iQUANTI™ INSIGHTS

Driving Decisions With Data: iQuanti's Hybrid Approach to Attribution Modeling

Ajay Rama, Pushpendra Kumar

TABLE OF CONTENTS

SYNOPSIS

Brands with large marketing budgets must prove the effectiveness of their advertising spend. When acquisition marketing tactics are deployed online and offline across a complex matrix of physical locations, online offerings, and product diversity, it presents a significant challenge. iQuanti aims to simplify and unify the aggregation, collection, and modeling of marketing data to build a comprehensive marketing strategy for enterprise brands. Here, we will provide detailed insights into iQuanti's approach to data modeling and interpretation.

INTRODUCTION - THE MARKETER'S DILEMMA

The explosive growth of media, channels, digital devices, and software applications has provided firms with unprecedented opportunities to mine data for better business outcomes. Data can be leveraged to better personalize the customer experience, extract more value from current customers, and home in on the right prospects.

Yet when organizations execute marketing spend across

a variety of channels – including TV, paid search, display, promotions and affiliates – and the competitive and market landscapes are in constant flux, it is a challenge to understand how data can actually be harnessed to grow revenue.

In this environment, data-driven analyses are necessary for identifying the underlying relationships between these variables – while also driving key benefits such as:

- **Quantifying successful marketing efforts and their impact on business objectives**
- **Prioritizing marketing spend for maximum impact**
- **Identifying the channels and tactics that provide the best return on investment.**

By combining media mix modeling, or econometric modeling, and multi-channel attribution modeling, iQuanti is able not only to define key enterprise-marketing performance metrics, but also to identify the impact of individual marketing channels. The holistic view of individual channel contributions provided by these modeling techniques is essential for optimizing overall marketing performance.

This document provides detailed insights into iQuanti's approach to modeling, and the business impact this approach is capable of driving.

1. MEDIA MIX MODELING (MMM)

Media mix modeling (MMM) is a technique that aims to quantify the impact of multiple marketing inputs on sales, market share, or other key business goals. The end goal of using MMM is to understand how each marketing input contributes to sales, and how much to spend on each marketing input to maximize return.

MMM's key strength lies in its ability to analyze offline variables that affect media performance: market elasticity, marginal profit, point of diminishing returns, seasonality, and how other media types impact consumer behavior.

MMM requires the creation of a mathematical equation to explain the sales pattern of a product as a function of numerous factors: paid search, display, paid social, email, broadcast media (TV and radio), etc. media mix modeling thrives on "variation" in the data set to identify the lift that results from individual channel activity.

1.1. DATA SELECTION AND PREPARATION

Before modeling can begin, the organization identifies the key business objectives to be measured. The next step is data discovery to determine what data is available and where it comes from. Data selection and preparation is typically the most time-consuming portion of a modeling project, but it is vital to achieving high-quality results.

Data categories required may include:

- **Market-level media measure (GRP/TRP + spend)**
- **Channel-level metrics such as traffic, impressions, clicks, etc.**
- **Marketing events and sponsorships**
- **New accounts/sales by product line**

Key data characteristics are:

- **Weekly aggregated data for each category**
  - **> Campaign or creative level**
  - **> Reach/delivery frequency**
  - **> By DMA or ZIP code**
- **Consistent for all media elements.**

A key element of a media mix model is the dependent variable, which is the variable of interest to the organization that needs to be predicted. For banking and financial organizations, for example, the more typical dependent variables are new accounts opened, or application forms submitted, while the same could be total product sales for a retail organization.

Independent variables, also referred to as predictors, are quantifiable measures which influence the dependent variable. Typical independent variables include TV, newspaper, and magazine spend, emails, direct mailers, and other means of reaching and engaging prospective customers.

Once the data set is fully integrated and cleansed of dependent and independent variables, a correlation analysis is done to check for multi-collinearity. This will reveal independent variables that are closely related to each other. Multi-collinearity can skew the model to make some variables appear more or less impactful than they really are. Care must be taken to eliminate highly interrelated variables and use a smaller number of relatively unrelated predictors to achieve a more robust model.

1.2. iQUANTI'S APPROACH TO MEDIA MIX MODELING

iQuanti uses the principle of multi-regression. The dependent variable and independent variables serve as inputs to this multi-regression model. One model may be sufficient to achieve the measurement goals of a study, but iQuanti often considers multiple models. This is especially meaningful if marketing strategy varies by region or sales channel. Results from multiple models can then be consolidated to create a system-wide view of marketing effectiveness.

