DIVERSIFYING WITH DATA

SIMIOCLOUD

DEMYSTIFYING “DATA” & HOW IT IS USED

- What is really meant by the term “data”?
- What are the most important data points for fundraising?
- Raw data leads to donor predictions

CONSUMER DATA

survey response

What do you say about yourself?

credit worthiness

wealth indicators

What is your financial strength?

search activity

What do you search?

geo location

Where do you go?

Where do you live?

Who are you?

lifestyle interests

demographics

segmentation products

What do you buy?

merchandise purchases

service contracts

charitable donations

consumer services spend

travel & hospitality spend

subscriptions

What do you do online?

social profiles

site visits

likes

follows

clicks

Donor Segmentation

$0.47

Average Gross Income
per Piece Mailed

$0.37

$0.24

$0.21

$0.17

$0.20

$0.13

$0.11

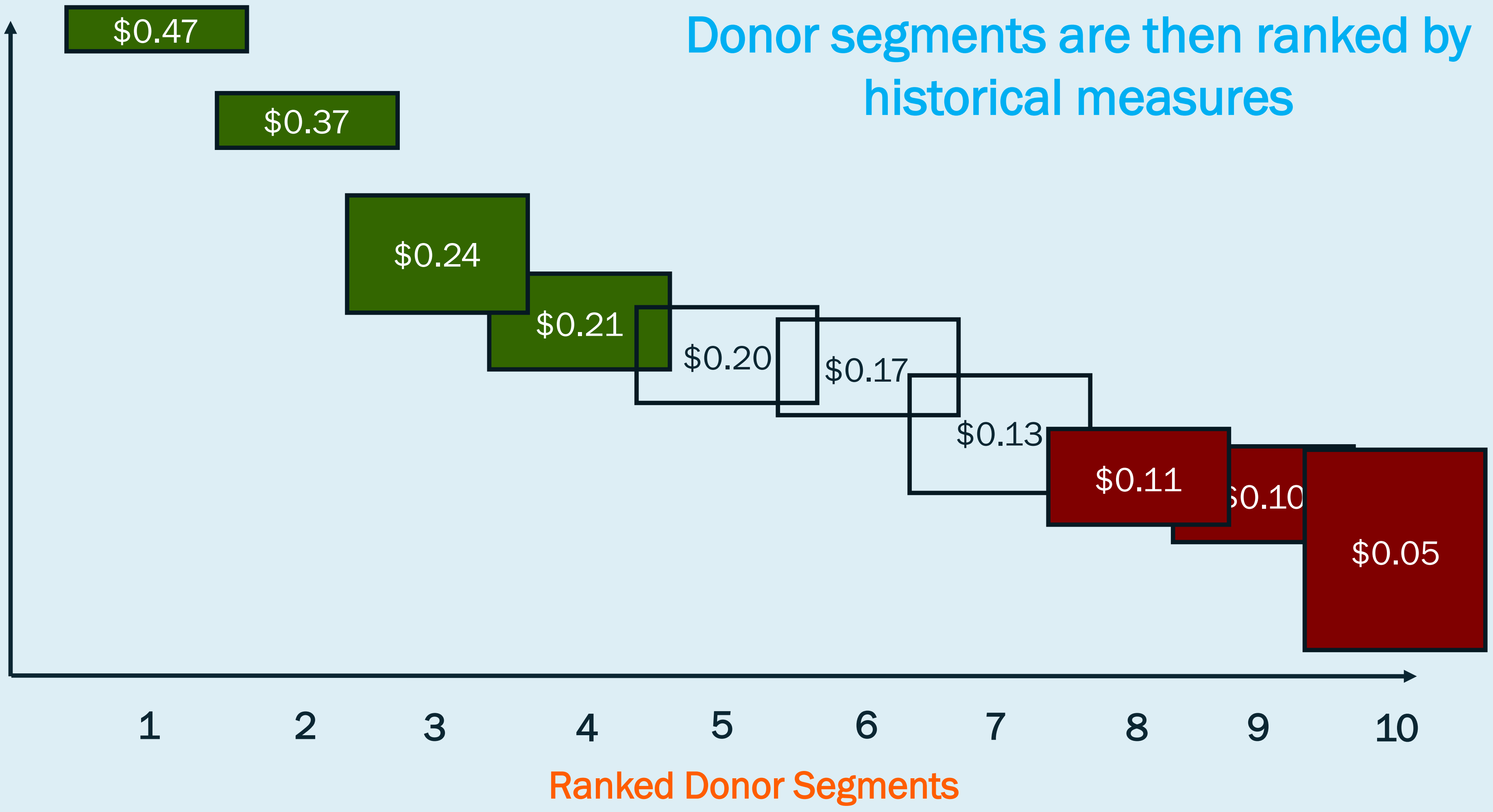
$0.10

$0.05

Donor segments are created from intuitive data elements like “recency of last gift”, “frequency” and “total $s”

