Logistics: Project

- Project presentation
  - Dec 7/9 during lectures
  - Everyone is expected to attend both lectures
  - 10 minutes for presentation + 1~2 minutes for QA and transition

  - A good practice to leverage what you learned (through giving presentations and observing others) to prepare for this final presentation

Logistics: Project

- Project reports
  - Due: Dec 12 (no late submissions)
  - Up to 6 pages (plus additional pages for only references/citations)
  - No strict format requirements
    - You are encouraged to use standard templates, such as AAAI format or NeurIPS format
  - For research projects
    - Your report should be structured in a way similar to the research papers we have read throughout the semester. (e.g., include introduction, related work, research problem or formulation, your proposed approach, results, conclusions).
  - For literature surveys
    - Do not summarize papers one by one.
      Find a theme, categorize papers, and put them in context.
    - Example: Making Better Use of the Crowd: How Crowdsourcing Can Advance Machine Learning Research. Vaughan. JMLR 2018.

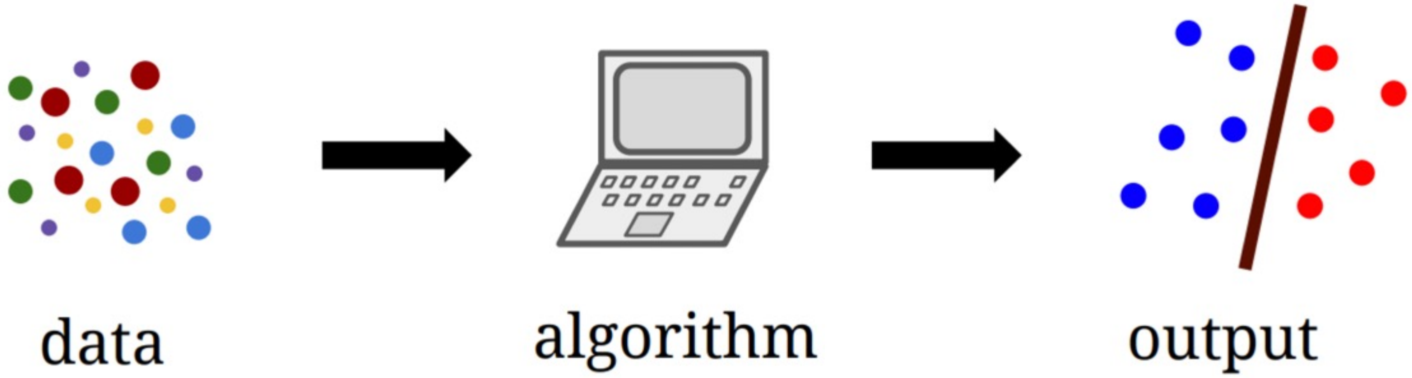
Lecture 21
Strategic Classification

Nov 16	Selected Recent Topics: Strategic Machine Learning	**Required** Strategic Classification. Hardt et al. ITCS 2016. Note: This is a more math-heavy reading. It is okay to skip the analysis in Section 2~4. But please try to understand the formulation and the main results. **Optional** How Do Classifiers Induce Agents To Invest Effort Strategically? Kleinberg and Raghavan. EC 2019. The Disparate Effects of Strategic Manipulation. Hu et al. FAT* 2019. Performative Prediction. Perdomo et al. ICML 2020.

Instructor: Chien-Ju (CJ) Ho

Classification

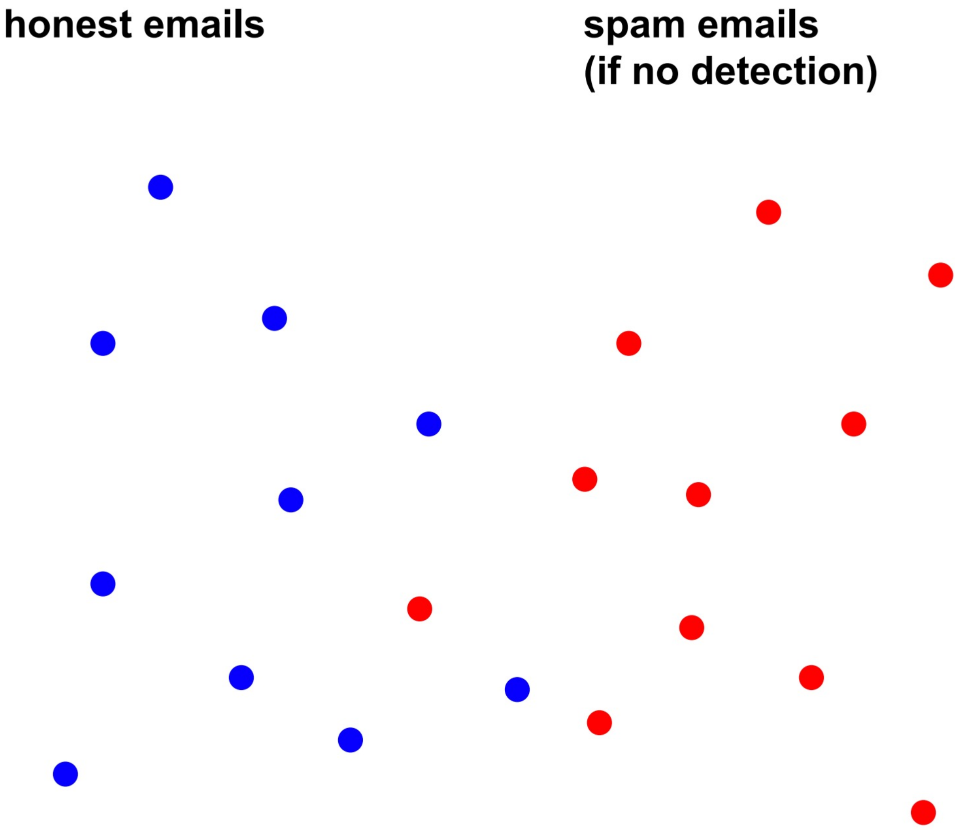
- Standard setup of (supervised) machine learning



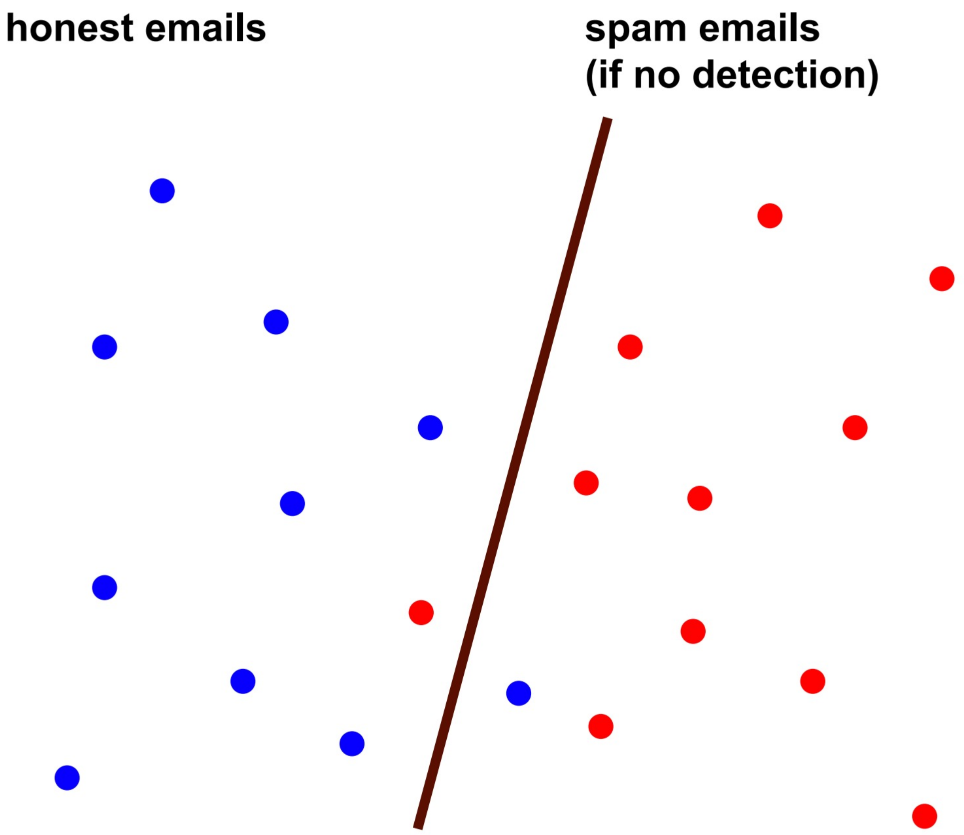
  - Finding patterns from the given training datasets
  - Use the pattern to make predictions on new testing data

- Fundamental assumption:
  - Training and testing data points are i.i.d. drawn from the same distribution

