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User-Based Cannibalization Mitigation in an Online Marketplace

Vivian Guo, Yan Qu

Abstract**—**Online marketplaces are not only digital places where consumers buy and sell merchandise, and they are also destinations for brands to connect with real consumers at the moment when customers are in the shopping mindset. For many marketplaces, brands have been important partners through advertising. There can be, however, a risk of advertising impacting a consumer's shopping journey if it hurts the use experience or takes the user away from the site. Both could lead to the loss of transaction revenue for the marketplace. In this paper, we present user-based methods for cannibalization control by selectively turning off ads to users who are likely to be cannibalized by ads subject to business objectives. We present ways of measuring cannibalization of advertising in the context of an online marketplace and propose novel ways of measuring cannibalization through purchase propensity and uplift modeling. A/B testing has shown that our methods can significantly improve user purchase and engagement metrics while operating within business objectives. To our knowledge, this is the first paper that addresses cannibalization mitigation at the user-level in the context of advertising.

Keywords**—**Cannibalization, machine learning, online marketplace, revenue optimization, yield optimization.

I. Introduction

ONLINE marketplaces are not only the places where people buy and sell products, they are also the platform for brands to connect with real consumers when customers are in the shopping mindset. For many marketplaces, brands are the important partners through advertising. However, it is possible that advertising could impact a consumer's shopping journey if the ads slow down page loads, distract the consumers, etc. Ultimately poor user experience can lead to the loss of transaction revenue for the marketplace. Manual efforts of mitigating ad impact by shutting off ads can improve user experience and recover transaction revenue, but it is generally done in an ad hoc manner.

While advertising impact on user experience can be measured through site speed, usability, etc., in this paper, we propose using a measure that links directly to a user's intent on a marketplace to make a purchase. Instead of looking at the individual aspects of user experience, we use a cannibalization measure that determines the loss of transactional revenue as a result of the individual factors.

In this paper, we present methods of user-based cannibalization control, which selectively turn off ads to users who are likely to be cannibalized by ads subject to business objectives. Cannibalization has been an important concept in marketing [11]-[14], but has not been much studied in the context of advertising. We first define cannibalization of advertising in the context of an online marketplace and describe metrics that can be used for quantifying cannibalization. In particular, we use a metric called bought item (BI) lift to measure the difference in BI between those users who are in the ads-off and ads-on group. BI lift measures the impact of ads on purchases on the marketplace. We describe how the BI lift is measured through long-running A/B testing.

We postulate that cannibalization can be mitigated by turning off ads to users who are sensitive to ads. We explore two ways to estimate the sensitivity to ads. First, for a user segment, we can compare users in the segment who are exposed to ads and who are not exposed to ads in terms of their BI. Segments with higher BI lift suggest that users in that segment are more impacted by ads. Such a BI lift measure is not feasible at an individual user level, as a user cannot have both ads on and ads off. The first method requires one to define user segments. We describe a rule-based method for user segmentation based on the frequency and purchase amount of user purchases. With the second method, we measure at the individual level the sensitivity by comparing the difference in purchase propensity between ads on and ads off. We use the uplift modeling technique [23], [24] to model the incremental impact of ads on a user's purchase behavior. The uplift model is built upon more dynamic features of user behaviors than the first method. Our analysis shows that it improves significantly over the rule-based method.

Although turning off ads could increase BI and site transactional revenue, it also results in the loss of ad revenue. Mitigation solutions often need to operate within certain business objectives such as ad revenue goals. Instead of simply eliminating cannibalization by switching off all ads, we need to balance cannibalization control and ad revenue loss. Constraints from the business side include:

- Ad revenue loss budget: the upper bound of ad revenue loss incurred due to turning ads off.
- BI lift target: the lower bound for expected BI lift in terms of cannibalization mitigation.
- Positive net gain: the recovered transactional revenue should be greater than the ad revenue loss.

The contribution of this paper is summarized as follows: We present ways of measuring the cannibalization impact of advertising in an online marketplace. We propose ways of measuring ad impact either through BI lift or through an uplift

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score in purchase propensity. We present a system of cannibalization mitigation by turning off ads to users who are sensitive to ads. We show that our methods significantly improve user purchase and engagement metrics while operating within the business objectives. To our knowledge, this is the first paper in the topic of cannibalization mitigation of advertising.

