

# Make Up Your Mind: The Price of Online Queries in Differential Privacy

or: An Excuse to Survey Differential Privacy Lower Bounds

Taiwan Theory Day

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# The Challenge of Data Privacy

**Protect  
privacy of  
subjects**

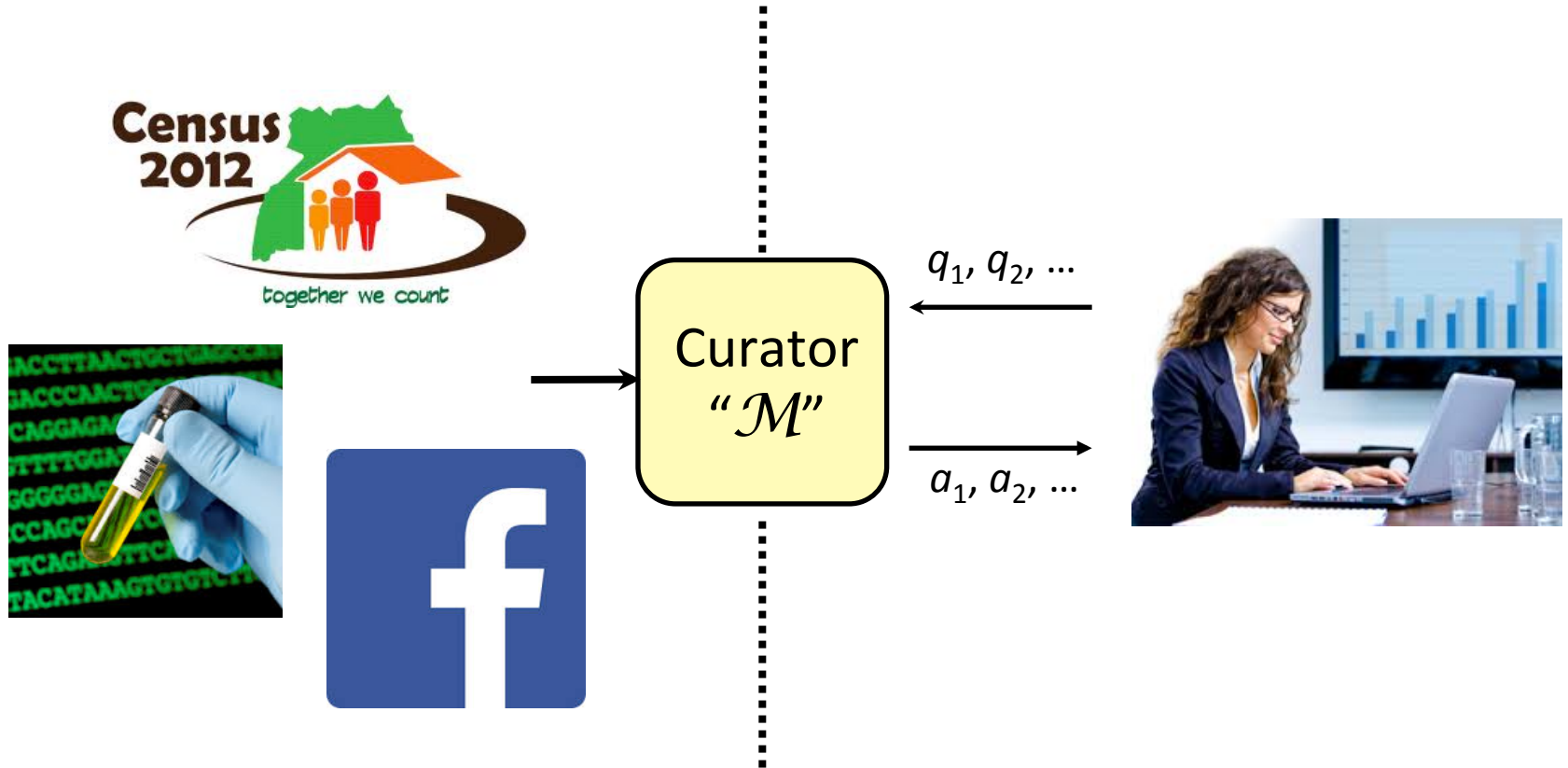


**Enable useful  
statistical  
analyses**

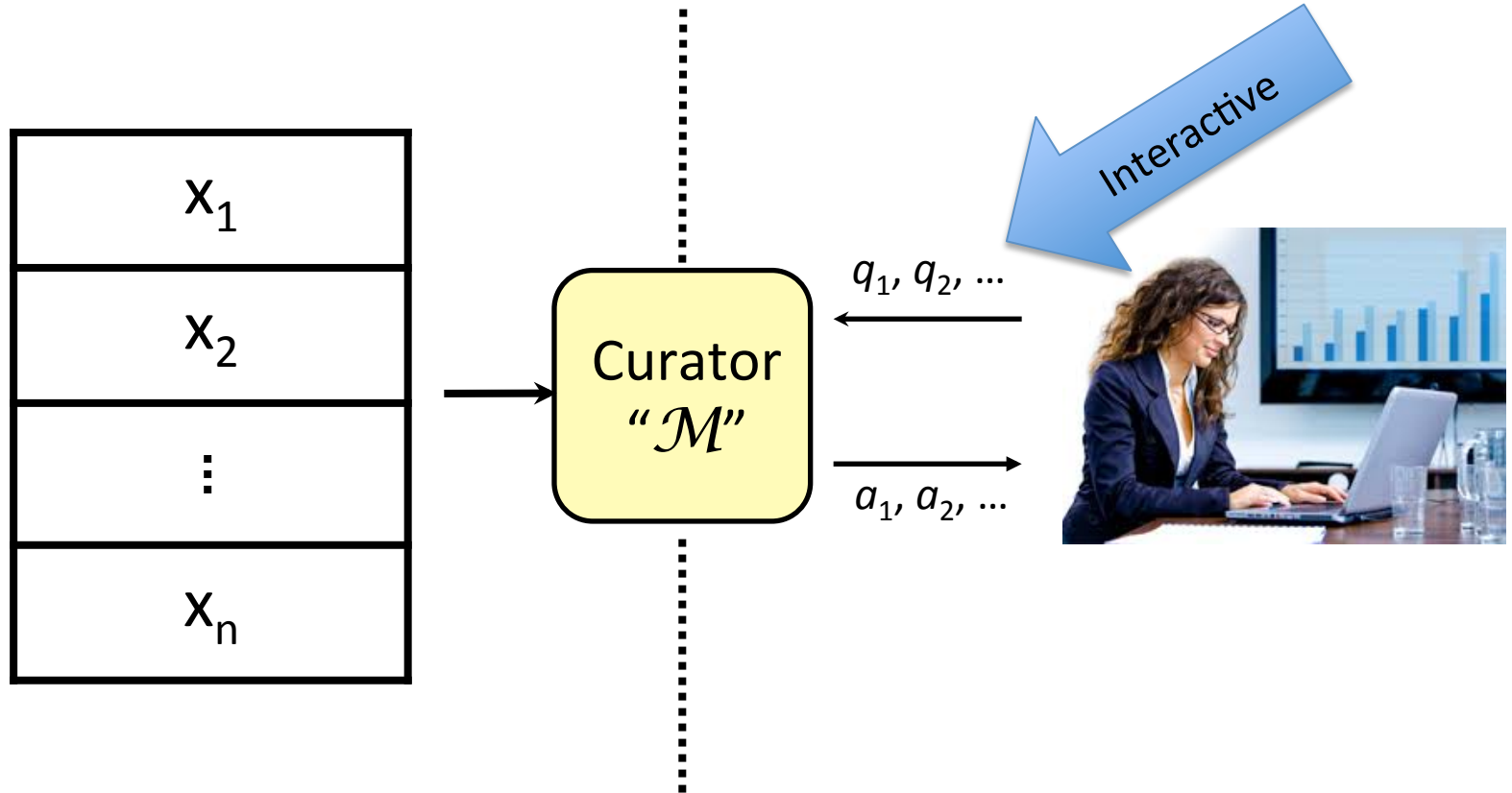
Census Data  
Medical Records  
Social Networks  
Location Data

Social science research  
Identifying genes  
Replicating studies  
Recommendation services

# Privacy-Preserving Data Analysis



# Privacy-Preserving Data Analysis



# How Should We Model Interaction?

- “Offline”: Analyst chooses all of her queries in advance and receives answers together
- “Adaptive”: Analyst chooses/asks queries one at a time
  - ...or another possibility?
- **This work:** How does changing the model of interaction affect what can be accomplished with differential privacy?

# Why Might This Matter?

- Rich theory of differential privacy – sophisticated algorithms matched by strong lower bounds
- Differential privacy prevents false discovery, even in *adaptive* data analysis

[Dwork-Feldman-Hardt-Pitassi-Reingold-Roth14, Hardt-Ullman14]

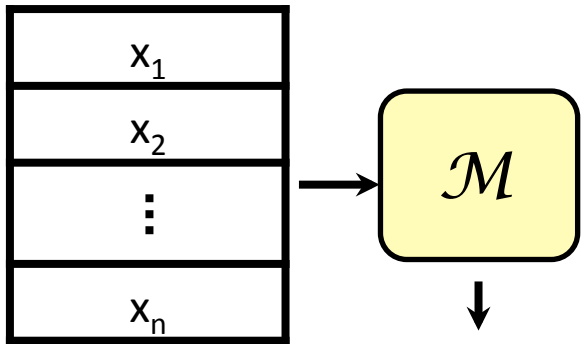


Does handling adaptivity in DP really come for free?

# Differential Privacy

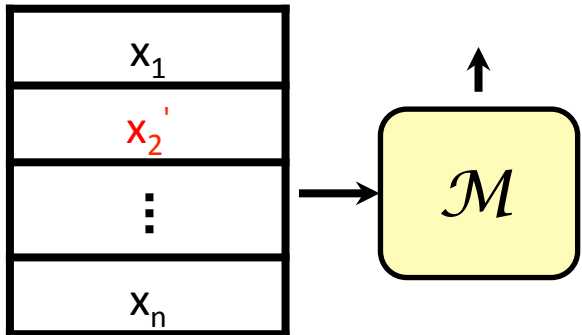
Dinur-Nissim03+Dwork, Dwork-Nissim04, Blum-Dwork-McSherry-Nissim05,  
Dwork-McSherry-Nissim-Smith06, Dwork-Kenthapadi-McSherry-Mironov-Naor06

$D$



$D$  and  $D'$  are **neighbors** if they differ on one row

$D'$



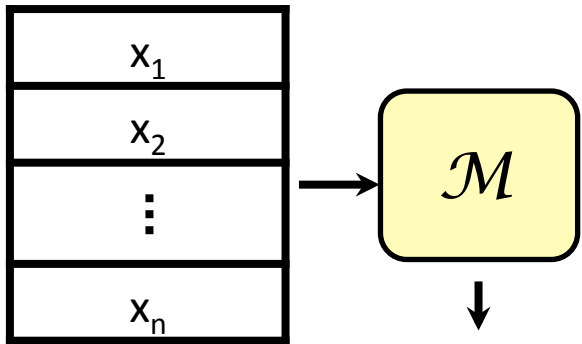
$\mathcal{M}$  is **differentially private** if for all neighbors  $D, D'$ :

$$\mathcal{M}(D) \approx \mathcal{M}(D')$$

# Differential Privacy

Dinur-Nissim03+Dwork, Dwork-Nissim04, Blum-Dwork-McSherry-Nissim05,  
Dwork-McSherry-Nissim-Smith06, Dwork-Kenthapadi-McSherry-Mironov-Naor06

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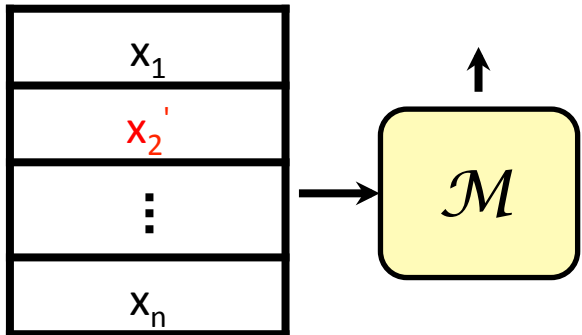


$D$  and  $D'$  are **neighbors** if they differ on one row

small const., e.g.  $\epsilon = 0.1$

“cryptographically small”  
require  $\delta \ll 1/n$ , often  $\delta = \text{negl}(n)$

$D'$



$\mathcal{M}$  is  **$(\epsilon, \delta)$ -differentially private** if for all neighbors  $D, D'$  and  $S \subseteq \text{Range}(\mathcal{M})$ :

$$\Pr[\mathcal{M}(D') \in S] \leq (1 + \epsilon) \Pr[\mathcal{M}(D) \in S] + \delta$$



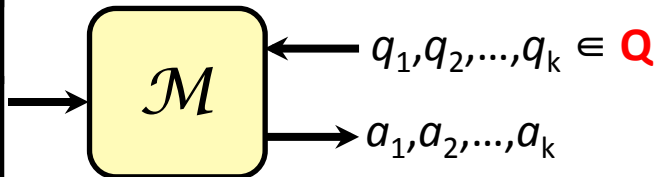
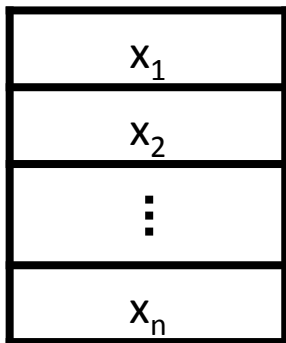
# Counting Queries

“What fraction of the rows of  $D$  satisfy some property  $q$ ?”

