Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2016)

Week 12: Real-Time Data Analytics (1/2)

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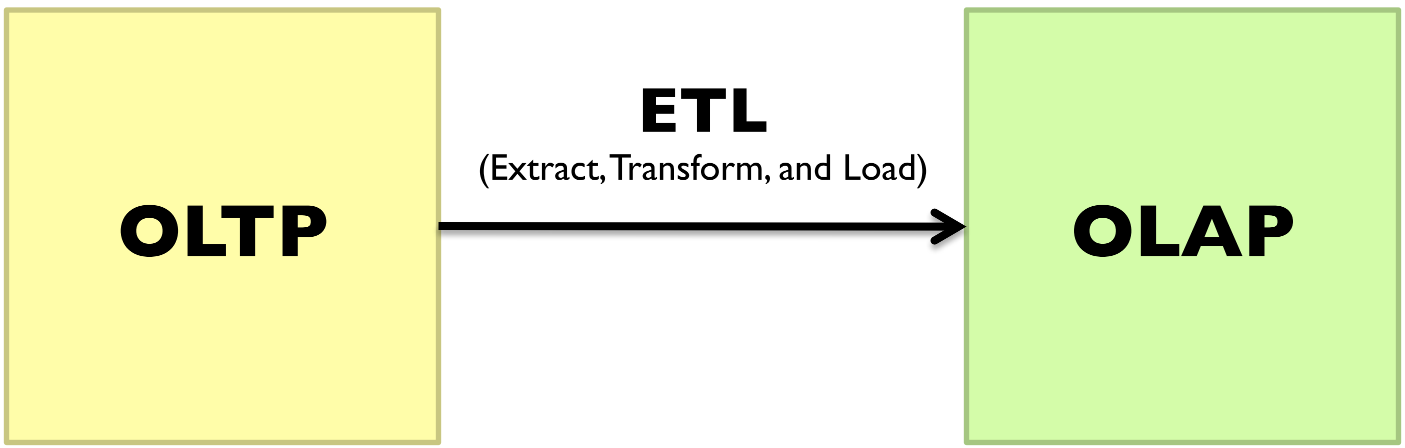
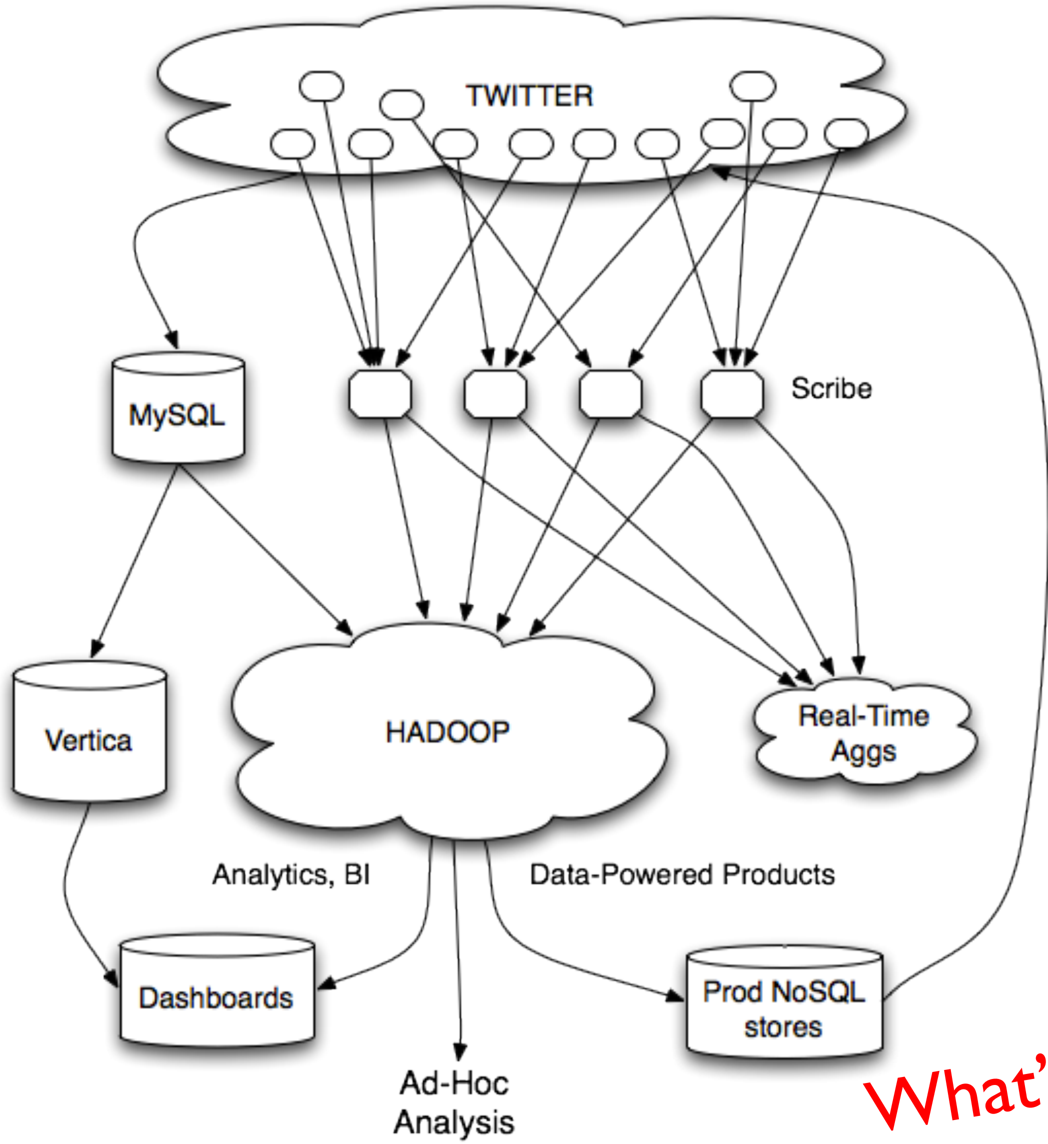
These slides are available at http://lintool.github.io/bigdata-2016w/

OLTP/OLAP Architecture





What's the issue?

Twitter's data warehousing architecture

real-time

vs.

online

vs.

streaming

What is a data stream?

- Sequence of items:
  - Structured (e.g., tuples)
  - Ordered (implicitly or timestamped)
  - Arriving continuously at high volumes
  - Sometimes not possible to store entirely
  - Sometimes not possible to even examine all items

What to do with data streams?

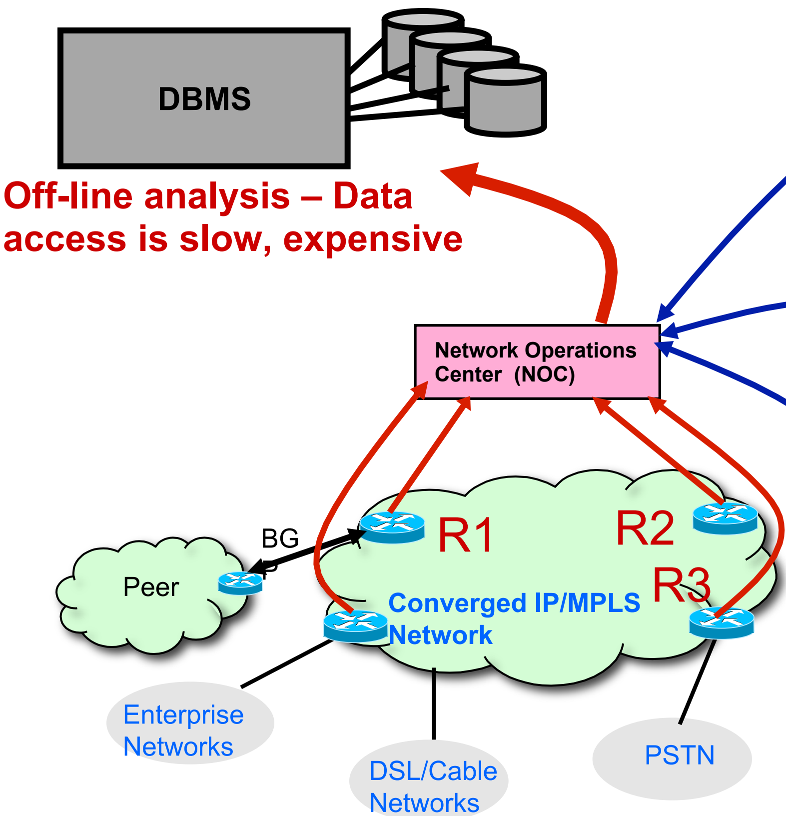
- Network traffic monitoring
- Datacenter telemetry monitoring
- Sensor networks monitoring
- Credit card fraud detection
- Stock market analysis
- Online mining of click streams
- Monitoring social media streams

What's the scale? Packet data streams

- Single 2 Gb/sec link; say avg. packet size is 50 bytes
  - Number of packets/sec = 5 million
  - Time per packet = 0.2 microseconds
- If we only capture header information per packet: source/destination IP, time, no. of bytes, etc. – at least 10 bytes
  - 50 MB per second
  - 4+ TB per day
  - **Per link!**

What if you wanted to do deep-packet inspection?

Source: Minos Garofalakis, Berkeley CS 286



What are the top (most frequent) 1000 (source, dest) pairs seen by R1 over the last month?

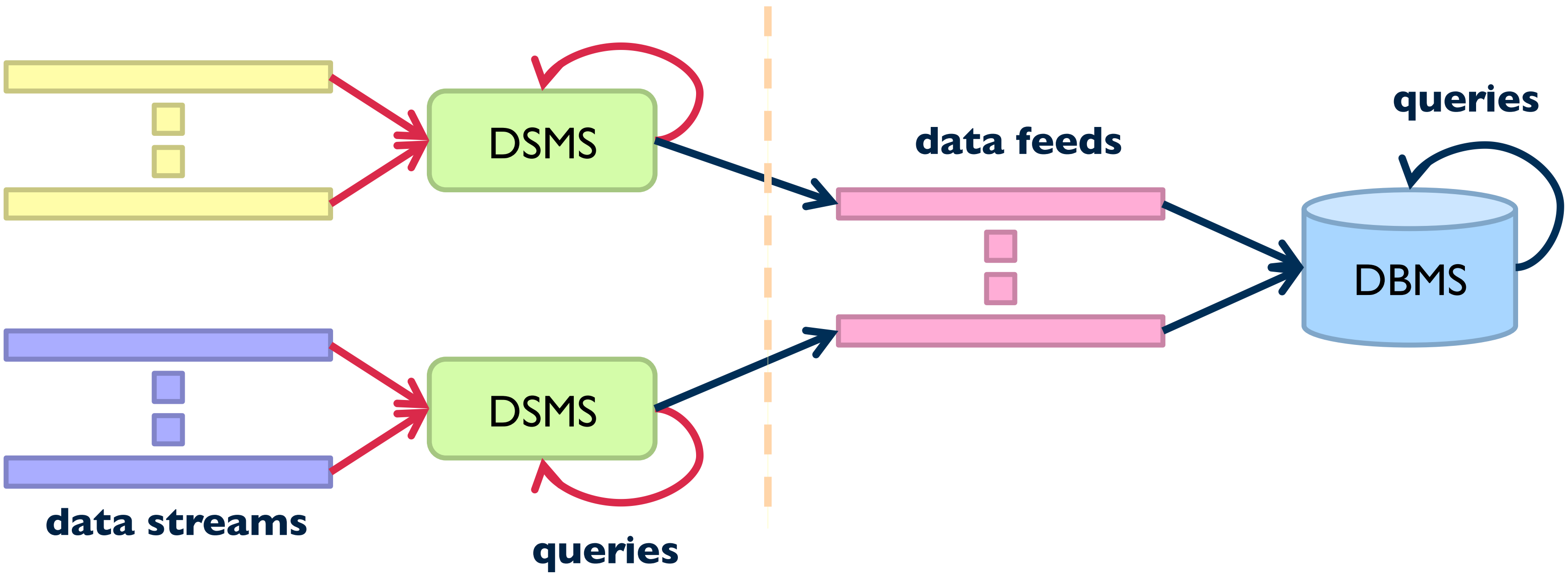
How many distinct (source, dest) pairs have been seen by both R1 and R2 but not R3?

