Fairness

Machine Learning for Behavioral Data

May 16, 2022

Today's Topic

Week	Lecture/Lab
9	Spring Break
10	Guest Lecture: Neuroscience
11	Unsupervised Learning
12	Unsupervised Learning
13	**Ethical Machine Learning**
14	Ethical Machine Learning
15	Project Presentations

- **Fairness**
- **Explainability**

Agenda

1) **Introduction to fairness – Cécile Hardebolle**
2) Fairness in machine learning:
   - Sources of unfairness
   - Fairness metrics – evaluating model predictions
3) Example on real world data (if time permits)
4) Discussion of indicative feedback

Getting ready for today's lecture…

- **If not done yet**: clone the repository containing the Jupyter notebook and data for today's lecture into your Noto workspace
- SpeakUp room for today's lecture:

https://go.epfl.ch/mlbd-lecture

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2) **Fairness in machine learning**:
   - **Sources of unfairness**
   - **Fairness metrics – evaluating model predictions**
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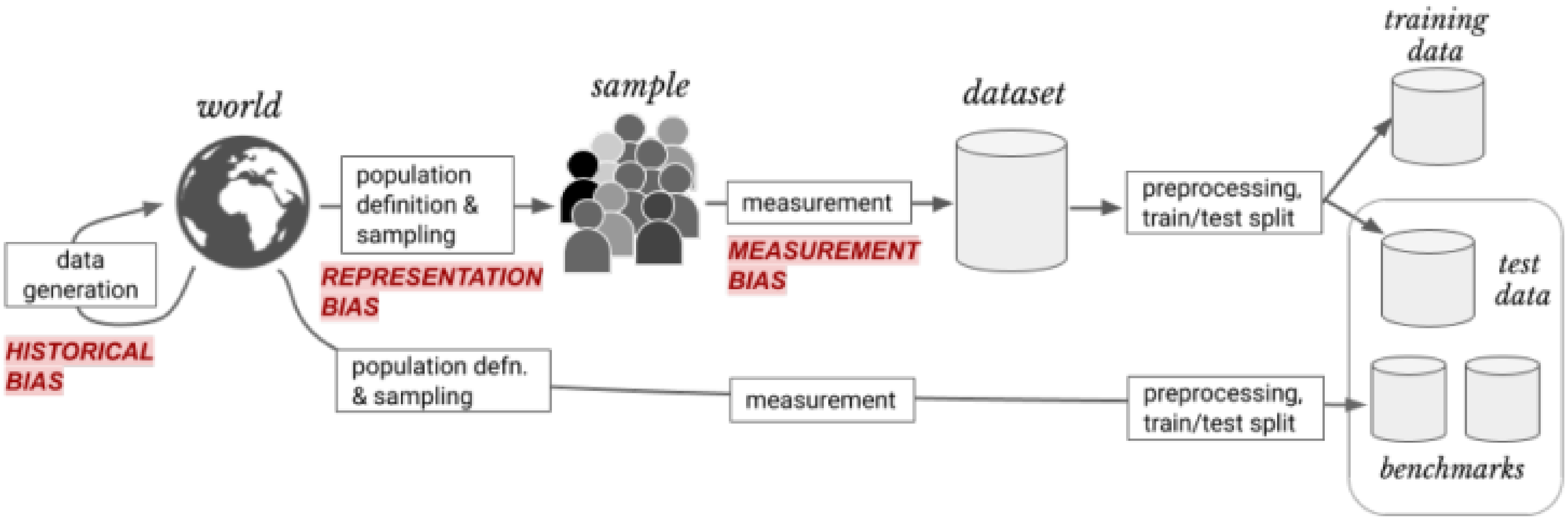
Learning Objectives

You should be able to:

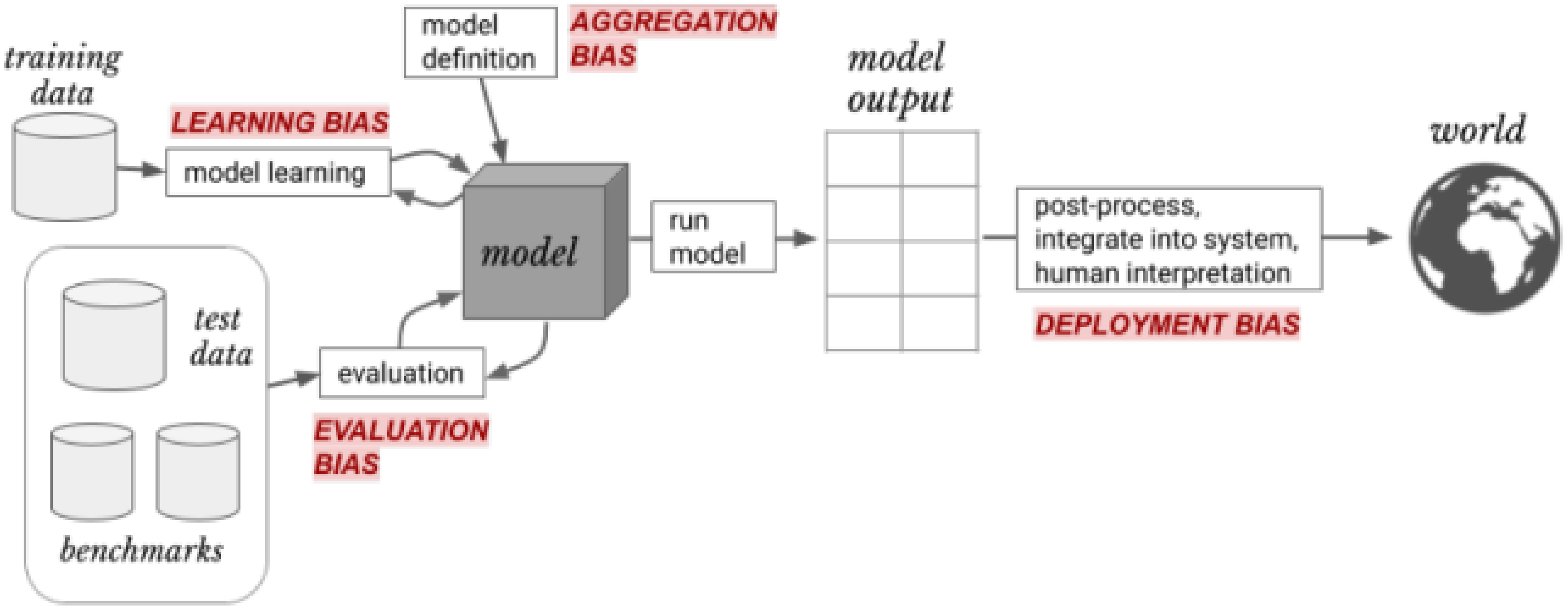
- Name and explain the sources of unfairness in a machine learning pipeline
- Explain and implement the most popular metrics for fairness
- Perform a fairness evaluation of a machine learning model using an appropriate fairness metric

Sources of Unfairness – Data Generation



[A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle]

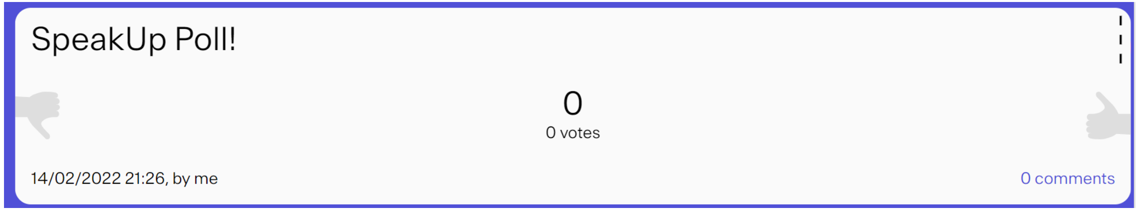
Sources of Unfairness – Model Building



[A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle]()

Fairness Through Blindness

- Idea: we ignore all protected attributes in our model (e.g., we do not use protected attributes such as gender, race, etc. as features)



Will this idea lead to a fair model?

a) Yes b) No

Fairness Through Awareness

- There is not one mathematically agreed definition of fairness
- Popular fairness metrics are
  - model-agnostic
  - defined for classification problems

Problem Formalization

Notation:

- X is the input to the model
- $\hat{Y}$ is the prediction of the model
- T is the true label
- A is the protected attribute

