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WORKING PAPER

Assessing and exploiting the profit function by modeling the net impact of targeted marketing

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Abstract

The success of a direct marketing campaign is driven by the ability of companies to estimate customers' future contribution to their profitability. Especially when considering that in retailing companies are wasting resources when targeting customers who will make purchases even in case they would not receive a mailing. We present an advanced profit evaluation, which rates customers for the *net* impact of a campaign on their buying behavior. Moreover, in contrast to current practices and theory, we model each part of the profit function to improve the accuracy of expected customer value. We employ logistic regression and multiple linear regression to estimate future purchase probabilities and customer expenditures. Variables of different types are considered and a variable selection technique is used to avoid overfitting. To validate our findings, we implemented the method into the mailing system of a European retailer. Our results are of major importance for direct marketing managers, since they make the company's total profit increase by 5 per cent. This result can be attributed to both a reduction of the optimal mailing depth by 65 per cent, which shows that current procedures lead to systematic 'overmailing', and a modified ranking of the customers in the segmentation list.

1. INTRODUCTION

For many years marketers have recognized direct marketing as an effective and efficient way of communicating with customers. However, it seems that it has not yet reached the height of its power. Since the foundation of their Quarterly Business Review in 2002, the Direct Marketing Association (DMA) reported a positive expansion of the direct marketing industry for the sixth consecutive quarter (The Direct Marketing association 2004). The latest published figures of 2004 show a record growth index and direct marketers are expecting this trend to continue in 2005. Moreover, currently, more than 50 per cent of all advertisement expenditure is made on direct marketing.

Several reasons can be found to account for this continuing development. Most authors ascribe the progress to the constant reduction of data storage costs, the available amount of computing power and the rising number of software packages (Bult and Wansbeek 1995, Rossi et al. 1996, Bult 1993). These trends enable companies to collect more and more individual (detailed) customer data, so more well-founded decisions can be taken. In addition, and maybe even more important, companies are now more aware that by implementing these facilities and using innovative modeling techniques to improve customer relationships, profitability and sales increase (The Direct Marketing Association 2004). This growing awareness stimulates further research into better procedures and techniques.

It also explains why direct marketing has received the level of attention in customer relationship management (CRM) literature it has over the last decades.

Several studies have already tackled different aspects of direct marketing in order to optimize mailing strategies. Response modeling is a well known technique commonly used by direct marketing analysts (Desarbo and Ramaswamy 1994). It has proven to be a profitable tool in fine-tuning direct marketing strategies (Elsner et al. 2004) since even small improvements attributed to modeling can create great financial gains (Malthouse 1999).

Different elements define the success of a direct marketing campaign. Bult and Wansbeek (1995) consider the most important one to be the composition of the mailing list. Many authors confirm this hypothesis (Levin and Zahavi 2001, Bitran and Mondschein 1996, Bhattacharyya 1999). Bitran and Mondschein (1996, p. 1366), for example, put it this way:

> ”One of the most important decisions that a manager must make in the catalog sales industry is defining the mailing policy, i.e., which rental lists to employ and the fraction of the people in those lists that should receive a catalog”.

So, basically, such selection boils down to two major steps: first, for each customer, one has to define how useful it is to send him or her a mailing and, secondly, a meaningful cut off point needs to be set to determine the number of customers to be targeted (mailing depth). Evidently, all these steps have to be taken while keeping in mind the maximization of company profits (Bhattacharyya 1999).

A good many studies discussed one or both of the above mentioned steps. However, to the best of our knowledge, the currently proposed procedures are still open to improvement. Nearly all of the examined studies recognize the importance of profit functions to resolve their targeting challenge (step 1 and step 2). A profit function is applied to balance revenues and costs of a direct mailing to determine valuable targets (see next section). However, none of the studies is employing the possibilities of predictive modeling to substitute all of the elements in these functions. As a consequence, the solutions provided in these studies concerning steps 1 and 2, can still be optimized.

First, most studies only make use of purchase propensity and neglect the level of expenditures to determine customer value. Second, retailers are generating traffic by distributing catalogs to a subset of their customers. However, in several settings it is common that also customers who were not targeted make purchases. If a company wants to be efficient in its targeting, such customer behavior should be integrated into the profit function in order to optimize the justification of outgoing mailings: only the net effect of a marketing action on company profit should be considered. Throughout this paper, this last phenomenon is referred to as the ‘clearance’ of customer profit. Finally, the majority of direct mailing studies do not establish optimal mailing depth. All these shortcomings are considered crucial when companies aim to maximize profit. To the best of our knowledge, no such a study exists, which exploits the full potential of modeling each item of individual expected profit functions when defining both a customer list and the optimal mailing depth for direct marketing purposes. Moreover, no studies were found in which the profit function only accounts for the ‘net’ effect of sending a mailing.

This article is organized as follows: Section 2 reviews the existing literature concerning list segmentation, establishing mailing depth and cleared profits. We point to the existing gaps in direct marketing literature from which the contributions of this paper arise. Section 3 explains the methodology we applied and gives mathematical details of our models. Our real-life application is explained in Section 4. Section 5 considers the results and Section 6 ends this paper with conclusions, a discussion and issues for further research.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Profit function

The existing literature concerning direct marketing has shown a tremendous growth during the last decades. Many authors recognize the traditional procedure of composing a mailing selection: score and rank customers in accordance with their usefulness and choose the ideal depth of the target list. Regardless of the scoring technique used, the mathematical computation of the customers’ value involves the consideration of an expected profit function. An early article of Magidson (1988) about direct marketing already stated that, when one needs to define the depth of a mailing and profits are the purpose, a financial analysis should be performed by making use of the outputs of the scoring models. Bult (1993) makes this idea more concrete and states that only those people should be mailed whose expected contribution margin is higher than the cost of the mailing. These thoughts result in the following generally acknowledged individual profit function:

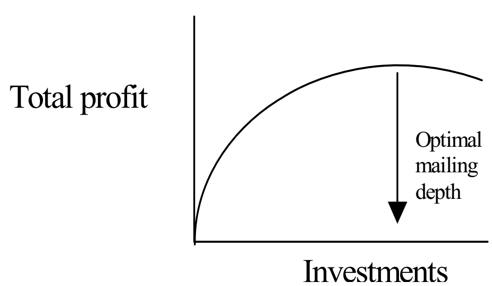
$$\pi_i = (R_i \cdot M) - C \qquad (1)$$

Where 'π_i' is the profit or the contribution of customer 'i', 'R_i' equals the individual revenue, 'M' is the general margin of the company and 'C' is the cost of sending the mailing. The customer's revenue can be subdivided (equation (2)):

$$\pi_i = ((E_i \cdot P_i) \cdot M) - C \tag{2}$$

In this profit function, 'P_i' is the customer's probability of purchasing and 'E_i' represents the customer's individual expenditures when a visit is made. If the profit is positive it is wise to put the particular customer in the mailing list. Consequently, if customers are ranked in accordance with the individual profit functions, management should invest in sending mailings up to the point of diminishing overall returns (Campbell et al. 2001) (see Figure 1).