Set-Expression Query

```
SELECT COUNT (R1.source, R1.dest)
FROM  R1, R2
WHERE R1.source = R2.source
```

SQL Join Query

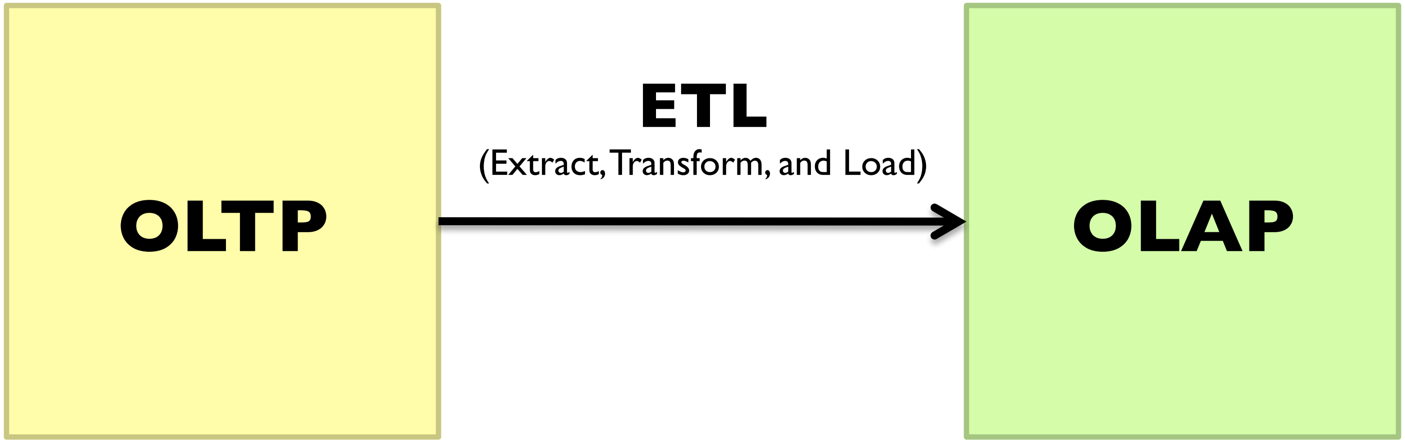
Common Architecture



- Data stream management system (DSMS) at observation points
  - Voluminous streams-in, reduced streams-out
- Database management system (DBMS)
  - Outputs of DSMS can be treated as data feeds to databases

Source: Peter Bonz

OLTP/OLAP Architecture



DBMS vs. DSMS

DBMS	DSMS
Model: persistent relations	Model: (mostly) transient relations
Relation: tuple set/bag	Relation: tuple sequence
Data update: modifications	Data update: appends
Query: transient	Query: persistent
Query answer: exact	Query answer: approximate
Query evaluation: arbitrary	Query evaluation: one pass
Query plan: fixed	Query plan: adaptive

Source: Peter Bonz

What makes it hard?

- Intrinsic challenges:
  - Volume
  - Velocity
  - Limited storage
  - Strict latency requirements
- System challenges:
  - Load balancing
  - Unreliable and out-of-order message delivery
  - Fault-tolerance
  - Consistency semantics (at most once, exactly once, at least once)

What exactly do you do?

- "Standard" relational operations:
  - Select
  - Project
  - Transform (i.e., apply custom UDF)
  - Group by
  - Join
  - Aggregations
- What else do you need to make this "work"?

Issues of Semantics

- Group by… aggregate
  - When do you stop grouping and start aggregating?
- Joining a stream and a static source
  - Simple lookup
- Joining two streams
  - How long do you wait for the join key in the other stream?
- Joining two streams, group by and aggregation
  - When do you stop joining?

What's the solution?

Windows

- Mechanism for extracting finite relations from an infinite stream
- Windows restrict processing scope:
  - Windows based on ordering attributes (e.g., time)
  - Windows based on item (record) counts
  - Windows based on explicit markers (e.g., punctuations)
  - Variants (e.g., some semantic partitioning constraint)

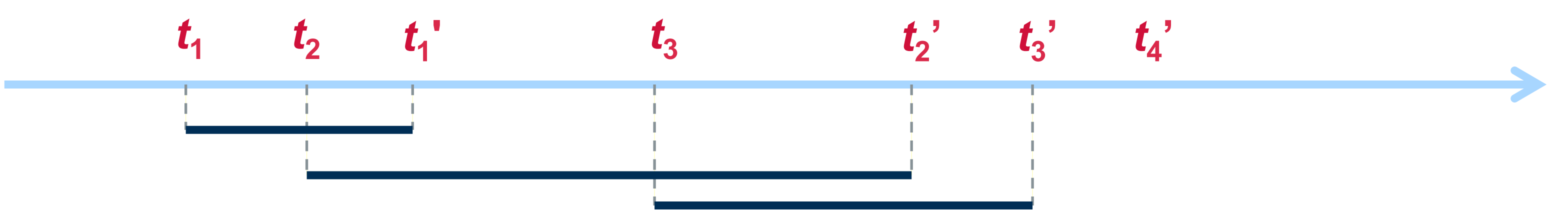
Windows on Ordering Attributes

- Assumes the existence of an attribute that defines the order of stream elements (e.g., time)
- Let T be the window size in units of the ordering attribute

Source: Peter Bonz

Windows on Counts

- Window of size *N* elements (sliding, tumbling) over the stream
- Challenges:
  - Problematic with non-unique timestamps: non-deterministic output
  - Unpredictable window size (and storage requirements)



Source: Peter Bonz

Windows from "Punctuations"

- Application-inserted "end-of-processing"
  - Example: stream of actions… "end of user session"
- Properties
  - Advantage: application-controlled semantics
  - Disadvantage: unpredictable window size (too large or too small)

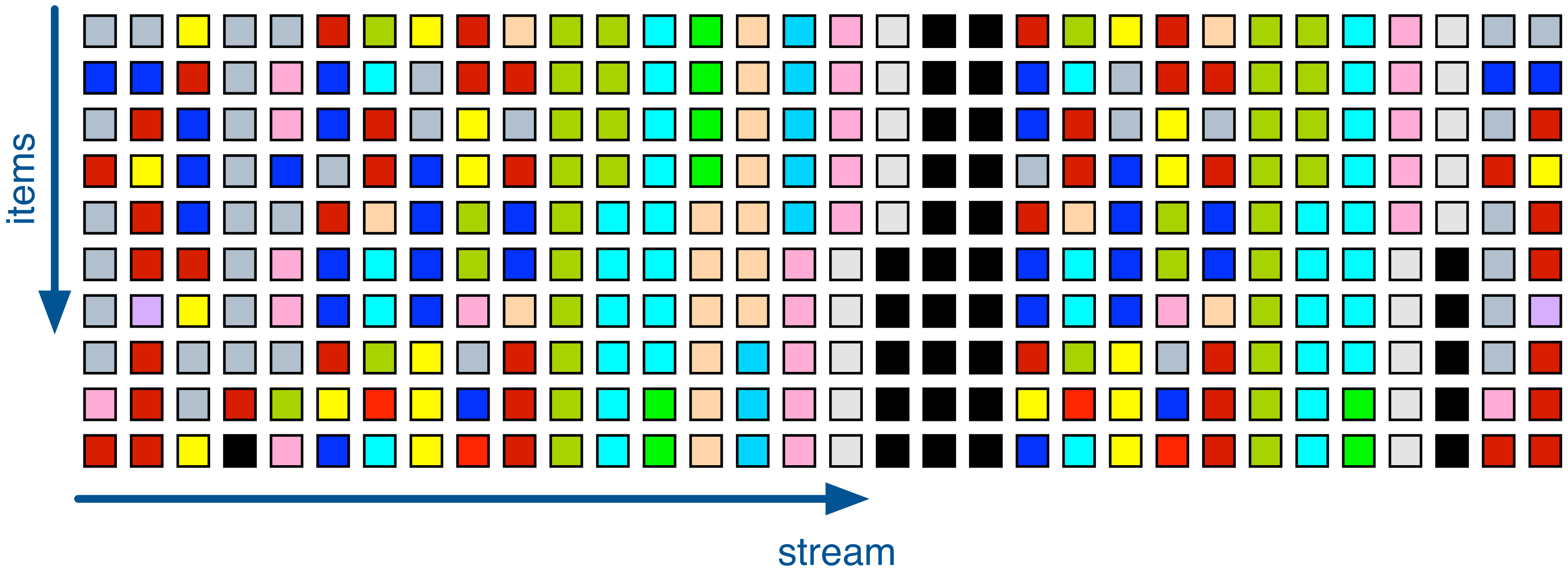
Common Techniques

Source: Wikipedia (Forge)

"Hello World" Stream Processing

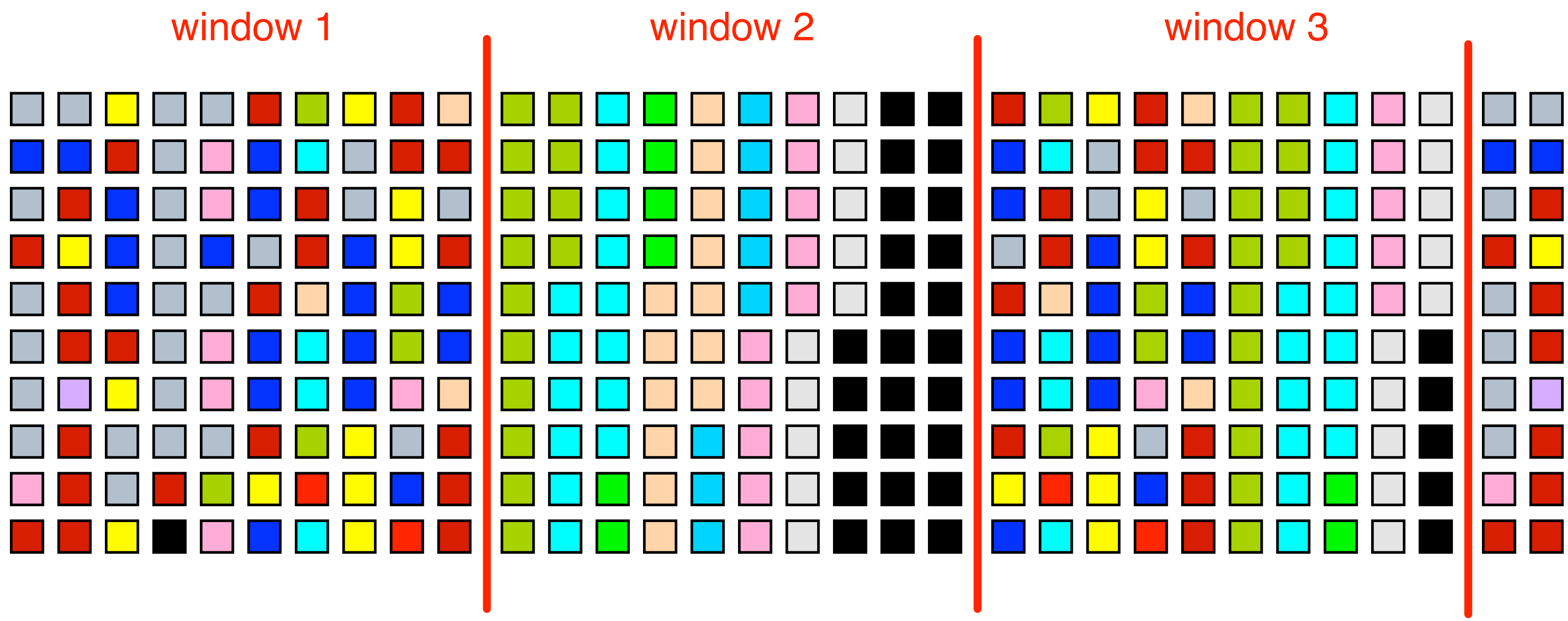
- Problem:
  - Count the frequency of items in the stream
- Why?
  - Take some action when frequency exceeds a threshold
  - Data mining: raw counts → co-occurring counts → association rules

The Raw Stream...



