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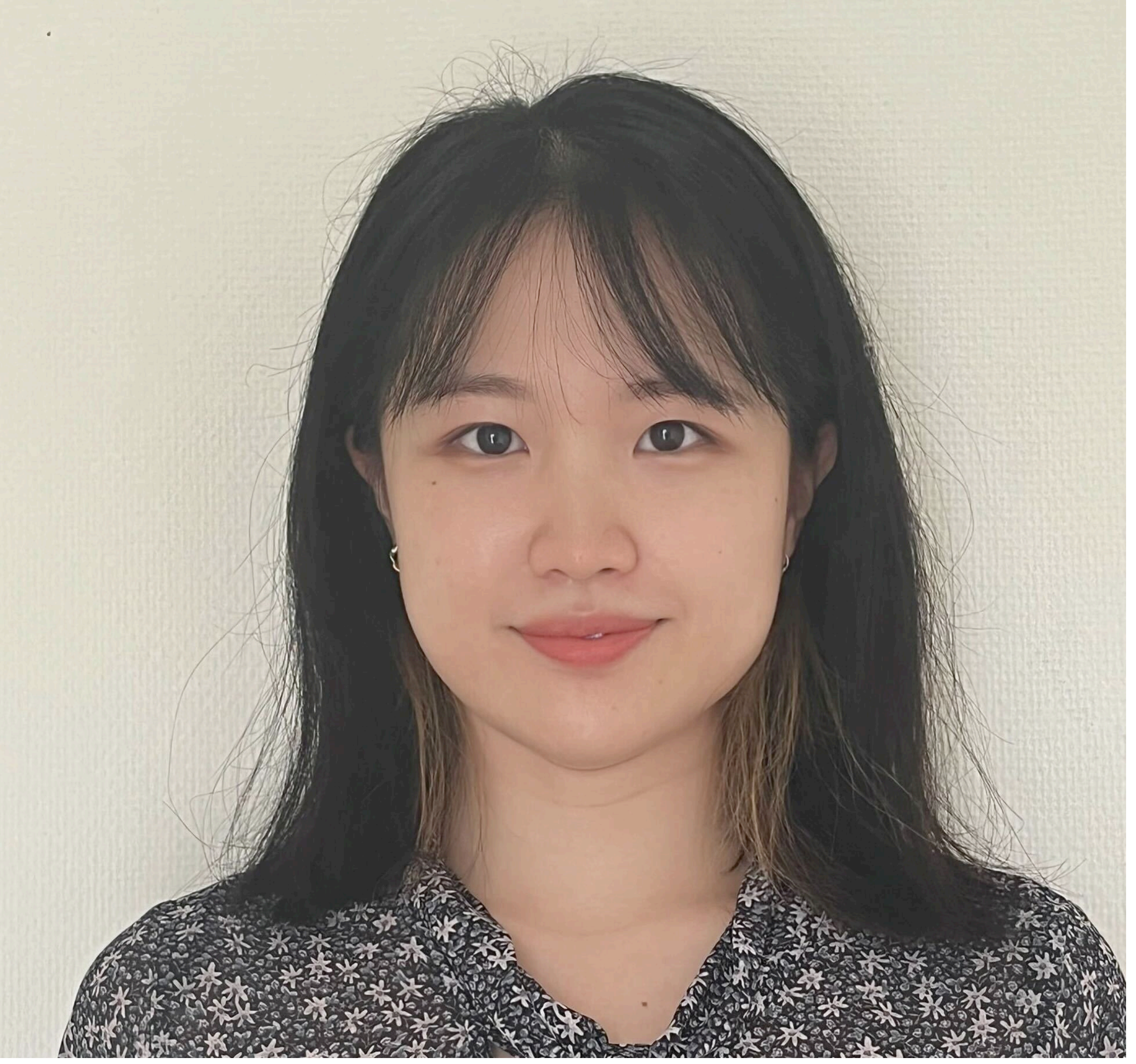
ETH zürich

ETH AI CENTER

How unfair is private learning ?

Amartya Sanyal, Yaxi Hu, Fanny Yang

Amartya



Yaxi

Fanny

Privacy and Fairness

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THIS WORK: The interaction of Privacy and Fairness of nearly **accurate algorithms.**

Differential Privacy

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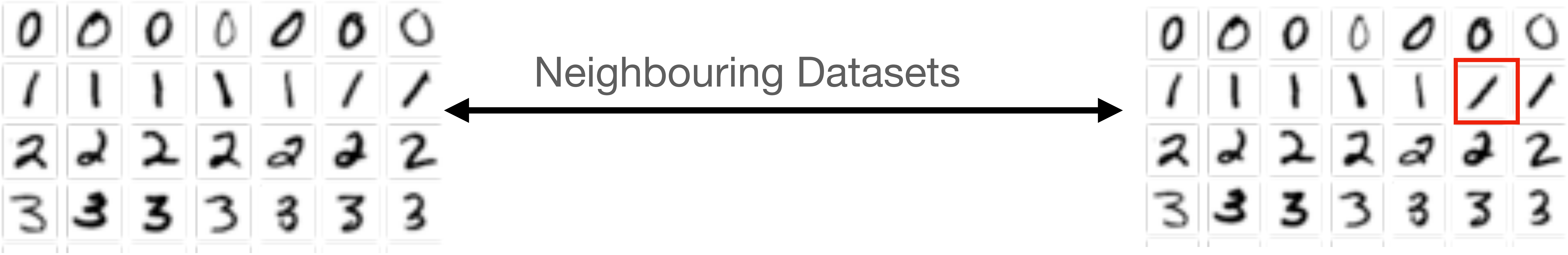

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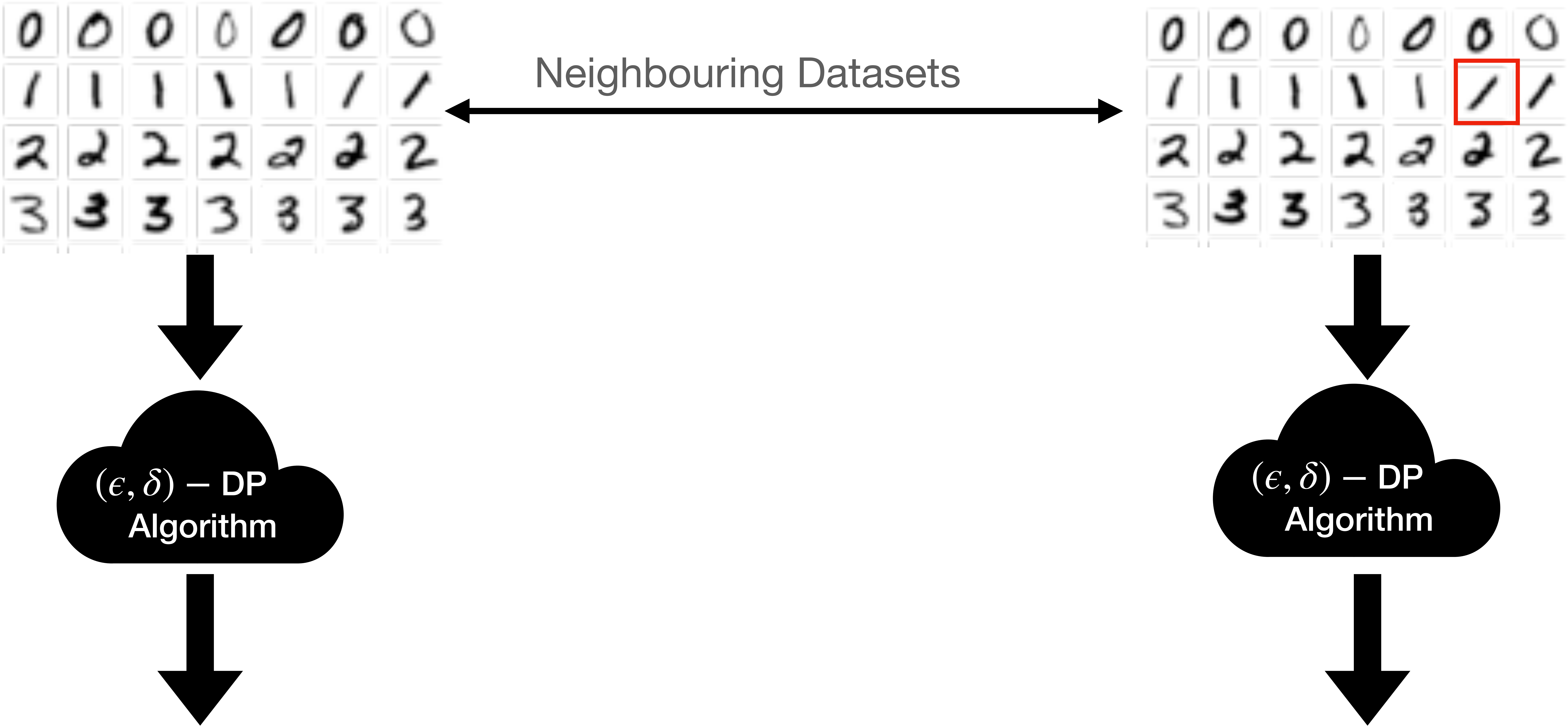

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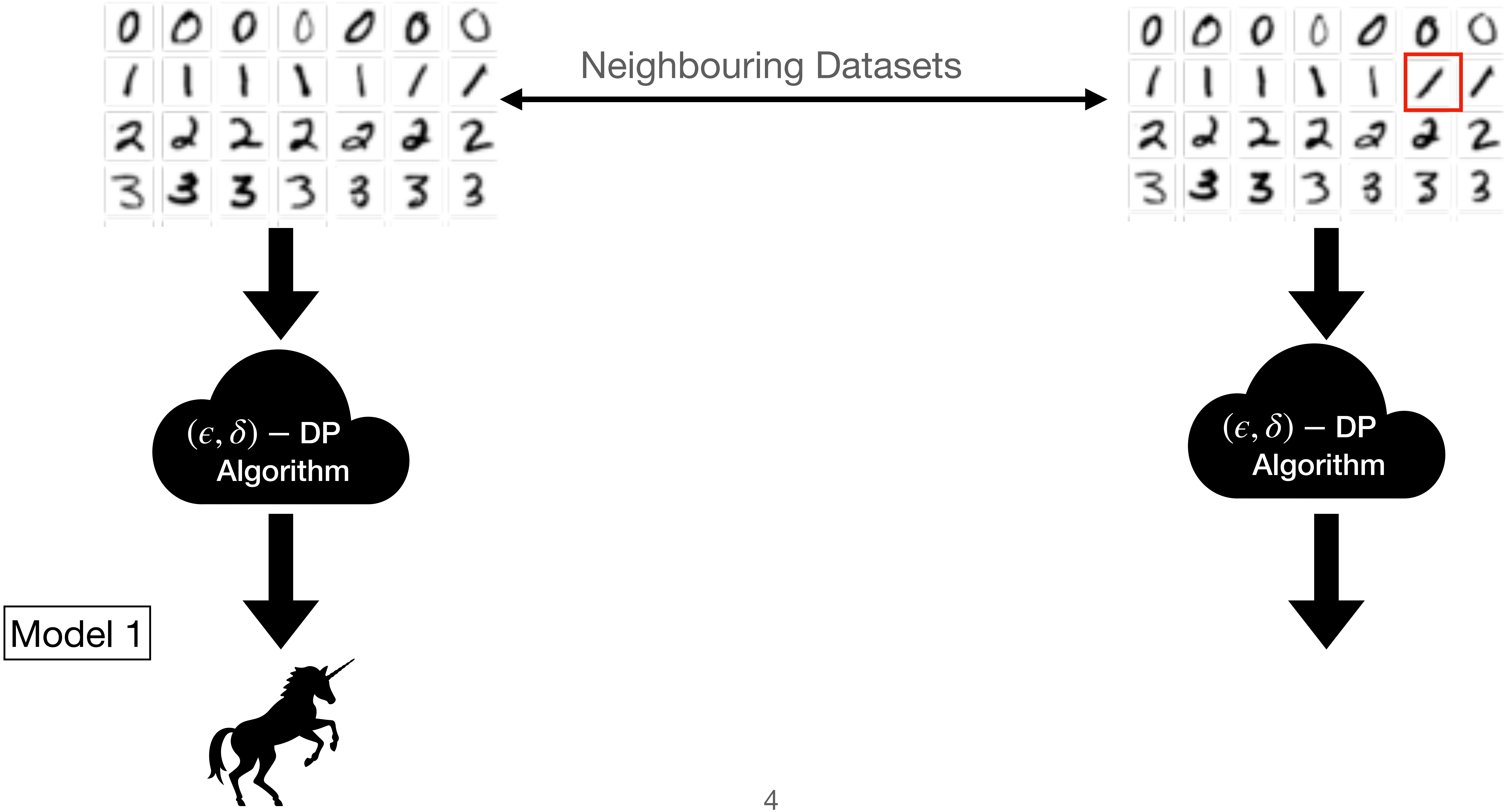

