Filters (Bloom & Quotient)

CSCI 333

Video Outline

- Filter Motivation
- Filter Operations
- Filter Designs
  - Bloom Filter
    - Parameters
    - Example
    - Limitations
  - Quotient Filter
    - Quotienting idea
    - Data structure
    - Example

Filter Motivation

- Sometimes, we're asked to perform an operation on a piece of data that doesn't actually exist
  - Consider a library. If we know the call number of a book we want, we can: (1) walk to the correct floor, (2) find the shelf with the correct range, and (3) scan for the book on the shelf.
    - If the book was checked out, all of that work was wasted!
  - These steps are surprisingly similar to the process of looking for an item in a data structure so large that it exceeds RAM
- What does this have to do with filters?
  - Filters compactly represent a set so we can check for the existence of an item. If the filter can confirm that the item does not exist, then we don't need to do the expensive search!

Filters: the BIG idea

- Filters are not exact. By embracing approximation, filters can be *memory efficient* data structures
  - Some false positives are allowed
    - Claim something is in the set when it is actually not present
  - But false negatives are never tolerated
    - Claim that something is absent when it is actually present

- Many applications are OK with this behavior
  - Typically filters are used in applications where a wrong answer just wastes work, but does not harm correctness
    - Recall the library example from before:
      - If we confirm the book doesn't exist, we don't search (correct)
      - If we mistakenly say the book exists, all we do is waste the time that we would have needed in the absence of the filter (correct, but slow)

Filter Operations

- Since filters *approximately* represent sets, a filter *must* support:
  - Insertions: `insert(key)`
  - Queries: `lookup(key)`

- Filters *may* also support other operations:
  - Deletion: `remove(key)`
  - Union: `merge(filter`$_a$`, filter`$_b$`)`

Filter Case Study: Bloom

Bloom Filters

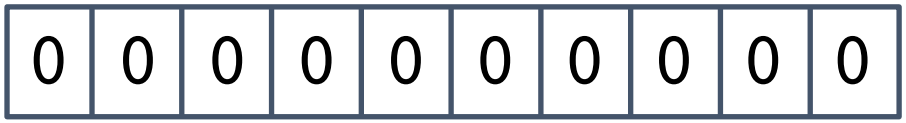
Goal: approximately represent a set of **n** elements using a bit array

- Returns either:
  - Definitely NOT in the set
  - Possibly in the set

Parameters: **m**, **k**

- **m**: Number of bits in the array
- **k**: Set of **k** hash functions { h_1, h_2, …, h_k }, each with range {**0**…**m−1**}

Concrete Example: k=3, m=10

M = 

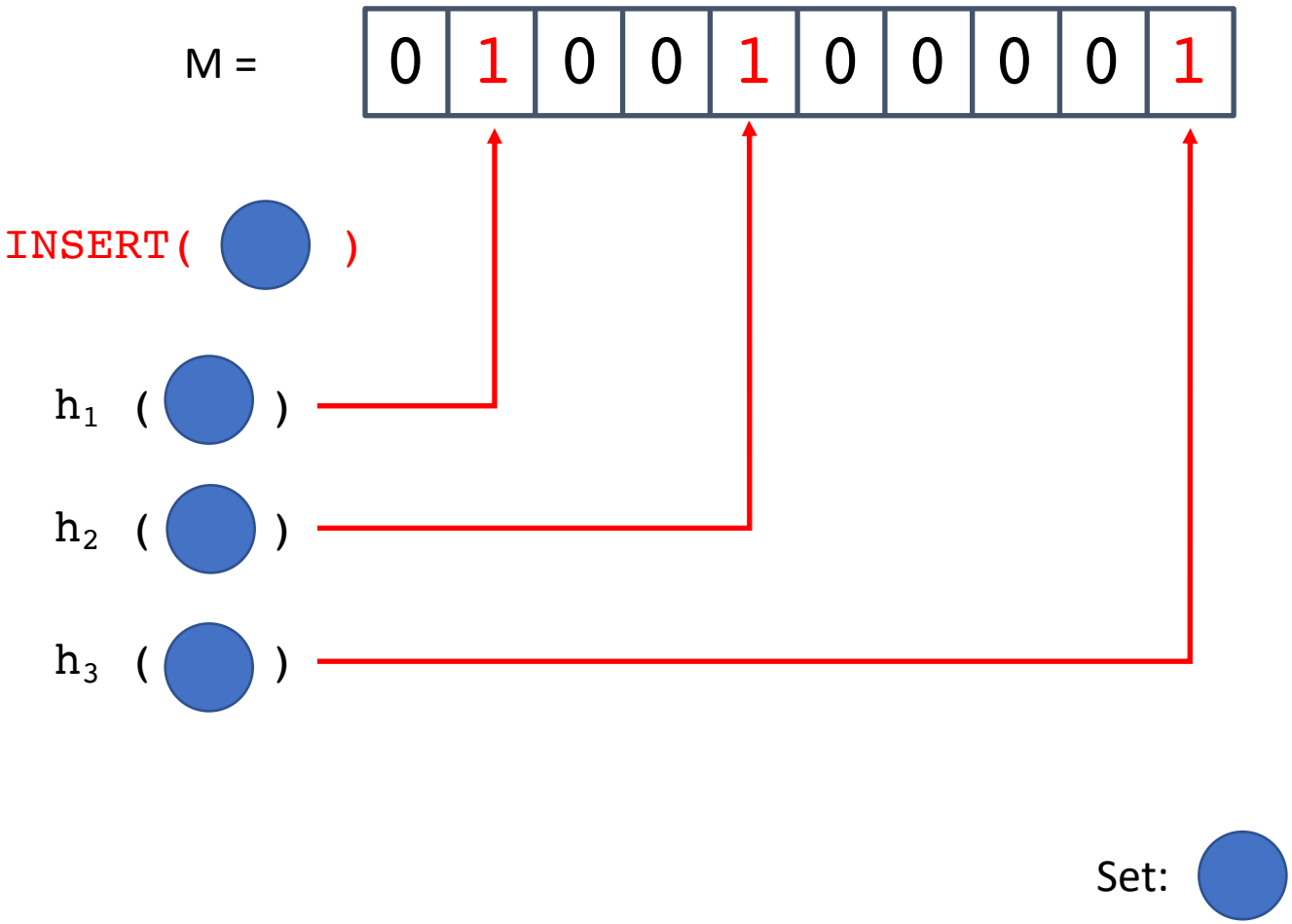
INSERT()

