

Universal Hashing, Perfect Hashing

Lecture 8

A weakness of hashing

Problem: For any hash function h , a set of keys exists that can cause the average access time of a hash table to skyrocket.

- An adversary can pick all keys from $\{k \in U : h(k) = i\}$ for some slot i .

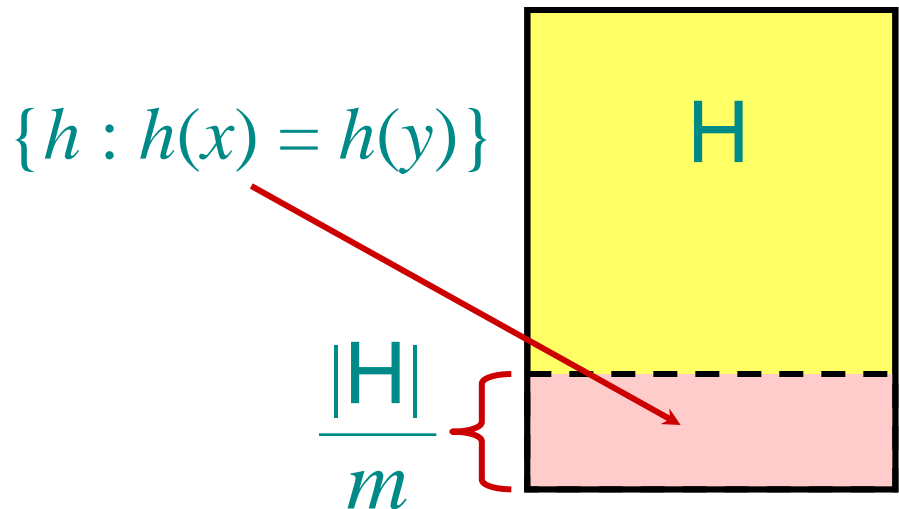
IDEA: Choose the hash function at random, independently of the keys.

- Even if an adversary can see your code, he or she cannot find a bad set of keys, since he or she doesn't know exactly which hash function will be chosen.

Universal hashing

Definition. Let U be a universe of keys, and let H be a finite collection of hash functions, each mapping U to $\{0, 1, \dots, m-1\}$. We say H is *universal* if for all $x, y \in U$, where $x \neq y$, we have $|\{h \in H : h(x) = h(y)\}| = |H|/m$.

That is, the chance of a collision between x and y is $1/m$ if we choose h randomly from H .



Universality is good

Theorem. Let h be a hash function chosen (uniformly) at random from a universal set H of hash functions. Suppose h is used to hash n arbitrary keys into the m slots of a table T . Then, for a given key x , we have

$$E[\text{\#collisions with } x] < n/m.$$

Proof of theorem

Proof. Let C_x be the random variable denoting the total number of collisions of keys in T with x , and let

$$c_{xy} = \begin{cases} 1 & \text{if } h(x) = h(y), \\ 0 & \text{otherwise.} \end{cases}$$

Note: $E[c_{xy}] = 1/m$ and $C_x = \sum_{y \in T - \{x\}} c_{xy}$.

Proof (continued)

$$E[C_x] = E \left[\sum_{y \in T - \{x\}} c_{xy} \right]$$

- Take expectation of both sides.

Proof (continued)

$$\begin{aligned} E[C_x] &= E \left[\sum_{y \in T - \{x\}} c_{xy} \right] \\ &= \sum_{y \in T - \{x\}} E[c_{xy}] \end{aligned}$$

- Take expectation of both sides.
- Linearity of expectation.

Proof (continued)

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- Take expectation of both sides.
- Linearity of expectation.
- $E[c_{xy}] = 1/m$.

Proof (continued)

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$$= \sum_{y \in T - \{x\}} E[c_{xy}]$$

$$= \sum_{y \in T - \{x\}} 1/m$$

$$= \frac{n-1}{m} \cdot \square$$

- Take expectation of both sides.
- Linearity of expectation.
- $E[c_{xy}] = 1/m$.
- Algebra.

