ADTA 5230 Data Analytics II

Analysis and Prediction on Donations

Final Project Report: Group 6

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**Introduction/Business understanding/Analytics questions:**

Business savant Warren Buffet is credited with saying that the fundamental rules of business are “Rule No. 1: Never lose money. Rule No. 2: Never forget rule No.1” (Buffett & Clark, 2006)[[1]](#footnote-1). Presented with the information that sending everyone within the population a personalized donation request would result in a net loss of -$0.55 per requestion, we were hired to improve the cost-effectiveness of your direct marketing campaigns to prior donors. Because we cannot decrease the fixed $2 cost of making and sending a donation request, we believed that the biggest problem facing your organization is the lackluster response rate of 10%. Each non-response would result in a loss of $2. So, we sought out how to increase the overall response rates to drive up net donation dollars after cost. To achieve this, we asked ourselves many questions in our analysis, such as:

1. Who should we target?
2. What are the biggest factors that dictate whether a person donates?
3. What are the factors that most influence the dollar amount for a donation?

These questions were addressed by using developed classification models to predict the likelihood of donation for each potential donor, and then targeting those individuals with a higher probability of donating with the direct marketing campaign. By doing so, the non-profit organization could increase the response rate, and consequently, the expected net profit from the campaign. To better understand the factors that influence the amount of donations, we developed a prediction model that estimates the expected donation amount based on the predictor variables, which would help identify the factors that are most important for determining donation amounts. Lastly, the organization could use the developed models for future campaigns and overall fundraising strategies.

**Data understanding/EDA**:

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the dataset, “nonprofit”, presented to us, we utilized a software called SAS Enterprise Miner, which we used for the entirety of project, to assist us with our analysis. Before building models and drawing conclusions, we had to understand and investigate the data by conducting an exploratory data analysis (EDA). One of the first steps of EDA was to observe the data and obtain an understanding of the size and scope of the data. SAS Enterprise Miner has a node called “StatExplore” that we used to help us with this step. For the “nonprofit” dataset as seen in the figure above, the dataset contains 6002 records with 6002 non-missing and 0 missing values and that 2,994 of the 6,002 people or 50.12% in this dataset would be donors. For further analysis of the data, we had to partition the data for the construction and testing of our models; having 6,002 records in the dataset gave us enough records to do such partition. Additionally, we also looked at the breakdown and demographics of the 6,002 records in the “nonprofit” dataset. Based on the summary statistics found in the first figure, the most common/average statistics for a person in our 6,002 records included: was in the 4th income group; owned a house; lived in region “ter2”; was female; was in the 8th group for wealth rating, averaged $11.68 per donation; had a lifetime donation total of $115.80; donated $22.98 as their largest donation; donated $15.65 as their most recent donation, had a neighborhood home average of 183.905 in thousands of dollars; had a neighborhood average household income of 56.79 in thousands of dollars; had a neighborhood median household income of 43.95 in thousands of dollars; had 1.58 kids; had donated 6.31 months between their 1st and 2nd donations; had a neighborhood low income rate of 13.88%; had last donated 18.79 months ago; and had received 61.35 lifetime promotions.

Univariate Analysis:

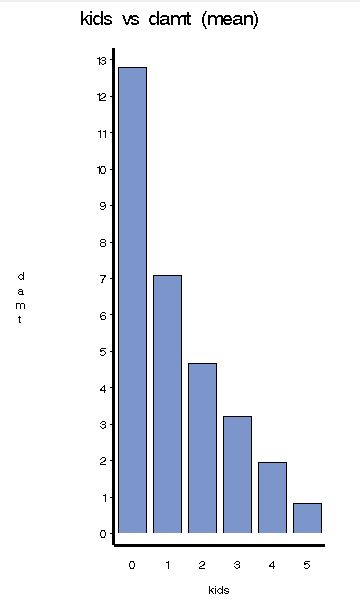
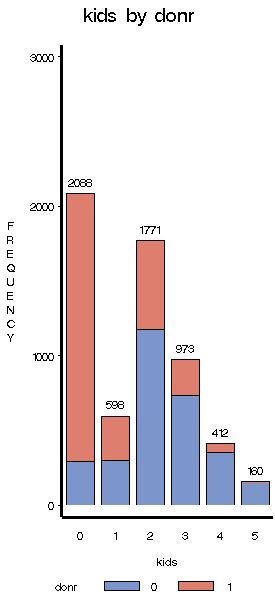
The information shown in the first figure also helped us with our analysis on the distribution within the variables of the “nonprofit” dataset. We looked at the results for skewness and kurtosis because they measure the shape of the variables’ distributions. The closer skewness and kurtosis were to zero than the data distribution would be more uniform; so, variables that had a high skewness and kurtosis such as “gifl”, which had the highest skewness of 7.180352 and kurtosis of 94.36788, indicated that the data within these variables contained extreme an extreme range of values. “gifl” had a large range of 639 considering its mean of 22.98 and standard deviation of 29.36. By looking at a univariate boxplot below for variable “gifl” we saw the full picture of its distribution, which showed the numerous circles outside the upper whisker representing outliers. For additional information about the distribution of other variables in the dataset, we have provided their associated boxplots for all interval variables in the appendix of this report. With the knowledge A picture containing chart

Description automatically generatedthat outliers existed, we knew that we had to address them before creating prediction models.

![Table

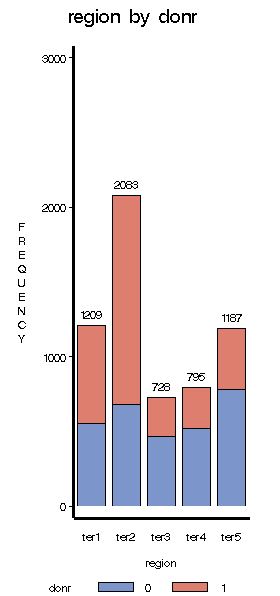
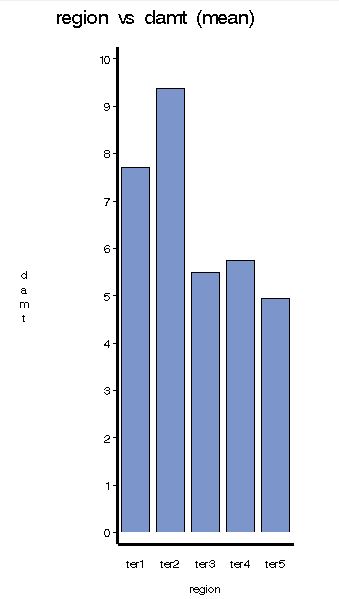
Description automatically 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Analysis:

The most notable correlation was the relatively strong negative correlation “kids” had with variable “DAMT”. When looking how to answer which factors dictate whether a person donates, we saw that the number of kids has the largest correlation to one of our target variables; because the correlation was negative, this would indicate that the higher the number of kids an individual has then the less likely chance that parent would donate.