II. Related Work

Related work falls into the following four areas: (1) advertising impact on users' purchase decision; (2) revenue cannibalization; (3) ad revenue optimization; (4) predicting user purchase propensity.

Online advertising can impact user experience and purchase decision. Research has focused on the online display advertising affecting user experiences of websites [1], [9], [10] and the impact of different types of ads on purchasing decision such as the banner ads [2], social media ads [3] and keyword-based ads [4]. It is also demonstrated that ads affect users' behavior along the purchase funnel [5], [6]. Quantitative studies have also looked into the effects of Exposure Frequency for advertising from traditional and online channels [7], [8].

The problem that we are solving here is beyond quantifying the ads impacts on the purchase decision. In our specific case, serving ads potentially cannibalize the transactional revenue on an online marketplace. There is literature studying revenue cannibalization between multiple channels. However, they mainly focus on cannibalization between different product lines in the market [11], [14], between new and re-manufactured products [12] and cannibalization of search revenue by different search engines [13]. Not much research has been done on transactional revenue cannibalization in the context of advertising.

We solve revenue optimization by looking at the two sides – ad revenue loss and recovery of cannibalized revenue. Various existing research has looked at some sort of trade-off in ads revenue optimization [15]. For example, one paper studied ad revenue optimization towards the trade-off between the short-term revenue from ad exchange with the long-term benefits of delivering good spots to the reservation ads [15].

Our machine learning model is largely dealing with purchase propensity prediction. There are many existing studies around this area [16]-[24]. There is a particular paper that illustrates the logistic regression method of predicting purchase propensity [16]. Our paper has compared statistics across multiple methodologies. Other papers demonstrated prediction of user behavior and purchase propensity in other use cases [17]-[20], but none of them have integrated explicitly the impact of ad exposure into modeling. We derived an uplift score measuring the cannibalization likelihood in our paper and this relates to some methodologies in marketing [21]-[24].

III. Methodology

In this section, we first present various metrics for measuring cannibalization. Then we present the overall architecture for cannibalization mitigation. We then drill down into two solutions: one is rule-based with limited user dimensions; while, the other is based on modeling purchase propensity and employs more user behavior features. The rule-based method serves as the basic line for comparing the model-based solution.

A. Cannibalization Measurement

Cannibalization is a real threat to online e-commerce sites. However, there has been little empirical work on formulating the problem. There are various ways of measuring cannibalization in product marketing [25], [26], but there is no standard measure of the concept. For an online marketplace, we propose measuring ad cannibalization as the percentage change in purchases between ads on and ads off. For our research, we employ a long-running A/B test, in which 3% traffic is prevented from showing any ads and the rest are exposed to ads. The 3% of users are randomly assigned on an ongoing basis. Since the assignment is random, the 3% of users differ from the rest of 97% only in whether or not they are exposed to ads. We define the cannibalization rate as the BI lift as follows:

$$\frac{BI_{ads\_off} - BI_{ads\_on}}{BI_{ads\_on}}$$

where BI_{ads_off}, BI_{ads_on} denote the number of the BI per user in the ads-off and ads-on group, respectively. Users are identified based on user ID and cookie information.

Cannibalized revenue is calculated as the change of transactional revenue based on BI lift as follows:

$$r * \frac{BI_{ads\_off} - BI_{ads\_on}}{BI_{ads\_on}} \quad (1)$$

where r is the site transactional revenue.

In addition to BI lift for capturing cannibalization by ads, we also look at ad's impact on user experience via user purchase funnel measurements:

- Number of success events: success events are defined as one of the following: buy it now, bid, best offer, watch, and add to cart.
- View→success event: conversion rate from item view page to success events.
- Search→View→success event: conversion from search page to view item page and then to success events
- Reactivated users: users who do not have a visit in the last 12 months.

Through cannibalization mitigation, we can recover certain cannibalized revenue while losing ad revenue. A good solution should balance between the recovered transactional revenue and ad revenue loss. We look at two metrics to monitor the balance.

Clawback revenue: Clawback revenue is the difference between the recovered transactional revenue and the ad revenue loss. A successful mitigation solution should be minimally net positive in clawback revenue.

Ad multiplier: Ad multiplier is the ratio between ad revenue and the cannibalized revenue. Formally:

$$\frac{ad\ revenue}{(likelihood\ of\ being\ cannibalized) * purchase\ value}.$$

A higher multiplier means that a unit of cannibalization revenue can be compensated by a higher ad revenue number. A multiplier of 1 ensures the clawback revenue is always net positive.

