Estimating Ad Impact on Clicker Conversions for Causal Attribution: A Potential Outcomes Approach

Joel Barajas*¹, Ram Akella¹, ², Marius Holtan³, Aaron Flores³

¹UC Santa Cruz, Santa Cruz CA, USA
²UC Berkeley, Berkeley, CA USA
³AOL Research, Palo Alto CA, USA
Introduction and Motivation

User Clicks and Causality: Why We Care about Them
Online Display Advertising Framework

- In performance-based online advertising (CPA campaigns), visiting users are targeted based on how likely they are to convert.

- Targeted and non-targeted users convert in the advertiser’s website potentially (observed by tracking cookies).

- Converting users regardless of the ad exposure have motivated the causal analysis of campaign effect.
Introduction and Motivation

- Are user clicks to online ads informative of campaign success?
  - **Advertiser**: “All I care about are user conversions”

- Is it a good idea to target users based on user clicks?
  - **Issues**: low click-through-rates, noisy clicks
  - **Benefits**: conversion rates are even lower

- Dalessandro *et al.* 2012: “Evaluate” click-based user targeting using prediction metrics (e.g. Area Under the Curve AUC)
  - **Conclusion**: User targeting based on clicks is statistically indistinguishable from random guessing
  - **Consequence**: User clicks are often ignored in the user targeting unless they appear to be “effective” to Machine Learning techniques (conversion prediction)
Our Proposal

• Use randomized experiments to measure the ad exposure effect on the user conversion probability of the clickers
  • Running randomized experiments (a.k.a A/B testing) is becoming the standard practice to measure the causal ad attribution effectively

• Is it possible to do design a clean focused randomized experiment?
  • Unfortunately NO!!
  • Reason: We need to show the ad to know the population of interest

• We use the standard Ad evaluation practice and find the Local Average Treatment Effect on the clicker conversion probability
  • Even though we design an experiment, we need causal modeling to find this effect
  • Reason: We do not observe the user clicks in the control group
Randomized Design

Use A/B Testing: what’s the big deal?
**Ideal Experimental Design**

- We can not design a parallel placebo campaign for the control group

*BY THE TIME WE KNOW THE POPULATION OF INTEREST, WE HAVE SHOWN THE AD ALREADY!!*
Experimental Design: Ad Evaluation

- Targeted user sub-population is possible to replicate (under certain conditions)

WE FIND THE LOCAL AD EFFECT ON THE SUB-POPULATION OF CLICKERS
Experimental Design Data

- Targeted Population

- Study
  - Yes
  - No

- Control
  - Z=0, S=0, Y=0
  - Z=1, S=0, Y=1
  - Z=1, S=0, Y=0
  - Z=1, S=1, Y=1

Converting User?

- Yes
  - Z=0, S=0, Y=1
  - Z=1, S=0, Y=1

- No
  - Z=0, S=0, Y=0

Clicking User?

- Yes
  - Z=1, S=0, Y=0

- No
  - Z=1, S=0, Y=0

- Decision
- Chance
- End

- Nobody click on the ad in the control group by definition.

FIND THE AD EFFECT CONDITIONAL ON THE CLICKER POST-TREATMENT VARIABLE
Effect Estimation

Wait a minute: you ran an experiment, why you need to infer causality?
Effect Estimation

Because the effect is conditional on a post-treatment (non-ignorable) variable

• Pre-treatment variable: Observed before the treatment assignment is made (e.g. demographics)
• Post-treatment variable: Observed after the treatment assignment is made (e.g. behavioral features, and user clicks)
Causal Estimation: Potential Outcomes

• We use the Principal Stratification framework, developed in Potential Outcomes Causal Model, to model the user selection as a post-treatment variable.

• In Potential Outcomes, everything framed in terms of: Units, Treatments, and Potential Outcomes.

