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Towards Private and Fair Machine Learning: Group-Specific Differentially Private Stochastic Gradient Descent with Threshold Optimization

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Outline

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1. Introduction

2. Related Work

3. Methodology

4. Experimental Study

5. Conclusion

1.Introduction

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Emphasize the importance of data privacy protection.

《GDPR》

Technique

- Differential Privacy
- Homomorphic Encryption
- Federated Learning

……

➢ **Differential Privacy (DP) has emerged as the predominant choice for ensuring data privacy[1].**

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1.Introduction

《ECOA》

Explicitly prohibits discrimination based on protected traits.

Existing ML algorithms exhibit varying degrees of discrimination in their decisions.

Fairness measurements

- Demographic Parity
- Accuracy Parity

Fairness-aware ML methods

- Pre-process
- In-process
- Post-process

1.Introduction

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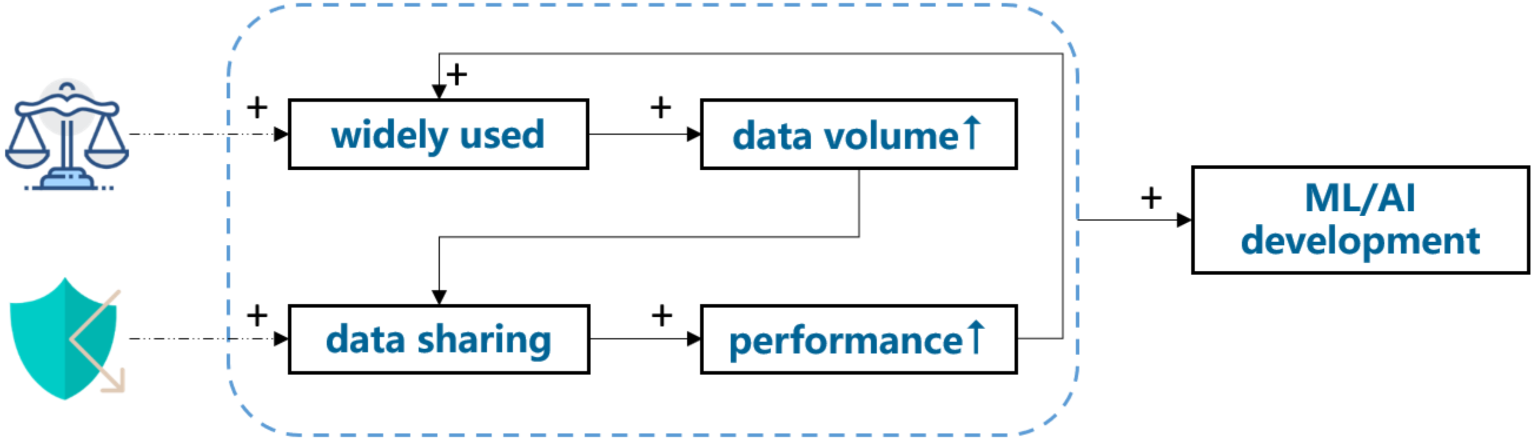
- From both ethical and legal perspectives, **fairness** and **privacy** are two crucial aspects for the development of ML/AI.



They are interrelated research issues rather than isolated challenges.

1.Introduction

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- Combining privacy and fairness poses challenges in two main categories: **addressing amplified unfairness due to DP** and **achieving outcome fairness in the ML model.**
- However, current methods often address the two objectives in isolation, overlooking their combined impact.
- To bridge this gap, we introduce **a group-specific DP stochastic gradient descent (DP-SGD) training mechanism with classification threshold optimization**, which concurrently addressing accuracy and outcome fairness issues in differentially private models.