h_1 ()

h_2 ()

h_3 ()

Concrete Example: k=3, m=10



Concrete Example: k=3, m=10

M = 

INSERT(★)

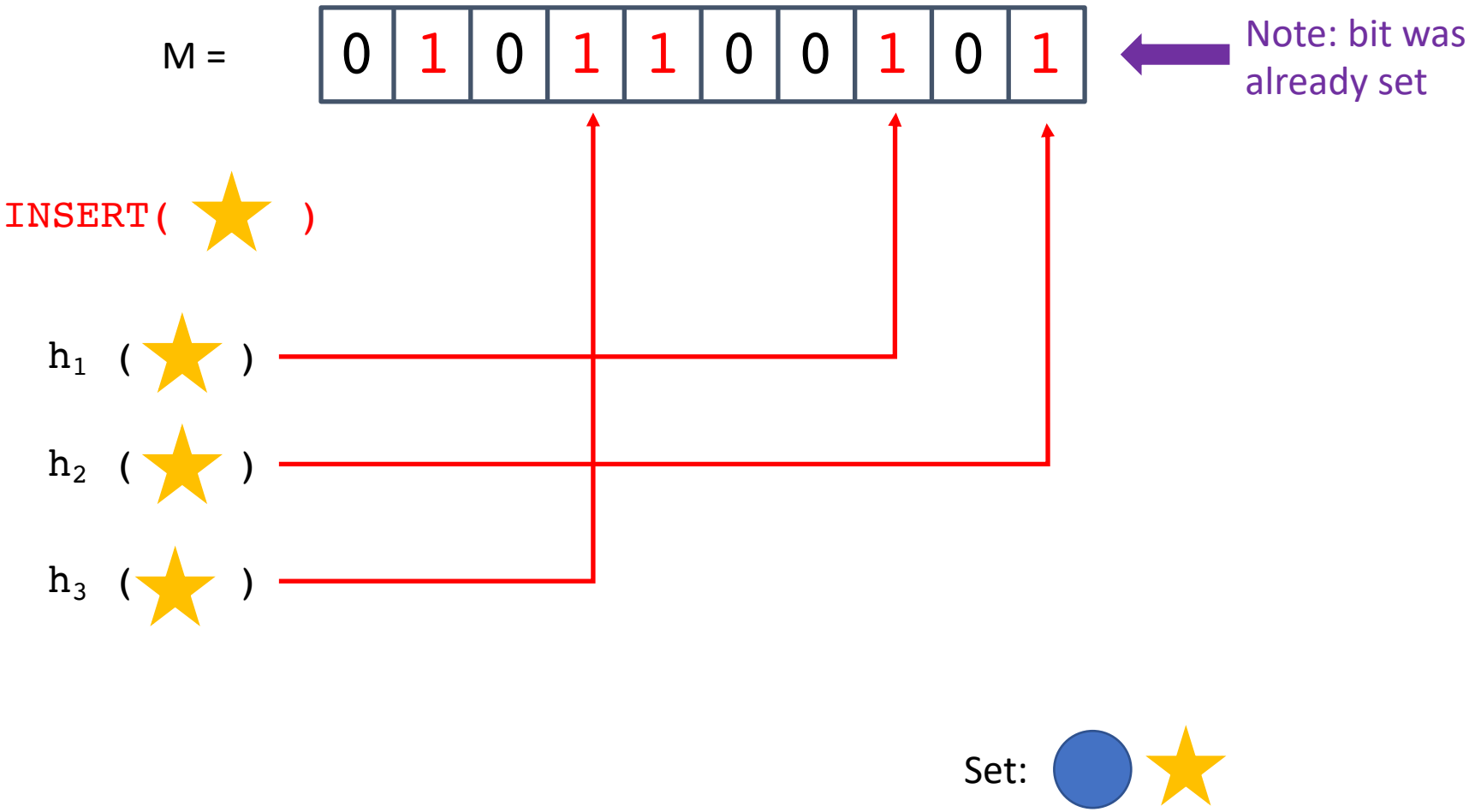
h_1 (★)

