

Probability and Computation: Problem sheet 2 Solutions

You are encouraged to submit your solutions at student reception or by emailing them to nr454 by 2pm Friday 07th of February

Algorithms

Question 1. In this question we consider the following NP-complete problem called *VERTEX-COVER*

Instance: A graph $G = (V, E)$.

Output: Subset $S \subseteq V$ such that each edge has an end in S and $|S|$ is minimized.

- (i) Can you come up with a simple randomised algorithm for *VERTEX-COVER*?
- (ii) Is this algorithm correct? (That is, does it always output a valid vertex-cover S)
- (iii) Can you show that, for any graph G , the expected size of the vertex cover S produced by your algorithm is at most twice the size of an optimal one?

Solution: Our algorithm **Rand-VC** is as follows:

For each $e = uv \in E$, if e is not already covered, add u to S with probability $1/2$, otherwise add v .

To see part (ii), each edge has at least one of its endpoints in S and so every edge is covered.

Part (iii) is the following result:

Proposition. Let S be the vertex cover output by **Rand-VC** and C be an optimal vertex cover. Then

$$\mathbf{E}[|S|] \leq 2|C|.$$

Proof. To begin we partition the edges by assigning them to vertices in C , an optimal vertex cover. Let e_1, \dots, e_k be the edges assigned to some $v \in C$. For each edge e_i examined by the algorithm, at most one vertex was added to the vertex cover S output by **Rand-VC**. Let S_v denote the set of such vertices added to S by the edges e_1, \dots, e_{k_v} assigned to $v \in C$.

Claim. For all $v \in C$, $\mathbf{E}[|S_v|] \leq 2$.

Proof of claim. We prove the claim by induction on the number of edges $k = k_v$ associated with v . If $k_v = 0$ the claim holds vacuously since no edge is adjacent to v and so cannot contribute any vertices to S_v . Assume the claim holds for any $n \leq k - 1$ edges then if v is associated with k edges and we start by considering $e_k = uv$ then

$$\begin{aligned} \mathbf{E}[|S_v|] &= \mathbf{E}[|S_v| \mid v \text{ added to } S_v] \cdot \mathbf{P}[v \text{ added to } S_v] + \mathbf{E}[|S_v| \mid u \text{ added to } S_v] \cdot \mathbf{P}[u \text{ added to } S_v] \\ &\leq 1 \cdot (1/2) + (1 + \mathbf{E}[|S'|]) \cdot (1/2), \end{aligned}$$

where S' is the set of vertices added **Rand-VC** when it considers the edges e_1, \dots, e_{k-1} . Thus by the inductive hypothesis $\mathbf{E}[|S'|] \leq 2$ and so

$$\mathbf{E}[|S_v|] \leq 1/2 + (1 + 2) \cdot (1/2) \leq 2,$$

as claimed. Alternatively one could see that, if the number of edges covered by v in the optimal cover was infinite, then $|S_v| \sim \text{Geo}(1/2)$ would have geometric distribution with parameter $1/2$. This is since each time we terminate with probability $1/2$ if we pick v and add it to S_v , or we add the other endpoint to S_v and keep going. \diamond

Now to prove the proposition, by the Claim, we have

$$\mathbf{E}[|S|] = \sum_{v \in C} \mathbf{E}[|S|] \leq \sum_{v \in C} 2 \leq 2|C|,$$

since the total number of vertices in the cover S found by **Rand-VC** is the sum of the vertices added by the edges associated with each $v \in C$. \square

Conditional Expectation

Question 2. Show properties 2 – 6 of slide 7 of Lecture 5.

Solution: Property 4: Let a be a possible value of X . Since X is independent of Y we have $\mathbf{P}[Y = y|X = a] = \mathbf{P}[Y = y]$ then

$$\mathbf{E}[Y|X = a] = \sum_y y \mathbf{P}[Y = y|X = a] \stackrel{indep}{=} \sum_y y \mathbf{P}[Y = y] = \mathbf{E}[Y],$$

deducing that $\mathbf{E}[Y|X] = \mathbf{E}[Y]$.

