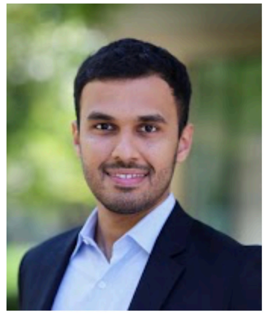
Bridging Algorithms, Law and Practice: Hiring and Beyond

Swati Gupta
Fouts Family Early Career Professor,
and Assistant Professor,
Lead of Ethical AI, NSF AI Institute AI4OPT,
School of Industrial and Systems Engineering
Georgia Institute of Technology

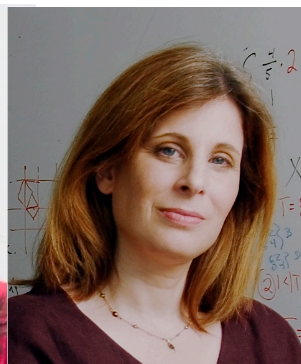
30 January, 2023
Texas A&M University

How to make algorithms with positive impact on society?

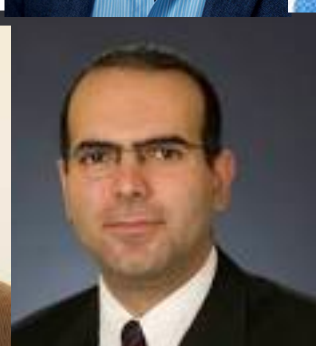










How to make algorithms with positive impact on society?

What is Bias/Fairness?

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Archive > Volume 551 > Issue 7679 > Comment > Article

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Rafael Yuste, Sara Goering, Blaise Agüera y Arcas, Guoqiang Bi, Jose M. Carmena, Adrian Carter, Joseph J. Fins, Phoebe Friesen, Jack Gallant, Jane E. Huggins, Judy Illes, Philipp Kellmeyer, Eran Klein, Adam Marblestone, Christine Mitchell, Erik Parens, Michelle Pham, Alan Rubel, Norihiro Sadato, Laura Specker Sullivan, Mina Teicher, David Wasserman, Anna Wexler, Meredith Whittaker & Jonathan Wolpaw

08 November 2017

What is Bias/Fairness?

“**Bias.** When scientific or **technological decisions** are based on a narrow set of systemic, structural or **social concepts and norms**, the resulting technology can **privilege certain groups** and harm others.” – Nature comment

Amazon to Bring Same-Day Delivery to Roxbury After Outcry

by **Spencer Soper**

April 26, 2016, 5:19 PM EDT *Updated on* April 26, 2016, 8:22 PM EDT

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Rating systems may discriminate against Uber drivers

By Leslie Morris | December 15, 2016

Amazon to Bring Same-Day Delivery to Roxbury After Outcry

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April 26, 2016, 5:19 PM EDT *Updated on* April 26, 2016, 8:22 PM EDT

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MACHINE BIAS

Facebook Lets Advertisers Exclude Users by Race

Facebook's system allows advertisers to exclude black, Hispanic, and other "ethnic affinities" from seeing ads.

by **Julia Angwin** and **Terry Parris Jr.**, Oct. 28, 2016, 1 p.m. EDT

Amazon to Bring Same-Day

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Russian Hacker Suspected of LinkedIn Attack Indicted in U.S.


Settl Mobi Plans

DIGITS

Google Mistakenly Tags Black People as 'Gorillas,' Showing Limits of Algorithms

By *Alistair Barr*

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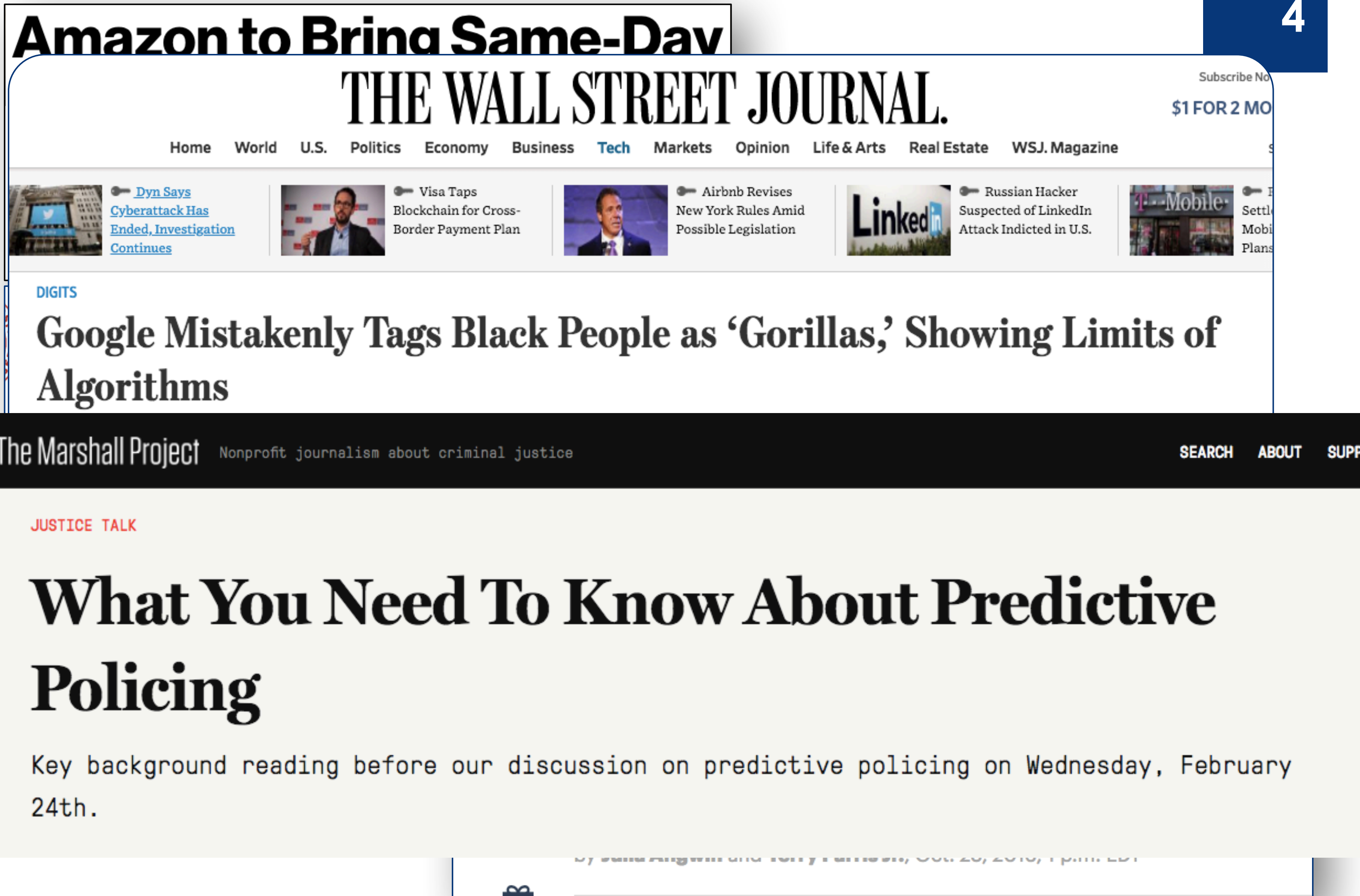

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The Marshall Project Nonprofit journalism about criminal justice

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JUSTICE TALK

What You Need To Know About Predictive Policing

Key background reading before our discussion on predictive policing on Wednesday, February 24th.

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DIGITS

Google N
Algorith

DE GRUYTER OPEN Proceedings on Privacy Enhancing Technologies 2015; 2015 (1):92–112

Amit Datta*, Michael Carl Tschantz, and Anupam Datta

Automated Experiments on Ad Privacy Settings

A Tale of Opacity, Choice, and Discrimination

Abstract: To partly address people's concerns over web tracking, Google has created the Ad Settings webpage to provide information about and some choice over the profiles Google creates on users. We present AdFisher, an automated tool that explores how user behaviors, Google's ads, and Ad Settings interact. AdFisher can run browser-based experiments and analyze data using machine learning and significance tests. Our tool uses a rigorous experimental design and statistical analysis to

serious privacy concern. Colossal amounts of collected data are used, sold, and resold for serving targeted content, notably advertisements, on websites (e.g., [1]). Many websites providing content, such as news, outsource their advertising operations to large third-party ad networks, such as Google's DoubleClick. These networks embed tracking code into webpages across many sites providing the network with a more global view of each user's behaviors.

The Marshall Proje

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JUSTICE TALK

What
Policing

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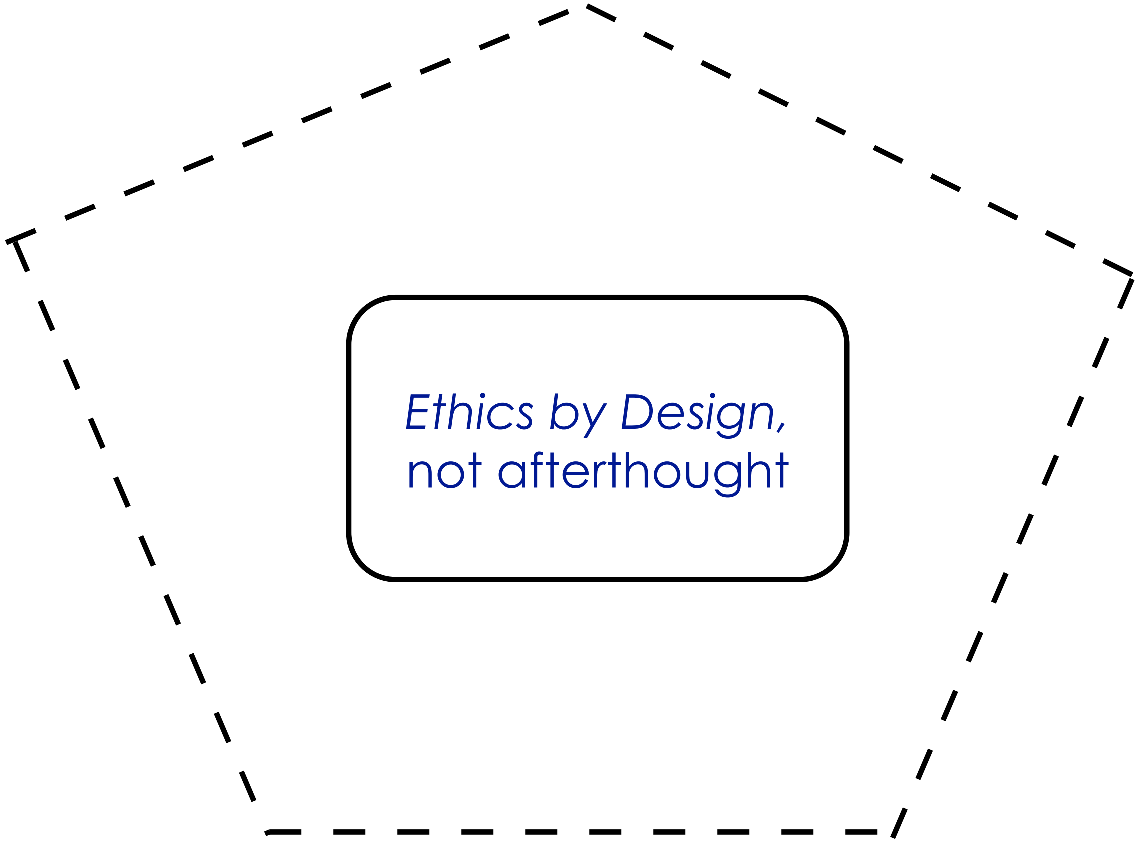
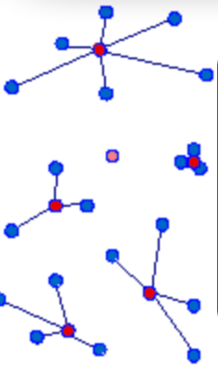
My research



My research

Walgreens and VillageMD to Open 500 to 700 Full-Service Doctor Offices within Next Five Years in a Major Industry First



Fairness definitions in static and dynamic env: e.g., facility location, reliability in energy networks

Ethics by Design, not afterthought

My research

STARRING ROLE

To fix racial bias in the gig economy, start with the ra

Keeping bias out of job applications and school admissions

By Ashley Kilgore

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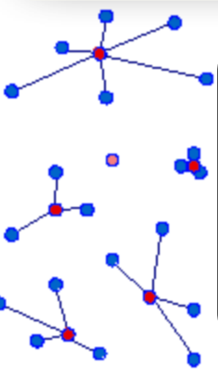
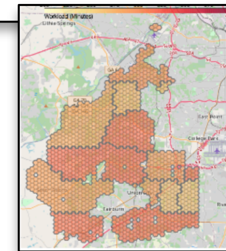


Impact of Bias in Data: e.g., School Admissions, Hiring and Screening Out, Police Districting, Gig economy



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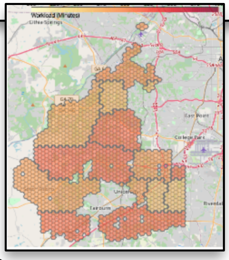

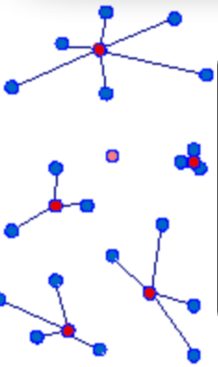

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Georgia enacts new congressional district map

By Douglas Kronaizl / In State / January 4, 2022 at 10:02 PM

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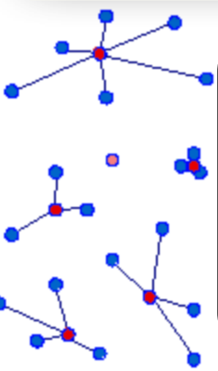

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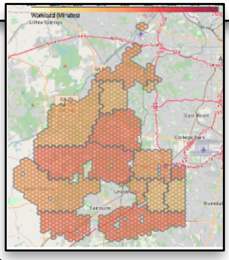

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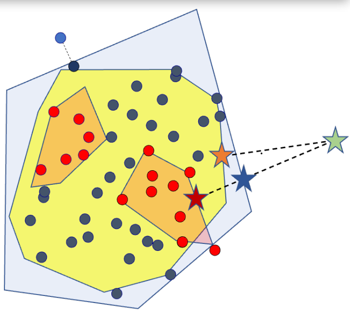

Racial Bias in Pulse Oximetry Measurement

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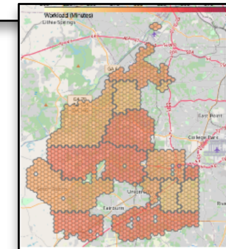

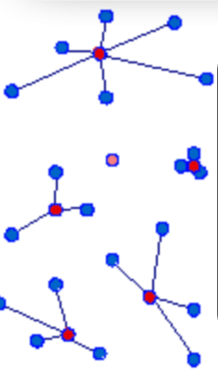

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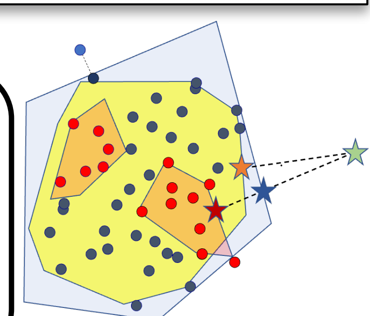
The EU General Data Protection Re (GDPR) is the most important chan data privacy regulation in 20 years

The regulation will fundamentally reshape the way in which d across every sector, from healthcare to banking and beyond.

Changing Legal Landscape: e.g., Title VII, CCPA, Price gouging, Voting Rights, Rooney Rule

Translating Domain Constraints: e.g., **trust scores** for rapid prediction of sepsis, **demand learning**



California Consumer Privacy Act (CCPA)

Home / Privacy / California Consumer Privacy Act (CCPA)

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Hiring in Practice

Hiring in Practice

- **Summer 2020**: Microsoft, Wells Fargo, Adidas, Google, Boeing announce major programs to address racial disparities in employment.

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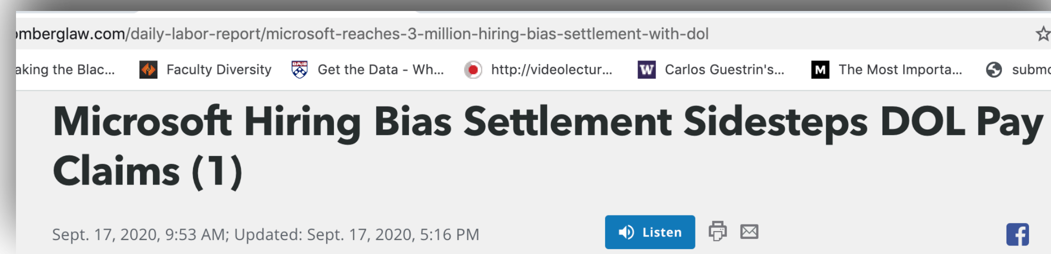

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mberglaw.com/daily-labor-report/microsoft-reaches-3-million-hiring-bias-settlement-with-dol

aking the Blac... Faculty Diversity Get the Data - Wh... http://videolectur... Carlos Guestrin's... The Most Importa... submod

Microsoft Hiring Bias Settlement Sidesteps DOL Pay Claims (1)

Sept. 17, 2020, 9:53 AM; Updated: Sept. 17, 2020, 5:16 PM Listen

- **October 2020**: Labor Department goes after Microsoft and Wells Fargo asking to prove hiring practices designed to increase racial diversity are not discriminating based on race

TECH

Labor Department Questions Microsoft and Wells Fargo Over Pledges to Hire More Black Employees

Agency letters ask if diversity initiatives constitute discriminaton; companies say they comply with employment law

Legal Basis: Title VII

Cannot use protected classes for making decisions in regulated domains: education, employment, housing, public accommodation, and credit (Civil Rights Act 1964)

Race (Civil Rights Act of 1964), **Color** (Civil Rights Act of 1964), **Religion** (Civil Rights Act of 1964), **National Origin** (Civil Rights Act of 1964), **Citizenship** (Immigration Reform and Control Act), **Age** (Age discrimination in Employment Act of 1967), **Pregnancy** (Pregnancy Discrimination Act), **Familial status** (Civil Rights Act of 1968), **Disability status** (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990), **Veteran Status** (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act), **Genetic Information** (Genetic Information Nondiscrimination Act)

Disparate treatment and disparate impact

Tension between disparate impact and disparate treatment.

How should an entity like Microsoft fix the underrepresentation in their hiring pipeline - without resorting to disparate treatment?

How should an entity like Microsoft fix the underrepresentation in their hiring pipeline - without resorting to disparate treatment?

Let's first model it mathematically.

Outline of the talk

- The Microsoft Paradox
- **Modeling Bias**
- Biased Online Secretary Problem
- Title VII: Anti-Discrimination Law
- Extensions
- Future Work

Data is biased

Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination

Marianne Bertrand

Sendhil Mullainathan

AMERICAN ECONOMIC REVIEW
VOL. 94, NO. 4, SEPTEMBER 2004
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Alexander W. Watts
Jun 2 2014

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Magnus Carlsson, Henning Finseraas, Arnfinn H Midtbøen, Guðbjörg Linda Rafnsdóttir

European Sociological Review, jcaa050, https://doi.org/10.1093/esr/jcaa050
Published: 25 November 2020 **Article history ▾**

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Harvard Business Review

Hiring | All the Ways Hiring Algorithms Can Introduce Bias

Hiring

All the Ways Hiring Algorithms Can Introduce Bias

by Miranda Bogen

May 06, 2019

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Bogen

RETAIL OCTOBER 10, 2018 / 7:04 PM / UPDATED 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

8 MIN READ

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Hiring | **All the Ways Hiring Algorithms Can Introduce Bias**

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RETAIL OCTOBER 10, 2018 / 7:04 PM / UPDATED 2 YEARS AGO

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By Jeffre

!!: Currently, ***97% of Fortune 500 companies organizations rely automated algorithms*** for resume tracking and screening, as it is impossible for humans to sift through millions of resumes or test scores or health records. [Raghavan et. al 2020], [Sánchez-Monedero et. al 2021]

Okay, this seems like a huge problem. But what can we do about it?

Is it possible to quantify bias?

It's unclear.

The Effects of Stereotype Threat and Double-Minority Status on the Test Performance of Latino Women

Patricia M. Gonzales, Hart Blanton, Kevin J. Williams

First Published May 1, 2002 | Research Article

https://doi.org/10.1177/0146167202288010

Does stereotype threat affect test performance of minorities and women? A meta-analysis of experimental evidence.

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Stereotype Threat and African-American Student Achievement

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Does stere ... s of

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EXPORT

Stereotype Threat and African-American Student Achievement

CLAUDE STEELE

But maybe we know whether *under* or *over*-estimation.

Our proposal [Salem, **Gupta** 2020]

"poset" model of bias (*partially ordered sets* [Birkhoff, 1948])

Only ***some*** *pairwise comparisons can be made with certainty*

e.g., candidates with varied interview scores,
SAT scores with adversity accounted for.

Our proposal [Salem, **Gupta** 2020]

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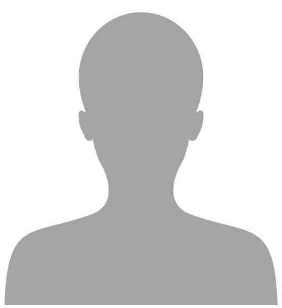
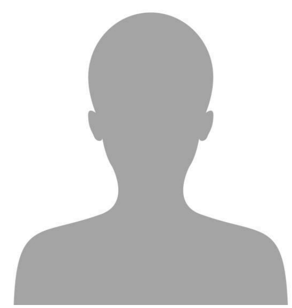
GPA: 3.5
Part-time job: 0



Work-ex: 0 years
GPA: 3.35
Part-time job: 2



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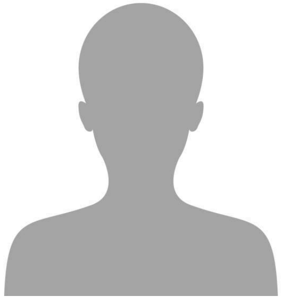

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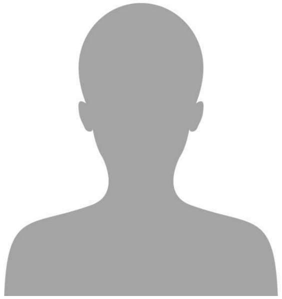

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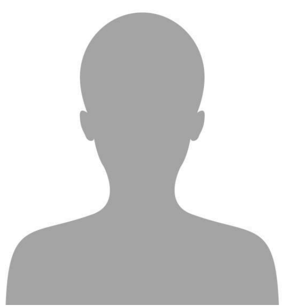

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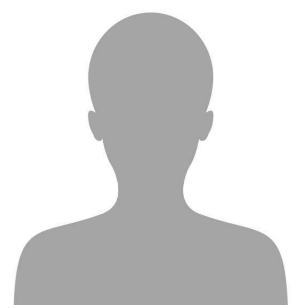

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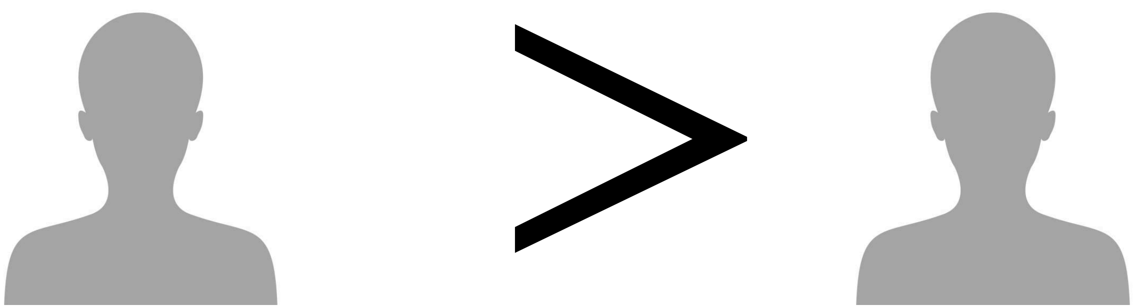

Special case: Group model

Each candidate belongs to a **known group**: $G_1, G_2, \ldots, G_k$

Observed potentials incorporate **unknown bias**:

$$\tilde{Z}_i = Z_i / \beta_j \text{ if } i \in G_j, \beta_j \geq 1$$

[Kleinberg, Raghavan 2018]

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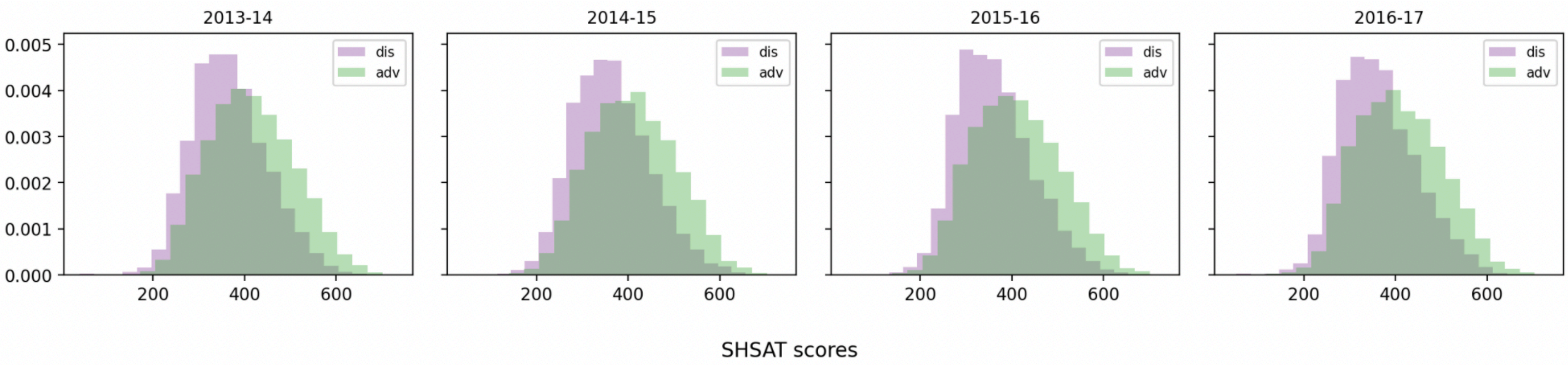

Discovering Opportunities in New York City's Discovery Program: an Analysis of Affirmative Action Mechanisms, Faenza, Gupta, Zhang, submitted to EC 2022.

