

9/25/2018 Week 4 Hash table

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Bloom filter

Hash table

⇒ array that is indexed by the value in it.

Purpose: Maintain a possible evolving set of stuff.
(transactions, people associated data, IP addresses)

(
Insert: Add new record
Delete: delete existing record
Lookup: Check for a particular record
}) All by using key.
Run by O(1).

Used often in "dictionary" structure but it is not maintaining the ordering of the elements.

- Constant time can be ensured only when implemented correctly, and data is non-pathological.

Application ① De-duplication

⇒ When new object x arrives
- lookup x in hash table H .
- if not found, Insert x into H .

Application ② The Two-sum problem

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Input : Unsorted array A of n integers. Target sum t .

Goal : Determine whether or not there are two numbers x, y in A with $x + y = t$.

Naive solution : $O(n^2)$ time via exhaustive search.

Better : ① Sort A ($n \log n$ time)

② for each x in A ,

look for $t - x$ in A via binary search.

$O(n \log n) \rightarrow$ Repeating lookup

\Rightarrow hash table allow to do it in $O(n)$.

Because the lookup in hash is constant $O(1)$ and faster than binary search ($\log n$).

Hash ① Insert elements of into hash table H

② for each x in A , lookup $t - x$ in H .

\Rightarrow Used for symbol table in compilers, ~~data~~ blocking network traffic, searching algorithms.

= Use hash table to avoid exploring any configuration (Node) more than once.

High level idea

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Setup: Universe U (All the ^{the} possibilities of data)
e.g. all IP address, all names etc.

[Really big]

Goal: Want to maintain evolving set $S \subseteq U$
[Reasonable size]

Naive Solution

① Array-based solution [indexed by U]

— $O(1)$ operations but $\Theta(|U|)$ space.

② list-based solution

— $O(|S|)$ space but $\Theta(|S|)$ ~~loop~~ lookup.

Solution: ① Pick $n = \#$ of "buckets" with $n \geq |S|$.

(for simplicity, assume $|S|$ doesn't vary too much)

(In real number of elements change dynamically.)
(Usually it doubles the length of array)

② Choose a hash function $h: U \rightarrow \{0, 1, 2, 3, \dots, n-1\}$
function to change
key \rightarrow position in array.

③ Use array A of length n , store x in $A[h(x)]$

\Rightarrow Use element itself as a index

Issue (Collisions)

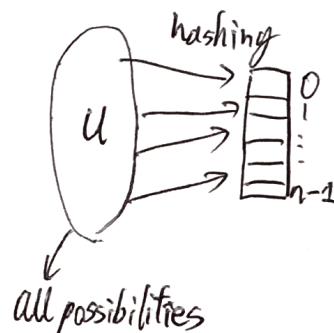
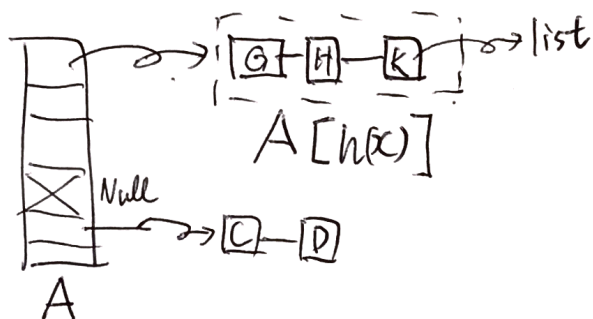
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Collision = Distinct $x, y \in U$ such that $h(x) = h(y)$

→ hash function

Solution #1 (Separate) chaining

- Keep the linked list in each bucket.



- Given a key/object x , perform Insert/Delete/Loopup in the list in $A[h(x)]$.

Solution #2 : open addressing (Only one object per bucket)

- Try to find the open bucket if the bucket is already full. Sequentially probing the open address. (Probe sequence)
 $\{h_1(x), h_2(x), h_3(x), \dots\}$

- e.g. linear probing (Check one after another)
double hashing (Use two hashing)

⇒ Both right. Depend on the situation.

If space is premium: Open addressing.

If deletion is crucial function: Separate Chaining.

Running time of hash function in each case

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- Hash table with chaining, Insert is $O(1)$. Insert new object x at front of the list in $A[hash]$
- Lookup is $O(\text{list length})$.

→ Could be anywhere from $\frac{m}{n}$ to m for $\frac{m}{n}$ objects.
Equal-length list
all objects in same bucket.
→ # of buckets

⇒ The shorter is the better for list length.

⇒ Want to distribute the object equally in the buckets.

(Not only for Separate Chaining but for Open addressing too)

"Good" hash function

- Spread the data out for good performance.
(Gold standard: Completely random hashing) ⇒ Impossible to actually implement.
- Run in constant time. (Hash function will be used everytime using either insertion/deletion/lookup.)
- ⇒ Should be easy to store/very fast to evaluate.

"Bad" hash function

e.g. keys = phone numbers (10-digits) 10^{10}

- Terrible hash function: $h(x) = \text{1st 3 digits of } x$ ⇒ want to make buckets that size of $n = 10^3$. Have to "map" 10^{10} to 10^3 .
- mediocre hash function: $h(x) = \text{last 3 digits of } x$
[still vulnerable to patterns in last 3 digits].

