Predictive Modeling in Enrollment Management: New Insights and Techniques
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This year’s class is different. A simultaneous shift across demographics, socioeconomics and technology is beginning to challenge and change the traditional enrollment process in higher education. Increasingly, institutions are turning to big data, complex models and strategic planning to make more informed decisions during the recruitment cycle.

This report examines the growing importance of predictive models within the context of college choice and today’s students. While relying on traditional enrollment indicators continues to be an important part of an institution’s strategic plan, new datasets that incorporate latent variables in a student’s decision-making process are becoming available. Social behavioral data, or students’ interactions with peers and staff online, can yield deeper visibility into students’ college choice, while also enhancing the strength of institutions’ existing predictive models.
College choice refers to a student’s decision of whether and where to go to college, and historically, has been framed through either economic, sociological or psychological theoretical perspectives (Bergerson, 2010). The economic perspective considers how students weigh the associated costs and benefits of a postsecondary education to maximize their return on investment. The sociological perspective addresses group status and how individual predispositions (e.g., ethnicity, family income) and family background (e.g., parental education and expectations) influence students’ decision to enroll in college. The psychological perspective focuses on how perceptions of self (e.g., self-efficacy) and institution (e.g., academic rigor) affect students’ college choice.

Thereafter, the college choice paradigm shifted to a more comprehensive model, in which researchers regarded college choice as a process and examined how economic, sociological and psychological factors at different stages in life influenced a student’s decision of whether and where to enroll (Hossler & Gallagher, 1987). Comprehensive models were applied to all college-intending students. However, given students’ increasingly diverse backgrounds and experiences, researchers are reevaluating their understanding of college choice to acknowledge that not all factors influence students in the same way, particularly among the growing population of underrepresented groups in higher education. For example, Perna’s (2006) model accounts for college choice differences across groups by examining economic, sociological and psychological factors within nested contextual layers (e.g., individual, family, institution, economy and public policy). Overall, research (Paulson, 1990; Bergerson, 2010) demonstrates that the path to enrollment is not universal, but varies across ethnic, socioeconomic and other groups based on individual differences and experiences.

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Figure 1. Traditional college choice model.
To understand college choice and aid in the process of student enrollment, higher education has seen an increase in the use of predictive analytics which utilizes past behavior to predict future behavior (Berg, 2012). Typically, enrollment managers use economic, sociological and psychological factors in their predictive models, all of which explain a significant amount of variance in a student’s enrollment decision. However, there may be additional variance accounted for in predictive enrollment models aside from these traditional factors.

As a university-branded, app community, Uversity’s Schools App with Enrollment Intelligence provides a platform to accelerate engagement with an institution by connecting students with peers and facilitating interactions with student ambassadors and admissions counselors. Enrollment Intelligence (EI) uses students’ interactions within the app community, or social behavioral data, to predict which students are most likely to enroll at an institution. Quantifying students’ social behavioral data into a ranked score can add further explanatory value to existing enrollment management models. By capturing students’ online interactions in real-time, EI accounts for an additional amount of variance that has not been accounted for previously in college choice models.

Figure 2. Alternative college choice model.
Neural Networks: Finding Complex Patterns in Data

To quantify students’ social behavioral data, EI uses a neural network analysis, the objective of which is to train the predictive model on a dataset with known predictor and outcome variables and learn from the data by finding the values of unknown parameters (Warner & Misra, 1996). Enrollment managers have a clear understanding of which traditional factors affect an admitted student’s decision to enroll, such as family income and campus visit. However, they do not necessarily know the level of importance associated with social behavioral predictors or how these predictor variables relate to one another and the enrollment outcome.

There are a couple advantages to using neural networks. First, neural networks are able to discover complex patterns in the data and their association with the enrollment outcome (Gonzalez & DesJardins, 2002, Luan, 2002). Specifically, neural network analysis is suitable for non-linear problems in which the nature of the predictor-outcome relationships is unknown (Gonzalez & DesJardins, 2002; Luan, 2002; Paliwal & Kumar, 2009; Warner & Misra, 1996). Such unknown relationships are evident in enrollment scenarios wherein it may be less clear how predictor variables relate to the enrollment outcome. For example, deposit behavior may exhibit a linear or curvilinear relationship with enrollment. Enrollment Intelligence uses a neural network analysis to examine the unknown relationships between students’ online social behaviors and their enrollment outcome as this concept has yet to be explored in the conversation around college choice.

