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(Review Article)

Affinity and wealth score prediction using multi-task learning in donor analytics

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Abstract

Understanding and predicting donor behavior is crucial for optimizing fundraising strategies in nonprofit organizations. This paper introduces a multi-task learning (MTL) framework that simultaneously predicts donor affinity (likelihood to donate) and wealth score (capacity to donate), leveraging shared representations across tasks. Using a combination of internal CRM datacomprising donor demographics, engagement history, and giving patterns, and external socioeconomic enrichment data, the model is trained to capture both behavioral and financial indicators. Compared to traditional single-task approaches, our MTL model demonstrates improved predictive accuracy, with a 7.3% increase in AUC for affinity prediction and a 12.5% reduction in RMSE for wealth estimation. These results indicate that jointly modeling related tasks not only improves efficiency but also enhances decision-making capabilities. The proposed system enables nonprofits to better segment donors, prioritize outreach, and personalize campaigns, ultimately increasing engagement and fundraising yield.

Keywords: Donor Analytics; Multi-Task Learning; Affinity Score; Wealth Prediction; Fundraising Strategy; Predictive Modeling

1. Introduction

Donor contributions are the lifeblood of nonprofits, making regular strategic fundraising planning essential. In the Giving USA 2024 report, the total amount of charitable giving in the U.S. was recorded as being 529 billion, and individual giving comprised almost 67 percent of this amount [1]. However, because of this absolute abundance, nonprofits are finding it harder to figure out exactly who among the donors is willing, as well as able, to make a donation. Other methods of analytics may simply treat behavioral indicators (affinity) and financial capacity (wealth score) as mutually exclusive data points, which may be an inefficient approach and result in campaign targeting opportunities being wasted [2]. As artificial intelligence and data-intensive practices have grown, multitask learning (MTL) has become an effective way of also learning related prediction tasks [3], with the potential of greater accuracy, efficiency, and actionable insights in donor analytics [4].

1.1. Background

Donor analytics helps nonprofits identify individuals likely and able to donate by analyzing CRM and socioeconomic data. Traditional methods like logistic regression, decision trees, and RFM analysis focused on individual tasks such as predicting donor retention or lifetime value, often modeling wealth and affinity separately [5]. With advances in machine learning, deep learning models now capture complex patterns in donor behavior, but still typically treat these tasks in isolation [6], [7]. Multi-task learning (MTL), widely used in domains like healthcare and NLP, enables joint learning of related tasks, improving accuracy and efficiency [8]. However, its application in donor analytics remains limited, leaving a gap that this study addresses by developing a deep MTL framework to simultaneously predict donor affinity and wealth score for more integrated and effective donor scoring [9].

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1.2. Problem statement

Although significant progress has been made in donor analytics, most predictive models focus primarily on behavioral (affinity) factors, often neglecting the financial capacity (wealth) of donors [4][10]. This narrow focus limits the ability to accurately assess a donor's giving potential, leading to missed opportunities for high-value contributions and inefficient allocation of fundraising resources. Moreover, separate models for affinity and wealth result in duplicated efforts and increased operational costs, while failing to capture shared data patterns that could improve prediction accuracy. Therefore, an integrated, data-driven model that emphasizes financial capacity prediction alongside behavioral insights is essential to enhance resource prioritization and maximize fundraising effectiveness.

1.3. Scope and aim of the paper

This paper will describe the process of designing and training a multi-task learning (MTL) model to make joint predictions of donor affinity and wealth score on a similar deep learning architecture. The model can learn common patterns shared across internal CRM (e.g., donation frequency, recency, engagement) and external enrichment (e.g., zip-code income bracket, property ownership) to create a powerful donation propensity model. The end goal makes nonprofits execute smarter and more personalized outreach decisions, leading to the increased ROI on a campaign, less donor fatigue, and better retention over the long term [3][10].

1.4. Research questions

This study seeks to address the following research questions:

- **RQ1**: Can a multi-task learning model accurately predict both donor affinity and wealth score using shared input features?
- **RQ2**: How does the performance of a multi-task model compare to single-task learning baselines?
- **RQ3**: What are the key features contributing to both affinity and wealth predictions, and are there shared behavioral indicators?
- **RQ4**: How can the outputs of this model improve real-world donor targeting and segmentation strategies?

