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Optimizing Campaign Effectiveness: Identifying Target Customers via Recommender Engine

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***Abstract*—In today's competitive business environment, the success of campaigns relies not only on their creation but also on effectively reaching the right customers. Campaigns often feature products that customers may not have considered or are unaware of, including popular items. This research aims to enhance retailer sales by leveraging an efficient recommender system that reminds targeted customers to purchase their preferred products and suggests additional items they hadn't initially considered during a campaign. Our focus is on utilizing the recommender system to identify potential customers for a curated set of products selected by the marketing team for a specific campaign. Communicating with all customers, can be time-consuming and costly, and irrelevant messages may harm customer loyalty. Therefore, the primary objective is to strategically select the right customers for a campaign, increasing sales and reducing communication costs. This paper provides valuable insights into connecting with the right customer segments to optimize revenue generation for businesses.**

The analysis shows that high-value customers (those generating the highest revenue) contributed to increases in average basket size, while win-back customers (with low engagement) and about to churn customers (those at risk of attrition) improved the effectiveness of marketing contacts by increasing engagement and reducing churn. Targeted communication, focused on revenue, also enhanced the quality of the relationship between the customer and the firm, helping to lower churn rates by engaging customers with suitable campaigns. This research provides empirical evidence supporting the theoretical benefits of targeting the right customers for a campaign.

***Index Terms*—Recommendation, ALS, Marketing Campaigns, Target Customers, Churn**

I. INTRODUCTION

In the landscape of e-commerce business, characterized by a vast product range and an extensive customer base, effective communication channels such as email, phone calls, and notifications are essential for customer interaction. However, these channels often require significant resources in terms of manpower and expenses. Unlike broad-scale communication, targeted communication is crucial for identifying specific groups of customers more likely to respond positively to a given campaign. This strategic approach has yielded substantial benefits for business, leading to significant savings in both communication costs and time.

Our databases contain detailed transactional data and records of purchased products, which form the basis of our recommendation system. By analyzing 12 months of past purchases, we have developed a recommendation model capable of predicting the top 100 potential next purchases for each customer. Storing this information in our databases and incorporating input from the marketing team about upcoming campaigns is a critical step in identifying top customers who can significantly contribute to maximizing revenue.

Our objective is twofold: to nurture customer loyalty by ensuring effective communication about the campaign reaches them, thereby strengthening their allegiance to our brand, and to optimize profitability by targeting communication efforts towards potential customers who are most likely to respond positively. This approach involves identifying customers based on various parameters, including those who regularly purchase items featured in the campaign (high value customers), those who were previously active but have become less engaged (win-back customers), and those who are at risk of churning or have shown declining engagement.

In reality, campaigns aimed at gaining customer loyalty and expanding the customer base can sometimes result in losses for companies rather than profits. To maintain the effectiveness of campaigns while ensuring profitability, it is imperative to focus on reducing communication costs. This can be achieved by identifying potential customers for the given campaign and communicating exclusively with them.

II. RELATED WORK

Many studies has been done to find target customers for Marketing Campaigns utilizing different strategies. In 2004 [1] employed collaborative filtering to compile a customer list for a campaign. Target customer selection using Fuzzy Model [2], [3] is referenced. This paper utilizes RFM features such as weeks since the last purchase and response time to emails to cluster customers and pinpoint those with the highest likelihood of responding to a campaign. [4] Along with RFM features this paper also aim in detecting interaction detection variable in order to find customers with high probability of respond to the campaign

In 2017 [5], the authors employed a hybrid approach that combined classification and clustering techniques. Initially, they classified customers' interests in a set of products, followed by clustering customers with similar interests for targeted marketing. [6] explores Segmentation approach to find best set of customers for target marketing. In 2017 [7] utilized forecasting approach to find target selection.

[8]–[10] discussed implementation of personalized recommendation model for e-commerce.

