



Conference Paper

Optimizing Fairness in AI for Credit Scoring: Constraint-Based and Adversarial Approaches

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Abstract

Artificial intelligence (AI) is transforming decision-making processes in finance, notably in credit scoring, where machine learning (ML) models enhance predictive accuracy. However, these models often rely on historical data containing biases, leading to unfair treatment of certain demographic groups based on race or gender. This paper presents two optimisation-based methods to enforce fairness in ML for credit scoring. The first approach uses constraint-based optimisation to reduce bias by regularising the decision boundary, while the second employs adversarial learning to equalise score distributions across demographic groups. Applied to real-world datasets, these methods achieve demographic parity, upholding fairness without significantly sacrificing predictive performance. The findings suggest that integrating fairness constraints into AI models can help finance applications mitigate discrimination, leading to more equitable outcomes in credit scoring.

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INTRODUCTION

Lately, AI (ML) and computerised reasoning (artificial intelligence) have acquired an unmistakable quality in high-stakes dynamic situations. Uses of ML calculations have been proposed for regions, for example, credit scoring [1], customised medication [2], and recidivism prediction [3].

Given the far-reaching reception of ML/simulated intelligence innovations, it is pivotal to guarantee that their execution doesn't propagate cultural shamefulness. ML models intrinsically rely upon authentic information to recognise examples and make forecasts. Nonetheless, verifiable shameful acts against safeguarded subgroups might bring inclination to the information. Preparing models on such one-sided details can bring about oppressive calculations. Involving these one-sided calculations in basic navigation can prompt further treacheries and create a cycle of criticism that supports cultural imbalances. Consequently, it is vital to create techniques to uphold decency in ML forecasts. This paper introduces two enhancement-based techniques to address this test. These techniques adjust the goal elements of ML calculations, integrating reasonableness imperatives as regularisation terms. The proposed approaches utilise brain organisations, which have made outstanding progress in various fields.

Our analyses use the *Adult Pay Dataset*, obtained from the 1994 statistics [4]. The outcomes exhibit that the proposed techniques essentially lessen inclination, characterised as *disparate impact*, while keeping up with wanted degrees of *demographic parity* with negligible exactness loss.

A. Related Work

The field of fair ML has been filled because of the disclosure of biases in calculations utilised in basic applications.

One generally examined case is COMPAS, a model used in the US equity framework to forecast recidivism probabilities. Despite its prescient abilities, [5] COMPAS excessively affected African-American respondents contrasted with Caucasian partners.

Inside the ML writing, various decency rules have been proposed to evaluate and alleviate biases. For example, [6] presented *equality of odds*, which guarantees equivalent Genuine Positive and Bogus Positive Rates across safeguarded gatherings [7]. proposed *counterfactual fairness*, a causal way to deal with decency. A far-reaching survey by [8] illustrated 21 reasonableness definitions and their cultural ramifications. This paper centres around *demographic parity*, one of the earliest and least difficult reasonableness measures with huge legitimate ramifications for recognising separation.

A few systems have been created to relieve predispositions considering race, orientation, and different variables. Early methodologies included pre-handling information to learn fair portrayals [9, 10]. Nonetheless, these strategies frequently experienced flighty precision compromises.

Limitation-based approaches brought decency requirements into model preparation. For instance, [11] added punishments to

calculated relapse classifiers to lessen predisposition, while [12] proposed a generalizable structure by punishing choice limit properties.

Ill-disposed learning has likewise been applied to authorise reasonableness. [13] utilised shared secret layers across organisations to guarantee segment equality. [14] used ill-disposed networks where an indicator expands exactness, and a foe upholds reasonableness.

In this paper, the strategies outlined in [12] and [14] are expanded upon to design classifiers that balance fairness and accuracy.

BACKGROUND

A. Adult Pay Dataset

The grown-up pay dataset [4] contains information gathered from $N = 32,561$ respondents during the 1994 US Registration. Every individual n is portrayed by $J = 14$ properties, addressed as $\mathbf{x}_n = \{x_n^{(1)}, x_n^{(2)}, \dots, x_n^{(J)}\}$, including elements, for example, training level, occupation type, capital additions, capital misfortunes, and weekly working hours. The goal is to foresee a double factor $y_n \in \{0, 1\}$, where $y_n = 1$ shows a yearly pay surpassing \$50,000.

