

# Accuracy Disparities and Social Choices in the Deployment of Privacy Mechanisms

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UMass**Amherst**

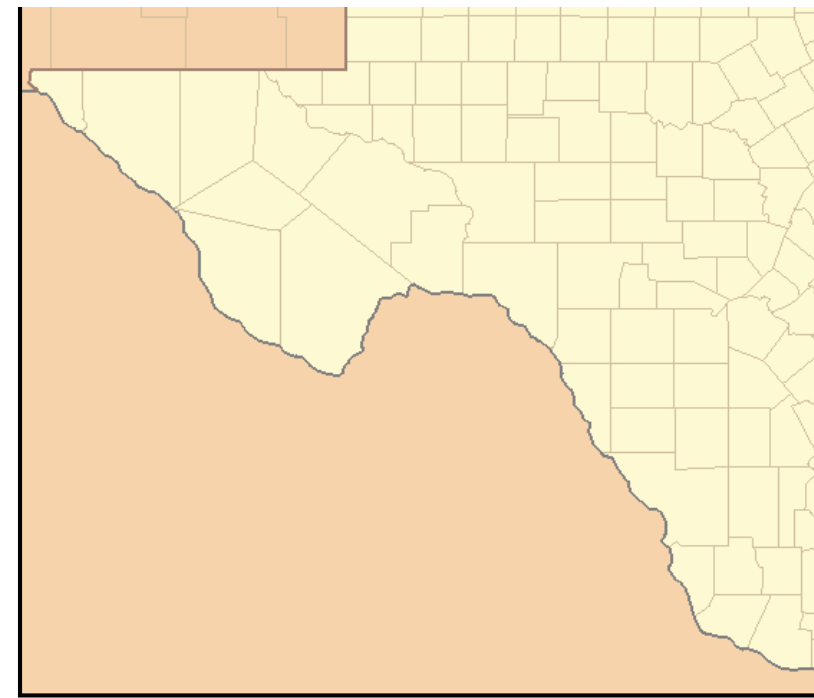
Joint work with:

**Ashwin Machanavajjhala (Duke), Michael Hay (Colgate), Ryan McKenna (UMass), David Pujol (Duke), Satya Kuppam (UMass)**

**The opinions expressed in this talk are my own and not those of the U.S. Census Bureau**

# Assignment

- A: universe of disjoint **assignee populations**
- M: assignment method (deterministic)
- O: outcome space



$$\begin{pmatrix} a_1 \\ \vdots \\ a_n \end{pmatrix}$$

Query

$$\begin{aligned} Q(a_1) &= (x_1, y_1) \\ &\vdots \\ Q(a_n) &= (x_n, y_n) \end{aligned}$$

Assign  
M

$$\begin{pmatrix} o_1 \\ \vdots \\ o_n \end{pmatrix}$$

$$o_i = \begin{cases} 1, & \text{if } q(a_i) > T \\ 0, & \text{otherwise} \end{cases}$$

Assignee population	
$a_1$	Anderson County
$a_2$	Andrews County
$a_3$	Angelina County
...	...
$a_n$	Zavala County

Statistics
(123, 7483)
(598, 8341)
...
(382, 7937)

Outcome
<input checked="" type="checkbox"/> Qualified
<input type="checkbox"/> Not Qualified
<input type="checkbox"/> Not Qualified
...
<input checked="" type="checkbox"/> Qualified

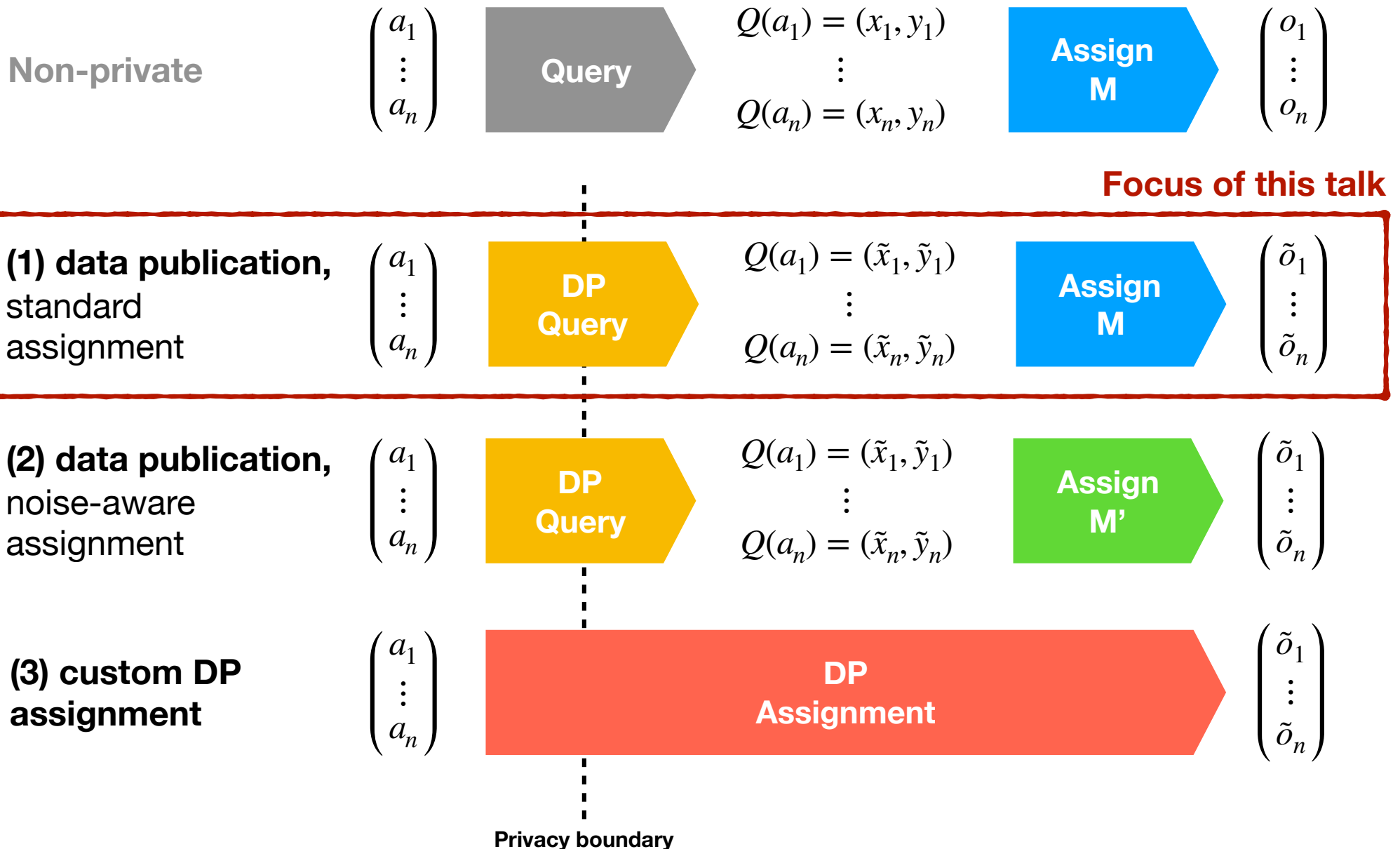
# Assignment problems

Problem	Assignee Populations	Population Statistics	Outcome space
→ Federal funds allocation	states, counties, school districts, ...	population counts	\$
Congressional apportionment	states	resident counts	seats
→ Minority language voting rights benefit	voting districts	voting-age citizens, limited English, and illiteracy.	{0,1}
Urban/Rural classification	census tracts	population counts	{0,1}
Redistricting tests	districts	population counts	{0,1}

# Consequences of inaccuracy

<b>Problem</b>	<b>Consequence</b>
<b>Federal funds allocation</b>	funds misallocated
<b>Congressional apportionment</b>	seats in house misallocated: unfair representation
<b>Minority language voting rights benefit</b>	minority language voters disenfranchised; or jurisdictions waste money on unnecessary voting materials
<b>Urban/Rural classification</b>	urban benefits misallocated
<b>Redistricting tests</b>	valid district plans rejected; invalid district plans accepted

