

Cross-Channel Marketing Analytics Integrating Offline and Online Data for Holistic Campaign Analysis

Mickey Singh

Marketing Analytics Manager, Affirm Inc. MS in Applied Statistics from Rochester Institute of Technology, NY"

INTRODUCTION

Marketing in the modern world is not dependent on the provision of things for sale. It is a thorough process of meeting the needs and wants of customers. Marketing research is a method of an art which paves the way for a managerial change. Various studies have well-defined marketing research. One research defines "Marketing research is the systematic and objective search for and analysis of information relevant to the identification and solution of any problem in the field of marketing." Another definition says "Marketing research is a company's efforts to know what is there; discern facts and get a grasp on the environment in which its activity is to develop; to understand the apprehension, attitudes, and behavior of people it deals with and to forecast the future in the light of available information." (Malhotra et al., 2020)(Nunan et al., 2020)

Importance of Cross-Channel Marketing Analytics

If a marketing campaign is started without any plan of process monitoring and follow-up analysis, what are the odds that it will be repeated? That's exactly what happens when the effectiveness of a marketing sector is not determined. A brand might think that they have a general understanding of what works best for them, but without hard data they cannot be sure. Without recognizing the most successful methods, marketing strategies are often repeated without desired results. This can be a costly and self-defeating process. With the knowledge of what has been the most effective, a brand can focus their efforts on the most successful sectors increasing the overall effectiveness of the marketing strategy. (Castellana et al.2020)

It is a well-known fact that businesses can determine better marketing strategies through the use of marketing data. In today's world, if there is one thing that successful businesses are proud of, it is their extensive and sophisticated data-driven marketing strategy. It's also no secret that in today's digital age, there are more online marketing channels than you can shake a stick at. It can be easy to be overwhelmed and overextend marketing strategies that spread a brand thin. The most successful marketing strategies come from a deep understanding of what works and what doesn't. An in-depth study of the effectiveness of each marketing channel can provide a means to discover the most successful sectors for a brand. Cross-channel marketing analytics is a method to study the progress of marketing strategies across all online and offline channels to determine which methods are most effective.

Challenges in Integrating Offline and Online Data

Data on such initiatives is usually aggregate level. How many copies of the magazine were sold? Did the bus ad lead to an increase in sales in a particular region? What was the response rate to the direct mail campaign? Often, answering these questions will involve a market research study which might only sample a small percentage of the population. Offline marketing data tends to be less available and when it is, the quality can be questionable. High-level brand marketing campaigns may have murky goals and vague timelines making it difficult to measure the initiative's success and assess the data used. (Shankar and Kushwaha, 2021)

By contrast, offline marketing consumer behavior simply cannot be tracked at the same level of granularity. For example, it's impossible to know exactly how many people read a particular article in a magazine, notice a certain ad on a bus, or remember a specific piece of direct mail. (Ratchford et al., 2022)

The online marketing world is built on user-level data which is perfectly trackable. Each ad impression, click or site visit is recorded in a log file somewhere. Cookies are seeded to users' computers allowing web analytics systems to track user behavior over time whether they return to the site via a search click or an email campaign, etc. This data is incredibly

granular and when properly analyzed can provide a wealth of information on user behavior and the effectiveness of online marketing initiatives. (de Sousa et al., 2020)

In an ideal world, offline and online marketing data would be merged to create a single customer view with every marketing touch captured and analyzed. In reality, integrating data from offline and online channels presents a number of challenges, which will be addressed in the following.

Offline Data Analysis

Most often, offline media data is cleaned, catalogued, and organized in a way that is specific to each medium (i.e. TV, print, radio). It is necessary to store the data in a way that allows for integration with other data and facilitates the mining process. Specifically, data needs to be stored at a level of analysis that is actionable. For example, data from a TV ad might be best stored at the airing schedule level, rather than the individual spot level. Changes in profitability or market conditions may affect when ads are run in the future, and one would not want to make decisions based on outdated comparative data. If a certain time period proves to be infeasible, TV ads can be cancelled and the data up to that point would still be valuable. (In an academic example, learning whether or not to run an ad at an academic conference, certain demographic targeted cable stations, or during a specific show are comparisons that would be impossible to make if the data from the cancelled conference ads were unavailable). Once a certain level of analysis will no longer be used, the data should be aggregated to avoid system slowdown as the size of the data warehouse grows. (Sides et al., 2022)(Nian et al., 2021)