In this specific situation, the safeguarded ascribes \mathbf{z}_n for individual n , *sex* and *race*. Authentic differences have brought about the underrepresentation of women and African Americans, earning over \$50,000 yearly. Utilising an innocently prepared model on this dataset for high-stakes choices, for example, credit endorsements or pay assurance, might propagate inclination, highlighting the requirement for reasonableness-conscious preparation strategies.

B. Disparate Effect and Segment Parity

Disparate impact emerges when one-sided model forecasts lead to results that lopsidedly weakness or advantage people in light of delicate properties. This idea was first expressed by [12]. Simply barring delicate characteristics \mathbf{z} from the dataset while preparing on the excess attributes $\mathbf{x} \setminus \mathbf{z}$ may in any case yield one-sided expectations because of connections among \mathbf{z} and $\mathbf{x} \setminus \mathbf{z}$ [15].

To address the unique effect, the aim is to enforce *demographic parity*, which requires that the prediction distribution remains invariant to changes in protected class membership. Let $p^*(y = 1)$ address the model's anticipated likelihood for the positive class. Segment equality is officially characterised as:

$$P(\hat{y} = 1 \mid \mathbf{z} = k_1) = P(\hat{y} = 1 \mid \mathbf{z} = k_2), \quad (1)$$

where k_1 and k_2 are unmistakable acknowledgements of the safeguarded characteristic \mathbf{z} . For example, if \mathbf{z} means orientation, k_1 could address Male and k_2 , Female. Instinctively, this implies that adjusting the safeguarded quality shouldn't influence the model's expectations.

Taking on segment equality as a reasonableness metric enjoys a few benefits. Outstandingly, it is upheld by legal points of

reference in the US. In 1978, administrative organisations like the EEOC, Branch of Work, and Division of Equity laid out the four-fifths rule to assess antagonistic unique effects [16]. In particular, the standard requires:

$$\min \left\{ \frac{P(\hat{y} = 1 | \mathbf{z} = k_1)}{P(\hat{y} = 1 | \mathbf{z} = k_2)}, \frac{P(\hat{y} = 1 | \mathbf{z} = k_2)}{P(\hat{y} = 1 | \mathbf{z} = k_1)} \right\} \geq \frac{q}{100}, \quad (2)$$

where $q = 80$ in the lawful definition, while $q = 100$ relates to consummate segment equality. [17] further contended that the momentary requirement of segment equality encourages long-haul value in labour markets.

Methods for Implementing Segment Parity

We present two streamlining-based methodologies for accomplishing segment equality in brain organisations. A brain network comprises a progression of direct and nonlinear changes applied to an info vector \mathbf{x} to deliver a result \mathbf{h}_L [18]. An L -layer brain organisation can be communicated as:

$$\mathbf{h}_1 = f_1(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1), \quad (3)$$

$$\mathbf{h}_2 = f_2(\mathbf{W}_2 \mathbf{h}_1 + \mathbf{b}_2), \quad (4)$$

$$\dots \quad (5)$$

$$\mathbf{h}_L = f_L(\mathbf{W}_L \mathbf{h}_{L-1} + \mathbf{b}_L), \quad (6)$$

where each \mathbf{W}_ℓ and \mathbf{b}_ℓ address the weight lattice and inclination vector for layer ℓ , f_ℓ is a component-wise nonlinear actuation capability, and \mathbf{h}_ℓ is the secret state at layer ℓ . For paired characterisation, the last layer regularly utilises a sigmoid initiation $\sigma(a) = \frac{1}{1+e^{-a}}$, compelling the result $\hat{p} = \mathbf{h}_L$ to $[0,1]$ and empowering probabilistic translation. Given nonlinearity decisions $\{f_\ell\}_{\ell=1}^L$, the boundaries $\{\mathbf{W}_\ell, \mathbf{b}_\ell\}_{\ell=1}^L$ are enhanced by limiting the *binary get entropy loss* Q_0 over the dataset:

$$Q_0 = - \sum_{n=1}^N [y_n \log \hat{p}_n + (1 - y_n) \log(1 - \hat{p}_n)], \quad (7)$$

where \hat{p}_n is the model’s anticipated likelihood for test n .