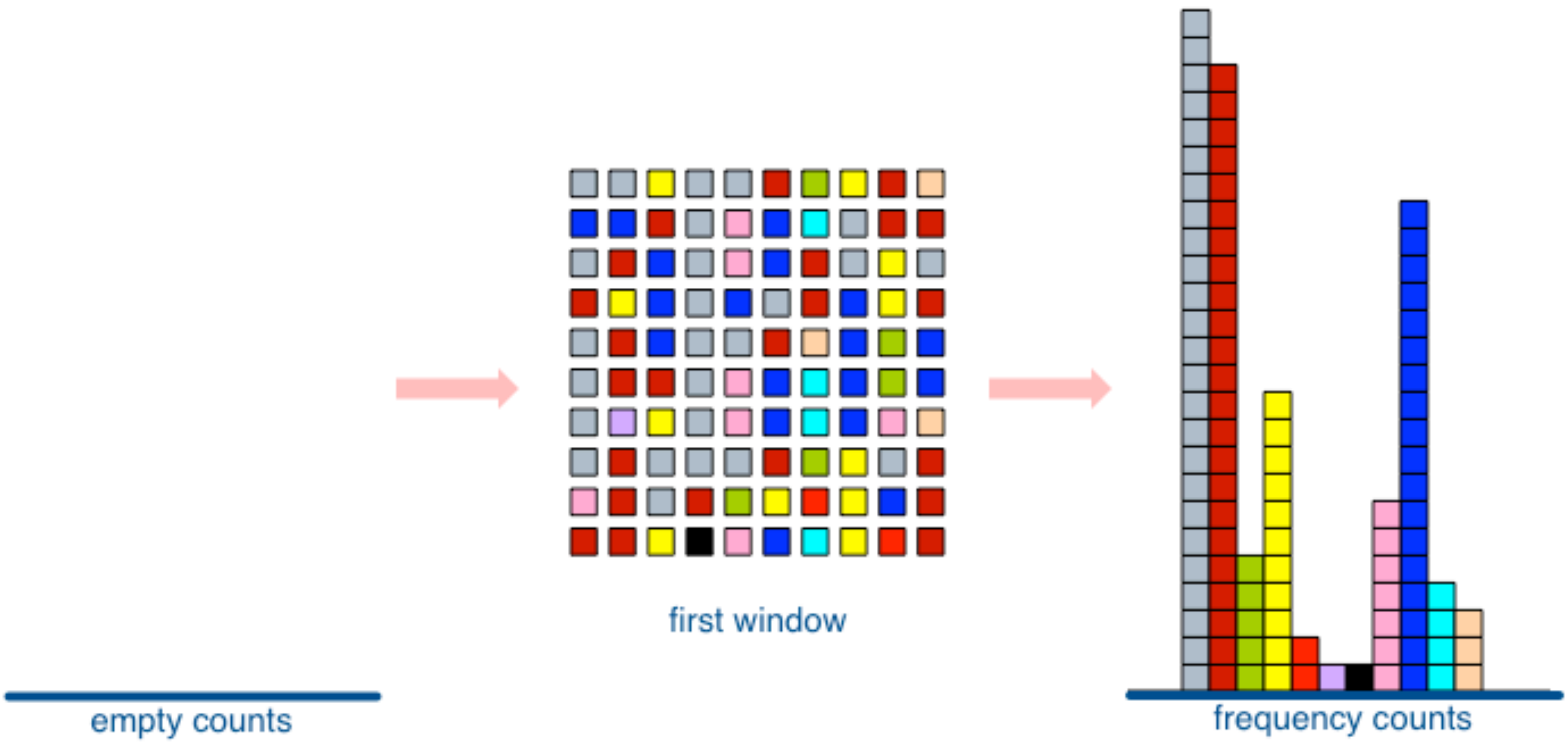
Source: Peter Bonz

Divide Into Windows...



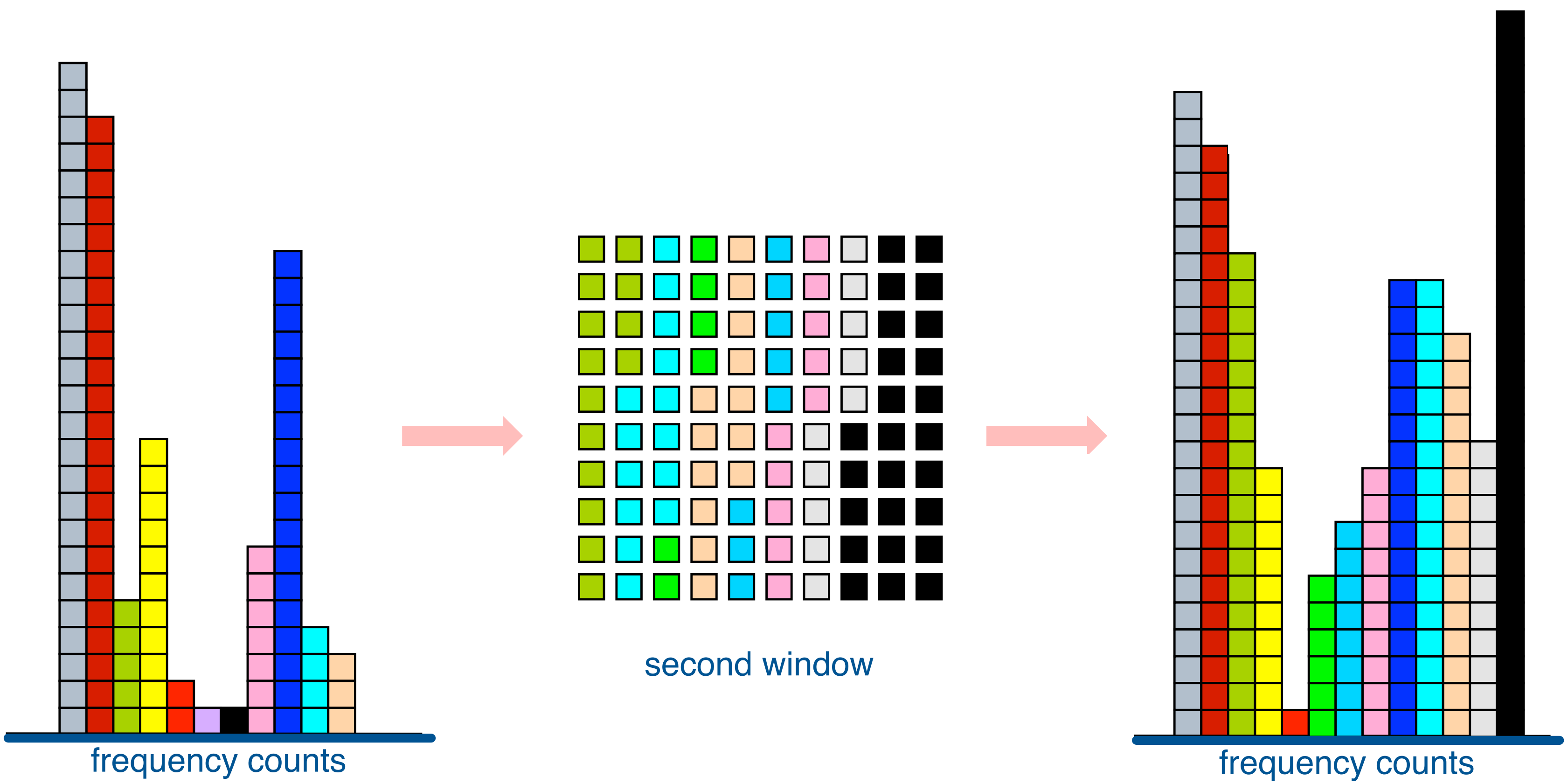
Source: Peter Bonz

First Window



Source: Peter Bonz

Second Window



Source: Peter Bonz

Window Counting

- What's the issue?

Lessons learned?
Solutions are approximate (or lossy)

General Strategies

- Sampling
- Hashing

Reservoir Sampling

- Task: select *s* elements from a stream of size *N* with uniform probability
  - *N* can be very very large
  - We might not even know what *N* is! (infinite stream)
- Solution: Reservoir sampling
  - Store first *s* elements
  - For the *k*-th element thereafter, keep with probability *s*/*k* (randomly discard an existing element)
- Example: *s* = 10
  - Keep first 10 elements
  - 11th element: keep with 10/11
  - 12th element: keep with 10/12
  - …

Reservoir Sampling: How does it work?

- Example: $s = 10$
  - Keep first 10 elements
  - 11th element: keep with 10/11

    If we decide to keep it: sampled uniformly by definition
    probability existing item is discarded: $10/11 \times 1/10 = 1/11$
    probability existing item survives: 10/11

- General case: at the $(k + 1)$th element
  - Probability of selecting each item up until now is s/k
  - Probability existing item is discarded: $s/(k+1) \times 1/s = 1/(k + 1)$
  - Probability existing item survives: $k/(k + 1)$
  - Probability each item survives to $(k + 1)$th round:
    $(s/k) \times k/(k + 1) = s/(k + 1)$

Hashing for Three Common Tasks

- Cardinality estimation — HashSet — HLL counter
  - What's the cardinality of set *S*?
  - How many unique visitors to this page?
- Set membership — HashSet — Bloom Filter
  - Is *x* a member of set *S*?
  - Has this user seen this ad before?
- Frequency estimation — HashMap — CMS
  - How many times have we observed *x*?
  - How many queries has this user issued?

