Increasing Debit Card Utilization and Generating Revenue using SUPER Segments

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1. Abstract

Debit card is the second largest non-interest income generating source for retail banks currently. Increasing the number of customers using debit card on the POS terminal can help banks earn higher interchange income. Most of the current marketing strategies are aimed at encouraging customers to swipe debit cards on POS terminals versus paying cash for their transactions. Institutions are analyzing and segmenting account holders by their payment behaviors to develop a deeper understanding of debit card usage. This allows institutions to create, implement, and manage personalized and cost-effective marketing strategies and loyalty programs that address the needs of both the account holder and the financial institution. Using the insights gained through deep exploratory data analysis, these segments can help capture more wallet share and increase revenue, besides mapping the customers to appropriate tiers in the incentive programs.

This study presents a novel approach that can help banks understand the behavior of their customers and their needs. Targeting the right set of customers and educating them can play an important role in saving marketing spend substantially for the bank. The proposed two stage SUPER (**S**pend **U**sage Merchant **PER**formance) segmentation technique can help banks identify the customers who are not naturally (without education or incentive) induced to spend more, but have a strong potential to spend on additional merchant categories. With this segmentation model, we can rapidly increase customer's utilization. Providing correct incentives can help increase the usage and also reduce campaign cost by eliminating customers that should not be targeted. Using a combination of business rule and statistical segmentation across customer spend, usage and performance across various merchants will give strong insights into the "gap" opportunity and can be exploited with actionable marketing plans to increase spend across various merchant categories where customers have potential to increase spend.

2. Introduction

By analyzing and segmenting customers, based on their buying and payment behaviours, organizations are able to develop a deeper understanding of their habits, need, and spend behaviour. Understanding the debit card customers through their past spending behaviour and level of engagement, is the key to unlock the strategy of effective marketing. Sample questions that might help to formulate the analysis strategy are:

- Which customer is most engaged with FI's (Financial Institutions) and why?
- Which account holders use debit card to pay at retail locations but not at restaurants?
- Which customer is not using debit card for purchases at all, but is still withdrawing cash at ATMs?
- Which customer has received a debit card but has not yet activated it?
- Which customer has more opportunity of growth in future?

- How would you target the growth potential?

Finding answers to these questions can help the FI to target the right customers with right offers and generate strong ROI on their campaign investments. Customer segments created, based on their debit card usage, spend and behaviour can help us find hidden opportunities to grow customer penetration as well as transaction frequency. To grow the customer value, we need to know which customer to grow by how much and across which merchant categories. Required opportunity analysis has been done in the two stage SUPER segmentation study to answer to the questions of whom, what, and where.

3. Research background

Each year, numerous methods are developed in an attempt to segment customers according to the business requirements. Different segments are needed for different purposes. A group that responds to one message may not have the same response as a group to a second message. A common mistake is to use a segmentation developed for one purpose in a different context. Segments can be made based on risk, value, response, spend behavior, profitability, fraud potential etc. Traditional segmentation techniques like recency, frequency monetary (RFM) models are commonly used to understand the customers better. Segmentation of customers to understand their spend behavior using RFM models helps cluster similar customers into buckets of similar behavior. However, this approach lacks in its ability to understand the customer spend behavior and lifestyle. Traditional segmentation finds out the quantitative spend behavior of a customer and defines hurdles on transaction counts to decide the incentive to be offered to increase the usage. But these incentives might be very general and might not leverage the customer's interest. Instead, with SUPER segmentation, we will be able to design a more customized incentive, based on their life style from the spend behavior across merchants. This precision approach to marketing the right incentive/education to the right customer will help drive interchange revenue from the customer base.

4. Framework for 2 stage SUPER segmentation

Today, a bank needs to devise more effective, targeted strategies for different customer groups and offer relevant, tailored incentives to influence decisions. The SUPER segmentation, with its two stage segmentation technique, aims at grouping customers in segments and matching each group with the right incentives. Data driven tailored segments require past transaction history made on the card of the customers.

First stage of segmentation is similar to any traditional business rules based segmentation, which uses past transaction history of frequency of transactions (F), monetary value of transactions (M), merchant information (M), and periodicity of transactions (P), to calculate a FMMP score for each customer. FMMP score is an average measure of customer's spends characteristics like transaction frequency, average number of days between two consecutive transactions, count of different merchants the card was swiped at, etc. Based on the FMMP score, customers are grouped into three segments–high activity group called “card burners”, medium activity group called “card regulars”, and light activity group called “card lite”.