A. Regularising Choice Limit Covariance

To uphold segment equality, [12] presented the idea of regularising the covariance between the choice limit distances of a classifier and the safeguarded credits z . Their technique, initially intended for strategic relapse and backing vector machines, can reach out to brain organisations.

For a brain network parallel classifier depicted in Condition 6, the choice limit distance $d^{(n)}$ of a preparation model n is characterised as:

$$d^{(n)} = \mathbf{W}^{(L)} \mathbf{h}_{L-1}^{(n)} + \mathbf{b}^{(L)}, \quad (8)$$

where $d^{(n)}$ addresses the worth before applying the last nonlinearity. This value demonstrates the classifier’s certainty level, with positive qualities leaning toward class 1 and negative qualities leaning toward class 0. Segment equality infers that the covariance between d and z ought to be zero, implying that expectations are free of the safeguarded trait z . The exact covariance can be assessed as:

$$\text{Cov}(z, d) \approx \frac{1}{N} \sum_{n=1}^N (z^{(n)} - \bar{z}) \cdot d^{(n)}, \quad (9)$$

where $\bar{z} = \frac{1}{N} \sum_{n=1}^N z^{(n)}$. For brain organisations, this covariance is incorporated as a regularisation term in the goal capability. The changed parallel cross-entropy misfortune becomes:

$$Q_1 = \sum_{n=1}^N y^{(n)} \log \hat{p}^{(n)} + (1 - y^{(n)}) \log(1 - \hat{p}^{(n)}) \quad (10)$$

$$+ \lambda \cdot \left| \frac{1}{N} \sum_{n=1}^N (z^{(n)} - \bar{z}) \cdot d^{(n)} \right|, \quad (11)$$

where λ is the regularisation boundary controlling the tradeoff between precision and reasonableness. By changing λ , the model can accomplish segment equality without seriously compromising precision.

Regularising with Antagonistic Networks

Antagonistic preparation, at first presented by [19] for generative ill-disposed networks (GANs), can likewise be applied to decency in AI [14]. The ill-disposed structure comprises two organisations: the *primary classifier* G , which predicts the objective name, and the *adversary* A , which predicts the shielded characteristic z from the logits of G .

For the essential classifier G , the logits $d^{(n)}$ for preparing model n are given by:

$$d(n) = \sigma^{-1}(p^{(n)}), \quad (12)$$

Where σ is the sigmoid capability. The enemy A figures out how to foresee z utilising $d^{(n)}$. Its misfortune capability is characterised as:

$$Q_A = \sum_{n=1}^N z^{(n)} \log A(d^{(n)}) + (1 - z^{(n)}) \log(1 - A(d^{(n)})). \quad (13)$$

The essential classifier G is prepared to limit its arrangement misfortune Q_0 while amplifying the enemy’s misfortune Q_A . The consolidated misfortune for G is:

$$Q_2 = Q_0 - \alpha \cdot Q_A, \quad (14)$$

Where α is a hyperparameter that totals exactness and decency. At the point when Q_A is boosted, A can’t foresee z from G ’s results, showing that G has accomplished segment equality.

The antagonistic preparation process limits the Jensen-Shannon (JS) uniqueness [19] between the restrictive circulations $q_1 = d|z = k_1$ and $q_2 = d|z = k_2$. The JS dissimilarity is:

$$JS(q_1, q_2) = \frac{1}{2} \text{KL}(q_1 || q_{12}) + \frac{1}{2} \text{KL}(q_2 || q_{12}), \quad (15)$$

where and KL signifies the Kullback-Leibler difference. Limiting this dissimilarity guarantees that the circulations $d | z = k_1$ and $d | z = k_2$ are undefined, accomplishing decency according to segment equality.

RESULTS

Our examinations, led on the Grown-up Pay dataset, assess the exhibition of a gauge brain organisation and feature how it experiences dissimilar effects. Along these lines, Techniques enforcing demographic parity are implemented to address this issue, with all experiments conducted using the PyTorch library [20].

