Predictive Modeling:
Using Existing Data to Segment Prospects and Improve Fundraising Results

April 28, 2017

NEDRA
An Apra Chapter

Agenda

- What is Predictive Modeling?
- Top 10 Use Cases
- Keys to Building a Model
- Major Giving → *Attachment*
- Annual Giving → *Non-Donor Segmentation*
- Q&A

Predictive Modeling

- "Uses mathematical tools and statistical algorithms to examine and determine patterns in one set of data . . .
- . . . in order to predict behavior in another set of data
- Integrates well with in-memory-data and data visualization"

Top 10 Use Cases

Major Giving

1. Attachment Scores
2. Expected Ask Values
3. Ranked List for a Program
4. Planned Giving

Annual Giving

5. Segment Non-Donors (most attractive to solicit)
6. Ask Amounts
7. Best Appeal Messages

Other

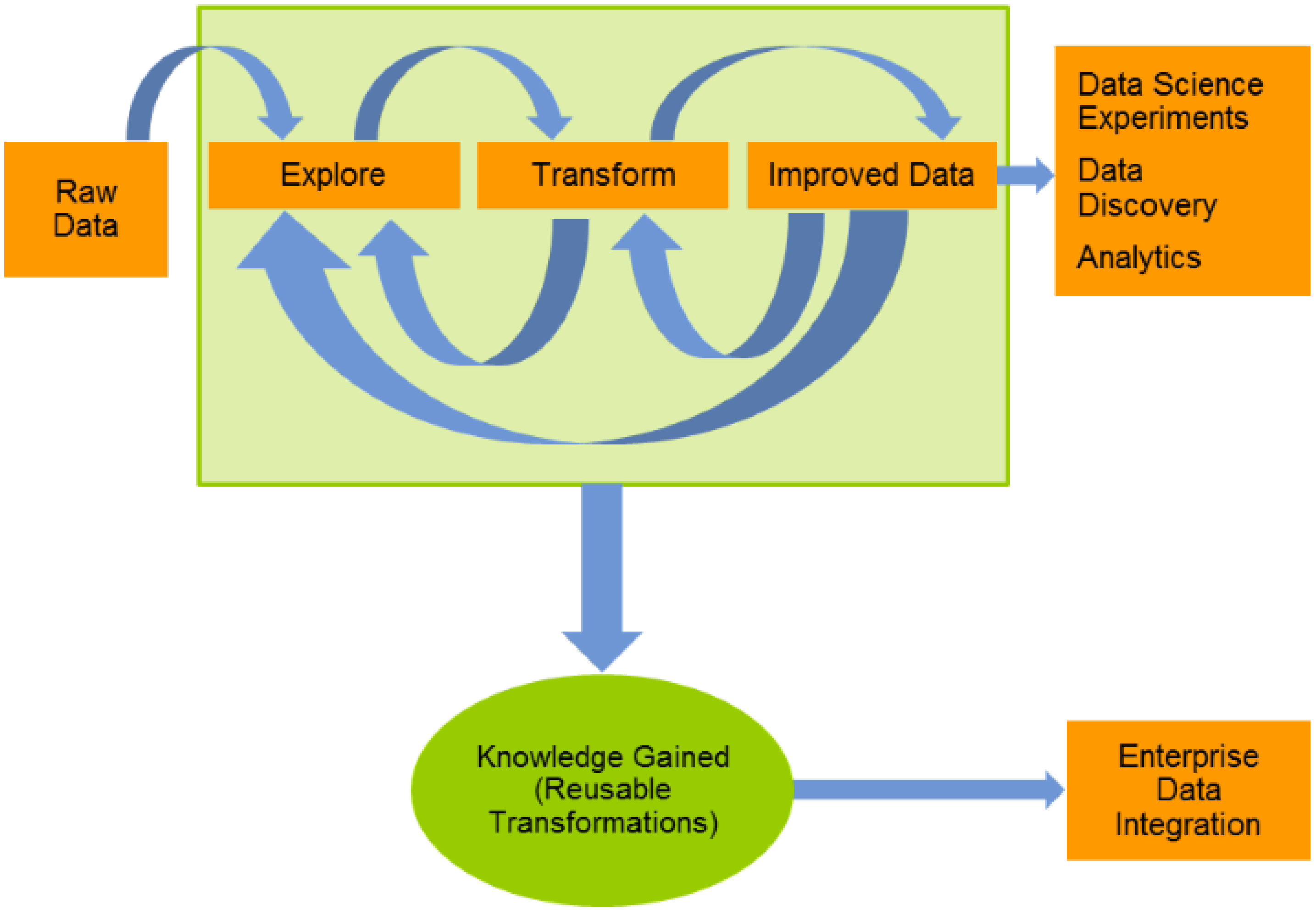
8. Patient Potential (from patient encounters)
9. Event Attendance (who is likely to attend)
10. Ad Hoc Hypothesis Testing

Source: ADVIZOR Fundraising Clients

Predictive Modeling Basics

- Target
  - Behavior that you want to examine
    - Classification Model: Target = a group to be compared with the base population (“selected subset”)
    - Regression Model: Target = a numeric field in your data
- Base Population
  - Group that has the potential to have the same experiences and behavior as the Target
- Explanatory Factors
  - Factors that might explain why the Target is different than other entities in the Base Population; or what drives the variation
  - Data fields from your various data tables
- Causation (≠ Correlation)

Iterative Process



Source: Gartner (March 2015)

