Predictive Model for Donation Campaign

MSIA 401: Predictive Analytics I

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Executive Summary

An analysis of donor data for a non-profit organization finds that similar factors influence both the probability of donation in response to solicitation, and the predicted amount of a donation. Key predictors include the amount of a donor's latest contribution, the total lifetime contribution dollars, the first contribution, largest contribution, sex of donor, and contribution code. In addition, the average time between donations, average dollar amount, and whether or not a donor's contributions have been increasing in quantity are also significant predictors. The findings in this paper are largely intuitive; such as predicted probability of donation and donation amount both increase with dollar amount of latest contribution, and decrease with prolonged average time between donations. It is suggested that these key attributes of donors, among others, are used to target those with the highest expected donation, by combining the predicted probability of donation and the predicted amount. By fitting various models that used these attributes, it was found that just over $10,500 could be raised by targeting only 1000 donors.

1 Introduction

Many non-profit organizations solicit contributions from past donors and this can be a tedious and time-consuming process. Furthermore, response rate for donations is low. It can be extremely beneficial to target donors based on the likelihood that they will actually donate, as well as the expected amount. One such non-profit is interested in developing predictive models to do just this. Donor data from 10/2001 to 12/2010 were provided, which include the donation responses to a solicitation sent in 10/2010. With the provided dataset on past donors, models were developed to predict the probability a given donor will donate, and the amount that will be donated. This paper describes the process of building such models and the results that follow.

To use the data for building predictive models, some pre-processing steps were taken, which are described in Section 2. This includes filling in missing values and calculating new variables that may serve as significant predictors. Section 2.1 covers exploratory data analysis, used to understand the provided data and to exploit any obvious relationships between the independent and dependent variables. Certain predictor variables are intuitive and expected to influence the expected donation of an individual, such as the size of dollar amount of their contributions and the number of times contributed. Others, such as solicitation code, may or may not play a significant role. Calculated variables, which will be described in further detail in section 2.2, such as whether donations have increased in quantity over time, are expected to have a positive relationship with probability of donation.

In order to predict whether or not a given donor will donate, logistic models were built. For predicting the donation amount, multiple linear regression models were built. Sections 3.1 and 3.2

respectively cover, in detail, the process for creating these models. The approach to model building was to begin with a simple model and progressively add quadratic and interaction terms as needed, all while eliminating insignificant predictor variables with each step. The logistic models were compared using the AUC (area under the ROC curve) and the linear models were compared using the Adjusted-R squared values. This section also includes model diagnostics, such as detection of influential observations and normalizing transformations.

Section 4 covers the model validation and how the chosen logistic and linear regression models were tested against the test data set. This includes the calculation of expected donations for each individual in the test data set and how well the top 1,000 predicted customers perform in terms of contributions. Finally, section 5 will draw conclusions from the analysis and sections 6 and 7 contain the respective references and appendices.

2 Data

2.1 Data Cleaning

Before any models could be fit to the data, the data had to be cleaned and pre-processed. Missing values had to be filled in, multiple data sets had to be merged together, errors had to be corrected, and redundant information had to be deleted. The following paragraphs describe all of the data cleansing steps that were applied to the raw data before model fitting.

The first step in the data cleaning process was filling in all missing values in the CNDOL2 and CNDOL3 columns. These columns represent the dollar amounts of a person's second most recent donation and third most recent donation. Since many people had only donated to the organization once, they did not have a second most recent donation or third most recent donation. The data set originally had missing values for these cases, so the missing values were set to “0”.

Next, the contribution and solicitation codes were categorized according to their type. The raw data set originally had these codes stored as four-digit numbers in the columns CNCOD1, SLCOD1, CNCOD2, SLCOD2, CNCOD3, and SLCOD3. The last four of those columns were dropped because they contained many missing values that could not be imputed. For values in the first two of those columns, corresponding code types (A, B, C, D, or M) were assigned and stored in new columns ContType1 and SolType1, allowing the contribution and solicitation codes to be used as a categorical variable in our models. The original columns that contained the four-digit codes were subsequently deleted.

The STATCODE column of the raw data listed the state (or territory) that each donor resided in. This column contained 61 unique levels, which was too many for this column to be a useful predictor. To make this information more useful, the state codes were grouped into ten different regions. The regions corresponded to 9 regions of the United States and an “Other” category for locations that were not in the continental United States. Thus, the Region categorical variable was used in lieu of state.

A few columns in the data set were either meaningless or redundant. The ID column represented a donor’s id number, which would not be useful for prediction. The columns CNDAT1, CNDAT2, and CNDAT3 contained the dates for a person’s most recent contribution, second most recent contribution, and third most recent contribution. The data set also had columns CNMON1, CNMON2, and CNMON3 that represented the number of months since a person’s most recent contribution, second most recent contribution, and third most recent contribution. For a given donation, if you know one of these two pieces of information, you can deduce the other since the current date minus the months since donation is equal to the contribution date. There would be a multicollinearity problem if both sets of variables were kept in the model, so the CNDAT columns were deleted.

Some errors were found in the column named CNMONF, which represents the months since a person's largest contribution. The column contained mostly values between 0 and 162, but a few values of 1146 were present. The 1146 values are very high and unrealistic since they would mean that people donated to the organization over 90 years ago. The 1146 values are likely the results of a typo, so they were all replaced with the value 146.

After all of the preceding clean up steps were completed, there were still some missing values in the data set. The missing values occurred in columns CNMON2 and CNMON3 for people that did not have more than one donation. Since it is not possible to impute these values, the columns were kept to allow for the various models to be fit with and without the columns included in order to find the best possible fit.

2.2 Added Calculated Variables

In addition to the variables that were given in the raw data, a few calculated variables were added to the data set that may potentially be significant in the predictive models. The calculated variables avg, avgTime, don2, don3, and incr_don are described below.

The variable avg represents the average of all of a person's donations. If the person only donated once, avg was set equal to CNDOL1. If the person donated twice, avg was set equal to the average of CNDOL1 and CNDOL2. If a person donated three times, avg was set equal to the average of CNDOL1, CNDOL2, and CNDOL3.

The variable avgTime represents the average amount of time between a person's donations. If a person has donated more than one time, then avgTime is set equal to (CNMONF - CNMON1)/(CNTMLIF-1). CMONF is the month of a person's first donation and CNMON1 is the month of a person's most recent donation. CNTMLIF is the total number of times that a person has contributed in their lifetime. If a person has only donated once in their lifetime, then avgTime is set equal to 0.

The variable don2 is a binary variable that represents if a person has donated at least twice to the organization (1 if they have, 0 if they haven't). The variable don3 is also a binary variable; it represents whether a person has donated at least three times to the organization or not (1 if they have, 0 if they haven't).

Lastly, the variable incr_don is a binary variable that represents whether or not a person's most recent donation was larger than their second most recent donation. If it is, this variable is set equal to 1, otherwise it is set equal to 0. If a person does not have two donations, then this variable is also set equal to 0.

2.3 Exploratory Data Analysis

Univariate Continuous Distributions

Information is available for 66,134 different donations for a non-profit solicitation company (from the training set). For each donor, there are features regarding latest contributions, first, second and third donations, months since a contribution was made, state and region, gender and total contributions. For each continuous variable, histograms were made to visualize variable centralities, spread, potential outliers and skewness. These general characteristics are described below and demonstrated in Figures 1 and 2 in the Appendix.