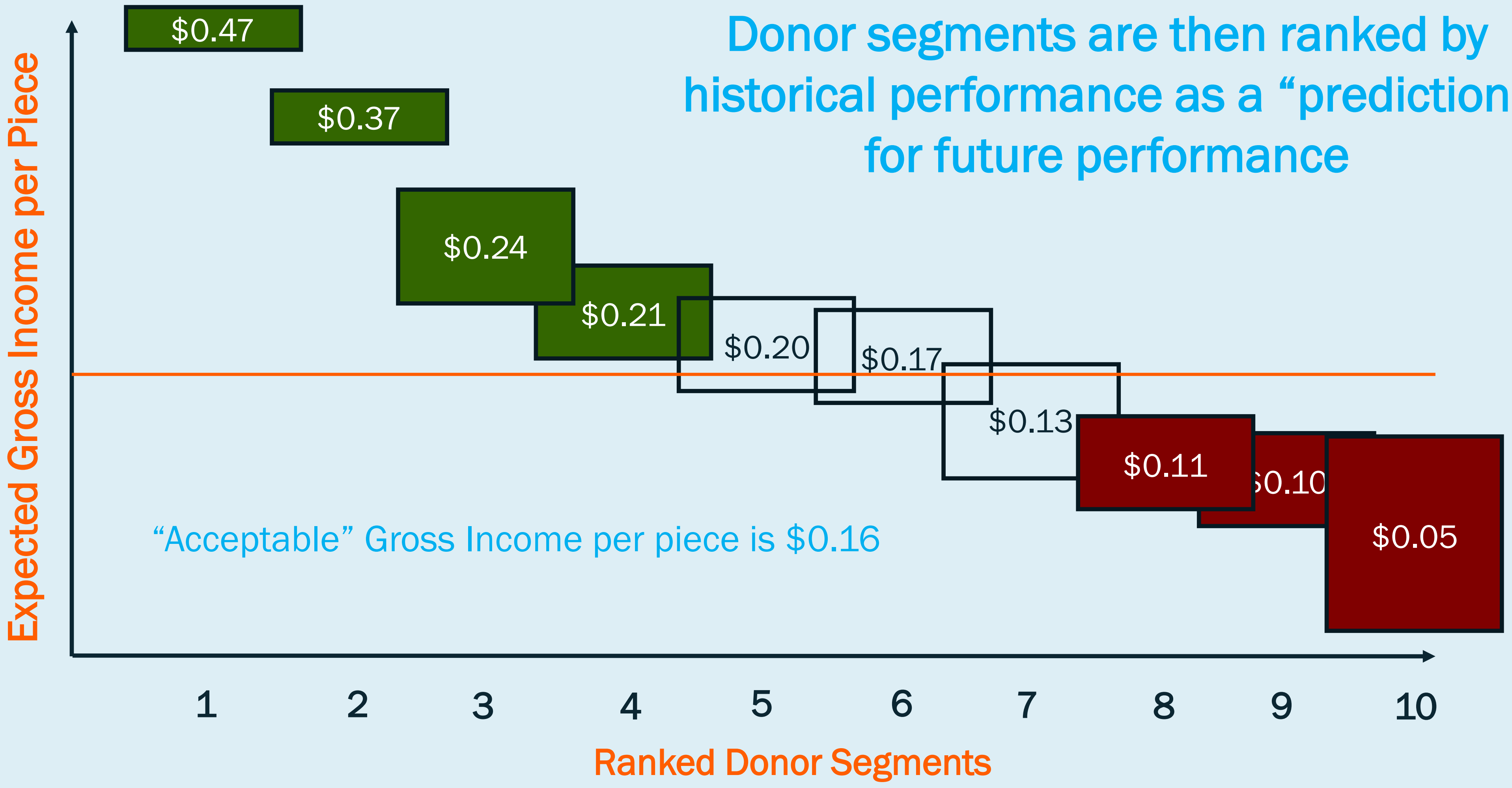
Ranked Donor Segments

Donor segments are then ranked by historical measures



Selected Segments

Donor segments are then ranked by historical performance as a "prediction" for future performance



Predictive Model Definition

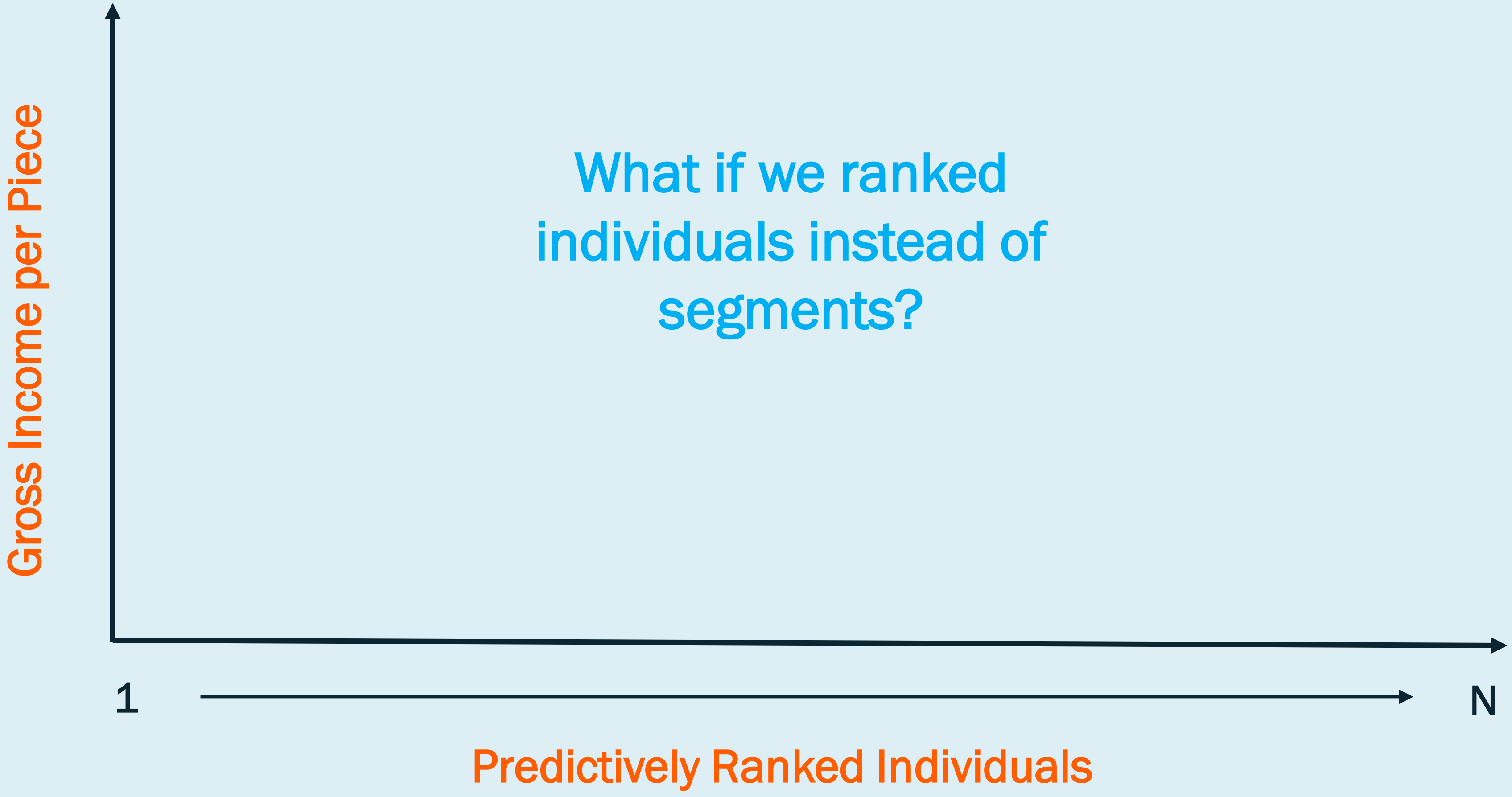
A predictive model is a mathematical statement created using statistical methods to assign a predicted value for a desired outcome

Scores!