Figure 1: Optimal mailing depth curve



The better the expected probabilities and expenditures reflect customers' 'real' behavior, the better customers can be ranked according to their contribution and the better the optimal mailing depth point can be defined. Most of the studies, however, only made use of predictive models to define the propensity of purchasing (P_i) (Gönül et al. 2000, Hansotia and Rukstales 2002, Gönül and Shi 1998, Bult and Wansbeek 1995, Muus et al. 1996, Bult 1993, Bauer 1988, Magidson 1988). Whereas the assessment of individual customer expenditures (E_i) is just as crucial to get a more accurate expectation of customers' profit. More specifically, some studies totally ignore the expenses (E_i) in the profit function so no meaningful evaluation can be made concerning expected revenues and the cut off point in the target list must be set arbitrary or is defined by budget constraints (Gönül et al. 2000, Bhattacharyya 1999, Bult 1993, Bauer 1988, Magidson 1988, Prinzie and Van den Poel 2005). Other studies include an average expenditure that is calculated across all customers (Elsner et al. 2004, Gönül and Shi 1998, Bult and Wansbeek 1995, Muus et al. 1996). Still, an average does not reflect the variance of the purchase levels across customers. Furthermore, Bult and Wansbeek (1995) underline the inclusion of heterogeneity in customer returns in their issues for future research. A few studies do make predictions of customers' expenses. But only the study of Campbell et al. (2001) uses this information to complete all parts of the profit function and to define the depth of their mailing. Bhattacharyya (1999) who uses genetic algorithms to model profit is restricted to budget constraints while Malthouse (1999) who applies ridge regression does not use this information to accomplish step 2, establishing mailing depth.

2.2 Cleared profits

We want to stress that the most prevalent objective of direct marketing procedures is to increase cost efficiency by precluding superfluousness of mailings being sent (Elsner et al. 2004). Certainly in retail settings, customers are able to make purchases even if they did not receive a mailing or catalog. So targeting such customers is a waste and higher profits can be achieved when these customers can be left out of the target list. This study proposes to extend the profit function (2) to take such behavior into account by including the purchase probability and the expected expenditure in case an individual does not receive a mailing. That way, the expected profit is discounted in accordance with the propensity of purchasing and the related expenditures of each individual when (s)he is not being mailed. This addition is valuable to the extent that customers are able to make purchases without being targeted. Only a few recent direct marketing studies did cover compensations for such kind of customer behavior. Gönül, Kim and Shi (2000) use a ratio of two hazard function models in order to decrease similar wasteful mailings. However, they do not consider heterogeneity of expenditures across customers. Furthermore, they make no distinction between the spending level of mailed and not mailed customers, whereas we expect the spending of mailed customers to differ from the spending of customers who did not receive a catalog. Hansotia and Rukstales (2002) calculated individual net incremental expected profits but also focused on purchase propensity only and did not take into account expected revenue. These studies point to the importance of compensating for customer behavior when no treatment is performed (the term 'treatment' is used throughout this paper to indicate that a catalog is sent to the customer). However, none of them fully exploit the elements of the profit function.

A summary of the literature shows that none of the present studies makes use of a profit function where: a) both purchase propensity and expected revenue are substituted by means of individual prediction models; b) customers' contribution is discounted for their behavior in case no treatment would occur. In contrast, we are convinced that these shortcomings have a serious impact on the customer ranking (step 1) and on the optimal depth of mailing (step 2), whereas both steps are considered to be among the most important in direct mailing strategies. These gaps can be checked in Table 1, which gives an overview of the studies cited. It is not our intention to give an exhaustive overview of all previous work in the area of direct marketing. To reduce the number of references, this table focuses only on studies that explicitly considered a procedure to define optimal mailing depths, modeled customer expenditures or considered some kind of profit clearance. It shows which techniques were applied for each of the predictive models and how the results were evaluated. The table highlights the contributions of this paper.

Our study adds to the existing literature in a number of ways. We propose a profit function in which individuals are evaluated depending on the 'net' effect of a mailing. Besides, we are the first to substitute each item of such an advanced profit function, which implies that we use four different predictive models. The contributions of using individual predictions instead of substituting average expenses are shown. Two different predictive techniques are analyzed: multiple regression and logistic regression. A variable selection technique is used to overcome overfitting problems. In addition, for each of the response models we detect the most important predictors in order to define what customer behavior is essential when making purchase predictions with and without sending a mail. Finally, to evaluate the results, we implemented our findings in a real-life experiment where we were able to manipulate an entire mailing stream of a collaborating company.

Table 1: Literature review

Author	Techniques				Evaluation level
	Prediction probability (treatment)	Prediction expenses (treatment)	Prediction probability (no treatment)	Prediction expenses (no treatment)	estimation/ validation/ field test
Bhattacharyya (1999)	-	genetic algorithm	-	-	estimation/validation
Bult and Wansbeek (1995)	CHAID, logit, profit max., semiparam. method	-	-	-	estimation/validation
Campbell, Erdahl, et al. (2001)	regression and linear programming	regression	-	-	field test
Elsner, Kraft and Huchzermeier (2004)	markov-chain, CHAID	-	-	-	field test
Gönul, Kim and Shi (2000)	proportional hazard function	-	ratio of hazards	-	estimation/validation
Gönül and Shi (1998)	algorithm of probits	-	-	-	estimation
Hansotia and Rukstales (2002)	logit, CHAID	-	profit function	-	estimation/validation
Malthouse (1999)	-	ridge regression	-	-	estimation/validation
Muus, Van der Scheer and Wansbeek (1996)	Bayes (normal posterior, laplace, MCMC)	-	-	-	estimation/validation
This study	logit	regression	logit	regression	estimation/validation/field test

3. METHODOLOGY

3.1 Profit function

The proposed optimization of direct mailing campaigns comes down to an adaptation of a customer's expected profit function (2) by taking into account purchase probabilities and expected expenditures with and without treatment. So, we need for each customer two different probabilities and two different expenditures. P_i^m, being the purchase propensity after receiving a catalog; P_i^n, being the purchase propensity if no catalog is received; E_i^m, the expenditures when the individual receives a mailing and makes purchases and E_i^n, the expenditures when the individual receives no mailing but does make purchases. Such a decomposition of company revenue can also be found in a recent study by van Heerde and Bijmolt (2005). Since we want to maximize the profitability of our entire customer base, the mathematical representation of our decision problem becomes:

$$Max\sum_{i=1}^{n}\left[((E_i^{\,m}\cdot P_i^{\,m})\cdot M)\cdot x_i-(C\cdot x_i)+((E_i^{\,n}\cdot P_i^{\,n})\cdot M)\cdot(1-x_i)\right] \qquad (3)$$

$$\sum_{i=1}^{n}x_i\le T \qquad (4)$$

where:

n represents the number of customers in the database

$E_i^{m/n}\cdot P_i^{m/n}$ represents the expected revenues of customer i given mail (m) or no mail (n)

M is the general margin of the company

C is the cost of sending one mailing

x_i represents the decision whether or not to mail to customer *I*

T represents the total number of customers to be mailed

Equation (4) represents the budget constraint. Rewriting equation (3) of this maximization problem indicates that we need to consider the difference between customer contribution generated if treatment occurs and their contribution in case no treatment takes place. Which means that this complex maximization problem can be simplified to:

$$Max\sum_{i=1}^{n}\left[(((E_i^{\;m}\cdot P_i^{\;m})-(E_i^{\;n}\cdot P_i^{\;n}))\cdot M)\cdot x_i-(C\cdot x_i)+((E_i^{\;n}\cdot P_i^{\;n})\cdot M)\right] \qquad (5)$$

The first part of this equation represents the net contribution by sending the mailing. The last part accounts for the regular purchase behavior of customers in case no action occurs. The individual profit function then becomes:

$$\pi_i = (((E_i^{m} \cdot P_i^{m}) - (E_i^{n} \cdot P_i^{n})) \cdot M) - C \qquad (6)$$

We emphasize the importance of estimating all the items of the profit function. This entails that four different predictive models are required to get accurate individual expectations about profit generated by customers.