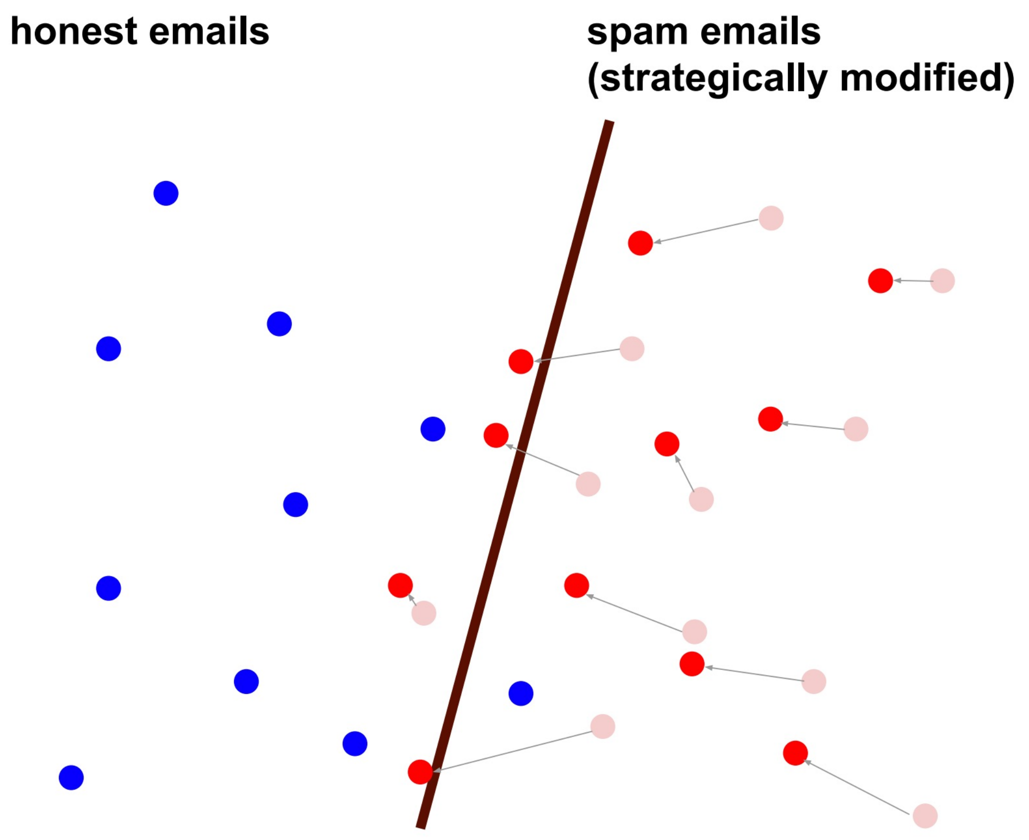
Example: Spam Filter



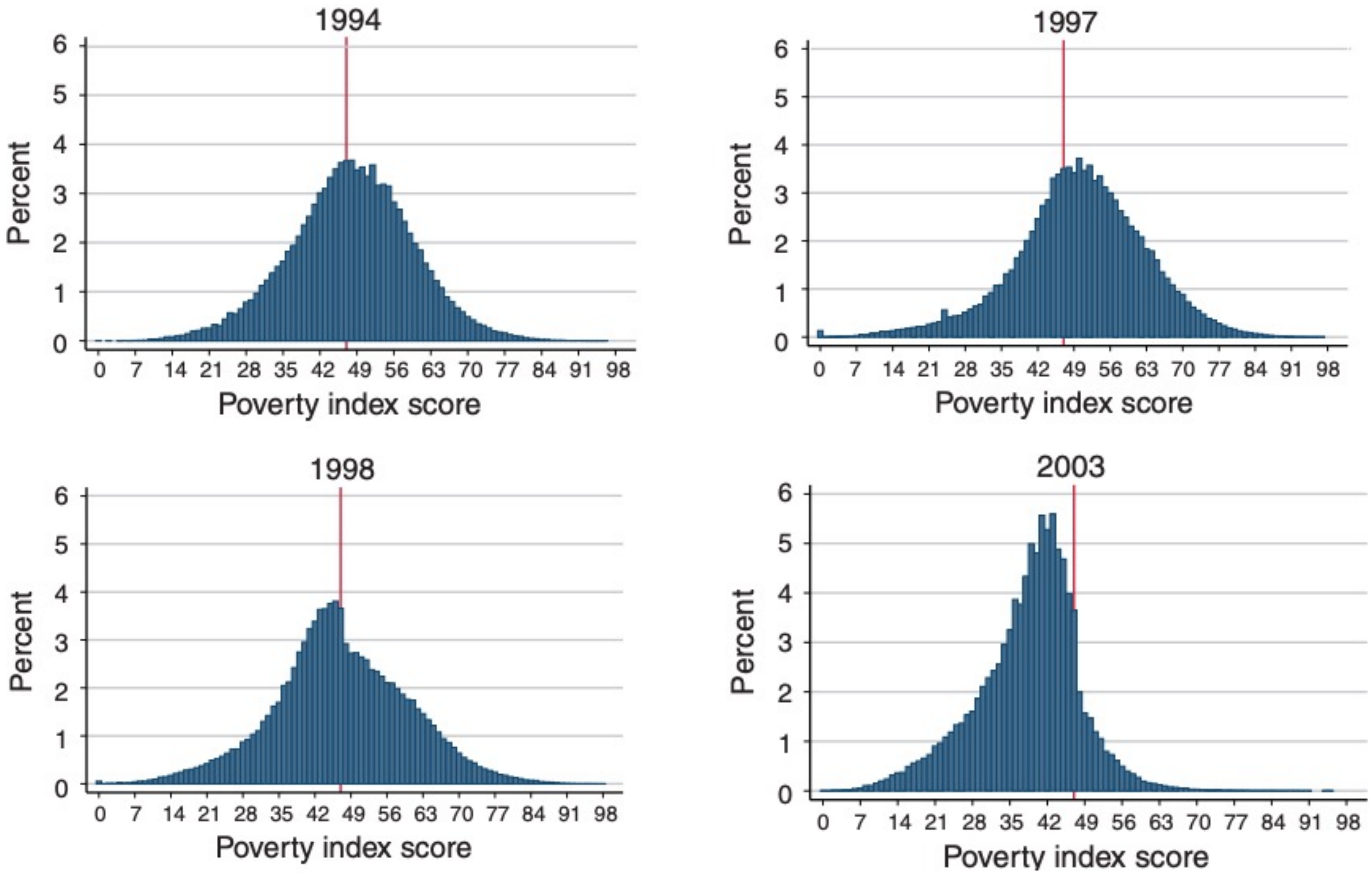
Example: Spam Filter



Example: Spam Filter

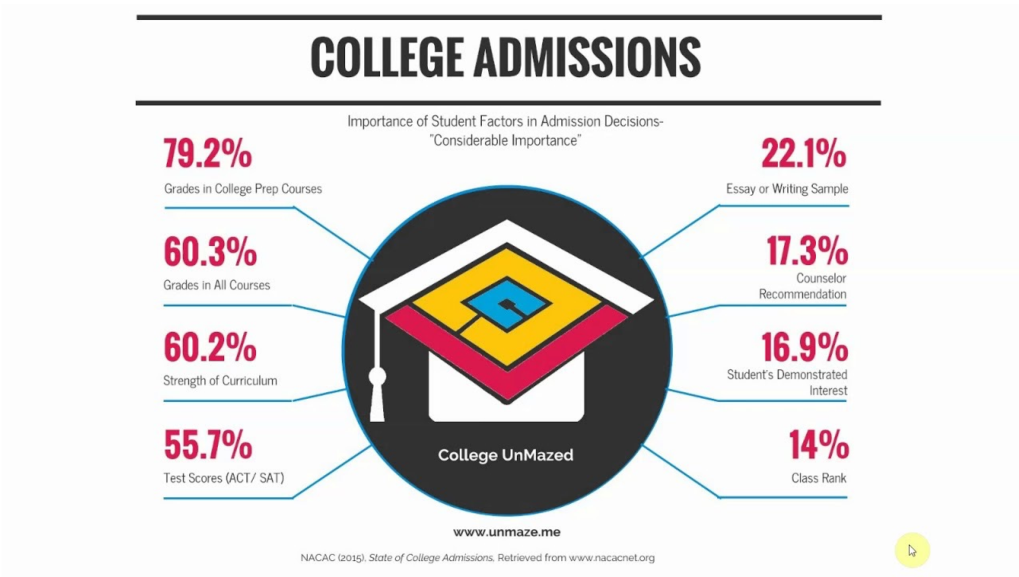


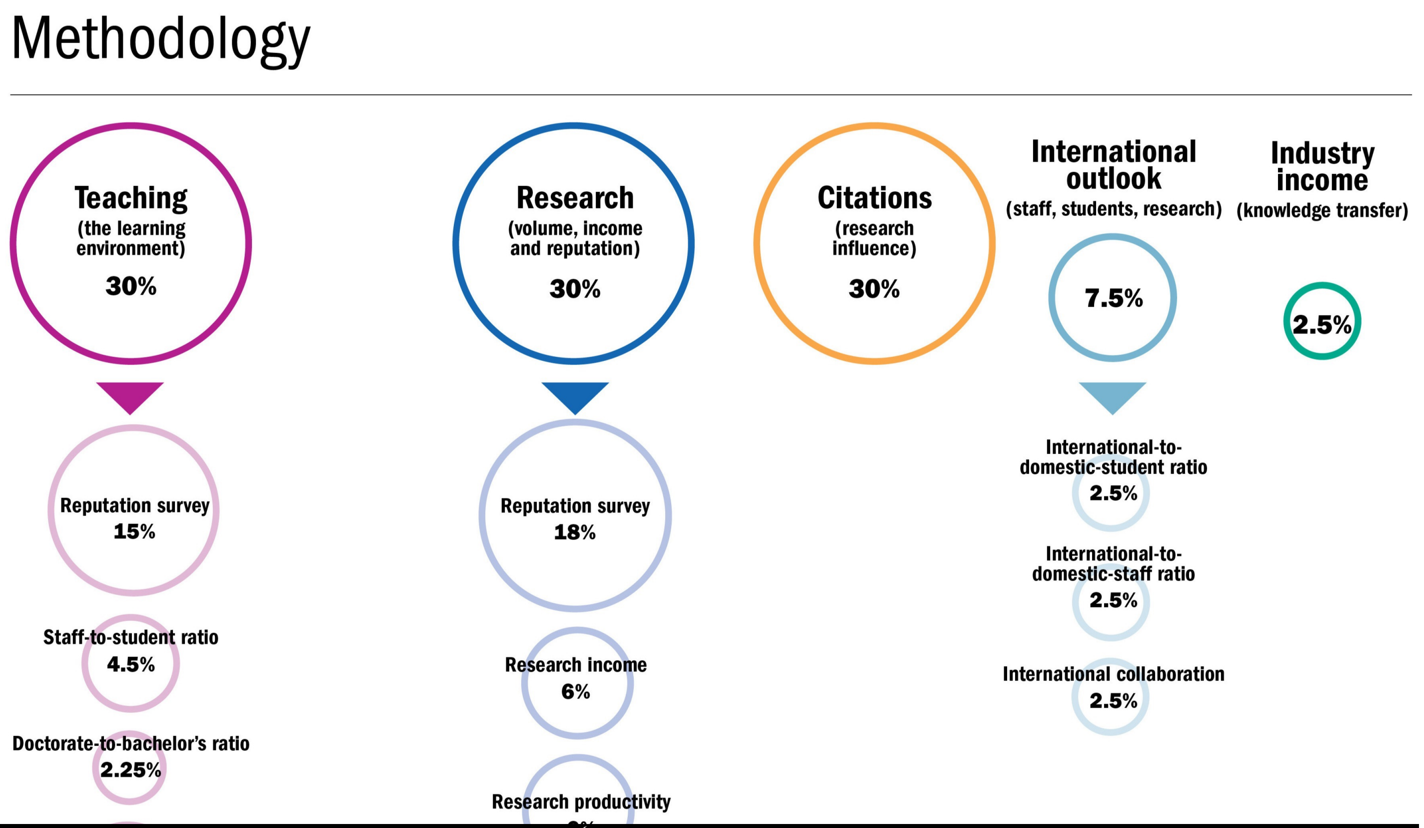
Social Program Eligibility [Camacho and Conover, 2012]

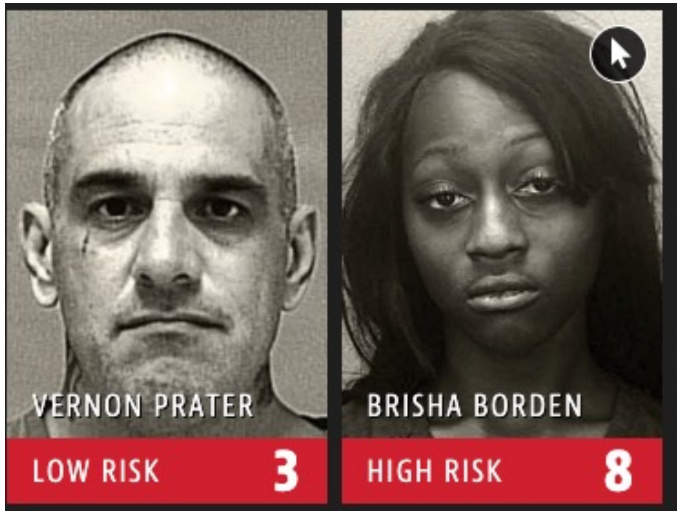


