



Customer Analytics: Maximizing the lifetime value of your customer segments


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Too often companies expend considerable effort developing and maintaining segmentation systems and targeting models with little consideration into who should be targeted when. They do little analysis on who is targeted, how often and how that affects long-term results. Many customer analytic models and segmentation systems provide insight into who should be targeted or what message to deliver, but the models themselves rarely offer an optimum long-term contact strategy.

In simple terms, if the model scores and segments are not updated often or the models are based on data that is static, then it is possible to target the same household with the same offer and message over-and-over. Many terms exist in the direct marketing industry for this including 'name fatigue' and 'name mix', but in all cases the result is poor performance over time as the marketing processes do not make the best use of the analytics and campaign management efforts. Additional customer analytic, data warehouse and database marketing techniques and processes must be tapped to ensure consistent performance throughout the customer lifecycle. We will see that the modeling and segmentation techniques are the same or very similar – it is the application of the models and other various marketing practices that differ.

BUSINESS IMPLICATIONS

Many individuals or departments may be focused on one portion (metric) of profitability. Bad debt percentage comes to mind – a short-term company focus may be on reducing bad debt when, in fact, incorrect short-term bad debt reduction methods may also reduce long-term profit as the efforts could remove potentially profitable customers. It is important to maintain and track all factors of customer performance, but the only true metric that a company is evaluated on is long-term profitability. This is especially true when moving toward a customer lifecycle approach to marketing as individual components of profitability may not improve or in some cases worsen. A basic example that is present in many industries is that highly responsive prospects tend not to turn into highly profitable customers. In certain instances, it may be necessary to take an initial hit on response and customer acquisition in order to build up a loyal and profitable customer base.



Before embarking on this journey companies should identify, analyze and adjust all processes that may be affected. Fine-tuning the contact management schedule could have far reaching implications outside the analytic realm including short-term and long-term forecasting. In addition, forecasting is usually tied to the budgeting process as well as bonus schedules. A long-term campaign management system may suppress short term profitability in order to maximize profitability over the customer lifespan. Clear and distinct rules, guidelines and processes must be in place that will reward long-term profitability.

DATA REQUIREMENTS

Data is the lifeblood of any and all database marketing operations. Without open access to customer and campaign history an organization cannot optimize long-term marketing performance. As such, an organization's direct marketing potential is directly related to the availability and format of historical customer, prospect & campaign data.

Unfortunately, 'Master Files' are still prevalent in today's highly technical workplace. Master files are simply a means to aggregate customer data during a specified period (usually monthly) to provide a snapshot of what the customers look like at that point in time. Any production type 'database' environment where data is processed and history is archived may be classified as a Master File environment. Master Files are usually a good first step to gain an initial understanding of the customer base; however, many organizations should place additional efforts towards developing a historical database in order to move to the next level of database marketing optimization.

Initially the differences between Master Files and a historical marketing data warehouse may seem minor, but the differences are considerable and may be measured in the amount of potential information that may be extracted from each. A few of the differences are listed below:

- Information is limited to the derived attributes on a master file.
- A master file environment is a production process whereby predetermined variables are calculated and all other information is thrown aside. A master file does not support an ongoing test-and-learn process as it is difficult to understand what works over time.
- True history is not available on a master file: Long-term behavior and changes in behavior can only be determined over time. Determining customer behavior is crucial in accurately predicting an individual's interests, potential actions and ultimately potential worth.

The true difference is competitive advantage - a marketing data warehouse enables an organization to move toward an optimized long-term database marketing program.



ANALYTIC TECHNIQUES

Once the business and data issues are resolved an organization may start to enhance, organize and adjust its Enabling Technologies, *Information Assets & Appropriate Measurements* in a manner that facilitates a long-term profitable database marketing environment. Effective Processes (people & technology processes) are also required to ensure proper use and control of the tools and techniques.

Step1:

Assess all analytic assets including the predictive models and segmentation systems and make certain that these systems are as robust as possible.

If customer history data is available the segmentation systems (segments or clusters) should place customers into distinct groups that have similar purchase and payment behavior. Many organizations do not spend enough effort developing well formed clusters of customers that may be used to significantly enhance targeting and messaging. For example, females in a specific ethnic group who reside in rural counties is not a well-defined cluster as individuals within that segment will have significantly different interests and purchase behaviors. Use customer history (purchases, payments, customer service calls, captured interests,..) and a proven clustering technique such as K-Means to develop clusters of customers who have the same interests and spending habits.

Verify that reliable predictive models (response, activation, cross-sell, profitability..) exist are not out of date. The segmentation power and predictive reliability of many models erode over time as the business and customer base evolves.