3.2 Model techniques

For the execution of the different predictions in equations (5) and (6), we need binary classification models to predict the individual purchase probabilities and regression models to estimate the expenditures.

Several studies support the use of logistic regression to analyze the probability of an event. It is a commonly used nonlinear technique, which has shown to perform very well in database marketing (Bult 1993, Zahavi and Levin 1997, Magidson 1988) and is used to explain discrete customer choice behavior (purchase or no-purchase). Other studies have pointed to the dominant position which logistic regression has compared to other techniques (Baesens et al. 2003). Finally, the output of a logistic regression can easily be transformed into a probability between 0 and 1, which is a requirement for incorporation in our advanced profit function. For more details about logistic regression, we refer to Anderson (1982).

For estimating customers' expenditure we make use of another commonly used technique: multiple linear regression. This technique has been discussed widely in many studies and therefore will not be handled in detail in this paper (Cohen and Cohen 2003). Moreover, it is already being used in other targeted marketing studies to assess customers' expenditure (Campbell et al. 2001).

3.3 Variable selection and performances

Many studies show the relevance of using a variable selection technique and determine the selection of input variables as a critical step in response modeling (Ha et al. 2004). Overfitting to the estimation data is a well-known problem in predictive modeling (Bhattacharyya 1999) and is our main reason to apply feature selection. This issue becomes even more important when a large number of predictors is used so the model becomes more complex (Ha et al. 2004), which entails that for such a complex model the performance on the estimation data can be misleading and performance may decrease dramatically on the validation data.

Backward selection and forward selection procedures are probably the most well-known selection techniques. However, these techniques often fail to select the best performing model due to their linear selection procedure. Therefore, we make use of the global score algorithm proposed by Furnival and Wilson (1974). This technique selects the best predictors in accordance with the score chi-square statistic. The branch and bound algorithm avoids performing a complete search of the variable space, being the set of all possible variable combinations, and consequently computation time is reduced.

The performance of the binary models is evaluated by the area under the receiver operating characteristic curve (AUC), which is a widely accepted criterion since it evaluates the ranking for different thresholds (Ha et al. 2004). The continuous models are evaluated by the R^2, the adjusted R^2 and the RMSE thresholds.

4. EMPIRICAL STUDY AND REAL-LIFE TEST

4.1 Data

For our empirical study we collaborated with a European retailer selling both products that are offered in grocery shops (food, beverages, cosmetics,…), as well as general merchandise products (electronics, apparel, do-it-yourself,…). In the remainder of this study, the first category of products is called the ‘food’ category and the second category is called the ‘non food’ category. Since the use of a member card is mandatory to purchase at the store, we are ensured to have information on buying patterns for food or non-food products for all customers of the company (over 1 million). The data delivered were very elaborate and contained customer demographics, ticket-line purchase information and information concerning past mailing actions. It was tracked at the individual customer level during more than five years: from July 1999 till March 2005 and concerned all of their outlets.

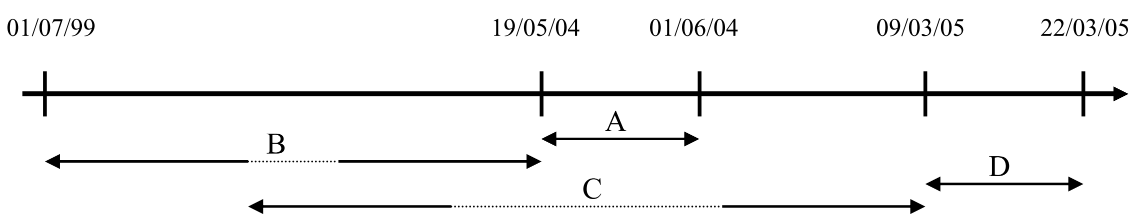
4.2 Real-life test for the usefulness of cleared profits

The encouraging results of the models (see results in Section 5), convinced our collaborating company to perform a real-life test, so we could validate our results in a subsequent mailing period. The purpose of this test was to find out whether or not the inclusion of cleared profits into the profit function leads to a reduction of the optimal number of mails and higher profits can be achieved by saving catalog costs. So, during one mailing period two sets of randomly chosen clients (two times 9898 clients) were put at our disposal for which we could manipulate the entire mailing list. One set of customers was treated by using a profit function that does not take into account the cleared profits (profit function (2)), while for the other set customers’ expected purchase probability and expenses were compensated for their behavior when no catalog would be sent (profit function (6)). For both samples, the optimal mailing depth was defined by considering the point of diminishing overall returns (Figure 1). The resulting number of customers was sent a catalog. Traditionally, the performance of models used for direct marketing purposes is evaluated by comparing the response rate of the customers being mailed (Haughton and Oulabi 1993) or by the percentage of observations that are correctly classified (Bult 1993). In our case, however, the goal is to eliminate customers from the target list who would shop even without receiving a mailing. So, it is important to include the response of the customers who are not mailed. The evaluation of the real-life test is done by considering the response rate and total profit generated by all 9898 customers, in each of the manipulated sets.

4.3 Random Samples

As our profit function indicates, we need four different models in order to substitute each of the function's parameters. Typically, these models have to be estimated based on randomly drawn data from the complete customer base (Bult 1993). So, to build our models, the company mailed a random selection of customers in order to model behavior after treatment. And, to model customer behavior without treatment, the retailer left out of her mailing list, by design, a randomly chosen set of 15,540 customers. In all our models, fifty per cent of the available data were used for estimation and twenty-five per cent was used in the test and the validation sets. Figure 2 shows which data are used to build the four models and to test them in real-life.

Figure 2: Periods of observation for independent and dependent variables



Part A represents the company's mailing period of two weeks that was used to compute the dependent variables (buying or not buying and the expenditures customers made) for the estimation of the models. Thereby, we aggregated all expenditures made during these two weeks. Part B covers the time period used to compute the independent variables for all model estimations. Next, all transactional data during time period C were used to compute independent variables for our real-life test and, finally, customers' behavior in period D is used to compute the real-life results.

Table 2 shows an overview of customer behavior in each of the four estimation sets that were used in each of the different models. It reports the size of the data sets and indicates the response rate and the average spending levels for the probability and the expenditure models respectively.

