MEASURING CAMPAIGN EFFECTIVENESS USING INFLUENCE METRIC AND HOLISTIC CONSUMER BEHAVIOR

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Synopsis

Digital media presents an opportunity for advertisers to reach consumers anywhere and at any time, ultimately affecting the likelihood of consumer engagement. Even still, quantitative measurement of campaign effectiveness can be challenging characterized by lack of accurate metrics.

Critical decisions regarding the effectiveness and ROI of online campaigns are made based on the simplistic metrics that attribute the conversion entirely to the measured campaign. Traditional approaches often miss three key issues – the impact of all pre and post ad viewing events (brand interactions - e.g. social, video, search, reviews, etc.) on the consumer conversion. The second is the user intent. Often campaigns are viewed by consumers who would convert regardless. The third aspect is the online user behavior. Online behavioral patterns specific to the user are critical in understanding the frequency requirements for brand interactions that result in maximum positive impact and conversion.

We present an approach that uses longitudinal user level panel data to measure the chronology of various ad events and brand interactions experienced by the user. We apply unsupervised learning models to detect patterns of baseline behavior. Integrating this knowledge with online consumer behavior we create behavioral segments based on the purchasing patterns of consumers. An influence metric estimates the impact of campaigns in the consumer purchase decision for each of the segments. We present results using an online ad campaign in the wireless industry that contrasts the influence of the campaign using traditional effectiveness measures and the estimates using the methodology described above. The conclusion using our methodology indicates a much more effective digital campaign in targeted populations than indicated by traditional methods.

Background

Over the past several years the industry has seen an increased demand for proving ROI on digital media. As media options continue to expand digital budgets are increasingly scrutinized. A fully integrated digital medium presents an opportunity for brands to have a significant impact on an appealing segment of consumers to interact with the brand and products. This also creates a challenge for brands to be able to measure the attribution of media. In order to understand the attribution of media it is imperative to understand the true influence of ad campaigns on the purchase decision of consumers. Are Ad campaigns targeting consumers who would have converted in any case? Traditional attribution model would classify this scenario as a successful ad campaign. But in terms of ROI, the campaign has not delivered by increasing awareness or conversions. In order to understand the true influence it is imperative to create behavioral segments as emerged from data and measure the influence of the campaign on each segment thereby creating an understanding of digital influence for future ad spend.

We present a consumer-centric approach to attribution analysis. This analysis concentrates on the sequence and intensity of each relevant behavior that may eventually impact a consumer's decision. Exposure to an ad is another stimuli as are a review site, the use of a search engine on an aggregator site, seeing a product placement in a YouTube video, etc. The approach is data driven- no prior assumptions are made about consumers' behaviors. The models emerge from the data reducing bias from estimation. Setting the model in this framework lends itself to estimating segments based on consumer journey. The influence of the ad, as a stimulus is then measured in each of these segments. This presents information to brands about consumer targets. Brands already know about consumers that interact with the brand. This approach helps brands locate segments of consumers that provide the most incremental return on the ad spend and provides information about locating these segments of consumers ultimately helping brand strategy.

Objective

The objective of the study was to create a holistic consumer centric attribution analysis. A wireless provider conducted an online campaign for 30 days and wanted to quantify the lift on conversion to build the case for increased digital spend. The brand hypothesized that the ad campaign was targeting consumers that were already bound to make a purchase. The brand wanted to focus on discovering behavioral segments of consumers that emerged from the data based on the consumer purchase journey and quantifying the influence of the ad campaign on each of the segments. Further the brand wanted to create targets for future digital spend and estimating the effectiveness of the campaign
Specifically the brand wished to quantify

- The lift attributable to online digital campaign
- Behavioral segments based on purchase journey
- Influence of the campaign on the behavioral segments
- Targets for future digital spend.

