UNIVERSITY OF NORTH TEXAS

Dr. Quintanar [ADTA 5230 Fall 2023]

Final Project Report

Predictive Modeling for Nonprofit Donations

GROUP:13

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1 Introduction

The nonprofit organization is facing a big challenge in making their direct marketing to past donors more cost-effective. Recent data shows that about 10% of people respond to their campaigns, and those who do donate around $14.50 on average. However, each campaign costs $2.00 for making and sending, which leads to a loss of -$0.55 for each mailing. To tackle this issue, the organization wants to get better at predicting which people are likely to donate. They plan to use data from their latest campaign to build a model, so they do not take a loss. The goal is to send the campaign to people who are more likely to donate and more likely to donate bigger amounts to achieve a net profit.

The dataset provided an opportunity to explore patterns within a nonprofit organization's donor database to predict future donations. The primary business question addressed was whether it's possible to accurately predict whether an individual would donate (DONR variable), and the potential donation amount (DAMT variable) based on demographic, financial, and donation history as well as predicting the best model for the project. good interpretation here

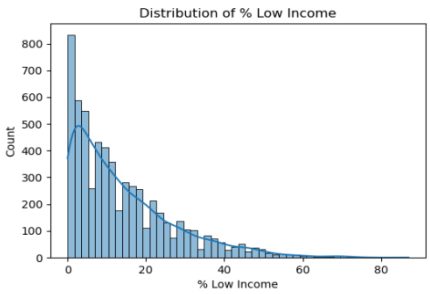
2 Exploratory Data Analysis (EDA)

The first analysis included figuring out how the dataset was organized, finding any missing values, and evaluating the distribution of the data. The dataset includes historical donation statistics, income indicators, and a variety of demographic characteristics. Several columns had missing values, which were handled by inputting the mean of the numerical features. Histograms and count plots were two important visualizations that provided information about the distribution of categories and numerical variables. The data set provided an opportunity to explore patterns within a nonprofit organization's donor database to predict future donations. The primary business question addressed was whether it's possible to accurately predict whether an individual would

donate (DONR variable), and the potential donation amount (DAMT variable) based on demographic, financial, and donation history.

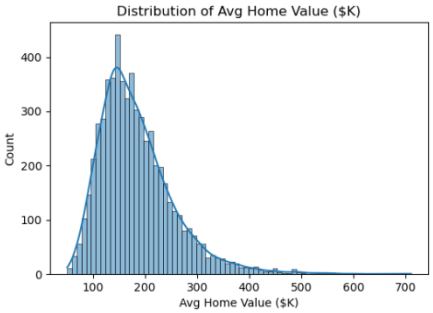
2.1 EDA analysis with Business questions

2.1.1 How does the percentage of low income affect the likelihood of making a large donation?



The graph shows the distribution of donations by percentage of low income. The graph is right skewed, which means that most donations are relatively small, but there are a few exceptionally large donations. Donations are more likely to be made by people who are lower in income than those who are higher in income.

2.1.2 Does the avg home value determine the amount of donations?

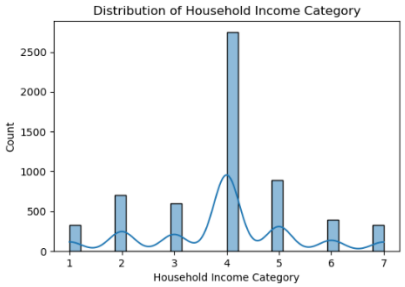


The donation distribution depending on average home value is displayed in the graph. The graph indicates that most donations come from homeowners whose average property worth is between $200,000 and $300,000. Additionally, a sizable portion of donations come from individuals whose

Again, you are one of the only groups to focus y

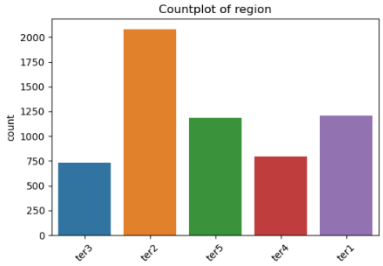
homes are worth between $300,000 and $400,000. People who own properties outside of or above this range, however, donate much less frequently.

2.1.3 What is the average donation amount for each income category?



The average donation amount varies by income category. Households in the $2,000-$2,500 income category make the largest average donations. Households in the $500-$1,000 income categories make the smallest average donations.

