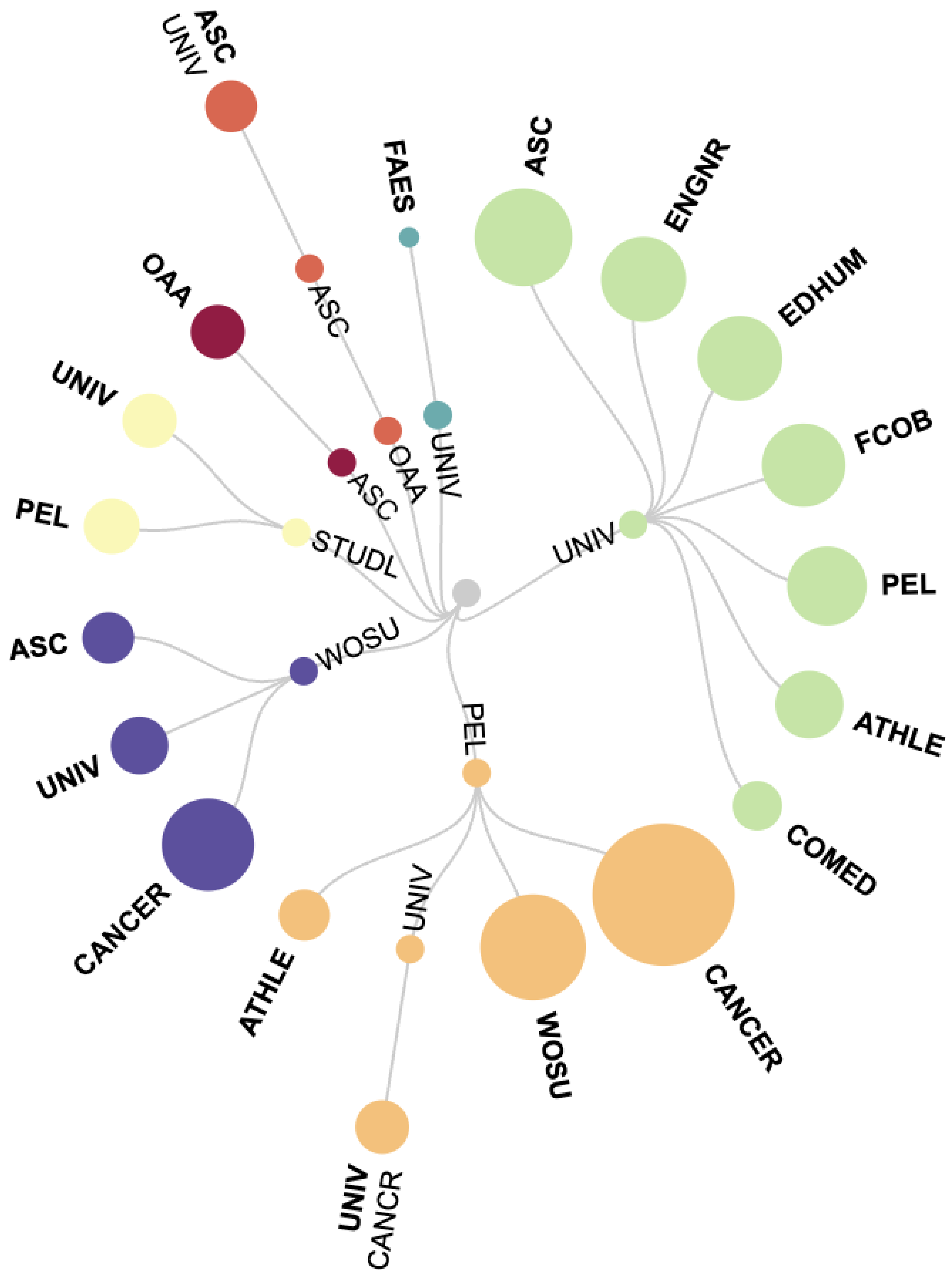
PREDICTING DONATION DESIGNATION

PROJECT 2 STATISTICS 4911

BY GROUP 4:
CAROLINE PIER, XIDAN KOU,
CARLI WERNER TROY STEIN, SONGYUAN WU, AND KAT HUSAR

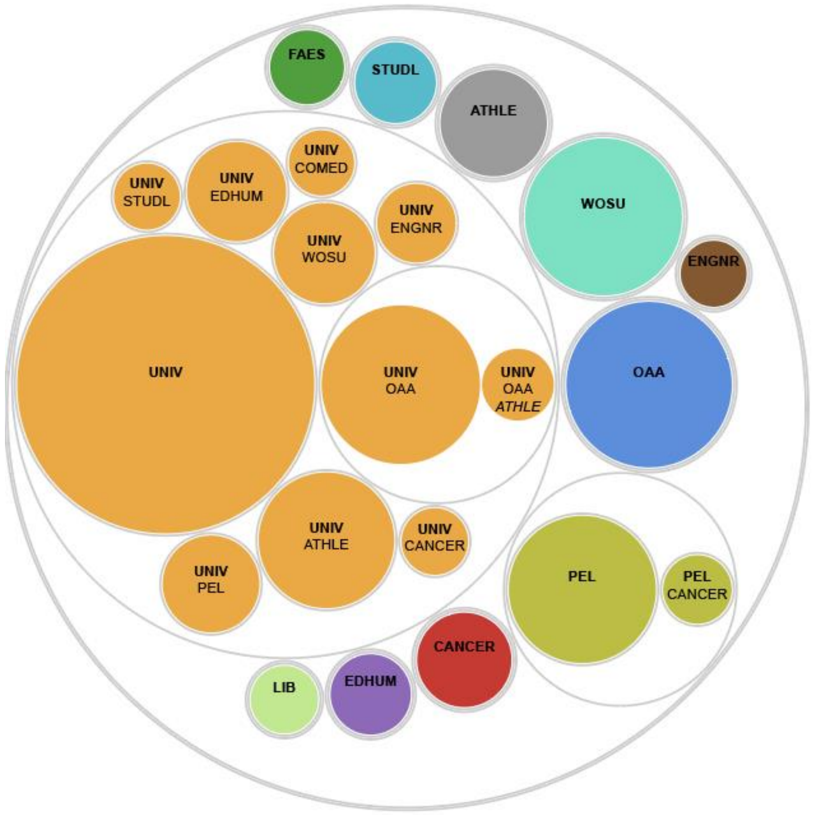
Top 20 Giving Combinations



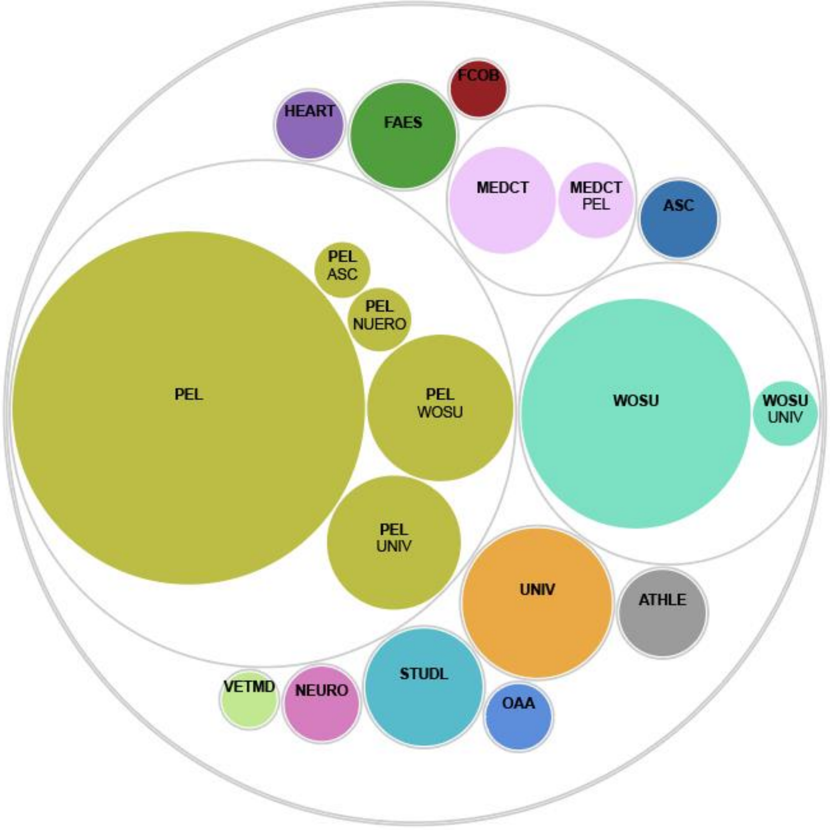
Top Giving Combinations by Designation
Designation Category + X + Y + Z

- Notable number of ***multiple designations*** for those having donated to *Arts and Sciences*
- Arts and Sciences donations tend to **overlap** with donations to the **University** and individual **university colleges**
- Cancer donations tend to overlap with **Pelotonia**, **Neurology**, the **Medical Center**, and **WOSU**
- Donations to **WOSU** notably overlap with Pelotonia, cancer, the Arts and Sciences, and the university

