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Data Governance and Stewardship in Fundraising: Estimating Donor Lifetime Value with Explainable AI

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Abstract:
The advent of Artificial Intelligence (AI) has the potential to transform fundraising by providing accurate estimates of Donor Lifetime Value (DLV). The challenge lies in the fact that standard-AI models lack transparency, create risks of algorithmic bias, and invite skepticism as trust erodes. In this paper, we suggest that the effective, ethical, and productive application of AI to DLV estimation requires a solid data governance framework. We argue that Explainable AI (XAI) is an important part of providing the transparency required to demystify predictions that allow fundraising professionals to personalize engagement with donors and to build stronger relationships. This supports a human-in-the-loop model in which AI augments professional fundraising capability, rather than replacing it.

Keywords: Explainable AI (XAI), Donor Lifetime Value (DLV), Data Governance, Fundraising, Ethical AI.

I. INTRODUCTION

The long-term viability of non-profit organizations is dependent upon the ability to build and maintain strong relationships with their donor base. In this context, DLV has come to represent an important indicator providing, forward-looking estimates of a donor's long-term financial prospects as well as providing strategic guidance on how to allocate limited resources. Traditional statistical methods to estimate DLV are weak, relying on historical data and often missing the complex, multi-dimensional reality of donor engagement in contemporary fundraising. While AI can provide a potential solution for this; being capable of processing large data (in-depth) to produce accurate predictions, AI is frequently constrained by the 'Black-Box' problem; algorithms which lack transparency could invariably create skepticism while limiting actionable insights. This article argues, that only when AI for DLV estimation is developed and implemented through thinking with a rigorous data governance and ethical stewardship framework, can we unlock its transformative power.

II. LITERATURE REVIEW

A. The Evolution of Fundraising Analytics

The increase of fundraising analytics in non-profits exemplifies a new epistemological leap from analytic thinking - moving from static historic reports to predictive analytics for fundraising activity in the future. Previously history was historic - reviewing reports of historic campaigns, and final gift allotments, counting up the total number of major gifts donated. There was some utility in retaining and discussing reports with the organizations, though historically much more as a reflective exercise in hindsight - even though we can see now (or potentially even then) the reports provided the organizations little descriptive understanding of the contexts surrounding great fundraising success, at all - nor did it provide any strategic tendency to act on the basis of that kind of reporting. The next evolutionary stage that was a natural progression from longitudinal reporting was the ability to move from historic reporting to historic reporting that also presented up statistical descriptors, giving the organizations a chance to then categorize

their donor database into very basic segments based on giving history, and if there were some demographic data - this stage of reporting allowed charities to start to think about some target segmented messaging to some of the donors, and it is worth noting that so far, it has still mainly been reactive messaging - but it's a start. Now, I feel there is a clearer indication of the transition from just reporting, to analytic thinking and the beginning of predictive thinking [1].

B. Traditional Models of Donor Lifetime Value (DLV)

"Donor Lifetime Value" (DLV) has been used as a key metric of strategic fundraising for many years, designed to estimate the total financial gift potential of a donor over their lifetime with an organization. Several traditional models have been built to quantify DLV, the most popular of which is the Recency, Frequency, Monetary (RFM) model. RFM provides a classification of donors based on how recently they have donated, how frequently they have donated and the monetary value of those donations. While utilizing RFM provides a straightforward and simple model to apply, its limitations are that it is also a historical view, only extending past donor behavior into the future, without being mindful of potential changes in the donor's circumstances or motivations. As a result, it can often be a blunt tool, and tentative in trying to value new donors or donors who give sporadically. Other statistical based approaches, like regression analyses, probability models, etc., provide greater sophistication but like DLV models, they also draw on a base of structured historical data that may fail to account for the variable, non-linear, emergent nature of donor engagement [3].

C. Artificial Intelligence in the Non-Profit Sector

Whether the use of AI is deterrent or more demonstrative, AI is not merely another alternative conversation in non-profit but is quickly becoming a more dependable conversation of advancing reliability of efficiency and objective facilitation. Just by demonstrating where AI is used conveys, at a basic level, an intention for the use of AI for the betterment of use(s) and depth of use for sustainability and impact. AI appears to establish a component of an organic state of biological AI through non-profit organization fundraising appears in order. In the organic state of developing AI, fundraising charities have utilized machine learning algorithms that take a greater amount of random data to formulate convoluted correlations of donor engagement which would be astronomically beyond the usability capabilities of TBM analysts utilizing standard data analysis.