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2.Related Work

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■Fairness measurements:

- Demographic Parity (DemParity) [2]:

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

- Accuracy Parity (AccParity) [3]:

$$|P(\hat{y} = y|s = s_a) - P(\hat{y} = y|s = s_b)| \leq \theta$$

2.Related Work

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- **Differentially Private Stochastic Gradient Descent (DP-SGD)[4]:**

Algorithm 1 DP-SGD

Input: Training dataset $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, the parameterized model $f_w(\cdot)$, loss function $\ell(\hat{y}, y)$ for prediction $\hat{y}$ and label y, iterations T, batch size b, learning rate η, noise scale σ, gradient norm bound C.

```
1: Initialize w^(0) randomly.
2: for t = 0, 1, ..., T − 1 do
3:     Sample a batch B^(t) from D with sampling probability b/N for each data point.
4:     for i ∈ B^(t) do
5:         g_i ← ∇ℓ(f_{w^(t)}(x_i), y_i)
6:         ḡ_i ← g_i · min(1, C/||g_i||_2)
7:     end for
8:     g̃ ← (1/b)(Σ_{i∈B^(t)} ḡ_i + N(0, σ²C²I))
9:     w^(t+1) ← w^(t) − ηg̃
10: end for
```

Output: Model $f_{w^{(T)}}(\cdot)$ and accumulated (ϵ, δ).

$$\bar{g}_i \leftarrow g_i \cdot min(1, \frac{C}{\|g_i\|_2})$$

$$\tilde{g} \leftarrow \frac{1}{b}\left(\sum_{i \in B^{(t)}} \bar{g}_i + \mathcal{N}(0, \sigma^2 C^2 \mathbf{I})\right)$$

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2.Related Work

- **Mitigating the unfairness amplified by DP.** Recent studies have found that incorporating DP into models can increase AccParity measurement between sensitive groups[3, 5-6]. Various efforts have been made to address this issue[6, 7].

- **Achieving outcome fairness in differentially private models.** Several works study how to achieve outcome fairness using fairness-aware learning when enforcing DP in the private model[8, 9].

3.Methodology

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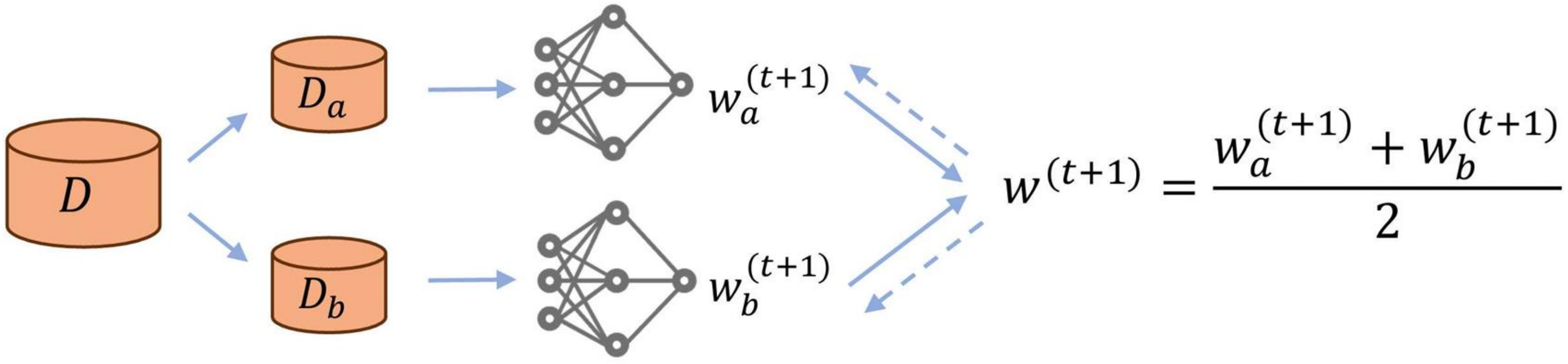
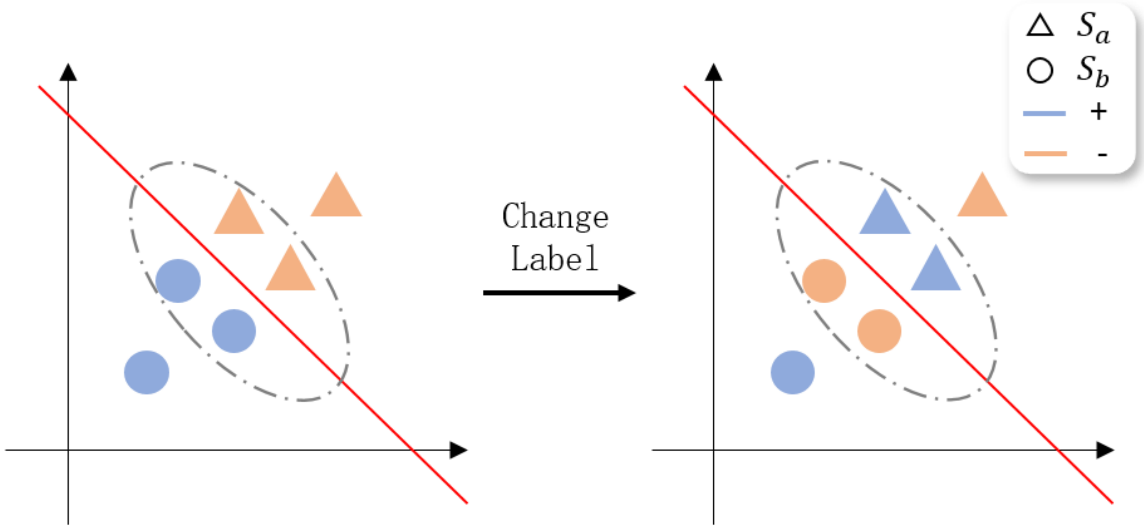
- We introduce GS-DP-SGD, a group-specific training strategy for DP-SGD that aims to alleviate the accuracy discrepancy exacerbated by DP-SGD.