• In Principal Stratification, the effect estimation is conditioned on user classes characterized by the value of the post-treatment variable under both treatment groups, control and study.
The Estimation Model: Mechanics

• \( Z_i \in \{0,1\} \): Treatment assignment \{control, study\}
• \( S_i \in \{0,1\} \): Non-clicking/clicking ad user
• \( Y_i \in \{0,1\} \): Non-converting/converting user

Define

\[
S_i^P = \{(S_i(0)), (S_i(1))\} = \{(0), (1)\}
\]

Define

\[
C_i = \begin{cases} 
0 & \text{if } S_i^P = (0,0)' \\
1 & \text{if } S_i^P = (0,1)'
\end{cases}
\]

- \( C_i = 1 \) defines the principal stratum of users who click on the ad when assigned to the study group (clicker-if-assigned)

- \( C_i = 0 \) defines the principal stratum of users who never click on the ad regardless of the treatment group (never-clicker)
What we do and do not Know

<table>
<thead>
<tr>
<th>User Counts</th>
<th>Potential Control</th>
<th>Outcomes Study</th>
<th>Treatment Assignment</th>
<th>Principal Stratum</th>
<th>C_i</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S_i(0)</td>
<td>Y_i(0)</td>
<td>S_i(1)</td>
<td>Y_i(1)</td>
<td>Z_i</td>
</tr>
<tr>
<td>N^0_{0,1}</td>
<td>0</td>
<td>0</td>
<td>*</td>
<td>*</td>
<td>0</td>
</tr>
<tr>
<td>N^1_{0,1}</td>
<td>0</td>
<td>1</td>
<td>*</td>
<td>*</td>
<td>0</td>
</tr>
<tr>
<td>N^0_0</td>
<td>0</td>
<td>*</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>N^1_0</td>
<td>0</td>
<td>*</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>N^0_1</td>
<td>0</td>
<td>*</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>N^1_1</td>
<td>0</td>
<td>*</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

We know all necessary data of the study group
What we do and do not Know

<table>
<thead>
<tr>
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<th>$C_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{0}^{0}$</td>
<td>$S_i(0)$</td>
<td>$S_i(1)$</td>
<td>$Y_i(0)$</td>
<td>$Y_i(1)$</td>
<td>$Z_i$</td>
</tr>
<tr>
<td>$N_{0}^{1}$</td>
<td>$0$</td>
<td>$0$</td>
<td>$*$</td>
<td>$*$</td>
<td>$0$</td>
</tr>
<tr>
<td>$N_{1}^{0}$</td>
<td>$0$</td>
<td>$1$</td>
<td>$*$</td>
<td>$*$</td>
<td>$0$</td>
</tr>
<tr>
<td>$N_{01}$</td>
<td>$0$</td>
<td>$*$</td>
<td>$0$</td>
<td>$0$</td>
<td>$1$</td>
</tr>
<tr>
<td>$N_{0}^{1}$</td>
<td>$0$</td>
<td>$*$</td>
<td>$0$</td>
<td>$1$</td>
<td>$1$</td>
</tr>
<tr>
<td>$N_{11}$</td>
<td>$0$</td>
<td>$*$</td>
<td>$1$</td>
<td>$0$</td>
<td>$1$</td>
</tr>
<tr>
<td>$N_{1}^{1}$</td>
<td>$0$</td>
<td>$*$</td>
<td>$1$</td>
<td>$1$</td>
<td>$1$</td>
</tr>
</tbody>
</table>

We need to infer the principal stratum of the control group
The Inference Problem

By randomization, the probability of clicker-if-assigned (the principal stratum) is the same for both treatment groups

\[ P(Y, Z, D, \Theta) = P(\Theta) \times \prod_{i} P(C_i | \pi) P(Z_i) P(Y_i | C_i = c, Z_i = z, \theta_{cz}) \]
The Inference Problem

By *randomization*, the probability of *clicker-if-assigned* (the principal stratum) is the same for both treatment groups.

