Bloom Filters

A Problem

Lookup five-word sequences, return count (or not found)

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Handle some misses locally

$$\Longrightarrow$$

Reduce network

Bloom Filter

Represent a set, probabilistically.

`insert(key)` Add `key` to the set.

`query(key)` If `key` is in the set, return `maybe`.
If `key` is not in the set, return `no` or `maybe`.

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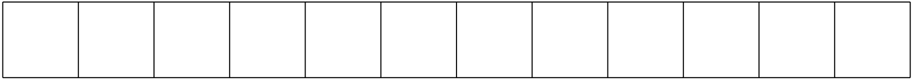
Usage

Ask a Bloom filter locally.

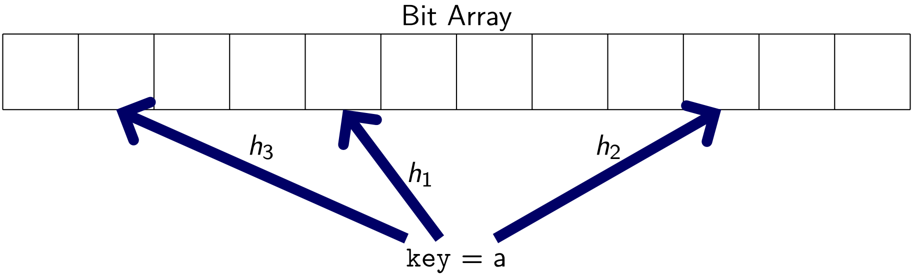
`no` Key is definitely not found $\rightarrow$ avoid network.

`maybe` Ask the network.

Bit Array



1. Initially the array is all 0s.



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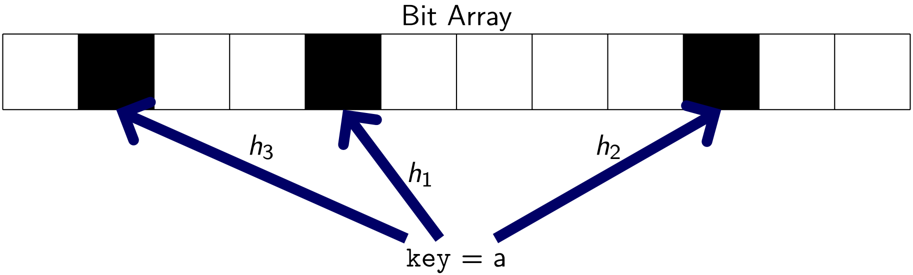
2. Hash functions assign bit positions to keys.



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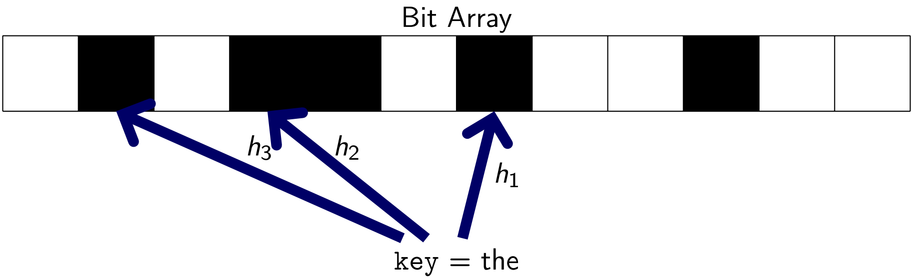
2. Hash functions assign bit positions to keys.
3. Insertion sets the corresponding bits to 1.



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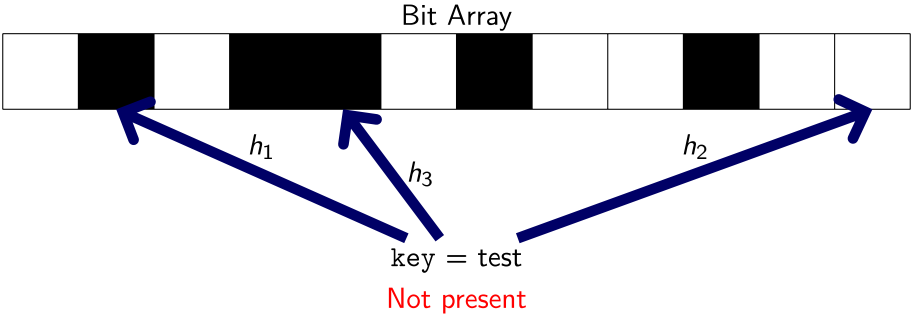

