

# Randomized Algorithms for Tracking Distributed Count, Frequencies, and Ranks

Zengfeng Huang, Ke Yi

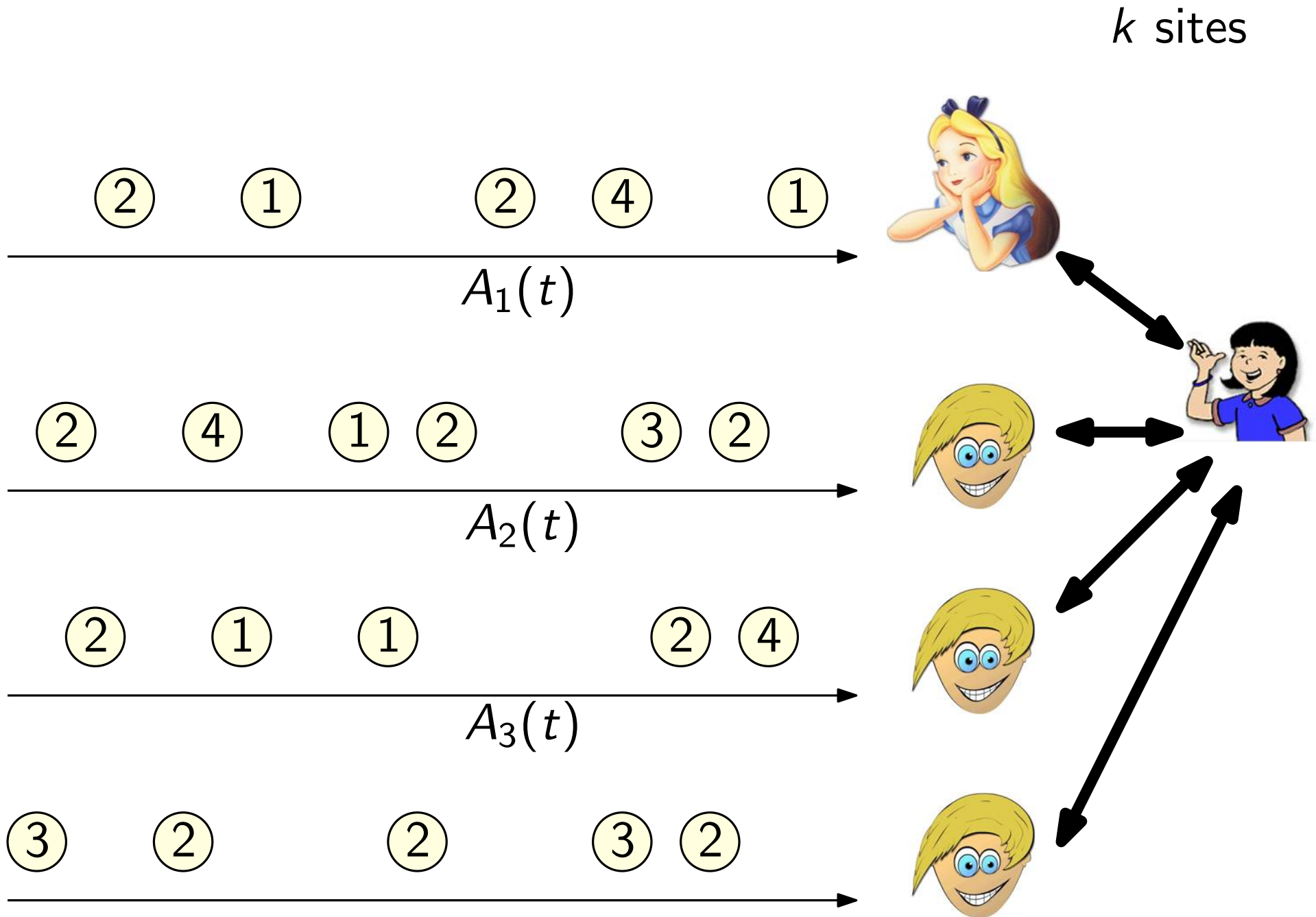
HKUST

Qin Zhang

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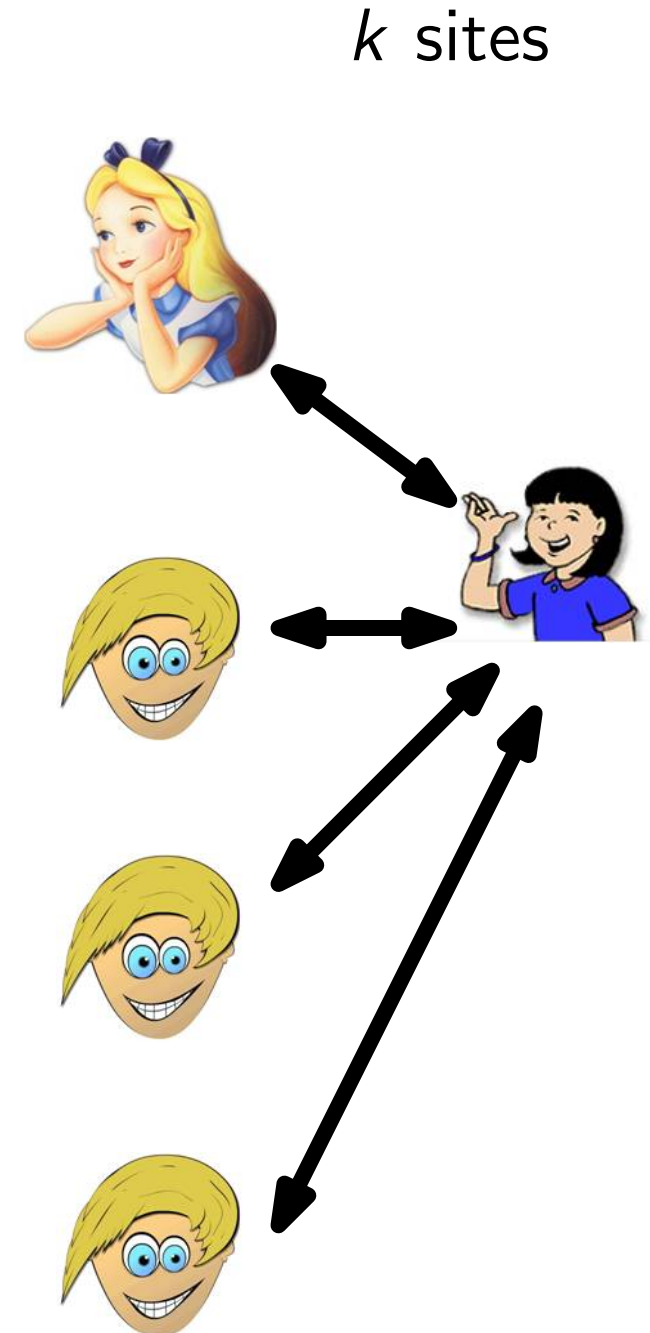
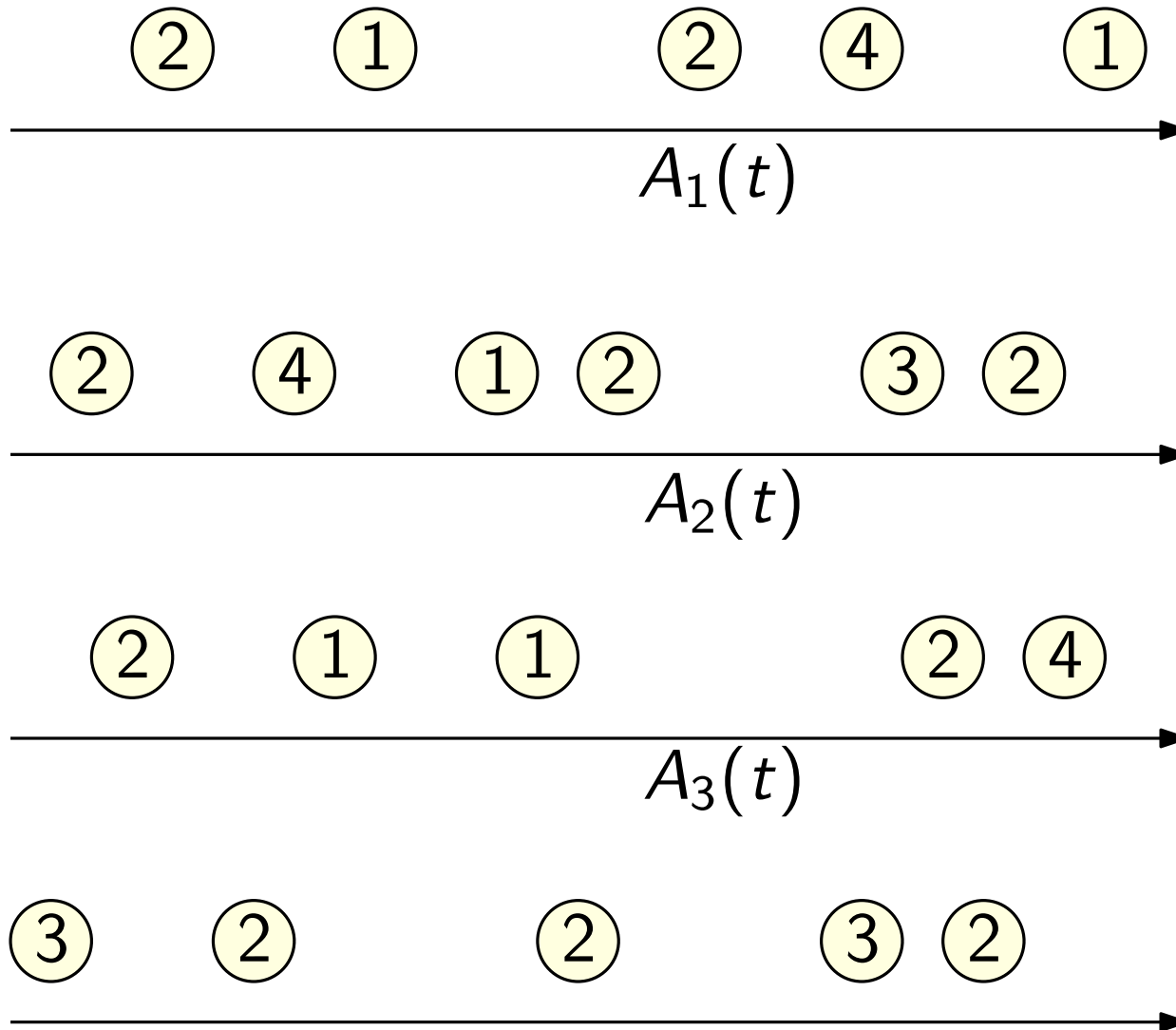
PODS'12

# The Model

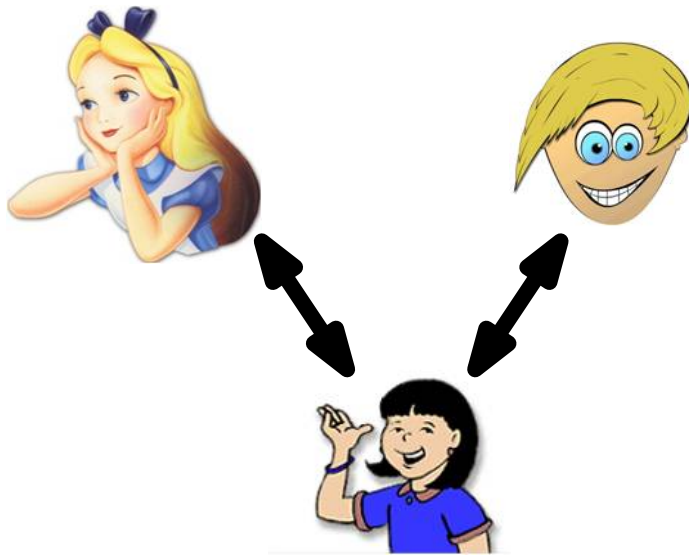
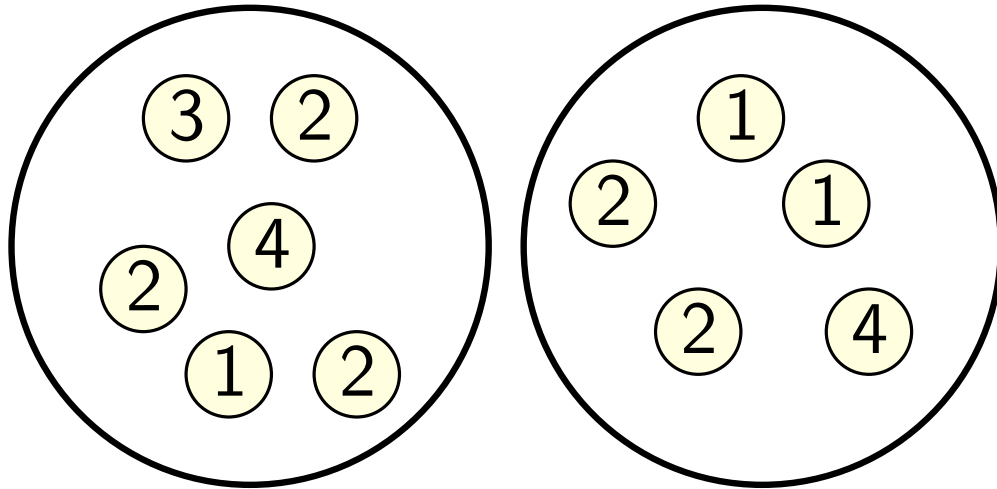


