Fair and Private Deep Learning

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github.com/magnetar-iiith/FairPrivateDL

Agenda

Motivation

Proliferation of AI

- Autonomous Driving, Robotics, LIama, Computer Vision

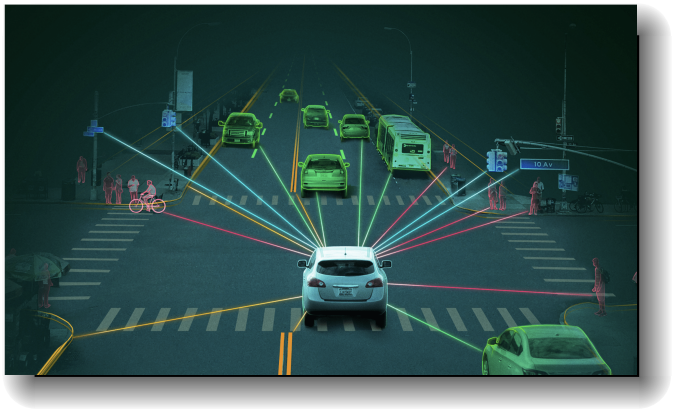

Figure: Ubiquitous AI systems [a]

[a] Image Credits: Manisha Padala Thesis

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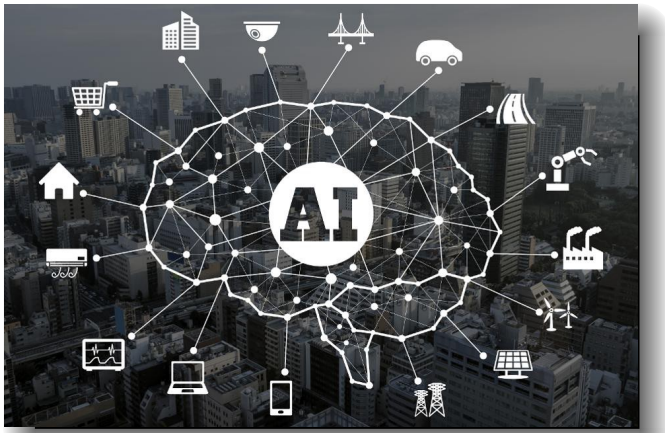
  - Resource Allocation, Course Allocation, Ride Shares, Rent SharesResource Allocation, Course Allocation, Ride Shares, Rent Shares



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Does historical unfairness matter?

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Are these concerns real or hyped?

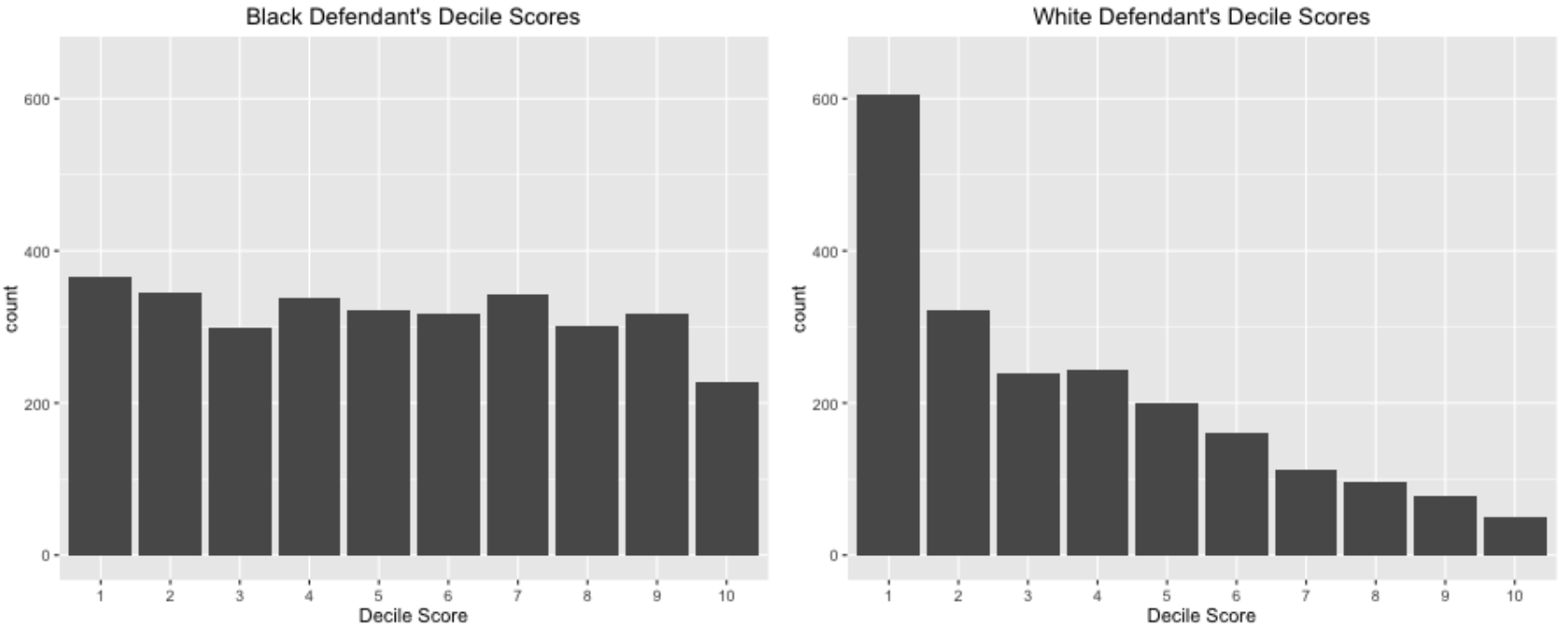
COMPAS

- Correctional Offender Management Profiling for Alternative Sanctions
  - Used by U.S. courts to assess the likelihood of a defendant becoming a recidivist (repeat offender)
- Prior to COMPAS (even before statistics and technology)
  - Human prejudices (e.g., against blacks) – may mark somebody for high risk
- COMPAS: general and violent recidivism, and for pre-trial risk assessment
- Machine Bias (ProPublica)

COMPAS

Source: Machine Bias (ProPublica)

COMPAS



Source: Machine Bias (ProPublica)

COMPAS

- "Scores like this – known as risk assessments – are increasingly common in courtrooms across the nation. They are used to inform decisions about who can be set free at every stage of the criminal justice system, from assigning bond amounts, to even more fundamental decisions about defendants' freedom." – Machine Bias (ProPublica)

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- Unfortunately for COMPAS (and those who suffered the consequences of their software), it turns out the algorithm gave **disproportionately higher** risk scores to **black** defendants than it did to white defendants.

COMPAS

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

Source: Machine Bias (ProPublica)

Other Instances

- Amazon same-day delivery – appeared to be racist

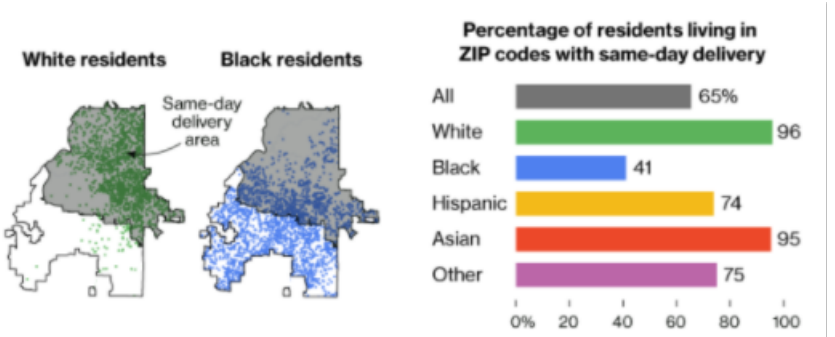

Fig 3: Source - Bloomberg

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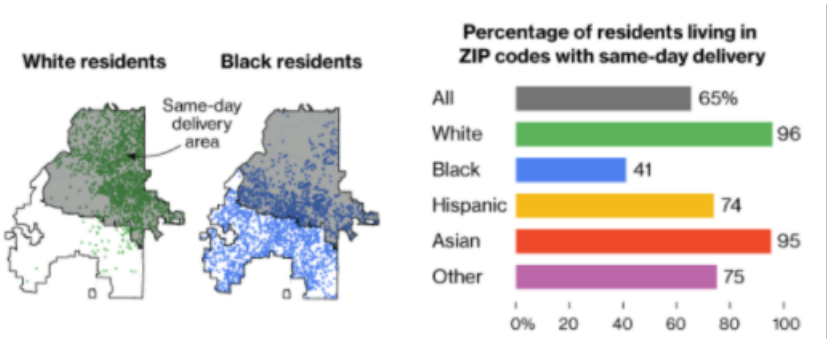
  - The Northern half of Atlanta, home to 96% of the city's white residents, has same-day delivery. However, southern Atlanta, where 90% of the residents are black, is excluded from same-day delivery



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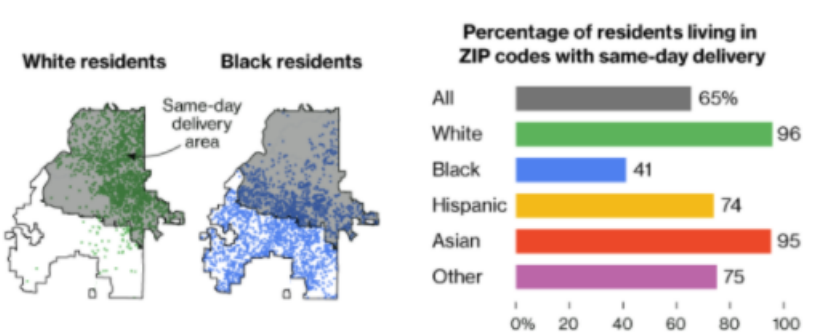
- Interesting: AMAZON never used race as a feature in their data while training their DL model



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Other Instances

Search query	Work experience	Education experience	Profile views	Candidate	Xing ranking
Brand Strategist	146	57	12992	male	1
Brand Strategist	327	0	4715	female	2
Brand Strategist	502	74	6978	male	3
Brand Strategist	444	56	1504	female	4
Brand Strategist	139	25	63	male	5
Brand Strategist	110	65	3479	female	6
Brand Strategist	12	73	846	male	7
Brand Strategist	99	41	3019	male	8
Brand Strategist	42	51	1359	female	9
Brand Strategist	220	102	17186	female	10

TABLE II: Top k results on www.xing.com (Jan 2017) for the job serach query "Brand Strategist".

Image Credit: Lahoti *et al.* []

Other Instances

- Algorithms that Demonstrate Artificial Intelligence Bias[1]
  - PredPol – Predicting crimes in US; Racial minorities
- Amazon recruitment tool
  - Biased against females
- ChatGPT Rift and Bias[2][3]

[1] https://www.geeksforgeeks.org/5-algorithms-that-demonstrate-artificial-intelligence-bias/
[2] ChatGPT Is Like Many Other AI Models: Rife With Bias (insider.com)
[3] Potential for bias based on prompt - ChatGPT and Generative Artificial Intelligence (AI)

Privacy Concerns in AI

FORBES > TECH

How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

Kashmir Hill Former Staff

Welcome to The Not-So Private Parts where technology & privacy collide

Feb 16, 2012, 11:02am EST

Source: Forbes

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- Data was completely anonymized
- Researchers still linked Netflix users to IMDb
- Many complex attacks are possible

Privacy Concerns in AI

- DL-based classifiers have been shown to be susceptible to privacy attacks

Figure 1: An image recovered using a new model inversion attack (left) and a training set image of the victim (right). The attacker is given only the person's name and access to a facial recognition system that returns a class confidence score.