Above we stated the negative correlation between “DAMT” and “kids” which led us to conduct an additional examination for this variable. As seen above, the figures compare variables “kids” to the target variables “Donr” and “DAMT”. In the left figure, the red represents the portion of the group that are donors while the blue represents non-donors. “0 kids” is the largest group among the 6,002 records. Astonishingly, this group also had the highest donation rate at 86.06%, 1,797 donors out of a possible 2,088. Because of the high donation rate, the average DAMT for “0 kids” was also the highest among the 5 groups at $12.78. Conversely, “5 kids” which was the smallest represented group containing 60 records also had the lowest donation rate at 6.25%, 10 donors out of a possible 160 and average DAMT of $0.81. With a quick glance of figure above, we could draw a conclusion that sending a donation request to those with 4 or 5 kids would prove unprofitable as both groups had an average DAMT under $2, which is the cost to mail out the requestion. However, this would eliminate the records of those with 4 or 5 kids that do donate; those with 4 kids who donate give an average of $13.30 and those with 5 kids who donate give an average of $13.00.

Looking at the “region” variable also provided us with additions insights on the demographics for the data. The “region” variable was depicted in the below figures. Region “ter2” was the most represented region in the dataset with 2083 records, accounting for 34.71% of the records; “ter2” also had the highest response/donor rate of 63.71%, 1402 donors out of 2083 records. Additionally, “ter2” had the highest average donation amount at $9.36. The number of records from “ter1” and “ter5” were almost equal; however, the response/donation rate for “ter1” is greater than “ter5”. Regions “ter3” and “ter4” were also of similar sizes to each other and have similar response/donation rates and average DMATs. Something that stood out was that “ter5” had more donors than “ter3” and “ter4” but “ter5” had the lowest average DMAT amongst the 5 regions.



Multivariate Analysis:

Chart

Description automatically generatedWith the data provided, we determined that there are two target variables, “donr” and “Damt”. “donr” was a classification response variable where “1” represented that the recipient of the donation request was a donor and where “0” represented that the recipient of the donation request was a non-donor. Our second target variable was “DAMT”, which was a prediction response variable that represented donation amount in dollars.

Looking over the variables within the dataset, we determined that the dataset does contain historical values for the target variables. These variables were “npro”, “gifdol”, “gifl”, “gifr”, “mdon”, “lag”, and “gifa” as they contained information regarding previous donations and donation amounts. Knowing our target variables, we started looking at the relationship between each of the variables with each other and with the target variables. Based on the variable correlation plot above, we determined which variables were correlated to each other based on the color of the respective boxes. The more red a box was then the more positive the correlation would be; the more gray a box was then the weaker the correlation; and the more blue a box was then the more negative the correlation. Variables such as “hv”, “incavg”, and “incmed” all had strong positive correlations to each other; conversely, “low” and these three variables had a relatively strong negative correlation. Variables such as “gifa”, “gifl”, and “gifr” also seemed to have a relatively strong positive correlation. Having groups of variables being highly correlated to one another can lead to the presence multicollinearity in the dataset, which would need to be addressed during the modeling.

**Data Preparation:**

To ensure the best and most accurate models, we first had to prepare the dataset for both regression models and classification models. Our first step in data preparation was splitting the data into three data groups: training, validation, and testing. Data splitting was conducted to assist with the evaluation and the accuracy of our models. The training data was used to help build the models. The validation data was used to tune the models’ hyperparameters. And the testing data was used to evaluate the final performances after the models have been tuned. All models for this project used a 70% split for training data, a 10% split for validation data, and 20% for testing.

Some models would be sensitive to outliers and the overall distribution of the data, so to ensure the accuracy of our models we had to transform and standardize our numerical variables in the dataset except for “Damt”. Models that factor distances between variables would inadvertently create bias based on variables with larger ranges which would lead to errors in the evaluation of the data. We used range standardization on our data to eliminate the biases created from variables with large ranges, such as “gifl” mentioned above. For this report, we used our range standardized data for the following models: linear regression and neural network.

As mentioned above in the EDA/ Data Understanding section, there was potential for multicollinearity in the dataset. Another part of our data preparation was to delete or reject one of the independent variables that was highly correlated with one or more independent variables during model building to predict the dependent variable. The independent variables of concern included the grouping of “gifa”, “gifl”, and “gifr” and the grouping of “hv”, “incavg”, and “incmed”. We created multiple models testing various variables combinations to eliminate the multicollinearity effect.

**Data Modeling**

Table

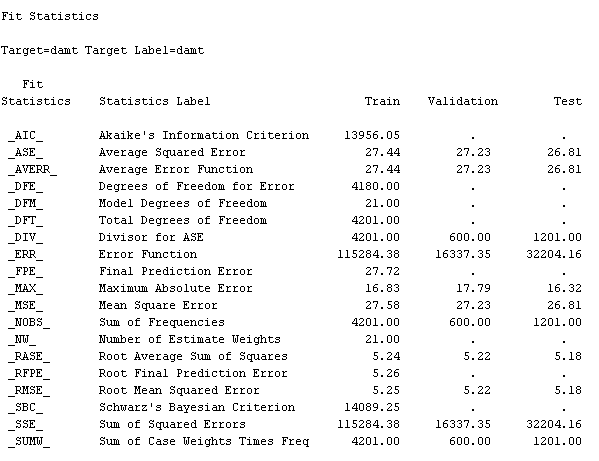
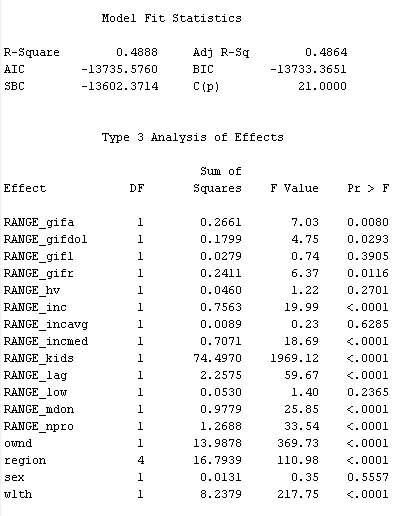
Description automatically generatedTable

Description automatically generated With our two target variables “donr” and “Damt”, we split our models into two categories: regression and classification. For our regression models, we used “Damt” as the target variable while rejecting the “donr” variable. Conversely, for our classification models, we used “donr” as our target variable while rejecting the “Damt” variable. Before each model we had to assign roles for each variable which can be seen in the figure below. After assigning the roles, we partitioned the data as mentioned above in the data preparation section.

A screenshot of a computer

Description automatically generated with medium confidenceThe regression models we utilized during the progression of the project included: linear regression, decision tree, gradient boosting, and neural networks. As stated above, the models for regression rejected the “donr” variable and used “Damt” as the target variable. For our regression models we measured the performance based off average squared error as it will always be a positive value and is the squared differences between the predicted values and the actual values. Our regression models can be seen in the Figure below. Throughout our process we also conducted Principal Component Analysis for the regression models.

We created linear regression models due to their simplicity for models measuring target and predictor variables. However, some of the drawbacks of a linear regression model included required standardization of the data, sensitivity to outliers and multicollinearity, and its limitation to modeling only linear relationships. After the range standardization of our interval variables, we ran the model which resulted in an average squared error (ASE) of 27.23 for the validation dataset and Adjusted Squared of 48.64% which represents that the independent variables could explain 48.64% of the variation in the target “Damt” variable. The regression model results are shown in the figure below.



