Probabilistic data structures. Part 1. Membership

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PROBABILISTIC DATA STRUCTURES

ALL YOU WANTED TO KNOW BUT WERE AFRAID TO ASK

PART 1: MEMBERSHIP

Andrii Gakhov tech talk @ ferret

MEMBERSHIP

Agenda:

- Bloom Filter
- Quotient filter

THE PROBLEM

 To determine membership of the element in a large set of elements

BLOOM FILTER

BLOOM FILTER

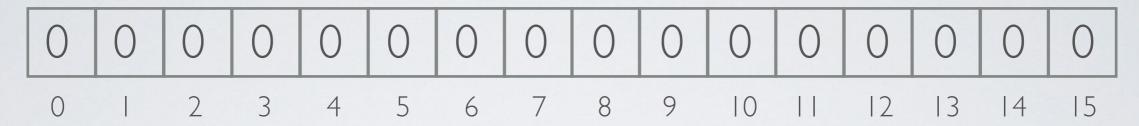
- proposed by Burton Howard Bloom, 1970
- Bloom filter is a realisation of probabilistic set with 3 operations:
 - add element into the set
 - test whether an element is a member of the set
 - test whether an element is not a member of the set
- Bloom filter is described by 2 parameters:
 - m length of the filter
 (proportional to expected number of elements n)
 - **k** number of different hash functions (usually, k is much smaller than m)
- It doesn't store elements and require about 1 byte per stored data

BLOOM FILTER: ALGORITHM

- Bloom filter is a bit array of m bits, all set to 0 at the beginning
- To insert element into the filter calculate values of all k hash functions for the element and set bit with the corresponding indices
- **To test** if element is in the filter calculate all **k** hash functions for the element and check bits in all corresponding indices:
 - if all bits are set, then answer is "maybe"
 - if at least 1 bit isn't set, then answer is "definitely not"
- Time needed to insert or test elements is a fixed constant O(k),
 independent from the number of items already in the filter

BLOOM FILTER: EXAMPLE

Consider Bloom filter of 16 bits (m=16)



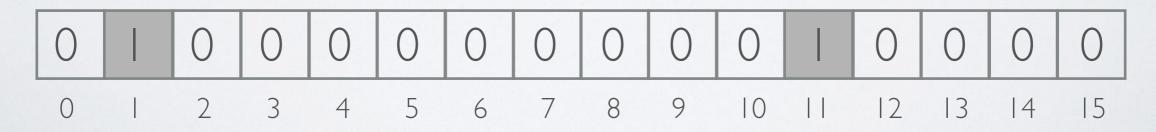
Consider 2 hash functions (k=2):

MurmurHash3 and Fowler-Noll-Vo

(to calculate the appropriate index, we divide result by mod 16)

• Add element to the filter: "ferret":

MurmurHash3("ferret") = 1, FNV("ferret") = 11



BLOOM FILTER: EXAMPLE

Add element to the filter: "bernau":

MurmurHash3("bernau") = 4, FNV("bernau") = 4



• Test element: "berlin":

MurmurHash3("berlin") = 4, FNV("berlin") = 12

Bit 12 is not set, so "berlin" definitely not in the set

• Test element: "paris":

MurmurHash3("paris") = 11, FNV("paris") = 4

Bits 4 and 11 are set, so the element maybe in the set (false positive)

BLOOM FILTER: PROPERTIES

• False positives are possible.

$$P(e \in \Im \mid e \notin \Im) \approx \left(1 - e^{\frac{kn}{m}}\right)^k$$

(element is not a member, but filter returns like it is a member)

- False negatives are not possible. $P(e \notin \Im 1e \in \Im) = 0$ (filter returns that elements isn't a member only if it's not a member)
- Hash functions should be independent and uniformly distributed. They should also be as fast as possible. (don't use cryptographic, like sha1)
- By choice of **k** and **m** it is possible to decrease false positives probability. $k^* = \frac{m}{n} \ln 2$