D. The "Black Box" Problem and the Rise of Explainable AI (XAI)

There are not many who would argue that AI, especially in the aspects of neural networks or complex ensemble methods, offers substantial predictive capability but its curse is always sometime worse for its incomprehensible dark side. This is often referred to as the "black box" problem where the logic is so complex that the developers do not, and cannot, understand how it concluded it reached. This presents significant barriers in even the best situations for fundraising; an AI system can predict a sufficiently high DLV from a specific donor, but if the system cannot provide any rationale or transparency into how it made that prediction, then fundraisers cannot accept, trust or use the prediction in their engagement strategy. This lack of transparency diminishes accountability and also increases the possibility that fundraisers could be acting on inaccurate or biased predictions. In response to this challenge, the field of Explainable AI (XAI) has formed [4].

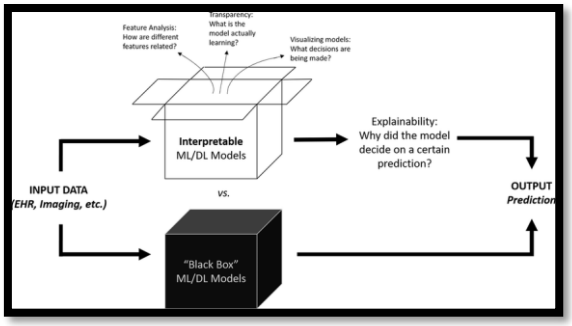

Fig 1: Black box AI models versus interpretable and explainable AI models

III. THE FRAMEWORK: DATA GOVERNANCE AND STEWARDSHIP

A. Defining Data Governance in a Non-Profit Context

Data governance is a deliberate arrangement of people, processes and technology to govern the organization's data as a strategic asset. In the non-profit world, it is more than managing data. It is about creating a formal data governance structure for managing the data lifecycle or managing data from acquisition to archiving. Policies should outline your organization's data standards, data applications, data security, etc. The same principle applies to roles and responsibilities. It is important to have data stewards for each data type and to understand that data stewards are active enablers of data quality and compliance, not passive bystanders. This is also necessary for moving from many disparate data points to a trusted and secure source of information. For a non-profit organization, data governance is not simply a technical issue, but a foundation for the organization to make strategic decisions with less concern about the "what ifs", knowing they are properly caring for their organizational assets, information, while meeting any legislative requirements, and for them to build off that foundation (over the following years) to develop any next-level analysis, e.g., AI-based Donor Lifetime Value models.

Fig 2: AI Ethics on Governance

B. Ethical Data Stewardship: Privacy, Consent, and Donor Trust

Ethical data stewardship is both a reasonable and ethical approach and demonstrates the organization's commitment to utilizing and safeguarding donors' data responsibly and ethically, while prioritizing the donor and their rights and expectations. Ethical data stewardship is linked to an organization's accountability of the trust they are trying to develop with their donors for strong stewardship and is a fundamental building block of philanthropy. Ultimately, philanthropy is stewardship which requires an openness to data collection on the part of the organization so it can be clear about what data is being collected, for what purpose, and how it will ultimately be used to achieve its organizational mission [7].

C. Data Quality and Hygiene as a Prerequisite for AI

The effectiveness of any Artificial Intelligence system is wholly reliant on the data it has been trained on. Given the aphorism "garbage in, garbage out" - particularly when it comes to predicting things based on modelling - if the training data has problems, then the outputs (if they exist) will be incorrect, problematic and potentially biased, hence data quality and hygiene is not an extra, but a prerequisite to effectively implementing and applying AI for estimating Donor Lifetime Value. This means that it is fundamental that workflows are established for data cleansing in order to find and correct mistakes, remove duplicates, and standardize formats were appropriate from different data sources. It also necessitates maximal data completeness, filling all fields on items of most importance, and data enrichment, adding relevant external information to internal data, and doing this where ethically right. Data hygiene should be an ongoing commitment, not a one-off project. By committing to the integrity of their foundational data assets, non-profits are ensuring that their AI models will be trained on the best available representation of their donor landscape, thus generating the best predictions and incremental strategic value for their insights [8].