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"poset" model of bias (*partially ordered sets* [Birkhoff, 1948])

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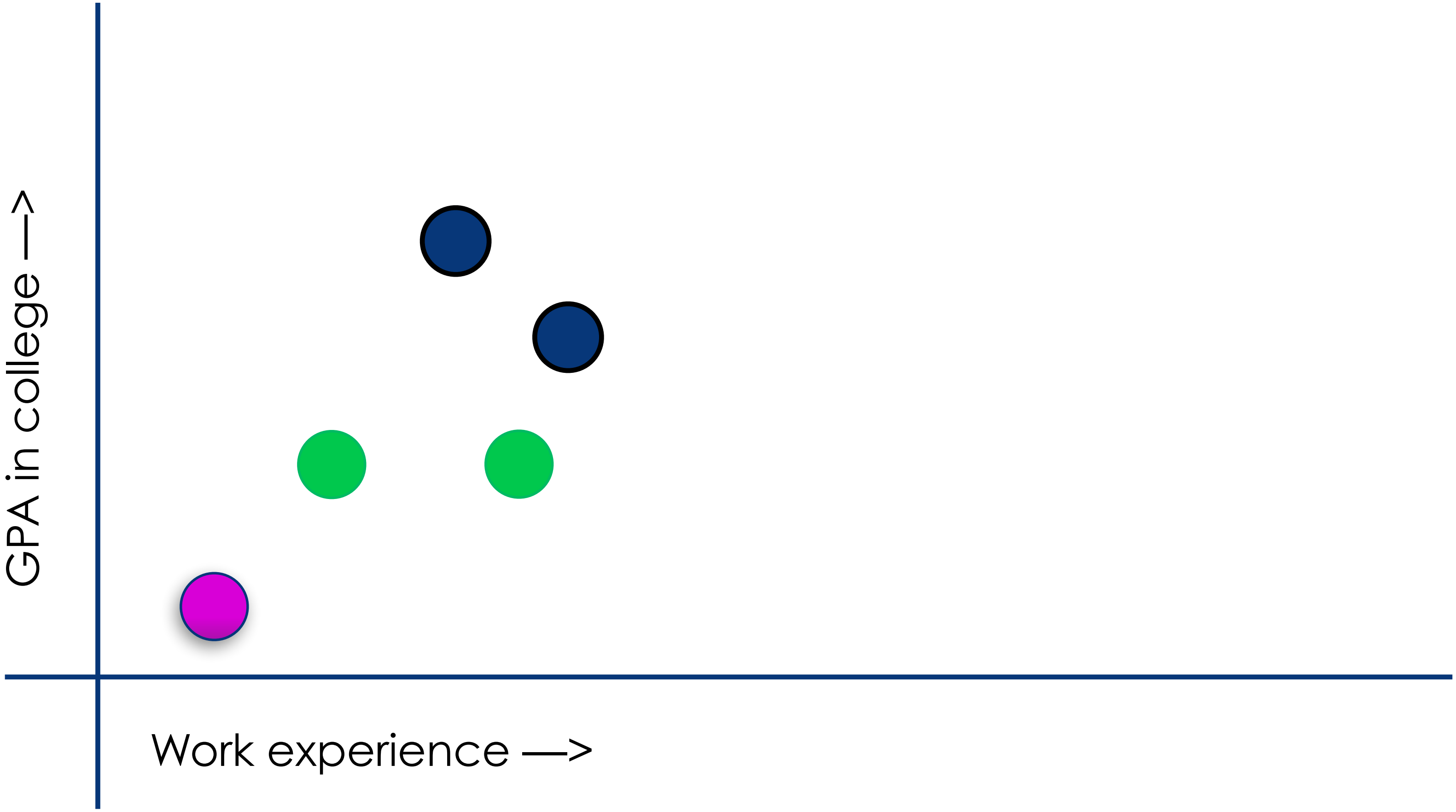

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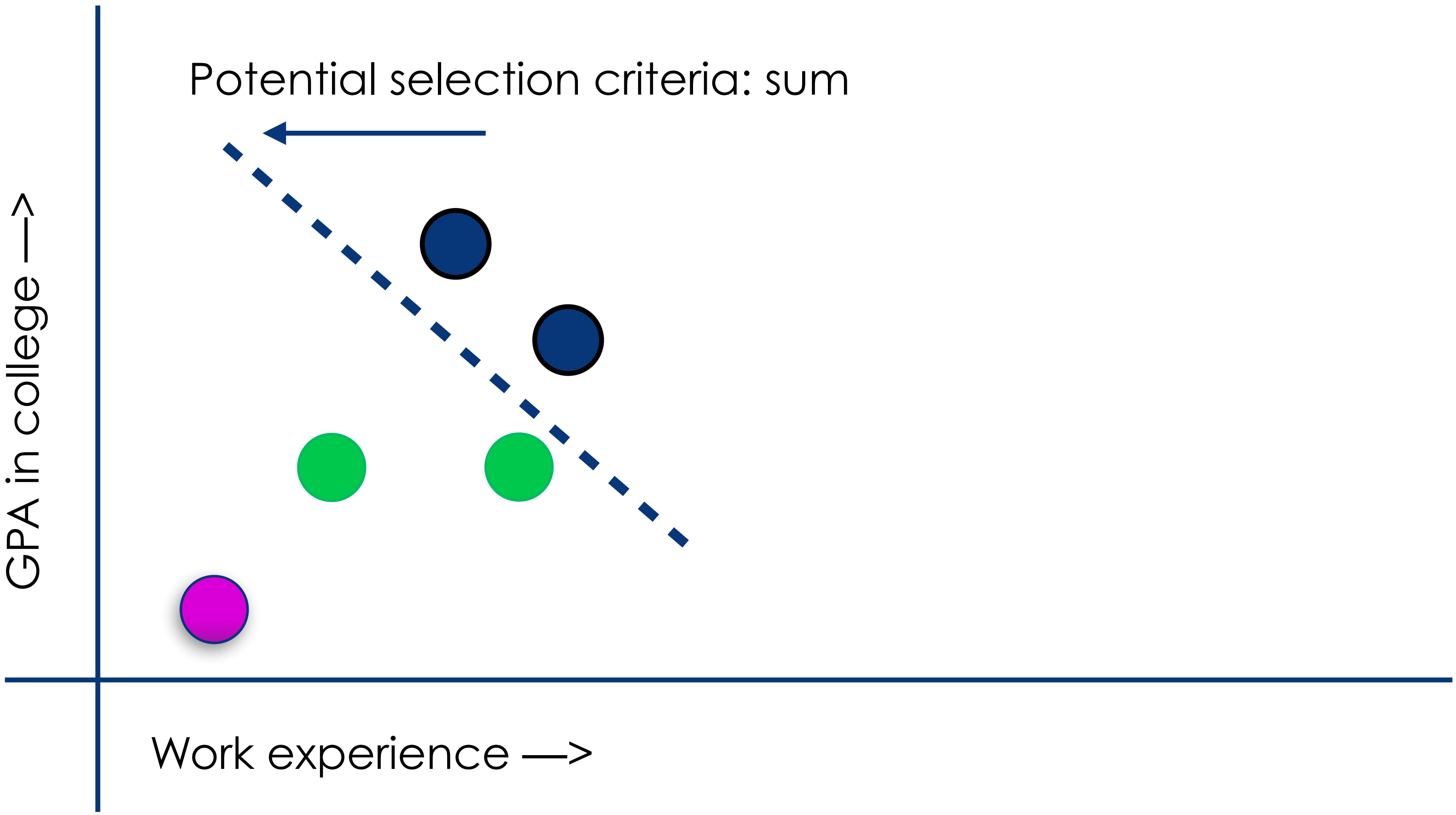

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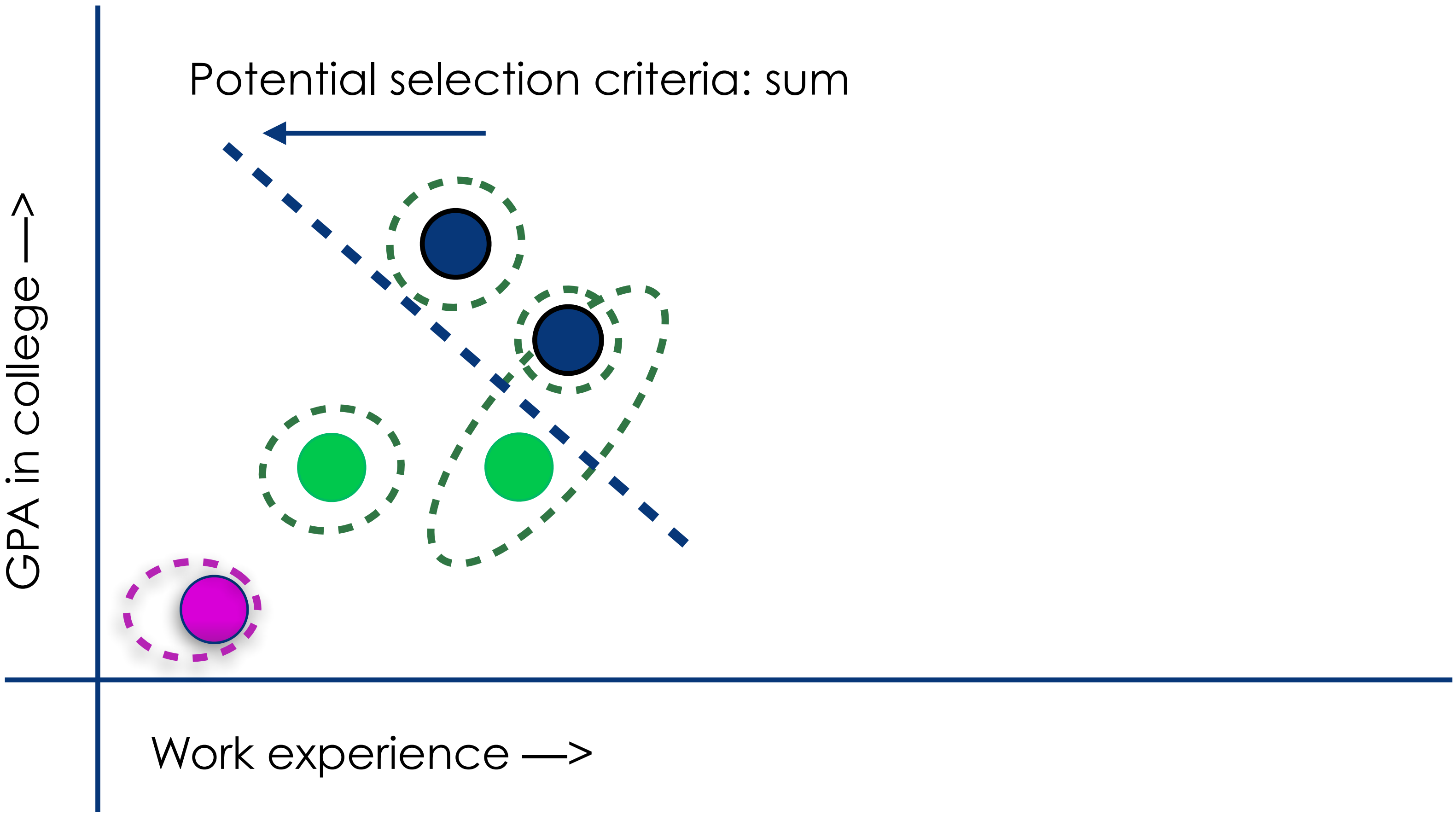

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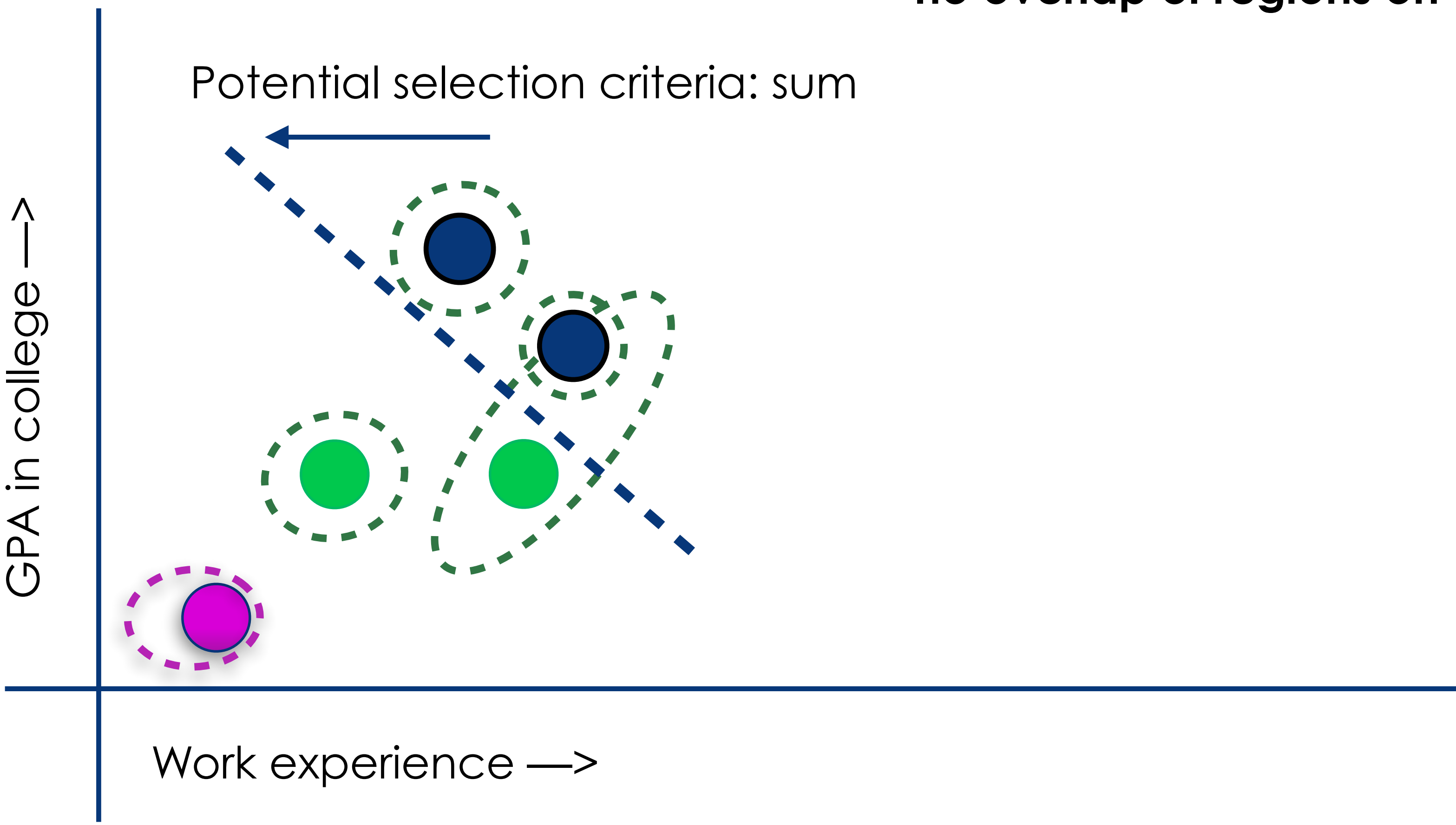

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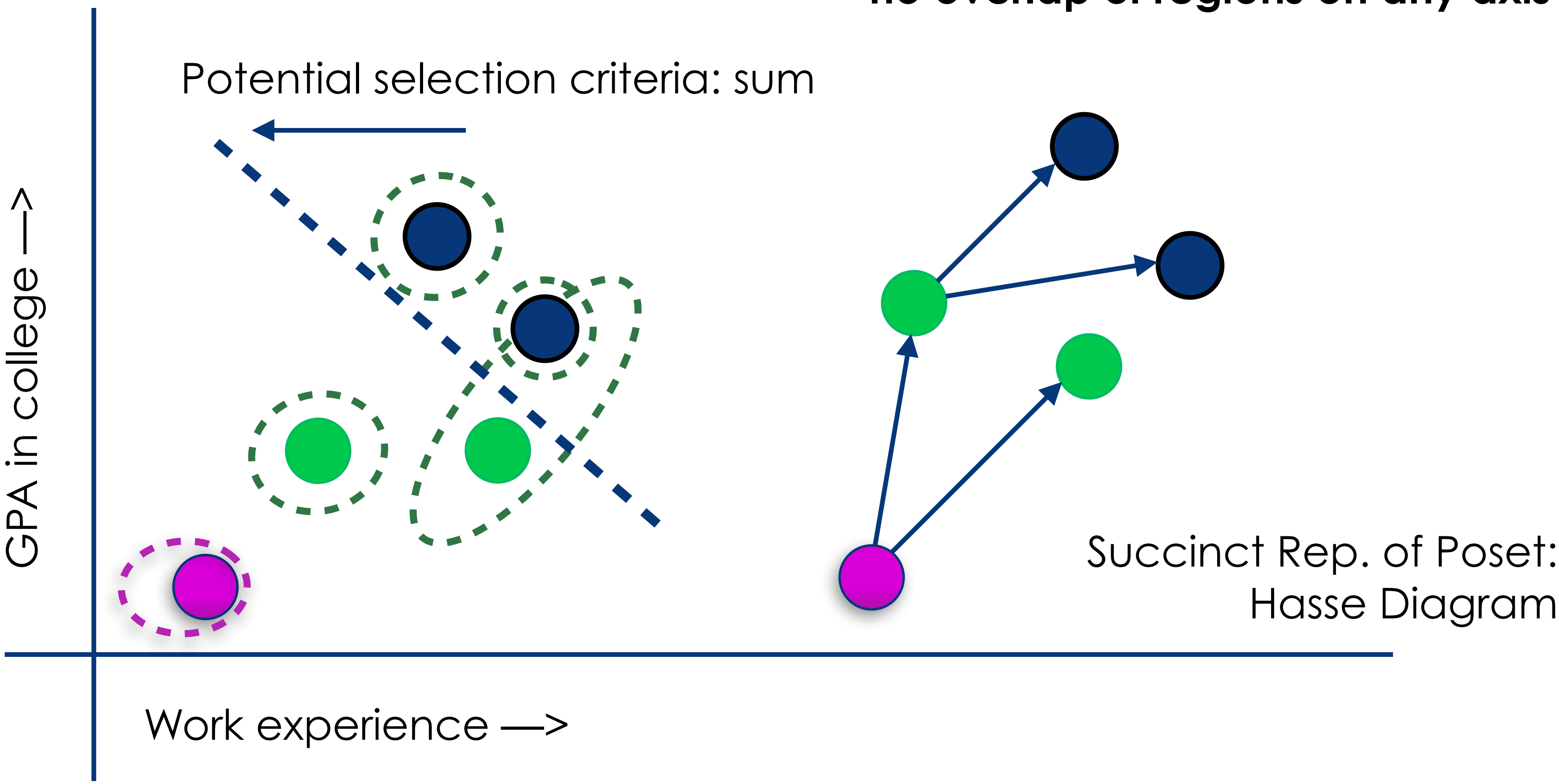

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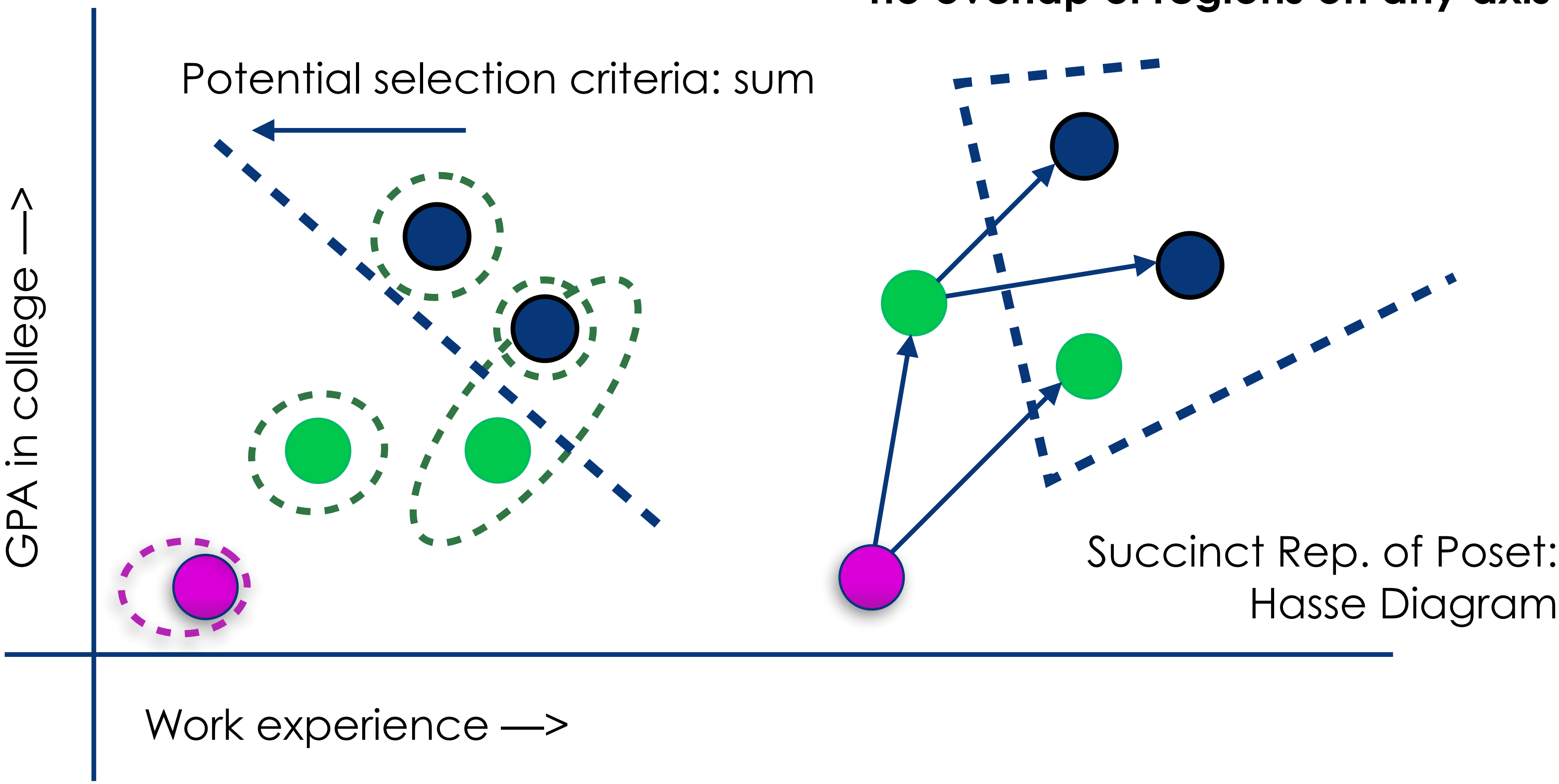

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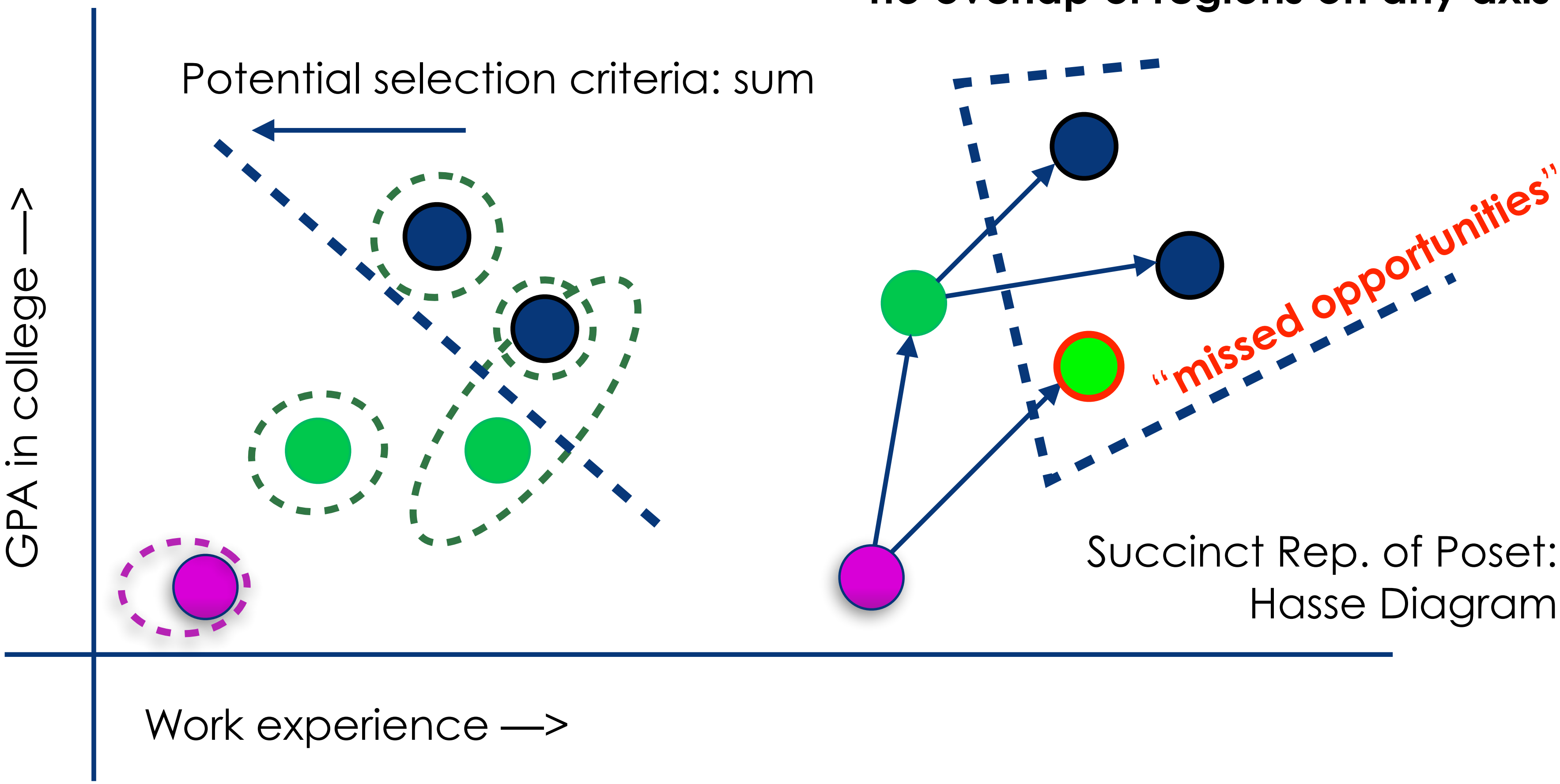

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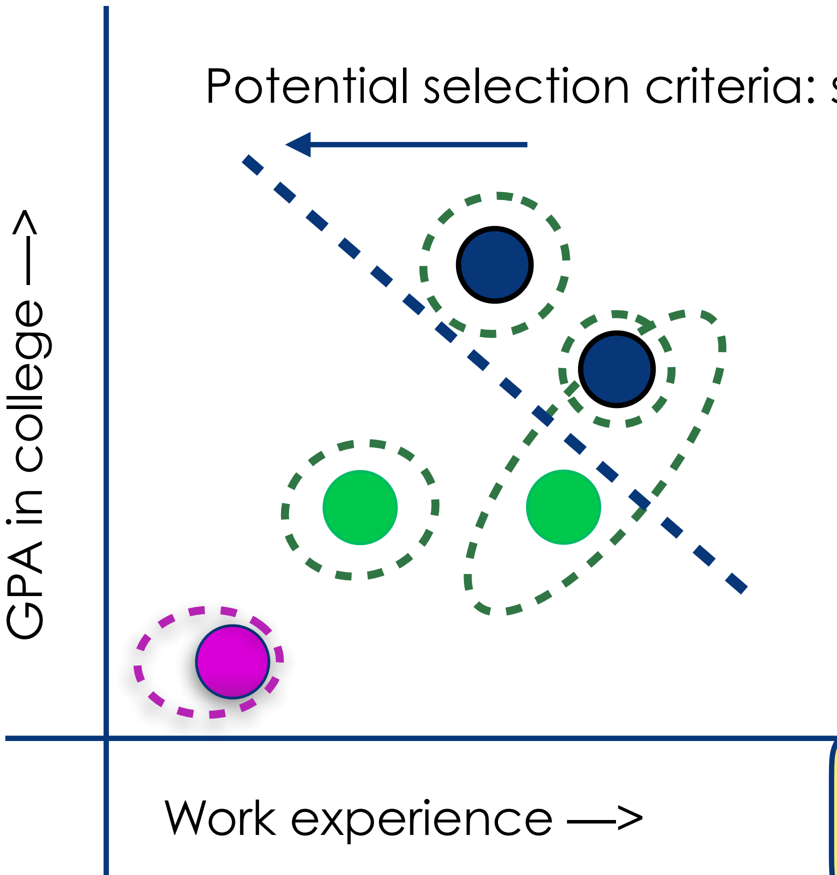
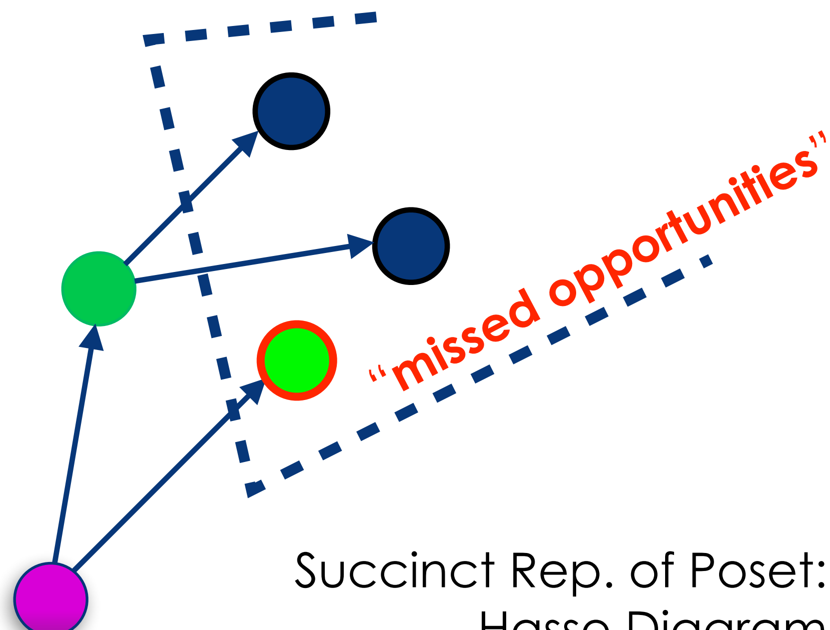




Succinct Rep. of Poset:
Hasse Diagram

How to construct these posets?
Connections to robust optimization?

