BANKING ANALYTICS DATA ASSETS

Best practices for marketing management

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Big Ideas

- Advanced analysis of customer transactional and account data can dramatically increase the value of operational data by synthesizing new business metrics and creating behavioral segmentation schemes and predictive scores of future behavior
- Successful customer partitions can be reused when a consistent customer segmentation schemes are developed across the organization and campaigns.
- The requirements for large numbers of customers in each campaign can be controlled by optimally sizing offer cells to the metric of interest and the degree of precision desired, and by using innovations in cell design.
- Pursuing faster development and deployment of predictive models and scores is likely to have significant strategic payoff. Faster development is driven by technological innovation on the tactical dimension, and by disciplined test-and-learn approaches on the strategic dimension.
- Holistically measuring changes in customer behavior (across the lifecycle or across multiple touch points and offers) is a powerful way to account for the overall impact of all interactions on customers and their behavior. This approach transforms performance tracking into a truly closed-loop process of observation, testing, and measurement that is not merely tied to a single offer or marketing contact.

Industry Context

Banking marketers, particularly those who develop marketing strategies for high-transaction-velocity products such as deposit, credit, debit, online, mobile and brokerage banking portfolios, routinely use performance data regarding accounts to manage relationships with customers. These organizations have been actively gathering together massive data files of customer transactions in an effort to deliver value to internal and external business partners. A driving factor in this value is the scope of the data that a bank marketer maintains across transactions, accounts, customers, merchants, and securities, but the scope of these data files is of only finite value when comprised of raw data.

Banking marketers have recently sought to add more value to raw transaction data by analyzing the behavior of customers and synthesizing new business metrics, behavioral segmentation schemes, and predictive scores of future behavior.

This research brief describes some of the information assets that can be created from detail-level transaction and account data. Information assets are analytically-enriched data elements, created by marketing business analysts and data scientists, that are stored and maintained in the bank's data warehouse for re-use by marketers to improve insight and targeting effectiveness. These assets represent opportunities to develop intellectual property that can be packaged for consumption by their internal and external business partners.

Behavioral Profiling Tags

Transaction records in the payments domain define which customer purchased from which merchant on which date for what spend volume. Transaction records in the brokerage domain typically define which positions, sales or redemptions were made by which customer on which date for what transaction size. Traditional reports provide views of this raw historical data. Most client organizations in this space can significantly enhance this data by identifying behavioral concepts, defining business rules to classify customer transaction data that characterizes these behaviors, and storing the "tags" (data fields) that track whether each customer exhibited these behaviors in a specified period of observation in data files.

Behavioral tags should typically be tied to business initiatives such as offers or segmentation schemes that drive targeting or product development objectives. The results of tag definition and execution should be stored in central data files designed for periodic refresh and retrieval by analysts. Tag definitions will typically involve the evaluation of rules defined across multiple metrics and dimensions, such as "customers who purchased at least $50 per week over a three-week period from merchants in both the petroleum merchant category code and convenience store merchant category code, at least once in the last six months." Tag identification may involve advanced computing techniques for discovery, refinement, and execution in order for the business process to be scalable. Examples of innovative and powerful behavior tags include the following:

- Spending bin tags, representing the number of customers who spent between $X and $Y (either total or per transaction) in a period of observation
- Geographical spend tags such as regional or metropolitan area spending patterns, representing the intensity of each customer's spend in a single regional area compared with the average customer whose bill is sent to that area
- Merchant category tags, representing the intensity of customer spend with merchant categories, merchant DBAs, merchant competitive sets, and individual merchants, as well as combinations of these tags (e.g., travel merchant tags combined or overlaid with restaurant merchant tags)
- Transaction sequence tags, representing a composite set of behaviors across merchants or geographies in a period of observation
- Trend, trajectory, and transition tags, representing a customer's recent increase or decrease in spend relative to their historical cyclical trend, or the presence of a spend lapse, or the transition from one behavioral state to another
- Small purchase tags, representing customers who exhibit the behavior of using the debit and credit card as the form of payment for everyday items
- Repeat purchase tags, representing customers who visit the same merchant or competitive set of merchants on a routine basis, given a definition of what is characterized by "routine" spend for that set of merchants.

