

CS 473: Algorithms

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Fingerprinting

Lecture 11

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Most slides are courtesy Prof. Chekuri

Bloom Filters

Hashing:

- 1 To insert x in dictionary store x in table in location $h(x)$
- 2 To lookup y in dictionary check contents of location $h(y)$

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Bloom Filter: tradeoff space for false positives

- 1 What if elements (x) are unwieldy objects such as long strings, images, etc with *non-uniform* sizes.
- 2 To insert x in dictionary, set *bit* at location $h(x)$ to **1** (initially all bits are set to **0**)
- 3 To lookup y if bit in location $h(y)$ is **1** say yes, else no.

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Issue: False positives due to collisions.

Bloom Filters

Bloom Filter: tradeoff space for false positives

Reducing false positives:

- 1 Pick k hash functions $h_1, h_2, \dots, h_k$ *independently*
- 2 Insert x : for $1 \leq i \leq k$ set bit in location $h_i(x)$ in table i to 1

Bloom Filters

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- ② Insert x : for $1 \leq i \leq k$ set bit in location $h_i(x)$ in table i to **1**
- ③ Lookup y : compute $h_i(y)$ for $1 \leq i \leq k$ and say yes only if each bit in the corresponding location is **1**, otherwise say no. If probability of false positive for one hash function is $\alpha < 1$ then with k independent hash function it is

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Take away points

- ① Hashing is a powerful and important technique for dictionaries. Many practical applications.
- ② Randomization fundamental to understand hashing.
- ③ Good and efficient hashing possible in theory and practice with proper definitions (universal, perfect, etc).
- ④ Related ideas of creating a compact fingerprint/sketch for objects is very powerful in theory and practice.

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As you may have guessed, fingerprint functions are hash functions.

Use of hash functions for designing fast algorithms

Problem

Given a text T of length m and pattern P of length n , $m \gg n$, find all occurrences of P in T .

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Karp-Rabin Randomized Algorithm

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Karp-Rabin Randomized Algorithm

It involves:

- Sampling a prime
- String equality via $\text{mod } p$ arithmetic
- Rabin's fingerprinting scheme – rolling hash
- Karp-Rabin pattern matching algorithm: $O(m + n)$ time.

Part I

Sampling a Prime

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Given an integer $x > 0$, sample a prime uniformly at random from all the primes between 1 and x .

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Checking if p is prime

- Agrawal-Kayal-Saxena primality test: deterministic but slow
- Miller-Rabin randomized primality test: fast but randomized outputs 'prime' when it is not *with very low probability*.

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For a fixed prime $p^* \leq x$, $\Pr[\text{algorithm outputs } p^*] = 1/\pi(x)$.

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$\Pr[A \cap B] = \Pr[B] = 1/x$. Why?

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$$\Pr[B|A] = \frac{\Pr[A \cap B]}{\Pr[A]} = \frac{\Pr[B]}{\Pr[A]} = \frac{1/x}{\pi(x)/x} = \frac{1}{\pi(x)}$$



Sampling a prime: Expected number of samples

Procedure

- 1 Sample a number p uniformly at random from $\{1, \dots, x\}$.
- 2 If p is a prime, then output p . Else go to Step (1).

Running time in expectation

Q: How many samples in expectation before termination?

A: $x/\pi(x)$. Exercise.

How many primes between 0 and x

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J. Hadamard and C. J. de la Vallée-Poussin (1896)

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- $y \sim \{1, \dots, x\}$ u.a.r., then y is a prime w.p. $\frac{\pi(x)}{x} > \frac{1}{\lg x}$.
- If we want $k \geq 4$ primes then $x \geq 2k \lg k$ suffices.

$$\pi(x) \geq \pi(2k \lg k) = \frac{2k \lg k}{\lg 2 + \lg k + \lg \lg k} \geq \frac{k(2 \lg k)}{2 \lg k} = k$$

Part II

String Equality

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 - If $x \neq y$, then $\Pr[\text{Bob says un-equal}] = 0.9999$.

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HOW?

String Equality: Randomized Algorithm

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(Recall) If $M = \lceil 2(5N) \lg 5N \rceil$, then $5N$ primes in $\{1, \dots, M\}$.

