The Multiplier Effect

Contents

1. Abstract.....2
2. Introduction.....3
   2.1. Importance of Predictive Analytics.....4
   2.2. The Multiplier Effect - Concept.....5
3. Methodology Overview.....6
   3.1. Variable Creation.....7
   3.2. Modelling Techniques.....7
   3.3. Model Illustration.....10
   3.4 Model Validation.....12
4. Customer Preferred Channel.....12
5. Conclusion.....16

Exhibits

Exhibit 1: Customer Satisfaction – Current Scenario.....3
Exhibit 2: Three Pillars of Multiplier Effect.....6
Exhibit 3: Variable Categories.....7
Exhibit 4: The Multiplier Effect – Products & Actions.....8
Exhibit 5: Quantile Analysis - Use.....9
Exhibit 6: Markov Chain Process.....10
Exhibit 7: Model Lift Curve.....10
Exhibit 8: Best product to Prioritize to the Customer.....12
Exhibit 9: Customer Transaction Trends across Channels.....13
Exhibit 10: Communication Channels with Attribute.....13
Exhibit 11: Outline for Identifying Customers' Channel Preferences.....14
Exhibit 12: Multi-level Clustering Approach.....14

1. Abstract

Banking is one of those few industries that has a plethora of data, which in hindsight is also its biggest asset. Indubitably, predictive analytics in banking has been ever-evolving, and most banks have leveraged its power in the past. However, like the analytics arena, it is also in the landscape of consumer needs that changes rapidly. In such times, it is all the more challenging for banks to adapt to this new reality and create prospects for themselves to deliver highly personalized and relevant products to its customers, which drives their happiness, profitability and loyalty - all at once.

Amid such dynamism, capitalizing opportunities become more thought-provoking as multiple lines of business and economic factors play a crucial role in determining lending rates. Moreover, other factors including compliance, policy, security, risk, and bureau cannot be overlooked either.

Therefore, as a wholesome solution towards forming the next best action for existing customers, the idea of the Multiplier Effect (ME) was conceptualized. The three pillars of the ME are - propensity, profitability and personalization. This concept provides a holistic framework in shaping the next best opportunities for the bank by enabling the prediction of customers' needs with utmost accuracy while also maximizing bank's revenue thereby propelling them to the next stage of evolution.

ME is an end-to-end framework for customer personalization, which solves for three main problems: Whom to target? What to sell? How to communicate?

Effective personalized communication with customer preferred channel to maximize conversions, reduce customer fatigue from mass bombardment of communications and lower costs.

ME ensures that customers would be contacted for products and services that have a high conversion likelihood, receive deals and offers based on past and potential revenue and get personalized communications through their preferred channels.

Customer preferences are changing constantly and it's crucial that we capitalize on it by evolving with the times. With the right implementation of the ME, companies can optimize customer communications and add value to the end-users' times. By getting communications that are relevant to them, customers would gravitate favorably towards these companies thereby driving acquisitions and conversions. With digital adoption taking centre stage in the current climate, companies can expect further cost reductions from non-digital channels.

2. Introduction

How many times have you received a call or a text message for a personal loan or a loan on card when you were actually looking to invest your money?

While a good experience keeps a customer satisfied, continuously bombarding the customer with calls for irrelevant sales pitch leads to customer dissatisfaction and eventually customer churn. According to Walker's 2020 research, 62% of companies are now rapidly investing money in research and analytics to meet the changing needs of customers. It has become extremely critical to understand customers' needs & preferences and communicate in a relevant way.

According to Esteban Kolsky, 72% of customers will share a positive experience with six or more people, but if they're not, 13% of them will share their experience with fifteen or more. As also explained by Malcolm Gladwell in the book The Tipping Point - the power of word-of-mouth cannot be underestimated in today's time, mainly because it helps explain why social epidemics have become more pervasive in the last hundred years. The Internet allows people to reach an unprecedented number of new people, and it only takes the power of a few special people to 'tip' the ideas into popularity.

Exhibit 1: Customer Satisfaction – Current Scenario

In 2018, Emirates NBD's digital marketing team reduced customer communications by 18% and by further 9% in 2019, leading to a decrease in marketing activities by 21% and 8% respectively. Therefore, focusing on lesser but relevant customer communication increases marketing effectiveness & customer experience.

Improving customer experience is the key to grow customers and retain existing ones, and this can be achieved by proactively providing best in class services through personalization and engagement.

2.1. Importance of Predictive Analytics

With the booming availability of information and advancements in IT, banks today are sitting on vast amounts of data, which if amalgamated with the power of analytics can unleash a world of opportunities that vastly improves decision making. Making use of extensive data to extract relevant and practical insights is extremely crucial in a customer-oriented space. From launching new products to acquiring customers, from managing & growing portfolios to retaining and winning back customers, everything requires predictive analytics. It not only helps in identifying key segments and problem areas but also in assessing future trends and setting targets. According to McKinsey's analytics "*Across all industries, companies that are more analytically driven realize financial growth three times higher than their less analytical competitors*".

Why Predictive Analytics?

With a booming availability of information and advancements in IT, banks today are sitting on huge amounts of data, which if amalgamated with the power of analytics can unleash a world of opportunities that vastly improves decision making.

From launching new products to acquiring customers, from managing & growing portfolios to retaining and winning back customers, everything requires predictive analytics.

Although a lot of major banks have adopted predictive analytics to monitor fraud, measure credit risk, maximize cross-sell/up-sell opportunities and retain customers, a lot of them are unable to convert their data into meaningful insights due to lack of domain knowledge and foresight for end objective. Product recommendations are being pushed to customers left and right, at times irrelevant and based on recent behavior using big data algorithms. While the predictability of AI models is generally high, if not developed carefully, such models often lead to overfitting and do not work during out of time validations. If useful metrics and controls are not used, then recommendations from a model with '90% accuracy' may effortlessly be overwhelming to the management but riotously unsuitable for the end objective. Such recommendations based on reinforced learning might be performing well in the e-commerce world where products can be an impulsive buy, but in industries like banks, products are mostly an 'involved' buy.

