KPMG 1A: Driving Donations
AI Studio Final Presentation

December 5th, 2024

Meet our team!

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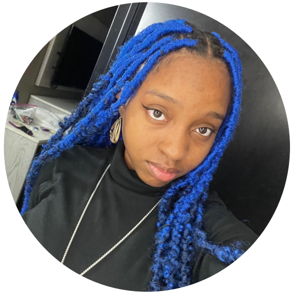

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Background on Project Focus

About C5LA

- 501(c)(3) charitable non-profit organization
- Youth Leadership
- Summer Camp + Hiking
- College/Career access and success program
- Push students out of comfort zone with fun outdoor activities and foster higher education and initiative in the community
- Fun Fact: Founded by Coca Cola CEO!

The goal was simple: help C5LA increase donations. How? Identify who is likely to donate again.

Business Impact

- Improved donor retention strategies
- Targeted Marketing and Outreach Campaigns
- Review of past decade’s success in growing donations

Our Approach

Explore data and
possible features

**Sprint 1:
Data Exploration**

Sprint 2: Data Preprocessing

- Clean and preprocess data
- Handle missing values
- Feature engineering

- Select techniques for ML model
- Validate and enhance model

**Sprint 3: Data Analysis
and Modeling**

Sprint 4: Finalize Product

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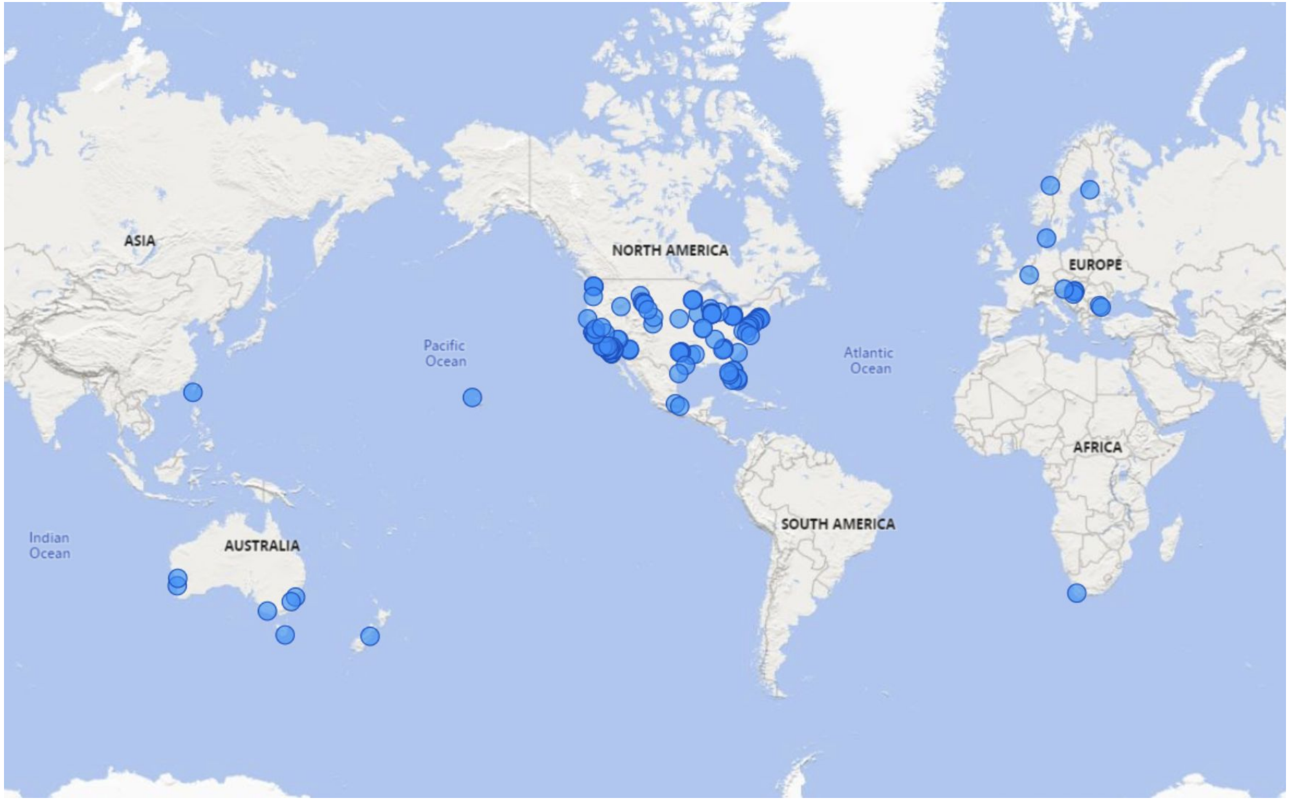
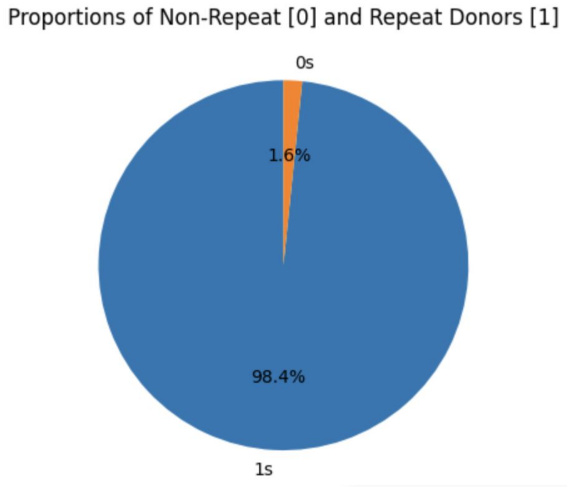
Data Preparation and Analysis