A. Baseline Brain Network

We train a basic brain network with $L = 2$ layers that perform well on the Grown-up Pay dataset. The info highlights are $\mathbf{x} \setminus \mathbf{z}$, barring delicate properties like sex and race. The engineering incorporates a secret layer $h^{(1)}$ with 64 units. The enactment capabilities are ReLU for $f^{(1)}$ and sigmoid for $f^{(2)}$. Loads and predispositions $\{W^{(1)}, W^{(2)}, b^{(1)}, b^{(2)}\}$ are introduced from $N(0, 1)$. The dataset comprises $N = 32,561$ people, split into a preparation set D_{train} of 26,048 tests and a test set D_{test} of 6,513 tests (80%-20% split). Preparing improves the parallel cross-

entropy misfortune capability from Condition 7, utilising the ADAM enhancer [21] with a batch size of 1,024 for 20 epochs.

In one test set, t , the model achieves an exactness of 85.00

a) Disparate Impact

Figure 1 envisions the bit thickness evaluations of anticipated probabilities $p^*(y = 1)$ across genders (Male versus Female) and races (Minorities versus White) in D_{test} . Dispersions contrast quite. Allow $D_{\text{test}}^{\text{Male}}$ and $D_{\text{test}}^{\text{Female}}$ to address subsets of D_{test} in view of sex. The reasonableness metric q , estimating adherence to segment equality, is characterised as:

$$q = \frac{|D_{\text{test}}^{\text{Female}}| - 1 \sum_{n \in D_{\text{test}}^{\text{Female}}} \hat{p}_n}{|D_{\text{test}}^{\text{Male}}| - 1 \sum_{n \in D_{\text{test}}^{\text{Male}}} \hat{p}_n}, \quad (16)$$

where \hat{p}_n signifies the anticipated likelihood for test n . For sex, $q = 41.82\%$ shows a huge predisposition against females.

Also, subsets $D_{\text{test}}^{\text{Minorities}}$ and $D_{\text{test}}^{\text{White}}$ feature racial difference, with $q = 63.63\%$. The two qualities abuse the 80% rule ordinarily utilised in legal and reasonableness settings. Table I sums up the mean anticipated probabilities for delicate gatherings.

Table 1: Mean anticipated probabilities of procuring over 50k for sensitive groups in the benchmark neural network.

Female	Male	Minorities	White
0.128	0.304	0.160	0.252

These differences show the dataset’s one-sided nature and the benchmark model’s constraints on fair dynamics in touchy settings.

B. Regularising Choice Limit Covariance

We take on the methodology point by point in Area III-A to address the unique effect in the vanilla brain network depicted in Segment. The engineering and preparation of hyperparameters are consistent with the previous design. Notwithstanding, rather than utilising the standard parallel cross-entropy loss L_0 , a regularised objective L_1 is introduced, which penalises selection boundary covariance, as expressed in Condition.

