Clever AI

How to use Marketing Mix Modelling

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Improve your RoAS with Marketing Mix Modelling insights

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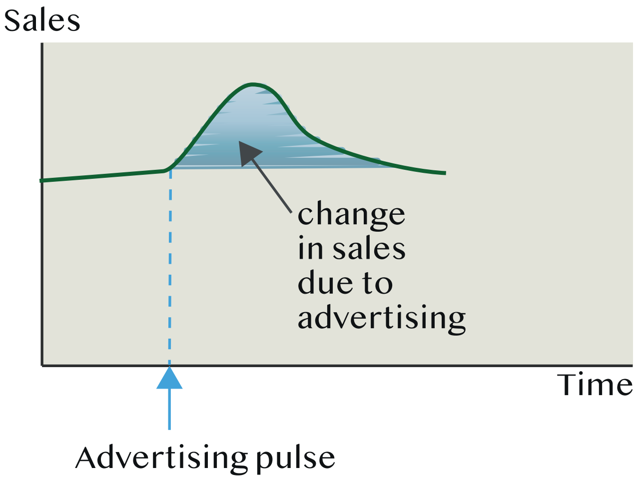
The marketing mix involves influencing elements to boost a brand's sales or market share. It focuses on how audiences and markets respond to advertising, assuming that past data holds valuable information for predicting future consumer reactions.
Understanding patterns of market response to advertising and pricing is the first step. These patterns, also known as effects, are basic insights gained from Marketing Mix Modeling (MMM).
The most important effects for MMM models are the following:

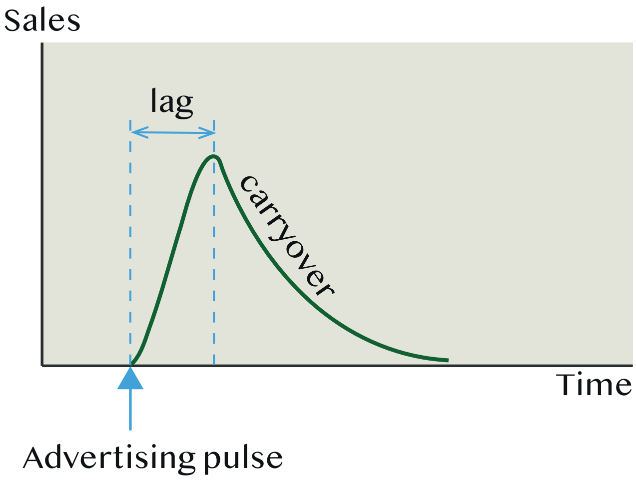
1. Current effect

The current effect of advertising is the change in sales caused by an exposure (or pulse) of advertising occurring at the same time period as the exposure.



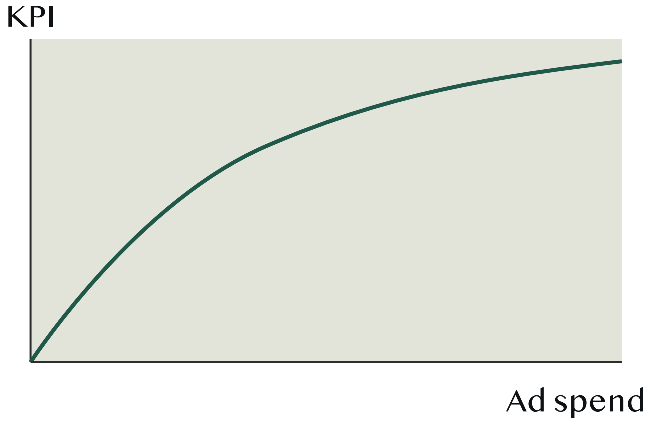
2. Carryover effect

The carryover effect of advertising is that portion of its effect that occurs in time periods following the pulse of advertising.



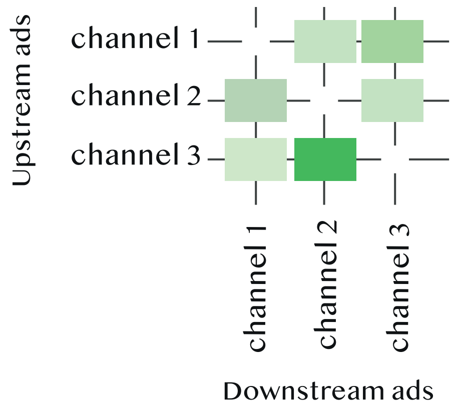
3. Shape Effect

The shape of the effect, sometimes called consumer response curve, refers to the change in sales in response to increasing intensity of advertising in the same time period.



4. Funnel effect

When one ad channel has an effect on the influence level of another ad channel in addition to increasing the KPI. Investing in an upstream channel increases the impact of a downstream channel.



The goal of an MMM model is to link advertising spending across several channels to a key performance indicator, such as sales. The model must be able to estimating what percentage of sales are generated by each channel. To achieve this, the Marketing Mix model must be capable of discovering all of these effects in order to correctly allocate sales generated by each channel.

