Fairness and Explainability: Bridging the Gap Towards Fair Model Explanations

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for code and more details

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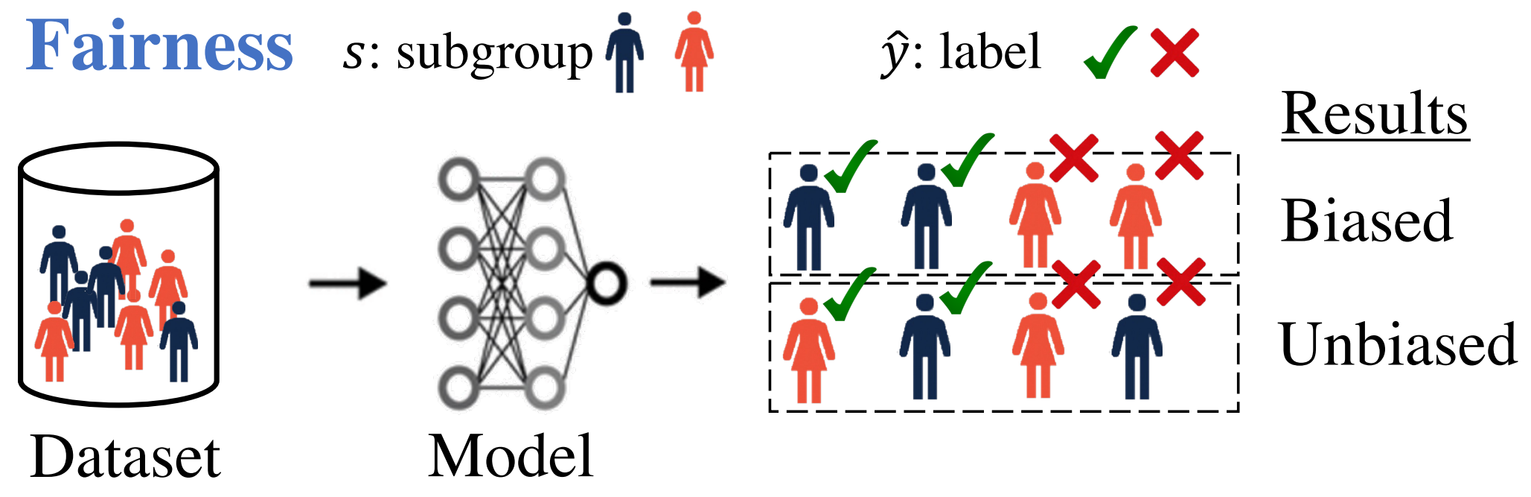
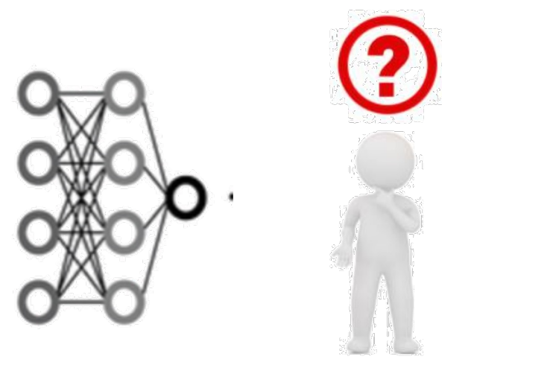
Fairness and Explainability



