

# Responsible AI:

## Seminar on Fairness, Safety, Privacy and more

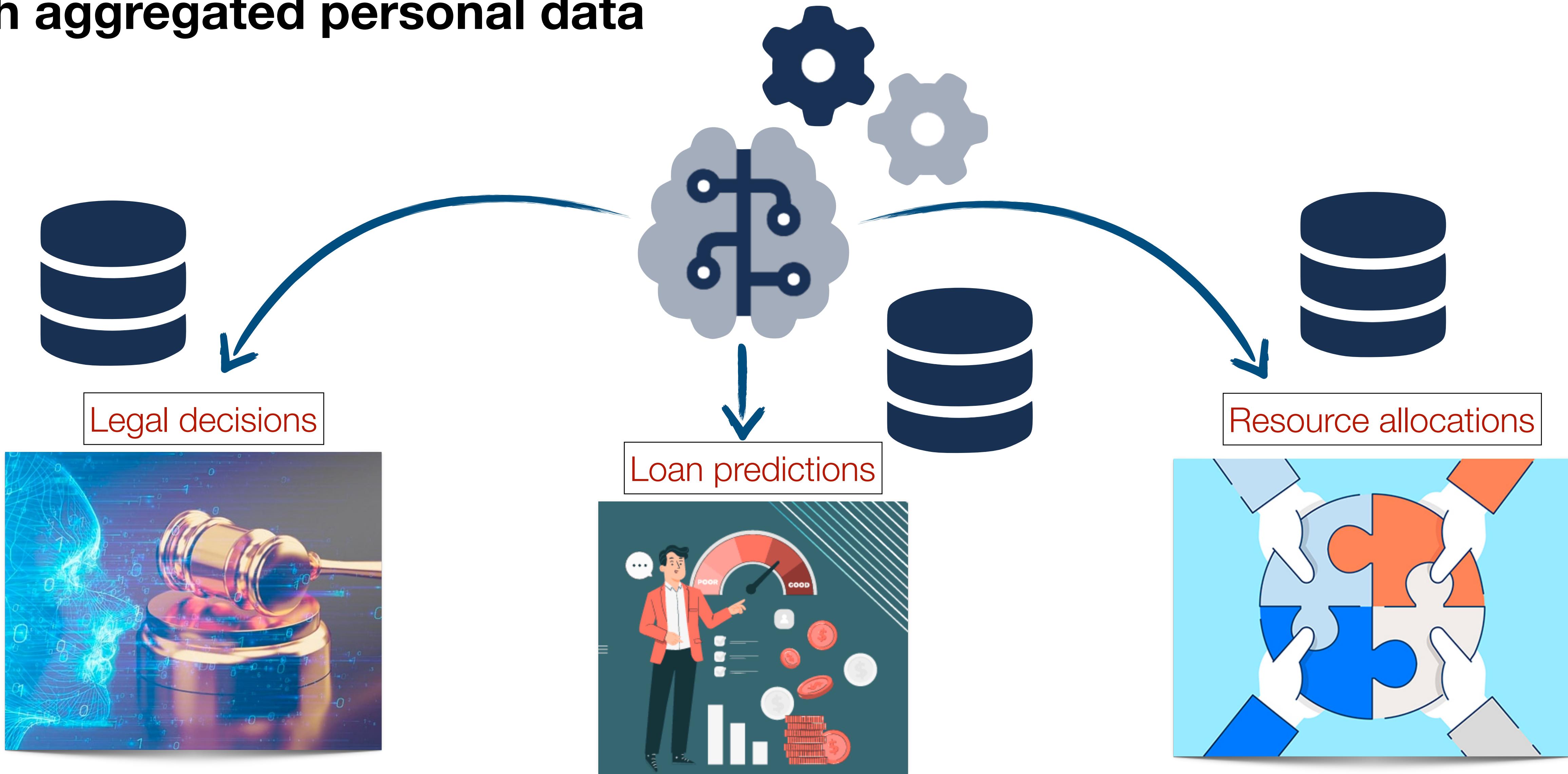
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Ferdinando Fioretto @UVA Spring 2024

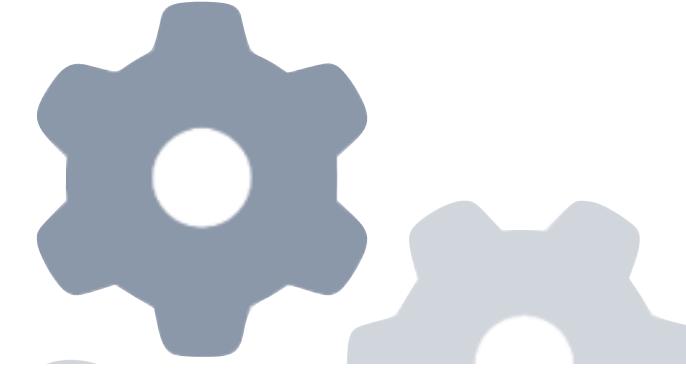


# AI-driven decision making

## with aggregated personal data



# Key concerns



President Biden Signs  
Executive Order Advancing  
Racial Equity and  
Imposing Equity Principles  
on Government A.I.

February 16, 2023



# Privacy

# Fairness

# Key concerns



# Privacy

- Differential Privacy has become the paradigm of choice for protecting data privacy.
- Deployments are growing at a fast rate.

Google testing new differential privacy strategy with Gboard for And

Chance Miller - Apr. 6th 2017 9:11 pm PT @ChanceHMiller

## Facebook Outlines New Differential

WIR ED BACKCHANNEL BUSINESS CULTURE GEAR IDEAS SCIENCE SECURITY SIGN IN SUBSCRIBE

ANDY GREENBERG SECURITY 07.13.2017 10:02 AM

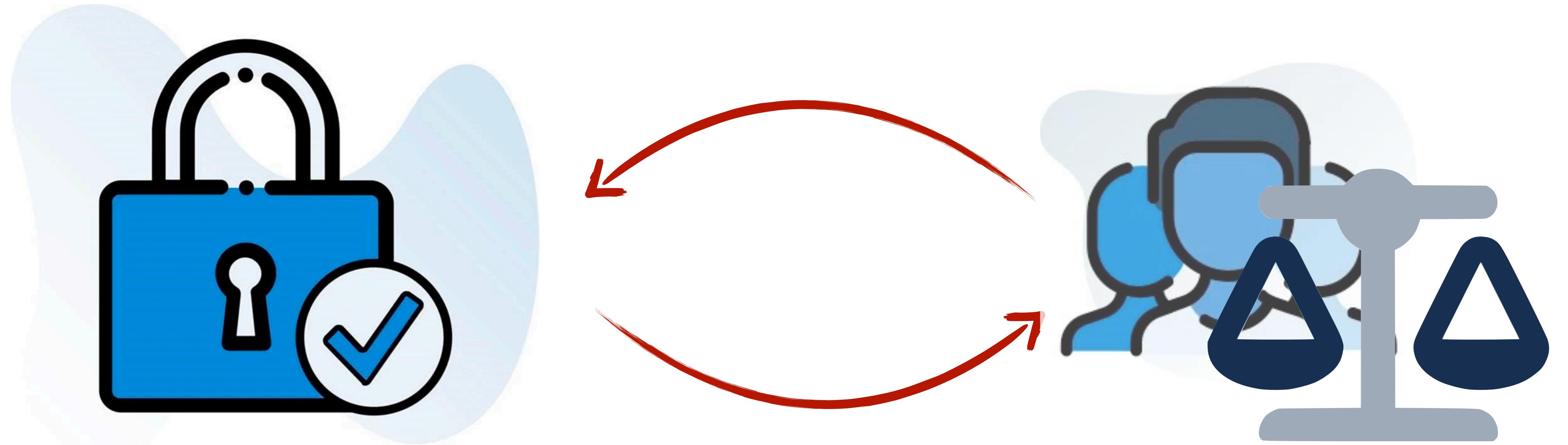
### Uber's New Tool Lets Its Staff Know Less About You

The controversial ride-sharing service is making a push for "differential privacy," a method that masks users' individual data.

### Data---But Not Your Data

At WWDC, Apple name-checked the statistical science of learning as much as possible about a group while learning as little as possible about any individual in it.

# Key concerns



Privacy

Fairness

# Disproportionate impacts in decision making

## Title 1 allotment

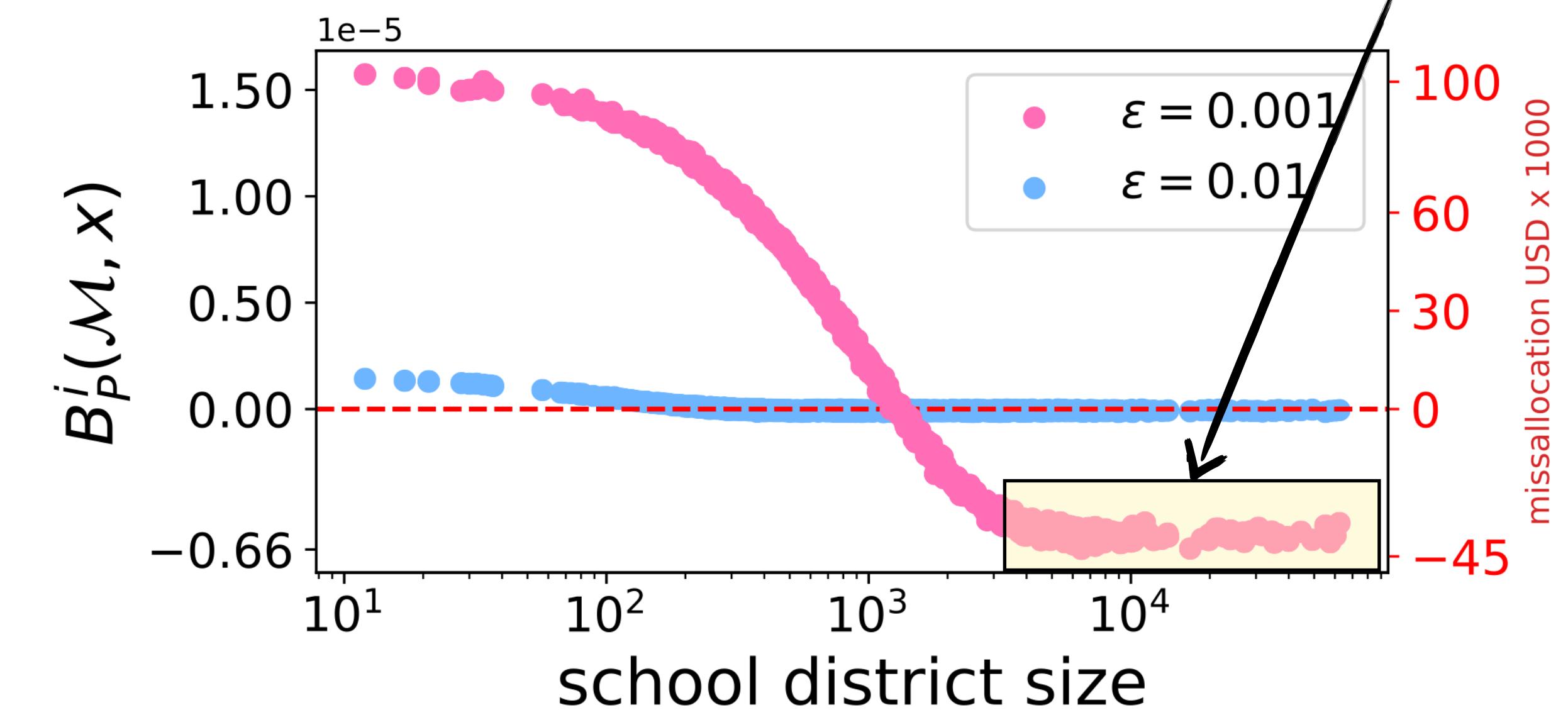
- Title I of the Elementary and Secondary Education Act is one of the largest U.S. program offering educational assistance to disadvantaged children.
- In the fiscal year 2021 alone, it distributed about \$11.7 billion through several types of grants.
- **Allotment:**

count of children 5 to 17 in district i

$$P_i^F(x) \stackrel{\text{def}}{=} \left( \frac{x_i \cdot a_i}{\sum_{i \in [n]} x_i \cdot a_i} \right)$$

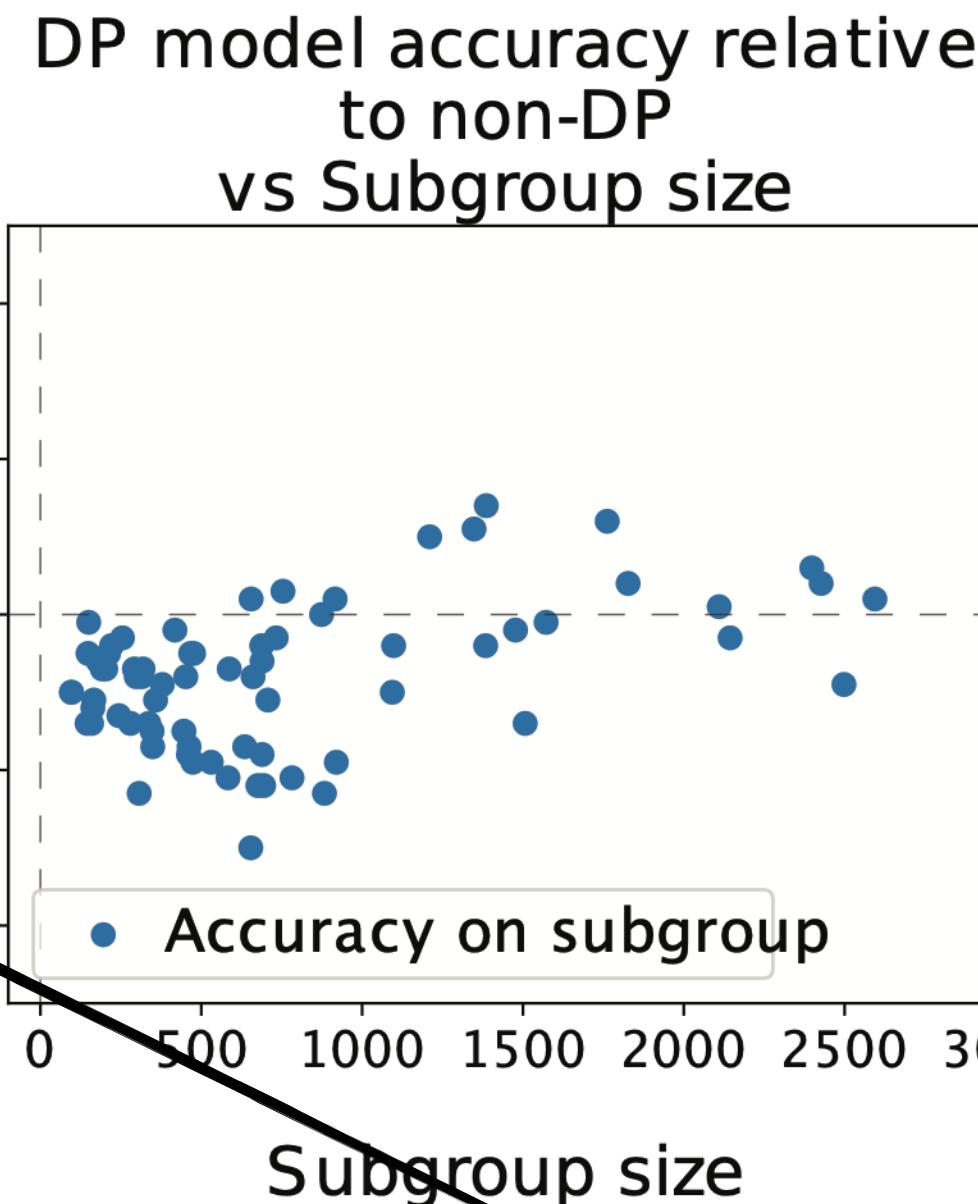
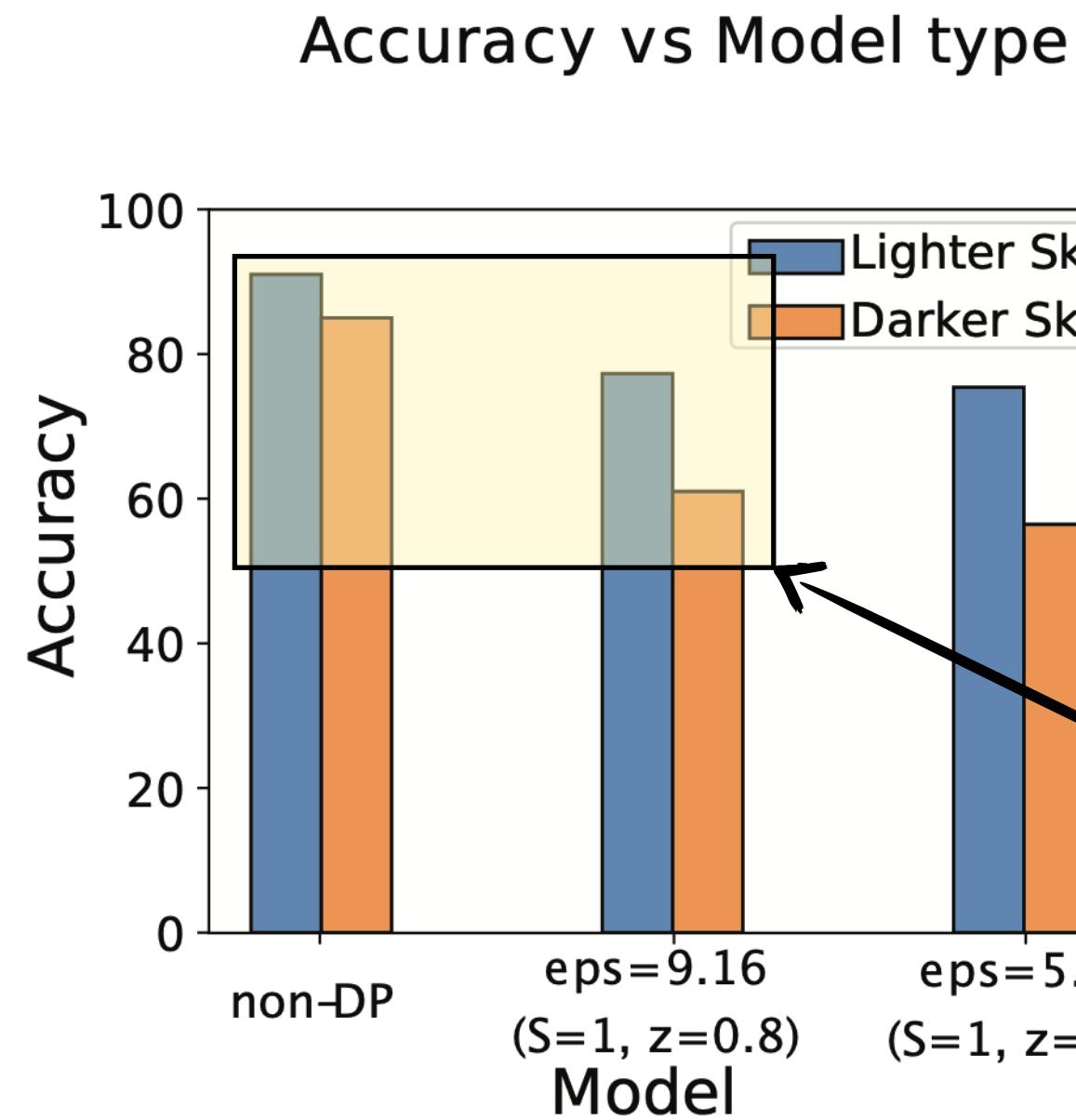
student expenditures in district i

Districts receiving up to 42K less than warranted

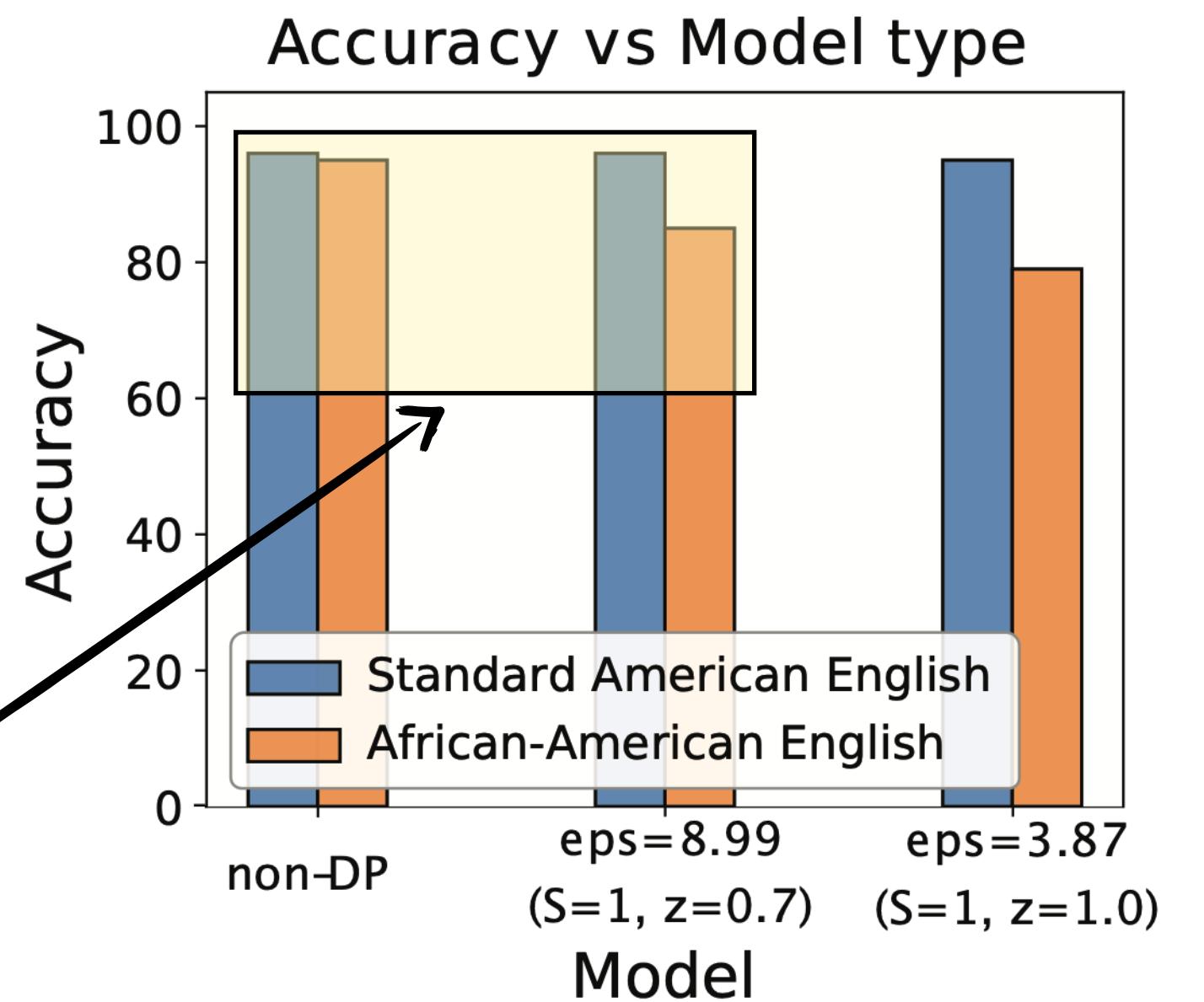


# Disproportionate impacts in learning tasks

Gender and age classification on facial images



Sentiment analysis of tweets



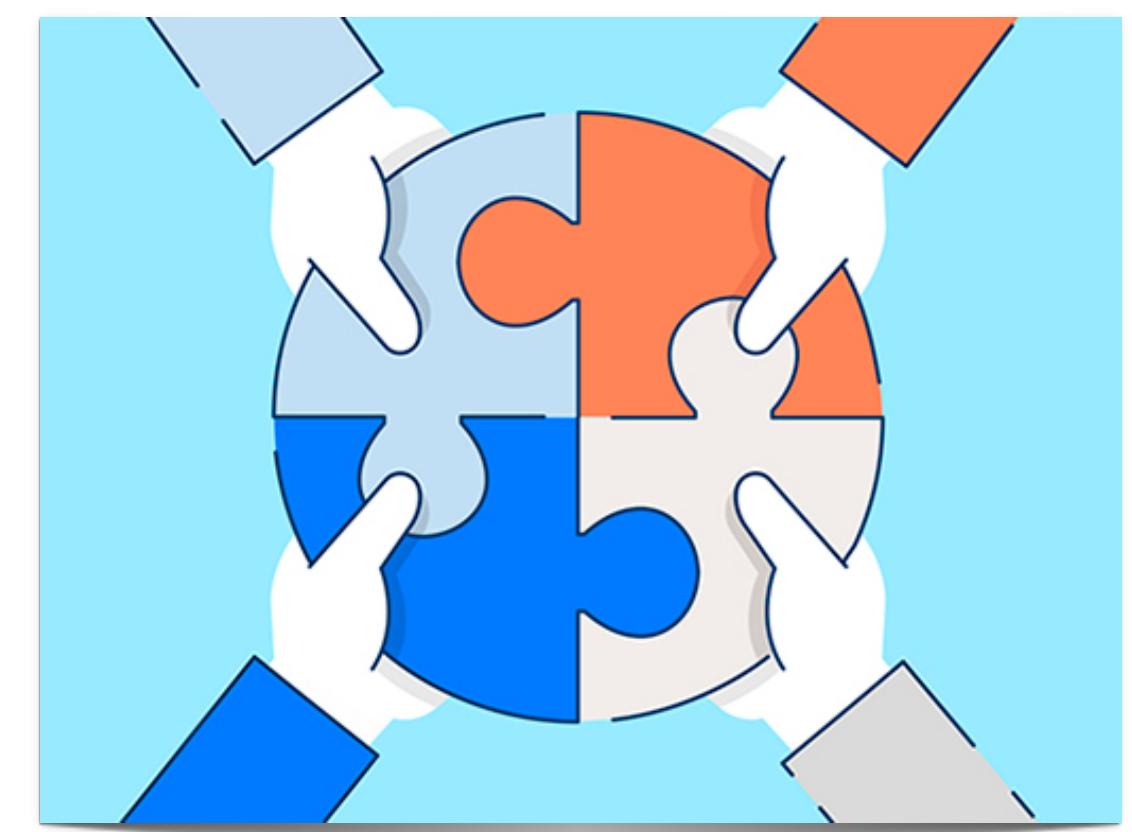
As the privacy increases the accuracy disparity of the learning task increases

# Societal impact

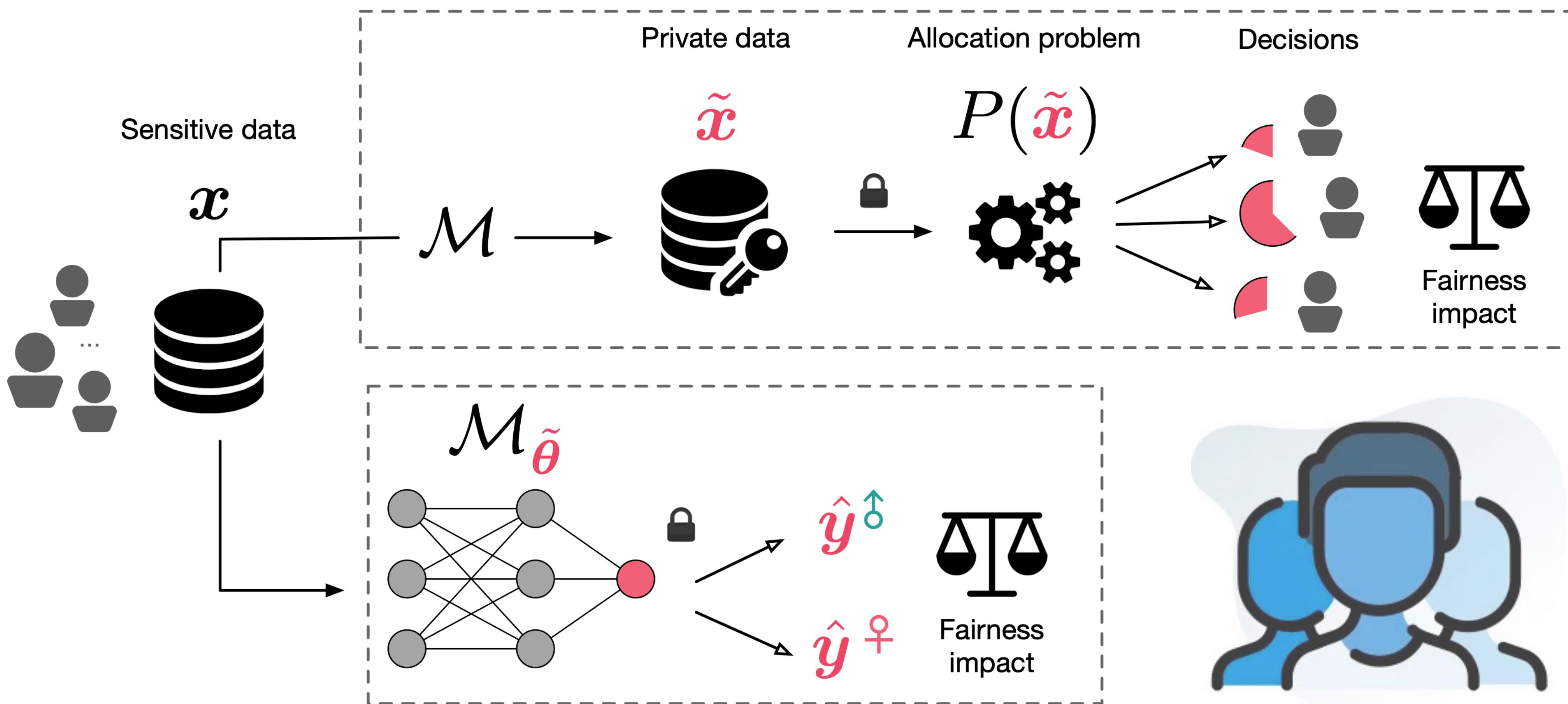
The resulting outcomes can have significant societal and economic impacts on the involved individuals:

- **Classification errors** may penalize some groups over others in important determinations including criminal assessment, hiring, or landing.
- **Biased decisions** can result in disparities regarding the allocation of critical funds, benefits, and therapeutics.

