Modeling Charity Donations:

Target Selection, Response Time and Gift Size*

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Abstract

Charitable organizations often consider direct mailings to raise donations. Obviously it is important for a charity to make a profitable selection from available mailing lists, which can be its own list or a list obtained elsewhere. For this purpose, a charitable organization usually has to address the following four questions:

1. Who should we send a mailing?
2. Who is likely to respond to that mailing?
3. How much time will it take for this individual to respond?
4. How much money will this individual donate?

Several techniques for addressing one or more of these questions have been suggested in the literature. For example, Bult and Wansbeek (1995) develop a model that addresses the second question. Otter *et al.* (1997) develop a model that jointly considers the second and the fourth question. In practice one often relies on techniques such as RFM-based decision rules (Bauer, 1988) in order to answer the first question.

In this paper we develop a model which enables a charitable organization to make an optimal selection from its own mailing list, while simultaneously considering the four questions above. Hence, our model consists of four components with a possible non-zero correlation structure. The explanatory variables in each of these components are RFM-type variables, where these are allowed to have different effects on the various variables to be explained. In particular, we show that the first component is essential when a target selection model is applied to a database. Neglecting this component can generate a substantial sample selection bias in the results of subsequent analysis. The various model parameters are estimated by maximum likelihood.

We illustrate our model using a random drawing of about 5,300 individuals from the database of a large Dutch charitable organization. Our empirical results indicate the relevance of the non-zero correlation across the model components, and the relevance of taking account of the target selection part. We find some RFM variables to have effects with opposite signs on the probability to respond, the time for response and the donation. It is found that the most profitable individuals are not the ones who have maximum scores on the RFM variables. We conclude with a discussion of various further research topics.

Key words: charity donations, target selection, time to response, duration model, censored regression

1 Introduction and Motivation

Charitable organizations often consider direct mailings to raise donations. These mailings are sent to prospective charity donors, while usually at the same time charity uses television and radio commercials in order to arouse attention for the upcoming mailings. Obviously, charitable organizations aim to maximize the total amount of the donations, and hence they are well known to draw heavily on their own mailing lists in order to improve target selection. The own mailing list contains information on current or previous charity donors, while a newly acquired list can contain variables that should have a predictive value for the probability that individuals would respond to a charity direct mailing.

In this paper we focus on an analysis of the own database with known characteristics of current or recent donors. Given such a database, a charitable organization usually has to address the following four questions:

1. Who should we send a mailing? (target selection)

2. Who is likely to respond to that mailing? (response)

3. How much time will it take for this individual to respond? (time to response)

4. How much money will this individual donate? (size of gift)

The first issue, that is, target selection, involves the selection of those individuals from the database who are in some way likely to yield a positive return for charity. Indeed, a charity database can contain information on as many as millions of individuals, and when mailings are to be sent out a few times per year, it is usually considered impossible and inefficient to send mailings to all these individuals. Hence a selection has to be made. This selection can be based on previous response, on previous donations and on the frequency of response, and on other variables such as household size, income and age (assuming that the relevant information is available). Oftentimes, only Recency, Frequency and Monetary value (RFM) variables are available, and one tends to select targets based on some weighted combination of these past performance measures. Additionally, CHAID type techniques are also used, as well as binary response models, see Haughton and Oulabi (1993).

Once the mailing has been sent out, it is important to examine the second issue, that is, who actually responds. It seldom occurs that all selected individuals respond, and hence something is to be learned from the characteristics of the responding donors. Ideally one would want to incorporate these findings into a next round of target selection. The analysis of dichotomous response variable (that is, yes or no) is usually carried out by considering binary choice models such as the logit and probit models, see for example Bult and Wansbeek (1995), or by using alternative non-parametric or semi-parametric classification methods, see for example Bult (1993).

The third issue, that is, the time to response, is also found to be an important topic in direct mailing, see for example Basu *et al.* (1995). Indeed to speed up response, a charitable organization can resort to considering additional marketing instruments, like advertising on television and radio, in order to alert prospective donors. The underlying idea may be that awareness leads to response, and also that individuals who postpone sending their gifts are likely to forget that they were indeed willing to contribute to charity in the first place. A typical econometric model that would be useful to analyze this time to response would be a so-called duration model, see Kiefer (1988). Although these models have been extensively applied in marketing research studies, see for example Jain and Vilcassim (1991), Helsen and Schmittlein (1993) and Gönül and Srinivasan (1993), it seems that they are not widely applied to model response times for charity donations.

Finally, the fourth issue concerns the size of the charitable contribution. The importance of this topic in conjunction with RFM variables originates from the notion that frequent contributors may perhaps donate less than infrequent donors. Hence, when one aims to maximize the total monetary value of the donations, it can be useful to be able to characterize the various types of individuals in this respect. As only individuals who respond to the mailing actually contribute, one has to consider so-called censored regression (Tobit) models for proper empirical analysis, see for example Otter *et al.* (1997).

Obviously, the four issues discussed so far constitute a single stage of an iterative process which should lead, all other aspects being constant, to an optimal target selection rule. A first step in this process is that a charity sends out a mailing, based on certain selection rules. Second, one analyzes the response data (response, time to response, and size of gift). Finally, with the results from this analysis one constructs a new rule for target selection. Note again that in this paper we confine our focus to current or past donors, and the selection of new donors is beyond the topic of this paper.

Given that the four issues all concern one round of fund raising, it seems natural to analyze the relevant empirical data using a single model framework, while thereby allowing for interdependencies between the four model components. Interestingly, to our knowledge this has never been done before, at least not while using formal econometric models. For example, Otter *et al.* (1997) implement a censored regression model (which is found to collapse to a two-part model) without incorporating the target selection rules used by the charitable organization. Hence, their analysis potentially suffers from sample selection bias, see Manski and Lerman (1977). In this paper, we therefore put forward a model that jointly considers the four aforementioned issues. We apply our model to a random draw of about 5,300 individuals from the database of a large Dutch charitable organization and consider a mailing that was sent out in February 1998. This charitable organization has information on about 800,000 individuals in its database.

The outline of our paper is as follows. As the charity organization under consideration extensively uses RFM variables, we provide a brief survey of the relevant literature on these variables in Section 2. In this section we also discuss the possible effects these RFM variables may have on each of the four aforementioned questions. Then, in Section 3, we put forward our novel model. We discuss representation, parameter estimation using maximum likelihood, and inference. In Section 4, we apply our model to the random draw from the available database. We provide some details on the data and discuss estimation results. To examine the interaction of RFM variables and the four issues, we consider various hypothetical individuals with different RFM histories. We also discuss target selection, given the results for the fully specified model. Finally, in Section 5, we discuss managerial implications. Additionally, we provide some limitations, which in turn suggest topics for further research.

2 Literature Review

In this section we provide a brief discussion of the literature on charity donations, on direct mailing and on the use of RFM variables. This discussion is intentionally not comprehensive, and therefore we refer to various other studies for more details. We conclude with a subsection on how one may expect RFM variables to have an effect on target selection, response, time to response and the size of the gift.

2.1 Charity and Direct Marketing Concepts

The motivations for gift giving in general and donating to charitable institutions in particular have been investigated intensively. Jones and Posnett (1991) document that the propensity of individuals to donate to charity is influenced by income, the tax-price of giving and some demographic variables. The amount donated is primarily influenced by income. Schervish (1997) also examines the factors that mobilize individuals to donate to charity. He reports that individuals who are socially active, in the sense that they actually participate in groups and organizations, and individuals who are approached directly to donate, are more inclined to donate. Schervish does not find any evidence that the size of income would influence the decision to donate to charity. Finally, Wolpert (1997) considers the demographics of charity donors. His results show that donations are presumably affected by the value that individuals assign to the services and benefits provided by the fund raisers.

