



PRESENTATION HANDOUT



The Evolution of Predictive Modeling

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Admissions circa 1980s

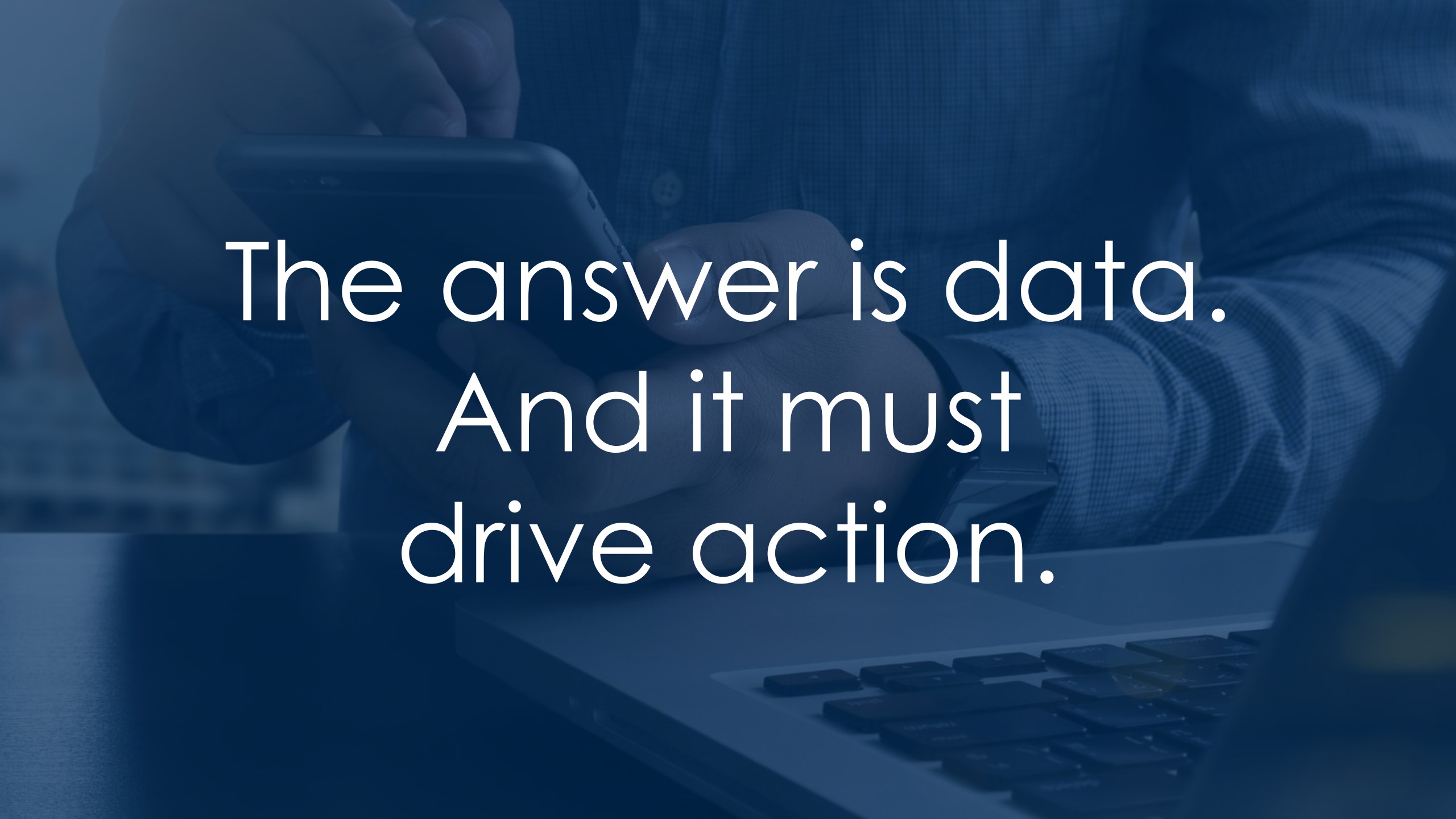


Funnel Time

The start of predictive modeling

Where it started

- It all starts with Performance Indicators (PI) and Key Performance Indicators (KPI)
- Over 25 years ago, the most important predictors were location-based proxies for socio-economic factors.
- In the last 5 years, the most important predictors for enrollment tend to be proxies for behavioral information and preferences.
 - Event RSVPs, online inquiries specific to your institution, visits (in-person and virtual)
 - Interest in majors / departments / athletics remain important

A person wearing a blue checkered shirt is holding a smartphone in their right hand and has their left hand on a laptop keyboard. The entire image is overlaid with a semi-transparent blue filter. The text is centered in white.

