Enhancing Fundraising Success with Custom Data Modeling

Abstract
The majority of nonprofit organizations rely heavily on contributions to fund their mission-critical activities. Because building relationships with donors is critical to the success of nonprofits, organizations must be able to transform their data on prospective donors into an action plan that will optimize the yield of their fundraising efforts. This paper offers a methodology for targeting individuals most likely to make a charitable contribution, by building custom response models using the rich donor data maintained by many nonprofit organizations as well as overlaid demographic information. The methodology is able to efficiently utilize a large volume of variables, while being flexible enough to use large categorical variables, such as postal code, and capture non-linear relationships between the independent variables and the likelihood to give.

Introduction
Fundraising in today's world is increasingly difficult, yet nonprofits continue to rely heavily on contributions to fund their mission-critical activities. Recently, nonprofit watchdog groups have encouraged nonprofit organizations to keep fundraising and administrative expenses to less than 50% of total funds raised. Higher postal and printing costs, and wage demands have put additional economic pressures on nonprofit organizations. Growth in telemarketing and direct mail marketing means that it is increasingly difficult to reach those individuals most likely to make a charitable donation. Because of these economic pressures today's development offices must determine the number of prospects to mail, phone and set up personal interviews with, so that total expected contributions are maximized within a fixed operating budget. This paper offers a methodology for targeting individuals most likely to make a charitable contribution, through the use of regression analysis on past donation history.

Response modeling is a common data mining technique in direct marketing. Numerous studies have examined ways to improve the efficacy of a direct mail campaign using response models. The effectiveness of response models in direct mail campaign have met with relatively limited success. Much of this is due to the fact that most for-profit direct mail campaigns must use purchased lists of names that have limited information about each prospect and little association with the organization.

Nonprofit organizations have a distinct advantage over for-profit organizations because they often have built-in prospect pools and thus do not need to rely as much on purchased lists of names. Many nonprofit organizations have large prospect pools through memberships, in the case of museums and some foundations, past-patients in the case of hospitals and alumni, parents of alumni and students in the case of schools. The advantage of prospect pools such as these is that they are continually increasing, and the organization may have quite a bit of information about each prospect.

Universities, for example, often times have information about an individual's age, gender,
A development office can use the predicted likelihood to make a charitable contribution to decide which prospects are worth a personal interview, which are worth a telephone call and which prospects should receive a mailing only.

Building a response model utilizing this information enables a nonprofit organization to combine the many characteristics of their givers into one score that can be used to rank each prospect’s likelihood to make a charitable contribution. A development office can use the predicted likelihood to make a charitable contribution to decide which prospects are worth a personal interview, which are worth a telephone call and which prospects should receive a mailing only.

Using data from a private Catholic high school, this paper describes a methodology for building a response model that captures the characteristics of those individuals most likely to make an annual gift. The methodology presented is efficient enough to handle many potential independent variables, while fully utilizing the rich data available to many organizations. The process uses an Empirical Bayes method for transforming categorical variables such as postal code and major, which because of the large number of categories, are typically difficult to use in a regression analysis, into continuous numeric variables that can be utilized in a regression. The process is also able to capture non-linear relationships, such as quadratic relationships, between the independent variables and the propensity to give to an organization.

**The Methodology**

The data utilized in this study come from a small, private, Catholic high school in the Northeast region of the United States. The high school has a database of 10,828 individuals. For each individual the high school has provided six years of giving history, which has been annualized. The goal is to produce a model that identifies individuals who are likely to give based on their characteristics. The dependent variable is based on information from the most recent year of giving. A “giver” is defined to be someone who gave an annual gift in the most recent year. Individuals who gave are therefore coded as a “1” and individuals who did not give in the most recent year are coded as a “0”. A probit regression is used to model the likelihood that an individual gave in the most recent year.

The high school has information on every individual’s age, class year (if they are alumni), gender, and the relationship of each individual to the school, i.e., alumnus, parent, friend, etc. In addition to these data elements, the high school’s data are overlaid with credit and census data. The overlaid credit data provides information about each prospect’s income and wealth, with variables such as mortgage and auto loan information, estimated home value, and use of premium and upscale retail bankcards. The census survey data is aggregated at the block group level (about 300 households) and provides information such as average monthly mortgage, average yearly income, education level, family size, and religious affiliations. With the overlaid credit and census variables, plus the data provided by the school, over 100 variables are utilized in the modeling process.

