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ENHANCING FUNDRAISING STRATEGIES IN HIGHER EDUCATION THROUGH MACHINE LEARNING

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ENHANCING FUNDRAISING STRATEGIES IN HIGHER EDUCATION THROUGH MACHINE LEARNING

by

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Enhancing Fundraising Strategies in Higher Education Through Machine Learning

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This thesis presents a comprehensive application of machine learning techniques, namely Fine Gaussian SVM and RUS Boosted Trees, to enhance fundraising strategies in higher education institutions. Analyzing a rich dataset from Blackbaud Raiser's Edge NXT, spanning 2012 to 2022, the study focuses on donor profiles, including demographics, donation history, and engagement patterns.

Key demographic insights include the increasing engagement of younger donors (20-29 age group) and significant contributions from older donors (70-99 age group). Geographical trends are also examined, revealing distinct patterns based on donors' city, state, and ZIP code.

The Fine Gaussian SVM model demonstrates moderate discriminatory power, with an AUC-ROC of 0.9105, indicating a strong ability to differentiate potential donors from non-donors. It particularly excels in identifying true positives but shows some limitations in accurately predicting negatives. The RUS Boosted Trees model, tailored for the dataset's imbalance, achieves a higher AUC-ROC of 0.9416, indicating superior performance in distinguishing repeat donors. These models are evaluated using accuracy, precision, recall, F1 score, and AUC-ROC to ensure robustness and applicability.

CHAPTER ONE
INTRODUCTION

In higher education, fundraising is an essential component that guarantees the ongoing improvement and expansion of academic programs, facilities, and research capacities in universities and colleges. The significance of this technique has increased as a result of the need for alternate sources of finance in the face of restricted government assistance, especially in countries such as US, UK, EU, and other nations like Malaysia [1].

There are several different aspects that are the focus of fundraising efforts in higher education. It involves ensuring educational quality, controlling tuition expenses, and boosting philanthropic engagement. Getting involved with alumni is important in this situation since they make up a large percentage of the donor base and give to their university out of a feeling of loyalty and personal connection [2]. Donations from alumni may range from modest individual gifts to major endowments, providing a wide range of monetary amounts.

Additionally, philanthropic organizations and corporations contribute significantly to university fundraising. These organizations often provide assistance to certain projects or research endeavors. As compensation, individuals may be granted recognition such as the privilege to name facilities or academic positions [3].

Nevertheless, the dependence on fundraising poses many obstacles. Achieving an appropriate balance between maintaining academic integrity and satisfying donor expectations requires the implementation of strategic planning. Higher education leaders encounter new obstacles as charitable contributions become essential for their longterm sustainable existence [4].

When it comes to fundraising for higher education, ethics are crucial. The influence of substantial gifts on university rules and admissions procedures is a subject of ongoing dispute. Concerns about this have been brought up by the way charitable financing has changed over time, moving from being beneficial to society to perhaps having political power [5].

The fundraising strategies have been significantly altered by technological breakthroughs. According to [6], the use of digital platforms, social media, and online giving has become crucial in effectively reaching a broader audience and enabling fundraising efforts.

Improving fundraising tactics is crucial for higher education because it makes it easier for institutions to achieve their financial objectives. The use of machine learning within this particular context has significant benefits, since it has the capability to enhance multiple aspects of fundraising.

Through the analysis of donor behavior and preferences, machine learning may improve fundraising techniques and support institutions in their charitable endeavors. This has significant importance within the framework of economic difficulties and the necessity for alternate avenues of support. According to [1], Higher education institutions may enhance communication channels and create effective fundraising campaigns by using machine learning methods, drawing inspiration from models used by private U.S. higher education institutions [7].

Using machine learning in finance to improve methodologies and apply evolutionary algorithms creates a more complete framework for financial machine learning applications [8]. A comparison study utilizing deep learning showed that crowdfunding campaign fundraising forecasts may be improved [9]. K-means clustering and artificial neural networks are strong machine learning and AI approaches that may enhance fundraising strategies. These tactics improve targeting and segmentation of potential donors, boosting the likelihood of fundraising success. according to [10].

1.1 Aim/Objective

The primary objective of this dissertation is to explore the potential of machine learning in revolutionizing fundraising strategies in higher education institutions. This involves using advanced machine learning algorithms to analyze, enhance, and predict fundraising outcomes more effectively. The key objectives are:

- Advancing Fundraising Models: Employing machine learning methodologies to construct persistent models capable of effectively analyzing donor data, hence improving the ability to forecast donor behavior and improve the efficiency of fundraising methods within the domain of higher education.
- Comprehensive Data Analysis: Examining current data on fundraising to find patterns, trends, and important variables that affect the spending habits and contribution amounts of donors. The present investigation will provide a robust basis for the development of machine learning models that are more efficient and impactful.
- Model Validation and Refinement: Thoroughly evaluating the precision and reliability of the constructed machine learning models in forecasting fundraising results. These models

will be continuously improved and optimized to meet the specific demands and circumstances of higher education institutions.

- Strategic Implementation for Successful Fundraising: Converting the machine learning models' insights and forecasts into workable plans. The objective of these techniques is to enhance the fundraising endeavors of institutions of higher education, with the intention of increasing their focus, effectiveness, and achievement.

1.2 Motivation

This argument is driven by the growing significance of fundraising in higher education, particularly in light of the decline of more established financing sources such as government subsidies. Higher education institutions are now experiencing increased budgetary constraints, which has prompted the need for a reassessment and improvement of their fundraising approaches.

Throughout history, fundraising endeavors have mostly relied upon either qualitative analysis or conventional statistical models. Nevertheless, these approaches may not adequately tackle the complicated and changing dynamics of modern donor behavior in a digitalized environment. Machine learning presents a potentially viable resolution to these mentioned issues. Machine learning can efficiently handle and evaluate large amounts of alumni information by using sophisticated algorithms. This algorithm allows organizations to generate more precise forecasts about prospective contributors and the probable magnitudes of their donations, so guaranteeing enhanced donor targeting and engagement [11].

This thesis is motivated by the need to investigate and include machine learning breakthroughs to revive fundraising methods within the field of higher education, enhancing their efficiency, effectiveness, and alignment with current digital progress.

1.3 Thesis contributions

This thesis introduces an important progression in the combination of fundraising in higher education and machine learning, providing innovative contributions in a field where data-driven methodologies are still developing. The focus of this thesis is to create an advanced prediction model that utilizes machine learning methods such as Fine Gaussian SVM, Boosted Trees. This model is specially designed to meet the fundraising requirements of higher education institutions. This methodology departs significantly from conventional techniques by integrating the complex and distinctive characteristics of educational fundraising, therefore addressing a need in the current field of research.

An essential element of this study is its inventive approach to addressing significant missing data in the database, which is a prevalent yet difficult problem in real-life situations. By tackling this issue, the thesis goes beyond conventional data analytics methods, improving the strength and usefulness of machine learning approaches under imperfect circumstances. This methodology not only evaluates the robustness of these algorithms but also facilitates the development of techniques for efficient data imputation and analysis, representing a substantial advancement in the domain of predictive modeling with incomplete datasets.

The anticipated results of this study are diverse. This thesis provides a practical and adaptable set of tools for users, specifically in university fundraising departments, to efficiently navigate and take advantage of missing data. This has the potential to result in more accurate and efficient fundraising campaigns. From an academic standpoint, this study enhances the existing body of knowledge by providing fresh perspectives on the use of machine learning in situations when data limitations exist. It establishes a standard for future investigations in this field. In general, the thesis aims to overcome the obstacles presented by inadequate data to transform the approach and effectiveness of fundraising for higher education by incorporating modern data analytics into its fundamental procedures.

1.4 Organization of Thesis

This thesis consists of five chapters. Chapter 1 introduces the research topic, objectives, and organization of the thesis. The second chapter provides a review of the literature concerning the principles and technologies of machine learning and their application in higher education fundraising. Chapter 3 describes the research methodology, including model design and data analysis. The results of the model development and insights are presented in Chapter 4. Finally, Chapter 5 summarizes the research findings and discusses their significance.