# The Model

Coordinator tries to compute  
 $f(A_1(t) \uplus A_2(t) \cdots A_k(t))$  for all  $t$

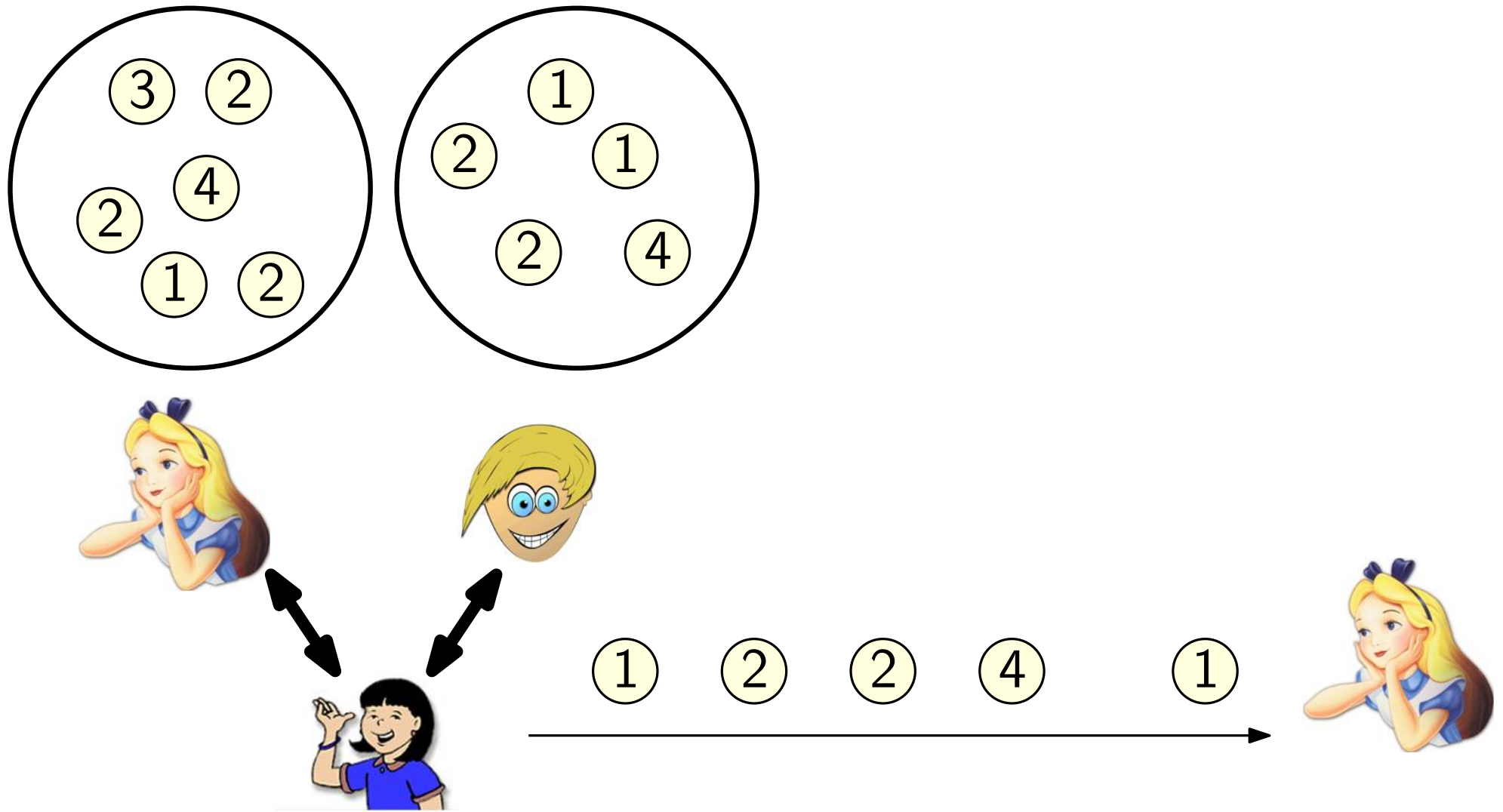


# Generalization of Two Models



Communication model  
(One-shot model)

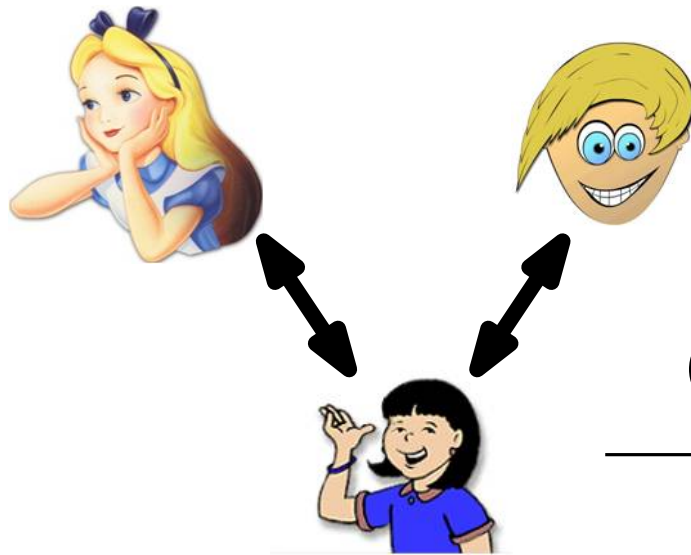
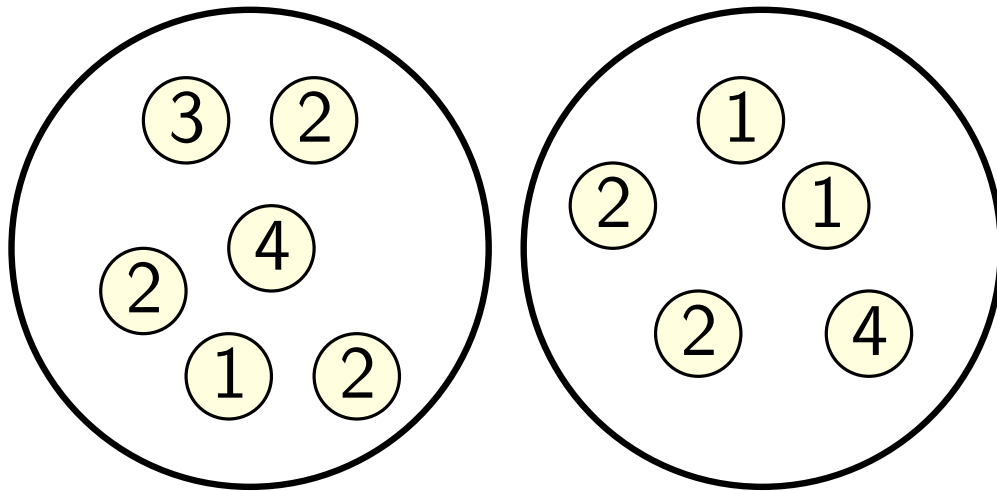
# Generalization of Two Models



Communication model  
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Data stream model

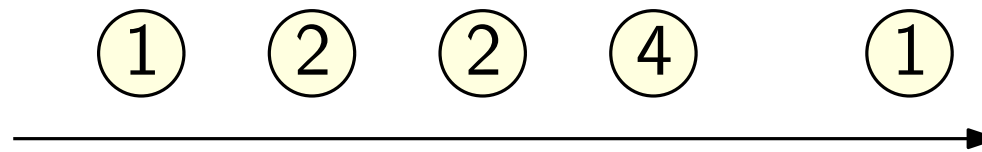
# Generalization of Two Models



Communication model  
(One-shot model)

## Goal

- Communication cost
- Space



Data stream model

# Warm Up: Count tracking

$$f(A) = |A(t)| \quad (\text{Trivial in previous models})$$

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$$f(A) = |A(t)| \quad (\text{Trivial in previous models})$$

Let  $n_i = A_i(t)$  be the local count

Track  $n = \sum_i n_i$  continuously within additive error  $\varepsilon n$  at any time



# Count tracking

Communication:  $O(k/\varepsilon \cdot \log n)$

Space per site:  $O(1)$

Tight

[Yi, Zhang, PODS'09]

# Count tracking

Communication:  $O(k/\varepsilon \cdot \log n)$   
Space per site:  $O(1)$   
Tight

[Yi, Zhang, PODS'09]

Communication:  $O(\sqrt{k}/\varepsilon \cdot \log n)$   
Space per site:  $O(1)$   
Tight

New

# Deterministic

Each site sets some thresholds

Sends a message when  $n_i$  exceed a threshold

$t_3$ —

$t_2$ —

$t_1$ —

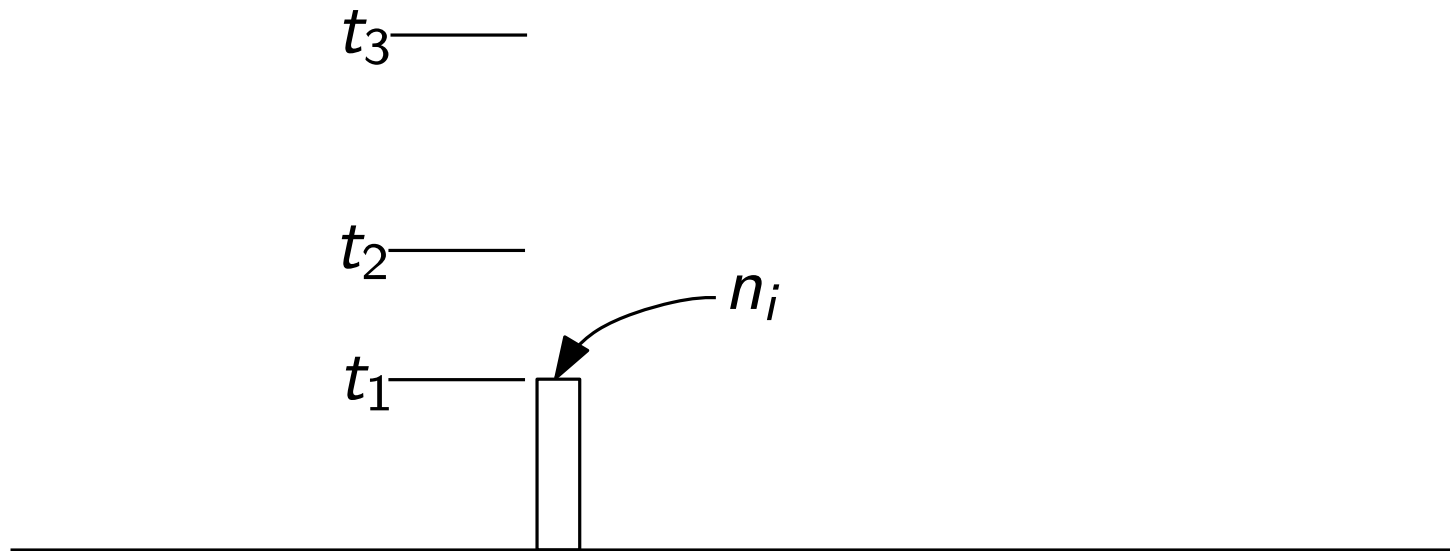
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[Yi, Zhang, PODS'09]

# Deterministic

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Sends a message when  $n_i$  exceed a threshold

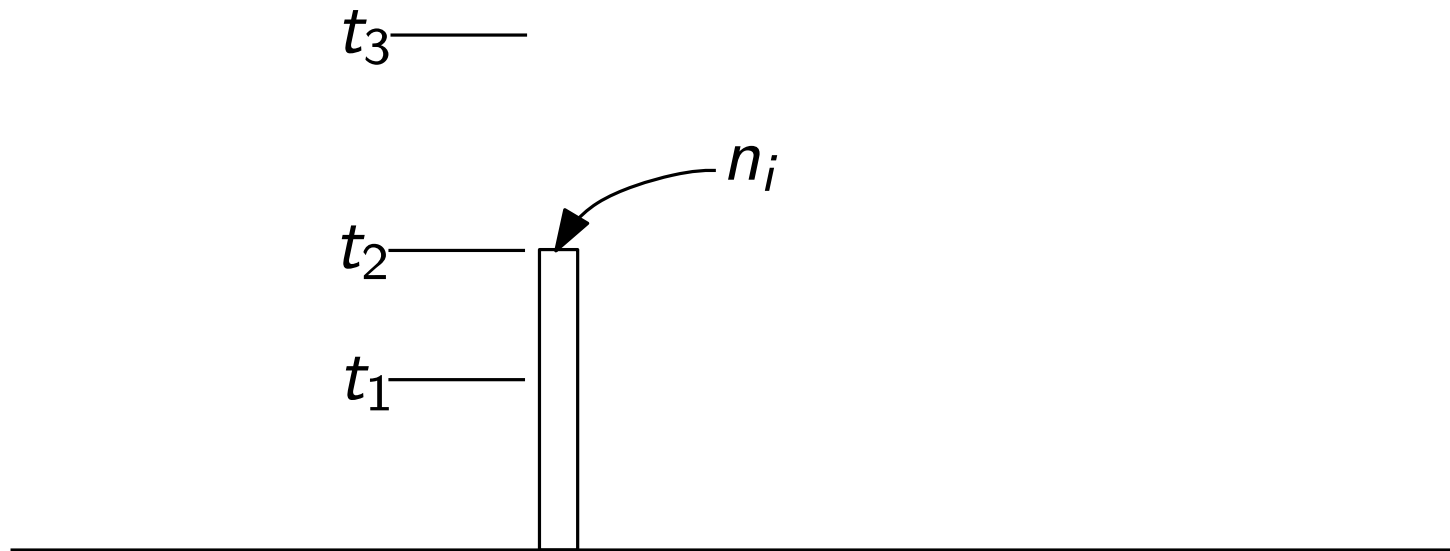


[Yi, Zhang, PODS'09]

