Average Individual Fairness

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Based on Joint Work with:
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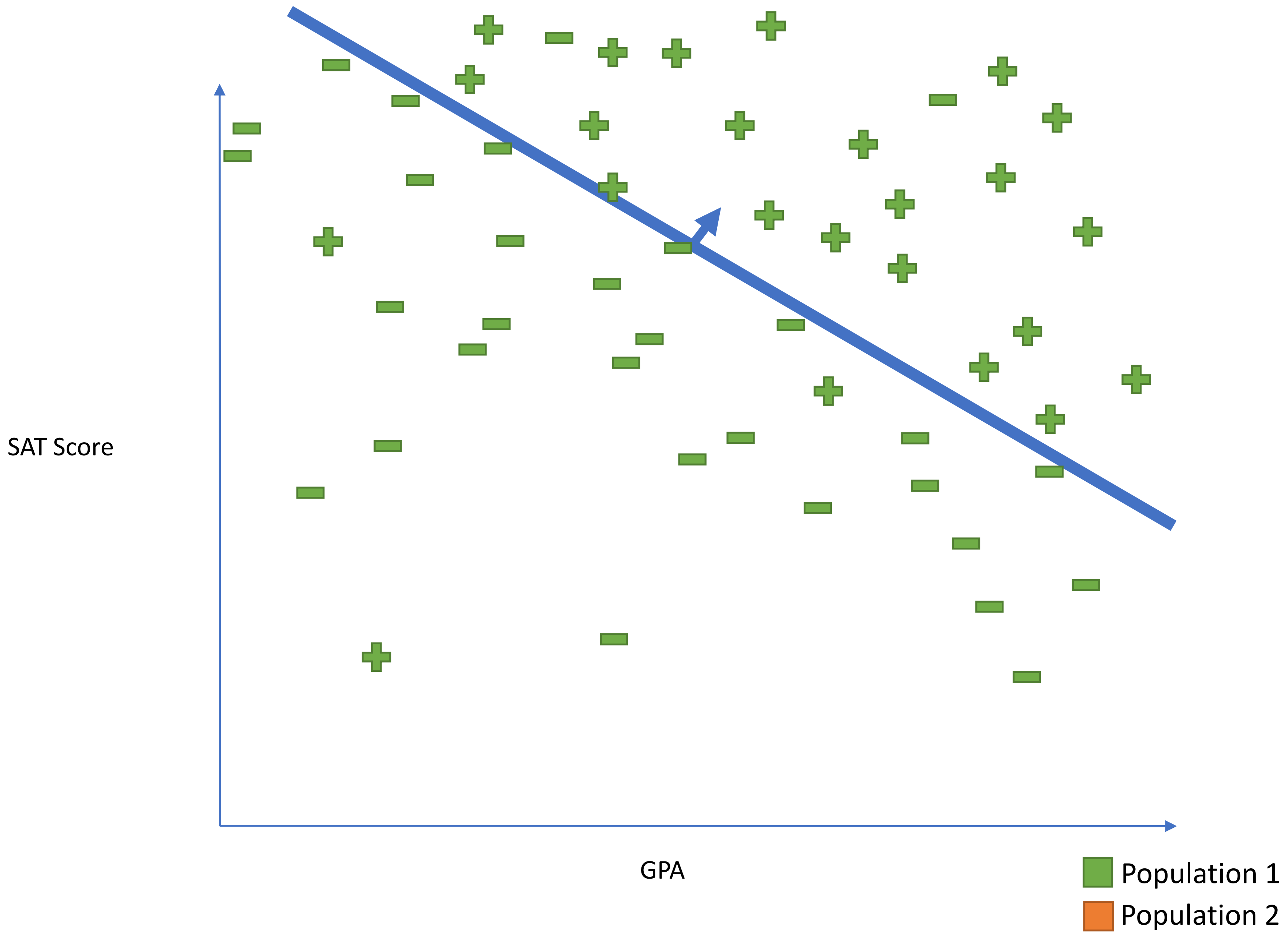
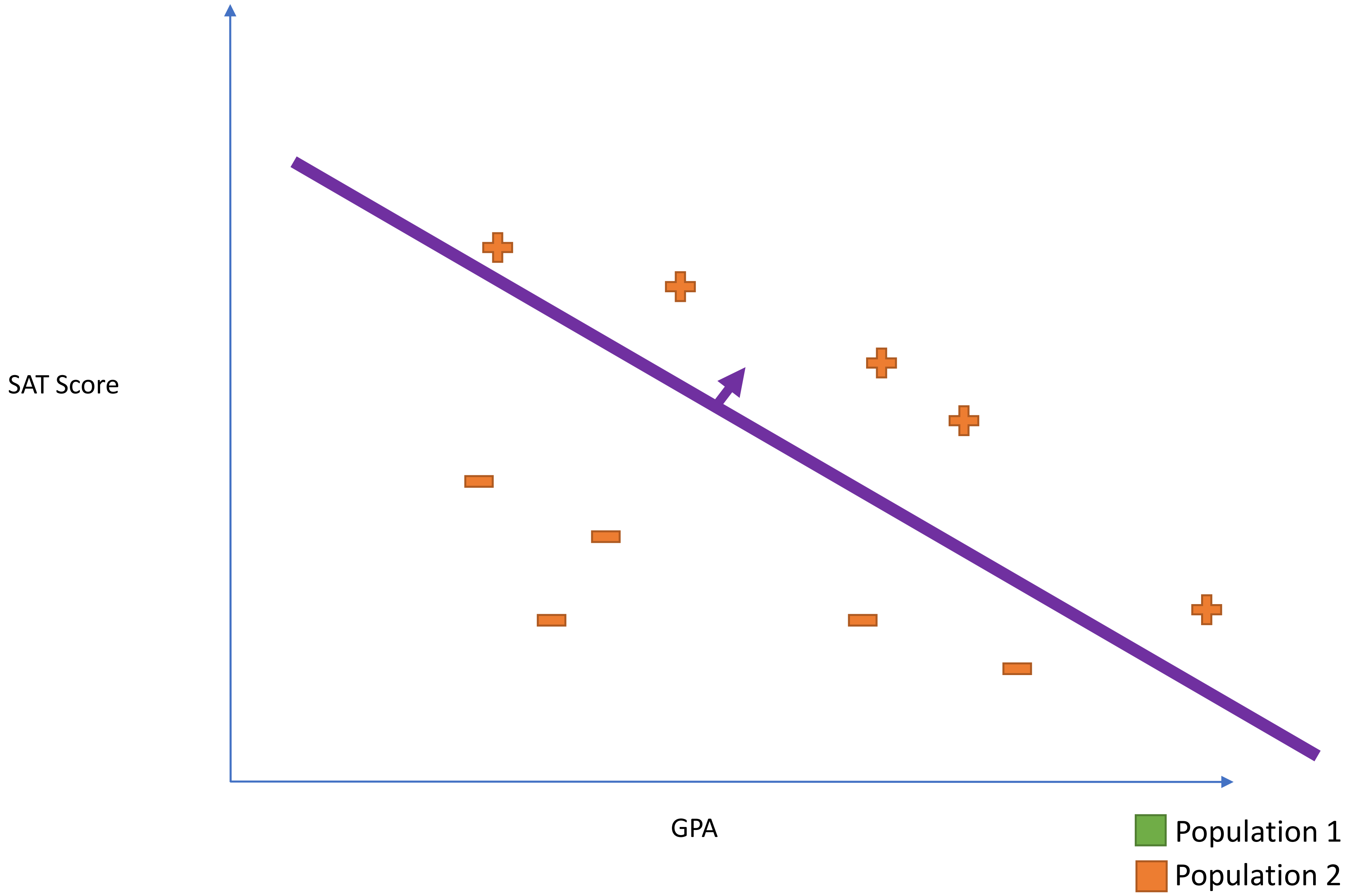