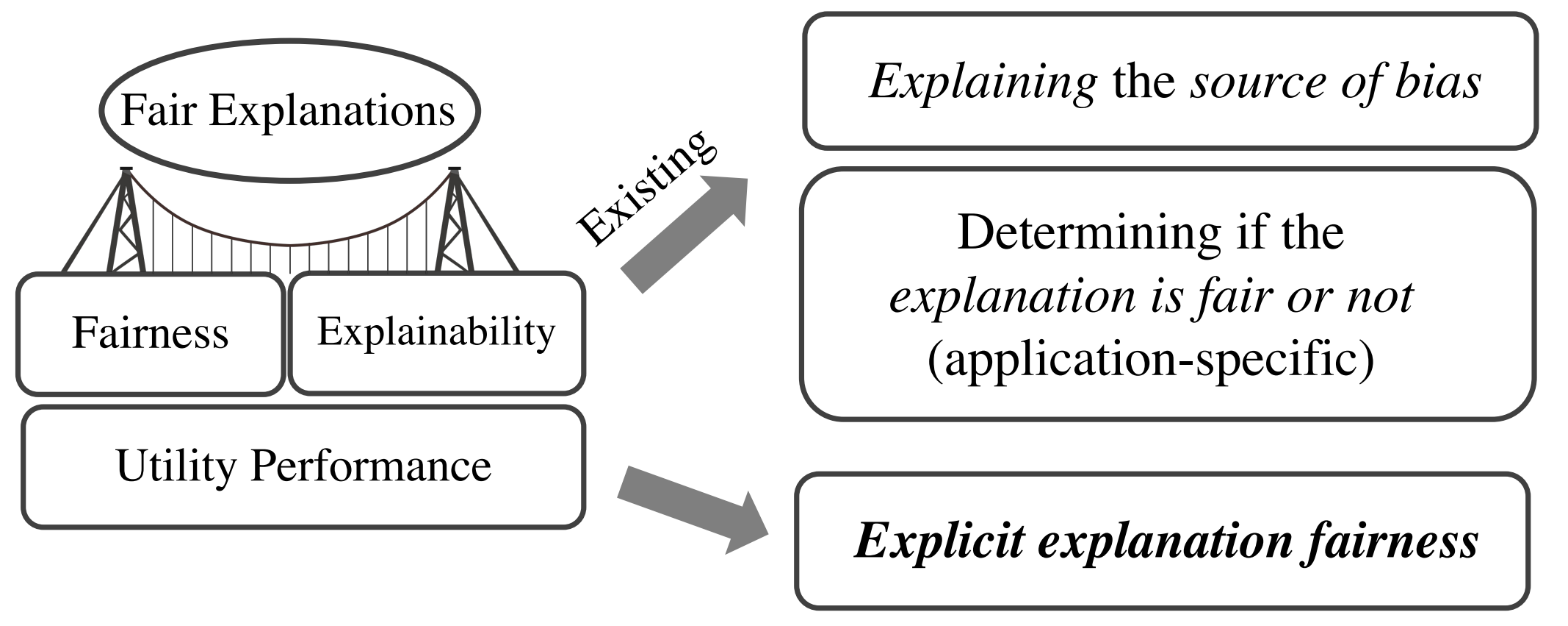
Explainability



Why should we trust the model?

Why did the model make a certain decision?

Fairness and Explainability

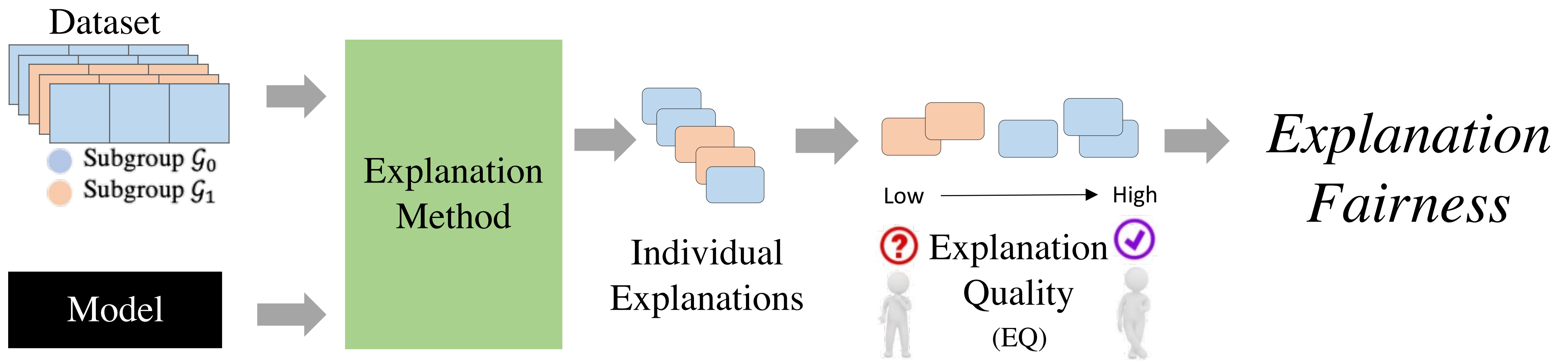


Explaining the *source of bias*

Determining if the *explanation is fair or not* (application-specific)

