Course Project

Predict 422 Section 56

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1. Introduction

A charitable organization wishes to develop a machine learning model to improve the costeffectiveness of their direct marketing campaigns to previous donors. According to their recent mailing records, the typical overall response rate is 10%. Out of those who respond (donate) to the mailing, the average donation is $14.50. Each mailing costs $2.00 to produce and send; the mailing includes a gift of personalized address labels and assortment of cards and envelopes. It is not cost-effective to mail everyone because the expected profit from each mailing is 14.50 x 0.10 – 2 = -$0.55. I will develop a classification model using data from the most recent campaign that can effectively capture likely donors so that the expected net profit is maximized.

The entire charity dataset consists of 3984 training observations, 2018 validation observations, and 2007 test observations. Weighted sampling has been used, over-representing the responders so that the training and validation samples have approximately equal numbers of donors and non-donors. The response rate in the test sample has the more typical 10% response rate. I will build a prediction model to predict expected gift amounts from donors. The data for the prediction model will consist of the records for donors only.

2. Exploring and Preparing Data

Examining Variable Type
I begin by examining the Data Dictionary provided in the Course Project introduction document to see what kind of variables are included in the data. Based on the quick preview of the data and the description below, I can also determine the variable type. There are 2 response variables: DONR and DAMT, which have several missing observations and an index variable, ID. All of the missing data are in the test sets as indicated by the PART variable which I will have to fill in with predicted values. These 4 non-predictor variables are highlighted in yellow in the table below in order to distinguish them from the other (predictor) variables. When the data is initially loaded in, all of the remaining predictor variables are quantitative variables of "int" type (integer values) except for agif which is "num" (decimal values). The region variables (REG1, REG2, REG3, and REG4), HOME, GENF, DONR are dummy (indicator) variables. Region may have been a 5 class categorical variable which has now been converted to 4 dummy variables with REG5 serving as the reference. In addition to the dummy variables, 2 of the int type variables, can be utilized as categorical variables: HINC and WRAT. I will need to examine the data distribution of these variables to see if they will be better utilized as categorical variables.

Variable	Type	Description
ID	Index	Index of observations
REG1, REG2, REG3, REG4	Binary Categorical	Region (There are five geographic regions; only four are needed for analysis since if a potential donor falls into none of the four he or she must be in the other region. Inclusion of all five indicator variables would be redundant and cause some modeling techniques to fail. A "1" indicates the potential donor belongs to this region.)
HOME	Binary Categorical	(1 = homeowner, 0 = not a homeowner)
CHLD	Continuous	Number of children
HINC	Continuous/ Categorical	Household income (7 categories)
GENF	Binary Categorical	Gender (0 = Male, 1 = Female)
WRAT	Continuous/ Categorical	Wealth Rating (Wealth rating uses median family income and population statistics from each area to index relative wealth within each state. The segments are denoted 0-9, with 9 being the highest wealth group and 0 being the lowest.)
AVHV	Continuous	Average Home Value in potential donor's neighborhood in $ thousands

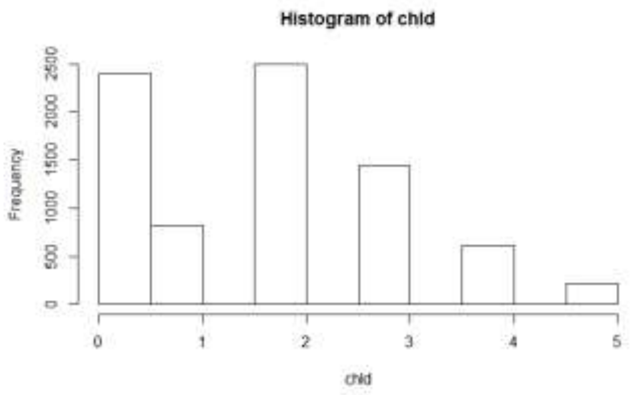
INCM	Continuous	Median Family Income in potential donor's neighborhood in $ thousands
INCA	Continuous	Average Family Income in potential donor's neighborhood in $ thousands
PLOW	Continuous	Percent categorized as “low income” in potential donor's neighborhood
NPRO	Continuous	Lifetime number of promotions received to date
TGIF	Continuous	Dollar amount of lifetime gifts to date
LGIF	Continuous	Dollar amount of largest gift to date
RGIF	Continuous	Dollar amount of most recent gift
TDON	Continuous	Number of months since last donation
TLAG	Continuous	Number of months between first and second gift
AGIF	Continuous	Average dollar amount of gifts to date
DONR	Binary Categorical	Classification Response Variable (1 = Donor, 0 = Non-donor)
DAMT	Continuous	Response Variable: Donation Amount in dollars
PART	Categorical	Indicates whether the observation is part of the training (train), test (test), or validation (valid) set

Examining Variables
In this next section, I will examine the histograms of the continuous variables and the frequency tables of the categorical variables.

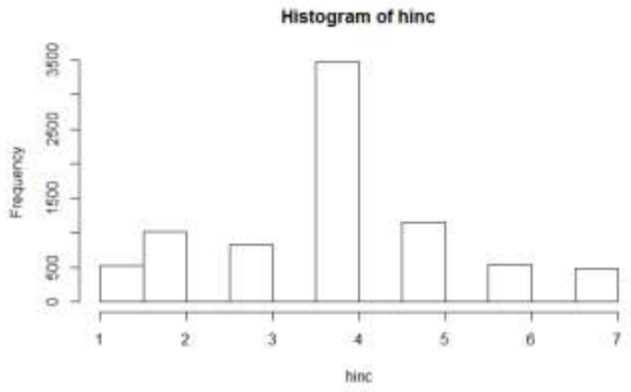
REGx (all 5 Region variables)
By taking the sum of each REGx variable, I find the instances for each of the 5 geographical regions (displayed in the following table). I also find the correlation coefficient of each REGx variable with DONR in the training set. Region 2 (REG2) has the most instances and the highest correlation with DONR.

Region	# Instances	Correlation with DONR
Region 1	1605	0.05645603
Region 2	2555	0.2470784
Region 3	1071	-0.1043229
Region 4	1117	-0.1262810
Region 5	1661	-0.1548909

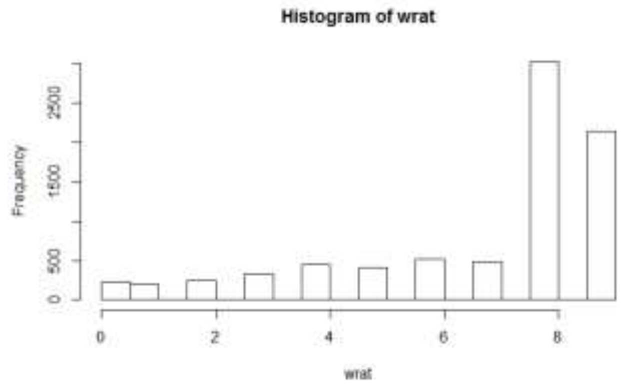
CHLD
The CHLD histogram is zero inflated. The highest count is for 2 children followed by 0 children. Even without the zero inflation, the histogram would appear positively skewed with a long right tail.



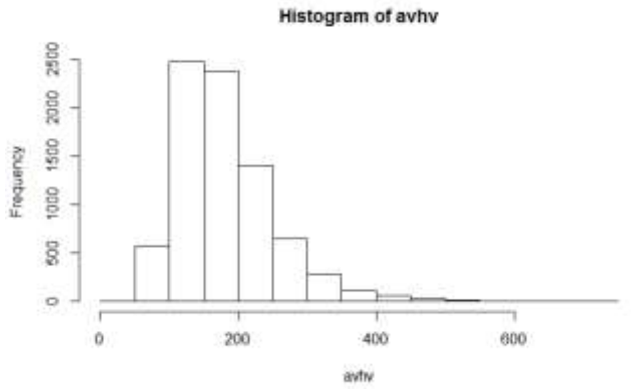
HINC
The HINC histogram appears evenly distributed except with a strong singular central spike at 4 which is also its median and mode. This spike makes the distribution highly kurtotic. The Anderson-Darling test for normality p-value < 2.2e16 meaning that the HINC histogram does not resemble a normal distribution.



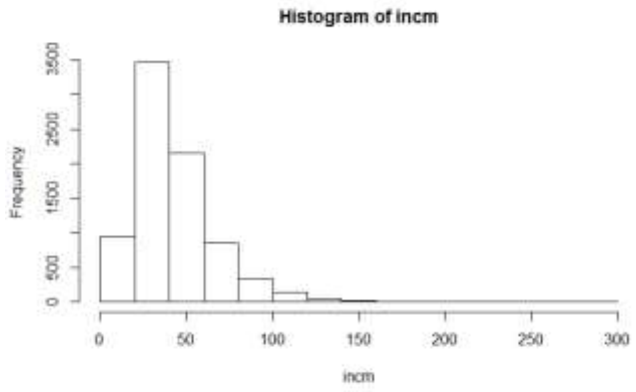
WRAT
The WRAT histogram is extremely negatively skewed. The distribution gradually increasing from 1 to 7 but then jumps up at 8 and drops slightly at 9. The highest frequency wealth group is 8 which is also its median and mode.



AVHV
The AVHV histogram is positively skewed with a long right tail. The median is 169 and the mean is 182.6, which are both close to the highest bin with the peak.

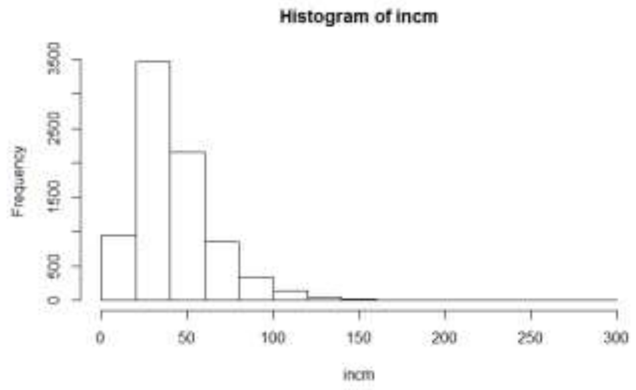


INCM
The INCM histogram is positively skewed with a long right tail. The median is 38 and the mean is 43.47, which are contained in the highest bin with the peak.



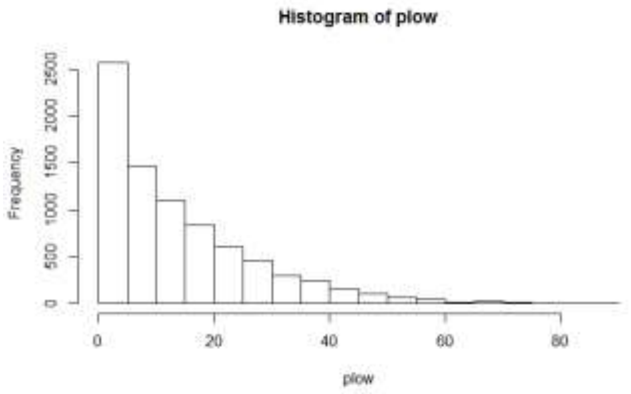
INCA

The INCA histogram is positively skewed with a long right tail. The median is 169 and the mean is 182.6, which are both contained in the highest bin with the peak.



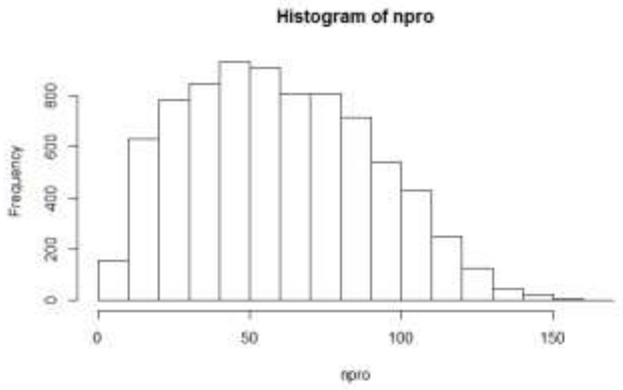
PLOW

The PLOW histogram is shaped like a poisson distribution that decays from left to right. The histogram is zero inflated with a long right tail extending out to a maximum of 87.

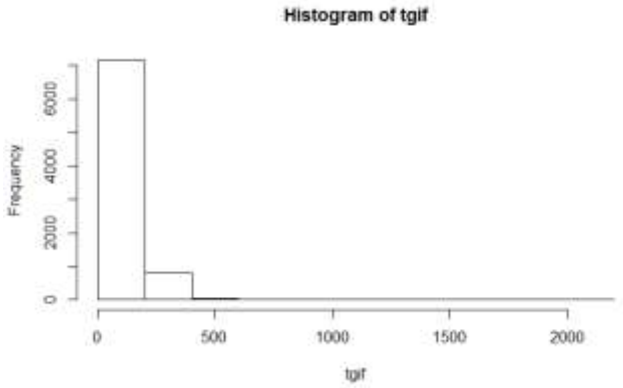


NPRO

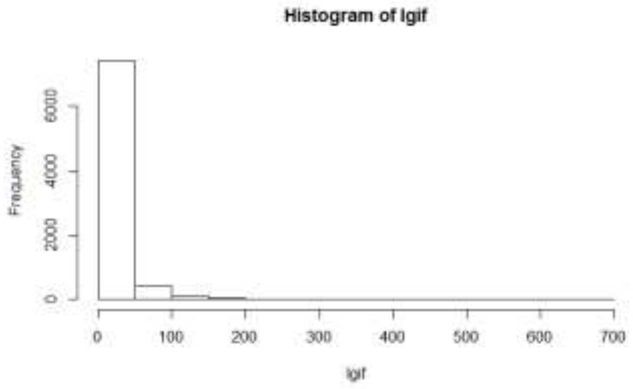
The NPRO histogram sharply increases from its first to second bin then after the peak gradually descends with a longer right tail. The Anderson-Darling test for normality p-value < 2.2e16 meaning that the HINC histogram does not resemble a normal distribution.



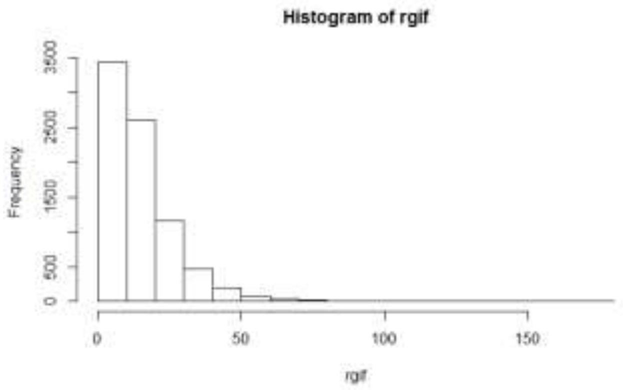
TGIF
The TGIF histogram is shaped like a poisson distribution that decays from left to right. The histogram has a long right tail extending out to a maximum of 2057.



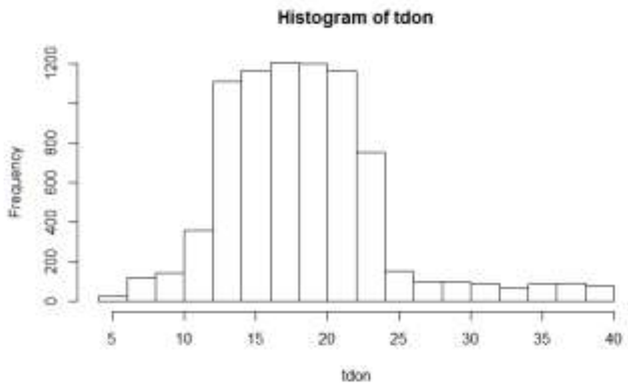
LGIF
The LGIF histogram is shaped like a poisson distribution that decays from left to right. The histogram has a long right tail extending out to a maximum of 681.



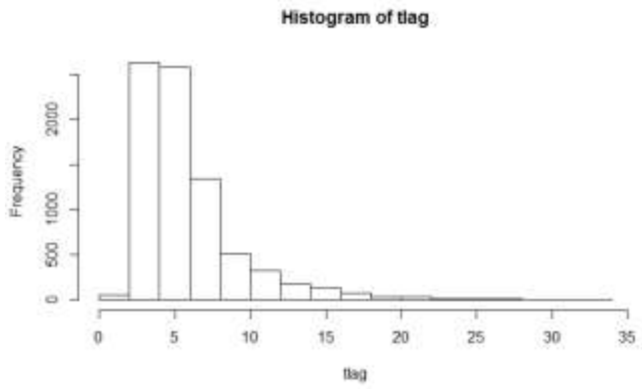
RGIF
The RGIF histogram is shaped like a poisson distribution that decays from left to right. The histogram has a long right tail extending out to a maximum of 173.



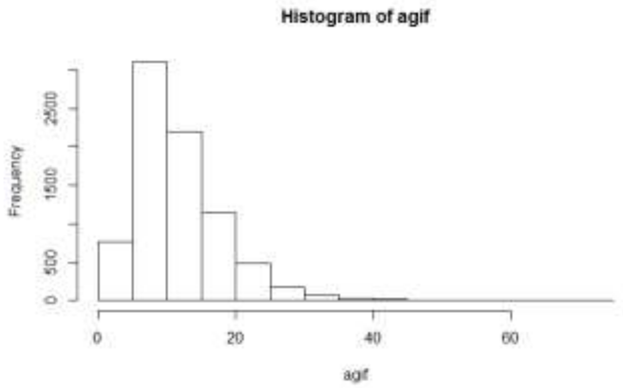
TDON
The TDON histogram is sharply jump up at 12 and stays relatively flat between 13 to 24, and sharply drops at 22. The median is 18 and the mean is 18.86 and both are contained on the top of plateau. The right tail extends out to 40. TDON may the variable closest to resembling a normal distribution, however the Anderson-Darling test for normality p-value < 2.2e16 meaning that the HINC histogram does not resemble a normal distribution.