SAT Score
GPA
Population 1
Population 2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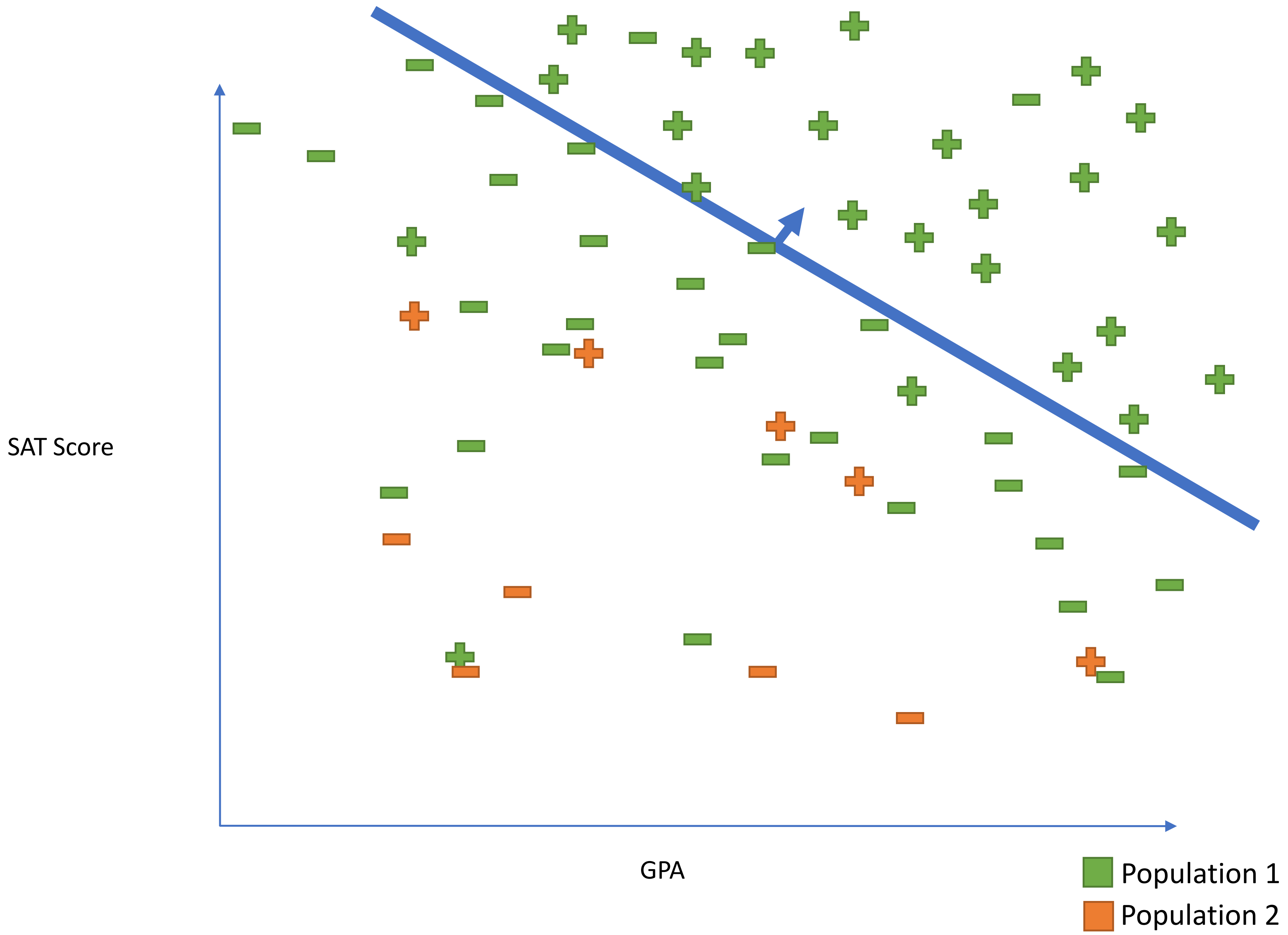
SAT Score
GPA
Population 1
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Why was the classifier “unfair”?

