# Ruffalo Noel Levitz Project

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## Today's Agenda





Data Gathering and Preparation





Modeling



**Conclusion** 

#### Introduction

- 1. Assumptions
- 2. Challenges
- 3. Original Dataset



## Assumptions



No external factors



Correct data



Use original dataset



Most important target variable

#### Challenges



#### Other Challenges

• Group members in different sections

#### **Data Challenges**

- Ignoring columns
- Missing values
- Incomplete rows





#### **Modeling Challenges**

- Too much time prepping data
- Unknown modeling techniques

#### Original Dataset

Name: Pledge

Number/Letter: 39, AM Description: Pledge flag

Format of Column: Single digit (1 or blank)

Column Type in R: Integer

Number of Missing/NAs in R: 244787

Questions About Column: What data is currently used that would cause someone to have a "pledge flag?"

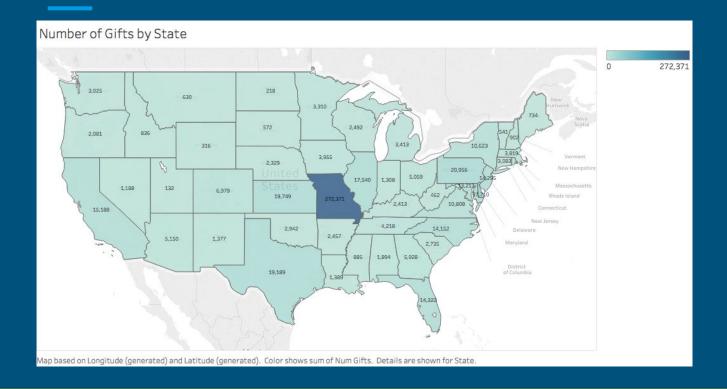
Any person with data populated in PledgeAmt (Column BI) and PledgeTot (Column BJ) (excluding where the pledge amounts/totals = 0) should be flagged as pledges. These fields are also numeric versions of the FY17\_PLEDGE\_AMOUNT column which was character in the original data for some reason

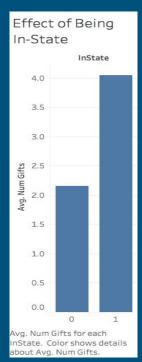
Any Similar Columns/Do Number Match Up?: Pldg

ACTION: DELETE - the column Pldg is the exact same but that one is formatted as a binary variable (0,1) with no blank lines

- 15,000,000+ cells
- Data Dictionary
  - Column descriptions
  - Number/text format
  - Column type in R
  - Missing values
  - Related columns
  - Questions
- Data Visualizations

## Original Dataset





# Data Gathering and Preparation

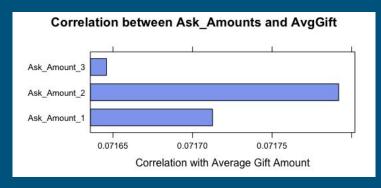
- 1. Data Cleaning
- 2. Data Selection
- 3. Dataset Used For Modeling

