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Measuring Campaign Performance by Using Cumulative Gain and Lift Chart

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ABSTRACT

The primary goal of a direct mail marketing (DM) campaign is to send mailers to group of customers who are likely to respond. To determine the likely responders for the offer, it is a common practice to build predictive models based on past experience, using historical data. It is not unusual to evaluate the campaign performance by comparing the results with the model. In this study, lift charts and cumulative gains have been used to measure the effectiveness of several marketing campaigns for telecom strategic products. The results provide important insights into the model, as well as performance measurement. This identifies the best customers and helps improve the profitability of subsequent campaigns.

INTRODUCTION

Direct marketing (DM) paradigm focuses on predicting economic behavior of a group of customers in order to predict and reduce attrition, predict likely responders, risk analysis, and fraud detection. The applications of such models are very apt in Financial Service Industry, Telecom, large Retailers, Direct Mail, email commerce etc. Validating the performance of a model is a critical step in the campaign process.

The cumulative gains and lift charts is an excellent way to show the performance of a model. The lift, a measure of the effectiveness of predictive model, is calculated as the ratio between the results obtained with and without the predictive model. The lift chart shows the likelihood of respondents from customers based on the predictive model and randomly chosen list of customers.

Figure 1a & 1b show the cumulative gains chart with baseline and lift curves A& B respectively. Response rate curve A, called the baseline curve, is for all customers chosen at random. Whereas the lift-curve B is the response of customers that were chosen from a model-score ranked list. The customers of curve B are expected to generate higher response rate compared to customers of curve A. Thus, the area under the curve would be bigger for a model with high predictive accuracy. For the campaign models with low predictive accuracy, the lift curve rises slowly and has a smaller area under the curve. The greater the area between the lift curve and baseline, the better the model is.

ESTIMATING THE AREA UNDER THE CUMULATIVE GAINS CURVE

SAS tools are integral part of our development work for marketing campaign analysis. For gains calculations and lift measurement SAS was instrumental as well. It is much easier to handle mathematical manipulations in SAS. The gains chart compares the predictive performance of the campaign model and a random model. The greater the area between the lift curve and the baseline (random) is, the better the model is. Mathematically the area under cumulative gains curve can be expressed as:

$$L_{area} = \int_0^a f(x)dx \qquad [1]$$

$$0 \le x \le a$$

In equation 1, the function *f(x)* can be expanded as follows:

$$\sum_{i=0}^{a} \tfrac{1}{2} \times [(CR_i - BL_i) + (CR_{i+1} - CR_{i+1})] \times (D_{i+1} - D_i) \qquad [2]$$

Where *CR* - cumulative gain percent *i*
BL – baseline at *i*
D - Decile at *i* .

Solving equation [1], yields the area under the cumulative gains curve:

$$L_{area} = \sum_{i=0}^{a} \tfrac{1}{2} \times [(CR_i - BL_i) + (CR_{i+1} - CR_{i+1})] \times (D_{i+1} - D_i) \qquad [3]$$

SAS was used to read in and integrate the campaign data from disparate data sources including SQL & Excel tables and manipulating data into a task orientated format. Once data was cleaned up and integrated the business rules were applied and, the following code was used to assign decile information:

```
data cust_dat;
   set &file;
      if model_ code in ('000', '') then decile='unk';
      else if model_code le 10 then decile='1';
      else if model_code le 20 then decile='2';
      else if model_code le 30 then decile='3';
      else if model_code le 40 then decile='4';
      else if model_code le 50 then decile='5';
      else if model_code le 60 then decile='6';
      else if model_code le 70 then decile='7';
      else if model_code le 80 then decile='8';
      else if model_code le 90 then decile='9';
      else if model_code le 100 then decile='10';
      else decile='unknown';
   run;
```

Cumulative responses were calculated using the following code:

```
data cumcall;
 set allreg;
 retain cum_MW cum_SW cum_W cum_E cumcall;
    cum_mw+mw_call;
      cum_sw+sw_call;
      cum_w+w_call;
      cum_e+e_call;
 run;
```

CAMPAIGN RESPONSE MODEL PERFORMANCE

A response model is supposed to predict the type of customers who will respond to a marketing campaign. Response models are typically used for developing customer insight and predictions of customers' behavior and campaign performance. For DM campaigns of telecom clients cumulative response and lift were evaluated for four strategic telecom products, that we will designate here as products I, II, III & IV.