Interestingly, the above findings do not take into account that many charitable organizations keep detailed records of all individuals who (ever) donated to their charity in the (recent) past. Hence, it is assumed that, besides from characteristics as income and degree of social activity, one can learn about charity donors from looking at their actual behavior. Based on this behavior, a charitable organization can apply a variety of target selection techniques, while aiming to select the most profitable donors. These techniques are often used in direct marketing. This selection is typically based on RFM variables, see

Cullinan (1977). These variables measure the Recency, Frequency and Monetary value of the donations, usually at the individual level. Recency indicates the time that elapsed since the individual has last donated. Frequency measures how often an individual has responded to mailings sent during a certain period of time. Finally, Monetary value indicates the value of the donations made by an individual during a certain period of time. The RFM variables are often combined into an individual score, which is then used to rank the individuals who are most likely to respond (Bauer, 1988), although other criteria are also possible. For example, Spring *et al.* (1999) use RFM variables together with characteristics of the mailing in a binary response model to predict the probability that someone will respond to a mailing. When RFM variables are used, it is assumed that individuals who rank high on all three dimensions are more profitable. The construction of the RFM variables depends on the data available and on the purpose of use. In the literature we find that different operational measures have been proposed, see for example Baier (1983), Nash (1986) and Roberts and Berger (1989). Van den Poel *et al.* (1998) report that RFM variables are the most important variables in currently applied models of mail-order buying behavior.

Although the single scores based on RFM variables are widely applied, more sophisticated methods for the selection of individuals have also been suggested. To determine target segments of potential contributors, one can also use decision-tree-based methods such as CHAID and CART, see for example Haughton and Oulabi (1993). Also, neural networks have been considered, see Zahavi and Levin (1997). There are also more advanced methods which focus at the individual level. For example, Bult (1993) develops a semi-parametric classification model. Furthermore, Bult and Wansbeek (1995) consider probit and logit models, where they advocate to estimate the parameters using a semi-parametric method. So far, the above models only concern the probability to donate, and there is no focus on the size of the gift. Recently however, Otter *et al.* (1997) propose to combine both the probability to respond and the amount donated into a censored regression (Tobit) model, where they illustrate the model to charity data. Other studies with a focus on charity data where similar models are used include Muus *et al.* (1996), Bult and

Wittink (1996) and Bult *et al.* (1997).

2.2 RFM Variables and Charity Donations

Before we turn to a discussion of our model, we first summarize the expected effects of RFM variables on target selection, response, time to response and the size of the charitable donation.

As discussed above, the effects of RFM variables on target selection are generally expected to be positive. Those individuals who rank high on frequently donating large sums of money, and also those who did so recently, are likely to obtain a high RFM score. Hence, the relevant effects are all expected to be positive. Below we will propose to use a binary probit model to capture the implemented target selection rule. Whether the parameters in this model are also significant is merely a statistical matter.

There is ample evidence in the literature which suggests that RFM variables have a positive effect on the probability to respond, see Roberts and Berger (1989), Van den Poel *et al.* (1998) and Spring *et al.* (1999). Additionally, as charitable organizations may send mailings also to individuals who are not likely to respond, we expect there to be a negative correlation between the probability to be included in a target selection and the probability to respond. The size of this correlation can be viewed as a measure of the quality of the target selection rule used by the charity fund.

There are not many indications what the effect of RFM variables on the duration of response should be. Individuals who respond frequently in the past may do so more rapidly as they might be considered to be more involved with the particular charity. Also, we would have no prior thoughts about the correlation between the duration and probability to responds and the size of the donation. One would expect, though, that advertising would reduce the response time. Unfortunately, we do not have data on advertising, and hence we abstain from a detailed discussion on this issue.

Finally, one may expect that RFM variables have a positive effect on the amount of the donation. Individuals who gave more in the past are likely to continue to do so in the future. Additionally, we expect there to be a significant correlation between the model component describing response and the censored regression model modeling the size of the gift. If an individual donates frequently and did so in the recent past, it may well be that he or she only donates small amounts. Hence, we expect a negative correlation. In the next section we put forward the model which correlates RFM variables with the various aspects of charity donations.

3 The Model

To analyze the response behavior of individuals to mailings of a charitable organization, we propose a new model. In Section 3.1 it is shown that the model combines four well-known econometric models. Section 3.2 deals with the estimation of the model parameters, while in Section 3.3 we discuss interpretation of the model.

3.1 Representation

The new model to describe the response behavior of individuals to mailings of a charitable organization consists of four components. With the first component we model the decision of the charity to send a mailing to an individual in their database. The second component describes the decision of an individual to respond to the mailing and hence to give a donation. The last two components concern the time between receiving the mailing and the response and the size of the donation. The first component of the model may seem to be redundant as we may not be interested in specifically analyzing the mailing strategies of a charitable organization. However, this step is important as the individuals who receive a mailing do not constitute a random sample from the database of the charity. In fact, only individuals who are considered likely to respond according to the measures used by the charitable organization will receive a mailing. Neglecting this first component may thus lead to a sample selection bias, see Manski and Lerman (1977). Therefore, we explicitly need to capture the mailing strategy in the first part of the model.

Before we can describe our model, we first have to introduce some notation. Let d_i^s be a 0/1 dummy variable that is 1 if the charitable organization decides to include individual i in the mailing and 0 if not, $i = 1, \ldots, I$. We define d_i^r to be a 0/1 dummy variable that is 1 if individual i responds to the mailing if he or she receives one, and 0 otherwise. Let t_i be the time between mailing and response for an individual i and let y_i be the donation of individual i. In this paper we measure t_i by weeks and y_i by Dutch guilders. Obviously, both quantities are only observed if individual i receives the mailing and responds to it.

The dichotomous variables d_i^s and d_i^r can be modelled by a probit model. Conditional on the response of individual i, we describe the time between receiving the mailing and the response by a duration model with a lognormal distribution function. Given response and the response time, we model the logarithm of the amount of the donation by a standard regression model. Now we turn to give more precise expressions for these four models.

The decision by the charitable organization concerning sending a mailing to individual i is modeled by

$$d_i^s = \begin{cases} 1 & w_i^s \geq 0 \\ 0 & w_i^s < 0, \end{cases} \tag{1}$$

where

$$w_i^s = \alpha_1 + x_i'\beta_1 + \varepsilon_{1,i}, \tag{2}$$

with α_1 an intercept, β_1 a k-dimensional parameter vector, x_i a k-dimensional vector with explanatory RFM variables for individual i and where $\varepsilon_{1,i} \sim \mathrm{N}(0,1)$. Hence, the probability that an individual will not receive a mailing is

$$\begin{aligned} \Pr[d_i^s = 0] &= \Pr[\varepsilon_{1,i} < -\alpha_1 - x_i'\beta_1] \\ &= \int_{-\infty}^{-\alpha_1 - x_i'\beta_1} \phi(\varepsilon_i) d\varepsilon_i \\ &= \Phi(-\alpha_1 - x_i'\beta_1), \end{aligned} \tag{3}$$

where ϕ and Φ are the density function and the cumulative density function of a standard univariate normal distribution, respectively.

