Use of Differential Privacy Techniques to Measure Incrementality of Ad Performance on Digital Platforms without Exchange of PII

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Abstract

Incrementality measurement is critical for evaluating the causal impact of digital ad campaigns. Typically, these analyses rely on precise user-level data for randomized control trials (RCTs), often necessitating the exchange of Personally Identifiable Information (PII) between ad platforms and advertisers. Differential Privacy (DP) offers a robust solution to this challenge by introducing noise into the data, thereby ensuring privacy without the need for PII exchange. This paper presents a detailed methodology for applying DP to incrementality measurement in digital advertising. We formulate the problem mathematically, outline a framework for incorporating DP mechanisms, and explore practical considerations such as privacy budget management, noise scaling, and the balance between privacy and utility. We also provide an in-depth simulation study to quantify the effectiveness of DP in protecting user privacy while maintaining accurate causal lift estimation.

Keywords: Privacy enhancing technologies (PETs), Causal inference, Randomized control Trials, Differential Privacy

Introduction

In the digital advertising ecosystem, understanding the incremental effect of an advertising campaign is paramount. Incrementality refers to the causal lift produced by an ad campaign compared to a control group. Traditionally, ad platforms and advertisers conduct randomized control trials (RCTs) to estimate lift, with randomization at the user level and conversion measurement at the advertiser level. However, this approach requires extensive access to granular user data, raising significant privacy concerns.

Differential Privacy (DP) is a mathematical framework that allows organizations to aggregate and analyze data without exposing individual user information. By adding controlled noise to the data, DP ensures that the inclusion or exclusion of any single data point (such as a user) does not significantly affect the overall result. In this paper, we propose an approach that applies DP to incrementality measurement, focusing on preserving user privacy while ensuring accurate causal inferences.

Mathematical Framework for Differential Privacy

1. Differential Privacy Mechanisms

A randomized mechanism is said to be differentially private if the presence or absence of any single individual in the dataset does not significantly change the outcome of any analysis. Formally, a mechanism M provides ε-Differential Privacy if:

$$Pr[M(D) \in S] \leq e\text{^}\varepsilon \cdot Pr[M(D') \in S] \, \forall \, S \subseteq Range(M)$$

Where:

- D and D' are neighboring datasets differing by one individual,
- S is any subset of the output space,
- ε is the privacy parameter that governs the amount of noise added to the data.

The mechanism typically adds noise that scales with the "sensitivity" of the function being computed. Sensitivity measures how much the output of a function can change when one individual's data is altered.

Laplace Mechanism

For functions that involve counting or summing over users, the Laplace mechanism is commonly used, adding noise drawn from the Laplace distribution:

$$M(D) = f(D) + Laplace(0, \Delta f/\varepsilon)$$

Where $f(D)$ is the function (e.g., conversion rate), and Δf is the sensitivity of the function, which measures the maximum possible change in the output when any individual's data is altered.

Gaussian Mechanism

For functions that require less stringent privacy guarantees (e.g., for higher utility), the Gaussian mechanism can be used, where noise is added from a Gaussian distribution with variance proportional to sensitivity:

$$M(D) = f(D) + N(0, \Delta f^2/\varepsilon^2)$$

Application to Incrementality Measurement

1. Definition of Incrementality (Lift)

Incrementality measures the causal effect of an ad campaign by comparing the behavior of users exposed to the ad (test group) against those not exposed (control group). The lift (incrementality) is typically expressed as the percentage difference between the conversion rates of the test and control groups:

$$L = (CR\_test - CR\_control) / CR\_control$$

Where:

- CR_test is the conversion rate of the test group (ad-exposed users),
- $CR\_control$ is the conversion rate of the control group (ad-unexposed users).

In the DP context, the conversion rates for the test and control groups are computed with added noise to preserve privacy.

2. Adjusting for Differential Privacy

In practice, to ensure that the conversion rates computed for the test and control groups adhere to differential privacy, noise is added as follows:

For the test group:

$$CR\_test = CR\_test + Laplace(0, \Delta f/\varepsilon)$$

For the control group:

$$CR\_control = CR\_control + Laplace(0, \Delta f/\varepsilon)$$

Thus, the DP-adjusted lift is:

$$L = (\hat{}CR\_test - \hat{}CR\_control) / \hat{}CR\_control$$

Where $\hat{}CR$ represents the noisy estimates of the conversion rates.

3. Privacy Budget and Noise Scaling

Managing the privacy budget is a crucial part of the DP framework. The total privacy loss is accumulated over multiple queries or mechanisms. If multiple lift measurements are performed (e.g., across different campaigns), the privacy budget is allocated accordingly. This can be controlled using advanced composition theorems that help track the total privacy loss across multiple uses of the mechanism.

Challenges in DP-based Incrementality Measurement

1. Misclassification Due to Randomization Misalignment

A key challenge in applying DP to incrementality measurement is the misclassification that arises from the misalignment of randomization units and measurement units. For example, if randomization occurs at the user level on the ad platform, but measurement occurs at the account level on the advertiser side, households with multiple users can be randomly split between test and control groups. This misclassification can distort lift estimates, and the added DP noise further complicates this issue.

To address this, we propose modeling the misclassification as a probabilistic event where users in the test group may be attributed to the control group and vice versa. Statistical techniques, such as Bayesian models or Markov Chain Monte Carlo (MCMC) methods, could be used to correct for these biases and refine lift estimates under DP constraints.

2. Privacy-Utility Trade-Off

Differential Privacy inherently introduces noise into the analysis, which reduces the accuracy of lift estimates. The extent of noise depends on the privacy parameter ε, with smaller values of ε offering stronger privacy guarantees but introducing greater noise. Finding the optimal balance between privacy and utility is critical.

3. Household-Level Effects

Another challenge is the presence of household-level effects, where one member of a household is exposed to an ad, and another is in the control group. This introduces potential "halo effects" where the exposure of one individual influences the behavior of others, which may lead to under- or over-estimation of the true lift.

Simulation Study and Results

Setup

- **Number of Users**: 100,000
- **Test-Control Split**: 50% test, 50% control
- **Baseline Conversion Rate**: 1% for control

- **True Lift**: 5%
- **Privacy Parameter (ε)**: 0.1, 0.5, 1.0
- **Mechanism**: Laplace mechanism applied to conversion rates

Results

The simulation revealed that as the privacy parameter ε decreases, the variance in the measured lift increases due to the higher noise introduced by the DP mechanism. However, when the number of users in the sample increases, the noise impact diminishes, improving the reliability of the incrementality estimate.

Impact of Misclassification

The misclassification due to randomization misalignment was shown to cause a significant understatement in measured lift, especially for households with multiple users. Adjustments using DP noise compounded this effect but also ensured that the privacy of user-level data was maintained.

Conclusion

Differential Privacy provides a powerful tool for ensuring privacy-preserving incrementality measurement in digital advertising. While challenges remain in mitigating the impact of misclassification and household-level effects, the proposed DP framework offers a mathematically sound and scalable solution to privacy concerns in causal lift analysis. By balancing the privacy budget and carefully managing noise scaling, DP can be used to provide reliable, privacy-compliant incrementality insights.

Future work will focus on refining the models to better account for household-level effects and optimize the trade-off between privacy and utility in real-world advertising contexts.

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