3.Methodology

- To mitigate the outcome unfairness of the private model trained by GS-DP-SGD, we incorporate a post-processing method called reject option based classification (ROC)[10] .



Algorithm 4 Threshold Optimization based Classification (TOC)

Input: Validation dataset $D_{valid} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{M}$, fairness constraint θ, model $f_{w^{(T)}}$.

for $\gamma \in$ `linspace(0.5, 1, 100)` **do**
    for $\mathbf{x}_i \in D_{valid}$ **do**
        $\hat{y}_i = \mathrm{ROC}(f_{w^{(T)}}(\cdot), \gamma, \mathbf{x}_i)$
    end for
    $m_\gamma = |P(\hat{y}=1|s=s_a) - P(\hat{y}=1|s=s_b)|$
    if $m_\gamma \le \theta$ **then Return** γ
end for
Return the γ that has minimal m_γ

Output: The threshold γ.

3.Methodology

- Overall, we implement GS-DP-SGD with Threshold Optimization (referred to as GS-DP-SGD-TO) to address both the exacerbated accuracy disparity (i.e., AccParity)and the outcome fairness (i.e., DemParity) issues.

Algorithm 5 GS-DP-SGD-TO

Input: Training dataset D_{train}, validation dataset D_{valid}, the parameterized model $f_w(\cdot)$, loss function $\ell(\cdot,\cdot)$, iterations T, batch size b, learning rate η, noise scale σ, gradient norm bound C, fairness constraint θ.

1: $f_{w^{(T)}}, (\epsilon, \delta) = \text{GD-DP-SGD}(D_{train}, f(\cdot), \ell(\cdot,\cdot), T, b, \eta, \sigma, C)$

2: $\gamma = \text{TOC}(D_{valid}, \theta, f_{w^{(T)}})$

Output: The ROC model $\text{ROC}(f_{w^{(T)}}, \gamma, \cdot)$ and the accumulated (ϵ, δ).

