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Revolutionizing Market Mix Models - Robyn

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Marketing refers to activities that promote the buying or selling of goods or services. The promotion is done for the product to reach its target customers. The end goal of marketing is to increase sales with a limited budget allotted to marketing. At the start of the century, the number of channels to promote a product are limited, such as TV, Radio, Billboards, etc., which can be humanly manageable. But in today's digital world, more channels were added to promote a product, such as Facebook, YouTube, Instagram, etc. Hence, when a specific Marketing budget is allotted, how much money has to be spent on different channels to maximize a firm's sales is the burning question for any company's marketing team. This is where AI/ML helped them make data-driven decisions by creating the Market Mix Modeling (MMM) technique.

MMM technique helps understand how much each marketing input contributes to sales and the amount to spend on each marketing input to maximize sales. The initial MMM techniques employed Multi-Linear Regression with sales or Market share as the dependent variable, and independent variables are marketing inputs such as Price, TV spends, Digital platform spends, etc. This model lacks the ability to consider Diminishing Returns & Carry-over effects by advertising inputs on the sales. Diminishing Returns mean the reduction in increment of sales for a unit increase in market input amount (i.e., some advertising inputs such as TV advertising spend do not have a linear impact on sales). It becomes zero after a certain threshold. The carry-over effect is the impact on future sales caused by the amount spent today on advertising.

To include the impact of Diminishing Returns and Carry-over effect on marketing campaigns, the Weibull or geometric ad-stock functions are used in the model.

Recently, Facebook introduced the Robyn MMM technique, which revolutionized the MMM techniques by using the time series concept to model the impact of marketing inputs on sales.

Robyn technique uses Facebook's Prophet library to decompose time series into the components of Trend, Seasonality, and Holiday. Robyn time series forecasting is based on an additive model where the Trend component consists of ad-stock and linear functions. The remaining nonlinear component consists of the Seasonality and Holiday effect. The Seasonality component is modeled as a periodic function of time using the Fourier series. The use of the Fourier series enables the model to quickly adapt to change in the seasonality component by increasing the number of Fourier components. The Holiday component is independent and helps to incorporate the effect of holidays and events into the model.

Fourier Series Equation:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos \frac{2\pi n t}{P} + b_n \sin \frac{2\pi n t}{P} \right)$$

Where $0 \leq t < P$, P is the period of the time series & N is the number of sine and cosine components in the Fourier series.

In MMM, the sales are divided into two components (i.e., Baseline Sales and Incremental Sales) which will help us to calculate Marketing Return on Investment (MROI) most effectively. Baseline variables are created to include the impact of non-media variables (such as temperature, unemployment, etc.) on sales. The expected volume of sales in the absence of in-store and online promotions is called Baseline Sales. The expected additional sales volume above Baseline Sales generated by marketing activities is called Incremental Sales.

Robyn MMM uses the Bhattacharya coefficient of statistics to split data into train and test with high similarity. Robyn MMM also applies Ridge regression to avoid Multi-collinearity and Over-fitting problems. Ridge regression is a regularization technique used to reduce variance by introducing a small amount of bias. The optimal value for penalizing tuning parameter (λ) of Ridge regression is also obtained automatically.

Normally, the MMM model contains high cardinality (number) of parameters (i.e., thetas, alphas, gammas, shapes, and scales), these increase further as the number of marketing channels increases. The high dimensions (cardinality) of parameters makes the model more complex, and it takes more time to obtain optimal point using a gradient optimization algorithm. But in Robyn MMM, the value of parameters (near to optimal point) is obtained by using a gradient-free optimization algorithm called Latin Hypercube Sampling (LHS). LHS is a statistical method to generate a near-random sample of parameter values from a multi-dimensional distribution. The MROI response functions of all the market and non -marketing inputs are obtained from the parameter values given by LHS. A Nonlinear optimization problem is designed using the obtained parameters with an objective function to maximize the sales or Market share under the Marketing Budget and other constraints.

Robyn MMM is not just limited to providing the optimal market mix inputs that intend to maximize MROI within the allotted Market budget. It helps to understand the effects of holidays, weather, functioning of institutions, and the market on advertising. It enables the marketing teams to compare varying marketing techniques by stimulating their impact on future sales. In addition, it reduces human bias and helps to understand the lag and decay effect of advertising to take control of cross-media budget allocation.