Multiple Approaches to Assessing the Impacts of Student Success Initiatives: Three Examples at UNLV

John (Skip) Crooker, Qingmin Shi,
Tina Nelson, and Shiloh Bradley

Office of Decision Support
University of Nevada, Las Vegas

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Overview

1. Experimental Challenges
2. Decision Making
3. Student Success Initiatives
   a. First Year Seminar (FYS)
   b. 15-to-Finish
   c. Student Outreach Specialists (SOS)
4. Discussion and Questions

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Experimental Challenges

- Evaluating the effects of any initiatives:
  - Non-experimental data
  - No random sampling
  - No random assignment
  - Selection bias
  - Empirically separate the intervention impacts from those of other factors (complexity of the factors related)

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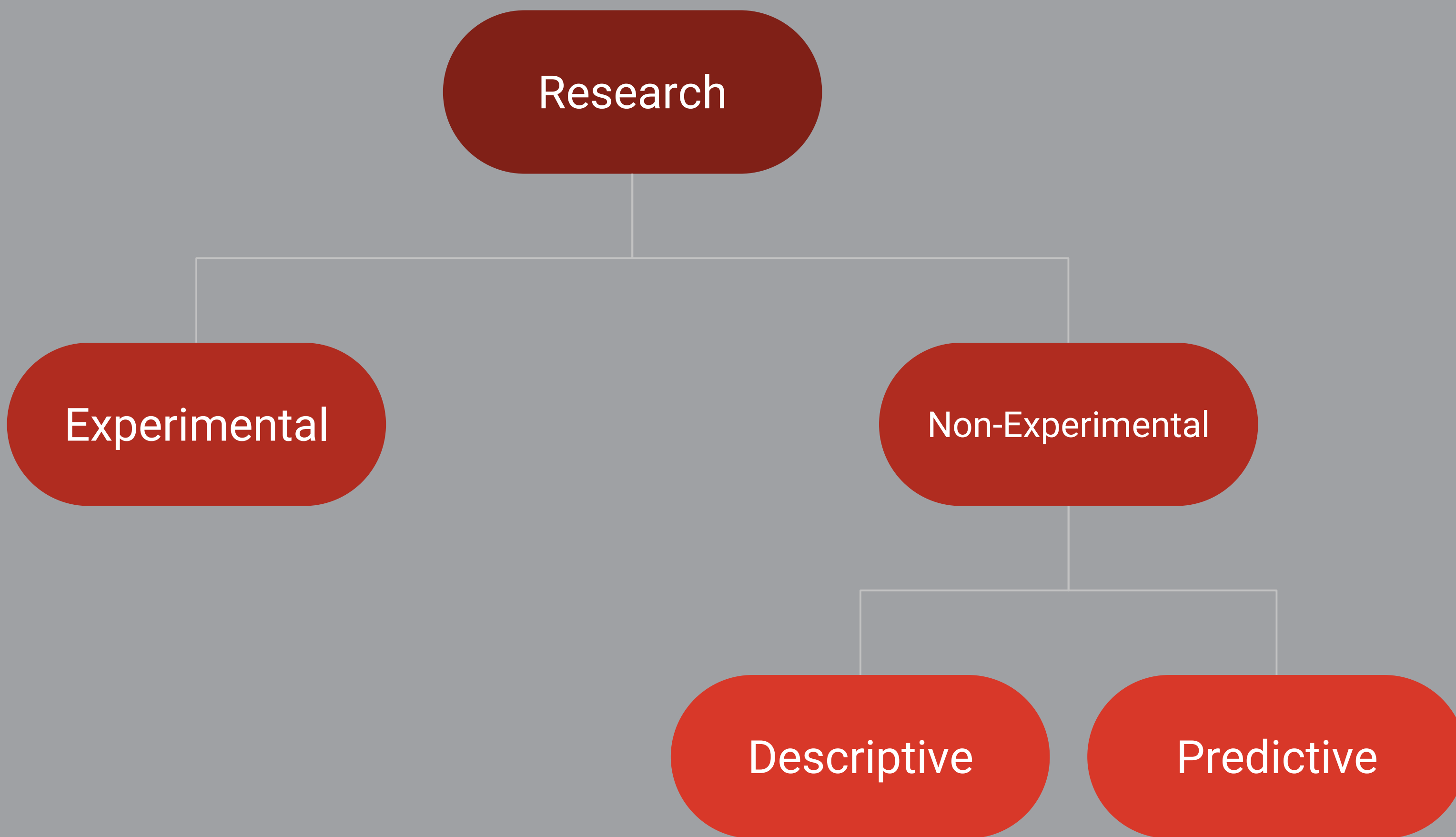
Making Decisions



