Using Machine Learning to Combat Inequity & Predict Student Success

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April 13, 2023

UNIVERSITY OF OREGON | Academic Data Analytics

Welcome

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Session Roadmap

1. Organizational background
2. Winter retention case study
3. Approach to machine learning
4. Discussion

Organizational Background

Academic Data Analytics

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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

Winter Retention Case Study

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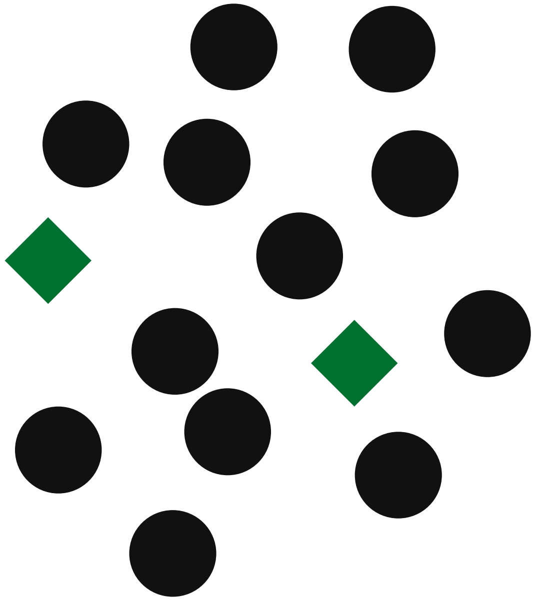
Prediction Task



Which incoming students will not persist to their second term?

