Reducing Age Bias in Machine Learning:
An Algorithmic Approach

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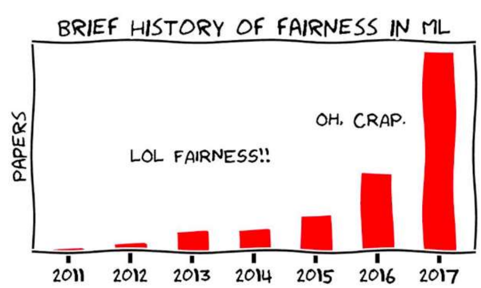
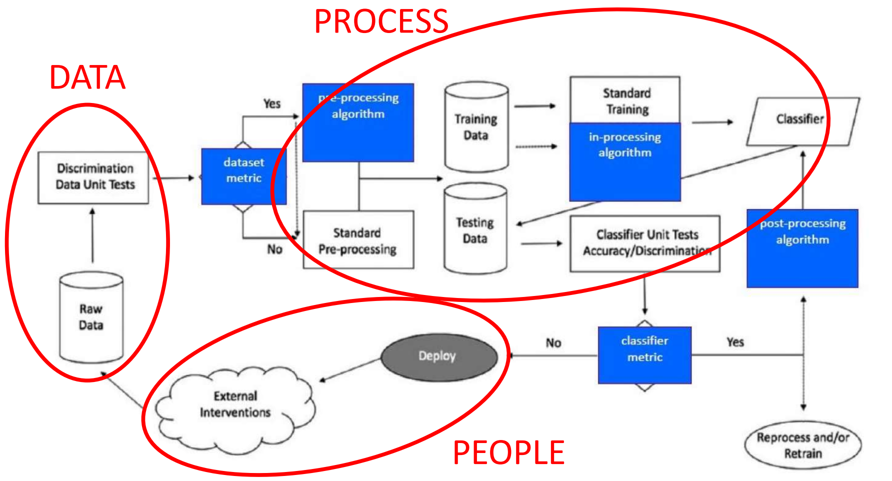
Bias in Machine Learning



Taken from Moritz Hardt lecture notes.

Is it BIASED because it is UNFAIR?
Is it FAIR because it is UNBIASED?

Bias in Machine Learning



https://aif360.mybluemix.net/

Bias in Machine Learning

PROCESS

Intervention Points

Pre-Processing

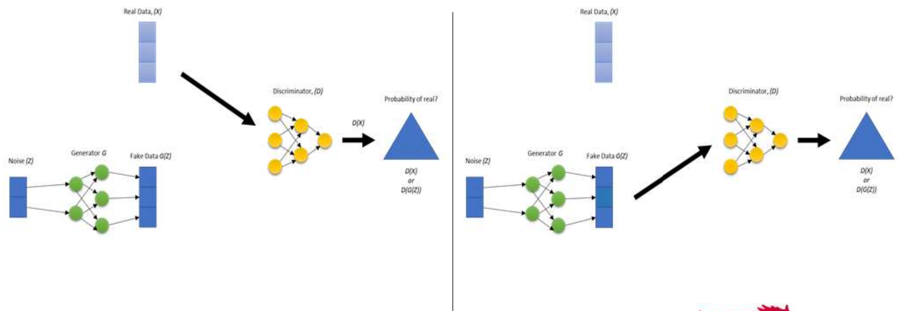
In-Processing

Post-Processing

- Classification
- Regression
- AI Fairness 360
  Prejudice Remover
- **Adversarial Debiasing**

GAN Overview

https://ya-webdesign.com/imgdownload.html



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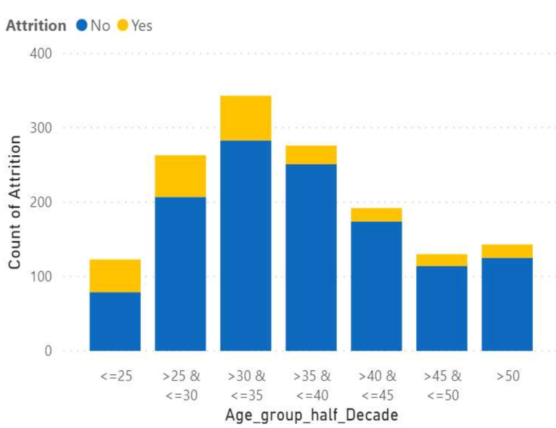
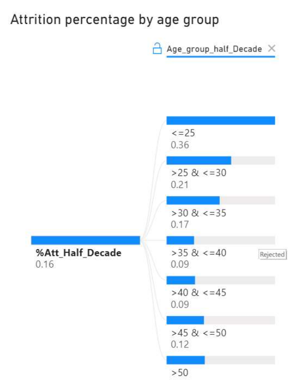
Experiment

