Information Discrepancy in Strategic Learning

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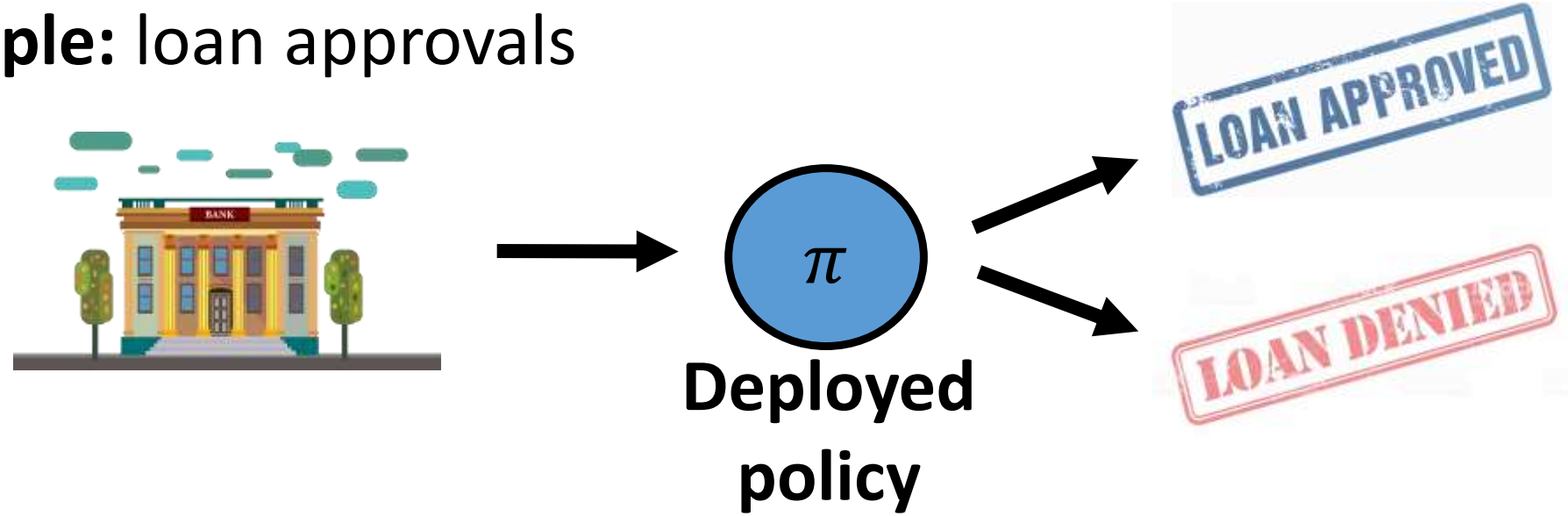
Strategic Learning

Settings which:

1. Involve decision making over human individuals.
2. Certain outcomes more desirable than others.

Example: loan approvals



Deployed policy

Strategic Learning

Individuals would like to receive
more favorable assessments
→ Act <u>strategically</u>
→ Strategic feature modifications

Example: loan approvals

π

Deployed policy

Strategic Feature Modification

π

Deployed policy

$x \in R^d$

$x' \in R^d$

$\pi(z)$=0 — **"Likely to default"**

$\pi(z)$=1 — **"Likely to repay"**

Ideally:

1. $\pi(x') >> \pi(x)$.
2. $Cost(x, x')$ is small.