While these observations are becoming more apparent ***their causes are still largely understudied.***



# Setting and talk outline

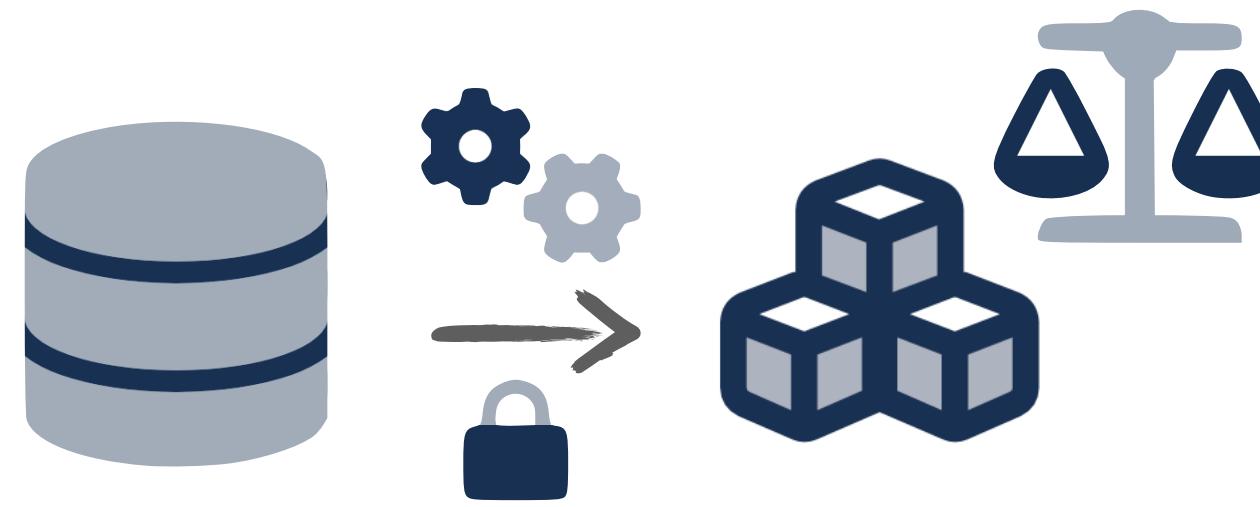


# Agenda

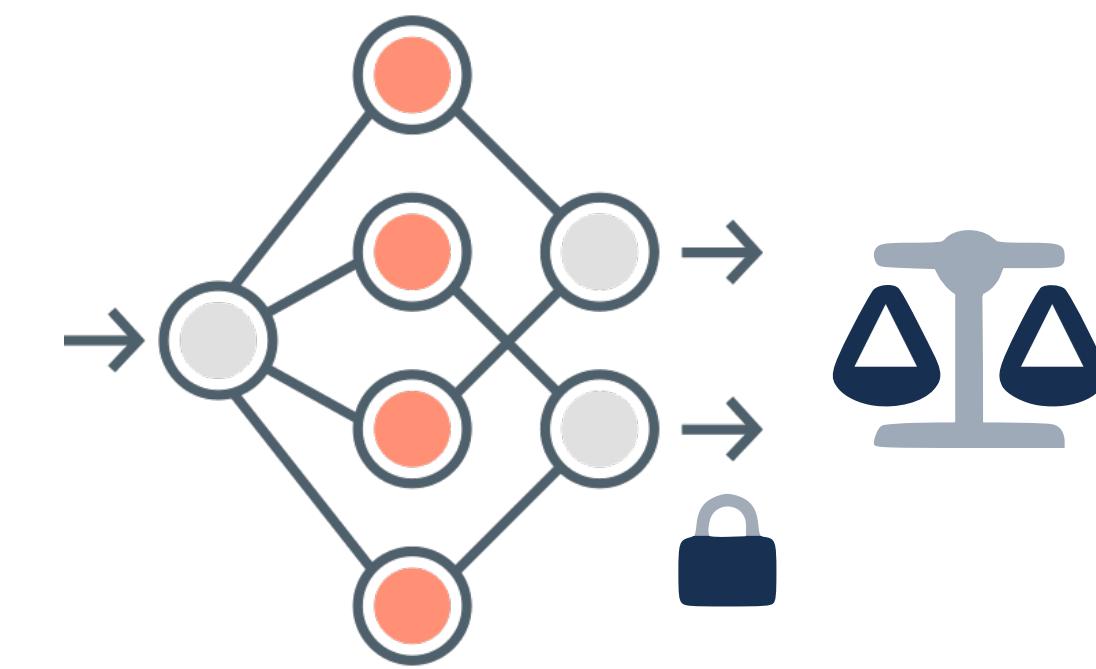
## Preliminaries



## Fairness impacts of DP in decision making



## Fairness impacts of DP in learning



## What's next?

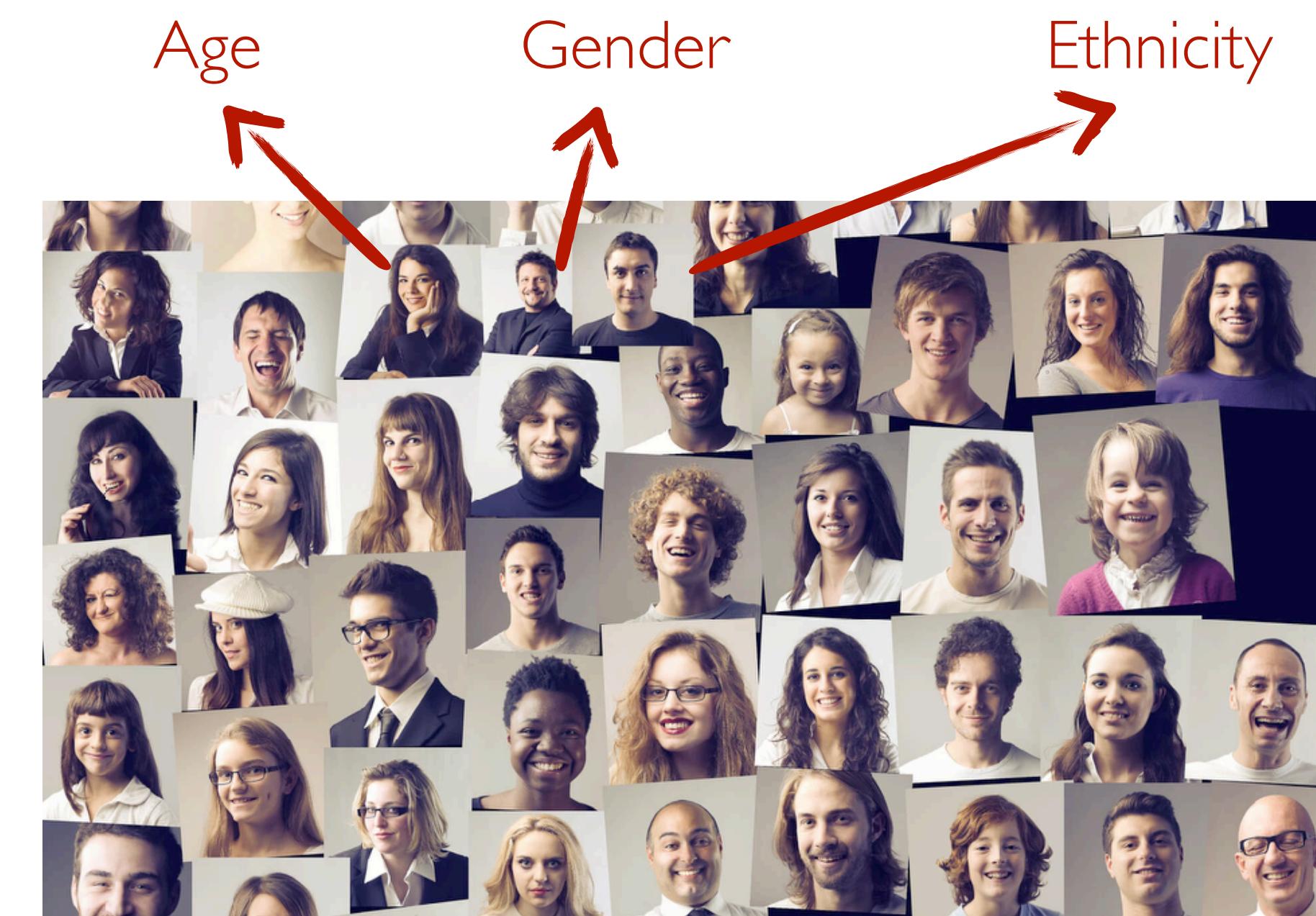
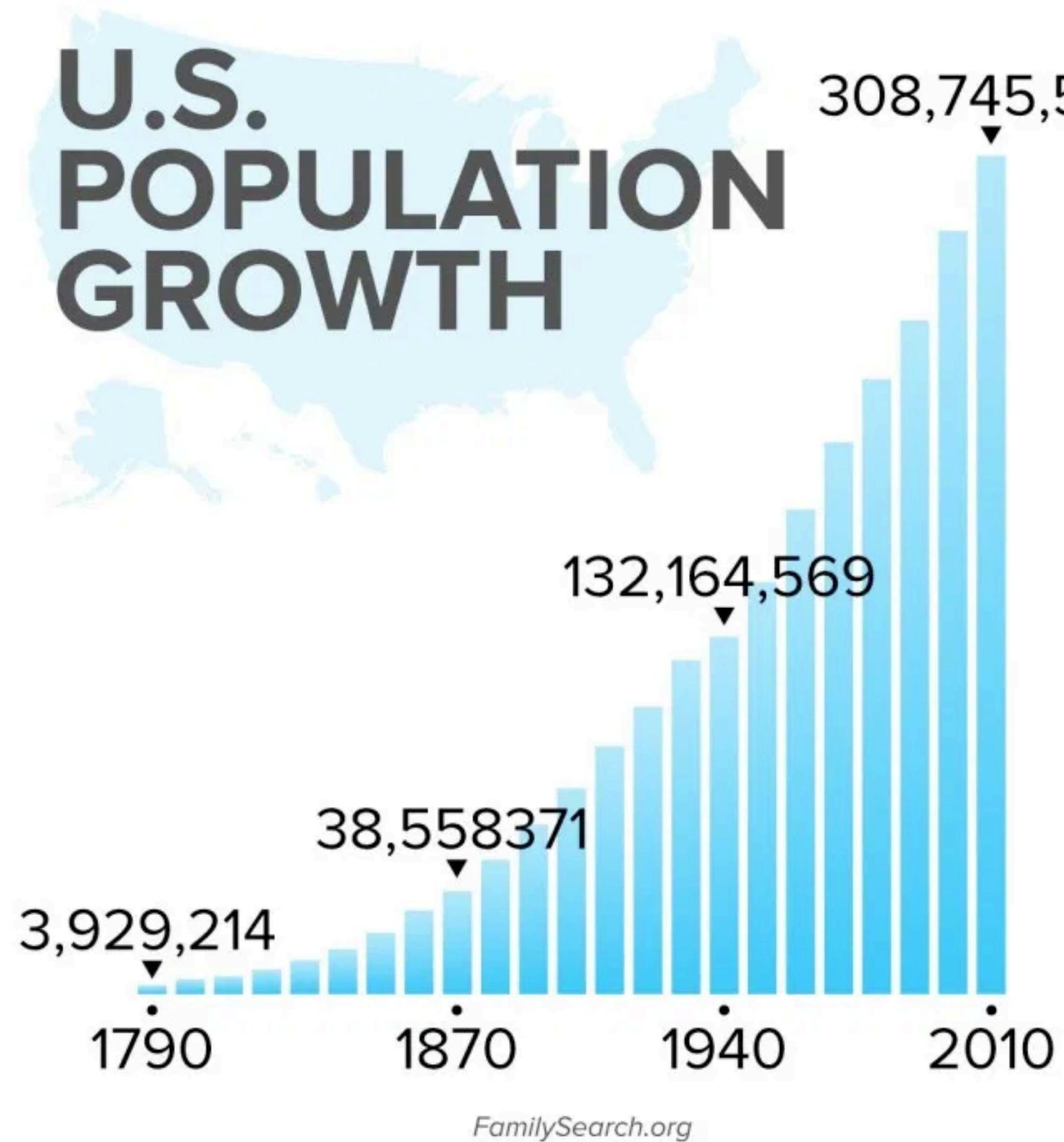


# Counting and Stats Publishing

## A Census data-release perspective

# US Census data collection

Enumeration of the total population living the US



# US Census data collection

## Accurate count is important

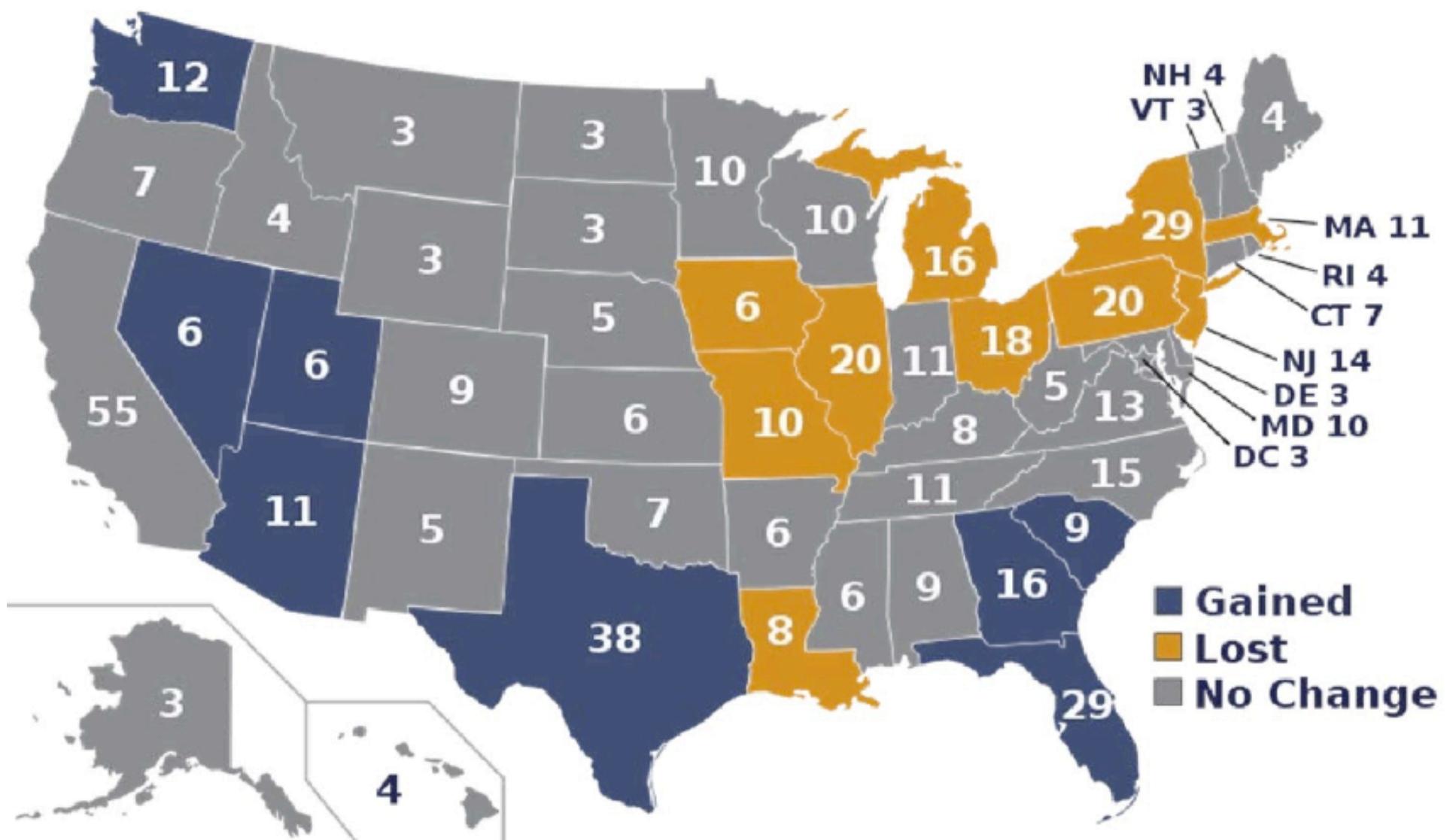
- Used to apportion multiple federal funding streams.
- \$665 billions allocated to 132 economic security programs (2022) other than health insurance or social security benefits.



Highway Planning and Construction



U.S. DEPARTMENT OF EDUCATION

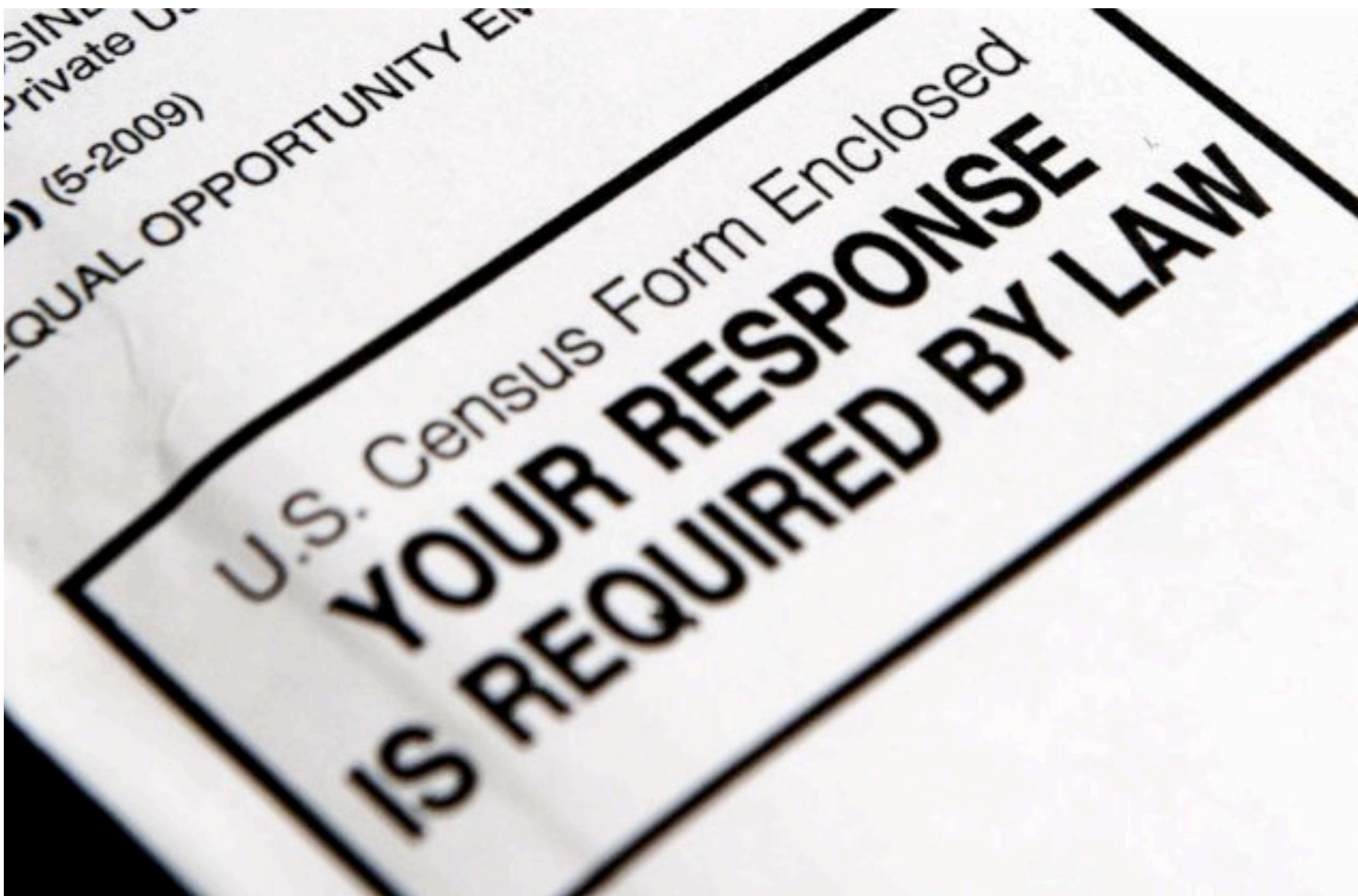


Determine the number of seats that states get in the US House of Representatives.

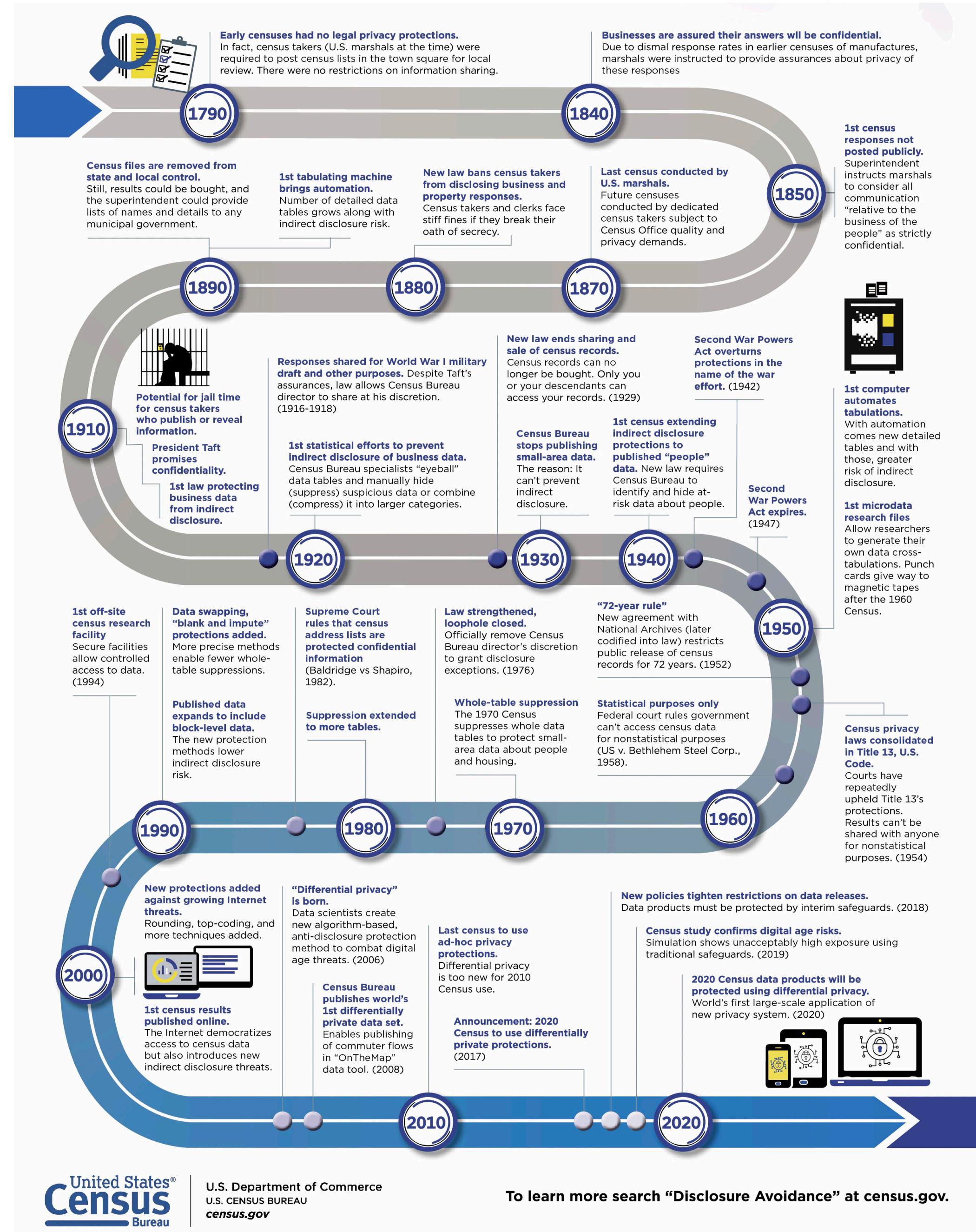
# US Census data collection

## Privacy is required by law

Because of the importance to have accuracy count congress makes the data collection mandatory.



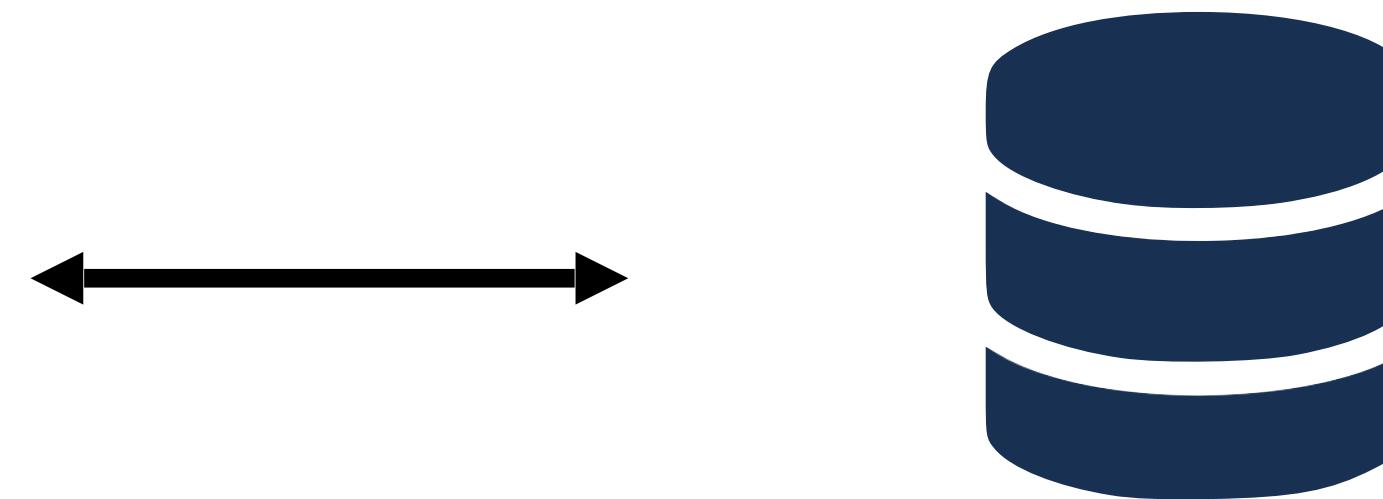
Title 13: Census is required to retain data confidentiality.



# Reconstruction Attacks



U.S. Department of Commerce  
Economics and Statistics Administration  
U.S. CENSUS BUREAU  
[census.gov](http://census.gov)



308,745,548 people in 2010 release which implements some “protection”

Commercial databases

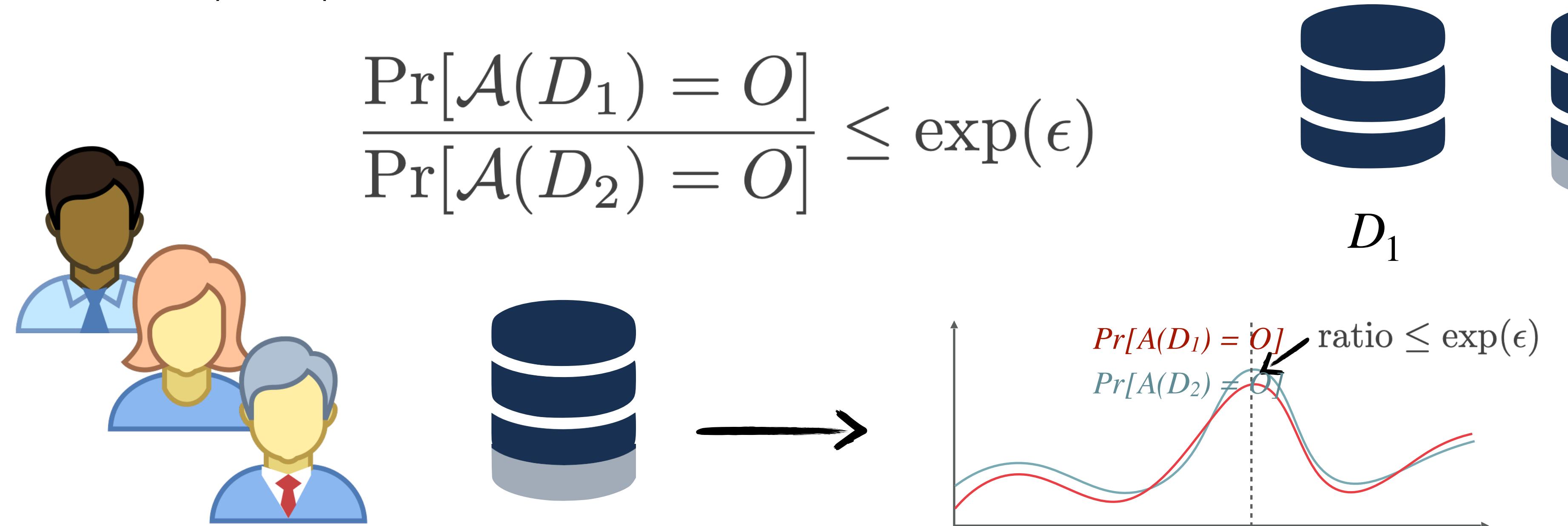
Linkage Attacks — Results from UC Census:

- Census blocks correctly reconstructed in all 6,207,027, inhabited blocks.
- Block, sex, age, race, ethnicity reconstructed:
  - Exactly: 46% of population (142M).
  - Allowing age +/- 1 year: 71% of population (219M).
- Name, block sex, age, race, ethnicity:
  - Confirmed re-identification: 38% of population.

# Differential Privacy

## Definition

A randomized algorithm  $\mathcal{A}$  is  $\epsilon$ -differentially private if, for all pairs of inputs  $D_1, D_2$ , differing in one entry, and for any output  $O$ :



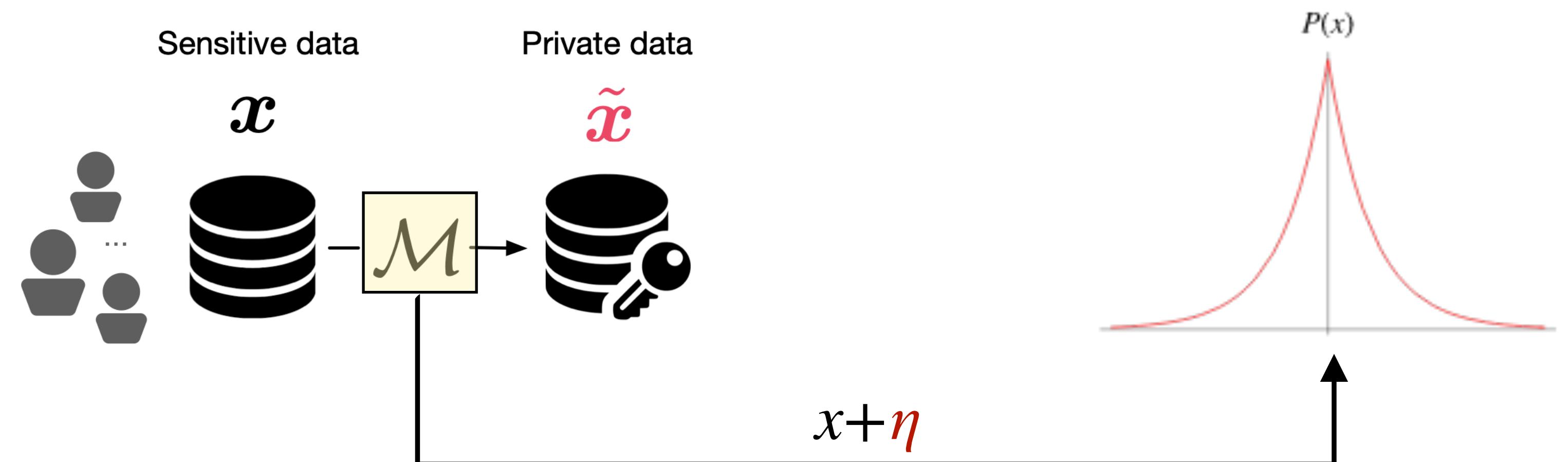
**Intuition:** An adversary should not be able to use output  $O$  to distinguish between any  $D_1$  and  $D_2$ .

# Differential Privacy

## Notable properties

- Immune to linkage attack: Adversary knows arbitrary auxiliary information.
- Composability: If  $A_1$  enjoys  $\epsilon_1$ -differential privacy and  $A_2$  enjoys  $\epsilon_2$ -differential privacy, then, their composition  $A_1(D), A_2(D)$  enjoys  $(\epsilon_1 + \epsilon_2)$ -differential privacy.
- Post-processing immunity: If  $A$  enjoys  $\epsilon$ -differential privacy and  $g$  is an arbitrary data-independent mapping, then  $g \circ A$  is  $\epsilon$ -differential private.

DP algorithms rely on randomization

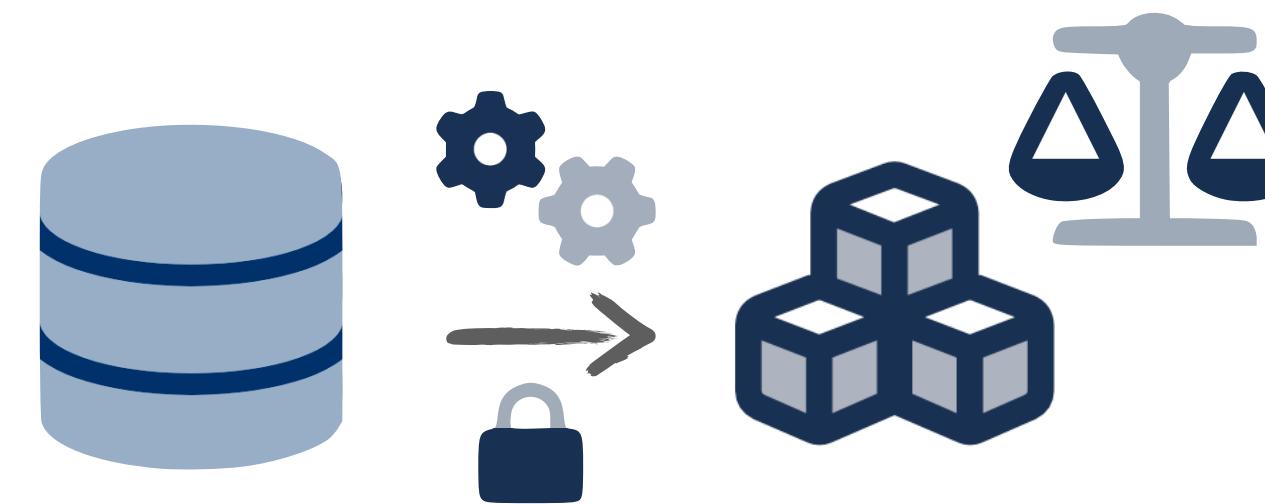


# Agenda

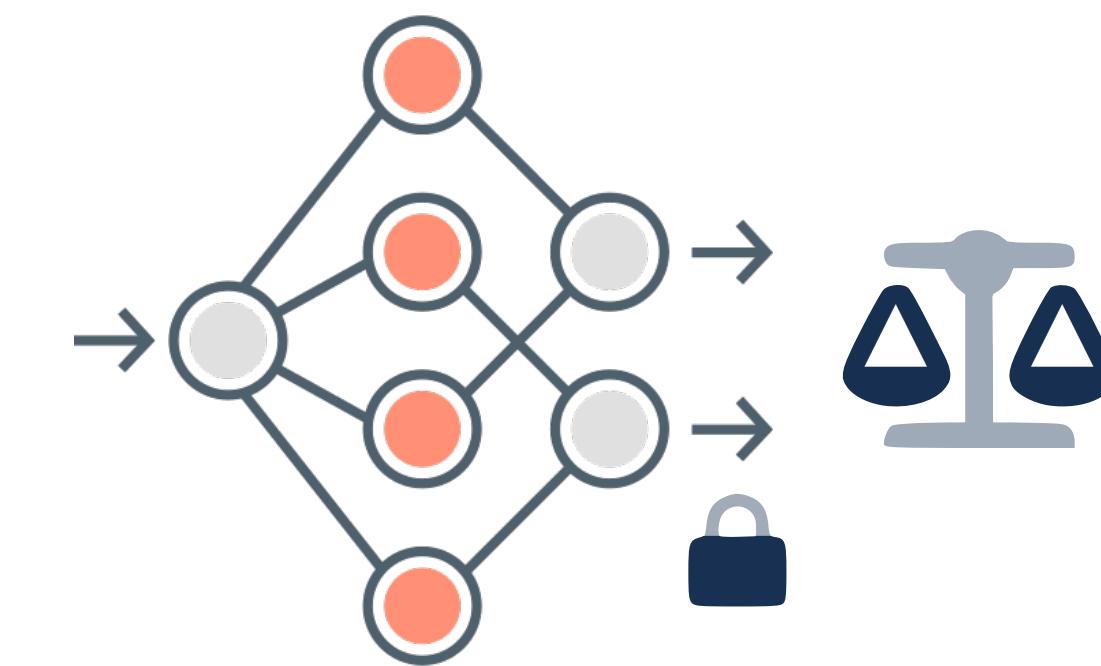
Preliminaries



## Fairness impacts of DP in decision making



## Fairness impacts of DP in learning

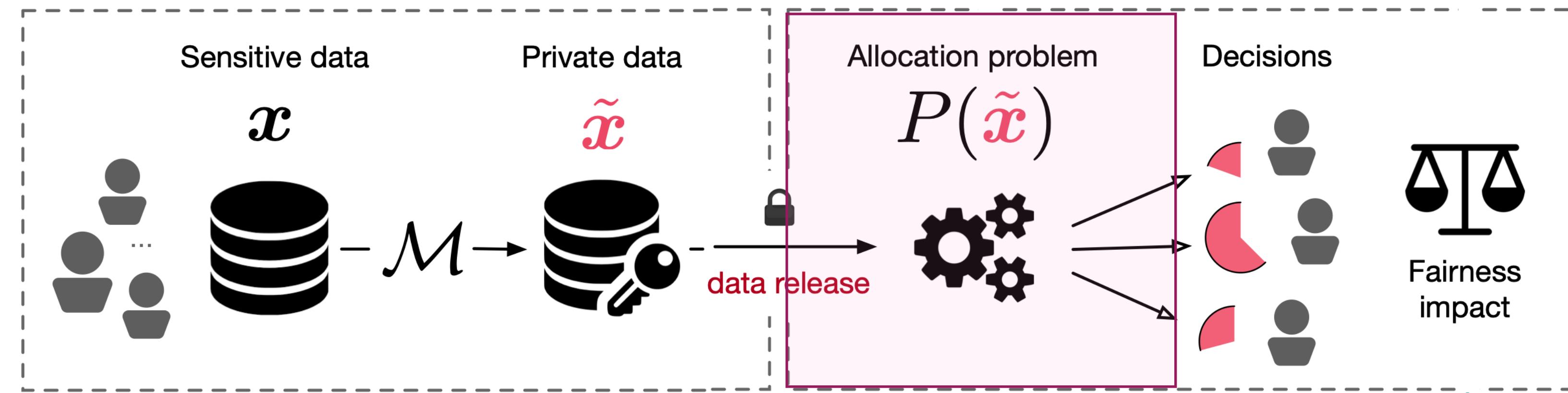


What's next?



