# Algorithms and Computation (grad course)

Lecture 11: Randomized Algorithms II

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Fall 2021

#### Problems with one-sided error algorithms:

- RP (Randomized Polynomial time)
- coRP (Complement of Randomized Polynomial time)

#### **Problems with zero-error algorithms:**

**ZPP** (Zero-error Polynomial time)

#### Problems with two-sided error algorithms:

- ▶ **PP** (Probabilistic Polynomial time)
- ▶ **BPP** (Bounded-error Probabilistic Polynomial time)

#### One-sided Error Algorithms

**Definition**: The class **RP** (Randomized Polynomial time) consists of all languages L that have a randomized algorithm A that runs in polynomial time such that for any input  $x \in \Sigma^*$ 

- $ightharpoonup x \in L \Rightarrow Pr[A(x) \text{ accepts}] \ge \frac{1}{2}$
- $x \notin L \Rightarrow Pr[A(x) \text{ accepts}] = 0$

**Definition**: The class  ${\bf coRP}$  consists of all languages L that have a randomized algorithm A that runs in polynomial time such that for any input  $x \in \Sigma^*$ 

- $x \in L \Rightarrow Pr[A(x) \text{ accepts}] = 1$
- $x \notin L \Rightarrow Pr[A(x) \text{ accepts}] \le \frac{1}{2}$

# One-sided error algorithms: Examples

- Verifying polynomial identity
- Verifying matrix multiplication

$$A \times B = C$$
?

Choose random vextor x and check if ABx = Cx

Global min-cut in graphs

#### Zero-error randomized algorithms

**Definition**: The language L belongs to the class **ZPP** if and only if there is a randomized algorithm A that given  $x \in \Sigma^*$  gives the correct answer on the question whether  $x \in L$  or not. The running time of the algorithm A is polynomial in expectation.

In some literature, algorithm A is called a Las Vegas algorithm. Monte Carlo algorithms are randomized algorithms with non-zero error probability.

#### Expectation

**Definition**: Let X be a discrete random variable taking values from the domain U. The expectation of X defined by

$$E[X] = \sum_{u \in U} u Pr[X = u]$$

**Example:** Let X be the outcome of rolling a dice. We have

$$E[X] = 1\frac{1}{6} + 2\frac{1}{6} + 3\frac{1}{6} + 4\frac{1}{6} + 5\frac{1}{6} + 6\frac{1}{6} = 3.5$$



## **Expected Running time**

Expected running time of algorithm A on input x:

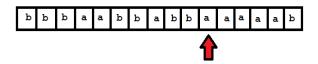
$$E[\text{running time}(A, x)] =$$

$$\sum_{\text{A stops on } x \text{ and } r_1, \dots, r_t} = \frac{1}{2^t} \times \text{running time}(A, x, r_1, \dots, r_t)$$

Expected running time of algorithm A on input of length n:

$$E[\text{running time}(A)] = \max_{x,|x|=n} \{E[\text{running time}(A,x)]\}$$

Example: Given an array A of length n containing n/2 number of a's and n/2 number of b's, find the position of an a.



Randomized Algorithm: Randomly pick a position and check if it is an a. Repeat this until an a is found.

Analysis: Pr[failure] = 0. The algorithm succeeds with probability 1.

Expected running time = 
$$\sum_{i=1}^{\infty} \frac{i}{2^i} = 2$$

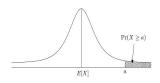
- ▶ Linearity of expectation. E[X + Y] = E[X] + E[Y]
- ▶ Markov Inequality. Given random variable X that takes positive values, for a > 0

$$Pr[X \ge a] \le \frac{E[X]}{a}$$

Setting a = tE[X] where t > 0, we get

$$Pr[X \ge tE[X]] \ge \frac{1}{t}$$

$$\begin{split} E[X] &= \sum_x x P(x) \\ &= \sum_{x \le a} x P(x) + \sum_{x \ge a} x P(x) \\ &\geq \sum_{x \ge a} x P(x) \\ &\geq \sum_{x \ge a} a P(x) \\ &= a \sum_{x \ge a} P(x) \\ &= a P(x > a), \end{split}$$



### Example: Waiting for a first success

Suppose we have a biased coin that comes up HEAD with probability  $\it p$ .

What is the expected number of coin tosses until a HEAD comes up?

Let X be the random variable equal to the number of tosses performed.

For 
$$j > 0$$
, we have  $Pr[X = j] = (1 - p)^{j-1}p$ 

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

**Theorem**:  $ZPP = RP \cap coRP$ .

**Lemma**:  $ZPP \subseteq RP \cap coRP$ .

**Proof**: Let L be a decision problem in **ZPP**. There is a randomized algorithm A that decides  $x \in L$ . Let f(n) be the expected running time of A on an input of size n. f(n) is a polynomial function.

