MSI at the ARF
MARKETING SCIENCE INSTITUTE

MSI Webinar:

Part 3 – Analytics Rebroadcast: Close Enough? A Large-Scale Exploration of Non-Experimental Approaches to Advertising Measurement

December 13, 2022 | Virtual | 12:30 PM – 1:00 PM EST

Speaker:

Brett R. Gordon - *Northwestern University*

Overview:

In part 3 of the MSI Series on Causal Measurement of Advertising Effects, speaker Brett R. Gordon (Northwestern University) discussed work he did with Robert Moakler (Meta) and Florian Zettelmeyer (Northwestern University). In his introduction, Gordon remarked that measuring the effects of advertising has always been a difficult endeavor and still remains somewhat elusive in the digital era. He pointed to a "fundamental problem in causal measurement: no person can see and not see an ad at the same time." Gordon echoed his colleagues in this MSI Series by noting that randomized controlled trials (RCTs) are "recognized as the gold standard to measure incremental effects" in understanding causality. However, he also indicated that there are times when RCTs cannot be conducted.

Gordon noted that observational methods are often used as a substitute when conducting a full-fledged experiment is not an option. He presented a team effort by the Kellogg School of Management and Facebook to understand the extent to which information aggregated from previous RCTs can fill in the void of missing data. This can be done by using previous RCTs~~,~~ to generate an "estimated lift." Compared to data from earlier RCTs, results from a Double/Debiased Machine Learning-based Observational Model (DML) showed improvements over other approaches but still overestimated the impact of advertising. He indicated that there were areas for improvement in the machine-based method to increase its effectiveness.

Takeaways:

- The "fundamental problem in causal measurement" is that "no person can see and not see an ad at the same time."

- **"Randomized controlled trials (RCTs)** are recognized as the **'gold standard'** to measure incremental effects."
    - In this type of experiment, the audience is split into two groups with one being exposed to an ad or marketing intervention (treated) and one being the control (unexposed). The two groups are compared to find the lift from the treatment.
- An **observational method** that relies on non-experimental variation in ad exposure, by comparing "outcomes between people who saw versus did not see the ad campaign" can assist in the understanding lift using existing data.
    - **Challenges from observational methods** can be addressed by finding "unexposed users" who look similar to exposed users "based on observable characteristics." The more observable characteristics used, the more reliable the results will be.
- An experiment conducted by Kellogg and Facebook was designed to **understand how to capture lift if an advertiser had not implemented a campaign using an RCT.**
    - What ad effect would they have to estimate by using an observational method?
        - **Information aggregated from previous "statistically significant" RCTs on Facebook can fill in the void of missing data** by comparing the estimate of the RCT lift from previous experiments to the estimate that would have been generated if the control group was ignored and instead used a model to generate estimated lift.
    - An example that **compared data from previous RCTs with results of a Double/Debiased Machine Learning-based Observational Model** (DML) showed improved results.
        - Ad lift results from the DML model were promising, though they were noticeably higher than the results from the standard RCT. DML was noted as good at "correcting bias."
        - Currently, "given the data available" **DML does not adequately measure the true effect of advertising** but is relatively better for "prospecting campaigns and those with low baseline conversion rates." **More granular data is needed from ad platforms to make this method more effective.**