1.3. MODEL CONSIDERATIONS

Most predictors in a linear model are treated as though they have a steady impact on the dependent variable, but this is not always true. iQuanti studies the underlying relationships between variables, which can then be incorporated in the model for better predictions. For example, certain variables like TV advertisements have a non-linear relationship with sales. This means that an increase in TV GRP does not always correlate directly to an increase in sales beyond a certain threshold.

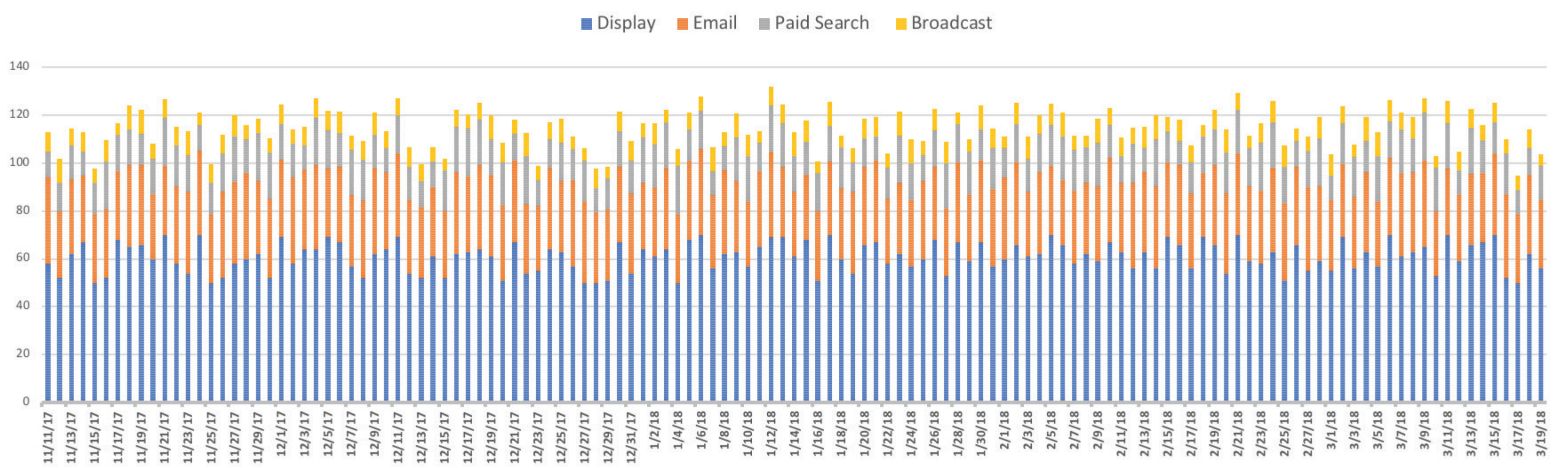
Another example is search spend and display spend, both of which typically produce diminishing returns beyond a certain saturation level. In these cases, a logarithmic or other type of transformation to the predictor variable can reflect a more realistic situation in the marketplace.

iQuanti studies the relationships between independent variables and the dependent variable as part of an initial exploratory data analysis to create more meaningful models.

The model equation is then formed between the dependent variables and predictors and is trained using historical data to come up with the best predictive function f().

$$Y_t = a + f(TV_t, TV_{t-1}, Radio_t, Radio_{t-1}, DM_t, Display_{t-1}, Display_{t-1}) + \varepsilon_t$$

This function f(variables) can be linear or non-linear depending on the relationship between the dependent variable and various marketing inputs.



The betas generated from regression analysis help in quantifying the impact of each of the inputs on the business goal under study. Essentially, the beta illustrates how a single unit increase in an input value would increase the sales/profit by **β** units, keeping all other marketing inputs constant.
The above visualization of sales trends represents a typical output from Media Mix Modeling, where the colored components are daily sales contributed by different marketing channels.

1.4. MIXED EFFECT MODEL

An alternate approach to MMM is suitable if more granular data, such as sales and advertising variables at the regional level, are available.
Mixed-effect models incorporate the individual impact of different regions' features in a single model.