Goodhart’s law:

“If a measure becomes the public’s goal, it is no longer a good measure.”








The Washington Post
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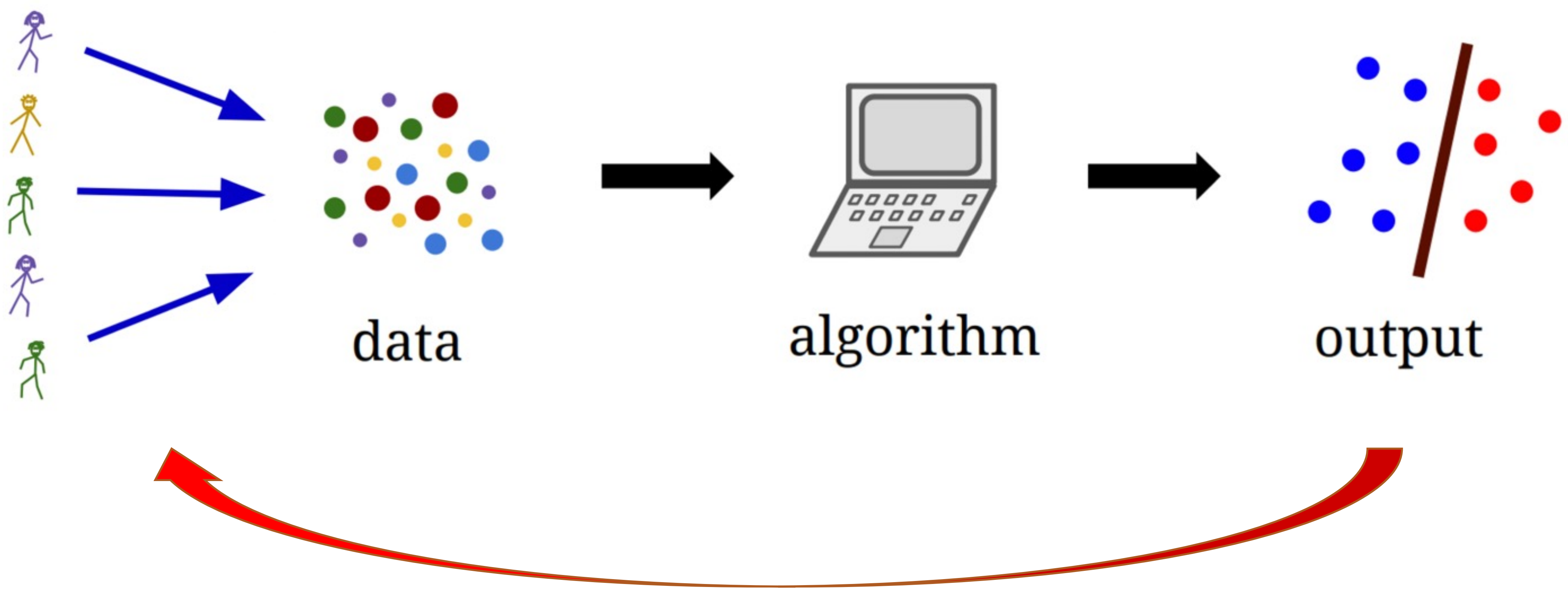
Opinion: I lead America's top-ranked university. Here's why these rankings are a problem.

