

# Machine Learning Based Approach for Measuring Promotion Effectiveness in Multiple Parallel Promotions' Scenarios

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**Abstract**—Promotion is a key element in the retail business. Thus, analysis of promotions to quantify their effectiveness in terms of Revenue and/or Margin is an essential activity in the retail industry. However, measuring the sales/revenue uplift is based on estimations, as the actual sales/revenue without the promotion is not present. Further, the presence of Halo and Cannibalization in a multiple parallel promotions' scenario complicates the problem. Calculating Baseline by considering inter-brand/competitor items or using Halo and Cannibalization's impact on Revenue calculations by considering Baseline as an interpretation of items' unit sales in neighboring nonpromotional weeks individually may not capture the overall Revenue uplift in the case of multiple parallel promotions. Hence, this paper proposes a Machine Learning based method for calculating the Revenue uplift by considering the Halo and Cannibalization impact on the Baseline and the Revenue. In the first section of the proposed methodology, Baseline of an item is calculated by incorporating the impact of the promotions on its related items. In the later section, the Revenue of an item is calculated by considering both Halo and Cannibalization impacts. Hence, this methodology enables correct calculation of the overall Revenue uplift due a given promotion.

**Keywords**—Halo, cannibalization, promotion, baseline, temporary price reduction, retail, elasticity, cross price elasticity, machine learning, random forest, linear regression.

## I. INTRODUCTION

### A. Background

PROMOTIONS are one of the most utilized strategies to boost sales in the retail industry. Whenever a retailer runs a promotion, there is always a challenge to measure the promotion's effectiveness. The uplift in the sales unit cannot be used as the sole criteria to measure the promotion's effectiveness. This is because retailers reduce their gross margin, by discounts, during promotions. Thus, there could be scenarios where the net unit uplift of promotion is positive on average, but the net Revenue uplift may be negative. Therefore, the most important criterion to measure the effectiveness of promotion is its impact on the Revenue. However, Revenue uplift is a derived quantity, and it is dependent on the Baseline. Thus, accurate measurement of the Baseline becomes essential for proper assessment of Revenue impact. Further, in a multiple parallel promotions' environment, the situation becomes more complicated due to the mutual Halo and Cannibalization impact of different items on each other. The Halo and Cannibalization impacts are defined as the uplift and the down-lift of sales due

to the promotion of a complementary or a substitute item.

Baseline is defined as the sales of an item had there been no promotion on it. However, there can be multiple permutations in which some or all related items (i.e., complementary or substitute) may be in promotion. Therefore, the Baseline of an item, calculated in one scenario where a subset of related items was promoted, would vary if the subset changes. Hence, this paper's primary focus is to address this variability in Baseline calculation and model it with Machine Learning to calculate proper Promotion Effectiveness.

### B. Literature Survey

This section briefly discusses studies related to the various strategies to measure promotions' effectiveness by calculating the Baseline or by considering the Halo and Cannibalization impact during Revenue calculation.

Loyal customer's basket analysis can be utilized to capture the Halo and Cannibalization impacts in case of promotion [1]. The method to estimate effect of promotion is addressed by creating multivariate multi structure models. However, such methodology relies heavily on basket analysis and will not work for slow-selling items. Further, Halo and Cannibalization impacts depend on the correctness of the substitute and complementary lists. As basket analysis is one of the methods to identify them, relying only on it may not be exhaustive.

Few studies utilize a simple Baseline formulation (like moving average), rule-based methods to calculate the gross lift and subsequently the Halo and Cannibalization impacts to capture promotion effectiveness [2], [3]. Such methodologies suffer due to the percolation of error from the naïve Baseline calculations, and also, the rule-based nature makes them rigid and non-adaptive. In these methodologies, the reverse impact of promotions on the complementary and the substitute items, which impacts the concerned item, are not considered during the Baseline calculation of the concerned item.

Other methodologies utilize similar Baseline assumptions like [2] and [3] but use learning-based methods to calculate the Halo and Cannibalization impacts instead of rule-based methods [5]. However, due to its reliance on naïve Baseline, it also suffers from the same inadequacies of [2] and [3].

Many researches focus only on calculating the Baseline accurately by incorporating market factors like seasonality, trend, etc. [4], [6]-[9]. However, they do not consider Halo impact on Baseline calculation and overall impact on Revenue.