Two popular models in this category are:

- **Fixed effect model**
- **Random effect model**

1.5. ADVANCE MODELS

This category of models takes into account both the direct effect as well as the indirect effect of advertising channels on sales. These are advanced analytical techniques and may require domain knowledge, as well as some research into the types of answers to be solved through modeling.

Two main techniques used in this category are:

- **Bayesian network approach:** Here, a probabilistic graphical model is created to target sales data and all the advertising variables, which are considered to be nodes in the graph. Using this network, one can detect the influence of each node on other nodes.
- **Vector auto regressive models (VAR):** The VAR is the generalization of the univariate autoregressive process to the multivariate space to model both the direct and indirect impacts of independent variables on the dependent variable.

1.6. MACHINE LEARNING APPROACHES

iQuanti also leverages machine learning models, such as random forest, to address any seasonality which might be present in the data sets. These models have historically offered better prediction capabilities.

1.7. MODEL EVALUATION

Several iterations of regression analysis are typically required to create a robust model. Measures of statistical fit such as R2, MAPE (mean absolute percent error), and significance testing for individual predictors are essential to determine the model's accuracy. The R2 score of a model indicates the variation in output that can be explained by input variations. Essentially, this confirms the accuracy of the independent variables – such as traffic, online marketing spend, or offline marketing spend – in explaining the dependent variable (product sales, company revenue, etc.) Multiple models are evaluated on these parameters to determine the best model fit.

1.8. MODEL VALIDATION

Validation is the final step in model building. This involves applying model coefficients to a subset of data not initially included in the model: the Hold Out Validation Set. The HOVS is not used for model creation; it is only used for model validation once the function f() has been predicted.

High accuracy for the validation set confirms that the model is accurate using new, previously unseen data points. It proves that the model can be applied to future data sets and is not overfitted. In other words, that it will be accurate in all cases, not just with the data that is being used for modeling purposes.

There are two approaches to selecting the validation set: either using data from a fixed period, or subsampling at random from the original dataset. The second is iQuanti's preferred approach, as it helps address data bias and seasonality, which can arise in the first case. The data and model will periodically be refreshed so changing channel interactions and behaviors may be incorporated.

2. ATTRIBUTION

Attribution is about identifying how to parse out credit for conversions at a granular level – a device, a person, an ad, a keyword or a channel.

Attribution serves several objectives within a company. The first is budgeting. Attribution helps ensure that money is invested where the most profit is generated. Another benefit to attribution is bid optimization. The granular data it provides can help optimize ad placements across digital channels such as search, display, and social. And, finally, companies rely on attribution for general targeting refinement.

2.1. ALGORITHMIC ATTRIBUTION MODELING

Though Google Analytics provides seven predefined attribution models which are predominantly heuristic (rule-based) in nature, iQuanti prefers algorithmic attribution. Algorithmic attribution takes advantage of advanced statistics and machine learning to objectively determine the impact of marketing touches along a customer's journey toward conversion, leading to a better understanding of campaign effectiveness.

This approach analyzes both converting and non-converting consumer paths across all online channels to identify latent channel influences. Most importantly, it uses data to uncover the correlations and success factors within a brand's marketing efforts.

There are two key highlights to our attribution modeling approach:

- **All online channel data (e.g. paid search, display) are comprehensively integrated; and**
- **Offline conversions (e.g. in-branch, using identity resolution partners such as LiveRamp, Tealium, etc) and cross-device customer conversions are tracked.**

2.2. DATA AVAILABILITY AND TECHNICAL READINESS

The data required for attribution may take time to collect, and isn't necessarily available right away. Two key data categories are needed for this modeling:

Online Data: There are two basic methodologies for obtaining the online data necessary for attribution. The first involves deploying tags to paid media and tracking website conversions; the second involves using historical data from a brand's web analytics platforms and ad partners.

Offline Data: Offline customer conversion data can be identified with the help of third-party data providers such as LiveRamp or Tealium.

For optimal modeling, the data should be:

- **Granular (i.e., customer-level)**
- **Inclusive of all customer touches**
- **Timestamped for each touchpoint**
- **By DMA, ZIP code, etc**
- **Consistent for all media elements.**

2.3. ATTRIBUTION MODEL BASED ON MARKOV CHAINS

Attribution modeling does depend on data access. Issues can arise if third-party data is not available, or if match rates are limited between a brand's customer database and third-party data.