Given that individual i receives a mailing from charity ($d_i^s = 1$), we model the decision to respond to the mailing by

$$d_i^r = \begin{cases} 1 & w_i^r \geq 0 \\ 0 & w_i^r < 0, \end{cases} \tag{4}$$

where

$$w_i^r = \alpha_{2,i} + x_i'\beta_2 + \varepsilon_{2,i}, \tag{5}$$

with $\alpha_{2,i}$ an individual-specific intercept, β_2 a k-dimensional parameter vector and $\varepsilon_{2,i} \sim \mathrm{N}(0,1)$. We denote the correlation between $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ by σ_{12}.

Given that an individual i responds to the mailing ($d_i^r = 1$) we model the time t_i between receiving the mailing and the actual response by a duration model. To reduce potential complications when modelling the correlations between the duration and the donated amount and decision to respond, we assume a lognormal distribution for t_i and we opt for an accelerated lifetime model, see Kiefer (1988). This leads to the following linear regression model for $\ln t_i$, that is,

$$\ln t_i = \alpha_{3,i} + x_i'\beta_3 + \varepsilon_{3,i} \tag{6}$$

where $\alpha_{3,i}$ is an individual-specific intercept, β_3 a k-dimensional parameter vector and $\varepsilon_{3,i} \sim \mathrm{N}(0, \sigma_3^2)$, see Kalbfleisch and Prentice (1980, p. 24).

Finally, the size of the donation y_i given response $d_i^r = 1$ and response time t_i is described by a linear regression model for $\ln y_i$, that is,

$$\ln y_i = \alpha_{4,i} + x_i'\beta_4 + \gamma \ln t_i + \varepsilon_{4,i}, \tag{7}$$

where $\alpha_{4,i}$ is an individual-specific intercept, β_4 a k-dimensional parameter vector, γ a scalar parameter and where we assume that $\varepsilon_{4,i} \sim \mathrm{N}(0, \sigma_4^2)$. Note that all four models include the same set of x_i variables. In practice one may of course consider other possibilities.

Finally, we model the correlation between the choices, the duration and the donated amount through a covariance matrix on $(\varepsilon_{1,i}, \varepsilon_{2,i}, \varepsilon_{3,i}, \varepsilon_{4,i})'$. This covariance matrix is given by

$$\Sigma = \begin{pmatrix} 1 & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & 1 & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_4^2 \end{pmatrix} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}, \tag{8}$$

where the $\Sigma_{i,j}$ are (2×2) matrices, $i = 1, 2$, $j = 1, 2$.

3.2 Estimation

To estimate the model parameters for each individual $\theta_i = (\alpha_1, \alpha_{l,i}, l = 2, 3, 4, \beta_j, j = 1, 2, 3, 4, \gamma, \Sigma)$, we use the method of maximum likelihood. Notice that the γ and σ_{34} parameters of our model as presented above are not jointly identified. Hence, to estimate the model we have to impose that one of the two equals zero. We stress here that it does not matter which restriction is imposed as both options lead to the same model with the same interpretation.[1] To derive the likelihood function of the model, we first derive the joint density function of $(d_i^s, d_i^r, \ln t_i, \ln y_i)$.

Using a similar approach as for the type-2 Tobit model, see Amemiya (1985, p. 385–386), we start with decomposing the density function of $(w_i^s, w_i^r, \ln t_i, \ln y_i)$ as

$$\begin{aligned} f(w_i^s, w_i^r, \ln t_i, \ln y_i; \theta_i) &= f(w_i^s, w_i^r | \ln t_i, \ln y_i; \theta_i) f(\ln t_i, \ln y_i; \theta_i) \\ &= f(w_i^s, w_i^r | \ln t_i, \ln y_i; \theta_i) f(\ln y_i | \ln t_i; \theta_i) f(\ln t_i; \theta_i). \end{aligned} \tag{9}$$

The final term in (9) corresponds with the unconditional density function of $\ln t_i$, which is simply given by

$$f(\ln t_i; \theta_i) = \frac{1}{\sigma_3 \sqrt{2\pi}} \left(-\frac{1}{2\sigma_3^2} (\ln t_i - \alpha_{3,i} - x_i' \beta_3)^2 \right). \tag{10}$$

The distribution of $\ln y_i$ given $\ln t_i$ is normal with mean $\alpha_{4,i} + x_i'\beta_4 + \gamma \ln t_i + \sigma_{43}\sigma_3^{-2}(\ln t_i - \alpha_{3,i} - x_i'\beta_3)$ and variance $\tilde{\sigma}_4^2 = \sigma_4^2 - \sigma_{43}^2\sigma_3^{-2}$. Hence, the conditional density function of $\ln y_i$ given $\ln t_i$ is given by

$$\begin{aligned} &f(\ln y_i | \ln t_i; \theta_i) = \\ &\quad \frac{1}{\tilde{\sigma}_4 \sqrt{2\pi}} \left(-\frac{1}{2\tilde{\sigma}_4^2} (\ln y_i - \alpha_{4,i} - x_i'\beta_4 - \gamma \ln t_i - \sigma_{43}\sigma_3^{-2}(\ln t_i - \alpha_{3,i} - x_i'\beta_3))^2 \right). \end{aligned} \tag{11}$$

To derive the probabilities for the two probit models we need to distinguish three cases, that is $d_i^s = 0$, $(d_i^s = 1, d_i^r = 0)$ and $(d_i^s = 1, d_i^r = 1)$. The probability that an individual is not selected by charity, $\Pr[d_i^s = 0; \theta_i]$, is given in (3). The probability that

[1] In our application below we show the results for $\sigma_{34} = 0$.

an individual is selected but does not respond to the mailing ($d_i^s = 1, d_i^r = 0$) is given by

$$
\begin{aligned}
\Pr[d_i^s = 1, d_i^r = 0; \theta_i] &= \Pr[\varepsilon_{1,i} > -\alpha_1 - x_i'\beta_1 \wedge \varepsilon_{2,i} < -\alpha_{2,i} - x_i'\beta_2] \\
&= \int_{-\alpha_1 - x_i'\beta_1}^{\infty} \int_{-\infty}^{-\alpha_{2,i} - x_i'\beta_2} |\Sigma_{11}|^{-\frac{1}{2}} \phi_2(\Sigma_{11}^{-\frac{1}{2}} \varepsilon_{12,i}) d\varepsilon_{1,i} d\varepsilon_{2,i},
\end{aligned} \tag{12}
$$

where $\varepsilon_{12,i} = (\varepsilon_{1,i}, \varepsilon_{2,i})'$ and where ϕ_2 is the density function of a bivariate normal distribution with mean zero and an identity covariance matrix. Finally, in order to derive the probability that an individual is selected and responds to the mailing ($d_i^s = 1, d_i^r = 1$), we use that the distribution of $w_i = (w_i^s, w_i^r)$ given $(\ln t_i, \ln y_i)$ is multivariate normal with mean

$$
\bar{w}_i = \begin{pmatrix} \alpha_1 + x_i'\beta_1 \\ \alpha_{2,i} + x_i'\beta_2 \end{pmatrix} + \Sigma_{12}\Sigma_{22}^{-1} \begin{pmatrix} \ln t_i - \alpha_{3,i} - x_i'\beta_3 \\ \ln y_i - \alpha_{4,i} - x_i'\beta_4 - \gamma \ln t_i \end{pmatrix} \tag{13}
$$

and variance $\tilde{\Sigma}_{11} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$. The probability that an individual responds to a received mailing equals $\Pr[w_i^s > 0 \wedge w_i^r > 0 | \ln t_i, \ln y_i]$, which can be expressed as

$$
\Pr[d_i^s = 1, d_i^r = 1; \theta_i] = \int_0^{\infty} \int_0^{\infty} |\tilde{\Sigma}_{11}|^{-\frac{1}{2}} \phi_2(\tilde{\Sigma}_{11}^{-\frac{1}{2}}(w_i - \bar{w}_i)) dw_i^s dw_i^r. \tag{14}
$$