Figure 3. A neural network maps predictor variables (x) located in the input layer to an outcome variable (y) located in the output layer. Hidden variables (a) in the hidden layer(s) are connected to all predictor and outcome variables via weights, also known as parameters. A constant or bias terms is also included in the model to allow for shifts in the sigmoid function.
Second, a neural network can counteract the effects of overfitting. A model with too many factors is prone to overfitting which implies that the model fits the training dataset well (i.e., minimal error between predicted and actual results), but does not generalize or make as accurate predictions with new datasets (Naik & Ragothaman, 2004). In the recruitment process, it is often assumed that admitted students exhibit similar behaviors year over year, and thus, one can use the past behaviors of previous admit cohorts to predict enrollment of new admit cohorts. This assumption, however, may lead to less accurate enrollment predictions when considering a model with a large set of factors. A model with too many predictors will calculate accurate enrollment predictions for the training set of previous admit cohorts, but to produce as accurate enrollment predictions for the current admit cohort, students must exhibit similar behaviors across all those factors year over year. Enrollment Intelligence uses a neural network analysis to adjust for changes in the online social behaviors that influence a student’s decision to enroll, and add visibility into how each student is different. Furthermore, EI calculates ranked scores daily, providing real-time enrollment predictions throughout the entire recruitment cycle.

Evaluating Performance: New Insights with Social Behavioral Data

Enrollment Intelligence quantifies students’ social behavioral data into scores, ranks students by score in descending order, and buckets students into ten equal groups from one (most likely to enroll) to ten (least likely to enroll) such that each group contains the same number of students. A visual representation for evaluating the performance of EI called a gains chart shows a comparison of ranked scores against actual enrollment outcomes. Because ranked scores are calculated daily, a gains chart can be created for any given day. For example, consider one partner institution’s gains chart during the recruitment cycle.

Figure 4. Anonymized gains chart evaluating model performance on March 1st.
Going back to March 1st (see Figure 4.), the average student at this institution had a 29% likelihood to enroll based on the school’s historical yield. Without EI, enrollment managers would expect that three in every ten students would actually enroll in their institution. Utilizing EI, students in the first rank were predicted to have the highest probability of enrolling and, in hindsight, the gains chart shows that they did have the highest enrollment compared to the historical yield and other ranks. Moreover, students in ranks one through ten were predicted to have a decreasing enrollment likelihood and the downward slope illustrates the strength of EI predictions. Snapshots of EI predictions on other days in the recruitment cycle follow this trend, demonstrating the effectiveness of using social behavioral data in a model to predict students’ college choice. Used in conjunction with institutions’ existing predictive models or enrollment strategies, EI may strengthen enrollment predictions by accounting for additional variance not previously factored into college choice models. See how three partner institutions utilized EI ranked scores to increase visibility into their students’ enrollment decision-making process.

Figure 5. A cumulative gains chart is an alternative representation for measuring model performance as it aggregates EI predictions as a percent of the enrolled class.
As a result of demographic shifts in Illinois’ student population and increased competition within the state, Western Illinois University, a medium-sized public institution with 10,000+ undergraduates, has experienced a decline in enrollment rates over the past eight years. To generate growth in enrollment, Andrew Borst, Director of Admissions, depends on data to execute his strategic enrollment management plan. Using a predictive modeling approach, he incorporates static metrics, such as admissions counselor interactions, campus visits, and deposit status, into a logistic regression model which indicates the strength of each metric as a predictor of enrollment. Logistic regression, however, is a point-in-time comparison that measures where the class ended up last year with where the class is right now, and as such, uses metrics that cannot be adjusted or measured again until the end of the enrollment cycle.

This year, Andrew integrated dynamic metrics based on social behavioral data, such as students’ engagement level, EI ranked scores, and in-app poll responses, to enhance the value of the existing model. The addition of this dataset improved the accuracy of the predictive model by approximately 15%, and ensured that Andrew was allocating resources to the right students without the cost of focusing on students who were likely to change their minds later in the decision timeline. Furthermore, the enhancements to the predictive model helped build trust in university leadership who were allocating financial aid and marketing funds. Andrew demonstrated how they could influence on-the-fence students based on their online social behavior, so that more resources could be apportioned to strategically recruit that group of students.

“\nThe main benefit of Enrollment Intelligence is that it gives me real-time information about how students are interacting with one another and our school, providing valuable information to build our class.\n”

Andrew Borst, Director of Admissions, Western Illinois University
Find, Track and Contact Students On-the-Fence

The University of Nebraska, Kearney is the third-largest institution in the state of Nebraska with a total enrollment of 7,000 undergraduate students. After experiencing its highest enrollment in history, the institution struggled to meet its target enrollment last year, missing the goal by nearly 100 students. Brad Green, Assistant Director of Recruitment, decided to explore predictive models as part of his admissions strategy. He turned to EI to triangulate its real-time predictions with historical enrollment data in an effort to shape his admissions strategy and gain more visibility into students’ likelihood to enroll.

