ICANN23
32nd International Conference on Artificial Neural Networks

An Explainable Feature Selection Approach for Fair Machine Learning

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Sep. 2023

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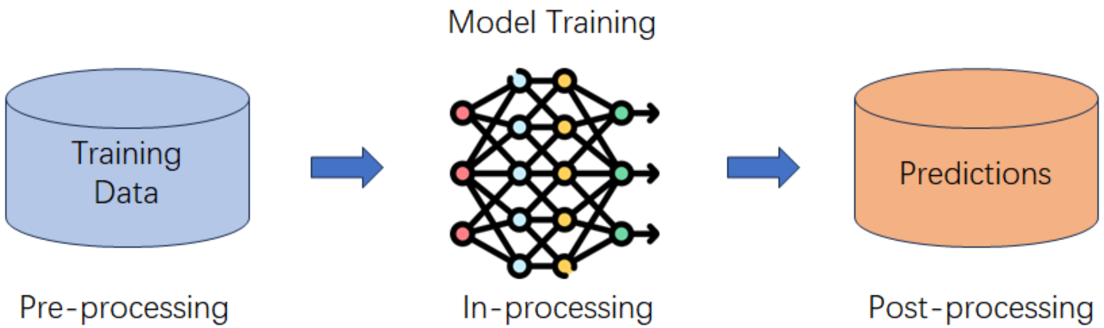
1. Introduction

- Machine learning (ML) algorithms are increasingly adopted in more and more fields and have brought significant impact on our daily lives and society.
- However, discriminatory behavior in algorithmic decision-making hinders the widespread adoption of machine learning. For instance, the software product COMPAS used to predict future criminals was found to be biased against blacks.
- Thus, **fairness in machine learning(ML) has received considerable attention and discussions in the last decades [1].**

[1] Huang, C., Zhang, Z., Mao, B., Yao, X.: An overview of artificial intelligence ethics. IEEE Transactions on Artificial Intelligence pp. 1–21 (2022). https://doi.org/10.1109/TAI.2022.3194503

1. Introduction

- There are many fairness-enhancing methods. Each type of method shows its advantages and limitations and there was no conclusively dominating method.



- The existing methods all lack **explainability** for fairness-enhancement mechanisms.
- We proposed an **explainable feature selection (ExFS)** approach to mitigate the unfairness based on an explainable artificial intelligence (XAI) approach.

2. Related Work

- Three widely used fairness measurements:
  - Demographic Parity(DP) [2]:

$$m_{DP} = |P(\hat{y} = 1|s = s_a) - P(\hat{y} = 1|s = s_b)|$$

  - Equal Opportunity(EOp) [3]:

$$m_{EOp} = |P(\hat{y} = 1|s = s_a, y = 1) - P(\hat{y} = 1|s = s_b, y = 1)|$$

  - Equalized Odds(EOd) [3]:

$$m_{EOd} = |P(\hat{y} = 1|s = s_a, y = 0) - P(\hat{y} = 1|s = s_b, y = 0)| + |P(\hat{y} = 1|s = s_a, y = 1) - P(\hat{y} = 1|s = s_b, y = 1)|$$

Note: s_a and s_b represent the different group between sensitive attribute.

[2] Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., Ntoutsi, E.: A survey on datasets for fairness-aware machine learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 12(3), 1–59 (2022)
[3] Lou, Y., Caruana, R., Gehrke, J., Hooker, G.: Accurate intelligible models with pairwise interactions. In: Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. p. 623–631. KDD ’ 13, Association for Computing Machinery, New York, NY, USA (2013)