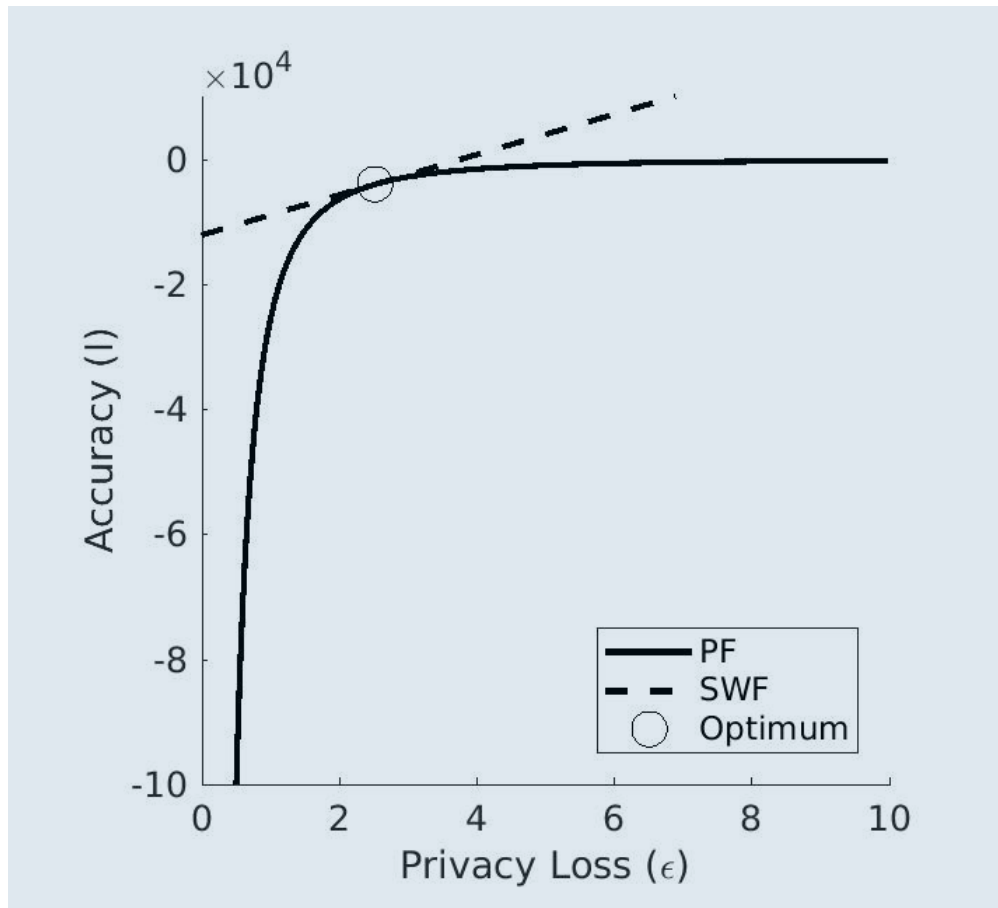
# Alternatives for private assignment



# Common statistical agency practices

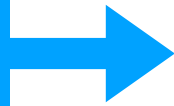
- Census tables based on **surveys** include estimates of sampling error (not the impact of disclosure limitation)
- Critical assignment problems may receive special treatment:
  - Redistricting and apportionment: no disclosure limitation on some supporting statistics.
  - Voting rights determinations: special variance reduction.
- In general, published tables **treated as true** for assignment problems.

# Social choice: accuracy vs. privacy loss



Total Error

Utilitarian  
social  
welfare: sum  
of individual  
utilities



*Abowd and Schmutte. An economic analysis of privacy protection and statistical accuracy as social choices. American Economic Review, 109(1), 2019.*

# Accuracy disparity

## Given:

- a fixed privacy loss budget and
- the best available privacy mechanism

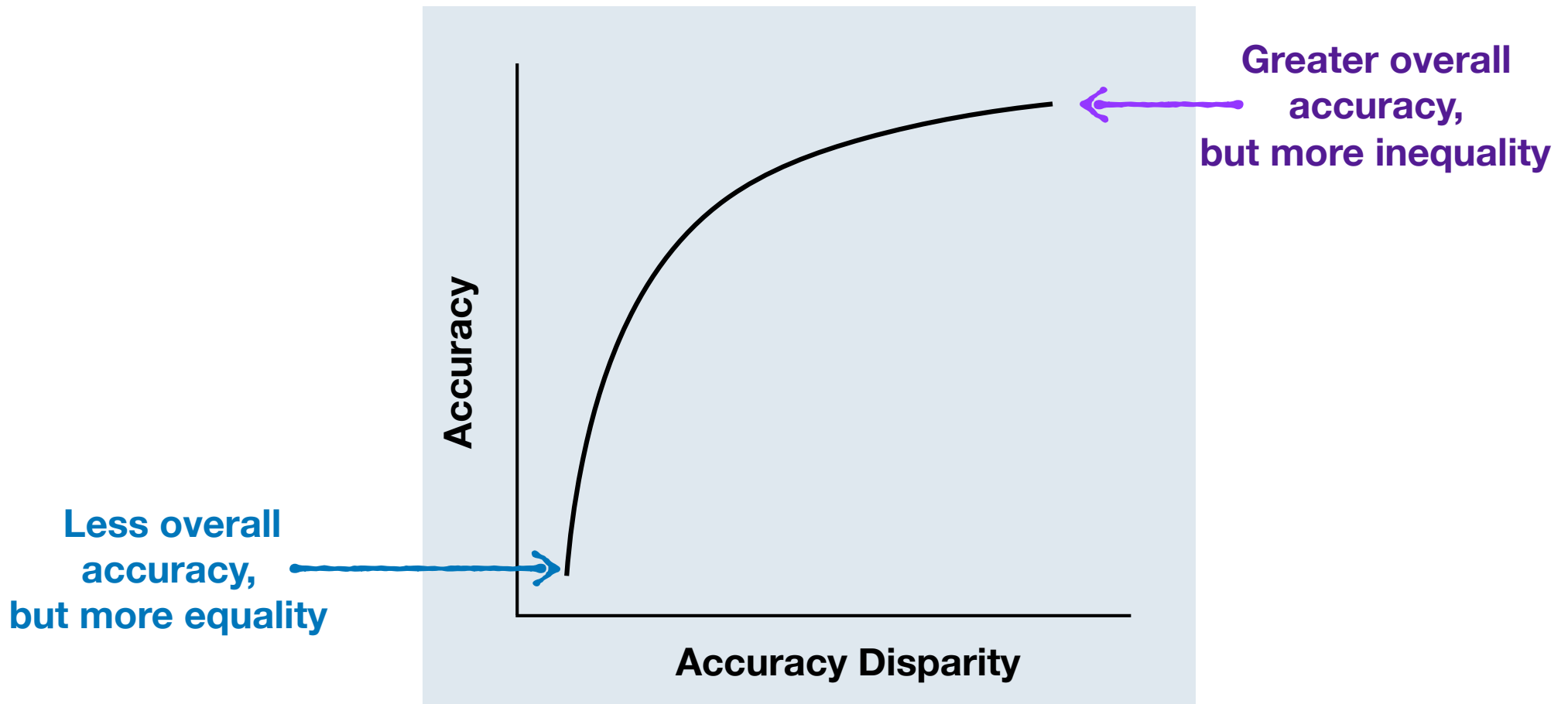
Do assignee populations bear the burden of inaccuracy equally?

