International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 08 | Aug - 2022 SJIF Rating: 7.185 ISSN: 2582-3930

Improvement in Minimum Detectable Effects in Randomized Control Trials: Comparing User-Based and Geo-Based Randomization

Varun Chivukula

varunvenkatesh88@berkeley.edu

Abstract
In digital advertising, randomized control trials (RCTs) are a fundamental method for evaluating campaign effectiveness. The randomization approach, whether user-based or geo-based—can substantially impact the statistical power and precision of detecting treatment effects. This paper explores the influence of these randomization methods on the Minimum Detectable Effect (MDE), focusing on how intra-cluster correlation (ICC) in geo-based randomization inflates variance and increases sample size requirements. Through mathematical modeling and simulation, we demonstrate that user-based randomization is more efficient, particularly for detecting small advertising effects, and offer recommendations for optimizing experimental designs in digital advertising contexts.

Keywords: Causal inference, Randomized Control Trials, Digital Advertising, Minimum Detectable Effect

1. Introduction

Digital advertising campaigns often require randomized control trials (RCTs) to assess the effectiveness of various treatments, such as ad creatives, bidding strategies, or targeting techniques. The method of randomization—user-based or geo-based—determines how treatment groups are assigned, affecting the accuracy with which advertisers can detect small treatment effects.

In geo-based randomization, entire geographic regions (e.g., cities or ZIP codes) are assigned to treatment or control groups. This approach often results in high intra-cluster correlation (ICC), as users within the same geographic area may share similar characteristics or behaviors. User-based randomization, on the other hand, assigns individual users to treatment or control groups, reducing ICC and the resulting variance.

This paper examines how these randomization strategies influence the MDE, which is crucial for determining the smallest effect that can be reliably detected in an ad campaign. We present a theoretical framework for calculating MDE under each randomization method and use simulations to evaluate the impact on sample size and power in digital advertising trials.

2. Methodology

2.1 Minimum Detectable Effect (MDE) Formula

The MDE in an RCT can be calculated using the following formula:

$$\text{MDE} = (Z_{\alpha/2} + Z_\beta) \cdot \sqrt{\frac{\sigma^2}{n_t} + \frac{\sigma^2}{n_c}}$$

Where:

- $Z_{\alpha/2}$ is the critical value for the desired confidence level (e.g., 1.96 for 95% confidence),
- Z_β is the critical value for the desired statistical power (e.g., 0.84 for 80% power),
- σ^2 is the variance in the outcome (e.g., click-through rate, conversion rate),
- n_t and n_c are the sample sizes in the treatment and control groups, respectively.

2.2 Variance Inflation in Geo-Based Randomization

In geo-based randomization, the variance is inflated by ICC, which is the correlation between users within the same geographic cluster. This inflated variance is represented as:

$$Vgeo = \sigma 2 \cdot (1 + (n^{-} - 1) \cdot ICC)$$

Where:

- $\bar{n}$ is the average number of users per geographic cluster,
- ICC is the intra-cluster correlation coefficient, which measures the degree to which users within the same geographic region are similar in behavior.

For **user-based randomization**, the variance does not suffer from clustering effects and is simply:

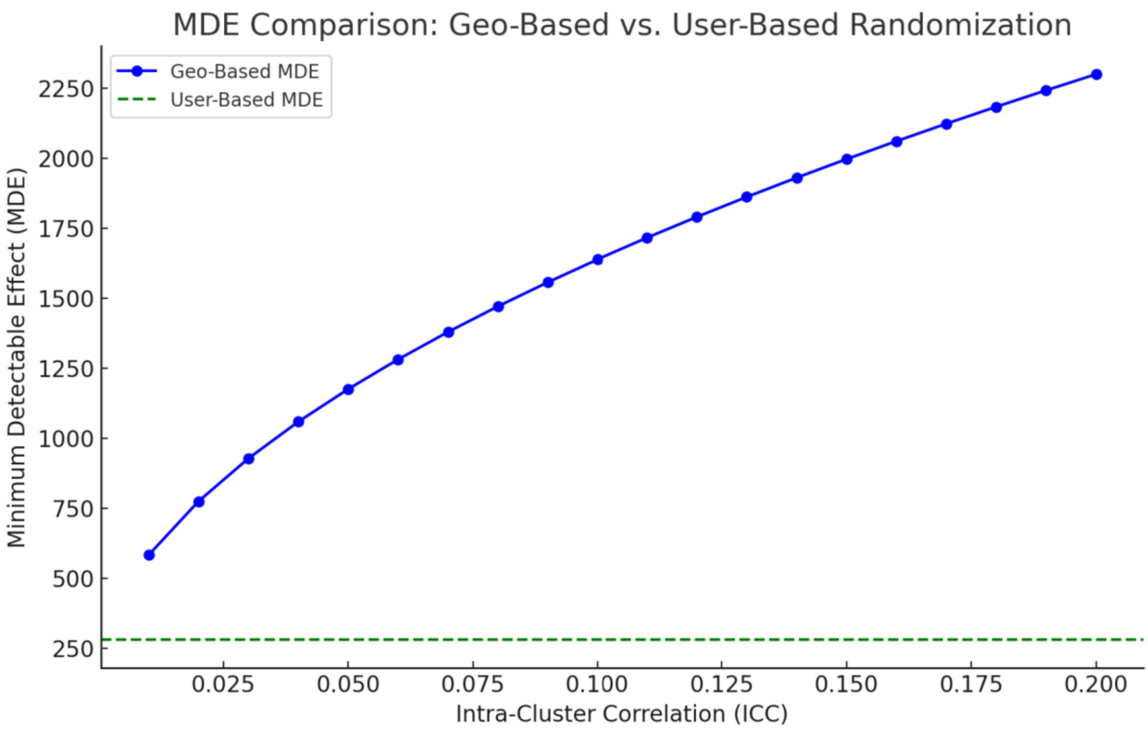
$$V_{\text{user}} = \sigma^2$$

2.3 Simulation Parameters

Simulations were performed to compare the MDE under both randomization methods, using the following parameters:

