ULB

INFO-H420
Management of Data Science and Business Workflows

Part II
Fairness

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2023-2024

How do people feel about interacting with AI systems?

survey of 5,000 consumers by Pegasystems about people interacting with Artificial Intelligence (AI) systems

- 34% say they interact with AI systems
- machines **not trustworthy**
  - only 9% very comfortable interacting
- machines **can be biased**
  - 53% say it’s possible for systems to show bias in their decisions
- machines **cannot be moral**
  - 56% don’t believe it is possible to develop systems that behaves morally

Responsible Data Science

- Responsible data science is the practice of using data and data-driven techniques in a way that is **ethical**, **transparent**, and **respectful of the rights** and interests of **individuals** and **society**

- Key concepts:
  - **Data privacy** and security, to protect sensitive data of individuals
  - **Transparency** about data sources, methods, and limitations
  - Exhibit desirable **ethical** principles
  - Put **human in control**, allow them to understand and control

ChatGPT, December 2022

Responsible AI/ML/Data Science

- Algorithmic Decisions (e.g., from ML/AI models) are ubiquitous, permeate many aspects of **society**
- more and more questions of **responsible use** arise

Fairness Accountability Transparency Ethics

- dedicated conferences
  - ACM Conference on Fairness, Accountability, and Transparency (FAccT)
  - AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society (AIES)
- topics appear in almost all CS venues
- courses: in Berkeley, Cornell, Princeton
- EU high-level expert group on AI: Ethics Guidelines for Trustworthy AI
- EU upcoming regulation: AI Act

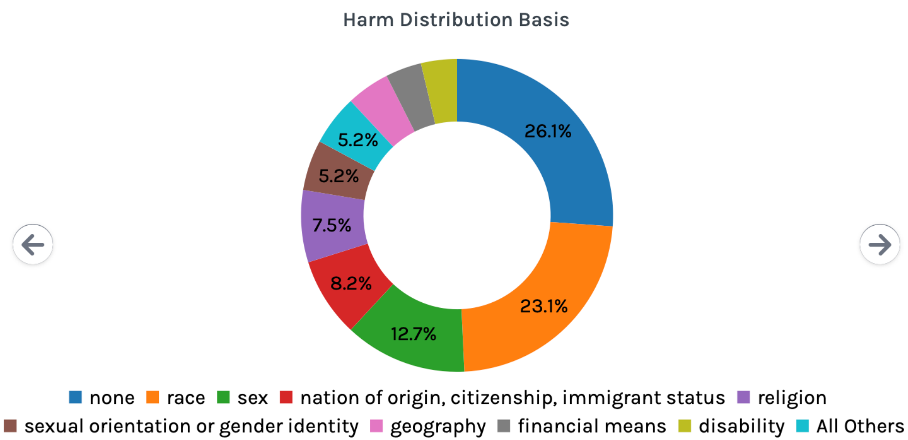
Irresponsible AI

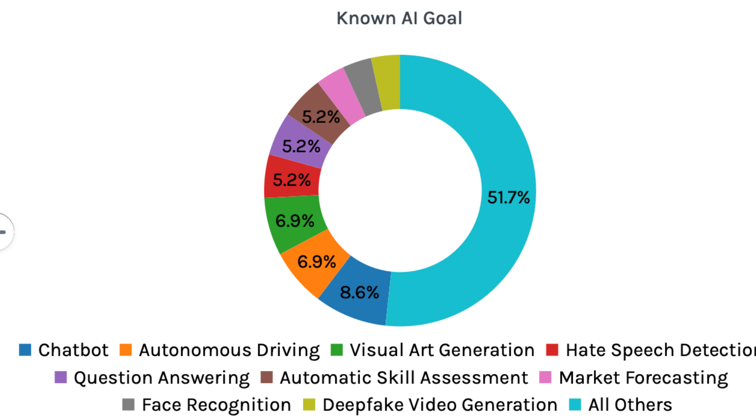
Welcome to the

AI Incident Database

Search over 2000 reports of AI harms

Search | Discover





https://incidentdatabase.ai

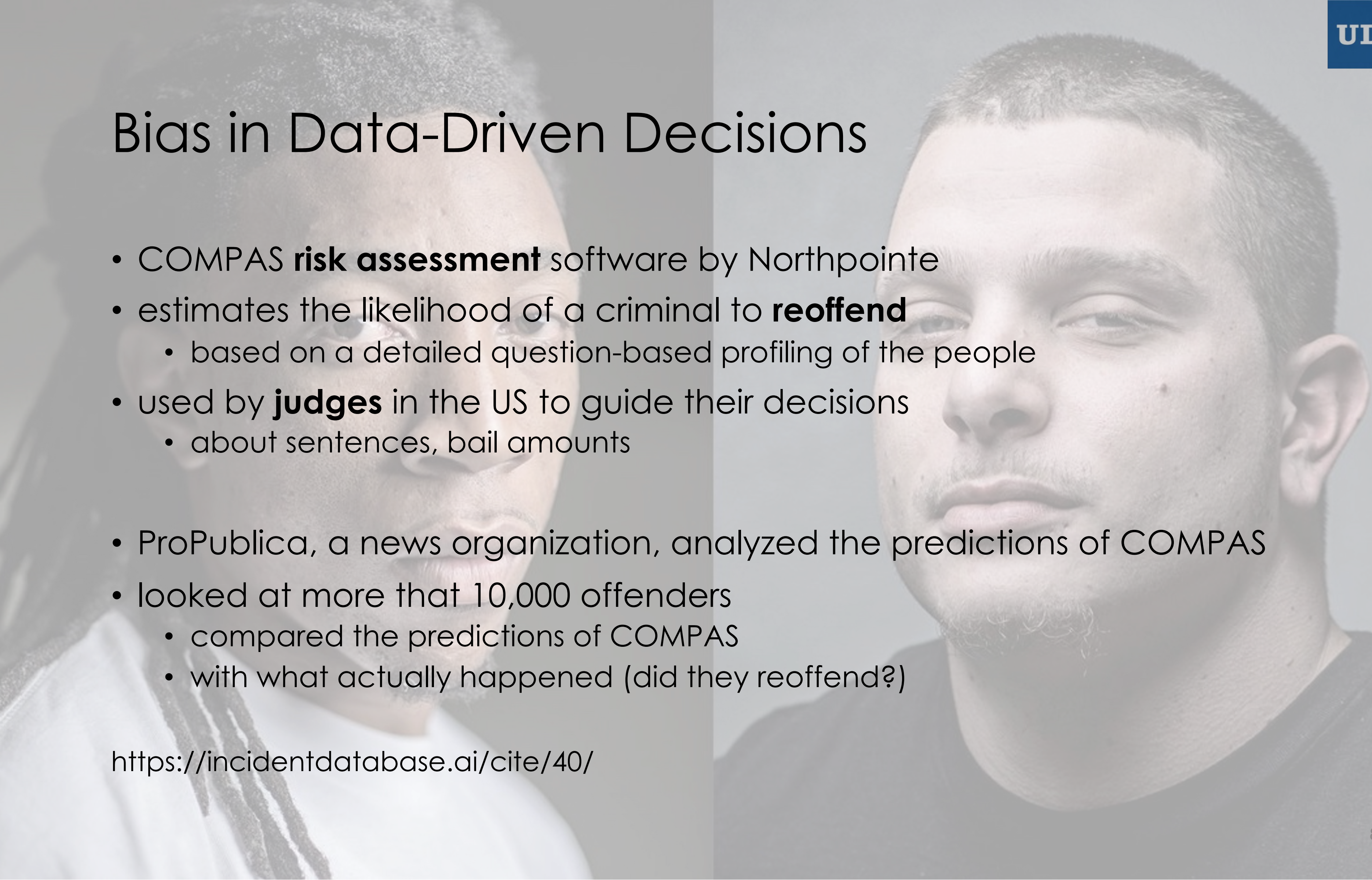
Ethical Principles

- review of 84 AI ethics guidelines
- trust is the "end goal"

Ethical principle	Number of documents	Included codes
Transparency	73/84	Transparency, explainability, explicability, understandability, interpretability, communication, disclosure, showing
Justice & fairness	68/84	Justice, fairness, consistency, inclusion, equality, equity, (non-)bias, (non-)discrimination, diversity, plurality, accessibility, reversibility, remedy, redress, challenge, access and distribution
Non-maleficence	60/84	Non-maleficence, security, safety, harm, protection, precaution, prevention, integrity (bodily or mental), non-subversion
Responsibility	60/84	Responsibility, accountability, liability, acting with integrity
Privacy	47/84	Privacy, personal or private information
Beneficence	41/84	Benefits, beneficence, well-being, peace, social good, common good
Freedom & autonomy	34/84	Freedom, autonomy, consent, choice, self-determination, liberty, empowerment
Trust	28/84	Trust
Sustainability	14/84	Sustainability, environment (nature), energy, resources (energy)
Dignity	13/84	Dignity
Solidarity	6/84	Solidarity, social security, cohesion

[2019 Nature Machine Intelligence A. Jobin et al.] *Artificial Intelligence: the global landscape of ethics guidelines*

Fairness



Bias in Data-Driven Decisions

- COMPAS **risk assessment** software by Northpointe
- estimates the likelihood of a criminal to **reoffend**
  - based on a detailed question-based profiling of the people
- used by **judges** in the US to guide their decisions
  - about sentences, bail amounts

- ProPublica, a news organization, analyzed the predictions of COMPAS
- looked at more that 10,000 offenders
  - compared the predictions of COMPAS
  - with what actually happened (did they reoffend?)

https://incidentdatabase.ai/cite/40/

Bias in Data-Driven Decisions

results of the study:

- correctly predicts reoffending for black and white at the same rate
    - same **recall** (true positive rate, sensitivity)

but **mistakes** paint a different picture:

- blacks are almost **twice as likely** as whites to be labeled a **higher risk** but not actually reoffend
    - more **false positives** for blacks
- black are **much less likely** than whites to be labeled **lower risk**, but actually reoffend
    - less **false negatives** for blacks

Algorithmic Decisions

- main result of the study:

discrimination against blacks

- but there is some controversy to the study results
  - https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing
  - https://www.documentcloud.org/documents/2998391-ProPublica-Commentary-Final-070616.html
  - https://www.propublica.org/article/technical-response-to-northpointe
  - http://www.crj.org/assets/2017/07/9_Machine_bias_rejoinder.pdf

Algorithmic Decisions

What are the issues here?

- **fairness** – is the system actually fair to racial groups?
- **transparency** – we don't know what the algorithm does
- **accountability** – who is to hold responsible?

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What is Fairness?

