Algorithm Design: A Fairness-Accuracy Frontier

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background

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- patients assigned to same risk score have substantially different actual health risks depending on race (Obermeyer et al., 2019)
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algorithm designers increasingly optimize not only for accuracy but also "fairness" (maintain comparable error rates across groups)

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   - characterize what part of this frontier can be achieved through appropriate garbling of inputs
   - ask whether the optimal garbling might involve excluding a covariate (group identity, test scores) entirely

part i:

designer chooses algorithm

setup

- single designer and population of (non-strategic) subjects

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- each subject is described by three variables:
  - **type** Y taking values in $\mathcal{Y}$
    (e.g. need for medical procedure)
  - **group** $G \in \mathcal{G} = \{r, b\}$
    (e.g. race)
  - **covariate** vector X taking values in $\mathcal{X}$
    (e.g. image scans, # past hospital visits, blood tests)

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- X is observed by the designer, Y and G are not directly observed (but may be revealed by X)

how covariates, group identity, and type are related

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  - e.g., consumption patterns predict gender and correlate highly with other group identities (Bertrand and Kamenica, 2020)

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- X is systematically biased up or down for one group
  - e.g., test scores may be shifted up for a high-income group
- X is more informative about Y for one group than the other
  - e.g., the covariate is selectively reported or more accurately measured for one group

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the designer chooses an **algorithm**

$$a : \mathcal{X} \to \Delta(\mathcal{D})$$

for determining (distributions over) decisions based on the observed covariate vector

group errors

fix a **loss function** $\ell : \mathcal{D} \times \mathcal{Y} \to \mathbb{R}$

- measures inaccuracy or harm for a given subject
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Definition

the **error** for group $g \in \mathcal{G}$ given algorithm a is

$$e_g\left(a\right) := \mathbb{E}_{D \sim a(X)}\left[\ell\left(D, Y\right) \mid G = g\right]$$

i.e., the average/expected loss for subjects in group g

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- improving **accuracy**: lowering e_r and e_b
- improving **fairness**: lowering $|e_r - e_b|$

how to trade off fairness and accuracy?

- there is a large literature on social preferences
- this literature documents substantial heterogeneity in how individuals trade off equity and efficiency
  - Fehr and Schmidt (1999), Andreoni and Miller (2002), Charness and Rabin (2002), Sullivan (2022)
- moreover, no evidence of consensus on how to make this tradeoff for real applications of algorithmic prediction rules

preferences

we consider a broad class of designer preferences:

Definition (fairness-accuracy (FA) dominance)

let $>_{FA}$ be the partial order on $\mathbb{R}^2$ satisfying $(e_r, e_b) >_{FA} (e'_r, e'_b)$ if

$$\underbrace{e_r \leq e'_r, \quad e_b \leq e'_b,}_{\text{higher accuracy}} \quad \text{and} \quad \underbrace{|e_r - e_b| \leq |e'_r - e'_b|}_{\text{higher fairness}}$$

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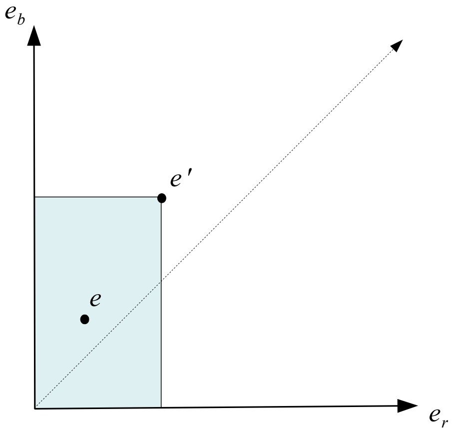
Definition

a **fairness-accuracy preference** $\succeq$ is any total order on $\mathbb{R}^2$ such that $e \succ e'$ whenever $e >_{FA} e'$

fairness-accuracy dominance



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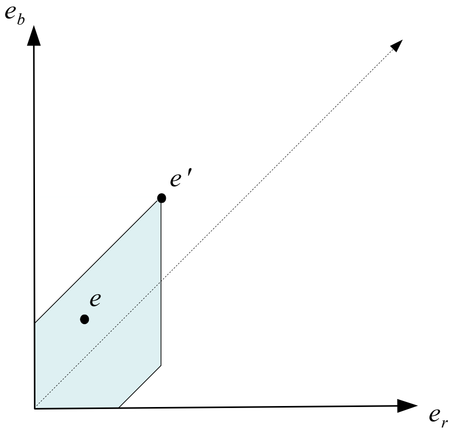

set of error pairs that **all** designers agree improve upon e'

example FA preferences

1. **utilitarian:** $w_u(e_r, e_b) = -p_r e_r - p_b e_b$ where p_r and p_b are the proportions of either group
   - generalizations of this rule put other weights on the two groups (Charness and Rabin, 2002; Dworczak et al., 2021)