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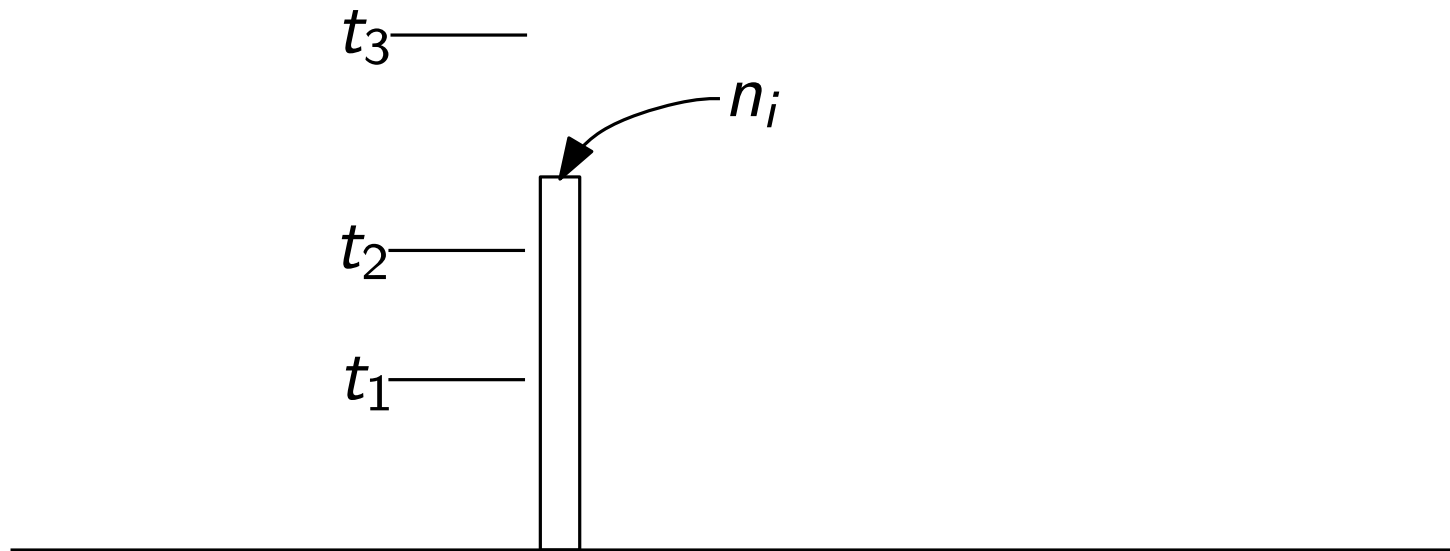


[Yi, Zhang, PODS'09]

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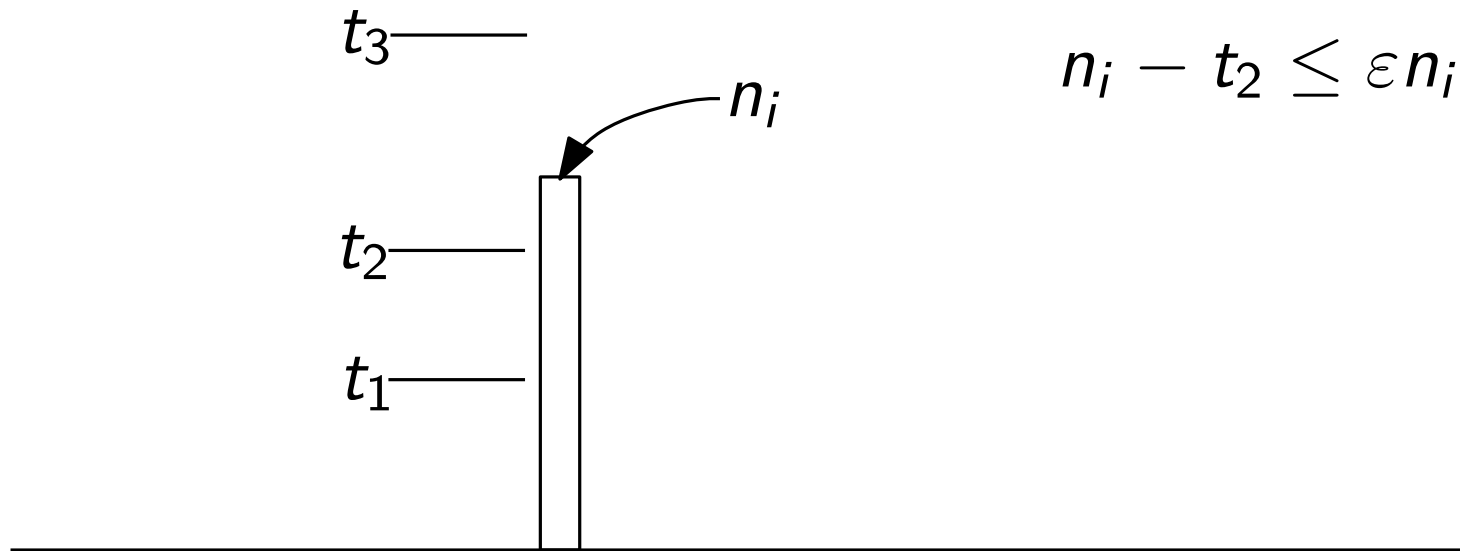


[Yi, Zhang, PODS'09]

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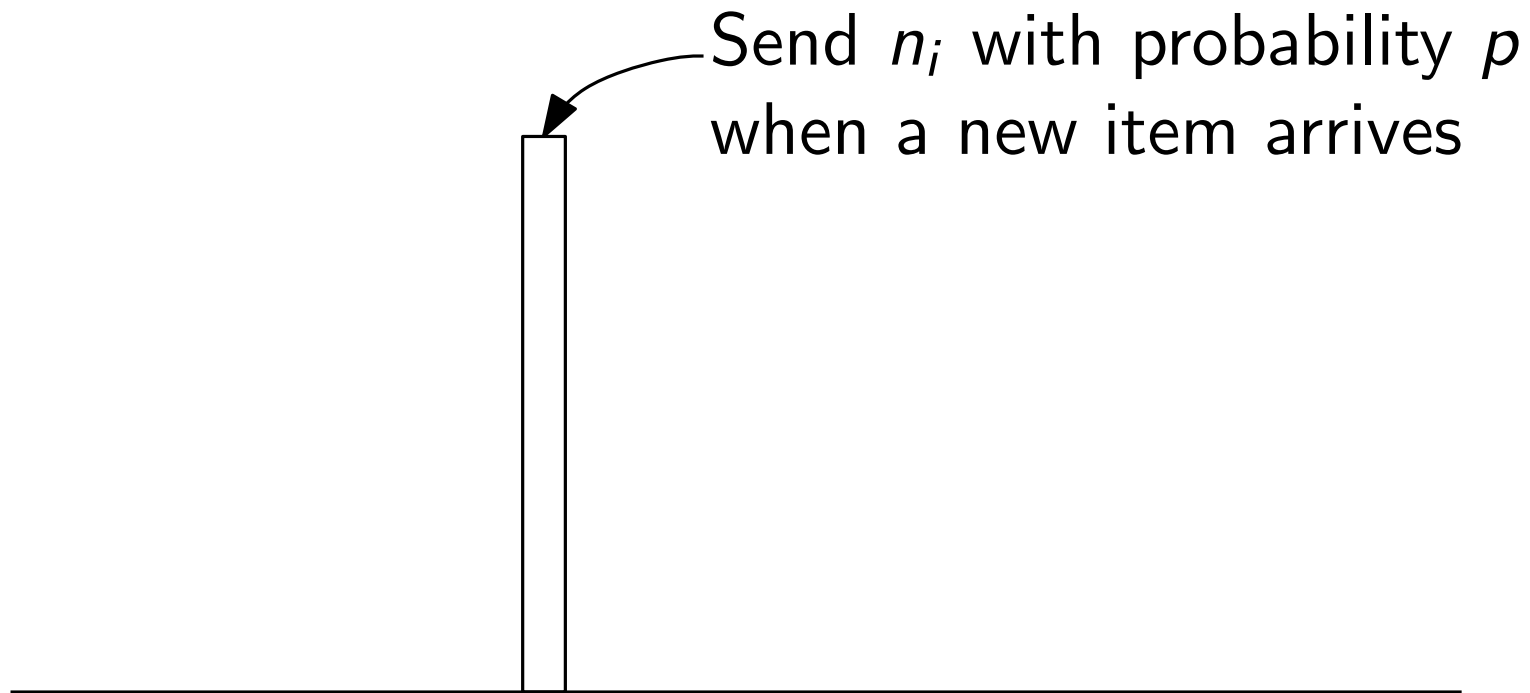
Sends a message when  $n_i$  exceed a threshold



[Yi, Zhang, PODS'09]

# Randomized algorithm

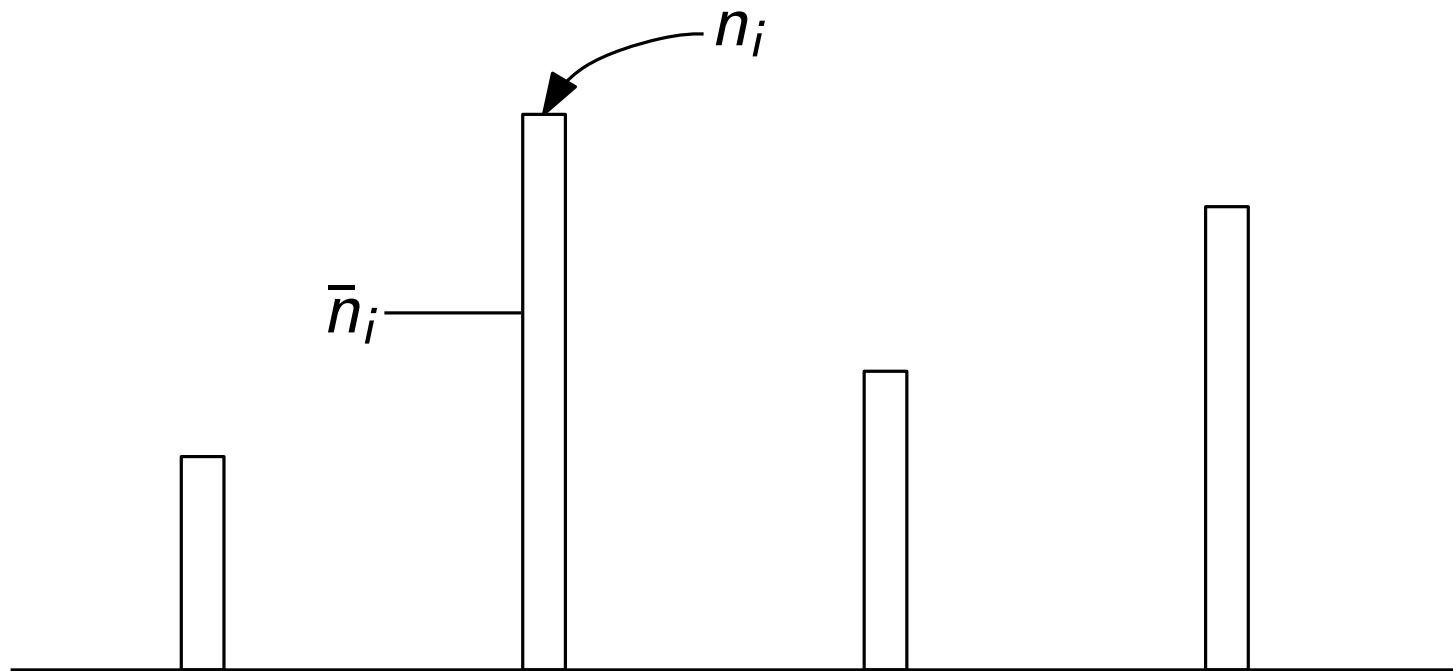
Make decision based on random bits





# Analysis

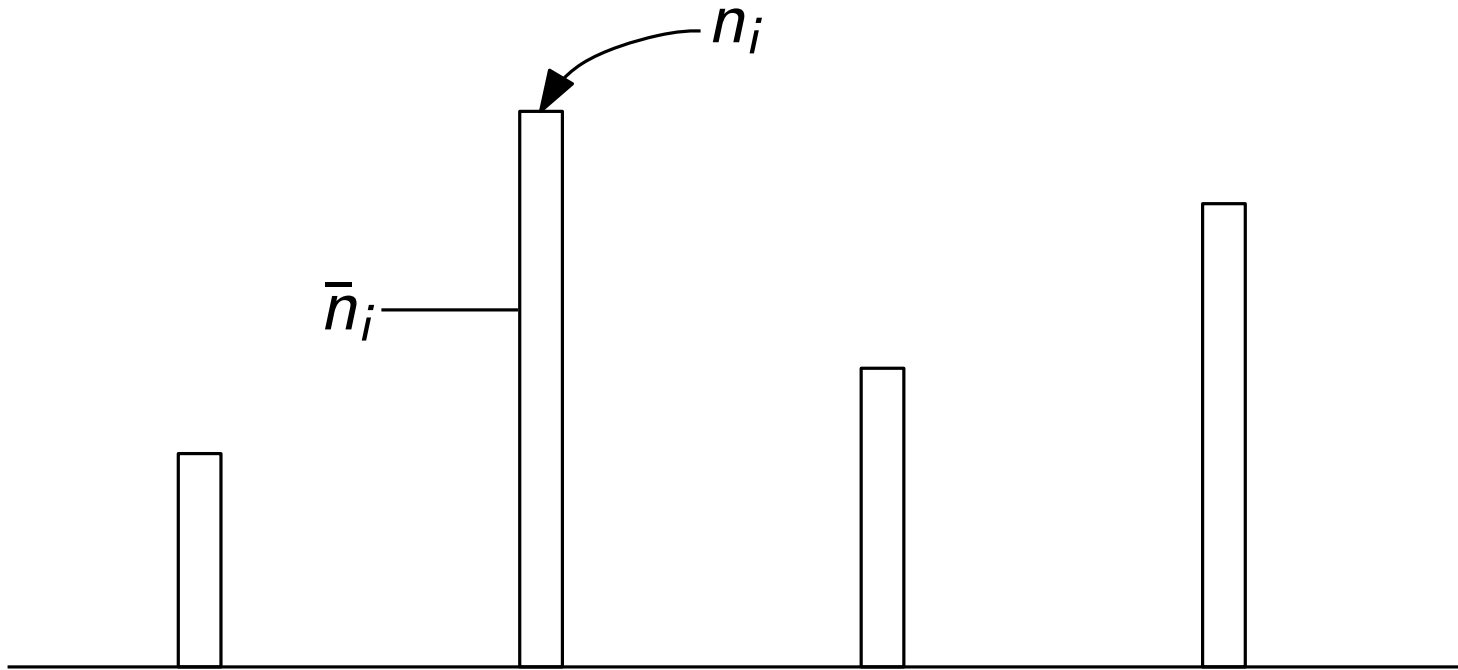
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# Analysis