E.g. **attribute** means  
 $q = \text{HasMouth?}$   
 $q(D) = 2/4$



	HasMouth?	Bakes?	Clothed?	OnJet?
	0	1	1	1
	1	0	1	1
	1	0	0	1
	0	1	1	1







$\mathcal{M}$  is accurate for  $k$  queries from  $Q$  if  
 $|a_i - q_i(D)| < 0.05$  for every  $i$   
(with high probability)

# (Privately) Answering Attribute Means

[DN03, DN04, BDMN05, DMNS06]

$d$  binary attributes

$n$  people

	HasMouth?	Bakes?	Clothed?	OnJet?
	0	1	1	1
	1	0	1	1
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	0	1	1	1





$\frac{1}{2}$   
+  
Noise( )

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$1/2$   
+  
Noise( $O(1/n)$ )

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$1/2$

+

Noise(

)

$1/2$

+

Noise(

)

$3/4$

+

Noise(

)

$1$

+

Noise(

)





**Disclaimer:** This talk hides  
all polylogs

# (Privately) Answering Attribute Means

[DN03, DN04, BDMN05, DMNS06]

$d$  binary attributes

$n$  people

	HasMouth?	Bakes?	Clothed?	OnJet?
	0	1	1	1
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	1	0	0	1
	0	1	1	1
	1/2 +	1/2 +	3/4 +	1 +
	Noise( $O(d^{1/2}/n)$ )	Noise( $O(d^{1/2}/n)$ )	Noise( $O(d^{1/2}/n)$ )	Noise( $O(d^{1/2}/n)$ )

Non-trivial accuracy requires  $d < n^2$

$\Rightarrow$  can answer  $k = d = \Omega(n^2)$  queries

**Disclaimer:** This talk hides all polylogs

# Not Just Attribute Means

[DN03, DN04, BDMN05, DMNS06]

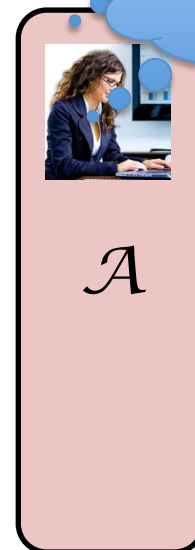
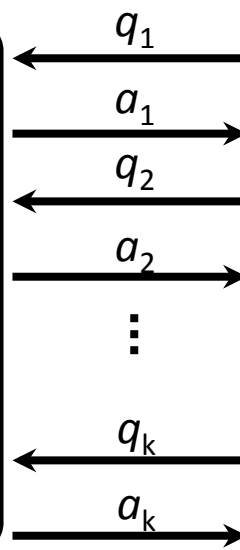
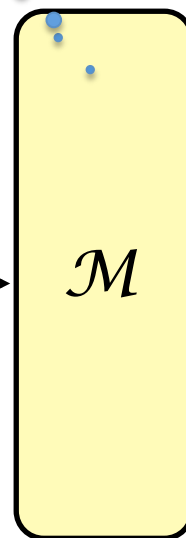
$$a_2 = q_2(D) + \text{Noise}(O(k^{1/2}/n))$$

$d$  binary attributes

$n$   
ppl



	Has Mouth	Bakes	Clothed	OnJet
	0	1	1	1
	1	0	1	1
	1	0	0	1
	0	1	1	1



$$q_1 = \text{HasMouth}$$
$$q_2 = \text{Bakes} \vee \text{Clothed}$$

Can answer  $k = \Omega(n^2)$  adaptively chosen counting queries





# ...And Not Just $n^2$ Queries

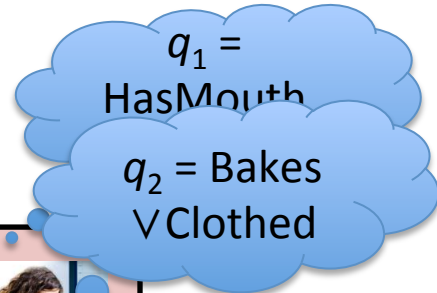
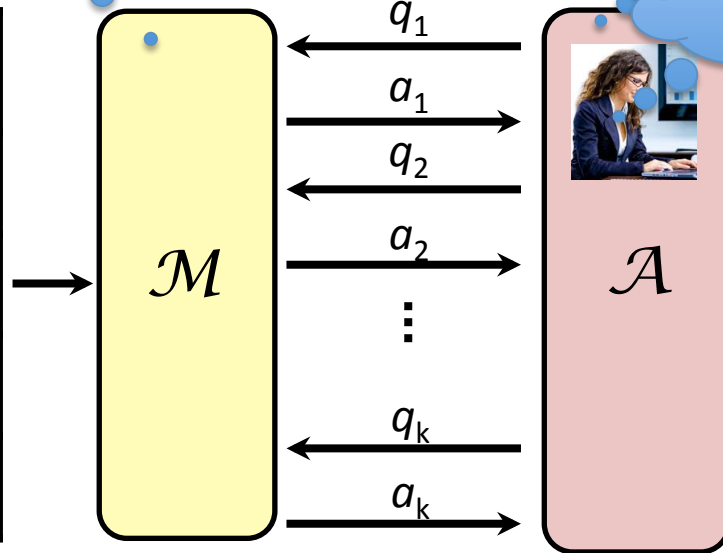
[Blum-Ligett-Roth08, Roth-Roughgarden10, Hardt-Rothblum10]



$d$  binary attributes

$n$  ppl

	Has Mouth	Bakes	Clothed	OnJet
	0	1	1	1
	1	0	1	1
	1	0	0	1
	0	1	1	1



“Private Multiplicative Weights” [Hardt-Rothblum10]

Can answer  $k = \exp(\Omega(n/d^{1/2}))$  *adaptively chosen* counting queries  
 (= exponentially many queries when  $n \gg d^{1/2}$ )

(Counting)

# How Many Queries Can We Answer?

( $\epsilon = 0.1, \delta = o(1/n)$ ) –  
differential privacy

Upper bound:  $n \ll d^{1/2}$   
(Independent Noise)

Upper bound:  $n \gg d^{1/2}$   
("Advanced Algorithms")

Adaptive

$\forall Q: k = \Omega(n^2)$ [...DMNS06]
$\forall Q: \exp(\Omega(n/d^{1/2}))$ [HR10]



# Matching Lower Bounds

- Can't answer more than  $k = \exp(O(n))$  queries

[Dinur-Nissim03]

## “Reconstruction Attack”

$\log n$  bits

1 bit

	Public “ID”		Sensitive “b”
	0	0	1
	0	1	0
	1	0	0
	1	1	1

$n$   
ppl

Ask *all*  $2^n$  counting queries of the form:  
 $q_S(x) = (x_{ID} \in S) \wedge x_b$  where  $S \subseteq \{0,1\}^{\log n}$

Reconstruct any database  $D'$  with  
 $|q_S(D') - q_S(D)| < 0.05$  for all  $q_S$

Claim: (0.05)-accurate answers  $\Rightarrow$   
 $b'$  agrees with  $b$  in 80% of entries

Proof: If  $|b' - b|_1 > 0.2$ , then  
 $|q_S(D') - q_S(D)| > 0.1$  for either  
 $S^> = \{i : b_i > b'_i\}$  or  $S^< = \{i : b_i < b'_i\}$

# Matching Lower Bounds

- Can't answer more than  $k = \exp(O(n))$  queries  
[Dinur-Nissim03]  
...
- Independent noise is tight for attribute means:  
Can only answer  $O(n^2)$  queries [B.-Ullman-Vadhan14]
- Private mult. weights is tight for conjunctions:  
Can only answer  $\exp(O(n/d^{1/2}))$  queries [B.-Ullman-Vadhan14]
- All lower bounds apply to a *fixed set* of queries

(Counting)

# How Many Queries Can We Answer?

( $\epsilon = 0.1, \delta = o(1/n)$ ) –  
differential privacy

Offline

Adaptive

Upper bound:  $n \ll d^{1/2}$   
(Independent Noise)



$\forall Q: k = \Omega(n^2)$   
[...DMNS06]

Upper bound:  $n \gg d^{1/2}$   
("Advanced Algorithms")



$\forall Q: \exp(\Omega(n/d^{1/2}))$   
[HR10]

Lower bound:  $n \ll d^{1/2}$   
(Attribute Means)

$\exists Q: O(n^2)$   
[BUV14]



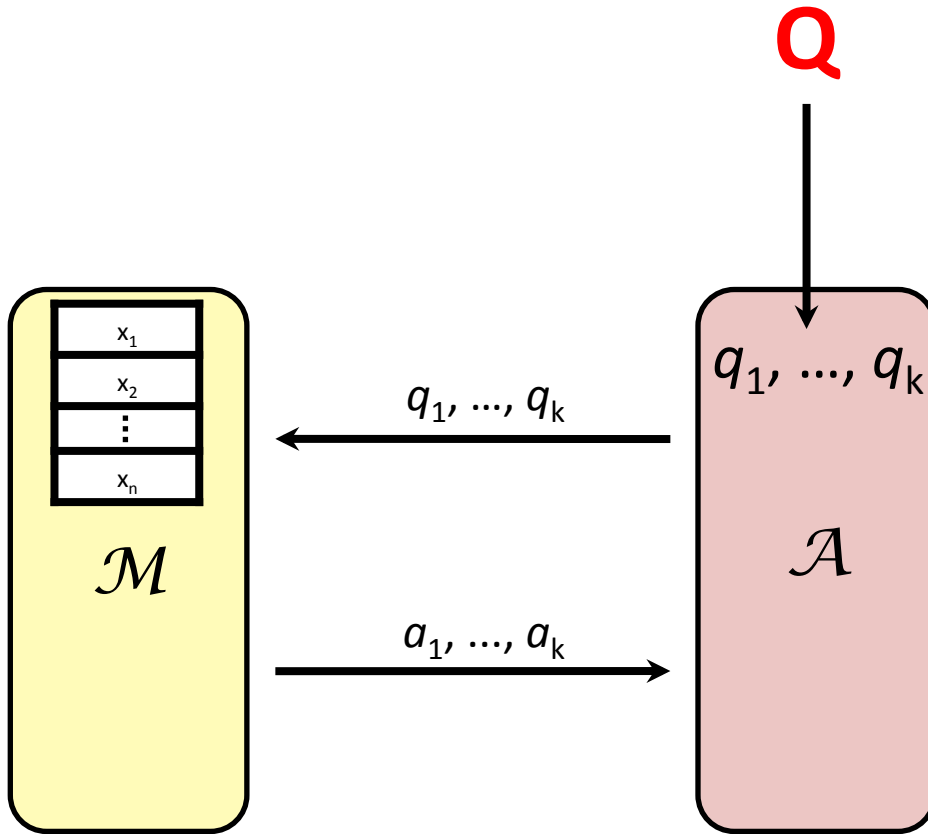
Lower bound:  $n \gg d^{1/2}$   
(Conjunctions)

$\exists Q: \exp(O(n/d^{1/2}))$   
[BUV14]



