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Identification of True Incremental Effects and Budget Reallocation Mechanisms in Digital Advertising under Bias-Corrected Multi-Touch Attribution

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Abstract: Due to more stringent privacy regulations, fractured cross-platform data and disjointed advertising channels have reduced the traceability of digital advertising results, and now people are only focused on changes in scale. Existing research has not yet combined propensity score correction, counterfactual incremental estimation, Shapley decomposition and marginal iROAS constraints in an auditable attribution pipeline. A bias-corrected multi-touchpoint attribution framework is proposed in this paper to remove the natural conversion baseline and redistribute channel credit. As shown in the illustrative channel-level application, observed attribution can differ from corrected incremental contribution by as much as 11 percentage points; for example, retargeting marginal iROAS dropped to 0.72, and 17 per cent of the budget was shifted among channels. Based on the above results, the attribution share should not be directly correlated with true increment; thus, budget allocation should shift away from high-relevance but low-incremental harvesting channels and towards scalable channels that offer better marginal incremental returns.

1. Introduction

The problem of digital advertising is not whether a channel is present in the conversion path, but whether the conversion would still happen without that ad touchpoint. Users are exposed to multiple times via search, social media, videos, displays, remarketing, email, etc., and will often click, visit or revisit them before finally buying. Multi-touchpoint attribution can improve path explanation, but its foundation is still observational association; channels near the conversion point or frequently logged by the platform tend to receive too much credit. Therefore, this paper addresses the following two research questions: (1) How large is the gap between the observed attribution share and bias-corrected incremental contribution? (2) Under what conditions should marginal iROAS constraints drive budget reallocation rather than platform-reported ROAS?

The three categories of existing research are as follows: Randomized experiments identify advertising incremental effects but are affected by opportunity costs and sample interference [2];

MMM models the overall channel response, but lack path-level explanations [3]; and saturation-based budget optimisation mitigates misallocation caused by static ROAS, but does not address user-level selection bias [4]. Therefore, this paper uses the corrected increment as the decision object and proposes a closed-loop mechanism of identification, correction, decomposition, allocation, and retesting.

2. Analysis of the Current Situation of the Research Topic

2.1 Advertising Measurement Shifts from Path Attribution to Incremental Identification

The typical indicators of advertising performance, such as click-through rate (CTR), conversion rate, customer acquisition cost (CAC) and attributable ROAS, are relatively easy to collect every day, but it is difficult to distinguish how many purchases were due to organic sources from those that resulted from advertising. Users who are already motivated to buy will purchase without seeing advertisements. Counting these conversions as advertising contributions overestimates channel value. Incremental measurement is the difference in potential results when exposed to and not exposed to the factor. That is to say,

$$\tau\_i = Y\_i(1) - Y\_i(0) \tag{1}$$

τ_i is the individual incremental effect of user i, Y_i(1) is the potential conversion result after ad exposure, and Y_i(0) is the potential conversion result in the absence of ad exposure. Therefore, the criterion for judging the effectiveness of an advertisement is not whether a conversion is achieved, but rather whether it generates additional conversions than would have been obtained without the advertisement (the counterfactual baseline).

2.2 Multi-Touchpoint Attribution Still Has Operational Value

Table 1. Comparison of Advertising Measurement Methods

Method	Data Level	Main Output	Strength	Limitation	Horizon
Last Touch	User Path	Attributed Conversions	Simple Audit	End-Point Bias	Daily
Rule-Based MTA	User Path	Fractional Credit	Easy Deployment	Heuristic Weight	Weekly
Data-Driven MTA	User Path	Contribution Score	Sequence Learning	Selection Bias	Weekly
Incrementality Test	User/Geo	Causal Lift	Strong Identification	Costly Holdout	Campaign
MMM	Aggregate Series	Response Curve	Privacy Robust	Low Granularity	Quarterly
Corrected MTA	Hybrid	Incremental Credit	Actionable Causality	Model Dependence	Monthly

Multi-touchpoint attribution can show how the touchpoints for user awareness, interest, comparison and purchase change over time, and is suitable for analyzing short-cycle campaigns and adjusting creatives, bids and audience packages. Although it is not exactly the same as causal effects, it can be used as an input feature for incremental models. Some research has used experimental samples to explore how the features of advertising campaigns relate to incremental changes in behaviour and has found that, even after adjustment, attribution indices retain some predictive power [2].