Understanding Employee Attrition





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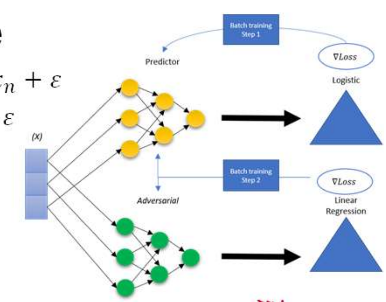
Experiment

- Overview Experiment
  - Age(Z) is protected
  - Age(Z) Correlated with explanatory (X) of predictor model
- Goals
  - Good Accuracy
  - Demographic Parity
    - Both protected and unprotected classes receive a positive outcome at equal rates.
    - Demographic Parity = True Positives + False Positives

Experiment

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



Experiment Results: Fairness

Goal: Improve group fairness based on demographic parity

- Evaluated differences in **accuracy** and **demographic parity** between the baseline model and a GAN model
- Calculated standard metrics to evaluate performance
- Calculated several other metrics to evaluate group fairness
- Metrics were calculated for 7 age groups in 5-years increments

Experiment Results: Accuracy

- Initial step to evaluate **Accuracy** of both models when predicting Attrition
- Accuracy from GAN model was compared to accuracy baseline model

ACCURACY	<= 25	(25, 30]	(30, 35]	(35, 40]	(40, 45]	(45, 50]	>50	OVERALL
Baseline/Pre-Gan	0.7576	0.8400	0.8315	0.9138	0.9464	0.8696	0.7941	0.8587
Post-Gan	0.6970	0.800	0.8314	0.8966	0.8929	0.9130	0.7941	0.8315

Table 1: Accuracy Comparison of Baseline and Adversarial Models by Age Group

- Accuracy in both models was expected to be similar
- Accuracy from GAN was lower across all groups
- Groups less than 35 and older population over 50, resulted in a lower accuracy on Attrition
- Attributed this to larger number of observations in the middle age groups

Experiment Results: Demographic Parity

- **Demographic Parity (DP) is achieved when:**
  - Each group has equal likelihood to be assigned a positive outcome
  - Proportion of positive predictions in the subgroups is close to each other

DEMOGRAPHIC PARITY	<= 25	(25, 30]	(30, 35]	(35, 40]	(40, 45]	(45, 50]	>50	OVERALL
Baseline/Pre-Gan	0.9394	0.9600	0.9438	0.9655	0.9464	0.9565	1.000	0.9375
Post-Gan	1.000	1.000	0.9888	0.9828	1.0000	1.000	1.000	0.9973

Table 2: Demographic Parity Comparison of Baseline and Adversarial Models by Age Group

- **Improved <u>DP</u> range across all groups:**

  Baseline between 94-100%; **GAN** range 98-100%

- **Small trade-off between Accuracy and Fairness GAN:**

  Accuracy decreased 2% but <u>DP</u> increased 6%.

Conclusions

- **Most adversarial debiasing work focused** on protected groups such as race, sex and gender bias; we considered binned data
- Achieved **Demographic Parity** based on results from a comparative analysis between the baseline model and the GAN model
- Our focus was on <u>Age debiasing</u>, and how age bias can be <u>prevented in deep learning models</u>

Conclusions

- **Bias must be addressed in advance and throughout the ML lifecycle – NOT as an afterthought**
- Mitigating bias using adversarial network architecture shows promise, yet we cannot be confident that systems are unbiased and fair

We <u>cannot</u> and <u>must not</u> replace the inquisitiveness, skepticism, moral imagination, compassion, and the sensitivity to foresee consequences that <u>humans</u> bring to bear on machine learning.

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Bias in Machine Learning: An Adversarial Approach

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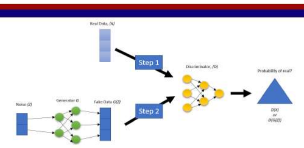
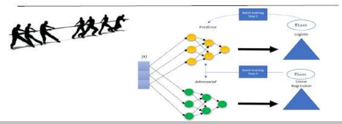
Introduction

- 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**

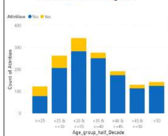
Data Overview

IBM Employee Attrition Dataset

Attrition: 84% NO / 16% YES

Age binned in 5-year ranges

More attrition <= age 35



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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.