Target Dollars: The mean target dollars, the response variable, is $2.38 and ranges from no donation up to $1500 donated. The distribution is strongly right skewed and centered at approximately 2 dollars. 73% of the donors did not donate in the fall 2010 donation cycle. The most commonly occurring donations are $2, $3, $5, $10 and $15 making up 23.6% of the whole training set. The $1500 donation is further examined as a potential outlier or influential observation after the model fitting, as it is significantly higher than any other donation.

Latest Contributions: The mean dollar amount for each of the latest contributions is $9.37, $9.25 and $8.95 respectively. For each subsequent contribution, each mean donation decreases slightly although the centrality and spread remains similar. Each distribution is strongly right skewed with the maximum values also decreasing for each subsequent latest contribution ($1000, $750, $600). The maximum donation for each of the three latest contributions could be examined as potential outliers that would need further testing to determine if those are actual outliers.

Largest Contribution: The largest contribution ranges from $2 to $1000 with a mean value of $10.53. The distribution doesn't appear to follow any known distribution but appears to be bimodal with a peak at roughly $5 and another peak at $20. The distribution is slightly right skewed with no blatant outliers upon observation.

First Contribution: The distribution for the first contribution is bimodal with a peak at roughly $5 and another peak at $20. The mean amount for the first contribution is $8 with the minimum amount being nothing donated and the maximum amount being $100. Upon inspection, the first contribution appears to be less in value to the largest contribution. The distribution is slightly skewed to the right with no clear outliers from observation.

Lifetime Contribution: The cumulative lifetime contribution has a mean of $33.40 with a minimum value of $2 and a maximum value of $3750. The distribution has a long right tail and is strongly right skewed as well. There are no apparent outliers from inspection.

Months Since First Donation was Made: The mean number of months since the first donation was made is 8.97 months. The distribution is right skewed slightly with the maximum months donated being 126 months and the minimum months being right after. There are two modes that occur at approximately 3 months and 25 since the first donation. From inspection, there appear to be no clear outliers

Average Time Since First Donation: The mean average time since the first donation is 4.21 months and the distribution appears to be bimodal with a mode at approximately 1 month and 5 months. There appear to be no evident outliers. The maximum average time since first donation is 71 months and the minimum average time is 0 months since first donation.

Univariate Relationships for Categorical Variables

The main feature to summarize univariate categorical relationships was looking at counts and proportions per variable. This can be seen in Table 1 in the Appendix. For Sex, married couples have the highest donation rate, followed by males. The latest contribution code with the highest donation rate is A, followed by B. The latest solicitation code B has the highest donation rate. No information is available to determine what the individual contribution and solicitation codes are, however the slight differences in donation rate suggest the codes could be meaningful predictors of donation probability.

Bivariate Relationships

Figure 2 demonstrates the pairwise bivariate relationships for all continuous variables. The lower diagonal shows pairwise scatter plots and the upper diagonal shows pairwise correlations between respective variables. The diagonal itself shows the univariate distribution against time. There is strong evidence of multicollinearity present indicated by the pairwise scatter plot. Several of the pairwise correlations are greater than 0.7, namely that between the largest contribution and the first donation, second and third dollar donations with lifetime and largest donations, and months since first contribution to times contributed lifetime. In addition, several other pairwise correlations have moderate evidence of multicollinearity evidenced by a correlation greater than 0.3. Thus, it is worthwhile to explore pairwise inter actions between all variables. Another interesting formulation for the pairwise scatterplots is that there could be a quadratic relationship between several of the predictors. This is worth an examination for modeling in addition to formulating the interactions from this exploratory data analysis overview.

3 Model Fitting

3.1 Logistic Regression Model

A logistic regression model was created to estimate the probability that a person in the test set will donate in response to a future solicitation sent out by the organization. The response variable for the model was a binary variable called donated. If a person made a donation in the test time period from 10/2010 to 12/2010 then their value for donated was set equal to 1. Otherwise their value for donated was set equal to 0.

Many variations of the logistic model were created and tested in order to find the best fitting model. The first model created was very simple and over time more complex models were created. To evaluate the models, the two primary metrics used were AUC (the area under the curve on the ROC plot) and the CCR (correct classification rate). Below is a description of each variation of the logistic regression model and the reasoning for trying it out. A formula for each model is listed in the Appendix.

Basic Logistic Regression Model

The initial model included all of the variables that were present in the cleaned-up data set. No quadratic or interaction terms were included in this model and no transformations were made. Just simple first order terms were included. This model was used as a baseline to compare with the more complex models made later on and is shown as model 1 in Table 2.

Name: logModel (1)   AUC: 0.716036   CCR: 0.753039

Forwards and Backwards Stepwise Logistic Regression Model

The next logistic regression models were created using forwards and backwards stepwise algorithms on the basic logistic regression model. Since not all of the variables used in the first model were significant, a potentially better model could be created by filtering down the selected variables to only those that are good predictors.

The forwards stepwise algorithm was run with the starting point being a blank model and the upper bound being the full basic logistic regression model. The algorithm added and removed variables one at a time and selected the best model based on the Akaike Information Criterion (AIC).

Name: forwards (2)   AUC: 0.716004   CCR: 0.753191

The backwards stepwise algorithm worked the same way as the forwards stepwise algorithm, except instead of starting with a blank model, the backwards algorithm starts with the full model. Variables were removed one at a time and the best model was selected based on Akaike Information Criterion (AIC). The resulting model is the same as the model that resulted from forwards stepwise algorithm.

Name: backwards (3) AUC: 0.716004 CCR: 0.753191

The models that resulted from the stepwise algorithm have similar AUCs and CCRs as the original model, but include less predictors.

Quadratic Terms Logistic Regression Model

Based on the exploratory data analysis completed earlier, it was decided that some quadratic terms (squared terms) should be included in the model in addition to the original predictors. This could potentially increase the AUC and/or CCR of the model. For the first quadratic model, a squared term was added for each numeric variable in the cleaned data set. The resulting model is shown below. As you can see, it has better AUC and CCR values than the previous models.

Name: logModel.quad (4) AUC: 0.719477 CCR: 0.755066

Backwards Stepwise, Quadratic Terms Logistic Regression Model

The backwards stepwise algorithm was then performed on the quadratic logistic model to rid the model of insignificant predictors. The resulting model has less terms than the full quadratic model, but near equivalent AUC and CCR values.

Name: backwards.quad (5) AUC: 0.719499 CCR: 0.755005

Interaction Terms and Quadratic Terms Logistic Regression

Next, interaction terms were added to the model since there may be a complex relationship between the response variable and multiple predictors. All possible interaction terms for numeric variables were included in the model. This model resulted in the highest AUC so far, but the lowest CCR. The stepwise algorithms were not run on this model since it is so large.

Name: logModelInter (6)   AUC: 0.729066   CCR: 0.760419

Quadratic Terms and Log Transformation Logistic Regression

Next, log transformations were made on various predictor variables since they did not display homoscedasticity. All variables that included a dollar amount (CNDOL1, CNDOL2, etc.) were transformed within the quadratic model. The results for this model were recorded and then some of the log transformations were removed to see if a better model could be produced. All possible combinations of log transformations for dollar amount variables were tested and the best combination is shown below. The AUC of this model was fairly low, but its CCR was fairly high.