Confusion Matrix

		True Label	
		$T = 1$	$T = 0$
Predicted Label	$Y = 1$	True Positive (TP)	True Positive (TP)
	$Y = 0$	False Negative (FN)	True Negative (NP)

Demographic Parity

- Requires equal proportion of positive predictions in each group

$$\boxed{\mathrm{p}(\hat{Y} = 1 | A = 1) = \mathrm{p}(\hat{Y} = 1 | A = 0)}$$

Demographic Parity - Example

- Admittance to *Fruits* University
- Students from two schools apply: *Apple* and *Peach*
- School *Peach* has a better program, resulting in more qualified students

Peach	**Qualified**	**Unqualified**
Admitted	45	2
Rejected	45	8

Apple	**Qualified**	**Unqualified**
Admitted	5	18
Rejected	5	72

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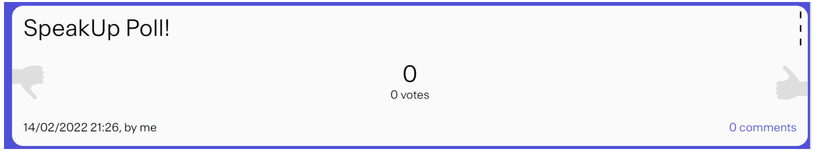

Is demographic parity fulfilled?

a) Yes b) No

Equalized Odds

- For any label and attribute, a classifier predicts the label equally well for all values of that attribute

$$\boxed{\begin{aligned} \mathrm{p}\big(\hat{Y} = 1 \big| A = 1, T = 1\big) = \mathrm{p}\big(\hat{Y} = 1 \big| A = 0, T = 1\big) \\ \mathrm{p}\big(\hat{Y} = 1 \big| A = 1, T = 0\big) = \mathrm{p}\big(\hat{Y} = 1 \big| A = 0, T = 0\big) \end{aligned}}$$

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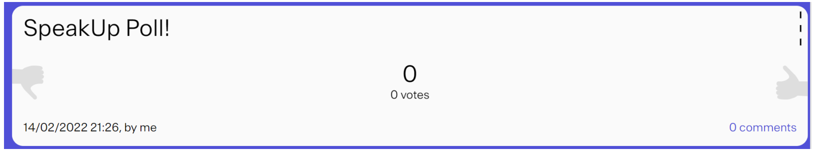

Are equalized odds fulfilled?

a) Yes b) No

Predictive Value Parity

- Probability of a sample with positive (negative) predictive value to truly belong to the positive (negative) class should be the same across attributes

$$\boxed{\begin{gathered} \mathrm{p}(T = 1 | A = 1, \hat{Y} = 1) = \mathrm{p}(T = 1 | A = 0, \hat{Y} = 1) \\ \mathrm{p}(T = 0 | A = 1, \hat{Y} = 0) = \mathrm{p}(T = 0 | A = 0, \hat{Y} = 0) \end{gathered}}$$

Predictive Value Parity - Example

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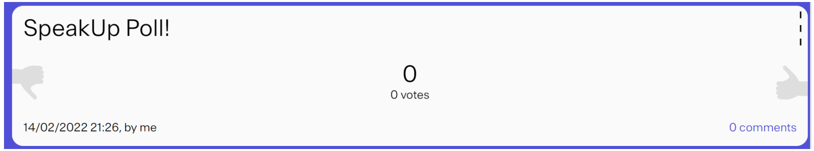

Is predictive value parity fulfilled?

a) Yes b) No

Impossibility Result

- Any two of the three criteria are mutually exclusive
  1. If A and T are not independent, then *demographic parity* and *predictive value* parity cannot simultaneously hold
  2. If A and $\hat{Y}$ are not independent of T, then *demographic parity* and *equalized odds* cannot simultaneously hold
  3. If A and T are not independent, then *equalized odds* and *predictive value parity* cannot simultaneously hold

Impossibility Result

Note that these requirements hold for *most* classifiers in real contexts:

- Base-rates of outcomes rarely are equal across groups
- A and T are usually associated when issues of fairness are relevant for the group in question
- $\hat{Y}$ and T are usually associated, if your classifier is any good

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Flipped Classroom – Your Turn

- Participants: 214 EPFL students of a course taught in *flipped classroom* mode with a duration of 10 weeks
- We have trained a classifier to predict whether a student will pass or fail the course based on their clickstream data
- Your task:
  1. Choose one of the fairness metrics introduced in class and compute the metric for the flipped classroom classifier
  2. Tell us: is the classifier fair according to the selected metric? Why did you choose this metric?

