TATARI

Brand Measurement Study

Introduction

Direct vs. Brand Response

When a TV ad runs, we can identify two main types of responders: immediate and latent. Immediate represent those viewers who respond to an ad within a few minutes after airing, while latent represent those who respond with a time delay (i.e. after a few hours, days, weeks, or even months). As such, immediate responders help us measure direct response, while latent ones help us measure the brand response (as shown in Figure 1 below).

We can calculate the direct response by measuring the lift in the advertiser's desired KPI (for example, cost per visitor or cost per install) within a narrow time window after an ad has aired.

Brand response is typically assessed through a survey (for instance, by measuring aided or unaided brand awareness). At Tatari, however, we leverage various statistical methodologies to model the relationship between direct and brand response. This relationship is expressed as the drag factor, a multiplier we use to calculate the brand response from direct response.

$$\text{drag factor} = \frac{\text{total response}}{\text{direct response}}$$

or

$$\text{drag factor} = \frac{(\text{direct response} + \text{brand response})}{\text{direct response}}$$

or

$$\text{drag factor} = 1 + \frac{\text{brand response}}{\text{direct response}}$$

direct response · brand response

t=0 · few minutes* · time

Figure 1 Direct vs. Brand Response in TV advertising. t=0 denotes time at which the viewers saw the advertiser's ad. *The threshold for direct vs. brand response will differ across advertisers.

If we have no way of following viewers from the time they see the ad to the time they make an action (e.g. visit the advertiser's website or install the app), we have to model this relationship. However, the modeled drag factor doesn't give us the most accurate representation of the brand response, which is why we prefer to measure it instead. A closed-loop study is our way of measuring (as opposed to modelling) the drag factor.

The Basics Of A
Closed-Loop Study

To perform a closed-loop study, we first obtain data from sources such as smart TV, mobile apps, and set-top boxes. It gives us information on the exposure of a particular (anonymized) IP address to a specific spot airing. Put differently, we are able match the IP address of a TV viewer with the timestamps of the advertiser's creatives (i.e. when they aired and on which networks). If we observe that the same IP address later comes back to the advertiser's website or app store, we have created a "closed loop" between the TV ad and the website or appstore visit.

## The benefits of a closed-loop study are multi-fold:

1. **Measurement of brand response:** By calculating the drag effect, we can discern the likelihood of viewers visiting the advertiser's website or installing the app after some time (e.g. few days) has passed since the ad aired. This provides measurement of the brand response.

2. **Insight into true incrementality:** By applying statistical analysis, we can discern those viewers who would have visited the advertiser's website or installed the app without seeing the advertiser's TV ads. This step is essential to performing correct calculation of the drag factor.

3. Gaining better insights into **reach and frequency.**

4. Gaining insight into **conversion rates by response time.**

5. Assessing differences in **conversion rates by programming category.**

This white paper focuses specifically on the first two benefits: measurement of the brand response and insight into true incrementality.

Client Case Study

Data Collection
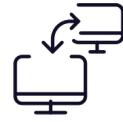
For this study, we focused on a mobile-app client. We collected the client's viewership and installation data during May 2017. Before performing the analysis, we cleaned up the data by removing extra devices that were registered to the same IP address and resolving for IP cycling. We also set a maximum threshold for installation time to align viewership and installation periods.

Data Analysis

Our closed-loop analysis for the client consisted of three steps:

1. Constructing a cumulative installation maturity curve

2. Adjusting for incrementality

3. Obtaining the final installation maturity curve and the drag factor

Step 1: Constructing A Cumulative Installation Maturity Curve

We first collected the client's viewership and clickstream datasets, which we call the primary dataset. This allowed us to visualize the installation likelihood, which we call the cumulative installation maturity curve (Figure 2). This curve helps us understand what the cumulative probability of installing the client's app is at a particular time point after last seeing the client's TV ad. For instance, after 200 hours (or approximately 8 days) of seeing the client's TV ad, 0.7% viewers were likely to have installed the client's app.
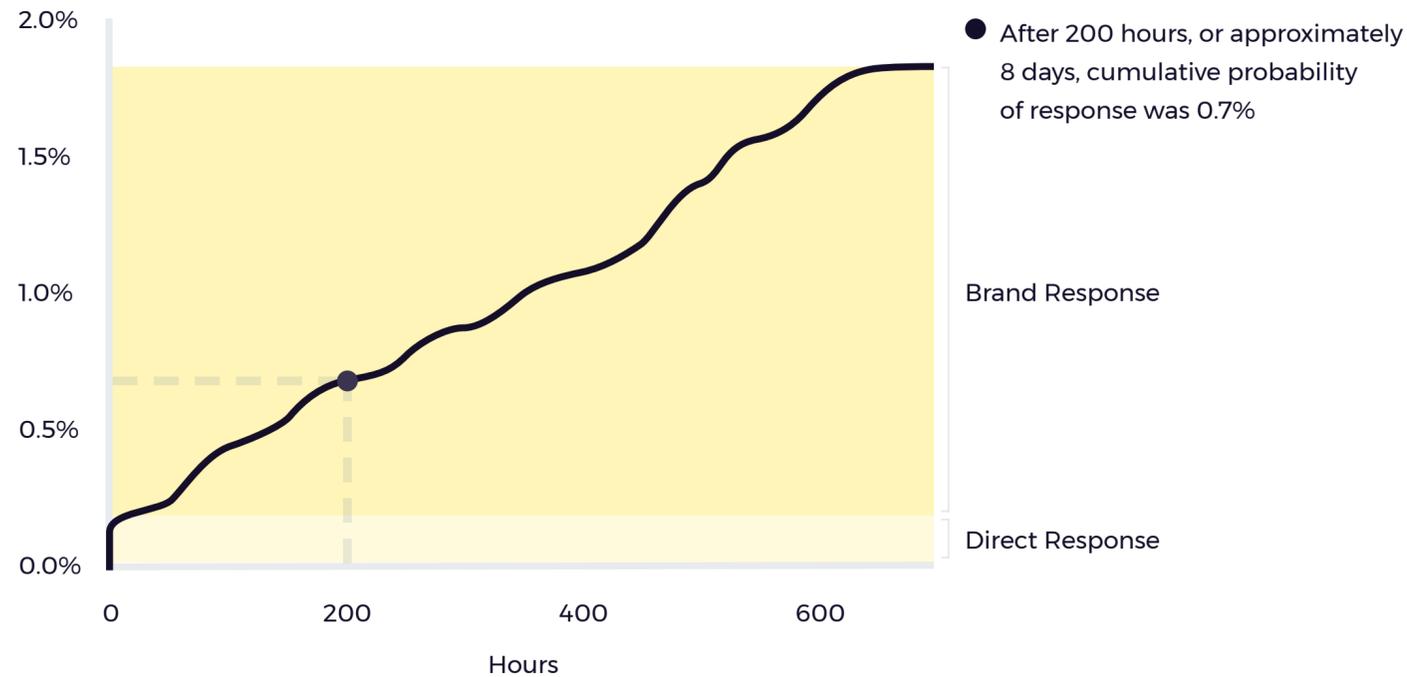

Figure 2 Client's cumulative installation maturity curve (0 < time < 600 hrs). t=0 denotes time at which the viewers saw the last client ad.

We can use the primary dataset to calculate the initial drag factor (shown in Figure 3 below), by using the quick formula:

$$\text{drag factor} = \frac{\text{total response}}{\text{direct response}}$$
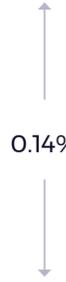
Client TV Long-Term Response			
Time Since	Total Response	Direct Response	Drag Factor
7 min	0.14%		1.00
1 day	0.27%		1.95
7 days	0.68%	0.14%	4.86
30 days	1.91%		13.64

Figure 3 Initial "cumulative" drag factor. Note that the direct-response attribution window for this client was 7 minutes (which is why the drag factor equals to 1.0 at the 7 min mark).

For this client, direct response was equal to 0.14% during the 7-minute attribution window. If we use the formula to calculate the value of the drag factor after 30 days, we can see that dividing 1.91% (total response) by 0.14% (direct response) yields a drag factor of 13.64.

However, because the cumulative installation curve does not distinguish those viewers who would have installed the client's app even without seeing the client's TV ad, this drag factor is too high, which is why we need to adjust for incrementality.

