Predictive Models for Annual Fundraising and Major Gift Fundraising

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For most nonprofit organizations, the selection process for determining the best individual prospects for capital campaigns or annual fund drives are ad hoc and intuitive. Our research provides two statistical models developed from the alumni database at Northwestern University for both major gifts and annual fund prospects. One model predicts which individuals will give $100,000 or more over three years, the other, $1,000 or more. Our work provides a means of more efficiently selecting fundraising prospects. In our analysis, we combine geo-demographic data with the internal data typically found in alumni databases. A metric is presented to test the viability of the models when compared to single-criterion models. We show that past giving is the strongest single factor in predicting future giving. However, full models provide superior overall results.

THE starting point for most fundraising efforts is the development of a strategy for defining the pool of potential prospects. When approaching either a capital campaign or an annual fund drive, development officers need to make basic decisions about who to approach and how large a gift to solicit. Typically, the population of potential donors for any institution or organization consists of tens of thousands, if not hundreds of thousands, of individuals. In a capital campaign, the critical need for face-to-face individual solicitations further reinforces the need to reduce the number of potential prospects to no more than a few thousand. In the case of a small institution, a target group of several hundred individuals may be all that can be visited. Even if one is considering a telephone or direct mail campaign for annual funds, it may be impossible or financially imprudent to contact everyone in the population.

For years, for-profit businesses have used census data to identify characteristics of likely customers living in particular geographical areas. Typically, this identification is done by associating an individual with the average characteristics of others living in the same block or group of blocks. This information is then used to determine which individuals are more likely to be customers, which then allows a firm to target its approaches. This technique of geo-demographics is represented by such products as PRIZM by Claritas, ACORN by CACI, and VISION by National Decision Systems.

Over the past five years, consulting firms such as Bentz, Whaley, Flessner; John Grenzebach and Associates, Inc.; and Marts and Lundy, Inc.; and alumni directory firms such as Publishing Concepts, Inc., and Harris, Inc., have begun to use geo-demographic data to assist universities and other nonprofits in identifying potential donors. The likelihood of individuals making a gift is determined by the characteristics of the neighborhoods where they reside. This information is then used to determine which prospects should be visited.

Many higher education institutions also have internal data on their alumni that are of potential value. It is typical to have data on alumni's year of graduation, major, and whether they have a spouse or children who attended the institution. Institutions know about special alumni and giving clubs to which prospects belong. If they keep detailed information, they may also know something about salary, job title, attitude toward the university, and participation in class activities.

Other nonprofits that might consider using the techniques outlined in this article have corresponding internal data. For hospitals, the patient lists provide a start. For museums and arts organizations, the list of patrons, sponsors, and participants will make up the database. Organizations lacking extensive internal information will benefit all the more from external coding.

Internal data and external geo-coded information can be combined to develop statistical models to predict giving at different levels. This information then can be used to rank order prospects in terms of their giving potential. This allows a development office to allocate an officer's time more efficiently with respect to personal visits and target solicitation levels.

In this article, we discuss how statistical analyses that combine geo-demographic and institution-specific data can help identify individuals who are most likely to be donors. We develop a scale of donor potential by examining past giving behavior, other internal data, and external geo-demographic data of 140,000 alumni at Northwestern University. A statistical technique similar to regression analysis known as *logit analysis* is used to determine which combination of variables best predicts giving. Employing these results, a scale is constructed using individuals' values on variables with variable coefficients as weights.

Common Practice and Previous Research

The informal use of particular characteristics of individuals to break down a database into populations of potential prospects is common to fundraising operations. For instance, one may select on the past giving behavior of individuals and decide to visit only individuals who have already given a certain amount, or one may choose individuals who meet certain criteria typical of wealth.

There are three problems with approaches of this type. First, this culling process often ignores important information that when used in combination can aid in predicting the giving behavior of individuals in the prospect population. Second, although characteristics used to sort a population are related to giving behavior, the specific rules applied may be very ad hoc. Third, there is the problem of variability in individual experience when used as a basis to formulate a rule.

The argument for statistical analyses is that they allow us to utilize a considerable amount of information simultaneously. We can use not only our own experiences, but those of others, both within our own and in other institutions. Statistical models involving many variables and individuals can be estimated on computers, and as a result, it is possible both to use large amounts of information and to precisely determine the best rules for selection.

Brittingham and Pezzullo (1990, pp. 39–44) provide an excellent summary of the predictors that have been considered by researchers (usually in dissertations based on a single institution) over the past years. They divide the predictors into two major groups: characteristics of alumni when they were students and current characteristics of alumni. Only the latter have shown promise of being strong predictors. There was no conclusive pattern to support differences based on entering ability, patterns of attendance, participation in student organizations, place of residence, choice of major, grade-point average, or financial aid.

Brittingham and Pezzullo note that certain current characteristics of alumni were found to be predictors in some studies; but not others. Income, age, number of degrees from the institution, emotional attachment to the school, participation in alumni events, and participation in and donation to other voluntary and religious groups were found to be predictors. The areas where studies disagreed were the following:

Sex (three studies show no effect, two show men give more)
Marital status (three studies show no effect, one shows married give more)

Spouse alumnus (two studies show no effect, one shows an effect when spouse has given gifts)
Status of children (three studies show no effect, two show some effect in certain cases)
Distance from school (three studies show no effect, one indicates farther, one indicates closer)
Occupation (three show no effect, three show some effect in some cases)