Finding churn customers in e-commerce and customer rentention strategies are explained well in [11], [12]

The primary focus of existing research is on segmentation and RFM features to identify suitable target customers. However, our proposed method aims to collectively identify customers with diverse characteristics, such as high revenue, win-back potential, and churn retention. This is achieved by leveraging the existing recommendation engine and churn model to optimize target selection, thereby maximizing revenue and fostering customer loyalty. Consequently, this approach is particularly viable for organizations equipped with a recommendation engine, ensuring alignment of marketing strategies with the current system.

III. Methodology

The proposed methodology consists of three distinct sections. The initial section focuses on identifying high-value customers through the recommendation engine, which analyzes and ranks customers based on their yearly revenue contribution for specific items. As illustrated in Fig. 1, this segment involves comprehensive analysis of historical purchase data to identify patterns and behaviors characteristic of high-value customers. Understanding these purchasing patterns enables measurement of customer impact on campaign performance, including their sales contribution and engagement levels. This analytical approach facilitates the development of targeted campaign strategies, ultimately optimizing resource allocation and maximizing campaign effectiveness.

The second section delves into identifying and analyzing win-back customers, defined as those who have a set of items included in their recommendations but currently exhibit lower engagement with these items. This involves examining historical transaction data to identify these lapsed customers and understanding the reasons behind their decreased activity. Strategies are then developed to re-engage these customers, such as personalized offers or targeted marketing messages aimed at reigniting their interest in the brand. The third section utilizes a churn model to identify customers who are about to churn or are showing signs of declining engagement. By targeting these at-risk customers with specific campaigns and offers designed to retain them, we aim to reduce churn rates and improve customer retention.

This comprehensive approach ensures that communication efforts are effectively directed towards the most impactful customer segments, thereby enhancing campaign outcomes and supporting long-term business growth.

A. Recommendation Engine

We have developed ALS-based recommendation engine utilizing historical transaction of all customers in order to predict customers' preferences and purchasing behaviors.

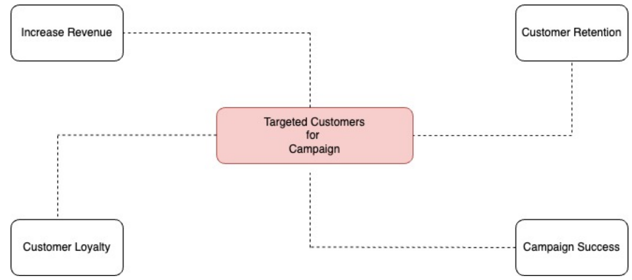

Fig. 1. Benefits of Targeting Customers for a campaign.

The ALS model is a collaborative filtering technique that efficiently handles large-scale data by alternating between fixing user and item latent factors and minimizing the error in predicting user-item interactions. By analyzing extensive historical purchase data, the ALS model identifies latent factors that capture underlying customer preferences and product attributes. This enables the recommendation engine to generate personalized product suggestions for each customer based on their purchase behavior and the behavior of similar customers. The model's robustness in handling sparse datasets and its ability to uncover complex patterns make it well-suited for enhancing the accuracy and relevance of recommendations, ultimately driving increased customer engagement and sales for the retail firm. Table I shows the output of ALS model. This approach enables the segmentation of customers based on their likelihood to respond positively to specific campaign items, ensuring that marketing efforts are both efficient and effective. The results demonstrate that utilizing the ALS model with extensive transaction data not only enhances the precision of customer targeting but also optimizes campaign outcomes by aligning product recommendations with customer interests and purchase history.

B. Churn Prediction

This project aims to understand the customer life cycle by identifying and analyzing patterns among customers at risk of ending their relationship with the business. Utilizing churn prediction techniques, we segment the customer base into distinct groups based on their likelihood of churn and the factors influencing their behavior. This segmentation provides a detailed understanding of customer dynamics, enabling targeted interventions to retain at-risk customers, optimize marketing strategies, and ultimately enhance customer loyalty and profitability.