Step2:

Introduce additional data sources into the models and segmentation systems. The additional data sources will provide enhanced segmentation and data volatility. Increased data volatility allows the marketing systems to identify groups of customers that may be interested at certain periods of time.

As an example a large insurance organization noticed that their current models and contact strategy selected the same individuals repeatedly within groups of similar offers. They had a strong analytic team with access to fairly good data (a data warehouse was years away at this time). Since robust historical data was not available they decided to look for additional data sources that would help the models identify pockets of individuals that may be interested in certain products during varying time periods. As a result, they incorporated life-events, industry seasonality indicators and economic data into their models with good success as individuals tend to purchase insurance at certain points of life and with increased velocity during certain economic times.

AVAILABLE DATA SOURCES

- ▶ **Behavioral data:** The simplest type of customer behavioral data are RFM purchase statistics (Recency, Frequency & Monetary). Other examples include customer tenure and historical purchases. Behavioral data also includes external credit sources as they track an individual's purchase and payment tendencies over time.

- ▶ **Life-events:** Move, birth, new job and graduations are examples of life-events that trigger an increase or adjustment in spending activity.
- ▶ **Contact history variables:** Number of contacts for each type of offer over a period of time and/or amount of time until last offer. Contact history variables allow the models to learn how contact fatigue effects future campaign performance.
- ▶ **Non-Behavioral data:** Industry specific customer header data and enhancement data, which includes geography, demographics and other compiled data sources.
- ▶ **Outside factors:** Industry seasonality indicators, economic indicators, weather data & holidays.
- ▶ **Marketing mix variables:** All previous marketing events aggregated to a specific time period (i.e. monthly).

Step3:

Develop additional analytic systems and tests to be used to help optimize contact timing and contact sequencing. Specifically, if not already available develop retention models to predict the amount of time until a customer leaves (survival or hazard models) or the probability of leaving over a specific period of time. Retention or hazard models, if developed properly and incorporated into well sequenced marketing strategies, provide an integral role in the advancement of 'timely' retention targeting. These models use advanced statistical and data processing techniques to develop a normal customer behavior profile. When a customer deviates from their normal behavior the model will notice the change and adjust the model score accordingly.

Step4:


Develop the update procedures and processes required to score the models and segments. In most instances it is best to retain control of the scoring functions within the analytic department. This will reduce the potential for errors and will provide an environment for future analyses as previous scores may be used in subsequent models and clusters.

IT, Marketing and Analytics should work together to determine the most appropriate scoring interval. Spending considerable time developing an automated nightly rescore system may only be warranted when the data and ultimately model scores change enough to affect marketing performance. Data and score volatility as well as campaign timeliness are the predominant factors in determining how often the customer scores and segments should be updated.

CUSTOMER BEHAVIORAL MONITORING SYSTEMS: ADVANCED TRIGGERS

Advanced customer monitoring software is available, which may be programmed (or may learn) to identify normal behaviors and significant changes in customer behavior over time. When the software identifies a significant change rules may route the individual customer to the most appropriate action (up-sell offer, retention action,..). Examples of this type of software include MarketSoft/Triggers and Synapse Technology/ SynapseEBM™

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suite. The software and embedded analytical techniques provide an advanced triggering capability, which significantly enhances offer timing beyond the typical marketing campaign schedule.

Customer monitoring systems are quickly gaining momentum in high volume customer contact environments such as financial institutions. These systems provide an advanced targeting method where the customer's actions trigger an event. In many industries the near real-time aspect of these systems provides the mechanism to drive incremental revenue. The same or similar techniques are available in segmentation systems and targeting models, but they are only acted upon when a campaign is executed – and most campaigns are executed on periodic schedules and require, at best, days to complete. Knowing that an individual or small group of individuals took an action that results in 10 times the typical attrition rate within the next week is great, but only when the organization acts on that knowledge immediately. The normal campaign schedule will miss out on the majority of this potentially enormous opportunity.

PUTTING ALL THE PIECES IN PLACE: A HORIZONTAL, TIME BASED, CONTACT MANAGEMENT STRATEGY

A true horizontal contact management strategy may have several levels of contact tactics based on where the customer resides in the customer lifecycle. The most basic includes two strategies – one for prospects and another for the current customers. Data availability drives the need to separate prospects from customers as prospects do not have historical interactions with the organization.

Prospects:

With all available models create a Net Present Value (NPV) statistic for each product or group of products at the prospect level. NPV calculations use the predictive models as well as other metrics (risk, product profitability, attrition,..) to determine the predicted profitability of a prospect for one product or product group.

▶ NPV = Probability of Activation * A Risk measure * Average NPV of a product discounted over time

- Probability of Activation: Response and activation models.
- Risk measure: Payment risk model or actuarial tables (if appropriate).
- Average NPV: The overall average NPV of all customers discounted over the average lifespan.