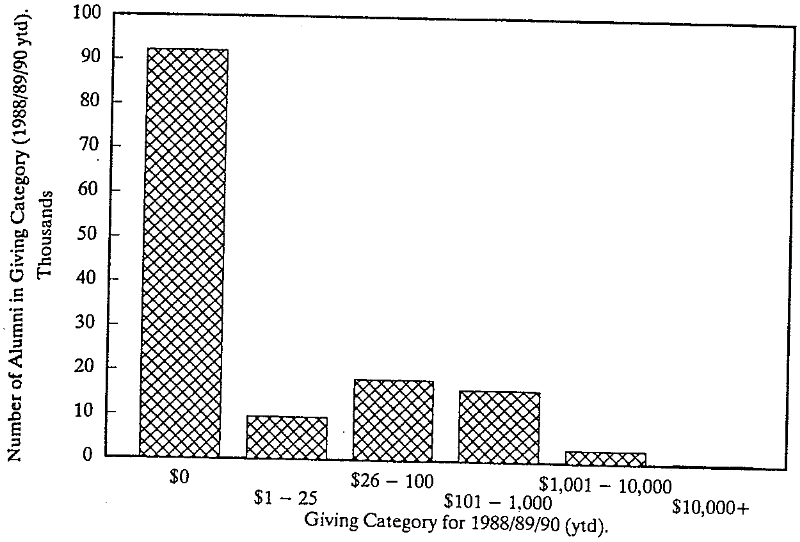
All of the characteristics where there were conflicts in past studies were included in the research for this study. Those that did not show significant and relatively strong effects (either individually or as a group) were eliminated from the models early in the process. The one variable that was never considered in these earlier studies but that was incorporated in our study was past giving. This characteristic has been used informally by development officers over the years as the best predictor of future giving. Yet until this study, it had not been used in formal studies of giving behavior. In our analysis, we found that it is the strongest single predictor of current giving. This is not surprising; we would expect past giving to be an excellent indicator of both an individual's current inclination and capacity to give.

We would expect past giving to be an excellent indicator

Most of the research done in this area has made use of linear techniques to predict giving. Connolly and Blanchette (1986) used discriminant analysis, and Melchiori (1988) used a classification analysis to predict donor behavior, both types of linear regression. These techniques are inappropriate when the object is to predict rare events, such as giving over $100,000, or when the dependent variable has an upper or lower bound and there are a large number of individuals at the bound, as with giving where there are numerous individuals with zero giving (see Maddala, 1983). As described below, because the outcome we are interested in is whether an individual made a gift of a certain size, we use logit analysis, a nonlinear variant of regression analysis, which is suitable for giving data (see Hanushek and Jackson, chap. 7, for an introduction). Figure 1 indicates the distribution of total gifts from alumni at Northwestern in the years 1988–1990.

To evaluate and compare models using a metric relevant to development officers, we examine the total number of dollars given by the best prospects identified by each model. A model is judged superior to another if the total number of dollars received by the top predicted donors is substantially higher within the range of prospects that might be solicited using a particular technique employed (for example, the limit might be under 1,500 prospects for personal solicitation of major gift prospects). We develop two predictive models that incorporate both the geodemographic information and the internal information typically present in a university database. Our major gifts model predicts

Figure 1. Distribution of Alumni by Level of Giving



which individuals will give over $100,000 in a three-year period. Our annual fund model predicts giving at the $1,000-and-up level over the same time frame after removing the top 1,500 major gift prospects from the data set.

Data and Methodology

We used the Northwestern University alumni/development database in this study. It consists of approximately 190,000 "mailable" individuals, 140,000 of which are alumni. Our analysis only uses alumni. The information in the files has been assembled over the past twenty-five years from several sources. Questionnaires have been sent to alumni from undergraduate (through the reunion program) and professional schools at various intervals from the late 1970s to the present. During the past two years, Northwestern carried out a National Resources Program that involved peer evaluation of the gift-giving potential of alumni. Approximately 25,000 alumni were rated, some multiple times. Each year, current graduates are added to the system, increasing the database by approximately 4,000 records.

Appended to the main database are PRIZM codes and affluence ratings provided by John Grenzebach and Associates from the Claritas Corporation. These variables are derived from census block–level data. PRIZM Cluster Codes provide a market segmentation system that is based on the principle that people with similar backgrounds, means, and consumer behavior cluster in neighborhoods suited to their chosen life-styles. Through a statistical analysis of the demographic characteristics and actual consumer behavior, every neighborhood in the nation is assigned to one of the forty PRIZM Clusters.

As an example, the following is a description of "Blue Blood Estates" (Code S1-28). According to their marketing literature, these are America's wealthiest socioeconomic neighborhoods, populated by super-upper established managers, professionals, and heirs to "old money," accustomed to privilege and living in luxurious surroundings. One in ten millionaires can be found in Blue Blood Estates, and there is a considerable drop from these heights to the next level of affluence.

Affluence ratings are only used in the annual fund model (see description of models below). This rating is a composite score of several census data elements, including average household income, education level, and home value. The score ranges from 0 to 99, with 99 being the score for the wealthiest neighborhoods in the nation.

People with similar backgrounds, means, and consumer behavior cluster in neighborhoods

Analysis Design

The basic design of the analysis is to use giving in the recent past as the dependent variable and total prior giving along with other information to predict recent giving. In our analysis, we use two levels of total giving between 1988 and 1990 as the dependent variables and giving prior to this time as an independent variable. In the first level, the major gift dependent variable is simply a zero-one dichotomy indicating whether an individual gave $100,000 or more over the three-year period (1-yes, 0-no). The alumni-giving dependent variable is defined similarly at the $1,000-and-up level.

Our procedure attempts to re-create a file that represents the information that would have been available in December 1987 and then uses this information to predict which alumni were most likely to make a gift between 1988 and 1990. For the nongiving variables, only currently stored values are known, so these are used. Since these variables have no dates associated with them (except for address information), the major assumption we make is that these variables have not changed in the past three years. Obviously, for some variables this is not problematic (for example, sex and degree), while for others, changes may have occurred (for instance, business occupation and salary).

