Introduction to Fairness

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Table of contents

Problem characterization

Introducion

- Discrimination-Aware classification was first introduced[1,2] to avoid unwanted dependencies between the attributes.
- Given a set of *sensitive attributes*, such as race, color, religion, sex, age, pregnancy
- The goal is to learn statistical models avoiding bias, discrimination or prejudice with respect to the sensitive attributes.
- Due to historical issues, human data may have, intentionally or not, harmful bias against some groups.

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[1] Dino Pedreschi, Salvatore Ruggieri, and Franco Turini. "Discrimination-aware data mining". In: *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD 08* (2008), p. 560.

[2] Faisal Kamiran and Toon Calders. "Classifying without discriminating". In: *2009 2nd International Conference on Computer, Control and Communication, IC4 2009* (2009).

Causes of unfairness

Causes of unfairness

- There are, at least, three causes of unfairness[3]
- Prejudice
  - Direct prejudice
  - Indirect prejudice
- Underestimation
- Negative legacy

[3] Toshihiro Kamishima et al. “Fairness-aware classifier with prejudice remover regularizer”. In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 7524 LNAI.PART 2 (2012), pp. 35–50.

Fairness criterias

Fairness criterias

- Anti-classification
  - Protected attributes and their proxies are not explicitly used to make decisions
- Classification parity
  - Measures of predictive performance (e.g., false positive and false negative rates) are equal across groups defined by the protected attributes
- Calibration
  - Outcomes are independent of protected attributes af- ter controlling for estimated risk

Fairness criterias

- Threshold rules[4]
  - Treat similarly risky people similarly
- Rich subgroup fairness[5]
  - Fairness constraint (say, equalizing false positive rates across protected groups), hold over an exponentially or infinitely large subgroups

[4] Sam Corbett-Davies et al. *The Measure and Mismeasure of Fairness: A Critical Review of Fair Machine Learning **. Tech. rep. 2018.

[5] Michael Kearns et al. *An Empirical Study of Rich Subgroup Fairness for Machine Learning*. Tech. rep. 2018.

Redlining effect

Redlining effect

- Simply removing sensitive attributes from training data is not enough to solve this problem
- The statistical model could indirectly learn bias through related features, phenomena known as *redlining effect*[6].
- For example, ethnicity may be strongly related to zip code.

[6] Gregory D. Squires. "Racial Profiling, Insurance Style: Insurance Redlining and the Uneven Development of Metropolitan Areas". In: *Journal of Urban Affairs* 25.4 (2003), pp. 391–410.

Approaches

α-protector

- Algorithm based on association and classification rules[7]
- Manually define a α-protector threshold for increasing confidence
- Direct and indirect discrimination versions

[7] Dino Pedreschi, Salvatore Ruggieri, and Franco Turini. "Discrimination-aware data mining". In: *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD 08* (2008), p. 560.

Data massaging

- *Massaging* the data to remove discrimination[8].
- Instances are ranked by learning a model trained without sensitive attributes
- Select candidates for *promotion* and *demotion*
- Invert labels to avoid discrimination

[8] Faisal Kamiran and Toon Calders. "Classifying without discriminating". In: *2009 2nd International Conference on Computer, Control and Communication, IC4 2009* (2009).

Bayesian models

- Proposes three models based on Naive Bayes[9]
  1. *Post-processing* phase that modify the probability of the decision being positive by changing the probabilities in the model
  2. Train *one model by value* of every sensitive attribute and *balance* them
  3. Add a *latent variable* in the Bayesian model that represents an unbiased, discrimination-free label and optimize the model parameters for likelihood using expectation maximization

[9] Toon Calders and Sicco Verwer. "Three naive Bayes approaches for discrimination-free classification". In: *Data Mining and Knowledge Discovery* 21.2 (2010), pp. 277–292.

Decision tree

- Proposes two models based on Decision Tree[10]
  1. Evaluates the *discrimination caused by each split*, not only its contribution to accuracy
  2. *Leaf relabeling* to lower discrimination

[10] Faisal Kamiran, Toon Calders, and Mykola Pechenizkiy. "Discrimination aware decision tree learning". In: *Proceedings - IEEE International Conference on Data Mining, ICDM* (2010), pp. 869–874.