Name: logModel.quad.log (7)   AUC: 0.720162   CCR: 0.756669

Optimal p* for Best Logistic Regression Model

In order to classify observations 1 or 0 (donate or do not donate), a threshold probability, p*, must be calculated. The optimal p* value will minimize the number of incorrectly classified observations. For the model which maximized CCR, the optimal p* value is .5. If this model were to be put into production at the non-profit, they may associate a higher cost with predicting that a donor will donate when in reality they don’t, or a false positive. Thus, a higher cost may be associated with false positives. When using a cost function that follows this logic, Cost = 2*FP + 1*FN, where FP is the number of false positives and FN is the number of false negatives, the optimal p* value becomes .37. Cost curves can be seen in Figure 3.

3.2 Multiple Linear Regression Model

A multiple linear regression model was built to estimate the dollar amount that a person in the test set would donate in the future time period. The response variable used was TARGDOL. To train the model, only donors with a TARGDOL > 0 were used. This prevents the many records (73%) with a TARGDOL = 0 from biasing the predictions downwards. We will be using this model in conjunction with the logistic model that predicts if a donor will donate, so this is a reasonable assumption.

An array of multiple linear regression models were built with various degrees of complexity. Each model was evaluated by looking at its Multiple R-Squared and Adjusted R-Squared value, which is shown in Table 3. Below is a description of each model.

Basic Multiple Linear Regression Model

The first model includes all variables present in the cleaned-up data set. There were no interactions or higher order terms added. This model is the simplest and serves as a benchmark for the later models.

Name: lmModel (1)   Multiple R-squared: 0.8390   Adjusted R-squared: 0.8387

Backwards Stepwise Multiple Linear Regression Model

This model uses the same variables as the basic multiple regression model, but a backwards stepwise algorithm is run to find the best model (based on AIC) by removing one variable at a time. This was explored because not every variable in the first model was found to be significant. The resulting model and its performance is shown below. The backwards stepwise model has similar performance metrics to the original, but some of the predictors were removed.

Name: backwards.lm (2) Multiple R-squared: 0.8388 Adjusted R-squared: 0.8387

Quadratic Terms Multiple Linear Regression Model

Including quadratic terms could possibly provide more information than just their first order counterparts. For each numeric column, an additional column was included that had the squared values of the numeric column. The resultant dataset was fit to a linear model. As expected, the Multiple R-squared is higher since there are more variables than in the original model. The Adjusted R-squared also increased, which is a positive sign.

Name: lmModel.quad (3) Multiple R-squared: 0.8804 Adjusted R-squared: 0.8801

Backwards Stepwise, Quadratic Terms Multiple Linear Regression Model

A backwards stepwise was again fitted, this time including all of the squared terms. This model was fit because many predictors in the initial quadratic model were insignificant. As expected, many variables were removed. The Multiple R-squared dropped very slightly, with the Adjusted R-squared remaining the same.

Name: backwards.lm.quad (4) Multiple R-squared: 0.8803 Adjusted R-squared: 0.8801

Interaction Terms and Quadratic Terms Multiple Linear Regression

In addition to including the squared versions of numeric predictors, this time the interactions between numeric variables was also included. This model shows a great increase in both performance metrics.

Name: lmModel.inter (5)   Multiple R-squared: 0.8930   Adjusted R-squared: 0.8922

Removed Influential Observations, Multiple Linear Model

The possibility of influential observations skewing the fit of the regression was explored. The influence.measures function in the stats package was used to identify influential observations. The simplest multiple linear regression model was fit with the remaining, uninfluential data points.

Name: lmModel.rminf (6)   Multiple R-squared: 0.6745   Adjusted R-squared: 0.6740

This version of the model performed worse. Both r-squareds decreased greatly. This is surprising, but is not unexplainable. There were a total of 1236 influential observations removed, a rather sizable chunk of the training set. This much of a change in the training set can cause this much of a change in the output.

Removed Influential Observations, Quadratic Multiple Linear Model

The influential observations were also removed from the quadratic model. This had a similar result as the previous model, the model fit decreased greatly from the fit without removing those observations.

Name: lmModel.quad.rminf (7)   Multiple R-squared: 0.6852   Adjusted R-squared: 0.6844

Quadratic terms, Log of some terms, Multiple Linear Regression

Before fitting, this time the log was taken of many of the numerical predictors. These predictors were chosen based on their distributions. There was some trial and error testing done to find the best subset of predictors to log.

Name: lmModel.quad.log (8)   Multiple R-squared: 0.8675   Adjusted R-squared: 0.8672

4 Model Validation

This section discusses how we selected our final models and then validated them against the test set. It also includes the results for how much our top 1000 predicted donors actually donated.

4.1 Division of Data into Training Set and Test Set

The cleaned data was divided into a training set and a test set. The training set was used to fit all of our predictive models and the test set was used to test our predictive models to see how well they performed. Every third observation from the original data into the test set was placed into the test set, making training set to test set size ratio 2:1.

4.2 Final Models Chosen

From the array of logistic and multiple regression models that were fit to the data, one model of each type had to be selected to predict how much each person in the test set would donate. The logistic model calculated the probability that each person would donate and the multiple regression model calculated their predicted donation. Each person's probability value was multiplied by their predicted donation to calculate their expected donation. Then, the donors with the top 1000 expected donations were selected and their actual donations were added together. Individually, the logistic model, which minimized AUC, was model (6) which included interaction terms with an AUC of 0.729066. The multiple linear regression model which maximized Adjusted R-squared was model (5) which included interaction terms with an Adjusted R-squared of 0.8922.

Since the selected models had to work together, it was not appropriate to select the two best models independently. The models had to be tested together so that the total donation from the top 1000 expected donors could be calculated. All possible combinations of the logistic and multiple regression models were tested together and the results from each test were recorded. The top five model combinations are shown below in Table 4, and the full results are shown in the appendix.

As you can see, the best combination of models was the logistic regression model that included quadratic and interaction terms, and the multiple regression model that included quadratic terms. The total expected donation from the top 1000 expected donors was $10,514.73. Both models are statistically significant. The Residual deviance for the logistic model is 68871, compared to a Null deviance of 77703. The linear regression model has an F statistic of 2576 and is significant at the 1% significance level. The classification table for the logistic model is seen in Table 5. The model correctly classified 96% of observations that did not donate, and 22% of those that did, so the model performed better in predicting who won't donate.

Key predictors for both models include the amount of a donor's latest contribution, the total lifetime contribution dollars, the first contribution, largest contribution, sex of donor, and contribution code. In addition, the average time between donations, average dollar amount, and whether or not a donor's contributions have been increasing in quantity are also significant predictors. Predicted probability of donation and donation amount both increase with dollar amount of latest contribution, and decrease with prolonged average time between donations.

A residual analysis was performed with the chosen linear model to ensure that the linear regression assumptions were met. Each predictor was plotted against the residuals and then visually inspected. Most predictors showed no warning signs, but some showed some minor violations of the homoscedasticity assumption. For example, the plots in Figure 4 show that the residuals versus AVG, CNMONF, and CONTRFST violate no assumptions. But the plot showing average time versus the residuals shows a higher variance among the observations with a lower average time. Since the homoscedasticity assumption was only violated slightly by a few of the many predictors, it was decided to still move forward with this model. It had the best performance on the test set, and that was the ultimate goal of this project (to get the most money possible from the top 1000 predicted donors). In the sake of time it was decided not to analyze the residual plots for the other inferior models. Figure 5 shows that the normality assumptions for the linear regression model are violated slightly. The points form a curve, which aligns with our exploratory data analysis that the data are long tailed with more extreme values than expected in a Normal distribution.

