

Assignment 3: Solution Sketch

Itay Hazan

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1 Generalized Bonferroni Inequalities

1.a. Let $S \in \binom{[n]}{r}$ be a set of r indices.

$$\begin{aligned} \Pr \left[\bigwedge_{i \in S} E_i \wedge \bigwedge_{i \notin S} \neg E_i \right] &= \Pr \left[\bigwedge_{i \in S} E_i \right] \cdot \Pr \left[\bigwedge_{i \notin S} \neg E_i \mid \bigwedge_{i \in S} E_i \right] \\ &= \Pr \left[\bigwedge_{i \in S} E_i \right] \cdot \sum_{t=0}^{n-r} (-1)^t \sum_{T \in \binom{[n] \setminus S}{t}} \Pr \left[\bigwedge_{j \in T} E_j \mid \bigwedge_{i \in S} E_i \right] \\ &= \sum_{t=0}^{n-r} (-1)^t \sum_{T \in \binom{[n] \setminus S}{t}} \Pr \left[\bigwedge_{i \in S \cup T} E_i \right]. \end{aligned}$$

Observe that $\Pr[X = r] = \sum_{S \in \binom{[n]}{r}} \Pr \left[\bigwedge_{i \in S} E_i \wedge \bigwedge_{i \notin S} \neg E_i \right]$, and therefore:

$$\begin{aligned} \Pr[X = r] &= \sum_{S \in \binom{[n]}{r}} \Pr \left[\bigwedge_{i \in S} E_i \wedge \bigwedge_{i \notin S} \neg E_i \right] \\ &= \sum_{S \in \binom{[n]}{r}} \sum_{t=0}^{n-r} (-1)^t \sum_{T \in \binom{[n] \setminus S}{t}} \Pr \left[\bigwedge_{i \in S \cup T} E_i \right] \\ &= \sum_{t=r}^n (-1)^{t-r} \binom{t}{r} \sum_{T \in \binom{[n]}{t}} \Pr \left[\bigwedge_{i \in T} E_i \right]. \end{aligned}$$

1.b. Following similar calculations to those in (1a) proves the following inequalities:

$$\begin{aligned} \Pr[X = r] &\leq \sum_{t=r}^k (-1)^{t-r} \binom{t}{r} \sum_{T \in \binom{[n]}{t}} \Pr \left[\bigwedge_{i \in T} E_i \right] && \text{when } 2 \mid k - r, \\ \Pr[X = r] &\geq \sum_{t=r}^k (-1)^{t-r} \binom{t}{r} \sum_{T \in \binom{[n]}{t}} \Pr \left[\bigwedge_{i \in T} E_i \right] && \text{when } 2 \nmid k - r. \end{aligned}$$

1.c. Let $p = \frac{\log n + c}{n}$. For every $S \subset [n]$, let E_S be the event that all vertices in S are isolated. It holds that

$$\begin{aligned} \Pr[E_S] &= \left(1 - \frac{\log n + c}{n} \right)^{\binom{|S|}{2} + |S|(n-|S|)} \\ &= \left(1 - \frac{\log n + c}{n} \right)^{|S|n} \cdot \left(1 - \frac{\log n + c}{n} \right)^{-O(|S|^2)} \\ &= (1 \pm o(1)) e^{-|S|(\log n + c)} \cdot (1 - o(1)) \\ &= (1 \pm o(1)) \frac{e^{-|S|c}}{n^{|S|}}. \end{aligned}$$

Using the equality in (1a), and since $\binom{m}{k} = (1 \pm o(1)) \frac{m^k}{k!}$, then:

$$\begin{aligned} \Pr[X_n = r] &= \sum_{t=r}^n (-1)^{t-r} \binom{t}{r} \sum_{S \in \binom{[n]}{t}} (1 \pm o(1)) \frac{e^{-|S|c}}{n^{|S|}} \\ &= (1 \pm o(1)) \sum_{t=r}^n (-1)^{t-r} \binom{t}{r} \binom{n}{t} \frac{e^{-tc}}{n^t} \\ &= (1 \pm o(1)) \sum_{t=r}^n (-1)^{t-r} \frac{t!}{r!(t-r)!} \frac{n^t e^{-tc}}{t! n^t} \\ &= (1 \pm o(1)) \sum_{t=r}^n (-1)^{t-r} \frac{e^{-tc}}{r!(t-r)!} \\ &= (1 \pm o(1)) \sum_{k=0}^n (-1)^k \frac{e^{-(k+r)c}}{r!k!} && \text{(renaming } k = t - r) \\ &= (1 \pm o(1)) \frac{e^{-rc}}{r!} \sum_{k=0}^n (-1)^k \frac{e^{-kc}}{k!} \\ &\xrightarrow{n \rightarrow \infty} \frac{e^{-rc}}{r!} e^{e^{-c}} = \Pr[P = r]. \end{aligned}$$

