Using Machine Learning to Predict Student Success and Combat Inequity

Nathan Greenstein Grant Crider-Phillips

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Welcome



Nathan Greenstein

Assistant Director of Machine Learning Academic Data Analytics, University of Oregon ngreenst@uoregon.edu



Grant Crider-Phillips

Machine Learning Analyst
Academic Data Analytics, University of Oregon
criderg@uoregon.edu

Academic Data Analytics



Academic Data Analytics

https://provost.uoregon.edu/analytics

- Office of the Provost
- Culture of data-driven decision-making
 - Shape policy
 - Prioritize equity
 - Increase transparency
- Focus areas:
 - Predicting student success
 - Understanding student feedback
 - Visualizing complex data
 - Understanding student and faculty progression

1. Project overview

2. Motivation

- 3. Our process
- 4. Early results and reflections
- 5. Discussion

Session Roadmap

Learning Goals

Understand applications of machine learning

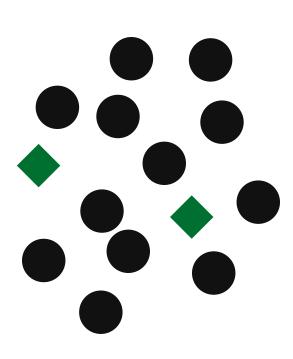
Engage with interplay between machine learning and **equity**

Identify implementation opportunities at home institutions

Project Overview • 0000



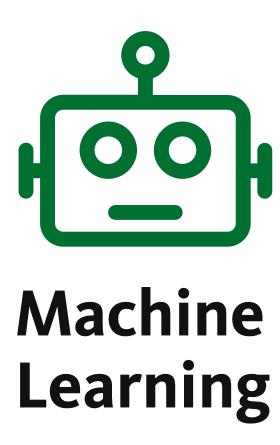
Prediction Task



Which incoming students will not persist to their second term?

- Predict before students matriculate
- Include all incoming first-time firstyear students
- Each year, use predictions to target early advising intervention

- Many varieties; today's focus is predictive analytics
- Harnesses large amounts of data and computing power
- Searches for **relationships** between inputs and outputs
- Finds patterns more complex than human eyes and traditional methods can handle
- Not magical, but powerful in the right situation



Motivation

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Central Challenge

Non-Retention

- Damaging to students and university
- Disproportionately impacts most
 vulnerable students

Timely Intervention

- **Difficult to recover** from early negative experiences
- Proactive
 interventions are
 more effective than
 reactive ones

Finite Resources

- **Fewer advisors** than students
- Must choose who receives a given intervention first

Central Challenge

Can we predict which incoming students will not persist to their second term?

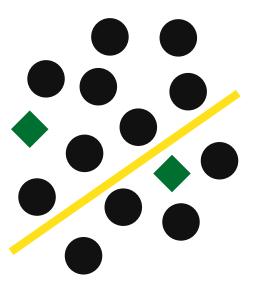
How early can we make our predictions?

Non-Retention

Timely Intervention

Finite Resources

- Early advising already in place
- Mathematical model already in use
 - Predicts first-term GPA
 - Traditional linear regression
 - Unable to predict second-term retention
- A useful tool, but a compromise
- Not evaluated for equity



Status Quo **Promises**

- Greater predictive power
- Better equipped for **challenging outcomes**
- Harnesses bigger, messier data

Concerns

- Will human stakeholders lose their voice?
- Might the algorithm be biased or inequitable?
- How much transparency will be offered?

