Re-formalization of Individual Fairness

Toshihiro Kamishima
National Institute of Advanced Industrial Science and Technology (AIST), Japan

The 6th FAccTRec Workshop: Responsible Recommendation
in conjunction with RecSys2023 @ Singapore, Sep. 18, 2023

START

Outline

Re-formalization of Individual Fairness

Individual Fairness: the principle of “Treating Like Cases Alike”

Mapping similar individuals in an original space into similar positions in a fair space

↓

Conditioning fairness criterion by individuals

Outline

- Brief summary of formal fairness
- Our re-formalized individual fairness is compatible with that of Dwork et al.
- Extend equalized odds and sufficiency by applying our new re-formalized individual fairness

Formal Fairness

Formal Fairness

In fairness-aware machine learning, we maintain the influence:

sensitive information —Influence→ **target / objective**

- socially sensitive information
- information restricted by law
- information to be ignored

- university admission
- credit scoring
- crick-through rate

Formal Fairness

The desired condition defined by a formal relation between sensitive feature, target variable, and other variables in a model

- How to related these variables
- Which set of variables to be considered
- What states of sensitives or targets should be maintained

Notations of Variables

$\boxed{Y}$ **target variable / object variable**

An objective of decision making, or what to predict

Ex: loan approval, university admission, what to recommend

$\boxed{Y}$ = observed / true, $\boxed{\hat{Y}}$ = predicted

$\boxed{S}$ **sensitive feature**

To ignore the influence to the sensitive feature from a target

Ex: socially sensitive information (gender, race), items' brand

- Specified by a user or an analyst depending on his/her purpose
- It may depend on a target or other features

$\boxed{\mathbf{X}}$ **non-sensitive feature vector**

All features other than a sensitive feature

Accounts of Discrimination

[Lippert-Rasmussen 06]

Why an instance of discrimination is bad?

- **harm-based account:** Discrimination makes the discriminatees worse off
- **disrespect-based account:** Discrimination involves disrespect of the discriminatees and it is morally objectionable
  - An act or practice is morally disrespectful of X

    ⇔ It presupposes that X has a lower moral status than X in fact has

⇓

Techniques of Fairness-Aware Machine Learning based on the harm-based account

The aim of FAML techniques remedy the harm of discriminatees

Judgements
Related to Formal Fairness

[Ishiguro+ 14, Bareinboim+ 21, Pearl+ 18]

Hazelwood School District v. United States, 433 U.S. 299 (1977)

- Where **gross statistical disparities** can be shown, they alone may, in a proper case, constitute *prima facie* proof

Gross Statistical Disparity: Discrimination in employment is determined whether the ratio of protected and non-protected groups of employees is diverged from the corresponding ratio in general population

Jack Gross, Petitioner, v. FBL Financial Services, US Supreme Court (2008)

- To establish a disparate-treatment claim under this plain language, a plaintiff must prove that age was **the but-for cause** of the employer's adverse decision
- A plaintiff must prove by a preponderance of the evidence (which may be direct or circumstantial), that age was **the but-for cause** of the challenged employer decision

Baselines in Harm-based Account

[Lippert-Rasmussen 06]

A harm-based account requests a baseline for determining whether the discriminatees have been made worse off

↓

- **Ideal outcome:** the discriminatees are in just, or the morally best
  ➡ **association-based fairness:** letting predictors get ideal outcomes
- **Counterfactual:** the discriminatees had not been subjected to the discrimination
  ➡ **counterfactual fairness:** comparing with the counterfactuals that a status of a sensitive feature was different

Individual Fairness

Individual Fairness

Individual Fairness: the principle of "Treating Like Cases Alike"

We re-formalize individual fairness
as conditioning a fairness criterion by $\mathbf{X}$

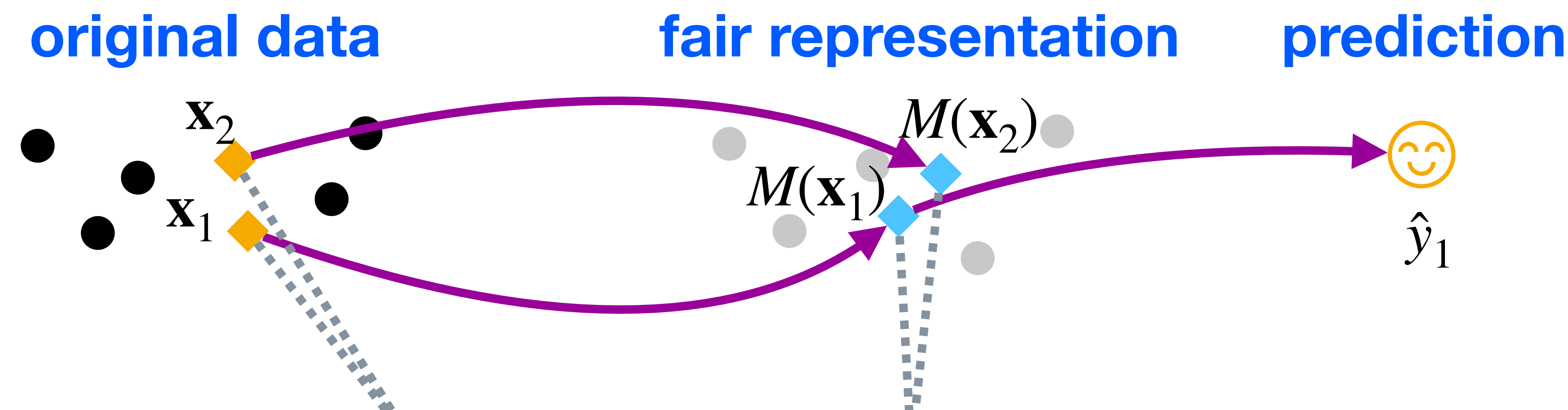
$$\hat{Y} \perp\!\!\!\perp S \xrightarrow{\text{conditioned by } \mathbf{X}} \hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$$