Nevertheless, it is also essential to decipher the end goal clearly – model accuracy or interpretation. Comprehending the difference between the two and knowing the trade-off is equally vital in the world of statistical learning. From a banking perspective, transactions that include complex structures and their relationships with each other need to be studied carefully. Hence, predictive analysis models that educate itself on customers' past behavior, personas, price sensitivity, credit risk, seasonality and market conditions are deemed most important for an effective Multiplier Effect framework.

2.2. The Multiplier Effect - Concept

Most banks commonly use a product-centric approach that targets customers for all products/actions, based on a customer's eligibility rather than their interests or behaviors. The Multiplier Effect is a revolutionizing concept aimed to enable banks to move from a product-centric to a customer-centric approach. The term 'Multiplier Effect' has been coined to define the next best action strategy for existing bank customers. It is an end-to-end framework for personalization, which addresses three main problems faced by banks when looking to expand its portfolio –

What is The Multiplier Effect?

It's a 360 degree approach which predicts customer's needs and also simultaneously achieves bank's revenue maximization objectives.

It guides the organization to move away from "I have a product, who can I target?" approach to "my customer needs this product".

1) **Whom to target?**
   The Multiplier Effect focuses on right targeting by using propensity models across all bank products ranging from current accounts to loans, wealth & forex and across all portfolio actions such as acquisition, activation, build/deepening, retention and win back.

   For instance, a customer with a current account can be targeted for a credit card based on his product propensity whereas a customer with a credit card can be targeted for diversifying his spend on travel based on the deepening model.

2) **What to sell?**
   While customer propensities across products and actions help understand their preferences, the aim is also to maximize a bank's revenue in parallel, for which it is imperative to identify high revenue generating products & actions for every customer. The solution is simple! Develop revenue models that take into account the various financial attributes for every product & action associated with each customer and compute the Net Estimated Potential (NEP) at a customer level.

   The NEP is the annualized revenue potential for any product offered to a customer or any action taken for him based on various income & cost parameters. It is based on the net revenue generated in the next year when a similar customer or segment used a product in the past. The key attributes are identified by developing segmentation models and then using the same to create revenue-based customer segments. For instance, if a current account customer takes a credit card, the revenue the bank will make in the next year is the NEP here.

   Marrying the propensities with NEP will not only target the right customer for any plan but also help maximize revenue & achieve targets. For instance, a customer who has similar propensities to take up any product, offering one with higher NEP will help maximize revenue.

3) **How to Communicate?**
   Execution is as important as strategizing a plan for which assessing and identifying the most optimal channel effectiveness across products, actions and customer segments becomes critical. The optimal channel should be based on a variety of factors such as customer preferences and persona, channel cost, reach and conversion rate.

The ME models are developed using 3000+ transactional, demographic, macro-economic variables including trends & ratios across all products. The end solution has been designed in such a way that operational challenges, business requirements and one-off events are already taken into consideration.

For instance, in the mid of 2019, cards business was behind its targets and to achieve the same, we shifted the focus from maximizing revenue to maximizing volumes with the lower pricing of installment plans.

Exhibit 2: Three Pillars of Multiplier Effect

Primarily, the framework is built on three pillars – p (propensity), π (value) and c (right channel), which allows tapping value by targeting customers for the right product, at the right time and through the right channel. It guides the organization to move away from "I have a product, who can I target?" approach to "My customer needs this product", in turn reducing effort and time spent on communicating different products to the customer.

The ME for all existing customers prioritizes actions based on the maximum propensity and NEP; it is a 360-degree approach to predicting customers' needs that also simultaneously achieves a bank's revenue maximization objectives. It also takes into account customer personas along with transactional behavior, risk behavior, price sensitivity and maps customer level preferences with product features**.**

What makes the ME approach different from other existing NBP/A models used by other banks? The current NBP/A modelling approach typically looks at customers in isolation and enables banks to create attractive opportunities for cross-sell and up-sell their products with more focus on profitability for the bank. The Multiplier Effect framework not only merges the portfolio goals with customer needs but also amalgamates personalized communication of each offer through the customer's preferred channel. The framework is created to enhance customer experience through personalization while maximizing revenue for the Bank.

3. Methodology Overview

There are a variety of problems encountered in the development of the next best product & action framework, the most common of which are listed below:

1. Assessing probabilities of response to numerous portfolio actions – a typical classification problem with predictors coming from past customer behaviors
2. Measuring propensities of signing up for various banking products – a typical classification problem with predictors coming from past customer behaviors
3. Understanding customer personas based on demographics, spend behavior, saving habits, borrowing habits etc.
4. Evaluate profitability/revenue impact of purchasing a new product / responding to a portfolio action through Markov models of cash flow movement trends

To estimate the probabilities and propensities, different kinds of techniques such as regression analysis, decision trees, random forests, gradient boosting & quantiles were used. While random forest and gradient boosting give better results, it is often prone to weak model stability and inexplicability of factors/reasons for predictions.

3.1. Variable Creation

Data preparation and exploration is the second step in the modelling process, which follows the problem definition and scope. It accounts for at least 75% of the overall effort and is always a prerequisite for great models. The more thought through and appropriate the variables are, the better the model. Since the ME framework spans across various products, variable creation was carefully planned by creating different categories for all attributes such as –