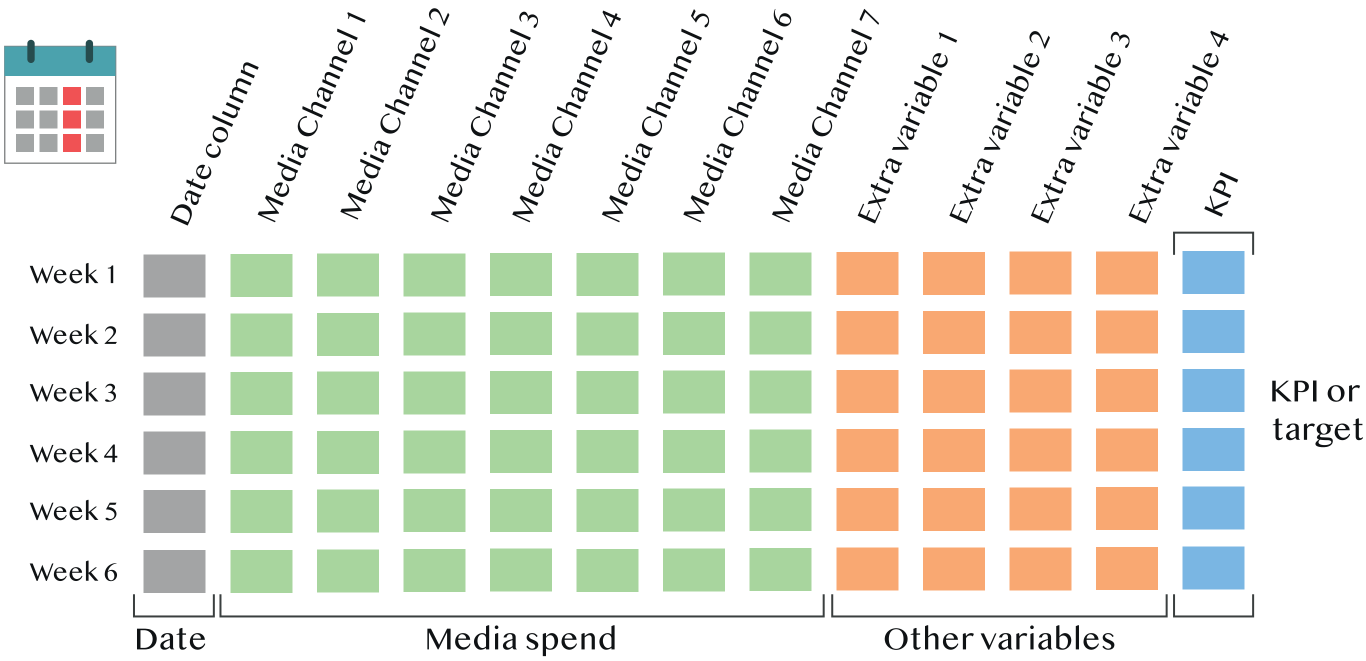
There are several factors influencing the progression of a potential consumer from being exposed to an ad, to becoming actively engaged or converted. These factors might include the transition rate from exposure to engagement, from capturing attention to actual conversion and the transition rate from building interest to making a purchase decision. Some online media channels offers information about rates like the conversions. In general the this exposure to purchase decision rate is encoded in the consumer response curve for each channel, determining the

A Marketing Mix model can contain multiple inputs:

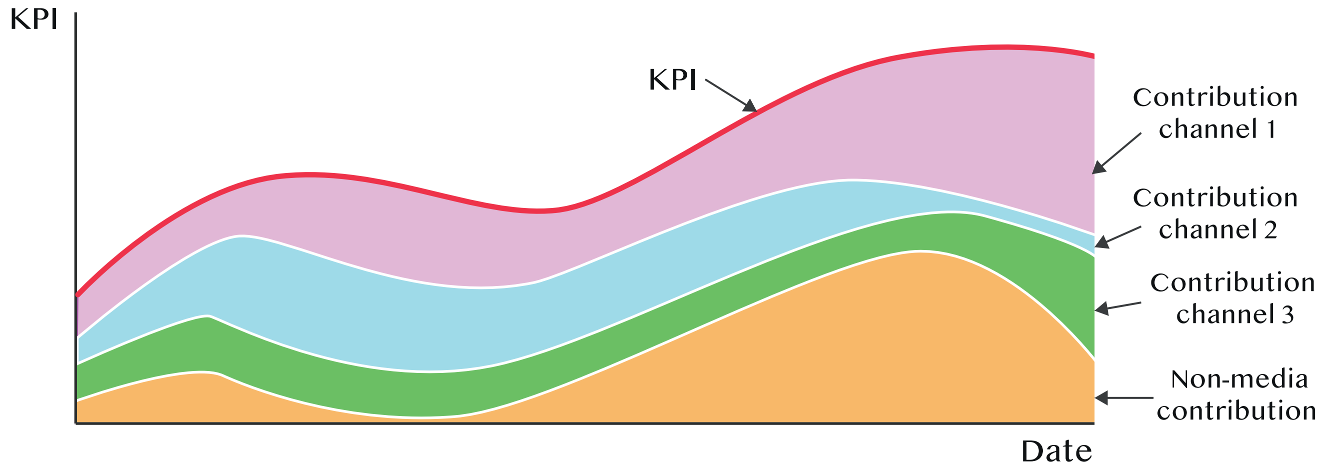
a) Channel spending on a daily, weekly, or monthly basis. This is the amount of money spent on a particular channel at a given frequency.

b) KPI: This is the variable we want to tie to ad spend. It might be sales, the number of new customers, market share, or any other indicator we use to track the performance of our business or brand.