Image Credit: Fredrikson et al. [18]

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- **Membership Attacks:** To discover whether a particular instance was present in the training set.
- **Model Inversion Attacks:** To reverse engineer the input data that led to a particular model's output.
- **Reconstruction Attacks:** To reconstruct sensitive information from the model's output (without necessarily focusing on the specific input data that led to that output)

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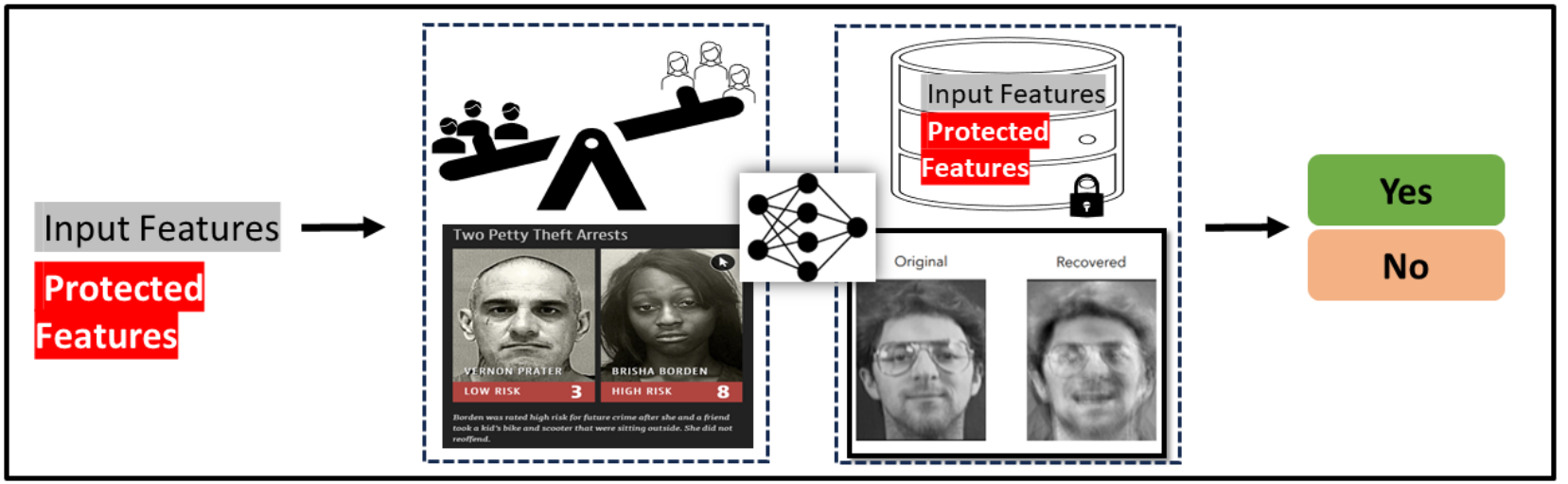

Fairness in Deep Learing

Notations and Model

Input: $X = \{x_1, \ldots, x_n\}$

Labels: $Y = \{y_1, \ldots, y_n\}$, $y_i \in \{0, 1\}$

Output: $\hat{Y} = \{\hat{y}_1, \ldots, \hat{y}_n\}$, $\hat{y}_i \in \{0, 1\}$

Protected Attribute: $A = \{\mathrm{A}_1, \ldots, \mathrm{A}_n\}$, $\mathrm{A}_i \in \{a^1, a^2\}$

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Model $h(x)$ gives the prediction probabilities (scores) and we obtain $\hat{y}$ after thresholding

Calibration

Definition

A classifier h is said to be calibrated if

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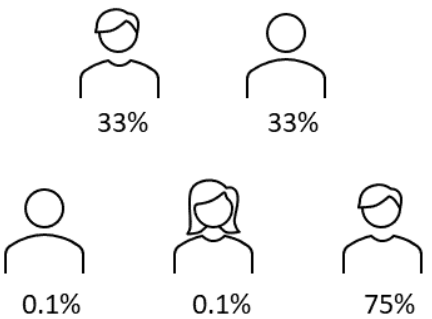

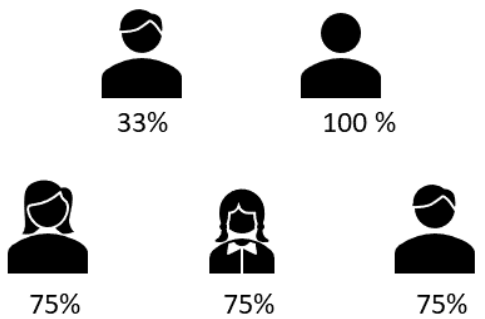

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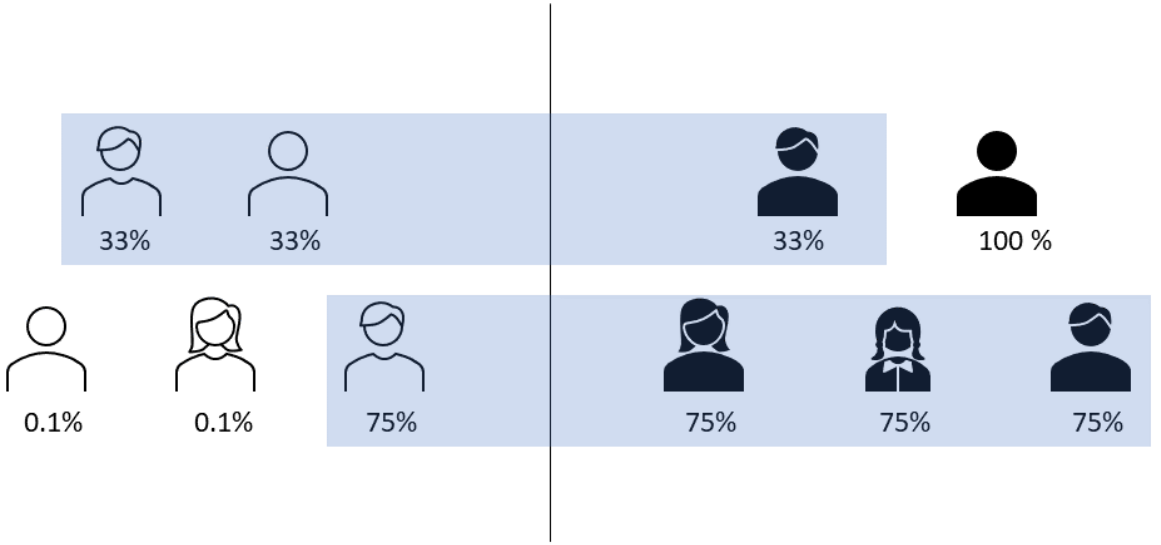

Group Fairness Criteria

Independence	**Separation**	**Sufficiency**
$\hat{Y} \perp A$	$\hat{Y} \perp A \vert Y$	$Y \perp A \vert \hat{Y}$

- Independence - predictions are independent of sensitive attribute
- Separation - independence within each target class
- Sufficiency - calibration per group

Independence

$\hat{Y} \perp A$

- Demographic Parity,
  Statistical Parity

  $$\mathbb{P}(\hat{Y} = 1 | A = a^1) = \mathbb{P}(\hat{Y} = 1 | A = a^2)$$

- Disparate Impact, p%-rule

  $$\frac{\mathbb{P}(\hat{Y} = 1 | A = a^1)}{\mathbb{P}(\hat{Y} = 1 | A = a^2)} \geq p$$

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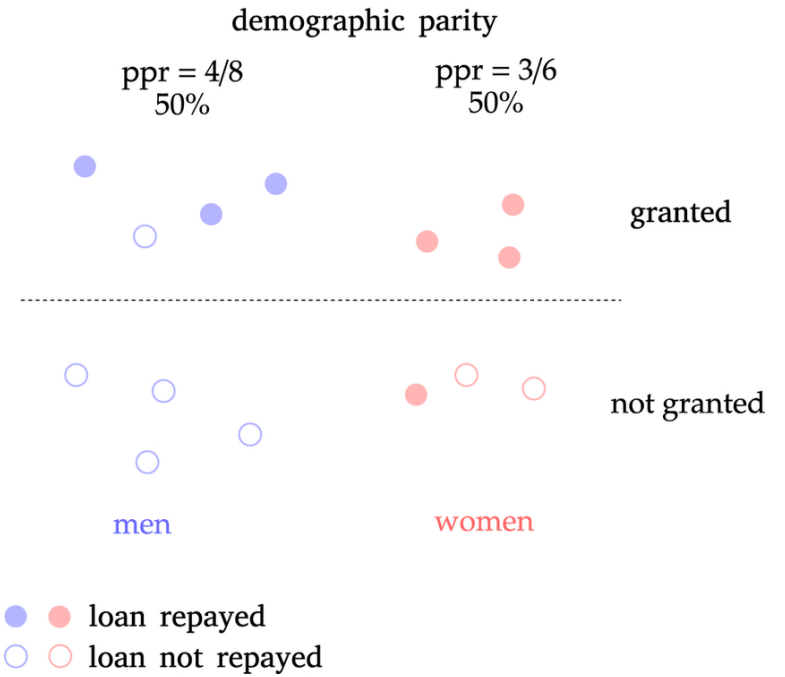


Independence

Note

- All groups have equal claim to acceptance
- Convenient technical properties
- Hiring qualified individuals from a^1 but not so qualified individuals from a^2 just to ensure fairness

Separation

$\hat{Y} \perp A \mid Y$

- False Negative Parity (FNP)

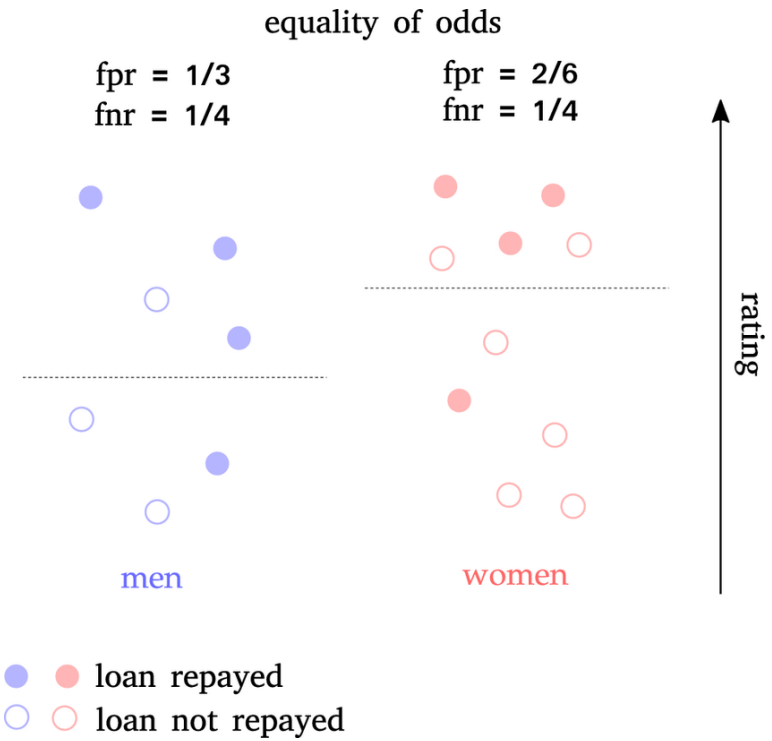
$$\mathbb{P}(\hat{Y} = 0 | A = a_1, Y = 1) = \mathbb{P}(\hat{Y} = 0 | A = a_2, Y = 1)$$

- False Positive Parity (FPP)