Property 5: Let a be a possible value of X , then

$$\begin{aligned} \mathbf{E}[YZ|X = a] &= \mathbf{E}[F(X)Z|X = a] = \sum_x \sum_z F(x)z \mathbf{P}[X = x, Z = z|X = a] \\ &= F(a) \sum_z z \mathbf{P}[Z = z|X = a] = F(a) \mathbf{E}[Z|X = a], \end{aligned}$$

deducing that $\mathbf{E}[YZ|X] = Y \mathbf{E}[Z|X]$.

Question 3. Let X_1, \dots, X_n be independent discrete random variables and let $Z = f(X_1, \dots, X_n)$ for some function f . Prove that

$$\mathbf{E}[Z|X_1, \dots, X_i] = \sum_{x_{i+1}, \dots, x_n} f(X_1, \dots, X_i, x_{i+1}, \dots, x_n) \mathbf{P}[X_i = x_{i+1}, \dots, X_n = x_n]$$

Solution: Let (a_1, \dots, a_n) be a possible value of (X_1, \dots, X_n) , then

$$\begin{aligned} \mathbf{E}[Z|X_1 = a_1, \dots, X_n = a_n] &= \sum_{x_1} \sum_{x_2} \dots \sum_{x_n} f(x_1, \dots, x_n) \mathbf{P}[X_1 = x_1, \dots, X_n = x_n | X_1 = a_1, \dots, X_i = a_i] \\ &= \sum_{x_{i+1}} \dots \sum_{x_n} f(a_1, \dots, a_i, x_{i+1}, \dots, x_n) \mathbf{P}[X_{i+1} = x_{i+1}, \dots, X_n = x_n]. \end{aligned}$$

Question 4. Conditional Variance. Define the conditional variance of Y given X as

$$\mathbf{Var}[Y|X] = \mathbf{E}[(Y - \mathbf{E}[Y|X])^2|X].$$

(i) Prove that $\mathbf{Var}[Y] = \mathbf{E}[\mathbf{Var}[Y|X]] + \mathbf{Var}[\mathbf{E}[Y|X]]$

(ii) Consider n bins and a random number M of balls, where $\mathbf{E}[M] = \mu$ and $\mathbf{Var}[M] = \sigma^2$. Compute the variance of the number of balls that are assigned to the first bin.

Solution: Remember that $\mathbf{Var}[Y] = \mathbf{E}[(Y - \mathbf{E}[Y])^2]$, and, equivalently, $\mathbf{Var}[Y] = \mathbf{E}[Y^2] - \mathbf{E}[Y]^2$.
By definition we have that

$$\mathbf{E}[\mathbf{Var}[Y|X]] = \mathbf{E}[\mathbf{E}[(Y - \mathbf{E}[Y|X])^2|X]] \stackrel{p1}{=} \mathbf{E}[(Y - \mathbf{E}[Y|X])^2] = \mathbf{E}[Y^2 - 2Y\mathbf{E}[Y|X] + \mathbf{E}[Y|X]^2]$$

(p1 refers to the properties of Lecture 6, slide 19). By p1 we get

$$\mathbf{E}[Y\mathbf{E}[Y|X]] \stackrel{p1}{=} \mathbf{E}[\mathbf{E}[Y\mathbf{E}[Y|X]|X]] \stackrel{p5}{=} \mathbf{E}[\mathbf{E}[Y|X]^2]$$

by linearity of conditional expectation (p3) we get

$$\mathbf{E}[\mathbf{Var}[Y|X]] = \mathbf{E}[Y^2] - \mathbf{E}[\mathbf{E}[Y|X]^2] \quad (1)$$

Also, note that $\mathbf{E}[\mathbf{E}[Y|X]] = \mathbf{E}[Y]$ then

$$\mathbf{Var}[\mathbf{E}[Y|X]] = \mathbf{E}[\mathbf{E}[Y|X]^2] - \mathbf{E}[Y]^2 \quad (2)$$

By adding equations (1) and (2) we get the result.

