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Implementing Multi-Touch Attribution at Scale for a Global Sales and Marketing Team in an Enterprise Environment

Shreesha Hegde Kukkuhalli
hegde.shreesha@gmail.com

I. Abstract

Multi-touch attribution (MTA) offers a sophisticated, data-driven approach to distributing credit across touchpoints within the customer journey [1] [2], thereby enabling more precise insights into channel and campaign performance. However, implementing MTA at scale for a global enterprise's sales and marketing team presents unique challenges, including the need to integrate disparate data sources, handle vast data volumes, apply advanced attribution models, and provide insights in real-time. This paper presents the design and implementation of a scalable MTA framework tailored to the needs of a global sales and marketing team, leveraging cloud-native infrastructure, big data processing, and machine learning algorithms to achieve accurate and actionable insights at scale. The proposed MTA solution addresses data heterogeneity by creating a unified data pipeline that integrates structured and unstructured data from CRM systems, web analytics, social media, paid media platforms, and offline sources.

Keywords: Multi-touch attribution, sales and marketing, data integration, machine learning, cloud computing, enterprise analytics.

II. Introduction

In traditional single-touch attribution models, credit for conversions is often assigned to either the first or last touchpoint, disregarding the role of intermediate interactions that may be essential to the decision-making process. While these models are easy to implement, they lack the depth required to understand the complete customer journey, potentially leading to suboptimal marketing strategies and budget allocation [6]. Multi-touch attribution, on the other hand, assigns value to each interaction a customer has with a brand, offering a more holistic view of campaign performance. As a result, MTA has emerged as a preferred approach for large enterprises that aim to align marketing and sales efforts with precise, data-driven insights. By accurately capturing the contribution of each touchpoint, MTA allows enterprises to enhance their marketing return on investment (ROI) and achieve more effective cross-channel coordination [3].

The objective of this study is to present a scalable, data-driven MTA framework tailored to the requirements of a global enterprise. The proposed solution leverages a combination of traditional attribution models (such as linear and U-shaped models) and machine learning techniques to achieve flexible, accurate credit allocation across touchpoints. The system architecture is built on a cloud platform, utilizing big data frameworks for parallel processing and auto-scaling capabilities to handle large and fluctuating data volumes. Additionally, a unified data pipeline enables seamless integration of data from multiple channels, while real-time streaming and interactive dashboards provide the global marketing and sales teams with accessible, actionable insights.

III. Main Body

Background and Related Work: The development of attribution models has evolved significantly, driven by the increasing complexity of digital marketing ecosystems and the need for accurate insights into the customer journey. Attribution models play a crucial role in assessing the effectiveness of marketing channels and campaigns, allowing enterprises to optimize their strategies and budget allocations. This section provides an overview of the evolution from single-touch to multi-touch attribution, discusses various MTA model types, and reviews recent advancements and case studies in implementing MTA at scale.

A. Single-Touch vs. Multi-Touch Attribution: Early attribution models in marketing were limited to single-touch approaches, where credit for a conversion was assigned to one touchpoint in the customer journey. Common single-touch models include *first-touch* and *last-touch* attribution. First-touch attribution assigns full credit to the first interaction a customer has with a brand, while last-touch attribution gives credit to the final interaction before a conversion. These models are simple to implement but fail to account for the multiple interactions that often occur throughout a customer's decision-making process, which can lead to inaccurate conclusions about channel effectiveness.

To address these limitations, multi-touch attribution (MTA) models were developed, recognizing that conversions [4] result from a series of interactions rather than a single touchpoint. MTA assigns partial credit to multiple touchpoints, creating a more comprehensive view of the customer journey. Different MTA models distribute credit differently; for example, the *linear model* assigns equal credit to each interaction, while the *U-shaped model* gives more weight to the first and last interactions. Other models, such as *time-decay attribution*, assign higher credit to interactions that occur closer to the conversion. The choice of model often depends on business goals, the nature of the product or service, and customer behavior patterns.