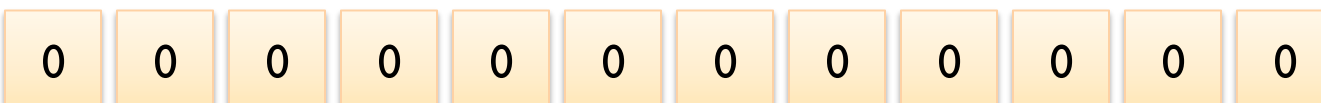
HyperLogLog Counter

- Task: cardinality estimation of set
  - size() → number of unique elements in the set
- Observation: hash each item and examine the hash code
  - On expectation, 1/2 of the hash codes will start with 1
  - On expectation, 1/4 of the hash codes will start with 01
  - On expectation, 1/8 of the hash codes will start with 001
  - On expectation, 1/16 of the hash codes will start with 0001
  - …

How do we take advantage of this observation?

Bloom Filters

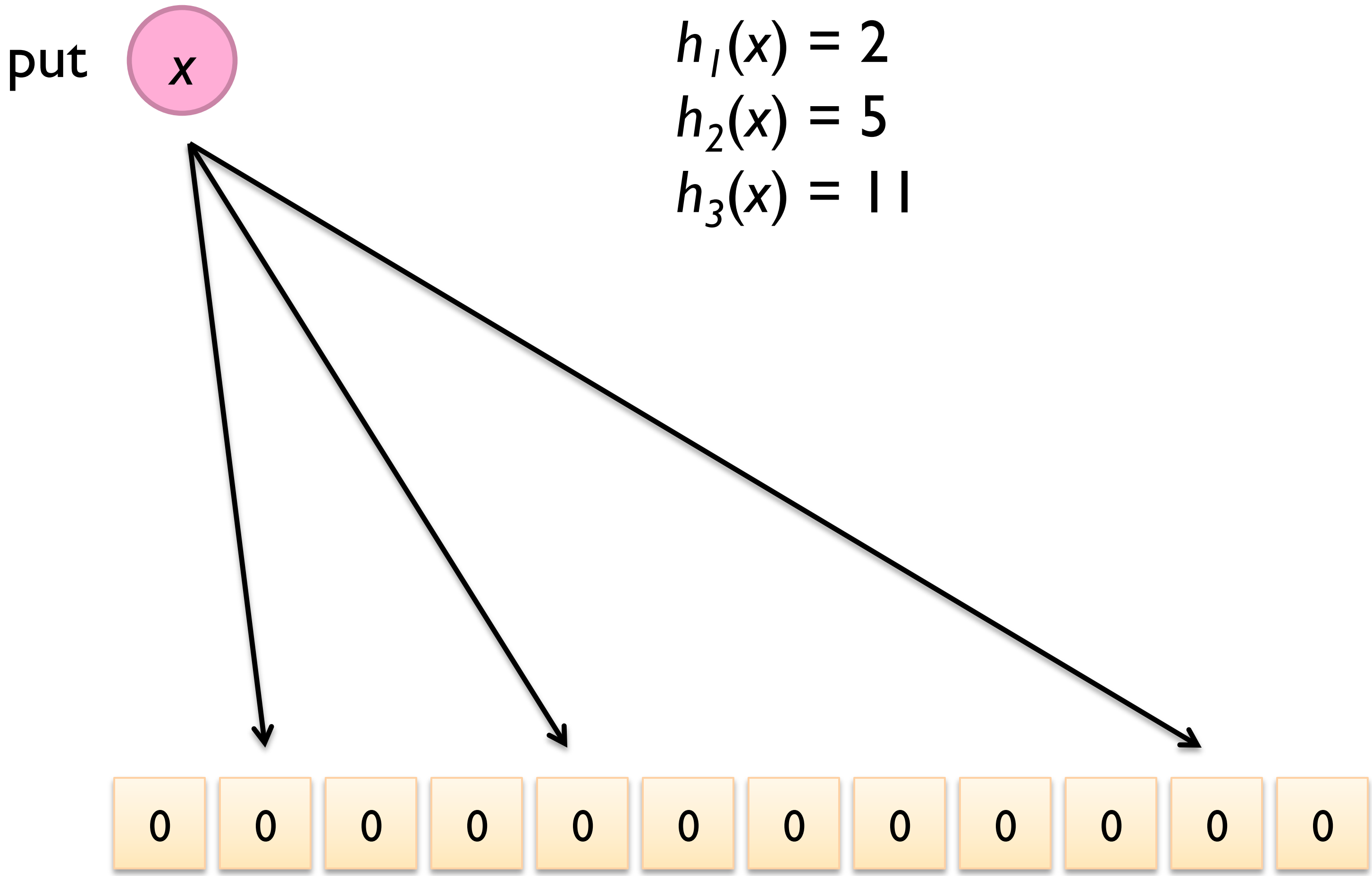
- Task: keep track of set membership
  - put(*x*) → insert *x* into the set
  - contains(*x*) → yes if *x* is a member of the set
- Components
  - *m*-bit bit vector



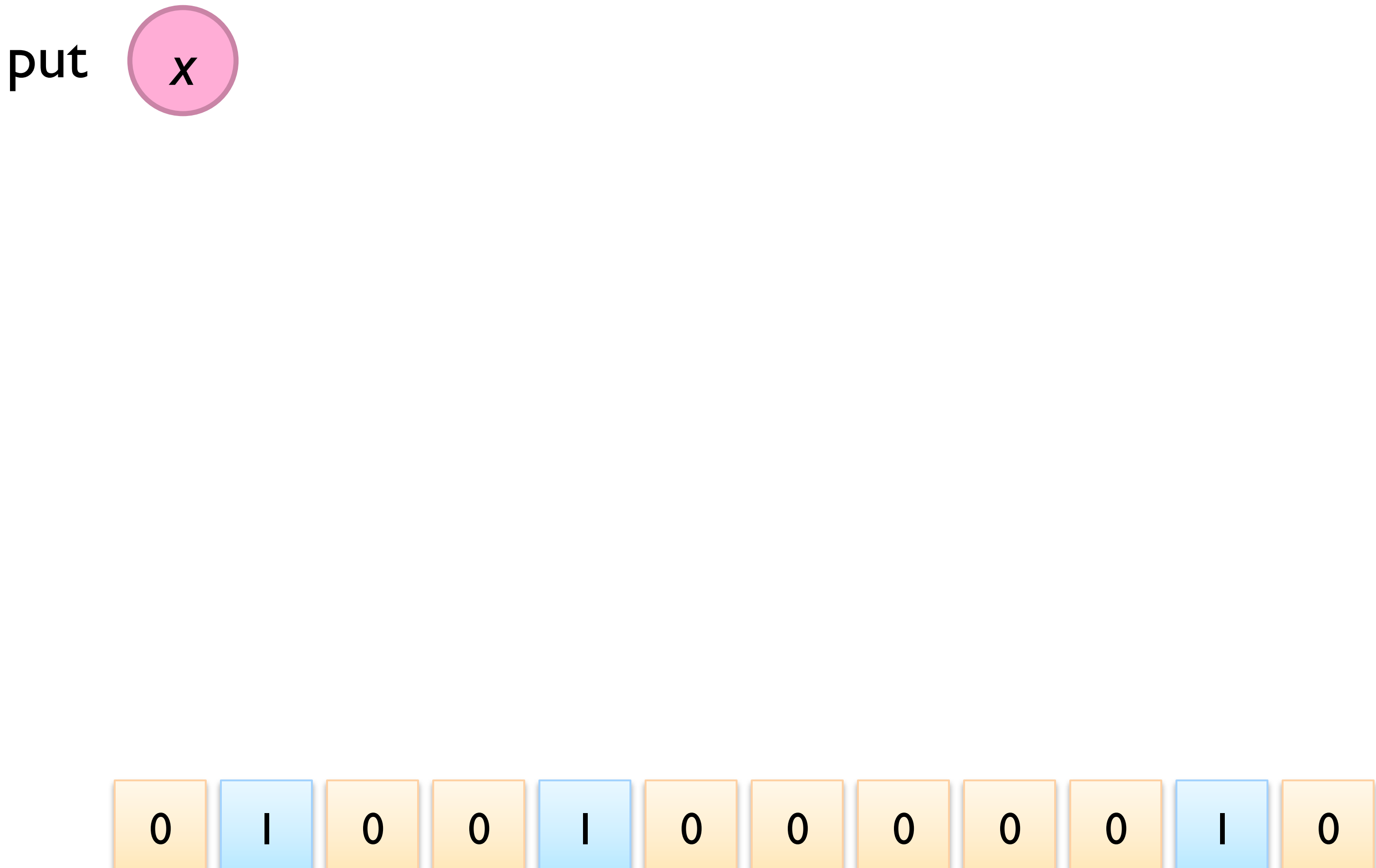
  - *k* hash functions: $h_1 \ldots h_k$