By Christopher L. Eisgruber
October 21, 2021 at 2:39 p.m. EDT

Strategic Classification

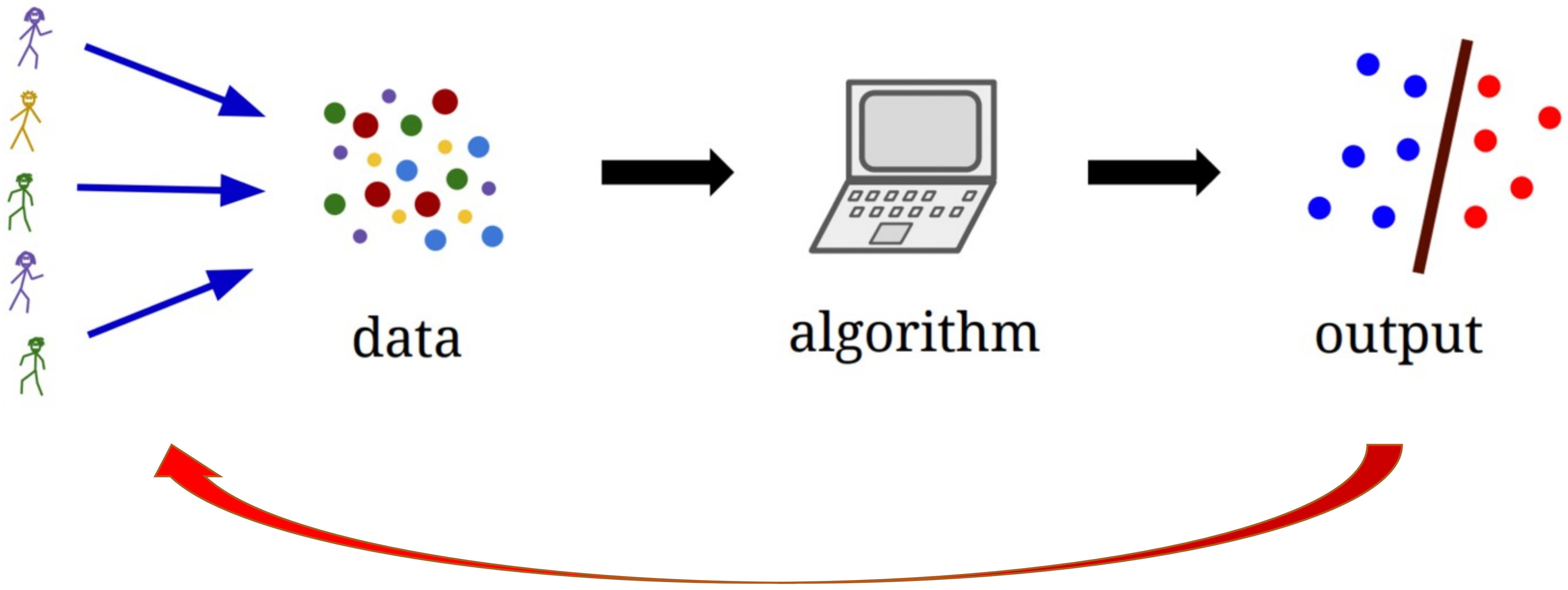


Warm-Up Discussion

- What are other examples of strategic classifications in the real world? What are the potential consequences of not considering the issues of strategic manipulations?

- On a high-level, what do you think can be done to help mitigate or address the issues of strategic manipulations?
  - As an example, Google keep secret of their ranking algorithms in the search results. Then companies that focus on SEO (search engine optimization) try to find out how the algorithms works. Is secrecy a good approach? What other options do we have?

Strategic Classification



How to take this interaction between ML algorithms and data-holders into account?

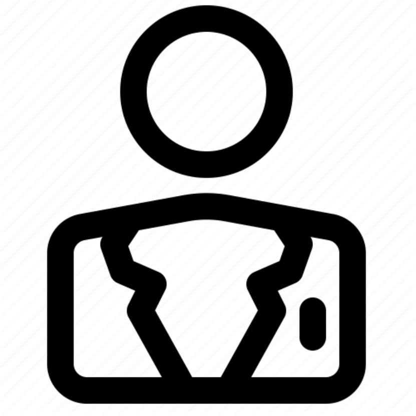
Game theoretical modeling

Game Theoretical Modeling

- Key elements:
  - Players, actions, payoffs

- Players: Jury (e.g., university) and Contestants (student applicants)
- Actions:
  - First, Jury decides on the machine learning model (binary classification)
  - Then, Contestant decides how to alter their features based on the model
- Payoffs
  - Jury wants to maximize the probability of **correct** predictions
  - Contestants want to be **selected** (being predicted as 1)

Choose a classifier
$f: X \to \{0,1\}$



Represented by initial features
$\vec{x}$ = (SAT score, GPA, etc)

True label $y = h(\vec{x}) \in \{0,1\}$

Choose manipulation (new $\vec{x}'$)
cost(initial $\vec{x}$, new $\vec{x}'$)

Student distribution D

Given f, student with $\vec{x}$ chooses to manipulate her feature to $\vec{x}'$ to maximize

$$f(\vec{x}') - cost(\vec{x}, \vec{x}')$$

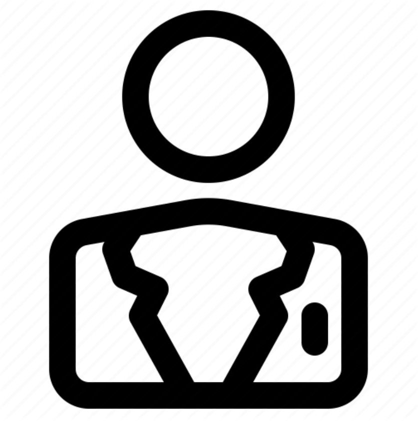
The university chooses the classifier f with the goal to maximize

$$\Pr_{\vec{x} \sim D}[f(\vec{x}') = h(\vec{x})]$$

Stackelberg Game
- Similar to the "contract design" problem
- The "classifier" is a contract

Choose a classifier

$f: X \to \{0,1\}$



Represented by initial features

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True label $y = h(\vec{x}) \in \{0,1\}$

Choose manipulation (new $\vec{x}'$)

cost(initial $\vec{x}$, new $\vec{x}'$)

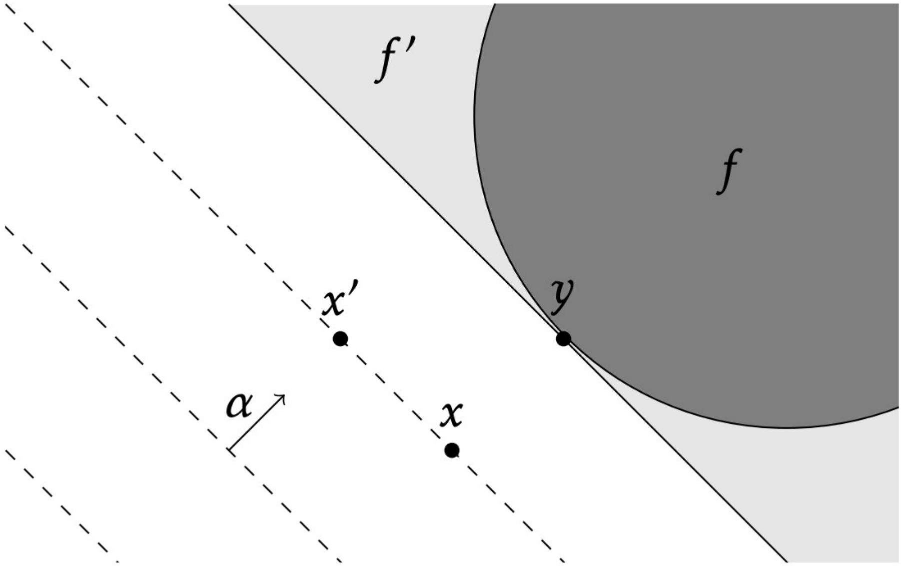
Student distribution D

Research question of the required reading:

Design the algorithm for computing the optimal f when taking strategic manipulations into account.

Main Results

- In general cases, finding the classification rule with near-optimal performance is NP-hard.
- In special cases, there exist efficient algorithms
  - E.g., when $\text{cost}(\vec{x}, \vec{x}') = \vec{\alpha} \cdot (\vec{x}' - \vec{x})$



More Aspects of Strategic Classification

1. Evaluation vs. Incentive
2. Social costs

Types of Manipulations

- Say that your insurance company wants you to stay healthy (so they can pay less) and decide to reward you if you hit the step target on your phone.

Gaming vs. Improvement

- Gaming
  - Alter the decision by manipulating proxy features without changing the underlying label
    - Unjustifiable or pointless effort
    - Considered in the required reading
- Improvement
  - Change the decision by manipulation that changes the underlying label
    - Maybe this is the positive effect that we want to utilize

The Purposes of Decision Rules

- To evaluate the candidates
  - Assume there is a true unobservable quality that we care about
    - e.g., whether the student will succeed or not
  - Unobservable quality leads to observable but manipulatable features
  - Aims to classify based on the true quality with gaming behavior

- To incentivize the candidates
  - Assume the true unobservable quality can be improved
  - Incentivize candidates to perform desired improvements