TLAG
The TLAG histogram sharply jumps up at 4 and then resembles a poisson distribution that decays with a long right tail that extends out to 34.



AGIF
The AGIF histogram sharply jumps up at 5 (the mode is 5.31) and then resembles a poisson distribution that decays with a long right tail that extends out to 72.27.



Adding New Variables
There were 11 continuous variable histograms that were positively skewed (AVHV, INCM, INCA, PLOW, NPRO, TGIF, LGIF, RGIF, TDON, TLAG, and AGIF) and 1 continuous variable histogram that was negatively skewed (WRAT). The square root and natural logarithm transforms can help fix the positively skewed distributions to appear more normal, while the square (to power of 2) or cube (to the power of 3) transforms can adjust negatively skewed distributions to appear more normal. Data points zero or less are undefined when I take the natural logarithm, so I set these values to zero for the natural logarithm transformed variables. Since CHLD was zero inflated, I create CHLD0 as an indicator variable set to 1 when CHLD0 = 0 and set to 0 otherwise. I know that REG5 is an implied reference point for all of the REGx (region) variables, but in order to actually include it into as an automated variable selection input variable, I need to explicitly add the variable. The following table indicates all of the new variables that I added to the charity data set.

Natural Logarithm Transform	Square Root Transform	Square Transform	Cube Transform	Indicator Variables
LN_CHLD	SR_CHLD	HINC2	HINC3	CHLD0
LN_AVHV	SR_AVHV	WRAT2	WRAT3	REG5
LN_INCM	SR_INCM			
LN_INCA	SR_INCA			
LN_PLOW	SR_PLOW			
LN_NPRO	SR_NPRO			
LN_TGIF	SR_TGIF			
LN_LGIF	SR_LGIF			
LN_RGIF	SR_RGIF			
LN_TDON	SR_TDON			
LN_TLAG	SR_TLAG			
LN_AGIF	SR_AGIF			

Preparing Data
Prior to building models, I have to choose between standardizing the data and then splitting up the data into training, test, and validation sets or splitting up the data and then standardizing the data. There are disadvantages to both sequences. When you perform standardization after splitting the data set, you are additionally testing the separation of the means and variances of the variables of each subset. When you perform standardization before before splitting the data set, you will be polluting your validation and test samples by incorporating information from the means and variances of the training set. For this project, I will generate a set of models for both sequences.

First, I divide up the data into training, test, and validation sets. The PART variable indicates which set each observation is assigned. The entire charity dataset consists of 3984 training observations, 2018 validation observations, and 2007 test observations. Next, I take the mean and standard deviation of all variables for all sets in order to standardize all variable data to have zero mean and unit standard deviation. I then create a separate dataframe for each set to classify DONR and a separate dataframe for each set to predict DAMT. Second, I perform standardization for the whole data set so that all variable data has zero mean and unit standard deviation. Then, I split up the data into training, test and validation sets. Both sequences end up with the following data variables.

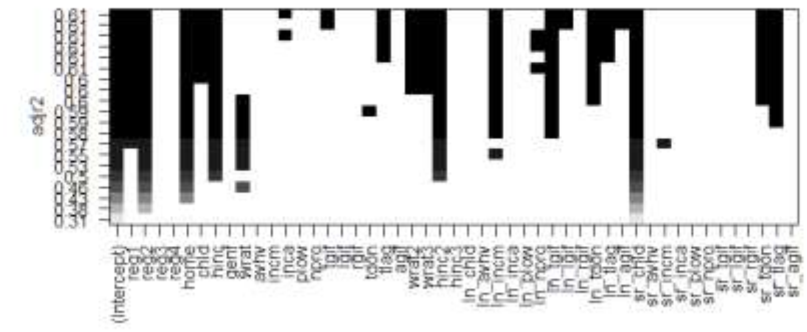
Data set	# Obs	# Var	Purpose
data.train	3984	55	Unstandardized training set
data.train.std.c	3984	52	To classify DONR
data.train.std.y	1995	52	To predict DAMT
data.valid	2018	55	Unstandardized validation set

data.valid.std.c	2018	52	To classify DONR
data.valid.std.y	999	52	To predict DAMT
data.test	2007	55	Unstandardized test set
data.test.std	2007	51	Standardized test set with missing response variable observations

3. Building Classification Models

The next step is to find the best subset of variables to use when building models. The original data set included 24 variables with 2 response variables, 1 index variable, and 1 data set specification variable (PART). Thus, there were only 20 predictor variables in the original charity data set. Even though the variable set has expanded to 51 predictor variables, I still expect the best model to have the same number of variables as the original data set or less.

First, I run an automated variable selection procedure on the training data set with the function REGSUBSETS in the LEAPS package with the "exhaustive search" method to find the best 20 variables out of the total 51 variables (including the newly added variables) for classifying DONR. The following plot is a graphical representation of the best models with 1 through 20 variables, where black colored squares indicate that the particular variable was included in that model. The y-axis orders the models by Adjusted R-Squared values. This figure indicates that the model with 20 variables has the highest Adjusted R-Squared value.



I do not immediately assume that the model with 20 variables has the best performing subset of variables. There are many redundant variables that may add unwanted multicollinearity problems such as the original variable and their transformed variant. Even if multicollinearity issues do not arise, it will be better to go with a more parsimonious model rather than a more complex model if performance is similar. More complex models will tend to perform well on the training set but perform worse on the test set due to overfitting. The following table shows the variables that appear more than once in different forms in the REGSUBSETS best model.

Redundant Variables		
CHLD	SR_CHLD	
HINC	HINC2	
WRAT2	WRAT3	
TGIF	LN_TGIF	
TLAG	LN_TLAG	SR_TLAG
LN_TDON	SR_TDON	

In order to trim the subset even more, I choose the variant that appears the most frequently and more than twice in the above graphical representation of the automated variable selection procedure. If multiple variants of the same variable appear in many of the 20 models, then each will be added to this new trimmed subset. The result is the following trimmed subset of 12 variables. I've included the default subset of all original 20 predictor variables (plus HINC2 and LN_AVHV added into the given code) and the variable selection subset of 20 variables with this trimmed subset.

Default original set (DO)	Variable selection subset (VS)	Trimmed subset (TS)
REG1	REG1	REG1
REG2	REG2	REG2
REG3	HOME	HOME

REG4	CHLD	SR_CHLD
HOME	HINC	HINC
CHLD	INCA	HINC2
HINC	TGIF	WRAT2
HINC2	TLAG	WRAT3
GENF	WRAT2	LN_TGIF
WRAT	WRAT3	SR_TDON
LN_AVHV	HINC2	SR_TLAG
INCM	LN_INCM	LN_INCM
INCA	LN_TGIF	
PLOW	LN_LGIF	
NPRO	LN_TDON	
TGIF	LN_TLAG	
LGIF	LN_AGIF	
RGIF	SR_CHLD	
TDON	SR_TDON	
TLAG	SR_TLAG	
AGIF		

Model Building Procedure
I will calculate profit for a particular classification model applied to the validation data. Each donor donates $14.50 on average and each mailing costs $2.00. Therefore, in order to find an ordered profit function (ordered from most likely donor to least likely), I will calculate the posterior probabilities for the validation dataset. Next, I will sort DONR in order of the posterior probabilities from highest to lowest. Then, I will calculate the cumulative sum of (14.5 x DONR – 2) as I go down the list. After that, I will find the maximum of this profit function. Lastly, I will create a classification table (or confusion matrix) to visualize the results. I will repeat this 5 step process for each subsequent model. As classification tables may be arranged or formatted differently, the following table indicates the format for my classification tables.

	Actual	
Predicted	**0**	**1**
0	True Negatives	False Negatives
1	False Positives	True Positives

Please note that when I compare the model results below I do not mention Models e through f because for the most part they are exactly the same as their models a through c counterparts.

Classification Model 1: Logistic Regression
The first method I will apply is classic Logistic Regression with each subset of variables of the standardized training set to classify DONR and test the model's performance on the standardized validation set. Logistic Regression will serve as a good starting point and standard for model comparison. The following table shows the classification table for all 6 Logistic Regression classification models. Models 1a, 1b, and 1c are built on the training where splitting was performed before standardization. Model 1b performs the best with the highest true positives and true negatives and the lowest false positives and false negatives.

Classification Model 1a: DO subset Splitting Before Standardization		**Classification Model 1b: VS subset Splitting Before Standardization**		**Classification Model 1c: TS subset Splitting Before Standardization**	
709	18	752	12	677	5
310	981	267	987	342	994

Classification Model 1d: DO subset Standardization Before Splitting		**Classification Model 1e: VS subset Standardization Before Splitting**		**Classification Model 1f: TS subset Standardization Before Splitting**	
709	18	752	12	677	5
310	981	267	987	342	994

Classification Model 2: Linear Discriminant Analysis
Next, I perform Linear Discriminant Analysis (LDA) with each subset of variables of the standardized training set to classify DONR and test its performance on the standardized validation set. LDA is not normally used with qualitative predictors however at this stage the model building process, however the goal is to ultimately to find good predictive models. Model 2b performed the best with the most true positives plus true negatives and least false positives plus false negatives.

Classification Model 2a: DO subset	**Classification Model 2b: VS subset**	**Classification Model 2c: TS subset**

Splitting Before Standardization		Splitting Before Standardization		Splitting Before Standardization	
675	14	719	6	667	5
344	985	300	993	352	994

Classification Model 2d: DO subset Standardization Before Splitting		Classification Model 2e: VS subset Standardization Before Splitting		Classification Model 2f: TS subset Standardization Before Splitting	
675	14	719	6	667	5
344	985	300	993	352	994

Classification Model 3: Quadratic Discriminant Analysis
Then, I build models with Quadratic Discriminant Analysis with each subset of variables of the standardized training set to classify DONR and test its performance on the standardized validation set.

Classification Model 3a: DO subset Splitting Before Standardization		Classification Model 3b: VS subset Splitting Before Standardization		Classification Model 3c: TS subset Splitting Before Standardization	
610	36	499	16	493	22
409	963	520	983	526	977

Classification Model 3d: DO subset Standardization Before Splitting		Classification Model 3e: VS subset Standardization Before Splitting		Classification Model 3f: TS subset Standardization Before Splitting	
610	36	499	16	493	22
409	963	520	983	526	977

Classification Model 4: K Nearest Neighbors
Next, I build models using the non-parametric K Nearest Neighbors (KNN) method. I can generate 6 KNN models by varying the smoothness parameter k where k = 1 through 6. In order to guarantee reproducibility of results I use set.seed(1). Apparently, this is the only instance when splitting before or after standardization actually affects the results. All of the models perform similarly, however Model 4e performs of the 12 KNN models because it has the highest true positives plus true negatives.

Classification Model 4a: k = 1 Splitting Before Standardization		Classification Model 4b: k = 2 Splitting Before Standardization		Classification Model 4c: k = 3 Splitting Before Standardization	
784	85	775	100	781	64
235	914	244	899	238	935

Classification Model 4d: k = 4 Splitting Before Standardization		Classification Model 4e: k = 5 Splitting Before Standardization		Classification Model 4f: k = 6 Splitting Before Standardization	
771	59	771	49	766	51
248	940	248	950	253	948

Classification Model 4g: k = 1 Standardization Before Splitting		Classification Model 4h: k = 2 Standardization Before Splitting		Classification Model 4i: k = 3 Standardization Before Splitting	
785	88	772	83	782	61
234	911	247	916	237	938

Classification Model 4j: k = 4 Standardization Before Splitting		Classification Model 4k: k = 5 Standardization Before Splitting		Classification Model 4l: k = 6 Standardization Before Splitting	
777	63	767	51	760	50
242	936	252	948	259	949

Classification Model 5: Logistic Regression using GAM with Natural Splines
Following that, I build logistic regression models with natural splines using the GAM package and function. I only apply natural splines to continuous variables (not to any variables that can be considered categorical variables) with 4 degrees of freedom. Model 5b performs horribly compared to the other natural spline logistic regression models. Model 5c performs the best with the most true positives and true negatives and least false positives and false negatives.

Classification Model 5a: DO subset Splitting Before Standardization		Classification Model 5b: VS subset Splitting Before Standardization		Classification Model 5c: TS subset Splitting Before Standardization	
713	14	486	545	764	10
306	985	533	454	255	989

Classification Model 5d: DO subset		Classification Model 5e: VS subset		Classification Model 5f: TS subset	

Standardization Before Splitting		Standardization Before Splitting		Standardization Before Splitting	
713	14	486	545	764	10
306	985	533	454	255	989

Classification Model 6: Logistic Regression using GAM with Smoothing Splines
After that, I build logistic regression models with smoothing splines using the GAM package and function. I only apply smoothing splines to continuous variables (not to any variables that can be considered categorical variables) with 4 degrees of freedom. All of the smoothing spline logistic regression models perform fairly well. Model 6c performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives.

Classification Model 6a: DO subset Splitting Before Standardization		Classification Model 6b: VS subset Splitting Before Standardization		Classification Model 6c: TS subset Splitting Before Standardization	
659	5	740	7	764	10
360	994	279	992	255	989

Classification Model 6d: DO subset Standardization Before Splitting		Classification Model 6e: VS subset Standardization Before Splitting		Classification Model 6f: TS subset Standardization Before Splitting	
659	5	740	7	764	10
360	994	279	992	255	989

Classification Model 7: Logistic Regression using GAM with Local Regression (span = 0.2)
Next, I build logistic regression models with local linear regression smoothing with spans covering 20% of the observations. I only apply local regression smoothing to continuous variables (not to any variables that can be considered categorical variables). Model 7b performs the best with highest true positives plus true negatives and lowest false positives and false negatives.

Classification Model 7a: DO subset Splitting Before Standardization		Classification Model 7b: VS subset Splitting Before Standardization		Classification Model 7c: TS subset Splitting Before Standardization	
705	13	786	15	770	8
314	986	233	984	249	991

Classification Model 7d: DO subset Standardization Before Splitting		Classification Model 7e: VS subset Standardization Before Splitting		Classification Model 7f: TS subset Standardization Before Splitting	
705	13	786	15	770	8
314	986	233	984	249	991

Classification Model 8: Logistic Regression using GAM with Local Regression (span = 0.5)
Next, I build logistic regression models with local linear regression smoothing with spans covering 50% of the observations. I only apply local regression smoothing to continuous variables (not to any variables that can be considered categorical variables). Model 8c performs the best with most true positives and true negatives and least false positives and false negatives.

Classification Model 8a: DO subset Splitting Before Standardization		Classification Model 8b: VS subset Splitting Before Standardization		Classification Model 8c: TS subset Splitting Before Standardization	
663	6	737	6	741	6
356	993	282	993	278	993

Classification Model 8d: DO subset Standardization Before Splitting		Classification Model 8e: VS subset Standardization Before Splitting		Classification Model 8f: TS subset Standardization Before Splitting	
663	6	737	6	741	6
356	993	282	993	278	993

Classification Model 9: Decision Tree
Now I build a full classification decision tree with all 3 subsets of variables using the tree function in the TREE package. In order to guarantee reproducibility of results, I use set.seed(1). Without any pruning of the decision tree, Model 9b and 9c perform exactly the same and Model 9a performs the best with the most true positives and true negatives and least false positives and false negatives.

Classification Model 9a: DO subset Splitting Before Standardization		Classification Model 9b: VS subset Splitting Before Standardization		Classification Model 9c: TS subset Splitting Before Standardization	
645	37	631	69	631	69
374	962	388	930	388	930

Classification Model 9d: DO subset Standardization Before Splitting		Classification Model 9e: VS subset Standardization Before Splitting		Classification Model 9f: TS subset Standardization Before Splitting	
645	37	631	69	631	69
374	962	388	930	388	930

Classification Model 10: Bagging
Next, I apply bagging to the 3 subsets using the randomForest package in R. Bagging is simply constructing regression trees using bootstrapped training sets, and averaging the resulting predictions. These trees are grown deep, and are not pruned. Hence each individual tree has high variance, but low bias. Bagging is simply a special case of a random forest with m = p (m = number of predictors considered for each tree, p = number of predictors). For bagging, I set the number of trees to 500. In order to guarantee reproducibility of results, I use set.seed(1). Model 10b performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives.

Classification Model 10a: DO subset Splitting Before Standardization		Classification Model 10b: VS subset Splitting Before Standardization		Classification Model 10c: TS subset Splitting Before Standardization	
693	14	748	23	693	15
326	985	271	976	326	984

Classification Model 10d: DO subset Standardization Before Splitting		Classification Model 10e: VS subset Standardization Before Splitting		Classification Model 10f: TS subset Standardization Before Splitting	
693	14	710	17	693	15
326	985	309	982	326	984

Classification Model 11: Random Forests
Next, I apply random forests to the 3 subsets using the randomForest package in R. For random forests, m = round(sqrt(p)). In building a random forest, at each split in the tree, the algorithm is not even allowed to consider a majority of the available predictors. In this way, strong and dominant predictors do not have as much influence on the tree structure as they would in bagging when all predictors are considered. For random forests, I set the number of trees to 500. In order to guarantee reproducibility of results, I use set.seed(1). Model 11a performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives. Model 11a also produced most true negatives than any other method used thus far.