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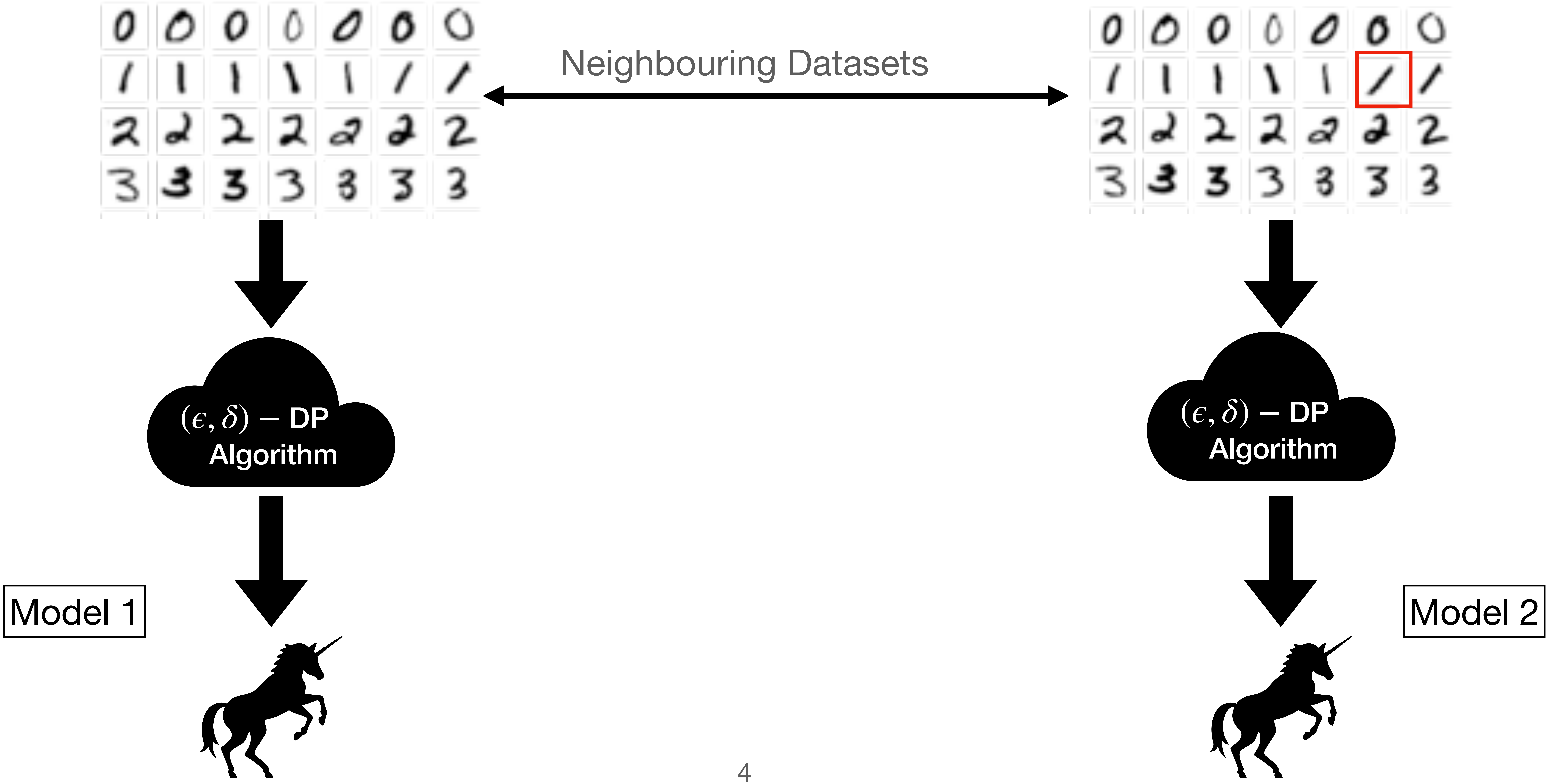

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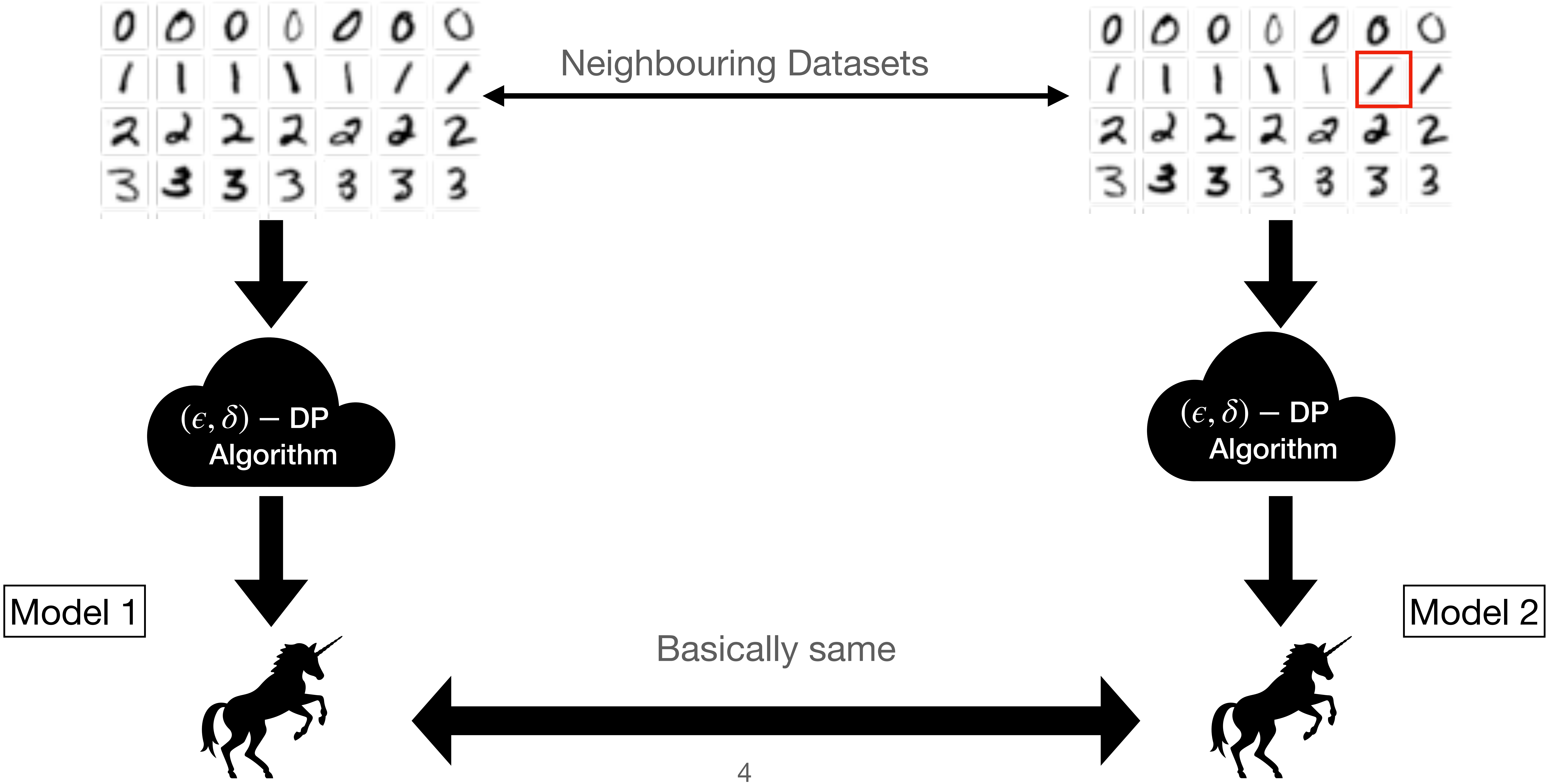

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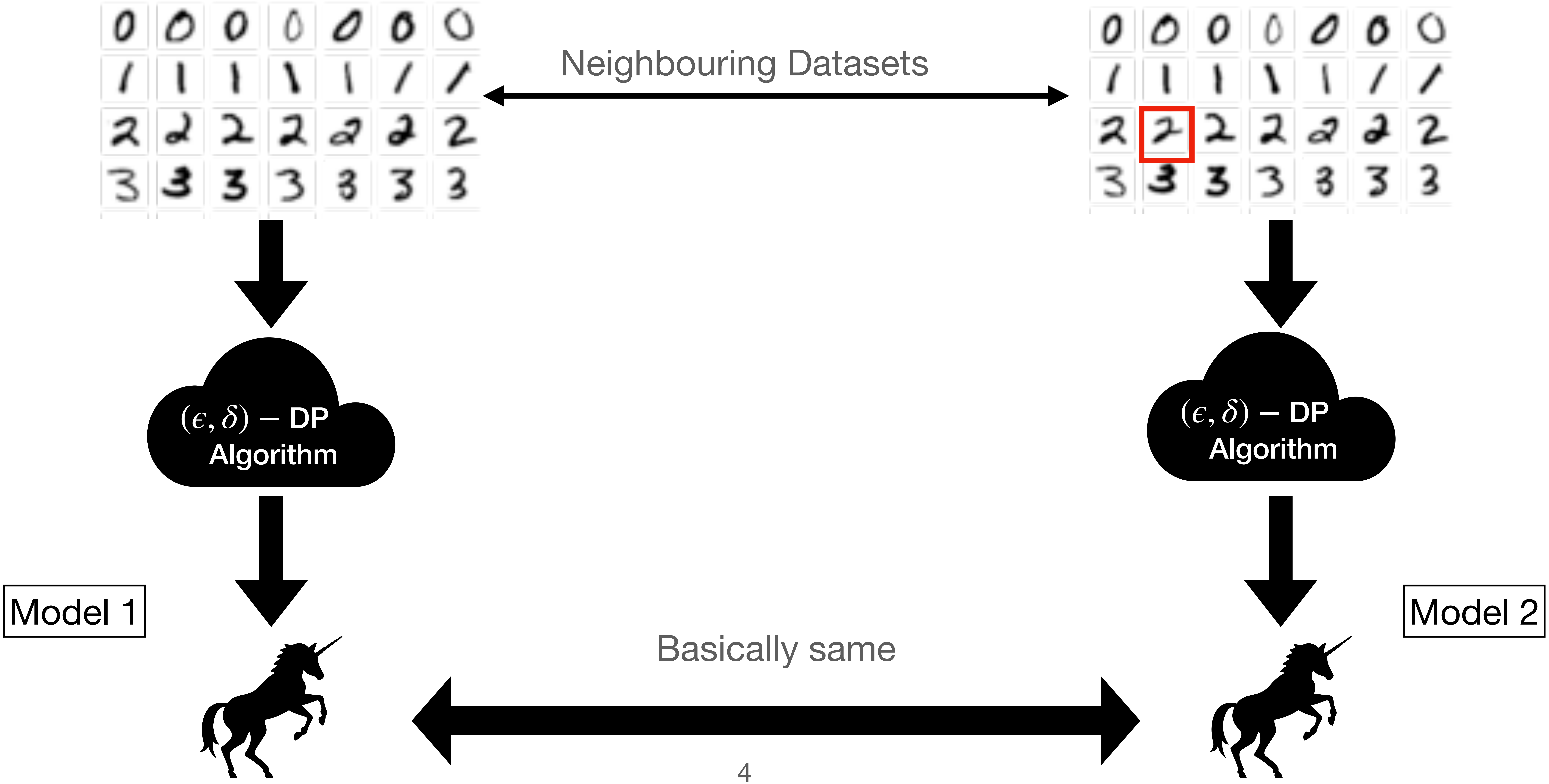