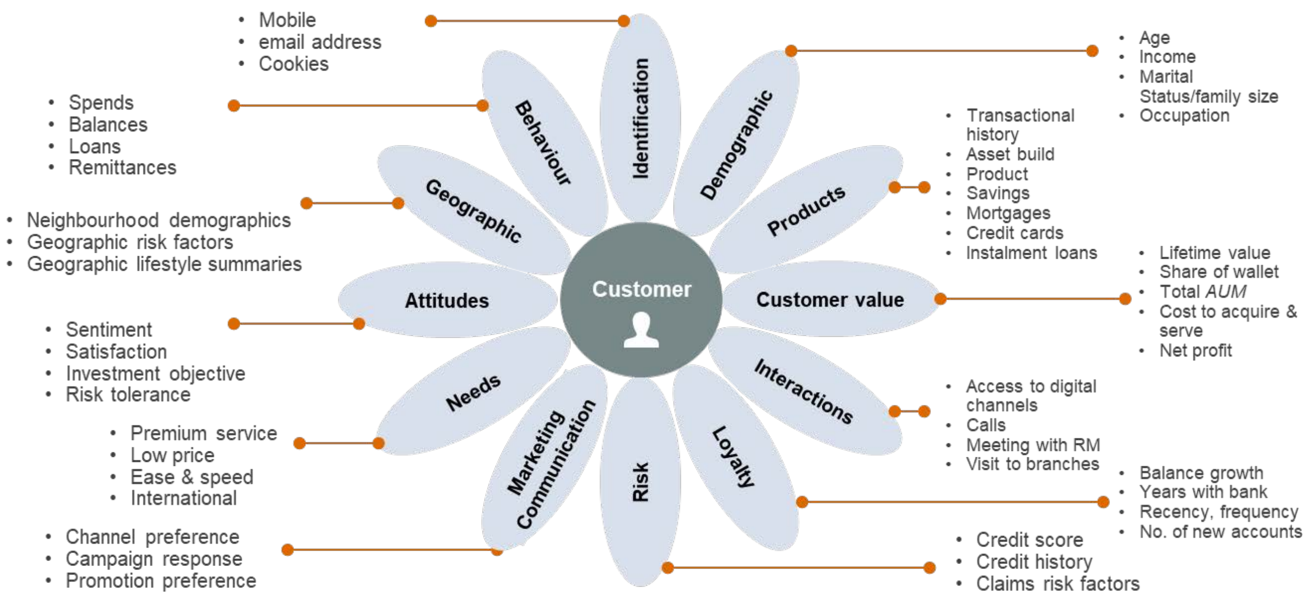

Exhibit 3: Variable Categories

Around 3,000+ new variables were created from the raw data available. Within each variable class, various types of attributes such as trend, ratio, categorical (ordinal & binary) & continuous (medians & averages) were created to enhance the explicability of each variable and in turn leading to a robust model predictive power. Post this, sanity checks were also performed on the data, which is one of the most critical steps to avoid poor/misleading model results. Standard methods such as outlier treatment, missing value treatment, validation and junk value treatment were employed.

3.2. Modelling Techniques

Imagine a clustering exercise with all variables in millimeters and one variable in kilometers. With the advent of machine learning, it is easy to use the latest techniques for solving business problems. However, overlooking the importance of understanding your data and how different model types work has exacerbated the problem of overfitting. Nevertheless, having a vast repository of variables alone is not enough; thus, for every model developed, choosing the right model type and technique was as crucial as data cleansing.

The ME framework consists of 35 different events representing 7 products across 5 potential customer actions (refer to Exhibit 4 below). Each event has a probability score and a corresponding value denoting the expected monetary gain. Different techniques were used to arrive at the probability values including logistic regression, linear regression, clustering and look-alike modelling. All of these techniques require data in various forms for effective analysis, which is why specific variable creation was done across products.

PRODUCTS	ACQUIRE	ACTIVATE	BUILD	RETAIN	WINBACK
LIABILITIES	✔	✔	✔	✔	✔
CREDIT CARDS	✔	✔	✔	✔	✔
FX	✔	✔	✔	✔	✔
ASSETS	✔		✔	✔	✔
WEALTH/ INSURANCE	✔		✔		✔
DEBIT CARDS	✔	✔	✔	✔	✔
TRADE FINANCE	✔		✔	✔	✔

Exhibit 4: The Multiplier Effect – Products & Actions

Regression Analysis was used when enough responders were present in the dataset. For most of the classification problems involving a binary dependent variable, logistic regression was used.
The above technique has been used very widely in the ME framework, particularly for assessing product propensities and probabilities of portfolio actions. One use case of such a technique is when the likelihood of taking up a credit card was to be assessed. In this problem, the aim is to determine how likely is a customer willing to apply for a credit card product given his behaviour on other products, especially his current/checking account and debit card usage, and his demographics (age, affluence, nationality). For this customer, the behaviour (X variables) is observed on his existing products over 12 months period (observation window) before a cut-off date. In the performance period, it is observed if the customer has actually obtained a credit card (Y = 1 if a credit card was taken and 0 if otherwise) or not.

To identify the most important variables from the list of 1000+, a variable selection process was run in SAS Enterprise Miner, which uses a chi-square test based assessment framework to arrive at a set of most powerful predictors (X'). These final set of predictors are then run through a Dmine regression process in SAS E-miner which does the following:

1. Uses AOV16 variables to identify non-linear relationships between interval variables and the target variable
2. Uses group variables to reduce the number of levels of classification variables.
3. Computes all 2-way interactions of classification variables.
4. Computes a forward stepwise least-squares regression. In each step, an independent variable that contributes maximally to the model R-square value is selected.

The resulting model demonstrates a strong separation between non-targets vs targets with the top 30% most probable customer base accounting for nearly 75% of the actual card sales in the next quarter.

Decision Tree (CHAID) have been used in cases where respondents are fewer than what is needed for regression analysis. A use case of this is assessing the probability of bringing down their bank balance. This framework was used to evaluate the propensities to subscribe to wealth products. Behavior of customers was assessed for a specific observation window, and their response was computed over the performance period with a binary performance definition (Y = 1 if the customer has taken a wealth product in the performance window, 0 if he hasn't).

CHAID decision trees are built using Chi-Square tests which study the interaction between categorical response variables. The final decision tree assists in identifying a few nodes that have higher response rates, which helps target them more effectively. The top 5 nodes account for 35% of the customers and 78% of the wealth product subscribers from the performance period.

Quantiles have been used to identify portfolio deepening opportunities for several products, e.g. Foreign Exchange usage, Wealth. Active customers in these products were considered, and a CHAID exercise was performed considering demographic profiles as above. For nodes with higher than portfolio response rate, we look at their wealth / FX distribution across four quartiles.