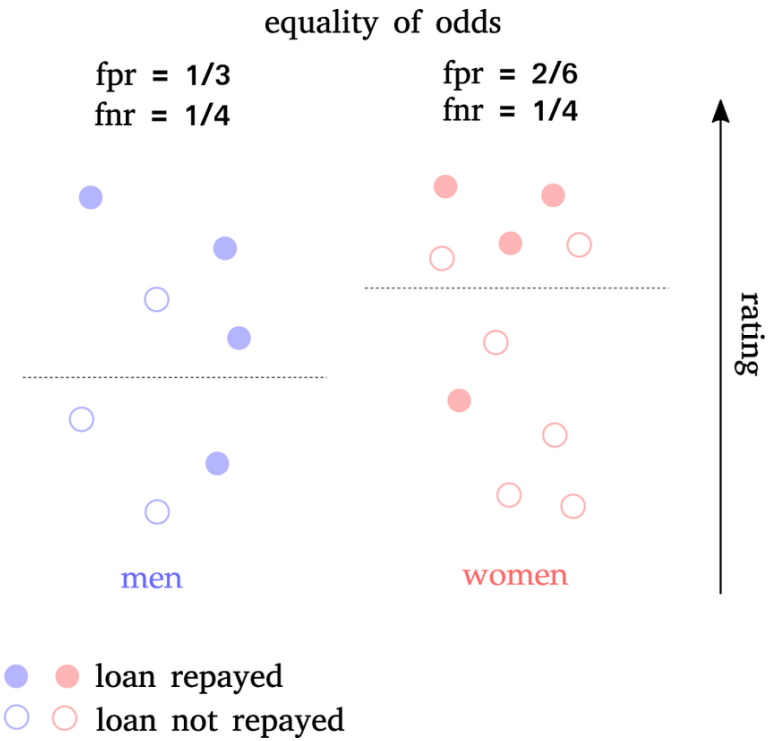
$$\mathbb{P}(\hat{Y} = 1 | A = a_1, Y = 0) = \mathbb{P}(\hat{Y} = 1 | A = a_2, Y = 0)$$

- Accuracy Parity - FP + FN parity
- Equalized Odds - FP and FN parity

Separation


equality of odds
fpr = 1/3
fnr = 1/4
fpr = 2/6
fnr = 1/4
rating
men
women
loan repayed
loan not repayed

Separation



- Opportunity is denied to eligible candidates at equal rate.
- Optimal classifier does not equalize error rates.
  - Who bears the burden of mis-classification?

Sufficiency

$Y \perp A|\hat{Y}$

- Sufficiency

$$\mathbb{P}(Y = 1|h(x) = r, A = a_1) = \mathbb{P}(Y = 1|h(x) = r, A = a_2)$$

- Calibration by groups

$$\mathbb{P}(Y = 1|h(x) = r, A = a_1) = r$$

Sufficiency

- In theory unconstrained supervised learning imply group calibration (Liu, Simchowitz, and Hardt 2019 [34])

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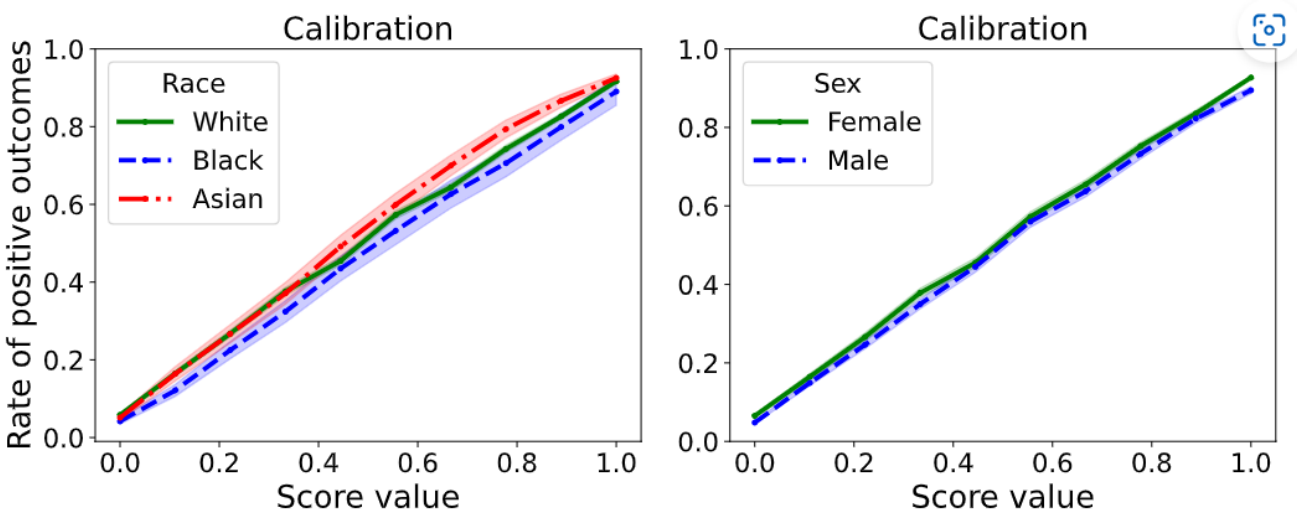

Figure: Group Calibration on Census ACS Data [3]

Impossibilities

Can we achieve any two fairness conditions together?

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- Independence $\implies A \perp \hat{Y}$
- Sufficiency $\implies Y \perp A \mid \hat{Y}$

Hence, $A \perp Y$

Unless $A \perp Y$, we cannot achieve both!

Impossibilities

Independence and Separation	$A \not\perp Y$ or $\hat{Y} \not\perp Y$
Independence and Sufficiency	$A \not\perp Y$
Sufficiency and Separation	$A \not\perp Y$ and full support

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On Fairness and Calibration [44]

Unless base rates are same (i.e., $\mathbb{P}(Y = 1|A = a_1) = \mathbb{P}(Y = 1|A = a_2)$) or h is a perfect classifier it is impossible to have both equalized odds and calibration

Impossibility

For calibration by group we require

$$\mathbb{P}(Y = 1|\hat{Y} = 1, A = a_1) = \mathbb{P}(Y = 1|\hat{Y} = 1, A = a_2)$$

Let $PP_1 = \mathbb{P}(Y = 1|\hat{Y} = 1, A = a_1)$, by Bayes rule,

$$PP_1 = \frac{\mathbb{P}(\hat{Y} = 1|Y = 1, A = 1)\mathbb{P}(Y = 1|A = 1)}{\mathbb{P}(\hat{Y} = 1|Y = 1, A = 1)\mathbb{P}(Y = 1|A = 1) + \mathbb{P}(\hat{Y} = 1|Y = 0, A = 1)\mathbb{P}(Y = 0|A = 1)}$$

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Given the base rate $p_1 = \mathbb{P}(Y = 1|A = a_1)$

$$PP_1 = \frac{TPR_1 \times p_1}{TPR_1 \times p_1 + FPR_1 \times (1 - p_1)}$$

Impossibility

We assume that Equalized Odds is satisfied that is,

- Let $u = TPR_1 = TPR_2$
- $v = FPR_2 = FPR_2$

Then calibration is satisfied when $PP_1 = PP_2$ or,

$$PP_1 = PP_2 \implies \frac{u \times p_1}{u \times p_1 + v \times (1 - p_1)} = \frac{u \times p_2}{u \times p_2 + v \times (1 - p_2)}$$

The above is true when

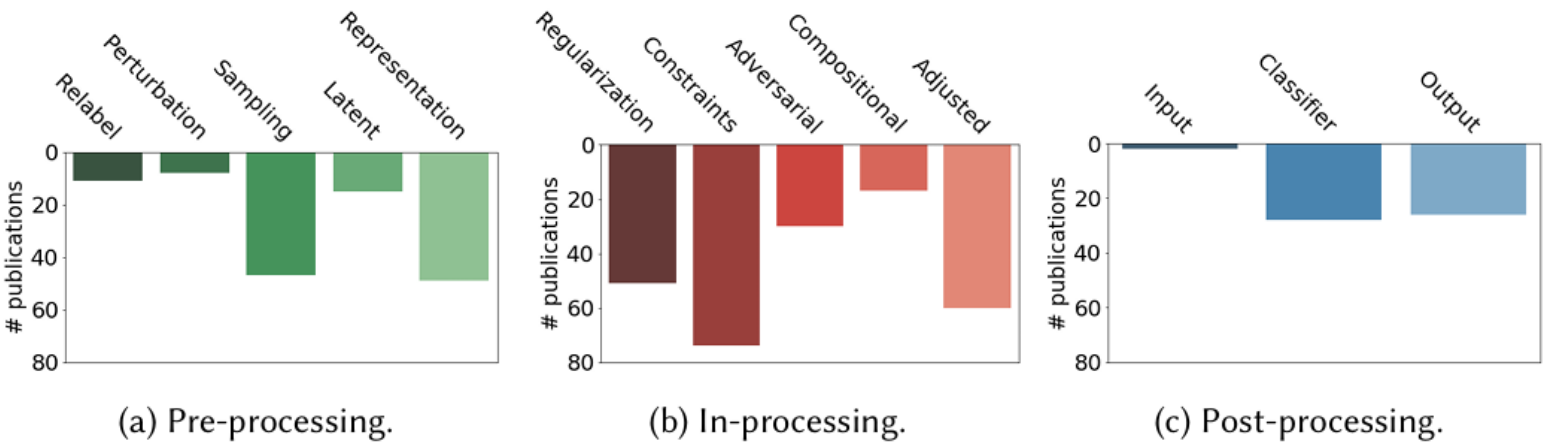
- Same base rates: $p_1 = p_2$
- Perfect predictor: $u = 1, v = 0$

Existing Approaches

In order to fit into ML framework, there are three approaches

(PRP)	Pre-processing	Input Features
(INP)	In-processing	Model
(POP)	Post-processing	Output Predictions

Existing Approaches



(a) Pre-processing. (b) In-processing. (c) Post-processing.

Figure: Summary of the approaches [23]

PRP: Relabeling and Perturbation

- Massaging - change ground truth labels
  - Kamiran and Calders 2009 [25], 2012 [27]
  - Žliobaite, Kamiran, and Calders 2011 [53]
  - Luong, Ruggieri, and Turini 2011 [36]

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- Perturbation - modifying input features
  - Feldman, Friedler, Moeller, Scheidegger, and Venkatasubramanian 2015 [16]
  - Lum and Johndrow 2016 [35]

PRP: Massaging Data [25]

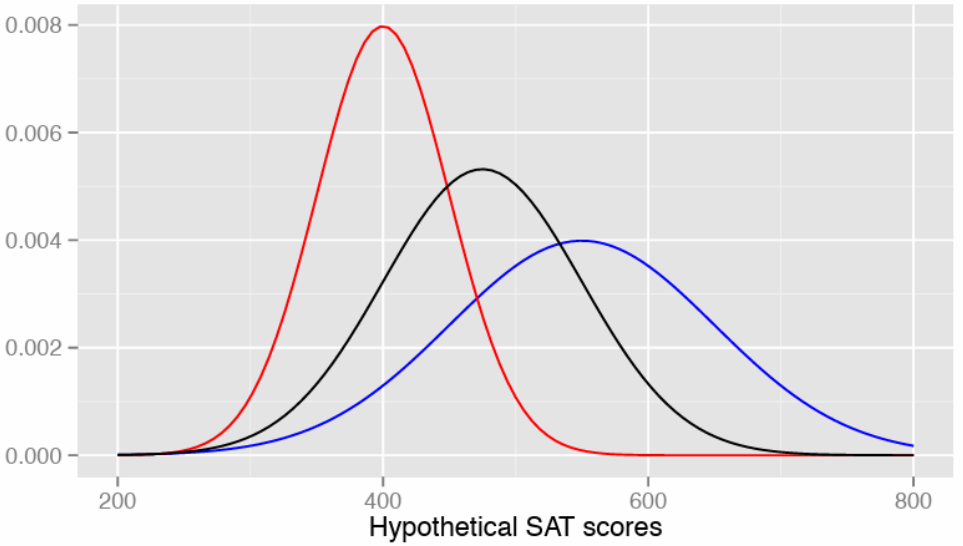
Fairness Notion: Demographic Parity (positive outcome supplied to both the groups equally)

X	A	Y
x_1	M	$+$
x_2	M	$-$
x_3	M	$-$
x_4	M	$+$
x_5	M	$-$
x_6	F	$+$
x_7	F	$+$
x_8	F	$+$
x_9	F	$+$
x_{10}	F	$-$

X	A	Y	$\mathbb{P}_+$
x_1	M	$+$	62%
x_2	M	$-$	6%
x_3	M	$-$	49%
x_4	M	$+$	67%
x_5	M	$-$	3%
x_6	F	$+$	76%
x_7	F	$+$	89%
x_8	F	$+$	90%
x_9	F	$+$	60%
x_{10}	F	$-$	10%

X	A	Y
x_1	M	$+$
x_2	M	$-$
x_3	M	$+$
x_4	M	$+$
x_5	M	$-$
x_6	F	$+$
x_7	F	$+$
x_8	F	$+$
x_9	F	$-$
x_{10}	F	$-$

PRP: Perturbation



Modifying continuous input (ordered) while ensuring the rank is maintained within the group. Red curve (male scores $\mu = 400, \sigma = 50$), Blue curve (female scores $\mu = 550, \sigma = 100$), Black curve (modified values $\mu = 475, \sigma = 75$) [16]

- Male students in 95^{th} percentile (≥ 500) are given scores ≥ 625 and remain in 95^{th} percentile.