Although the AUC and ROC was the main method to validate the model against the test set, cross validation was a method that was examined. The issue with cross validation is that it is formulated on the basis of splitting the training set into a set number of folds and then validating on the left out fold. For each iteration, a different fold will be left out and the average will be calculated across all the left out folds to get an averaged cross validated error. This does not explicitly use the test set (although “test sets” are formulated from the training set) so it was a method explored but not used due to a test set of donators being provided.

5 Conclusions

Table 7 shows the mean donation from the top 1000 donors is $11.86. The most significant key predictors include the total lifetime contribution dollars, the first contribution, largest contribution, sex of donor, and contribution code. The added calculated variables were also significant predictors, such as the average time between donations, average dollar amount, and whether or not a donor's contributions have been increasing in quantity are also significant predictors. The findings are largely intuitive; such as predicted probability of donation and donation amount both increase with dollar amount of latest contribution, and decrease with prolonged average time between donations.

The predictors, that are significant, with the largest impact on probability of donation (magnitude of coefficient) are the sex of the donor, the contribution code, and number of lifetime contributions. Married couples exhibit the highest probability of donation, as expected from the frequency table. The predictors with the largest impact on donation amount are the dollar amount of the latest contribution and if the donations have been increasing in magnitude.

The non-profit should utilize this information to try to maximize expected donations. For example, putting more emphasis on soliciting donations from married couples, or people who have contributed several times, could result in increased probability of donation. Trying to influence the donation amount, perhaps with suggested donations that are slightly higher than a donor's previous donation, can help increase the amount of future donations.

Further analysis can be done in order to segment donors to customize solicitation methods in attempts to maximize the expected donations. Perhaps it should be a priority to try and create lifetime donors, rather than one-time donors. Solicitations can be somewhat customized for groups of donors who exhibit similar characteristics in order to focus on key factors that influence each group. As mentioned previously, soliciting for a donation of 5% more than a donor's previous donation can help influence a trend of increasing donations, which was an important factor in increasing expected donation amount.

More information on the contribution and solicitation codes would be beneficial to the analysis, as there may be information associated with each code that could provide further details about the donor or the donor segment they should belong to. Information on donation incentives may also have been helpful in this analysis. For example, donors who have some direct connection to the non-profit may be more likely to donate than those who do not. In addition, certain donation amounts may be associated with perks, such as giveaways from the non-profit, or entry to a donor appreciation events.

The analysis presented in this paper shows an exhaustive approach to finding the best predictive models for expected future donations form donors of a non-profit as a result of a solicitation effort. Additional predictor variables are likely the best approach to improving the predictions. The suggested information above is just a subset of possible significant factors. In the meantime, it is suggested that the key attributes of donors, among others, are used to target those with the highest expected donation, by combining the predicted probability of donation and the predicted amount.

6 References

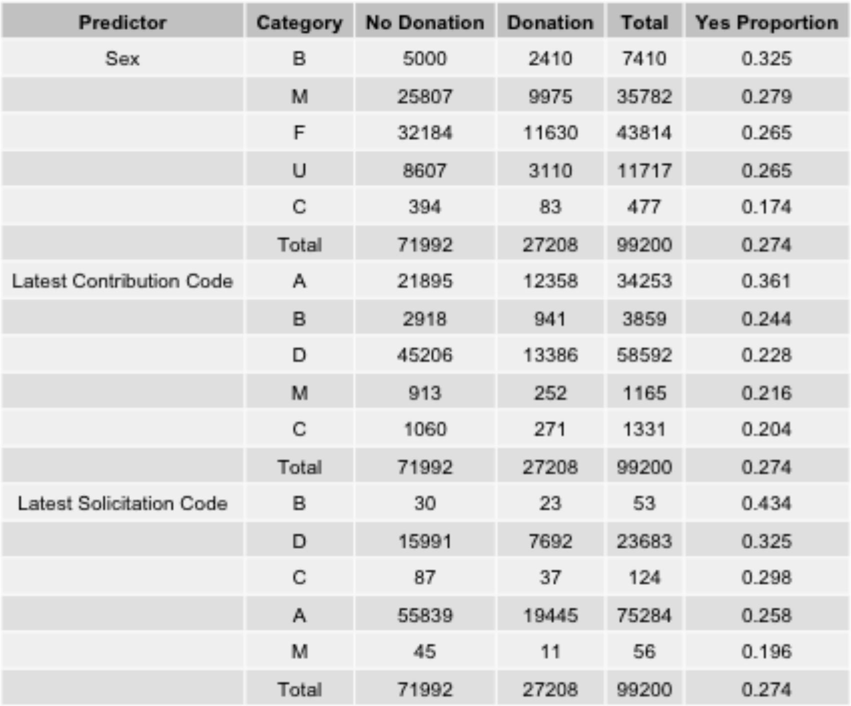
Link to our GitHub Repository: https://github.com/MSIA/PredictiveProjectADDK

Tamhane, A. C., & Malthouse, E. C. (2016). Predictive Analytics: Parametric Models for Regression and Classification. Evanston, IL. John Wiley & Sons Inc.

7 Appendix (Tables, Figures, Formulas)

Tables

Table 1: Frequency Table for Categorical Variables



Predictor	Category	No Donation	Donation	Total	Yes Proportion
Sex	B	5000	2410	7410	0.325
	M	25807	9975	35782	0.279
	F	32184	11630	43814	0.265
	U	8607	3110	11717	0.265
	C	394	83	477	0.174
	Total	71992	27208	99200	0.274
Latest Contribution Code	A	21895	12358	34253	0.361
	B	2918	941	3859	0.244
	D	45206	13386	58592	0.228
	M	913	252	1165	0.216
	C	1060	271	1331	0.204
	Total	71992	27208	99200	0.274
Latest Solicitation Code	B	30	23	53	0.434
	D	15991	7692	23683	0.325
	C	87	37	124	0.298
	A	55839	19445	75284	0.258
	M	45	11	56	0.196
	Total	71992	27208	99200	0.274

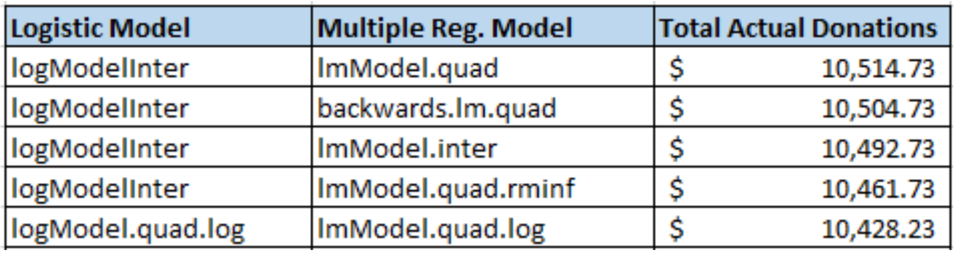
Table 2: Logistic Regression Models

Logistic Regression Models			
Model	Name	AUC	CCR
1	logModel	0.716036	0.753039
2	forwards	0.716004	0.753191
3	backwards	0.716004	0.753191
4	logModel.quad	0.719477	0.755066
5	backwards.quad	0.719499	0.755005
6	logModelInter	0.729066	0.760419
7	logModel.quad.log	0.720162	0.756669

Table 3: Multiple Linear Regression Models

Multiple Linear Regression Models			
Model	Name	R-squared	Adj R-squared
1	lmModel	0.8390	0.8387
2	backwards.lm	0.8388	0.8387
3	lmModel.quad	0.8804	0.8801
4	backwards.lm.quad	0.8803	0.8801
5	lmModel.inter	0.8930	0.8922
6	lmModel.rminf	0.6745	0.6740
7	lmModel.quad.rminf	0.6852	0.6844
8	lmModel.quad.log	0.8675	0.8672

