

# Northeastern University: Planned Gift Propensity Modeling



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# *Project Overview*

**Predict** planned-gift likelihood using models tailored to an extremely rare donor outcome.

**Identify** and rank high-value prospects by isolating the top 1–10%

**Engineer** behavioral and engagement features to strengthen model performance despite demographic missingness.

**Create** actionable donor segments that Advancement can use to prioritize outreach and optimize cultivation strategy.

**Which donors are most likely to make a planned gift of \$100,000+?**

# Handling Missing Values

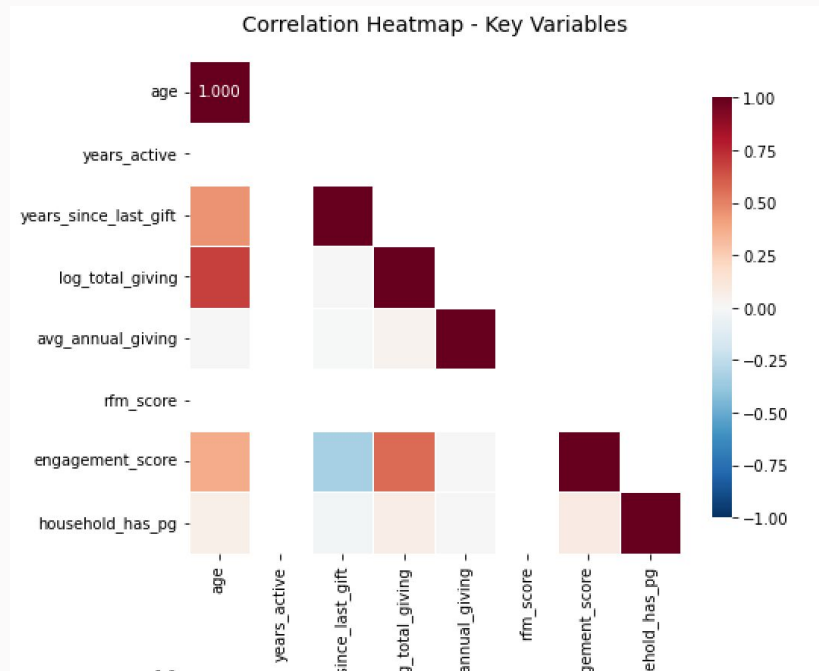
## Why Age Cannot Be Imputed

- **53.9% missing** — too incomplete for reliable imputation.
- **Missingness is not random** — PG rate is **5x lower** when age is missing.
- **No strong proxy** — other age-related fields also have high missingness.

## Our Solution

- Use **variables highly correlated with age** to capture similar information.
- Key proxies: **years since last gift, log total giving, engagement score**.
- Together, they reflect **donor maturity and wealth**

**effects** — the behavioral drivers behind age.



### Planned Giving Rates:

Category	PG Count	Total	PG Rate	vs Overall
Has Age	245	146,669	0.1670%	1.75x
Missing Age	59	171,533	0.0344%	0.36x
Overall	304	318,202	0.0955%	1.00x



# Feature Engineering

- **Captured donor behavior** through interaction terms that combine capacity, engagement, and relationship signals.
- **Prioritized high-signal features** with low missingness and strong correlation to planned giving.
- **Replaced unusable demographics** with behavioral proxies.

## Built 3 feature sets:

- A **transparent, low-missing set** for Logistic Regression
- A **broader behavioral + capacity set** for XGBoost to model complex patterns
- An **expanded set leveraging all engineered variables** to maximize predictive lift for LightGBM

# Logistic Regression Model

**PR-AUC = 0.0211**

- 21 times better than random (0.01% positive cases in data set)