PRP: Sampling

Calders, Kamiran, and Pechenizkiy 2009 [6]

- Reweighing - instance is weighed according to its label and protected attribute
- Uniform Sampling - duplicate or removal of samples
- Preferential Sampling - duplicate or removal of samples based on decision boundary

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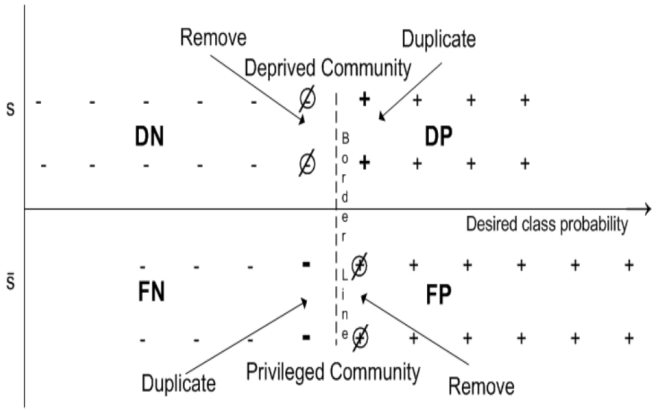
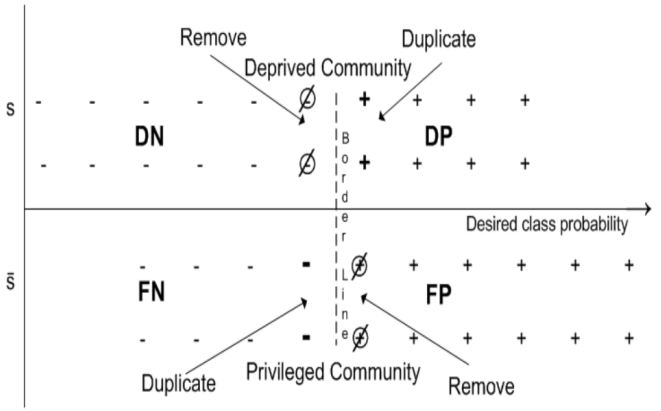
- SMOTE: Synthetic Minority Oversampling TEchnique (Chakraborty, Majumder, and Menzies 2021 [7])

PRP: Sampling



Preferential Duplication and Removal [26]

PRP: Sampling



Preferential Duplication and Removal [26]

SMOTE: $X_{new} = X + \text{rand}(0, 1) \cdot (X - X')$

PRP: Representation Learning

Learn representations such that

- sensitive information is removed
- target information is preserved

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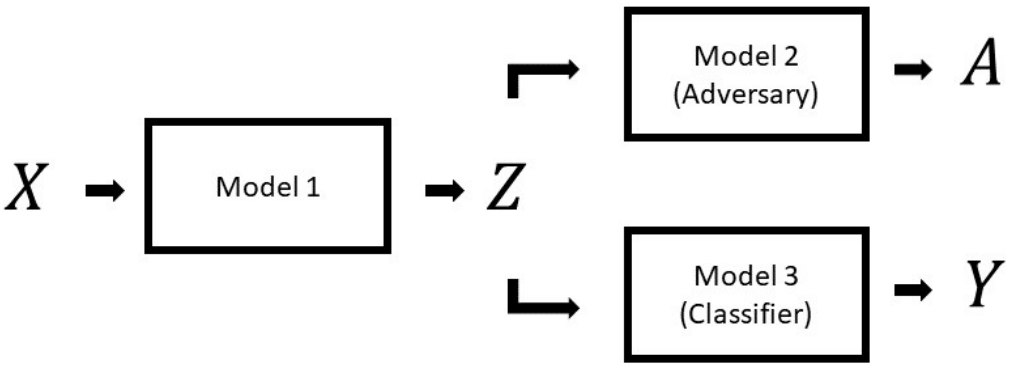
- target information is preserved

- Variational Autoencoders (Creager, Madras, Jacobsen, Weis, Swersky, Pitassi, and Zemel 2019 [9])
- Neural Style Transfer (Quadrianto, Sharmanska, and Thomas 2019 [45])
- Adversarial Learning (Zhu, Zheng, Liao, Li, and Luo 2021 [52])
- Contrastive Learning (Gupta, Ferber, Dilkina, and Ver Steeg 2021 [20])

PRP: Adversarial Learning



POP

Post processing - fair predictions from an existing trained model

POP: Input Correction

- Perturbing test input data
  - Adler, Falk, Friedler, Nix, Rybeck, Scheidegger, Smith, and Venkatasubramanian 2018 [2]
  - Li, Meng, Chen, Yu, Wu, Zhou, and Xu 2022 [33]

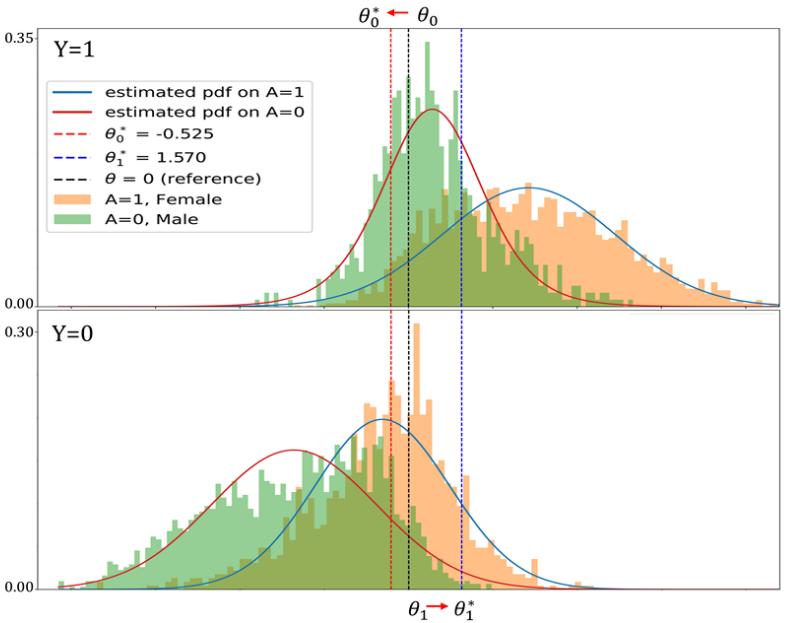
POP: Model Correction

The classifiers are modified

- From unfair classifier to fair classifier by solving an optimization for fairness loss [21] and extended by [49]
- Train two classifiers (h_1, h_0), return class mean instead of $h_1(x)$ w.p. α to ensure EO [44]
- Modifying decision trees by relabelling leaf nodes (iteratively find the leaf node with highest $\frac{fairness-gain}{accuracy-drop}$) [28]
- Boosting of classifiers to enhance fairness [31]

POP: Output Correction

- Learning thresholds for predicted probabilities (Menon and Williamson 2018 [38])
- Learning thresholds specific to a group (Jang, Shi, and Wang 2022[24])



INP

In-processing - train a model to be fair using modified loss function or training approaches

INP: Adversarial

PRP learns Z an intermediate representation, here we try to learn $\hat{Y}$ that is robust to bias

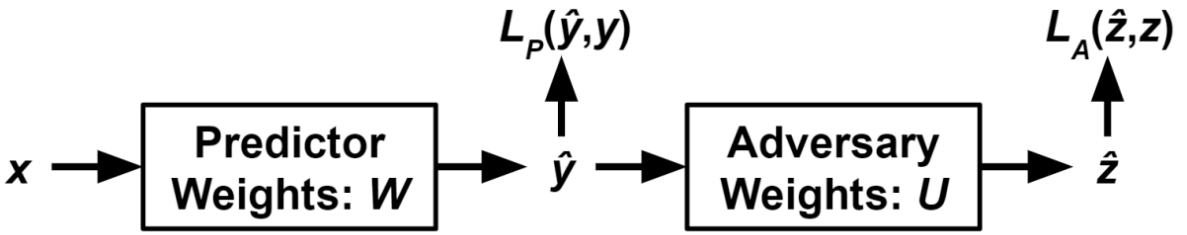


Figure: Zhang, Lemoine, and Mitchell 2018 [51]

- Minimize L_P
- Maximize L_A

INP: Compositional Learning

- Learning different classifiers for different groups using transfer learning (Dwork, Immorlica, Kalai, and Leiserson 2018 [14], Ustun, Liu, and Parkes 2019 [48])
- Ensemble of multiple classifiers for different metrics of fairness (Li, Meng, Chen, Yu, Wu, Zhou, and Xu 2022 [33])

INP: Adjusted Learning

- Active Learning - (Obermeyer, Powers, Vogeli, and Mullainathan 2019 [40])
- Rejection Learning - (Madras, Creager, Pitassi, and Zemel 2018 [37])
- Distributional Robust Optimization - (Hashimoto, Srivastava, Namkoong, and Liang 2018 [22])

INP: Constrained Based

- Loss function consists of performance loss and fairness loss
- Fairness loss is non-convex and complex

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- Loss function consists of performance loss and fairness loss
- Fairness loss is non-convex and complex
- Convexification (Bilal Zafar, Valera, Gomez Rodriguez, and Gummadi 2015 [5], Kamishima, Akaho, and Sakuma 2011, [29])

INP: Convexification [5]

Fairness Notion: Disparate Impact

$$\min \left\{ \frac{\mathbb{P}(\hat{y}_i = 1 | a_i = 0)}{\mathbb{P}(\hat{y}_i = 1 | a_i = 1)}, \frac{\mathbb{P}(\hat{y}_i = 1 | a_i = 1)}{\mathbb{P}(\hat{y}_i = 1 | a_i = 0)} \right\} \geq 0.8$$

Non-convex and complex so define a proxy loss that is convex.

