Vidyavardhini's College of Engineering & Technology

Department of Computer Engineering

Experiment No.6

Data Stream Algorithms:

Implement Bloom filter algorithm using any programming language

Date of Performance: 21/08/23

Date of Submission: 04/09/23

<u>**AIM**</u>:

Data Stream Algorithms:

Implement bloom filter algorithm using any programming language

THEORY:

Bloom filter algorithm approximates the number of unique objects in a stream or a database in one pass. If the stream contains n elements with m of them unique, this algorithm runs in O(n) time and needs $O(\log(m))$ memory.

CSL702: Big Data Analytics Lab



Vidyavardhini's College of Engineering & Technology

Department of Computer Engineering

Algorithm:

- 1. Create a bit vector (bit array) of sufficient length L, such that 2L>n, the number of elements in the stream. Usually a 64-bit vector is sufficient since 264 is quite large for most purposes.
- 2. The i-th bit in this vector/array represents whether we have seen a hash function value whose binary representation ends in 0i. So initialize each bit to
- 3. The i-th bit in this vector/array represents whether we have seen a hash function value whose binary representation ends in 0i. So initialize each bit to
- 4. The i-th bit in this vector/array represents whether we have seen a hash function value whose binary representation ends in 0i. So initialize each bit to
- 5.Once input is exhausted, get the index of the first 0 in the bit array (call this R). By the way, this is just the number of consecutive 1s (i.e. we have seen 0,00,...,0R-1 as the output of the hash function) plus one.
- 6.Calculate the number of unique words as $2R/\phi$, where ϕ is 0.77351. A proof for this can be found in the original paper listed in the reference section.
- 7.The standard deviation of R is a constant: $\sigma(R)=1.12$. (In other words, R can be off by about 1 for 1 0.68 = 32% of the observations, off by 2 for about 1 0.95 = 5% of the observations, off by 3 for 1 0.997 = 0.3% of the observations using the Empirical rule of statistics). This implies that our count can be off by a factor of 2 for 32% of the observations, off by a factor of 8 for 0.3% of the observations and so on.

CODE:

```
n = 20 #no of items to add p = 0.05 #false positive probability
```

```
bloomf = BloomFilter(n,p)
print("Size of bit array:{}".format(bloomf.size)) print("False
positive Probability:{}".format(bloomf.fp_prob)) print("Number
of hash functions:{}".format(bloomf.hash_count))
```

CSL702: Big Data Analytics Lab



Vidyavardhini's College of Engineering & Technology

Department of Computer Engineering

```
# word not added
word absent = ['bluff','cheater','hate','war','humanity',
         'racism', 'hurt', 'nuke', 'gloomy', 'facebook',
         'geeksforgeeks','twitter']
for item in word present:
  bloomf.add(item)
shuffle(word present)
shuffle(word absent)
test words = word present[:10] +
word absent shuffle(test words) for word in
test words:
  if bloomf.check(word):
     if word in word absent:
        print("'{}' is a false positive!".format(word))
     else: print("'{{}}' is probably
       present!".format(word))
  else: print("'{}}' is definitely not
     present!".format(word)) Output:
```

```
ubuntugubuntu-HP-Elite-Tower-600-G9-Desktop-PC:~/bloomfilter$ python3 bloom_test.py
Size of bit array:124
False positive Probability:0.05
Number of hash functions:4
'gloomy' is definitely not present!
'cohesive' is probably present!
'geeksforgeeks' is definitely not present!
'bluff' is definitely not present!
'abundant' is probably present!
'abundant' is probably present!
'ruke' is definitely not present!
'twitter' is a false positive!
'cheater' is definitely not present!
'generosity' is probably present!
'generosity' is probably present!
'genial' is probably present!
'humanity' is a false positive!
'comfort' is probably present!
'war' is definitely not present!
'war' is definitely not present!
'generous' is probably present!
'facebook' is definitely not present!
'thurt' is definitely not present!
```

Vidyavardhini's College of Engineering & Technology Department of Computer Engineering

CONCLUSION:

The small data structure created for membership checking, the Bloom filter, stands out. When dealing with huge data sets, where it is acceptable to occasionally accept false positives, it excels. However, there is a risk for false positives, which implies that it could mistakenly classify an element as belonging to the set even while it doesn't. The quantity of hash functions utilised and the size of the bit array depend on the delicate balance between space efficiency and the probability of false positives. In situations involving network routers, spell checks, and distributed systems, bloom filters are frequently used, especially when memory resources are limited and quick membership tests are required.

CSL702: Big Data Analytics Lab