- Dictionary: "***the state of being free from bias or injustice***"

- Political Science: "*distributive justice discusses **fair allocation of resources** among diverse members of a community*"
  - "A Theory of Justice" by J. Rawls (American philosopher)
    - "justice as fairness"; "social cooperation should be fair to all citizens regarded as free and as equals"
  - but what is a *fair allocation*?
    - ***equality of outcome***: each person get the same amount
    - ***equality of opportunity***: equal grounds for competing for resources
    - ***social welfare***: what benefits the society the most

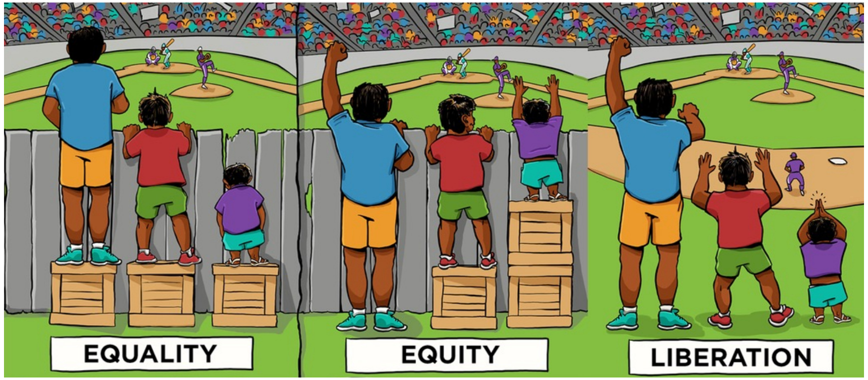
What is Fairness?

- Legal Systems: ***"fairness as non-discrimination"***
  - ***disparate treatment***: intentional discrimination on *protected groups* (defined on race, color, sex, etc.); not "*color-blind*"
    - e.g., only African American applicants are required to take a pre-employment assessment test
  - ***disparate impact***: a procedure that has disproportionate impact on protected groups
    - e.g., all applicants are tested but only African Americans are eliminated based on the results of the assessment.
  - ***affirmative action***: promote non-discrimination and support historically disadvantaged groups; *quota systems*
    - e.g., to address gender imbalance in STEM

Algorithmic Fairness

- Data-Driven Systems often make **decisions** on behalf of humans
  - high-stake decisions: likelihood to reoffend; grant a loan application
  - innocuous decisions: which article to read; what to buy in a store
    - or not so innocuous? fake news, filter bubbles

Algorithmic Fairness: machine made decisions should *not discriminate* against individuals



Group vs Individual Fairness

Group Fairness

- a specific **protected** group defined by a **sensitive** attribute (e.g., race, gender) should be treated/impacted similarly to the other (non-protected) groups
    - typically two groups protected (disadvantaged) and non-protected (advantaged)

Individual Fairness

- a specific **individual** should be treated/impacted similarly **to a similar other** individual

Classification based on Tasks

Fairness depends on the type of task and its outcomes

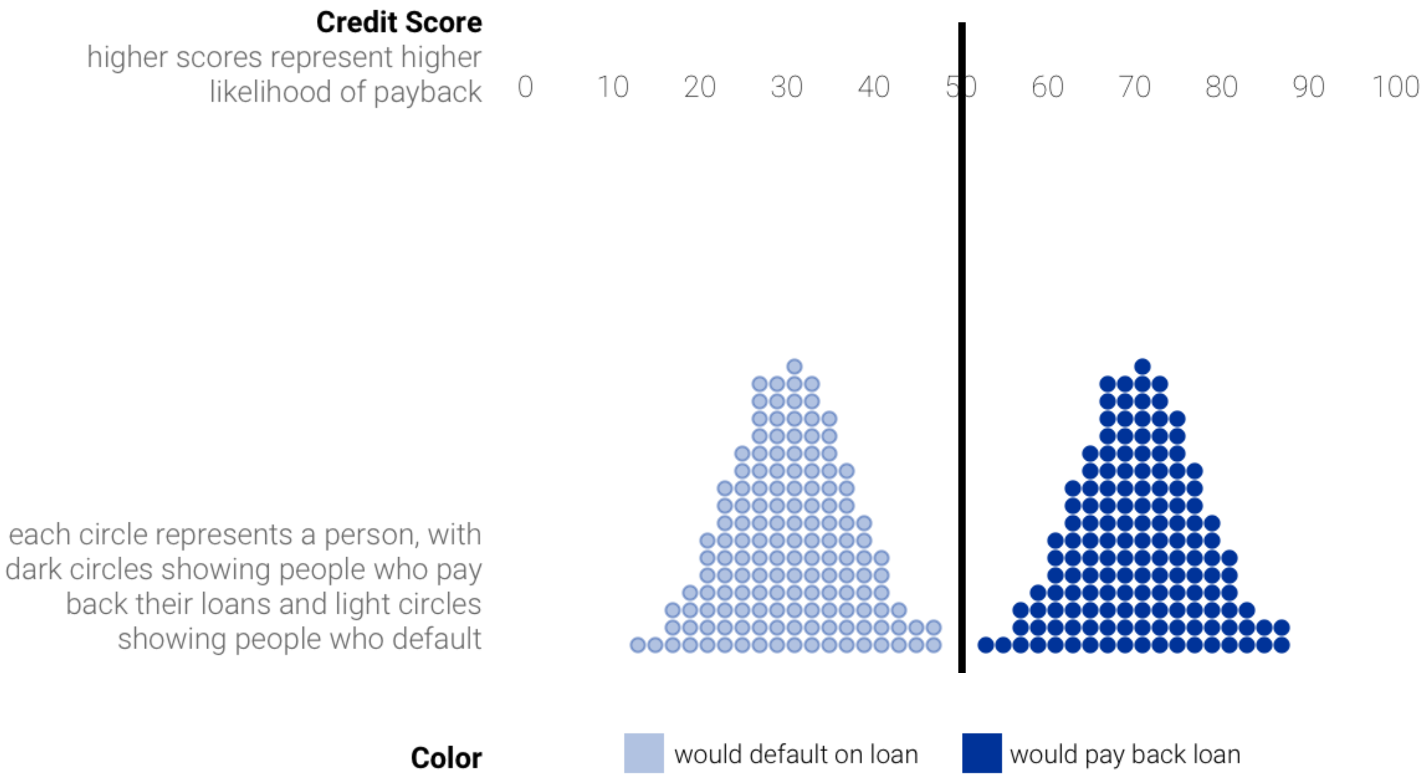
- Classification
- Ranking
- Recommendation

Fairness in Classification

Classification

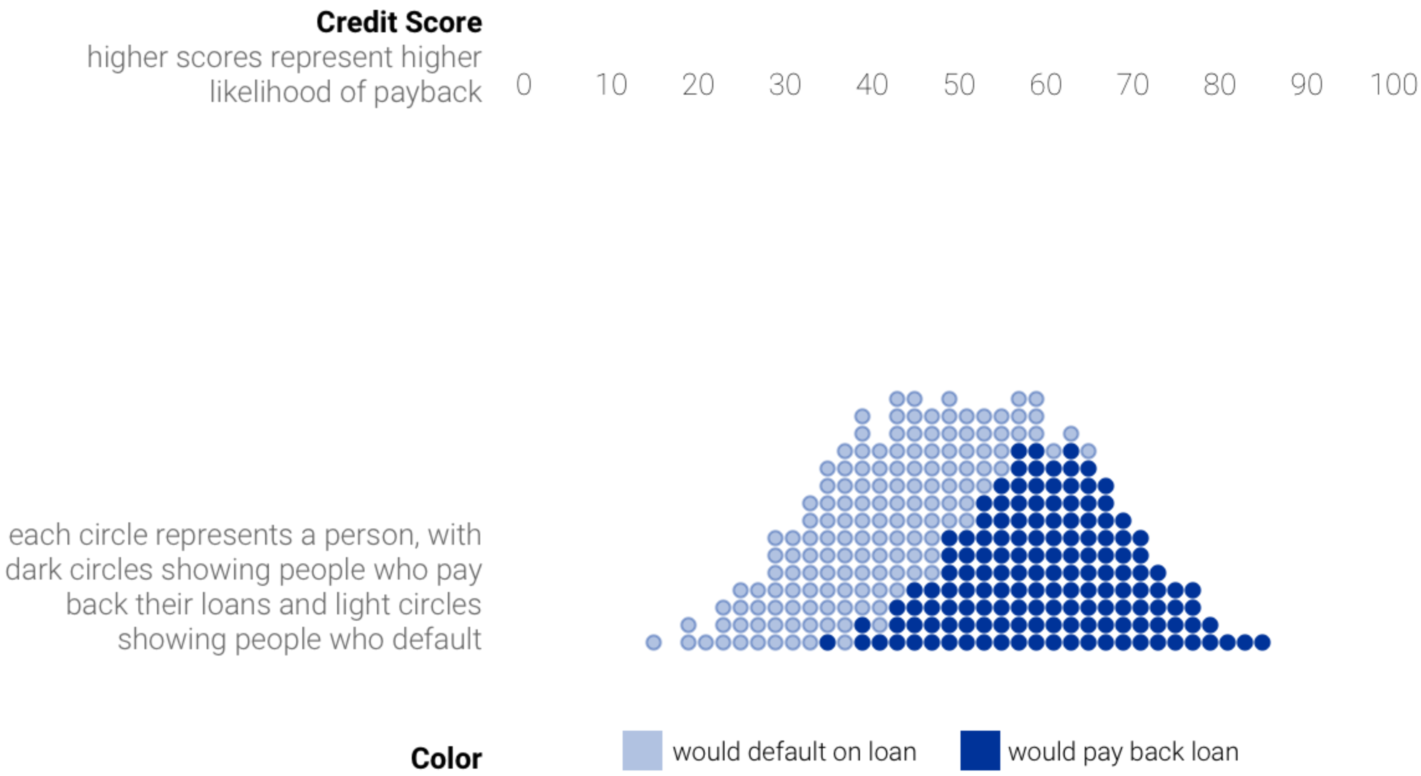
- assume **binary** classification (positive or negative classes)
  - e.g., accept a loan
- assume group fairness: **protected** vs. **non-protected** group
- assume that some **score** predicts the likelihood of being in the positive class
  - e.g., a credit score
- a score **threshold** determines the classification outcome
  - e.g., scores above threshold mean positive

How should we set the threshold?



http://research.google.com/bigpicture/attacking-discrimination-in-ml/

How about now?