B. System Flow

Our method of automatic cannibalization mitigation aims to improve user experience by turning ads off to users who are sensitive to advertising in their purchase journey and at the same time minimizing ad revenue loss. Fig. 1 is a high-level flow of cannibalization mitigation. The real-time components are above the dotted line; the components below the dotted line are offline processes. First, the ad call from the ad client is sent to the cannibalization decision engine (1). The cannibalization decision engine looks up the users in the ad call from the online user store (2) and returns the user score(s) to the decision engine (3). The cannibalization decision engine applies rules or thresholding to decide whether the decision to serve the ad or not and passes the decision back to the ad client (4). If the decision is ads off, no ad will be shown.

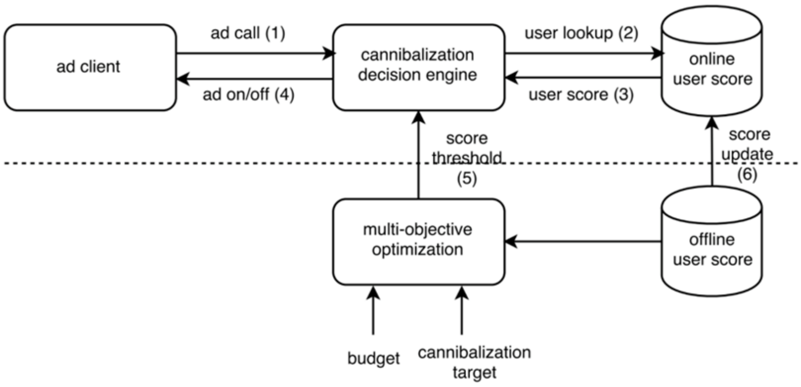

Fig. 1 High-level flow for cannibalization decision engine

The offline process consists of three major steps: 1) compute users' sensitivity to advertising; 2) compute users' ad revenue contribution; and 3) use multi-objective optimization to maximize cannibalization reduction by turning off ads while observing business constraints such as ad revenue goals.

The results of step 1) and step 2) are kept in the offline user store. The scores are updated daily and fed to the online user store. In the following subsections, we will present in more detail on how to compute these scores at user segment level and at individual user level.

The multi-objective optimization component takes user scores and various objectives such as ad budget goal and cannibalization mitigation goals and performs multi-objective optimization. The result of the optimization is a set of decision rules that inform the system of to whom and when to turn advertising off.

C. Segment-Based Cannibalization Mitigation

As discussed in Section III.*A*, BI lift can be used to measure advertising impact on users' purchase behaviors. We first apply this metric to measure ad sensitivity of different groups of users. One way of segmenting the users is by their frequency of purchases and the total spent on the site. Fig. 2 gives some examples of such segments and their respective BI lifts. We can see that users in different segments vary in their overall sensitivity to advertising. In general, high spenders tend to have high BI lift numbers.

Our optimization problem is two-sided. Recovering cannibalized revenue is at the cost of loss in ad revenue. Therefore, we should also look at the ad revenue contribution.

To calculate a user's contribution to ad revenue, we compute a weighted 30-day ad exposure count and translate it to the ad revenue number. Fig. 3 illustrates the ad revenue contribution by different percentile ad exposure buckets. One can see that almost 60% of ad revenue contribution comes from the top 10% percentile (90-100%) bucket. Because of this skewness of ad revenue contribution, mitigation decisions by shutting off ads should be taken with care so that business objectives such as ad revenue goals can be maintained.

Segment ID	% BI	% User	BI Lift
12	32.4%	16.4%	6.7%
10	10.7%	3.8%	5.5%
11	17.0%	9.0%	4.9%
13	12.1%	16.3%	3.7%
14	8.1%	11.1%	2.2%
15	8.0%	10.8%	1.8%
1	5.2%	5.2%	1.8%
2	4.4%	4.6%	1.0%

Fig. 2 Cannibalization across different user segments. As an example, segment 12 is the most cannibalistic segment (BI lift 6.7%); 16.8% of users belong to this group, but they contribute to 32.4% of BI

Our solution is to choose the segments S of users such that it maximizes the expected lift in the number of BI per user subject to: (1) ad revenue loss within budget; (2) lift in BI

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meeting a pre-given target for cannibalization improvement; and (3) net revenue gain is positive. The optimal solution looks as "for FM segment i, to turn off ads for users below jth percentile of ad impressions". Formally:

$$\max_{S} E(BI\ lift)$$
$$subject\ to\!: E(ad\ revenue\ loss) \leq budget$$
$$E(BI\ lift) \geq target$$
$$r * E(BI\ lift) - E(ad\ revenue\ loss) \geq 0$$

where r is the site transactional revenue.