To ensure the best insights are extracted from the information that is available, iQuanti employs Markov models for attribution modeling. A Markov model is a probabilistic model which seeks to calculate the chance that an interaction in one channel – or state, for Markov modeling purposes – will result in a transition to another state (i.e., a conversion).

Every customer journey, or sequence of touchpoints, is represented as a chain in a directed Markov graph where each vertex is a possible state (channel/touchpoint) and the edges represent the probability of transition between the states, including conversion.

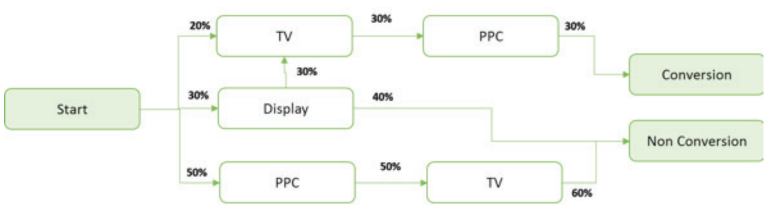
By computing the model and estimating transition probabilities, every marketing channel/touchpoint may be attributed probabilistically.

2.4. ILLUSTRATION

Assume customer journeys contain three unique channels: email, paid search, and display. In addition, three special states – (start), (conversion), and (null) – can be added to each graph to represent a starting point, purchase, or conversion, including unsuccessful conversions. Transitions from identical channels are possible (e.g. paid search --> paid search) but are omitted for this illustration.

Assume as well that there are three unique customer journeys:
Start --> Display --> Email --> Paid Search --> Purchase
Start --> Display --> Unsuccessful Conversion
Start --> Paid Search --> Email --> Unsuccessful Conversion

These journeys help build transition maps like the one below. The percentages, which represent the probability of transition from one state to another, are derived from historical data. The percentages can be modeled to reflect the proportion of conversions or customer values.



Next, the probability of transition from one state in the chain to another – such as a display ad interaction producing a click-through to the company's website – is calculated.

Finally, every contribution of each touchpoint to a conversion is estimated using the principle of removal effect. The aim of removal effect is to remove each channel from the graph consecutively and measure how many conversions (or how much value) would be made (or earned) without it.

The Markov chain model is effective because it uses superior, proven statistical methods to derive the value of each touch on the customer journey and estimate what combination of touches will be most effective.

This knowledge allows for more informed, objective decisions, rather than just assigning equal weights or subjective judgments, leading a brand's marketing efforts to become **more quantifiable and thus more effective.**

In most of the predictive models (such as MMM and random forest), where we eventually see what the true future values are and can compare them to predicted values, in attribution modeling there is no "true" attribution value against which to verify our values. iQuanti's unique approach to evaluate attribution models is to measure and communicate path-specific conversion probability to actual conversion probability driven through same path for a Hold-Out Validation Set.

2.5. MODEL EVALUATION & MODEL REFRESH

Typically, three months of customer journey data is selected as training data to be leveraged for model building. Attribution modeling typically uses data from a shorter time frame than Media Mix Modeling, so as to identify short-term trends. iQuanti uses a month's worth of customer interaction data to serve as the HOVS for model evaluation.

2.6. MODEL VALIDATION

The predicted probability of conversion for individual paths in the validation set is derived from model transition probabilities and can be compared to the path-specific conversion probability to determine model accuracy.

If the attribution model correctly or closely predicts the actual results, the model is mathematically sound. If the outcome does not match the model, the model requires recalibration.

Model accuracy can also be measured using statistical methods such as K-L divergence, which measures the convergence or divergence of two probability distributions. Higher-order [0-4] Markov chains may be included to further enhance accuracy.

Validation doesn't end with model selection but is a continuous Kaizen process. Model performance requires regular monitoring to keep up with changes in business environment, customer behavior or other inputs. Some of these changes may be due to factors like seasonality, which could be included in modeling or changing customer behavior.

Recent data is often most relevant for model accuracy, as customer interaction behavior is constantly in flux.
The models need to be refreshed on a regular basis to learn from the latest data and remain insightful.

Model refreshes may need to occur at least on a quarterly basis. The frequency of refreshes should closely resemble the time it takes for a customer to successfully convert from his/her first touchpoint. By incorporating recent conversion data, this refresh cycle ensures key model parameters are updated to most effectively predict attribution characteristics.

2.7. ADDITIONAL BUSINESS BENEFITS

Markov chains offer an effective way of marketing channel attribution.