For the second part, let X be the number of balls that are assigned to the first bin. We compute $\mathbf{Var}[X] = \mathbf{E}[\mathbf{Var}[X|M]] + \mathbf{Var}[\mathbf{E}[X|M]]$. In lecture 6 slide 24 we computed $\mathbf{E}[X|M] = \sum_{i=1}^{\infty} \mathbf{1}_{\{i \leq M\}} = M/n$. Moreover, by definition of conditional variance, we get

$$\begin{aligned} \mathbf{Var}[X|M] &= \mathbf{E}[(X - M/n)^2|M] \stackrel{p3,p5}{=} \mathbf{E}[X^2|M] - 2(M/n)\mathbf{E}[X|M] + (M/n)^2 \\ &= \mathbf{E}[X^2|M] - (M/n)^2 \end{aligned}$$

We just need to compute $\mathbf{E}[X^2|M]$. Let X_i be 1 if ball number i is assigned to the first bin, otherwise X_i is 0. Then $X = \sum_{i=1}^{\infty} X_i \mathbf{1}_{\{i \leq M\}}$ and therefore

$$X^2 = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} X_i X_j \mathbf{1}_{\{i,j \leq M\}}$$

Note that $X_i^2 = X_i$, then

$$\mathbf{E}[X^2|M] = \sum_{i=1}^{\infty} \mathbf{E}[X_i|M] + 2 \sum_{1=i < j < \infty} \mathbf{E}[X_i X_j|M] \mathbf{1}_{\{i,j \leq M\}}$$

Finally, use that the location of a ball is independent of how many balls we assigned in total. Therefore $\mathbf{E}[X_i|M] = 1/n$ and $\mathbf{E}[X_i X_j|M] = 1/n^2$ for $i \neq j$. We conclude that

$$\mathbf{Var}[X|M] = M/n + M(M-1)/n^2 - (M/n)^2 = M/n - M/n^2$$

and $\mathbf{E}[\mathbf{Var}[X|M]] = (\mu/n)(1 - \frac{1}{n})$

On the other hand, remember that $\mathbf{E}[X|M] = M/n$. Then

$$\mathbf{Var}[\mathbf{E}[X|M]] = \mathbf{Var}[M/n] = \frac{1}{n^2} \mathbf{Var}[M] = \sigma^2/n^2.$$

By adding $\mathbf{Var}[\mathbf{E}[X|M]]$ and $\mathbf{E}[\mathbf{Var}[X|M]]$ we get the result.

Question 5. Consider a coin that shows head with probability p . What is the expected number of flips required to observe a run of n consecutive heads?

Solution: To get a run of n heads, we first need to get a run of $n-1$ head. After that we either get another head, or we get a tail and restart the process. Denote by T_n the number of coins needed to get

a run of n heads, and T'_n be the number of coins needed to get a run of n heads after restarting. Denote by X_n the indicator variable that tells us if we have to restart after T_{n-1} or not. Then

$$T_n = T_{n-1} + 1 + X_n T'_n$$

Note that X_n is independent of T'_n since T'_n does not depend on the previous coins. Then $\mathbf{E}[T_n] = \mathbf{E}[T_{n-1}] + 1 + \mathbf{E}[X_n] \mathbf{E}[T'_n] = \mathbf{E}[T_{n-1}] + 1 + (1-p)\mathbf{E}[T'_n]$ Using that $\mathbf{E}[T'_n] = \mathbf{E}[T_n]$ we get the recursion

$$\mathbf{E}[T_n] = \frac{1}{p}\mathbf{E}[T_{n-1}] + \frac{1}{p}.$$

By iterating the previous recursion, and by using that $\mathbf{E}[T_1] = \frac{1}{p}$ we conclude that

$$\mathbf{E}[T_n] = \frac{1}{p^n} + \dots + \frac{1}{p}.$$

Hint.

Q5: Recall how we deduce the expectation of a geometric random variable in class.