Strategic feature modification

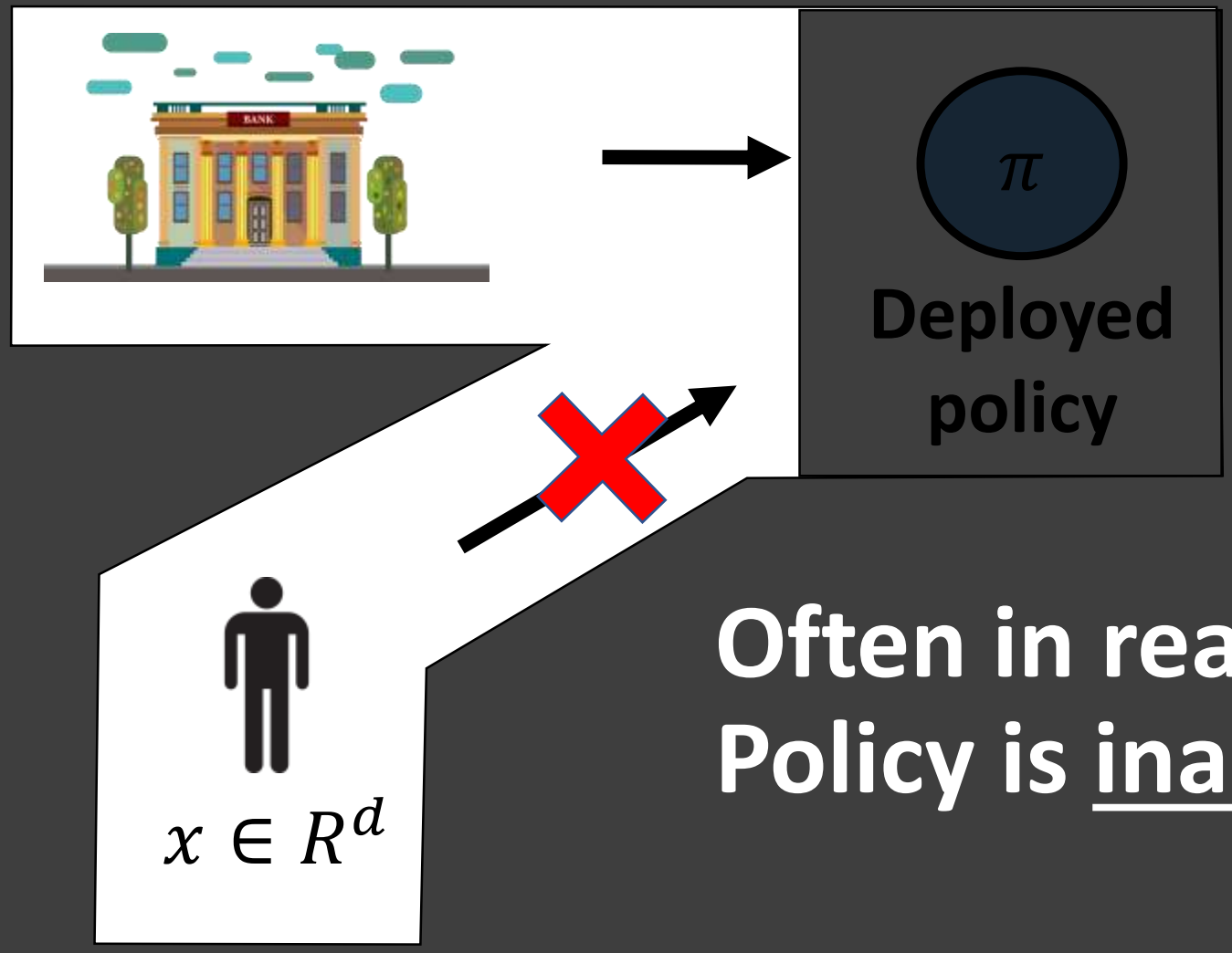
π

Deployed policy

$x \in R^d$

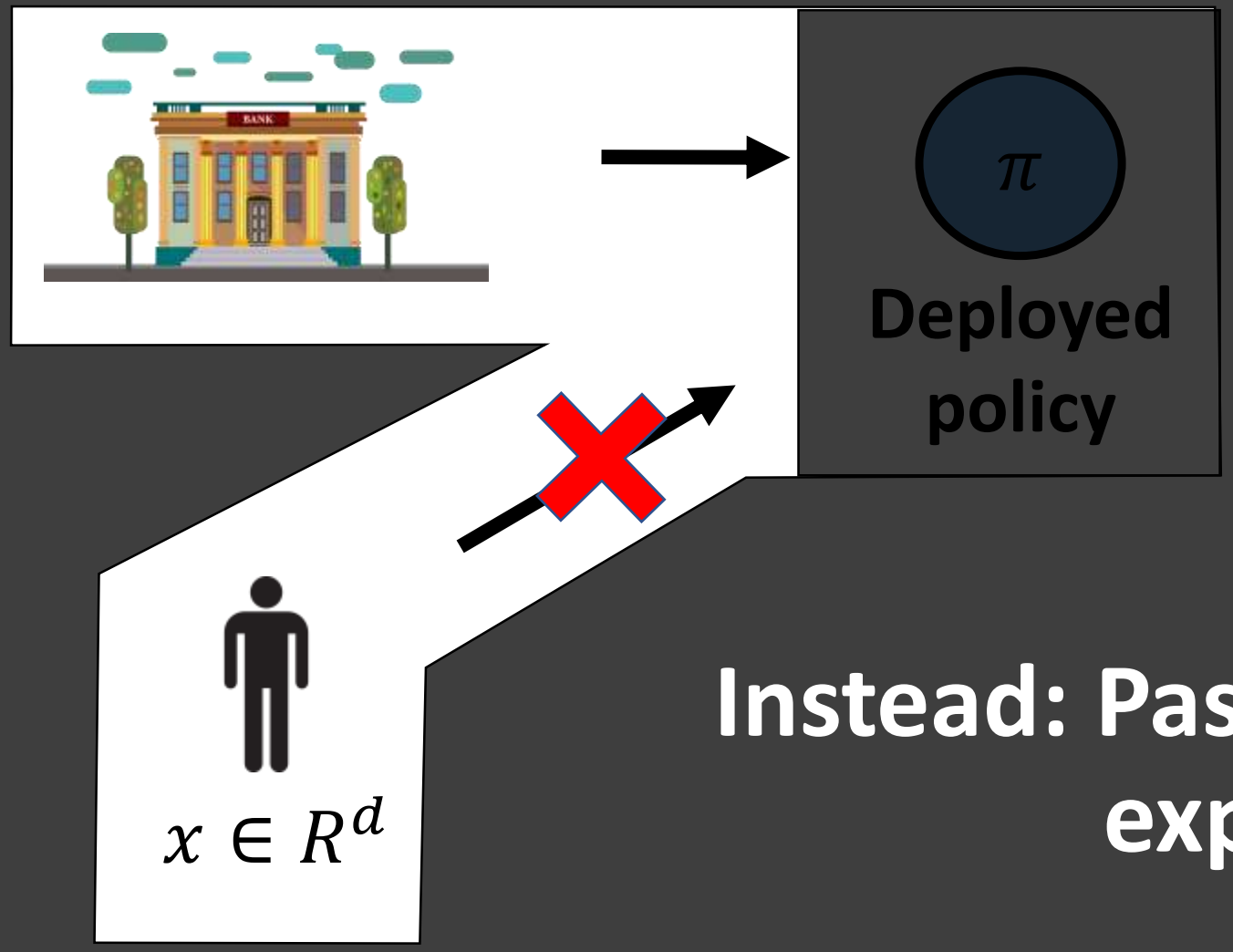
Key assumption: deployed policy is accessible.

Strategic feature modification



Often in reality:
Policy is <u>inaccessible</u>.

Strategic feature modification



Instead: Past labelled examples, explanations, …

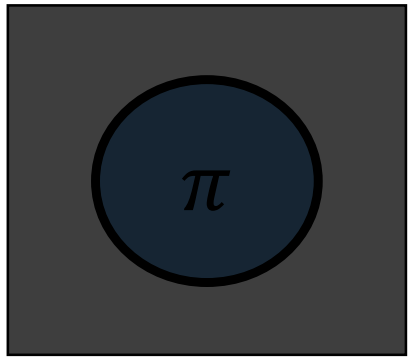
Our Work

Focus on strategic learning when decision rules are **inaccessible**.