IV. METHODOLOGY: A FRAMEWORK FOR XAI-DRIVEN DLV ESTIMATION

A. Data Sourcing and Preparation for DLV Modeling

The first step in building a DLV model is executing the systematic acquisition and consolidation of relevant data from across a non-profit's information ecosystem. Data is most commonly resident in a single platform, namely, the Customer Relationship Management (CRM) system, which contains the core donor profile data, donor transactional data, and donor interaction data [6]. Engagement data from online fundraising platforms will also supply more complete, granular and detailed information about online active campaigns, peer-to-peer give, and donor responses to specific appeals. Integrated engagement data (email marketing, event management and volunteer management) is also required to build a more complete picture of a donor's relationship with the organization. After acquisition, this heterogeneous data must now be prepared. This important process, known as ETL (extract, transform, load), is to extract the data from its original data source, transform the data into a consistent and standardized format, and load it into one central readily available analytical database. This preparation is integral to preserving the data integrity of a single dataset that is acceptable for use in advanced machine learning applications [9].

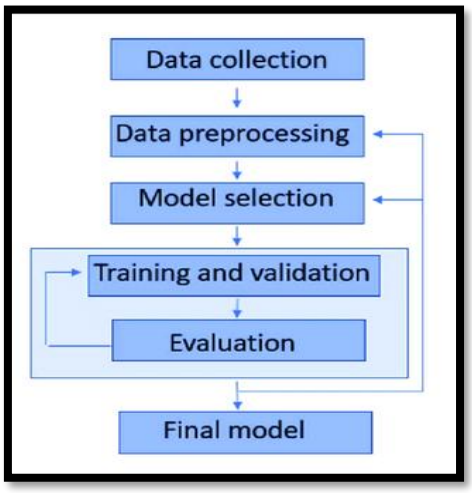

Fig 3: Machine Learning Workflow

B. Feature Engineering for a 360-Degree Donor View

Feature engineering is the construction of a definitive set of informative variables or features from raw articulated data to be used in a model for the purpose of making a prediction. Feature Engineering becomes important with respect to representing the multidimensional nature of donor behavior, which can come from more than transactional data. In the case of a more comprehensive Donor Lifetime Value (DLV)

model, we want to create features that represent the multifaceted nature of donor relationships that include transactional features (average dollar amount, number of transactions, time since last transaction, cumulative amount given to date), and Donor Interaction Value (DiV) features, which relates strictly to what we were concerned with as part of a donor's non-financial relationship to the organization (i.e. email opens and clicks, any attendance at events, hours volunteered). Collecting demographics and wealth indicator data is another completely ethical and legal way to finish up the feature creation stage. We take this comprehensive approach to ensure we complete a sufficiently detailed set of features that will allow for AI to at least be able to see every donor through the 360-degree lens and understand the complex inter-relationships which can be complex, multi-level, and in both directions, which feed into that decision towards value and commitment [10].

C. Implementing an Explainable AI Model

We stated that the selection and implementation of the analytic model is the most basic part of the model. There are many machine learning algorithms available, we will select to study algorithms such as XG-Boost (Extreme Gradient Boosting) or Random Forest due to the demonstrated predictive power of the models, were relevant also due to the reasonable treatment of complicated tabular data, hence using the model that was tested in the methodology. XG-Boost and Random Forest are both types of ensemble methods that take in many predictions from many different decision trees and form a single decision based on an ensemble approach. An ensemble method is a challenge when trying to take the "Black box" out of a model, because we will generate a predicted value, but we may not know what the predictors were involved in, and therefore, not understand what predictive factors were behind that individual prediction. The model has now been placed within the framework, which offers adequate support from an Explainable AI (XAI) perspective and solution environment and therefore provides a transparent solution [11].

D. Interpreting Model Outputs for Actionable Insights

The last step in the process is to take the outputs from the XAI model and put the outputs into insights that have strategic value. The XAI process will formulate two outputs, instead of a DLV score, for all donors. The outputs from the XAI enabled process will be the prediction and the explanation. The explanation (often a SHAP force plot, or summary plot) reveals which of the features contributed (positively and/or negatively) to the score for your donor. For example, yes, the model could predict a very high DLV for a donor based on historical donations, but if the donor engaged significantly with a specific campaign or content, shortly before the prediction for DLV made in days or weeks before, that also matters. This information reframes the DLV score from a static to a dynamic evaluation. The fundraising teams could take this outputs and look at what if any of the drivers of loyalty and value for segments of donors were primary or secondary factors in determining loyalty and value, to test what … they had assumed, or to reflexively challenge their assumptions to be more strategic in their follow-up[12].

