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Net Lift Model for Effective Direct Marketing Campaigns at 1800flowers.com

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ABSTRACT

This paper describes basic concepts, benefits and challenges of implementation of Net Lift Models in direct marketing campaigns at 1800Flowers.com. Net lift models predict which customer segments are likely to make a purchase ONLY if prompted by a marketing undertaking. The modeling work was conducted using stepwise logistic regression in SAS Enterprise Miner ®.

The paper provides examples how net lift probability decomposition models leveraged differences between purchasers in test group and control group to predict which customer segments need a marketing contact and which customers segments are likely to make purchasing decision without a nudge.

TRADITIONAL APPROACH TO DIRECT MARKETING LIST MODELING

Majority of direct marketing campaigns are based on purchase propensity models, selecting customer email, paper mail or other marketing contact lists based on customers' probability to make a purchase.

Scoring Rank	Response Rate	Lift
1	28.1%	3.41
2	17.3%	2.10
3	9.6%	1.17
4	8.4%	1.02
5	4.8%	0.58
6	3.9%	0.47
7	3.3%	0.40
8	3.4%	0.41
9	3.5%	0.42
10	0.1%	0.01
Total	**8.2%**	

Table 1. Example of standard purchase propensity model output used to generate direct campaign mailing list at 1800Flowers.com

This purchase propensity model had a 'nice' lift (rank's response rate over total response rate) for the top 4 ranks on the validation data set. Consequently, we would contact customers included in top 4 ranks. After the catalog campaign had been completed, we conducted post analysis of mailing list performance vs. control group. The control group consisted of customers who were not contacted, grouped by the same purchase probability scoring ranks.

1800Flowers.com sample campaign post analysis results:

	Mailing Group	Control Group	
Scoring Rank	**Response Rate**	**Response Rate**	**Incremental Response Rate**
1	27.0%	27.9%	-0.91%
2	20.3%	20.9%	-0.56%
3	10.7%	10.0%	0.66%
4	8.9%	7.5%	1.38%
Total	**16.7%**	**16.5%**	**0.15%**

Table 2. Campaign Post analysis

As shown the table 2, the top four customer ranks selected by propensity model perform well for both mailing group and control group. However, even though mailing/test group response rate was at decent level – 16.7%, our incremental response rate (mailing group net of control group) for combined top 4 ranks was only 0.15%. With such low incremental response rate, our undertaking would be likely generating a negative ROI.

What was the reason that our campaign shown such poor incremental results? The purchase propensity model did its job well and we did send an offer to people who were likely to make a purchase. Apparently, modeling based on expected purchase propensity is not always the right solution for a successful direct marking campaign. Since there was no increase in response rate over control group, we could have been contacting customers who would have bought our product without promotional direct mail. Customers in top ranks of purchase propensity model may not need a nudge or they are buying in response to a contact via other channels. If that is the case, the customers in the lower purchase propensity ranks would be more 'responsive' to a marketing contact.

We should be predicting incremental impact – additional purchases generated by a campaign, not purchases that would be made without the contact. Our marketing mailing can be substantially more cost efficient if we don't mail customers who are going to buy anyway.

Since customers very rarely use promo codes from catalogs or click on web display ads, it is difficult to identify undecided, swing customer based on the promotion codes or web display clickthroughs.

Net lift models predict which customer segments are likely to make a purchase ONLY if prompted by a marketing undertaking.

Purchasers from mailing group include customers that needed a nudge, however, all purchasers in the holdout/control group did not need our catalog to made their purchasing decision. All purchasers in the control group can be classified as 'need no contact'. Since we need a model that would separate 'need contact' purchasers from 'no contact' purchasers, the net lift models look at differences in purchasers in mailing (contact) group versus purchasers from control group.

In order to classify our customers into these groups we need mailing group and control group purchases results from

similar prior campaigns. If there are no comparable historic undertakings, we have to create a small scale trial before the main rollout.

All models described in this project used stepwise logistic regression on data partitioned into test and validation sets. All data prep work was done in base SAS ® and all modeling was done in SAS Enterprise Miner ®.

NET LIFT MODELING APPROACH – PROBABILITY DECOMPOSITION MODELS

Segments used in probability decomposition models:

	Contacted Group	Control Group
Purchasers prompted by contact	**A**	**D**
Purchasers not needing contact	**B**	**E**
NonPurchasers	**C**	**F**

Figure 2. Segments in probability decomposition models

Standard purchase propensity models are only capable of predicting all purchasers (combined segments A and B). The probability decomposition model predicts purchasers segments that need to be contacted (segment A) by leveraging two logistic regression models, as shown in the formula below [1].

$$P(A \mid AUBUC) = P(AUB \mid AUBUC) \times (2 - 1/P(AUB \mid AUBUE))$$

Probability of purchase prompted by contact	**Probability of purchase out of contact group**	**Probability of purchaser being in contact group out of all purchasers**

Summary of probability decomposition modeling process:

1. Build stepwise logistic regression purchase propensity model (M1) and record model score for every customer in a modeled population.

2. Use past campaign results or small scale trial campaign results to create a dataset with two equal size sections of purchasers from contact group and control group. Build a stepwise regression logistic model predicting which purchasers are from the contact group. The main task of this model will be to penalize the score of model built in the step 1 when purchaser is not likely to need contact.

3. Calculate net purchasers score based on probability decomposition formula

Results of the probability decomposition modeling process for floral marketing offer mailing at 1800Flowers.com.

Scoring Rank	Contact Group Response %	Control Group Response %	Incremental Response Rate
1	18.8%	12.9%	5.9%
2	7.8%	5.4%	2.4%
3	6.9%	4.5%	2.5%
4	4.3%	3.6%	0.7%
5	3.9%	3.5%	0.4%
6	4.1%	4.1%	0.0%
7	3.7%	4.0%	-0.2%
8	4.7%	4.1%	0.6%
9	5.0%	6.7%	-1.7%
10	11.0%	15.7%	-4.7%

Table 3. Post analysis of campaign leveraging probability decomposition model

Scoring Ranks 1 thru 6 show positive incremental response rates. The scoring ranks are ordered based on the incremental response rates.

CONCLUSION

The probability decomposition model is just one in a group of methods known as net lift models. The net lift models help maximize ROI of marketing campaigns as they let us avoid contacting customers or prospects who are highly likely to buy a product or service anyway. The traditional purchase propensity model may do a good job ranking customers based on their probability to make a purchase but it does not have the ability to select the true responders, the customers who will only make a purchase if contacted. The probability decomposition model has its challenges; it is relatively difficult to interpret as it combines scores of two separate model scores. Following is a list of conditions required for net lift model:

- presence of randomized control group

- analyzed marketing contact is not the only communication leading to purchase

- purchase rate is not correlated to lift, purchase propensity model is not sufficient

- presence of similar/repetitive marketing campaigns or small scale tests

- variation in average lift across scoring ranks

OTHER APPLICATIONS OF NET LIFT MODELS:

1. Businesses – customer attrition
2. Medical field – personalized treatment of patients

REFERENCES

1. Jun Zhong, VP Targeting and Analytics, Card Services Customer Marketing, Wells Fargo in the presentation: "Predictive Modeling & Today's Growing Data Challnges" at Predictive Analytics World in San Francisco, CA in 2009.

CONTACT INFORMATION

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