$n_i - \bar{n}_i$  is a random variable

$$\hat{n}_i = \begin{cases} \bar{n}_i - 1 + 1/p, & \text{if } t > 0; \\ 0, & \text{else.} \end{cases}$$



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$$E[\hat{n}_i] = n_i, \text{Var}[\hat{n}_i] = 1/p^2$$

$$\hat{n} = \sum \hat{n}_i$$

$$E[\hat{n}] = \sum \hat{n}_i = n, \text{Var}[\hat{n}] = k/p^2$$

# Rounds

## Chebyshev

SD less than  $\varepsilon n \rightarrow p = O(\sqrt{k}/\varepsilon n)$   
constant probability of success

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SD less than  $\varepsilon n \rightarrow p = O(\sqrt{k}/\varepsilon n)$   
constant probability of success

- Track a 2-approximation  $\bar{n}$  of  $n$ 
  - Broadcast  $\bar{n}$  whenever  $\bar{n}$  doubles
  - Set  $p = \frac{\sqrt{k}}{2\bar{n}}$
- Divide the tracking period into rounds
  - $n$  approximately doubles in a round
  - $p$  is fixed in a round

# Rounds

- Communication cost
  - Tracking a constant approximation  $O(k \log n)$
  - number of messages in a round:  $O(np) = O(\sqrt{k}/\varepsilon)$
  - Total:  $O(k \log n + \sqrt{k}/\varepsilon \cdot \log n)$

# Randomized lower bound

One-way communication lower bound:  $\Omega(k/\varepsilon \cdot \log n)$



# Randomized lower bound

One-way communication lower bound:  $\Omega(k/\varepsilon \cdot \log n)$

- No global information
- Can not distinguish 2 extremes:
  1. Evenly distributed
  2. All the items arrive at one site

# Randomized lower bound

Communication lower bound:  $\Omega(\sqrt{k}/\varepsilon \cdot \log n)$

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## 1-BIT problem

Set  $s$  to  $k/2 + \sqrt{k}$  or  $k/2 - \sqrt{k}$  randomly

Randomly pick  $s$  sites with input 1, others 0

Goal: determine  $s$

# Randomized lower bound

## Lemma

Any deterministic algorithm that solves 1-bit problem has communication cost  $\Omega(k)$

# Randomized lower bound

## Lemma

Any deterministic algorithm that solves 1-bit problem has communication cost  $\Omega(k)$

Main idea:

- Communicate less than  $o(k)$  bits, the uncertainty is still high
- The algorithm has good chance to make a mistake

# Randomized lower bound

## Hard input in round $i$

Divide the round into  $\frac{1}{\varepsilon\sqrt{k}}$  subrounds

In any subround  $r$ :

Set  $s$  to  $k/2 + \sqrt{k}$  or  $k/2 - \sqrt{k}$  randomly

Randomly pick  $s$  sites, send them  $2^i$  items each.

# Randomized lower bound

## Hard input in round $i$

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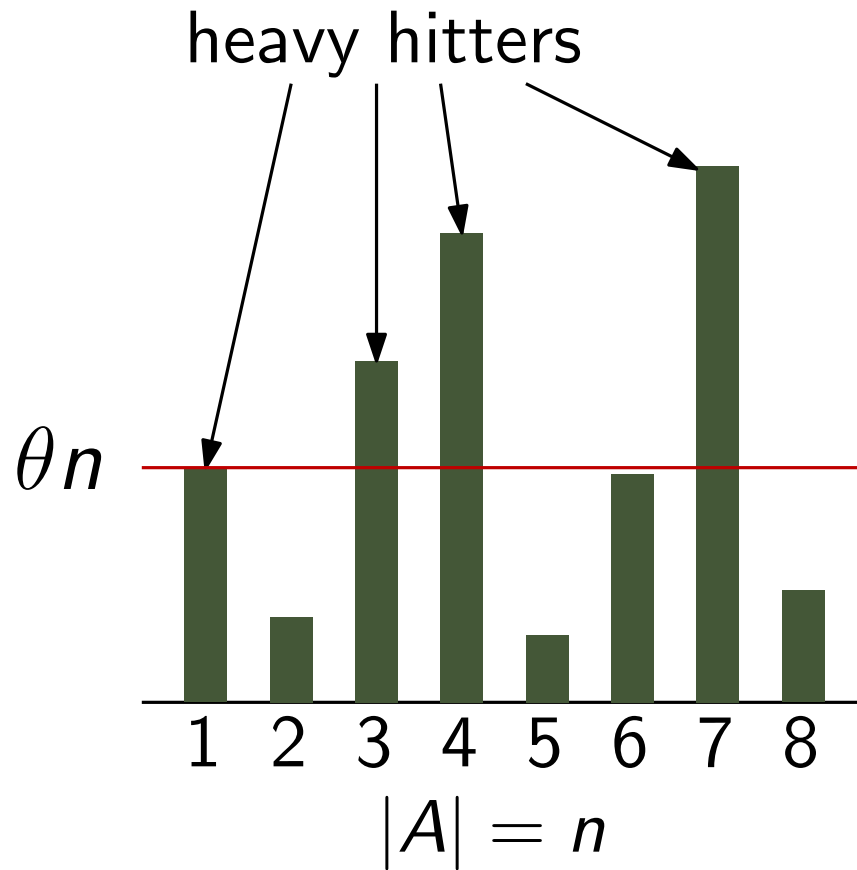
Cost in a subround is  $O(k)$ :

$$n \leq O(\sqrt{k}/\varepsilon \cdot 2^i)$$

$$\text{Error allowed: } O(\sqrt{k}2^i)$$

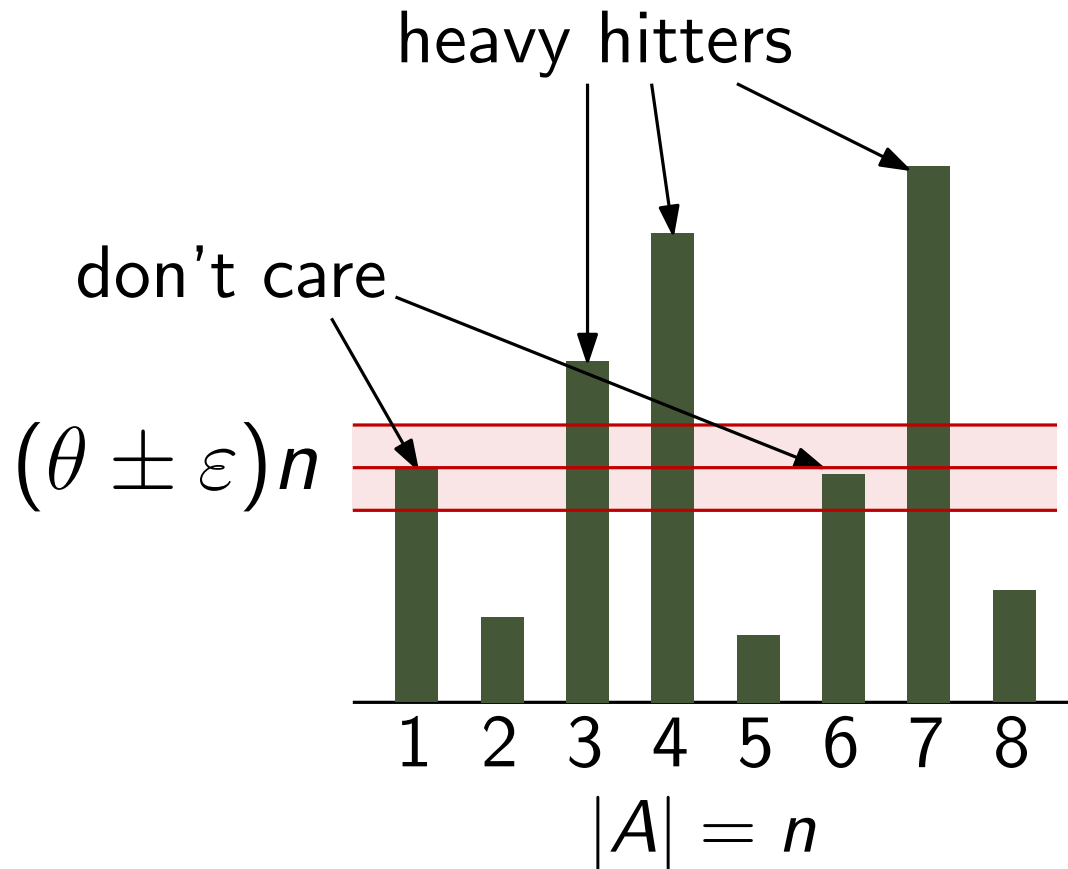
Cost in a round is  $O(\sqrt{k}/\varepsilon)$ :