4.Experimental Study

■Experimental Setup：

- ***Datasets:*** Six commonly used binary classification datasets relevant to fairness research: **Adult, Dutch, Bank, Credit, Compas, and Law**.
- ***Comparison Methods:*** Methods aiming to reduce accuracy disparity: **DP-SGD-F[6], DP-SGD-A[7], and GS-DP-SGD.** Methods aiming to achieve fairness in model decisions: **FairDP[8] and DP-SGD-P[9].**
- ***Model:*** **MLP** with two hidden layers of 256 units each, a maximum of 20 iterations.
- ***Evaluation Metrics:*** Two common group fairness metrics: **Accuracy Parity (AccParity) and Demographic Parity (DemParity)**.

4.Experimental Study

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■Compare with methods of alleviating the accuracy unfairness intensified by DP.

Dataset	Method	ϵ	Acc (↑)	AccParity (↓)	DemParity (↓)
Adult	SGD		0.848 ± 0.003	0.114 ± 0.008	0.191 ± 0.007
	DP-SGD	2.654	0.789 ± 0.005	0.154 ± 0.010	0.064 ± 0.005
	DP-SGD-F	2.667	0.829 ± 0.003	0.112 ± 0.008	0.210 ± 0.005
	DP-SGD-A	2.661	0.848 ± 0.003	0.114 ± 0.007	0.191 ± 0.010
	GS-DP-SGD	2.657	0.832 ± 0.005	0.116 ± 0.010	0.199 ± 0.057
	GS-DP-SGD-TO	2.658	0.837 ± 0.005	0.108 ± 0.015	0.047 ± 0.015
Dutch	SGD		0.834 ± 0.003	0.070 ± 0.006	0.335 ± 0.016
	DP-SGD	2.269	0.793 ± 0.005	0.111 ± 0.011	0.231 ± 0.033
	DP-SGD-F	2.280	0.812 ± 0.005	0.092 ± 0.008	0.232 ± 0.024
	DP-SGD-A	2.275	0.834 ± 0.004	0.069 ± 0.006	0.332 ± 0.017
	GS-DP-SGD	2.267	0.805 ± 0.008	0.081 ± 0.015	0.208 ± 0.064
	GS-DP-SGD-TO	2.267	0.786 ± 0.006	0.070 ± 0.026	0.052 ± 0.020
Compas	SGD		0.673 ± 0.014	0.027 ± 0.015	0.291 ± 0.021
	DP-SGD	4.118	0.623 ± 0.025	0.041 ± 0.022	0.170 ± 0.057
	DP-SGD-F	4.204	0.632 ± 0.021	0.035 ± 0.019	0.184 ± 0.044
	DP-SGD-A	4.161	0.678 ± 0.013	0.024 ± 0.016	0.281 ± 0.020
	GS-DP-SGD	4.113	0.676 ± 0.011	0.024 ± 0.020	0.287 ± 0.037
	GS-DP-SGD-TO	4.113	0.668 ± 0.010	0.029 ± 0.017	0.073 ± 0.060
Law	SGD		0.898 ± 0.004	0.160 ± 0.014	0.190 ± 0.018
	DP-SGD	3.671	0.888 ± 0.004	0.202 ± 0.015	0.000 ± 0.000
	DP-SGD-F	3.694	0.888 ± 0.004	0.202 ± 0.015	0.001 ± 0.001
	DP-SGD-A	3.683	0.898 ± 0.004	0.158 ± 0.015	0.182 ± 0.017
	GS-DP-SGD	3.679	0.895 ± 0.004	0.163 ± 0.021	0.139 ± 0.053
	GS-DP-SGD-TO	3.679	0.894 ± 0.004	0.176 ± 0.017	0.049 ± 0.024
Bank	SGD		0.900 ± 0.003	0.036 ± 0.007	0.035 ± 0.004
	DP-SGD	2.831	0.884 ± 0.004	0.050 ± 0.006	0.002 ± 0.001
	DP-SGD-F	2.845	0.887 ± 0.004	0.047 ± 0.007	0.007 ± 0.003
	DP-SGD-A	2.838	0.902 ± 0.003	0.036 ± 0.006	0.037 ± 0.005
	GS-DP-SGD	2.837	0.888 ± 0.005	0.043 ± 0.013	0.048 ± 0.031
	GS-DP-SGD-TO	2.837	0.901 ± 0.004	0.037 ± 0.008	0.026 ± 0.013
Credit	SGD		0.812 ± 0.004	0.024 ± 0.010	0.030 ± 0.006
	DP-SGD	3.365	0.778 ± 0.005	0.031 ± 0.008	0.000 ± 0.000
	DP-SGD-F	3.381	0.779 ± 0.006	0.029 ± 0.008	0.005 ± 0.006
	DP-SGD-A	3.373	0.817 ± 0.005	0.023 ± 0.011	0.033 ± 0.007
	GS-DP-SGD	3.366	0.809 ± 0.004	0.031 ± 0.013	0.035 ± 0.023
	GS-DP-SGD-TO	3.366	0.821 ± 0.006	0.026 ± 0.009	0.020 ± 0.009