Question: Who was harmed?

Possible Answer: The qualified applicants mistakenly rejected.

False Negative Rate: The rate at which harm is done.

Fairness: Equal false negative rates across groups?

[Chouldechova], [Hardt, Price, Srebro], [Kleinberg, Mullainathan, Raghavan]

Statistical Fairness Definitions:

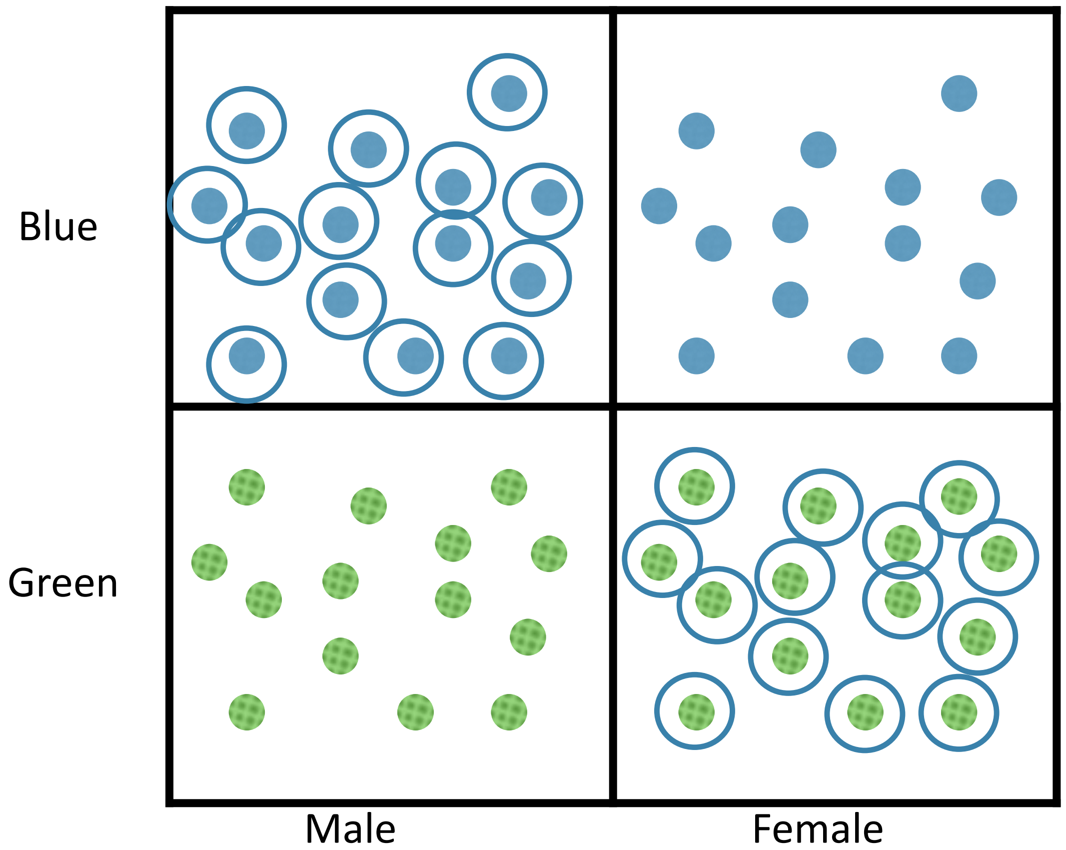
1. Partition the world into groups (often according to a “protected attribute”)
2. Pick your favorite statistic of a classifier.
3. Ask that the statistic be (approximately) equalized across groups.

But…

- A classifier equalizes false negative rates. What does it promise you?
  - The *rate* in false negative rate assumes you are a uniformly random member of your population.
  - If you have reason to believe otherwise, it promises you nothing…

For example

- Protected subgroups: “Men”, “Women”, “Blue”, “Green”. Labels are independent of attributes.
- The following allocation equalizes false negative rates across all four groups.



Sometimes individuals are subject to more than one classification task…

The Idea

- Postulate a distribution over *problems* and *individuals*.
- Ask for a *mapping between problems and classifiers* that equalizes false negative rates across every pair of individuals.
- Redefine *rate*:

Averaged over the problem distribution.

An *individual* definition of fairness.

