The UNIVERSITY of OKLAHOMA

Retention and Recruitment: Using a Predictive Analytic Model to Build and Implement a Strategic Graduation and Retention Action Plan

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Background

- Critical teacher shortage first documented in Oklahoma in 1948 (Dodson).
- Fast forward to 2017 and the same teacher shortage still exists (Blatt, 2016; Denwalt, 2015).
- During the 2016-2017 academic year Oklahoma faced a 1000 teacher shortfall (Englebright, 2015).
- The critical teacher shortage is at crisis level in surrounding states and across much of the U.S. (Sutcher, Darling-Hammond & Carver-Thomas, 2016).
- Current predictions show that if the current teacher supply trends continue, the annual teacher shortfall in the U.S. will reach 112,000 by 2018 (Camera, 2016).

Literature Review: Overview

Strong predictors and predictor themes of student retention and graduation:

- Importance of academic advising, coaching/mentoring and high impact practices (Tinto, 2006; Ruffalo Noel Levitz, 2013; Lowe & Toney, 2000; Martinez, 2015; Mat et al., 2013; Moore, 2015; Provencher & Kassel, 2017; Meléndez, 2007; Young-Jones et al., 2013).
- Appropriate financial support in the form of aid, grants and scholarships (Cabrera et al., 1992; Dowd, 2004; DesJardins, Ahlburg, & McCall, 2002; Wohlgemuth et al., 2007).
- Relationship of grades and GPA to retention and graduation (Cabrera et al., 1992; Gershenfeld et al., 2016; Vandamme et al., 2007; Vare et al., 2003; Wolniak, 2016).
- Exam scores specifically, ACT/SAT composite scores (Gershenfeld et al., 2016; Vandamme et al., 2007; Vare et al., 2003; Wohlgemuth et al., 2007; Wolniak, 2016).
- Gender (Gershenfeld et al., 2016; Wolniak, 2016).

What We Know

- Early identification of at-risk students for intervention programs or redirection into appropriate parallel degree paths can improve campus and college retention and graduation rates.
- Guidance, mentoring and information the student receives from academic advisors and college personnel can be an important factor in increased retention and graduation rates (Lowe & Toney, 2000; Tinto, 2006; Young-Jones, Burt, Dixon & Hawthorne, 2013).
- Predictive analytics is a promising method in the quest to increase student success at the university and college level (Delen, 2011; Mah, 2016; Mat, Buniyamin, Arsad, & Kassim, 2013; Oztekin, 2016; Vandamme, Meskens & Superby, 2007).
- In 2015, the Department of Education funded a 9-million-dollar grant for a study on the impact of analytics and effectiveness of academic advising or coaching on student retention (Department of Education Awards, 2015).

Model Development

Working with data scientists at the University of Oklahoma, a predictive analytic model was designed to aid in the recruitment, retention, and graduation of future educators.

- Our predictive analytic model utilizes a machine learning algorithm, extreme gradient boosted machine.
- The prediction model, built on historical data, is now being applied to current student populations as a retention and recruitment tool.
- A preliminary strategic graduation and retention action plan, based on the model, is in use by academic advisors and advising administrators.

Methodology

Methodologically, this work has evolved over several years.

- We have carefully defined the student population that we are including.
- Identified the strongest predictive variables.
- Utilized many different statistical estimating techniques in an effort to more accurately estimate the likelihood a student will get a degree.
- The current estimator is a machine learning algorithm, extreme gradient boosted machine (Friedman, 2001).
- Using cross validation techniques, it was determined that about 8400 decision trees optimizes our ability to predict if a student will get a degree in the College of Education.
- In terms of accuracy, the cross validation indicates we are correctly classifying (i.e., degree/no degree) over 95% of the students.

Model Sample

- Sample data are all students who had declared Education as their major between Spring 2010 and Fall 2016
- N=1070
- Gender: 86.4% Female/13.6% Male
- 826 Received a degree
- 244 Did not receive a degree

Model Demographics

Gender

- 86.4% Female
- 13.6% Male
  - 20% of females did not receive a degree
  - 40% of males did not receive a degree
  - Males are much more likely to not receive a degree from the JRCoE program.