h_2 (★)

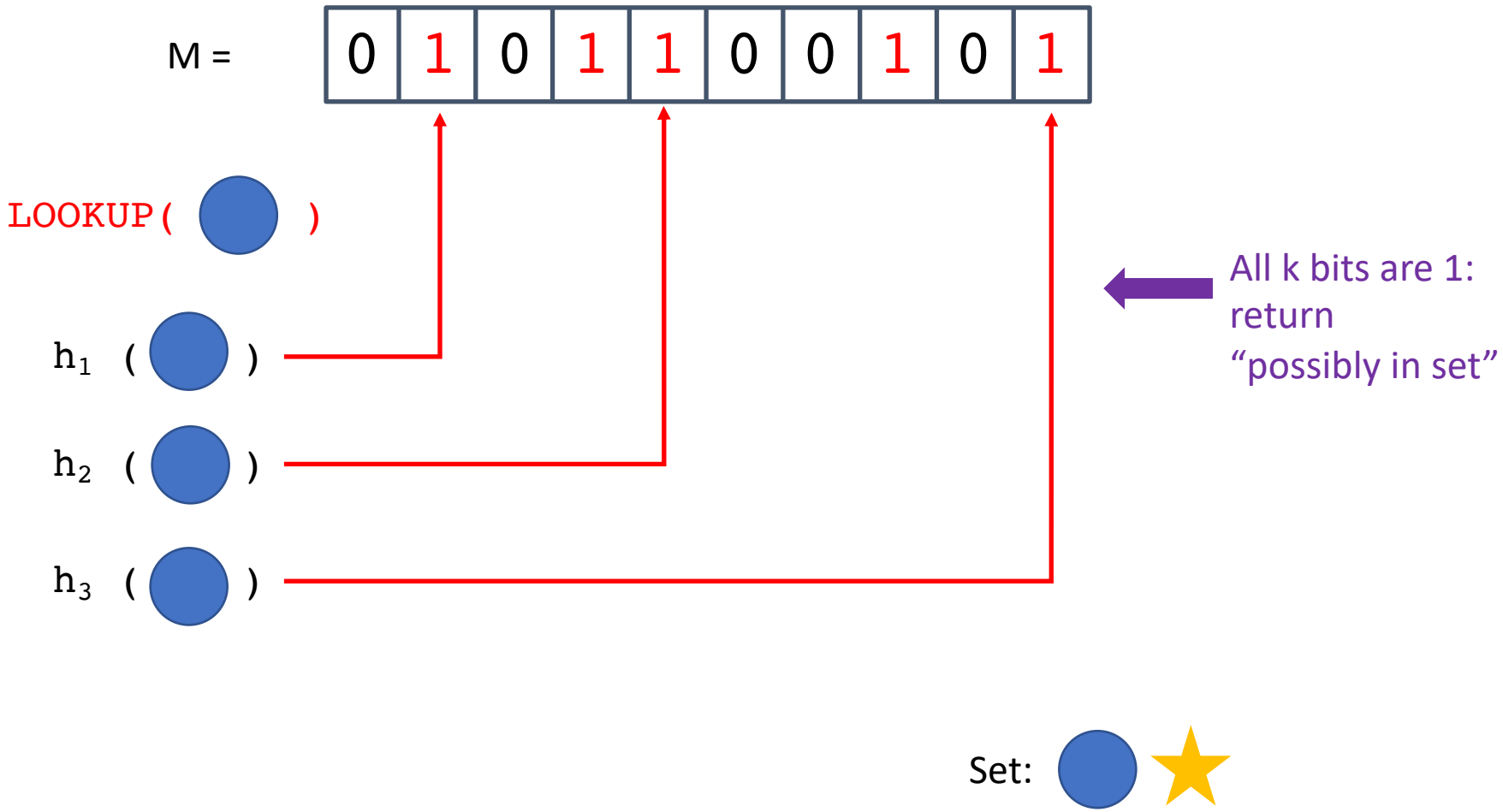
h_3 (★)