The joint density function of $(d_i^s, d_i^r, \ln t_i, \ln y_i)$ is now given by the product of (3), (12), (14), (10) and (11), that is,

$$
\begin{aligned}
f(d_i^s, d_i^r, \ln t_i, \ln y_i; \theta_i) = {} & \Pr[d_i^s = 0; \theta_i]^{I[d_i^s = 0]} \Pr[d_i^s = 1, d_i^r = 0; \theta_i]^{I[d_i^s = 1, d_i^r = 0]} \\
& (\Pr[d_i^s = 1, d_i^r = 1; \theta_i] f(\ln t_i; \theta_i) f(\ln y_i | \ln t_i; \theta_i))^{I[d_i^s = 1, d_i^r = 1]}
\end{aligned} \tag{15}
$$

where $I[\cdot]$ is an indicator function which is 1 if the argument is true and zero otherwise. The log likelihood function equals the sum of the log joint density functions in (15) over the individuals, that is,

$$
\ell(D^s, D^r, \ln T, \ln Y; \theta) = \sum_{i=1}^{I} \ln f(d_i^s, d_i^r, \ln t_i, \ln y_i; \theta_i), \tag{16}
$$

where $\theta = \{\theta_i, i = 1, \ldots, I\}$ and $(D^s, D^r, \ln T, \ln Y) = \{(d_i^s, d_i^r, \ln t_i, \ln y_i), i = i, \ldots, I\}$.

The individual-specific intercepts $\alpha_{l,i}$, $l = 2, 3, 4$ model allow for heterogeneity in the donation behavior of individuals. For example, some individuals may be less likely to respond but if they respond they give more than the average donation, while other individuals can be more likely to respond but donate less than the average amount. If we do not have enough observations for each individual, it is not possible to estimate individual-specific intercepts, see for example Rossi and Allenby (1993) for a discussion. To allow for possible heterogeneity across individuals in this case, we assume that there are m groups of individuals with the same intercepts and model these groups by a finite mixture model with $m-1$ mixing proportions p_j, $j = 1, \ldots, m-1$ with $p_m = 1 - \sum_{j=1}^{m-1} p_j$, see Kamakura and Russell (1989) for a similar approach in brand choice models. Denote θ_j as the parameter belonging to mixture component j, $j = 1, \ldots, m$. The log likelihood function becomes

$$\ell(D^s, D^r, \ln T, \ln Y; \theta_j, p_j, j = 1, \ldots, m) = \sum_{i=1}^{I} \ln \left(\sum_{i=1}^{m} p_j f(d_i^s, d_i^r, \ln t_i, \ln y_i; \theta_j) \right). \quad (17)$$

To estimate the model parameters, we maximize (17) over the parameters θ_j, $j = 1, \ldots, m$. This maximization can be done with standard numerical optimization algorithms[2], like Newton-Raphson. As starting values for maximum likelihood estimation, we use maximum likelihood estimates of the separate components (thereby setting the covariance matrix in (8) to a diagonal matrix). In this paper we opt for the BHHH-algorithm of Berndt *et al.* (1974). The advantage of this algorithm is that it only requires the first-order derivative of the log likelihood and not the second-order derivatives. The maximum likelihood estimates are asymptotically normally distributed with a mean equal to the true parameter values and with a covariance matrix equal to the inverse of the information matrix. To estimate this information matrix we use the scores average outer product, see Judge *et al.* (1985, p. 180). This estimator also does not require the second-order derivatives of the likelihood. Statistical testing for the number of mixture components (groups) is not possible as under the restriction $\theta_j = \theta_k$ for $k \neq j$ one of the mixing proportions p_j is not identified. This phenomenon is known as the Davies (1977) problem. Therefore, to determine the number of mixture components (or groups) m, we increase the number of

[2]To restrict the mixing parameters p_j between 0 and 1, we apply the logit transformation. Furthermore, to ensure that the covariance matrix Σ is positive definite we define Σ as $S'S$, where S is a lower diagonal matrix.

mixture components until the BIC does not decrease anymore, see Jain *et al.* (1994) for a similar and successful approach to brand choice models.

3.3 Interpretation

Before we apply our model to the data from a Dutch charitable institution, we first discuss the interpretation and the potential use of the model for forecasting and target selection.

First we consider the probability that an individual with RFM characteristics x_i is selected by the charity for a mailing, that is,

$$\Pr[d_i^s = 1; \theta_i] = \Pr[\varepsilon_{i,1} > -\alpha_1 - x_i'\beta_1] = 1 - \Phi(-\alpha_1 - x_i'\beta_1). \tag{18}$$

The probability that this individual will respond to the mailing given that he or she receives a mailing equals

$$\begin{aligned}\Pr[d_i^r = 1 | d_i^s = 1; \theta_i] &= \frac{\Pr[d_i^s = 1 \wedge d_i^r = 1; \theta_i]}{\Pr[d_i^s = 1]} \\ &= \frac{\int_{-\alpha_1 - x_i'\beta_1}^{\infty} \int_{-\alpha_{2,i} - x_i'\beta_2}^{\infty} |\Sigma_{11}|^{-\frac{1}{2}} \phi_2(\Sigma_{11}^{-\frac{1}{2}} \varepsilon_{12,i}) d\varepsilon_{1,i} d\varepsilon_{2,i}}{1 - \Phi(-\alpha_1 - x_i'\beta_1)}.\end{aligned} \tag{19}$$

For practical purposes the previous two probabilities are however not so interesting. In fact, we are interested in the marginal probability that an individual responds to a mailing and in his or her expected donation. These follow from the marginal model (4)–(7). Again, this may suggest that the first probit model (4) that concerns the probability that an individual receives a mailing is redundant. This is however not the case as the first step in our model takes into account the fact that the charitable organization is likely to send mailings to individuals whom it expects to respond. Hence, this components describes the target selection strategy of the charity and it takes into account that the individuals who receive a mailing are not selected at random.