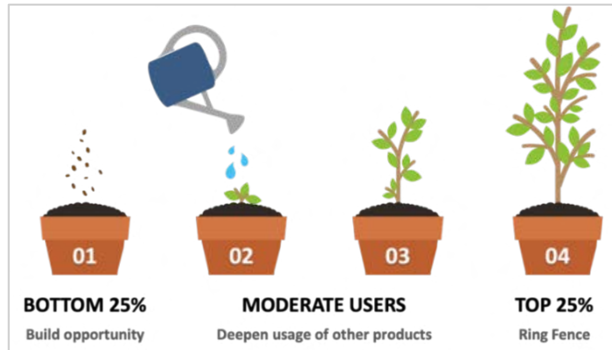

Exhibit 5: Quantile Analysis - Use

Cluster Analysis was used to identify the spend profile of customers, which was subsequently used in identifying spend diversification opportunities as well as developing an understanding of customer personas.

The objective of cluster analysis is to assign objects into clusters proposed by the data not determined a priori, such that objects in a given group tend to be similar to each other in some sense and objects in other clusters tend to be dissimilar. This is achieved through calculation of Euclidean distances between vectors created at a customer level from percentage of spends at various MCCs, percentage of weekend spends, premium and online spends etc. and grouping vectors with lesser distances together such that each cluster is homogenous with a similar set of customers.

The analysis is done using the HPCLUS procedure in SAS E-miner, which uses k-means algorithm to cluster observations in such a way that customers belonging to the same cluster are homogenous but customers in different clusters are heterogeneous. The results of the analysis help us identify groups of customers whose spends are concentrated on specific categories and there are diversification opportunities or groups whose spends are diverse but not that frequent. The analysis also helps us identify the four main groups of spenders which help in arriving at different customer personas such as online spends, hotel/travel, premium and mass.

Personas are a combination of the above spend clusters and segmentation of customers basis their demographics such as age, income, affluence, digital savviness, location, cuisine preference etc.

Markov Chain are used in assessing the impact of 'change in state'. These have been used to study the impact on profitability for accounts/credit cards, as customers move across different months on books. We also use this framework to study foreclosure rates for asset products and fixed deposits.

This framework was used for assessing credit card revenue movement across time. For this, a particular metric like card utilization, account attrition, loan pre-closure etc. was observed across different months on books. The build-up of these across the life of a customer was then used to assess the profitability of the customers. The portfolio was segmented into homogenous buckets based on utilization, credit limit, spend band, pay ratio, revolve pattern (transactor/occasional revolvers/consistent revolvers), card type (Super Premium/Premium/Platinum/Others).

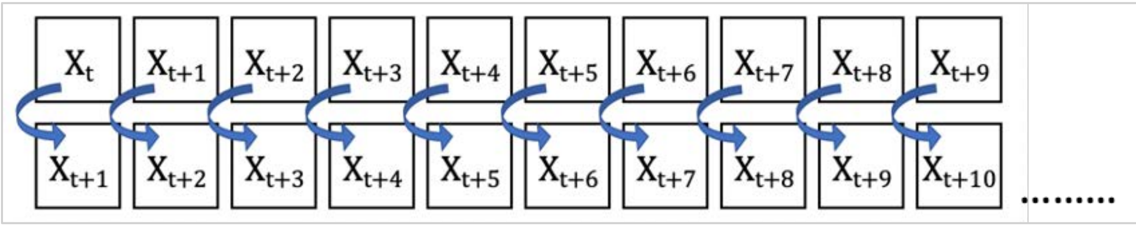

Exhibit 6: Markov Chain Process

For each segment, the median revenue (X) across different months on books (t), as shown above, was used to assess the rate of change in a month for each month on book. To ensure stability in the rates, this rate was considered for a period of 6 months. The output of this exercise was a transition matrix of revenues π^j_t for t=1,2,3…. and j=1,2,3… where t = months on books and j = segment. This π^j_t were used in arriving at the revenue potential of a card customer belonging to segment j at 't' months on books.

3.3. Model Illustration

All credit card customers were sold both Loan on Card (DAC) and Balance Conversion (BALCON) based on their card balances and Open to Buy (OTB) on credit limit. They were called by call center agents and reached out to via digital channels, which led to customer dissatisfaction due to irrelevant calls and increasing number of calls.

To make this process more effective, a Plan Optimization strategy which builds separate propensity models for both DAC & BALCON at customer level was developed. It achieved -

- ✓ Propensities from both DAC and BALCON model to help target the right customer.
- ✓ Avoiding calls to customers with very low propensities to further drive customer satisfaction.

To develop propensity models, a base of credit card customers eligible for a plan (excluding delinquent & high risk customers) was created. Various independent variables capturing customer behavior across different attributes, change in customer behavior in last three and six months, average & median values for 3, 6, 9 and 12 months, ratio variables, customer personas and affluence and demographics were computed at the customer level. Since a customer is likely to take up both DAC & BALCON at the same time, separate propensity models for both were developed. With the DAC model, 80% of the DAC takers can be targeted based on propensities by communicating with just 30% of the eligible customer base. Key attributes of the model included plans taken in the last 12 months, change in portfolio balance, change in utilization, plan balance as a ratio of the card balance, risk-based customer segments, and change in card balance. Without the model, conversion/good rate was 6%, and with the model, it had gone up to 27% in the 1st decile.

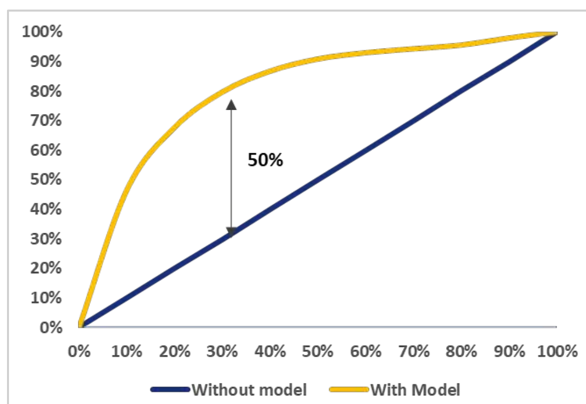

Exhibit 7: Model Lift Curve

Similarly, with the BALCON model, 3/4th of the BALCON takers can be targeted with just 30% of the customer base.

The usage of these propensity models will not just target the right customers with higher likelihood but also reduce irrelevant communication to customers not interested in these plans and further reduce communication costs.