Classification Model 11a: DO subset Splitting Before Standardization		Classification Model 11b: VS subset Splitting Before Standardization		Classification Model 11c: TS subset Splitting Before Standardization	
806	26	744	15	780	20
213	973	275	984	239	979

Classification Model 11d: DO subset Standardization Before Splitting		Classification Model 11e: VS subset Standardization Before Splitting		Classification Model 11f: TS subset Standardization Before Splitting	
804	26	744	15	780	20
215	973	275	984	239	979

Classification Model 12: Boosting
Next, I apply boosting to the 3 subsets using the GBM package in R. Boosting works in a similar way as bagging, except that the trees are grown sequentially: each tree is fit using the residuals from previously grown trees so that learning takes place. The major advantage of boosting is that it is very resistant against overfitting although it can occur very slowly. For boosting, I set the number of trees to 5000. In order to guarantee reproducibility of results, I use set.seed(1). Model 12a performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives. Model 12a ties Model 12a for producing the most true negatives than any other method used thus far.

Classification Model 12a: DO subset Splitting Before Standardization		Classification Model 12b: VS subset Splitting Before Standardization		Classification Model 12c: TS subset Splitting Before Standardization	
806	18	764	7	760	6
213	981	255	992	259	993

Classification Model 12d: DO subset Standardization Before Splitting		Classification Model 12e: VS subset Standardization Before Splitting		Classification Model 12f: TS subset Standardization Before Splitting	
800	18	751	5	760	6
219	981	268	994	259	993

Classification Model 13: Artificial Neural Network

After that, I fit a neural network with a single hidden layer of 20 nodes with 100 iterations and decay of 0.001 to the 3 subsets using the NNET package in R. Artificial neural networks are relatively crude electronic networks of neurons based on the neural structure of the brain. They process observations one at a time, and learn by comparing their classification of the observation with the known actual classification of the observation. The errors from the initial classification of the first observation is fed back into the network, and used to modify the network's algorithm for further iterations. In order to guarantee reproducibility of results, I use set.seed(1). Model 13f performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives.

Classification Model 13a: DO subset Splitting Before Standardization		**Classification Model 13b: VS subset Splitting Before Standardization**		**Classification Model 13c: TS subset Splitting Before Standardization**	
793	90	672	15	823	113
226	909	347	984	193	886

Classification Model 13d: DO subset Standardization Before Splitting		**Classification Model 13e: VS subset Standardization Before Splitting**		**Classification Model 13f: TS subset Standardization Before Splitting**	
780	71	688	19	808	63
239	928	331	980	211	936

Classification Model 14: Support Vector Machine (linear kernel)
After that, I use support vector machine with a linear kernel to the 3 subsets using the E1071 package in R. A support vector machine is a discriminative classifier formally defined by a separating hyperplane. For model 14, the hyperplane is based on a linear kernel. In order to guarantee reproducibility of results, I use set.seed(1). Model 14b performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives.

Classification Model 14a: DO subset Splitting Before Standardization		**Classification Model 14b: VS subset Splitting Before Standardization**		**Classification Model 14c: TS subset Splitting Before Standardization**	
660	14	699	6	649	6
359	985	320	993	370	993

Classification Model 14d: DO subset Standardization Before Splitting		**Classification Model 14e: VS subset Standardization Before Splitting**		**Classification Model 14f: TS subset Standardization Before Splitting**	
659	14	695	6	649	6
360	985	324	993	370	993

Classification Model 15: Support Vector Machine (radial kernel)
After that, I use support vector machine with a linear kernel to the 3 subsets using the E1071 package in R. For model 15, the hyperplane is based on a radial kernel. In order to guarantee reproducibility of results, I use set.seed(1). Model 15d performs the best with the highest true positives plus true negatives and lowest false positives plus false negatives.

Classification Model 15a: DO subset Splitting Before Standardization		**Classification Model 15b: VS subset Splitting Before Standardization**		**Classification Model 15c: TS subset Splitting Before Standardization**	
625	7	653	10	664	10
394	992	366	989	355	989

Classification Model 15d: DO subset Standardization Before Splitting		**Classification Model 15e: VS subset Standardization Before Splitting**		**Classification Model 15f: TS subset Standardization Before Splitting**	
613	5	648	11	655	10
406	994	371	988	364	989

4. Selecting the Best Classification Model

In order to select the best model, I compute a whole host of classification metrics based off of the confusion table values. The following table shows all of the classification that I use and whether the value should be maximized or minimized to indicate a better fit.

Metrics	**Goal**
Number of True Positives (TP)	Higher
Number of True Negatives (TN)	Higher
Number of False Positives	Lower
Number of False Negatives	Lower
Misclassification Rate (Misclass.Rate)	Lower

Area under the ROC curve (AUC)	Higher
Accuracy	Higher
Sensitivity (or Recall)	Higher
Specificity	Higher
Precision	Higher
Fall out	Lower
False Discovery Rate or False Positive Rate (FDR)	Lower
Miss Rate or False Negative Rate	Lower
F Measure (weighted avg of precision and recall)	Higher
Matthews correlation coefficient: correlation coefficient between the observed and predicted binary classifications, values between -1 and +1 (MCC)	Higher
Number of Mailings	Higher
Profit	Higher

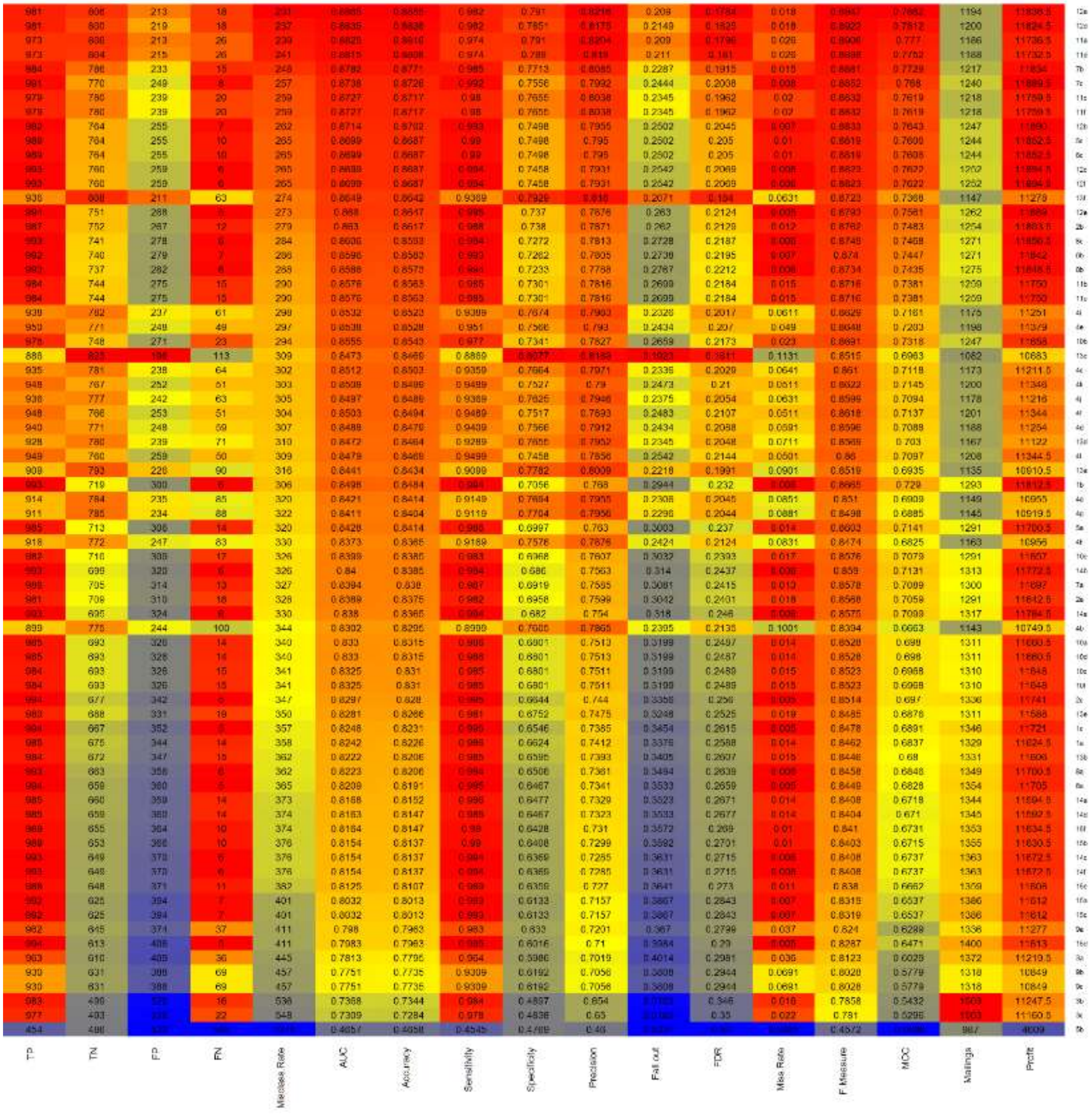
I scale all of the values to be a proportion of the highest score minus the lowest score for each metric so that I can compare the models against each other. I then calculate the mean value of the scaled scores and then generate a color based heat map to visualize the best model. Here the worst models have values in blue colored cells and the best models have values in red colored cells. The color gradient moves from blue to yellow to red, therefore the best classification model will be most deeply colored red.

As you can see in the color based heat map, the boosting and random forest models performed the best. Model 12a, a boosting (boosted random forest of classification decision trees) model using the default original set of variables with data that was standardized before data splitting, performed the best based on these classification metrics out of all the classification models. With this specific boosting model, I used 5000 trees, a shrinkage parameter of 0.01, and an interaction depth (tree size) of 4.

I am not surprised that boosting generated the best model. It is one of the most powerful methods that we learned this quarter in Predict 422. Boosting, like bagging, is an approach for improving prediction results for various machine learning methods. It particularly well suited to decision trees. Rather than resampling the data, boosting weights on some examples during learning. In boosting, trees are grown sequentially so that each tree is grown using information from previously grown trees. Unlike fitting a single large decision tree to the data, which amounts to fitting the data hard and potentially overfitting, the boosting approach instead learns slowly. By fitting small trees to the residuals, we slowly improve the tree modeling function in areas where it does not perform well. The shrinkage parameter λ slows the process down even further, allowing more and different shaped trees to attack the residuals.

As the Model labels are too small to easily read, here are the models ranked by mean value of scaled scores from best to worst.

Model	**Rank**	**Model**	**Rank**	**Model**	**Rank**	**Model**	**Rank**	**Model**	**Rank**	**Model**	**Rank**
12a	1	12f	13	13c	25	5a	37	2c	49	14f	61
12d	2	13f	14	4c	26	4h	38	13e	50	15e	62
11a	3	12e	15	4k	27	10e	39	1c	51	15a	63
11d	4	2b	16	4j	28	14b	40	1a	52	15c	64
7b	5	8c	17	4f	29	7a	41	13b	53	9a	65
7c	6	6b	18	4d	30	2a	42	8a	54	15d	66
11c	7	8b	19	13d	31	14e	43	6a	55	3a	67
11f	8	11b	20	4l	32	4b	44	14a	56	9b	68
12b	9	11e	21	13a	33	10a	45	14d	57	9c	69
5c	10	4i	22	1b	34	10d	46	15f	58	3b	70
6c	11	4e	23	4a	35	10c	47	15b	59	3c	71
12c	12	10b	24	4g	36	10f	48	14c	60	5b	72



