Product Offer and Pricing Personalization in Retail Banking

Wei Ke
Columbia Business School, USA

Rogan Johannes Vleming
Simon Kucher & Partners, Canada

Rohan Shah
Simon Kucher & Partners, Canada

INTRODUCTION

Over the past decade, retail banks have leveraged advanced analytics to power pricing and campaign optimization strategies in deposits. These models collected and analyzed historic data, competitors' pricing, economic conditions, demand elasticities, and other factors to optimize the pricing and marketing of deposit products to consumers. However, these efforts were applied to single-product lines and conducted in silos without consideration for the customer's broader relationship with the bank. Deposit marketing campaigns often had myopic objectives that sometimes ran counter to larger institutional goals, and a broad stroke approach meant marketing-yield efficiency were usually very low.

The rise of parametric (e.g., classic regression and optimization) and non-parametric modeling (e.g. machine learning, multi-armed bandits, etc.) capabilities has opened up new possibilities for banks to shift from this fragmented, product-centric approach towards orchestrated one-to-one marketing where the bank is able to automate and tailor communications, pricing and products offers to speak directly to their customers in context-appropriate, relevant ways. Developed using internal and external data, these models can consider a customer's wider relationship with the bank, to personalize next-best offers, adapt messages based on reactions and feedback, and nudge customers towards desired actions with high-levels of accuracy and relevance.

Several types of parametric and non-parametric models are needed to support one-to-one marketing orchestration capabilities. These include flow of funds, response models, and customer lifetime measurement and segmentation clustering models. Data on product usage and transaction patterns can support customer segmentation models that anticipate and predict future customer needs to trigger up-selling and other tailored communications, while behavioral science can refine machine-learning models to deliver nudges and improve decision making.

Additionally, intangible objectives like financial well-being, customer lifetime value and customer satisfaction must be made measurable and tangible. A dynamic score, similar to a FICO metric, to measure a customer's financial well-being and reflect how well the customer is managing his/her finances based on banking behaviors and transactions, should be considered.

The transition from a marketing and pricing organization that executed blanket marketing campaigns to one capable of delivering the right message to the right customer at the right time for the right product

DOI: 10.4018/978-1-7998-9220-5.ch116

through the right channel, is a multistep and complex undertaking. For banks, there are challenges at the analytical and organizational levels.

Ideally price setting should be integrated with marketing. However, many banks separate these functions where pricing decisions for savings, certificate-of-deposits, mortgages and other retail banking products are made by the bank's treasurer responsible for managing the bank's daily cash flow and liquidity-of-funds to meet regulatory, operational, financial, and risk requirements. For larger banks, a product promotion campaign might also require the involvement of multiple departments. The result are teams operating with fragmented views at the product level, as well as at the marketing execution and pricing level. The barriers preventing a bank from greater personalization in marketing and customer communications, are often related to its organizational structure and not because the bank lacks analytical capabilities.

One-to-one marketing orchestration can be challenging for organizations with segregated teams, inadequate systems and untargeted marketing. Any project must begin with an assessment to identify gaps and maturity along organizational, conceptual and implementation dimensions to ensure the requisite capabilities including internal collaboration, data and analytics capabilities and transformation processes are present.

A well-executed one-to-one marketing strategy can deliver many benefits to a retail banking including higher customer retention, bigger share of wallet, sales profitability per customer and customer satisfaction. Personalization also directly impacts sales growth, marketing efficiency and profitability.

This article's contribution is a unique perspective on the value of combining personalization engines built on customer lifetime value and flow-of-funds modeling into a unified framework to make retail banking product offer and pricing decisions. It takes a classic approach that builds out the behavioral modeling components. Data scientists, marketers, practitioners and decision makers in the field will find the tools, methodologies and approaches in this article useful. There will be sections on designing customer lifetime value models for commercial effectiveness, flow of funds modeling, enhanced data capture for customer interactions, and behavior-based customer segmentation grids. The retail banking deposit, lending, and private banking markets are used as implementation examples.

BACKGROUND

There are three streams of research that precede this piece of work. The first stream comes from economic studies of retail banking product competition and elasticity measurement at the market level. Egan et al. (2017) developed a structural model to study the demand for deposit products. They argue that demand is influenced by product differentiation and the behavior of the banks, e.g., by setting interest rates for the deposit products. Chiu and Hill (2017) estimated elasticity of demand for retail deposits in the United Kingdom, again at the market level. Their modeling approach is based on a highly stylized single period, linear, partial equilibrium model. Karlan and Zinman (2019) estimated long-run elasticity of demand for credit products in Mexico, on the other side of the balance sheet using ordinary least squares. Hong et al. (2021) built a two-period model of revolving credit with asymmetric information and adverse selection to study pattern of changes to interest rates and balance transfer activities before and after the enactment of the CARD Act. Calomiris and Pornrojnangkool (2009) used a log-linear model to estimate the effects of relationship pricing on market demand for industrial loans. Our work assumes the perspectives of an individual bank (as opposed to the market) that wishes to optimize and personalize its pricing for its customer base.

Related Content

Role of AI in the Inventory Management of Agri-Fresh Produce at HOPCOMS
Raghavendra A. N.and Amalanathan S. (2023). *Advanced Machine Learning Algorithms for Complex Financial Applications (pp. 115-131).*
www.irma-international.org/chapter/role-of-ai-in-the-inventory-management-of-agri-fresh-produce-at-hopcoms/317020

An Exploration of Python Libraries in Machine Learning Models for Data Science
Jawahar Sundaram, K. Gowri, S. Devaraju, S. Gokuldev, Sujith Jayaprakash, Harishchander Anandaram, C. Manivasaganand M. Thenmozhi (2023). *Advanced Interdisciplinary Applications of Machine Learning Python Libraries for Data Science (pp. 1-31).*
www.irma-international.org/chapter/an-exploration-of-python-libraries-in-machine-learning-models-for-data-science/330569

Investigating Machine Learning Techniques for User Sentiment Analysis
Nimesh V. Pateland Hitesh Chhinkaniwala (2022). *Research Anthology on Machine Learning Techniques, Methods, and Applications (pp. 681-692).*
www.irma-international.org/chapter/investigating-machine-learning-techniques-for-user-sentiment-analysis/307478

Comparison of Brainwave Sensors and Mental State Classifiers
Hironori Hiraishi (2022). *International Journal of Artificial Intelligence and Machine Learning (pp. 1-13).*
www.irma-international.org/article/comparison-of-brainwave-sensors-and-mental-state-classifiers/310933

Features Selection Study for Breast Cancer Diagnosis Using Thermographic Images, Genetic Algorithms, and Particle Swarm Optimization
Amanda Lays Rodrigues da Silva, Maíra Araújo de Santana, Clarisse Lins de Lima, José Filipe Silva de Andrade, Thifany Ketuli Silva de Souza, Maria Beatriz Jacinto de Almeida, Washington Wagner Azevedo da Silva, Rita de Cássia Fernandes de Limaand Wellington Pinheiro dos Santos (2021). *International Journal of Artificial Intelligence and Machine Learning (pp. 1-18).*
www.irma-international.org/article/features-selection-study-for-breast-cancer-diagnosis-using-thermographic-images-genetic-algorithms-and-particle-swarm-optimization/277431