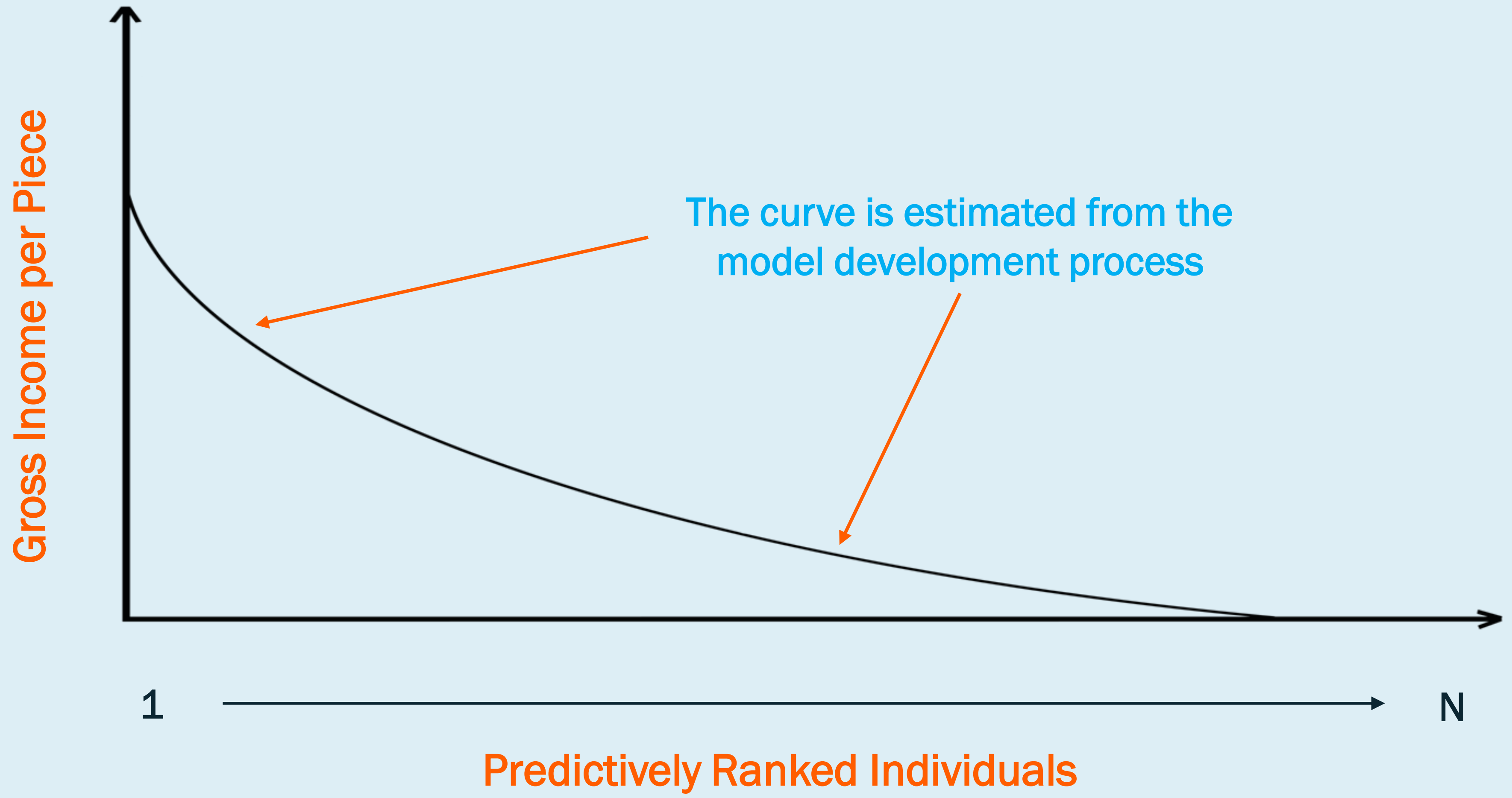
Regression,
Elastic Net,
Machine Learning