Explicit explanation fairness

Novel Procedure-Oriented Fairness Perspective



(1) Ratio-based Fairness Δ_{REF}

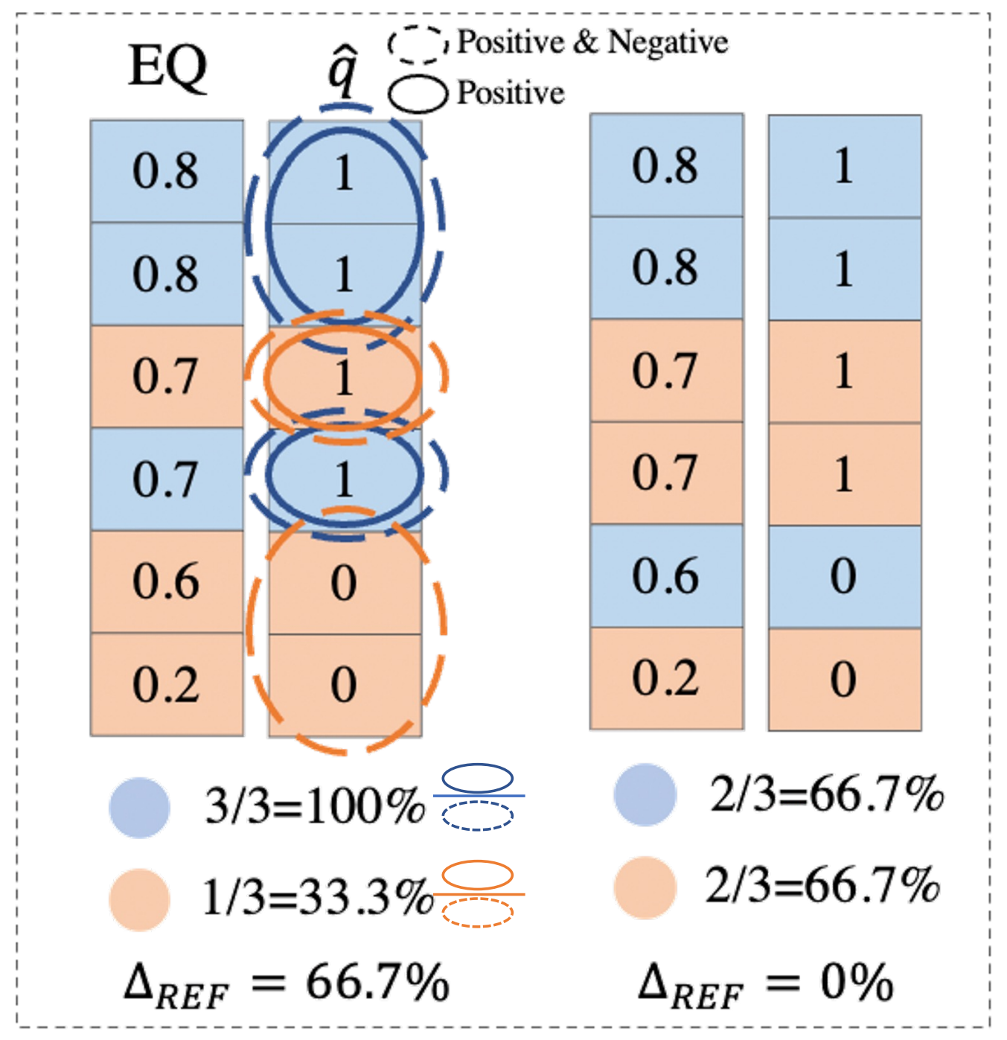
$$\Delta_{SP} = |P(\hat{y}=1|s=0) - P(\hat{y}=1|s=1)|$$