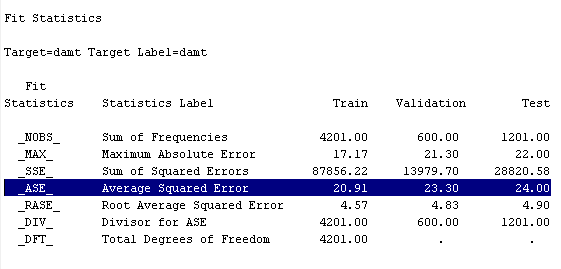
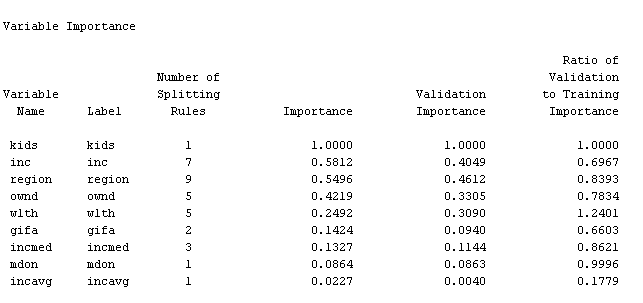
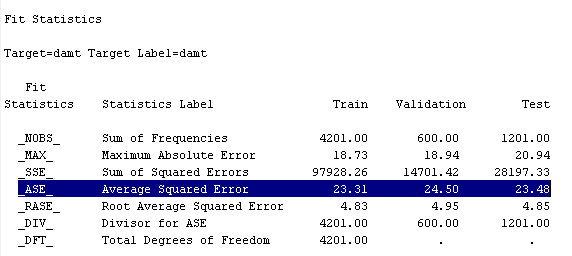
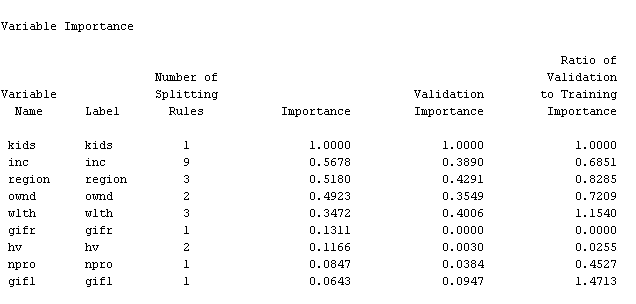
Diagram

Description automatically generatedAnother model created was a decision tree model because of its strength to highlight important variables, its ability to handle non-linear relationships, and its simplicity to interpret the model’s results. Despite the advantages, decision tree models were prone to overfitting and sensitivity to changes. We created two decision tree models: one had a maximum branch of 2 and depth of 6, seen below, and the other had a maximum branch of 6 and depth of 20.

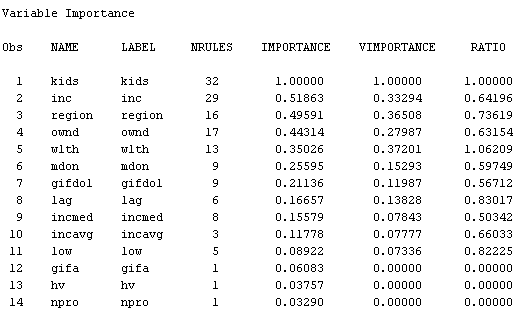
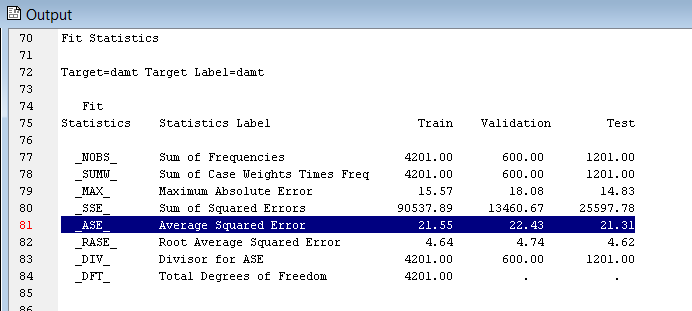
A picture containing graphical user interface

Description automatically generatedAs for the results for the 6 branch 20 deep model, they can be seen below.

The takeaways for both decision tree models were that “kids”, “inc”, and “region” were the most impactful independent variables in our dataset. Both models used “kids” for the first split. We looked at the ASE to compare the two models to determine which one would be better suited for the dataset; having a lower ASE would determine which model fits better. Because our 6 branch 20 deep model had an ASE of 23.30 on validation compared to the 2 branch 6 deep’s ASE of 24.50, we determined that the 6 branch 20 deep would be the better decision tree model. The measures on the left were for 2 branch 6 deep and the right were for 6 branch 20 deep.



We also created a gradient boosting model which performs like a decision tree model as it provides insight on the importance of variables. Additional benefits include its accuracy and its ability to handle both categorical and numerical data. However, like many other models, gradient boost would be susceptible to overfitting. After running the gradient boosting model, we once again were shown that variables “kids”, “inc”, and “region” held the most importance. As for the performance of the gradient boosting model, the ASE for the validation data was 22.43.



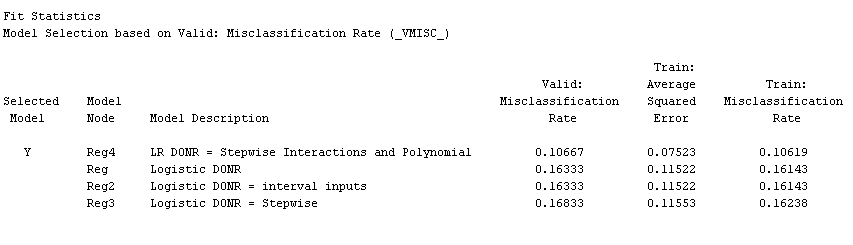
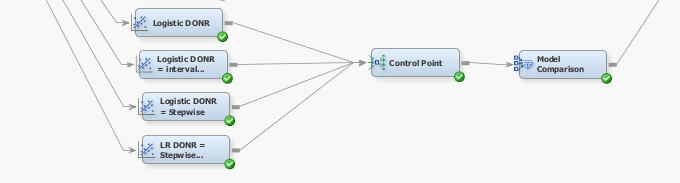
The last model we used for our regression models targeting “Damt” was a neural network model. Using a neural network had certain advantages given the nature of this dataset as neural networks are designed to quickly wrangle datasets of larger sizes. However, they are not without their disadvantages as neural networks could be affected by overfitting. We created three different neural network models with one model using backpropagation as the training technique and all used average error for the model selection criteria. We created one model with 3 neurons, one model with 16 neurons, and we created the third model with 32 neurons. Based on the results on the validation set, the neural network model with 16 neurons performed the best as it had an ASE of 19.15; the neural network model with 32 neurons had an ASE of 20.29 while the neural network model with 3 neurons performed slightly worse with ASE of 20.63. The results can be seen in the image below.

