CMPT 210: Probability and Computing

Lecture 11

Sharan Vaswani February 9, 2023 **Q**: For $n \times n$ matrices A, B and D, is D = AB?

Algorithm:

- Generate a random *n*-bit vector *x*, by making each bit *x_i* either 0 or 1 *independently* with probability 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].
- 2. Compute t = Bx and y = At = A(Bx) and z = Dx.
- 3. Output "yes" if y = z (all entries need to be equal), else output "no".

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 $O(n^2)$.

(Basic) Frievald's Algorithm

Let us analyze the algorithm for general matrix multiplication.

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

YesNo
$$D = AB$$
10 $D \neq AB$ $< \frac{1}{2}$ $\geq \frac{1}{2}$

Table 1: Probabilities for Basic Frievalds Algorithm

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 $\exists (i, j) \text{ s.t. } E_{i, j} \neq 0$.

$$Pr[Algorithm outputs "yes"] = Pr[y = z] = Pr[r = 0]$$

=
$$Pr[(r_1 = 0) \cap (r_2 = 0) \cap \ldots \cap (r_i = 0) \cap \ldots]$$

=
$$Pr[(r_i = 0)] Pr[(r_1 = 0) \cap (r_2 = 0) \cap \ldots \cap (r_n = 0) | r_i = 0]$$

(By def. of conditional probability)

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

(Basic) Frievald's Algorithm

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

 $\Pr[r_i = 0] = \Pr[r_i = 0 | \omega = 0] \Pr[\omega = 0] + \Pr[r_i = 0 | \omega \neq 0] \Pr[\omega \neq 0]$ (By the law of total probability)

$$\Pr[r_i = 0 | \omega = 0] = \Pr[x_j = 0] = \frac{1}{2}$$

$$\Pr[r_i = 0 | \omega \neq 0] = \Pr[(x_j = 1) \cap E_{i,j} = -\omega] = \Pr[(x_j = 1)] \Pr[E_{i,j} = -\omega | x_j = 1]$$
(By def. of conditional probability)

$$\implies \Pr[r_i = 0 | \omega \neq 0] \leq \Pr[(x_j = 1)] = \frac{1}{2} \qquad (\text{Probabilities are in } [0, 1], \ \Pr[x_j = 1] = \frac{1}{2})$$
$$\implies \Pr[r_i = 0] \leq \frac{1}{2} \Pr[\omega = 0] + \frac{1}{2} \Pr[\omega \neq 0] = \frac{1}{2} \Pr[\omega = 0] + \frac{1}{2} [1 - \Pr[\omega = 0]] = \frac{1}{2} (\Pr[E^c] = 1 - \Pr[E])$$
$$\implies \Pr[\text{Algorithm outputs "yes"}] \leq \Pr[r_i = 0] \leq \frac{1}{2}.$$

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.

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*.

Frievald's Algorithm

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.
- 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".

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: $O(mn^2)$ 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.

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

Probability Amplification - Analysis

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

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

- $= \Pr[\mathcal{A}_1 \text{ outputs Yes } \cap \mathcal{A}_2 \text{ outputs Yes } \cap \ldots \cap \mathcal{A}_m \text{ outputs Yes } | \text{ true answer is Yes }]$
- $= \prod_{i=1}^{n} \Pr[\mathcal{A}_i \text{ outputs Yes } | \text{ true answer is Yes }] = 1$ (Independence of runs)

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

i = 1

- $= 1 \mathsf{Pr}[\mathcal{B} \text{ outputs Yes} \mid \mathsf{true} \text{ answer is No }]$
- $= 1 \Pr[\mathcal{A}_1 \text{ outputs Yes } \cap \mathcal{A}_2 \text{ outputs Yes } \cap \ldots \cap \mathcal{A}_m \text{ outputs Yes } | \text{ true answer is No }]$ $= 1 \prod_{m}^{m} \Pr[\mathcal{A}_i \text{ outputs Yes } | \text{ true answer is No }] \ge 1 \frac{1}{2m}.$

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.

Questions?

Random Variables

Definition: A random "variable" R on a probability space is a total function whose domain is the sample space S. The codomain is usually a subset of the real numbers.

Example: Suppose we toss three independent, unbiased coins. Let C be the number of heads that appear.

 $S = \{HHH, HHT, HTH, HTT, THH, THT, TTH, TTT\}$

C is a total function that maps each outcome in S to a number as follows: C(HHH) = 3, C(HHT) = C(HTH) = C(THH) = 2, C(HTT) = C(THT) = C(TTH) = 1, C(TTT) = 0.

C is a random variable that counts the number of heads in 3 tosses of the coin.

Example: I toss a coin, and define the random variable R which is equal to 1 when I get a heads, and equal to 0 when I get a tails.

Bernoulli random variables: Random variables with the codomain $\{0, 1\}$ are called Bernoulli random variables. E.g. *R* is a Bernoulli r.v.

Q: Suppose we throw two standard dice one after the other. Let us define R to be the random variable equal to the sum of the dice. What is the domain, range of R?

Ans: $R : \{1, 2, 3, 4, 5, 6\} \times \{1, 2, 3, 4, 5, 6\} \rightarrow \mathbb{N} \cap [2, 12].$ R((4, 7)) = 11, R((4, 1)) = 5, R((1, 1)) = 2, R((6, 6)) = 12.

Q: Three balls are randomly selected from an urn containing 20 balls numbered 1 through 20. The random variable *M* is the maximal value on the selected balls. What is the domain, range of *M*? Ans: $M : \{1, 2, ..., 20\} \times \{1, 2, ..., 20\} \times \{1, 2, ..., 20\} \rightarrow \{1, 2, ..., 20\}$

Q: In the above example, what is $2 \times M((1,4,6))$? Is *M* an invertible function? Ans: 12, No since *M* maps both $\{1,2,5\}$ and (3,4,5) to 5.

Indicator Random Variable: An indicator random variable maps every outcome to either 0 or 1. *Example*: Suppose we throw two standard dice, and define M to be the random variable that is 1 iff both throws of the dice produce a prime number, else it is 0.

 $M: \{1, 2, 3, 4, 5, 6\} \times \{1, 2, 3, 4, 5, 6\} \rightarrow \{0, 1\}.$ M((2, 3)) = 1, M((3, 6)) = 0.

An indicator random variable partitions the sample space into those outcomes mapped to 1 and those outcomes mapped to 0.

Example: When throwing two dice, if *E* is the event that both throws of the dice result in a prime number, then random variable M = 1 iff event *E* happens, else M = 0.

The indicator random variable corresponding to an event E is denoted as \mathcal{I}_E , meaning that for $\omega \in E$, $\mathcal{I}_E[\omega] = 1$ and for $\omega \notin E$, $\mathcal{I}_E[\omega] = 0$. In the above example, $M = \mathcal{I}_E$ and since $(2,4) \notin E$, M((2,4)) = 0 and since $(3,5) \in E$, M((3,5)) = 1.