Model Demographics

Self reported IPED Categories

IPEDS Categories	Total	No Degree	Degree	Percent not receiving a degree
American Indian or Alaska Native	46	17	29	37%
Multi Race	61	20	41	32.8%
Hispanic	54	16	38	29.6%
Black or African American	28	8	20	28.6%
White	822	173	649	21%
Do not wish to report	44	6	38	13.6%

Model Demographics

Curriculum

Major	Total	No Degree	Degree	Percent not receiving a degree
Education-Undecided	10	10	0	100%
Mathematics Ed	42	15	27	35.7%
Social Studies Ed	97	30	67	30.9%
Science Ed	43	13	30	30.2%
Special Ed	64	18	46	28.1%
Language Arts Ed	96	21	75	21.9%
Early Childhood Ed	184	39	145	21.2%
Elementary Ed	502	78	424	15.5%

Model Demographics

Average Term Hours

Average Credit Hour	No Degree	Degree
0-8 hours	9.8%	4%
8-12 hours	24.2%	19.2%
12-15	26%	67.9%
15-17	6.1%	4.4%
17-21	1.2%	2.2%
Missing	32%	2.3%

Model Demographics

OU Retention Undergraduate GPA

GPA range	Total	No Degree	Degree	Percent not receiving a degree
1.0-1.99	57	57	0	100%
2.0-2.49	37	36	1	97.3%
2.5-2.74	31	29	2	93.5%
2.75-2.99	44	25	19	56.8%
3.00-3.49	392	45	347	11.5%
3.5-4.0	479	22	457	4.6%

Model
Built on Historical Data

Features and Statistical Techniques

Statistical Modeling Techniques

Extreme Gradient Boosted Machine

- XGB uses a ensemble of decision trees and is an more optimized version of the Gradient Boosted Machine Algorithm. Known as a multiple imputation model, can be useful to impute missing data in both linear and logistic regression models (Milletich, 2016).

Logistic Regression

- In cases where the response is one of two outcomes, logistic regression produces a single linear function using a logit transformation to help find the maximum likelihood of each case (Tabachnick & Fidell, 2007).

LASSO Regression

- A linear regression method that applies an L1 penalty to control the size of the coefficients. Lasso will cause some of the coefficients to reach 0 which is a sort of continuous subset selection (Tibshirani, 1996).

Receiver Operation Characteristic (ROC) Curves and Area Under the Curve (AUC)

- In a ROC curve the true positive rate (Sensitivity) is plotted as a function of the false positive rate (1 - Specificity) for a variety of cut-off points. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold (Fawcett, 2006).
- The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two diagnostic groups (No Degree/Degree).

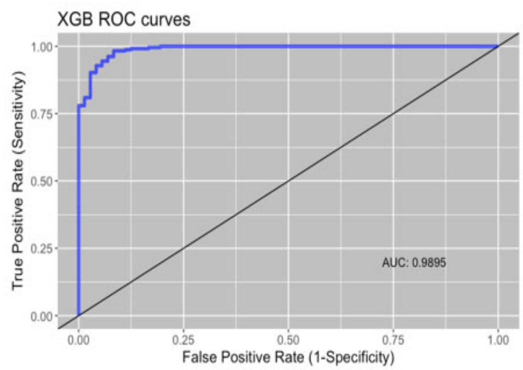
We initially started with 51 modeling features and 1 response variable

- fe_ is a feature we engineered
- r_ is a feature that was transformed
- missing_ identifies features that are dummy coded features representing missing data

[1] "OBTAINED_DEGREE"	"GENDER_CODE"	"IPEDS_CATEGORY_DESC"
[4] "OU_RETN_UG_GPA"	"COMB_RETN_UG_GPA"	"TERM_CODE"
[7] "TERM_HOURS"	"HONORS_IND"	"SCHOLAR_IND"
[10] "fe_mean_pell_dollars"	"fe_mean_loan_dollars"	"fe_ewma10_mean_loan_dollars
[13] "fe_mean_scholarship_dollars"	"fe_mean_tuition_waiver_dollars"	"fe_mean_grant_sans_pell_dollars"
[16] "fe_ewma_mean_tuition_waiver_dollars"	"fe_mean_unmet_need"	"fe_female"
[19] "fe_ipeds_white"	"fe_ipeds_am_indian"	"fe_major_early_childhood"
[22] "fe_major_elementary"	"fe_major_lang_arts"	"fe_major_math_edu"
[25] "fe_major_science_edu"	"fe_major_social_studies"	"fe_major_special_edu"
[28] "missing_act_sat_max"	"r_ACT_SAT_CONV_MAX"	"missing_hs_percent"
[31] "r_HS_PERCENTILE"	"missing_hs_class_size"	"r_HS_CLASS_SIZE"
[34] "missing_hs_gpa"	"r_HS_GPA"	"missing_trans_gpa"
[37] "r_TRANS_RETN_UG_GPA"	"missing_trans_gpa_hours"	"r_TRANS_RETN_UG_GPA_HOURS"
[40] "r_IPEDS_CATEGORY_DESC"	"r_HONORS_IND"	"r_SCHOLAR_IND"
[43] "r_CURRIC1_MAJOR_DESC"	"r_CURRIC2_MAJOR_DESC"	"mean_sp.fall"
[46] "mean_sum.hrs"	"r_no_ta"	"missing_curric1"
[49] "missing_curric2"	"missing_ipeds"	"missing_ou_term"
[52] "missing_term_hours"		