Diagram

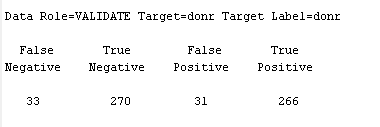
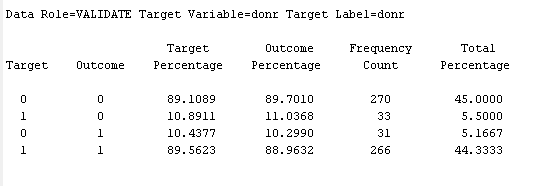
Description automatically generatedTable

Description automatically generatedThe classification models we utilized during the progression of the project included: logistic regression, decision tree, gradient boosting, random forest, neural networks, and Bayesian network. As stated above, the models for classification rejected the “Damt” variable and used “donr” as the target variable. To gauge the performance of the models, we used misclassification rate and the confusion matrix. For the confusion matrix, a true positive meant the model predicted the person would be a donor correctly; a false positive meant the model predicted that a person be a donate incorrectly; a true negative meant the model predicted the person would not be a non-donor correctly; and a false negative meant the model predicted the person would not be a non-donor incorrectly. Classification models would need to have a low misclassification rate. See below for the all the classification models we have implemented.

The first model that we implemented to model the classification data was logistic regression. Logistic regression would not require data to be standardized, would be very easy to implement, would be able to handle many independent variables, and it would produce probabilities of a binary outcome, which for this project is 1 for donor and 0 for non-donor. Some drawbacks of logistic regression would be its susceptibility to overfitting and multicollinearity amongst the variables. The logistic regression models we implemented include standard logistic regression, logistic regression considering only interval variables, stepwise logistic regression, and logistic regression with stepwise interactions and polynomial.



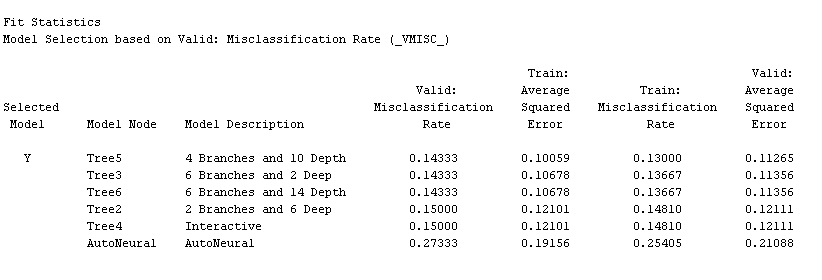
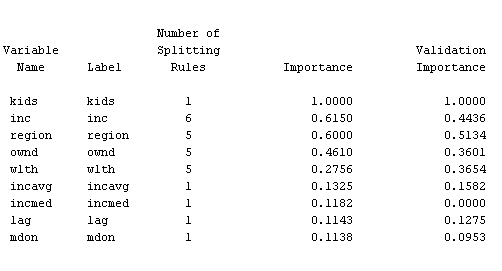
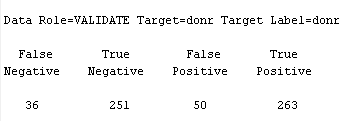
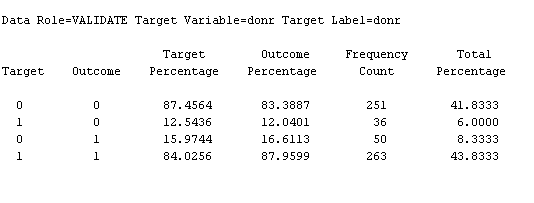
The best performing logistic regression model was the logistic regression with stepwise interactions and polynomial as it had a misclassification rate of 0.10667 for the validation data. For this model, it predicted that 44.33%, 266 of 600, in our validation dataset would be correctly classified as donors and 45.00%, 270 of 600, would be correctly classified as non-donors. Additionally, this model would predict 5.50%, 33 of 600, of the records being incorrectly classified as a non-donor while 5.17%, 31 of 600, being incorrectly classified as a donor. These results for the classification table and confusion matrix can be found below.



Diagram

Description automatically generatedWe once again used a decision tree model because of its ability to handle numerical and categorical variables. Similar to the decision tree models to predict “Damt”, we used decision tree models that were 2 branch 6 deep and 6 branch 20 deep; however, we also created models that were 4 branch 10 deep and 6 branch 14 deep. We created several models to tune and find which configuration produced the best results for this type of model.

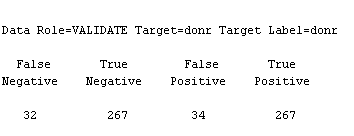
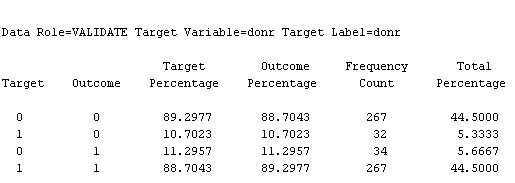
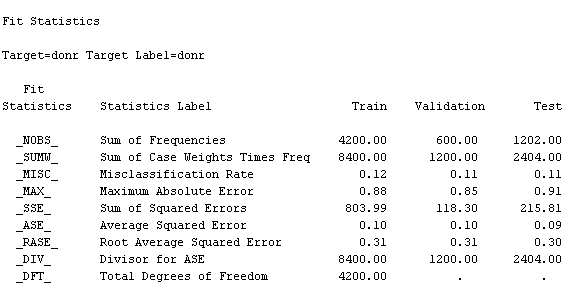
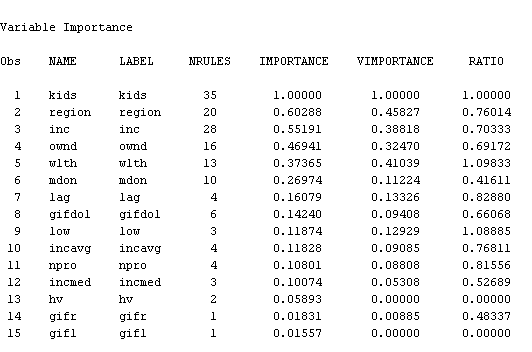
All models had the first split using “kids”; for variable importance, “kids”, “inc”, and “region” were the top three except the 2 branch 6 deep model where “kids”, “ownd”, and “region” were the top three. Comparing these four decision tree models, the 4 branch 10 deep, 6 branch 20 deep, and the 6 branch 14 deep models all had a validation misclassification rate of 0.14333. However, we observed minimal variation in the training set, so we decided to proceed with the 4 branch 10 deep branch for the classification chart confusion matrix because it had the lowest training misclassification rate of 0.13000. For the 4 branch 10 deep model, it predicted that 43.833%, 263 of 600, in our validation dataset would be correctly classified as donors and 41.83%, 251 of 600, would be correctly classified as non-donors. Additionally, this model would predict 6.00%, 36 of 600, of the records being incorrectly classified as a non-donor while 8.33%, 50 of 600, being incorrectly classified as a donor.