Set: 

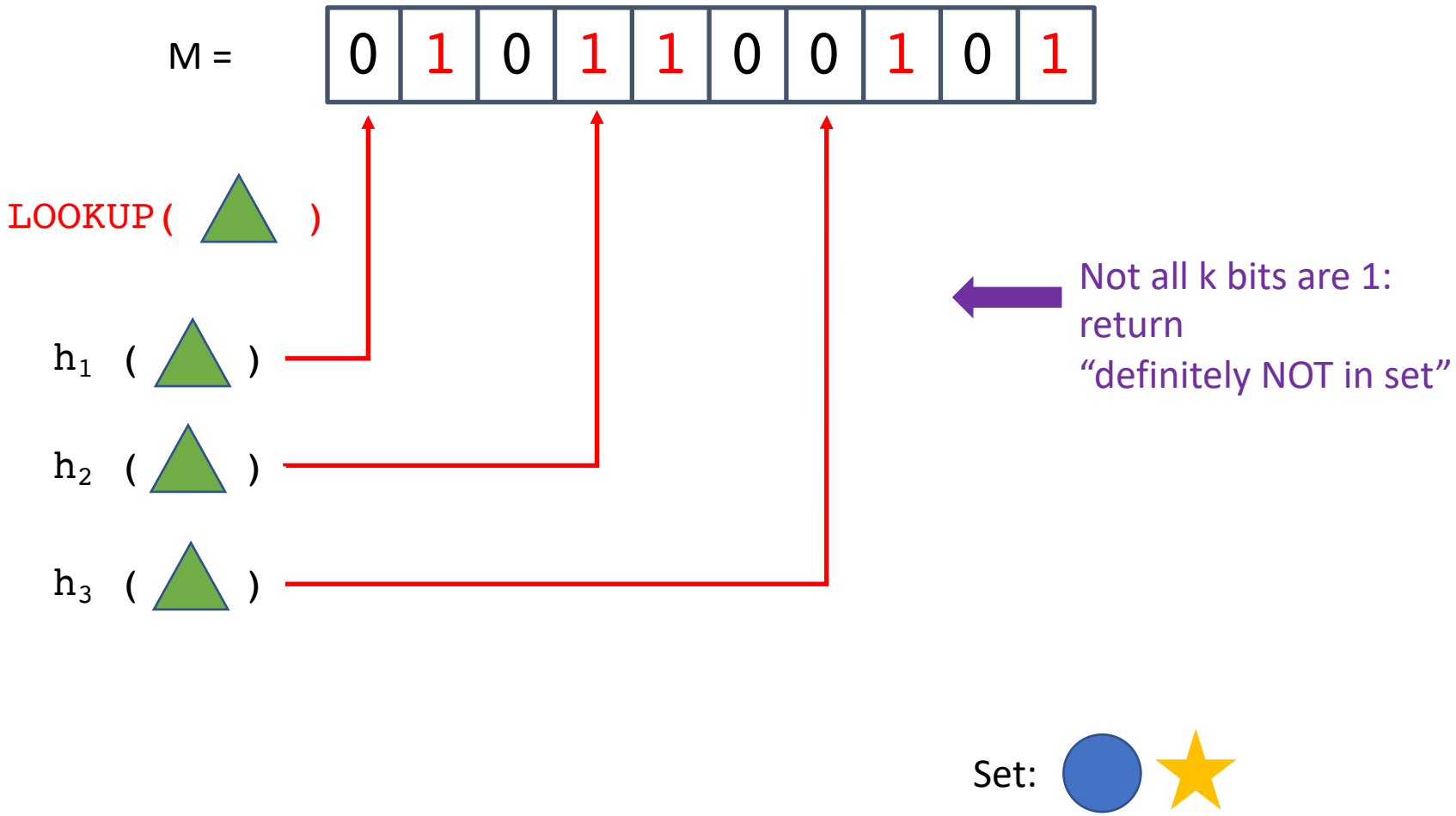
Concrete Example: k=3, m=10



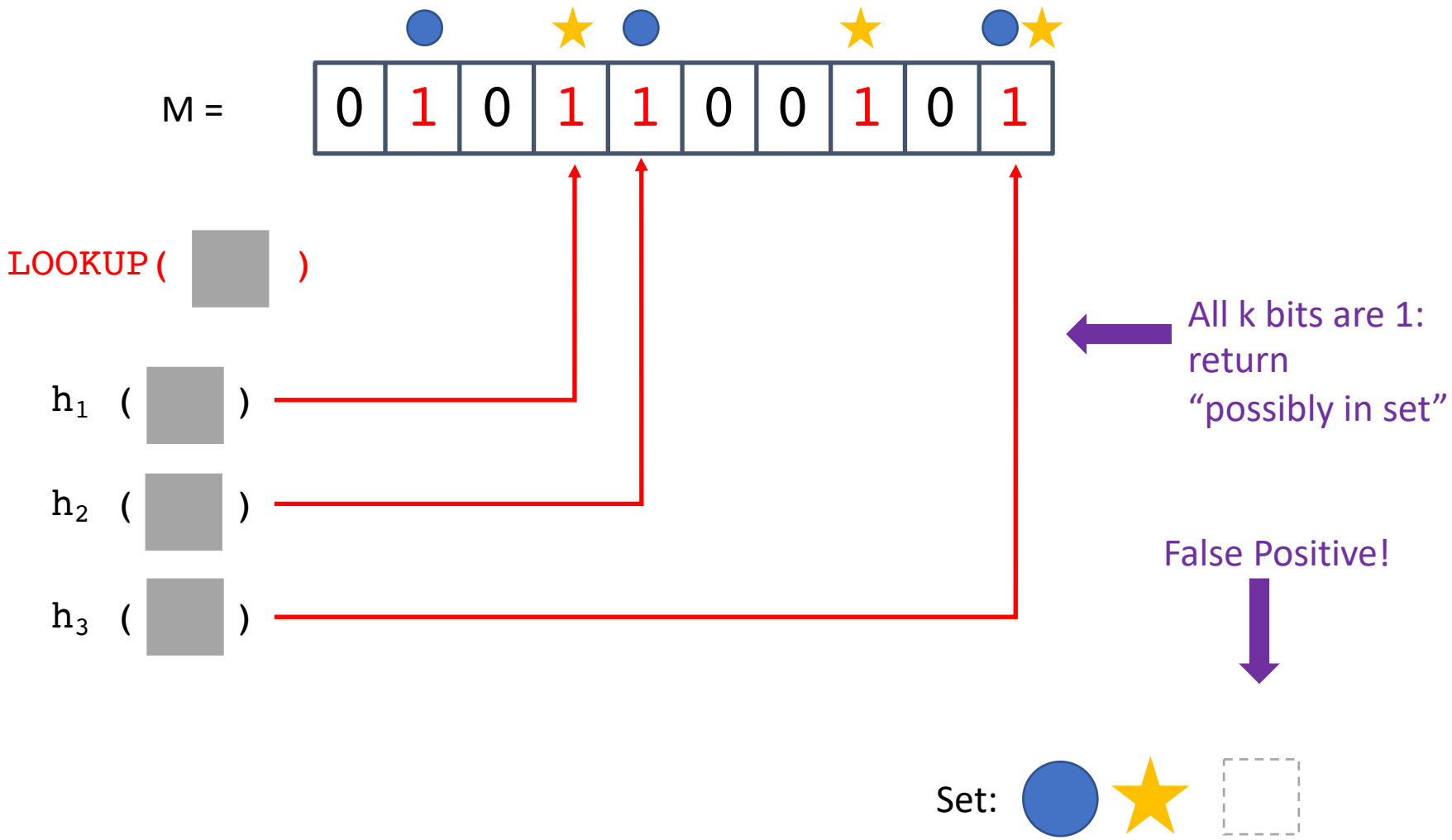
Concrete Example: k=3, m=10



Concrete Example: k=3, m=10



Concrete Example: k=3, m=10



Tuning False Positives

- What happens if we increase `m`?
- What happens if we increase `k`?

- False positive rate `f` is:

$$f = \left(1 - \left(1 - \frac{1}{m}\right)^{kn}\right)^k \approx \left(1 - e^{-\frac{kn}{m}}\right)^k$$

P(a given bit is still 0 after n insertions with k independent hash functions)

Bloom Filters

- Are there any problems with Bloom filters?
  - What operations do they support/not support?
  - How do you grow a Bloom filter?
  - What if your filter itself exceeds RAM (how bad is locality)?
    - What does the cache behavior look like?

Bloom Filters: Challenges

- How do you grow a Bloom filter?
  - Short answer: you can't
    - Filter only stores bits: no way to "invert" bits to recover items
  - Longer answer: rebuild
    - If you wanted to grow a Bloom filter, you could allocate a new (empty) filter of the target size, then read through all items and insert them to the new filter
      - Note: the underlying data may or may not be available!