Where are the Donations From?

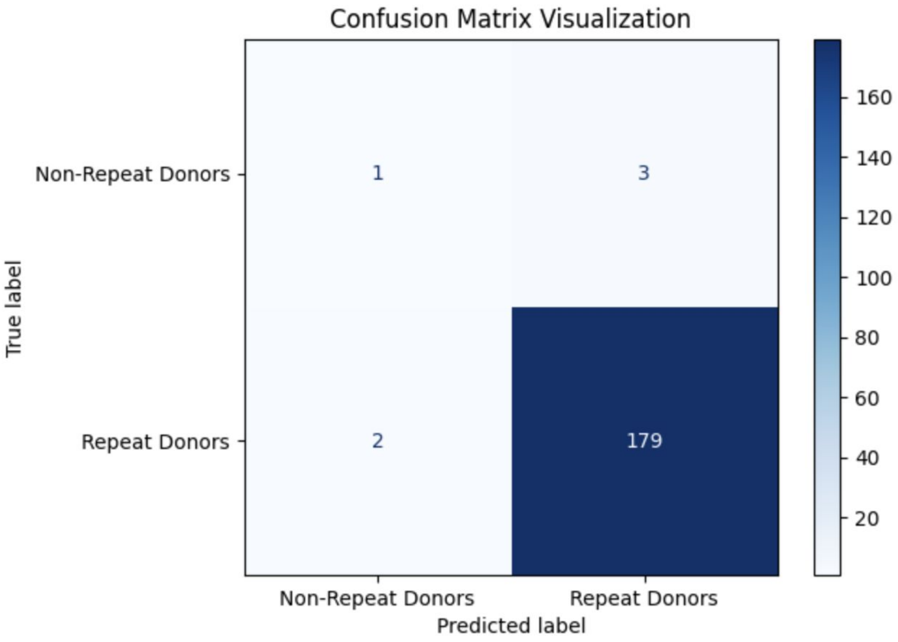


Summary of Data Collected

- 3122 donations collected between 2014 and 2021
- 616 unique donors
- 606 repeat donors
- 10 non-repeat donors



Summary


Confusion Matrix Visualization
Non-Repeat Donors
Repeat Donors
True label
1
3
2
179
Non-Repeat Donors
Repeat Donors
Predicted label
160
140
120
100
80
60
40
20

Data Analysis Key Takeaways

- Mapped ZCTA and zip codes to see how many times a donor's name popped up, which gave us intel on whether they were a repeat donor
- Did feature engineering to create repeat_donor feature
- Amount donated was highly correlated with whether someone would be a repeat donor
- Processed features to get percentage instead of absolute number for demographics data

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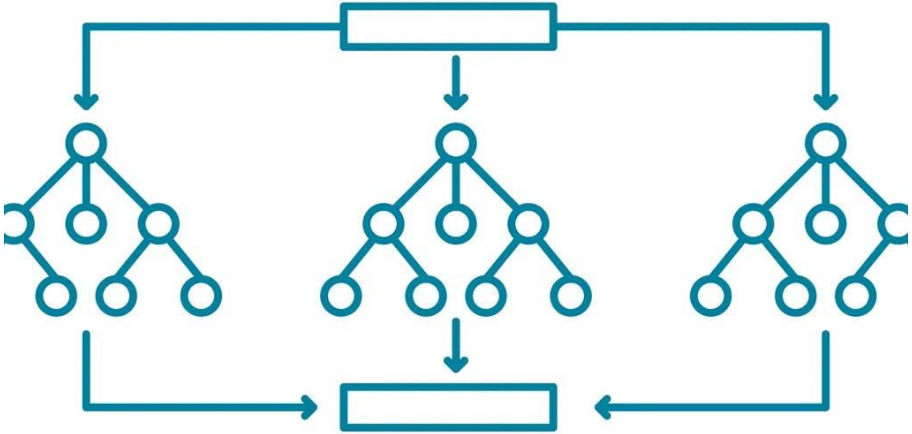
Building and Improving the Model