2. Related Work

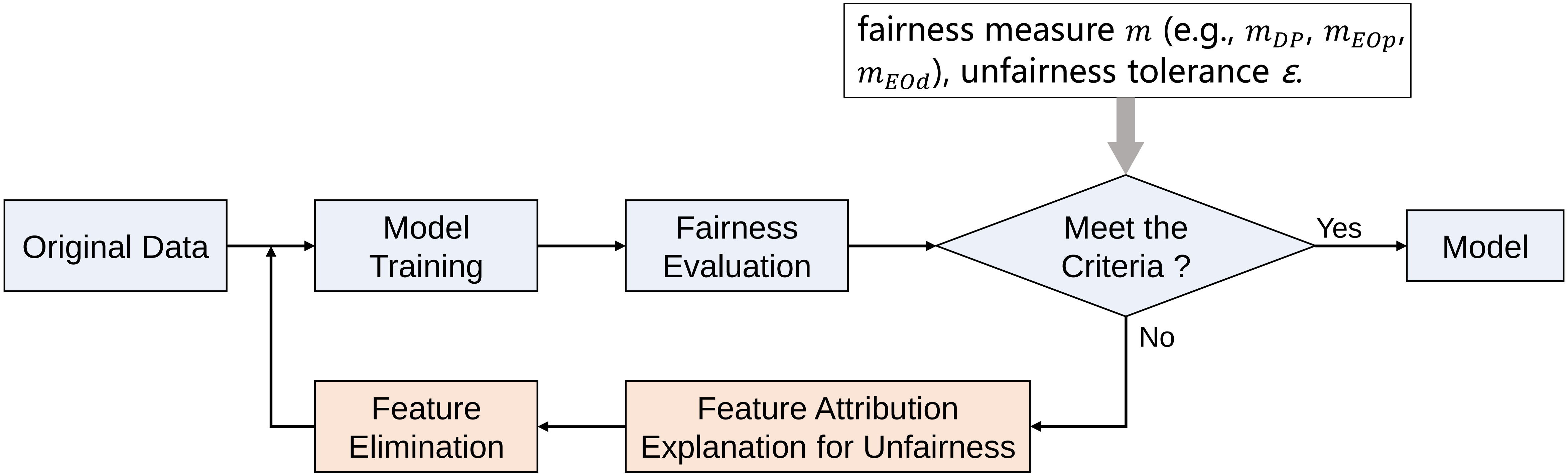
- Recently, there is a growing body of work that uses feature selection(FS) to improve the fairness of ML [4], which is referred to as fairness-aware FS [5].
  - **Fairness-Aware Filter FS:** filter method is computationally efficient, but its performance may be inferior to a wrapper method due to not considering the adopted model.
  - **Fairness-Aware Wrapper FS:** wrapper methods usually can provide good results but involve high computational costs.

Neither filter nor wrapper fairness-aware FS approaches can offer the rationale or cause why removing some features can lead to fairness enhancement.

[4] Grgic-Hlaca, N., Zafar, M.B., Gummadi, K.P., Weller, A.: The case for process fairness in learning: Feature selection for fair decision making. In: NIPS Symposium on Machine Learning and the Law. vol. 1, p. 11. Barcelona, Spain (2016)
[5] Khodadadian, S., Nafea, M., Ghassami, A., Kiyavash, N.: Information theoretic measures for fairness-aware feature selection. arXiv preprint arXiv:2106.00772 (2021)

3. Explainable Feature Selection

■ The Overall Procedure of ExFS



Key Steps:

- Calculate the feature attribution for unfairness, i.e., the contribution of each feature to the unfairness.
- Eliminate the feature that has largest contribution to unfairness, so as to reduce the unfairness.

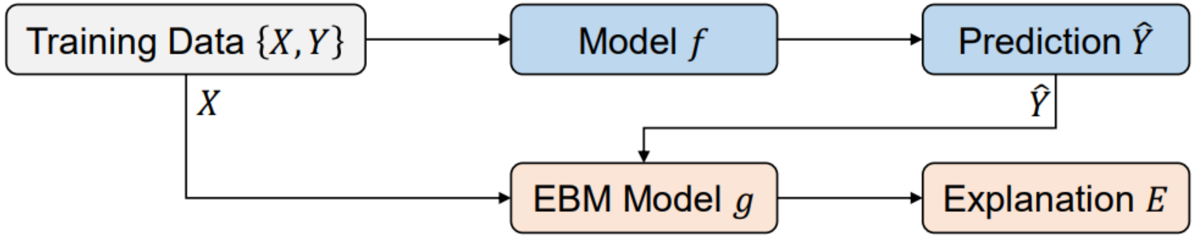
3. Explainable Feature Selection

■ Feature Attribution Explanation Method

- SHAP (Shapley Additive Explanations) is a post-hoc approach that can provide both global and local explanations. It has an expensive computational cost.
- LIME (Local Interpretable Model-Agnostic Explanation) is a post-hoc approach that can provide local explanations.
- EBM (Explainable Boosting Machine) is an intrinsic approach that can provide both global and local explanations, it requires a cheap computational cost than others.