Bloom Filters: put

$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$

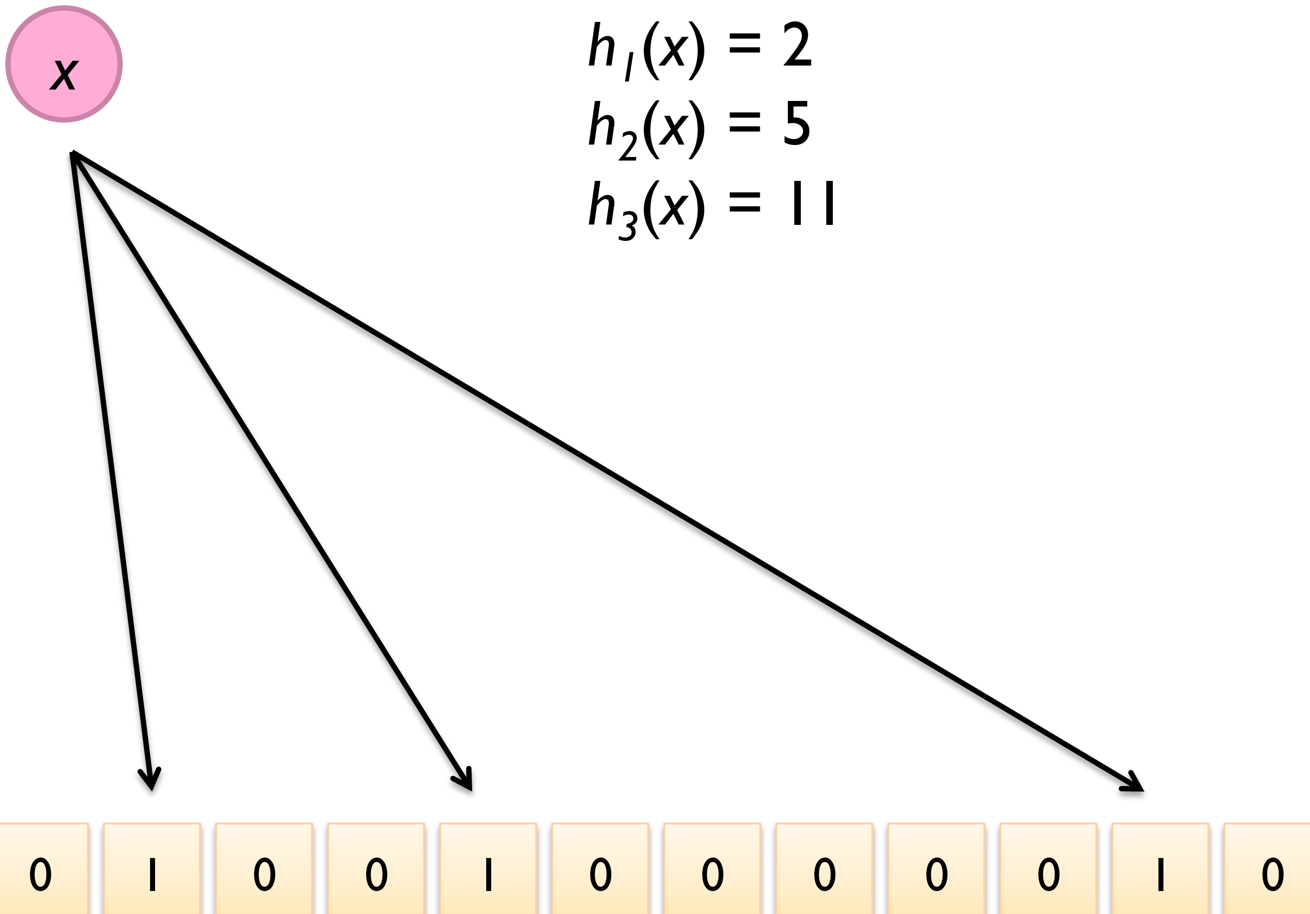


Bloom Filters: put



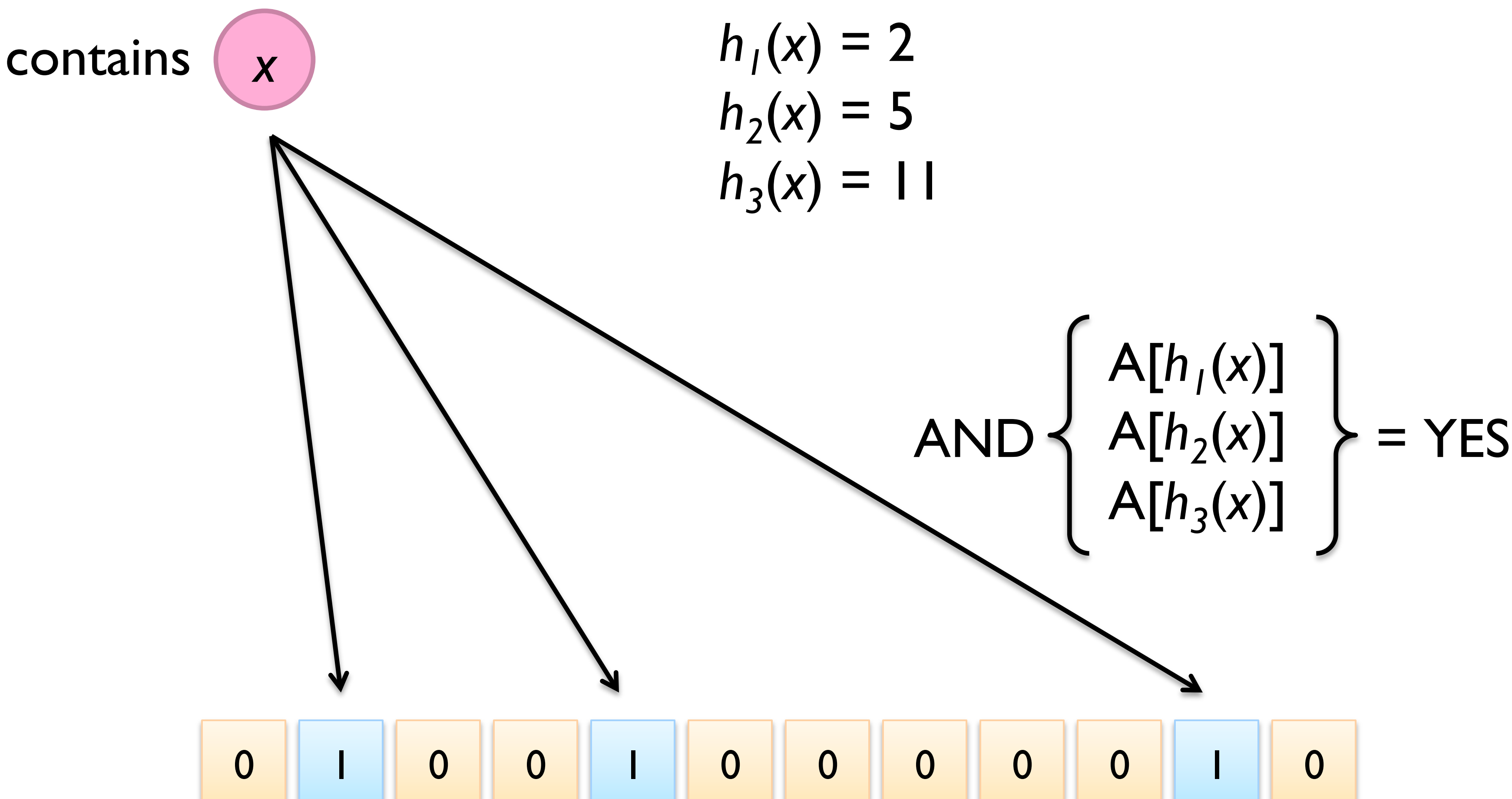
Bloom Filters: contains

contains

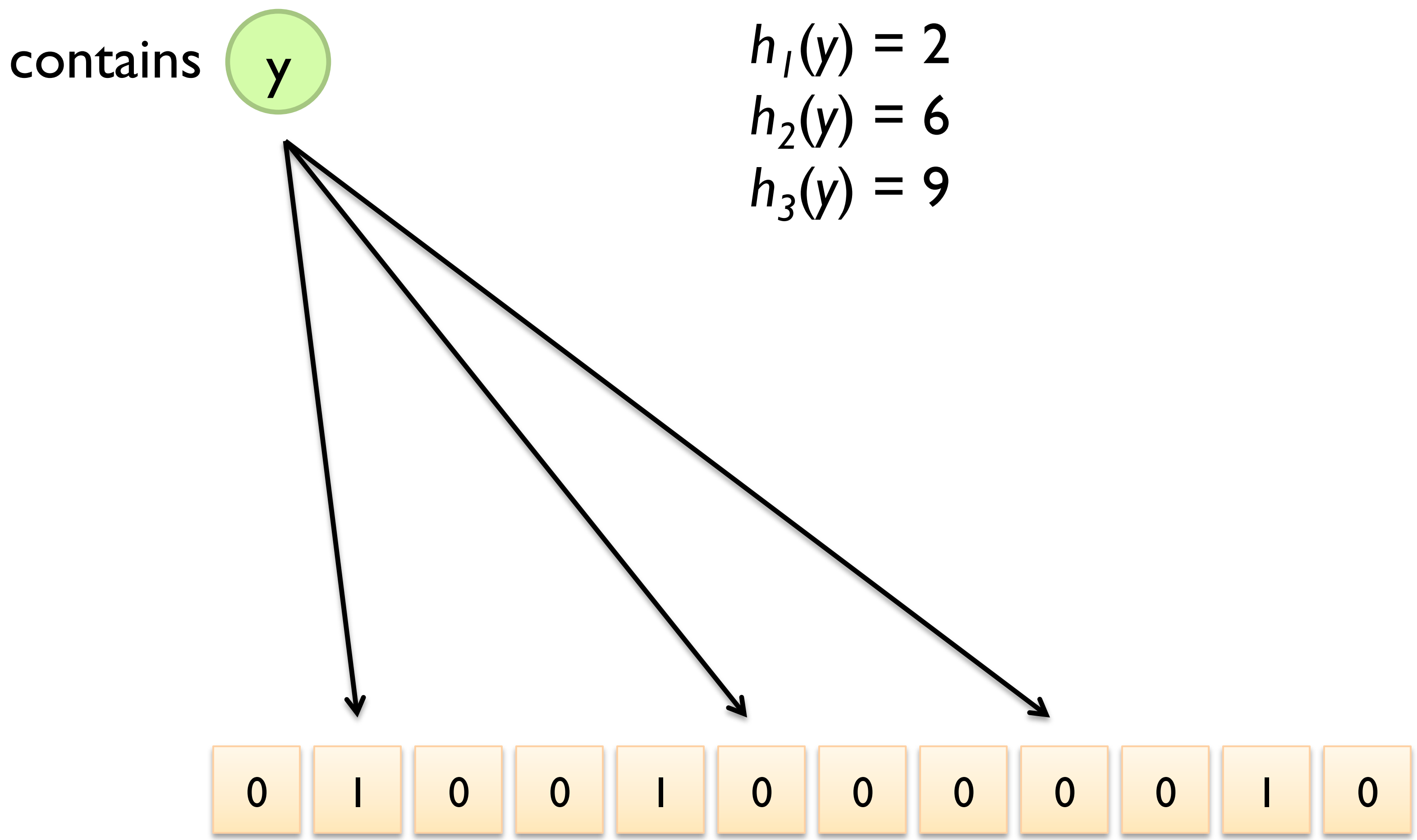


$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$

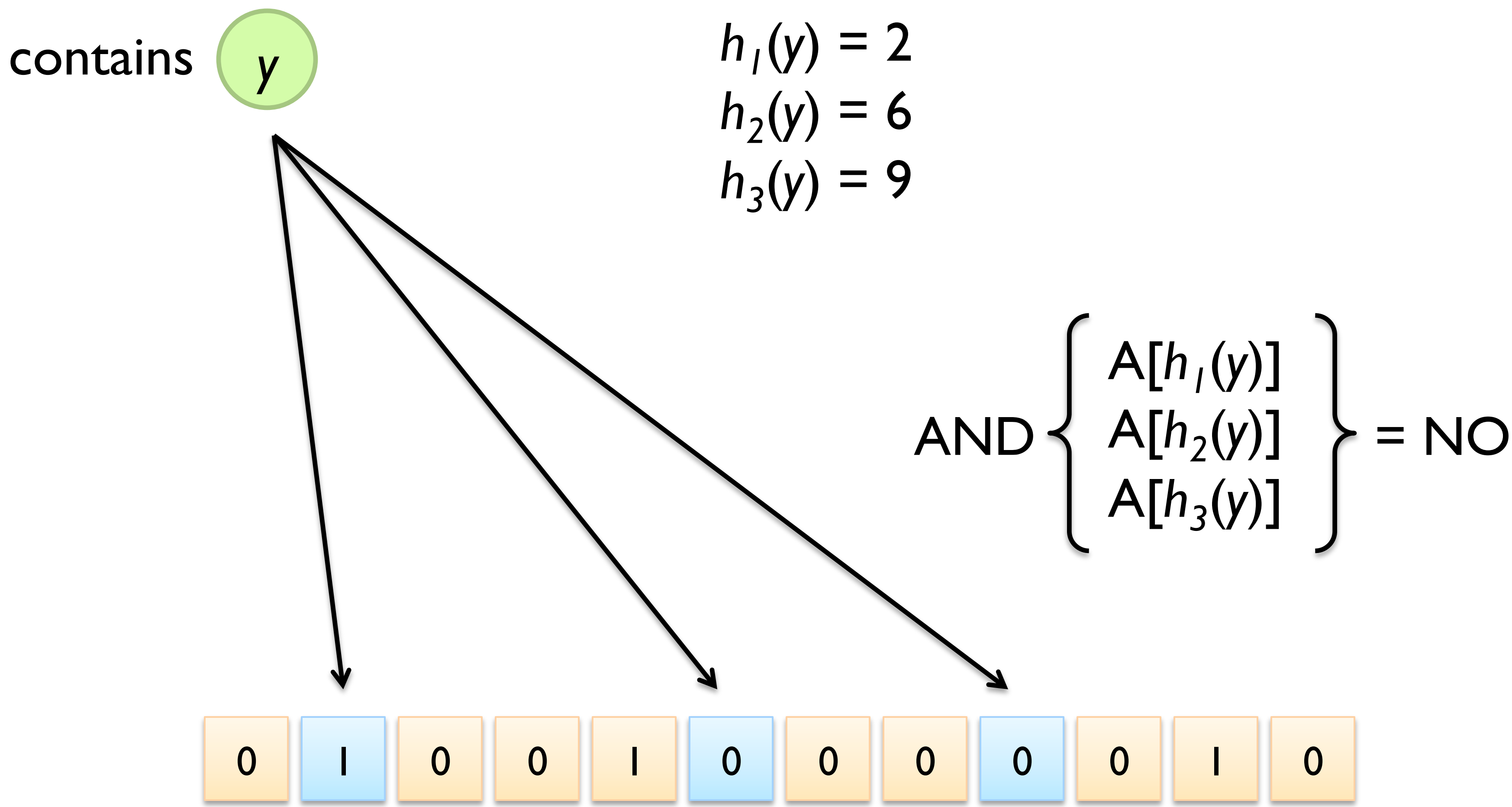
Bloom Filters: contains



Bloom Filters: contains



Bloom Filters: contains



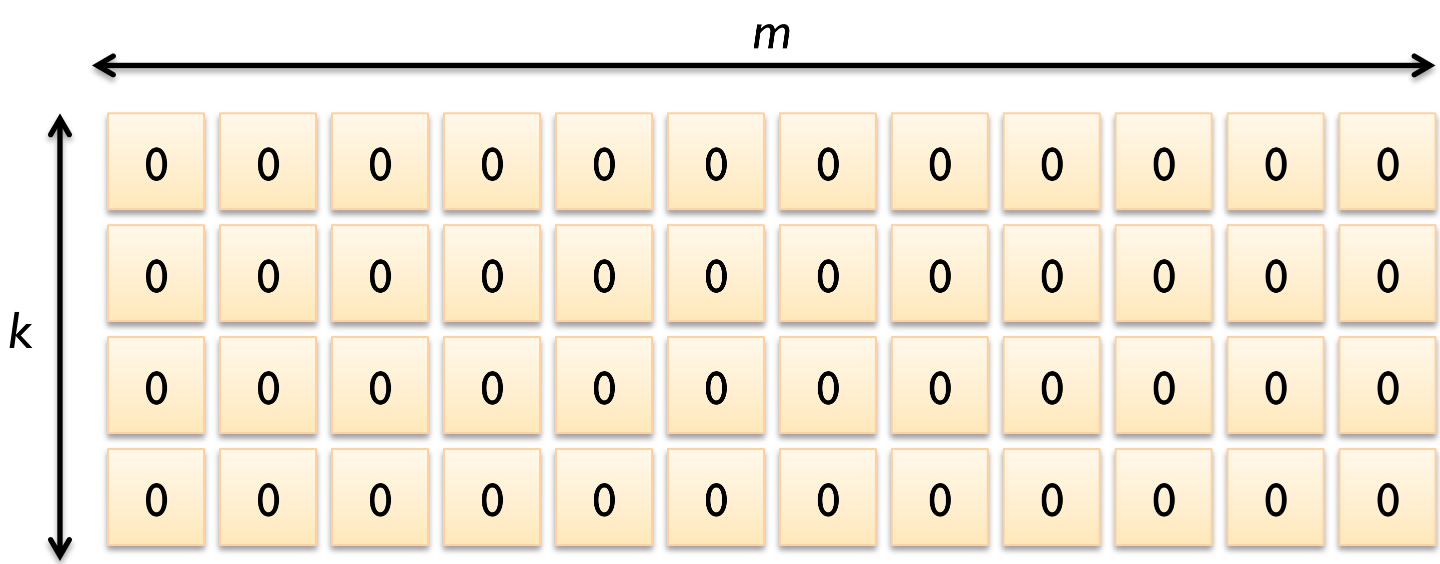
What's going on here?