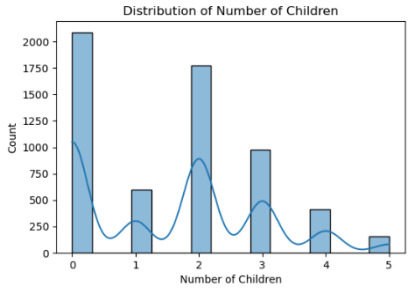
2.1.4 What are the key takeaways from the distribution of donations by region?



The chart shows the number of donations by region. The regions with the highest number of donations are ter2, ter1and5 with over 1250 donations e. Ter3and ter4 have the fewest donations, with less than 1000 donations each. (we considered geographic regions ter1, ter2, ter3, ter4, ter5)

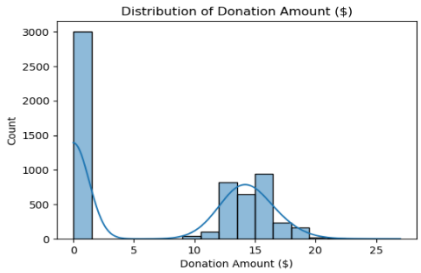
discussion of what these values represent would be helpful for the reader to frame th

2.1.5 Do you think families with more children are more likely or less likely to donate to charity? Why?



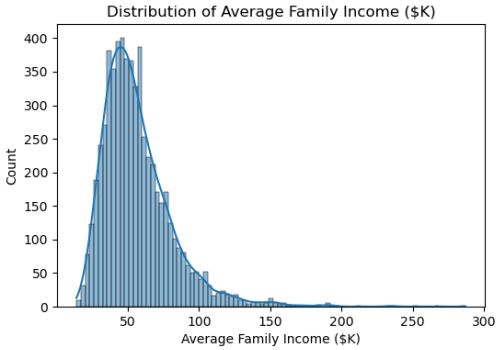
The graph shows that the majority of families have 0 or 2 children, followed by families with 3 children. The number of families with 1 or more than 4 children decreased significantly. Families with 2 children may be more likely to have a sense of civic responsibility and feel a need to give back to their community, which could lead to higher donation amounts overall. Families with more than 2 children may have less disposable income, which could lead to lower donation amounts.

2.1.6 What are general Insights of the donation amount distribution?



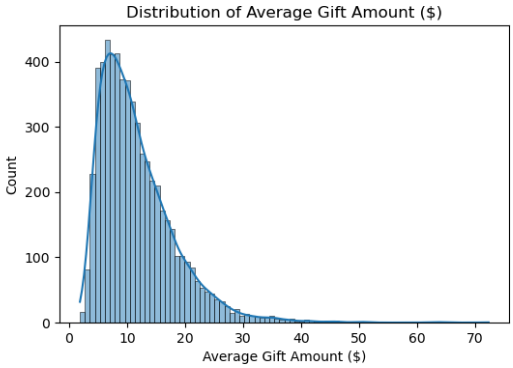
The graph shows the distribution of donation amounts. The donation amounts range from $0 to $3000, with the most common donation amount being between $10 and $20. There is a long tail of larger donations, with a few donations over $1000.

2.1.7 What is the distribution of average family income for the donations?



The graph shows the distribution of donation amounts based on the average home value. The graph shows that most donations are made by people who have homes with an average value of $30,000-$70,000. However, the number of donations made by people with homes above or below this range decreases significantly.

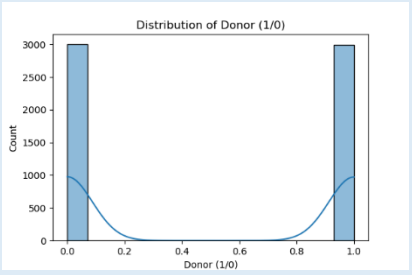
2.1.8 What are the insights for the average gift amount?



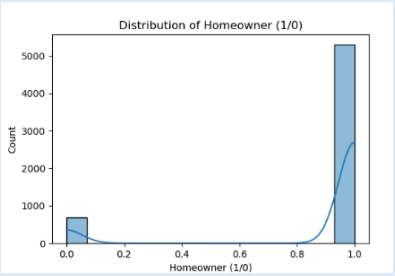
The graph shows the distribution of average gift amount by donation count. The most common average gift amount is around $10, but it can be as low as $0 or as high as $400.

The graph is skewed to the right, meaning that there are more donations with a lower average gift amount than donations with a higher average gift amount. This is because there are many small donations, but there are also a few exceptionally large donations.