The marginal probability that an individual with characteristics x_i responds to a mailing is

$$\Pr[d_i^r = 1; \theta_i] = \Pr[\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] = 1 - \Phi(-\alpha_{2,i} - x_i'\beta_2). \tag{20}$$

The expected (log) duration time between receiving the mailing and the response, given response, for an individual with characteristics x_i is

$$\begin{aligned}
\mathrm{E}[\ln t_i|d_i^r = 1;\theta_i] &= \mathrm{E}[\alpha_{3,i} + x_i'\beta_3|d_i^r = 1;\theta_i] + \mathrm{E}[\varepsilon_{3,i}|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \alpha_{3,i} + x_i'\beta_3 + \mathrm{E}[\mathrm{E}[\varepsilon_{3,i}|\varepsilon_{2,i}]|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \alpha_{3,i} + x_i'\beta_3 + \mathrm{E}[\sigma_{2,3}\varepsilon_{2,i}|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \alpha_{3,i} + x_i'\beta_3 + \sigma_{2,3}\frac{\phi(-\alpha_{2,i} - x_i'\beta_2)}{1 - \Phi(-\alpha_{2,i} - x_i'\beta_2)},
\end{aligned} \tag{21}$$

where we use that $\mathrm{E}[\varepsilon_{3,i}|\varepsilon_{2,i}] = \sigma_{2,3}\varepsilon_{2,i}$ and $\mathrm{E}[\varepsilon_{2,i}|\varepsilon_{2,i} > c] = \phi(c)/(1 - \Phi(c))$, see Maddala (1983, p. 365). As expected duration does in general not equal the exponent of the expectation of the logarithm of duration, we have to consider

$$\begin{aligned}
\mathrm{E}[t_i|d_i^r = 1;\theta_i] &= \mathrm{E}[\exp(\ln t_i)|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{3,i} + x_i'\beta_3)\mathrm{E}[\mathrm{E}[\exp(\varepsilon_{3,i})|\varepsilon_{2,i}]|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{3,i} + x_i'\beta_3 + \frac{1}{2}(\sigma_3^2 - \sigma_{2,3}^2))\mathrm{E}[\exp(\sigma_{2,3}\varepsilon_{i,2})|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{3,i} + x_i'\beta_3 + \frac{1}{2}(\sigma_3^2 - \sigma_{2,3}^2))\exp(\frac{1}{2}\sigma_{2,3}^2)\frac{(1 - \Phi(-\alpha_{2,i} - x_i'\beta_2 - \sigma_{2,3}))}{1 - \Phi(-\alpha_{2,i} - x_i'\beta_2)} \\
&= \exp(\alpha_{3,i} + x_i'\beta_3 + \frac{1}{2}\sigma_3^2)\frac{(1 - \Phi(-\alpha_{2,i} - x_i'\beta_2 - \sigma_{2,3}))}{1 - \Phi(-\alpha_{2,i} - x_i'\beta_2)}, \qquad (22)
\end{aligned}$$

where we use that $\mathrm{E}[\exp(\gamma\varepsilon_{2,1})|\varepsilon_{2,i} > c] = \exp(\frac{1}{2}\gamma^2)(1 - \Phi(c - \gamma))/(1 - \Phi(c))$, see Maddala (1983, p. 366).

Likewise, we can derive the expected log donation given response of an individual with characteristics x_i, that is,

$$\begin{aligned}
\mathrm{E}[\ln y_i|d_i^r = 1;\theta_i] &= \mathrm{E}[\ln y_i|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \alpha_{4,i} + x_i'\beta_4 + \gamma\mathrm{E}[\ln t_i|d_i^r = 1;\theta_i] + \mathrm{E}[\varepsilon_{4,i}|\varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \alpha_{4,i} + x_i'\beta_4 + \gamma\mathrm{E}[\ln t_i|d_i^r = 1;\theta_i] + \sigma_{2,4}\frac{\phi(-\alpha_{2,i} - x_i'\beta_2)}{1 - \Phi(-\alpha_{2,i} - x_i'\beta_2)}
\end{aligned} \tag{23}$$

and the expected donation given response can be derived to equal

$$
\begin{aligned}
\mathrm{E}[y_i | d_i^r = 1; \theta_i] &= \mathrm{E}[\exp(\ln y_i) | \varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{4,i} + x_i'\beta_4 + \gamma(\alpha_{3,i} + x_i'\beta_3)) \\
&\qquad \mathrm{E}[\mathrm{E}[\exp(\varepsilon_{4,1} + \gamma\varepsilon_{3,i}) | \varepsilon_{2,i}] | \varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{4,i} + x_i'\beta_4 + \gamma\alpha_{3,i} + \gamma x_i'\beta_3 + \frac{1}{2}(\sigma_{3+4}^2 - (\gamma\sigma_{23} + \sigma_{24})^2)) \\
&\qquad \mathrm{E}[\exp((\gamma\sigma_{23} + \sigma_{24})\varepsilon_{2,i}) | \varepsilon_{2,i}] | \varepsilon_{2,i} > -\alpha_{2,i} - x_i'\beta_2] \\
&= \exp(\alpha_{4,i} + x_i'\beta_4 + \gamma\alpha_{3,1} + \gamma x_i'\beta_3 + \frac{1}{2}\sigma_{3+4}^2) \\
&\qquad \frac{(1 - \Phi(-\alpha_{2,i} - x_i'\beta_2 - \gamma\sigma_{23} - \sigma_{24}))}{1 - \Phi(-\alpha_{2,i} - x_i'\beta_2)},
\end{aligned} \tag{24}
$$

where $\sigma_{3+4} = \gamma^2\sigma_3^2 + \sigma_4^2 + 2\gamma\sigma_{34}$.

Notice again that the expectations (21)–(24) are unconditional on whether an individual receives a mailing but conditional on the response of the individual. Unconditional expectations can be constructed in a straightforward way. For example, the unconditional expected donation equals

$$
\begin{aligned}
\mathrm{E}[y_i; \theta_i] &= \mathrm{E}[y_i | d_i^r = 1; \theta_i] \Pr[d_i^r = 1; \theta_i] + \mathrm{E}[y_i | d_i^r = 0; \theta] \Pr[d_i^r = 1; \theta_i] \\
&= 0 + \mathrm{E}[y_i | d_i^r = 1; \theta_i] \Pr[d_i^r = 1; \theta_i].
\end{aligned} \tag{25}
$$

Hence the unconditional expected donation is always smaller than the expected donation given response.

If it is not possible to estimate individual-specific intercepts $\alpha_{l,i}$ and one opts for a mixture approach, the probabilities to respond and the expectations discussed above are just weighted averages of the expectations and/or probabilities for different values of θ_j with the mixing proportions p_j as weights.

The charitable organization can now use the derived probabilities and expectations to select which individuals from their database should receive a mailing in a next round. One may then decide to send the individuals who are most likely to respond a mailing or otherwise to send a mailing to individuals who have the largest unconditional expected donation. In the application in the next section we provide some illustrations.

4 Application to Dutch Charity Donations

We illustrate the new model presented in the previous section for a sample of a database of a large Dutch charitable organization. In Section 4.1, we provide a short description of the data under consideration. In Section 4.2, we discuss the empirical results. Finally, in Section 4.3, we discuss target selection with the estimated model.

4.1 Data

Our database contains information on the donation behavior of almost 800,000 individuals for a large Dutch charitable organization for the period 1994–1998. For each mailing, the charity makes a selection of these individuals based on RFM variables. It is known for each individual in the database whether a mailing has been sent, whether the individual responds to this mailing, the time between the moment the mailing has been sent and the response, and the amount of the donation in guilders. Notice that we have to assume that all mailings which are sent are also received.

We draw a random sample of 5,274 individuals from the database, concerning the mailings of February 1998. The information concerning earlier mailings is used to construct RFM variables to explain response, time to response and the size of the gift. To be able to construct these RFM variables, we only consider individuals who are active contributors, in the sense that they donated at least once in the period 1994–1997.

Before we turn to the description of the RFM variables, we first report some characteristics of the variables that we want to explain with our new model. About 80% of the individuals in our random draw receive a mailing in February 1998. About 40% of these individuals respond to the mailing and donate money. The average donation given response is 18.60 guilders with a maximum of 250 guilders and a minimum of 2 guilders[3]. The average time to respond given response is 4.35 weeks. More than 90% of the individuals respond within 10 weeks.