Assess Bank's NEP of DAC and BALCON for each customer –

When a customer takes a plan (DAC or BALCON), the bank earns the interest income based on the loan amount, tenure and eligible price as per the tenure and customers' riskiness. But it also loses on the cost of funds which is lent to the customers.

Moreover, in case of foreclosures, the bank loses on the interest not earned on the remaining tenure, but it charges a foreclosure fee and gains on the cost of funds.

The NEP computation takes into account the above metrics and scenarios and assesses the net interest income earned from a customer upon receiving a plan. Booking amount is based on the balance used for BALCON and OTB for DAC while tenure is taken as an average for that customer behavioral segment. Price is based on his transactor/revolver behavior, spend or plan activities and months on book.

We reviewed all plans foreclosed in the last 48 months and assessed their tenure served, balance foreclosed and computed %balance foreclosed every month for every loan tenure of DAC & BALCON. The %balance foreclosed is then used to calculate NEP used as the percentage of the loans that will foreclose.

Net Estimated Potential for DAC and BALCON was assessed for every customer to identify the product with higher revenue potential.

$$\boldsymbol{NEP} = \sum_{N=0}^{Tenure} \Big(f(NPV) \times [f\big((Yield - Cost\ of\ Fund) \times PC\big) + f(PC\ Charges)]\Big)$$

where,
NEP = Net Estimated Potential, PC = Loan Pre-closure, NPV = Net Present Value

Offer products where propensity adjusted NEP is higher thereby maximizing both conversion & revenue:

- ✓ Marrying the propensities with NEP will not only target the right customer for any plan but also help achieve revenue goals.
- ✓ For customers who have similar propensities for taking any plan, offering the plan with higher NEP will help maximize revenue.

Offering the best plan which maximizes conversion and revenue –

$$\text{PLAN OPTIMIZATION} = \underset{\text{IPP}}{\overset{\text{DAC}}{f}}[MAX\{f(Plan)\}]$$

where,

$$f(Plan) = f(Booking\ Amount) \times f(Plan\ Propensity) \times f(Plan\ NEP)$$

When the propensities for DAC and IPP along with the NEP is calculated for every customer eligibility separately for a plan, the product with higher propensity adjusted NEP is prioritized as shown in the table below (where booking amount for DAC is Dacable amount & IPP is Principal balance) –

CUSTOMER NO	CREDIT LIMIT	EVER INST	AVG UTIL	DACABLE AMOUNT	PRICE SEGMENTS	PRIN BAL	ENR 1VSL6M	NC ENR 1VSL6M	UTIL L3M	UTIL 1VSL6M	%CORE ENR	PROB DAC	PROB BALCON	DAC NEP*	BALCON NEP*	BEST PRODUCT
C1	112,500	1	71.3%	50,495	N	47,787	1.41	1.27	31%	0.94	52%	8.47%	5.02%	68	296	BALCON
C2	28,950	1	2.4%	26,055	N	2,459	1.53		1%	1.87	100%	2.53%	0.64%	11	2	DAC
C3	100,000	1	0.0%	90,000	X	-	.	.	0%	-	.	4.46%	.	24	.	DAC
C4	50,000	1	9.2%	25,000	V	3,992	0.62	.	6%	0.68	100%	2.02%	5.14%	49	28	DAC
C5	61,300	1	70.1%	16,045	V	45,240	1.48	.	53%	1.06	100%	10.26%	29.74%	160	1,868	BALCON
C6	16,500	1	51.7%	5,946	W	5,394	1.55	0.86	34%	1.66	69%	1.42%	27.89%	8	269	BALCON
C7	47,200	1	2.6%	35,400	W	1,230	1.96	.	3%	1.85	100%	2.90%	2.68%	100	6	DAC
C8	120,000	0	78.5%	19,213	B	11,959	1.70	1.76	34%	1.30	11%	18.06%	39.68%	562	1,601	BALCON
C9	174,000	1	1.3%	100,000	B	1,355	0.39	.	1%	-	100%	2.54%	1.40%	411	6	DAC
C10	52,000	0	18.2%	37,330	C	14,886	1.41	.	8%	1.29	100%	3.86%	9.10%	263	511	BALCON
C11	48,000	1	84.0%	1,202	D	39,368	1.56	-	36%	1.44	100%	2.96%	33.71%	8	5,005	BALCON
C12	119,700	0	68.4%	57,413	D	4,386	1.35	1.89	29%	0.84	5%	32.72%	39.66%	4,189	656	DAC
C13	8,800	1	60.9%	3,922	A	45	2.40	3.33	26%	1.62	1%	14.92%		65		DAC
C14	50,000	0	29.1%	23,998	A	14,520	2.19	3.55	12%	2.45	54%	1.81%	7.84%	48	141	BALCON

Exhibit 8: Best product to Prioritize to the Customer

Initial implementation of some strategies have yielded promising results, with the performance of few as listed below –

1. Card customers who were earlier pitched both DAC & BALCON, are now pitched the best product based on the ME by both Call Center and digital campaigns driving conversions by almost 10%.
2. Debit Card Retention Campaigns based on the ME generated 33% incremental spends.
3. FX Propensity Activation Model in a targeted segment captured 60% of activations from just 30% customers.

3.4 Model Validation

All propensity & revenue models across all products will be validated every six months to assess the change in population and key attributes by computing the Population Stability Index (PSI) and Characteristic Stability Index (CSI).

If the PSI > 0.25 for any model, referring to a major shift in population, it needs a variable level deep dive. Then, CSI will help identify the variables where the impact of the population shift is significant. In such cases, the model will be re-calibrated based on population shift or re-developed using the recent population.

Model validations might also be required during instances of change in economic situations, for example, COVID-19, bank rate cuts, and other macro-economic events likely to a cause change in GDP, income, demand and customer behavior.

4. Customer Preferred Channel

With an increase in digital adoption across banks, customers now prefer to do banking at their fingertips. Same is evident from the graph below, which shows an increase in transactions on Online/Mobile Banking channel while customer visits to Branch have decreased over the last five years. However, still, a significant proportion of customers continue to use other channels for various needs and products. Customers contact the bank through multiple channels based on their reason for interaction, the complexity of request, resolution time and ease of access. A customer applies for a loan on card through mobile banking, but he talks to the call center agent to enquire on various investment plans.