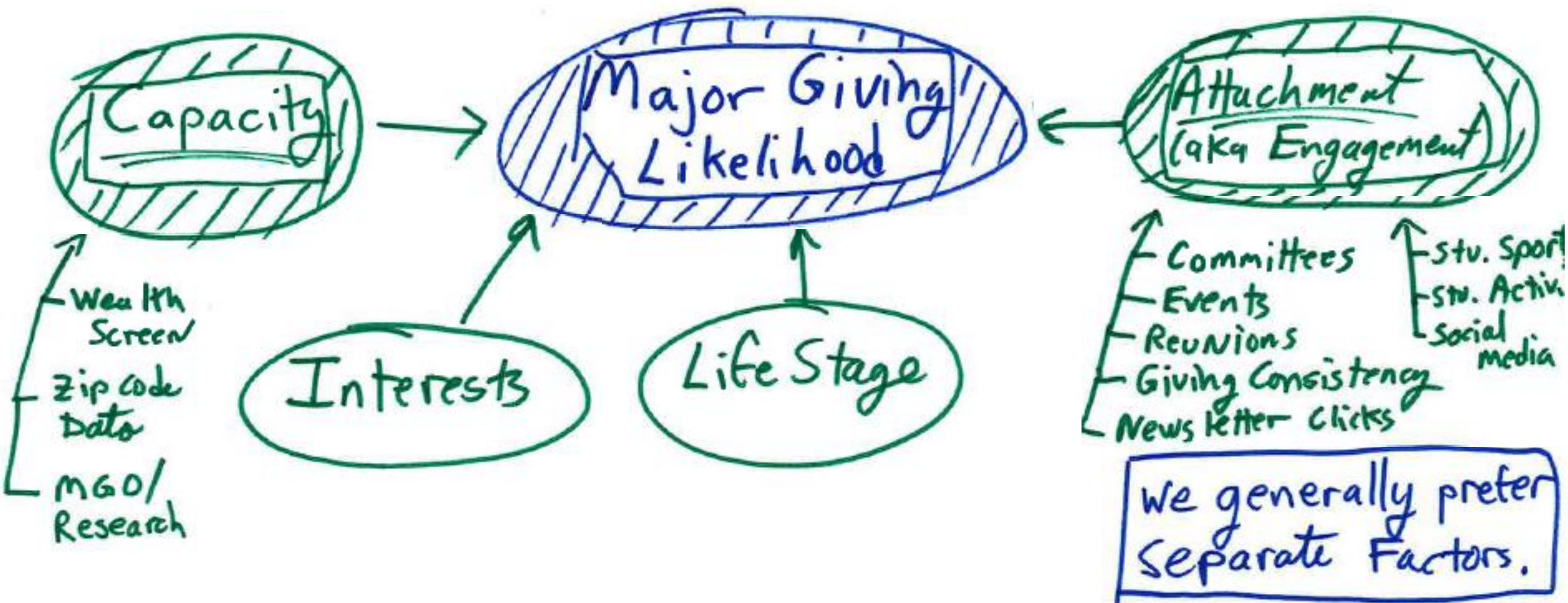
MAJOR GIVING

- Question(s) to answer
- Composite score or separate factors
- One model or several
- How to prep the data
- Setting up and building the model

ATTACHMENT MODEL

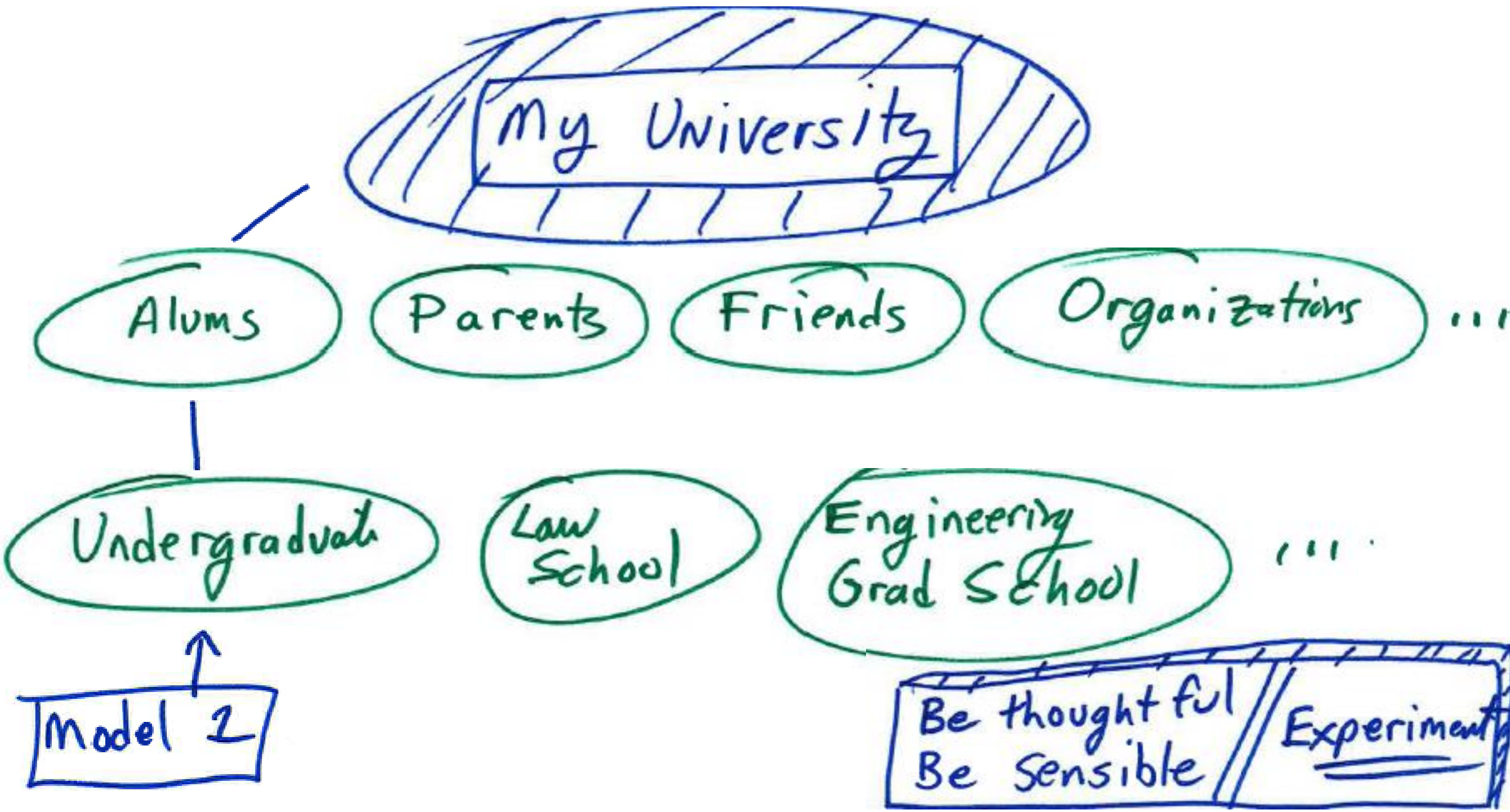
Getting Started

- What question are you trying to answer?
  - What are the characteristics of my top donors?
  - Who else has those characteristics + should be staffed?
- Composite Score or Separate Factors?