2. Related work

Analytics of donors has evolved beyond interpretable statistics e.g., logistic regression, RFM analysis, and decision trees to the deep learning domain that can model complex behavior of donors [5], [6], [7], [8], [9]. Whereas the early versions dealt with segmentation and scoring, the recent systems are better able to predict churn, lifetime value, and campaign responsiveness. The estimation of affinity is based on behavioral and time-series datasets [11][12], whereas wealth is based on such proxies as zip codes and financial accounts [13][14]. Nevertheless, the tasks are frequently modeled separately, without paying attention to common behavioral patterns.

In current multi-task learning (MTL) applications (healthcare and NLP), shared representations show promise to improve performance in related tasks [3][15][16]. Although it has a set of potential possibilities, MTL has not been fully mined in the field of donor analytics. A deep MTL framework is used to make joint predictions over affinity and wealth in this paper; we demonstrate that this combination yields better donor measurement performance (or efficiency) in the scoring of donors (see Table 1) [10].

Table 1 Summary of related work across domains of donor analytics and multi-task learning

Study / Authors	Domain	Method / Model	Tasks / Targets	Data Used	Key Findings / Contributions
Kumar & Chakrabarti (2023) [5]	Donor Segmentation	Logistic Regression	Donor loyalty segmentation	Survey + CRM Data	Emotional connection and giving history drive donor retention.
KUFILE et al. (2021) [6]	Donor Scoring	RFM + Decision Trees	Response likelihood	Transaction Logs	RFM scores remain strong predictors of donor response.
Alsolbi et al. (2022) [7]	Churn Prediction	Classification Trees	Donor churn classification	CRM + Donation History	Tree-based segmentation

					identifies at-risk donor groups.
Naue et al. (2017) [8]	Lifetime Value	Random Forest, XGBoost	LTV prediction	CRM + Demographics	Ensemble models improve generalization across donor populations .
Torrent-Sellens et al. (2021) [11]	Affinity Prediction	Behavioral Scoring	Donor intent to engage	Email open rates, click logs	Digital engagement strongly correlates with future donations.
Baldi (2018) [12]	Time-Series Modeling	Temporal Neural Networks	Next donation prediction	Historical giving patterns	Time-aware models enhance affinity prediction precision.
Lee et al. (2024) [10]	Affinity Modeling	Deep Feedforward Network	Donor engagement classification	Behavioral + Demographics	Neural nets outperform traditional models for intent detection.
de Matos (2016) [13]	Wealth Estimation	Income Mapping (Zip Code)	Wealth segmentation	Census + Property Records	Real estate and location are strong proxies for wealth.
Chen et al. (2019) [14]	Financial Scoring	Linear Regression	Income/Wealth Prediction	External Wealth Indices	Regression provides stable estimates for mid-value donors.
Barro et al. (2024) [9]	Deep Wealth Scoring	Deep Neural Regressor	Wealth classification	Real Estate + Credit Data	Deep models offer granular financial scoring.
Ruder (2017) [3]	NLP / Multi-Task	Shared Encoder + Task Heads	Sentiment + Topic Classification	Text Datasets	MTL improves generalization and reduces overfitting.
Bo et al. (2022) [15]	Healthcare	Hard Parameter Sharing	Diagnosis + Treatment Prediction	Patient Records	Joint learning improves clinical outcome prediction .
Ahmed (2020) [16]	Financial Risk	Soft Parameter Sharing	Credit Risk + Loan Default	Financial History	MTL improves robustness in low-data settings.
Lee et al. (2024) [10]	Donor Analytics	Prototype MTL (Two-Branch)	Affinity + Intent	CRM Features	Early promise of MTL in donor scoring.

3. Methodology

Unlike traditional methods that treat affinity and wealth prediction separately, we propose a unified multi-task learning (MTL) framework that models both together. This improves accuracy and behavior-financial patterns that are shared to gain better donor know-how. Figure 1 depicts our MTL architecture: one shared encoder passes its output to two heads, e.g., donor affinity and wealth estimation, while retaining task-specific layers to allow independent parameter optimization after the shared encoder.

