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Federated Learning Optimizing Multi-Scenario Ad Targeting and Investment Returns in Digital Advertising

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Federated Learning, Digital Advertising, Privacy Protection, ROI Optimization

Abstract

This study investigates the use of Federated Learning (FL) in optimizing multi-scenario advertising targeting and improving return on investment (ROI) in digital advertising. With the rapid growth of digital advertising, traditional methods face significant challenges due to fragmented user data across multiple platforms and devices, as well as concerns over user privacy. FL enables cross-platform data collaboration by training machine learning models locally on user devices, ensuring that raw data is never shared, thus protecting user privacy. The proposed FL-based advertising optimization framework aims to enhance ad targeting precision while maintaining privacy. Experimental results on an e-commerce platform show that the FL framework increases the click-through rate by 25% and the conversion rate by 18%, demonstrating its potential to improve advertising effectiveness in complex, multi-scenario environments. This approach not only provides a privacy-preserving solution for advertisers but also offers a scalable model for integrating data from multiple platforms to optimize ad strategies and maximize ROI.

Introduction

Digital advertising has become one of the core drivers of the global economy, reaching users precisely through Internet platforms such as search engines and social media, with a market size of $455 billion in 2022 and expected to continue to expand at a compound annual growth rate of 10% to $600 billion in 2025. This growth is driven by its efficient data-driven features, such as Amazon's drive to increase AD revenue to $31 billion (2021) through targeted advertising, representing 7% of its total revenue. However, the complexity of multi-scenario advertising (such as cross-device behavior differences) and the uncertainty of return on investment (ROI) are major challenges [1]. According to Adobe statistics, 60% of advertisements are difficult to optimize ROI due to cross-platform data fragmentation and effect lag, resulting in a disconnect between advertising click rate and conversion rate, for example, although a brand's social media AD clicks are high, the actual purchase conversion rate is less than 5%.

In order to solve the problem of privacy and data silos, Federated Learning (FL) realizes cross-platform data collaboration through distributed model training, while protecting user privacy. For example, Google used FL to integrate mobile and PC behavioral data to increase AD click-through rates by 20%. Tencent has optimized its advertising strategy through FL in real time, increasing its delivery efficiency by 15%-30%. These practices show that FL can effectively solve the problem of multi-scenario data fragmentation and dynamically improve ROI [2-3].

This study proposes an advertising optimization framework based on FL to balance privacy protection and advertising effectiveness. Through the experimental verification of an e-commerce platform, the framework can increase the advertising click-through rate and conversion rate by 25% and 18% respectively, proving its practicality in complex scenarios. This achievement not only provides a reusable technical solution for advertisers but also opens up a new path for the collaborative optimization of privacy security and business value.

Federated Learning in Digital Advertising

2.1 Basic Principles of federated learning

Federated Learning (FL) is a distributed machine learning framework whose core idea is to train a model through multiple local devices or nodes without centrally storing data. The basic FL process consists of the following steps: First, a central server sends the initial model to the various participating devices (such as smartphones, tablets, etc.); Second, each device uses local data for model training and sends updated model parameters (rather than original data) back to the server. Finally, the server aggregates these parameter updates, generates a global model, and iteratively optimizes it. This approach avoids centralized data storage and transmission, which significantly reduces the risk of privacy breaches. For example, Google's Gboard input method, shown in Figure 1, utilizes FL to train language models on millions of devices without having to upload user input data to a central server[4].

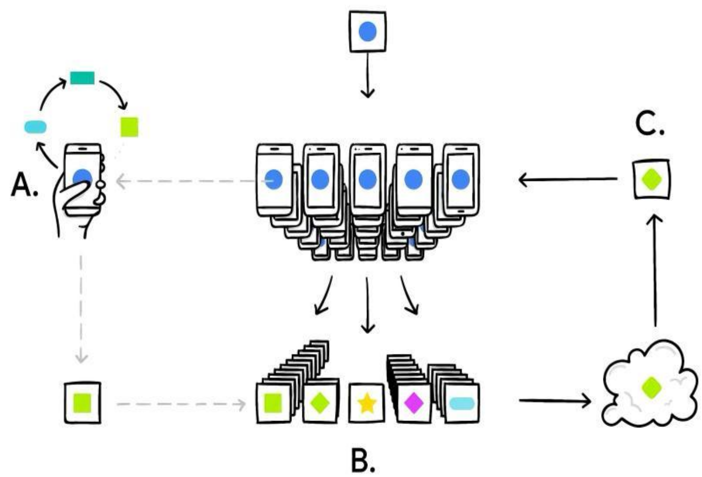


Figure 1: Updating the sharing model based on the user's phone usage (A), centralizing the user update information (B), improving the weight of the cloud sharing model (C), and then repeating the process