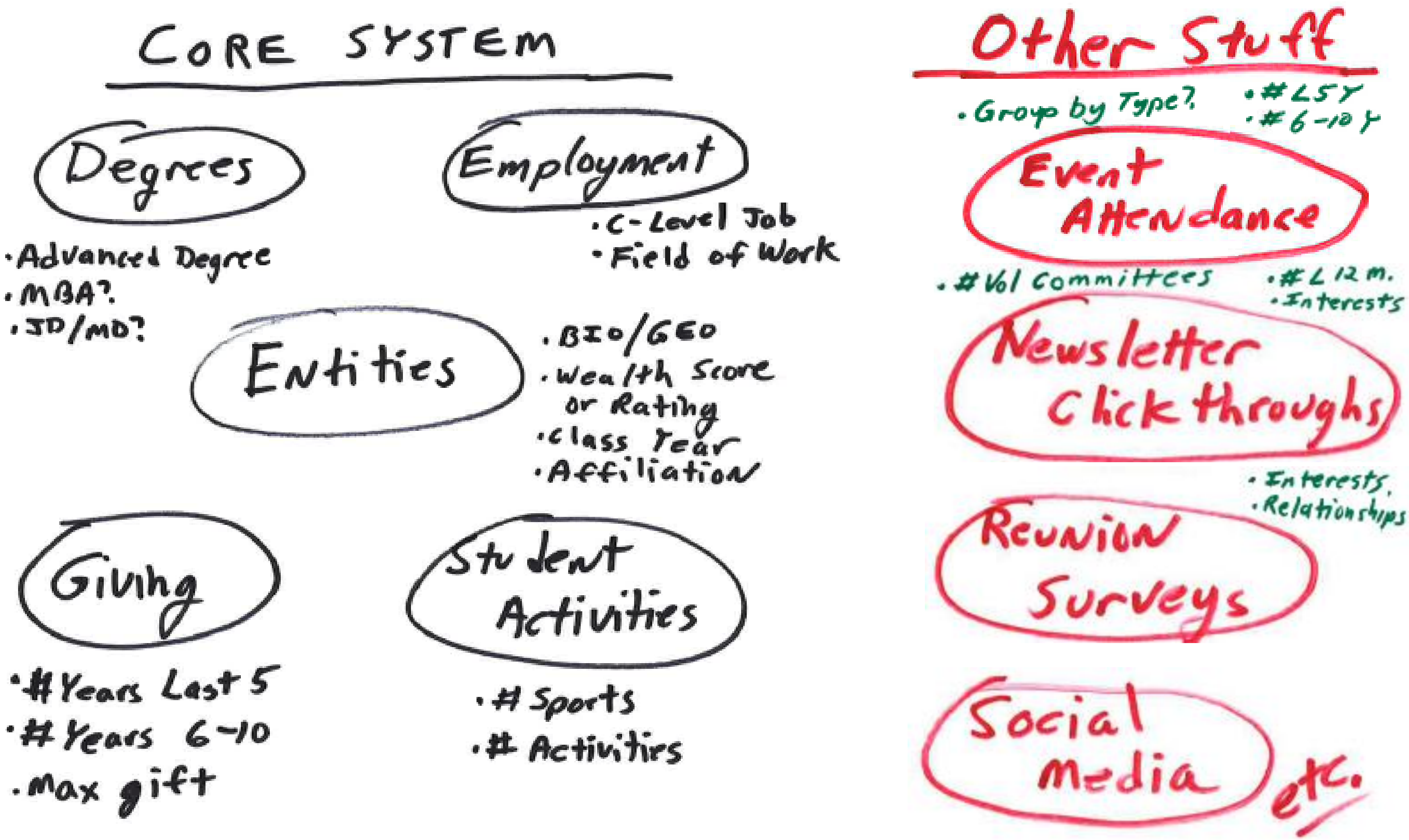
One Model or Several

- Can everybody have the same experience?



What about the Data?

- *What factors might influence undergraduate alums to give?*
- *Who else has those characteristics?*



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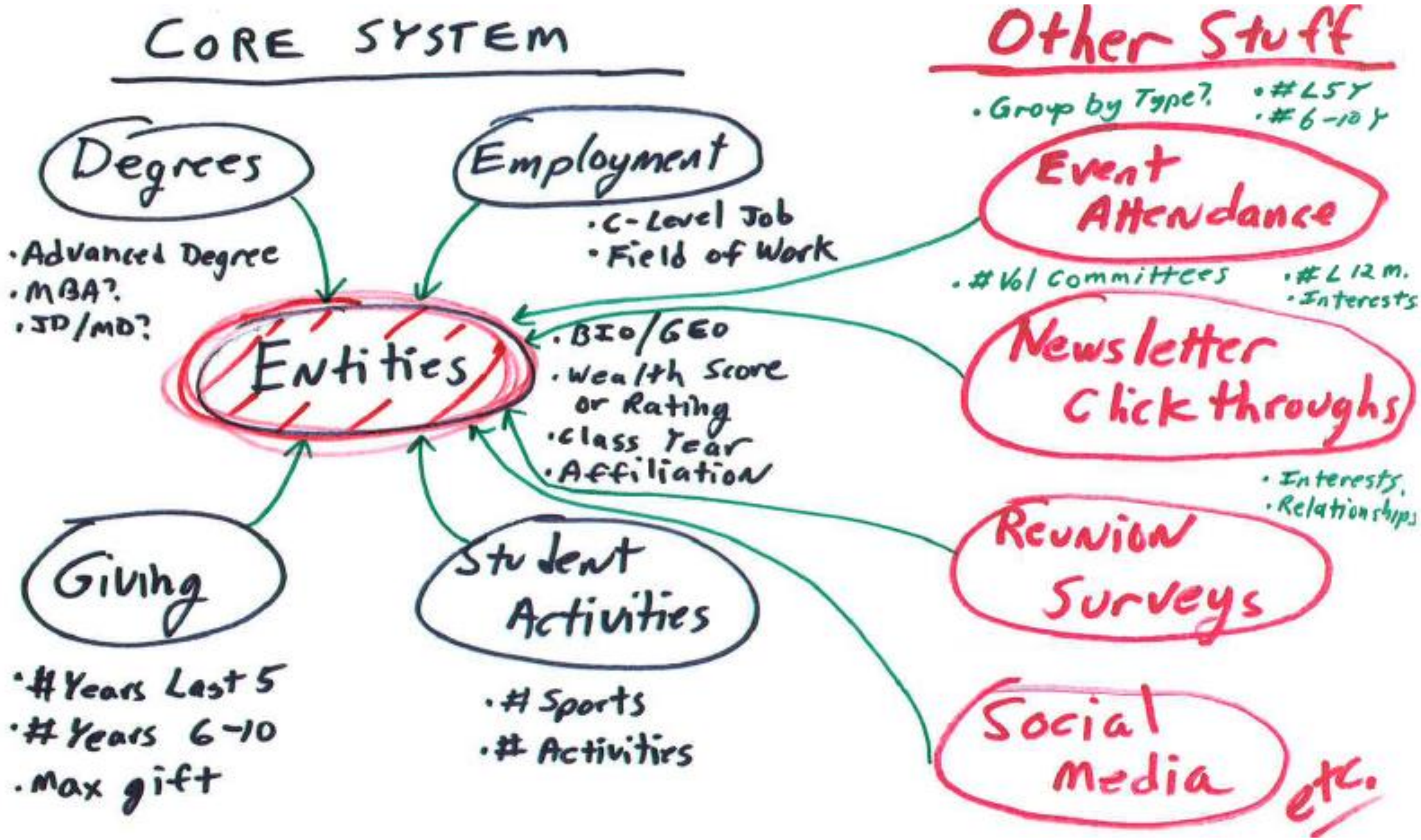


Let’s Build one!!

