

# The Design and Analysis of Algorithms

## Lecture 27 Randomized Algorithms II

Zhenbo Wang

Department of Mathematical Sciences, Tsinghua University



# Content

Universal Hashing

Load Balancing

# Dictionary Data Type

- *Dictionary*. Given a universe  $U$  of possible elements, maintain a subset  $S \subseteq U$  so that *inserting*, *deleting*, and *searching* in  $S$  is efficient.
- *Dictionary interface*.

create(): initialize a dictionary with  $S = \emptyset$ .

insert( $u$ ): add element  $u \in U$  to  $S$ .

delete( $u$ ): delete  $u$  from  $S$  (if  $u$  is currently in  $S$ ).

lookup( $u$ ): is  $u$  in  $S$ ?

- *Challenge*. Universe  $U$  can be extremely large so defining an array of size  $|U|$  is infeasible.
- *Applications*. File systems, databases, Google, compilers, checksums P2P networks, associative arrays, cryptography, web caching, etc.

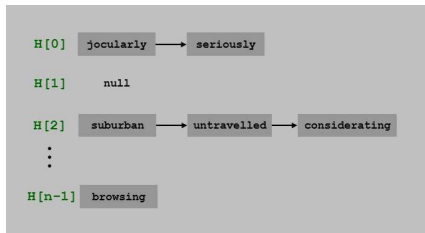


# Hashing

- *Hash function.*  $h : U \rightarrow \{0, 1, \dots, n-1\}$ .
- *Hashing.* Create an array  $H$  of size  $n$ . When processing element  $u$ , access array element  $H[h(u)]$ .
- *Collision.* When  $h(u) = h(v)$  but  $u \neq v$ .

A collision is expected after  $\Theta(\sqrt{n})$  random insertions (Birthday Problem).

Separate chaining:  $H[i]$  stores linked list of elements  $u$  with  $h(u) = i$ .



# Hashing Performance

- *Ideal hash function.* Maps  $m$  elements *uniformly at random* to  $n$  hash slots.

Running time depends on length of chains.

Average length of chain  $= \alpha = m/n$ .

Choose  $n \approx m \Rightarrow$  on average  $O(1)$  per insert, lookup, or delete.

- *Challenge.* Achieve idealized randomized guarantees, but with a hash function where you can easily find items where you put them.
- *Approach.* Use randomization in the choice of  $h$ .



# Universal Hashing

- *Universal family of hash functions.* [Carter-Wegman 1980s]

For any pair of elements  $u, v \in U$ ,  $\Pr_{h \in H}[h(u) = h(v)] \leq 1/n$ .

Can select random  $h$  efficiently.

Can compute  $h(u)$  efficiently.

Ex.  $U = \{a, b, c, d, e, f\}$ ,  $n = 2$ .

	a	b	c	d	e	f
$h_1(x)$	0	1	0	1	0	1
$h_2(x)$	0	0	0	1	1	1

$$\begin{aligned} H &= \{h_1, h_2\} \\ \Pr_{h \in H}[h(a) = h(b)] &= 1/2 \\ \Pr_{h \in H}[h(a) = h(c)] &= 1 \\ \Pr_{h \in H}[h(a) = h(d)] &= 0 \\ &\dots \end{aligned}$$

not universal

	a	b	c	d	e	f
$h_1(x)$	0	1	0	1	0	1
$h_2(x)$	0	0	0	1	1	1
$h_3(x)$	0	0	1	0	1	1
$h_4(x)$	1	0	0	1	1	0

$$\begin{aligned} H &= \{h_1, h_2, h_3, h_4\} \\ \Pr_{h \in H}[h(a) = h(b)] &= 1/2 \\ \Pr_{h \in H}[h(a) = h(c)] &= 1/2 \\ \Pr_{h \in H}[h(a) = h(d)] &= 1/2 \\ \Pr_{h \in H}[h(a) = h(e)] &= 1/2 \\ \Pr_{h \in H}[h(a) = h(f)] &= 0 \\ &\dots \end{aligned}$$

universal



# Universal Hashing: Analysis

- *Proposition.* Let  $H$  be a universal family of hash functions; let  $h \in H$  be chosen uniformly at random from  $H$ ; and let  $u \in U$ . For any subset  $S \subseteq U$  of size at most  $n$ , the expected number of items in  $S$  that collide with  $u$  is at most 1.

**Pf.** For any element  $s \in S$ , define indicator random variable  $X_s = 1$  if  $h(s) = h(u)$  and 0 otherwise.

Let  $X$  be a random variable counting the total number of collisions with  $u$ .

$$E_{h \in H}[X] = E\left[\sum_{s \in S} X_s\right] = \sum_{s \in S} \Pr[X_s = 1] \leq \sum_{s \in S} \frac{1}{n} = |S| \frac{1}{n} \leq 1. \quad \square$$

**Q.** OK, but how do we design a universal class of hash functions?



# Designing a Universal Family of Hash Functions

## Theorem 1 (Chebyshev 1850)

*There exists a prime between  $n$  and  $2n$ .*

- *Modulus.* Choose a prime number  $p \approx n$ .
- *Integer encoding.* Identify each element  $u \in U$  with a base- $p$  integer of  $r$  digits:  $x = (x_1, x_2, \dots, x_r)$ .
- *Hash function.* Let  $A =$  set of all  $r$ -digit, base- $p$  integers. For each  $a = (a_1, a_2, \dots, a_r)$  where  $0 \leq a_i < p$ , define

$$h_a(x) = \sum_{i=1}^r a_i x_i \pmod{p}.$$

- *Hash function family.*  $H = \{h_a : a \in A\}$ .