After overlaying the high school’s database with the credit and census data, the data set is split into two halves for model validation. “Validation” refers to the process of confirming the efficacy of a model as applied to a data set that is independent of the data used to build the model. By
setting aside a portion of the high school’s data, generally called the “hold-out sample”, the models can be tested to see which models perform at the optimal level. The validation process is discussed further below.

Probit analysis restricts relationships between the independent and dependent variable to be linear. To capture non-linear relationships several transformations of the independent variables are done. To do this, the independent variables are categorized into three types of variables and transformed according to these types. The three types of variables are categorical variables, such as constituency code and postal code; continuous numeric variables such as age and income; and dummy variables such as gender and presence of a mortgage. Categorical variables are transformed using an Empirical Bayes method, utilizing the hold-out data set. Standard numeric variables are transformed in two ways to account for any possible quadratic relationships and to normalize any variables with a highly skewed distribution. Dummy variables are created on such variables as whether an individual has a mortgage, by transforming them so that any individual who has a mortgage receives a “1” and individuals who do not have a mortgage receive a “0”.

Categorical Variables Transformation:
A common transformation of categorical variables such as constituent code requires the creation of several dummy indicator variables for all but one of the categories. However, variables, such as postal code and major, have far too many categories to create a dummy variable for each category. In order to utilize these variables in a probit analysis categorical variables are transformed into numeric values using an Empirical Bayesian method.3,4,5,6,7

The intuition behind the Bayesian method is quite simple. A variable such as postal code is converted into a numeric data element by first determining the proportion of individuals who made a donation in the most recent year for each postal code.

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It is possible to use this proportion of givers in each postal code in a regression analysis; however this transformation has problems. For postal codes with a large number of prospects, it is likely that the proportion of givers in the database is representative and may be used to infer the likelihood of any individual to give in that postal code. However, for postal codes with few prospects, it is unlikely that the proportion of givers in the database is representative.

It is desirable therefore to “weight” those postal codes with fewer prospects different than those postal codes with a large number of prospects. Using an Empirical Bayes method described in Morrison2 and Casella1 the proportion of individuals who gave in a particular postal code is shrunk towards the overall mean for the entire database. The amount of shrinkage depends on the number of prospects in each postal code.

In Bayesian data analysis the researcher’s prior knowledge of the problem at hand is incorporated into the statistical analysis. In this case the overall percentage of givers on the hold-out data set is used as the prior. The prior is then combined with the actual observed percentage of prospects who have given within each postal code, on the hold-out data set. The manner in which the prior and the actual percentage of givers is combined depends on the number of prospects in a given
postal code. The fewer the prospects in a postal code the more weight is placed on the prior and the less weight placed on the actual percentage of givers in a postal code. Thus for postal codes with fewer prospects more shrinkage towards the mean occurs. In this case the mean is the overall percentage of givers on the hold-out data set.

Note that the Empirical Bayesian method is modified slightly here, to avoid “peeking” at the data prior to building the model. By creating the numeric transformations of the categorical variables on the hold-out data set and then applying those numeric transformations to the model building data set peeking at the data prior to building the model is avoided and thus the possibility that the categorical variables will be falsely predictive is avoided.

The categorical variable transformation does have a drawback in that it does not capture the possible ordinal relationship of some categorical variables. Postal codes, for example, may also be used to measure distance from an organization, which is likely to be a determinate of propensity to make a donation. Certainly an individual living close to a museum is more likely to donate to that museum than someone living 1000 miles away. However, in the method described above those postal codes closer to the organization will receive a higher numeric transformation than those further away, provided that there is a relationship between giving and distance from the organization.