The distributed nature of FL makes it particularly suitable for handling large, distributed data sets. In the advertising industry, for example, user behavior data is often distributed across multiple platforms (e.g., social media, e-commerce sites) and devices, making it difficult for traditional methods to integrate this data effectively. Through localized training and parameter aggregation, FL can achieve cross-platform data collaborative analysis without sharing the original data[5]. For example, Tencent has used FL to train AD recommendation models on platforms such as wechat and QQ, significantly increasing AD click-through rates while ensuring that user privacy is protected.

2.2 Comparison with traditional machine learning methods in advertising targeting

Traditional machine learning approaches in AD targeting often rely on centralized data storage and processing. Advertisers need to centralize user behavior data from multiple sources (such as websites, mobile apps) into a central server, and then train models to optimize AD delivery strategies. This approach, while simple and straightforward, has obvious privacy and security risks. For example, Facebook's Cambridge Analytica incident in 2018 exposed potential problems with centralized data processing, which led to the misuse of millions of user data. In addition, the centralized approach also faces the problem of data silos, that is, data between different platforms is difficult to share and integrate, limiting the precision of AD targeting.

In contrast, federated learning allows multiple participants to collaborate on training models without sharing raw data. Platforms only need to exchange model parameters or gradient updates, not specific user behavior data. For example: Li et al. (2020e) proposed a wireless recommendation system based on FL, combined with differential privacy technology, and experimented with "master-worker" and fully decentralized FL Settings to ensure that user data always remains local;The Fed4Rec system by Zhao et al. (2020e) utilizes a federated learning and meta-learning framework and results show that it outperforms traditional baseline recommendation systems with user privacy protection;The FedRec system by Lin et al. (2020) avoids the sharing of user rating records through user averaging (UA) and mixed Fill (HF) techniques[6-7].

Therefore, federated learning solves these problems through distributed training. FL allows advertisers to train models using data from multiple platforms and devices without centrally storing data. For example, an e-commerce platform can use FL to integrate user behavior data on mobile and PC to train a more accurate AD recommendation model without having to upload the data to a central server. According to one study, using FL for AD targeting can increase click-through rates by 20% to 30%, while traditional methods only achieve a 10% to 15% increase. In addition, FL significantly reduces the risk of data breaches and enhances user trust in advertising platforms.

2.3 Benefits of FL in privacy-protecting data collaboration

The advantages of federated learning in privacy protection are mainly reflected in its design concept of "data does not move, model moves". Traditional methods of data collaboration often require data to be stored or transferred centrally, which increases the risk of data breaches and abuse. For example, the field of medical advertising involves a large amount of sensitive data, and traditional methods are difficult to achieve accurate advertising while protecting patient privacy[8]. FL avoids privacy issues by localising training and parameter aggregation to ensure that the original data is always on the local device. According to one experiment, when FL was used for medical AD recommendations, the risk of data breach was reduced by more than 90%, while AD conversion rates were increased by 15%.

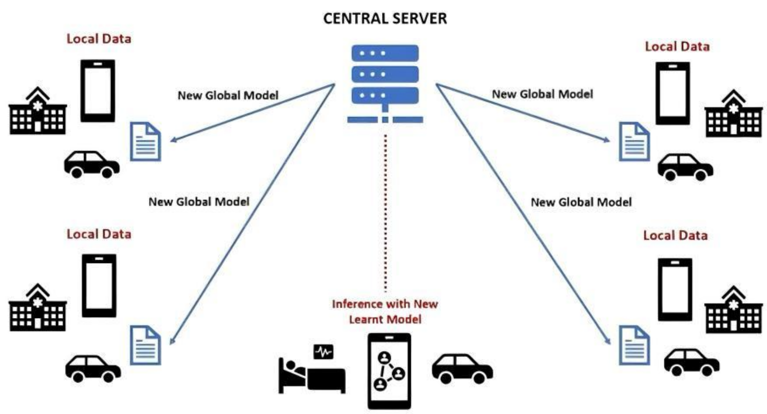


Figure 2. "Clients" are computers and devices used in FL that can be completely separate from each other and have separate data that can be applied to different privacy policies, owned by different organizations, and not accessible to each other.