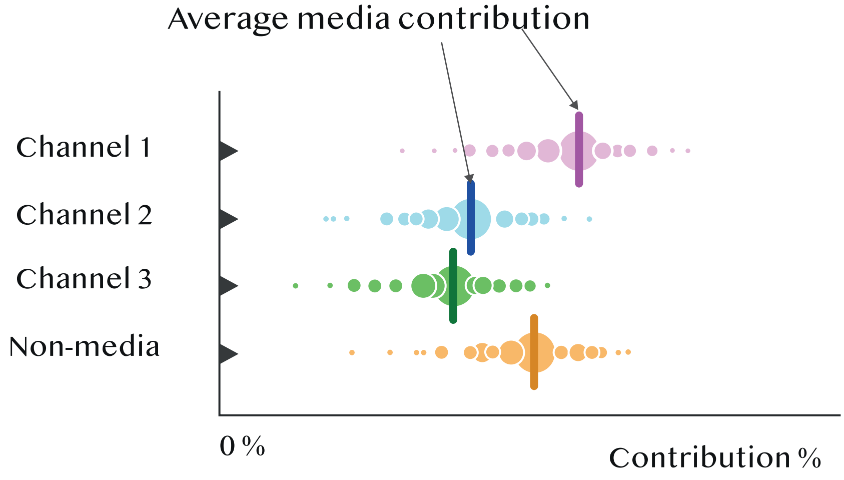
c) There are multiple variables that we agree can affect our KPI but are unrelated to channel spending. This variables could be related to brand awareness, macroeconomic data, weather data, competitor data, and so on. A MMM will use these variables to explain the non-media influence on the given KPI.



1. Channels contribution



Channel contribution varies over time partly due to a range of factors such as audience behavior or funnel effects. This is why we usually want to know the average media contribution as a way to compare different channels.

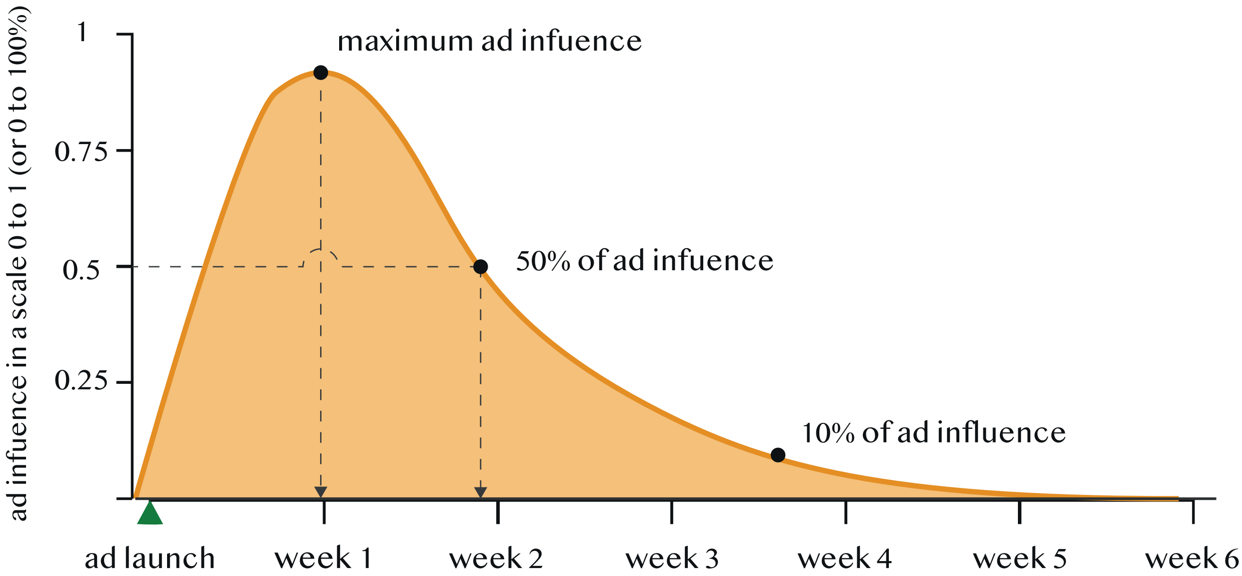


The model attempts to correlate media investment with KPI, however there is always a portion of the KPI that the model is unable to associate with media spend. This part is frequently referred to as the baseline or non-media contribution. This baseline can contain seasonality, brand, or other factors that, until we give more variables to fill this gap, will remain hidden.

2. Carryover effect

The ad effect is not showing its full influence strength at when we launch it. A lag between the launch moment and the maximum capability deployment moment is common. When the ad has reached its maximum influence, it will begin to decline to zero. This weareout can be fast or slow, resulting in a declining curve that prolong the add influence for some time.