The answer is data.
And it must
drive action.

How Predictive Modeling Drives Success

Data-driven decisions

- Territory Management
- Manage Communication Flow
- Prioritize Outreach
- Relationship Building



RNL enhances socioeconomic variables to aid in increasing prediction

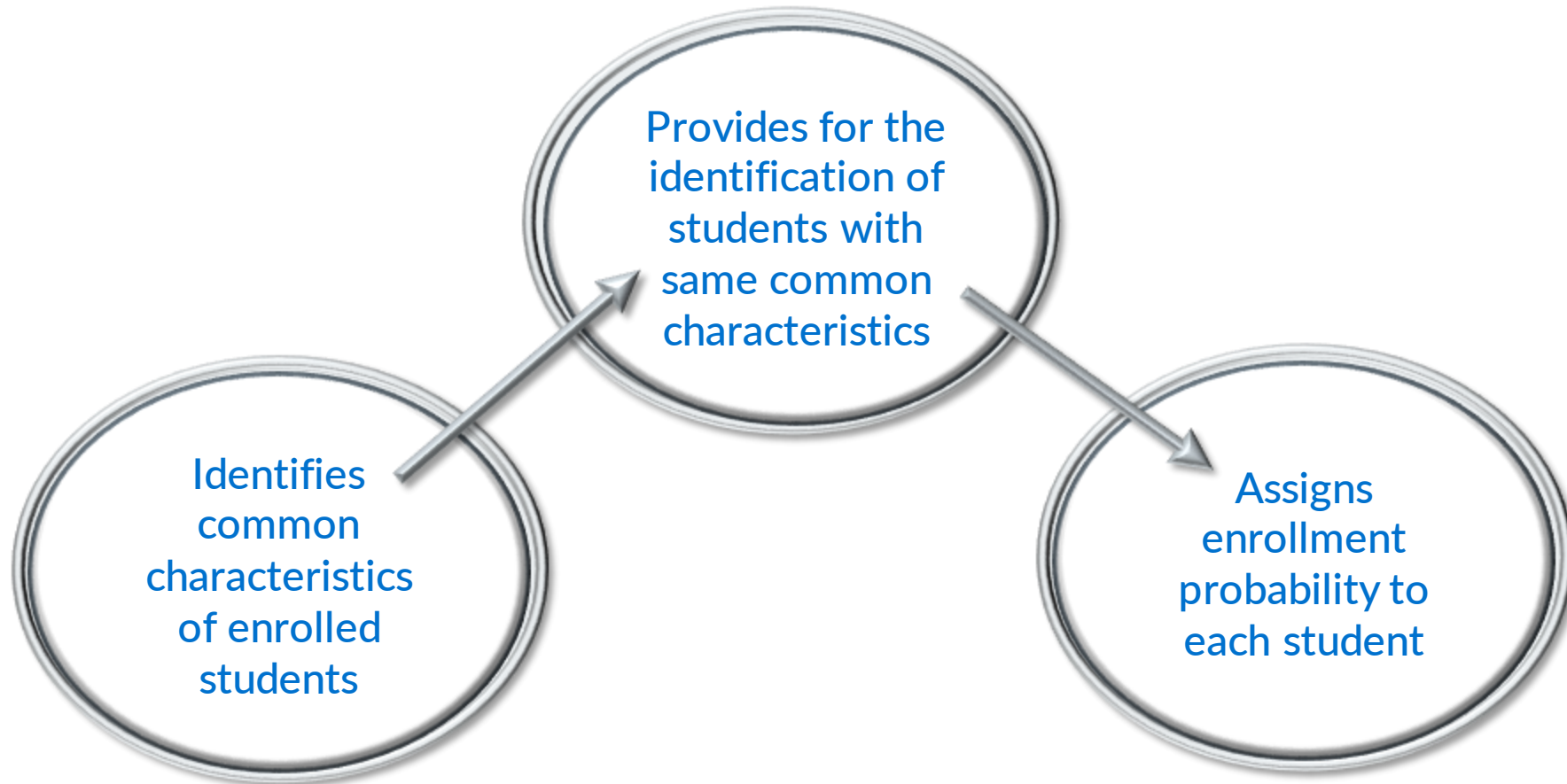


- 70 Personix cluster definitions
- 21 Life Stage Cluster Groups
- Appended data based on ZIP+4

