A Decision Support System for fund raising management in medium-sized Organizations

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Abstract. In fund raising management, quantitative methods based on a structured Data Base of (potential) donors have a great importance. A modern approach is founded on a rigorous mathematical modelling, that has been specialized for different kind of Non Profit Associations, in order to maximize the effectiveness of the proposed Decision Support System (DSS) related to the available information and the level of computerization, which are normally strictly dependent on the size of the Organization. In the present contribution we propose a DSS specifically performed and focused on the medium-sized Organizations, which are not yet specifically considered by the literature. Both the mathematical modelling and the available data structure are specialized for this kind of Associations, by using a dynamic DB management approach that integrates the issues of the so called fund raising pyramid into the algorithm, by an automatic evaluation of the data set by time. Furthermore the key feature in estimating the probability of "giving" is enhanced, thanks to a refining process that is implemented for donors that have enough historical information.

Keywords. Social Economics, Fund Raising Management, Medium-Sized Organizations, Decision Support Systems, Empirical Estimation.

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1 Introduction

In Social Economics area the Non Profit Organizations (NPO) management has a great importance. A crucial support for NPOs is the fund raising activity, in

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which the resources for the mission of the Association are collected ([1] and [18]). In organising fund raising campaigns, Organizations need the donors' support, which donate for the mission and more specifically for the goal of the current campaign, see e.g. [8], [20] and [12]. Managing donors efficiently is therefore essential for the survival of the Organization and for the achievement of its aims ([13], [16]). Classical operational literature emphasizes on the use of quantitative methods in order to manage the donors list, employing Data Bases (DB) technologies ([9] and [11]). Econometric literature also dealt with (potential) donors profiles that match some specific gift inclination, see e.g. [7] and [6]. Recently an innovative approach has been performed in this field by [2], that introduces the use of mathematical modelling and Decision Support Systems (DSS) techniques, in order to help Associations both to decide the kind of campaign they have to organize and the features to implement, and the donors of the DB list which must be contacted, in order to maximize the expected return of the campaign, satisfying time and cost constraints. This quantitative approach has been specialized for different kind of Organizations. On one hand [3] and [5] dealt with large-sized Associations, international also, that have lists of millions of donors and a powerful organizational system requiring a very sophisticated DSS. On the other hand, [4] consider also small-sized Organizations and developed a DSS based only on essential information with no need of an organized DB. This approach has been validated both in the operative world by Associations that test it (as documented in [3], [4] and [5]) and in the pertaining literature (see [21]).

In this contribution, we study the detailed features of medium-sized Organizations and we develop a DSS based on a specific mathematical model and targeted for this kind of Associations. In particular we integrate the practitioners' issues contained in the so called "giving pyramid" (see e.g. [13] or [5] pp. 133-135) into a unique model (differently to [5]) simplifying in this way the structure of the system and making the results more understandable by the management staff of the NPO. Furthermore we improve also some general features of the previous models, like e.g. the estimation of the probability of giving and, consequently, the estimation of the expected total return of the campaign. The mathematical approach consists in a ranking algorithm that, differently from the previous literature, fits data of each donor considering also the specific historical dataset of that donor. In this way the fund raising pyramid is dynamically integrated into the calculation process and not given at each evaluation to the algorithm as in [5], avoiding in this way an explicit step of maintenance of the dataset.

The data structure is an organized data base (DB) ([14] and [10]), where only the usual information on donors is contained and any other additional information is required, differently from e.g. [3] and [5], in order to be effectively usable by medium-sized Associations. A key point of the algorithm is to evaluate the probability of "giving". In the literature, this has previously performed by following the indications of operative literature, which are however quite qualitative and do not explore the estimation properties. In this contribution, an improvement has been made in this point, due to the refining of the estimation for all donors for which the historical dataset is robust enough, considering the frequency of gift over the total of request, both for the entire period and for a recent time window to capture possible dynamic shifts.

This improves the quality of estimation and gives additional information that will be used in evaluating the total return and the general performance of the employed strategy.

The obtained DSS is based on a robust dynamic mathematical model, but at the same time it is usable and targeted for the management of a medium-sized Organization. The goal is obtained including inside the computational process the principal instances of fund raising management, simplifying in this way the structure of the system, that is completely enclosed in the DB management context and not includes sophisticated and labourious to manage information techniques, like *artificial intelligence* tools, as for instance in [3], [5].