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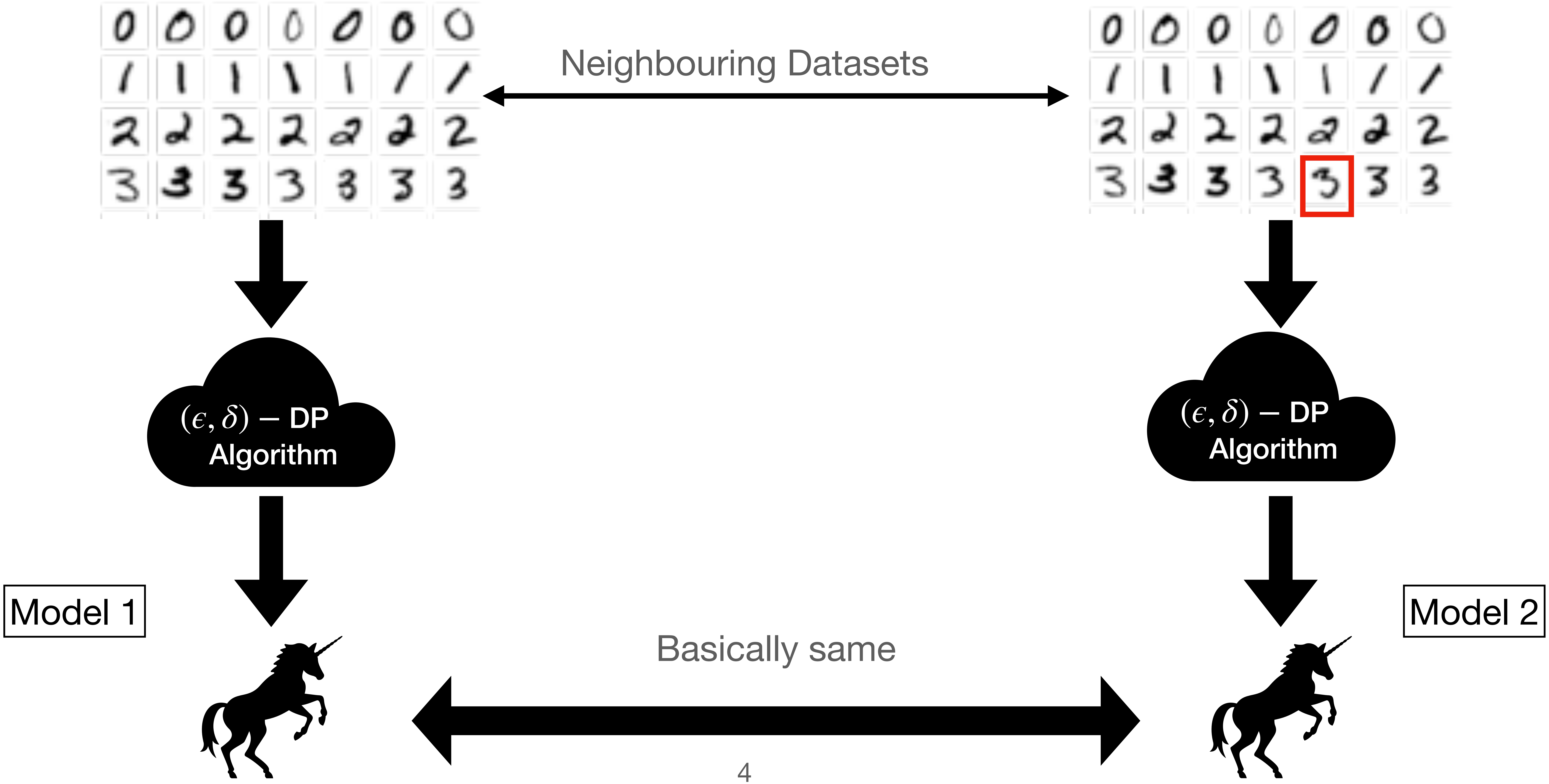

(Un) Fairness (Accuracy Discrepancy)

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Genre

Thrillers

Superhero

B&W

Mimes

Silent

Puppet

Ostern

(Un) Fairness (Accuracy Discrepancy)

Genre	Thrillers	Superhero	B&W	Mimes	Silent	Puppet	Ostern
Proportion	40%	40%	4%	4%	4%	4%	4%

(Un) Fairness (Accuracy Discrepancy)

Minority subpopulations

Genre	Thrillers	Superhero	B&W	Mimes	Silent	Puppet	Ostern
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(Un) Fairness (Accuracy Discrepancy)

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ML Problem: Is the movie safe to watch for kids ?

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	Majority Error = 5%		Minority Error = 70%				

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Total Error = 18%

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Total Error = 18%

Accuracy Discrepancy = Minority Error - Total Error

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Total Error = 18%

Accuracy Discrepancy = 70 - 18 = 52%

Example dataset

CelebA

Example dataset

CelebA

Example dataset

CelebA

40 binary attributes with each image

Eyeglasses

Bangs

Pointy Noise

Example dataset

CelebA

40 binary attributes -> **2^{40} subpopulations.**

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40 binary attributes -> **2^{40} subpopulations.**

- **Subpopulation 1**: Eyeglasses, bangs, …, pointy nose.

40 binary attributes with each image

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Example dataset

CelebA

<u>40 binary</u> <u>attributes -> **2^{40} subpopulations.**</u>

- **Subpopulation 1**: Eyeglasses, bangs, …, pointy nose.
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<u>40 binary attributes with each image</u>

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CelebA

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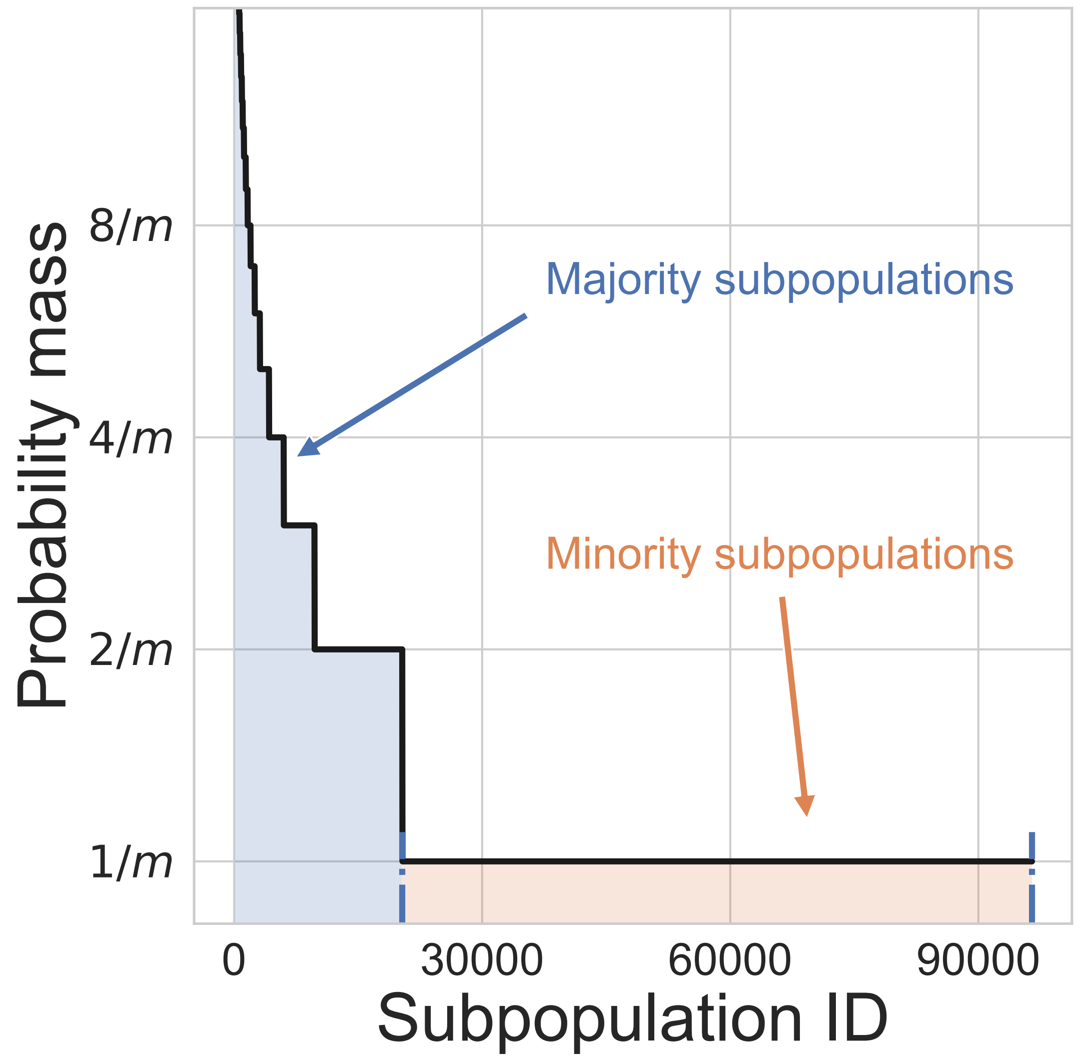

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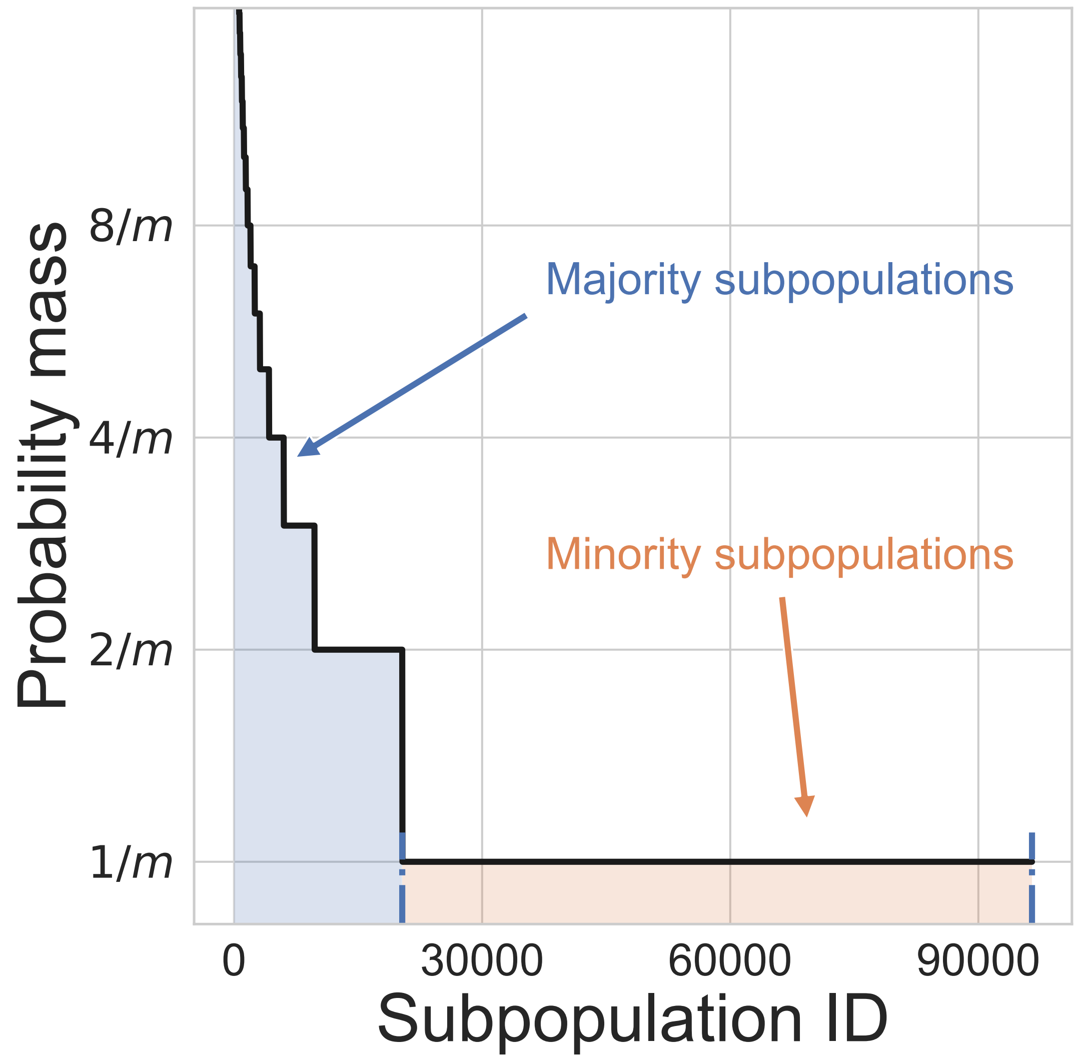