BLOOM FILTER: APPLICATIONS

- Google BigTable, Apache HBase and Apache Cassandra use Bloom filters to reduce the disk lookups for non-existent rows or columns
- Medium uses Bloom filters to avoid recommending articles a user has previously read
- Google Chrome web browser used to use a Bloom filter to identify malicious URLs (moved to PrefixSet, Issue 71832)
- The Squid Web Proxy Cache uses Bloom filters for cache digests

BLOOM FILTER: PROBLEMS

- The basic Bloom filter doesn't support deletion.
- Bloom filters work well when they fit in main memory
 - ~1 byte per element (3x-4x times more for Counting Bloom filters, that support deletion)
- What goes wrong when Bloom filters grow too big to fit in main memory?
 - On disks with rotating platters and moving heads, Bloom filters choke. A rotational disk performs only 100–200 (random) I/Os per second, and each Bloom filter operation requires multiple I/Os.
 - On flash-based solid-state drives, Bloom filters achieve only hundreds of operations per second in contrast to the order of a million per second in main memory.
- Buffering can help. However, buffering scales poorly as the Bloom-filter size increases compared to the in-memory buffer size, resulting in only a few buffered updates per flash page on average.

BLOOM FILTER: VARIANTS

- Attenuated Bloom filters use arrays of Bloom filters to store shortest path distance information
- **Spectral Bloom filters** extend the data structure to support estimates of frequencies.
- Counting Bloom Filters each entry in the filter instead of a single bit is rather a small counter. Insertions and deletions to the filter increment or decrement the counters respectively.
- Compressed Bloom filters can be easily adjusted to the desired tradeoff between size and false-positive rate
- Bloom Filter Cascade implements filtering by cascading pipeline of Bloom filters
- Scalable Bloom Filters can adapt dynamically to the number of elements stored, while assuring a maximum false positive probability

BLOOM FILTER: PYTHON

- https://github.com/jaybaird/python-bloomfilter
 pybloom is a module that includes a Bloom Filter data structure along with an implementation of Scalable Bloom Filters
- https://github.com/seomoz/pyreBloom
 pyreBloom provides Redis backed Bloom Filter using
 GETBIT and SETBIT

BLOOM FILTER: READ MORE

- http://dmod.eu/deca/ft_gateway.cfm.pdf
- https://en.wikipedia.org/wiki/Bloom_filter
- https://www.cs.uchicago.edu/~matei/PAPERS/bf.doc
- http://gsd.di.uminho.pt/members/cbm/ps/dbloom.pdf
- https://www.eecs.harvard.edu/~michaelm/postscripts/ im2005b.pdf

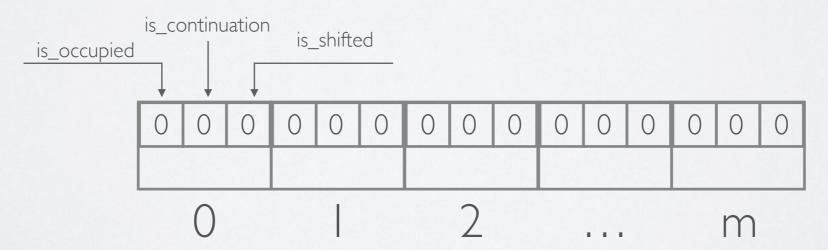
QUOTIENT FILTER

QUOTIENT FILTER

- introduced by Michael Bender et al., 2011
- Quotient filter is a realisation of probabilistic set with 4 operations:
 - add element into the set
 - delete element from the set
 - test whether an element is a member of a set
 - test whether an element is not a member of a set
- Quotient filter is described by:
 - p size (in bits) for fingerprints
 - single hash function that generates fingerprints
- Quotient filter stores p-bit fingerprints of elements