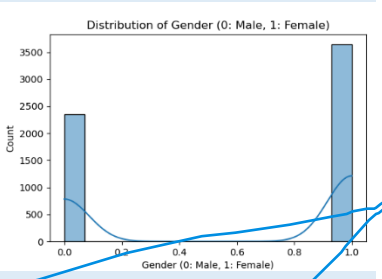
2.2 EDA plots



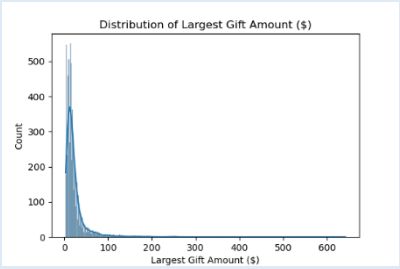
This graph showes there are equal number of donators and non donators



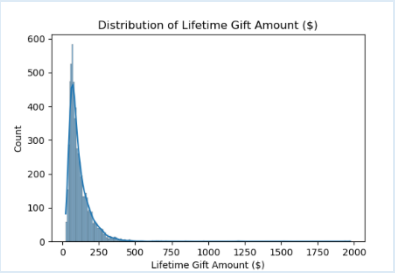
This graph shoes that there are more number of homeowners



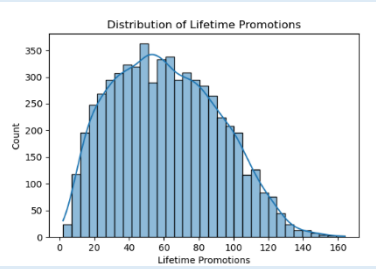
This graph is left skew and tells there are enormous number of females. for formal



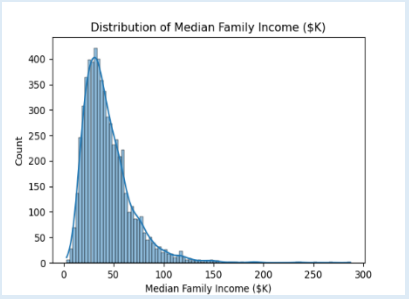
This graph is right skew and shows that large amount of gifts are between 0-100$.



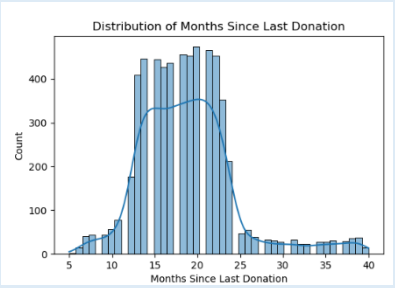
This graph is right skew and showes that lifetime gift amount are more in between 0- 250$.



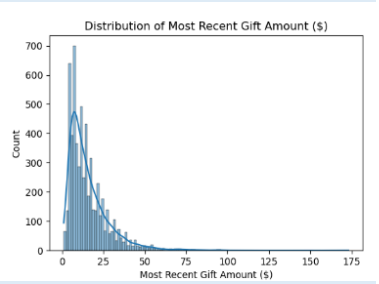
This graph is right skew the count is decreasing as the lifetime promotions are increasing.



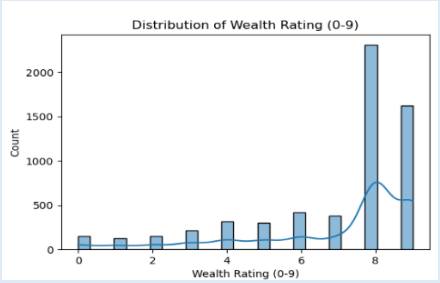
The median family income is right skew has more count in between 0-100



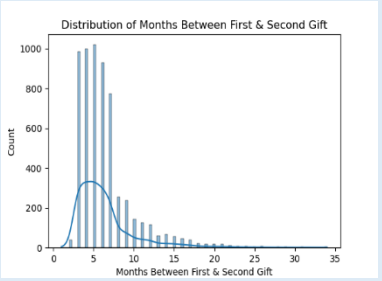
The past dontation are high from in15-25 months.



This graph shows a right skew the count is less for larger gift amounts.



With the count of more than 2000 wealth rating 8 are more.



There is more 5-to-10-month difference first and second gift.

3 Data Preparation

To prepare the data, it was necessary to remove unnecessary columns, deal with missing values (which were none), and use one-hot encoding to encode categorical variables. For the purposes of classification (DONR) and regression (DAMT), the dataset was divided into predictors (ID, DONR, and DAMT excluded) and target variables. Numerical features underwent standard scaling to get the dataset ready for modeling.

3.1 Dropping Unnecessary Columns:

The rationale behind excluding columns such as 'ID,' 'donr,' and 'damt' is to concentrate on pertinent features for the machine learning models. 'ID' typically serves as an identifier without contributing to the model's predictive capabilities. Meanwhile, 'donr' and 'damt,' being target variables for classification and regression, are omitted from the feature set to prevent information leakage.