Assignee population		True outcome	Correct Classification
$a_1$	Anderson County	<input checked="" type="checkbox"/> Qualified	54%
$a_2$	Andrews County	<input type="checkbox"/> Not Qualified	85%
$a_3$	Angelina County	<input type="checkbox"/> Not Qualified	95%
...	...	...	
$a_n$	Zavala County	<input checked="" type="checkbox"/> Qualified	89%



# Social choice: accuracy vs. accuracy disparity

FOR A FIXED EPSILON:



# Remainder of the talk

1. Introduction

**2. Causes of accuracy disparities**

3. Cases studies

- Voting rights benefits
- Title I education funding

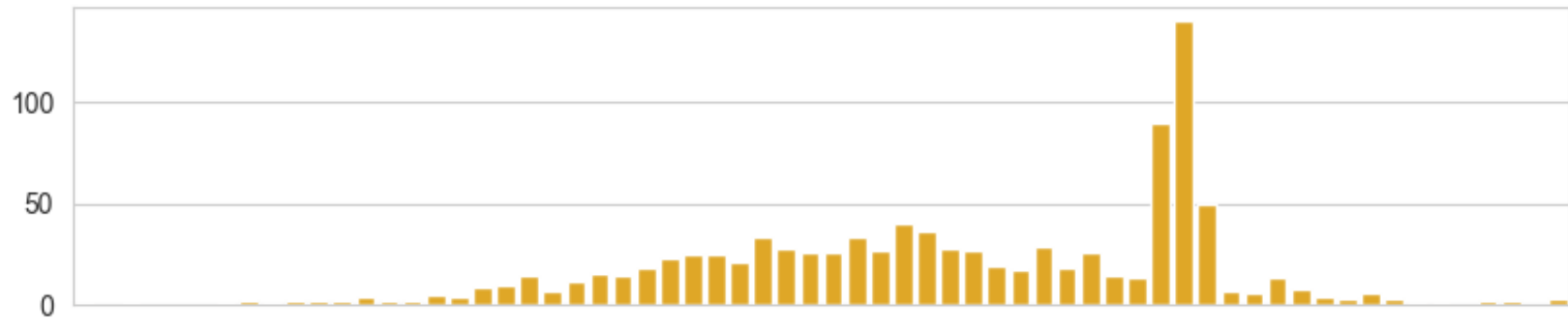
4. Discussion and conclusion

# Accuracy disparities

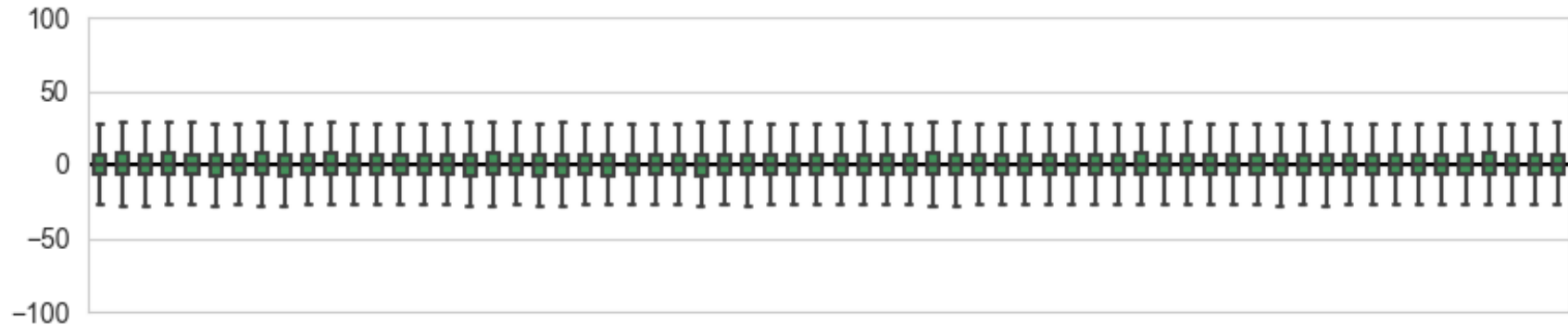
- Different groups may experience:
  - **unequal error** rates in estimated counts.
  - **bias** in estimated counts
  - **unequal outcomes**
- Algorithmic techniques that contribute to this:
  - post-processing → **bias**
  - data-adaptive algorithms → **bias**
  - optimizing total error on a workload → **unequal error**
  - threshold conditions in assignment → **unequal outcomes**

# Laplace mechanism

True sensitive data

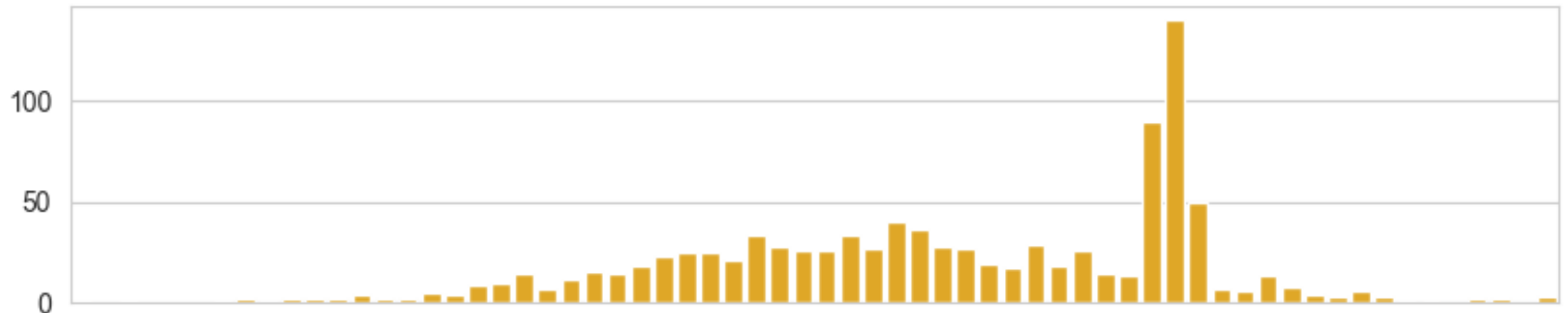


eps=.1 Expected L1 per query error = 9.98



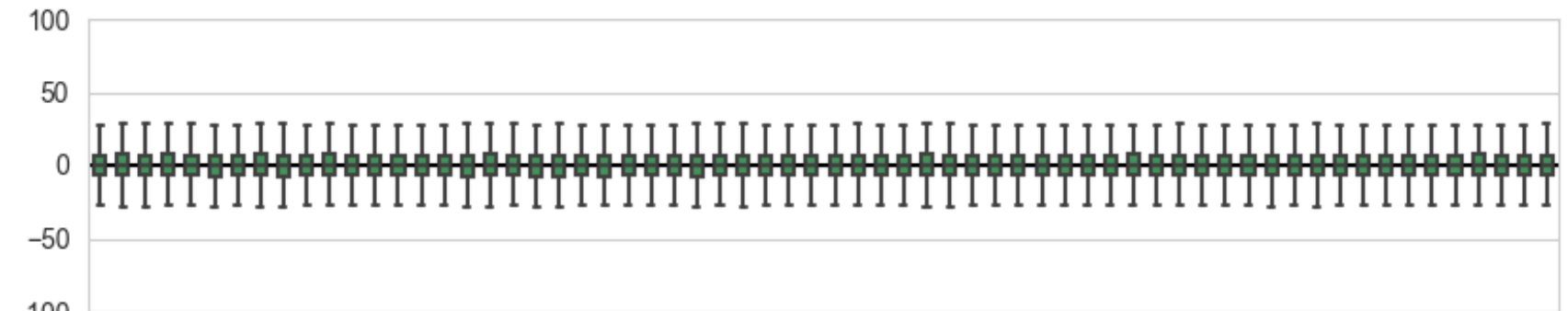
# Alternative mechanisms

input data:

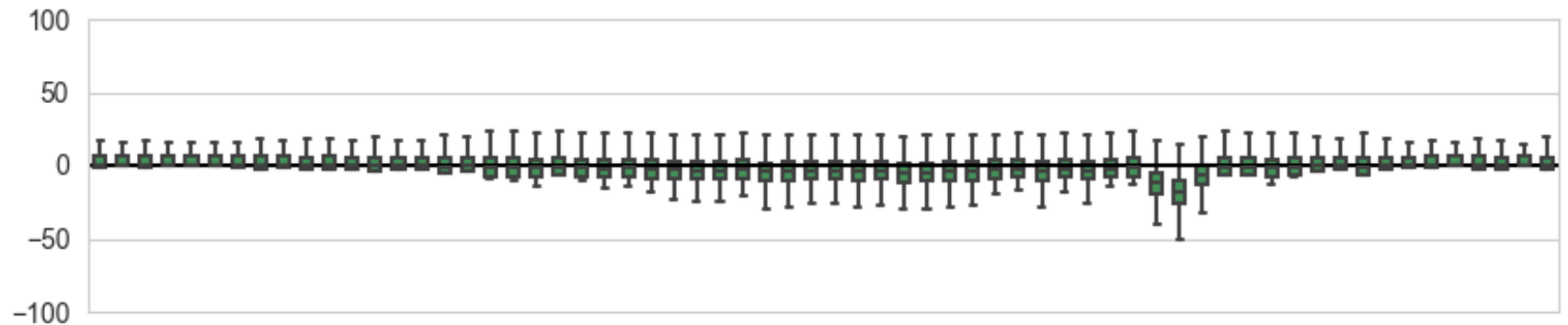


eps=.1

Laplace  
error=9.98



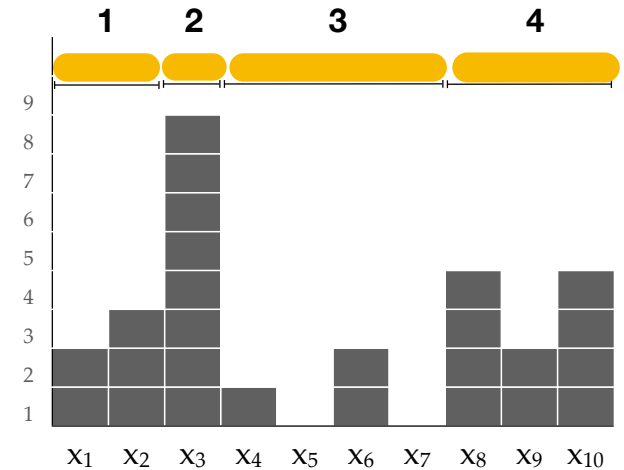
Laplace w/  
rounding  
error=7.67



# Data-adaptive mechanisms

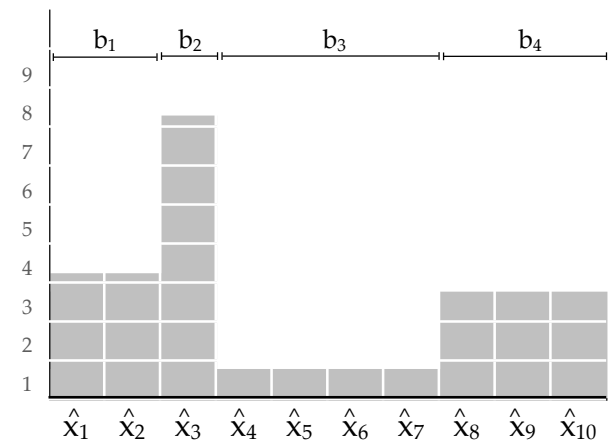
## DAWA

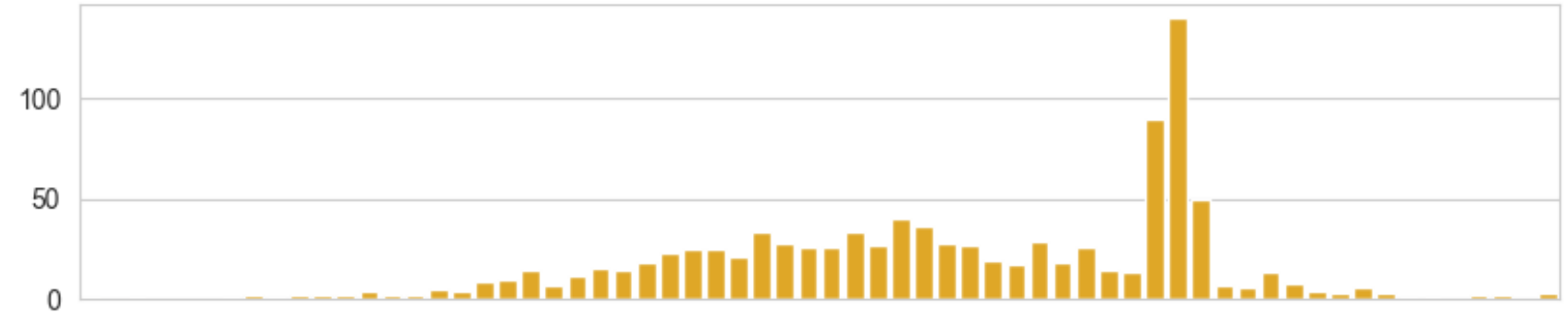
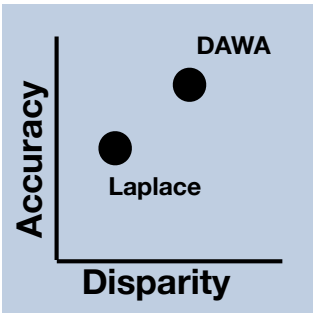
- Private data reduction
- Workload-adaptive measurements
- Least-squares inference



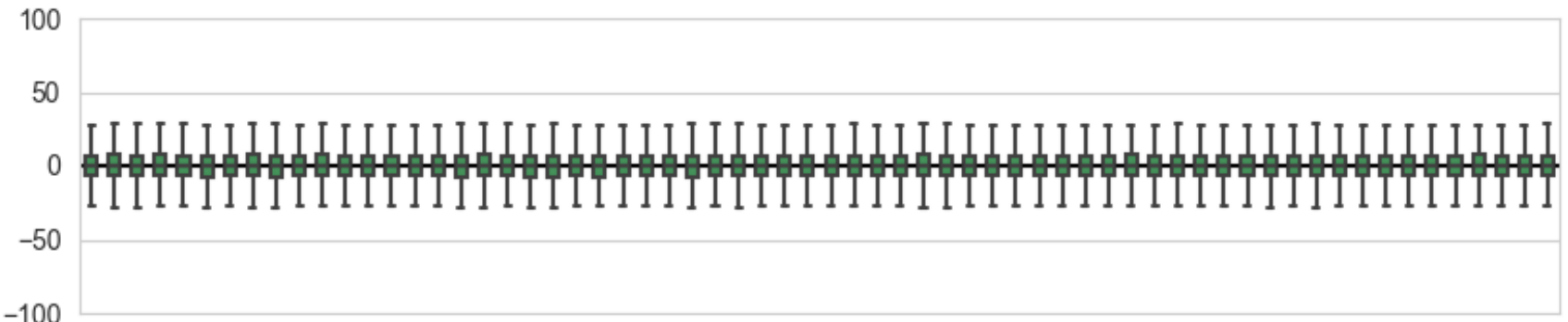
## MWEM

- Uniform starting estimate
- Iterate:
  - measurement selection using Exponential Mechanism
  - Multiplicative weights inference