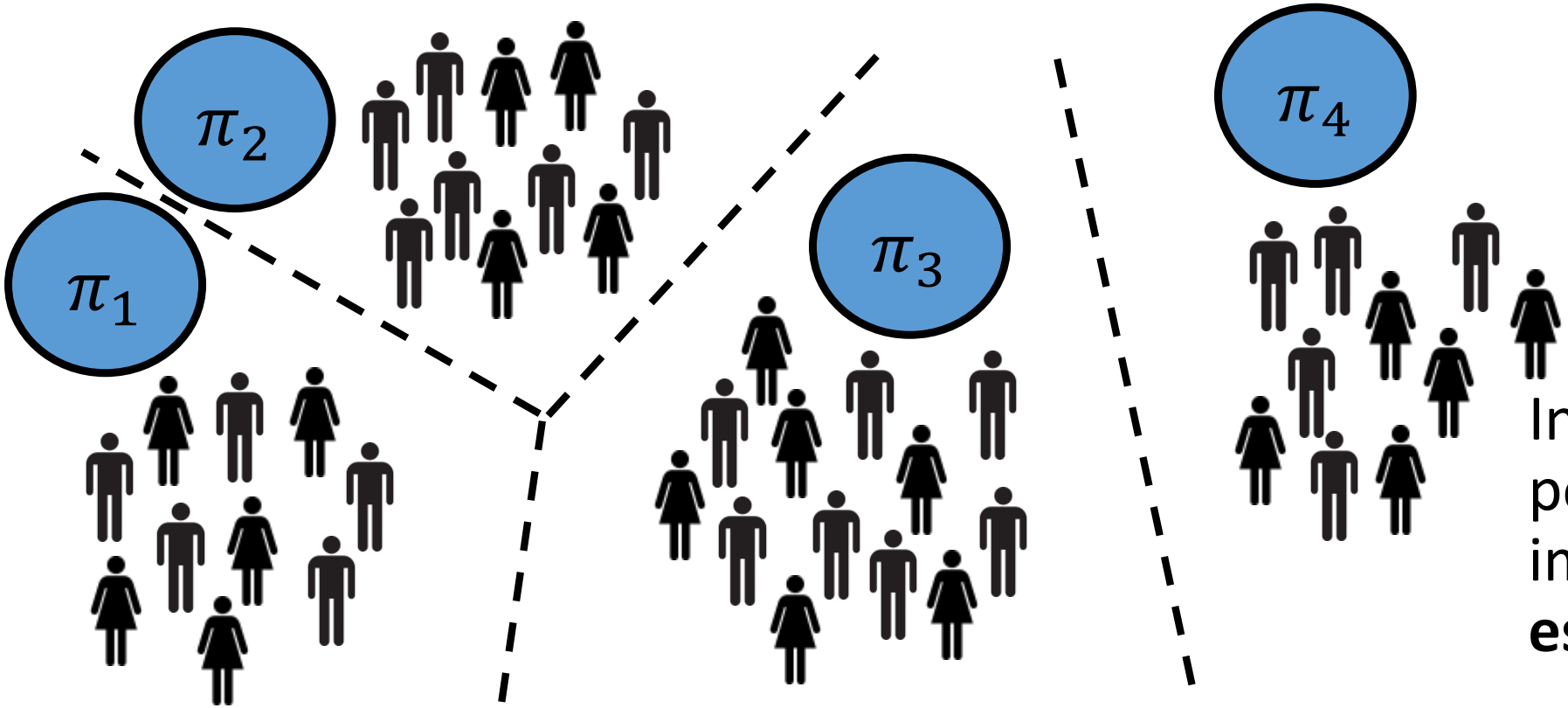
Model based on **learning from peers**.

Instead of observing the decision rule, individuals try to learn about it from friends, acquaintances **who applied previously**.

Strategic Learning with Inaccessible rules



Due to information discrepancy, different peer-networks may form **different estimates** of the deployed rule.



Individuals in each sub-population attempt to improve using **its own estimation** of the rule.

Strategic Learning with Inaccessible rules

Q: What are the effects of information discrepancy between different sub-populations on the ability of individuals to improve?

Adult Dataset

Publicly available at UCI repository.