(includes variables such as household income level, ethnicity, and distance from campus)

Assessing Historical Data

The power of a good model



Two major reasons to qualify your pool



Strategically reallocate
limited resources

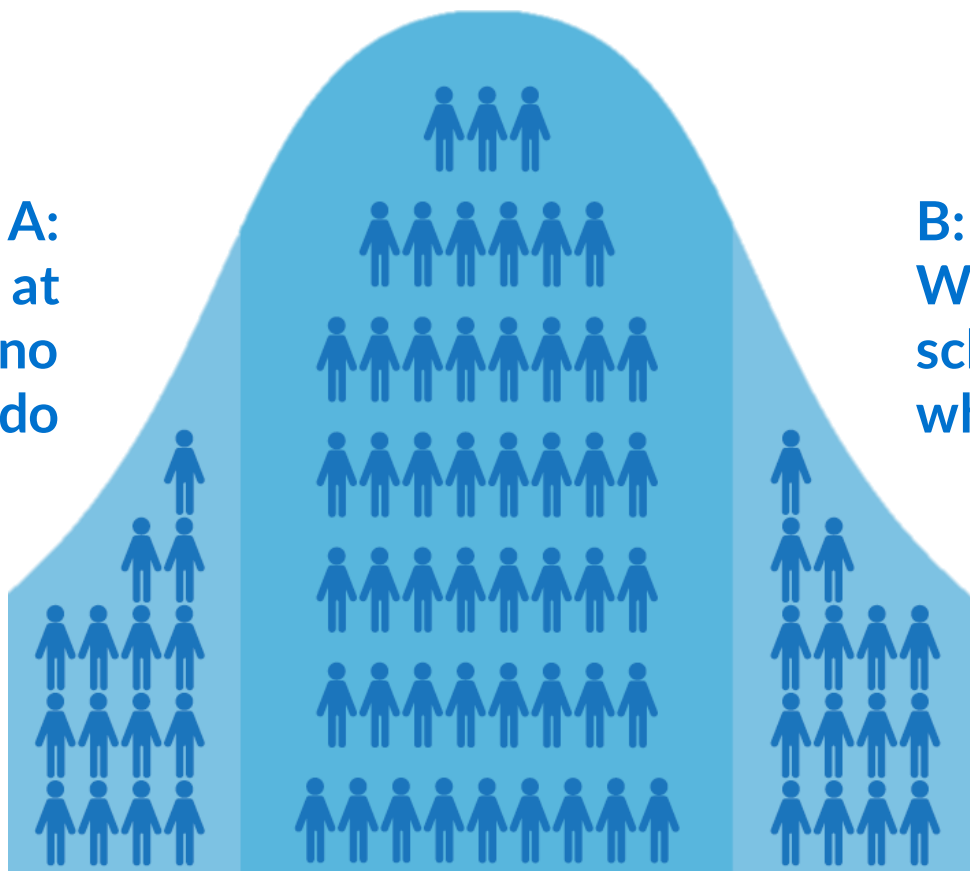
Manage the
recruitment process

A known fact about student choice, interest, and behavior

C: Area of influence

A:
Will not enroll at
your school no
matter what you do

B:
Will enroll at your
school no matter
what you do



What indicators do you use for prioritization?

Are you qualifying your pool?

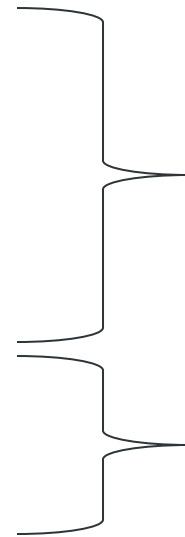
- Funnel Data
- Geographic
- Student information
- Engagement
- Other?

Modeling Tournament Approach

Build multiple types of models, both traditional and machine learning. Based on one or more criteria, a champion model will be identified

Models to Consider:

- Stepwise Regression
- Backwards Regression
- Decision Tree
- Gradient Boosting
- Neural Network



Traditional methods

Machine learning

Model Tournament

Terms and Definitions

Model Tournament Overview

After splitting the modeling data into training and validation data sets, the data is reduced to a set of variables that have demonstrated a relationship to the event of interest. The data is then sent to a tournament using multiple modeling techniques to fit the data. These techniques include traditional and machine learning methods. Based on fit statistics and model performance, a champion model is determined. Of most importance is how the models perform on the validation set as this represents an estimate of how the model will perform on future scoring data.