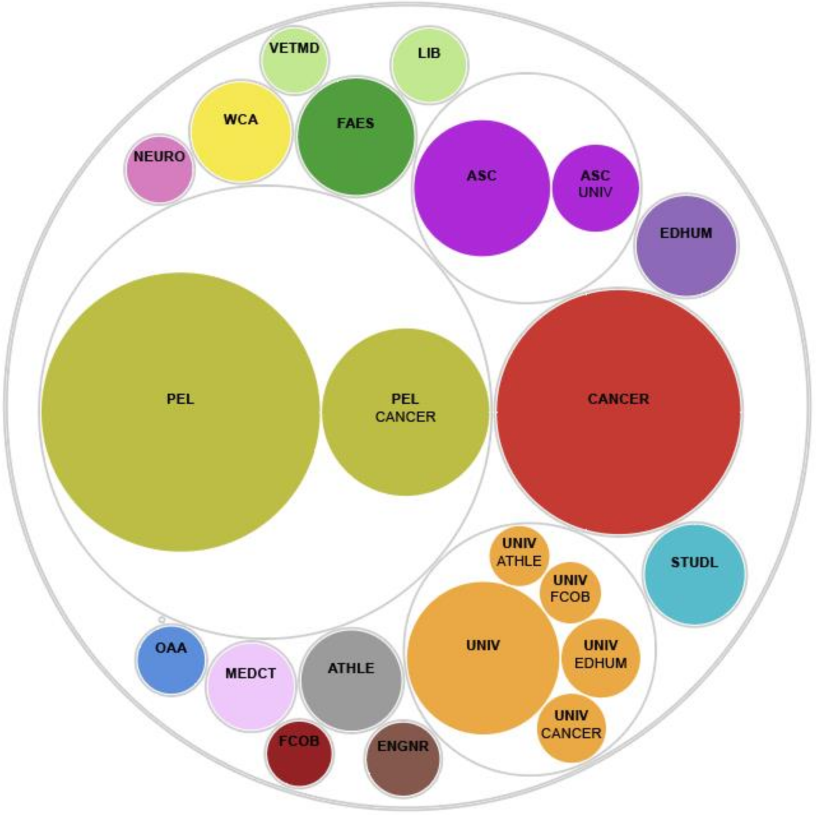
ARTS AND SCIENCES



CANCER



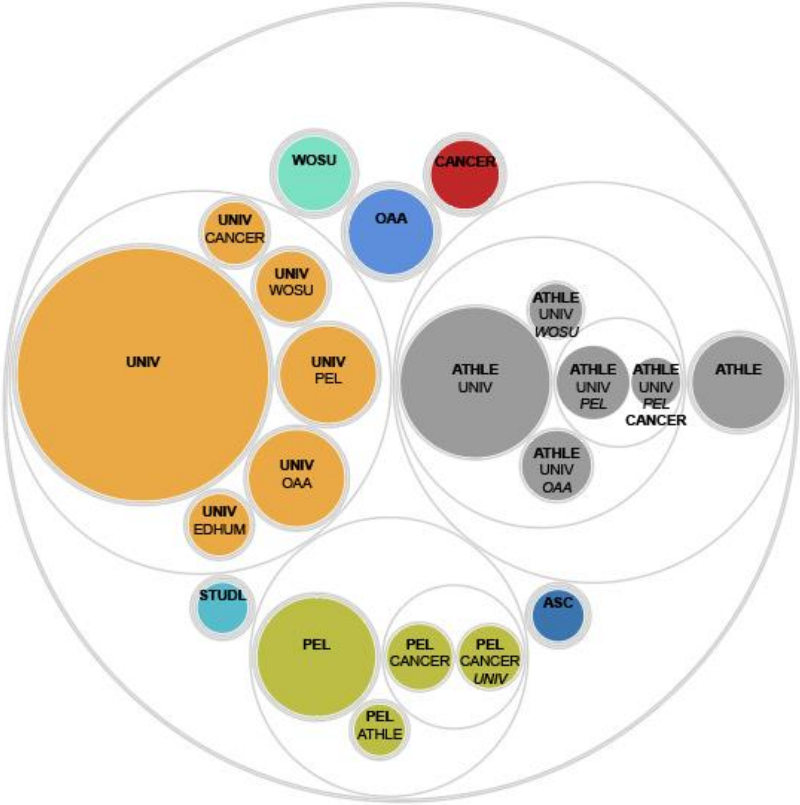
WOSU



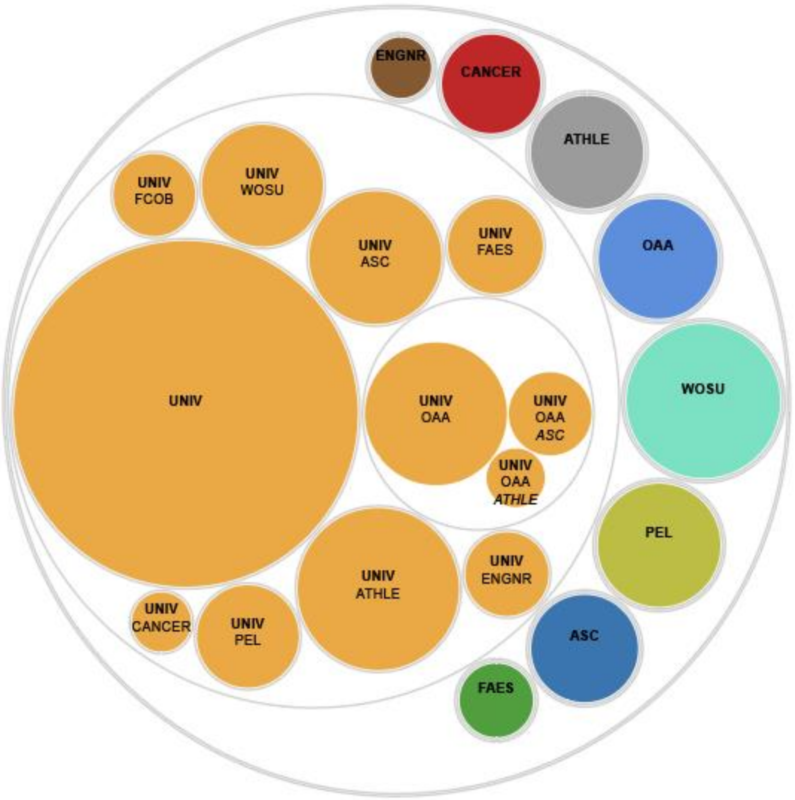
Top Giving Combinations by Designation
Designation Category + W + X + Y +Z

- Fisher College of Business tends to have more donations toward Athletics and Pelotonia
    - Those donating to FCOB also tend to donate to a **variety** of designations
- The College of Education and Human Ecology tends to have more donations toward the **university** and the university in combination with other designations
- Office of Academic Affairs tends to have more donations not heavily weighted toward another designation in particular but among ASC, FCOB, and UNIV then College of Engineering and Student Life