Second stage segmentation is based on a statistical technique, which is a non- hierarchical segmentation, called k-means clustering algorithm, to further disintegrate the three segments, namely card burner, card regular and card lite, This segmentation is based on percentage of usage across merchants. The success of K-Means clustering algorithm largely depends on the efficiency of the initialization of the cluster centers. We have to be aware of potential issues with k-means clustering algorithm such as-

- In order to minimize the squared distances between the observed data and the cluster centers, the algorithm might converge to the local minima instead of the global minima.
- A cluster center might be initialized too far away from the observed data or too close to other active cluster centers in dense data regions. This cluster center turns into a dead center as it is difficult to associate any observed data with this point, based on minimum squared distance.

Top merchant categories (we used 13) are identified and percentage of total transaction counts is calculated across each category for all customers. For example, if a cardholder has made 10 transactions in the development period where four are for Groceries, three for Gas and three for Bills, then the percentage of usage would be 40%, 30%, and 30% in these categories respectively. Rest of the categories will have 0% usage. Based on this merchant spend distribution, clustering is done to arrive at an optimum number of clusters. The technique used is non–hierarchical, for clustering all the customers into four segments. The optimum number of clusters is decided by viewing the non-hierarchical model statistics, like R-square, CCC, and Pseudo-F statistic. Fig.1 shows how we arrived at the four clusters. On the graph, we see each of the three statistics plotted by cluster. The left axis is for Pseudo-F and CCC multiplied by 1000. The right axis is for approximate overall R-Square. The trend to examine in this graph is the pseudo-F and CCC statistics peak and where the R-square tapers off (remember R-square will always be higher as the number of clusters increases.) Analyzing the graph below, it shows that the CCC and pseudo-F peak at 4 and R-square tapers off at 4 cluster. Hence, we arrive at four statistical segments based on performance across merchants.

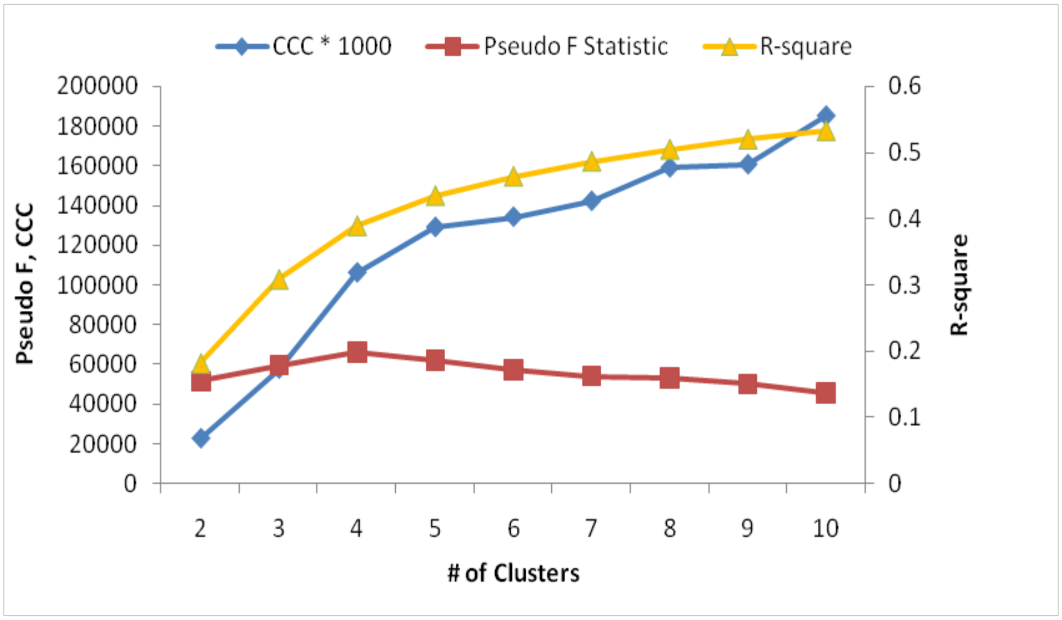

Fig1.

