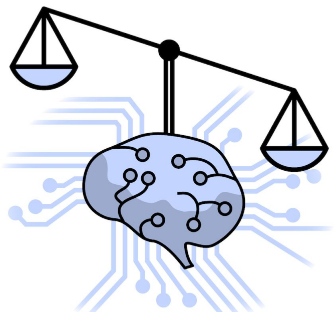

MoFlipTest: Multi-Objective FlipTest

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25th June, 2021

Outline

- Motivation
- Counterfactuals in ML
- The problem we want to tackle
- Related works
  - FlipTest
  - MOC
  - QII & MCS
- Notations
- Proposed Idea

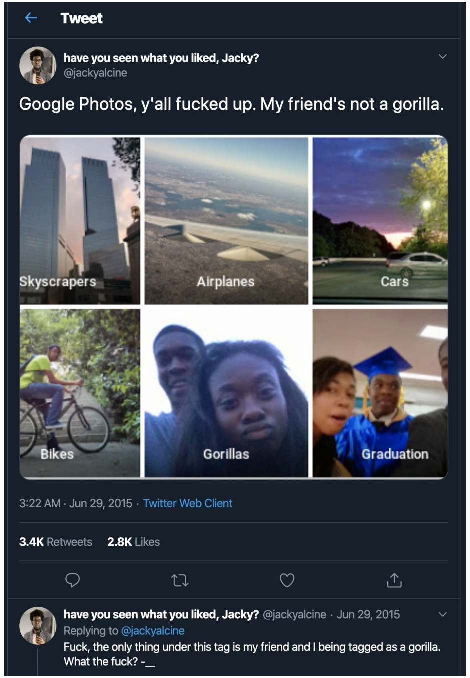
Motivation

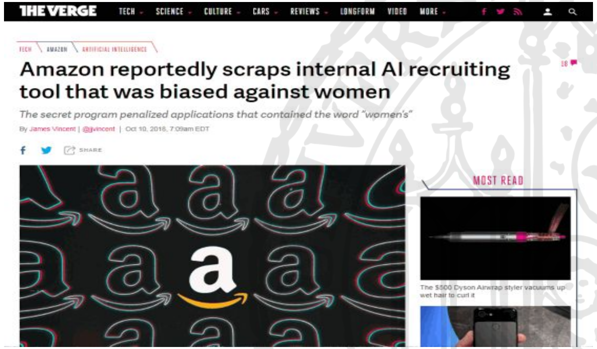
Erik Carter

China Is Collecting DNA From Tens of Millions of Men and Boys, Using U.S. Equipment

Even children are pressed into giving blood samples to build a sweeping genetic database that will add to Beijing's growing surveillance capabilities, raising questions about abuse and privacy.

Published June 17, 2020
By Sui-Lee Wee



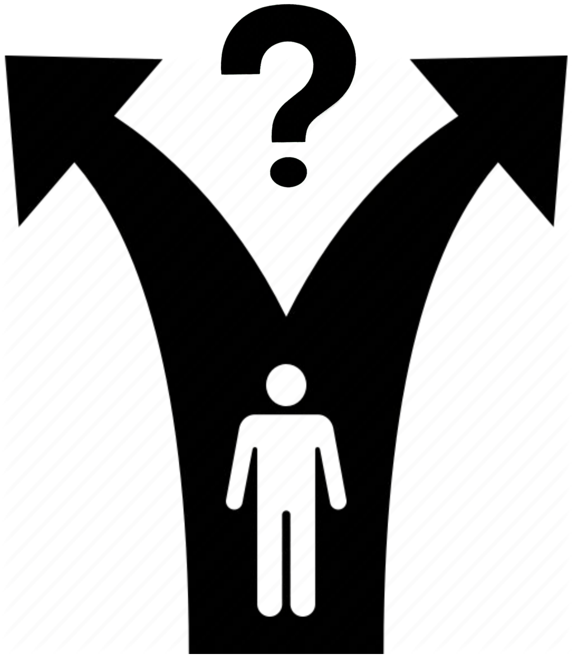


Motivation: bias against protected classes

Legally recognized ‘protected classes’

Race; Color; Sex; Religion; National origin; Citizenship; Age; Pregnancy; Familial status; Disability status; Veteran status; Genetic information [4]

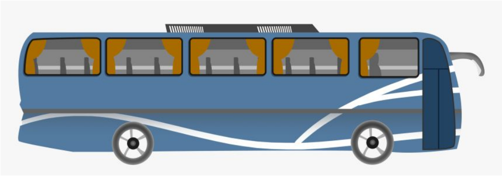
Counterfactuals



Counterfactuals cntd.

"What if I had taken the public bus instead of a taxi, I might have reached office earlier"

- Idea of two fictitious world
- Different Interpretations



Counterfactuals in ML

- Used to explain predictions
- Used to check if an ML model is fair
- Used for local explanation of a model (individual instance)
- Counterfactual explanations for reversing unfavorable outcome

The problem we want to tackle

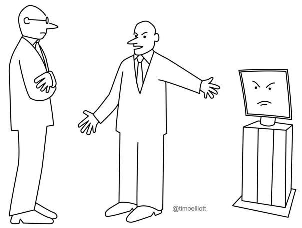
“Given a fitted model *f*, we want to test whether it is fair or not with respect to the definition of counterfactual fairness:

A predictor is fair if it would give the same prediction in a world where we were different [4]”

Related works

FlipTest [1]:

- A fairness testing approach
- Generates counterfactuals by optimal transport mapping of the predicted probabilities of the two groups
- Idea of Flipsets
    - Positive Flipset (F+)
    - Negative Flipset (F-)
- Transparency report
- Works for binary classifiers

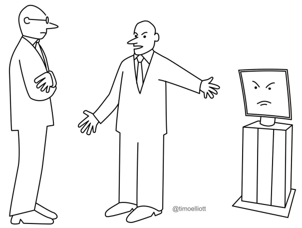


His decisions aren't any better than yours — but they're WAY faster...