Of the two models, the major gifts model is the simplest. Only a few individuals have given gifts totaling over $100,000 in three years ($N = 61$). As a result, our effective sample size is quite small and only a small number of independent variables are statistically important (using a chi-square test). A considerably larger number of individuals have made gifts over $1,000 ($N = 3{,}266$). Consequently, the power of our sample to detect whether particular variables are important is much greater. The annual fund model contains an additional eight variables beyond the major gifts model. The variables in our two models are described in Table 1.

As discussed below, we arrived at the above list of variables for our two models by testing a wide variety of models against our data. We need, however, to at least touch on the conceptual relevance of these variables for predicting giving behavior. If one conceptualizes individual giving as being the result of both inclination and capacity to give, one can see that some of the above variables capture one or the other of these dimensions, and other variables capture both. Past giving, neighborhood, and estate planning interest capture both inclination and capacity. We would suspect that recency of gift, relation to the university, location, whether one's spouse is an alumnus, questionnaire information, and religious activity would principally capture inclination. Year since graduation, salary, affluence, an individual's national resource rating, and possibly sex and school should reflect capacity.

Logit Analysis

Logit analysis solves the problems of using regression analysis to predict rare events

We use logit analysis to develop the two models of donor behavior. It specifies a nonlinear relationship between the probability of an event occurring (a gift being made) and the variables used to predict that event. By positing a nonlinear relationship, logit analysis solves the problems of using regression analysis to predict rare events such as gifts over $100,000 and the problem of there being substantial numbers of individuals who have not given at all. For further discussion of logit models, see Chapter 7 in Hanushek and Jackson (1977).

An obvious question is why we have not just used simple regression analysis or the more sophisticated tobit analysis, which takes into account in a statistically appropriate way the fact that there are a large number of never givers (for an introduction to tobit models, see Maddala, 1983). Both of these techniques use the precise amount that an individual has given in estimating the effects of different variables. In our logit analysis, giving is simply coded as being above or below some threshold. We did try both of the above techniques. The regression model test results were not nearly as strong as the results using logit analysis (using the metric described later on in the article, fewer dollars were "raised" when this model was used). The tobit model showed mixed test results, with some levels of selection (300 alumni) having higher dollars and other levels (600 and 1,000) having lower dollars than the logit model for major gifts. The tobit estimates were not always reasonable. For example, years since degree has a highly nonmonotonic and unstable effect on giving.

An important question is why the logit model might do better than either standard regression or the tobit model. Our interest is in predicting individuals who are likely to be at the very upper

Table 1. Description of Variables for Major Gifts and Annual Fund Models

Field	Description[a]
Major Gifts Model	
Past Giving	
PAST10K	Past years giving $10,000 plus (pre-1988) including family giving.
PAST3K	Past years giving $3,000 plus (pre-1988) including family giving.
PAST1K	Past years giving $1,000 plus (pre-1988) including family giving.
PAST5C	Past years giving $500 plus (pre-1988) including family giving.
PAST1C	Past years giving $100 plus (pre-1988) including family giving.
PAST1	Past years giving $1 plus (pre-1988) including family giving.
Recency of Last Gift	
RECENT87	Last gift given in 1987
RECENT86	Last gift given in 1986
RECENT85	Last gift given in 1985
Relation to University	
FATTACH	Attachment to the university (not through giving programs)—trustees, relative on system, admissions mailing list, theater mailing list, spouse is a trustee, spouse is on admissions list, spouse is on theater mailing list.
Year of Graduation	
DYS11	Years since last degree (any school) 11–30
DYS31	Years since last degree (any school) 31–40
DYS41	Years since last degree (any school) 41–50
DYS51	Years since last degree (any school) 51+
Neighborhood	
DPRIZM2	Claritas PRIZM scores 21, 28, and 39 (Urban Gold Coast, Blue Blood Estates, and Gray Power)
Salary	
SAL2HIGH	Self-reported salary $200,000 and over
SAL2MED	Self-reported salary $100,000 to $199,999
SAL2LOW	Self-reported salary under $100,000
Estate Planning Interest	
FDIFFLAG	Dealing-in-futures (estate planning mailer) respondent
National Resource Program	
SPOTEN	High giving potential (lifetime $250,000 to all causes)—initially loaded via national resources program
Annual Fund Model (includes Major Gifts Model variables)	
Location	
CHICAGOA	Address in Chicagoland area
Sex	
RSEX	Sex of alumnus
Spouse Information	
SPALUM	Whether the spouse is also an alum
Affluence Rating	
AFFMED	Geo-coded affluence rating 50 to 69 (100 pt scale)
AFFHIGH	Geo-coded affluence rating 70 to 89
AFFVHIGH	Geo-coded affluence rating 90+

Table 1. *(continued)*

Field	*Description* [a]
Questionnaire Information	
FRESPON	Responded to a questionnaire at some time (since 1975)
HIGHPOS	Self-reported high position (for example, president, CEO, partner, senior vice-president)
School Information	
MEDICAL	Alumnus has a degree from the medical school
LAW	Alumnus has a degree from the law school
CAS	Alumnus has a degree from the college of arts and sciences
Religious Activity	
RELIGACT	Alumnus participated in a religious activity while a student

[a] Values are all discrete (0 or 1).

extreme in the giving distribution. Individuals who have given over $100,000 represent 0.04 percent and individuals who have given over $1,000 represent 2.3 percent of the database. Logit analysis appears to do a better job precisely because it only makes distinctions at the extremes. Regression and tobit analysis, because they attempt to accurately differentiate between individual levels of giving in the other 97.7 percent of the population, apparently do worse. Thus, by ignoring information on the precise amount of individuals' giving and only focusing on the distinctions that are relevant to development officers—potential major gift and significant annual fund prospects—logit analysis does a better job of identifying individuals.