The Empirical Bayes transformation described above has the added advantage of allowing for other relationships between geography and the likelihood to give. For example, if an analyst wanted to build a model that predicts individuals most likely to make a planned gift, it is conceivable that individuals who live in areas more populated by retirees are more likely to make a contribution. In this case then, the postal codes with the highest numeric transformations may not be those closest to the organization but rather those in states such as Florida and Arizona where there are larger numbers of retired individuals. The Empirical Bayesian transformation described above is able to capture these types of relationships.

**Continuous Numeric Variables**

Probit regression restricts the relationship between the independent variables and the dependent variable to be strictly linear. That is, the likelihood to give is assumed to be either always positively related to the explanatory variable or always negatively related to the explanatory variables. Yet some variables, such as age, may not exhibit a strictly linear relationship with the propensity to make a donation.

In some instances the relationship can be quadratic in nature. For example, it is possible that the likelihood to donate to an organization increases with age up until an individual retires. Upon retirement the individual is now faced with a fixed income and thus has fewer resources available for charitable contributions. Thus, around 65 years old, the relationship between age and giving might become negative.

To capture possible quadratic relationships such as these, a variable is created that includes the quadratic nature in its scope. This is done by regressing the independent variable and the square of the independent variable on the likelihood to make a donation, using the hold-out data set. The coefficients from this regression are then used to create a new variable in the model building
data set. For example, regressing age and age squared on giving in the most recent year for the Catholic high school, yields the following regression equation:

\[ Y = -0.267 + 0.00226(AGE) + -0.00247(AGE^2). \]

This regression equation is used to create a new variable with the quadratic relationship built in. For a person who is 30 years old the value for the new variable is \(-2.35\), for a person who is 50 years old the value for the new variable is \(3.81\) and for a person who is 80 the value is \(-15.89\). The equation indicates that the relationship between giving and age appears to be increasing up until age 50 or so and then decreasing after that.

Similar to the creation of the categorical variables, these quadratic relationships are built on the hold-out data set, and applied to the model building data set, so that we do not run the risk of creating variables that are highly correlated with the dependent variable merely because we have “peeked” at the data. Additionally, logged values of all continuous variables are created in case any of the independent variables are highly skewed, as is often the case with variables such as income.

**Model Creation**

After transforming and creating all of the variables there are more than 170 potential independent variables. Many of these variables are highly correlated with one another, particularly the logged, quadratic, and standard numeric forms of the same variable. The highly intercorrelated variables can lead to problems with multicollinearity, which occurs when the independent variables are highly correlated and can lead to severe estimation problems.

It is also extremely time-consuming to build models using this many variables, many of which may have no correlation with the likelihood make a donation. For these reasons the number of potential variables in the final model is limited by examining the simple correlations between the independent variables and the dependent variable.

During this step, the correlations of the logged, quadratic and standard numeric forms of each variable are examined, and the form that has the highest correlation with giving is kept for the final modeling stage. The intercorrelations of the independent variables are also examined to avoid problems with multicollinearity. Variables such as average household income and median household income are highly correlated and thus only one will be chosen for the final modeling stage. The 50 variables that are most correlated with the dependent variable are kept for the modeling process, taking into account the intercorrelations among the independent variables.

Using the best subset option in SAS the best one to ten variable models are built using the 50 variables kept from the correlation analysis. The “best subset” option in SAS builds the best one variable model, by building all of the possible one variable models, but choosing the model yielding the highest residual chi-square statistic.\(^8\) The best two through ten variable models are created in a similar way.

**Model Validation**

Once the best one through ten variable models have been determined by SAS, the performance of each of these models is examined using the hold-out data set. Since, the goal is to predict future

\(^2\) The presence of multicollinearity causes the variances of the estimates of the parameters to be quite large. Thus, multicollinearity can lead a researcher to the false conclusion that a variable is not a significant factor.
giving, it is important to ensure that the models do not suffer from “over-fitting,” which occurs when too many variables are included in the model. Models that are over-fit perform very well in-sample; since model performance generally increases as more variables are added. By examining each model on an “out-of-sample” data set, where performance is best with a modest number of variables and declines when too many or too few variables are included, the problem of “over-fitting” is avoided.

