

# Solutions for Week 11

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## 1

### 1.1

Because this problem has "self-reducibility" property, we can solve it using FPRAS. Suppose  $M_0, M_1, \dots, M_n$  is the satisfying assignments that when we fix the first bit equal to either 0 or 1. Without loss of generality, we assume that we fix them all to 0 (If the fraction of 1 for each bit is larger than  $\frac{1}{2}$ , we set it to 1 for that bit). Then we can use equations as follows

$$\#\phi = M_0 = \frac{M_0}{M_1} \frac{M_1}{M_2} \dots \frac{M_{n-1}}{M_n} M_n$$

Obviously,  $M_n = 1$ . Suppose that  $q_i = \frac{M_i}{M_{i-1}} > \frac{1}{2}$ , we can get

$$\#\phi = M_0 = \frac{1}{q_1} \frac{1}{q_2} \dots \frac{1}{q_n}$$

As we can see, the  $N_0$  in the problem is

$$N_0 = \frac{1}{q_2} \dots \frac{1}{q_n}$$

and  $p$  in the problem is  $q_1$ . So we need to get  $N_0$  recursively. And get  $p = q_1$  using approximate counting.

With Chernoff Bound, to  $(\epsilon/n, \delta/n)$  approximate counting, we should set sample size  $m$

$$m = \frac{6n^2 \ln(2n/\delta)}{\epsilon^2}$$

Here we use the assumption that  $\mu \geq \frac{1}{2}$ .

The algorithm to compute each  $q_i$  is as follows.

Using each  $q_i$  and equations above, we can get approximate counting for number of  $\#\phi$ .

### 1.2

We can efficiently generate uniform samples as follows: Suppose we have  $\phi_k(x) = (X_1, X_2, X_3, \dots, X_k = x, \dots, X_n)$ , which the  $k$  bit is fixed by  $x$ . For each bit of this uniform sample, we can determine it using equation

$$X_k = \begin{cases} 1 & \text{w.p. } \frac{\#\phi_k(1)}{\#\phi} \\ 0 & \text{w.p. } \frac{\#\phi_k(0)}{\#\phi} \end{cases}$$

which  $\phi_k(1)$  and  $\phi_k(0)$  can be computed by black box C.

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**Algorithm 1** FPRAS for Computing Ratio  $q_i$  with  $(\delta/n, \epsilon/n)$

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**Require:** Satisfying assignments fixed the first  $i - 1$  bits to 0

**Ensure:** The Ratio  $q_i$

$$m = \frac{6n^2 \ln 2/\delta}{\epsilon^2}$$

$$C_i = 0$$

$$C_{i-1} = 0$$

**for**  $i = 1$  to  $m$  **do**

    Sample  $x$  from satisfying assignments fixed the first  $i - 1$  bits to 0

$$C_{i-1} = C_{i-1} + 1$$

**if** the  $i$ -th bit of  $x$  is also 0 **then**

$$C_i = C_i + 1$$

**end if**

**end for**

$$q_i = C_i/C_{i-1}$$

**return**  $q_i$

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## 2

### 2.1

Proof: When we fix  $Z = z$ , then  $\mathbb{E}[X|Y, Z]$  is a random variable on  $Y$ .

$$\begin{aligned} \mathbb{E}[\mathbb{E}[X|Y, Z]|Z = z] &= \sum_y \mathbb{E}[X|Y = y, Z = z] Pr[Y = y|Z = z] \\ &= \sum_y \sum_x x Pr[X = x|Y = y, Z = z] Pr[Y = y|Z = z] \\ &= \sum_y \sum_x x \frac{Pr[X = x, Y = y, Z = z]}{Pr[Y = y, Z = z]} \frac{Pr[Y = y, Z = z]}{Pr[Z = z]} \\ &= \sum_y \sum_x x \frac{Pr[X = x, Y = y, Z = z]}{Pr[Z = z]} \\ &= \sum_x x \frac{Pr[X = x, Z = z]}{Pr[Z = z]} \\ &= \sum_x x Pr[X = x|Z = z] \\ &= \mathbb{E}[X|Z = z] \end{aligned}$$

Since  $\mathbb{E}[[X|Y, Z]|Z]$  is random variable on  $Y$ ,

$$\begin{aligned} \mathbb{E}[[X|Y, Z]|Z] &= \sum_z \mathbb{E}[\mathbb{E}[X|Y, Z]|Z = z] \\ &= \sum_z \mathbb{E}[X|Z = z] \\ &= \mathbb{E}[X|Z] \end{aligned}$$

Q.E.D.

## 2.2

We prove these lemma in turn. Proof: When  $y$  is a constant,

$$\begin{aligned}\mathbb{E}[XY|Y = y] &= \mathbb{E}[yX|Y = y] \\ &= y\mathbb{E}[X|Y = y]\end{aligned}$$

From the definition of conditional expectation, we get

$$\mathbb{E}[XY|Y] = Y\mathbb{E}[X|Y]$$

Take expectation on both sides,

$$\begin{aligned}\mathbb{E}[XY] &= \mathbb{E}[\mathbb{E}[XY|Y]] \\ &= \mathbb{E}[Y\mathbb{E}[X|Y]]\end{aligned}$$

Q.E.D.

## 3

### 3.1

Let  $X_i$  indicate whether vertex  $i$  is a isolated vertex. Thus  $X = \sum_{i=1}^n X_i$ . For each edge, there are  $\binom{n}{2}$  options. For each vertex, there are at most  $(n-1)$  degree. So

$$Pr[deg(v_i) = 0] = (1 - \frac{\binom{n}{2} - (n-1)}{\binom{n}{2}})^N = (1 - \frac{n-2}{n})^{cn}$$

With linearity of expectation,

$$\begin{aligned}\mathbb{E}[X] &= \mathbb{E}[\sum_{i=1}^n X_i] \\ &= \sum_{i=1}^n \mathbb{E}[X_i] \\ &= n(1 - \frac{n-2}{n})^{cn} \\ &= n(\frac{2}{n})^{cn}\end{aligned}$$

### 3.2

As we can see,  $X$  is a function of edges  $E_1, E_2, \dots, E_{cn}$ . Now we define doob edge exposure martingale, for every  $i \in [0, cn]$

$$Z_i = \mathbb{E}[X|E_1, \dots, E_i]$$

Obviously,  $Z_0 = \mathbb{E}[X]$  and  $Z_{cn} = X$ . Now we prove that  $Z_{i=0}^n$  is a martingale w.r.t  $(X_i)$ .

$$\begin{aligned}\mathbb{E}[Z_i|E_1, \dots, E_{i-1}] &= \mathbb{E}[\mathbb{E}[X|E_1, \dots, E_i]|E_1, \dots, E_{i-1}] \\ &= \mathbb{E}[X|E_1, \dots, E_{i-1}] \\ &= Z_{i-1}\end{aligned}$$

The first equality is the definition of  $Z_i$ , the second from the fact in section 2.1, and the last from the definition of  $Z_{i-1}$ . Now we can use Azuma to this doob martingale. For each  $E_i$ , it will decrease the isolated vertices at most 2 or increase isolated vertices at most 2, which means

$$|Z_i - Z_{i-1}| \leq 2$$

With Azuma-Hoeffding's inequality,

$$\begin{aligned}Pr[|Z_n - Z_0| \geq 2\lambda\sqrt{cn}] &\leq 2e^{-\frac{(2\lambda\sqrt{cn})^2}{2cn*2^2}} \\ &= 2e^{-\frac{4\lambda^2 cn}{8cn}} \\ &= 2e^{-\frac{\lambda^2}{2}}\end{aligned}$$

Q.E.D.