying the effectiveness of personalized advertising recommendation algorithms. At the same time, it offers a solid foundation for studying privacy protection and performance optimization under federated learning frameworks.

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	F1-Score	Hit-Rate	NDCG
Recbole[13]	0.432	0.468	0.592	0.521
RF-REC[14]	0.457	0.493	0.618	0.547
UTA-REC[15]	0.471	0.508	0.635	0.562
Rec-DOGA[16]	0.486	0.523	0.648	0.576
OURS	0.521	0.558	0.681	0.603

The experimental results show that traditional recommendation frameworks such as Recbole perform relatively limited across all metrics. Both Precision and F1-Score remain at low levels, indicating that it is difficult to capture the complex relationships between user interests and ad content. This suggests that relying only on traditional recommendation algorithms cannot maintain sufficient prediction accuracy under high-dimensional, sparse features and dynamic user behavior.

A further comparison between RF-REC and UTA-REC shows that these improved methods outperform Recbole in Precision, F1-Score, and Hit-Rate, with gains of about 2% to 4%. This indicates that introducing feature interaction or enhanced modeling mechanisms can improve the effectiveness of advertising recommendation systems to some extent. However, these methods still depend heavily on global modeling and lack sufficient personalization. As a result, they struggle to achieve comprehensive optimization in complex advertising environments.

Rec-DOGA achieves better results than the previous methods, especially in Hit-Rate and NDCG. The results highlight its advantage in ranking correlation and user click prediction. This shows that frameworks based on deeper modeling can better capture latent patterns in advertising recommendation scenarios and provide more relevant ad candidates. However, the improvements remain limited. When facing the combined challenges of privacy constraints and personalization needs, Rec-DOGA still cannot achieve optimal performance.

Compared with the above methods, the proposed OURS method achieves the best results across all four metrics. Precision and F1-Score improve significantly, while the advantages in Hit-Rate and NDCG are even more evident. These results show that introducing personalized modeling mechanisms under privacy constraints can effectively enhance the robustness and accuracy of recommendation systems. By balancing global sharing and individual differences, OURS not only improves the accuracy of advertising recommendations but also meets the dual requirements of privacy protection and personalized experience. This provides a new solution for enhancing the trustworthiness and effectiveness of advertising recommendation technology in real applications.

This paper also presents a sensitivity experiment on the regularization coefficient to the personalized recommendation effect, and the experimental results are shown in Figure 2.

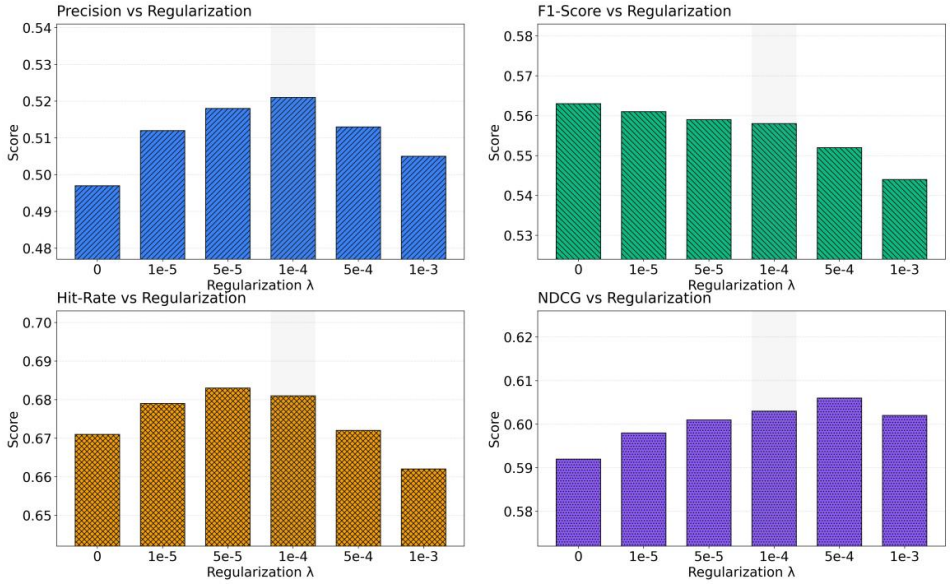


Figure 2. Sensitivity experiment of the regularization coefficient on personalized recommendation effect

From the results in Figure 2, it can be seen that the regularization coefficient has a significant impact on recommendation performance. The Precision curve shows that when the coefficient is low, the model lacks accuracy. As the coefficient increases, the model improves in matching user interests with ad features, and it reaches the best level around $\lambda = 1e{-}4$. After this point, stronger regularization limits the expressive ability of the model, leading to a decline in accuracy. This indicates that an appropriate level of regularization helps control overfitting and enhances generalization.