Modeling Types

Stepwise Regression

Using logistic regression, this technique first fits the best 1-variable model. The algorithm then determines what variable can be added to produce the best 2-variable model. The process of adding variables one at a time continues until the improvement in the model fails to meet model fit criteria and no additional variables surpass a certain level of significance.

Backwards Regression

Using logistic regression, this technique starts with all viable input variables in the model and iteratively removes the weakest variable in the model. This continues until all remaining variables meet a predetermined significance level.

Gradient Boosting

A machine learning method that iteratively re-samples the data. With each sample, a simple model (typically a decision tree) is fit and then a secondary model is fit to the error produced by the initial model. Based on performance within each sample, the models are weighted and combined to produce a final prediction. The frequency in which variables are used within the models determines the importance level of each variable.

Neural Network

A machine learning method that takes inputs and finds both simple and complex relationships between the inputs and the outcome. By detecting complex nonlinear relationships in data, neural networks can help to make predictions about real-world problems. Neural networks are especially useful when the relationship between inputs and outputs is not known and where prediction is more important than explanation. Proxy models, typically decision trees, are used to identify which variables play a strong role in a neural network model.

Decision Tree

A simple modeling method that identifies what variable best splits the data based on the outcome event. All leaves are then further split as long as there is a variable that produces a significant split and each resulting leaf has a sufficient number of records. Splitting ceases when these conditions are no longer met. The result of a decision tree is a set of simple rules that segments the data into similar groups.

Students are then assigned a probability based on how likely they are to enroll

| ENROLLED | 1.0 | A | ENROLLED |
|----------------|-----|---|-----------------|
| Kate Black | .99 | | Highly Likely |
| Mike Miller | .85 | | Highly Likely |
| Dave Hamilton | .72 | | Likely |
| Jerrica Zwick | .68 | | Likely |
| Angie Mabeus | .46 | | Somewhat Likely |
| Audrey Keppler | .41 | | Somewhat Likely |
| Brian Schuler | .21 | | Less Likely |
| Jordan Clouser | .17 | | Less Likely |
| NOT ENROLLED | .01 | | J |

RNL Prediction for Top of the Funnel

Maximize and inform your search purchase

SEARCH MODELING

- Predictive inquiry-to-application model for up to four markets specific to your institution
- Inform strategic decisions across all vendors targeting your search purchases

Tailor post-purchase/pre-inquiry outreach and strategy

RNL AFFORDABILITY PREDICTOR

- A capability exclusive to RNL
- Establishes each student's likely EFC range (low, moderate, high)
- Provide more nuanced and specific aid-related outreach

Understand your inquirers and drive pool to apply and deposit

FORECASTPLUS™

- RNL inquiry-to-enrollment; applicant-to-enrollment; and admit-to-enrollment modeling options combined with our survey results
- Focus on the right students with ongoing scoring