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Some methodologies focus on the impact of promotions on consumers' purchase behavior but do not consider the implications of the same on Baseline or Revenue uplift calculations [10], [13].

Pre and post-promotion dips due to stockpiling and brand switching during the promotional period can be captured [11], [12]. However, such methodologies do not consider Baseline or Revenue uplift calculations.

Baseline sales of predictable items can be calculated using a machine learning approach after classification an item as predictable or random by analyzing its historical sales [14]. However, the impact of promotions on complementary and substitute items was not considered.

All the above cited literatures do not utilize a combined approach of calculating the Baseline and Revenue calculation for accurate measurement of Promotion Effectiveness. Hence, these methods fall short of considering the mutual Halo and Cannibalization impacts in multiple parallel promotions' scenarios.

Most of the time, industries use naïve approaches for Baseline estimation. Such techniques either use the same value of sales as one of the previous reliable observations or by using the first point of each promotion and compare it by the last point when the promotion ends like [5] or by using window-based moving average techniques [3]. However, such Baseline estimates do not incorporate the Halo and Cannibalization impacts on a multiple-parallel promotions' environment. Hence, a Machine Learning based methodology to incorporate such impacts during the Baseline calculation is proposed. This calculated Baseline is utilized in the subsequent Revenue Uplift calculation while incorporating Halo and Cannibalization impacts. Halo and Cannibalization impacts need to be considered in both baseline and Revenue calculation separately. This is because Halo and Cannibalization in baseline capture the impact on the concerned item of its promoted complementary and substitute items. On the other hand, the Halo and Cannibalization impact during Revenue calculation captures the concerned item's promotion impact on its complementary and substitute items. The description of the proposed methodology is in the next section.

## II. METHODOLOGY

The proposed methodology is divided into two sections. In the first section, the Baseline of an item "j" is calculated by incorporating the impact of the promotions on related items for which the item "j" is complementary or substitute. In the second section, the Revenue of an item is calculated by considering the positive impact of its promotion on complementary items (Halo impact) and the negative impact on its substitute items (Cannibalization impact). Thus, the Halo and Cannibalization impact on item "j" for calculating the Baseline of item "j" is considered. However, the Halo and Cannibalization impact of item "j" on its complementary and substitute is considered to estimate the Revenue due to a promotion correctly. This enables correct calculation of the overall Revenue uplift.

The definitions and pre-requisites along-with the methodology is explained in the subsequent subsections.

### A. Definitions and Pre-requisites

**Baseline.** Baseline sales is an estimate of sale of an item "j" on week "t" had there been no promotion on item "j".

**Halo and Cannibalization.** Halo impact of item "i" can be defined as the increase in sales of items in the set "C<sub>i</sub>" due to promotion on item "i", where "C<sub>i</sub>" is the set of items which are complementary to item "i". Similarly, the Cannibalization impact of item "i" can be defined at the decrease in sales of items in the set "S<sub>i</sub>" due to promotion on the item "i", where "S<sub>i</sub>" is the set of items that are substitutes of item "i". It is assumed that the list of complementary and substitute items is already available. Along with this list, their sales, promotion information and strength of the complementary and substitute relationship is also available. Similarity scores like cosine similarity and lift values from Market Basket Analysis are possible candidates for quantifying the strength of relationship with substitute and complementary items respectively.

**Temporary Price Reduction.** Temporary Price Reduction or TPR is one of the most common promotions in the Retail Sector. It refers to the reduction in the price of items by providing a percentage discount. There are also other types of promotions. However, in this analysis only TPR promotions are considered.

**Cross price elasticity.** Cross price elasticity measures change in demand of quantity of one product when price of another product changes. Substitute goods have a positive cross price elasticity, as the price of one good increases, the demand for the second good increases. Complementary goods have a negative cross price elasticity, as the price of one good increases, the demand for the second good decreases. Equation (1) is the mathematical formulation of cross price elasticity using the log-log model.

$$\ln Q_j = b_0 + b_1 \ln P_j + b_2 \ln P_i \quad (1)$$

where  $Q_j$  : Quantity sold for item "j",  $P_j$  : Price of item "j", such that "j"  $\in$  "S<sub>i</sub>" or "C<sub>i</sub>",  $P_i$  : Price of promoted item "i",  $b_1$  : is the price elasticity of item "j",  $b_2$  : is the cross-price elasticity coefficient, thus  $b_2$  is the estimated percent change in dependent variable ( $Q_j$ ) for a percent change in independent variable ( $P_i$ ).