# Fairness in downstream decisions

## Setting

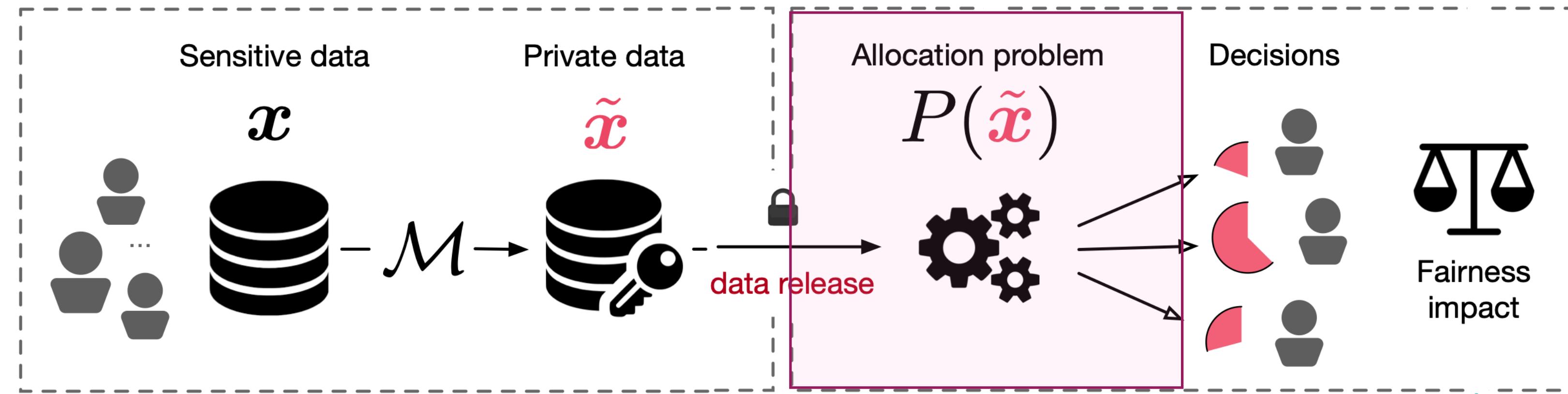


Analyze the unintended fairness impacts of a DP data-release mechanism to the outcome of a **decision problem**.

1. **Allotment problems**: which distributes a finite set of resources to some entity.
2. **Decision rules**: which determines whether an entity qualifies for some benefit.

# Fairness in downstream decisions

## Setting



Bias:  $B_P^i(M, x) = \mathbb{E}_{\tilde{x} \sim M(x)}[P_i(\tilde{x})] - P_i(x)$

**Definition ( $\alpha$ -Fairness).** A data-release mechanism  $M$  is said  $\alpha$ -fair w.r.t. a problem  $P$  if, for all datasets  $x \in \mathcal{X}$  and all  $i \in [n]$

$$\xi_B^i(P, M, x) = \max_{j \in [n]} |B_P^i(M, x) - B_P^j(M, x)| \leq \alpha$$

# Disproportionate impacts in downstream decisions

## Title 1 allotment

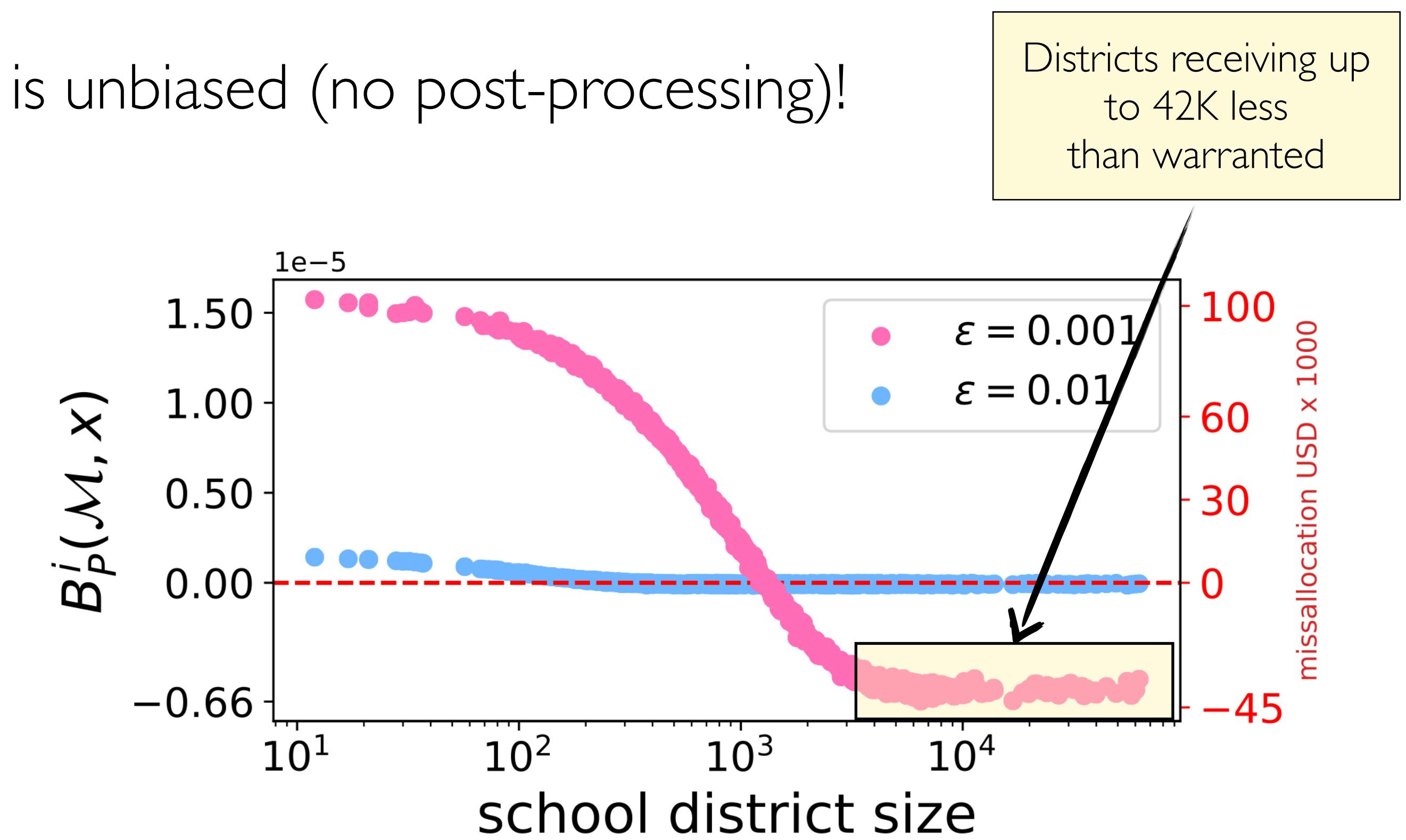
- Even a simple allocation rule, applied on top of noisy data may produce biased decisions with significant fairness issues.
- This is true even if the DP mechanism is unbiased (no post-processing)!

### Allotment:

count of children 5 to 17 in district i

$$P_i^F(x) \stackrel{\text{def}}{=} \left( \frac{x_i \cdot a_i}{\sum_{i \in [n]} x_i \cdot a_i} \right)$$

student expenditures in district i



# Shape of the decision problem

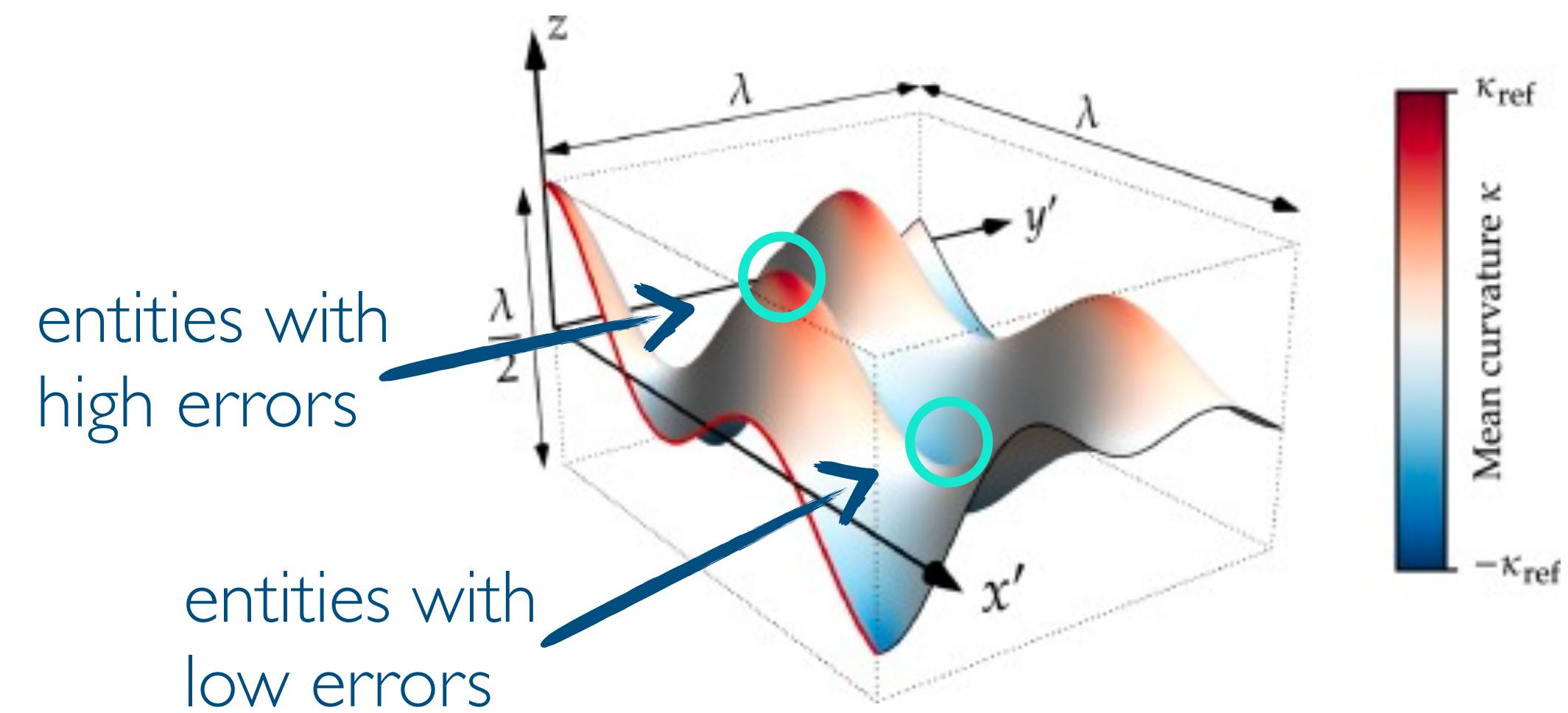
## First key result

- **Theorem (informal):** It is the “**shape**” of the decision problem that characterizes the unfairness of the outcomes, even using an **unbiased DP mechanism**.
- The problem bias can be approximated as (when  $P_i$  is at least twice differentiable):

$$\begin{aligned} B_P^i(\mathcal{M}, \mathbf{x}) &= \mathbb{E}[P_i(\tilde{\mathbf{x}} = \mathbf{x} + \eta)] - P_i(\mathbf{x}) \\ &\approx \frac{1}{2} \boxed{H P_i(\mathbf{x})} \times \boxed{\text{Var}[\eta]} \end{aligned}$$

↗      ↗

Local curvature of problem  $P_i$       Variance of the noisy input (depends on  $\epsilon$ )



- Fairness can be bounded whenever the problem local curvature is constant across entities, since the variance is also constant and bounded.

# Shape of the decision problem

## First key result

- **Theorem (informal):** It is the “**shape**” of the decision problem that characterizes the unfairness of the outcomes, even using an **unbiased DP mechanism**.
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$$B_P^i(\mathcal{M}, \mathbf{x}) = \mathbb{E}[P_i(\tilde{\mathbf{x}} = \mathbf{x} + \eta)] - P_i(\mathbf{x})$$

$$\approx \frac{1}{2} \mathbf{H}P_i(\mathbf{x}) \times \text{Var}[\eta]$$

Local curvature of  
problem  $P_i$

Variance of the  
noisy input  
(depends on  $\epsilon$ )

A data release mechanism  $M$  is  $\alpha$ -fair w.r.t.  $P$ , for some finite  $\alpha$ , if for all datasets  $x$ , exists constants  $c_{jl}^i \in \mathbb{R}$ , ( $i \in [n], j, l \in [k]$ )

$$(\mathbf{H}P_i)_{j,l}(\mathbf{x}) = c_{j,l}^i \quad (i \in [n] \ j, l \in [k]).$$

- **Corollary:** (Perfect)-fairness cannot be achieved if  $P$  is any non-linear function, as in the case of the allocations considered.

# Disproportionate impacts in downstream decisions

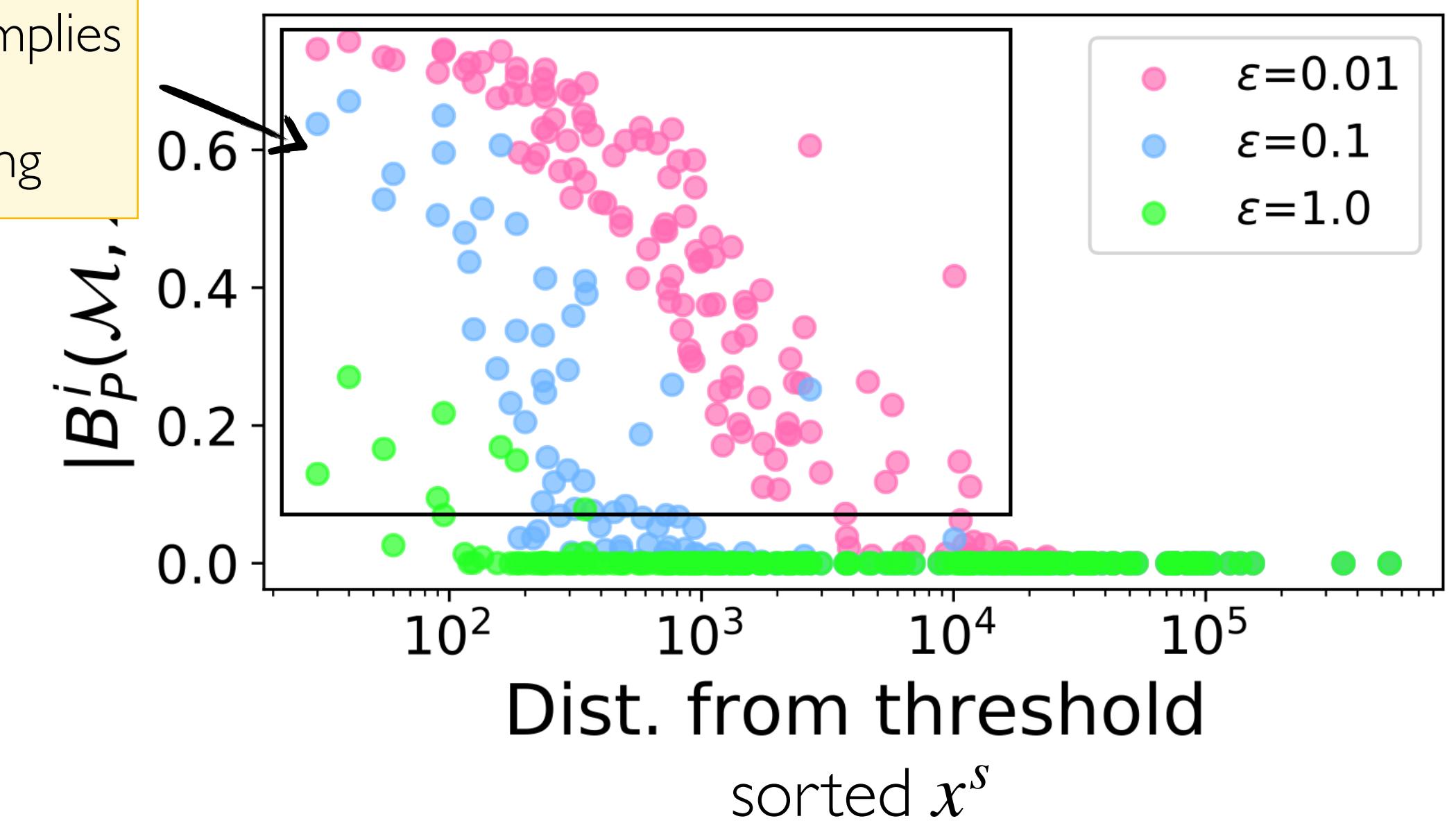
## Minority language voting rights

- The Voting Rights Act of 1965 provides a body of protections for racial and language minorities.
- Section 203 describes the conditions under which local jurisdictions must provide minority language voting assistance during an election.
- Jurisdiction  $i$  must provide language assistance (including voter registration, ballots, and instructions) iff decision rule  $P_i^M(x)$  returns true with:

$$P_i^M(x) \stackrel{\text{def}}{=} \left( \frac{x_i^{sp}}{x_i^s} > 0.05 \vee x_i^{sp} > 10^4 \right) \wedge \frac{x_i^{spe}}{x_i^{sp}} > 0.0131.$$

+ < 5<sup>th</sup> grade education  
 no. of ppl in  $i$  speaking minority language  $s$   
 + limited English proficiency

Misclassification implies potentially disenfranchising

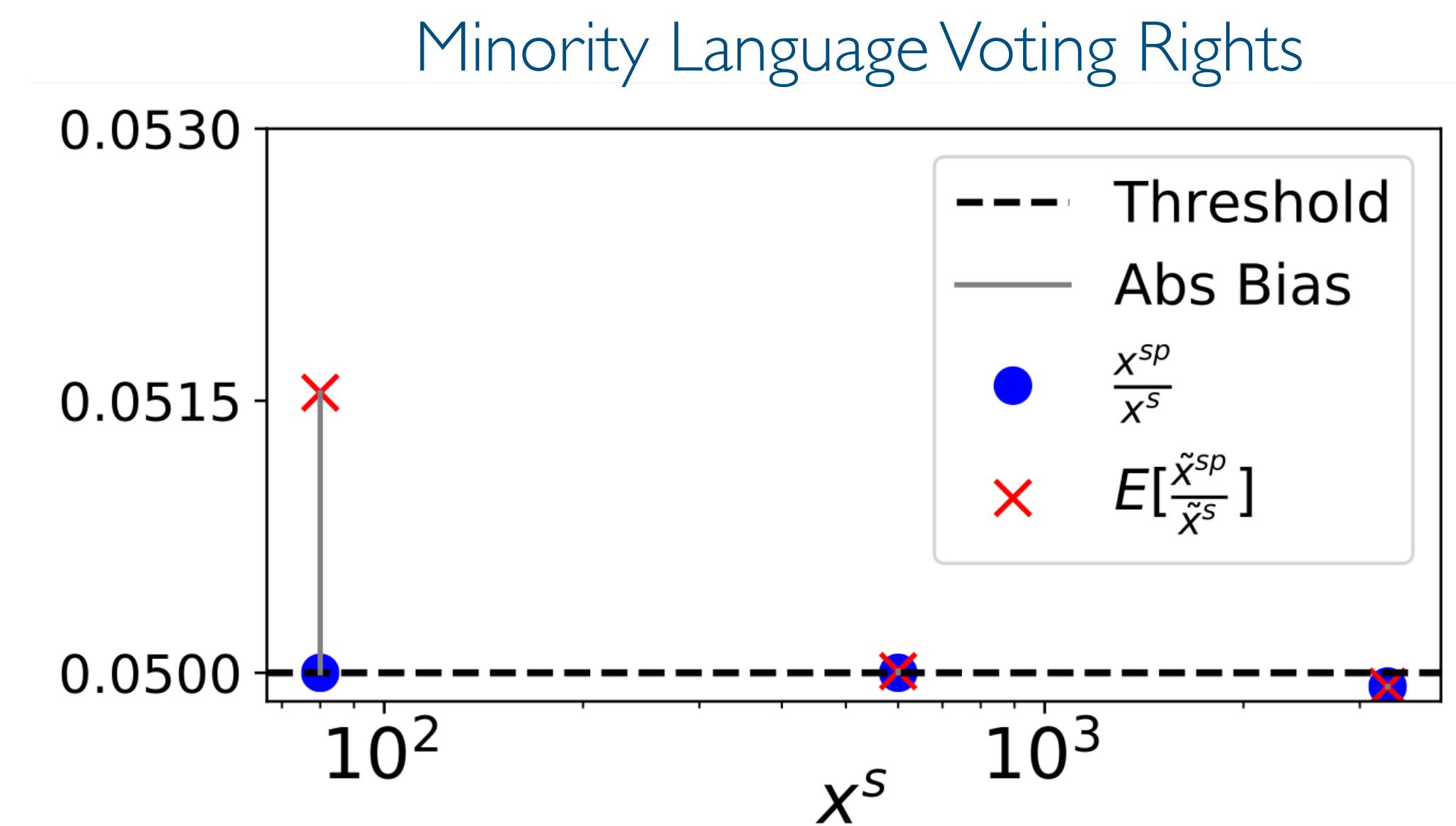


# Fair Decision Rules

## Ratio Functions

$$P_i^M(x) \stackrel{\text{def}}{=} \left( \frac{x_i^{sp}}{x_i^s} > 0.05 \vee x_i^{sp} > 10^4 \right) \wedge \frac{x_i^{spe}}{x_i^{sp}} > 0.0131.$$

- Loving county, TX, where  $x_{sp}/x_s = 0.05 = \frac{4}{80}$
- Terrell county, TX, where  $x_{sp}/x_s = 0.05 = \frac{30}{600}$
- Union county, NM, where  $x_{sp}/x_s = 0.049 = \frac{160}{3305}$



- **Theorem (informal):** The perturbation induced by the DP mechanism affects more the county with lower numerator / denominator.

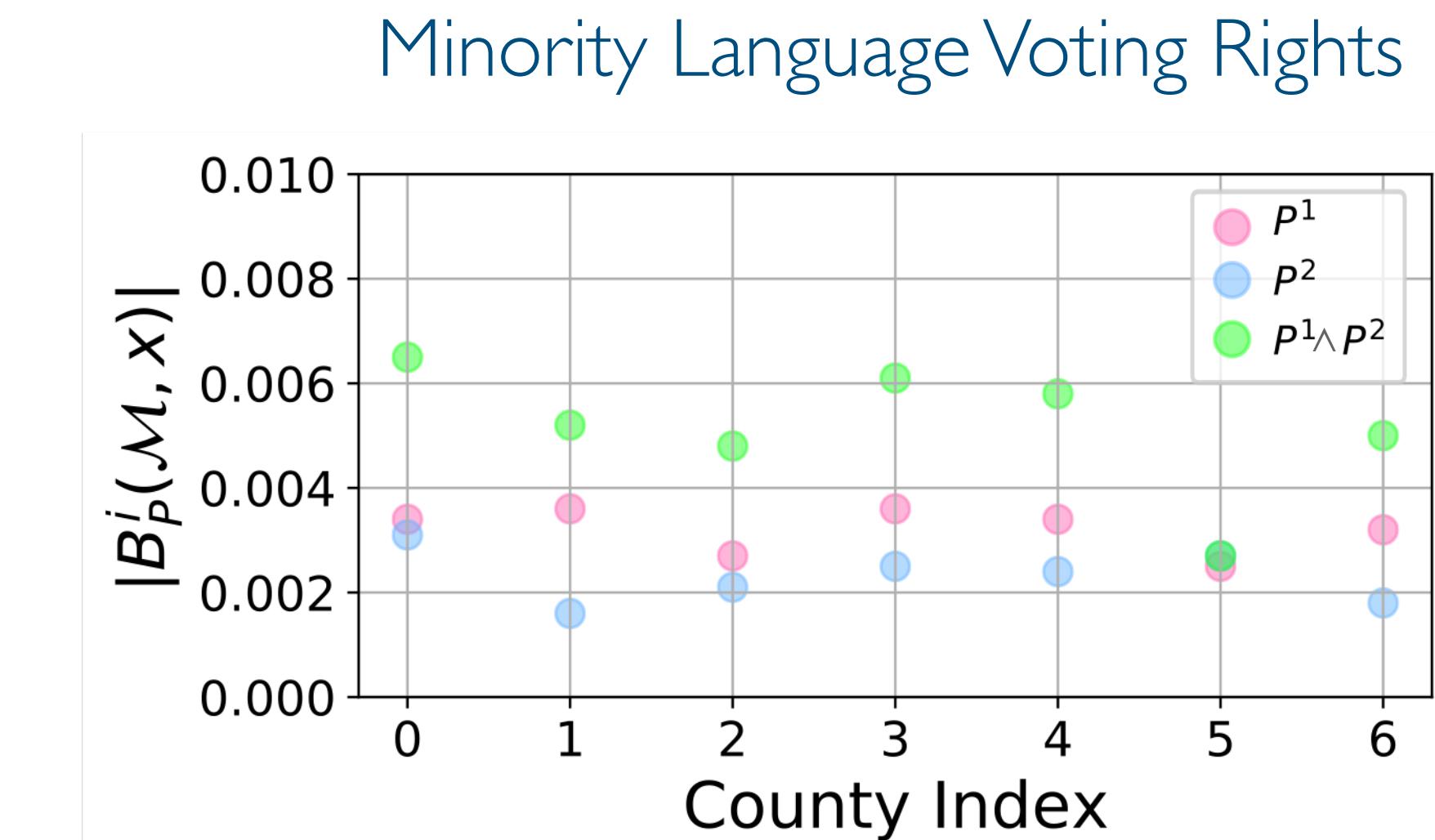
# Fairness composition

## Second key result

$$P_i^M(x) \stackrel{\text{def}}{=} \left( \frac{x_i^{sp}}{x_i^s} > 0.05 \vee x_i^{sp} > 10^4 \right) \wedge \frac{x_i^{spe}}{x_i^{sp}} > 0.0131.$$

$$P^1(x^{sp}) = \mathbb{1}\{x^{sp} \geq 10^4\}$$

$$P^2(x^{sp}, x^{spe}) = \mathbb{1}\left\{\frac{x_i^{spe}}{x_i^{sp}} > 0.0131\right\}$$



- Small bias when considered individually
- However, when they are combined using logical connector  $\wedge$ , the resulting absolute bias increases substantially, as illustrated by the associated green circles.

- **Theorem (informal):** The logical composition of two  $\alpha_1$ - and  $\alpha_2$ -fair mechanisms is  $\alpha$ -fair with  $\alpha \geq \max(\alpha_1, \alpha_2)$ .
- The unfairness induced by “composing” predicates is no smaller than that of their individual components.