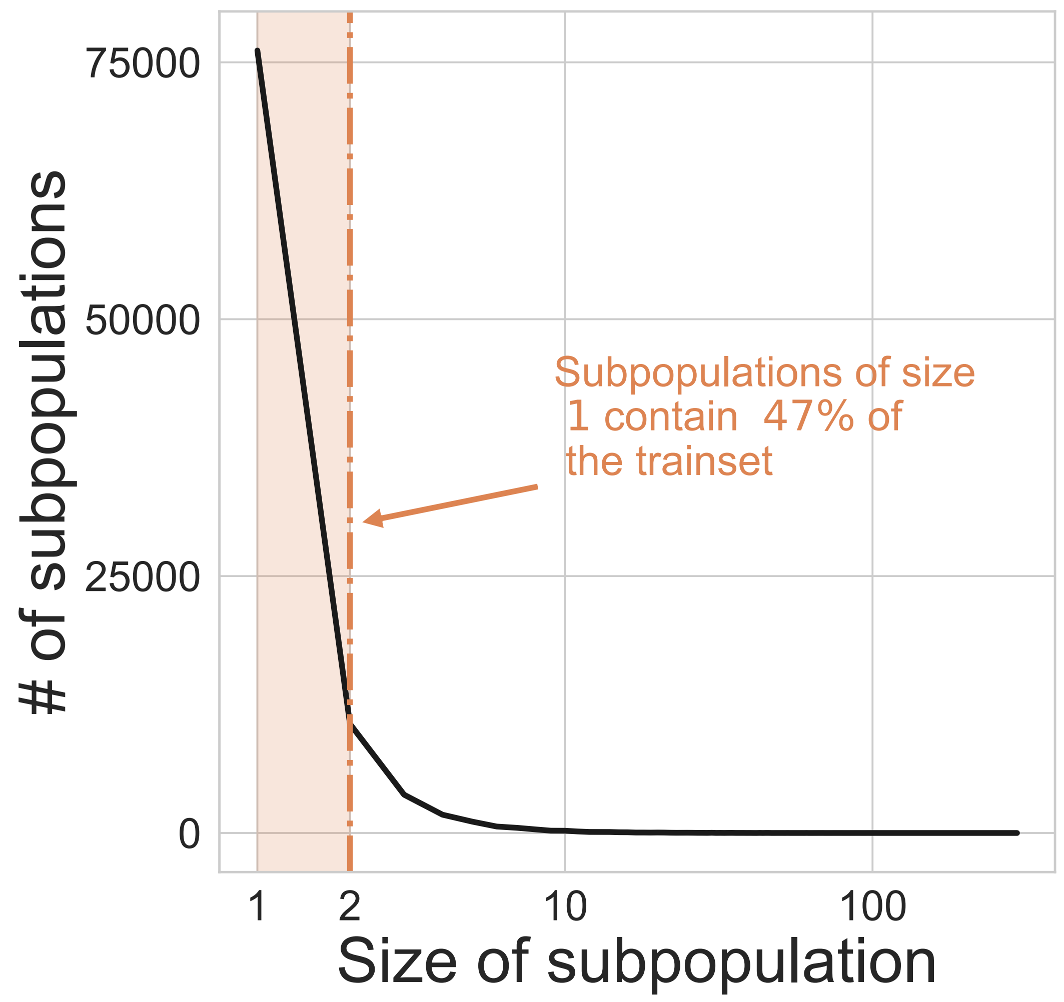

Privacy vs Fairness

CelebA

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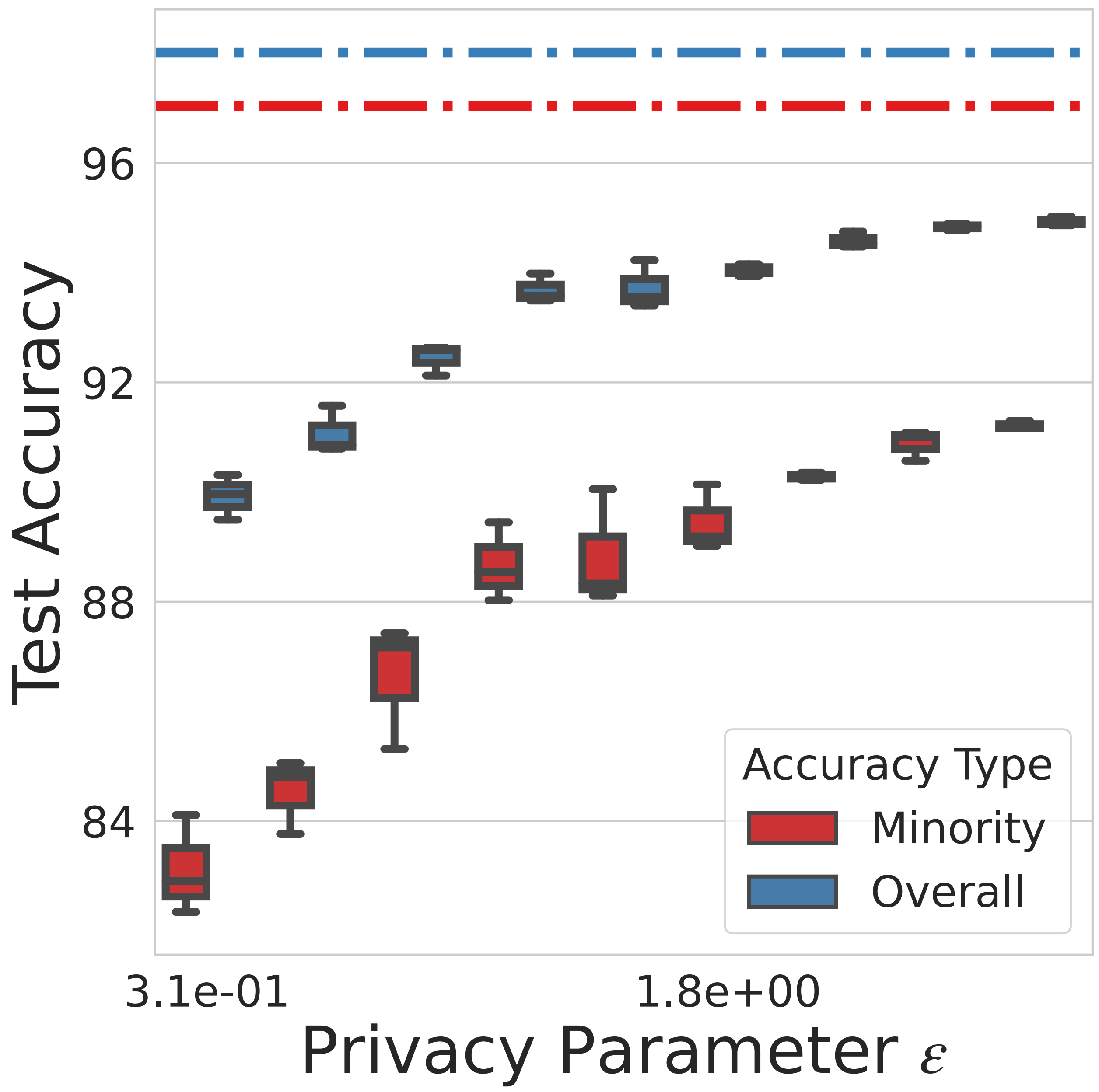

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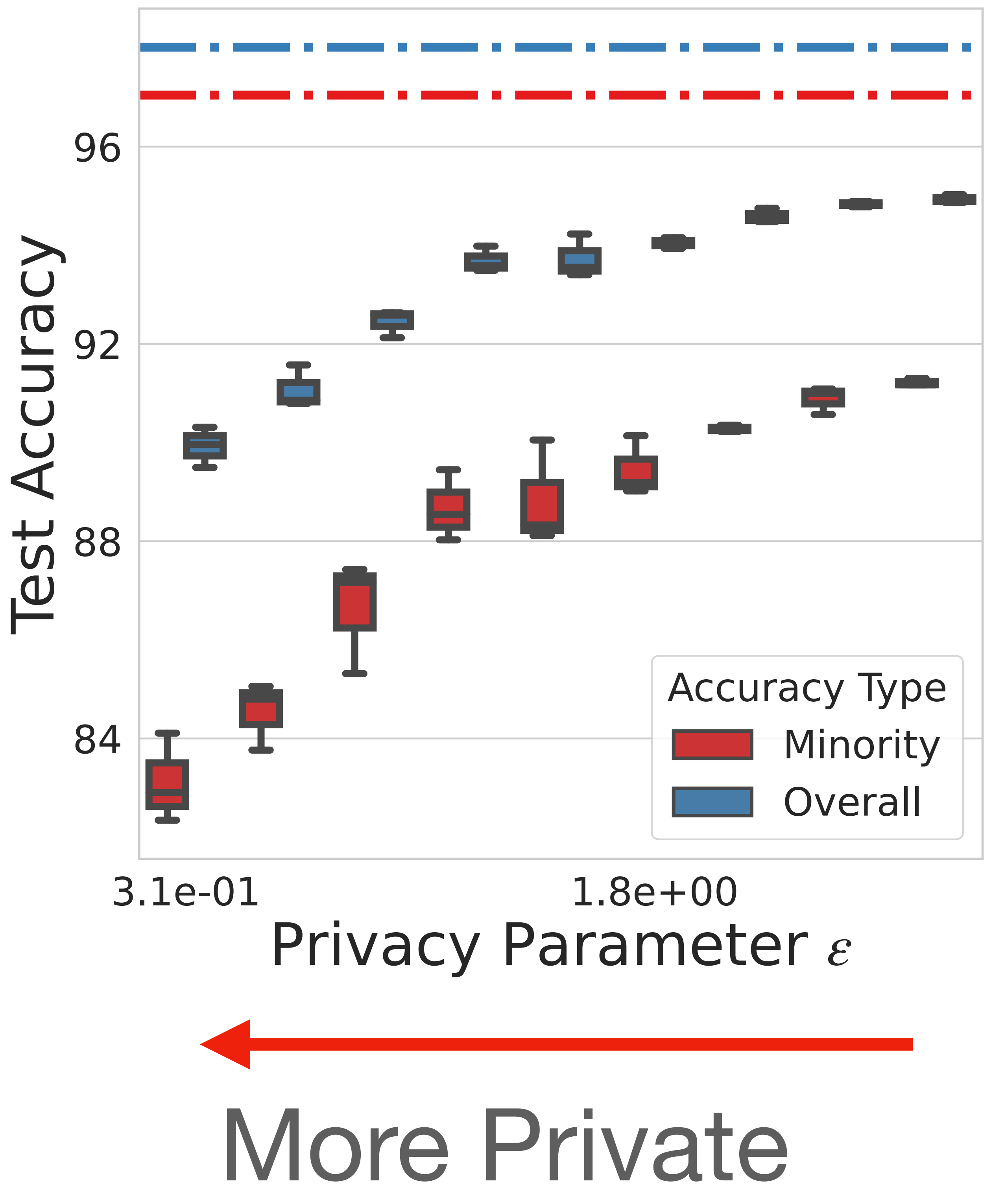

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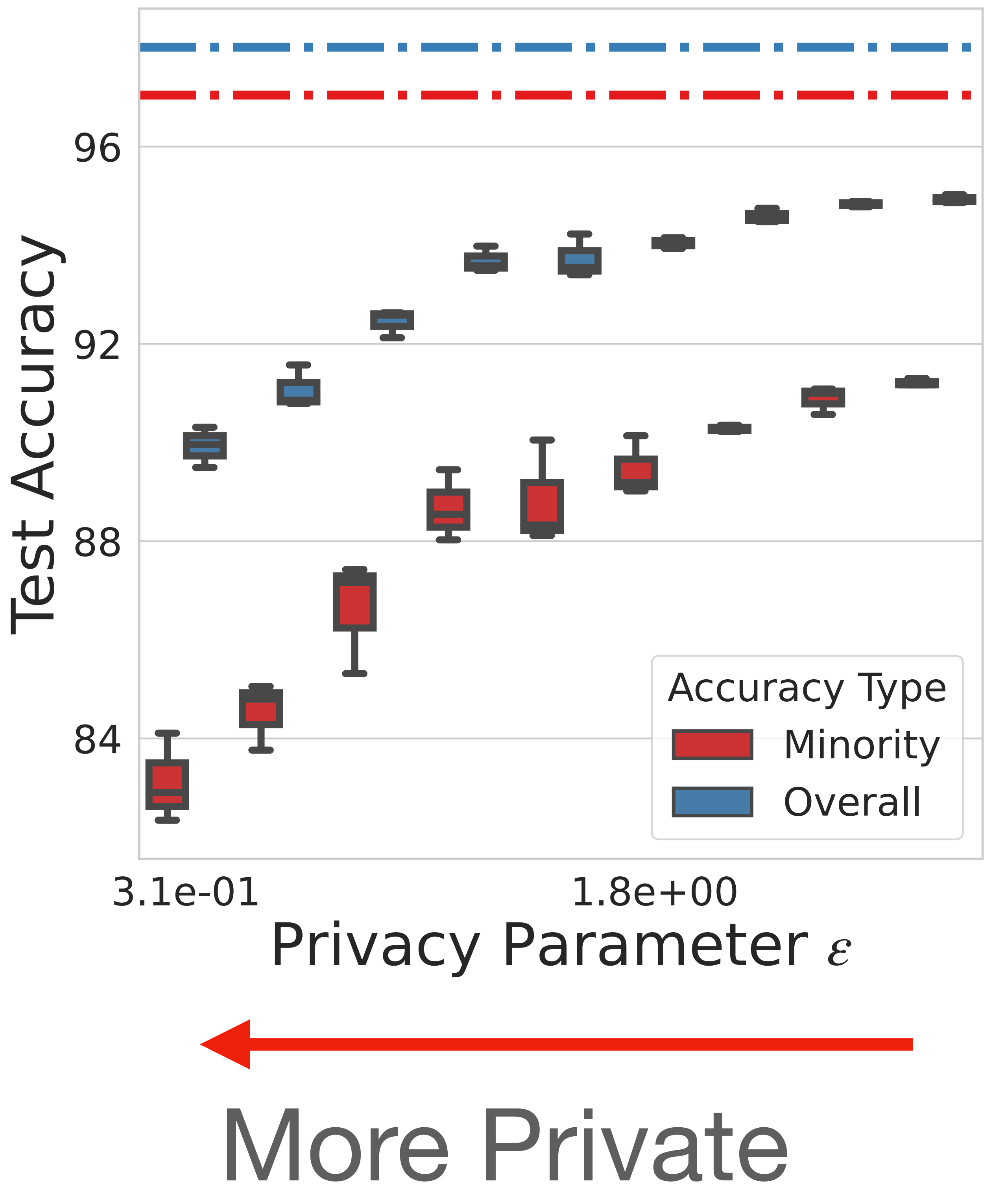