Table 1 shows that the different measurement methods are not equivalent. Last-click and rule-based attribution are suitable for low-cost monitoring but have a considerable bias; experimental identification has the highest causality but limited coverage; and MMM is suitable for long-term budget assessment under privacy constraints but lacks explanation of touchpoint sequence. Bias-corrected multi-touchpoint attribution combines path granularity and incremental logic to help allocate budgets based on attribution results.

2.3 Privacy Constraints and Platform Disconnection Amplify Measurement Bias

Privacy policies, browser restrictions and walled-garden platforms are all limiting the full collection of user paths. Apple's App Tracking Transparency has reduced the accuracy of ad targeting and measurement, and weakened cross-platform conversion tracking [6]. Research on large-scale short-form video advertising has shown that the effect outside the platform under study is also included in the total effect [7]. Therefore, to conduct causal inference, bias correction is needed; otherwise, it is not data cleaning.

A relatively high average ROAS does not guarantee that the new budget will also be effective. With the expansion of channel coverage and a decrease in audience engagement, the incremental benefit per unit of advertising will decline, and there is a risk of ad fatigue. Recently, saturation functions, combinatorial arm slot machines and change-point detection have been applied to optimise advertising budgets; therefore, given the non-linearity of channels and changes in the market, the budget mechanism needs to be adjusted [4].

Table 2: Channel-Level Corrected Attribution and Budget Indicators.

Channel	Current Budget %	Observed Attribution %	Corrected Incremental %	Marginal iROAS	Recommended Budget %
Search	30	32	24	1.18	25
Social	25	26	18	1.05	19
Video	16	18	22	1.42	23
Display	12	11	14	1.21	14
Retargeting	10	9	7	0.72	6
Email	7	4	15	1.35	13

The differences in observed attribution and corrected increments are shown in Table 2. Search and social channels have a relatively large proportion but drop after correction; thus, they are considered to be driven by organic demand. Video and email have larger corrected increments; thus, the impact of demand stimulation and repeat-purchase reactivation is likely underestimated in the raw paths. The suggested budget percentages are based on the marginal iROAS constraint and the saturation assumption in Eq. (5), not on platform-reported attribution alone; they should be understood as an analytically calibrated allocation example.

3. Raising Questions

3.1 Correlation attribution is unable to find the real increment.

Advertising impression allocation will be driven by algorithms in conjunction with users' past behaviour and bidding auctions, as well as targeted reach-outs. Users who are more likely to purchase will be selected by the advertising system for more frequent contact and thus have a higher probability of converting after being exposed to a touchpoint. If credit is directly assigned based on observed paths, the model may incorrectly count the user's own purchase intention as an advertisement's contribution. Let D_i be the indicator that user i has been reached, and let X_i be the set of covariates such as past behaviour, location, device type, etc. Propensity Score is:

$$e(X_i) = P(D_i = 1|X_i) \tag{2}$$

e(X_i) is the propensity score, the probability that user i will be reached under covariate conditions X_i; D_i indicates whether it was reached or not; and X_i is the observed covariate vector. Estimate e(X_i) and then use weighting or matching to make the observable characteristics of the reached group and the control group closer, thereby reducing selection bias.

3.2 Cross-channel interference distorts the contribution of a single touchpoint

User conversion is not the sum of touchpoints. Raise the public's awareness of the brand, have more people look for it online, show customised advertisements in various parts of extended remarketing networks, and use a dual marketing path of email and social media distribution to drive frequent purchases. These paths are treated as hypothesized mechanisms here and are in line with recent evidence on platform spillover in short-form video advertising [7] and paid-organic complementarity in mobile app advertising [8]. If the model does not consider spillover, it may underestimate the upstream channel and overestimate harvesting touchpoints near conversion.

3.3 Budget adjustments do not have a cause-and-effect relationship.

Many enterprises' advertising funds have been planned by considering the published ROAS of the platform; however, such high ROAS may not reflect significant extra-normal earnings growth. Brand searches and retargeting are usually high-conversion-rate channels because they address existing demand. If the budget keeps going to these channels, the firm will be recording conversions instead of creating them. Frequent and large-scale budget adjustments can also disrupt the learning period of the platform; thus, any reallocation needs to be considered in light of adjusted increments, marginal iROAS, and budget-smoothing constraints simultaneously.

