CMPT 210: Probability and Computing

Lecture 11

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As an example, let us focus on A, B being binary 2×2 matrices.

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

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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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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].

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

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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 $\geq \frac{1}{2}$.

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_

$$Pr(R = 0 \mid D \mid = AB)$$

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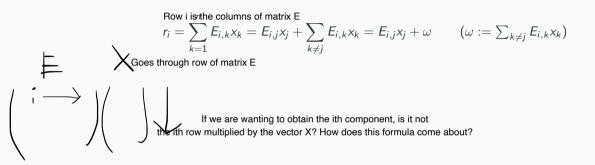
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To complete the proof, on the next slide, we will prove that $\Pr[r_i = 0] \leq \frac{1}{2}$.



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

$$\Pr[r_i = 0] = \Pr[r_i = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_i = 0 | \omega \neq 0] \Pr[\omega \neq 0]$$
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$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2}$$
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if w is 0, then Eij must be zero.

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$$(\Pr[E^{c}] = 1 - \Pr[E])$$

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

$$\Pr[r_{i} = 0] = \Pr[r_{i} = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_{i} = 0 | \omega \neq 0] \Pr[\omega \neq 0]$$

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

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$$(\Pr[E^{c}] = 1 - \Pr[E])$$

 \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:

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- 1 Run the Basic Frievald's Algorithm for *m* independent runs.
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- 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

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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.

 ${f Q}$: 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

If A_i denotes run i of Algorithm A, then

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

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

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