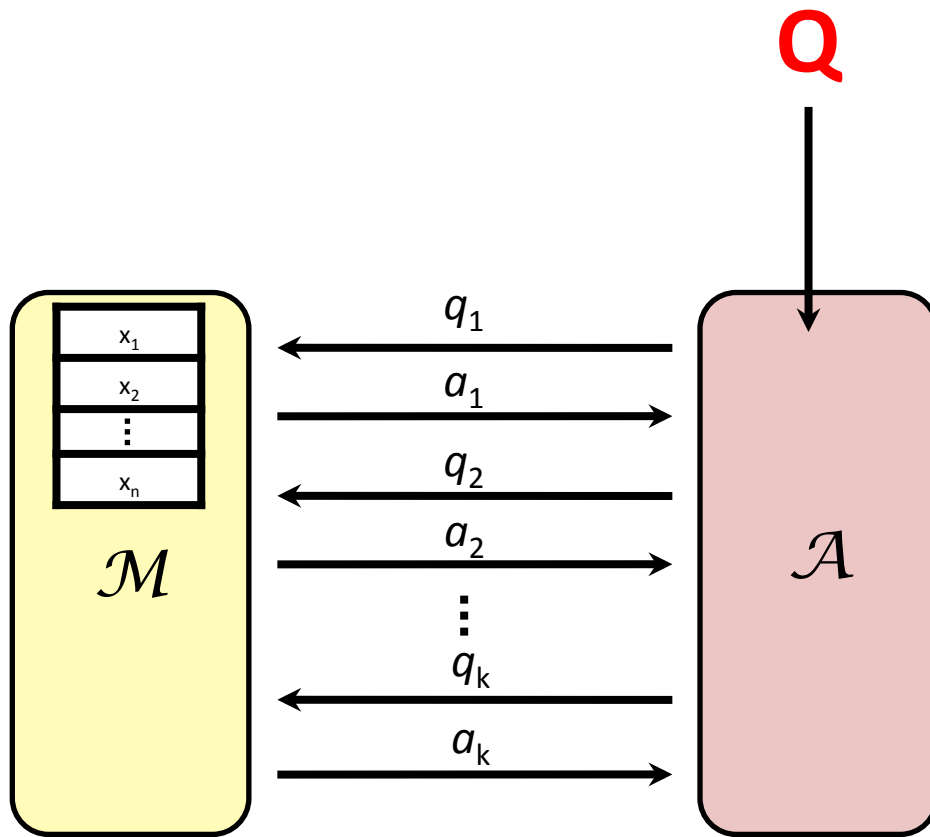
**Question:** Are these models equivalent?

# The OFFline Model



1.  $\mathcal{A}$  chooses  $k$  queries  $q_1, \dots, q_k$  from  $Q$
2.  $\mathcal{A}$  gives queries to  $\mathcal{M}$  in a single batch
3.  $\mathcal{M}$  releases answers  $a_1, \dots, a_k$

# The Adaptive Model

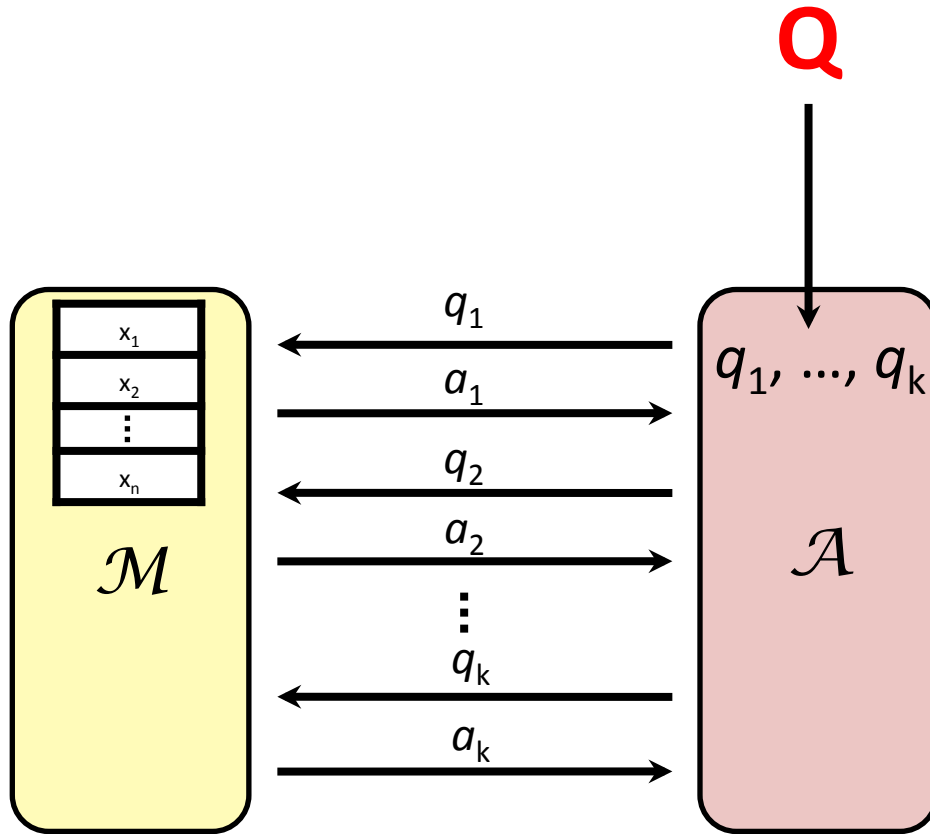


In each round  $j = 1, \dots, k$ :

1.  $\mathcal{A}$  chooses a query  $q_j$  (depending on  $q_1, a_1, \dots, q_{j-1}, a_{j-1}$ )
2.  $\mathcal{M}$  must release  $a_j$  before seeing  $q_{j+1}$

# The ONLINE Model

(Non-adaptive)



1.  $\mathcal{A}$  chooses  $k$  queries  $q_1, \dots, q_k$  from  $Q$

2. In each round  $j = 1, \dots, k$ :

$\mathcal{M}$  must release  $a_j$  before seeing  $q_{j+1}$

# Our Results

All three models are distinct

- **Offline  $\neq$  Online**

Family  $Q_{\text{prefix}}$  of counting queries

**Offline:** Can answer  $k = \exp(\Omega(n^{1/2}))$  queries

**Online:** Can only answer  $k = O(n^2)$  queries

- **Online  $\neq$  Adaptive**

Family  $Q_{\text{corr}}$  of “search” queries

**Online:**  $k = \exp(\Omega(n))$  queries

**Adaptive:**  $k = O(1)$  queries

# Offline vs. Online

## “Prefix queries”

$$Q_{\text{prefix}} = \{ q_S : \{0,1\}^d \rightarrow \{0,1\} \}$$

For  $S = \{y_1, \dots, y_m \in \{0,1\}^{\leq d} : m \leq d\}$  and  $x \in \{0,1\}^{\leq d}$  :

Define  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

## Example

$$S = \{0, 10, 001, 110\} \subseteq \{0,1\}^{\leq 4}$$

$$x = 1010 \in \{0,1\}^{\leq 4}$$



# Offline vs. Online

## “Prefix queries”

$$Q_{\text{prefix}} = \{ q_S : \{0,1\}^d \rightarrow \{0,1\} \}$$

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## Example

$$S = \{0, \mathbf{10}, 001, 110\} \subseteq \{0,1\}^{\leq 4}$$

$$x = \mathbf{10}10 \in \{0,1\}^{\leq 4}$$

$$\Rightarrow q_S(x) = 1$$

# Offline vs. Online

## “Prefix queries”

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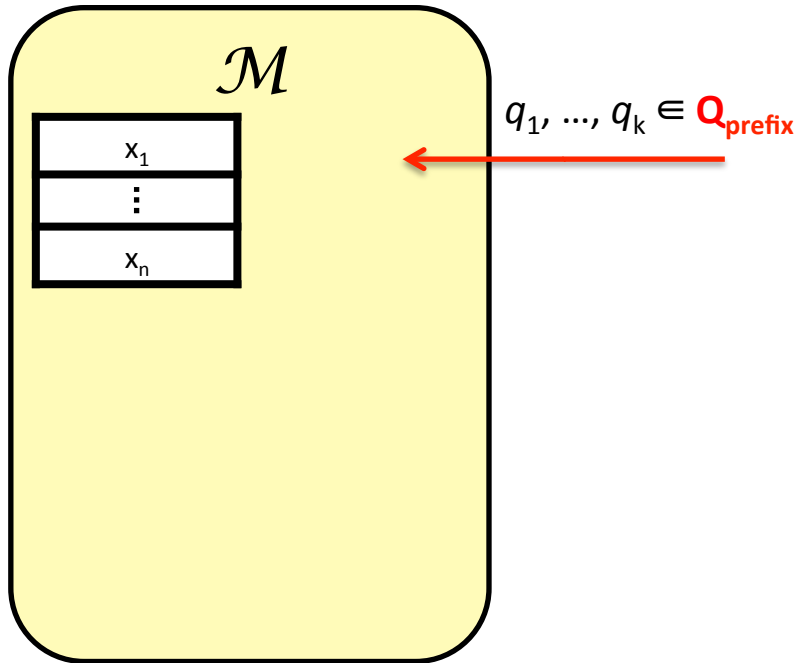
Define  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

## Intuition for separation

**Offline:** Structure of queries enables dimensionality reduction

**Online:** As hard as *attribute means*

# An Offline Algorithm

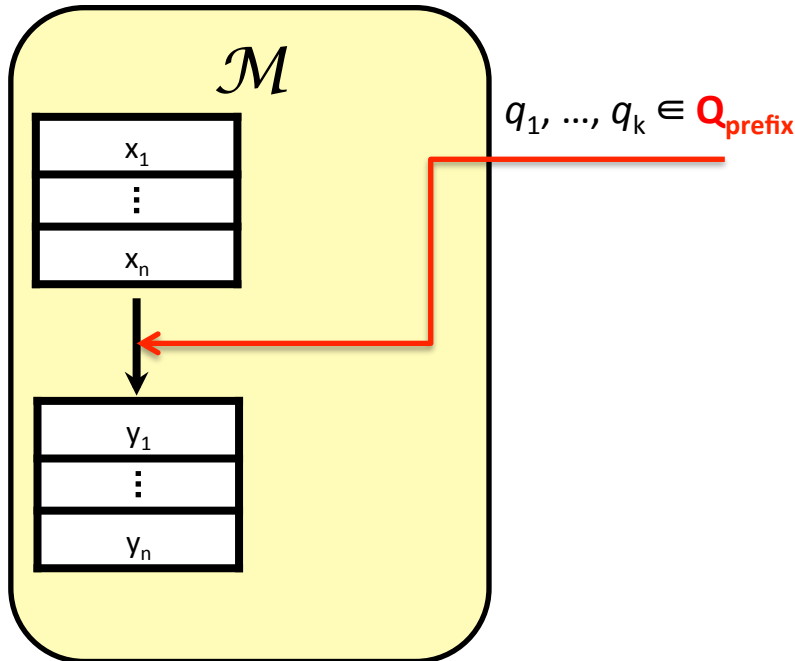


## Algorithm $\mathcal{M}$

Input: queries  $q_1, \dots, q_k$  corresponding to sets  $S_1, \dots, S_k$

1. Let  $S = S_1 \cup S_2 \cup \dots \cup S_k$
2. Replace each  $x_i$  with longest  $y_i \in S$  which is a prefix of  $x_i$
3. Run your favorite “advanced algorithm” on  $(y_1, \dots, y_n)$