Segmentation Schemes

Segmentation schemes are created by using one or more metrics, customer or merchant business dimensions, and behavioral tags, combined with analyst-defined breakpoints on any combination of these analytic elements to place customers into groups. Traditional campaigns frequently use segmentation schemes, but they tend to be defined within the context of each campaign and aren't typically stored or shared across campaigns. The centralization of segmentation definitions allows sharing and evaluation for potential re-use, particularly when segmentation schemes are identified to successfully partition strongly performing groups of customers (often called "cells") from poorly performing groups. Marketers should have a clear line of sight into groups of customers that perform well in marketing strategies, so they can repeat those strategies, and into groups that don't perform well, so those strategies can be tuned and refined. This leads to organic improvement in strategy performance over the long haul. Other aspects of modern, behaviorally-driven segmentation are as follows:

- Recency, frequency, and monetary segmentation commonly used when characterizing consumer spend with retailers; this scheme is a hallmark of many campaigns
- Customer lifecycles indexed by their vintage
- Merchants segmented into merchant category codes and, in the context of partner merchant-oriented campaigns, categorized into merchant competitive sets
- Customers segmented into groups that characterize their spending behavior across one or more behavioral dimensions through the use of behavioral tags (e.g., business versus leisure travelers, business spenders, luxury spenders, high spenders, everyday spenders, and big city spenders)
- Powerful segmentation schemes defined by combining and cross-classifying multiple behavioral profiles and tags (e.g., Chicago-intensive luxury-oriented high spenders versus their counterparts in San Francisco and Los Angeles).

Test & Learn Strategies and Contact Strategies

Test and learn strategies have long been embraced by large banks in their efforts to identify which variations of marketing and risk management strategies have the greatest effectiveness on meeting performance objectives such as acquisition, activation, spend stimulation, balance retention, and active spender retention. These strategies are composed of frequent tests of relatively large numbers of offer cells designed and executed in a disciplined, planned manner over a period of months and quarters in advance. This approach is one that should be explored by mid-tier banks as they mature their analytics capabilities.

The intention of these test and learn strategies is to gain analytic insights into offer cell performance, instead of only maximizing response in any one campaign wave. By optimally sizing cells to the metric of interest and the degree of precision desired in results compared across cells, and by using innovations in cell design, the requirements for large numbers of customers in each campaign can be controlled.

Examples of test and learn strategies include the following:

- Different segments targeted across cells
- Different incentives across cells
- Different offer qualification requirements across cells
- Different bundling of offer features across cells
- Combinations of segments, incentives, qualifications, and offer features across cells.

Contact strategies govern the maximum number of contacts and combinations of contacts across offers per customer in a given time period. The purpose of contact policies is to manage the number of impressions received by customers so that the effect of each is sustained and customer responsiveness is not reduced by receiving too many offers. For instance, one prominent payments processor utilizes contact strategies that restrict to no more than four contacts within a 12-month period. Other organizations have developed even more detailed contact strategies, such as rules that limit duplicate offers over time, or enforce cross-channel follow-up. Banks should consider whether they possess the infrastructure and strategies that will support contact strategies such as these, adopted by leading bank marketers and risk managers:

- Maximum contacts per customer across multiple offers
- Minimum contacts per customer across offers, or for certain offers
- Setting different contact strategies by customer segment, or establishing a specific segmentation designed to capture contact strategy explicitly
- Identifying "high contact" customers
- Identifying "no contact" customers
- Seasonal contact strategies, such as "maximum of five contacts per customer per quarter"
- Rolling contact strategies, such as "maximum of two contacts per customer in a rolling six-week time window"
- Agent-based strategies that enforce contact through intermediary channels for customers, such as those who enjoy a private banker relationship, or are dedicated to a branch

Test and learn and contact strategies leverage the same infrastructure and customers and deliver similar benefits in terms of increased overall effectiveness of customer contact in the long run. There are trade-offs for each strategy in terms of short-run contact volumes and potential response rates per cell, particularly for large-volume, low-response, broadly targeted offers. These trade-offs can be measured and evaluated on an on-going basis and decisions can be made by marketing analysts and business partners using dollar-weighted metrics in order to adjudicate across various contact options.