Method	Intrinsic vs. Post-hoc	Computing Cost	Scope
SHAP	Post-hoc	High	Global and Local
LIME	Post-hoc	Medium	Local
EBM	Intrinsic	Low	Global and Local

■ Using EBM to Explain Black-box Model’s Predictions



3. Explainable Feature Selection

■ Calculating the Feature Attributions for Fairness Measurement

- Let $e(\mathbf{x}) \in \mathbb{R}^{\mathrm{d}}$ denotes the explanation of prediction provided by EBM, we use $E_a = \{e(\mathbf{x}^{(i)}) \mid \mathbf{x}^{(i)} \in \mathcal{D}_a\}$, $E_b = \{e(\mathbf{x}^{(j)}) \mid \mathbf{x}^{(j)} \in \mathcal{D}_b\}$ represent the explanation sets for the two subsets (or groups) $\mathcal{D}_a$ and $\mathcal{D}_b$ of dataset $\mathcal{D}$ associated with the sensitive attribute. Based on [6, 7], We calculate how each feature contribute to the m_{DP} by,

$$FA_{DP} = mean(E_a) - mean(E_b) = \frac{\sum_{\mathbf{x}^{(i)} \in \mathcal{D}_a} e(\mathbf{x}^{(i)})}{|\mathcal{D}_a|} - \frac{\sum_{\mathbf{x}^{(j)} \in \mathcal{D}_b} e(\mathbf{x}^{(j)})}{|\mathcal{D}_b|}$$

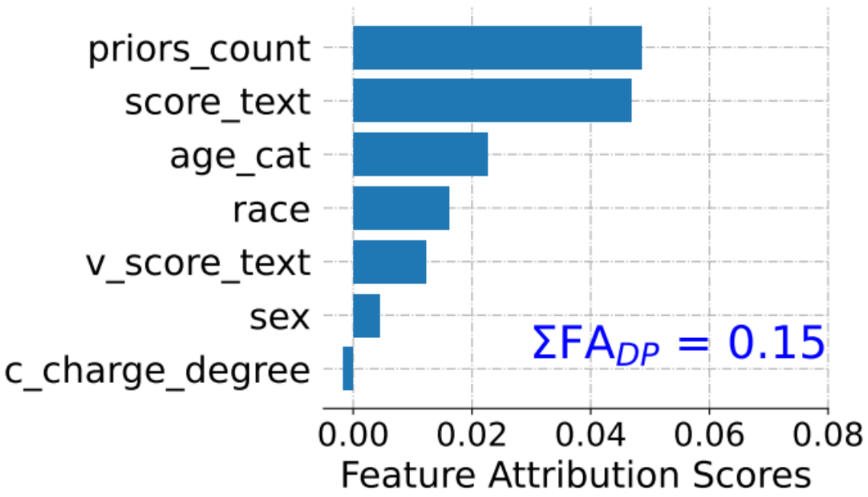
FA_{DP} is a vector that includes the contributions of each feature to the DP measure, and $\sum FA_{DP}$ indicates the DP value. The feature attribution for other group fairness measurements (EOp and EOd) can be derived in a similar way as that for DP described above.

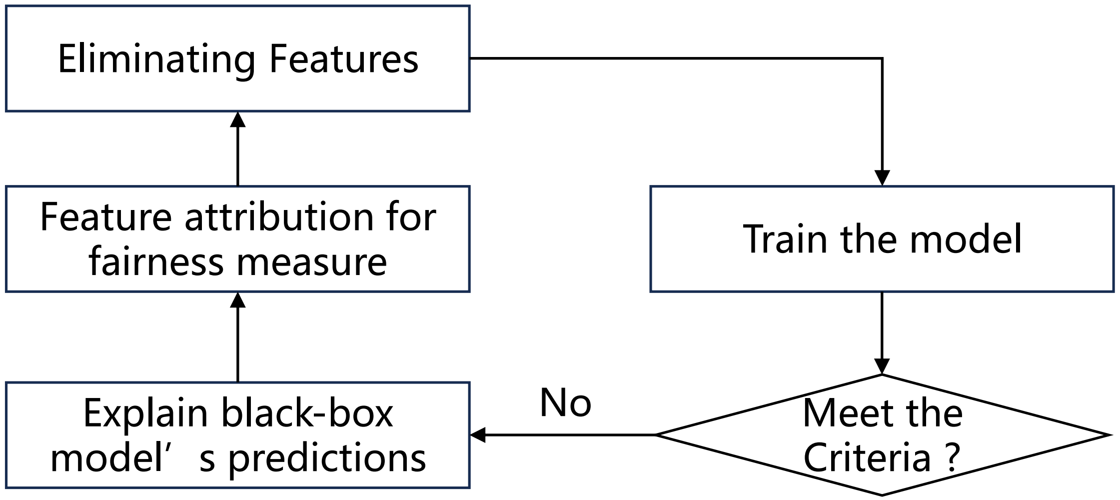
[6] Thampi, A.: Interpretable AI: Building explainable machine learning systems. Manning Publications Co. (2022)
[7] Lundberg, S.M.: Explaining quantitative measures of fairness. In: Fair & Responsible AI Workshop@ CHI2020 (2020)