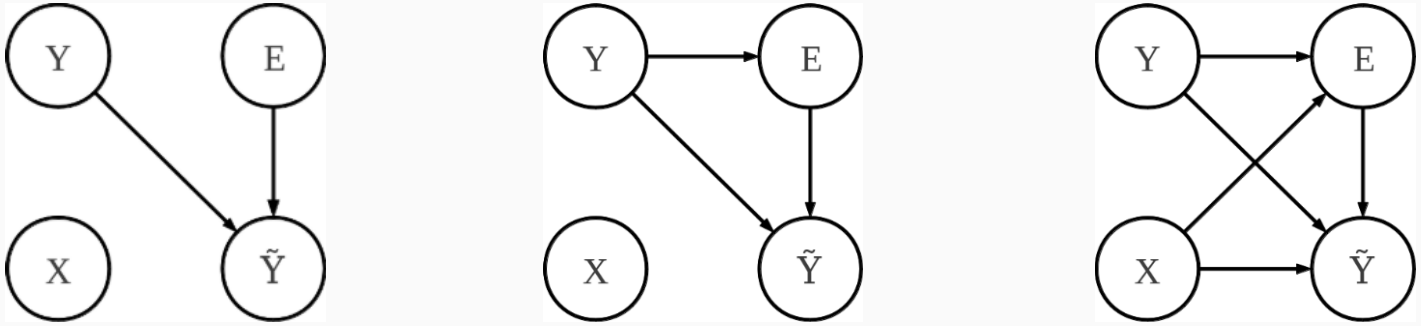
Heuristics for rich subgroups

- Two-player zero-sum game[11]
  1. Learner (the primal player)
  2. Auditor (the dual player)

[11] Michael Kearns et al. “Preventing Fairness Gerrymandering: Auditing and Learning for Subgroup Fairness”. In: (Nov. 2017).

Noise Taxonomy

Noise Taxonomy



(a) NCAR (b) NAR (c) NNAR

Figure 1: Noisy Models

Noisy Completely at Random The occurrence of an error E is independent of the other random variables, including the true class itself. So called uniform label noise.

Noisy at Random The probability of occurrence of na error is dependent on true lable. Different classes may have different label error rates.

Noisy Not at Random The occurrence of an error may depend not only on true label, but even on features.

Proposal #1

Proposal #1

- Handle fairness as a *waekly supervised learning problem*
- Apply Loss Factorization[12]
- Given a *transition matrix*, use forward and backward to correct prediction[13]

[12] Giorgio Patrini et al. *Loss Factorization, Weakly Supervised Learning and Label Noise Robustness*. Tech. rep. 2016. URL: http://proceedings.mlr.press/v48/patrini16.pdf.

[13] Filipe Braida do Carmo. "Considerando o ruído no aprendizado de modelos preditivos robustos para a filtragem colaborativa". PhD thesis. Universidade Federal do Rio de Janeiro.

Proposal #1

- We can define transition matrices for fairness:

$$T_{FP} = \begin{bmatrix} fpb_{1,1} & \dots & fpb_{1,n} \\ fpb_{2,1} & \dots & fpb_{2,n} \\ \vdots & & \vdots \\ fpb_{n,1} & \dots & fpb_{n,n} \end{bmatrix} \quad T_{FN} = \begin{bmatrix} fnb_{1,1} & \dots & fnb_{1,n} \\ fnb_{2,1} & \dots & fnb_{2,n} \\ \vdots & & \vdots \\ fnb_{n,1} & \dots & fnb_{n,n} \end{bmatrix}$$

- Where:
  - T_{FP} False positive transition matrix
  - T_{FN} False negative transition matrix
  - $fpb_{i,j}$ False positive bias caused by features i, j
  - $fnb_{i,j}$ False negative bias caused by features i, j

Experiments on Adult Income Dataset

Dataset characterization

Size

Total size	32561
Train size	29304
Test size	3257

Target

Positive	$>$ 50k (7841)
Negative	$<=$ 50k (24720)

Features

age	continuous.
workclass	Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
fnlwgt	continuous.
education	Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
education-num	continuous.

Dataset characterization

marital-status	Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
occupation	Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
relationship	Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
race	White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
sex	Female, Male.

