# CMPT 210: Probability and Computing

Lecture 11

Sharan Vaswani

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As an example, let us focus on A, B being binary  $2 \times 2$  matrices.

Example: 
$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$
,  $B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$  then  $C = AB = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$ 

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**Trivial way**: Do the matrix multiplication ourselves, and verify it using  $O(n^3)$  (or  $O(n^{2.373})$ ) operations.

**Frievald's Algorithm**: Randomized algorithm to verify matrix multiplication with high probability in  $O(n^2)$  time.

**Q**: For  $n \times n$  matrices A, B and D, is D = AB?

#### Algorithm:

1. Generate a random n-bit vector x, by making each bit  $x_i$  either 0 or 1 independently with probability  $\frac{1}{2}$ . E.g, for n=2, toss a fair coin independently twice with the scheme – H is 0 and T is 1). If we get HT, then set  $x=[0\,;\,1]$ .

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- 2. Compute t = Bx and y = At = A(Bx) and z = Dx.

Since we are only doing matrix vector multiplication, it is  $O(n^2)$ 

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- 2. Compute t = Bx and y = At = A(Bx) and z = Dx.
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**Computational complexity**: Step 1 can be done in O(n) time. Step 2 requires 3 matrix vector multiplications and can be done in  $O(n^2)$  time. Step 3 requires comparing two n-dimensional vectors and can be done in O(n) time. Hence, the total computational complexity is  $O(n^2)$ .

Let us run the algorithm on an example. Suppose we have generated x = [1; 0]

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad ; \quad B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \quad ; \quad D = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

$$Bx = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad ; \quad y = A(Bx) = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad ; \quad z = Dx = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

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Hence the algorithm will correctly output "no" since  $D \neq AB$ .

Q: Suppose we have generated x = [0; 0]. What is y and z?

In this case, y=z and the algorithm will incorrectly output "yes" even though  $D \neq AB$ .

Correctness of algorithm depends on vector x

Let us run the algorithm on an example. Suppose we have generated x = [1; 0].

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad ; \quad B = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \quad ; \quad C = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$$
$$Bx = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad ; \quad y = A(Bx) = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad ; \quad z = Cx = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

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Hence the algorithm will correctly output "yes" since C = AB.

Q: Suppose we have generated x = [0; 1]. What is y and z?

In this case again, y=z and the algorithm will correctly output "yes".

Let us analyze the algorithm for general matrix multiplication.

Case (i): If D = AB, does the algorithm always output "yes"?

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Case (i): If D = AB, does the algorithm always output "yes"? Yes! Since D = AB, for any vector x, Dx = ABx.

**Case (ii)** If  $D \neq AB$ , does the algorithm always output "no"?

**Claim**: For any input matrices A, B, D if  $D \neq AB$ , then the (Basic) Frievald's algorithm will output "no" with probability  $\geq \frac{1}{2}$ .

What is the non-basic version?

Let us analyze the algorithm for general matrix multiplication.

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**Case (ii)** If  $D \neq AB$ , does the algorithm always output "no"?

**Claim**: For any input matrices A, B, D if  $D \neq AB$ , then the (Basic) Frievald's algorithm will output "no" with probability  $\geq \frac{1}{2}$ .

Table 1: Probabilities for Basic Frievalds Algorithm

One sided in the sense that an error only occurs if D != AB

*Proof*: If  $D \neq AB$ , we wish to compute the probability that algorithm outputs "yes" and prove that it less than  $\frac{1}{2}$ .

Let 
$$E = AB - D$$

If D != AB, there is at least an (i,j) such that  $e_i = 0$ .

If E only has zeros, AB = D

$$Ex = ABX - DX = (AB - D)X$$

*Proof*: If  $D \neq AB$ , we wish to compute the probability that algorithm outputs "yes" and prove that it less than  $\frac{1}{2}$ .

Define E := (AB - D) and r := Ex = (AB - D)x = y - z. If  $D \neq AB$ , then  $\exists (i,j)$  s.t.  $E_{i,j} \neq 0$ .

*Proof*: If  $D \neq AB$ , we wish to compute the probability that algorithm outputs "yes" and prove that it less than  $\frac{1}{2}$ .

