

Advanced Algorithms – COMS31900

Hashing part one

Chaining, true randomness and universal hashing

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Dictionaries

In a **dictionary** data structure we store (key, value)-pairs

such that for any *key* there is at most one pair (*key*, *value*) in the dictionary.

Often we want to perform the following three operations:

add(x, v) Add the the pair (x, v).

lookup(x) Return v if (x, v) is in dictionary, or NULL otherwise.

delete(x) Remove pair (x, v) (assuming (x, v) is in dictionary).

There are many data structures that will do this job, e.g.:

Linked lists

Red-black trees

Binary search trees

Skip lists

► (2,3,4)-trees

van Emde Boas trees (later in this course)

these data structures all support extra operations beyond the three above

but none of them take O(1) worst case time for all operations...

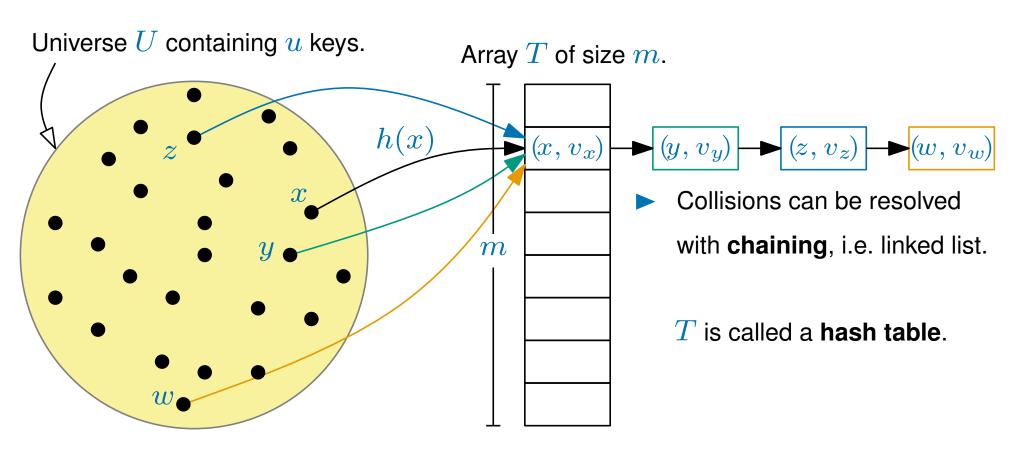
so *maybe* there is room for improvement?



Hash tables

We want to store n elements from the universe, U in a dictionary.

Typically u = |U| is much, much larger than n.



A hash function $h:U\to [m]$ maps a key to a position in T.

We write [m] to denote the set $\{0, \ldots, m-1\}$.

We want to avoid **collisions**, i.e. h(x) = h(y) for $x \neq y$.



Time complexity

We cannot avoid collisions entirely since $u \gg m$;

some keys from the universe are bound to be mapped to the same position.

(remember u is the size of the universe and m is the size of the table)

By building a hash table with chaining, we get the following time complexities:

Operation	Worst case time	Comment
$\operatorname{add}(x,v)$	O(1)	Simply add item to the list link if
		necessary.
lookup(x)	$O(\mbox{length of chain containing }x)$	We might have to search through the whole list containing \boldsymbol{x} .
delete(x)	$O(\mbox{length of chain containing }x)$	Only $O(1)$ to perform the actual deletebut you have to find x first

So how long are these chains?



True randomness

THEOREM

Consider any n fixed inputs to the hash table (which has size m),

i.e. any sequence of n add/lookup/delete operations.

Pick h uniformly at random from the set of *all* functions $U \to [m]$.

The expected run-time per operation is $O(1 + \frac{n}{m})$, or simply O(1) if $m \ge n$.

PROOF

Let x, y be two distinct keys from U. \longrightarrow iff means if and only if.

Let indicator r.v. $I_{x,y}$ be 1 iff h(x) = h(y).

we have that,
$$\Pr\left(h(x) = h(y)\right) = \frac{1}{m}$$

this is because h(x) and h(y) are chosen uniformly and independently from [m].

Therefore,
$$\mathbb{E}(I_{x,y}) = \Pr(I_{x,y} = 1) = \Pr(h(x) = h(y)) = \frac{1}{m}$$
.

We have that,
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True randomness

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PROOF

Let indicator r.v. $I_{x,y}$ be 1 iff h(x) = h(y).

We have that, $\mathbb{E}(I_{x,y})=rac{1}{m}$.