CHAPTER TWO
LITERATURE SURVEY

Within the field of higher education, conventional fundraising tactics have been essential in closing the disparity between the requirements of institutions and the resources at their disposal. These conventional approaches often include yearly fundraising initiatives, capital campaigns, endowments, special events, and soliciting gifts from alumni. The efficacy of these tactics is contingent upon the establishment of enduring connections, the implementation of strategic planning, and a comprehensive comprehension of donor behavior [12].

Nevertheless, fundraising in higher education encounters several obstacles. The principal obstacle is the growing financial demands brought on by the reduction in government assistance and the escalating expenses of schooling. The increasing dependence of institutions on charitable donations has underscored the need of implementing efficient fundraising tactics [13]. Furthermore, it is essential for institutions to continuously adjust their methods due to the ever-changing nature of donor habits and preferences.

Fundraising in higher education in the United States has evolved into a meticulously structured procedure, including an annual sum of tens of billions of dollars. There is a need for proficient fundraising experts that can effectively handle the complicated obstacles in this field, such as ethical concerns, donor interactions, and the optimal utilization of fundraising technology [14].

Furthermore, the development of fundraising strategies has been shaped by several circumstances, including the emergence of digital platforms and shifting cultural norms. Institutions are investigating new approaches, such as grassroots initiatives and student-led philanthropy, to build a sense of community and relieve financial difficulties [15]. In addition to offering financial assistance, these efforts also include the broader community, including students, professors, and alumni, in the process of fundraising.

Interest has been growing in the use of machine learning in fundraising, with numerous studies investigating its potential to revolutionize the conventional approaches utilized in this field. An essential aspect of emphasis is in the optimization of donor targeting. In [16], the use of machine learning algorithms has the potential to greatly enhance the effectiveness of fundraising campaigns by effectively identifying ideal targets, prioritizing former contributors, and limiting outreach efforts towards those who have not previously made gifts.1. Machine learning techniques have been used in the realm of crowdfunding, which has similarities to fundraising in higher education, to forecast the success of campaigns. The effectiveness of Support Vector Machines (SVM) in forecasting the outcomes of donation-based campaigns has been shown, providing valuable insights into the determinants of donor involvement [17].

Additional research has shown that machine learning algorithms can assess social media activity and donors' human capital to forecast crowdfunding project performance, suggesting that these strategies have wider fundraising applications [18]. The accuracy of ensemble neural networks in predicting fundraising results has been well acknowledged.

In addition to predictive analytics, machine learning may help identify complicated, nonlinear interactions between factors that drive fundraising performance. The use of this approach has shown significant utility in the examination of crowdfunding for art projects, since conventional linear models may not sufficiently include the intricacies involved [19].

In [19], the author presents a thorough examination of the use of machine learning techniques in improving the comprehension and forecasting of crowdfunding achievements, with a special emphasis on art projects on the crowdfunding platform Kickstarter. The author employs four machine learning methodologies, namely gradient boosted decision trees, random forests, shallow neural networks, and support vector machines, to assess their effectiveness in comparison to conventional logistic regression models. The research provides evidence that the use of these techniques, namely gradient boosted decision trees, yields enhanced predictive capabilities in the identification of successful crowdfunding campaigns. Through an examination of 14,612 art projects sourced from the crowdfunding platform Kickstarter, the author uncovers noteworthy non-linear associations among crucial factors such as the social capital possessed by the project creator, the financial objective of the campaign, and the probability of achieving success. Significantly, the research reveals that include text factors such as 'Business' and 'Location' enhances the model's ability to make accurate predictions. In the test dataset, the gradient boosted decision trees model demonstrated superior performance, achieving an Area Under the Curve (AUC) of roughly 88.72%. This performance surpassed that of the logistic regression model, which exhibited an AUC of approximately 86.7%. This study highlights the effectiveness of machine learning in understanding intricate dynamics within the field of crowdfunding and offers significant insights for enhancing crowdfunding methods.

The use of machine learning in the fundraising techniques of Yemego

NGO has resulted in notable improvements in donor engagement and contributions. They customized outreach to diverse donor groups by using clustering algorithms for donor segmentation and data such as gift history and engagement levels. By integrating historical contribution quantities and economic factors, their predictive analytics for donation forecasting allows for precise anticipation of giving patterns. By using A/B testing and evaluating campaign indicators like as open and click-through rates, fundraising efforts have been enhanced, resulting in increased effectiveness. Utilizing Natural Language Processing and social media analytics has strengthened connections with donors, hence improving donor engagement. The use of Robotic Process Automation has optimized the donation procedures, resulting in more efficient operations. Significantly, the classification model used by the researchers uses logistic regression to identify prospective contributors. This model integrates demographic data, engagement data, and past contribution history, resulting in significant increases in conversion rates and reductions in marketing expenses. These tactics have not only resulted in a significant rise in contributions and enhanced donor loyalty, but also increased operational effectiveness, showcasing the profound influence of technology on fundraising for non-profit organizations [20].

The research conducted in [17] used machine learning algorithms to examine the many aspects that impact the effectiveness of donation-based crowdfunding campaigns. More precisely, the researchers used a dataset consisting of 9,935 campaigns from GoFundMe. They employed several machine learning methods, such as the Support Vector Machine (SVM), to forecast the performance of the campaigns. This prediction was based on a variety of parameters that were known at the beginning of the campaign and during its entire course. The results indicated that certain characteristics, such as the quantity of social media shares and the number of 'likes', had a substantial impact on the daily contribution amounts of the campaigns. Specifically, their Support Vector Machine (SVM) model exhibited exceptional predictive precision, making it a powerful instrument for predicting the results of crowdfunding campaigns. The research highlights the effectiveness of machine learning in augmenting comprehension and strategic planning of crowdfunding endeavors, offering practical insights for campaign coordinators.

The author in [21] aims to create predictive models for charitable giving by using Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), and Support Vector Regression (SVR). These models are built using demographic data obtained from zip codes in the United States. The research emphasized the importance of variables such as population, educational attainment, and prior year's philanthropic contributions in forecasting future donations. The artificial neural network (ANN) model demonstrated superior effectiveness, exhibiting the greatest level of accuracy in prediction, followed by the support vector regression (SVR) and multilayer regression (MLR) models. The evaluation process assessed the important performance metrics of these models, therefore showcasing their capacity to reliably predict philanthropic donations.

Table 2-1: Comparative performance metrics of MLR, ANN, and SVR in predictive modeling.

Criteria	MLR	ANN	SVR
SMAPE	0.829	0.765	0.759
MAE	0.067	0.055	0.057
RMSE	0.111	0.098	0.105
NRMSE	0.396	0.350	0.374
MSE	0.012	0.010	0.011
Residual	23.294	18.268	20.837
R2	0.753	0.807	0.783
Max Error	0.933	0.611	0.877
R	0.868	0.898	0.885

Table2-illustrates the comparative efficiency of each model in terms of various accuracy measures, with ANN showing a distinct edge in terms of lower error rates and higher explanatory power.

The authors utilized various machine learning algorithms, such as K-Nearest Neighbor (K-NN), Naïve Bayes, Logistic Regression, Random Forest, and Neural Networks, in [22] The purpose of this analysis was to gain insights into donor behavior and project approval factors by examining the DonorsChoose dataset. The K-NN technique had a higher accuracy rate of over 60%, exhibiting superior performance when applied to smaller datasets. Conversely, Naïve Bayes shown more effectiveness when using the Bag of Words vectorizer, suggesting its efficacy in simpler models. The usefulness of Logistic Regression and Neural Networks in managing complicated datasets and textual data has been established, as they have shown promise in increasing accuracy scores over 70%. The Random Forest model demonstrated its versatility by achieving an accuracy of above 60%. These findings highlight the wide-ranging possibilities of machine learning algorithms in forecasting the success of crowdfunding endeavors and enhancing techniques for keeping donors inside crowdfunding platforms.