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4. **constrained optimization** (e.g., Hardt et al., 2016):

$$\min_{a:\mathcal{X}\to\Delta(\mathcal{D})} \quad p_r e_r(a) + p_b e_b(a) \quad \text{s.t. } |e_r(a) - e_b(a)| \leq \varepsilon$$

fairness-accuracy frontier

Definition

the **feasible set** given X is

$$\mathcal{E}(X) := \{(e_r(a), e_b(a)) : a \in \mathcal{A}_X\}$$

where $\mathcal{A}_X$ is the set of all algorithms $a : \mathcal{X} \to \Delta(\mathcal{D})$

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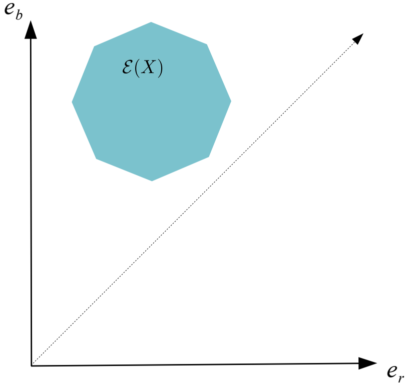
- describes optimal points across the broad range of preferences consistent with FA-dominance

feasible set of group error pairs

lemma: for any X, the feasible set $\mathcal{E}(X)$ is compact and convex

(if $\mathcal{X}$ is finite, it is a convex polygon)



important points

group-optimal points:

$$R_X := \arg\min_{e \in \mathcal{E}(X)} e_r \qquad B_X := \arg\min_{e \in \mathcal{E}(X)} e_b$$

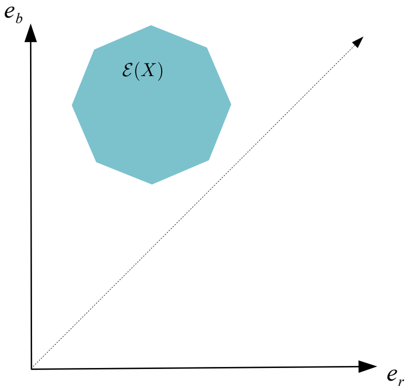
fairness-maximizing point:

$$F_X := \arg\min_{e \in \mathcal{E}(X)} |e_r - e_b|$$

(break all ties in favor of aggregate accuracy)

important points

easy to locate geometrically:



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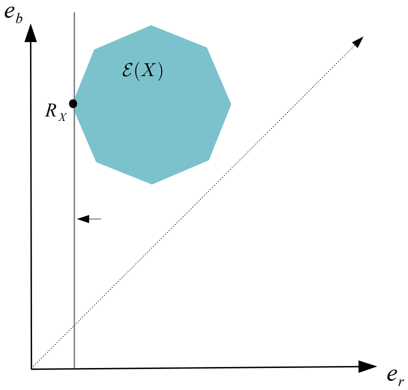

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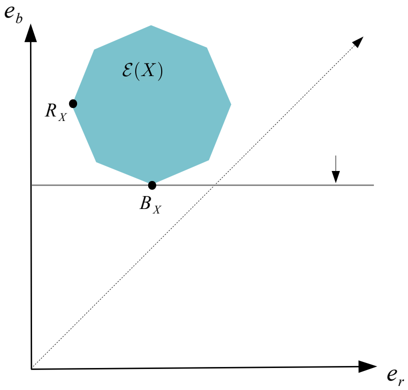

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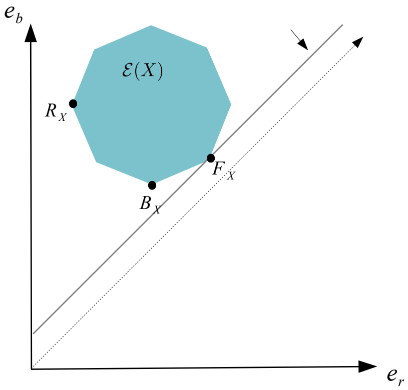