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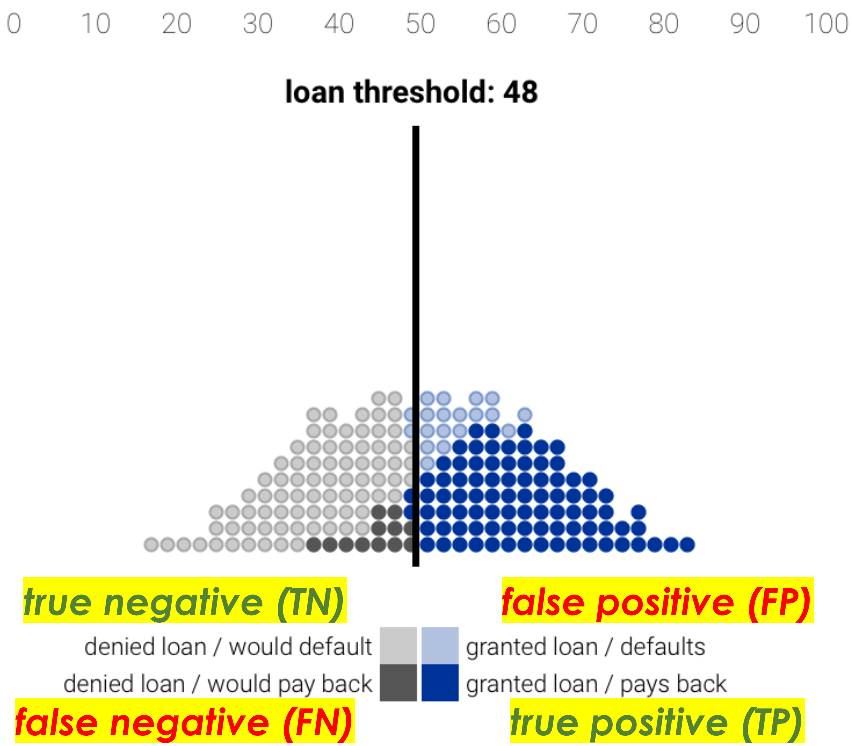
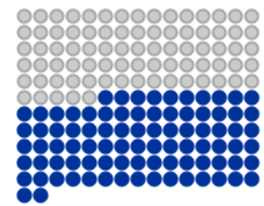


accuracy

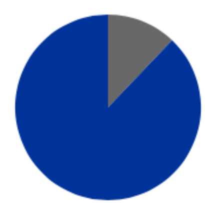
Correct 84%
loans granted to paying applicants and denied to defaulters



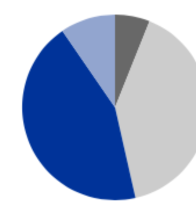
Incorrect 16%
loans denied to paying applicants and granted to defaulters

recall

True Positive Rate 88%
percentage of paying applications getting loans

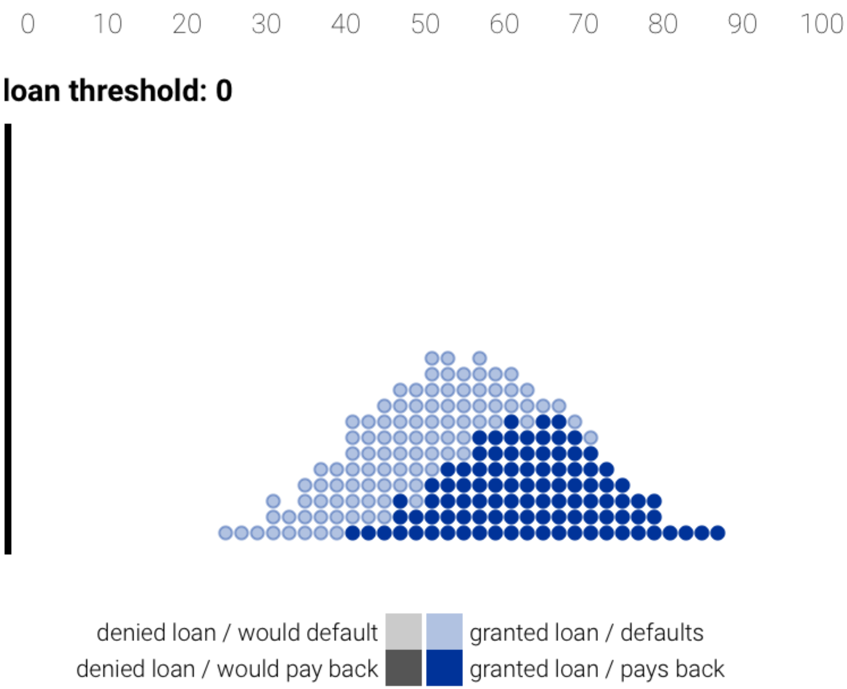


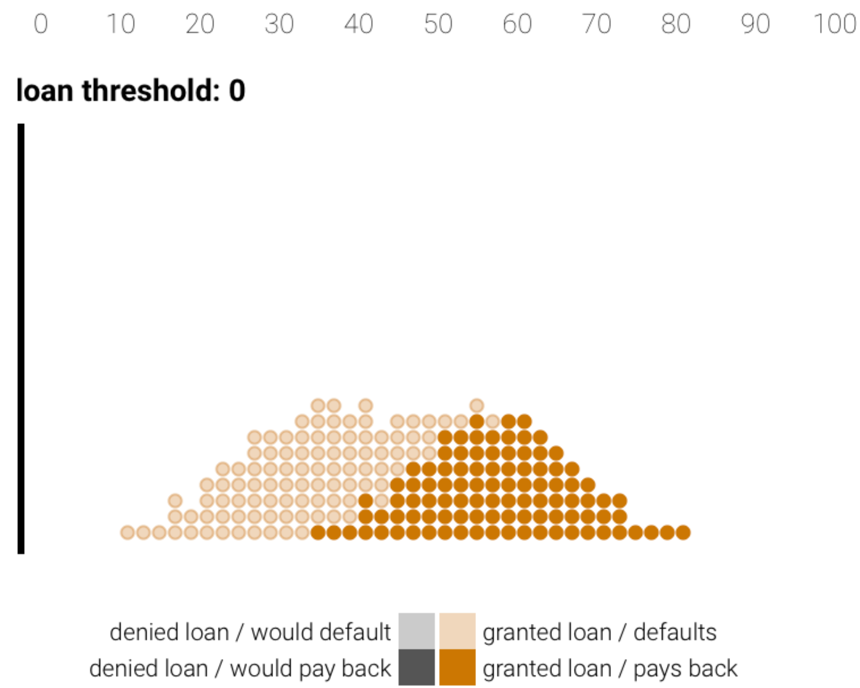
Positive Rate 54%
percentage of all applications getting loans



Two groups: Blue and Orange

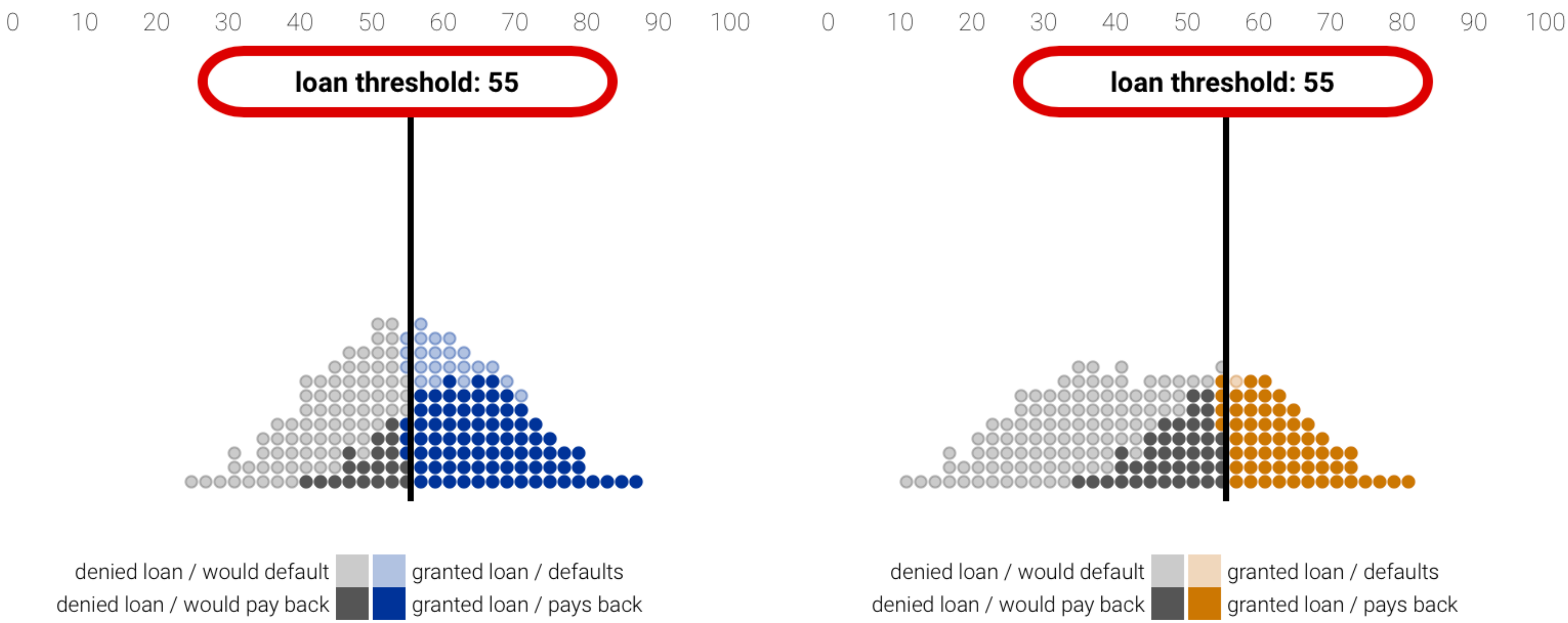
How should we set the thresholds for the two groups?





Equal Treatment (Color-Blindness)

We don't look at color, set the **same threshold.**



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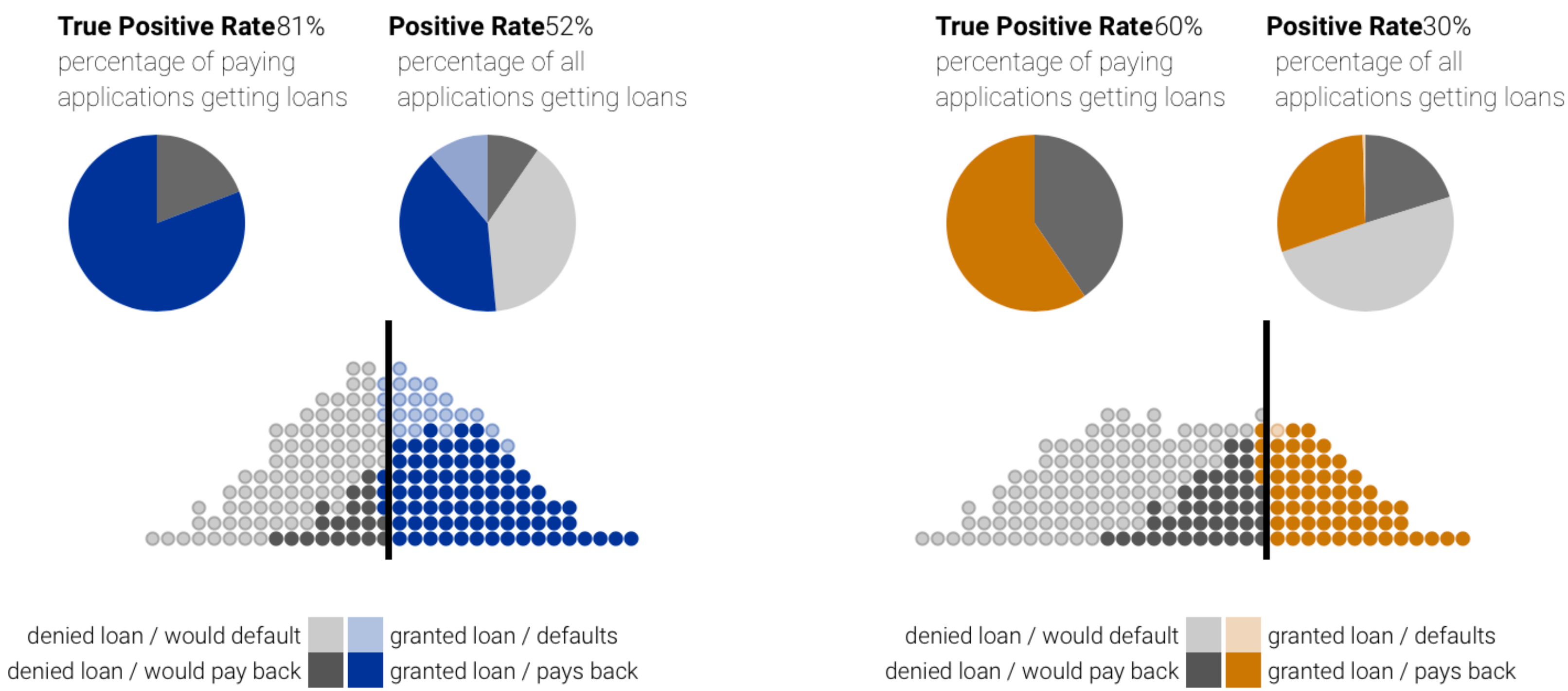