Same opportunity of having positive prediction

$$\Delta_{REF} = |P(\hat{q}=1|s=0) - P(\hat{q}=1|s=1)|$$

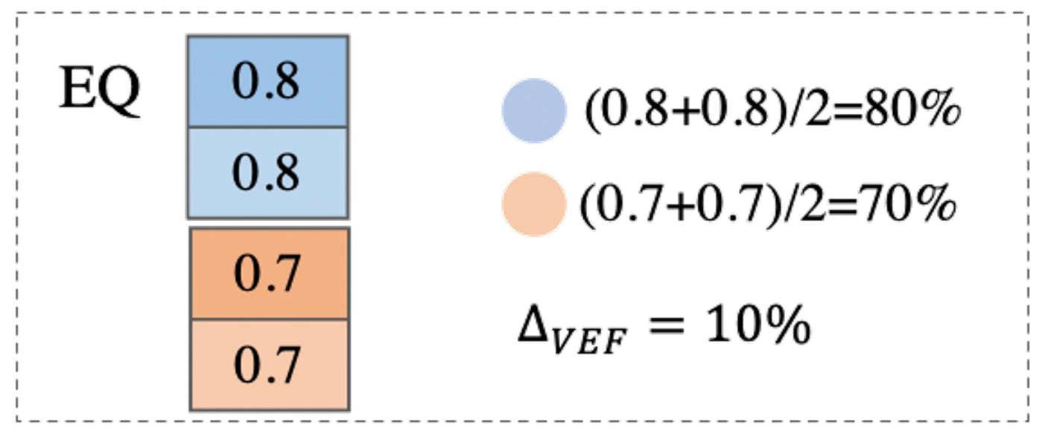
Same opportunity of having high-quality explanations

$\hat{y}$: prediction $\hat{q}$: explanation quality s: sensitive labels



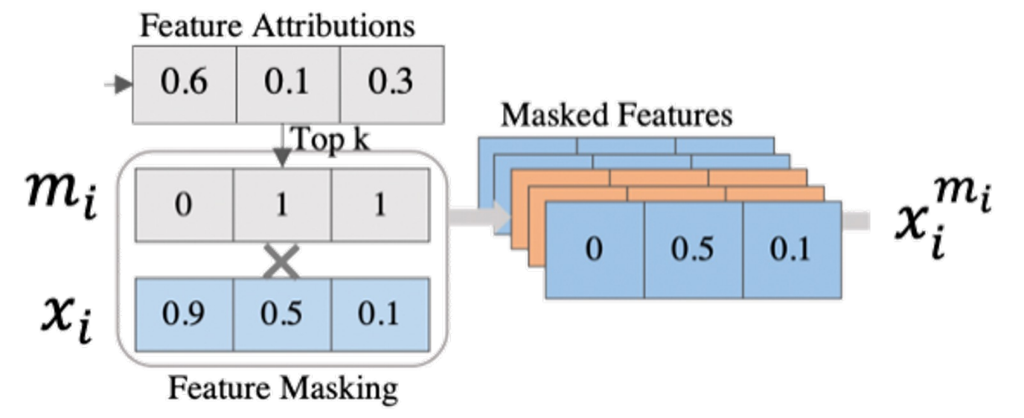
(2) Value-based Fairness Δ_{VEF}

$$\Delta_{\mathrm{VEF}} = \left| \frac{1}{|\mathcal{G}_0^K|} \sum_{i \in \mathcal{G}_0^K} \mathrm{EQ}_i - \frac{1}{|\mathcal{G}_1^K|} \sum_{i \in \mathcal{G}_1^K} \mathrm{EQ}_i \right|$$