## FEATURE IMPORTANCE

### 1. spouse\_X\_alumni (0.43)

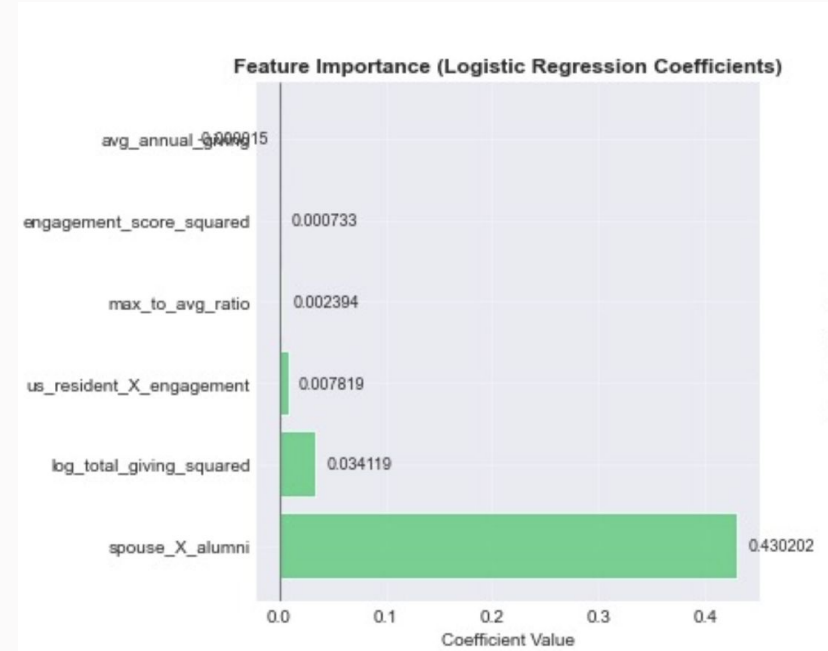
- Alumni who have a spouse connection to the university show significantly elevated planned giving propensity
- The dual household connection creates deeper institutional ties

### 2. log\_total\_giving\_squared (0.034)

- Cumulative wealth effect accelerates at high giving levels

### 3. us\_resident\_X\_engagement (0.008)

- US residents with high engagement show elevated PG propensity



# Logistic Regression Model (engagement metrics)

PR-AUC = 0.0086

- 8 times better than random (0.01% positive cases in data set)

## FEATURE IMPORTANCE

### 1. unique\_opportunity\_types (0.877)

- Donors who've experienced multiple "entry points" for giving are more likely to have planned gifts than single-opportunity donors

### 2. unique\_designations (0.337)

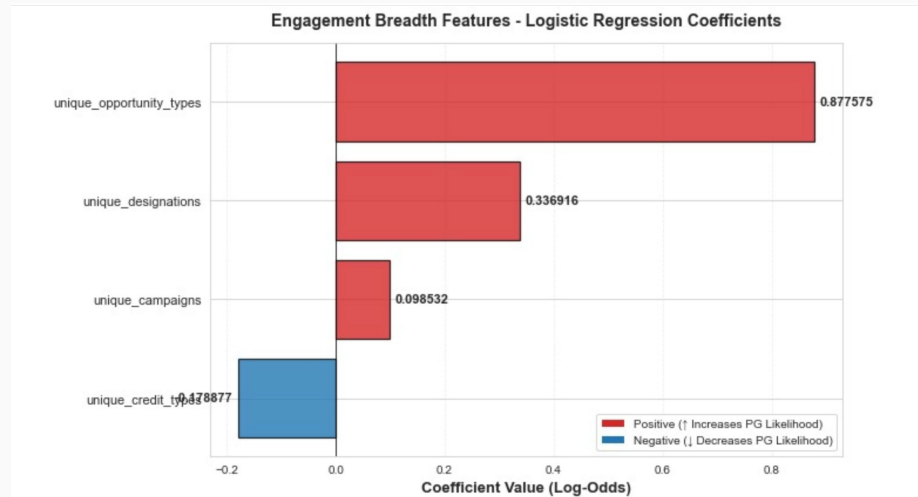
- A donor supporting 5 different designations is significantly more likely to have PG than someone giving exclusively to one program

### 3. unique\_credit\_types (-0.179)

- Planned gift's may have simpler payment structures (data artifact, not indicative of donor interest)

### 4. unique\_campaigns (0.098)

- Campaign participation matters less than *how* donors give (opportunity types) or *what* they support (designations) - time-based campaign cycles are less predictive than enduring program interests