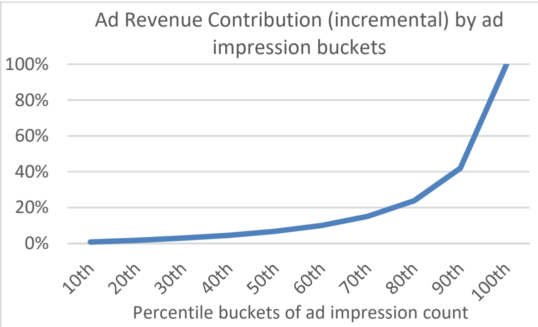

Fig. 3 Ad revenue contribution (cumulative) by impression buckets: almost 60% of ad revenue (y-axis) comes from the top 10% bucket of users (x-axis)

D. User-Level Cannibalization Mitigation

The algorithm described in Section III.*C* has limitations in that it clusters users based on only two features (weighted ad impression count and frequency/purchase segmentation), while we know there are many behavioral and demographic features that could potentially affect users' purchase decisions;

The segmentation method is not very dynamic and does not react to a user's behavior quickly.

The next algorithm considers more user behavior features and provides decisions on user level. On a high level, we score and rank users on a daily basis.

Specifically, for each user, we compute a multiplier which is to be updated on a daily basis. The multiplier is defined as the ratio of ad revenue and cannibalized revenue and it captures the trade-off between ad revenue and cannibalization.

In the following sections, we will demonstrate how each component of the multiplier is derived: Likelihood of cannibalization; estimation on daily ad revenue and purchase value.

1) Purchase Propensity

We develop a machine learning model 1 that predicts a user's purchase propensity. The set of user features consists of:

- Different types of online behaviors such as search, view, and purchase by product categories over the recently passed 1 day, 3 days, 7 days and 30 days;
- Buyer and seller status features such as their respective feedback scores;
- Demographic features such as age, gender, and state;
- Time factors such as "day of the week" that capture temporal seasonality;
- "Treatment group" that indicates whether a user is in the ads on or ads off group since exposing to ads may impact one's purchase propensity.

We use 1-week of site traffic data with about 20 million users. We split the raw data in the ratio of [0.6, 0.4] for the training and test sets. In our raw dataset, each row represents a user's feature and target variable *is_purchased_binary* for each user on each given date. Each user is represented by a set of 171 features.

Feature selections are done in GBM (gradient boost machine). Three randomly generated noise variables are served as benchmarks for feature importance. Forty features with an importance score higher than the noises are selected as important variables. Note that the variable *treatment_group* shows higher importance than noise, meaning that being exposed to ads indeed influence ones' purchase decisions.

Various predicting models are applied to train the data: logistic regression, random forest, and GBM. Fig. 4 presents the results from the test set. GBM performs best compared with the others in terms of a higher AUC and F1 score.

2) Likelihood of Cannibalization

Purchase propensity predicts the likelihood of making a purchase. However, it does not necessarily imply cannibalization. It is possible that a user with high purchase propensity knows exactly what he wants to buy and therefore is insensitive to ads.

Our hypothesis is that users may be distracted by seeing ads through purchase funnel and have their purchase decisions impacted. The likelihood of cannibalization can be interpreted as the difference in the conditional probability of a purchase given a user is in the ads-off and ads-on group. We capture this difference by the uplift score. Formally:

$$uplift\ score = probability(purchase|ads\ off) - probability(purchase|ads\ on)$$

The uplift score captures the difference in purchase propensity, given a user is exposed to ads or not. Leveraging the purchase propensity model which has the *treatment_group* as a user feature, we can obtain two scores for each user by setting *treatment_group* = "ads off" and *treatment_group* = "ads on". The difference between the two scores gives the uplift score.

The other hypothesis is that the uplift score is not sufficient for signaling being cannibalized. Suppose a user's purchase propensity is very low, a high uplift score may not necessarily imply a change in the purchase decision.