TP	TN	FP	FN	Misclass Rate	AUC	Accuracy	Sensitivity	Specificity	Precision	Fall out	FDR	Miss Rate	F Measure	MCC	Mailings	Profit	
981	806	213	18	231	0.8865	0.8855	0.982	0.791	0.8216	0.209	0.1784	0.018	0.8947	0.7882	1194	11836.5	12a
981	800	219	18	237	0.8835	0.8826	0.982	0.7851	0.8175	0.2149	0.1825	0.018	0.8922	0.7812	1200	11824.5	12d
973	808	213	26	239	0.8825	0.8816	0.974	0.791	0.8204	0.209	0.1796	0.026	0.8906	0.777	1186	11736.5	11a
973	804	215	26	241	0.8815	0.8806	0.974	0.789	0.819	0.211	0.181	0.026	0.8898	0.7752	1188	11732.5	11d
984	786	233	15	248	0.8782	0.8771	0.985	0.7713	0.8085	0.2287	0.1915	0.015	0.8881	0.7729	1217	11834	7b
991	770	249	8	257	0.8738	0.8726	0.992	0.7556	0.7992	0.2444	0.2008	0.008	0.8852	0.768	1240	11889.5	7c
979	780	239	20	259	0.8727	0.8717	0.98	0.7655	0.8038	0.2345	0.1962	0.02	0.8832	0.7619	1218	11759.5	11c
979	780	239	20	259	0.8727	0.8717	0.98	0.7655	0.8038	0.2345	0.1962	0.02	0.8832	0.7619	1218	11759.5	11f
992	764	255	7	262	0.8714	0.8702	0.993	0.7498	0.7955	0.2502	0.2045	0.007	0.8833	0.7643	1247	11890	12b
989	764	255	10	265	0.8699	0.8687	0.99	0.7498	0.795	0.2502	0.205	0.01	0.8819	0.7606	1244	11852.5	5c
989	764	255	10	265	0.8699	0.8687	0.99	0.7498	0.795	0.2502	0.205	0.01	0.8819	0.7606	1244	11852.5	6c
993	760	259	6	265	0.8699	0.8687	0.994	0.7458	0.7931	0.2542	0.2069	0.006	0.8823	0.7622	1252	11894.5	12c
993	760	259	6	265	0.8699	0.8687	0.994	0.7458	0.7931	0.2542	0.2069	0.006	0.8823	0.7622	1252	11894.5	12f
936	808	211	63	274	0.8649	0.8642	0.9369	0.7929	0.816	0.2071	0.184	0.0631	0.8723	0.7368	1147	11279	13f
994	751	268	5	273	0.868	0.8647	0.995	0.737	0.7876	0.263	0.2124	0.005	0.8793	0.7561	1262	11889	12e
987	752	267	12	279	0.863	0.8617	0.988	0.738	0.7871	0.262	0.2129	0.012	0.8762	0.7483	1254	11883.5	2b
993	741	278	6	284	0.8606	0.8593	0.994	0.7272	0.7813	0.2728	0.2187	0.006	0.8749	0.7468	1271	11850.5	8c
992	740	279	7	286	0.8596	0.8583	0.993	0.7262	0.7805	0.2738	0.2195	0.007	0.874	0.7447	1271	11842	6b
993	737	282	6	288	0.8586	0.8573	0.994	0.7233	0.7788	0.2767	0.2212	0.006	0.8734	0.7435	1275	11848.5	8b
984	744	275	15	290	0.8576	0.8563	0.985	0.7301	0.7816	0.2699	0.2184	0.015	0.8716	0.7381	1259	11750	11b
984	744	275	15	290	0.8576	0.8563	0.985	0.7301	0.7816	0.2699	0.2184	0.015	0.8716	0.7381	1259	11750	11e
938	782	237	61	298	0.8532	0.8523	0.9389	0.7674	0.7983	0.2326	0.2017	0.0611	0.8629	0.7161	1175	11251	4i
950	771	248	49	297	0.8538	0.8528	0.951	0.7566	0.793	0.2434	0.207	0.049	0.8648	0.7203	1198	11379	4e
976	748	271	23	294	0.8555	0.8543	0.977	0.7341	0.7827	0.2659	0.2173	0.023	0.8691	0.7318	1247	11858	10b
886	823	196	113	309	0.8473	0.8469	0.8869	0.8077	0.8189	0.1923	0.1811	0.1131	0.8515	0.6963	1082	10683	13c
935	781	238	64	302	0.8512	0.8503	0.9359	0.7664	0.7971	0.2336	0.2029	0.0641	0.861	0.7118	1173	11211.5	4c
948	767	252	51	303	0.8508	0.8499	0.9489	0.7527	0.79	0.2473	0.21	0.0511	0.8622	0.7145	1200	11346	4h
936	777	242	63	305	0.8497	0.8489	0.9369	0.7625	0.7946	0.2375	0.2054	0.0631	0.8599	0.7094	1178	11216	4j
948	766	253	51	304	0.8503	0.8494	0.9489	0.7517	0.7893	0.2483	0.2107	0.0511	0.8618	0.7137	1201	11344	4f
940	771	248	59	307	0.8488	0.8479	0.9409	0.7566	0.7912	0.2434	0.2088	0.0591	0.8596	0.7089	1188	11254	4d
928	780	239	71	310	0.8472	0.8464	0.9289	0.7655	0.7952	0.2345	0.2048	0.0711	0.8569	0.703	1167	11122	13d
949	760	259	50	309	0.8479	0.8469	0.9499	0.7458	0.7856	0.2542	0.2144	0.0501	0.86	0.7097	1208	11344.5	4l
909	793	226	90	316	0.8441	0.8434	0.9099	0.7782	0.8009	0.2218	0.1991	0.0901	0.8519	0.6935	1135	10910.5	13a
993	719	300	6	306	0.8498	0.8484	0.994	0.7056	0.768	0.2944	0.232	0.006	0.8665	0.729	1293	11812.5	1b
914	784	235	85	320	0.8421	0.8414	0.9149	0.7694	0.7955	0.2306	0.2045	0.0851	0.851	0.6909	1149	10955	4k
911	785	234	88	322	0.8411	0.8404	0.9119	0.7704	0.7956	0.2296	0.2044	0.0881	0.8498	0.6885	1145	10919.5	4g
985	713	306	14	320	0.8428	0.8414	0.986	0.6997	0.763	0.3003	0.237	0.014	0.8603	0.7141	1291	11700.5	5a
916	772	247	83	330	0.8373	0.8365	0.9169	0.7576	0.7876	0.2424	0.2124	0.0831	0.8474	0.6825	1163	10956	4a
982	710	309	17	326	0.8399	0.8385	0.983	0.6968	0.7607	0.3032	0.2393	0.017	0.8576	0.7079	1291	11657	10c
993	699	320	6	326	0.84	0.8385	0.994	0.686	0.7563	0.314	0.2437	0.006	0.859	0.7131	1313	11772.5	14b
986	705	314	13	327	0.8394	0.838	0.987	0.6919	0.7585	0.3081	0.2415	0.013	0.8578	0.7089	1300	11697	7a
981	709	310	18	328	0.8389	0.8375	0.982	0.6958	0.7599	0.3042	0.2401	0.018	0.8568	0.7059	1291	11642.5	2a
993	695	324	6	330	0.838	0.8365	0.994	0.682	0.754	0.318	0.246	0.006	0.8575	0.7099	1317	11784.5	14a
899	775	244	100	344	0.8302	0.8295	0.8999	0.7605	0.7865	0.2395	0.2135	0.1001	0.8394	0.6663	1143	10749.5	4b
985	693	326	14	340	0.833	0.8315	0.986	0.6801	0.7513	0.3199	0.2487	0.014	0.8528	0.698	1311	11680.5	10a
985	693	326	14	340	0.833	0.8315	0.986	0.6801	0.7513	0.3199	0.2487	0.014	0.8528	0.698	1311	11680.5	10d
984	693	326	15	341	0.8325	0.831	0.985	0.6801	0.7511	0.3199	0.2489	0.015	0.8523	0.6968	1310	11648	10e
984	693	326	15	341	0.8325	0.831	0.985	0.6801	0.7511	0.3199	0.2489	0.015	0.8523	0.6968	1310	11648	10f
994	677	342	5	347	0.8297	0.828	0.995	0.6644	0.744	0.3356	0.256	0.005	0.8514	0.697	1336	11741	2c
980	688	331	19	350	0.8281	0.8266	0.981	0.6752	0.7475	0.3248	0.2525	0.019	0.8485	0.6878	1311	11588	13e
994	667	352	5	357	0.8248	0.8231	0.995	0.6546	0.7385	0.3454	0.2615	0.005	0.8478	0.6891	1346	11721	1c
985	675	344	14	358	0.8242	0.8226	0.986	0.6624	0.7412	0.3376	0.2588	0.014	0.8462	0.6837	1329	11624.5	1a
984	672	347	15	362	0.8222	0.8206	0.985	0.6595	0.7393	0.3405	0.2607	0.015	0.8446	0.68	1331	11606	13b
993	663	356	6	362	0.8223	0.8206	0.994	0.6506	0.7361	0.3494	0.2639	0.006	0.8458	0.6848	1349	11700.5	8a
994	659	360	5	365	0.8209	0.8191	0.995	0.6467	0.7341	0.3533	0.2659	0.005	0.8449	0.6828	1354	11705	6a
985	660	359	14	373	0.8168	0.8152	0.986	0.6477	0.7329	0.3523	0.2671	0.014	0.8408	0.6718	1344	11594.5	14c
985	659	360	14	374	0.8163	0.8147	0.986	0.6467	0.7323	0.3533	0.2677	0.014	0.8404	0.671	1345	11592.5	14d
989	655	364	10	374	0.8164	0.8147	0.99	0.6428	0.731	0.3572	0.269	0.01	0.841	0.6731	1353	11634.5	16f
989	653	366	10	376	0.8154	0.8137	0.99	0.6408	0.7299	0.3592	0.2701	0.01	0.8403	0.6715	1355	11630.5	15b
993	649	370	6	376	0.8154	0.8137	0.994	0.6369	0.7285	0.3631	0.2715	0.006	0.8408	0.6737	1363	11672.5	14e
993	649	370	6	376	0.8154	0.8137	0.994	0.6369	0.7285	0.3631	0.2715	0.006	0.8408	0.6737	1363	11672.5	14f
988	648	371	11	382	0.8125	0.8107	0.989	0.6359	0.727	0.3641	0.273	0.011	0.838	0.6662	1359	11608	16c
992	625	394	7	401	0.8032	0.8013	0.993	0.6133	0.7157	0.3867	0.2843	0.007	0.8319	0.6537	1386	11612	16a
992	625	394	7	401	0.8032	0.8013	0.993	0.6133	0.7157	0.3867	0.2843	0.007	0.8319	0.6537	1386	11612	15c
962	645	374	37	411	0.798	0.7963	0.963	0.633	0.7201	0.367	0.2799	0.037	0.824	0.6288	1336	11277	9a
994	613	406	5	411	0.7983	0.7963	0.995	0.6016	0.71	0.3984	0.29	0.005	0.8287	0.6471	1400	11613	16d
963	610	409	36	445	0.7813	0.7795	0.964	0.5986	0.7019	0.4014	0.2981	0.036	0.8123	0.6025	1372	11219.5	3a
930	631	388	69	457	0.7751	0.7735	0.9309	0.6192	0.7056	0.3808	0.2944	0.0691	0.8028	0.5779	1318	10849	9b
930	631	388	69	457	0.7751	0.7735	0.9309	0.6192	0.7056	0.3808	0.2944	0.0691	0.8028	0.5779	1318	10849	9c
983	499	520	16	536	0.7368	0.7344	0.984	0.4897	0.654	[illegible]	0.346	0.016	0.7858	0.5432	1503	11247.5	3b
977	493	526	22	548	0.7309	0.7284	0.978	0.4838	0.65	[illegible]	0.35	0.022	0.781	0.5296	1503	11160.5	3c
454	498	[illegible]	[illegible]	[illegible]	0.4657	0.4658	0.4545	0.4789	0.46	[illegible]	[illegible]	[illegible]	0.4572	[illegible]	987	4009	5b

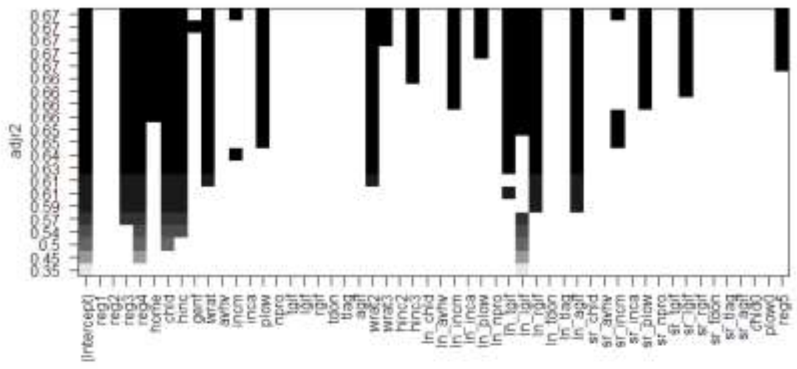
Next, I calculate the posterior probabilities for the test data set. Then, I sort DONR in order of the posterior probabilities from highest to lowest. I calculate the cumulative sum of (14.5 x DONR – 2) while going down the list. Then, I find the maximum of this profit function. Based on Model 12a applied to the test data set, I will mail to the 278 highest posterior probabilities.

Best classification model = Model 12a: Boosting (standardization before splitting)

Classification Model 12a: DO subset Splitting Before Standardization	
806	18
213	981

5. Building Prediction Models

In the following prediction models, I will use data where standardization was performed before splitting and splitting was performed before standardization. Similar to the process with classification models, I will start out this section by identifying the best variable set to predict donation amount in the response variable DAMT. First, I run an automated variable selection procedure on the training data set with the function REGSUBSETS in the LEAPS package with the “exhaustive search” method to find the best 20 variables out of the total 51 variables (including the newly added variables) for predicting DAMT. The following plot is a graphical representation of the best models with 1 through 20 variables, where black colored squares indicate that the particular variable was included in that model. The y-axis orders the models by Adjusted R-Squared values. This figure indicates that the model with 20 variables has the highest Adjusted R-Squared value.



It is very interesting that the other 3 region variables (REG3, REG4, and REG5) that were not selected than when classifying DONR (REG1 and REG2) were selected for predicting DAMT. It may just be a coincidence as the situation is completely different (classifying DONR vs predicting DAMT), so there may be no relationship between the variables selected with REGSUBSETS. There is a noticeable lack of TDON and TLAG variables which appeared in almost all of the classifying DONR subsets. Otherwise, the remaining selected variables are relatively similar to those for the classifying DONR list. Once again, I identify redundant variables in the REGSUBSETS subset in order to choose a more parsimonious and reduced subset.

Redundant Variables		
WRAT	WRAT2	WRAT3
PLOW	LN_PLOW	SR_PLOW
LN_INCM	SR_INCM	
LN_LGIF	SR_LGIF	

Only variables that appear in REGSUBSET results more than twice are included in the variable selection subset. Both WRAT and WRAT2 are included in a majority of the subsets, however WRAT3 is only included in 3, so it is eliminated from the trimmed subset. Similarly, PLOW is included in a majority of the subsets, however LN_PLOW and SR_PLOW are only in 4 and 5, respectively, so they are taken out of the trimmed subset. The same reasoning is applied for leaving out SR_INCM and SR_LGIF. Please note that the default original set does not include HINC2, which was included in the set of variables used to classify DONR.

Default original set (DO)	Variable selection subset (VS)	Trimmed subset (TS)
REG1	REG3	REG3
REG2	REG4	REG4
REG3	HOME	REG5
REG4	CHLD	HOME
HOME	HINC	CHLD
CHLD	WRAT	HINC
HINC	PLOW	PLOW
GENF	WRAT2	WRAT
WRAT	WRAT3	WRAT2
LN_AVHV	HINC3	HINC3
INCM	LN_INCM	LN_INCM
INCA	LN_PLOW	LN_LGIF

PLOW	LN_TGIF	LN_TGIF
NPRO	LN_LGIF	LN_RGIF
TGIF	LN_RGIF	LN_AGIF
LGIF	LN_AGIF	
RGIF	SR_INCM	
TDON	SR_PLOW	
TLAG	SR_LGIF	
AGIF	REG5	

In order to compare models I will compute and analyze goodness of fit and model performance metrics including mean squared error (MSE), standard error (Std Error), R Squared value (R2), Adjusted R Squared value (Adj R2), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Prediction Model 1: OLS Linear Regression
The first method I will apply is classic ordinary least squares regression with each subset of variables of the standardized training set to predict DAMT and test the model's performance on the standardized validation set. Least Squares Regression will serve as a good starting point and standard for model comparison. The following table shows the classification table for all 6 Linear Regression classification models. Models 1a, 1b, and 1c are built on the training where splitting was performed before standardization. Model 1b performs the best with the lowest MSE, lowest Standard Error, highest R Squared, highest Adjusted R Squared, lowest AIC, and lowest BIC

Metrics\Models	**Prediction Model 1a: DO subset Splitting Before Standardization**	**Prediction Model 1b: VS subset Splitting Before Standardization**	**Prediction Model 1c: TS subset Splitting Before Standardization**
MSE	1.867523	1.3547	1.392546
Std Error	0.1696615	0.1501628	0.1520951
R2	0.5722429	0.668497	0.6604173
Adj R2	0.5679089	0.6651383	0.6578434
AIC	6646.579	6138.016	6176.056
BIC	6784.96	6276.396	6282.987

Prediction Model 2: Ridge Regression with GLMNET
The next method I will apply is ridge regression using the GLMNET function which applies a tuning parameter to all estimated coefficients (not including the intercept) shrinking them towards 0 (but never actually equal to 0) as specified by the lambda value (λ). When λ = 0, the penalty term has no effect, and ridge regression will produce the least squares estimates. However, as $\lambda \to \infty$, the impact of the shrinkage penalty grows, and the ridge regression coefficient estimates will approach 0. I use cross validation to identify the optimal lambda from a grid of 10000 lambda values (between 0 and 10e+10) for each model. I have to specify a random seed first so my results will be reproducible, since the choice of the cross-validation folds is random.

The GLMNET package does not provide R Squared, Adjusted R Squared, AIC, or BIC values. The reason for this is that standard errors are not very meaningful for strongly biased estimates that arise from penalized estimation methods. Penalized estimation is a procedure that reduces the variance of estimators by introducing substantial bias. The bias of each estimator is therefore a major component of its mean squared error, whereas its variance may contribute only a small part.

Unfortunately, in most applications of penalized regression it is impossible to obtain a sufficiently precise estimate of the bias. Any bootstrap-based calculations can only give an assessment of the variance of the estimates. Reliable estimates of the bias are only available if reliable unbiased estimates are available, which is typically not the case in situations in which penalized estimates are used. Reporting a standard error of a penalized estimate therefore tells only part of the story. It can give a mistaken impression of great precision, completely ignoring the inaccuracy caused by the bias. Model 2b performs the best with the lowest MSE and lowest Standard Error.

Metrics\Models	**Prediction Model 2a: DO subset Splitting Before Standardization**	**Prediction Model 2b: VS subset Splitting Before Standardization**	**Prediction Model 2c: TS subset Splitting Before Standardization**
MSE	1.868898	1.363563	1.420405
Std Error	0.1703007	0.151085	0.1545045
λ	0.0399264	0.01	0.01

Prediction Model 3: Lasso with GLMNET

The next method I will apply is the lasso using the GLMNET function which applies a tuning parameter to all estimated coefficients (not including the intercept) shrinking them towards 0 (where some actually equal to 0) as specified by the lambda value (λ). When λ = 0, the penalty term has no effect, and the lasso will produce the least squares estimates. However, as $\lambda \to \infty$, the impact of the shrinkage penalty grows, and the ridge regression coefficient estimates will approach and may equal 0. Therefore, the difference between ridge regression and the lasso are that some coefficient estimates are forced to be exactly equal to zero when the tuning parameter λ is sufficiently large. I use cross validation to identify the optimal lambda from a grid of 100 lambda values for each model. I have to specify a random seed first so my results will be reproducible, since the choice of the cross-validation folds is random. In the chart below, I list the lambda value and the number of coefficient estimates set exactly to 0. Model 3b performs the best with the lowest MSE and lowest Standard Error.

Metrics\Models	**Prediction Model 3a: DO subset Splitting Before Standardization**	**Prediction Model 3b: VS subset Splitting Before Standardization**	**Prediction Model 3c: TS subset Splitting Before Standardization**
MSE	1.861808	1.412496	1.462396
Std Error	0.1694304	0.1537956	0.1566224
λ	0.01	0.66832615	0.01
Num β= 0	1	2	0

Prediction Model 4: Principal Components Regression

Now, I add models built using Principal Components Regression. The result of running a Principal Components Regression model is a table of variance explained for each number of principal components included. I compute the ten-fold cross-validation error for each possible value of number of PCs used. I have to specify a random seed first so my results will be reproducible, since the choice of the cross-validation folds is random. The cross validation score which is reported as root mean squared error is computed for each number of PCs. I report the smallest cross validation error when all PCs are included in the model along with the mean square error and standard error. Model 4b performs the best with the lowest MSE and lowest Standard Error.

Metrics\Models	**Prediction Model 4a: DO subset Splitting Before Standardization**	**Prediction Model 4b: VS subset Splitting Before Standardization**	**Prediction Model 4c: TS subset Splitting Before Standardization**
MSE	2.272426	1.981271	2.02648
Std Error	0.1924591	0.183062	0.1807794
CV Error	1.286	1.132	1.142

Prediction Model 5: Partial Least Squares

Now, I add models built using Partial Least Squares which works similar to Principal Components Regression. The result of running a Partial Least Squares model is a table of variance explained for each number of principal components included. I compute the ten-fold cross-validation error for each possible value of number of PCs used. I have to specify a random seed first so my results will be reproducible, since the choice of the cross-validation folds is random. The cross validation score which is reported as root mean squared error is computed for each number of PCs. I report the smallest cross validation error when all PCs are included in the model along with the mean square error and standard error. Model 5b performs the best with the lowest MSE and lowest Standard Error.

Metrics\Models	**Prediction Model 5a: DO subset Splitting Before Standardization**	**Prediction Model 5b: VS subset Splitting Before Standardization**	**Prediction Model 5c: TS subset Splitting Before Standardization**
MSE	1.891649	1.455105	1.51345
Std Error	0.1712315	0.1548187	0.157661
CV Error	1.286	1.132	1.142

Prediction Model 6: Least Squares Regression using GAM with Natural Splines

Following that, I build logistic regression models with natural splines using the GAM package and function. I only apply natural splines to continuous variables (not to any variables that can be considered categorical variables) with 4 degrees of freedom. Model 6b performs horribly compared to the other natural spline least squares regression models. Here GAM does not provide R Squared or Adjusted R Squared values. Here Model 6b produces a very high error rate about 10 times as much as the other models. Model 6c performs the best with the lowest MSE and lowest Standard Error.

