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Personalization: University Fundraising

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Personalization: University Fundraising

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Abstract. University fundraising campaigns, which are typically a multi-year endeavor, help institutions build a strong financial foundation to enable a unique student experience. At the heart of effective fundraising is having strong relationships and partnerships with certain audiences that provide the best donation opportunities. Generally, alumni networks and the local community makeup these audiences as strong fundraising bases. Therefore, universities have a significant responsibility in developing these relationships to gain deeper insights into their constituents' needs and interests. This enables them to tailor effective engagement strategies, thereby increasing the likelihood of meeting donation expectations. This research explores how machine learning techniques can be used to predict who is most likely to donate and generate personalized email communication content at an individual level to maximize donations. The opportunity to automate email campaigns with a personalized touch with the goal of increasing the lifetime value of each donor can be beneficial to SMU over several years.

1 Introduction

Private universities make up approximately 68% of postsecondary educational institutions in the United States. Traditionally, private, and public universities have differed in their primary funding sources. From 2020-21, 46% of funding for private non-profit institutions came from private investments, reflecting a 36-percentage point increase compared to the previous year. Meanwhile, 40% of funding for public universities came from government sources (National Center for Education Statistics, n.d.). The increase in private investments for both private and public institutions indicate a shift towards a reliance on fundraising.

Historically, public universities rely on funding from state and federal sources since they are usually absent from the endowment and donation networks that are usually associated with private universities. In the fiscal year of 2022, higher education institutions received a combined funding of $120.7 billion from state and local governments, marking a 5% increase, with an additional $2.5 billion sourced from federal funding. (State Higher Education Finance [State Higher Education Finance], 2023). This is representative of the current state of higher education in which national enrollment has decreased, which has led to increasing funding commitments at the state level. As a result, public university revenues made up of students' tuition dollars have decreased. Meaning when government funding decreases, universities must find alternative funding sources, often resorting to higher tuition fees to bridge that gap. Public universities rely on the state's discretion, influenced by fluctuating economic factors and evolving priorities regarding funding allocations for higher education annually. Given this inherent uncertainty, it behooves them to seek out more stable revenue streams capable of sustaining their operations and academic endeavors in the long run.

Public universities are evidently adopting fundraising strategies like those employed by private institutions, establishing ambitious campaigns aimed at bolstering education affordability for students and advancing various university initiatives. According to The Texas Tribune, Texas A&M launched a nine-year campaign called "Lead by Example" back in 2015 that raised $4.25 billion, surpassing its original goal of $4 billion. Not to be left out, in 2016, The University of Texas at Austin launched the "What Starts Here" campaign with the goal of raising $6 billion, which is the third-largest campaign of any public university in the country (McGee, 2024).

These endeavors, led by well-known institutions boasting substantial alumni donor bases known for their generous contributions, serve as models for both private and public universities to follow. The success of these campaigns is driven by a cohesive community supporting the university, comprising alumni, non-alumni, and foundations that share in the belief of the university's capacity to deliver value and enact positive change locally and globally. Another measure of success lies in the quality of the relationship between the university and its alumni. When the university adeptly engages with its alumni in different ways that appeal to them, it becomes easier for them to offer financial support or volunteer their time. The breakdown of donations received by Texas A&M's "Lead by Example" campaign illustrates this point: former students accounted for over 60 percent of campaign gifts, with nearly 40 percent coming from non-alumni and various public and private foundations (Clark, 2021).

Private universities rely heavily on fundraising due to the absence of local and federal support that public universities receive. As result, they must continuously demonstrate their value to stakeholders, who play a crucial role in sustaining and securing their future viability. Typically, for private universities, there are three different types of donations. Money donated towards research and/or sports facilities is known as capital projects. In most cases, the donor decides which projects those funds should be allocated to. Another type of donation is for an endowment. These are usually large funds created through donations, investments, and other financial contributions that generate income that can be used to provide long-term financial support and stability. Lastly, donors can provide funds to support immediate needs such as purchasing lab equipment, as well as ongoing operations like ground maintenance.