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

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

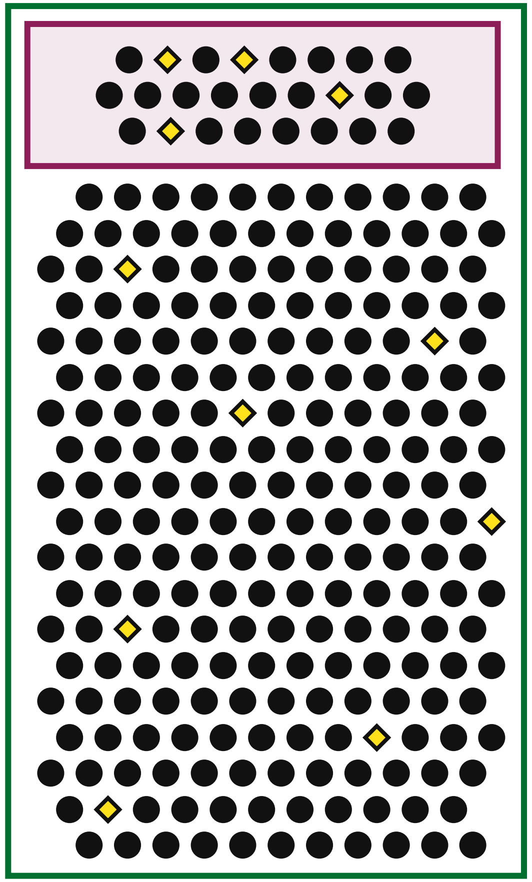
Timely Intervention

Finite Resources

Model Performance, 2021 Cohort

ADA Model

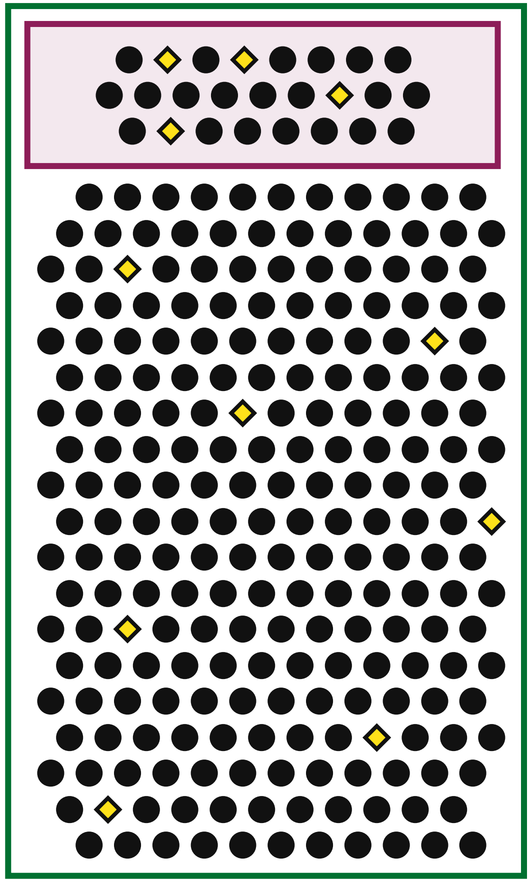
2021 Cohort



Model Performance, 2021 Cohort

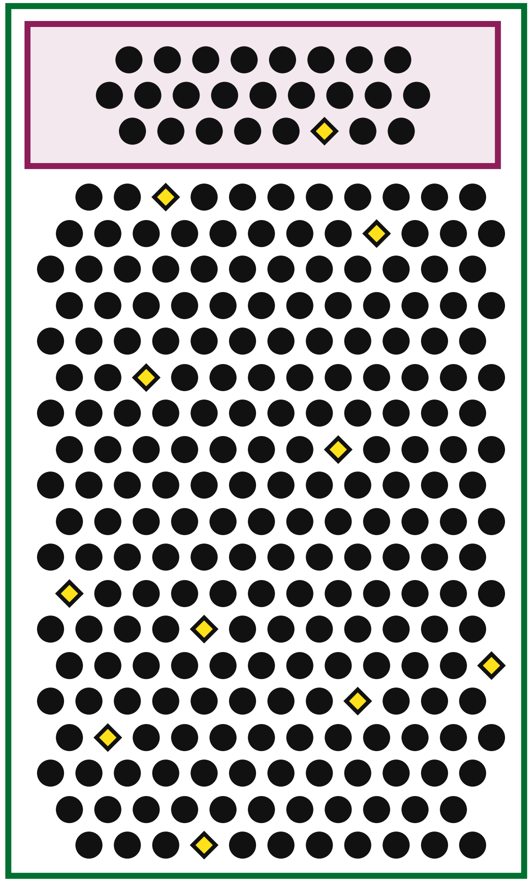
ADA Model

2021 Cohort



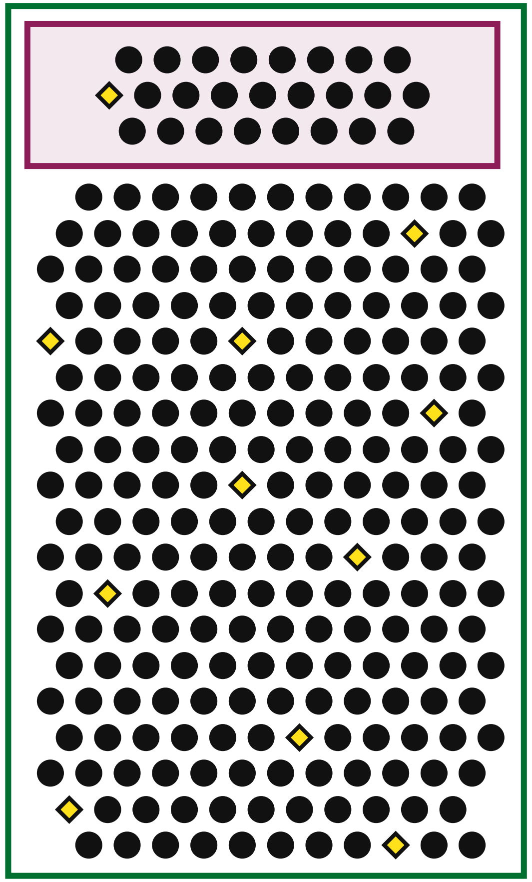
GPA Alternative

2021 Cohort



Random Lottery

2021 Cohort



Approach to Machine Learning

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Machine Learning

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?

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

Discussion

Thank you!

Nathan Greenstein
Grant Crider-Phillips

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Office of the Provost
University of Oregon

https://provost.uoregon.edu/analytics

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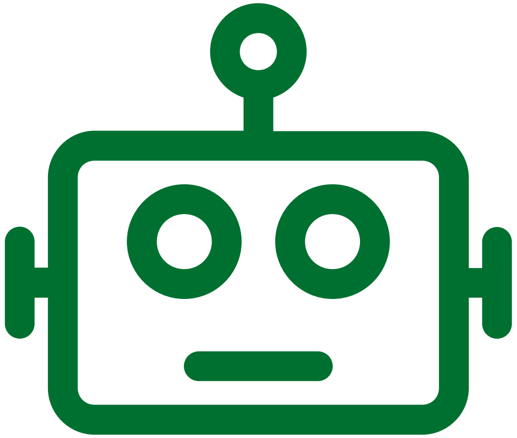
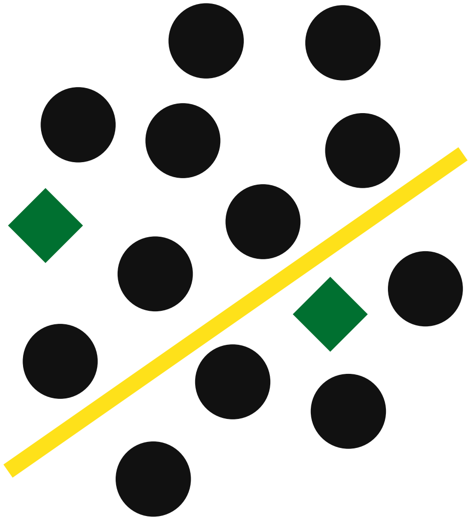
Appendix