Gift Amount or
Response Rate

Predictive Models Ranking Individuals

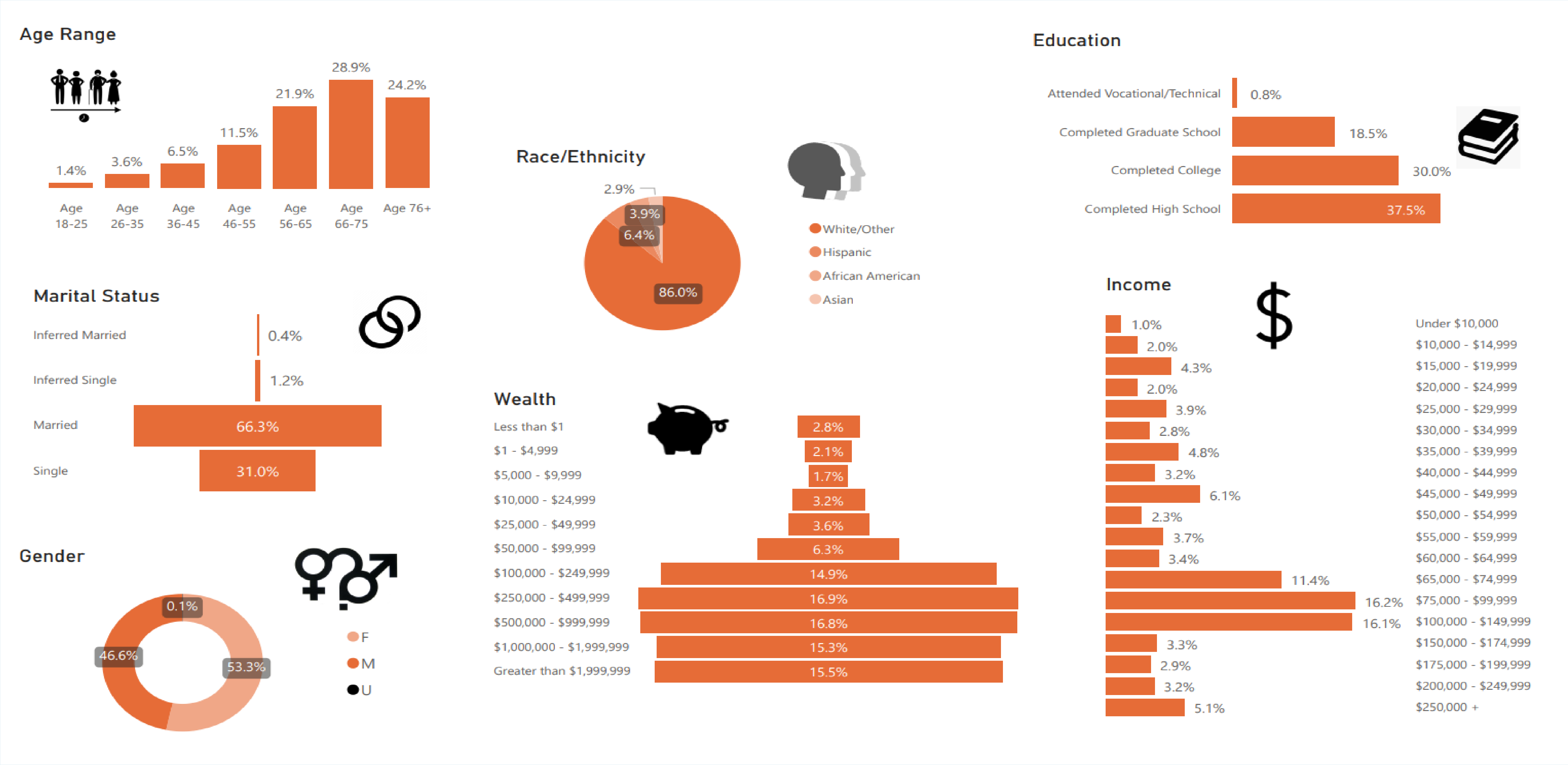


Predictive Models "Shape the Curve"

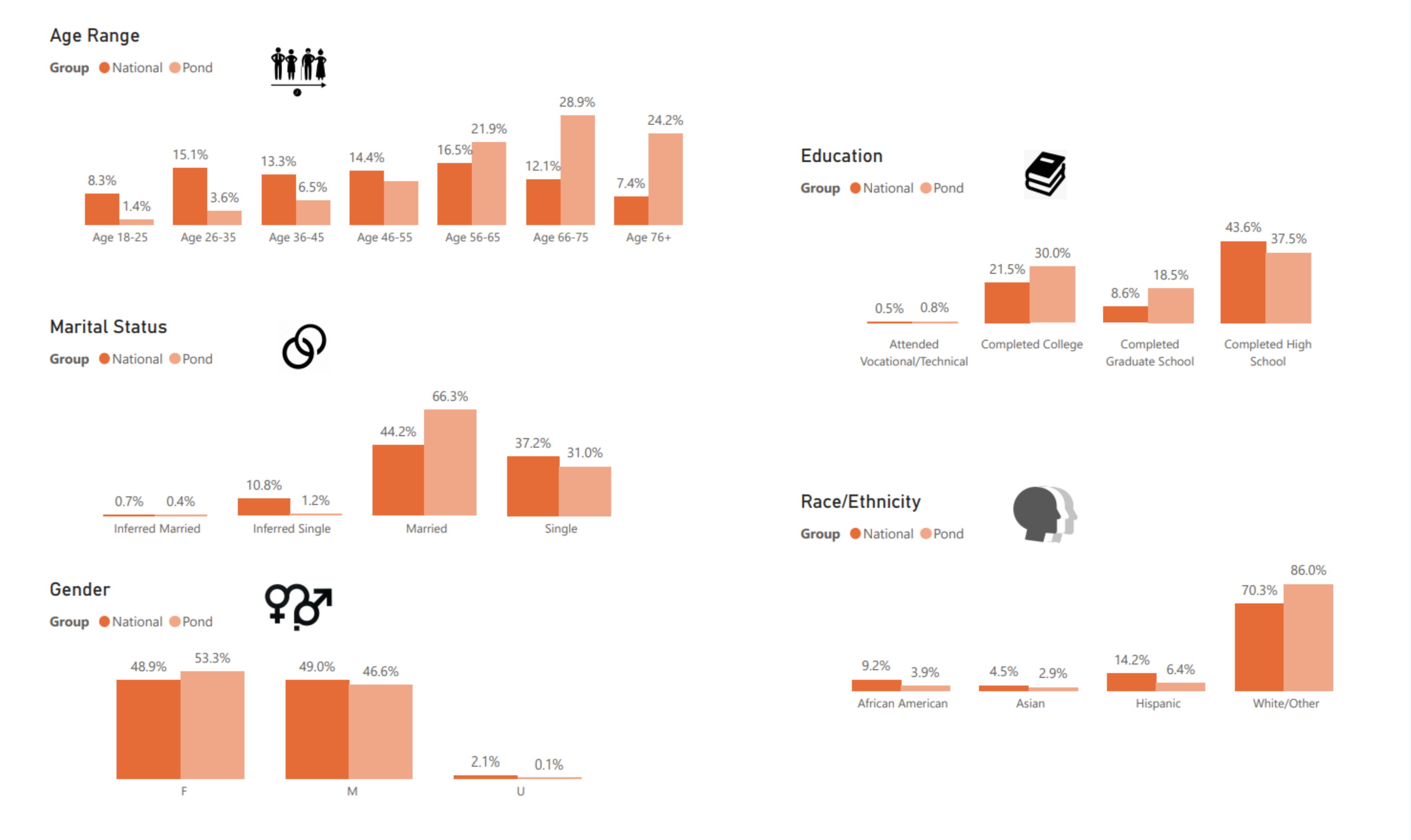


IS ALL OF THE FUNDRAISING OF TODAY "FISHING FROM THE SAME POND"?