### B. Details of the Proposed Methodology

**Baseline.** The proposed methodology utilizes regression-based learning to model the Baseline of a concerned item, "j". As the sales of an item is influenced by promotions on "j" as well as the promotions on the items for which "j" is substitute or complementary. Hence the Baseline is formulated as:

$$\beta_{jt} = f(P_{jt}, P_{St}, P_{Ct}) \quad (2)$$

where  $\beta_{jt}$  : is the Baseline sales of item "j" on week "t",  $P_{jt}$  : is the Promotion flag of item "j" on week "t",  $P_{St}$  : is the Promotion flag of items in the set  $RS_j$  on week "t",  $P_{Ct}$  : is the Promotion flag of items in the set  $RC_j$  on week "t",  $RS_j$  : is the set of items for which item "j" is substitute,  $RC_j$  : is the set of

items for which item “j” is complementary.

The Baseline formulation in this paper is not restricted only to accommodate inter-brand/competitive reactions (i.e., Cannibalization) but also incorporates Halo impact. Further, the modeling function “f” is not restricted to be linear. This enables “f” to capture complex relationships between the independent and the dependent variables. However, to prove the proposed methodology's effectiveness, a comparison with the linear model is also performed. The Baseline calculated using linear and nonlinear modeling functions is represented as “lm” and “rf” respectively.

Net Revenue Uplift. Revenue of an item during promotion is calculated as:

$$\mathcal{R}_{jt} = Q_{jt} * \overline{Pr}_{jt} \quad (3)$$

where  $\mathcal{R}_{jt}$ : Revenue earned on item “j” on week “t”,  $Q_{jt}$ : Quantity sold of item “j” during promotion week “t”,  $\overline{Pr}_{jt}$ : Promotion price or reduced price of item “j” during promotion week “t”.

To measure the correct impact of a promotion, the fact that promotion on an item may impact sales of its complementary items positively and can be responsible for loss in sales of substitute items should also be considered. Hence while calculating Revenue earned due to promotion on an item, the Revenue earned on its complementary items should be added and Revenue lost in sales of its substitute items should be subtracted. Using (2) and (3), the Net Revenue can be calculated as:

Net Revenue = Revenue – Cannibalized Revenue + Halo Revenue

$$N\mathcal{R}_{jt} = \mathcal{R}_{jt} - (\sum_{i=1}^n U_{it} * WS_{ji} * Pr_i) + \sum_{k=1}^m U_{kt} * WS_{jk} * Pr_k \quad (4)$$

where n: number of substitute items of item “j” which are not in promotion, m: number of complementary items of item “j” which are not in promotion,  $U_{it}$ : Uplift in number of units sold of item “i” during week “t”, where item “i” is substitute/complementary of item “j”, calculated as  $U_{it} = |\beta_{it} - Q_{it}|$ ,  $WS_{ji}$ : Quantifies the weighted strength of substitute/complementary relationship in the range [0,1] of item “i” w.r.t item “j”. It is the weighted mean across all items to which item “i” is complementary or substitute. Strength of complementary or substitute relationship is described in Section II A.  $Pr_j$ : Base-price or non-promotional price of item “j”

In a multiple parallel promotions' scenario, the drop in sales of an item “i” cannot be attributed to a single substitute i.e., item “j”, as there may be many substitutes of item “i” which can be in promotion in the week “t” and have cannibalized the sales of item “i”. The Cannibalization impact is assumed to be directly proportionate to the Weighted Strength ( $WS_{ji}$ ). Similarly, the Halo impact on complementary items is calculated.

Finally, to observe the efficiency of promotion on any product, Revenue uplift is calculated using (2) and (4), using the formula below:

$$\text{Revenue Uplift } (\mathcal{RU}_{jt}) = N\mathcal{R}_{jt} - (\beta_{jt} * Pr_j) \quad (5)$$

Further, the promotion effectiveness for all items in a promotion can be computed as:

$$\text{Promotion Effectiveness} = \sum_{z=1}^h RU_{zt} \quad (6)$$

where h: number of items in the given promotion, t: week of promotion.