3. Explainable Feature Selection

■ Eliminating Features based on Explanations

- The larger value of items in FA_{DP} vector indicates the corresponding features contribute more to the fairness measure, i.e., causing unfairness.
- Hence, we can eliminate the feature that have largest contribution score to fairness measure for reducing unfairness.
- We recursively eliminate the feature that contributes mostly to the computed fairness measure.





4. Experimental Study

■ 4.1 Experimental Setting

- **Compared Approaches :**
  - Feature Selection based on Mutual Information (FS-MI)
  - Feature Selection based on Pearson Correlation Coefficient (FS-PCC)
  - Feature Selection using Genetic Algorithm (FS-GA)
  - Feature Selection using NSGA-II (FS-NSGA-II)
- **Datasets :** Adult, Compas, Dutch.
- **Models :** Logistic Regression (LR), Random Forest(RF), Multi-layer Perceptron(MLP).
- **Evaluation Metrics :** DP, EOp and EOd.

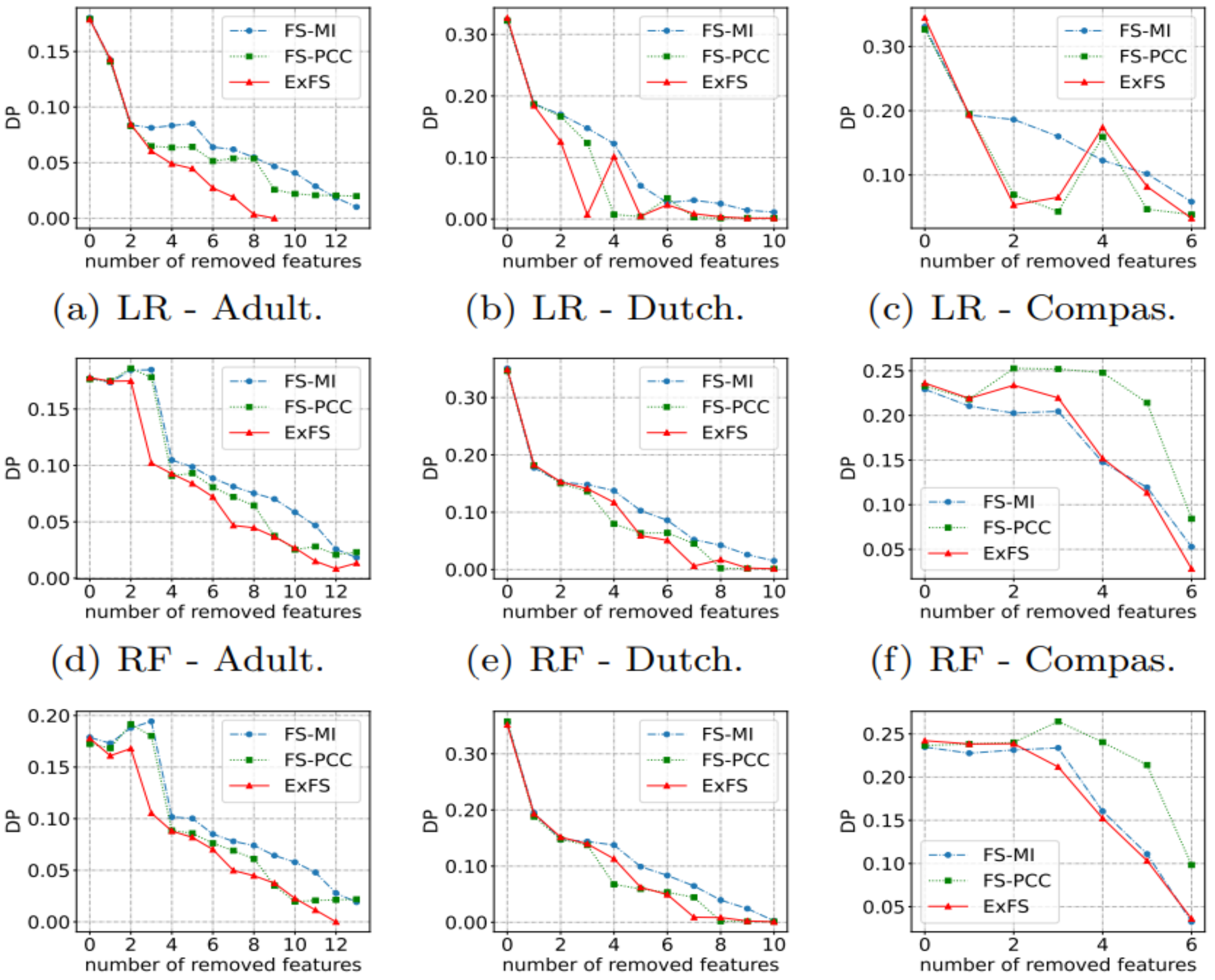
The train and test dataset split ratio is 7:3.