Constructing a set of universal hash functions

Let m be prime. Decompose key k into $r + 1$ digits, each with value in the set $\{0, 1, \dots, m-1\}$. That is, let $k = \langle k_0, k_1, \dots, k_r \rangle$, where $0 \leq k_i < m$.

Randomized strategy:

Pick $a = \langle a_0, a_1, \dots, a_r \rangle$ where each a_i is chosen randomly from $\{0, 1, \dots, m-1\}$.

Define $h_a(k) = \sum_{i=0}^r a_i k_i \bmod m$.

*Dot product,
modulo m*

How big is $H = \{h_a\}$?

$$|H| = m^{r+1}.$$

REMEMBER THIS!

Universality of dot-product hash functions

Theorem. The set $\mathbf{H} = \{h_a\}$ is universal.

Proof. Suppose that $x = \langle x_0, x_1, \dots, x_r \rangle$ and $y = \langle y_0, y_1, \dots, y_r \rangle$ be distinct keys. Thus, they differ in at least one digit position, wlog position 0.

For how many $h_a \in \mathbf{H}$ do x and y collide?

We must have $h_a(x) = h_a(y)$, which implies that

$$\sum_{i=0}^r a_i x_i \equiv \sum_{i=0}^r a_i y_i \pmod{m}.$$

Proof (continued)

Equivalently, we have

$$\sum_{i=0}^r a_i(x_i - y_i) \equiv 0 \pmod{m}$$

or

$$a_0(x_0 - y_0) + \sum_{i=1}^r a_i(x_i - y_i) \equiv 0 \pmod{m},$$

which implies that

$$a_0(x_0 - y_0) \equiv -\sum_{i=1}^r a_i(x_i - y_i) \pmod{m}.$$

Fact from number theory

Theorem. Let m be prime. For any $z \in \mathbb{Z}_m$ such that $z \neq 0$, there exists a unique $z^{-1} \in \mathbb{Z}_m$ such that

$$z \cdot z^{-1} \equiv 1 \pmod{m}.$$

Example: $m = 7$.

z	1	2	3	4	5	6
z^{-1}	1	4	5	2	3	6

Back to the proof

We have

$$a_0(x_0 - y_0) \equiv -\sum_{i=1}^r a_i(x_i - y_i) \pmod{m},$$

and since $x_0 \neq y_0$, an inverse $(x_0 - y_0)^{-1}$ must exist, which implies that

$$a_0 \equiv \left(-\sum_{i=1}^r a_i(x_i - y_i) \right) \cdot (x_0 - y_0)^{-1} \pmod{m}.$$

Thus, for any choices of a_1, a_2, \dots, a_r , exactly one choice of a_0 causes x and y to collide.

Proof (completed)

Q. How many h_a 's cause x and y to collide?

A. There are m choices for each of a_1, a_2, \dots, a_r , but once these are chosen, exactly one choice for a_0 causes x and y to collide, namely

$$a_0 = \left(\left(- \sum_{i=1}^r a_i (x_i - y_i) \right) \cdot (x_0 - y_0)^{-1} \right) \bmod m.$$