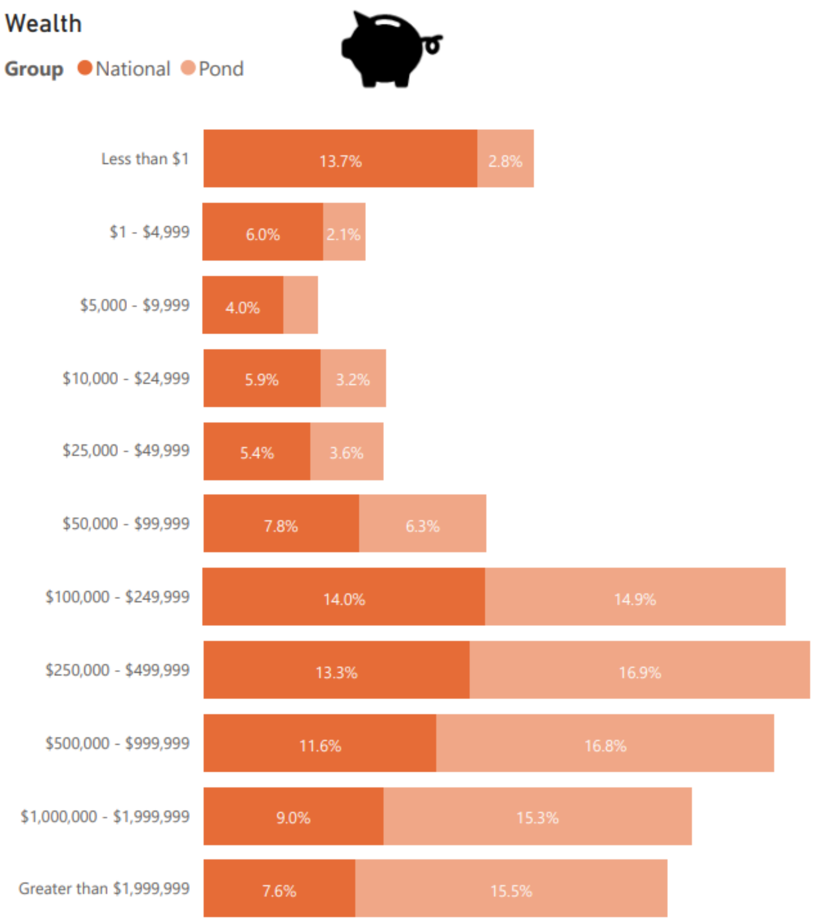
The “POND”

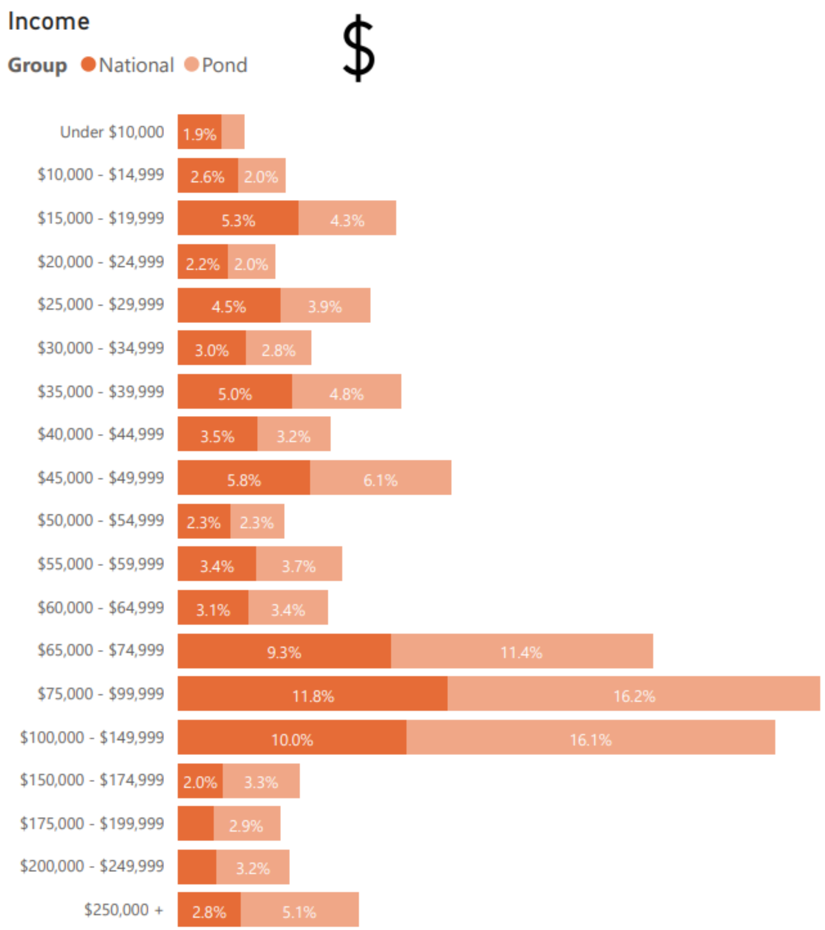

Age Range
1.4%
3.6%
6.5%
11.5%
21.9%
28.9%
24.2%
Age 18-25
Age 26-35
Age 36-45
Age 46-55
Age 56-65
Age 66-75
Age 76+
Race/Ethnicity
2.9%
3.9%
6.4%
86.0%
White/Other
Hispanic
African American
Asian
Education
Attended Vocational/Technical 0.8%
Completed Graduate School 18.5%
Completed College 30.0%
Completed High School 37.5%
Marital Status
Inferred Married 0.4%
Inferred Single 1.2%
Married 66.3%
Single 31.0%
Wealth
Less than $1 2.8%
$1 - $4,999 2.1%
$5,000 - $9,999 1.7%
$10,000 - $24,999 3.2%
$25,000 - $49,999 3.6%
$50,000 - $99,999 6.3%
$100,000 - $249,999 14.9%
$250,000 - $499,999 16.9%
$500,000 - $999,999 16.8%
$1,000,000 - $1,999,999 15.3%
Greater than $1,999,999 15.5%
Income
$
Under $10,000 1.0%
$10,000 - $14,999 2.0%
$15,000 - $19,999 4.3%
$20,000 - $24,999 2.0%
$25,000 - $29,999 3.9%
$30,000 - $34,999 2.8%
$35,000 - $39,999 4.8%
$40,000 - $44,999 3.2%
$45,000 - $49,999 6.1%
$50,000 - $54,999 2.3%
$55,000 - $59,999 3.7%
$60,000 - $64,999 3.4%
$65,000 - $74,999 11.4%
$75,000 - $99,999 16.2%
$100,000 - $149,999 16.1%
$150,000 - $174,999 3.3%
$175,000 - $199,999 2.9%
$200,000 - $249,999 3.2%
$250,000 + 5.1%
Gender
0.1%
46.6%
53.3%
F
M
U

The Pond versus the National Average



The Pond versus the National Average





Discrimination Bias in Modeling

- Is there a circular effect in current acquisition audience targeting?
- Are data companies limited to the “pond” with their modeling solutions?
- Or are organizations contributing to the problem by limiting donor data?

Certainly……Potentially……YES!

Discrimination Bias in Modeling

- Bias: "outcomes which are systematically less favorable to individuals within a particular group and where there is no relevant difference between groups that justifies such harms".*
- Algorithms are not intentionally discriminatory, but they ARE the culmination of a series of human judgements which may result in unintended discriminatory effects.
- Examples: predictions for recidivism for parole decisions, credit scoring, and job candidate screening
- In the context of fundraising, bias in algorithms has generally resulted in the self-reinforcing "pool" of donor prospects
- But is this necessarily a "bad" outcome?