Summary

- There are multiple sources of unfairness in a machine learning pipeline
- There is no consensus on the mathematical definition of fairness metrics
- Different metrics assess different aspects of the classifier
- Often, fairness metrics are mutually exclusive
- Fairness evaluation of a classifier includes exploration of relevant characteristics of our data

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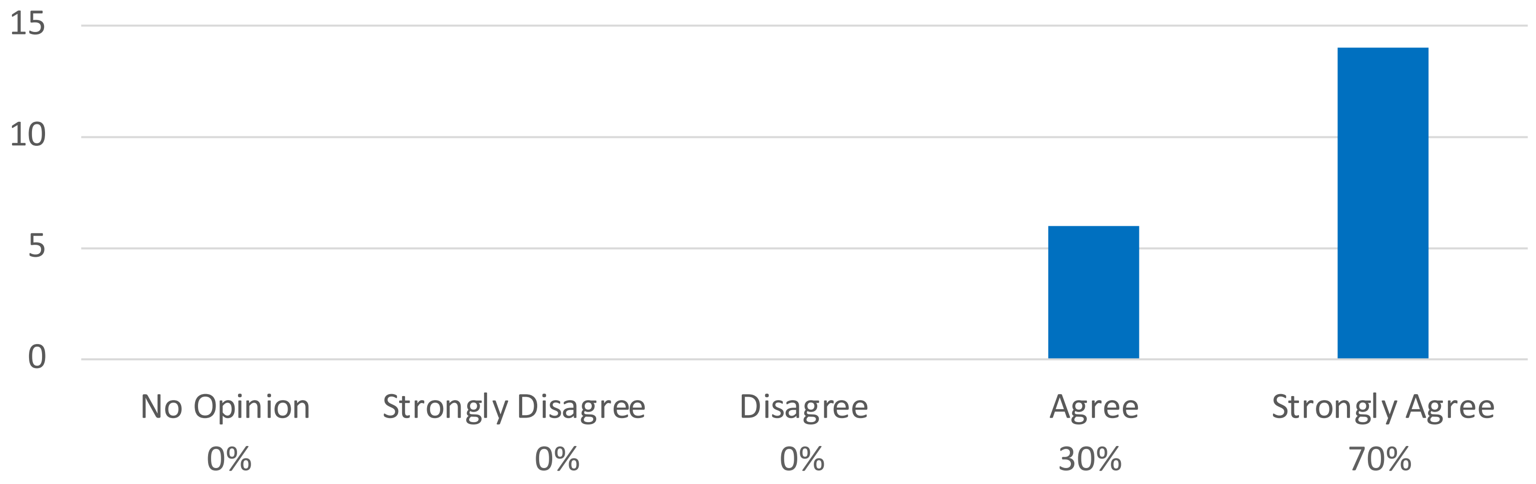
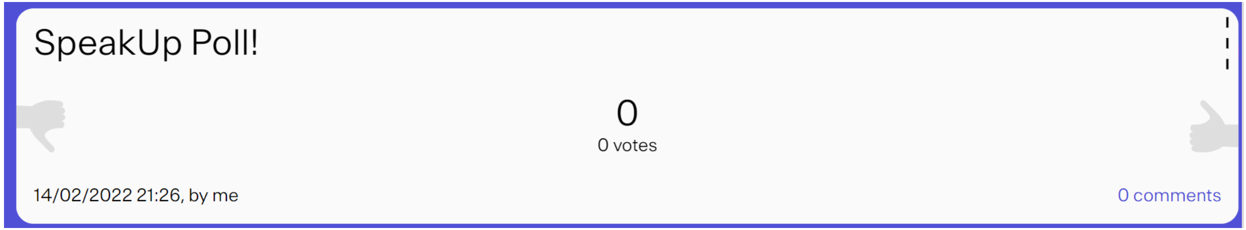
Indicative Feedback

- Overall, I think this course is good (based on 20 answers)



Indicative Feedback

- Learning Objectives
- More practice opportunities



a) Yes
b) No

Would you regularly come to lab sessions to solve additional practice talks?