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Student Success Initiatives

Our approaches to assessing the impacts of three campus-wide student success initiatives:

1. First-year seminars (FYS)
2. 15-to-Finish
3. Student Outreach Specialists (SOS) program

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Context of FYS

- Established as an academically rigorous 2-3 credit course in Fall 2012, the purposes of FYS are:
  - To introduce students to the research university's academic environment, and expectations, and UULOs as well.
  - To provide students with an understanding of the GE curriculum, academic success strategies, and career exploration.

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Context of FYS

- Estimate the impacts of FYS on retention and graduation
- Compared with FYS non-participants during the earlier period time (fall 2010 to fall 2011):
  - Are FYS students retained at a higher rate?
  - Do FYS students graduate within six years at a higher rate?
  - If students enroll in FYS, how do retention and graduation differ by FYS grade?

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Methods

- Cross-sectional data to estimate the effect of FYS on retention and graduation odds and likelihood:
  - Use probit model to estimate the probability of retention and graduation focusing on the effects of FYS enrollment and FYS grade
  - Calculate the odds ratios for retention and graduation by FYS enrollment and FYS grade
  - Learning Outcome Survey (LOS) data to assess student engagement and satisfaction with FYS

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Example of Results

Retention Odds Ratios by FYS Grade

Description	Odds Ratio
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=F)	2.663
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=D-)	1.819
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=D)	1.437
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=D+)	1.353
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=C-)	1.376
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=C)	1.227
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=C+)	1.157
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=B-)	1.081
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=B)	1.085
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=B+)	1.059
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|Grade=A-)	1.012

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Example of Results

Retention Odds Ratios by FYS Enrollment

Description	Odds Ratio
Pr(RET 2nd Fall|Grade=F)/Pr(RET 2nd Fall|No FYS)	0.629
Pr(RET 2nd Fall|Grade=D-)/Pr(RET 2nd Fall|No FYS)	0.921
Pr(RET 2nd Fall|Grade=D)/Pr(RET 2nd Fall|No FYS)	1.166
Pr(RET 2nd Fall|Grade=D+)/Pr(RET 2nd Fall|No FYS)	1.238
Pr(RET 2nd Fall|Grade=C-)/Pr(RET 2nd Fall|No FYS)	1.218
Pr(RET 2nd Fall|Grade=C)/Pr(RET 2nd Fall|No FYS)	1.366
Pr(RET 2nd Fall|Grade=C+)/Pr(RET 2nd Fall|No FYS)	1.448
Pr(RET 2nd Fall|Grade=B-)/Pr(RET 2nd Fall|No FYS)	1.551
Pr(RET 2nd Fall|Grade=B)/Pr(RET 2nd Fall|No FYS)	1.544
Pr(RET 2nd Fall|Grade=B+)/Pr(RET 2nd Fall|No FYS)	1.582
Pr(RET 2nd Fall|Grade=A-)/Pr(RET 2nd Fall|No FYS)	1.656
Pr(RET 2nd Fall|Grade=A)/Pr(RET 2nd Fall|No FYS)	1.676

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Why we chose this model

- Probit model estimates the probability of discrete outcomes
  - Binary classification model
  - Retention is a discrete outcome
- Odds ratio shows the ratio between the predicted probabilities from the probit model