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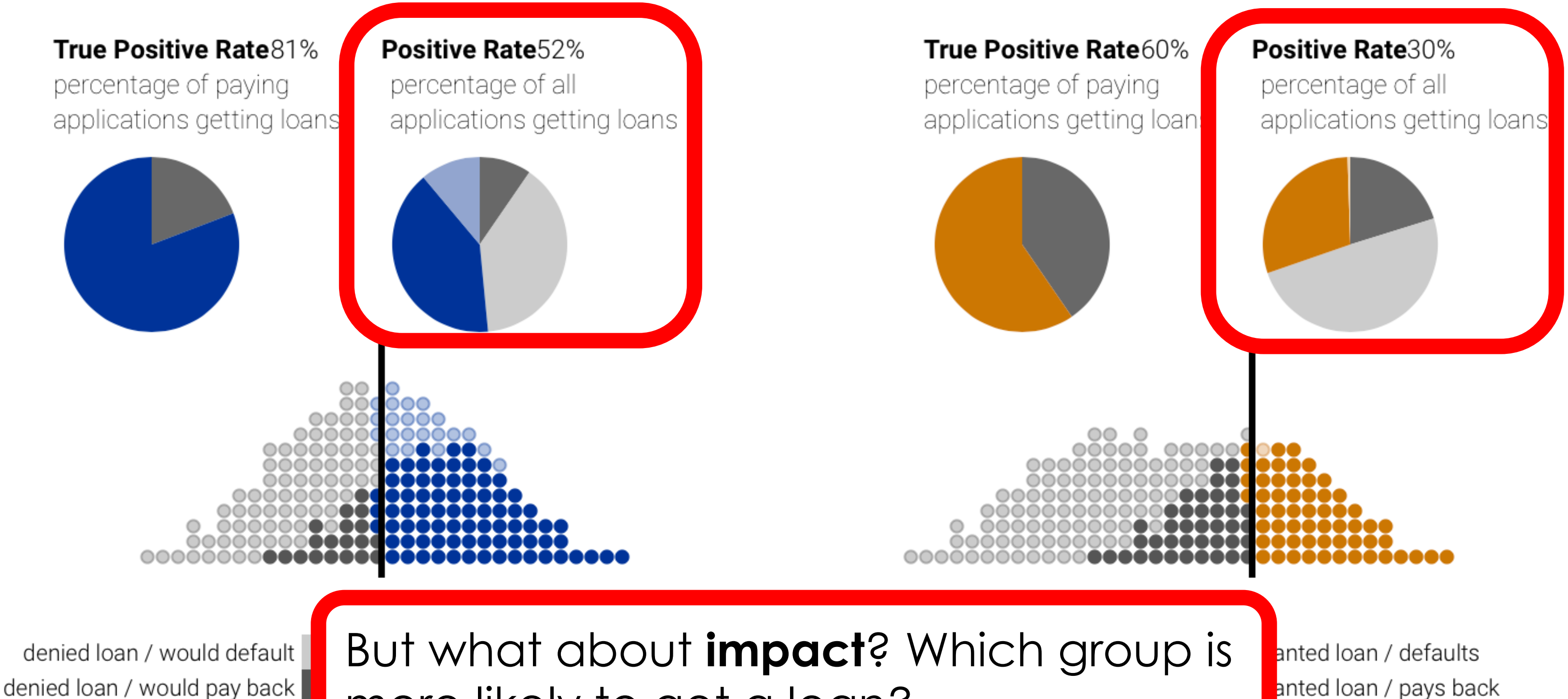
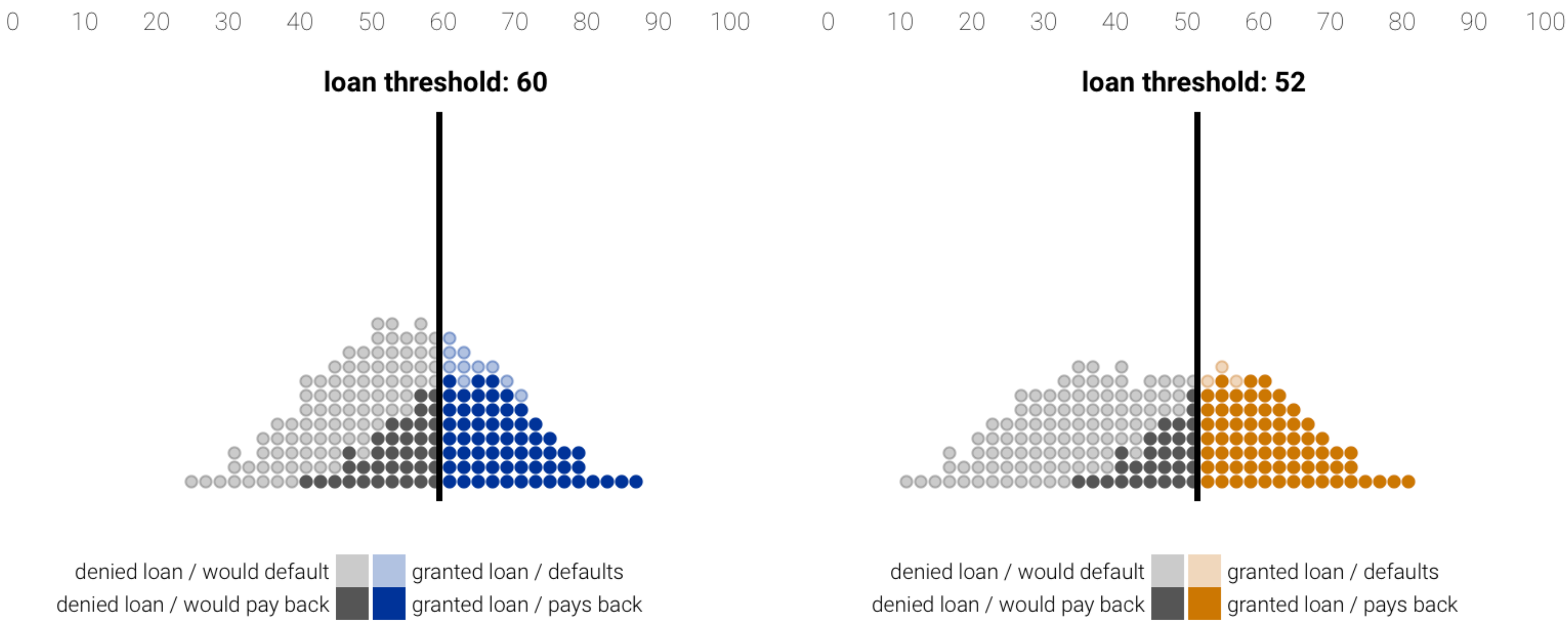


But what about **impact**? Which group is more likely to get a loan?

Group (Demographic/Statistical) Parity

Set **different thresholds** so that groups have equal chance of getting a loan (*equal impact*)



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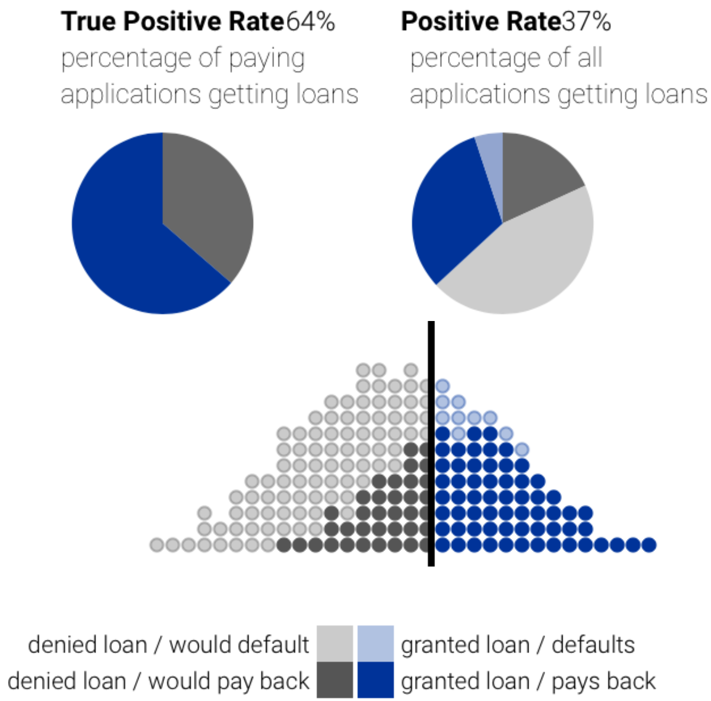