To examine out-of-sample model performance, the predicted likelihood of giving a gift is compared with the actual outcome on the hold-out data set. Measures adopted from signal detection theory, including the Receiver Operator Characteristic (ROC) and $d'$, are employed. The ROC compares the actual outcome in the hold-out data set to the predicted outcome for all possible criterion scores by examining the tradeoff between “hits” and “false alarms.” Any model score can be used as a cut-off or criterion point, which defines a hit and false alarm rate.

Hits occur when prospects gave in the previous year and were given a score equal to or greater than the cut-off point. False alarms occur when prospects did not give in the previous year and were given a score equal to or greater than the criterion. When models are performing above chance, the hit rate will be greater than the false alarm rate for any criterion score. The hit and false alarm rates for the seven variable model are illustrated in a ROC graph in Figure 1. The diagonal line indicates chance performance; the bow above it indicates the performance of the model. The more predictive the model, the more the bow sweeps towards the upper left corner of the graph.

By taking the probit of the hit and false alarm rates, the axes are rescaled and the bows “straighten out” (see Figure 2). $D'$ indicates the number of common standard deviations separating the score distributions for the givers and non-givers. $D'$ can be calculated by taking the distance between the tangent of the straight line and the origin.

The $d'$ is calculated using the hold-out data set for the one through ten variable models, to determine which model is most predictive. The $d'$ for the one through ten variable models built on the Catholic high school’s data ranged from approximately 1.23 to 1.25, indicating that about 1.2 standard deviations separate the distribution of givers from the distributions of non-givers. Based on the $d'$ and the chi-square statistics for individual variables in the models, the seven variable model was chosen. Table 1 shows the final model chosen.

The strongest variable in the model is the number of years a prospect has given gifts in the past. In this instance those that are most likely to give are most likely to have consistently given in the past – this is an outcome that, not surprisingly, is frequent.

The significance of the City and State variable illustrates the effectiveness of the Bayesian transformation on large categorical variables. A variable such as this is difficult to use in a regression analysis because the number of categories makes it difficult to transform into several dummy indicator variables. Using the empirical Bayesian method described above makes it possible to fully utilize this important information in a regression model.

Table 2 illustrates the transformation of this variable. The third column gives the observed
proportion of individuals in a city and state who gave to the organization. The fourth column shows the Empirical Bayes estimates of the same proportion. Note that for cities with very few observations, such as Village 4, the Empirical Bayes estimate is much closer to the overall proportion of givers cities with a large number of prospects.

Age is also an important variable in the propensity to give and shows the ability of the methodology to capture non-linear relationships between giving and the independent variables. The relationship between age and the likelihood to give is quadratic. Figure 3 shows this quadratic relationship. Figure 3 indicates that the likelihood to give increases with age up until around 50 years of age, and then declines. This shows that individuals with children of high school age have a propensity to give to this Catholic high school.

Income appears to be another strong indicator of the likelihood to make a gift to this private high school. The Upscale Retail High Credit/Credit Limit indicates that individuals who are more likely to give have access to upscale retail credit cards, which is indicative of higher income individuals. The likelihood that an individual will make a donation also increases as the individual’s mortgage amount increases. The model also indicates that individuals with at least one auto loan are more likely to make a charitable contribution to this high school. These three income-related variables are positive and significant, indicating that the likelihood to give to this private Catholic High School increases with income.

Finally, the positive sign on the dummy gender variable indicates that males are more likely to make a gift than females.

**Application to Other Organizations**

To examine how well the process described here works on different types of nonprofit organizations, a model predicting the likelihood to make a charitable donation has been built for a large metropolitan museum in the mid-western region of the United States. This organization has 160,484 individuals on their database; 4,233 of which have given a gift in the most recent year. The museum has provided information on the length and level of museum memberships, museum interests of every individual, whether the individual has been on a museum sponsored trip, committee participation, and number of children.

The museum’s data was overlaid with the same credit and census data that were overlaid on the Catholic high school’s data file and the model was built using the methodology outlined above.