A Formalization

- An unknown distribution P over individuals $x_i \in X$
- An unknown distribution Q over *problems* $f_j : X \rightarrow \{0,1\}$, $f_j \in F$
- A hypothesis class $H \subseteq \{0,1\}^X$ (Note f_j's not necessarily in H)
- Task: Find a *mapping from problems to hypotheses* $\psi \in (\Delta H)^F$
    - A new "problem" will be represented as a new labelling of the training set.
    - Finding the hypothesis corresponding to a new problem shouldn't require resolving old problems. (Allows online decision making)

What to Hope For (Computationally)

- Machine learning learning is already computationally hard [KSS92,KS08,FGKP09,FGPW14,…] even for simple classes like halfspaces.
- So we shouldn’t hope for an algorithm with worst-case guarantees…
    - But we might hope for an efficient reduction to unconstrained (weighted) learning problems.
- “Oracle Efficient Algorithms”
    - This design methodology often results in practical algorithms.

Computing the Optimal Empirical Solution.

Initialize $\lambda_i^1 = 1/n$ for each $i \in \{1, \dots, n\}$

For $t = 1$ to $T = O\left(\frac{\log n}{\epsilon^2}\right)$

- **Learner Best Responds**:
  - For each problem j, solve the learning problem $h_j^t = A(S_j^t)$ for $S_j^t = \left\{\left(\lambda_i^t + \frac{1}{n}, x_i, f_j(x_i)\right)\right\}_{i=1}^n$
  - Set $\gamma^t = \mathbf{1}[\sum_i^n \lambda_i^t \geq 0]$
- **Auditor Updates Weights**:
  - Multiply λ_i^t by $(err(x_i, h^t, \hat{Q}) - \gamma)$ for each expert i and renormalize to get updated weights λ_i^{t+1}.

Output the weights λ_i^t for each person i and step t.

Defining ψ

- Parameterized by the sequence of dual variables $\lambda^T = \{\lambda^t\}_{t=1}^T$

$\psi_{\lambda^T}(f)$:

For $t = 1$ to T

- Solve the learning problem $h^t = A(S^t)$ for $S^t = \left\{\left(\lambda_i^t + \frac{1}{n}, x_i, f(x_i)\right)\right\}_{i=1}^n$

Output $p_f \in \Delta H$ where p_f is uniform over $\{h^t\}_{t=1}^T$

(Consistent with ERM solution)

Computing the Optimal Empirical Solution.

