Fairness

Machine Learning for Behavioral Data

May 6, 2025

Today's Topic

Week	Lecture/Lab
9	Unsupervised Learning
10	Spring Break
11	Unsupervised Learning
12	**Fairness**
13	Explainability
14	Reserve
15	Poster Presentations

- **What is fairness?**
- **Fairness metrics**
- **Interpreting neural networks**

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/speakup-mlbd2025

Agenda

1) **Introduction to ethics in ML**
2) Fairness in machine learning:
   - Sources of unfairness
   - Fairness metrics – evaluating model predictions
3) Example on real world data

Fairness in ML game

EPFL has developed a game-based approach to introduce students to the topic of fairness in ML

https://companion.epfl.ch/game/7d7zs7/

Agenda

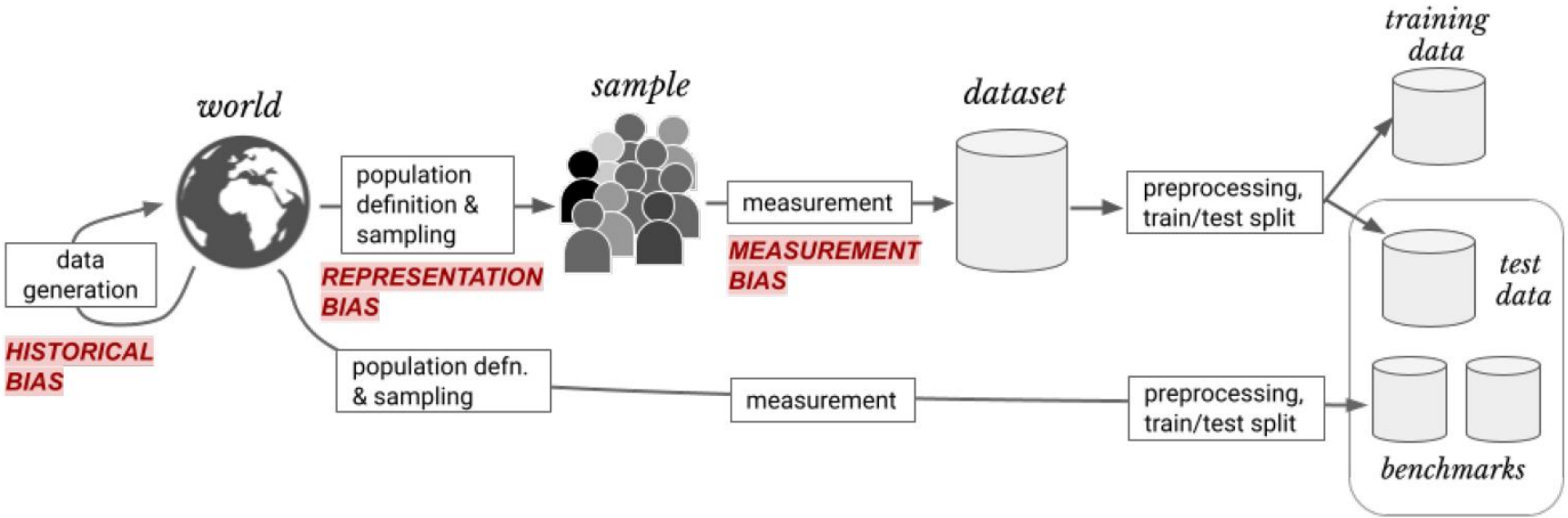
1) Introduction to ethics in machine learning
2) **Fairness in machine learning**:
   - **Sources of unfairness**
   - **Fairness metrics – evaluating model predictions**
3) Example on real world data

Learning Objectives

You should be able to:

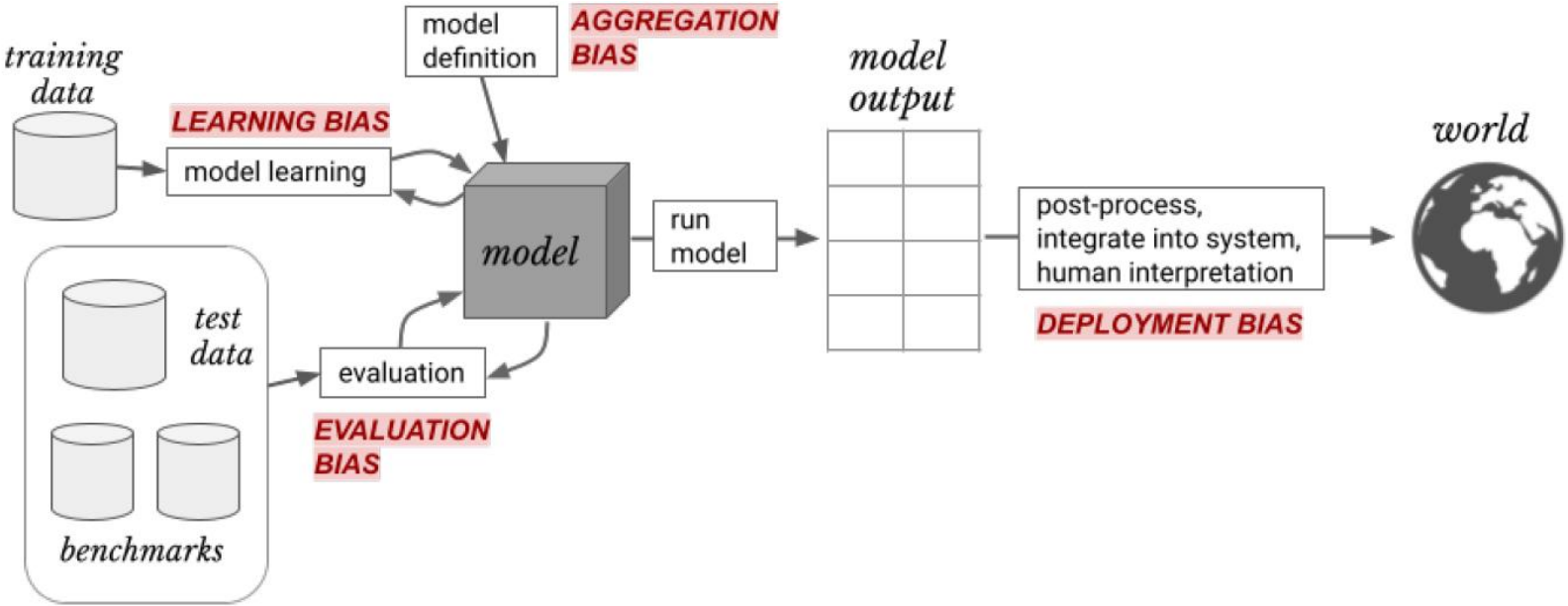
- Name and explain the sources of unfairness in a machine learning pipeline
- Explain and implement the most popular metrics for fairness
- Perform a fairness evaluation of a machine learning model using an appropriate fairness metric

Sources of Unfairness – Data Generation



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

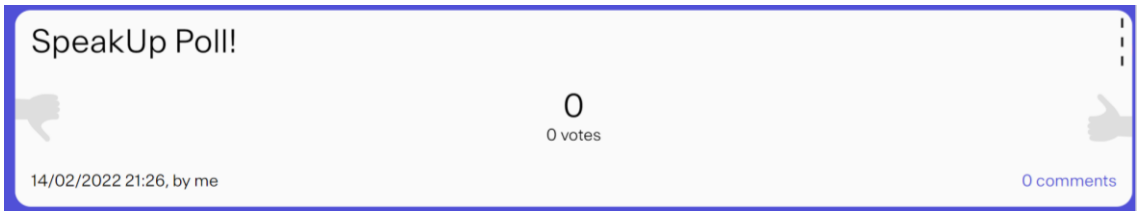
Sources of Unfairness – Model Building



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)	False Positive (FP)
	$Y = 0$	False Negative (FN)	True Negative (TN)

Demographic Parity

- Requires equal proportion of positive predictions in each group

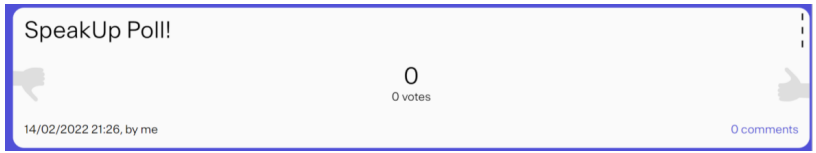
$$\mathrm{p}(\hat{Y} = 1 | A = 1) = \mathrm{p}(\hat{Y} = 1 | A = 0)$$

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



Is demographic parity fulfilled?

a) Yes b) No

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Equalized Odds

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

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

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

Equalized Odds - Example

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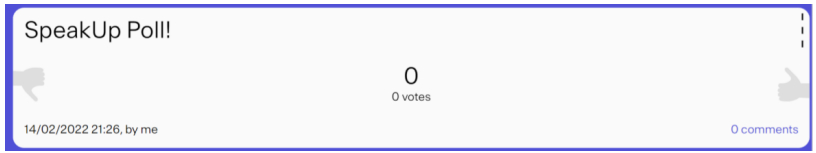

Are equalized odds fulfilled?

a) Yes b) No

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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

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

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

Predictive Value Parity - Example

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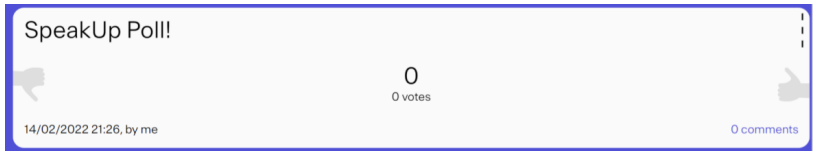

Is predictive value parity fulfilled?

a) Yes b) No

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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