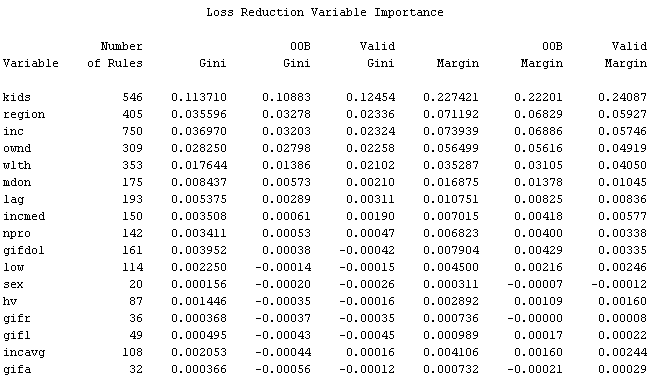
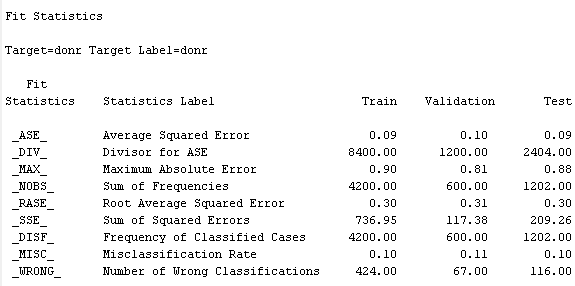
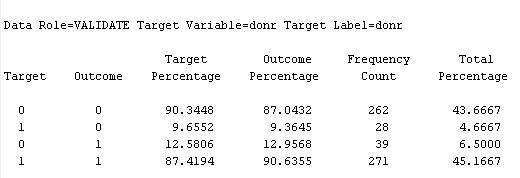
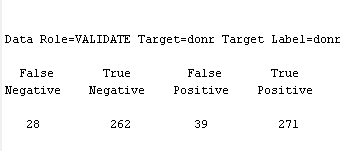
Diagram

Description automatically generated Another three classification models we implemented were gradient boosting, random forest, and Bayesian network. We looked into each of these models in detail below.

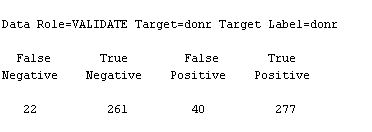
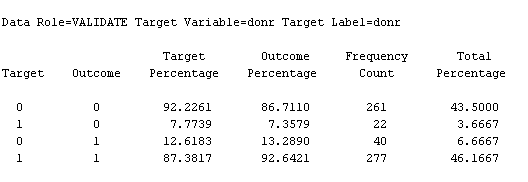
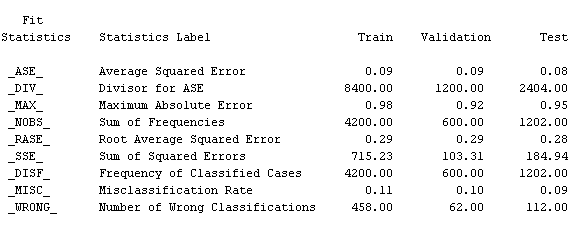
Gradient boosting was selected again because it can also handle numerical and categorical variables. This model once again showed that the three most important independent variables were “kids”, “inc”, and “region”. Our gradient boosting model had a misclassification rate of 0.11 and correctly predicted that 44.50%, 267 of 600, in our validation dataset would be donors. Coincidently, it also correctly predicted that 44.50% would be non-donors. It also predicted 5.67%, 34 of 600, would be incorrectly classified as donors and 5.33%, 32 of 600, would be incorrectly classified as non-donors. The variable important table, classification table, and event classification table can be seen in the figure below.



Random forest models also highlighted which variables were most important. Additional benefits included being unaffected to outliers, not requiring standardization of the data, and being able to reduce variance and the effect of overfitting. The primary drawback of random forest models would be its tendency to overfit. For our random forest model, it produced the best model of 1 tree with 41 leaves; this model had a validation misclassification rate of 0.19. Regarding variable importance, “kids”, “inc”, and “region” were once again the top three. Additionally, this model predicted that 45.17% or 271 of 600 in our validation dataset would be correctly classified as donors; 43.67% or 262 of 600 would be correctly classified as non-donors. It also predicted 6.50%, 39 of 600, would be incorrectly classified as donors and 4.67%, 28 of 600, would be incorrectly classified as non-donors. The variable importance table, classification table, and event classification table can be seen in the figure below.



Another classification model we utilized was a Bayesian network model. Some of the advantages of a Bayesian network model would be its high goodness of fit for predicting a future event based on history, which in our case would be “donr”. One of the disadvantages of a Bayesian network model would be its complexity and its sensitivity to the independent variables being modeled, which could lead to bias. For our Bayesian network model, we had a validation misclassification rate of 0.10. This model predicted that 46.17%, 277 of 600, of the validation dataset would be correctly classified as a donor while 43.50%, 261 of 600, would be correctly classified as a non-donor. Additionally, the model predicted that 6.67%, 40 of 600, would be incorrectly classified as donors and 3.67%, 22 of 600, would be incorrectly classified as non-donors. The model’s fit statistics, classification table, and event classification table can be seen below.



Lastly, we implemented several neural networks because they could also be used for both regression and classification. We created three different neural network models: one with 3 hidden neurons, one with 16 hidden neurons, and one with 22 neurons.

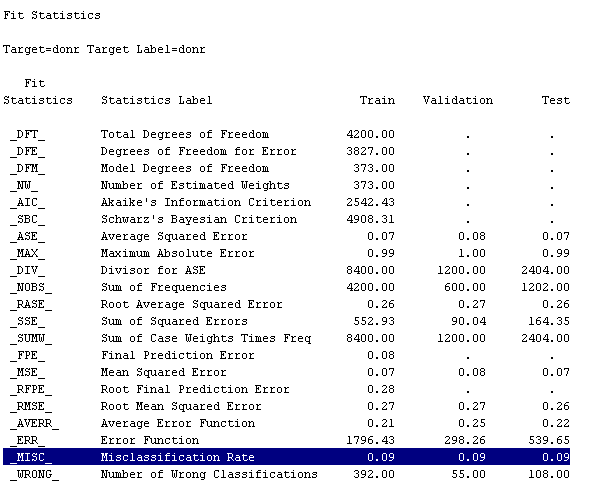
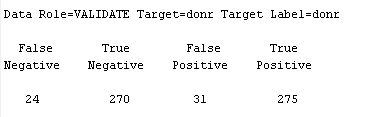
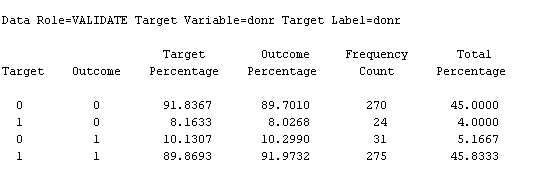
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**A close-up of a document

Description automatically generated with low confidence**To properly implement a neural network model, we had to standardize the data. We determined that the ideal number of neurons in the hidden layer was 16 neurons as it produced the best/lowest validation misclassification of 0.09167.

In the neural network with 16 neurons model, 45.83%, 275 of 600, of the validation data would be classified correctly as a donor while 45.00%, 270 of 600, would be classified correctly as a non-donor. Additionally, 5.17%, 31 of 600, would be incorrectly classified as donors and 4.00%, 24 of 600, would be incorrectly classified as non-donors. The model’s fit statistics, classification table, and event classification table can be seen below.