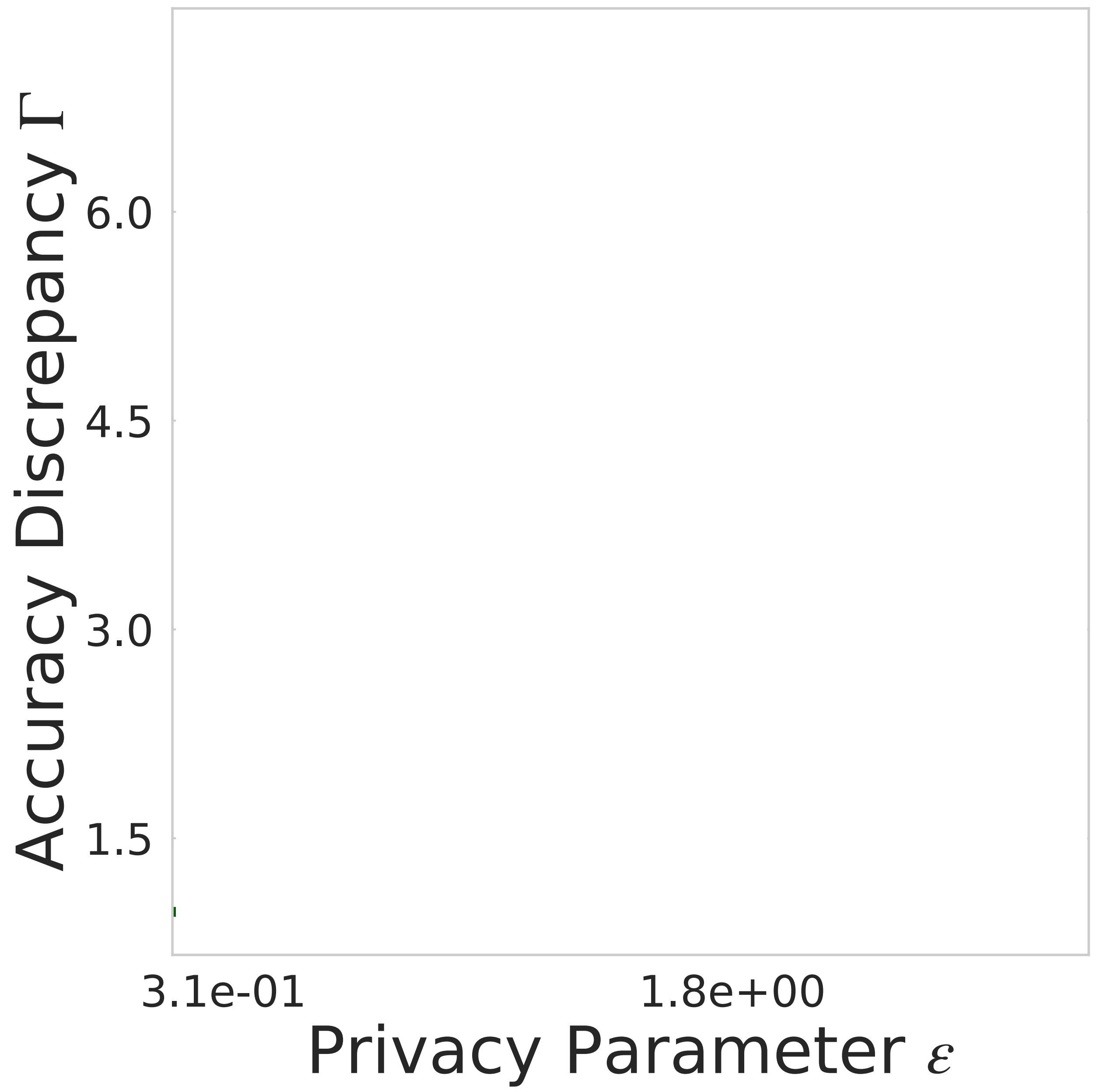

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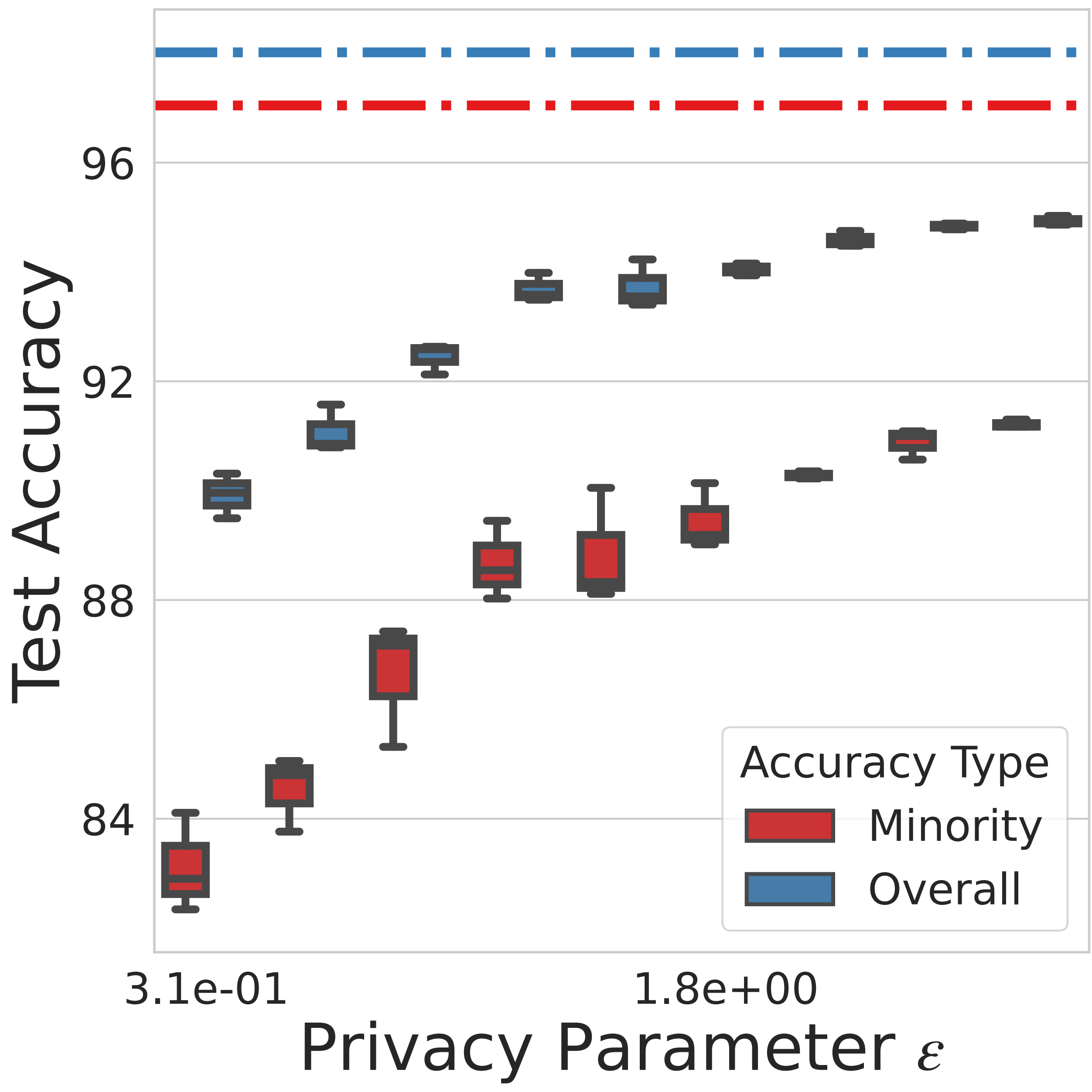
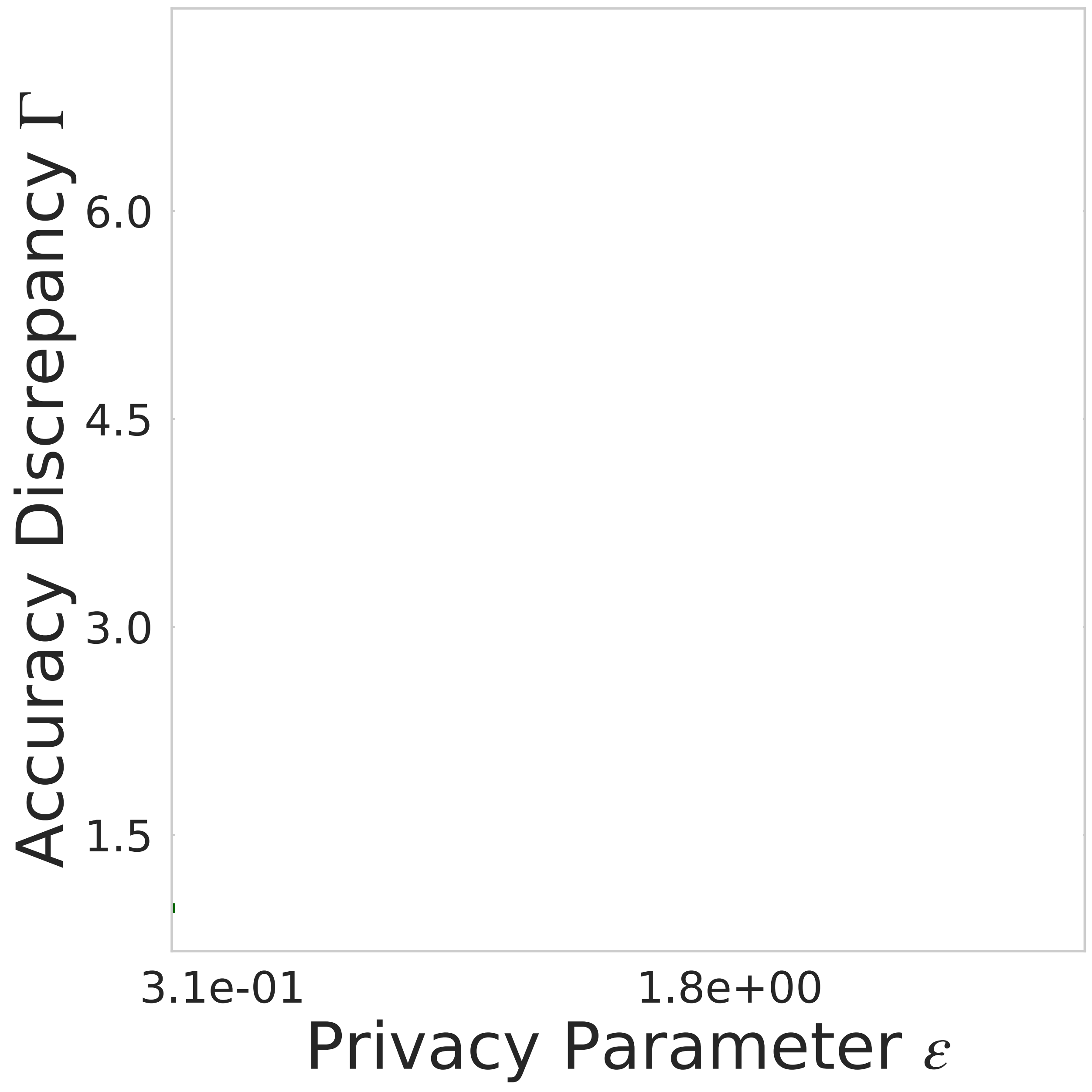


