Lecture 16: Hashing

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Bloom Filter 1

Let $U = \{0, 1, \dots, N-1\}$ be a huge universe of possible elements. Our goal is to maintain a subset $S \subseteq U$ of size m where $m \ll N$, so that we can efficiently check if an element $x \in S$ or not. For example, U is the set of all possible password strings, and S is the set of unacceptable passwords. We hope to have fast queries, small space, simple algorithms, and low false positive rate.

A Bloom filter maintains a 0-1 table/array H of size n=cm, and uses k hash functions $h_1,\ldots,h_k:U\to$ $\{0,1,\ldots,n-1\}$. The table H is initialized to be all-zero, i.e., for each j=0 to n-1 we set H[j]=0. We consider two tasks, inserting an element x into S and checking if an element $x \in S$ or not. Deletions are not allowed.

Algorithm 1 Insertion

```
Input: x \in U to be inserted into S
 1: for i = 1 to k do
 2:
        Compute h_i(x)
        H[h_i(x)] \leftarrow 1
 4: end for
```

Algorithm 2 Membership query

```
Input: x \in U (for which we want to check if x \in S)
 1: for i = 1 to k do
 2:
        Compute h_i(x)
        if H[h_i(x)] = 0 then
 3:
           Return No & Halt
 4:
 5:
        end if
 6: end for
 7: Return Yes
                                                                               \triangleright Happen iff H[h_i(x)] = 1 for all i
```

If $x \in S$, then Algorithm 2 outputs Yes always. Meanwhile, if $x \notin S$, then it might incorrectly output Yes; this is called a *false positive*. The false positive rate is the probability of getting a false positive, i.e., the failure probability. Our goal is to estimate the false positive rate as a function of k which is the number of hash functions used, and c = n/m which is the ratio between sizes of the table H and the set S. Observe that increasing c (i.e., having a larger table H) always decreases the false positive rate; however, how it depends on k, the number of hash functions, is not so obvious. Our goal is to find the optimal choice of kfor a given value of c.

For any location j, we have that

$$\Pr\left(H[j] = 0\right) = \left(\left(1 - \frac{1}{n}\right)^k\right)^m = \left(1 - \frac{1}{cm}\right)^{km} \approx e^{-k/c},$$

assuming m is large. Suppose the input x to Algorithm 2 is not in S. Then we have

Pr (output Yes) = Pr
$$(\forall i : H[h_i(x)] = 1) \approx (1 - e^{-k/c})^k$$
.

Therefore, the false positive rate is approximately given by

$$f(c,k) = \left(1 - e^{-k/c}\right)^k.$$

Now fix c, and we aim to find the optimal k which minimizes f(c, k). By calculus, the minimizer k turns out to satisfy

$$\frac{k}{c} = \log 2.$$

So, we set $k = (\log 2)c \approx 0.693c$ (or $c \approx 1.443k$). The false positive rate then becomes

$$\Pr(\text{false positive}) \approx \left(1 - e^{-k/c}\right)^k = \frac{1}{2^k}.$$

Therefore, increasing k (i.e., using more hash functions) while maintaining $k/c = \log 2$ (so c is increasing at the same time) allows us to decrease the false positive rate exponentially fast, at a price of larger time and space complexity.

Remark 1. When $k/c = \log 2$, we have

$$\Pr(H[j] = 0) \approx e^{-k/c} = \frac{1}{2}.$$

So H is a uniformly random 0-1 string after inserting all m elements.

2 Cuckoo Hashing

In Cuckoo hashing, we maintain a hash table H of size n=cm and use two hash functions $h_1, h_2: U \to \{0, 1, \ldots, n-1\}$. Each element $x \in U$ has two possible locations $h_1(x)$ and $h_2(x)$ given by the hash functions. When inserting x, we use whichever is empty. If neither of the locations is empty, then we add x to one of the locations, say $h_2(x)$, and move the element y previously at $h_2(x)$ to the other possible location of y. Note that y is still at one of its possible locations $h_1(y)$ and $h_2(y)$. If the other location of y is empty, then we are done after moving y to there. Otherwise, we put y there and move the element z previously there to its other location. We will repeat this process until success.