Predictive Models and Scores

Most banking marketers have developed at least some predictive models that target initiatives in the acquisition, marketing, account management and risk management disciplines. Nonetheless, few organizations have honed their practices and processes to reduce the time for model development and deployment to the level of market leaders, which are able to update and deploy models in a few days, as opposed to the typical timeframe of months. Given the high return on investment for these practices and investments, more banking marketers should be pursuing faster development and deployment of predictive models and scores.

Leading banks have streamlined the predictive modeling and scoring processes to design and refresh models in much the same fashion as segmentation scheme and behavioral tags. The up-front development cycle for these predictive models is longer and requires more specialized labor as compared to segmentation scheme and behavioral tags, but the strategic payoff is likely to be significant given the increase in customer insights that can be delivered, as well as the reduction in cycle time to define and roll out new custom models for every individual offer or contact strategy. Evidence from leading banks supports the hypothesis that a generalized catalog of response and revenue contribution models tied to strategies and treatments are likely to produce better returns than using non-score-based offer prioritization or ranking. In the marketing domain, examples of predictive models that would be useful for most banking marketers include the following at a minimum:

- Response
- Incremental response (i.e., incentive responsiveness, compared to no incentive)
- Direct response (product offer A results in a sale for product A) and indirect response (product offer A results in a sale for product B)
- Offer revenue contribution
- Spend stimulation contribution
- Cross-offer and/or cross-contact spend lift
- Channel preference

The next step in the predictive analytics process is model deployment, which generates scores at the segment and customer levels and places those scores in data files accessible to analysts for use in ranking and prioritizing strategies and offers for customers. These scoring processes can be compute-intensive, so planning and administration of this task is very valuable. Some scores will be more relevant only for subsets of the customer population (for example, only on credit products or only for certain segments).

Account and Volume Forecasts and Projections

On a variety of banking platforms, such as payments, online, mobile and brokerage, it is easier for customers to transact, and hence the volume of transactions over time and per unit of time is increasing rapidly. This is evident in several trends, for instance, the increase in the use of cards as the preferred form of payment by consumers for many types of purchases, and with the inherent growth rate in debit and credit card spend volume; the increase in online trading velocity; the increased use of online payments. Coincident with these transaction volume trends, there is a coincident rise in the value of being able to project that volume accurately several months or quarters in advance. Bankers will find it valuable to generate spend volume projections by groups of customers broken out by segments or behavioral tag groups, as well as by more traditional means such as card products, geographies, and credit quality tiers.

A forecasting and projection infrastructure for this purpose should have several key attributes, as follows:

- Generate projections of accounts and spend volumes by multiple business hierarchies (including those that are user-defined) for several months and/or quarters in the future
- Take underlying trends, seasonality, and business cycles explicitly into account
- Take bank, industry, calendar, and user-defined events into account
- Be flexible enough to accommodate analyst-defined metrics, analyst-defined business hierarchies, and subsets of the customer population of interest to analysts
- Use forecast scenarios as a means of comparing which sets of input assumptions driving growth, including campaigns, naturally-occurring cross-sell, attrition, and the economy, have the greatest impact on overall account and spend volumes
- Determine the cross-product impacts of marketing and pricing on adoption and medium-term account openings and balances as a function of the performance correlations over time

Optimal Offer Allocation and Customer Treatment Decisions

One rapidly growing approach within the bank analytics space is the use of mathematical optimization to allocate optimal offers or treatments to customers. These optimization approaches allow analysts to evaluate the economic trade-offs of alternative offer and targeting strategies and attach fiscal metrics to each strategy, thereby allowing decision-makers to determine the best overall approach for the marketing organization and its stakeholders.