In [23], the author used Gaussian Naive Bayes, Random Forest, and Support Vector Machine (SVM) algorithms in "A Machine Learning Approach to Fundraising Success in Higher Education" to improve fundraising techniques in higher education. The aim was to discover possible new contributors and forecast promising donors. The research shown that when used effectively as a targeting approach, these algorithms have the potential to secure over 85% of new donations and more than 90% of new major donors while soliciting a mere 40% of the candidates. The most effective algorithm achieved an overall accuracy of 97% in identifying potential donors in the test set. It successfully identified over 85% of possible donors while only soliciting 26% of applicants. The findings of this study highlight the efficacy of machine learning in enhancing donor targeting tactics, demonstrating the substantial impact of these technologies on fundraising endeavors inside higher education establishments.

CHAPTER THREE
METHODS AND MODELING

3.1 Data Acquisition and Dataset Description

3.1.1 Data Source

The primary source of data for this study is derived from Blackbaud Raiser's Edge NXT, a widely used cloud-based software for fundraising and donor management in educational institutions. The selection of this platform was based on its strong data collection capabilities, which enable the capture of a diverse range of donor-related information that is crucial for the conducted research. The procedure of retrieving data included a cooperative endeavor with the university's administration to guarantee access to relevant information while upholding ethical principles and privacy rules.

3.1.2 Dataset Characteristics

The dataset has a significant quantity of records, providing comprehensive information on multiple aspects of donor profiles and their involvement with the institution spanning the years 2012 to 2022. The dataset comprises a wide range of data categories, which include, but are not limited to, donor demographics such as age and gender, as well as donation history including the amount and frequency. This particular selection offers a comprehensive and diverse perspective on the behavior and interactions of donors over a substantial duration. The dataset exhibits a noteworthy level of complexity, as it has interconnected records that provide valuable insights into the continuous trends of donor involvement and donation habits.

3.1.3 Data Quality

Raiser's Edge NXT's comprehensive data management techniques are responsible for the dataset's high degree of correctness and consistency. Initial evaluations revealed minor concerns about the completeness or inconsistencies of the data, which were resolved using conventional data cleaning methods.

3.1.4 Time Frame

The selected period from 2012 to 2022 is noteworthy, since it covers a 10-year duration that offers a historical perspective on donor conduct and fundraising patterns. This time frame has significant relevance as it encompasses the dynamic characteristics of donor interaction methods and the use of digital technology in fundraising methodologies. Moreover, the presence of data before 2012 provides opportunities to expand the research to a wider temporal framework, perhaps yielding more comprehensive understandings of enduring patterns and the influence of past occurrences on fundraising.

3.1.5 Data Preparation for Analysis

Prior to analysis, the dataset was subjected to extensive preprocessing, which included feature engineering, normalization, and data cleansing (e.g., management of absent values). To be able to get trustworthy and insightful analysis findings, this procedure was crucial in ensuring that the data was suitable for the use of the RUS Boosted Trees and Fine Gaussian Support Vector Machine (SVM) algorithms.

3.2 Ethical Considerations and Data Privacy

3.2.1 Ethical Approval

This work went through a comprehensive ethical review procedure before data collection began, in accordance with academic research rules of ethics. As part of this approach, the study team presented a comprehensive proposal to the appropriate ethical review board at the institution, which included the research goals, techniques, and data management processes. Ensuring compliance to institutional rules and regulations related to research involving human beings was accorded particular emphasis.

Furthermore, all members of the study team signed a confidentiality agreement. The access to the Blackbaud Raiser's Edge NXT database was regulated by an agreement established by our educational institution. The policy required a strict commitment to maintaining data confidentiality and ensuring ethical use of the obtained information. The agreement functions as a fundamental element in preserving the reputation of the research process and maintaining the highest ethical principles.

3.2.2 Data Anonymization

Anonymizing personal data was an important part of preserving ethical integrity in our investigation. Before analysis, all personally identifying information in the dataset was eliminated or made difficult to read in order to protect donor privacy. Donors were mostly identified using constituent IDs as the only means of anonymization. The identification numbers assigned to each donor are distinct, however they don't reveal any personal details, thereby ensuring the preservation of subject confidentiality.

The anonymization procedure has been carefully designed to achieve an ideal balance between protecting the usefulness and authenticity of the data while also ensuring the confidentiality of people. The study team conducted a thorough examination of donor behavior and trends by specifically examining constituent IDs, while ensuring the confidentiality of the data participants. By using these steps, the research complies with ethical standards and data privacy laws, guaranteeing that the study is carried out with regard and accountability for the privacy and rights of the persons whose data is being examined.

3.3 Data Preprocessing and Feature Engineering

3.3.1 Data Cleaning Steps

The initial phase of data preprocessing involved a comprehensive evaluation of the dataset to identify and address any data quality issues. The dataset, consisting of donor information and their donation history, required several key cleaning steps:

The first stage of data preparation included doing a thorough assessment of the dataset in order to detect and resolve any potential data quality concerns. Several essential cleaning stages were necessary for the dataset, which included donor information and their giving history.

1. Handling Missing Values: The process of addressing missing data included doing a comprehensive scan across many variables, including 'Age', 'Zip Code', and contribution amounts. In light of the fundamental features of the dataset, whereby the presence of missing values has the potential to introduce bias into donor profiles and donation patterns, several techniques were used. These techniques include mean or median imputation for continuous variables, as well as mode imputation for categorical variables.

2. Outlier Detection: The process of outlier detection was used to examine the contribution amounts over several years, using statistical methods such as the Interquartile Range (IQR). The

assessment of outliers was conducted to ascertain if they were anomalies or valid extreme values.

3. Data Formatting: Formatting data was conducted to guarantee uniformity, with a special focus on standardizing data formats for categorical variables such as 'Gender', 'City', and 'State'. This stage included the combining of text forms and the resolution of any differences in classification.

3.4 Model Selection

In this study, the choice of employing Fine Gaussian SVM and RUS Boosted Trees as the primary analytical models was influenced by the specific characteristics of the dataset and the research objectives.

1. Fine Gaussian SVM: The selection of Fine Gaussian Support Vector Machine (SVM) was driven by its capability to manage large datasets efficiently and its exceptional performance in classification tasks, especially with continuous or normally-distributed data. The Fine Gaussian SVM uses a Gaussian (radial basis function) kernel to transform the data and then finds an optimal boundary between the possible outputs. This is particularly beneficial for our dataset, which includes continuous variables such as donation amounts and donor ages. The model's ability to handle complex relationships in data makes it ideal for analyzing patterns and making predictions about donor behavior.

2. RUS Boosted Trees: The adoption of RUS (Random Under-Sampling) Boosted Trees was motivated by the necessity to tackle the imbalanced nature of the dataset, where non-donors are likely more prevalent than donors. This approach effectively merges the strengths of boosting, a potent ensemble technique, with random under-sampling. This enhancement improves the model's performance on the minority classes, such as the actual donors, by focusing more on their data during the training process.

3.5 Model Evaluation

Model assessment in machine learning is crucial for assessing a model's ability to make accurate predictions and its resilience. The present study aimed to assess the performance of the Fine Gaussian SVM and RUS Boosted Trees models using a comprehensive set of evaluation measures. These metrics provided valuable insights into several facets of model performance. The evaluation of accuracy was based on its direct measurement of total performance, which is the proportion of accurate forecasts out of all predictions produced. Nevertheless, the presence of a possible imbalance in the dataset, whereby one class may have a substantial numerical advantage over the other, may lead to incorrect conclusions based only on accuracy.

To mitigate this issue, the use of accuracy was implemented, a crucial aspect in the realm of fundraising, as it serves to prevent the overestimation of possible contributors. Precision is defined as the ratio of accurately predicted positive instances to the total number of positive instances, and it is influenced by the model's capacity to accurately identify real donors. On the other hand, recall, also known as sensitivity, refers to the ratio of accurately detected real positives by the model. To mitigate the risk of neglecting prospective donors, it is essential to maintain a high recall rate in donor prediction models. The F1 score, a statistic that integrates accuracy and recall by calculating their harmonic mean, was also used. This approach is particularly advantageous in situations where it is crucial to strike a harmonious equilibrium between the identification of a substantial number of genuine donors and the assurance of a substantial degree of certainty in these prognostications.

Furthermore, the AUC-ROC, which stands for Area Under the Receiver Operating Characteristic Curve, played a crucial role in this investigation. The receiver operating characteristic (ROC) curve illustrates the relationship between the true positive rate and the false positive rate across different threshold values. On the other hand, the area under the curve (AUC) measures the model's overall capability to differentiate between the positive and negative classes. A high likelihood of accurately identifying a random positive case greater than a random negative instance is indicated by an AUC value near to 1.