For both public and private universities, excelling in fundraising is essential in any context, as it can unlock unprecedented levels of donations and philanthropic support. These resources enable universities to implement multi-year strategies, solidifying their credibility and advancing their institutional goals. For instance, in 2021, Southern

Methodist University (SMU), the subject of this research, launched a $1.5 billion campaign for impact called “SMU Ignited”. The O’Donnell Foundation, recognized as one of Dallas’ leading philanthropic entities, contributed $30 million to SMU. This donation aims to establish 10 endowed academic positions in data science and engineering, bolstering associated research endeavors. (O’Donnell, 2023). This donation enables the university to cement itself as a leader in technology innovation.

The different fundraising campaigns mentioned so far highlight the importance of engagement, especially with alumni. While students naturally become alumni of an institution and may already have some degree of connection, this may not always be sufficient to persuade them to become donors. Therefore, establishing a deeper connection that resonates with their interests, values, and vision creates a shared interest that universities can leverage to effectively communicate with future donors. Universities often hold fundraising events, typically for higher-level donors, to facilitate personal connections and help them understand the needs and impact they can have. Likewise, customizing various events to cultivate personal connections can prove beneficial in broadening and nurturing a donor pipeline, that can effectively attract new or prospective donors. In 2023, Boise State University introduced Gravyty, an AI-powered fundraising platform, with the aim of enhancing interaction with alumni who possess the capacity to become significant donors, thereby supporting efforts to build a robust donor pipeline. During the initial three months, the university raised over $118,000, with $60,000 stemming from new or enhanced contributions, and deployed nearly 4,500 personalized emails to individuals within their portfolio of potential donors (Gravyty, 2023).

In fundraising circles, it's often referred to as an "art," (Lee et al.,2020) but institutions are increasingly embracing analytics to derive insights into the giving behavior of donors. This involves storing relevant information about donors' interactions with the university, allowing for a more data-driven approach to fundraising strategies. Institutions need to understand donors at an individual level and communicate with them as such, but this can be challenging considering budget and technical limitations that can impact engagement approaches. Therefore, this research aims to use donor demographic data, interaction history, and machine learning algorithms to predict which donors, among those with a current lifetime value of less than $100,000, are most likely to donate. Additionally, the goal includes generating personalized email communication for a particular donor.

2 Literature Review

The literature review focuses on the following key areas: alignment of university brands with fundraising campaigns, machine learning applications with personalized marketing strategies, and university fundraising with machine learning applications.

2.1 Alignment of University Brands & Fundraising Campaigns

This study focuses on improving fundraising strategies that can help institutions meet their campaign goals. Therefore, investigating how institutions have built brand equity to attract students, alumni, and donors to support their initiatives is key for shaping effective strategies.

As per a study conducted in 2020, enrollment in higher education institutions remains lower than pre-pandemic figures, with a decline of approximately 1.09 million students (Current Term Enrollment Estimates | National Student Clearinghouse Research Center, n.d.). This makes the pool of students that are considering higher education much more competitive, in which universities must distinguish themselves from other universities to attract students.

Building brand authenticity is no easy feat for universities. They must carefully consider how to uniquely position themselves among competitors, achieve student enrollment benchmarks, and construct fundraising campaigns that align with their objectives. This pursuit is often called the 'Holy Grail' (Sevilla, 2018). While these efforts are common, they are seldom achieved. At any rate universities must understand that to effectively drive engagement from their audiences it needs to build a cohesive brand that speaks on behalf of the university but appeals to different interests at the same time.

This study references two case studies on how University of Toronto (U of T) and Georgia State University demonstrated best practices in brand development that drove success in fundraising and provided benefits to other areas within the university. In the U of T case study, it was apparent that the research university predominantly functioned in a decentralized manner and struggled with consistent storytelling which impacted its identity. This realization sparked the creation of a collaborative working group and advisory group led by the University Advancement team who are responsible for fundraising activities with the purpose of establishing a culture of collaboration throughout the campaign brand development process. (Sevilla, 2018). These collaborations revealed a lack of clear values that were not always understood by external audiences. As a result, U of T created a brand platform where their $2 billion "Boundless" campaign originated fostering a message of togetherness. The campaign was effectively adopted by various divisions within U of T for mass media brand-building campaigns, student recruitment campaigns, and divisional marketing (Sevilla, 2018).

Georgia State is similarly as broad as U of T in that it has 7 campuses throughout Atlanta, Georgia and has 12 colleges and schools. Their $300 million "Burning Bright" campaign focused on its student success as its brand identity (Sevilla, 2018). This resonated with students, alumni, and donors. The process of finding its brand identity is like U of T in that they conducted interviews to gage audience perceptions about what makes Georgia State unique.