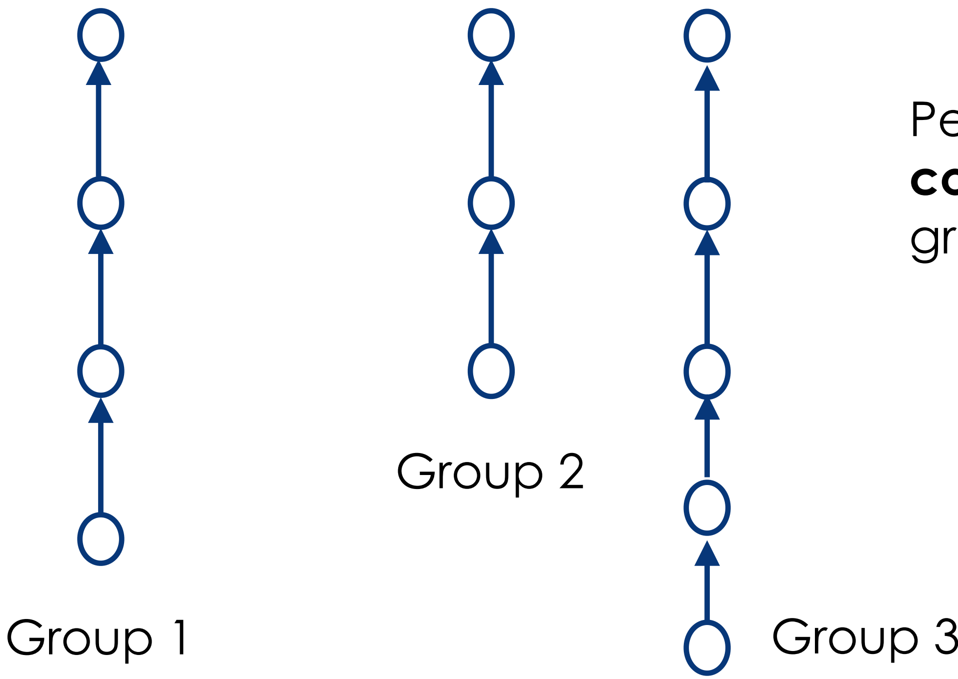
Special case: Group model

Each candidate belongs to a **known group**: $G_1, G_2, \ldots, G_k$

Observed potentials incorporate **unknown bias**:

$$\tilde{Z}_i = Z_i/\beta_j \text{ if } i \in G_j, \beta_j \geq 1$$

[Kleinberg, Raghavan 2018]



People **within a group are comparable**, but **not across** groups.

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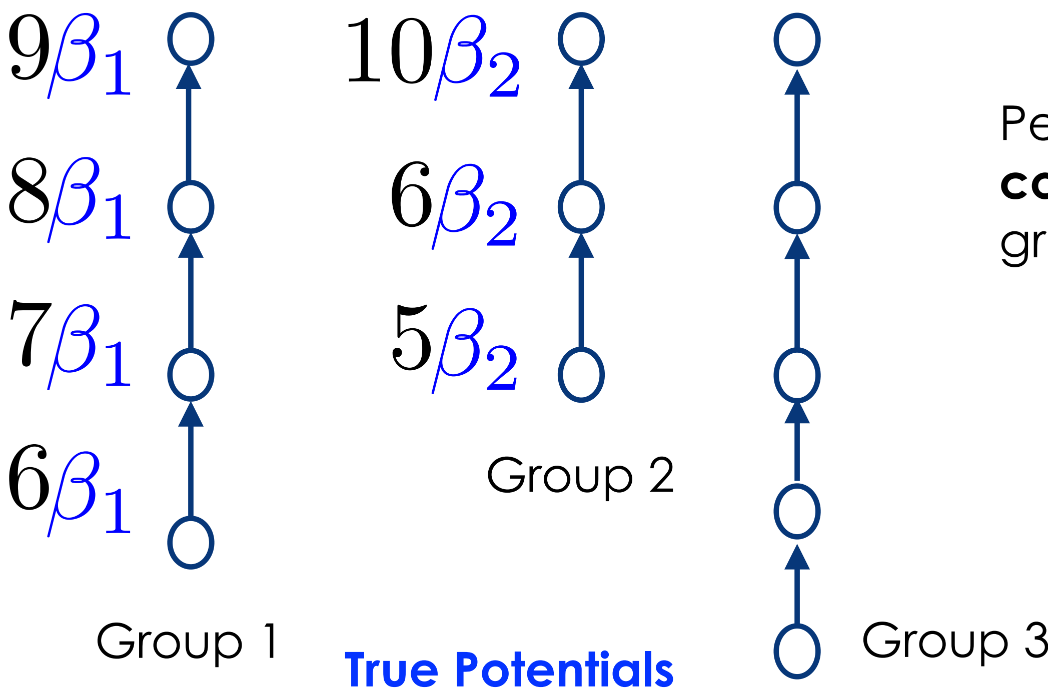

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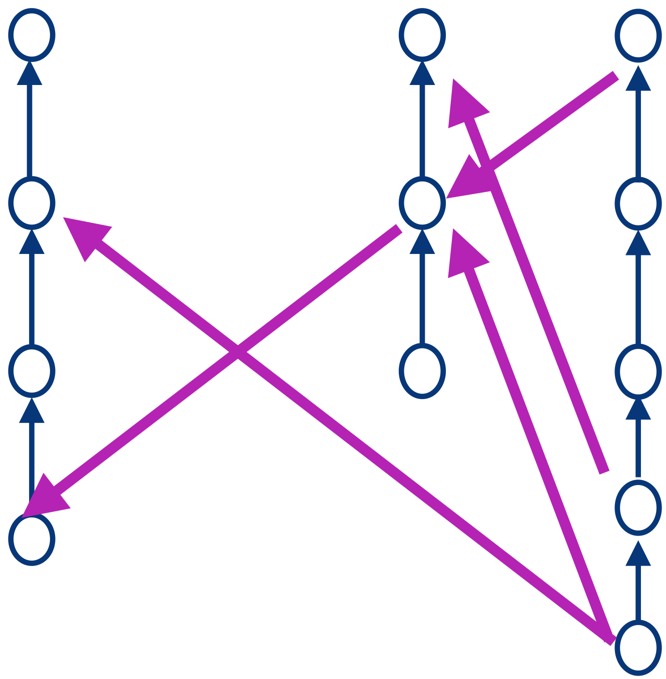

People **within a group are comparable**, but **not across** groups. **This is a coarse approximation.**

Posets would add more comparisons, allow finer treatment.

Experimental Study

Aspiring Minds Employability Outcomes 2015 Dataset

Gender	10percent	12percent	College tier	College GPA	College city tier	English	Logical
-16.95	-0.2193	0.2372	-18.50	1.182	1.563	0.02541	0.1429

Quant	Domain	ElectronicsAndSemicon	Computer science	Mechanical eng.	Electrical eng.
0.1199	177.5	-0.09960	0.006473	-0.3314	-80.72

Telecom. eng.	Civil eng.	Conscientiousness	Agreeableness	Extraversion	Neuroticism
-80.72	0.4119	-4.598	2.649	-3.256	-4.508

Openness to experience	Graduation age
3.565	0.1764

Coefficients (partial derivatives) of the linear prediction model for computer programming.

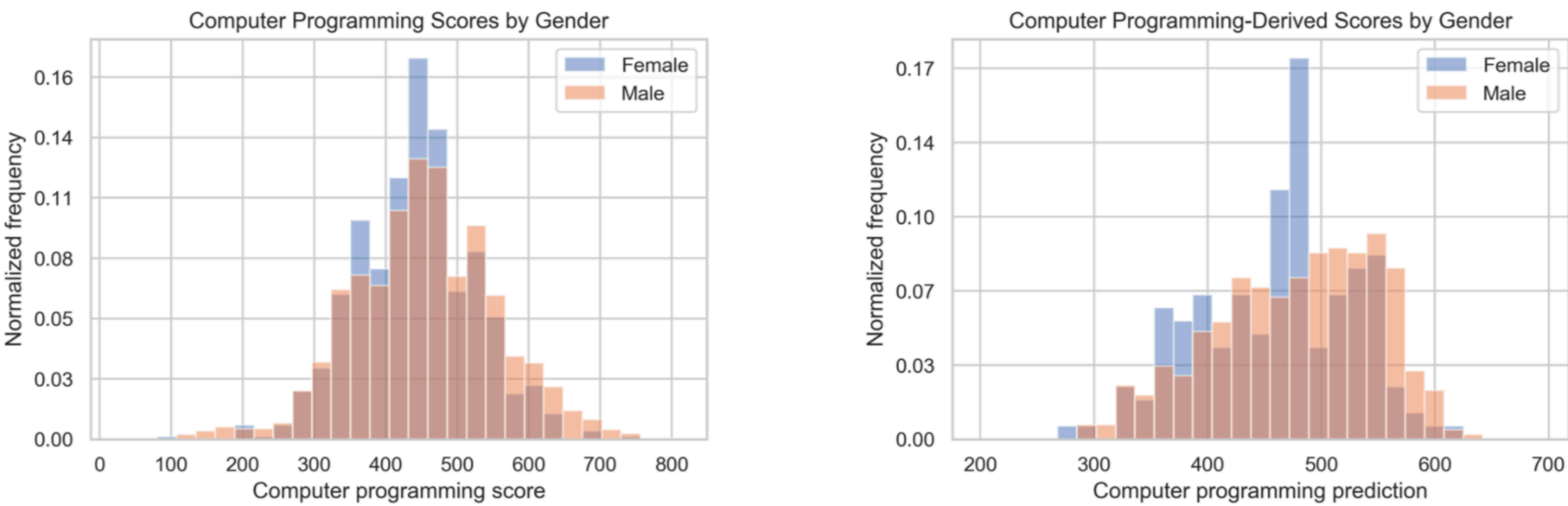

Figure 3 **The left figure plots the true computer programming scores by gender for the entire dataset. The right figure plots the predicted computer science scores by gender for the test dataset.**

$R^2 = 0.567$ (m), 0.627 (f)

Potential Partial Order:

non-binary?

Consider the two groups based on data: female and male.
Center their error distributions, using training data:

$$\left[\frac{\sigma_y}{\sigma_{\widehat{y}}}\left(\widetilde{w}(a) - \mu_{\widehat{y}}\right) + \mu_y - \lambda\sigma_j,\ \frac{\sigma_y}{\sigma_{\widehat{y}}}\left(\widetilde{w}(a) - \mu_{\widehat{y}}\right) + \mu_y + \lambda\sigma_j\right]$$

$$= [\widehat{y}_{\text{transf.}}(a) - \lambda\sigma_j, \widehat{y}_{\text{transf.}}(a) + \lambda\sigma_j]$$

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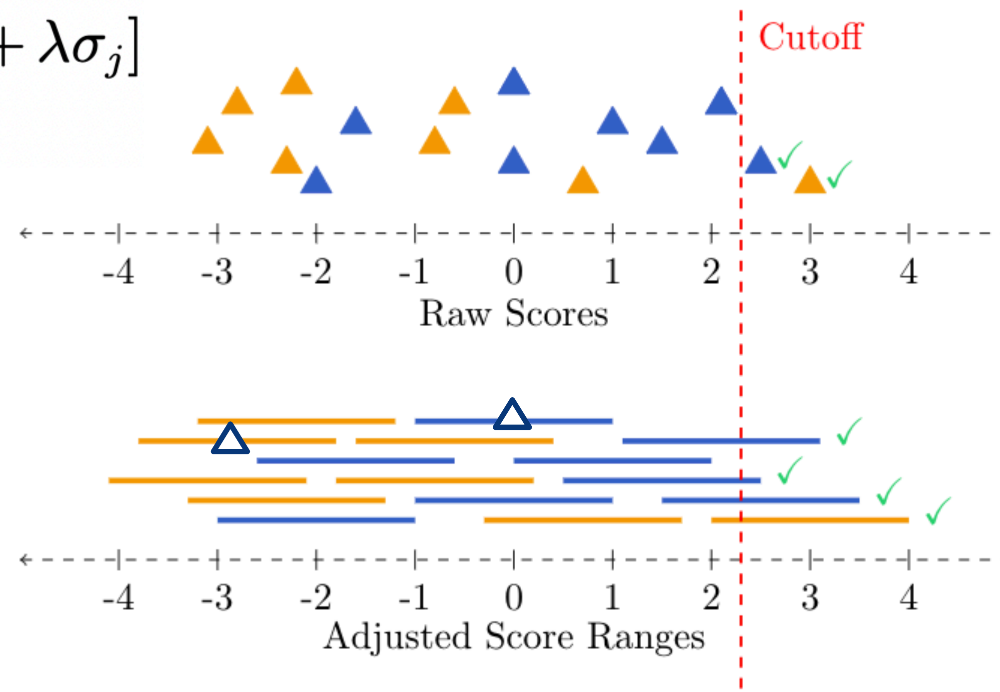

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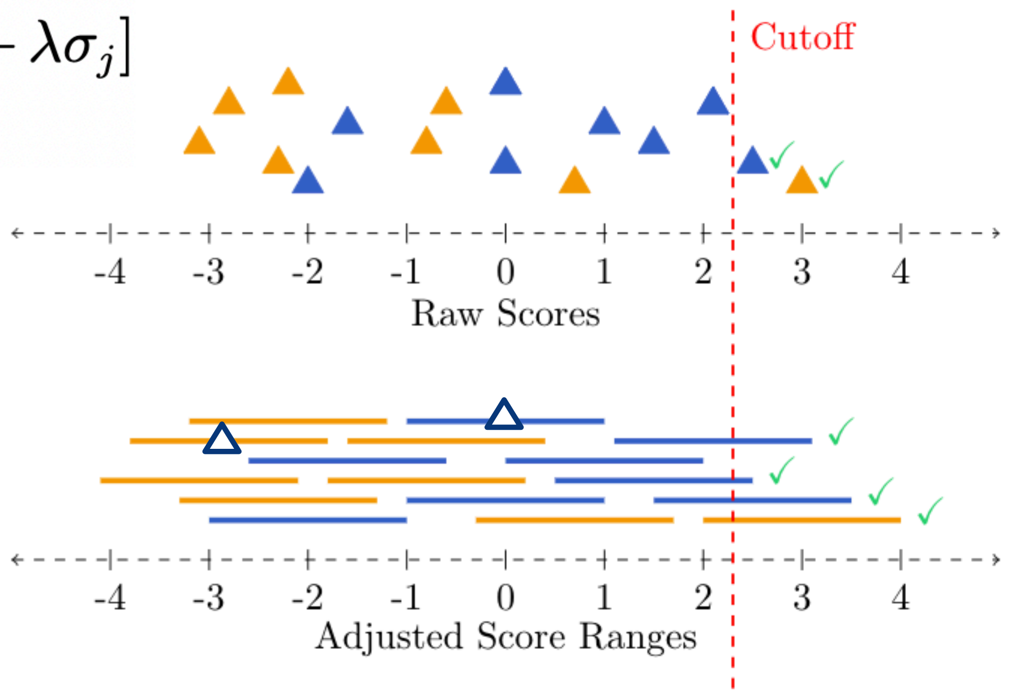


Can we design **efficient algorithms** and provide **meaningful interventions**?

Outline of the talk

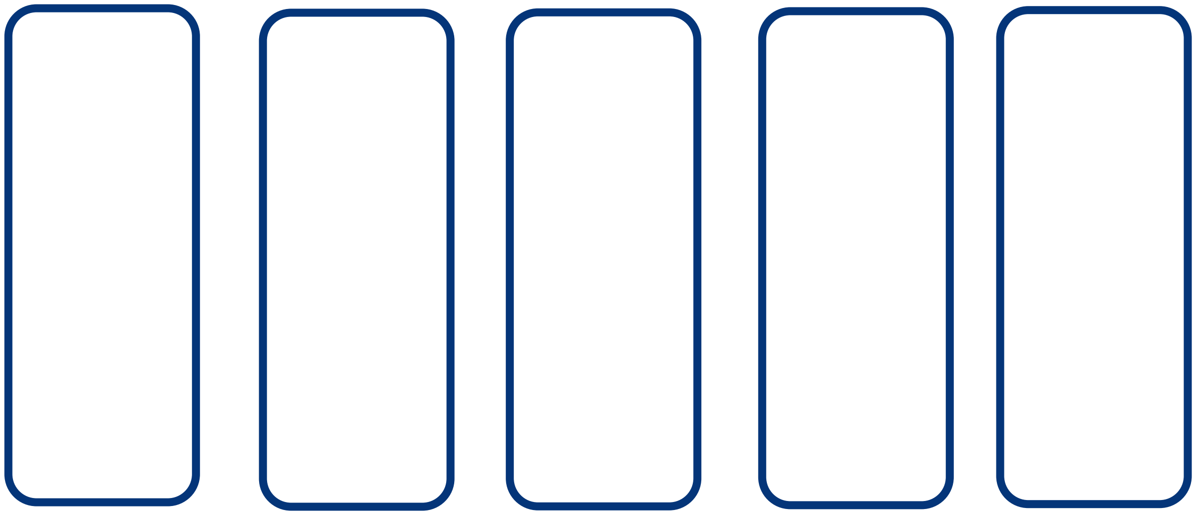
- The Microsoft Paradox
- Modeling Bias
- **Biased Online Secretary Problem**
- Title VII: Anti-Discrimination Law
- Extensions
- Future Work

Online "Secretary" Problem

**Applications
For
Olympiad
Team of Two
People**

Online "Secretary" Problem

Applications For Olympiad Team of Two People



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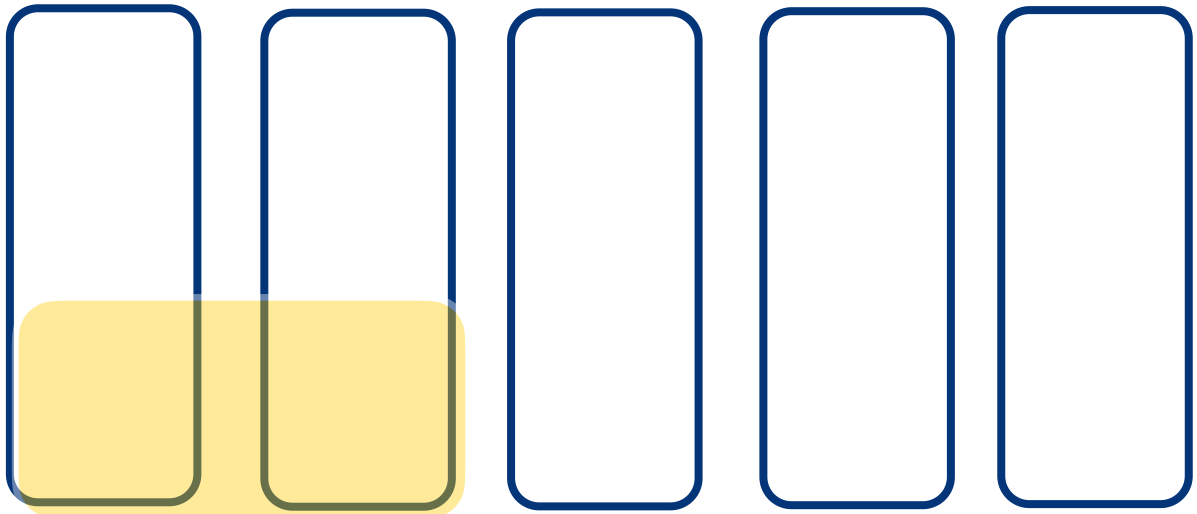

Online "Secretary" Problem

Applications For Olympiad Team of Two People

90

Pilar

Online "Secretary" Problem

Applications For Olympiad Team of Two People

90

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70

Sam

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Applications For Olympiad Team of Two People

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Sam

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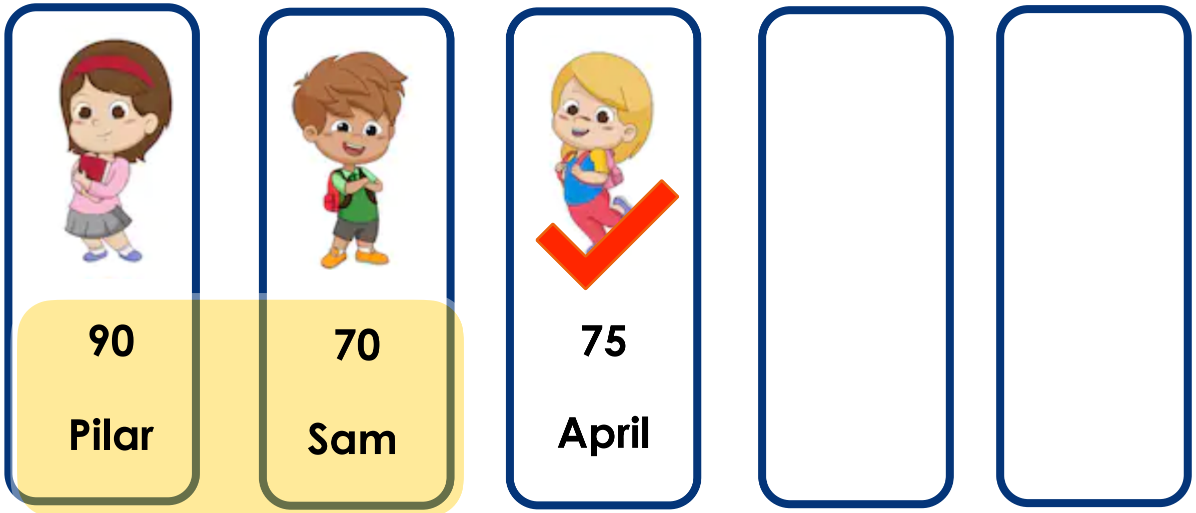
April

Online “Secretary” Problem

Applications For Olympiad Team of Two People



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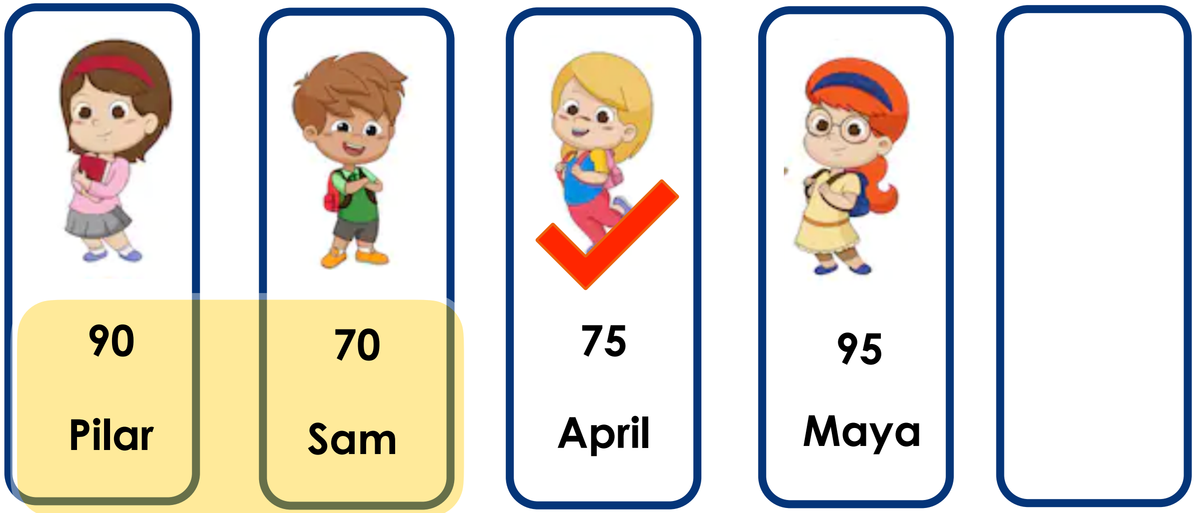

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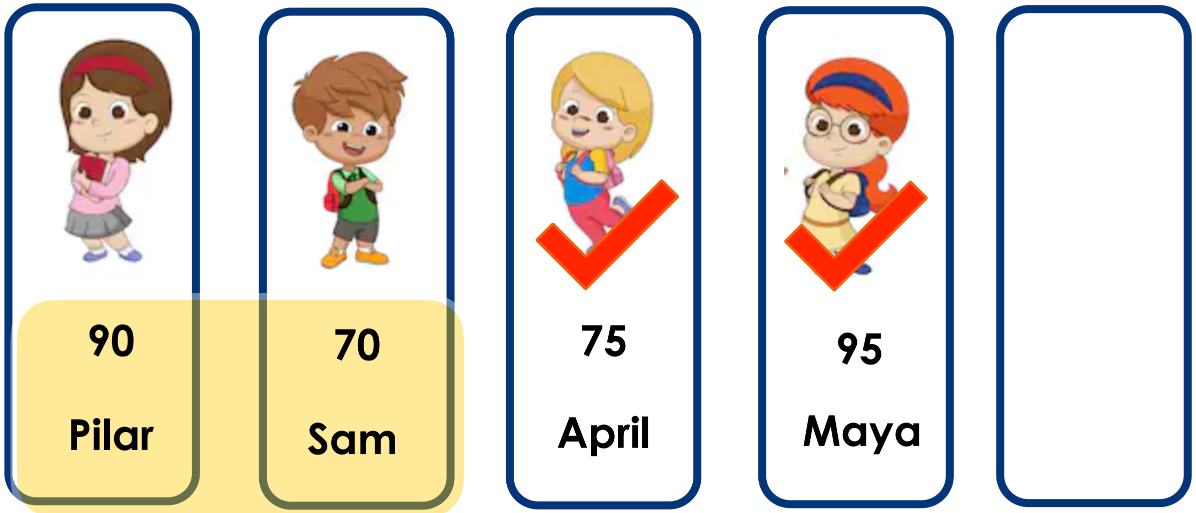