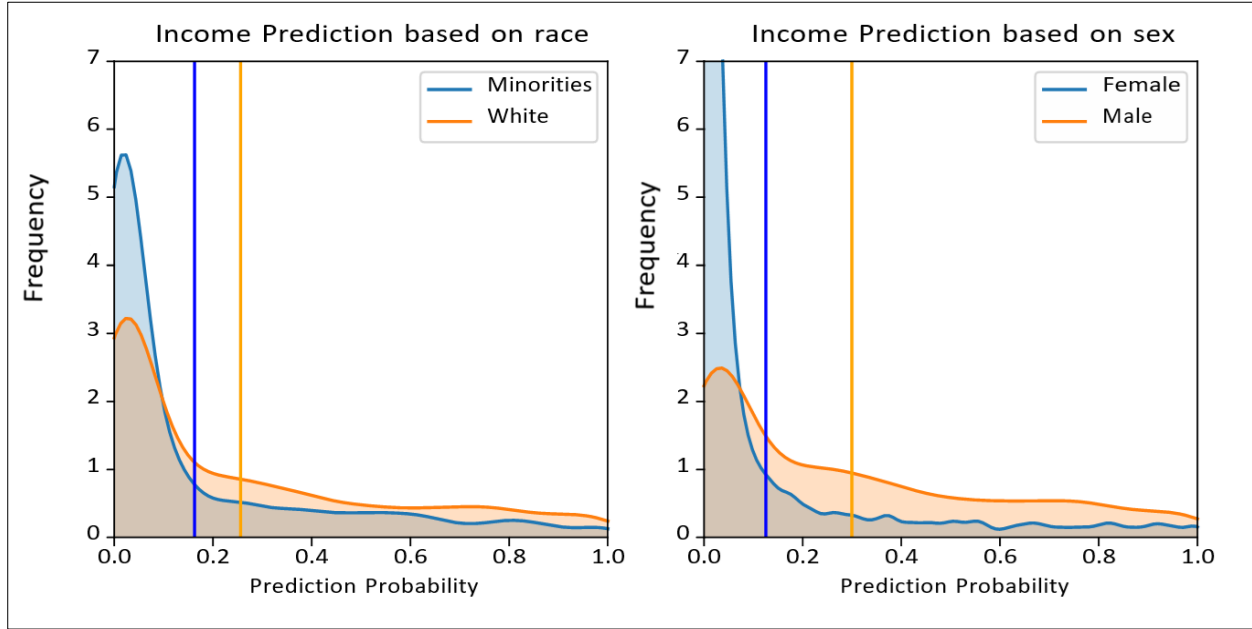


Fig 1: Kernel thickness appraisals of anticipated probabilities for various races (left) and genders (right) in the pattern brain organisation. Run lines address implies (Table I).

In the examination, the regularisation boundary λ is shifted to assess its effect on exactness and reasonableness in the brain network classifier. The upsides of λ tried incorporate $\{3 \times 10^{-2}, 1 \times 10^{-2}, 3 \times 10^{-3}, 1 \times 10^{-3}, 3 \times 10^{-4}, 1 \times 10^{-4}\}$, which steadily decline by elements of around three.

Charts and mathematical outcomes for the touchy trait *sex* on the preparation and test datasets are introduced in Figure 2 and Table II separately. The outcomes demonstrate that picking a fitting λ can guarantee segment equality without essentially compromising exactness. For instance, from Figure 2 and Table

II, the compromise bend shows a particular curve at $\lambda = 3 \times 10^{-3}$, pursuing it as an ideal decision.

Additionally, results for the touchy property *race* are given in Figure 3 and Table III. For this case, $\lambda = 1 \times 10^{-3}$ seems to actually provide surplus exactness and reasonableness.

Figure 4 shows how regularisation works on the arrangement of expectation dispersions for delicate characteristics. As contrasted in the figure, huge additions in segment equality are apparent. The tables likewise uncover that the test precision diminishes by all things considered 1.2% for the picked λ values, an insignificant compromise.

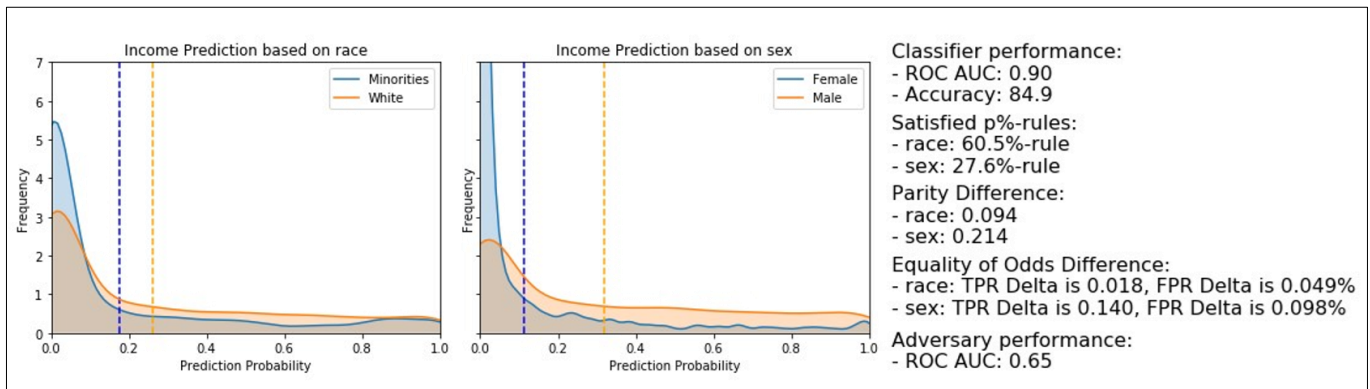


Fig 2: Trade-off among exactness and segment equality for *sex* by changing λ . Preparing set results (left) and test set results (right).