With no set deposit deadline, Brad worked closely with the data team to monitor their student information system, measuring their incoming class at given points in time against static metrics from the previous year. By integrating historically powerful indicators of enrollment, such as email open rates, housing sign-ups, orientation registration, with social behavioral predictors, Brad was able to build a more complete picture of individual students and their decision to enroll. One such student who signed up for housing, but did not register for new student orientation was flagged as at risk of not enrolling. Based on her social behavioral interactions, however, EI identified the student as highly engaged with the institution. Using the combination of traditional enrollment indicators and real-time student behavior, Brad recognized that she was on-the-fence about her decision to enroll, and worked with her to register for orientation and complete the enrollment process. The additional layer of insight helped Brad more effectively find, track and contact individual students on-the-fence to secure his incoming class.

“I think social behavioral data is new and exciting, and definitely see potential for Enrollment Intelligence to be a larger part of how we approach enrollment. It gives our team validity and provides the assessment to make sure we’re on track.”

Brad Green, Assistant Director of Recruitment, University of Nebraska, Kearney
Chestnut Hill College, a small, private institution with less than 2,500 undergraduates, has experienced consecutive enrollment shortfalls due to a struggling Philadelphia school district and an increase in first-generation students. As the new Director of Admissions, Jamie Gleason’s biggest challenge was adapting to students’ changing demographics and needs, so that he could better distribute financial aid dollars to those at-risk students most likely to enroll and thrive at Chestnut Hill. In an effort to improve yield for his incoming class, Jamie used EI to complement existing enrollment strategies and provide more complete student profiles.

Jamie focused his efforts on students who were susceptible to falling off his radar. After cross-referencing Enrollment Intelligence predictions with traditional enrollment indicators, he discovered that there were highly engaged students expressing significant interest in attending Chestnut Hill, but who had not deposited. Concerned with the inconsistency between datasets, Jamie considered the reasons why those students had not deposited, including that they were unable to commit financially to the institution. In order to secure one particular student’s enrollment, Jamie was able to reallocate financial aid dollars and increase his offer by $9,000. For his first year at Chestnut Hill, Jamie set an aggressive enrollment goal. He wanted to implement strategies that would have an immediate impact, and EI provided the visibility he needed to make every student count.

“The fact that there is a model working on understanding how [social behavioral] interactions affect students’ college choice and processing all of the factors I cannot see is reassuring. Enrollment Intelligence helps us to find, track and contact those students who are falling off”

Jamie Gleason, Director of Admissions, Chestnut Hill College
Conclusion

To a certain extent, the student’s journey to college has always been clouded in uncertainty for enrollment managers. But as students’ backgrounds and experiences become increasingly diverse, post-secondary institutions are left leaving more to chance during the enrollment process than ever before. Traditional methods of interpreting a student’s college choice in economic, sociological, and psychological terms may not be enough to develop a full understanding of whether or not that student will enroll and persist at a certain institution.

The good news is that advancements in technology and data science mean institutions no longer have to rely solely on historical, or point-in-time, datasets to assess the trajectory of this year’s student. Incorporating real-time, social behavioral data into a predictive model, such as EI, can increase visibility into a student’s enrollment decision, enhance the overall accuracy of existing models, and help institutions more efficiently define, target and enroll the right students.
About Author

Alexandra Sigillo is a researcher and data analyst at Uversity, Inc. focused on predictive modeling, survey research, and institutional partnerships. She combines data and storytelling to communicate how social behavioral metrics impact student enrollment and success. Prior to joining Uversity in 2012, Alexandra received her Ph.D. in social psychology from the University of Nevada, Reno.

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About Uversity

Uversity partners with over 150 colleges and universities to provide an industry-leading student engagement platform that improves enrollment and student success. Through UChat and Schools App, we are connecting over 4.5 million students with the right information and people during the admissions process, and leveraging these student-to-student interactions to help higher education institutions proactively shape today’s incoming class.

We help our partners:

• Provide an engaging, mobile experience for prospective and admitted students
• Create and deliver targeted outreach to best-fit students
• Grow, shape and manage enrollment

To learn more about how our mobile student experience, communication platform and predictive analytics can benefit your institution, connect with a member of our team at contact@uversity.com.
References