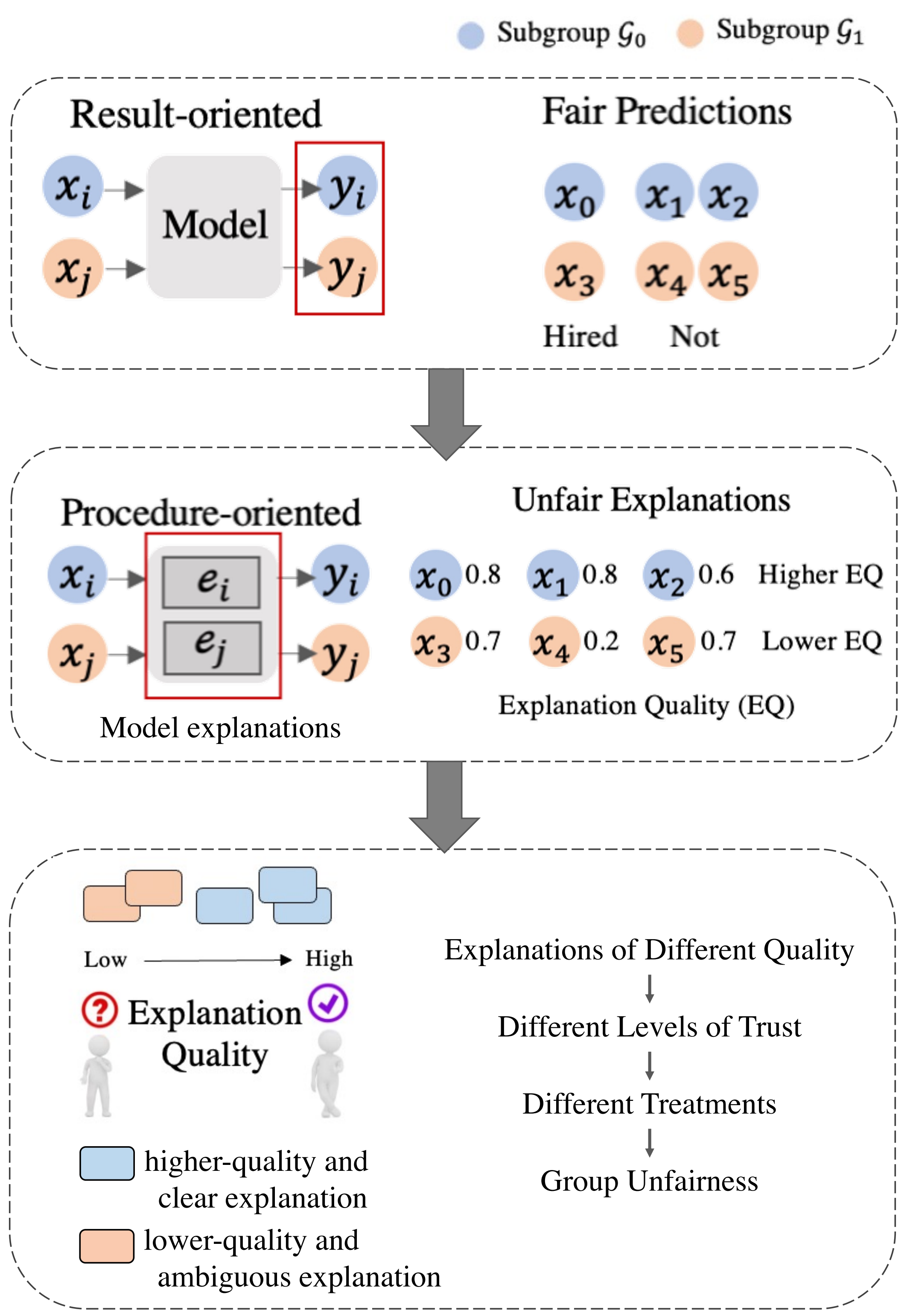


EQ: Fidelity of Model

$$\Delta_{F_i} = P(\hat{y}_i = y_i | x = x_i) - P(\hat{y}_i = y_i | x = x_i^{m_i})$$