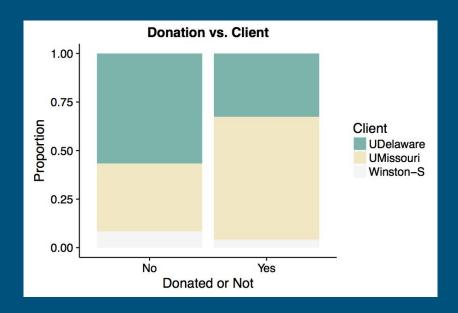


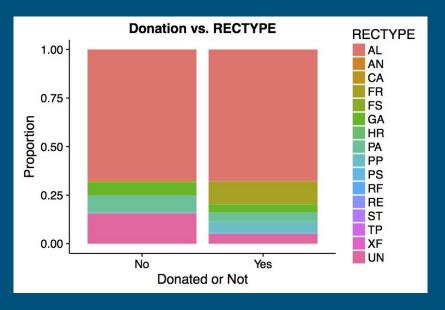
#### Data Cleaning

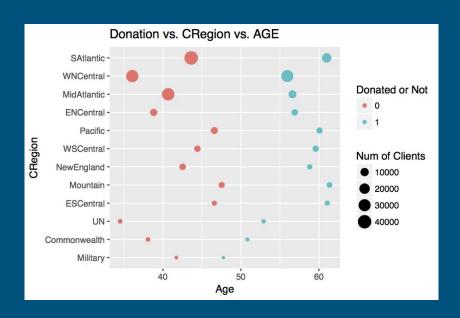
- After examination,
  - Removed errors and outliers: negative talk time and age below 3
  - Transformed some columns to improve interpretability
    - STATE: change to CRegion to reduce the number of levels
    - RecentGradYr, LastGradYr: change to YearSinceRecentGrad to have numeric values
  - Deleted 32 irrelevant and duplicate columns such as PHONE\_RESEARCH, PAYMENT\_TYPE
- Changed missing values to 0, except of AGE
  - Normally missing values of AGE are replaced to mean/median of AGE, but to avoid misleading impact of 53,161 NAs of AGE on models, separated dataset into:
    - 1) Dataset without NAs of AGE
    - 2) Dataset with replaced NAs of AGE to median

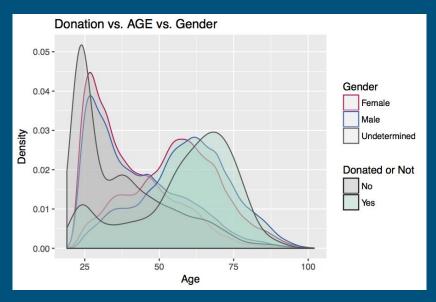
- For models to predict whether donate or not,
  - Transformed NumGifts into Donor01 to have binary values
  - Further removed 11 columns like FSTGFTA, FSTGFTD, LSTGFTD
  - Extracted 4 highly correlated columns:
    - AGE YearSinceGrad & YearSinceRecentGrad
    - Ask\_Amount\_2 Ask\_Amount\_1 & Ask\_Amount\_3

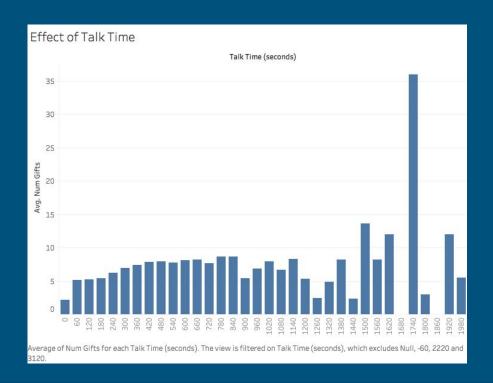


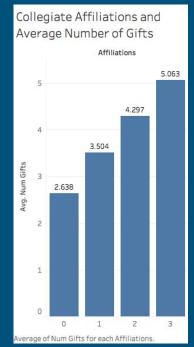












- Left 14 columns with 252,725 rows
  - Predictors: SCHOOL, AGE, RECTYPE, GENDER, NumDegrees, SuccCont, AffilCount, client, Ask\_Amount\_2, InState, TotAttempts, TALK\_TIME, and CRegion
  - Target: Donor01

#### Dataset Used for Modeling

- Had multiple datasets that we could use:
  - Depending on AGE:
    - trainset\_rmAGE Dataset without NAs of AGE
    - trainset\_medAGE Dataset with replaced NAs of AGE to median of AGE (45)
  - Depending on client, (no Winston-S due to too many incomplete rows):
    - trainset\_UD Dataset for UDelaware
    - trainset\_UM Dataset for UMissouri
  - Depending on balancing methods that we used\*:
    - trainset\_under Dataset with undersampling target variable
    - trainset\_both Dataset with over and undersampling target variable