Collecting and Organizing Offline Data

Independent companies and data aggregators collect offline advertising data from multiple sources such as television, radio, print media, and other non-digital marketing channels. To conduct a thorough cross-channel advertising analysis, marketers must first compile this data together into a centralized database. Television monitoring companies are able to provide extremely accurate data on when and where a particular advertisement aired. Many radio monitoring companies are able to provide similar data on radio advertisements. However, the abundance of radio station and program information can make it difficult to link specific data on when an ad aired with data on ad effectiveness. Print media data can be very difficult to obtain, as it often requires manual entry of coupon codes and other special offers into a database for later analysis. These data collection methods may seem archaic compared to methods of data collection for digital advertising, but the importance of having accurate historical records of various advertisements cannot be understated. (Gordon et al., 2023)

Analyzing Offline Campaign Performance

Offline campaign data is often available at a level of granularity much greater than that for online campaigns. For example, in television advertising, second by second information on when the advertisements were played is available, and promotion codes in direct mail can provide a link to specific advertisements and individuals' responses. We might consider television advertising as just another online channel and attempt to assess its impact in the short run through changes in online brand search or site visitation induced by a TV ad. In this case, the online response variables have become intermediate outcomes. (Kefford et al.2023)However, it is more common to view the offline campaign as having a long-term effect on the brand such that changes in the brand's market conditions can be attributed to the campaign for an extended period. In either case, it is useful to link the online and offline data. This can be done by modifying the online tracking and data collection so that it is consistent with the key offline variables. For example, we might tag key web pages with the specific period of a TV campaign and make sure that the data on these pages is about the product categories and market regions targeted by the TV ads. This allows us to defer the analysis of the online brand response to a secondary step where the web tracking data is filtered on the relevant periods and compared against the overall TV campaign schedule. In cases where the online variables are intermediate, it may be possible to store them as a series of short-run changes and carry out a transfer function analysis to relate them to the TV ads. Step one in linking the online and offline data is to fully understand the response function of the online variables and this will be a major area of research in the future. (Timoumi et al., 2022)

Extracting Insights from Offline Data

Leveraging offline data for extracting insights. In the previous section, we discussed the methods used for analyzing the effectiveness of offline campaigns. When crafting campaigns, marketing managers typically decide on the product of interest and an associated group of consumers to target. The decision on how to allocate resources across different types of advertisements and promotions is driven by both the nature of the product and the groups selected for targeting. This suggests the decision on how to allocate resources can be mapped to a product's marketing mix. A marketing mix refers to the specific set of advertisements and promotions for a product. It's widely recognized as the "4Ps": product, price, place, and promotion. (Eriksson et al., 2020)(Li et al., 2021)For each type of advertisement and promotion, there should be an effect on sales. Thus given a marketing mix, the expected result is an increase in sales volume. By relating cause and effect between marketing mix and sales, we can track the impact of specific types of advertisements and promotions on sales

volume. The most effective way to do this is by conducting controlled experiments. In a controlled experiment, data is collected in an environment where the experimenter has the ability to control the effects of extraneous variables. This is done by trying to manipulate the variable of interest, while holding all other potential influences on the dependent variable constant. In the context of this research, data accumulated from store scanner is considered to be sales data. The goal is to use this sales data to measure the impact of various forms of promotions on the sales of a specific product. An example of a promotion would be discounting the product price by a certain percentage. The data collected from this type of a promotion can later be compared to previous sales data at regular price, in order to evaluate the effectiveness of the promotion on price and thus the promotion as a part of the product's marketing mix. (Argente et al.2021)

ONLINE DATA ANALYSIS

Online data analysis is an extremely broad topic. In the context of cross-channel marketing analytics, online data specifically refers to the English language digital data on promotional marketing efforts. This may include a wide array of promotional executions, ranging from simple web-advertising campaigns to complex and integrated cross-channel promotions. Digital data analysis is often used to assess and optimize the ROI of a specific promotional tactic, but can also be used as a tool for understanding the effects of various marketing efforts on the brand equity of a product or company. In general, data analysis can be used as a tool to both evaluate and improve marketing effectiveness. In this context, we attempt to provide a framework and best practices for specific types of online promotion.

Gathering and Consolidating Online Data

Data from a variety of sources is often available online and is generally inexpensive to collect. Online data has a number of potential sources - directly collected website data, syndicated data (data collected hosted by a third party on behalf of a company), and competitive intelligence from a variety of sources. Channel competitive intelligence involves understanding what competitors are doing in terms of their online marketing and trying to obtain data on their online marketing strategy. This may involve aggregating data on competitor websites, search engine meta data, or information on banner advertising. At this stage, the key goal is to obtain data in as raw a format as possible. Frequently data obtained will be in multiple formats and stored in different locations, so a robust data consolidation plan will need to be put in place. This will involve creating a single data repository and storing data in a format that will make it easily accessible for later stages of analysis. This activity is somewhat complex and time consuming but is an important prerequisite to effectively analysing online data. (Penedo et al.2023)