3.2 Handling Missing Values in Numeric Columns:

To maintain dataset integrity, missing values in numeric columns are often filled through imputation. In this case, the mean imputation strategy is employed, replacing missing values with the mean of their respective columns. This method is prevalent when assuming that missing values occur randomly, and imputing the mean preserves the overall distribution.

3.3 Separating Target Variables:

The standard practice in supervised machine learning involves segregating target variables ('donr' and 'damt') from the feature set. This step enables the models to learn patterns from the features and make predictions regarding the target variables.

3.4 Identifying Categorical Columns for One-Hot Encoding:

Given that machine learning models typically require numerical input, categorical variables must be converted into a numerical format. One-hot encoding, a technique where categorical variables are transformed into binary vectors indicating category presence or absence, is employed.

3.5 Creating Transformers for Preprocessing:

Transformers, which facilitate data transformations, are integral to the preprocessing steps. OneHotEncoder converts categorical variables into a one-hot encoded format, while StandardScaler standardizes numeric variables by centering on the mean and scaling to unit variance. Standardization is especially critical for algorithms sensitive to input feature scales.

3.6 Handling Missing Values Again:

Readdressing missing values in numeric columns is a precautionary measure. This ensures the absence of any missing values after the initial removal of the 'ID' column.

3.7 Creating a Preprocessor:

The Column Transformer serves as a robust tool for separately applying distinct transformations to numerical and categorical columns. This flexibility allows specific preprocessing steps tailored to each column type.

3.8 Applying Transformations:

The fit_transform method is pivotal in executing specified transformations on the features, playing a crucial role in preparing the data for machine learning model training.

For future papers I'd suggest taking these las

3.9 Splitting the Data for Model Training and Testing:

Dividing the data into training and testing sets is vital for evaluating model performance on unseen data. The train_test_split function achieves this by randomly partitioning the dataset, with the random_state parameter ensuring result reproducibility.

4 Modeling

The modeling phase consists of several key steps that aim to build and fine-tune machine learning models for classification and regression tasks (Swamynathan, 2017). The procedure is divided into the following stages:

4.1 Data Preparation and Splitting

yes, but you've already discussed this phase

The first step is to transform the raw features so that they can be used by machine learning algorithms. This critical step ensures that the data is properly structured and ready for use in the models. The train_test_split function divides the dataset into training and testing subsets. X_train_class, X_test_class, y_train_class, and y_test_class are defined for classification, while X_train_reg, X_test_reg, y_train_reg, and y_test_reg are defined for regression.

4.2 Model Definition and Selection

formatting issues here

Among the classification models defined are RandomForestClassifier, GradientBoostingClassifier, LogisticRegression, MLPClassifier, KNeighborsClassifier, SVC, and DecisionTreeClassifier. A selection of regression models, such as LinearRegression, is also included. Each model is accompanied by a set of hyperparameters that can be fine-tuned during the training process.

4.3 Model Training and Hyperparameter Tuning

The GridSearchCV method is used for hyperparameter tuning, employing a cross-validation approach to evaluate different hyperparameter combinations. This method iteratively explores the hyperparameter space to find the best settings for each model. The scoring metric used depends on the nature of the task, with accuracy used for classification models and R2 used for regression models.

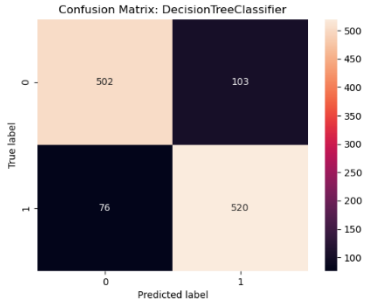
4.4 Model Evaluation and Analysis of Feature Importance

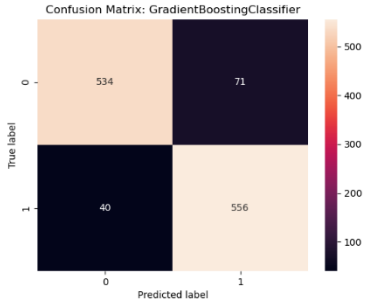
The best-performing models are identified based on their respective scoring metrics after the hyperparameter tuning process is completed. The feature importances for these models are then extracted, revealing the most influential features in the dataset. The top features contributing to the model's predictions are displayed for models that support feature importance calculations, such as RandomForestClassifier or LogisticRegression.