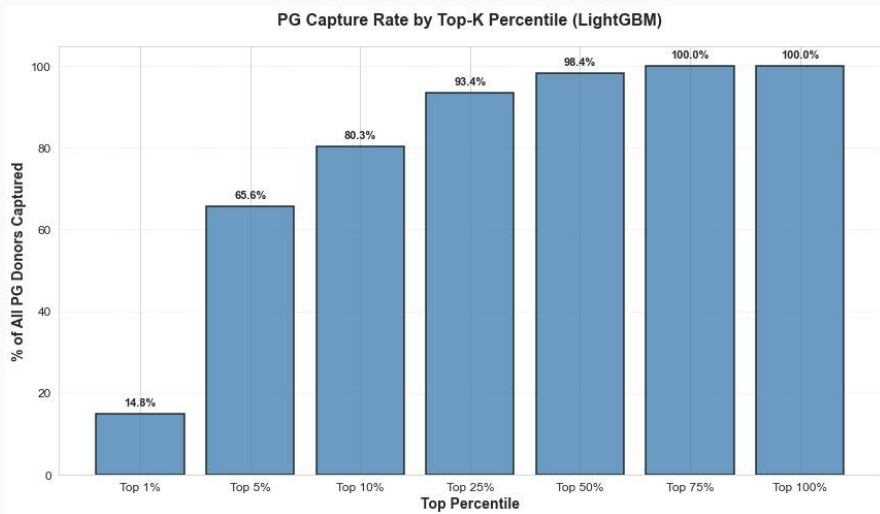
# XGBoost vs LightGBM

## XGBoost Model (PR-AUC = 0.051)

- By contacting top 1% (636 people), captures **37.7%** of all PG donors
- By contacting top 5% (6,364 people), captures **67%** of all PG donors

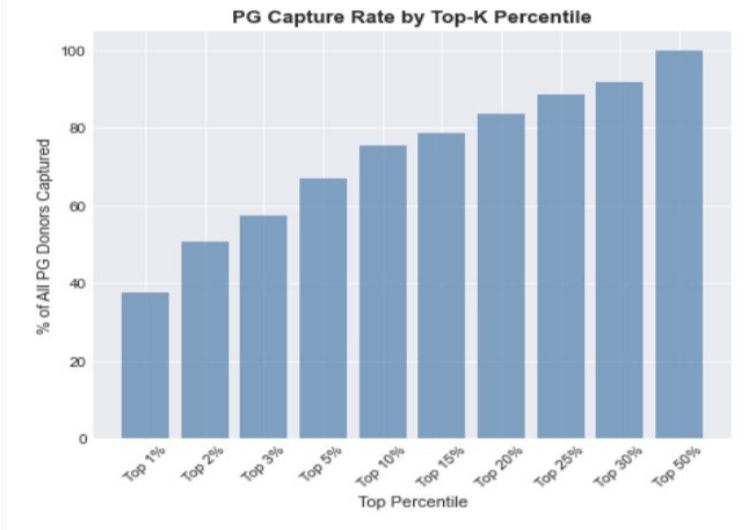
## LightGBM Model (PR-AUC = 0.3266)

- By contacting top 1% (636 people), captures **14.8%** of all PG donors
- By contacting top 10% (6,364 people), captures **80.3%** of all PG donors



## Recommendation

- LightGBM performs better on entire dataset
- XGBoost performs better for top 1% and 5% which is more useful for targeted segmentation





# Model Performance

Metric	XGBoost	LightGBM	Winner
PR-AUC Score	0.051	0.327	LightGBM
Improvement over Random	53x	341x	LightGBM
Top 1% Capture Rate	37.7%	14.8%	XGBoost
Top 5% Capture Rate	67%	65.6%	XGBoost
Top 10% Capture Rate	75%	80.3%	LightGBM



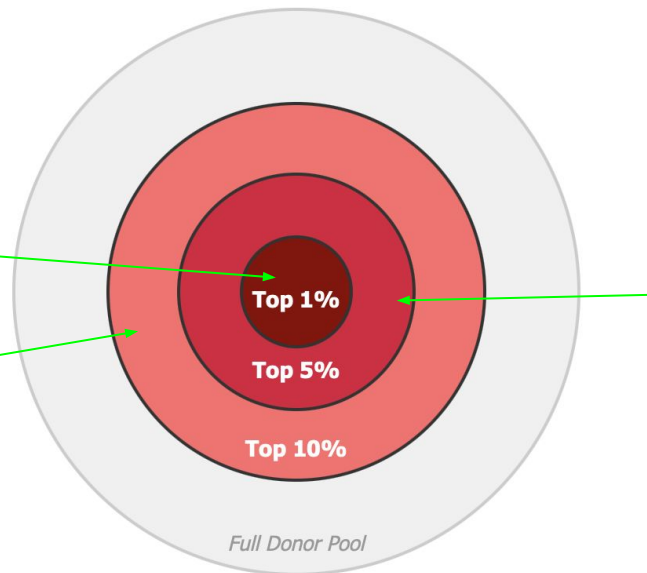
# Donor Segmentation

## Top 1% (3,182 donors)

Contains 37.7% of all likely planned-gift donors and should be prioritized for personal outreach and estate-planning conversations.

## Top 10% (31,820 donors)

Accounting for 75% of likely PG donors, this group represents emerging prospects suited for educational content and early cultivation.