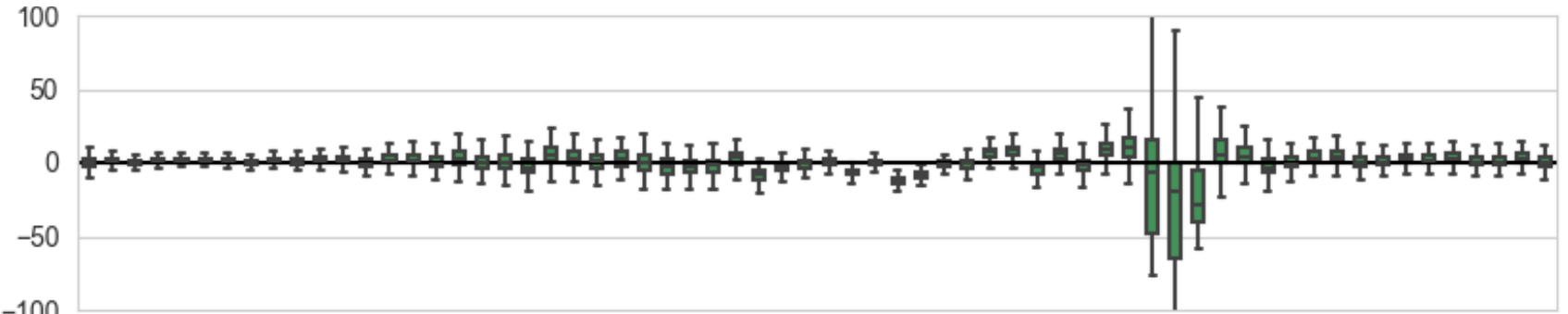




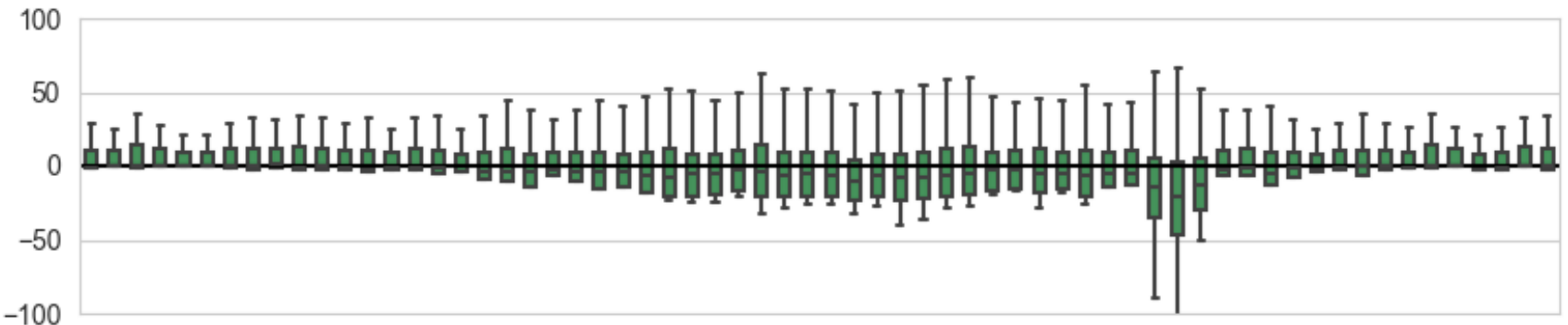
**Laplace**  
(error=9.98)



**DAWA**  
(error=6.51)



**MWEM**  
(error=17.31)



# Matrix mechanism: workload adaptivity

Matrix Mechanism (MM)  
[Li et al, PODS 2010]

$\mathbf{x}$	$\leftarrow$	vectorize(R)
$\mathbf{W}$	$\leftarrow$	vectorize(W)
$\mathbf{A}$	$\leftarrow$	$\text{OPT}_{\text{MM}}(\mathbf{W})$
$\Delta_{\mathbf{A}}$	$\leftarrow$	$\ \mathbf{A}\ _1$
$\mathbf{a}$	$\leftarrow$	$\mathbf{A}\mathbf{x}$
$\mathbf{y}$	$\leftarrow$	$\mathbf{a} + \text{Lap}(\Delta_{\mathbf{A}}/\epsilon)$
$\underline{\mathbf{x}}$	$\leftarrow$	$\mathbf{A}^+\mathbf{y}$
ans	$\leftarrow$	$\mathbf{W}\underline{\mathbf{x}}$

**Given workload  $\mathbf{W}$ , find strategy  $\mathbf{A}$  that minimizes total squared error on  $\mathbf{W}$**

select a “good”  $\mathbf{A}$  for  $\mathbf{W}$

Laplace mechanism on  $\mathbf{A}$

Reconstruct answers to  $\mathbf{W}$  from noisy  $\mathbf{A}$  answers

**Key properties:**

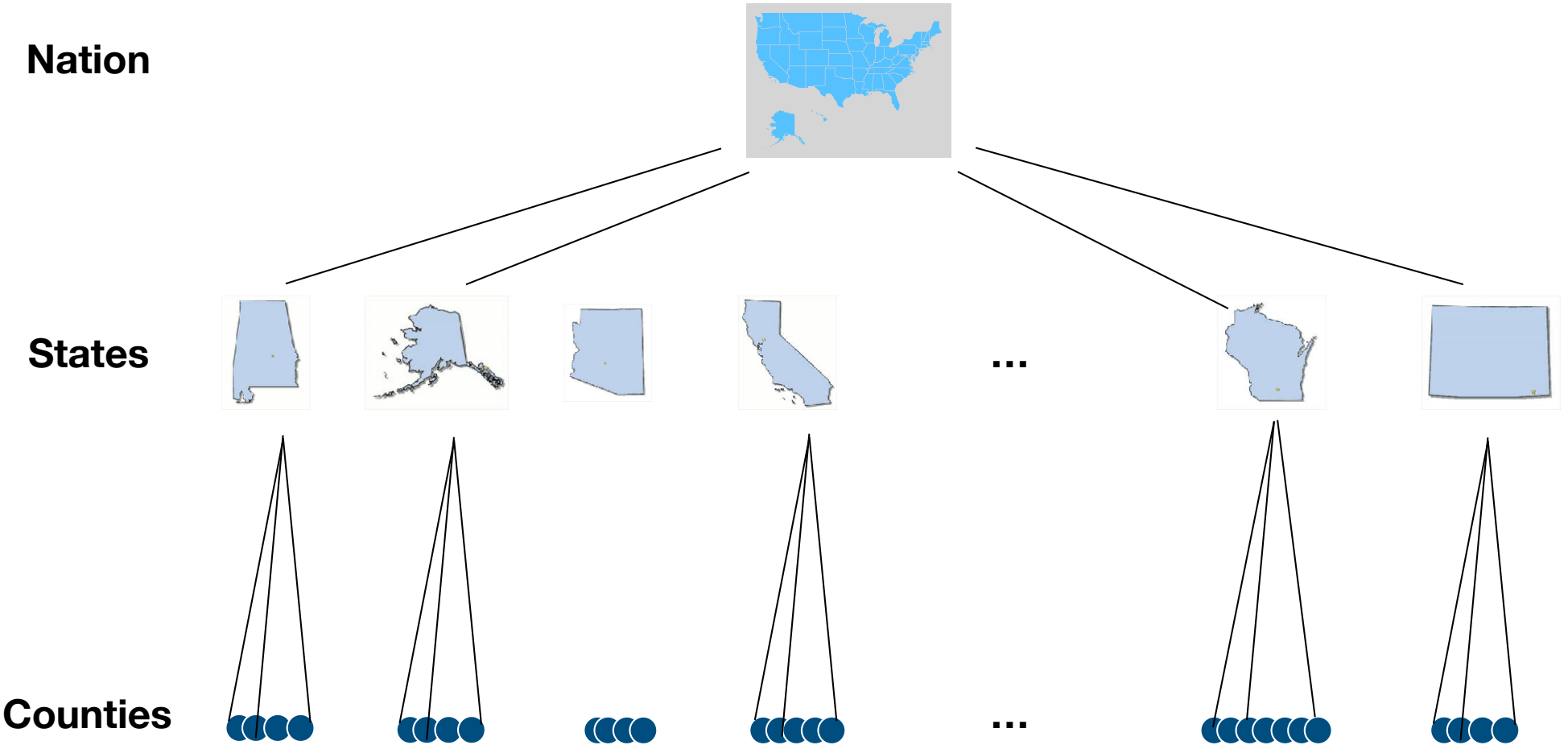
➡ **Unbiased answers to workload queries**

