Measuring Promotion Effectiveness in Multiple Parallel Promotions’ Scenarios

**Abstract.** Promotion is a key element in retail business. Thus, analysis of promotions to quantify their effectiveness in terms of revenue and/ margin is an important 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. Most of the current research focuses on calculating baseline by considering inter brand/ competitor items. Others focus on accounting for Halo and Cannibalization impact on revenue calculations by considering baseline as interpretation of items’ unit sales in neighboring nonpromotional weeks. Such approaches individually may not be able to capture the overall revenue uplift in case of multiple parallel promotions. Hence, we propose a Machine Learning based method for calculating the revenue uplift by considering the Halo and Cannibalization impact on the baseline as well as on the revenue. We implemented the same on our organization’s data. However, due to data confidentiality issue we used simulated data to prove the effectiveness of our method.

**Keywords:** Halo, Cannibalization, Promotion, Baseline, Temporary Price Reduction, Retail, Elasticity, Cross Price Elasticity, Machine Learning, Random forest, Linear Regression

1. Introduction
   1. Background

Promotions are one of the most utilized strategies to boost the sales in the retail industry. Whenever a retailer runs a promotion, there is always a challenge to measure the effectiveness of the promotion. The uplift in sales unit cannot be used as the sole criteria to measure the effectiveness of the promotion. This is because retailers reduce their gross margin, by discounts, during promotions. Thus, there could be scenarios where net unit uplift of a promotion is positive on average, but the net revenue uplift maybe negative. Therefore, the most important criteria to measure the effectiveness of a 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 baseline becomes important for proper assessment of revenue impact. 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 on a complementary or a substitute item respectively. In a multiple parallel promotions’ environment, related (i.e., substitute or complementary) items maybe on promotion at the same time and therefore, would impact the sales of each other.

* 1. Literature Survey

This section briefly discusses about studies related to the various strategies to measure the effectiveness of promotions by calculating baseline or by considering the Halo and Cannibalization impact during revenue calculation.

The common points among the available literature are that many researches looked only into baseline calculation by considering inter brand/competitor impacts for promotion effectiveness calculation. Others focused on revenue calculation due to promotion considering Halo and Cannibalization impact.

[1],[2], and [4] focusses on calculating and incorporating the Halo and Cannibalization impact of an anchor item’s promotion on its complementary and substitute items. However, the reverse impact of promotions on the complementary and the substitute items which impacts the anchor item are not considered during the baseline calculation of the anchor item. Hence, these methods cannot handle multiple and parallel promotions’ scenarios.

[3],[5] and [6], focusses only on calculating the baseline accurately by incorporating competitive reactions, seasonality, trend etc but don’t consider halo impact. Further, they have not analysed the impact on revenue calculation.

Most of the times, industries use very naïve approaches for baseline estimation. Such techniques either use same value of sales as one of the previous reliable observations or by using first point of each promotion and compare it by last point when the promotion ends like [4] or by using window based moving average techniques like [2]. However, such baseline estimates don’t incorporate the halo and cannibalization impacts on a multiple-parallel promotions’ environment. Hence, we have developed a Machine Learning based methodology to incorporate such impacts during the calculation of baseline. This calculated baseline is utilized in the subsequent Revenue Uplift calculation while incorporating Halo and Cannibalization impacts. We describe our methodology in the next section.

1. Methodology

Our proposed methodology is divided into two sections. In the first section, we calculate the baseline of an item “*j*” by incorporating the impact of the promotions on related items for which the item “*j”* is complementary or substitute. In the second section, we calculate the revenue of an anchor item by considering the positive impact of its promotion on complementary items (Halo impact) and negative impact of promotion on its substitute items (Cannibalization impact). In short, we consider the Halo and Cannibalization impact on item “*j*” for calculating the baseline of item “*j*”. However, we incorporate the Halo and Cannibalization impact of item “*j*” on its complementary and substitute to correctly estimate the revenue due to a promotion. This enables us to calculate the overall revenue uplift correctly.

We explain the definitions and pre-requisites along-with our methodology in the subsequent sub-sections.

* 1. 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 “” due to promotion on item “*i*”, where “” is the set of items which are complementary to item “*i*”. Similarly, cannibalization impact of item “*i*” can be defined at the decrease in sales of items in the set “” due to promotion on item “*i*”, where “” is the set of items which are substitutes of item “*i*”.We are assuming the list of complementary and substitute items along with their sales and promotion information are available.

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

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. For, Complementary goods have a negative cross- price elasticity, as the price of one good increases, the demand for the second good decreases

 Below is the mathematical formulation of cross price elasticity using log-log model.

ln ln

Where,

: Quantity sold for item “*j*”

: Price of item “*j*”, such that “*j*” ∈ “” or “”

: Price of promoted item “*i*”

: is the price elasticity of item “*j*”

: is the cross-price elasticity coefficient, thusis the estimated *percent change* in dependent variable () for a *percent change* in independent variable ().

