Bias in Machine Learning: An Adversarial Approach

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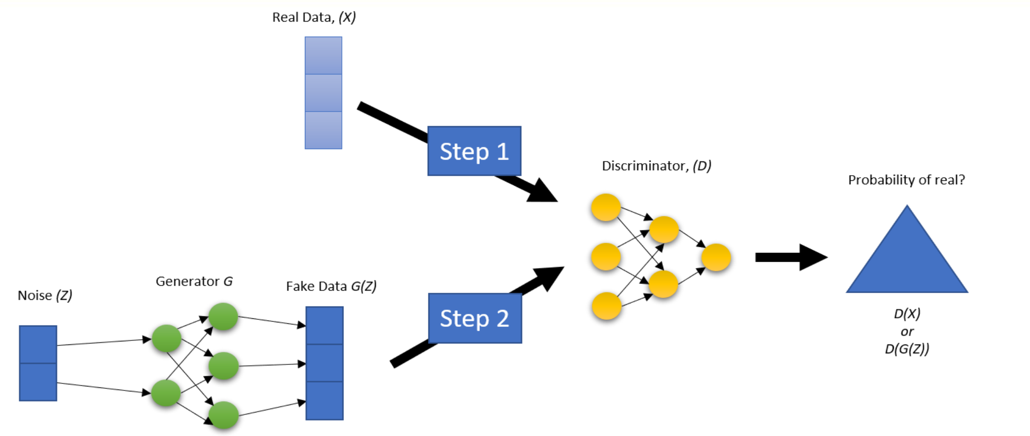
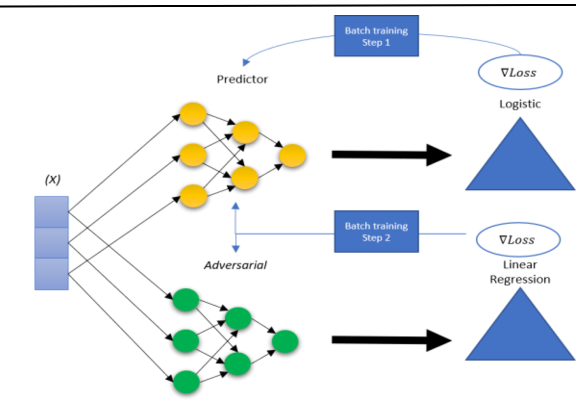
Introduction

- Bias is very prevalent, occurring in ML models at pre-process, in-process, post-process stages.
- Examples of ML bias are widely known – COMPAS, Amazon hiring algorithm/resume scan, Word2Vec. Most are binary: protected class vs unprotected class.
- Our study focuses on eliminating bias stemming from AGE when predicting employee attrition.

Main Topics

- Adversarial learning can be leveraged to mitigate bias and unfairness.
- Competing models of GAN, where Predictor (P) tries hinder Discriminator (D) with fake data, while feedback from D tries to hinder P prediction ability.
- Our study: P -- predict employee prediction; D -- predict age.
- Goal: improve group fairness via demographic parity (DP) (all equally likely of positive outcome (TP + FP)).





Model Architecture

Baseline Model

- Logistic Model
- $\hat{y}_{Attrition} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_n x_n + \varepsilon$

Adversarial Models

- $\hat{y}_{Attrition} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_n x_n + \varepsilon$
- $\hat{A}_{Age} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_n x_n + \varepsilon$
- $Loss = -\alpha \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$

Results

- **Improved DP**: range Pre-GAN for all groups between 94-100%; Post-GAN range 98-100%.
- **Small trade-off between Accuracy and Fairness Post-GAN:** accuracy decreased 2% but DP increased 6%.
- **Demonstrate work beyond binary classes**: can work toward having more than one unprotected group.
- **See Results Chart**

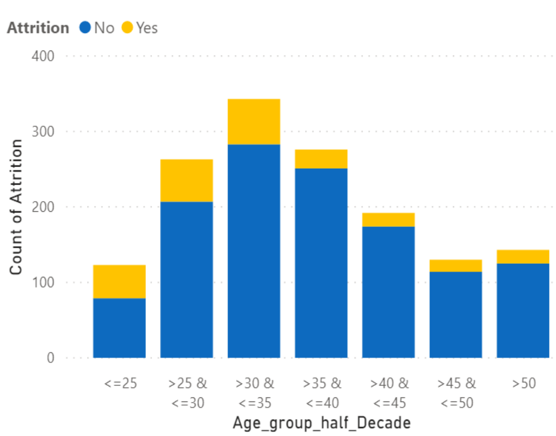
Data Overview

IBM Employee Attrition Dataset

Attrition: 84% NO / 16% YES

Age binned in 5-year ranges

More attrition <= age 35



ACCUR	< = 25	(25, 30]	(30, 35]	(35, 40]	(40, 45]	(45, 50]	> 50	Overall
Pre GAN	0.7575	0.84	0.8315	0.9138	0.9464	0.8696	0.7941	0.8587
Post GAN	0.6970	0.8	0.8315	0.8966	0.8929	0.9130	0.7941	0.8315

DEMO PARITY	< = 25	(25, 30]	(30, 35]	(35, 40]	(40, 45]	(45, 50]	> 50	Overall
Pre GAN	0.9394	0.96	0.9438	0.9655	0.9464	0.9565	1.0	0.9375
Post GAN	1.0	1.0	0.9888	0.9828	1.0	1.0	1.0	0.9972

Conclusions / Future Work

- Bias must be addressed in advance and throughout – NOT as an afterthought.
- Re-run study with larger, real dataset and/or pre-processed data that balances attrition % or sampled differently.
- Refine code with Early Stop, when the adversary has sufficiently mitigated bias and correlation is no longer detected in the adversarial model for Z(x), Age.
- We CANNOT and MUST NOT replace the inquisitiveness, skepticism, mortal imagination and compassion that humans bring to bear on Machine Learning.