Table 4: Top 5 Model Combinations for Expected Donation

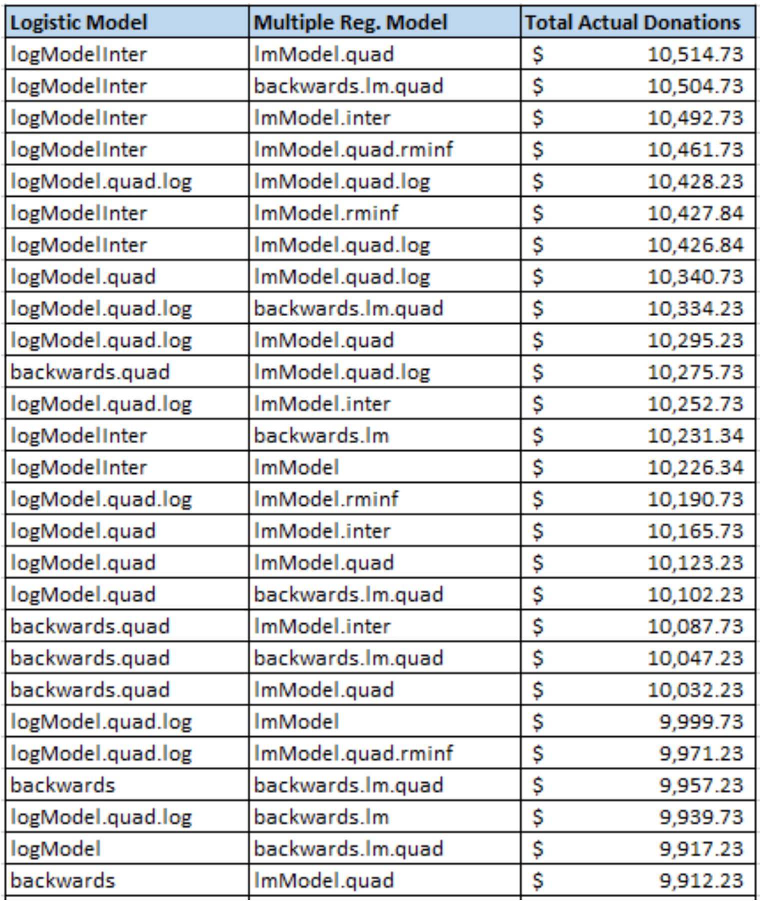


Logistic Model	Multiple Reg. Model	Total Actual Donations
logModelInter	lmModel.quad	$ 10,514.73
logModelInter	backwards.lm.quad	$ 10,504.73
logModelInter	lmModel.inter	$ 10,492.73
logModelInter	lmModel.quad.rminf	$ 10,461.73
logModel.quad.log	lmModel.quad.log	$ 10,428.23

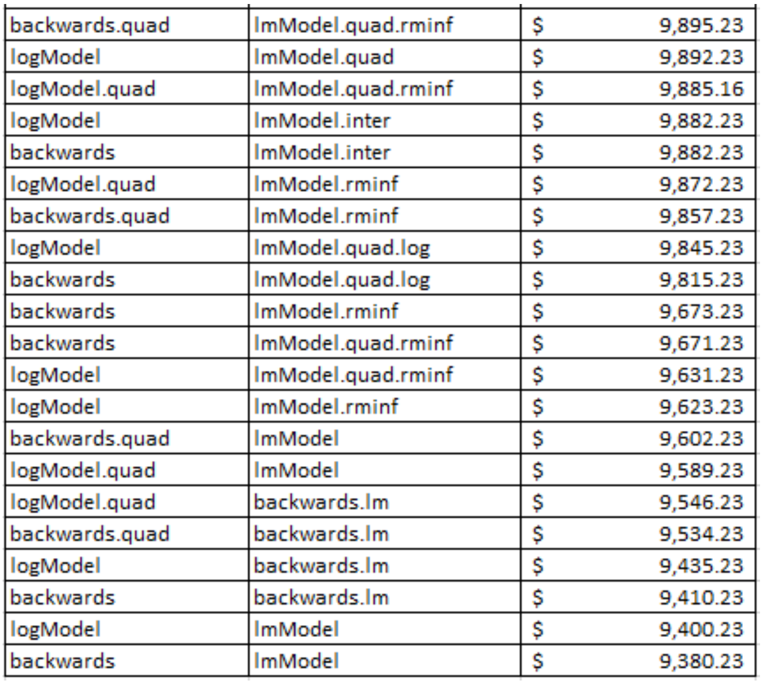
Table 5: Classification Table

	Predicted	
Actual	0	1
0	23069	928
1	7118	1951

Table 6: Results from Every Combination of Models



Logistic Model	Multiple Reg. Model	Total Actual Donations
logModelInter	lmModel.quad	$ 10,514.73
logModelInter	backwards.lm.quad	$ 10,504.73
logModelInter	lmModel.inter	$ 10,492.73
logModelInter	lmModel.quad.rminf	$ 10,461.73
logModel.quad.log	lmModel.quad.log	$ 10,428.23
logModelInter	lmModel.rminf	$ 10,427.84
logModelInter	lmModel.quad.log	$ 10,426.84
logModel.quad	lmModel.quad.log	$ 10,340.73
logModel.quad.log	backwards.lm.quad	$ 10,334.23
logModel.quad.log	lmModel.quad	$ 10,295.23
backwards.quad	lmModel.quad.log	$ 10,275.73
logModel.quad.log	lmModel.inter	$ 10,252.73
logModelInter	backwards.lm	$ 10,231.34
logModelInter	lmModel	$ 10,226.34
logModel.quad.log	lmModel.rminf	$ 10,190.73
logModel.quad	lmModel.inter	$ 10,165.73
logModel.quad	lmModel.quad	$ 10,123.23
logModel.quad	backwards.lm.quad	$ 10,102.23
backwards.quad	lmModel.inter	$ 10,087.73
backwards.quad	backwards.lm.quad	$ 10,047.23
backwards.quad	lmModel.quad	$ 10,032.23
logModel.quad.log	lmModel	$ 9,999.73
logModel.quad.log	lmModel.quad.rminf	$ 9,971.23
backwards	backwards.lm.quad	$ 9,957.23
logModel.quad.log	backwards.lm	$ 9,939.73
logModel	backwards.lm.quad	$ 9,917.23
backwards	lmModel.quad	$ 9,912.23



backwards.quad	lmModel.quad.rminf	$	9,895.23
logModel	lmModel.quad	$	9,892.23
logModel.quad	lmModel.quad.rminf	$	9,885.16
logModel	lmModel.inter	$	9,882.23
backwards	lmModel.inter	$	9,882.23
logModel.quad	lmModel.rminf	$	9,872.23
backwards.quad	lmModel.rminf	$	9,857.23
logModel	lmModel.quad.log	$	9,845.23
backwards	lmModel.quad.log	$	9,815.23
backwards	lmModel.rminf	$	9,673.23
backwards	lmModel.quad.rminf	$	9,671.23
logModel	lmModel.quad.rminf	$	9,631.23
logModel	lmModel.rminf	$	9,623.23
backwards.quad	lmModel	$	9,602.23
logModel.quad	lmModel	$	9,589.23
logModel.quad	backwards.lm	$	9,546.23
backwards.quad	backwards.lm	$	9,534.23
logModel	backwards.lm	$	9,435.23
backwards	backwards.lm	$	9,410.23
logModel	lmModel	$	9,400.23
backwards	lmModel	$	9,380.23