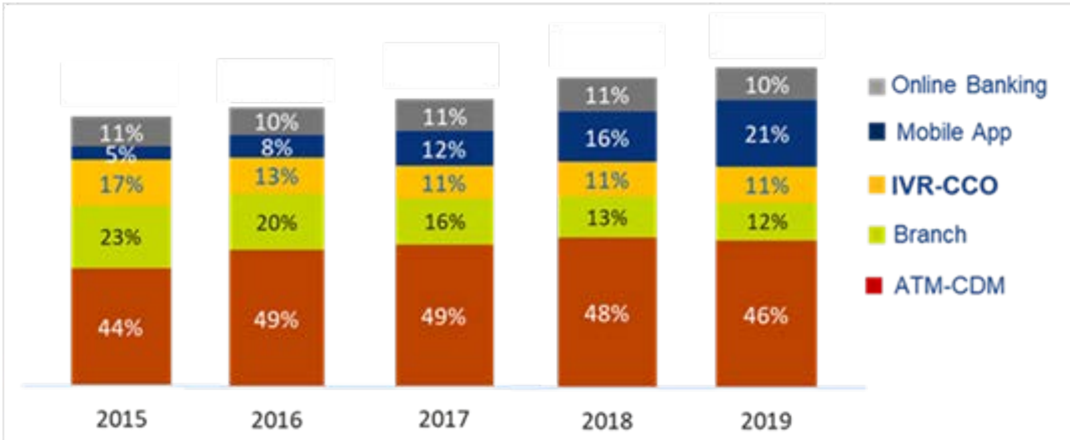

Exhibit 9: Customer Transaction Trends across Channels

While on one hand, customers have their preferred channel for reaching out to the bank, the bank currently communicates through a variety of channels for pitching its banking services.

	EDM	SMS	Website	Online / Mobile	CCO - IVR	CCO-Inbound	ATM / CDM	Online Banking Logout page	Mobile App Notification
Valid Mobile		●			●	●			
Valid Email	●								
DNC	●	●	●	●			●	●	●
DNS	●		●	●	●	●	●	●	●
Open Rate	●	●		●				●	●
SMS delivery		●							
Website Visit			●						
Online / Mobile registration				●				●	●
Online / Mobile Active			●	●				●	●
ATM Active							●		
CCO call - IVR		●			●				
CCO call - Agent					●	●			

Exhibit 10: Communication Channels with Attribute

Thus, it is imperative to understand both customer preference and engagement across channels where either the customer reaches out to the bank or the bank sends communication to the customer. For instance, assessing email open rate for any communication can help understand customer's engagement on the Email channel for any product.

The need to identify the customer's preferred channel stems from the need to "Right Serve" the customers. While the previous sections of this paper cover elements of identifying customer propensity towards banking products and services, it is important these solutions be relayed in the best possible manner to the customers.

The selection of channels (which later serve as cluster variables) for the analysis was done based on identifying which ones had a significant group of customers using only those channels. This caused a split between channels operating through the same physical system (ATM-CDM, CCO-IVR) while newer ones had minimal to no monopoly over a customer's interactions (ITMs combined with ATMs).

This is followed by a two-pronged approach to ensure that the customer's Interactions and Marketing Responses are addressed independently despite there being common channels between the two.

	Transaction Channel	Marketing Channel
Channels Considered	ATM, Branch, Inbound calls (CCO), CDM, IVR, Mobile App, Online Banking	Email, Mobile App, Online Banking
Eligibility Criteria	At least 1 financial or non-financial interaction	Greater than 70th percentile of marketing channel open rate
Selection Criteria	Transaction channel(s) with highest Interaction	Marketing channel(s) with highest Open Rate
Outcome	**Identification of top 3 channels where customer is most likely to read the communication**	

Exhibit 11: Outline for Identifying Customers' Channel Preferences

A multi-level clustering framework was used to identify the customer's preferred transaction channels. The process involved segmenting within clusters to form sub-clusters, with each cluster representing a channel preference associated to customers within the groups. The interactions considered included –

- Financial transactions such as credit card payments, utility bill payments, FX transfers, local transfers & cash withdrawals.
- Non-financial interactions such as service calls, complaint calls, enquiries & surveys.

While the clusters could inherently mask the preferences of an individual to an extent, multi-level clustering safeguarded those interests, while also accounting for look-alike preferences across other customers within the same segment.

The grouping of customers was done using k-means clustering on customer-level channel interaction percentages, thereby ensuring consistency of the scale. Based on the data fed to the process, 53 clusters were created out of 11 customer segments, with each cluster corresponding to a preferred channel, acting as the Main Preferred Transacting Channel for the customers in the cluster.

Further to this, 219 second-level clusters were created on top of the 53 groups created earlier, with the re-computation of the channel-interaction percentages post removal of the channel obtained from the first clustering exercise.

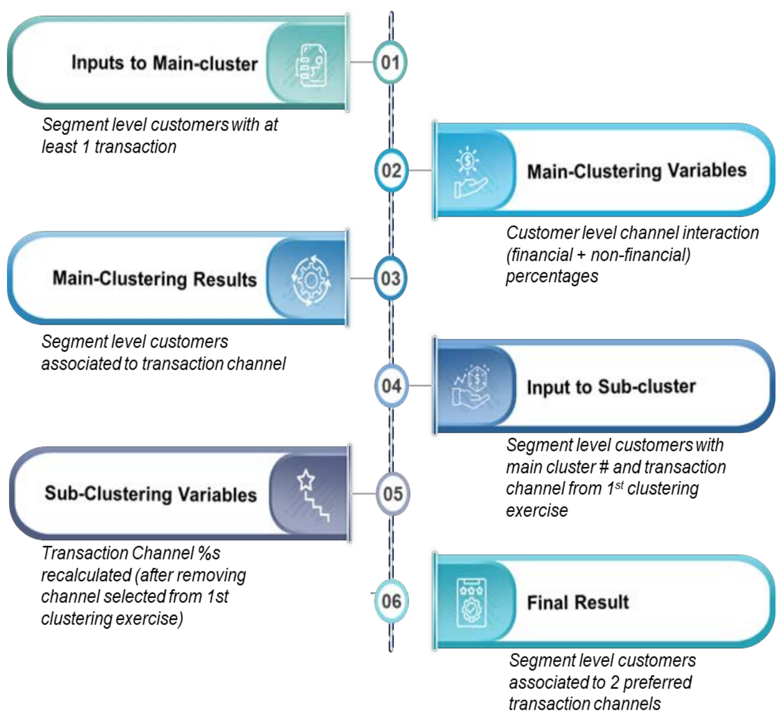

Exhibit 12: Multi-level Clustering Approach

The identification of the top 2 preferred transacting channels per customer is followed by arriving at Preferred Marketing Channels.