B. Types of Multi-Touch Attribution Models: MTA models can be broadly categorized into rule-based and data-driven models. Rule-based models apply predefined heuristics to allocate credit, such as linear, U-shaped, and time-decay attribution. These models are simple and interpretable but lack the flexibility to adapt to changes in customer behavior. In contrast, *data-driven attribution* models use machine learning algorithms to dynamically determine the contribution of each touchpoint based on historical data. By learning patterns from large datasets, data-driven models provide more accurate and customized attributions but require significant computational resources and sophisticated data infrastructures.

- **Linear Attribution**: This rule-based model assigns equal credit to each touchpoint in the customer journey. Linear attribution is easy to understand and implement but may dilute the impact of more influential touchpoints.

- **U-Shaped Attribution**: Also known as the position-based model, U-shaped attribution emphasizes the importance of the first and last touchpoints, assigning them higher credit while distributing the remaining credit equally among the intermediate interactions.
- **Time-Decay Attribution**: This model assumes that touchpoints closer to the conversion event are more influential, assigning them higher credit. Time-decay models are particularly useful for short sales cycles where recent interactions are likely more impactful.
- **Data-Driven Attribution**: Data-driven or algorithmic attribution models use statistical and machine learning techniques to analyze historical data and determine the contribution of each touchpoint based on its observed impact on conversions. Common approaches include logistic regression, Markov chains, and neural networks. Data-driven models are highly adaptable and can provide personalized insights, though they require large datasets and computational power. [5]

C. Machine Learning and Advanced Algorithms in MTA: Machine learning algorithms have been increasingly used to enhance the accuracy and scalability of MTA models. Techniques such as *logistic regression*, *Markov chain models*, and *neural networks* are particularly effective for handling the non-linear and complex nature of customer journeys. For example, Markov chain models estimate the probability of each touchpoint leading to conversion by examining historical transition patterns, while neural networks can capture the interaction effects among touchpoints. These methods allow for a more flexible and context-aware attribution but often come with challenges related to model interpretability and computational demands.

D. Scalability and Infrastructure Challenges in MTA: One of the major challenges of implementing MTA in large enterprises is scalability. With the volume of interactions generated across global sales and marketing channels, MTA models must process vast amounts of data while maintaining accuracy and efficiency. The rise of *cloud computing* and *big data technologies* has enabled enterprises to build scalable data pipelines for MTA. Technologies such as *Apache Spark, Hadoop*, and *Kubernetes* allow parallel data processing and auto-scaling, making it feasible to handle large datasets in real-time.

Recent advances in cloud-native architectures have further enhanced scalability. Cloud providers offer managed services, such as Amazon Web Services (AWS), Azure and Google Cloud Platform (GCP), which support large-scale data processing and machine learning model deployment.

Problem Statement: Global enterprises face the challenge of analyzing and attributing credit across numerous channels, from digital ads and social media to CRM touchpoints. The main objectives of this study are:

1. Develop an MTA model that accurately captures the value of each touchpoint.
2. Scale the model to handle large data volumes from global marketing and sales channels.
3. Enable real-time or near-real-time analytics for timely insights.

Proposed Solution

Data Collection and Integration: Data collection is the backbone of MTA, requiring the integration of structured and unstructured data from various sources, including CRM, web analytics, social media, and transactional data. This section describes a scalable data pipeline built using cloud services, ensuring efficient data ingestion and transformation.

- **Data Sources**: CRM systems, website interaction logs, web visit platforms such as Adobe, email marketing systems, content sharing platforms, paid media platforms, social media channels, retail stores and offline sources.
- **Data Processing**: Cleaning, de-duplication, and harmonization to ensure data consistency.
- **Data Storage**: Use of a data lake or cloud data platform such as data bricks, snowflake to store raw data and a data warehouse for processed, analysis-ready data.