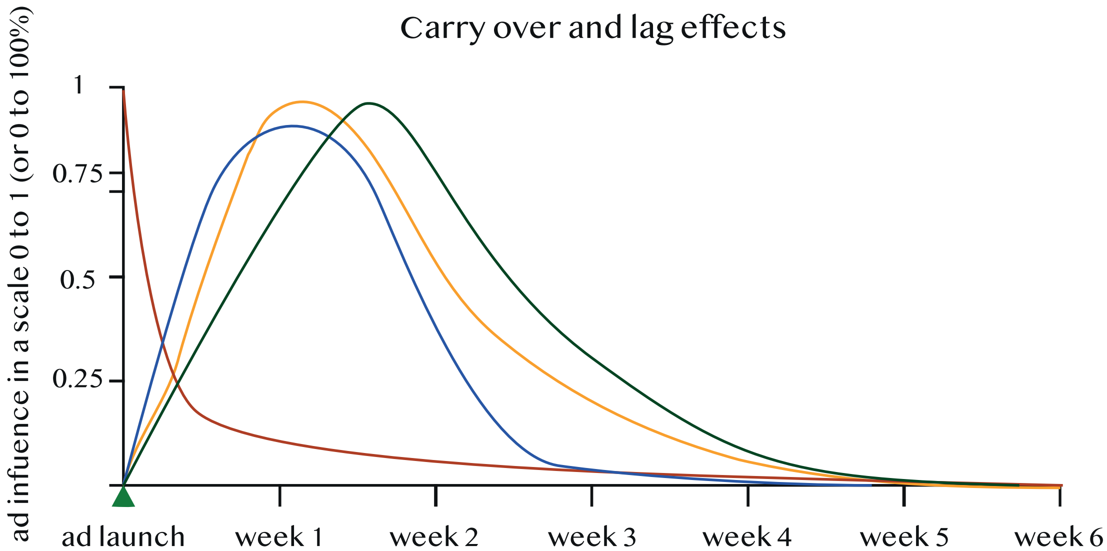
Consumer response curve

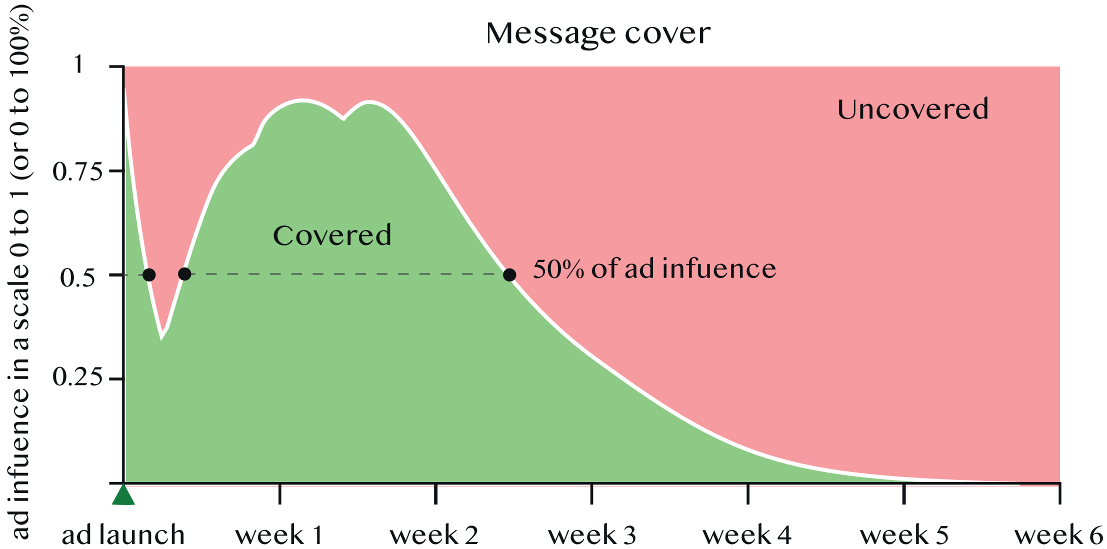


The above curve shows that the ad in a specific channel deploys its maximum influence approximately one week after its launch. Then it begins to decline, so that two weeks after its launch, it is still deploying 50% of its capacity. After nearly four weeks, the ad has lost strength and is only deploying 10% of its total capacity.