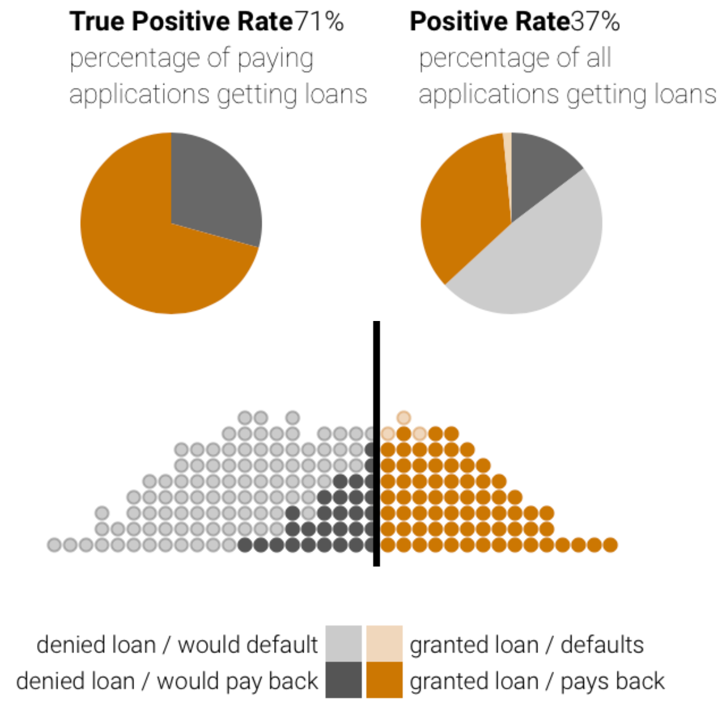

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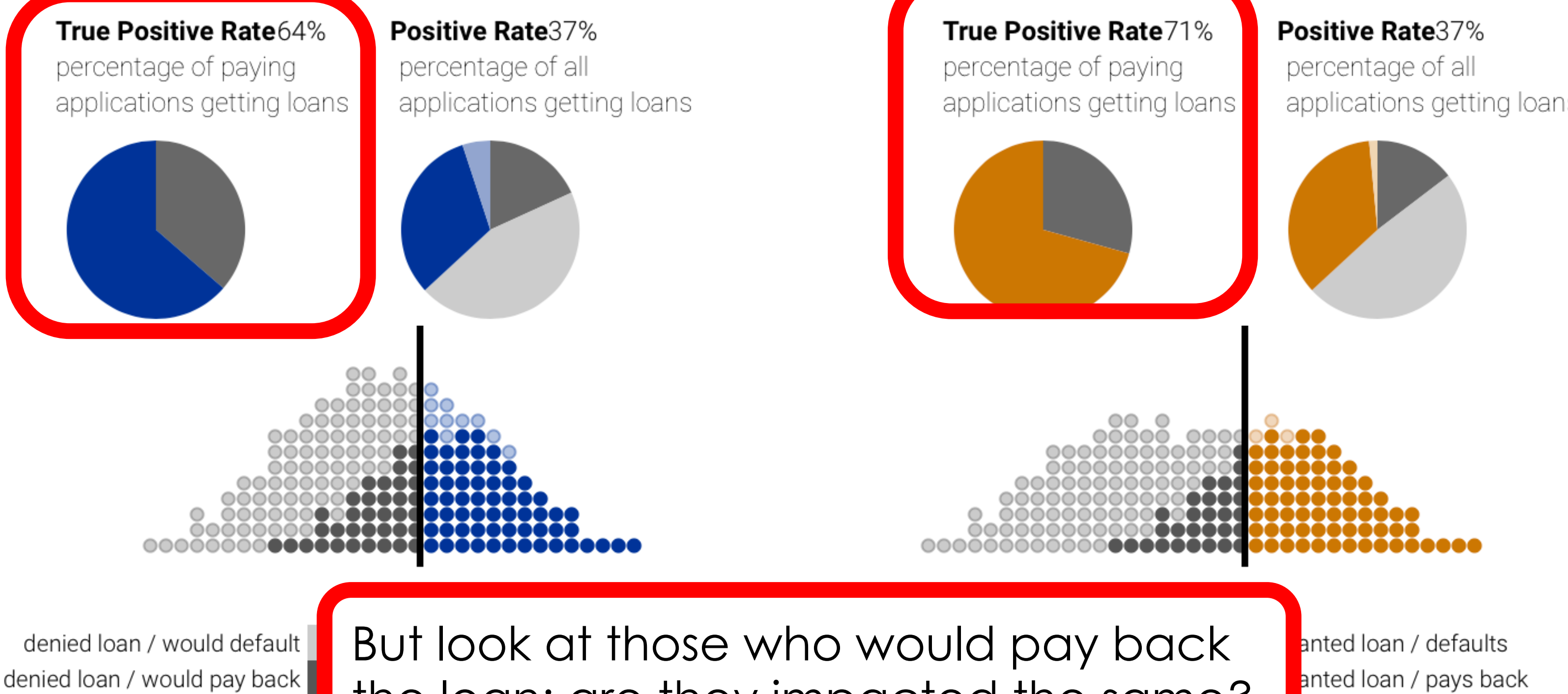
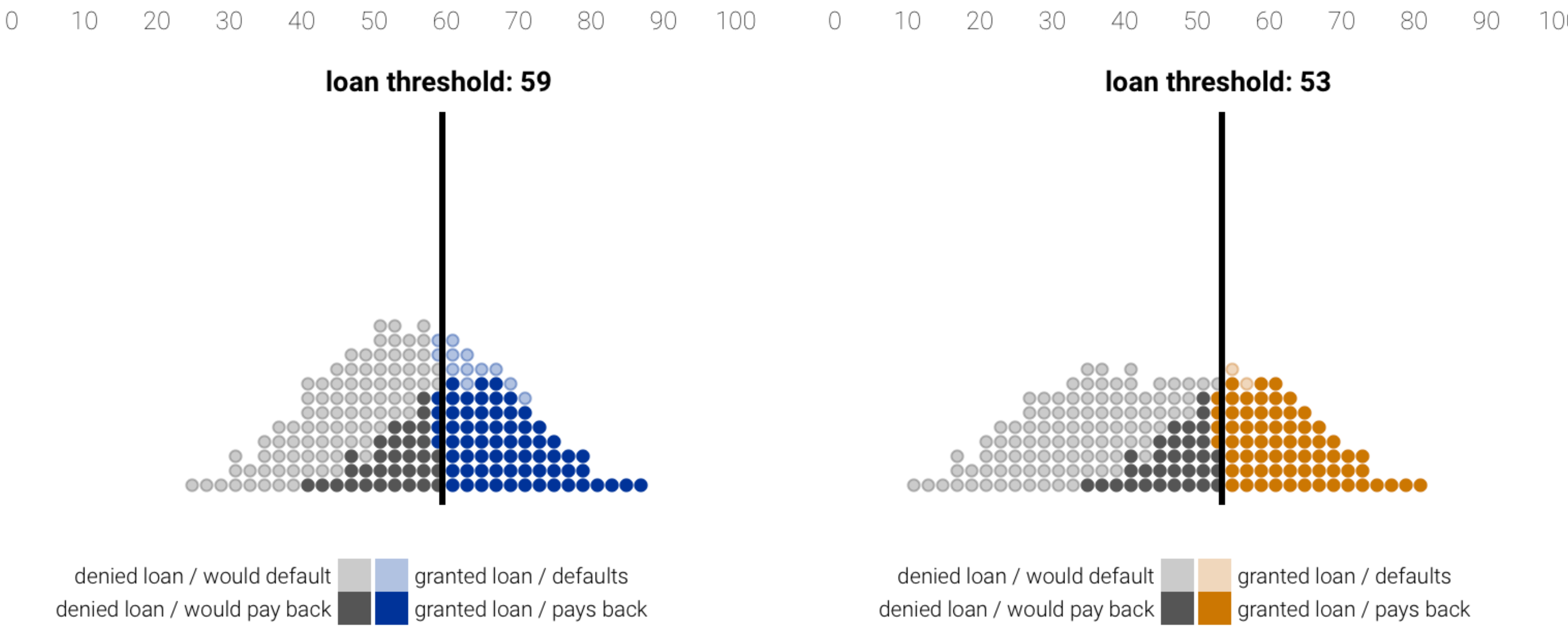


But look at those who would pay back the loan; are they impacted the same?

Equal Opportunity

Aim to be fair for those that would pay back the loan



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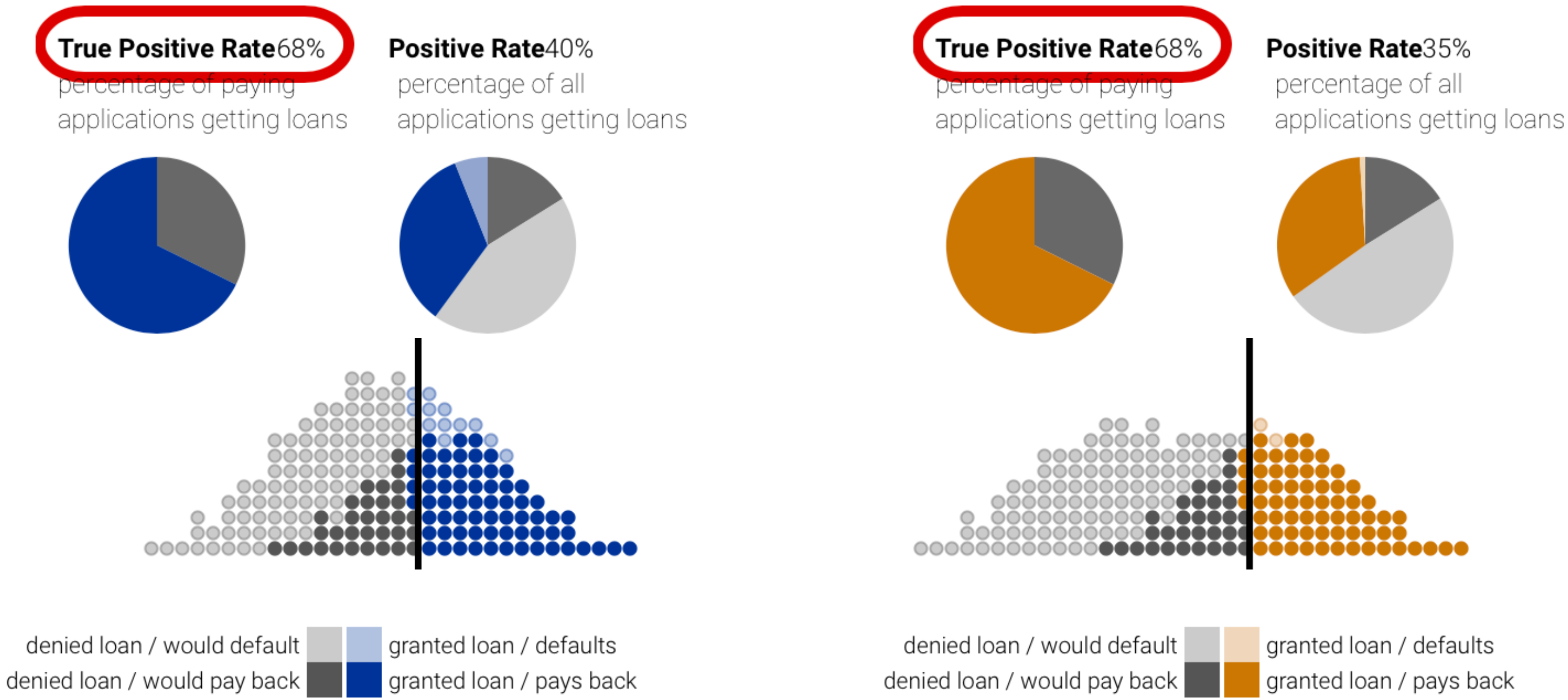


Fairness Notions

- **equal treatment** (color-blindness, fairness by unawareness): same threshold
- **group parity** (demographic or statistical parity): same positive rate
- **equal opportunity**: same true positive rate (recall)

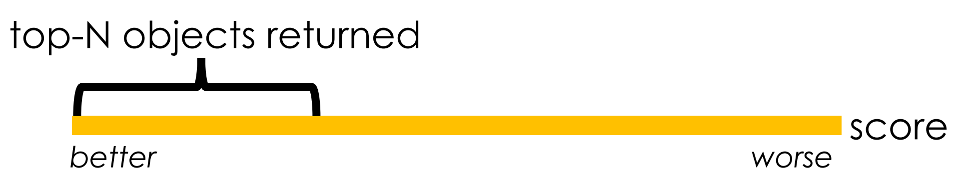
- you cannot have it all!
- there are various impossibility theorems related to fairness in classification