# An Offline Algorithm

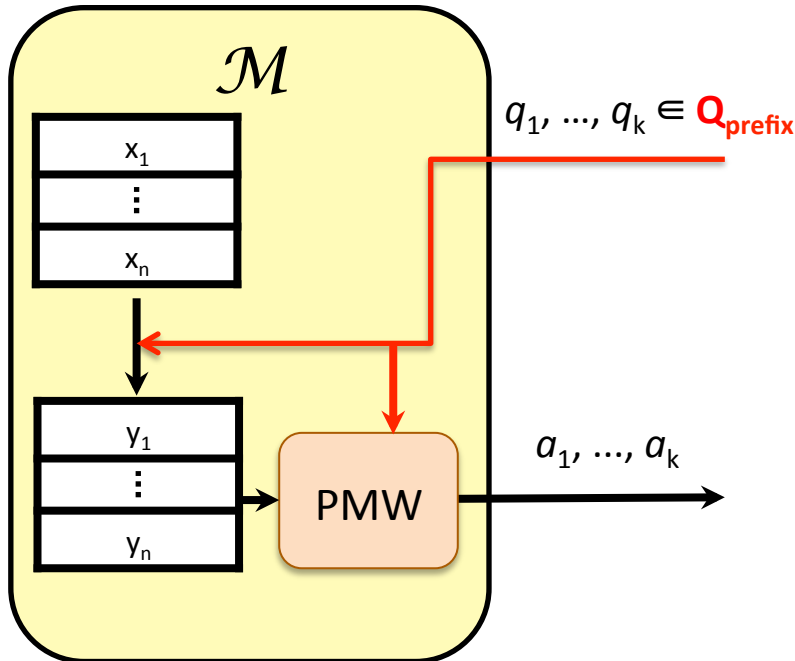


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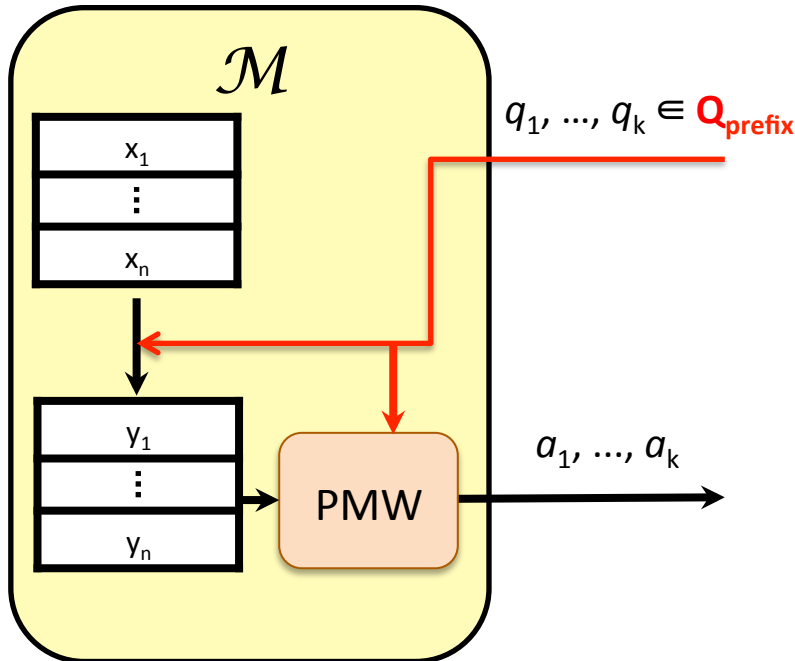


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# An Offline Algorithm

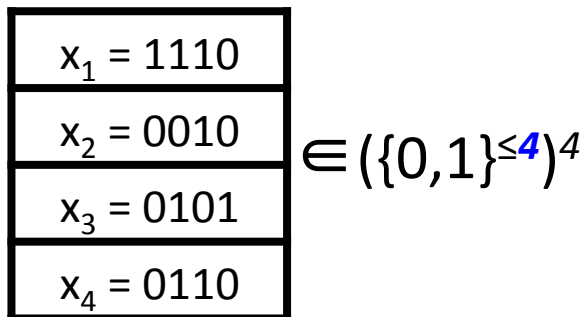


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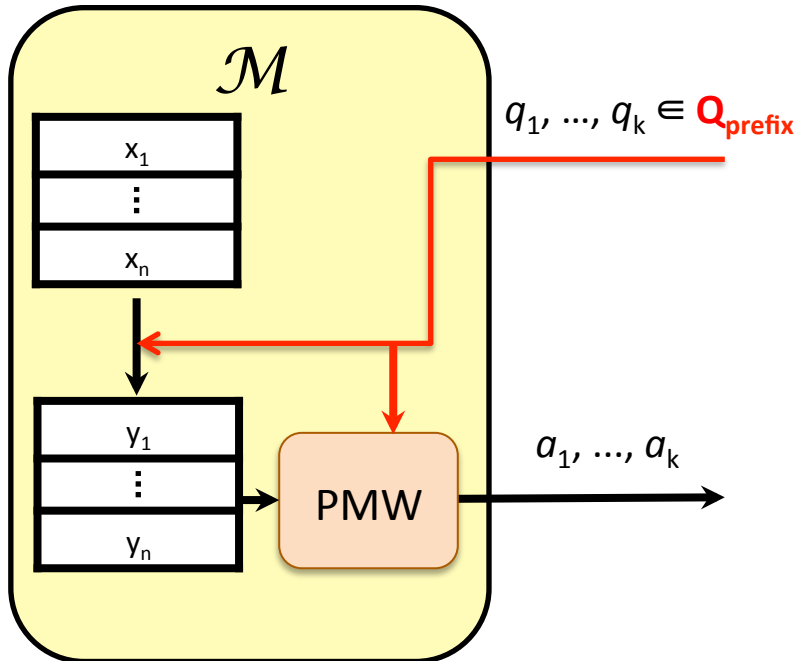


$$S_1 = \{1\}$$

$$S_2 = \{01, 10\}$$

$$S_3 = \{001, 011\}$$

# An Offline Algorithm

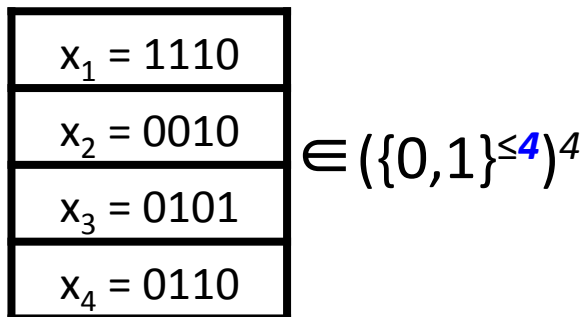


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## Example:



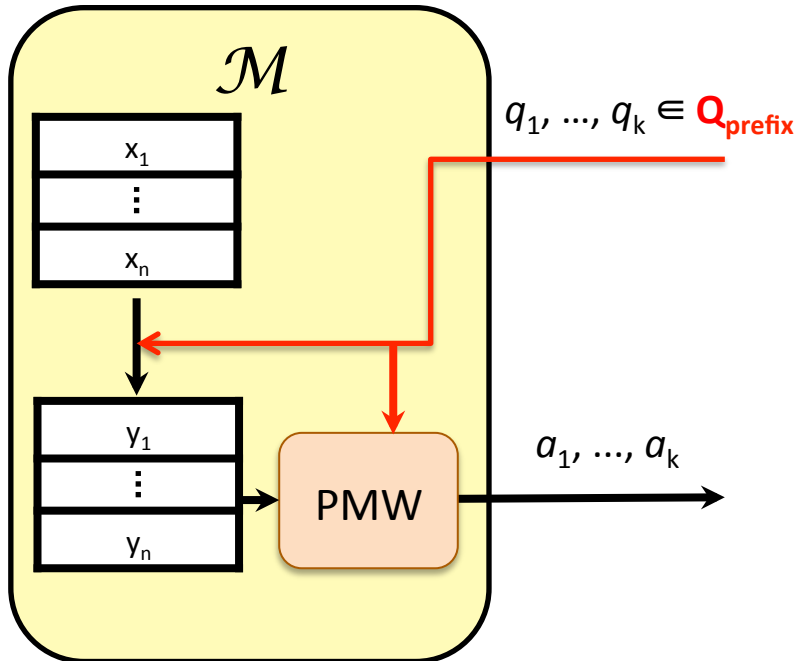
$$S_1 = \{1\}$$

$$S_2 = \{01, 10\}$$

$$S_3 = \{001, 011\}$$

$$\Rightarrow S = \{1, 01, 10, 001, 011\}$$

# An Offline Algorithm



## Algorithm $\mathcal{M}$

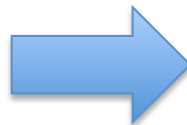
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## Example:

$x_1 = 1110$
$x_2 = 0010$
$x_3 = 0101$
$x_4 = 0110$

$\in (\{0,1\}^{\leq 4})^4$



$y_1 = 1$
$y_2 = 001$
$y_3 = 01$
$y_4 = 011$

$\in S^4$

$$S_1 = \{1\}$$

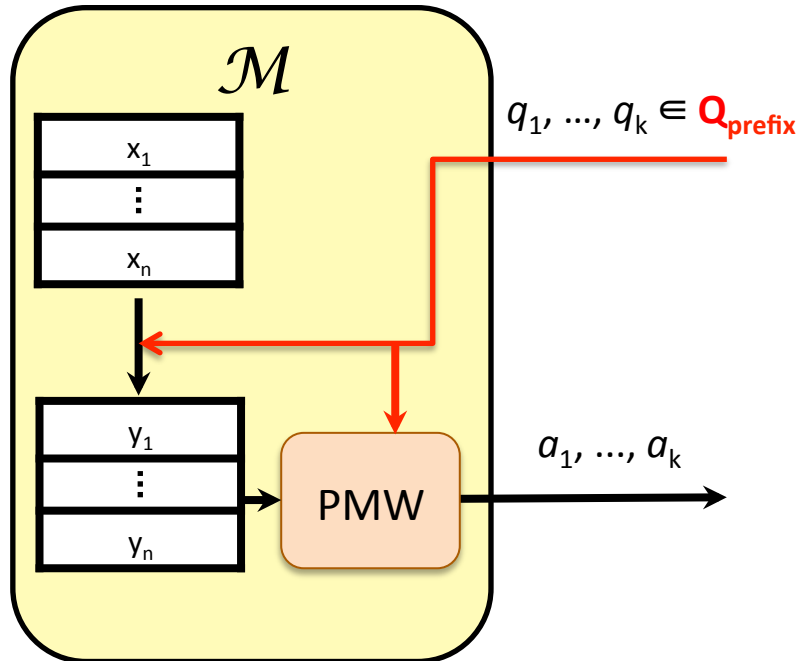
$$S_2 = \{01, 10\}$$

$$S_3 = \{001, 011\}$$

$$\Rightarrow S = \{1, 01, 10, 001, 011\}$$



# An Offline Algorithm



## Algorithm $\mathcal{M}$

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Fact 1: All  $q_j(y_i) = q_j(x_i)$  (since  $z \in S$  is a prefix of  $x_i$  iff  $z$  is a prefix of  $y_i$ )

Fact 2:  $y_i$ 's come from a universe of size only  $kd$  (i.e. dimension  $\log(kd)$ )

$\Rightarrow$  Private Mult. Weights can answer  $k = \exp(\Omega(n/\log^{1/2}(kd)))$  queries

For  $d = \text{poly}(n)$ , solve to get  $k = \exp(\Omega(n^{1/2}))$

# Our Results

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Family  $Q_{\text{corr}}$  of “search” queries

**Online:**  $k = \exp(\Omega(n))$  queries

**Adaptive:**  $k = O(1)$  queries

# An Online Lower Bound

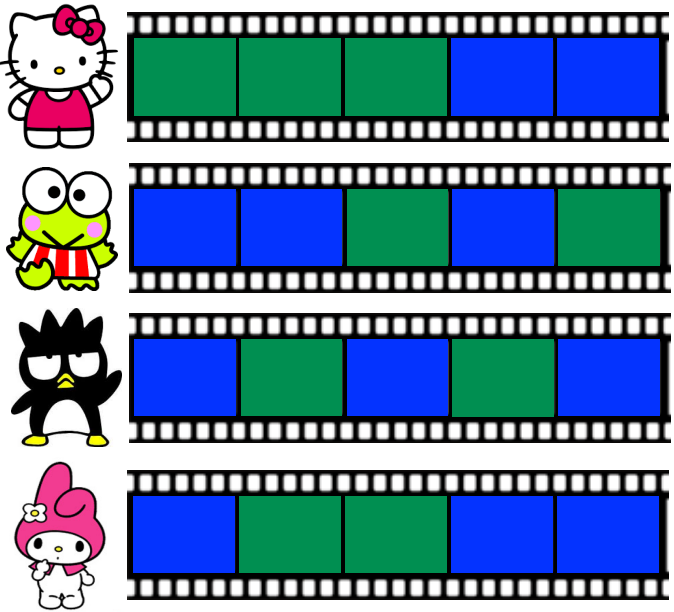
- Lower bound for attribute means via fingerprinting codes [B.-Ullman-Vadhan14]
- “Embed” attribute means into online prefix queries