Define 
$$E:=(AB-D)$$
 and  $r:=Ex=(AB-D)x=y-z$ . If  $D\neq AB$ , then  $\exists (i,j)$  s.t.  $E_{i,j}\neq 0$ . Pr(y = z | D |= AB\_Pr(R = 0 | D |= AB)

Pr[Algorithm outputs "yes"] = Pr[
$$y = z$$
] = Pr[ $r = \mathbf{0}$ ]  
= Pr[ $(r_1 = 0) \cap (r_2 = 0) \cap ... \cap (r_i = 0) \cap ...$ ]

$$Pr(R = 0) = Pr(r1 = 0 \& r2 = 0 \& ..... rn = 0 | D != AB)$$

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This can be at most Prive def. of conditional probability)

 $\implies$   $\Pr[\mathsf{Algorithm\ outputs\ "yes"}] \le \Pr[r_i = 0]$  (Probabilities are in [0,1])

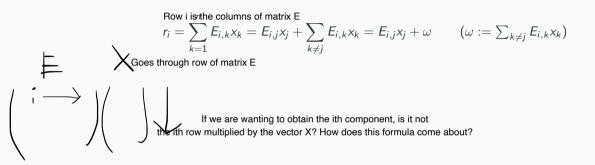
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$$\implies$$
  $\Pr[\mathsf{Algorithm\ outputs\ "yes"}] \leq \Pr[r_i = 0]$  (Probabilities are in  $[0,1]$ )

To complete the proof, on the next slide, we will prove that  $\Pr[r_i = 0] \leq \frac{1}{2}$ .



$$r_i = \sum_{k=1}^n E_{i,k} x_k = E_{i,j} x_j + \sum_{k \neq j} E_{i,k} x_k = E_{i,j} x_j + \omega \qquad (\omega := \sum_{k \neq j} E_{i,k} x_k)$$

$$\Pr[r_i = 0] = \Pr[r_i = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_i = 0 | \omega \neq 0] \Pr[\omega \neq 0]$$
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$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2}$$
(Since  $E_{i,j} \neq 0$  and  $\Pr[x_j = 1] = \frac{1}{2}$ )

if w is 0, then Eij must be zero.

 $\implies \Pr[r_i = 0 | \omega \neq 0] \leq \Pr[(x_i = 1)] = \frac{1}{2}$ 

$$r_i = \sum_{k=1}^n E_{i,k} x_k = E_{i,j} x_j + \sum_{k \neq j} E_{i,k} x_k = E_{i,j} x_j + \omega \qquad (\omega := \sum_{k \neq j} E_{i,k} x_k)$$
 
$$\Pr[r_i = 0] = \Pr[r_i = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_i = 0 | \omega \neq 0] \Pr[\omega \neq 0]$$
 Where did - w come from? (By the law of total probability) 
$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2} \qquad (\text{Since } E_{i,j} \neq 0 \text{ and } \Pr[x_j = 1] = \frac{1}{2})$$
 
$$\Pr[r_i = 0 | \omega \neq 0] = \Pr[(x_j = 1) \cap E_{i,j} = -\omega] = \Pr[(x_j = 1)] \Pr[E_{i,j} = -\omega | x_j = 1]$$
 If w is not zero, then x\_j must equal 1. (By def. of conditional probability)

(Probabilities are in [0,1],  $Pr[x_i=1]=\frac{1}{2}$ )

$$r_i = \sum_{k=1}^{n} E_{i,k} x_k = E_{i,j} x_j + \sum_{k \neq j} E_{i,k} x_k = E_{i,j} x_j + \omega$$
  $(\omega := \sum_{k \neq j} E_{i,k} x_k)$ 

 $\Pr[r_i=0]=\Pr[r_i=0|\omega=0]\Pr[\omega=0]+\Pr[r_i=0|\omega\neq0]\Pr[\omega\neq0]$  We are not given that it is equally likely that  $\mathbf{x}_j$  can either be 0 or non-zero the law of total probability)