Table 7: Top Expected Donor Summary Statistics

Min	7.20
1st Quantile	8.03
Median	9.17
Mean	11.86
3rd Quantile	11.28
Max	795.30

Figures

Figure 1: Univariate Relationships

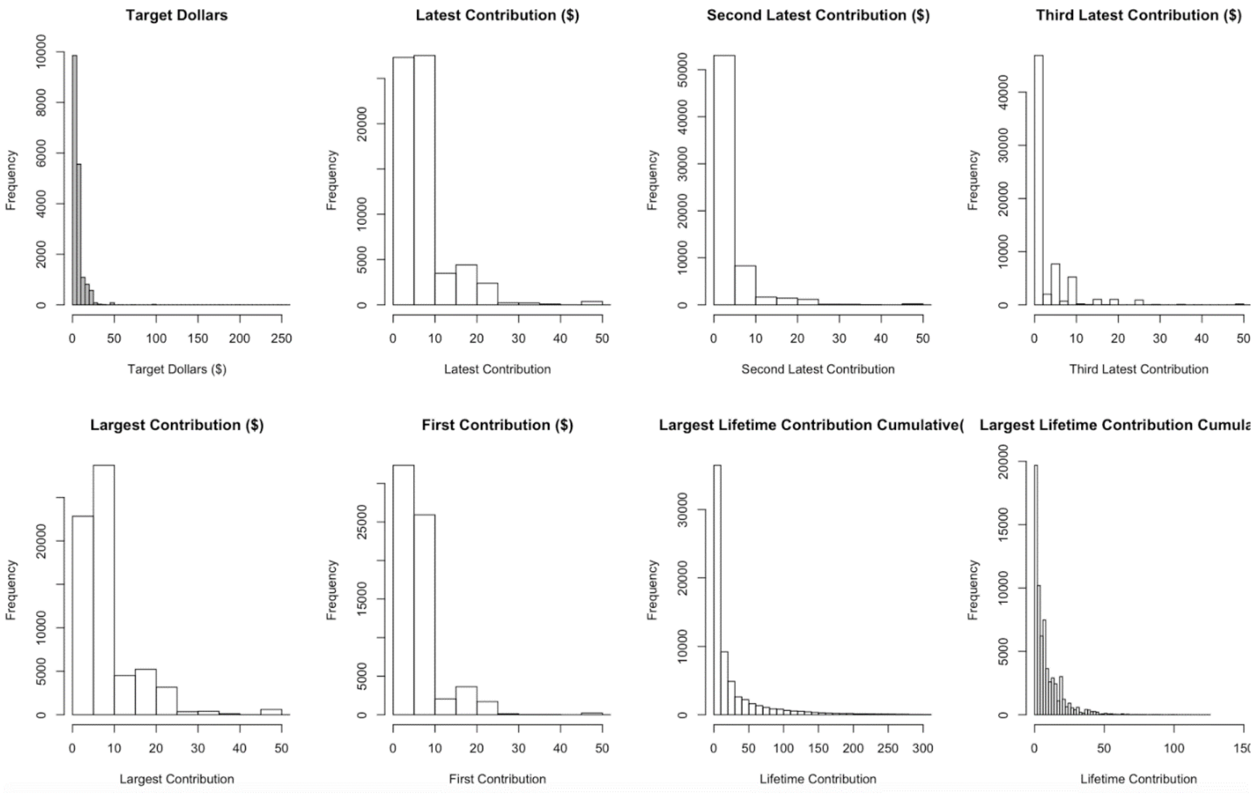


Figure 2: Bivariate Relationships (Continuous Variables)