Other bad example of hash function

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e.g. keys = memory locations (will be multiples of a power of 2)
 $n = 10^3$

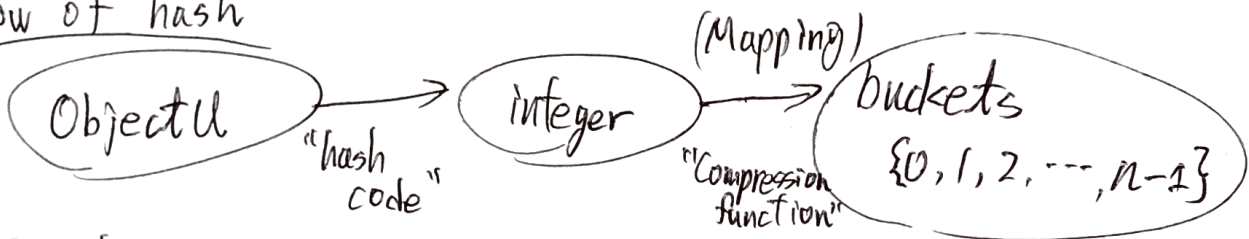
- Terrible: $h(k) = x \% 1000$

⇒ all odd buckets guaranteed to be empty. Waste of memory spaces.

⇒ Making good hash function is an art. Should be different in each application. New way of hashing is coming out every year.

Quick-and-Dirty hash function

Flow of hash



* Sometimes (when the object is already $\$int$) "hash code" step might be skipped.

- "hash code": e.g. subroutine to convert string to integer. (Using ~~ASCII~~ ASCII code)
- "Compression func.": e.g. like mod n function (~~$\% 1000$~~ $\% n$ function)

How to choose $n = \#$ of buckets? (Rule of thumb)

- ① Choose n to be a prime num. (with in constant factor of $\#$ of object in table)
(If key is all divisible by 2, and hash function's modulus is also ~~divisible~~ divisible by 2, it ~~shares~~ shares a common factor 2, so all the odd buckets remained empty)
⇒ By using " $\%$ prime" function, any bucket have chance to be filled.

② Not too close to power of 2.

③ Not too close to power of 10.

Universal hashing

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load of the hash table

$$\text{load factor } \alpha := \frac{\# \text{ of objects in hash table}}{\# \text{ of buckets of hash table}}$$

- ① $\alpha = 1$ or less to run operation in constant time. (Otherwise $O(\text{list length})$.)
- ② With open addressing, need to be $\alpha \ll 1$.

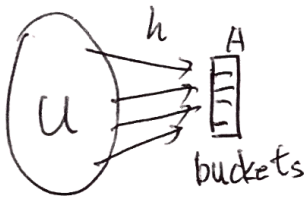
⇒ Controlling the load is important to keep the performance of hash function.

⇒ Usually increasing the buckets of hash table according to the # of objects in the hash table. (Double the length is typical implementation.)

Pathological Data sets

⇒ There is no de-all-end-all hash function.

⇒ Every single hash function has a pathological data set!



⇒ Possible to make the data set that make the data stored in same bucket.
(e.g. Store all the data in $A[31]$)

Hash's performance is not same in any input

Quick sort : $n \log n$

Merge sort : $n \log n$

DFS : n

BFS : n

hash function : $\Rightarrow ?$

⇒ Pathological data can be used for system attack.

how can we cope with the pathological data?

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① Use cryptographic hash function. (e.g. SHA-2)

⇒ Infeasible to reverse engineer a pathological data set.

② Use randomization.

- Design a family \mathcal{H} of hash functions such that in average, "almost all" functions $h \in \mathcal{H}$ spread S out "pretty evenly".

⇒ Since randomization is real time, even reading the source code, cannot reverse engineer the pathological data.

→ Universal hashing (Randomized solution)

Part 1: Definition of "Good random hash function"

Part 2: Concreate example of simple + practical function

Part 3: Justification of definition of "Good random hash function" lead to "Good performance".

Bloom Filter

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Supported Operation

Purpose of using Bloom Filter

⇒ Fast insert and lookup. (→)

Pros: ⇒ More space efficient than Hash table (↑)

Cons: ⇒ ① Cannot store an associated object.
② No deletions
③ Small false positive probability.

Application of Bloom Filter

Original: Early spell checker.

Cononical: List of forbidden passwords.

Modern: Network routers

} All doesn't care about the possibility of false positives.

⇒ If critical, use hash

How it work?

Ingredients: ① Array of n bits. (So $\frac{n}{|S|} = \#$ of bits per object in data set S . Let's say 8bits)
② k hash functions h_1, h_2, \dots, h_k ($k = \text{small constant like } 3, 5$)

Inserts: For $i=1, 2, \dots, k$
set $A[h_i(x)] = 1$ (No matter the existing bit in $A[h_i(x)]$)

Lookup: Return True $\Leftrightarrow A[h_i(x)] = 1$ for every $i=1, 2, \dots, k$.

Note: No false negative. (If x has inserted, $\text{Lookup}(x)$ guaranteed to succeed)
But: false positive if all k $h_i(x)$'s already get to 1 by other insertions.

How useful is Bloom Filter?

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Intuition: Should be a trade-off between space and error prob.

⇒ Basically, the bigger the space Bloom Filter use, the smaller the false positive prob. is.

⇒ Way to set the right num. of k . (# of hash function)
 b : Number of bits representing the object.

$$k \approx (\log 2) \cdot b$$

⇒ Prob. of error

$$\epsilon \approx \left(\frac{1}{2}\right)^{(\log 2)b} \quad \text{or} \quad b \approx 1.44 \cdot \log_2 \frac{1}{\epsilon}$$

E.g. with $b=8$, choose $k=5$ or 6 , error prob. only $\approx 2\%$