Table 2: Customer behavior with or without treatment on the estimation set

Model		Case	
		With treatment	*Without treatment*
Purchase probability	Number of customers in estimation set	370,616	7,770
	Response rate	30.82%	18.40%
Expenditures	Number of customers in estimation set	114,236	1,430
	Average Spending during visit	€ 162	€ 144

As we expected, the response rate and the spending of customers that received a catalog exceed the one of customers without treatment. These data make it possible to decompose the effect of a promotional action, by analogy with van Heerde and Bijmolt (2005). Namely, the change in total revenue can be attributed to increased customer spending and an enhanced number of customers that visited one of the stores (response rate).

4.4 Variables

The quantity of data delivered by the retailer is extensive. As a result, we could calculate an elaborate set of predictors, which are used in both the models that explain purchase propensities as well as the models that predict customers' expenditure. In total 68 explanatory variables were computed. Appendices 1 and 2 summarize the input, together with a brief description of how they are calculated, based on demographic data, individual purchase history and mailing information. Rossi et al. (1996) pointed to the enormous potential of making use of household purchase histories for direct marketing models. The estimate results are also reported in this table but will be discussed in a next section of this paper. The variable set can be subdivided into different types.

The first type of variables are RFM related predictors. There exists virtually no study dealing with direct marketing strategies that does not include one or more of these widely known variables. Recency, frequency and the amount purchased are all considered to be effective predictors for future purchase behavior. Bauer (1988) made clear assumptions about the signs of the estimates of these variables. Both the frequency of purchasing and the amount of money spent will increase the likelihood of future purchasing while a higher recency might be the indication of lower purchase chances. However, this last assumption might only be true in case of fast moving consumer goods. Other studies indicate that for durables, for example, the response rate might increase with the recency (Bitran and Mondschein 1996). Therefore we included different operationalizations of these variables. First, all RFM variables are calculated using the entire purchasing data. Furthermore, the same variables, except for one, are calculated by considering purchases done in the food category and the non food category separately. Since no agreement exists on how these predictors have to be measured (Bauer 1988) and Heilman et al. stress the importance of choosing the right amount of data that needs to be incorporated (2003), we used several measuring methods for these predictors. The spending and frequency variables are measured by using the entire purchase history, the last two years, the last year, the last six months, the last month and the last two weeks of data. Next to the typical recency variables concerning all purchases (Recency), purchases in the food category (Frecency) and purchases in the non food category (Nfrecency), we also included the average number of days between customers' purchases, being the interpurchase time (Ipt, F_ipt and NF_ipt). Since the time window of the estimated models had to be observed, for some customers no information was available to compute recency related variables. The dummies FRec_dum and NFRec_dum compensated for these cases. Finally, we also included some relative figures: the average spending (rSpend_freq, rFSpend_freq and rNFSpend_freq) and the amount spent relative to the length of customer's relationship (rSpend_lor, rFspend_lor and rNFSpend_lor).

Bhattacharyya (1999) indicated that the response to previous mailings might contain interesting information for future purchasing behavior. Consequently, we included the percentage of times someone went to the shop when (s)he received a mailing (PercResp_Leaf). We also add the percentage of times a customer made a visit when (s)he was not in the target list (PercResp_Noleaf). Besides, we measured how many times an individual came to the store more than once during one and the same mailing period, since we expect that customers who are very likely to come to the store without having received a mailing will come regardless of the existing mailing periods (Morethanonce). Finally, a relative measure of this last variable (Perc_morethanonce) and a dummy to indicate whether or not sufficient data were available to compute the mailing-related variables for a customer (Respdum), were added to the models.

Several studies have considered the use of returned goods to express the strength of a relationship (Reinartz and Kumar 2002, Buckinx and Van den Poel 2005). That is why the total value of returned goods and the total value of returned empty bottles were worked out (Retour, Amount_deposit). Finally, we included several demographics. The availability of most of this information was dependent on the voluntariness of the customer at his or her registration. We assume that customers who provide more demographic information, have a more positive attitude towards the company and therefore have a higher purchase propensity. That is why we added as an input category whether or not customers provided their fax number, phone number or e-mail (Fax_dum, Phone_dum, Email_dum). Furthermore, some customers have more than one customer card, which might indicate a more intense relationship (Cardholders_dum). We also included the distance between the customer's residence and the nearest store as a predictor in the model (Distance) and we included whether customers are living in a house or a flat (Box_dum). Further, customers who also purchase products for a company, might have different purchase intentions or quantities (VAT_dum) and in order to incorporate geodemographics we included the native language of a customer (Language_dum). Magidson (Magidson 1988), finally, points to the importance of the length of customer's relationship with the firm (Lor).

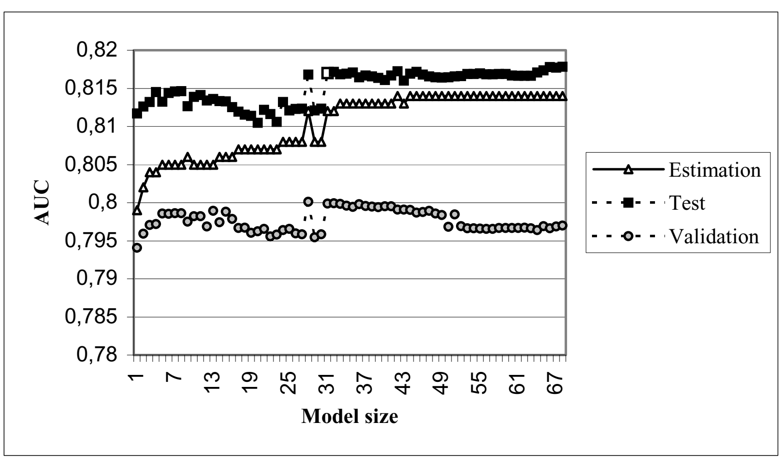
5. RESULTS

5.1 Model Performance

5.1.1 Variable selection

For the multiple linear regressions and the logistic regressions, we applied a variable selection procedure to avoid overfitting and to ensure optimal predictive performance. Our dataset was split in three parts: an estimation set was used to estimate the models, a hold-out test set was used to make an appropriate model choice with the feature selection procedure and a hold-out validation set was kept to check for the resulting predictive performance. The optimal model size was defined by selecting the smallest model size whose performance did not significantly differ from the performance of the model with the best performance. We illustrate this selection procedure for one of the four models. Figure 3 shows the performance on the estimation, test and validation set for the prediction of purchase probability without treatment. The model with the best performance on the test set (highest AUC) was the model with size 68. However, all models with a model size larger than 30 show a performance that is not significantly different (Delong et al. 1988) from the one with 68 variables, so

Figure 3: Feature selection, purchase probability without treatment



model ‘31’ was chosen as the optimal model since it is the one with the lowest number of predictors (see white colored square within the test performances). Such subset selection was done for all models. The optimal model size for the prediction of purchase propensity after receiving a catalog is twenty-two. For the prediction of expenses with treatment the most favorable size is one variable and for the determination of expected expenses without treatment the best number of variables to use is two. Appendices 1 and 2 give an overview of these final models together with the standardized parameter estimates of the variables. The tables also present the univariate standardized parameter estimates of all the variables. These results can be used for the interpretation of the relevance of the different predictors whereas the multivariate results show which variable set presents the best predictive performance.