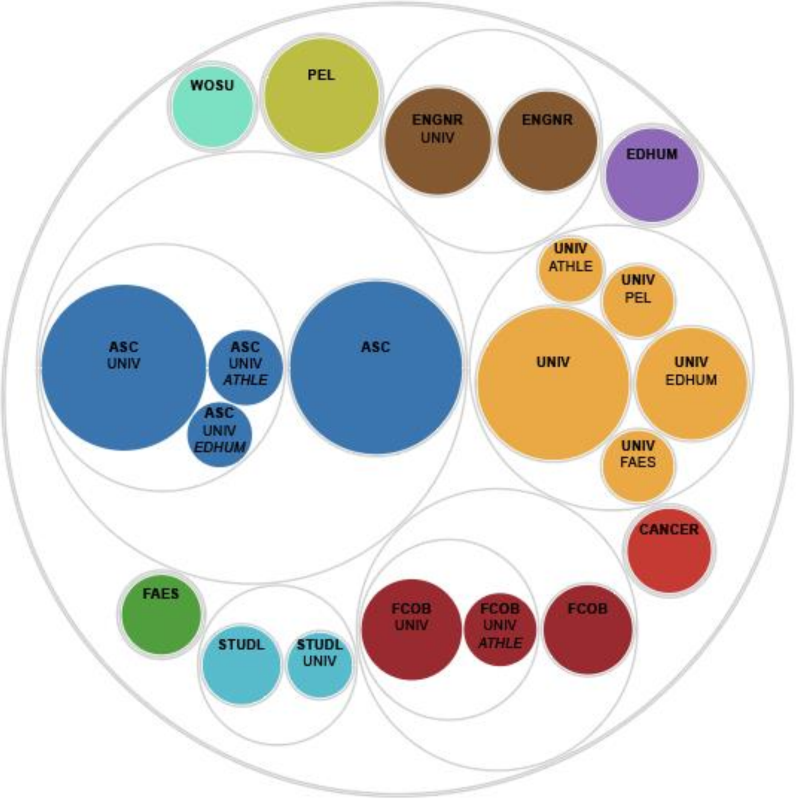
FISHER COLLEGE OF BUSINESS



COLLEGE OF EDUCATION AND HUMAN ECOLOGY

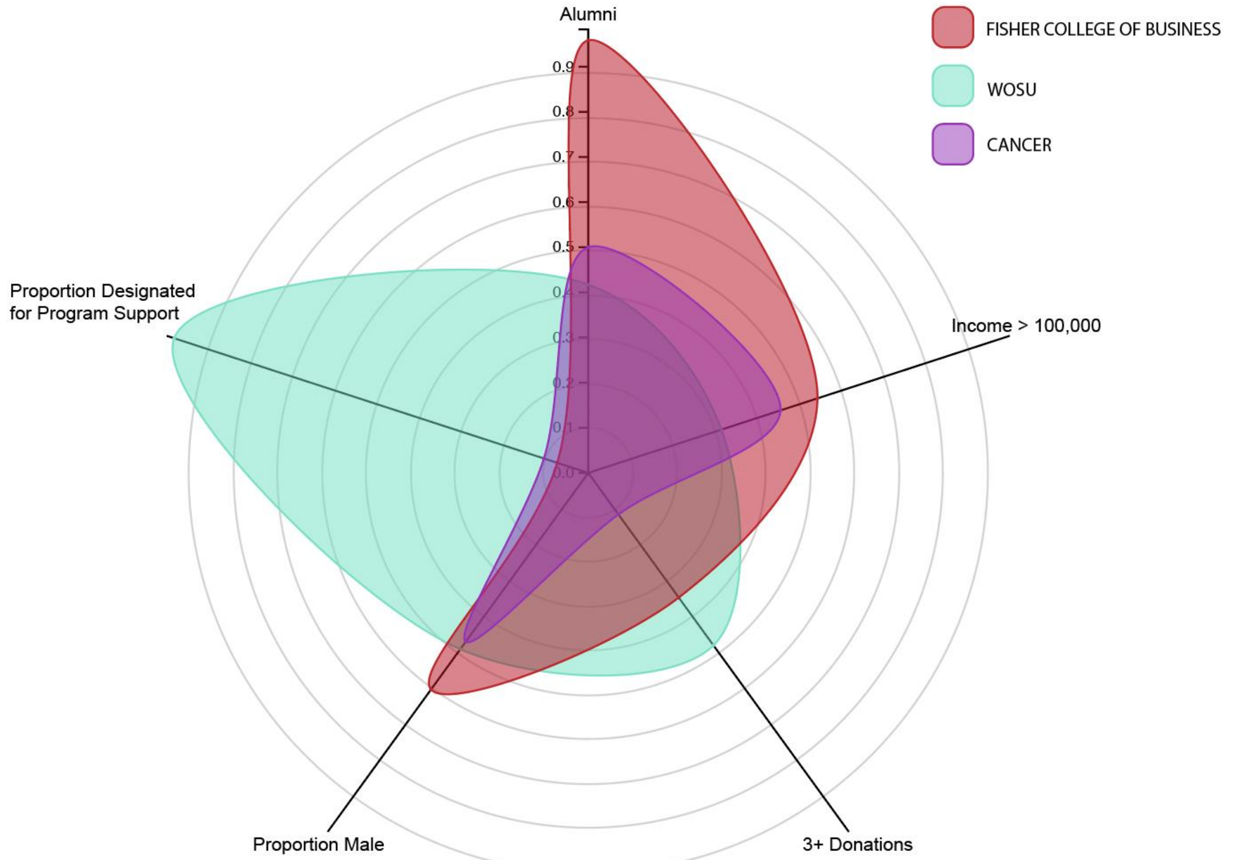


OAA



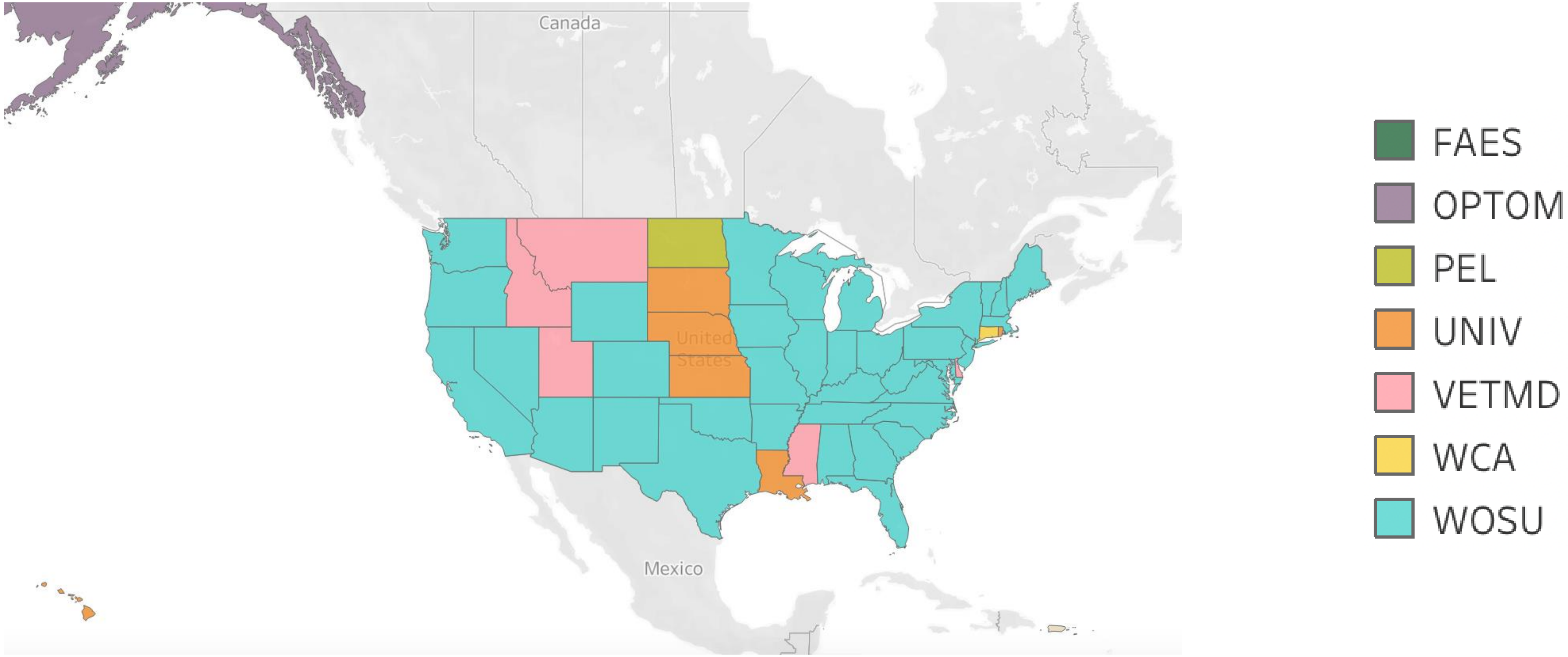
Donor Composition by Designation

- Fisher College of Business has significantly more alumni donors than the other two categories
  - The college also has higher income donors and the highest proportion of male donors compared to the other two
- WOSU donors have more lifetime donations followed by FCOB followed by Cancer
- WOSU donations are often designated for Program Support



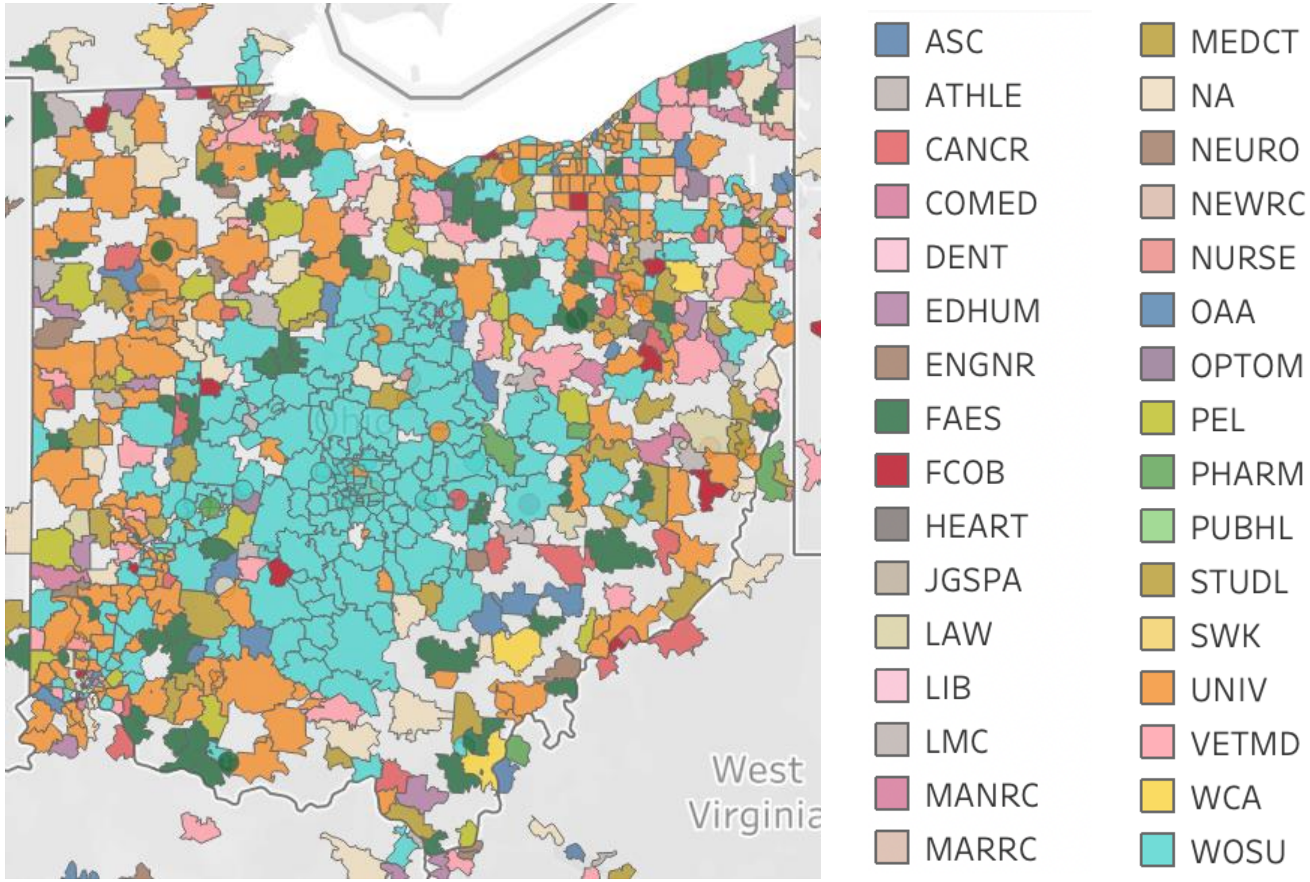
Where are donations coming from?

