robustBF: A High Accuracy and Memory Efficient 2D Bloom Filter

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Abstract—**Bloom Filter is an important probabilistic data structure to reduce memory consumption for membership filters. It is applied in diverse domains such as Computer Networking, Network Security and Privacy, IoT, Edge Computing, Cloud Computing, Big Data, and Biometrics. But Bloom Filter has an issue of the false positive probability. To address this issue, we propose a novel robust Bloom Filter, robustBF for short. robustBF is a 2D Bloom Filter, capable of filtering millions of data with high accuracy without compromising the performance. Our proposed system is presented in two-fold. Firstly, we modify the murmur hash function, and test all modified hash functions for improvements and select the best-modified hash function experimentally. Secondly, we embed the modified hash functions in 2D Bloom Filter. Our experimental results show that robustBF is better than standard Bloom Filter and counting Bloom Filter in every aspect. robustBF exhibits nearly zero false positive probability with more than $10\times$ and $44\times$ lower memory consumption than standard Bloom filter and counting Bloom Filter, respectively. Source code is available at https://github.com/patgiri/robustBF.**

Index Terms—**Bloom Filter, Membership Filter, Approximation Algorithms, Data Structures, Algorithms.**

I. INTRODUCTION

Bloom Filter [1] is a membership filter that is capable of filtering a large number of data with a tiny amount of memory. Therefore, Bloom Filter meets diverse applications and it is applied in diverse domains, namely, Computer Networking [2], [3], Network Security [4] and Privacy [5], IoT [6], Big Data [7], Cloud Computing [8], Biometrics [9] and Bioinformatics [10]. There are diverse variants of Bloom Filter available [11]–[13]; however, these filters are unable to provide high accuracy using tiny memory without compromising query performance. Moreover, the false positive probability is an issue of Bloom Filter, and it cannot be reduced without increasing the memory size. There are many fast filters available, for instance, Morton Filter [14] and XOR Filter [15]. Morton Filter is faster than Cuckoo Filter. Morton Filter extends Cuckoo Filter and implements a compressed Cuckoo Filter.

In this paper, we propose a novel Bloom Filter, called robustBF, is to reduce the false positive probability. robustBF is a 2D Bloom Filter, which modifies the murmur hash function for better performance. The outcomes of the proposed system are outlined as follows-

- robustBF is a fast filtering Bloom Filter, and it is faster than standard Bloom Filter (SBF) [16] and counting Bloom Filter (CBF) [17]. robustBF is $2.038\times$ and $2.48\times$ faster in insertion of 10M data than SBF and CBF respectively.
- robustBF consumes $10.40\times$ and $44.01\times$ less memory than SBF and CBF on an average, respectively.
- robustBF exhibits false positive probability almost zero in the desired false positive probability setting of 0.001 with lower memory consumption. Thus, the accuracy of robustBF is almost 100%.

We compare robustBF with SBF and CBF. We found that robustBF is better in the false positive probability and more efficient in memory consumption than the other filters' variants. To the best of our knowledge, robustBF is the only Bloom Filter that can increase its accuracy and lower the memory footprint without compromising the filter's performance.

The paper is organized as follows- Section II discusses on the preliminaries on Bloom Filter and its terminologies. Section III establishes the propose systems, called robustBF. Section IV demonstrates the performance of robustBF experimentally. Section V analyses on proposed systems and its memory consumption. Finally, Section VI concludes the paper.

II. PRELIMINARY

Bloom Filter is introduced by Burton Howard Bloom in 1970 [1]. Bloom Filter has the potentiality of improving many systems. Bloom Filter is not a complete system, and it is just an enhancer of a system. Therefore, it is applied in many domains, including Networking, Security, Big Data, Bioinformatics, etc., to enhance its performance. The capability of Bloom Filter is limited to $true$ or $false$. Let, $\mathbb{B}$ be the Bloom Filter by size m bits, $\mathcal{S} = \{x_1, x_2, x_3, \ldots, x_\eta\}$ be the inserted set, U be the universe where $\mathcal{S} \subset$ U and η be the total number of keys inserted into $\mathbb{B}$ using κ independent hash functions. Let x_i be the random query, then true positive, false positive, false negative, and true negative. There are no false negatives in the conventional Bloom Filter. The true positive, false positive, false negative and true negative are defined in Definitions 1, 2, 3 and 4 respectively.

Definition 1: If $x_i \in \mathbb{B}$ and $x_i \in \mathcal{S}$, then the result of Bloom Filter is called true positive.

Definition 2: If $x_i \in \mathbb{B}$ and $x_i \notin \mathcal{S}$, then the result of Bloom Filter is called false positive.

Definition 3: If $x_i \notin \mathbb{B}$ and $x_i \in \mathcal{S}$, then the result of Bloom Filter is called false negative.

Definition 4: If $x_i \notin \mathbb{B}$ and $x_i \notin \mathcal{S}$, then the result of Bloom Filter is called true negative.

A. Operations

Algorithm 1 Insertion of an input item κ into Bloom Filter $\mathbb{B}$ using three hash functions.