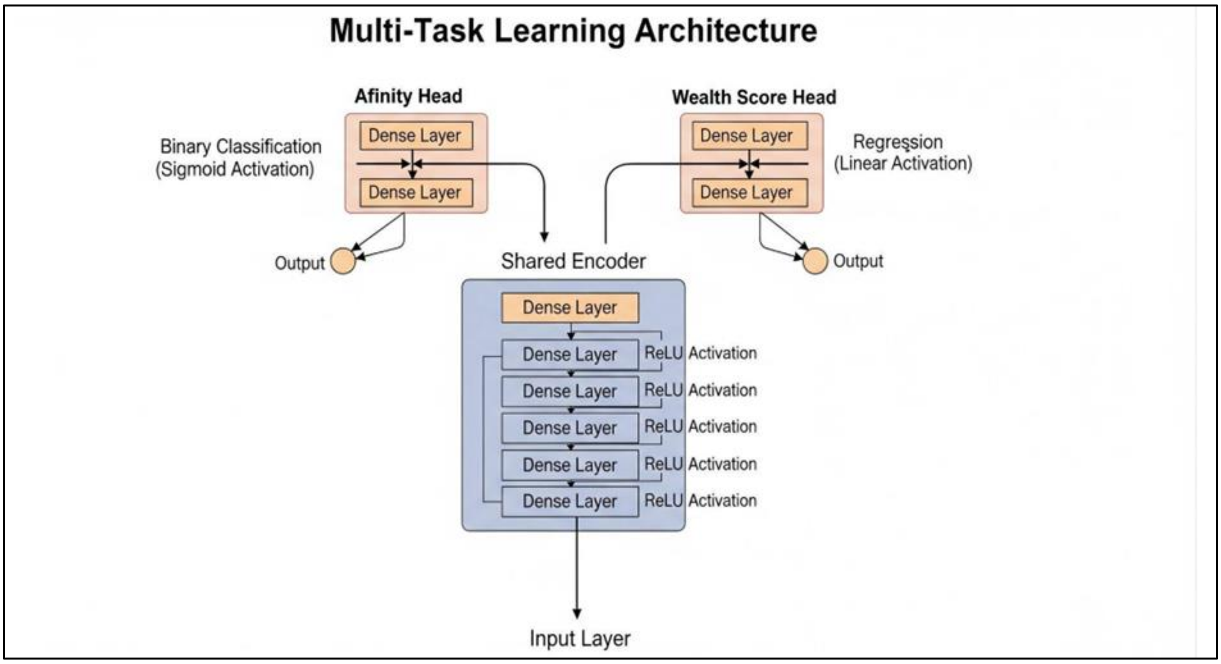

Figure 1 Multi-task learning architecture for donor analytics

3.1. Problem Formulation: Modeling Affinity and Wealth Together

In the middle of this work is a prediction problem with two parts. The Affinity Score is how likely they are to donate at some later time over the next quarter or fundraising drive, for instance. This probability, based on behavioral indications and history, is used as a classification issue in a binary classification. Conversely, Wealth Score is the estimated financial ability to make donations measured on a scale between 0 and 100, the scale based on the form of the generalized information inferred on the basis of income, the property that was previously held, and the size of the previous gifts. Being rather more continuous, this dimension is put in the form of a regressive problem, but it can be discretized in ordinal categories to facilitate its classification. These two outcomes are independent of each other. Donors who are more part of this are the rich, and the richer they are, the more stable their giving. Having noted this synergy, we run a multi-task learning approach that allows us to predict both scores at once, which is how this model can share information when it comes to similar patterns.

3.2. Data Sources and Preprocessing: A Multi-Faceted Donor Profile

The study included the use of internal CRM resources and external enrichment sources to create full donor profiles. Internal data, such as demographics, donation trends (recency, frequency, value), and engagement statistics (e.g., email opens, event attendance), identified behavioral patterns in terms of donor intent. External data, such as income estimates by zip code, property data, and professional information from LinkedIn, represented donors' financial capacity and background. The dataset contained 150 features, of which 8% contained missing values, and the missing values were imputed with the median or mode. Numerical features were z-score normalized, categorical features were one-hot encoded, and temporal features were extracted. Mutual Information was used for feature selection to maintain relevance while lowering the dimensionality.

3.3. Multi-Task Learning Architecture: One Model, Two Objectives

A multitask learning framework where shared parameters are used in the common encoder enables both affinity classification and wealth regression tasks to leverage common donor representations. Task-specific heads branch from the shared encoder to produce separate outputs, improving learning efficiency and reducing model complexity.