Discussion

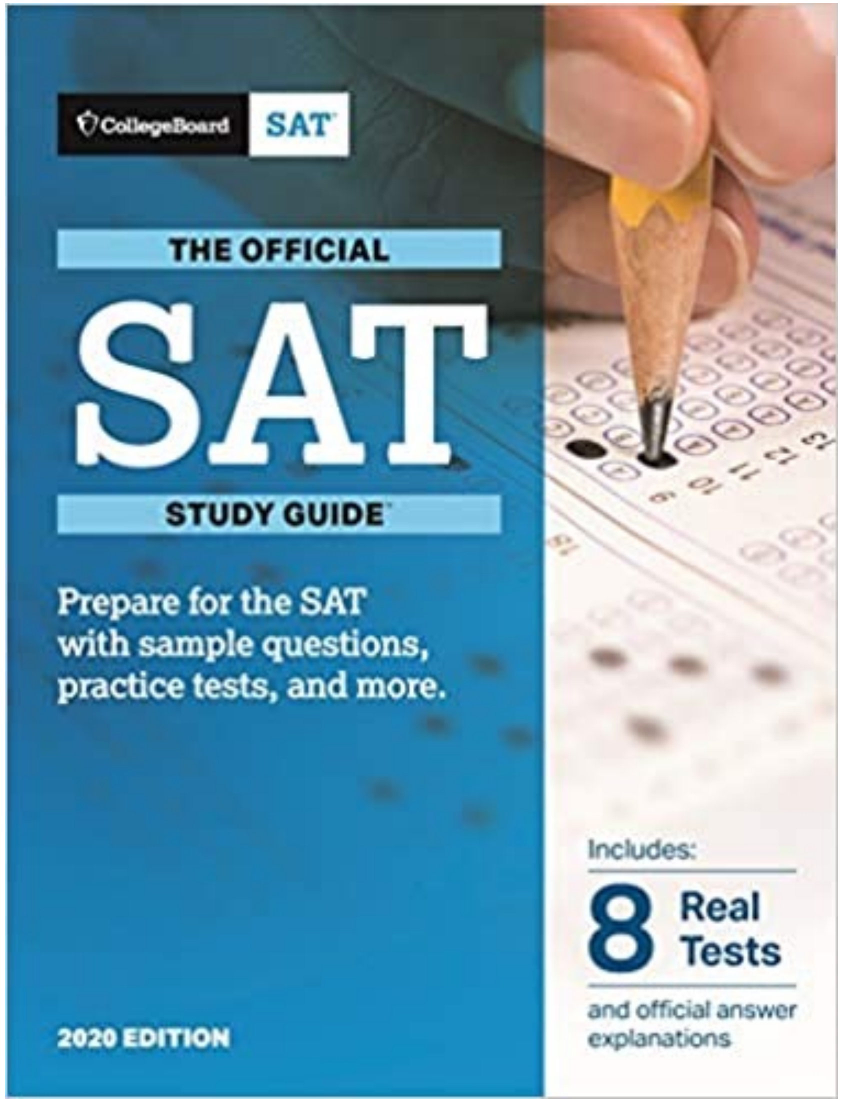
- Think about examples that we can use classification as incentive to motivate desired actions.

- How can we design the incentives?
  - Informally, what behavior do you want to encourage, and how to make the classification rule achieve that?
  - Formally, how the classification rule should look like? How to find the "optimal" rule?

- Example: how the course grades are split up would impact what you do for the course. What's the "best" way to design the grades? (What should be the desired behavior?)

How do classifiers induce agents to invest effort strategically?

Kleinberg and Raghavan. EC 2019.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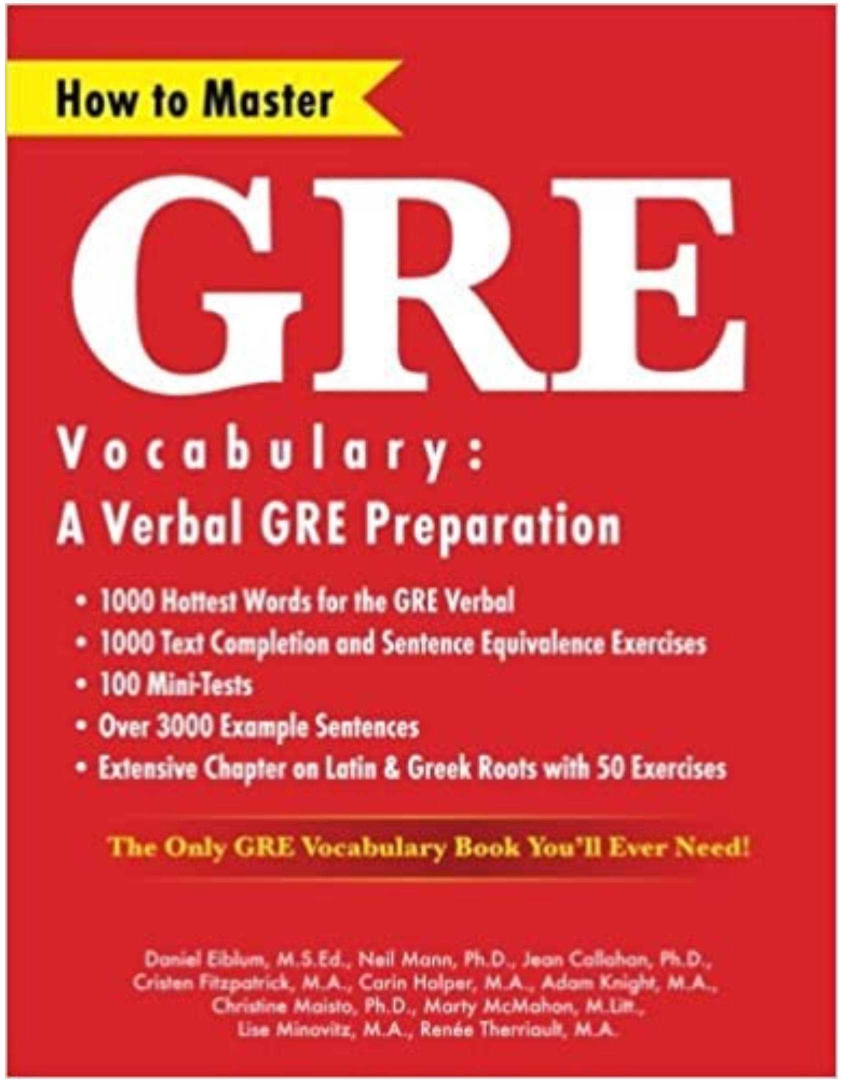
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Vocabulary:
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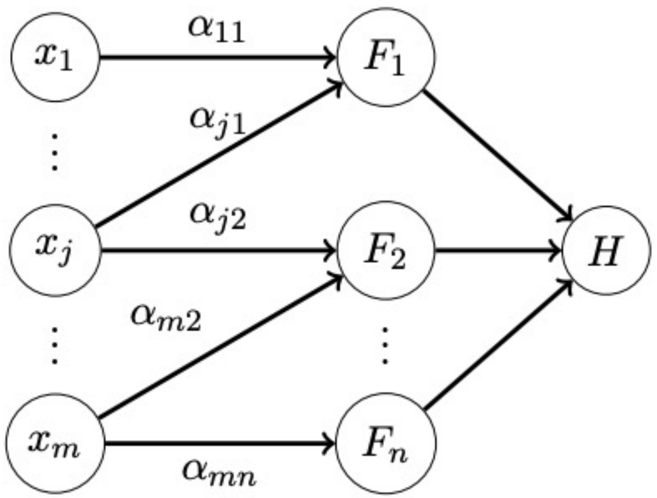
Daniel Eiblum, M.S.Ed., Neil Mann, Ph.D., Jean Callahan, Ph.D., Cristen Fitzpatrick, M.A., Carin Halper, M.A., Adam Knight, M.A., Christine Maisto, Ph.D., Marty McMahon, M.Litt., Lise Minovitz, M.A., Renée Therriault, M.A.

- “Test preparation has been the focus of intense argument for many years, and all sorts of different terms have been used to describe both good and bad forms. . . I think it’s best to. . . distinguish between seven different types of test preparation: Working more effectively; Teaching more; Working harder; Reallocation; Alignment; Coaching; Cheating. The first three are what proponents of high-stakes testing want to see”
- - Daniel Koretz, Measuring Up.

How to induce the desired behavior?

Graphical Representation of the Model

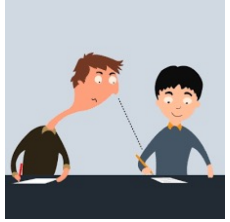
- Consider a single student
  - $x_1, \ldots, x_m$: the effort students spent on actions
    - E.g., studying, working in a reading group, copying answers online
  - $F_1, \ldots, F_n$: the set of observable features after actions
    - E.g., homework grades, exam grades
  - $\alpha_{i,j}$: the contribution to feature F_i from action x_j
    - $F_i = f(\sum_{j=1}^{m} \alpha_{j,i} x_j)$



- The teacher designs the final grades H based on F
  - $H = \sum_{i=1}^{n} \beta_i F_i$