Evaluating Online Campaign Effectiveness

Causal Impact Modelling is necessary when the main goal of the campaign is to increase the distribution of brand advertising, and it is important to decide what algorithm should be implemented based on the nature of the advertising. A transfer function model can be seen as two linked regression models. Google preaches that it is often better to use simpler statistical models to decide where to use the resources. A simpler alternative is to use change point detection, and a good approach for this is to use the method of Granger causality. (Timoumi et al., 2022)

Most online marketers would evaluate the effectiveness of a campaign run on another channel using the success of that campaign in its own channel. For example, an affiliate would evaluate a TV campaign by the increase in traffic driven from the search channel with the search terms used in the TV advert. However, it is important to know whether the increase in search traffic was due to the TV campaign or other factors. If the increase was solely due to other factors, then the TV campaign was not effective in this case. This type of evaluation can only be done by using Causal Impact Modelling.

Evaluating the effectiveness of a campaign is an essential part of any marketing activity. It is the only way to gauge the relative success or failure of the campaign and can provide learning which can be useful in future activities.

Identifying Key Online Metrics

Online metrics are imaginary scales defined by marketers to measure consumers' behavior on a website. This is the starting point for data collection since all data is, at its core, based on these metrics. For example, the consumer behavior metrics might be "Visits", "Page Views", "Conversion", and "Retention". Visits and page views are fairly straightforward, representing the number of times users entered the site and the number of pages they viewed. Conversion is a key metric that varies in definition by site. It can be a sale, a lead, a registration, a download, etc. Conversion rate is then a comparison of conversions to visits. Finally, Retention measures how many of the original visitors return over a specific period of time. (Miu et al.2021)The method of data collection can affect the interpretation of these metrics. For example, the accuracy of a visit is questionable if the site uses session cookies to define visits, and the cookies have a short expiration time. In this case, if a user exits the site and returns after the expiration time, it will be counted as two visits. Data can be collected using direct tracking or event tracking. Direct tracking is generally more accurate and involves the use of a tracking code to send

data directly to the data collection server. Event tracking adds function calls to the site to collect data upon specific user actions. This method allows more detailed data collection and is offered by Google Analytics. (collaboration, 2020)

HOLISTIC CAMPAIGN ANALYSIS

In the previous chapter, we developed methods for measuring the success of individual online marketing activities and devising optimal strategies for targeting such activities to certain types of customers. If successful, those strategies will increase the diversity of marketing contacts to customers, both in terms of the types of activities and the targeting dimensions. This increase in marketing complexity creates a need for tools and methods to help marketers coordinate their online marketing strategies and tactics across different activities and customer segments, and to understand how these various interactions influence overall customer acquisition and retention. This is the goal of the following two chapters, where we shift our focus from individual marketing activities to a complex array of cross-channel interactions and develop analysis and optimization methods to aid in such endeavors. (Siqin, 2022).

This type of cross-channel analysis is commonly referred to as marketing mix modeling when it employs aggregated data to measure the impact of various marketing activities on sales. Because this kind of modeling has been so successful in optimizing offline advertising, there is growing interest in applying similar analysis to the online world. The hoped-for nirvana is a single model that measures the impact of both online and offline marketing activities on sales, enabling companies to optimize their marketing mix across the two domains. While the promise is great, the reality is that building such a model is currently infeasible due to the lack of a unifying identifier that can track individuals across online and offline marketing interactions. This fundamental issue will require its own dedicated research to resolve. An alternative and more feasible form of cross-channel analysis is to measure the impact of online marketing activities on offline transactions, such as the effect of display ads or search keywords on increasing calls to a sales center or branded search activity. This kind of analysis is best done with experiment and or quasi-experimental methods and can utilize the same customer data and IDs to track both the online marketing exposure and offline customer behavior. A final thrust of cross channel analysis is to use customer level data and analysis to understand how a sequence of cross channel contacts influences a consumer's brand attitude and purchase behavior, in order to optimize the timing and targeting of marketing contacts across the channels. All of these forms of cross channel analysis while disparate in the techniques used and type of marketing being analyzed, share the common goal of understanding how online marketing activities can best complement marketing in other channels, and each represent important areas for future research. (Wang et al.2021)(Forghani et al.2022).

The task of quantifying the effects of online marketing on sales and profits presents many challenges. For one, the data necessary to do so is housed in various data systems, such as web analytics, ad serving, and customer databases. Much of the data also resides in different organizations, such as multiple publishers and marketing service providers. Further, the data exists in different formats and employs different user identifiers, usually cookies for online data and name/address for offline data. These challenges, while not impossible to overcome, increase the difficulty and cost of measuring online marketing effectiveness.