Next, create a Life Time Value (LTV) statistic to determine the final contact cutoff decisions. The LTV statistic incorporates cross-sell probabilities as well as lapse probabilities to determine the final predicted LTV of a prospect. The lapse probabilities are determined by creating attrition models - A lapsed prospect model calculates the probability of lapsing over the typical customer lifecycle. Finally, deduct the campaign



marketing expense to determine **the total potential for a prospect over time given all goods and services sold.**

$$\text{LTV} = \text{Lapsed probability} * (\text{sum of (all cross-sell probabilities times the cross-sell product's NPV)} + \text{NPV of the product offered}) - \text{marketing expenses}$$

Once all the models and NPV calculations are available the prospects may be scored for each product from which future campaign selection decisions may be executed. An example LTV prospect score report is provided below for one product (product A).

Product 'A' LTV: Prospect campaign selection report

Decile	Prospects	Average Marketing Cost	Activation %	Risk Indicator	TTL Predicted Cross-sell \$	Product 'A' average NPV	Average \$ ¹	Average LTV \$ ²	Average Cumulative LTV\$	Sum Cumulative LTV\$
1	64,985	\$ 0.55	8.10%	0.89	\$ 24	\$ 9	\$ 3.00	\$ 2.45	\$ 2.45	\$ 159,432
2	64,985	\$ 0.55	4.95%	0.93	\$ 22	\$ 9	\$ 1.63	\$ 1.08	\$ 3.54	\$ 229,763
3	64,985	\$ 0.55	4.05%	0.92	\$ 21	\$ 9	\$ 1.32	\$ 0.77	\$ 4.31	\$ 279,844
4	64,985	\$ 0.55	3.45%	0.97	\$ 20	\$ 9	\$ 1.03	\$ 0.48	\$ 4.79	\$ 311,130
5	64,985	\$ 0.55	3.00%	1.03	\$ 19	\$ 9	\$ 0.83	\$ 0.28	\$ 5.06	\$ 329,017
6	64,985	\$ 0.55	2.40%	1.02	\$ 20	\$ 9	\$ 0.68	\$ 0.13	\$ 5.20	\$ 337,618
7	64,985	\$ 0.55	1.65%	1.04	\$ 20	\$ 9	\$ 0.45	\$ (0.10)	\$ 5.10	\$ 331,432
8	64,985	\$ 0.55	1.05%	1.02	\$ 19	\$ 9	\$ 0.28	\$ (0.27)	\$ 4.83	\$ 314,198
9	64,985	\$ 0.55	0.75%	1.08	\$ 18	\$ 9	\$ 0.19	\$ (0.36)	\$ 4.47	\$ 290,491
10	64,985	\$ 0.55	0.60%	1.10	\$ 16	\$ 9	\$ 0.14	\$ (0.41)	\$ 4.06	\$ 263,610
Total	649,850	\$ 0.55	3.00%	1.00	\$ 20	\$ 9	\$ 0.96	\$ 0.41		

1-Average\$ Activation% * (1/Risk Indicator) * (TTL Predicted Cross-sell\$ + Product 'A' average NPV)
 2-Average LTV\$: Average\$ - Average Marketing Cost

The above decile report shows prospects in 10% groupings sorted descending by Average LTV\$. Notice that deciles 1 to 6 show a profitable LTV (Average LTV\$ column). Assuming the prospect contact strategy is to only contact an individual if their overall predicted LTV was positive then only those prospects in deciles 1-6 would be contacted as the cumulative LTV is maximized at \$337,618. Deciles 7 through 10 each show a lifetime loss. It is important to notice that although the Average LTV decreases continuously by decile the individual components (risk,..) may not.

Customers:

The LTV process is very similar for customers however, additional data is available to build more robust models. The above prospect LTV report does not include a lapsed indicator as it tends to be difficult to predict the probability of a prospect lapsing over the typical customer life cycle. Customer retention models will allow for this additional lapsed indicator and provide additional LTV segmentation.

Time is added as a dimension to the customer LTV system as similar customers may behave differently depending on where they fit in the customer lifecycle. Two groups of customers who are in the same LTV decile and customer segment may behave differently if they have significantly different tenure. When developing a clear customer contact strategy tenure is a vital factor.

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The report below shows an example of a customer time-segmentation by three dimensions:

LTV Decile: Deciles 1, 5 & 10 are only visible to show the segmentation power of this method – a typical LTV report would show all deciles. LTV calculation at the customer level is similar to prospect LTV. Some differences exist:

- ▶ Retention models are used (multiply by a lapsed indicator)
- ▶ This LTV report does not subtract marketing expenses. Once the contact strategy is determined by cell the predicted marketing costs may be included.