### III. EXPERIMENTAL ANALYSIS

In this section, the experimental analysis to validate the proposed methodology is discussed. Due to privacy concerns, the proprietary data from our organization could not be used. Further, any open-source dataset which fulfills all the requirements of the proposed methodology was not found. Hence, the sales and promotions of items along with their Halo and Cannibalization impacts are simulated. The use of a simulated dataset enabled to have the true Baseline of the items, which was used as ground truth for our analysis. In the subsequent subsections, the simulator and experimental results for calculating the Baseline are discussed.

#### A. Simulator

A simulator was developed with 40 items, and each item is having 5 complementary and 5 substitutes. The complementary and substitute items were computed from a similarity matrix with randomized similarity values. After identification of the complementary and substitutes, their cross-price elasticities are created. Then the Baseline sales was created assuming a normal distribution (mean = 120 and standard deviation = 5) of sales volume for the items. Further, random promotion flags were created for each of the items, which was then utilized along with cross-price elasticities to compute the actual sales. Gaussian noise (mean = 30 and standard deviation = 18) was added to the actual sales. In this analysis only “Temporary Price Reduction” promotions with 20% discount were considered. However, the proposed methodology can be applied for any other promotion type and percentage discount.

#### B. Experimental Results

The simulator was run to generate the required dataset. This dataset was split into train and test sets in the ratio of 75:25. The Baseline(lm) and Baseline(rf) models were trained on the train dataset and calculated the Baseline for each by setting the promotion flag for the concerned item as “0”. This enabled the computation of the Baseline when there was a promotion on the item.

In Table I, a sample of training data is shown. The column “j\_Pf” represents the promotion flag on the concerned item “j” for which Baseline has to be calculated. The columns starting with “i” represents the  $i^{th}$  item's promotion flag, where “i” varies from 1 to n as in (4). Similarly, the columns stating with “j” represent the promotion flags of the  $j^{th}$  item, where “j” varies from 1 to k as in (4). The column “target\_j” represents the actual sales of item “j” on the week “t”, such that “t” is represented by the row number of Table I.

TABLE I

SAMPLE OF TRAINING DATA

$j\_P$ $F$	$i\_1\_P$ $F$	$i\_2\_P$ $F$	$i\_3\_P$ $F$	$k\_1\_P$ $F$	$k\_2\_P$ $F$	$k\_3\_P$ $F$	$k\_4\_P$ $F$	$k\_5\_P$ $F$	$target$ $j$
0	0	1	1	0	0	1	1	0	130
0	0	1	0	0	0	0	0	1	122
1	0	1	0	0	1	0	0	0	169
0	0	0	0	1	1	0	1	1	128
0	0	1	1	0	0	0	1	0	112
0	0	0	1	1	1	0	0	0	93

A model, linear or non-linear, is trained using the training data as shown in Fig. 1. This enables the model to learn the sales based on the promotion flags of the concerned item and the items for which the concerned item is substitute or complementary. After training, during the prediction phase,

“ $j\_PF$ ” was set as 0 for those weeks when item “ $j$ ” was in promotion (i.e. when “ $j\_PF$ ”=1) to predict the Baseline. This predicted Baseline is compared with the actual Baseline to measure the error. Root Mean Square Error (RMSE) is used as the error metric in the analysis.

The simulator was run 50 times to generate 50 different datasets with different promotion flags and the corresponding difference in actual sales. The average RMSE values were calculated corresponding to each of the 3 Baseline calculation methodologies viz. 3 weeks moving average (3weeks), linear model(lm) and Non-linear model based on Random Forest (rf) for each of the 40 items. The average RMSE was the mean RMSE of the concerned item across all the 50 datasets.