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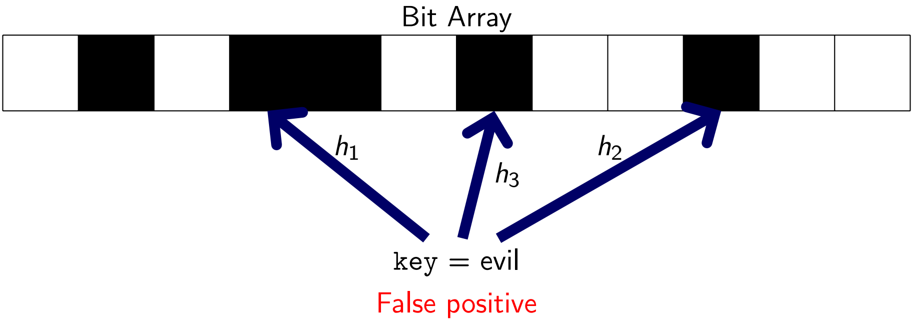

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Not done yet:

- Need multiple hash functions.
- What is the false-positive probability?
- How many hash functions?

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We need independent hash functions:

$$h_1(\texttt{the}), h_2(\texttt{the}), h_3(\texttt{the}), \ldots$$

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Just use one good hash function h and concatenate with key:

$$h(\texttt{1\_key}), h(\texttt{2\_key}), h(\texttt{3\_key}), \ldots$$

The optimal number of hashes is

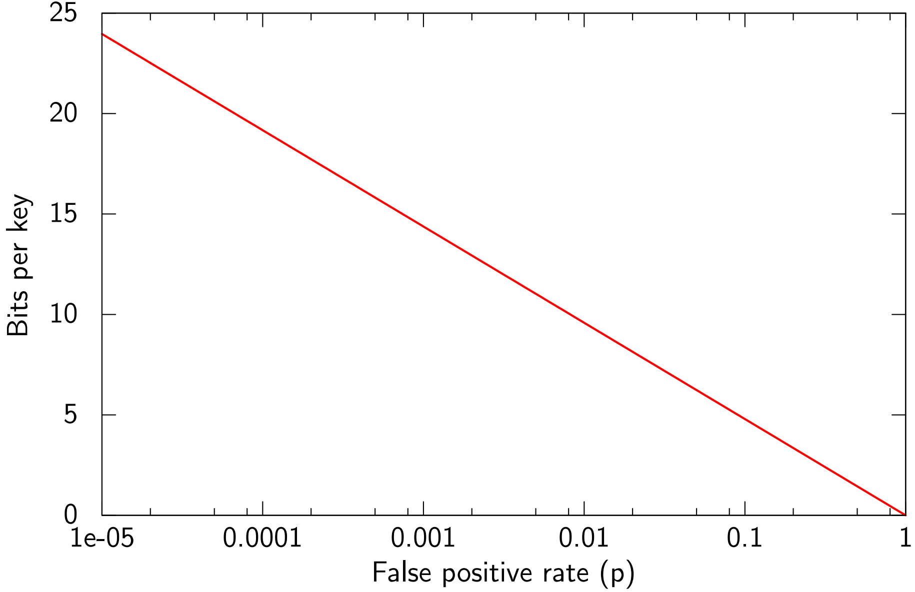
$$\text{hashes} \approx \frac{\text{bits}}{\text{entries}} \ln 2$$

To satisfy false-positive probability p, Bloom filters use

$$\approx \frac{-\log_2 p}{\ln 2}$$

bits per key.

Don't worry about the exact equations.
But deriving them is fun!


25
20
15
10
5
0
Bits per key
1e-05
0.0001
0.001
0.01
0.1
1
False positive rate (p)

Summary

Approximately represent a very large set in small memory.

Used to reduce expensive lookups in SSTable, BigTable, ...

Also useful in isolation for error-tolerant tasks.