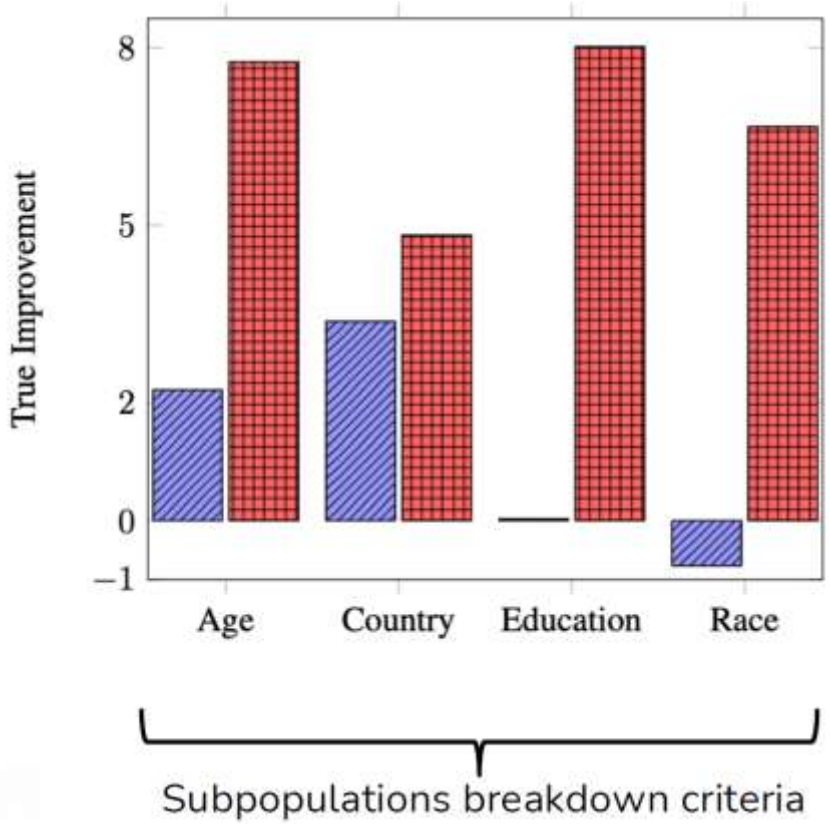
- ~50K datapoints
- 14 attributes including Age, Country, Workclass, Education, Race, etc.
- Label (annual income): = 50K Our process:
- 4 experiments separating subpopulations based on:

Characteristic	Subpopulation 1	Subpopulation 2
Age	<35 yrs old	>=35 yrs old
Country	All others	Western countries
Education	All others	Above high school
Race	All others	White

Predict **income improvement** (final income – original income) for each sub-population.

Results Snapshot: Adult Dataset

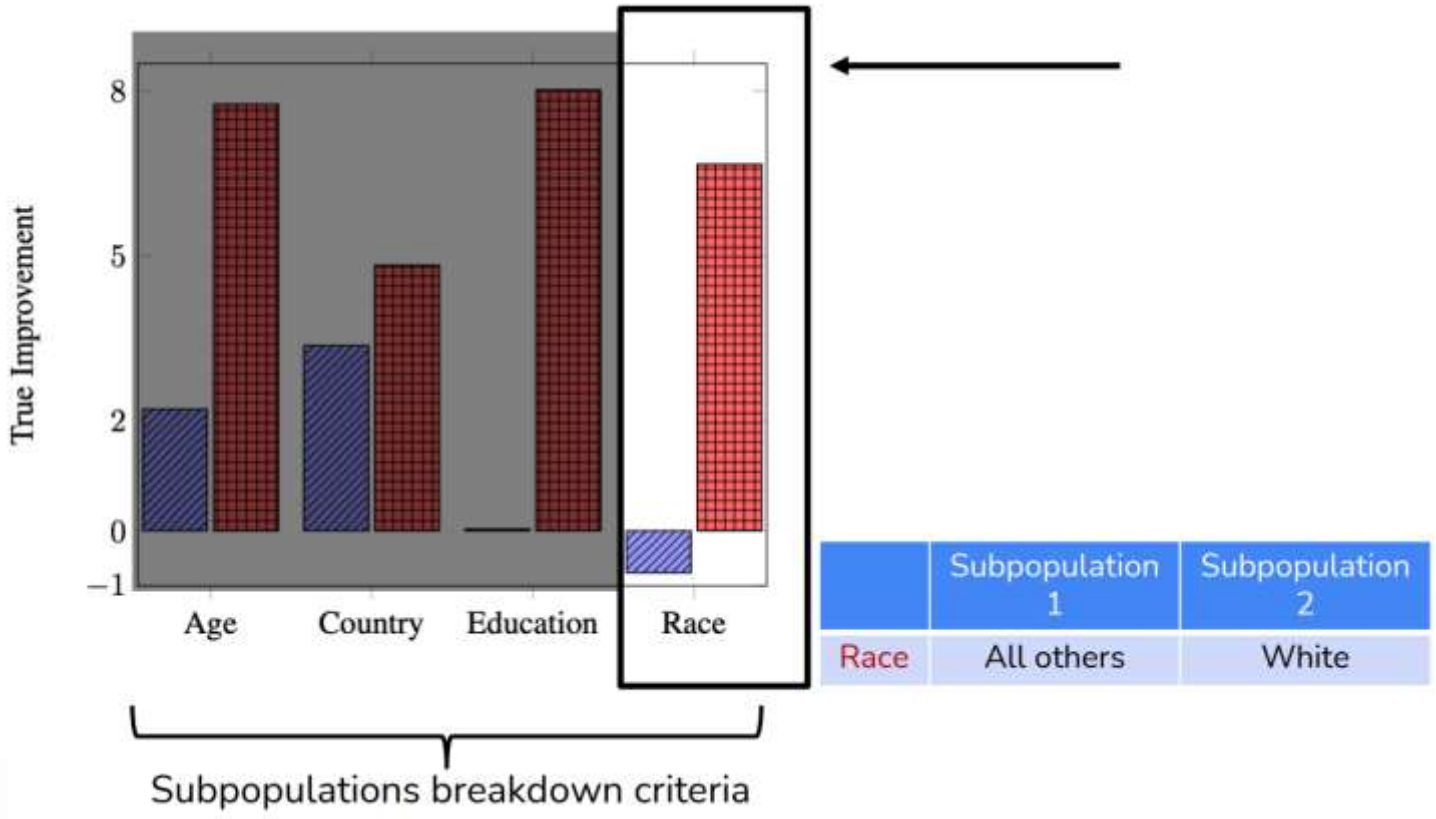
- Total income improvement currently subpopulation 1
- Total income improvement currently subpopulation 2