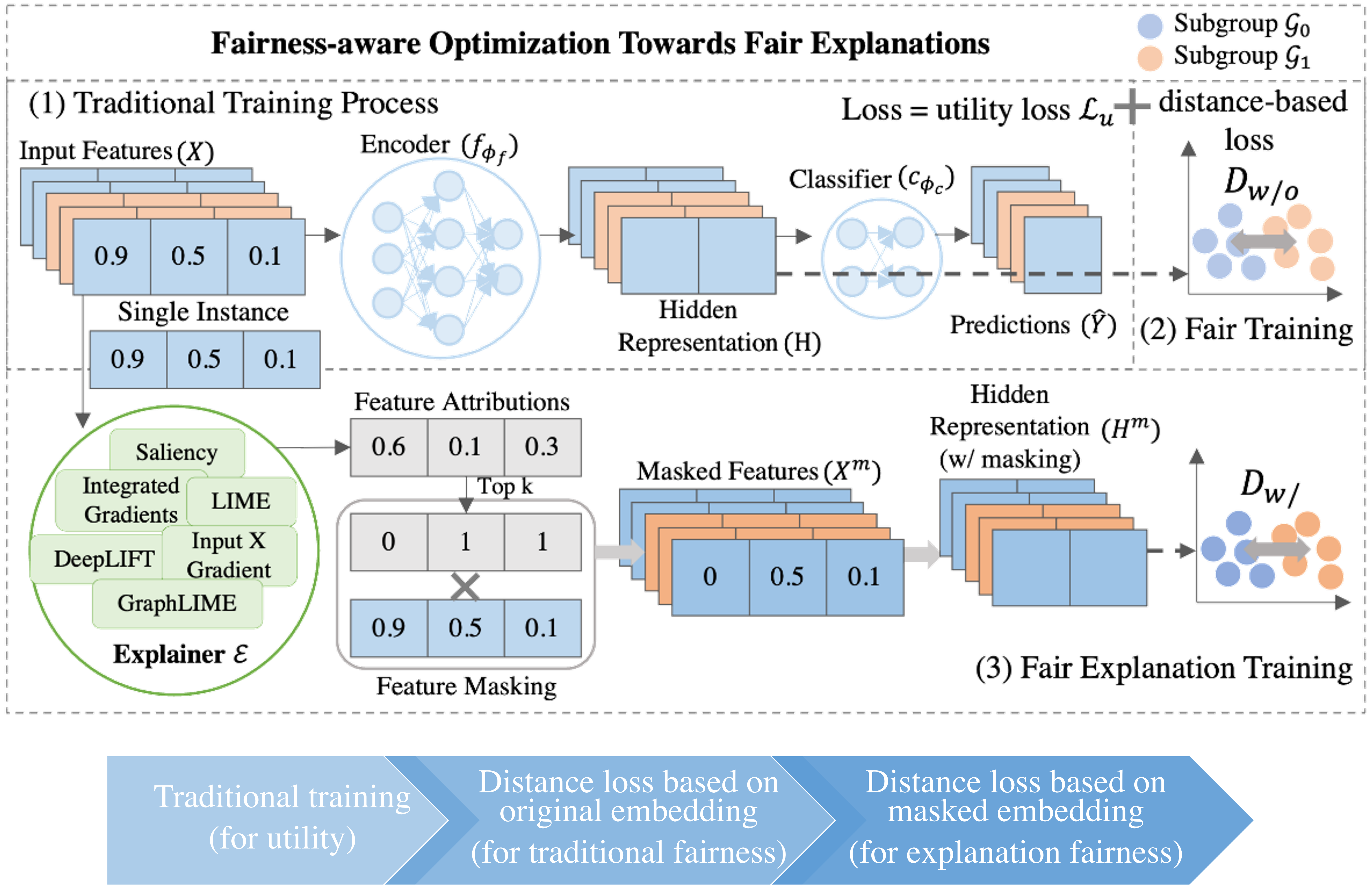


Motivation



Explanations of Different Quality
↓
Different Levels of Trust
↓
Different Treatments
↓
Group Unfairness

Comprehensive Fairness Algorithm (CFA)



Fairness-aware Optimization Towards Fair Explanations

(1) Traditional Training Process

Loss = utility loss $\mathcal{L}_u$ + distance-based loss

(2) Fair Training

(3) Fair Explanation Training

Traditional training (for utility) → Distance loss based on original embedding (for traditional fairness) → Distance loss based on masked embedding (for explanation fairness)