statistical parity → **individual fairness** (individual statistical parity)

1. This formulation is compatible with the one proposed by Dwork et al.
2. This newly formalized criterion can be used for in- or post- process methods as well as pre-process methods of fairness
3. This formalization can be applied to fairness criteria, equalized odds or sufficiency

Dwork's Individual Fairness

[Dwork+ 12]



distance between original data

$$d\left(\mathbf{x}_1, \mathbf{x}_2\right) \geq d^{\circ}\left(M(\mathbf{x}_1), M(\mathbf{x}_2)\right)$$

distance between fair representations

Lipschitz condition

To formalize the principle "Treating Like Cases Alike,"

1. Similar original data are mapped to similar fair representations
2. Predictors make similar predictions for similar representations

No sensitive information in fair representations

⬇

The predictions satisfy a Fairness through Unawareness condition

Fairness through Unawareness

Fairness through Unawareness: Prohibiting to access individuals' sensitive information during the process of learning and inference

This is a kind of procedural fairness, in which a decision is fair, if it is made by following pre-specified procedure

$\Pr[\, \hat{Y} \mid \mathbf{X}, S \,]$

A **unfair model** is trained from a dataset including sensitive and non-sensitive information

$\Pr[\, \hat{Y} \mid \mathbf{X} \,]$

A **fair model** is trained from a dataset eliminating sensitive information

A unfair model, $\Pr[\, \hat{Y} \mid \mathbf{X}, S]$, is replaced with a fair model, $\Pr[\, \hat{Y} \mid \mathbf{X} \,]$

$$\Pr[\, \hat{Y}, \mathbf{X}, S \,] = \Pr[\, \hat{Y} \mid \mathbf{X}, S] \Pr[\, S \mid \mathbf{X} \,] \mathrm{P}[\, \mathbf{X} \,] \Rightarrow \Pr[\, \hat{Y} \mid \mathbf{X} \,] \Pr[\, S \mid \mathbf{X} \,] \Pr[\, \mathbf{X} \,]$$

Fairness through Unawareness: $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$

Re-formalization of Individual Fairness

Distributions of a target variable are equal for all possible sensitive groups given a specific non-sensitive values

$$\Pr[\,\hat{Y} \mid S, \mathbf{X}{=}\mathbf{x}\,] = \Pr[\hat{Y} \mid \mathbf{X}{=}\mathbf{x}],\ \forall \mathbf{x} \in \mathrm{Dom}(X) \Rightarrow \hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$$

II

We re-formalize Individual fairness

as conditioning fairness criteria by $\mathbf{X}$

⬇

This formula, $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$, is coincident with

Fairness through Unawareness

Dwork's Individual Fairness ⟷ Fairness through Unawareness ⟷ Our re-formalized individual fairness

Our re-formalized individual fairness is compatible with Dwork's

Extended Individual Fairness

Equalized Odds and Sufficiency

Fairness in errors of predictions to mitigate an inductive bias

Equalized Odds	**Sufficiency**
$\hat{Y} \perp\!\!\!\perp S \mid Y$	$Y \perp\!\!\!\perp S \mid \hat{Y}$
Matching false positive ratio (FPR) and true positive ratio (TPR), if Y is binary	Matching positive and negative predictive values (PPV & NPV), if Y is binary

- The ProPublica pointed out the recidivism score, the COMPAS, does not satisfy equalized odds [Angwin+ 2016]
- The US Court refuted that the score is designed to satisfy a sufficiency condition [Flores+ 2016]

Extended Individual Fairness

Conditioning by $\mathbf{X}$ can convert Equalized Odds and Sufficiency to individual versions of them