- *Top Designation by State*
- By State there is an overall trend of donating to WOSU.

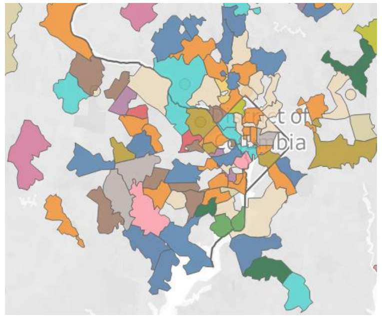


Where are donations coming from?

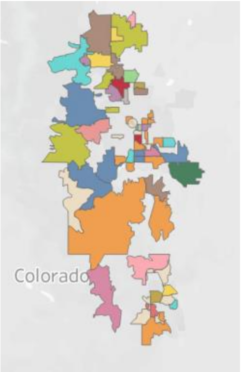
- *Top Designation by Zipcode*
- By Zipcode those in central Ohio tend to donate more to WOSU
    - Those further out tend to donate to the University, Fisher College of Business, Pelotonia, Cancer, and some other university colleges.



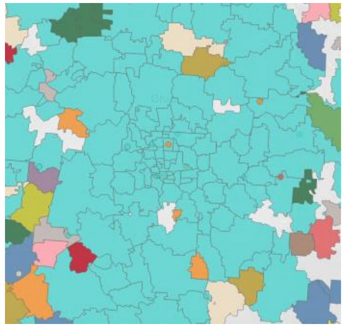
D.C.



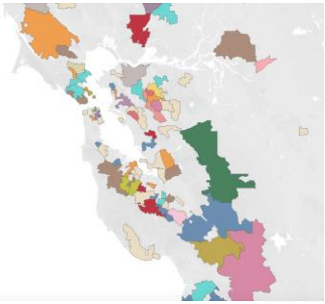
Denver



CENTRAL OHIO

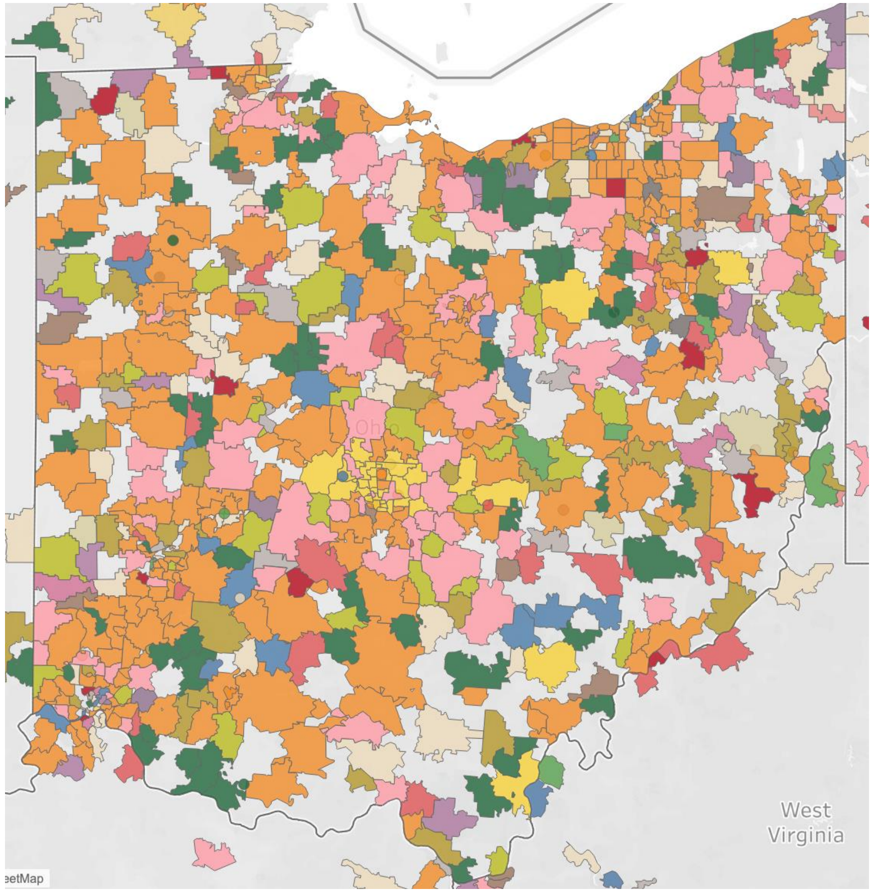


San Fran



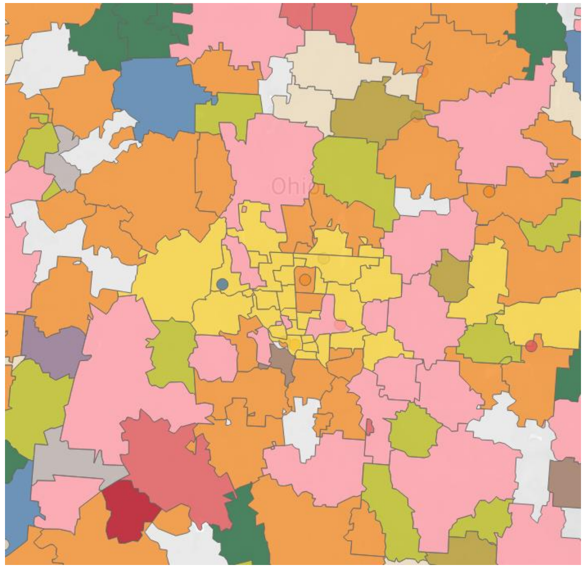
Where are donations coming from?

- *Top Designation by Zipcode*
- **Excluding WOSU** – Central Ohio Designations tend to go toward WCA – *Wexner Center for the Arts*
- *College of Food, Agriculture, and Environmental Sciences* and University Donations are notable



ASC
ATHLE
CANCR
COMED
DENT
EDHUM
ENGNR
FAES
FCOB
HEART
JGSPA
LAW
LIB
LMC
MANRC
MARRC
MEDCT
NA
NEURO
NEWRC
NURSE
OAA
OPTOM
PEL
PHARM
PUBHL
STUDL
SWK
UNIV
VETMD
WCA
WOSU