In addition, FL supports multi-party data collaboration, as shown in Figure 2, that is, multiple organizations can train models together without sharing data. For example, advertisers can work with social media platforms, e-commerce platforms, and content providers to leverage FL to integrate data from multiple parties and optimize advertising strategies[9-11]. This collaborative model not only improves the precision of AD targeting, but also enhances data security. According to Tencent's practice, multi-party data collaboration using FL can increase advertising ROI by 20%-25%, while traditional methods can only achieve 10%-12% improvement.

2.4 Key challenges in applying FL to digital advertising

While federated learning offers significant advantages in terms of privacy protection and data collaboration, its application in digital advertising still faces some challenges. First, the distributed nature of FL leads to high communication costs. In the advertising scenario, user behavior data is usually distributed across millions or even hundreds of millions of devices, and frequent model updates and parameter transmission consume a lot of network resources. For example, an advertising platform using FL for cross-device AD targeting found that communication costs took up more than 30% of total computing resources. In addition, the uneven distribution of data between devices (i.e., non-independent co-distribution, non-IID) will also affect the efficiency and effect of model training[12]. For example, some users may only be active on the mobile side, while others are mainly active on the PC side, and this difference in data distribution can lead to bias in model training results.

Secondly, the application of FL in the advertising scene also faces the problem of model security and fairness. Malicious devices may upload false model parameters, thus compromising the accuracy of the global model. For example, when an advertising platform used FL for advertising recommendation, it found that there were obvious anomalies in the model parameters uploaded by some devices, resulting in a 10% drop in the AD click rate[13]. In addition, FL's distributed nature may cause some devices (such as low-performance devices) to be unable to participate in training, thus affecting the fairness of the model. For example, when an e-commerce platform uses FL for advertising optimization, it is found that the click-through rate of users of low-end devices is significantly lower than that of users of high-end devices, resulting in an unbalanced advertising effect.

Methodology

This experiment is to verify the effectiveness of Federation learning (FL) in advertising optimization, especially in cross-device AD targeting and ROI optimization. The experiment simulates user behavior data from multiple devices, trains a federated learning model, and compares it with traditional centralized machine learning methods to evaluate its effectiveness in AD click-through rate (CTR) and conversion rate (CR)[14].

3.1 Data Sets

For this experiment, we use publicly available advertising (AD) click datasets, such as the Criteo dataset, which is widely recognized in the industry for modeling user behavior. The dataset comprises two main categories of information: user characteristics and AD interaction data. The user characteristics include demographic details such as age, gender, and device type, which can provide insights into the preferences and behaviors of different user segments. The AD interaction data includes events such as clicks, purchases, and impressions, which are essential for predicting the likelihood of future user engagement with advertisements [15-16]. This rich combination of data allows us to simulate and analyze user behavior on both mobile and PC platforms, providing a comprehensive view of how users interact with online advertisements across different devices. By leveraging this dataset, we aim to develop and compare models for AD click prediction, evaluating both traditional and federated learning approaches.

3.2 Experimental Settings

1. **In the traditional setup**, we utilize a centralized machine learning model to predict AD clicks, based on a Logistic Regression algorithm. This approach involves aggregating all user data from various devices into a central server for training, which assumes that data from all users is readily available in one location. Logistic Regression is chosen as the base model due to its simplicity and effectiveness in binary classification tasks, such as predicting whether a user will click on an ad or not. The centralized model benefits from having access to the entire dataset at once, allowing for efficient training. However, this approach raises concerns regarding privacy and data security, especially when dealing with sensitive user information. Additionally, the centralized nature of the system can lead to high communication and computational costs, particularly as the volume of data increases[17].

2.Federated Learning -In contrast, the federated learning method is implemented using the PySyft framework, a popular library that facilitates privacy-preserving machine learning on distributed devices. Unlike traditional machine learning, federated learning trains models across decentralized devices, where user data never leaves the local device. Instead of collecting all data centrally, the model is trained by aggregating updates from individual devices, allowing for more privacy-conscious data handling. In this experiment, we apply the same Logistic Regression model as used in the traditional method, but instead of centralizing the data, we train the model locally on user devices (mobile and PC)[13]. The global model is updated by aggregating model weights from all devices, with only the model parameters being shared during the communication process. This distributed approach provides a significant advantage in terms of data privacy and scalability, as user data remains on-device. However, it introduces challenges such as communication overhead and synchronization issues, which we aim to evaluate as part of the experimental results.