5.1.2 Predictive performance

This section describes the predictive power of the different models. Table 3 is divided in four subparts and demonstrates for each model the performance of either the multiple regression or the logistic regression, dependent on the type of the model. We compare the results of the *full* model – being the model that incorporates all 68 predictors – with the results of the *final* model – being the model that remains after the subset-selection procedure.

The evaluation shows that we obtained acceptable results for all of the models: all of them exhibited a significance level below 0.0001. Concerning the prediction of purchase probabilities, the logit models did not show an overfitting problem. The performances on the full model are very comparable to the ones on the final model. Apparently, the predictive accuracy of someone’s visit propensity in case (s)he did not receive a catalog is remarkably better than the one of the model that predicts the visiting behavior when someone did receive a catalog. In both cases, the power of the models exceeds the 0.5 benchmark of the null model.

In contrast, the models that predict customers' expenses do signal overfitting difficulties. For both models, the adjusted R^2 of the full models are considerably lower than the ones of the final models. In other words, the predictive performance of our models increases by selecting the relevant predictors, which supports the application of our model selection technique. And again, considering the results, the prediction of the expenditures when no catalog was sent leads to superior results compared to the case where customers received a catalog.

Table 3: Model performance

Table A: Purchase probability with catalog

	Logistic regression	
	Full model	Final model (v=22)
AUC	0.7368	0.7367

Table C: Purchase probability without catalog

	Logistic regression	
	Full model	Final model (v=31)
AUC	0.7970	0.7999

Table B: Expected expenses with catalog

	Multiple linear regression	
	Full model	Final model (v=1)
R^2	0.0046	0.2026
Adj R^2	0.0035	0.2026
RMSE	579.0103	297.9283

Table D: Expected expenses without catalog

	Multiple linear regression	
	Full model	Final model (v=2)
R^2	0.2760	0.3769
Adj R^2	0.2027	0.3752
RMSE	202.3815	179.8794

As mentioned in the literature section, in previous studies it was a rare practice to model customers' expenditures as input for the profit function. Additionally, the prediction of expenditures when no catalog was sent was never done before. Instead, in previous studies, the expected expenses in the profit functions were mostly substituted with the average past expenses across all customers and sometimes by the average spending of a customer. Table 4 and 5 show the R^2 and the adjusted R^2 in case one would use the average past expenditures per customer to approximate expected expenditures. The performance of the averages is lower than the ones of our models (see Table 3, B and D), which supports the necessity of modeling all aspects of the profit function.

Table 4: Expected expenses with treatment, model fit of past individual average expenses

	Model fit
R^2	0.1768
Adjusted R^2	0.1768

Table 5: Expected expenses without treatment, model fit of past individual average expenses

	Model fit
R^2	0.3689
Adjusted R^2	0.3681

5.1.3 Variable Importance

The univariate standardized parameter estimates indicate which variables are most important for each of the predictions. To model purchase propensities, virtually all variable types are relevant. More specifically, demographic variables have the lowest standardized estimates whereas variables related to the return of goods and recency related variables have the highest estimates for the prediction of purchase probabilities with treatment, and purchase propensity without treatment respectively. In contrast, more distinctions can be made between the predictors when explaining the purchase amounts. Here, variables related to customers' overall spending, spending in the food category and relative spending variables have the most notable standardized estimates. Remarkably, frequency-related variables, recency-related variables and variables concerning past mailings have lower estimates compared to the predictions of purchase probabilities. Again, demographics are among the ones with the slightest relevance. These results confirm the findings of Gupta (1988). His study showed that most of the variation in the purchase quantity is accounted for by customers' average past purchase quantity. In addition, again similar to our hypotheses, interpurchase time did not show up to be an important predictor in his model.

5.2 Real-life test

5.2.1 Expected results

We were able to implement our proposed procedure during one of the mailing periods of the European retailer. In this real-life test, the proposed profit function (6) was used to define the optimal mailing depth and the resulting target list. As a benchmark, the traditional profit function (2) was used for another (similar) set of customers. In both cases customers were ranked based on the result of their individual profit function (step 1). The components of these functions were substituted by the outcomes of the multiple linear regressions and the logistic regressions.

Figure 4: Optimal mailing depth, profit function (2)

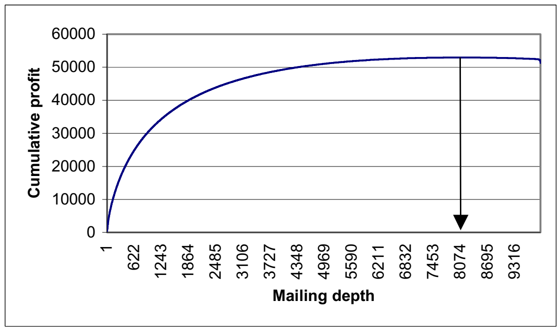
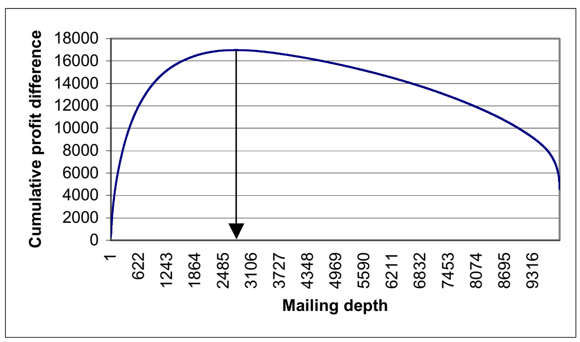


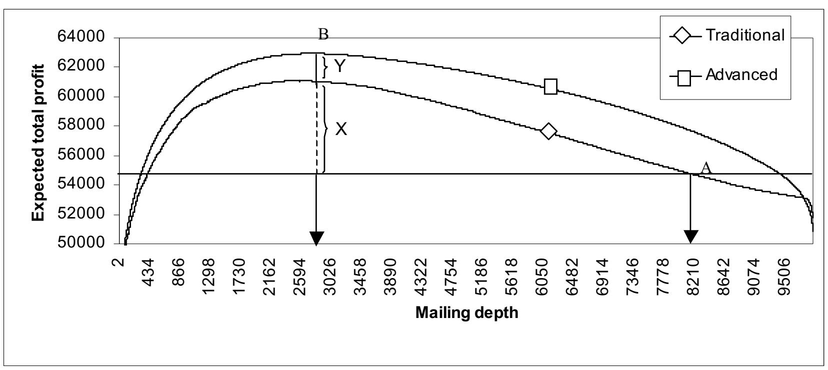
Figure 5: Optimal mailing depth, profit function (6)



Figures 4 and 5 show the optimal mailing depth (step 2) - being the maximum of the accumulated outcomes of the profit functions - for our proposed model and the benchmark model respectively. These results show that indeed far fewer customers need to be mailed when we incorporate cleared profits. The optimal number of clients that had to be mailed – on a total of 9,898 clients in each test case - was 2,761 (Figure 5) for the advanced profit function and 8,094 for the traditional approach (Figure 4).