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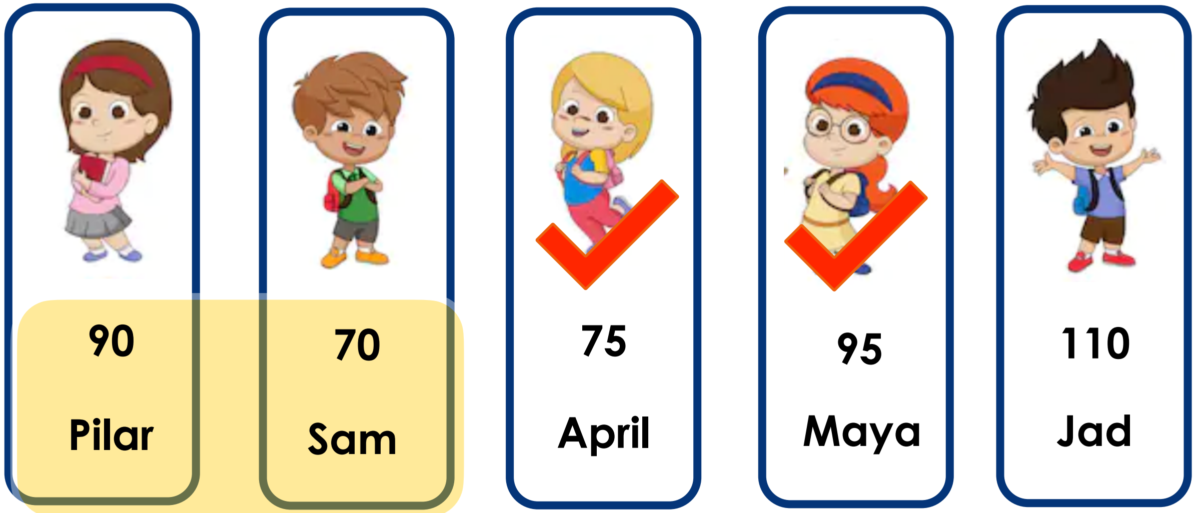

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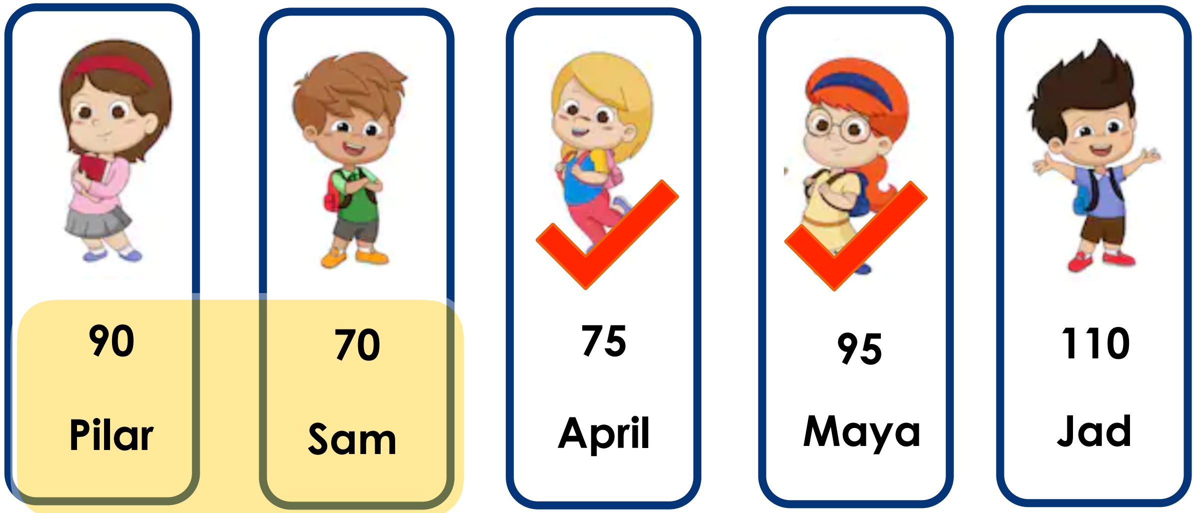

Secretary Problem: Maximize total utility of hired candidates

Competitive Ratio: minimize "worst case" OPT/E(ALG)

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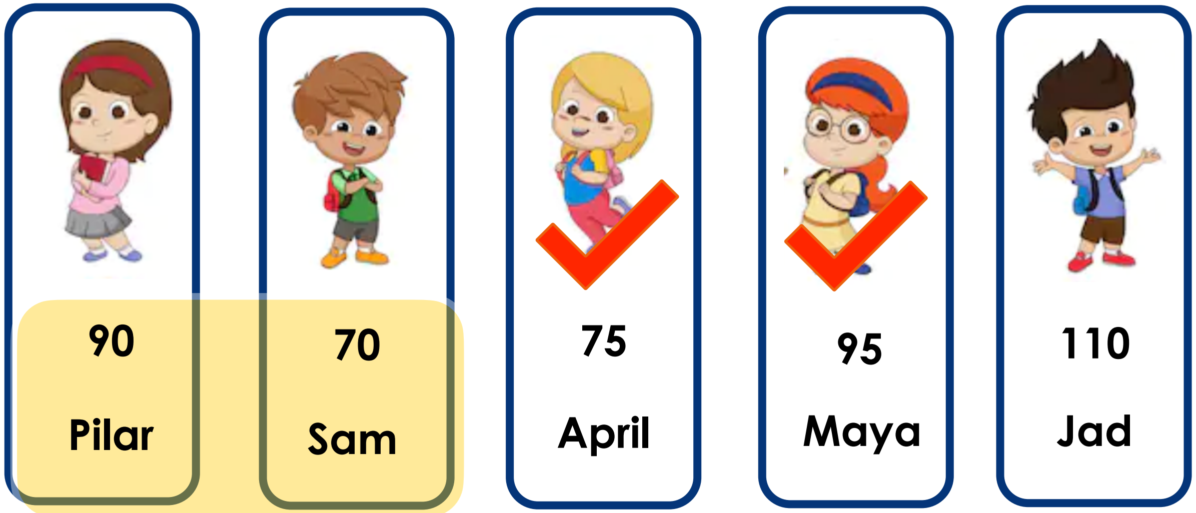

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What if some students had an extra job while preparing for the test?

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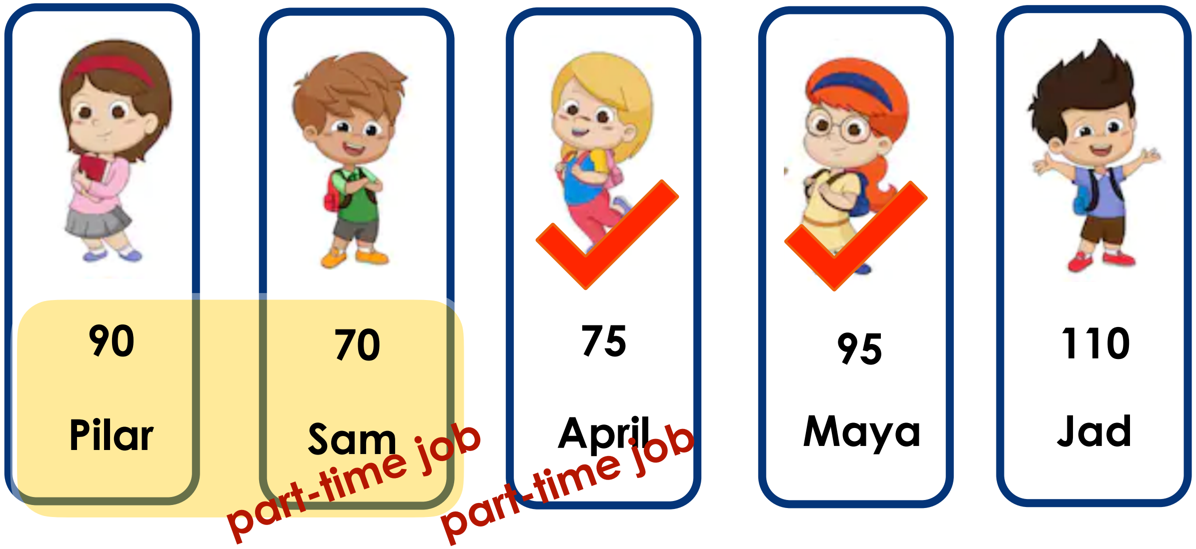

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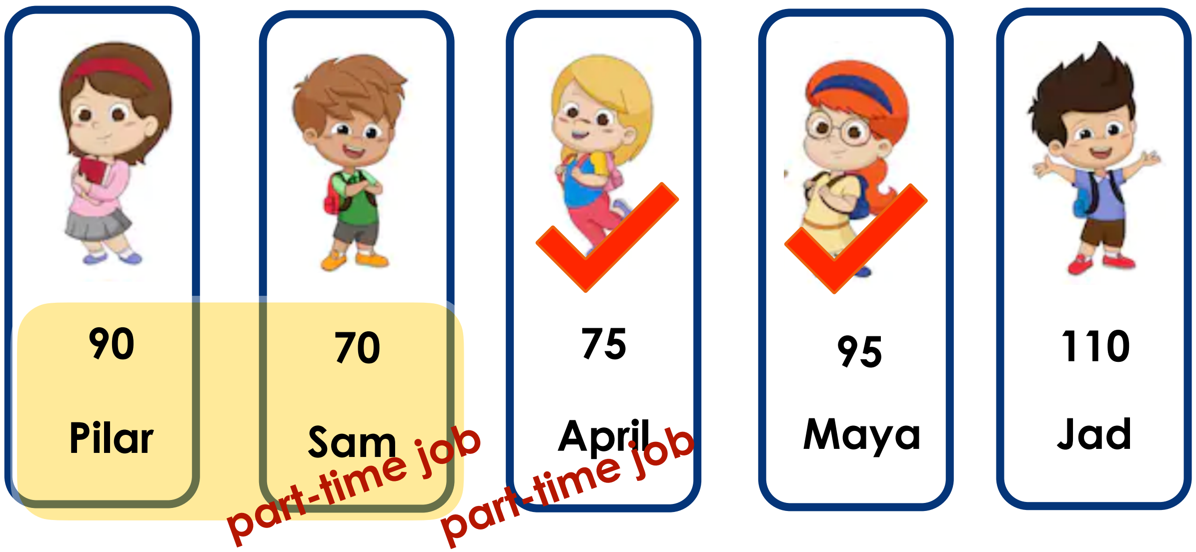

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Secretary problems: Dynkin (O(e), 1963), Kleinberg (2005), Babaioff-Immorlica-Kleinberg (matroid, 2007), Kumar-Lattanzi-Vassilvitskii-Vattani (2011), Buchbinder-Jain-Singh (2014), Feldman-Svensson-Zenklusen (2015), Soto (2013), etc.

Biased Secretary Problem [Salem, **Gupta** 2020]

*Individuals arrive over time, **poset relations** are observed, irrevocable selection decisions to maximize total true utility (known to OPT, any utility consistent with poset).*

order of arrival: random or adversarial after sample.

Minimize the **Competitive ratio**

(for fully adversarial)

$$\sup_{\mathcal{P},\omega} \frac{\mathrm{Opt}(\omega)}{\mathbb{E}[\mathrm{Alg}(\mathcal{P},\omega)]}$$

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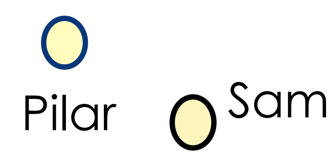

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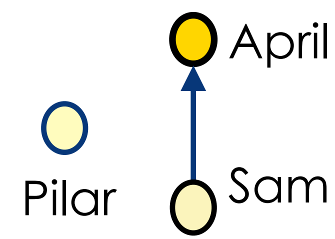

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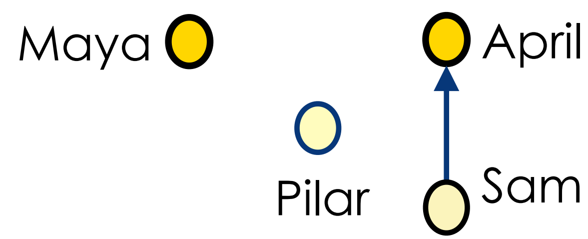

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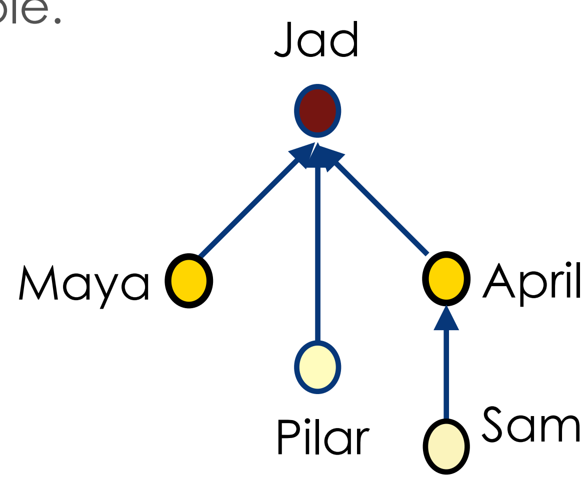

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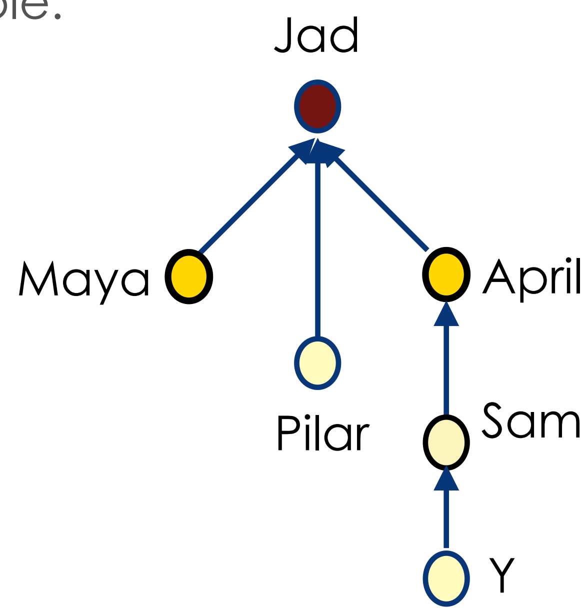

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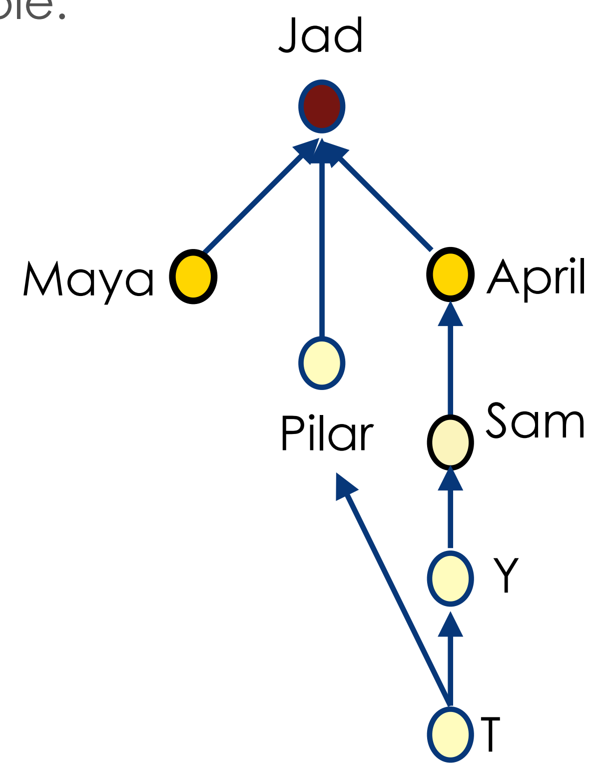

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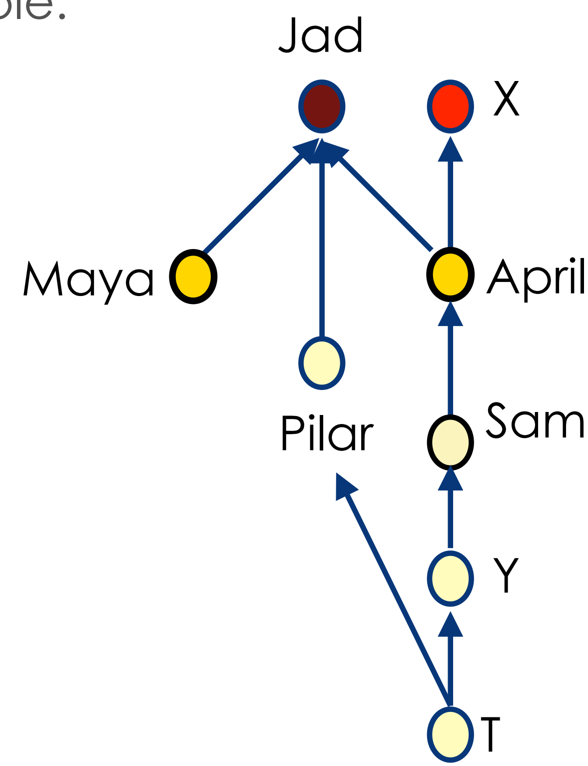

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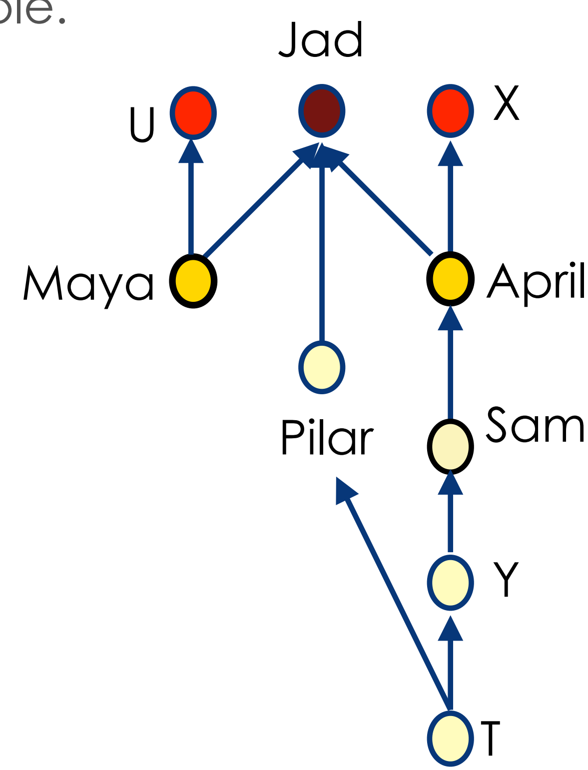

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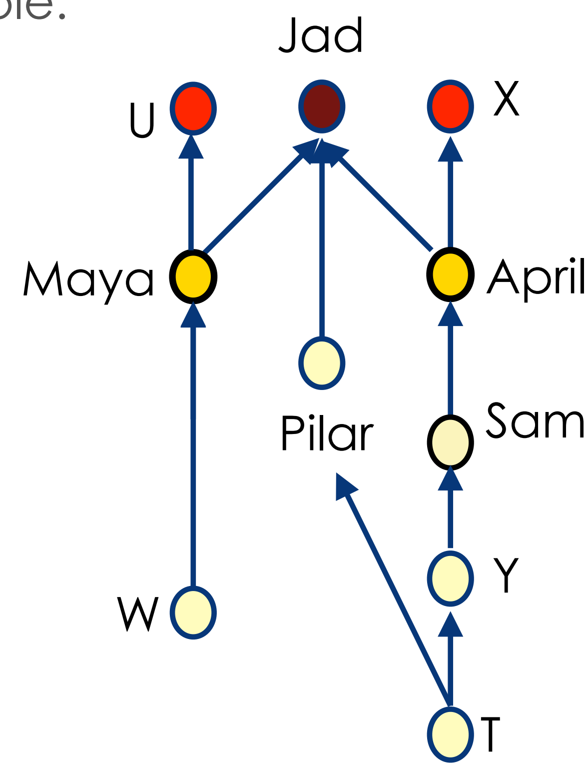

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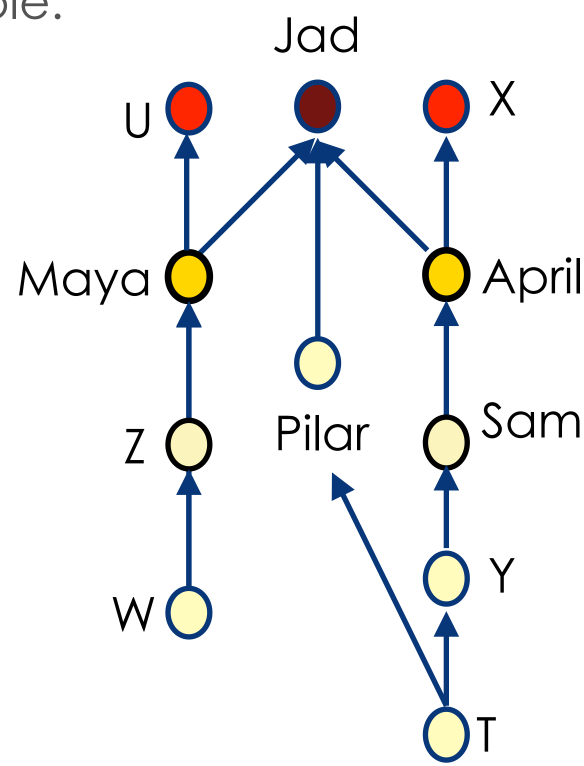

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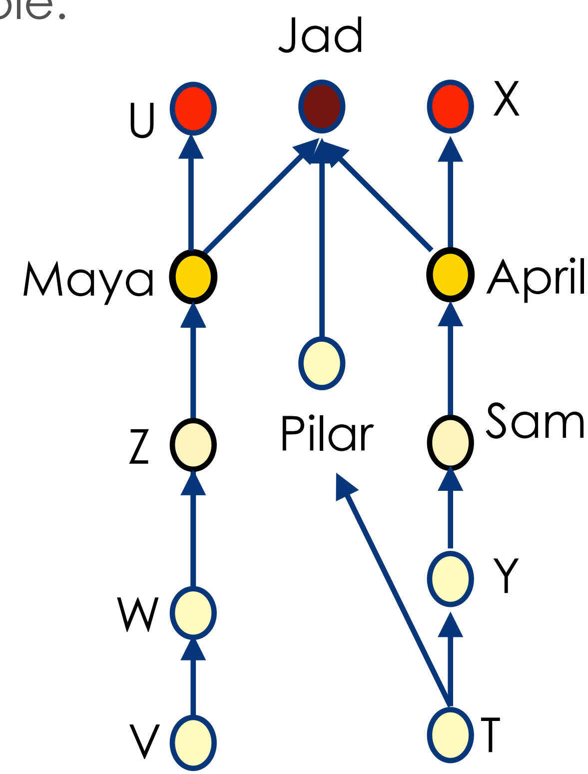

Desired Fairness

- Perhaps equal opportunity to **equally qualified** is ideal, but we only know so much.
- **Ranked demographic parity (RDP):**
  - Probability of selection should increase with better poset comparison,

$$a \succ b \implies \mathbb{P}(a = \checkmark) \geq \mathbb{P}(b = \checkmark)$$

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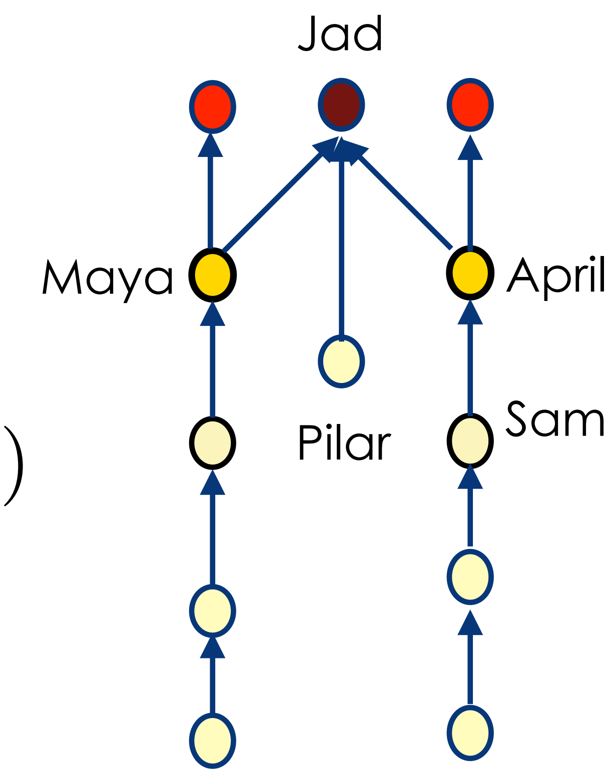

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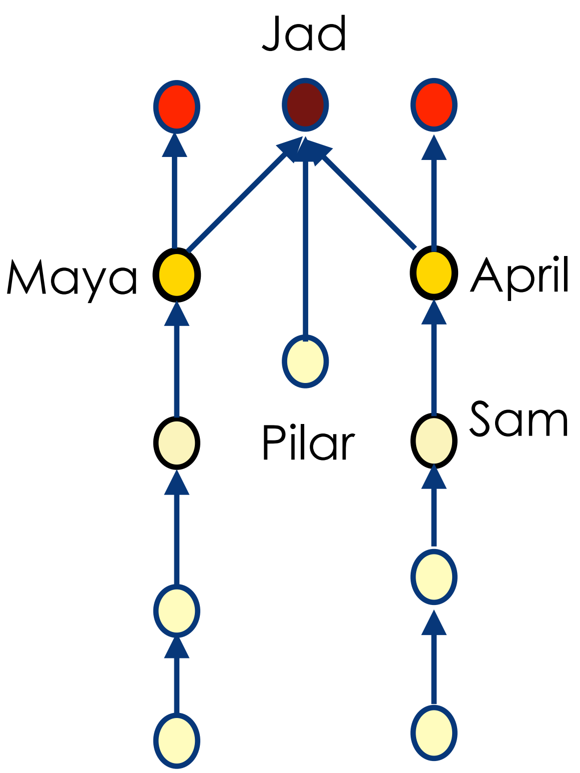
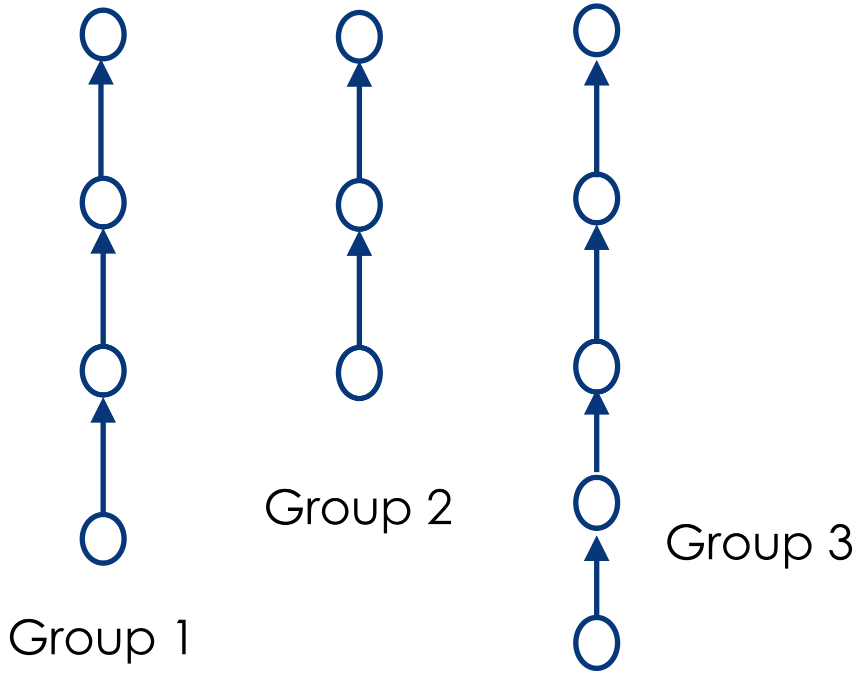


Obs. Let $\mathcal{P}$ be a poset, and suppose an algorithm has the property that $a \prec b$ implies $\mathbb{P}(a \text{ is selected}) \leq \mathbb{P}(b \text{ is selected})$. If the algorithm makes decisions based solely on arrival order and $\mathcal{P}$, then it will satisfy RDP.