**Evaluation**

To start this project, we asked ourselves the following questions:

1. Who should we target?
2. What are the biggest factors that dictate whether a person donates?
3. What are the factors that most influence the dollar amount for a donation?

To find the answers to the first two questions we looked at the results from our classification models. We evaluated the models and have provided our findings below. The evaluation criteria was based on the misclassification rate because the overall performance of the model across all classes would be measured as opposed to focusing on the individual classes. The misclassification rate also would represent the proportion of records in the dataset that was misclassified by the model. To avoid the problems associated with overfitting, we compared the misclassification rate of the training dataset to the misclassification of the validation dataset to ensure there would be no significant difference. For evaluating the best model, we considered only the misclassification rate on the validation data for all the models. We had four sub-sections of classification models.

A screenshot of a computer

Description automatically generated with low confidenceThe first section consisted of decision models, which can be seen in the image below.

A picture containing text, font, screenshot, receipt

Description automatically generated

A picture containing line, diagram, white, screenshot

Description automatically generatedOf all the decision tree models that we implemented, the decision tree with 4 branches and 10 depth provided us with the best validation misclassification rate of 0.1433. This model had a training misclassification rate of 0.1300 which showed that there was no overfitting with the model and would provide accurate predictions on unseen data.

A close-up of a document

Description automatically generated with low confidence The next sub-section of models included the neural network models, that can be seen above. Based on the validation misclassification results below, we determined that the best neural network model had 16 neurons in the hidden layer.

A picture containing line, diagram, white, parallel

Description automatically generated This model had a validation misclassification rate of 0.09167; this model did not experience overfitting because there was not a significant difference between the validation and training misclassification rates. The training misclassification rate for the 16-neuron model was 0.09333 and can be found in the image below.

A close-up of a document

Description automatically generated with low confidence The third sub-section of classification models consisted of gradient boosting, random forest, and Bayesian network models. A display of this sub-section can be seen above. Comparing these models together resulted in us determining that the Bayesian network was the best performing model out of this group.

A screenshot of a computer

Description automatically generated with low confidenceAs seen above, the validation misclassification rate for the Bayesian network model “HP BN Classifier” was 0.10333. Having a training misclassification rate of 0.10905 showed that there was not a significant difference between the misclassification rates meaning there was no overfitting.

A close-up of a document

Description automatically generated with low confidence The last sub-section of our classification models was our logistic regression models. This sub-section can be seen in the image above. Based on the model comparison between the logistic regression models the best preforming model was the logistic regression model with stepwise interactions and polynomial.

As seen in the image above, the logistic regression model with stepwise interactions and polynomial had a validation misclassification rate of 0.10667. The difference between the validation and training misclassification was minimal so there was no overfitting.

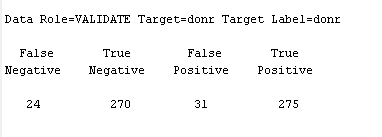
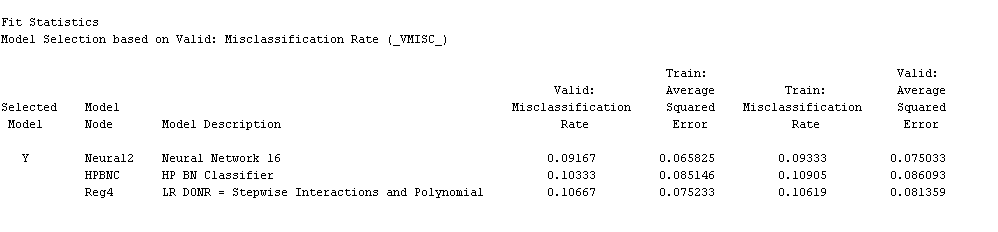
A screenshot of a computer

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A close-up of a receipt

Description automatically generated with low confidence After determining the best model within each sub-section, we conducted an additional model comparison amongst these models. The detailing of the final model comparison can be seen above. Our evaluation criteria remained the same for this model comparison as we were looking to see which model had the lowest/best misclassification rate on the validation data. The results of this model comparison can be seen below.

Based on the preceding image, the neural network model with 16 neurons in the hidden layer was our best performing classification model with a validation misclassification rate of 0.09167. Because of these results, we used the confusion matrix of the neural network model with 16 neurons to ultimately predict the number of people who would be a donor.



So, the final classification model selected was the neural network model with 16 neurons in the hidden layer that had a misclassification rate of 0.09167 for the validation data. The above confusion matrix showed that out of 600 observations, there were 299 donors and 301 non-donors. This model correctly identified 275 donors and 270 non-donors; however, it misclassified 24 donors as non-donors and 31 non-donors as donors.

To further evaluate this model's performance, we used the following statistical criteria: sensitivity, specificity, precision, accuracy, and F1 score. The sensitivity of the model was 0.9197 which indicated that the model correctly identifies 91.97% of the donors. The specificity of the model was 0.8970 which indicated that the model correctly identifies 89.70% of the non-donors. The precision of the model was 0.8987 which indicated that when the model predicts that a person will donate there is an 89.87% chance that the specific person will donate. The accuracy of the model was 0.9083 which indicated that the model correctly classified 90.83% of the records in the dataset. The F1 score of the model was 0.9091 which is a harmonic mean of precision and sensitivity. The calculations for these statistical criteria can be found below.

Sensitivity = TP/(TP+FN) = 275 / (275 + 24) = 0.9197

Specificity = TN/(TN+FP) = 270 / (270 + 31) = 0.8970

Accuracy = (TP + TN) / (TN + FP + FN + TP) = (275 + 270) / (275 + 270 + 24 + 31) = 0.9083

Precision = TP / (TP + FP) = 275 / (275 + 31) = 0.8987

F1 Score = (2 \* Precision \* Sensitivity) / (Precision + Sensitivity)

F1 Score = (2 \* 0.8987 \* 0.9197) / (0.8987 + 0.9197) = 0.9091

Because this dataset provided had oversampled the number of donors, we had to reweigh our model to find the true sensitivity, specificity, precision, accuracy, and F1 score. In the dataset you have provided, donors made up 49.88% of the sample but were only 10% of the whole data; conversely, non-donors made up 50.12% of the sample but represented 90% of the whole data. To reweigh the data, we performed the following calculations:

The sampling factor for actual donors is 49.88/10 = 4.98.

The sampling factor for actual non-donors is 50.12/90 = 0.556.