INP: Convexification [5]

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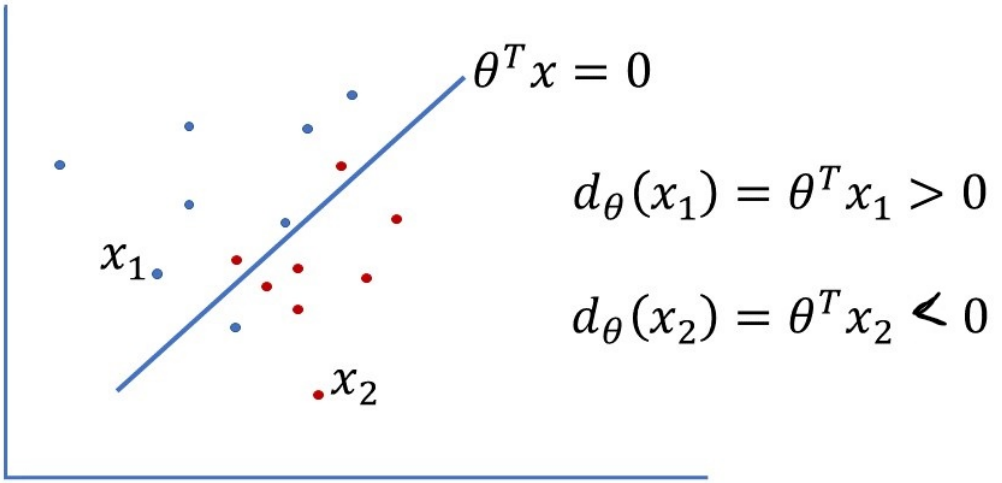

$$\mathbb{P}(d_\theta(x_i) > 0|a_i = 0) = \mathbb{P}(d_\theta(x_i) > 0|a_i = 1)$$

INP: Convexification [5]

$\mathbb{P}(d_\theta(x) > 0 | a_i = 0) = \mathbb{P}(d_\theta(x_i) > 0 | a_i = 1)$
Perfect DI implies $Covariance(d_\theta(x), a) = 0$

$$Cov(d_\theta(x), a) = \frac{1}{n} \sum_{i=1}^{n} (a - \mu_a) \theta^T x$$

- Convex w.r.t. θ hence included in many classifier formulations

INP: FNNC

FNNC: Fair Neural Network Classifier [41]

- We introduce a penalty term in the loss and train a NN-classifier
- Provide sample bounds why the penalty term helps minimize fairness

Padala Manisha, Sujit Gujar. "*FNNC: Achieving Fairness through Neural Networks*".**(IJCAI '20)**

Loss Function and Optimizer

Cross-entropy loss with DP constraint (batch of S samples)

$$l_{CE}(h(x_i), y_i) = -y_i \log(p_i) - (1 - y_i) \log(1 - p_i)$$

$$\hat{l}_{CE}(h(X), Y) = \frac{1}{S} \sum_{i=1}^{S} l_{CE}(h(x_i), y_i)$$

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$$const^{DP}(z_S) = \left| \frac{\sum_{i=1}^{S} p_i a_i}{\sum_{i=1}^{S} a_i} - \frac{\sum_{i=1}^{S} p_i (1 - a_i)}{\sum_{i=1}^{S} 1 - a_i} \right|$$

$$l_{DP}(h(X), \mathcal{A}, Y) : \frac{1}{B} \sum_{l=1}^{B} const^{k}(z_S^{(l)}) - \epsilon \leq 0$$

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Lagrangian Multiplier

The overall loss for the network.

$$\boxed{L_{NN} = \hat{l}_{CE} + \lambda l_{DP}} \quad \lambda : \text{Lagrangian Multiplier}$$

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$$\min_{\theta} \max_{\lambda} L_{NN}$$

Perform SGD twice, once for minimizing the loss w.r.t. θ and again for maximizing the loss w.r.t. λ at every iteration

Results - Equalized Odds

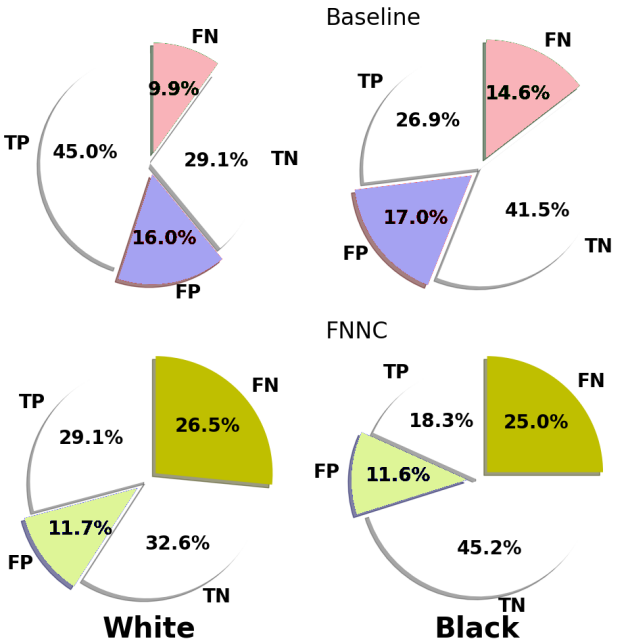


Figure: Compass dataset: FPR and FNR is comparable across race in FNNC as observed in the bottom left and right pie charts

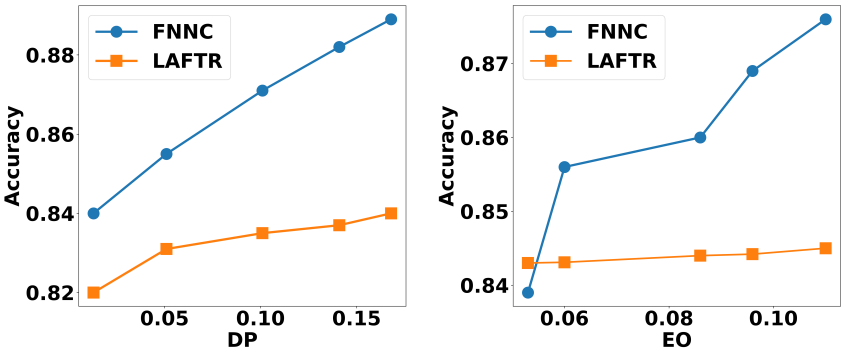


Figure: FNNC vs LAFTR [37] on Adult dataset

Dataset	ϵ	FNNC	COCO[39]	LinCon [39]
adult	0.05	0.28 (0.027)	0.33 (0.035)	0.39 (0.027)
compass	0.20	0.32 (0.147)	0.41 (0.206)	0.57 (0.107)
crimes	0.20	0.28 (0.183)	0.32 (0.197)	0.52 (0.190)
default	0.05	0.29 (0.011)	0.37 (0.032)	0.54 (0.015)

Q-mean loss s.t. DP is within ϵ (actual DP in parentheses)

Bounds on DP and EO

Theorem

For each of $k \in \{DP, EO\}$, *the relation between the statistical estimate of the constraint given batches of samples,* z_S, $\mathbb{E}_{z_S}[const^k(z_S)]$, *and the empirical estimate for* B *batches of samples is listed below. Given that* $const^k(z_S) \leq 1$, *for a fixed* $\delta \in (0,1)$ *with a probability at least* $1-\delta$ *over a draw of* B *batches of samples from* $(h(X), \mathcal{A}, Y)$, *where* $h \in \mathcal{H}$,

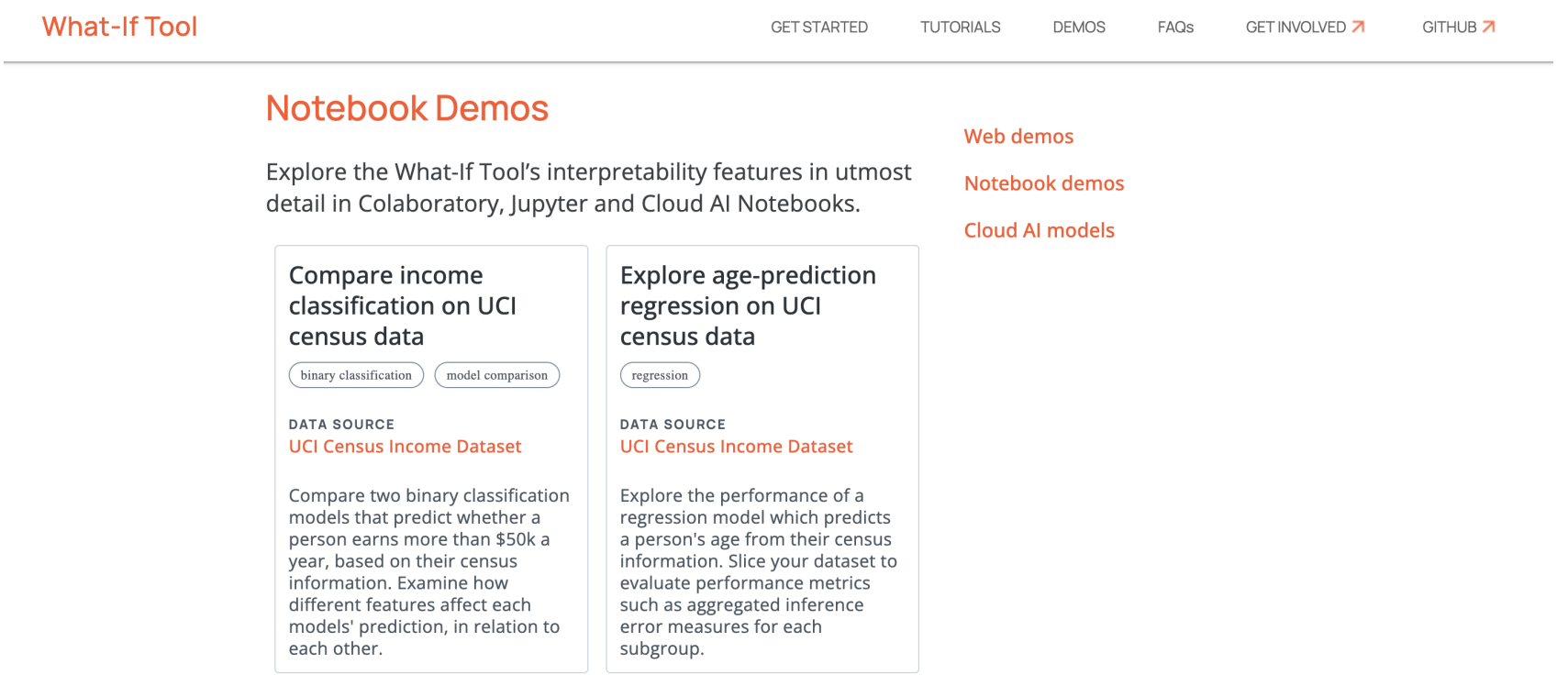
$$\mathbb{E}\left[const^k(z_s)\right] \leq \frac{1}{B}\sum_{\ell=1}^{B} const^k\left(z_S^{(\ell)}\right) + 2\Omega_k + C\sqrt{\frac{\log(\frac{1}{\delta})}{B}}$$

$$\Omega_{DP,EO} = \inf_{\mu>0}\left\{\mu + \sqrt{\frac{2\log\left(\mathcal{N}_\infty(\mathcal{H}, \mu/2S)\right)}{B}}\right\}$$

Bounds on covering numbers leads to the following (Dutting *et al.* [10]), For the network with R hidden layers, D parameters, and vector of all model parameters $\| w \|_1 \leq W$. Given that w_l is bounded, the output of the network is bounded by some constant L.

$$\Omega_{DP} = \Omega_{EO} \leq \mathcal{O}\left(\sqrt{RD\frac{\log(WBSDL)}{B}}\right)$$

Fairness in DL: Getting Started



Source: `pair-code.github.io/what-if-tool/explore/`

Fairness in DL: Getting Started

Source: `ai-fairness-360.org/`

Privacy in Deep Learning

What is Differential Privacy (DP)?

