

# Chap 5 – Probability Analysis and Randomized Algorithms

5.1 The hiring problem

5.2 Indicator random variable

5.3 Randomized algorithms

5.4. ... further uses of indicator random ...

# 5.1 The hiring problem

- The hiring problem (maximization or minimization)

HIRE-ASSISTANT( $n$ )

$best = 0$  // least-qualified dummy candidate

**for**  $i = 1$  **to**  $n$

    interview candidate  $i$  // interview cost  $c_i$

    if candidate  $i$  is better than candidate  $best$

$best = i$

    hire candidate  $i$  // hire cost  $c_h$

If  $n$  candidates, and we hire  $m$  of them, the cost is

$O(nc_i + mc_h)$

Assume that  $c_h > c_i$ , we shall concentrate on analyzing  $mc_h$ .

# 5.1 The hiring problem

- Worst case analysis
  - In the worst case, the candidates appear in increasing order of quality and the hiring cost is  $O(nc_h)$ .
- Probabilistic analysis (Average case analysis)
  - Depend on probabilistic assumption about input distribution
  - Usually, the assumption is uniform random permutation, i.e. all of the  $n!$  permutations are equally likely.
  - The algorithm is deterministic.
- Randomized algorithm
  - The  $n$  candidates are permuted uniformly at random to enforce the probabilistic assumption.

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- A discrete random variable  $X$  is a function  
 $X: S \rightarrow$  real or integer values  
where  $S$  is a finite or countably infinite sample space.
- The event  $X = x$  denotes the set  $\{s \in S \mid X(s) = x\}$ .
- The probability of occurrence of the event  $X = x$  is

$$\Pr\{X = x\} = \sum_{s \in S: X(s) = x} \Pr\{s\}$$

- The expectation of  $X$  is

$$E[X] = \sum_x x \Pr\{X = x\}$$

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- Example

Let  $X$  be a random variable denoting the number of times number 6 appears in 3 dice casts, then

$X: S \rightarrow \{0,1,2,3\}$ , e.g.  $X(5,6,6) = 2$

where  $S = \{(d_1, d_2, d_3) \mid 1 \leq d_i \leq 6\}$  is the sample space  
 $X = 2$

- denotes the event "two of 3 dice casts are 6"
- denotes  $S' = \{(6,6,d), (6,d,6), (d,6,6) \mid 1 \leq d \leq 5\}$
- occurs with probability

$$\Pr\{X = 2\} = \sum \Pr\{s\} = \sum \frac{1}{216} = \frac{15}{216}$$

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- Example (Cont'd)

We also have

$$\Pr\{X = 0\} = 125/216$$

$$\Pr\{X = 1\} = 75/216$$

$$\Pr\{X = 3\} = 1/216$$

The expected number of times 6 appears in 3 dice casts is

$$\begin{aligned} E[X] &= \sum_{x=0}^3 x \Pr\{X = x\} \\ &= 0 \cdot \frac{125}{216} + 1 \cdot \frac{75}{216} + 2 \cdot \frac{15}{216} + 3 \cdot \frac{1}{216} = \frac{1}{2} \end{aligned}$$

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- Example

Let  $X$  be a random variable denoting the number of times 6 appears in  $n$  dice casts

Then,  $0 \leq X \leq n$

We have

$$\begin{aligned} E[X] &= \sum_{x=0}^n x \binom{n}{x} \left(\frac{1}{6}\right)^x \left(\frac{5}{6}\right)^{n-x} \\ &= \sum_{x=1}^n x \frac{n}{x} \binom{n-1}{x-1} \left(\frac{1}{6}\right)^x \left(\frac{5}{6}\right)^{n-x} \end{aligned}$$

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)
  - Example (Cont'd)

$$\begin{aligned} E[X] &= \frac{n}{6} \sum_{x=1}^n \binom{n-1}{x-1} \left(\frac{1}{6}\right)^{x-1} \left(\frac{5}{6}\right)^{n-x} \\ &= \frac{n}{6} \sum_{x=0}^{n-1} \binom{n-1}{x} \left(\frac{1}{6}\right)^x \left(\frac{5}{6}\right)^{n-x-1} \\ &= \frac{n}{6} \left(\frac{1}{6} + \frac{5}{6}\right)^{n-1} = \frac{n}{6} \end{aligned}$$