A potential problem of Algorithm 3 is the cycle of moves which causes an infinite loop. If this happens, we start over with two new hash functions (rehash), and insert all elements of S from the beginning.

We observe and establish the following properties of Cuckoo hashing, assuming c = n/m is sufficiently large:

- O(1) query time and no errors;
- O(1) expected insertion time;
- Probability of rehashing is at most 1/2.

Definition 2 (Cuckoo Graph). The Cuckoo graph G is a multigraph (with possibly multiple edges and self-loops) associated with the hash table H and hash functions h_1, h_2 . Vertices of G are locations/entries of H, so there are n vertices. Edges of G show possible locations for all elements of G. More specifically, for each G and edge G and edge G and label this edge by G by G by G and edges.

We have the following crucial observation.

Observation 3. If G has no cycles (i.e., G is a forest), then all m insertions succeed.

Algorithm 3 Insertion

```
Input: x \in U to be inserted into S
 1: Compute h_1(x)
 2: if H[h_1(x)] is empty then
         H[h_1(x)] \leftarrow x \& \mathbf{Halt}
 4: end if
 5: Compute h_2(x)
 6: if H[h_2(x)] is empty then
         H[h_2(x)] \leftarrow x \& \mathbf{Halt}
 8: end if
 9: y \leftarrow H[i] where i = h_2(x)
10: H[i] \leftarrow x
11: if i = h_1(y) then
12:
        Move y from i to h_2(y)
                                                                                                                   \triangleright i = h_2(y)
13:
    else
        Move y from i to h_1(y)
14:
16: Repeat for y (from step 9) if necessary
```

Algorithm 4 Membership query

```
Input: x \in U (for which we want to check if x \in S)

1: Compute h_1(x) and h_2(x)

2: if H[h_1(x)] = x or H[h_2(x)] = x then

3: Return Yes

4: else

5: Return No

6: end if
```

In the rest of this section, we assume that $n \ge 6m$, i.e., $c = n/m \ge 6$. For any locations i, j, and any element $x \in S$, the probability that $\{i, j\}$ is an edge of G labeled by x is equal to $2/n^2$ if $i \ne j$, and $1/n^2$ if i = j. First consider the probability of rehashing:

$$\begin{split} \Pr\left(\text{rehashing}\right) & \leq \Pr\left(\exists \text{ cycle in } G\right) \\ & \leq \sum_{\ell=1}^{\infty} \Pr\left(\exists \text{ cycle of length } \ell \text{ in } G\right) \\ & \leq \sum_{\ell=1}^{\infty} n^{\ell} \cdot m^{\ell} \cdot \left(\frac{2}{n^2}\right)^{\ell} \\ & \leq \sum_{\ell=1}^{\infty} \left(\frac{2m}{n}\right)^{\ell} \\ & \leq \sum_{\ell=1}^{\infty} \left(\frac{1}{3}\right)^{\ell} = \frac{1}{2}. \end{split}$$

The expected insertion time of an element x to some location i is controlled by:

$$\begin{split} \mathbb{E}\left[\text{length of a longest path from }i\right] &\leq \mathbb{E}\left[\#\text{ of vertices connected to }i\right] \\ &= \sum_{j \neq i} \Pr\left(i \text{ and } j \text{ are connected}\right). \end{split}$$

For any $j \neq i$, we have

$$\begin{split} \Pr\left(i \text{ and } j \text{ are connected}\right) &\leq \sum_{\ell=1}^{\infty} \Pr\left(\exists \text{ path from } i \text{ to } j \text{ of length } \ell\right) \\ &\leq \sum_{\ell=1}^{\infty} n^{\ell-1} \cdot m^{\ell} \cdot \left(\frac{2}{n^2}\right)^{\ell} \\ &\leq \frac{1}{n} \sum_{\ell=1}^{\infty} \left(\frac{2m}{n}\right)^{\ell} \\ &\leq \frac{1}{2n}. \end{split}$$

Therefore,

 $\mathbb{E}\left[\text{length of a longest path from }i\right] \leq \frac{1}{2}.$