After examining the best one through ten variable models, a seven variable model was chosen. The d’ for this model is 1.29, which is similar to the d¢ for the Catholic high school’s model above. The model, described in Table 4, indicates, not surprisingly, that the museum’s donors look quite different than the Catholic high school’s donors. The museum’s donors are individuals who have a strong association with the museum through membership, who have strong interests in certain types of exhibits and who have been on one of the trips offered through the museum. In other words, donors have a strong affiliation with the museum.

The model also indicates that the likelihood to donate a gift increases with a person’s wealth. Propensity to give increases with estimated home value and with the proportion of households in
Tree generating techniques, such as CHAID and CART, have been widely used for the purpose of predicting response to some sort of solicitation.

A block group with monthly mortgage amounts greater than $2,000, indicating that donors live in areas with greater home values. The Revolving High Credit/Credit variable indicates that donors have more access to revolving credit than non-donors.

In contrast to the model built for the Catholic high school, where age was a significant factor in the likelihood to give a donation, the museum’s donors do not appear to differ in age from the museum’s non-donors. This is likely because a museum appeals to a large variety of ages, while a Catholic high school appeals to individuals with high school age children.

**Brief Comparison With Other Techniques and Future Research**

Tree generating techniques, such as CHAID and CART, have been widely used for the purpose of predicting response to some sort of solicitation. CHAID or Chi Square Automatic Interaction Detector can be applied to situations where all variables, dependent and explanatory, are categorical. At the initial stage a contingency table is built for the response variable with each explanatory variable. By choosing the most significant contingency table, as measured by the Bonferoni adjusted p-value of the corresponding chi-square test, the best first variable is selected and the best combination of categories. The file is split according to the first variable and then another contingency table is built for each node. The process continues until the resulting tree is a certain size.

One of the biggest disadvantages to the CHAID technique is that all explanatory variables must be categorical. Therefore, the researcher must decide how to split continuous variables into categorical variables prior to analysis. Often times these decisions are completely arbitrary. With large numbers of variables, many of which are continuous, the use of CHAID becomes quite cumbersome.

CART is another tree generating technique that addresses the limitations of CHAID.\(^3\)\(^4\) CART stands for Classification and Regression Trees. CART examines splits of the form \(X < C\) where \(C\) is some real number ranging from the minimum value of \(X\) to its maximum value. For example, if \(X\) stands for the individual’s age, and \(C\) is 60, then “splitting on \(X < 60\)” means that all individuals less than 60 years old go to the left and the rest go to the right. One of the advantages of CART is that the data is allowed to decide how to split continuous variables without any arbitrary choice by the analyst.

A drawback of CART is that with response rates of .01% to 10% which is not an uncommon response rate in a fundraising campaign, particularly a capital or planned giving campaign, Cart will often build no tree and classify the whole file as a non donor. One study suggests using a file with as many donors as non donors will get around this problem.\(^1\) This is not an optimal solution if the number of donors in a campaign is very low like in the case of a capital gift campaign.

CART and CHAID are both useful techniques to identify important variables and significant interactions that can then be used in a probit regression. Future research would incorporate these techniques into the methodology described in this paper.

\(^3\) See Haughton, D., Oulabi, S. (11) for a more complete description of CHAID.
Conclusion

This paper describes a method for building response models that characterize an organization’s donors and provides the nonprofit organization with a single indicator of propensity to make a donation. With this indicator the nonprofit organization can target those prospects that have a high propensity to donate.

The methodology described is efficient enough to utilize a large number of variables from a variety of sources. Through a method adopted from Empirical Bayesian data analysis, large categorical variables such as postal code can be utilized in a probit regression. A process for capturing non-linear relationships between the independent variables and the likelihood to give is also described.

By building models for a small, Catholic high school and a large metropolitan museum, the methodology is shown to work for different types of nonprofit organizations.