More Private



More Private

Privacy vs Fairness

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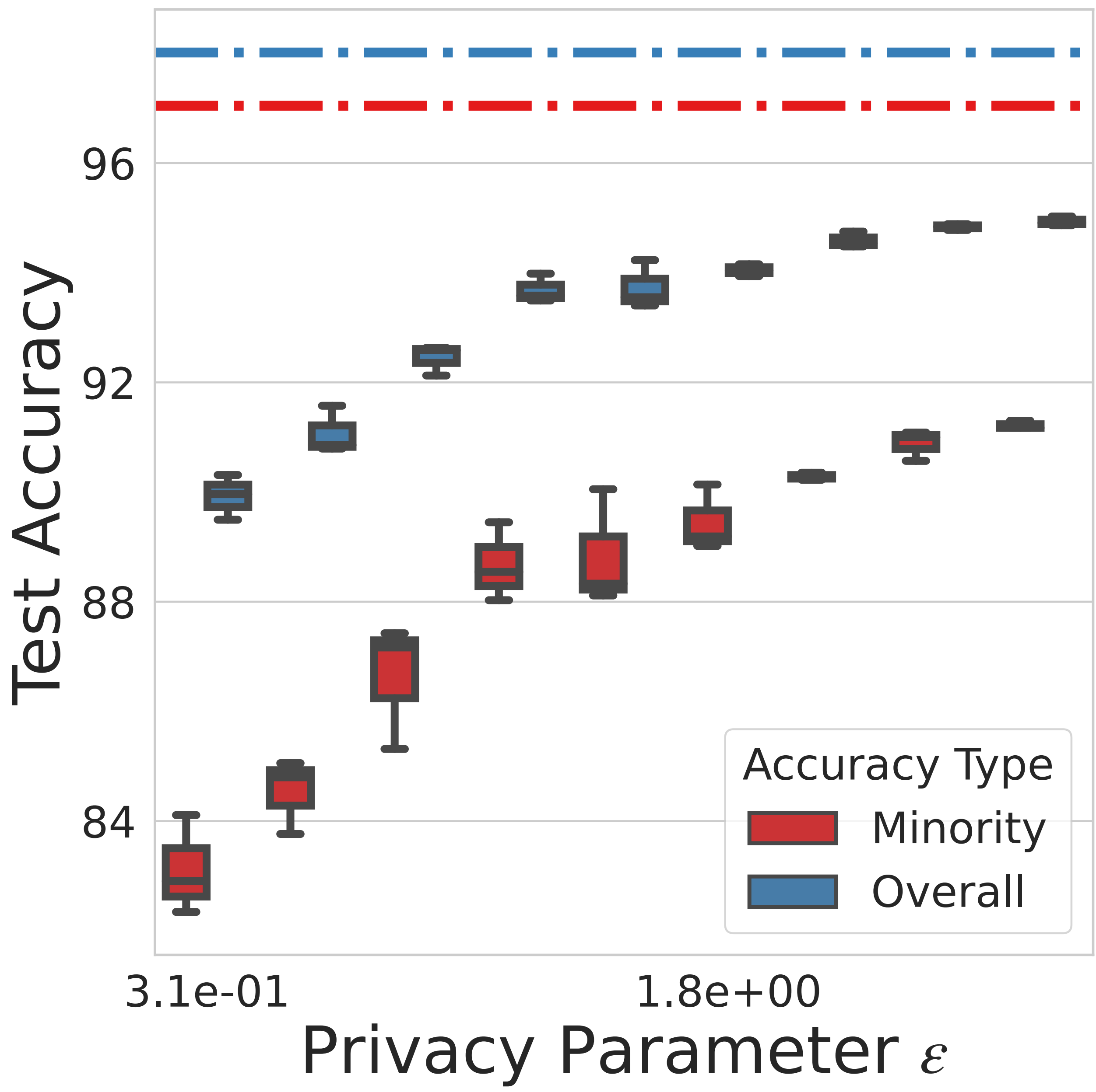
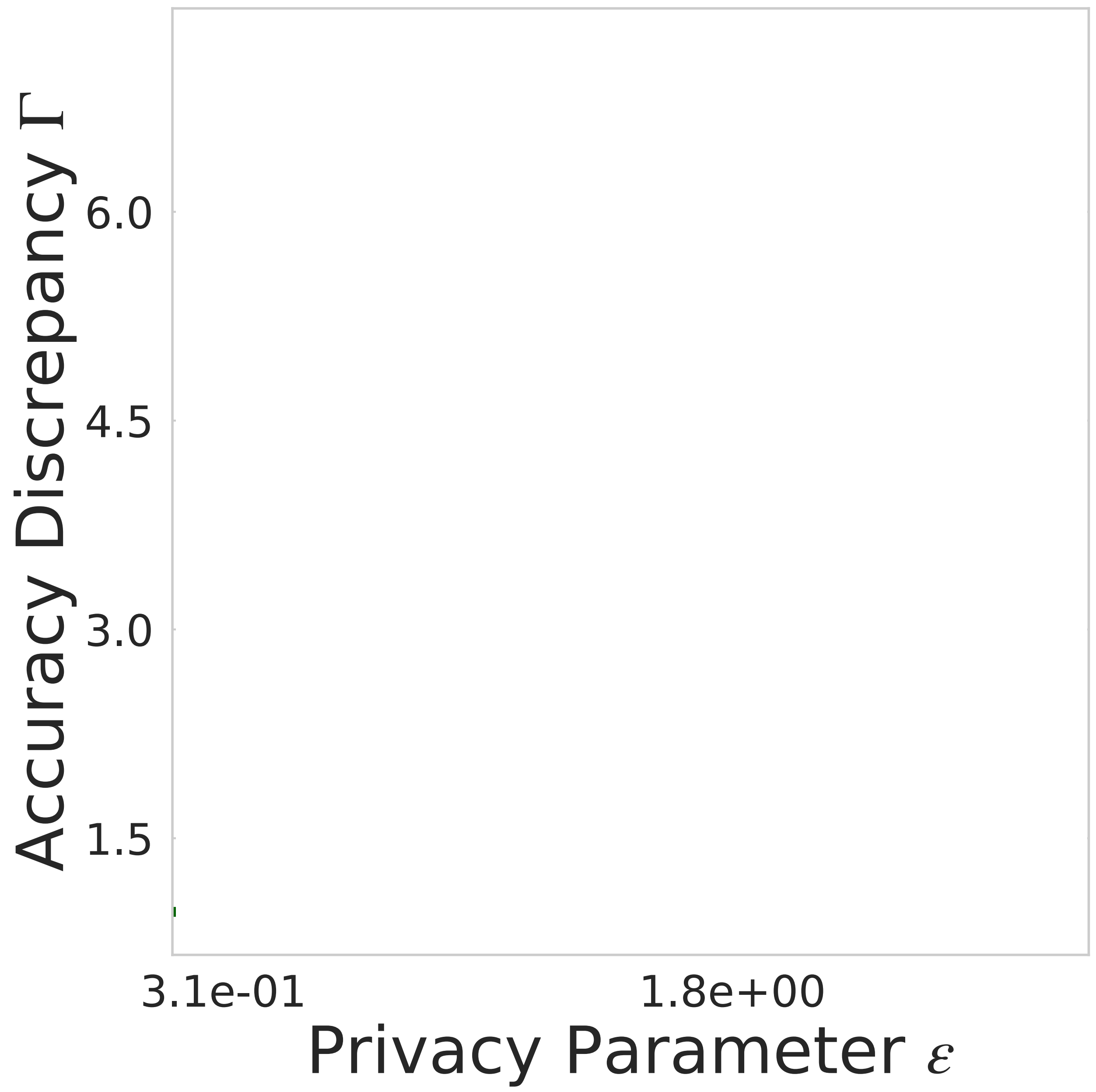


More Private

Less Fair



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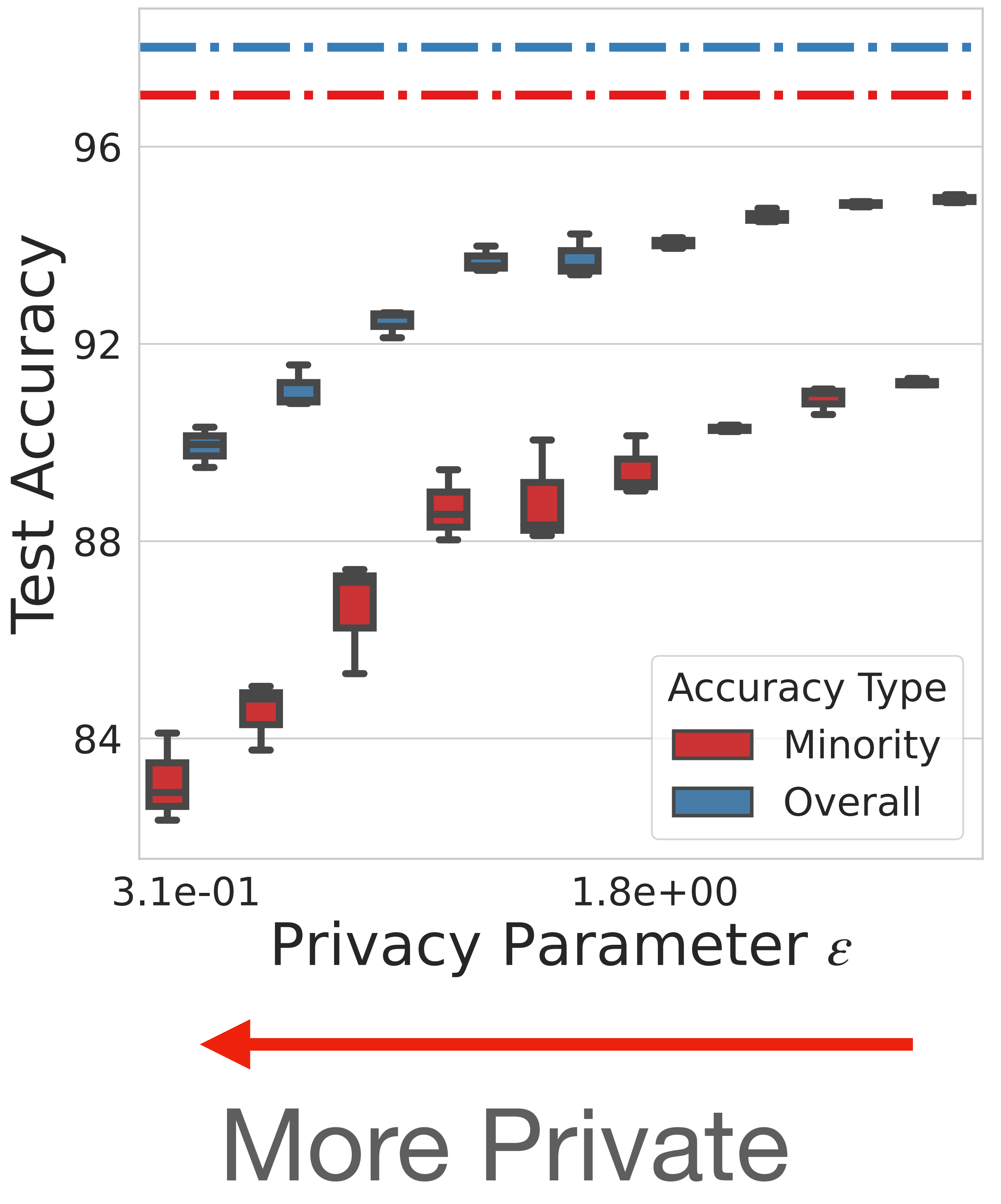
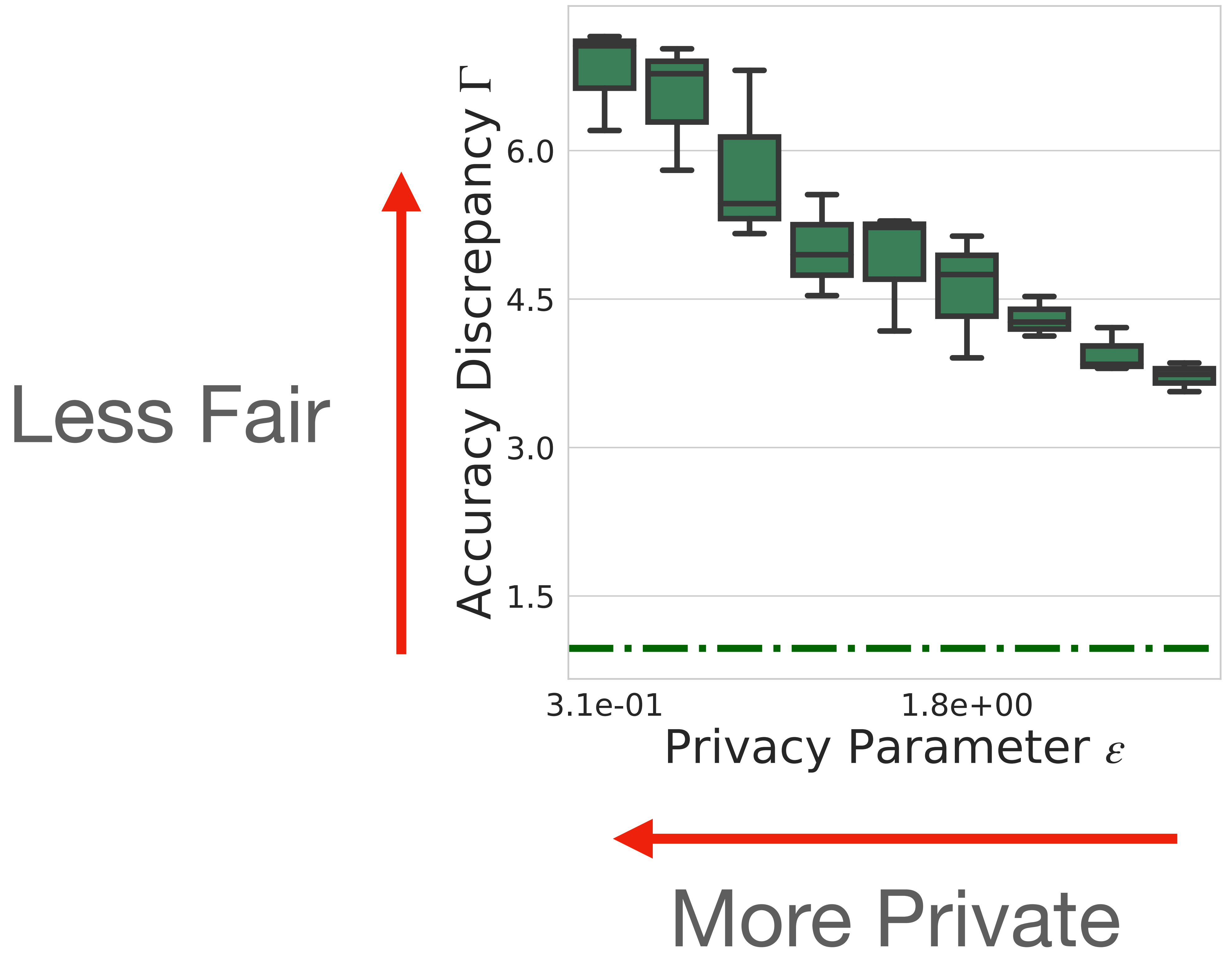
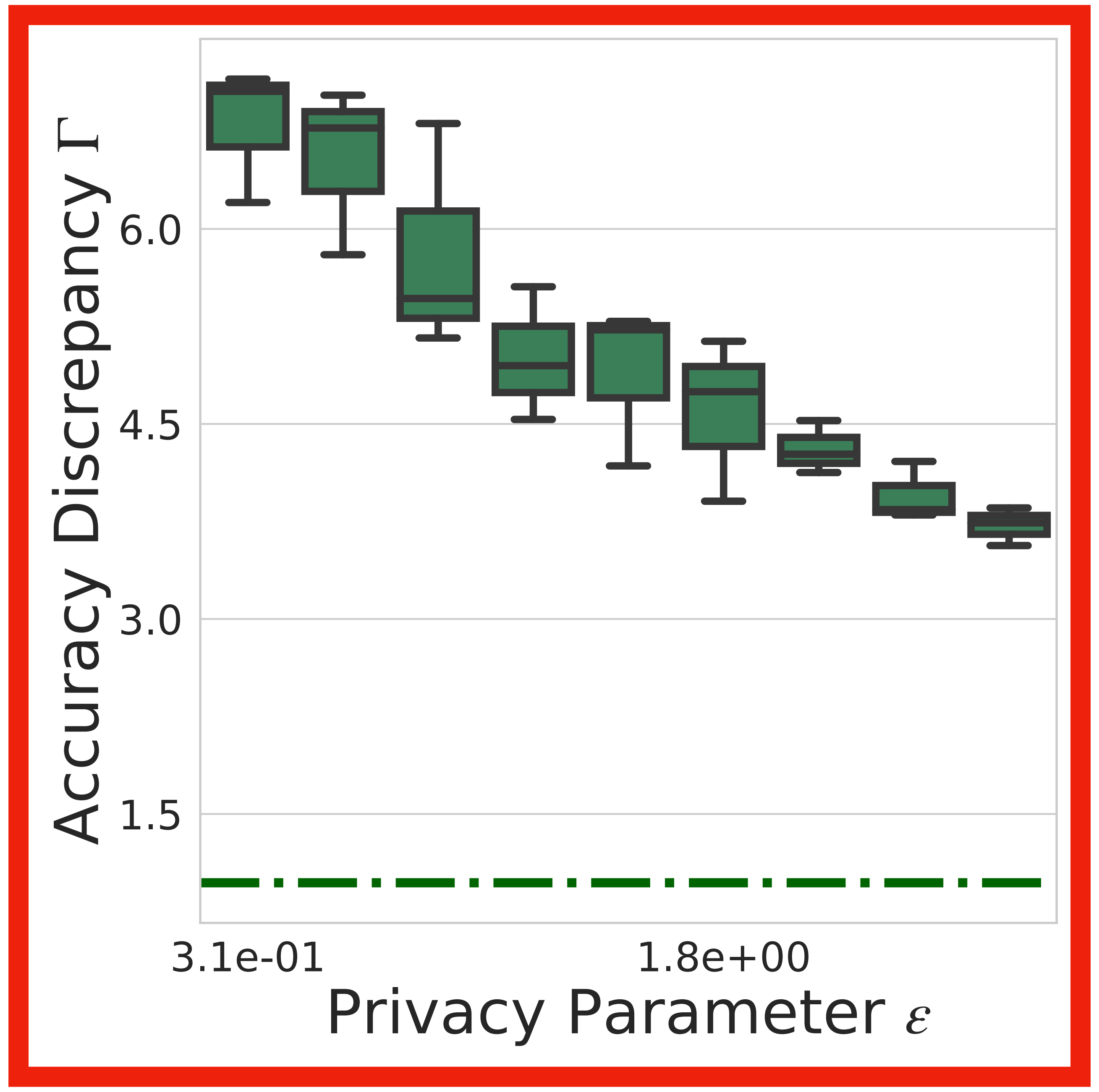
CelebA