2 The donor's gift forecasting model

We assume that the NPO has a structured DB with donors historical information. For each donor, either quantitative or qualitative data are usually collected. Quantitative data used in this approach are essentially the historical path of past donations for each kind of campaign. Other quantitative or coded information (e.g. age, gender, profession, educational qualification, income, number of children) and qualitative information (like interests, hobbies, preferences, social relationships), that are generally included in a structured DB, are not considered in this model, because it is focused on the most important variables in order to be effective but not too sophisticated. The advantage of it is making usable the resulting model by that Associations which don't have an advanced DB, like the small-medium sized and the poorly computerized medium-sized ones.

The Association Management (i.e. the Decision Maker, DM for brevity) has to organize a fund raising campaign that is focused on one of the interests of its mission, by deciding the donors to contact and the contacting strategy, and considering the costs, which depend on the contact way (the higher the cost, the greater the gift probability). Moreover, the DM has to specify the campaign budget and the target (global return) to achieve.

A strategy involves therefore a list of possible actions (characterized by a certain effectiveness and cost; higher the cost, greater the effectiveness) and a list of potential donors, characterized by DB's information.

In this contest, we will not distinguish between the different types of requests. Thus the conceptual model will include the series of *requests* (in broad and abstract sense) and the corresponding *answer* (the gift, if any, or zero). In this way, the available data consist of the sampled time series of past gifts for each donor, that is the sequence of the request dates and the corresponding contingent gift (if any, zero otherwise). All the observations are aligned at the current time t, therefore the series conventionally starts from $t - n_i$ up to t for each $i - th$ donor, thus its length is n_i. Given that the model needs to be applied to every donor, we suppose that n_i does not differ too much among donors.

After fixing the time origin in t_0, the time conventionally corresponding to the beginning of the NPO activity (or later), the available data consist of the time sequence for the $i-th$ donor: $\{t_i(1), t_i(2), ..., t_i(n_i)\}$, with $t_i(k) > t_0, \forall k$, being n_i the number of contacts for the $i-th$ donor, and being the corresponding gift sequence: $\{D_i(1), D_i(2), ..., D_i(n_i)\}$, with $D_i(j) \geq 0$. If $D_i(j) = 0$ no gift was given. Moreover, as for the conceptual model, we suppose that the donor gives the gift, if he does, at the same time of the contact; thus the delay between the contact and the gift (if any) is negligible. The value $D_i(k)$ corresponds to the gift (or null gift) given by the $i-th$ donor at time $t_i(k)$.

Then each donor is characterized by the *profile* d_i:

$$d_i = \{(t_i(1), D_i(1)), (t_i(2), D_i(2)), ..., (t_i(n_i), D_i(n_i)\}$$

We suppose that at time t, the *current* time, with $t \geq max_i(t_i(n_i))$, an ordered list of donors has to be produced in function of some desired characteristics, and subsequently the reaching of the fixed target has to be evaluated. The DM preferences are expressed by a set of parameters, that reflect the DM requests about the donor characteristics. For instance, a donor will be selected only if he has given a gift at least at a fixed percentage of the past requests. Again the donor must have been contacted at least a fixed number of times, otherwise he is discarded, given that the DM judges the past observations as insufficient[1]. Thus the DM has to specify:

1) The fixed minimum value for the global gift, G, i.e. the sum of the gift of all donors (the campaign target) ("Select donors whose average gift is *at least* G euro");

2) a minimum value for the *robustness*, i.e. minimum number of requests, r_{min};

3) a minimum value for the gift sampled frequency (observed in the past), f_{min};

4) a penalization function for the elapsed time in function of the frequency, $\mu(ET)$ (see later);

5) a time window w to compute the empirical frequency of the last gifts in order to include the *coldness* effect, see below.

The algorithm will select the donors which satisfy the DM's preferences expressed by the thresholds previously assigned. At the same time, it will produce a donor *ranking list*. For this purpose, we define:

[1] From now on this characteristic will be called *robustness*.

i) $PD_i(t)$: the estimated gift probability at time $(t+1)$ for the $i-th$ donor, calculated at time t;

ii) The gift's frequency for the $i-th$ donor, between τ_1 and τ_2, with $t_0 \leq \tau_1 \leq \tau_2 \leq t$:

$$f_i(\tau_1, \tau_2) = \frac{\sum_{\tau_1 \leq t_i(j) \leq \tau_2} I(D_i(j))}{\sum_{\tau_1 \leq t_i(j) \leq \tau_2} j} \tag{1}$$

being $I(x)$ the indicator function of x:

$$I(x) = \begin{cases} 1, \, x > 0 \\ 0, \, x \leq 0 \end{cases}$$

iii) The average gift (*positive* values only) for the $i_t h$ donor, between τ_1 and τ_2:

$$V_i(\tau_1, \tau_2) = \frac{\sum_{\tau_1 \leq t_i(j) \leq \tau_2} D_i(j)}{\sum_{\tau_1 \leq t_i(j) \leq \tau_2} j} \tag{2}$$