# Shape of the decision problem

## Important conclusion

*Using DP to generate private inputs of decision problems commonly adopted to make policy determination will necessarily introduce fairness issues, despite the noise being unbiased!*

# Mitigation solution

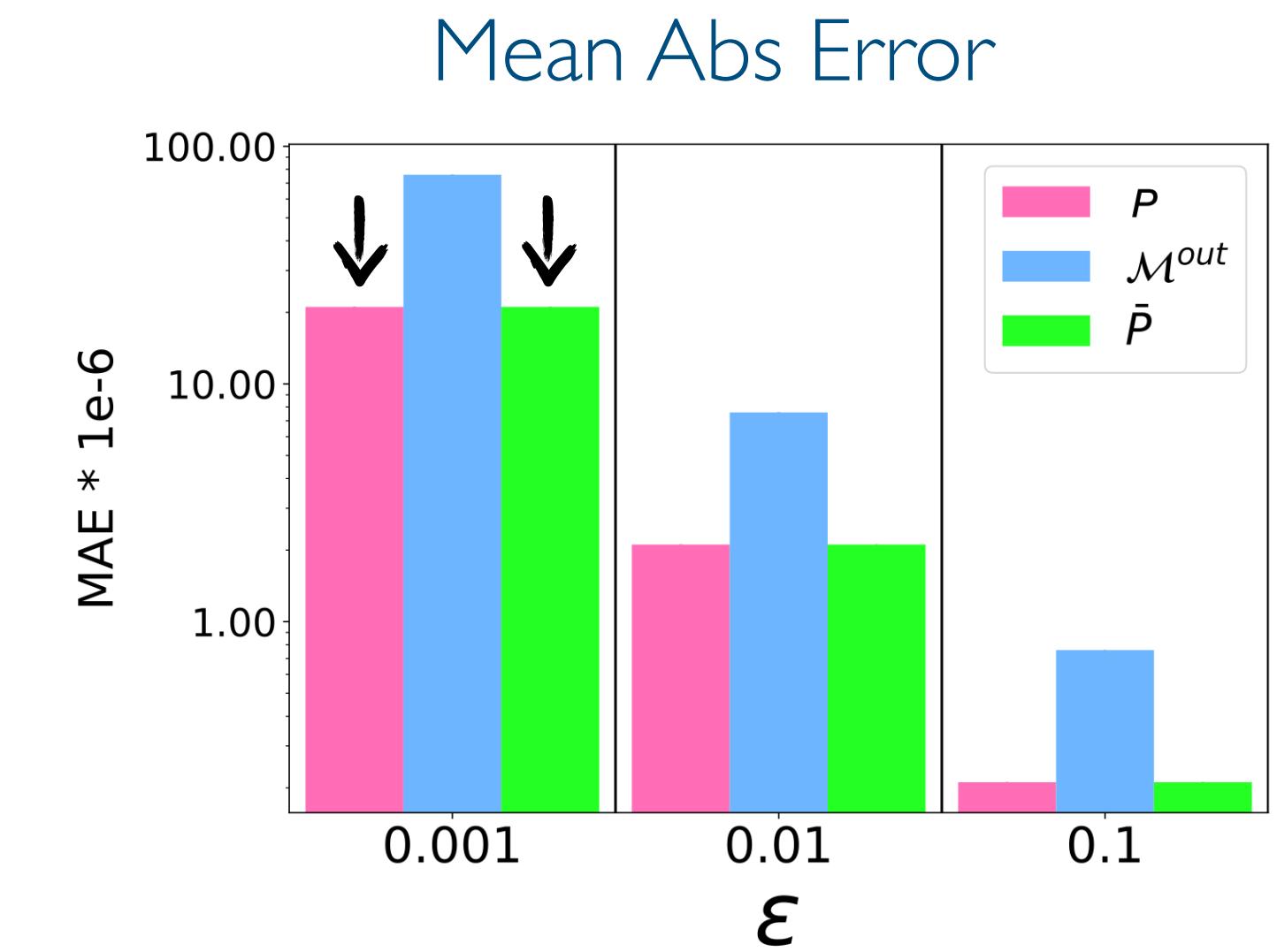
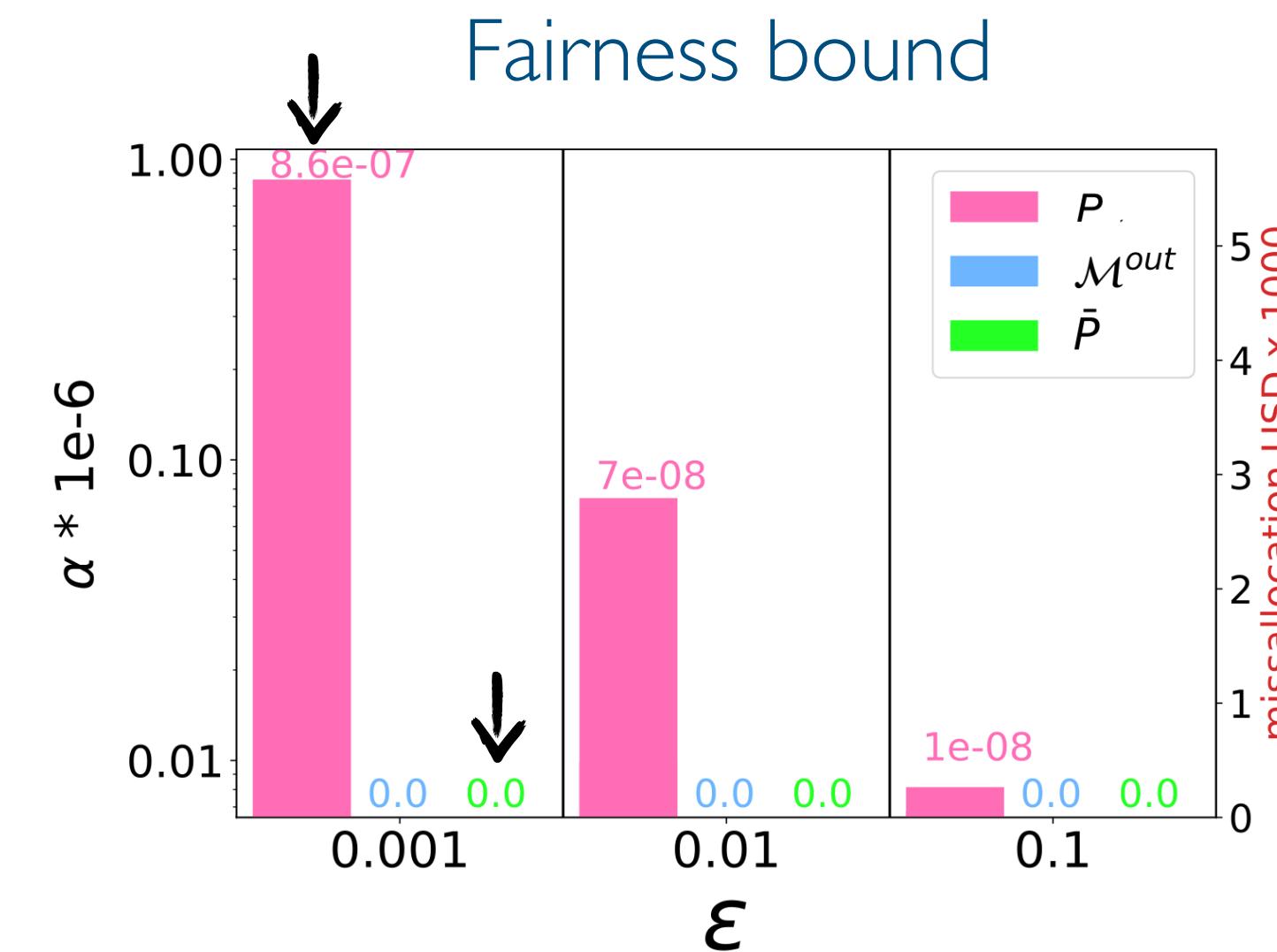
## Fair allocations

- Note that the observed issues are **not data-driven, but problem-driven**.
- **Corollary:** If  $P$  is a linear function, then mechanism  $M$  is fair w.r.t.  $P$ .
- **Linearizing the allotment problem** — General idea: Given a problem  $P_i$ , derive a linear approximation  $\tilde{P}_i$  of  $P_i$

Redundant data release

$$P_i^F(x) \stackrel{\text{def}}{=} \left( \frac{x_i \cdot a_i}{\sum_{i \in [n]} x_i \cdot a_i} \right)$$

Release its (noisy) version  
as a constant



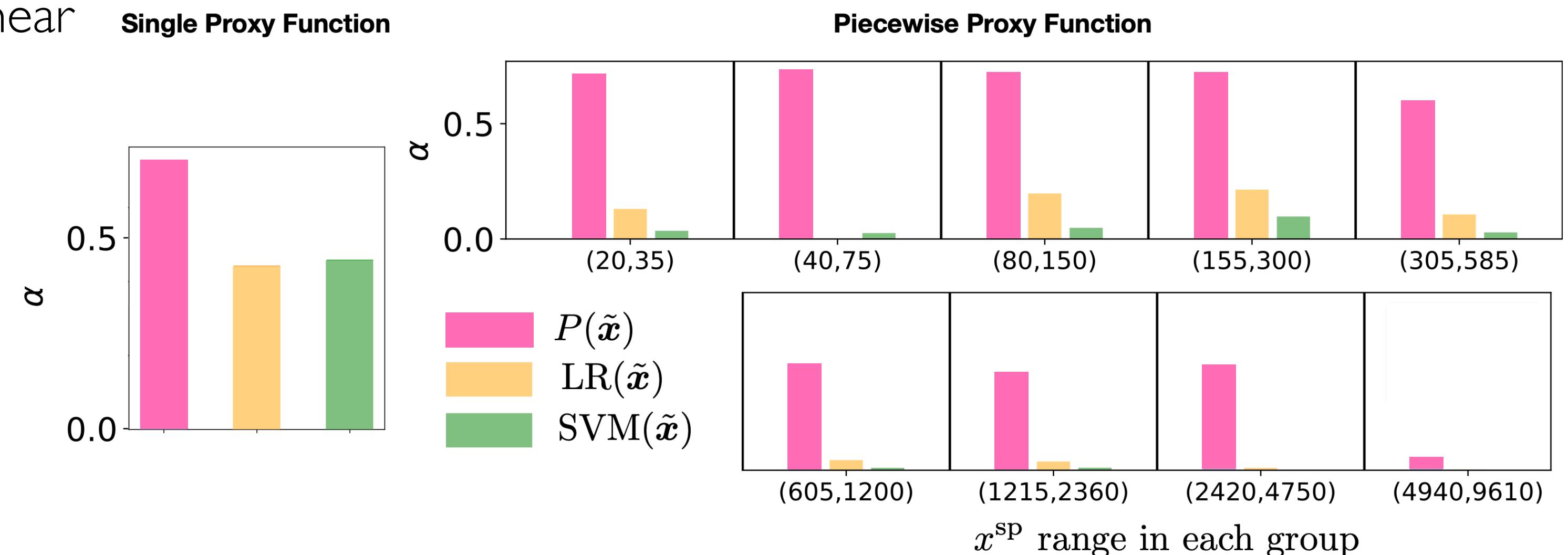
# Mitigation solution

## Fair Decision Rules

- Much more difficult scenario. But we could resort to the linear approximation trick again.

1. Partition dataset into groups  $x^{sp}$
2. Train subgroups using features  $x$  using a linear classifier
3. Use the parameters of the proxy linear model  $LR(x)$  or  $SVM(x)$  to make a decision i.e., to approximate  $P_i^M$

$$P_i^M(x) \stackrel{\text{def}}{=} \left( \frac{x_i^{sp}}{x_i^s} > 0.05 \vee x_i^{sp} > 10^4 \right) \wedge \frac{x_i^{spe}}{x_i^{sp}} > 0.0131.$$

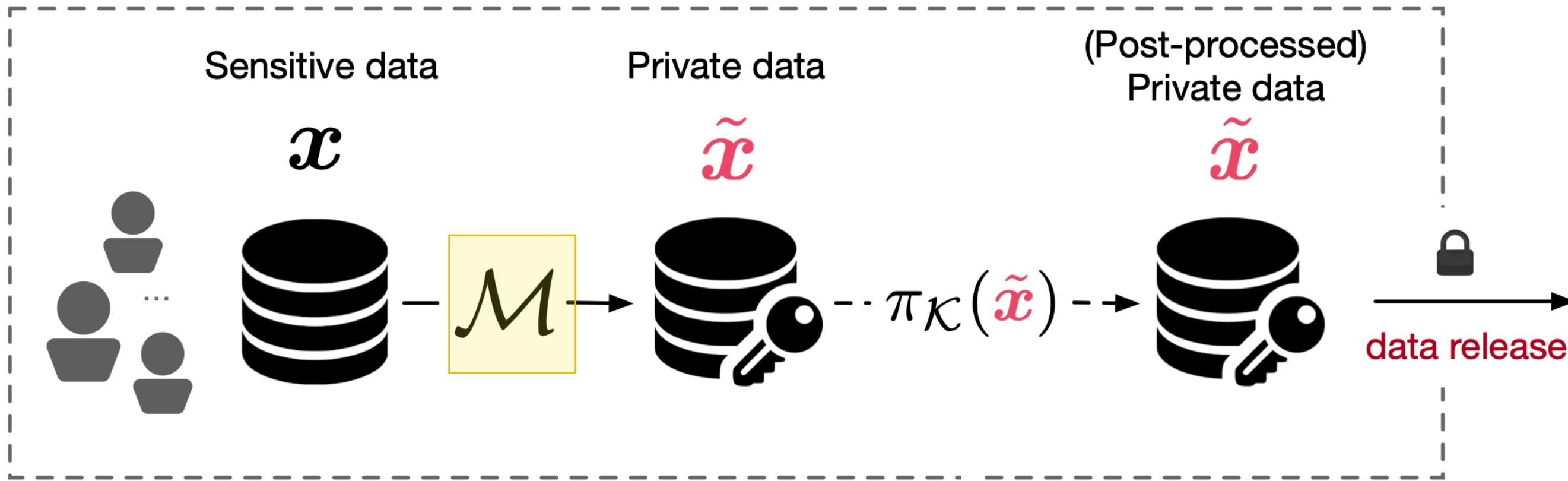


**Result summary:** Fairness violation decreases substantially, within each subgroup.

# DP Post-processing

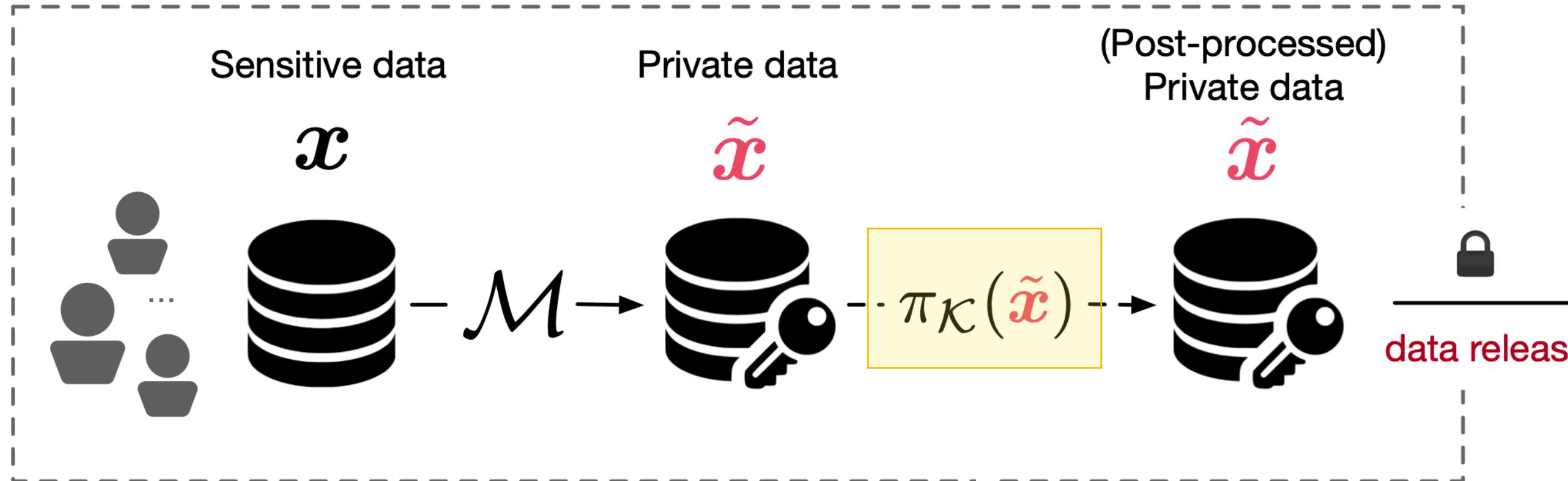
## Fairness impact

# DP data release with post-processing



I. Apply noise with appropriate parameter  $\tilde{x} = x + \text{Noise}$

# DP data release with post-processing

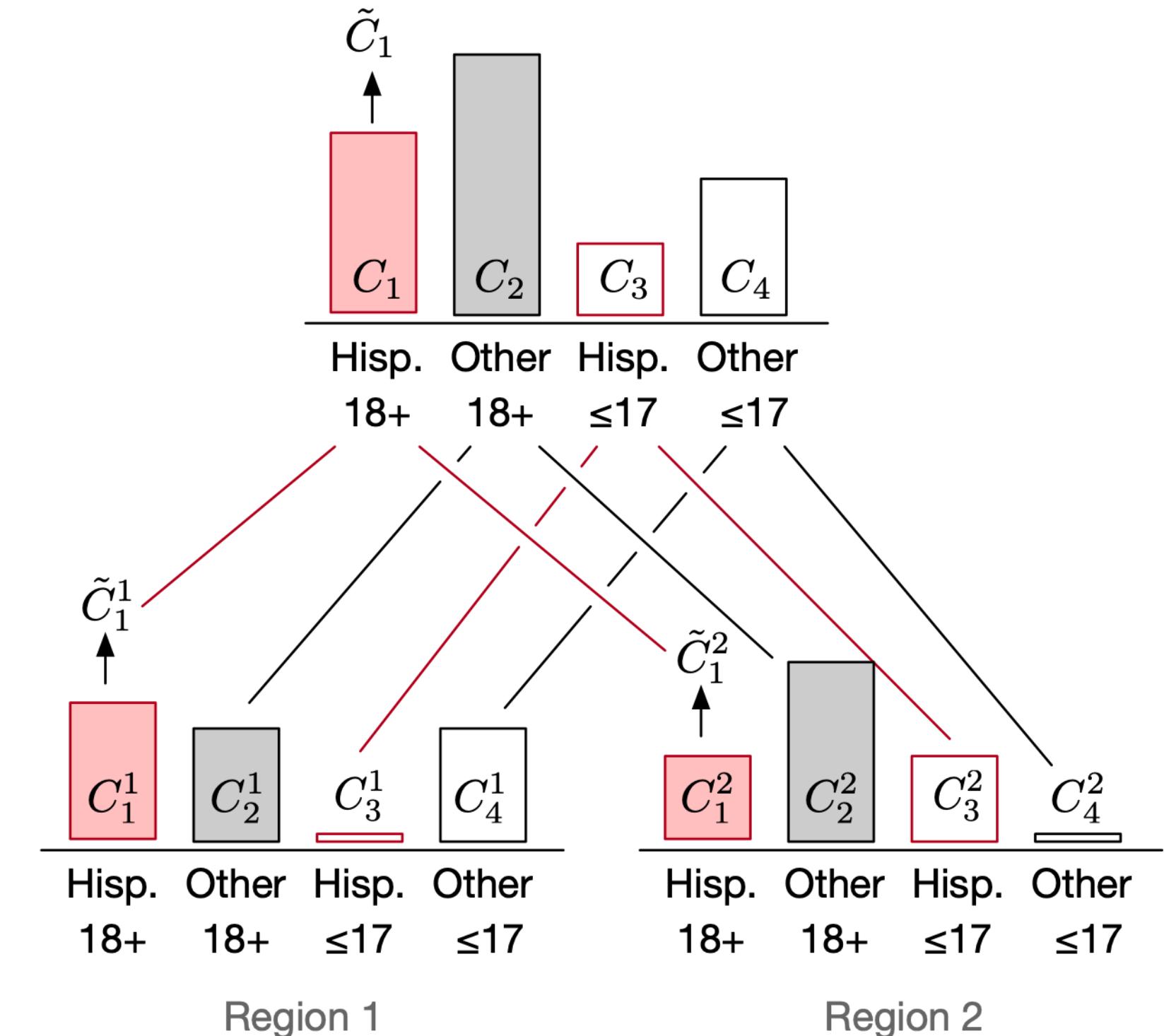


1. Apply noise with appropriate parameter  $\tilde{\mathbf{x}} = \mathbf{x} + \text{Noise}$
2. Post-process output  $\tilde{\mathbf{x}}$  to enforce consistency

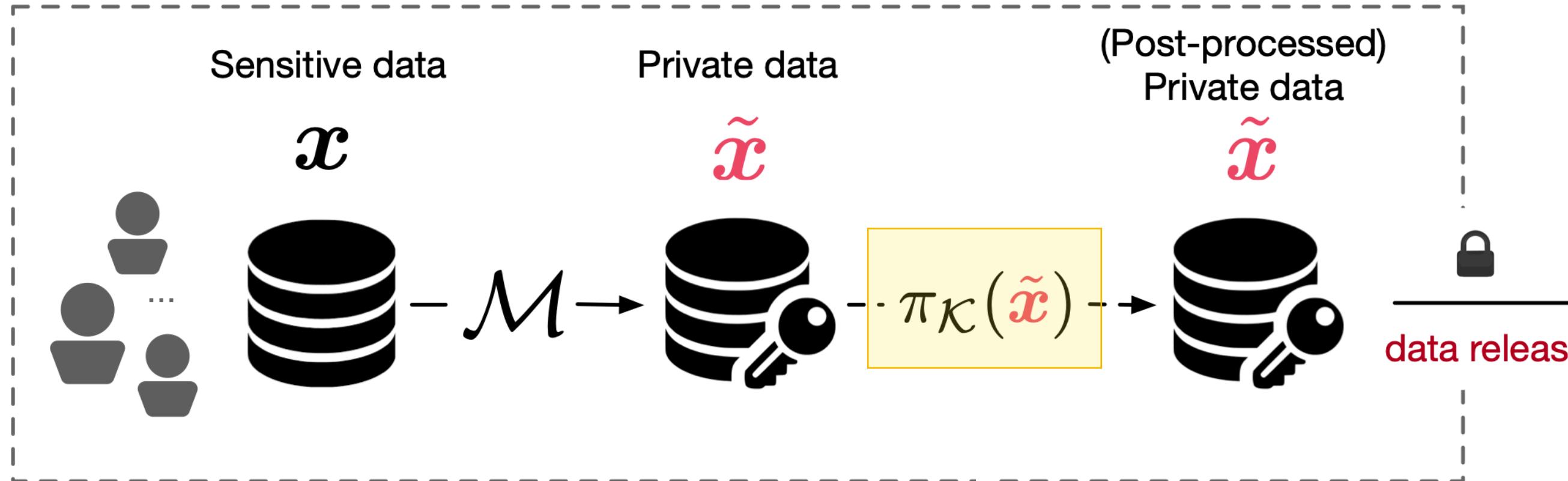
$$\pi_{\mathcal{K}}(\tilde{\mathbf{x}}) : \operatorname{argmin}_{\mathbf{v} \in \mathcal{K}} \|\mathbf{v} - \tilde{\mathbf{x}}\|_2$$

with feasible region defined as

$$\mathcal{K} = \left\{ \mathbf{v} \mid \sum_{i=1}^n v_i = C, \mathbf{v} \geq 0 \right\}$$



# DP data release with post-processing



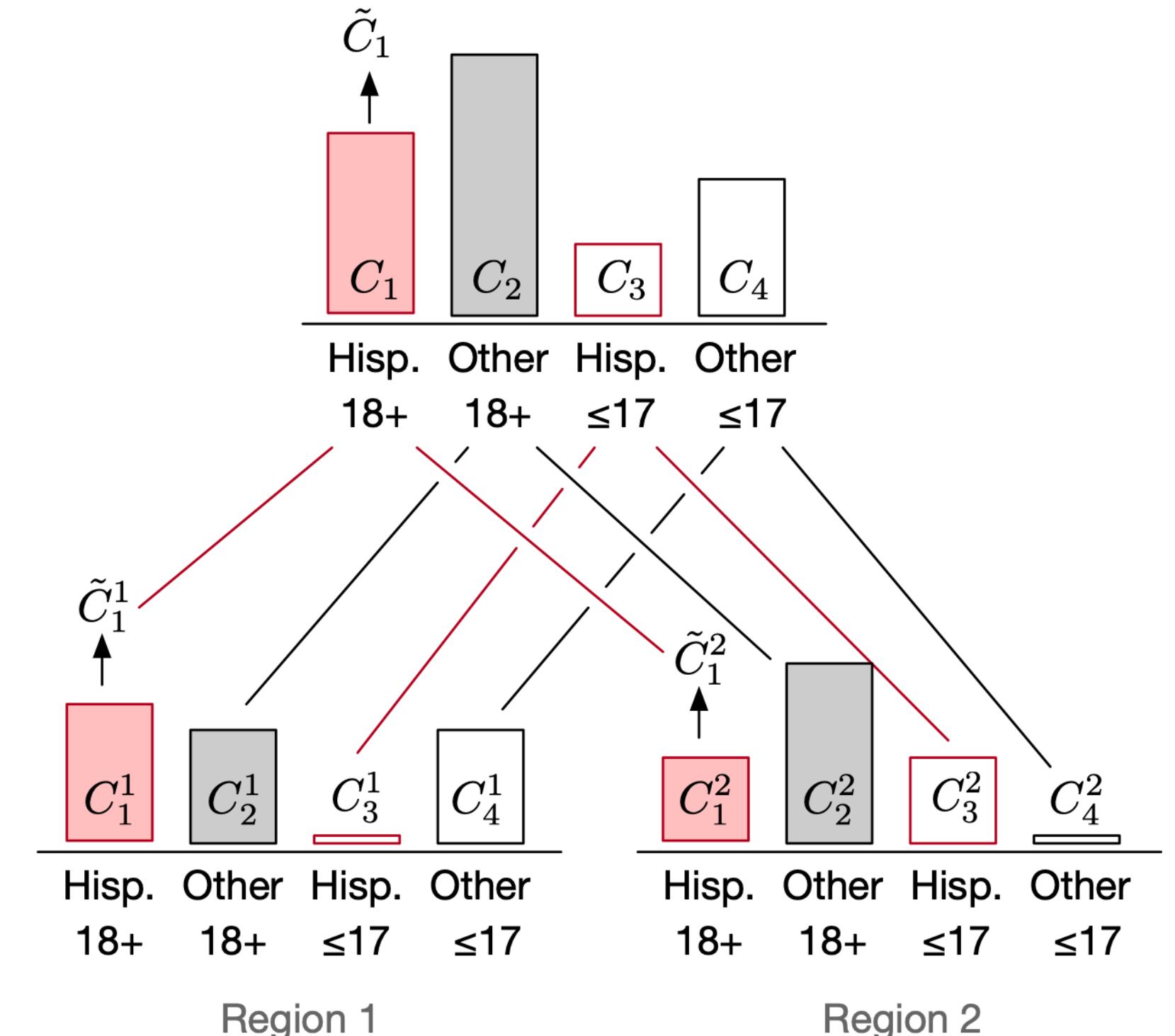
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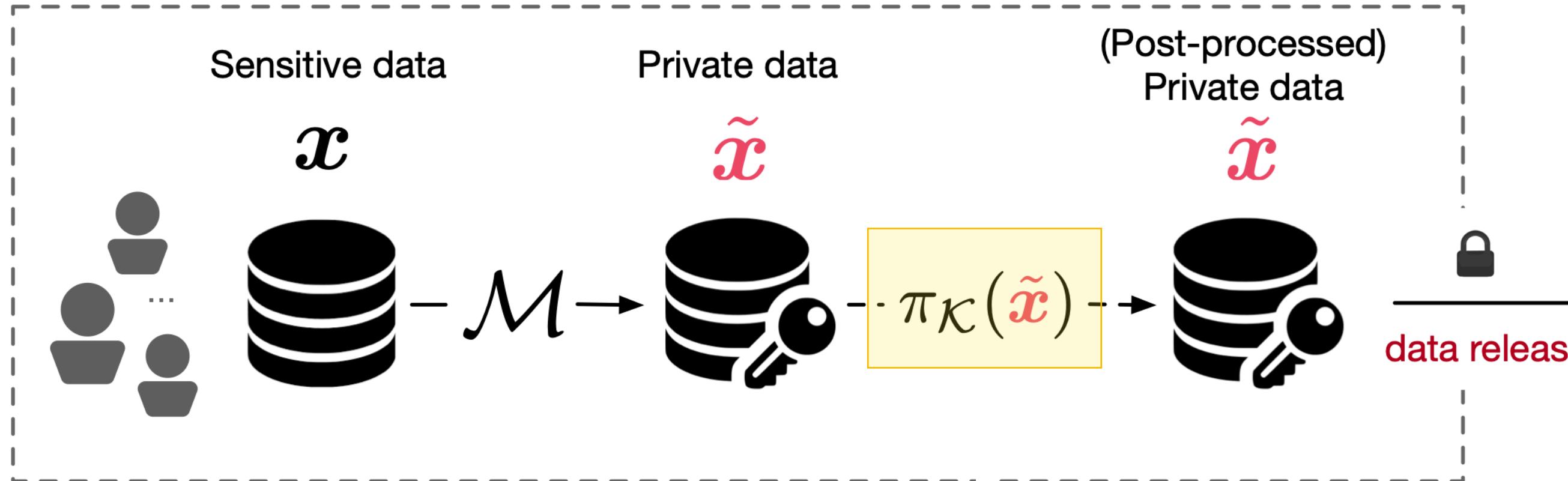
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# DP data release with post-processing

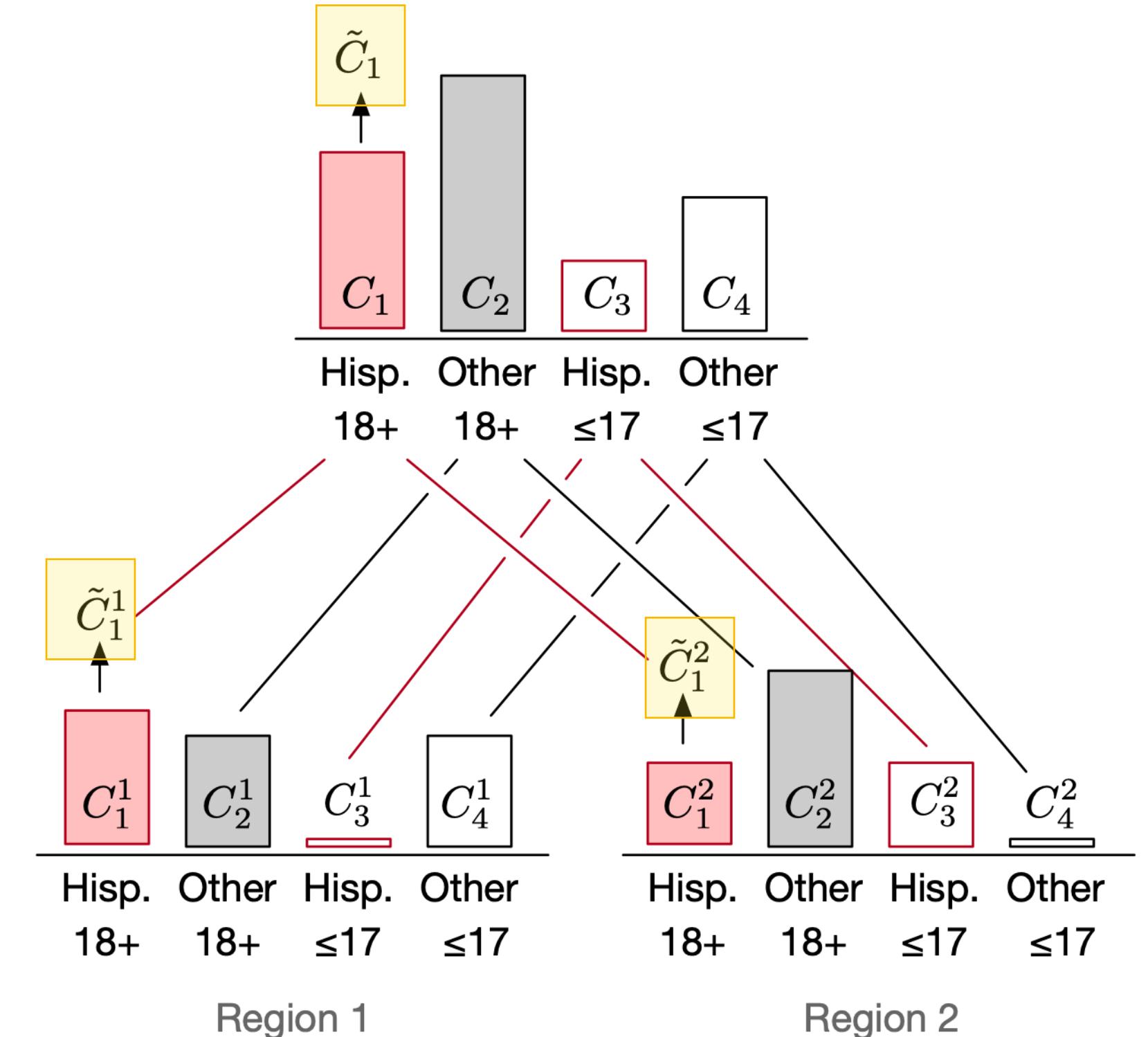


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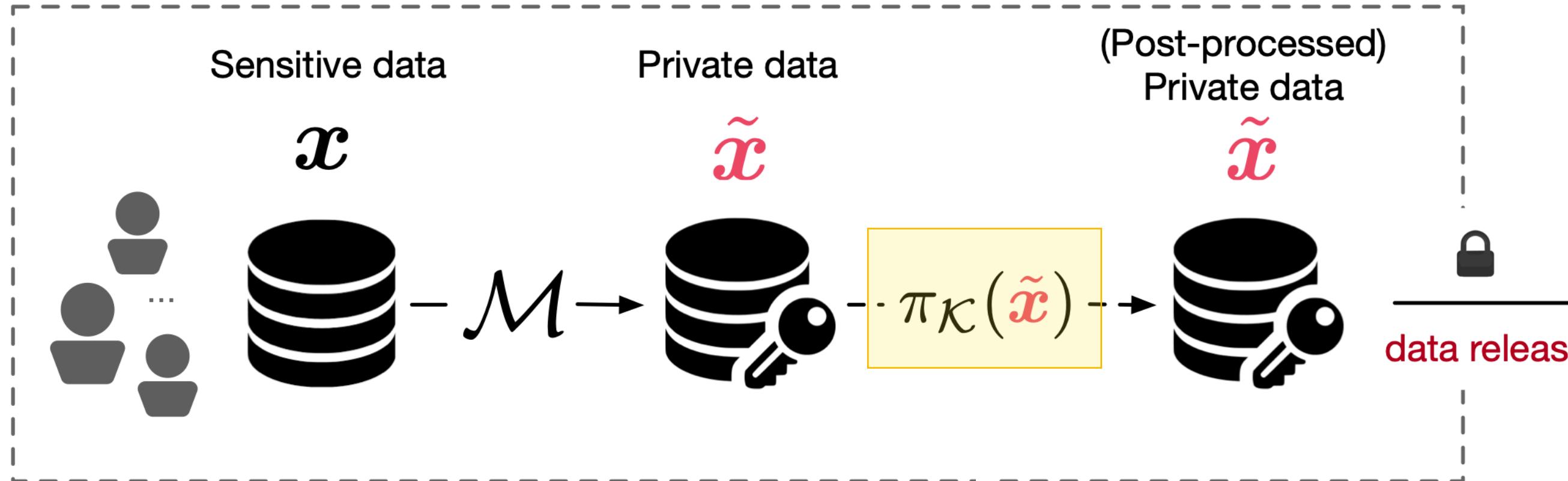
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# DP data release with post-processing

