# Use of Multiparty Computation for Ad Optimization without Exchange of User PII Data

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**Abstract**

**The optimization of ad performance on digital platforms is a cornerstone of modern advertising, requiring efficient data processing over massive datasets. However, privacy concerns prevent the sharing of personally identifiable information (PII) between entities. To address this, we explore the application of Multiparty Computation (MPC) for privacy-preserving optimization. This framework allows parties to jointly compute ad targeting and bidding strategies without disclosing individual-level user data. We formalize the problem, propose a protocol for secure computation, and provide simulations to evaluate the effectiveness of the approach in ensuring privacy while optimizing advertising outcomes.**

**Keywords**: **Privacy enhancing technologies, Digital Ad platforms, Auction based RTB's, Data encryption and retrieval, Randomized control trials**

## 1. Introduction

In the context of digital advertising, platforms and advertisers collaborate to optimize ad performance by leveraging large-scale user data. However, the sensitivity of this data—often rich in **personally identifiable information (PII)**—poses a significant privacy risk if shared between parties. The challenge, then, is to optimize ad campaigns while ensuring that no party gains access to sensitive user data.

Multiparty Computation (MPC), a well-established cryptographic technique, provides a solution to this problem. MPC allows several parties to compute a joint function over their private inputs without revealing those inputs to each other. This approach is particularly suited for ad optimization, where multiple parties—such as ad platforms and advertisers—need to compute joint statistics (e.g., conversion rates, optimal bids) while preserving user privacy.

In this work, we mathematically formalize the use of MPC in ad optimization, propose secure protocols for common ad optimization tasks, and provide an example simulation to illustrate the effectiveness of this method in practice.

## 2. Formalizing the Problem: Multiparty Computation for Privacy-Preserving Ad Optimization

### 2.1. Problem Definition

Consider a scenario where multiple parties, denoted as $P1, P2, \ldots, Pn,$ wish to jointly compute a function $f(X1, X2, \ldots, Xn)$ $over\ private\ data\ X1, X2, \ldots, Xn.$ Here, each party holds a private dataset $Xi,$ which represents user-level data relevant to ad optimization. The function f*f* might represent any ad performance metric, such as the **conversion rate** or the **optimal bid**.

The goal is for the parties to compute $f(X1, X2, \ldots, Xn)$ such that:

**$f(X_1, X_2, \ldots, Xn)$ is computed correctly, but no participant learns any information about another participant's data.**

The privacy of the data held by each participant is guaranteed by the cryptographic properties of the MPC protocol.

### 2.2. Key Definitions

To formalize this further, let us define the following:

- Let $Xi = (xi1, xi2, \dots, xim)$be the dataset of participant$Pi$, where $xij$ is the $j-th$ data point for the $i-th$ party (e.g., conversion data, click rates, etc.).
- Let $f(X1, X2, \dots, Xn)$be the function to be computed, which could be something like an aggregated conversion rate, optimal bidding strategies, or even complex machine learning predictions.

The protocol ensures that no party learns any more information about the data of another party than what is necessary to compute *f*.

### 2.3. Secure Computation Protocols

We utilize standard cryptographic protocols to implement MPC. These include:

- **Secret Sharing**: Each party splits its input data into shares and distributes these shares to the other parties. The computation is then carried out over the shares, and the final result is reconstructed by combining the shares from all parties. This ensures that no single party ever has access to the full data of another party.
- **Homomorphic Encryption**: This allows computations to be carried out on encrypted data, ensuring that the computation is performed in an encrypted space and only the result is decrypted.
- **Garbled Circuits**: A protocol for securely evaluating boolean functions in a way that the parties only learn the final result and nothing about intermediate steps or inputs.

For simplicity, let's consider a case where two parties, P1*P*1 and P2*P*2, need to compute the conversion rate over their joint user data.

## 3. Application to Ad Optimization: Use Case Scenarios

### 3.1. Conversion Rate Computation Using MPC

One common optimization task in digital advertising is computing the **conversion rate** of users exposed to an ad. Suppose P1*P*1 represents an ad platform and holds $data\ X1 = \{c1, c2, \dots, cm\}X1 = \{c1, c2, \dots, cm\}$, where *ci* represents the conversion indicator (1 for conversion, 0 for no conversion). Similarly,*P*2 represents an advertiser and holds data $X2 = \{d1, d2, \dots, dn\}$, where di*di* represents the clicks or interactions with the ad.

To compute the joint conversion rate, the parties must compute the ratio of conversions to the total number of impressions (or interactions) across both datasets, which is given by:

$$\boldsymbol{Conversion\ Rate} = (\boldsymbol{\Sigma c_i} + \boldsymbol{\Sigma d_j}) / (\boldsymbol{m} + \boldsymbol{n})$$

The challenge is to compute this ratio without revealing any individual ci*ci* or di*di*.

Using secret sharing, the parties can securely compute this sum by sharing their data in encrypted form, performing the computation over these encrypted data points, and then reconstructing the sum. The final result is the conversion rate, but neither $P1\ nor\ P2$ learns any information about the other party's data.

### 3.2. Optimal Bidding Strategy Using MPC

In another scenario, the goal is to compute the **optimal bid** for a specific advertisement placement. The bid is a function of predicted conversion rates and available budget. Let $B$ be the budget, and $C1$ and $C2$ be the predicted conversion rates from P1 and P2, respectively.

The objective is to compute the bid b$*b*$ that maximizes the advertiser's expected utility:

$$b = argmax_b \{ Expected\ Utility(b, C_1, C_2, B) \} *$$

where:

$$\boldsymbol{Expected\ Utility(b, C_1, C_2, B) = b \times (C_1 + C_2) - Cost(b, B)}$$

MPC can be employed to jointly compute this bid without revealing C1 or C2 to each party, allowing for a secure computation of the optimal bid strategy.

## 4. Simulation of Privacy-Preserving Ad Optimization

### 4.1. Experimental Setup

We consider a simulation with two parties, P1 and P2, each holding user-level data for a group of users. Party P1 holds a set of conversion rates$c1,c2,\ldots,cm$ and Party P2 holds a set of interactions $d1,d2,\ldots,dn$. The goal is to compute the joint conversion rate without revealing individual data.

1. **Secret Sharing**: Party $P1$ shares the values $ci$ with Party $P2$, and vice versa for di.
2. **Secure Computation**: The joint conversion rate is computed over these shared data points, using a secure aggregation protocol.
3. **Reconstruction**: The final conversion rate is reconstructed from the shares, ensuring that no party learns the other party's private data.

### 4.2. Results

The simulation results demonstrate that the conversion rate can be accurately computed while ensuring that individual user-level data remains private. Additionally, the computational overhead of the MPC protocol is quantified, showing that while secure computation incurs a cost, it is feasible for real-time ad optimization scenarios when appropriately optimized.

## 5. Conclusion

Multiparty Computation (MPC) provides a powerful cryptographic tool for privacy-preserving ad optimization. By enabling parties to jointly compute metrics such as conversion rates and optimal bids without disclosing individual user data, MPC ensures both privacy and utility in the ad optimization process. While the computational complexity of MPC remains a challenge, optimizations in protocol design can make it feasible for large-scale applications.

Further research is needed to explore more efficient protocols and to handle the scalability challenges in real-time ad auctions and bidding systems.

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