Randomized algorithms II

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Random Variables and Expectation

Randomized algorithms

- · Last week
 - · Contention resolution
 - · Global minimum cut
- Today
- · Expectation of random variables
 - · Guessing cards
- · Hash functions and hash tables







Random variables

- · A random variable is an entity that can assume different values.
- The values are selected "randomly"; i.e., the process is governed by a probability distribution.
- Examples: Let X be the random variable "number shown by dice".
 - · X can take the values 1, 2, 3, 4, 5, 6.
 - If it is a fair dice then the probability that X = 1 is 1/6:
 - Pr[X=1] = 1/6.
 - · Pr[X=2] = 1/6.
 - ٠ ..

Expected values

- · Let X be a random variable with values in $\{x_1, ... x_n\}$, where x_i are numbers.
- · The expected value (expectation) of X is defined as

$$E[X] = \sum_{j=1}^{n} x_j \cdot \Pr[X = x_j]$$

- · The expectation is the theoretical average.
- · Example:
- X = random variable "number shown by dice"

$$E[X] = \sum_{j=1}^{6} j \cdot \Pr[X = j] = (1 + 2 + 3 + 4 + 5 + 6) \cdot \frac{1}{6} = 3.5$$

Waiting for a first succes

- Coin flips. Coin is heads with probability p and tails with probability 1 p. How many independent flips X until first heads?
 - Probability of X = j? (first succes is in round j)

$$Pr[X = j] = (1 - p)^{j-1} \cdot p$$

· Expected value of X:

$$E[X] = \sum_{j=1}^{\infty} j \cdot \Pr[X = j] = \sum_{j=1}^{\infty} j \cdot (1 - p)^{j-1} \cdot p = \frac{p}{1 - p} \sum_{j=1}^{\infty} j \cdot (1 - p)^{j}$$
$$= \frac{p}{1 - p} \cdot \frac{1 - p}{p^{2}} = \frac{1}{p}$$

$$\sum_{k=0}^{\infty} k \cdot x^k = \frac{x}{(1-x)^2} \quad \text{for } x < 1.$$

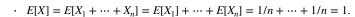
Properties of expectation

- If we repeatedly perform independent trials of an experiment, each of which succeeds with probability p > 0, then the expected number of trials we need to perform until the first succes is 1/p.
- If *X* is a 0/1 random variable, then E[X] = Pr[X = 1].
- · Linearity of expectation: For two random variables X and Y we have

$$E[X + Y] = E[X] + E[Y]$$

Guessing cards

- Game. Shuffle a deck of n cards; turn them over one at a time; try to guess each card.
- Memoryless guessing. Can't remember what's been turned over already. Guess a card from full deck uniformly at random.
- · Claim. The expected number of correct guesses is 1.
- $X_i = 1$ if i^{th} guess correct and zero otherwise.
- · X = the correct number of guesses $= X_1 + ... + X_n$.
- $E[X_i] = \Pr[X_i = 1] = 1/n$.







Guessing cards

- · Game. Shuffle a deck of n cards; turn them over one at a time; try to guess each card.
- · Guessing with memory. Guess a card uniformly at random from cards not yet seen.
- Claim. The expected number of correct guesses is $\Theta(\log n)$.
 - $X_i = 1$ if i^{th} guess correct and zero otherwise.
- X = the correct number of guesses $= X_1 + ... + X_n$.
- $E[X_i] = \Pr[X_i = 1] = 1/(n-i+1)$.
- $E[X] = E[X_1] + \dots + E[X_n] = 1/n + \dots + 1/2 + 1/1 = H_n$

 $\ln n < H(n) < \ln n + 1$

Coupon collector

- Coupon collector. Each box of cereal contains a coupon. There are n different types of coupons.
 Assuming all boxes are equally likely to contain each coupon, how many boxes before you have at least 1 coupon of each type?
- Claim. The expected number of steps is $\Theta(n \log n)$.
 - Phase j = time between j and j + 1 distinct coupons.
 - X_i = number of steps you spend in phase j.
 - $X = \text{number of steps in total} = X_0 + X_1 + \cdots + X_{n-1}$.
 - $E[X_i] = n/(n-j).$
 - · The expected number of steps:

$$E[X] = E[\sum_{i=0}^{n-1} X_j] = \sum_{i=0}^{n-1} E[X_j] = \sum_{i=0}^{n-1} n/(n-j) = n \cdot \sum_{i=1}^{n} 1/i = n \cdot H_n.$$

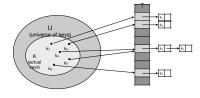
Hashing

Dictionaries

- Dictionary problem. Maintain a dynamic set of S ⊆ U subject to the following operations:
 - Lookup(x): return true if $x \in S$ and false otherwise
 - Insert(x): Set $S = S \cup \{x\}$
 - Delete(x): Set $S = S \setminus \{x\}$
- · Universe size. Typically |U| = 2^64 and |S| << |U|.
- · Satellite information. Information associated with each element.
- · Goal. A compact data structure with fast operations.
- · Applications. Many! A key component in other data structures and algorithms.