Any competitive algorithm must hedge



$$c = \sup_{\beta > 0, w} \frac{\mathrm{Opt}(w)}{\mathbb{E}[\mathrm{Alg}(\beta, w)]}$$

If there is zero probability on any maximal element then competitive ratio is infinity.

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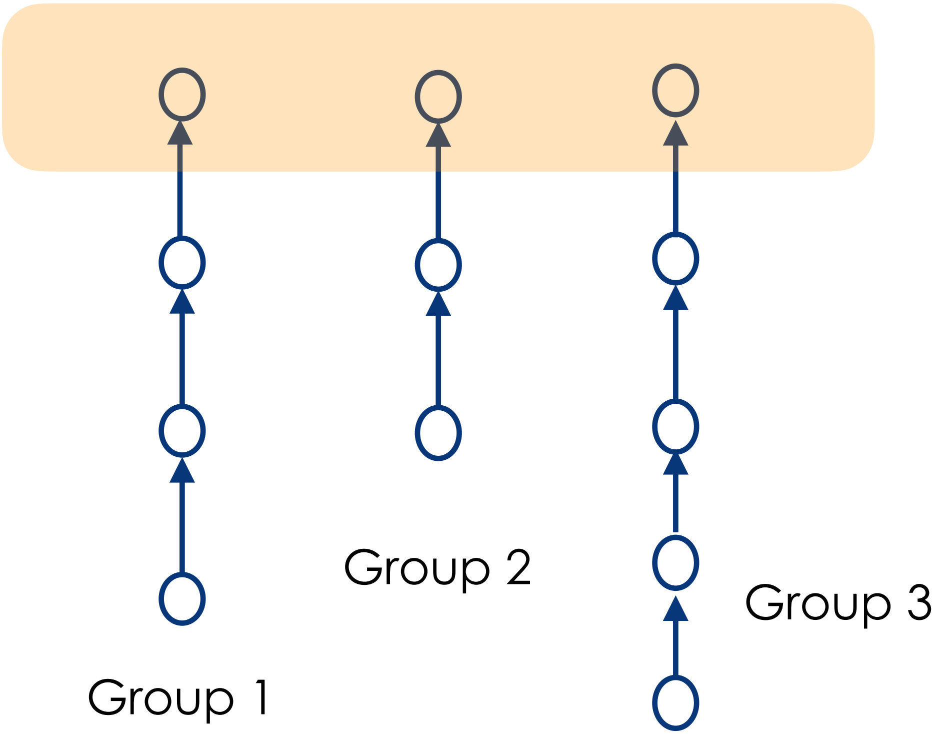

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If there is zero probability on any maximal element then competitive ratio is infinity.

[Salem, G.] *Any algorithm for the poset k-secretary problem with access to only partial ordinal rankings with respect to a partial order of width ω is $\Omega(\omega)$-competitive.*

Warm-Up: k-secretary problem

Algorithm 1: [Dynkin 1963]

Sample N/e elements
Select first element better than sample

N= 10, N/e = 3.67, $|S|$ = 3, k = 1

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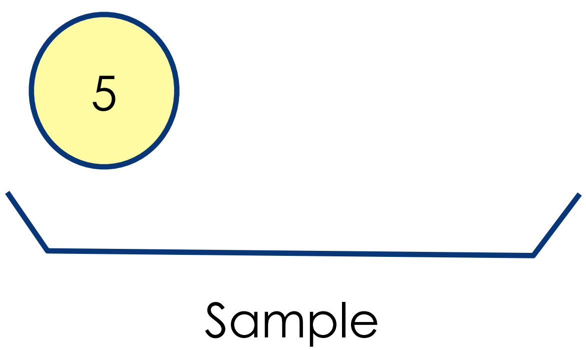

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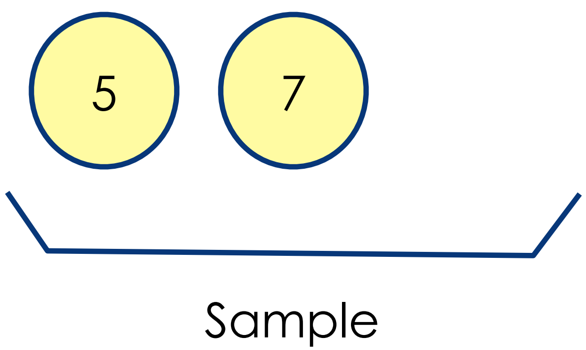

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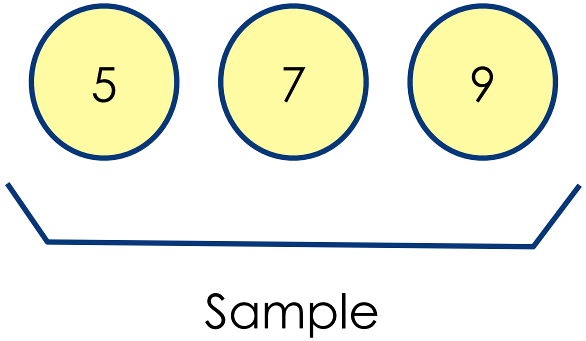

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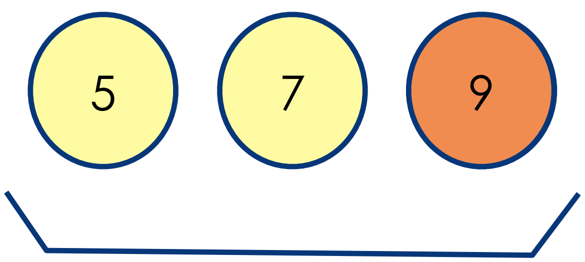

Sample

Highest in sample = 9

Warm-Up: k-secretary problem

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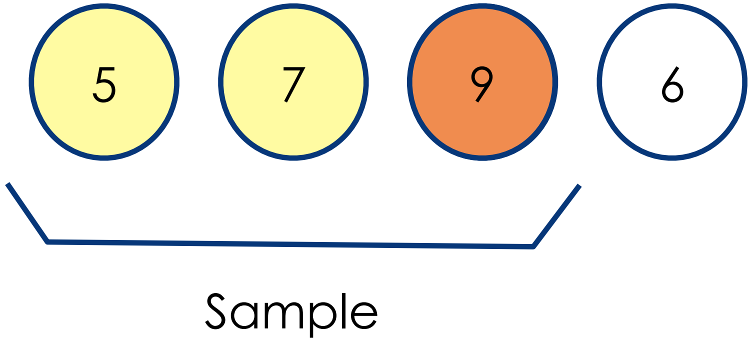

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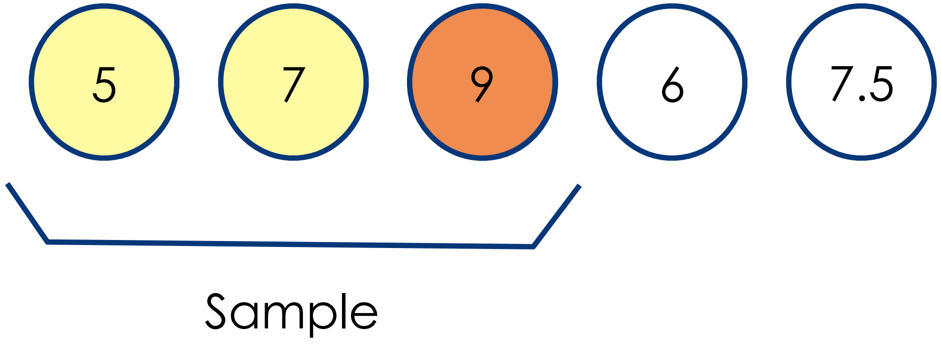

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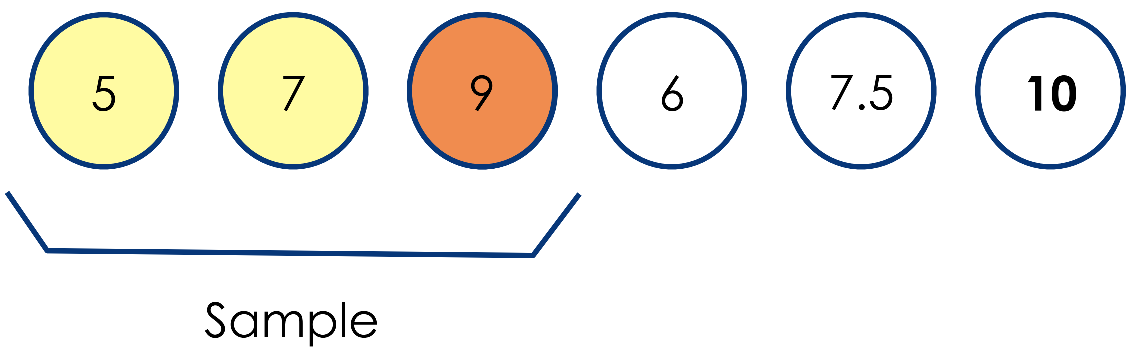

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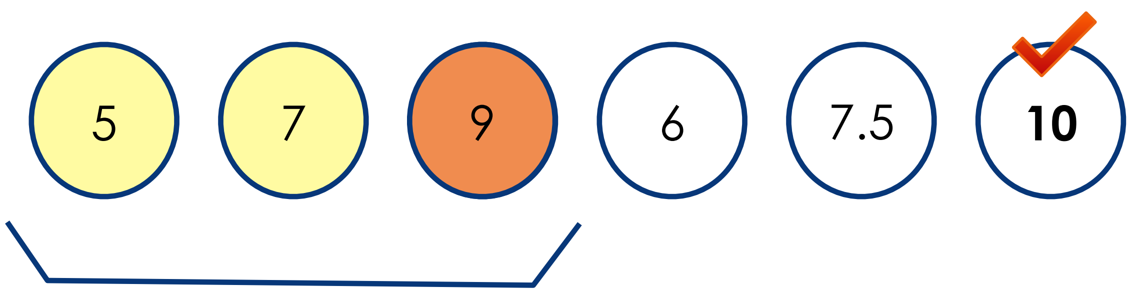

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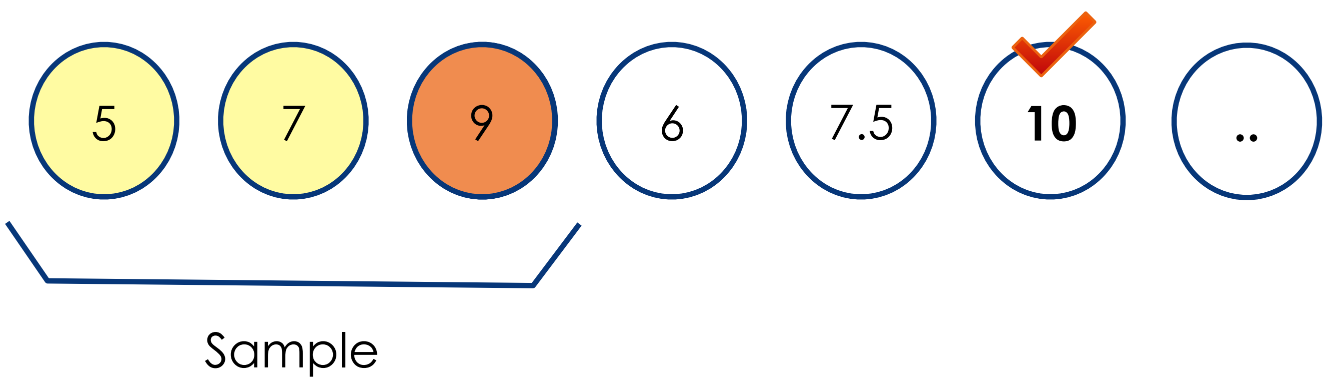

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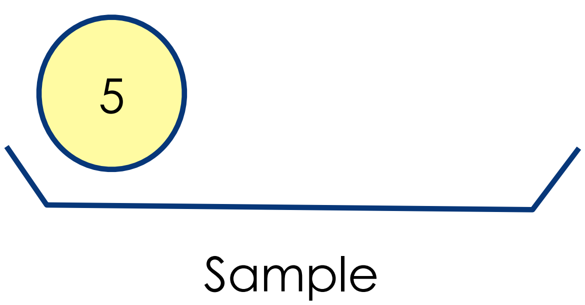

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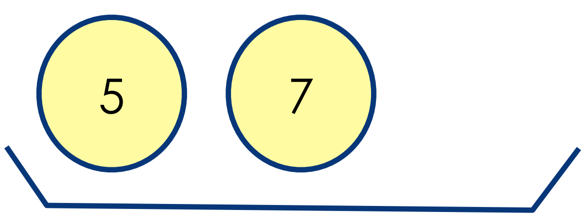

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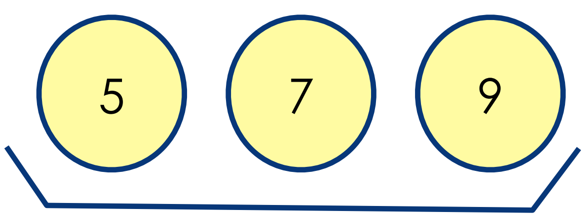

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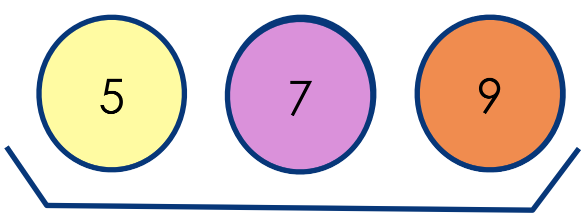

Sample

2nd highest so far = 7

Warm-Up: k-secretary problem

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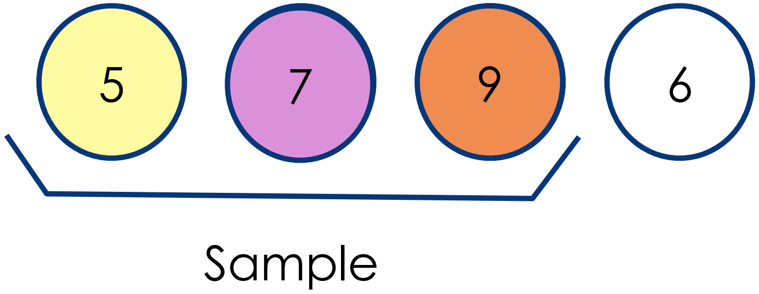

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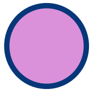

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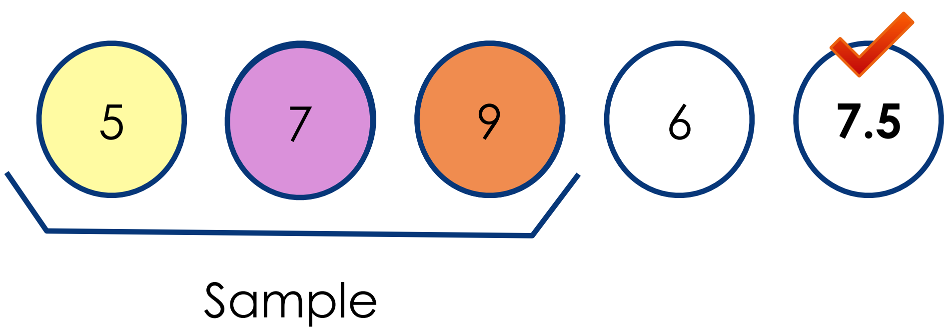

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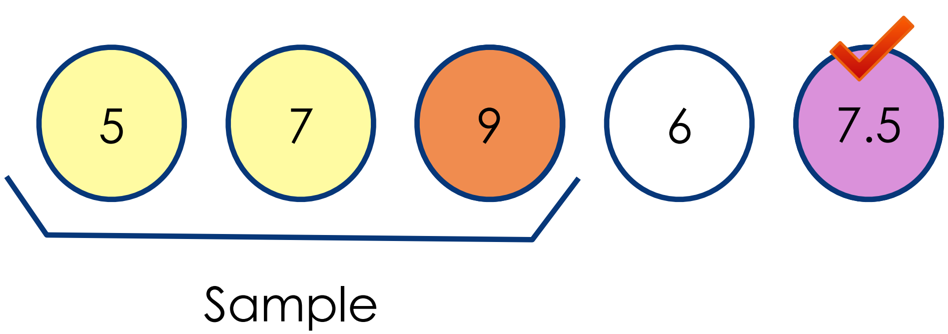

2nd highest so far = 7.5

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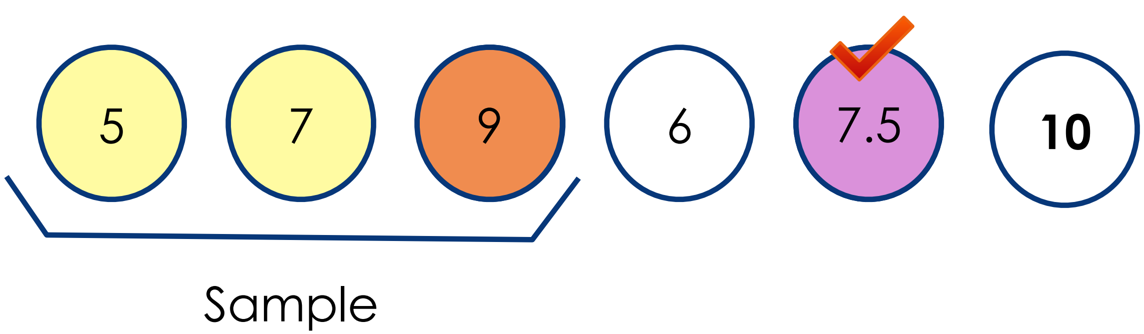

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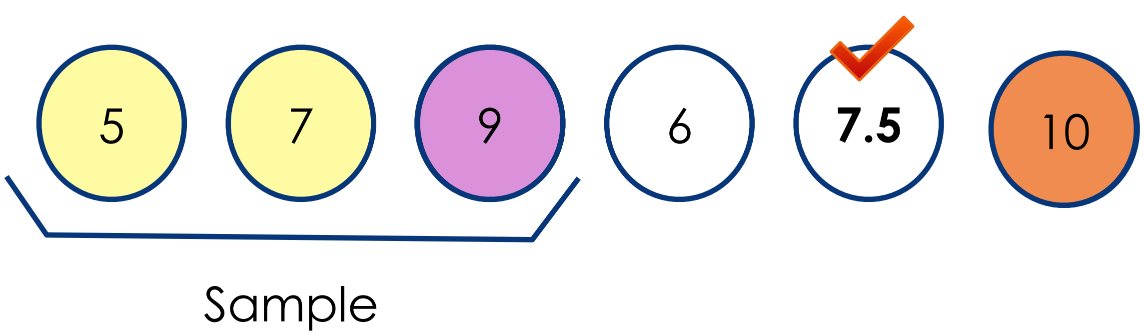

2nd highest so far = 9

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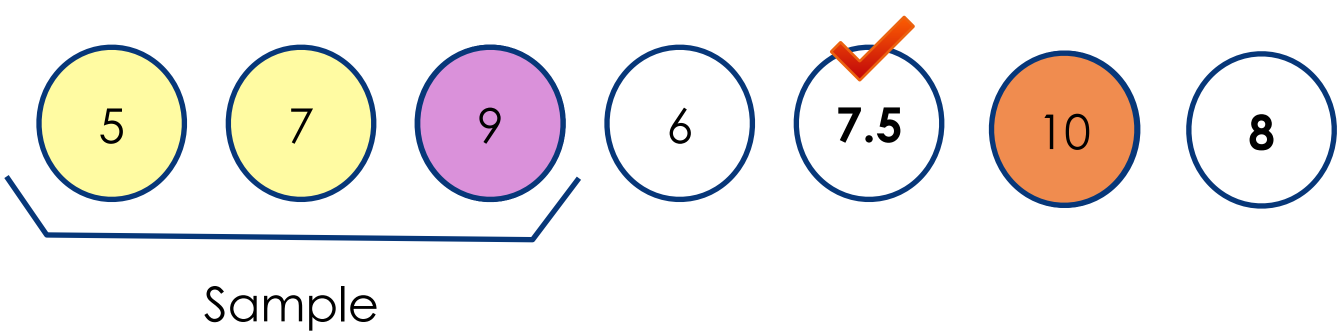

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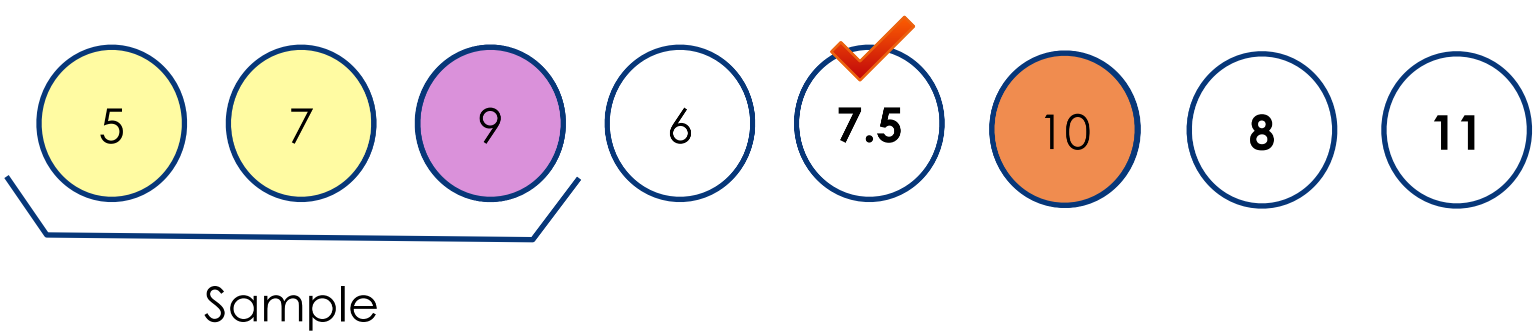

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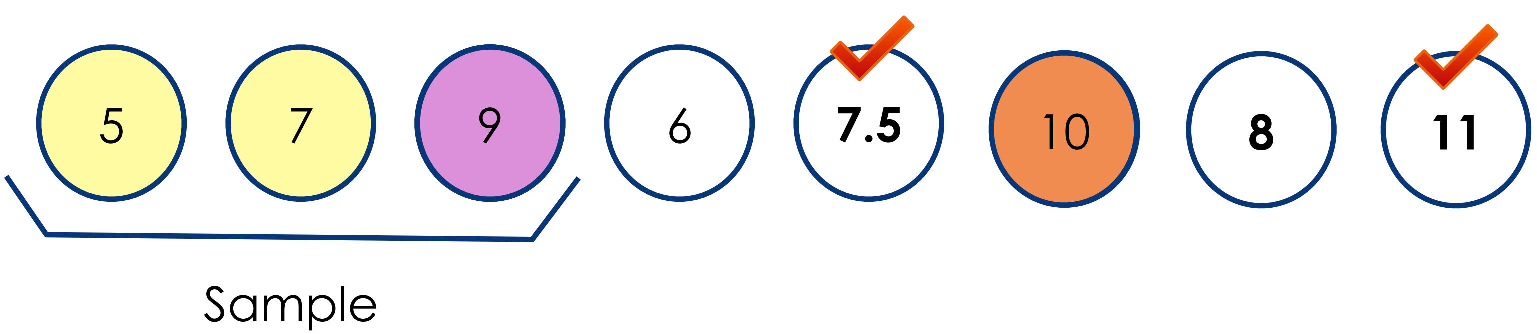

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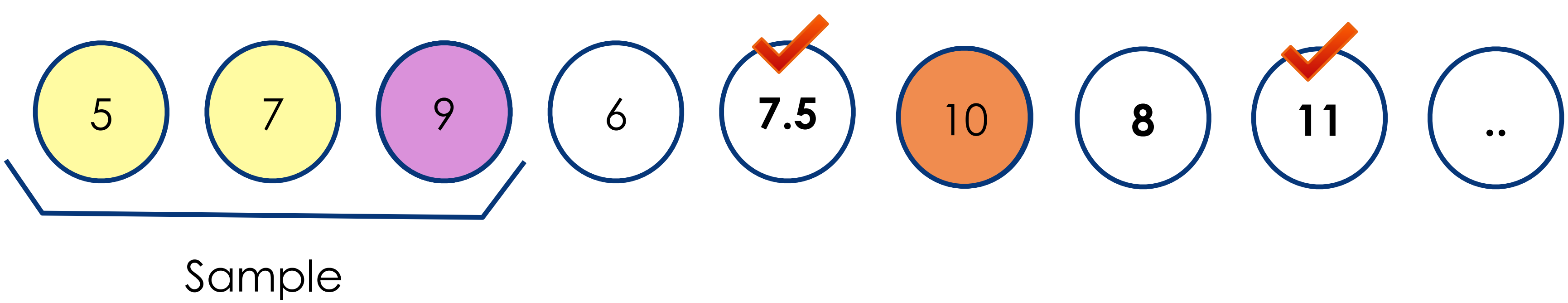

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Requires to **know N** [Gh,V11], which will be an issue for posets.

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Sample

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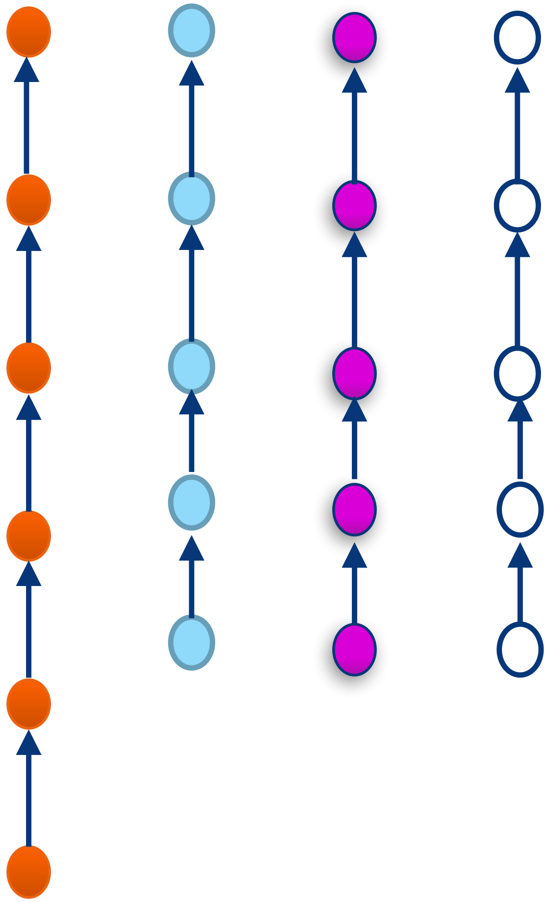
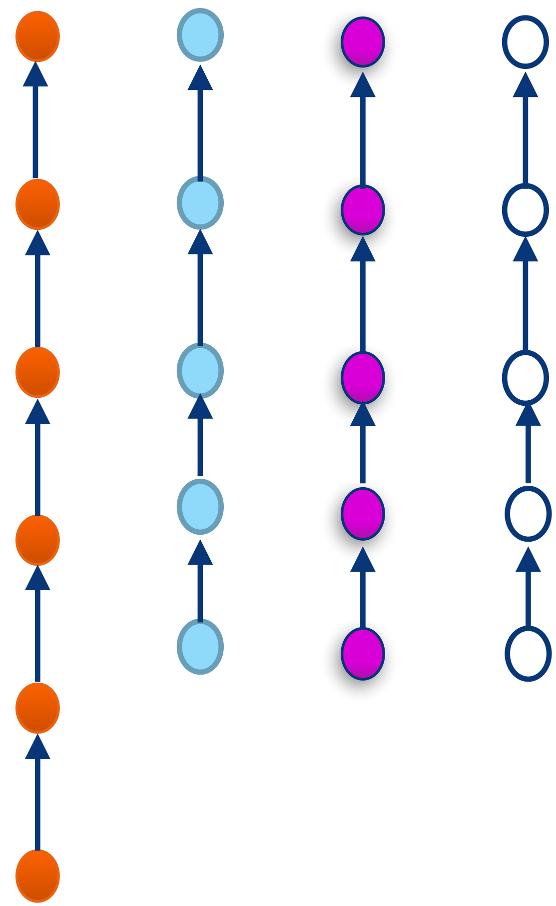
Biased Secretary with Poset



Biased Secretary with Poset

1. 4 groups given with known sizes, want to select 5 candidates.