*Lee, Resnick, Barton: "Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms"

The “Pool” Was Formed

Intuitive Donors

Promoted

Responders

Non-Responders

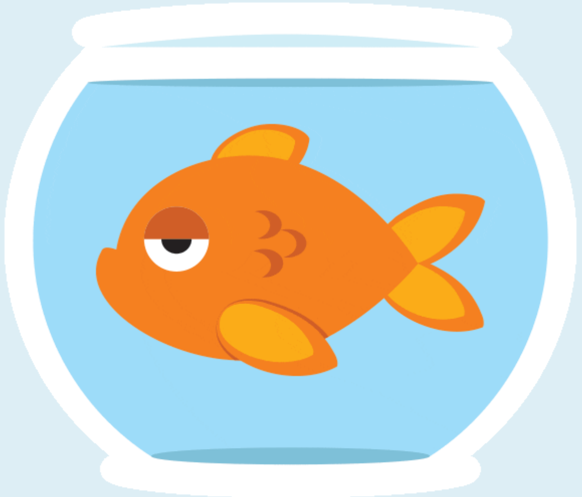
Algorithm targets responders

Responder Look-Alikes

Individuals “Left Behind”

Algorithm is based on the data provided to it, which in this case means no “Left Behind” representation

Some individuals were left out of the cycle because they were thought to be unresponsive or lacked financial means



ETHICS & LEGALITIES OF DATA IN MODELING

Consumer Privacy

The U.S. lacks a uniform Federal data privacy law with respect to the collection, use, and sharing of consumer personal information that applies to the private sector.

Increasingly more U.S. states have stepped into this void and are passing their own consumer data privacy laws:

- California Consumer Privacy Protection Act (CCPA): Effective January 1, 2018
- California Consumer Privacy Rights Act (CPRA): Takes effect in 2023
- Colorado Privacy Act: Takes effect in 2023
- Virginia Consumer Data Protection Act: Takes effect in 2023

The EU's General Data Protection Regulation (known as GDPR), and now the CCPA and CPRA, have provided the blueprint for other states to pass legislation regarding consumer data privacy.

State Laws

These new state laws create a variety of challenges for data providers and marketers alike, as the legislative landscape is increasingly more a patchwork of regulations:

- Compliance challenges
- Costs (in both people and technology)
- Negative effects on consumers

The Unintended Impact on Consumers

New laws should be of significant concern for fundraisers as they attempt to reach historically underrepresented and underserved communities.

For instance, consider the new Colorado and Virginia laws

- The laws categorize a consumer's race and ethnicity as sensitive data
- There will need to be additional opt-in requirements met for the processing of that data
- Therefore, it will be increasingly a challenge for fundraisers to meet its commitments to DEI initiatives if you can't identify and target audiences with data

Marketers and Fundraisers, along with their Data Solutions providers will need to adapt to meet these challenges with creative data modeling practices.

Compliance with Data Legislation & Data Ethics

- Comply with the law(s) applicable to the consumer data you are receiving and using in your business / organization

- Treat every record as if there is a live person behind it

- Strive to not only comply with applicable data laws, but take steps to ensure that a consumer will not be harmed in the use of their personal information

Omitted Variable Bias

- Addressing possible discriminatory bias in models is not easy

- Simply removing protected data can still result in *bias*
  - Other attributes are potentially correlated with protected data

- Statistical methods can help with the problem:
  - Fit the model and retain any predictive protected characteristics to prevent other variables from acting as proxies
  - When *scoring* the model, set the values of the protected characteristics to the population means for all individuals to maintain model blindness to those characteristics

TACTICS FOR FUNDRAISERS IN SEARCH OF NEW “POOLS”

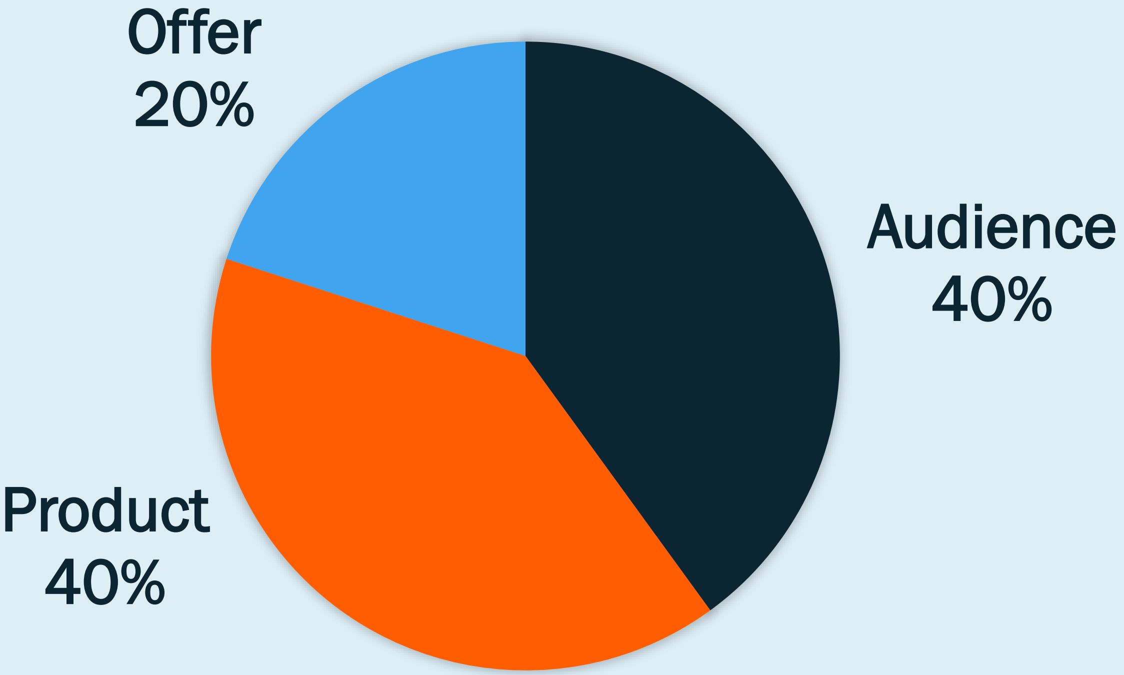
Common Questions

- How can we obtain younger donors?
- How can we expand into new markets / regions?
- How can we attract more Hispanic donors?
- How can we find donors who are only loyal to our organization?