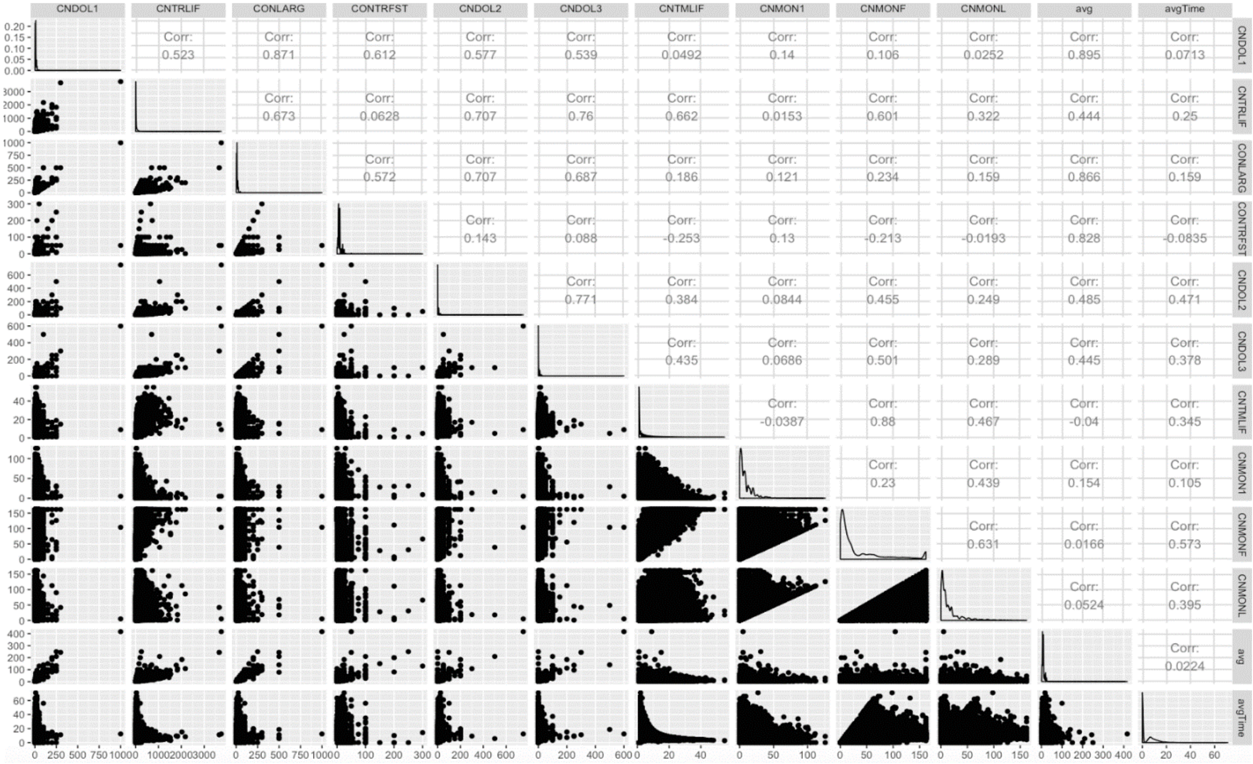


Figure 3: Cost Curves and Optimal p*

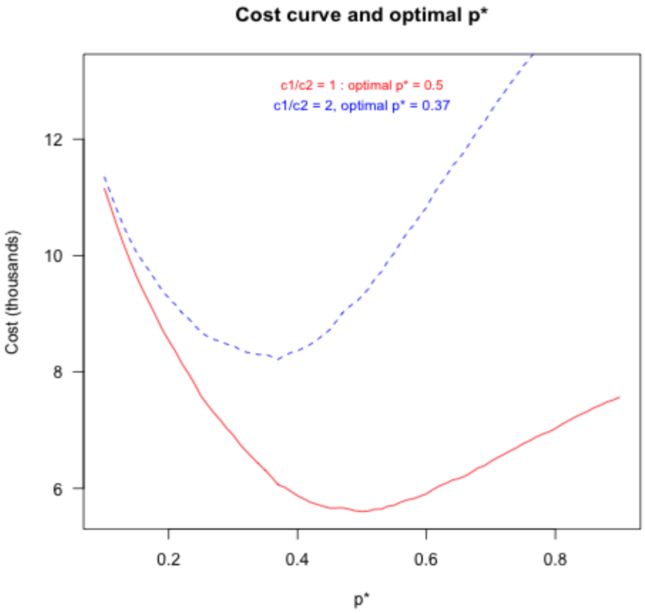


Figure 4: Residual Analysis of Linear Model with Quadratic Terms

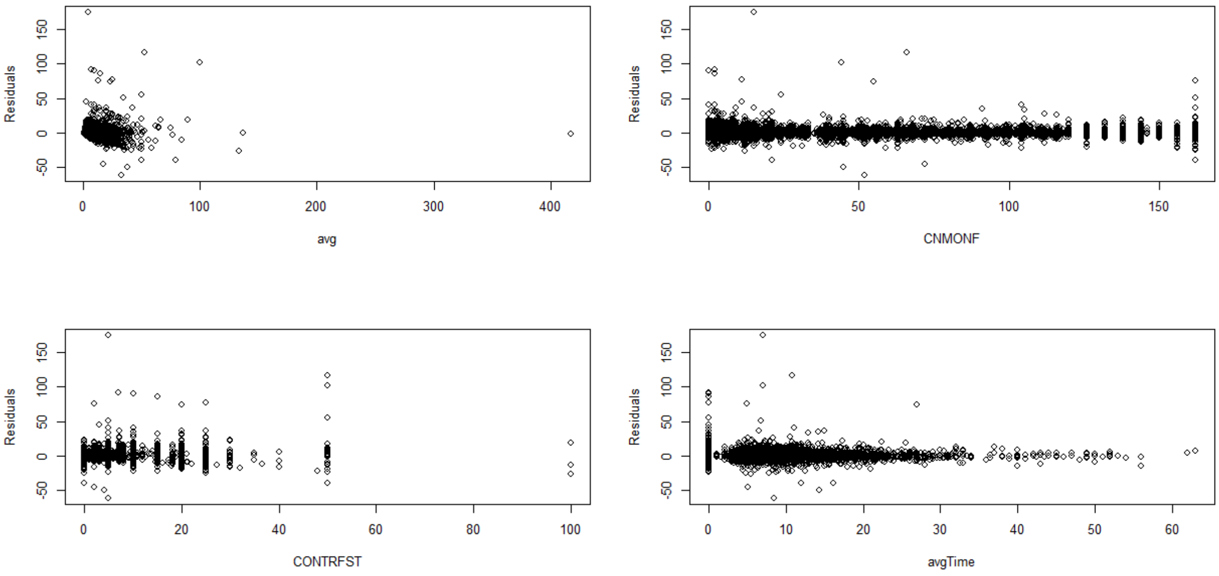
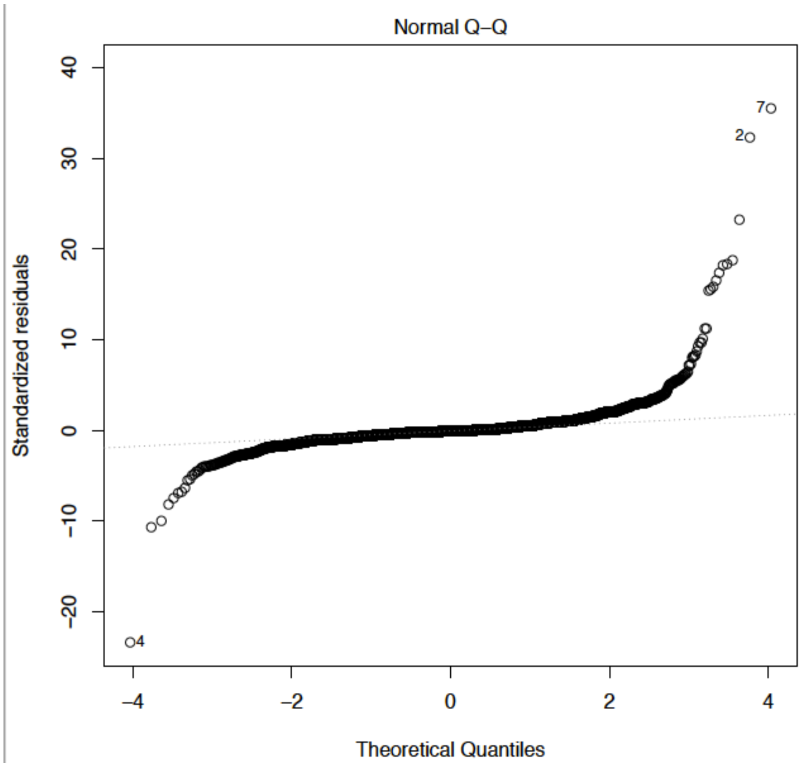


Figure 5: Normality Assumptions of Linear Model



Formulas

Logistic Model Formulas

Model Name	Formula
logModel	donated ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + CNMON1 + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + SEX + ContType1 + SolType1 + Region
forwards	donated ~ CNMON1 + CNMONL + CNTMLIF + CNMONF + ContType1 + CONTRFST + SolType1 + incr_don + SEX + don2 + avgTime + CNTRLIF + CNDOL2 + CNDOL1 + CONLARG + don3 + Region
backwards	donated ~ CNMON1 + CNMONL + CNTMLIF + CNMONF + ContType1 + CONTRFST + SolType1 + incr_don + SEX + don2 + avgTime + CNTRLIF + CNDOL2 + CNDOL1 + CONLARG + don3 + Region
logModel.quad	donated ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 + incr_don + Region + sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + sq_avg + sq_avgTime
backwards.quad	donated ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNTMLIF + CNMON1 + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + SEX + ContType1 + SolType1 + Region + sq_CNDOL1 + sq_CONLARG + sq_CNDOL2 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONL + sq_avg + sq_avgTime
logModel.quad.log	donated ~ log(CNDOL1) + CNTRLIF + log(CONLARG) + log(CONTRFST+1) + log(CNDOL2+1) + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 +incr_don + Region + log(sq_CNDOL1) + sq_CNTRLIF + log(sq_CONLARG) + log(sq_CONTRFST+1) + log(sq_CNDOL2+1) + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + log(sq_avg) + sq_avgTime
logModelInter	donated ~ sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + sq_avg + sq_avgTime + CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + CNMON1 + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + CNDOL1.CNTRLIF + CNDOL1.CONLARG + CNDOL1.CONTRFST + CNDOL1.CNDOL2 + CNDOL1.CNDOL3 + CNDOL1.CNTMLIF + CNDOL1.CNMON1 + CNDOL1.CNMONF + CNDOL1.CNMONL + CNDOL1.avg + CNDOL1.avgTime + CNDOL1.don2 + CNDOL1.don3 + CNDOL1.incr_don + CNTRLIF.CONLARG + CNTRLIF.CONTRFST + CNTRLIF.CNDOL2 + CNTRLIF.CNDOL3 + CNTRLIF.CNTMLIF + CNTRLIF.CNMON1 + CNTRLIF.CNMONF + CNTRLIF.CNMONL + CNTRLIF.avg + CNTRLIF.avgTime + CNTRLIF.don2 + CNTRLIF.don3 + CNTRLIF.incr_don + CONLARG.CONTRFST + CONLARG.CNDOL2 + CONLARG.CNDOL3 + CONLARG.CNTMLIF + CONLARG.CNMON1 + CONLARG.CNMONF + CONLARG.CNMONL + CONLARG.avg + CONLARG.avgTime + CONLARG.don2 + CONLARG.don3 + CONLARG.incr_don + CONTRFST.CNDOL2 + CONTRFST.CNDOL3 + CONTRFST.CNTMLIF + CONTRFST.CNMON1 + CONTRFST.CNMONF + CONTRFST.CNMONL + CONTRFST.avg + CONTRFST.avgTime + CONTRFST.don2 + CONTRFST.don3 + CONTRFST.incr_don + CNDOL2.CNDOL3 + CNDOL2.CNTMLIF + CNDOL2.CNMON1 + CNDOL2.CNMONF + CNDOL2.CNMONL + CNDOL2.avg + CNDOL2.avgTime + CNDOL2.don2 + CNDOL2.don3 + CNDOL2.incr_don +