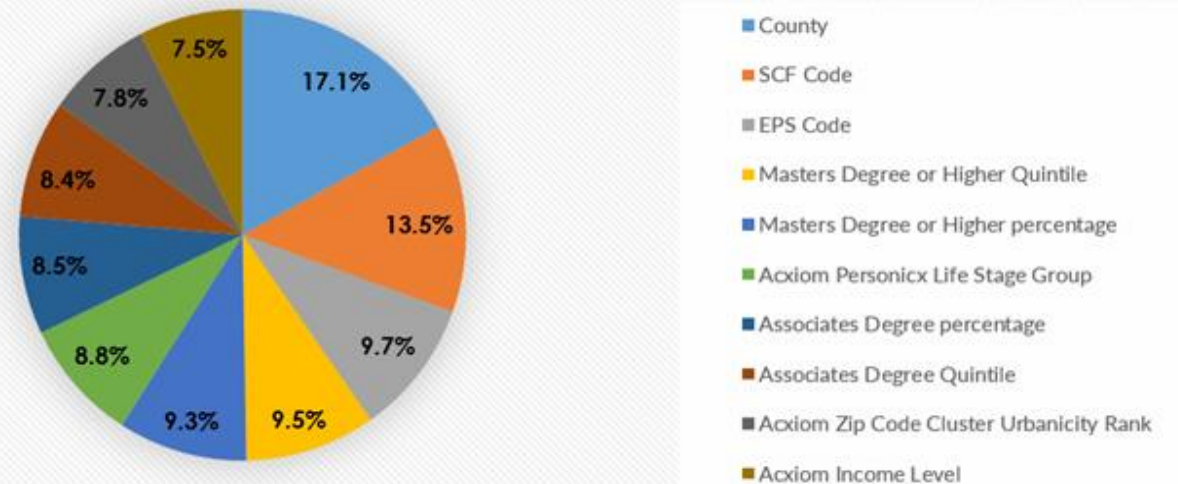
Sample of Search and Inquiry Models

Inquiry-to-Enrollment Model

| Variable | Importance | Relative Strength |
|---|------------|-------------------|
| First Major as Inquiry (YN056) | 1.00 | 23.5% |
| Primary County Code of Student (XTG_N | 0.96 | 22.6% |
| Sectional Center Facility Code (XTG_N23 | 0.61 | 14.3% |
| Enrollment Planning Service Code (YTG_ | 0.45 | 10.7% |
| Personix Segmentation Cluster (YN720) | 0.38 | 9.0% |
| Initial Source Code (YN020) | 0.37 | 8.7% |
| Categorized No. of Days as Inquiry (XCN | 0.21 | 5.0% |
| Income Level (XN460) | 0.14 | 3.3% |
| High School CEEB Code (YTG_N086) | 0.13 | 2.9% |

Search-to-Apply Model

Variables in Model and Relative Impact



RNL Prediction for yielding, retaining students and gaining donors

Maximize institution dollars and improve yield

Improve campus retention immediately when students arrive to campus

Increase your donor pool and understand who is more likely to give

ECONOMETRIC MODELING

- Admit-to-enrollment model helps prioritize student outreach to make informed enrollment projections.
- Identify students who are more likely to enroll when provided additional aid which enables you to strategically allocate dollars for maximum impact.
- Model helps understand price elasticity and impact on changes in net student charges.

STUDENT RETENTION PREDICTOR

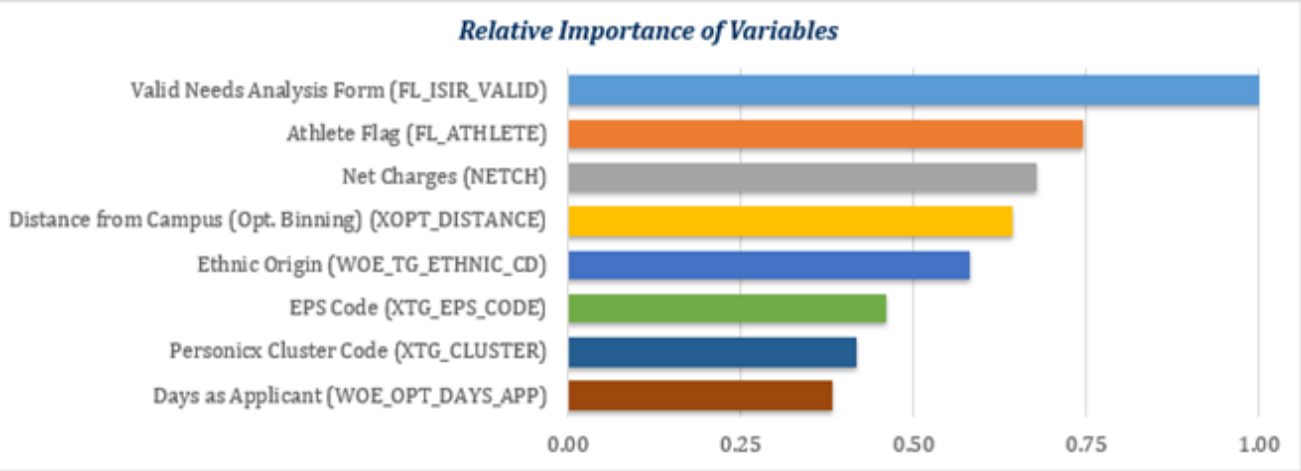
- Model measures students' likelihood of attrition based on observed risk factors
- Establishes yield qualification for first-year re-enrollment plan

