Cross-attribute evaluation of fairness mechanisms

Student: Razvan-Andrei Morariu

Supervisors: Univ.-Prof. Dr. Benjamin Roth, Pedro Henrique Luz de Araujo, Anastasiia Sedova



Introduction

Fairness in ML ensures that algorithms produce unbiased outcomes, treating all individuals equally regardless of characteristics like race, gender, or age.

ML models used on certain datasets yield biased and unfair outcomes. As a result, mechanisms ensuring fairness in ML have emerged.



German Credit Dataset

The dataset has:

- 1000 entries
- 20 features/descriptors (such as age, gender, credit amount, purpose)
- 2 sensitive features: age and gender

Binary classification : If the credit of a person is good or bad in terms of

risk



Bias



Fairness mechanisms: pre-process, in-process, **post-process Post-process** : Do the fairness optimization on the predictions of ML model

Measure: Equal opportunity difference : $|P(\hat{Y} = 1|Y = 1, A = 1) - P(\hat{Y} = 1|Y = 1, A = 0)| \in [0, 1]$



Goal of the Project

One very common source of bias is under-representation bias. There are bias injection methods to simulate this type of bias in order to understand its consequences.

Entire dataset + chose a category to be underrepresented

Probability p: keep every positive sample from the selected category Probability 1-p: discard it

Biased dataset

Pipeline: Inject bias at different levels and check the effects on fairness optimization algorithms





Fairness can be evaluated w.r.t. different features (age, gender, race). How does fairness optimization for one feature influence the others? 0.6 0.5 0.4 Equal opp 6 Fairness Fairness for age for gender 0.1 0.0 0.2 0.3 0.4 0.5 0.6



Similar results were obtained for gender.

There is no clear correlation between age fairness improvement and gender fairness improvement.



There might be a negative correlation between age fairness improvement and accuracy.

Selected References

Avrim Blum, Kevin Stangly: Recovering from Biased Data: Can Fairness Constraints Improve Accuracy? Moritz Hardt, Eric Price, Nathan Srebro: Equality of Opportunity in Supervised Learning Yuji Roh, Kangwook Lee, Steven Euijong Whang, Changho Suh: Sample Selection for Fair and Robust Training XiaoqianWang, Heng Huang: Approaching Machine Learning Fairness through Adversarial Network