1: **procedure** INSERT($\mathbb{B}[]$, κ, S_1, S_2, S_3)
2:     $i_1 = $ MURMUR(κ, $length$, S_1) $\% \mu$
3:     $i_2 = $ MURMUR(κ, $length$, S_2) $\% \mu$
4:     $i_3 = $ MURMUR(κ, $length$, S_3) $\% \mu$
5:     $\mathbb{B}[i_1] \leftarrow 1$
6:     $\mathbb{B}[i_2] \leftarrow 1$
7:     $\mathbb{B}[i_3] \leftarrow 1$
8: **end procedure**

Algorithm 2 Lookup an item κ in Bloom Filter using three hash functions

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1: **procedure** LOOKUP($\mathbb{B}[]$, κ, S_1, S_2, S_3)
2:     $i_1 = $ MURMUR(κ, $length$, S_1) $\% \mu$
3:     $i_2 = $ MURMUR(κ, $length$, S_2) $\% \mu$
4:     $i_3 = $ MURMUR(κ, $length$, S_3) $\% \mu$
5:     **if** $\mathbb{B}[i_1]$ AND $\mathbb{B}[i_2]$ AND $\mathbb{B}[i_3]$ **then**
6:         **return** $True$
7:     **else**
8:         **return** $False$
9:     **end if**
10: **end procedure**

There are two key operations of Bloom Filter, namely, insert and lookup (query) operations. Algorithm 1 presents a key to Bloom Filter's insertion process using three hash function. The same process is applied in the lookup of a key, which is shown in Algorithm 2.

B. rDBF

Definition 5: Let, a set $\mathcal{S} = \{x_1, x_2, x_3, \ldots x_\eta\}$ and multidimensional bit array $\mathbb{B}_{d_1, d_2, d_3, \ldots, d_i}$ where η is the total number of elements in the set $\mathcal{S}$ and d_i is the dimension. The multidimensional Bloom Filter maps the elements set $\mathcal{S}$ in the multidimensional bit array $\mathbb{B}_{d_1, d_2, d_3, \ldots, d_i}$ using k distinct hash functions similar to conventional Bloom Filter.

r-Dimensional Bloom Filter (rDBF) is purely a multidimensional Bloom Filter that uses multidimensional Bloom array to reduce false positives and enhance computation time [18]. rDBF derives many variants, namely, 2DBF, 3DBF, 4DBF, 5DBF and so on, where $r = 2, 3, 4, \ldots$ in rDBF and defined in Definition 5. 2DBF uses two-dimensional Bloom array. Similarly, 3DBF uses three-dimensional Bloom array. rDBF uses **unsigned long int** instead of bitmap. rDBF uses Murmur non-cryptic hash function which is the fastest hash function.

Moreover, rDBF uses fast operators except hash functions and modulus operator.

III. ROBUSTBF- THE PROPOSED SYSTEMS

We propose a novel Bloom Filter based on 2D Bloom Filter (2DBF) [18], called robustBF. We modify the existing hash function and embed the modified hash function to constructs a new Bloom Filter. robustBF modifies the hashing technique to increase its performance. The performance of robustBF depends on the murmur hash functions, which introduces some biases and the number of hash function calls. This bias helps in improving the accuracy, and hence, reduces the false positive probability. robustBF is designed by aiming to provide high accuracy and memory-efficient Bloom Filter.

A. Selection of a hash function

The performance of the Bloom Filter depends on the hash functions. There are many hash functions available, namely, xxHash, SuperFastHash, FastHash, FNV, and murmur hash functions. Murmur hash function is the finest hash function among all non-cryptography string hash functions [19]. There are also cryptographic string hash functions, namely, SHA1, SHA2, and MD5. These string hash functions are the best for security purposes. However, these cryptographic string hash functions are unable to reduce the false positive probability [20]. Moreover, it degrades the performance of the Bloom Filter and it is proven in Patgiri *et al.* [20]. Thus, we modify the murmur hash functions and evaluated the best modification among the modified hash functions. Murmur hash function depends on the bit mixture and scanning of the input, and thus, we modify the murmur hash function and term it as H1, H2, H3, H4, H5, H6, and H7. The modified murmur hash function H1 reads 3 bytes of data at a time. Similarly, the modified murmur hash function H2 reads 4 bytes at a time. Thus, H3, H4, H5, H6, H7, H8, and H9 reads 5, 6, 7, 8, 9, 10, and 11 bytes of data at a time. It shows a huge difference in changing the reading of data at a time in murmur hash functions. The experimental results show that the H4 exhibits the best performance.

B. Designing the 2D Bloom Filter

The detailed architecture of 2D Bloom Filter is depicted in 1. Each cell of 2DBF of Figure 1 contains β bits. Initially, an item is hashed into 2DBF using k distinct hash functions, i.e., the item is mapped into k cells of 2DBF and the bits are set to 1. Let, $\mathbb{B}_{X,Y}$ be the 2D Bloom Filter (2DBF) where X and Y are the dimensions, and these are prime numbers. Let, $\mathcal{H}()$ be the modified murmur hash function, and $\mathcal{K}$ is an item to be inserted. Let, $\mathbb{B}_{i,j}$ and is the particular cell in $\mathbb{B}_{X,Y}$ filter. To insert, Equation (1) is invoked.