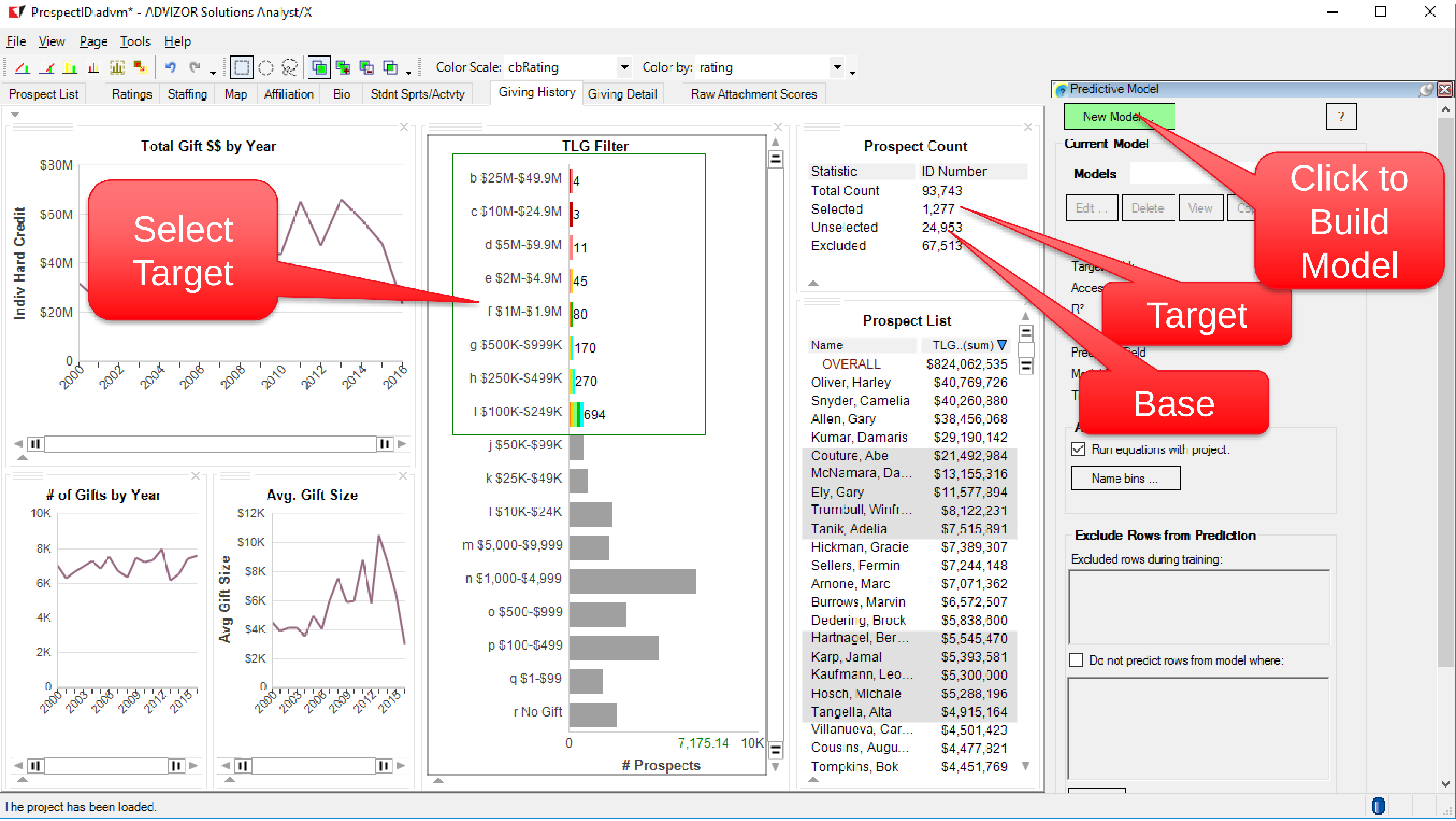
MAJOR GIVING: ATTACHMENT MODEL

Attachment Model

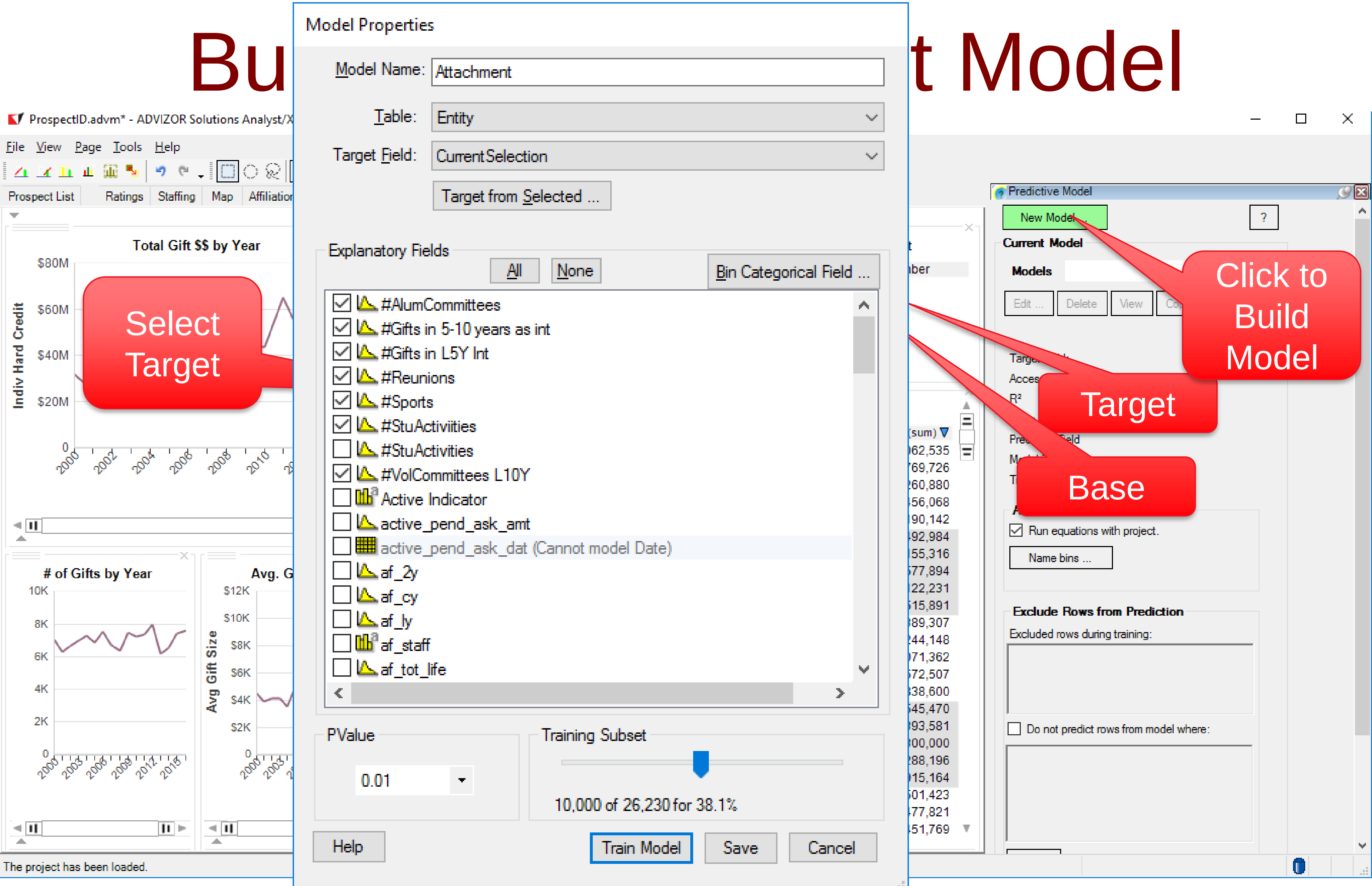
- Question: What causes some people to give at or above their capacity? Who else looks like that?