Based on that research, it was able to formulate a distinct positioning statement, emphasizing its advantages as a large research institution situated in the growing Atlanta metropolitan area, with access to a wide range of opportunities. (Georgia State

University, 2023). The university successfully aligned its identity and brand with the "Burning Bright" campaign by creatively integrating the visual of the flame found in the GSU logo. The university raised $298 million, and regarding student success, scholarships increased by over 50 percent. These results exemplify the impact of a consistent brand that relates to their target audiences.

2.2 Machine Learning Applications with Personalized Marketing Strategies

In today's marketing landscape, personalization has emerged as a key strategy. Research indicates that 90% of consumers are drawn to personalized advertisements, while 95% of businesses implementing personalization techniques have experienced a threefold increase in return on investment (Choi & Lim, 2020). This demonstrates that personalization now has become a necessity as consumers expect businesses or organizations to deliver stand-out experiences apart from what they've already grown accustomed to.

The aim of personalization is simple, yet its execution can be challenging: to create unique content for individual consumers based on collected data. Personalization encompasses a wide range of delivery methods, including customized email communications, targeted advertisements, and tailored e-commerce experiences. This means reaching the right person at the right time with the right message (Lin, 2023). Doing this effectively allows organizations to understand what their consumers want and deliver experiences that resonate with them, which can lead to increased engagement and retention.

However, in a survey conducted by Gartner Inc. from November to December 2020, involving 350 marketing leaders, it was found that 63% of marketing leaders encounter difficulties in providing personalized experiences to their consumers (Gartner Says 63% of Digital Marketing Leaders Still Struggle with Pers, n.d.). One of the factors contributing to this is that businesses haven't scaled the adoption of artificial intelligence (AI) and machine learning (ML) capabilities at an enterprise level that matches their customer acquisition and retention roadmaps. The survey also shows that only 17% of marketing leaders are using AI/ML across various marketing areas. (Gartner Says 63% of Digital Marketing Leaders Still Struggle with Pers, n.d.). Deploying AI/ML solutions within the marketing domain requires an integrated approach between marketing and data science teams to map marketing objectives to tangible solutions that can be measured and assess whether it delivered upon expectations.

In terms of machine learning applications, in the context of personalization there are many use cases. For instance, personalized marketing relies heavily on consumer data to adapt the user experience and generate customized recommendations. In Burberry's case it leverages big data and machine learning to combat counterfeit products and enhance both sales and customer relations. Central to the company's sales growth strategy is the maintenance of intimate, personalized connections with its clientele.

Through reward and loyalty programs, Burberry collects valuable data to refine and personalize the shopping journey for every individual consumer (Marr & Co, 2017).

Another application involves optimizing advertising performance, utilizing machine learning to analyze ad effectiveness across various platforms and offer recommendations for performance improvements. For example, Google Ads uses advanced machine learning techniques in pay-per-click (PPC) campaigns. Through bidding, machine learning algorithms analyze extensive datasets to make highly precise predictions across a given account, informing decisions on bid amounts and their potential impact on conversions (Nikolajeva & Teilāns, 2021). The depth of insight gained from these algorithms holds significant influence over ad placement, dictating optimal timing and positioning. Machine learning techniques along with human input allow marketers to gain a deeper understanding of its audiences.

2.3 University Fundraising with Machine Learning Applications

The adoption of machine learning algorithms to enhance donor engagement represents a growing approach with promising potential. Researchers (Lee et al., 2020) developed a model based on previous interactions taken by donors and the university with respect to the donor for a given email campaign. This model is then used to determine the most appropriate action to take next with a donor individually. Their work focused on optimizing models to predict donation amounts and then suggest appropriate email parameters that foundations should use to increase donations. In their research, they used recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to train these models on the sequence of actions taken by the donor and university. They experimented with various window sizes encompassing previous actions and feature data characterizing the donor. Their research builds upon prior efforts, which achieved a 36% reduction in mean absolute error (MAE) using CNNs. The researchers also found that RNNs and CNNs with similar MAEs chose similar email parameters meaning they learned similar outcomes but with different architectures.