$$\mathbb{B}_{i,j} \leftarrow \mathbb{B}_{i,j} \ OR \ \mathbb{P} \tag{1}$$

where $h = \mathcal{H}(\mathcal{K})$, $i = h\%X$, $j = h\%Y$, $\rho = h\%\beta$ and $\mathbb{P} = (1 \ll \rho)$, where $\%$ is modulus operator, β is the size of a cell and $\ll$ is bitwise left shift operator. The β should be also prime number. Let us assume, **unsigned long int** occupies 64
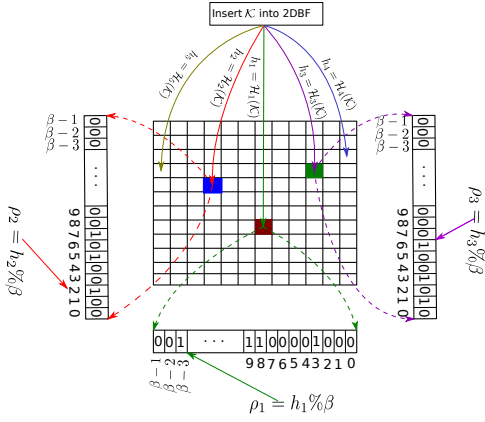
Fig. 1: Insertion or lookup process in 2D Bloom Filter.

bits, then the the nearest prime number is 61. Therefore, β should be 61 but it cannot be greater then the size of a cell in 2DBF.

The deletion operation is performed using XOR operator. To remove $\mathcal{K}$ from 2DBF, Equation (2) is invoked.

$$\mathbb{B}_{i,j} \leftarrow ((\mathbb{B}_{i,j} \ AND \ \mathbb{P}) == \mathbb{P}? \ (\mathbb{B}_{i,j} \oplus \mathbb{P}) : \mathbb{B}_{i,j}) \quad (2)$$

For lookup operation (query operation) of an item $\mathcal{K}$, Equation (3) is invoked.

$$\mathcal{F}_{2DBF} \leftarrow (\mathbb{B}_{i,j} \ AND \ \mathbb{P}) \gg \rho \quad (3)$$

If $\mathcal{F}_{2DBF}$ is 1, then the key is a member of 2DBF and otherwise, it is not a member of 2DBF. Equation (1), (2) and (3) depends on the hash function $\mathcal{H}()$.

IV. EXPERIMENTAL RESULTS

We evaluate the accuracy, false positive probability, query and insertion performance, and memory consumption of robustBF. We have conducted our experiment in Desktop PC with the configuration of Intel CoreTH i7-7700 CPU @ 3.60GHz × 8, 8GB RAM, 1TB HDD, Ubuntu 18.04.5 LTS, and GCC- 7.5.0.

A. Test cases

We have created four different test cases to validate the accuracy, performance, memory efficiency and false positive rate. The four test cases are Same Set, Mixed Set, Disjoint Set and Random Set which are defined in Definition 6, 7, 8 and 9 respectively [20]. These test cases are used to evaluate the strengths and weaknesses of Bloom Filter in every aspect. Let, $\mathcal{S} = \{s_1, s_2, s_3, \ldots, s_m\}$ be the input set and input into the robustBF.

Definition 6: Let, $\mathcal{Q}$ is a set queried where $\mathcal{Q} = \mathcal{S}$, then the set $\mathcal{Q}$ is called Same Set.

Definition 7: Let, $\mathcal{Q} = \{Q^1, Q^2\}$ be a query set where $Q^1 = \{Q_1^1, Q_2^1, Q_3^1, \ldots\}$ and $Q^1 = \{Q_1^2, Q_2^2, Q_3^2, \ldots\}$ such that $Q^1 \subset \mathcal{S}$ and $Q^2 \cap \mathcal{S} = \phi$, then the set $\mathcal{Q}$ is called Mixed Set.

Definition 8: Let, $\mathcal{Q}$ be a query set where $\mathcal{Q} \cap \mathcal{S} = \phi$, then the set $\mathcal{Q}$ is called Random Set.

Definition 9: Let, $\mathcal{Q}$ be a query set randomly generated, then the set $\mathcal{Q}$ is called disjoint set.

B. Experiments

This section presents the accuracy of Bloom Filters and its memory requirements. robustBF inherits the properties from rDBF [18]. We compare robustBF with standard Bloom Filter (SBF) [16] where SBF is a standard Bloom Filter to benchmark. The robustBF, SBF, and CBF are single-threaded Bloom Filter. Single-threaded Bloom Filters are useful as an enhancer of a system, while multi-threaded Bloom Filter is a complete system. robustBF outperforms SBF and CBF in every aspect, which is presented in this section.
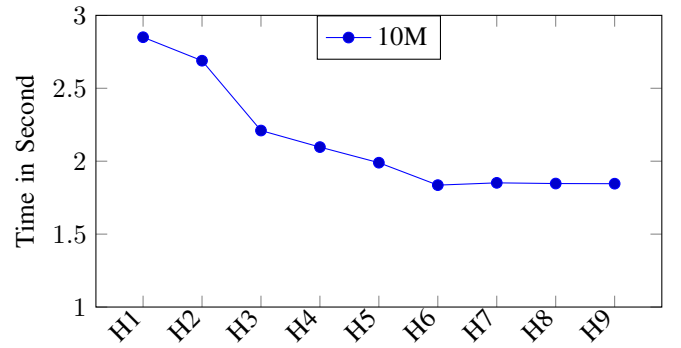
C. Hash function experimentation

Fig. 2: Insertion time of modified murmur hash functions H1, H2, H3, H4, H5, H6, H7, H8 and H9. Lower is better.