To test this hypothesis, we evenly bucket the users in the test set along two dimensions: by their purchase propensity and uplift scores. We compare the BI lift across treatment and

[1] Our data science platform is built on H2O and Spark, which can do scalable machine learning with hundreds of GB data.

control groups.

Fig. 5 takes users from the ads-on group and looks at the user distribution across uplift buckets for any given bucket for purchase propensity. Users are concentrated along the diagonal cells, meaning that buyers from higher purchase propensity buckets are likely to come from the more cannibalistic uplift buckets.

Fig. 6 shows the percentage of BI lift contribution by users from each purchase propensity and uplift buckets.

This is consistent with our earlier hypothesis on purchase propensity. The high uplift score does not necessarily imply cannibalization. Those 16.42% users with both high (in the top 75^{th} - 100^{th} percentile) purchase propensity and uplift score appear to be the most cannibalistic and account for 66.88% of BI lift.

To take into account the impact of both the purchase propensity and uplift score, we compute the likelihood of cannibalization as a composite of the two:

$$Sqrt(purchase\ propensity) * sqrt(uplift\ score)$$

3) Purchase Value and ad Revenue

The estimation of user-level purchase value and ad revenue is mainly derived from a user's previous activity.

For each user, we collect a profile of daily ad revenue for the last 30 days and daily purchase amount for the past year. We take the median instead of the average of data points, as the former is more robust to distribution skewness. However, there could be data sparsity issues for users who were not actively visiting and buying. We process the data according to the rule below.

For users with enough data points (visiting days or purchase days more than 5): we take the median of the past daily purchase value and ad revenue.

For users with sparse data points (visiting days or purchase days less than 5): we take on the default value of his corresponding FM segment; i.e., the median value aggregated across all users in that FM segment.

Inspecting the data for user-level purchase value and ad revenue, we found that the distribution of data has long tails. See Fig. 7. To mitigate the large outliers' impact on multiplier, we take logarithm to normalize the values. The purpose is to prevent a big outlier value from dominating the impact on the multiplier. Fig. 8 gives the distribution after normalization.

4) Multiplier

Combining all components, we generate the user-level multiplier. The multiplier reflects the trade-off between ad revenue and cannibalized revenue. The higher the multiplier, the more ad revenue a user brings in relative to cannibalization. For users with a multiplier greater than one, we expect positive clawback revenue for showing ads to them.

For cannibalization mitigation, we compute a multiplier threshold for deciding what users to turn off ads so that: The multiplier value less than a critical point of positive net revenue gain; the expected ad revenue loss is within budget.

To see the effect of cannibalization and ad revenue change upon multiplier, we use one week of traffic data and rank users by their multiplier and compare the percentage of contribution in BI and ad revenue.

Users are evenly divided into 10 percentile buckets according to their multiplier values. Both shares in transactional and ad revenue decreases with the value of the multiplier. It is consistent with some previous analytics work that those who shop a lot are also more exposed to ads, the 0-10^{th} percentile multiplier bucket for instance. In the low percentile buckets, the contribution of ad revenue is low compared to BI. As we go to high multiplier buckets, share in ad revenue dominates the share in BI. Fig. 11 illustrates the percentage of contribution in BI and ad revenue by multiplier values.

	AUC	Precision	Recall	F1 Score	Accuracy
Random Forest	0.763	0.267	0.437	0.329	0.826
GBM	0.767	0.262	0.445	0.334	0.826
Logistic Regression	0.708	0.215	0.426	0.286	0.791

Fig. 4 Statistics in model evaluations – GBM performs better than others

	Purchase Propensity				
Uplift	0-25^{th} percentile	25-50^{th} percentile	50-75^{th} percentile	75-100^{th} percentile	Grand Total
0-25^{th} percentile	14.79%	5.60%	2.79%	1.82%	25.00%
25-50^{th} percentile	8.00%	9.57%	5.84%	1.59%	25.00%
50-75^{th} percentile	2.15%	8.05%	9.64%	5.17%	25.00%
75-100^{th} percentile	0.07%	1.78%	6.73%	16.42%	25.00%
Total	25.00%	25.00%	25.00%	25.00%	100.00%