Summary of the Approach

To discern the knowledge about the influence of the ad campaign, we used three types of input data. The same data are utilized to create segments of users based on user behavior and the purchase journey experience by the users. The three sources of input data are -

1. Longitudinal user level data

   These are click stream activity from each user that records every web page, the time stamp of the click-stream activity and the time spent by the user on each web page.
2. Definition of brand interaction

   Brand activity or touch points are defined based on the brand, the brand category; the products and other brand related activity. Typical examples of touch points are review sites about brand/product, manufacturer site, social media interaction specific to the product, etc. Each touch point is defined as a collection of web pages. User visitation to any of the web pages defined as a touch point gets defined as a user visitation to the touch point.

3. User Interaction with touch points

   These are longitudinal data representing the exact time that the user interacted with a touch point and the amount of time the user spent on the touch point. Implicit within these data is information about the order of touch points, the frequency of visitation to these touch points the reach of each touch point.

For the case study we utilized the data available from the Millward Brown Digital panel. MBD has a panel of 2 million active users online. Consequentially data are collected and processed using MBD data process. The panel is assimilated from multiple technology sources to mitigate some of the technology bias associated with a specific data collection technology. MBD uses a patented methodology for biased adjustment from the data source and projecting to the online browsing universe. The details of the methodology are out of scope for this paper and any specific algorithm details described here utilize the existing panel projection methodology.

The existing panel projection methodology can be detailed in the following way –

$$Reported\ Metrics = \sum_{i=1}^{n} I_i * user_i * wt_i$$

where,

n = Total number of panellists

$User_i$ = the raw metric recorded for user *i*

Wt_i = weight of the user *i*

$$I_i = \begin{Bmatrix} 1\ if\ i\ \epsilon\ metric \\ 0\ otherwise \end{Bmatrix}$$

As stated above, the scope of this paper does not allow for detailing the projection methodology. We will continue to extend the projection methodology as stated above towards the application in understanding the impact and influence on consumer path to purchase.

The data collection process consisted of aggregating user level data across defined period of time and for a consumer journey for defined period for each user. The first step in the process is defining an end state. Typical end state tend to be conversion (product purchase), but in specific cases could also be approximated as product add to cart or other defined activity. Based on the definition of an end state and a defined shopping period, users are identified in the system. The user selection is conducted based on reaching the end state during the defined period.

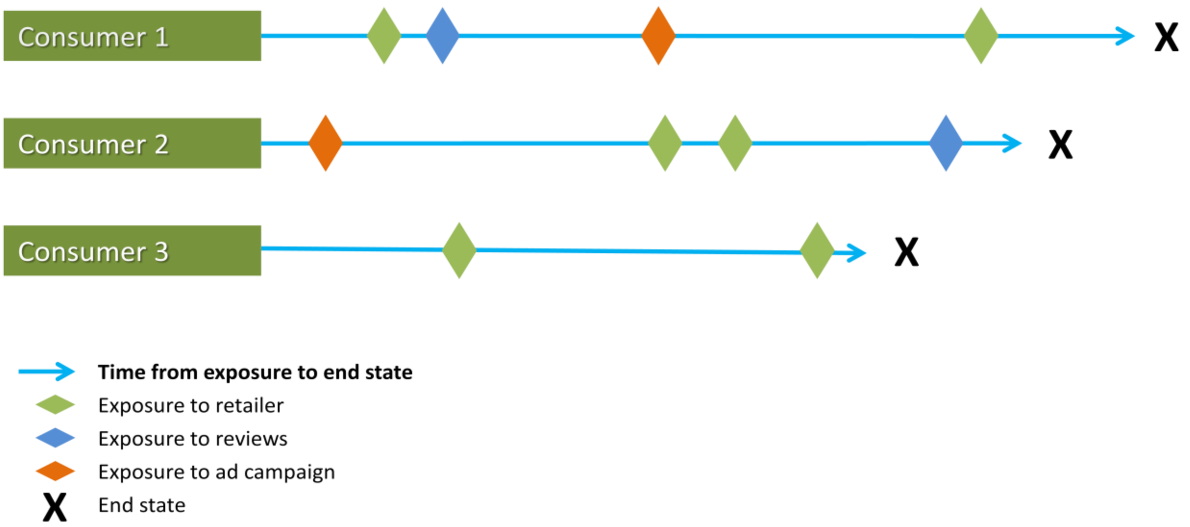
The next step in the process is to define the touch points. A touch point is defined as a collection of web pages that are related based on a common theme. For example, a 'retailer' touch point can be defined as visitation to a defined set of online retailers and all the subsequent brand/product pages on the retailer. Based on the specific study multiple retailers can be clustered into one. Te touch point definition can be as aggregated or granular as required by the specific brand and product campaign. As a continued example, all online retailers can be considered in a single touch point or at the other end of the spectrum; each retailer can be its own touch point. The developed model can handle the granularity of touch points or aggregation of touch points as well as the frequency of visitation in the inferential procedure. In the context of the model set up, viewing an ad campaign is added to the data as an additional touch point.