Chained Hashing

- · Chained hashing [Dumey 1956].
 - \cdot n = |S|.
 - Hash function. Pick some crazy, chaotic, random function h that maps U to $\{0, ..., m-1\}$, where $m = \Theta(n)$.
 - · Initialise an array A[0, ..., m-1].
 - · A[i] stores a linked list containing the keys in S whose hash value is i.



Uniform random hash functions

- E.g. $h(x) = x \mod 11$. Not crazy, chaotic, random.
- · Suppose |U| ≥ n²: For any hash function h there will be a set S of n elements that all map to the same position!
 - => we end up with a single linked list.
- · Solution: randomization.
- For every element $u \in U$: select h(u) uniformly at random in $\{0, ..., m-1\}$ independently from all other choices.
- Claim. The probability that h(u) = h(v) for two elements $u \neq v$ is 1/m.
- Proof.
 - m² possible choices for the pair of values (h(u),h(v)). All equally likely.
- · Exactly m of these gives a collision.

Chained Hashing with Random Hash Function

- Expected length of the linked list for h(x)?
- Random variable L_x = length of linked list for x. $L_x = \{y \in S \mid h(y) = h(x)\}$
- · Indikator random variable:

$$I_y = \begin{cases} 1 & \text{if } h(x) = h(y) \\ 0 & \text{otherwise} \end{cases} \qquad L_x = \sum_{y \in S} I_y \qquad \qquad E[I_y] = \Pr[h(y) = h(x)] = \frac{1}{m} \text{ for } x \neq y.$$

· The expected length of the linked list for x:

$$E[L_x] = E\left[\sum_{y \in S} I_y\right] = \sum_{y \in S} E[I_y] = 1 + \sum_{y \in S \setminus \{x\}} \frac{1}{m} = 1 + (n-1) \cdot \frac{1}{m} = \Theta(1).$$

Chained Hashing with Random Hash Function

- · Constant time and O(n) space for the hash table.
- · But:
- · Need O(|U|) space for the hash function.
- · Need a lot of random bits to generate the hash function.
- · Need a lot of time to generate the hash function.
- · Do we need a truly random hash function?
- · When did we use the fact that h was random in our analysis?

Chained Hashing with Random Hash Function

- Expected length of the linked list for h(x)?
- Random variable L_r = length of linked list for x. $L_r = \{y \in S \mid h(y) = h(x)\}$
- · Indikator random variable:

$$I_{\mathbf{y}} = \begin{cases} 1 & \text{if } h(\mathbf{x}) = h(\mathbf{y}) \\ 0 & \text{otherwise} \end{cases} \qquad L_{\mathbf{x}} = \sum_{\mathbf{y} \in \mathcal{S}} I_{\mathbf{y}} \qquad E[I_{\mathbf{y}}] = \Pr[h(\mathbf{y}) = h(\mathbf{x})] = \frac{1}{m} \text{ for } \mathbf{x} \neq \mathbf{y}.$$

· The expected length of the linked list for x:

$$E[L_x] = E\left[\sum_{y \in S} I_y\right] = \sum_{y \in S} E[I_y] = 1 + \sum_{y \in S \setminus \{x\}} \frac{1}{m} = 1 + (n-1) \cdot \frac{1}{m} = \Theta(1).$$

Universal hash functions

- · Universal hashing [Carter and Wegman 1979].
 - Let H be a family of functions mapping U to the set $\{0, ..., m-1\}$.
- · H is universal if for any $x, y \in U$, where $x \neq y$, and h chosen uniformly at random in H,

$$\Pr[h(x) = h(y)] < 1/m.$$

· Require that any $h \in H$ can be represented compactly and that we can compute the value h(u) efficiently for any $u \in U$.