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Procedure

Define $h_p(x) = x \bmod p$

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Lemma

If $x = y$ then Bob always says equal.

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Lemma

If $x \neq y$ then, $\Pr[\text{Bob says equal}] \leq 1/5$ (error probability).

String Equality: Randomized Algorithm

x, y : N -bit strings.

(Recall) If $M = \lceil 2(sN) \lg sN \rceil$, then sN primes in $\{1, \dots, M\}$.

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Lemma

If $x \neq y$ then, $\Pr[\text{Bob says equal}] \leq 1/s$ (error probability).

Question.

Let $x = 6 = 2 * 3$. If we draw a p u.a.r. from $\{2, 3, 5, 7\}$, then what is the probability that $x \bmod p = 0$?

- (A) 0.
- (B) 1.
- (C) $1/4$.
- (D) $1/2$.
- (E) none of the above.

Question.

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Now, let $y = 21$. What is the probability that $(y - x) \bmod p = 15 \bmod p = 0$?

- (A) 0.
- (B) 1.
- (C) $1/4$.
- (D) $1/2$.

String Equality: Randomized Algorithm

Error probability

x, y N -bit string, $M = \lceil 2(sN) \lg sN \rceil$, and $h_p(x) = x \bmod p$

Lemma

If $x \neq y$ then, $\Pr[\text{Bob says equal}] = \Pr[h_p(x) = h_p(y)] \leq 1/s$

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- $D = |x - y|$, then $D \bmod p = 0$, and $D \leq 2^N$.

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- $D = p_1 \dots p_k$ prime factorization.

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- $2^k \leq D \leq 2^N \Rightarrow k \leq N$. D has at most N divisors.

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- Probability that a random prime p from $\{1, \dots, M\}$ is a divisor
$$= \frac{k}{\pi(M)} \leq \frac{N}{\pi(M)}$$

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- $2^k \leq D \leq 2^N \Rightarrow k \leq N$. D has at most N divisors.
- Probability that a random prime p from $\{1, \dots, M\}$ is a divisor
$$= \frac{k}{\pi(M)} \leq \frac{N}{\pi(M)} \leq \frac{N}{M/\lg M} = \frac{N}{2(\textcolor{red}{s}N) \lg \textcolor{red}{s}N} \lg M \leq \frac{1}{\textcolor{red}{s}}$$



Error Probability and Communication

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Amount of Communication

Each round sends 2 integers $\leq M$. # bits: $2 \lg M \leq 4(\lg s + \lg N)$.

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Second approach will send $10(2 \lg (10N \lg 5N)) \leq 1280$ bits.

Part III

Karp-Rabin Pattern Matching Algorithm

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Solution $S = \{1, 8\}$.

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Given a string T of length m and pattern P of length n , s.t. $m \gg n$, find all occurrences of P in T .

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T =abracadabra, P =ab.

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$O(mn)$ run-time.

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Pick a prime p u.a.r. from $\{1, \dots, M\}$. $h_p(x) = x \bmod p$.

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Can we compute $h_p(T_{i+1 \dots i+n})$ using $h_p(T_{i \dots i+n-1})$ fast?

Let a and b be (non-negative) integers.

$$(a + b) \bmod p = ((a \bmod p) + (b \bmod p)) \bmod p$$

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$x = T_{i\dots i+n-1}$ and $x' = T_{i+1\dots i+n}$.

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$x = 1011001$, and $x' = 0110010$ (or $x' = 0110011$).

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Can it contain unmatched positions? YES!

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- To ensure S is correct with at least **0.99** probability, we need

$$1 - \frac{m}{s} = 0.99 \Leftrightarrow \frac{m}{s} = \frac{1}{100} \Leftrightarrow s = 100m$$

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64-bit arithmetic is doable on laptops!

Take away points

- ① Hashing is a powerful and important technique. Many practical applications.
- ② Randomization fundamental to understand hashing.
- ③ Good and efficient hashing possible in theory and practice with proper definitions (universal, perfect, etc).
- ④ Related ideas of creating a compact fingerprint/sketch for objects is very powerful in theory and practice.