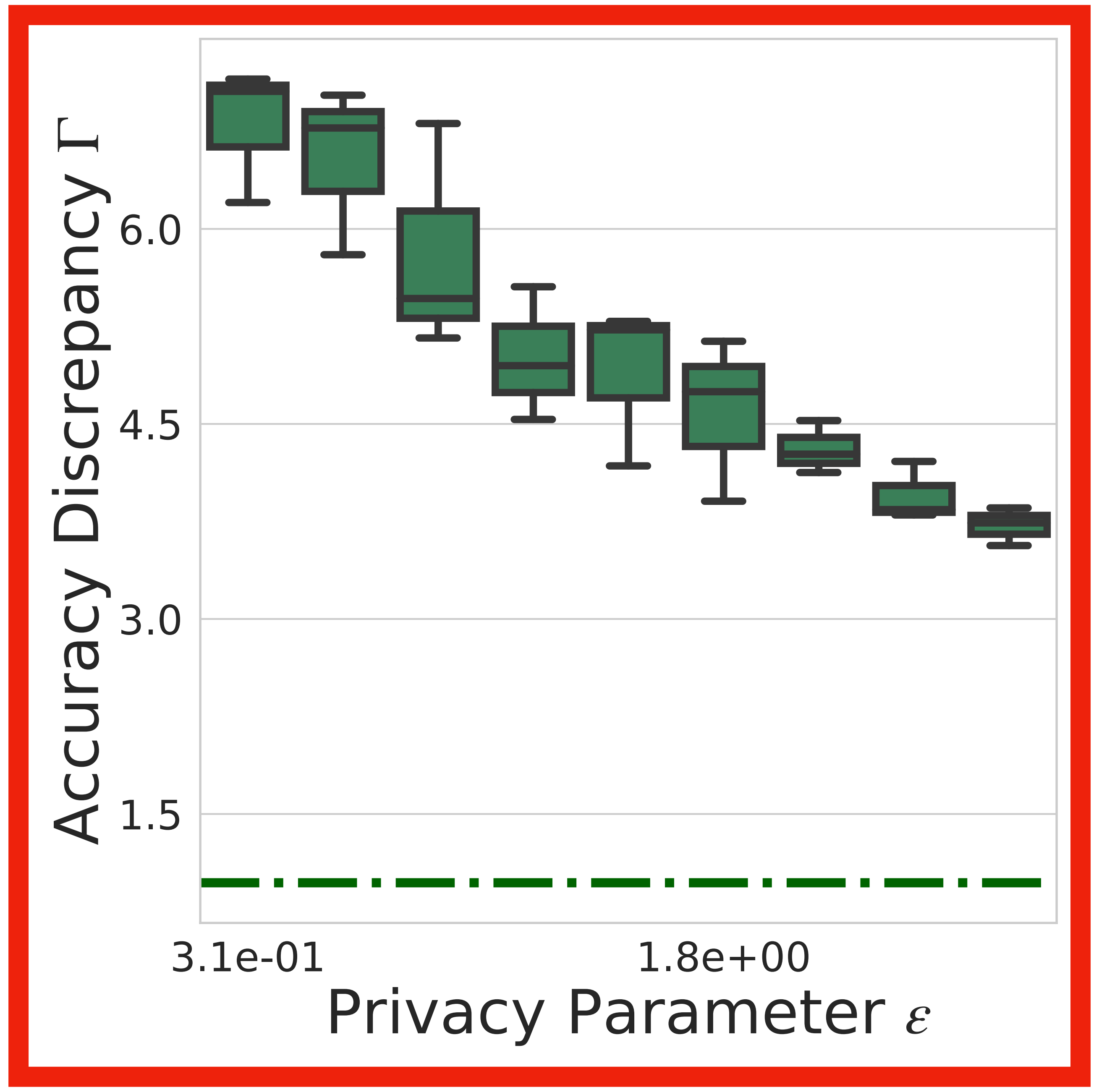


Is this trend systematic?



Is this trend systematic?

Main Contribution:
We prove this trend in a model-agnostic setting



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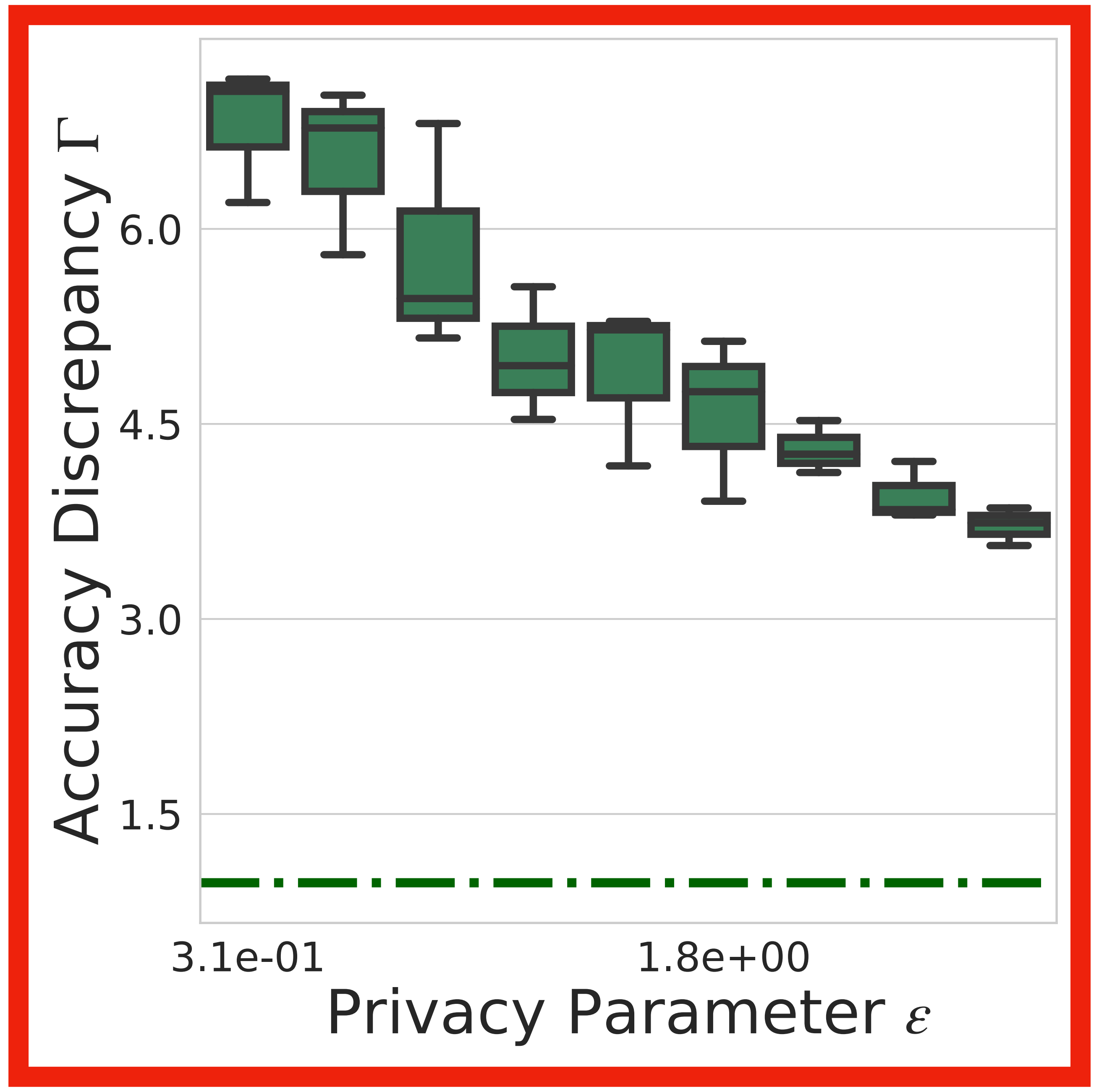