Attribution Modeling: This section introduces the mathematical models behind MTA, focusing on machine learning techniques for more dynamic, data-driven attributions. The proposed approach uses a combination of traditional attribution models and machine learning algorithms.

- **Model Selection**: A comparative study of model types (e.g., linear, U-shaped, neural networks) for enterprise-specific needs.
- **Data-Driven Attribution**: Custom machine learning models are trained to dynamically assign credit based on historical customer journey data.
- **Evaluation Metrics**: RMSE, R2 score, and lift analysis are used to assess model accuracy.

Infrastructure and Scalability: The MTA model requires infrastructure capable of processing high data volumes quickly. This section details the deployment of cloud-native solutions and big data frameworks.

- **Technology Stack**: Spark, Hadoop, and Kubernetes are used for parallel processing.
- **Scalability**: Auto-scaling features in cloud platforms handle fluctuating data loads.
- **Real-Time Processing**: Streaming technologies (e.g., Apache Kafka, AWS Kinesis) enable real-time data ingestion.

Real-Time Analytics and Dashboarding: To facilitate data access for global teams, real-time analytics and interactive dashboards are developed.

- **User Interfaces**: Custom dashboards provide actionable insights and are integrated with enterprise reporting tools.
- **Data Visualization**: Visual elements (e.g., graphs, heatmaps) make attribution data easily interpretable.
- **Access Control**: Role-based access ensures data security and aligns with global data privacy laws.

Case Study

Background: Large global B2B (business to business) technology enterprise with more than $75B in annual revenue wanted to understand more on channels that are contributing to an opportunity. Company had both digital and non-digital channels, digital channels include: Web sites, CRM platform where as non-digital channels include: company sponsored events, conferences. Enterprise had multiple data sources for digital and non-digital channels, some key sources were: Core metrics, Unica, Tealium. Marketing team of the technology company decided to build a large scale multi touch attribution model to quantify and assign credit to each channel for every win or loss opportunity.

Implementation: Following key steps are followed during implementation:

- All marketing data was brought into a central data platform built using Hadoop on cloud.
- Data ingestion and transformation pipelines to derive features were built using spark on Scala
- MTA models are trained on random sample using SPSS
- Trained models are converted to Spark on Scala and scored against full set of data.

MTA data flow diagram

Results and benefits

- More than 20% in marketing cost savings by optimizing marking spend on channels with meaningful contribution to opportunity
- > $20M in annual revenue by industrializing and implementing trained MTA model for other enterprises (customers).

IV. Conclusion

The impact of this implementation is substantial, as it enables the marketing team to gain a granular understanding of customer engagement, revealing the true influence of individual channels, campaigns, and content on conversion rates. Additionally, by quantifying the relative impact of each touchpoint, the enterprise can optimize budget allocation, prioritize high-performing channels, and adjust strategies in real-time. This empowers decision-makers with actionable insights that promote more informed and agile marketing strategies across regions.
Future work will focus on addressing these challenges through enhanced privacy-preserving techniques, such as federated learning, to enable secure and compliant data sharing. Additionally, we plan to incorporate more advanced machine learning techniques, including deep learning models, to capture the nonlinear relationships between touchpoints and conversions. Extending the model to include customer lifetime value (CLV) as an additional factor will provide a more comprehensive view of long-term customer profitability. Moreover, we aim to refine the real-time analytics component to support predictive analytics, which would allow the marketing team to anticipate customer behavior and optimize campaigns proactively.

In conclusion, this scalable MTA framework represents a significant step toward data-driven decision-making in enterprise marketing [7]. By accurately assessing the value of each touchpoint and equipping global teams with timely insights, this model lays the groundwork for a more customer-centric, ROI-focused approach to global marketing and sales. As enterprises continue to prioritize digital transformation, scalable, AI-powered MTA models such as the one proposed in this study will be indispensable for maintaining competitive advantage and fostering long-term customer relationships.

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