Step 2: Adjusting For Incrementality

We collected the viewership dataset from other TV ads running at the same time, which we call the secondary dataset. This allowed us to follow viewers who saw non-client ads, but still installed the client's app. From a testing standpoint, this is the control group (those people who would have installed the app without seeing client's ad). This process is shown in Figure 4 below.
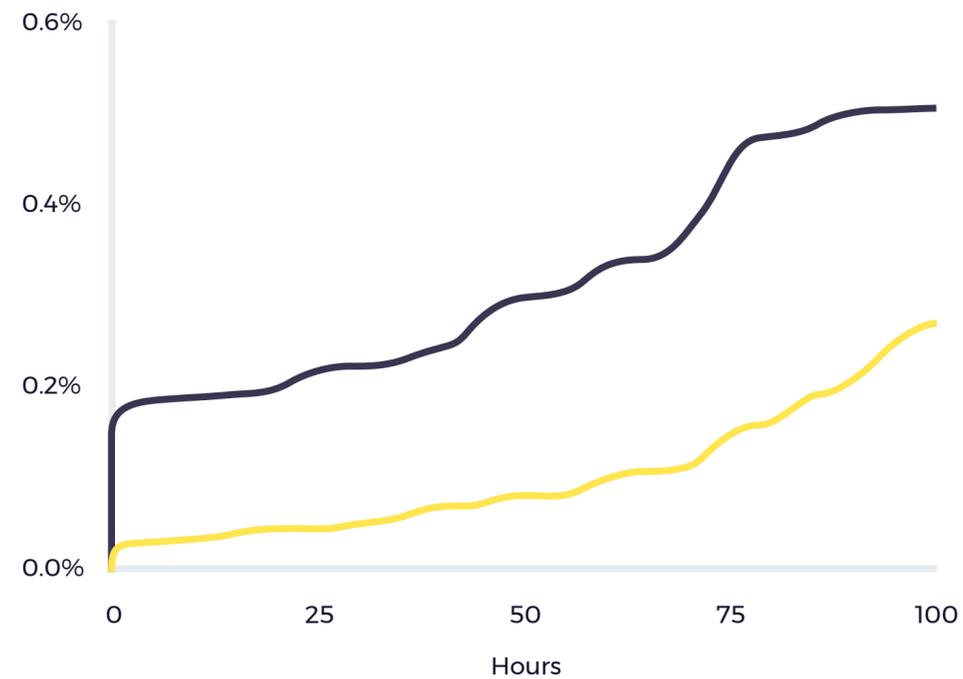
The secondary dataset was then subtracted from the primary dataset to obtain the incremental installation curve (Figure 5). By doing this, we obtained an estimated installation curve for only those viewers who installed the client's app as a result of seeing the client's TV ad (hence the name incremental).
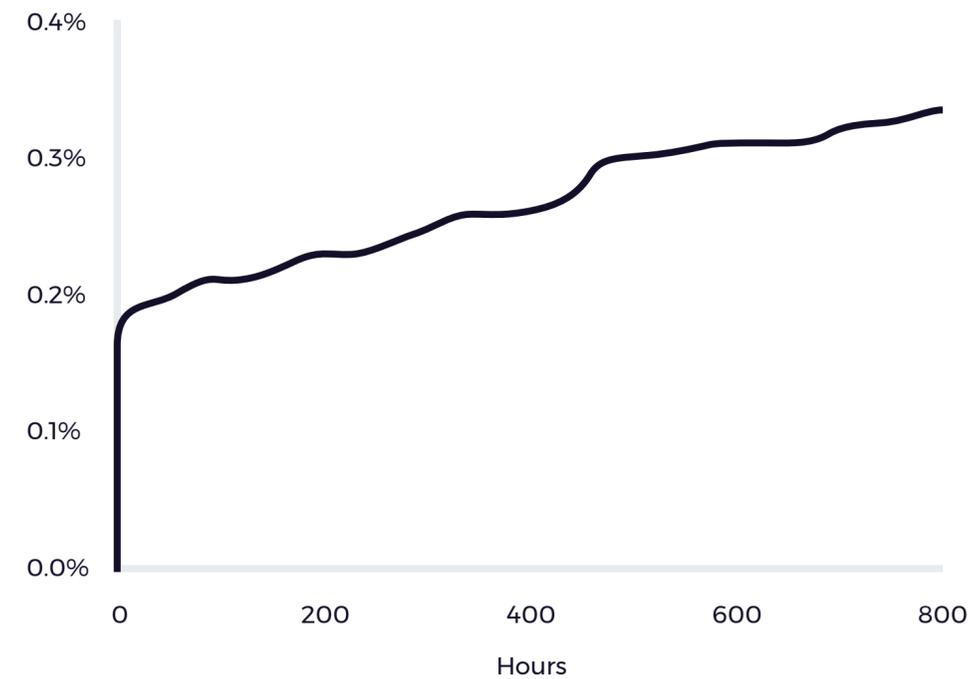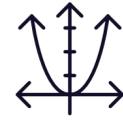

Figure 4 Control group (in yellow) shown next to cumulative installation curve (0 < time < 100 hrs). t=0 denotes time at which the viewers saw the last client ad.