Bloom Filters: Challenges

- What if your filter itself exceeds RAM?
  - What does the cache behavior look like?
    - Good hash functions intentionally create a uniform distribution to avoid “clumping”
    - So even if the filter fits in RAM, the cache locality is poor due to k random accesses
  - If the data set is truly large, there are a few options:
    - Use fewer bits per item (sacrifice precision)
    - Tolerate higher false positive rates
    - Use caching techniques, adding potential for expensive misses

Bloom Filters: Challenges

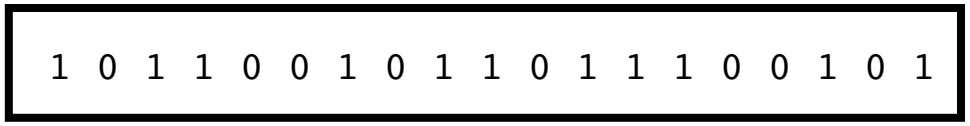
- What operations do they support/not support?
  - insert? Yes!
  - query? Yes!
  - delete? No! (Multiple items may have “set” any given bit)
  - rename? No! (rename = delete + insert)
  - “count”? No! (maybe/no answers only)

Bloom filter extensions that add support for additional operations do exist, but these operations are not supported by the standard data structure.

Filter Case Study: Quotient

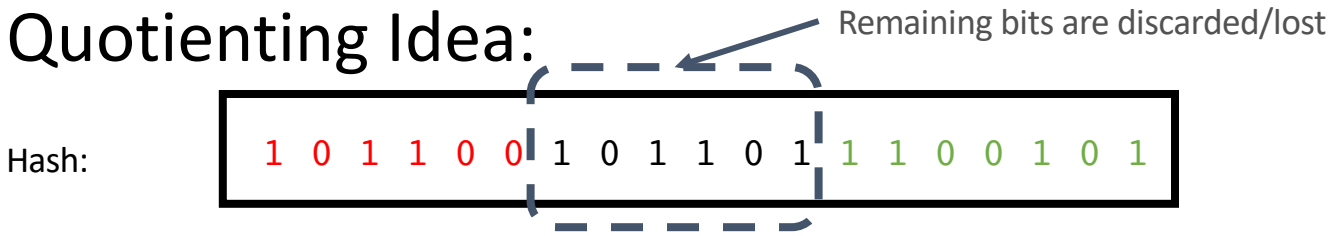
Quotient Filters

- Based on a technique from a homework question in Donald Knuth's "The Art of Computer Programming: Sorting and Searching, volume 3" (Section 6.4, exercise 13)
- Quotienting Idea:

Hash: 

Quotient Filters

- Based on a technique from a homework question in Donald Knuth's "The Art of Computer Programming: Sorting and Searching, volume 3" (Section 6.4, exercise 13)
- Quotienting Idea:



Building a Quotient Filter

- The quotient is used as an index into an **`m`**-bucket array, where the remainder is stored.
  - Essentially, filter is a hashtable that stores a remainder as the value
  - The quotient is *implicitly* stored because it is the bucket index

- Collisions are resolved using linear probing and 3 extra bits per bucket
  - **`is_occupied:`** whether a slot is the canonical slot for *some* value currently stored in the filter
  - **`is_continuation:`** whether a slot holds a remainder that is part of a run (but not the first element in the run)
  - **`is_shifted:`** whether a slot holds a remainder that is not in its canonical slot

- A canonical slot is an element's "home bucket", i.e., where it belongs in the absence of collisions.