# Designing a Universal Family of Hash Functions

## Theorem 2

$H = \{h_a : a \in A\}$  is a universal family of hash functions.

**Pf.** Choose a prime number  $p \approx n$ .

Let  $x = (x_1, \dots, x_r)$  and  $y = (y_1, \dots, y_r)$  be two distinct elements of  $U$ .

Since  $x \neq y$ , there exists an integer  $j$  such that  $x_j \neq y_j$ .

We have  $h_a(x) = h_a(y)$  iff  $a_j(y_j - x_j) = \sum_{i \neq j} a_i(x_i - y_i) \pmod{p}$ .

Can assume  $a$  was chosen uniformly at random by first selecting all coordinates  $a_i$  where  $i \neq j$ , then selecting  $a_j$  at random. Thus, we can assume  $a_i$  is fixed for all coordinates  $i \neq j$ .

Since  $p$  is prime,  $a_j z = m \pmod{p}$  has at most one solution among  $p$  possibilities.

Thus  $\Pr[h_a(x) = h_a(y)] \leq 1/n$ .  $\square$



# Number Theory Fact

**Fact.** Let  $p$  be prime, and let  $z \not\equiv 0 \pmod{p}$ . Then  $\alpha z = m \pmod{p}$  has at most one solution  $0 \leq \alpha < p$ .

**Pf.** Suppose  $\alpha$  and  $\beta$  are two different solutions.

Then  $(\alpha - \beta)z \equiv 0 \pmod{p}$ ; hence  $(\alpha - \beta)z$  is divisible by  $p$ .

Since  $z \not\equiv 0 \pmod{p}$ , we know that  $z$  is not divisible by  $p$ ; it follows that  $(\alpha - \beta)$  is divisible by  $p$ .

This implies  $\alpha = \beta$ .  $\square$



# Chernoff Bounds

## Theorem 3

*Suppose  $X_1, \dots, X_n$  are independent 0 – 1 random variables. Let  $X = X_1 + \dots + X_n$ . Then for any  $\mu \geq E[X]$  and for any  $\delta > 0$ , we have*

$$Pr[X > (1 + \delta)\mu] < \left( \frac{e^\delta}{(1 + \delta)^{1+\delta}} \right)^\mu;$$

*for any  $\mu \leq E[X]$  and for any  $0 < \delta < 1$ , we have*

$$Pr[X < (1 - \delta)\mu] < e^{-\delta^2 \mu / 2}.$$



# Load Balancing

- *Load balancing.* System in which  $n$  jobs arrive in a stream and need to be processed immediately on  $n$  identical processors. Find an assignment that balances the workload across processors.
- *Centralized controller.* Each processor receives one job.
- *Decentralized controller.* Assign jobs to processors uniformly at random.

How likely is it that some processor is assigned "too many" jobs?



# Load Balancing: Analysis

- Let  $X_i$  = number of jobs assigned to processor  $i$ .
- Let  $Y_{ij} = 1$  if job  $j$  assigned to processor  $i$ , and 0 otherwise.
- We have  $E[Y_{ij}] = 1/n$ .
- Thus,  $X_i = \sum_j Y_{ij}$ , and  $\mu = E[X_i] = 1$ .
- Applying Chernoff bounds with  $\delta = c - 1$  yields  $\Pr[X_i > c] < \frac{e^{c-1}}{c^c}$ .
- Let  $\gamma(n)$  be number  $x$  such that  $x^x = n$ , and choose  $c = e\gamma(n)$ .

$$\Pr[X_i > c] < \frac{e^{c-1}}{c^c} < \left(\frac{e}{c}\right)^c = \left(\frac{1}{\gamma(n)}\right)^{e\gamma(n)} = \left(\frac{1}{n}\right)^e < \frac{1}{n^2}$$

- Union bound  $\Rightarrow$  with probability  $\geq 1 - 1/n$  no processor receives more than  $e\gamma(n) = \Theta(\log n / \log \log n)$  jobs.



# BPP, RP and ZPP

**BPP.** Decision problems solvable with probability  $\geq 2/3$  in poly-time.

**RP.** Decision problems solvable with one-sided error in poly-time.

If the correct answer is *no*, always return *no*.

If the correct answer is *yes*, return *yes* with probability  $\geq 1/2$ .

**coRP.** Complementary of *RP*.

**ZPP.** Decision problems solvable in *expected* poly-time.



# BPP, RP and ZPP

## Theorem 5

$$\begin{aligned}\mathbf{RP} &\subseteq \mathbf{BPP} \\ \mathbf{coRP} &\subseteq \mathbf{BPP} \\ \mathbf{ZPP} &= \mathbf{RP} \cap \mathbf{coRP}\end{aligned}$$

## Theorem 6

$$P \subseteq ZPP \subseteq BPP, RP \subseteq NP.$$

- *Fundamental open questions.* To what extent does randomization help?
- Does  $P = ZPP$ ? Does  $ZPP = BPP$ ? Does  $RP = NP$ ? Does  $BPP = NP$ ?



# Homework

- Read Chapter 13 of the textbook.
- Exercise 9 & 18 in Chapter 13.

