

Net lift and return maximization

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It was a dark and
stormy night...

afternoon



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Waynette Tubbs
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Dear Readers,

Today is the first day of [Predictive Analytics World](#) (PAW) in San Francisco. I hope you're there and your day is packed with presentations of the brightest minds talking about **advanced predictive analytic methods** including uplift modeling (net lift), text analytics, massively parallel analytics and in-cloud deployment. If you're not there, I should tell you that SAS is launching [SAS Text Analytics](#).

SAS is shipping [SAS Sentiment Analysis](#), [SAS Content Categorization](#), [SAS Ontology Management](#) and [SAS Text Miner](#) (SAS Text Miner 4.2 is now available). All draw on Teragram's natural language processing and linguistic technologies. This suite gives a more complete picture of the insights hidden in the text



Could I have been wrong all along...?

There has been recent mentions of a target selection (i.e.: case selection) technique referred to as *net lift*, *uplift*, *incremental response*, *differential response*, and possible other names.

When posed as a *return maximization* problem, net lift and the *usual* target selection practice coincide.

Net lift applies to target selection in situations with a binary treatment; *return maximization* provides direction on how to handle problems in situations with more than one treatment.

Problem statement

Given the following data:

- cases $P = \{1, \dots, n\}$,
- treatments $J = \{1, \dots, U\}$,
- expected return $R(i, t)$ for each case i and treatment t ,
- non-negative integers n_1, \dots, n_U such that

$$n_1 + \dots + n_U = n ;$$

find a treatment assignment

$$f : P \rightarrow J$$

so that the total return

$$\sum_{i=1}^n R_{if(i)}$$

is maximized, subject to the constraints that the number of cases assigned to treatment j is not to exceed n_j ($j = 1, \dots, U$).

Example 1: Mailing campaign

- P : a group of customers,
- two treatments:
 1. treatment 1: send a promotional coupon; R_{i1} is the expected return if a coupon is sent to customer i ,
 2. treatment 2: no coupon is sent; the expected return is zero: $R_{i2} = 0$

Solution to the maximization problem:

- assign treatment 1 to the customers with the n_1 largest values of R_{i1}
- assign treatment 2 to the remaining customers

This solution can also be derived from the Neyman-Pearson lemma.

Example 2: Marketing action case

- P : a group of customers,
- two treatments:
 1. treatment 1: exercise some marketing action;
 R_{i1} is the expected return if treatment 1 is given to customer i ,
 2. treatment 2: exercise no the marketing action;
let R_{i2} be the expected return if treatment 2 is given to customer i .

Solution to the maximization problem:

$$\begin{aligned}\sum_{i=1}^n R_{if(i)} &= \left(\sum_{i \in (f=1)} R_{i1} \right) + \left(\sum_{i \in (f=2)} R_{i2} \right) = \left(\sum_{i \in (f=1)} R_{i1} \right) + \left(\sum_{i=1}^n R_{i2} - \sum_{i \in (f=1)} R_{i2} \right) = \\ &= \left(\sum_{i \in (f=1)} R_{i1} - R_{i2} \right) + \left(\sum_{i=1}^n R_{i2} \right)\end{aligned}$$

The second sum does not involve f , so maximizing total return is equivalent to maximizing the first term

$$\sum_{i \in (f=1)} R_{i1} - R_{i2}$$

As for to the solution to Example 1, to attain the maximum return:

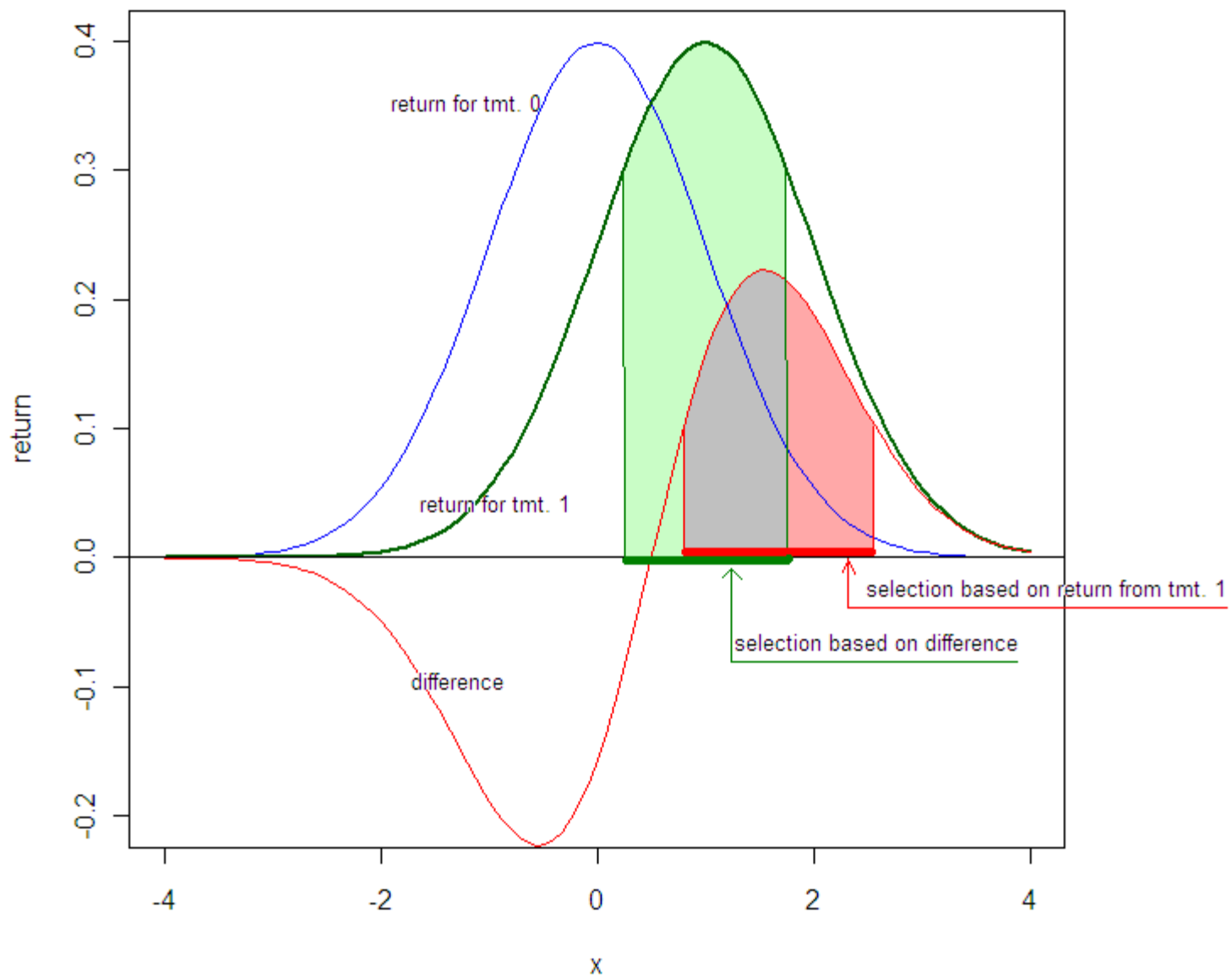
- assign treatment 1 to the customers with the n_1 largest values of $R_{i1} - R_{i2}$
- assign treatment 2 to the remaining customers

The difference $R_{i1} - R_{i2}$ is called *net lift*, *uplift*, *incremental response*, *differential response*, etc.

If one considers only the response to treatment 1, bases targeting on a model built out of responses to previous marketing actions, one is proceeding as if the situation were as in Example 1. One would mistakenly maximize

$$\sum_{i \in (f=1)} R_{i1}$$

Such maximization would not yield the maximum return. One needs to consider the return from cases subjected to no marketing action.