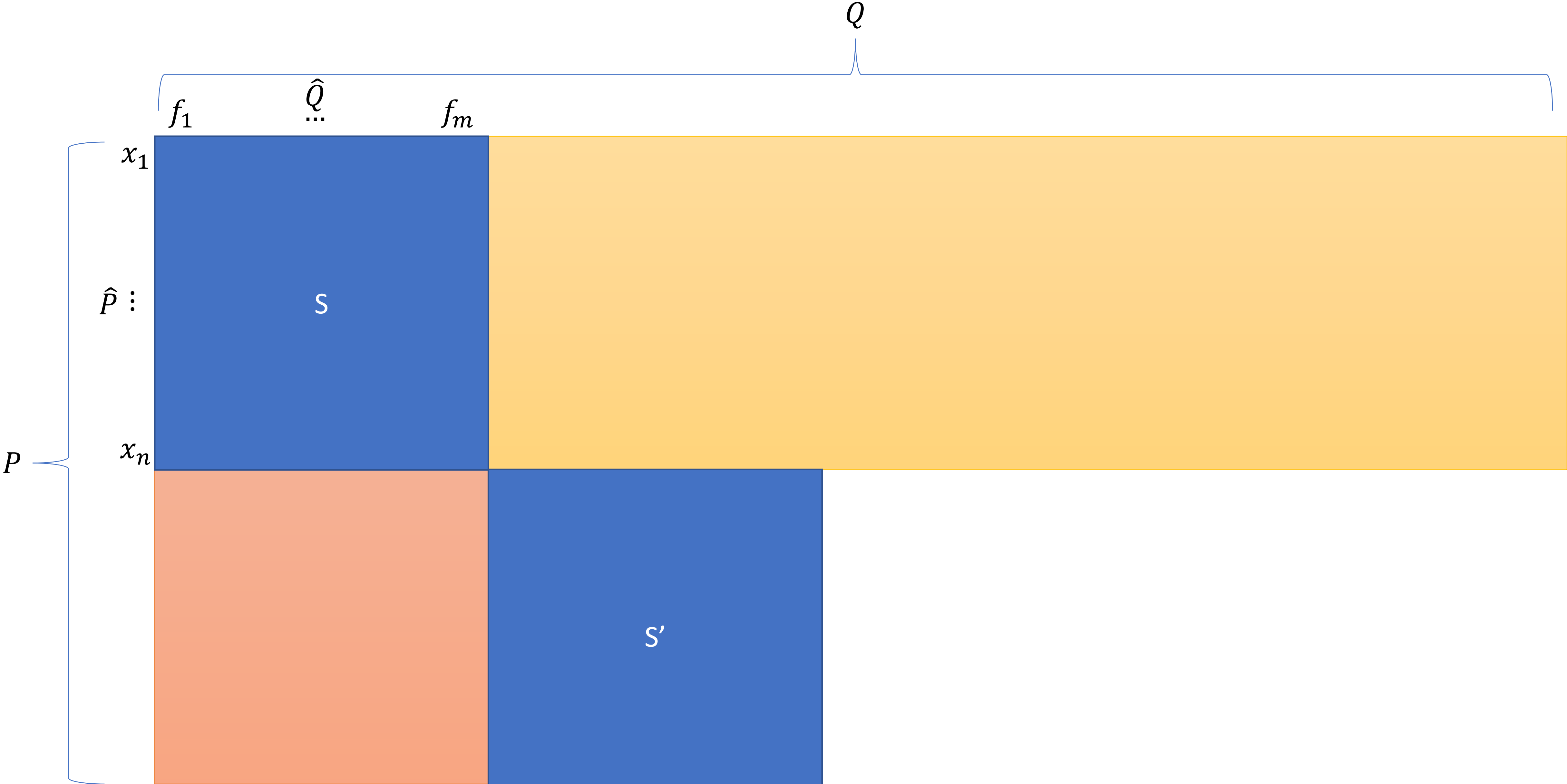
Theorem: After $O\left(m \cdot \frac{\log n}{\epsilon^2}\right)$ calls to the learning oracle, the algorithm returns a solution $p \in (\Delta H)^m$ that achieves empirical error at most:

$$OPT\left(\alpha, \hat{P}, \hat{Q}\right) + \epsilon$$

and satisfies for every $i, i' \in \{1, \dots n\}$:

$$\left|FN\left(x_i, p, \hat{Q}\right) - FN\left(x_{i'}, p, \hat{Q}\right)\right| \le \alpha + \epsilon$$

Generalization: Two Directions



Generalization

Theorem: Assuming

1) $m \geq \text{poly}\left(\log n, \frac{1}{\epsilon}, \log\frac{1}{\delta}\right)$,

2) $n \geq poly\left(m, VCDIM(H), \frac{1}{\epsilon}, \frac{1}{\beta}, \log\frac{1}{\delta}\right)$

the algorithm returns a solution ψ that with probability $1-\delta$ achieves error at most:

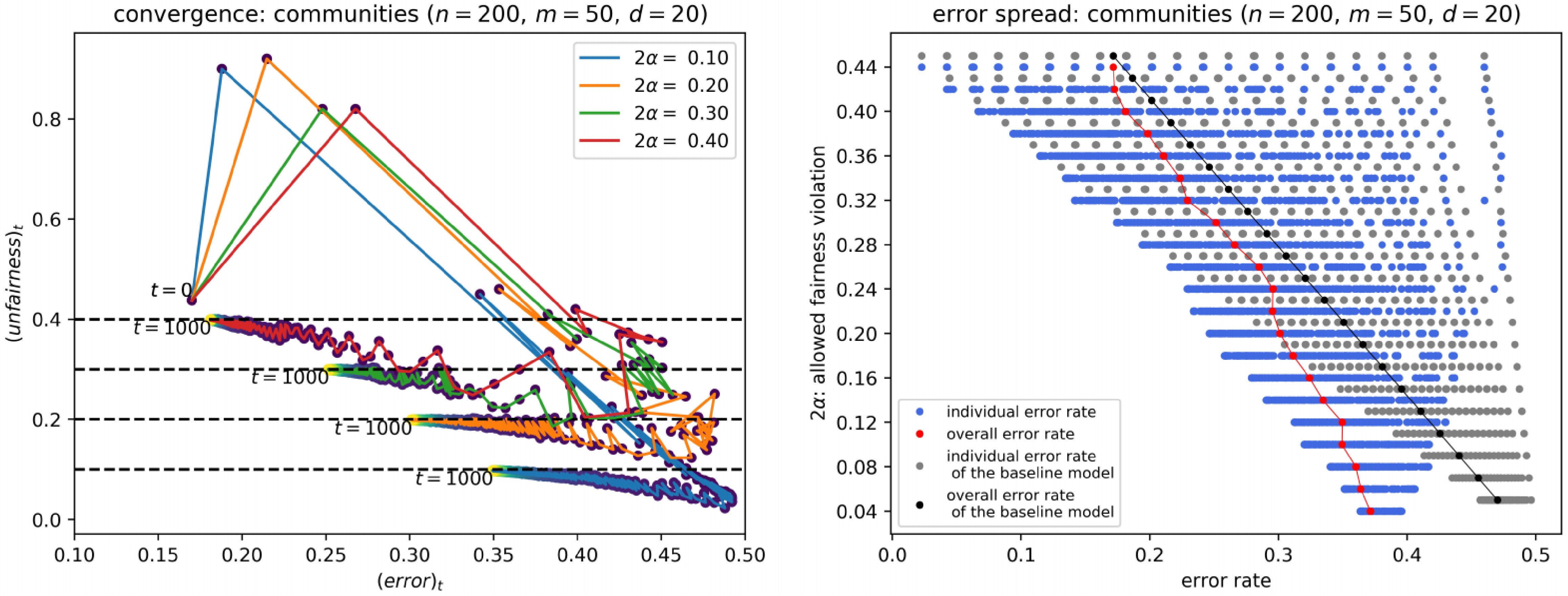
$$OPT(\alpha, P, Q) + \epsilon$$

and is such that with probability $1-\beta$ over $x, x' \sim P$:

$$|FN(x, \psi, Q) - FN(x', \psi, Q)| \leq \alpha + \epsilon$$

Does it work?

- It is important to experimentally verify “oracle efficient” algorithms, since it is possible to abuse the model.
  - E.g. use learning oracle as an arbitrary NP oracle.
- A brief “Sanity Check” experiment:
  - Dataset: Communities and Crime
  - First 50 features are designated as “problems” (i.e. labels to predict)
  - Remaining features treated as features for learning.


convergence: communities ($n = 200$, $m = 50$, $d = 20$)
$2\alpha =$ 0.10
$2\alpha =$ 0.20
$2\alpha =$ 0.30
$2\alpha =$ 0.40
$t = 0$
$t = 1000$
$t = 1000$
$t = 1000$
$t = 1000$
$(unfairness)_t$
$(error)_t$
error spread: communities ($n = 200$, $m = 50$, $d = 20$)
2α: allowed fairness violation
error rate
individual error rate
overall error rate
individual error rate of the baseline model
overall error rate of the baseline model

Takeaways

- We should think carefully about what definitions of “fairness” really promise to individuals.
- Making promises to individuals is sometimes possible, even without making heroic assumptions.
- Once we fix a definition, there is often an interesting algorithm design problem.
- Once we have an algorithm, we can have the tools to explore inevitable *tradeoffs*.

Thanks!

Average Individual Fairness:
Algorithms, Generalization and Experiments
Michael Kearns, Aaron Roth, Saeed Sharifimalvajerdi

Shameless book plug:
The Ethical Algorithm
Michael Kearns and Aaron Roth