Metrics\Models	**Prediction Model 6a: DO subset Splitting Before Standardization**	**Prediction Model 6b: VS subset Splitting Before Standardization**	**Prediction Model 6c: TS subset Splitting Before Standardization**
MSE	1.679664	11.97154	1.399422
Std Error	0.14687	0.547503	0.1391948
AIC	6303.19	6142.199	6140.123

BIC	6649.142	6469.281	6360.274

Prediction Model 7: Least Squares Regression with Smoothing Splines
Following that, I build logistic regression models with smoothing splines using the GAM package and function. I only apply smoothing splines to continuous variables (not to any variables that can be considered categorical variables) with 4 degrees of freedom. Model 6b performs horribly compared to the other smoothing spline least squares regression models. Here GAM does not provide R Squared or Adjusted R Squared values. Here Model 6b produces a very high error rate about 10 times as much as the other models. Here Model 7a performs the best with the lowest MSE, however Model 7c has the lowest Standard Error, AIC, and BIC

Metrics\Models	**Prediction Model 7a: DO subset Splitting Before Standardization**	**Prediction Model 7b: VS subset Splitting Before Standardization**	**Prediction Model 7c: TS subset Splitting Before Standardization**
MSE	1.1569567	1.346153	1.335262
Std Error	0.1595578	0.1501249	0.1487894
AIC	6326.331	6148.189	6129.225
BIC	6464.712	6286.569	6236.156

Prediction Model 8: Least Squares Regression using GAM with Local Regression (span = 0.2)
Next, I build least squares regression models with local linear regression smoothing with spans covering 20% of the observations. I only apply local regression smoothing to continuous variables (not to any variables that can be considered categorical variables). Model 8c performs the best with the lowest MSE, Standard Error, AIC, and BIC.

Metrics\Models	**Prediction Model 8: DO subset Splitting Before Standardization**	**Prediction Model 8b: VS subset Splitting Before Standardization**	**Prediction Model 8c: TS subset Splitting Before Standardization**
MSE	2.208205	1.341621	1.334256
Std Error	0.6697493	0.1463981	0.1458805
AIC	6351.096	6229.713	6154.597
BIC	6489.477	6368.094	6261.528

Prediction Model 9: Least Squares Regression using GAM with Local Regression (span = 0.5)
Next, I build least squares regression models with local linear regression smoothing with spans covering 50% of the observations. I only apply local regression smoothing to continuous variables (not to any variables that can be considered categorical variables). Model 9c performs the best with the lowest MSE, Standard Error, AIC, and BIC.

Metrics\Models	**Prediction Model 9a: DO subset Splitting Before Standardization**	**Prediction Model 9b: VS subset Splitting Before Standardization**	**Prediction Model 9c: TS subset Splitting Before Standardization**
MSE	1.625461	1.345475	1.341848
Std Error	0.1700076	0.1492391	0.1484047
AIC	6334.956	6155.241	6132.99
BIC	6473.337	6293.622	6239.921

Prediction Model 10: Regression Tree
Now I build a full regression decision tree with all 3 subsets of variables using the tree function in the TREE package. Regression trees are very similar to classification trees. Instead of stratifying data into regions based on class proportions, it stratifies data by cutoff thresholds. In order to guarantee reproducibility of results, I use set.seed(1). Without any pruning of the decision tree, Models 10a, 10b, and 10c all perform exactly the same.

Metrics\Models	**Prediction Model 10a: DO subset Splitting Before Standardization**	**Prediction Model 10b: VS subset Splitting Before Standardization**	**Prediction Model 10c: TS subset Splitting Before Standardization**
MSE	2.241075	2.241075	2.241075
Std Error	0.1920681	0.1920681	0.1920681
Deviance	1.917	1.917	1.917

Prediction Model 11: Bagging
Next, I apply bagging to the 3 subsets using the randomForest package in R. For bagging, I set the number of trees to 500. In order to guarantee reproducibility of results, I use set.seed(1). I post the highest R Squared value out of all 500 trees generated. Model 11b performs the best with lowest MSE, Standard Error, and second highest highest R Squared (just slightly less than of Model 11c).

Metrics\Models	**Prediction Model 11a: DO subset**	**Prediction Model 11b: VS subset**	**Prediction Model 11c: TS subset**

	Splitting Before Standardization	Splitting Before Standardization	Splitting Before Standardization
MSE	1.70452	1.680767	1.690726
Std Error	0.1746157	0.1700015	0.1717354
Highest R2	0.6026312	0.6069172	0.607098

Metrics\Models	**Prediction Model 11d: DO subset Standardization Before Splitting**	**Prediction Model 11e: VS subset Standardization Before Splitting**	**Prediction Model 11f: TS subset Standardization Before Splitting**
MSE	1.706585	1.681794	1.691131
Std Error	0.1748117	0.1701418	0.1717578
Highest R2	0.6015721	0.6066416	0.6063775

Prediction Model 12: Random Forests
Next, I apply random forests to the 3 subsets using the randomForest package in R. For random forests, I set m = round(sqrt(p)) and the number of trees to 500. In order to guarantee reproducibility of results, I use set.seed(1). I post the highest R Squared value out of all 500 trees generated. Model 12c performs the best with the lowest MSE, lowest Standard Error, and highest R Squared value than any previous prediction model I've built.

Metrics\Models	**Prediction Model 12a: DO subset Splitting Before Standardization**	**Prediction Model 12b: VS subset Splitting Before Standardization**	**Prediction Model 12c: TS subset Splitting Before Standardization**
MSE	1.66794	1.632706	1.609385
Std Error	0.1733482	0.1732356	0.1702943
Highest R2	0.604422	0.6152546	0.6217699

Metrics\Models	**Prediction Model 12d: DO subset Standardization Before Splitting**	**Prediction Model 12e: VS subset Standardization Before Splitting**	**Prediction Model 12f: TS subset Standardization Before Splitting**
MSE	1.670802	1.6341	1.610562
Std Error	0.1735235	0.1733228	0.1704411
Highest R2	0.6039727	0.6151073	0.6213717

Prediction Model 13: Boosting
Last, I apply boosting to the 3 subsets using the GBM package in R. For boosting, I set the number of trees to 5000. GBM does not provide any R Squared or Adjusted R Squared values. In order to guarantee reproducibility of results, I use set.seed(1). Model 13a performs the best

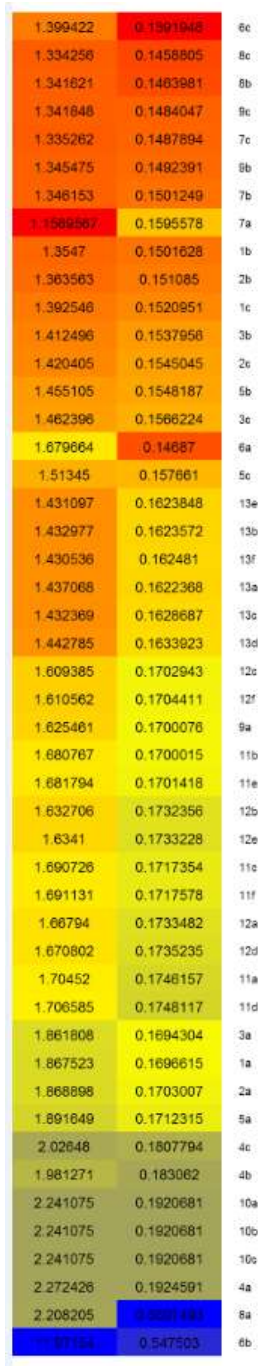
Metrics\Models	**Prediction Model 913: DO subset Splitting Before Standardization**	**Prediction Model 13b: VS subset Splitting Before Standardization**	**Prediction Model 13c: TS subset Splitting Before Standardization**
MSE	1.437068	1.432977	1.432369
Std Error	0.1622368	0.1623572	0.1628687

Metrics\Models	**Prediction Model 13d: DO subset Standardization Before Splitting**	**Prediction Model 13e: VS subset Standardization Before Splitting**	**Prediction Model 13f: TS subset Standardization Before Splitting**
MSE	1.442785	1.431097	1.430536
Std Error	0.1633923	0.1623848	0.162481

6. Selecting the Best Prediction Model

Similar to the process for choosing the best classification model, I also use a color based heat map to compare prediction models and select the model with the highest scaled mean value of scores which should appear as the top of the heat map and the most deeply red colored. For some methods and models, it was not meaningful to report AIC, BIC, R Squared, or Adjusted R Squared values so I compare models based on mean squared error (MSE) and standardized error (Std Error).

I am slightly surprised that GAMs with natural splines, smoothing splines, and local regression outperformed the tree based methods. Decision trees and random forests may not perform very well when all of the data is numeric. I believe that parametric methods based on least squares regression work well when there are unseen but present relationships between the response variables and predictor variables that can be modeled with a regression equation. However, in this situation for predicting DAMT, the GAM approach to nonparametric regression produces better fitting models than the parametric approaches. Some of the most powerful nonparametric methods we learned this quarter in Predict 422 are least squares regression with GAM using splines.



MSE	Std Error	
1.399422	0.1391948	6c
1.334256	0.1458805	8c
1.341621	0.1463981	8b
1.341848	0.1484047	9c
1.335262	0.1487894	7c
1.345475	0.1492391	9b
1.346153	0.1501249	7b
1.1589567	0.1595578	7a
1.3547	0.1501628	1b
1.363563	0.151085	2b
1.392546	0.1520951	1c
1.412496	0.1537958	3b
1.420405	0.1545045	2c
1.455105	0.1548187	5b
1.462396	0.1566224	3c
1.679664	0.14687	6a
1.51345	0.157661	5c
1.431097	0.1623848	13e
1.432977	0.1623572	13b
1.430536	0.162481	13f
1.437068	0.1622368	13a
1.432369	0.1628687	13c
1.442785	0.1633923	13d
1.609385	0.1702943	12c
1.610562	0.1704411	12f
1.625461	0.1700076	9a
1.680767	0.1700015	11b
1.681794	0.1701418	11e
1.632706	0.1732356	12b
1.6341	0.1733228	12e
1.690726	0.1717354	11c
1.691131	0.1717578	11f
1.66794	0.1733482	12a
1.670802	0.1735235	12d
1.70452	0.1748157	11a
1.706585	0.1748117	11d
1.861808	0.1694304	3a
1.867523	0.1696615	1a
1.868898	0.1703007	2a
1.891649	0.1712315	5a
2.02648	0.1807794	4c
1.981271	0.183062	4b
2.241075	0.1920681	10a
2.241075	0.1920681	10b
2.241075	0.1920681	10c
2.272426	0.1924591	4a
2.208205	[illegible]	8a
[illegible]	0.547503	6b

As you can see in the color based heat map, the least squares regression models using a generalized additive model with natural splines, smoothing splines, and local regression performed the best. Model 6c, a least squares regression model using GAM with natural splines using the trimmed subset of variables with data that was standardized before data splitting, performed the best based on mean squared error and standardized error metrics (common for all out of all the prediction models. With this specific GAM with natural splines, I used 4 knots for all continuous variables based on default settings (automatically placed according to percentiles).

Best prediction model = Model 6c: Boosting (standardization before splitting)

Metrics\Models	**Prediction Model 6c: TS subset Splitting Before Standardization**
MSE	1.399422
Std Error	0.1391948
AIC	6140.123

BIC	6360.274

Finally, I save the predicted DONR and DAMT values for the test set in a CSV file entitled “JP.csv”. The column named “chat” contains all the predicted DONR values (0 = not donor, 1 = donor) and the column named “yhat” contains all the predicted DAMT values or donation amounts.

7. Conclusion

A charitable organization wishes to develop a machine learning model to improve the cost-effectiveness of their direct marketing campaigns to previous donors. In this course project, I developed a classification model using data from the most recent campaign to effectively capture likely donors so that the expected net profit is maximized. I also developed a prediction model to predict donation amounts for donors (consisting of the records for donors only).

I explored the data and analyzed the shape of the histogram of continuous variables. I added variable transformations based on the particular skewness of the variables including square root, natural logarithm, square, and cube transforms. I standardized the data both before and after splitting the data into training, test, and validation sets and then build many models based on various methods we covered in this quarter in Predict 422. For classification models, I used logistic regression, linear discriminant analysis, quadratic discriminant analysis, k nearest neighbors, logistic regression using GAM with natural splines, logistic regression using GAM with smoothing splines, logistic regression using GAM with local regression smoothing (span = 0.2, 0.5), decision tree, bagging, random forests, boosting, artificial neural networks, and support vector machines (linear and radial kernels). For prediction models, I used least squares regression, ridge regression, the lasso, principal components regression, least squares regression using GAM with natural splines, least squares regression using GAM with smoothing splines, least squares regression using GAM with local regression smoothing (span = 0.2, 0.5), decision tree, bagging, random forests, and boosting. The best classification model and method was boosting (5000 trees, interaction depth = 4, shrinkage parameter = 0.01) and the best prediction model and method was least squares regression using GAM with natural splines (4 knots). I should always pursue the simplest model to predict or explain dependent variables, but sometimes data does not cooperate and the search for good models leads to very complex, data-driven, nonparametric models as it did for the charity data set. However, sometimes the most powerful and complex models do not significantly outperform simpler models, and in these cases, it may be preferable to choose the parsimonious model for practicality, interpretation, and implementation reasons. Although they perform very well and can be very accurate, decision trees and random forests can take a very long time to train. The best methods for generating classification models are not always the best methods for generate prediction models.

I am grateful for the opportunity to have learned so many new and powerful machine learning algorithms and methods for analytical modeling. This project was a wonderful way to utilize and apply everything we learned about different methods of building models on a real world data set.