Direct Marketing Theory: The Relative Importance of Campaign Components

There are three main components to a marketing appeal:

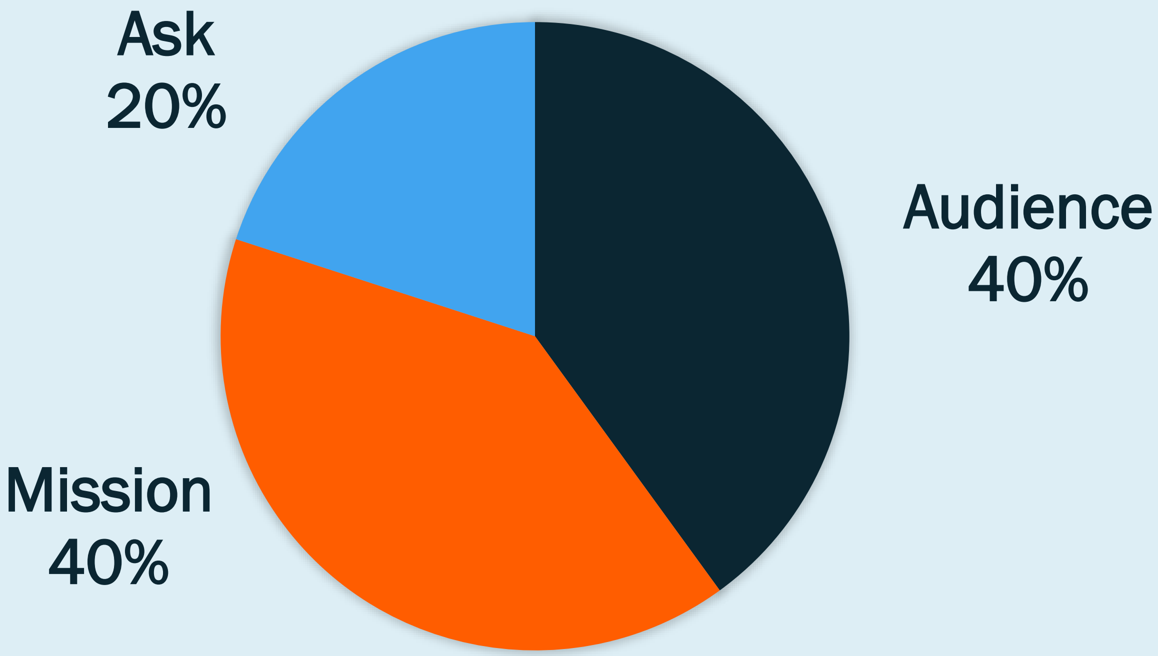
- Audience
- Product
- Promotion or Offer



In Fundraising Terms

There are three main components to a fundraising appeal:

- Audience Segments
- The Mission as conveyed through creative / copy
- The Ask $