4.Experimental Study

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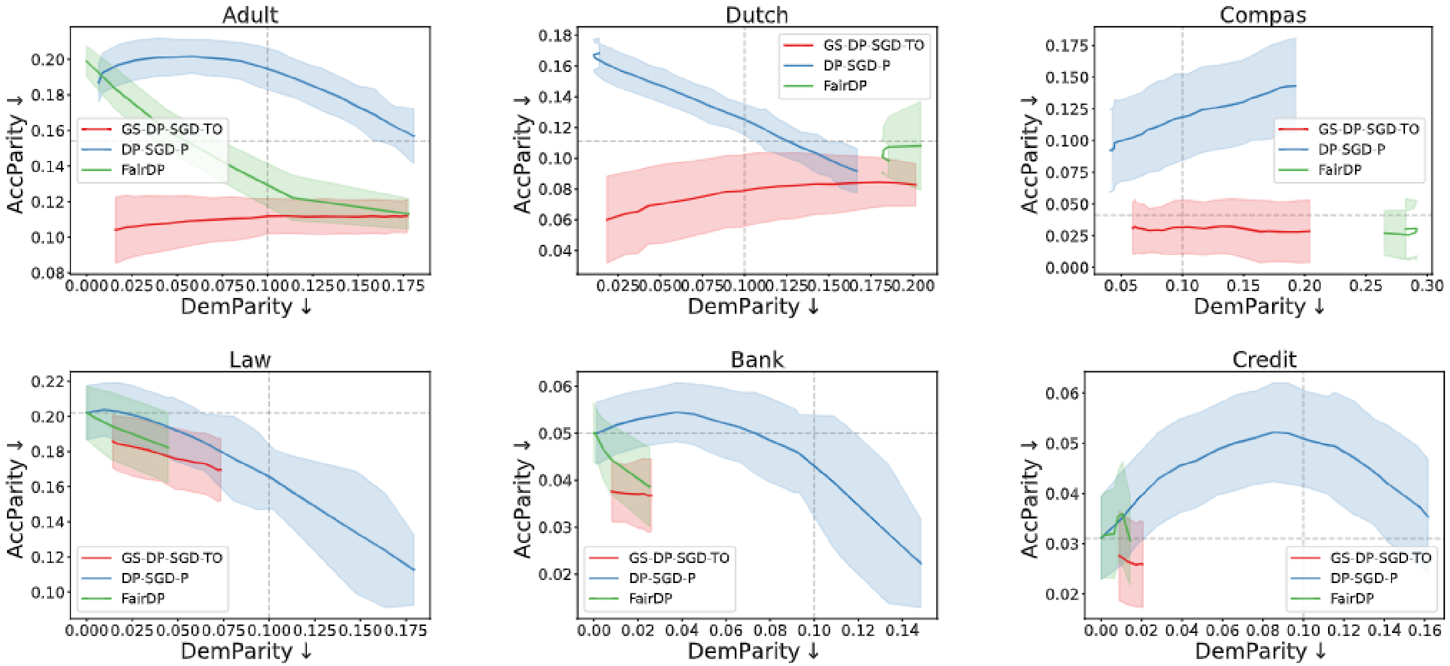
■Compare with methods of mitigating outcome unfairness for differentially private models.