Appendix: R Code

```r
# PREDICT 422 Practical Machine Learning
# Course Project
# Winter 2016
# Joshua Peng

# OBJECTIVE: A charitable organization wishes to develop a machine learning
# model to improve the cost-effectiveness of their direct marketing campaigns
# to previous donors.

# 1) Develop a classification model using data from the most recent campaign that
# can effectively capture likely donors so that the expected net profit is maximized.

# 2) Develop a prediction model to predict donation amounts for donors - the data
# for this will consist of the records for donors only.

# Load the data
charity <- read.csv("charity.csv") # load the "charity.csv" file
attach(charity)

# Identify Variables with Missing Values
colnames(charity)[colSums(is.na(charity)) > 0]

# Adding in reference reg5 to analyze correlations
sum(reg1)
sum(reg2)
sum(reg3)
sum(reg4)
8009-(1605+2555+1071+1117)
reg5 = rep(0,nrow(charity))
for(i in 1:nrow(charity)) {
  if (reg1[i]==0 && reg2[i]==0 && reg3[i]==0 && reg4[i]==0) {reg5[i]=1}}
```

```
charity$reg5 = reg5
charity.train <- charity[charity$part=="train",]
rm(charity.train)

# Analyzing REGx
library('corrplot') #package corrplot
regx_cor = cor(charity.train[,c(2:5,25,22)])
corrplot(regx_cor, method = "number") #plot matrix

# normality tests
library(nortest)
ad.test(hinc)
ad.test(npro)
ad.test(tdon)

# descriptive summary of variables
library(modeest)
summary(charity)
mfv(hinc)[1]
mfv(wrat)[1]
mfv(avhv)[1]
mfv(tlag)[1]
mfv(agif)[1]

# histograms
hist(reg1) # dichotomous
hist(reg2) # dichotomous
hist(reg3) # dichotomous
hist(reg4) # dichotomous
hist(home) # dichotomous
hist(chld) # zero inflated
hist(hinc) # median spike
hist(genf) # dichotomous
hist(wrat) # left skewed
hist(avhv) # right skewed
hist(incm) # right skewed
hist(inca) # right skewed
hist(plow) # right skewed, poisson
hist(npro) # right skewed
hist(tgif) # right skewed, poisson
hist(lgif) # right skewed, poisson
hist(rgif) # right skewed, poisson
hist(tdon) # slightly right skewed
hist(tlag) # right skewed
hist(agif) # right skewed

# predictor transformations
charity$wrat2 = wrat^2
charity$wrat3 = wrat^3
charity$hinc2 = hinc^2
charity$hinc3 = hinc^3
charity$ln_chld = log(chld)
charity$ln_avhv = log(avhv)
charity$ln_incm = log(incm)
charity$ln_inca = log(inca)
charity$ln_plow = log(plow)
charity$ln_npro = log(npro)
charity$ln_tgif = log(tgif)
charity$ln_lgif = log(lgif)
charity$ln_rgif = log(rgif)
charity$ln_tdon = log(tdon)
charity$ln_tlag = log(tlag)
charity$ln_agif = log(agif)
charity$sr_chld = sqrt(chld)
charity$sr_avhv = sqrt(avhv)
charity$sr_incm = sqrt(incm)
charity$sr_inca = sqrt(inca)
charity$sr_plow = sqrt(plow)
charity$sr_npro = sqrt(npro)
charity$sr_tgif = sqrt(tgif)
charity$sr_lgif = sqrt(lgif)
charity$sr_rgif = sqrt(rgif)
charity$sr_tdon = sqrt(tdon)
charity$sr_tlag = sqrt(tlag)
charity$sr_agif = sqrt(agif)
chld0 = rep(0,nrow(charity))
plow0 = rep(0,nrow(charity))
reg5 = rep(0,nrow(charity))
for(i in 1:nrow(charity)) {
if(chld[i]==0) {chld0[i]=1}
if(plow[i]==0) {plow0[i]=1}
if(reg1[i]==0 && reg2[i]==0 && reg3[i]==0 && reg4[i]==0) {reg5[i]=1}}
charity$reg5 = reg5
charity$chld0 = chld0
charity$plow0 = plow0
charity$ln_plow[charity$ln_plow <= 0] = 0
charity$ln_chld[charity$ln_chld <= 0] = 0
attach(charity)

# histograms after data transformations
```

```
hist(hinc2)
hist(hinc3)
hist(wrat2)
hist(wrat3)
hist(ln_chld)
hist(ln_avhv)
hist(ln_incm)
hist(ln_inca)
hist(ln_plow)
hist(ln_npro)
hist(ln_tgif)
hist(ln_lgif)
hist(ln_rgif)
hist(ln_tdon)
hist(ln_tlag)
hist(ln_agif)
hist(sr_chld)
hist(sr_avhv)
hist(sr_incm)
hist(sr_inca)
hist(sr_plow)
hist(sr_npro)
hist(sr_tgif)
hist(sr_lgif)
hist(sr_rgif)
hist(sr_tdon)
hist(sr_tlag)
hist(sr_agif)

# Set up data for analysis (initial steps)
data.train <- charity[charity$part=="train",]
x.train <- data.train[,c(2:21, 25:55)]
c.train <- data.train[,22] # donr
n.train.c <- length(c.train) # 3984
y.train <- data.train[c.train==1,23] # damt for observations with donr=1
n.train.y <- length(y.train) # 1995
data.valid <- charity[charity$part=="valid",]
x.valid <- data.valid[,c(2:21, 25:55)]
c.valid <- data.valid[,22] # donr
n.valid.c <- length(c.valid) # 2018
y.valid <- data.valid[c.valid==1,23] # damt for observations with donr=1
n.valid.y <- length(y.valid) # 999
data.test <- charity[charity$part=="test",]
n.test <- dim(data.test)[1] # 2007
x.test <- data.test[,c(2:21, 25:55)]

# Set up data for analysis (data splitting before standardization)
rm(data.train.std.y, data.train.std.c, data.valid.std.y, data.valid.std.c, data.test.std)
x.train.mean <- apply(x.train, 2, mean)
x.train.sd <- apply(x.train, 2, sd)
x.train.std <- t((t(x.train)-x.train.mean)/x.train.sd) # standardize to have zero mean and unit sd
apply(x.train.std, 2, mean) # check zero mean
apply(x.train.std, 2, sd) # check unit sd
data.train.std.c <- data.frame(x.train.std, donr=c.train) # to classify donr
data.train.std.y <- data.frame(x.train.std[c.train==1,], damt=y.train) # to predict damt when donr=1
x.valid.std <- t((t(x.valid)-x.train.mean)/x.train.sd) # standardize using training mean and sd
data.valid.std.c <- data.frame(x.valid.std, donr=c.valid) # to classify donr
data.valid.std.y <- data.frame(x.valid.std[c.valid==1,], damt=y.valid) # to predict damt when donr=1
x.test.std <- t((t(x.test)-x.train.mean)/x.train.sd) # standardize using training mean and sd
data.test.std <- data.frame(x.test.std)

# Set up data for analysis (Data splitting after standardization)
rm(data.train.std.y, data.train.std.c, data.valid.std.y, data.valid.std.c, data.test.std)
x.charity = charity[,c(2:21, 25:55)]
c.charity = charity[,22] # donr
n.charity.c = length(c.charity) # 8009
y.charity = charity[c.charity==1,23] # damt for observations with donr=1
n.charity.y = length(y.charity) # 5001
x.charity.mean = apply(x.charity, 2, mean)
x.charity.sd = apply(x.charity, 2, sd)
x.charity.std = t((t(x.charity)-x.charity.mean)/x.charity.sd) # standardize to have zero mean and unit sd
apply(x.charity.std, 2, mean) # check zero mean
apply(x.charity.std, 2, sd) # check unit sd
data.charity.std.c = data.frame(x.charity.std, donr=c.charity, part=charity$part) # to classify donr
data.charity.std.y = data.frame(x.charity.std[c.charity==1,], damt=y.charity) # to predict damt when donr=1
data.charity.std.y0 = data.frame(x.charity.std, part=charity$part) # add in part
data.charity.std.y1 = data.frame(data.charity.std.y0[c.charity==1,], damt=y.charity) # to predict damt when donr=1
i.train.c = which(data.charity.std.c$part=="train")
i.train.y = which(data.charity.std.y1$part=="train")
i.valid.c = which(data.charity.std.c$part=="valid")
i.valid.y = which(data.charity.std.y1$part=="valid")
i.test = which(charity$part=="test")
data.train.std.c = data.charity.std.c[i.train.c,]
data.train.std.y = data.charity.std.y[i.train.y,]
data.valid.std.c = data.charity.std.c[i.valid.c,]
data.valid.std.y = data.charity.std.y[i.valid.y,]
data.train.std.c$part = NULL
data.train.std.y$part = NULL
data.valid.std.c$part = NULL
data.valid.std.y$part = NULL
data.test.std = x.charity.std[i.test,]

##### CLASSIFICATION MODELING ######

library(MASS)
library(leaps)
library(gam)
library(ROCR)
library(AUC)
vs1 = regsubsets(donr ~ ., data = data.train.std.c, nvmax = 20)
plot(vs1, scale="adjr2")

# Logistic Regression

# M1c: Trimmed subset of 12 variables
model.log2 = glm(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag, data.train.std.c, family=binomial("logit"))
# M1b: Best 20 variable model from regsubsets
model.log2 = glm(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                   wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                   ln_agif + sr_chld + sr_tdon + sr_tlag, data.train.std.c, family=binomial("logit"))
# M1a: Default Original subset
model.log2 <- glm(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data.train.std.c, family=binomial("logit"))

##### My Logistic Regression Model
post.valid.log2 <- predict(model.log2, data.valid.std.c, type="response") # n.valid post probs
profit.log2 <- cumsum(14.5*c.valid[order(post.valid.log2, decreasing=T)]-2)
plot(profit.log2) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.log2) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.log2)) # report number of mailings and maximum profit
cutoff.log2 <- sort(post.valid.log2, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.log2 <- ifelse(post.valid.log2>cutoff.log2, 1, 0) # mail to everyone above the cutoff
table(chat.valid.log2, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.log2, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)
#####

model.log1 <- glm(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data.train.std.c, family=binomial("logit"))
post.valid.log1 <- predict(model.log1, data.valid.std.c, type="response") # n.valid post probs
# calculate ordered profit function using average donation = $14.50 and mailing cost = $2
profit.log1 <- cumsum(14.5*c.valid[order(post.valid.log1, decreasing=T)]-2)
plot(profit.log1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.log1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.log1)) # report number of mailings and maximum profit
# 1291.0 11642.5
cutoff.log1 <- sort(post.valid.log1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.log1 <- ifelse(post.valid.log1>cutoff.log1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.log1, c.valid) # classification table
#                c.valid
#chat.valid.log1   0   1
#               0 709  18
#               1 310 981
# check n.mail.valid = 310+981 = 1291
# check profit = 14.5*981-2*1291 = 11642.5
# Results
# n.mail Profit  Model
# 1329   11624.5 LDA1
# 1291   11642.5 Log1

# Linear Discriminant Analysis

# M2c: Trimmed subset of 12 variables
model.lda2 = lda(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag, data.train.std.c)
# M2b: Best 20 variable model from regsubsets
model.lda2 = lda(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                   wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                   ln_agif + sr_chld + sr_tdon + sr_tlag, data.train.std.c)
# M2a: Default Original subset
model.lda2 <- lda(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data.train.std.c) # include additional terms on the fly using I()

##### My Linear Discriminant Analysis
post.valid.lda2 <- predict(model.lda2, data.valid.std.c)$posterior[,2] # n.valid.c post probs
profit.lda2 <- cumsum(14.5*c.valid[order(post.valid.lda2, decreasing=T)]-2)
plot(profit.lda2) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.lda2) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.lda2)) # report number of mailings and maximum profit
cutoff.lda2 <- sort(post.valid.lda2, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.lda2 <- ifelse(post.valid.lda2>cutoff.lda2, 1, 0) # mail to everyone above the cutoff
```

```
table(chat.valid.lda2, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.lda2, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)
#####

model.lda1 <- lda(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data.train.std.c) # include additional terms on the fly using I()
# Note: strictly speaking, LDA should not be used with qualitative predictors,
# but in practice it often is if the goal is simply to find a good predictive model
post.valid.lda1 <- predict(model.lda1, data.valid.std.c)$posterior[,2] # n.valid.c post probs
# calculate ordered profit function using average donation = $14.50 and mailing cost = $2
profit.lda1 <- cumsum(14.5*c.valid[order(post.valid.lda1, decreasing=T)]-2)
plot(profit.lda1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.lda1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.lda1)) # report number of mailings and maximum profit
# 1329.0 11624.5
cutoff.lda1 <- sort(post.valid.lda1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.lda1 <- ifelse(post.valid.lda1>cutoff.lda1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.lda1, c.valid) # classification table
#               c.valid
#chat.valid.lda1   0   1
#              0 675  14
#              1 344 985
# check n.mail.valid = 344+985 = 1329
# check profit = 14.5*985-2*1329 = 11624.5

# Quadratic Discriminant Analysis

# M3c: Trimmed subset of 12 variables
model.qda2 = qda(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag, data.train.std.c)
# M3b: Best 20 variable model from regsubsets
model.qda2 = qda(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                   wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                   ln_agif + sr_chld + sr_tdon + sr_tlag, data.train.std.c)
# M3a: Default Original subset
model.qda2 <- qda(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data.train.std.c) # include additional terms on the fly using I()

post.valid.qda2 <- predict(model.qda2, data.valid.std.c)$posterior[,2] # n.valid.c post probs
profit.qda2 <- cumsum(14.5*c.valid[order(post.valid.qda2, decreasing=T)]-2)
plot(profit.qda2) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.qda2) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.qda2)) # report number of mailings and maximum profit
cutoff.qda2 <- sort(post.valid.qda2, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.qda2 <- ifelse(post.valid.qda2>cutoff.qda2, 1, 0) # mail to everyone above the cutoff
table(chat.valid.qda2, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.qda2, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)
#####

# K Nearest Neighbors
library(class)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=1)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=2)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=3)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=4)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=5)
set.seed(1)
model.knn1=knn(data.train.std.c,data.valid.std.c,c.train,k=6)

post.valid.knn1 <- as.integer(as.character(model.knn1))
profit.knn1 <- cumsum(14.5*c.valid[order(post.valid.knn1, decreasing=T)]-2)
plot(profit.knn1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.knn1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.knn1)) # report number of mailings and maximum profit
cutoff.knn1 <- sort(post.valid.knn1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.knn1 <- ifelse(post.valid.knn1>cutoff.knn1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.knn1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.knn1, c.valid)
perf <- performance(pred,"tpr","fpr")
```

```
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Logistic Regression using GAM with Natural Splines
library(gam)
# M5c: Trimmed subset of 12 variables
model.ns1 = gam(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                ns(ln_incm,4) + ns(ln_tgif,4) + ns(sr_tdon,4) + ns(sr_tlag,4),
                data.train.std.c, family=binomial("logit"))
# M5b: Best 20 variable model from regsubsets
model.ns1 = gam(donr ~ reg1 + reg2 + home + chld + hinc + ns(inca,4) + ns(tgif,4) + ns(tlag,4) + wrat2 +
                   wrat3 + hinc2 + ns(ln_incm,4) + ns(ln_tgif,4) + ns(ln_lgif,4) + ns(ln_tdon,4) +
                   ns(ln_tlag,4) + ns(ln_agif,4) + sr_chld + ns(sr_tdon,4) + ns(sr_tlag,4),
                   data.train.std.c, family=binomial("logit"))
# M5a: Default Original subset
model.ns1 <- gam(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ns(ln_avhv,4) + ns(incm,4) + ns(inca,4) + ns(plow,4) + ns(npro,4) + ns(tgif,4) +
                  ns(lgif,4) + ns(rgif,4) + ns(tdon,4) + ns(tlag,4) + ns(agif,4),
                  data.train.std.c, family=binomial("logit"))

post.valid.ns1 <- predict(model.ns1, data.valid.std.c, type="response") # n.valid post probs
profit.ns1 <- cumsum(14.5*c.valid[order(post.valid.ns1, decreasing=T)]-2)
plot(profit.ns1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.ns1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.ns1)) # report number of mailings and maximum profit
cutoff.ns1 <- sort(post.valid.ns1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.ns1 <- ifelse(post.valid.ns1>cutoff.ns1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.ns1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.ns1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Logistic Regression using GAM with Smoothing Splines
library(gam)
# M6c: Trimmed subset of 12 variables
model.ss1 = gam(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                s(ln_incm,4) + s(ln_tgif,4) + s(sr_tdon,4) + s(sr_tlag,4),
                data.train.std.c, family=binomial("logit"))
# M6b: Best 20 variable model from regsubsets
model.ss1 = gam(donr ~ reg1 + reg2 + home + chld + hinc + s(inca,4) + s(tgif,4) + s(tlag,4) + wrat2 +
                wrat3 + hinc2 + s(ln_incm,4) + s(ln_tgif,4) + s(ln_lgif,4) + s(ln_tdon,4) +
                s(ln_tlag,4) + s(ln_agif,4) + sr_chld + s(sr_tdon,4) + s(sr_tlag,4),
                data.train.std.c, family=binomial("logit"))
# M6a: Default Original subset
model.ss1 <- gam(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                 s(ln_avhv,4) + s(incm,4) + s(inca,4) + s(plow,4) + s(npro,4) + s(tgif,4) +
                 s(lgif,4) + s(rgif,4) + s(tdon,4) + s(tlag,4) + s(agif,4),
                 data.train.std.c, family=binomial("logit"))

post.valid.ss1 <- predict(model.ss1, data.valid.std.c, type="response") # n.valid post probs
profit.ss1 <- cumsum(14.5*c.valid[order(post.valid.ss1, decreasing=T)]-2)
plot(profit.ss1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.ss1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.ss1)) # report number of mailings and maximum profit
cutoff.ss1 <- sort(post.valid.ss1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.ss1 <- ifelse(post.valid.ss1>cutoff.ss1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.ss1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.ss1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Logistic Regression using GAM with Local Regression Smoothing (span=0.2)
library(gam)
# M7c: Trimmed subset of 12 variables
model.lo1 = gam(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                lo(ln_incm,span=0.2) + lo(ln_tgif,span=0.2) + lo(sr_tdon,span=0.2) + lo(sr_tlag,span=0.2),
                data.train.std.c, family=binomial("logit"))
# M7b: Best 20 variable model from regsubsets
model.lo1 = gam(donr ~ reg1 + reg2 + home + chld + hinc + lo(inca,span=0.2) + lo(tgif,span=0.2) +
                  lo(tlag,span=0.2) + wrat2 + wrat3 + hinc2 + lo(ln_incm,span=0.2) + lo(ln_tgif,span=0.2) +
                  lo(ln_lgif,span=0.2) + lo(ln_tdon,span=0.2) + lo(ln_tlag,span=0.2) + lo(ln_agif,span=0.2) +
                  sr_chld + lo(sr_tdon,span=0.2) + lo(sr_tlag,span=0.2),
                  data.train.std.c, family=binomial("logit"))