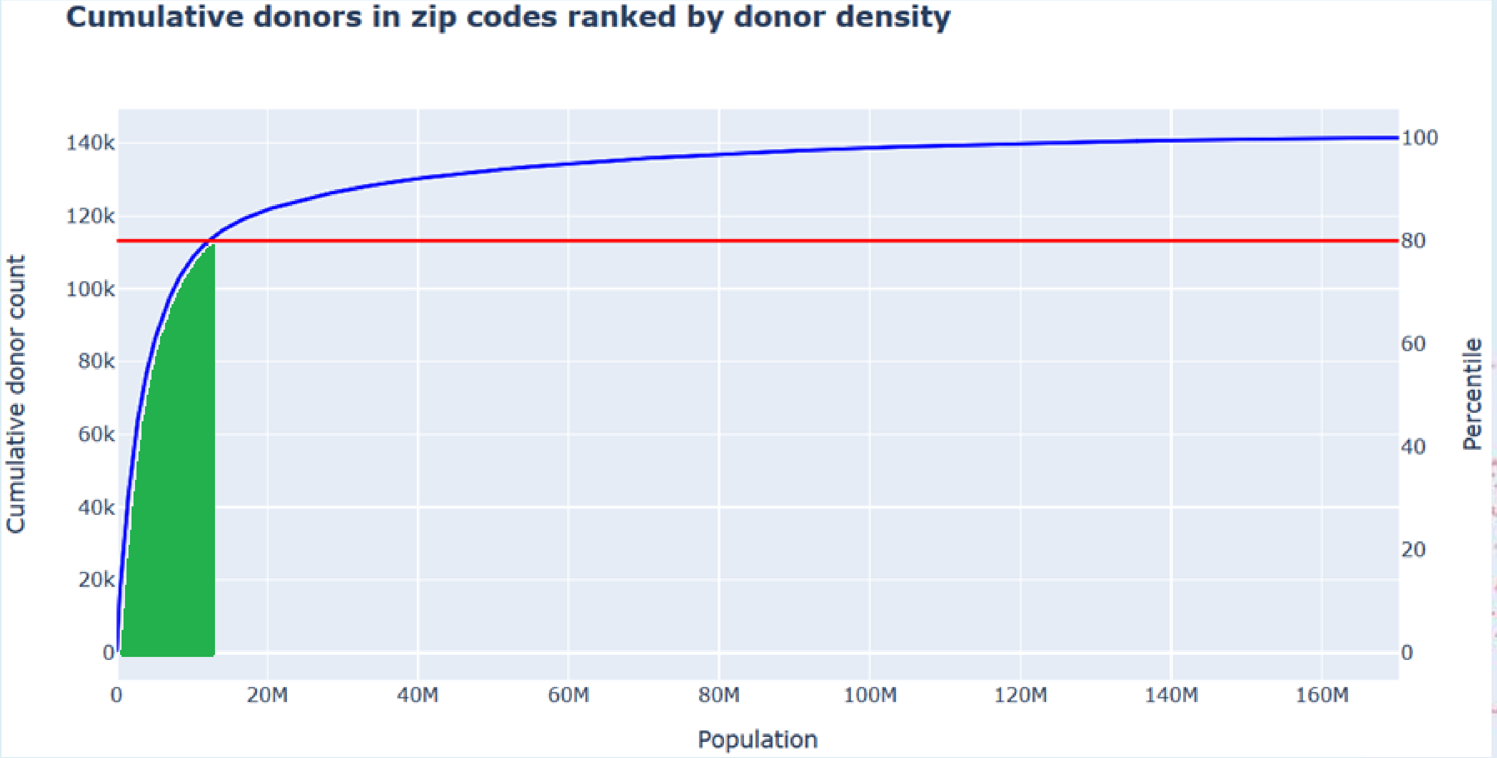
The Younger Donor Problem

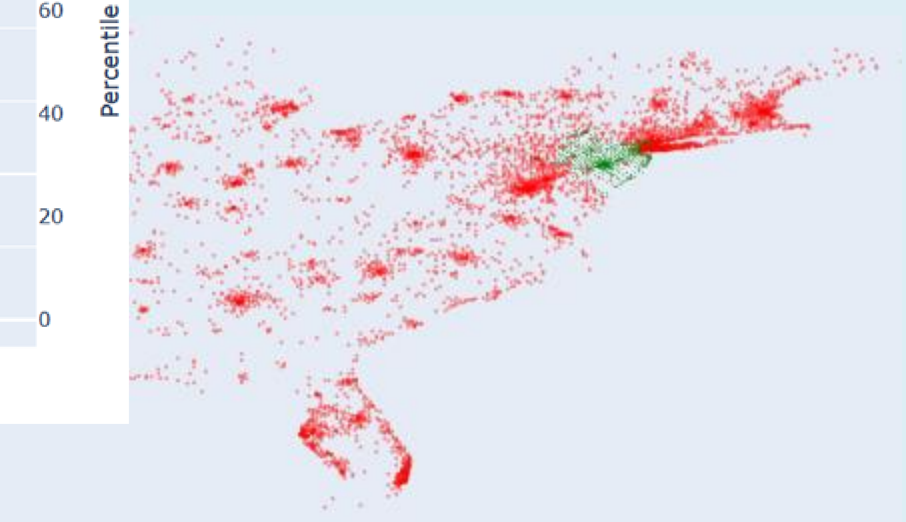
- Organizations want to attract younger donors as their current base ages and passes
- Is the Ask, Messaging and Copy appropriate and appealing to the younger generation?
- Is the Mission relevant to the younger generation?
- “Age-band” models can be created, tested, and refined based on initial outcomes

Age Band	Quantity	% of File	Response Rate	Index
18-34	1,403	0.2%	0.42%	17
35-44	14,932	1.8%	0.64%	26
45-54	57,383	6.7%	1.76%	71
55-64	189,353	22.2%	2.13%	86
65-74	432,931	50.8%	2.89%	117
75+	156,324	18.3%	2.22%	90
Total	852,326		2.48%	

Expanding Into New Markets

- ➢ Use historical donor information to understand current “market”
- ➢ Design analytical datasets focused on regions outside of the current market
- ➢ Develop a model free of geographic bias, test carefully, and refine the model based on test outcomes





Hispanic Marketing

Table 3.

Population by Race and Ethnicity: Projections 2030 to 2060

The non-Hispanic White population is projected to shrink by nearly 19 million people by 2060.

(In thousands)

Characteristics	Population						Change from 2016 to 2060	
	2016		2030		2060			
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Total population	**323,128**	**100.0**	**355,101**	**100.0**	**404,483**	**100.0**	**81,355**	**25.2**
One race								
White	248,503	76.9	263,453	74.2	275,014	68.0	26,511	10.7
Non-Hispanic White	197,970	61.3	197,992	55.8	179,162	44.3	-18,808	-9.5
Black or African American	43,001	13.3	49,009	13.8	60,690	15.0	17,689	41.1
American Indian and Alaska Native	4,055	1.3	4,663	1.3	5,583	1.4	1,528	37.7
Asian	18,319	5.7	24,394	6.9	36,815	9.1	18,496	101.0
Native Hawaiian and Other Pacific Islander	771	0.2	913	0.3	1,125	0.3	354	45.9
Two or More Races	8,480	2.6	12,669	3.6	25,255	6.2	16,775	197.8
Hispanic	57,470	17.8	74,807	21.1	111,216	27.5	53,746	93.5

*https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf

Hispanic Marketing: Acculturation Level

Acculturation Level: How immersed within the surrounding culture?

- Generally, it takes 10-15 years
- Longer for Hispanics due to pride in values and heritage that is past on to the next generation
- Modern Hispanics tend not to assimilate as quickly for 2 reasons:
  - Technology allows for easy connection with their homeland
  - "Diversity" is now celebrated whereas in the past it was not socially acceptable

Hispanic Marketing: Targeting Issues

Segmentation Issues:

- U.S. population is graying, but Hispanics are younger
  - Median age is 28 versus overall age of 37
- Consumption patterns for Hispanics are different
- Technology and Media use are distinctly different
  - Due to language, culture and ownership dynamics
  - 68 more time watching video on the internet
  - 20 more time watching video on their mobile device
- Hispanic data via traditional compilation methods is poor

*https://www.gallowayresearch.com/expertise/hispanic-market-research/

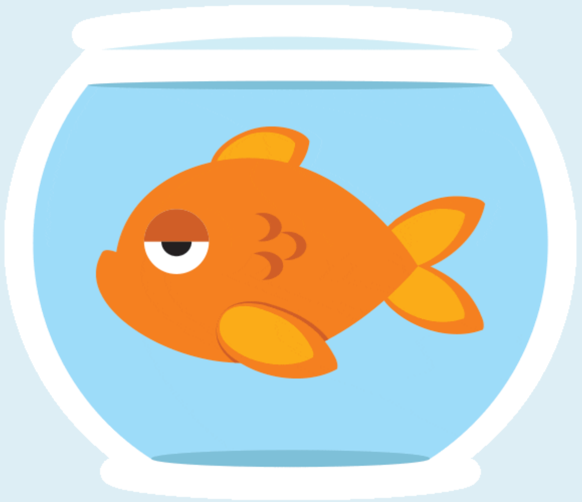
The Pond is Always Changing

General Axiom

On average, prospect audiences <u>without</u> demonstrated past donation history will significantly underperform

Final Thoughts

- There is no "Easy Button" for Acquisition & Donor Fundraising
- Advanced <u>data resources</u> and <u>data science methodologies</u> are a necessity
- There is nothing wrong with <u>intelligent</u> fishing from the same "pond"
- Fundraisers will need to <u>invest</u> to cultivate, attract and catch the new "fish"



QUESTIONS?

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ADVANCING MOORE AS A MARKETING TECHNOLOGY LEADER

THANK YOU

For more information, contact:

Doug Kaczmarek

dkaczmarek@mooredmgroup.com