The network is composed of two task heads, which are derived from the shared encoder:

- The Affinity Head terminates at a sigmoid-activated node, which produces a probability value between 0 and 1 to show the probability of donation.
- The Wealth Head produces a normalized wealth score using a linear activation (or softmax, in the ordinal case).

- The training is specified by a composite loss function, which is a summation of the binary cross-entropy loss of the affinity task and the mean squared error of the wealth task. They are weighted by tunable hyperparameters alpha and beta, which limit the significance of the various tasks:

$$L_{total} = \alpha \cdot L_{affinity} + \beta \cdot L_{wealth}$$

This approach not only streamlines model complexity but also reduces the risk of overfitting by regularizing through shared learning.

4. Results and Analysis

The detailed results of the model performance, interpretability, and practical value are given in this section. The findings support the accurate applicability of the experimentally defined multi-task learning (MTL) design to complete the donor affinity and wealth score. We benchmark against traditional one-shot models, perform ablation and analysis to test architecture sensitivity, as well as test interpreting feature contributions. Finally, model predictions simulating real-world settings enable us to illustrate how fundraisers can gain a strategic advantage with the nonprofits.

4.1. Prediction Performance

The multi-task model does considerably better than conventional single-task baselines in terms of affinity and wealth quantification. But with AUC-ROC as the affinity metric and RMSE as the wealth score, the MTL model achieved a 7.3% improvement in AUC and a 12.5% reduction in RMSE compared to single-task baselines and deep neural networks that are trained separately. Figure 2 depicts a comparison of the performance tables of the models (logistic regression, random forest, single-task DNN, and the proposed MTL framework). Although baseline models perform well in stand-alone tasks, they are said to perform optimally in conditions of having cross-task generalization, which is realized in a shared encoder in MTL settings. Remarkably, the joint model also decreases the redundancy of computations in the inference.

