LECTURE 8 (September 19th)

More Probability & Randomized Algorithms

RECAP Equality Testing
Given two binary vectors
$$u, v \in \{0,1\}^n$$

Decide if they are equal or not
Only operation that is allowed : DOTPRODUCT $(a, b) \rightarrow \text{Time B}(n)$
take dot product $(\text{Ind } 2)$ of any two binary vectors $a, b \in io, 1^n$
i.e. output is
 $(a, b) \mod 2 = \sum_{i=1}^n a_i b_i \pmod{2} = \begin{cases} 1 & \text{if } (a, b) \text{ is odd} \\ 0 & o/\omega \end{cases}$
if coordinate
Deterministically let $e_i \in [00 \cdots 0]$ be the it standard basis vector
Invoking DOTPRODUCT (u, e_i) for $i=1$ to n , tells us what u or v is
Time $= O(n \cdot B(n))$
Algorithm $\cdot \text{Pick}$ a random vector $r \in \{0,1\}^n$
 $\cdot \text{If } (u, r) = (u, r) \text{ mod } 2$, then output EQUAL
 $\cdot \text{Else}$ output NOT EQUAL
Theorem $\mathbb{P}[\text{ Algorithm errs }] \leq \frac{1}{2}$ and is running time is $O(n + B(n))$
 $obvious$
 $\frac{Proof}{}$ Algorithm only errs if $u \neq v$
 $\text{Then }, \langle u, r \rangle = \sum_{i=1}^{n-1} u_i r_i + u_n \tau_n$
 $\langle v, r \rangle = \sum_{i=1}^{n-1} u_i r_i + v_n \tau_n$
 $(v, r) = \sum_{i=1}^{n-1} u_i r_i + v_n \tau_n$
 $i = \frac{p \mod 2}{2}$ wp. $\frac{1}{2}$ $r_n = 0$, so $\langle 0, r \rangle \neq \langle v, r \rangle$
 \boxed{P} Now, there are two cases
 $\boxed{\frac{1}{2} \alpha \neq p \mod 2}$ wp. $\frac{1}{2} r_n = 1$, so $\langle u, r \rangle \neq \langle v, r \rangle$
Thus, $\mathbb{P}[\text{ Algorithm errs }] \leq \frac{1}{2}$ \overleftarrow{This} is not very small
 $Can we make it \leq \delta$?

Repetition/Amplification That
Repetition/Amplification That
If any execution says NOT EQUAL
$$\Rightarrow$$
 output EQUAL
 $a_{(N)} \Rightarrow autput EQUAL$
Again, algorithm only errs if $u \neq v$,
 $\mathbb{P}[Algorithm errs] = \mathbb{P}[all is iteration return EQUAL]$
 $= \frac{t}{10} \frac{1}{2} = 2^{-t} = 2^{-\left\lceil \log \frac{1}{2} \right\rceil} = 5$
Runtime is now $O(n + B(n) \cdot \log \frac{1}{5})$
Testing Matrix Product
Given Boolean matrices B(C, D $\in i_0, i_0^{nm}$
 $decide if BC = D (mod 2)$
Matrix Multiplication takes $O(n^{2,3\cdots})$ time.
Randonness allows us to do it in roughly $O(n^2)$ time.
Randonness allows us to do it in roughly $O(n^2)$ time.
Algorithm
Take a random Boolean vector $r \in i_0, i_0^m$
 $\cdot Compute Dr = y$
 $\cdot Compute BCr = B(Cr) = x$
 $\cdot If x \neq y$, return NOT EQUAL $d_{(N)}$ return EQUAL
 $Error Analysis$
If $BC = D \Rightarrow$ algorithm is always correct
If $BC + D \Rightarrow$ algorithm may fail
 $(mod 2)$
 $H BC + D \Rightarrow$ algorithm may fail
 $(mod 2)$
 $H C = mov of BC and D are not equal
 $Let u = i^m$ row of BC and D are not equal
 $Let u = i^m$ row of BC. Then, $u \neq u$ by astumption
 $v = i^m$ row of D
By previous lemma, $\mathbb{P}[\langle u, r \rangle \mod 2 = \langle v, r \rangle \mod 2] = \frac{1}{2}$
We can make the error at most S, by reperting log $\frac{1}{2}$, times$

Random Variable

A random variable is a function $X: \Omega \longrightarrow V$ \mapsto value set

We write $\mathbb{P}[X=x]$ or $\mathbb{P}[X\leq x]$ or $\mathbb{P}[X=Y]$ to denote events about random variables

Expectation For real/complex/vector valued random variable X

$$\mathbb{E}[X] = \sum_{x} x \mathbb{P}[X=x] = \frac{1}{2}$$

Note Random variables over infinite sample spaces (e.g. integers) may not have finite expectations