Fairness in Ranking

Ranking

- algorithm computes some **score** that encodes/predicts *goodness*
  - e.g., **merit**, relevance
- we want to **rank** objects (usually people) based on that score
  - e.g., candidates for a job position

- similarity with classification task: algorithm computes scores
- difference with classification task: there is **no threshold**; just the length (cut-off) of the ranked list



- so to achieve fairness we can only change the **scoring function**

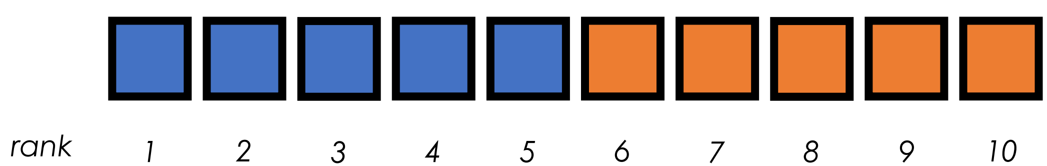
Group Parity

- how does **group parity** translate in ranking?
- remember for classification: group parity = achieve equal positive rate in each group
  - positive (predicted as relevant) = you appear in the ranked list

- so if we look at the top-N objects:
- group parity = *half* from protected, *half* from non-protected

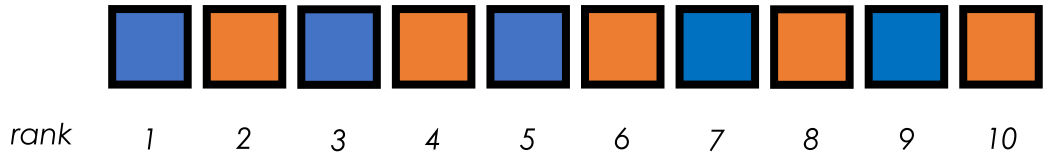
example: rank 10 people from two groups

- is this fair? how can we fix it?



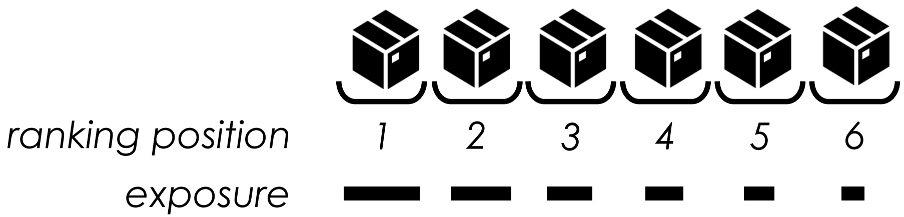
Group Parity

- stronger requirement: **for every prefix** of the ranked list, there should be group parity



- generalize a bit: assume we have a **target ratio**/mix of groups
  - e.g., 40% blue, 60% orange
- how can you achieve this?

Exposure in rankings



- a ranked list **exposes** items to the user
- the amount of exposure depends on the **ranking position**
  - top positions give higher exposure (aka *position bias*)

- the exposure of an item **does not depend** on relevance, utility, user satisfaction, etc.; just on ranking position

Fairness of Exposure

- a ranking **exposes** objects at varying degrees
  - **position bias**: higher ranked items are exposed more

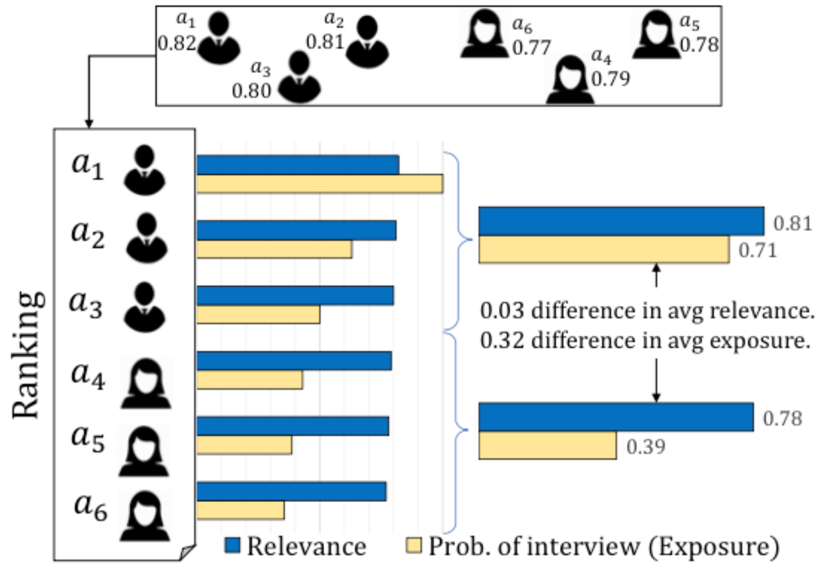
- fairness aspect: **exposure** should be **proportional** to **merit**
  - if an item is x times better than another, it should receive x times more exposure

Fairness of Exposure

- fairness = exposure ~ merit (relevance)
- can we achieve this? almost never
  - exposure is **fixed**
  - merit **depends** on ranking scores

job applicants

ranking by merit



high discrepancy in group exposure

[2018 KDD A. Singh T. Joachims] *Fairness of Exposure in Rankings*

Fairness of Exposure

- what can we do then?
  - be fair in the long-term: **amortized fairness**
  - or be fair **probabilistically**: probabilistic rankings

- formulate an optimization problem
  - **maximize** relevance **subject to** equal exposure, or
  - **minimize** exposure discrepancy **subject to** relevance quality drop

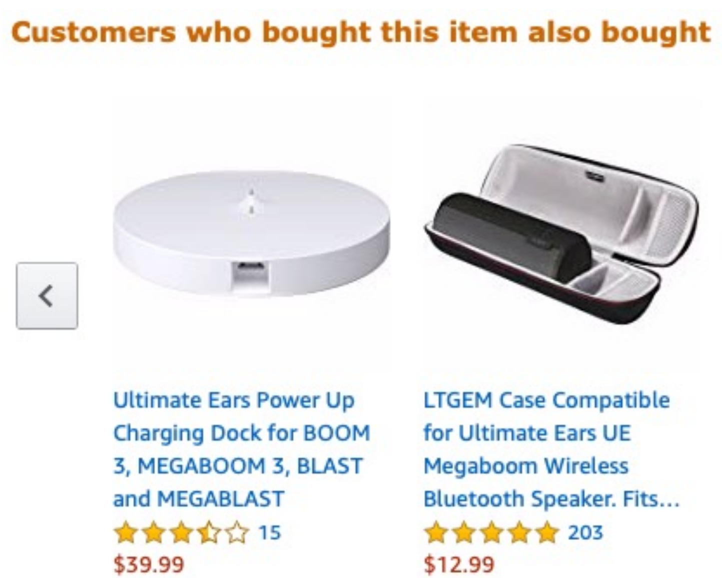
[2018 SIGIR A. Biega et al.] *Equity of Attention: Amortizing Individual Fairness in Rankings*
[2018 KDD A. Singh T. Joachims] *Fairness of Exposure in Rankings*

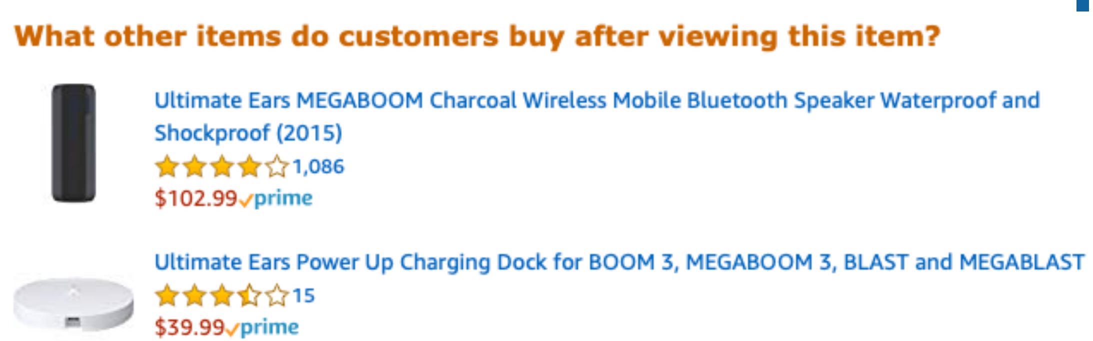
Fairness in Recommendations

What are recommender systems?

We Have Recommendations for You

Sign in to see personalized recommendations

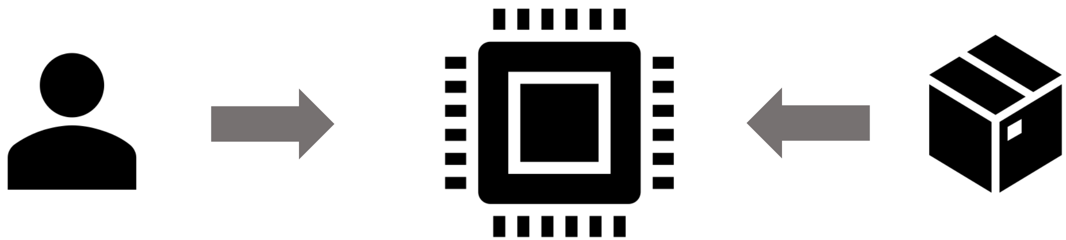




Stakeholders in recommender systems

recommenders = match **users** with **items**

users *recommender* *items*



consumers **system provider** **producers**

a multi-sided market with possibly conflicting interests
and various **fairness concerns**

Fairness in recommendations

fairness is the **fair distribution** of a **resource**

to make it less abstract and cyclic, answer three questions:

- fair **for whom?** (which are the *protected groups*)
  - **consumers** (end users, buyers)
  - **producers** (item providers, creators, sellers)
- distribution **of what** resource?
  - **accuracy** (effectiveness, utility, satisfaction, quality of service, etc.)
    - e.g., items are good matches for users; users are good matches to items
  - **exposure** (attention)
    - e.g., what users see; to whom items are recommended
- **when** is the distribution fair?
  - specify the **optimal state** of fairness
  - quantify how far the optimal state is = define some (**un-**)**fairness measure**

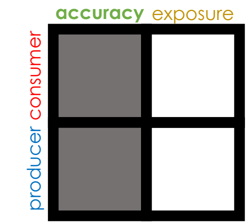
Taxonomy of fairness definitions in recommenders

of what?

for whom?