robustBF is a two-dimensional Bloom Filter and depends on the murmur hash function. The insertion performances of H1, H2, H3, H4, H5, H6, H7, H8, and H9 are demonstrated in Figure 2. A total of 10M data is inserted into robustBF. The performance of robustBF is the lowest in H1 and the highest in H9. However, the insertion performance is not as important as the lookup operation.
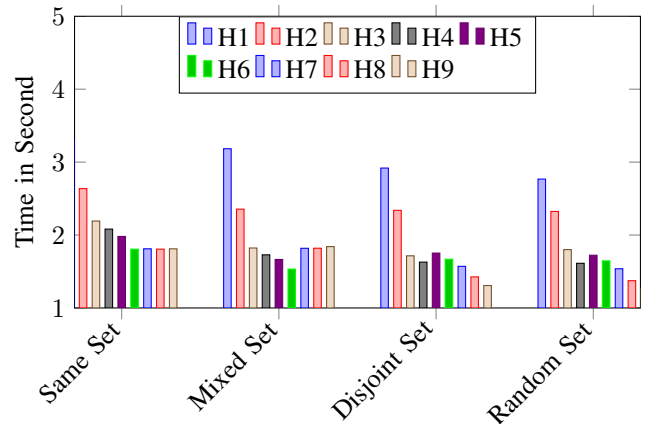

Fig. 3: Lookup time of modified murmur hash functions H1, H2, H3, H4, H5, H6, H7, H8 and H9. Lower is better.

The Bloom Filter is designed to provide higher lookup performance with a tiny amount of memory usage. robustBF is evaluated its performance in Same Set, Mixed Set, Disjoint Set, and Random Set to reveal the strength and weakness. robustBF is evaluated with modified murmur hash function H1, H2, H3, H4, H5, H6, H7, H8, and H9. robustBF exhibits a similar lookup performance of 10M queries in H3, H4, H5, H6, H7, H8, and H9. Therefore, we select a modified murmur hash function from H3, H4, H5, H6, H7, H8, and H9. However, it is challenging to conclude the best performer because their performance differs in different test cases.
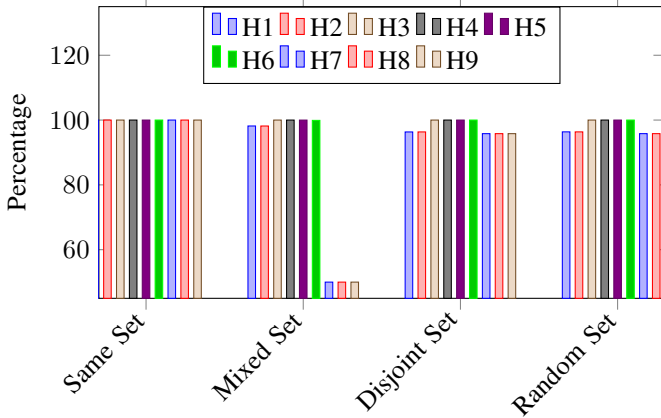
Fig. 4: Accuracy of modified murmur hash functions H1, H2, H3, H4, H5, H6, H7, H8 and H9. Higher is better.
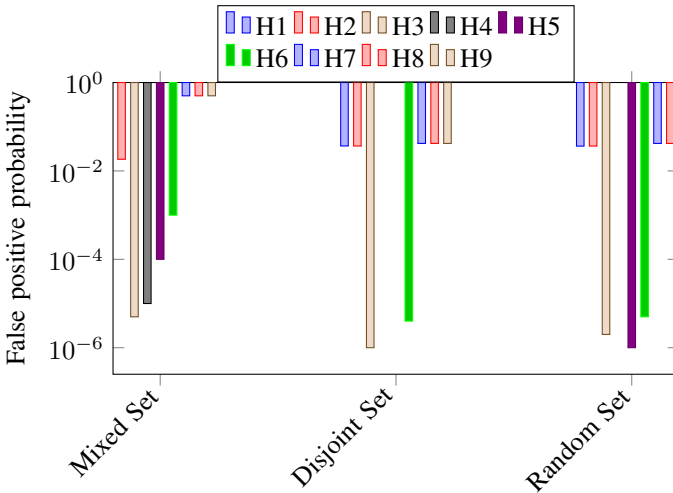

Fig. 5: False positive probability of Lookup of modified murmur hash functions H1, H2, H3, H4, H5, H6, H7, H8 and H9. Lower is better.

robustBF measures its accuracy as $\mathcal{A} = 1 - \mathcal{FPP}$ since there are no false negatives. Figure 4 demonstrates the accuracy of robustBF using modified murmur hash functions H1, H2, H3, H4, H5, H6, H7, H8, and H9. As per our observation, the H4 has the highest accuracy and lowest false positive probability in all test cases. The false positive probability is demonstrated

in Figure 5. The H6, H7, H8, and H9 exhibit the highest performance; however, the false positive probability of these hash functions is poor. Therefore, we are simply striking out the modified murmur hash function H6, H7, H8, and H9. The remaining hash functions are H3, H4, and H5 to compare their performance.
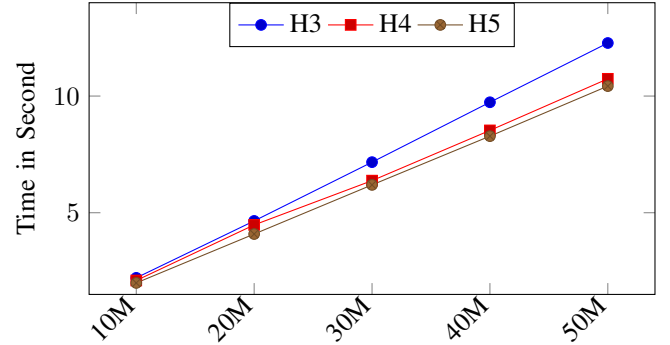