Experiments

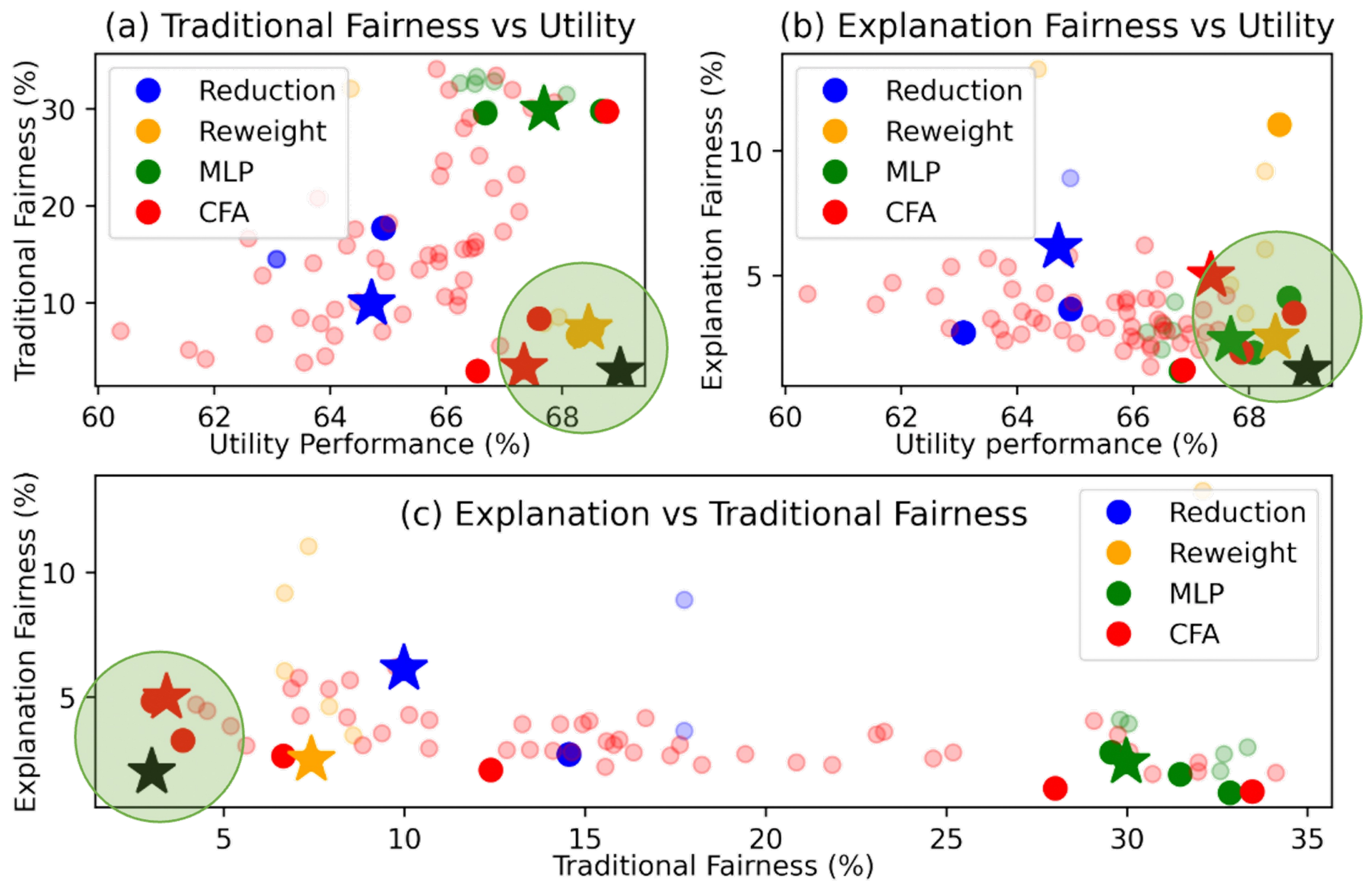
RQ1: Bias Mitigation

Dataset	Metric	MLP	Reduction	Reweight	CFA
Recidivism	AUC↑	86.12 ± 1.91	81.17 ± 0.00	**89.24 ± 0.00**	89.02 ± 0.86
	F1↑	76.54 ± 2.52	76.69 ± 0.00	72.99 ± 0.00	**81.28 ± 1.35**
	Acc↑	83.48 ± 1.53	84.66 ± 0.00	83.70 ± 0.00	**87.17 ± 0.84**
	Δ_{SP} ↓	6.07 ± 2.18	2.04 ± 0.00	4.27 ± 0.00	**1.16 ± 0.49**
	Δ_{EO} ↓	3.19 ± 0.73	4.66 ± 0.00	3.37 ± 0.00	**1.14 ± 0.39**
	Δ_{REF} ↓	4.45 ± 2.96	**0.53 ± 0.00**	1.34 ± 0.91	1.98 ± 1.23
	Δ_{VEF} ↓	2.1 ± 1.38	**2.06 ± 0.00**	3.22 ± 0.00	2.70 ± 0.78
	Score ↑	74.15 ± 2.03	76.19 ± 0.00	75.88 ± 0.00	**82.33 ± 0.62**
Por	AUC↑	90.86 ± 0.35	67.64 ± 0.00	89.07 ± 0.00	**91.30 ± 0.55**
	F1↑	58.41 ± 4.10	51.43 ± 0.00	51.43 ± 0.00	**60.55 ± 4.73**
	Acc↑	89.57 ± 0.78	89.57 ± 0.00	89.57 ± 0.00	**89.82 ± 1.00**
	Δ_{SP} ↓	2.08 ± 0.75	1.93 ± 0.00	1.93 ± 0.00	**1.00 ± 0.72**
	Δ_{EO} ↓	32.35 ± 7.07	**20.59 ± 0.00**	**20.59 ± 0.00**	27.65 ± 5.44
	Δ_{REF} ↓	8.68 ± 3.18	**1.37 ± 0.00**	8.68 ± 0.00	4.66 ± 3.76
	Δ_{VEF} ↓	4.44 ± 2.22	**0.00 ± 0.00**	7.69 ± 0.00	4.70 ± 3.67
	Score ↑	55.83 ± 3.97	57.60 ± 0.00	57.25 ± 0.00	**61.55 ± 3.26**