\*undersampling: reduce the number of majority class in target variable \*oversampling: increase the number of minority class in target variable

### Modeling

- 1. Hypotheses
- 2. Modeling Techniques
- 3. Results
- 4. Evaluation Criteria



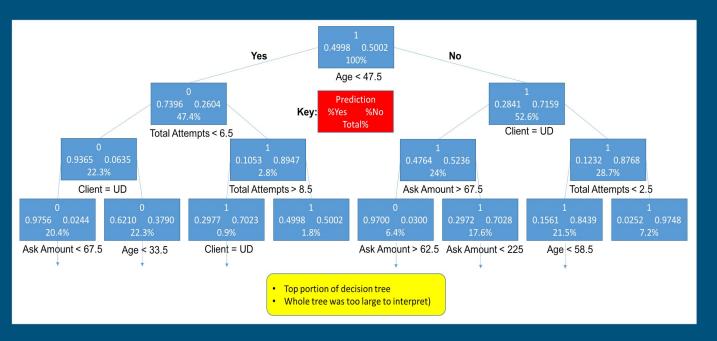
### Hyphotheses

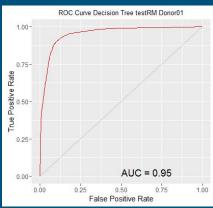
- Based on the findings:
  - Chance to donate
    - People living in certain areas or in-state tend to donate more than those living in other areas or out-of-state
    - Older individuals are more likely to donate than younger individuals
    - People with more call attempts tend to donate more than those with less call attempts
    - People with longer talk time have a higher chance of donating
    - Males have a higher chance to donate

#### Modeling Techniques Explored

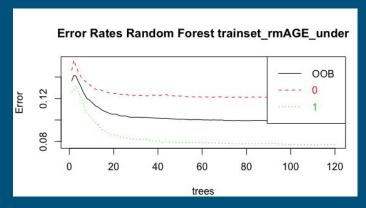
- Decision Tree:
  - Used R-packages to help pick optimum parameters for min split, min bucket, max depth and complexity values
- Random Forest: advanced decision tree
  - Number of trees: the larger the better, but the longer to compute, results stops getting significantly better beyond a critical number
  - Number of variables: the lower the greater reduction of variance, but also the greater increase in bias
- Support Vector Machine (SVM):
  - Kernel: Radial Basis (rbfdot)
  - o Options: The parameter has been set from 0-1.
- Used Rattle and R-packages to build three models

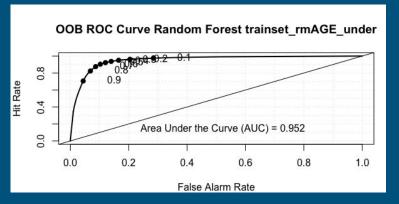
#### Results -Decision Tree





#### Results -Random Forest





```
Tree 1 Rule 34 Node 2796 Decision 1

1: TALK TIME <= 41.5

2: CRegion IN ("Military", "Pacific", "ESCentral", "WSCentral", "Mountain", "WNCentral", "ENCentral"

3: SCHOOL IN ("Agriculture and Natural Resources", "Applied Science", "Continuing Education", "Educa

4: client IN ("UDelaware")

5: AffilCount <= 0.5

6: NumDegrees > 0.5

7: SuccCont IN ("0")

8: TotAttempts > 2.5

9: Ask_Amount 2 > 67.5

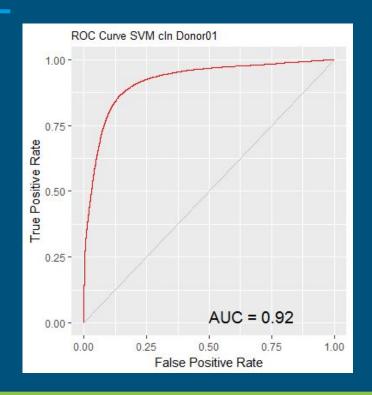
10: TotAttempts <= 7

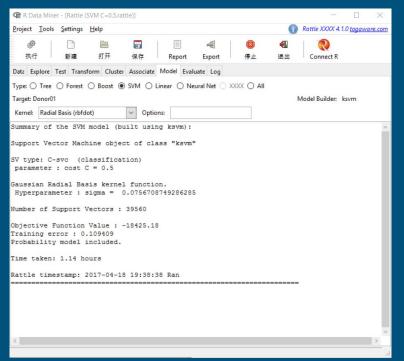
11: TotAttempts <= 4.5

12: GENDER IN ("M", "U")

13: CRegion IN ("M", "Pacific", "ESCentral", "Mountain", "NewEngland", "Commonwealth", "SAtla
```