There are several additional uses of the approach:

- **Markov model can be deployed for customer lifetime value (CLV) prediction**
- **Additional channel interactions – such as call center activity, offline promotions, or in-store sales activity – can be built in**
- **A "likely to buy" predictive model can be developed using machine-learning algorithms.**

3. HYBRID MODEL - COMBINING MEDIA MIX AND ATTRIBUTION MODELS

To get the most out of one's marketing efforts, fast and efficient measurement is crucial. Using measurement tools that combine the high-level diagnosis of media mix modeling provides insight into the ROI of each marketing channel and the granularity of attribution. This reveals the interplay between channels, giving marketers more precise insights, as opposed to using these approaches separately. Media mix modeling (MMM) is a time-tested way to measure the overall business impact of a range of marketing and media tactics on business. It helps guide investment decisions by showing which channels and tactics work better than others. Multi-touch attribution modeling, meanwhile, analyzes the large amounts of data generated by the impact of digital media (particularly paid search, display advertisements and email) on individual consumers. This information ideally includes every exposure the consumer has had to a marketer's messages and his/her response (or lack thereof). Leveraging granular insights from MTA with aggregated data from MMM identifies the true contributions of digital and offline channels. iQuanti's hybrid approach uses MMM to assign a fraction of a brand's overall sales to offline media, then rewards the remaining credit to user/channel-level behaviors through MTA reporting.

This hybrid approach allows for:

- **Measurement of both the direct and indirect impact of marketing spend on outcomes**
- **Higher accuracy**
- **More strategic decision-making around investments and tactical operational campaign adjustments**

CONCLUSION

Media mix modeling (MMM) may be likened to attribution modeling's big brother. While MMM is a top-down approach that helps allocate spend between channels on a macro level, attribution modeling, specifically digital modeling, focuses on a bottoms-up approach – involving more granular planning, as well as optimization on a more frequent basis. The output of attribution models can be applied to fine-tune MMM's longer-term predictions with more recent trends.

iQuanti's hybrid approach, combining the best of MMM and attribution modeling, offers more insight into the true performance of both online and offline acquisition marketing for an organization.

iQuanti's modeling approach, using a diverse toolset of advanced models and machine learning, drives marketing decisions based on data, along with defined evaluation and validation approaches that ensure true business value generation.

ATTRIBUTION - WHY IT MATTERS FOR FINANCIAL SERVICES ORGANIZATIONS

Business Case for Attribution

- Large financial services organizations deploy their acquisition marketing spend both online and offline, across a complex matrix of physical locations, online offerings, and product diversity.
- By virtue of this multiplicity of channels, product offerings and locations, the true contribution of each channel is opaque. Advanced analytical approaches can illuminate patterns in channel performance.
- Media Mix Modeling and attribution modeling provide brands with a deep understanding of the contributions that multiple channels make towards their business goals.

Analytical Approaches

- iQuanti's Media Mix Modeling strategy involves multiple analytical approaches, from multi-regression models to advanced models (mixed effects models, vector auto regressive models) and machine learning. A Markov/chain-based approach to attribution modeling, in particular, would prove highly effective in attributing individual channel contributions to overall marketing outcomes.

Models and Effectiveness

- iQuanti's hybrid approach to attribution, which leverages both MMM (to identify long term channel contributions) and attribution modeling (to identify shorter-term trends) helps to identify the true contributions of individual marketing channels.
- iQuanti's algorithmic approach to attribution modeling is a significant upgrade from rule-based attribution modeling. It removes subjective decision making and uncovers hidden or latent data patterns leading to meaningful channel attribution.

Business Outcome

- Media Mix Modeling provides high-level insights into how online and offline channels contribute to an organization's acquisition funnel.
- Attribution models unlock insights into the customer journeys and key channel touchpoints that lead to conversions, ultimately resulting in higher conversions.

Citations:
- Anderl E., Schumann J.H. (2014). Analyzing the Customer Journey:Attribution Modeling for Online Marketing Exposures in a Multi- Channel Setting, Retrieved from http://wcai.wharton.upenn.edu
- Martech: Analytics & Data(2016), Beyond heuristics: Algorithmic multi-channel attribution, Retrieved from https://martechtoday.com
- Bhattacharya P. (2018), Marketing Mix Modeling: Techniques and Challenges, Retrieved from https://analytics.ncsu.edu/