Our models can be represented by the following equation:

$$\text{Score}_i = \text{Weight}_1\text{Attribute}_1 + \text{Weight}_2\text{Attribute}_2 + \ldots + \text{Weight}_n\text{Attribute}_n$$

where Score is a measure of an individual's propensity to give at a specified level, Weight is the logit coefficient associated with the particular attribute, indicating its importance, and Attribute is a variable taking on the value 1 if the particular alumnus has the attribute and 0 if the particular alumnus does not.

Once the weights for the formula are established with statistical procedures, a score can be produced for each prospect in the institution's database by simply adding up the appropriate weights. The score can then be converted to a probability for each of the two models. At Northwestern, the converted scores are displayed on the prospect tracking report (prospect "card") and assist the development staff in deciding who to visit.

Attempted Models

Many models were estimated using different variables. Initially, we used stepwise procedures to identify variables of potential importance. We chose the major gifts and alumni models that "raised" the most money over an appropriate range of selected alumni. In the process of identifying these two models, we explored several different options. Several variables were considered and later rejected because either they lacked significance (via chi-square criteria tested both individually and in groups) or did not contribute greatly to the model. Among these were the following: marital status, sports participation as a student, and largest single-gift amount. As mentioned earlier, marital status and sports participation as a student were considered by other investigators over the years with little success. The largest single-gift amount was not important as long as the more fundamental variable—average total past giving—was included in the analysis.

Average past giving decoupled the effects of age from the propensity to give

Second, different methods of handling past giving were investigated. We use average past giving since the earliest degree instead of total past giving because it decoupled the effects of age from the propensity to give. Both continuous and discrete setups were considered for past giving. The continuous specification (piecewise linear) setup was far superior. We did not use a fully continuous specification of the past giving variable directly in our model because of the large amount of resources needed for such a setup using logit analysis. When we did use continuous specifications for past giving with regression analysis, the results were not as strong. A discussion of stability and collinearity concerns can be found in the appendix.

Table 2 describes the coefficients for each variable, along with the standard errors. Each model is described separately in the next two sections of the article.

Major Gifts Model

The first column in Table 2 indicates the effects of the eight variables used in the major gifts model. Since the categories of the major gifts variables are all coded as zero-one dummy variables, the relative size of their coefficients can be directly compared. Determining the absolute size of the logit coefficients is discussed in the appendix.

The sole exception to this zero-one coding is past giving, where the dummy variables are coded so that the effects are cumulative. For example, the effect of giving \$10,000 or more is the sum of the effects for that level and all lower levels: 1.22 + 1.70 + .84 + 2.60 = 6.36. The effect of having given at least \$1,000 will be .84 + 2.60 = 3.44. The use of this cumulative coding scheme, as opposed to a sum-of-effects method, is somewhat arbitrary—the same exact results are determined either way—but we use it to show the incremental effects of giving.

Past giving has by far and away the largest effect on current giving (b = 6.36 for individuals who have given over \$10,000).

Table 2. Estimated Major Gifts and Annual Fund Models

	Logit Coefficients (Weight/Standard Error)			
Attributes	Major Gifts Model (100k+)		Annual Fund Model (1k+)	
AVG PAST YEARS $10K+	1.22	0.54		
AVG PAST YEARS $3K+	1.70	0.54		
AVG PAST YEARS $1K+	0.84	0.74		
AVG PAST YEARS $5C+	2.60	0.72		
AVG PAST YEARS $1C+	0.00		2.72	0.05
AVG PAST YEARS $1+	0.00		0.72	0.16
NONDONOR	0.00		0.00	
RECENT 87 DONOR	0.92	0.47	1.90	0.10
RECENT 86 DONOR	0.00		0.92	0.13
RECENT 85 DONOR	0.00		0.66	0.16
SALARY HIGH	1.34	0.43	0.60	0.12
SALARY MEDIUM	0.00		0.32	0.08
SALARY LOW	0.00		-0.30	0.06
SALARY INFO MISSING	0.00		0.00	
DIF MAILING RESPONDENT	2.33	0.49	1.34	0.20
DIF MAILING NON-RESPONDENT	0.00		0.00	
NRP RATING VERY HIGH	1.52	0.40	0.51	0.11
NRP RATING NOT VERY HIGH	0.00		0.00	
PRIZM CODE (21,28 OR 39)	0.73	0.37	0.17	0.06
PRIZM CODE NOT (21,28 OR 39)	0.00		0.00	
NON-GIFT PROG PARTICI	0.50	0.36	0.22	0.06
NON-GIFT PROG NON-PART	0.00		0.00	
1 TO 10 YRS SINCE DEG	0.00		0.00	
11 TO 30 YRS SINCE DEG	0.00		1.05	0.10
31 TO 40 YRS SINCE DEG	2.66	0.82	1.14	0.11
41 TO 50 YRS SINCE DEG	3.18	0.83	1.17	0.12
51 PLUS YRS SINCE DEG	3.51	0.82	1.31	0.13
MALE			0.24	0.06
FEMALE			0.00	
SPOUSE ALUMNUS			0.46	0.06
SPOUSE NOT ALUMNUS/MISSING			0.00	
AFFLUENCE SCORE VERY HI			0.48	0.11
AFFLUENCE SCORE HIGH			0.36	0.06
AFFLUENCE SCORE MEDIUM/LOW			0.00	
RESPONDENT TO QUESTIONNAIRE			0.32	0.08
NON-RESPONDENT TO QUESTIONNAIRE			0.00	
HIGH POSITION			0.33	0.07
NON-HIGH POSITION			0.00	

Table 2. *(continued)*

	Logit Coefficients (Weight/Standard Error)	
Attributes	*Major Gifts Model (100k+)*	*Annual Fund Model (1k+)*
CHICAGO AREA ADD	0.15	0.05
NON-CHICAGO AREA ADD	0.00	
MEDICAL DEGREE	1.34	0.07
LAW DEGREE	0.76	0.08
CAS DEGREE	0.23	0.06
RELIGIOUS ACTIVITY AS STUDENT	0.54	0.29
NO RELIGIOUS ACT AS STUDENT/MISSING	0.00	

The variables that were in question in past studies were not significant

This variable was not used in earlier studies, and yet traditionally the fundraising community uses it as the main criterion for selecting prospects.