Drawback: Hard to compute



## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- Example (Cont'd)

Alternative analysis

Let  $X_i$  be a random variable denoting the number of times 6 appears in the  $i^{\text{th}}$  dice cast

Then,

$X_i = 0$  or  $1$

$$\Pr\{X_i = 0\} = 5/6$$

$$\Pr\{X_i = 1\} = 1/6$$

The expected number of times 6 appears in any dice cast is

$$E[X_i] = 0 \cdot \frac{5}{6} + 1 \cdot \frac{1}{6} = \frac{1}{6} = \Pr\{X_i = 1\}$$

## 5.2 Indicator random variables

- Expected value of a random variable (Appendix C.3)

- Example (Cont'd)

Next,

linearity of expectation

$$X = \sum_{i=1}^n X_i$$

$$E[X] = E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i] = \sum_{i=1}^n \frac{1}{6} = n/6$$

$X_i$  is called an indicator random variable, i.e.

$X_i = 1$ , if the event "the  $i^{\text{th}}$  dice cast comes out 6" occurs  
= 0, if the event doesn't occur

## 5.2 Indicator random variables

- Indicator random variables

Given a sample space and an event  $A$ , define the indicator random variable:

$$\begin{aligned} I\{A\} &= 1 && \text{if } A \text{ occurs} \\ &= 0 && \text{if } A \text{ doesn't occur} \end{aligned}$$

**LEMMA** For an event  $A$ , let  $X_A = I\{A\}$ . Then,  $E[X_A] = \Pr\{A\}$

*Proof*

Letting  $\bar{A}$  be the complement of  $A$ , we have

$$\begin{aligned} E[X_A] &= E[I\{A\}] \\ &= 1 \cdot \Pr\{A\} + 0 \cdot \Pr\{\bar{A}\} \\ &= \Pr\{A\} \end{aligned}$$

## 5.2 Indicator random variables

- Probability analysis of the hiring problem

Assume that the candidates arrive in a random order.

Define indicator random variables  $X_1, X_2, \dots, X_n$ , where

$X_i = \{\text{candidate } i \text{ is hired}\}$

Then,

$$E[X_i] = \Pr\{\text{candidate } i \text{ is hired}\}$$

$$= \Pr\{\text{candidate } i \text{ is the best so far}\} = 1/i$$

$\because$  Assumption that the candidates arrive in a random order

$\Rightarrow$  candidates 1, 2, ...,  $i$  arrive in random order

$\Rightarrow$  any one of these first  $i$  candidates is equally likely to be the best one so far

## 5.2 Indicator random variables

- Probability analysis of the hiring problem

Let  $X$  be a random variable that equals the number of times we hire a new office assistant. Then,

$$X = \sum_{i=1}^n X_i$$

$$E[X] = E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i] = \sum_{i=1}^n 1/i = \ln n + O(1)$$

### LEMMA 5.2

Assuming that the candidates are presented in a random order, algorithm HIRE-ASSISTANT has an average hiring cost of  $O(c_h \ln n)$ .

## 5.3 Randomized algorithms

- Randomized hiring assistant

RANDOMIZED-HIRE-ASSISTANT( $n$ )

randomly permute the list of candidates

HIRE-ASSISTANT( $n$ )

### LEMMA

The expected hiring cost of RANDOMIZED-HIRE-ASSISTANT is  $O(c_h \ln n)$ .

### *Proof*

After permuting the input array, we have a situation identical to the probabilistic analysis of deterministic HIRE-ASSISTANT.