Fig. 6: Insertion time of robustBF of 10M, 20M, 30M, 40M, and 50M by H3, H4 and H5 murmur hash functions. Lower is better.

robustBF performance is measured using H3, H4, and H5 by inserting 10M, 20M, 30M, 40M, and 50M data. robustBF performance is similar to H4 and H5; however, its performance is lower in H3 as depicted in Figure 6. We observed that the H4 is the best performer among the modified murmur hash functions. However, H4 is not the best performer in insertion and lookup, but it is best in false positive probability. Therefore, we conclude that H4 is the best choice for robustBF. The rest of the experiment of robustBF is performed using the H4 function because H4 exhibits its best performance in the false positive probability, which is crucial for Bloom Filter.
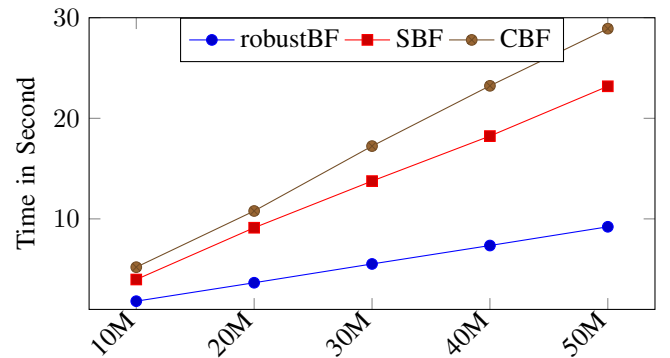
D. Comparison of robustBF with other filters

Fig. 7: Insertion time of robustBF, SBF and CBF. Lower is better.

The comparison of insertion time of robustBF and SBF is demonstrated in Figure 7. robustBF, SBF, and CBF perform 5.426 million operations per second (MOPS), 2.182 MOPS, and 1.79 MOPS on average, respectively. robustBF is faster than SBF in insertion.
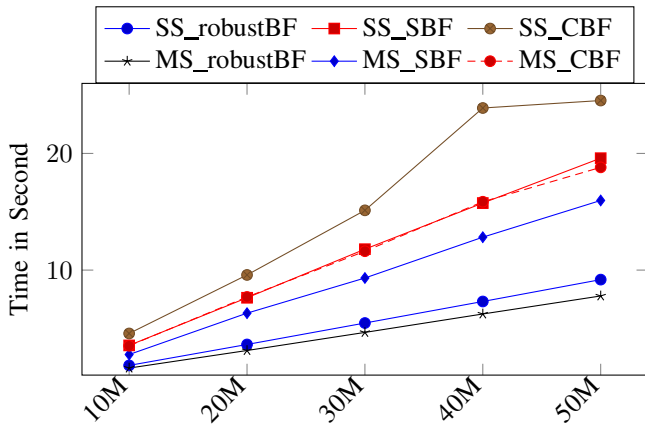
Fig. 8: Lookup time of robustBF, SBF, and CBF in Same Set (SS) and Mixed Set (MS). Lower is better.
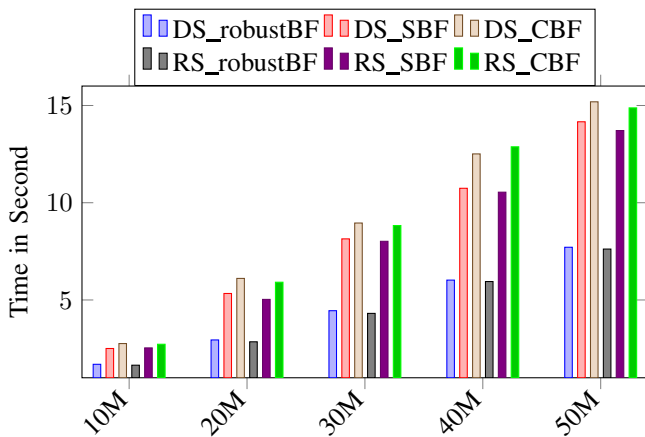

Fig. 9: Lookup time of robustBF, SBF, and CBF in Disjoint Set (DS) and Random Set (RS). Lower is better.

Figure 8 and 9 demonstrate the lookup time taken by robustBF and SBF in different test cases, namely, Same Set (SS), Mixed Set (MS), Disjoint Set (DS), and Random Set (RS). robustBF is faster than SBF and CBF in every aspect. robustBF performs 5.463 MOPS, 6.373 MOPS, 6.369 MOPS, and 6.423 MOPS in the Same Set, Mixed Set, Disjoint Set, and Random Set, respectively. On the other hand, SBF performs 2.554 MOPS, 3.178 MOPS, 3.667 MOPS, and 3.727 MOPS in the Same Set, Mixed Set, Disjoint Set, and Random Set on an average, respectively. Similarly, CBF performs 1.994 MOPS, 2.642 MOPS, 3.347 MOPS, and 3.384 MOPS in the Same Set, Mixed Set, Disjoint Set, and Random Set on an average, respectively.

Table I shows the false positive probability of robustBF and SBF in different test cases with 10 million to 100 million of dataset. robustBF and SBF do not exhibit any false positive probability in the Same Set. However, there is a false positive probability in other test cases. robustBF exhibits the highest false positive probability in Mixed Set, which is much lower than SBF. It is almost zero false positive probability. However,

the configuration of SBF and CBF is 0.001, and hence, it shows a constantly similar false positive probability.