# M7a: Default Original subset
model.lo1 <- gam(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                 lo(ln_avhv,span=0.2) + lo(incm,span=0.2) + lo(inca,span=0.2) + lo(plow,span=0.2) +
                 lo(npro,span=0.2) + lo(tgif,span=0.2) + lo(lgif,span=0.2) + lo(rgif,span=0.2) +
                 lo(tdon,span=0.2) + lo(tlag,span=0.2) + lo(agif,span=0.2),
                 data.train.std.c, family=binomial("logit"))

post.valid.lo1 <- predict(model.lo1, data.valid.std.c, type="response") # n.valid post probs
```

```
profit.lo1 <- cumsum(14.5*c.valid[order(post.valid.lo1, decreasing=T)]-2)
plot(profit.lo1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.lo1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.lo1)) # report number of mailings and maximum profit
cutoff.lo1 <- sort(post.valid.lo1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.lo1 <- ifelse(post.valid.lo1>cutoff.lo1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.lo1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.lo1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Logistic Regression using GAM with Local Regression Smoothing (span=0.5)
library(gam)
# M8c: Trimmed subset of 12 variables
model.lo2 = gam(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                  lo(ln_incm,span=0.5) + lo(ln_tgif,span=0.5) + lo(sr_tdon,span=0.5) + lo(sr_tlag,span=0.5),
                  data.train.std.c, family=binomial("logit"))
# M8b: Best 20 variable model from regsubsets
model.lo2 = gam(donr ~ reg1 + reg2 + home + chld + hinc + lo(inca,span=0.5) + lo(tgif,span=0.5) +
                  lo(tlag,span=0.5) + wrat2 + wrat3 + hinc2 + lo(ln_incm,span=0.5) + lo(ln_tgif,span=0.5) +
                  lo(ln_lgif,span=0.5) + lo(ln_tdon,span=0.5) + lo(ln_tlag,span=0.5) + lo(ln_agif,span=0.5) +
                  sr_chld + lo(sr_tdon,span=0.5) + lo(sr_tlag,span=0.5),
                  data.train.std.c, family=binomial("logit"))
# M8a: Default Original subset
model.lo2 <- gam(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                   lo(ln_avhv,span=0.5) + lo(incm,span=0.5) + lo(inca,span=0.5) + lo(plow,span=0.5) +
                   lo(npro,span=0.5) + lo(tgif,span=0.5) + lo(lgif,span=0.5) + lo(rgif,span=0.5) +
                   lo(tdon,span=0.5) + lo(tlag,span=0.5) + lo(agif,span=0.5),
                   data.train.std.c, family=binomial("logit"))

post.valid.lo2 <- predict(model.lo2, data.valid.std.c, type="response") # n.valid post probs
profit.lo2 <- cumsum(14.5*c.valid[order(post.valid.lo2, decreasing=T)]-2)
plot(profit.lo2) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.lo2) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.lo2)) # report number of mailings and maximum profit
cutoff.lo2 <- sort(post.valid.lo2, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.lo2 <- ifelse(post.valid.lo2>cutoff.lo2, 1, 0) # mail to everyone above the cutoff
table(chat.valid.lo2, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.lo2, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Decision Tree
library(tree)
# M9c: Trimmed subset of 12 variables
set.seed(1)
model.tr1 = tree(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag, data=data.train.std.c)
# M9b: Best 20 variable model from regsubsets
set.seed(1)
model.tr1 = tree(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                   wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                   ln_agif + sr_chld + sr_tdon + sr_tlag, data=data.train.std.c)
# M9a: Default Original subset
set.seed(1)
model.tr1 <- tree(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                    ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                    data=data.train.std.c) # include additional terms on the fly using I()

post.valid.tr1 <- predict(model.tr1, data.valid.std.c) # n.valid post probs
profit.tr1 <- cumsum(14.5*c.valid[order(post.valid.tr1, decreasing=T)]-2)
plot(profit.tr1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.tr1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.tr1)) # report number of mailings and maximum profit
cutoff.tr1 <- sort(post.valid.tr1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.tr1 <- ifelse(post.valid.tr1>cutoff.tr1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.tr1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.tr1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Bagging
library(randomForest)
# M10c: Trimmed subset of 12 variables
set.seed(1)
model.bag1 = randomForest(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag, data=data.train.std.c,
                   mtry=12, ntree=500, importance=T)
```

```
# M10b: Best 20 variable model from regsubsets
set.seed(1)
model.bag1 = randomForest(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                   wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                   ln_agif + sr_chld + sr_tdon + sr_tlag, data=data.train.std.c,
                   mtry=20, ntree=500, importance=T)
# M10a: Default Original subset
set.seed(1)
model.bag1 = randomForest(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data=data.train.std.c, mtry=21, ntree=500, importance=T)

post.valid.bag1 <- predict(model.bag1, data.valid.std.c) # n.valid post probs
profit.bag1 <- cumsum(14.5*c.valid[order(post.valid.bag1, decreasing=T)]-2)
plot(profit.bag1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.bag1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.bag1)) # report number of mailings and maximum profit
cutoff.bag1 <- sort(post.valid.bag1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.bag1 <- ifelse(post.valid.bag1>cutoff.bag1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.bag1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.bag1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Random Forests
library(randomForest)
# M11c: Trimmed subset of 12 variables
set.seed(1)
model.rf1 = randomForest(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                         ln_incm + ln_tgif + sr_tdon + sr_tlag, data=data.train.std.c,
                         mtry=3, ntree=500, importance=T)
# M11b: Best 20 variable model from regsubsets
set.seed(1)
model.rf1 =  randomForest(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                         wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                         ln_agif + sr_chld + sr_tdon + sr_tlag, data=data.train.std.c,
                         mtry=4, ntree=500, importance=T)
# M11a: Default Original subset
set.seed(1)
model.rf1 <-  randomForest(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                           ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                           data=data.train.std.c, mtry=5, ntree=500, importance=T)

post.valid.rf1 <- predict(model.rf1, data.valid.std.c) # n.valid post probs
profit.rf1 <- cumsum(14.5*c.valid[order(post.valid.rf1, decreasing=T)]-2)
plot(profit.rf1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.rf1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.rf1)) # report number of mailings and maximum profit
cutoff.rf1 <- sort(post.valid.rf1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.rf1 <- ifelse(post.valid.rf1>cutoff.rf1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.rf1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.rf1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Boosting
library(gbm)
# M12c: Trimmed subset of 12 variables
set.seed(1)
model.boo1 = gbm(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                        ln_incm + ln_tgif + sr_tdon + sr_tlag, data=data.train.std.c,
                        distribution="gaussian", n.trees=5000,
                        interaction.depth=4,shrinkage=0.01,verbose=F)
# M12b: Best 20 variable model from regsubsets
set.seed(1)
model.boo1 =  gbm(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                         wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                         ln_agif + sr_chld + sr_tdon + sr_tlag, data=data.train.std.c,
                         distribution="gaussian", n.trees=5000,
                         interaction.depth=4,shrinkage=0.01,verbose=F)
# M12a: Default Original subset
set.seed(1)
model.boo1 <-  gbm(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + I(hinc^2) + genf + wrat +
                          ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                          data=data.train.std.c, distribution="gaussian", n.trees=5000,
                          interaction.depth=4,shrinkage=0.01,verbose=F)

post.valid.boo1 <- predict(model.boo1, data.valid.std.c, n.trees=5000) # n.valid post probs
profit.boo1 <- cumsum(14.5*c.valid[order(post.valid.boo1, decreasing=T)]-2)
plot(profit.boo1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.boo1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.boo1)) # report number of mailings and maximum profit
```

```
cutoff.boo1 <- sort(post.valid.boo1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.boo1 <- ifelse(post.valid.boo1>cutoff.boo1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.boo1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.boo1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Artificial Neural Network
library(nnet)
xc_vars = c("reg1","reg2","home","sr_chld","hinc","hinc2","wrat2","wrat3",
            "ln_incm","ln_tgif","sr_tdon","sr_tlag")
xb_vars = c("reg1","reg2","home","chld","hinc","inca","tgif","tlag","wrat2",
            "wrat3","hinc2","ln_incm","ln_tgif","ln_lgif","ln_tdon","ln_tlag",
            "ln_agif","sr_chld","sr_tdon","sr_tlag")
xa_vars = c("reg1","reg2","reg3","reg4","home","chld","hinc","hinc2","genf","wrat",
            "ln_avhv","incm","inca","plow","npro","tgif","lgif","rgif","tdon",
            "tlag","agif")
xc1 = data.train.std.c[,xc_vars]
xb1 = data.train.std.c[,xb_vars]
xa1 = data.train.std.c[,xa_vars]
xvc1 = data.valid.std.c[,xc_vars]
xvb1 = data.valid.std.c[,xb_vars]
xva1 = data.valid.std.c[,xa_vars]

# M12c: Trimmed subset of 12 variables
set.seed(1)
model.nn1 = nnet(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag,
                   data=data.train.std.c, size=20, maxit=100, decay=.001)
newdata=xvc1
# M12b: Best 20 variable model from regsubsets
set.seed(1)
model.nn1 =  nnet(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                    wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                    ln_agif + sr_chld + sr_tdon + sr_tlag,
                    data=data.train.std.c, size=20, maxit=100, decay=.001)
newdata=xvb1
# M12a: Default Original subset
set.seed(1)
model.nn1 <-  nnet(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + hinc2 + genf + wrat +
                     ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                     data=data.train.std.c, size=20, maxit=100, decay=.001)
newdata=xva1

post.valid.nn1 <- predict(model.nn1, newdata) # n.valid post probs
profit.nn1 <- cumsum(14.5*c.valid[order(post.valid.nn1, decreasing=T)]-2)
plot(profit.nn1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.nn1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.nn1)) # report number of mailings and maximum profit
cutoff.nn1 <- sort(post.valid.nn1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.nn1 <- ifelse(post.valid.nn1>cutoff.nn1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.nn1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.nn1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Support Vector Machines (Linear kernel)
library(e1071)

# M12c: Trimmed subset of 12 variables
set.seed(1)
model.svm1 = svm(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                 ln_incm + ln_tgif + sr_tdon + sr_tlag,
                 data=data.train.std.c, kernel="linear", cost=0.1, scale=FALSE)
# M12b: Best 20 variable model from regsubsets
set.seed(1)
model.svm1 =  svm(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                  wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                  ln_agif + sr_chld + sr_tdon + sr_tlag,
                  data=data.train.std.c, kernel="linear", cost=0.1, scale=FALSE)
# M12a: Default Original subset
set.seed(1)
model.svm1 = svm(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + hinc2 + genf + wrat +
              ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
              data=data.train.std.c, kernel="linear", cost=0.1, scale=FALSE)

post.valid.svm1 <- predict(model.svm1, data.valid.std.c) # n.valid post probs
profit.svm1 <- cumsum(14.5*c.valid[order(post.valid.svm1, decreasing=T)]-2)
plot(profit.svm1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.svm1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.svm1)) # report number of mailings and maximum profit
cutoff.svm1 <- sort(post.valid.svm1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
```

```
chat.valid.svm1 <- ifelse(post.valid.svm1>cutoff.svm1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.svm1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.svm1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

# Support Vector Machines (Radial Kernel)
library(e1071)

# M12c: Trimmed subset of 12 variables
set.seed(1)
model.svm1 = svm(donr ~ reg1 + reg2 + home + sr_chld + hinc + hinc2 + wrat2 + wrat3 +
                   ln_incm + ln_tgif + sr_tdon + sr_tlag,
                 data=data.train.std.c, kernel="radial", cost=0.1, scale=FALSE)
# M12b: Best 20 variable model from regsubsets
set.seed(1)
model.svm1 =  svm(donr ~ reg1 + reg2 + home + chld + hinc + inca + tgif + tlag + wrat2 +
                    wrat3 + hinc2 + ln_incm + ln_tgif + ln_lgif + ln_tdon + ln_tlag +
                    ln_agif + sr_chld + sr_tdon + sr_tlag,
                  data=data.train.std.c, kernel="radial", cost=0.1, scale=FALSE)
# M12a: Default Original subset
set.seed(1)
model.svm1 = svm(donr ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + hinc2 + genf + wrat +
                   ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                 data=data.train.std.c, kernel="radial", cost=0.1, scale=FALSE)

post.valid.svm1 <- predict(model.svm1, data.valid.std.c) # n.valid post probs
profit.svm1 <- cumsum(14.5*c.valid[order(post.valid.svm1, decreasing=T)]-2)
plot(profit.svm1) # see how profits change as more mailings are made
n.mail.valid <- which.max(profit.svm1) # number of mailings that maximizes profits
c(n.mail.valid, max(profit.svm1)) # report number of mailings and maximum profit
cutoff.svm1 <- sort(post.valid.svm1, decreasing=T)[n.mail.valid+1] # set cutoff based on n.mail.valid
chat.valid.svm1 <- ifelse(post.valid.svm1>cutoff.svm1, 1, 0) # mail to everyone above the cutoff
table(chat.valid.svm1, c.valid) # classification table
## computing a simple ROC curve (x-axis: fpr, y-axis: tpr)
library(ROCR)
pred <- prediction(chat.valid.svm1, c.valid)
perf <- performance(pred,"tpr","fpr")
auc.perf = performance(pred, measure = "auc")
auc.perf@y.values
plot(perf)

model.best.c = model.boo1 # model 12a
profit.best.c = profit.boo1
# select best model to have maximum profit in the validation sample
post.test <- predict(model.best.c, data.test.std, n.tree = 5000) # post probs for test data
# Oversampling adjustment for calculating number of mailings for test set
n.mail.valid <- which.max(profit.best.c)
tr.rate <- .1 # typical response rate is .1
vr.rate <- .5 # whereas validation response rate is .5
adj.test.1 <- (n.mail.valid/n.valid.c)/(vr.rate/tr.rate) # adjustment for mail yes
adj.test.0 <- ((n.valid.c-n.mail.valid)/n.valid.c)/((1-vr.rate)/(1-tr.rate)) # adjustment for mail no
adj.test <- adj.test.1/(adj.test.1+adj.test.0) # scale into a proportion
n.mail.test <- round(n.test*adj.test, 0) # calculate number of mailings for test set
cutoff.test <- sort(post.test, decreasing=T)[n.mail.test+1] # set cutoff based on n.mail.test
chat.test <- ifelse(post.test>cutoff.test, 1, 0) # mail to everyone above the cutoff
table(chat.test)
#    0    1
# 1676  331
# based on this model we'll mail to the 331 highest posterior probabilities

##### PREDICTION MODELING ######

library(leaps)
library(stats)
vs2 = regsubsets(damt ~ ., data = data.train.std.y, really.big = T, nvmax = 20)
plot(vs2, scale="adjr2")

# Least Squares Regression

# M1c: Trimmed subset of 15 variables
model.ls1 = lm(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
               hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
               data.train.std.y)
# M1b: Best 20 variable model from regsubsets
model.ls1 = lm(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
              wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
              ln_agif + sr_incm + sr_plow + sr_lgif, data.train.std.y)
# M1a: Default Original subset
model.ls1 <- lm(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                data.train.std.y)

pred.valid.ls1 <- predict(model.ls1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.ls1)^2) # mean prediction error
# 1.867523
```

```
sd((y.valid - pred.valid.ls1)^2)/sqrt(n.valid.y) # std error
# 0.1696615
summary(model.ls1)$r.squared
summary(model.ls1)$adj.r.squared
AIC(model.ls1)
AIC(model.ls1,k=8.290042) # for BIC, k=ln(#obs in training set)

# Ridge Regression

library(glmnet)
grid=10^seq(10,-2,length=10000)
y = as.matrix(data.train.std.y$damt)
xc_vars = c("reg3","reg4","reg5","home","chld","hinc","plow","wrat","wrat2",
            "hinc3","ln_incm","ln_lgif","ln_tgif","ln_rgif","ln_agif")
xb_vars = c("reg3","reg4","reg5","home","chld","hinc","plow","wrat","wrat2",
            "wrat3","hinc3","ln_incm","ln_plow","ln_tgif","ln_lgif","ln_rgif",
            "ln_agif","sr_incm","sr_plow","sr_lgif")
xa_vars = c("reg1","reg2","reg3","reg4","home","chld","hinc","genf","wrat",
            "ln_avhv","incm","inca","plow","npro","tgif","lgif","rgif","tdon",
            "tlag","agif")
xc = as.matrix(data.train.std.y)[,xc_vars]
xb = as.matrix(data.train.std.y)[,xb_vars]
xa = as.matrix(data.train.std.y)[,xa_vars]
xvc = as.matrix(data.valid.std.y)[,xc_vars]
xvb = as.matrix(data.valid.std.y)[,xb_vars]
xva = as.matrix(data.valid.std.y)[,xa_vars]

# M2c: Trimmed subset of 15 variables
set.seed(1)
cv.out = cv.glmnet(xc,y,alpha=0,lambda=grid)
bestlam = cv.out$lambda.min
newdata = xvc
model.rr1 = glmnet(xc,y,alpha=0,lambda=bestlam, standardize=FALSE)
# M2b: Best 20 variable model from regsubsets
set.seed(1)
cv.out = cv.glmnet(xb,y,alpha=0,lambda=grid, standardize=FALSE)
bestlam = cv.out$lambda.min
newdata = xvb
model.rr1 = glmnet(xb,y,alpha=0,lambda=bestlam, standardize=FALSE)
# M2a: Default Original subset
set.seed(1)
cv.out = cv.glmnet(xa,y,alpha=0,lambda=grid)
bestlam = cv.out$lambda.min
newdata = xva
model.rr1 = glmnet(xa,y,alpha=0,lambda=bestlam, standardize=FALSE)

pred.valid.rr1 = predict(model.rr1, newx=newdata, s=bestlam) # validation predictions