In some cases, a donor can show more or less stability in his gift attitude, depending on many latent variables (liquidity availability, position in the market, management change, etc.). This phenomenon can be modeled as follows: the probability $PD_i(t)$ is estimated as a monotone[2] function $F(f_i(t_0, t), f_i(t-w, t))$ of the *global* empirical frequency, $f_i(t_0, t)$, and the empirical frequency in the last time window of width w, $f_i(t-w, t)$. If $f_i(t-w, t) < f_i(t_0, t)$ a clear tendency to *coldness* can be inferred. Conversely, if $f_i(t-w, t) > f_i(t_0, t)$, the donor becomes more *generous* and this phenomenon can be captured by this simple heuristic rule.

Again, if the donor's attitude in the considered instant depends on many variables (often not observable), a critical role is played by the time passed since the last donation, the *elapsed time* $ET_i(t) = t - t_i(n_i)$, given that a donor is generally less prone to give a gift if he has gifted more recently. Thus we could expect that the shorter ET_i, the lower the gift probability. For this purpose $PD_i(t)$ has to be modified by a not decreasing function $\mu(ET_i(t))$, determined by the DM. Supposing a limited *memory effect*, this penalty will be applied only for a limited time horizon.
In the simplest case the function $F(,)$ is a linear combination of $f_i(t_0, t)$ and $f_i(t-w, t)$ with coefficients ω_L and $\omega_S = 1 - \omega_L$, thus:

$$PD_i(t) = [(\omega_L \times f_i(t_0, t) + \omega_S \times f_i(t-w, t)] \times \mu(ET_i(t)) \tag{3}$$

[2] The function $F(,)$ is monotone in both its arguments.

Similarly, the average gift is a linear combination (with the same parameter values) of the Long term sampled gift and the Short term sampled gift:

$$V_i(t) = \omega_L \times V_i(t_0, t) + \omega_S \times V_i(t - w, t) \tag{4}$$

In this way, we enhance the classical estimation technique of the probability of giving, initially proposed by the operational literature, and then adopted by the academic one (without exploiting the possibilities given by a rigorous mathematical approach). In fact, in the literature, the probability of giving is computed by considering the past gifts as having the same weight, while in our approach we dynamically analyze the past behavior of each donor by explicitly considering the memory effect.
Finally we compute the average expected gift for the $i - th$ donor as usual: $PD_i(t) \times V_i(t)$.

Thus the algorithm consists of the following steps:

1) Fix the input parameters: $r_{min}, V_{min}, f_{min}, \omega_L, \omega_S$, the function μ and the target G;

2) At the current time t, select all the donors d_i for which $r_i \geq r_{min}$, $V_i(t_0, t) \geq V_{min}$ and $f_i \geq f_{min}$;

3) For all the donors d_i previously selected, compute $PD_i(t)$ and $V_i(t)$ and their product $PD_i(t) \times V_i(t)$;

4) Sum up all the values $PD_i(t) \times V_i(t)$: $Sum = \sum_i PD_i(t) \times V_i(t)$.

If $Sum \geq G$ then the campaign target is reached; otherwise enlarge the donors set or modify some of the input parameters $r_{min}, V_{min}, f_{min}$.
Finally, we underline that our method doesn't require a priori knowledge about the statistical distribution of the involved variables, therefore only an *empirical* estimation of the probability of giving and an average gift are provided, see [15]. Even though, on one hand, this approach can be debatable, on the other hand it can be applied to every available data set, supposing only statistical independence among the events (gifts sequence). Nevertheless, including both the coldness and the elapsed time effect, the obtained model intends to emulate a real DM behavior. Therefore the proposed algorithm falls in the category of machine learning and artificial intelligence, see [19], rather than in the statistical estimation methods.