	CNDOL3.CNTMLIF + CNDOL3.CNMON1 + CNDOL3.CNMONF + CNDOL3.CNMONL + CNDOL3.avg + CNDOL3.avgTime + CNDOL3.don2 + CNDOL3.don3 + CNDOL3.incr_don + CNTMLIF.CNMON1 + CNTMLIF.CNMONF + CNTMLIF.CNMONL + CNTMLIF.avg + CNTMLIF.avgTime + CNTMLIF.don2 + CNTMLIF.don3 + CNTMLIF.incr_don + CNMON1.CNMONF + CNMON1.CNMONL + CNMON1.avg + CNMON1.avgTime + CNMON1.don2 + CNMON1.don3 + CNMON1.incr_don + CNMONF.CNMONL + CNMONF.avg + CNMONF.avgTime + CNMONF.don2 + CNMONF.don3 + CNMONF.incr_don + CNMONL.avg + CNMONL.avgTime + CNMONL.don2 + CNMONL.don3 + CNMONL.incr_don + avg.avgTime + avg.don2 + avg.don3 + avg.incr_don + avgTime.don2 + avgTime.don3 + avgTime.incr_don + don2.don3 + don2.incr_don + don3.incr_don + targdol + SEX + ContType1 + ContType2 + ContType3 + SolType1 + SolType2 + SolType3 + Region

Multiple Regression Model Formulas

Model Name	Formula
lmModel	targdol ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 + incr_don + Region
backwards.lm	targdol ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNTMLIF + CNMONF + CNMONL + avg + don2 + don3 + incr_don + ContType1 + SolType1
lmModel.quad	targdol ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 + incr_don + Region + sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + sq_avg + sq_avgTime
backwards.lm.quad	targdol ~ sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONL + sq_avg + sq_avgTime + CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + SEX + ContType1 + SolType1
lmModel.rminf	targdol ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 + incr_don + Region
lmModel.quad.rminf	targdol ~ CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + SEX + CNMON1 + CNMONF + CNMONL + ContType1 + SolType1 + avg + avgTime + don2 + don3 + incr_don + Region + sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + sq_avg + sq_avgTime
lmModel.quad.log	targdol ~ log(sq_CNDOL1) + sq_CNTRLIF + log(sq_CONLARG) + log(sq_CONTRFST+1) + log(sq_CNDOL2+1) + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + I(log(sq_avg)) + sq_avgTime + log(CNDOL1) + CNTRLIF + log(CONLARG) + log(CONTRFST+1) + log(CNDOL2+1) + CNDOL3 + CNTMLIF + CNMON1 + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + SEX + ContType1 + SolType1 + Region
lmModel.Inter	targdol ~ sq_CNDOL1 + sq_CNTRLIF + sq_CONLARG + sq_CONTRFST + sq_CNDOL2 + sq_CNDOL3 + sq_CNTMLIF + sq_CNMON1 + sq_CNMONF + sq_CNMONL + sq_avg + sq_avgTime + CNDOL1 + CNTRLIF + CONLARG + CONTRFST + CNDOL2 + CNDOL3 + CNTMLIF + CNMON1 + CNMONF + CNMONL + avg + avgTime + don2 + don3 + incr_don + CNDOL1.CNTRLIF + CNDOL1.CONLARG + CNDOL1.CONTRFST +

	CNDOL1.CNDOL2 + CNDOL1.CNDOL3 + CNDOL1.CNTMLIF + CNDOL1.CNMON1 + CNDOL1.CNMONF + CNDOL1.CNMONL + CNDOL1.avg + CNDOL1.avgTime + CNDOL1.don2 + CNDOL1.don3 + CNDOL1.incr_don + CNTRLIF.CONLARG + CNTRLIF.CONTRFST + CNTRLIF.CNDOL2 + CNTRLIF.CNDOL3 + CNTRLIF.CNTMLIF + CNTRLIF.CNMON1 + CNTRLIF.CNMONF + CNTRLIF.CNMONL + CNTRLIF.avg + CNTRLIF.avgTime + CNTRLIF.don2 + CNTRLIF.don3 + CNTRLIF.incr_don + CONLARG.CONTRFST + CONLARG.CNDOL2 + CONLARG.CNDOL3 + CONLARG.CNTMLIF + CONLARG.CNMON1 + CONLARG.CNMONF + CONLARG.CNMONL + CONLARG.avg + CONLARG.avgTime + CONLARG.don2 + CONLARG.don3 + CONLARG.incr_don + CONTRFST.CNDOL2 + CONTRFST.CNDOL3 + CONTRFST.CNTMLIF + CONTRFST.CNMON1 + CONTRFST.CNMONF + CONTRFST.CNMONL + CONTRFST.avg + CONTRFST.avgTime + CONTRFST.don2 + CONTRFST.don3 + CONTRFST.incr_don + CNDOL2.CNDOL3 + CNDOL2.CNTMLIF + CNDOL2.CNMON1 + CNDOL2.CNMONF + CNDOL2.CNMONL + CNDOL2.avg + CNDOL2.avgTime + CNDOL2.don2 + CNDOL2.don3 + CNDOL2.incr_don + CNDOL3.CNTMLIF + CNDOL3.CNMON1 + CNDOL3.CNMONF + CNDOL3.CNMONL + CNDOL3.avg + CNDOL3.avgTime + CNDOL3.don2 + CNDOL3.don3 + CNDOL3.incr_don + CNTMLIF.CNMON1 + CNTMLIF.CNMONF + CNTMLIF.CNMONL + CNTMLIF.avg + CNTMLIF.avgTime + CNTMLIF.don2 + CNTMLIF.don3 + CNTMLIF.incr_don + CNMON1.CNMONF + CNMON1.CNMONL + CNMON1.avg + CNMON1.avgTime + CNMON1.don2 + CNMON1.don3 + CNMON1.incr_don + CNMONF.CNMONL + CNMONF.avg + CNMONF.avgTime + CNMONF.don2 + CNMONF.don3 + CNMONF.incr_don + CNMONL.avg + CNMONL.avgTime + CNMONL.don2 + CNMONL.don3 + CNMONL.incr_don + avg.avgTime + avg.don2 + avg.don3 + avg.incr_don + avgTime.don2 + avgTime.don3 + avgTime.incr_don + don2.don3 + don2.incr_don + don3.incr_don + donated + SEX + ContType1 + SolType1 + Region