GS-DP-SGD-TO reliably and effectively reduces the AccParity value.

4.Experimental Study

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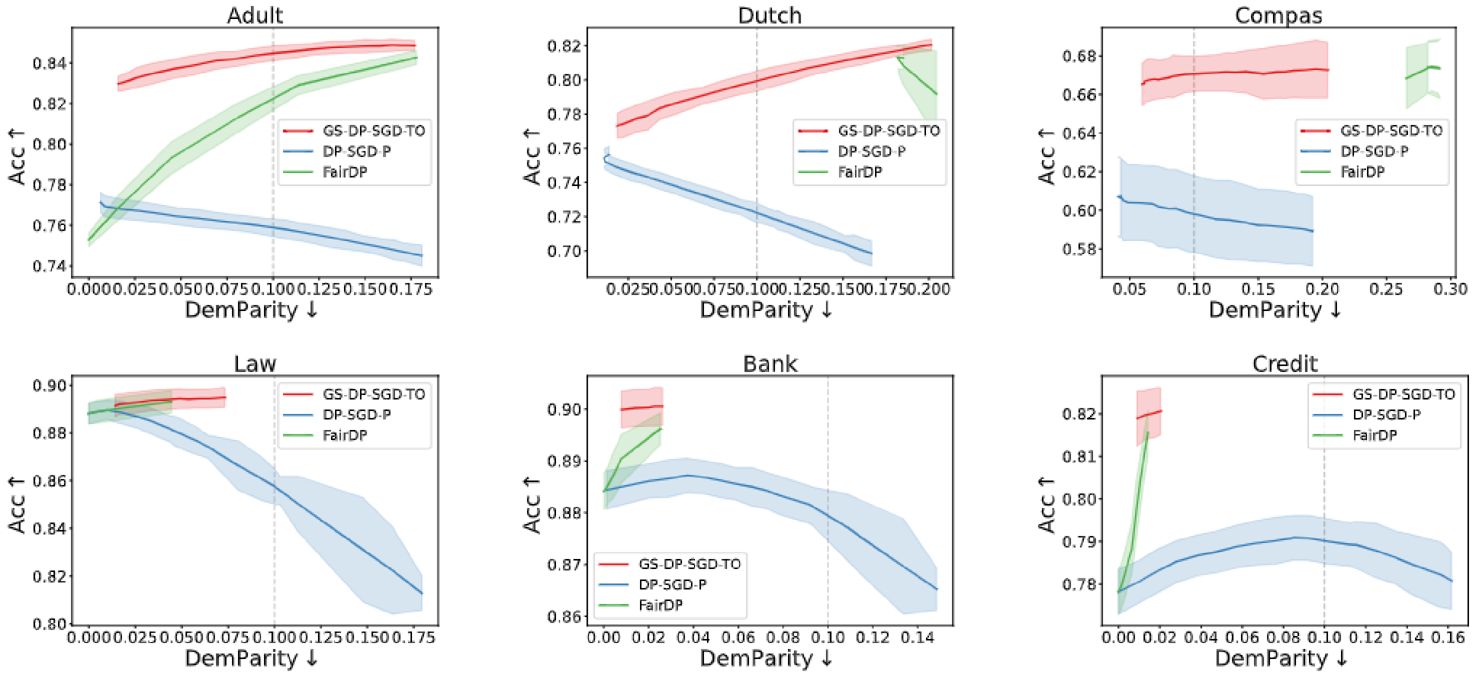

GS-DP-SGD-TO achieves the highest accuracy at the same DemParity value.

5.Conclusion

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- Our approach uses group-specific DP-SGD during training to reduce accuracy disparity, followed by threshold optimization to improve outcome fairness.

- Extensive experiments confirm its effectiveness across datasets, balancing AccParity and DemParity with reasonable utility.

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5.Conclusion

■Limits:

- The outcome fairness metric may exceed the predefined constraint due to threshold selection based on the validation set.

- It currently applies only to binary classification tasks and single sensitive attributes.

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Thank you!

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