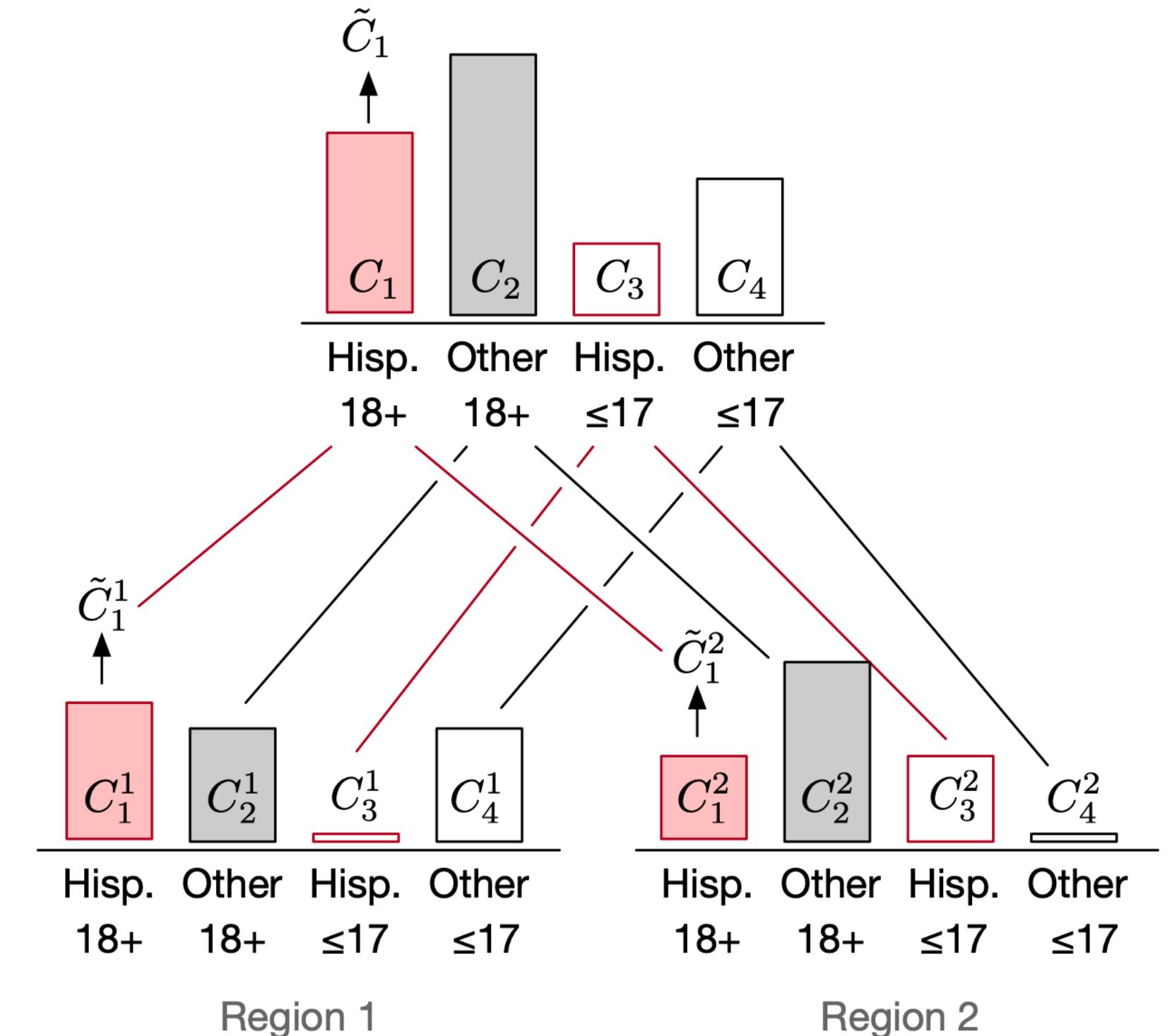


1. Apply noise with appropriate parameter  $\tilde{x} = x + \text{Noise}$
2. Post-process output  $\tilde{x}$  to enforce consistency

$$\pi_{\mathcal{K}}(\tilde{x}) : \operatorname{argmin}_{\mathbf{v} \in \mathcal{K}} \|\mathbf{v} - \tilde{x}\|_2$$

with feasible region defined as

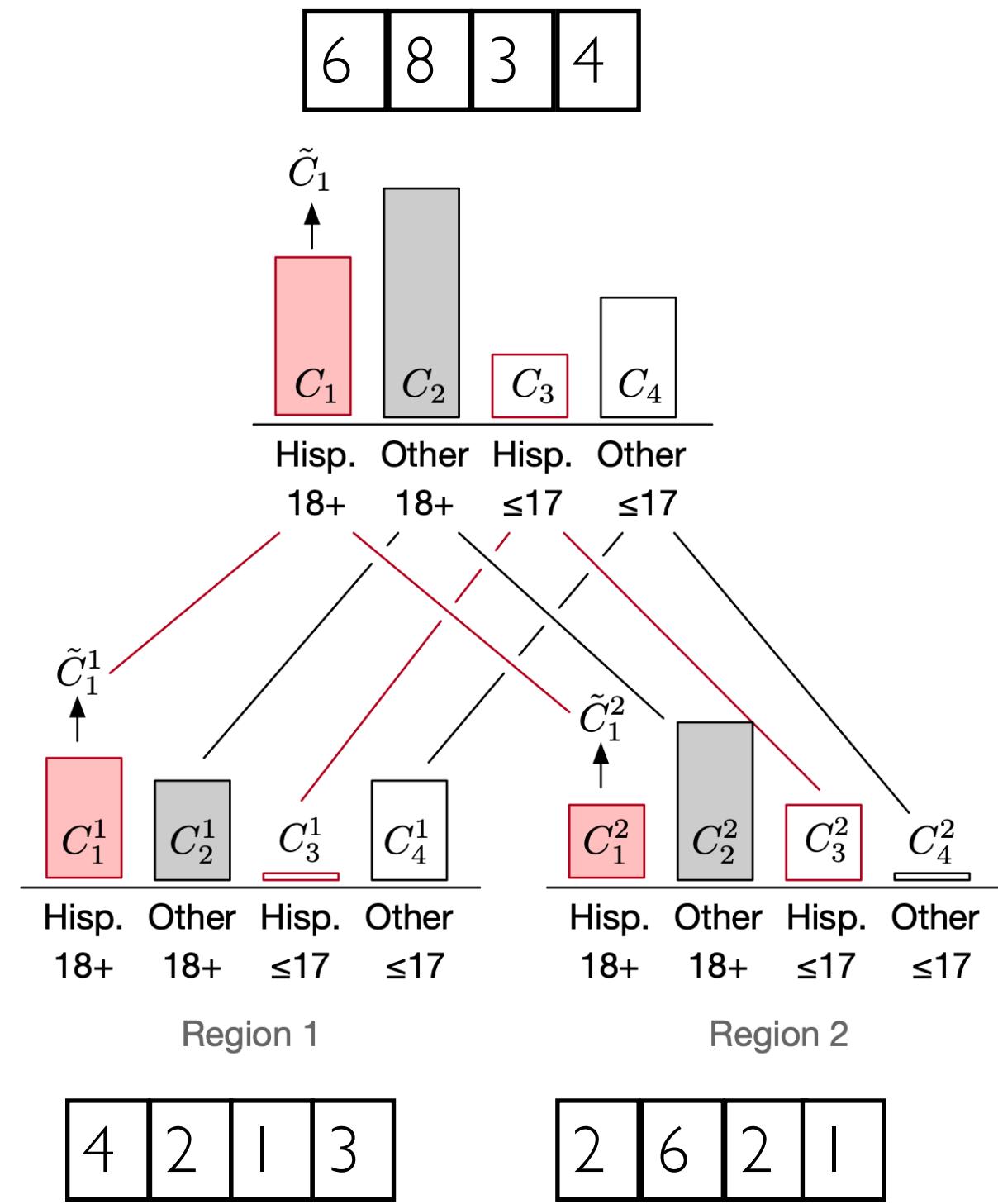
$$\mathcal{K} = \left\{ \mathbf{v} \mid \sum_{i=1}^n v_i = C, \mathbf{v} \geq 0 \right\}$$



Satisfies DP due to post-processing immunity

# DP post-processing

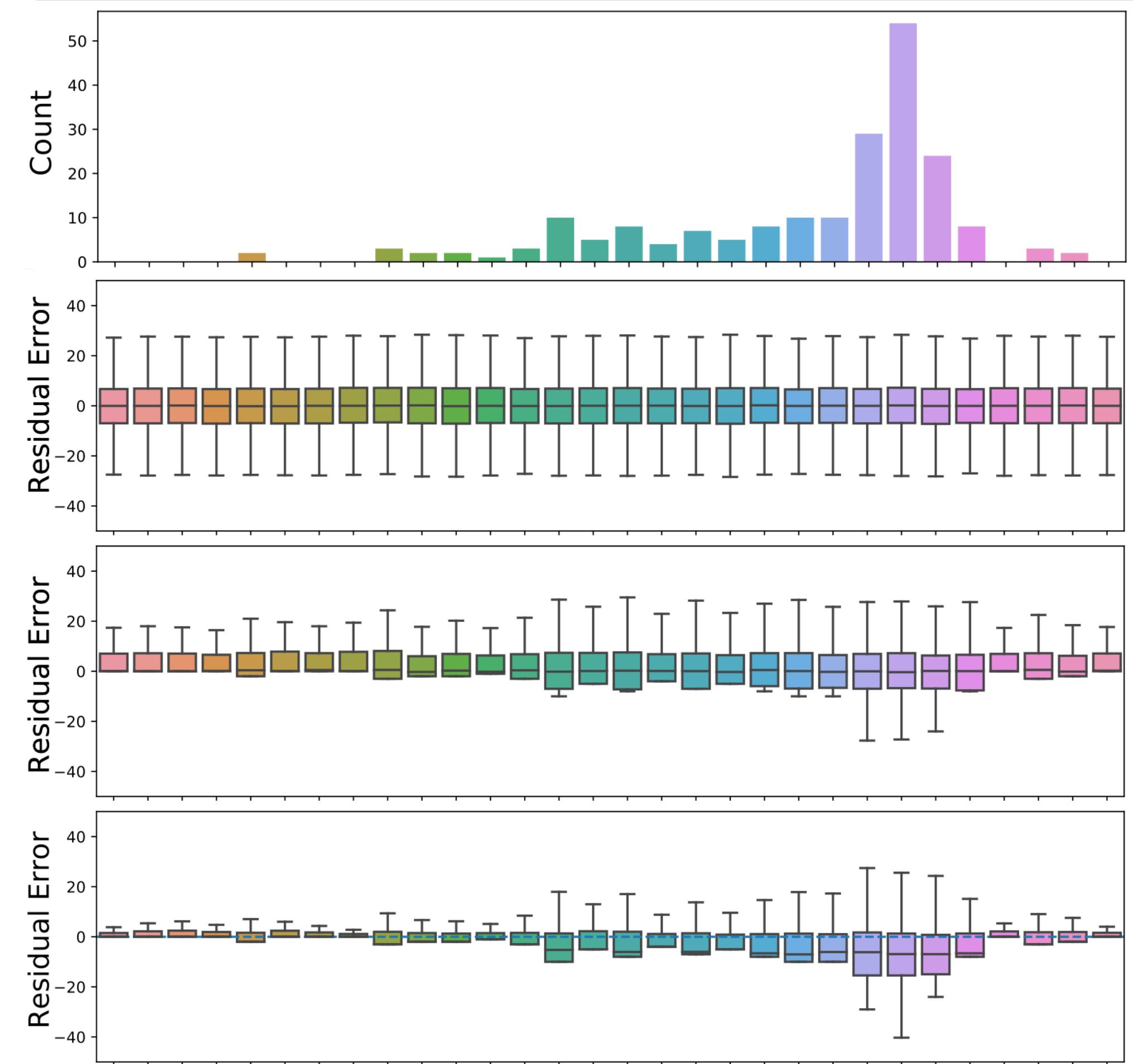
## Error and bias



$$\pi_{\geq 0} := \operatorname{argmin}_{v \geq 0} \|v - \tilde{x}\|_2$$

$$\pi_{\mathcal{K}_S} := \operatorname{argmin}_{v \in \mathcal{K}_S} \|v - \tilde{x}\|_2, \quad \mathcal{K}_S = \{v \in \mathbb{R}^n \mid \sum_i v_i = \tilde{S}, v_i \geq 0\},$$

Laplace  
mechanism



# DP post-processing

## Error and bias

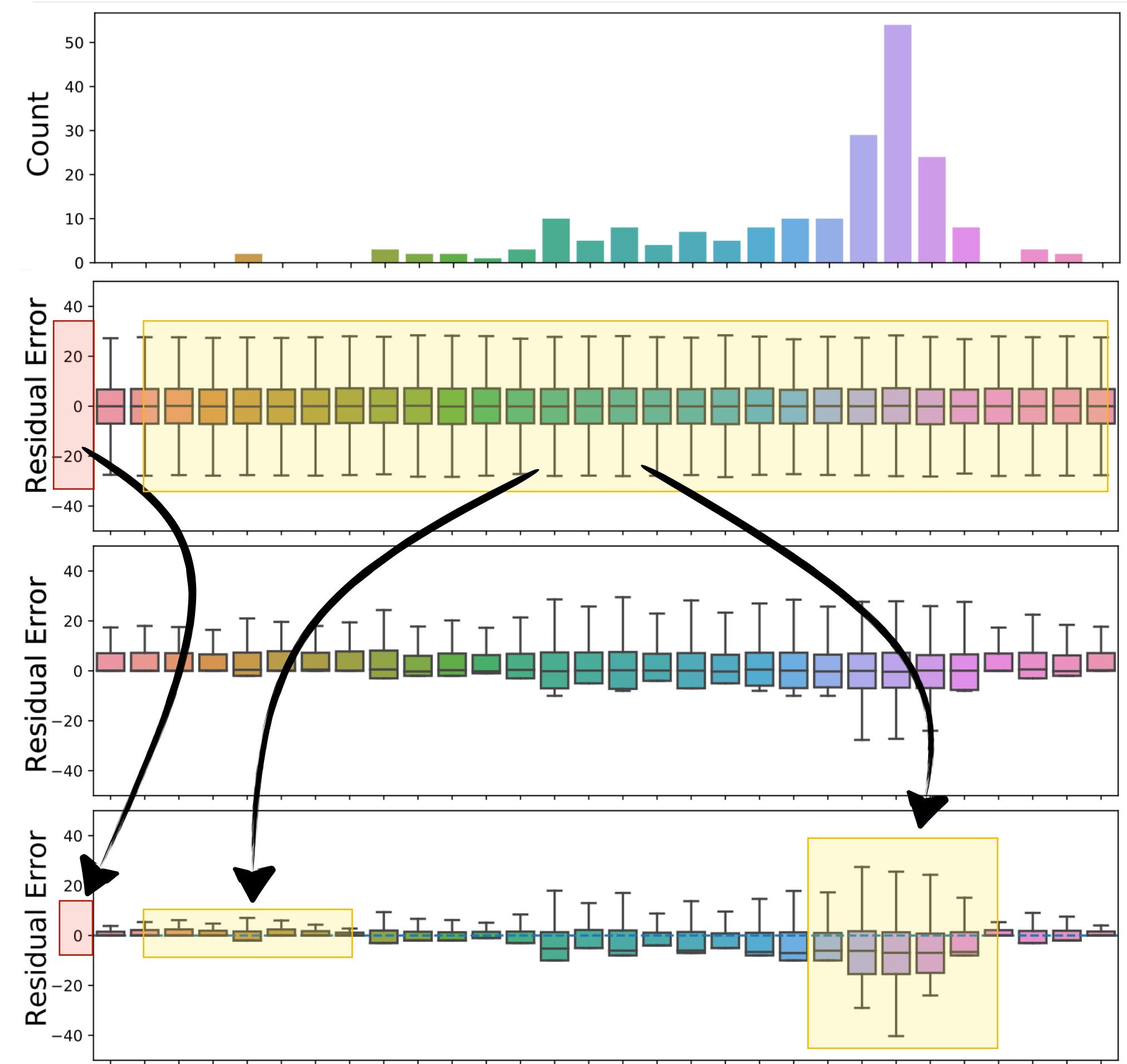
Observe that post-processing **reduces the errors.**

However, **it increases unfairness!**

Laplace  
mechanism

$$\pi_{\geq 0} := \operatorname{argmin}_{v \geq 0} \|v - \tilde{x}\|_2$$

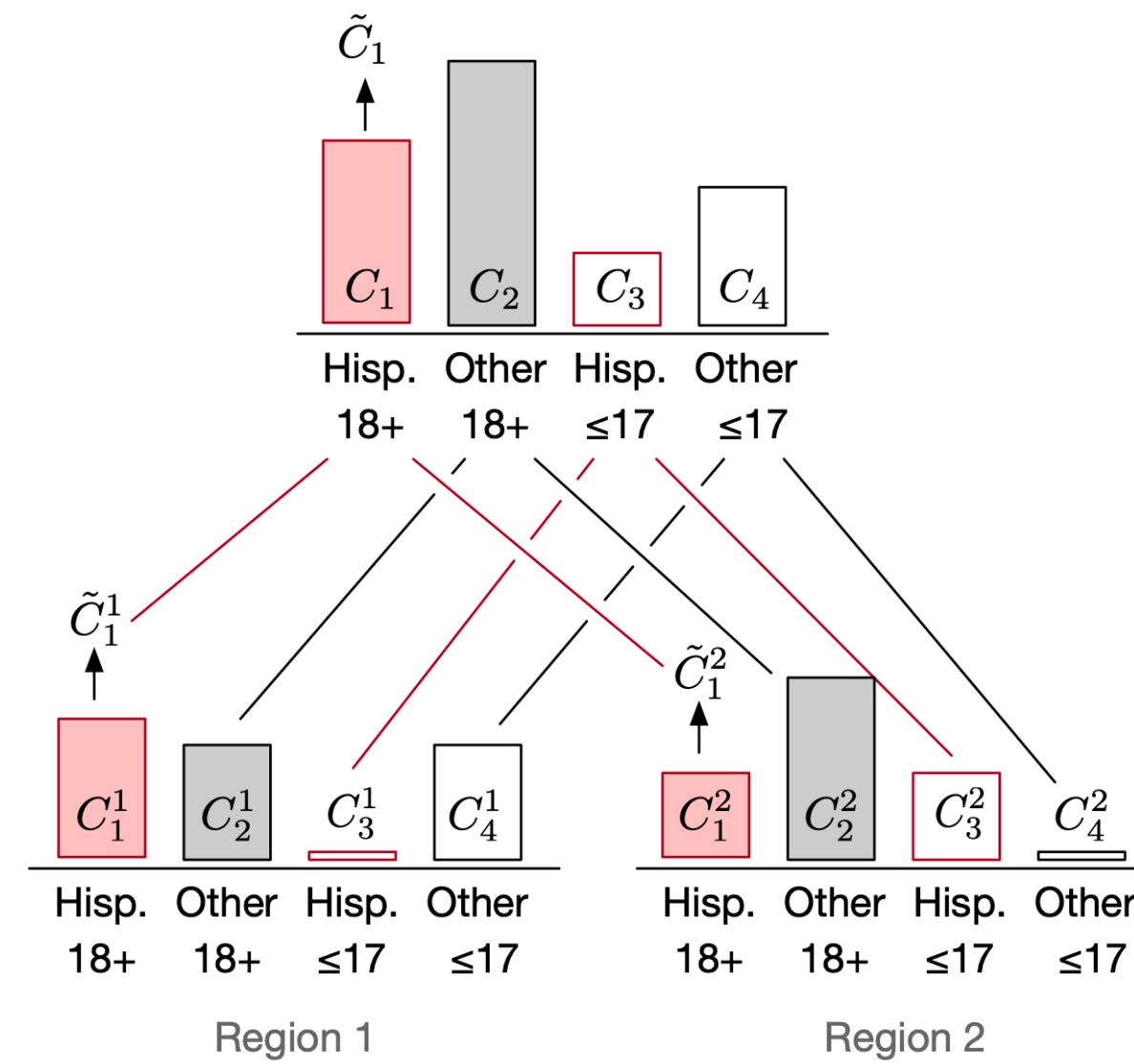
$$\pi_{\mathcal{K}_S} := \operatorname{argmin}_{v \in \mathcal{K}_S} \|v - \tilde{x}\|_2, \quad \mathcal{K}_S = \{v \in \mathbb{R}^n \mid \sum_i v_i = \tilde{S}, v_i \geq 0\},$$



# Bias of post-processing

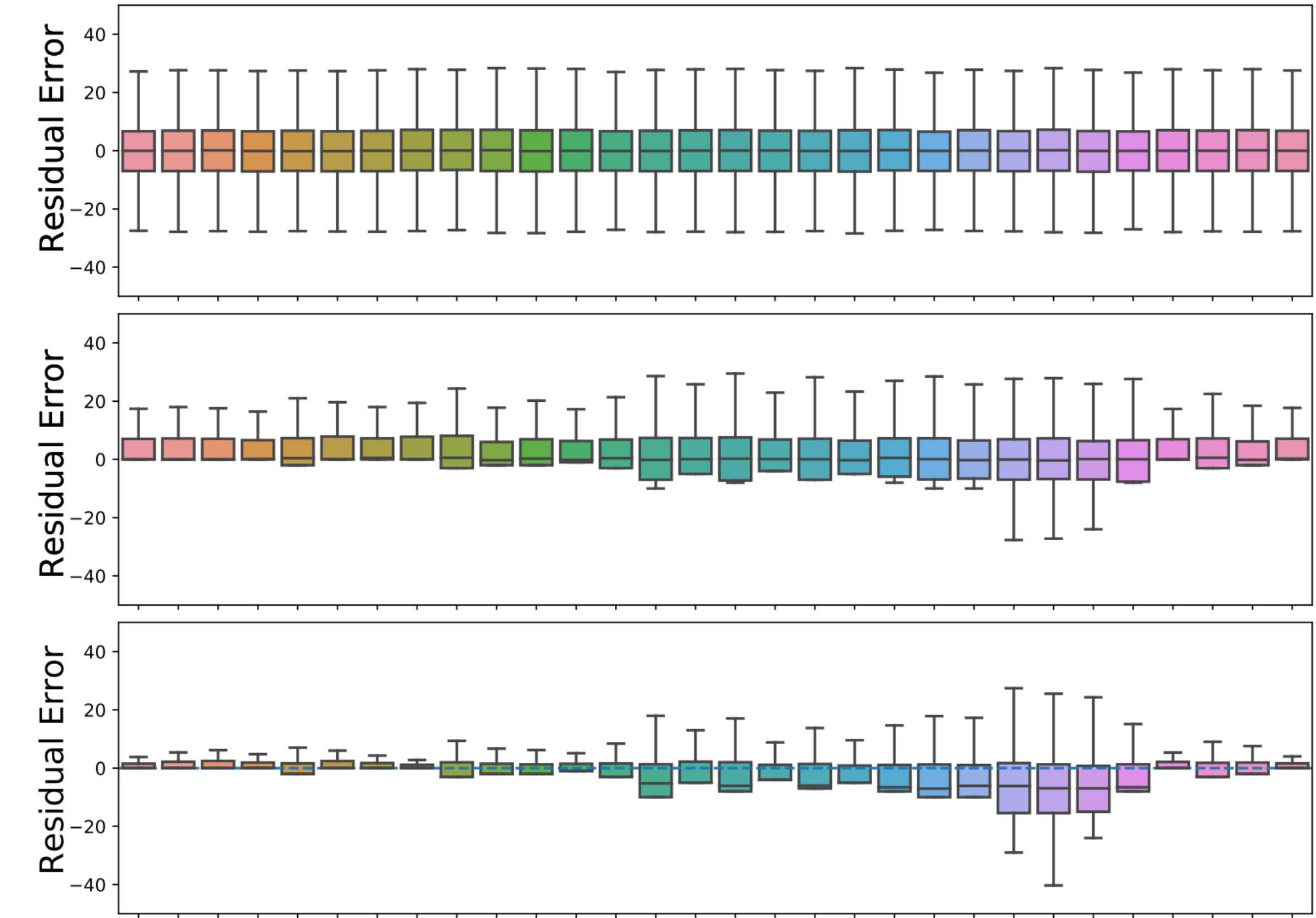
## Key result

- Thm (informal): The bias is caused by the presence of **non-negativity constraints!**



$$\pi_{\geq 0} := \operatorname{argmin}_{v \geq 0} \|v - \tilde{x}\|_2$$

$$\pi_{\mathcal{K}_S} := \operatorname{argmin}_{v \in \mathcal{K}_S} \|v - \tilde{x}\|_2, \quad \mathcal{K}_S = \{v \in \mathbb{R}^n \mid \sum_i v_i = \tilde{S}, v_i \geq 0\},$$

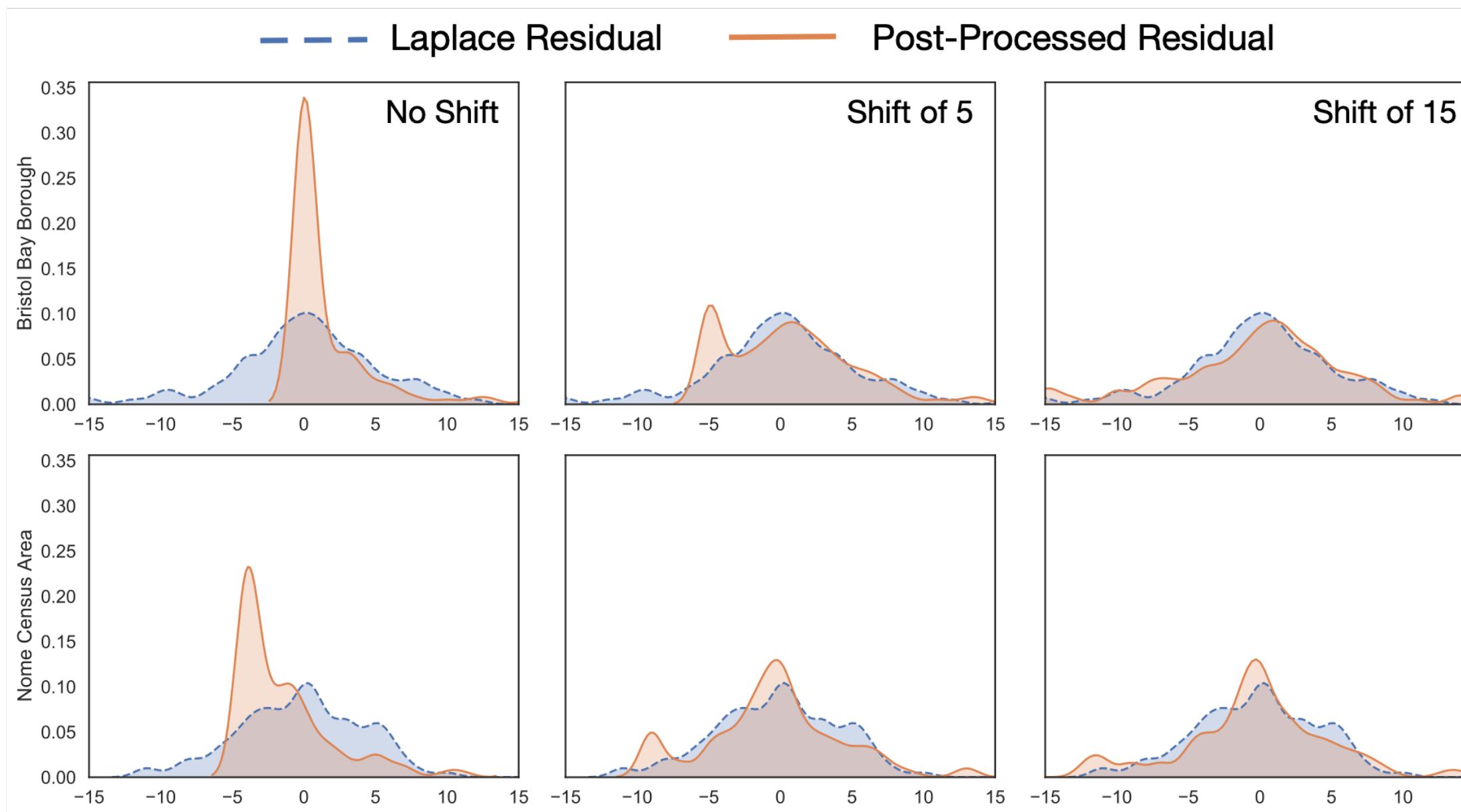


# Quantifying bias in post-processing

**Theorem:** Suppose that the noisy data  $\tilde{x}$  is the output of the Laplace mechanism with scale  $\lambda$ . The bias of the post-processed solution  $\pi_{\mathcal{K}^+}$  of program  $(L^+)$  is bounded, in  $l_\infty$  norm, by

$$\|B_{L^+}(\mathcal{M}, \mathbf{x})\|_\infty = \left\| \mathbb{E}_{\tilde{\mathbf{x}} \sim \mathcal{M}(\mathbf{x})} [\pi_{L^+}(\tilde{\mathbf{x}}) - \mathbf{x}] \right\|_\infty \leq C' \cdot \exp\left(\frac{-r_m}{\lambda}\right) \cdot \sum_{i=0}^{n-1} \frac{(r_m)^i}{i! \cdot \lambda^i},$$

where  $C'$  represents the value  $\sup_{v \in \mathcal{K}^+} \|v - \mathbf{x}\|_\infty$ , which is finite due to the boundedness of the feasible region  $\mathcal{K}^+$ .

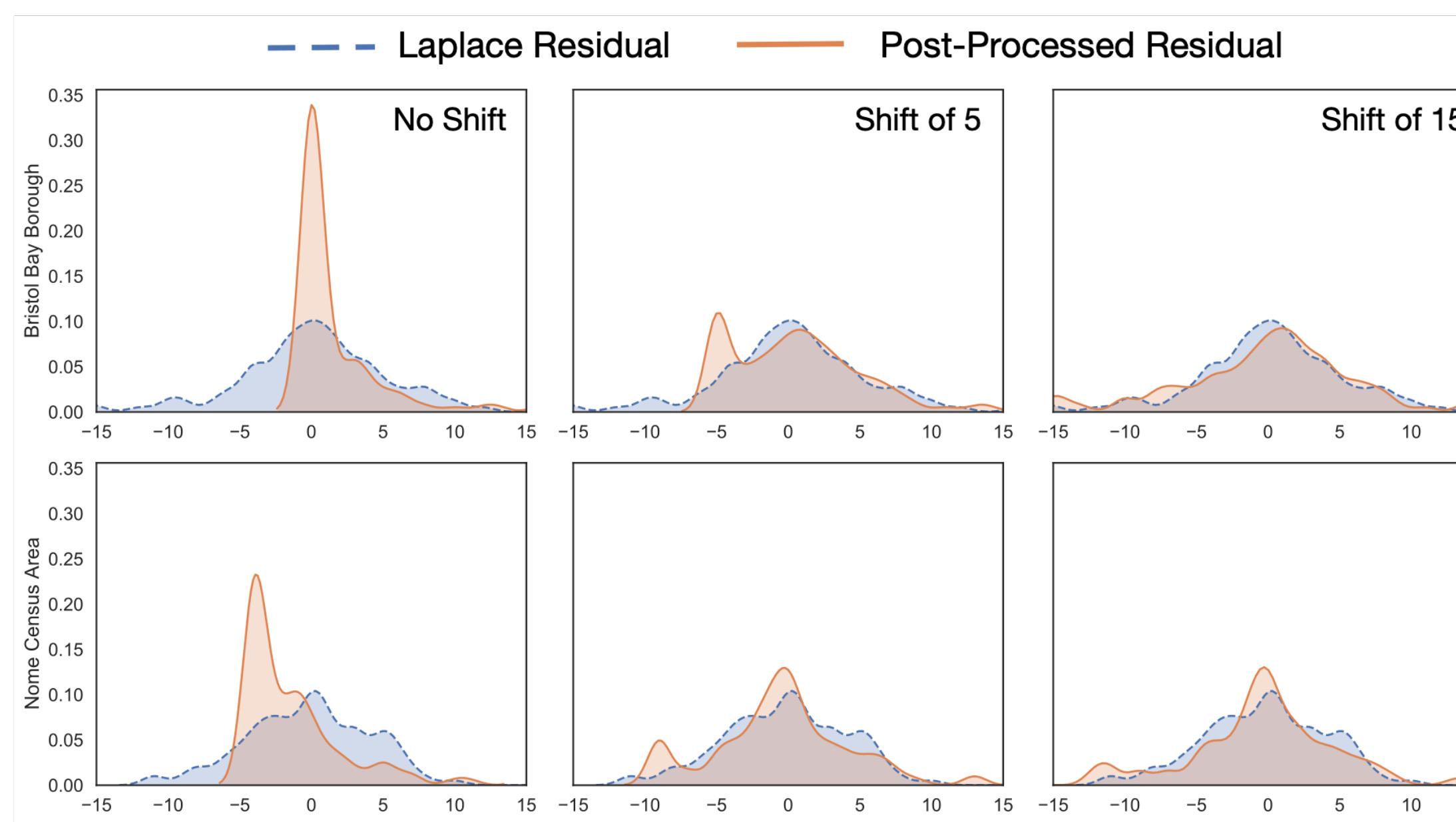


There is an  $\ell_1$ -ball of radius  $r_m = \min_i x_i$  and centered in  $\mathbf{x}$  which is a feasible subspace where there is no bias.

Shifting increases the value of  $r_m$  and the bias progressively disappear.

# Practical considerations

- Post-processing reduces the variance of the noise differently in different “regions”. Regions with many subregions (e.g., counties, census blocks, etc.) will have more variance than regions with few subregions.
- It creates situations where counties will be treated fundamentally differently in decision processes.



Variance	
Arizona (pop: 2.37ML in 15 counties)	186.67
Texas (pop: 8.89ML in 254 counties)	200.01
~6.5% difference which may affect allocations!	