Machine Learning

Our Process





Process Commitments

PARTICIPATORY

Engage meaningfully with a range of stakeholders

TRANSPARENT

Report honestly and accessibly on process and outcomes

EQUITY-ORIENTED

Apply lens throughout; demonstrably advance equity

Process Highlights

Participatory

- Partner closely with
 Undergraduate
 Education and
 Student Success
- Converse with other offices
- Reflect student body through diverse data sources

Transparent

- Report actively to UESS throughout
- Publicly disseminate methods and results
- Acknowledge strengths and limitations

Equity-Oriented

- With stakeholders,
 define equity
 standards
- Ground our work in existing scholarship
- Thoroughly vet model for equity and revise as necessary

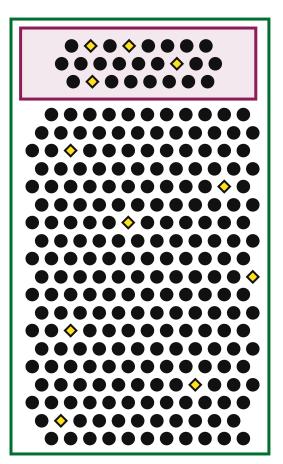
Early Results & Reflections ••••



Model Performance, 2021 Cohort

ADA Model

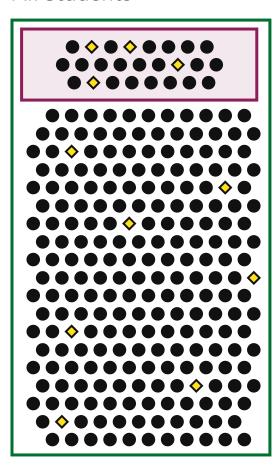
All Students



Model Performance, 2021 Cohort

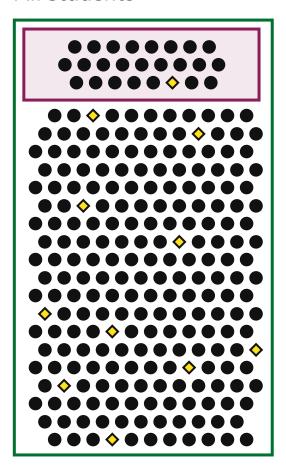
ADA Model

All Students



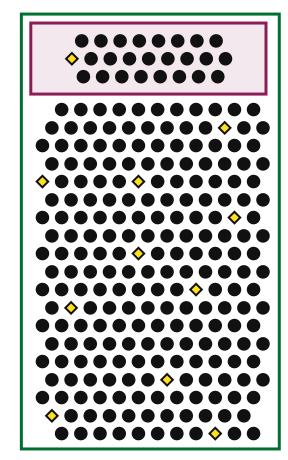
GPA Alternative

All Students



Random Lottery

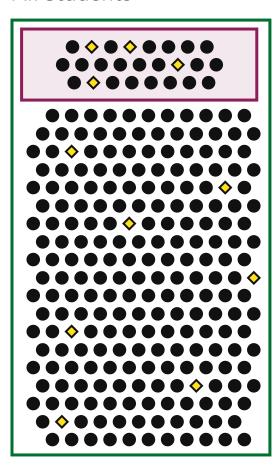
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Model Performance, 2021 Cohort

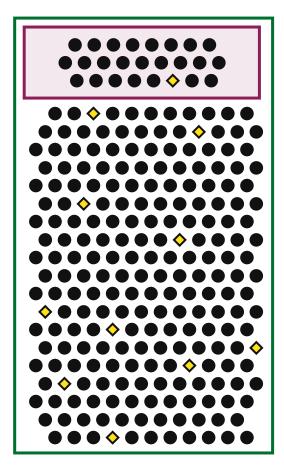
ADA Model

All Students



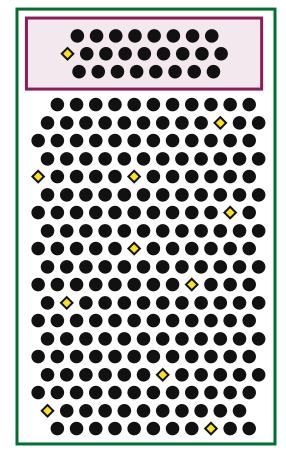
GPA Alternative

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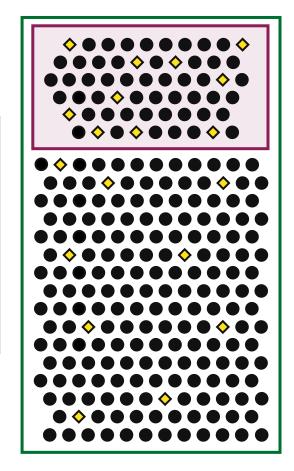
Random Lottery