Bloom Filters

- Error properties: contains(*x*)
  - False positives possible
  - No false negatives
- Usage:
  - Constraints: capacity, error probability
  - Tunable parameters: size of bit vector *m*, number of hash functions *k*

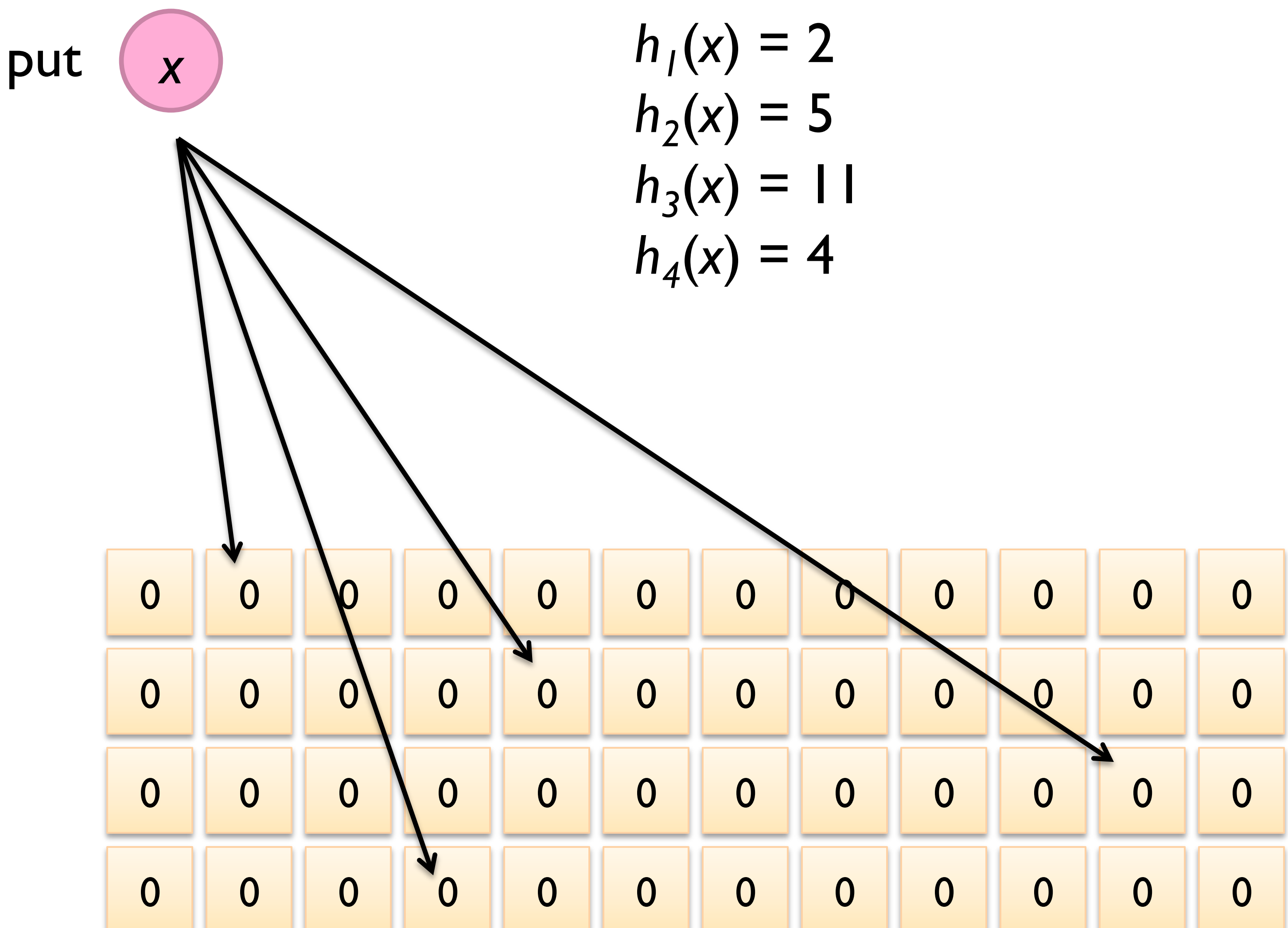
Count-Min Sketches

- Task: frequency estimation
  - put(x) → increment count of x by one
  - get(x) → returns the frequency of x
- Components
  - k hash functions: $h_1 \dots h_k$
  - m by k array of counters