2. Carryover effect and message coverage

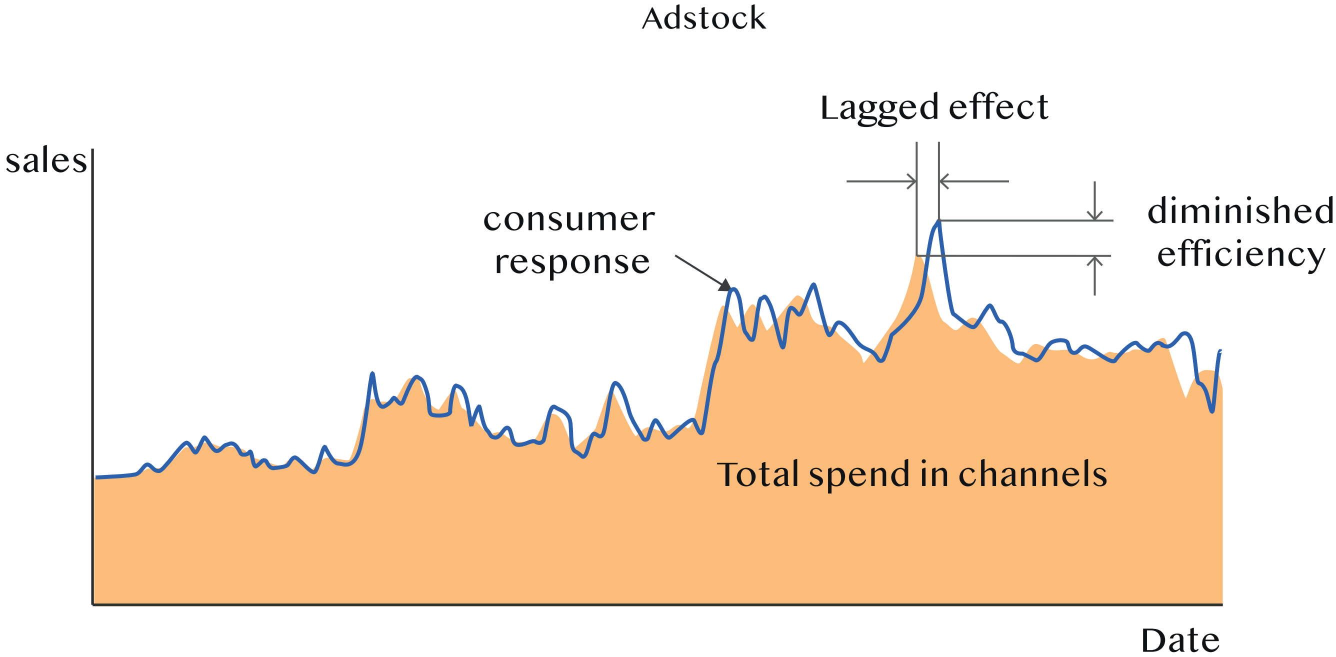
The goal of launching a campaign through a variety of media channels is to extend the message's impact as much as possible. We can have for examples different channels with a similar carryover curve shape with a maximum deployment after one week, followed by a high decrease in to the second week. Then we haven't a right coverage during the first 7 days and also we have a poor coverage during after the day 16-17.





3. Adstock (consumer response)

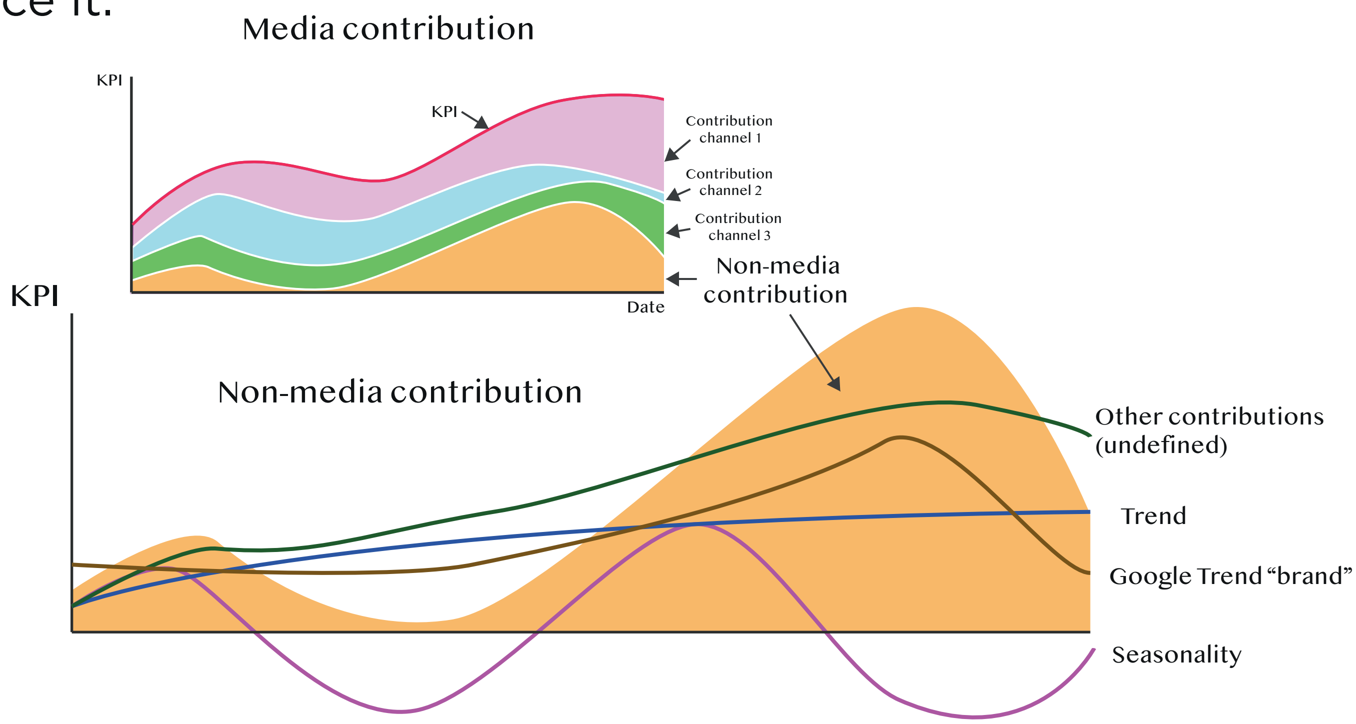
In customer response, "adstock" describes how an advertising effect lasts longer than the time it takes to deliver the message. This is typically represented in a sales chart as a tailing off of the incremental sales that occur after the advertising period.