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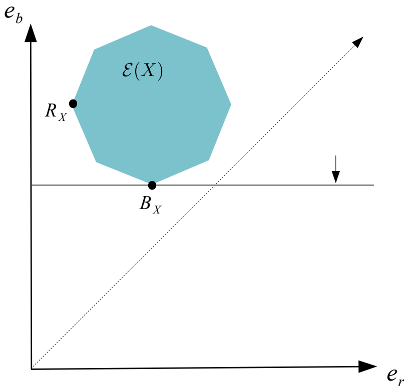


group-skewed vs group-balanced

Definition

covariate vector X is

- r-**skewed** if $e_r < e_b$ at R_X and $e_r \leq e_b$ at B_X

  "group r's error is lower both at group r's favorite point and also at group b's favorite point"

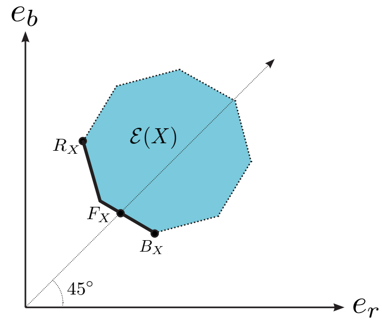
- b-**skewed** if $e_b < e_r$ at B_X and $e_b \leq e_r$ at R_X
- **group-balanced** otherwise

characterization of fairness-accuracy frontier

Theorem

$\mathcal{F}(X)$ is lower boundary of $\mathcal{E}(X)$ between

- *R_X and B_X if X is group-balanced*



characterization of fairness-accuracy frontier

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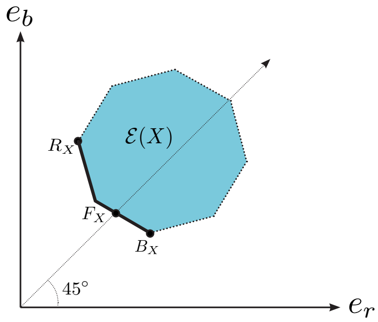

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$\mathcal{F}(X)$ is lower boundary of $\mathcal{E}(X)$ between

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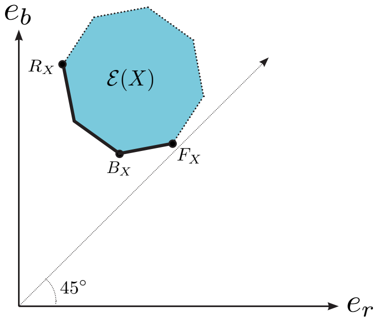
- *G_X and F_X if X is g-skewed*



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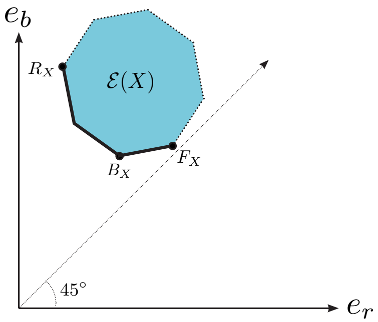

strong fairness-accuracy conflict

- compare the error pairs $e = (1/2, 1/2)$ and $e' = (1/3, 1/4)$
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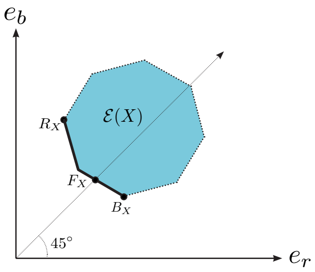
Definition

e, e' are a **strong accuracy-fairness conflict** if

- $e_r \leq e'_r$ and $e_b \leq e'_b$ (with at least one inequality strict)
- $|e_r - e_b| > |e'_r - e'_b|$

strong fairness-accuracy conflict

corollary: suppose $F_X \notin \{R_X, B_X\}$; then X is group-skewed $\iff$ some $e, e' \in \mathcal{F}(X)$ represent a strong accuracy-fairness conflict



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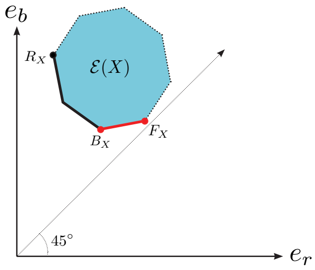