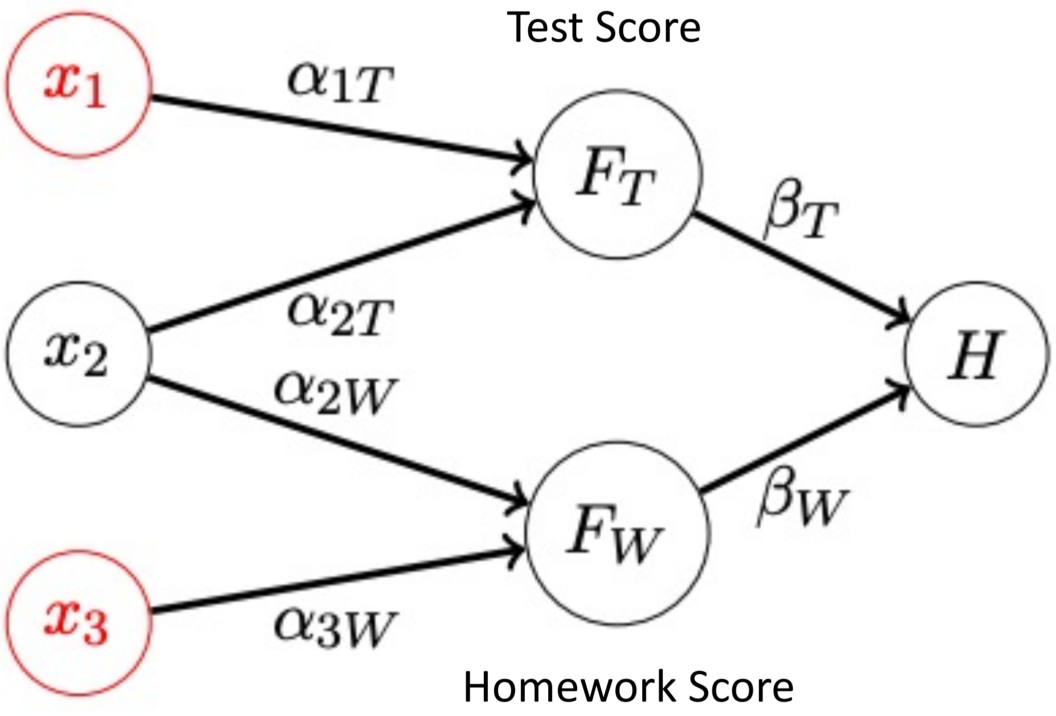
Example: Course Grades

cheating

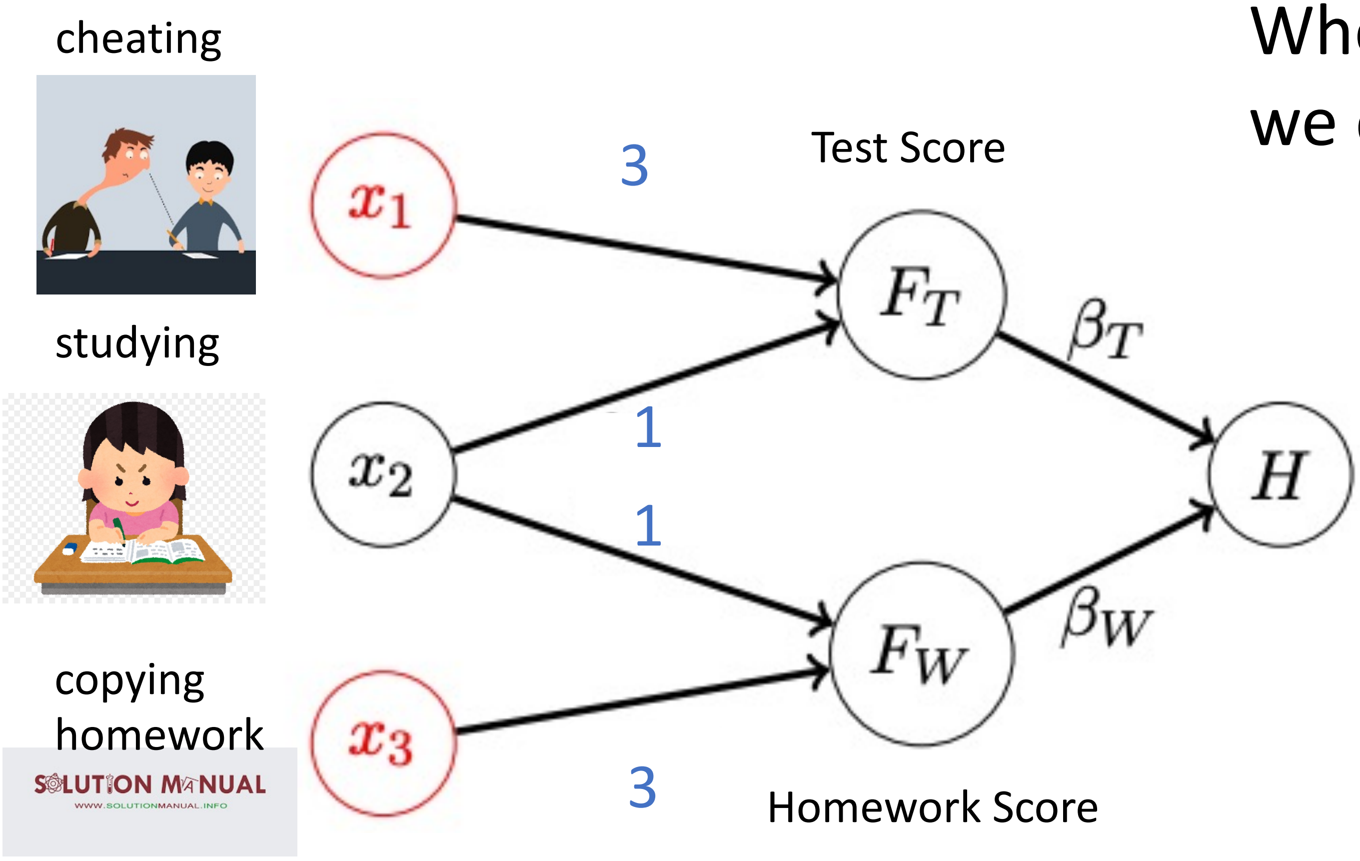


studying

copying homework



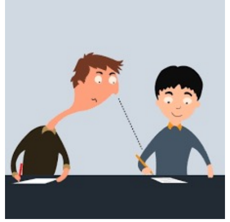
Example: Course Grades



When the desired effort is substitutable, we can't incentivize that effort.

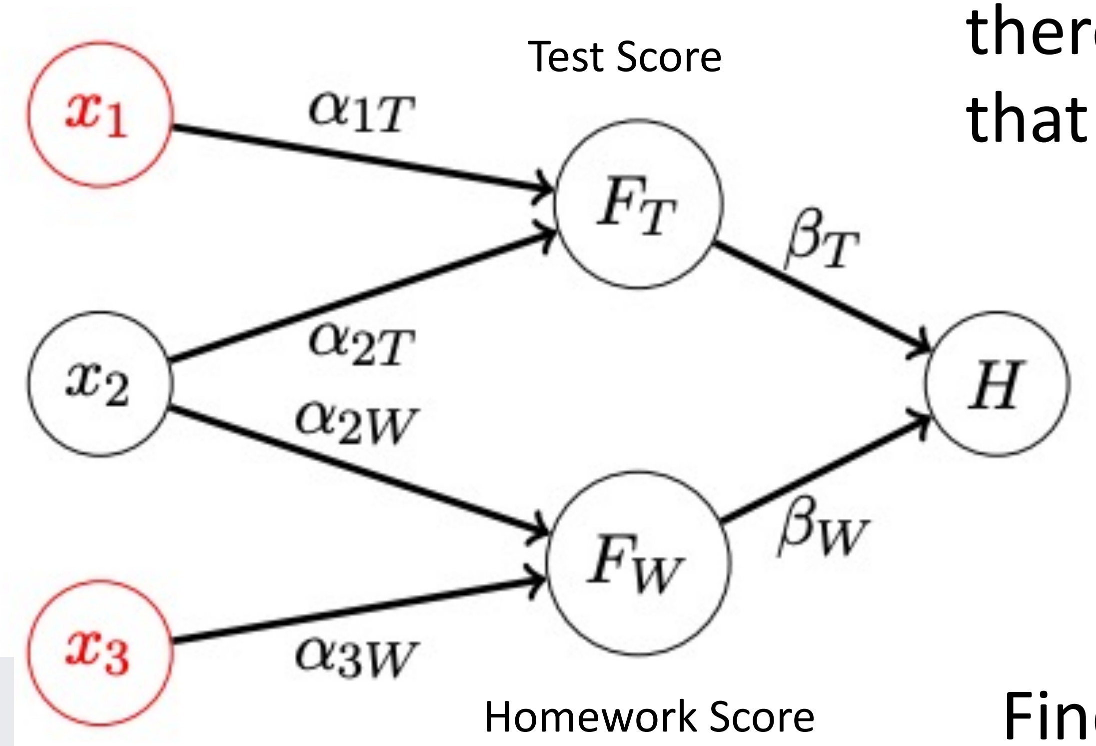
Example: Course Grades

cheating



studying

copying homework



When the effort is not substitutable, there is a linear mechanism incentivizing that effort.

Finding that mechanism is NP-hard.

