Birdwatching: False Negatives In Cuckoo Filters

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ABSTRACT
Cuckoo filters are a probabilistic data structure for approximate set membership queries. Their lookup queries are designed to return either “probably in the set” (with probability of error $\epsilon$) or “definitely not in the set”. We show that the latter does not necessarily hold in practice, meaning that these filters may suffer from both false positives and false negatives. Specifically, we analyze state-of-the-art cuckoo filter implementations, and identify a source of false negatives arising from an interplay between partial-key hashing and cuckoo evictions in filters that are close to full. We further show that for practical implementations of cuckoo filters, there is a trade-off between space efficiency and incurring a certain amount of false negatives. Finally, we compare state-of-the-art cuckoo filter implementations with their Bloom filter counterparts. We show that for a false positive rate below 3%, Bloom filters achieve better space efficiency than cuckoo filters for most of the filter sizes.

CCS CONCEPTS
• Theory of computation → Bloom filters and hashing;

KEYWORDS
Cuckoo filters, Bloom filters

ACM Reference Format:

1 INTRODUCTION
Cuckoo filters are an approximate set membership data structure that support Insert, Lookup, and Delete operations. They were introduced by Fan et al. [4] in 2014, and have since been adopted in a wide range of network applications in which Bloom filters were utilized beforehand. To maximize their space efficiency and operations throughput (i.e., number of operations per second), cuckoo filters make their Lookup approximate, admitting a fraction $\epsilon$ of false positives. By design, cuckoo filters are supposed to not incur any false negatives for Lookup.

Our contributions are summarized as follows:

- We conduct experiments to measure the space efficiency of cuckoo filters [1], showing that they may use up to twice the theoretically expected amount of memory.
- We compare the space efficiency of cuckoo filters [1] with Bloom filters implementation in Bitcoin Core [2] and identify conditions under which Bloom filters are smaller than cuckoo filters (See Fig. 2).
- Finally, we identify the potential source of false negatives in some cuckoo filters and evaluate their effect in practical filter configurations (See Fig. 1).

2 STRUCTURE OF CUCKOO FILTERS
A cuckoo filter is a two-dimensional bit array divided logically into slots, buckets and fingerprints. The number of slots per bucket ($b$), number of buckets ($m$), and bits per slot ($f$) are fixed and uniform throughout the filter. We write $n_{\text{max}}$ to denote the maximum capacity of the filter, $n$ to denote the number of currently inserted elements, and $\alpha = n/(b \times m)$ to denote the current load factor. Cuckoo

Figure 1: Empirical false negatives rate for $b = 4, f = 8$ cuckoo filters, with $m$ not a power of two.

Figure 2: Space utilization of space optimized cuckoo [1] and Bloom filters [2].
filters also make use of two independent hash functions: the fingerprint hash \( x_f \) and bucket hash \( H \). These two hash functions participate in partial-key cuckoo hashing — the procedure of identifying the two buckets into which a fingerprint \( \phi_x \) of an item \( x \) may be stored. The fingerprint hash determines the fingerprint of an item, while the bucket hash determines the two candidate buckets (denoted \( i_1 \) and \( i_2 \)) into which the fingerprint may be stored. The fingerprint of each successfully inserted item is stored in only one of the two candidate buckets, depending on which bucket has sufficient space. If no bucket has space to store the fingerprint, a bucket (\( i_1 \) or \( i_2 \)) is chosen uniformly at random and the recursive process of cuckoo eviction is triggered [4]. Partial-key cuckoo hashing is thus calculated as follows (for fingerprint function \( \phi_x = x_f(x) \)):

\[
\begin{align*}
i_1 &= H(x) \pmod{m} \\
i_2 &= i_1 \oplus H(\phi_x) \pmod{m}
\end{align*}
\]

Importantly, \( i_1 \) and \( i_2 \) represent the indices of the buckets, and thus must be translated into the bucket range \([0, m-1]\) to prevent illegal memory references. State-of-the-art implementations [1] use modulo operation for this purpose. When \( m \) is a power of two, this modulo operation is reduced to a bit-wise “and”, which eventually allows for higher operations throughput on modern hardware.

Additionally, most probabilistic filters are designed with a targeted false positive rate \( \epsilon > 0 \). For example, given the false positive rate \( \epsilon \), a space-optimized Bloom filter uses \( \frac{1}{m} \log_2(\frac{1}{\epsilon}) \) bits per item. On the other hand, cuckoo filters use \( f \) bits to fingerprint each item, and the minimal fingerprint size for a given false positive rate \( \epsilon \) and bucket size \( b \) is \( f = \lceil \log_2(1/\epsilon) + \log_2(2b) \rceil \) [4]. Thus, for the fixed \( \epsilon \) we can choose \( b \) and \( f \) to make cuckoo filters that are smaller than corresponding Bloom filters. This property of cuckoo filters makes them a plausible alternative to Bloom filters when we need to minimize memory consumption.

3 CAUSES OF FALSE NEGATIVES

The partial-key alternative bucket calculation given in (1) is false negatives free only when \( m \) is a power of two. Otherwise, when \( m \) is not constrained to powers of two, we have the following observations:

Observation 1. There exist cuckoo filters that permit evictions to an incorrect bucket \( i \), such that \( i \neq i_1 \), and \( i \neq i_2 \).

Observation 2. An element \( x \) that is evicted to an incorrect bucket is a false negative when there is no previously inserted \( x' \) such that:

\[
(\phi_{x'} = \phi_x) \text{ and } (H(x') = H(x) \pmod{m}).
\]

When the condition from (2) holds, we observe not only the false positives (dictated by parameter \( \epsilon \)), but also observe false negatives. For traditional applications of probabilistic filters, a significant amount of false negatives is unacceptable.

Graf and Lemire [5] have recently proposed an alternative version of partial-key cuckoo hashing to replace (1) and avoid modulo operation. However, their version results in a twofold degradation in the throughput of the Insert operation [5], which may be unacceptable in traditional network applications.

REFERENCES