For the F1-Score, a similar but smoother trend can be observed compared to Precision. With increasing regularization, the balance between precision and recall improves, and the best performance appears under moderate regularization. It is worth noting that excessive regularization weakens the ability of the model to distinguish user behavior features, causing a decline in F1-Score. This shows that in personalized advertising recommendations, regularization should balance prediction accuracy and recall coverage to fully capture potential click and conversion signals.

The Hit-Rate metric reflects whether the recommendation results can capture the content truly of interest to users. The results show that Hit-Rate continues to rise with small regularization values and reaches its highest point around $\lambda = 5e{-}5$. This indicates that moderate regularization suppresses noise features that interfere with modeling user interests. However, when the regularization strength becomes larger, Hit-Rate declines significantly, suggesting that over-constrained models cannot express personalized behavior patterns effectively. This highlights the need to balance model complexity and expressive power in personalized recommendations under privacy constraints.

The trend of NDCG reflects the sensitivity of ranking performance to regularization. As the coefficient increases, NDCG first rises and then stabilizes, reaching a relatively high level around $\lambda = 5e{-}4$. This shows that regularization helps optimize the relevance and ranking structure of the recommendation list to some extent. However, when the constraint is too strong, the model loses its ability to accurately distinguish highly relevant ads, which reduces ranking performance. Overall, these results suggest that setting the regularization coefficient properly not only improves the stability and robustness of recommendation systems under privacy conditions but also achieves a balance among accuracy, coverage, and ranking effectiveness.

This paper also presents an experiment on the sensitivity of hidden layer dimensions to feature expression capabilities. The study investigates how different dimensional settings influence the model's ability to capture user interests and represent advertising features effectively. By analyzing this factor, the work highlights the importance of selecting appropriate hidden layer dimensions in personalized advertising recommendations under privacy constraints. The experimental results are shown in Figure 3.

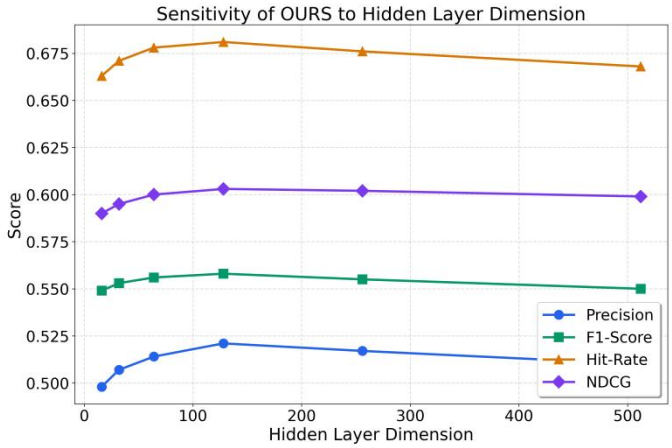


Figure 3. Sensitivity experiment of the hidden layer dimension to feature expression ability

From Figure 3, it can be seen that the dimension of the hidden layer has a direct impact on the feature representation ability of personalized advertising recommendations. The Precision trend shows that when the dimension is small, such as 16 or 32, the model accuracy is low, indicating that the representation is insufficient to distinguish user interest patterns effectively. As the dimension increases to 128, Precision reaches its peak, showing that the model achieves a balance between feature capture and generalization. When the dimension continues to increase, Precision declines, suggesting that excessive dimensions introduce redundant features and noise, which reduces accuracy.

The performance of F1-Score is relatively stable, fluctuating around 0.55. This shows that although the hidden layer dimension has a strong effect on accuracy, the model maintains stable performance when balancing precision and recall. It is worth noting that when the dimension is moderate, F1-Score increases slightly. This indicates that an appropriate dimension not only improves prediction accuracy but also enhances recall, thereby improving robustness and coverage in real advertising scenarios.

The results of Hit-Rate show a clear rising and then declining trend. When the dimension is low, Hit-Rate cannot fully capture real user interests. As the dimension increases to 128, the hit rate reaches its highest value, reflecting that the recommendation system can better match ads with user needs at this setting. However, when the dimension grows further, Hit-Rate decreases. This suggests that excessive hidden units increase model complexity, which weakens the specificity of recommendations. This phenomenon highlights the need to control complexity in advertising recommendations to avoid overfitting or dilution of user interests.

