Bloom Filters
A Problem

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

In General
Distributed storage
New keys are broadcast (or read-only)
High miss rate
Handle some misses locally

⇒
Reduce network
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Bloom Filter
Represent a set, probabilistically.

\texttt{insert(key)} Add key to the set.

\texttt{query(key)} If key is in the set, return \texttt{maybe}.
If key is not in the set, return \texttt{no} or \texttt{maybe}.
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*.

**Usage**
Ask a Bloom filter locally.
*no* Key is definitely not found → avoid network.
*maybe* Ask the network.
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.
Initially the array is all 0s.

1. Hash functions assign bit positions to keys.

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Initially the array is all 0s.

Hash functions assign bit positions to keys.

Insertion sets the corresponding bits to 1.

Queries check that the corresponding bits are 1.
Bit Array

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

key = evil

False positive
Bloom Filters: memory efficient
...but some probability of false positives.
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Not done yet:
- Need multiple hash functions.
- What is the false-positive probability?
- How many hash functions?
We need independent hash functions:

$$h_1(\text{the}), h_2(\text{the}), h_3(\text{the}), \ldots$$
Multiple Hash Functions?

We need independent hash functions:

\[ h_1(\text{the}), h_2(\text{the}), h_3(\text{the}), \ldots \]

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

\[ h(1\_\text{key}), h(2\_\text{key}), h(3\_\text{key}), \ldots \]
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

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

bits per key.

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