- The user conversion probability for both principal strata in the control group is **not identifiable**.

\[
P(Y, Z, D, \Theta) = P(\Theta) \times \prod_{i} P(C_i|\pi)P(Z_i)P(Y_i|C_i = c, Z_i = z, \theta_{cz})
\]
The Inference Problem

By **randomization**, the probability of *clicker-if-assigned* (the principal stratum) is the same for both treatment groups.

- The user conversion probability for both principal strata in the control group is **not identifiable**.

- We assume **POSITIVE campaign effect**

\[
P(Y, Z, D, \Theta) = P(C)I_{[0, \theta_{01})}(\theta_{00})I_{[0, \theta_{11})}(\theta_{10})
\times \prod_{i} P(C_{i}|\pi)P(Z_{i})P(Y_{i}|C_{i} = c, Z_{i} = z, \theta_{cz})
\]
The Inference Problem

By **randomization**, the probability of clicker-**if**-assigned (the principal stratum) is the same for both treatment groups.

We assume **POSITIVE campaign effect**

\( \theta_{c1} \geq \theta_{c0} \quad \forall c \in \{0,1\} \)

\[
P(Y, Z, D, \Theta) = P(\Theta)I_{[0, \theta_{01})}(\theta_{00})I_{[0, \theta_{11})}(\theta_{10})
\times \prod_{i} P(C_i|\pi)P(Z_i)P(Y_i|C_i = c, Z_i = z, \theta_{cz})
\]
The Inference Problem

By randomization, the probability of clicker-if-assigned (the principal stratum) is the same for both treatment groups.

We use the paper for the Gibbs algorithm sampling expressions and positive campaign effect.

\[
P(Y, Z, D, \Theta) = P(\Theta)I_{[0,\theta_{01})}(\theta_{00})I_{[0,\theta_{11})}(\theta_{10})
\]

\[
\times \prod_{i} P(C_i|\pi)P(Z_i)P(Y_i|C_i = c, Z_i = z, \theta_{cz})
\]
Causal Effect Metrics

- Causal **average ad effect on conversion rate**

$$\begin{align*}
LATE_{Click} &= E[Y_i|C_i = 1, Z_i = 1, \theta_{11}] - E[Y_i|C_i = 1, Z_i = 0, \theta_{10}] = \theta_{11} - \theta_{10} \\
LATE_{NoClick} &= E[Y_i|C_i = 0, Z_i = 1, \theta_{01}] - E[Y_i|C_i = 0, Z_i = 0, \theta_{00}] = \theta_{01} - \theta_{00}
\end{align*}$$

- Observational and post-treatment **biased effects**

$$\begin{align*}
ATE^{obs}_{Click} &= E[Y_i|S_i(1) = 1, Z_i = 1] - E[Y_i|S_i(1) = 0, Z_i = 1] \\
ATE^{post}_{Click} &= E[Y_i|S_i(1) = 1, Z_i = 1] - E[Y_i|S_i(0) = 0, Z_i = 0]
\end{align*}$$

- **$ATE^{obs}_{Click}$** is similar to a prediction “evaluation”

$$\begin{align*}
ATRB_{Click} &= LATE_{Click} \\
&\times \frac{(N_{11}^0 + N_{11}^1)}{(N_{01}^1 + N_{11}^1)} \\
ATRB_{NoClick} &= LATE_{NoClick} \\
&\times \frac{(N_{01}^0 + N_{01}^1)}{(N_{01}^0 + N_{11}^1)}
\end{align*}$$

- Attributed converting users respect to the observed study conversions
Causal Effect Metrics

- Causal average ad effect on conversion rate

\[
\begin{align*}
\text{LATE}_{\text{Click}} &= E[Y_i | C_i = 1, Z_i = 1, \theta_{11}] - E[Y_i | C_i = 1, Z_i = 0, \theta_{10}] = \theta_{11} - \theta_{10} \\
\text{LATE}_{\text{NoClick}} &= E[Y_i | C_i = 0, Z_i = 1, \theta_{01}] - E[Y_i | C_i = 0, Z_i = 0, \theta_{00}] = \theta_{01} - \theta_{00}
\end{align*}
\]