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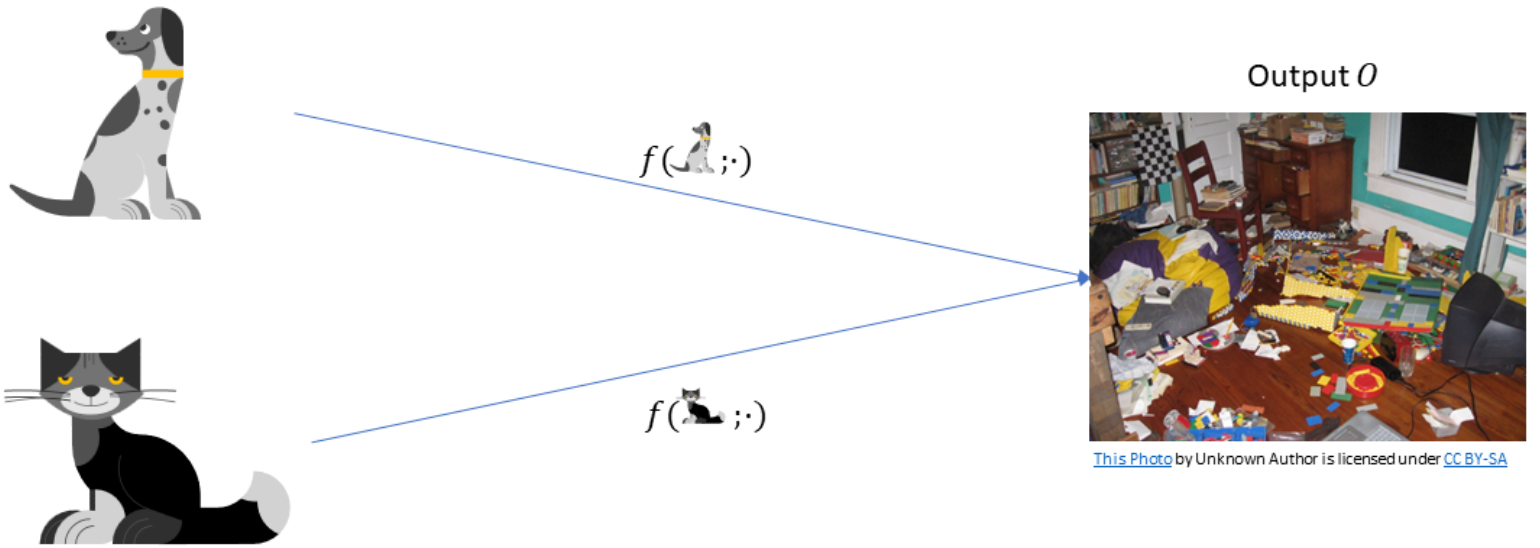
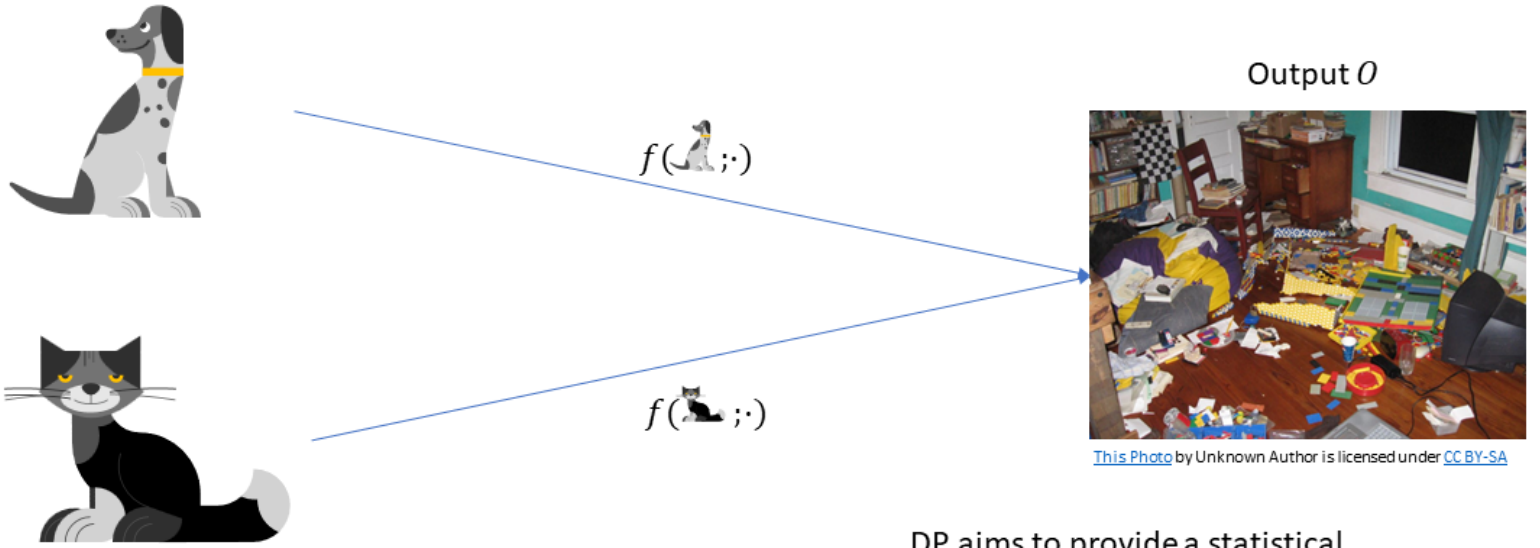


What is Differential Privacy (DP)?



DP aims to provide a statistical guarantee against a database that the inclusion or exclusion of any single entry will not significantly impact the results of the statistical analysis.

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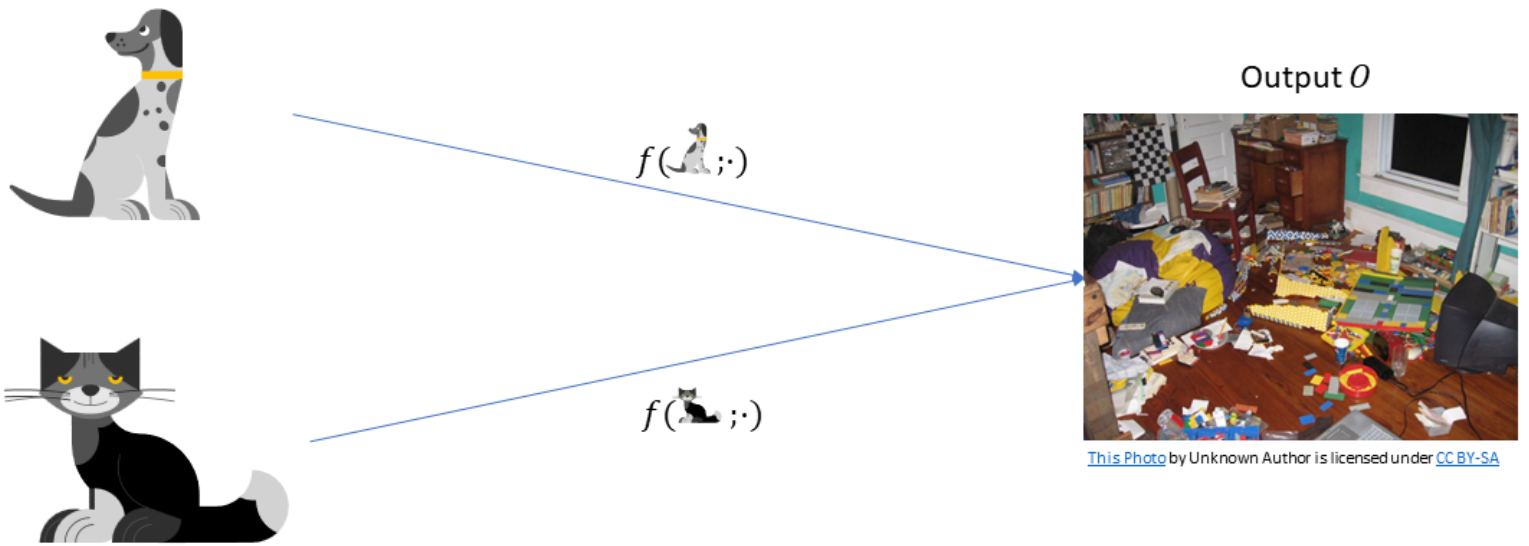

Both the cat and the dog have Plausible Deniability ☺

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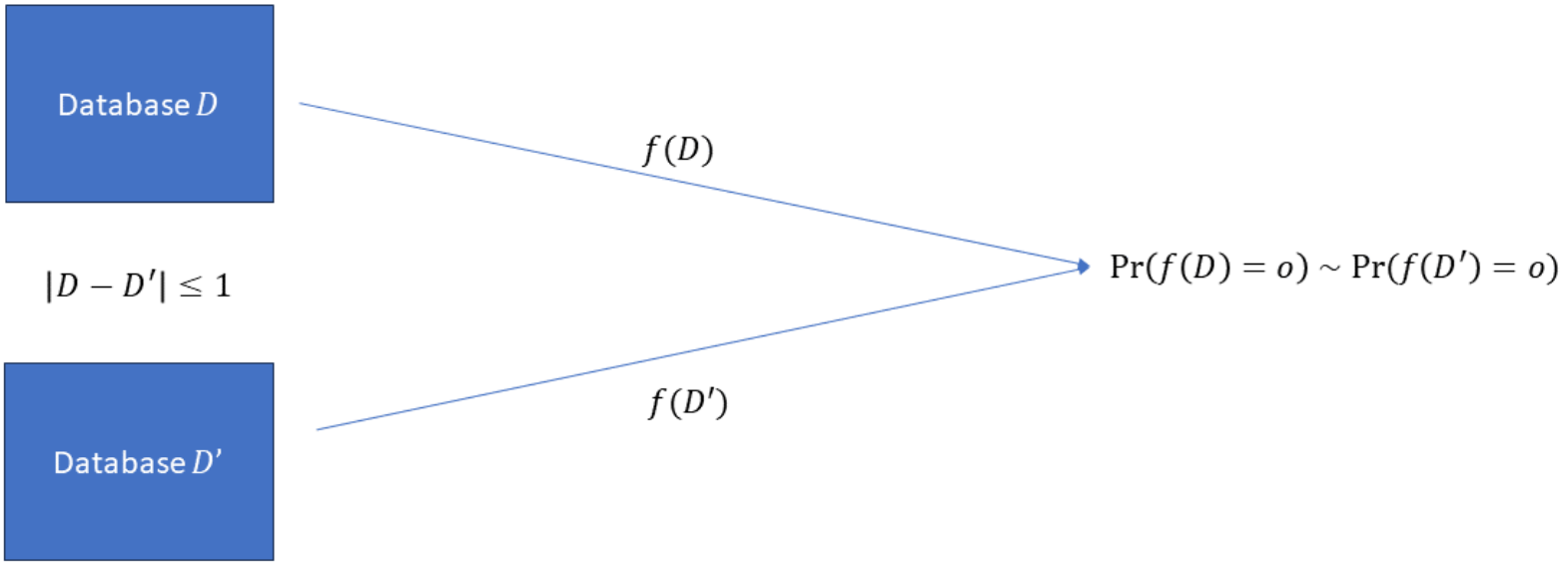

