FAHT: An Adaptive Fairness-aware Decision Tree Classifier

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Bias in Machine Learning

The image quality is not good. it's the original image, I am not sure how to get a better one, I'll try.



Current studies tackle fairness as a static/batch problem.

Notions of Fairness

Introduction

The figure again does not look nice

- More than twenty fairness-related measures has been proposed thus far. Add citation
- We adopt the widely used statistical parity:

$$Disc(D) = \frac{FG}{FG + FR} - \frac{DG}{DG + DR}$$





- **DR** (deprived-rejected): females rejected a benefit.
- **DG** (deprived-granted): females granted a benefit.
- FR (favored-rejected): males rejected a benefit.
- FG (favored-granted): males granted a

Fairness-aware Learning approaches

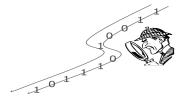
- Add regularization terms to the Mixed-Integer
 Programming model to penalize discrimination [Aghaei et al., 2019].
- Closer to ours: introduce a splitting criterion w.r.t. sensitive attribute and class label [Kamiran et al., 2010].
- Two distinctions:
 - Fairness is directly defined in terms of the discrimination difference of the induction of a split, i.e., the fairness gain due to the split.
 - Our model operates in an online setting rather than upon a static/batch dataset.

Stream Classification

Is it fine to say concept drift explicitly? I didn't as not sure if will be asked how we handle drift

- Continuous flow of data.
- Main challenge: changes in the joint data distribution over time

 concept drifts.



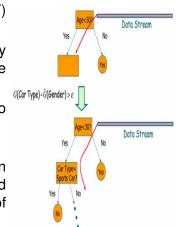
- The learning methods therefore should adapt to changes by learning incrementally from new instances [Krawczyk et al., 2017], and by carefully considering historical information into the model [Melidis et al., 2018].
- Our approach integrates fairness-aware solution and the online approach to maintain a fair and up-to-date classifier for infinite data streams.

Vanilla Hoeffding Tree

- Our Fairness-Aware Hoeffding Tree (FAHT) builds upon the Hoeffding Tree (HT).
- HT scans each instance in the stream only once and stores sufficient information in the leaves for tree growing.
- The crucial decisions are when and how to split a node by Hoeffding bound:

$$\triangle \overline{G} = \overline{G}(X_a) - \overline{G}(X_b) > \epsilon$$

 Such decisions are based on information gain to optimize predictive performance and do not consider fairness. Again the quality of the figure



Fairness-Aware Hoeffding Tree Classifier

FAHT extends the HT model in two ways:

- Introduce a new splitting criterion that jointly considers the gain of an attribute split w.r.t. classification and also w.r.t. discrimination.
- Maintain sufficient statistics at each node to enable the computation of the new splitting criterion values.

The Fair Information Gain Splitting Criterion

HT model:

 Information gain (IG): exclusively accuracy-oriented and fairness is inconceivable.

The Fair Information Gain Splitting Criterion

- Information gain (IG): exclusively accuracy-oriented and fairness is inconceivable
- To overcome this, we propose to alter the splitting criterion to also consider the fairness gain (FG):

$$FG(D,A) = |Disc(D)| - \sum_{v \in dom(A)} \frac{|D_v|}{|D|} |Disc(D_v)|$$

- D_v , $v \in dom(A)$ are the partitions induced by A (attribute)
- $Disc(D_v)$ is computed based on *statistical parity*.
- The idea of *FG* align with *IG* but focuses on discrimination and is also the higher the merrier.
- Directly defined in terms of the reduction in discrimination rather than mediating between the entropy w.r.t. sensitive attribute.

The Fair Information Gain Splitting Criterion

Fair Information Gain (FIG):

• Combine FG and IG to a joint objective:

$$FIG(D,A) = \left\{ egin{array}{l} IG(D,A) & , if \ FG(D,A) = 0 \\ IG(D,A) imes FG(D,A) & , otherwise \end{array}
ight.$$

- Evaluate the suitability of a splitting attribute in terms of both accuracy and fairness.
- For splits that do not change the distribution of discrimination, FIG is reduced to IG.
- Multiplication is favoured: two metrics are not necessary in the same scale and encourage fair splits.

The FAHT System

- Pre-pruning. For the null attribute of FIG, the current class distribution is used to represent the IG and the FG is evaluated as the current level of discrimination.
- Sufficient statistics. Keep track of the counts/maintain Gaussian distribution for discrete attributes and numeric attributes, respectively, to evaluate the FG.
- Memory. The required memory becomes O((d+2)vc) from O(dvc), which incurs negligible extra costs especially when d ≫ 2.

Evaluation Metrics and Goals

- The predictive- vs fairness-performance
- Prequential evaluation: first test, on both aggregatedWhat are the aggregated measures?You wrote it before camera ready due, I guess you meant aggregated for window based? measures and over the stream performance, then train.
- Understand the effects of the proposed splitting criterion in the structure of the resulting decision tree models.

Datasets

- Still short of datasets for fairness-aware research, this challenge is further magnified by the demanding requirement for big non-stationary streams.
- The ones that best meet streaming requirements are the Adult and Census datasets both aiming to predict whether individual's annual income will exceed a certain amount.
- Render them as discriminated data streams by randomizing the order of the instances and processing them in sequence.