🟧 Utility Performance
🟦 Traditional Fairness
🟩 Explanation Fairness
🟨 Overall Score

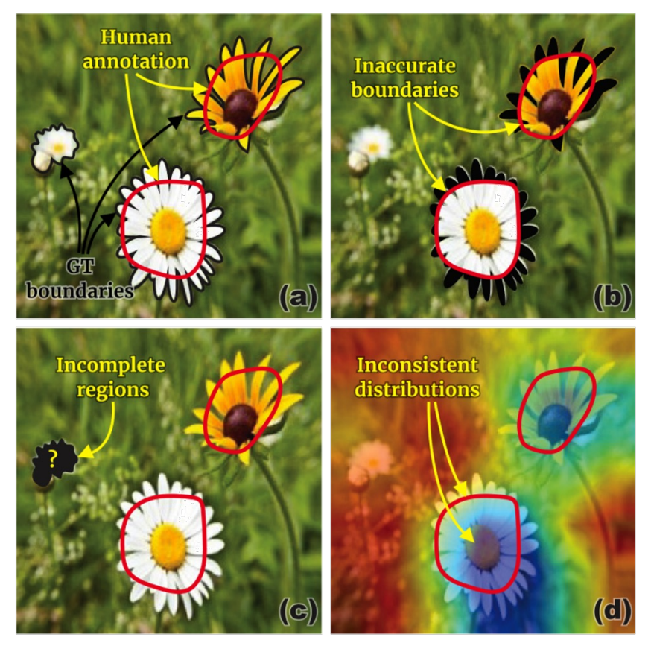
Overall score: $\frac{\mathrm{AUC+F1+ACC}}{3} - \frac{\Delta_{SP}+\Delta_{EO}}{2} - \frac{\Delta_{VEF}+\Delta_{REF}}{2}$ (model selection)

RQ2: Multi-objective Tradeoff

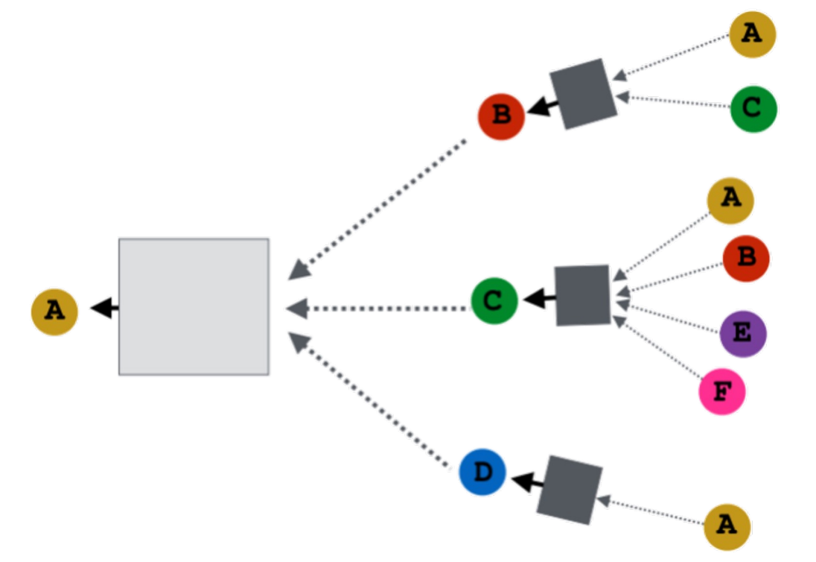


Future Directions

Extending CFA
- Data types
- EQ metrics



Fair and Explainable Graph Neural Networks



Fair Explanation for Inherently Explainable Models (e.g., Decision Tree)