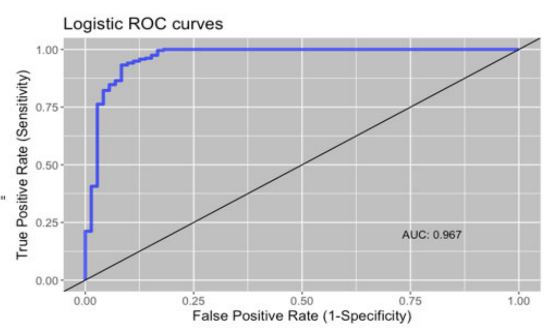
Extreme Gradient Boost - XGBoost

Most Important Variables:
[1] "OU_RETN_UG_GPA"
[2] "TERM_HOURS"
[3] "mean_sum.hrs"
[4] "r_CURRIC2_MAJOR_DESC"
[5] "r_HS_CLASS_SIZE"
[6] "r_TRANS_RETN_UG_GPA_HOURS"



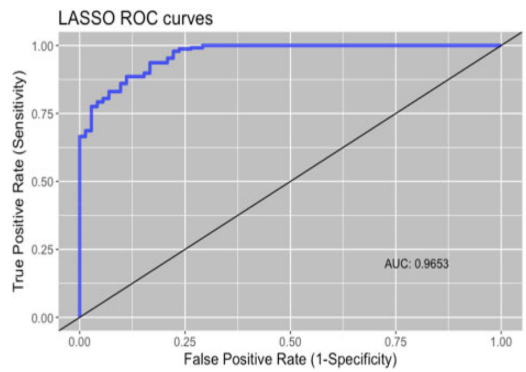
Logistic Regression

Most Important Variables:
[1] "mean_sum.hrs"
[2] "r_CURRIC2_MAJOR_DESCNONE"
[3] "OU_RETN_UG_GPA"
[4] "missing_act_sat_max"
[5] "r_TRANS_RETN_UG_GPA_HOURS"
[6] "r_ACT_SAT_CONV_MAX"
[7] "r_CURRIC2_MAJOR_DESCElementary School"
[8] "COMB_RETN_UG_GPA"
[9] "mean_sp.fall"
[10] "r_HS_CLASS_SIZE"

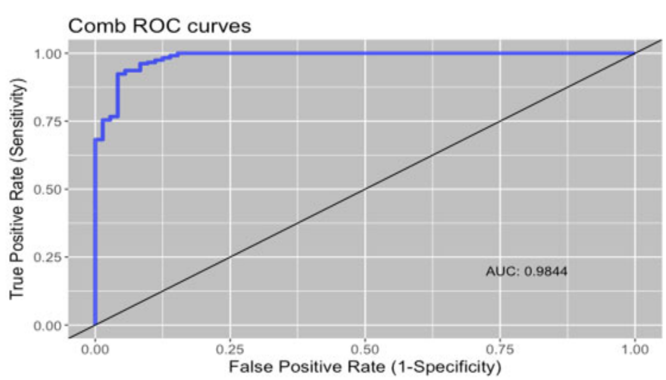


LASSO - GLMNET

Most Important Variables:
[1] "OU_RETN_UG_GPA"
[2] "missing_term_hours"
[3] "fe_major_science_edu"
[4] "fe_major_special_edu"
[5] "fe_major_lang_arts"
[6] "missing_curric1"
[7] "HONORS_IND"
[8] "fe_major_math_edu"
[9] "missing_curric2"
[10] "fe_major_early_childhood"



Combine the Predictions



Results and Discussion on Model

There are 51 features identified in the current model of which 15-24 are strong predictors (Slides 17-20). The other features were not meaningful in all modeling techniques. Finally, in terms of accuracy, the cross validation indicates that in our current model we are correctly classifying (i.e., degree/no degree) over 95% of the students.