In addition, we can define the expected profit difference between each of the customer bases. Therefore, it is not sufficient to compare the resulting profits in Figure 4 and Figure 5 since the first one reports the total profit and the second figure reports the net impact on the profit (cleared profits). Recall that in our case it is not adequate to consider the revenue of the customers being mailed. We need the expected profits of the entire customer base since our intention is to consciously leave certain customers out of the target list. So, the total profit is the profit generated by all mailed and all not mailed customers. For each customer we can calculate his/her expected individual profit contribution given that (s)he is mailed and given that (s)he is not mailed, which results, after accumulation in the total expected profits. Further, instead of reporting the expected profits for both selected mailing depths (8,094 and 2,761 customers), we show the expected profits for all mailing depths in each of the two cases (see Figure 6). Both curves do not start at the origin. This can be attributed to the profit that all clients are expected to generate in case none of them receives a catalog.

Figure 6: Attribution of profit difference to mailing depth and ranking changes



Secondly, the figure shows that defining target lists based on the advanced profit function is beneficial at each mailing depth. Moreover, when considering that the test involves less than 1 per cent of the total customer database, the expected profit difference between the advanced and the traditional method is substantial: 62,939 euros (point B) versus 54,840 euros (point A). Moreover, the curves show that the optimal mailing depth of the advanced method indeed guarantees the optimal profit level. Whereas this is not the case for the traditional procedure.

Finally, it is clear that the profit difference between the two approaches can be attributed to a) the savings made by reducing the mailing cost, and b) the alternative ranking of the customers in the segmentation list. This is shown in Figure 6 where the total profit difference between point A and B can be split in part X (attribution a) and Y (attribution b) respectively.

5.2.2 After implementation

To check whether these expectations hold in a real-life environment, the optimal number of mailings, according to each method were distributed to the respective customer sets. Table 6 shows the results of both systems.

The results of our real-life test confirm the expectations: the figures prove that our advanced method indeed generates more profit than the traditional method. The customers in the set of the traditional procedure, generate more revenue in total, but, since their total mailing cost is significantly higher, the remaining profit, after considering margin and mailing costs, is 2,151 euros lower. An extrapolation to the total customer base yields more than 200,000 euros per mailing, being an increase of the total company profitability of five per cent.

Table 6: Results of real-life test, traditional and advanced profit function methods

	Traditional	Advanced
Number of customers	9,898	9,898
Number of mailings sent	8,094	2,761
Total Revenue by all clients	€ 332,997	€ 317,117
Mailing costs	€ 6,880	€ 2,347
Profit[1]	€ 43,070	€ 45,221
Response rate mailed (%)	2,043 (25.24%)	1,042 (37.74%)
Response rate not mailed (%)	94 (5.21%)	1,017 (14.25 %)

[1] Considering a profit margin of 15 per cent.

6. DISCUSSION AND EXTENSIONS

The success of a direct marketing campaign depends on how a company is able to define customers' value and to what extent it can determine the optimal size of its target list. Both these decisions are considered to be the most important steps for direct marketing management and are driven by the profit function applied.

We propose a new direct mailing method, which makes use of a more advanced profit function that values customers based on the net effect of companies' targeting actions. This seems appropriate since in retail settings customers are able to make purchases even if they do not receive a mailing. In addition, we are the first to use individual predictive models to substitute each item of this elaborate function. The degree to which expected purchase probabilities and expected expenses correspond to real behavior has a direct impact on the significance of the profit function and therefore on the success of the selection method. By accounting for customers' cleared profits and providing a more reliable approximation of probabilities and expenses, we present an improved mailing method that selects customers who need a stimulus to make purchases and disregards customers who will buy anyhow.

We used logistic regression and multiple linear regression to estimate the purchase probability and the expenses in case a customer is treated and in case a customer is not being treated. Sixty-eight predictors of different types were used as explanatory variables. All the models show valid prediction performance. The individual prediction of expected expenses has a better fit with customers' real expenses compared to the use of past average expenses. Moreover, the amount spent with treatment differs from the expenses without treatment. This demonstrates the contribution of applying modeling techniques for all items of the profit function. A feature-selection procedure, based on the algorithm of Furnival and Wilson (1974), chooses the optimal number of inputs for each of the models. The results show that mainly the predictions of future expenses experience overfitting problems, for which variable selection demonstrates its usefulness. For the prediction of purchase propensities almost every variable type is of relevance. In contrast, the modeling of customers' expenses is mainly explained by spending-related variables.

Most interestingly, in collaboration with a European retailer, we implemented the method presented in this paper in a real-life environment. The results show that companies, whose customers have the possibility to make purchases without being treated, are sending too many mailings when applying traditional profit functions for customer evaluation. The use of our advanced profit function causes a substantial reduction in the number of mailings that need to be sent, while the total profit increases significantly. This can be attributed to the elimination of customers from the mailing list, who make purchases regardless of whether they receive a catalog. Moreover, our results show that the profit difference can be credited to both the reduction of the number of mailings and to changing the order of the customers in the segmentation list. Additionally, the expected profit curves across all mailing depths indicate that this profit difference exists at each mailing size. Consequently, even if the optimal number of customers cannot be targeted, for example, due to budgetary constraints, or if the company wants to mail more customers than the optimal mailing depth suggests, it is more profitable to use the advanced profit function to compose the customer ranking. To conclude, these findings are particularly interesting for marketing management since with the proposed method, higher profits can be generated with lower marketing expenditure. Furthermore, applying the advanced profit function causes substantial changes in the profile of the customers being targeted. Whereas traditional approaches typically target the 'best' customers, our method focuses on customers who need to be stimulated the most. That way, less 'promising' clients are also in the target list which means they are reactivated and shrinkage of the active customer base over time might be avoided (Elsner et al. 2004).

This study is not without limitations. In our case, customers are able to shop regardless of the treatment they received, which is common practice for traditional store retailers. The inclusion of cleared profits in the profit function gains importance to the extent that customers who are not targeted generate sales. In a mail-order setting where catalogs are distributed with constantly changing catalog content, for example, it is rather impossible to make purchases if no mailing is received. Further research needs to investigate the contributions of the advanced profit function in other settings, which use direct marketing to stimulate purchase behavior.

The power of the models has a direct influence on the predictive performance of the profit function and is therefore crucial for the entire mailing strategy. So, the use of modeling techniques with a predictive ability that outperforms the ones presented in this study will result in increased accuracy, better customer ranking and higher profits. The inclusion of other relevant explanatory variables might increase the performance of the models as well.

In our method, customer value is evaluated based on their contribution during a single mailing. Some studies, however, suggest that customers' profits need to be maximized over a longer period, including more than one mailing (Jonker et al. 2004, Bitran and Mondschein 1996). So, the inclusion of the advanced profit function into such methodologies is worth investigating.