Count-Min Sketches: put

$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$
$h_4(x) = 4$



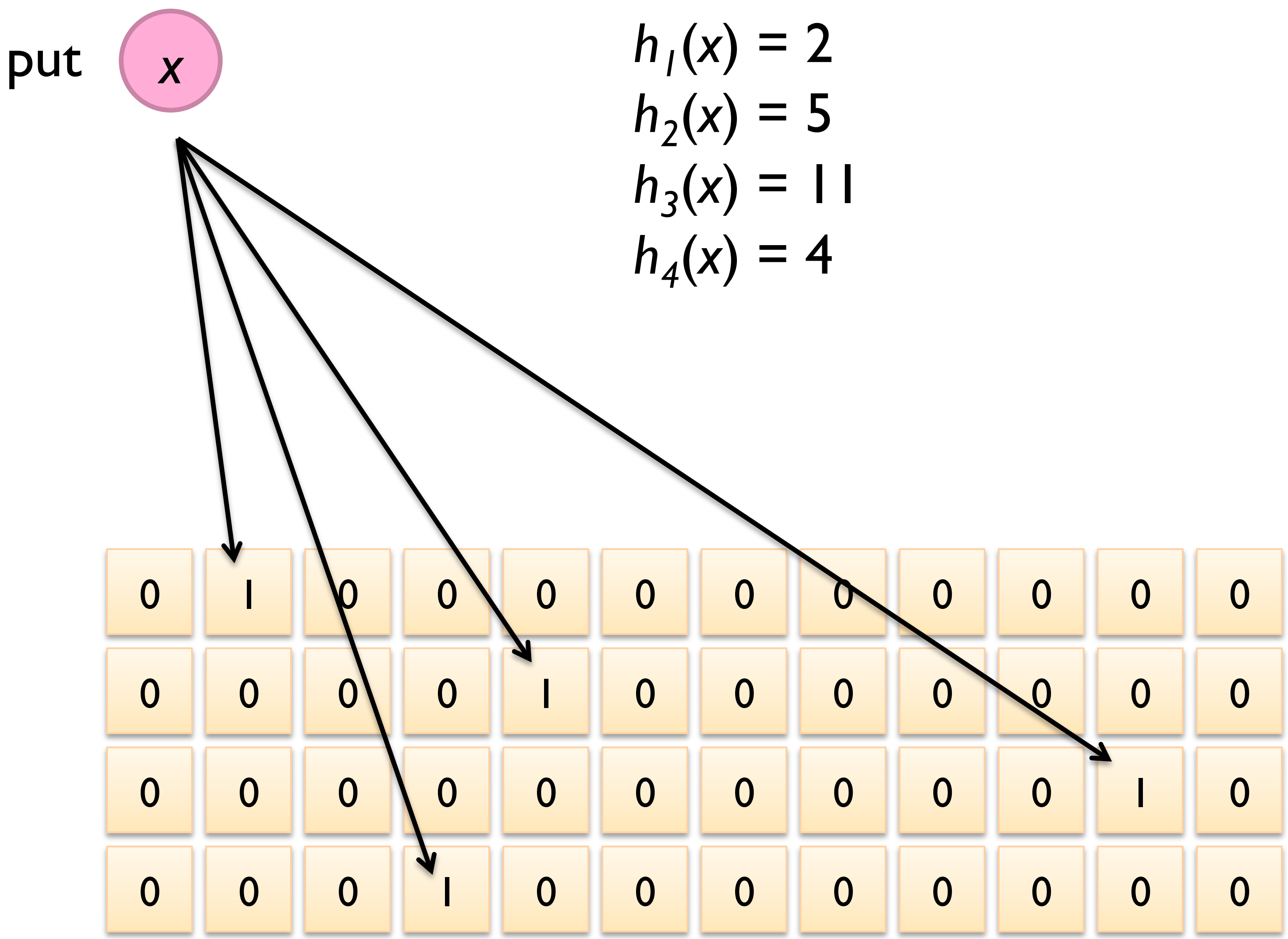
Count-Min Sketches: put

put *x*

0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	0	0	0

Count-Min Sketches: put

$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$
$h_4(x) = 4$



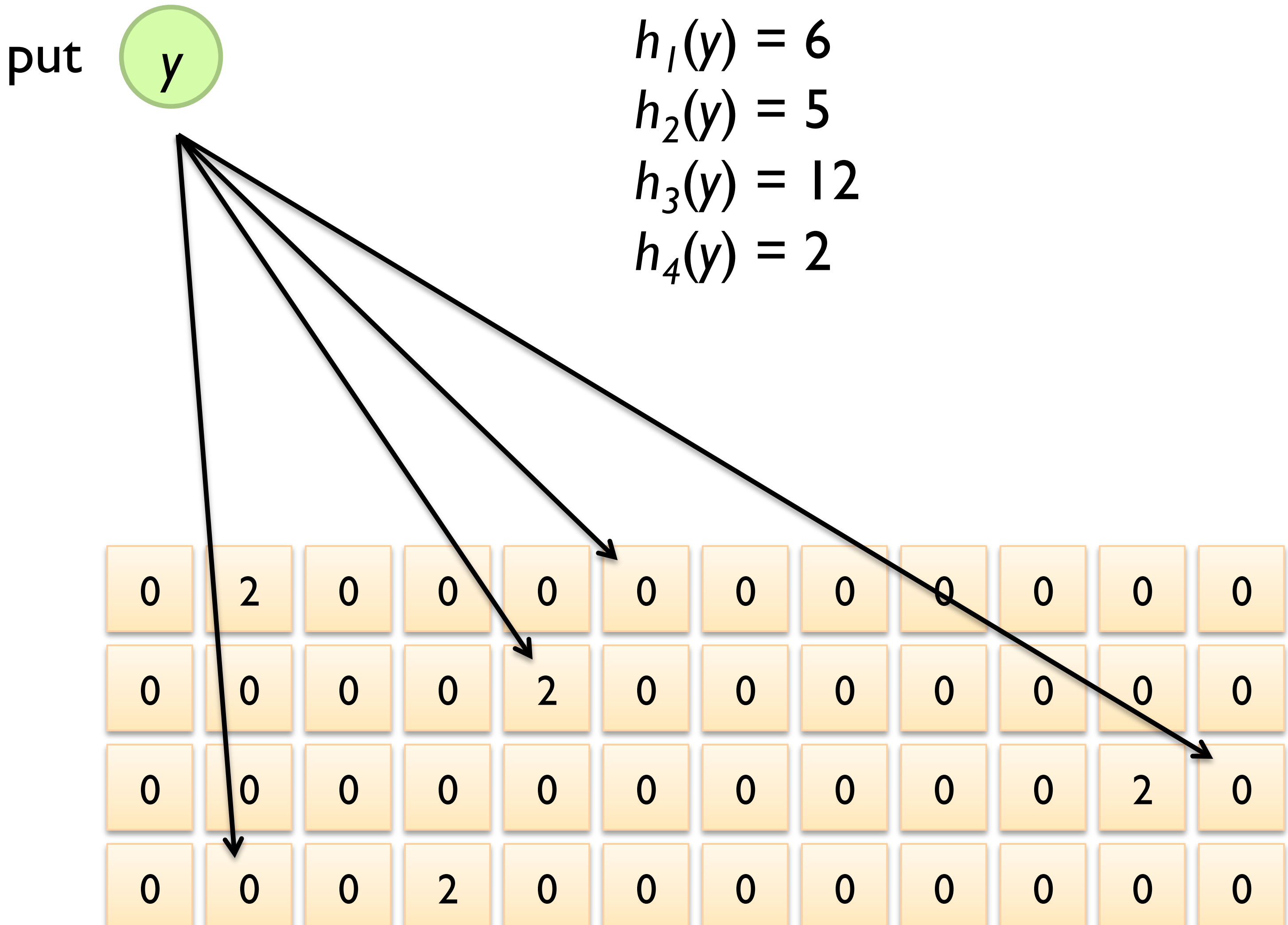
Count-Min Sketches: put

put *x*

0	2	0	0	0	0	0	0	0	0	0	0
0	0	0	0	2	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	2	0
0	0	0	2	0	0	0	0	0	0	0	0

Count-Min Sketches: put

$h_1(y) = 6$
$h_2(y) = 5$
$h_3(y) = 12$
$h_4(y) = 2$



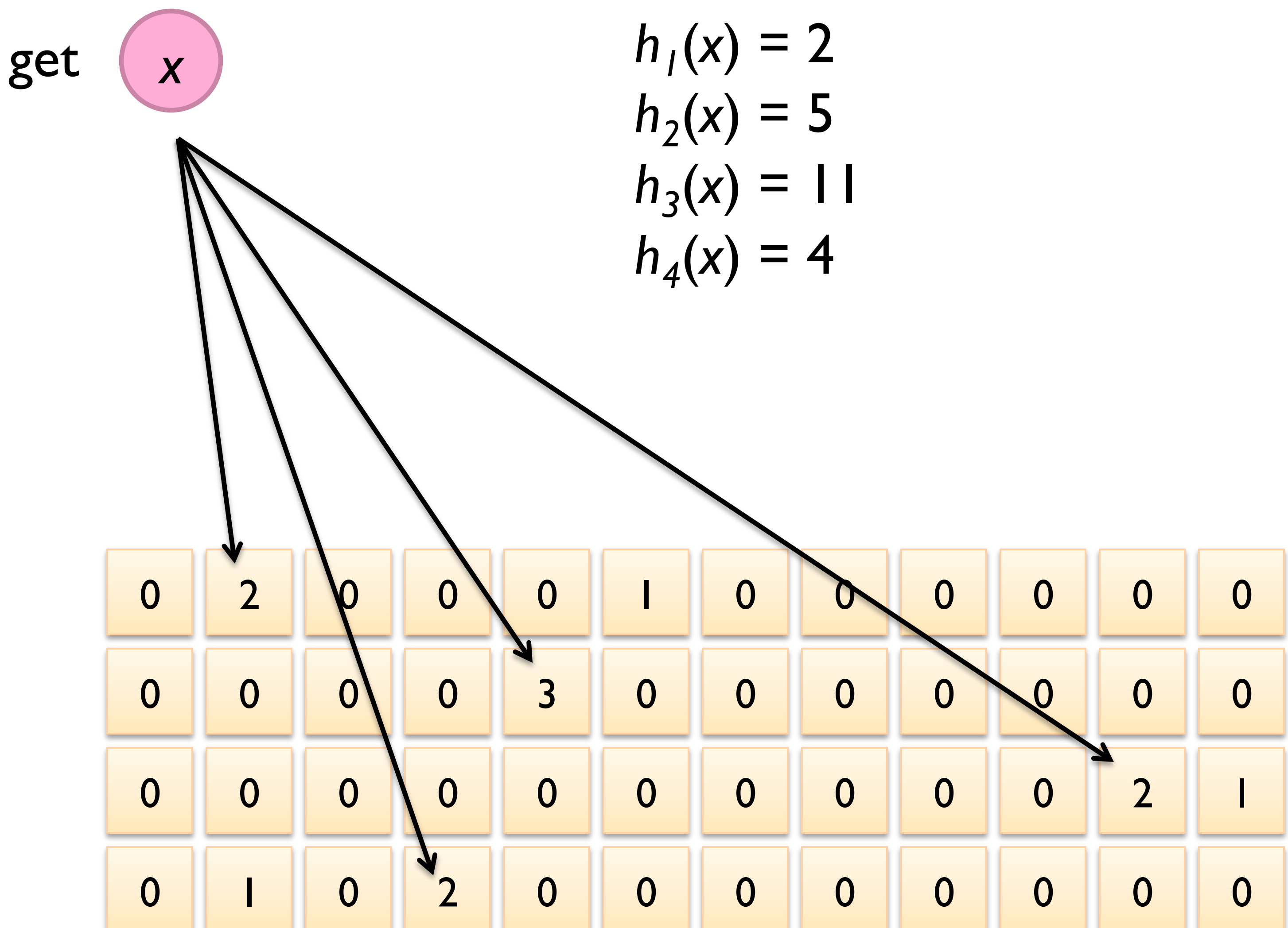
Count-Min Sketches: put

put y

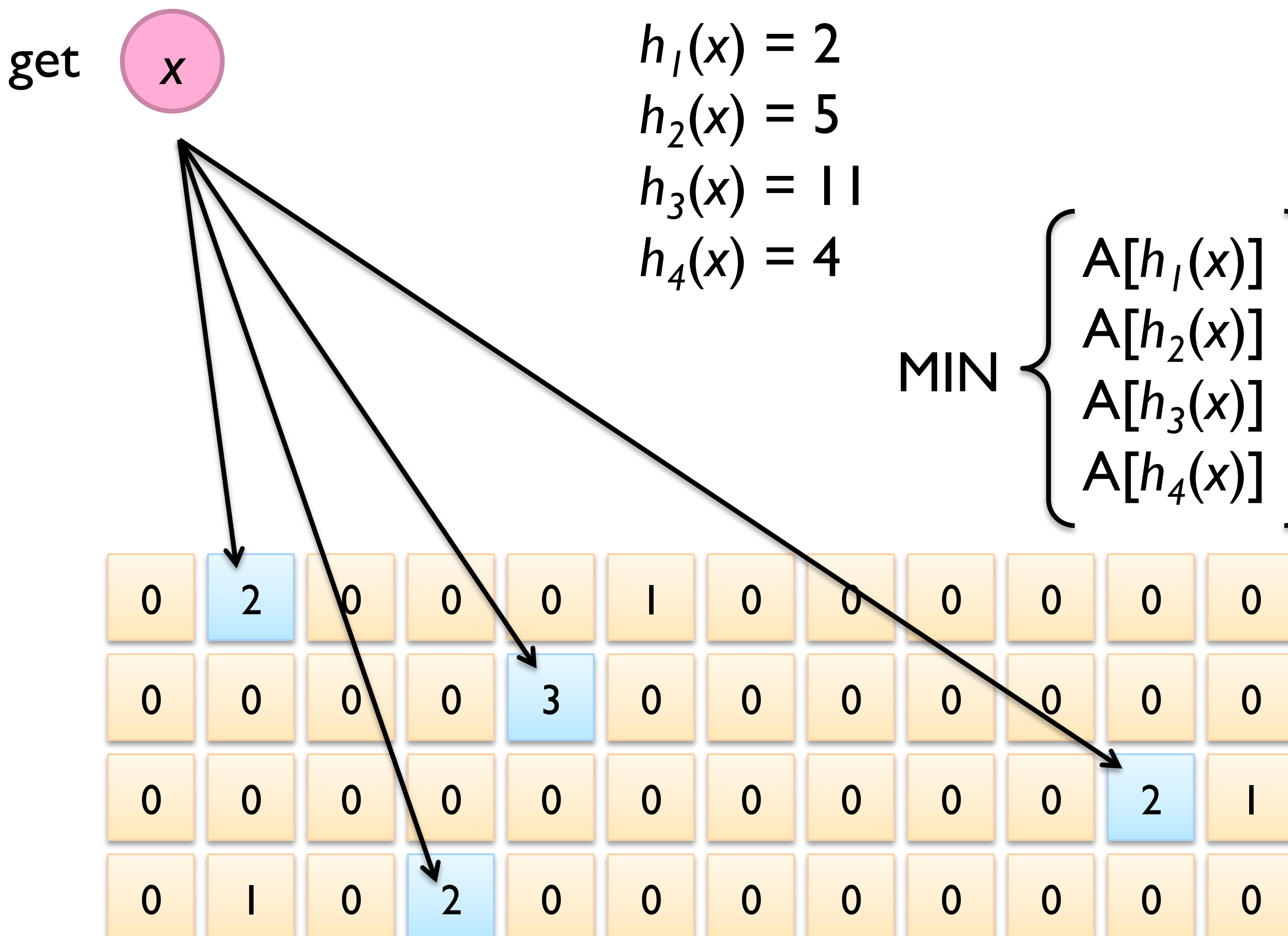
0	2	0	0	0	1	0	0	0	0	0	0
0	0	0	0	3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	2	1
0	1	0	2	0	0	0	0	0	0	0	0