Related works cntd.

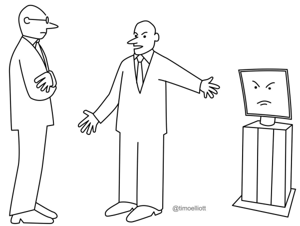
MOC (Multi-Objective Counterfactual method) [2]:

- Model-agnostic
- Focuses on four objectives
  - Counterfactual prediction close to desired prediction
  - Counterfactual close to instance
  - Sparse feature changes
  - Counterfactuals having likely feature values or combinations
- Works for numerical and categorical features
- Works for classifiers and regression



His decisions aren't any better than yours — but they're WAY faster...

Related works (for extension) cntd.



His decisions aren't any better than yours — but they're WAY faster...

QII (Quantitative input influence) [3]:

- Captures the degree of influence of inputs on outputs of systems
- Takes into account the correlated inputs

MCS (Model-based Counterfactual Synthesizer) [6]:

- Synthesizes model-based counterfactuals for prediction reasoning

Notations

x: original instance

y: original prediction

x': counterfactual instance

y': counterfactual prediction

Proposed idea (MoFlipTest)

- Multi-Objective Counterfactual method
- Model-agnostic
- Transparency report
- Flipsets
  - Positive Flipset (F+)
  - Negative Flipset (F-)
- Will work for numerical and categorical features

Proposed idea (MoFlipTest) cntd.

- Focuses on three objectives of MOC:
  - Counterfactual close to instance x'→x
  - Sparse feature changes
  - Counterfactuals having likely feature values or combinations (hard to achieve)

- Observe the difference between y'→y
  - Comparing outcomes with flipsets

Proposed idea (An extension) cntd.

An extension to our idea:

- We would like to use QII for finding out the exact features that are responsible for discrimination

Proposed idea (example)

A loan application example

Sex	Income	Height	Education	Age	Y
female	50k	5’4”	Bachelors	28	✗
male	60k	5’9”	Masters	30	✓

✗ = Loan denied

✓ = Loan accepted

Proposed idea (example) cntd.

1st objective and 2nd objective: x' close to x and small #feature changes

Sex	Income	Income'	Height	Education	Age	Y	Y'
female	50k	60k	5’4”	Bachelors	28	✗	✓
male	60k	60k	5’9”	Masters	30	✓	✓

Proposed idea (example) cntd.

3rd objective: counterfactuals should have likely feature values or combinations

Sex	Income	Height	Education	Education'	Age	Age'	Y	Y'
female	50k	5’4”	Bachelors	Masters	28	32	✗	✓
male	60k	5’9”	Masters	Masters	30	30	✓	✓

Proposed idea (example) cntd.

Suppose our method generated a counterfactual where the sensitive attribute is changed from female to male and changed the outcome:

Sex	Sex'	Income	Height	Education	Age	Y	Y'
female →	male	50k	5'4"	Bachelors	28	✗	✓
male →	female	60k	5'9"	Masters	30	✓	✓

Proposed idea (example) cntd.

It means our model might be biased based on an individual’s sex or gender

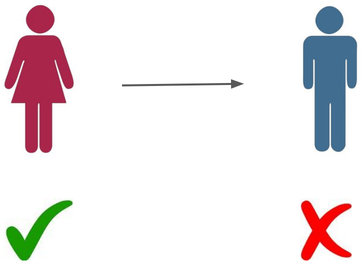
Sex	Sex'	Income	Height	Education	Age	Y	Y'
female	male	50k	5’4”	Bachelors	28	✗	✓
male	female	60k	5’9”	Masters	30	✓	✓

Proposed idea (example) cntd.

Flipset: the set of women who had a different model outcome post translation

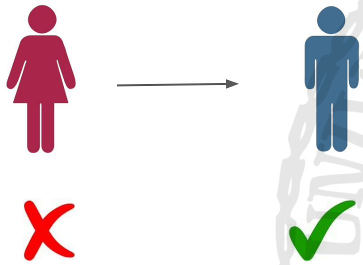
F(+)

Positive Flipset



F(-)

Negative Flipset



Proposed idea (example) cntd.

Information from flipset:

- Compare flipset distribution to overall female population to uncover potential discrimination

Proposed idea (example) cntd.

Transparency Report: it gives the insight about how the model discriminates.

- Here, $h : X \rightarrow \{0, 1\}$ is a binary classifier, $G(x) \rightarrow$ function for MOC counterfactual generation. $F(h, G)$ is the corresponding flipset

$$\frac{1}{|F^{\star}(h,G)|} \sum_{\boldsymbol{x} \in F^{\star}(h,G)} \boldsymbol{x} - G(\boldsymbol{x}), \ \ and$$

$$\frac{1}{|F^{\star}(h,G)|} \sum_{\boldsymbol{x} \in F^{\star}(h,G)} \operatorname{sign}(\boldsymbol{x} - G(\boldsymbol{x}))$$

$$Here, \star \in \{+, -\}$$

Proposed idea (challenges to tackle)

- Generalize to regression
- Making it multi-objective

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6. Fan Yang, Sahan Suresh Alva, Jiahao Chen and Xia Hu. “Model-Based Counterfactual Synthesizer for Interpretation”.