CENTRAL OHIO

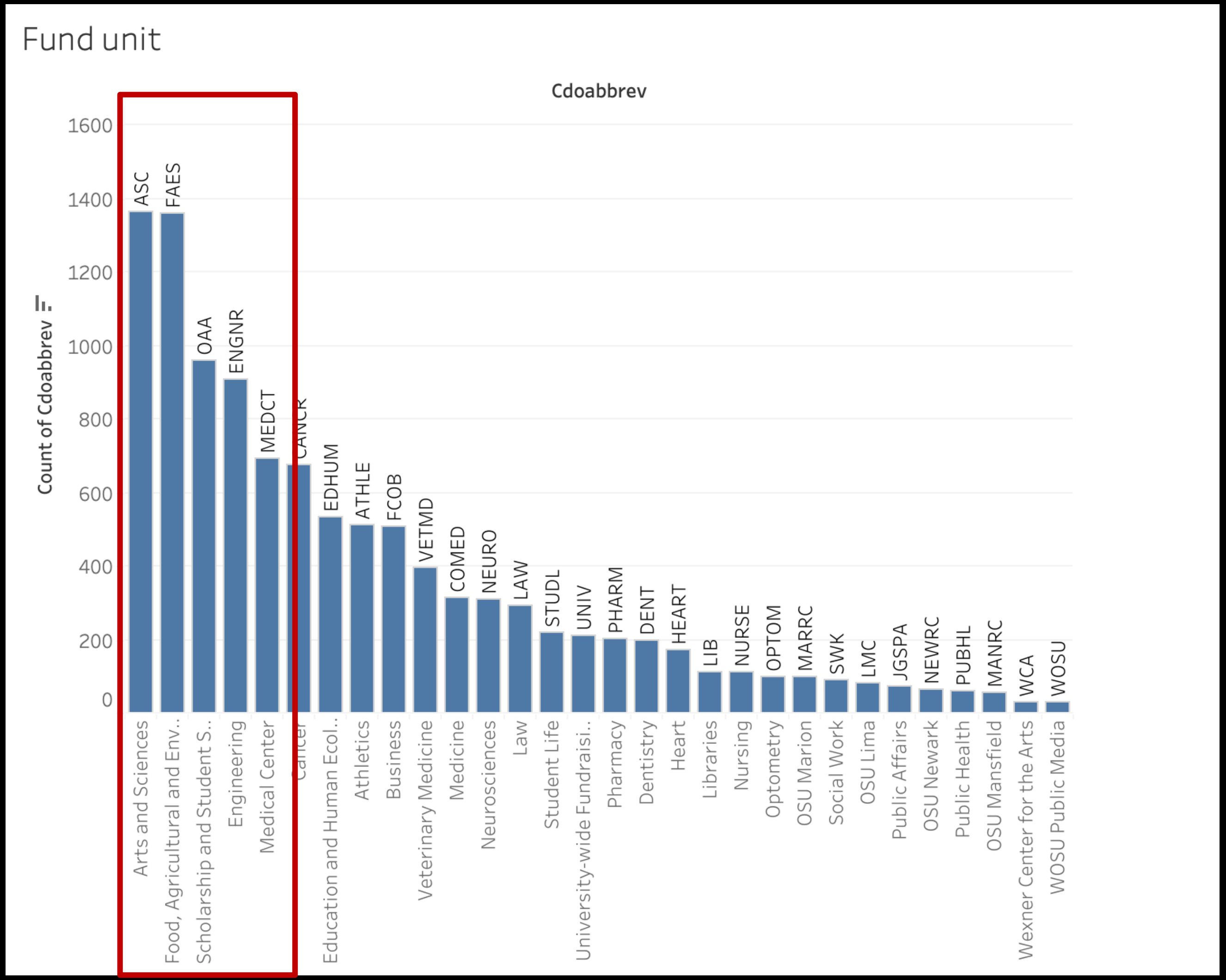


ANALYSIS ON TOP FIVE FUND UNIT

Response variable : cdo (Fund unit)

Explanatory variables

- 30 variables
- Degree :ASC / FAES / …
- Relationships to OSU: OSU alumni / OSU parent/ …



ANALYSIS PROCESS

Variable Selection:
Lasso
Boosting

Variables with Positive Lasso Coefficient

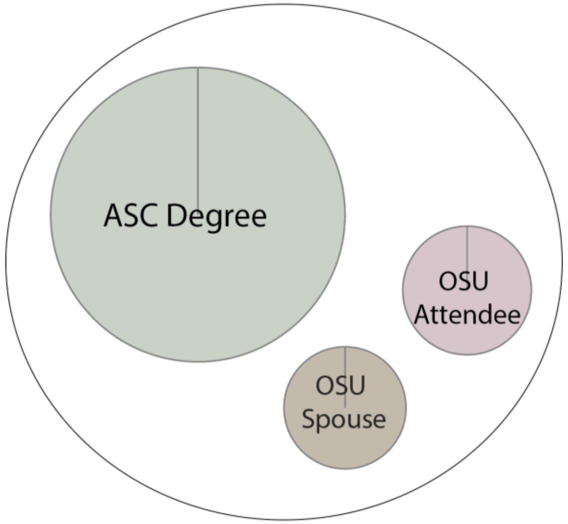
Prediction Model:
Logistic Regression

Note: Only keep the positive coefficient from Lasso because we only want variables that will cause this person to donate the fund. We don't want variables that will cause the person don't donate to the fund.

Response:

Giving To ASC

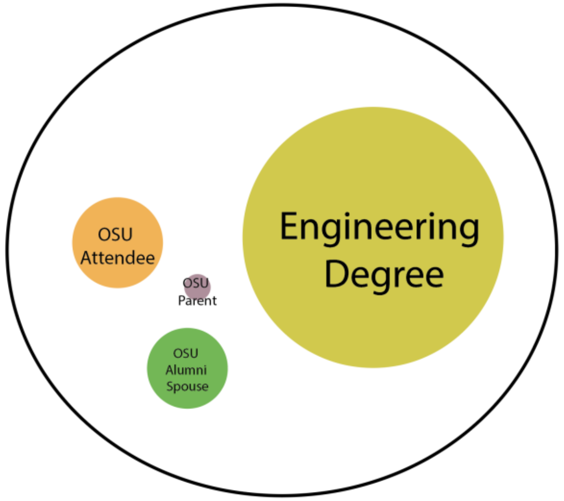
Predictors:



Response:

Giving To Engineering

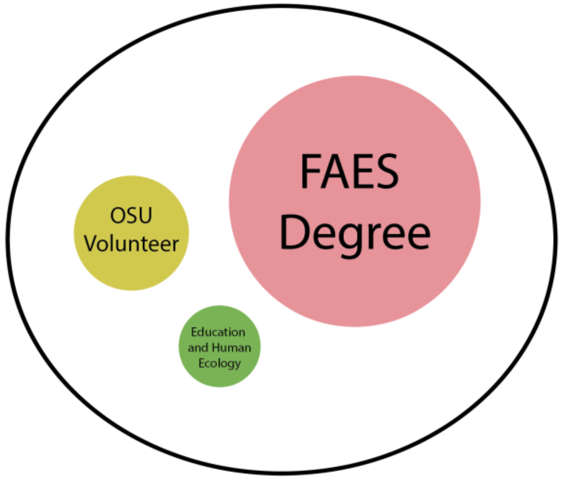
Predictors:



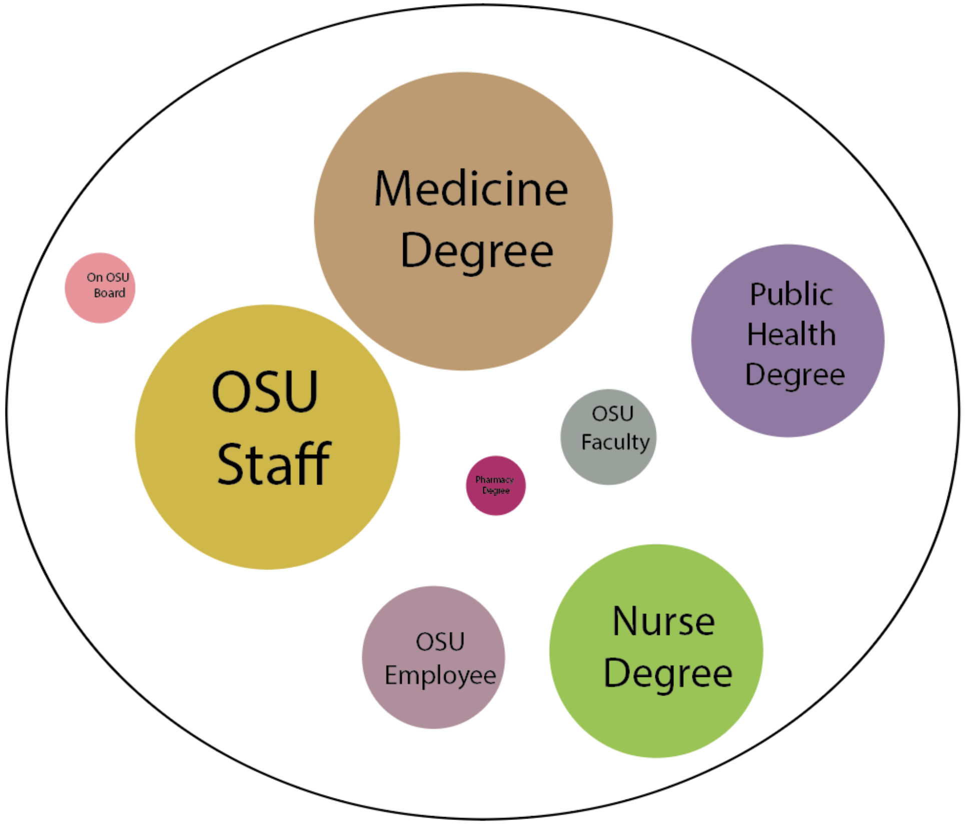
Response:

Giving to Food, Agricultural And Environmental Sciences

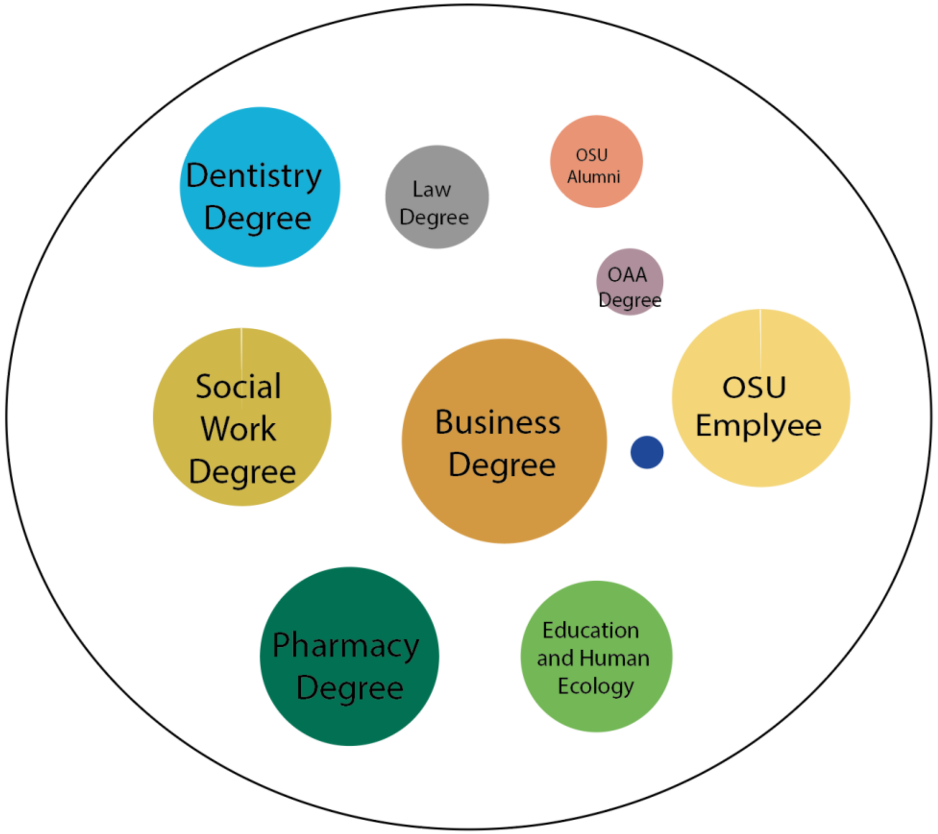
Predictors:



Giving To Medical Center



Giving to *OAA:* Scholarship and Student Support



	Demographics	Odds
Person A	Social Worker degree	0.329
Person B	Social Worker degree + OSU Employee	0.688
Person C	Business Degree + OSU Alumni	0.426
Person D	Pharmacy Degree + OSU Employee	0.886
Person E	OSU Alumni	0.089

GIVING TO OAA

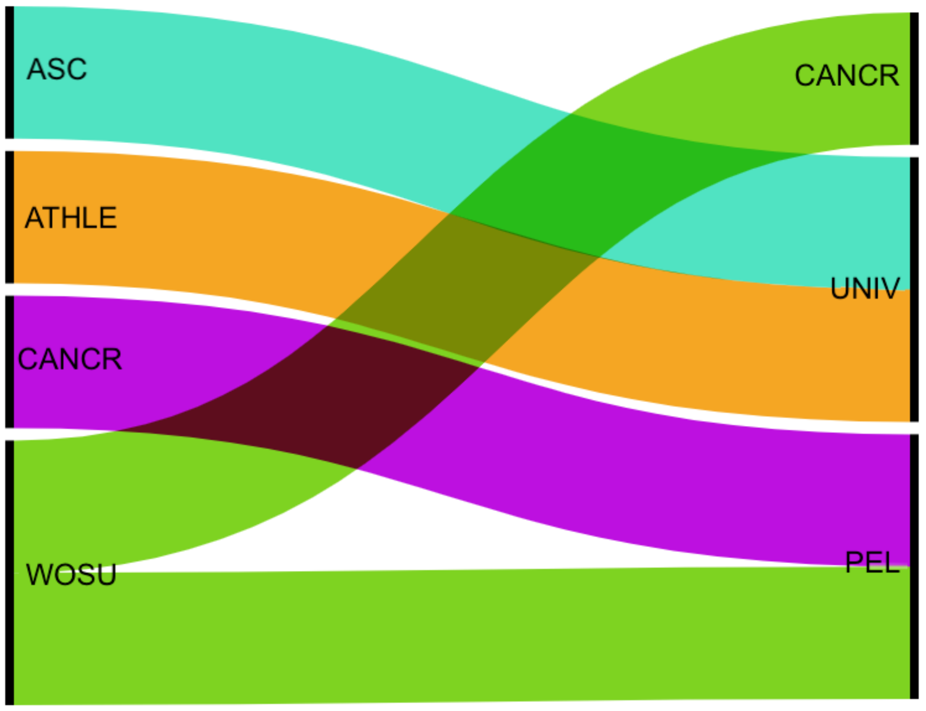
ASSOCIATION ANALYSIS

ASSOCIATION ANALYSIS

- Rules creations:
  - Clean data:
    - Remove inactive organizations
    - Remove constituents donating to one fund only
  - What combinations do we see often together?
    - Apriori algorithm to find frequent itemsets (combinations) fast
  - Accounting for overall frequency of specific fund:
    - Use lift metric

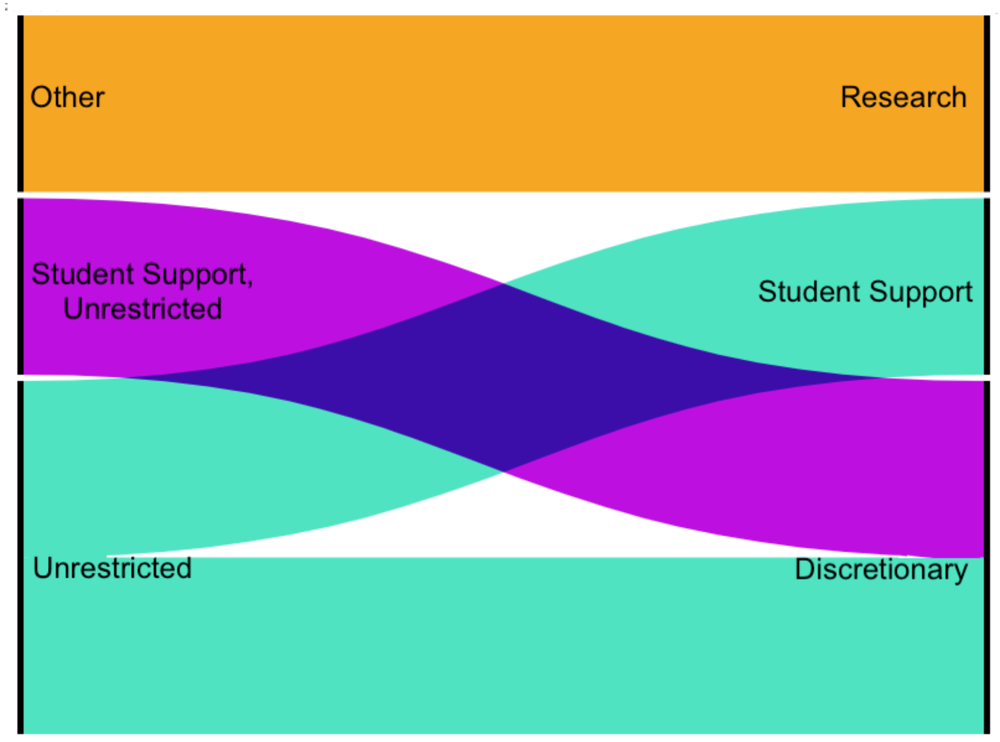
UNIT CODE RULES

antecedents	consequents	support	confidence	lift
(ASC)	(UNIV)	0.116368	0.606317	1.214478
(ATHLE)	(UNIV)	0.133747	0.642066	1.286085
(CANCR)	(PEL)	0.162818	0.514221	1.367692
(WOSU)	(CANCR)	0.100505	0.352338	1.112774
(WOSU)	(PEL)	0.118299	0.414719	1.103041



DESIGNATION PURPOSE RULES

antecedents	consequents	support	confidence	lift
(Unrestricted)	(Discretionary)	0.204452	0.852045	1.712548
(Other)	(Research)	0.378080	0.905018	1.521475
(Student Support, Unrestricted)	(Discretionary)	0.105970	0.849671	1.707776
(Unrestricted)	(Discretionary, Student Support)	0.105970	0.441626	1.803066



CHARACTERISTIC - BASED ASSOCIATION ANALYSIS

- Do a collection of donors who participated in the same activity frequently donate to any specific funds?
  - Student life variables: honor society, religious organizations, etc.

THE OHIO STATE UNIVERSITY

HONORS AND SCHOLARS CENTER

Did donors who were in honor society frequently donate to pelotonia?

