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Bias within Rule based Attribution Models for Evaluating ROI of Digital Advertising Spend

Varun Chivukula

USA

ABSTRACT

Rule-based attribution models, such as first-touch, last-touch, and linear attribution, are widely used in digital marketing to assign credit for conversions across the customer journey. While these models are simple and easy to implement, they often fail to capture the complexity of multi-channel marketing and the causal relationships between touchpoints. When not calibrated using randomized control trials (RCTs), rule-based models introduce systematic biases, leading to distorted performance metrics, inefficient budget allocation, and suboptimal decision-making.

This paper delves deeply into the biases inherent in uncalibrated rule-based attribution, illustrating their effects with detailed simulated examples. It explores the overestimation of specific touchpoints, the underestimation of incremental impacts, and the inability to capture synergies between channels. The discussion emphasizes how RCTs address these challenges by isolating causal relationships and recalibrating attribution models to reflect true campaign performance. The paper also provides actionable recommendations for marketers seeking to improve the accuracy and reliability of their attribution frameworks.

***Corresponding author**

Varun Chivukula, USA..

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Introduction

Attribution models are critical tools in evaluating the performance of marketing campaigns, as they assign credit for conversions to specific touchpoints along the customer journey. Rule-based attribution models, such as first-touch, last-touch, and linear attribution, remain dominant in the industry due to their simplicity, accessibility, and compatibility with existing analytics platforms [1,2].

Despite their widespread adoption, rule-based models fail to account for the causal relationships between marketing activities and user behavior. This limitation results in systematic biases that distort campaign performance metrics and lead to inefficient resource allocation [3]. For instance, last-touch attribution, which assigns all credit to the final interaction before a conversion, overemphasizes lower-funnel activities while undervaluing top-of-funnel efforts like display ads and brand awareness campaigns [4]. Similarly, first-touch attribution exaggerates the role of initial interactions, ignoring the influence of downstream touchpoints.

In today's multi-channel marketing landscape, where users interact with numerous touchpoints across multiple devices, the limitations of rule-based attribution are particularly glaring. These models are ill-equipped to capture the synergies between channels or the incremental impact of individual touchpoints. Without calibration using RCTs, they fail to provide a reliable foundation for marketing decision-making. This paper explores these biases in depth, presenting detailed simulated examples and discussing how RCTs can mitigate these issues.

Systematic Biases in Rule-Based Attribution

Overemphasis on Touchpoints Close to Conversions

Rule-based attribution models disproportionately allocate credit to touchpoints near the conversion event. Last-touch attribution, for example, credits 100% of the conversion to the final interaction, disregarding the upstream touchpoints that nurtured the user.

Simulated Example

Consider a user journey consisting of the following interactions:

- Display Ad (Day 1): Introduces the user to the brand.
- Search Ad (Day 3): Guides the user to explore the website.
- Email Campaign (Day 4): Prompts the user to return.
- Conversion (Day 5): User completes a purchase.

In a last-touch attribution model, the email campaign receives 100% of the credit for the conversion. This overemphasis misrepresents the contributions of the display and search ads, leading marketers to overinvest in email campaigns while undervaluing top- and mid-funnel channels that play essential roles in driving long-term brand growth [5].

Underestimation of Incremental Impacts

Uncalibrated rule-based models fail to differentiate between organic conversions and those driven by marketing interventions. This limitation leads to an underestimation of the true incremental value of campaigns, resulting in skewed ROI metrics.

Simulated Example

An advertiser runs a social media campaign that generates 1,500 conversions. However, an RCT reveals that only 60% of these conversions are incremental, while the remaining 40% would have occurred organically. A rule-based model, which assumes all 1,500 conversions are attributable to the campaign, inflates the ROI calculation, prompting overinvestment in social media advertising [6].

Ignoring Synergistic Effects
Rule-based attribution models treat touchpoints as isolated entities, ignoring the synergies between them. For example, the combined effect of display and search ads often exceeds the sum of their individual contributions, but rule-based models fail to account for this interaction.

Simulated Example
A company runs concurrent campaigns:
- **Display Ads:** Drive 1,000 visits and 200 conversions.
- **Search Ads:** Drive 1,500 visits and 300 conversions.
- **Combined Display + Search Ads:** Drive 2,800 visits and 700 conversions.

A rule-based model independently credits display and search ads without accounting for the additional 200 conversions generated by their combined effect. This omission undervalues integrated strategies and encourages siloed decision-making [7].

Randomized Control Trials: A Solution to Attribution Bias
RCTs offer a robust methodology for calibrating rule-based attribution models by isolating causal relationships between marketing activities and conversions [8]. By randomizing users into treatment and control groups, RCTs enable marketers to measure the true incremental impact of campaigns and adjust attribution weights accordingly.

Adjusting Attribution Weights
RCTs provide empirical data to recalibrate attribution models. For example, if an RCT determines that display ads generate a 25% lift in conversions, this insight can be used to adjust attribution weights to more accurately reflect the channel's contribution [9].

Quantifying Incrementality
RCTs allow marketers to separate organic conversions from those directly influenced by marketing efforts. This distinction is critical for accurately calculating ROI and informing budget allocation decisions [10].

Practical Implications for Marketing Strategy
Budget Allocation
Uncalibrated attribution models often result in inefficient budget allocation. For instance, channels like retargeting ads, which appear highly effective in last-touch models, may receive disproportionate funding at the expense of top-funnel activities like video advertising.
Simulated Example
An e-commerce company allocates 70% of its budget to retargeting ads based on a last-touch attribution model. After calibrating the model with RCT data, the company discovers that only 50% of retargeting conversions are incremental, prompting a reallocation of funds to upper-funnel channels such as influencer campaigns and programmatic display ads [11].

Performance Metrics
Calibrating rule-based models with RCTs ensures that performance metrics accurately reflect campaign effectiveness. This accuracy enhances marketers' ability to justify investments, optimize strategies, and align budgets with business objectives [12].

Future Directions
Hybrid Models
Combining rule-based frameworks with machine learning algorithms calibrated by RCTs can improve scalability and accuracy. These hybrid models can dynamically adjust attribution weights based on real-time data and causal insights [13,14].

Cross-Platform Attribution
Addressing data silos in walled gardens like Meta and Google remains a critical challenge. Future research should focus on leveraging cryptographic techniques and federated learning to enable cross-platform attribution without compromising user privacy [15,16].

Real-Time Calibration
Developing real-time RCT frameworks will enable dynamic calibration of attribution models as campaigns evolve. This approach is particularly valuable for fast-paced industries like e-commerce and programmatic advertising [17].

Conclusion
Rule-based attribution models, while simple and widely adopted, introduce systematic biases that distort marketing measurement and decision-making. Without RCT calibration, these models overestimate the impact of certain touchpoints, underestimate incremental effects, and fail to account for channel synergies. By integrating RCT insights into attribution frameworks, marketers can improve the accuracy of their performance metrics, optimize budget allocations, and enhance the overall efficiency of their campaigns. As the complexity of digital advertising continues to grow, adopting advanced attribution techniques is no longer optional-it is a strategic imperative.

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