# DP post-processing

## Important conclusion

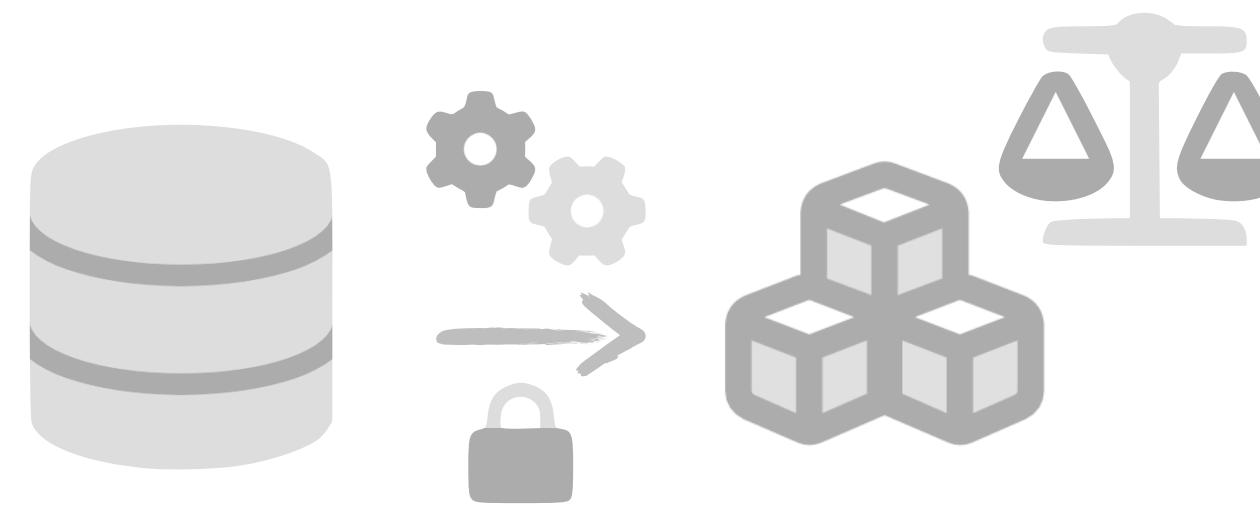
*Although post-processing reduces errors,  
its application to policy determinations  
should take into account fairness issues.*

# Agenda

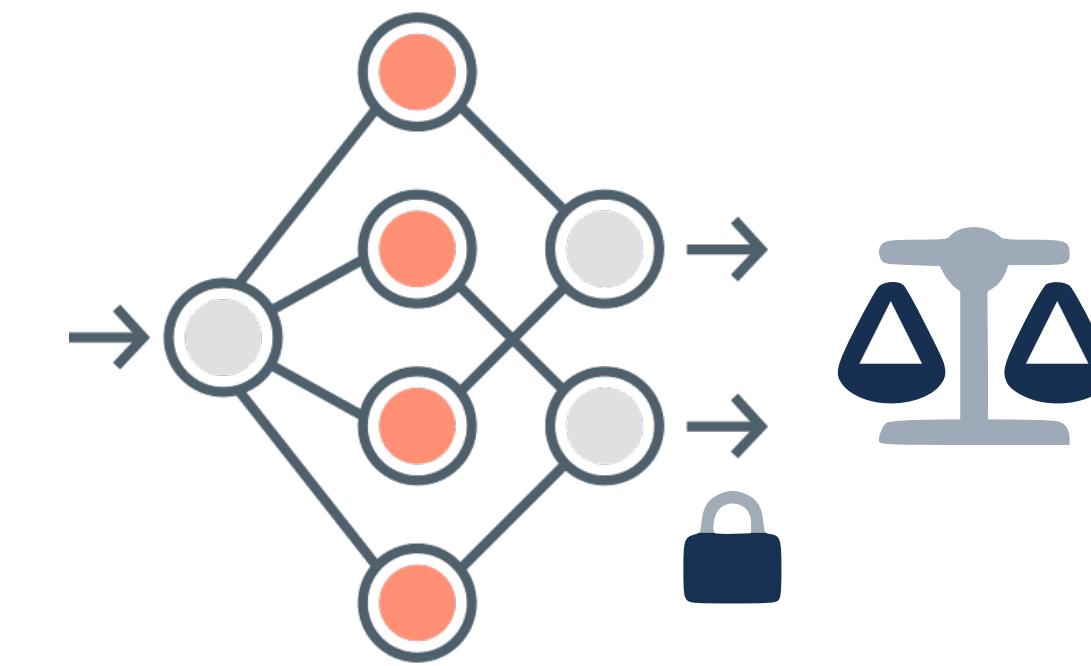
## Preliminaries



## Fairness impacts of DP in decision making



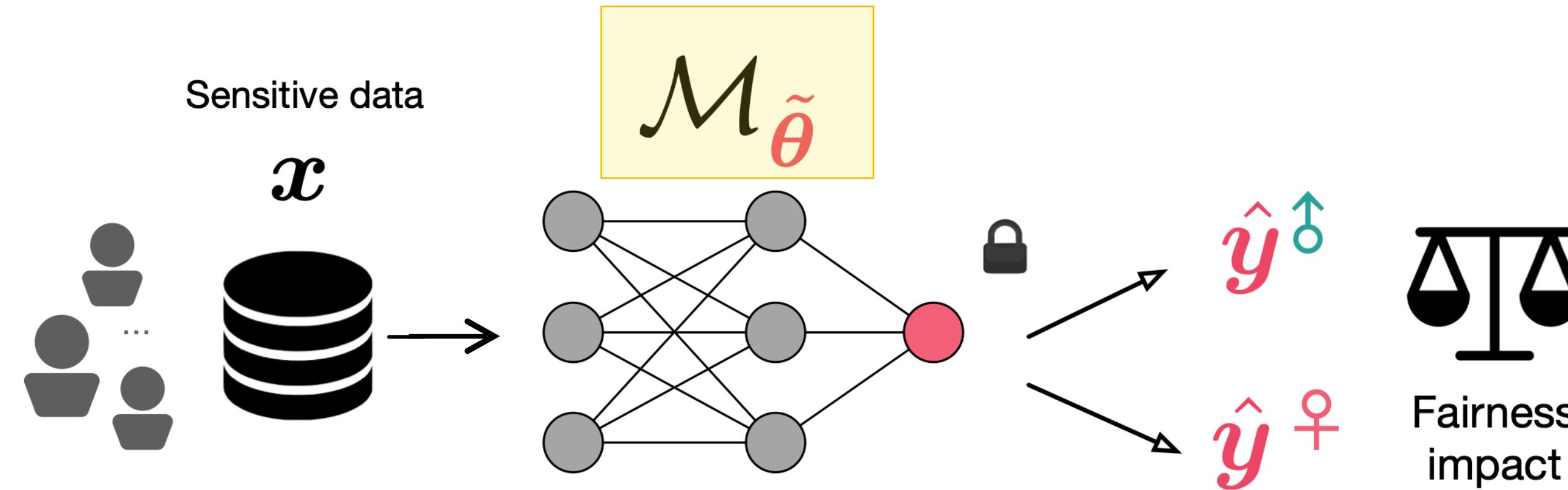
## Fairness impacts of DP in learning



## What's next?



# Fairness in DP learning tasks



- Given a dataset consisting of data points  $(X_i, A_i, Y_i)$  the goal is to learn a classifier  $f_\theta$  that guarantees privacy of the individual data points and the learning task minimizes

$$\min_{\theta} \mathcal{L}(\theta; D) = \frac{1}{n} \sum_{i=1}^n \ell(f_\theta(X_i), Y_i)$$

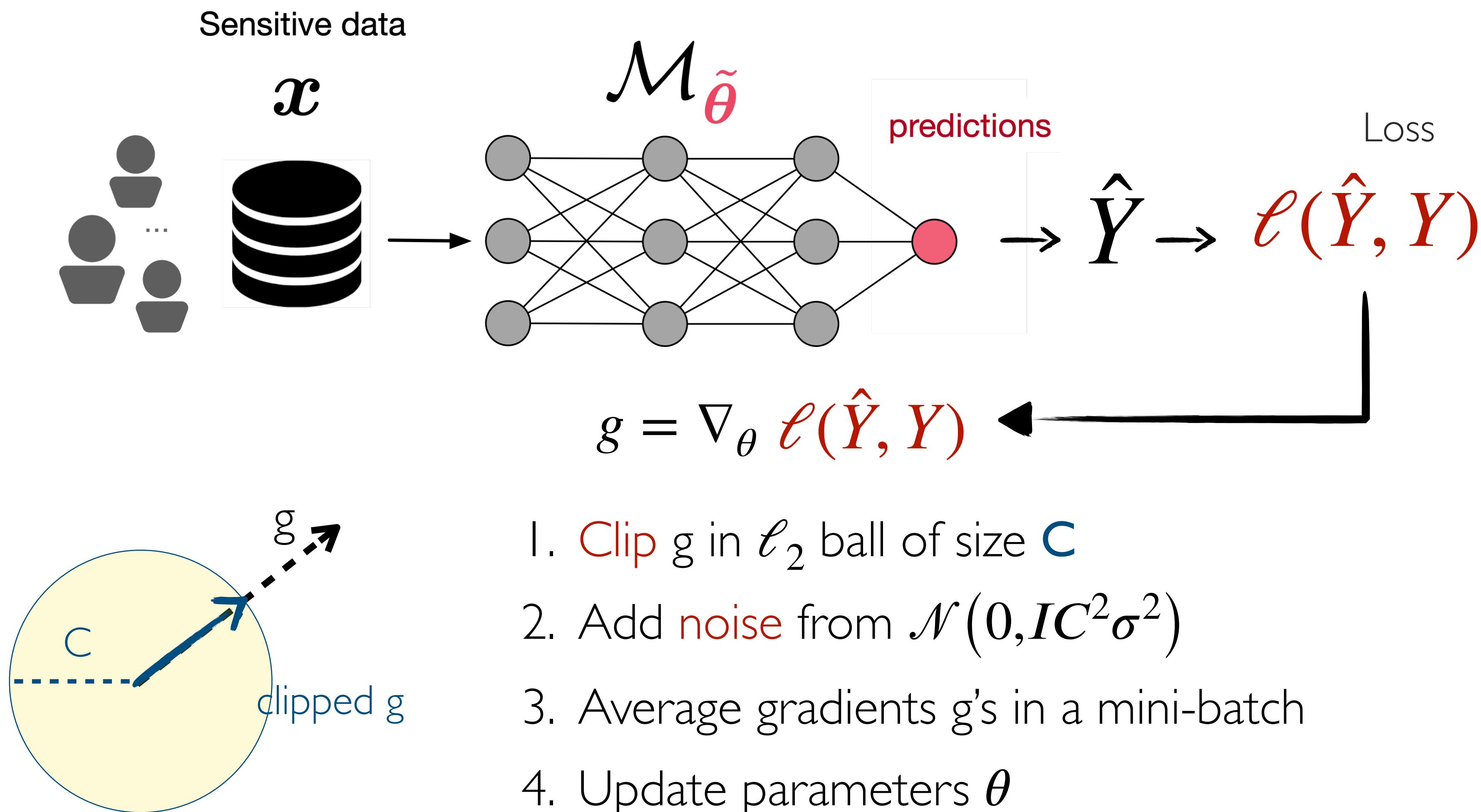
- Fairness focuses on the notion of excessive risk:  $R(\theta, D) = \mathbb{E}_{\tilde{\theta}} [\mathcal{L}(\tilde{\theta}; D)] - \mathcal{L}(\theta^*; D)$ , and is measured with respect to the excessive risk gap

$$\xi_a = |R_a(\theta) - R(\theta)|$$

↗ ↘

group-level population level

# DP Stochastic Gradient Descent



# Fairness issues in DP-SGD

**Theorem:** Consider an ERM problem with twice differentiable loss w.r.t. the model parameters. The expected loss of a group a at iteration  $t+1$  is:

$$\begin{aligned}\mathbb{E} [\mathcal{L}(\theta_{t+1}; D_a)] &= \underbrace{\mathcal{L}(\theta_t; D_a) - \eta \langle g_{D_a}, g_D \rangle + \frac{\eta^2}{2} \mathbb{E} [g_B^T H_\ell^a g_B]}_{\text{non-private term}} \\ &\quad + \underbrace{\eta (\langle g_{D_a}, g_D \rangle - \langle g_{D_a}, \bar{g}_D \rangle) + \frac{\eta^2}{2} (\mathbb{E} [\bar{g}_B^T H_\ell^a \bar{g}_B] - \mathbb{E} [g_B^T H_\ell^a g_B])}_{\text{private term due to clipping}} \quad (R_a^{\text{clip}}) \\ &\quad + \underbrace{\frac{\eta^2}{2} \text{Tr}(H_\ell^a) C^2 \sigma^2}_{\text{private term due to noise}} \quad (R_a^{\text{noise}}) \\ &\quad + O(\|\theta_{t+1} - \theta_t\|^3),\end{aligned}$$

where the expectation is taken over the randomness of the private noise and the mini-batch selection, and the terms  $g_Z$  and  $\bar{g}_Z$  denote, respectively, the average non-private and private gradients over subset  $Z$  of  $D$  at iteration  $t$  (the iteration number is dropped for ease of notation).

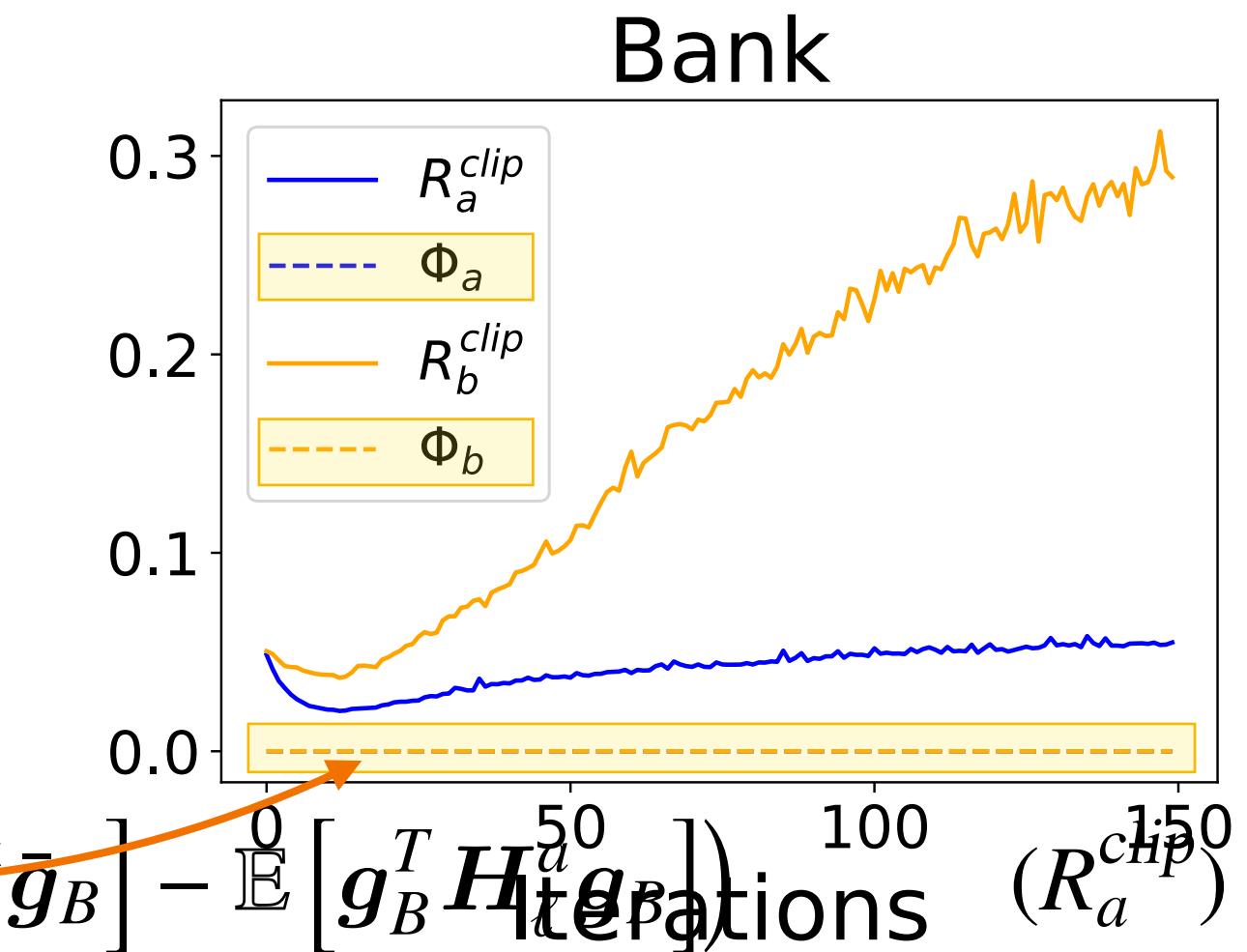
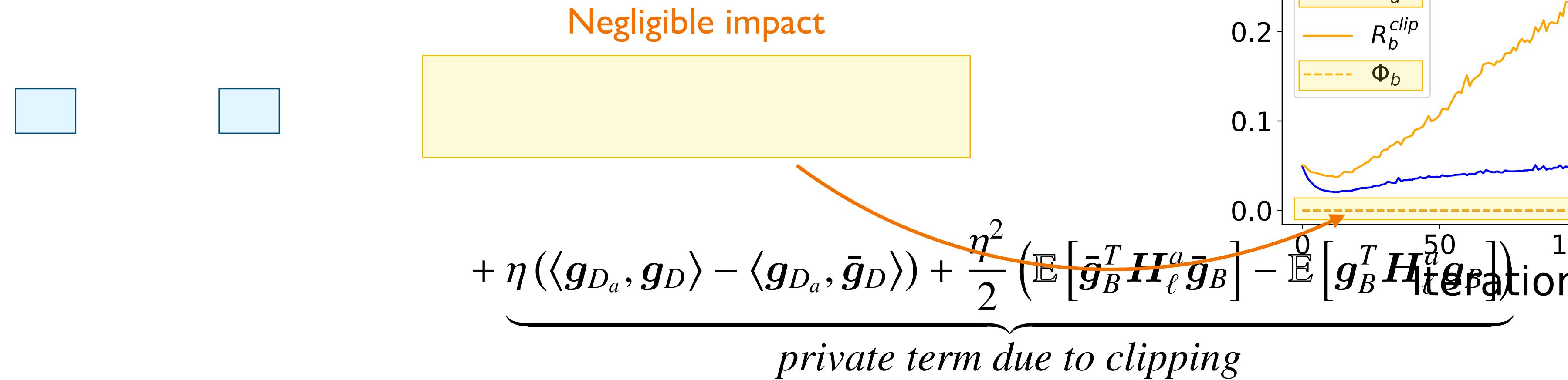
# Why clipping causes unfairness?

## Gradient norms and excessive risk

$$+ \underbrace{\eta (\langle \mathbf{g}_{D_a}, \mathbf{g}_D \rangle - \langle \mathbf{g}_{D_a}, \bar{\mathbf{g}}_D \rangle) + \frac{\eta^2}{2} (\mathbb{E} [\bar{\mathbf{g}}_B^T \mathbf{H}_\ell^a \bar{\mathbf{g}}_B] - \mathbb{E} [\mathbf{g}_B^T \mathbf{H}_\ell^a \mathbf{g}_B])}_{\text{private term due to clipping}} \quad (R_a^{\text{clip}})$$

# Why clipping causes unfairness?

## Gradient norms and excessive risk



# Why clipping causes unfairness?

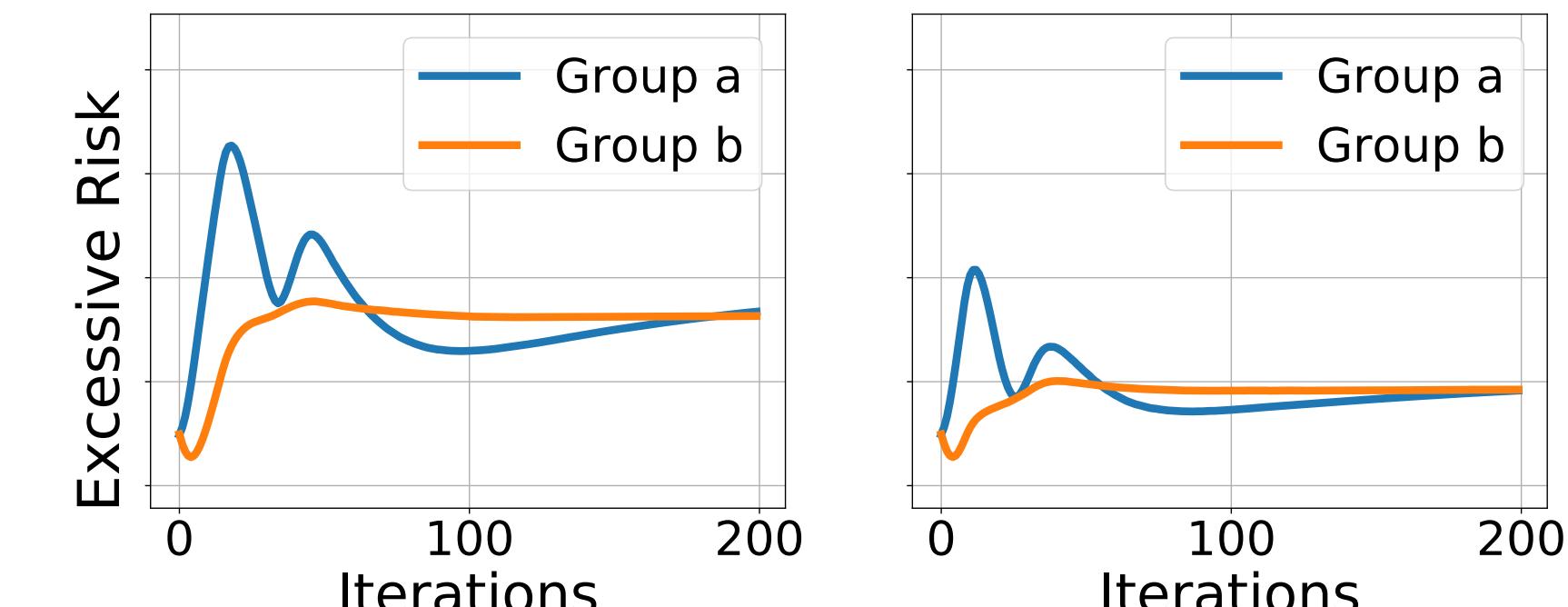
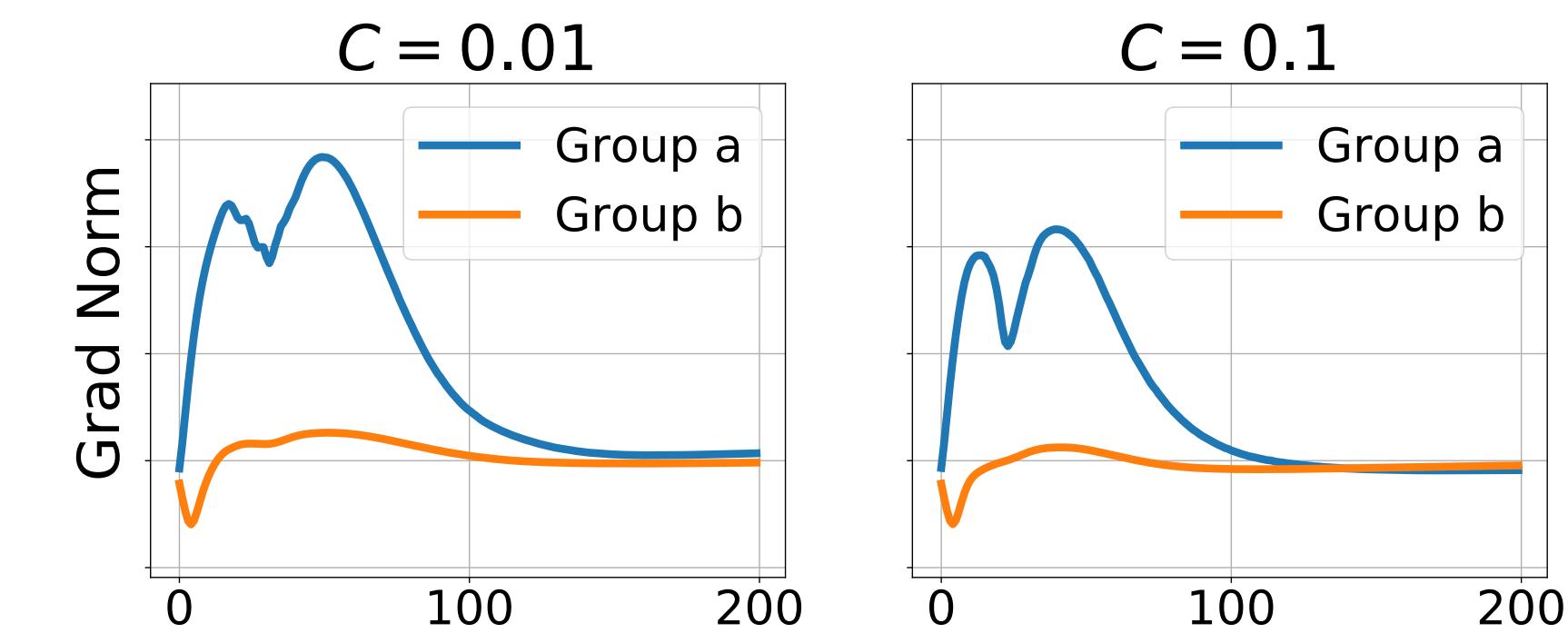
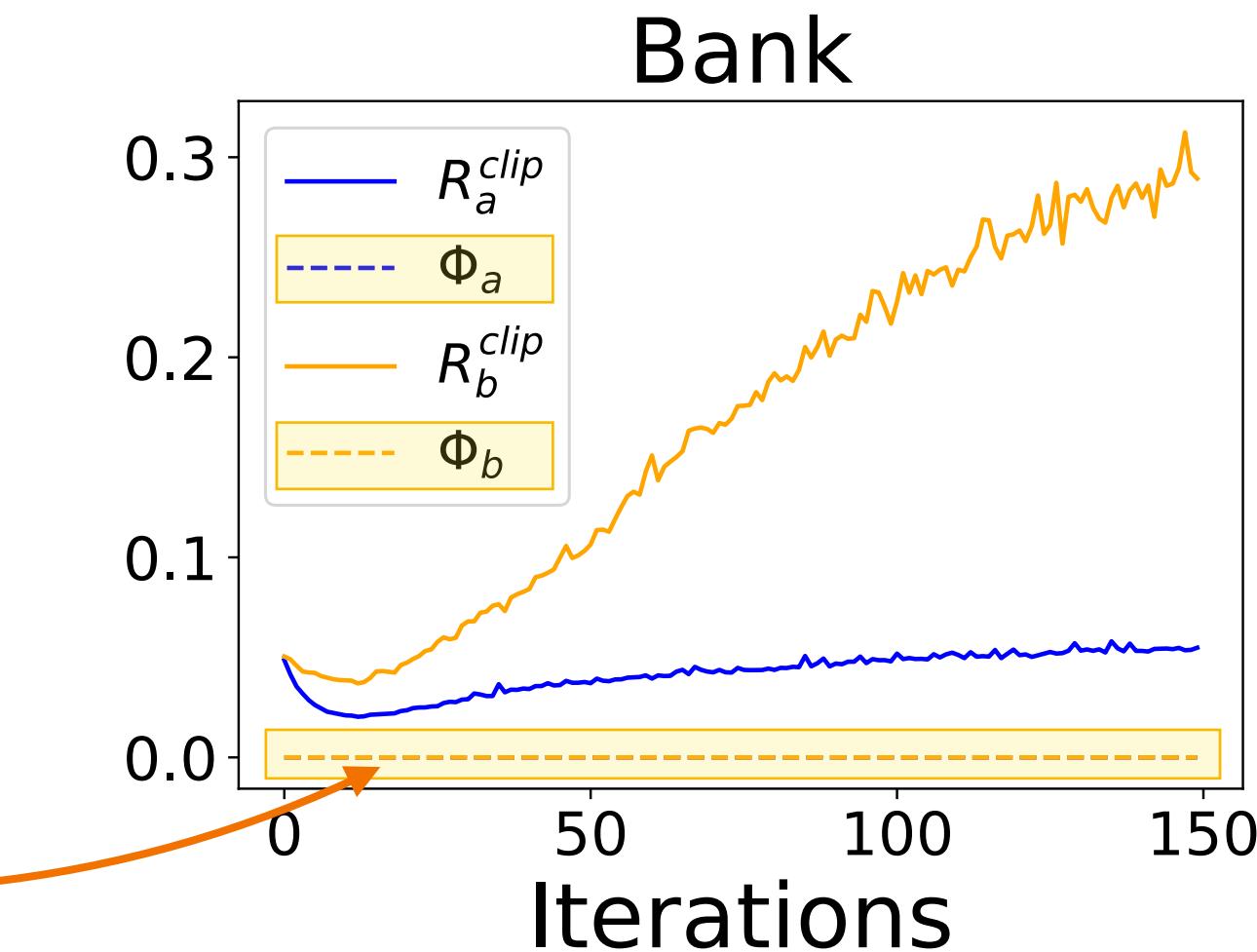
## Gradient norms and excessive risk

$$\underbrace{\eta (\langle \mathbf{g}_{D_a}, \mathbf{g}_D \rangle - \langle \mathbf{g}_{D_a}, \bar{\mathbf{g}}_D \rangle) + \frac{\eta^2}{2} (\mathbb{E} [\bar{\mathbf{g}}_B^T \mathbf{H}_\ell^a \bar{\mathbf{g}}_B] - \mathbb{E} [\mathbf{g}_B^T \mathbf{H}_\ell^a \mathbf{g}_B])}_{\text{private term due to clipping}}$$

Negligible impact

Crucial Proxy to Unfairness (due to clipping)

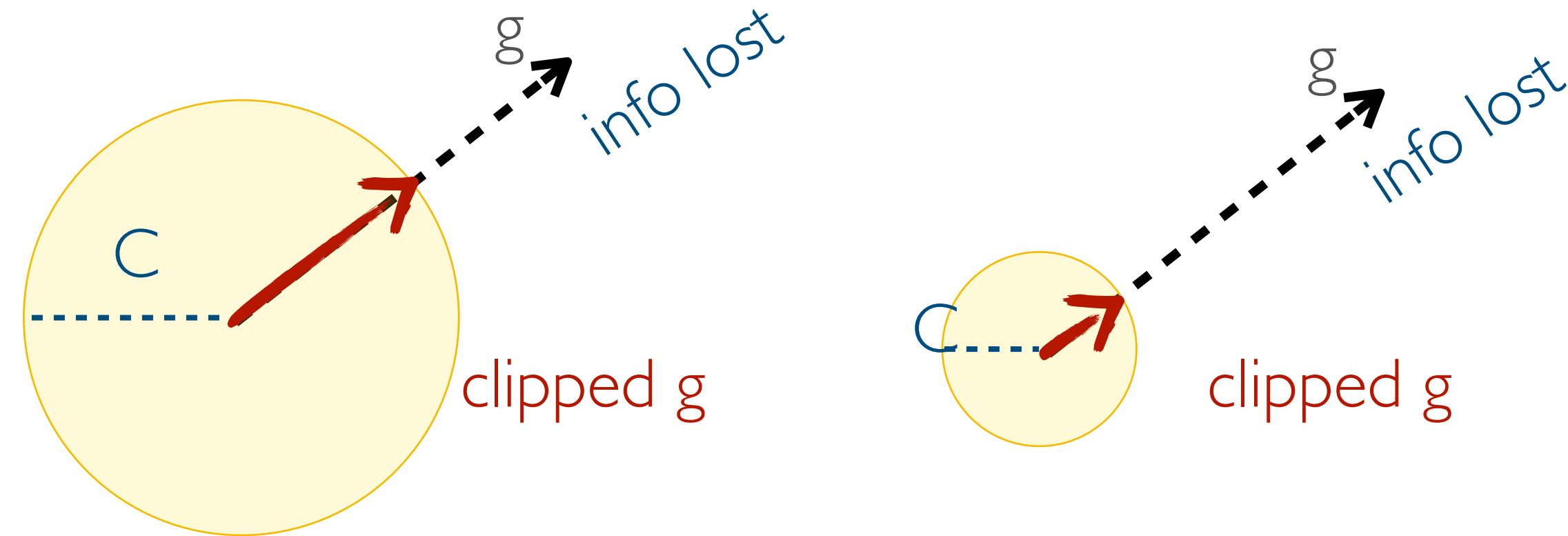
Theorem (informal): Gradient flow affects the excessive risk (unfairness) of the individuals and groups.



