Online Advertising Incrementality Testing And Experimentation: Industry Practical Lessons

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ABSTRACT

Online advertising has historically been approached as user targeting and ad-to-user matching problems within sophisticated optimization algorithms. As the research area and ad tech industry have progressed over the last couple of decades, advertisers have increasingly emphasized the causal effect estimation of their ads (aka incrementality) using controlled experiments (or A/B testing). Even though observational approaches have been derived in marketing science since the 80s including media mix models, the availability of online advertising personalization has enabled the deployment of more rigorous randomized controlled experiments with millions of individuals.

These evolutions in marketing science, online advertising, and the ad tech industry have posed incredible challenges for engineers, data scientists, and marketers alike. With low effect percentage differences (or lift) and often sparse conversion rates, the development of incrementality testing platforms at scale suggests tremendous engineering challenges in the measurement precision and detailed implementation. Similarly, the correct interpretation of results addressing a business goal within the marketing science domain requires significant data science and experimentation research expertise. All these challenges on the ongoing evolution of the online advertising industry and the heterogeneity of its sources (social, paid search, native, programmatic, etc).

In the current tutorial, we propose a practical, grounded view in the incrementality testing landscape, including:

- The business need
- Solutions in the literature
- Design and choices in the development of incrementality testing platform
- The testing cycle, case studies, and recommendations to effective results delivery
- Incrementality testing evolution in the industry

We will provide first-hand lessons on developing and operationalizing such a platform in a major combined DSP and ad network; these are based on running tens of experiments for up to two months each over the last couple of years.

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CCS CONCEPTS

• Applied computing → Marketing; **Economics**; **• Information systems → Computational advertising**; **Display advertising**; **• General and reference → Experimentation**; **• Mathematics of computing → Probability and statistics**.

KEYWORDS

Marketing Incrementality, Controlled Randomized Experiments, A/B Testing, Computational Advertising, Causal Inference

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1 OFFERINGS AND TOPICS COVERED

1.1 Intended Audience

Practitioners and Researchers in the field of online advertising and marketing. General knowledge of online advertising, familiarity with A/B testing is a plus.

1.2 Previous Related offerings

Econometric Analysis and Digital Marketing: How to Measure the Effectiveness[6]. This tutorial was given at the time ad effectiveness testing was gaining popularity in the industry. Our current tutorial shows the eight-year evolution of the methods, real-world practices, and operationalization of those practices.

1.3 Learning Outcomes

Topics Reviewed:

- Experiment design and A/B testing
- Causal inference
- Ad tech architectures
- Business use cases in advertising and marketing analytics
- Practical recommendations to successful significant incrementality experiments

Participants will:

(1) Identify and formulate key approaches to measuring the effectiveness of online advertising.
(2) Execute relevant statistics for hypothesis testing, power analysis in experiment planning and simulate experiment scenarios.
(3) Be able to define key ingredients of an operational incrementality testing platform and their trade-offs.
(4) Understand the business need for incrementality testing.

(5) Identify the necessary conditions to increase the likelihood of successful test given minimum detectable lift, conversion type, test duration among others.

Take-away material:

Cheatsheet of statistical tools including python notebooks and spreadsheets for statistical power analysis

Summary of recommendations handout document for operationalization addressing the challenges and trade-offs of operationalizing testing

Categorization of business use cases handout document addressing typical needs and focus of incrementality testing

2 TUTORIAL OUTLINE

Part 1 The basics: context and challenges [7]
- The problem
- How channel-level testing fits within other forms of testing
- Business Use cases

Part 2 Incrementality Testing: concepts, solutions and literature [2, 3, 8, 10]
- Literature and Industry practices
- Estimation Frameworks

Part 3 From concept to production: platform building, challenges, case studies [3, 9]
- Building the experiment platform journey
- The identity graph and treatment groups
- User holdout design within modern Ad tech serving systems
- Data Logging and Analysis

Part 4 Deployment at Scale: test cycle and case studies
- Experiment execution cycle
- Case Studies

Part 5 Emerging trends: identity challenges, industry trends and solutions [1, 4, 5]
- Advertisers Testing without Ad Network holdouts
- Geo-testing
- Challenges with user ids

3 AUTHORS BIOGRAPHY

Joel Barajas, Sr Research Scientist, has over 11 years of experience in the online advertising industry with research contributions at the intersection of Ad tech, Marketing Science, and Experimentation. He has experience with Ad load personalization and experimentation in a publisher marketplace. Within Marketing Data Science, he has supported regular budget allocation and Media Mix Models in multi-channel advertising. With a PhD dissertation focussed on ad incrementality testing, his published work has appeared in top outlets including INFORMS Marketing Science Journal, ACM CIKM, ACM WWW, SIAM SDM. He led the science development and marketing analytics of the incrementality testing platform in a multidisciplinary team. He currently oversees most incrementality tests in Verizon Media ad network (previously yahoo!) and DSP (previously AOL advertising.com). Joel also leads the science development in CTV and linear TV measurement modeling. He holds a B.S. (with honors) in Electrical and Electronics Engineering from the Tecnológico de Monterrey, and a PhD in Electrical Engineering (with emphasis on statistics) from UC Santa Cruz.

Narayan Bhamidipati, Sr Director of Research, has over 14 years of experience in Computational Advertising and Machine Learning. He currently leads a team of researchers focused on providing state-of-the-art ad targeting solutions to help ads be more effective and relevant. This includes creating various contextual targeting products to reduce the company's reliance on user profiles and help improve monetization in a more privacy aware world. Alongside that, Narayan ensures that the user profile based ad targeting products continue to improve despite the decline of tracking data. In addition, Narayan is keen on developing the most accurate ad effectiveness measurement platform which would help the company attract more revenue by proving the true value of the ad spend on our platforms. He holds B.Stat(Hons), M.Stat and PhD(CS) degrees, all from the Indian Statistical Institute, Kolkata.

Dr. James G. Shanahan has spent the past 30 years developing and researching cutting-edge artificial intelligence systems, splitting his time between industry and academia. For the academic year 2019-2020, Jimi held the position of Rowe Professor of Data Science at Bryant University, Rhode Island. He has (co) founded several companies that leverage AI/machine learning/deep learning/computer vision in verticals such as digital advertising, web search, local search, and smart cameras. Previously he has held appointments at AT&T (Executive Director of Research), NativeX (SVP of data science), Xerox Research (staff research scientist), and Mitsubishi. He is on the board of Anvia, and he also advises several high-tech startups including Aylien, ChartBoost, DigitalBank, LucidWorks, and others. Dr. Shanahan received his PhD in engineering mathematics and computer vision from the University of Bristol, U. K. Jimi has been involved with KDD since 2004 as an author, as a tutorial presenter, and as a workshop co-chair; he has actively been involved as a PC/SPC member over the years also.

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