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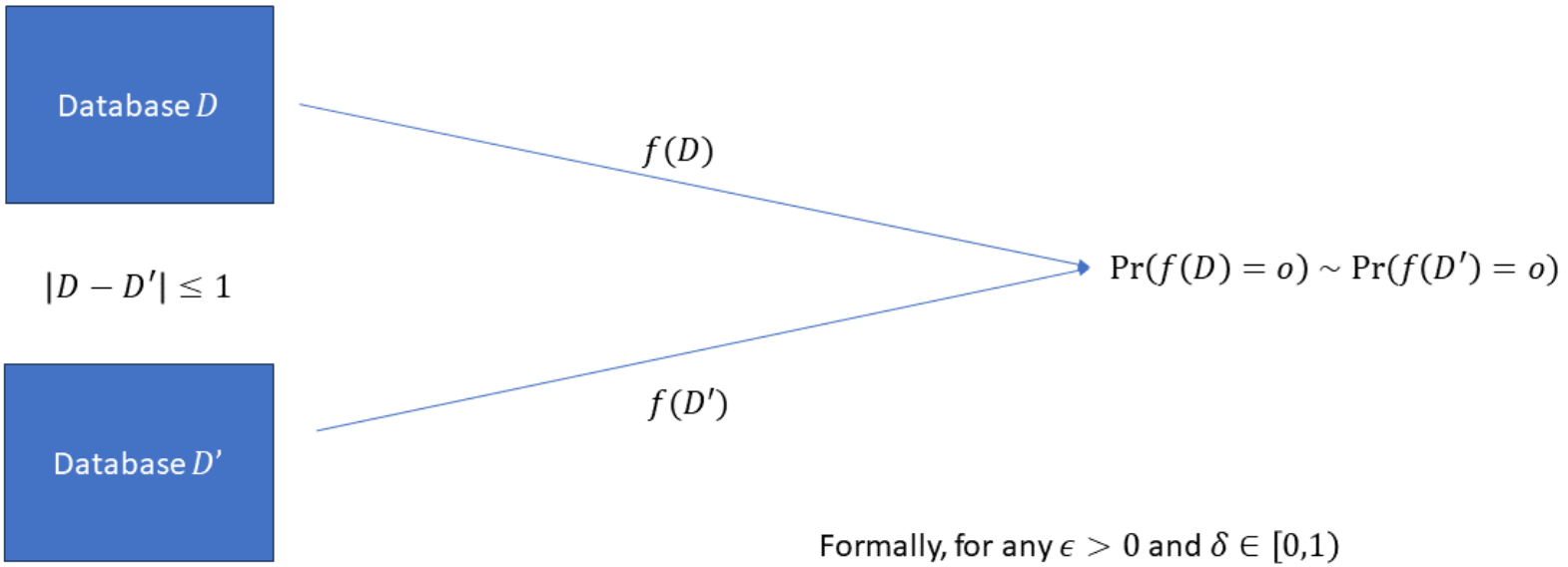

Formally, for any $\epsilon > 0$ and $\delta \in [0,1)$

$$\Pr(f(D) = o) \leq e^{\epsilon} \cdot \Pr(f(D') = o) + \delta$$

Differential Privacy (DP)

Definition (Differential Privacy (DP) [13, 11, 12])

For a set of databases $\mathcal{X}$ and the set of noisy outputs $\mathcal{Y}$, a randomized algorithm $\mathcal{M} : \mathcal{X} \to \mathcal{Y}$ is said to be (ϵ, δ)-DP if $\forall D, D' \in \mathcal{X}$, s.t. $|D - D'| \leq 1$, and $\forall S \subseteq \mathcal{Y}$ the following holds,

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Why is this a reasonable notion of privacy?

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4. DP protects against reconstruction, membership attacks

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5. $\delta > 0 \implies$ "approximate"-DP (ignore unlikely events)

Differential Privacy (DP)

Definition (Differential Privacy (DP) [13, 11, 12])

For a set of databases $\mathcal{X}$ and the set of noisy outputs $\mathcal{Y}$, a randomized algorithm $\mathcal{M} : \mathcal{X} \to \mathcal{Y}$ is said to be (ϵ, δ)-DP if $\forall D, D' \in \mathcal{X}$, s.t. $|D - D'| \leq 1$, and $\forall S \subseteq \mathcal{Y}$ the following holds,

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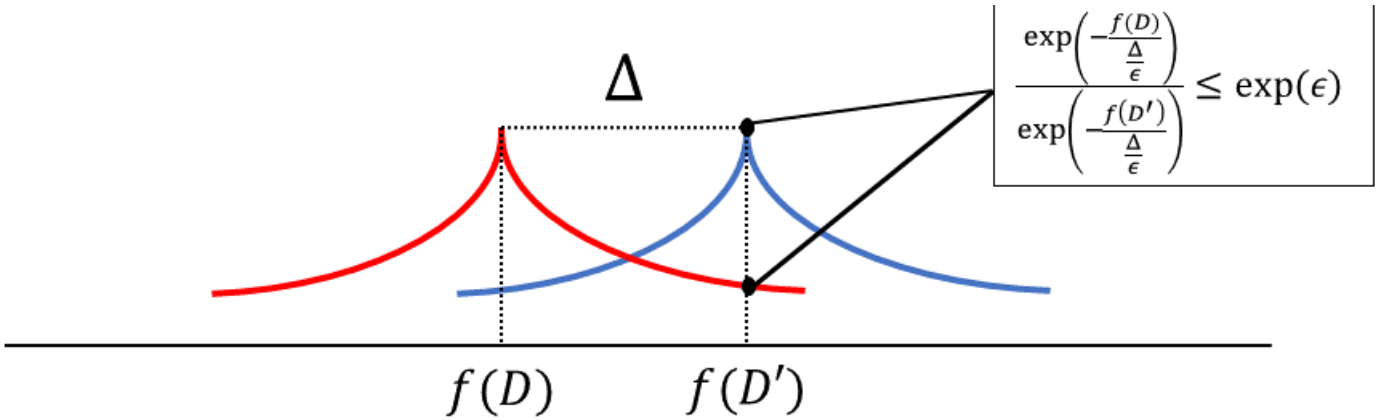

Figure: Laplace Mechanism: Illustration

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Stochastic Gradient Descent (SGD)

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Implementation: `github.com/tensorflow/privacy`

DP-SGD: Does it Work?

- MNIST [32]: Classify black and white images as digits
- An "easy" ML task
  - Non-private ML model's test accuracy $\approx 100\%$
- Abadi *et al.* [1]: 97% for $\epsilon = 8$
- Tramer and Boneh [47]: 98-99% for $\epsilon \in [1, 3]$
- DP-SGD performs well for "easy" tasks
  - CIFAR-10: 98% (non-private) and 69% (for $\epsilon = 3$ [47])

Figure: Examples from the MNIST database (Credit [32])

Other Advances

PATE [43]: Private Aggregation of Teacher Ensembles

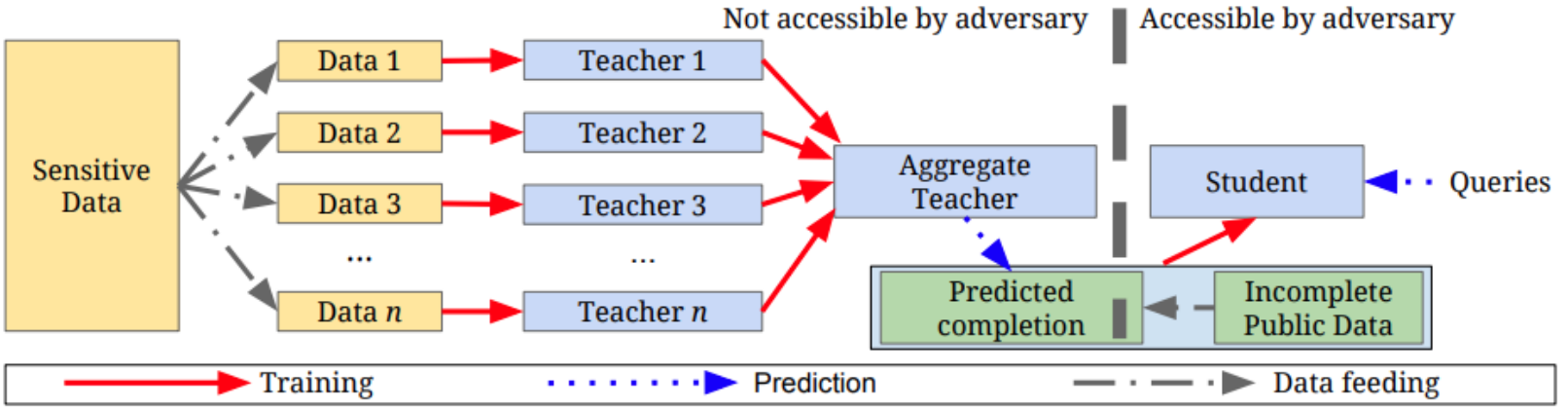

Figure: Overview of PATE (Credit [43])

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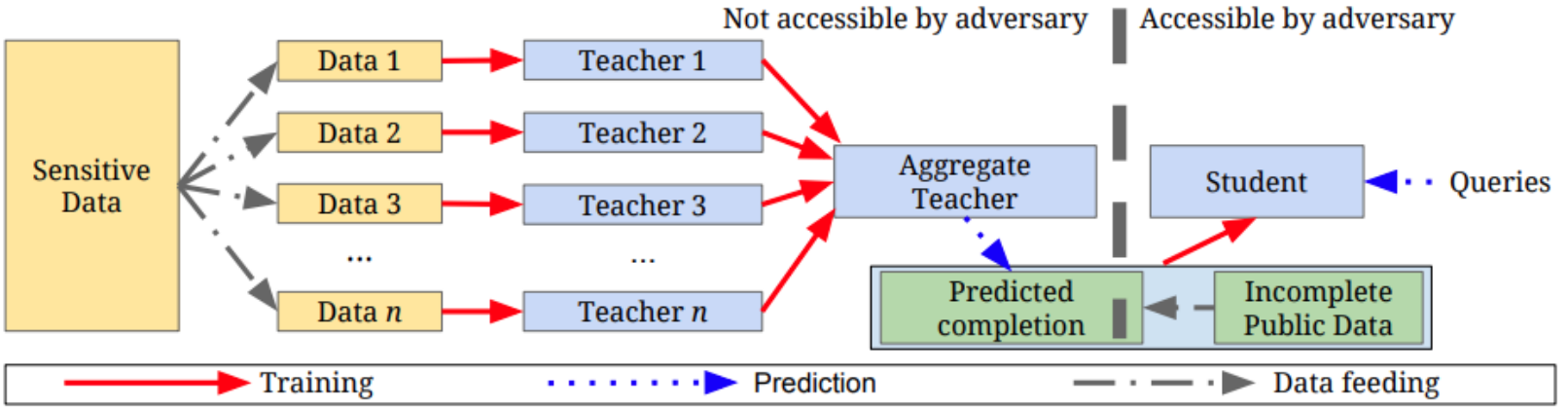

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Performance on MNIST: 98.5% test accuracy for $\epsilon \approx 2$

Other Advances

Yu *et al.* [50]: Differentially private Fine-tuning of Language Models

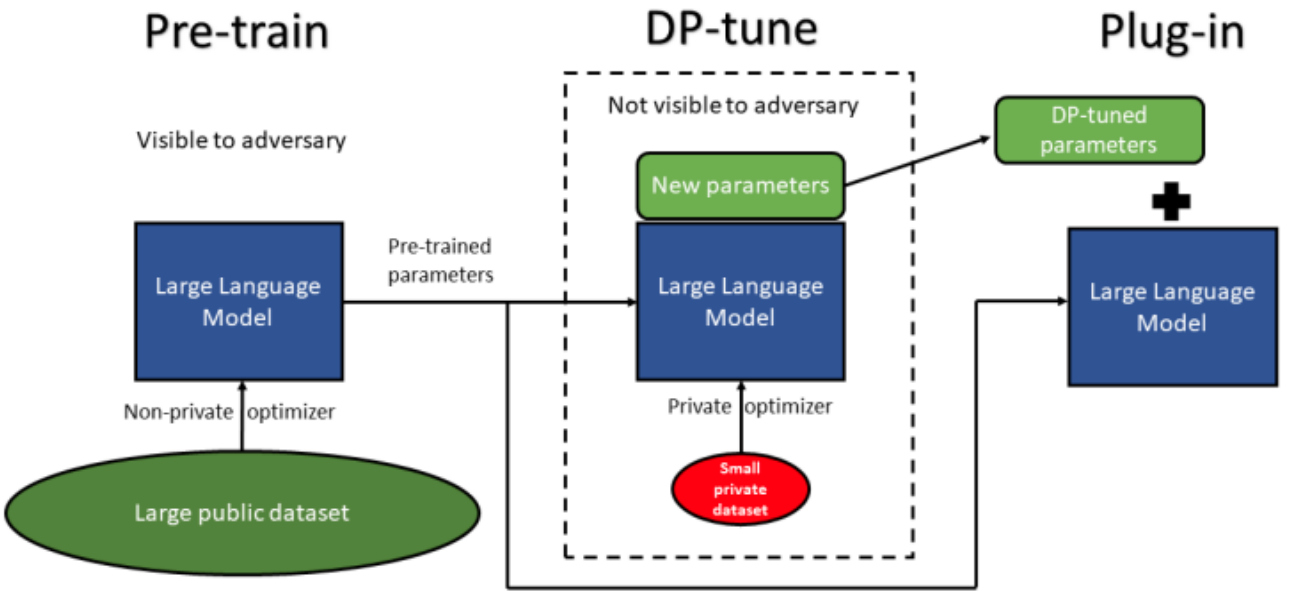

Figure: Overview of the framework (Credit [50])