All reported results are the average results on the test set obtained from 15 different random splits.

4. Experimental Study

■ 4.2 Experimental results

We can see that the ExFS method tends to be **the most efficient method** for improving the DP metric, especially on the Adult dataset.



(a) LR - Adult. (b) LR - Dutch. (c) LR - Compas.

(d) RF - Adult. (e) RF - Dutch. (f) RF - Compas.

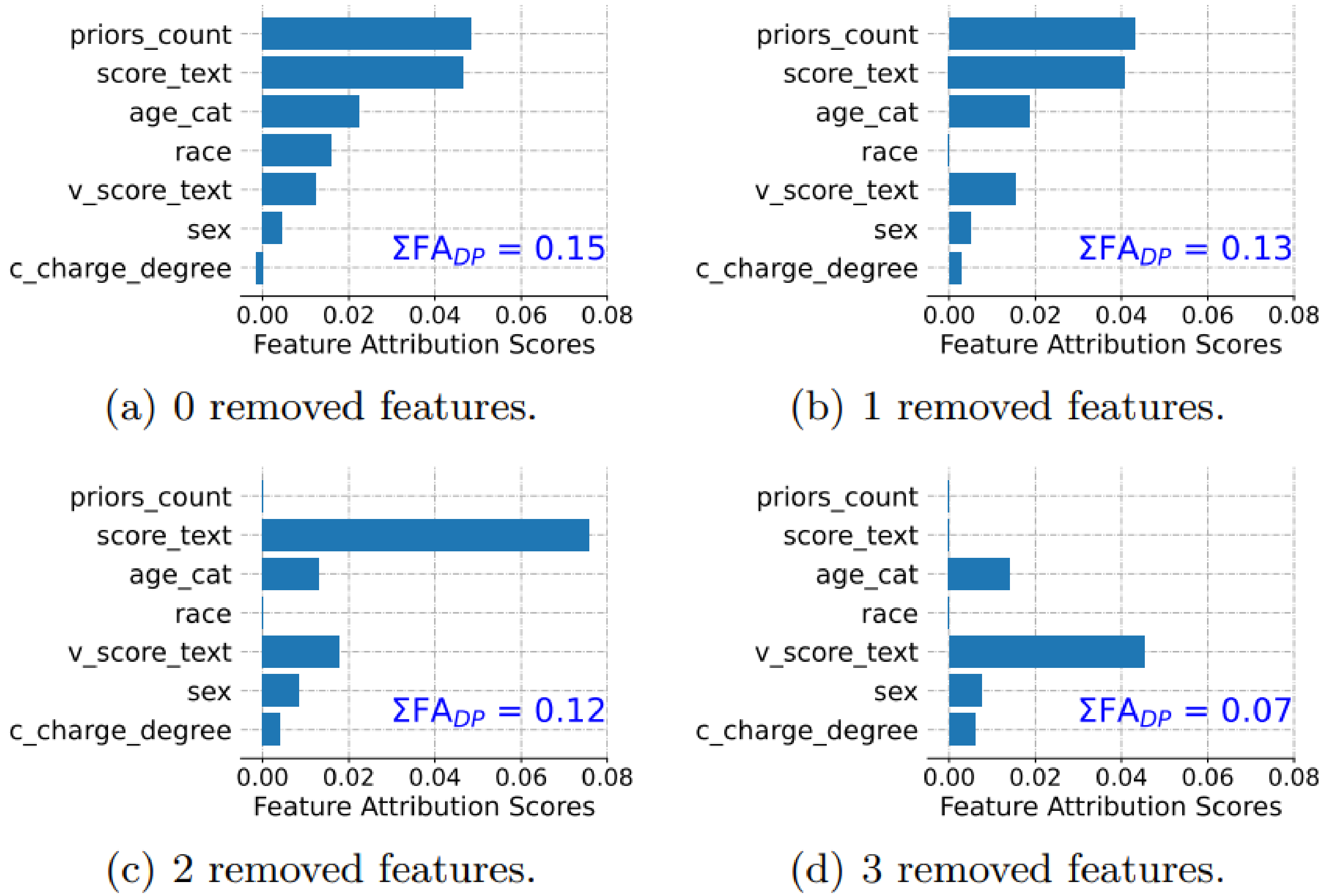
(g) MLP - Adult. (h) MLP - Dutch. (i) MLP - Compas.