Universal Hashing

- Positional number systems. For integers x and b, the base-r representation of x is x written in base b.
- · Example.
- $(10)_{10} = (1010)_2 (1 \cdot 2^3 + 0 \cdot 2^2 + 1 \cdot 2^1 + 0 \cdot 2^0)$
- $(107)_{10} = (212)_7 (2 \cdot 7^2 + 1 \cdot 7^1 + 2 \cdot 7^0)$

Universal Hashing

• Hash function. Given a prime p and $a = (a_1 a_2 ... a_r)_p$, define

$$h_a((x_1x_2...x_r)_p) = a_1x_1 + a_2x_2 + ... + a_rx_r \mod p$$

- · Example.
- $\cdot p = 7$
- $a = (107)_{10} = (212)_7$
- $\cdot x = (214)_{10} = (424)_7$
- $h_a(x) = 2 \cdot 4 + 1 \cdot 2 + 2 \cdot 4 \mod 7 = 18 \mod 7 = 4$
- · Universal family.
- $\cdot H = \{h_a \ (a_1 a_2 ... a_r)_p \in \{0, ..., p-1\}^r\}$
- · Choose random hash function from H ~ choose random a.
- · H is universal (analysis next).
- · O(1) time evaluation.
- O(1) space.
- Fast construction.



Uniform Hashing

• Lemma 1. For any prime p, any integer $z \neq 0 \mod p$, and any two integers α, β :

$$\alpha z = \beta z \mod p \quad \Rightarrow \quad \alpha = \beta \mod p.$$

- · Proof.
 - Show $(\alpha \beta)$ is divisible by p:
 - $\cdot \alpha z = \beta z \mod p \implies (\alpha \beta)z = 0 \mod p.$
 - By assumption z not divisible by p.
 - Since p is prime $\alpha \beta$ must be divisible by p.
 - Thus $\alpha = \beta \mod p$ as claimed.

Universal Hashing

- Goal. For random $a=(a_1a_2...a_r)_p$, show that if $x\neq y$ then $\Pr[h_a(x)=h_a(y)]\leq 1/p$.
- Recall: $x = (x_1 x_2 ... x_r)_p$ and $y = (y_1 y_2 ... y_r)_p$:

$$x \neq y \Leftrightarrow (x_1 x_2 ... x_r)_p \neq (y_1 y_2 ... y_r)_p \Rightarrow x_i \neq y_i$$
 for some j.

• Lemma 2. Let j be such that $x_j \neq y_j$. Assume the coordinates a_i have been chosen for all $i \neq j$. The probability of choosing a_i such that $h_a(x) = h_a(y)$ is 1/p.

$$\cdot \ h_a(x) = h_a(y) \quad \Leftrightarrow \quad \sum_{i=1}^r a_i x_i \mod p = \sum_{i=1}^r a_i x y_i \mod p \quad \Leftrightarrow \quad a_i (x_j - y_j) = \left[\sum_{i \neq j} a_i (x_i - y_i) \mod p \right] = \mathbf{c}$$

fixed value $z \neq 0$

all a₁ fixed for i≠i.

- There is exactly one value $0 \le a_i < p$ that satisfies $a_i z = c \mod p$.
- Assume there was two such values a_i and a'_i .
- Then $a_j z = a'_j z \mod p$.
- · Lemma 1 $\Rightarrow a_j = a_j' \mod p$. Since $a_j < p$ and $a_j' < p$ we have $a_j = a_j'$.
- Probability of choosing a_i such that $h_a(x) = h_a(y)$ is 1/p.

Universal Hashing

- Lemma 2. Let j be such that $x_j \neq y_j$. Assume the coordinates a_i have been chosen for all $i \neq j$. The probability of choosing a_i such that $h_a(x) = h_a(y)$ is 1/p.
- Theorem. For random $a=(a_1a_2...a_r)_p$, if $x\neq y$ then

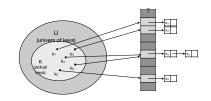
$$\Pr[h_a(x) = h_a(y)] = 1/p$$
.

- · Proof.
- E: the event that $h_a(x) = h_a(y)$.
- F_b : the event that the values a_i for $i \neq j$ gets the sequence of values b.
- Lemma 2 shows that $Pr[E | F_b] = 1/p$ for all b.
- Thus

$$\Pr[E] = \sum_{b} \Pr[E \mid F_b] \cdot \Pr[F_b] = \sum_{b} \frac{1}{p} \cdot \Pr[F_b] = \frac{1}{p} \sum_{b} \cdot \Pr[F_b] = \frac{1}{p}$$

Dictionaries

- · Theorem. We can solve the dictionary problem (without special assumptions) in:
- · O(n) space.
- · O(1) expected time per operation (lookup, insert, delete).



Universal Hashing

- · Other universal families.
- For prime p > 0.

$$h_{a,b}(x) = ax \mod p$$

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

• Hash function from k-bit numbers to l-bit numbers.

$$h_a(x) = (ax \mod 2^k) \gg (k-l)$$

$$H = \{h_a \mid a \text{ is an odd integer in } \{1, \ldots, 2^k-1\}\}$$