# CMPT 210: Probability and Computing 

Lecture 11

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## Recap - (Basic) Frievald's Algorithm

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

## 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 $H T$, then set $x=[0 ; 1]$.
2. Compute $t=B x$ and $y=A t=A(B x)$ and $z=D x$.
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 $O\left(n^{2}\right)$ time. Step 3 requires comparing two $n$-dimensional vectors and can be done in $O(n)$ time. Hence, the total computational complexity is $O\left(n^{2}\right)$.

## (Basic) Frievald's Algorithm

Let us analyze the algorithm for general matrix multiplication.
Case (i): If $D=A B$, does the algorithm always output "yes"? Yes! Since $D=A B$, for any vector $x, D x=A B x$.

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

$$
\begin{array}{|c|c|c|} 
& \text { Yes } & \text { No } \\
D=A B & 1 & 0 \\
D \neq A B & <\frac{1}{2} & \geq \frac{1}{2}
\end{array}
$$

Table 1: Probabilities for Basic Frievalds Algorithm

## (Basic) Frievald's Algorithm

Proof: If $D \neq A B$, we wish to compute the probability that algorithm outputs "yes" and prove that it less than $\frac{1}{2}$.
Define $E:=(A B-D)$ and $r:=E x=(A B-D) x=y-z$. If $D \neq A B$, then $\exists(i, j)$ s.t. $E_{i, j} \neq 0$.

$$
\begin{aligned}
\operatorname{Pr}[\text { Algorithm outputs "yes" }] & =\operatorname{Pr}[y=z]=\operatorname{Pr}[r=\mathbf{0}] \\
& =\operatorname{Pr}\left[\left(r_{1}=0\right) \cap\left(r_{2}=0\right) \cap \ldots \cap\left(r_{i}=0\right) \cap \ldots\right] \\
& =\operatorname{Pr}\left[\left(r_{i}=0\right)\right] \operatorname{Pr}\left[\left(r_{1}=0\right) \cap\left(r_{2}=0\right) \cap \ldots \cap\left(r_{n}=0\right) \mid r_{i}=0\right]
\end{aligned}
$$

(By def. of conditional probability)
$\Longrightarrow \operatorname{Pr}[$ Algorithm outputs "yes" $] \leq \operatorname{Pr}\left[r_{i}=0\right]$ (Probabilities are in $[0,1]$ )

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

## (Basic) Frievald's Algorithm

$$
\begin{array}{r}
r_{i}=\sum_{k=1}^{n} E_{i, k} x_{k}=E_{i, j} x_{j}+\sum_{k \neq j} E_{i, k} x_{k}=E_{i, j} x_{j}+\omega \quad\left(\omega:=\sum_{k \neq j} E_{i, k} x_{k}\right) \\
\operatorname{Pr}\left[r_{i}=0\right]=\operatorname{Pr}\left[r_{i}=0 \mid \omega=0\right] \operatorname{Pr}[\omega=0]+\operatorname{Pr}\left[r_{i}=0 \mid \omega \neq 0\right] \operatorname{Pr}[\omega \neq 0] \\
\text { (By the law of total probability) } \\
\operatorname{Pr}\left[r_{i}=0 \mid \omega=0\right]=\operatorname{Pr}\left[x_{j}=0\right]=\frac{1}{2} \quad \begin{array}{c}
\text { (Since } \left.E_{i, j} \neq 0 \text { and } \operatorname{Pr}\left[x_{j}=1\right]=\frac{1}{2}\right) \\
\operatorname{Pr}\left[r_{i}=0 \mid \omega \neq 0\right]=\operatorname{Pr}\left[\left(x_{j}=1\right) \cap E_{i, j}=-\omega\right]=\operatorname{Pr}\left[\left(x_{j}=1\right)\right] \operatorname{Pr}\left[E_{i, j}=-\omega \mid x_{j}=1\right]
\end{array} \\
\text { (By def. of conditional probability) } \\
\Longrightarrow \operatorname{Pr}\left[r_{i}=0 \mid \omega \neq 0\right] \leq \operatorname{Pr}\left[\left(x_{j}=1\right)\right]=\frac{1}{2} \quad \begin{array}{l}
\text { (Probabilities are in } \left.[0,1], \operatorname{Pr}\left[x_{j}=1\right]=\frac{1}{2}\right) \\
\Longrightarrow \operatorname{Pr}\left[r_{i}=0\right] \leq \frac{1}{2} \operatorname{Pr}[\omega=0]+\frac{1}{2} \operatorname{Pr}[\omega \neq 0]=\frac{1}{2} \operatorname{Pr}[\omega=0]+\frac{1}{2}[1-\operatorname{Pr}[\omega=0]]=\frac{1}{2} \\
\quad\left(\operatorname{Pr}\left[E^{c}\right]=1-\operatorname{Pr}[E]\right)
\end{array} \\
\Longrightarrow \operatorname{Pr}[\text { Algorithm outputs "yes" }] \leq \operatorname{Pr}\left[r_{i}=0\right] \leq \frac{1}{2} .
\end{array}
$$