- Effect size = 1% (0.01),
- Baseline conversion rate = 5% (0.05),
- Sample size = 10,000 users for user-based randomization and 30 geo clusters (e.g., cities) for geo-based randomization.

We ran simulations with ICC values ranging from 0.01 to 0.20 to observe how increasing clustering affects the MDE in geo-based randomization.



3. Results

3.1 Variance Analysis

Geo-based randomization inflates the variance as ICC increases. This means that for higher ICC values (more similarity between users in the same geographic area), a larger sample size is required to detect the same treatment effect. For user-based randomization, the variance remains constant, regardless of ICC, allowing for smaller sample sizes and better detection of smaller effects.

3.2 Minimum Detectable Effect (MDE)

As ICC increases, the MDE for geo-based randomization grows due to the inflated variance. The formula for calculating MDE under geo-based randomization is:

$$\mathrm{MDE}_{\mathrm{geo}} = (Z_{\alpha/2} + Z_{\beta}) \cdot \sqrt{\frac{V_{\mathrm{geo}}}{n_t} + \frac{V_{\mathrm{geo}}}{n_c}}$$

For user-based randomization, the MDE is given by:

$$\mathrm{MDE}_{\mathrm{user}} = (Z_{\alpha/2} + Z_{\beta}) \cdot \sqrt{\frac{\sigma^2}{n_t} + \frac{\sigma^2}{n_c}}$$

These equations highlight that the MDE for geo-based randomization increases with ICC, making it harder to detect smaller effects as clusters become more similar.

4. Discussion

4.1 Practical Implications in Digital Advertising

1. **User-Based Randomization:**

   In digital advertising, user-based randomization is highly efficient for detecting small changes in key metrics like click-through rate (CTR) or conversion rate. This approach is particularly effective for testing ad creatives, bidding strategies, or targeting algorithms, where interactions are individual-based, and there is little concern about spillover effects between users.

2. **Geo-Based Randomization:**

   Geo-based randomization may be necessary for some digital advertising experiments, particularly those that involve geographic targeting or regional variations in behavior. However, geo-based randomization often leads to inflated variance, requiring larger sample sizes to achieve the same statistical power. In such cases, techniques like stratification (randomizing within geographic subgroups) or covariate adjustment can help reduce the impact of ICC.

4.2 Recommendations

- For **digital advertising experiments**, especially those focused on individual-level interventions (e.g., personalized ads), **user-based randomization** is recommended due to its efficiency and smaller sample size requirements.
- In cases where geo-based randomization is necessary (e.g., region-specific campaigns), **stratification** should be used to control for ICC, and **covariate adjustment** can help reduce the bias introduced by clustering effects.
- **Pre-trial simulations** should be conducted to estimate the ICC for different geographic regions, allowing advertisers to optimize their experimental design based on the expected degree of clustering.

5. Conclusion

User-based randomization significantly improves the efficiency of digital advertising experiments by reducing the MDE and required sample size. This method is particularly valuable in contexts where the treatment effects are small, and statistical power is crucial. However, geo-based randomization remains an option for experiments with regional interventions or where spillover effects are present, provided that strategies are in place to control for ICC.

References

1. Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences*. Cambridge University Press.
2. Angrist, J. D., & Pischke, J. S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
3. Dube, J.-P., Chintagunta, P. K., & Chintagunta, P. K. (2010). "Tipping and Targeting in Digital Advertising." *Marketing Science*, 29(5), 844-862.

4. Zhang, H., & Choi, J. (2019). "Impact of Randomization Strategy on Estimating Effects in Digital Advertising." *Journal of Marketing Analytics*, 7(2), 89-101.
5. Gerber, A. S., & Green, D. P. (2012). *Field Experiments: Design, Analysis, and Interpretation.*
6. Kohavi, R., Tang, D., & Xu, Y. (2020). *Trustworthy Online Controlled Experiments: A Practical Guide to A/B Testing.*
7. Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences.*
8. Xu, Y., Chen, N., & Xiong, J. (2020). "Evaluation of Geo-Based Versus User-Based Randomization in Online Advertising Experiments."
9. Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods.*
10. Bakshy, E., Eckles, D., & Yan, R. (2012). "Unbiased Estimation in A/B Tests with Interference."
11. Lewis, R. A., & Rao, J. M. (2015). "The Unfavorable Economics of Measuring the Returns to Advertising."
12. Higgins, J. P. T., & Green, S. (Eds.). (2011). *Cochrane Handbook for Systematic Reviews of Interventions.*
13. Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models.*