Up on defining touch points and the segment of sites that constitute the touch points, a set of users is defined by selecting all users in the panel who exhibited an end state behavior, and exposure to the ad campaign within the predefined time frame. A default time frame is usually 4 months but can extend longer or shorter depending on brand and products.

The next step in the process is to select the longitudinal activity of the defined set of users. For each user, their activity in a predefined time frame prior to reaching the end state is selected. Based on this activity, the variables collected are the user, their path (eg. search -> retail ->reviews ->retail ->END state). For each user the time spent on each touch point and the time spent between touch points is also collected. And the total time spent online is used as a variable to normalize their activity on touch points.

The above list of variables represents a comprehensive set of brand related activity exhibited by the users. Implicit in the list of variables is the order of the touch points, the frequency of visitation to each of the touch points. These are important modeling parameters that define the criticality of the path to the user as well as the criticality of each touch point within the user path towards purchase. Another critical aspect surrounds touch point definitions. Ad campaigns are considered to be another touch point in the users' path to purchase. The advantage of this modeling approach is that attribution is estimated in the context of the entire user activity as opposed to a exposed and control design where normalizing exposed and controls to other stimuli is not feasible. Any regressive model used to normalize across the exposed and control groups is prone to bias related to correlation of variables. Utilizing the longitudinality in combination with the behavior of the user paints a larger picture that estimates the true underlying attribution of the ad campaign in the context of the consumer journey and the path to purchase.

The consumer centric attribution methodology can be represented as follows



The figure represents a the data layout of the consumer centric attribution model. Each user is exposed to stimuli at specific points of the path to purchase along with the ad campaign. The frequency of exposure to the touch points is different for each user. There are some users who are not exposed to the ad campaign and reach the end state and still others who are exposed to the ad campaign and do not reach the end state.

Consumer Centric Attribution Model

The consumer centric attribution model consists of two steps –

Step I: Segments using consumer behaviour

In the initial step we create segments or clusters of users based on paths, observed visitation behavior and the time spent on each path. To do this we use fuzzy c-means clustering. In fuzzy clustering, data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. This differs to other hard-clustering methods such as k-means or hierarchical clustering methods where each element is assigned to only one cluster based on similarity or dissimilarity scores. Fuzzy clustering is a process of assigning these membership levels, and then using the membership levels to assign data elements to one cluster.

Step II: consumer centric attribution model

In the second step we create an attribution model by estimating a 4 parameter logistic curve for each user and creating an influence metric for each touch point for each user. A 4 parameter logistic model assumes an underlying 'S-shaped' curve for the probability of reaching an end state. Using the 4 parameter logistic model, consumer journey is represented as a connection of touch points such that the influence of each touch point is estimated in the probability of making the user continue along the purchase journey. As the consumer gets closer to reaching the end state the model intrinsically adjusts for the change in frequency and time between touch points to reach the end state and utilizes this adjustment in estimating the influence of each touch point. Using this scale, the influence is estimated so that for every consumer reaching the end state, the sum of influences from all touch points equals 1.