"Antecedent"

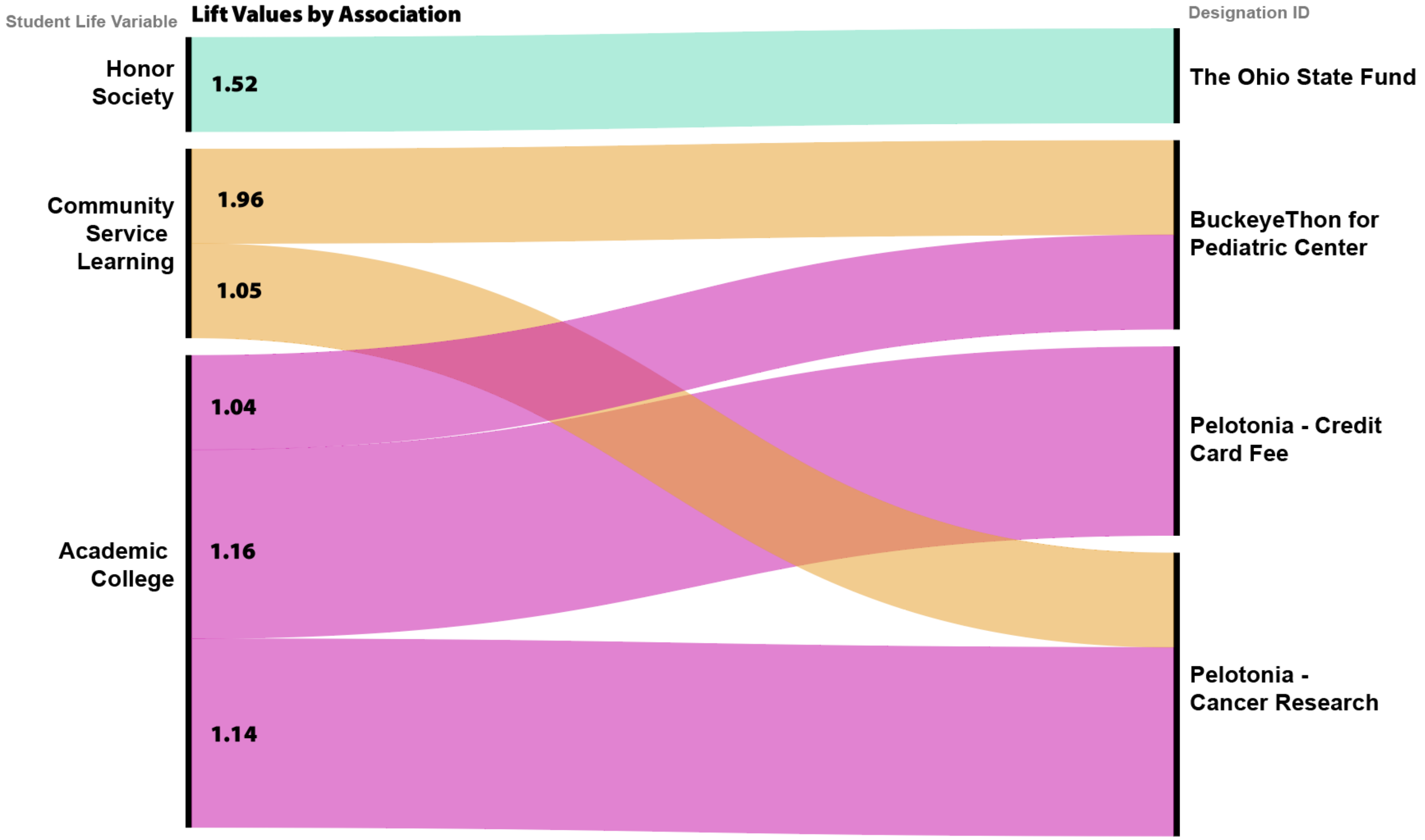
"Consequent"

antecedents	consequents	support	confidence	lift
Community Service Learning	BuckeyeThon Fund for Pediatric Cancer	0.054	0.354	1.957
Honor Society	The Ohio State Fund	0.062	0.248	1.520
Academic College	Pelotonia Credit Card Fee Operating Fund	0.066	0.159	1.164
Academic College	Pelotonia Fund for Cancer Research, Pelotonia Credit Card Fee Operating Fund	0.065	0.157	1.162
Academic College	Pelotonia Fund for Cancer Research	0.149	0.359	1.141
Community Service Learning	Pelotonia Fund for Cancer Research	0.051	0.330	1.048
Academic College	BuckeyeThon Fund for Pediatric Cancer	0.078	0.189	1.044
Honory Society	Pelotonia Fund for Cancer Research	0.073	0.291	0.923

THE ALGORITHM

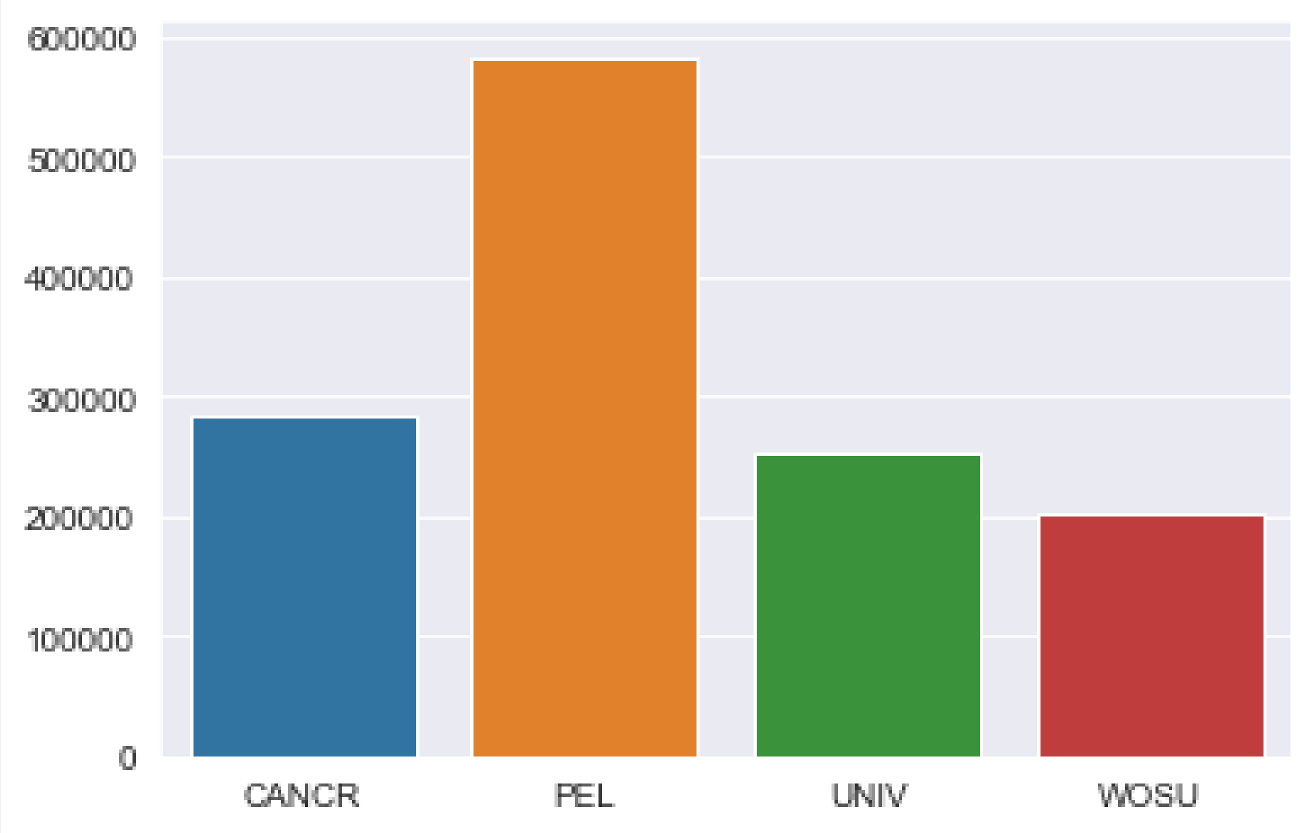
- 5% of donors must participate in a variable for it to be considered
- Similarly, a fund must be donated to in 5% of all donations to be considered
  - This 'support' threshold must be specified for running the algorithm
- Lift > 1 means the values are associated!