Fig. 5 User distributions across purchase propensity and uplift buckets

	Purchase Propensity				
Uplift	0-25^{th} percentile	25-50^{th} percentile	50-75^{th} percentile	75-100^{th} percentile	Total
0-25^{th} percentile	0.00%	4.29%	0.00%	0.00%	4.29%
25-50^{th} percentile	0.00%	0.00%	2.52%	0.00%	2.52%
50-75^{th} percentile	2.13%	8.53%	1.94%	4.39%	16.99%
75-100^{th} percentile	0.00%	3.83%	5.50%	66.88%	76.21%
Total	2.13%	16.65%	9.95%	71.27%	100.00%

Fig. 6 Percentage of BI lift contribution by users from each purchase propensity and uplift buckets – 66.88% of BI lift are contributed by 16.42% of users from the top purchase propensity and uplift score bucket

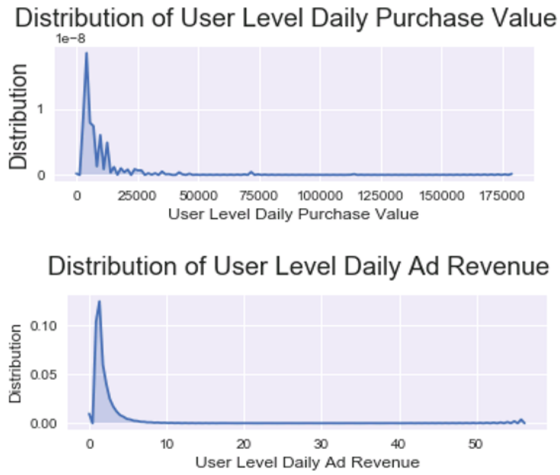

Fig. 7 Distribution of user-level daily purchase value and ad revenue long tails

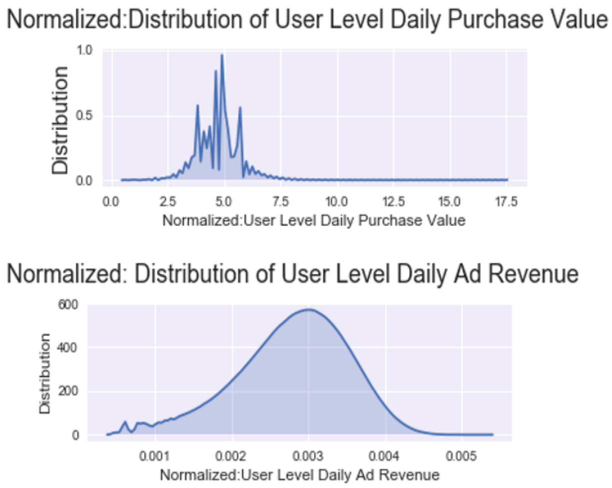

Fig. 8 Logarithm normalization for user-level daily purchase value and ad revenue, to mitigate the impacts of outliers in the long tail

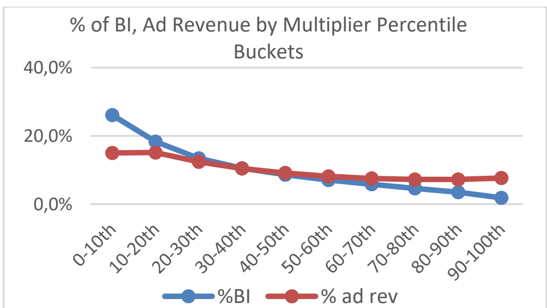

Fig. 9 Percentage of contribution in BI and ad revenue by multiplier

IV. Evaluation

A. Results for Segment-Based Mitigation

We evaluated our method on an e-commerce site for three weeks in November 2016. The experiment was set up as an A/B test with 50% traffic with automatic cannibalization mitigation and 50% without.

We observed statistically significant 0.39% lift in BI and 0.37% lift in Gross Merchandise Bought (GMB).

In addition, we observed statistically significant lifts with purchase funnel related metrics, such as item view page to successful conversion and search to item view to successful conversion. We also observed statistically significant lift with reactivated users who ended up buying. See Fig. 9.

Metric	Lift	p-value
Gross Merchandise Bought (GMB)	0.37%	0.032
BI	0.39%	0.001
Reactivated Buyers	0.58%	0.027
Success Events	0.38%	0.009
Search→View→Success Event	0.17%	0.000
View Item→Success Event	0.14%	0.000

Fig. 10 Experiment Result: statistically significant lifts in user purchase and purchase funnel related metrics

It is worth noting that those online results appear to be quite aligned with the offline simulation. See Fig. 11.

