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Marketing Mix Modelling Using Multi-objective Hyperparameter Optimization

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ABSTRACT

Marketing mix modelling (MMM) is an important technique in marketing measurement to define effectiveness and efficiency of marketing investment. MMM is a complex combination of various statistical models and data transformation functions. Traditional MMM is subject to analyst bias and is slow and expensive. This disclosure describes automated techniques that reduce the analyst bias in MMM and make the model building process fast, flexible, and inexpensive. The techniques described in this disclosure overcome analyst bias through a multi-objective hyperparameter optimization that is achieved by using an evolutionary algorithm.

KEYWORDS

- Marketing Mix Modelling (MMM)
- Marketing optimization
- Marketing measurement
- Hyperparameter optimization
- Online advertising
- Ad Attribution
- Evolutionary algorithm
- Time series forecasting
- Pareto optimality

BACKGROUND

Marketing mix modelling (MMM) is an important technique in marketing measurement to define effectiveness and efficiency of marketing investment. It has been in existence for decades and is gaining popularity again, even in verticals such as e-commerce that were earlier not interested in MMM. Verticals that had access to more granular data typically relied on other solutions such as multi touch attribution (MTA) for estimating marketing effectiveness and efficiency. However, such solutions are unsuitable in the current climate of increasing data privacy requirements. MMM as a completely privacy-safe solution is gaining momentum in the broader ecosystem as a tool/methodology and is becoming a central element in measurement stacks.

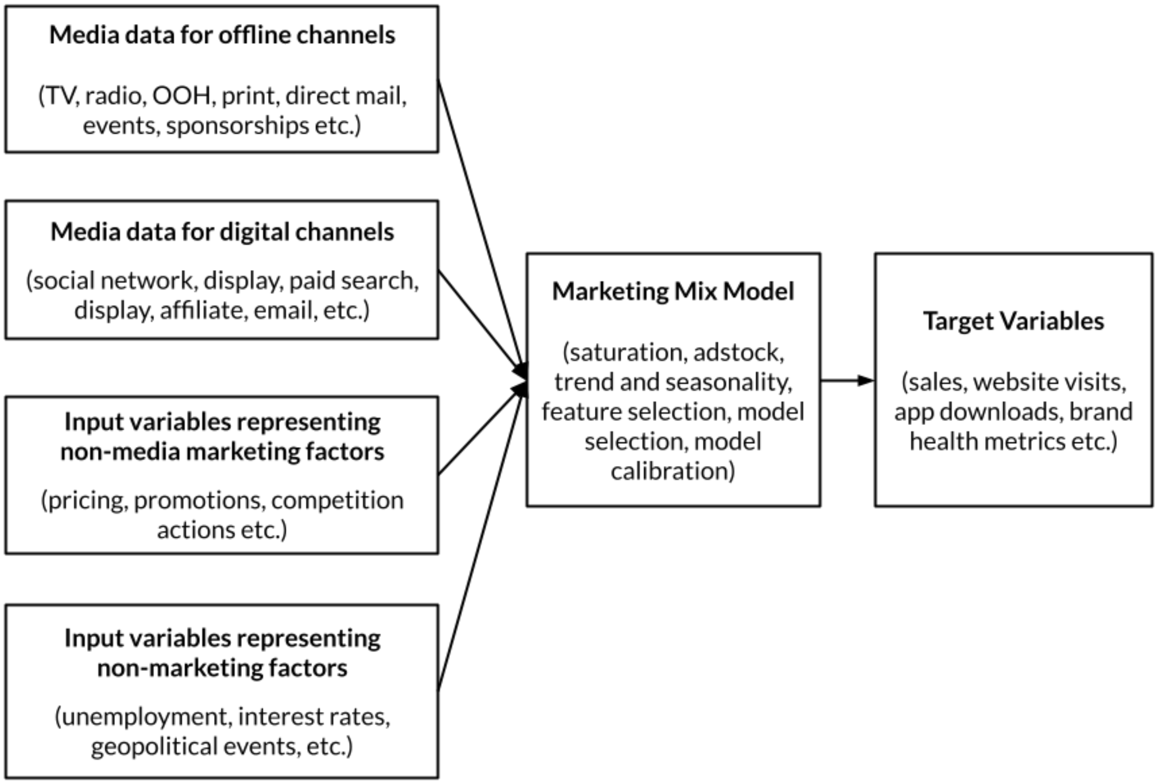

Fig. 1: Diagrammatic Representation of a Marketing Mix Model (MMM)