Our approach integrates business insights with model training using XGBoost to detect segments such as Newbie, Infrequent, Declining, About to Churn, Goner, and Stable customers. Newbie customers are those who registered within the last 12 months, while Infrequent customers exhibit random purchase patterns on the platform. The marketing focus is on three segments: Declining, About to Churn, and Goner. Goner customers have not made any transactions in the last three months, Declining customers show a drop in basket size (sales) of 70 percent or more, and About to Churn customers are predicted to make no sales in the upcoming three months. Table II depicts the output of churn prediction model. By targeting these three segments for given campaign we can increase customer retention at out Platform.

C. Target Customers

The systematic process of customer targeting for campaign execution is depicted in Fig. 2.
High Value customers: Our research prioritizes increasing sales among high-potential customers identified through recommendation algorithms. Specifically, we have developed a method to select top-purchasing customers based on their historical sales data. By focusing on customers with significant purchases of promotional campaign items, we aim to strategically enhance their basket size and overall sales. This targeted approach ensures that marketing efforts are directed towards customers with the highest propensity to increase their spending, thereby optimizing the effectiveness of promotional campaigns.

Win-Back Customers: Our research focuses on re-engaging lapsed customers by leveraging the recommendation engine to identify individuals whose recommendation sets include campaign promotional items, yet who have shown no recent interaction with these items. By targeting these win-back customers, we aim to increase uplift and re-acquire their engagement with the promoted items. This strategy is designed to rejuvenate interest and boost purchase activity among customers who have previously disengaged, thereby enhancing the overall effectiveness of our marketing efforts.

Churn/Declining Customers: Our approach aims to prevent customers from churning and transitioning to the goner segment by utilizing the recommendation engine to identify at-risk individuals. These customers are recommended items from the campaign as their next potential purchases. To retain and re-engage them, we will specifically target these churn/declining customers with the given campaign, thereby mitigating the risk of further disengagement and promoting continued interaction with our offerings. This targeted intervention is crucial for maintaining customer loyalty and sustaining revenue growth.

This approach of selecting a diverse set of customers for a campaign maximizes total revenue by incorporating strategies to boost revenue from slow customers and retain those who are at risk of churning or declining.

IV. Data Preparation

We have varied set of customers with different purchase patterns. Utilizing their past 12 months of historical information along with product details we have store output of each module: Recommendation Engine and Churn Prediction.
Sample Recommendation Engine and Churn Model outputs are shown tables I and II respectively.

TABLE I
RECOMMENDATION OUTPUT

Customer Id	Product Num	Dept	Class	Subclass	Product Score
10000	999	Fresh Food	Carrot	Chinese carrot	0.94
10000	665	Dry Food	Salt	Rock Salt	0.86
10000	829	Fresh Food	Bean	Peanut	0.80
10000	709	Non Food	Disposable	Plastic Cup	0.63
10001	990	Non Food	Stationary	Pen	0.89
10001	827	Fresh Food	Meat ball	Fish ball	0.71

TABLE II
CHURN OUTPUT

Customer Id	Segment
10000	Goner
10001	About to churn
10002	Stable
10003	Declining
10004	Stable
10001	Infrequent

A. Finding Target Customers

High Value:

- Select all customers that have recommendations for promotional items.
- Sort these customers based on their average monthly revenue.

Win Back:

- From the set of all customers that have recommendations for promotional items, select customers who have not done any sales on the recommended items in last 2 weeks.
- Sort customers' list based on number of recommended items from potential items in their recommendations.

Churn/Declining:

- Merge the set of all customers that have recommendations for promotional items, with churn output.
- Select customers based on three segments: ”About to churn”, ”Declining” and ”Goner”.
- Sort the above customers' list based on number of recommended items from potential items in their recommendations.

Select top customers based on threshold on number of target customers for a campaign.