Count-Min Sketches: get

$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$
$h_4(x) = 4$



Count-Min Sketches: get

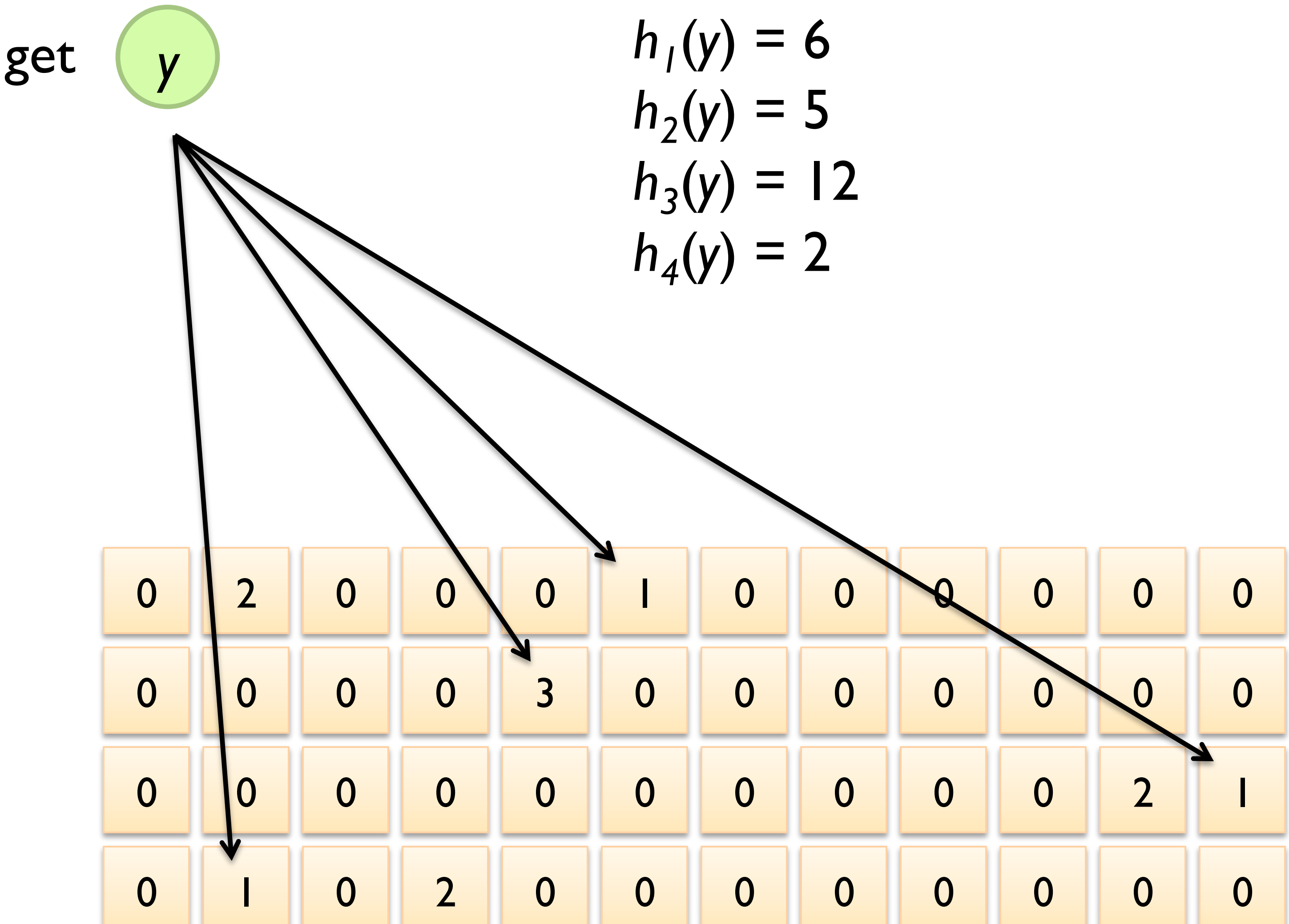


$h_1(x) = 2$
$h_2(x) = 5$
$h_3(x) = 11$
$h_4(x) = 4$

$$\text{MIN} \begin{Bmatrix} A[h_1(x)] \\ A[h_2(x)] \\ A[h_3(x)] \\ A[h_4(x)] \end{Bmatrix} = 2$$

Count-Min Sketches: get

$h_1(y) = 6$
$h_2(y) = 5$
$h_3(y) = 12$
$h_4(y) = 2$

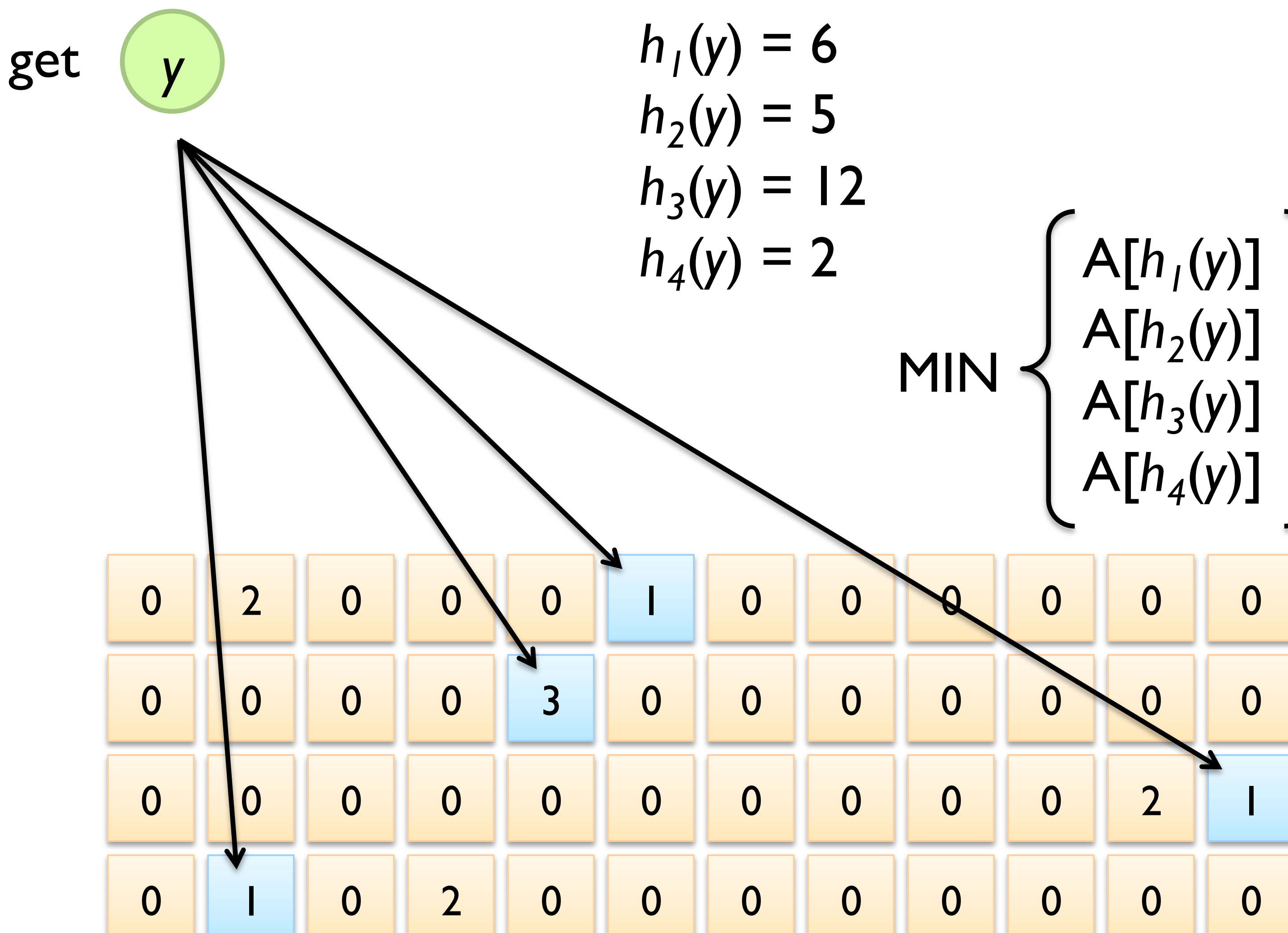


0	2	0	0	0	1	0	0	0	0	0	0
0	0	0	0	3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	2	1
0	1	0	2	0	0	0	0	0	0	0	0

Count-Min Sketches: get

$h_1(y) = 6$
$h_2(y) = 5$
$h_3(y) = 12$
$h_4(y) = 2$

$$\text{MIN} \left\{ \begin{array}{l} A[h_1(y)] \\ A[h_2(y)] \\ A[h_3(y)] \\ A[h_4(y)] \end{array} \right\} = 1$$



Count-Min Sketches

- Error properties:
  - Reasonable estimation of heavy-hitters
  - Frequent over-estimation of tail
- Usage:
  - Constraints: number of distinct events, distribution of events, error bounds
  - Tunable parameters: number of counters m, number of hash functions k, size of counters

Three Common Tasks

Cardinality estimation	HashSet	HLL counter
Set membership	HashSet	Bloom Filter
Frequency estimation	HashMap	CMS

- Cardinality estimation
  - What's the cardinality of set *S*?
  - How many unique visitors to this page?
- Set membership
  - Is *x* a member of set *S*?
  - Has this user seen this ad before?
- Frequency estimation
  - How many times have we observed *x*?
  - How many queries has this user issued?


Next time:
Stream Processing Architectures
Source: Wikipedia (River)

Source: Wikipedia (Japanese rock garden)