4. Problem-Solving and Strategies

4.1 Constructing an Incremental Attribution Model for Deviation Correction

Bias-corrected multi-touchpoint attribution first computes the propensity score, then calculates the incremental conversion of ads relative to the counterfactual baseline, and finally decomposes this incremental part among path touchpoints. Not all conversions are included in the ads' attribution; therefore, a natural baseline is removed first. The mean treatment effect under inverse probability weighting can be expressed as:

$$\hat{A}TE\_IPW = (1/n)\ \Sigma\_i\ [D\_(iY\_i\ )/e(X\_i\ ) - ((1 - D\_i\ )\ Y\_i)/(1 - e(X\_i\ )\ )] \tag{3}$$

ATE_hat_IPW in the formula is the sample average incremental effect estimated by inverse probability weighting; n is the sample size; Y_i is the conversion result or conversion value; D_i is the reach status; e(X_i) is the propensity score. The estimator needs overlap and positivity; that is, users with similar covariates should have non-zero probabilities of being reached and unreached. Extreme weights should be truncated or clipped in the implementation, such as at the 99th percentile, because propensity scores close to 0 or 1 can invalidate the estimator and increase noise.

4.2 Shapley Decomposition of Contact Marginal Contribution

Find the overall increase and then determine how the various channels have distributed this increase. Use the Shapley marginal contribution method to compare the change in corrected increment before and after adding a channel to different touchpoint sets.

$$\varphi\_j = \Sigma\_\{S \subseteq N\{j\}\}[|S|!\,(M - |S| - 1)!/M!][v(S \cup \{j\}) - v(S)] \quad (4)$$

φ_j is the incremental contribution of channel j; N is the full set of channels; M is the number of channels; S is any subset that does not contain channel j; and v(S) is the corrected incremental value of subset S. Exact Shapley calculation enumerates 2^M subsets. This is feasible for the six-channel example, but when M is greater than about 15, KernelSHAP or permutation sampling need to be used to approximate marginal contributions at a reasonable computational cost.