METRIC	Offline Projected	Online Result
BI lift (segment)	0.48% (+/-19%)	0.39% (+/- 0.17%)

Fig. 11 Offline Projection vs. Online Result for the segment-based approach

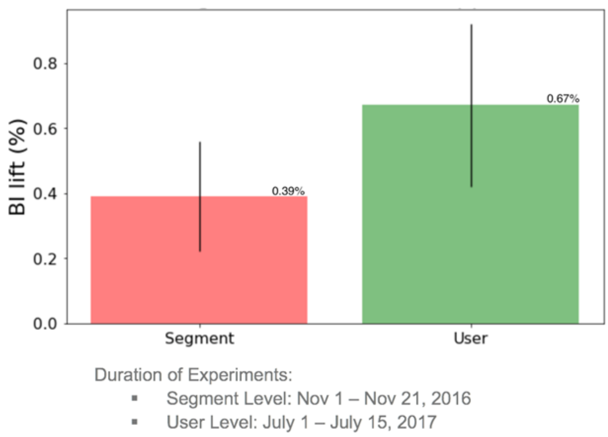

Fig. 12 BI lift comparison between the segment-level and user-level approaches

B. Results for User-Based Mitigation

Although Version 1 of the algorithm has successful online test results, it makes cannibalization mitigation decisions at the user segment level. Version 2 improves from version 1 in the sense that it tailors the cannibalization mitigation decision to each individual user. The decision will take into account a user's state in the purchase funnel and their sensitivity to advertising.

We launched an online experiment to test the user-based mitigation in July 2017. The experiment was set up as an A/B test with 50% traffic with automatic cannibalization mitigation and 50% without.

The user-based approach has improved from the segment-based approach in terms of BI lift (Fig. 12) and clawback revenue (Fig. 13). For the two weeks of experiment in July 2017, we achieved a BI lift of 0.67% (+/- 0.25%) and net revenue gain of $95,848.

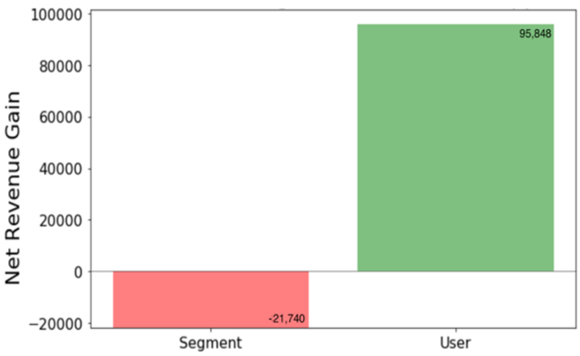

Fig. 13 Clawback revenue comparison between the segment-level and user-level approaches

V. Conclusion and Future Work

In this paper, we propose gauging the impact of advertising on user experience through a cannibalization measure based on transactional revenue loss. We present two versions of data science approaches that automatically reduce cannibalization while maintaining the business objectives at the same time. The first approach is from user segmentation and the second approach is to rank users by their ad revenue contribution relative to cannibalization.

The segment-based mitigation algorithm (in Section III.*C*) has been launched as experiments and shown significant lifts on user experience with both BI and other purchase funnel related metrics. Compared to its previous version, the user-level mitigation algorithm (in Section III.*D*) is more responsive to user-level behavior changes and thus better identifies potential cannibalization impacts. Offline simulation results for the second version of the algorithm shows a much stronger recovery of cannibalized revenue as well as net revenue gain, given the same ad revenue budget.

The user-level cannibalization mitigation algorithm (as illustrated in Section III.*D*) can be improved in terms of precision. We currently infer a user's expected purchase value from his past purchase values. However, this is not a precise estimation since the value of the purchase depends on the category of items. For example, a purchase in the motor category is likely more expensive than that in toys category. To better estimate a user's purchase value, we may just estimate future purchase value based on his recently searched or viewed items.

We can also further extend this algorithm to a floor pricing model. Currently, the two approaches being demonstrated in this paper only give binary decisions of whether to show ads for a particular user or not. We can further extend this to a floor pricing model for ad placement bidding. Therefore, the model would not be just limited to binary decisions. By setting the reserve price for an ad placement equal to the expected cannibalization, we realize a positive net gain from showing ads.

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