Analyzing CRM Results: It's Not Just About Software and Technology

One of the key factors in conducting successful CRM programs is the ability to both track and interpret results. Many of the technological advancements in CRM have been on the tracking side. Without the ability to capture and track the right information, it becomes meaningless to discuss analysis and interpretation of results. Yet, in today's environment, we are seeing the proliferation of campaign management systems that now facilitate the proper tracking of information for organizations. Organizations can now quickly access the information they need. But the question still remains. Are they accessing the right information and are they drawing the right conclusions from this information? In many cases, the answer would be no to both questions. Why? Many organizations focus on the technical and mathematical skills as the key requirements for a data analyst. There is no question that these skills are required, yet organizations fail to integrate the level of experience into the overall mix. Analysts in many cases are simply considered as messengers of information. It then becomes the marketing department's job to interpret and derive the meaningful conclusions from the information. A sub-optimal culture exists here since the key persons working with the information (analysts) are not involved in the interpretative stage of the analysis. Organizations having analysts as both messengers and interpreters of information have a competitive advantage, which has been developed from many years of both interpreting results and drawing conclusions. The best analysts are those that constantly challenge the information even if the results look favorable. With their invaluable experience of applying many different solutions in many different environments, they have the keen insights to determine the integrity of results. But what does this exactly mean? How do we provide a concrete example that depicts the meaningfulness of this type of expertise? The best way to really appreciate this type of expertise is to understand at a high level some of the thought processes that an experienced data analyst might go through in a given analytical exercise. The very first question an analyst should consider is whether or not the analysis is for strategic or tactical purposes. This type of consideration will dictate the type of approach used in the analysis. Let's look at the approach used for a more tactical type exercise.

Tactical exercises are analyses based off information that will be used for an upcoming campaign. In this exercise, the first area of consideration is the establishment of control groups, as we need to have a point of reference or benchmark in evaluating overall results. Let us look at the following example:

Campaign 1

Test 1	21% response rate
Control 1	20% response rate
Performance Lift	5%

Campaign 2

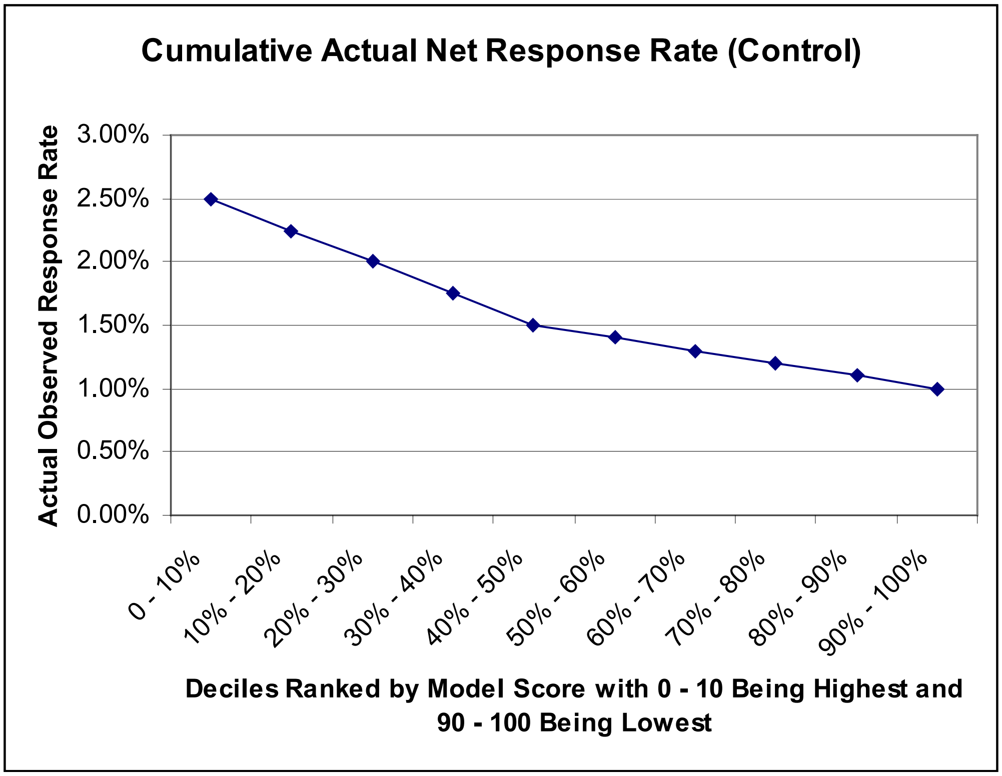
Test 2	.5% response rate
Control 2	.25% response rate
Performance Lift	50%

In the two campaigns, we obtain response rates of 21% and .5%. Does that mean the 21% response rate is the better campaign. The answer is no, since the control group response rate in this case was 20% for an overall performance lift of 5% (21%/20%) while in the other case the control response rate was .25% for an overall performance lift of 50% (.50%/.25%).