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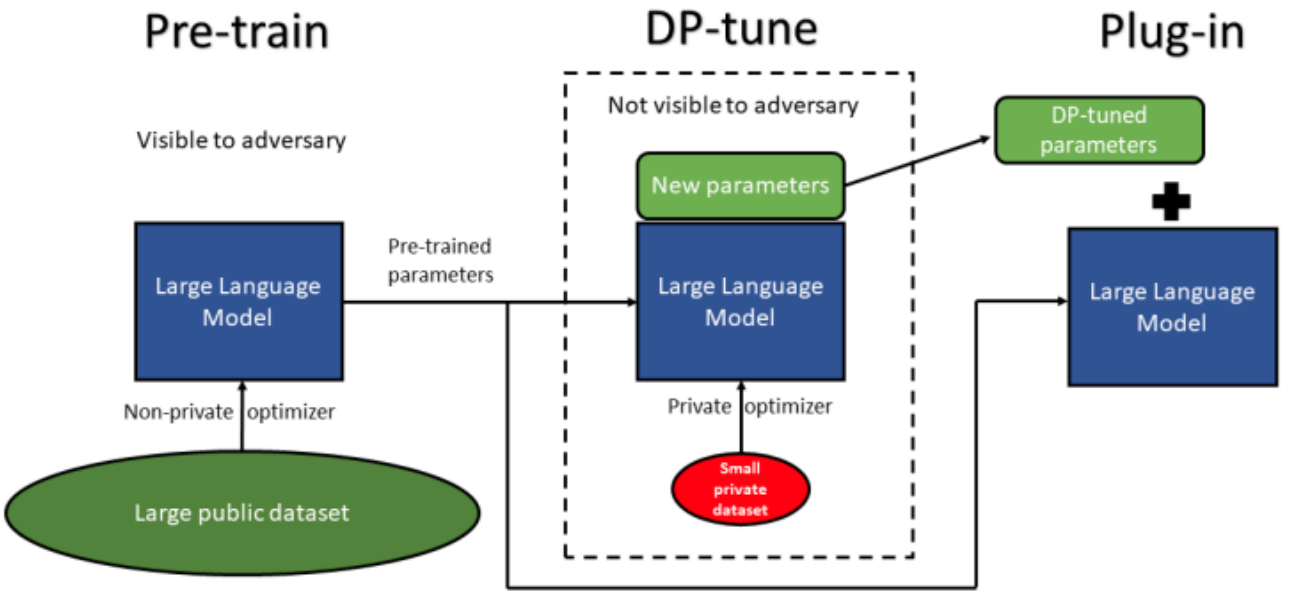

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Tighter privacy accounting using [19]

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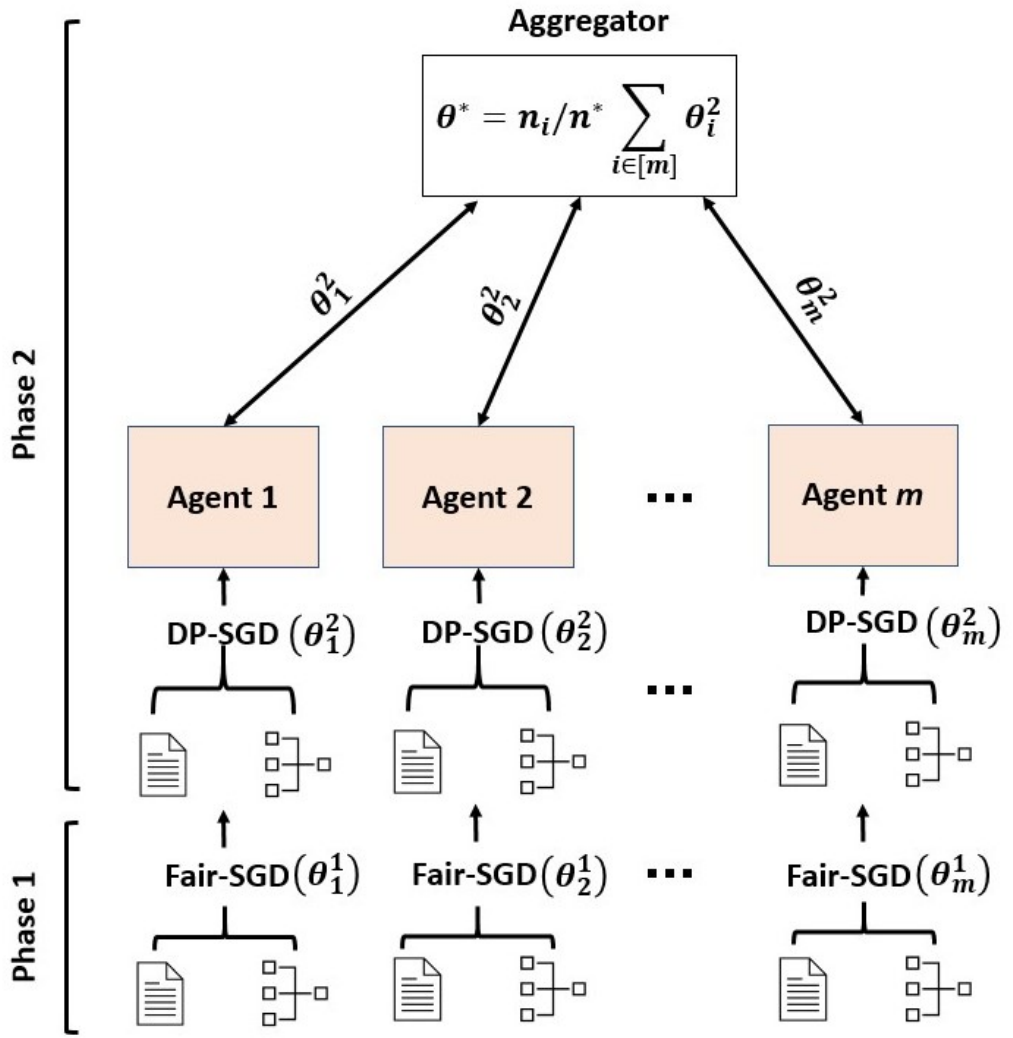
FPFL: Fair and Private Federated Learning

Our Model


Aggregator
$\theta^* = n_i/n^* \sum_{i\in[m]} \theta_i^2$
θ_1^2
θ_2^2
θ_m^2
Phase 2
Agent 1
Agent 2
...
Agent m
DP-SGD (θ_1^2)
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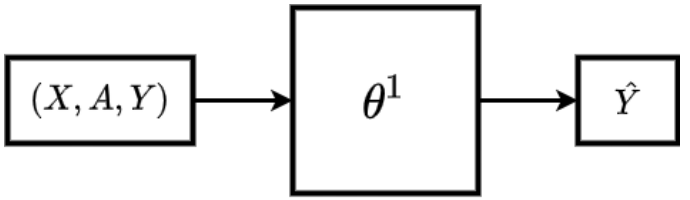
Phase 1: Fair-SGD

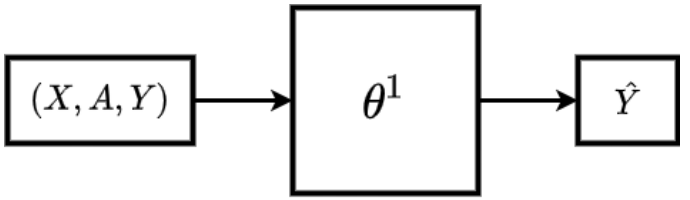
For each agent,



Multi-layer Neural Network

Phase 1: Fair-SGD

For each agent,



Multi-layer Neural Network

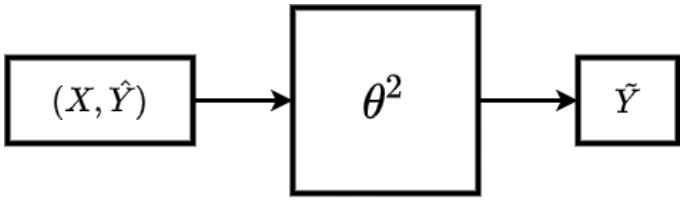
- Loss function [41]:

$$L(\cdot) = \text{Cross entropy loss}(Y, \hat{Y}) + \lambda \cdot \text{DemP Loss}(A, \hat{Y})$$

- Optimization:

$$\min_{\theta^1} \max_{\lambda} L(\cdot)$$

Phase 2: DP-SGD



Multi-layer Neural Network

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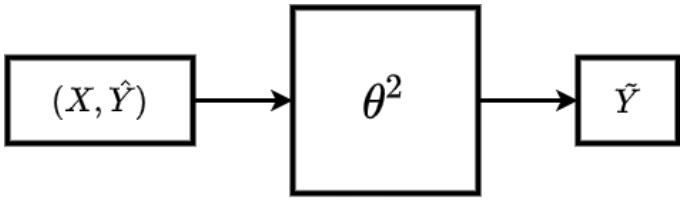

Multi-layer Neural Network

- We train the network in this phase to learn the predictions from Fair-SGD
- We add Gaussian noise to the gradients provided by SGD to ensure data confidentiality [1]

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- Reduces the number of epochs $\implies$ Reduction in explosion of ϵ

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- As agents broadcast only θ^2, our ϵ, δ bounds follow from moments accountant [1, Theorem 1]

Federated Learning Meets Fairness and Differential Privacy [42]

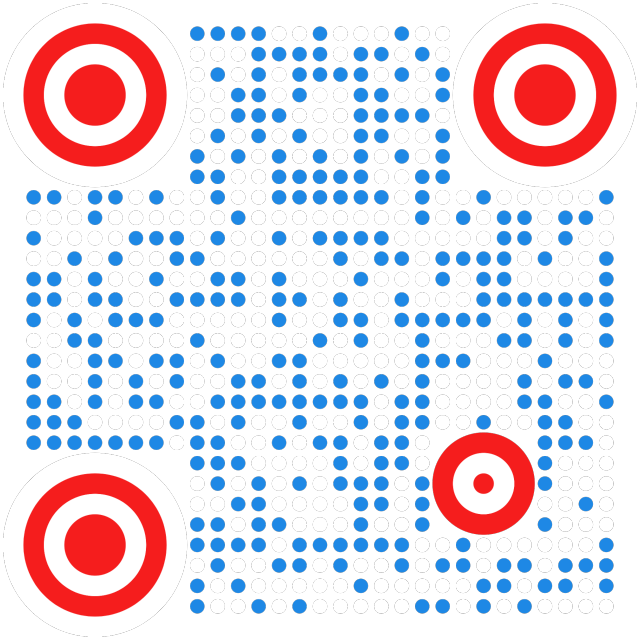
Implementation

Demo Implementation on Colab: Take me there!

Further Reading

- The Algorithmic Foundations of Differential Privacy [12]
- Fairness and Machine Learning [4]
- Differential Privacy and Fairness in Decisions and Learning Tasks: A Survey [17]
- Privacy and Fairness in Federated Learning: on the Perspective of Trade-off [8]
- A systematic review of federated learning from clients' perspective: challenges and solutions [46]

Thank you!



github.com/magnetar-iiith/FairPrivateDL

mll.iiit.ac.in

References I

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