Figure 1 is a diagrammatic representation of a typical marketing mix model. A marketing mix model is an equation that can be used to predict target variables such as sales, website visits, app downloads etc. based on media data from offline media such as television, radio, out-of-home advertising (OOH), etc.; digital media such as social media, paid search, email, affiliate marketing, etc.; non-media marketing factors such as pricing, promotions, etc.; and other non-marketing variables such as macroeconomic data, geopolitical events, etc. as inputs.

A marketing mix model is essentially a complex combination of various statistical models and data transformation functions. Due to this complexity, MMM is traditionally an expensive solution and thus, has only been affordable for larger advertisers. Among the highly dynamic and fast-growing e-commerce, digital native, disruptor and heavy-direct-response advertising verticals, traditional MMM may be considered unsuitable due to problems such as:

1. **MMM is biased:** Traditionally, building MMM requires a lot of human judgement which can lead to "analyst bias" when setting model parameters. Analyst bias plays a role in the following critical activities in the model building process:
    - Feature selection: the analyst decides which explanatory variables should be used in the model.
    - Trend and seasonality: the analyst decides how trend/seasonal variables are constructed.
    - Adstock: the analyst decides the adstock rate for each media channel.
    - Saturation: the analyst decides the saturation curve for each media channel.
    - Model selection: the analyst decides which model result is to be chosen.
    - Calibration: the analyst compares model result and experiment manually.
    - Recommendation: all of the above can lead to potential incorrect media allocation and business decision harming the business growth and/or lead to inefficiency.

As a result of the major role played by such analyst bias, traditional MMM can be subjective, inflexible, and difficult to build.

2. **MMM is slow:** Traditional MMM is slow. It can take months or even a whole year to build an initial model which is typically updated once or twice a year. Additionally, input data availability and granularity also slow down the process. Due to this, insights from traditional MMM are usually not applicable for on-the-fly campaign insights and optimization. Due to

the manual modelling process, model extensions such as nested structure and interaction require even more effort and time, and can introduce further bias.

3. **MMM is expensive:** To set model parameters appropriately, advertisers need either a team of experienced data scientists and/or a third-party partner that may charge substantial fees.

DESCRIPTION

This disclosure describes techniques that can reduce the analyst bias in MMM, and can make the model building process fast, flexible, and inexpensive. The techniques described in this disclosure overcome analyst bias through multi-objective hyperparameter optimization that is achieved by using an evolutionary algorithm.