(b) X is r-skewed

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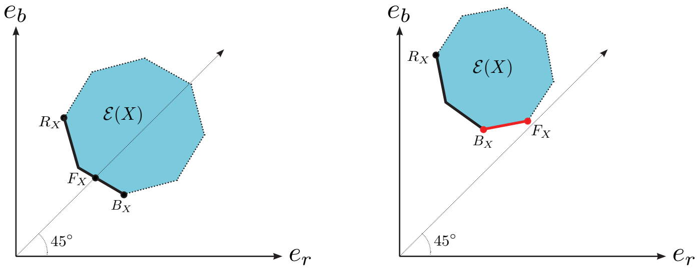

(a) X is group-balanced (b) X is r-skewed

in practice, moving up that red line could correspond to choosing not to condition on certain available information

POLICYMAKER

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ACADEMIC

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“**Yes**, they are **group-balanced**.”

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“Your proposal is not optimal for you by your own preferences, **regardless** of how you tradeoff fairness and accuracy.”

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"**No**, they are **group-skewed**."

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"If you care sufficiently about fairness relative to accuracy, then your proposal **may be optimal** for your goals."

which of group balance and group skew is more common?

difficult to anticipate without an empirical analysis

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why might X be **group-balanced**?

- X has a group-dependent meanings
  - high X implies high Y for group r, but low Y for group b
- different inputs in X are informative for either group
  - $X = (X_1, X_2)$ where X_1 is uninformative about Y for group r and X_2 is uninformative about Y for group b

which of group balance and group skew is more common?

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why might X be **group-skewed**?

- X is asymmetrically informative
  - $Y \mid X, G = r$ more dispersed than $Y \mid X, G = b$
- e.g., medical data is recorded more accurately for high-income patients than low-income patients

generalizations

beyond absolute difference

- results extend when unfairness is measured as $|\phi(e_r) - \phi(e_b)|$ where ϕ is some continuous strictly increasing function
- if ϕ is log, then this corresponds to evaluating fairness using the ratio of errors rather than their difference

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different loss functions for evaluating fairness and accuracy

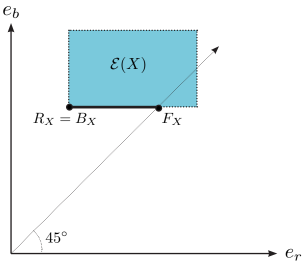
- qualitative result extends whenever the two loss functions aren't "directly opposed"
- group-balance generalizes to whether F_X belongs to usual Pareto frontier
  - X is group-balanced $\Longrightarrow$ FA frontier is usual Pareto frontier
  - X fails group-balance $\Longrightarrow$ FA frontier is union of the Pareto frontier and a positively-sloped sequence of lines

special case: X reveals G

in special cases, the frontier simplifies further.

Proposition

suppose $G \mid X$ is degenerate; then, $\mathcal{E}(X)$ is a rectangle with sides parallel to axes and $\mathcal{F}(X)$ is the line segment from $R_X = B_X$ to F_X



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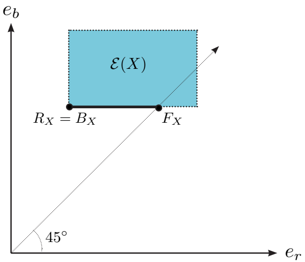

- frontier is **rawlsian**: worse-off group gets best feasible error

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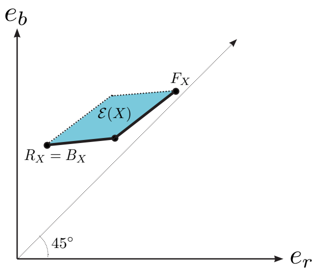

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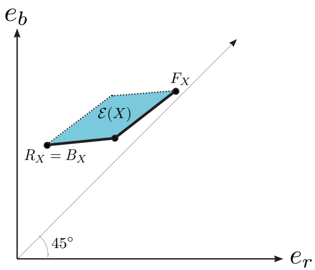

