# A sampling of Randomized Algorithms

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2 Verifying polynomial Identities







Verifying polynomial Identities









### Verifying polynomial Identities

3 Verifying Matrix Multiplication



A Randomized Min-Cut Algorithm







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Verifying polynomial Identities Verifying Matrix Multiplication A Randomized Min-Cut Algorithm Coupon Collector problems

# Recap

### Main points

Probability spaces, Random Variable,

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Probability spaces, Random Variable, Distribution of a random variable (pmf), Expected Value, Variance.

Verifying polynomial Identities Verifying Matrix Multiplication A Randomized Min-Cut Algorithm Coupon Collector problems

Polynomial Identities and the verification problem

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#### Definition

A function f() of one variable x, is called a polynomial function, if it satisfies,

$$f(\mathbf{x}) = \sum_{i=0}^{n} a_{n-i} \cdot \mathbf{x}^{n-i}.$$

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A univariate polynomial function can also be expressed in the form:

$$f(x) = \prod_{i=1}^n (a_i x - b_i)$$

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- (ii) Accordingly, a polynomial function in the canonical form can be written as:

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and a polynomial function in product form can be written as:

$$g(x) = \prod_{i=1}^n (x_i - c_i)$$

# Statement of Problem

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Subramani Sample Analyses

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#### Theorem

Every polynomial function has a unique canonical representation.

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What is the running time?  $\Theta(n^2)$ ! Can we do better?

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### **Function** RANDOMIZED-VERIFY-POLYNOMIAL-IDENTITY(f(), g())

1: Pick an integer *r* uniformly from the interval  $\{1, 2, \dots, 2 \cdot n\}$ .

2: Compute 
$$s = f(r)$$
 and  $t = g(r)$ .

3: if 
$$(s = t)$$
 then

4: f() and g() are identical.

#### 5: **else**

6: 
$$f()$$
 and  $g()$  are **not** identical.

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If the algorithm declares that  $f() \neq g()$ , then the algorithm is correct.

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#### Note

If the algorithm declares that  $f() \neq g()$ , then the algorithm is correct. If the algorithm declares that f() = g(), then it is possible that  $f() \neq g()$ . We need to bound the probability of this event.

Recap

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A polynomial of degree n has exactly n roots (not necessarily distinct). (Fundamental theorem of algebra).

#### Observation

Two distinct polynomials f() and g() can be equal only at the roots of the polynomial f() - g().

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Two distinct polynomials f() and g() can be equal only at the roots of the polynomial f() - g(). The polynomial f() - g() has at most n distinct roots. Recap

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# Bounding the error probability (contd.)

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## Observation

The only way for the randomized algorithm to give an incorrect answer when  $f() \neq g()$ , is if the integer r that it picked, is a root of the polynomial f() - g().

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#### Theorem

On "yes" instances, the randomized algorithm does not err. On "no" instances, the probability that the algorithm errs is at most  $\frac{1}{2}$ .

Matrix multiplication and Verification

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**Problem Statement** 

Given 2 square  $n \times n$  matrices **A** and **B**, compute **C** = **A** · **B**.

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How to verify Strassen?

A randomized approach to verification

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## Function RANDOMIZED-VERIFY-MATRIX-PRODUCT(C, A, B)

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### Main idea

We will show that if **r** is chosen uniformly from  $\{0,1\}^n$ , then the probability that  $\mathbf{A} \cdot \mathbf{B} \cdot \mathbf{r} = \mathbf{C} \cdot \mathbf{r}$ , when  $\mathbf{A} \cdot \mathbf{B} \neq \mathbf{C}$  is at most  $\frac{1}{2}$ .

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#### Lemma

There is no difference between choosing **r** uniformly from  $\{0,1\}^n$  and choosing each of its components uniformly over the set  $\{0,1\}$ .

# Analysis (contd.)

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## Bounding the error

Subramani Sample Analyses

# Analysis (contd.)

### Bounding the error

(i) Assume that  $\mathbf{A} \cdot \mathbf{B} \neq \mathbf{C}$ , but that  $\mathbf{A} \cdot \mathbf{B} \cdot \mathbf{r} = \mathbf{C} \cdot \mathbf{r}$ .

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- (iii) Without loss of generality assume that the first element of the first row of **D**, i.e.,  $d_{11}$  is not 0.

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- (iii) Without loss of generality assume that the first element of the first row of **D**, i.e.,  $d_{11}$  is not 0.
- (iv) Since  $\mathbf{D} \cdot \mathbf{r} = 0$ , it means that  $\sum_{i=1}^{n} d_{1i} \cdot r_i = 0$ .

(v) Therefore, 
$$r_1 = -\frac{\sum_{j=2}^{n} d_{ij} \cdot r_j}{d_{11}}$$
.

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- (iii) Without loss of generality assume that the first element of the first row of **D**, i.e.,  $d_{11}$  is not 0.
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#### Note

The above method of analysis is called the Principle of Deferred Decisons.

The Min-cut problem on undirected unweighted graphs

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Recap

Sample Analyses

Subramani

#### Verifying polynomial Identities Verifying Matrix Multiplication A Randomized Min-Cut Algorithm Coupon Collector problems

The Randomized approach

## The Randomized approach

## The Contract Operation

## Function CONTRACT-EDGE(G, e)

- 1: {We will contract edge e in G.}
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## Randomized Min-cut

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## The Randomized Algorithm

Function Randomized Min-Cut( $\mathbf{G} = \langle \mathbf{V}, \mathbf{E} \rangle$ )

- 1: while there are more than 2 vertices in G do
- 2: Pick an edge e uniformly and at random from the edge set E
- 3: CONTRACT-EDGE(G, e)

### 4: end while

- 5: Let a and b denote the last two vertices that remain.
- 6: Output the edges between *a* and *b* as the min-cut of **G**.

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#### Note

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$$(1 - \frac{2}{n \cdot (n-1)})^{n \cdot (n-1) \cdot \ln n} \leq e^{-2 \cdot \ln n} (\operatorname{since} (1-x) \leq e^{-x})$$
$$= \frac{1}{n^2}$$

# Coupon Collector problems

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### Problem Statements

Subramani Sample Analyses

# Coupon Collector problems

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- (i) For a fixed  $t \ge N$ , what is the probability that at least *t* coupons need to be collected to ensure that we have at least one coupon of each type?
- (ii) What is the expected number of coupons to be collected, to ensure that each coupon type has been collected?

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You are required to collect coupons in a series of iterations. Assume that each coupon belongs to one of N types, where N is a fixed number. The coupons are drawn uniformly and at random from the N coupon types. Several questions are of interest:

- (i) For a fixed t ≥ N, what is the probability that at least t coupons need to be collected to ensure that we have at least one coupon of each type?
- (ii) What is the expected number of coupons to be collected, to ensure that each coupon type has been collected?
- (iii) Suppose you are given a *K* coupons (usually less than *N*). What is the expected number of distinct coupon types in these *K* coupons?

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We focus on the following question: What is the expected number of coupons to be collected, to ensure that each coupon type has been collected? Let *X* denote the total number of coupons to be drawn, before we have at least one coupon of each of the *N* distinct types. Let  $X_i$  denote the number of coupons that need to be drawn, after (i-1) distinct coupon types have been collected, in order to draw a coupon of a type that has not been collected.

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variable with parameter  $p_i$ . Therefore,

$$E[X] = \sum_{i=1}^{N} E[X_i]$$
$$= \sum_{i=1}^{N} \frac{1}{p_i}$$

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$$= N \cdot \ln N + \Theta(N), \text{ since } H_{N} = \ln N + \Theta(1)$$