RESULTS


Student Life Variable
Lift Values by Association
Designation ID
Honor Society
1.52
The Ohio State Fund
Community Service Learning
1.96
1.05
BuckeyeThon for Pediatric Center
Academic College
1.04
1.16
1.14
Pelotonia - Credit Card Fee
Pelotonia - Cancer Research

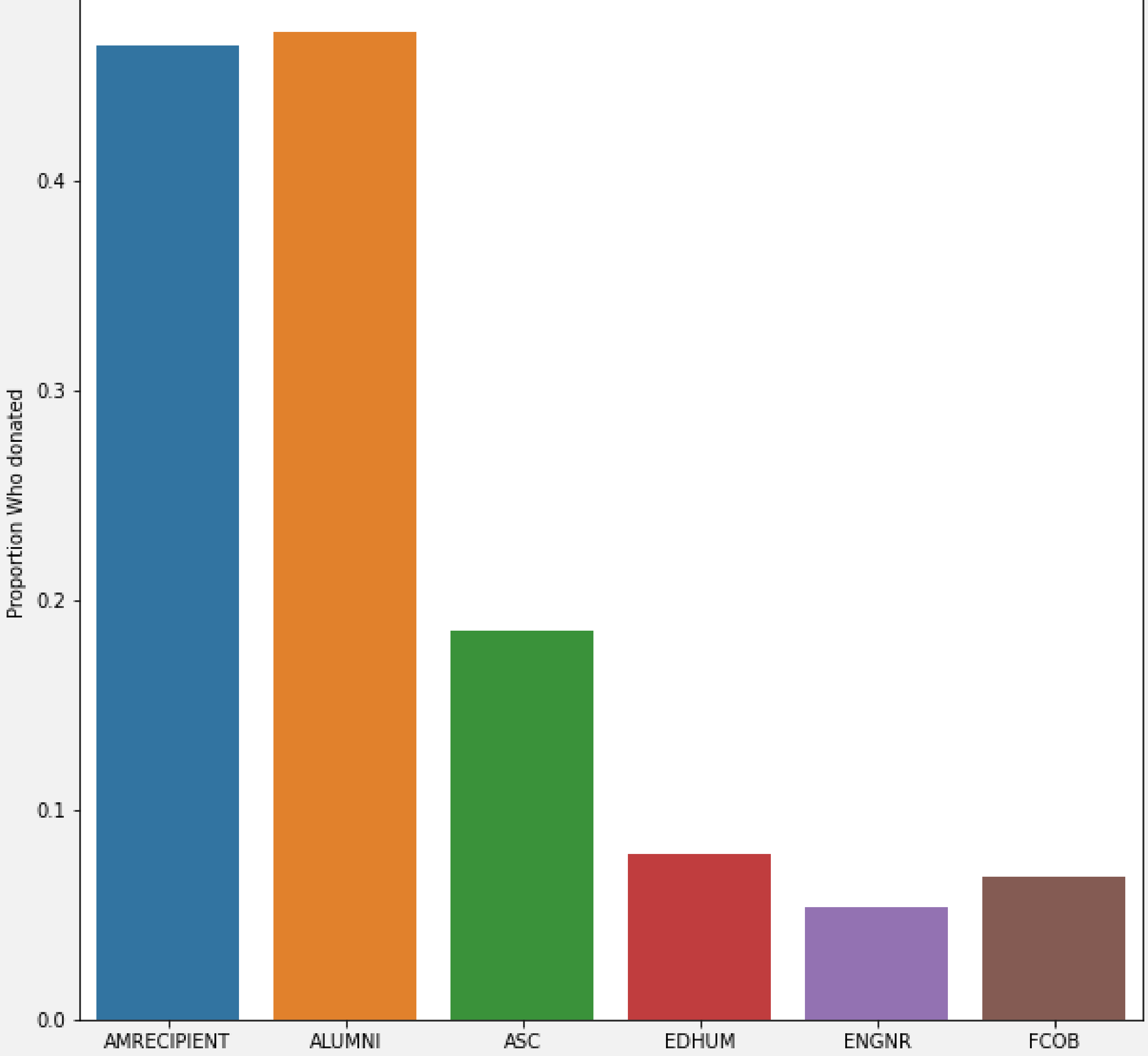
PELOTONIA, WHO DONATES THERE?

- What does a donor look like for Pelotonia?
- Treated demographics categorical (i.e. College graduated from)
- Why Pelotonia?
  - One of the largest events (one of the cdo codes for top 6 funds)
  - Opportunistic to find many new donor



WHERE ARE PEOPLE COMING FROM?

- Pelotonia Donors



MODEL MADE

- Logistic Regression model using previous 6 demographics illustrated
- 57% accuracy
- Less demographics to pay attention to same power

CONCLUSIONS

- Target Donors who graduated from: ARTSCI, EDHUM, ENGNR, or FCOB
- Alumni are important they have an odds of 1/3
- OSAMRECIPIENT also valuable

USER-BASED COLLABORATIVE RECOMMENDATION SYSTEM

Main assumption: Similar person would always have similar tastes and incentives for the same thing.

1. Input any constituent A in the database

2. Finding the most similar k constituents based on cosine similarity method

3. Using the designations to which similar constituents donate to give recommendations for constituent A

STEP 1: CALCULATE EACH SIMILARITY MATRIX

- # Events and corresponding donation amount (N_EVENTS,FY_EVENTS_LAST,etc)
- Consistency (VAL_DONOR_LT_CONSISTENCY, N_DONOR_LT_CONSECFYS, etc**)**
- Payment Approaches **(IS_DONOR_PAY_STOCK, etc)**
- Relationship with OSU **(IS_MEMBER_PC, VAL_SCORE_ENGAGEMENT)**

Consistency Subset

Constituent_ID	VAL_DONOR_LT_CONSISITENCY	N_DONOR CONSECFYS	N_DONOR_GIVENGFYS
10	0.3871	3	12
11	0.5982	3	12
12	1	1	3
13	0.6111	1	5
14	0.8766	6	22

Similarity Matrix

Similarity Matrix	Constituent 10	Constituent 11	Constituent 12	Constituent 13	Constituent 14
Constituent 10	1	0.88	0.74	0.65	0.92
Constituent 11	0.83	1	0.66	0.45	0.86
Constituent 12	0.59	0.47	1	0.73	0.55
Constituent 13	0.75	0.92	0.38	1	0.76
Constituent 14	0.91	0.33	0.42	0.69	1

STEP 2: COMBINE COSINE SIMILARITY MATRICES

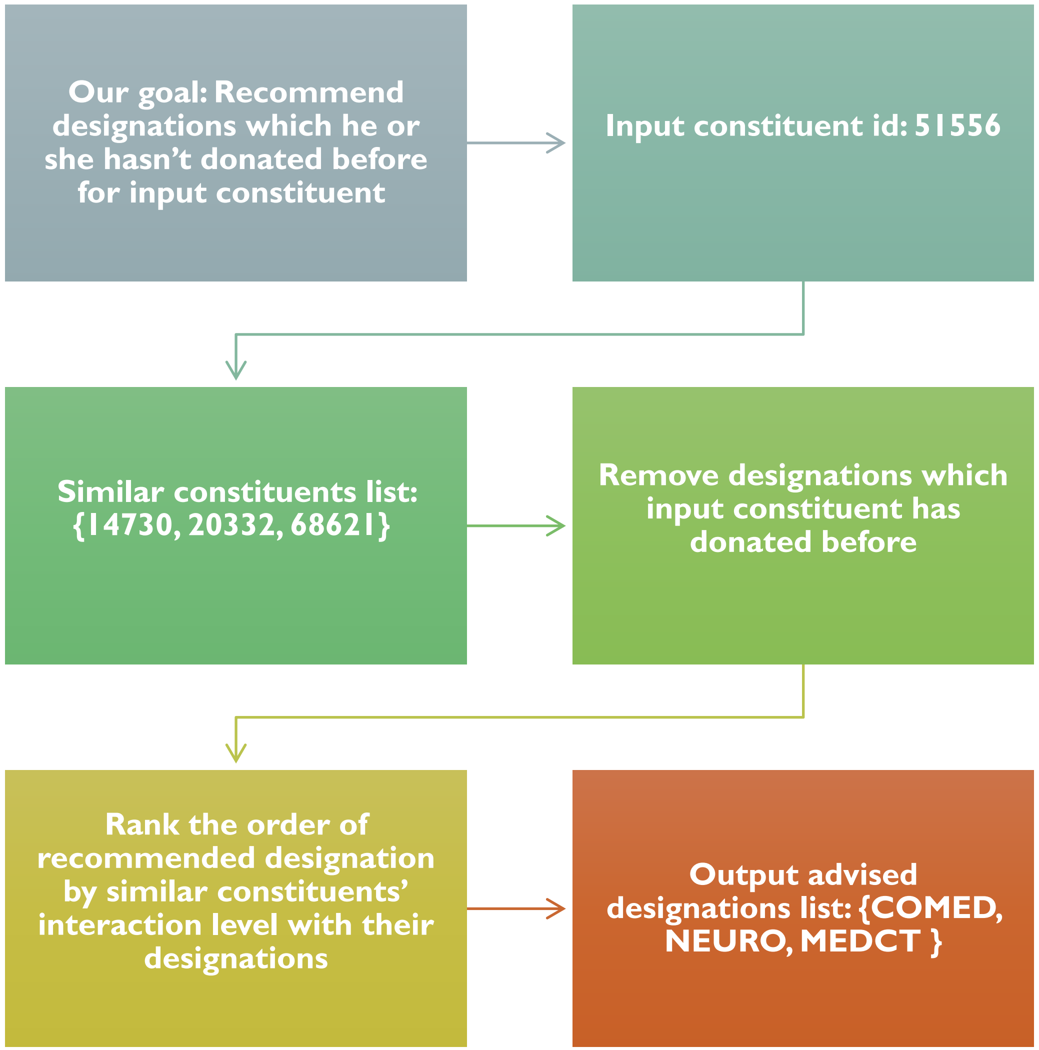
Weights_Events: 0.3

Weigths_Payment: 0.1

Weights_Consistency: 0.2

Weights_Rela: 0.4

Improvement: Current weights are based on the intuition and experiment which are not scientific and persuative enough. I would find one scientific way to measure the weights of each variable subsets and evaluate much more accuarate cosine similarity score.



FINAL STEP: OUTPUT RECOMMENDED DESIGNATIONS

THANK YOU!

Any Questions?