Another method for exploring donation behavior involves employing graph models to predict the likelihood of a prospective alumna/us contributing to specific funds. For instance, as evidenced by a recent study (Dong, 2022), incorporating relationships between entities and their interactions yields improved outcomes compared to machine learning models that sequentially analyze input features. More specifically, the node embeddings or connections represented in the graph encompass contributions to various funds, linked with documented records of donor engagements with outreach initiatives, revealing individual interests (Dong, 2022). An example of a node embedding in their research is an 'alumnus embedding' to represent each alumnus based on their history of clicks on newsletter articles. This is represented numerically to capture their interests, as these interactions are deemed valuable for understanding their preferences. Graph representations are used to enclose the connections between nodes for instance connecting an alumnus to a newsletter that they clicked on and the fund that they have donated to. This is enabled via a learning method called node2vec (Dong, 2022). The alumni behavior graph model constructed can be used to identify which funds may interest a particular alum by looking at their similarities. The predictive power of this model can provide insights into the funds an alum is likely to donate to, which can inform the development of target strategies to engage specific audiences.

Applying a non-parametric technique such as Multi-Layer Perceptron to predict donors' behavior offers an alternative means of predicting both the quantity and sizes of donations by leveraging donors' individual characteristics and past donation records as evidenced in a study conducted from the Ca'Foscari University of Venice (Barro et al., 2024). Simply an MLP can be seen as a network of artificial neurons organized into layers: input, hidden, and output. The input layer receives data from the environment, the hidden layer processes the computation, and the output layer provides the result. This study used three different MLP based prediction models where two of the models were a seven-input-one-output MLP. These models differ in that the gift amount is one of the input features of MLP1 and vice versa, the output label of MLP1 is one of the input features of MLP2. The third is six-input-two-output MLP. MLP3 differs from MLP1 and MLP2 where it has two output labels. Also, it attempts to predict attributes of the donations based solely on information about the donors themselves, without considering any additional factors (Barro et al., 2024). MLP1 turned out be a single-hidden-layer MLP with 12 nodes in the hidden layer. The training was iterated 25 times. MLP2 and MLP3 had 13 hidden nodes. To determine the performance of the model the researchers used R^2 which indicates how well the independent variable(s) explain the variation in the dependent variable between a range of 0 to 1. MLP1 achieved an R^2 of 0.9065 which indicates that the independent variable(s) effectively account for nearly all the variability observed in the dependent variable. MLP2 and MLP3 achieved an R^2 of 0.6842 and achieved an 0.4322 respectively (Barro et al., 2024). The findings from the models perform satisfactorily well except for MLP3 when the goal is to predict one specific variable without considering other variables simultaneously, the models are effective at achieving accurate predictions for that variable. For practical reasons, this approach may not be efficient if there are multiple attributes that need to be considered. However, considering that institutions may have data limitations, it could be beneficial. For future considerations, the researchers will focus on hyperparameter tuning of the models to improve forecasting capabilities.

3 Methods

The data used in this analysis was sourced directly from SMU's Marketing and Communications department (MARCOM), which is actively involved in the university's current fundraising initiative, "SMU Ignited". The data was pulled from different department CRM systems that includes information about the constituents, the emails associated with a particular marketing campaign, and subsequent actions taken by the constituents once an email has been received. Table 1 provides a breakdown of the datasets covered in this analysis.

Table 1. Description of the datasets provided by MARCOM.

Dataset	Description
Constituents	CSV with basic information about each constituent such as education background, macro-demographics, communication preferences.
Gifts	CSV with unique identifiers for constituents, gifts, and source code tied to marketing effort.
Email pdfs	Email communications sent to constituents.
Email Actions	Separate CSV files of received, opened, clicks with constituent and source code ids.

The modeling will be structured so that each row represents a constituent with columns that describe different characteristics like marital status, simple constituency (alumni, friend, parent), and age as examples. Considering the data is contained within several different files, the restructuring process is detailed below in the Data Processing section.

3.1 Data Processing

The first step in data preprocessing was consolidating all the email actions datasets into a single dataset that will eventually be combined with other datasets that were mentioned above in Table 1. The email actions dataset comprises the “Source Code” serving as the marketing ID for a particular marketing effort, along with the subsequent email actions from a constituent like “Received_Timestamp”, “Opened_Timestamp”, and “Clicked_Timestamp” that are associated with a “Source Code”. Next, we combined the email actions dataset with the gifts dataset to associate a constituent with a gift known as the “Revid_seq_id”. This is achieved by using the constituent ID known as “Seq_id” and “Source Code”. Next, we combined the last dataset with the constituent's dataset to include constituent demographics using the “Seq_id”.