Figures 1a & 1b show performance results of DM campaign for product I. Lift curve B shows the percentage of positive responses. When campaign model has high predictive accuracy, the lift curve rises quickly, as shown in Figures 1a & 1b. Y-axis in cumulative gains chart in Figure 1a shows the percentage of total positive responses. Whereas the X-axis shows the decile of customers contacted. Our telecom client uses decile to group its customers. It is a common practice to rank customers and divide them into ten groups (or bands). Baseline curve A is the overall response rate for the customers contacted at random. The ratio of responders for modeled customers who received the DM and baseline is called the lift and it is plotted in Figure 1b. Four product groups that were selected for evaluation of cumulative gains and lift are listed in the product table:

Product Table

Product Group	Campaign - Service Type
I	Offer 1- multiple communications services
II	Offer 2- with added incentives to purchase
III	Offer 3- Single communications service
IV	Offer 4- Bundle-combination of two services

SAS routine was developed for calculating the key performance indicators of marketing campaigns of four distinct product groups as illustrated in the Product Table. Campaign data like customer responses, cumulative response percentage, lift, and lift area were calculated as shown in Tables 1 through 4. Lift at each decile demonstrates the model's ability to beat the random approach / average performance. Both charts consist of a lift curve and a baseline. The greater the area between the lift curve and the baseline, the more effective the model is.

Table 1

Product I Campaign				
Deciles	Calls	Cumulative Responses	Lift	Lift Area
1	375	24.88%	2.49	0.0744
2	326	46.52%	2.33	0.2070
3	346	69.48%	2.32	0.3300
4	286	88.45%	2.21	0.4396
5	164	99.34%	1.99	0.4890
6	10	100.00%	1.67	0.4467
7	0	100.00%	1.43	0.3500
8	0	100.00%	1.25	0.2500
9	0	100.00%	1.11	0.1500
10	0	100.00%	1.00	0.0500

Table 2

Product II Campaign				
Deciles	Calls	Cumulative Responses	Lift	Lift Area
1	187	26.95%	2.69	0.0847
2	170	51.44%	2.57	0.2419
3	134	70.75%	2.36	0.3610
4	102	85.45%	2.14	0.4310
5	80	96.97%	1.94	0.4621
6	15	99.14%	1.65	0.4305
7	4	99.71%	1.42	0.3442
8	2	100.00%	1.25	0.2486
9	0	100.00%	1.11	0.1500
10	0	100.00%	1.00	0.0500

Tables 1 and 2 correspond to Figures 1a &1b and 2a & 2b respectively. The lift values of 2.49 and 2.69 fall in decile 1. This means that compared to overall averages, the customers in decile 1 were 2.49% more likely to respond for Product Group I. Also, the customers were 2.69% more likely to respond for Product Group II. However, for product groups III & IV the lift values in all deciles in Table 3 and 4, turned out to be very small implying that the customer's responses were random. The cumulative responses in Tables 1 and 2 for the first three deciles, show that models perform 69.48% and 70.75% better than average, as compared to 32.24% and 30.54% in Tables 3 and 4 respectively.