Statistical Parity
$Y \perp\!\!\!\perp S \mid \hat{Y}$

Equalized Odds
$\hat{Y} \perp\!\!\!\perp S \mid Y$

Sufficiency
$Y \perp\!\!\!\perp S \mid \hat{Y}$

conditioned by $\mathbf{X}$

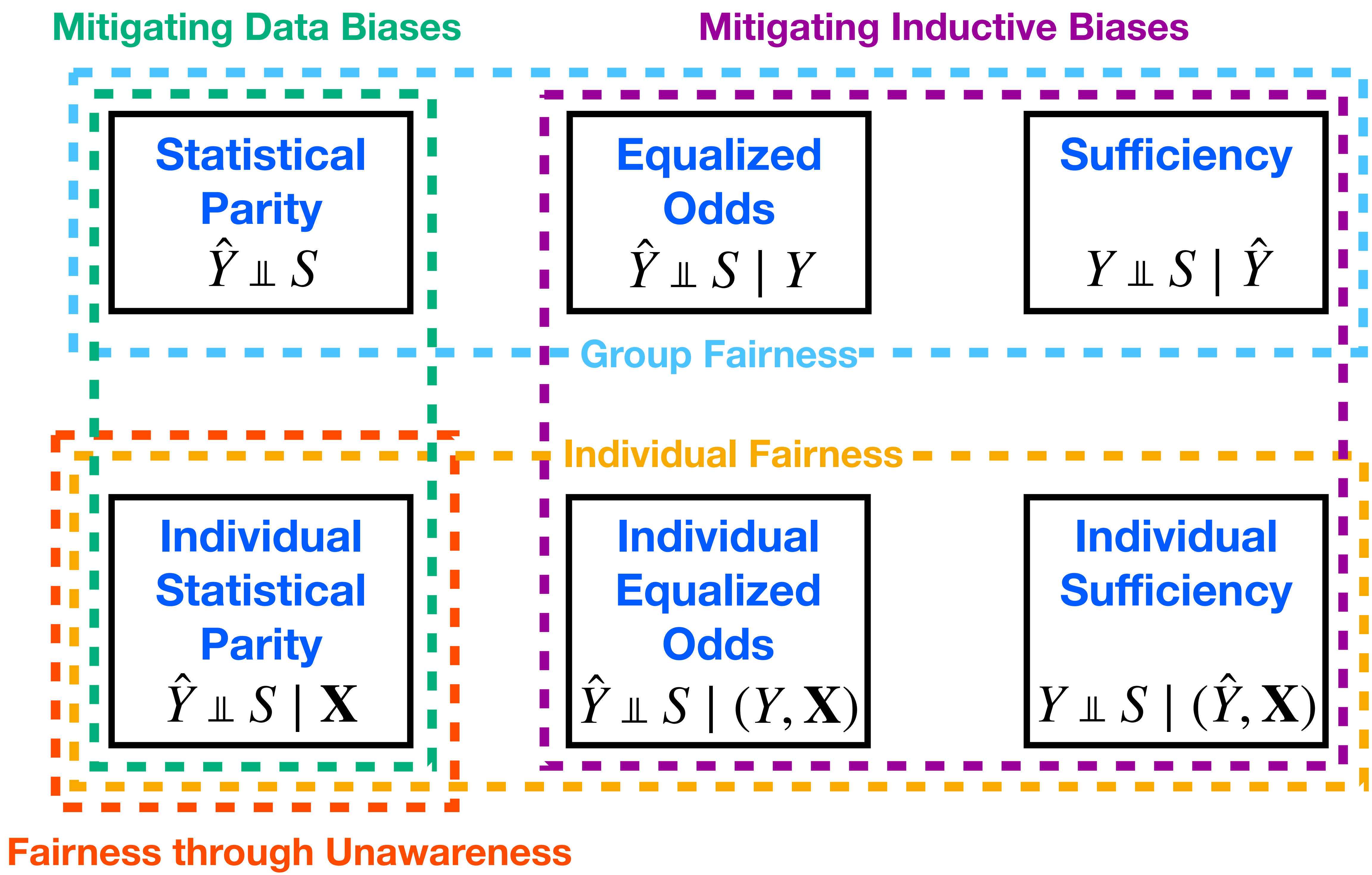
Individual Statistical Parity
$Y \perp\!\!\!\perp S \mid \mathbf{X}$

Individual Equalized Odds
$\hat{Y} \perp\!\!\!\perp S \mid (Y, \mathbf{X})$

Individual Sufficiency
$Y \perp\!\!\!\perp S \mid (\hat{Y}, \mathbf{X})$

The phrase, “treating alike,“ means predicting in similar error rate

Summary of Formal Association-based Fairness



Conclusion

Conclusion

- We re-formalize the notion of individual fairness by conditioning by $\mathbf{X}$
  - Compatible with that of Dwork et al.
  - Equalized odds or sufficiency can be extensible to their corresponding individual versions
  - Our individual fairness can be used in in in-process or post-process approaches as well as pre-process approaches

Future work

- One of the limitation is an interpretation of the term, *like*
  - if non-sensitive features take exactly the same values, two assumptive individuals are considered as *like*
  - To relax the limitation, the introduction of similarities between individuals would be required

My FAML tutorial slide: https://www.kamishima.net/archive/faml.pdf