The above illustration effectively illustrates two basic effects: diminishing efficiency, which occurs when consumer response is low to support the investment, and the lag effect, which occurs when consumers react to ads later than the ad exposure.

4. Non-media contribution

Non-media influence is the part of KPI that the model has not been able to correlate with media spend. The magnitude of this influence can vary depending on the number of channels used, the maturity of the business, or brand awareness. The source of this influence could potentially be diverse, and we must uncover additional factors or variables capable of explaining a certain amount of this influence. These variables can be brand-related variables such as brand interest, macro-economical variables such as consumer price index, weather-related variables such as feeling temperature or rain level, or even competitor information. As marketers, we understand the context of the business we are analyzing, and therefore we must provide the model with variables that we suppose can influence it.



5. Funnel effects

Today, people use a number of media at the same time, especially when it comes to social media. Generation Z, for example, uses mobile devices to watch television or read magazines while also communicating with their peers via social networks. In this scenario, identifying which channel truly influenced that user's conversion into a customer can be exceptionally difficult. The funnel effect aims to establish a relationship between the different media so that we can assess whether one media has been able to increase the influence of another in our MMM model.
This effect is very important for two reasons: it allows us to accurately allocate the influence of each channel, and it makes it possible us to identify synergies across channels, indicating which channels share a specific

The amount of money we put into this channels during the time of the analysis...

	channel 1	channel 2	channel 3	channel 4	channel 5
channel 1		0%	1%	4%	6%
channel 2	5%		2%	1%	0%
channel 3	1%	3%		1%	4%
channel 4	8%	0%	-4%		0%
channel 5	5%	15%	4%	-1%	

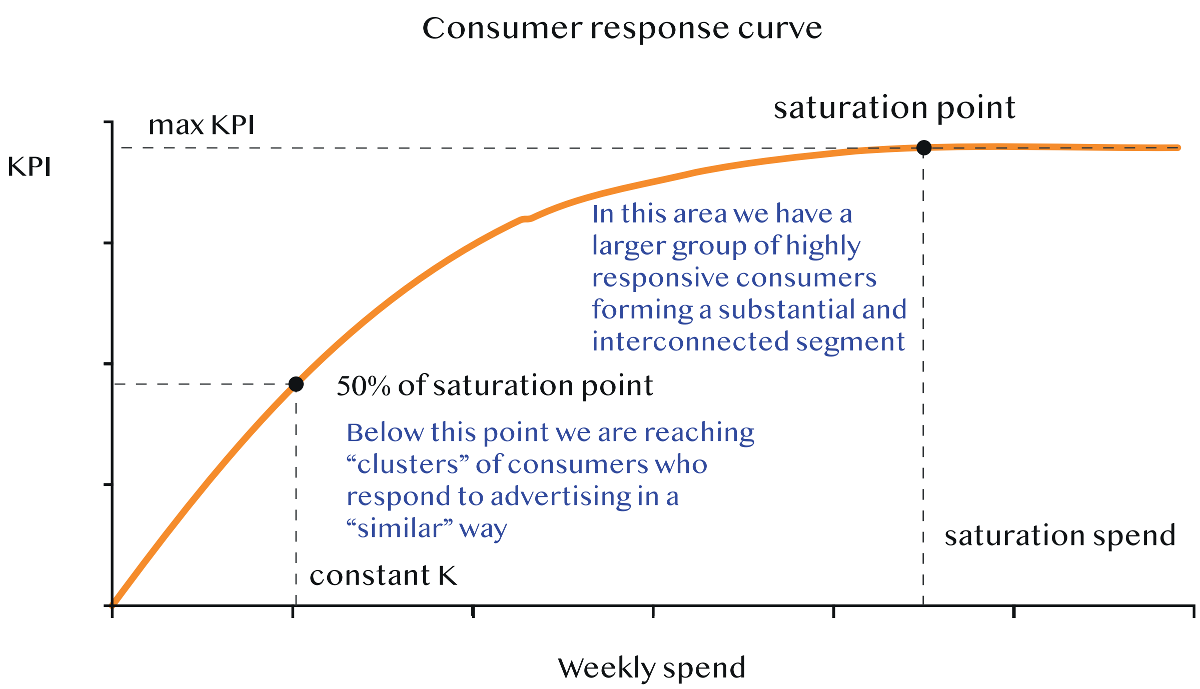
...has affected how much impact these other channels have gained or lost.

What does this values mean?

What we invested in Channel 3 during the time period that corresponds to the entry data has helped to raise the influence on Channel 5's KPI by 4%.

6. Shape effect or consumer reponse curve

One of the most important insights that we are going to get from an MMM model is the consumer response curve. This curve appears to depict the relationship between the increase in KPI attained by increasing spending on a specific channel. This curve looks simple at first glance, but it is able to reveal several significantly more complex underlying phenomena.