➡ **Data-independent expected error**

➡ **Expected error varies across workload**

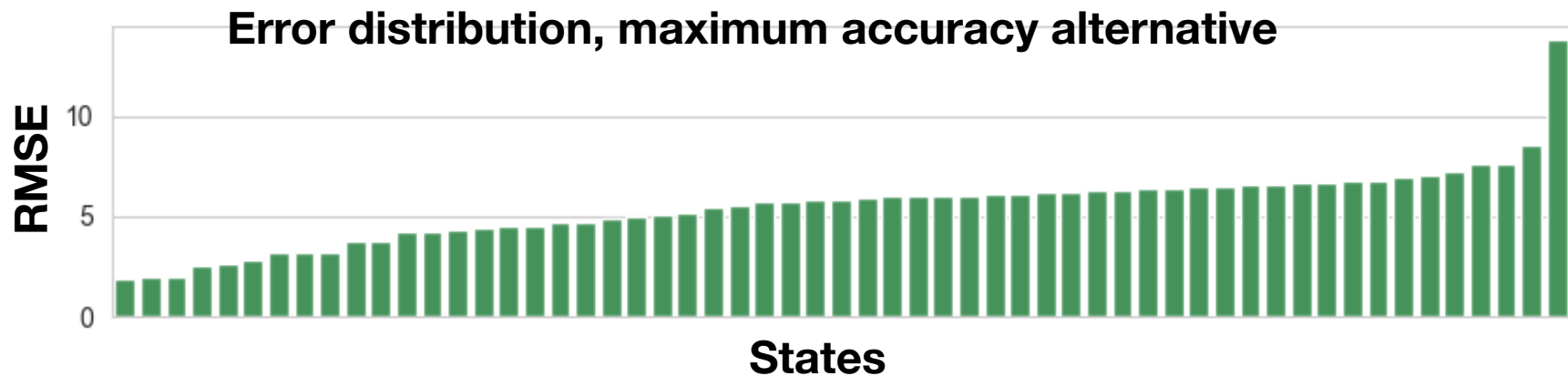
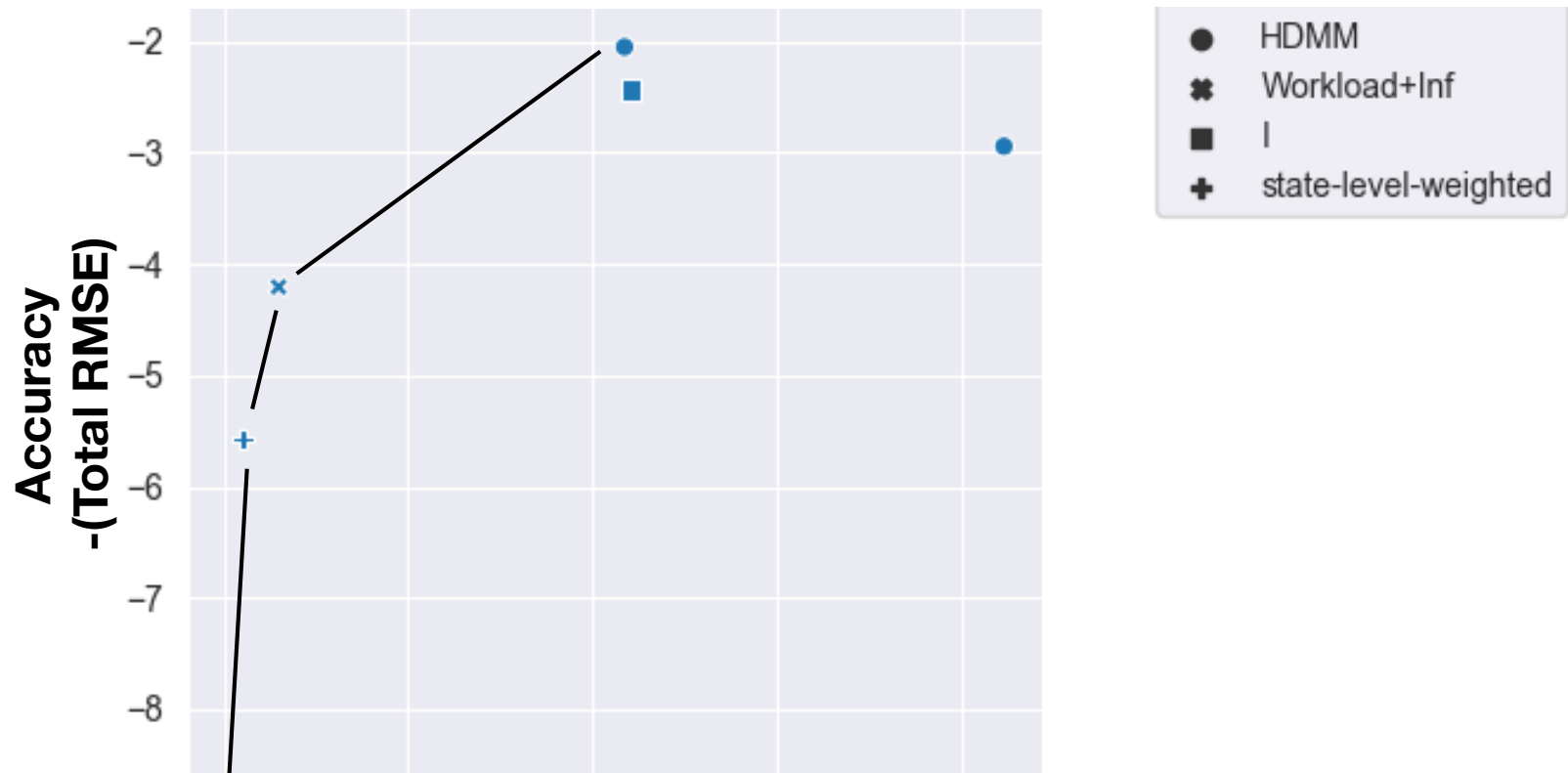


# Geographic hierarchy

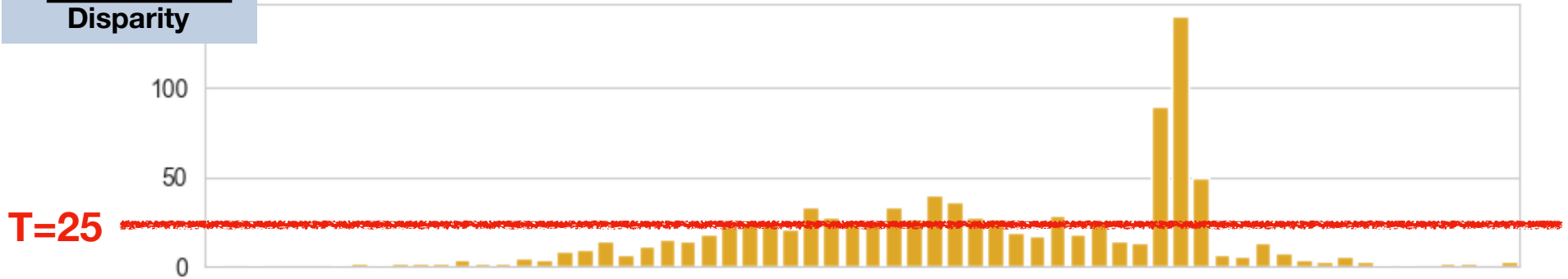
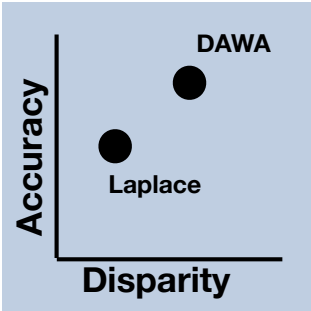