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Appendices

Appendix 1: Description and standardized parameter estimates for multivariate and univariate models of purchase probabilities

Variable	Description	Models: Purchase with treatment		Purchase without treatment	
		Multivariate	Univariate	Multivariate	Univariate
Frequency	Number of purchases in total history.	0.0464 ***	0.4840 ***		0.5093 ***
Frequency_2Y	Number of purchases during last two years.	-0.2578 ***	0.5605 ***	-0.1344	0.5839 ***
Frequency_1Y	Number of purchases during last year.	0.2108 ***	0.5803 ***	0.2552 ***	0.6081 ***
Frequency_6M	Number of purchases during last six months.	0.0400 ***	0.5500 ***		0.5779 ***
Frequency_1M	Number of purchases during last month.	0.0291 ***	0.3448 ***		0.4147 ***
Frequency_2W	Number of purchases during last two weeks.		0.2228 ***		0.2612 ***
FFrequency	Number of purchases in total history in food category.	-0.0277 ***	0.4395 ***	0.0688	0.4492 ***
FFrequency_2Y	Number of purchases during last two years in food category.		0.5143 ***		0.5159 ***
FFrequency_1Y	Number of purchases during last year in food category.		0.5363 ***	-0.1260 **	0.5361 ***
FFrequency_6M	Number of purchases during last six months in food category.	0.0516 ***	0.5116 ***		0.5174 ***
FFrequency_1M	Number of purchases during last month in food category.		0.3160 ***		0.3709 ***
FFrequency_2W	Number of purchases during last two weeks in food category.		0.1984 ***	0.0324	0.2308 ***
NFFrequency	Number of purchases in total history in non food category.		0.4342 ***		0.4926 ***
NFFrequency_2Y	Number of purchases during last two years in non food category.	0.0811 ***	0.4836 ***	0.0310	0.5470 ***
NFFrequency_1Y	Number of purchases during last year in non food category.		0.4866 ***		0.5553 ***
NFFrequency_6M	Number of purchases during last six months in non food category.		0.4522 ***		0.5227 ***
NFFrequency_1M	Number of purchases during last month in non food category.		0.2686 ***	0.0584 **	0.3525 ***
NFFrequency_2W	Number of purchases during last two weeks in non food category.		0.1759 ***	-0.0422 *	0.2146 ***
Spending	Spending in total history.	-0.0494 ***	0.5944 ***		0.4311 ***
Spending_2Y	Spending in last 2 years.		0.7064 ***	10.9362 **	0.5123 ***
Spending_1Y	Spending in last year.		0.6666 ***		0.5104 ***
Spending_6M	Spending in last 6 months.	0.0978 ***	0.6027 ***		0.5003 ***
Spending_1M	Spending in last month.		0.2923 ***		0.3164 ***
Spending_2W	Spending in last 2 weeks.	0.0225 ***	0.1953 ***		0.2146 ***
FSpending	Spending in total history in food category.		0.6305 ***		0.3566 ***
FSpending_2Y	Spending in last 2 years in food category.		0.7811 ***	-7.1288 **	0.4400 ***
FSpending_1Y	Spending in last year in food category.		0.7670 ***	0.1848 ***	0.4340 ***
FSpending_6M	Spending in last 6 months in food category.		0.7401 ***		0.4269 ***
FSpending_1M	Spending in last month in food category.		0.4173 ***	0.0203	0.3076 ***
FSpending_2W	Spending in last 2 weeks in food category.		0.2681 ***		0.2177 ***
NFSpending	Spending in total history in non food category.		0.3044 ***		0.3756 ***
NFSpending_2Y	Spending in last 2 years in non food category.		0.3281 ***	-6.0760 **	0.4241 ***
NFSpending_1Y	Spending in last year in non food category.		0.3057 ***		0.4230 ***
NFSpending_6M	Spending in last 6 months in non food category.		0.2636 ***	0.0634 **	0.4197 ***
NFSpending_1M	Spending in last month in non food category.		0.1321 ***		0.2118 ***
NFSpending_2W	Spending in last 2 weeks in non food category.		0.0914 ***		0.1377 ***
Recency	Number of days since last purchase.	-0.0780 ***	-0.4238 ***	-0.4343 ***	-1.2270 ***
FRecency	Number of days since last purchase in food category.		-0.2276 ***		-0.6684 ***
NFRecency	Number of days since last purchase in non food category.		-0.3022 ***	0.0909	-0.9540 ***
Ipt	Average number of days between store visits.		-0.6004 ***		-1.8109 ***
F_ipt	Average number of days between store visits in food category.		-0.2160 ***		-0.5615 ***
NF_ipt	Average number of days between store visits in non food category.		-0.5007 ***		-1.2961 ***
FRecdum	Dummy to indicate absence of data to compute Frecency		-0.0592 ***		-0.1953 ***
NFRecdum	Dummy to indicate absence of data to compute NFrecency	0.0077 ***	-0.0153 ***		-0.0662 **
rSpend_freq	Average Spending in a visit.		-0.0811 ***	0.0361	-0.1568 ***
rFSpend_freq	Average Spending in a visit in the food category.		0.0288 ***	-0.1036 ***	0.0190 *
rNFSpend_freq	Average Spending in a visit in the non food category.		-0.1613 ***		-0.2528 ***
rSpend_lor	Relative Spending to the length of customer's relationship		0.5479 ***	-2.5684 *	0.4239 ***
rFSpend_lor	Relative Spending in the food category to the length of customer's relationship.		0.5789 ***	1.7231 *	0.3591 ***
rNFSpend_lor	Relative Spending in the non food category to the length of customer's relationship.		0.2979 ***	1.3201 *	0.3582 ***
PercResp_Leaf	Percentage of times a purchase is made in case a promotion leaflet was received.	0.2848 ***	0.4971 ***	0.2895 ***	0.6043 ***
PercResp_Noleaf	Percentage of times a purchase is made in case no promotion leaflet was received.	0.0150 ***	-0.3192 ***	-0.0608 *	-0.4175 ***
Morethanonce	Number of times that a customer visits more than once in one and the same promotion period.	0.1292 ***	0.4639 ***	0.0428	0.5261 ***
Perc_morethanonce	MoreThanOnce divided by the number of times a customer bought at least once in a promotion period.	-0.0504 ***	0.2038 ***	-0.0281	0.2907 ***
Respdum	Dummy to control for missing data concerning mailing information	-0.0376 ***	0.0793 ***	0.0297	0.5076 ***
Retour	Total value of returned goods.		0.9671 ***		0.2018 ***
Amount_deposit	Total value of empty botles returned.		0.6762 ***		0.1448 ***
Language_dum	Customer's language (1=Dutch, 0 = French)	-0.0149 ***	-0.0147 ***		0.0959 ***
Vat_dum	Customer has VAT number or not (1/0)	-0.0090 ***	-0.0268 ***		-0.0645 ***
Fax_dum	Fax number in database (1= yes, 0= no)		0.0056 ***	-0.0304	-0.0419 **
Phone_dum	Phone number in database (1= yes, 0= no)		-0.0011		0.0417 **
Remark_dum	Remark in database (1= yes, 0= no)		-0.0108 ***	-0.0216	-0.0217
Email_dum	E-mail address in database (1= yes, 0= no)		-0.0038 *		-0.0232
Box_dum	Living in flat (1= yes, 0= no)		-0.0049 **	-0.0261	0.0030
Cardholders_dum	2 cardholders (1= yes, 0= no)		0.0391 ***		0.2046 ***
Relation_dum	Relation indication in database (1= yes, 0= no)		-0.0118 ***	0.0580 ***	0.0763 ***
Distance	Distance to the store	-0.0306 ***	-0.1309 ***	-0.0410 **	-0.1904 ***
Lor	Length of customer's relationship.	0.0068 ***	0.0808 ***		0.1118 ***