- the only difference across designers that matters is how they choose to resolve strong fairness-accuracy conflicts

part ii:

designer regulates inputs

regulating algorithmic inputs

- so far we've given the designer control of the algorithm

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  (Chan and Eyster, 2003)
- we'll model this as an information design problem

input design model

there is a primitive covariate vector X

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Definition

the **input design feasible set** given X is

$$\mathcal{E}^* (X) := \{e (a_T) \ : \ T \text{ is a garbling of } X\}$$

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Definition

the **input design fairness-accuracy frontier** given X, denoted $\mathcal{F}^*(X)$, is the set of all FA-undominated points in $\mathcal{E}^*(X)$

example garblings

real examples of such garblings are abundant

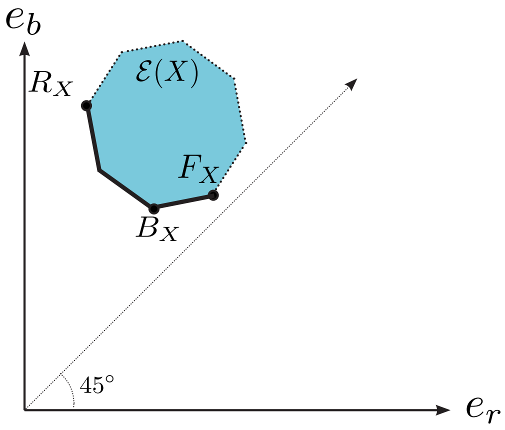
- **drop an input:**
  - "Ban the Box" campaign prohibited employers from asking about criminal history (Agan and Starr, 2018)
  - some researchers advocate for race-blind algorithms in the context of health predictions (Manski, 2022)
- **coarsen an input:**
  - essentially any test score
- **add noise:**
  - differential privacy initiatives adopted by the US Census Bureau, Apple, and Google

input design versus control of the algorithm

we'll ask two questions:

- how powerful is input design relative to control of the algorithm?
- could it be optimal for the designer to exclude an input altogether?

how powerful is input design?



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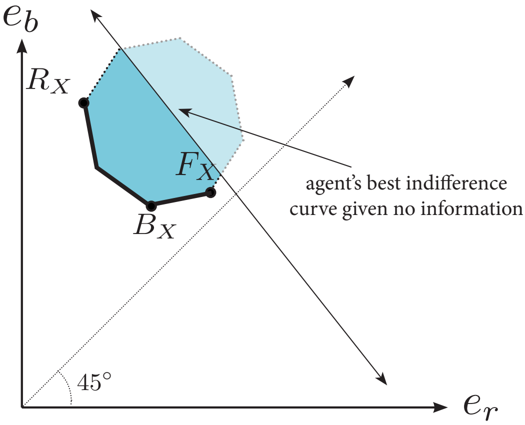

let e_0 be the minimal achievable aggregate error given no information

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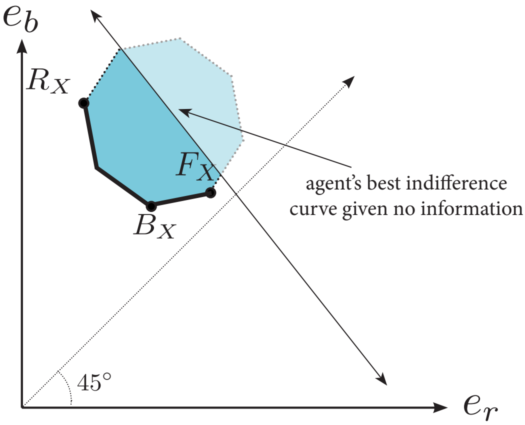

cannot force the agent to implement an error pair (e_r, e_b) satisfying $p_r e_r + p_b e_b > e_0$

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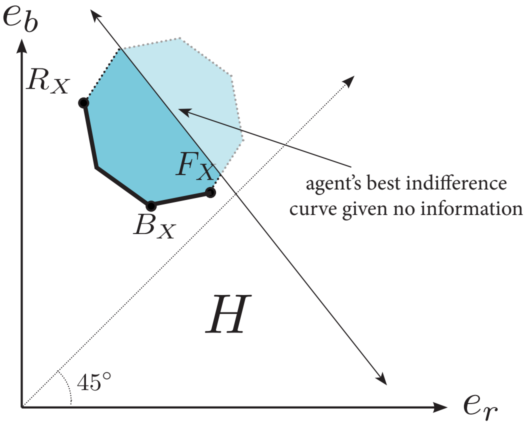
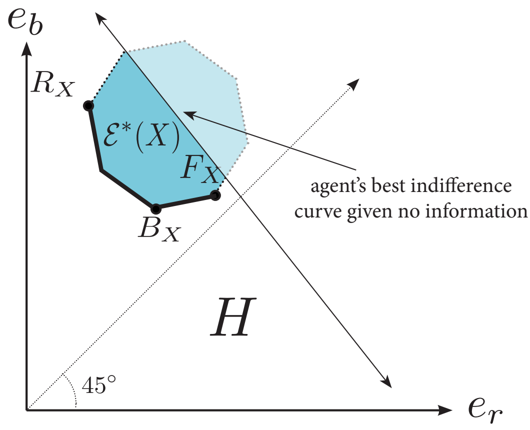