To guarantee the reliability of applying the models to unseen data, a twofold technique was used for model validation. One often used initial validation option is the holdout method, which entails dividing the dataset into separate groups for training and testing purposes. This methodology enables the assessment of the model's efficacy on novel data subsequent to its training on the training dataset. In addition, k-fold cross-validation was used to reduce any bias in the data partitioning process and to gain a more comprehensive evaluation of the model's performance. K-fold cross-validation involves partitioning the dataset into 'k' subsets, often known as folds. The training process involves training the model on 'k-1' folds, followed by validation on the remaining fold. The aforementioned procedure is iterated 'k' times, whereby each sequence is used as the validation set once. The procedure of cross-validation offers a complete assessment of the model's performance across different subsets of the data, hence providing assurance in the model's stability and capacity to generalize.

To ensure a comprehensive investigation of the prediction models, the selection of these assessment measures and validation procedures was made. This systematic methodology guarantees that the results are based on solid evidence and that the models created are strong enough to be used effectively in improving fundraising methods in higher education.

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Features Engineering

The objective of the feature engineering method was to convert unprocessed data into significant variables that could efficiently be used as input for the Fine Gaussian SVM and RUS Boosted Trees models.

1. Demographic Information: The contributors' demographic profiles were created using variables such as 'Age', 'Gender', and 'Zip Code'. Understanding donor segments and forecasting contribution behavior heavily relies on these characteristics.

- Age

The attempt to estimate university financing using machine learning requires a comprehensive examination of factors that may impact forecasting accuracy. The clarification of donor age as an important feature within our models is of utmost importance in this endeavor. Age provides an abundance of information regarding donation patterns and the subtle shift over life's financial periods as a proxy for different socioeconomic circumstances.

This section of our study examines the historical donation data that has been divided into different donor age groups. Through this analysis, we can identify patterns that highlight the tendency towards donating and the changes in donor involvement across the years. By analyzing these patterns, we explain the underlying reasoning for choosing age as a crucial technical characteristic in our algorithms. The objective of this study is to provide light on the relationship between life phases, as indicated by age, and philanthropy giving. By doing so, we want to develop a more comprehensive and knowledgeable predictive model for university financing.

By using the predictive capabilities of age in our machine learning framework, our objective is to not only forecast the fluctuations in university funding, but also provide a more detailed comprehension of donor behavior. The present study plays a fundamental role in our efforts to develop a predictive model that is both insightful and accurate. This model will enable us to make strategic interactions that are grounded in facts and closely aligned with the donor community.

The age ranges have been divided into eight distinct groups for the sake of our study. These categories are '20-29', '30-39', '40-49', '50-59', '60-69', '70-79', '80-89', and '90-99'. This age-based classification, which runs from twenty to ninety, allows us to better understand the demographic distribution in terms of the total number of people in each age group, the quantity of new donors, the value of their contributions, and the patterns of consistent giving for each age group.

The data indicates a distinct pattern of declining donor engagement as age rises, with the youngest group (20-29) exhibiting the greatest proportion and the oldest group (90-99) displaying the lowest.

The examination of contributor percentages across different age groups at a university shows an important pattern: the 20-29 age group shows the highest percentage of donors (34.32%), indicating a significant level of involvement among recent graduates or young alumni. As individuals get older, there is an obvious decrease in the proportion of donors, with substantial reductions seen in each succeeding age cohort. This decline may be attributed to heightened financial obligations and transformative life events.

The proportion of individuals in the 30-39 age group decreases to 18.94%, most likely as a result of variables such as starting families and purchasing houses. This is followed by more declines in older age groups, with 40.44% in the 40-49 age group, 10.72% in the 50-59 age group, and 9.80% in the 60-69 age group.

The observed pattern persists, with the most pronounced decreases in the age groups of 70-79 (7.27%), 80-89 (3.01%), and 90-99 (0.45%). These drops may potentially be attributed to less income upon retirement, lower population numbers, and decreased involvement with the institution, as shown in table 4-1.

Table 4-1: Sample of donors categorized by age group.

Age	Donor	% of Total
20-29	1652	34.32%
30-39	912	18.95%

40-49	743	15.44%
50-59	516	10.72%
60-69	472	9.81%
70-79	350	7.27%
80-89	145	3.01%
90-99	22	0.46%

- Age and Amount of giving

An initial glance at the distribution of total donation amounts from 2019 to 2022 across various age brackets reveals a telling story: the propensity to give increases with age. The younger donor, those aged 20-29, begin their philanthropic journey with modest contributions. As donors progress through subsequent decades of their lives, there is a discernible augmentation in the scale of giving, culminating in the 80-89 age group bestowing the highest cumulative donations. This ascending trajectory suggests that donor age encapsulates a blend of increased financial stability, a heightened sense of legacy, and perhaps a deepening affinity for the university.

The figure below shows the amounts given by donors from different age groups between the years 2019-2022.

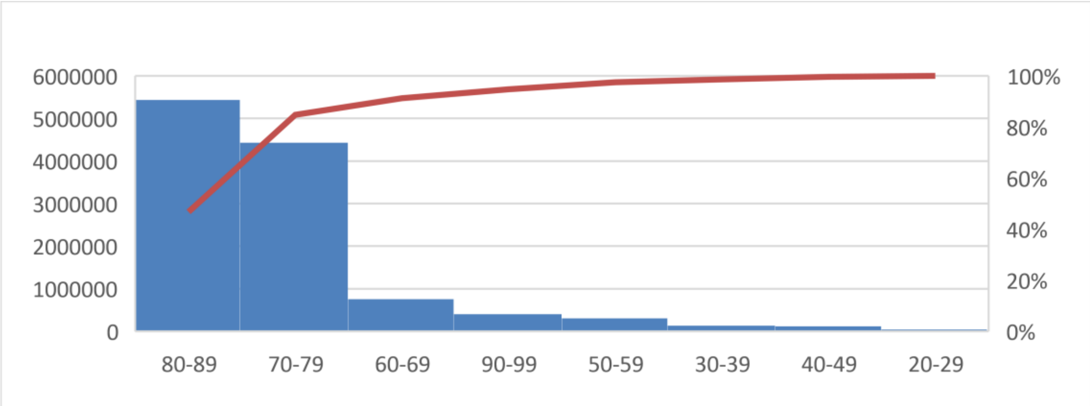


Figure 4-1: The amounts given by donors from different age groups between the years 2019-2022.

- Age and Repeated Donor Engagement

The historical data on repeated donations from 2019 to 2022 further elucidates the pattern of sustained giving across age groups. With each advancing age bracket, there is a notable increase in repeated donor counts, reflecting a deepening commitment to the institution. Remarkably, even as the population size diminishes in the oldest cohorts, the loyalty, as measured by repeat donations, remains strong. This steadfastness, especially pronounced in donors aged 60 and above, underscores the importance of recognizing age as a marker of long-term engagement.

The figure presents a table showing the history of repeated donations by age group for the years 2019-2022, 2020-2022, and 2021-2022. This table likely illustrates the number of donors who have made donations repeatedly during these periods.