The Purposes of Decision Rules

- To evaluate the candidates
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  - Aims to classify based on the true quality with gaming behavior

- To incentivize the candidates
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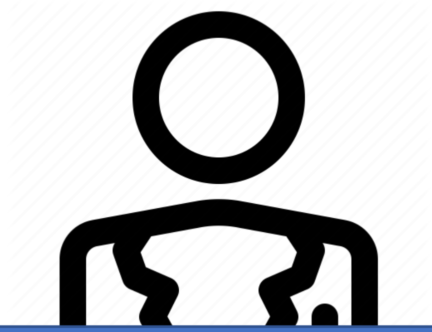
More Aspects of Strategic Classification

1. Evaluation vs. Incentive
2. Social costs

There Are Two Parties in Strategic Classification

Choose a classifier
$f: X \to \{0,1\}$



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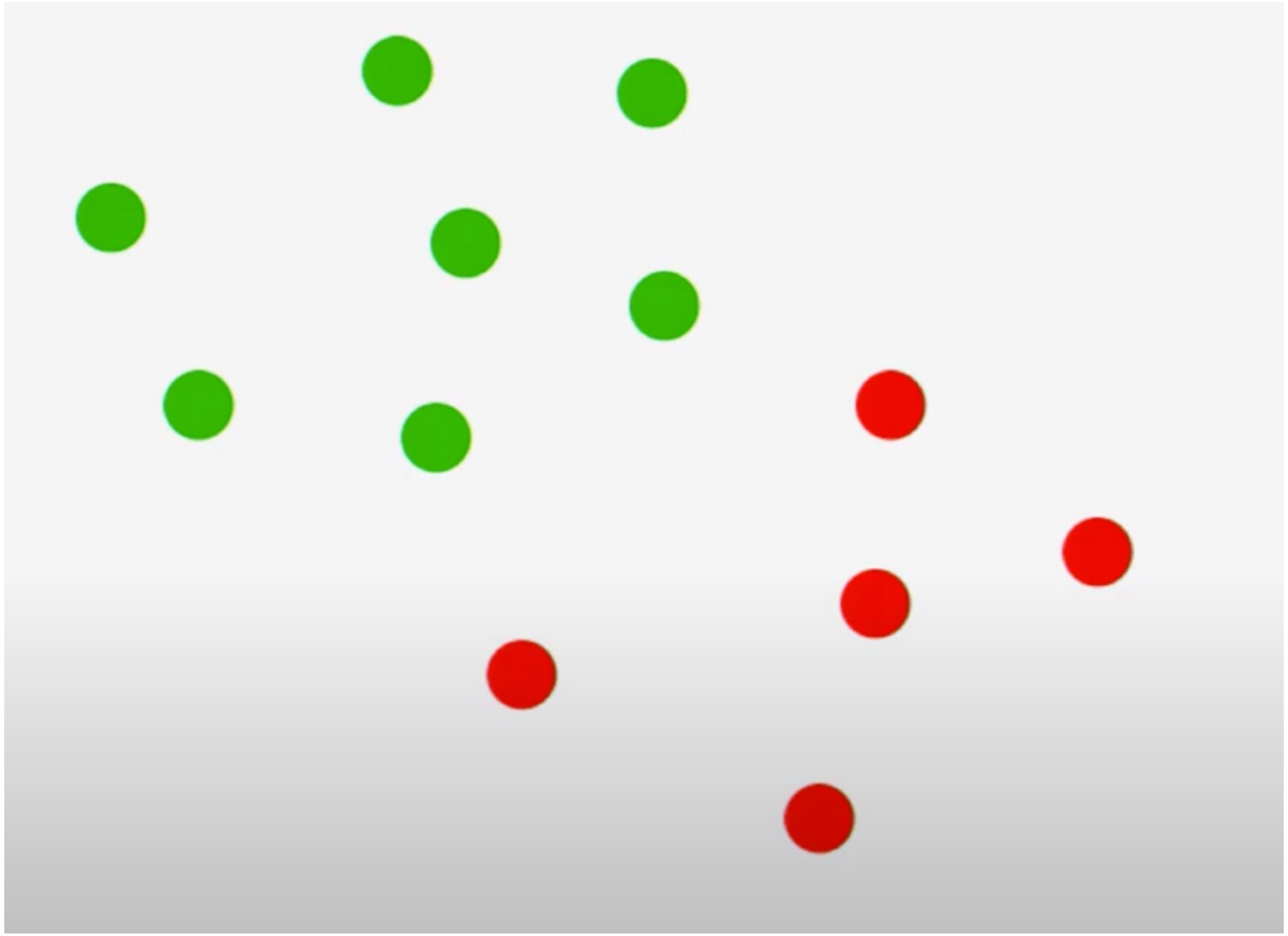
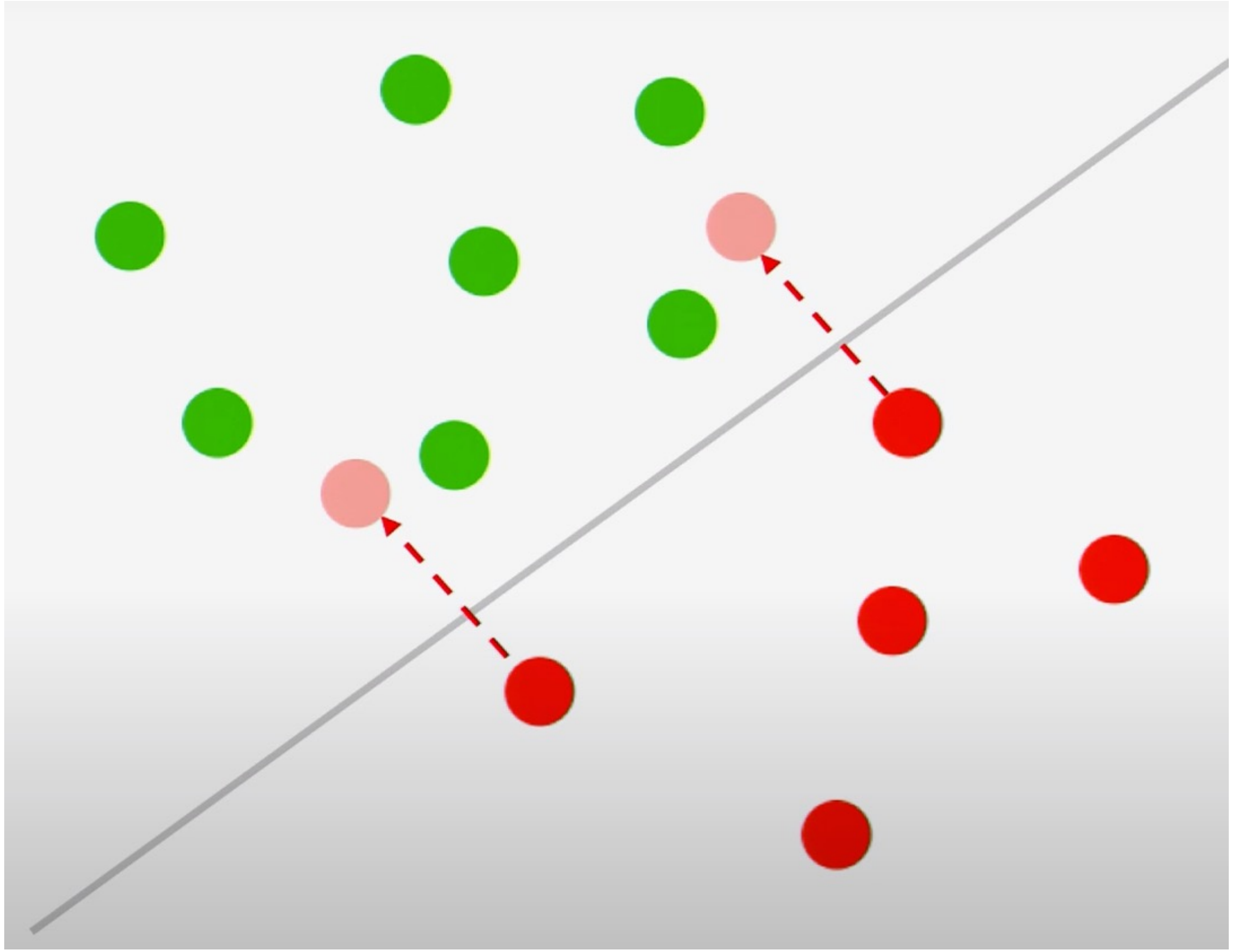
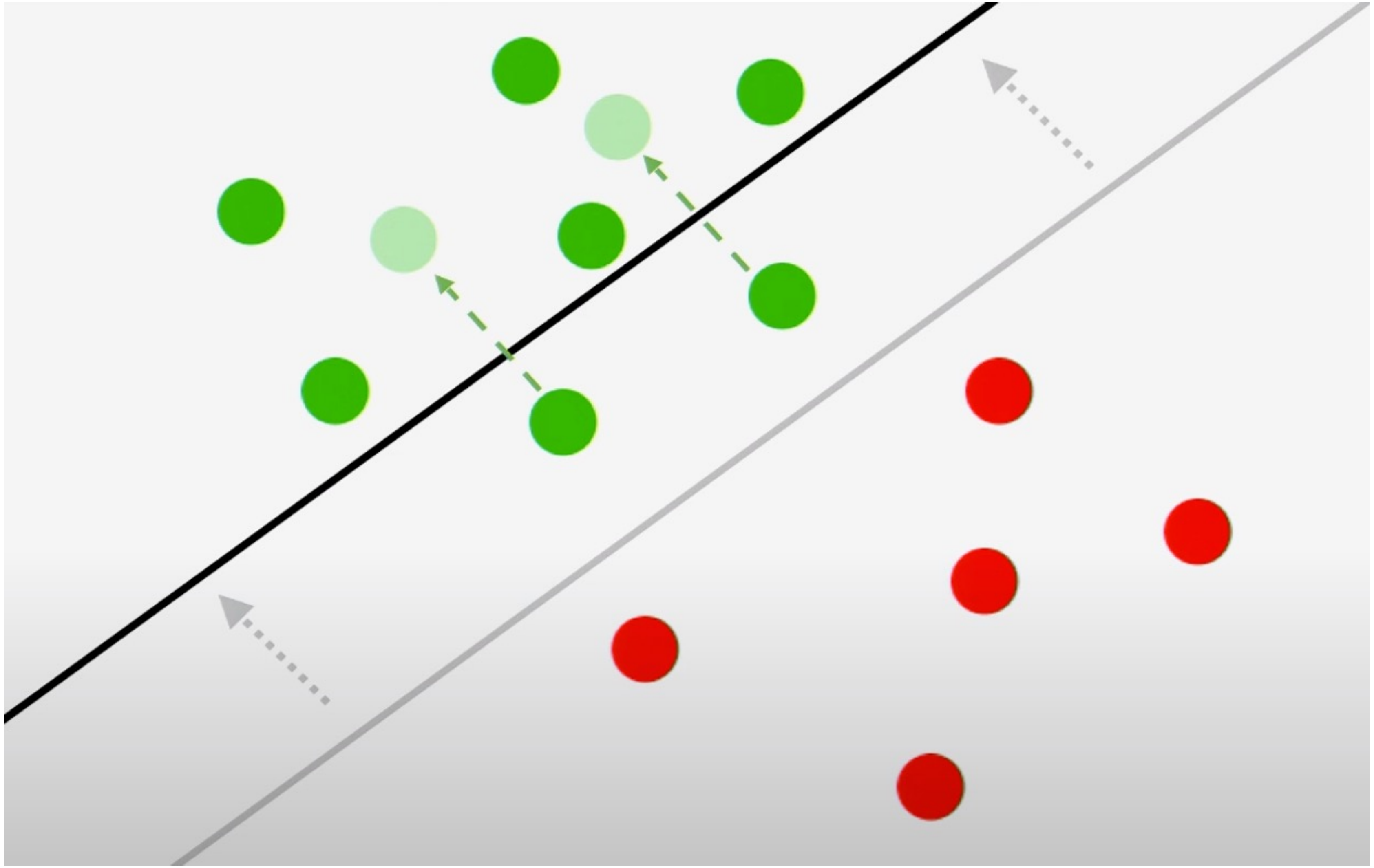
Choose manipulation (new $\vec{x}'$)
$\vec{x}$, new $\vec{x}'$)