- Target: undergraduate alums who have given over $100k
- Base Population: all undergraduate alums rated $100k+
- Explanatory Factors: things that indicate opt in interest
  - Committees, events, reunions, giving, newsletter clicks, student sports, student activities, etc.
- Algorithms Used: Regression in ADVIZOR
  - Point-and-click interface
  - Need Excel skills; no stats degree or database query skills required:
    - Data prep in integrated "in-memory pool"
      - Combinations, aggregation, binning, cross-table calculations
    - Test, iterate and explore using interactive visualization
    - Models complete rapidly – typically .2 to 4 minutes

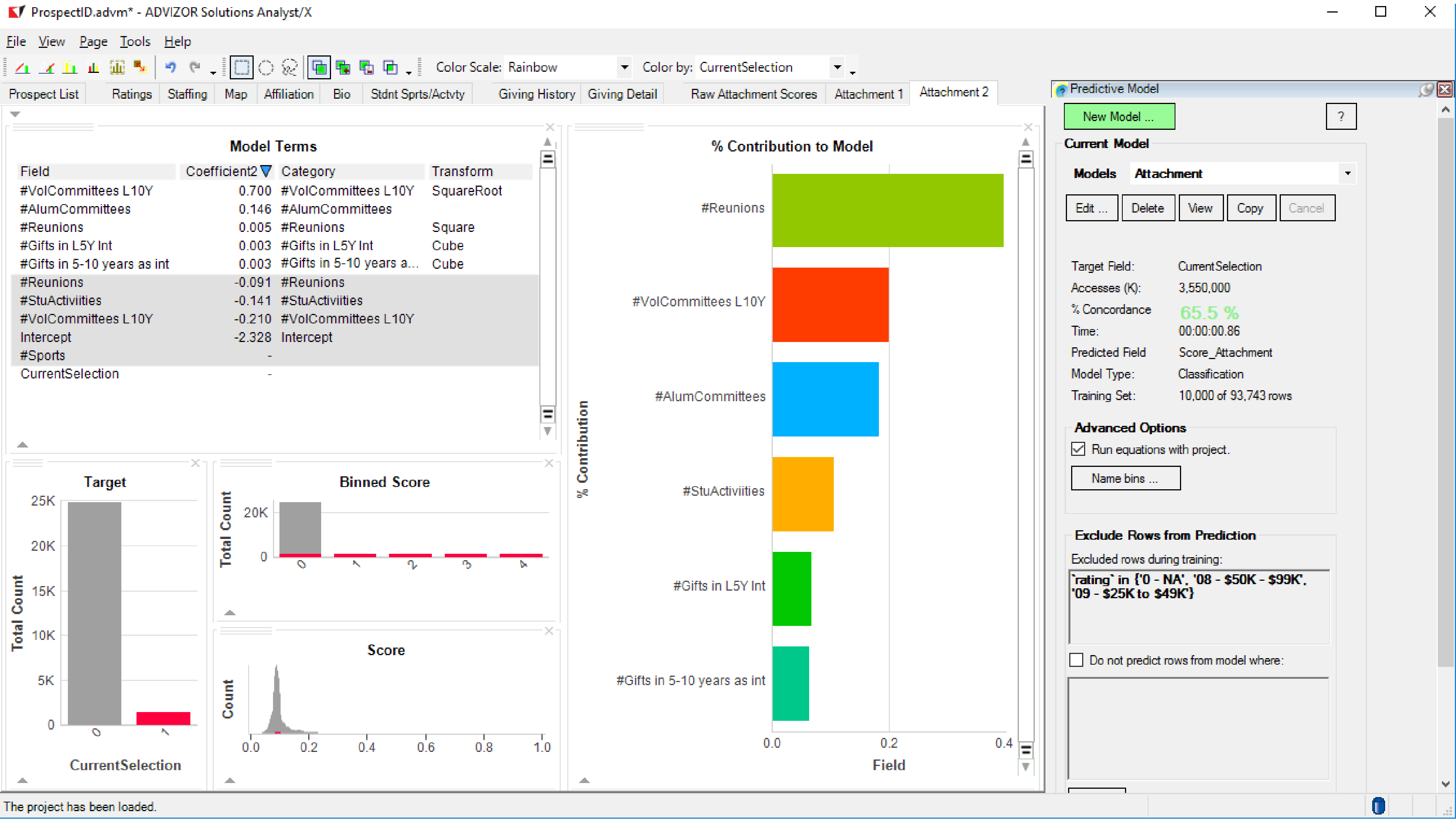
Build an Attachment Model



Bu t Model

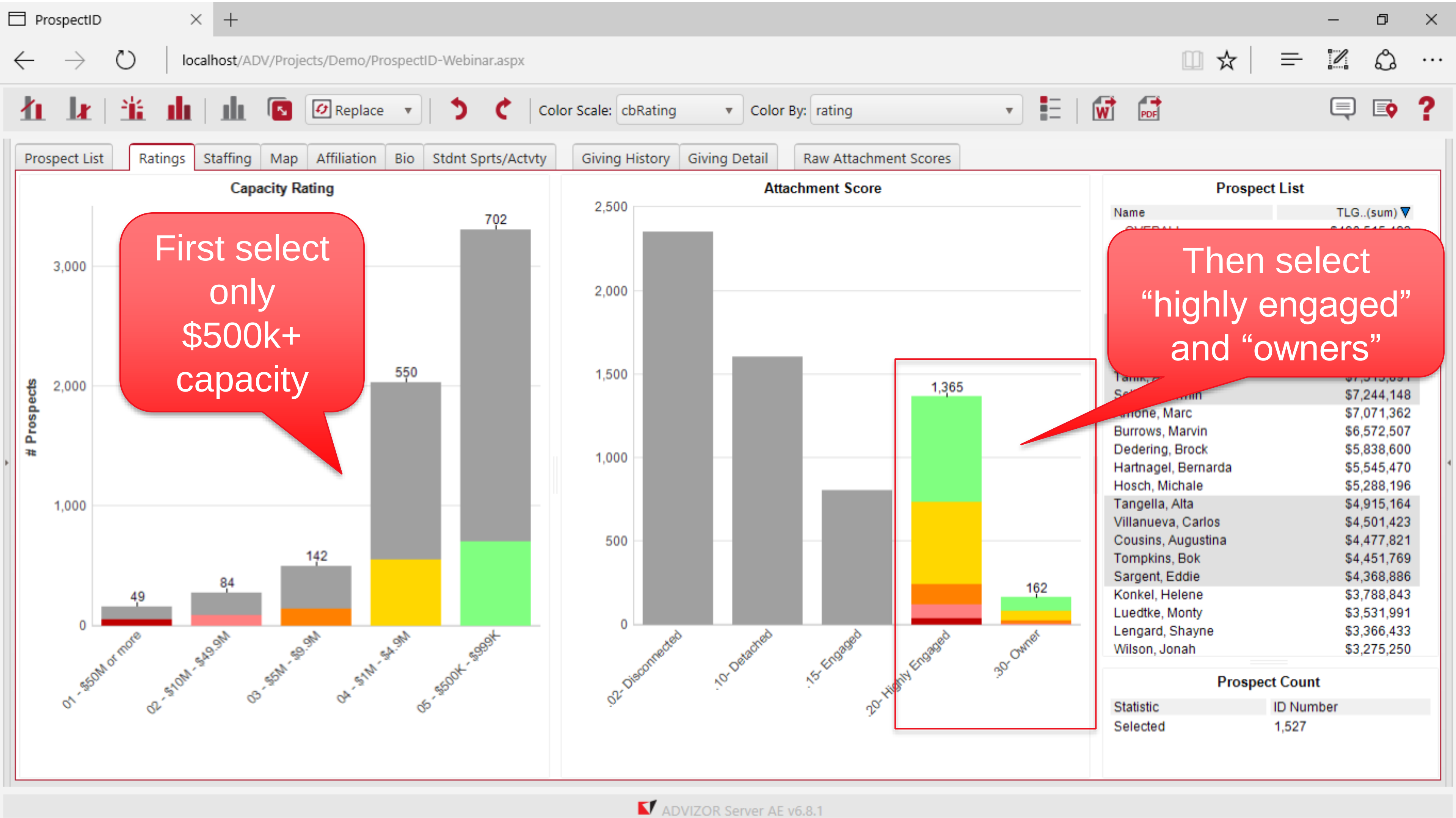

Model Properties
Model Name: Attachment
Table: Entity
Target Field: CurrentSelection
Target from Selected ...
Explanatory Fields
All
None
Bin Categorical Field ...
#AlumCommittees
#Gifts in 5-10 years as int
#Gifts in L5Y Int
#Reunions
#Sports
#StuActivities
#StuActivities
#VolCommittees L10Y
Active Indicator
active_pend_ask_amt
active_pend_ask_dat (Cannot model Date)
af_2y
af_cy
af_ly
af_staff
af_tot_life
PValue
0.01
Training Subset
10,000 of 26,230 for 38.1%
Help
Train Model
Save
Cancel
ProspectID.advm* - ADVIZOR Solutions Analyst/X
File View Page Tools Help
Prospect List
Ratings
Staffing
Map
Affiliation
Total Gift $$ by Year
Indiv Hard Credit
# of Gifts by Year
Avg Gift Size
The project has been loaded.
Select Target
Predictive Model
New Model ...
Current Model
Models
Edit ...
Delete
View
Run equations with project.
Name bins ...
Exclude Rows from Prediction
Excluded rows during training:
Do not predict rows from model where:
Click to Build Model
Target
Base