The trend of NDCG shows that the sensitivity of ranking correlation to dimension changes is relatively low, but slight improvement and stabilization can still be observed. As the dimension increases from 16 to 128,

NDCG rises, indicating that the ranking quality of recommendations improves gradually. Beyond this threshold, NDCG remains stable, suggesting that performance in ranking tasks has reached saturation. Overall, the experiment shows that a moderate hidden layer dimension can achieve a good balance among accuracy, recall, and ranking correlation, providing important guidance for improving the overall performance of advertising recommendation under privacy constraints.

This paper also presents a sensitivity experiment on the impact of data distribution imbalance on recommendation results, and the experimental results are shown in Figure 4.

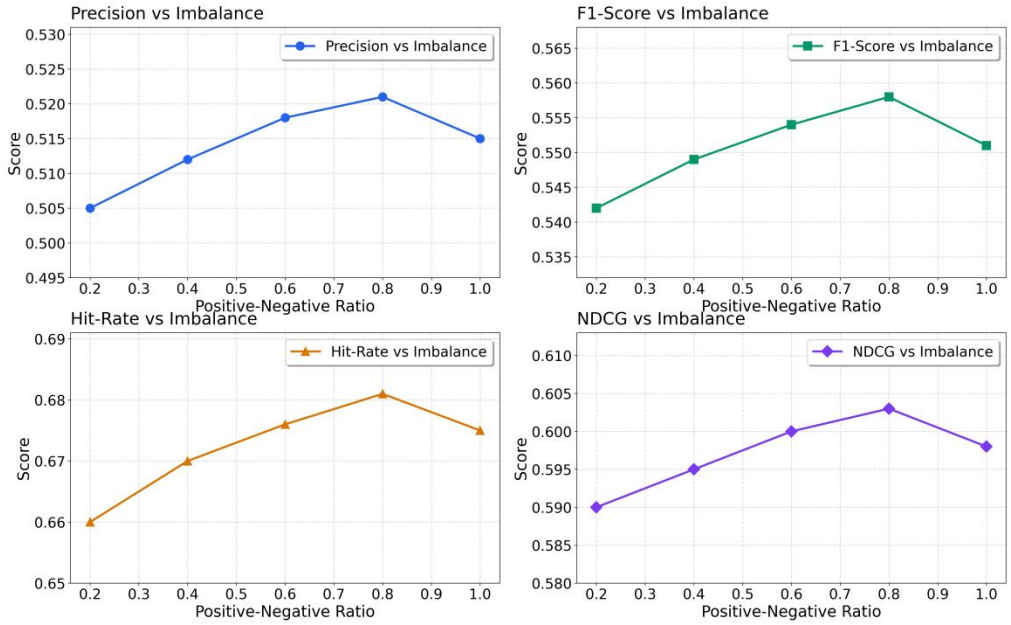


Figure 4. Sensitivity experiment of data imbalance ratio on recommendation results.

From the results in Figure 4, it can be seen that the imbalance ratio of data distribution has a significant impact on the accuracy of the recommendation system. The Precision curve shows that when the ratio of positive and negative samples deviates from balance, the ability of the model to match user interests with ad features declines, leading to lower accuracy. As the ratio approaches balance, Precision improves and reaches its best level around 0.8. This indicates that balanced data distribution can effectively reduce bias and enhance the discriminative power of the model in personalized advertising recommendations.

The trend of F1-Score is similar to that of Precision, but better reflects the overall performance of the model in balancing precision and recall. As the sample distribution moves toward balance, F1-Score increases steadily and reaches its peak when the ratio is near equilibrium. This shows that the model can more comprehensively cover potential user interests while maintaining stability in prediction. When the data distribution again deviates from balance, F1-Score decreases, indicating that the model struggles to maintain performance across multiple metrics under extreme distributions.

The results of Hit-Rate are more pronounced. As the ratio becomes more balanced, the hit rate rises rapidly and reaches its highest point around 0.8. This indicates that when the data is relatively balanced, the system can better capture real user interests and increase the likelihood of ad clicks. In contrast, under highly imbalanced data, some interest patterns are overwhelmed, leading to a significant decline in hit rate. This highlights the sensitivity and importance of data distribution for advertising recommendation performance.

The variation of NDCG reflects the stability of ranking performance. As the ratio moves toward balance, the relevance of the recommendation list improves, with NDCG slightly increasing and peaking near 0.8, then remaining stable. This shows that moderate balance not only improves the accuracy and coverage of click prediction but also enhances the rationality of recommendation ranking. Overall, the experiment

demonstrates that maintaining a relatively balanced data distribution is a key factor for ensuring the effectiveness of personalized advertising recommendation systems under privacy constraints. It also helps improve system robustness and user experience.