As explanatory variables for mail selection, response, time to response and the size of

[3] One guilder is about 0.45 euro.

the gift in our model, we use two measures of Recency, two measures of Frequency and two measures of Monetary value. The literature suggests that there are many different ways to construct RFM variables, see for example Baier (1983), Nash (1986), Roberts and Berger (1989). In the charity case, the response on each occasion can be seen as the sale of one product at different prices, making the construction of the Monetary value measures more straightforward. As Recency variables, we use the number of weeks that elapsed since the last response of an individual to a mailing and we consider a 0/1 dummy variable which indicates whether the individual has responded to the most recent mailing. As Frequency variables we take the proportion of responded mailings and the average number of mailings sent to an individual in a year. Finally, the Monetary value variables are taken to be the average gift in previous responded mailings and the amount that was donated in the last mailing to which was responded.

4.2 Empirical Results

To analyze the explanatory power of RFM variables to describe the charity donation behavior of individuals, we consider the four components model of Section 3. The first component of the model in (1) describes the mail selection procedure of the charitable organization. In the second probit equation in (4) we explain the response behavior of individuals. The time to respond and the size of the gift are modelled by the regressions in (6) and (7), respectively. The model with unrestricted covariance matrix (8) is estimated for the 5,274 individuals in our random sample.

We start with determining possible heterogeneity across the individuals. To capture possible differences in the behavior of individuals, we allow for different intercepts $\alpha_{l,i}$ in the probit model describing response and the regression models describing time to response and size of the donation. Recall that different intercepts may describe that some individuals are less likely to respond, while their donation is above average, while other individuals are more likely to respond, but donate less than the average amount. As we only have one observation per individual, this heterogeneity is modelled by a mixture model as described at the end of Section 3.2. However for our particular data, it turns out that there is not much evidence for heterogeneity. The BIC of a model with two mixture components $m = 2$ (=2.693) is larger than the BIC of a model without heterogeneity (=2.686). The same is true by the way, if we opt for AIC. The parameters corresponding to the RFM variables in the two component mixture model are almost the same as in the model without heterogeneity. Additionally, also the intercept parameters of the two components are almost the same. Therefore, we conclude that it is not necessary to incorporate heterogeneity in the model for the data set under consideration.

Table 1 shows the maximum likelihood estimates of the model parameters without heterogeneity with estimated standard errors in parentheses. We first discuss the first component of the model, that deals with the mail selection procedure of the charity. The parameter estimates suggest that individuals with many weeks since last response and/or who responded in the last mailing, are less likely to receive a mailing in this mailshot. The proportion of responded mailings has a positive effect on receiving a mailing, while the average number of mailings per year has a negative effect. Both monetary value variables, that is, average gift and gift in last response, have a negative influence on receiving a mail, but the effect of both variables is not significant at the 5% level.

The remaining three components of the model are of course of more interest as these indicate the characteristics of individuals, who are likely to respond and donate money to the charitable organization. We see that 7 out of the 18 parameters (excluding the three intercepts) are significant at the 5% level. We find for 3 of the 6 RFM variables a positive and significant influence on the probability to respond. This concerns both Frequency variables and the response to last mailing. Monetary value variables do not seem to have a significant influence on the probability to response.

The final column in Table 1 shows that the time between receiving a mailing and response has a positive effect on the size of the gift, but that this influence is not significant. Hence, individuals who respond faster do not significantly donate more. Monetary value variables have a positive significant influence on the amount donated. Furthermore, the proportion of responded mailings has a significant negative effect on the size of the donation. This suggests that individuals who often respond to a mailing, give a smaller

Table 1: Parameter estimates with estimated standard errors in parentheses[1] for the four component model (1)–(7).

variable	mail	response	duration	amount
intercept	6.581*	−1.920*	0.892	0.509*
	(0.269)	(0.291)	(0.648)	(0.198)
# weeks since last response	−1.264*	0.058	0.097	0.047
	(0.045)	(0.075)	(0.126)	(0.045)
response (0/1) to last mailing	−1.173*	0.302*	0.067	−0.016
	(0.082)	(0.087)	(0.144)	(0.050)
proportion of responded mailings	0.533*	1.838*	−0.324	−0.299*
	(0.124)	(0.127)	(0.205)	(0.050)
# mailings per year	−0.068	0.143*	−0.097*	−0.001
	(0.038)	(0.033)	(0.044)	(0.016)
average donation	−0.032	−0.025	0.073	0.631*
	(0.113)	(0.097)	(0.122)	(0.030)
donation in last response	−0.007	0.112	−0.020	0.274*
	(0.109)	(0.091)	(0.113)	(0.027)
time between mailing and response				0.023
				(0.035)

[1] Standard errors are computed using the scores average outer product.
* denotes significant at the 5% level.

amount. The effects of the other three explanatory variables are not significant.

The RFM variables do not have a significant effect on the time between receiving a mailing and response except for the average number of mailings per year. Apparently, individuals who receive more mailings per year, usually respond faster to the mailing.

The estimate of the covariance matrix of the four error terms with estimated standard error in parentheses equals

$$\begin{pmatrix} 1 & -0.453 & -0.003 & 0.053 \\ & (0.148) & (0.268) & (0.085) \\ -0.453 & 1 & -0.038 & -0.277 \\ (0.148) & & (0.163) & (0.025) \\ -0.003 & -0.038 & 0.909 & 0 \\ (0.268) & (0.163) & (0.018) & \\ 0.053 & -0.277 & 0 & 0.141 \\ (0.085) & (0.025) & & (0.009) \end{pmatrix}.$$

A likelihood ratio test statistic for the joint significance of the off-diagonal elements in this covariance matrix equals 85.26, which is significant as the 95% percentile of a $\chi^2(5)$ distribution equals 11.07. Hence, we should not simplify this covariance matrix to a diagonal matrix.

There is a large significant negative correlation of -0.453 between the mailing selection equation and the response equation. This indicates that individuals who receive a mailing, while the probit model (1) does not suggest sending them a mailing, are less likely to respond to the mailing. This suggests that a better target selection procedure is possible than the one now used by the charitable organization. The covariance matrix also shows a large significant negative correlation of -0.277 between the response model (4) and the donation equation (7). This suggest that individuals, who are more likely to respond than their RFM variables indicate, usually donate less than suggested by their RFM variables in the censored regression part of the model.

The significant correlation between response and donation is not found in the study by Otter *et al.* (1997). Their finding leads them to advocate a two-part model with no correlation between the probit response model and regression model describing the size of the donation. A possible explanation for this result is that Otter *et al.* (1997) do not

Table 2: Parameter estimates with estimated standard errors in parentheses[1] for the model without the mail selection component.

variable	response	duration	amount
intercept	-1.327^*	0.884	0.042
	(0.227)	(1.015)	(0.340)
#weeks since last response	-0.121^*	0.093	0.038
	(0.042)	(0.073)	(0.025)
response (0/1) to last mailing	0.146^*	0.066	0.022
	(0.066)	(0.089)	(0.031)
proportion of responded mailings	2.041^*	-0.308	0.039
	(0.110)	(0.780)	(0.266)
# mailings per year	0.155^*	-0.095	0.027
	(0.033)	(0.070)	(0.023)
average donation	-0.074	0.070	0.608^*
	(0.106)	(0.126)	(0.025)
donation in last response	0.125	-0.018	0.301^*
	(0.100)	(0.124)	(0.028)
time between mailing and response			0.017
			(0.010)

[1] Standard errors are computed using the scores average outer product.
* denotes significant at the 5% level.

consider the mail selection step of the charity in their model. Indeed, if we estimate our model where we leave out the first component (1) that takes care of the mailing selection strategy, we obtain the following covariance matrix

$$\begin{pmatrix} 1 & -0.028 & -0.005 \\ & (0.605) & (0.268) \\ -0.028 & 0.908 & 0 \\ (0.605) & (0.028) & \\ -0.005 & 0 & 0.095 \\ (0.268) & & (0.002) \end{pmatrix},$$

where the covariance term between response and donated amount is now found to be insignificant. Recall that the estimated parameters in this simplified model suffer from sample selection bias as the model parameters are estimated using a sample of individuals who are already likely to respond to the mailing according to the charity.