	accuracy	**exposure**
consumer	prediction accuracy [2017 NeurIPS S. Yao et al.] ranking accuracy [2018 FAT M. Ekstrand et al.]	equal exposure [2018 FAT R. Burke et al.]
producer	ranking accuracy [2019 KDD A. Beutel et al.]	exposure coverage [2018 CIKM, 2019 RecSys] equal exposure [2018 FAT R. Burke et al.] calibrated exposure [2018 RecSys]

some representative works



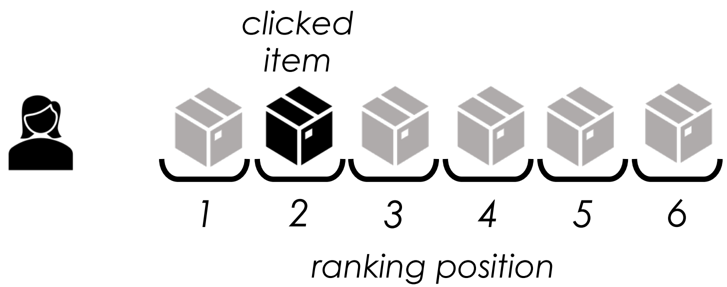
Accuracy in recommender systems

view 1: the recommender **matches** users with items

prediction accuracy: how good is the matching (regression task)

- metrics: absolute error (MAE), root mean square error (RMSE)

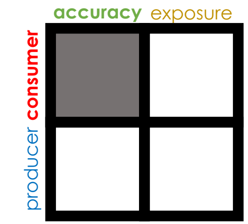
view 2: the recommender **ranks** items for a user



reciprocal rank (RR) = 1/2

ranking accuracy: how good is the ranking (ranking task)

- metrics: reciprocal rank (RR), discounted cumulative gain (DCG)

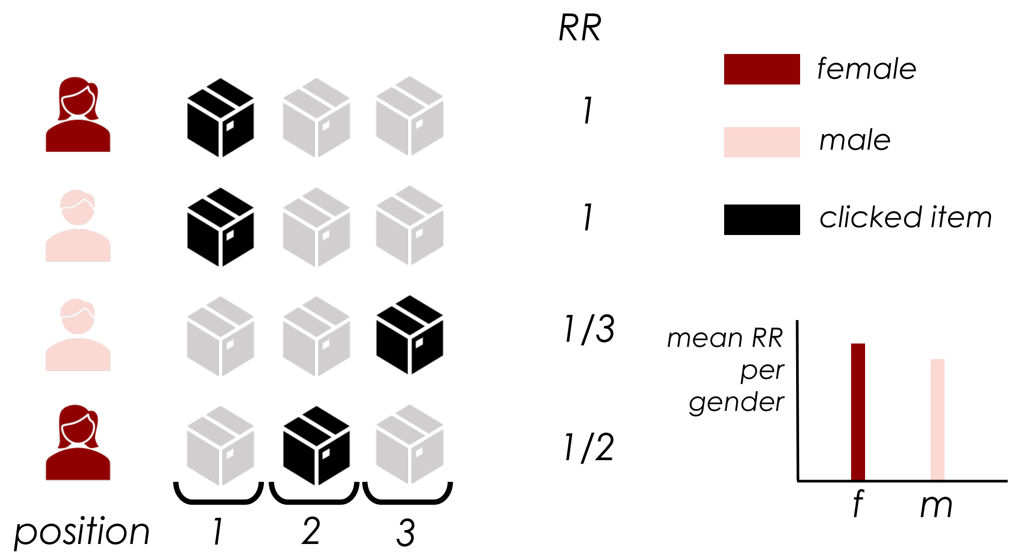


Fairness of **accuracy** for **consumers**

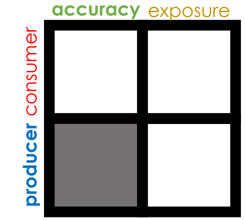
*“**Males** and **females** should experience the same quality of service.”*

operationalized as:

1. **group** users **by gender**
2. measure **total accuracy** per gender
3. **assess** if distribution is **fair**



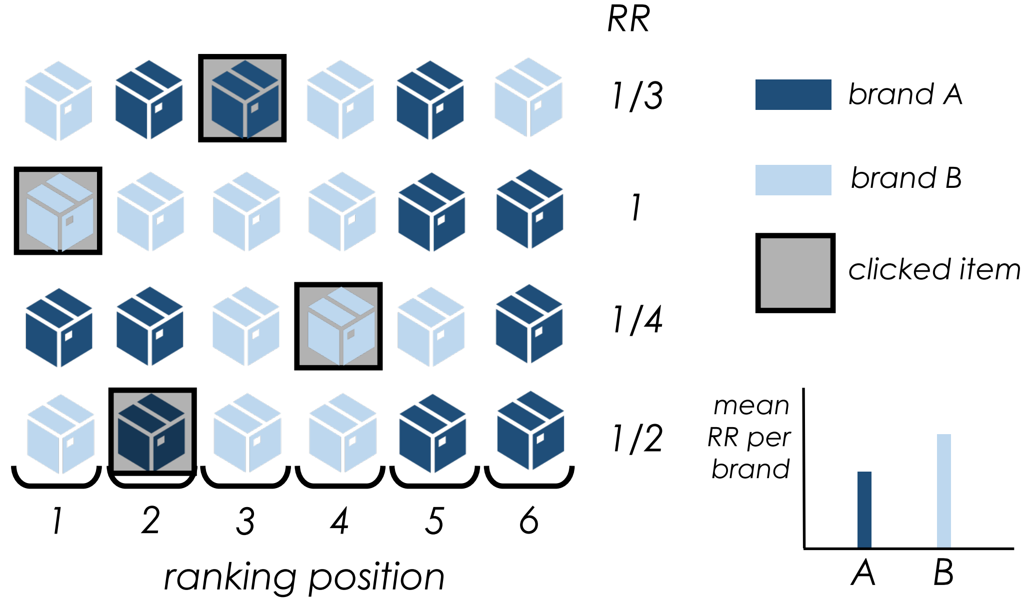
Fairness of accuracy for producers

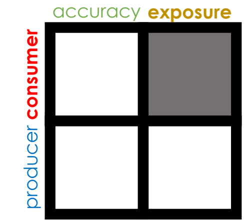


*"When recommending products, **all brands** should have similar accuracy."*

operationalized as:

1. **group** items **by brand**
2. measure **total accuracy** per brand
3. **assess** if distribution is **fair**



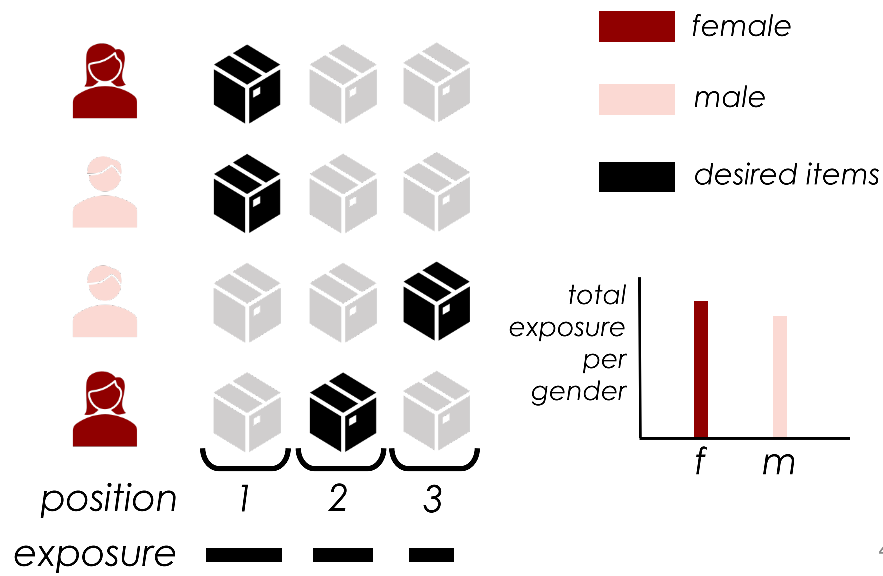


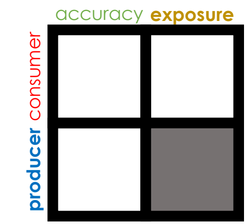
Fairness of exposure for consumers

"When recommending jobs, ***males*** *and* ***females*** *should see the same number of executive openings."*

operationalized as:

1. **group** users **by gender**
2. measure **total exposure** per gender
3. **assess** if distribution is **fair**



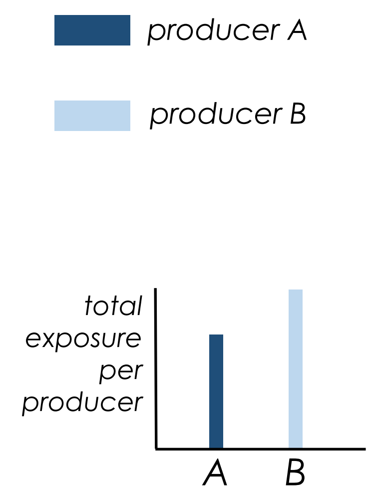


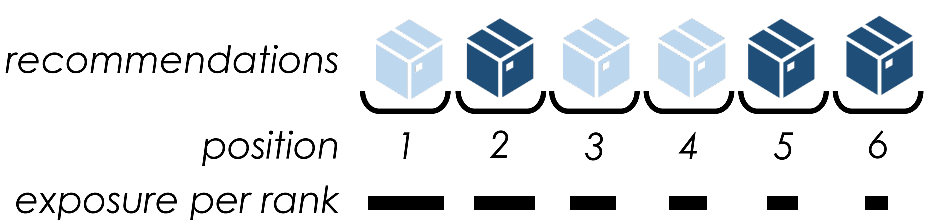
Fairness of **exposure** for **producers**

*"When recommending products, **all brands** should be fairly exposed."*

operationalized as:

1. **group** items **by producer**
2. measure **total exposure** per producer
3. **assess** if the distribution is **fair**





How to Achieve Fairness

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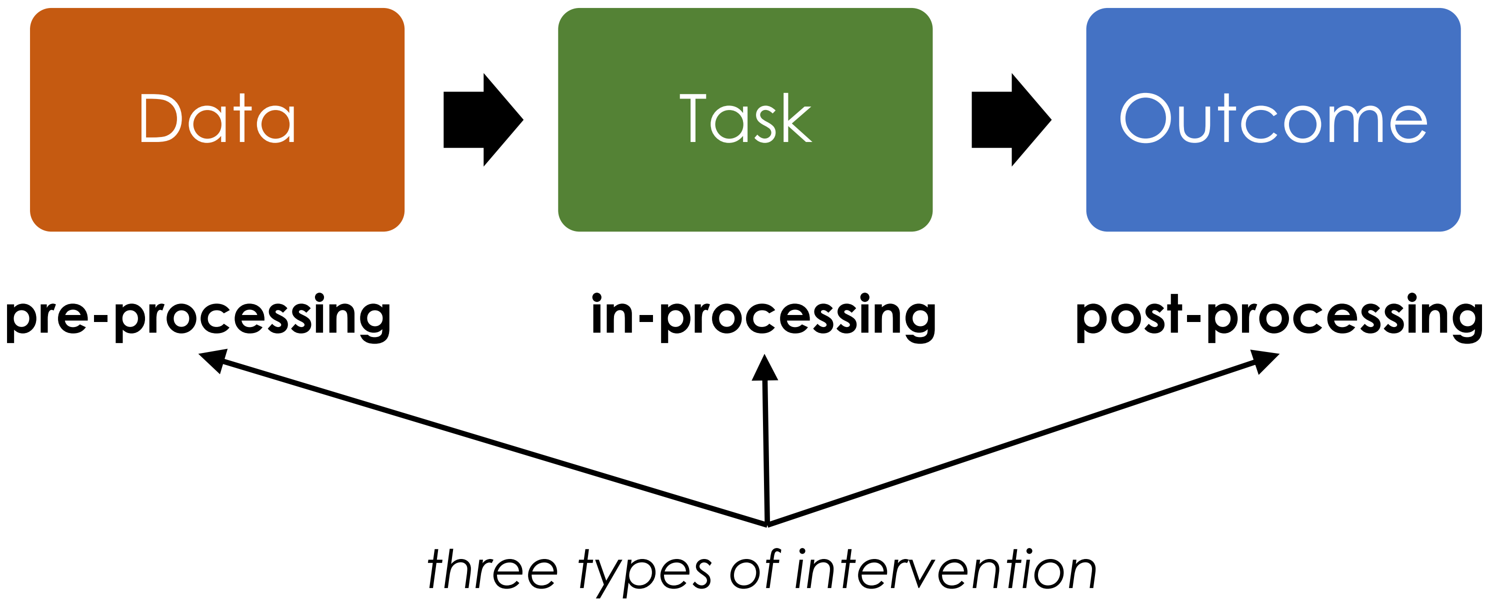