Customer segment: Typical segmentation systems contain several clusters as behavior and predictive performance will vary by segment. For simplicity the report below only shows one segment – Segment A ‘Trendy & Mobile’: Slightly younger upper income customers who predominantly purchase high-end products.

Time (Month): All individuals are standardized to their specific tenure month. Only those customers that remain in that month are used. The report shows 6 months in total. The size and total number of time periods vary by many factors including industry. It is usually best to track customers at least through the typical customer lifecycle – the point in time where 75%-90% the customers still exist.

The report below shows historically conservative to average customer segmentation results by the 3 dimensions yet cells exist that show 10 times the overall average predicted future LTV\$.

Segment	Decile	Data	Customers Remaining in Month					
			1	2	3	4	5	6
A: Trendy & Mobile	1	Avg\$ to Date	\$ 10.85	\$ 15.75	\$ 28.00	\$ 36.75	\$ 54.25	\$ 80.50
		Avg Future LTV\$	\$ 104.93	\$ 71.42	\$ 52.94	\$ 36.40	\$ 20.13	\$ 30.19
		%Customers remaining	99%	85%	66%	45%	30%	25%
	5	Avg\$ to Date	\$ 3.10	\$ 4.50	\$ 8.00	\$ 10.50	\$ 15.50	\$ 23.00
		Avg Future LTV\$	\$ 24.91	\$ 16.99	\$ 12.19	\$ 8.09	\$ 4.37	\$ 6.56
		%Customers remaining	93%	79%	60%	39%	24%	19%
	10	Avg\$ to Date	\$ 0.47	\$ 0.68	\$ 1.20	\$ 1.58	\$ 2.33	\$ 3.45
		Avg Future LTV\$	\$ 2.01	\$ 1.40	\$ 0.80	\$ 0.35	\$ 0.14	\$ 0.21
		%Customers remaining	83%	69%	50%	29%	9%	4%
Segment A Total		Avg\$ to Date	\$ 4.01	\$ 5.83	\$ 10.36	\$ 13.60	\$ 20.07	\$ 29.79
		Avg Future LTV\$	\$ 30.60	\$ 20.94	\$ 14.76	\$ 9.50	\$ 5.08	\$ 7.62
		%Customers remaining	93%	79%	60%	39%	22%	17%
Total - All Customers (All Segments)		Avg\$ to Date	\$ 2.23	\$ 3.80	\$ 6.80	\$ 9.30	\$ 13.50	\$ 18.50
		Avg Future LTV\$	\$ 13.84	\$ 9.14	\$ 5.74	\$ 3.88	\$ 1.85	\$ 2.78
		%Customers remaining	90%	75%	50%	20%	15%	10%

The number of cell combinations should be manageable as the customer contact strategies will vary by cell or groups of cells. Adjusting the marketing strategies by cell allows an organization to fine-tune its marketing efforts based on future predictive results as well as where the customer fits in the customer lifecycle. Adjusting contact strategies and messaging based on this time dependent segmentation will provide an optimized strategy and maximize customer profitability by segment over time.



CAMPAIGN MANAGEMENT IMPLICATIONS:

The environment described above will produce two contact categories:

- Real-time or near real-time: Those individuals identified within the customer behavioral monitoring software.
- A set or periodic campaign schedule based on the results of the LTV analyses. The customer behavioral monitoring system triggers are usually not incorporated with the ongoing campaign schedule as timing is critical. As customers are triggered by the monitoring software for real-time offers they need to be captured and possibly suppressed from the normal campaign schedule. It is important to set distinct rules for both types of campaigns so that they do not interfere with each other.

Transitioning from a one-off campaign environment to an analytic long-term database marketing strategy is challenging, but it is well worth the effort. Most of the tools and techniques are the same – they are now applied in a way that fits into a long-term profitability strategy. These analytic and marketing strategies, when applied correctly, will provide the means and groundwork towards ongoing and consistent profitability. Those organizations that challenge themselves to the limit of these analytic and marketing processes will gain a competitive advantage.

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About Quaero

Quaero is a marketing services company that helps Fortune 1000 enterprises accelerate marketing performance and improve customer relationships and profitability across channels, online and offline. We provide both consulting, onsite integration and fully hosted, outsourced marketing services. The company helps organizations generate significant growth by bridging the gap between marketing and technology, providing tools and processes that promote effective multi-channel marketing by harnessing the power of customer information and insights to drive marketing strategy and execution. Quaero serves category-leading clients in Financial Services, Pharmaceutical/Healthcare, Media and Publishing – online and offline, Travel and Leisure, Retail, Telecommunications, and Business Services.

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