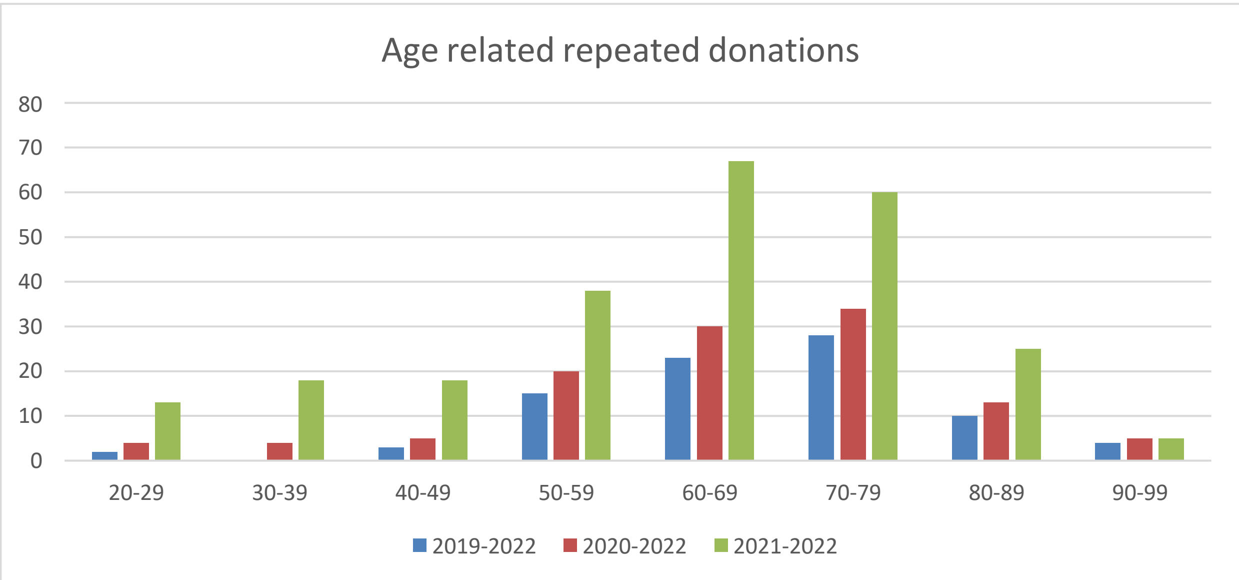


Figure 4-2: History of repeated donations by age group

The analyses demonstrate that donor age is more than a mere chronological measure; it is indicative of evolving donor motivation and capacity. As such, it becomes an indispensable feature in our predictive models. By integrating age, we can account for the natural graduation of donors into higher giving tiers over time, the potential for consistent engagement, and the propensity for making larger, legacy-focused contributions.

The role of age in predicting university funding is multi-dimensional. It is a proxy for the financial journey of alumni, reflective of their growing ability and willingness to give back as they advance in their careers and lives. Age, as a predictive feature, affords a nuanced understanding of donor behaviors, enhancing the predictive power of our machine learning models. In doing so, it guides universities to cultivate relationships with alumni across the life spectrum, ensuring a stable and flourishing culture of giving.

- Gender

The dataset provides an overview of the donor count for each gender during a span of four consecutive years, specifically from 2019 to 2022. There is a consistent upward trend in the number of donors for both genders in each successive year, with the most significant surge seen between the years 2019 and 2020.

The number of female donors has seen a significant and continuous annual increase. The number of male donors has seen a substantial growth, rising from 189 in 2019 to 1,270 by 2022, representing a more than six-fold increase. The number increased by more than four times, from 201 in 2019 to 845 in 2022. Although both genders see a rise in the number of donors, females have a larger annual growth rate.

Table 4-2: Number of donors for each gender and the number of new donors across four consecutive years—2019 through 2022.

	Number of donors				New donors			
Gender	2019	2020	2021	2022	2019	2020	2021	2022
Female	189	787	1129	1270	82	606	921	1067
Male	201	624	766	845	59	424	541	594

From table 3-2, there is a significant year-over-year growth for both genders, and t the number of female donors is higher than that of male donors, both in terms of total count and new donors

- Gender and age

The analysis of donors by age group and gender reveals several trends. Notably, female donors significantly outnumber male donors in the younger age brackets, with this pattern consistent up to the 60-69 age range. For example, in the 20-29 age group, the percentage was 64.29% Female, 35.71% Male.

As the age increases, the gender gap in donation counts begins to narrow. In the 50-59 and 60-69 age groups, the difference in the number of male and female donors decreases, A notable trend reversal occurs in the 70-79 age bracket, where male donors outnumber female donors for the first time, a pattern that continues into the 80-89 age group .In the oldest age group (90-99), the numbers are low for both genders, with 12 female and 10 male donors.

These findings indicate that while female donors lead in numbers in earlier life stages, the gap diminishes and eventually reverses in the later stages of life, as shown in figure 4-3.

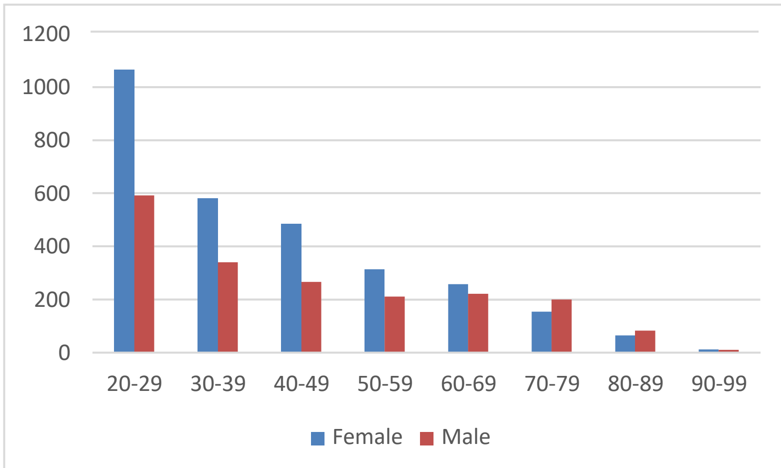


Figure 4-3: Distribution of donors by age group and gender

- Gender and amount of giving

The total giving amount for female was exceptionally high due to two donations that were above $9 million each in 2022, which are classified as outliers. When these outliers are removed, the total giving amounts and the average donation per female donor reduce considerably. The removal of the outlier donations results in a significant decrease in the total giving figure for females, highlighting the impact of very large donations on the overall metrics.

The figure below shows the amount of giving for each female donor in 2022:

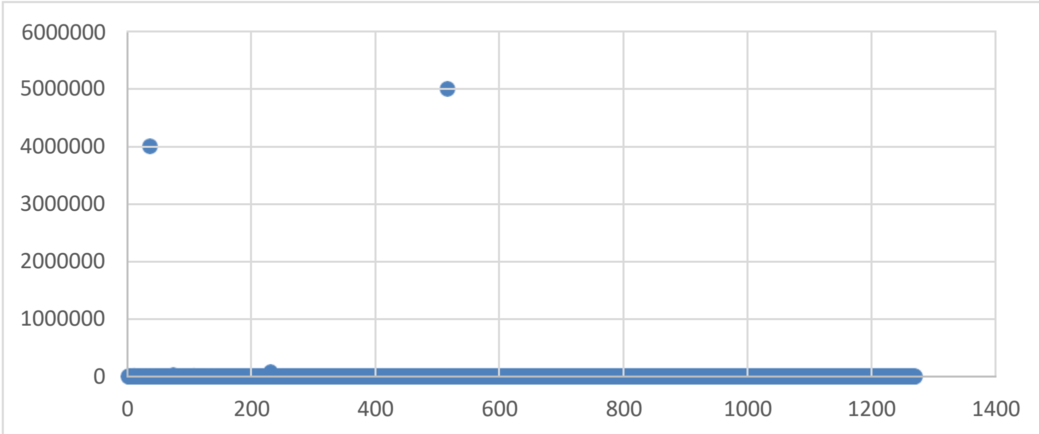


Figure 4-4: Amount of giving for each female donor in 2022

Table 4-3: Total amounts given by gender from 2019 to 2022

Gender	The Amount of giving	The Amount of giving without outliers
Female	10178523.03	1174266.53
Male	1469587.37	1469587.37

As shown in table 4-3, excluding the two outliers, the recalculated total amount contributed by female donors is $1,174,266.53, which brings it more in line with the total donations made by male donors. The total amount contributed by male donors $1,469,587.37, indicating a more consistent range of donations without such significant outliers.

The average donation amount for female donors $293,566.63, and the average donation amount for male donors is $367,396.84. those male donors, on average, contribute larger amounts than female donors.

- Age and Repeated Donor Engagement

The analysis of repeated donors by gender across three time periods (2019-2022, 2020-2022, and 2021-2022) reveals a consistent higher trend for both genders. Specifically, there is an important rise in the number of female repeated donors, with a significant increase from 30 in 2019-2022 to 106 in 2021-2022.