define $H = \{(e_r, e_b) : p_r e_r + p_b e_b \leq e_0\}$

how powerful is input design?



lemma: $\mathcal{E}^*(X) = \mathcal{E}(X) \cap H$

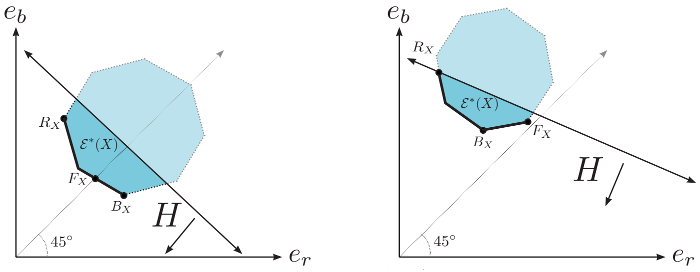
(see also Alonso and Camâra, 2016)

how powerful are informational constraints?

Proposition

(a) *If X is group-balanced, then $\mathcal{F}(X) = \mathcal{F}^*(X)$ iff $R_X, B_X \in H$*

(b) *If X is r-skewed, then $\mathcal{F}(X) = \mathcal{F}^*(X)$ iff $R_X, F_X \in H$*



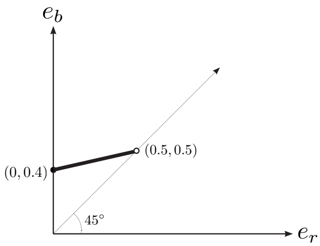
takeaway: under weak conditions, designer can implement favorite (unconstrained) outcome by designing the algorithmic inputs

add/ban covariates?

- constraints on algorithmic inputs sometimes take the form of a ban on use of a specific covariate
  - e.g., banning use of race in medical predictions, or banning test scores in college admissions
- because of misaligned preferences between the designer and agent, banning a covariate **can be optimal**

simple example where banning an input is optimal

- $Y \in \{0, 1\}$ with $P(Y = 1 \mid G = g) = 1/2$ for both groups g
- $X \in \{0, 1\}$ is a binary signal
  - $X = Y$ with probability 1 if $G = r$
  - $X = Y$ with probability 0.6 if $G = b$
- the designer is Egalitarian (payoff is $-|e_r - e_b|$)
- sending no information leads to a payoff of $|0.5 - 0.5| = 0$.
- sending **any** information about X leads to a negative payoff



uniform worsening of the frontier

at the other extreme:

Definition

excluding X' given X **uniformly worsens the frontier** if every point in $\mathcal{F}^*(X)$ is FA-dominated by a point in $\mathcal{F}^*(X, X')$

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remark: this is different from comparing the information policies of completely revealing X versus completely revealing (X, X')

two comparisons

excluding group identity:

garblings of X vs. garblings of (X, G)

excluding an arbitrary covariate when G is present:

garblings of (X, G) vs. garblings of (X, G, X')

compare X to (X, G)

Proposition

suppose $R_X, B_X \in H$. excluding G uniformly worsens the frontier if and only if X is group-balanced

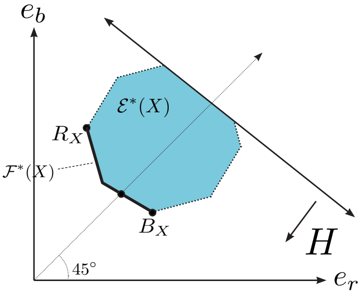

Figure: X is group-balanced

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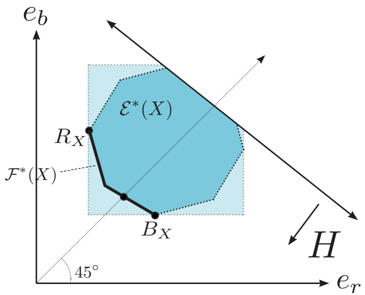