Whether one has given in 1987 ($b = .47$) and whether one's salary is high (> \$200,000, $b = 1.34$) is important in predicting gifts over \$100,000. The planned giving mailer variable is important ($b = 2.33$), as are the national resource ratings ($b = 1.52$). The PRIZM codes acquired from John Grenzebach and Associates have an effect ($b = .73$). Their measure of affluence, however, was not included because it was not a significant predictor. Involvement in the university has some effect ($b = .50$). Age is quite important, with having received one's degree more than fifty years ago being quite important ($b = 3.51$). The variables that were in question in past studies—status of children, distance from school, and occupation—were not significant for the major gifts model.

Using the Model

We have used the results from the major gifts logit analysis to calculate a score predicting an individual's likelihood of making a major gift for all alumni in the database (140,000). This score was calculated using the logit coefficients as weights and the individual's value on each attribute. The exception to this is past giving, where the effect of each individual's total prior giving is extrapolated from the coefficients in the model. The maximum combined score for an individual who had average giving over \$10,000 is 4.65 (including intercept –12.56), and the minimum score for an individual who has never given is –12.56. If an individual has the maximum score, his or her probability of making a major gift would be 99.05 percent. An individual with the minimum score would only have a 0.0004 percent probability of making a major gift. When prospects are rank ordered, the probability drops quickly to under 10 percent (at the 212th record). From this, we can see that the model cannot identify a great number of sure bets in terms of major gifts. However, it clearly indicates which individuals are not worth approaching.

In any capital campaign, the major gifts (irrevocable and outright) make up the large majority of the total dollars—usually somewhere between 80 and 90 percent. The cost of personally soliciting these major gift prospects is very high, involving many hours of professional, clerical, and volunteer time in the process. Identifying those individuals most likely to give a major gift is key to raising these dollars efficiently. The major gifts model was tested to determine if it is an appropriate method for this selection process.

Testing the Model

The test involves a comparison of the major gifts model with single-criterion models (for example, salary level) using a metric designed to estimate the selection effectiveness of each model. The metric we use is the sum of giving (including family giving) between 1988 and 1990 by the highest-ranked potential donors. Figure 2 indicates the dollars raised from the selected group over the future three years. The larger the number of dollars "raised" for the same number of selected alumni, the "better" the model—in other words, the better the model is at identifying the highest potential donors.

Figure 2. Total Gift Comparison—Major Gifts Model Versus Alternative Models

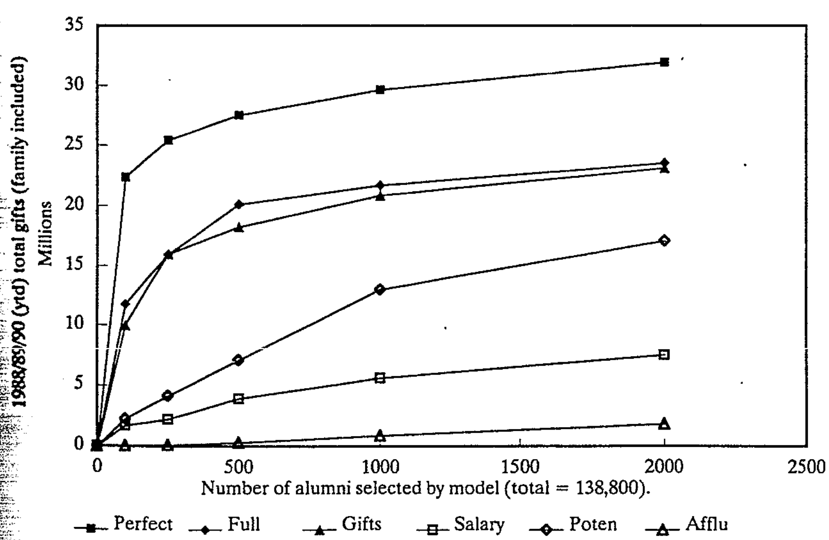


Figure 2 clearly shows that the average past giving model and the full major gifts models are the only contenders for selecting the best prospects. Although the gifts model does well at the start (under 500 prospects), *using the full model accounts for approximately $1 to $2 million more at the 500- and 1,000-prospect levels.* This level of difference would certainly account for any additional costs involved in doing a statistical analysis. Because of the high cost of personal visitation, every 100 to 200 prospects can translate into the cost equivalent of one full-time development officer.

Since average past giving appears to be such a strong indicator of future major gifts, the following question is of great importance: When is it worth the effort to personally visit a prospect who has great financial wealth, but who has not given much in the past? To address this question, a test was done of the model on three subpopulations of the full alumni database: (1) those alumni who have given on the average $250+ dollars per year since graduation (1,400 records), (2) those alumni who have given between $10 and $249 per year (26,300 records), and (3) those alumni who have given less than $10 per year since graduation (111,100 records). Past giving was determined by looking at giving only through 1987. Figure 3 indicates the dollars that came in between 1988 and 1990.

When is it worth the effort to personally visit a prospect?