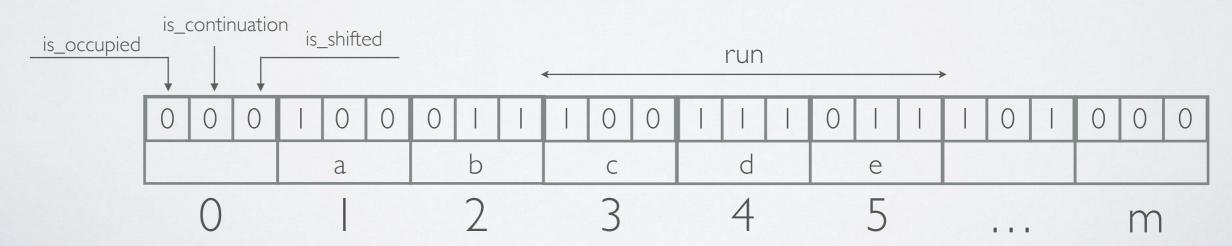
QUOTIENT FILTER: ALGORITHM

- Quotient filter is a compact open hash table with $m = 2^q$ buckets. The hash table employs *quotienting*, a technique suggested by D. Knuth:
 - the fingerprint **f** is partitioned into:
 - the **r least significant bits** ($f_r = f \mod 2^r$, the remainder)
 - the q = p r most significant bits ($f_q = \lfloor f/2^r \rfloor$, the quotient)
- The remainder is stored in the bucket indexed by the quotient
- Each bucket contains 3 bits, all 0 at the beginning: is_occupied,
 is_continuation, is_shifted



QUOTIENT FILTER: ALGORITHM

- If two fingerprints \mathbf{f} and $\mathbf{f'}$ have the same quotient ($\mathbf{f_q} = \mathbf{f'_q}$) it is a **soft collision**. All remainders of fingerprints with the same quotient are stored contiguously in a **run**.
- If necessary, a remainder is **shifted** forward from its original location and stored in a subsequent bucket, wrapping around at the end of the array.
 - is_occupied is set when a bucket j is the canonical bucket ($f_q = j$) for some fingerprint f, stored (somewhere) in the filter
 - is_continuation is set when a bucket is occupied but not by the first remainder in a run
 - is_shifted is set when the remainder in a bucket is not in its canonical bucket



QUOTIENT FILTER: ALGORITHM

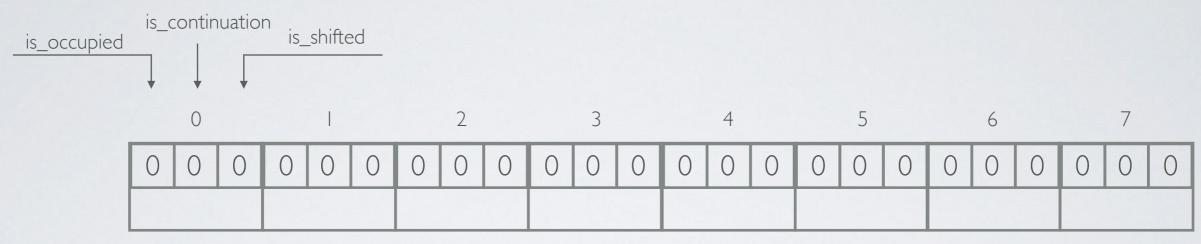
• To **test** a fingerprint **f**:

- if bucket $\mathbf{f_q}$ is not occupied, then the element with fingerprint \mathbf{f} definitely not in the filter
- if bucket f_q is occupied:
 - starting with bucket fq, scan left to locate bucket without set is_shifted bit
 - scan **right** with running count (is_occupied: +1, is_continuation: -1) until the running count reaches 0 when it's the quotient's *run*.
 - \bullet compare the remainder in each bucket in the quotient's run with $\mathbf{f_r}$
 - if found, than element is (probably) in the filter, else it is definitely not in the filter.

• To add a fingerprint **f**:

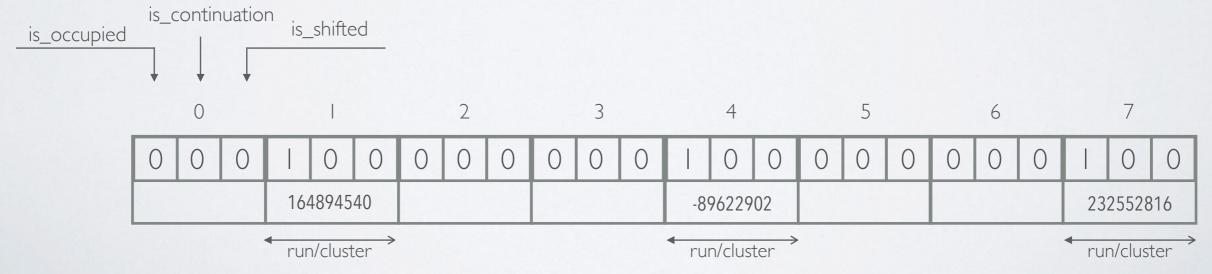
- follow a path similar to test until certain that the fingerprint is definitely not in the filter
- choose bucket in the current run by keeping the sorted order and insert reminder $\mathbf{f_r}$ (set is_occupied bit)
- shift forward all reminders at or after the chosen bucket and update the buckets' bits.

Consider Quotient filter with size p=8 and 32-bit signed
 MurmurHash3 as h



Add elements: "amsterdam", "berlin", "london"

 $f_q("amsterdam") = 1, f_q("berlin") = 4, f_q("london") = 7$ $f_r("amsterdam") = 164894540, f_r("berlin") = -89622902, f_r("london") = 232552816$ Insertion at this stage is easy since all canonical slots are not occupied

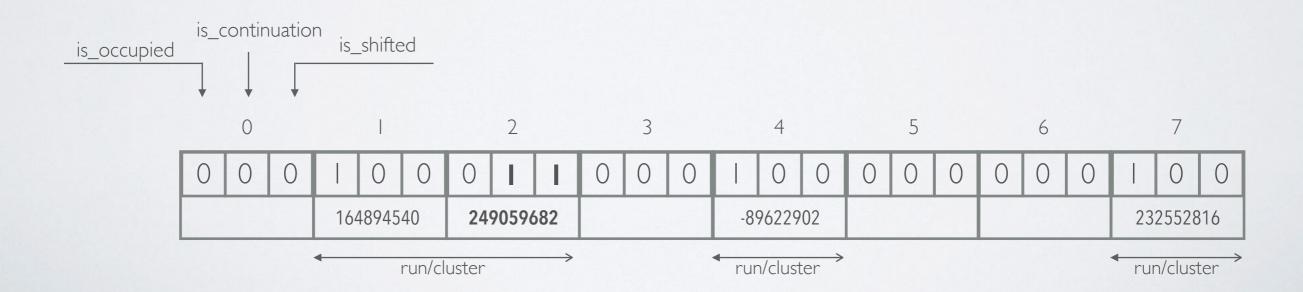


Add element: "madrid"

$$f_q("madrid") = 1, f_r("madrid") = 249059682$$

The canonical slot 1 is already occupied. The *shifted* and *continuation bits* are not set, so we are at the beginning of the cluster which is also the run's start.

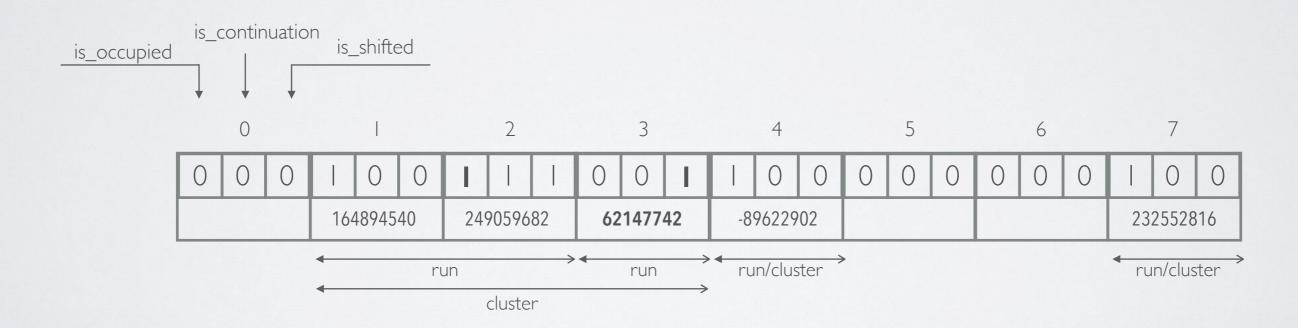
The reminder f_r("madrid") is *strongly bigger* than the existing reminder, so it should be shifted right into the next available slot 2 and *shifted/continuation bits* should be set (but not the *occupied bit*, because it pertain to the slot, not the contained reminder).