Using these calculations, we created the following adjusted validation confusion matrix.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Actual Non-Donors (0) | Actual Donors (1) | Total |
| Predicted  Non-Donors (0) | 270 / 0.556 = 485.612 | 24 / 4.998 = 4.802 | ~490 |
| Predicted  Donors (1) | 31 / 0.566 = 55.755 | 275 / 4.988 = 55.132 | ~110 |
| Total | ~540 | ~60 | 600 |

With our new reweighted confusion matrix, we reassessed our neural network with 16 neurons with the same statistical criteria as above, which are sensitivity, specificity, precision, accuracy, and F1 score. The calculations for these statistical criteria can be found below:

Sensitivity = TP/(TP+FN) = 55.132/ (55.132+ 4.802) = 0.9191

Specificity = TN/(TN+FP) = 485.612 / (485.612 + 55.755) = 0.8971

Accuracy = (TP + TN) / (TN + FP + FN + TP)

Accuracy = (55.132 + 485.612) / (55.132 + 485.612 + 4.802+ 55.755) = 0.9083

Precision = TP / (TP + FP) = 55.132 / (55.132 + 55.755) = 0.4973

F1 Score = (2 \* Precision \* Sensitivity) / (Precision + Sensitivity)

F1 Score = 2 \* (0.4973 \* 0.9191) / (0.4973 + 0.9191) = 0.6454

The reweighted sensitivity of the model was 0.9191 which indicated that the model correctly identifies 91.91% of the donors. The specificity of the model was 0.8971 which indicated that the model correctly identifies 89.71% of the non-donors. The precision of the model was 0.4973 which indicated that when the model predicts that a person will donate there is a 49.73% chance that the specific person will donate. The accuracy of the model was 0.9083 which indicated that the model correctly classified 90.83% of the records in the dataset. The F1 score of the model was 0.6454.

To find the answers to the last question we looked at the results from our regression models. We evaluated the models and have provided our findings below. The evaluation criteria was based on the average squared error (ASE) because it would measure the quality of the relationship between the dependent variable with the independent variables. To measure a model, the ASE would take the average of the squared differences between the predicted and actual values. For evaluating the best model, we only considered the ASE on the validation data for the A picture containing screenshot, line, text, diagram

Description automatically generatedmodels. During our modeling process, we created two sub-sections of regression models.

The first sub-section consisted of a stepwise logistic model, decision tree models, a gradient boosting model, a random forest model, and a high-performance regression model. This sub-section can be seen in the image above. Of all the models in this sub-section, the high-performance regression model provided us with the best/lowest ASE of 18.1269 for the validation dataset. The model comparison for this sub-section can be seen in the image below.

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A diagram of a network

Description automatically generated with low confidenceAs for the second sub-section of regression models, this group consisted of various neural network models: one with 16 neurons, one with 3 neurons, and one with 32 neurons. Note that these neurons were in the hidden layer of the neural networks. This sub-section of neural networks can be seen in the depiction below.

A picture containing text, screenshot, font, number

Description automatically generatedBased on the model comparison for the neural networls, the best performing model was the neural network with 16 neurons in the hidden layer. This model had the lowest validation ASE at 19.1518. The model comparison for this sub-section can be seen in the image below.

After determining the best model in both sub-sections of the regression models, we conducted an additional model comparison amongst these two models, the high-performing regression model and the neural network with 16 neurons. For the overall structure of our regression model analysis, we included a depiction below.

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A close-up of a computer error

Description automatically generated with low confidenceThe detailing of the final model comparison can be seen below. Our evaluation criteria remained the same for this model comparison as we were looking to see whether the high-performing regression model or the neural network with 16 neurons had the lowest/best ASE rate on the validation data. The results of this model comparison can be seen below.

Based on the image above, the neural network model with 16 neurons in the hidden layer beat out the high-performing regression model and proved to be our best performing classification model. This neural network model had a validation ASE of 19.1518. Because of these results, we looked at the variable importance to see which variables had the biggest impact on the target variable “Damt”. In order to achieve this, we utilized a score and reporter node in SAS Enterprise Miner.

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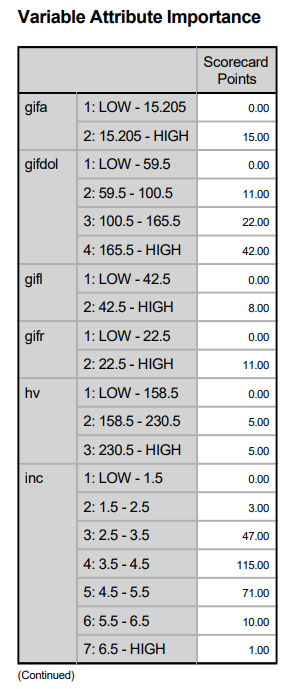
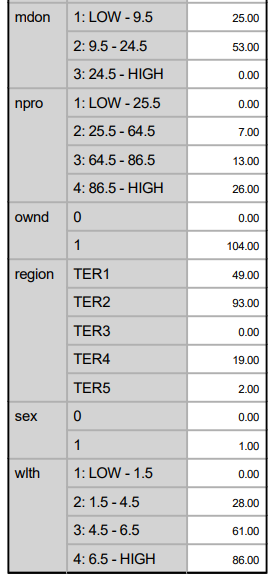
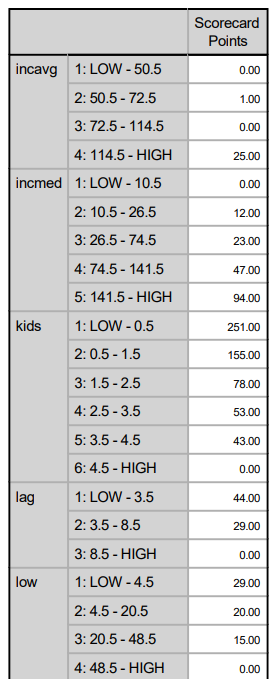
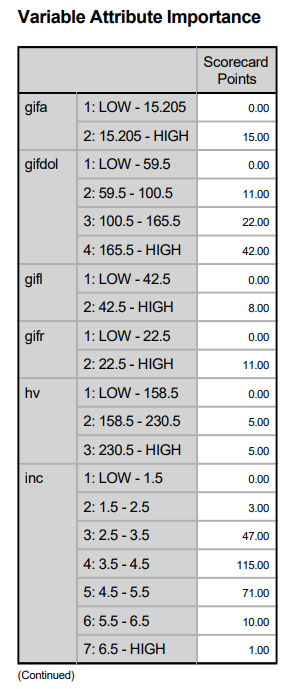
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After choosing the reporter node to report on “summary”, we were A picture containing text, screenshot, rectangle, diagram

Description automatically generatedpresented with the following information about the model’s variables.

As seen in the chart above, the “kids” variable had the highest variable importance. The remaining top five variables of highest importance were “inc”, “ownd”, “region” and “wlth”.

The variable importance of the values within each variable can be seen above. The key takeaways are noted here. The variable importance of “gifdol” increased as the dollar amount of lifetime gifts to date increased. The three groups with the highest variable importance within “inc” were “2.5 – 3.5”, “3.5” – 4.5”. The variable importance of “incmed” increased as the variable importance of “kids” significantly decreased as the number of kids increased. The “LOW – 0.5” group in the “kids” variable produced the largest variable importance overall of 251; the variable importance for “kids” proceeded to decrease as the number of kids increased. As “lag” and “low” increased, the variable importance of their values decreased. The grouping of “9.5 – 24.5” number of months since last donation had the largest variable for “mdon”. As “npro” increased, its variable importance increased as well. Owning a house had a variable importance of 110, which is the 4th highest among every grouping, while not owning a house had 0 variable importance. Regions “Ter2” and “Ter1” had significantly higher variable importance compared to the other three regions. The group with a wealth rating of “4.5-6.5” had the highest variable importance among “wlth”. Variables that had little (25 or lower variable importance) to no variable importance were “gifa”, “gifl”, “gifl”, “hv”, “incavg”, and “sex”.