# Why clipping causes unfairness?

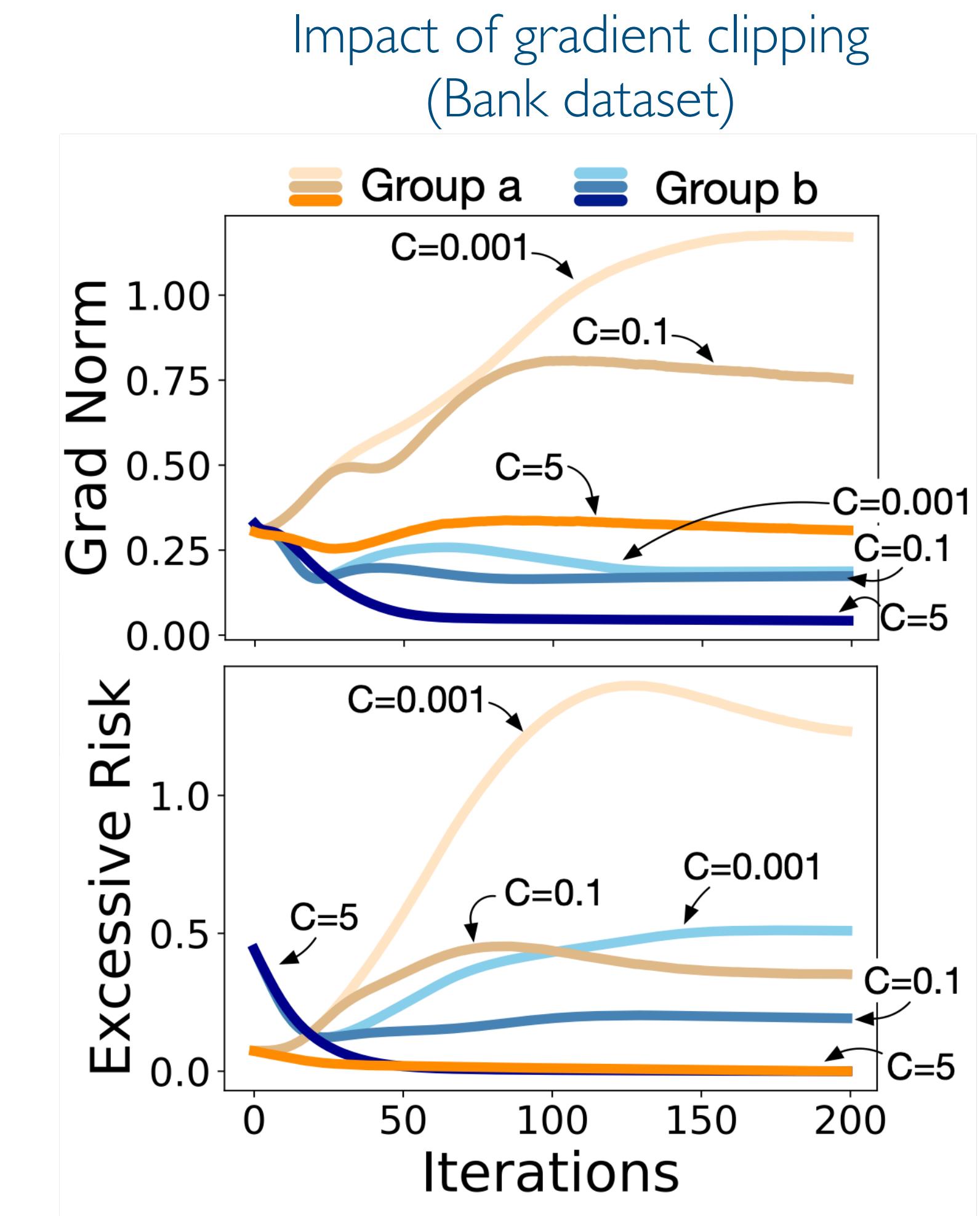
## Gradient norms and excessive risk

- When **clipping**, the smaller  $C$ , the higher is the information loss of the average gradients that are backpropagated.



**Theorem:** Let  $p_z = |D_z|/|D|$  be the fraction of training samples in group  $z \in \mathcal{A}$ . For groups  $a, b \in \mathcal{A}$ ,  $R_a^{\text{clip}} > R_b^{\text{clip}}$  whenever:

$$\|\mathbf{g}_{D_a}\| \left( p_a - \frac{p_a^2}{2} \right) \geq \frac{5}{2}C + \|\mathbf{g}_{D_b}\| \left( 1 + p_b + \frac{p_b^2}{2} \right).$$



# Why noise causes unfairness in DP-SGD?

$$+ \underbrace{\frac{\eta^2}{2} \text{Tr}(\mathbf{H}_\ell^a) C^2 \sigma^2}_{\text{private term due to noise}} \quad (R_a^{\text{noise}})$$

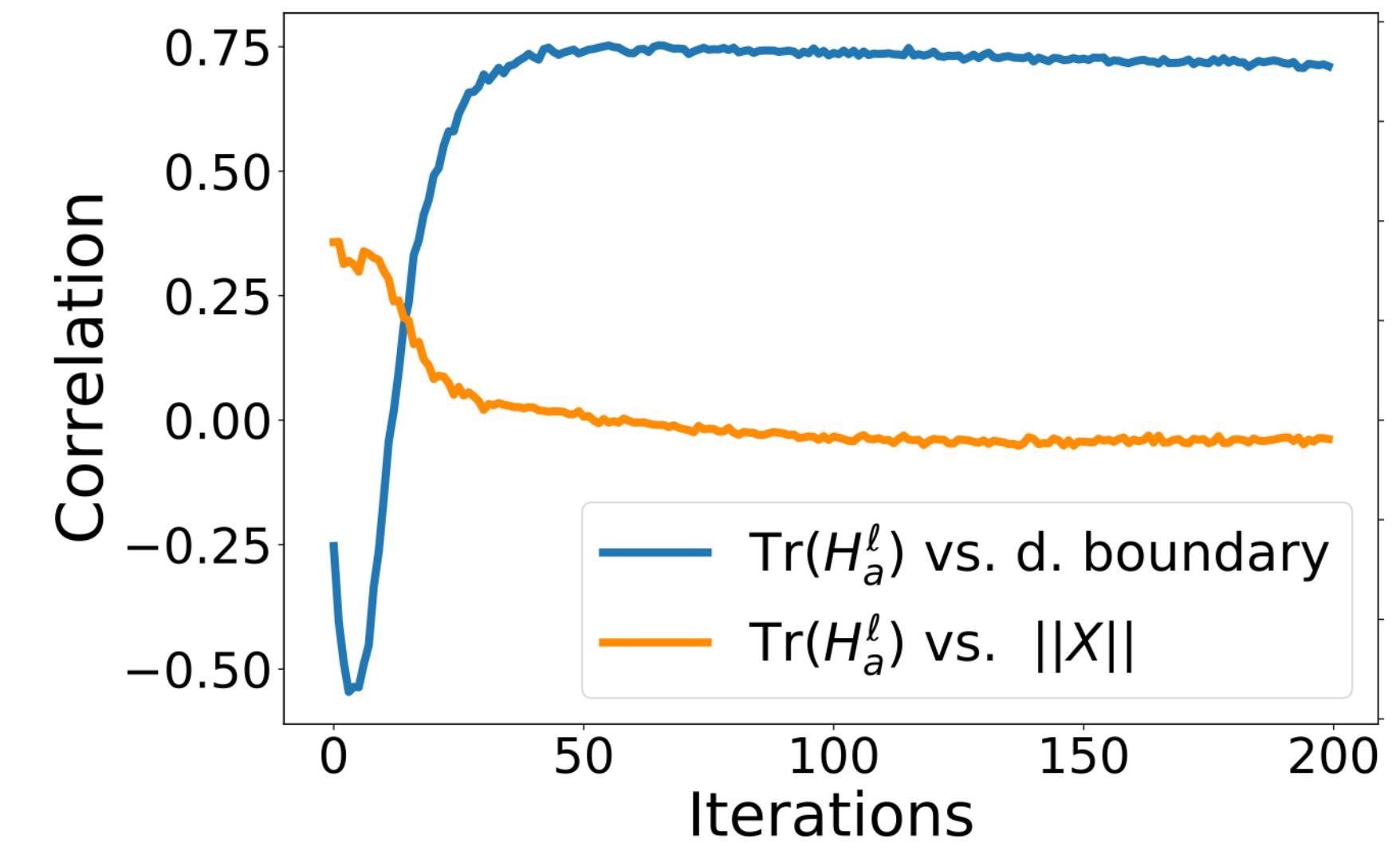
# Why noise causes unfairness in DP-SGD?

## Distance to the decision boundary and excess risk



$$+ \underbrace{\frac{\eta^2}{2} \text{Tr}(\mathbf{H}_\ell^a) C^2 \sigma^2}_{\text{private term due to noise}}$$

Correlation between Hessian trace and closeness to the decision boundary and input norms



# Why noise causes unfairness in DP-SGD?

## Distance to the decision boundary and excess risk

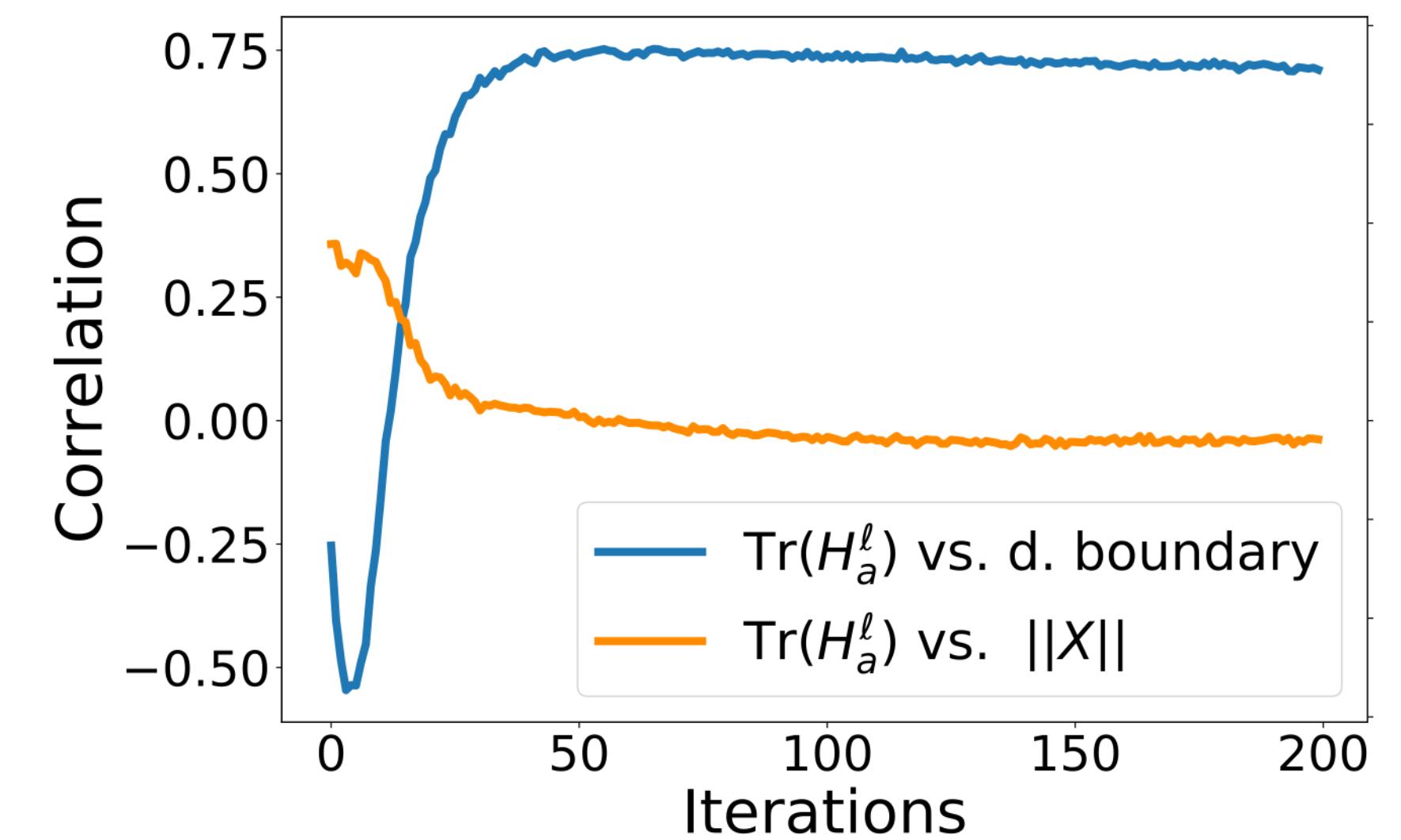
$$\underbrace{\frac{\eta^2}{2} \text{Tr}(\mathbf{H}_\ell^a) C^2 \sigma^2}_{\text{private term due to noise}}$$

Crucial Proxy to Unfairness (due to noise)

**Theorem (informal):** Individuals whose outputs are close to the **decision boundary** will have higher Hessian traces (high local curvatures of the loss).

Intuitively, the model decisions for samples which are close to the decision boundary are less robust to the presence of noise w.r.t. samples which are farther away from the boundary.

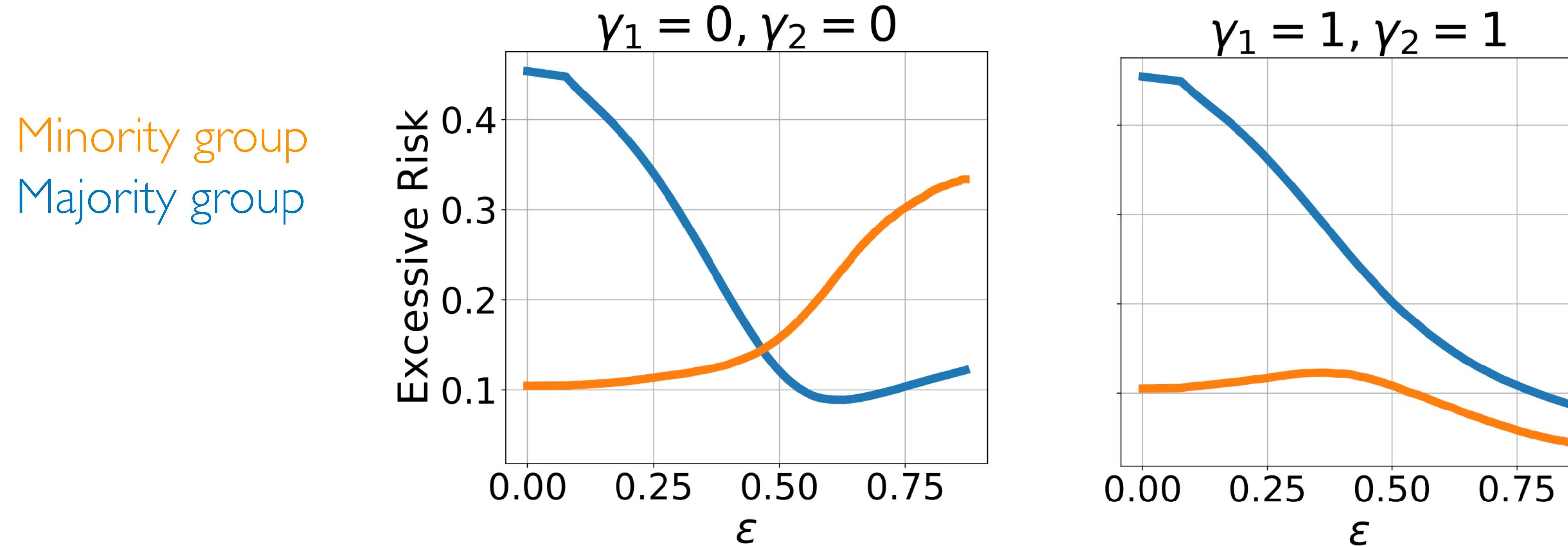
Correlation between Hessian trace and closeness to the decision boundary and input norms



# Mitigating solutions

Modify training so to equalize the factors affecting the excessive risk due to  
clipping and to noise addition

$$\min_{\theta} \mathcal{L}(\theta; D) + \sum_{a \in \mathcal{A}} \left( \gamma_1 \left| \langle g_{D_a} - g_D, g_{D_a} - \bar{g}_D \rangle \right| + \gamma_2 \left| \text{Tr}(H_\ell^a) - \text{Tr}(H_\ell) \right| \right),$$

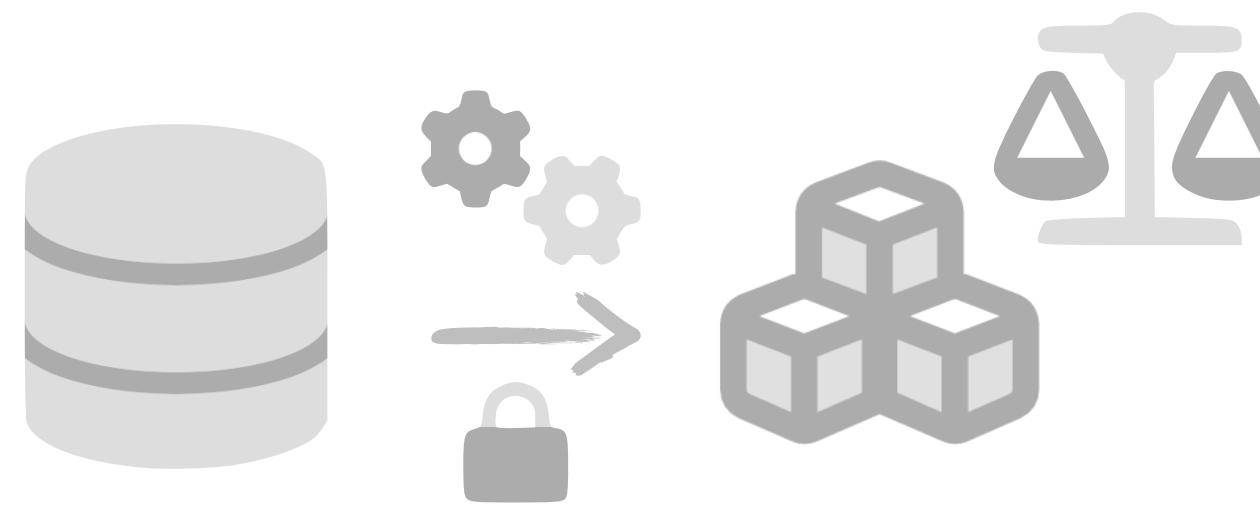


# Agenda

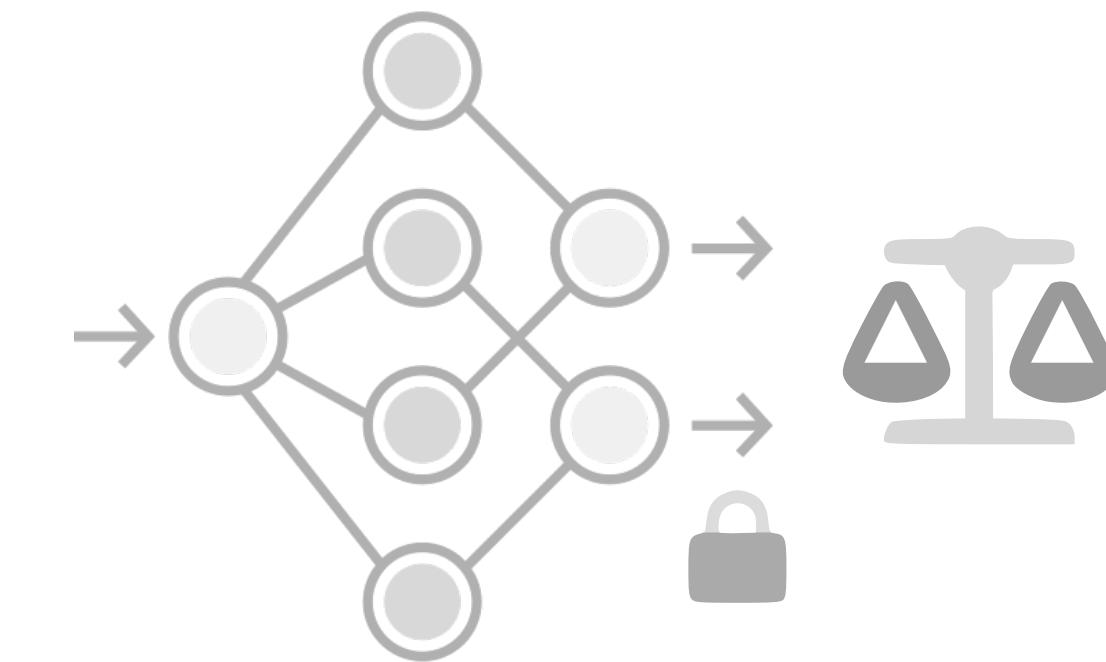
Preliminaries



Fairness impacts of DP  
in decision making



Fairness impacts  
of DP in learning



**What's next?**



# Privacy and Equity of decision making

## Need

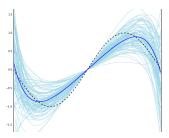
Analyze the cost of traditional disclosure avoidance techniques on public policy decisions.

## Challenges

How to compare traditional disclosure avoidance techniques with modern techniques (DP).



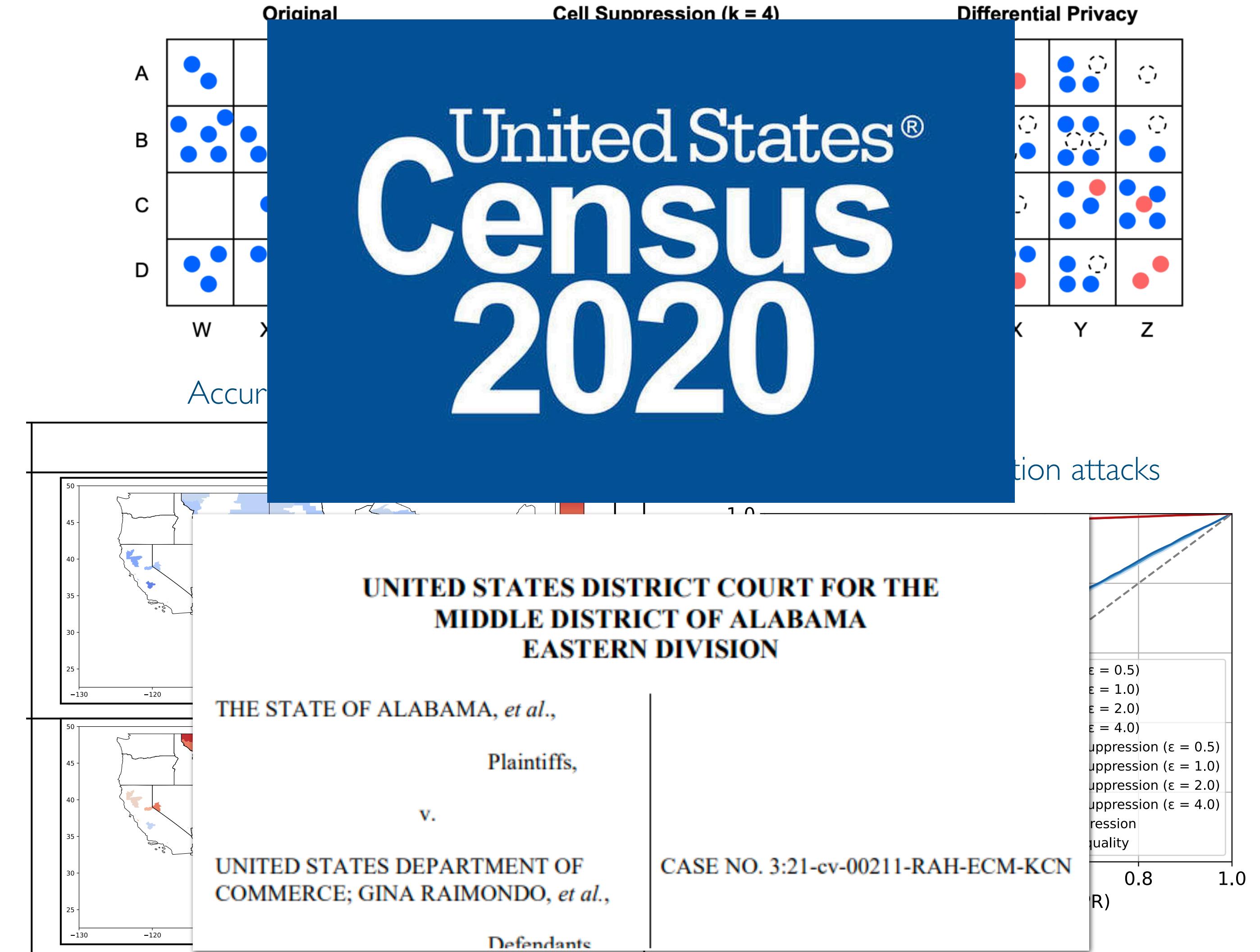
Privacy



Bias and Variance



Fairness



# Unfairness in Hardware Network Pruning

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Pruning has a disparate impact on model accuracy

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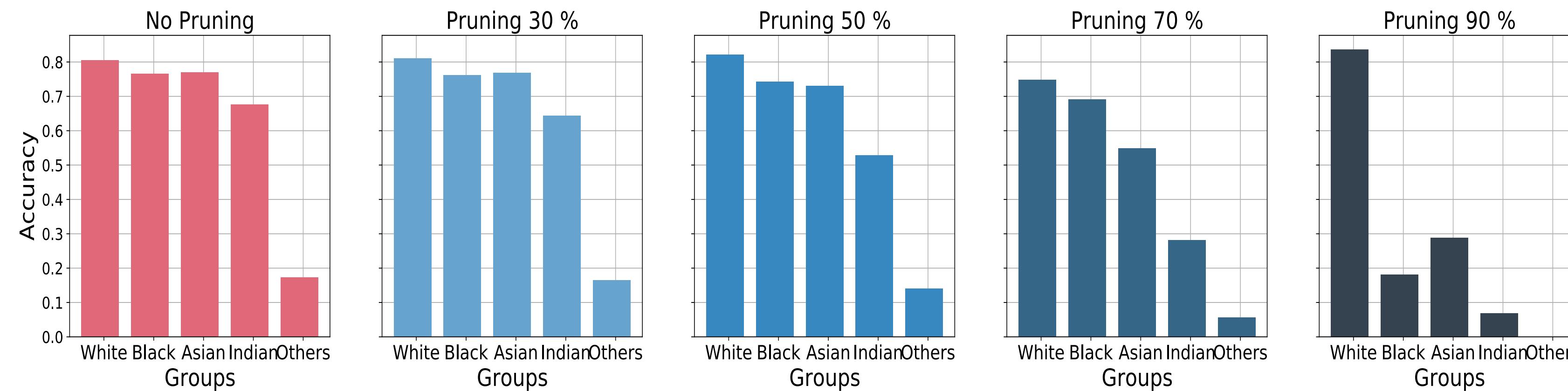


Figure 1: Accuracy of each demographic group in the UTK-Face dataset using Resnet18 [18], at the increasing of the pruning rate.

# Unfairness in Hardware Tooling

## ON THE FAIRNESS IMPACTS OF HARDWARE SELECTION IN MACHINE LEARNING

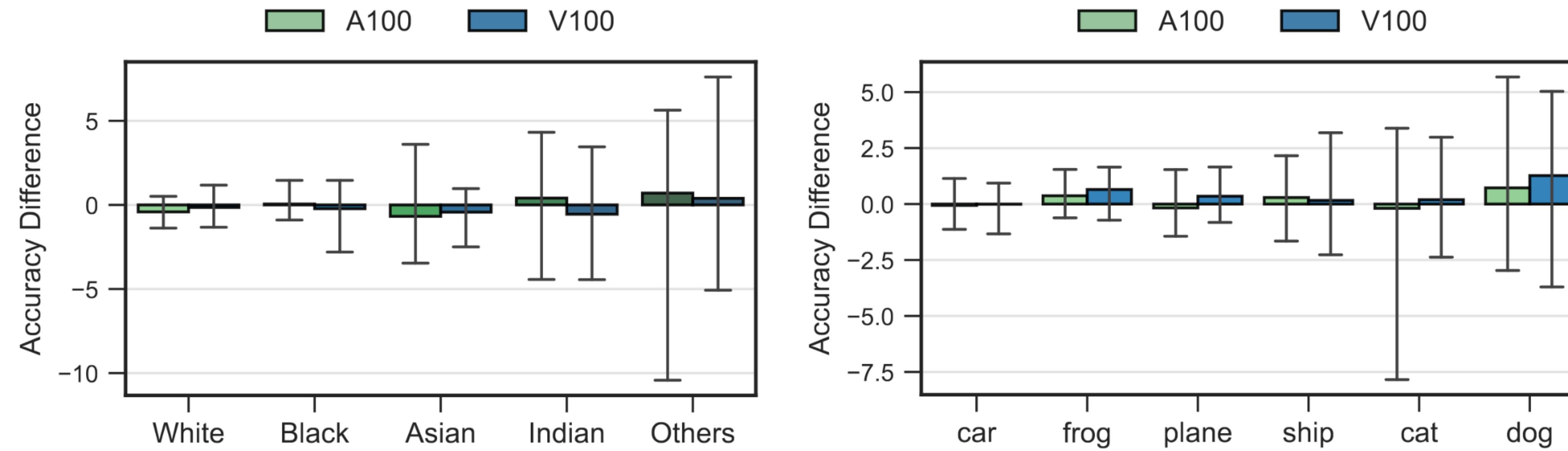
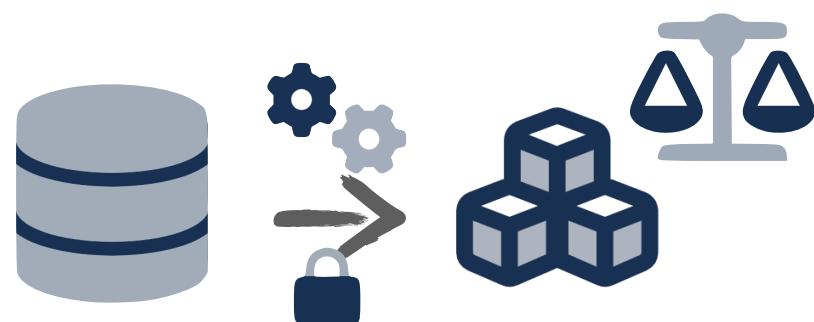


Figure 1: A training model (ResNet34) with the same parameters (random seeds, epochs, batch-size) on different hardware can have vastly different performance results, especially for minority groups (dark colors). The reference hardware is T4. **Left:** UTK-Face, **Right:** CIFAR-10.

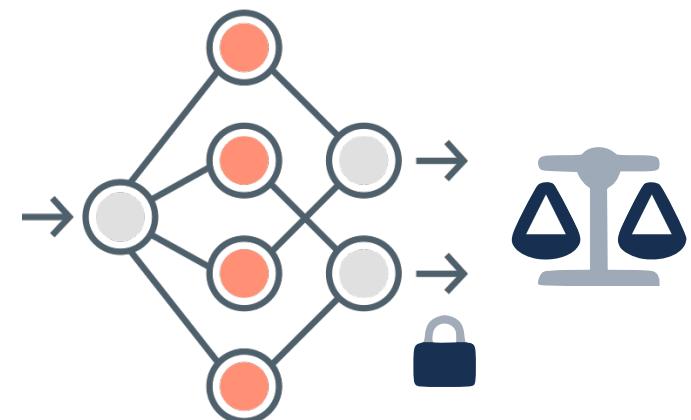
# Conclusions

## Unintended effects of DP on decisions and learning tasks

- Motivated by the use of rich datasets combined with black-box algorithms
- Proved that several problems with significant societal impacts (allocation of funding, language assistance) **exhibit inherent unfairness** when applied to a DP release of the census data.



**Decision making:** Characterized the conditions for which these problems have finite fairness violations and suggested guidelines to act on the decision problems or on the mechanisms to mitigate the fairness issues.



**Machine Learning:** Characterized the reasons for DP to disproportionately affect the accuracy of learning tasks and proposed mitigating solutions.

- Exciting research direction that requires close cooperation between multiple areas and can transform the way we approach ML and decision making to render these algorithms more aligned with societal values.

# Discussion

- In ML, there is often a trade-off between accuracy and fairness. Can you think of examples where this trade-off is evident? How should it be managed?
  - **Trade-offs:** When and when not DP may lead to fairness issues in AI models? How can these trade-offs be balanced or mitigated?
  - **Impact of DP on Data Representation:** Can DP affect representation of minority groups in datasets?
  - **Role of Differential Privacy in Bias Mitigation:** How can differential privacy be used as a tool to mitigate bias in AI models?
  - How does the concept of fairness intersect with other performance metrics of a model? Is it possible to achieve high fairness without sacrificing other metrics?
- **Policy considerations:**
  - Discuss the ethical implications of not addressing fairness and privacy in AI systems. Who is most at risk?
  - What role should policy and regulation play in ensuring fairness and privacy in AI?

# Responsible AI: Seminar on Fairness, Safety, Privacy and more

## Thank you!

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-  [@nandofioretto](#)



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"Differential Privacy of Hierarchical Census Data: An Optimization Approach".

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See <https://web.ecs.syr.edu/~ffiorett/publications.html> for papers links.

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See <https://web.ecs.syr.edu/~ffiorett/publications.html> for papers links.