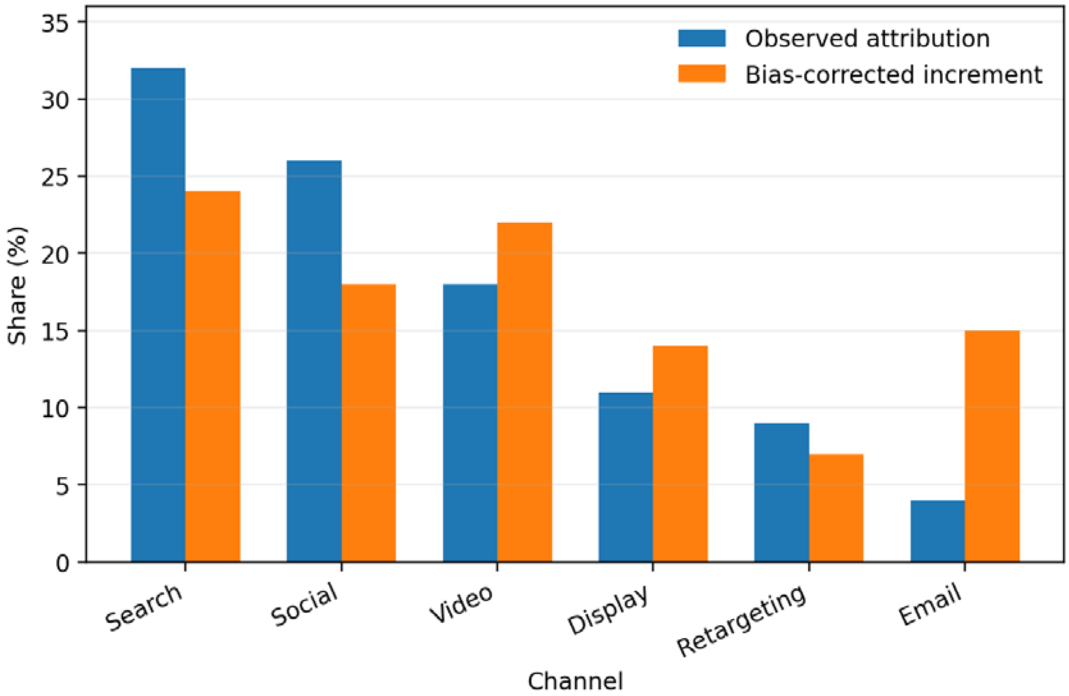

Figure 1. Attribution and Corrected Incremental Share

As shown in Figure 1, the observed attributions for Search and Social are 32% and 26%, respectively; the corrected increments are 24% and 18%, and both indicate natural demand recovery and path-proximity bias. The corrected increments for Video, Display and Email are higher than the observed attributions; thus, demand stimulation, cross-channel return traffic and repeat-purchase reactivation are likely underrepresented by raw attribution. Therefore, the budget decisions should be based on the corrected increment rather than the original attribution rank.

4.3 Establish a Budget Redistribution Mechanism Driven by Marginal iROAS

The purpose of budget re-allocation is to maximise the future additional benefits for the same total cost. Let B_j be the budget for channel j and R_j(B_j) be the corrected incremental revenue response of that channel. The optimisation problem is:

$$\text{Max}\_\{B\_1, \ldots, B\_M\}\Sigma\_\{j = 1\}\hat{}MR\_j(B\_j), s.t. \Sigma\_\{j = 1\}\hat{}MB\_j = B, B\_j \geq b\_j\hat{}min \quad (5)$$

M is the number of channels; R_j(B_j) is the corrected incremental revenue of channel j under budget B_j; B is the total budget; and b_j^min is the minimum operational budget threshold. To ensure the reproducibility of the recommendation, the revenue response is modeled as a Hill saturation function:

$$R_j(B_j) = (\alpha_j B_(j_j^\beta))/(\kappa_(j_j^\beta) + B_(j_j^\beta)),\ 0 < \beta_j \leq 1 \qquad (6)$$

In Eq. (6), α_j is the upper bound of incremental revenue, κ_j is the half-saturation budget, and β_j is response curvature. The above parameters can be obtained from historical spend-response series, experimental lift data or MMM priors, and the marginal iROAS is derived from the first derivative of R_j(B_j).

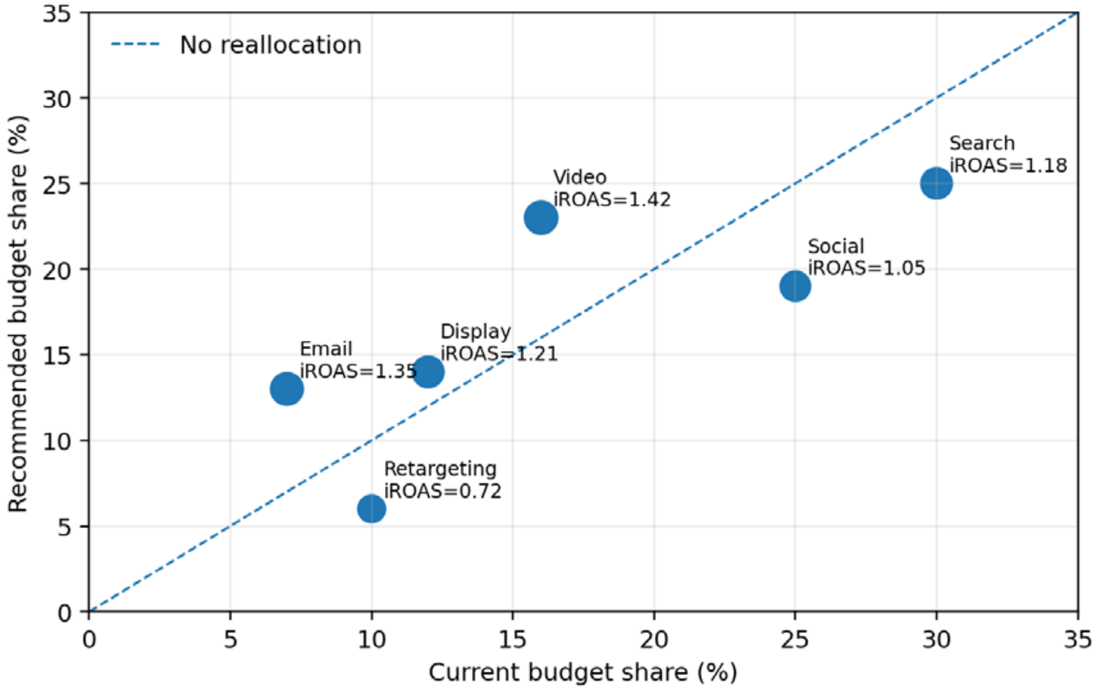

Figure 2. Budget Reallocation and Marginal iROAS.