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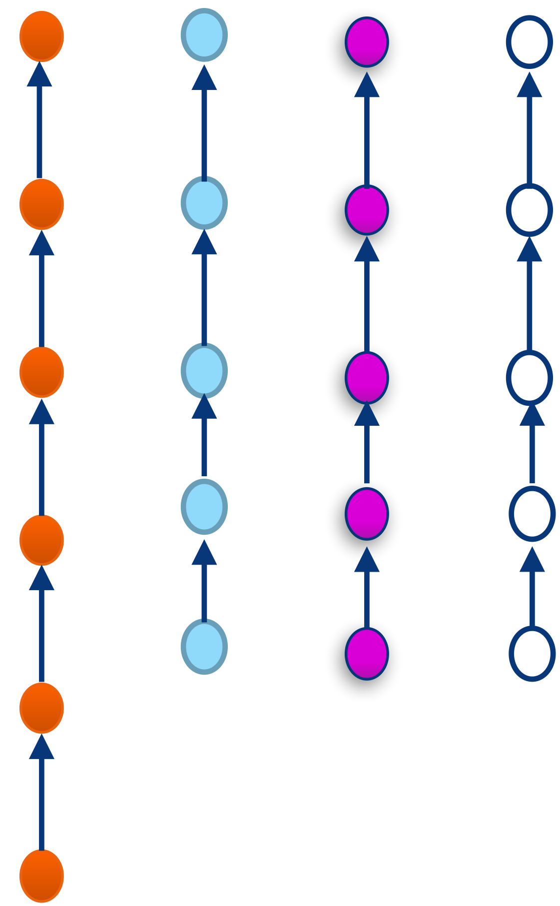

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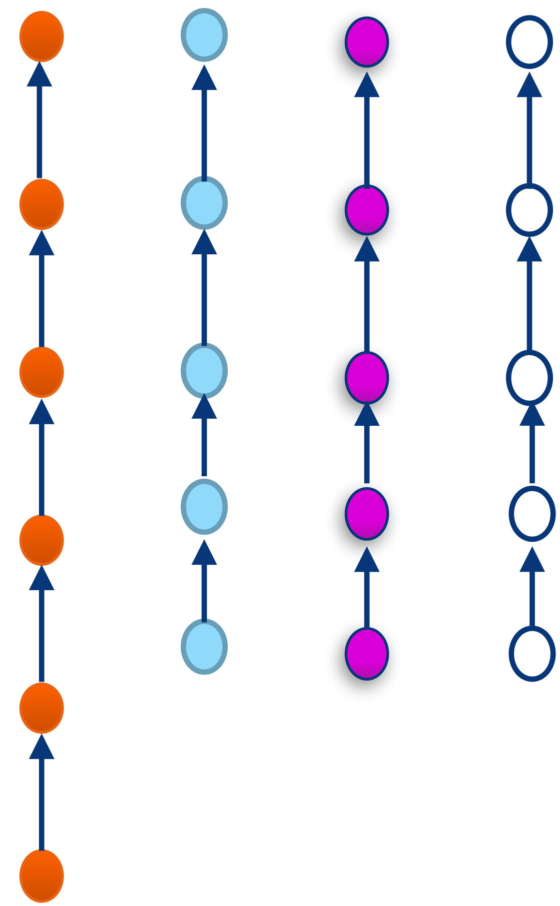

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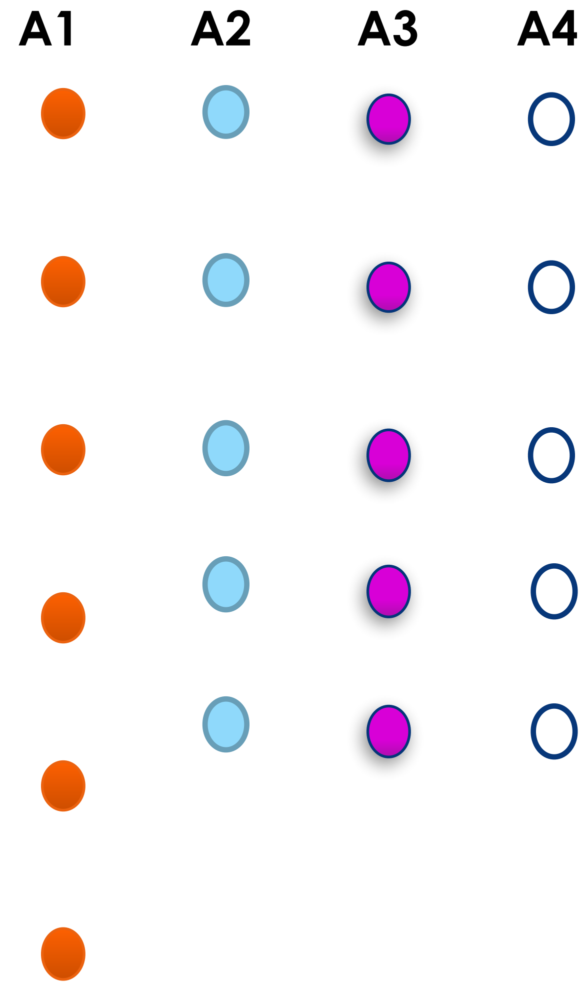

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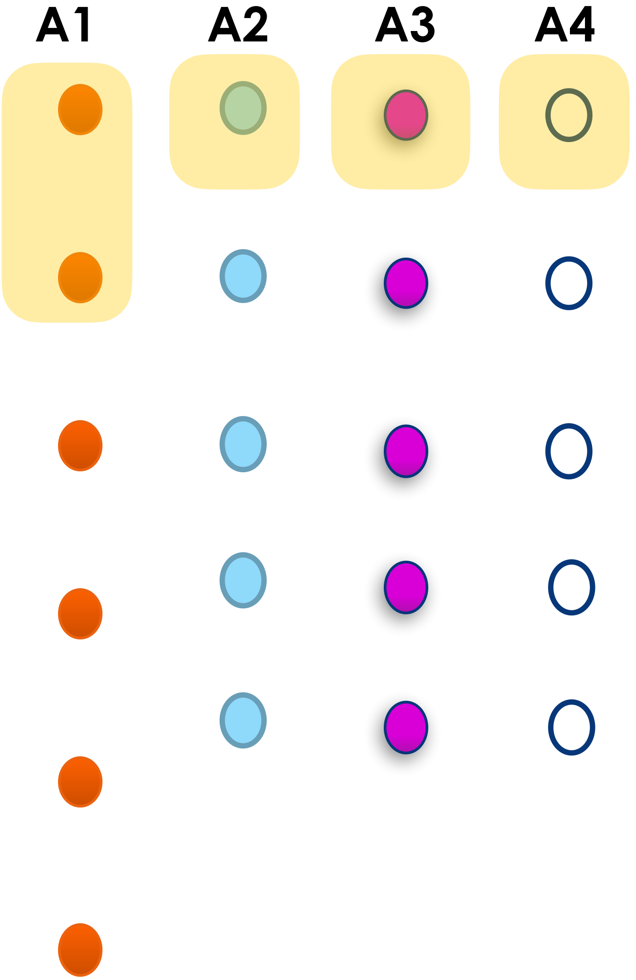

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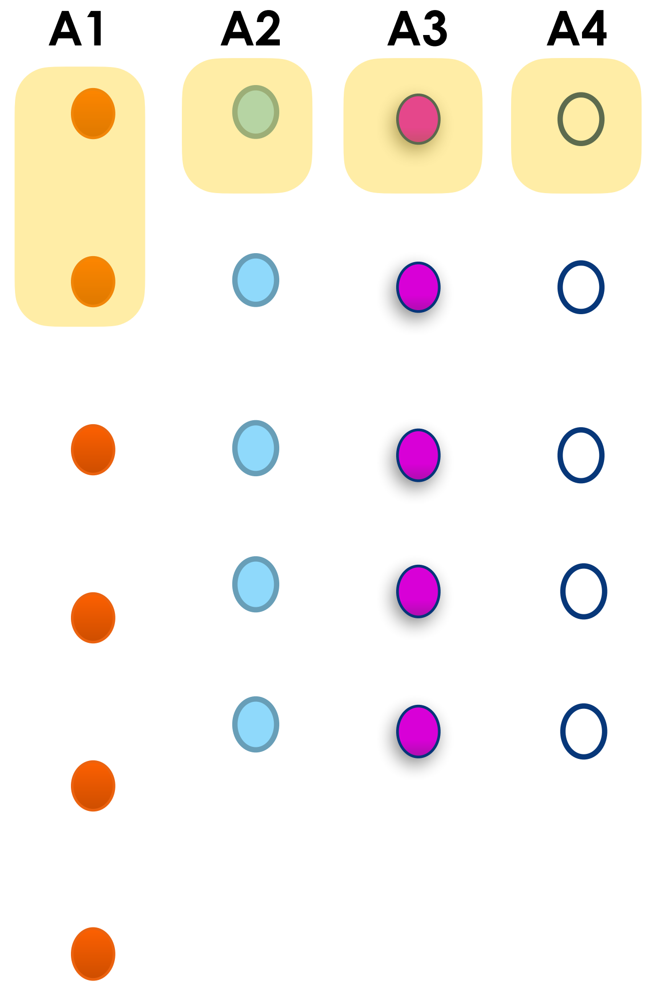

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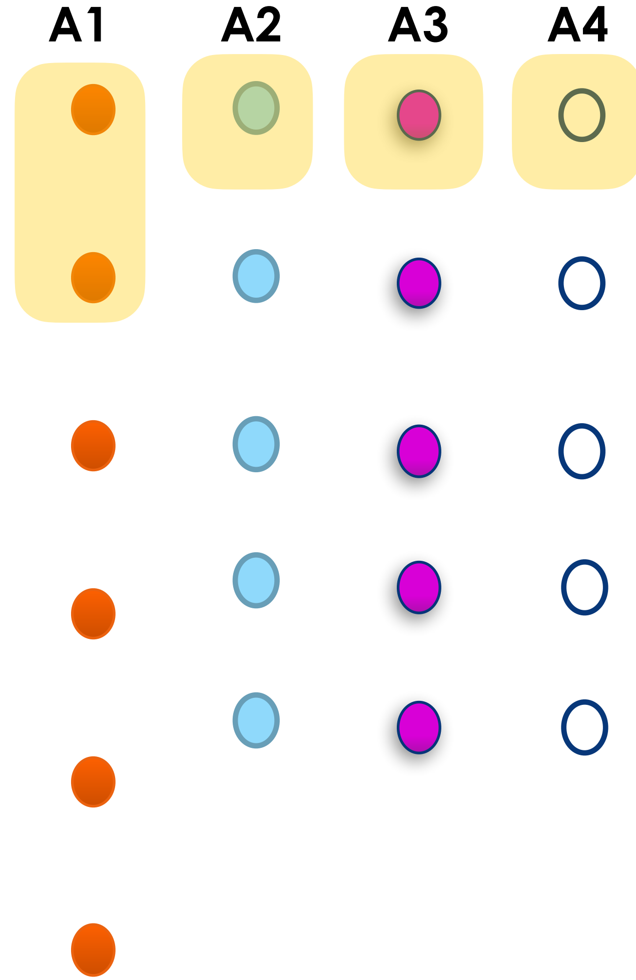
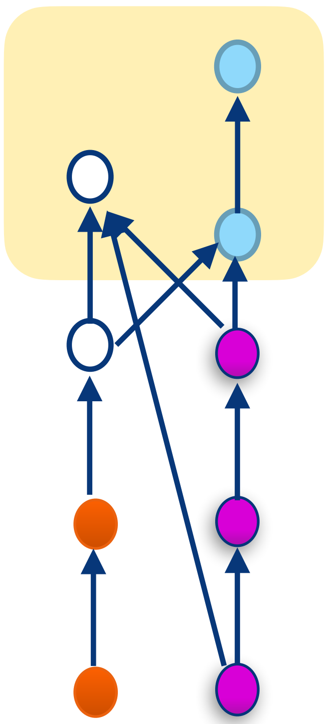


Quotas are illegal!!

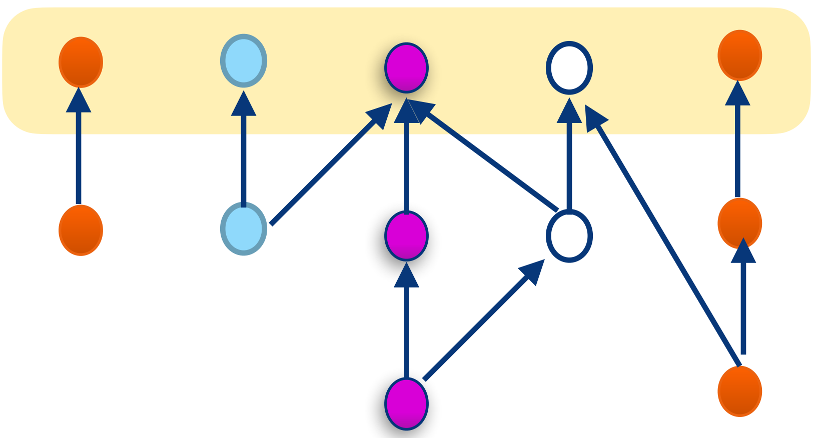
Poset Secretary Algorithms

We would like to select maximal elements as they arrive..

.. but we don't know the structure of the poset up front!



Poset 1 (width = 2)



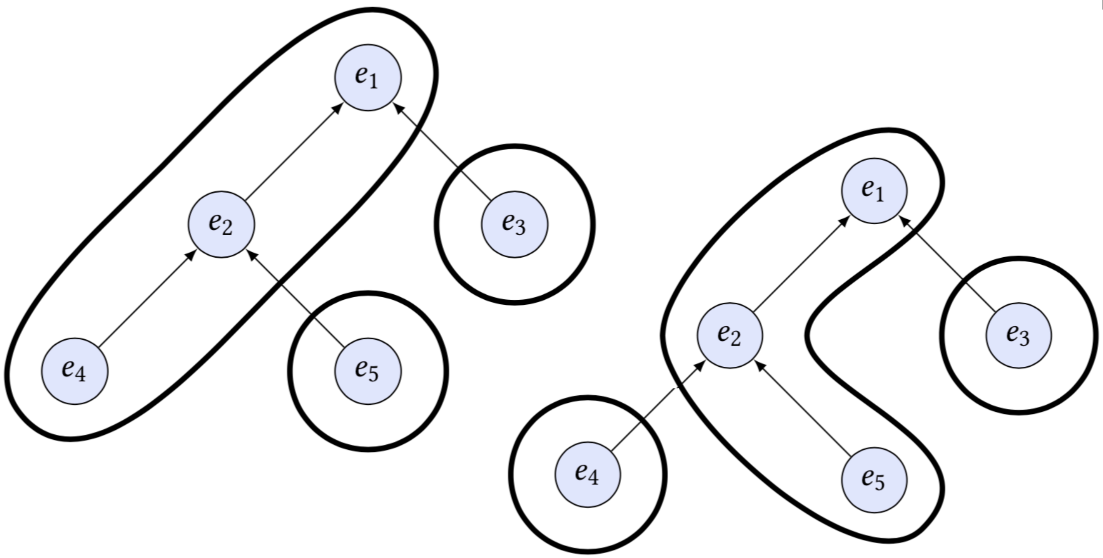
Poset 2 (width = 5)

Width dictates lower bound on competitive ratio.

Poset Secretary Algorithms

Width = minimum number of chains to decompose the poset

[Dilworth's Theorem, Rudnicki 2009]



Tempting to use **online chain partitioning** [e.g., Keirstead, Trotter (1981) for interval orders].

Still non-trivial due to **sizes of chains (N?)**.

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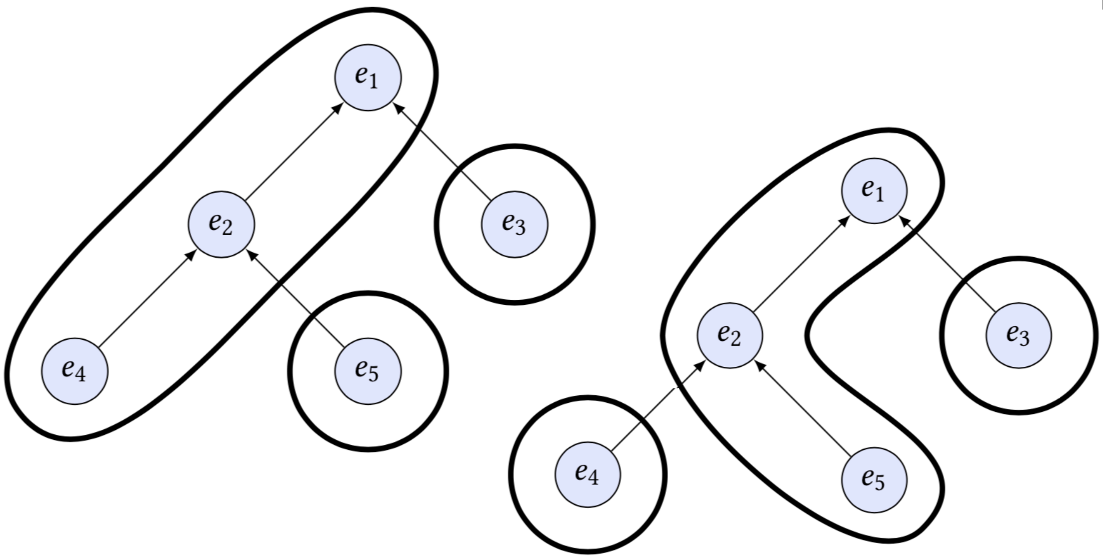

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We use a **random partitioning technique** [Soto, 2013], [Babaioff e.t al 2009]

Assign each candidate to an independent label,

Select a single candidate from each "label",

$O(3\omega' e^2)$

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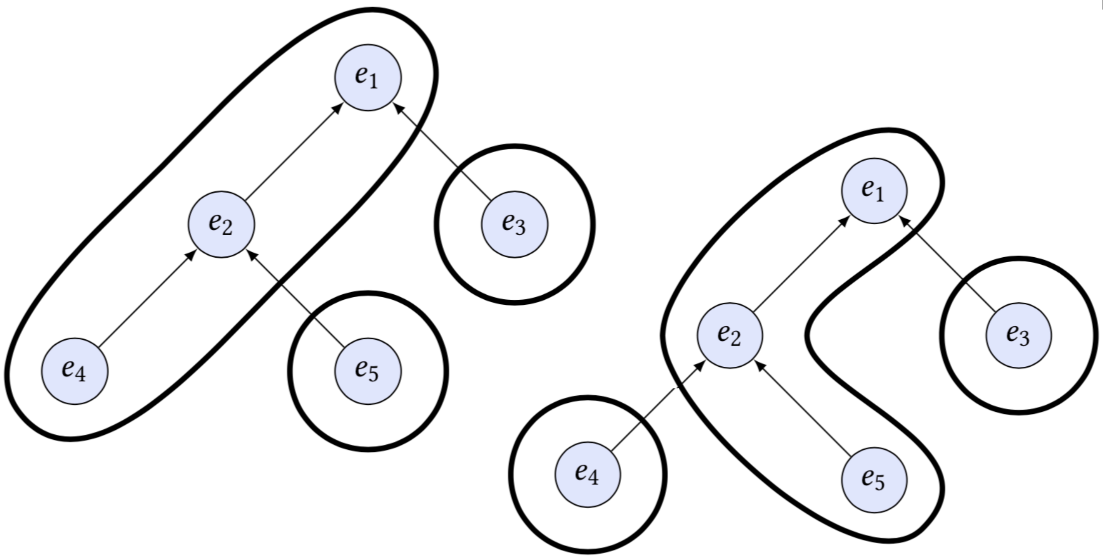

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but **RDP is not satisfied** (due to properties of chain decomposition).

Selection in the Poset Model

Algorithm Gap-K-POSET:

1. We will assign labels in [k] to each candidate.
2. Sample, estimate the width of full poset.
3. Correct sample size if needed.
4. Within each label, select maximal element compared to sample if none selected so far.

L1	L2	L3	L4

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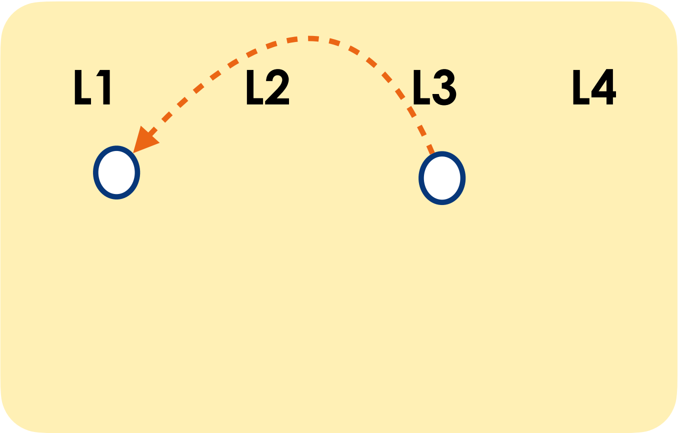

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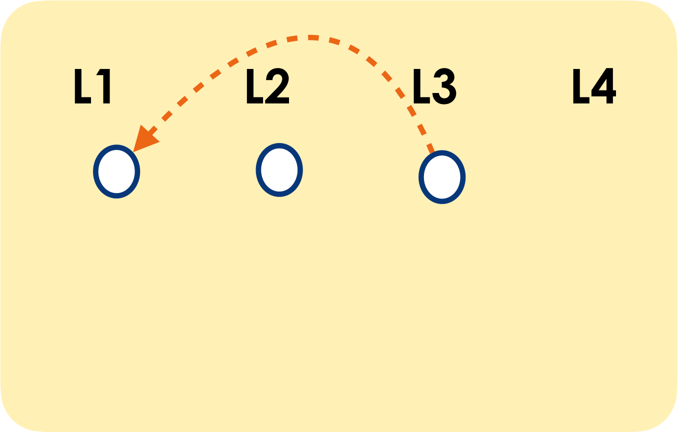

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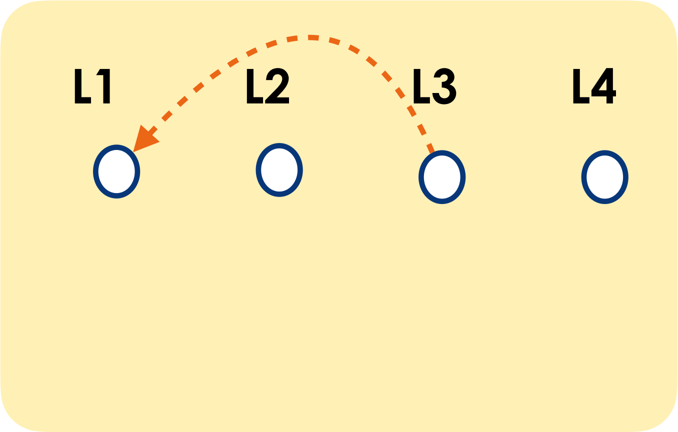

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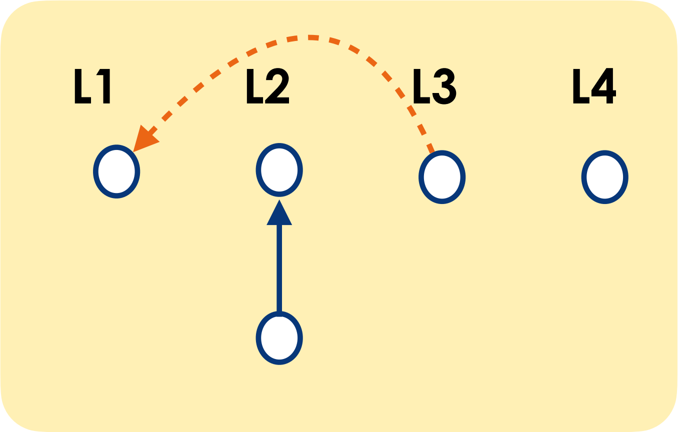

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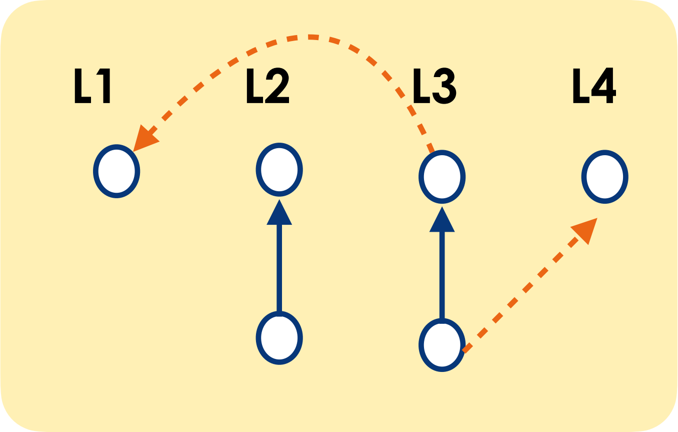

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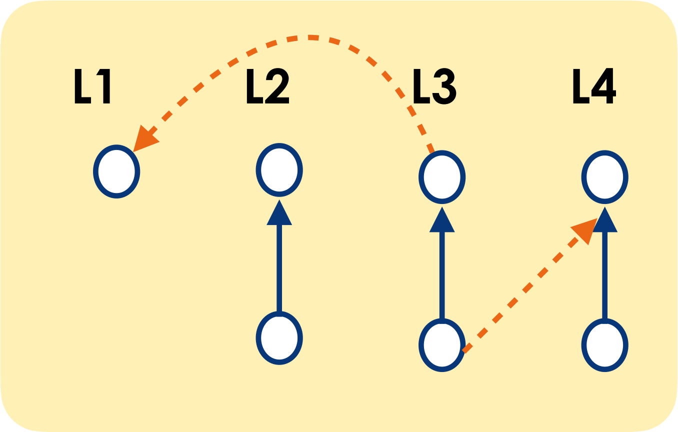

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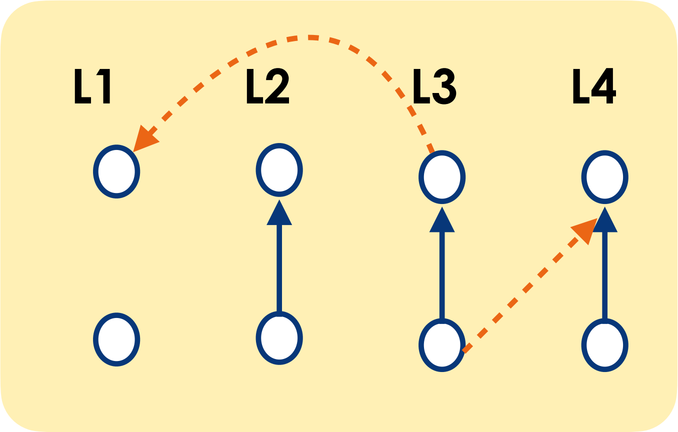