## Top 5% (15,910 donors)

Capturing 67% of all likely PG donors, this segment is ideal for targeted events, legacy-society invitations, and focused cultivation.

# Recommendations

## Top 1% - Top Priority

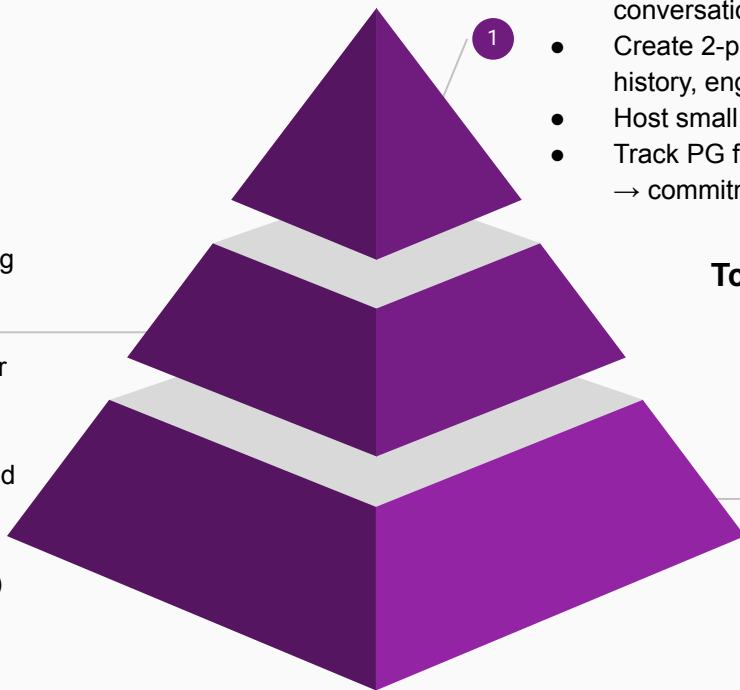
- 1:1 estate-planning meetings for every Tier 1 donor within 12–18 months.
- Assign two officers per donor for continuity and depth.
- Use key predictive features (spouse - alumni tie, lifetime giving, engagement) to script individualized conversations.
- Create 2-page donor portfolios summarizing giving history, engagement, and PG options.
- Host small, exclusive briefings with the Dean/President.
- Track PG funnel metrics monthly (discussion → proposal → commitment).

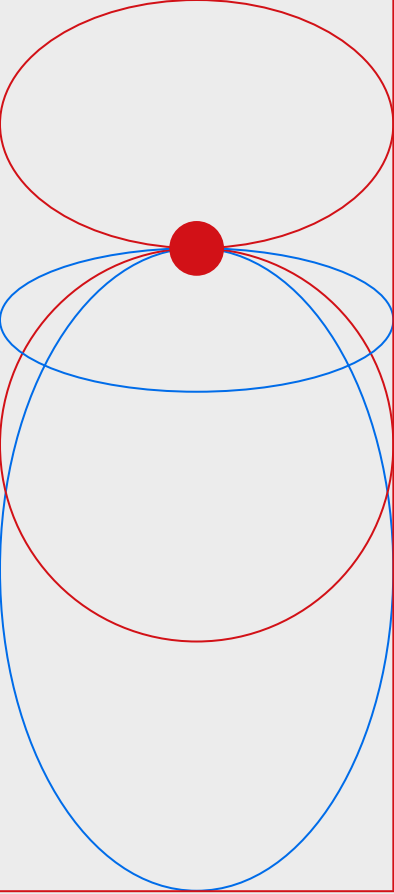
## Top 10% - Scalable Cultivation

- Send automated PG nurture flows (6–8 emails/year) tied to life stages.
- Invite donors to virtual PG info sessions with alumni success stories.
- Deploy a PG Readiness Survey to surface interest signals for tier upgrades.
- Use engagement analytics to flag Tier 3 donors behaving like Tier 2.
- Trigger alerts for sudden behavior changes (large gifts, new volunteering, increased event activity).

## Top 5% - High Potential Donors

- Run quarterly PG workshops on estate planning and giving vehicles.
- Send milestone-triggered PG packets (e.g., \$100K lifetime giving, 10-year giving streak).
- Monitor for “risers” whose engagement or giving accelerates.
- Require officers to complete 20–30 PG-intro calls per month using segmented scripts.
- Create micro-cohorts (Alumni Couples, Consistent Givers, Multi-Decade Donors) for targeted messaging.





*Thank You!*

*Q&A*