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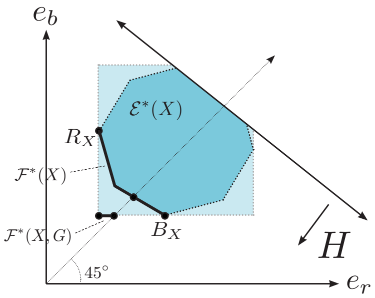

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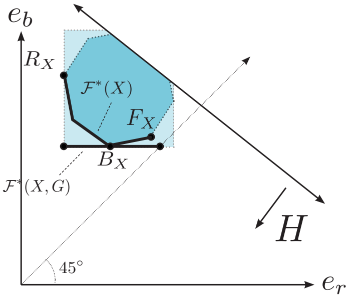

Figure: X is group-skewed

takeaways

- so long as X is group-balanced, then every designer can find a way of combining the information in G and X that is superior to sending information about X alone
- echoes previous findings that **disparate treatment** may be necessary to preclude **disparate impact**
  - Lundberg (1991), Chan and Eyster (2003), Ellison and Pathak (2022)
- here disparate treatment is via an asymmetric information policy rather than through the algorithm itself

compare (X, G) to (X, G, X')

definition: say that X' is **decision-relevant over** X **for group** g if there are realizations (x, x') and $(x, \tilde{x}')$ of (X, X') such that

$$\{1\} = \operatorname*{argmin}_{d \in \mathcal{D}} \mathbb{E}[\ell(d, Y) \mid X = x, X' = x', G = g]$$

while

$$\{0\} = \operatorname*{argmin}_{d \in \mathcal{D}} \mathbb{E}[\ell(d, Y) \mid X = x, X' = \tilde{x}', G = g]$$

i.e., the additional information in X' changes the optimal assignment for some individual in group g relative to X alone

compare (X, G) to (X, G, X')

Proposition

(a) *suppose* (X, G) *is* g*-skewed. then:*

excluding X' *given* (X, G) *uniformly worsens the frontier* $\iff$ X' *is decision-relevant over* X *for group* $g' \neq g$.

(b) *suppose* (X, G) *is group-balanced. then:*

excluding X' *given* (X, G) *uniformly worsens the frontier* $\iff$ X' *is decision-relevant over* X *for both groups.*

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consider the question of whether to ban test scores in admissions decisions

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test scores are likely to be decision-relevant for both groups, so our result suggests that:

- if G is available, then excluding test scores is welfare-reducing for all designers with the ability to garble available covariates
- if G is not available, then it may be better for a sufficiently fairness-minded designer to completely exclude test scores

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if affirmative action is banned nationwide, then universities with certain preferences may have reason to ban use of test scores

takeaways

- our framework abstracts away from many important features of the college admissions process
- but the link between the availability of G and the value of additional information holds more generally
- access to group identity has a positive spillover effect for the value of other covariates
- there is always some group-dependent garbling of the other information that aligns the agent and designer's incentives.

related literature

equity-efficiency tradeoffs: taxation (Saez and Stantcheva, 2016; Dworczak et al., 2021), policing (Persico, 2002; Jung et al., 2020), admissions (Chan and Eyster, 2003; Ellison and Pathak, 2021)

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$\longrightarrow$ we focus on a special equity-efficiency tradeoff motivated by...

algorithmic bias:

- empirical documentation of the disparate impact of algorithms (Obermeyer et al., 2019; Arnold et al., 2021; Fuster et al., 2021)
- much of the theoretical literature posits a particular objective criterion (Roth and Kearns, 2019), engagement with fairness accuracy tradeoffs in special cases (Menon and Williamson, 2018)

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⟶ we provide general results for how this tradeoff is moderated by the inputs to the algorithm, and also...

info design: model the design of algorithm inputs as information design (Kamenica and Gentzkow, 2011; Bergemann and Morris, 2019)

conclusion

- framework for evaluating the accuracy/fairness tradeoffs of algorithms
- characterized the fairness-accuracy frontier over different designer preferences for how to trade off these criteria
- explained how certain statistical properties of the algorithm's inputs impact the shape of this frontier
- in some cases (e.g., when the inputs are group-balanced), there are conclusions/policy recommmendations that hold **for all** designer preferences in a broad class

thank you

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