Let N_x be the number of keys stored in T that are hashed to h(x)

so, in the worst case it takes N_x time to look up x in T.

Observe that
$$N_x=\sum_{y\in T}I_{x,y}$$
 the keys in T Finally, we have that $\mathbb{E}(N_x)=\mathbb{E}\left(\sum_{y\in T}I_{x,y}\right)=\sum_{y\in T}\mathbb{E}(I_{x,y})=n\cdot\frac{1}{m}=\frac{n}{m}$ linearity of expectation.



Specifying the hash function

Problem: how do we specify an arbitrary (e.g. a truly random) hash function?

For each key in U we need to specify an arbitrary position in T, this is a number in $\lceil m \rceil$, so requires $\approx \log_2 m$ bits.

So in total we need $\approx u \log_2 m$ bits, which is a ridiculous amount of space! (in particular, it's much bigger than the table :s)

Why not pick the hash function as we go?

Couldn't we generate h(x) when we first see x?

Wouldn't we only use $n \log_2 m$ bits? (one per key we actually store)

The problem with this approach is recalling h(x) the next time we see x

Essentially we'd need to build a dictionary to solve the dictionary problem!

This has become rather cyclic... let's try something else!



Specifying the hash function

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So in total we need $\approx u \log_2 m$ bits, which is a ridiculous amount of space! (in particular, it's much bigger than the table :s)

Instead, we define a set, or *family of hash functions*: $H = \{h_1, h_2, \dots\}$.

As part of initialising the hash table,

we choose the hash function h from H randomly.

How should we specify the hash functions in H and how do we pick one at random?



Weakly universal hashing

ightharpoonup A set H of hash functions is **weakly universal** if for any two distinct keys $x, y \in U$,

$$\Pr\left(h(x) = h(y)\right) \leqslant \frac{1}{m}$$

where h is chosen uniformly at random from H.

OBSERVE

The randomness here comes from the fact that h is picked randomly.

THEOREM

Consider any n fixed inputs to the hash table (which has size m),

i.e. any sequence of n add/lookup/delete operations.

Pick h uniformly at random from a weakly universal set H of hash functions.

The expected run-time per operation is O(1) if $m \ge n$.

PROOF

The proof we used for true randomness works here too (which is nice)



Constructing a weakly universal family of hash functions

- Suppose U = [u], i.e. the keys in the universe are integers 0 to u-1.
- \blacktriangleright Let p be any prime bigger than u.
- For $a,b \in [p]$, let

$$h_{a,b}(x) = ((ax+b) \bmod p) \bmod m,$$

$$H_{p,m} = \{h_{a,b} \mid a \in \{1, \dots, p-1\}, b \in \{0, \dots, p-1\}\}.$$

THEOREM

 $H_{p,m}$ is a weakly universal set of hash functions.

PROOF

See CLRS, Theorem 11.5, (page 267 in 3rd edition).

OBSERVE

- $lackbox{a}x+b$ is a linear transformation which "spreads the keys" over p values when taken modulo p. This does not cause any collisions.
- ightharpoonup Only when taken modulo m do we get collisions.



True randomness vs. weakly universal hashing

For both,

true randomness

(h is picked uniformly from the set of all possible hash functions) and weakly universal hashing

(h is picked uniformly from a weakly universal set of hash functions)

we have seen that when $m \geqslant n$,

the expected lookup time in the hash table is O(1).

Since constructing a weakly universal set of hash functions seems much easier than obtaining true randomness, this is all good news!

isn't it?

What about the length of the *longest* chain? (the longest linked list)

If it is very long, some lookups could take a very long time...

LEMMA

If h is selected uniformly at random from all functions $U \to [m]$ then, over m fixed inputs,

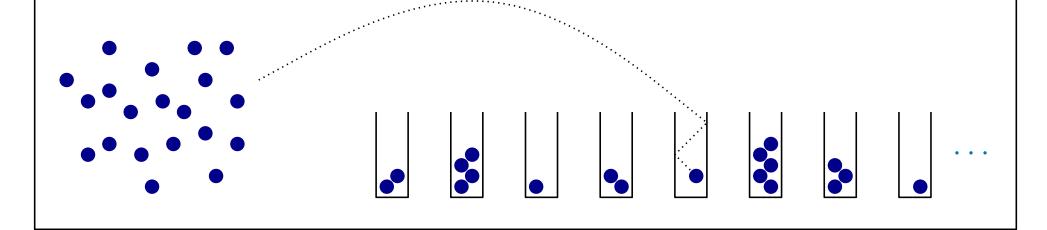
$$\Pr\left(\text{any chain has length} \geqslant 3\log m \right) \leqslant \frac{1}{m}.$$

OBSERVE

In this lemma we insert m keys, i.e. n = m.

