Online Advertising Incrementality Testing And Experimentation

Industry Practical Lessons

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Who we are ...

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Tutorial Parts

1. The basics: context and challenges
2. Incrementality Testing: concepts, solutions and literature
3. From concept to production: platform building, challenges, case studies
4. Deployment at Scale: test cycle and case studies
5. Emerging trends: identity challenges, industry trends and solutions

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Part 5

Emerging trends: identity challenges, industry trends and solutions

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Geo-Testing

Testing with aggregate time series and geo testing units

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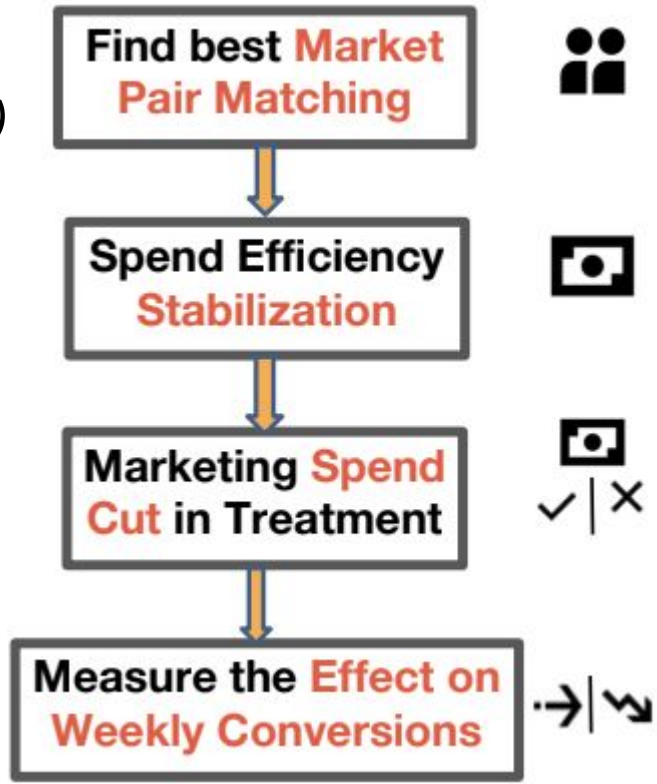
Controlled Geo-Experiment + Synthetic Control

Barajas et al. (2020), Blake et al. (2015), Abadie et al. (2010)



Without user level holdout, market pair testing is a viable solution

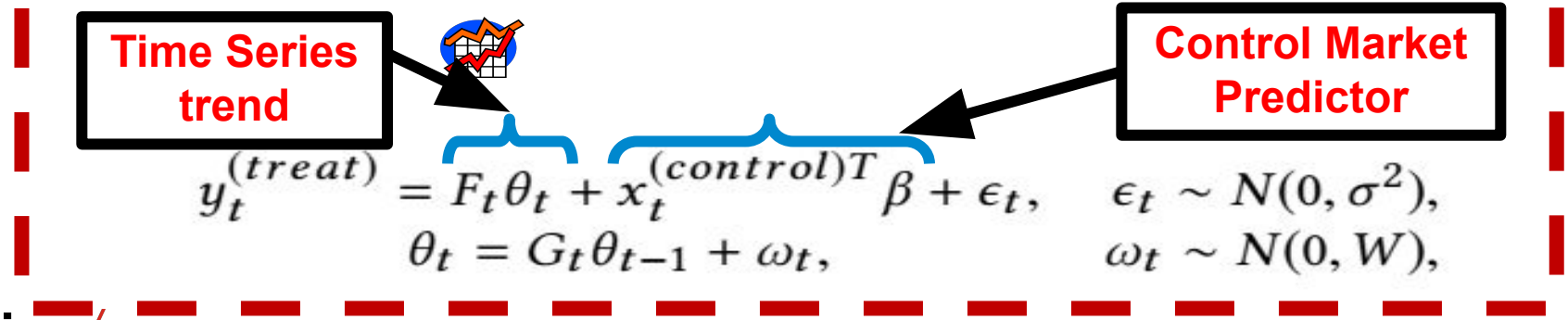
- Typical incrementality testing for advertisers when the ad network **does not support user-level holdouts**

Causal Estimation: Synthetic Control

Barajas et al. (2020)

Bayesian Structural framework with **time series and a regression component** from the control market conversions to predict the treatment conversions (synthetic control).