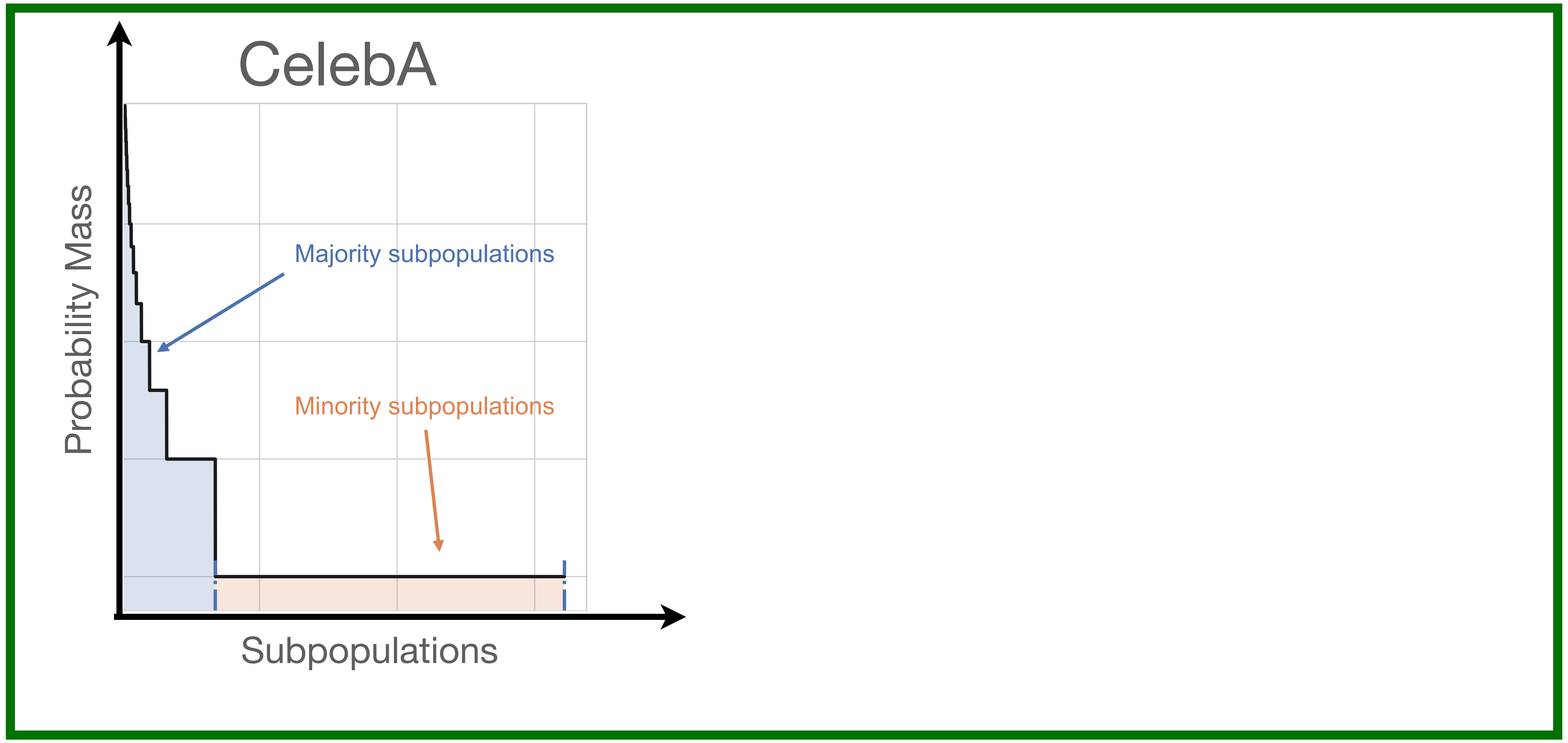

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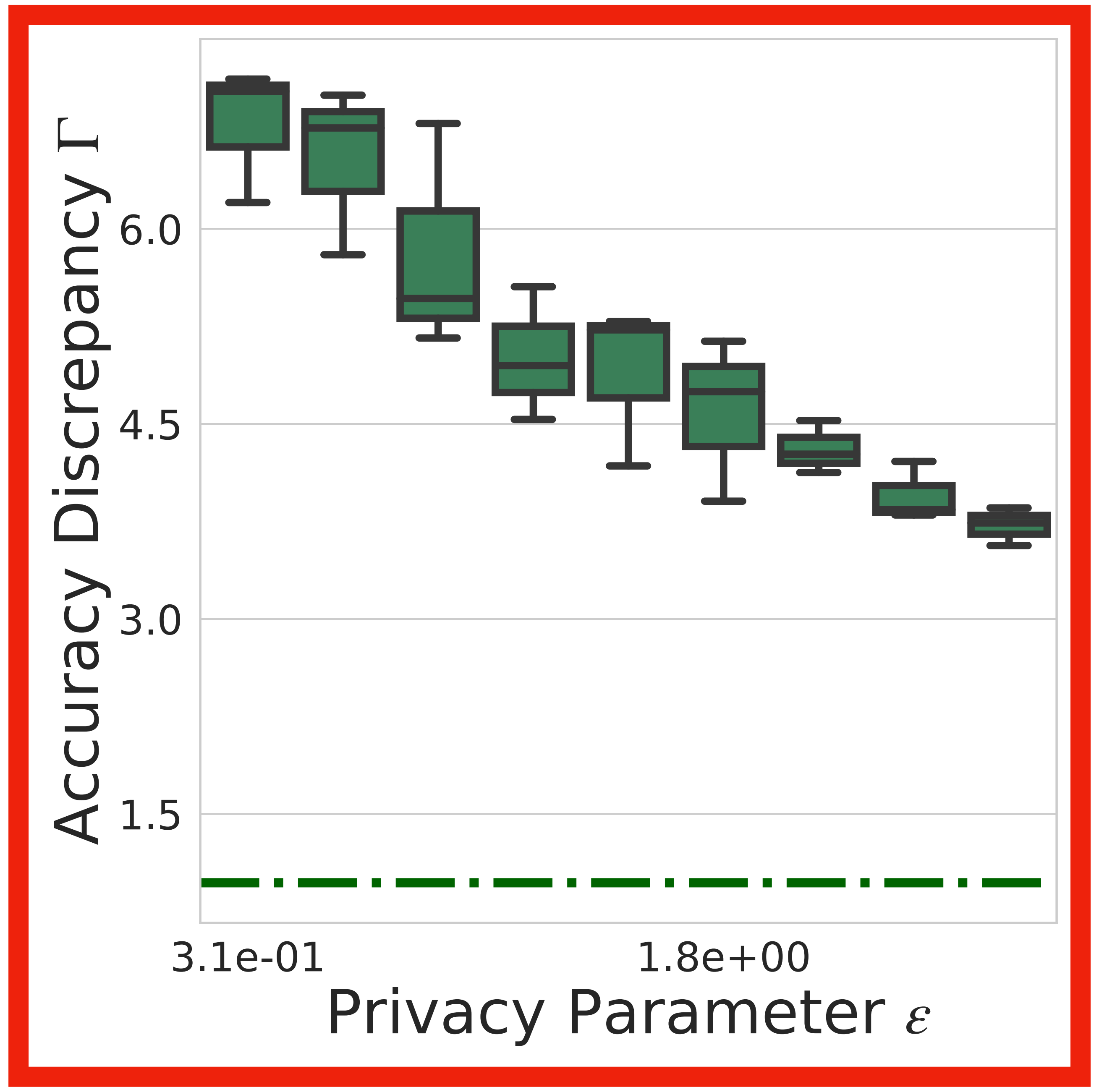

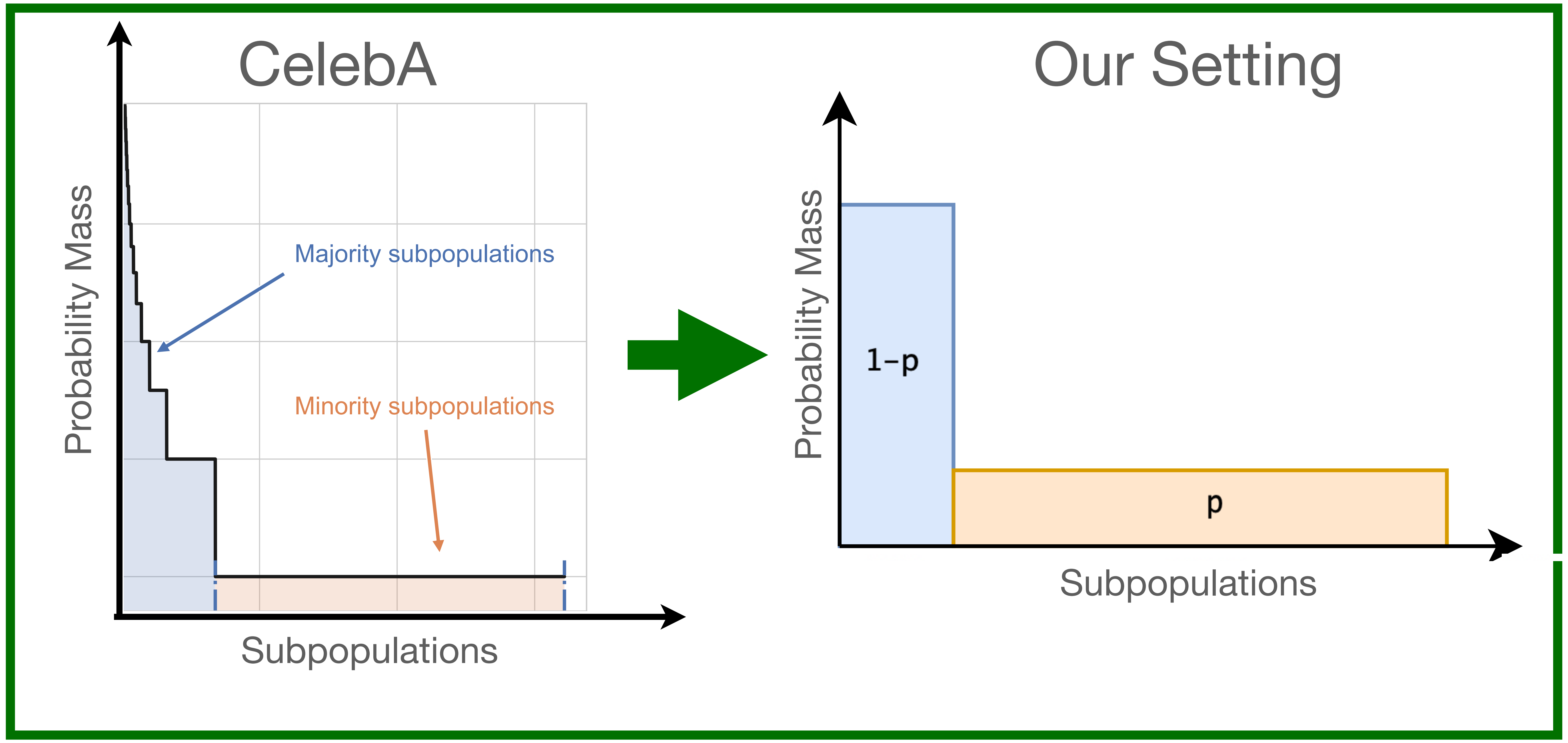

Definitions of error and fairness

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- Error

Definitions of error and fairness

- Error $\operatorname{err}(A, \Pi, F) =$

Definitions of error and fairness

- Error $\mathrm{err}\left(A, \Pi, F\right) =$

Learning Algorithm

Definitions of error and fairness

- Error

$$\text{err}\left(\boxed{A}, \boxed{\Pi}, F\right) =$$

Learning Algorithm

Data Distribution

Definitions of error and fairness

Prior distribution over labelling functions $\subseteq Y^X$

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Definitions of error and fairness

Prior distribution over labelling functions $\subseteq Y^X$

- Error

$$\mathrm{err}\left(A, \Pi, F\right) = \mathbb{P}\left[h(x) \neq f(x)\right]$$

Learning Algorithm

Probability is over $S \sim \Pi^m, f \sim F, h \sim A(S_f)$, and $x \sim \Pi_{p,N}$

Data Distribution

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- Accuracy Discrepancy

Definitions of error and fairness

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Learning Algorithm

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Data Distribution

- Accuracy Discrepancy

$$\Gamma\left(A, \Pi, F\right) = \mathrm{err}_{\mathrm{Minority}}\left(A, \Pi, F\right) - \mathrm{err}\left(A, \Pi, F\right)$$

Definitions of error and fairness

Prior distribution over labelling functions $\subseteq Y^X$

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Probability is over $S \sim \Pi^m, f \sim F, h \sim A(S_f)$, and $x \sim \Pi_{p,N}$

- Accuracy Discrepancy

Marginalised over minority subpopulations

$$\Gamma\left(A, \Pi, F\right) = \boxed{\mathrm{err}_{\mathrm{Minority}}\left(A, \Pi, F\right)} - \mathrm{err}\left(A, \Pi, F\right)$$

Privacy at the cost of fairness

Privacy at the cost of fairness

Consider any (ϵ, δ)**-DP algorithm** that obtains low error on a long-tailed distribution.

Privacy at the cost of fairness

Consider any (ϵ, δ)**-DP algorithm** that obtains low error on a long-tailed distribution.

(Informal Theorem A) We prove an asymptotic lower bound for accuracy discrepancy which

- (Privacy) Increases with privacy parameter ϵ.

Privacy at the cost of fairness

Consider any **(ϵ, δ)-DP algorithm** that obtains low error on a long-tailed distribution.

N: # Minority subpopulations
m: # Training points

(Informal Theorem A) We prove an asymptotic lower bound for accuracy discrepancy which

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Privacy at the cost of fairness

Consider any (ϵ, δ)-**DP algorithm** that obtains low error on a long-tailed distribution.

(Minority Subpopulations) Let $\frac{N}{m} \to c$ as $N, m \to \infty$.

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(Informal Theorem A) We prove an asymptotic lower bound for accuracy discrepancy which

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- (Long-tailed) Increases with (relative) # of minority subpopulations c.

Privacy at the cost of fairness

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(Minority Subpopulations) Let $\frac{N}{m} \to c$ as $N, m \to \infty$.

N: # Minority subpopulations
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F: Label prior

(Informal Theorem A) We prove an asymptotic lower bound for accuracy discrepancy which

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Privacy at the cost of fairness

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(Label prior Entropy) Define $\|F\|_\infty = \max_{x,y} \mathbb{P}_{f \sim F}\left[f(x) = y\right]$

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- (Privacy) Increases with privacy parameter ϵ.
- (Long-tailed) Increases with (relative) # of minority subpopulations c.
- (Label prior) Increases with entropy of the label prior.

Thank you