## (Basic) Frievald's Algorithm

Hence, if $D \neq A B$, the Algorithm outputs "yes" with probability $\leq \frac{1}{2} \Longrightarrow$ 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".

$$
\left\lvert\, \begin{array}{c|c|c|} 
& \text { Yes } & \text { No } \\
D=A B & 1 & 0 \\
D \neq A B & <\frac{1}{2^{m}} & \geq 1-\frac{1}{2^{m}}
\end{array}\right.
$$

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: $O\left(m n^{2}\right)$

## 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.

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

$$
\begin{aligned}
& \text { If } A_{i} \text { denotes run } i \text { of Algorithm } \mathcal{A} \text {, then } \\
& \quad \operatorname{Pr}[\mathcal{B} \text { outputs Yes } \mid \text { true answer is Yes }] \\
& =\operatorname{Pr}\left[\mathcal{A}_{1} \text { outputs Yes } \cap \mathcal{A}_{2} \text { outputs Yes } \cap \ldots \cap \mathcal{A}_{m} \text { outputs Yes } \mid \text { true answer is Yes }\right] \\
& =\prod_{i=1}^{m} \operatorname{Pr}\left[\mathcal{A}_{i} \text { outputs Yes } \mid \text { true answer is } \mathrm{Yes}\right]=1 \quad \text { (Independence of runs) } \\
& \operatorname{Pr}[\mathcal{B} \text { outputs } \mathrm{No} \mid \text { true answer is No }] \\
& =1-\operatorname{Pr}[\mathcal{B} \text { outputs Yes } \mid \text { true answer is No }] \\
& =1-\operatorname{Pr}\left[\mathcal{A}_{1} \text { outputs Yes } \cap \mathcal{A}_{2} \text { outputs Yes } \cap \ldots \cap \mathcal{A}_{m} \text { outputs Yes } \mid \text { true answer is No }\right] \\
& =1-\prod_{i=1}^{m} \operatorname{Pr}\left[\mathcal{A}_{i} \text { outputs Yes } \mid \text { true answer is } \mathrm{No}\right] \geq 1-\frac{1}{2^{m}} .
\end{aligned}
$$

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 $<\frac{1}{2^{m}} \ll \frac{1}{2}$. 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 $\mathcal{S}$. 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.
$\mathcal{S}=\{H H H, H H T, H T H$, HTT, THH, THT, TTH, TTT $\}$
$C$ is a total function that maps each outcome in $\mathcal{S}$ to a number as follows: $C(H H H)=3$, $C(H H T)=C(H T H)=C(T H H)=2, C(H T T)=C(T H T)=C(T T H)=1, C(T T T)=0$.
$C$ 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.

## Back to throwing dice

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: $M:\{1,2, \ldots, 20\} \times\{1,2, \ldots, 20\} \times\{1,2, \ldots, 20\} \rightarrow\{1,2, \ldots, 20\}$

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 .

## Random Variables and Events

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 $(3,5) \in E, M((3,5))=1$.