The significance of Marketing Channel as a Preferred Channel was assessed based on two criteria –

1. Number of campaigns per customer

2. Response percentage per customer-channel combination

Once the preferred transacting/interacting and marketing channels were identified for all customers, three rules were defined to prioritize between the two sets.

1. The first priority, in terms of Channel preference, is given to marketing channel with the highest response rate (based on an expert score response rate to a significant number of campaigns)
2. Transacting Channels that are also used for communication would require significant response rates to be considered as a Preferred Channel
3. In case of insignificant marketing communication or response, Channel preferences are assigned between transacting channels identified from clustering exercise

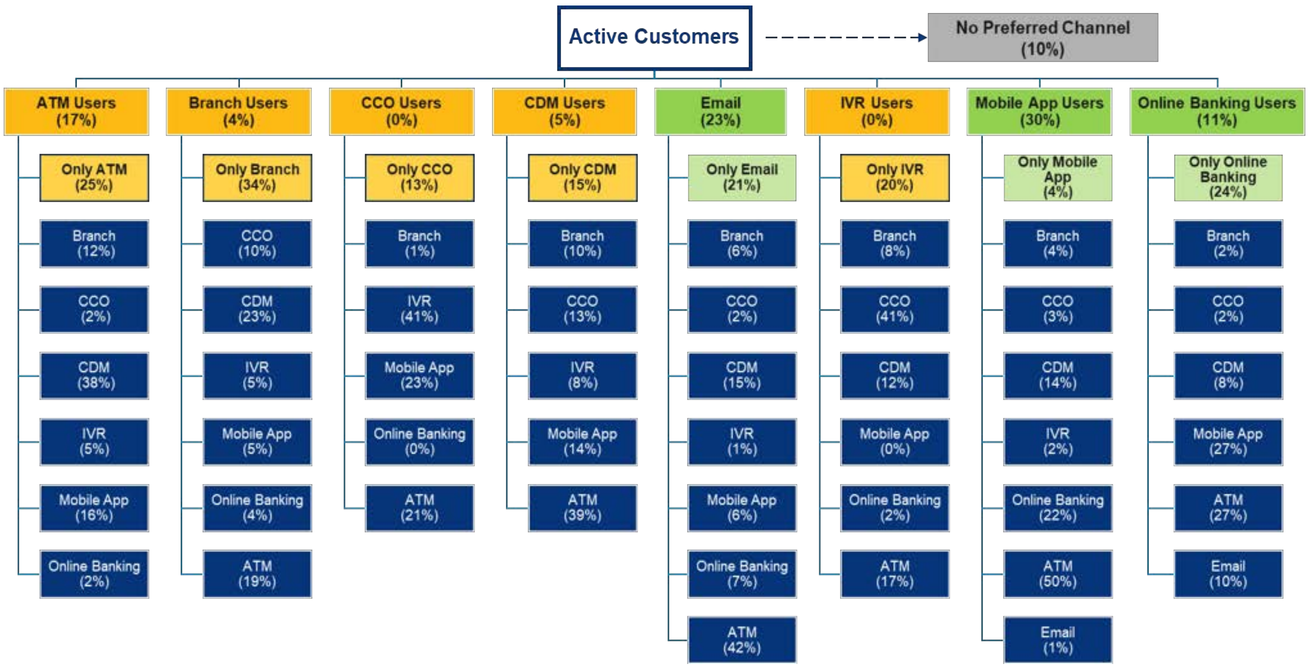

Exhibit 13: Customer split across Channels

The above-mentioned approach enabled tagging of at least two preferred channel to 75% of the active customer base with another 15% restricted to only one.

Nonetheless, the analysis and associated Marketing campaign data show an annualized cost save of ~72% in SMS sent to customers, while restricting the testing and resulting impact only to customers who have at least 2 preferred channels tagged to them.

In addition to the above, the plausible success of adoption of the preferred channels for outreach would provide a platform to asses and arguably curtail the frequency of queries towards the human workforce at call centers – giving immediate services for ~48% of the customer base through Mobile App, Online Banking or even Whatsapp.

Lastly, the cost per lead for each channel is also taken into consideration to communicate with the customer's preferred and cost-effective channel. For instance, it is more optimal to send online banking pop-ups for applying for a credit card to a digitally engaged customer rather than being called by a call center agent.

To summarize, using the customers' preferred channel based will lead to optimal communication not only driving conversions but also reducing the cost of communication through irrelevant channels and customer fatigue. As the third pillar of the Multiplier Effect, the next best product/actions for any customer will be communicated through this right channel framework.

5. Conclusion

"A person's name is to that person the sweetest most important sound in any language"

- Dale Carnegie

There is so much innovation going on with companies learning more about their customers every day and implementing new things all the time. There is much noise about customers being targeted by the competition through all channels possible. It is more of a necessity than wishful thinking to drive personalized interactions with customers to generate maximum value through targeted communication.

A few examples of companies personalizing their interactions successfully are -

1. Tips by Sberbank – it is a virtual assistant within the bank's mobile app that studies customer banking behavior to provide personalized recommendations. Customers can set their financial goals and get connected to the most suitable products to attain those goals. It also has in built alerts to remind customers if they can claim tax rebates on transactions.
2. The Coca Cola "Share a Coke" campaign – Coca Cola replaced the branding on their bottles and cans with the 150 most popular first names in Australia. When customers saw their name on the Coke bottles, it created a personalized experience even though the bottles were mass produced. The result was an extraordinary increase in sales prompting Coca Cola to launch this campaign in many other regions across the world.
3. Atom bank - An online only bank that does not have a fixed logo for its brand. Customers can design the interface, controlling how it looks or even branding it with a different name.