The comparison results of filter approaches to enhance DP fairness metric on different datasets using different models.

4. Experimental Study

■ 4.2 Experimental results

ExFS method not only makes the selection process **transparent and understandable** but also helps us to analyze the reasons for the results generated by this selection.



Feature attribution explanations for DP on Compas dataset using MLP model.

4. Experimental Study

■ 4.2 Experimental results

ExFS approach generally performs **better** than the two filter-based methods (FS-MI and FS-PCC) on three fairness measurements and achieves **comparable** results to the two wrapper-based approaches (FS-GA and FS-NSGA-II).

Dataset	Model	Method	Fairness Measurement DP	EOp	EOd
Adult	LR	FS-MI	0.010 ± 0.011	0.012 ± 0.011	0.015 ± 0.008
		FS-PCC	0.020 ± 0.004	0.015 ± 0.013	0.017 ± 0.014
		FS-GA	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$	0.021 ± 0.012
		FS-NSGA-II	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$
		ExFS	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$
	RF	FS-MI	0.018 ± 0.007	0.019 ± 0.016	0.024 ± 0.019
		FS-PCC	0.021 ± 0.003	0.014 ± 0.011	0.019 ± 0.008
		FS-GA	$\mathbf{0.000 \pm 0.000}$	0.054 ± 0.021	0.022 ± 0.016
		FS-NSGA-II	$\mathbf{0.000 \pm 0.000}$	0.121 ± 0.027	$\mathbf{0.000 \pm 0.000}$
		ExFS	0.008 ± 0.003	$\mathbf{0.012 \pm 0.008}$	0.017 ± 0.007
	MLP	FS-MI	0.019 ± 0.008	0.022 ± 0.015	0.021 ± 0.013
		FS-PCC	0.020 ± 0.005	0.016 ± 0.009	0.020 ± 0.010
		FS-GA	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$	0.022 ± 0.013
		FS-NSGA-II	$\mathbf{0.000 \pm 0.000}$	0.111 ± 0.221	0.023 ± 0.011
		ExFS	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$	$\mathbf{0.000 \pm 0.000}$

The comparison results of all investigated fairness-aware feature selection approaches to enhance different fairness measurements.

5. Conclusion

- In summary, we proposed an ExFS approach that is capable of explaining and mitigating unfairness in ML models. The results of our experiments demonstrate that:
  - The effectiveness of our approach in improving the fairness of ML models.
  - ExFS method is transparent and is able to provide explanations for the rationale of why removing some features can lead to fairness enhancement.

- Furthermore, ExFS is computationally efficient, which requires a lower computational cost compared to wrapper-based methods.

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Thank You !