Next was inspecting the final dataset to remove unnecessary attributes and handling missing values. Since this study focuses on email communications, it made sense to remove unrelated communication preferences like “Do Not Telephone”, and “Do Not Mail”. The dataset included various location related attributes so removed “City”, “County”, “Cbsa_name” which is known as Core-based statistical area description, and “Pmsa_name” which is known as Primary Metropolitan Statistical Area Identification. After removing those location related attributes relied on other location attributes like “State” and “Search_Postcode” which is the zip code. Also removed an attribute called

“Last Recognized Commitment Year” since there is another attribute that is similar called “Recognized Last Year of Giving”. Next, we reviewed categorical attributes that had a limited number of missing values that could be updated with the value "Unknown" so that we could have data completeness while maintaining data integrity. Those attributes included “Marital Status”, “Region”, “SMU Primary Degree” which refers to the degree category like Bachelor of Arts or Master of Arts, “SMU Primary Program” refers to degree program category, and “Primary School” refers to the name of the school from which the degree program originates.

The next step was addressing the numerous missing values in the "Source Code" field. To assign the appropriate code, we referred to another field called “Link” which is a link within in each email communication for either providing a gift or signing up for an event associated with a marketing effort. This link contains information such as the “Source Code” or the name of the marketing effort it is related to. Utilizing this information, we updated the missing values in the “Source Code” field, resulting in a reduction of missing values by 20%. To continue updating the missing values we decided to randomly assign the codes. Since most of the codes provided rolled up to 5 different marketing efforts, this approach ensures a broad distribution across various campaigns, maintaining data balance. Those missing codes also meant not having email actions so at a minimum we could only manually assign “Received_Timestamp” to those records. At this point all missing values have been addressed. The attributes listed below in Table 2 will be used for modeling.

Table 2. Description of attributes included in modeling set.

Variable	Description
Seq_id	Constituent id
Revid_seq_id	Gift id
Received_Timestamp	Timestamp of when constituent received email communication
Opened_Timestamp	Timestamp of when constituent opened email communication
Clicked_Timestamp	Timestamp of when constituent click link in email communication
Marketing Effort	Marketing campaign
Source Code	Marketing effort ID
Marital Status Code id	Marital Status
Gender	Gender
Simple_Constituency	Constituency Status
Primary_Classof	Graduating class year

Primary_School	Degree school
Age_Range	Age
State	State
Search_Postcode	Zip code
Region	Area
Cbsa	Core-based statistical area
Primary_Email_DoNotEmail	Email communication preference
SMU_Primary_Degree	Degree category
SMU_Primary_Program	Degree program category
RecognizedFirstYearOfGiving	Recognized first year of donation
RecognizedLastYearOfGiving	Recognized last year of donation
DoNotEmail	Email communication preference

Before modeling, we needed to standardize the data first. This was done by one hot encoding the categorical attributes and scaled the numerical attributes using Scikit-learn.

3.2 Modeling and Evaluation Methods

The response variable contains two categories and is based on the gift ID "Revid_seq_id." These categories indicate whether a constituent made a gift ("Gift") or not ("No Gift"). To assess the model's performance accurately, we will utilize a weighted F1 score. The dataset is balanced between the two categories. Based on this, it was determined that a deep neural network would be sufficient for binary classification.

The neural network used for this research is a simple feed forward sequential neural network with three dense layers. The first and second layers have 64 neurons with rectified linear unit (ReLU) activation function for the hidden layers. ReLU provides efficiency in how the network learns complex patterns from the input data. The third layer has one neuron with a sigmoid activation function that will support binary classification tasks. Batch normalization is applied after each layer to improve the training stability of the neural network. Batch normalization helps mitigate issues like vanishing gradients, where updates to the weights of early layers in a deep neural network are small or non-existent during training. This slowdown in learning can hinder the network's performance improvement. Batch normalization ensures the optimization process is efficient, leading to faster learning and potentially better model performance. The model setup includes specifying The Adam optimizer which helps the model learn from the training data and update parameters to minimize loss that will improve its ability to make accurate predictions on unseen data and binary cross entropy loss function for measuring the difference between the predicted output of the model and the actual binary labels of either "Gift" or "No Gift". The model is trained for 10 epochs with a batch size of 32.