ADVANCED ANALYTICS

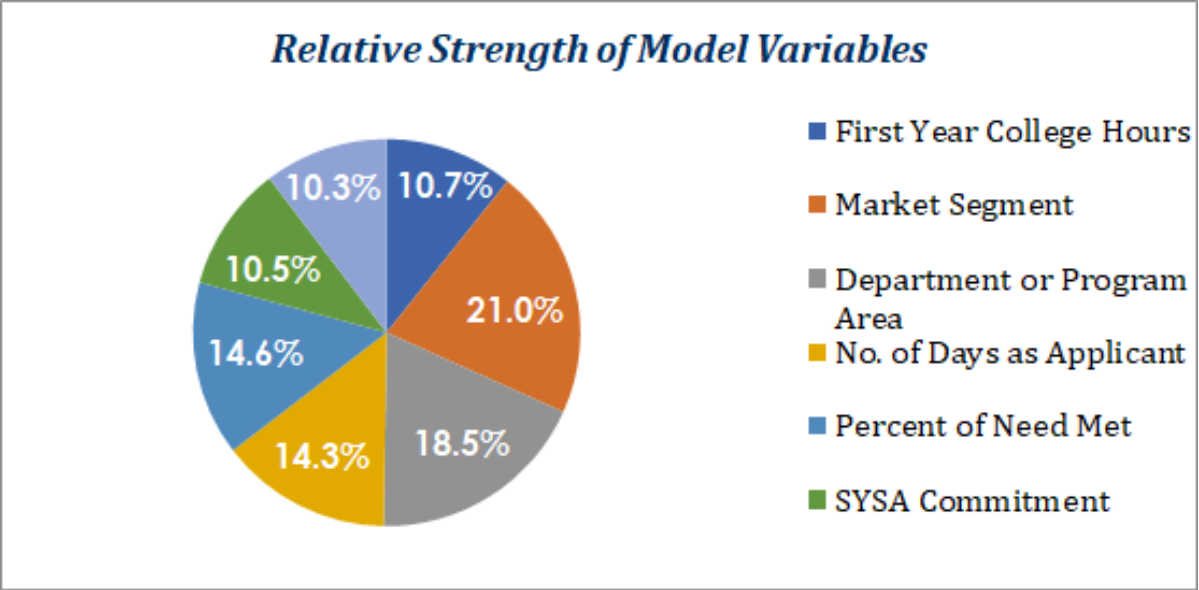
- Increase your donor population by targeting individuals who are more likely to give

Econometric and Student Success Modeling

Econometric Model



Student Retention Model



**Data
enhancements
shift modeling
strategy**

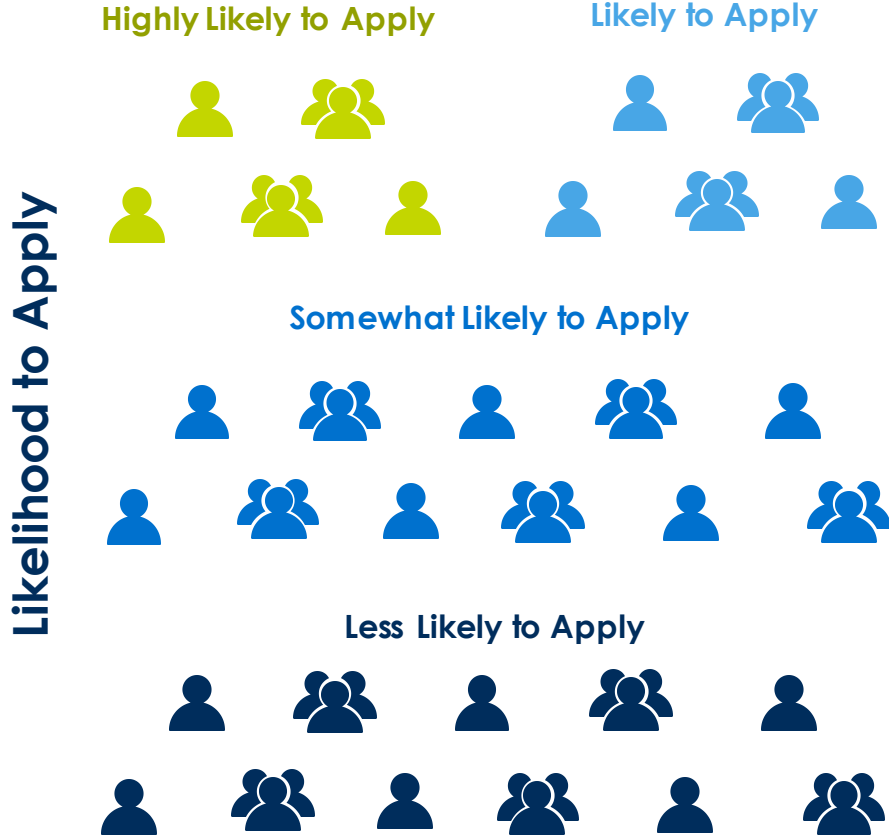


Predictive Modeling + Engagement Scores

Inquiry to Applicant

Engagement scores add another layer to show current engagement level and trending by funnel stage