Structural Equation



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Market Best Match: A/A tests

Barajas et al. (2020)

Best Pair selection given the conversion and estimation method

A/A test estimation: Given Causal Estimation Framework

Filter Best Pairs and Parameters: tightest and interval with zero effect

Algorithm 1 Control/Treatment Market Pair Selection

1: Ω: Set of Markets to consider
2: Φ: Set of placebo intervention times
3: Δ_t: Time length of historical data
4: Δ_{t_i}: Time after placebo intervention

Estimation Parameters: Markets, Intervention times, Train/follow-up Length

5: **for all** treatment market: $m \in \Omega$ **do**
6: **for all** control market: $n \in \{\Omega - m\}$ **do**
7: **for all** intervention time: $d \in \Phi$ **do**
8: **Fit** the synthetic control model of Eq 1:
9: **Find** Θ^s, $s = 1, \ldots, N_s$, given $\{y^{(m)}_{d-\Delta_t:d-1}, x^{(n)}_{d-\Delta_t:d-1}\}$
10: **Predict** $\hat{y^s}^{(m)}_{t_i}$, $\forall s \in \{s = 1, \ldots, N_s\}$ after intervention, $\forall t_i \in \{d, \ldots, d + \Delta_{t_i}\}$
11: **Estimate** Credible Intervals (CI) $lift_{cum(d+\Delta_{t_i})}$, Eq 3
12: **end for**
13: **end for**
14: $n^*, d^* \leftarrow$ tightest CI that include $lift_{cum(d+\Delta_{t_i})} = 0$
15: **Append** best control/treatment/time $V = \{V, (m, n^*, d^*)\}$
16: **end for**
17: **return** V

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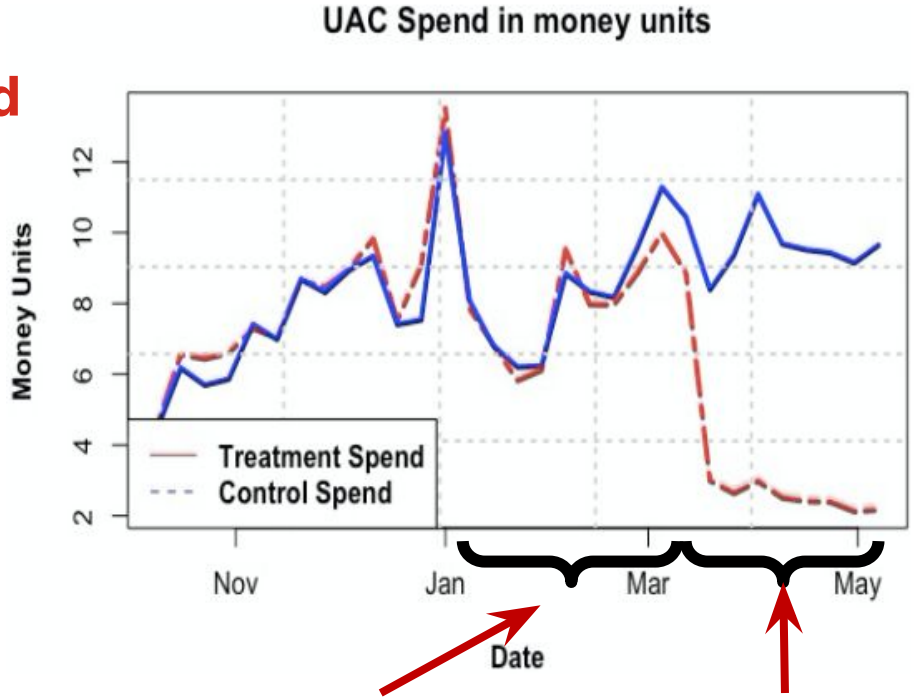
UAC Incrementality: Intervention