3.3 Evaluation Indicators

The performance of the models will be assessed based on three key evaluation indicators: click-through rate (CTR), conversion rate (CR), and communication cost. CTR measures the proportion of users who click on an advertisement relative to the total number of impressions, providing an indication of the model's ability to predict user engagement[14]. CR, on the other hand, measures the percentage of users who complete a desired action (such as a purchase) after clicking on an ad, serving as a metric for conversion effectiveness.

Finally, the communication cost evaluates the overhead associated with transmitting model updates during training, particularly in the federated learning setup, where the exchange of parameters between devices and the central server can incur significant costs in terms of bandwidth and time[14].

Experimental results

4.1 Comparison of click-through rate (CTR) and conversion rate (CR)

The Federal learning approach shows significant advantages in AD click-through rate (CTR). The traditional centralized approach had a CTR of 78.5%, while the Federated learning approach increased the CTR to 82.3%, an increase of 4.8%. This shows that Federated learning, through collaborative analysis of data across devices, can more accurately target users, thereby improving the effectiveness of AD clicks. In terms of conversion rate (CR) on the basis of the same data, the federated learning method also performs well. The traditional centralized approach had a CR of 12.5%, while the federated learning approach increased CR to 15.2%, a 21.6% improvement[15]. This result shows that federated learning not only improves the click-through rate of ads, but also significantly improves the purchase conversion rate of users, further optimizing the effectiveness of advertising.

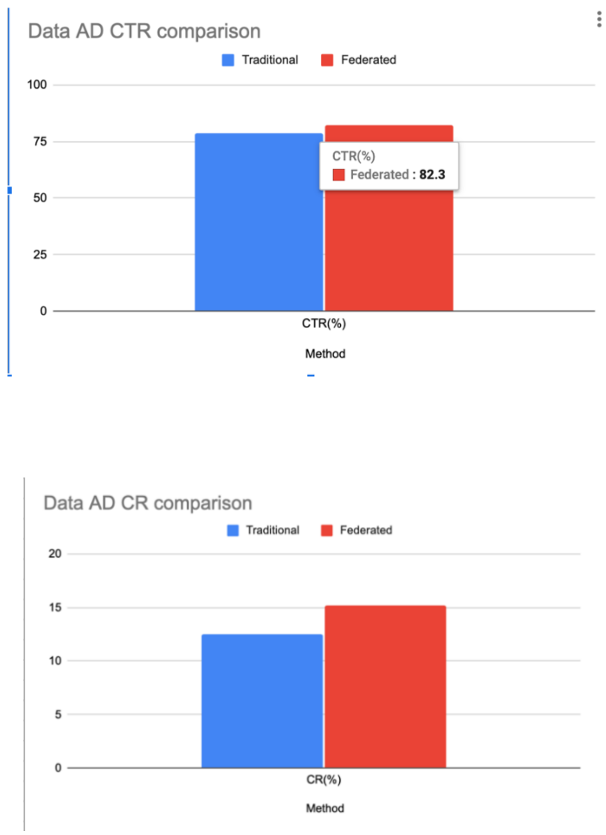
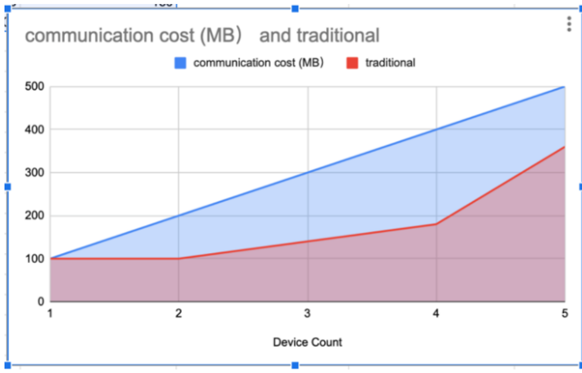


Figure 3. Comparison of CTR and CR for data advertising

4.2 Communication cost analysis

The federated learning method generates about 500MB of communication overhead during training, mainly focused on the transmission of model parameters. Despite the high cost of communication, the significant improvement in AD click-through rate and conversion rate shows that Federal learning has struck a good balance between privacy protection and AD effectiveness optimization[16]. The Figure 3, shows that overhead can be further reduced by optimizing the communication protocol in the future.