Overview of RFE

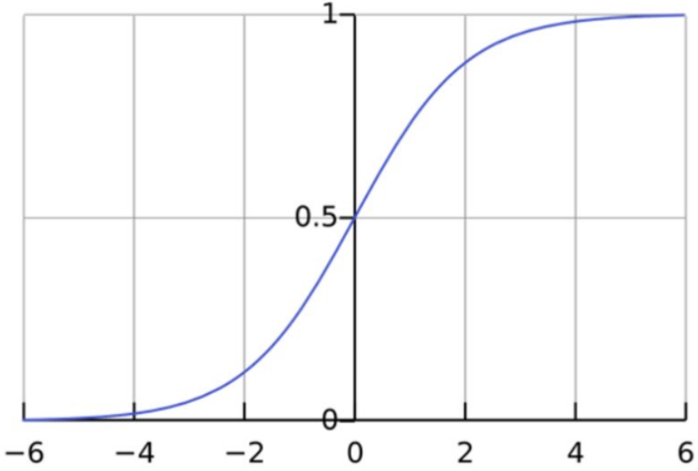
- Popular approach to choosing features is selecting ones that have high correlation with label
- RFE (Recursive Feature Elimination) trains model multiple times to eliminate the weakest label each time
- More powerful than selecting features with high correlations because it guarantees the features that remain will improve model performance
- Has to be performed during training stage, not data exploration stage

Modeling Components and Comparisons

'Billing Zip/Postal Code', 'ZCTA', 'Education Years', 'High school %', 'large_donation_flag', 'Account Type_Household'



Decision Tree



Logistic Regression

Model Comparison

Model Name	Description	Results	Pros	Cons
RF Decision Tree	Creates many branches to evaluate if a donor will donate again	98% precision :) Highly predicted people would donate again	Handles large datasets well	Prone to overfitting We have a small dataset
Logistic Regression	Does regression to classify beyond a threshold if someone will donate again	60% average accuracy...	Easy to set up Efficient training	Assumes linearity in relationships Bad for large datasets

Modeling Key Takeaways

- People are very much likely to donate again
- The amount donated is confirmed to be the best determinant of whether someone donates again
- %educated and %went to college were also important factors

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Summary and Next Steps

What We Learned

- Initial data processing is most important
- Determining the right features can make or break a model's performance
- Overfitting can easily happen with smaller datasets (like in our case)
- If our model just always predicted a donor will donate, it would be correct 98% of the time. C5LA is killing it!

Improving Model Performance

- Removing outliers … lowered model performance
- Using mean to impute null values improved performance by 1x10^-16

Controlled experiment - change one for each model

1. No outliers
2. Using mean to impute nulls
3. Features
   a. Try model 1: remove campaigns
   b. Try model 2: remove close year, close day
   c. Try model 3: reduce features to 6, or keep reducing features to see optimized performance
4. param_grid
   a. change parameters

Next Steps

- More data points focused on donors who did not donate again could help us identify trends in those who don't become repeat donors
- We have yet to explore how the following 3 changes may affect model performance:

3. Features
    a. Try model 1: remove campaigns
    b. Try model 2: remove close year, close day
    c. Try model 3: reduce features to 6, or keep reducing features to see optimized performance
4. param_grid
    a. change parameters

Resources we Leveraged

We primarily used Jupyter Notebook, GitHub, Python, scikit-learn, PowerBI, and pandas

Bonus: Appendix

Precision/Recall Data

	precision	recall	f1-score	support
0	$\boxed{0.33}$	0.25	0.29	4
1	0.98	0.99	0.99	181
accuracy			0.97	185
macro avg	0.66	0.62	0.64	185
weighted avg	0.97	0.97	0.97	185

AUC-ROC: 0.951657458563536

Out of all the predictions where the model predicted non-repeat donors, only **33%** were actually correct.

Precision/Recall Data

	precision	recall	f1-score	support
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Only 25% of the actual non-repeated donors were correctly identified by the model.

Precision/Recall Data

	precision	recall	f1-score	support
0	0.33	0.25	0.29	4
1	0.98	0.99	0.99	181
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macro avg	0.66	0.62	0.64	185
weighted avg	0.97	0.97	0.97	185

AUC-ROC: 0.951657458563536

Out of all predictions labeled as repeat donors, 98% were correct.

Precision/Recall Data

	precision	recall	f1-score	support
0	0.33	0.25	0.29	4
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AUC-ROC: 0.951657458563536

The model successfully identified 99% of the actual repeat donor instances.

Questions?

Thank you everyone :)