Table II demonstrates the accuracy of robustBF and SBF. Both robustBF, SBF, and CBF exhibit 100% accuracy in the Same Set. The accuracy of robustBF is much higher than SBF and CBF. The lowest accuracy of robustBF is 99.999% in 20M and 10M datasets with the Mixed Set test cases.
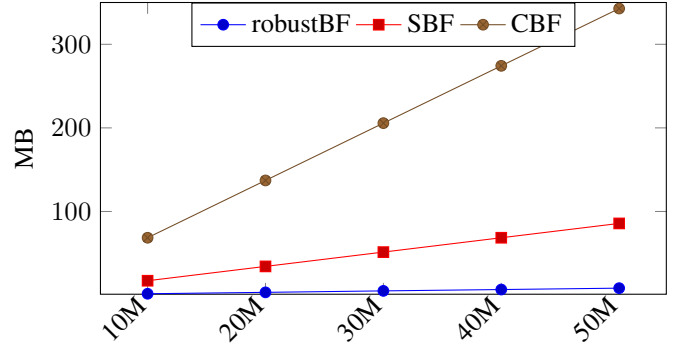

Fig. 10: Memory consumption of robustBF, SBF and CBF. Lower is better.

Interestingly, robustBF uses a tiny amount of memory. SBF uses higher memory than robustBF, as shown in Figure 10. robustBF, SBF, and CBF require 1.382 bits, 14.378 bits, and 57.511 bits memory per elements. Therefore, robustBF consumes $10.40\times$ and $44.01\times$ lower memory than SBF and CBF, respectively. Therefore, robustBF is better than SBF and CBF in memory consumption.
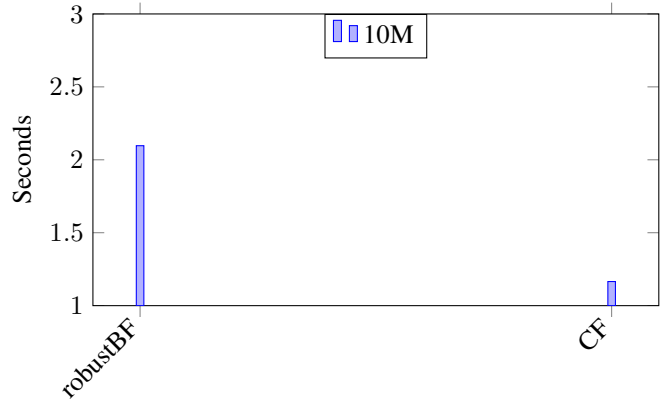

Fig. 11: Comparison of insertion time of 10M data into robustBF, and CF in second. Lower is better.

Now, let us compare robustBF with Cuckoo Filter [21] which is not a Bloom Filter. Cuckoo Filter is a membership filter based on cuckoo hashing. Figure 11 demonstrates the insertion time taken by robustBF, and CF. CF is the fastest in the insertion of 10M data than robustBF. Here, robustBF takes the highest times, which is much slower than CF.

Similar to insertion, robustBF is slower in lookup than CF, as shown in Figure 12. CF is the fast filter to perform the lookup of 10M data.

TABLE I: False positive probability of robustBF and SBF in various test cases. Lower is better.

Dataset	MS_robustBF	MS_SBF	MS_CBF	DS_robustBF	DS_SBF	DS_CBF	RS_robustBF	RS_SBF	RS_CBF
10M	0.000010	0.001028	0.001027	0.000000	0.001012	0.000996	0.000001	0.000989	0.000998
20M	0.000010	0.001009	0.000996	0.000001	0.001002	0.000999	0.000000	0.00098	0.001002
30M	0.000007	0.000998	0.000999	0.000000	0.001003	0.000996	0.000000	0.000981	0.000976
40M	0.000003	0.001019	0.001001	0.000000	0.001022	0.001003	0.000000	0.001	0.000977
50M	0.000002	0.001013	0.000994	0.000000	0.001008	0.000999	0.000000	0.000976	0.000986

TABLE II: Accuracy of robustBF, SBF, and CBF in Same Set (SS), Mixed Set (MS), Disjoint Set (DS) and Random Set (RS). Higher is better.

| Interval	MS_robustBF	MS_SBF	MS_CBF	DS_robustBF	DS_SBF	DS_CBF	RS_robustBF	RS_SBF	RS_CBF
10M	99.999	99.8972	99.8973	100	99.8988	99.9004	99.9999	99.9011	99.9002
20M	99.999	99.8991	99.9004	99.9999	99.8998	99.9001	100	99.902	99.8998
30M	99.9993	99.9002	99.9001	100	99.8997	99.9004	100	99.9019	99.9024
40M	99.9997	99.8981	99.8999	100	99.8978	99.8997	100	99.9	99.9023
50M	99.9998	99.8987	99.9006	100	99.8992	99.9001	100	99.9024	99.9014
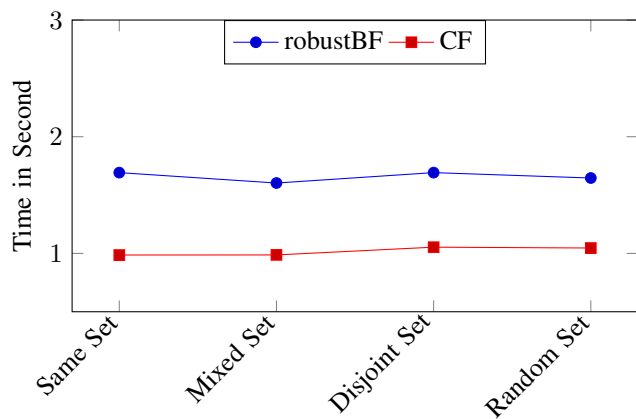
Fig. 12: Comparison of lookup time of 10M in robustBF, and CF in second. Lower is better.