Given the aggressive way in which companies are trying to personalize content and reach out to customers effectively, it is essential to ensure that all interactions with customers are meaningful and derive maximum value through effective implementation and sync between the 3 key pillars –

1. **Understand customer DNA** - It is important to know our customers, understand their banking DNA, behavior and preferences, the channels they use and prefer, transactions, credit behavior, and level of affluence, aspirations and propensities to all the products that are serviced by the bank.
2. **Analytics engine** - With this data in place, it is crucial to have a robust real-time analytical engine with an 'always on feedback' loop and recursive learning algorithms to generate real-time insights from customer data and use them for effective targeting.
3. **Personalized curriculum** - With the customer insights and the analytics engine in place, it is vital to have a personalized curriculum to drive customized interactions for every customer. For this, we need an integrated delivery platform - marketing automation, a customer 360 so all channels understand customers better and deliver a personal experience.

For large organizations to personalize at scale, it has to effectively sync the three pillars listed above like in an orchestra. They should always adopt an 'Always On' marketing approach - this refers to a future state where the organization can deliver marketing messages to customers when it is most relevant to them across all channels as opposed to a blanket marketing approach.

Explanatory Notes

The following abbreviations have been used –

ME	Multiplier Effect	**OTB**	Open to Buy
NEP	Net Estimated Potential	**AED**	United Arab Emirates Dirham
NBP/A	Next Best Product/Action	**PSI**	Population Stability Index
AOV	Analysis of Variance	**CSI**	Characteristic Stability Index
CHAID	Chi-square Automatic Interaction Detection	**ATM**	Automated Teller Machine
FX	Foreign Exchange	**CDM**	Cash Deposit Machine
MCC	Card Spend Categories	**CCO**	Call Center Operation
DAC	Loan on Card	**IVR**	Interactive Voice Response
BALCON	Balance Conversion	**ITM**	Interactive Teller Machine

References

https://www.walkerinfo.com/Portals/0/Documents/Knowledge%20Center/Featured%20Reports/WALKER-Customers2020.pdf

https://www.superoffice.com/blog/customer-experience-statistics/

https://www.mckinsey.com/industries/financial-services/our-insights/smarter-analytics-for-banks

https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/consultancy/deloitte-uk-con-next-best-action.pdf

https://www.sas.com/en_ca/insights/articles/marketing/local/art-science-next-best-action.html

https://medium.com/@NexJSystemsInc/next-best-action-smarter-faster-and-really-really-good-for-business-b6119c8ecedf

https://blog.treasuredata.com/blog/2019/10/16/next-best-action-recommendations-that-work/

https://www.cognizant.com/whitepapers/beyond-omnichannel-determining-the-right-channel-mix-codex2413.pdf

https://www.experian.co.uk/assets/marketing-services/documents/fmcg-guide2-finding-the-channels-that-drive-the-best-response.pdf

http://intranet.fucape.br/uploads/MATERIAIS_AULAS/33023-Decision_Process_Evolution_in_Customer_Channel_Choice.pdf

https://engagehub.com/wp-content/uploads/whitepaper/Financial%20Services%20eBook.pdf

https://wi2017.ch/images/wi2017-0316.pdf

https://www.bcg.com/publications/2019/what-does-personalization-banking-really-mean

https://www.sas.com/content/dam/SAS/en_gb/doc/other1/events/sasforum/slides/day2/I.Brown%20Advanced%20Modelling%20Techniques%20in%20SAS%20EM_IB.pdf

Picture credits – Shutterstock.com

Authors

Sachin Chandna
SVP, Head of CIE
Emirates NBD, Dubai
T: +971-501014201
E: SachinC@EmiratesNBD.com

Gourab Sengupta
AVP, Business Analytics, CIE
Emirates NBD, Dubai
T: +971-508718601
E: GourabS@EmiratesNBD.com

Anshika Gupta
Senior Analyst,
Business Analytics, CIE
Emirates NBD, Dubai
T: +971-523752396
E: AnshikaG@EmiratesNBD.com

Neha Saraswat
Senior Analyst,
Business Analytics, CIE
Emirates NBD, Dubai
T: +971-544906161
E: NehaSAR@EmiratesNBD.com

Balakiran Reddy Mareddy
AVP, Retail Information &
Data Management, CIE
Emirates NBD, Dubai
T: +971-553547158
E: BalakiranMR@EmiratesNBD.com

Joe Cyriack
Senior Analyst,
Business Analytics, CIE
Emirates NBD, Dubai
T: +971-506471324
E: JoeC@EmiratesNBD.com

Acknowledgements

The Multiplier Effect framework was developed by joint efforts of the Analytics & Data team at CIE. We thank Nithin Narayanan, Joby Jacob, Rashid Basheer, Maqsood Pasha, Sahil Kumar, Gautam Kapur, Joseph Abdou, Abinaya Viswanathan and Akshay Sandhu for their significant contribution to the whitepaper & the framework. In addition, we are grateful to Vikram Krishna (Head of Group Marketing & Customer Experience) for his valuable feedback and support. We would also like to thank the members of the CIE Data, Analytics and Digital team for orchestrating the development and implementation of the Multiplier Effect framework at ENBD.

We would also like to extend our appreciation to the members of the SAS team for their guidance and contribution to the whitepaper.

Emirates NBD

About Emirates NBD's Customer Intelligence & Engagement

Customer Intelligence & Engagement (CIE) unit at Emirates NBD Dubai is an Data, Analytics, Business Intelligence and Digital Marketing function of the bank supporting various business units and segments to lead initiatives in the areas of portfolio growth, customer experience enhancement, revenue maximization, cost optimization, marketing campaigns and digitization of banking.

sas

In collaboration with SAS

SAS is the leader in analytics. Through innovative software and services, SAS empowers and inspires customers around the world to transform data into intelligence. SAS gives you THE POWER TO KNOW®.

Learn more on www.sas.com/me