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METHOD FOR INTERPRETING CONVERSION PATH PERFORMANCE FROM UPPER-FUNNEL INTERACTIONS

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In digital marketing, most advertisers optimize to the interaction that occurs immediately before a conversion, commonly known as the "last click". With attribution, that scope is significantly widened to engage prospective customers across their entire journey, opening up opportunities for efficiency and performance. The challenge, however, is more than just how to allocate a budget, but also the time lag that occurs between spend and revenue.

In a "last click" approach, advertisers can invest and immediately measure impact. Pay for a click, measure if that visitor converted. Optimizations can also occur in near real-time.

But, with an alternate attribution strategy, investing across the entire funnel also means that the delay between marketing action and conversion begins to significantly widen. Within individual verticals, we have discovered that a retail advertiser may have to wait up to 3 weeks to measure the full impact of an upper-funnel investment. This means that assessing the performance of display campaign flighted during Thanksgiving could take up until the last week of the holiday shopping season in December to know whether it was successful. Other verticals, including travel, finance and education have even longer lag periods making the impact more significant.

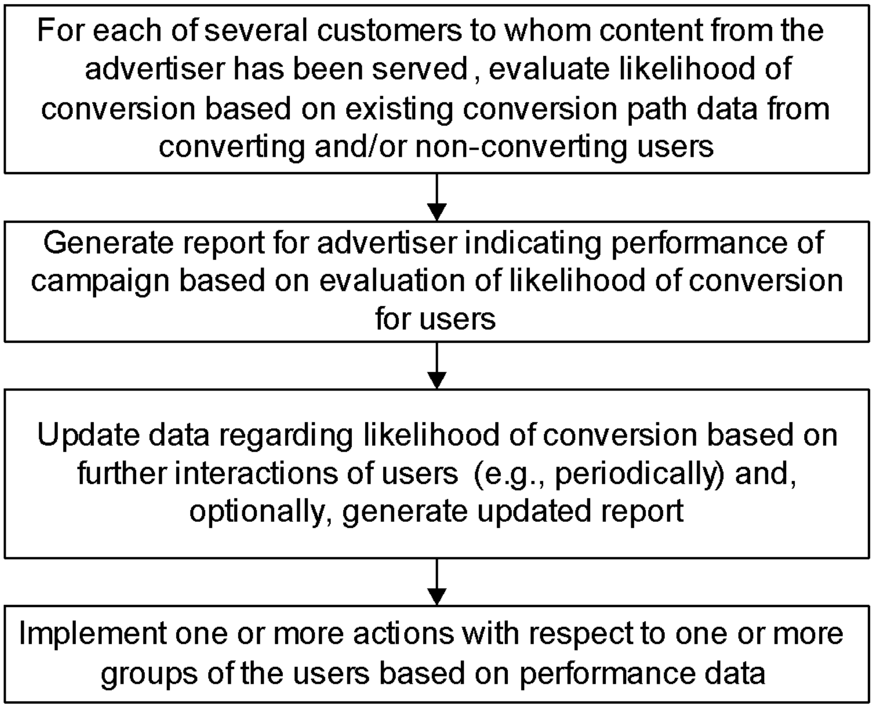
This problem is causing significant challenges to marketers in two key areas: risk and responsiveness.

In the first group, risk, advertisers are forced to wait for customer paths to develop in their entirety before they can begin to assess the overall impact on their conversions from their new approach. Continuing from the previous example, an advertiser may not be able to assess whether their holiday campaign was successful until it is far too late in the season to reverse any shortcomings. And, while an advertiser can limit risk by testing in smaller areas to avoid a sizable impact on their business, the lag period from test to results is still exponentially larger than anything they tried with a "last click" methodology, reducing the attractiveness of attribution, as a whole.

The second issue, responsiveness, presents a problem as it limits the amount of options a marketer has to improve their campaign performance. Each individual opportunity can take weeks before its performance can be assessed, limiting the amount of tests that can be run, as well as requiring increased budgets to ensure it can run evenly throughout the experiment.