55,000 Inquires

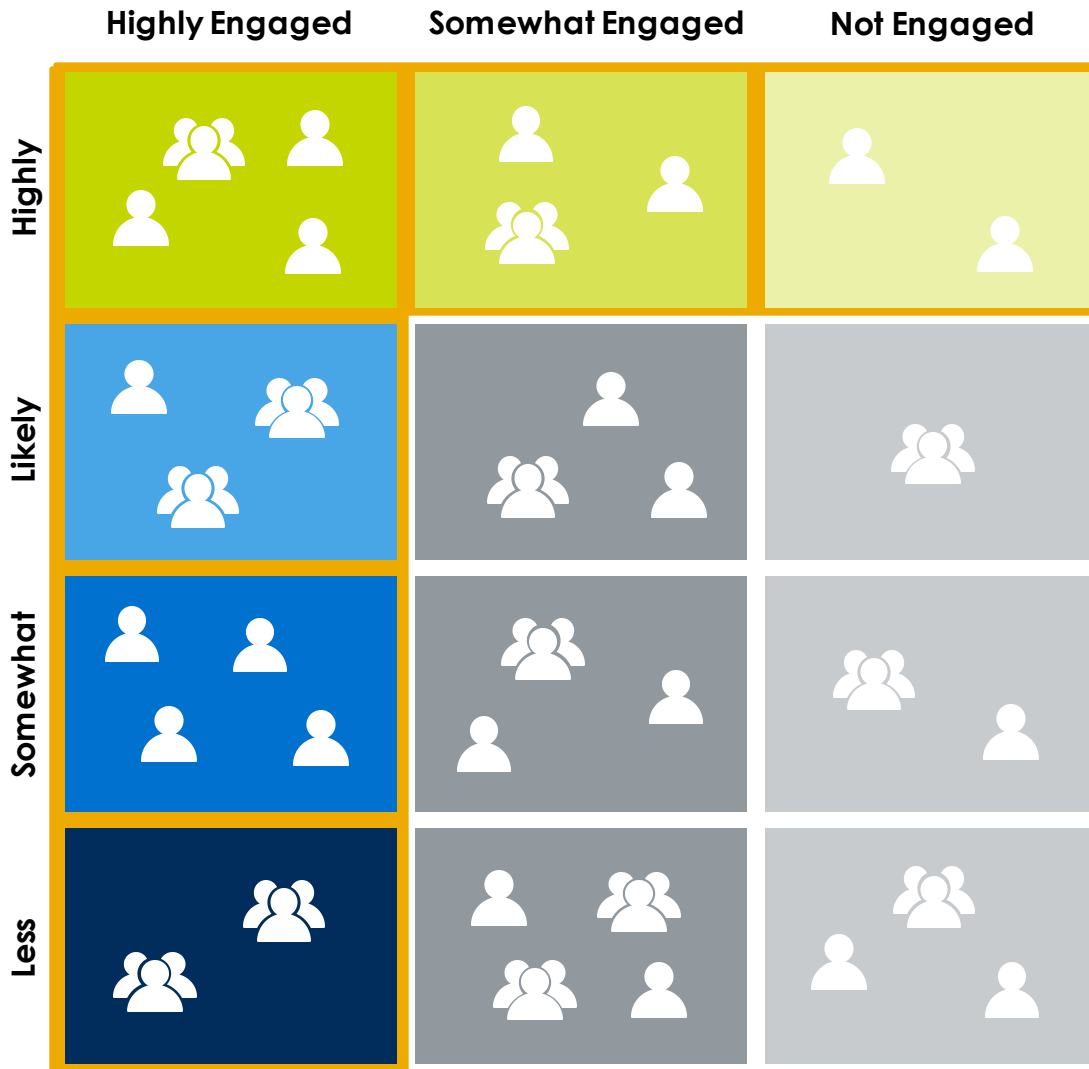


Highly Engaged Somewhat Engaged Not Engaged

| | Highly Engaged | Somewhat Engaged | Not Engaged |
|----------|----------------|------------------|-------------|
| Highly | | | |
| Likely | | | |
| Somewhat | | | |
| Less | | | |



Data-Driven Prescriptive Action: Enhanced Analytics



Modeling

Inquiry, Applicant, Admit (Example)

Action: Intensify marketing outreach for the students most likely to apply and those highly engaged.