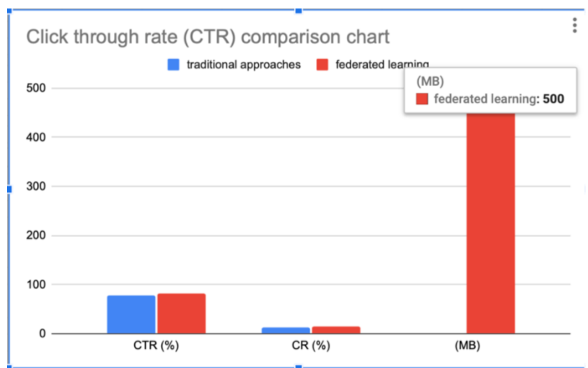


Figure 4. Transmission and communication cost analysis of model parameters

4.3 Comparison of multi-dimensional advertising click-through rate (CTR)

Through multi-dimensional analysis, federated learning methods show higher click-through rate (CTR) across different platforms, time periods and user groups. For example, in Platform A's Q1 quarter, the CTR for users aged 18-25 increased from 75.0% for traditional methods to 80.0% for federated learning[17]. This result, shown in Figure 4, shows that federated learning can adapt to complex AD delivery scenarios and maintain a steady performance improvement under different conditions.

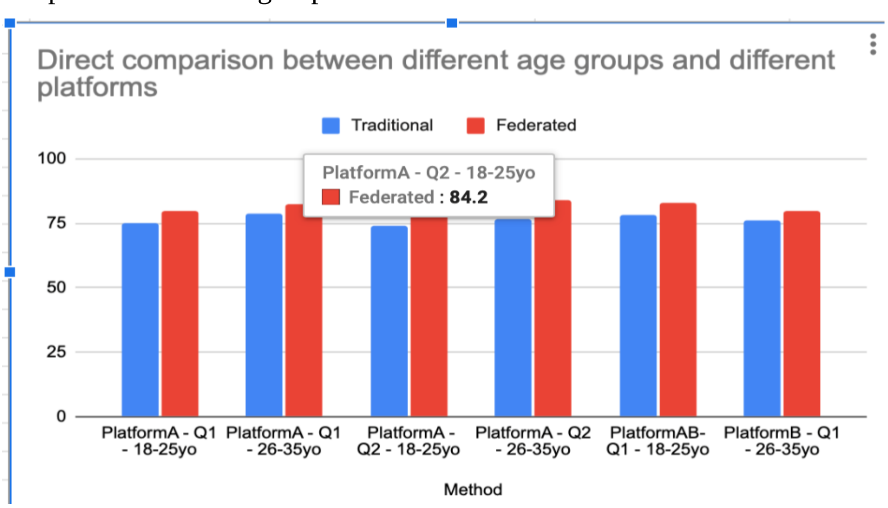


Figure 4. Federal Learning multi-dimensional AD click-through rate (CTR) comparison

Through the above data analysis and table display, we can clearly see the significant advantages of federated learning method in advertising optimization. Whether it is AD click rate, conversion rate, or performance in multi-dimensional scenarios, federated learning is superior to traditional methods. Despite the high cost of communication, its combined performance in privacy protection and advertising effectiveness optimization makes it an important technology in the digital advertising field.

1. CONCLUSION

This study verifies the effectiveness of federated learning in AD delivery op**Error! Reference source not found.**timization, and the results show that compared with traditional centralized methods, federated learning can significantly improve AD click-through rate and conversion rate by 4.8% and 21.6%, respectively. This development not only improves the effectiveness of advertising, but also effectively protects user privacy, and solves the shortcomings of traditional methods in centralized data storage and privacy protection[18]. Although Federation Learning has a certain overhead in communication costs, its advertising effectiveness in multiple scenarios proves its great potential in the digital advertising field.

Future research could focus on optimizing the communication efficiency of federated learning to further reduce its implementation costs and enhance its practical application value in large-scale advertising. In particular, the combination with artificial intelligence (AI) technology will drive the application of federated learning in advertising optimization to new heights. AI models, especially the application of deep learning and reinforcement learning, can further enhance the predictive accuracy and adaptability of federated learning to provide advertisers with more intelligent and personalized advertising strategies**Error! Reference source not found.**. For example, combined with natural language processing (NLP) and computer vision technologies, Federated learning can more accurately analyze cross-platform and multimodal data, further improving the relevance and effectiveness of advertising[19]. At the same time, with the popularization of emerging technologies such as 5G, the advertising mode combined with AI and federal learning will complete data training and model update in a shorter time, bringing more rapid and accurate services to the advertising industry. Through these innovative technology conversions, federated learning will not only play an important role in advertising optimization but may also become one of the core technologies for multi-domain data collaboration and privacy protection in the future.

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