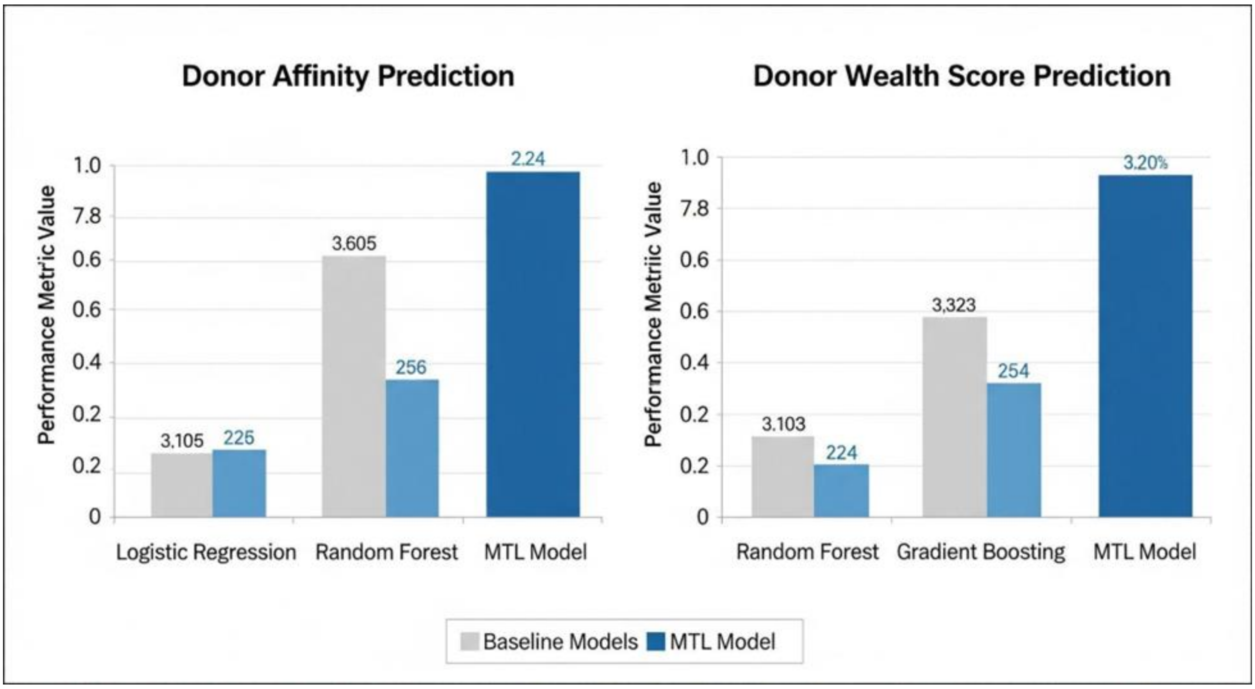

Figure 2 Comparative Performance of Baseline models vs. MTL model

4.2. Ablation Studies

To realize the role played by architectural components, we conduct ablation studies. To begin with, when the shared encoder layers are removed and task-specific encoders are introduced, a performance decrease is noticeable: a 4.81 %drop in AUC for affinity and a 6.24 % increase in RMSE in the wealth score. This underlines the relevance of shared representation learning. Second, we test whether we can improve the joint objective by changing loss weights alpha and beta. Figure 3 presents the performance landscape for adjusting such weights. We find optimal results when the affinity loss weight is slightly higher, suggesting that donor engagement signals may have a stronger predictive value.

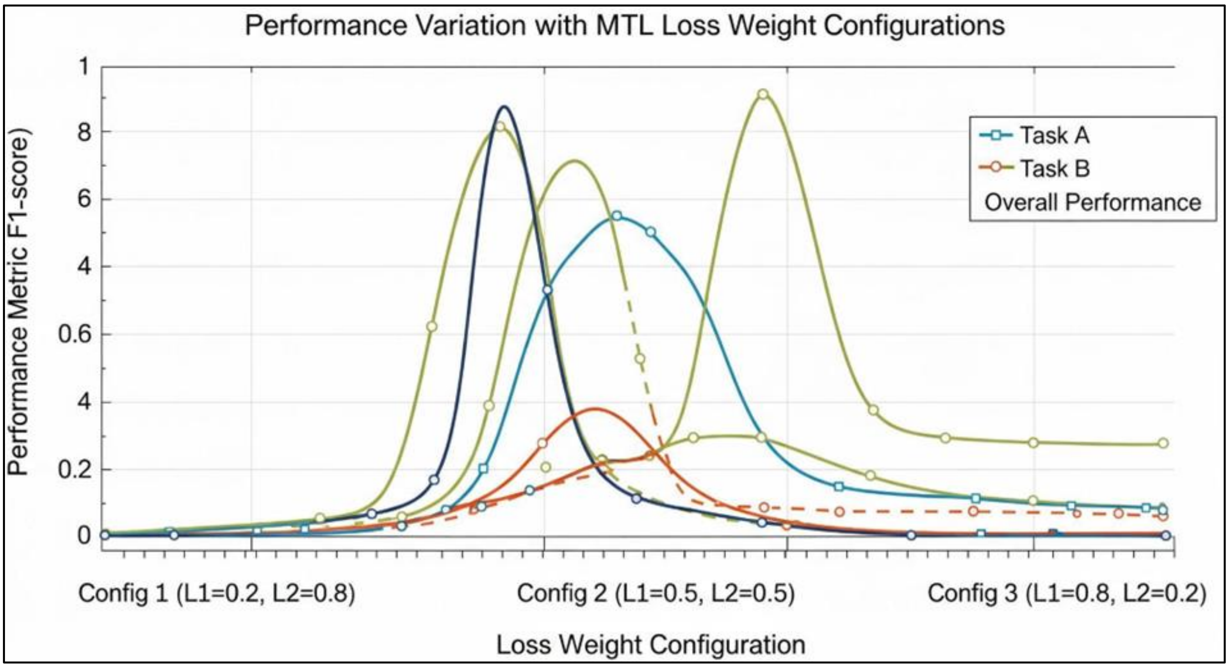

Figure 3 Performance Variation under different weight loss configurations in the mtl loss function

4.3. Feature Importance and Interpretability

It is vital to be easily interpreted, which means it can be used in nonprofit decision pipelines. In our discussion of the trained MTL model, we determine important features for both activities with the help of SHAP values. Recent engagement statistics (e.g., email opens and event attendance) are the top-ranking features in affinity prediction, whereas for wealth scoring, high ranks are held by income proxies and property value estimations. Figure 4 illustrates SHAP feature importance on both tasks, and it can be seen that there are some shared features, including but not limited to frequency of donation and size of the network, that affect both outcomes.