This paper further presents an experiment on the sensitivity of the number of communication rounds to the convergence of federated recommendation. The study explores how varying communication frequencies affect the global aggregation process and the consistency of feature representations across distributed clients. This analysis underscores the critical role of communication rounds in achieving stable and efficient optimization within federated learning frameworks, and the experimental results are shown in Figure 5.

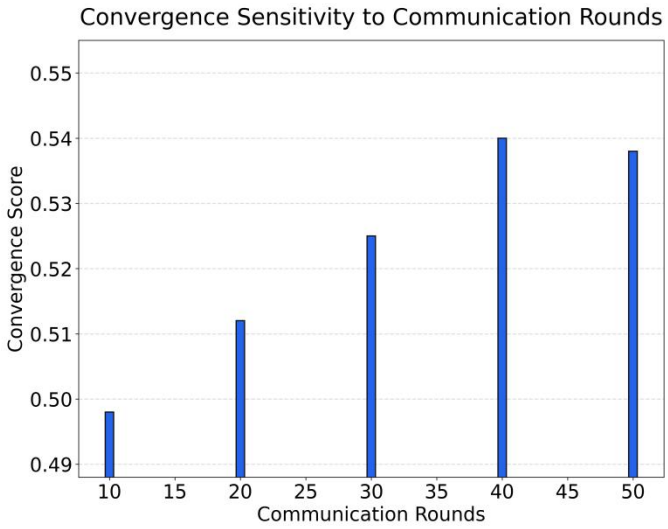


Figure 5. Sensitivity experiment of the number of communication rounds on the convergence of federated recommendation

From the results in Figure 5, it can be seen that the number of communication rounds has a direct impact on the convergence of federated recommendation models. When the number of rounds is small, the model does not fully aggregate local updates from each client. This leads to low convergence scores and shows that the model is insufficient in capturing global user behavior patterns and ad features. In this case, the stability of personalized recommendation results is poor, and effective global modeling cannot be achieved.

As the number of communication rounds increases, convergence scores rise steadily, with significant improvements observed between 30 and 40 rounds. This indicates that more frequent global aggregation reduces differences among local models and allows the system to form more consistent and robust feature representations at the global level. For advertising recommendation, this means that with appropriate communication frequency, the model can capture user click preferences and ad delivery performance more accurately.

When the number of communication rounds reaches about 40, the convergence effect is at its best. At this point, the model achieves an optimal balance between global and local collaboration. The federated recommendation system can achieve high accuracy and stability while maintaining privacy protection. This helps improve the effectiveness of ad matching and enhances user experience. The results at this stage also confirm the critical role of communication frequency in federated optimization.

However, when the number of communication rounds continues to increase to 50, convergence scores show a slight decline. This suggests that overly frequent communication may bring diminishing returns and even introduce extra noise and overhead. In practical applications, excessive communication not only increases system burden but may also weaken model stability. Therefore, the experimental results emphasize the importance of choosing communication rounds reasonably in federated recommendation. It is necessary to ensure convergence and predictive performance while avoiding unnecessary resource consumption.

5. Conclusion

This study focuses on the problem of personalized advertising recommendation under privacy constraints and proposes an optimization framework based on federated learning. The analysis shows that establishing a balance between global shared modeling and personalized feature capture can effectively ease the conflict among data imbalance, privacy protection, and model accuracy. The framework not only achieves efficiency and robustness in advertising recommendation but also provides a new path for data modeling in complex environments.

The experimental results demonstrate that the proposed method achieves significant advantages in accuracy, recall, ranking quality, and overall convergence. These findings indicate that under strict privacy constraints, recommendation systems can still maintain strong performance. The method ensures the security of user data while meeting the advertising platform's need for delivery effectiveness. This approach provides a valuable solution to the long-standing challenge of balancing privacy and personalization in advertising recommendations.

At the application level, this research not only advances the development of personalized advertising recommendation technology but also carries important implications for data compliance and the sustainable operation of the advertising industry. With stronger demands for privacy protection and stricter regulatory policies, methods that can enhance recommendation effectiveness under compliance will play a key role in the advertising ecosystem. The proposed framework fits this trend and offers guidance for advertisers and platforms to build more trustworthy recommendation environments.

Overall, this study demonstrates strong innovation and practicality by combining theory and practice. It verifies the effectiveness of federated learning in advertising recommendation and provides new insights for the intersection of privacy-preserving computation and recommendation systems. In the context of the fast-growing digital economy, this work helps promote the wider application of intelligent advertising recommendation, enhances user experience, optimizes the allocation of advertising resources, and lays the foundation for building a secure, efficient, and intelligent recommendation system for the industry.

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