# Frequent Items: Definition

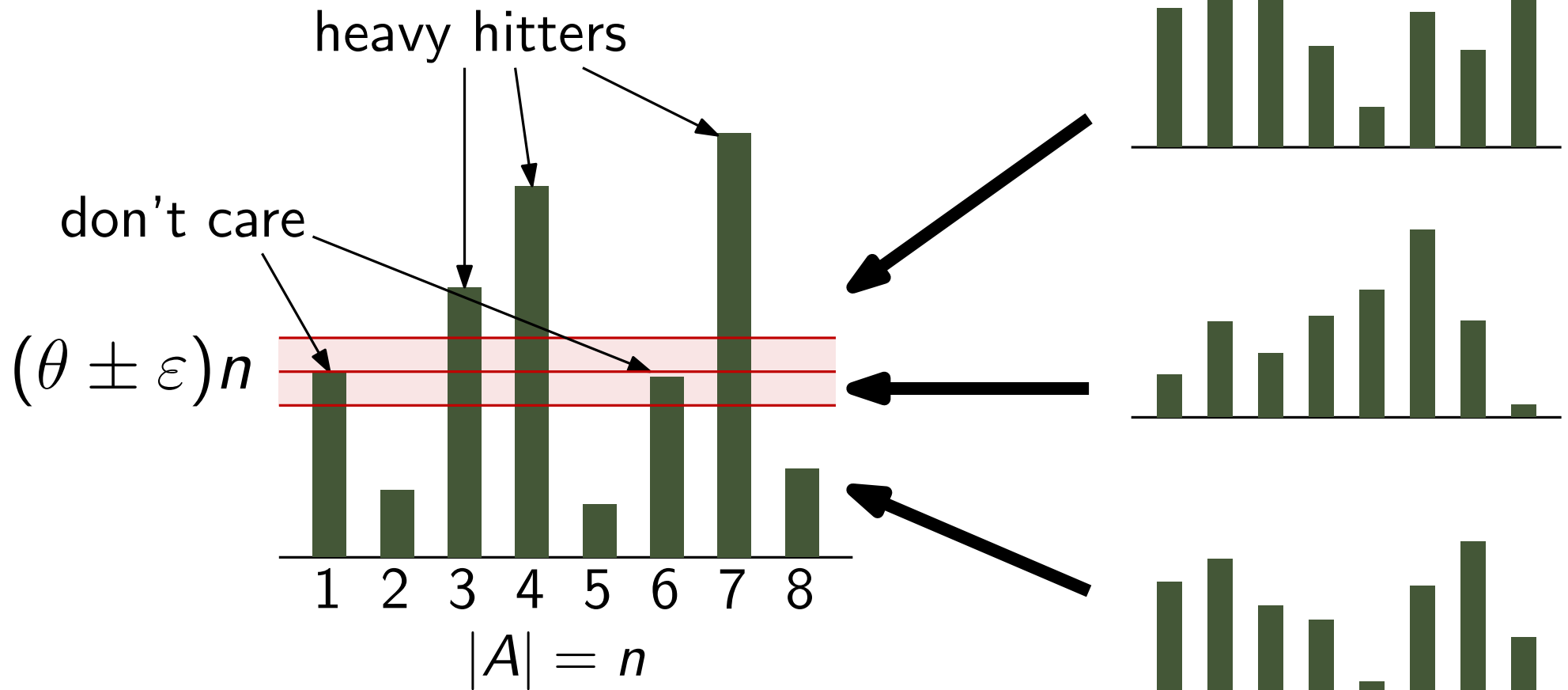




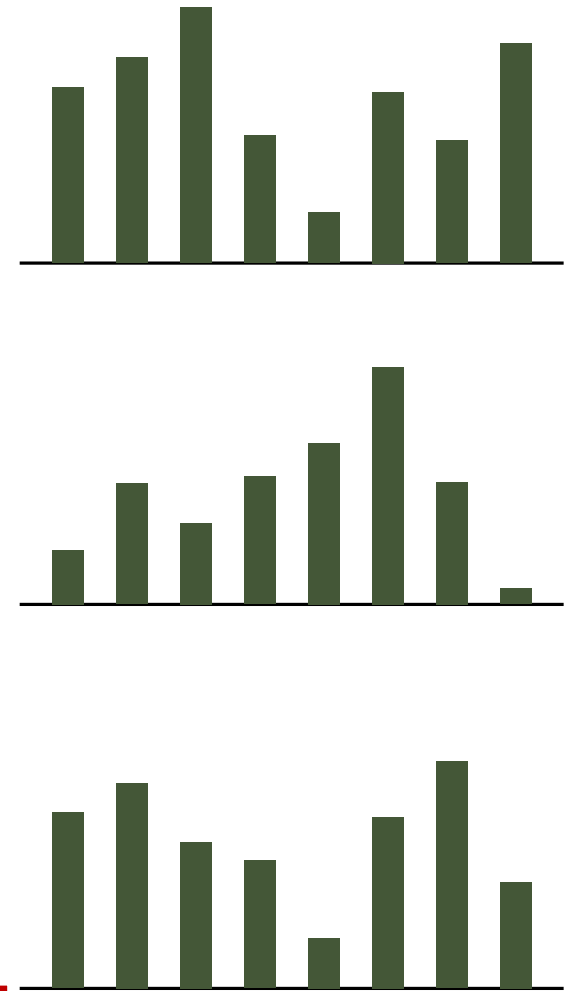
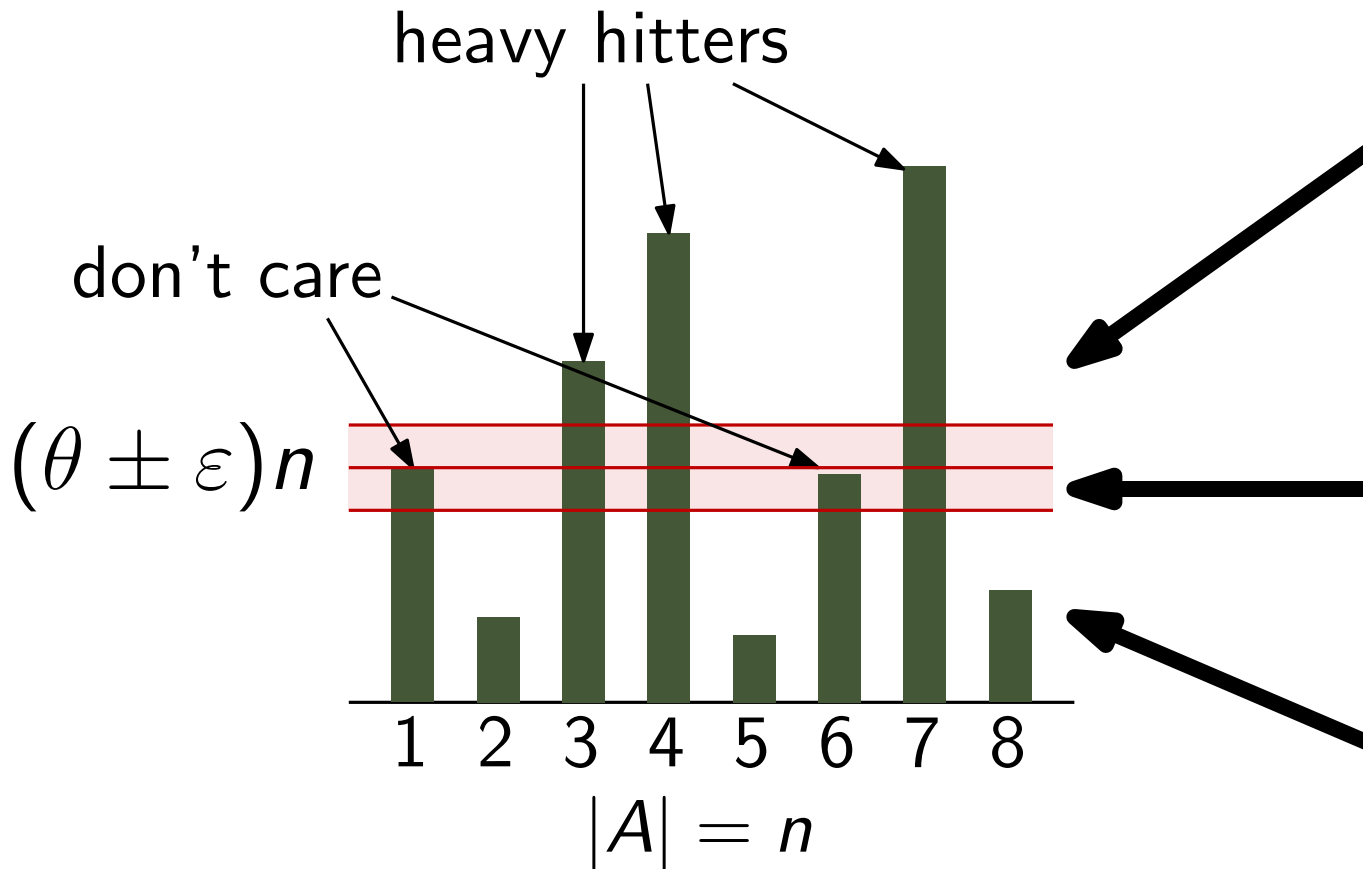
# Frequent Items: Definition



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# Frequent Items: Definition



## Frequency estimation with $F_1$ error

Estimate the frequency of every element with additive error  $\epsilon n$ .

# Frequent Items: Algorithm in a round

Use the previous algorithm on each item  $i$

- Maintain a count for each item at each site
- Space

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## Streaming algorithm

cost per site:  $O(1/\epsilon)$

- total:  $O(k/\epsilon)$
- improve to  $O(\sqrt{k}/\epsilon)$

# Frequent Items: algorithm

Idea: maintain only large enough counts

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$i$ :



Start to count  $i$  with  
probability  $p$

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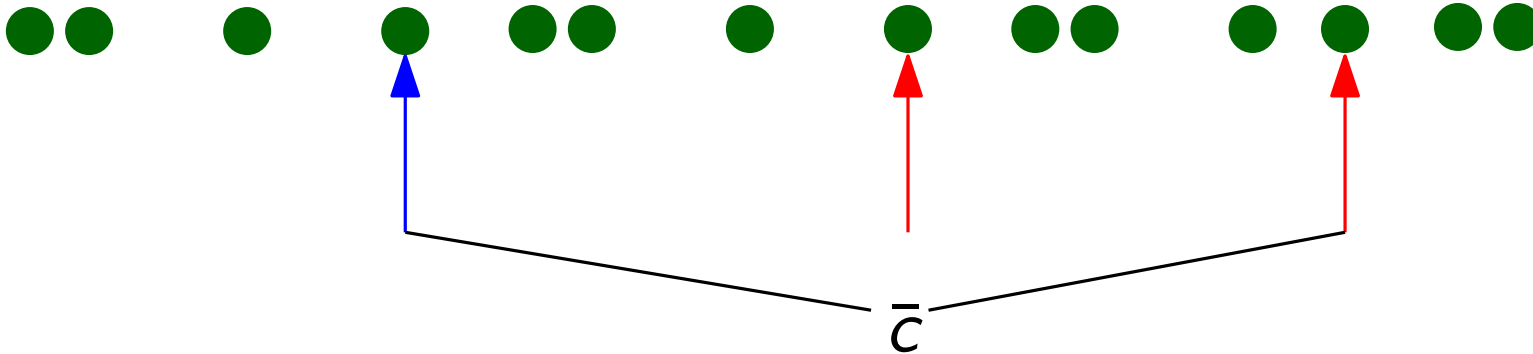


Start to count  $i$  with  
probability  $p$

Update the count  
with probability  $p$

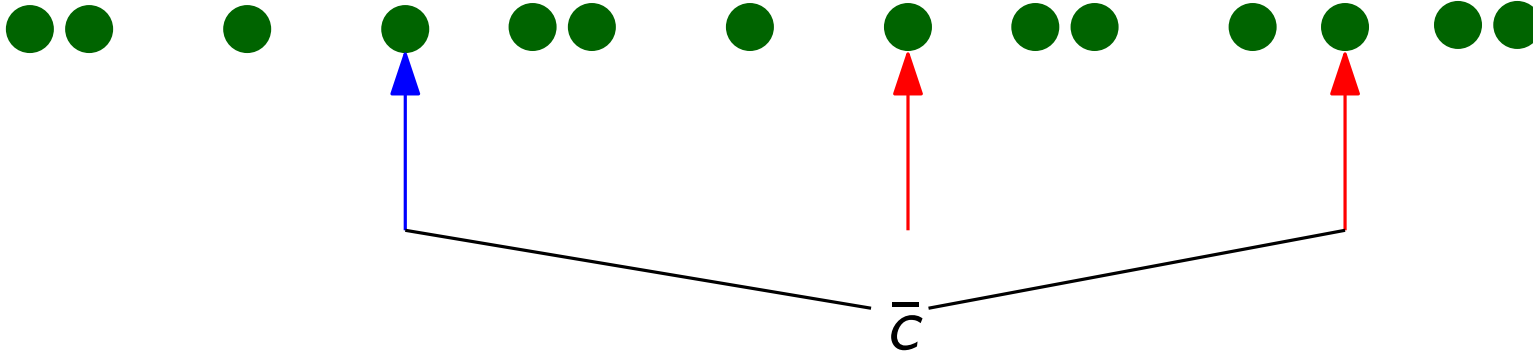


# Frequent Items: analysis



Coordinator only know  $\bar{c}$

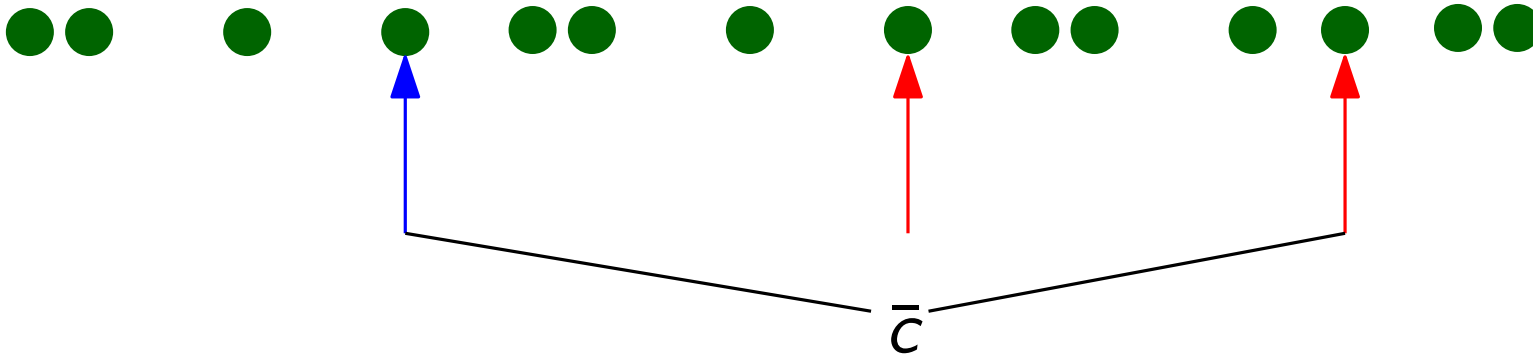
# Frequent Items: analysis



Coordinator only know  $\bar{c}$

$$\hat{f}_i = \begin{cases} \bar{c} - 1 + 2/p, & \text{if } \bar{c} > 0; \\ 0, & \text{else.} \end{cases}$$