All Students

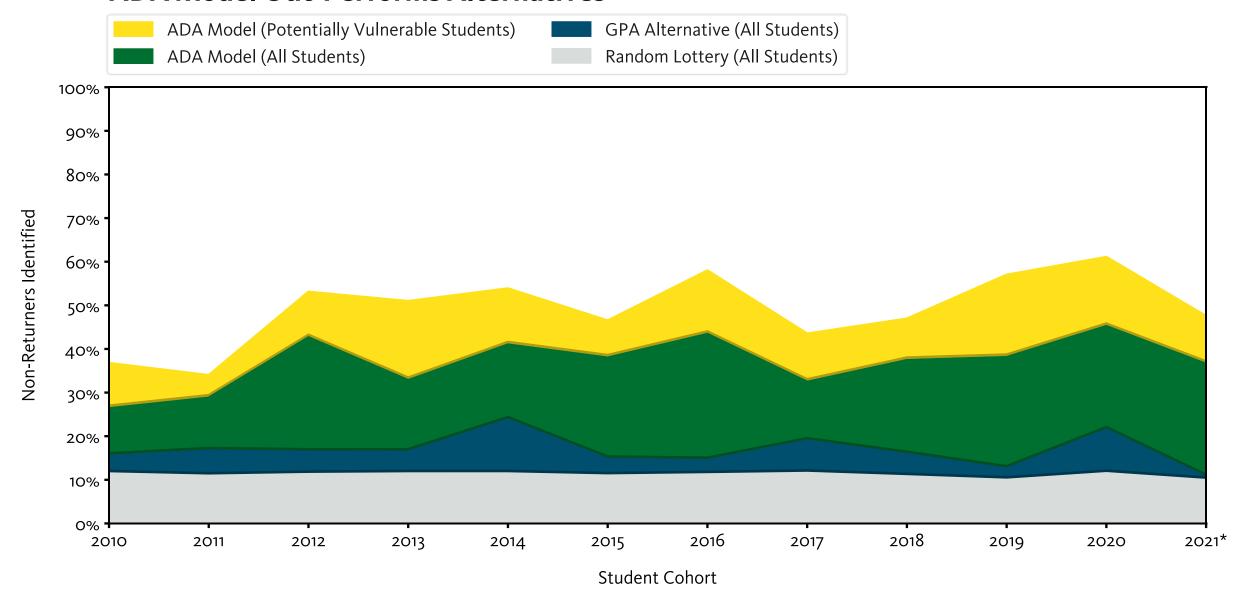


ADA Model

Potent. Vuln. Students



ADA Model Out-Performs Alternatives

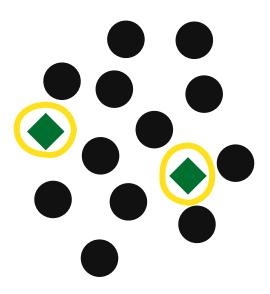


^{*} The 2021 cohort was hidden from the model during development. Each cohort's performance is based on a model trained with all cohorts' data, except the cohort in question and 2021.

- Refine model **performance**
- Expand equity analysis; make any necessary adjustments
- Deploy for incoming students this year



Reflections



- Confident that performance exceeds alternatives
- Room to continue improving
- Growing confidence in model equity
- Process was extremely successful
- Thoughtful approach, plus working in-house, enables responsible machine learning
- Ultimately, harnessed powerful new tools without undermining human stakeholders or potentially vulnerable students

Discussion •••••



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Open Discussion



Thank you!

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Academic Data Analytics Office of the Provost University of Oregon

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Academic Data Analytics