PROOF

The problem is equivalent to showing that if we randomly throw m balls into m bins, the probability of having a bin with at least $3\log m$ balls is at most $\frac{1}{m}$.



PROOF

continued...

Let X_1 be the number of balls in the first bin.

Choose any k of the m balls (we'll pick k in a bit)

the probability that all of these k balls go into the first bin is $\frac{1}{m^k}$.

So, the union bound gives us

$$\Pr(X_1 \geqslant k) \leqslant \binom{m}{k} \cdot \frac{1}{m^k} \leqslant \frac{1}{k!}.$$

THEOREM

Let V_1,\ldots,V_q be q events. Then

$$\Pr\left(\bigcup_{i=1}^{q} V_i\right) \leqslant \sum_{i=1}^{q} \Pr(V_i).$$



PROOF

continued...

Let X_1 be the number of balls in the first bin.

Choose any k of the m balls (we'll pick k in a bit)

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So, the union bound gives us

$$\Pr(X_1 \geqslant k) \leqslant {m \choose k} \cdot \frac{1}{m^k} \leqslant \frac{1}{k!}.$$

$${\binom{m}{k}} = \frac{m!}{k!(m-k)!} = \frac{m \cdot (m-1) \cdot (m-2) \cdot \dots \cdot (m-k+1) \cdot (m-k)!}{k!(m-k)!}$$

$$\leq \frac{m \cdot (m) \cdot (m) \cdot \dots \cdot (m)}{k!} \leq \frac{m^k}{k!}$$

PROOF

continued...

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the probability that all of these k balls go into the first bin is $\frac{1}{m^k}$.

So, the union bound gives us

$$\Pr(X_1 \geqslant k) \leqslant {m \choose k} \cdot \frac{1}{m^k} \leqslant \frac{1}{k!}.$$

By using the union bound again, we have that

 $\Pr(\text{at least one bin receives at least } k \text{ balls}) \leqslant m \cdot \Pr(X_1 \geqslant k) \leqslant \frac{m}{k!}.$

Now we set $k=3\log m$ and observe that $\frac{m}{k!}\leqslant \frac{1}{m}$ for $m\geqslant 2$, and we are done.

PROOF

continued...

Let X_1 be the number of balls in the first bin.

Choose any k of the m balls (we'll pick k in a bit)

Why is
$$\frac{m}{k!} \leqslant \frac{1}{m}$$
? (when $k = 3\log m$)
$$k! = k \times (k-1) \times (k-2) \dots \times 2 \times 1$$

$$k! > 2 \times 2 \times 2 \dots \times 2 \times 1 = 2^{k-1}$$
By us
$$k! > 2^{(3\log m - 1)} \geqslant 2^{2\log m} = (2^{\log m})^2 = m^2$$

$$\text{so } \frac{m}{k!} \leqslant \frac{m}{m^2} = \frac{1}{m}$$

Now we set $\kappa = 5 \log m$ and observe that $\frac{1}{k!} \leq \frac{1}{m}$ for $m \geq 2$ and we are done.

LEMMA

If h is selected uniformly at random from all functions $U \to [m]$ then, over m fixed inputs,

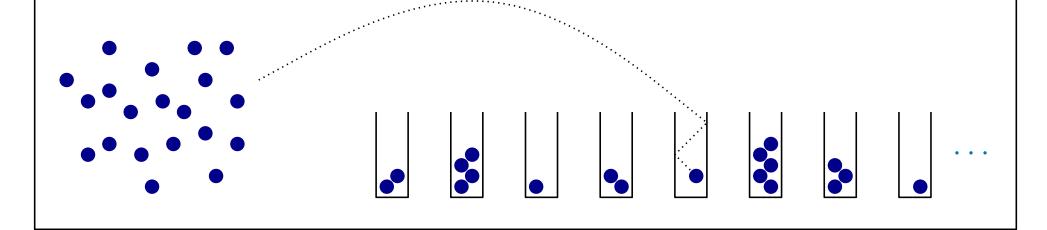
$$\Pr\left(\text{any chain has length} \geqslant 3\log m \right) \leqslant \frac{1}{m}.$$

OBSERVE

In this lemma we insert m keys, i.e. n = m.