Figure 5 Incremental installation curve (0 < time < 600 hrs). The initial spike at t=0 represents direct response.

Step 3: Obtaining The Final Installation Maturity Curve & The Drag Factor

The incremental installation curve is then smoothed to obtain the curve in Figure 6, which we call the final installation maturity curve. We can use the drag factor formula again on this data to calculate the new drag factor, as shown in Figure 7.
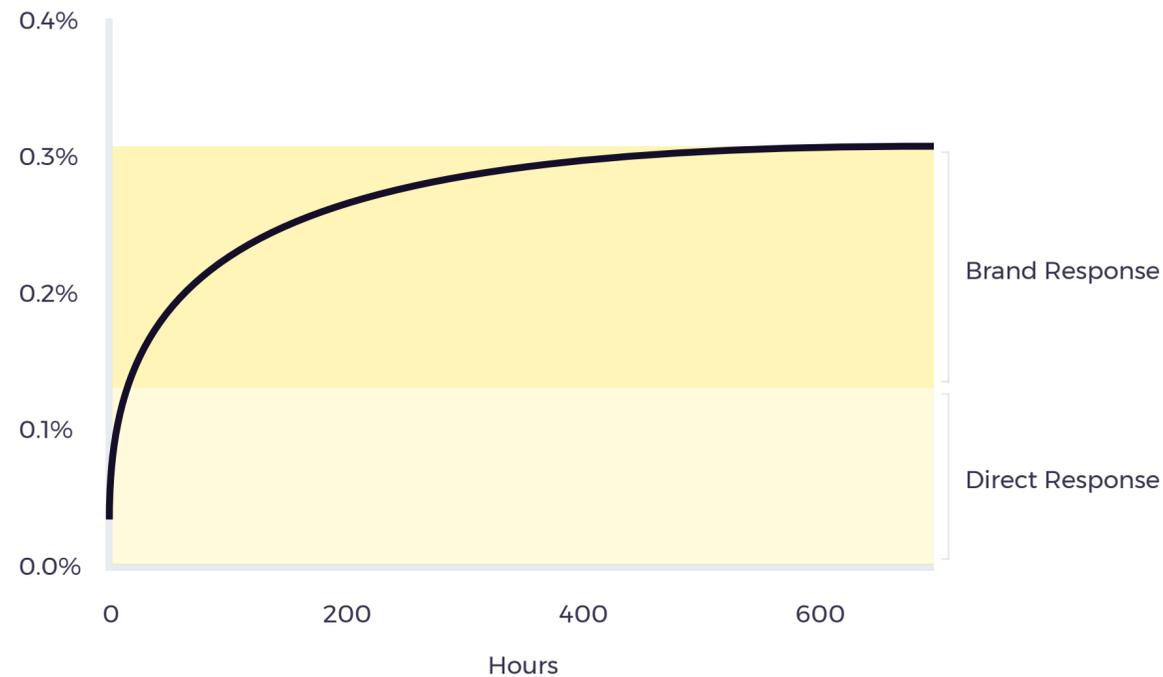
Client TV Long-Term Response			
Time Since	Total Response	Direct Response	Drag Factor
7 min	0.133%		1.00
1 day	0.20%		1.50
7 days	0.241%	0.133%	1.81
30 days	0.295%		2.22

Figure 7 Drag factor after adjusting for incrementality

In this case, after 30 days, when we divide the total response (0.295%) by the direct response (0.133%), we obtain a drag factor of 2.22.

Comparing the drag factor (2.22) to the cumulative one (13.64), we can see that it has significantly decreased after accounting for those viewers who would have installed client's app even without seeing client's TV ad (the control group).

We can also relate the total response to the cost per install (CPI) by noting the following:

$$\text{total response} = \text{direct response} + \text{brand response}$$

and

$$\text{CPI (total response)} = \frac{\text{CPI (direct response)}}{\text{drag factor}}$$

This shows that the CPI of total response decreases as the drag factor increases.

Figure 6 Final Installation Maturity Curve (0 < time < 600 hrs). t=0 denotes time at which the viewers saw the last client ad.

Conclusion

We were able to measure the drag factor (and therefore the brand response) for this client using a closed-loop analysis. The CPI calculated no longer holds any guessing around the brand impact. TV is fully and correctly attributed for, and can now be compared to other paid (digital) acquisition campaigns (measured at the margin and adjusted for isolating incrementality).

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Thank you.