Profiling the four segments based on their usage across 10 merchant categories will show the customer behavior in each of these segments. In Fig.2, each of the four segments represents a line in the spider chart. Customers falling in the segment represented by green line are more inclined towards using their cards for ATM withdrawals. Orange line represents customers who prefer using their cards mostly in restaurants.

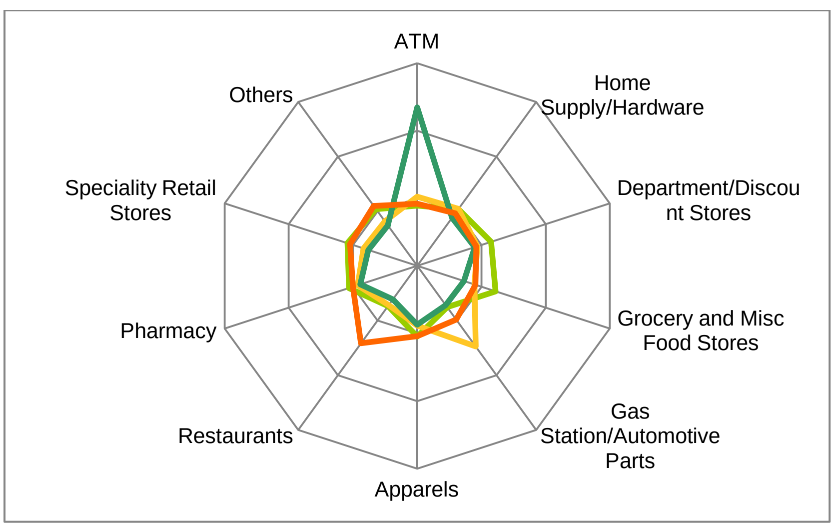

Fig. 2

Hence, based on the customer spend behavior across merchants, we arrive at four segments: Restaurant Goers, Grocery/Dept. Store Users, Gas fillers, and ATM users, within each of the three segments of card burner, card regular and card lite. Key feature of this statistical method of segmentation lies in picking the right seeds values and setting the right number of clusters to be formed.

Fig. 3 shows how a customer segment looks like.