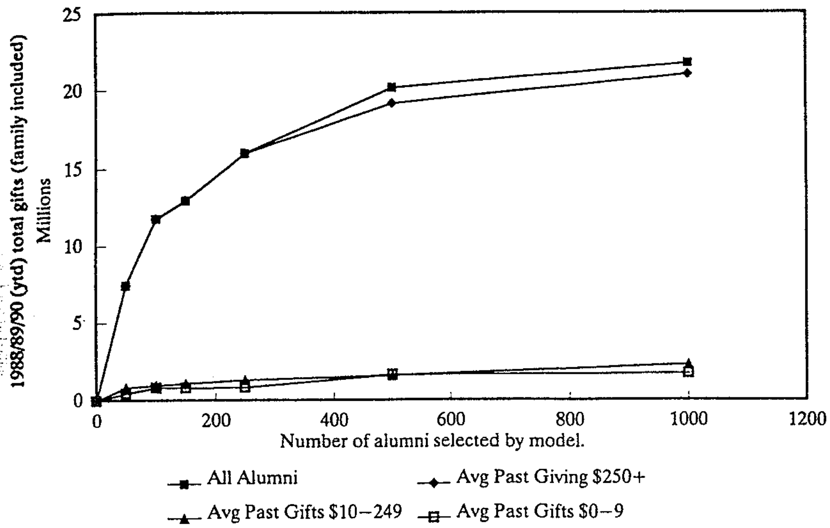
Figure 3 dramatically shows that most of the dollars will come from those who have given generously in the past. At the 500 level of selection, the gap between the all alumni group and the $250+ group indicates that low- and medium-level past givers are being brought in by the model. In another analysis that looked more closely at the individual prospects actually selected, the first person selected by the model who had less than $1,000 in total past giving was ranked number 421. There were a total of 49 alumni in the top 1,000 prospects whose total past giving level was under $1,000.

A further analysis was done to determine the marginal yearly increases in gift revenue provided by each level of selection and for each of the three subpopulations. Figure 4 shows that only after selecting around 500 prospects from the highest level of past giving will the marginal returns be comparable to the top 50 selected from either the low or medium levels of past giving. It is also clear that the lowest-level subpopulation is the most unstable with regard to marginals over levels of selection. There is less predictability in this population. For example, at the 500 level the marginal increase is greater than at the 150 or 250 selection levels.

Annual Fund Model

Fundraising programs do not consist entirely of major gifts fundraising, even in large capital campaigns. To generate operat-

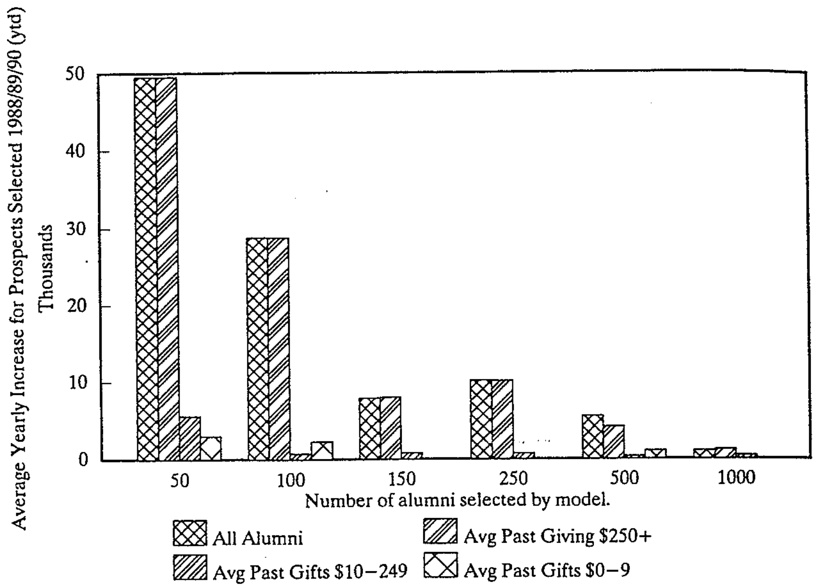
Figure 3. Total Gifts Raised from Subpopulations with Different Records of Past Giving (Using the Major Gifts Model)



ing funds and move donors up the fundraising pyramid, direct mail and phon-a-thon programs are used. These annual fund programs can also benefit from selection methodology that will allow only the most worthwhile prospects to be contacted. Or looking at it another way, the methodology can help to remove the most unlikely prospects, thereby saving postage or telephone costs with minimal risk. Instead of concentrating on hundreds of prospects, as is the case with the major gifts model, the direct mail and phon-a-thon programs need to select thousands of prospects for each solicitation.

The annual fund model was developed by first eliminating the top 1,500 major gift prospects using the major gifts model, since these individuals should be personally contacted by an appropriate representative of the institution. Using the remaining population, a logit model was used to predict which individuals had given $1,000 or more in the three-year period. Almost twice as many variables are included in the alumni model. Because there are many more individuals in this range over the three-year period (N = 2,803), the effects of more variables can be estimated precisely, and it is beneficial to utilize them in predicting future donor behavior.

Figure 4. Marginal Increases in Gift Revenue for Subpopulations with Different Records of Past Giving (Using the Major Gifts Model)



All of the variables used in the major gifts model are in the annual fund model. In many cases, different categorizations of these variables were useful. Past giving continues to have the largest effect ($b = 3.42$ for individuals with giving over $5,000), but distinctions at low as opposed to high levels of giving are important (most of the high-level past givers were essentially removed from the data at this point via the major gifts model). In annual giving, a more refined breakout of recency of gift is useful, with more recent givers, as expected, being more likely to give ($b = 1.90$ for 1987 givers). Also, a more refined categorization of salary is useful in predicting giving ($b = .6$ for high and .32 for medium). Perhaps somewhat surprisingly, the planned giving mailing ($b = 1.34$) and national resource program rating variables ($b = .51$) continue to be important in predicting giving. We would not have anticipated this with the low level of contribution that we are modeling, since these variables result from efforts explicitly set up to assist in the marketing of major gifts programs. PRIZM codes ($b = .17$) and participation in the university ($b = .22$) continue to predict giving. Year since graduation is only important in distinguishing between individuals who graduated in the past ten years and others ($b = 1.05$ for eleven to thirty years out).