See: [Bassily-Smith-Thakurta15, Dwork-Talwar-Thakurta-Zhang15, Steinke-Ullman15, B.-Nissim-Stemmer16]

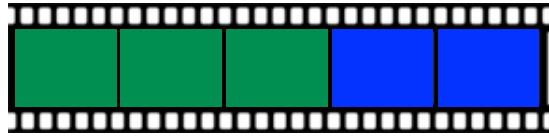
# Fingerprinting Codes [Boneh-Shaw95]

I want to distribute my new movie

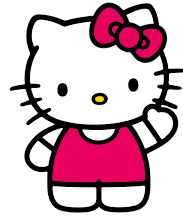
*Hello Kitty's  
Gradient Descent*



Pirate



Trace Algorithm

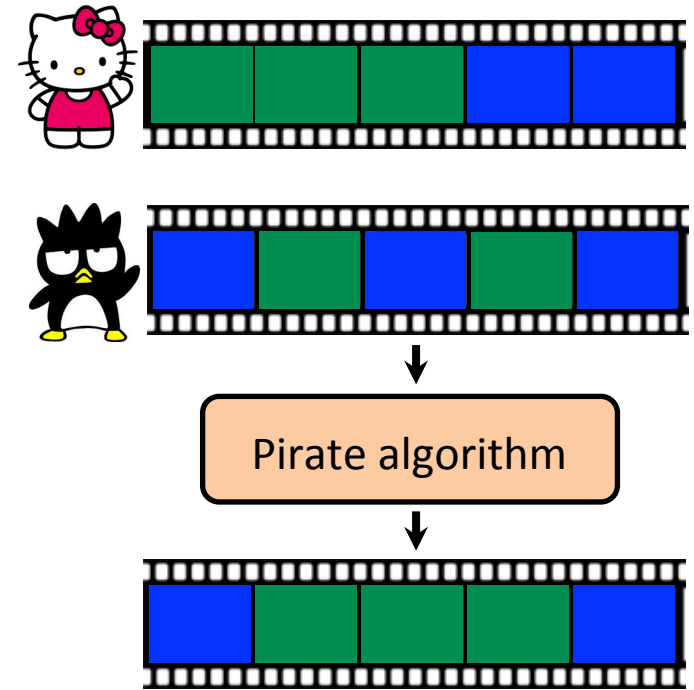
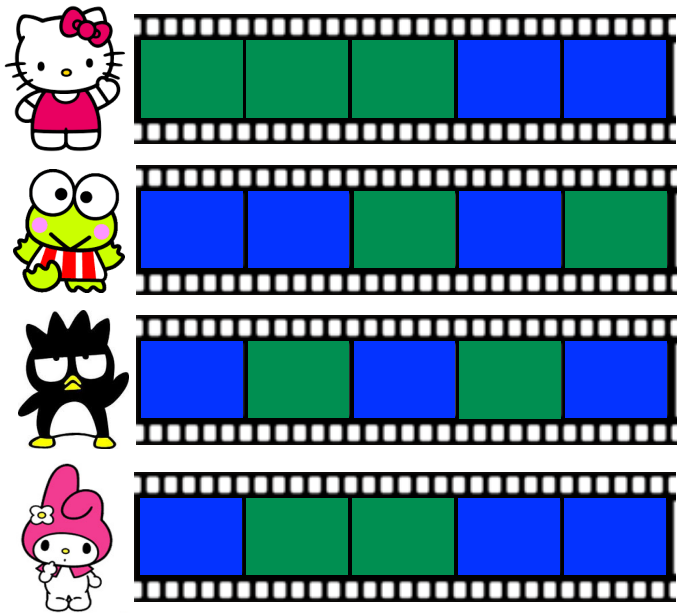


...but Sanriotown is full of pirates!

# Fingerprinting Codes [Boneh-Shaw95]

I want to distribute my new movie

Hello Kitty's  
Gradient Descent



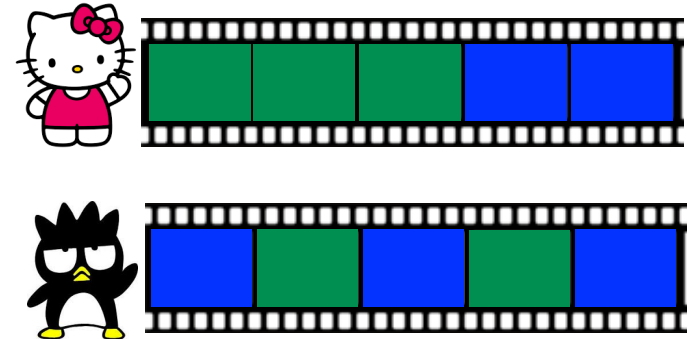
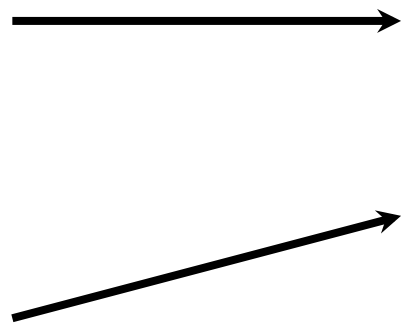
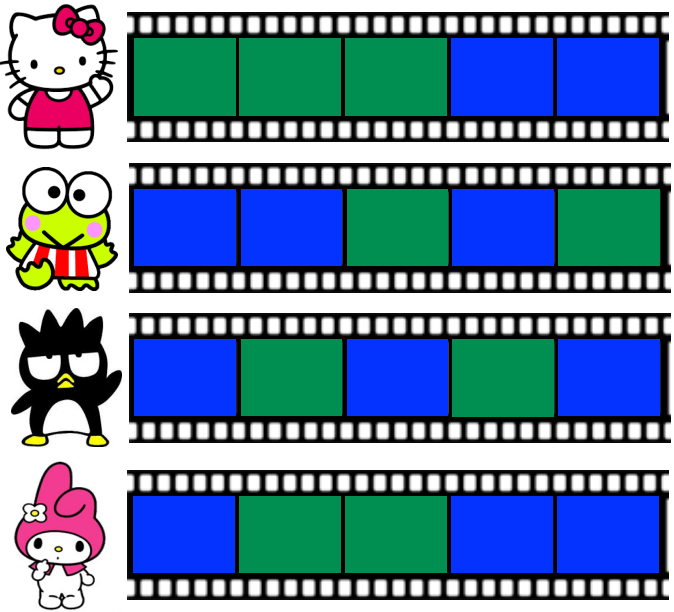
...but Sanriotown is full of pirates!

Who collude against me!

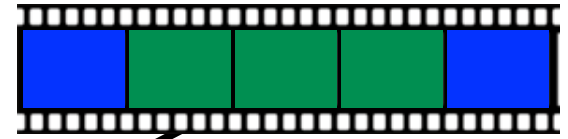
# Fingerprinting Codes [Boneh-Shaw95]

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Pirate algorithm

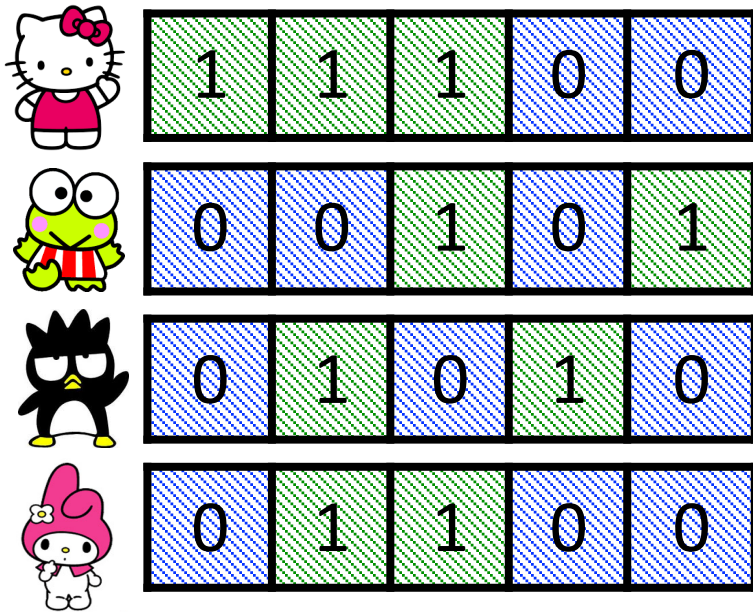


Trace algorithm

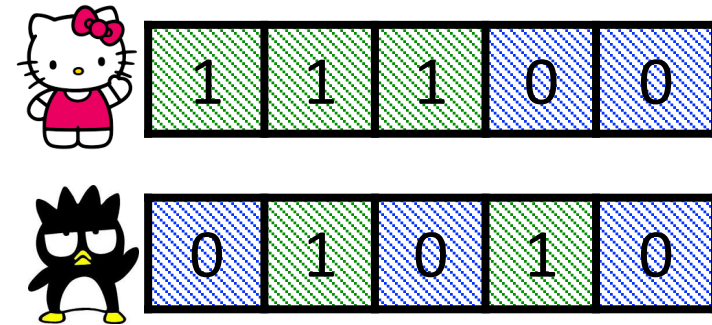


# Fingerprinting Codes [Boneh-Shaw95]

Gen( $1^n$ ) outputs  $C \in (\{0,1\}^d)^n$



Pirate coalition  $S \subseteq [n]$



Pirate algorithm



Feasible pirate codeword  $w$

Trace algorithm

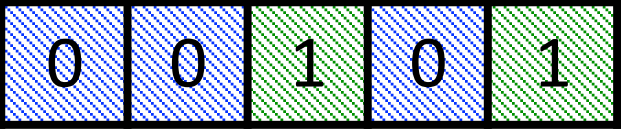
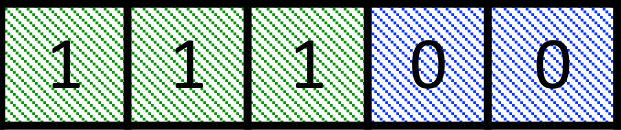


For all coalitions  $S$  and all pirate alg. for producing  $w$ ,

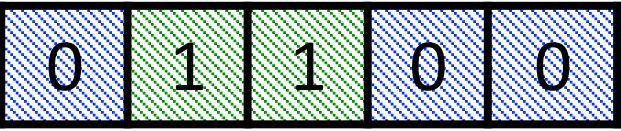
$$\Pr[\text{Trace}(w, C) \in S] \approx 1$$