**Workload:** counts (of some predicate) at county, state, and national level.

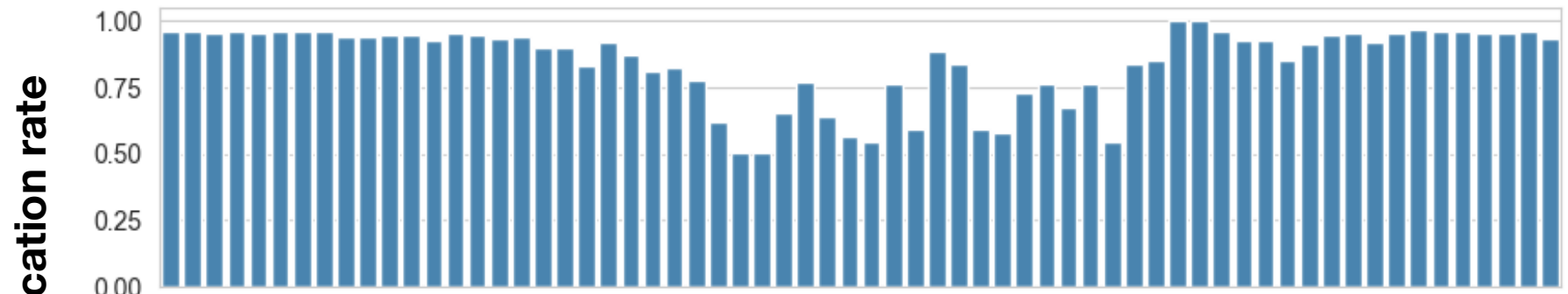
# Accuracy on state counts



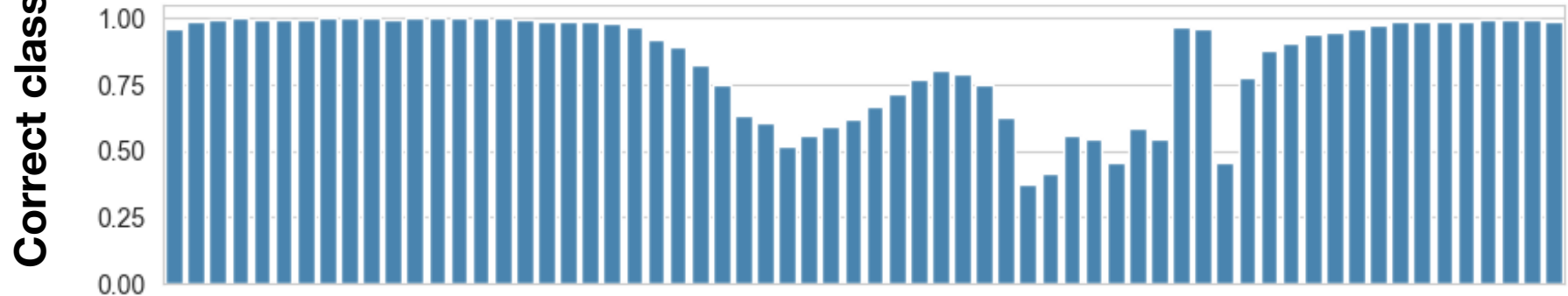
# Threshold assignment



Laplace



DAWA



# Outline

1. Introduction
2. Causes of accuracy disparities
- 3. Cases studies**
  - **Voting rights benefits**
  - **Title I education funding**
4. Discussion and conclusion

# Minority language voting benefits

- Section 203 of the 1965 Voting Rights Act (U.S.) specified conditions under which jurisdictions must provide language assistance.
- A jurisdiction determined to be “covered” for language L must provide all election information (voter registration, ballots, and instructions) in the language L.
- Determinations made by the Census Bureau every 5 years, using published data.
- Last determinations in 2016: 263 out of 8000 jurisdictions covered (across all languages). 21 million voters live in these jurisdictions.

# Minority language voting benefits

- For each jurisdiction  $j$ :
  - For each minority language  $L$ :
    - Define:
      - $q_{vac}(a_j)$  = voting age citizens in  $j$  speaking language  $L$
      - $q_{lep}(a_j)$  = voting age citizens in  $j$  speaking language  $L$  and limited-English proficient.
      - $q_{lit}(a_j)$  = voting age citizens in  $j$  speaking language  $L$  and limited-English proficient and less than 5th grade education.
    - If  $\left( \frac{q_{lep}(a_j)}{q_{vac}(a_j)} > 0.05 \vee q_{lep}(a_j) > 10000 \right) \wedge \frac{q_{lit}(a_j)}{q_{lep}(a_j)} > 0.0131$
    - Then  $a_j$  is covered for language  $L$

# Covered jurisdictions

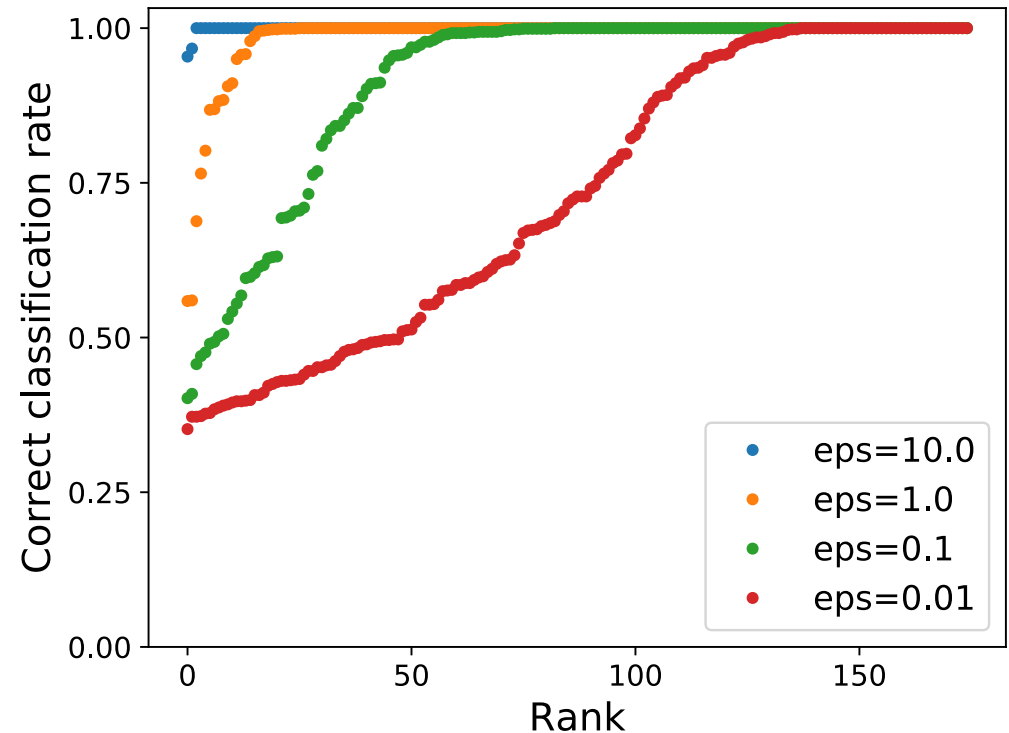
% jurisdictions with  
correct classification  
>95%