- \( \text{ATE}_{\text{Click}}^{obs} \) is sample prediction

- Attributed converting users respect to the observed study conversions

Confidence intervals are trivial to obtain from the posterior distribution Gibbs samples
Results

OK, OK, …, but show me the money
Results: Validation

- Given the model parameters:
  - We generate 100 count sets
  - We fit our model: 3000 samples
  - Concatenate the posterior samples or each run

- Settings:
  - Population: 23 Million Users
  - $P(Z=1)=0.5$
  - $P(Y=1|C=1,Z=1)=1\times10^{-3}$
  - $P(Y=1|C=1,Z=1)=9.82\times10^{-5}$
  - Lift LATE\_click = 14%
  - Lift LATE\_NoClick = 14%
  - Clicker Rate = 0.068%

**BOTTOM LINE:** WE RECOVER THE TRUE EFFECT ON THE CLICKER CONVERSION RATE
### Large-Scale Randomized Experiment Data

<table>
<thead>
<tr>
<th>Treatment Assignment $Z_i$</th>
<th>Principal Stratum $(S_i(0), S_i(1))$</th>
<th>$C_i$</th>
<th>User Counts $N_y^{cz}$</th>
<th>Campaign 1</th>
<th>Campaign 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>(0,*)</td>
<td>*</td>
<td>$N_{0,1}^0$</td>
<td>3,621,409</td>
<td>11,431,495</td>
</tr>
<tr>
<td>0</td>
<td>(0,*)</td>
<td>*</td>
<td>$N_{0,1}^1$</td>
<td>314</td>
<td>961</td>
</tr>
<tr>
<td>1</td>
<td>(0,0)</td>
<td>0</td>
<td>$N_{01}^0$</td>
<td>3,535,571</td>
<td>11,328,649</td>
</tr>
<tr>
<td>1</td>
<td>(0,0)</td>
<td>0</td>
<td>$N_{01}^1$</td>
<td>347</td>
<td>1,014</td>
</tr>
<tr>
<td>1</td>
<td>(0,1)</td>
<td>1</td>
<td>$N_{11}^0$</td>
<td>2,414</td>
<td>9,799</td>
</tr>
<tr>
<td>1</td>
<td>(0,1)</td>
<td>1</td>
<td>$N_{11}^1$</td>
<td>2</td>
<td>8</td>
</tr>
</tbody>
</table>

- **Pre-processing:**
  - **Total Population:** 7.16 Million | 22.7 Million
  - Use **tracking cookies** (users)
  - **Randomize users** based on the timestamp the cookie was born
  - Focus on the user cookies **born before** the campaign started
  - CPM (non-optimized) campaigns for the same advertiser
  - Use a **placebo campaign** to target users in the control group
  - **Objective:** perform an **exploratory** campaign effectiveness analysis
### Large-Scale Randomized Experiment Data

<table>
<thead>
<tr>
<th>Treatment Assignment $Z_i$</th>
<th>Principal Stratum $(S_i(0), S_i(1))$</th>
<th>User Counts $N^y_{CZ}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>(0,*)</td>
<td>$N_0^0$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$N^1_{10}$</td>
</tr>
<tr>
<td>1</td>
<td>(0,1)</td>
<td>$N^1_{11}$</td>
</tr>
</tbody>
</table>

| Total Population:         | 7.16 Million | 22.7 Million |

Clicker conversion rate in the study group is almost 10 times higher!!