To assess the model's effectiveness, we utilize the weighted F1-score, a metric that offers a balanced evaluation of precision (false positives) and recall (false negatives). By assigning greater significance to minority classes, this metric accounts for class imbalances, ensuring the model's proficiency across all classes, including those with fewer instances. In this context, the weighting accommodates variations in the number of instances within each donation class.

4 Results

The overall performance of the final neural network model was evaluated using the F1-score, which can also encompass additional information regarding our results, such as precision, recall, and overall accuracy. Tables 3 and 4 show performance statistics and confusion matrix.

Table 3. Classification report for neural network model.

Outcome Category	Precision	Recall	F1-Score
No Gift	0.99	0.99	0.99
Gift	0.99	0.99	0.99
Macro Average	0.99	0.98	0.98
Weighted Average	0.99	0.99	0.99
Overall Accuracy	-	-	0.99

Table 4. Confusion Matrix for test set predictions.

	Outcome Category	No Gift	Gift
True Label	No Gift	4538	42
	Gift	63	2749

Overall, the neural network model achieved an impressive performance; however, these results may not inherently translate to interpretability. On some level it demonstrates the model's ability to capture complex patterns, but it needs to be further evaluated by domain experts to understand true insights from model predictions and applicability to real world scenarios.

After performing model classification of whether constituents provided gifts or not, we can use GenAI to send personalized email communication content. This is to explore personalization strategies to improve engagement efforts around email communications to constituents. The concept of personalization is not new, as it offers individuals unique content or experiences based on their history, interests, and preferences. Therefore, we wanted to explore whether this approach could be applicable to the fundraising domain, potentially fostering better relationships with constituents.

When utilizing GenAI tools, we employed Google's AI Studio, which utilizes the Gemini 1.5 Pro model. This IDE, accessible through a browser, is used for prototyping generative models. Google AI Studio facilitates rapid model testing and experimentation with different prompts. We were able to take one of the marketing campaign emails that was provided to us that we could use as input to generate personalized email communication. We used the campaign that had the most gifts associated with it which was called “Campaign Update Winter 2023”. This campaign coincided with SMU’s announcement of their move to the Atlantic Coast Conference (ACC) which provided a natural opportunity to describe the impact gifts would have on an effective transition. Next, we simply uploaded the pdf into the IDE which served as user input along with a prompt asking the model to provide a thank you email to constituents that donated to the campaign. The model could only evaluate the text in the pdf and not the associated images or links. As output the model was able to generate a sample thank you email. Refer to Figure 1 on the results.

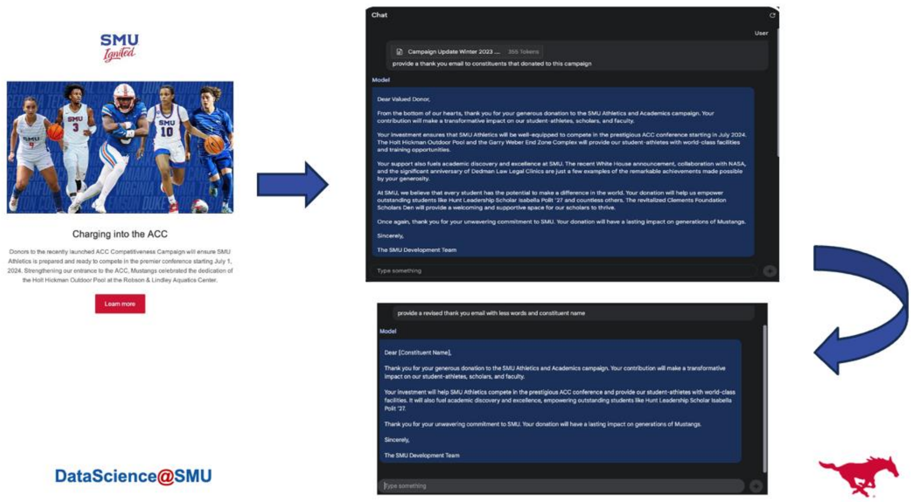

Figure 1 Results from GenAI Personalized Email Communication

5 Discussion

5.1 Limitations

The findings of this study may be influenced by certain limitations that could have impacted the model's overall performance. For instance, most records lacked a marketing effort id or "Source Code" that could be associated with the marketing efforts that were provided. As a result, we had to randomly assign the codes which changed the actual makeup of how the gifts can be tied to a particular marketing effort. This discrepancy may have stemmed from variations in how marketing efforts are identified across different departments in different CRM systems that contain constituent data. These discrepancies may indeed impact the reliability of the study findings. Nevertheless, acknowledging these shortcomings can lay the groundwork for future research aimed at addressing these limitations. This could involve developing or utilizing a platform capable of supporting inter-departmental data needs while fostering a shared understanding of constituent profiles, thereby facilitating various marketing engagement efforts.