# Frequent Items: analysis

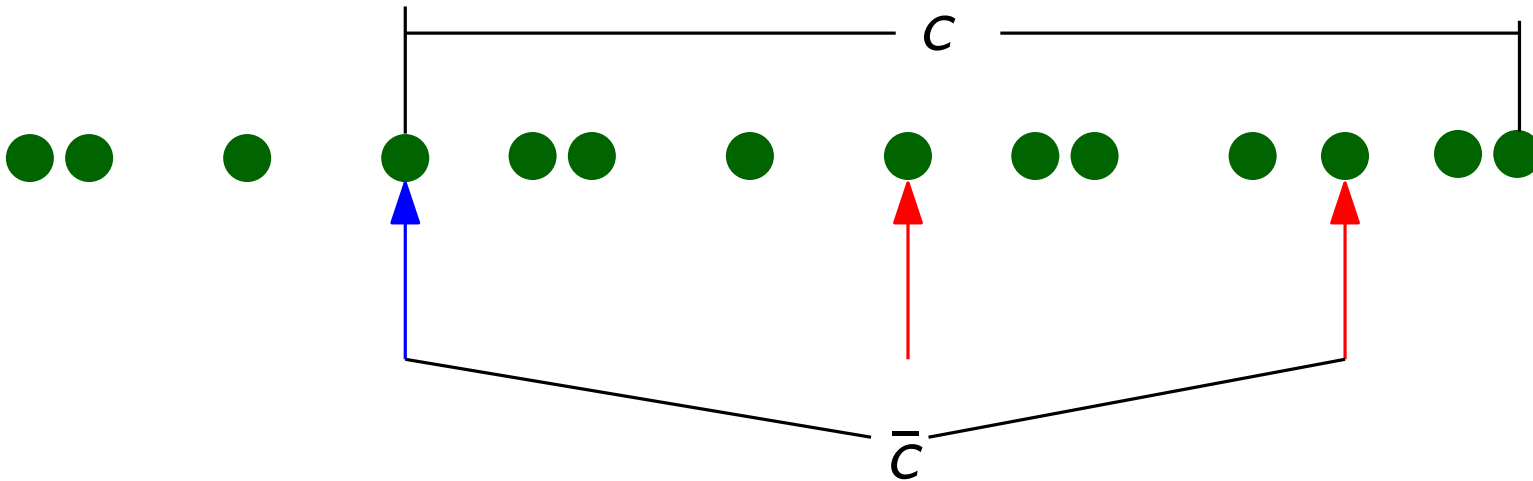


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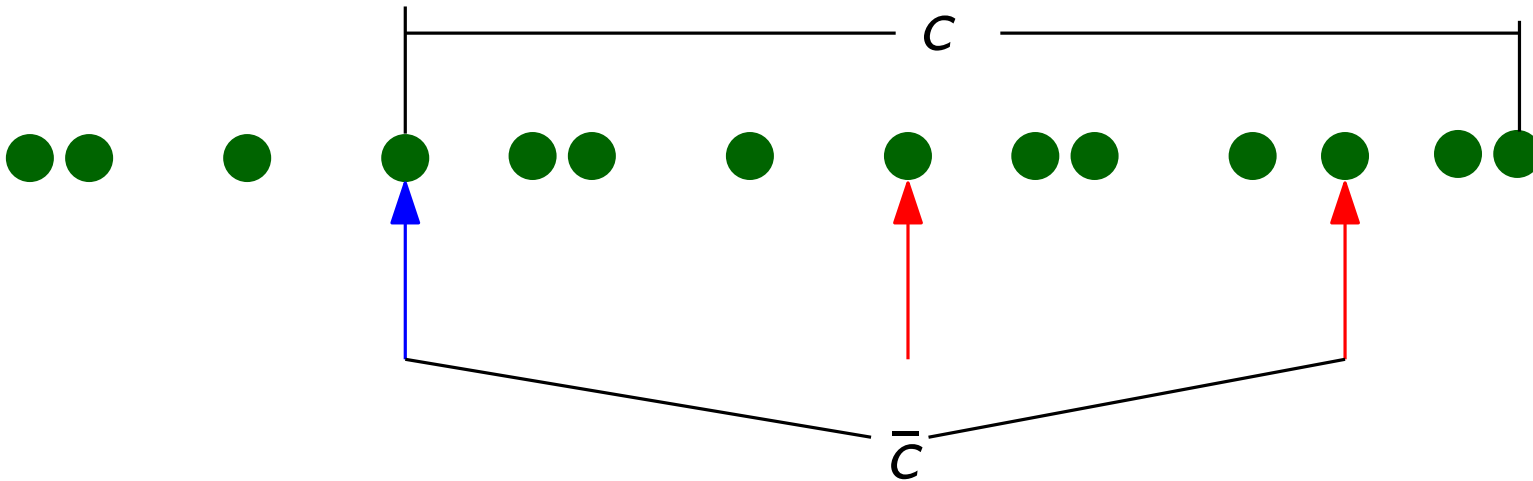
Bias might be as large as  $\varepsilon n / \sqrt{k}$

# Frequent Items: analysis



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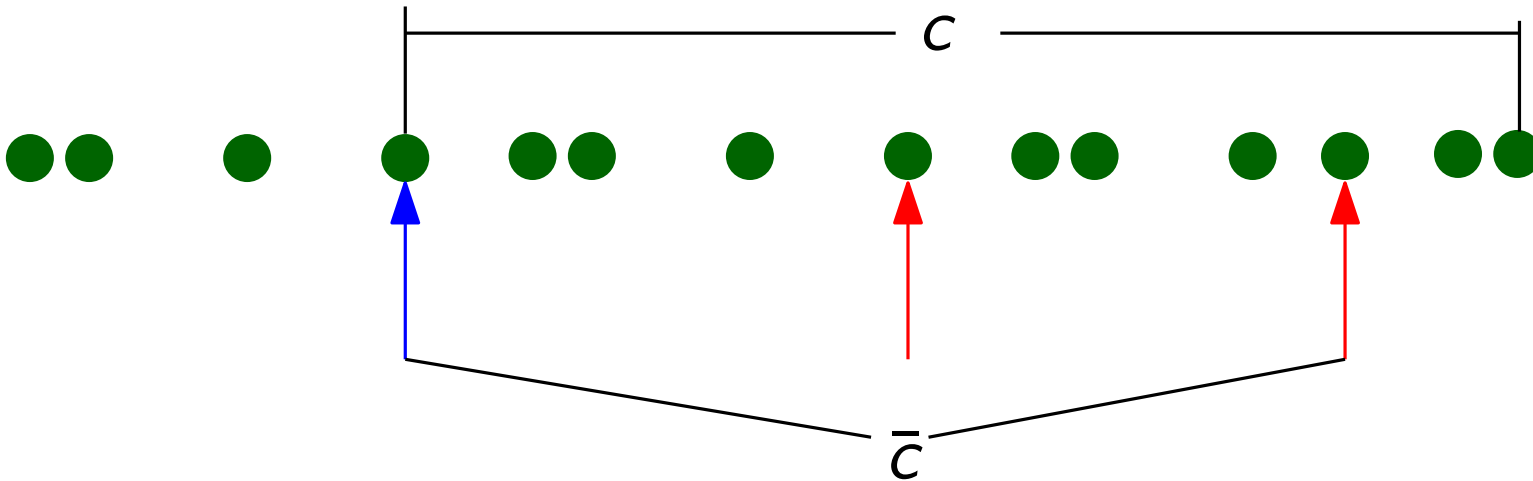
# Frequent Items: analysis



Coordinator only know  $\bar{c}$

$$\hat{f}_i = \begin{cases} c - 1 + 1/p, & \text{if } c > 0; \\ 0, & \text{else.} \end{cases}$$

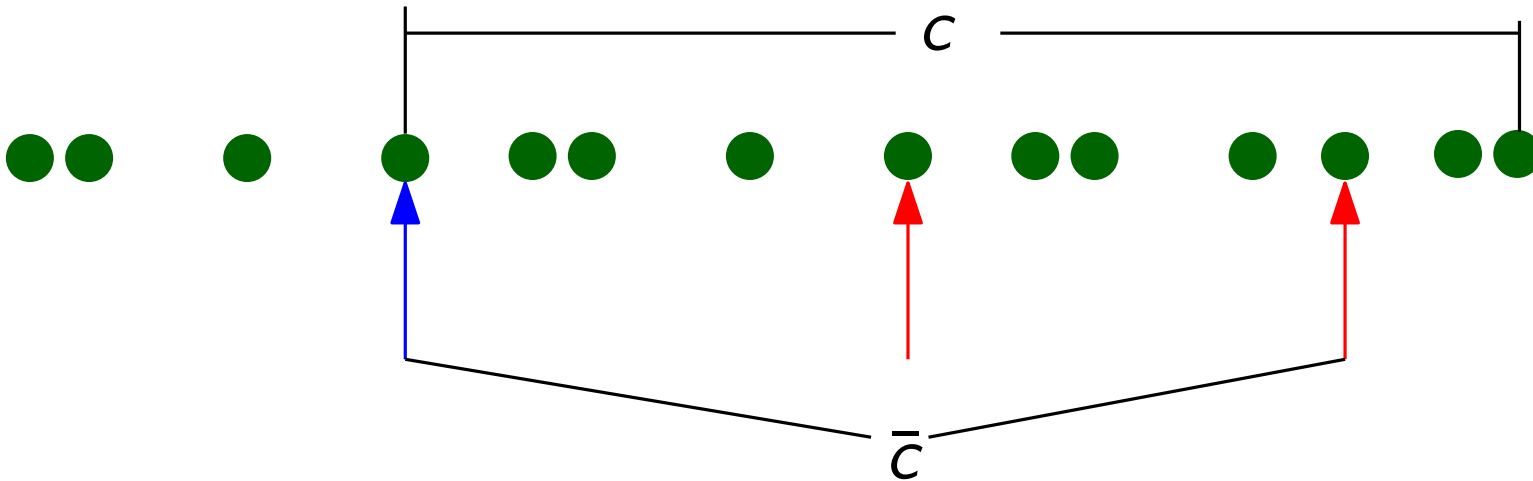
# Frequent Items: analysis



Estimate  $c$  by  $\bar{c}$

$$\hat{c} = \begin{cases} \bar{c} - 1 + 1/p, & \text{if } \bar{c} > 0; \\ 0, & \text{else.} \end{cases}$$

# Frequent Items: analysis



Combined

$$\hat{f}_i = \begin{cases} \bar{c} - 2 + 2/p, & \text{if } \bar{c} > 1; \\ 1/p, & \text{if } \bar{c} = 1; \\ 0, & \text{else.} \end{cases}$$

# Lower bound

- $E[\hat{f}_i] = f_i$
- $\text{Var}[\hat{f}_i] \leq 2/p^2$



# Lower bound

- $E[\hat{f}_i] = f_i$

- $\text{Var}[\hat{f}_i] \leq 2/p^2$

set  $p = O\left(\frac{\sqrt{k}}{\varepsilon n}\right)$

space:  $O(\sqrt{k}/\varepsilon)$

space per site:  $O(1/(\varepsilon\sqrt{k}))$

# Lower bound

- Communication lower bound still hold
- Space lower bound

# Lower bound

- Communication lower bound still hold
- Space lower bound
  - constant space
  - communication space tradeoff

# Space lower bound

## Theorem

Any randomized algorithm that solves the frequency tracking problem with communication  $C$  bits and uses  $M$  bits of space per site, we have  $C \cdot M = \Omega(\log n / \varepsilon^2)$ .

# Space lower bound

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Any randomized algorithm that solves the frequency tracking problem with communication  $C$  bits and uses  $M$  bits of space per site, we have  $C \cdot M = \Omega(\log n / \varepsilon^2)$ .

Communication cost:  $O(\sqrt{k} / \varepsilon \cdot \log n)$  bits

Space per site:  $\Omega(1 / (\varepsilon \sqrt{k}))$  bits

# Space lower bound

## Theorem

The  $k$ -party communication complexity for the one-shot frequency estimation problem is  $\Omega(\sqrt{k}/\varepsilon)$  bits.

[Woodruff, Zhang, STOC'12]

# Space lower bound

## Theorem

The  $k$ -party communication complexity for the one-shot frequency estimation problem is  $\Omega(\sqrt{k}/\varepsilon)$  bits.

## Direct-Sum theorem

Solve  $\ell$  instances of the frequency estimation problem simultaneously needs  $\Omega(\ell \cdot \sqrt{k}/\varepsilon)$  bits of communication.

[Woodruff, Zhang, STOC'12]

# Space lower bound

## Proof sketch

Let  $\mathcal{A}$  be a  $k$ -party tracking algorithm with communication  $C$  and space  $M$

Use  $\mathcal{A}$  to solve  $tk$ -party one-shot problem.