There are also eight new variables, including most of those with contradictory findings in other research. Sex has a modest effect ($b = .24$ for males). The effect of having a spouse who is an alumnus is of similar size ($b = .46$). Unlike in the major gifts model, the Grenzebach affluence score predicts giving ($b = .48$ for the highest group). Whether an individual has ever responded to a Northwestern questionnaire is a useful predictor ($b = .32$). Surprisingly, information about an individual's job title, which was not significant in the major gifts model, is useful in the annual fund model ($b = .33$). Finally, residence in the Chicago area ($b = .15$), degree ($b = 1.34$ for medical and $b = .76$ for law graduates), and religious involvement as an undergraduate ($b = .54$) all have an effect.

As with the major gifts model, a score was calculated for each individual that indicated his or her likelihood of having given over $1,000 in the three-year period. The logit coefficients were again used to weight the zero-one indicators of each individual's attributes to form a score. The maximum score an individual could receive is 5.1 (including the intercept at –8.25), equivalent to a probability of 99.33 percent of giving over $1,000. The minimum score was –8.55, equal to a probability of 0.03 percent.

Testing the Model

The annual fund model was tested using a methodology similar to that used earlier. Figure 5 compares the full annual fund model against models using single factors. The selection of the top 50,000 prospects (out of 137,398) provides the great majority (92 percent) of the dollars from this population over the three-year period in the test. Furthermore, the average past gifts only model is the only single-criterion model that comes close to the full model. Although this generally substantiates the collective development wisdom of the ages—and the direct mail marketing segmentation strategies of LYBUNTs (donors who gave Last Year But Unfortunately Not This), PYBUNTs (donors who gave Past Years But Unfortunately Not This), and NEVER GIVERS (no past giving ever)—the use of the full model would allow for a further refinement of the strategy and potentially greater overall levels of gift income. This is a small percent difference, but it is over a million dollars difference at many of the test points (10K, 20K, and 50K).

A marginal income analysis was conducted to determine the average yearly expected income levels per prospect at several different levels of selection. Figure 6 shows that marginal returns generally drop quickly at the 20,000-prospect level. After mixed results between 20,000 and 50,000 prospects, the returns drop precipitously to very low levels. Although we have not included marginal cost information in this article, our analysis appears to suggest (for Northwestern) not sending direct mail or phon-a-thon solicitations to alumni beyond the 60,000-person level.

Figure 5. Total Gift Comparison—Annual Fund Model Versus Alternative Models

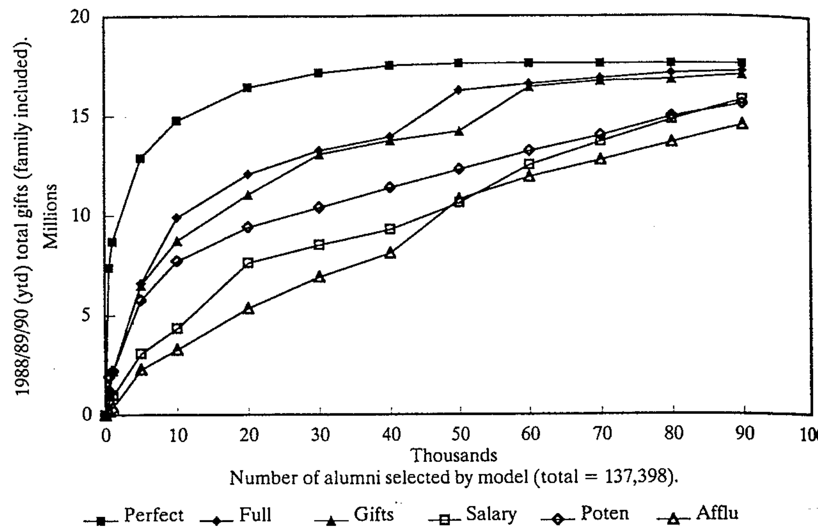
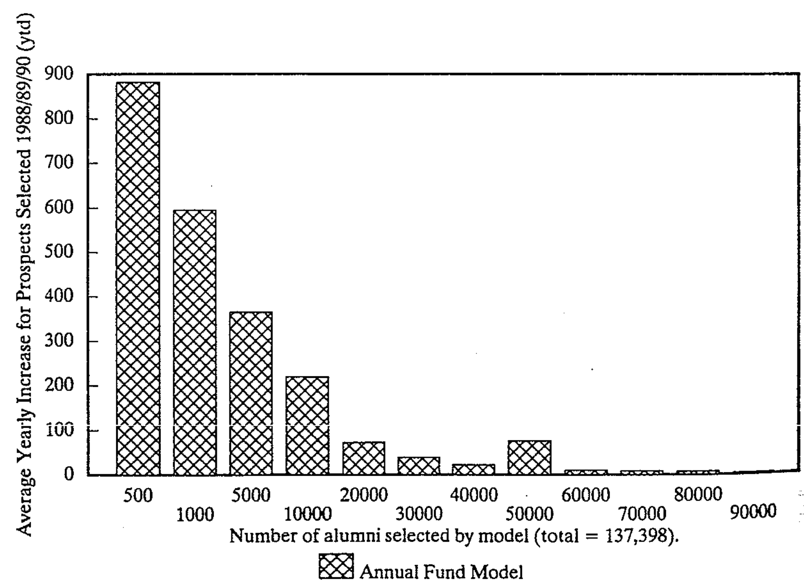


Figure 6. Marginal Increases in Gift Revenues Using Annual Fund Model



foundation, corporate, or government support will not be able to use this process. However, hospitals and museums should be able to create models that are customized for their needs. They will rely more heavily on the externally coded information, because often the only information they have will be name and current address. There is some question whether the past giving factor will be as strong for other nonprofits. Are alumni unique in their long-term commitments to their alma mater?