Example 3: A toy example

Consider the following toy example with a population of $n = 3$ cases, and $U = 3$ treatments, $n_1 = n_2 = n_3 = 1$ and returns:

Case	Treatment		
	1	2	3
1	9	15	7
2	13	18	11
3	6	7	3

Exercise: Show that the assignment that maximizes total return under the given constraints is:

Case	Assigned treatment	Return
1	2	15
2	3	11
3	1	6

Case	Treatment		
	1	2	3
1	9	15	7
2	13	18	11
3	6	7	3

Note that neither case 2 nor case 3 were assigned the treatment that maximize their return.

Case	Assigned treatment	Return
1	2	15
2	3	11
3	1	6

Although the possibility of a return of 18 exists, this possibility is not realized, since case 2 is not assigned treatment 2.

(In a case like this, one would probably advice that more resources be allocated to treatment 2, so that $n_2 > 1$.)

Example 4: General case

The problem can be cast as a standard integer linear programming problem. If we let

$$x_{ij} = \begin{cases} 1 & \text{if treatment } i \text{ is given to case } j \\ 0 & \text{otherwise} \end{cases}$$

then the problem can be written as:

$$\text{Maximize } \sum_{i=1}^n \sum_{j=1}^U R_{ij} x_{ij}$$

subject to the constraints:

$$\sum_{i=1}^n x_{ij} = n_j$$

$$\sum_{j=1}^U x_{ij} = 1 \quad \text{for } j = 1, \dots, U$$

$$x_{ij} = 0 \text{ or } 1 \quad \text{for } i = 1, \dots, n$$

Note:

In general, the best *assignment* that solves the linear programming problem does not vary continuously with the coefficients:

- small changes in the returns R_{ij} result in only small changes in the best total return,
- but: the assignment that yields the best return may vary considerably.

Example 5: A(n almost real) example and variation

Each week, a call centre is responsible for contacting a group of customers. The length n of the list is not fixed, but it does not vary much from week to week.

Based on what is known of the customers, and on historical observations, it is possible to estimate the expected probability of successfully contacting each customer at different combinations of time of the day and call type (“home” or “other”).

Un-adjusted probabilities of successful contact are not constant in time...

Rate	weekd					
	Mon	Tue	Wed	Thu	Fri	Sat
8	33.92	44.30	41.51	38.29	35.12	40.01
9	25.43	43.02	41.17	40.25	37.57	43.05
10	29.10	45.04	44.14	42.12	41.37	45.39
11	33.86	50.37	45.16	44.12	37.83	46.84
12	39.19	46.57	37.26	35.69	33.97	45.23
13	37.74	42.17	36.96	32.76	29.05	39.09
14	35.94	39.65	31.89	31.24	29.85	34.42
15	35.78	36.40	32.03	31.91	25.97	32.26
16	36.88	32.71	28.81	27.18	30.30	32.11
17	35.41	31.69	32.15	33.96	33.33	40.59
18	36.49	33.91	36.09	32.60	26.15	37.47
19	39.74	35.80	39.36	33.85	28.76	77.78

Problem: make a (calling time, weekday) assignment so that expected total number of contacts is maximized, subject to the constraint that the call centre capacity is limited.

Remarks:

- in general, we will only know an estimate of R_{ij} :

$$\hat{R}_{ij} = R_{ij} + \textit{remainder}_{ij}$$

which suggests that insisting on solving the full maximization problem is an over-kill

- in practice, proper call optimization is carried dynamically

A solution sketch:

- segment customers, including the probabilities of successful contact at different times as segmentation variables, so that the probability of contact is approximately constant for the segment
- solve the optimization problem for the fraction of each segment that has to be contacted at each time

Reference

Lo, Victor S.Y. The True Lift Model - A Novel Data Mining Approach to Response Modeling in Database Marketing, SIGKDD Explorations. Volume 4 (2002), Issue 2, pg 78-86

(February 16, 2010 fall during the Winter Olympics in Vancouver. The weather in the whole country was quite mild)