Examine Model Results

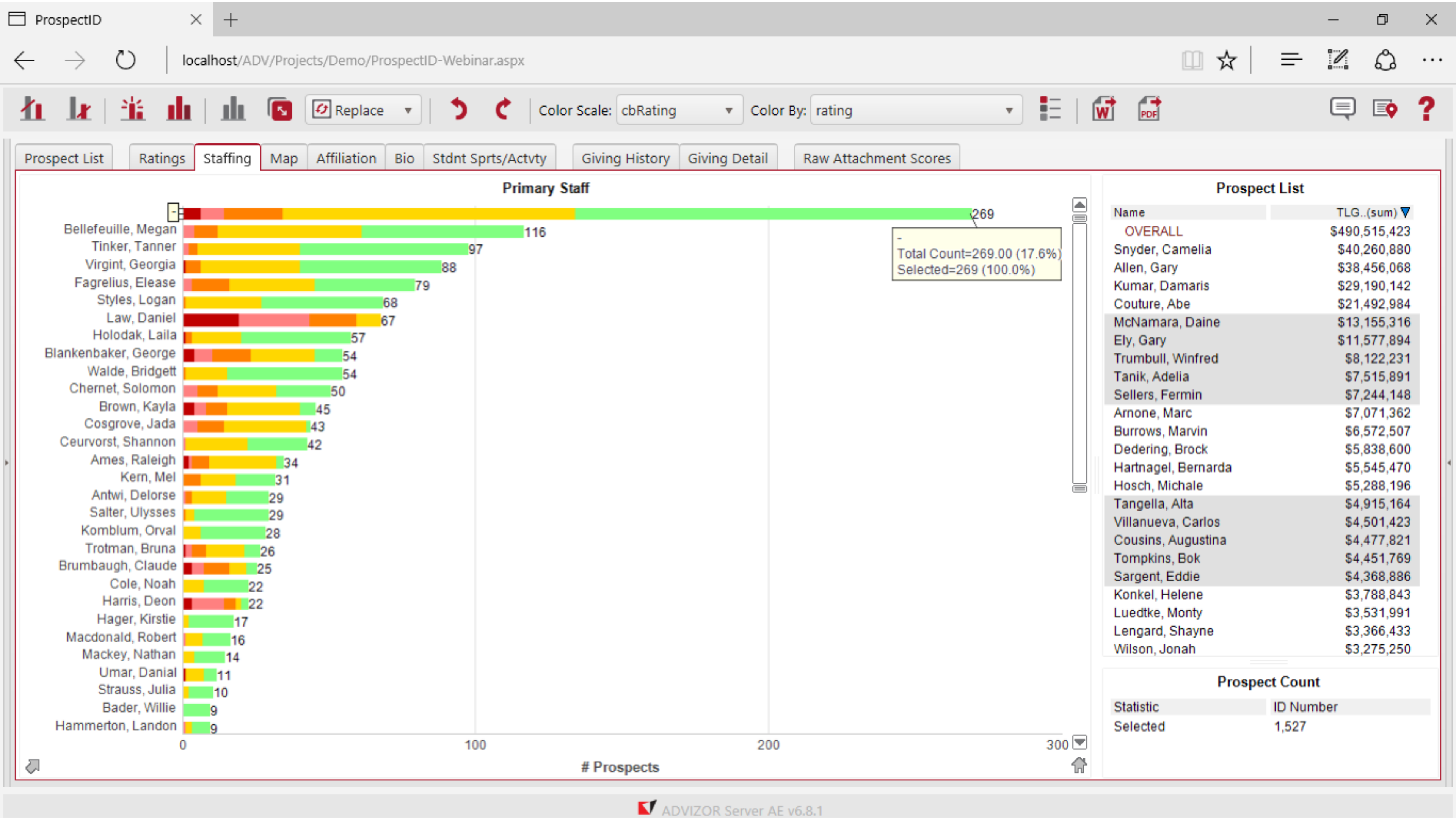


Put your Model In Play

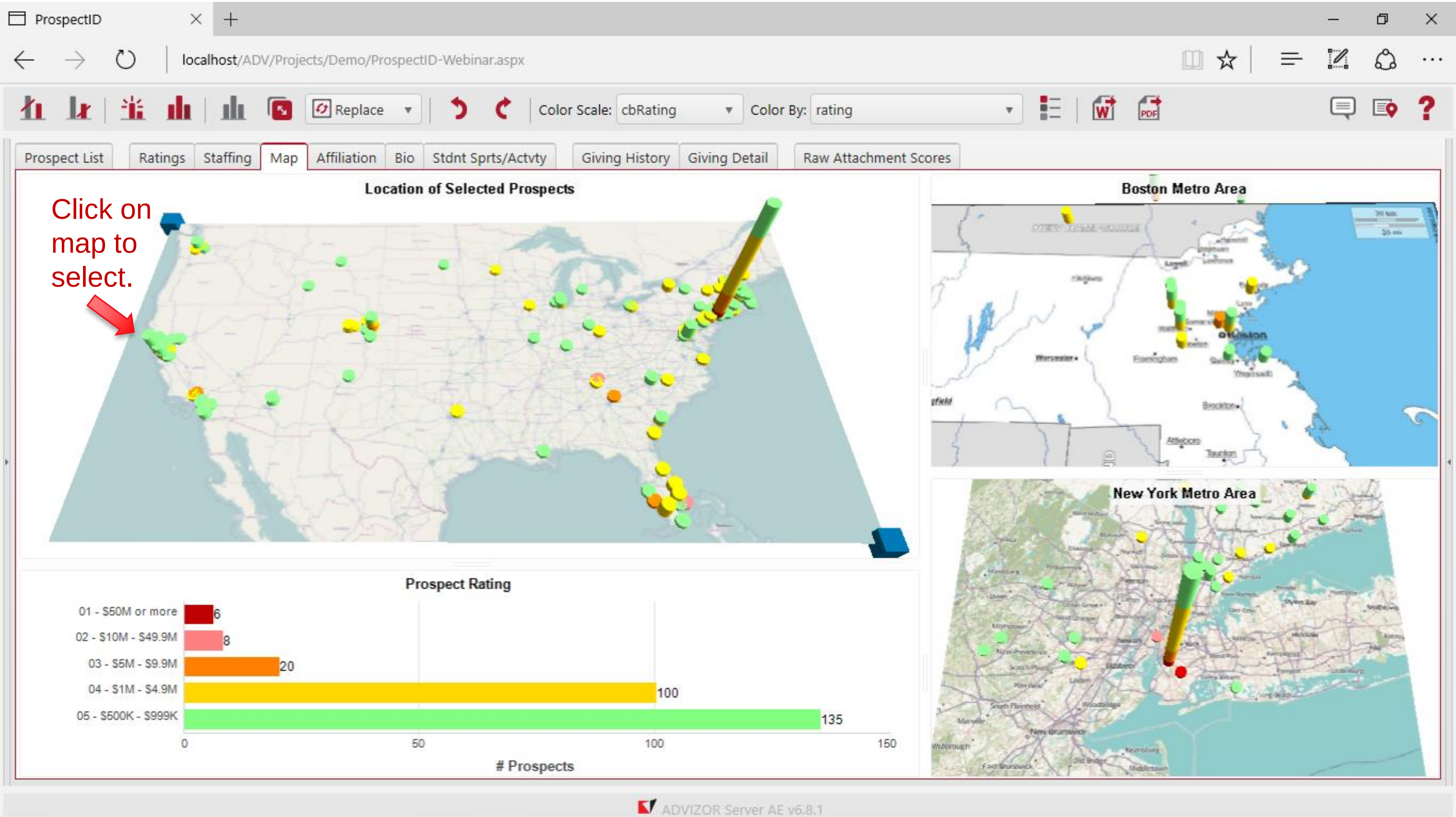
Select High Capacity and Highly Engaged Prospects – 1,527 people



269 out of the 1,527 are Not Staffed



Those 269 are all across the country; cluster of 24 in San Francisco Bay area – maybe a dinner out there?