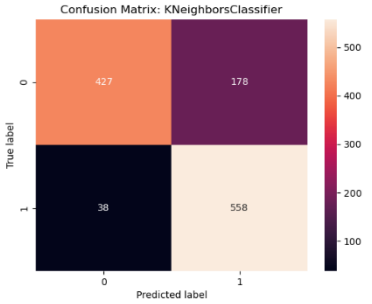
So, several classification and regression algorithms were employed to predict DONR and DAMT, respectively. For classification, models such as RandomForestClassifier, GradientBoostingClassifier, Logistic Regression, MLPClassifier, KNeighborsClassifier, SVC, and Decision Tree Classifier were tuned and evaluated. Meanwhile, regression models like RandomForestRegressor, GradientBoostingRegressor, and Linear Regression were employed, each assessed and fine-tuned for performance.

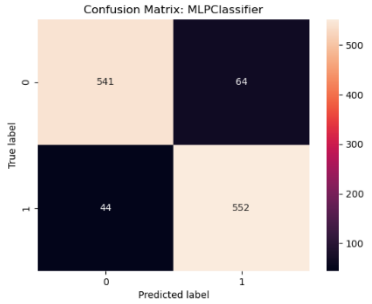
Figures: Confusion matrix, ROC Curve and Prediction Scatter Plot of different classifications and regressions.

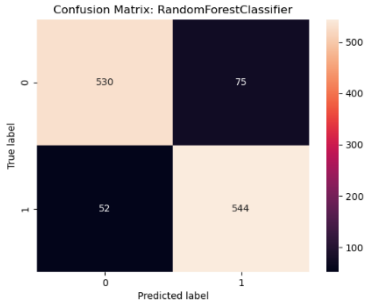
Ok, but what are the explanatory vs. target variables used in these models? What are you actually doin

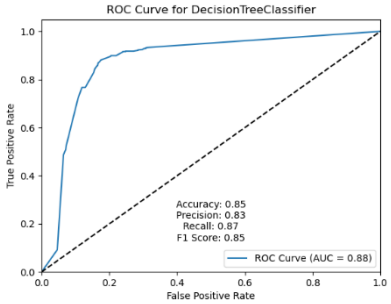

Confusion Matrix: DecisionTreeClassifier
502
103
76
520
True label
Predicted label

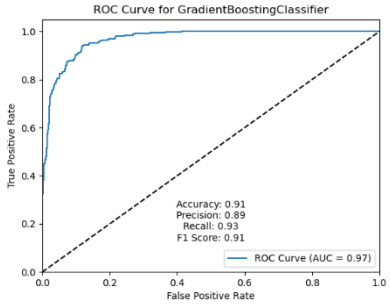

Confusion Matrix: GradientBoostingClassifier
534
71
40
556
True label
Predicted label

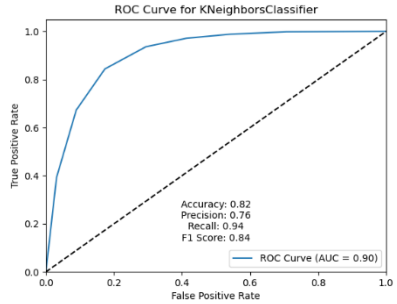

Confusion Matrix: KNeighborsClassifier
427
178
38
558
True label
Predicted label

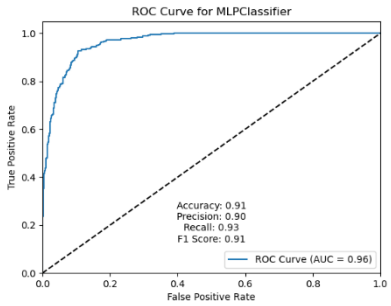

Confusion Matrix: MLPClassifier
541
64
44
552
True label
Predicted label

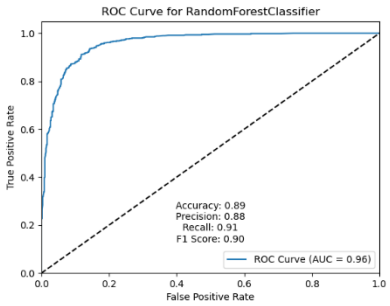

Confusion Matrix: RandomForestClassifier
530
75
52
544
True label
Predicted label