3 A numerical example

Consider now the following example:

The DM specifies (financial unit are expressed for instance in thousands of euro):

a) the campaign target $G = 100$,

b) the time horizon: $t = 48$ months ($t_0 = 0, t = 48$),

c) the time window $w = 24$ months,

d) $r_{min} = 5$, $f_{min} = 0.60$,

e) equal importance to low term and high term frequency: $\omega_1 = 0.5, \omega_2 = 0.5$,

f) the penalty function for the elapsed time will have no effect, thus will be equal to one, if $ET > 8$, equal to zero if $ET < 4$, and linearly increasing between 4 and 8, thus:

$$\mu(x) = \begin{cases} 0, & x < 4 \\ \frac{x-4}{4}, & 4 \leq x \leq 8 \\ 1, & x > 8 \end{cases}$$

Consider 5 hypothetical donors, each of them described by the following profiles:

$d_1 = \{(15, 100), (20, 0), (25, 200), (35, 100)\}$

$d_2 = \{(0, 100), (5, 50), (10, 0), (12, 0), (15, 50), (20, 0), (24, 80), (28, 40), (34, 0), (36, 50), (40, 50), (41, 100)\}$

$d_3 = \{(10, 100), (15, 0), (20, 300), (25, 0), (30, 0), (33, 300), (35, 0), (38, 400) (42, 0), (44, 0)\}$

$d_4 = \{(0, 80), (10, 100), (20, 0), (25, 100), (30, 50), (35, 0), (40, 100), (42, 50)\}$

$d_5 = \{(10, 50), (15, 0), (20, 100), (25, 70), (30, 0), (33, 100), (38, 80), (40, 300)\}$

Both the donors 1 and 3 are discarded, the first for the too low robustness (only 4 requests, while $r_{min} = 5$), the other for the too low frequency, even if characterized by high average gift and sufficient robustness (i.e. sufficient number of contacts).

As for the donor 2, we have $f_2(t_0, t) = f_2(0, 48) = 0.66$, given that for 8 cases over a total of 12 the donor gave a gift. Again, considering only the requests in the last 24 months, we have $f_2(t - w, t) = f_2(24, 48) = 0.83$, $ET_2 = 48 - 41 = 7$ therefore:

$$\begin{aligned} PD_2(48) &= [0.5 \times f_2(0, 48) + 0.5 \times f_2(24, 48)] \times \mu(7) = \\ &= [0.5 \times 0.66 + 0.5 \times 0.83] \times 0.75 = 0.56 \end{aligned} \quad (5)$$

given that the penalty function for the elapsed time is $\mu(7) = 0.75$. As for the average sampled gift we have:

$$V_2(48) = 0.5 \times V_2(0, 48) + 0.5 \times V_2(24, 48) = 0.5 \times 43.3 + 0.5 \times 53.3 = 48.3 \quad (6)$$

A similar computation for the two other donors d_4 and d_5 provides, being $ET_4 = 48 - 44 = 4$, $ET_5 = 48 - 40 = 8$:

$$PD_4(48) = [0.5 \times f_4(0, 48) + 0.5 \times f_4(24, 48)] \times \mu(6) = \\ = [0.5 \times 0.75 + 0.5 \times 0.8] \times 0.5 = 0.39 \quad (7)$$

$$PD_5(48) = [0.5 \times f_5(0, 48) + 0.5 \times f_5(24, 48)] \times \mu(8) = \\ = [0.5 \times 0.75 + 0.5 \times 0.8] = 0.77 \quad (8)$$

and:

$$V_4(48) = 0.5 \times V_4(0, t) + 0.5 \times V_4(24, t) = 0.5 \times 60.0 + 0.5 \times 60.0 = 60.0 \quad (9)$$

$$V_5(48) = 0.5 \times V_5(0, t) + 0.5 \times V_5(24, t) = 0.5 \times 87.5 + 0.5 \times 170 = 128.7 \quad (10)$$

Finally we compute the expected total gift for the campaign as:

$$Sum = \sum_i PD_i(t) \times V_i(t) = 0.66 \times 43.3 + 0.39 \times 60 + 0.77 \times 128.7 = 123.56 \quad (11)$$

and given that $Sum > G$ ($Sum = 123.56$, $G = 100$), the campaign target is reached with an expected margin higher than 20 per cent.

4 Conclusions

In the paper we develop a specific algorithm to construct a Decision Support System for the fund raising management in a medium-sized Organization, exploiting the specific characteristics of the examined case. At this aim we use specific mathematical techniques particularly suitable for the goal. The obtained system captures the most important properties of more sophisticated ones, previously developed in the literature, and at the same time results suitably usable for the Organization management. The estimation of the probability of giving typically used in the literature is also enhanced. A future work includes the extension of this integrated dynamic approach to some new claim, like the analysis of different kind of campaigns and the evaluation of different types of request mode. Furtheremore we intend to develop a deeper analysis for a further improvement in the estimation of probability of "giving", for instance applying a *naive* bayesian estimation as in [17] or a Markov chain approach.

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