Dataset characterization

capital-gain continuous.

capital-loss continuous.

hours-per-week continuous.

native-country United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

NAR Experiment on Adult Income

Given

False positive rate: fp

False negative rate: fn

We define transition matrix T as

$$T = \begin{bmatrix} 1 - fp & fp \\ fn & 1 - fn \end{bmatrix}$$

Also, forward correction as

```
def forward_categorical_crossentropy(T):
    def loss(y_true,y_pred):
        pred = dot(transpose(T), y_pred)
        return categorical_crossentropy(y_true, pred)
    return loss
```

NAR Experiment on Adult Income

Pre-processing
- One-hot-encoding
- Normalization (Min-Max Scaler)

Randomness
- Fixed seed

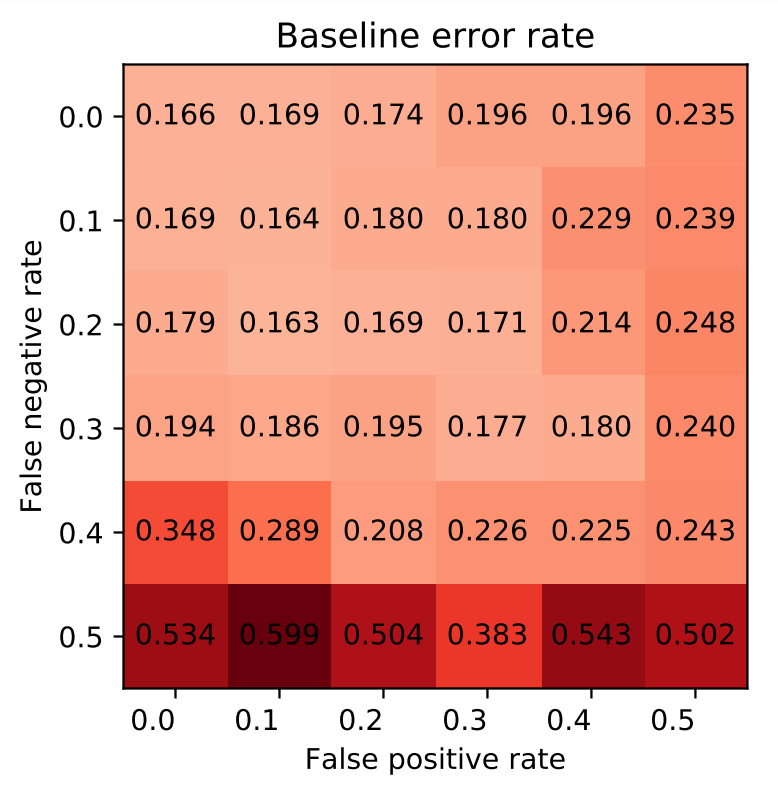
Network architecture
- $108 \rightarrow 128 \rightarrow \textit{ReLU} \rightarrow 2 \rightarrow \textit{softmax}$

```
traning_epochs = 5
model = keras.Sequential([
        keras.layers.Flatten(input_shape=(108,)),
        keras.layers.Dense(128, activation=tf.nn.relu),
        keras.layers.Dense(2, activation=tf.nn.softmax)
    ])
model.compile(optimizer='adam',
                loss=categorical_crossentropy,
                metrics=['accuracy'])
```

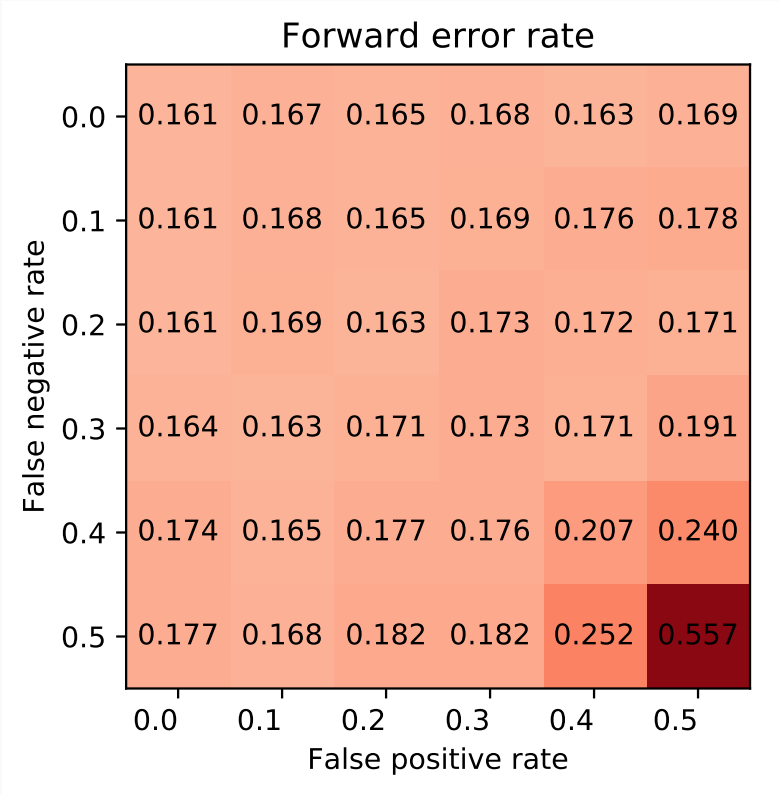
NAR Experiment on Adult Income

```
false_positive_rates = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5]
false_negative_rates = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5]

for fp in false_negative_rates:
    for fn in false_negative_rates:
        T = np.array([[1-fp,fp],[fn,1-fn]])

        polluted_y_train = pollute(y_train, T)
        forward_loss = forward_categorical_crossentropy(T)

        baseline_acc = evaluate(X_train, X_test,
                    polluted_y_train, y_test,
                    loss_function=categorical_crossentropy)

        forward_acc = evaluate(X_train, X_test,
                    polluted_y_train, y_test,
                    loss_function=forward_loss)
```