References


Figure 1
Catholic High School’s Receiver Operator Characteristic

Figure 2
Catholic High School’s Final Model D’ Line
Figure 3
Relationship Between Age and Charitable Giving for the Catholic High School

Table 1
Catholic High School Model

(n=10,828)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.97 (0.14)</td>
</tr>
<tr>
<td>Years of Consecutive Giving</td>
<td>0.61 (0.01)</td>
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<tr>
<td>Age Quadratic</td>
<td>2.25 (0.34)</td>
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<td>City and State</td>
<td>0.54 (0.11)</td>
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<td>Upscale Retail High Credit/ Credit Limit</td>
<td>0.0001 (0.00004)</td>
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<td>1st Mortgage High Credit</td>
<td>1.79E-6 (3.31E-7)</td>
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<tr>
<td>1st Auto Loan</td>
<td>0.14 (0.04)</td>
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<tr>
<td>Gender (Male =1)</td>
<td>0.21 (0.07)</td>
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<tr>
<td>d’</td>
<td>1.25</td>
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</tbody>
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Table 2
Sample of Empirical Bayes City and State Estimates
(City and State Names have been changed to maintain confidentiality of data)

<table>
<thead>
<tr>
<th>City and State</th>
<th>Number of Prospects</th>
<th>Observed Proportion of Givers</th>
<th>Empirical Bayes Estimate</th>
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<tbody>
<tr>
<td>Village 1, VT</td>
<td>152</td>
<td>36.18</td>
<td>32.60</td>
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<tr>
<td>Village 2, VT</td>
<td>148</td>
<td>34.46</td>
<td>31.17</td>
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<tr>
<td>Village 3, VT</td>
<td>101</td>
<td>33.66</td>
<td>29.49</td>
</tr>
<tr>
<td>Village 4, VT</td>
<td>18</td>
<td>50.00</td>
<td>28.59</td>
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<tr>
<td>Village 5, VT</td>
<td>116</td>
<td>31.90</td>
<td>28.58</td>
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<td>Village 6, MA</td>
<td>401</td>
<td>28.18</td>
<td>27.71</td>
</tr>
<tr>
<td>Village 7, VT</td>
<td>29</td>
<td>37.93</td>
<td>26.92</td>
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<td>Village 8, VT</td>
<td>63</td>
<td>31.75</td>
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<td>Village 9, MA</td>
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<td>26.09</td>
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<tr>
<td>Village 10, NY</td>
<td>127</td>
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<td>26.09</td>
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<tr>
<td>Village 11, NH</td>
<td>16</td>
<td>43.75</td>
<td>25.08</td>
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Table 3
Empirical Bayes Estimate of Constituent Code

<table>
<thead>
<tr>
<th>Constituent Code</th>
<th>Number of Prospects</th>
<th>Observed Proportion of Givers</th>
<th>Empirical Bayes Estimate</th>
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<tr>
<td>Trustee</td>
<td>10</td>
<td>60.00</td>
<td>54.47</td>
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<tr>
<td>Current Parent</td>
<td>836</td>
<td>50.72</td>
<td>50.66</td>
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<tr>
<td>Alumni</td>
<td>4077</td>
<td>24.90</td>
<td>24.90</td>
</tr>
<tr>
<td>Alumni and Parent</td>
<td>3408</td>
<td>15.93</td>
<td>15.94</td>
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<tr>
<td>Faculty/Staff</td>
<td>887</td>
<td>7.44</td>
<td>7.47</td>
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<tr>
<td>Friend</td>
<td>455</td>
<td>1.32</td>
<td>1.41</td>
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<tr>
<td>Grandparent</td>
<td>1151</td>
<td>0.00</td>
<td>.04</td>
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Table 4
Museum Model
(n=160,484)

<table>
<thead>
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<th>Variable</th>
<th>Coefficients(Standard Error)</th>
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<td>Years of Consecutive Giving</td>
<td>0.7271(0.02)</td>
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<td>Maximum Membership Level</td>
<td>.003(0.0001)</td>
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<td>Number of Interests</td>
<td>0.06(0.003)</td>
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<tr>
<td>Trip Taker</td>
<td>0.52(0.10)</td>
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<tr>
<td>Proportion Homes With Monthly Mortgage &gt; 2000</td>
<td>0.35(0.10)</td>
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<tr>
<td>Average Home Value</td>
<td>.17(.03)</td>
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<td>Revolving High Credit/Credit Limit</td>
<td>3.27E-6(5.98E-7)</td>
</tr>
<tr>
<td>d’</td>
<td>1.29</td>
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