To analyze the consequences of this sample selection bias on the effects of the RFM variables, we provide in Table 2 the maximum likelihood parameter estimates in case the first component is not included. If we compare the parameter estimates in Tables 1 and 2, we notice a number of differences. First of all, the estimate of the intercept in the response equation is substantially larger in the three component model, which suggests that individuals are more likely to respond. This is not surprising as the parameters in Table 2 are estimated using a data set of individuals who are already likely to respond. Also the intercept in the duration equation is somewhat smaller. If we consider the RFM variables, we notice some remarkable differences. For example, in the response equation the coefficient for the number of weeks since the last response to a mailing changes from 0.302 to -0.121. In both models this variable has a significant effect. In the amount equation the coefficient for the same variable changes from -0.299 to 0.039. However, this variable does not have a significant effect in the restricted model.

4.3 Model Interpretation and Target Selection

Our estimated model can be used to forecast which individuals are most likely to respond to a new mailing and their expected donation as described in Section 3.3. Before we turn to a discussion on target selection, we first intend to illustrate the properties of the model

Table 3: Expected donations to charity for individuals who responded to the last mailing they received 13 weeks ago.[1]

		proportion of responded mailings											
		0.25			0.50			0.75			1		
		#mailings/year			#mailings/year			#mailings/year			#mailings/year		
average donation	donation last resp.	1	2	3	1	2	3	1	2	3	1	2	3
		response to last mailing											
	10	2.62	3.20	3.85	4.42	5.14	5.89	6.38	7.10	7.80	8.06	8.63	9.16
10	25	3.91	4.72	5.61	6.36	7.31	8.29	8.89	9.80	10.67	10.92	11.62	12.24
	50	5.26	6.30	7.42	8.33	9.50	10.70	11.38	12.45	13.48	13.70	14.49	15.19
	10	4.53	5.55	6.68	7.69	8.96	10.29	11.19	12.47	13.73	14.22	15.26	16.20
25	25	6.77	8.19	9.76	11.08	12.78	14.53	15.61	17.24	18.81	19.29	20.55	21.68
	50	9.11	10.94	12.92	14.53	16.63	18.76	19.99	21.93	23.78	24.21	25.65	26.93
	10	6.84	8.40	10.14	11.69	13.65	15.70	17.11	19.10	21.05	21.83	23.46	24.95
50	25	10.24	12.41	14.82	16.87	19.48	22.19	23.89	26.43	28.87	29.66	31.63	33.40
	50	13.80	16.60	19.65	22.14	25.38	28.68	30.62	33.64	36.53	37.25	39.51	41.52

[1] The expectations are unconditional on response and computed using (25).

by considering the unconditional expected donation of individuals in (25) given different RFM histories. The expected donations thus depend on the probability to response in (20) and the expected donation given response in (24). We consider three reasonable but different values for each RFM variable. The results are summarized in Tables 3 through 5. Some cells in the tables are left empty as these combinations of RFM variables are not possible in practice. Note also that some combinations of RFM variables are seldom or never found in our database. Hence, the tables are just for illustrative purposes in order to gain understanding of the model properties.

Table 3 displays the expected donation of individuals who responded to the last mailing they received 13 weeks ago for different combinations of Frequency and Monetary value variables. Several conclusions can be drawn from this table, and we will only mention some of the interesting results. Higher values of the Monetary value variables lead to higher expected donations. A large average donation in the past turns out to be much more important for expected donation than a large donation in the last response. A higher proportion of response to the mailings in the past leads to a higher expected donation. The expected donation of individuals who received more than 1 mailing in the past is higher than the expected donation of those who have only received one mailing per year on average, although the differences are very small. This may be explained by the fact that individuals who receive more mailings may be more involved with charity.

The same patterns can be found in Tables 4 and 5, where we consider the expected donation of individuals, where the last response to a mailing was 52 and 104 weeks ago, respectively. The first panel in both tables displays the expectation if an individual responded to the last mailing and the second panel corresponds to the situation where he or she did not so. The expected donation of individuals, who did not respond to the last mailing, is smaller than for those who did responded to the mail. For example, individuals who did not receive a mailing in the last 104 weeks but who did respond to their last mailing have a higher expected donation than individuals who responded to a mailing only 52 weeks ago. A similar conclusion can be drawn if we consider individuals who did not respond to the last mailing but responded 104 weeks ago for the last time. The charitable organization should pay attention to these individuals.

Our model can be used to determine an optimal selection of individuals in a new round of mailings. This selection may for example be based on the probability to respond as in Bult and Wansbeek (1995). If we construct for every individual in the database the RFM variables, we can compute the probability to respond using (20) and select the individuals who are most likely to respond. As our model also incorporates the size of the gift, we may include the expected donation in the optimal selection procedure as in Otter *et al.* (1997). Target selection is usually based on a decision rule that incorporates both the magnitude of the probability to respond and the expected donation given response. We

Table 4: Expected donations to charity for individuals who responded 52 weeks ago for the last time.[1]

average donation	donation last resp.	proportion of responded mailings 0.25 #mailing/year			0.50 #mailing/year			0.75 #mailing/year			1 #mailing/year		
		1	2	3	1	2	3	1	2	3	1	2	3
		response to last mailing											
	10	3.16	3.82	4.55	5.17	5.96	6.78	7.28	8.04	8.78	9.00	9.59	10.11
10	25	4.68	5.60	6.59	7.39	8.44	9.50	10.09	11.05	11.96	12.15	12.85	13.47
	50	6.26	7.43	8.68	9.64	10.92	12.20	12.86	13.99	15.05	15.19	15.98	16.68
	10	5.46	6.62	7.91	9.01	10.41	11.86	12.78	14.15	15.46	15.89	16.95	17.91
25	25	8.10	9.72	11.48	12.90	14.76	16.65	17.74	19.46	21.09	21.47	22.47	23.87
	50	10.86	12.92	15.13	16.85	19.13	21.42	22.63	24.66	26.57	26.87	28.31	29.58
	10	8.26	10.04	12.01	13.71	15.87	18.12	19.56	21.68	23.73	24.42	26.09	27.59
50	25	12.27	14.75	17.45	19.66	22.53	25.46	27.17	29.85	32.40	33.03	35.03	36.81
	50	16.46	19.62	23.03	25.70	29.22	32.78	34.69	37.86	40.84	41.36	43.63	45.64
		no response to last mailing											
	10	2.02	2.52	3.11	3.67	4.37	5.12	5.70	6.48	7.25			
10	25	3.06	3.79	4.61	5.38	6.33	7.33	8.06	9.07	10.06			
	50	4.17	5.12	6.18	7.13	8.32	9.57	10.43	11.64	12.83			
	10	3.47	4.35	5.38	6.37	7.60	8.93	9.97	11.34	12.73			
25	25	5.27	6.54	7.99	9.34	11.01	12.80	14.11	15.90	17.68			
	50	7.20	8.86	10.72	12.40	14.51	16.73	18.27	20.44	22.57			
	10	5.22	6.57	8.13	9.66	11.54	13.58	15.20	17.32	19.47			
50	25	7.95	9.89	12.10	14.17	16.75	19.50	21.54	24.31	27.08			
	50	10.87	13.40	16.25	18.84	22.08	25.50	27.92	31.28	34.59			

[1] The expectations are unconditional on response and computed using (25).