# DP Post-processing

## Mitigating solution

**Definition 4** (Projection onto Simplex Mechanism (PoS)).  
The projection onto simplex mechanism *outputs the allocation as follows.*

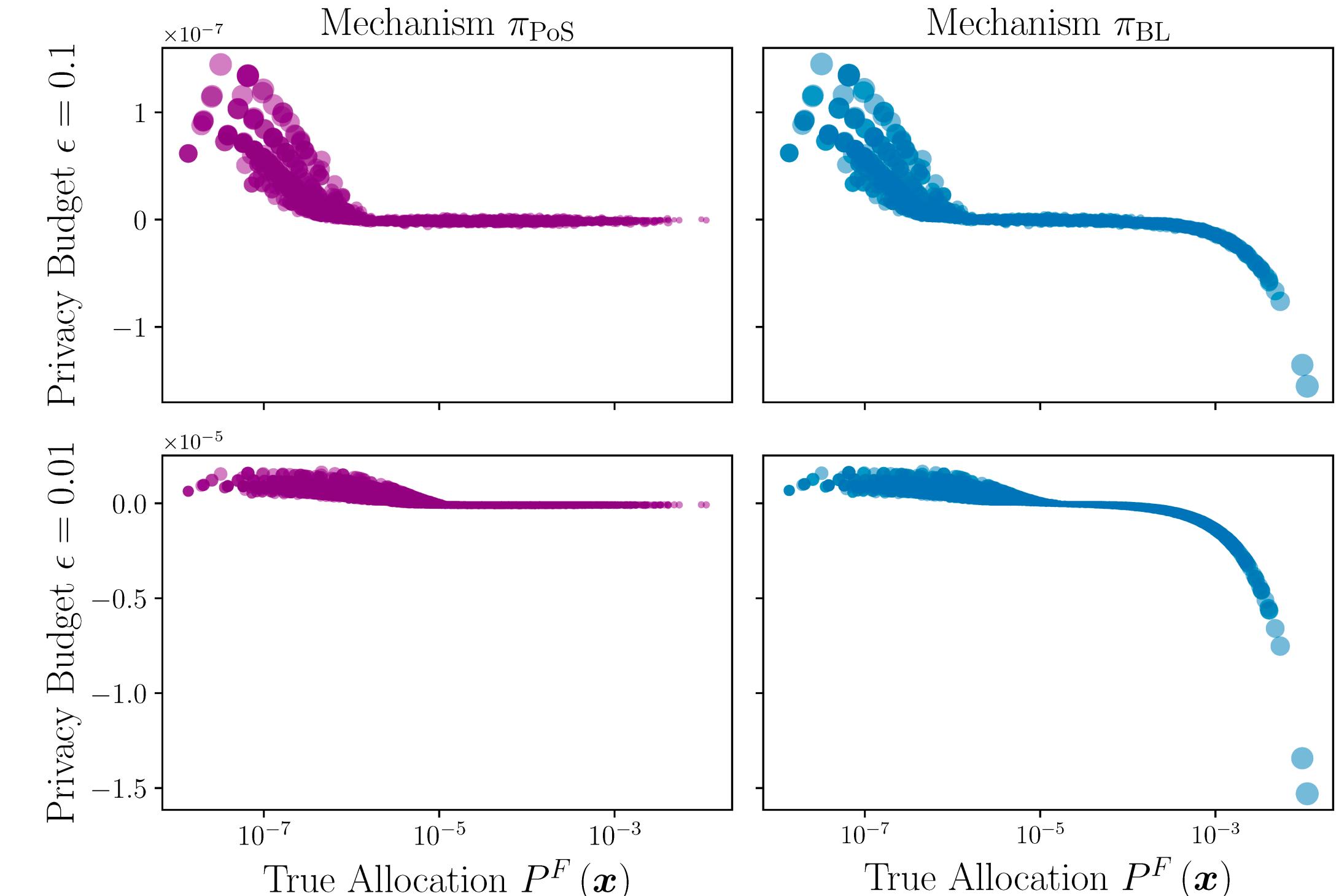
$$\pi_{\text{PoS}}(\tilde{\mathbf{x}}) := \arg \min_{\mathbf{v} \in \Delta^n} \|\mathbf{v} - P^F(\tilde{\mathbf{x}})\|_2 \quad (P_{\text{PoS}})$$

**Theorem (informal).** For any DP dataset  $\tilde{\mathbf{x}}$  the PoS mechanism generates the unique optimal solution to program

$$\pi_\alpha^*(\tilde{\mathbf{x}}) := \arg \min_{\mathbf{v} \in \Delta_n} \|\mathbf{v} - P^F(\tilde{\mathbf{x}})\|_{\perp\!\!\!\perp} \quad (P_\alpha)$$

which closely approximate the optimal post-processing mechanism

$$\pi^* := \min_{\pi \in \Pi_{\Delta_n}} \|\mathbb{E}_{\tilde{\mathbf{x}}} [\pi(\tilde{\mathbf{x}}) - P^F(\mathbf{x})]\|_{\perp\!\!\!\perp}$$



Privacy Budgets	$\epsilon = 0.1$		$\epsilon = 0.01$		$\epsilon = 0.001$	
Mechanisms	$\pi_{\text{BL}}$	$\pi_{\text{PoS}}$	$\pi_{\text{BL}}$	$\pi_{\text{PoS}}$	$\pi_{\text{BL}}$	$\pi_{\text{PoS}}$
$\alpha$ -fairness	3.00E-07	<b>1.50E-07</b>	1.70E-05	<b>1.75E-06</b>	8.06E-04	<b>2.23E-05</b>
Cost of Privacy	1.62E-05	<b>1.41E-05</b>	1.33E-03	<b>1.04E-03</b>	5.90E-02	<b>3.49E-02</b>

# Properties of the training data

Fairness impact

# Warm up: output perturbation

## Input norms

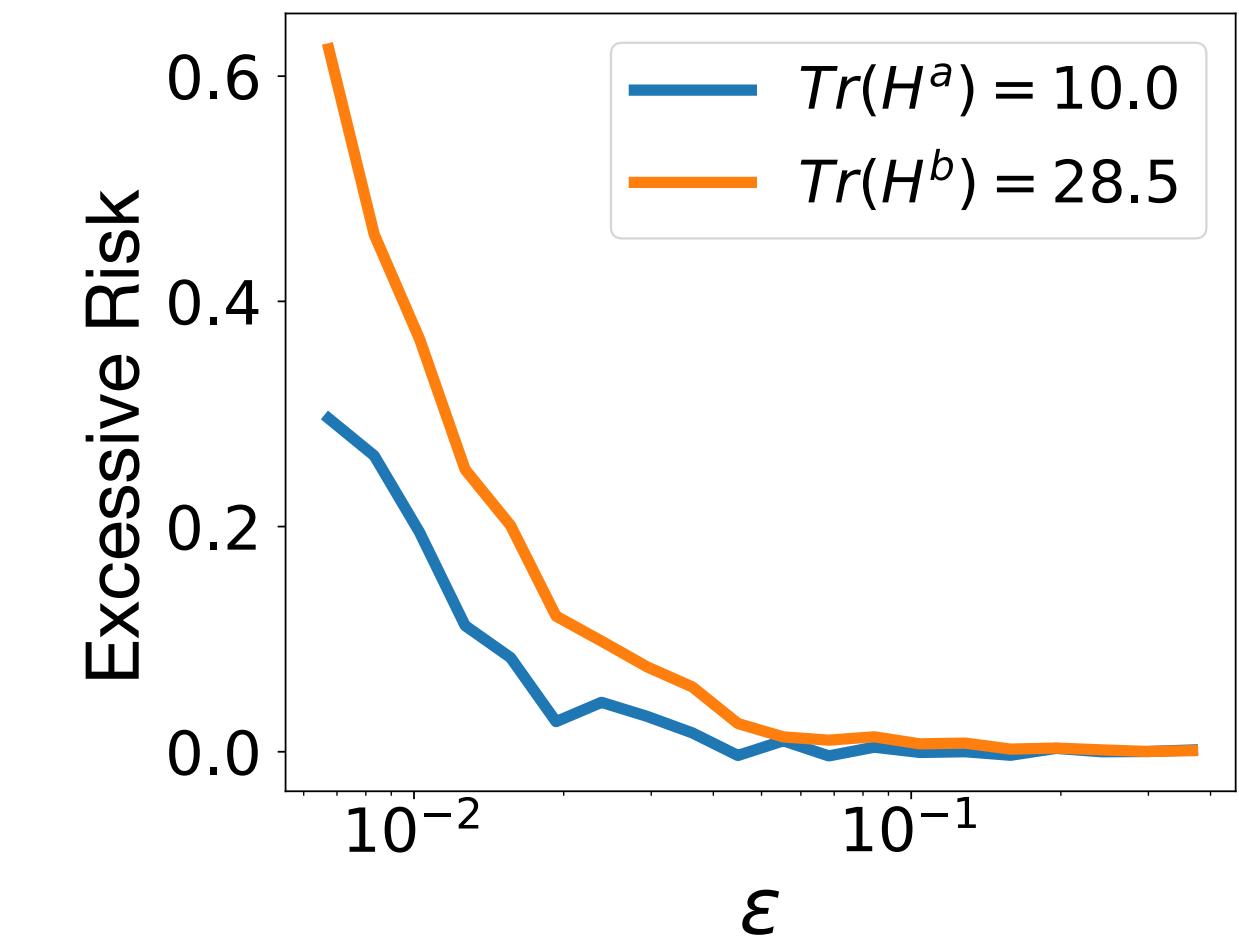
- Adds Gaussian noise  $\mathcal{N}(0, \Delta_\ell^2 \sigma^2)$  to the optimal model parameters  $\theta^*$
- **Thm:** For  $\ell$  twice differentiable convex functions, the excessive risk gap is approximated as

$$\xi_a \approx \frac{1}{2} \underbrace{\Delta_\ell^2 \sigma^2}_{\text{privacy parameters}} \left| \text{Tr}(\mathbf{H}_\ell^a) - \text{Tr}(\mathbf{H}_\ell) \right|,$$

local curvature of the losses

- Groups with larger Hessian traces may have larger ER compared to those with smaller Hessian traces
- **Corollary:** Consider the ERM for a linear model  $f_\theta(X) = \theta^\top X$  with  $\ell_2$  loss. Then output perturbation **cannot guarantee** pure fairness
- The Hessian of the  $\ell_2$  loss for a group depends solely on the input norms of the elements in  $D_a$

$$\text{Tr}(\mathbf{H}_\ell^a) = \mathbb{E}_{X \sim D_a} \text{Tr}(XX^\top) = \mathbb{E}_{X \sim D_a} \|X\|^2$$



# Properties of the training data

## Input norms

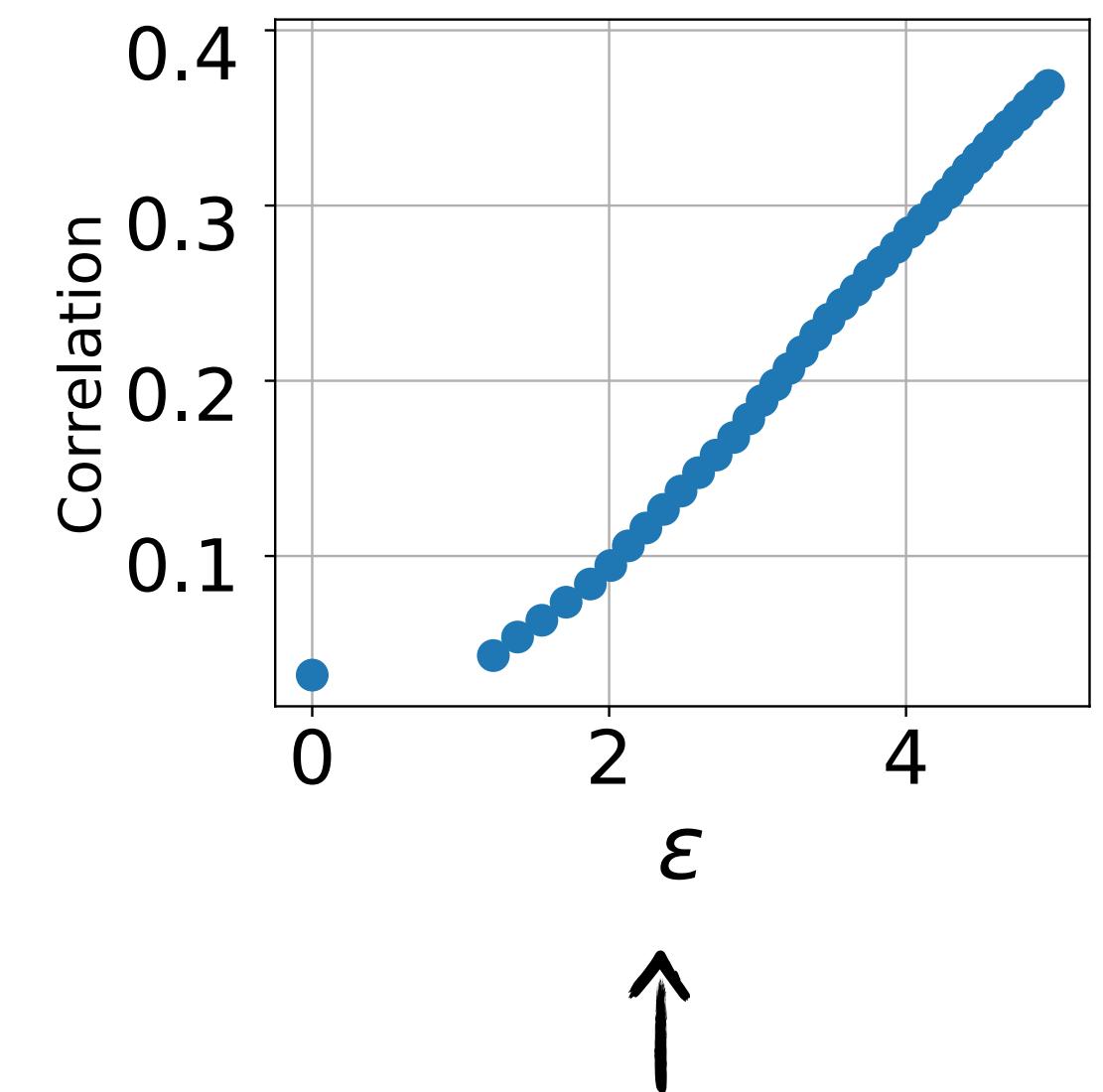
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↑      ↪      ↑  
privacy parameters      local curvature of the losses

- Groups with large input norms (often observed at the tail of the data distribution) may lead to large Hessian loss values.
- **Corollary:** For groups  $a$  and  $b$ , if their average group norms  $\mathbb{E}_{X_a \sim D_a} \|X_a\| = \mathbb{E}_{X_b \sim D_b} \|X_b\|$  have identical values, then output perturbation with  $\ell_2$  loss function achieves pure fairness.

correlation between input norms  
and excessive risk

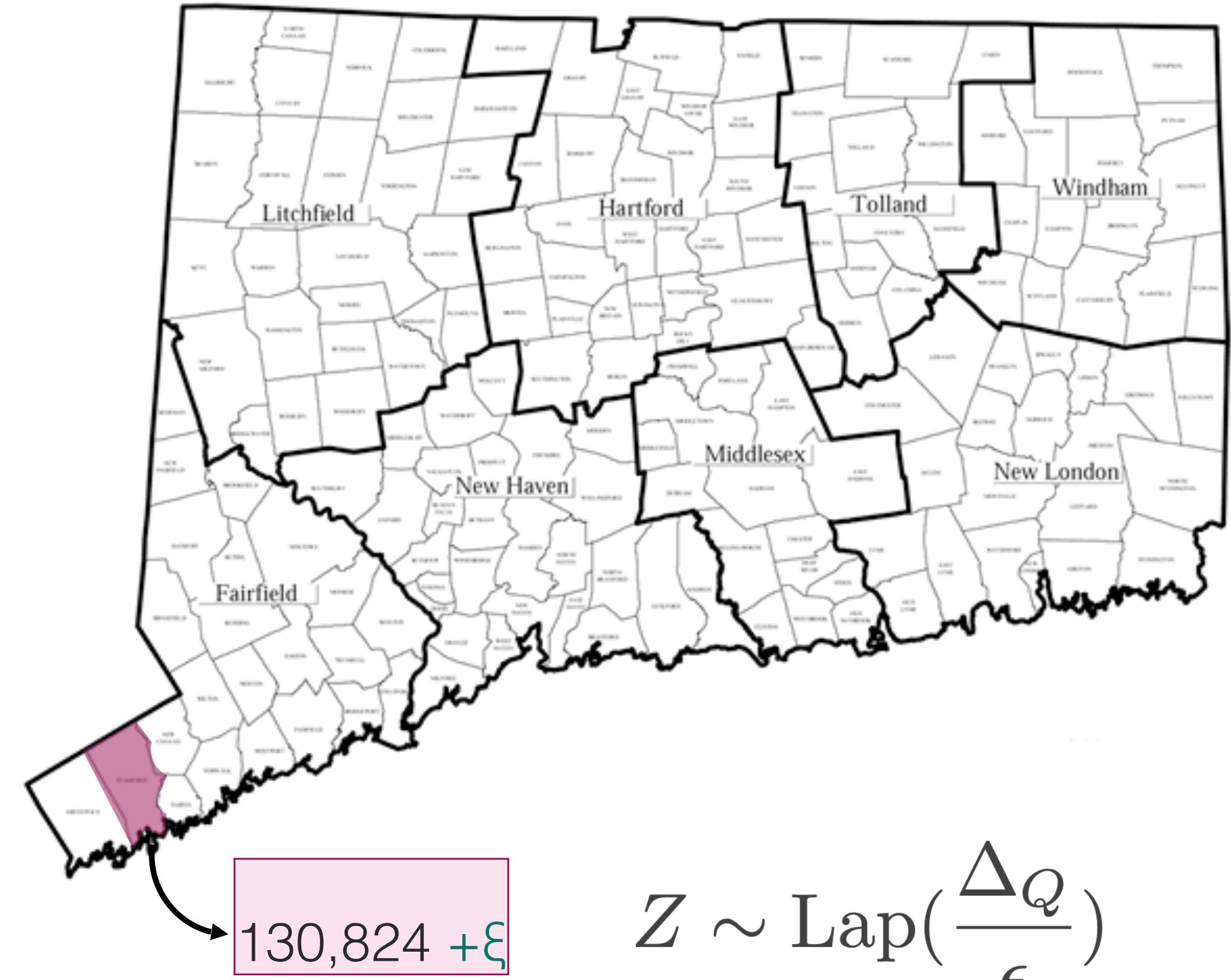
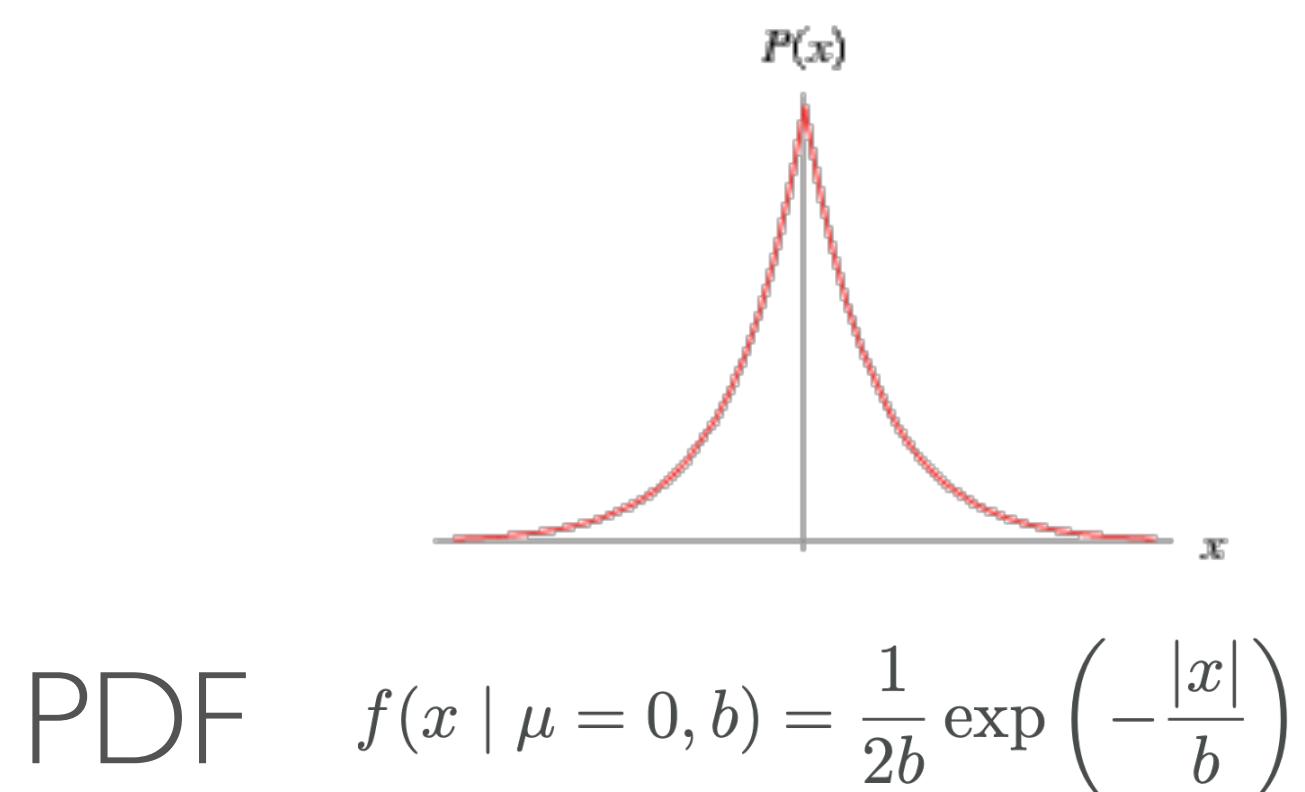


generated using a large non-linear  
(deep net) model!

# The Census Data Release Problem

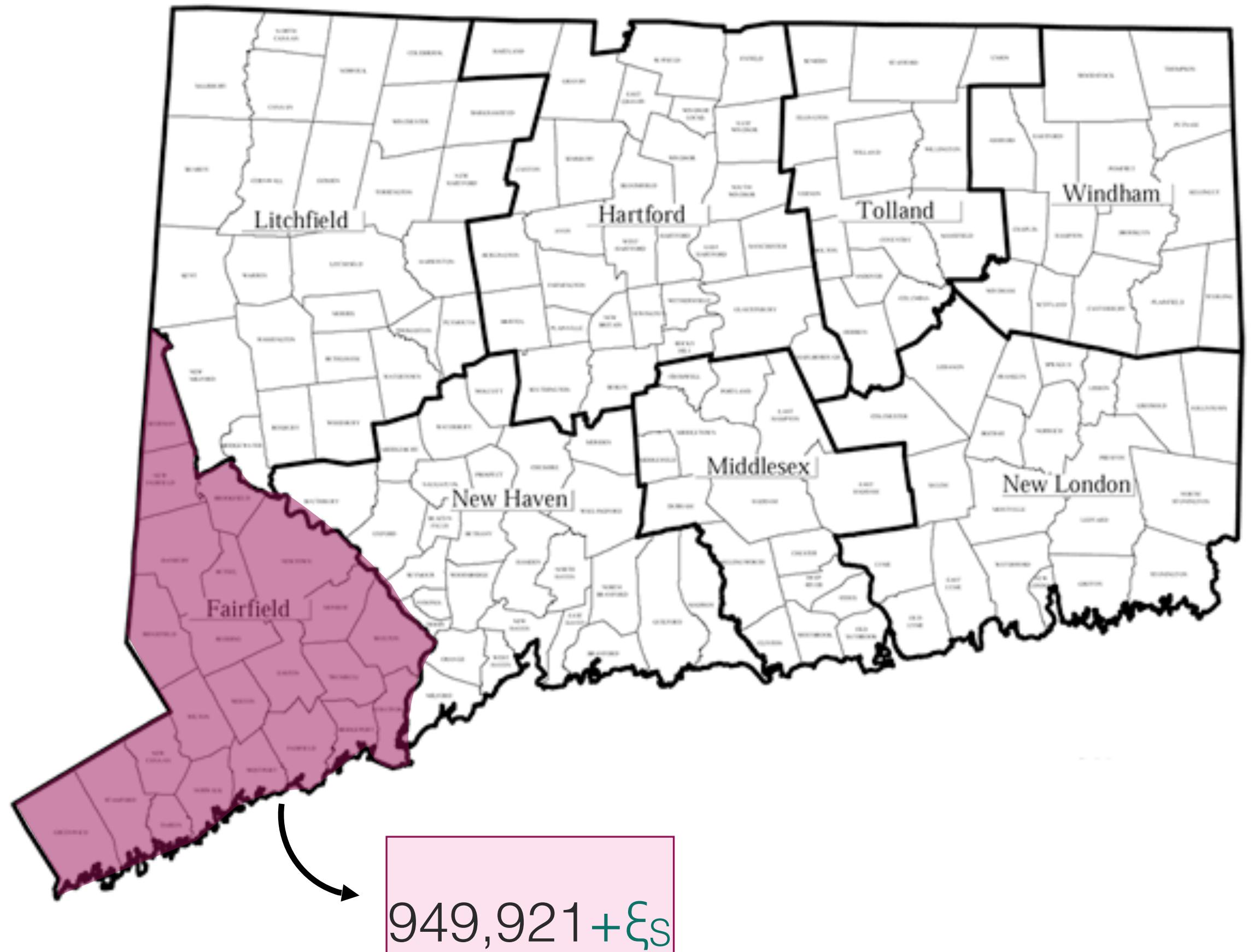
- GOAL: Release socio-demographic feature of the population grouped by:

1. Census blocks
2. Counties
3. States
4. National level



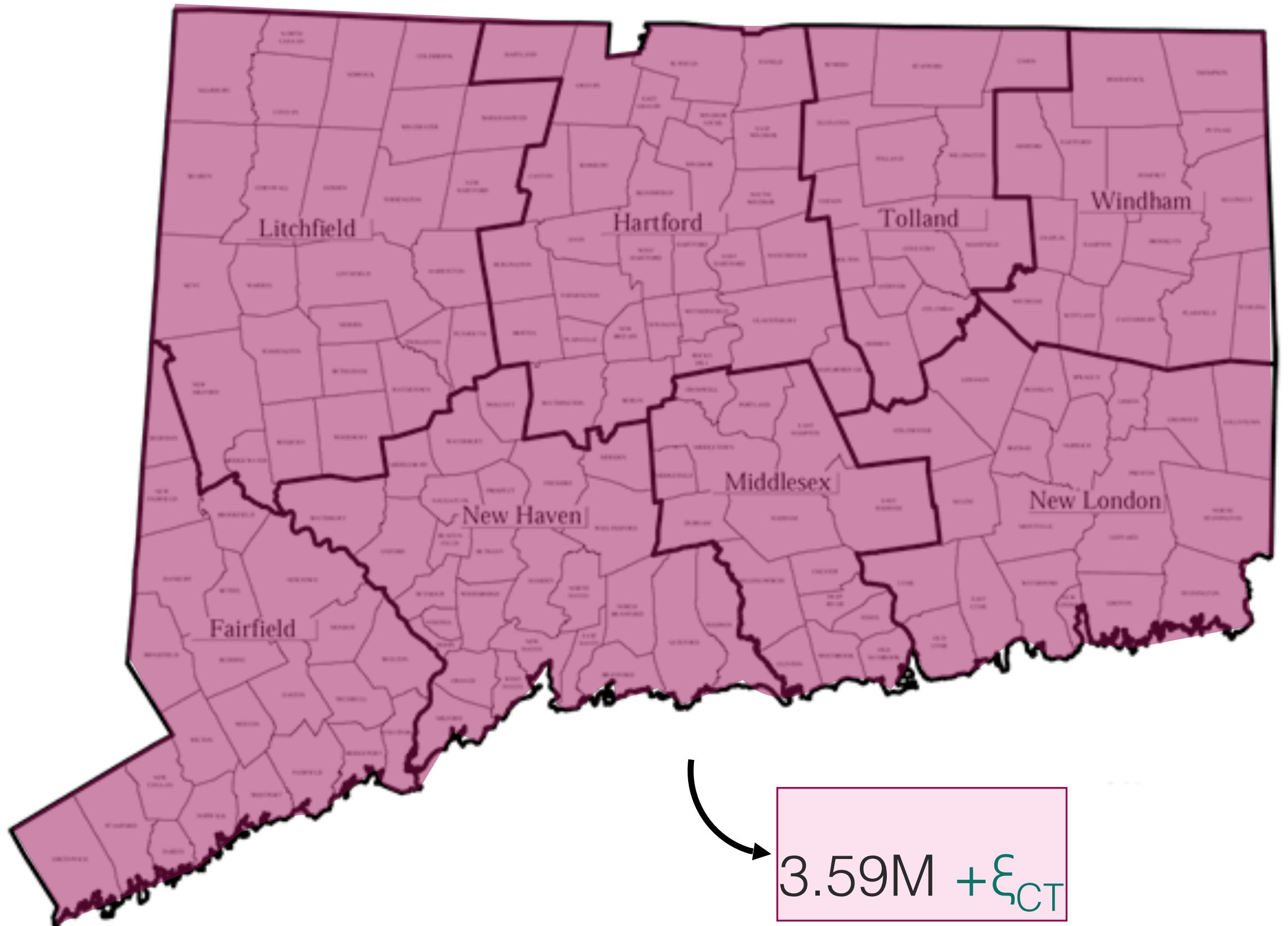
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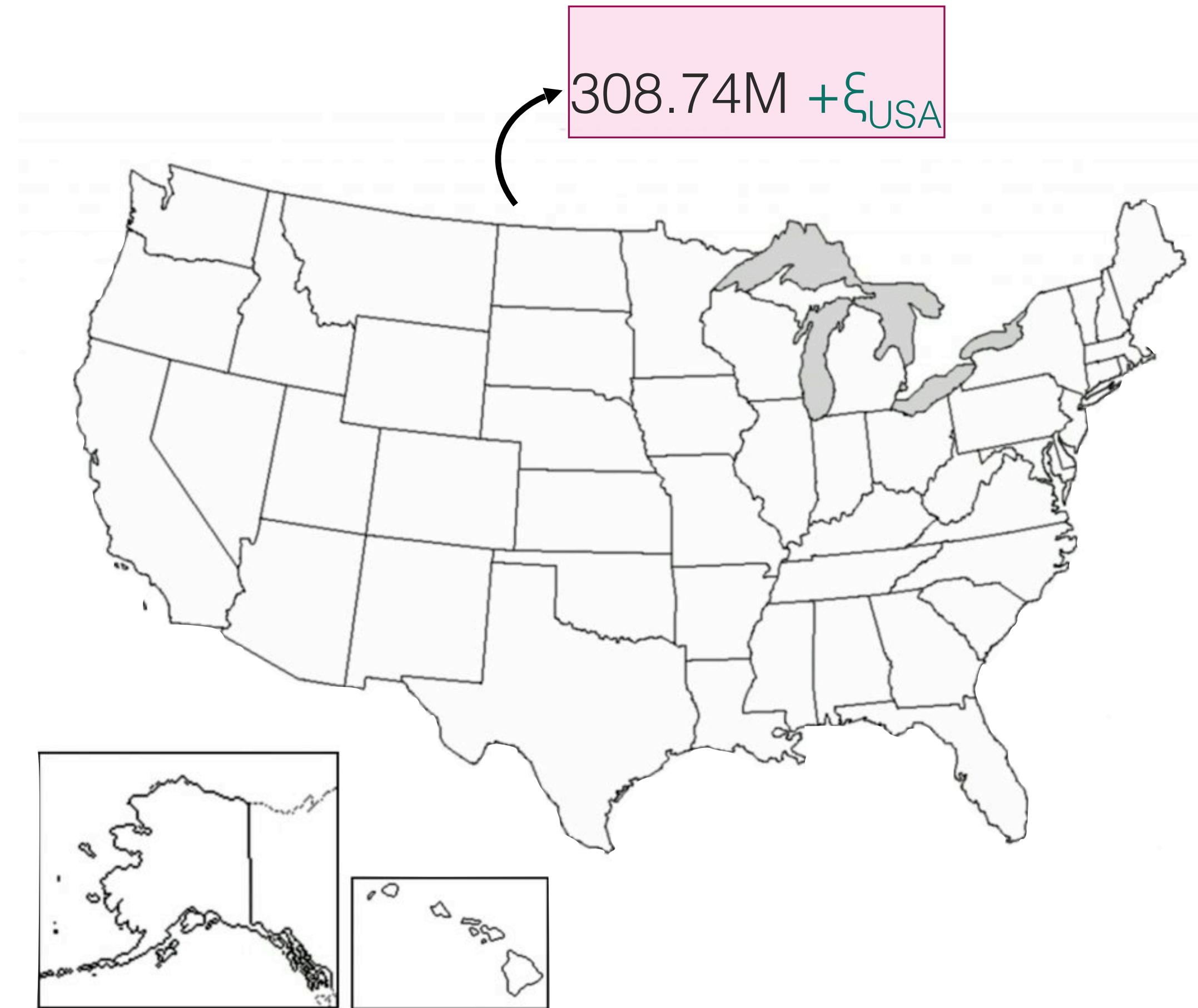
# The Census Data Release Problem

- GOAL: Release socio-demographic feature of the population grouped by:
  1. Census blocks
  2. Counties
  3. States
  4. National level



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# The consistency issue

- Requirements:
  1. Privacy
  2. Hierarchical **Consistency**
  3. **Validity:** The private values are non-negative
- Noise is applied independently to each estimate
- The noisy quantities at a “level” (e.g., state) are **inconsistent** with the sum of the noisy quantities at the “children levels” (e.g., counties of that state)