$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2}$$
 (Since  $E_{i,j} \neq 0$  and  $\Pr[x_j = 1] = \frac{1}{2}$ )

$$\Pr[r_i = 0 | \omega \neq 0] = \Pr[(x_j = 1) \cap E_{i,j} = -\omega] = \Pr[(x_j = 1)] \Pr[E_{i,j} = -\omega | x_j = 1]$$

Do we need x\_j to be 1 so that w is a non-zero value? (By def. of conditional probability)

$$\Rightarrow \Pr[r_{i} = 0 | \omega \neq 0] \leq \Pr[(x_{j} = 1)] = \frac{1}{2}$$
 (Probabilities are in [0, 1],  $\Pr[x_{j} = 1] = \frac{1}{2}$ )
$$\Rightarrow \Pr[r_{i} = 0] \leq \frac{1}{2} \Pr[\omega = 0] + \frac{1}{2} \Pr[\omega \neq 0] = \frac{1}{2} \Pr[\omega = 0] + \frac{1}{2} [1 - \Pr[\omega = 0]] = \frac{1}{2}$$
(Pr[E<sup>c</sup>] = 1 - Pr[E])

$$r_{i} = \sum_{k=1}^{n} E_{i,k} x_{k} = E_{i,j} x_{j} + \sum_{k \neq j} E_{i,k} x_{k} = E_{i,j} x_{j} + \omega \qquad (\omega := \sum_{k \neq j} E_{i,k} x_{k})$$

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 $\implies$  Pr[Algorithm outputs "yes"]  $\leq$  Pr[ $r_i = 0$ ]  $\leq \frac{1}{2}$ .

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 $\implies$  Pr[Algorithm outputs "yes"]  $\leq$  Pr[ $r_i = 0$ ]  $\leq \frac{1}{2}$ .

Hence, if  $D \neq AB$ , the Algorithm outputs "yes" with probability  $\leq \frac{1}{2} \implies$  the Algorithm outputs "no" with probability  $\geq \frac{1}{2}$ .

In the worst case, the algorithm can be incorrect half the time! We promised the algorithm would return the correct answer with "high" probability close to 1.

## (Basic) Frievald's Algorithm

Hence, if  $D \neq AB$ , the Algorithm outputs "yes" with probability  $\leq \frac{1}{2} \implies$  the Algorithm outputs "no" with probability  $\geq \frac{1}{2}$ .

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A common trick in randomized algorithms is to have *m* independent trials of an algorithm and aggregate the answer in some way, reducing the probability of error, thus *amplifying the* probability of success.



By repeating the Basic Frievald's Algorithm m times, we will amplify the probability of success. The resulting complete Frievald's Algorithm is given by:

 $1\,$  Run the Basic Frievald's Algorithm for m independent runs.

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- 1 Run the Basic Frievald's Algorithm for *m* independent runs.
- 2 If any run of the Basic Frievald's Algorithm outputs "no", output "no".
- 3 If all runs of the Basic Frievald's Algorithm output "yes", output "yes".

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Table 2: Probabilities for Frievald's Algorithm

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Table 2: Probabilities for Frievald's Algorithm

If m=20, then Frievald's algorithm will make mistake with probability  $1/2^{20}\approx 10^{-6}$ .

Computational Complexity:  $O(mn^2)$ 

### **Probability Amplification**

Consider a randomized algorithm  $\mathcal A$  that is supposed to solve a binary decision problem i.e. it is supposed to answer either Yes or No. It has a one-sided error – (i) if the true answer is Yes, then the algorithm  $\mathcal A$  correctly outputs Yes with probability 1, but (ii) if the true answer is No, the algorithm  $\mathcal A$  incorrectly outputs Yes with probability  $\leq \frac{1}{2}$ .

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Let us define a new algorithm  $\mathcal B$  that runs algorithm  $\mathcal A$  m times, and if any run of  $\mathcal A$  outputs No, algorithm  $\mathcal B$  outputs No. If all runs of  $\mathcal A$  output Yes, algorithm  $\mathcal B$  outputs Yes.

#### **Probability Amplification**

Consider a randomized algorithm  $\mathcal A$  that is supposed to solve a binary decision problem i.e. it is supposed to answer either Yes or No. It has a one-sided error – (i) if the true answer is Yes, then the algorithm  $\mathcal A$  correctly outputs Yes with probability 1, but (ii) if the true answer is No, the algorithm  $\mathcal A$  incorrectly outputs Yes with probability  $\leq \frac{1}{2}$ .