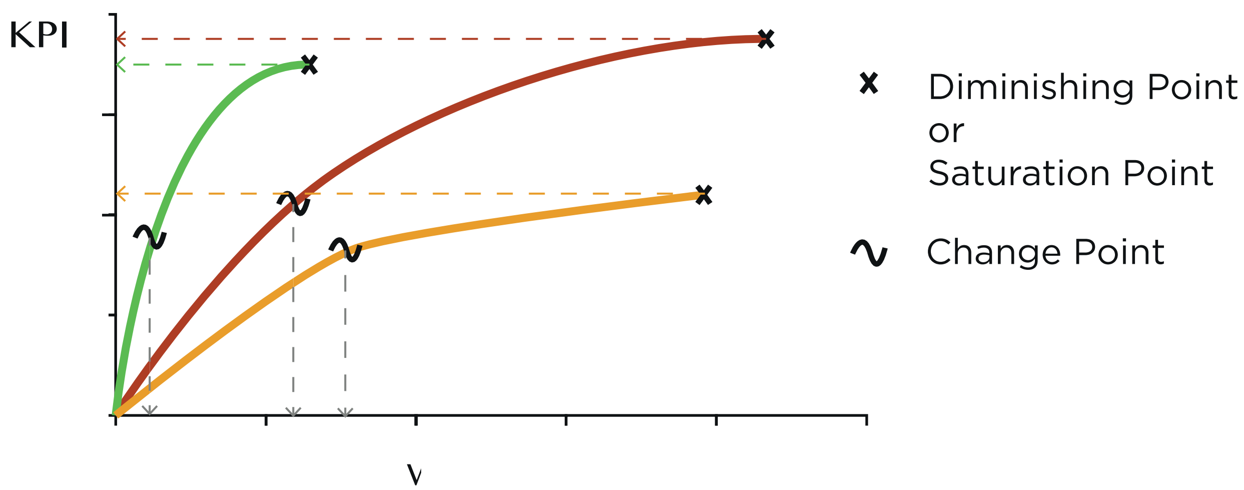


The first conclusion of this curve is how the channel's profitability changes based on the investment. This information is necessary for comparing different channels and planning future scenarios.

It's also important to note that the curve has a point where it shifts, which tells us a lot about how our clients react to ads in general and in every channel.

4. Audience response

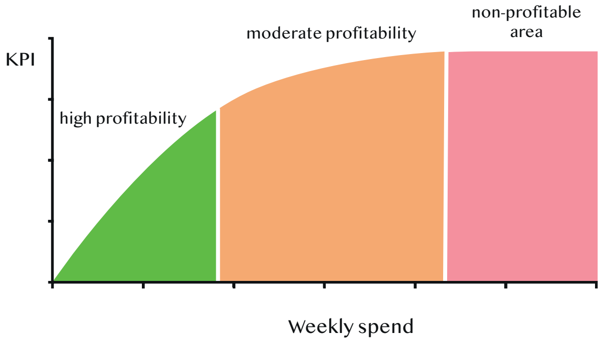
The consumer response curve to an ad in particular channels should be considered as a quantitative and qualitative tool. To fit the data to a curve, we use different mathematical models that describe physical processes that exhibit saturation behavior (diminishing or saturation point) and undergo a change or transition in their dynamics (change point).
We don't have a lot of data, thus the adjustment of this curve isn't very accurate. Even so, this analysis is quite useful for comparing the response curves of the different channels and for comparing both the diminishing points and the changing points. We don't have a lot of data, thus the adjustment of this curve isn't very precise. Even so, this analysis is quite useful for comparing the response curves of the different channels and for comparing both the declining points and the changing points. To illustrate the channel's convertibility, or the ease with which viewers go from ad exposure to interest to purchase (or lack thereof), consider the changing points. Additionally, at certain stages, we can deduce if we are communicating with a bigger, more homogeneous audience or with separate, more fragmented ones.



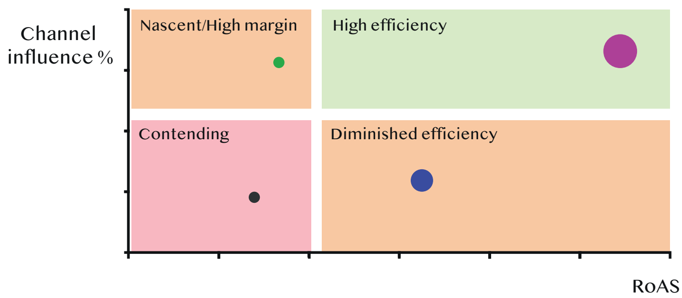
7. Channel assessment

The customer saturation curve, in turn, provides us with an important indicator: the profitability of each channel. Furthermore, the curve differentiates three different zones: the zone of high profitability, where any increase in spending is profitable, the zone of moderate profitability, where each increase in spending is profitable but to a smaller extent, and the zone of unprofitability, where the increase in spending does not correspond to an increase in the KPI.

Consumer response curve



Channel assessment

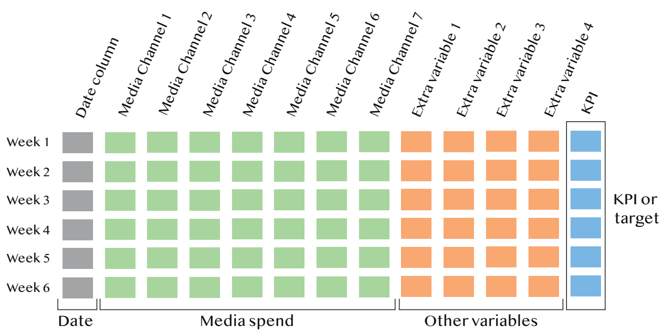


Finally, by plotting the average RoAS of each channel against the influence of each channel, we can perform a channel assessment. We can divide the channels into four groups: the most efficient, the most efficient but least influential, the channels with neither efficiency nor influence, and the channels with the potential to be efficient.