Forecasting models have been traditionally used by marketers to assess the impact of their spend decisions, but are limited in daily optimizations for advertisers. Similar to Media Mix Models (MMM), forecasting models are top-down, looking at large groups of marketing spend, usually at the channel-level in conjunction with larger business conditions (market, competition, seasonality) to project total sales. Attribution models, on the other hand, are attractive for their bottom-up approach, offering insight into individual keywords, campaigns and customers and, in turn, giving marketers more levers to pull on a customer-level. These components are often too small in size for a forecasting model to project accurately.

This disclosure uses existing conversion path data from both converting and non-converting users to a website to assess the probability of a customer's conversion path continuing towards a conversion, optionally reassessing this likelihood at each interaction. One implementation of the concept is illustrated in the flowchart below:



Consider a travel advertiser who is making a decision to invest in an upper-funnel display campaign to bring in new customers. During the first stage of the process, this method identifies, as a metric, how many new conversion paths were started. This is determined by users who have clicked on a particular display campaign, but have either not previously been to the website or, if selected by the advertiser, not within a period of time that would connect them with previous visits (e.g. 90-days).

Using the path data from previous customers, the system can then directly calculate the likelihood of a new customer continuing to convert based on that starting point. For example, if previous customer paths starting on a display click had a 1% chance of converting later in their path, the same may be assigned to new customers. This gives advertisers their daily benchmark, similar to last-click, to project how many sales may result from their spend.

As a front-end visualization, audience groups are broken down into separate reports based on their acquisition campaign as it provides a stronger signal to intent versus interactions that may happen elsewhere in the funnel. The advertiser can view the total number of prospective customers brought into the funnel from the campaign, their likeliness of converting based on previous path interactions, the confidence bands surrounding that estimate and the number of days before that spend is expected to be fully captured. It can also project out the costs from subsequent interactions. For example: if customers starting on a display path are likely to click on X search ads, the visualization can project what the likely search budget should be to continue to drive customers through the conversion funnel.

In some implementations, the system can update the estimated performance metrics (e.g., estimated likelihood of conversion) based on subsequent interactions. With each additional interaction (e.g., a second visit through paid search) or metrics surrounding an interaction (e.g., time on site, pages viewed), the projection can become even more precise, alerting the marketer to whether the campaign is over or under-performing based on historical performance data. For instance: A typical customer introduced through a display campaign may have only a 1% chance of conversion, but since the second visit came from paid search and occurred within the next 24 hours, we have a higher confidence that a conversion will eventually occur and adjust the formula accordingly. Equally, the process can detect if, say, the prospective customer set was not returning in the time predicted and therefore may be a wasted investment - even without waiting for the whole path to play out.

In some implementations, the advertiser may use the information discussed above to implement one or more actions. Suppose X% of customers who were expected to convert are not behaving as previous conversion paths suggest. The advertiser would have the option to proactively market to that segment either through a remarketing list or e-mail campaign in an attempt to change their behavior. The system could also construct probability models to guide the advertiser on what their level of success may be with the specified action given historical performance the associated costs. In other cases, the system may use marketing events to induce more desirable behavior (e.g., behavior more likely to lead to a conversion based on historical data). If customers returning to the site 24 hours after their first interaction was deemed a positive response, the system may recommend bidding more for those specific customers during the brief window surrounding the initial interaction.

In some implementations, the system may expand beyond marketing channels and into product-oriented projections. If you brought X customers in through a generic, upper-funnel travel campaign, it is reasonable to suggest that you could forecast inventory demands as their conversion paths begin to develop with a reasonable prediction as to when that inventory needs to be available to satisfy the customer's need.

Much of the work done in attribution has been to look backwards at conversion paths to assess whether a marketing action was impactful and how much credit should go to a respective action. This disclosure takes a forward-looking view based on the same historical performance, giving marketers greater control to understand and respond to the developing conversion paths instead of assuming that they are already predefined by the attribution model itself. Beyond using this particular type of approach, competitors would be limited to building individual forecasting models for clients, which are still subject to the limitations that were described above.

Abstract

A method for interpreting conversion path performance from upper-funnel interactions includes evaluating likelihood of conversion for each of several customers to whom content from the advertiser has been served based on existing conversion path data from both converting and/or non-converting users to a website. The method further includes generating a report for an advertiser indicating performance of campaign based on the evaluation of likelihood of conversion for users, updating data regarding likelihood of conversion based on further interactions of users, and optionally implementing one or more actions with respect to one or more groups of the users based on performance data.