However, this is still not the end. We may ask how the control group was derived. Was the control group randomly selected or was it based off some broad targetting criteria. Did we have enough names in the control group sample? If the number of names are minimal in a given control group, it will limit the confidence of any recommendations since we may not be able to attach a high degree of statistical significance to our findings. The use of more stringent targetting criteria in a control group will also limit the impact of the analysis. Solutions developed from a control using restrictive criteria can only be applied against a universe with those same restrictive criteria.

In analyzing results from a tactical perspective, the analyst must also identify the campaign objectives from a learning standpoint. Does the campaign have the appropriate testing structure in place? For instance, marketing may just want to determine whether a targetting strategy worked or did not work within a campaign. This kind of broad question can be answered by simply creating a test cell where the targetting strategy is applied and a control cell where names are randomly promoted. If the test cell outperforms the control cell assuming they both have the same offer and message, then we know that the targetting strategy has been effective. But what if the marketing department wants to become more granular and determine the optimum cutoff for selection of names by a given targetting approach. Furthermore, they may want to assess the level of performance for a given targetting approach as well as assessing the impact of a given communication strategy within different targetted portions of the list. In this case, we need to evaluate the model's ability to rank order names in order to both determine where the optimum cutoff is as well as the level of performance for this type of targetting approach. Different groups of cells will also be organized in order to evaluate the impact of the communication approach. In this case, tracking cells would be created at the quintile level (20%) or decile level (10%) depending on how granular we want our desired level of learning. These cells would be further split based on the different communication approaches being tested within the campaign. With this type of tracking system, we can achieve three key pieces of learning:

1. Performance of Model (i.e. how well does it rank order) represents the first piece of key learning



You can see from the above chart that the degree of rank ordering can be measured by the steepness or slope of the line. This line, called a Lorenz curve, is the most commonly used device in evaluating predictive models within the database marketing environment. Listed below is how the data from the graph on the previous page would appear within a chart.

% of Prospects Mailed (Rated by Desc. Model Score	Cumulative # of Names Mailed	Cumulative Actual Net Response Rate (Control)	ROI
0 - 10%	100000	2.50%	87.50%
10% - 20%	200000	2.25%	68.75%
20% - 30%	300000	2.00%	50.00%
30% - 40%	400000	1.75%	31.25%
40% - 50%	500000	1.50%	12.50%
50% - 60%	**600000**	**1.40%**	**5.00%**
60% - 70%	700000	1.30%	-2.50%
70% - 80%	800000	1.20%	-10.00%
80% - 90%	900000	1.10%	-17.50%
90% - 100%	1000000	1.00%	-25.00%

2. Optimum cutoff for selection of names represents the second piece of key learning.

   This chart reveals that the optimum cutoff from in terms of maximizing profit would be 60% as the interval ROI is still above zero.

3. Determine sensitivity of communication piece within model-ranked intervals represents the third piece of key learning.

The second type of purpose for analytical projects is to derive insights for strategy development. We have all heard how organizations need to reorient themselves with strategies that have a CRM focus. Analytics can provide the insights into building a foundation for a CRM strategy. Segmentation of the customer base based on profit or some other notion of value can be used as one means to group customers. Behavioural information could also be used as another criterion for segmenting customers. By overlaying behaviour with profit or value, we can then develop a basic segmentation strategy with specific marketing initiatives and programs created around these segments. Listed below is an example of what this initial segmentation strategy might look like.

Existing 1 yr+ Tenure Customers

	Low	Medium	High
Stable			
Grower			
Decliner			
Re-activator			
Decliner			

New Customers (Tenure is in Months)

		Tenure			
Avg. Monthly Value (YTD)	**Active (Last 3 Months)**	**0 – 3**	**4 – 6**	**7 – 9**	**10 – 12**
High	**Yes**				
	No				
Medium	**Yes**				
	No				
Low	**Yes**				
	No				

Lifecycle analysis as well as product sequence analysis can reveal underlying patterns about both what product to offer customers and when to offer it. It is this type of knowledge that can be used to formulate marketing strategy based on where the customer is within their lifecycle. Once again, the analysis may reveal that there are clear periods within a customer's lifecycle when a customer should be contacted or promoted by the company. Product sequencing can be used to develop strategies for cross-promoting new customers with the appropriate second and third product. With customers that are longer tenure in nature, product affinity analysis can identify the most appropriate product for that customer at that particular point in time.

Another key area in formulating marketing strategy relates to information around the campaign history of customers. With the influx of campaign management systems that have inundated the market, access and use of this information is more easily facilitated. For instance, through analysis, policies can be developed which relate to how often a given person is promoted within a given period of time as well as the length of time between promotions. This could also be extended based on promotion type. After all, we may find that promotion category A should be promoted more frequently than category B.

As one can surmise from the above discussion, analytics represents more than just applying mathematical tools and technology. The more competitive analysts all use technology but with a view to interpreting results with the key question: What does this really mean? Those analysts that spend more time challenging the results and looking for potentially different interpretations will create the real CRM opportunities for their organizations.