Similarly, male repeated donors show growth, with a rise from 55 in 2019-2022 to 138 in 2021-2022. At first, there was a greater number of male donors, but by 2021-2022, there has been a significant increase in female donors, although men still have a larger overall count, as shown in table 4-4.

Table 4-4: Number of donors ad male and female.

Gender	2019-2022	2020-2022	2021-2022
Female	30	45	106
Male	55	70	138

- State, City and Zip code.

The state with the largest proportion of donations was Texas (93%), while the city with the highest percentage was Tyler (26%), with the remaining percentage spread out over different cities in Texas, none topping 5% of total donors.

In relation to the ZIP code, the ZIP codes 75703, 75701, and 75707 showed the largest proportion of donors, accounting for 21.12% of the total. The remaining percentages were allocated among various other ZIP codes, with none surpassing 1% of the donors in Tyler and 2% throughout all cities.

2. Donation History and Patterns: Historical donation data from 2010 to 2022 was aggregated to create features such as total donation amount, average donation size, and frequency of donations. Additional features like the time since the last donation and the first donation year were engineered to capture donor loyalty and engagement over time.

3. Participation Indicators: Binary variables representing whether a donor participated in a donation for each year ('2012P', '2013P', etc.) were included to reflect the donor's active engagement with the university. These indicators are crucial for understanding patterns in giving behavior.

4. Geographical Insights: The 'City' and 'State' information, combined with 'Zip Code', was used to explore geographical trends in donations, potentially revealing regional differences in donor behavior.

4.2 Literature Features

The practice of predictive modeling is significantly influenced by the careful selection of relevant traits that have shown empirical significance in various research contexts. By thoroughly examining academic research and historical data patterns, a certain collection of features has been determined to have a significant impact on predicting the probability and extent of donations associated to universities.

Consistent with this research, we have enhanced our data gathering process to include the following features, which are easily accessible in our university database: Age, Gender, Preferred ZIP, Financial Information Amount, and Marital Status. The factors mentioned above have been methodically selected based on their established importance and frequency in predicting results associated with university development endeavors.

After applying each of Fine Gaussian SVM and RUS Boosted Trees

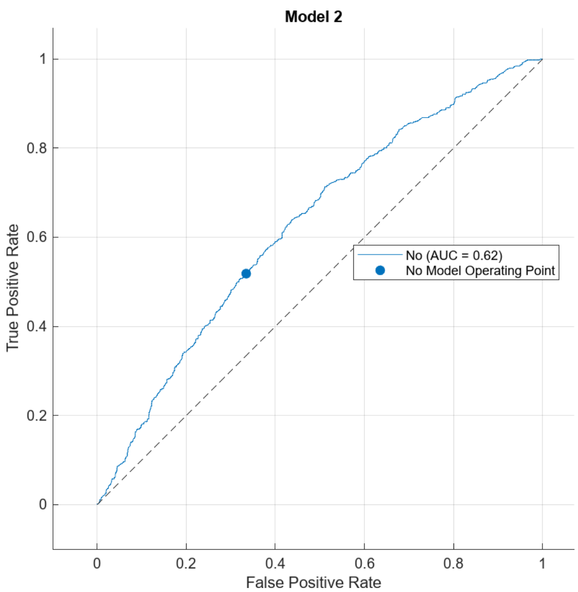


Figure 4-5: ROC for Fine Gaussian SVM

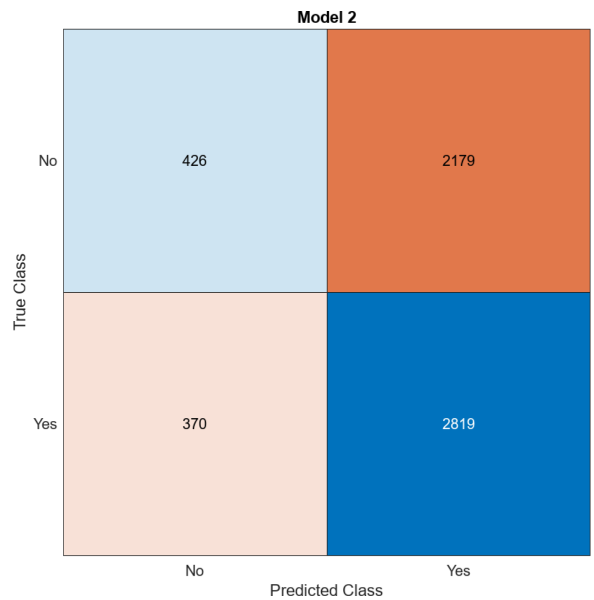
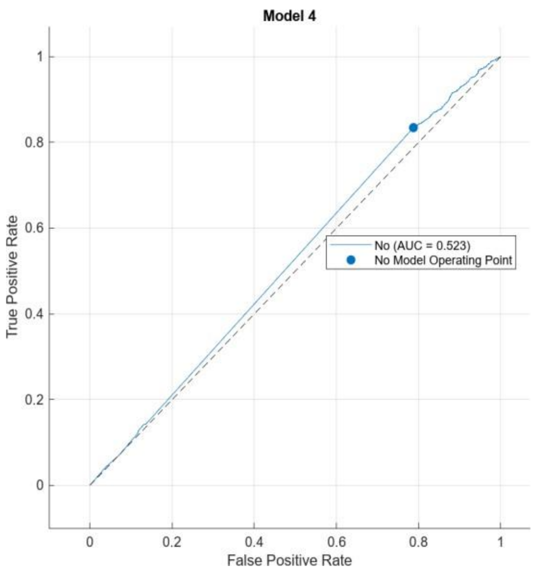


Figure 4-6: Confusion matrix for Fine Gaussian SVM

As shown in figure 4-5, AUC-ROC of 0.5999, reflecting a moderate ability to differentiate between classes. Its sensitivity, or recall rate, suggests a high true positive rate, indicative of the model's capability to identify the majority of the relevant cases. However, the specificity score indicates a challenge in accurately predicting negative cases, as seen by the lower true negative rate. The confusion matrix in figure 4-6, further substantiates these findings, with a high number of true positives and a considerable number of false positives.



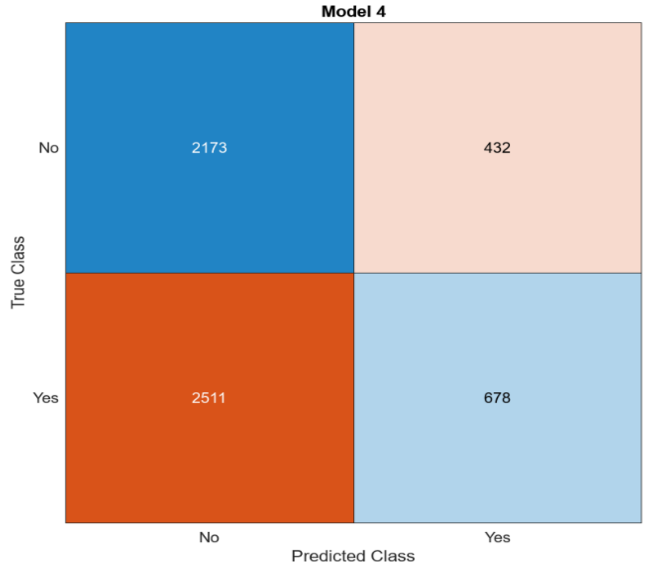


Figure 4-7: ROC for RUS Boosted Trees   Figure 4-8: Confusion matrix for RUS Boosted Trees

Conversely, figure 4-7, yielded an AUC-ROC of 0.523, which is closer to the baseline of random chance, denoting limited discrimination power. The sensitivity rate for this model is lower compared to fine gaussian , hinting at less effectiveness in identifying true positive instances. In terms of specificity, it achieved a better score, showing a stronger performance in recognizing true negative instances. The confusion matrix in figure 4-8, confirms this pattern, presenting a more balanced classification across the predicted classes, yet with a sizeable number of false negatives.

After discussing the classification outcomes, the subsequent application of the regression model to predict the actual amount of money donated yields unsatisfactory results as shown in figure 4-9 . The scatter plot reveals a poor fit, especially at higher donation amounts, which indicates that the model's predictive performance is inadequate. This suggests a need for model reassessment or refinement before it can be considered reliable for practical use.