lowest correct  
classification rate

$\epsilon$

10.0	100%	95%
1.00	92%	55%
0.10	74%	39%
0.01	33%	37%

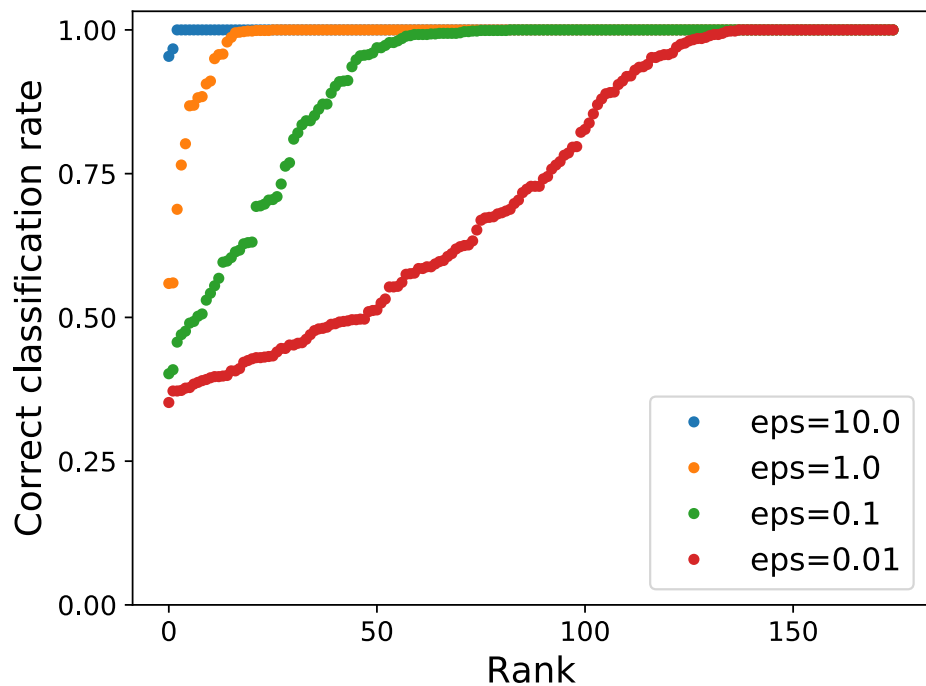
Laplace Mechanism



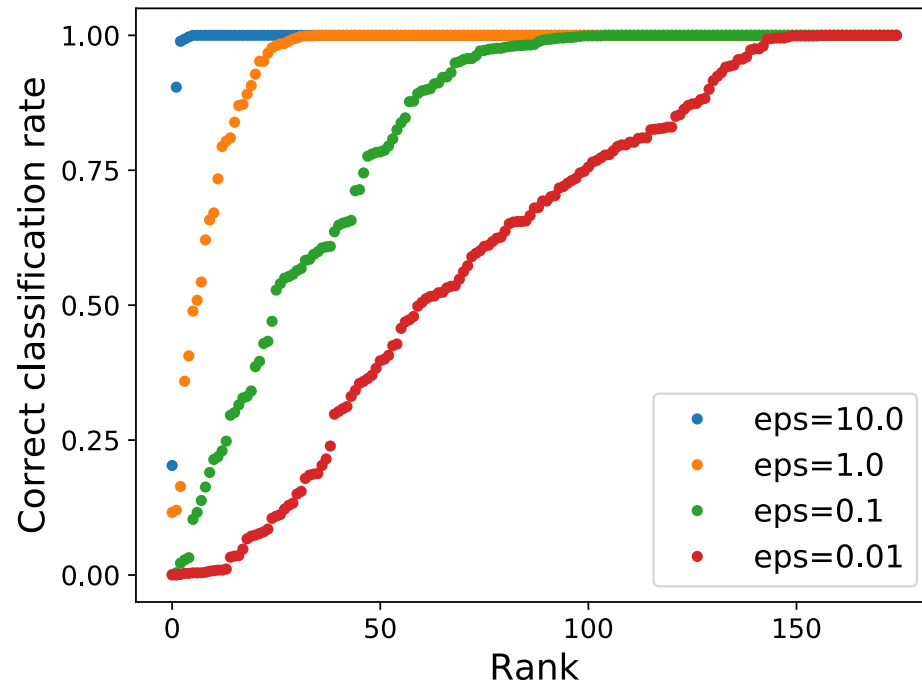
2016 public-use data (treated as ground truth)  
“Hispanic” minority language group  
175 positively classified jurisdictions

# Laplace vs. DAWA

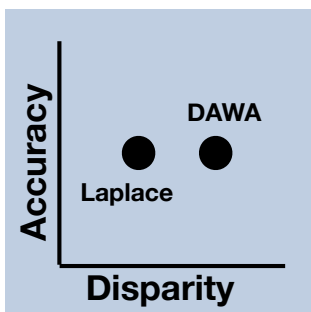
## Laplace Mechanism



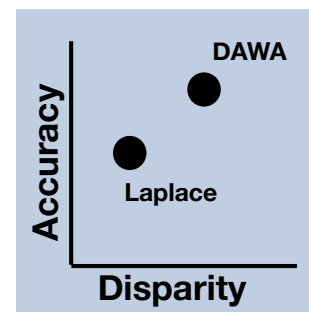
## DAWA Algorithm



At  $\epsilon = 0.1$  DAWA and Laplace have equal total error



At  $\epsilon = 0.01$  DAWA has 30% lower error than Laplace.





# Title I funds allocation

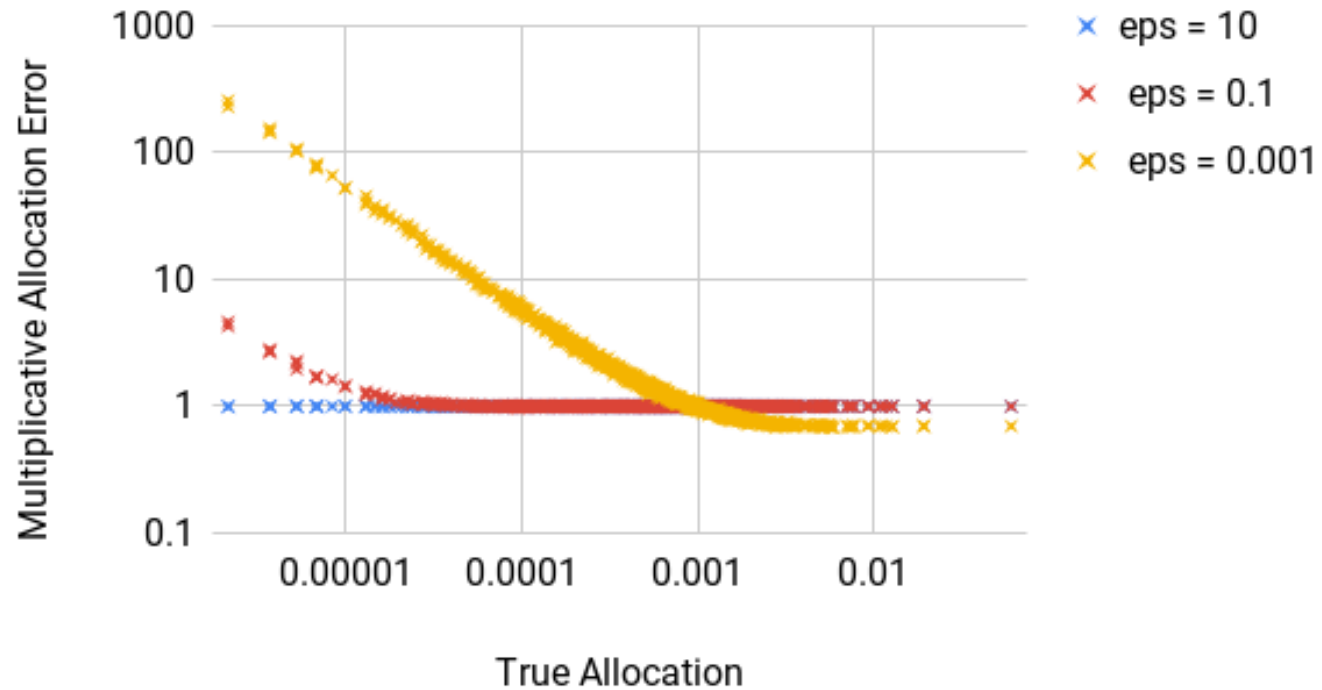
- The allocation of at least \$675 billion, annually, relies on Census data.
- Title I of the Elementary and Secondary Education Act of 1965 gives educational funding to school districts in proportion to number of children in financial need.
- In 2015, \$6.5 billion was given through Title I “Basic grants”

# Title I funds allocation

- Given total allocation **C**
- For each U.S. school district **d**
  - Define:
    - $q_{exp}(a_d)$  = average per student expenditure
    - $q_{eli}(a_d)$  = number of eligible students in district a.
  - Allocate to district **d**: 
$$\frac{Cq_{exp}(a_d)q_{eli}(a_d)}{\sum_i q_{exp}(a_i)q_{eli}(a_i)}$$

# Allocation error

State of Michigan, 888 districts



eps	small districts	large districts
10.0	1.01x ↑	0.001% ↓
0.10	10x ↑	0.05% ↓
0.001	500x ↑	50% ↓

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# Summary

- Assignee populations do not bear the utility cost of existing privacy mechanisms equally.
- Disparities have a variety of causes:
  - minimizing total error, small counts biased up, counts near a decision boundary, those who get “asked about” less often, outliers biased towards neighbors...

# Next steps?

- For what epsilons are disparities small enough to ignore?
- Can we develop privacy mechanisms that allow us to target more complex utility notions?
- Can we remedy disparities through post-processing or by adjusting assignment functions? Is this legally acceptable?
- Should individuals be able to choose how they weigh potential privacy harms against potential utility harms

# Thank you

Results in this talk were made with **€KTELO**

<https://github.com/ektelo/ektelo>