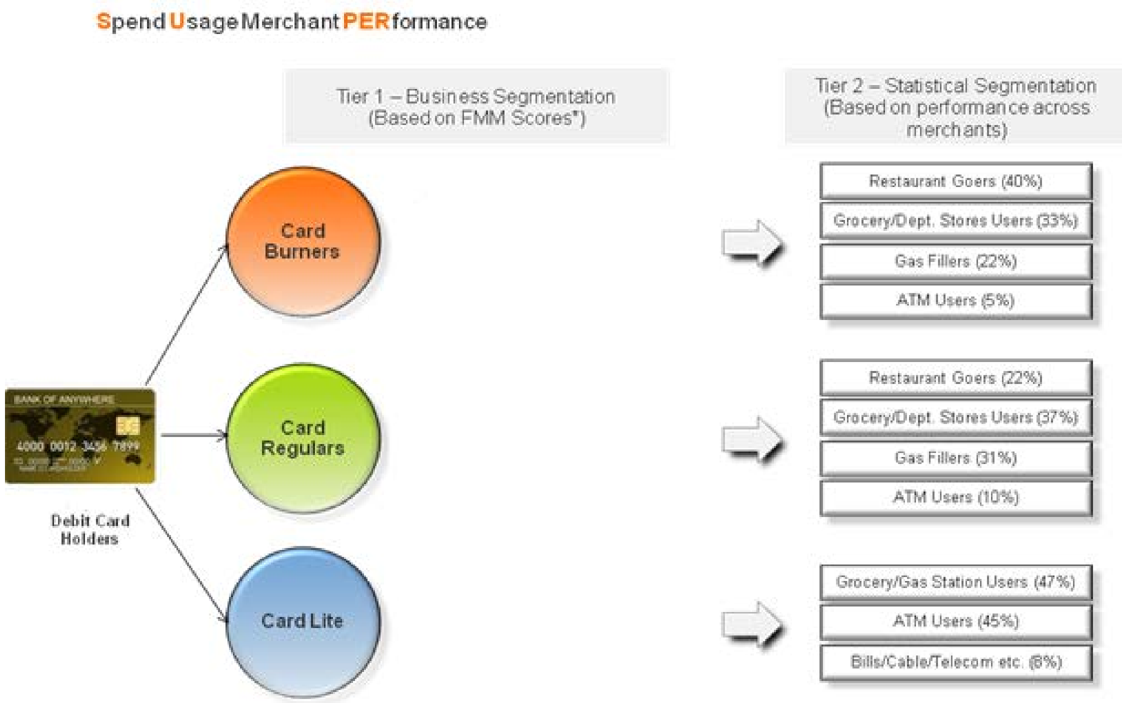

Fig. 3

5. Profiling of segments for campaign strategy planning, based on usage across merchants

Card burners, who are extensive card users, have little possibility to further increase their usage. In order to find opportunities where card burners can spend more, a profiling of these customers based on the second stage segments can be done. Card burners are customers who very adept with spending digital money and can be driven by the right educational offer to spend more in additional categories and do not need any monetary benefits for it. Campaigns that offer monetary benefits are expensive and not so easily profitable in the short term. Such offers might increase purchase behavior instantly but will not sustain the same behavior in the long term. Return on investments for monetary benefits are low and not sustainable for Card burners.

On the other hand, Card regular segment represent an opportunity to generate ROI using the following methods:

- Understanding the profiles of customers within card regulars that have enough opportunity to grow their usage
- Providing the customers monetary offers, based on spend behavior of each of the four-segments

On the card light segment, the bank should be careful in making investments through a marketing campaign, since the response levels to incentives might be low or not sustainable (i.e. migration opportunities to higher segments might be low).

6. Opportunity analysis for increasing card usage across different segments

Our objective is to make the customers increase their card usage. In order to achieve our objective we design marketing campaigns for these customers to incentivize them with offers they might find useful according to their personal spending habits. In order to understand their spending habits and lifestyle we segment customers into groups and sub-groups based on certain business rules and statistical methods. Once we obtain these segments which are based on customers spending habits we understand the specific behavior of each segment and how to utilize this information in designing campaigns and incentives. Each segment will have specific marketing strategy based on its performance and usage. We identify the segments where the customer spends the most. Next best opportunity is where we can incentivize the customer to spend more. Finding the 'next best' potential opportunity can be done by analyzing the correlation between spends in different spend segments. For example, within card burners if a customer spends in sub segment 'Grocery Users', it shows high correlation with customer spends in category "GAS Fillers". Then, we can assume that if the customers in card burner segment use their card primarily for buying groceries they might want to use it for filling gas as well. Additionally if we compare the Average Transaction Frequency (ATF) of 'Grocery users', who use their card for filling gas with the ATF of the overall group of customers, we may find a huge target opportunity .Fig4. shows how we identify the next best opportunity here. Hence, the next best potential opportunity of growth for grocery users lies in gas filling. Defining "hurdle rates" for offers given to grocery users based on this information can help them increase their card usage.

Card Burners

Tier 2 Segments

	Grocery Users (33%)	Gas Fillers (22%)	ATM Users (5%)	Restaurant Goers (40%)	Avg. Trans Freq
ATM	72% (2.85)	83% (4.04)	100% (16.4)	78% (2.98)	4.0
Dept Stores	89% (4.45)	79% (3.06)	75% (2.90)	80% (2.93)	3.5
Grocery Stores	99% (13.2)	99% (8.30)	95% (6.00)	99% (8.52)	9.9
Gas Station	95% (8.75)	100% (24.8)	89% (8.41)	98% (13.7)	14.4
Apparels	60% (2.16)	46% (1.48)	43% (1.47)	58% (2.16)	2.0
Restaurants	85% (8.21)	75% (8.64)	54% (4.83)	100% (31.6)	19.0

High Penetration but Low ATF in correlated merchants

Increase transaction frequency across Gas Station

Fig. 4

7. Conclusion

This novel technique of SUPER segmentation that couples 2 stages of segmentation divides the debit card customer base into critical segments, which have distinct characteristics of its own. By capturing these attributes related to the spending habits and lifestyle of each segment it is possible to design appropriate educational and promotional offers for each debit card. Theses insights gained when coupled with the right promotional offers to each segment, enables banks and financial institutions to improve profitability of their debit card portfolios, bolster card usage and customer relationships, and capture more wallet share; thereby, providing a sustainable growth.

8. References

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