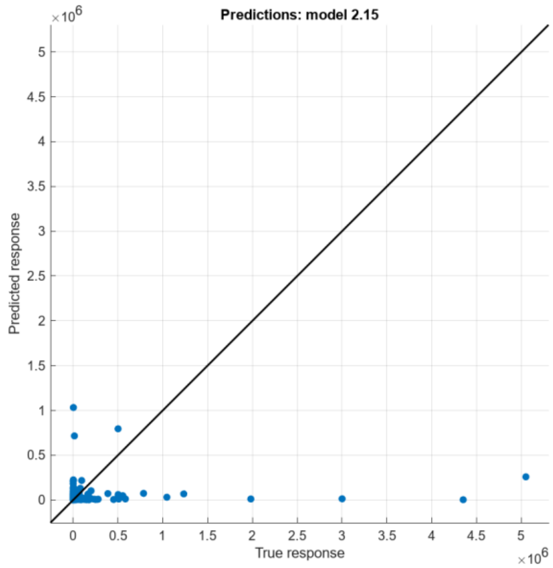


Figure 4-9: True response vs predicted response (Boosted Trees)

4.3 New Person in Town

In the evolution of our predictive analytics, we have built upon the foundation laid by features vetted through academic literature by incorporating additional, potentially predictive features available in our university's database. This augmentation is reflective of a strategic approach that combines empirical evidence with innovative data exploration to refine and enhance model performance, the enriched dataset now includes (age, gender, preferred ZIP code, total financial information, marital status, consecutive years of giving, total number of gifts).

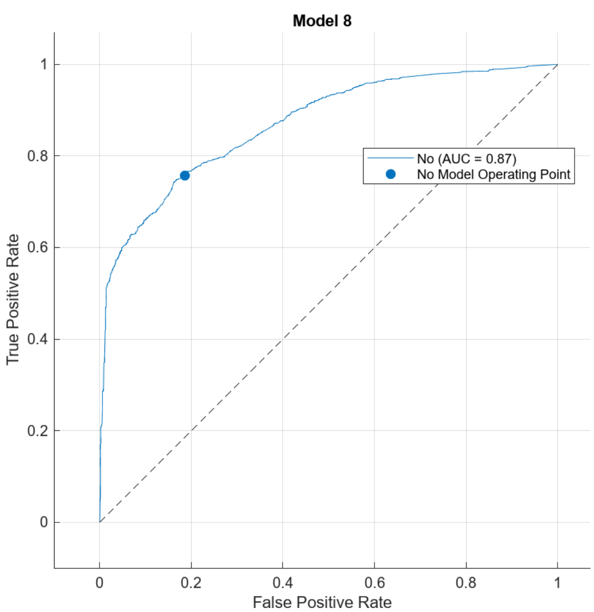


Figure 4-10: ROC for RUS Boosted Trees

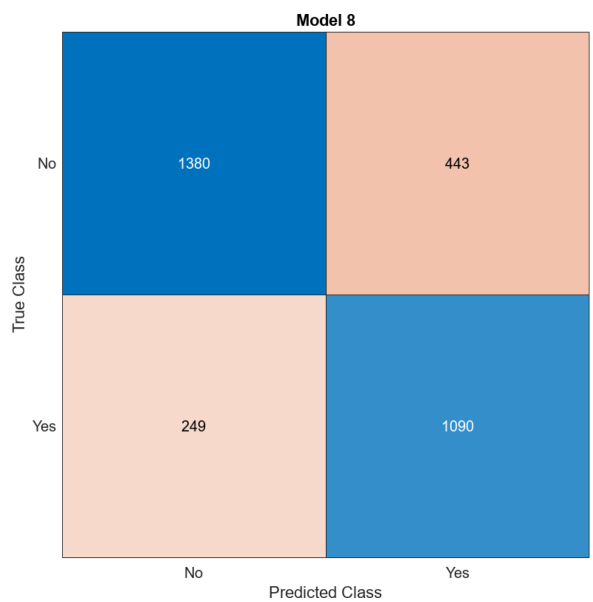


Figure 4-11: Confusion matrix for RUS Boosted Trees

Upon enhancing our model with a RUS Boosted Trees, a significant uptick in performance metrics was observed, as evidenced by the results encapsulated in figures above. The ROC curve in figure 4-10 demonstrates an AUC of 0.87, a substantial increase compared to previous iterations. This high AUC value suggests a strong discriminatory ability to distinguish between potential donors and non-donors.

The ROC curve, characterized by its steep ascent and plateau near the top left corner of the graph, indicates a high true positive rate with a low false positive rate at the selected model operating point. This balance underscores the model's precision in classifying true positive cases while minimizing false alarms.

The accompanying confusion matrix in figure 4-11 provides a numerical representation of the model's predictions, with 1090 true positive and 1380 true negative predictions, standing against 443 false positive and 249 false negative instances. From these values, we can derive a high sensitivity or recall, which implies that the model successfully identifies a large proportion of actual positive cases. However, the considerable number of false positives signals a need for caution, as this reflects on the precision of the model which might be lower due to the relatively high number of false positives.

The effectiveness of the regression model in predicting contribution amounts appears insufficient, as shown by the figure 4-12 that displays a notable difference, especially for higher donation values. The difference underscores the existing limitations of the model and underscores the need for further improvement or an entirely new approach to make it appropriate for real-world use. The model's projections for the contribution amounts may be anticipated to differ from the actual values by about 639.37, either overestimating or underestimating the genuine amount.

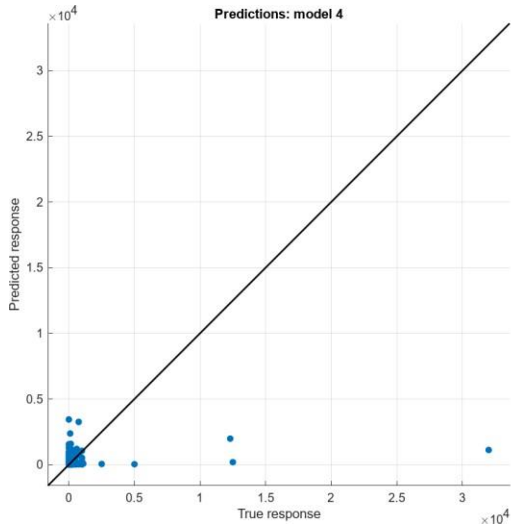


Figure 4-12: True response vs predicted response (Boosted Trees)

4.4 Giving History

The transformative power of predictive modeling is often harnessed by continually refining the features used to forecast outcomes. Initially, our models leveraged general demographic and financial indicators, yielding insights that, while valuable, fell short of our accuracy aspirations. It became apparent that a more nuanced approach was needed to enhance the predictive precision of our efforts. Thus, we turned our attention to the giving history of our alumni and donors, a rich tapestry of past behavior which could illuminate future actions.

Incorporating a temporal dimension, we crafted features representing the giving activity over the three years leading up to the predicted year (2019P, 2020P, 2021P) and the total amount donated prior to this period (Until 2019). This approach allowed us to view giving not merely as a series of transactions but as a narrative of engagement, mapping a donor's journey with the university. We opted to treat recent yearly donations as categorical variables, indicating the presence or absence of giving, which provided a clearer signal of ongoing donor engagement irrespective of the amount.