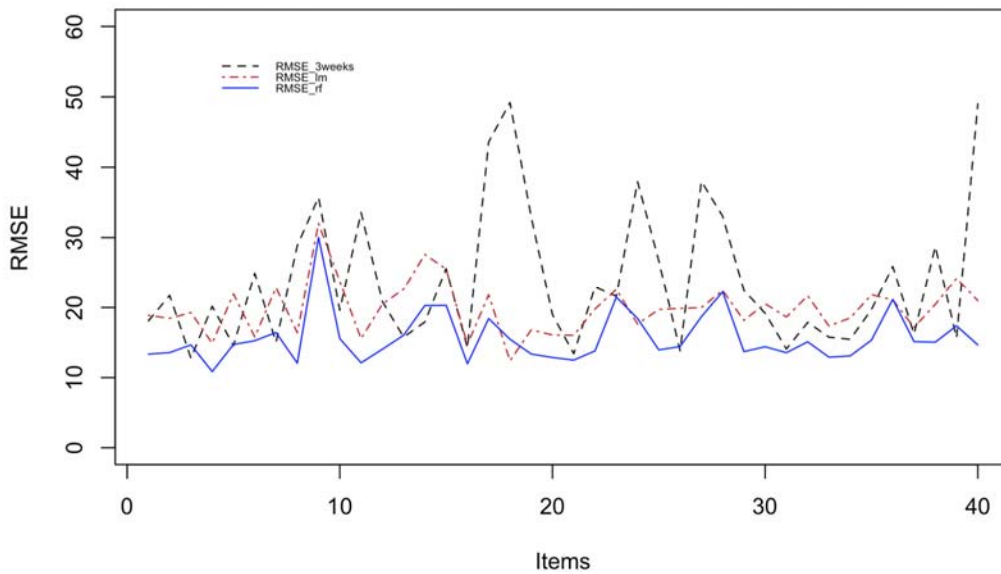


Fig. 1 Averaged RMSE values of the three methodologies for each of the 40 items across all the 50 runs

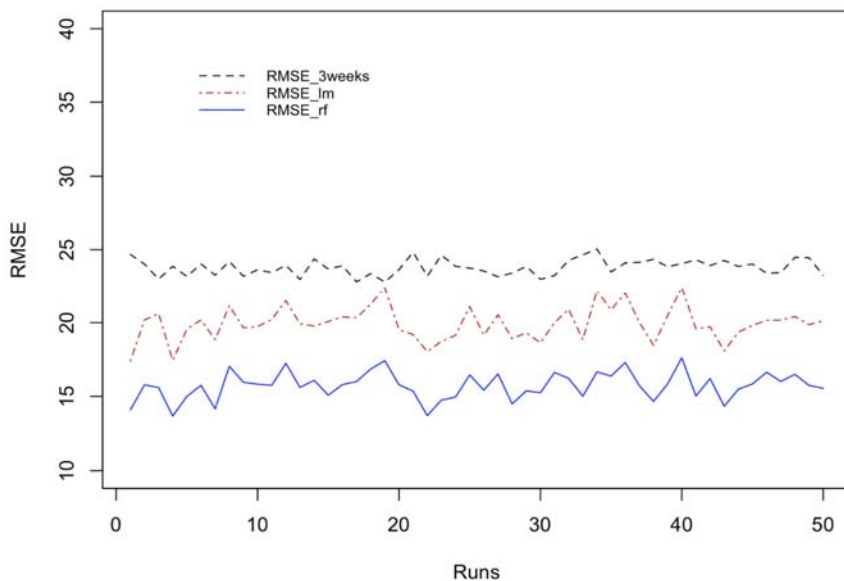


Fig. 2 Average RMSE values of the three methodologies for each of the 50 runs across all the 40 items

In Fig. 1 the average RMSE values for each of the three methodologies across all 40 items are shown. It is observed that for most of the items, the average RMSE value of Baseline(rf) is lower than that of Baseline(3weeks) and Baseline(lm). In Fig. 2 the average RMSE values for each of the three methodologies across all 50 runs are shown. As observed from Fig. 2, the average RMSE of Baseline(rf) is much lower than that of the other two methods.

#### IV. CONCLUSION AND FUTURE WORK

The proposed approach of utilizing Machine Learning to calculate the Baseline performed much better in terms of accuracy. Further, the Random Forest based implementation outperformed the Linear Regression based method. Thus, it can be concluded that the Random Forest based Baseline calculation is the nearest to the true Baseline. This would, in turn, enable for a more accurate estimation of the Net Revenue Uplift. The proposed methodology not only enables for computing promotion effectiveness in multiple-parallel promotions' scenarios, but it can also be utilized in forecasting the effectiveness of promotions in such scenarios. This would enable the business to leverage the benefits of promotions more effectively. The proposed formulation for Baseline calculation is regression based. In future, the proposed methodology will be refined by incorporating time-series forecasting algorithms with promotion flags as regressors to accommodate the trend and seasonality in sales, other types of promotions, pull-forwards effect, and return sales.

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