tribution D

Is it reasonable to only optimize the benefit of the institution?

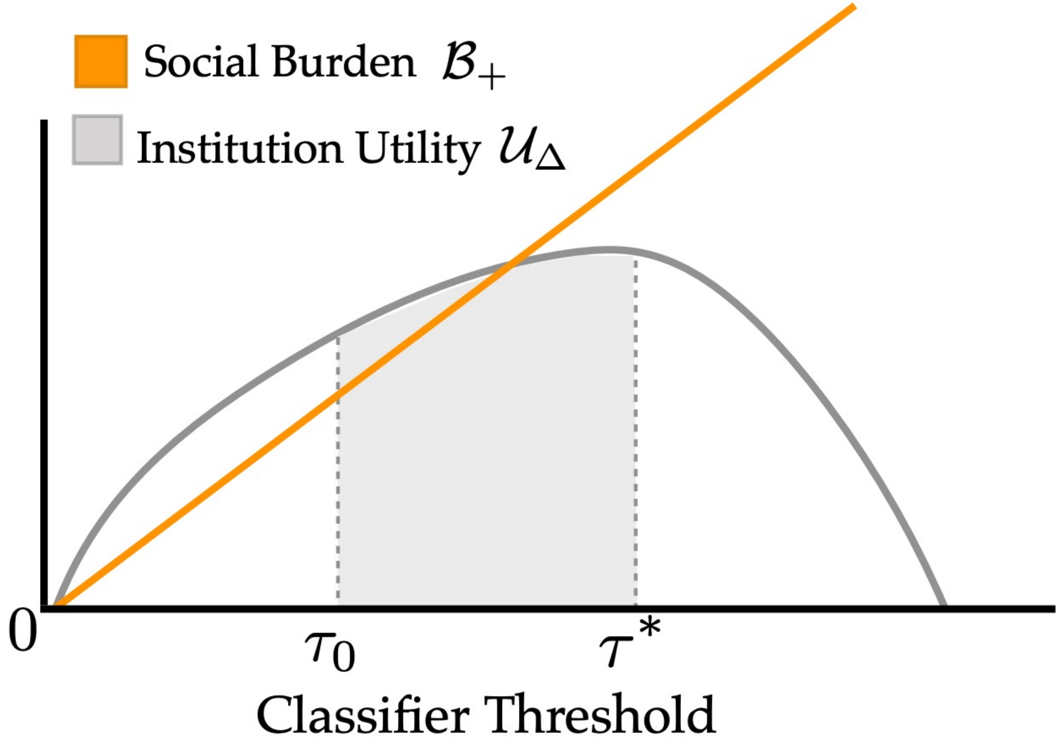






Institution Utility vs. Social Burden [Milli et al. 2018]

- Institution utility: the utility for deploying the decision rule
- Social burden: the amount of effort contestants need to put in



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CULTURA CREATIVE (RF) / ALAMY STOCK PHOTO

GREs don't predict grad school success. What does?

By Beryl Lieff Benderly | Jun. 7, 2017 , 8:30 AM

EDUCATION

The Problem With the GRE

The exam “is a proxy for asking ‘Are you rich?’ ‘Are you white?’ ‘Are you male?’”

VICTORIA CLAYTON MARCH 1, 2016

EDUCATION AND OUTREACH | NEWS

US graduate entry exams not a predictor of PhD success, says study

28 Jan 2019

ETS GRE

ETS Home > GRE Home > Research > Validity Evidence: Predicting Success in Graduate Education

GRE Research

› Validity Evidence: Predicting Success in Graduate Education

Validity Evidence: Constructs and Content

Fairness and Accessibility

Psychometric Issues

Developing New Measures

Other Research

Validity Evidence: Predicting Success in Graduate Education

Reports in this section support the validity arguments for the interpretation of scores from the *GRE*® General Test and Subject Tests.

Key Reports

- The Validity of *GRE* General Test Scores for Predicting Academic Performance at U.S. Law Schools
  By D. M. Klieger, B. Bridgeman, R. J. Tannenbaum, F. A. Cline, M. Olivera-Aguilar (2018)
  ETS Research Report No. RR-18-26
- The Validity of Scores from the GRE revised General Test for Forecasting Performance in Business Schools: Phase One
  By J. W. Young, D. Klieger, J. Bochenek, C. Li, and F. Cline (2014)
  GRE Board Report No.14-01
- The Role of Noncognitive Constructs and Other Background Variables in Graduate Education
  By P. C. Kyllonen, A. M. Walters, and J. C. Kaufman (2011)
  GRE Board Report No. 00-11
- Understanding What the Numbers Mean: A Straightforward Approach to GRE Predictive Validity
  By B. Bridgeman, N. Burton, and F. Cline (2008)
  GRE Board Report No. 04-03
- Predicting Long-Term Success in Graduate School: A Collaborative Validity Study
  By N. W. Burton and M. Wang (2005)
  GRE Board Report No. 99-14R

Discussion

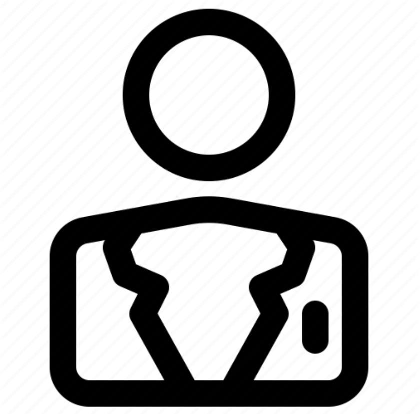
- People in advantage groups might be able to pay smaller costs to manipulate the features. What are the example applications that this could happen (e.g., SAT scores)?

- What do you think are the bad consequences with this imbalanced manipulations? What are potential ways we can deal with them?

The Disparate Effects of Strategic Manipulation

Hu, Immorlica, and Vaughan. FAT* 19.

Choose a classifier
$f: X \to \{0,1\}$



Represented by initial features
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True label $y = h(\vec{x}) \in \{0,1\}$

Choose manipulation (new $\vec{x}$)
cost(initial $\vec{x}$, new $\vec{x}$)

Student distribution D

Choose a classifier
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Represented by initial features
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True label $y = h(\vec{x}) \in \{0,1\}$

Choose manipulation (new $\vec{x}$)
cost(initial $\vec{x}$, new $\vec{x}$)

Student distribution D

What if this cost is different across groups?

Main Results

- Group differences
  - Group A: Advantage group
  - Group B: Disadvantage group

- Result 1: Reinforcing inequalities
  - Under mild conditions, the equilibrium classifier more likely to mistakenly exclude people from group B and mistakenly admit people from group A

- Result 2: Subsidy interventions?
  - There exists cases that both groups are worse-off when a subsidy is offered compared to no subsidy at all.

Summary: Strategic Classification

- Mitigate the effect of gaming
  - How do we ensure we still have a good classifier even if we know that people will game the system
- Using classification to incentivize improvements
  - Classification as incentives
- Social costs
  - The tradeoffs between the ML utility and the costs incurred on the individuals