Barajas et al. (2020)

Given **treatment/control pairs and the estimation method**, we execute the experiment

1. Cost-per-attributed-signup (CPA) **stabilization** both groups
2. **Suspend** spend for treatment market



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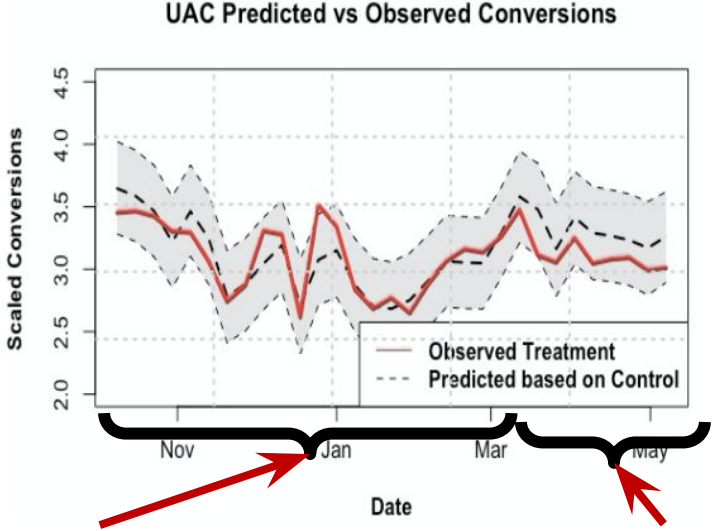
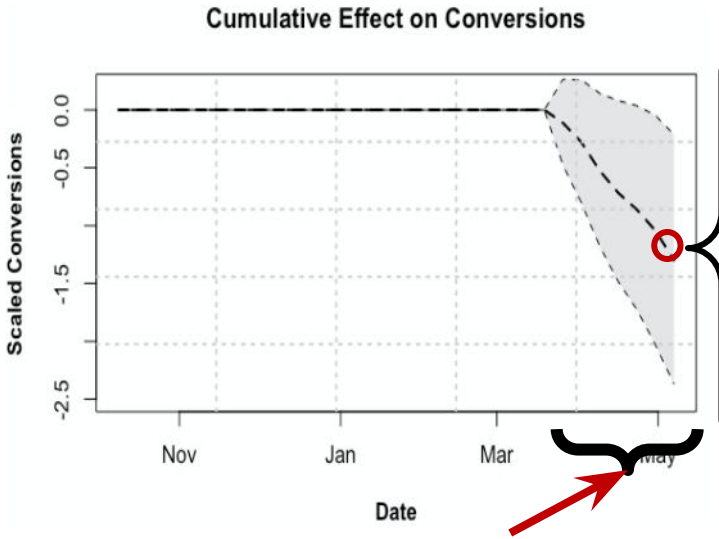
UAC Incrementality: Effect on Weekly Conversions

Barajas et al. (2020)

Consistently **lower predictive (synthetic control) treatment conversions** than observed





Conversion Lift:
-6.57%

Spend Lift:
-72.33%

Cost per Incremental Scaled conversion:
39.30 money units

Training period:
09/09 - 03/12

Intervention period.
Predictive vs observed
03/12 - 03/15

Cumulative effect and 95% credible intervals

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Limitations and Caveats

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Limitations and Caveats

1. Comparisons between aggregate market conversions **require large intervention effects (spend)** since we are **unable to identify users not exposed to the ads** leading to less precision.

2. Rigorously designed experiments provide **valuable data to build channel cost curves of incremental conversions** and to calibrate Media Mix Models for optimal spend allocation

3. **Testing during holidays is noisy and problematic**, which is a big limitation compared to user holdout testing

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Thank you!!!

Feedback welcome.

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