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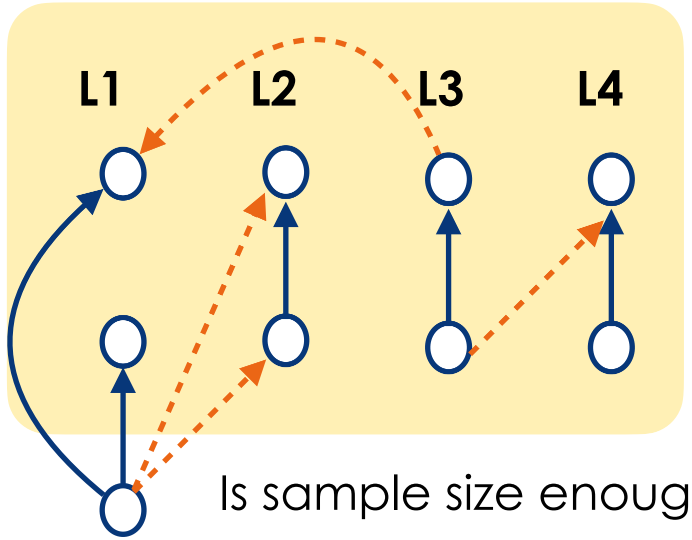

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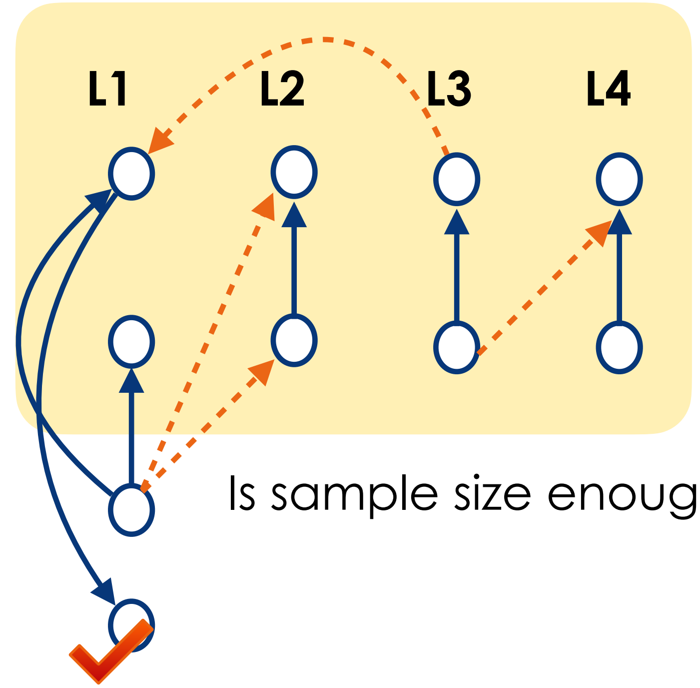

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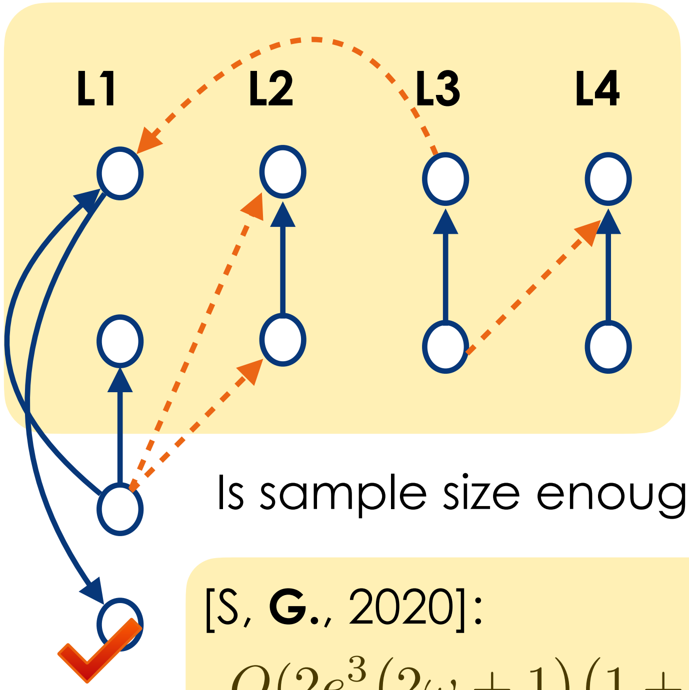

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[S, **G.**, 2020]:

$$O\left(2e^3\left(2\omega+1\right)\left(1+o(1)\right)\right)$$

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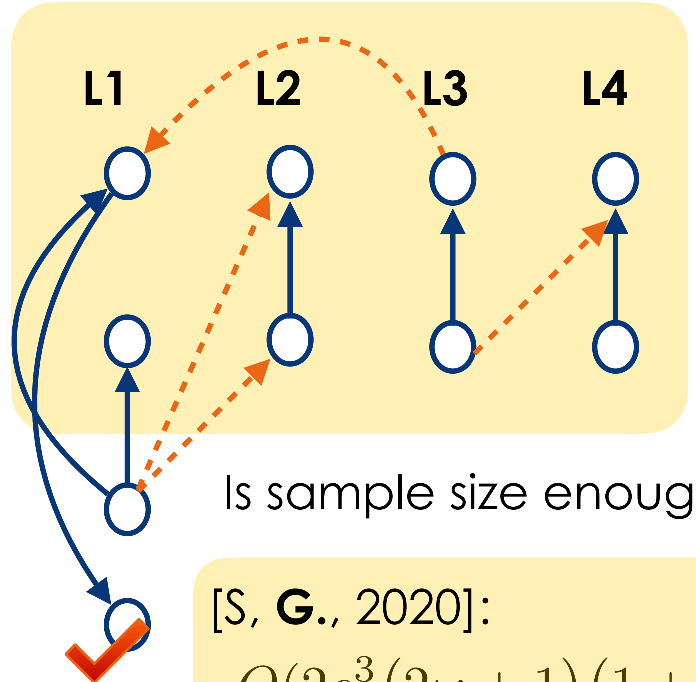

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Key takeaways are managerial:
- *Estimates* from prior samples,
- *Independent selection committees via labels*,
- *Select maximal* in each label,
- *Don't disregard comparative* information (RDP for posets),
- *Decrease width* of poset for better performance,
- **Asymptotic methods**: **adaptive thresholds** as more information.

Summary of competitive ratios

	Competitive ratio	Algorithm
Poset model		
ω known	$(\omega+1)e^2$ (Corollary 5.1)	GAP-K-LABEL (Algorithm 1)
ω unknown	$e^3(4\omega+2)(1+o(1))$ (Proposition 5.3)	GAP-K-POSET (Algorithm 2)
ω unknown $\omega \leq \log k$	$\omega\left(1-\frac{38\log N}{\sqrt{k}}\right)^{-1}$ (Corollary 5.2)	ADATHRESHOLD (Algorithm 3)

	Competitive ratio	Algorithm
Group model		
Adversarial	$(g+1)e^2$ (Corollary 5.1)	GAP-K-LABEL (Algorithm 1)
Adversarial	$gf(k/g)$ (Proposition 6.1)	GAP (Algorithm 4)
Stochastic	$2e(1+o(1))$ (Proposition 6.2)	GAP-K-CAP (Algorithm 5)

Open questions: width for posets (4e gap), asymptotic k without regimes, N unknown (constant not possible [GV, 2011]), privacy sensitive construction of posets, network models, biased matroid secretary (partition matroid), other applications: school admissions.

Experimental Study

Aspiring Minds Employability Outcomes 2015 Dataset

Gender	10percent	12percent	College tier	College GPA	College city tier	English	Logical
-16.95	-0.2193	0.2372	-18.50	1.182	1.563	0.02541	0.1429

Quant	Domain	ElectronicsAndSemicon	Computer science	Mechanical eng.	Electrical eng.
0.1199	177.5	-0.09960	0.006473	-0.3314	-80.72

Telecom. eng.	Civil eng.	Conscientiousness	Agreeableness	Extraversion	Neuroticism
-80.72	0.4119	-4.598	2.649	-3.256	-4.508

Openness to experience	Graduation age
3.565	0.1764

Coefficients (partial derivatives) of the linear prediction model for computer programming.

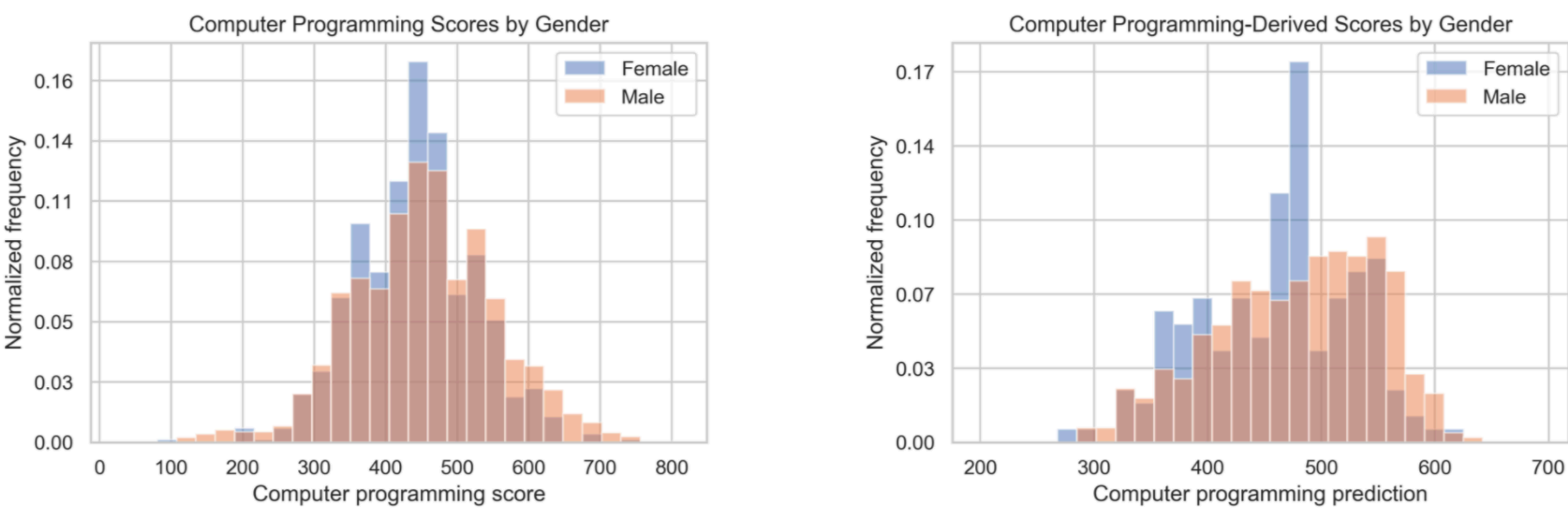
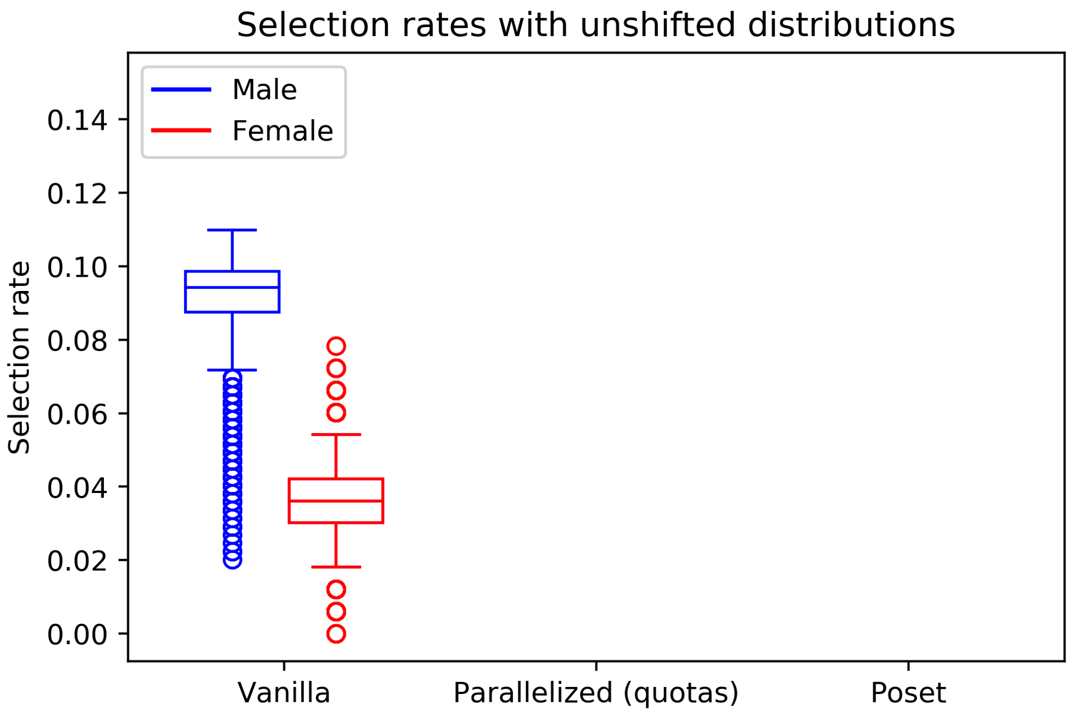


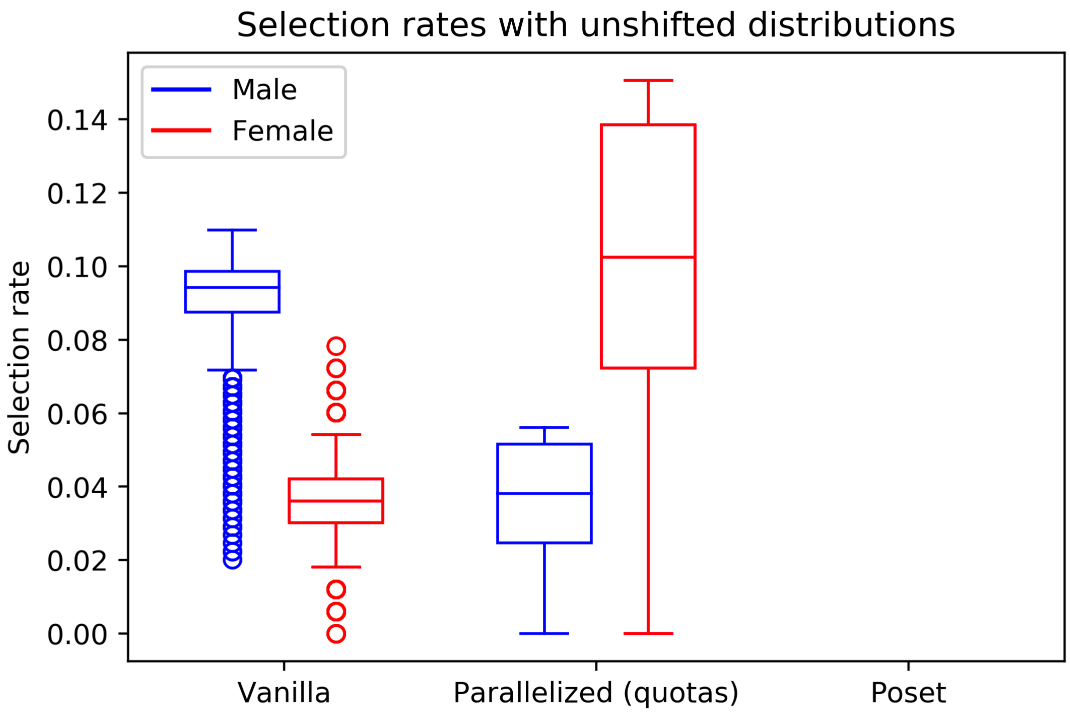
Figure 3 **The left figure plots the true computer programming scores by gender for the entire dataset. The right figure plots the predicted computer science scores by gender for the test dataset.** $R^2 = 0.567$ (m), 0.627 (f)

Experimental Study



Online selection of 25 candidates, from a pool of 612, using centered error distributions to construct the poset.

Experimental Study



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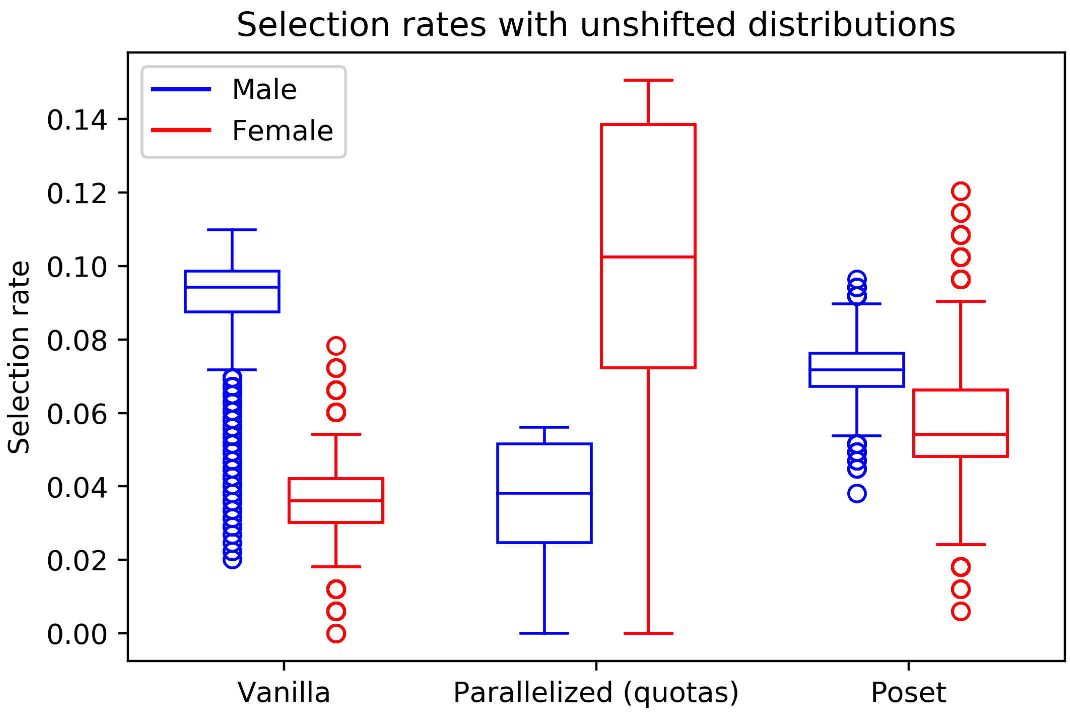

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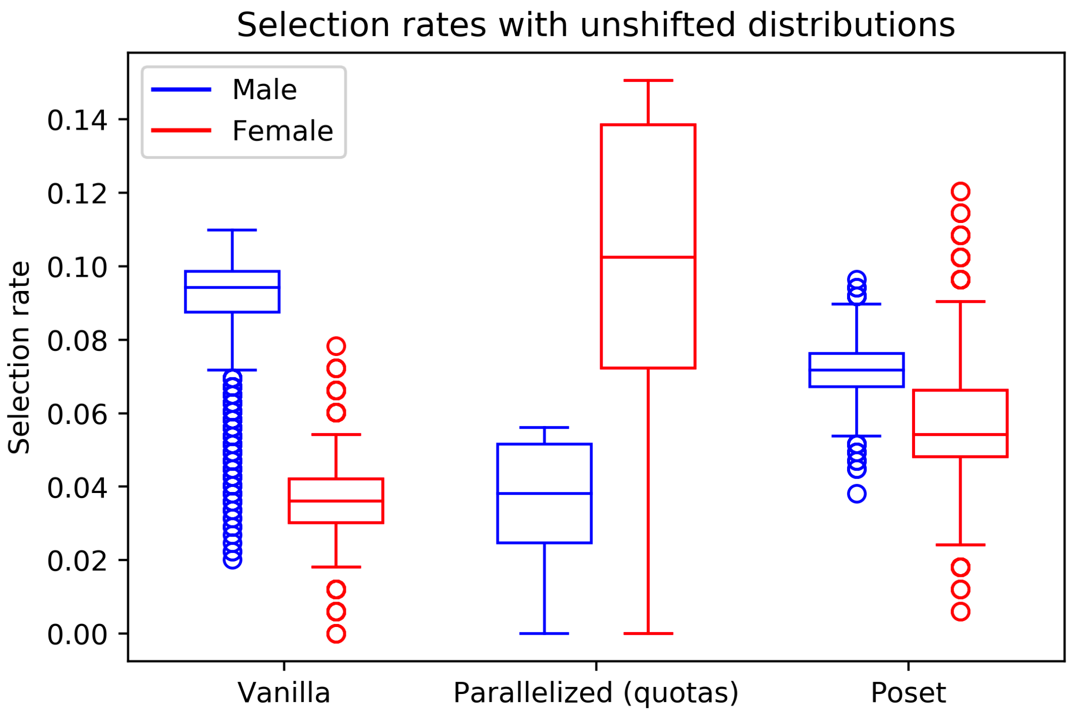

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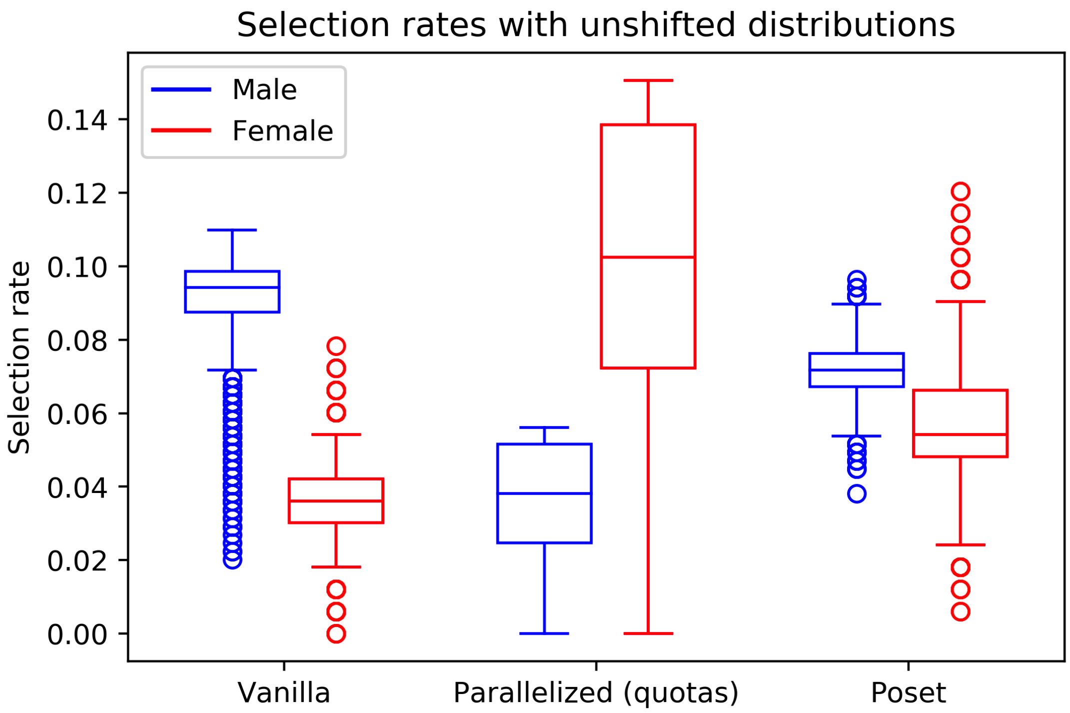

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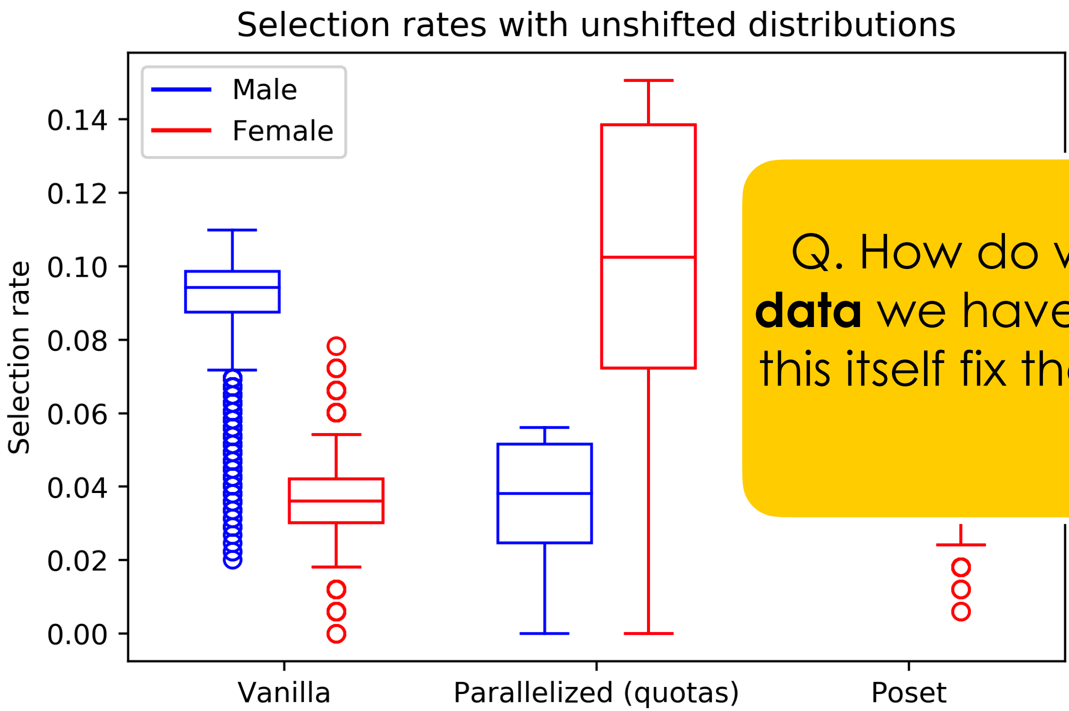

Q. How do we quantify the **variability in data** we have, **based on the context**? Can this itself fix the "unfairness" in downstream decisions?

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Outline of the talk

- The Microsoft Paradox
- Modeling Bias
- Biased Online Secretary Problem
- **Title VII: Anti-Discrimination Law**
- Other applications
  - impact, policy, audits, domain knowledge, law
- Future Work

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- **Posets:** transparent way for uncertainty in candidate evaluations. This allows an employer to design a "practice in order to provide a **fair opportunity for all individuals**, regardless of race" before deploying it. [*Ricci v. DeStefano*]

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- “**Are we there yet**”: adaptivity of uncertainty sets

Don’t let Ricci v. DeStefano Hold You Back: A Bias-Aware Legal Solution to the Hiring Paradox, Jad Salem, Deven Desai, Swati Gupta. FAccT 2022 and UC Davis Law Review 2023.

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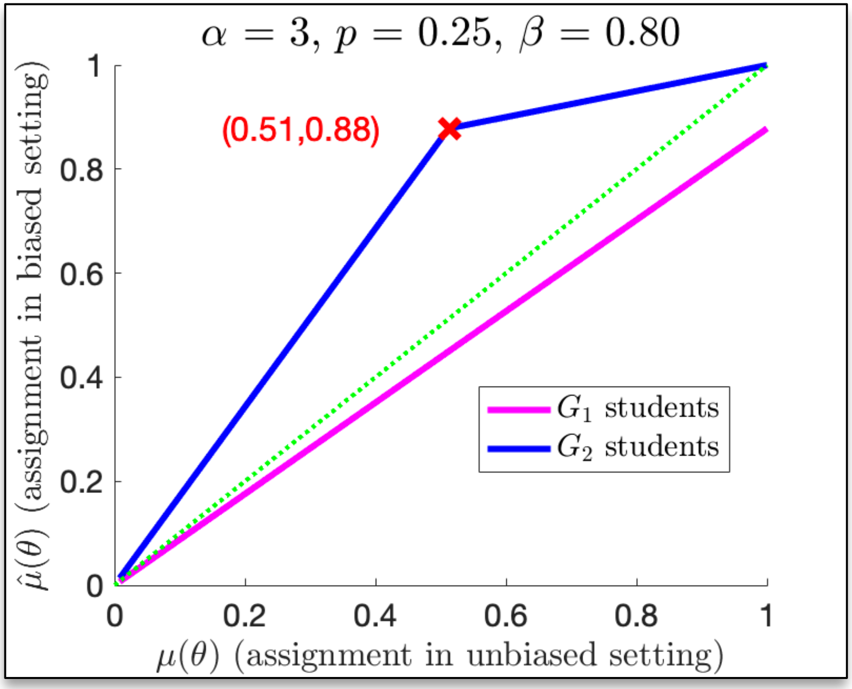
Models for variability in data can help us test **“what if” scenarios**, and help policy makers.