Table 5: Expected donations to charity for individual who responded 104 weeks ago for the last time.[1]

		proportion of responded mailings											
		0.25			0.50			0.75			1		
		#mailing/year			#mailing/year			#mailing/year			#mailing/year		
average donation	donation last resp.	1	2	3	1	2	3	1	2	3	1	2	3
		response to last mailing											
	10	3.46	4.16	4.94	5.58	6.41	7.26	7.77	8.55	9.30	9.50	10.09	10.62
10	25	5.10	6.08	7.14	7.96	9.05	10.15	10.74	11.71	12.64	12.79	13.50	14.11
	50	6.81	8.05	9.37	10.36	11.69	13.01	13.66	14.81	15.88	15.97	16.77	17.46
	10	5.98	7.22	8.59	9.74	11.21	12.72	13.64	15.04	16.39	16.78	17.85	18.81
25	25	8.84	10.56	12.43	13.90	15.84	17.80	18.88	20.64	22.30	22.62	23.90	25.03
	50	11.83	14.01	16.35	18.11	20.48	22.85	24.04	26.11	28.05	28.27	29.72	30.98
	10	9.05	10.96	13.05	14.82	17.09	19.43	20.88	23.06	25.16	25.80	27.48	28.99
50	25	13.41	16.04	18.91	21.19	24.19	27.23	28.93	31.67	34.27	34.82	36.82	38.60
	50	17.95	21.30	24.89	27.64	31.30	34.99	36.87	40.10	43.14	43.53	45.81	47.80
		no response to last mailing											
	10	2.23	2.78	3.41	4.00	4.74	5.53	6.13	6.93	7.74			
10	25	3.37	4.15	5.04	5.84	6.84	7.90	8.65	9.68	10.71			
	50	4.59	5.60	6.73	7.72	8.98	10.29	11.16	12.41	13.63			
	10	3.83	4.79	5.89	6.95	8.25	9.65	10.72	12.15	13.59			
25	25	5.81	7.18	8.73	10.15	11.92	13.79	15.14	16.99	18.82			
	50	7.92	9.70	11.68	13.44	15.66	17.99	19.56	21.80	23.99			
	10	5.78	7.24	8.92	10.54	12.53	14.69	16.35	18.57	20.79			
50	25	8.78	10.86	13.23	15.41	18.13	21.03	23.12	25.99	28.84			
	50	11.97	14.68	17.72	20.44	23.86	27.44	29.90	33.37	36.78			

[1] The expectations are unconditional on response and computed using (25).

would propose a much simpler selection rule. The charitable organization faces two types of costs, that is, the mailing cost c_m (letter and stamp) and the costs of cashing cheques c_c. The net unconditional expected donation of a individual with characteristics x_i is

$$\mathrm{E}[y_i|d_i^r = 1, x_i; \theta_i] \Pr[d_i^r = 1|x_i; \theta_i] - c_m - c_c \Pr[d_i^r = 1|x_i; \theta_i], \tag{26}$$

where $\mathrm{E}[y_i|d_i^r = 1, x_i; \theta_i]$ and $\Pr[d_i^r = 1|x_i; \theta_i]$ are defined in (24) and (20), respectively. The latter term corresponds to the expected costs of cashing a cheque. A target selection procedure involves computing the net unconditional expected donation of each individual in the database and select those individuals with the highest expected donation.

5 Conclusions

In this paper we proposed a new model, consisting of four interrelated components, with which we could describe one stage of an iterative process involving target selection and response analysis. We illustrated it for a random draw of a database of a charitable organization. In this section we discuss some managerial implications of our model. Additionally, we review possible limitations and the resulting topics for further research.

5.1 Managerial Implications

Our illustration of the model to charity data clearly indicated the relevance of putting all four components of the selection and analysis process into a single model. We showed that when the target selection part was deleted from the model, one would draw inaccurate conclusions concerning the effects of RFM variables. As the model involves various nonlinear functions of the explanatory variables and their respective parameters, we provided a simple method to evaluate the usefulness of the model by calculating expected donations given certain values of the input variables. This allowed us to understand that expected donation did not get maximized for large positive values of all RFM variables only. In fact, it turned out that, for example, individuals, who responded quite some time ago, had a higher expected donation than those who donated on the last occasion. Hence, the model can clearly indicate to whom one should better send mailings, instead of just sending mailings to individuals with the highest scores on RFM variables.

The four components of the model together constitute a single stage of the iterative process of targeting individuals and analyzing their response behavior. Obviously, it is of substantial interest to managers to base their decision process on a model that puts everything together in one framework. Indeed, our model yields clear-cut target selection rules for a next round. In this round, one should again consider the next three components, and given the model results, one can construct new target selection rules. As such, the process becomes an iterative process, where each time the model should suggest optimal selection rules. Needless to say that the model parameters should be re-estimated in each stage, as one should not expect that the effects of the various RFM variables are constant throughout the iterative process. It is perhaps of interest to mention here that the Dutch charitable organization, which allowed us to try out our model on their database, now allows us to experiment with our model in future stages of target selection and analysis. In subsequent work, we aim to discuss the empirical experience with our model.

5.2 Limitations and Topics for Future Research

There are a couple of limitations to our model and empirical analysis, although they all seem to generate interesting topics for further research. The first is that we considered only a static analysis of the data. As mentioned above, we believe that our model can best be used in a dynamic process of target selection and data analysis. It may now be that, given that we consider a similar kind of data in each round, we benefit from previous analysis by imposing prior expectations on the values of certain parameters. Hence, it seems best to incorporate our model into a Bayesian learning and updating strategy, where, so to say, we learn more about typical individuals who donate to charity each time we analyze their response behavior.

A second limitation concerns the fact that we only considered individuals who did donate before to the same charity. Indeed, only because of this focus we could construct RFM variables. However, for a charitable organization it is usually also of interest to acquire new donators. Oftentimes, new prospective charity donors are selected from mailing lists, which are provided by firms other than the charity itself. These firms provide lists of zip codes and addresses of individuals who they think might be willing to donate to charity. Hence, again there is a selection step, which should be included in the model in order to avoid sample selection bias. Even though one usually only knows some characteristics of individuals or households when they have certain zip codes, it should be possible to match this information with the RFM variables of individuals with for example the same zip codes. As this means that one has to draw inference on individuals on the basis of estimated characteristics of groups of individuals (for example, those who have the same zip codes), one has to resort to so-called ecological inference techniques.

Finally, a third limitation is that we found that RFM variables did not have much of an effect on the speed of response to a direct mailing. Indeed, one may expect that a variable such as advertising would have more effect. However, it seems impossible to collect advertising exposure and recall data at the individual level. The only option is to consider the effects of advertising in a longitudinal study, implying that one considers our model for several sequential mailshots. Given the availability of data on for example advertising expenditures, one then examines if advertising has an effect on whether, when and how much to donate to charity. We consider this as an interesting topic for further research.

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