Action: Optimize channel mix and test new strategies to drive engagement.

Analytics drives strategy and content for all audiences

Parent Engagement

Engage parents to turn them into enrollment influencers

- Prospective parents have a **40% higher email open rate on the platform.**
- Students with a parent using the platform are nearly **3x more likely to apply, yield rates up to 6% higher than average, and 3x more likely to enroll.**

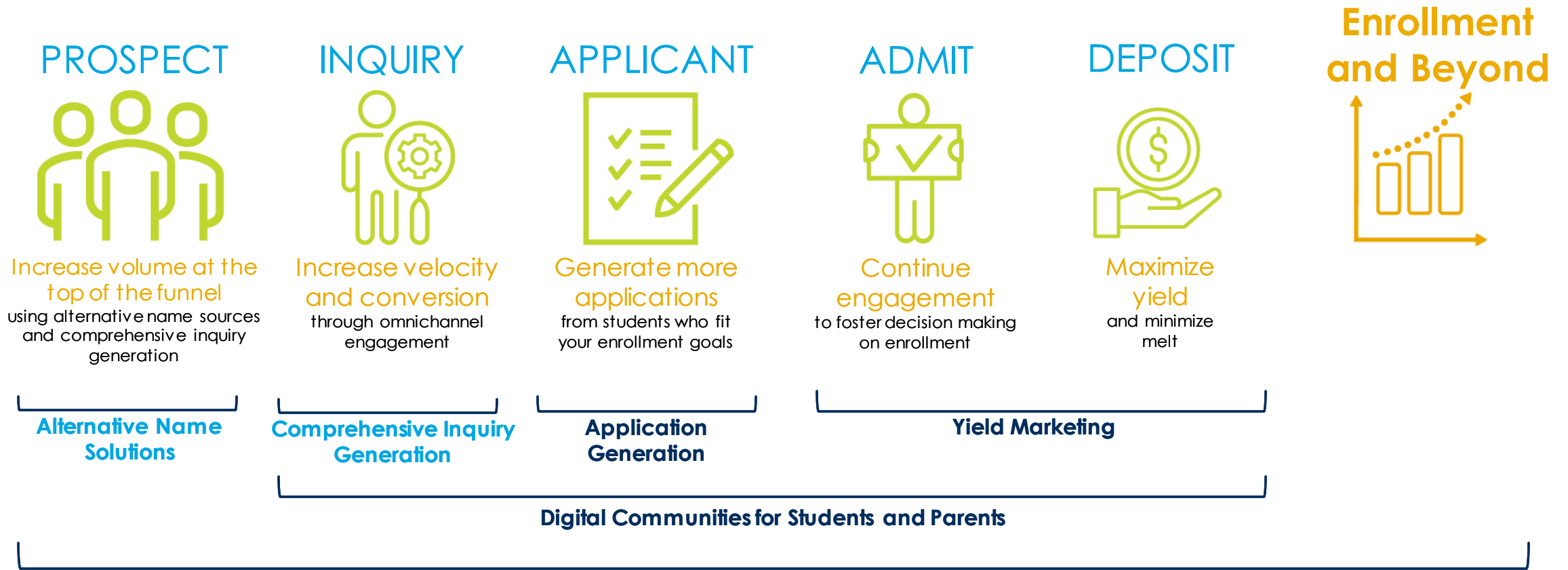


99% of parents are involved in the college process

- *Qualify their interest*
- *Nudge their behavior*
- *Guide communications with data*

Modeling for the Life Cycle of a Student

Continuous modeling from prospective student through alumni



Actionable Analytics and Dashboards, Digital Experiences, Supercharged Engagement

What's next?

1. Evaluation of Data Points
 - Use the data in your CRM to developed solid plans
 - Use the data to help drive holistic strategy decisions
2. Focus on Student Life Cycle – Pre-prospect through Donors
3. What will be next in the Evolution of Modeling???

Thank you

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