Add element: "ankara"

$$f_q("ankara") = 2, f_r("ankara") = 62147742$$

The canonical slot 2 is not occupied, but already in use. So, the fr("ankara") should be shifted right into the neared available slot 3 and its *shifted bit* should be set. In addition, we need to flag the canonical slot 2 as occupied by setting the *occupied bit*.



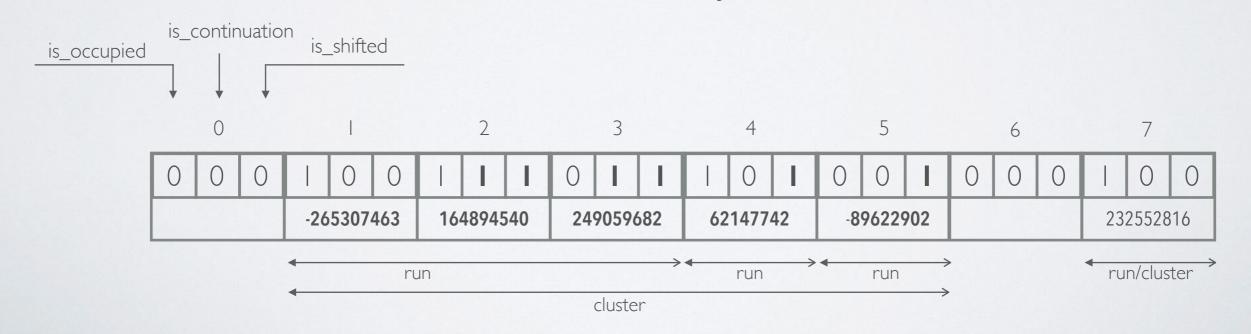
Add element: "abu dhabi"

 $f_q("abu dhabi") = 1, f_r("abu dhabi") = -265307463$

The canonical slot 1 is already occupied. The *shifted* and *continuation bits* are not set, so we are at the beginning of the cluster which is also the run's start.

The reminder f_r("abu dhabi") is *strongly smaller* than the existing reminder, so all reminders in slot 1 should be shifted right and flagged as continuation and shifted.

If shifting affects reminders from other runs/clusters, we also shift them right and set shifted bits (and mirror the continuation bits if they are set there).

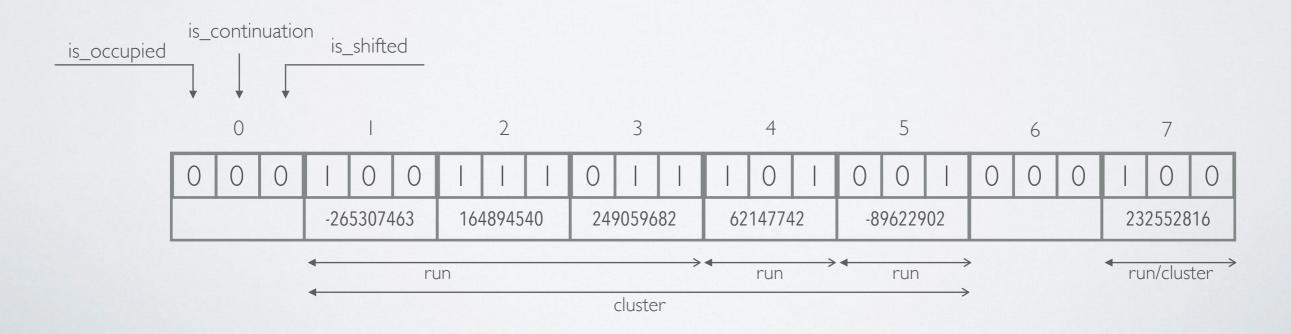


• Test element: "ferret"

$$f_q("ferret") = 1, f_r("ferret") = 122150710$$

The canonical slot 1 is already occupied and it's the start of the run. Iterate through the run and compare f_r ("ferret") with existing reminders until we found the match, found reminder that is strongly bigger, or hit the run's end.