We want to show  $L \in \mathbf{RP} \cap \mathbf{coRP}$ . In other words:

- ▶ There is a randomized algorithm  $A_1$  with polynomial time complexity where  $x \in L \Rightarrow Pr[A_1(x) \text{ accepts}] \geq \frac{1}{2}$  and  $x \notin L \Rightarrow Pr[A_1(x) \text{ accepts}] = 0$
- ▶ There is a randomized algorithm  $A_2$  with polynomial time complexity where  $x \in L \Rightarrow Pr[A_2(x) \text{ accepts}] = 1$  and  $x \notin L \Rightarrow Pr[A(x) \text{ accepts}] \leq \frac{1}{2}$

Algorithm  $A_1$ : Run the zero-error algorithm A on input x. Stop the execution before the running time exceeds 2f(n).

- If A accepts x before it is stopped, we accept x.
- If A rejects x before it is stopped, we reject x.
- ▶ Otherwise (if *A* is stopped before giving an answer) we accept *x*.

If  $x \in L$ , algorithm  $A_1$  always accepts x.

If  $x \notin L$ , algorithm  $A_1$  accepts x with probability at most  $\frac{1}{2}$ . This happens when the running time of A on x exceeds 2f(n). Let E be this event.

Let R be the running time of A on x. Since  $E[R] \le f(n)$ 

$$Pr[E] = Pr[R \ge 2f(n)] \le \frac{1}{2}$$
 (Markov inequality)

Therefore  $L \in \mathbf{coRP}$ . In the same manner, we can define the one-sided error algorithm  $A_2$  and show that  $L \in \mathbf{RP}$ . Therefore  $L \in \mathbf{RP} \cap \mathbf{coRP}$ .

**Lemma**:  $RP \cap coRP \subseteq ZPP$ .

**Proof**: Let  $L \in \mathbb{RP} \cap \mathbf{coRP}$ . It means

▶ There is a randomized algorithm  $A_1$  with polynomial time complexity where

$$x \in L \Rightarrow Pr[A_1(x) \text{ accepts}] \ge \frac{1}{2} \text{ and}$$
  
 $x \notin L \Rightarrow Pr[A_1(x) \text{ accepts}] = 0$ 

▶ There is a randomized algorithm  $A_2$  with polynomial time complexity where

$$x \in L \Rightarrow Pr[A_2(x) \text{ accepts}] = 1 \text{ and}$$
  
 $x \notin L \Rightarrow Pr[A_2(x) \text{ accepts}] \leq \frac{1}{2}$ 

We runs both algorithms  $A_1$  and  $A_2$  on input x. We act according to the following table.

| A1 accepts x                | A1 accepts x                           |
|-----------------------------|--|
| A2 accepts x stop $x \in L$ | A2 rejects $\mathbf{x}$ stop $x \in L$ |
| A1 rejects x                | A1 rejects x                           |
| A2 accepts x                | A2 rejects x                           |
| Repeat                      | stop $x \notin L$                      |

$$x \in L \Rightarrow Pr[A_1(x) \text{ accepts}] \ge \frac{1}{2}$$
  
 $x \notin L \Rightarrow Pr[A_1(x) \text{ accepts}] = 0$   
 $x \in L \Rightarrow Pr[A_2(x) \text{ accepts}] = 1$   
 $x \notin L \Rightarrow Pr[A_2(x) \text{ accepts}] \le \frac{1}{2}$ 

$$E_3$$
 (repeat) happens with probability at most  $\frac{1}{2}$ .  
 $Pr[A_1 \text{ rejects and } A_2 \text{ accepts } | x \in L] \leq \frac{1}{2} \times 1 = \frac{1}{2}$   
 $Pr[A_1 \text{ rejects and } A_2 \text{ accepts } | x \notin L] \leq 1 \times \frac{1}{2} = \frac{1}{2}$   
 $Pr[E_3] = Pr[A_1 \text{ rejects and } A_2 \text{ accepts}] \leq \frac{1}{2}$ 

**Recall**: Good event happens with probability p. Bad event happens with probability 1-p. Expected number of repetitions until a good event happens is most  $\frac{1}{p}$ .

Expected number of repetition until  $E_1 \cup E_2 \cup E_4$  happens for the first time is most  $\frac{1}{1/2} = 2$ 

Let  $f(n) = \max\{\text{running time of } A_1, \text{ running time of } A_2\}$ 

Let R be the running time of the proposed algorithm on input x. We have

$$E[R] \le 2f(n) \times \text{ expected number of repetitions } \le 2f(n) \times 2$$

Therefore the proposed algorithm has O(f(n)) expected running time and always gives the correct answer.