Table 2: Accuracy and segment equality as elements of λ for sex.

λ (Sex)	Train Acc	Train q	Test Acc	Test q
3×10^{-2}	0.759	0.994	0.759	0.996
1×10^{-2}	0.777	0.967	0.778	0.977
3×10^{-2}	0.834	0.934	0.838	0.957
1×10^{-2}	0.840	0.895	0.838	0.922
3×10^{-2}	0.849	0.771	0.843	0.801
1×10^{-2}	0.852	0.529	0.850	0.547

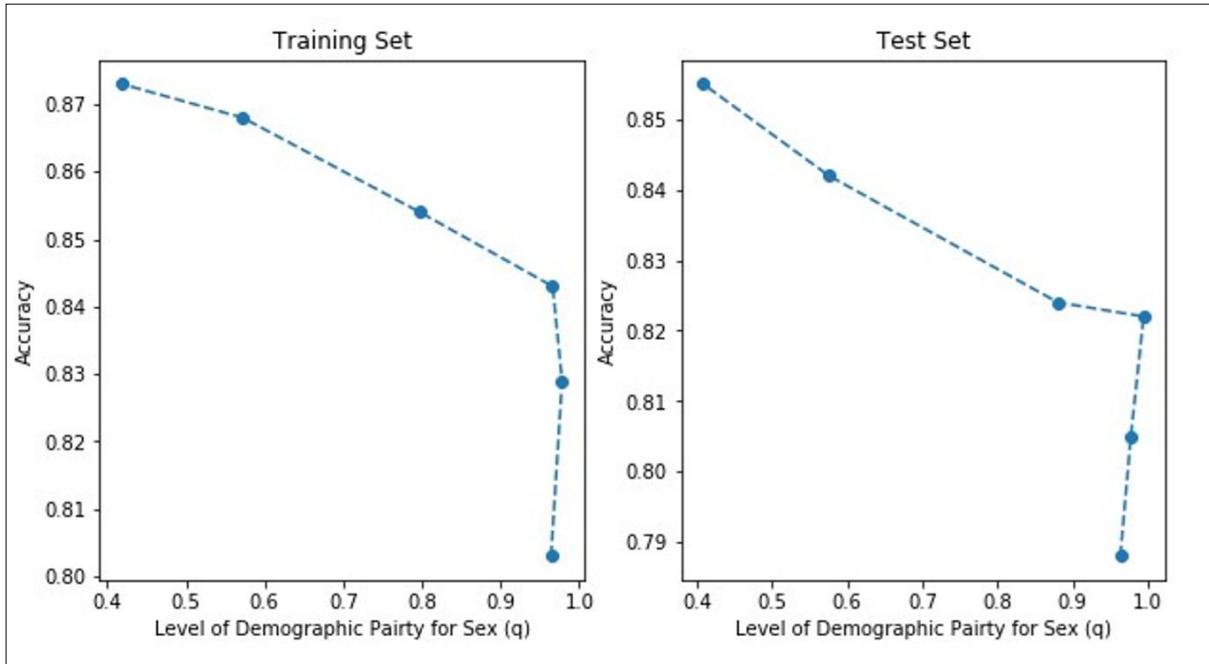


Fig 3: Trade-off among exactness and segment equality for *race* by changing λ . Preparing set results (left) and test set results (right).

DISCUSSION AND CONCLUSION

The discoveries introduced in this paper show a critical advancement in further developing segment equality when contrasted with the vanilla brain network model. The perceptions of score dispersions show how expectations for various segment groups, like race and sex, combine towards decency after applying the proposed strategies. Moreover, the mathematical measurements affirm that these strategies really meet the $q \geq 80$ edge, a basic benchmark in legal and administrative settings for solid AI models.

The outcomes show that the two techniques effectively improve decency measurements while maintaining exactness. The compromises noticed are negligible, showing that these methodologies can offset decency targets with execution requests in viable applications. For example, regularising choice limits covariance and integrates ill-disposed pre-preparation-owed reliable upgrades across different situations.