# FP Codes vs. Diff. Privacy

Coalition of  $n$  pirates



⋮



Feasible pirate codeword  $w$



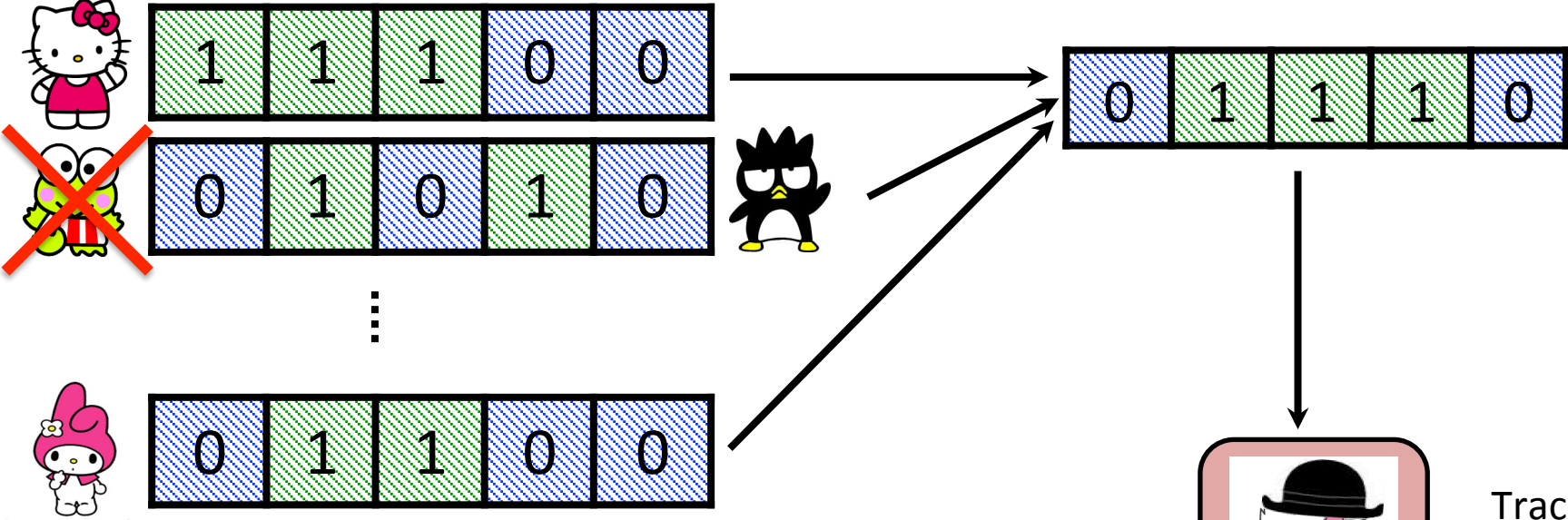
Trace Algorithm

$$\Pr[\text{Trace}(w, C) = \text{Frog}] \geq 1/n$$



# FP Codes vs. Diff. Privacy

Coalition of  $n$  pirates



$$\Pr[\text{Trace}(w, C) = \text{frog}] \ll 1/n$$

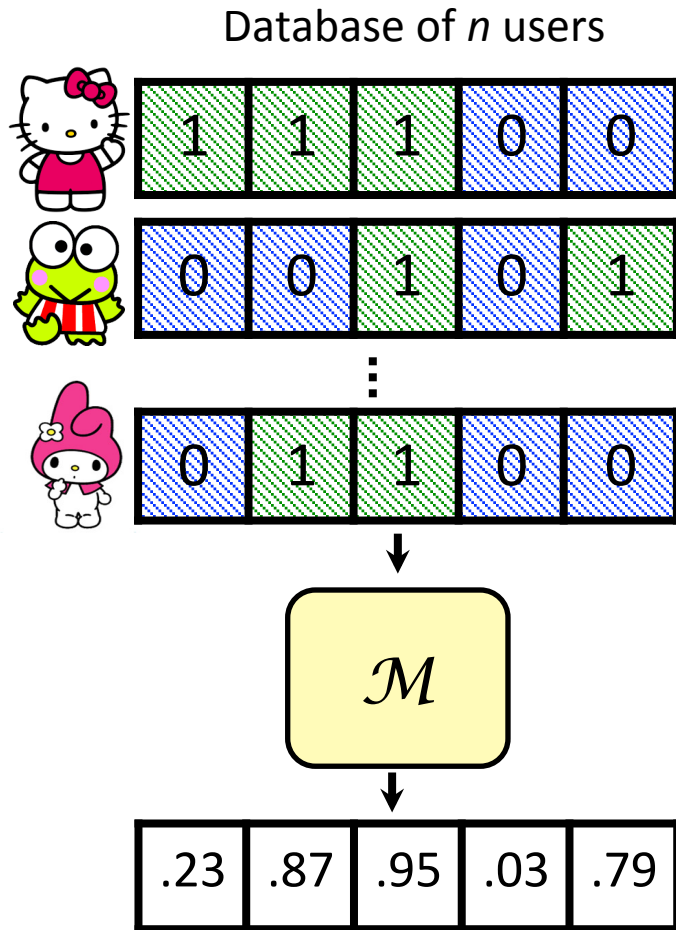
# FP Codes vs. Diff. Privacy

Trace behaves very differently depending on whether  is in the coalition



Fingerprinting codes are the “opposite” of differential privacy!

# Lower Bound for Attribute Means



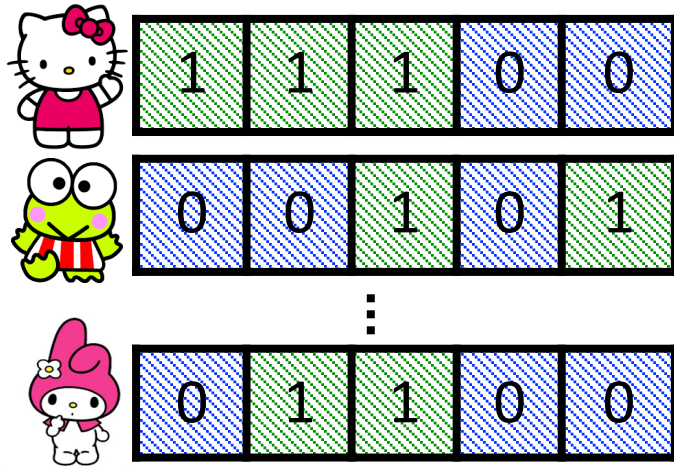
Suppose (for contradiction) we have

- A FP code of length  $k$  for  $(n+1)$  users
- A diff. private  $\mathcal{M}$  that is accurate for  $k$  attribute means

Reduction: Use  $\mathcal{M}$  to break security of the FP code

# Lower Bound for Attribute Means

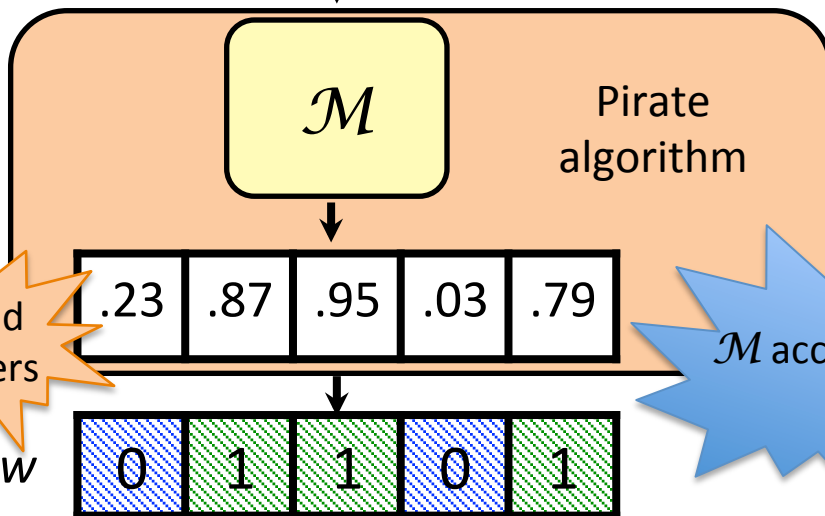
Database of  $n$  users = Coalition of  $n$  pirates



Suppose (for contradiction) we have

- A FP code of length  $k$  for  $(n+1)$  users
- A diff. private  $\mathcal{M}$  that is accurate for  $k$  attribute means

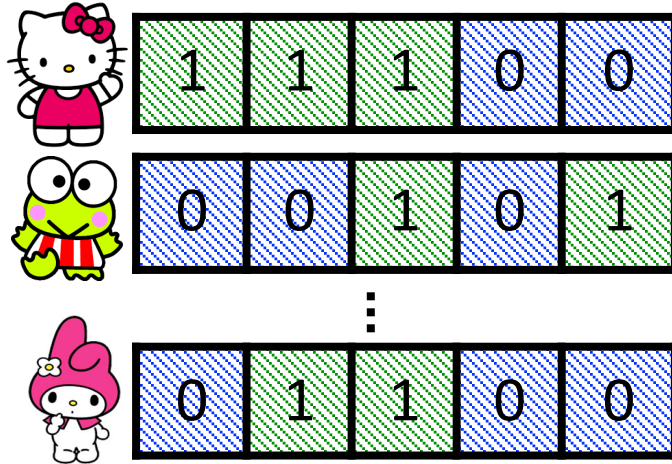
Reduction: Use  $\mathcal{M}$  to break security of the FP code



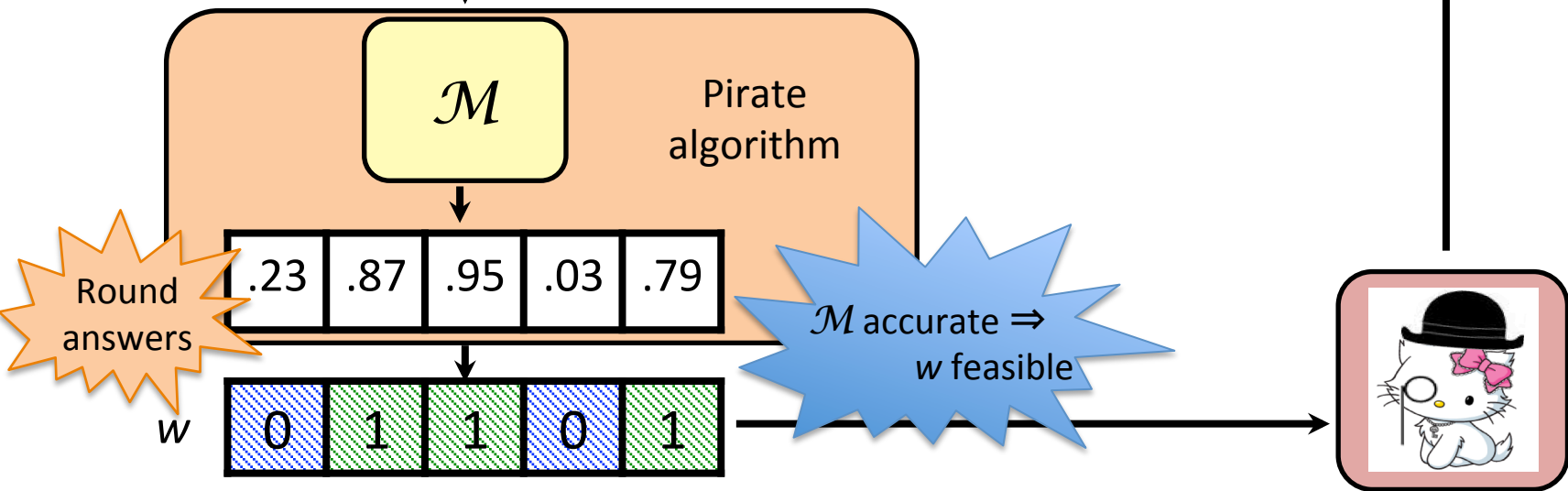
$\mathcal{M}$  accurate  $\Rightarrow$   $w$  feasible