V. DISCUSSION: STRATEGIC IMPLICATIONS AND CHALLENGES

A. From Prediction to Personalization: Leveraging XAI Insights

The strategic value in XAI to produce insights about predicting Donor Lifetime Value (DLV) is so much more than prediction accuracy and selecting the best choice from many varying approaches as it quite simply is a paradigm shift from traditional outreach to fully personal stewardships. Conventional DLV models give a single score, a what, that can help with high-level segmentation, whereas an XAI model can start to explain the why of that score. The XAI tool gives very specific information about which aspects of donor activity, fast dollar accumulators, frequent small gifts, attendance at a recent event, or active engagement with several of the campaign emails, positively likely contributed to the donor's predicted value, and therefore the recommended donor stewardship strategy; this again gives fund-raisers an opportunity to target the donor message with much more specificity. For example, let us say the XAI model suggested that for a particular donor, the high DLV was driven by their long-term commitment to the organization as a volunteer, as an organization you may want to engage them, so look at this as if it is

the first opportunity for a 'learning point' of inviting them to engage further from the perspective of personal experience versus generic calls for financial/monetary support even though they will contribute[13].

B. Enhancing Fundraiser Effectiveness and Donor Relationships

The evolution of technology means organizations can engage with donors over their decisions in ways they previously could not; this also has much wider implications for how a fundraiser may engage with a donor. Rather than the organization and technology shift the fundraiser to be a data administrator to a relationship manager. Importantly, from a relationship manager perspective, if the fundraisers embedded fundraising capabilities, instincts, judgement and assessment of donors as contributors remain there, that act of just completing an analysis and reporting from an XAI insightful system on your best prospects enables a thorough, engaging relevant discussion with the donor that uses the data as a supportive perspective element to the above comparison points. Importantly, the donor perspective goes so much deeper and therefore the engagement with the donor can also become more relevant and meaningful; for example, the 'commitment' was increased in some depth towards the organization. So, the technology does not replace the human element, it provides a deepening of the human element; because it establishes a systematic anchor, some rationale for the fundraiser to position the human element to build a relationship[15].

C. Critical Challenges: Algorithmic Bias and Implementation Hurdles

These challenges may include algorithmic bias (where an AI model, is trained with historic data that has both recognized bias, and unrecognized bias, for example, historic data where there has been limited or no engagement for specific demographic or geographic groups, and therefore were learning, and replicating possible bias, and quite possibly large-scale bias based on few variables.) We may be, mathematically underestimating the potential value of the un-invited donor, or we may be systematically underestimating value when looking at demographic groups, and thus unwittingly introducing self-fulfilling disengagement in a need to mitigate unintentional bias. To mitigate the possibility of producing the aforementioned bias, it will take more than just technical development, it would take significant data auditing, and fairness-aware machine learning, [14].

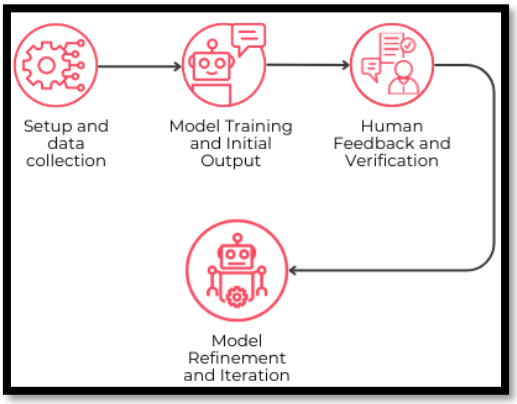

Fig 4: Human in the Loop

VI. CONCLUSION

The paper has prompted the conclusion that meaningful and ethical relationship with Artificial Intelligence in modelling Donor Lifetime Value does not exist unless you have ethical stewardship of the data and have a conscious choice to use transparent technology. In this paper I have mapped the links of the technologies of Explainable Artificial Intelligence (XAI) as an important intermediary between the predicted future literacy and sophistication of predictive analytics and machine learning to analyze the specific DLV

features of your current and likely future fundraising professional behavior. The ability to not only engage with sophisticated analytic tools could provide a goal of not measuring solely DLV in the future but gaining a deeper understanding in a subtle and nuanced sense of the specific triggers or levers that lead to donor loyalty represents a highly transformational and meaningful relationship that creates innovation whilst shaping and expressing the realities of the innovation of that relationship stage.

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