Results Snapshot: Adult Dataset

Sub-populations may end up **worse off**.

- Total income improvement currently subpopulation 1
- Total income improvement currently subpopulation 2

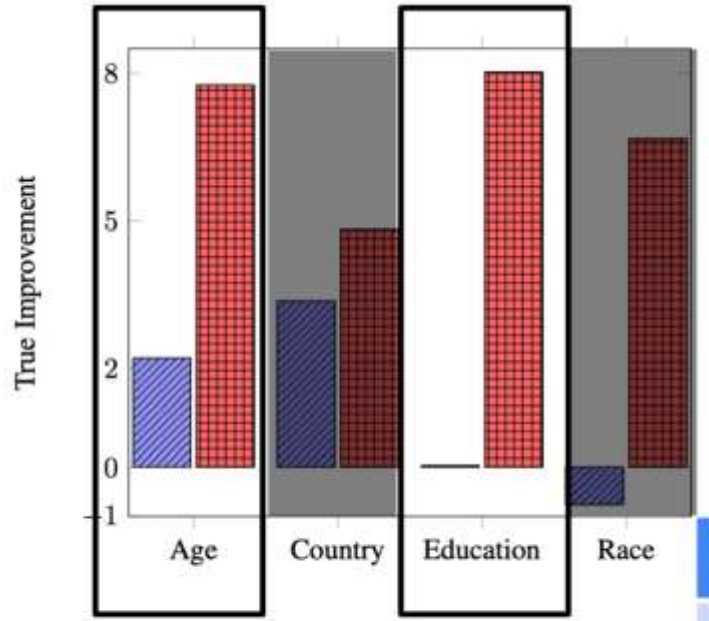


	Subpopulation 1	Subpopulation 2
Race	All others	White

Results Snapshot: Adult Dataset

Total improvement may be **very unequal** across sub-populations.

- Total income improvement currently subpopulation 1
- Total income improvement currently subpopulation 2



	Subpopulation 1	Subpopulation 2
Age	<35 yrs old	>=35 yrs old
Education	All others	Above HS

Results

We make explicit a connection between:

1. Information available to different sub-populations.
2. Ability of individuals to improve.

Theoretical characterizations for when, across all sub-populations:

1. Do-no-harm.
2. Equal improvements.
3. Effort is exerted optimally.

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Thank you!

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