24 in Bay Area: none have been on a committee ➔ *key cultivation step*

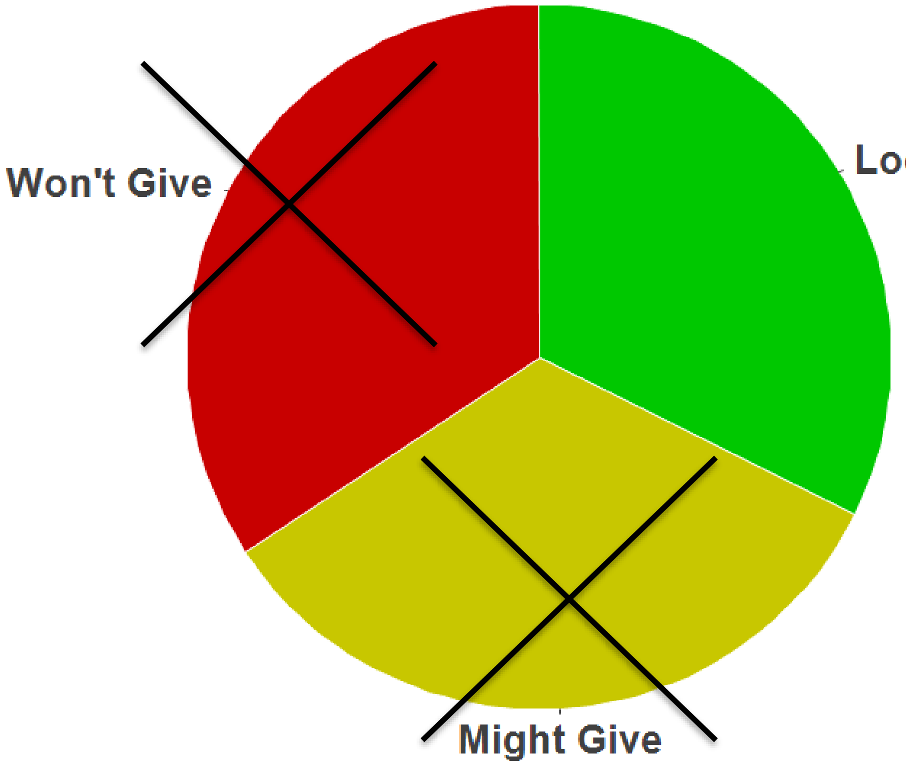
Attachment Score Details

ID Number	Name	Rating	TLG ▼	Attachment S... ▼	Attachment Group	#VolCommittees L10Y	#Gifts in L5Y Int	#Gifts in 5-10 years as int	#Reunions	#Sports	#StuActivities
42,395	Prado, David	05 - $500K - $999K	4,051	0.28	.30- Owner	0	5	5	11	2	7
40,435	Eliason, Abdul	05 - $500K - $999K	8,820	0.26	.20- Highly Engaged	0	5	5	12	1	1
43,016	Eckstein, Bethann	05 - $500K - $999K	89,934	0.25	.20- Highly Engaged	0	5	5	11	0	0
42,880	Hoyt, Deborah	05 - $500K - $999K	2,065	0.25	.20- Highly Engaged	0	5	5	11	0	0
76,254	Todt, Eusebio	05 - $500K - $999K	19,113	0.25	.20- Highly Engaged	0	5	5	6	0	2
49,240	Totedo, Cinthia	04 - $1M - $4.9M	47,967	0.25	.20- Highly Engaged	0	5	5	10	0	0
238,591	Leone, Candi	05 - $500K - $999K	9,650	0.25	.20- Highly Engaged	0	5	5	10	0	0
117,017	Chen, Virginia	03 - $5M - $9.9M	1,347,511	0.25	.20- Highly Engaged	0	5	5	9	0	0
58,987	Angle, Awilda	04 - $1M - $4.9M	54,741	0.25	.20- Highly Engaged	0	5	5	9	0	0
55,042	Gordon, Glinda	04 - $1M - $4.9M	27,805	0.25	.20- Highly Engaged	0	5	5	9	0	0
52,591	Gold, John	05 - $500K - $999K	29,226	0.23	.20- Highly Engaged	0	4	5	10	3	3
238,896	Galliers, Lucia	05 - $500K - $999K	5,280	0.22	.20- Highly Engaged	0	5	4	6	0	0
40,885	Hall, Brittany	05 - $500K - $999K	3,990	0.21	.20- Highly Engaged	0	4	5	12	0	0
227,477	Dykstra, Hanna	05 - $500K - $999K	5,465	0.21	.20- Highly Engaged	0	5	3	15	0	0
52,903	Mallikarjun, Georgie	03 - $5M - $9.9M	838,961	0.21	.20- Highly Engaged	0	4	5	10	0	0
70,521	King, Denisha	05 - $500K - $999K	29,580	0.21	.20- Highly Engaged	0	5	4	0	0	0
239,615	Krush, Elba	05 - $500K - $999K	3,435	0.20	.20- Highly Engaged	0	5	3	12	0	0
75,097	Riley, Natalie	03 - $5M - $9.9M	4,740	0.20	.20- Highly Engaged	0	4	5	7	0	0
228,874	Hurka, Samantha	05 - $500K - $999K	11,538	0.20	.20- Highly Engaged	0	4	5	5	0	0
237,832	Miller, Daisey	01 - $50M or more	210,720	0.19	.20- Highly Engaged	0	5	3	6	0	0
85,914	Ejvr, Adrian	05 - $500K - $999K	902	0.19	.20- Highly Engaged	1	4	3	5	1	4
72,614	Chan, Vern	05 - $500K - $999K	5,450	0.19	.20- Highly Engaged	0	4	4	7	0	3
124,421	Bechtoldt, Carlos	04 - $1M - $4.9M	1,488	0.19	.20- Highly Engaged	0	5	3	3	-	-
52,592	Cloonan, Karen	05 - $500K - $999K	6,103	0.18	.20- Highly Engaged	0	4	4	10	0	0

ANNUAL GIVING

Segment Non-Donors

Study non-donors who have been recently acquired. Who are they? What are their characteristics? Who else has similar characteristics??



For Graduates L5Y: Women, live in New York City, have degrees of MACC, JD, PHARMD, CERT, BBA, or BSHP*

For Graduates older than L5Y: Married, live in Virginia, Texas, or New York City, have Professional Degrees such as JDs, MBAs, BBAs, event attendees*

*Score based on weighted combination of all of these factors.

Focus on Successful Appeals …

- Typically 10 to 15% of the appeals work
- But teams often send everybody everything
  - Should measure and then focus on what works
  - And send primarily to “Look Like our Donors” segment
- Successful appeals are generally:
  - Higher “touch”:
    - For example, from a class agent who knows the prospect
    - Personalized letter or call
  - Theme based to prospects’ interest areas
    - For example, healthcare message to medical professionals …
    - … sport message to alum who always clicks on sports article in newsletter
    - Etc.

… with 6 to12 Touches per Year

- Goal: send each entity in target segment 6 to 12 effective appeals per year
- Problem: often “over touch” with unsuccessful appeals …
  - We have seen 50+ to over half the non-donor base
  - Heavy email
- … and “under touch” with successful appeals
  - At same client only 1 to 2 successful appeal touches per year to people in target segment because sent to too many other people
- Why: higher yield appeals generally cost more …
- … so segmenting the non-donor base to focus on “look like my donors” is important
- *Substantial improvement potential* → *next page*

Northern Illinois (11/15)

Results:

- All major mail solicitations were sent to less people and made more money each of the last three fiscal years
- Holiday Cards revenue tripled in one year while sending 5k less pieces (25% less)
- Revenue up over 70% since 2012
- Average gift size up 60%
- Acquired 17% more new donors in FY15 than FY14
- First time donor retention up from 23% to 30%

Webinar on this case study at: www.AdvizorSolutions.com/resources/webinars (11/15)

Predictive Modeling – Summary

- Focus on **Answering Questions**
- **Do it in house**; your team knows the data best
- **Start simple**; don't over complicate
  - "A simple model completed now is better than a complex model that takes forever"
- **Iterate and evolve**, experiment, use common sense
- **Use the data that you have**; don't go crazy with social media and other "extras"
- **Embed it** in your Data Discovery / Reporting system so that it updates and you can keep using it

Discussion, Q&A

Follow-up: Doug.Cogswell@AdvizorSolutions.com, +1.630.971.5201