Figure 1a

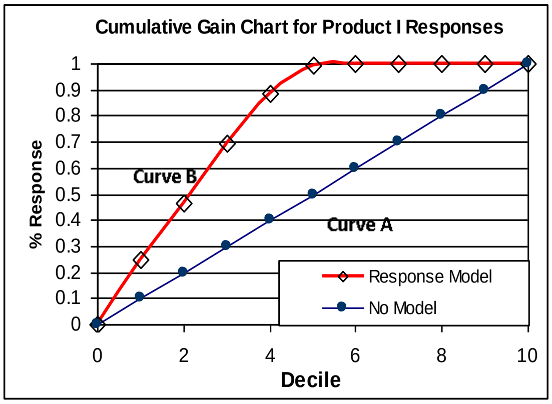


Figure 1b

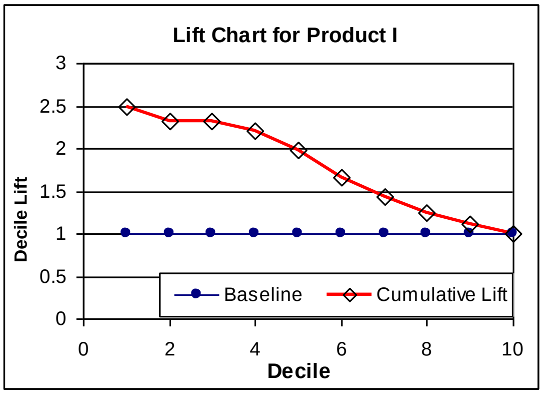


Figure 2a

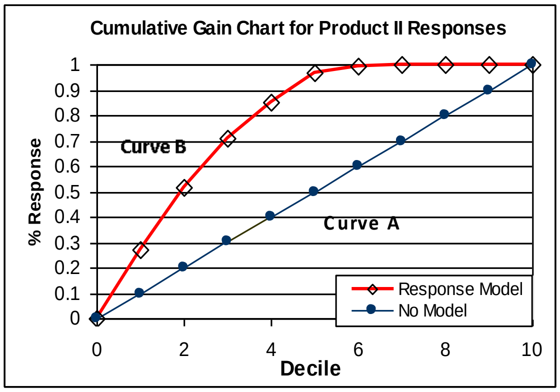


Figure 2b

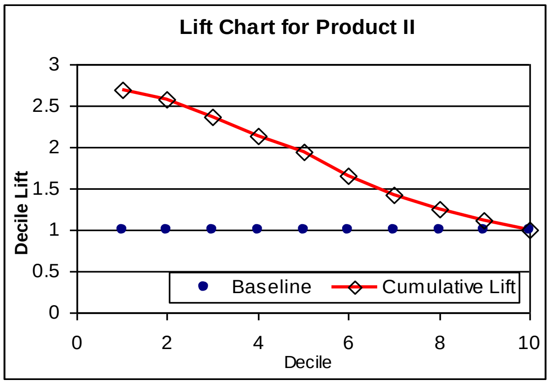


Table 3

Product III Campaign				
Deciles	Calls	Cumulative Responses	Lift	Lift Area
1	0	1.09%	0.11	(0.0445)
2	2	13.11%	0.66	(0.0790)
3	22	32.24%	1.07	(0.0232)
4	35	58.47%	1.46	0.1036
5	48	90.71%	1.81	0.2959
6	59	100.00%	1.67	0.4036
7	17	100.00%	1.43	0.3500
8	0	100.00%	1.25	0.2500
9	0	100.00%	1.11	0.1500
10	0	100.00%	1.00	0.0500

Table 4

Product IV Campaign				
Deciles	Calls	CumulativeResponses	Lift	Lift Area
1	70	9.63%	0.96	(0.0019)
2	80	20.63%	1.03	0.0013
3	72	30.54%	1.02	0.0058
4	74	40.72%	1.02	0.0063
5	85	52.41%	1.05	0.0156
6	91	64.92%	1.08	0.0367
7	96	78.13%	1.12	0.0653
8	73	88.17%	1.10	0.0815
9	86	100.00%	1.11	0.0909
10	0	100.00%	1.00	0.0500

Figures 1a and 2a show that by using models, the top two deciles captured about 50% of the responders. This is compared to a random baseline where two deciles would capture only 20% of the responders. Figures 1b and 2b illustrate that the customers at top 10% decile are 2.5 and 2.7 times more likely to respond than would be expected. The greater the area between the two lines, the more the model was able to concentrate responders in the top deciles. The lift charts (Figures 1b, 2b, 3b, & 4b) show how much more likely we are to receive responses from customers that were selected from predictive model than if we contact a random sample of customers.

