#### Designing Experiments to Measure Incrementality on Facebook

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# Facebook advertising has risen dramatically in importance

In 2017, \$204bn was spent on online advertising [1].

Amongst that, \$40bn was spent with Facebook targeting 2.13bn monthly active users [2].

We find advertising on Facebook allows us to continue inspire fashion-loving 20-somethings to express their best selves and achieve amazing things.



### The need to measure incrementality

Over time, we moved away from measuring our ad campaign's performance using ROI / ROAS in favour of incrementality.

This allows a fairer evaluation of a campaign's performance, and hence enabling better attribution.





# They offer incrementality measurement via lift studies

A controlled experiment where the target population is split into two:

- Test group: Adverts shown
- Control group: Adverts not shown

Difference in a metric (e.g. total sales, number of app installs) between the test and control groups is the incrementality of the campaign.





# ISN'T THAT JUST AN A/B TEST?



## A/B test with a few twists

<u>An unreached audience</u> Not every one in the test group gets to see an ad!

> <u>A scaled control group</u> The group size of the control group is scaled to match that of the test group for a meaningful comparison.

<u>A Facebook-controlled test/control split</u> Advertisers have no access to user-level data for data protection reasons - only the aggregated level result is reported.



# Comparing marketing strategies via multi-cell tests

Facebook can split the target population into multiple cells. Different campaigns + test-control splits can be run in each.

These can be used to compare strategies where the target audience exhibits a selection bias [3] (e.g. comparing campaigns that vary the bid size based on customer lifecycle).

We are interested in measuring the difference between incrementalities attained by the campaigns. This is not reported by Facebook.\*



Cell B: 70/30 Test/Control Split



## The current gap in literature

Advertising on Facebook

**Controlled Experiment Design** 





### AGENDA

 How does Facebook calculate incrementality and lift? (A quick overview of Gordon et al. [4])

- 2. How can we estimate the test power and sample size required to run a Facebook lift study?
  - 3. Can we generalise the test power and sample size required calculations to a multi-cell study?



## Calculating Incrementality & Lift in a Facebook Lift Study

A Quick Overview

We use # conversions as the running example, though the calculations apply to other metrics.

# Conversions

#### Test Control



We use # conversions as the running example, though the calculations apply to other metrics.

Facebook tracks and reports the following:

 $C_T$ : # conversions in the test group  $C_S$ : # conversions in the scaled control group\*  $R_T$ : # conversions in the reached audience of the test group





- $C_T$ : # conversions in the test
- $C_S$ : # conversions in the scaled control
- $R_T$ : # conversions in the reached audience of the test group

# conversions contains contribution from the reached and unreached audiences  $(U_T \& U_S)$ .

The conversion rate for unreached audiences & control are assumed to be the same.  $\Rightarrow U_T = U_S$ .





R<sub>T</sub>, U<sub>T</sub>: # conversions in the reached/unreached
audience of the test group
R<sub>S</sub>, U<sub>S</sub>: # conversions in the reached/unreached

audience of the scaled control group

The incrementality is the extra # conversions.

The lift is the incrementality relative to the # conversions in the reached audience of the scaled control. Facebook then runs a NHST to see if there is enough evidence for a non-zero lift.



Conversions

#



# Estimating the test power & sample size required

Filling in the missing piece

# We first require the distribution of the test statistic - lift

Two ways to do so:

- 1. Derive the analytical form of the CMF (assuming conversions follow a Poisson process):  $F_L(l) \approx \sum_{k=0}^{\infty} \sum_{j=0}^{\left\lfloor \left(l + \frac{1}{r}\right)(rs)(k)\right\rfloor} e^{-(\lambda_T + \lambda_C)} \frac{\lambda_T^j \lambda_C^k}{j!k!}, \ l \in \mathbb{Q}$
- 2. Simulating the distribution using Poisson samples.

We show the two methods are equivalent, it is faster to simulate, and we can swap in other distributions to model the # of conversions or other metrics.



#### BRYAN LIU

#### Test power

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### Test power

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- Derive the lift distribution under the null hypothesis, usually when expected lift = 0.
- 2. Find the critical value, usually the 95<sup>th</sup> percentile.
- Derive the distribution under the alternate hypothesis (expected lift = minimum detectable lift), and find the proportion of the distribution over the critical value.



![](_page_18_Picture_8.jpeg)

### Minimum sample size required

Given a target minimum detectable lift and test power (usually 80%), we can solve for the minimum sample size required using some rootfinding methods.

![](_page_19_Figure_3.jpeg)

![](_page_19_Picture_5.jpeg)

## Generalising to multi-cell lift studies

Same techniques, but a different test statistic

## **Comparing incrementalities**

Recall we were finding the incrementality/lift of an ad campaign.

![](_page_21_Figure_3.jpeg)

![](_page_21_Picture_5.jpeg)

### **Comparing incrementalities**

In a multi-cell lift study, we are also interested in comparing the *difference* between incrementalities/lifts, and see if there is statistical evidence that it is non-zero.

![](_page_22_Figure_3.jpeg)

![](_page_22_Picture_5.jpeg)

### Test statistic

The difference in lift is defined as the (absolute, not relative) difference between the lift in Cell B and that in Cell A.

We simulate the distribution of the difference in lift, as it is very difficult to obtain an analytical form of the distribution.

![](_page_23_Figure_4.jpeg)

Difference between lift of cells = Lift of Cell B – Lift of Cell A

![](_page_23_Picture_7.jpeg)

### The test statistic distribution is different!

The variance of the test statistic will increase even if the variance within each group stays the same, as multi-cell studies have more test/control groups.

![](_page_24_Figure_3.jpeg)

Single-cell study

Multi-cell study

Liu, Bettaney, Chamberlain. Designing Experiments to Measure Incrementality on Facebook.

![](_page_24_Picture_7.jpeg)

### The test statistic distribution is different!

Hence, a common pitfall in multi-cell studies is to use the test power and minimum sample size derived for single cell lift studies. Otherwise, the way to calculate test power is similar.

![](_page_25_Figure_3.jpeg)

![](_page_25_Picture_5.jpeg)

### SUMMARY

- We went through how Facebook calculate incrementality and lift. (A quick overview of Gordon et al.)
- 2. We fill in the gap in literature by providing a test power & minimum required sample size calculation.
- 3. We generalise the test power and sample size required calculations to multi-cell studies, and show these quantities are very different to that of single-cell studies.

![](_page_26_Picture_6.jpeg)

![](_page_27_Picture_0.jpeg)