Responsible Machine Learning*

Lecture 3: Discrimination Testing and Remediation

Patrick Hall

The George Washington University

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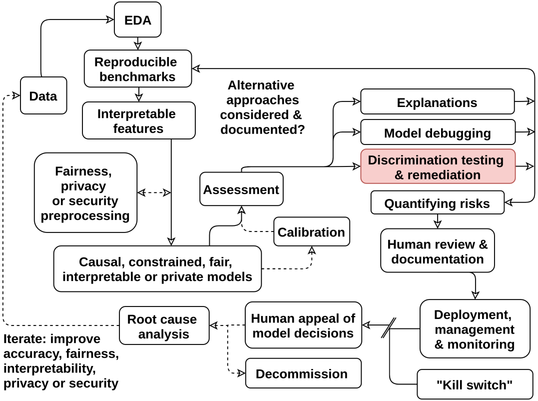
A Responsible Machine Learning Workflow[†]



[†] *A Responsible Machine Learning Workflow*

Why Care About Discrimination in Machine Learning?

- **Responsible practice of machine learning (ML)**: ML can affect millions of people! [7]
- **Discrimination is often illegal (in the U.S.)**: Non-compliance fines and litigation costs.
- **Reputational risk**: Upon encountering a perceived unethical ML system, 34% of consumers are likely to, "stop interacting with the company."‡

‡See: Why addressing ethical questions in AI will benefit organizations.

What Is Bias?

- Almost *all* data, statistical models, and ML models encode different types of *bias*, i.e., **systematic misrepresentations of reality**.
- Sometimes, bias is *helpful*.
    - Shrunken and robust β_j coefficients in penalized linear models.
- Other types of bias can be unwanted, unhelpful, discriminatory, or illegal.
- Many instances of discrimination in ML arise from sociologically biased experimental design, data collection, labeling, or storage processes.

What is Discrimination in ML?

In many applications[§], model predictions should ***ideally*** be independent of demographic group membership.

In these applications, a model exhibits discrimination if:

1. Demographic group membership is not independent of the likelihood of receiving a favorable or accurate model prediction.
2. Membership in a *subset* of a demographic group is not independent of the likelihood of receiving a favorable or accurate model prediction (i.e., *local or individual discrimination*).[3]

[§] e.g., Under the Equal Credit Opportunity Act (ECOA), as implemented by Regulation B, and the Fair Credit Reporting Act (FCRA)

What Kinds of Discrimination Occur in ML?

Several forms of discrimination may manifest in ML, including:

- Group disparities:
  - Overt discrimination against groups, i.e., *disparate treatment* (DT).
  - Unintentional discrimination against groups, i.e., *disparate impact* (DI).
  - Differing quality across demographic groups, i.e., *differential validity*.
- Local or individual discrimination.

How Does Discrimination Arise in ML?

Discrimination originates from poor experimental design:

- Asking biased questions, e.g., "can a face predict trustworthiness?", "can demographics predict creditworthiness?"
- Modeling biased phenomenon, e.g., healthcare spending vs. healthcare need.

Discrimination originates from training data:

- Incomplete or inaccurate data, e.g., under-representation of minorities. See Gender Shades [2].
- Accurate but differing patterns of causation, correlation, or dependency between demographic groups and past outcomes, e.g., traditional FICO credit scores.¶
- Explicit encoding of historical social biases into training data, e.g., criminal records.

¶See: https://shiftprocessing.com/credit-score/#race

How Does Discrimination Arise in ML?

ML models can perpetuate or exacerbate discrimination.

Group disparities, i.e., different or inaccurate treatment of entire demographic groups:

- Including direct or proxy identifiers for demographic group membership, i.e., *DT*.
- Learning different correlations between demographic groups and favorable model outcomes, i.e., *DI*.
- Exhibiting different accuracies across demographic groups, i.e., *differential validity*.

Locally, i.e., different or inaccurate treatment of similar individuals:

- Local response function or decision boundary form.
- Capacity to form local complex demographic proxies on a row-by-row basis.

Common Metrics of Discrimination in ML

Common metrics for DI and ***group*** disparities:

- Differential validity: $\frac{\text{quality}_p}{\text{quality}_r}$
- Adverse impact ratio: $\frac{\%\text{ accepted}_p}{\%\text{ accepted}_r}$
- Marginal effect: $\%\text{ accepted}_p - \%\text{ accepted}_r$
- Standardized mean difference: $\frac{\bar{\hat{y}}_p - \bar{\hat{y}}_r}{\sigma_{\hat{y}}}$

where, $p \equiv$ protected group and $r \equiv$ reference group (often white males).

There are many other, sometimes conflicting, mathematical definitions of discrimination. See 21 Definitions of Fairness and Their Politics.

Additional Considerations for Discrimination Testing

- Local discrimination, i.e., the model treats a small number of similar people differently.
  - Constrain problematic interactions.
  - Search around probability thresholds.
  - Adversarial models.
- Post-hoc explanation to understand drivers of discrimination:
  - To be conducted after discrimination is confirmed by standard tests.
  - Be aware of:
    - No demographic features in model.
    - Fairwashing [1] and scaffolding [8].

How to Fix Discrimination in ML?

Fix organizational processes: Lecture 6

Fix the data:

- Collect demographically representative training data.
- Label and annotate data carefully.
- Select features judiciously.
- Sample and reweigh training data to minimize discrimination.[4]

How to Fix Discrimination in ML?

Fix the model:

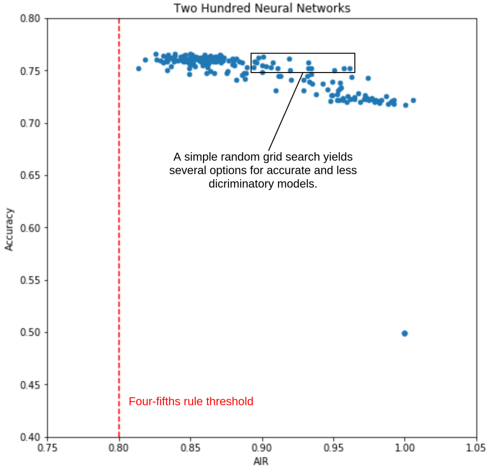
- Consider fairness metrics when selecting hyperparameters and cutoff thresholds.
- Train fair models directly:
  - Learning fair representations (LFR) and adversarial de-biasing.[9], [10]
  - Use dual objective functions that consider both accuracy and fairness metrics.
- Edit model mechanisms to ensure less biased predictions, e.g., with GA2M/EBM models.

Fix the predictions:

- Balance model predictions, e.g., reject-option classification.[5]
- Correct or override predictions with model assertions or appeal mechansims.[3], [6]

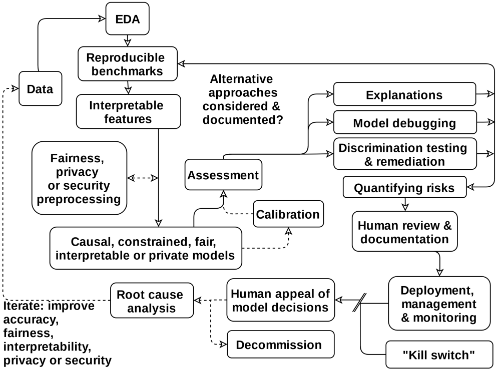
How to Fix Discrimination in ML?

Consider discrimination measures during model selection.



How to Fix Discrimination in ML?

As part of a responsible ML workflow.



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