Despite these victories, a few roads for future work remain neglected. One promising course involves assessing these strategies on a wider range of real-world datasets to determine their generalizability more likely. Besides, while the outcomes here are overwhelmingly experimental, determining hypothetical certifications would improve the interpretation of the conditions under which these strategies are effective. In particular, creating hypothetical limits on the exactness of misfortune expected to accomplish an objective degree of segment equality would provide important insights.

One area of interest is the assessment of decency beyond equality. The writing incorporates more than twenty meanings of decency, each pertinent to various application areas. Future work could strengthen strategies to assess their adequacy under elective decency definitions, like equivalent open door or individual reasonableness. In addition, investigating whether these strategies can simultaneously fulfil various reasonableness measures would essentially widen their utility.

Table 3: Numerical results of how accuracy and level of demographic parity change as functions of regularisation parameter λ for constraining prediction probabilities conditioned on *race*.

λ (Race)	Train Acc	Train q	Test Acc	Test q
3×10^{-2}	0.759	0.994	0.759	0.996
1×10^{-2}	0.819	0.967	0.822	0.960
3×10^{-2}	0.846	0.937	0.841	0.913
1×10^{-2}	0.848	0.930	0.845	0.910
3×10^{-2}	0.852	0.822	0.846	0.810
1×10^{-2}	0.853	0.707	0.849	0.700

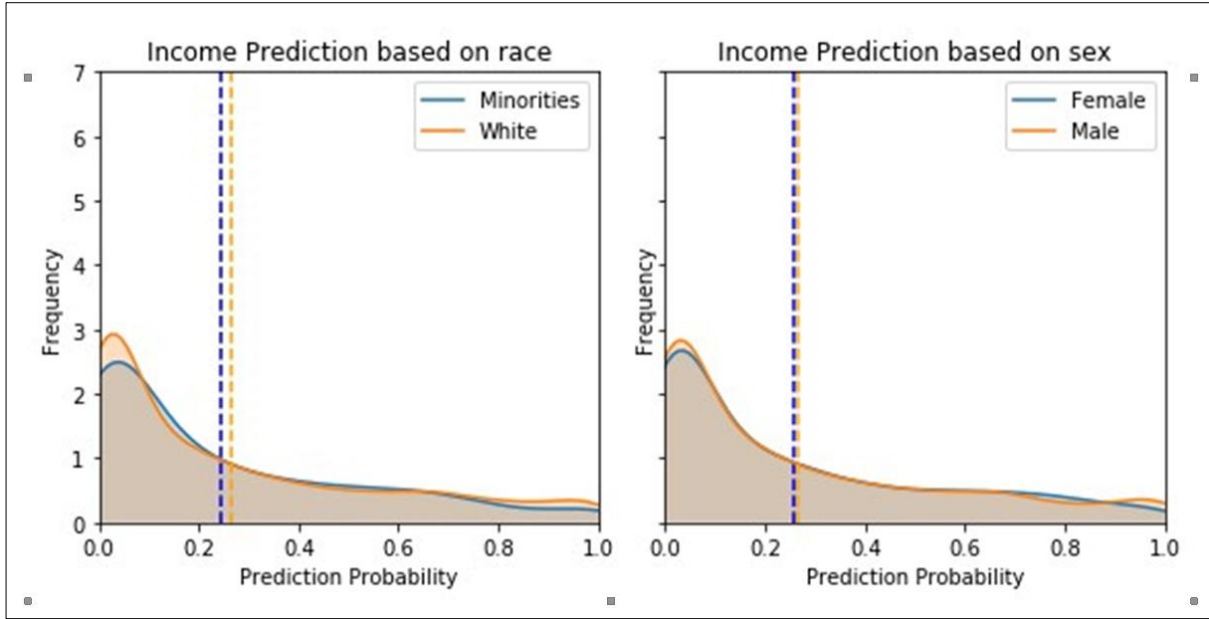


Fig 4: Kernel thickness assessments of anticipated probabilities for *sex* (right) and *race* (left) utilising regularised choice limits. Speckled lines show mean values.

Considering everything, this study’s consequences highlight the capability of designated regularisation and antagonistic preparation to make more attractive AI models. By considering illustrated future examination headings, these strategies could be refined and expanded, improving fair simulated intelligence frameworks that align with cultural and legitimate assumptions.

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