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Recommendations

- Easy and quick to use
  - *glm()* function in R
- Good for predicting a binary outcome

Context 15-to-Finish

- Fall 2013, the Nevada System of Higher Education Board of Regents approved a proposal to adopt the Enrollment Intensity and Student Achievement Campaign, known as 15-to-Finish
- Encouraging 18 to 24 year old undergraduate students to enroll in at least 15 credits per semester or 30 credits per year
- Implemented in Fall 2014

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Research Questions of 15-to-Finish

- How well does the trained model predict student 15-to-Finish enrollment behavior?
- What are the outcome differences in retention and graduation rates for students who enrolled 15 or more credits in the first-fall term relative to students who enrolled less than 15 credits?

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Methods

- Using the Synthetic Control Method (SCM) and *Synth* package for R
  - Enables to construct a composite comparison unit by selecting a weighted average of the outcome variable from a group of units similar to the treated group
  - Provides a more valid counterfactual estimate involving only one treated unit (15-to-Finish) and a few control units (Abadie & Gardeazabal, 2003; Abadie et al., 2010; Bifulco et al. 2017; Bouttell et al. 2018).

Methods

- Training a credit hour enrollment model using Fall 2010 to Fall 2012 census data (pre-treatment)
- Using trained model to predict sequential enrollment, retention, and graduation of Fall 2013 to Fall 2015 (post-treatment) by grouping post-treatment cohorts into 10 mutually exclusive bins based on this predicted likelihood

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Methods

In-Sample Model Prediction (Pretreatment) and Out-of-Sample Prediction (Posttreatment)

		Pretreatment			Posttreatment		
Bin	**Likelihood**	**< 15**	**≥15**	**% of ≥15**	**< 15**	**≥15**	**% of ≥15**
1	0%-10%	**88**	**7**	7.4	65	31	32.3
2	10% - 20%	830	154	15.7	535	351	39.6
3	20% - 30%	3,056	927	23.3	1,756	2,009	53.4
4	30% - 40%	1,370	801	36.9	693	1,595	69.7
5	40% - 50%	504	522	50.9	303	945	75.7
6	50% - 60%	188	233	54.3	141	412	74.5
7	60% - 70%	92	131	58.7	53	231	81.3
8	70% - 80%	33	75	69.4	38	110	74.3
9	80% - 90%	16	38	70.4	17	63	78.8
10	90% - 100%	12	20	62.5	5	41	89.1

Why we chose this model

- No control group
- Difference in differences approach using historical behavior

Recommendations

- May not be ideal
- Need randomly assigned treatment
- Second best approach

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Context of the SOS Program

- Proactively serves academically disadvantaged students by linking students with available campus resources designed to improve student success
- Connects with incoming freshman undergraduate students who are at-risk of not completing their academic program with the campus resources
- Fosters engagement with the university, and develops a support network for students that traditionally have low social and academic capital

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Methods

- Decide which variables are input and output
- Scale and normalize the variables
- Train and test data using R package *neuralnet*
- Use output data as validation against what the SOS staff anecdotally say makes a student "at-risk"

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Methods

- Develop a dashboard to visualize and validate the results
- Analyze the data collected from the Campus Connect (EAB) from outreach specialists to identify the issues or concerns