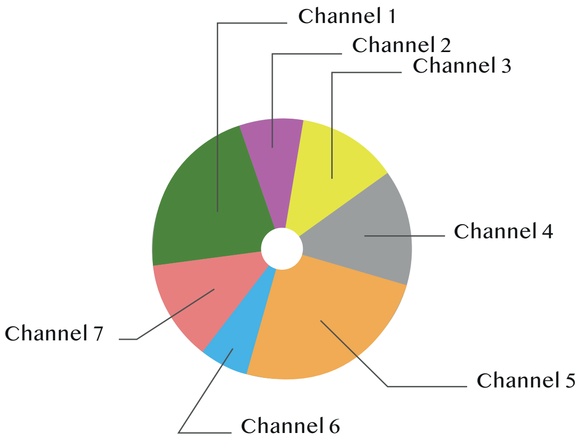
1. Optimal scenario

Once the model has integrated all of these insights, we can ask it, given the input data, what media mix should be used to maximize our KPI. The model will take into account the media's influence, the consumer response curve, the carryover effect, the media's RoAS, as well as seasonality and patterns learned during training. With this information, our model will build a scenario in which we could have earned the maximum KPI by adjusting the media mix.

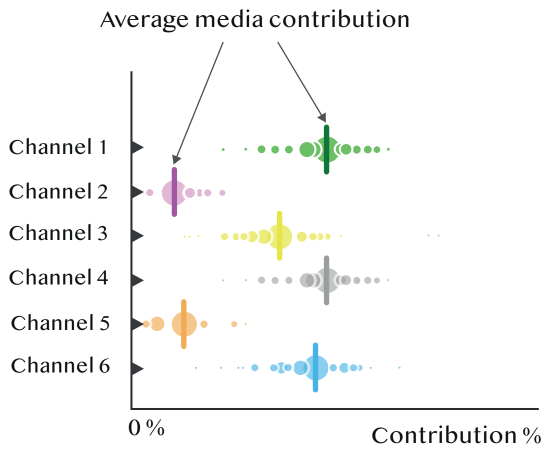
Input data



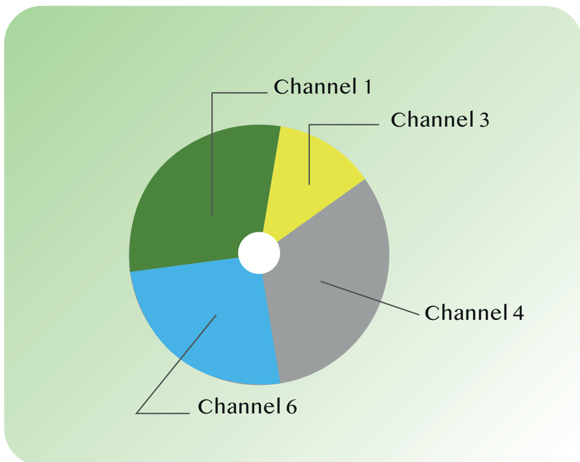
Input data media mix



Input media contribution



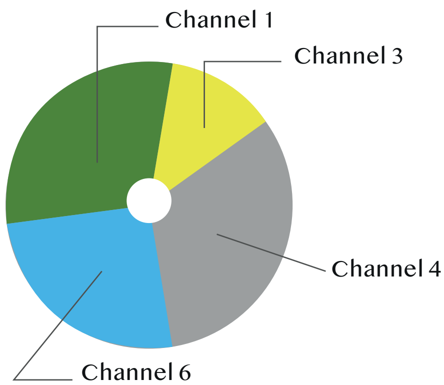
Optimal media mix



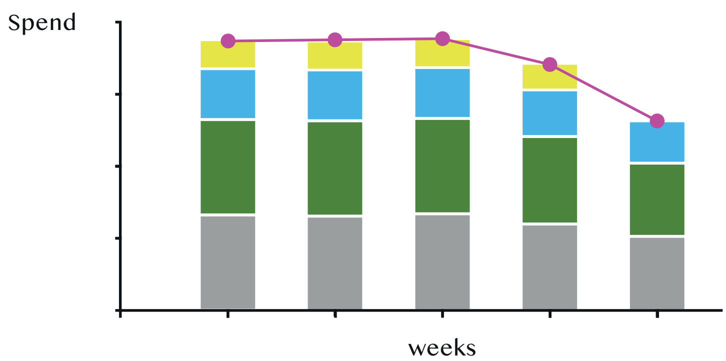
1. Future campaigns

Finally, we can use our model to plan prospective options. Starting from the last date the model saw in the input data, we could ask the model, given a particular amount for total spend and a time horizon, to give us the maximum KPI we can reach and the media mix we will require. The model will provide an optimal media mix and it's allocation during the next time steps.

Planned Marketing Mix



Planned spend



Planned RoAS