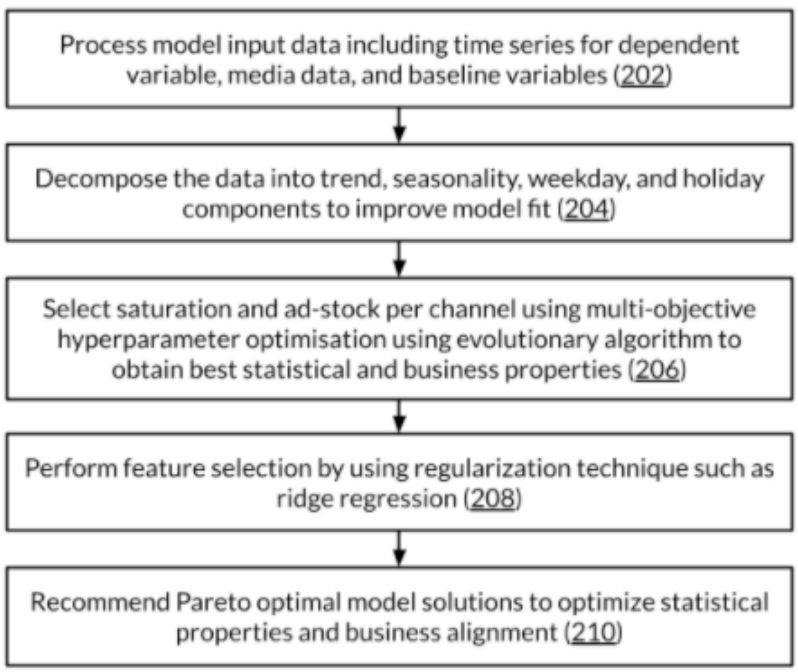

Fig. 2: Example process for MMM

Figure 2 illustrates an example process for marketing mix modelling, per the techniques of this disclosure. Model input data including time series for the dependent variable, media data and baseline variables is processed and made ready for the subsequent steps such as trend and seasonality detection, multi-objective hyperparameter optimization etc. (202). The dependent variable time series is automatically decomposed into trend, seasonality, weekday, and holiday components to achieve a better model fit (204).

The saturation and adstock for each channel are selected automatically by performing multi-objective hyperparameter optimization using an evolutionary algorithm to obtain the best statistical and business properties (206).

Consider a situation in which the advertiser runs ads on a social media platform and on television. In MMM, the adstock and saturation need to be defined for every channel. Adstock is the decay rate of the marketing effect over time for a certain channel (e.g., television). An adstock of 50% for social media spend implies that every dollar the advertiser spends on social media today has 0.5 dollars worth of effect remaining for the next day, 0.25 dollars remaining for the day after, and so on. Objectives used for optimization can include normalized root mean square error (NRMSE) which relates to model error, and decomposition distance which relates to business logic. Feature selection is performed automatically using a regularization technique such as ridge regression (208). Pareto optimal model solutions are recommended to optimize the statistical properties and business alignment of the model (210).

By performing multi-objective hyperparameter optimization using an evolutionary algorithm and feature selection using a regularization technique, the modelling process is substantially automated. It provides a set of optimal results with highly tuned adstock and saturation hyperparameters out-of-the-box in a short turnaround time.

The techniques have several valuable features that could be used by the data scientists and business users for ongoing marketing optimization. These include:

- A rolling update feature that allows any time grain cadence and thereby enables always-on reporting and attribution.
- The use of evolutionary algorithms with multi-objective capacity enables fast and automated hyperparameter optimization to support unbiased decisions (feature selection, trend and season selection, adstock selection, saturation selection and model selection).
- Machine learning libraries that support multicore and parallel computing enable scalability.
- Advanced models including nested model and interaction effect decomposition can be easily activated using built-in features.
- Building of mixed panel-time series models with time and additional dimension(s) can be supported.
- Measurement of the impact of organic traffic and sentiment on business outcomes is enabled.
- Measurement of long-term baseline effects and indirect effects of advertising can be supported.
- Subject to data availability, the techniques can be used to quantify role and impact of advertisement creatives on business outcomes.
- A set of best possible models with best statistical and business properties is auto selected using Pareto optimality criteria.
- Model selection logic rules can be customized to accommodate selection of business logic rules, per domain requirement.
- In addition to Pareto-selection, calibration features can be used to help further constrain the result towards groundtruth such as data-driven attribution or lift test result.
- Predictive algorithms can be used to support budget allocation decisions and make recommendations of budget split to optimize the desired business outcomes.

CONCLUSION

Marketing mix modelling (MMM) is an important technique in marketing measurement to define effectiveness and efficiency of marketing investment. MMM is a complex combination of various statistical models and data transformation functions. Traditional MMM is subject to analyst bias and is slow and expensive. This disclosure describes automated techniques that reduce the analyst bias in MMM and make the model building process fast, flexible, and inexpensive. The techniques described in this disclosure overcome analyst bias through a multi-objective hyperparameter optimization that is achieved by using an evolutionary algorithm.

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