Conditional Given an event A, the conditional expectation of X given A, is <u>Expectation</u>

$$\mathbb{E}[X|A] = \sum_{x} \mathbb{P}[X=x|A]$$

$$\mathbb{E}[X] = \mathbb{E}[X|A] \cdot \mathbb{P}[A] + \mathbb{E}[X|A] \cdot \mathbb{P}[A]$$

$$\mathbb{E}[X] = \sum_{y} \mathbb{E}[X|Y=y] \cdot \mathbb{P}[Y=y] = \mathbb{E}[\mathbb{E}[X|Y]]$$

Independence Two random variables X and Y are independent if for all x, y: the events X=x and Y=y are independent

If X and Y are independent, then $\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y]$

Similarly, if X,... Xn are fully independent, then

Linearity For any random variables $X_1 \dots X_n$ is reals $\alpha_1, \dots, \alpha_n$

$$\mathbb{E}\left[\sum_{j=1}^{n} \left(\alpha_{i} X_{i}^{\cdot}\right)\right] = \sum_{i=1}^{n} \alpha_{i} \cdot \mathbb{E}\left[X_{i}^{\cdot}\right]$$

<u>Example</u> Toss independent coins where each coin comes up heads w.p. $P \in [0, 1]$ Count $\mathbb{E}[\# heads]$

$$X_{i} = \begin{cases} 0 & \text{if coin is tails} \quad \text{and} \quad \mathbb{E}[X_{i}] = p \\ 1 & \text{if coin is heads} \end{cases}$$

$$Let X = \sum_{i=1}^{n} X_{i}$$

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_{i}\right] = \sum_{i=1}^{n} \mathbb{E}[X_{i}] = np$$

Example Toss independent coins where each coin comes up heads w.p. $P \in [0_1, 1]$ How many flips until first head?

$$\mathbb{E} \left[\# flips \right] = \mathbb{E} \left[\# flips \right] \text{ first flip is } \mathbb{P} \left[\text{first flip } \right] \\ = 1 \qquad \qquad = P \\ + \mathbb{E} \left[\# flips \right] \text{ first flip is } \mathbb{P} \left[\text{first flip } \right] \\ = 1 + \mathbb{E} \left[\# flips \right] \mathbb{P} \left[\text{first flip } \right] \\ = 1 + \mathbb{E} \left[\# flips \right] = 1 - p \\ = p + (1-p)(1 + \mathbb{E} \left[\# flips \right]) \\ \implies \mathbb{E} \left[\# flips \right] = \frac{1}{P} \\ \mathbb{E} \left[\# f$$

Sampling a Fair Coin from a Biased Coin

Suppose you have a biased coin that comes up heads with some unknown probability p How can you use it to get a fair coin toss?

Von Neumann in 1951 came up with a strategy

· Flip the biased coin twice

- If results of the two flips are different, return the first one HT \rightarrow return "Heads", TH \rightarrow return "Tails"
- Otherwise repeat until success

Why does this return a fair coin toss?

So, P[HT | flips diff]

$$= \frac{P(1-p)}{2p(1-p)} = \frac{1}{2}$$



How many flips do we need ?

 $\mathbb{P}[\text{ each iteration succeeds}] = 2p(1-p) = q \longrightarrow \text{ How many times do we need to flip} \\ a \text{ biased coin until it comes up H ?} \\ \mathbb{E}[\# \text{ times until success}] = \frac{1}{q} = \frac{1}{2p(1-p)}$

Note There are better algorithms if we know the value of p

Collecting Pokemons - Gotta Catch 'Em All

How many Pokemon cards you need to buy to collect all N pokemons?

Assume that each time we buy a card, we get a uniformly random Pokemon

Let Y = # cards to get all N pokemons

Let Yi = # cards after we have (i-1) pokemons to get i pokemons

$$y = y_1 + y_2 + \dots + y_N$$

What is $\mathbb{E}[Y]$? $Y_i = 1$

 $y_N = \#$ times we need to flip a $\frac{1}{N}$ - biased coin to see heads

 $\mathbb{E}[\lambda^N] = N$

Similarly, $Y_i = \#$ times we need to flip a $\frac{N-i+1}{N}$ - biased coin to see heads $E[Y_i] = \frac{N}{N-i+1}$

Thus, by linearity of expectation

$$E[Y] = \sum_{i=r}^{n} E[Y_i] = \sum_{i=r}^{N} \frac{N}{N-i+l} = N \sum_{i=r}^{N} \frac{1}{N-i+1} = N \sum_{j=r}^{N} \frac{1}{j} \qquad (j=N-i+1)$$
$$= N \cdot H_N$$
$$\longrightarrow N^{\text{th}} Harmonic Number$$
$$\approx N \cdot \ln N$$