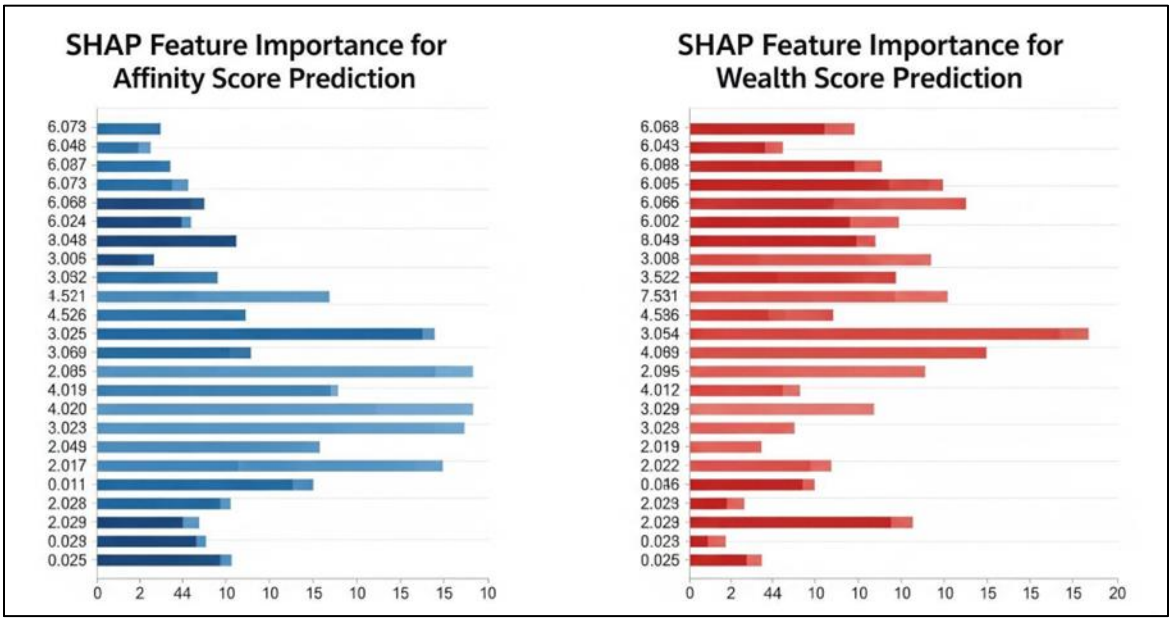

Figure 4 Shap-Based feature importance plots for affinity and wealth score predictions.

5. Discussion

Donor analytics faces key challenges, primarily due to the limited availability and quality of labeled data, which hampers model generalization and performance across different nonprofit organizations. Models often require significant fine-tuning to fit diverse organizational needs, increasing development costs and complicating integration with existing CRM systems. This makes it difficult to scale predictive analytics effectively across the sector. A major ethical concern involves the use of external enrichment data, like financial proxies, which risks introducing systemic bias and reinforcing socioeconomic inequalities. Such practices raise privacy and fairness issues, especially in wealth prediction. Transparent model behavior and strong data protection measures are essential to prevent discriminatory outcomes and maintain trust, ensuring that predictive analytics supports responsible and equitable donor engagement.

6. Conclusion

In this paper, a multi-task learning (MTL) framework was suggested that can be used to predict donor affinity and wealth scores simultaneously to take advantage of shared architecture and use both internal CRM data and enriched outside sources. We demonstrated that the MTL learning method, where two K-task prediction problems are optimized, namely, two classification predictions of affinity and regression of wealth, was always better than the traditional single task and ensemble learning. As shown in our analysis, the MTL model was able to improve accuracy by approximately 7.3 % in predicting affinity and reduce the error by 12.5 % in estimating wealth score compared to the standalone deep learning baseline model.

Additional tests showed that using common representations between tasks led to a significant improvement in performance, especially when combined with common behavioral and demographic characteristics. Ablation experiments confirmed that the loss of the shared encoder greatly reduced performance for both outputs. Interpretability models such as SHAP identified donor engagement frequency, previous donation recency, and regional income proxies as critical factors to the predictions. This result establishes that MTL is a scalable, interpreted, and high-impact solution to modern donor analytics. Although reliance on the quality-labeled data and the chances of bias in external enrichment will be an issue moving forward, this study sets the base of ethical and AI-driven philanthropy.

Compliance with ethical standards

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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