NAR Experiment on Adult Income



(a) Without correction



(b) Forward

Figure 2: Error rate by pollution level

NAR Experiment on Adult Income

Figure 3: Improvement: $\frac{without\_correction - forward}{without\_correction}$

NNAR Experiment on Adult Income

Given

- $fp_{male} = 0.3$
- $fn_{male} = 0.1$
- $fp_{female} = 0.05$
- $fn_{female} = 0.4$

We define transition matrix as

$$T_{male} = \begin{bmatrix} 1 - fp_{male} & fp_{male} \\ fn_{male} & 1 - fn_{male} \end{bmatrix},$$

$$T_{female} = \begin{bmatrix} 1 - fp_{female} & fp_{female} \\ fn_{female} & 1 - fn_{female} \end{bmatrix}$$

We define, male and female forward correction as

```
T_male = np.array([[1-fp_male, fp_male],
                   [ fn_male , 1-fn_male]])

T_female = np.array([[1-fp_female, fp_female],
                     [ fn_female , 1-fn_female]])

forward_male_loss = forward_categorical_crossentropy(T_male)
forward_female_loss = forward_categorical_crossentropy(T_female)
```

NNAR Experiment on Adult Income

```
polluted_male_labels = pollute(y_train_male, T_male)
polluted_female_labels = pollute(y_train_female, T_female)

X_train = np.vstack([X_train_male, X_train_female])
polluted_labels = np.vstack([polluted_male_labels,
    polluted_female_labels])

test_loss, test_acc = evaluate(X_train, X_test, y_train, y_test,
                        polluted_y_data=polluted_labels,
                        loss_function=categorical_crossentropy,
                        traning_epochs=6)
without_correction_result = test_acc
```

NNAR Experiment on Adult Income

```
model.compile(optimizer='adam',
              loss=forward_female_loss,
              metrics=['accuracy'])

model.fit(X_train_female, polluted_female_labels, epochs=3)

model.compile(optimizer='adam',
              loss=forward_male_loss,
              metrics=['accuracy'])

model.fit(X_train_male, polluted_male_labels, epochs=3)

test_loss, test_acc = model.evaluate(X_test, y_test)
forward_result = test_acc
```

NNAR Experiment on Adult Income

Error rates

Without pollute 0.166

Pollute without correction 0.186

Pollute with forward 0.169

Improvement 0.09 – 9%

Proposal #2

Propasal #2

- Let D a dataset
- Let p a protected feature
- Let G a generative model trained on D
- Let g a dataset generated by G

- Let D^{-p} the dataset without p
- Let G^{-p} a generative model trained on D^{-p}
- Let g^{-p} a dataset generated by G^{-p}
- Let g^{+p}, g^{-p} with p randomly filled

1. Can we compare g with g^{+p} to estimate T?

Proposal #3

Propasal #3

- Let D a dataset
- Let p a protected feature
- Let D^{-p} the dataset without p
- Let D^{+p}, D^{-p} with p randomly filled

1. Can we train an autoencoder to encode D to D^{+p} and use latent factors as a transition matrix?
2. Can we use this trained autocoder in some way to substitute forward/backward correction?