**Pre-processing:**

- **Use tracking cookies** (users)
- **Randomize users** based on the timestamp the cookie was born
- **Focus on the user cookies** born before the campaign started
- **CPM (non-optimized)** campaigns for the same advertiser
- **Use a placebo campaign** to target users in the control group
- **Objective**: perform an exploratory campaign effectiveness analysis

**Clicker conversion rate**

- 8.27e-4 vs 9.81e-5
- 8.16e-4 vs 8.95e-5
Analysis of Results

<table>
<thead>
<tr>
<th>Measure</th>
<th>Campaign 1 Low</th>
<th>Med</th>
<th>High</th>
<th>Campaign 2 Low</th>
<th>Med</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clicker Rate, $\pi$ (%)</td>
<td>0.0667</td>
<td>0.0588</td>
<td>0.0699</td>
<td>0.0851</td>
<td>0.0889</td>
<td>0.0988</td>
</tr>
<tr>
<td>$\text{ATE}^{\text{obs}}_{\text{Click}}$ (naive) (%)</td>
<td>-2.33</td>
<td>7.30</td>
<td>16.92</td>
<td>2.54</td>
<td>7.26</td>
<td>12.00</td>
</tr>
<tr>
<td>lift $\text{ATE}^{\text{obs}}_{\text{Click}}$ (%)</td>
<td>-237</td>
<td>743</td>
<td>1720</td>
<td>282</td>
<td>811</td>
<td>1340</td>
</tr>
<tr>
<td>$\text{ATE}^{\text{post}}_{\text{Click}}$ (biased) (%)</td>
<td>-2.21</td>
<td>7.41</td>
<td>17.04</td>
<td>2.54</td>
<td>7.26</td>
<td>12.00</td>
</tr>
<tr>
<td>lift $\text{ATE}^{\text{post}}_{\text{Click}}$ (%)</td>
<td>-255</td>
<td>855</td>
<td>1960</td>
<td>306</td>
<td>870</td>
<td>1400</td>
</tr>
<tr>
<td>$\text{ATE}_{\text{Camp}}$ (1e-5) (%)</td>
<td>0.37</td>
<td>1.28</td>
<td>4.99</td>
<td>-0.33</td>
<td>6.18</td>
<td>12.50</td>
</tr>
<tr>
<td>lift $\text{ATE}_{\text{Camp}}$ (%)</td>
<td>4.05</td>
<td>13.61</td>
<td>49.00</td>
<td>3.04</td>
<td>11.02</td>
<td>42.50</td>
</tr>
<tr>
<td>$\text{ATRB}_{\text{Camp}}$ (%)</td>
<td>3.76</td>
<td>11.78</td>
<td>20.22</td>
<td>0.99</td>
<td>6.45</td>
<td>13.53</td>
</tr>
<tr>
<td>$\text{LATE}_{\text{NoClick}}$ (1e-5) (%)</td>
<td>0.37</td>
<td>13.46</td>
<td>24.21</td>
<td>1.04</td>
<td>6.97</td>
<td>23.13</td>
</tr>
<tr>
<td>lift $\text{LATE}_{\text{NoClick}}$ (%)</td>
<td>3.81</td>
<td>15.46</td>
<td>24.21</td>
<td>1.04</td>
<td>6.97</td>
<td>23.13</td>
</tr>
<tr>
<td>$\text{ATRB}_{\text{NoClick}}$ (%)</td>
<td>3.48</td>
<td>11.78</td>
<td>20.22</td>
<td>0.99</td>
<td>6.45</td>
<td>13.53</td>
</tr>
<tr>
<td>$\text{LATE}_{\text{Click}}$ (1e-4) (%)</td>
<td>0.35</td>
<td>4.61</td>
<td>13.72</td>
<td>0.43</td>
<td>4.65</td>
<td>11.04</td>
</tr>
<tr>
<td>lift $\text{LATE}_{\text{Click}}$ (%)</td>
<td>7.28</td>
<td>150.77</td>
<td>874.20</td>
<td>7.21</td>
<td>145.85</td>
<td>813.12</td>
</tr>
<tr>
<td>$\text{ATRB}_{\text{Click}}$ (%)</td>
<td>0.02</td>
<td>0.32</td>
<td>0.95</td>
<td>0.04</td>
<td>0.45</td>
<td>1.06</td>
</tr>
<tr>
<td>C2C $\text{ATRB}$ (%)</td>
<td>-</td>
<td>0.57</td>
<td>-</td>
<td>-</td>
<td>0.78</td>
<td>-</td>
</tr>
</tbody>
</table>