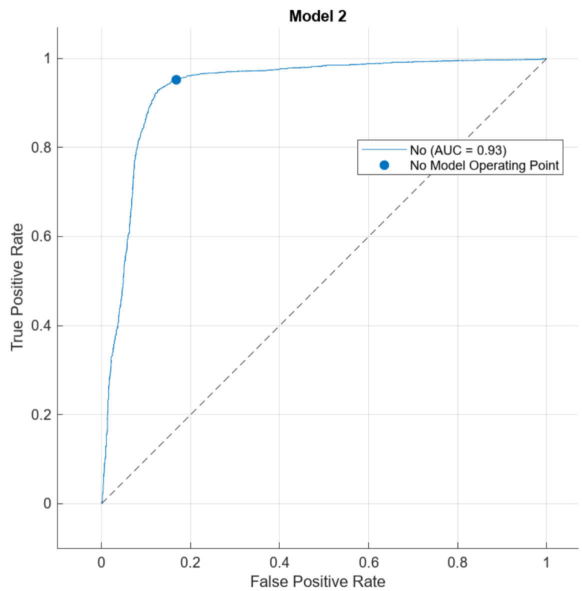


Figure 4-13: ROC for Fine Gaussian SVM

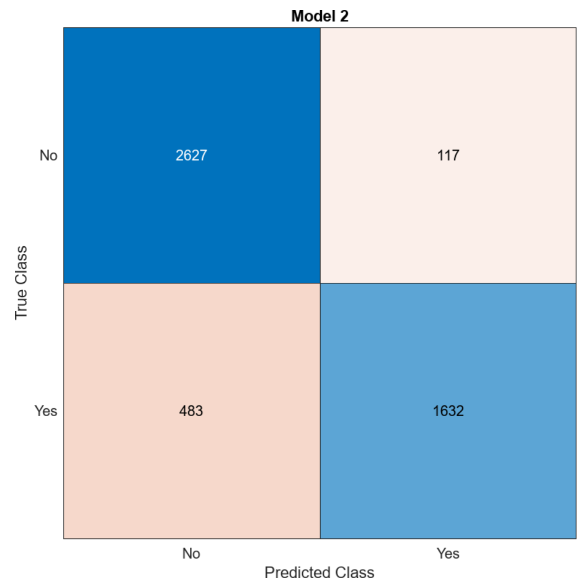


Figure 4-14: Confusion matrix for Fine Gaussian SVM

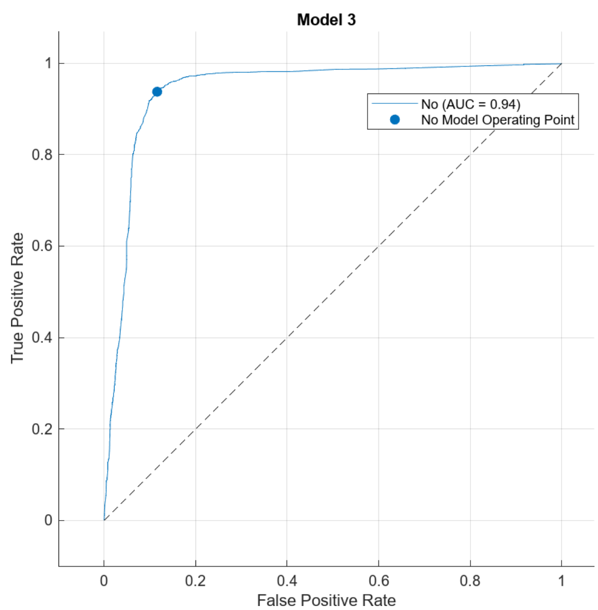


Figure 4-15: ROC for RUS Boosted Trees

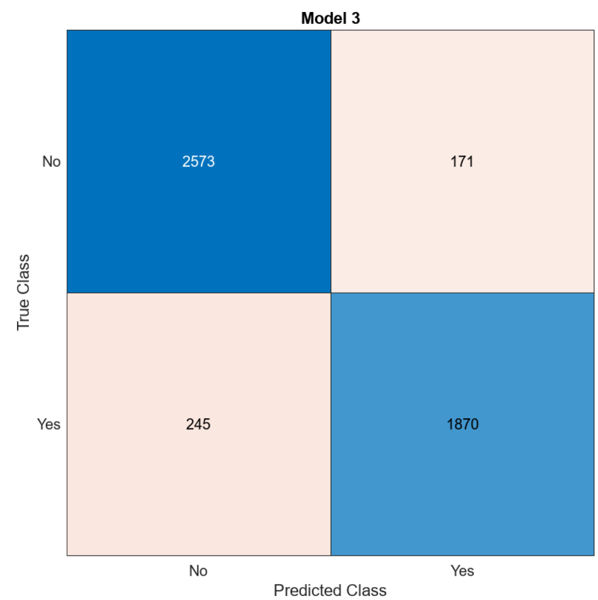


Figure 4-16: Confusion matrix for RUS Boosted Trees

With these refined features in our arsenal – Age, Gender, Zip Code, City, State, and the giving history – we applied advanced machine learning techniques. The Fine Gaussian Support Vector Machine and RUS Boosted Trees were deployed to discern patterns within this enriched dataset.

in figure 4-13 (Fine Gaussian SVM) demonstrated commendable performance, with an AUC of 0.9332, denoting a high ability to distinguish between classes. The confusion matrix revealed an accuracy that reinforced the model's efficacy, with a strong balance between sensitivity (recall) and precision. In figure 4-15 (RUS Boosted Trees), however, achieved an even higher AUC of 0.9416, suggesting an even finer distinction between donors likely to give again and those less inclined.

After examining the efficacy of the regression model in predicting contribution amounts, figure 4-17 analysis indicates a less than ideal fit, particularly at larger levels of actual donations. This conclusion highlights the limits of the model and emphasizes the need for more changes or a different methodology before it can be considered useful for practical purposes.

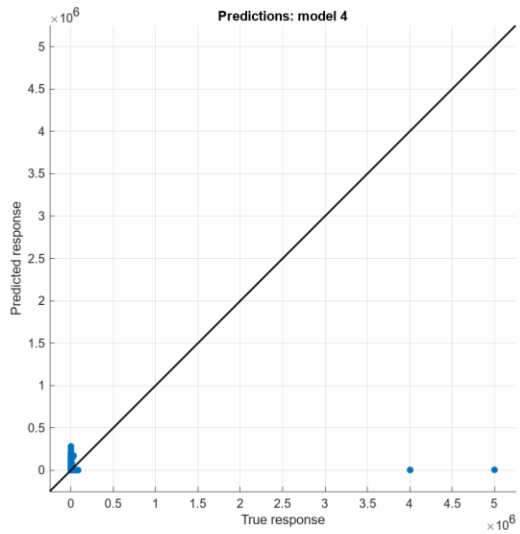


Figure 4-17: True response vs predicted response (Boosted Trees)

Table 3-5: Model development

Model	AUCROC	ACCURACY
Literature feature	0.62	56%
New person in town	0.87	78%
Giving history	0.94	91.5%

Table 3-5 above, shows the summary of all the classification stages and the improvement in each step.

CHAPTER FIVE

CONCLUSION

In conclusion, this dissertation has effectively explored the application of machine learning to enhance fundraising in higher education, using detailed analysis and predictive modeling. The research utilized a comprehensive decade-long dataset from Blackbaud Raiser's Edge NXT, focusing on demographics, donation patterns, and engagement metrics. This provided an in-depth view into donor behaviors from 2012 to 2022.

Crucial insights emerged, notably the increased engagement from younger donors and substantial contributions from older demographics. The data also unveiled significant geographical patterns in donor activities. These findings underscore the dynamic nature of donor behavior in higher education fundraising.

The research's core involved deploying Fine Gaussian SVM and RUS Boosted Trees models, each offering unique insights. The Fine Gaussian SVM model, with an AUC of 0.9105, showed a strong ability to identify potential donors, though it struggled with false positives. On the other hand, the RUS Boosted Trees, achieving a higher AUC of 0.9416, indicated improved efficacy in distinguishing repeat donors, despite a notable presence of false negatives.

These outcomes signify the transformative potential of machine learning in refining fundraising strategies. The adaptability and predictive accuracy of these models provide a framework for higher education institutions to tailor their fundraising efforts more effectively, taking into account the nuanced shifts in donor preferences and behaviors. The dissertation's findings point towards a future where machine learning not only aids in predicting donor behaviors but also in shaping more strategic, data-driven fundraising campaigns. This integration of technology and analytics is poised to redefine the landscape of educational fundraising, making it more efficient, targeted, and aligned with evolving donor trends.

CHAPTER SIX

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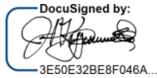
Javier Kypuros jkypuros@uttyler.edu Dean of the College of Engineering The University of Texas at Tyler Security Level: Email, Account Authentication (None)	 Signature Adoption: Drawn on Device Using IP Address: 104.28.77.5	Sent: 5/31/2024 8:33:27 AM Viewed: 5/31/2024 10:38:55 AM Signed: 5/31/2024 10:39:08 AM

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