* 1. Details of the Proposed Methodology

### **Baseline.** We formulate the problem of modeling the baseline of a concerned item, “*j”* as a regression problem. We assume that 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.

= *f* (,,)

Where,

: is the baseline sales of item “*j*” on week “*t*”

: is the Promotion flag of item “*j”* on week “*t*”

: is the Promotion flag of items in the seton week “*t*”

: is the Promotion flag of items in the seton week “*t*”

: is the set of items for which item “*j”* is substitute

: is the set of items for which item “*j*” is complementary

Our formulation is similar to the baseline formulation in [3], but we did not restrict our methodology to only accommodate inter-brand/competitive reactions (i.e. cannibalization). We have additionally incorporated the halo impact for baseline calculation. Further, we did not restrict the function “*f*” to be linear. This enables us to capture complex relationships between the independent and the dependent variables. However, to prove the effectiveness of our methodology we will compare it with the linear model too.

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

= \*

Where,

Revenue earned on item “*j*” on week “*t*”

Quantity sold of item “*j*” during promotion week “*t*”

Promotion price or reduced price of item “*j*” during promotion week “*t*”

To measure correct impact of a promotion we need to consider 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.

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.

Net Revenue = Revenue – Cannibalized Revenue + Halo Revenue

= ((

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

: Uplift in number of units sold of item “*i*” during week “*t*”, where item “*i*” is substitute/complementary of item “*j*”, calculated as

: 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.

: Base-price or non-promotional price of item “*j*”

In a parallel-multiple promotions’ scenario, the drop in sales of an item “*i*” cannot be attributed to a single substitute i.e. item “*j*” , as there maybe many substitutes of item “*i*” which can be in promotion in week “*t*” and have cannibalized the sales of item “*i*”. We are assuming that this cannibalization impact is directly proportionate to the Weighted Strength (). Similarly, we can compute the halo impact on complementary items.

Finally, to observe efficiency of promotion on any product, we check Revenue uplift using below formula:

Revenue Uplift () for item “*j*” = – (\* )

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

Promotion Effectiveness =

Where,

*h*: number of items in the given promotion

*t*: week of promotion

1. Experimental Analysis

In this section we will describe the Experimental Analysis that we performed on our proposed methodology. Due to privacy concerns we could not use the proprietary data from our organization. Also, we could not find any open source dataset which fulfills all the requirements of our methodology. Hence, we simulated sales and promotions of items along with their Halo and Cannibalization impacts. The use of simulated dataset enabled us to have the true baseline of the items which was used as ground truth for our analysis. In the subsequent sub-sections, we will discuss the simulator and experimental results for calculating the baseline.

* 1. Simulator

We developed a simulator with 40 items and each item 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, we created their cross-price elasticities. We then created the baseline sales 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. We also added Gaussian noise (mean=30 and standard deviation=18) to the actual sales. We considered promotions only of type “Temporary Price Reduction” with 20% discount.

* 1. Experimental Results

We ran the simulator and then split the dataset into train and test in the ratio of 75:25. We trained the Baseline(lm) and Baseline(rf) models on the train data and calculated the baselines for each by setting the promotion flag for the concerned item as “0”. This enabled us to compute the baseline when there was a promotion on the item.

We ran the simulator 50 times to generate 50 different datasets with different promotion flags and corresponding difference in actual sales. We calculated the average RMSE values 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.

In Fig.1. we plot the average RMSE values for each of the three methodologies across all 40 items. We see 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. we plot the average RMSE values for each of the three methodologies across all 50 runs. We see that in all the runs the average RMSE of Baseline(rf) is much lower than that of the other two methods.

Chart, line chart, histogram

Description automatically generated

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

Chart, line chart, histogram

Description automatically generated

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

1. Conclusion and Future Work

The proposed approach of utilizing Machine Learning to calculate baseline performed much better in terms of accuracy. Further, the Random Forest based implementation outperformed the Linear Regression based method. Thus, we can conclude that the Random Forest based Baseline calculation is the nearest to the true baseline. This would in turn enable for more accurate estimation of Net Revenue Uplift. Our methodology not only enables for computing promotion effectiveness in a 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 in a more effective manner.

We formulated the baseline calculation as a regression problem. However, in future we intend to use time-series forecasting algorithms with promotion flags as regressors to accommodate the trend and seasonality in sales. Further, we would incorporate other types of promotions, pull-forwards effect and also return sales for calculating the promotion effectiveness.

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