Results and Discussion on Model cont'd.

The results show that some of the strongest indicators of student retention based on the historical data in the College of Education and ultimately graduation include:

- University retention GPA and transfer retention GPA for transfer students
- Summer enrollment hours
- Average course enrollment in fall and spring
- Curriculum/Major
- Average unmet financial need

Additional predictors:

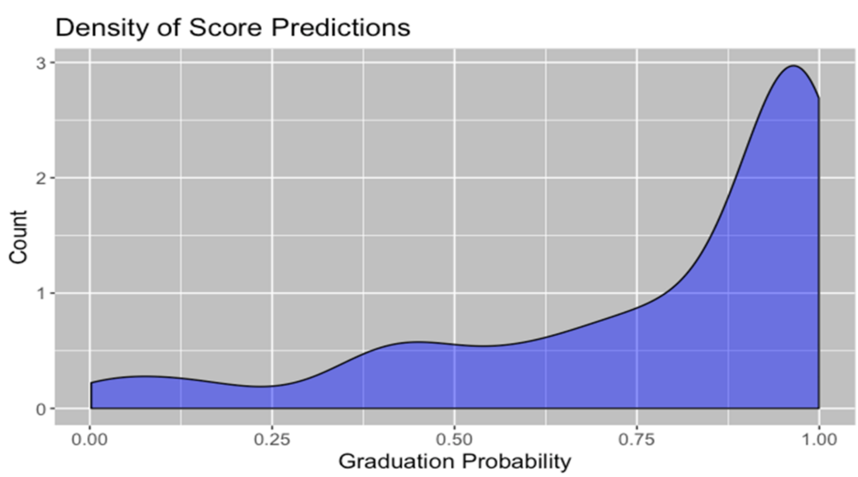
- The overall OGET score*
- OGET subtest 2 score** (communication skills)
- Number of advising appointments

Model with Active Students

Scoring data are those students at OU with Education declared as a major in the Spring 2017 term.

N=510

Scoring Predictions: Current Students



Scoring Predictions

	In Danger	Border	Safe
Count	35	80	395

≥ In danger < .4 < Border < .6 ≤ Safe ≤ 1

Use of Model:
Advisors and Administrators

- **STUDENT ≠ NUMBER!!!!**
- Identify students early who need a safety net.
- Identify students who need financial support.
- Coaching/ Targeted Advising sessions.
- Targeted interventions with students to improve graduation success.
- Refer students to identified services.
- Help students select appropriate education major.

Use of Model Results: Examples

- Identified students who may need financial support and guided them and/or families to money coaching, financial services, scholarship programs, work assistance tuition waiver or room and board programs before the students have bursar/enrollment holds on their accounts.
- Targeted funding support which allows the students to reduce the number of hours they work each week is another method to help at-risk students who have high unmet financial need. (Included Debt-Free Teacher, Graduation Office, Bursar's Office, Work Assistance Tuition Waiver, Teach Grant, Scholarships, Targeted requests from donors, Certification Exam help, etc.,.)
- Coaching or targeted advising sessions to help at risk students devise pathways for success by identifying and referring students to identified support services. We have designed targeted interventions with students to improve their graduation success including help selecting an appropriate education major or assist them in exploration of other degree options where they can be successful (parallel planning).

Other Uses of Model: Current and Future

Shape and refine our recruiting strategies:
- Working with our Office of Admissions and Recruitment on human capital and pipeline projects that will help us identify and recruit quality students who can be successful
- Identify quality students for recruitment into the college and specific shortage teaching areas such as STEM (Science, Technology, Engineering, and Mathematics).
- Aggressive and targeted outreach/recruitment of identified prospective students (Use of Slate, an integrated data base, Student Dashboard, DFT Alumni and student ambassadors.)

Identify best ways to effectively utilize financial support:
- Aggressive recruitment of identified candidates with scholarship funds to increase the number of underrepresented populations, males, and STEM applicants matriculating into the program.
- Identify areas of greatest need for targeted funding requests from donors such as Debt-Free Teacher initiative and certification exam funding.
- Increasing retention and graduation rates provides accountability for donors and other stakeholders by allowing them to see how their donations directly benefit students.