Accuracy vs. Fairness

 To the best of our knowledge, this is the first work to address discrimination in data stream classification, so we compare FAHT to HT and Kamiran's.

Metric	Adult	dataset	Census dataset			
Methods	Accuracy	Discrimination	Accuracy	Discrimination		
HT	83.91%	22.59%	95.06%	6.84%		
Kamiran's	83.92% (+0.01%)	22.61% (+0.09%)	94.82% (-0.25%)	6.59% (-3.65%)		
FAHT	81.83% (-2.48%)	16.29% (-27.89%)	94.28% (-8.20%)	3.20% (-53.22%)		

- HT induces discriminated trees, and Kamiran's method has little numerical differences comparing to HT.What is the discrimination of hte original HT?
- FAHT is capable of diminishing the discrimination to a lower level while maintaining a fairly comparable accuracy.

Accuracy vs. Fairness

FAHT	Adult c	lataset1	Census dataset ²			
HT	Granted	Rejected	Granted	Rejected		
Granted	527	310	824	963		
Rejected	523	14,832	564	153,424		

¹ Chi-squared = 53.954, df = 1, p-value = 2.052e-13

Table: McNemar's test on deprived community between HT and FAHT applied to each dataset, testing whether FIG worked to benefit the positive classification of the deprived group.

The anti-discrimination capability of FAHT is also statistically significant.

² Chi-squared = 103.74, df = 1, p-value < 2.2e-16

Accuracy vs. Fairness

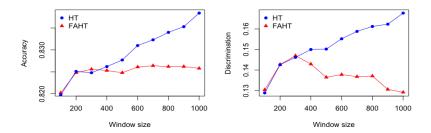


Figure: The Adult data stream is processed in sliding windows; Each window trains a base learner as the ensemble component, the oldest one will be replaced when the classifier window is full; The ensemble members stored in the classifier window will also get updated with the instances in the current sliding window.

- FAHT controls the discrimination propagation while maintaining a high prediction capability.

Structural Effects on the Tree Construction

should I highlight? This correlation isn't good actually, age is more correlated with sex than capital-gain. Or may be

I agree ... that is weird and maybe we should investigate it further. Probably remove this and keep only the one with the shorter trees Selected attributes on the tree construction:

- HT: capital-gain(root), capital-loss, relationship, native-country, education, age.
- **FAHT:** age(root), capital-gain, marital-status, relationship.

Attribute	age	education	marital.status	relationship	sex	capital.gain	capital.loss	hours.per.week	native.country	class
age	1.00	0.01	0.43	-0.22	-0.09	0.08	0.06	0.07	-0.01	0.23
education	0.01	1.00	0.01	0.05	0.00	0.02	-0.01	-0.05	0.06	-0.05
marital.status	0.43	0.01	1.00	0.02	0.18	0.01	0.01	0.01	0.00	0.00
relationship	-0.22	0.05	0.02	1.00	0.27	-0.04	-0.05	-0.18	0.04	-0.17
sex	-0.09	0.00	0.18	0.27	1.00	-0.05	-0.05	-0.23	0.00	-0.21
capital.gain	0.08	0.02	0.01	-0.04	-0.05	1.00	-0.03	0.08	-0.01	0.22
capital.loss	0.06	0.01	0.01	-0.05	-0.05	-0.03	1.00	0.05	0.00	0.15
hours.per.week	0.07	-0.05	0.01	-0.18	-0.23	0.08	0.05	1.00	-0.01	0.23
native.country	-0.01	0.06	0.00	0.04	0.00	-0.01	0.00	-0.01	1.00	-0.02

Structural Effects on the Tree Construction

Entity	Sensitive attribute	Predicted boundary	Actual boundary
Sensitive attribute	1:1	-0.20 : -0.16	-0.21 : -0.21
Predicted boundary	-0.20 : -0.16	1:1	0.52 : 0.44
Actual boundary	-0.21 : -0.21	0.52 : 0.44	1:1

Table: Pearson Correlation coefficients between sensitive attribute, predicted decision boundary and actual decision boundary on Adult dataset. The values before colon are from the HT and after are from FAHT.

 FAHT selects attributes that balance encoding and diminish discrimination of the training data.

Structural Effects on the Tree Construction

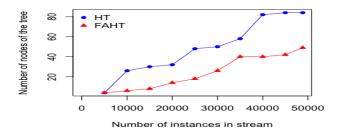
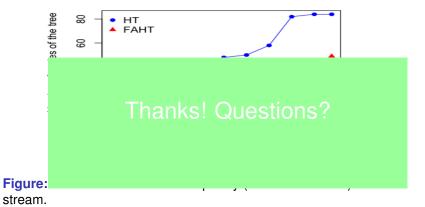


Figure: Adult dataset: Model complexity (number of nodes) over the stream.

 FAHT results in a shorter tree comparing to HT, as its splitting criterion FIG is more restrictive comparing to IG.



Contact data and Acknowledgements

Contact us:

Introduction

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Code and data:

Available at: +++

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