Using the Interactive Notebook: Fairness in Machine Learning

1 Getting Started

This notebook is designed as an interactive teaching tool to help computer science students explore ethical challenges in machine learning. It combines theoretical background with code, data exploration, and interactive tasks.

To use the notebook:

1. Required Files:
    - Clone or download the GitHub repository: https://github.com/LukasWel/ethical-challenges-in-ml
    - Inside the repository, you will find the following structure:
        - 'Fairness_Notebook/Notebooks/'
          Contains the seven Jupyter notebooks (Part 1 – Part 7) and all required images.
        - 'Fairness_Notebook/Data/'
          Contains all datasets needed for the practical studies.
        - 'Fairness_Notebook/User_Guide/'
          Contains this user guide.
        - 'Fairness_Notebook/Thesis/'
          Contains the corresponding master's thesis to this this notebook.
2. Open the Notebooks:
    - Use Jupyter Lab or Jupyter Notebook (e.g. via Anaconda)
    - Start with "Part1_Motivation" and proceed in numerical order
    - Each notebook page builds on concepts from the previous one
3. Run Cells Step-by-Step:
    - Execute each cell in order, from top to bottom
    - Markdown cells should already be rendered, but code blocks must be executed one by one
    - The blocks in each notebook depend on previous ones, so execution order matters
4. Additional Notes:
    - Some visualizations may take a few seconds to load
    - Make sure to maintain the original folder structure after downloading or cloning.
    - For the practical studies, make sure the CSV files and image paths in the notebooks are correctly set to your folder structure.
    - The UTKFace dataset was split into two parts due to file size limitations on GitHub. Please combine the contents of both folders (UTKFace 1 & UTK Face 2) into a single folder named UTKFace. This new folder should be placed in the same location where the two parts were located: 'Fairness_Notebook/Data/GenderClassification_Study/'

2 Solutions to Quizzes

Page 1

1. False
2. It showed different error rates between racial groups
3. Carefully auditing how features correlate with sensitive attributes

Page 2

1. False
2. Statistical Parity
3. If predictions are imperfect and sensitive attributes influence the outcome, different fairness goals can be in conflict

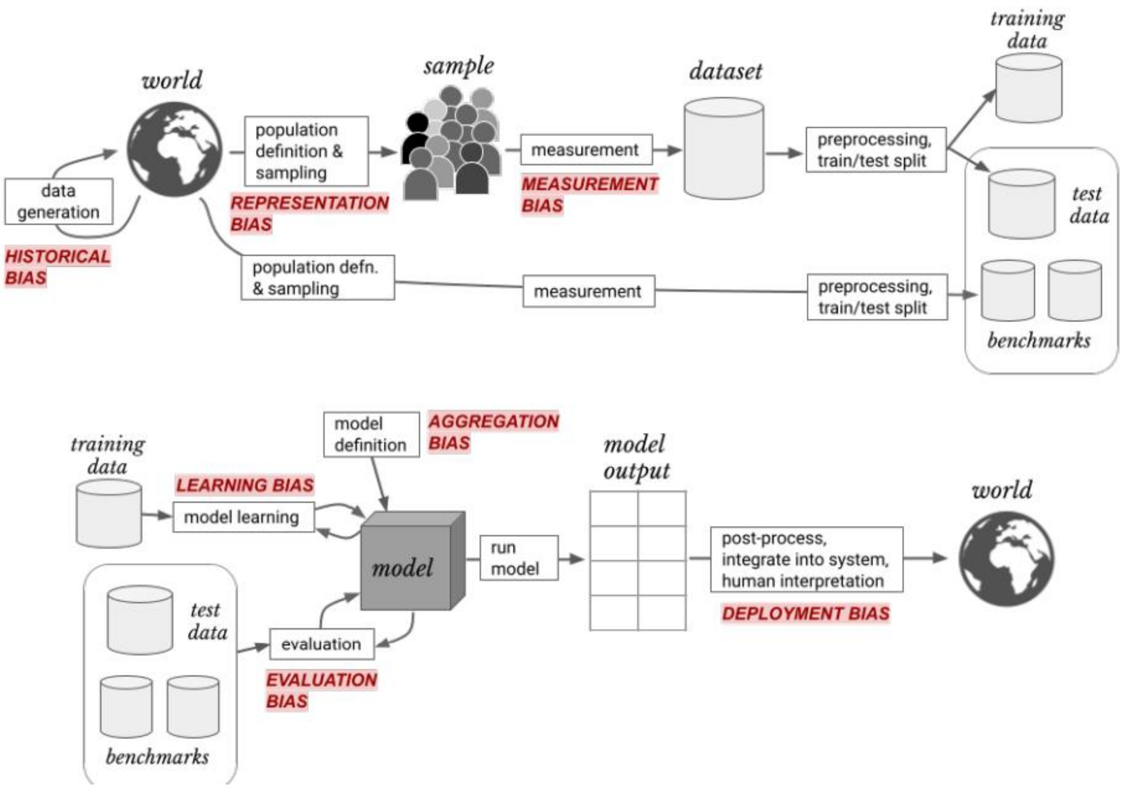
Page 3

1. True
2. Because it equalizes access to support by reducing false negatives
3. Different fairness metrics reflect different values and may conflict with one another

Page 4

1. False
2. A recidivism model uses "arrest record" as a label for "criminal behavior"
3. It can occur even in small datasets due to overfitting

Solution to the Exercise: Localize Forms of Bias in ML-Lifecycle:



Note. From Suresh & Guttag, 2021.

Page 5

1. False
2. It asks whether people are fairly represented, not fairly treated
3. Women were more often misclassified than men, especially Women of Color

Page 6

1. True
2. Misallocation of resources and distorted crime patterns
3. Down-weighting discovered incidents during training

Page 7

1. False
2. Ignoring fairness concerns at the decision boundary
3. An outcome where a better alternative exists for all groups

3 References

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