One potential data source for better understanding giving behavior is to solicit feedback from prospective constituents, aiming to understand either their ability or motivations toward giving. In a study conducted by Indiana University Lily Family School of Philanthropy it noted that organizations that adapt to using innovative digital practices is a critical skill in reaching prospective constituents. These efforts can potentially lead to more gifts, as younger audiences are more likely to respond to such initiatives (Osili et al., 2022). Other observations from this study analyzed the factors influencing giving decisions compared to social identities. One key finding was the recognition of privileges, which prompted self-reflection and spurred a desire to contribute to benefit the broader community. Additionally, among younger constituents, having the financial resources to contribute impacted their ability to do so (Osili et al., 2022). With this additional information, institutions can further inform their fundraising and engagement strategies, leading to improved constituent support.

5.2 Implications

The model built in this study has nearly perfect performance however researchers should still critically evaluate the learnings produced from the model and determine if the results are valid enough to truly provide insights that can be useful in the universities fundraising efforts.

The model's main application involved predicting whether a constituent donated, yet its potential extends to more nuanced predictions, such as identifying the campaigns to which a constituent is inclined to contribute based on their interests and past donation history. Future research could explore these possibilities further. As discussed in the literature review section, the usage of graph models can provide insights into the interconnectedness of donors and optimize campaign targeting strategies.

5.3 Ethics

Given the study's focus on data about the university's constituents and their interactions, ethical concerns were important. We collaborated closely with SMU MARCOM department to ensure that the data used protected individuals' personal information and couldn't be combined with other sources to identify them or be used maliciously, which was critical. Additionally, protecting donor privacy is essential for maintaining trust and ensuring the proper use of contributions and financial information.

Therefore, it’s important that organizations establish secure environments for platforms storing constituent data, with robust access control policies. Unfortunately, data breaches are a reality, so organizations must constantly evaluate and implement necessary procedures to protect their systems and data. Failure to do so can result in significant consequences, as noted in a 2023 incident where a cyber security researcher discovered nearly 1 million donor records exposed in an unprotected online database owned by DonorView, a cloud-based donor management system used by over 200,000 non-profits (GRF CPAs and Advisors, 2023). This breach compromised detailed donor information, including contact details and payment methods. Often, non-profits and other organizations rely on these types of vendor solutions when they lack the technical expertise to manage their own systems or find it more cost-effective for data management or fundraising capabilities. Consequently, such compromises highlight the importance of ensuring robust security measures, even when utilizing third-party solutions.

In fundraising, ethical practices are not always a given, but organizations are strongly encouraged by different laws and regulations that govern fundraising activities. Those responsible for fundraising are usually aligned with the university’s mission and gift acceptance policies. This can also be a point of contention with the larger community when there is controversy surrounding a donation and not having visibility into those policies. It was revealed that Yale and Columbia, along with other institutions, were found to have received millions from members of the Sackler family, who were facing lawsuits regarding their pharmaceutical company's involvement in the U.S. opioid crisis (Elliott, n.d.). Navigating situations where concerns surface post-gift can be complex, often leading to requests for greater clarity or participation in the protocols surrounding gift acceptance. There are different stances on what should guide universities regarding gift acceptance and how they should operate based on what they consider to be in the best interest of the organization. Nevertheless, it's important to keep in mind the moral implications of gift acceptance, especially if the availability of those funds was tainted by some injustice. It's crucial to weigh the consequences of such decisions carefully.

6 Conclusion

The university fundraising community can certainly benefit from improving the usage of fundamental marketing tools such as email communications to improve relationships with constituents. Being able to provide relevant content that resonates with a constituent's interests and values can improve retention and increase the lifetime value a constituent contributes to a university. This study didn't leverage interests and other activities outside of emails actions, but it would greatly improve modeling capabilities.

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