PROOF

The problem is equivalent to showing that if we randomly throw m balls into m bins, the probability of having a bin with at least $3\log m$ balls is at most $\frac{1}{m}$.





Longest chain – weakly universal hashing

The conclusion from previous slides is that with true randomness, the longest chain is very short (at most $3\log m$) with high probability.

LEMMA

If h is picked uniformly at random from a weakly universal set of hash functions then, over m fixed inputs,

$$\Pr\left(\text{any chain has length} \geqslant 1 + \sqrt{2m}\,\right) \leqslant \frac{1}{2}.$$

OBSERVE

This rubbish upper bound of $\frac{1}{2}$ does not necessarily rule out the possibility that the *tightest* upper bound is indeed very small. However, the upper bound of $\frac{1}{2}$ is in fact tight!



Longest chain - weakly universal hashing

PROOF

- For any two keys x, y, let indicator r.v. $I_{x,y}$ be 1 iff h(x) = h(y).
- Let r.v. C be the total number of collisions: $C = \sum_{x,y \in T, x < y} I_{x,y}$.
- lacksquare Using linearity of expectation and $\mathbb{E}(I_{x,y})=rac{1}{m}$ (h is weakly universal),

$$\mathbb{E}(C) = \mathbb{E}\left(\sum_{x,y\in T, x< y} I_{x,y}\right) = \sum_{x,y\in T, x< y} \mathbb{E}(I_{x,y}) = {m \choose 2} \cdot \frac{1}{m} \leqslant \frac{m}{2}.$$

- ▶ by Markov's inequality, $\Pr(C \geqslant m) \leqslant \frac{\mathbb{E}(C)}{m} \leqslant \frac{1}{2}$.
- Let r.v. L be the length of the longest chain. Then $C \geqslant {L \choose 2}$.

This is because a chain of length L causes $\binom{L}{2}$ collisions!



Longest chain - weakly universal hashing

PROOF

- For any two keys x, y, let indicator r.v. $I_{x,y}$ be 1 iff h(x) = h(y).
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$$\mathbb{E}(C) = \mathbb{E}\left(\sum_{x,y \in T, x < y} I_{x,y}\right) = \sum_{x,y \in T, x < y} \mathbb{E}(I_{x,y}) = {m \choose 2} \cdot \frac{1}{m} \leqslant \frac{m}{2}.$$

- ightharpoonup by Markov's inequality, $\Pr(C\geqslant m)\leqslant rac{\mathbb{E}(C)}{m}\leqslant rac{1}{2}$.
- lacksquare Let r.v. L be the length of the longest chain. Then $C\geqslant {L\choose 2}$.

Now,
$$\Pr\left(\frac{(L-1)^2}{2}\geqslant m\right)\leqslant \Pr\left(\binom{L}{2}\geqslant m\right)\leqslant \Pr\left(C\geqslant m\right)\leqslant \frac{1}{2}.$$
 this is because $\binom{L}{2}=\frac{L!}{2!(L-2)!}=\frac{L\cdot(L-1)}{2}\geqslant \frac{(L-1)^2}{2}$

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- ightharpoonup by Markov's inequality, $\Pr(C\geqslant m)\leqslant \frac{\mathbb{E}(C)}{m}\leqslant \frac{1}{2}$.
- Let r.v. L be the length of the longest chain. Then $C \geqslant {L \choose 2}$.
- $\qquad \qquad \text{Now, } \Pr\left(\frac{(L-1)^2}{2} \geqslant m\right) \leqslant \Pr\left(\binom{L}{2} \geqslant m\right) \leqslant \Pr\left(C \geqslant m\right) \leqslant \frac{1}{2}.$

By rearranging, we have that
$$\Pr\left(L\geqslant 1+\sqrt{2m}\right)\leqslant \frac{1}{2}$$
 , and we are done.

Conclusions

For both,

true randomness (h is picked uniformly from the set of all possible hash functions) and weakly universal hashing

(h is picked uniformly from a weakly universal set of hash functions)

we have seen that when $m \geqslant n$,

the expected lookup time in a hash table with chaining is O(1).

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If h is selected uniformly at random from all functions $U \to [m]$ then,

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LEMMA

If h is picked uniformly at random from a weakly universal set of hash functions,

$$\Pr\left(\text{any chain has length} \geqslant 1 + \sqrt{2m}\right) \leqslant \frac{1}{2}.$$