# Lower Bound for Attribute Means

Database of  $n$  users = Coalition of  $n$  pirates

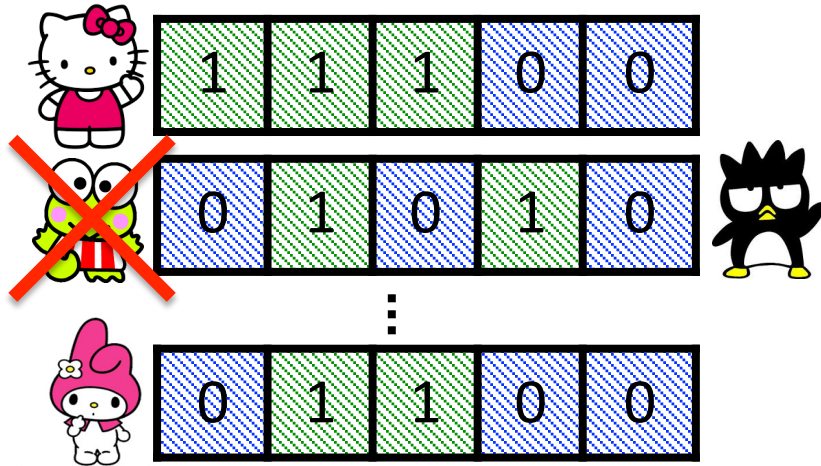


$$\Pr[\text{Trace}(w) = \text{frog}] \geq 1/n$$



# Lower Bound for Attribute Means

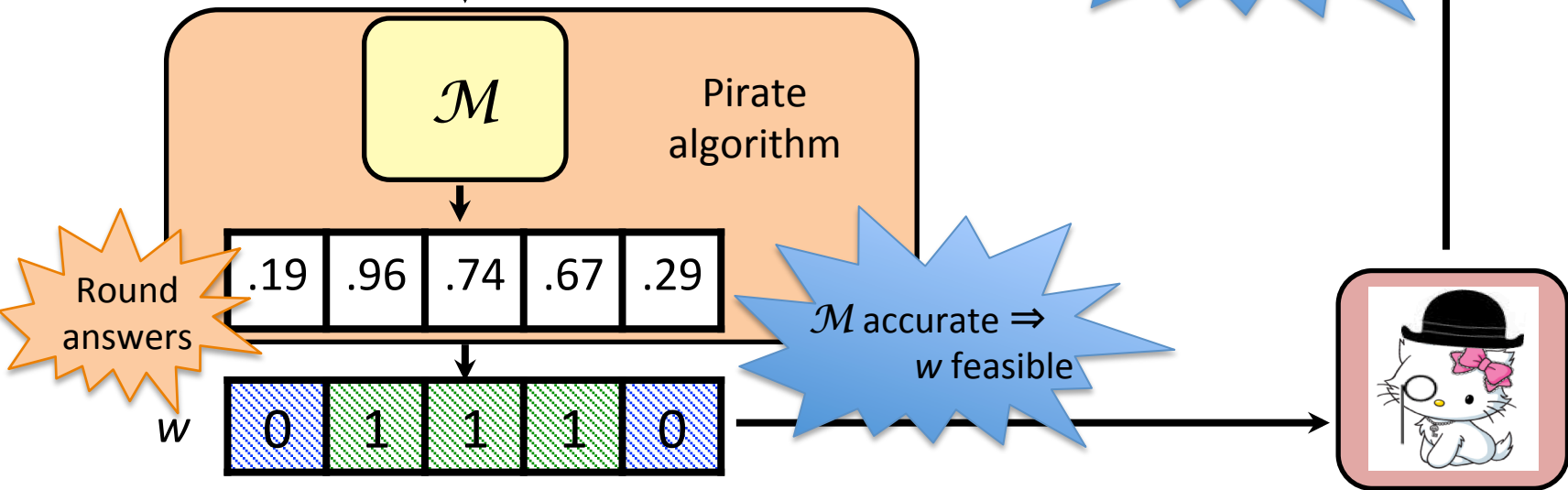
Database of  $n$  users = Coalition of  $n$  pirates



Contradicts security of FP code!

$$\Pr[\text{Trace}(w) = \text{Frog}] \geq \frac{(1/n) - \delta}{1 + \varepsilon}$$

$$\mathcal{M} \text{ private} \Rightarrow \text{Trace fails} \geq \frac{1}{3n}$$



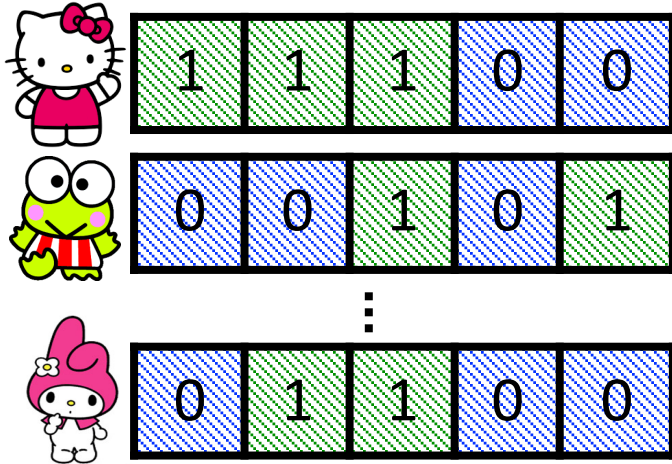
# Lower Bound for Attribute Means

- $\exists$  FP code for  $n$  users with length  $k$   
 $\Rightarrow n$  samples enables  $< k$  attribute means
- [Tardos03]  $\exists$  FP code for  $n$  users of length  $k = O(n^2)$   
 $\therefore$  attribute means require  $k \leq O(n^2)$

Next: How to embed attribute means into online prefix queries

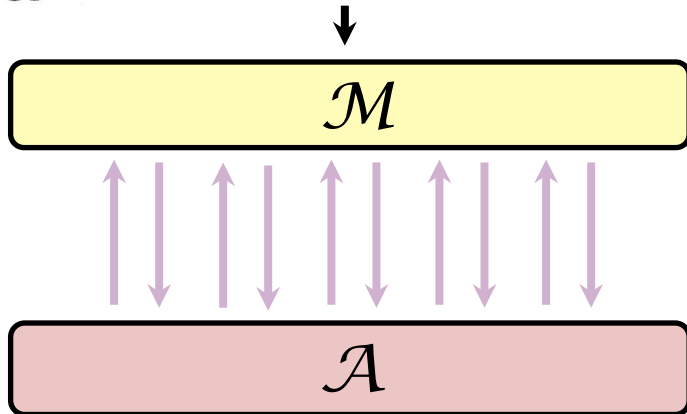
# Lower Bound for Prefix Queries

Database of  $n$  users



Suppose  $\mathcal{M}$  can answer  $k$  prefix queries presented online

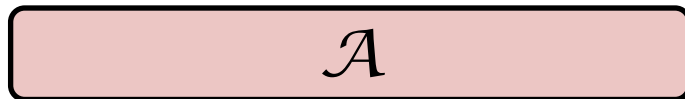
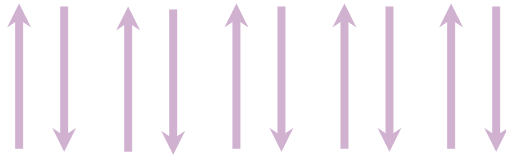
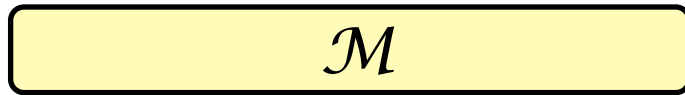
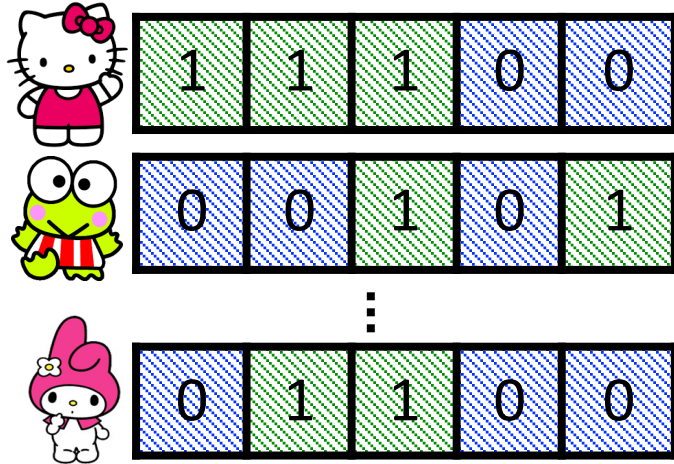
Reduction: Use  $\mathcal{M}$  to answer  $k$  attribute mean queries





# Lower Bound for Prefix Queries

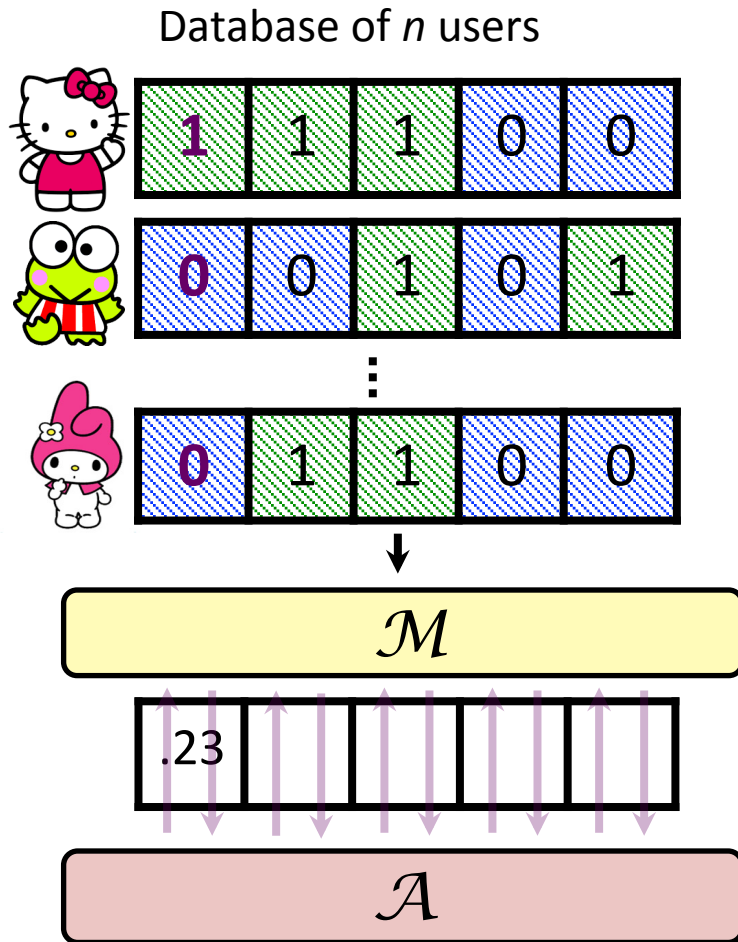
Database of  $n$  users



Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

# Lower Bound for Prefix Queries

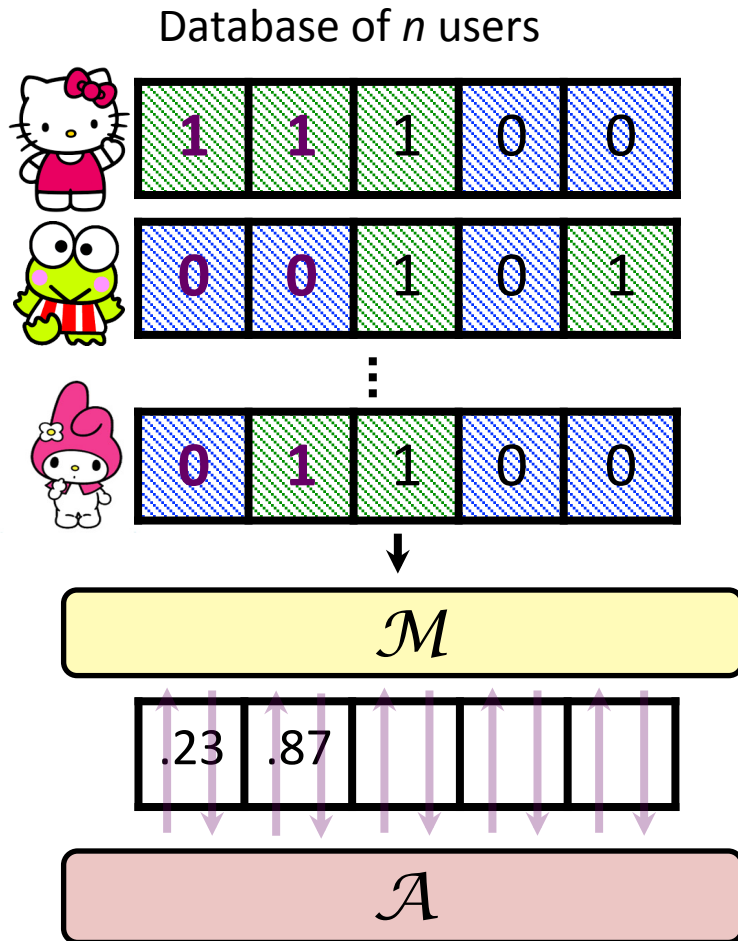


Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

$$S_1 = \{1, 1, \dots, 1\}$$

# Lower Bound for Prefix Queries



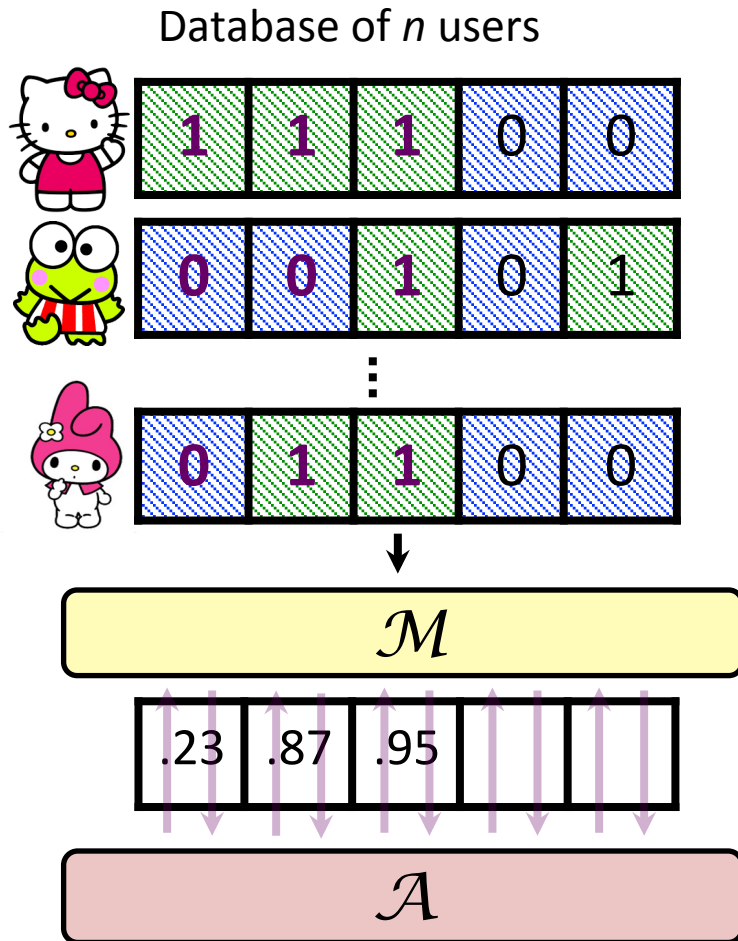
Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