Estimating Campaign effectiveness in a wireless study

We briefly present the model in estimating the influence of an ad campaign in a study in the wireless industry. A wireless provider conducted an online campaign for 30 days on major publishers and wished to quantify the influence of the campaign on the consumer purchase journey.

Approach in the wireless study

As defined earlier, we collected data from all users who reached an end state during the 30 day campaign and the following 30 days. The period of latency to be tested was determined to be 30 days post campaign. The following touch points were considered along with the ad campaign during the analysis –

- Ad Campaign
- Social Media
- Reviewer Sites
- Search
- OEM sites (Orignal equipment manufacturer – eg – Samsung, Nokia, etc.)
- Carrier Sites

Visitation to any of the sites as defined by the collection of web pages belonging to each touch point constituted as a visit to the touch point. The study collected a total of 2016 consumers who had converted i.e. purchased an online plan during the defined time frame. For each consumer, the study observed the consumer activity for 5 weeks prior to reaching the end state to record the engagement with the defined touch points.

Results for the case study

The study looked at all the different paths from the 2016 users. 2016 users constituted 1782 distinct paths. A path refers to a chronological set of touch points the user visited before reaching the end state. An example of a user path is – Search->Retailer->Review->End State. Out of the 2016 users, 1328 users were exposed to the ad campaign. These users constituted 32 million online impressions at a projection level. The average frequency of these impressions was 5.3
We used fuzzy clustering to create a set of segments based on user paths. The data segmented into four groups based on user behavior and the paths. The highlights of the paths are represented in the table below

	Segment 1	**Segment 2**	**Segment 3**	**Segment 4**
% of Users	20	24	45	11
Av. # of Steps	8	10	3	8
Average Time on Path	2.6 weeks	5.6 weeks	4 weeks	8 weeks

Table 1 – Summary of clusters for Shoppers

Based on the segments above, we estimated the influence of the advertising campaign based on the definition of step 2 above. The results of the influence are presented below –

Segment	Influence of Ad campaign
All users	19%
Segment 1	29%
Segment 2	23%
Segment 3	15%
Segment 4	16%

Table 2 – Influence of Ad campaign for each segment

Based on the segment the algorithm also created a list of touchpoints that are most influential for each segment. This defines where users in each segment can be acquired based on their behavior.

Segment	Influencial Touch points
Segment 1	Retailer, Time on first touch point
Segment 2	Search, Reviews
Segment 3	OEM, Aggregator
Segment 4	Total Research time, Search, Reviews

Table 3 – The Most influential touch points for each segment.

Based on these results, we were able to quantify the influence of the campaign not just in comparison to the exposed vs control setting but a more holistic influence on persuading consumers to convert. Based on the segmentation approach, we were able to provide a retargeting strategy in terms of segments that were more influenced by the ad campaign. This resulted in the brand being able to carve a more effective digital strategy moving forward. A detailed description of each of the segments in terms of their online behavior and demographics is out of the scope of this paper but based on this approach is a conclusion that can be reached. Our study showed that certain segments on users recognized by their online behavior tend to respond more to certain ad campaigns thus laying the foundation for creating a predictive model that can result in a more effective retargeting strategy and a better ad spend by the brand.

Conclusions

We do not believe that true attribution and campaign effectiveness can be measured by simply in a control and exposed setting. There are several other stimuli in terms of earned and paid media that the users are exposed to that contribute in conjunction with the advertising campaign. Furthermore, exposing users who would convert regardless of the exposure to the campaign can bias the attribution results towards inflating the impact of campaign.

We do believe that stimuli work differently on behavioral segments and such segments need to be dynamically created based on behavior of users and the patterns of touch points the users take to reach the conversion state. Once these segments are created, the effectiveness of ad campaigns can be utilized for effective retargeting and attribution modeling.