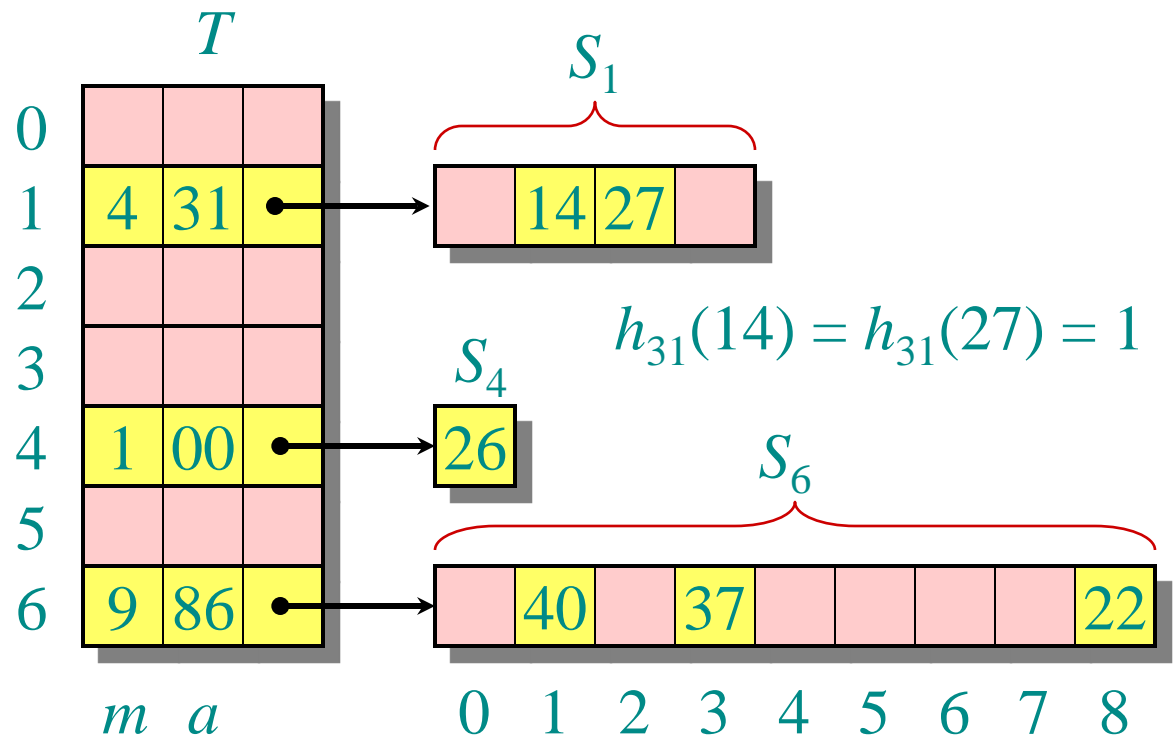
Thus, the number of h_a 's that cause x and y to collide is $m^r \cdot 1 = m^r = |\mathbf{H}|/m$. ◻

Perfect hashing

Given a set of n keys, construct a static hash table of size $m = O(n)$ such that **SEARCH** takes $\Theta(1)$ time in the *worst case*.

IDEA: Two-level scheme with universal hashing at both levels.

No collisions at level 2!



Collisions at level 2

Theorem. Let \mathbf{H} be a class of universal hash functions for a table of size $m = n^2$. Then, if we use a random $h \in \mathbf{H}$ to hash n keys into the table, the expected number of collisions is at most $1/2$.

Proof. By the definition of universality, the probability that 2 given keys in the table collide under h is $1/m = 1/n^2$. Since there are $\binom{n}{2}$ pairs of keys that can possibly collide, the expected number of collisions is

$$\binom{n}{2} \cdot \frac{1}{n^2} = \frac{n(n-1)}{2} \cdot \frac{1}{n^2} < \frac{1}{2}. \quad \square$$

No collisions at level 2

Corollary. The probability of no collisions is at least $1/2$.

Proof. Markov's inequality says that for any nonnegative random variable X , we have

$$\Pr\{X \geq t\} \leq E[X]/t.$$

Applying this inequality with $t = 1$, we find that the probability of 1 or more collisions is at most $1/2$. □

Thus, just by testing random hash functions in H , we'll quickly find one that works.

Analysis of storage

For the level-1 hash table T , choose $m = n$, and let n_i be random variable for the number of keys that hash to slot i in T . By using n_i^2 slots for the level-2 hash table S_i , the expected total storage required for the two-level scheme is therefore

$$E \left[\sum_{i=1}^m \Theta(n_i^2) \right] = \Theta(n),$$

since the analysis is identical to the analysis of bucket sort.