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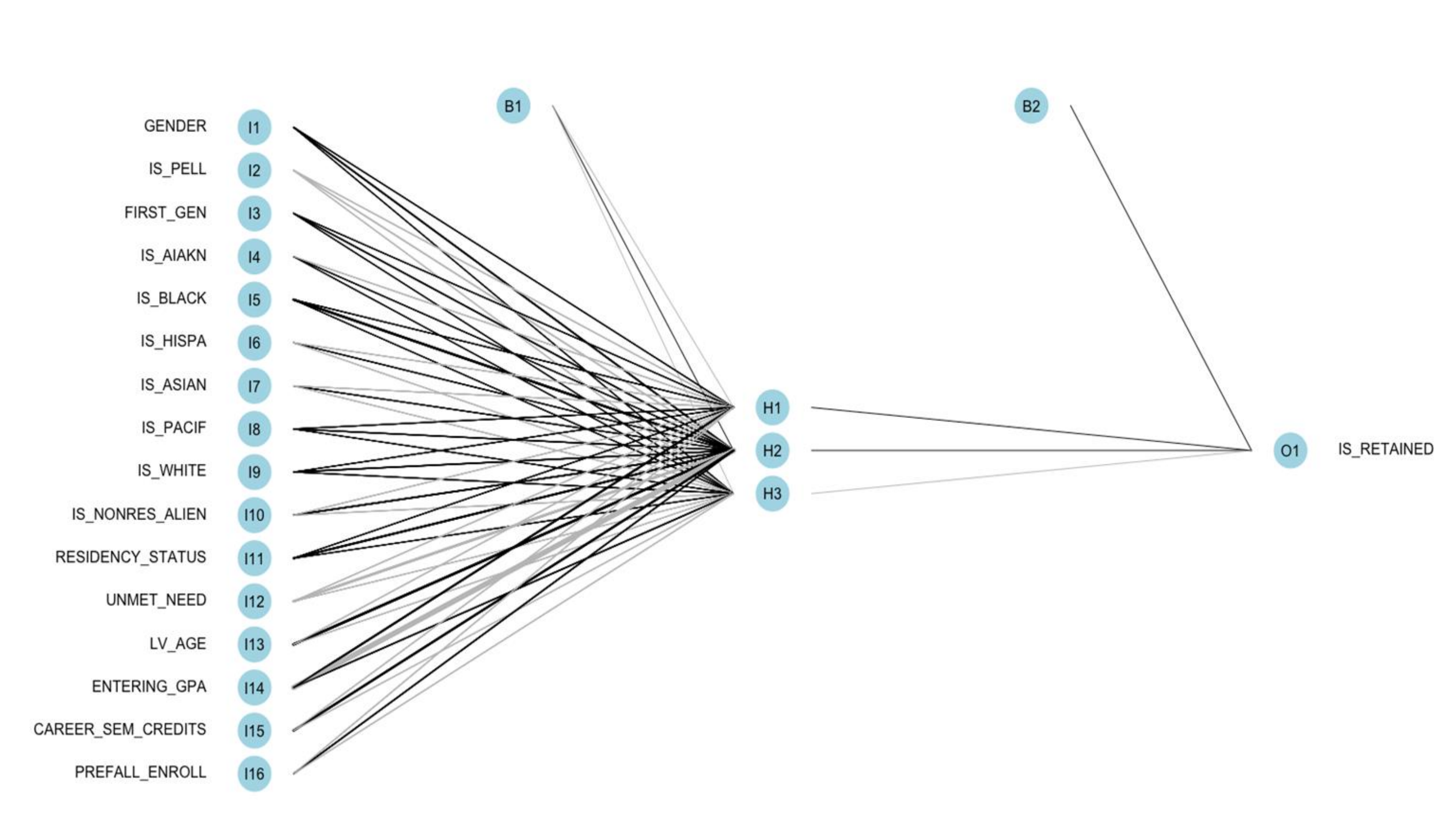
Example of Results



Example of Results

Fold <int>	RMSE <dbl>
1	0.3922480
2	0.3814138
3	0.3674106
4	0.3661701
5	0.3717440
6	0.3637305
7	0.3802578
8	0.3643151
9	0.3876821
10	0.3749915

	prediction	
actual	0	1
0	430	532
1	91	2663

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Why we chose this model

- Sounded fun
- Literature says model accuracy can be around 85-90%
- NN can perform cross-validation to obtain a more accurate and reliable estimate of model error

Recommendations

- Don't use this unless you have super high computing power or don't mind taking long breaks from work
- Models can take 30+ minutes to converge
- Accuracy is about the same as linear and logistic models which run in seconds

Discussion & Questions

Contact Us

iap@unlv.edu

ir.unlv.edu/IAP/

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Thank you!

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