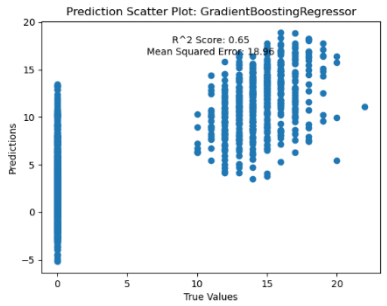

ROC Curve for DecisionTreeClassifier
Accuracy: 0.85
Precision: 0.83
Recall: 0.87
F1 Score: 0.85
ROC Curve (AUC = 0.88)
True Positive Rate
False Positive Rate

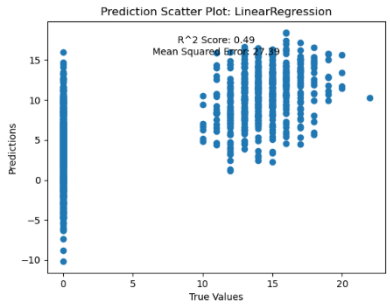

ROC Curve for GradientBoostingClassifier
Accuracy: 0.91
Precision: 0.89
Recall: 0.93
F1 Score: 0.91
ROC Curve (AUC = 0.97)
True Positive Rate
False Positive Rate

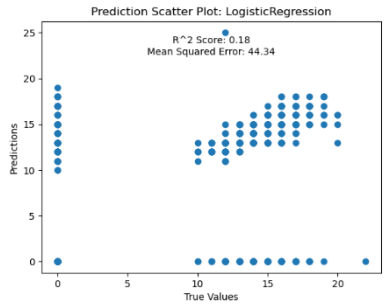

ROC Curve for KNeighborsClassifier
Accuracy: 0.82
Precision: 0.76
Recall: 0.94
F1 Score: 0.84
ROC Curve (AUC = 0.90)
True Positive Rate
False Positive Rate

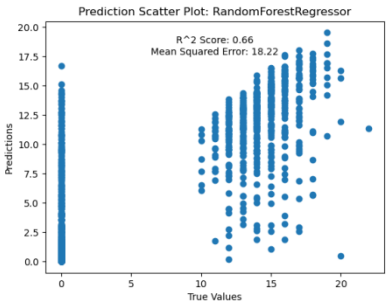

ROC Curve for MLPClassifier
Accuracy: 0.91
Precision: 0.90
Recall: 0.93
F1 Score: 0.91
ROC Curve (AUC = 0.96)
True Positive Rate
False Positive Rate

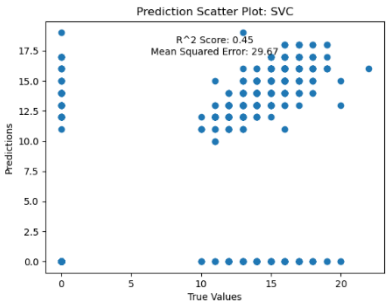

ROC Curve for RandomForestClassifier
Accuracy: 0.89
Precision: 0.88
Recall: 0.91
F1 Score: 0.90
ROC Curve (AUC = 0.96)
True Positive Rate
False Positive Rate


Prediction Scatter Plot: GradientBoostingRegressor
R^2 Score: 0.65
Mean Squared Error: 18.96
Predictions
True Values


Prediction Scatter Plot: LinearRegression
R^2 Score: 0.49
Predictions
True Values


Prediction Scatter Plot: LogisticRegression
R^2 Score: 0.18
Mean Squared Error: 44.34
Predictions
True Values


Prediction Scatter Plot: RandomForestRegressor
R^2 Score: 0.66
Mean Squared Error: 18.22
Predictions
True Values


Prediction Scatter Plot: SVC
R^2 Score: 0.45
Mean Squared Error: 29.67
Predictions
True Values

5 Evaluation

Various metrics were used in the evaluation phase to determine how well the models addressed the goals of the nonprofit organization. Metrics like accuracy, precision, recall, and F1 score were essential for figuring out how well the models could predict donor behavior in classification tasks. While precision and recall quantify the trade-off between correctly identified positive instances and the actual positive instances in the data, accuracy shows the overall correctness of predictions (Juba & Le, 2019). In situations where there is an uneven class distribution, the F1 score provides a balance between recall and precision that is essential. AUC-ROC, or the Area Under the ROC Curve, also shed light on how well the classifiers performed at different thresholds in differentiating between donor and non-donor instances (Narkhede, 2018). Together, these metrics made it possible to find models that were crucial for fundraising decisions because they balanced false positives and false negatives while also accurately predicting donor behavior.