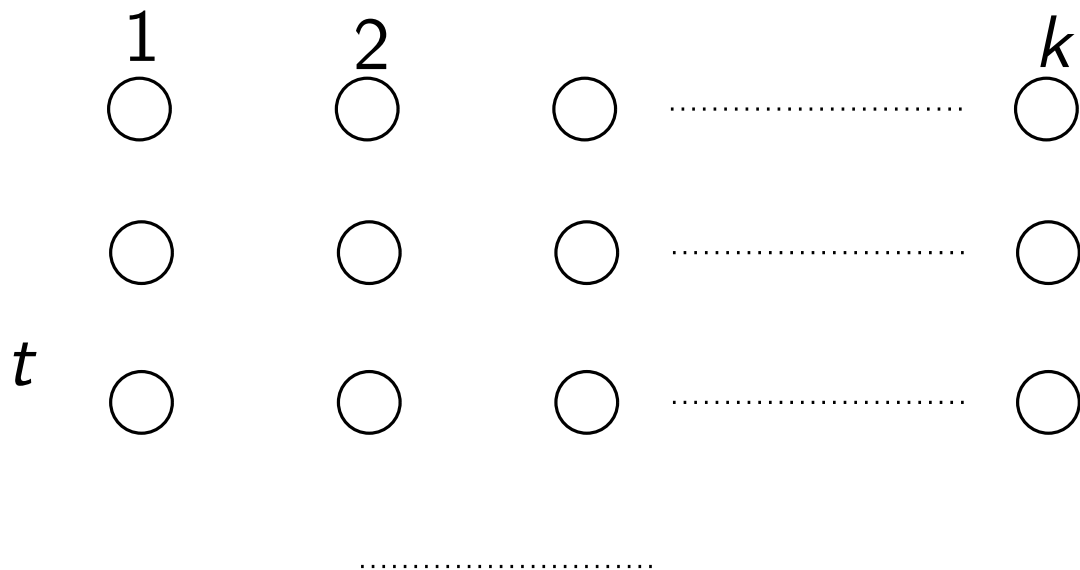


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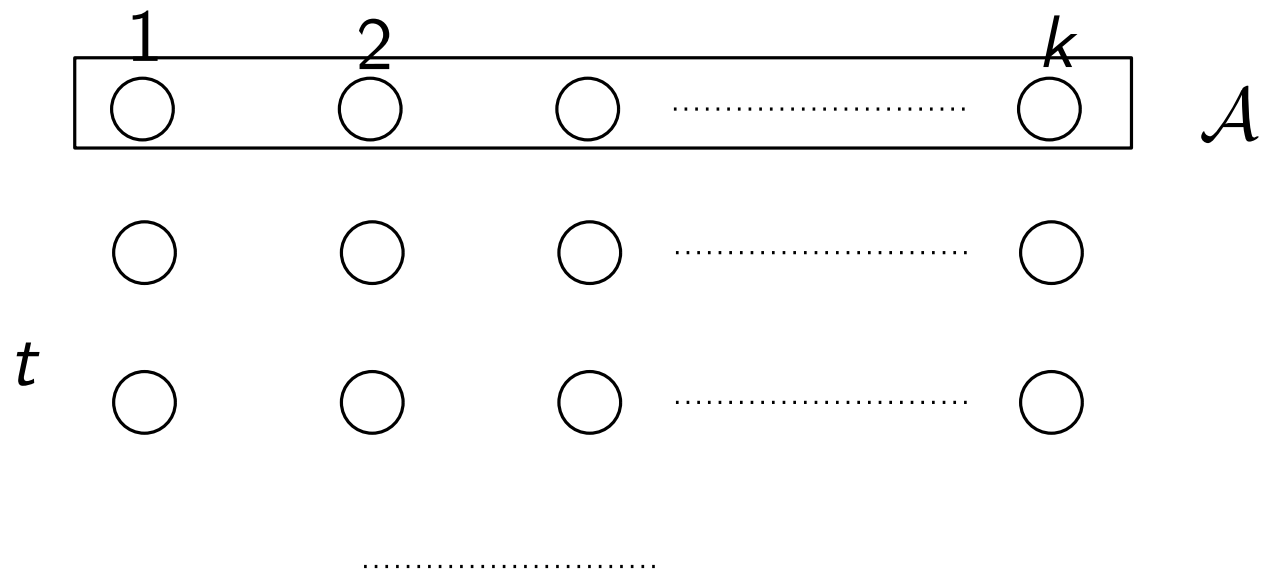


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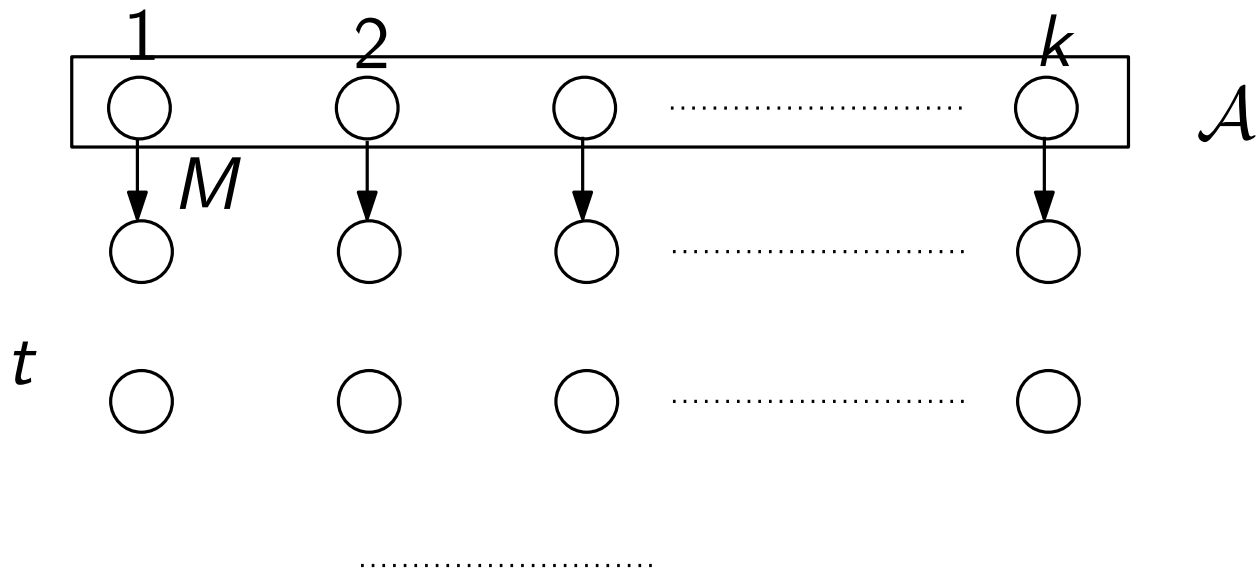


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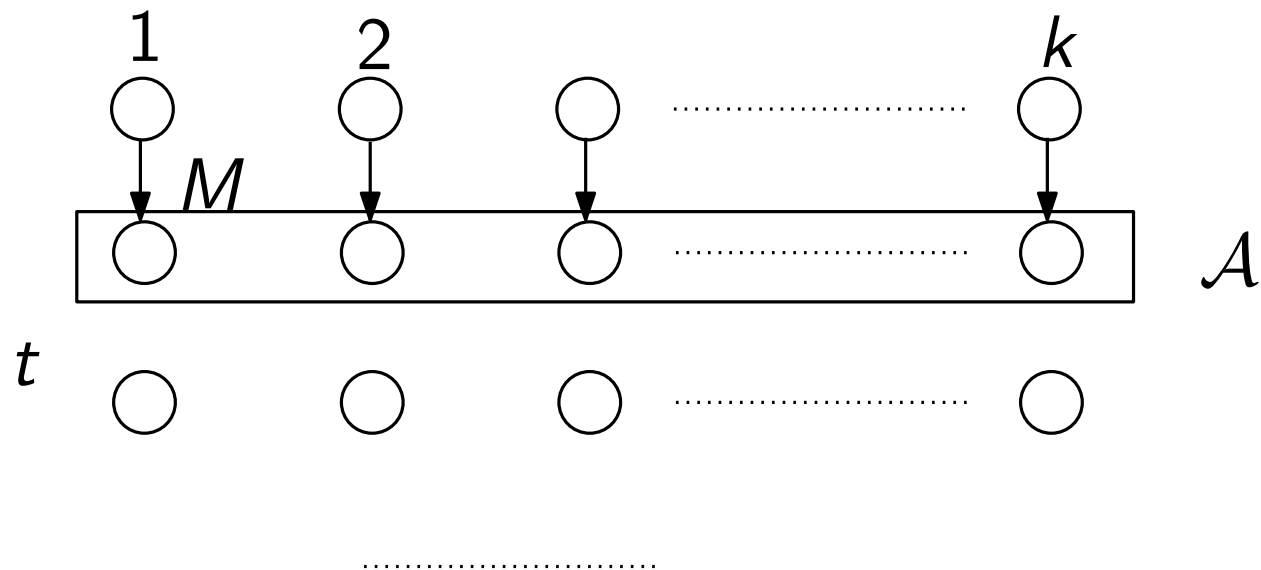


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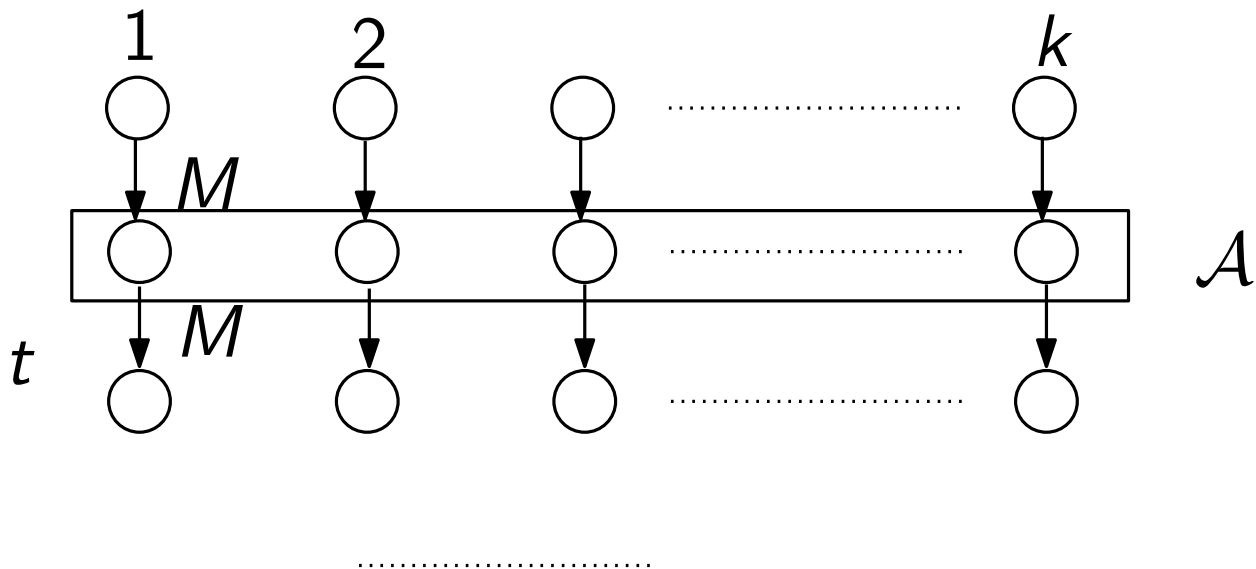


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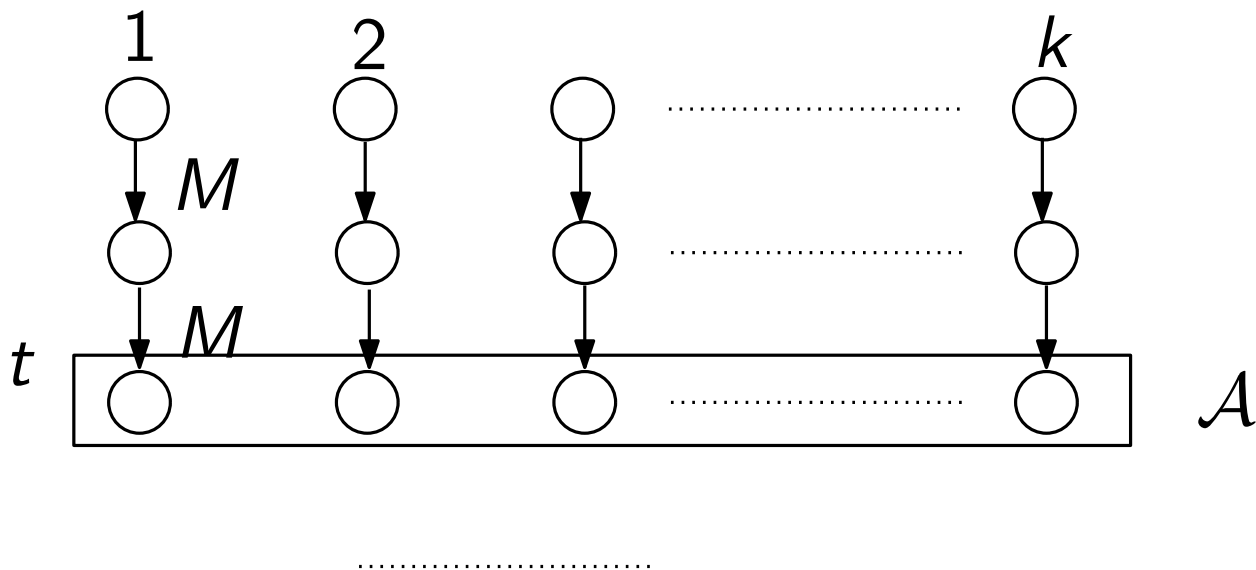


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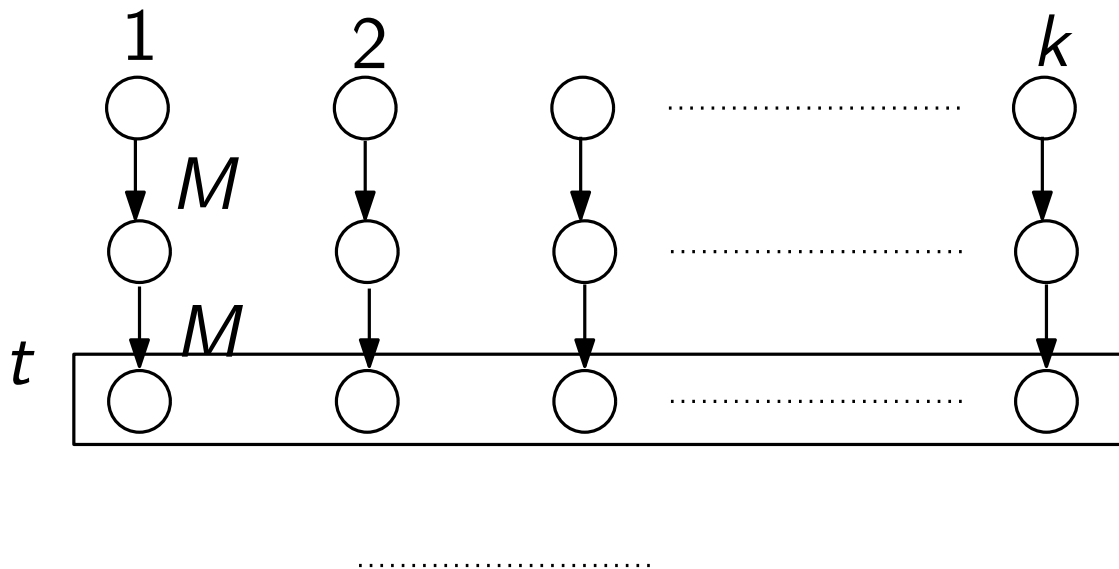