$$S_1 = \{1, 1, \dots, 1\}$$

$$S_2 = \{11, 01, \dots, 01\}$$

# Lower Bound for Prefix Queries



## Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

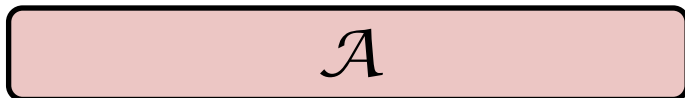
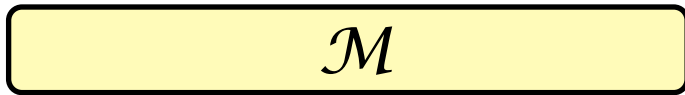
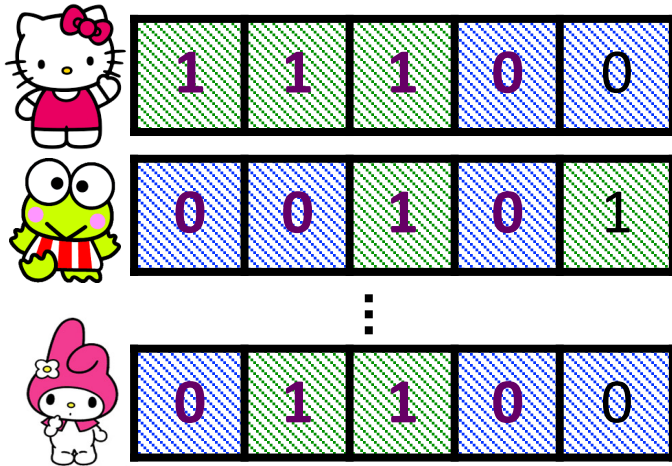
$$S_1 = \{1, 1, \dots, 1\}$$

$$S_2 = \{11, 01, \dots, 01\}$$

$$S_3 = \{111, 001, \dots, 011\}$$

# Lower Bound for Prefix Queries

Database of  $n$  users



Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

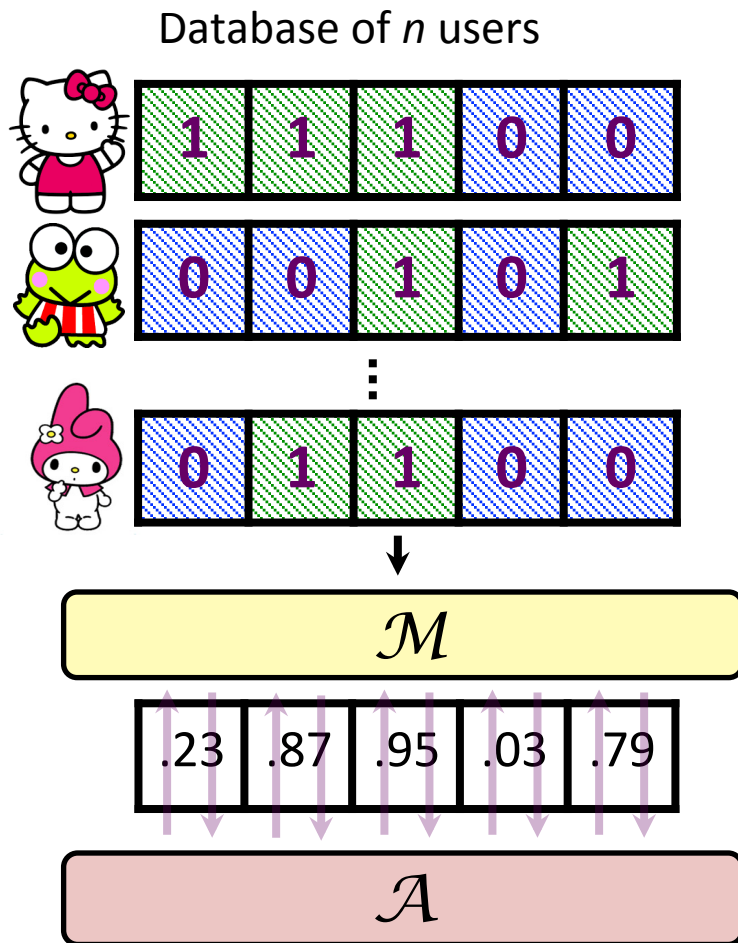
$$S_1 = \{1, 1, \dots, 1\}$$

$$S_2 = \{11, 01, \dots, 01\}$$

$$S_3 = \{111, 001, \dots, 011\}$$

$$S_4 = \{1111, 0011, \dots, 0111\}$$

# Lower Bound for Prefix Queries



## Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

$$S_1 = \{1, 1, \dots, 1\}$$

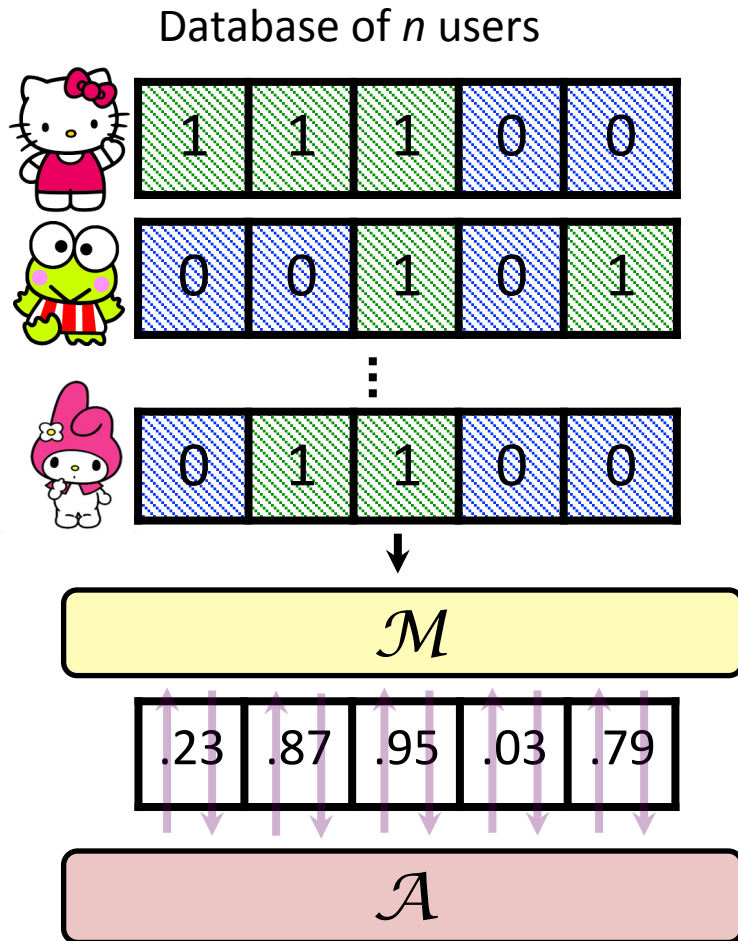
$$S_2 = \{11, 01, \dots, 01\}$$

$$S_3 = \{111, 001, \dots, 011\}$$

$$S_4 = \{1111, 0011, \dots, 0111\}$$

$$S_5 = \{11101, 00101, \dots, 01101\}$$

# Lower Bound for Prefix Queries



## Queries:

Recall  $q_S(x) = 1$  iff  $\exists y \in S$  that is a prefix of  $x$

$$S_1 = \{1, 1, \dots, 1\}$$

$$S_2 = \{C_{1,1}1, \dots, C_{n+1,1}1\}$$

$$S_3 = \{C_{1,1}C_{1,2}1, \dots, C_{n+1,1}C_{n+1,2}1\}$$

$$S_4 = \{C_{1,1}C_{1,2}C_{1,3}1, \dots\}$$

...

Fact 1:  $q_j(D) = j^{\text{th}}$  attribute mean

Fact 2:  $q_1, \dots, q_{j-1}$  reveal nothing about  $q_j$

(But  $q_j$  reveals answers to  $q_1, \dots, q_{j-1}$ !)

# Lower Bound for Prefix Queries

- $n$  samples suffice for  $k$  online prefix queries  
     $\Rightarrow n$  samples suffice for  $k$  attribute means\*
- Attribute mean lower bound  $k = O(n^2)$   
     $\therefore$  online prefix queries require  $k \leq O(n^2)$   
    (Even for  $d = O(n^2)$ )

\*Not quite black-box use of FPCs / attribute mean lower bound, but follows from FP code analysis of [Steinke-Ullman15, Dwork-Smith-Steinke-Ullman-Vadhan15]



# Our Results

All three models are distinct

- **Offline  $\neq$  Online**

Family  $Q_{\text{prefix}}$  of counting queries

**Offline:** Can answer  $k = \exp(\Omega(n^{1/2}))$  queries

**Online:** Can only answer  $k = O(n^2)$  queries

- **Online  $\neq$  Adaptive**

Family  $Q_{\text{corr}}$  of “search” queries

**Online:**  $k = \exp(\Omega(n))$  queries      **Adaptive:**  $k = O(1)$  queries

# Online vs. Adaptive (Idea)

$$Q_{\text{corr}} = \{ q_S : \{0,1\}^n \rightarrow \{0,1\} \}$$

\*Not counting queries\*

For  $S = \{y_1, \dots, y_m \in \{0,1\}^n\}$  and  $x \in \{0,1\}^n$ :

“Find me a vector  $z \in \{0,1\}^n$  that is highly correlated with  $x$ , but not too correlated with any  $y_j$ ”

## Intuition

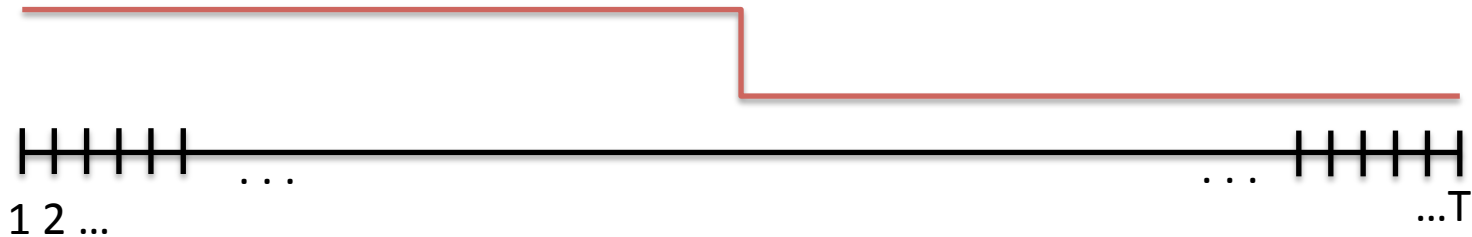
**Online:** Randomized response [Warner65] – Choose  $z$  once and for all with  $z_i = \text{Round}(x_i + \text{Noise}(1/\epsilon))$

**Adaptive:** Picking queries strategically enables a reconstruction attack

# Conclusions

- To answer many queries with differential privacy, it can help to “make up your mind”
- Open questions:
  - Can counting queries separate online vs. adaptive?
  - Are there *natural* tasks that separate these models?

Some evidence for one-dimensional thresholds



**Thank you!**