* p <.10
** p <.05
* **p <.01

Appendix 2: Description and standardized parameter estimates for multivariate and univariate models of expenditures

Variable	Description	Models			
		Expenses with treatment		Expenses without treatment	
		Multivariate	Univariate	Multivariate	Univariate
Frequency	Number of purchases in total history.		0.0990 ***		-0.0176
Frequency_2Y	Number of purchases during last two years.		0.1195 ***		-0.0013
Frequency_1Y	Number of purchases during last year.		0.1198 ***		0.0203
Frequency_6M	Number of purchases during last six months.		0.1150 ***		0.0310
Frequency_1M	Number of purchases during last month.		0.0916 ***		0.0508 *
Frequency_2W	Number of purchases during last two weeks.		0.0658 ***		-0.0055
FFrequency	Number of purchases in total history in food category.		0.1107 ***		-0.0071
FFrequency_2Y	Number of purchases during last two years in food category.		0.1280 ***		0.0162
FFrequency_1Y	Number of purchases during last year in food category.		0.1269 ***		0.0421
FFrequency_6M	Number of purchases during last six months in food category.		0.1243 ***		0.0545 **
FFrequency_1M	Number of purchases during last month in food category.		0.1036 ***		0.0660 **
FFrequency_2W	Number of purchases during last two weeks in food category.		0.0752 ***		0.0106
NFFrequency	Number of purchases in total history in non food category.		0.0454 ***		-0.0038
NFFrequency_2Y	Number of purchases during last two years in non food category.		0.0594 ***		0.0091
NFFrequency_1Y	Number of purchases during last year in non food category.		0.0652 ***		0.0315
NFFrequency_6M	Number of purchases during last six months in non food category.		0.0652 ***		0.0380
NFFrequency_1M	Number of purchases during last month in non food category.		0.0483 ***		0.0468 *
NFFrequency_2W	Number of purchases during last two weeks in non food category.		0.0326 ***		-0.0193
Spending	Spending in total history.		0.6787 ***		0.1860 ***
Spending_2Y	Spending in last 2 years.		0.6686 ***		0.2098 ***
Spending_1Y	Spending in last year.		0.6075 ***	0.1839 ***	0.2573 ***
Spending_6M	Spending in last 6 months.		0.6312 ***		0.2306 ***
Spending_1M	Spending in last month.		0.4281 ***		0.2225 ***
Spending_2W	Spending in last 2 weeks.		0.3234 ***		0.1244 ***
FSpending	Spending in total history in food category.	0.7027 ***	0.7027 ***		0.1633 ***
FSpending_2Y	Spending in last 2 years in food category.		0.6887 ***		0.1866 ***
FSpending_1Y	Spending in last year in food category.		0.6254 ***		0.2463 ***
FSpending_6M	Spending in last 6 months in food category.		0.6580 ***		0.2319 ***
FSpending_1M	Spending in last month in food category.		0.4623 ***		0.2100 ***
FSpending_2W	Spending in last 2 weeks in food category.		0.3566 ***		0.1695 ***
NFSpending	Spending in total history in non food category.		0.1584 ***		0.1433 ***
NFSpending_2Y	Spending in last 2 years in non food category.		0.1829 ***		0.1401 ***
NFSpending_1Y	Spending in last year in non food category.		0.1838 ***		0.1535 ***
NFSpending_6M	Spending in last 6 months in non food category.		0.1689 ***		0.1315 ***
NFSpending_1M	Spending in last month in non food category.		0.1201 ***		0.1359 ***
NFSpending_2W	Spending in last 2 weeks in non food category.		0.0999 ***		0.0188
Recency	Number of days since last purchase.		-0.0058 *		0.0703 ***
FRecency	Number of days since last purchase in food category.		-0.0162 ***		-0.0067
NFRecency	Number of days since last purchase in non food category.		-0.0038		0.0295
Ipt	Average number of days between store visits.		-0.0116 ***		0.0242
F_ipt	Average number of days between store visits in food category.		-0.0171 ***		-0.0226
NF_ipt	Average number of days between store visits in non food category.		-0.0047		0.0100
FRecdum	Dummy to indicate absence of data to compute Frecency		-0.0052 *		-0.0157
NFRecdum	Dummy to indicate absence of data to compute NFrecency		-0.0012		0.0125
rSpend_freq	Average Spending in a visit.		0.3360 ***	0.2285 ***	0.2876 ***
rFSpend_freq	Average Spending in a visit in the food category.		0.3564 ***		0.2807 ***
rNFSpend_freq	Average Spending in a visit in the non food category.		0.0576 ***		0.1160 ***
rSpend_lor	Relative Spending to the length of customer's relationship		0.6729 ***		0.1980 ***
rFSpend_lor	Relative Spending in the food category to the length of customer's relationship.		0.6962 ***		0.1690 ***
rNFSpend_lor	Relative Spending in the non food category to the length of customer's relationship.		0.1549 ***		0.1555 ***
PercResp_Leaf	Percentage of times a purchase is made in case a promotion leaflet was received.		0.0372 ***		-0.0294
PercResp_Noleaf	Percentage of times a purchase is made in case no promotion leaflet was received.		-0.0067 **		-0.0033
Morethanonce	Number of times that a customer visits more than once in one and the same promotion period.		0.0728 ***		0.0116
Perc_morethanonce	MoreThanOnce divided by the number of times a customer bought at least once in a promotion period.		0.0827 ***		0.0926 ***
Respdum	Dummy to control for missing data concerning mailing information		-0.0007		-0.0318
Retour	Total value of returned goods.		0.2870 ***		0.0722 ***
Amount_deposit	Total value of empty botles returned.		0.2587 ***		0.0709 ***
Language_dum	Customer's language (1=Dutch, 0 = French)		0.0187 ***		0.0592 **
Vat_dum	Customer has VAT number or not (1/0)		0.0593 ***		0.0870 ***
Fax_dum	Fax number in database (1= yes, 0= no)		0.0503 ***		0.0189
Phone_dum	Phone number in database (1= yes, 0= no)		0.0181 ***		0.0479 *
Remark_dum	Remark in database (1= yes, 0= no)		-0.0038		-0.0042
Email_dum	E-mail address in database (1= yes, 0= no)		0.0459 ***		0.0607 **
Box_dum	Living in flat (1= yes, 0= no)		-0.0174 ***		-0.0270
Cardholders_dum	2 cardholders (1= yes, 0= no)		-0.0011		0.0168
Relation_dum	Relation indication in database (1= yes, 0= no)		-0.0341 ***		-0.0282
Distance	Distance to the store		0.0284 ***		0.1015 ***
Lor	Length of customer's relationship.		-0.0022		-0.0119

* p <.10
** p <.05
* **p <.01

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