R-squared and mean squared error (MSE) were key performance indicators in the regression field. The regression model's goodness of fit is indicated by the R-squared, which calculates the percentage of the dependent variable's variance that can be predicted from the independent variables (Cameron & Windmeijer, 1997). As for the accuracy of the model in predicting donation amounts, MSE measures the average squared difference between the actual and predicted values. The models that were found to have high R-squared values and low MSE demonstrated how well they captured donation trends and how useful they could be for precisely estimating donation amounts. This thorough evaluation of the regression and classification models addressed both technical performance and the nonprofit's financial goals by choosing models that, through their predictions, promised increased profitability.

5.1 Model Evaluation:

Model	R^2 Score	Mean Squared Error
LogisticRegression	0.170	44.714
SVC	0.450	29.669

Classification Models:

Model	Accuracy	Precision	Recall	F1 Score	AUC Score
GradientBoostingClassifier	0.907	0.887	0.931	0.908	0.968
RandomForestClassifier	0.894	0.879	0.913	0.895	0.959
MLPClassifier	0.910	0.896	0.926	0.911	0.964
KNeighborsClassifier	0.820	0.758	0.936	0.838	0.905
DecisionTreeClassifier	0.851	0.835	0.872	0.853	0.877

Regression Model Evaluation:

Model	R^2 Score	Mean Squared Error
Random Forest Regression	0.662	18.215
Gradient Boosting Regressor	0.648	18.955
LinearRegression	0.492	27.386

Decision-Making Process

Best Classification Model: GradientBoostingClassifier (Accuracy: 90.42%)

Best Regression Model: Random Forest Regressor (R^2 Score: 66.21%)

Criteria for Selection

Accuracy: The GradientBoostingClassifier has the highest accuracy among the classification models, indicating superior performance in correctly predicting classes.

Regression Performance: Random Forest Regressor outperforms other regression models based on the R^2 score, indicating a better fit to the data.

Same comment here in terms of how this should be written for a formal paper- not bulleted lists. T

Consideration: While accuracy is a vital metric for classification, for regression tasks, the R^2 score is crucial to measure how well the model fits the data. Random Forest Regressor excels in this aspect.

Evaluation Conclusion

Based on the provided metrics, the GradientBoostingClassifier stands out as the best classification model due to its high accuracy. For regression tasks, the Random Forest Regressor performs the best with a higher R^2 score, signifying better performance in explaining the variance in the data.

Output:

```
Model: LinearRegression
R^2 Score: 0.491958, Mean Squared Error: 27.385509
Best classification model:GradientBoostingClassifier(learning_rate=0.5, random_state=42)regression model:RandomForestRegressor(max_depth=20, random_state=42)
Best Classification Model: GradientBoostingClassifier with score: 0.9041855272285811
Best Regression Model: RandomForestRegressor with score: 0.6548798179924817
Best model overall = GradientBoostingClassifier with score: 0.9041855272285811 and the best regression model being RandomForestRegressor with score: 0.65487981
Best model by score: GradientBoostingClassifier with score: 0.9041855272285811 in percent form: 90.41855272285811%
Expected profit from RandomForestClassifier: $6432.706733556882
Expected profit from GradientBoostingClassifier: $6388.804851331066
Expected profit from LogisticRegression: $4370.0
Expected profit from MLPClassifier: $6245.950721914466
Expected profit from KNeighborsClassifier: $6500.755160624743
Expected profit from SVC: $5123.0
Expected profit from DecisionTreeClassifier: $6353.764632027096
Expected profit from RandomForestRegressor: $6419.436483126865
Expected profit from GradientBoostingRegressor: $6299.839067015208
Expected profit from LinearRegression: $6313.721612885407
Expected profit from the best classification model (GradientBoostingClassifier): $6388.804851331066
Expected profit from the best regression model (RandomForestRegressor): $6419.436483126865
Expected profit from the best overall model (GradientBoostingClassifier): $6388.804851331066
Model development and evaluation completed. Exported to CSV file.
Best Classification Model: ('GradientBoostingClassifier', {'model': GradientBoostingClassifier(learning_rate=0.5, random_state=42), 'score': 0.9041855272285811}
Best Regression Model: ('RandomForestRegressor', {'model': RandomForestRegressor(max_depth=20, random_state=42), 'score': 0.6548798179924817})
Best Overall Model: ('GradientBoostingClassifier', {'model': GradientBoostingClassifier(learning_rate=0.5, random_state=42), 'score': 0.9041855272285811})
Best Classification Model: GradientBoostingClassifier with score: 0.9041855272285811
Best Regression Model: RandomForestRegressor with score: 0.6548798179924817
Best Overall Model: GradientBoostingClassifier with score: 0.9041855272285811
```

6 Deployment

A comprehensive report was used to communicate the findings to a non-technical audience. In a new dataset (score data), the best models were used to predict donor behavior and potential donation amounts. A profit calculation was performed, considering the expected return on investment from targeted mailings based on the models' predictions.