Once a preferred optimization scenario has been identified by analysts and stakeholders, the offer allocation logic can be converted into customer-centric data files and business rules that approximate the mathematically optimal results for making future offer allocation decisions. Examples of optimal offer allocation strategies relevant for a bank might include the following:

- Alternative offers within a single campaign
- Offers across campaigns
- Offers across multiple channels

- Alternative contact strategies
- Alternative optimization objectives (e.g., response rate, incremental response rate, and response-weighted margin contribution)

Notably, the use of optimal allocation of treatments to customers has not been limited to the marketing and account management disciplines; risk management and collections departments have also been very active in the pursuit of mathematical optimization routines applied to line assignment, credit line adjustment, pricing and re-pricing, delinquency and collections strategies.

Performance Tracking, Analysis, and Calibration

Most organizations maintain processes for tracking the effectiveness of offers, including standard reporting to support marketing and risk management treatment performance analysis. These results are typically presented in the format of printed reports along with annotations and remarks on analytic insights gathered through the performance analysis of the campaign or strategy. These result reports are typically evaluated at the end of a period of measurement, and the reporting on that offer or treatment concludes.

Less frequently, but more powerfully, a holistic measurement of changes in customer behavior (across the lifecycle or across multiple touch points and offers) is established to account for the overall impact on customers and their behavior. This approach transforms performance tracking into a truly closed-loop process of observation, testing, and measurement that is not merely tied to a single offer or marketing contact. The creation of a business analysis environment is consistent with this on-going measurement approach, although it will require stewardship from within the organization in order to be sustained over the long term. One benefit of this approach is that a view of all touches on a customer can be balanced with the customer's baseline experience and that of other customers who exhibit similar behaviors and inhabit similar segments. Features of this advanced type of performance tracking, analysis, and calibration framework include the following:

- Enhance performance reporting to make it more broadly available and delivered on a more timely basis
- Enable the completion of the feedback loop by converting offer-specific results into customer-level performance tags
- Support interactive analysis of offer performance as a function of performance tags
- Track changes in customer behavior in the short- (offer-specific, quarter-specific), mid- (multiple quarters), and long-term (annually, and segmented by customer vintage)
- Enable analysts to adjust performance expectations for subsequent customer strategies given current results tied to performance tags
- Capture and share analytic findings and insights: capture, publish, retrieve, and re-use.

Conclusion

Interested in learning about how Corios can help you get more from your models? Give Robin a call at **503.295.1685** or email him at **deploy@coriosgroup.com**.

About the Author

Robin Way

Robin Way is the Lead Faculty Member for Banking at the International Institute of Analytics, and is the founder and CEO of the management analytics consultancy, Corios. He has over 25 years of experience in the design, development, execution, and improvement of applied analytics models for clients in the credit, payments, lending, brokerage, insurance and energy industries. Robin was previously employed with SAS® Institute's Financial Services Business Unit as a managing analytics consultant for 12 years, in addition to another 10+ years in analytic management roles for several client-side and consulting firms.

Robin's professional passion is devoted to democratizing and demystifying the science of applied analytics. His contributions to the field correspondingly emphasize statistical visualization, analytical data preparation, predictive modeling, time series forecasting, mathematical optimization applied to marketing, and risk management strategies. Robin's undergraduate degree from the University of California at Berkeley and his subsequent graduate-level coursework emphasized the analytical modeling of human and consumer behavior.

About Corios

Corios is a leader in the discipline of management analytics consulting focused on helping clients across industries to bridge the gap between their data and their business decisions. The company's custom offerings provide analytical solutions for risk management and compliance, marketing, pricing, and big data initiatives. Corios' solutions have identified business improvements worth hundreds of millions of dollars for corporations across North America.

Corios believes that data-driven techniques are the key to making profitable business decisions, and that data should be simple, approachable, and implementable for both analysts and decision makers. The Corios team is persistent in their efforts to promote transparency and common process across the analytical discipline.

To learn more about how Corios is bridging the gap between data and business decisions, please visit **coriosgroup.com**.

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