Figure 3a

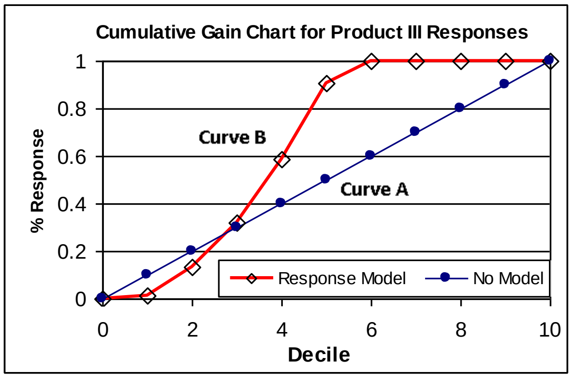


Figure 3b

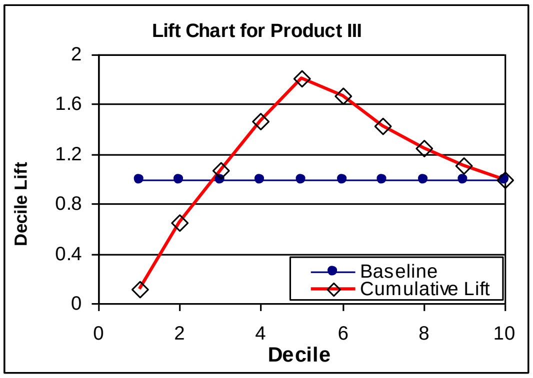


Figure 4a

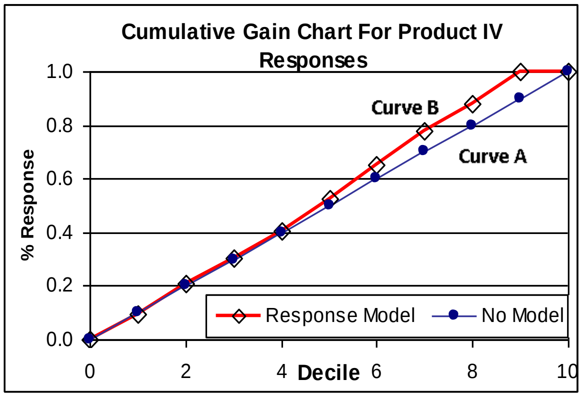
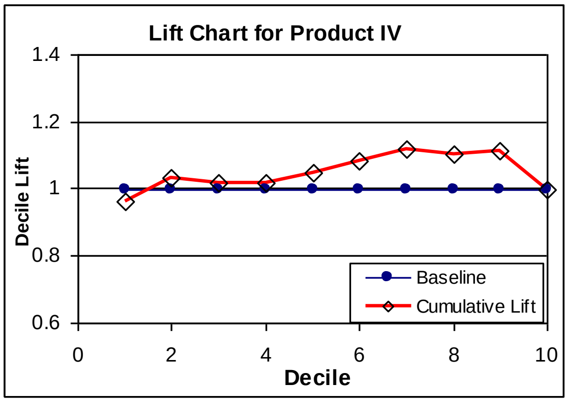


Figure 4b



In Figure 3b & 4b the lift curve is close to the baseline, and does not rise quickly. This implies that the model is not responding or it is not a good one. We can conclude that the campaign model used to create the lift curves in Figures 3a to 4b have low predictive accuracy. This low level of response can perhaps be achieved simply by flipping a coin.

CONCLUSION

The analysis presented here show that at top deciles, customers respond to campaign offers at a higher percentage. As such, a higher percentage of total mail quantity should be allocated to those groups of customers that have higher tendency to respond. Product groups I & II are good examples of targeting appropriate customers with the right offers. On the other hand, the campaign models for product groups III & IV do not look promising as they have a weaker model without any ability to predict or identify the strong responders.

REFERENCES

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