Post-Processing for Group Parity in Ranking

Step 1. Determine **minimum representation** from the **protected** group in each **prefix**

- Suppose we want at least $\lfloor 40\% N \rfloor$ orange at every top-N

N	1	2	3	4	5	6	7	8	9	10
# orange	0	0	1	1	2	2	2	3	3	4

Step 2. Create two sublists of objects (blue and orange), sorted on score

a b c d e f

better

g h i j k l

better

Step 3. Build the ranked list incrementally

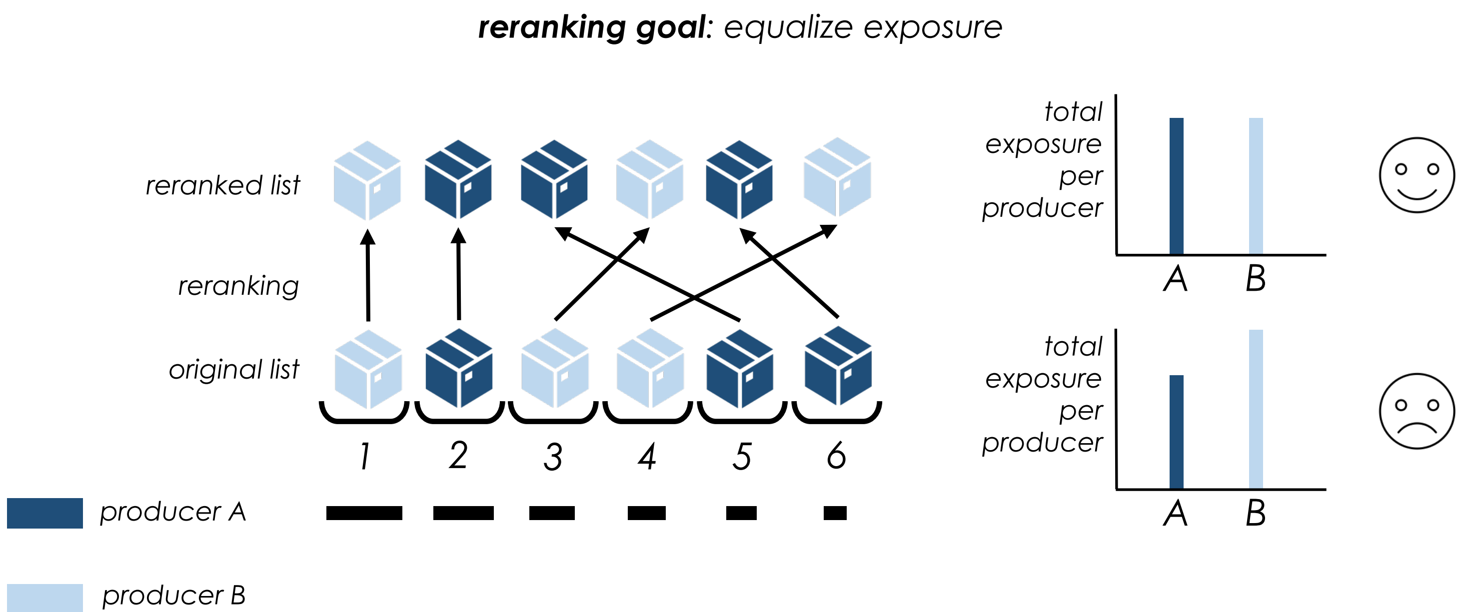
- at each rank choose the **best** from either group (why best?),
- **unless** you *must* choose from the protected (to ensure minimum representation)

rank	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
	a	b	g	c	h	d	e	i	f	j

Post-Processing for Fair Exposure in Ranking

change the position of items to improve fairness

trade-off between **fairness** and **accuracy**



Post-Processing for Ranking

the **original list** optimizes some **internal measure** of **utility**

- e.g., relevance, click-through rate

but to increase **fairness**, the list has to be reranked

- at the expense of **utility**

reranking must **trade-off** two objectives: **utility** and **fairness**

possibilities:

maxU	maximize **utility** given a constraint on **fairness**
maxF	maximize **fairness** given a constraint on **utility**
U+F	maximize a combination of **utility** and **fairness**

Other Fairness Challenges

Continuous Protected Attributes

- All definitions compare a **protected group** (e.g., blacks, women) against the **non-protected**

- What happens in the case of continuous protected attributes, e.g., **age**, **income**, ***location***

- Groups are not defined beforehand, and defining them can lead to **gerrymandering**
  - purposefully setting the group boundaries to **hide discrimination**

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Spatially Fair Distribution of Outcomes

X	O	X	O
O	X	O	X
X	O	X	O
O	X	O	X

Spatially Unfair Distribution of Outcomes

X	X	O	O
X	O	X	O
X	X	O	O
X	X	O	O

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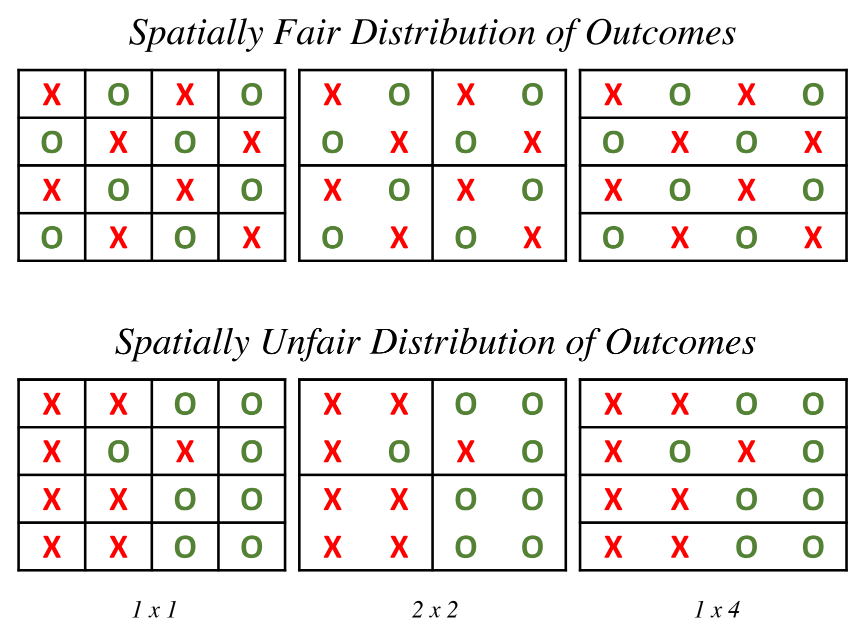
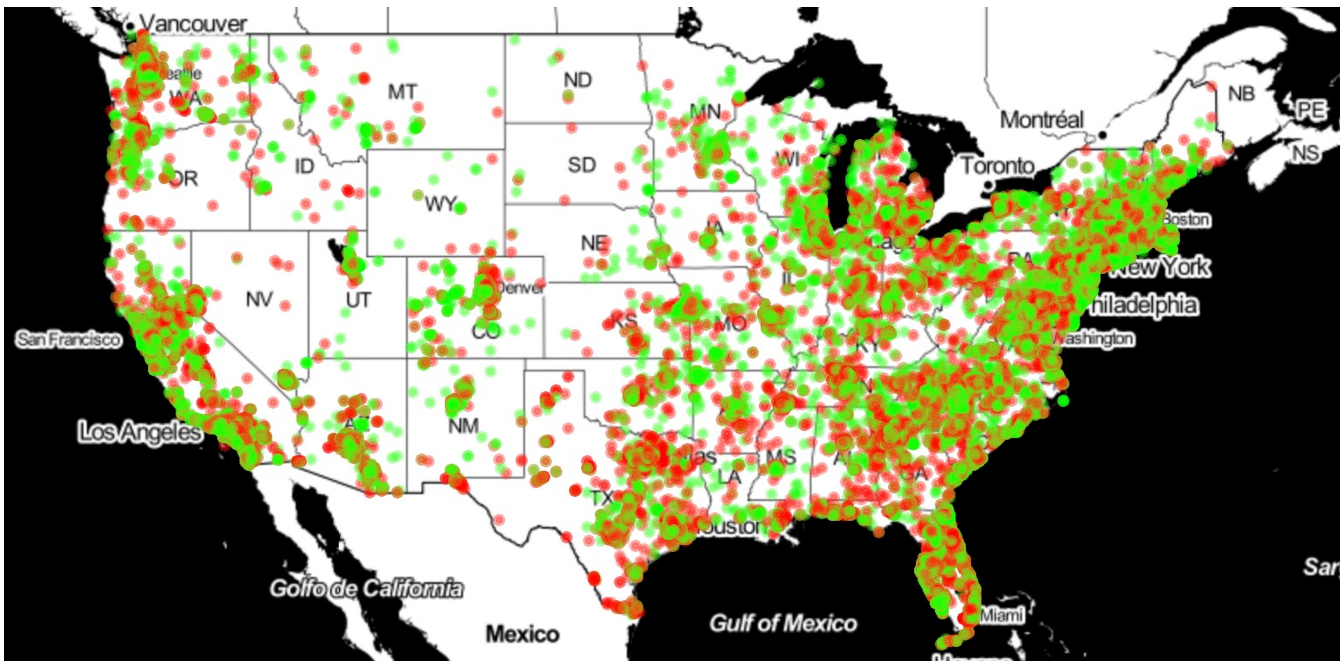


Location Fairness

- We want **outcomes** to be **independent of location**
- Consider **Loan Application** Accepts and Rejects per location
- Is this map **fair**?



Discover Unfairness via Explanations

- Previous definitions require the groups (protected vs. non-protected) to be fixed and known in advance
- Can you **discover** groups (or sub-groups) where discrimination occurs?

Counterfactual Explanations

- A person x **does not receive** a loan
  - x = {Race=Caucasian, Gender=Female, Income=Low}
- What are the **minimal changes** to **receive** the loan?
  - {Gender=Female} → {Gender=Male}

- This shows **discrimination** based on gender!