## 5.3 Randomized algorithms

- Deterministic vs randomized algorithms
  - Deterministic algorithms
    - Have best- or worst-case inputs
    - Talk of worst-case or average-case running time
    - For any particular input, the algorithm's behavior is reproducible.
  - Randomized algorithms
    - All input cases are equal – there are no best- or worst-case inputs, only "lucky or unlucky probability"
    - Talk of expected running time
    - For any particular input, the algorithm's behavior is not reproducible.

## 5.3 Randomized algorithms

- Randomly permuting arrays

PERMUTE-BY-SORTING( $A$ )

$n = A.length$

let  $P[1..n]$  be a new array

**for**  $i = 1$  **to**  $n$

$P[i] = \text{RANDOM}(1, n^3)$

sort  $A$ , using  $P$  as sort keys

// Example

//  $A = a_1, a_2, a_3$

//  $P = 17, 26, 5$

//  $A = a_3, a_1, a_2$

Drawbacks

1 Don't work in-place

2 Take  $\Theta(n \lg n)$  time

3 Need more random bits



## 5.3 Randomized algorithms

- Randomly permuting arrays

A better in-place  $\Theta(n)$  algorithm

RANDOMIZE-IN-PLACE( $A, n$ )

for  $i = 1$  to  $n$

    swap  $A[i]$  with  $A[\text{RANDOM}(i, n)]$

### LEMMA

RANDOMIZE-IN-PLACE computes a uniform random permutation.

### Terminology

Given  $n$  elements, a  $k$ -permutation is a permutation of  $k$  elements chosen from the  $n$  elements.

## 5.3 Randomized algorithms

- Randomly permuting arrays

**LEMMA** (Cont'd)

*Loop invariant:* Just before the  $i^{\text{th}}$  iteration,  $A[1..i-1]$  contains each possible  $(i-1)$ -permutation with probability

$$\frac{(n-i+1)!}{n!} \left( = \frac{1}{n} \times \frac{1}{n-1} \times \cdots \times \frac{1}{n-i+2} \right)$$

Termination:  $i = n + 1$

If the loop invariant is true, then at termination  $A[1..n]$  contains each possible  $n$ -permutation with probability

$$\frac{(n-(n+1)+1)!}{n!} = \frac{1}{n!}$$

as desired.

## 5.3 Randomized algorithms

- Randomly permuting arrays

**LEMMA** (Cont'd)

*Proof* of the loop invariant

Initialization:  $i = 1$

Since  $A[1..0]$  is an empty array and a 0-permutation has no elements, at the initialization  $A[1..0]$  certainly contains any 0-permutation with probability  $1 = (n - 1 + 1)!/n!$

Maintenance

$A[1..i - 1]$  contains each  $(i - 1)$ -permutation with prob.  
 $(n - i + 1)!/n!$

$\Rightarrow A[1..i]$  contains each  $i$ -permutation with prob.  $(n - i)!/n!$

## 5.3 Randomized algorithms

- Randomly permuting arrays

**LEMMA** (Cont'd)

$A[1..i]$  contains  $\langle x_1, x_2, \dots, x_i \rangle$  iff events  $E_1$  and  $E_2$  occur where

$E_1$ :  $A[1..i-1]$  contains  $\langle x_1, x_2, \dots, x_{i-1} \rangle$

$E_2$ :  $A[i]$  contains  $x_i$

By induction hypothesis, we have

$$\Pr\{E_1\} = \frac{(n-i+1)!}{n!}$$

Also, since  $x_i$  is chosen randomly from  $A[i..n]$ , we have

$$\Pr\{E_2|E_1\} = \frac{1}{n-i+1}$$

## 5.3 Randomized algorithms

- Randomly permuting arrays

**LEMMA** (Cont'd)

Therefore,  $A[1..i]$  contains  $\langle x_1, x_2, \dots, x_i \rangle$  with probability

$$\begin{aligned}\Pr\{E_2 \cap E_1\} &= \Pr\{E_2|E_1\} \Pr\{E_1\} \\ &= \frac{1}{n-i+1} \cdot \frac{(n-i+1)!}{n!} \\ &= \frac{(n-i)!}{n!}\end{aligned}$$