Applying these techniques to other nonprofits may be useful

In many respects, the modeling efforts here are crude. We need to consider separately modeling an individual's inclination and capacity to give. It may be that by explicitly taking account of the separate effects that variables have on inclination and capacity, we can further refine the models' ability to predict future giving behavior. We also need to explore the critical importance for giving behavior of development staff interactions with prospects. Lack of good information regarding contacts over the past few years has hampered this type of study. This is less of a factor with the annual fund model, since an assumption could be made that over the past ten years, all alumni with good addresses and phone numbers were solicited annually. In the case of the major gifts model, the following question lingers: If development staff had approached those with the highest capacity (regardless of past giving) over the past few years, would the results have been better than if the staff had approached alumni based primarily on past giving levels? So far, our results suggest that giving is certainly not unidimensional and at least involves differences across individuals in commitment and capacity. We are now investigating these issues.

Appendix

Collinearity and Stability. A correlation table was created for the variables in the models, and regressions of the independent variables against each other were done to check for collinearity. The major gifts model had no serious collinearity problems using either test. The highest correlation value other than with past giving was .156, which was between SPOTEN (National Resources Program Screening and Rating) and Past giving at the $500 plus level. The maximum R^2 is .4906, which is just below the maximum recommended level.

The annual gifts model had two groups of variables that were moderately correlated with each other. The first group consisted of the two geodemographic coding variables, PRIZM scores and the two affluence ratings (correlations .315 and .366). To test the stability of the model, these variables were removed separately. Although the PRIZM coefficient increased slightly when the affluence variables were removed, and the affluence coefficients in-

Predicting New Prospects

The models we have developed are being utilized at Northwestern for the identification of new prospects. To develop scores appropriate for this task, we combine giving prior to 1988 and giving from 1988 to the present to predict future donors. This allows us to use our models to predict who will be most likely to give in the next several years. This information is currently being used to organize campaign strategy and to determine visiting priorities.

The annual fund model has been used to reduce the size of certain mailings. For example, a recent athletic department mailing that normally would have gone to around 10,000 prospects was sent to a smaller group of 5,000 based on the model. A comparison test with last year's results is currently in process. Informally at this time, the development officer in charge feels that there was no falloff in dollars raised as a result of eliminating this group of 5,000 prospects from the mailing.

The annual fund model has been used to reduce the size of certain mailings

This fall, the annual fund model was used to cut back the mailing for the year-end appeal from 140,000 to 100,000 alumni (reunion classes and young alumni were included regardless of the model). The results of the mailing show annual fund donations are up slightly compared to last year. This together with the savings of not mailing to 40,000 people represents dramatic success in improving efficiency.

The predictor score, known as the Lindahl/Winship factor at Northwestern, is now printed out on every prospect tracking summary report (referred to as a prospect card at Northwestern). The number, printed on the bottom of each prospect's card, serves as an additional indicator to help put into perspective the other information that is listed as individual characteristics. When a planned and major gift officer selects prospects for a trip, the score is incorporated in decisions about who to contact and visit.

The difference the utilization of these models has made in terms of fundraising impact is noticeable, yet hard to evaluate because the development staff was significantly reduced over the past four to five years. This model has most likely helped the operation maintain levels of support with fewer staff. Before someone is cultivated or solicited, a development officer is now aware of the statistical chances of the person giving a major gift over the next three years. When they see a 10.303 percent rating, they know that it would definitely be worth their while to pursue the prospect. On the other hand, if someone was rated 0.022 percent, they would think twice before making contact, relying on other research or information about the person before placing the individual on their trip list.

Applying these techniques to other nonprofits may be useful, depending on the availability of a database comparable to alumni at a university or college. Nonprofits that rely almost entirely on creased slightly when the PRIZM variable was removed, the other parameters in the model remained very stable.

The second cluster of variables consisted of the following: Response to Questionnaire, Salary Low (from questionnaire form), Past giving over $1.00, and Most recent gift in 1987 (correlations between .257 and .547). Regressing independent variables on each other revealed only the problem between recent gifts and past giving (R^2 = .7006). A test was done to check for stability of the model when removing each of these variables separately. Although there were slight changes in the model, the only variable causing a large swing in other coefficients was the recent gift variable. This caused the Past giving over $1.00 coefficient to move from .7183 to 1.9828. This makes sense, since there are a large number of individuals who are repeat donors and would have both given in 1987 and given over $1.00. All of the variables in question were left in the model.

Besides using a chi-square test for determining whether a variable or sets of variables would be included in the model (a large sample size will cause certain variables to be significant, even though they will not contribute to the fit of the model), a likelihood ratio test was done to test the overall fit. The major gifts model has Likelihood chi-square of 210.27 with 443 df and a probability of 1.000, and the annual fund model has Likelihood chi-square of 8408.05 with 18190 df and a probability of 1.0000. In both cases, this indicates a very good fit of the model to the data. This is somewhat surprising, given the very large size of our sample.

Absolute Size of Logit Coefficients. The evaluation of the absolute size of logit coefficients is somewhat difficult. The dependent variable is the $\ln(p/(1-p))$ or, in words, the natural logarithm of the odds of an outcome. Perhaps the easiest interpretation is to exponentiate the coefficient, giving the increase that a one-unit change in the variable produces in the odds of a particular outcome. Thus, a coefficient of 1.5 when exponentiated approximately gives 4.5, indicating a multiplicative increase in the odds of an event of this amount. For instance, if the odds were originally 2 to 1, with the shift they would be 9 (or 2 X 4.5) to 1.

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