Fig. 13: Comparison of memory consumption 10M data by robustBF and CF. Lower is better.

TABLE III: Comparison of false positive probability in lookup of 10M in robustBF and CF. Lower is better.

Test cases	robustBF	CF
Same Set	0	0
Mixed Set	1E-05	0.0005592
Disjoint Set	0	0.5749
Random Set	0	0.995351

The false positive probability of robustBF is almost zero, which is demonstrated in Table III. But, CF exhibits good false positive probability in the Same Set and Mixed set, whereas it shows the worst in Disjoint Set and Random Set of data due to the kicking process.

Figure 13 demonstrates the memory consumption in 10M data by robustBF and CF. robustBF, and CF occupy 1.55MB, and 24MB for 10M data, respectively.

V. ANALYSIS

Let, m be the number of bits of the Bloom Filter $\mathbb{B}$ and the probability to be a particular bit is not set to 1 is $(1 - \frac{1}{m})$. There are k the number of hash functions and n number of total items to b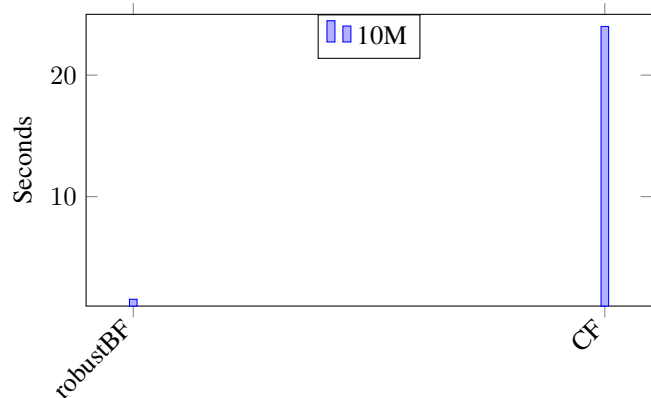e inserted into the Bloom Filter $\mathbb{B}$, then the probability of a bit not set to 1 is $\left(1 - \frac{1}{m}\right)^{nk}$. Therefore, the probability of a particular bit is set to 1 is

$$1 - \left(1 - \frac{1}{m}\right)^{nk} \tag{4}$$

Thus, the desired false positive probability is

$$\varepsilon = \left(1 - \left(1 - \frac{1}{m}\right)^{nk}\right) \approx \left(1 - e^{-kn/m}\right)^{k} \tag{5}$$

The number of hash functions k cannot be too large or too small. Bloom Filter requires an optimal number of hash functions. The assumption of the optimal number of hash function is $k = \frac{m}{n}ln2$. Optimal number of hash function is an assumption and it works well with conventional Bloom Filter. It gives the optimal number of hash functions. Solving Equation (5) using the assumption of number of hash functions, we get

$$\varepsilon = \left(1 - e^{-(\frac{m}{n}ln2)n/m}\right)^{\frac{m}{n}ln2} \tag{6}$$

By simplifying Equation (6), we get

$$ln\varepsilon = -\frac{m}{n}(ln2)^2, \quad \implies m = -\frac{n\,ln\varepsilon}{(ln2)^2} \tag{7}$$

The memory requirement is m depending on the desired false positive probability ε and number of input items n. robustBF uses approximately half of the desired memory calculated by Equation (7).

A. Memory requirements of robustBF

robustBF is a 2D Bloom Filter (2DBF), and thus, the memory requirement not only depends on the n and ε but also its dimensions of the array. Let, X and Y be the dimensions of robustBF. The dimensions $X \neq Y$ and these are prime numbers. If X and Y are not prime numbers, then false positive increases. We need to calculate X and Y from m. Let, P_i be the array of prime numbers and $q = \frac{m}{2*\beta}$ where the β is the number of bits per cell in robustBF. Now, we calculate $t = \sqrt{q}$ and call the function $i = \text{SELECTPRIME}(t)$ as shown in Algorithm 3.

Algorithm 3 Index calculation of prime number array P_i

1: **procedure** SELECTPRIME(t)
2:     **for** $i = 1$ to $TotalNumberOfPrime$ **do**
3:         **if** $P_i > t$ **then return** i;
4:         **end if**
5:     **end for**
6: **end procedure**

The dimension $X = P_{i+3}$ and $Y = P_{i-3}$. Thus, robustBF allocated **unsigned long int** 2D array, i.e., the total number of memory bit is $X \times Y \times \beta$ where β is the bit size of **unsigned long int**. Also, robustBF uses exactly half of the number of optimal hash functions calculated because it performs the modulus operation using dimensions X and Y to place an item in the filter.