Quotient Filter Example

Hash table with external chaining

Hash table with linear probing + bits

Table of objects with quotients/ remainders for reference

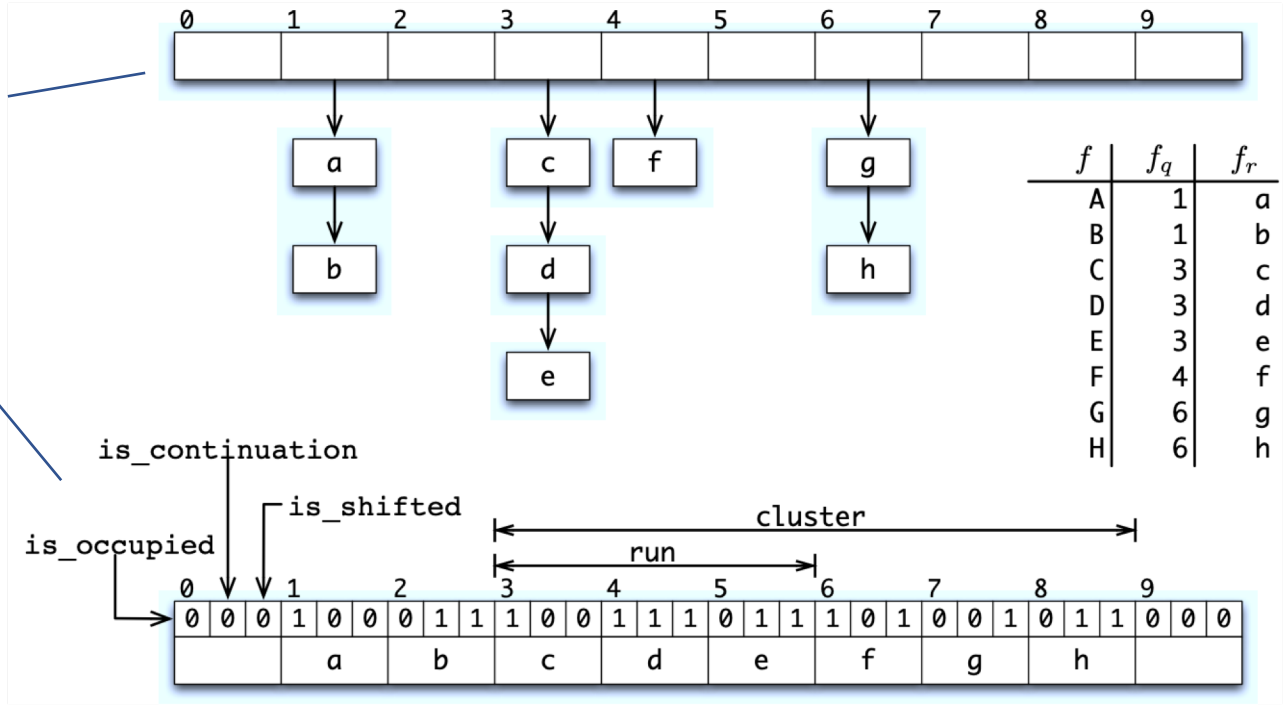


Figure 1: An example quotient filter and its representation.

[https://www.usenix.org/conference/hotstorage11/dont-thrash-how-cache-your-hash-flash]

Quotient Filter Example

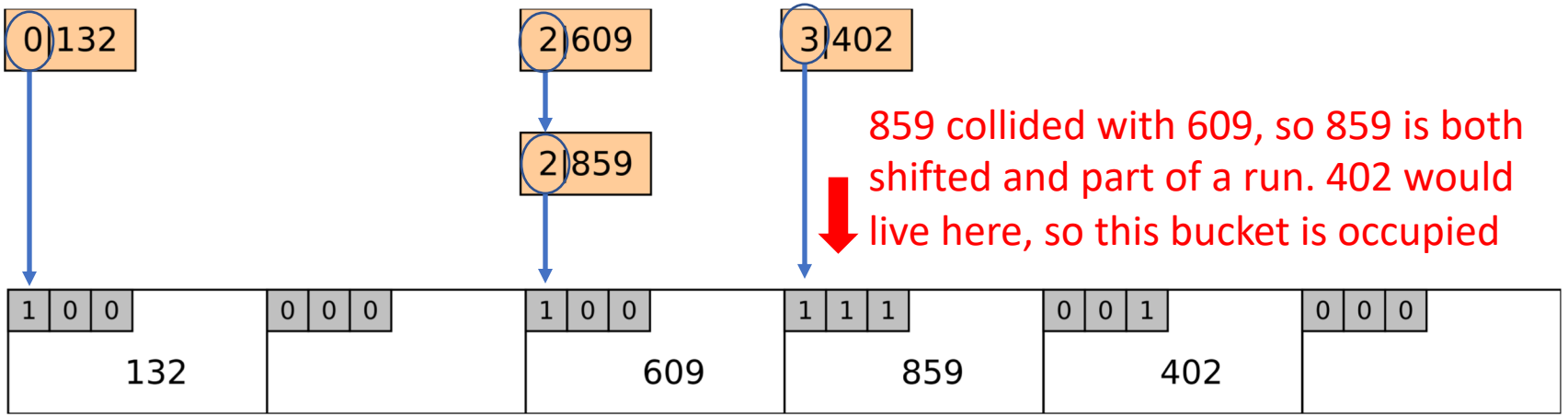
Parameters:

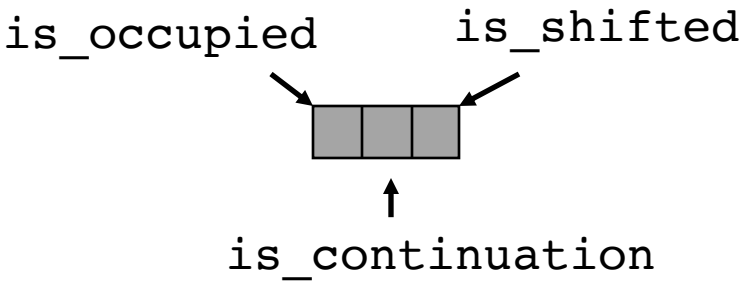
q = 1 bit

r = 3 bits

	Quotient (Bucket Index)	Remainder (Item Stored)
`put(` 0132 `)`	0	132
`put(` 2859 `)`	2	859
`put(` 2609 `)`	2	609
`put(` 3402 `)`	3	402

Quotient Filter Example





Quotient Filter Concept-check

- What are the possible reasons for a collision?
  - Which collisions are treated as “false positives”
- What parameters does the QF give the user? In other words:
  - What knobs can you turn to control the size of the filter?
  - What knobs can you turn to control the false positive rate of the filter?