Help us identify other specific support or resources we can offer or use to help our students be successful:
- Bridging Programs, Mentoring Programs, Find your Future, etc.
- Student retention and tracking dashboard

Next steps in the Action Plan: Continue to Identify, Refine and Develop

- Identify support sources/services for student success and retention or redirection.
- Refine process/protocol for supporting students with low predicted success rates (decision tree model for red, yellow and green zones).
- Develop and identify progress assessments and benchmarks for incoming vs. current students.
- Refine use as a recruitment tool for aggressive recruitment of quality future educators
- Accountability for donors and stakeholders.

Next steps in the Retention Predictive Model

- Changes to model – new research studies and new identified predictor variables.
- Refinement of model to address non-traditional and traditional student populations.
- Changes on predictor variables – access to same data availability of new data sources.
- Identify and test affective and other pertinent variables (dispositions, OSAT, etc.).
- Identification of proper teaching content focus areas early on.
- Longitudinal studies that look at longevity and success in the teaching field in relation to prediction model and pertinent indicators (OSAT, OPTE, OLI, etc.).

Conclusions and Future Research Plans

In the future we will continue to improve on our ability to predict the success of our students:

- Adding additional data sources that improve predictions: Learning Management System and card swipe data (e.g., lab usage, campus engagement), and survey responses.
- Continue to refine the current model: identify variables that address behaviors, dispositions or affective processes indicative of successful teachers (Social justice beliefs, beliefs about ESL and students with disabilities, Career Inventories, etc.).
- Collect data for Longitudinal studies that address longevity in the field in relation to the prediction model and identified pertinent retention indicators (teacher certification exams Oklahoma Subject Area Test (OSAT) and Oklahoma Professional Teaching Exam (OPTE), impact on student learning (OLI), etc.) that will assess the quality and impact of graduates from the teacher preparation program.

We want to ensure that teacher preparation programs graduate high quality and well-prepared teachers.

Questions?

Literature Review: Cont'd

Strong predictors of retention and graduation:

- GPA, high school grades, verbal and math aptitude scores are strong predictors of teacher preparation program completion and graduation (Vare, Dewalt, & Dockery 2003).
- Four-year graduation rates for specific colleges of study including Education, Design and Engineering were significantly lower than Liberal Arts and Sciences (Wohlgemuth et al., 2006).
- First-semester GPA, gender (female), and composite ACT scores are predictors of success in college (Gershenfeld, Hood, & Zhan, 2016; Vandamme, Meskens, & Superby, 2007).
- GPA, ACT and gender are strong predictors of four-year graduation rates (Wolniak, 2016).
- GPA strongly related to persistence and retention (Cabrera, Nora, & Castaneda, 1992).
- ACT, high school rank, gender, and financial aid (gifts and grants) are significant positive predictors of retention and graduation (Wohlgemuth et al. (2006).
- Strong correlation between years to degree and the type of financial aid students receive- greater amounts of gift aid (grants and scholarships) and work study aid as compared to receiving greater amounts of loan aid (Wohlgemuth et al., 2006).

Literature Review: Cont'd

- The probability increases that students will thrive, persist, and complete degrees when they are in an academic environment with mentors who provide clear and consistent information about the requirements and expectations of the institution and program (Tinto, 2006).
- Nationwide, student satisfaction surveys consistently find that academic advising is a top factor in a positive college experience for students (Ruffalo Noel Levitz, 2013).
- High impact practices such as coaching and mentoring by faculty and advisors increases student retention (Provencher & Kassel, 2017).
- Coaching or counseling sessions totaling as little as 3-4 hours in the fall are strong predictors of continuing enrollment for the spring semester (Cholewa & Ramaswami, 2015).
- Frequency of meeting with academic advisors and use of early college interventions increases success (Wolniak, 2016).
- Targeted interventions by trained academic advisors useful in increasing retention rates of at-risk and underrepresented populations (Young-Jones et al., 2013; Martinez, 2015).
- Academic advising and coaching is especially useful with Hispanic student populations (Meléndez, 2007).
- At-risk student populations working with an academic coach display higher levels of self-efficacy and responsibility (Moore, 2015).

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Original Model: OGET Test Subareas

*	OGET Test Subareas	Range of competencies	Percentage of test
I	Critical Thinking Skills: Reading and Communications	0001–0005	20%
II	Communication Skills	0006–0008	12%
III	Critical Thinking Skills: Mathematics	0009–0011	16%
IV	Computation Skills	0012–0014	12%
V	Liberal Studies: Science, Art and Literature, Social Sciences	0015–0020	20%
			80%
	Constructed-Response		
VI	Critical Thinking Skills: Writing	0021	20%