Let us define a new algorithm  $\mathcal B$  that runs algorithm  $\mathcal A$  m times, and if any run of  $\mathcal A$  outputs No, algorithm  $\mathcal B$  outputs No. If all runs of  $\mathcal A$  output Yes, algorithm  $\mathcal B$  outputs Yes.

 ${f Q}$ : What is the probability that algorithm  ${\cal B}$  correctly outputs Yes if the true answer is Yes, and correctly outputs No if the true answer is No?

### Probability Amplification - Analysis

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If A_i denotes run i of Algorithm A, then
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 $\mathsf{Pr}[\mathcal{B} \text{ outputs Yes} \mid \mathsf{true} \text{ answer is Yes }]$ 

$$= \text{Pr}[\mathcal{A}_1 \text{ outputs Yes } \cap \mathcal{A}_2 \text{ outputs Yes } \cap \ldots \cap \mathcal{A}_m \text{ outputs Yes } | \text{ true answer is Yes }]$$

$$=\prod_{i=1}^{m}\Pr[\mathcal{A}_{i} \text{ outputs Yes} \mid \mathsf{true} \text{ answer is Yes }] = 1 \tag{Independence of runs}$$

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# Probability Amplification - Analysis

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$$=\prod_{i=1}^m \Pr[\mathcal{A}_i \text{ outputs Yes} \mid \mathsf{true} \text{ answer is Yes }] = 1$$
 (Independence of runs)

 $\mathsf{Pr}[\mathcal{B} \text{ outputs No} \mid \mathsf{true} \text{ answer is No}]$ 

$$=1-\mathsf{Pr}[\mathcal{B} \text{ outputs Yes }| \text{ true answer is No }]$$

$$=1-\text{Pr}[\mathcal{A}_1 \text{ outputs Yes }\cap \mathcal{A}_2 \text{ outputs Yes }\cap \ldots \cap \mathcal{A}_m \text{ outputs Yes }| \text{ true answer is No }]$$

$$=1-\prod_{i=1}^m \Pr[\mathcal{A}_i ext{ outputs Yes} \mid ext{true answer is No }] \geq 1-rac{1}{2^m}.$$

# Probability Amplification - Analysis

If  $A_i$  denotes run i of Algorithm A, then

 $Pr[\mathcal{B} \text{ outputs Yes} \mid \text{true answer is Yes}]$ 

$$= \mathsf{Pr}[\mathcal{A}_1 \text{ outputs Yes } \cap \mathcal{A}_2 \text{ outputs Yes } \cap \ldots \cap \mathcal{A}_m \text{ outputs Yes } | \text{ true answer is Yes }]$$

$$=\prod_{i=1}^{m}\Pr[\mathcal{A}_{i} \text{ outputs Yes} \mid \text{true answer is Yes }]=1 \tag{Independence of runs}$$

 $Pr[\mathcal{B} \text{ outputs No} \mid \text{true answer is No}]$ 

- $=1-\mathsf{Pr}[\mathcal{B} \ \mathsf{outputs} \ \mathsf{Yes} \ | \ \mathsf{true} \ \mathsf{answer} \ \mathsf{is} \ \mathsf{No} \ ]$
- $=1-\text{Pr}[\mathcal{A}_1 \text{ outputs Yes }\cap \mathcal{A}_2 \text{ outputs Yes }\cap \ldots \cap \mathcal{A}_m \text{ outputs Yes }| \text{ true answer is No }]$

$$=1-\prod_{i=1}^m \Pr[\mathcal{A}_i ext{ outputs Yes} \mid ext{true answer is No }] \geq 1-rac{1}{2^m}.$$

When the true answer is Yes, both  $\mathcal B$  and  $\mathcal A$  correctly output Yes. When the true answer is No,  $\mathcal A$  incorrectly outputs Yes with probability  $<\frac{1}{2}$ , but  $\mathcal B$  incorrectly outputs Yes with probability  $<\frac{1}{2^m}<<\frac{1}{2}$ . By repeating the experiment, we have "amplified" the probability of success.