V. Experimental Results and Benefits

Campaign effectiveness can be quantified by measuring the total revenue generated from targeted customers, calculated using the formula illustrated in Fig. 3.

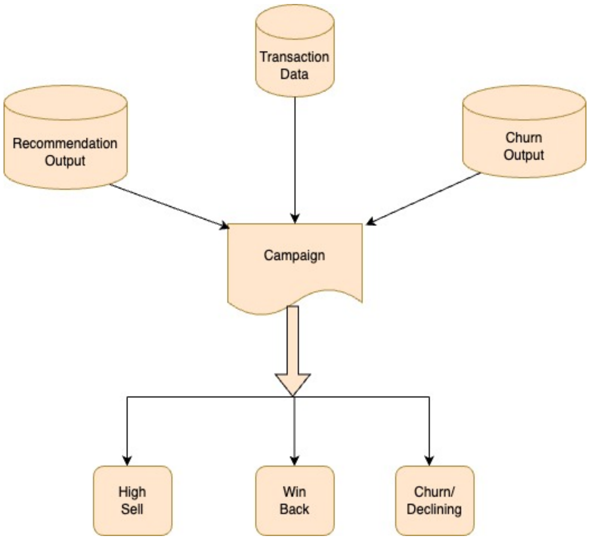

Fig. 2. Training Loss over 3000 steps.

Revenue calculation:
n:total set of recommended customers
k:total set of items in the given campaign
q:quantity purchased of each item
pp:promotional price of an item during campaign
date range: start to end date of a campaign
R=revenue earned from target set of customers

$$R = \sum_{i=1}^{n} \sum_{j=1}^{k} q * pp$$

Fig. 3. Revenue

The implementation of these three methodologies in one region led to the strategic targeting of 10 percent of customers, who subsequently generated 63 percent of the total campaign revenue. Analysis of the results, as illustrated in Fig. 4, revealed significant improvements across customer segments: ”High Value” customers demonstrated a 56% increase in average basket size, while ”Win Back” customers exhibited a remarkable 92% growth in average sales. Most notably, the campaign proved particularly effective in retaining customers classified as ”churn” and ”declining,” demonstrating the methodology’s impact on customer retention.

Identifying and targeting the best set of customers for a campaign and contacting them with relevant information provides several key benefits:

- Increased Sales and Revenue: By reaching out to customers who are most likely to respond positively to the campaign, businesses can significantly boost their sales and overall revenue.
- Improved Customer Engagement: Targeted campaigns ensure that customers receive information that is relevant to their interests and needs, leading to higher engagement rates.
- Enhanced Customer Experience: When customers receive personalized and pertinent offers, their overall experience with the brand improves, fostering stronger relationships and loyalty.
- Efficient Use of Resources: Focusing marketing efforts on a well-defined target audience reduces wasteful spending on broad, less effective campaigns, leading to more efficient use of marketing budgets and resources.
- Reduced Churn Rates: By engaging at-risk customers with targeted campaigns, businesses can address their needs and concerns, thereby reducing the likelihood of churn and improving customer retention.
- Competitive Advantage: Companies that effectively utilize targeted campaigns can differentiate themselves from competitors by offering more personalized and relevant communications.

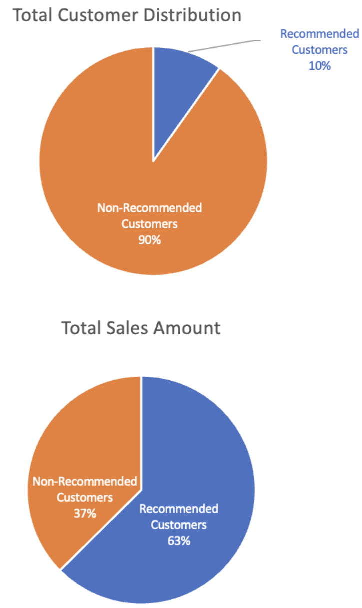

Fig. 4. customer vs sales distribution

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