Impact on Admissions

1. Can bias-models help us understand most impactful ways of providing resources?



(a) Quantify which students are impacted most due to bias in a continuous market

SCAN ME

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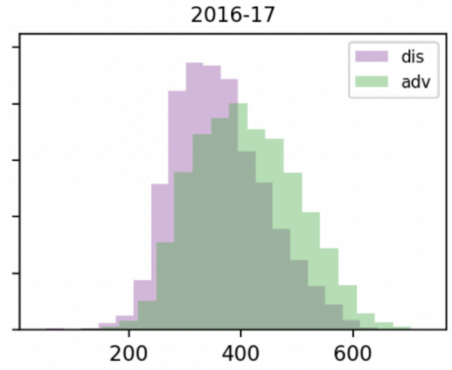

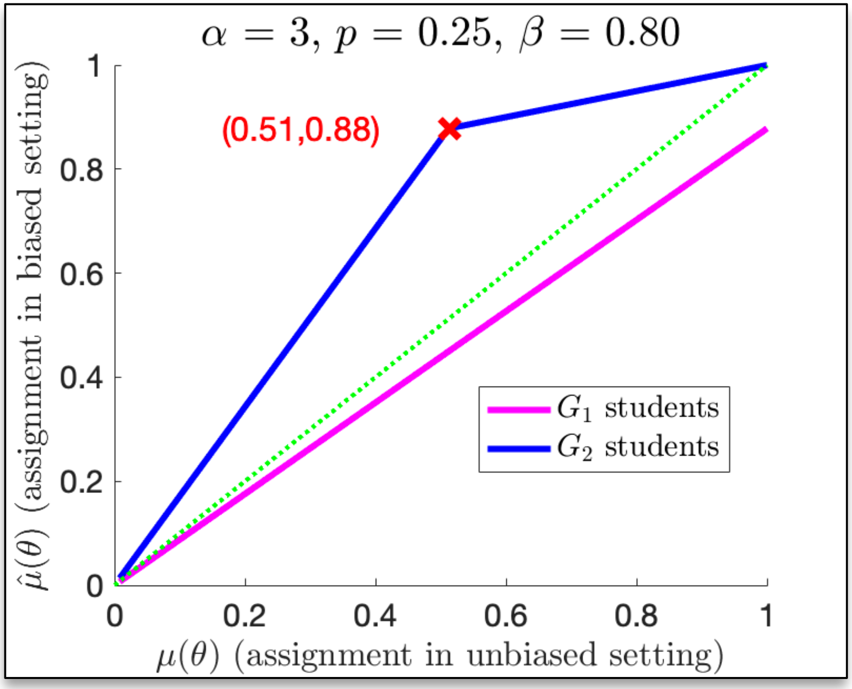

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Reducing the Feeder Effect in Public School Admissions: A Bias-aware Analysis for Targeted Interventions, Faenza, Gupta, Zhang, under submission to M&SOM.

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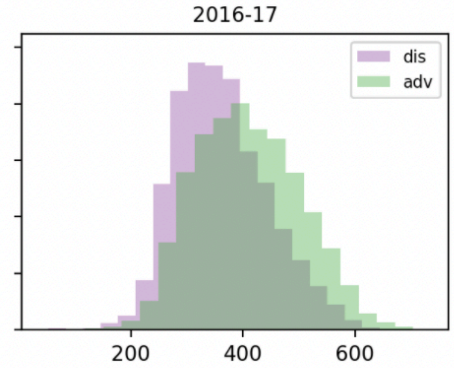

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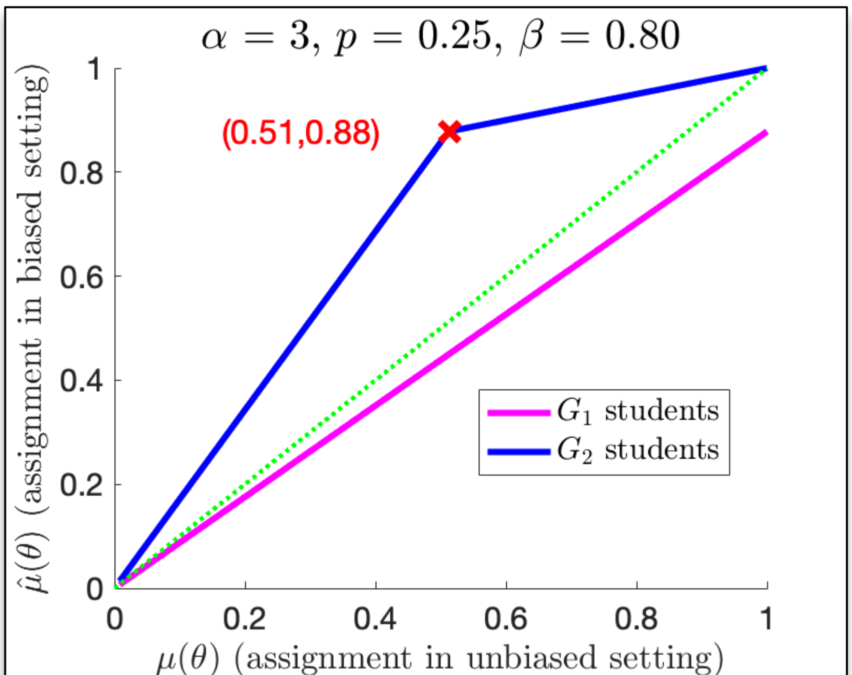

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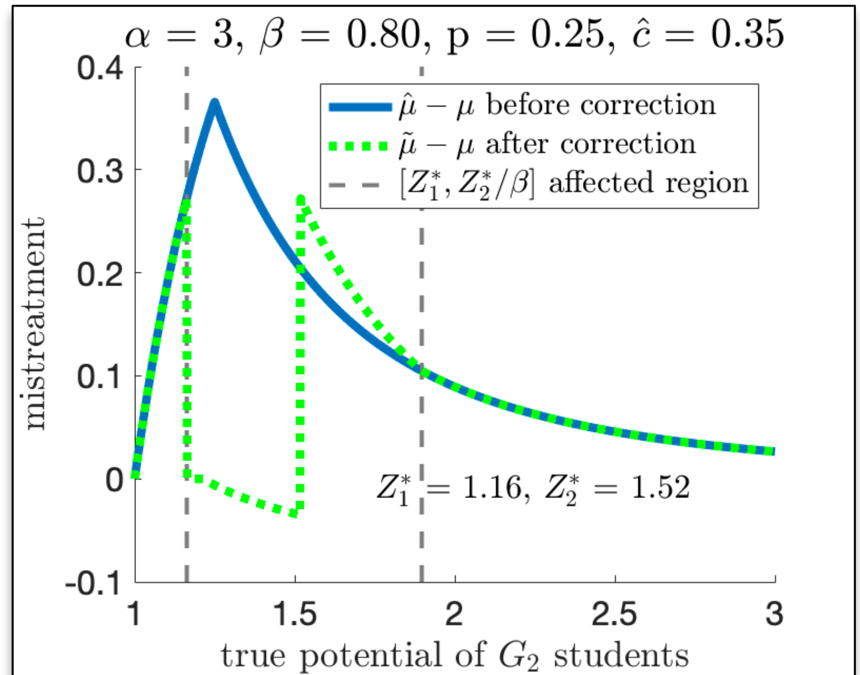

(b) Under continuous matching market, average performers benefit most by resources.

Reducing the Feeder Effect in Public School Admissions: A Bias-aware Analysis for Targeted Interventions, Faenza, Gupta, Zhang, under submission to M&SOM.

SCAN ME

Errors in observed/recorded data may be structured due to the problem domain.

Translating Domain Constraints

2. Bias-models help us quantify our trust in evaluations and allow for uncertainty. In what other ways can we quantify trust in data?

Racial Bias in Pulse Oximetry Measurement

Clinicians and ICU doctors can often look at charts and detect errors or discount untrustworthy labs. Can we translate their domain knowledge into **mathematical constraints**?

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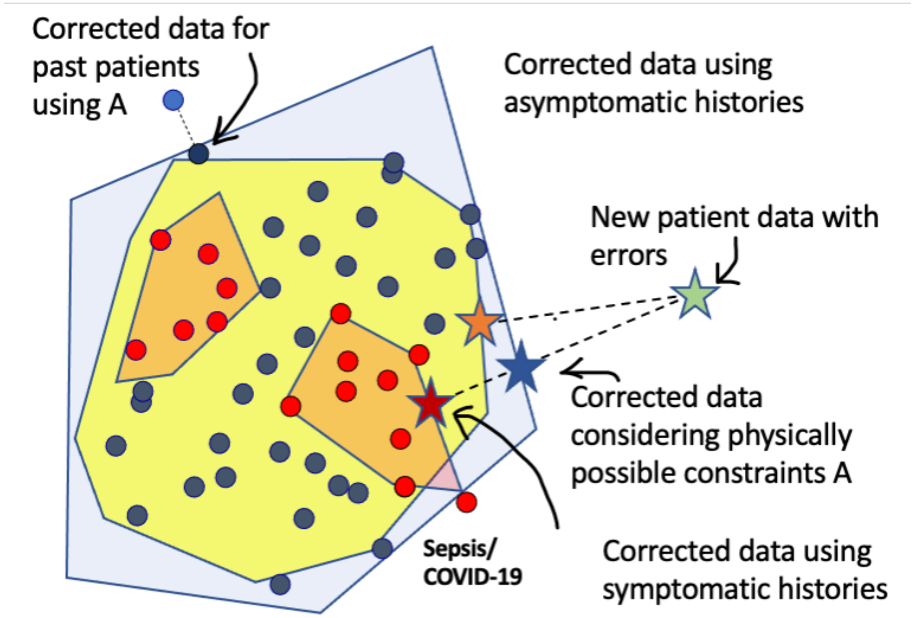


Distance of new patient data to different sets will guide confidence in the label for sepsis/COVID-19.

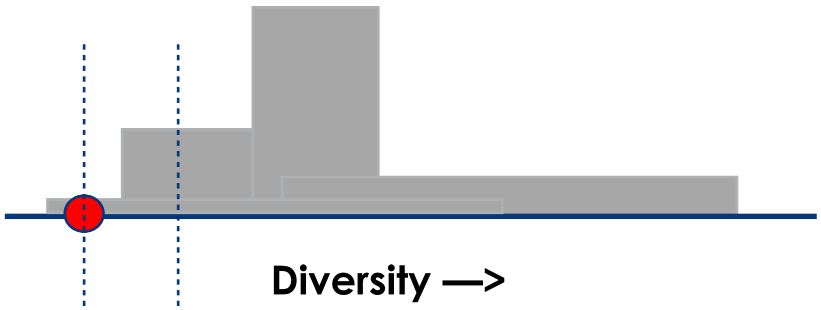
"Enabling Rapid and Trustworthy predictions of Sepsis via Translation of Clinical Domain Knowledge into High-Dimensional Mathematical Constraints", Mehak Arora, Hassan Mortagy*, Nathan Dwarshuis, Swati Gupta, Andre Holder, Rishi Kamaleswaran, under submission to PNAS.

Can OR help guide policy makers?

OR For Policy Impact

3. Can we provide a lever for audits for algorithms? dependent on uncertainty sets and algorithmic pipeline, this can give us a characterization of outcome space.

Histogram of diversity outcomes based on algorithmic choices



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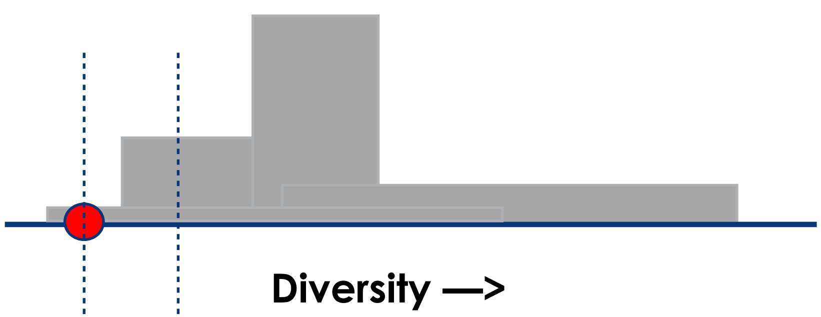
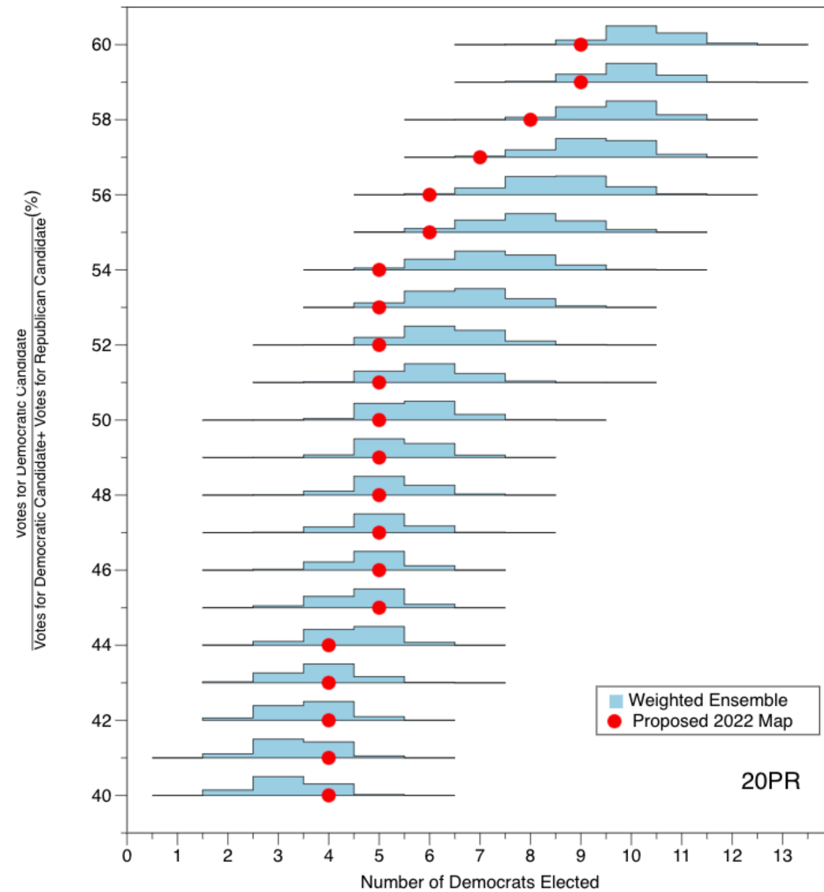


The Geeks Who Put a Stop to Pennsylvania's Partisan Gerrymandering



Mathematically Quantifying Gerrymandering and the Non-responsiveness of the 2021 Georgia Congressional Districting Plan, Joint work with J. Mattingly, D. Randall, G. Herschlag, C. Hettle, Z. Zhao, 2022, EAAMO 2022.

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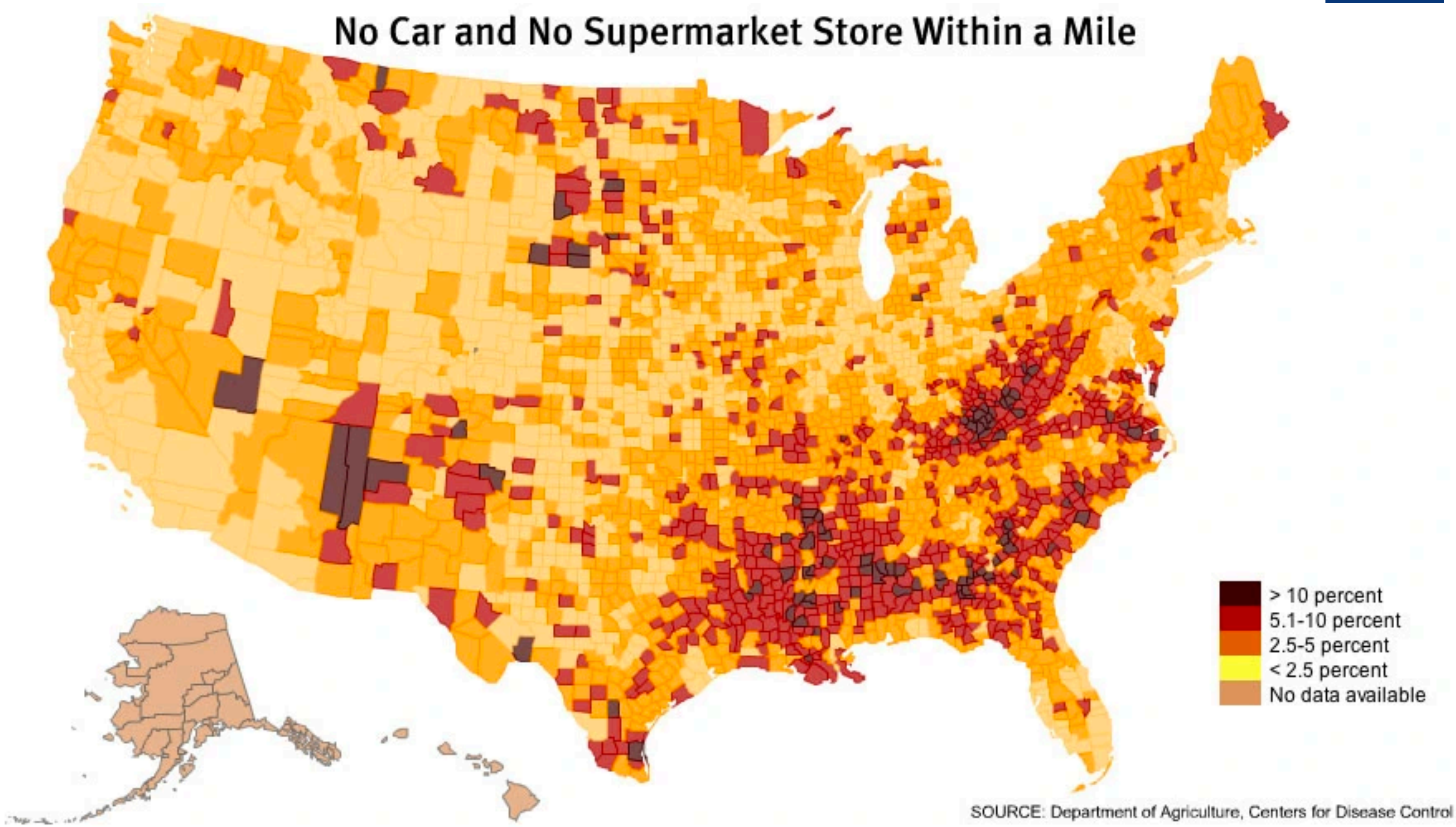

OR For Policy Impact

5. Can we guide policy-makers into taking informed decisions, by highlighting properties of potential solutions?

Fair Facility Location

$$\min \sum_{i \in F'} c_i + \left[\sum_{s \in [r]} \left(\frac{1}{|D_s|} \sum_{j \in D_s} d(j, \Pi(j)) \right)^p \right]^{1/p} .$$

Cost of opening facilities

"r" groups of people

Reduces to min max for p=infinity

Theorem [GMS22]. *There is a polynomial-time algorithm that gives a 4-approximation for the p-norm fair facility location problem for any* $p \in [1, \infty]$. *Moreover, we can find a set* S *of* $\log_2(r) - 1$ *solutions such that for all norms* $p \in [1, \infty]$, *there is some solution in* S *that is an 8-approximation to the p-norm fair facility location problem.*

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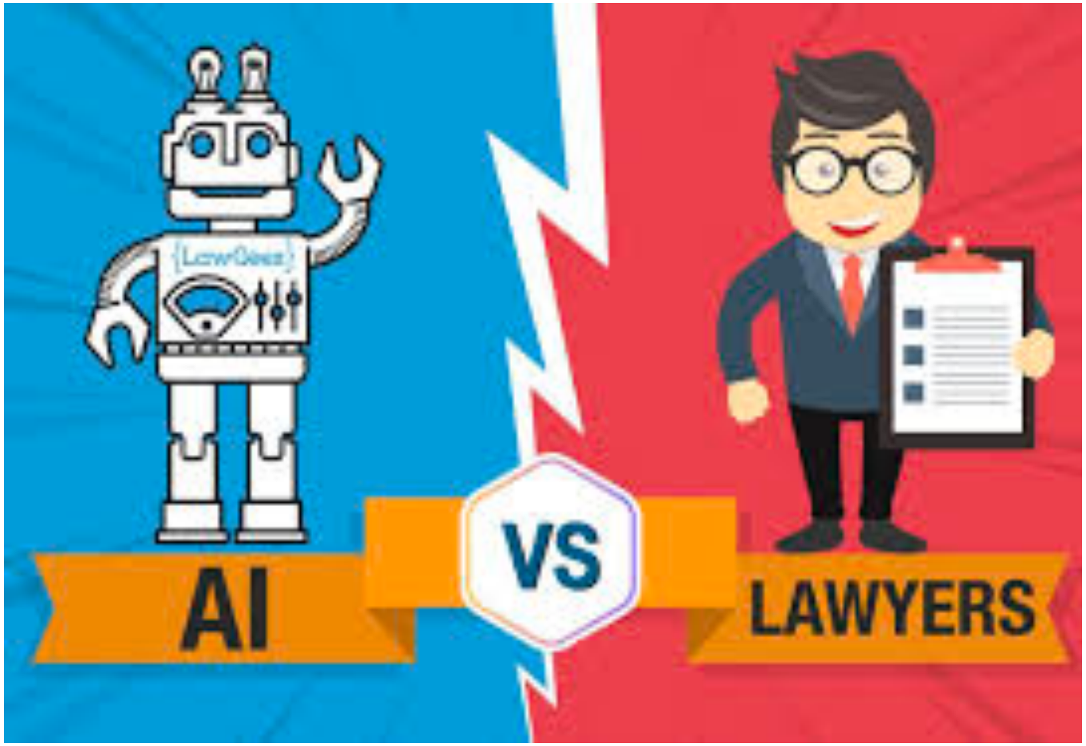
Socially Fair and Hierarchical Facility Location Problems, Joint work with Jai Moondra and Mohit Singh, 2022, under submission to Math of OR.

Can we design algorithms that are robust to lawsuits?



Changing legal landscape

5. To adapt our pursuits of efficiency and cost minimization to a changing legal landscape, we might need to enforce more domain constraints.

MARY McQUEEN and VICTORIA BALLINGER, on behalf of themselves and all others similarly situated, Plaintiffs, v. AMAZON.COM, INC., a Delaware corporation, Defendant.	No. CLASS ACTION COMPLAINT FOR VIOLATION OF CALIFORNIA'S UNFAIR COMPETITION LAW, UNJUST ENRICHMENT, AND NEGLIGENCE **JURY**

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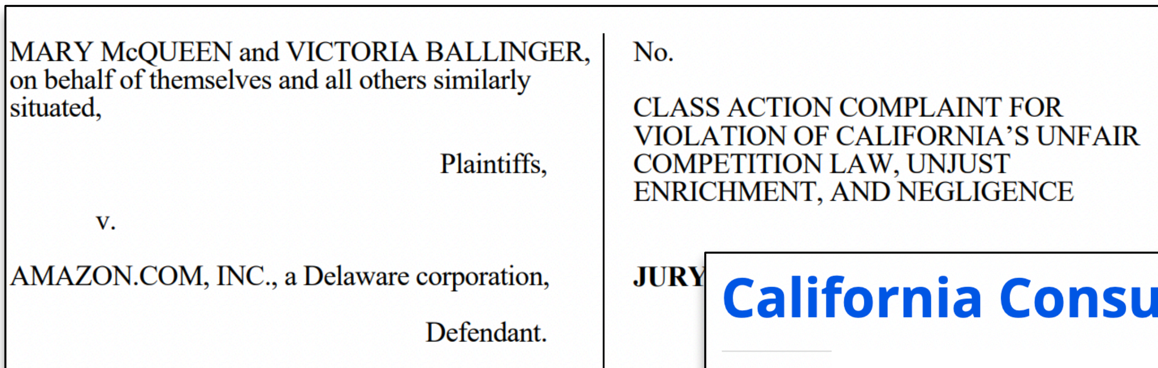

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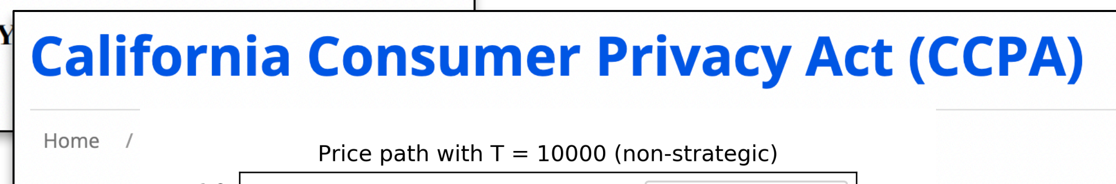

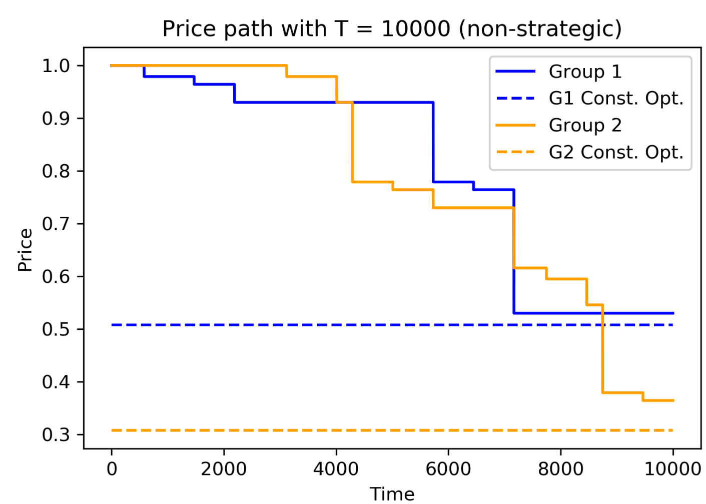

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"Algorithmic Challenges in Ensuring Fairness at the Time of Decision", Jad Salem, Vijay Kamble, Swati Gupta, WINE 2022. Under submission to Operations Research.

SCAN ME

Summary

1. **Models for bias**: partially ordered sets, e.g., interval, network, group
2. **Poset Online Secretary** with *ranked demographic parity*
3. **Lower bound** dependent on the width of the poset
4. For **poset bias**:
   - ✦ **Width and Labels:** $O(e^2(w+1))$ if known width, o/w $O(e^3(4w+2))$.
5. For **group bias**:
   - ✦ **Labels**: $O((g+1)e^2)$ in AG/AU, $O(ge)$ in RG/AU, $O(2e)$ in RG/RU
   - ✦ **Asymptotic**: $O(g(1+o(1)))$ for asymptotic k, in AG/AU setting.
6. **Legal basis**: built-in headwinds, no quotas using posets, individuals as numbers, banding, 4/5th rule is only a trigger.
7. **Extensions**: interventions for admissions, discovery program, audits as in districting, domain constraints for demand learning.

Questions? Thank you for listening!

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Questions?