Biased effects similar to the prediction based “effectiveness”

SEVERE OVER-ESTIMATION: UPPER BOUND LARGER THAN 1,400%
### Analysis of Results

**Very large confidence intervals due to low clicker rates and non-optimized CPM campaigns:** 0.0683%, 0.0865%

**EVEN IN A PESSIMISTIC ANALYSIS THE CLICKERS ARE MORE VALUABLE THAN THE NON-CLICKERS**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Campaign 1</th>
<th></th>
<th></th>
<th></th>
<th>Campaign 2</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low</td>
<td>Med</td>
<td>High</td>
<td></td>
<td>Low</td>
<td>Med</td>
<td>High</td>
</tr>
<tr>
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<td>0.0683</td>
<td>0.0699</td>
<td></td>
<td>0.0851</td>
<td>0.0865</td>
<td>0.0880</td>
<td></td>
</tr>
<tr>
<td>ATECamp ($/click) (1e-4)</td>
<td>9.32</td>
<td>7.88</td>
<td>16.22</td>
<td></td>
<td>2.54</td>
<td>7.26</td>
<td>12.00</td>
<td></td>
</tr>
<tr>
<td>ATRBCamp ($/click) (1e-4)</td>
<td>282</td>
<td>811</td>
<td>1340</td>
<td></td>
<td>254</td>
<td>726</td>
<td>1200</td>
<td></td>
</tr>
</tbody>
</table>

- **3.50e-5 vs 2.00e-5 = 75% increase**
- **4.30e-5 vs 1.22e-5 = 252% increase**
Small number of attributed converting users are clickers. Reason: more than 900 times larger non-clicker volume!!

Non-clickers: 0.32% vs Campaign: 12.17%

Non-clickers: 0.45% vs Campaign: 6.62%

EVEN THOUGH THE AD EFFECT IS HIGHER FOR CLICKERS, FEW CLICKERS ARE OBSERVED!!
A click-to-conversion attribution (C2C), where a user conversion is attributed to the last user click, tends to under-estimate the true campaign value.

<table>
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<th>Campaign 2 Low</th>
<th>Med</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATE</td>
<td>283</td>
<td>858</td>
<td>1568</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lift ATE</td>
<td>4.06</td>
<td>10.04</td>
<td>24.02</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>ATRB</td>
<td>3.74</td>
<td>12.17</td>
<td>20.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C2C</td>
<td>0.57%</td>
<td></td>
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<td>Campaign</td>
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Most of the users who are affected by the campaign do not click on the ad!!
Conclusion

Fine, this is too much detail… give me your recommendation
Business Implications

• Optimizing user clicks optimizes the causally generated conversions.
  • Positive correlation of clicks with incremental conversions

• Clicks must be a component of a combined user targeting policy, but not the only objective
  • Many positive affected users do not click on the ad

• C2C business model under-estimates the causal attribution, contradicting the general industry belief that C2C over-estimates the value
  • C2C does not consider the ad effects on the non-clickers
Conclusion

• We proposed a method to find the causal ad effect on the clicker conversions based on randomized experiments
  • The average campaign effect must not be negative.

• We found evidence suggesting a higher ad effect on the user conversion probability of the clickers
  • A pessimistic analysis supports this hypothesis

• Our method and analysis open a path for more studies of the user clicks
  • Why many users affected by the ad do NOT click on the ad is an open research problem
Joel Barajas*, Ram Akella, Marius Holtan, Aaron Flores

jbarajas AT soe.ucsc DOT edu
https://users.soe.ucsc.edu/~jbarajas/

Thank you!!