What is Bloom Filter?

A Bloom filter is a space-efficient probabilistic data structure that is used to test whether an element is a member of a set. For example, checking availability of username is set membership problem, where the set is the list of all registered username. The price we pay for efficiency is that it is probabilistic in nature that means, there might be some False Positive results. False positive means, it might tell that given username is already taken but actually it's not.
Interesting Properties of Bloom Filters.

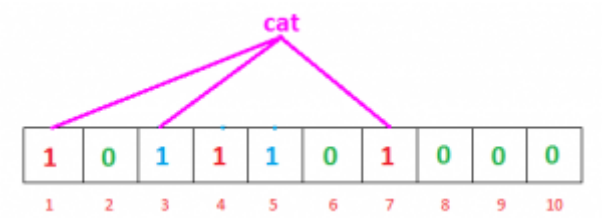
- Unlike a standard hash table, a Bloom filter of a fixed size can represent a set with an arbitrarily large number of elements.
- Adding an element never fails. However, the false positive rate increases steadily as elements are added until all bits in the filter are set to 1, at which point all queries yield a positive result.
- Bloom filters never generate **false negative** result, i.e., telling you that a username doesn't exist when it actually exists.
- Deleting elements from filter is not possible because, if we delete a single element by clearing bits at indices generated by k hash functions, it might cause deletion of few other elements. Example – if we delete "geeks" (in given example below) by clearing bit at 1, 4 and 7, we might end up deleting "nerd" also Because bit at index 4 becomes 0 and bloom filter claims that "nerd" is not present.

Working of Bloom Filter

A empty bloom filter is a **bit array** of **m** bits, all set to zero, like this –

We need **k** number of **hash functions** to calculate the hashes for a given input. When we want to add an item in the filter, the bits at k indices h1(x), h2(x), ... hk(x) are set, where indices are calculated using hash functions.
Example – Suppose we want to enter "geeks" in the filter, we are using 3 hash functions and a bit array of length 10, all set to 0 initially. First we'll calculate the hashes as follows:

```
h1("geeks") % 10 = 1
h2("geeks") % 10 = 4
h3("geeks") % 10 = 7
```



Now if we want to check "geeks" is present in filter or not. We'll do the same process but this time in reverse order. We calculate respective hashes using h1, h2 and h3 and check if all these indices are set to 1 in the bit array. If all the bits are set then we can say that "geeks" is **probably present**. If any of the bit at these indices are 0 then "geeks" is **definitely not present**.

False Positive in Bloom Filters

Operations that a Bloom Filter supports

- insert(x) : To insert an element in the Bloom Filter.
- lookup(x) : to check whether an element is already present in Bloom Filter with a positive false probability.
  NOTE : We cannot delete an element in Bloom Filter.

Probability of False positivity
Let **m** be the size of bit array, **k** be the number of hash functions and **n** be the number of expected elements to be inserted in the filter, then the probability of false positive **p** can be calculated as:

$$P = \left(1 - \left[1 - \frac{1}{m}\right]^{kn}\right)^k$$

Size of Bit Array
If expected number of elements **n** is known and desired false positive probability is **p** then the size of bit array **m** can be calculated as :

$$m = -\frac{n \ln P}{(ln2)^2}$$

Optimum number of hash functions

The number of hash functions **k** must be a positive integer. If **m** is size of bit array and **n** is number of elements to be inserted, then k can be calculated as :

$$k = \frac{m}{n} ln2$$

Choice of Hash Function

The hash function used in bloom filters should be independent and uniformly distributed. They should be fast as possible. Fast simple non cryptographic hashes which are independent enough include murmur, FNV series of hash functions and Jenkins hashes.
Generating hash is major operation in bloom filters. Cryptographic hash functions provide stability and guarantee but are expensive in calculation. With increase in number of hash functions k, bloom filter become slow. All though non-cryptographic hash functions do not provide guarantee but provide major performance improvement.