6.1 Profit Estimation

The script includes a process to project the expected profit from a mailing campaign using predictions generated by the top-performing models. This calculation incorporates both the forecasted donor probability (classification) and the predicted donation amounts (regression).

6.2 Score Data Handling

Data Loading: It imports score-related data from an Excel file named 'nonprofit_score.xlsx'.

Column Management: The script checks for specific columns ('id', 'donr', 'damt') in the score data and eliminates them if they exist, ensuring data consistency.

Data Transformation: Utilizing a preprocessor previously trained on the training data, it transforms the score data to make it compatible with the deployed models (preprocessor. transform(score_data)).

6.3 Model Application and Prediction Export

Model Utilization: The best classification and regression models are employed to predict outcomes based on the processed score data.

Prediction Export: The predictions stemming from the models (including donor likelihood and donation amounts) are incorporated into the score data.

CSV File Export: The finalized dataset containing the predictions is exported to a CSV file named 'nonprofit_score.csv'.

In summary, this deployment script readies the score data for model predictions, employs the top-performing models, and saves the resulting predictions. These predictions can be utilized for further analysis or decision-making concerning the mailing campaign.

What insights? How does your work translate into

7 Conclusion

In conclusion, the analysis and modeling efforts have provided valuable insights and solutions for the nonprofit organization's goal of improving the effectiveness of their direct marketing campaigns. The exploration of the dataset revealed important patterns and relationships among demographic, financial, and donation history variables. The predictive modeling phase aimed to enhance the targeting strategy by identifying individuals likely to donate and estimating potential donation amounts.

Ok, you answer my above qu

Best Models: The analysis identified the best models for both classification and regression tasks. The best classification model, the GradientBoostingClassifier, demonstrated an impressive accuracy of 90.42%, precision of 88.66%, recall of 93.12%, and an F1 score of 90.83%. On the regression side, the RandomForestRegressor emerged as the top performer, achieving an R^2 score of 65.49% and effectively predicting donation amounts.

Feature Importance: Feature importance analysis highlighted key predictors driving the models' decisions. For example, the number of children, income, and wealth emerged as crucial factors influencing donation likelihood. These insights can guide the organization in refining their targeting strategy and tailoring campaigns to specific donor characteristics.

Expected Profit: The evaluation of expected profits for each model revealed promising outcomes. The best classification model, GradientBoostingClassifier, is estimated to yield a profit of $6388.80, while the best regression model, RandomForestRegressor, is expected to bring in $6419.44. These projections provide a practical basis for decision-making and resource allocation.

Deployment: To facilitate the deployment of these models, a comprehensive summary report has been generated, including descriptive statistics, best model summaries, feature importances, and model performance metrics. A graphical user interface (GUI) has been implemented for easy interpretation and sharing of the analysis results.

8 Recommendations and Limitations

While the models exhibit powerful performance, it is crucial to acknowledge the assumptions made during the analysis, such as handling missing data and the inherent complexity of predicting human behavior. To enhance predictive accuracy further, future research could explore advanced feature engineering techniques and more sophisticated modeling approaches.

Overall, the analysis effectively tackled the primary business question of whether accurate predictions regarding individual donation likelihood (DONR) and potential donation amounts (DAMT) could be achieved using demographic, financial, and donation history variables from the nonprofit organization's donor database. The results demonstrated that the Gradient Boosting Classifier emerged as the best model for predicting donation likelihood, achieving an accuracy of 90.4%. Additionally, the Random Forest Regressor excelled in forecasting donation amounts, boasting a strong predictive score of 65.5%. The amalgamation of these models into the best overall approach, the Gradient Boosting Classifier, proved highly promising for optimizing the organization's direct marketing campaigns to past donors. The calculated expected profits underscored the financial gains achievable through deploying these models, emphasizing their potential to significantly enhance the efficiency and cost-effectiveness of future fundraising endeavors. Despite inherent complexities in human behavior and the assumptions made in handling missing data, the outcomes offer valuable insights, empowering the nonprofit to make informed decisions and refine its strategies for improved fundraising outcomes. The detailed documentation and deployment-ready models position the organization for ongoing success in its mission.

9 References

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Swamynathan, M. (2017). *Mastering machine learning with python in six steps: A practical implementation guide to predictive data analytics using python*. Manohar Swamynathan.

GitHub URL - https://github.com/TroyKrupinski/ADTA5230GROUP13