Quotient Filter Concept-check

- What are the possible reasons for a collision?
  - Collisions in the hashtable
    - Same quotient, but different remainders cause shifting
  - Collisions in the hashspace
    - Different keys may produce identical quotients/remainders
      - If a hash function collision -> not the QF's fault
      - If due to dropped bits during "quotienting" -> that is the QF's fault
  - Which collisions are treated as "false positives"
    - Collisions in the hash space
- What parameters does the QF give the user? In other words:
  - What knobs can you turn to control the size of the filter?
  - What knobs can you turn to control the false positive rate of the filter?
  - Quotient bits (number of buckets)
  - Remainder bits (how many unique bits per element to store)

Why QF over BF?

- QF supports deletes
- QF supports “merges”
- QF has good cache locality
  - How many locations accessed per operation?
  - Some math can show that runs/clusters are expected to be small when we size our array properly

- **Don’t Thrash, How to Cache Your Hash on Flash** also introduces the Cascade filter, a *write-optimized* filter made up of increasingly large QFs that spill over to disk.
  - Similar idea to Log-structured merge trees, which are an exciting topic for another unit!

Cascade Filter

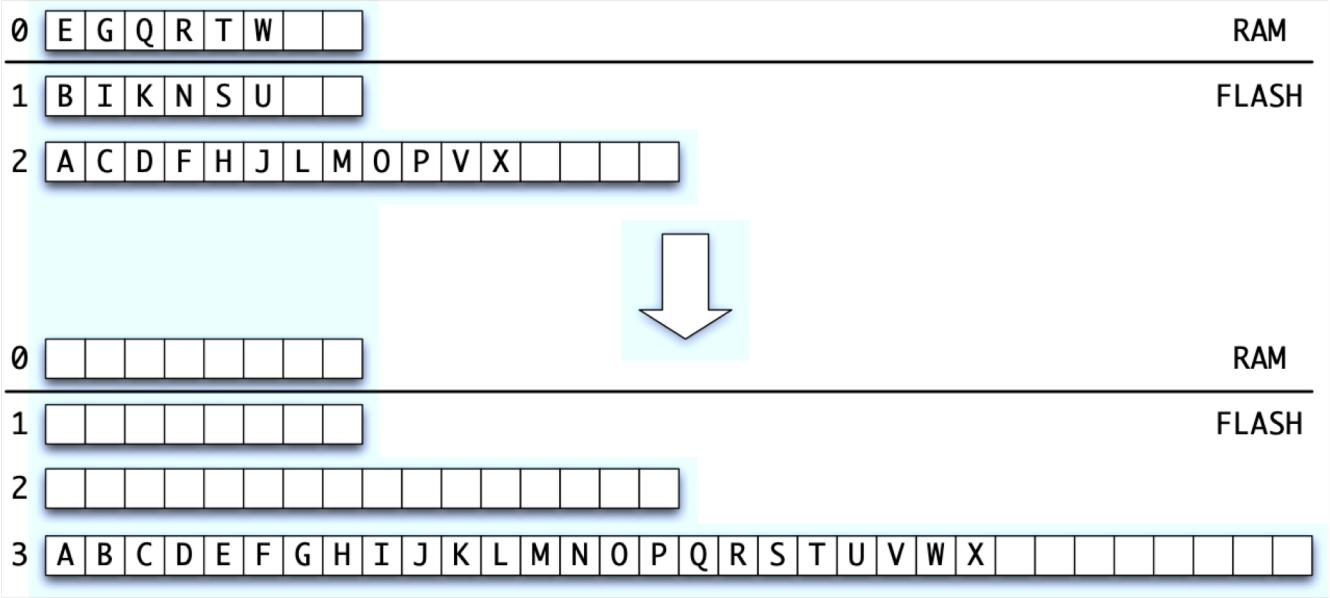


Figure 2: Merging QFs. Three QFs of different sizes are shown above, and they are merged into a single large QF below. The

[https://www.usenix.org/conference/hotstorage11/dont-thrash-how-cache-your-hash-flash]

Inserts are fast (duplicates are OK, so inserts only touch RAM level)
Lookups do 1 I/O per *level*

Takeaways

- Filter use case: save I/O in big data applications
- By embracing approximation, filters can compactly represent sets
  - Filters tolerate some false positives
  - Filters never allow false negatives
- Filter designs can be tuned to trade resources for accuracy or features, but…
- Not all filters are created equal
  - What operations are important?
  - How important is cache efficiency?