VI. CONCLUSION

In this paper, we present a novel Bloom Filter, called robustBF. We have demonstrated that robustBF is able to reduce the false positive probability to almost zero with desired false positive probability. Also, robustBF consumes approximately $10\times$ and $44\times$ less memory than SBF and CBF with the same settings. We have also demonstrated its accuracy, which is satisfactorily high. The lookup and insertion performance of robustBF is higher than SBF and CBF. No Bloom filter can increase its accuracy by lowering the memory footprint significantly to the best of our knowledge. There are diverse faster filters available than robustBF. The key objectives of robustBF is to improve accuracy and lower memory footprint without compromising the filter's performance. Therefore, the robustBF performance is compared with SBF and CBF. We agree that there are many faster filter available than robustBF, for instance, Morton Filter [14], and XOR Filter [15]; but these filters use large memory per items. Therefore, robustBF can improve various applications' performance using a tiny amount of memory in Computer Networking, Security and Privacy, Blockchain, IoT, Big Data, Cloud Computing, Biometrics, and Bioinformatics.

REFERENCES

[1] B. H. Bloom, "Space/time trade-offs in hash coding with allowable errors," *Comm. of the ACM*, vol. 13, no. 7, pp. 422–426, 1970.
[2] J. H. Mun and H. Lim, "New approach for efficient ip address lookup using a bloom filter in trie-based algorithms," *IEEE Transactions on Computers*, vol. 65, no. 5, pp. 1558–1565, 2016.
[3] H. Lee and A. Nakao, "Improving bloom filter forwarding architectures," *IEEE Communications Letters*, vol. 18, no. 10, pp. 1715–1718, 2014.
[4] R. Patgiri, S. Nayak, and S. K. Borgohain, "Preventing ddos using bloom filter: A survey," *EAI Endorsed Transactions on Scalable Information Systems*, vol. 5, no. 19, 11 2018.
[5] R. Patgiri, S. Nayak, and S. K. Borgohain, "Passdb: A password database with strict privacy protocol using 3d bloom filter," *Information Sciences*, vol. 539, pp. 157–176, 2020.
[6] A. Singh, S. Garg, S. Batra, N. Kumar, and J. J. Rodrigues, "Bloom filter based optimization scheme for massive data handling in iot environment," *Future Generation Computer Systems*, vol. 82, pp. 440 – 449, 2018.
[7] R. Patgiri, S. Nayak, and S. K. Borgohain, "Role of bloom filter in big data research: A survey," *International Journal of Advanced Computer Science and Applications(IJACSA)*, vol. 9, no. 11, 2019.
[8] A. Singh, S. Garg, K. Kaur, S. Batra, N. Kumar, and K. R. Choo, "Fuzzy-folded bloom filter-as-a-service for big data storage in the cloud," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2338–2348, 2019.
[9] C. Rathgeb, F. Breitinger, H. Baier, and C. Busch, "Towards bloom filter-based indexing of iris biometric data," in *2015 International Conference on Biometrics (ICB)*, 2015, pp. 422–429.
[10] S. Nayak and R. Patgiri, "A review on role of bloom filter on dna assembly," *IEEE Access*, vol. 7, pp. 66 939–66 954, 2019.
[11] L. Luo, D. Guo, R. T. B. Ma, O. Rottenstreich, and X. Luo, "Optimizing bloom filter: Challenges, solutions, and comparisons," *IEEE Communications Surveys Tutorials*, vol. 21, no. 2, pp. 1912–1949, 2019.
[12] H. Lim, J. Lee, and C. Yim, "Complement bloom filter for identifying true positiveness of a bloom filter," *IEEE Communications Letters*, vol. 19, no. 11, pp. 1905–1908, 2015.
[13] P. Reviriego, J. Martínez, and S. Pontarelli, "Cfbf: Reducing the insertion time of cuckoo filters with an integrated bloom filter," *IEEE Communications Letters*, vol. 23, no. 10, pp. 1857–1861, 2019.
[14] A. D. Breslow and N. S. Jayasena, "Morton filters: Faster, space-efficient cuckoo filters via biasing, compression, and decoupled logical sparsity," *Proc. VLDB Endow.*, vol. 11, no. 9, p. 1041–1055, May 2018. [Online]. Available: https://doi.org/10.14778/3213880.3213884
[15] T. M. Graf and D. Lemire, "Xor filters: Faster and smaller than bloom and cuckoo filters," *ACM J. Exp. Algorithmics*, vol. 25, Mar. 2020.
[16] A. Kirsch and M. Mitzenmacher, "Less hashing, same performance: Building a better bloom filter," *Random Struct. Algorithms*, vol. 33, no. 2, p. 187–218, Sep. 2008.
[17] L. Fan, P. Cao, J. Almeida, and A. Z. Broder, "Summary cache: A scalable wide-area web cache sharing protocol," *IEEE/ACM Trans. Netw.*, vol. 8, no. 3, pp. 281–293, Jun. 2000.
[18] R. Patgiri, S. Nayak, and S. K. Borgohain, "rDBF: A r-dimensional bloom filter for massive scale membership query," *Journal of Network and Computer Applications*, vol. 136, pp. 100 – 113, 2019.
[19] A. Appleby, "Murmurhash," Retrieved on September 2020 from https://sites.google.com/site/murmurhash/, 2020.
[20] R. Patgiri, S. Nayak, and N. B. Muppalaneni, "Is bloom filter a bad choice for security and privacy?" in *2021 International Conference on Information Networking (ICOIN)*, 2021, pp. 648–653.
[21] B. Fan, D. G. Andersen, M. Kaminsky, and M. D. Mitzenmacher, "Cuckoo filter: Practically better than bloom," in *Proceedings of the 10th ACM International on Conference on Emerging Networking Experiments and Technologies*, ser. CoNEXT '14. New York, NY, USA: Association for Computing Machinery, 2014, p. 75–88. [Online]. Available: https://doi.org/10.1145/2674005.2674994