Machine Learning

- 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**

- **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**



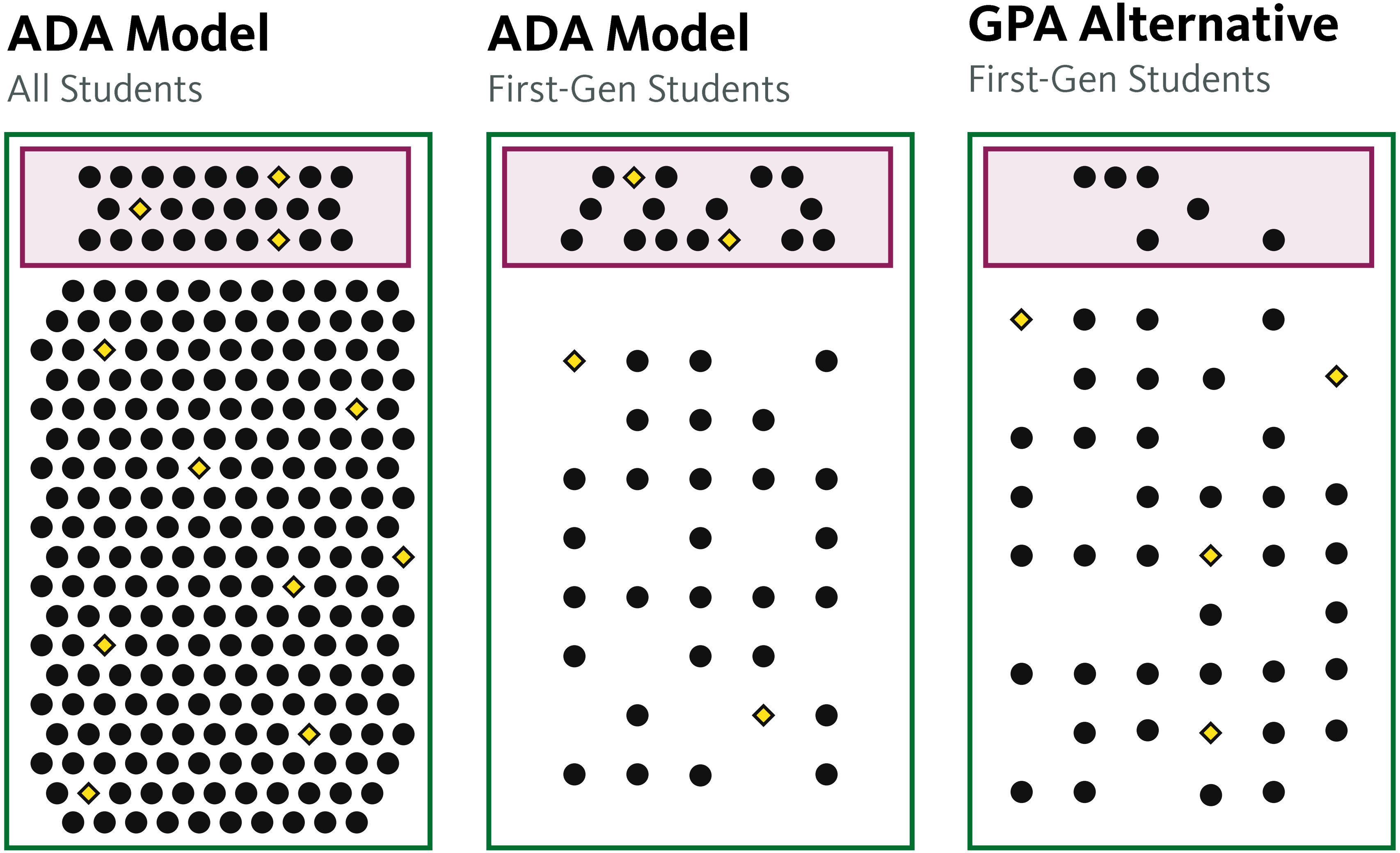
Status Quo

Initial Guardrails

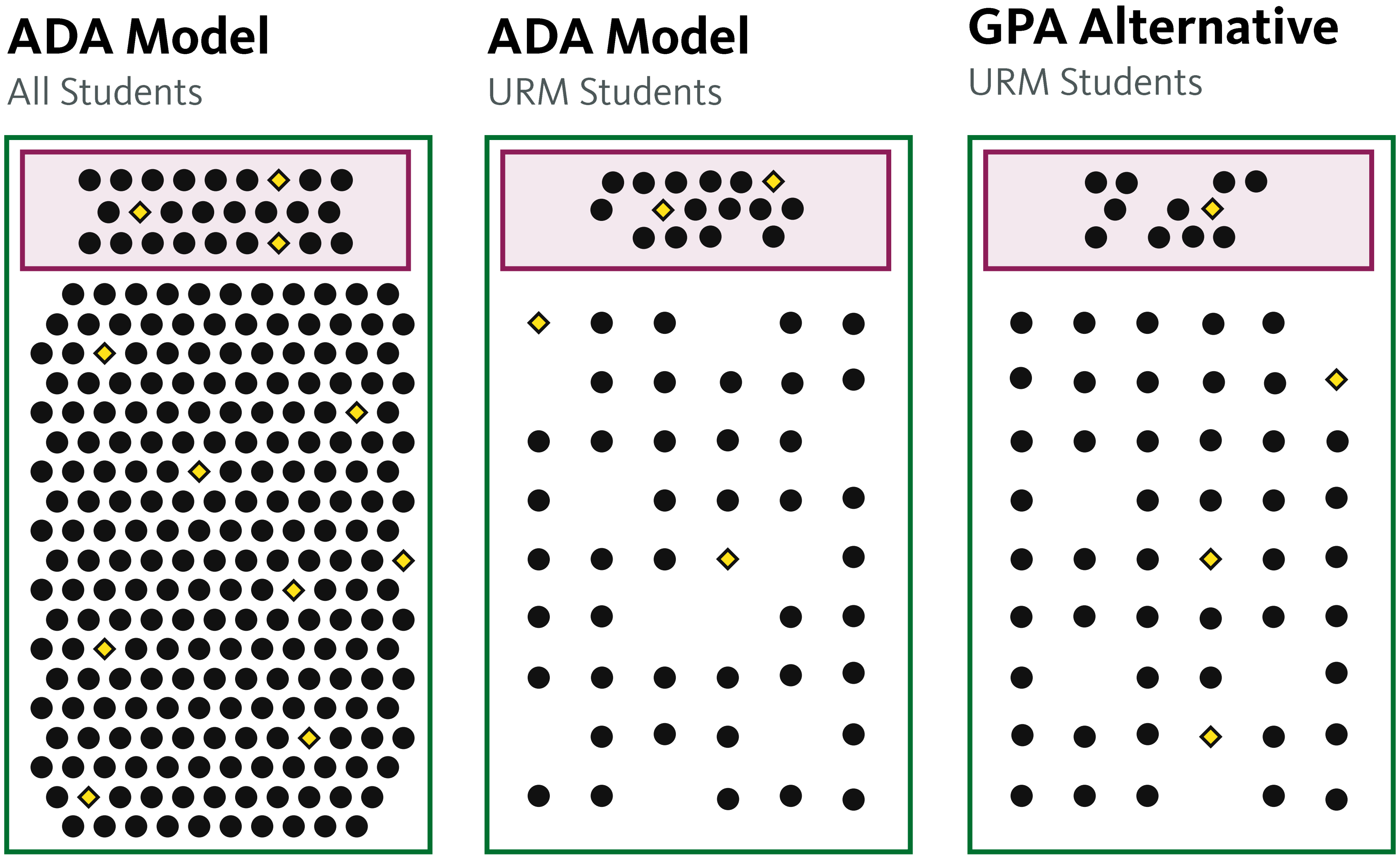
Do No Harm

- Focus on model **performance**
- Compare specific groups to **everyone**
- Ensure that:
  - **Vulnerable** groups: ≥ **85%**
  - **Privileged** groups: **≥ 75%***

First-Gen Performance, 2021 Cohort



URM Performance, 2021 Cohort



Equity Performance Comparison

Model Performance (% of Non-Returners Targeted)	All Students	First-Generation	URM Race/Ethnicity				
			All	Black / African American	American Indian / Alaskan Native	Native Hawaiian / Other Pacific Islander	Hispanic / Latinx
Training Cohorts (2010 thru 2020)	100%	149%	146%	172%	134%	103%	147%
Validation Cohort (2021)	100%	129%	149%	110%	120%	–	160%

Cells representing fewer than 10 students are not reported.

Including Race

- Equity depends on **real-world use**
  - Sometimes need parity
  - Sometimes need **dis**parity
- Withholding race **does not ensure equity**
  - Proxy variables
  - Unbalanced data
- Model bias can be **measured** and **corrected**
  - **Empirical** metrics quantify bias
  - Corrective technologies **adjust** model
  - Use together for real **accountability**