mean((y.valid - pred.valid.rr1)^2) # mean prediction error
sd((y.valid - pred.valid.rr1)^2)/sqrt(n.valid.y) # std error
bestlam

# Lasso

library(glmnet)
grid=10^seq(10,-2,length=10000)
y = as.matrix(data.train.std.y$damt)
xc_vars = c("reg3","reg4","reg5","home","chld","hinc","plow","wrat","wrat2",
            "hinc3","ln_incm","ln_lgif","ln_tgif","ln_rgif","ln_agif")
xb_vars = c("reg3","reg4","reg5","home","chld","hinc","plow","wrat","wrat2",
            "wrat3","hinc3","ln_incm","ln_plow","ln_tgif","ln_lgif","ln_rgif",
            "ln_agif","sr_incm","sr_plow","sr_lgif")
xa_vars = c("reg1","reg2","reg3","reg4","home","chld","hinc","genf","wrat",
            "ln_avhv","incm","inca","plow","npro","tgif","lgif","rgif","tdon",
            "tlag","agif")
xc = as.matrix(data.train.std.y)[,xc_vars]
xb = as.matrix(data.train.std.y)[,xb_vars]
xa = as.matrix(data.train.std.y)[,xa_vars]
xvc = as.matrix(data.valid.std.y)[,xc_vars]
xvb = as.matrix(data.valid.std.y)[,xb_vars]
xva = as.matrix(data.valid.std.y)[,xa_vars]

# M3c: Trimmed subset of 15 variables
set.seed(1)
cv.out = cv.glmnet(xc,y,alpha=1,lambda=grid)
bestlam = cv.out$lambda.min
newdata = xvc
model.las1 = glmnet(xc,y,alpha=1,lambda=bestlam, standardize=FALSE)
# M3b: Best 20 variable model from regsubsets
set.seed(1)
cv.out = cv.glmnet(xb,y,alpha=1,lambda=grid, standardize=FALSE)
bestlam = cv.out$lambda.min
newdata = xvb
model.las1 = glmnet(xb,y,alpha=1,lambda=bestlam, standardize=FALSE)
# M3a: Default Original subset
set.seed(1)
cv.out = cv.glmnet(xa,y,alpha=1,lambda=grid)
bestlam = cv.out$lambda.min
newdata = xva
model.las1 = glmnet(xa,y,alpha=1,lambda=bestlam, standardize=FALSE)
```

```
pred.valid.las1 = predict(model.las1, newx=newdata, alpha=1, s=bestlam) # validation predictions
mean((y.valid - pred.valid.las1)^2) # mean prediction error
sd((y.valid - pred.valid.las1)^2)/sqrt(n.valid.y) # std error
bestlam
lasso.coef = predict(model.las1, newx=newdata, s=bestlam, alpha=1, type="coefficients")
lasso.coef

# Principal Components Regression

# M4c: Trimmed subset of 15 variables
library(pls)
set.seed(1)
model.pcr1 = pcr(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
                 data=data.train.std.y, validation ="CV", scale = F)
# M4b: Best 20 variable model from regsubsets
set.seed(1)
model.pcr1 = pcr(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                 ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y,
                 validation ="CV", scale = F)
# M4a: Default Original subset
set.seed(1)
model.pcr1 <- pcr(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data=data.train.std.y, validation="CV", scale = F)

pred.valid.pcr1 <- predict(model.pcr1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.pcr1)^2) # mean prediction error
sd((y.valid - pred.valid.pcr1)^2)/sqrt(n.valid.y) # std error
summary(model.pcr1)

# Partial Least Squares

# M5c: Trimmed subset of 15 variables
set.seed(1)
model.pls1 = plsr(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                  hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
                  data=data.train.std.y, validation ="CV", scale = F)
# M5b: Best 20 variable model from regsubsets
set.seed(1)
model.pls1 = plsr(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                   wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                   ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y,
                   validation ="CV", scale = F)
# M5a: Default Original subset
set.seed(1)
model.pls1 <- plsr(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                    ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                    data=data.train.std.y, validation="CV", scale = F)

pred.valid.pls1 <- predict(model.pls1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.pls1)^2) # mean prediction error
sd((y.valid - pred.valid.pls1)^2)/sqrt(n.valid.y) # std error
summary(model.pls1)

# Least Squares Regression using GAM with Natural Splines
library(gam)
# M6c: Trimmed subset of 12 variables
model.ns1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + ns(plow,4) + wrat + wrat2 +
                hinc3 + ns(ln_incm,4) + ns(ln_lgif,4) + ns(ln_tgif,4) + ns(ln_rgif,4) + ns(ln_agif,4),
                data.train.std.y, family=gaussian("identity"))
# M6b: Best 20 variable model from regsubsets
model.ns1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + ns(plow,4) + wrat + wrat2 +
                  wrat3 + hinc3 + ns(ln_incm,4) + ns(ln_plow,4) + ns(ln_tgif,4) +
                  ns(ln_lgif,4) + ns(ln_rgif,4) + ns(ln_agif,4) + ns(sr_incm,4) +
                  ns(sr_plow,4) + ns(sr_lgif,4),
                  data.train.std.y, family=gaussian("identity"))
# M6a: Default Original subset
model.ns1 <- gam(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                   ns(ln_avhv,4) + ns(incm,4) + ns(inca,4) + ns(plow,4) + ns(npro,4) + ns(tgif,4) +
                   ns(lgif,4) + ns(rgif,4) + ns(tdon,4) + ns(tlag,4) + ns(agif,4),
                   data.train.std.y, family=gaussian("identity"))

pred.valid.ns1 <- predict(model.ns1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.ns1)^2) # mean prediction error
sd((y.valid - pred.valid.ns1)^2)/sqrt(n.valid.y) # std error
AIC(model.ns1)
AIC(model.ns1,k=8.290042) # for BIC, k=ln(#obs in training set)


# Least Squares Regression using GAM with Smoothing Splines
library(gam)
# M7c: Trimmed subset of 12 variables
model.ss1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + s(plow,4) + wrat + wrat2 +
                hinc3 + s(ln_incm,4) + s(ln_lgif,4) + s(ln_tgif,4) + s(ln_rgif,4) + s(ln_agif,4),
                data.train.std.y, family=gaussian("identity"))
# M7b: Best 20 variable model from regsubsets
model.ss1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + s(plow,4) + wrat + wrat2 +
                  wrat3 + hinc3 + s(ln_incm,4) + s(ln_plow,4) + s(ln_tgif,4) +
                  s(ln_lgif,4) + s(ln_rgif,4) + s(ln_agif,4) + s(sr_incm,4) +
                  s(sr_plow,4) + s(sr_lgif,4),
                  data.train.std.y, family=gaussian("identity"))
# M7a: Default Original subset
model.ss1 <- gam(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                   s(ln_avhv,4) + s(incm,4) + s(inca,4) + s(plow,4) + s(npro,4) + s(tgif,4) +
                   s(lgif,4) + s(rgif,4) + s(tdon,4) + s(tlag,4) + s(agif,4),
                   data.train.std.y, family=gaussian("identity"))

pred.valid.ss1 <- predict(model.ss1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.ss1)^2) # mean prediction error
sd((y.valid - pred.valid.ss1)^2)/sqrt(n.valid.y) # std error
AIC(model.ss1)
AIC(model.ss1,k=8.290042) # for BIC, k=ln(#obs in training set)

# Least Squares Regression using GAM with Local Regression Smoothing (span=0.2)
library(gam)
# M8c: Trimmed subset of 12 variables
model.lo1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + lo(plow,span=0.2) + wrat + wrat2 +
                  hinc3 + lo(ln_incm,span=0.2) + lo(ln_lgif,span=0.2) + lo(ln_tgif,span=0.2) +
                  lo(ln_rgif,span=0.2) + lo(ln_agif,span=0.2),
                  data.train.std.y, family=gaussian("identity"))
# M8b: Best 20 variable model from regsubsets
model.lo1 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + lo(plow,span=0.2) + wrat + wrat2 +
                  wrat3 + hinc3 + lo(ln_incm,span=0.2) + lo(ln_plow,span=0.2) + lo(ln_tgif,span=0.2) +
                  lo(ln_lgif,span=0.2) + lo(ln_rgif,span=0.2) + lo(ln_agif,span=0.2) + lo(sr_incm,span=0.2) +
                  lo(sr_plow,span=0.2) + lo(sr_lgif,span=0.2),
                  data.train.std.y, family=gaussian("identity"))
# M8a: Default Original subset
model.lo1 <- gam(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                   lo(ln_avhv,span=0.2) + lo(incm,span=0.2) + lo(inca,span=0.2) +
                   lo(plow,span=0.2) + lo(npro,span=0.2) + lo(tgif,span=0.2) +
                   lo(lgif,span=0.2) + lo(rgif,span=0.2) + lo(tdon,span=0.2) +
                   lo(tlag,span=0.2) + lo(agif,span=0.2),
                   data.train.std.y, family=gaussian("identity"))

pred.valid.lo1 <- predict(model.lo1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.lo1)^2) # mean prediction error
sd((y.valid - pred.valid.lo1)^2)/sqrt(n.valid.y) # std error
AIC(model.lo1)
AIC(model.lo1,k=8.290042) # for BIC, k=ln(#obs in training set)

# Least Squares Regression using GAM with Local Regression Smoothing (span=0.5)
library(gam)
# M9c: Trimmed subset of 12 variables
model.lo2 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + lo(plow,span=0.5) + wrat + wrat2 +
                  hinc3 + lo(ln_incm,span=0.5) + lo(ln_lgif,span=0.5) + lo(ln_tgif,span=0.5) +
                  lo(ln_rgif,span=0.5) + lo(ln_agif,span=0.5),
                  data.train.std.y, family=gaussian("identity"))
# M9b: Best 20 variable model from regsubsets
model.lo2 = gam(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + lo(plow,span=0.5) + wrat + wrat2 +
                  wrat3 + hinc3 + lo(ln_incm,span=0.5) + lo(ln_plow,span=0.5) + lo(ln_tgif,span=0.5) +
                  lo(ln_lgif,span=0.5) + lo(ln_rgif,span=0.5) + lo(ln_agif,span=0.5) + lo(sr_incm,span=0.5) +
                  lo(sr_plow,span=0.5) + lo(sr_lgif,span=0.5),
                  data.train.std.y, family=gaussian("identity"))
# M9a: Default Original subset
model.lo2 <- gam(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                   lo(ln_avhv,span=0.5) + lo(incm,span=0.5) + lo(inca,span=0.5) +
                   lo(plow,span=0.5) + lo(npro,span=0.5) + lo(tgif,span=0.5) +
                   lo(lgif,span=0.5) + lo(rgif,span=0.5) + lo(tdon,span=0.5) +
                   lo(tlag,span=0.5) + lo(agif,span=0.5),
                   data.train.std.y, family=gaussian("identity"))

pred.valid.lo2 <- predict(model.lo2, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.lo2)^2) # mean prediction error
sd((y.valid - pred.valid.lo2)^2)/sqrt(n.valid.y) # std error
AIC(model.lo2)
AIC(model.lo2,k=8.290042) # for BIC, k=ln(#obs in training set)

# Decision Tree
library(tree)
# M10c: Trimmed subset of 12 variables
set.seed(1)
model.tr1 = tree(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
                 data=data.train.std.y)
# M10b: Best 20 variable model from regsubsets
set.seed(1)
model.tr1 = tree(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                 ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y)
# M10a: Default Original subset
set.seed(1)
model.tr1 <- tree(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data=data.train.std.y) # include additional terms on the fly using I()

pred.valid.tr1 <- predict(model.tr1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.tr1)^2) # mean prediction error
sd((y.valid - pred.valid.tr1)^2)/sqrt(n.valid.y) # std error
```

```
summary(model.tr1)

# Bagging
library(randomForest)
# M11c: Trimmed subset of 12 variables
set.seed(1)
model.bag1 = randomForest(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
                 data=data.train.std.y, mtry=15, ntree=500, importance=T)
# M11b: Best 20 variable model from regsubsets
set.seed(1)
model.bag1 = randomForest(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                 wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                 ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y,
                 mtry=20, ntree=500, importance=T)
# M11a: Default Original subset
set.seed(1)
model.bag1 <- randomForest(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                  ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                  data=data.train.std.y, mtry=20, ntree=500, importance=T)

pred.valid.bag1 <- predict(model.bag1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.bag1)^2) # mean prediction error
sd((y.valid - pred.valid.bag1)^2)/sqrt(n.valid.y) # std error
max(model.bag1$rsq)

# Random Forests
library(randomForest)
# M12c: Trimmed subset of 12 variables
set.seed(1)
model.rf1 = randomForest(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                         hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif,
                         data=data.train.std.y, mtry=4, ntree=500, importance=T)
# M12b: Best 20 variable model from regsubsets
set.seed(1)
model.rf1 = randomForest(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                         wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                         ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y,
                         mtry=4, ntree=500, importance=T)
# M12a: Default Original subset
set.seed(1)
model.rf1 <- randomForest(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                          ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                          data=data.train.std.y, mtry=4, ntree=500, importance=T)

pred.valid.rf1 <- predict(model.rf1, newdata = data.valid.std.y) # validation predictions
mean((y.valid - pred.valid.rf1)^2) # mean prediction error
sd((y.valid - pred.valid.rf1)^2)/sqrt(n.valid.y) # std error
max(model.rf1$rsq)

# Boosting
library(gbm)
# M13c: Trimmed subset of 12 variables
set.seed(1)
model.boo1 = gbm(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                hinc3 + ln_incm + ln_lgif + ln_tgif + ln_rgif + ln_agif, data=data.train.std.y,
                 distribution="gaussian", n.trees=5000,
                 interaction.depth=4,shrinkage=0.01,verbose=F)
# M13b: Best 20 variable model from regsubsets
set.seed(1)
model.boo1 =  gbm(damt ~ reg3 + reg4 + reg5 + home + chld + hinc + plow + wrat + wrat2 +
                  wrat3 + hinc3 + ln_incm + ln_plow + ln_tgif + ln_lgif + ln_rgif +
                  ln_agif + sr_incm + sr_plow + sr_lgif, data=data.train.std.y,
                  distribution="gaussian", n.trees=5000,
                  interaction.depth=4,shrinkage=0.01,verbose=F)
# M13a: Default Original subset
set.seed(1)
model.boo1 <-  gbm(damt ~ reg1 + reg2 + reg3 + reg4 + home + chld + hinc + genf + wrat +
                   ln_avhv + incm + inca + plow + npro + tgif + lgif + rgif + tdon + tlag + agif,
                   data=data.train.std.y, distribution="gaussian", n.trees=5000,
                   interaction.depth=4,shrinkage=0.01,verbose=F)

pred.valid.boo1 <- predict(model.boo1, newdata = data.valid.std.y, n.trees=5000) # validation predictions
mean((y.valid - pred.valid.boo1)^2) # mean prediction error
sd((y.valid - pred.valid.boo1)^2)/sqrt(n.valid.y) # std error


# Colormap for classification models
library(gplots)
library(RColorBrewer)
d1 = read.csv("classmap2.csv", row.names = 1, header=T)
d2 = read.csv("classactual2.csv", row.names = 1, header=T)
rownames = rownames(d1)
#d1 = d1[,-c(16,17)]
#d2 = d2[,-c(16,17)]
d1 = as.matrix(d1)
d2 = as.matrix(d2)
# creates a own color palette from blue to red
my_palette <- colorRampPalette(c("blue","yellow","red"))(n = 299)
# (optional) defines the color breaks manually for a "skewed" color transition
```

```
col_breaks = c(seq(0,0.799,length=100),   # for blue
               seq(0.80,0.929,length=100),   # for yellow
               seq(0.93,1.0,length=100))   # for red
# creates a 5 x 5 inch image
png("classheatmap.png",     # create PNG for the heat map
    width = 11*300,        # 5 x 300 pixels
    height = 17*300,
    res = 300,            # 300 pixels per inch
    pointsize = 10)        # smaller font size
heatmap.2(d1,
          cellnote = d2,        # same data set for cell labels
          main = "Classification Metrics", # heat map title
          notecol="black",      # change font color of cell labels to black
          density.info="none",  # turns off density plot inside color legend
          trace="none",         # turns off trace lines inside the heat map
          margins =c(10,8),     # widens margins around plot
          col=my_palette,       # use on color palette defined earlier
          breaks=col_breaks,    # enable color transition at specified limits
          dendrogram="none",    # only draw a row dendrogram
          Colv=FALSE,           # turn off column clustering
          Rowv=FALSE,           # turn off row clustering
          keysize=25,
          lmat=rbind(c(2),c(3),c(1),c(4)),
          lhei=c(5,5,18,0),
          lwid=c(1))
dev.off()

# Colormap for prediction models
library(gplots)
library(RColorBrewer)
d3 = read.csv("predmap.csv", row.names = 1, header=T)
d4 = read.csv("predactual.csv", row.names = 1, header=T)
rownames = rownames(d3)
d3 = as.matrix(d3)
d4 = as.matrix(d4)
# creates a own color palette from blue to red
my_palette <- colorRampPalette(c("red","yellow","blue"))(n = 299)
# (optional) defines the color breaks manually for a "skewed" color transition
col_breaks = c(seq(0,0.03,length=100),   # for red
               seq(0.031,0.08,length=100),   # for yellow
               seq(0.081,1.0,length=100))   # for blue
# creates a 5 x 5 inch image
png("predheatmap.png",     # create PNG for the heat map
    width = 2.2*300,        # 5 x 300 pixels
    height = 14*300,
    res = 300,            # 300 pixels per inch
    pointsize = 9)        # smaller font size
heatmap.2(d3,
          cellnote = d4,        # same data set for cell labels
          main = "Classification Metrics", # heat map title
          notecol="black",      # change font color of cell labels to black
          density.info="none",  # turns off density plot inside color legend
          trace="none",         # turns off trace lines inside the heat map
          margins =c(12,10),     # widens margins around plot
          col=my_palette,       # use on color palette defined earlier
          breaks=col_breaks,    # enable color transition at specified limits
          dendrogram="none",    # only draw a row dendrogram
          Colv=FALSE,           # turn off column clustering
          Rowv=FALSE,           # turn off row clustering
          keysize=25,
          lmat=rbind(c(2),c(3),c(1),c(4)),
          lhei=c(5,5,18,0),
          lwid=c(1))
dev.off()

# select model.ls2 since it has minimum mean prediction error in the validation sample
model.best.y = model.ns1
yhat.test <- predict(model.best.y, newdata = data.test.std) # test predictions
# FINAL RESULTS
# Save final results for both classification and regression
length(chat.test) # check length = 2007
length(yhat.test) # check length = 2007
chat.test[1:10] # check this consists of 0s and 1s
yhat.test[1:10] # check this consists of plausible predictions of damt
ip <- data.frame(chat=chat.test, yhat=yhat.test) # data frame with two variables: chat and yhat
write.csv(ip, file="JP.csv", row.names=FALSE) # use your initials for the file name
# submit the csv file in Angel for evaluation based on actual test donr and damt values
```