#### Results -SVM





#### **Evaluation Criteria - Overall Dataset**

Dataset	rmAGE	medAGE	rmAGE_under	rmAGE_both	
Tree	15, 5, 15, 0.0001	21, 7, 10, 0.0001	21, 7, 10, 0.0001	21, 7, 10, 0.0001	
FPR	0.0816	0.0707	0.1077	0.1071	
FNR	0.1311	0.1639	0.1089	0.1061	
F	0.8695	0.8457	0.8464	0.8462	
Forest	120, 3	120, 3	30, 3	30, 3	
FPR	0.0827	0.0693	0.1190	0.1118	
FNR	0.1239	0.1402	0.0812	0.0882	
F	0.8623	0.8605	0.8575	0.8594	
SVM	2	0.5		2	
FPR	-	0.0984 F	FPR: false positive rate (predicted 0 was really 1)		
FNR	-		FNR: false negative rate (predicted 1 was really 0)		
F	-	0.8444	F score: overall accuracy for binary target		

## Evaluation Criteria - Client Specific

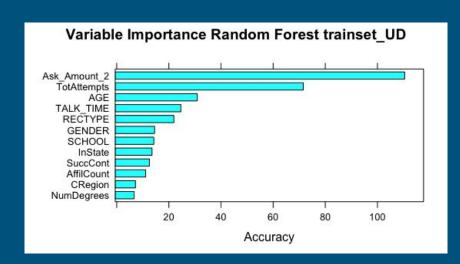
Dataset	UDelaware (UD)	UMissouri (UM)	UM_under	UM_both	
Tree	15, 5, 5, 0.0001	15, 5, 15, 0.0001	90, 30, 10, 0.0001	90, 30, 5, 0.0001	
FPR	0.0110	0.5014	0.4866	0.7421	
FNR	0.1556	0.1420	0.8543	0.6128	
F	0.8943	0.5674	0.1279	0.2487	
Forest	60, 3	90, 3	30, 3	30, 3	
FPR	0.0115	0.2879	0.8137	0.8239	
FNR	0.0969	0.1133	0.8401	0.8127	
F	0.9268	0.7045	0.1251	0.1251	
SVM	0.5	0.5	-	4	
FPR	0.0186	0.2199 F	FPR: false positive rate (predicted 0 was really 1)		
FNR	0.2232	0.1447 FN	FNR: false negative rate (predicted 1 was really 0)		
F	0.9628	0.5745	F score: overall accuracy for binary target		

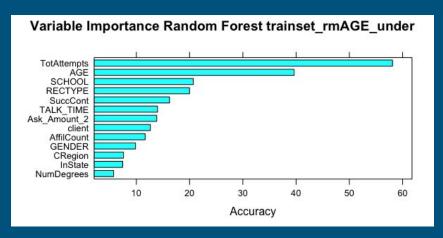
#### Conclusion

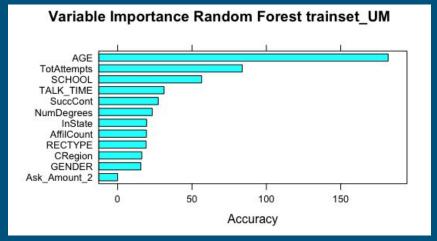
- 1. Final Best Model
- 2. Insights
- 3. Recommendations
- 4. Final Takeaways