We start from slot 1 which reminder is smaller, so we continue to slot 2. Reminder in the slot 2 is already bigger than f_r ("ferret"), so we conclude that "ferret" **definitely not in the filter**.



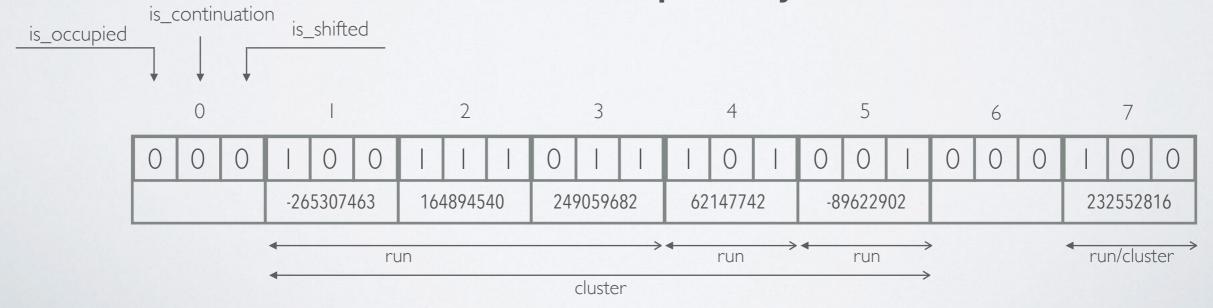
Test element: "berlin"

 $f_q("berlin") = 4$, $f_r("berlin") = -89622902$

The canonical slot 4 is already occupied, but shifted bit is set, so the run for which it is canonical slot exists, but is shifted right.

First, we need to find a run corresponding to the canonical slot 4 in the current cluster., so we scan left and count occupied slots. There are 2 occupied slots found (indices 1 and 2), therefore our run is the 3rd in the cluster and we can scan right until we found it (count slots with not set *continuation bit*).

Our run starts in the slot 5 and we start comparing f_r ("berlin") with existing values and found match, so we can conclude that "berlin" **probably in the filter**.



QUOTIENT FILTER: PROPERTIES

• False positives are possible.

$$P(e \in \Im \mid e \notin \Im) \le \frac{1}{2^r}$$

(element is not a member, but filter returns like it is a member)

• False negatives are not possible.

$$P(e \notin \Im \mid e \in \Im) = 0$$

(filter returns that elements isn't a member only if it's not a member)

- Hash function should generate uniformly distributed fingerprints.
- The length of most runs is O(1) and it is highly likely that all runs have length O(log m)
- Quotient filter efficient for large number of elements (~1B for 64-bit hash function)

QUOTIENT FILTER VS BLOOM FILTER

- Quotient filters are about 20% bigger than Bloom filters, but faster because each access requires evaluating only a single hash function
- Results of comparison of in-RAM performance (M. Bender et al.):
 - inserts: BF: 690 000 inserts per second, QF: 2 400 000 insert per second
 - lookups: BF: 1 900 000 lookups per second, QF: 2 000 000 lookups per second
- Lookups in Quotient filters incur a single cache miss, as opposed to at least two in expectation for a Bloom filter.
- Two Quotient Filters can be efficiently merged without affecting their false positive rates. This is not possible with Bloom filters.
- Quotient filters support deletion

QUOTIENT FILTER: IMPLEMENTATIONS

- https://github.com/vedantk/quotient-filter
 Quotient filter in-memory implementation written in C
- https://github.com/dsx724/php-quotient-filter
 Quotient filter implementation in pure PHP
- https://github.com/bucaojit/QuotientFilter
 Quotient filter implementation in Java

QUOTIENT FILTER: READ MORE

- http://static.usenix.org/events/hotstorage11/tech/ final_files/Bender.pdf
- http://arxiv.org/pdf/1208.0290.pdf
- https://en.wikipedia.org/wiki/Quotient_filter
- http://www.vldb.org/pvldb/vol6/p589-dutta.pdf

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