As shown in Figure 2, the recommended budgets for Video and Email are higher than the current budgets because their marginal iROAS values of 1.42 and 1.35 are still within the scalable range. Retargeting drops to 6 per cent and is no longer economically feasible. Search decreased from 30% to 25%; therefore, the channels for brand-demand harvesting should not be expanded indefinitely but should also not fall below the minimum required level for demand collection.

4.4 Establish Auditable Operating Rules

A series of identification, correction, allocation and retesting should be carried out on the model. First, combine impressions, clicks, conversions, order amount, user history, campaign cost and indicators for missingness of privacy. Next, analyse the difference between reached and unreached audiences and inspect propensity-score overlap. Then, estimate the counterfactual baseline and decompose only the incremental part. Then, according to the marginal iROAS, saturation, confidence interval width and business constraints, adjust the budget. Finally, make some modifications and conduct a small-scale test with ge or an audience. To avoid the model being a "black box", output attribution share, corrected incremental share, confidence interval, marginal iROAS, budget adjustment range and the threshold source for each action.

Table 3 shows the auditable budget adjustment rules. The thresholds are not taken as universal constants; they are guardrails based on the saturation response in Eq. (6), historical frequency distribution and retesting constraints. If the corrected increment is large and statistically significant, increase the funding; if the marginal iROAS falls below 1 after saturation checks, reduce the budget. When the missingness of the path is relatively large, MMM priors should be employed to mitigate misjudgments caused by incomplete user-level logs.

Table 3. Decision Rules for Budget Reallocation.

Condition	Diagnostic Signal	Action	Control Constraint	Review Cycle
High incremental share	Corrected − observed > 5 pp and CI excludes zero	Increase test budget	Weekly change cap < 20%	2 Weeks
Saturation risk	Marginal iROAS < 1 after frequency saturation check	Reduce budget	Minimum reach floor	Weekly
Harvesting bias	High ROAS and low causal lift	Hold or decrease	Preserve brand baseline	Monthly
Spillover effect	Assisted conversion growth or cross-platform lift	Increase test budget	Geo validation	4 Weeks
Data uncertainty	Wide CI or propensity overlap violation	Keep stable	Learning budget	2 Weeks
Privacy signal loss	Path missing rate > 35%	Use MMM prior	Aggregate check	Monthly

5. Conclusion

True incremental effect identification and budget reallocation under bias-corrected multi-touchpoint attribution are studied in this paper. Based on the above analysis, all conversions are not necessarily attributable to a path touchpoint in advertising measurement; they should first be evaluated in light of their contribution relative to the natural baseline. Although traditional multi-touch attribution is suitable for monitoring operations, it lacks propensity correction and counterfactual analysis, thus suffering from selection bias, platform self-attribution and the inclusion of natural conversions in the attribution. The above framework introduces propensity-score correction, inverse probability weighting, Shapley marginal contribution and marginal iROAS optimisation to transform attribution results into auditable budget migration rules.

Prioritize corrected incremental contribution, marginal return and stability constraints in budget reallocation. Channels with high observed attribution but low corrected increment should be expanded under controlled circumstances; channels with low observed attribution but high corrected increment should be gradually validated and expanded with experimental budgets; channels showing a decline in marginal iROAS or excessively wide confidence intervals should reduce frequency and budget or be maintained in an observation mode. The study also has some deficiencies: the channel-level figures in Table 2 are an allocation example and not a proprietary campaign dataset; the propensity model may be misspecified if important behavioural covariates are omitted; and Shapley additivity may be reduced in competitive ad markets with strategic channel interactions. In the future, geo-experiments, privacy-preserving aggregate modelling and reinforcement learning budget control will be used to construct a more adaptive incremental attribution system.

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