Integrating Offline and Online Data

However, these integrations are difficult to create in most web analytics tools. They typically require uploading offline conversion data into the tool, or using an API to send data from the tool to a company's CRM system. This may only solve for specific cases and not provide a holistic view of how online behavior affects offline conversions or vice versa. Furthermore, online and offline data typically is stored in different systems which are not designed to work together. For example, a recent survey of 200 senior-level marketers found that 88% of customer data was stored in more than one system, and 64% of these respondents stated that the data was stored in "too many" disparate systems. This can act as a barrier for integrating the data even if there are tools in place to do so. (Kihn and O'Hara, 2020).

Measuring attribution across online and offline channels is difficult, and integrating the data to understand the overall effects of marketing campaigns is an ongoing challenge for many companies. Cross-channel marketing makes this task even more complex, since customers are easily influenced by high converting online marketing channels to research products that are later purchased offline. Additionally, existing customers often begin purchase processes offline that were initiated by search marketing or display advertising, which are typically tracked with online web analytics. These are just a few examples of why integrating online and offline marketing data is crucial to understanding the effects of cross-channel marketing and making informed decisions for future marketing investments. (Timoumi et al., 2022).

Measuring Cross-Channel Attribution

The objective of the first part of the analysis process is to calculate how much value each marketing channel has provided. This is achieved by isolating each marketing channel and examining how it has contributed to desired outcomes, compared

to if it was turned off. For search and email, this is a relatively straightforward process and involves using pre-existing analytics data to examine the effect individual campaigns have had on predefined KPIs. However, for display and affiliate marketing, this is a more difficult task due to the nature of the channels. These channels are less targeted and often involve serving ads on a CPM basis for display and a flat rate with no specific action with an affiliate. The way in which display and affiliate marketing ads impact consumers is akin to a branding exercise in many cases, so we cannot always assume that a click was required to invoke a change in consumer behavior. (Ghosal et al., 2020)(Chattopadhyay2020)The next step is to take into consideration the change in consumer behavior the marketing activity provoked. For example, if a consumer makes a purchase after clicking a search ad, it is pretty clear that the ad has caused the purchase. However, often consumer behavior changes are not so clear-cut and consumers may justify a change in purchase path with a change in behavior. In these cases, it is important to consider all possible paths the consumer could make to the purchase and how the marketing activity influenced this. This information is then used to re-weight the value of the marketing activity. (Mathew and Soliman, 2021)

Optimizing Marketing Strategies

Optimization can also identify tactical changes that improve the effectiveness of marketing actions. For example, email offers may be very effective at generating responses, but the profitability of those responses could vary greatly by the type of offer, or the offer may cannibalize sales that would have been generated at a higher margin with a different promotion. By using optimization to target the most profitable responses, the email campaign could generate more net revenue with the same upfront cost. Simulation and optimization can run virtual tests for these changes, predicting the impact on sales and profit before the changes are implemented in the market. (Păvăloaia et al., 2020)

Marketing mix models can provide key decision support for this type of strategic marketing change. The simulation capability can quantify how changes to the marketing mix can affect the desired marketing outcome. In the prior example, the goal might be to increase market share with that customer segment with a minimum cost increase. The simulation can propose changes to the advertising mix that achieve the higher market share with an acceptable cost increase and compare it to the current strategy. (Lahtinen et al., 2020)

Each marketer aims to maximize the return on marketing spending. However, multiple constraints exist, including budget, channel capacity, competitive actions, and marketing 'noise'. These constraints force some marketing strategies to be infeasible, either because they target too few prospects, resulting in high average acquisition cost, or because they attempt to achieve a marketing goal using a suboptimal mix of marketing actions. Infeasible strategies could benefit from simple changes that free up resources to be applied more effectively. For example, a strategy to increase market share for a particular segment might be sound, but the current mix of TV and online advertising might be too costly. If the same level of market share could be achieved with less advertising, the savings could be applied to other marketing actions, or the cost savings could improve profitability or allow a price reduction to gain more market share. (Park and Mithas, 2020)

CONCLUSION

With advances in technology, we can now measure the impact of cross-channel marketing programs much more accurately. This allows us to move away from single channel, last click measurement techniques, and understand how each element of the marketing mix contributes to sales and customer acquisition. However, the complexity of marketing analytics is increasing, as more data becomes available and a wider variety of techniques are used to encourage customer purchase. This book has discussed the state of marketing analytics today and the range of techniques that can be used to measure the effectiveness of different marketing programs. We have also discussed some of the key research that has been conducted in this area. Key themes that have arisen throughout the book are: - Cross-channel effects: the majority of marketing activity is designed to have an impact on a product or brand's sales over a period of time rather than an immediate effect. Many current analytics techniques do not measure the long term impact of marketing. - Long term and dynamic marketing effectiveness: marketing strategy and execution should be an ongoing process of testing and refinement. Therefore, it is essential to have metrics that can compare the effectiveness of different programs and a feedback loop to help management decisions on an ongoing basis. Static models of marketing effectiveness are of limited use.

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