Therefore  $L \in \mathbf{ZPP}$ .

# a random joke

```
int getRandomNumber()
{
    return 4; // chasen by fair dice roll.
    // guaranteed to be random.
}
```

### Randomized approximation algorithm for 3-SAT

**Input**: A formula  $\phi$  with 3 - CNF format consisting of m clauses defined over n variables.

$$(x_1 \vee \overline{x_4} \vee x_3) \wedge (x_2 \vee \overline{x_4} \vee \overline{x_1}) \wedge \ldots \wedge$$

**Problem**: Find an assignment that satisfy the most number of clauses.

**Algorithm I**: Set each variable  $x_1, \ldots, x_n$  independently to False or True with probability  $\frac{1}{2}$  each.

What is the expected number of clauses satisfied by such random assignment?

Let  $Z_i = 1$  if clause  $C_i$  is satisfied otherwise  $Z_i = 0$ .

number of satisfied clauses = 
$$\sum_{i=1}^{m} Z_i$$
 =

expected number of satisfied clauses = 
$$E[\sum_{i=1}^{m} Z_i] = \sum_{i=1}^{m} E[Z_i] = \sum_{i=1}^{m} Pr[Z_i = 1] = \frac{7}{8}m$$

- ▶ **Observation**: Given any 3-CNF formula  $\phi$  there is always an assignment that satisfy at least  $\frac{7}{8}$  number of clauses in  $\phi$
- ▶ Follows from the fact that when E[X] = k there is an event where  $X \ge k$ .
- We want to find an assignment that satisfy  $\frac{7}{8}$  of the clauses.
- Let p be the probability that a random assignment satisfy  $\frac{7}{8}$  of the clauses?
- We prove a lower bound on p

- Let  $p_j$  denote the probability that a random assignment satisfy exactly j clauses
- expected number of satisfied clauses =  $\sum_{j=1}^{m} j p_j$
- $\sum_{j=1}^{m} j p_j = \frac{7}{8} m$
- $p = \sum_{j \ge \frac{7}{8}m} p_j$   $1 p = \sum_{j < \frac{7}{8}m} p_j$
- $\blacktriangleright \ \ \frac{7}{8}m = \sum_{j < \frac{7}{8}m} jp_j + \sum_{j \geq \frac{7}{8}m} jp_j$
- Let m' be the largest number smaller than  $\frac{7}{8}m$

$$p \ge \frac{\frac{7}{8}m - m'}{m} \ge \frac{\frac{1}{8}}{m} \ge \frac{1}{8m}$$

• p is the probability that a random assignment satisfy at least  $\frac{7}{8}$  of the clauses.

**Algorithm II**: Set each variable  $x_1, \ldots, x_n$  independently to <u>False</u> or <u>True</u> with probability  $\frac{1}{2}$  each. Check if  $\frac{7}{8}$  of the clauses are satisfied. If not, repeat.

- expected number of trails before success  $\leq \frac{1}{p} \leq 8m$
- ▶ Algorithm II has expected running time O(m(n+m)) and, given formula  $\phi$ , finds an assignment that satisfy at least  $\frac{7}{8}$  of the clauses in  $\phi$

## Two-sided error algorithms: class **PP**

**Definition**: The class **PP** (Probabilistic Polynomial time) consists of all languages L that have a randomized algorithm A that runs in polynomial time such that for any input  $x \in \Sigma^*$ 

- $ightharpoonup x \in L \Rightarrow Pr[A(x) \text{ accepts}] > \frac{1}{2}$
- $x \notin L \Rightarrow Pr[A(x) \text{ accepts}] < \frac{1}{2}$
- ▶ To boost the probability of success (for example to  $\frac{1}{4}$ ), we can repeat the algorithm and output the majority of the answers.
- Number of required repetitions could be exponential!
- Not very practical.

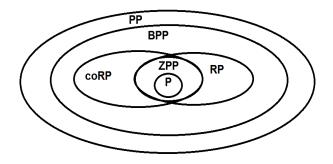
### Two-sided error algorithms: class BPP

**Definition**: The class **BPP** (Bounded-error Probabilistic Polynomial time) consists of all languages L that have a randomized algorithm A that runs in polynomial time such that for any input  $x \in \Sigma^*$ 

- $ightharpoonup x \in L \Rightarrow Pr[A(x) \text{ accepts}] > \frac{3}{4}$
- $ightharpoonup x \notin L \Rightarrow Pr[A(x) \text{ accepts}] < \frac{1}{4}$

Given  $x \in \Sigma^*$ , the probability of error of the algorithm on input x, is at most  $\frac{1}{4}$ .

**Fact:** The error probability of the algorithm can be reduced to  $\frac{1}{2^n}$  by polynomial number of repetitions.



Conjecture: BPP = P