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$$C + M \cdot tk \geq \Omega\left(\frac{\sqrt{kt}}{\varepsilon}\right)$$

# Approximate rank

value-to-rank queries

$$10 \quad r(10) = 7$$

① ③ ④ ⑥ ⑦ ⑨ ⑪ ⑬

Return any number within  $r(10) \pm \epsilon n$

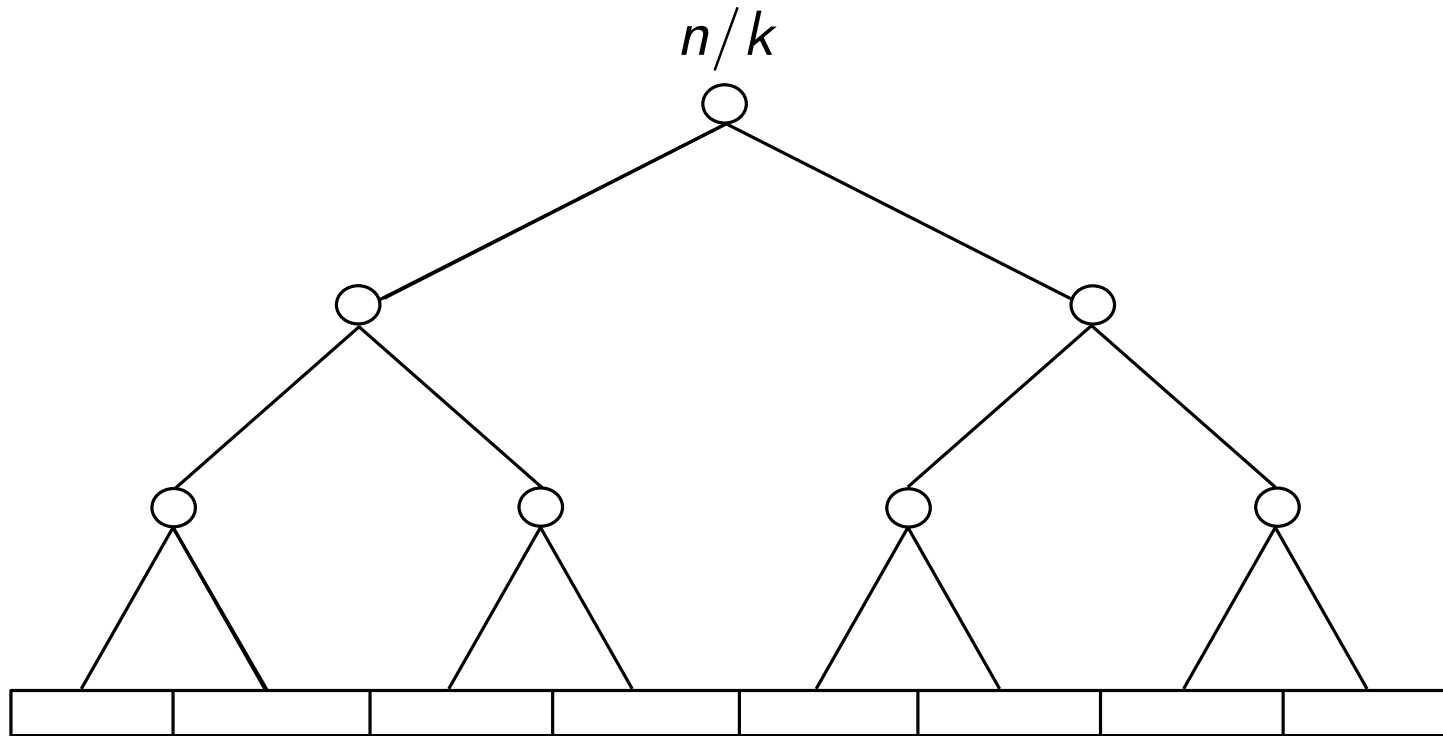


# Approximate rank

$$n/k$$

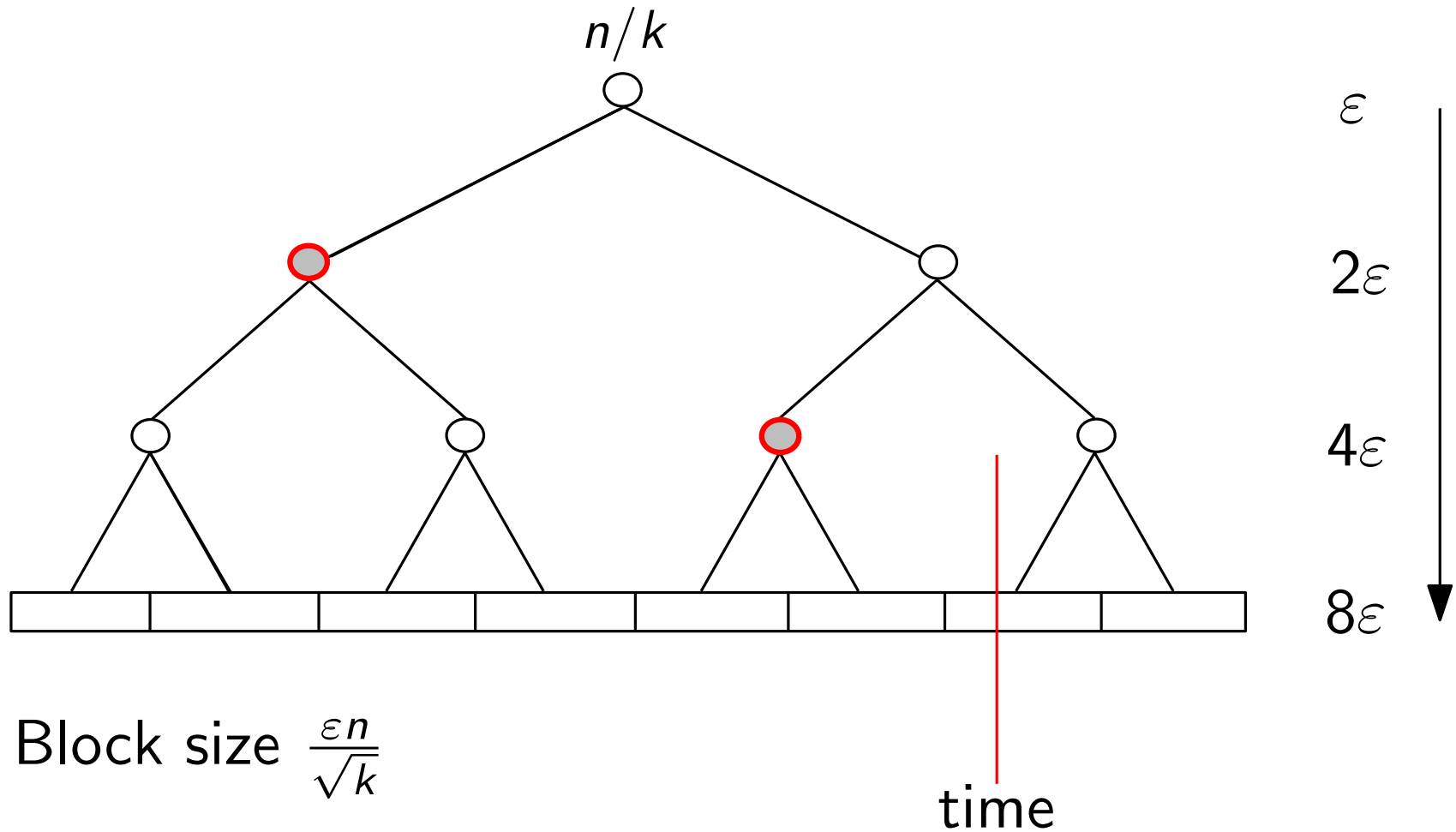


# Approximate rank



Block size  $\frac{\epsilon n}{\sqrt{k}}$

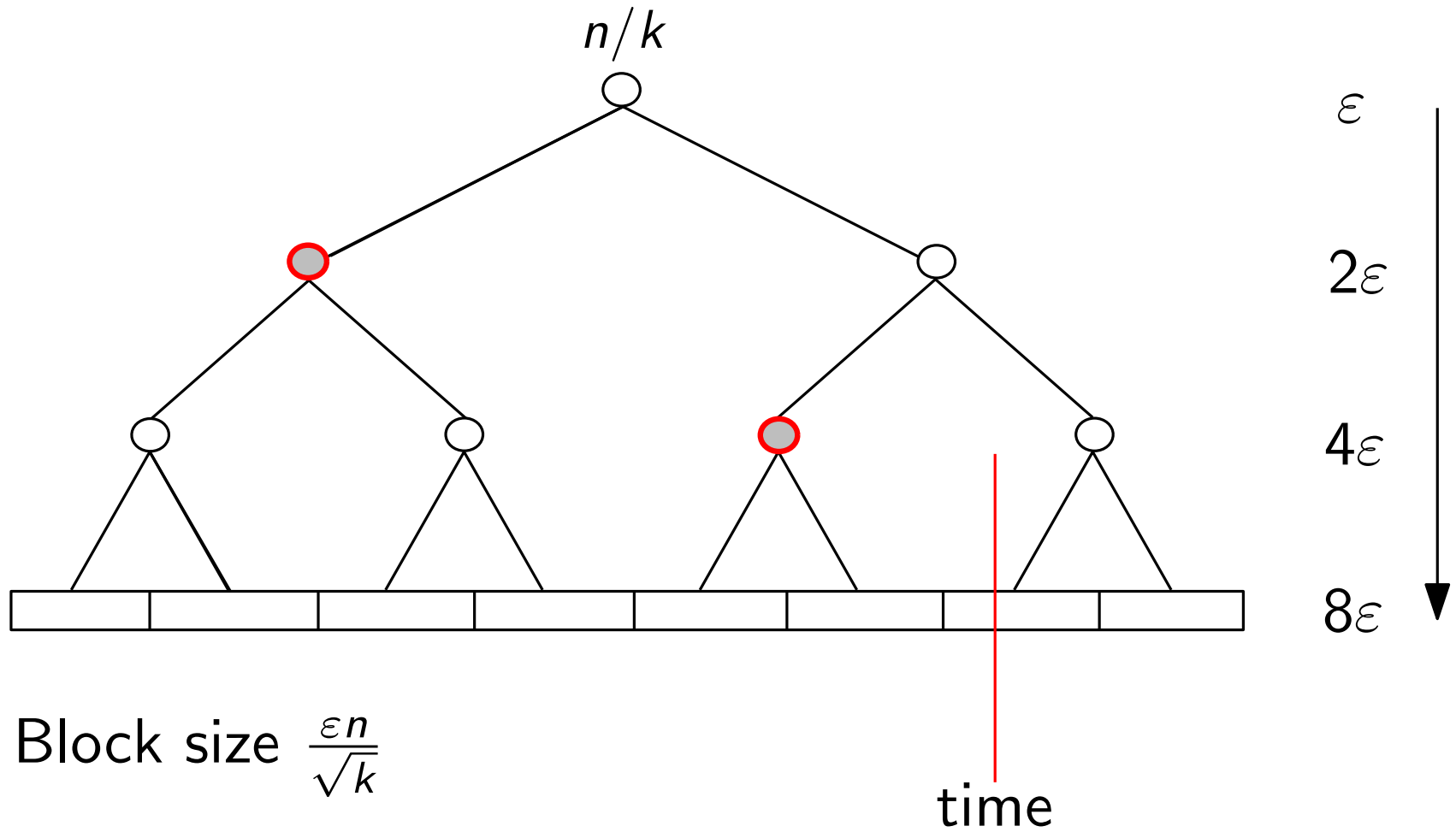
# Approximate rank



Each node will run a streaming algorithm

A node is full, send the sketch

# Approximate rank



Analysis omitted

# Approximate rank

Communication:  $O\left(\frac{k}{\varepsilon} \cdot \log n \log^2 \frac{1}{\varepsilon}\right)$   
Space per site:  $O\left(\frac{1}{\varepsilon} \cdot \log n\right)$

[Yi, Zhang, PODS'09]

Communication:  $O\left(\frac{\sqrt{k}}{\varepsilon} \cdot \log n \log^{1.5} \frac{1}{\varepsilon}\right)$   
Space per site:  $O\left(\frac{1}{\varepsilon \sqrt{k}}\right) \cdot \log^2 \frac{1}{\varepsilon}$

New

# Conclusion

- Improve the communication cost for 3 important problem by  $O(\sqrt{k})$
- Improve the space by  $O(\sqrt{k})$
- Prove matching randomized lower bound for communication and space

Thank you!