**Deployment**

We determined, based on our thorough analysis of the various models, that the neural network model with 16 neurons was the best fitting and most accurate model for both classification and regression to predict our target variables “donr” and “Damt”, respectively. We will be using this model to predict for the Non-Profit Score dataset. Based on this neural network model predictions on ‘donr’, 434 people are likely to donate out of 2,007 people in the score dataset in response to the direct marketing campaign. This translated to an effective response rate of 21.6%. We also concluded that the regression neural network model with 16 neurons was the best performing regression model to predict our regression target variable “Damt” for the Non-Profit Score dataset. This model predicted the average donation amount of all donors to be $10.75 with a standard deviation of 3.42. The highest predicted donation was $18.86; the lowest predicted donation was $1.29; and the median amount donated was $10.64.

Assuming the cost per mailing is $2, if we were to send to all 2,007 people in the score dataset, your cost would be $4,014. Based on the sample of 2,007, we calculated the total profit from the predicted 434 donors and multiplied it by the average donation amount from the sample, so 434 x $10.75 = $4,665.50. This resulted in an expected net profit of $4,665.50 - $4,014 = $651.50. However, it would be more profitable to only target those predicted to donate. If instead your organization were to only send out the personalized donation requests to people who were predicted to donate, your cost would be $868. So, the expected total of donations would remain $4,665.50, calculated by 434 \* $10.75. Subtracting the $868 cost of mailing from total donations $4,665.50 gave us an expected total profit of $3,797.50. See below for a display of how we aligned the predicted donors and their predicted donation amounts.

A screenshot of a table

Description automatically generated with low confidence

If we wanted to further narrow the model, targeting those whose donation amount is within two standard deviations of the mean could result in an even more profitable campaign. After all, some who are predicted to donate may only donate a very small amount, such as $2, which would result in a net loss due to the cost of mailing. For this new model, we eliminated predicted donors who would donate less than $2.00 from our mailing list and not decrease the size of the sample significantly. Instead, what if we targeted those who are predicted to donate a minimum of $4. There are only 9 individuals projected to donate less than that. We can save another $18 on shipping costs if we do not send them any campaign marketing materials, as well as raise the average donation amount to $10.93.

**Conclusion**

As mentioned in the introduction, the three questions we wanted to answer for this project included:

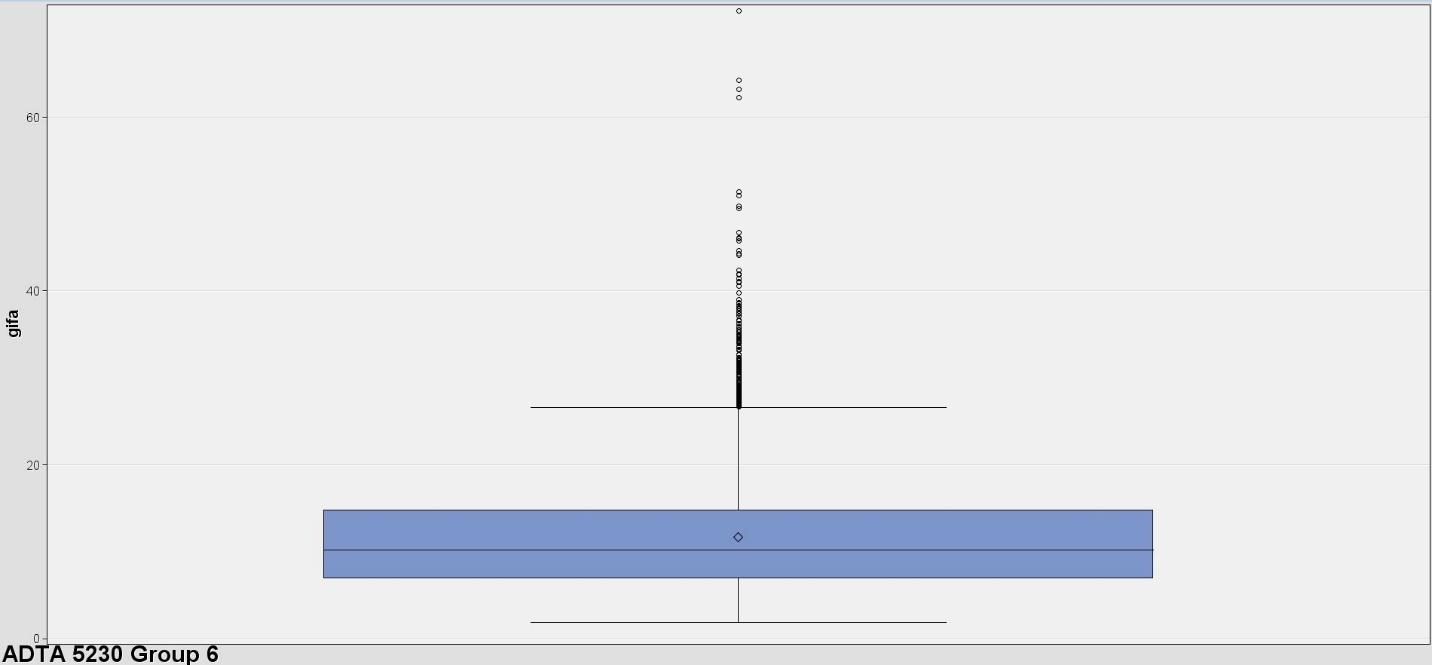
1. Who should we target?
2. What are the biggest factors that dictate whether a person donates?
3. What are the factors that most influence the dollar amount for a donation?

Our research suggested that your organization should target the individuals who were predicted to donate. We determined that the variables that had the greatest affect were “kids”, “inc”, “ownd”, “region” and “wlth.” So ideally, you would be looking for someone who has 0 kids, was in category 4 for household income, owns a house, lives in region “ter2”, and has a wealth rating above 6.5. A limitation of this data was the low significance of the variables with the target variables, the strongest being a moderately negative correlation between kids and DONR and DAMT. More information could be gathered about the population to learn more about the demographics of potential donors. These factors could include what charitable contributions have been made to other organizations, or how the allocation of the charitable proceeds impacts potential donors, etc. Another limitation of the data was the outliers, which can cause the data to skew. The outliers mostly existed in the areas of income and donation history, and future research could be conducted on the possible causes of variance between why a donor may donate much more or much less compared to past donations. However, we believe these outliers did not affect our overall results in a significant way.

In conclusion, our model produced a response rate of 21.6% as 434 out of the 2007 people in your sample compared to your population response rate of 10%. These predicted donors had an average donation amount of $10.75 compared to the population’s average donation amount of $14.50. So based on the score data, your organization would see a profit of $3,797.50 if you sent donation requests to our models’ 434 predicted donors.

Appendix

Boxplots for Univariate Analysis



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A screenshot of a computer

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A screenshot of a computer

Description automatically generated with low confidence

Overview of our Principal Components Analysis

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1. Buffett, M., & Clark, D. (2006). The Tao of Warren Buffett: Warren Buffett’s Words of Wisdom: Quotations and Interpretations to Help Guide You to Billionaire Wealth and Enlightened Business Management. [↑](#footnote-ref-1)