#### Final Best Model







#### **Important Factors**

- Age
- Total Attempts
- Talk Time

## Insignificant Factors

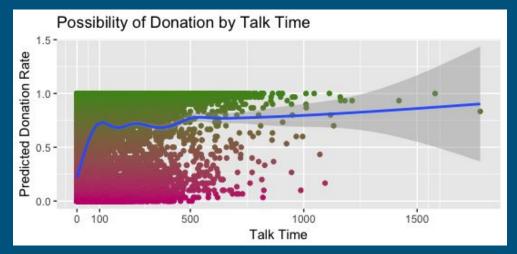
- Number of degrees
- Client's location
- Gender

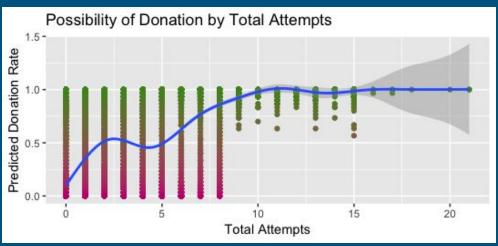
#### Strategic Recommendations

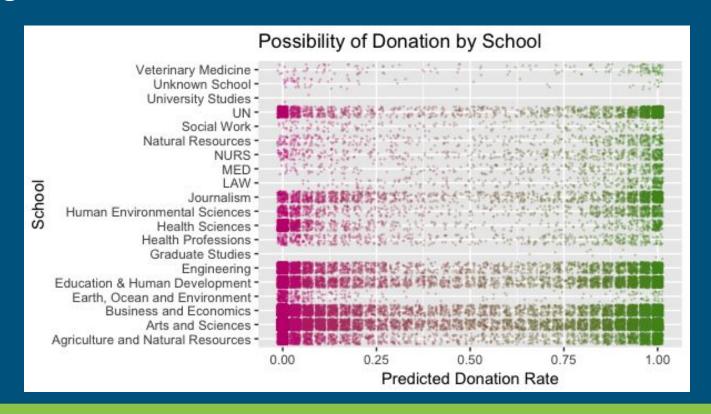
• Target people in the 55-75 age group

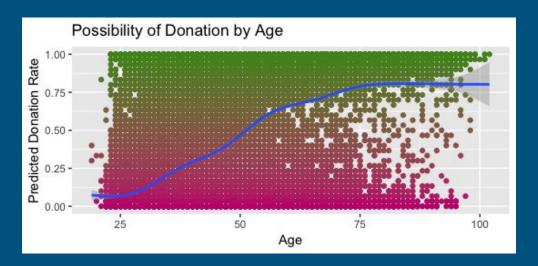
## Tactical Recommendations

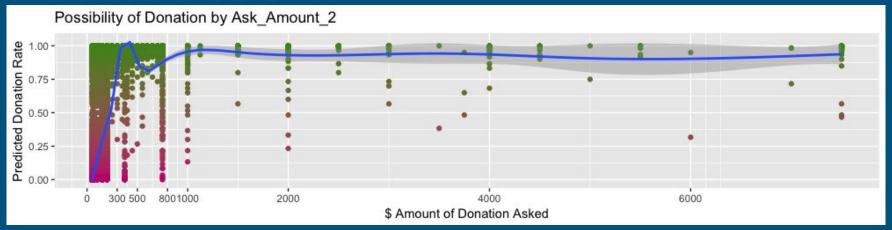
- Delaware clients: set optimal ask amount
- Missouri clients: focus on older people











# Final Takeaways

**THANK YOU!**