1.d. Let $\epsilon > 0$. Since $\sum_{r=0}^{\infty} \Pr[P = r] = 1$ is a series of nonnegative and monotonically decreasing elements, then there exists R for which $\sum_{r=R}^{\infty} \Pr[P = r] \leq \frac{\epsilon}{4}$. Furthermore, since $\Pr[X_n = r] \xrightarrow{n \rightarrow \infty} \Pr[P = r]$, then there exists N such that $|\Pr[X_n = r] - \Pr[P = r]| \leq \frac{\epsilon}{4R}$ for any $n \geq N$ and any $r \leq R$. Therefore, for any $n \geq N$,

$$\begin{aligned}
\sum_{r=0}^{\infty} |\Pr[X_n = r] - \Pr[P = r]| &= \sum_{r=0}^{R-1} |\Pr[X_n = r] - \Pr[P = r]| + \\
&+ \sum_{r=R}^{\infty} |\Pr[X_n = r] - \Pr[P = r]| \\
&\leq R \cdot \frac{\epsilon}{4R} + \sum_{r=R}^{\infty} \Pr[X_n = r] + \sum_{r=R}^{\infty} \Pr[P = r] \\
&\leq \frac{\epsilon}{4} + \left(1 - \sum_{r=0}^{R-1} \Pr[X_n = r]\right) + \sum_{r=R}^{\infty} \Pr[P = r] \\
&\leq \frac{\epsilon}{4} + 1 - \sum_{r=0}^{R-1} \left(\Pr[P = r] - \frac{\epsilon}{4R}\right) + \sum_{r=R}^{\infty} \Pr[P = r] \\
&\leq \frac{\epsilon}{4} + \left(1 - \sum_{r=0}^{R-1} \Pr[P = r]\right) + R \cdot \frac{\epsilon}{4R} + \sum_{r=R}^{\infty} \Pr[P = r] \\
&\leq \frac{\epsilon}{4} + \sum_{r=R}^{\infty} \Pr[P = r] + R \cdot \frac{\epsilon}{4R} + \sum_{r=R}^{\infty} \Pr[P = r] \\
&\leq \frac{\epsilon}{4} + \frac{\epsilon}{4} + \frac{\epsilon}{4} + \frac{\epsilon}{4} = \epsilon.
\end{aligned}$$

2 Google Interview Question

2.a. For any $i \in n$, let $X_k^i(m)$ denote the number of balls in the i th bin after m steps. Clearly, $X_k^i(m) \sim \text{Bin}(m, 1/n)$, and using the Poisson approximation for the Binomial distribution, we get that $X_k^i(m) \approx \text{Pois}(m/n)$. Therefore, by linearity of expectation we get that:

$$\mathbb{E}[X_k(m)] = \sum_{i=1}^n \mathbb{E}[\mathbf{1}_{\{X_k^i(m)=k\}}] \approx n \cdot e^{-m/n} \frac{(m/n)^k}{k!}.$$

A more careful analysis, that follows the footsteps of the proof of the Poisson limit theorem, proves that $\mathbb{E}[X_k(m)] = n \cdot e^{-m/n} \frac{(m/n)^k}{k!} + O(1)$, as required. For the variance of $X_k(m)$: for every i , the random variable $\mathbf{1}_{\{X_k^i(m)=k\}}$ is a Bernoulli indicator, and hence $\mathbb{V}[\mathbf{1}_{\{X_k^i(m)=k\}}] \leq 1$. Furthermore, it is fairly easy to see that

$$\text{Cov}(\mathbf{1}_{\{X_k^i(m)=k\}}, \mathbf{1}_{\{X_k^j(m)=k\}}) < 0.$$

Therefore:

$$\mathbb{V}[X_k(m)] = \sum_{i=1}^n \mathbb{V}\left[\mathbf{1}_{\{X_k^i(m)=k\}}\right] + 2 \sum_{i<j} \text{Cov}\left(\mathbf{1}_{\{X_k^i(m)=k\}}, \mathbf{1}_{\{X_k^j(m)=k\}}\right) = O(n).$$

2.b. Let $\tilde{\delta}(n) = n^{2/3}$. Let $t = n^{1/6}$, and define a set of $t + 1$ evenly-spread m_i s as follows: $m_i = \epsilon n + \frac{(C-\epsilon)n}{t}i$ for every $0 \leq i \leq t$. For every such m_i , Chebyshev's inequality yields

$$\Pr[|X_k(m_i) - \mathbb{E}[X_k(m_i)]| \geq \tilde{\delta}] \leq \frac{\mathbb{V}[X_k(m_i)]}{\tilde{\delta}^2} = \frac{O(n)}{n^{4/3}} = \frac{O(1)}{n^{1/3}}.$$

Now, applying a union bound, we get that

$$\Pr\left[\bigwedge_{i=0}^t |X_k(m_i) - \mathbb{E}[X_k(m_i)]| \geq \tilde{\delta}\right] \leq (t+1) \frac{O(1)}{n^{1/3}},$$

and since $t = o(n^{1/3})$ then this probability is $o(1)$; namely, with high probability, $|X_k(m_i) - \mathbb{E}[X_k(m_i)]| \leq \tilde{\delta}$ for all our m_i s. Now, let m be any natural number in the range $[\epsilon n, Cn]$. Let $i \in \{0, \dots, t\}$ be the index for which $m_i \leq m \leq m_{i+1}$. We therefore get:

$$\begin{aligned} |X_k(m) - \mathbb{E}[X_k(m)]| &= |X_k(m) - \mathbb{E}[X_k(m)] + X_k(m_i) - \mathbb{E}[X_k(m_i)] - \\ &\quad - X_k(m_i) + \mathbb{E}[X_k(m_i)]| \\ &\leq |X_k(m) - X_k(m_i)| + |\mathbb{E}[X_k(m)] - \mathbb{E}[X_k(m_i)]| + \\ &\quad + |X_k(m_i) - \mathbb{E}[X_k(m_i)]|. \end{aligned}$$

Since we throw a single ball in each step, then $|X_k(m) - X_k(m_i)| \leq |m - m_i| \leq 2\frac{(C-\epsilon)n}{t}$. Similarly, $|\mathbb{E}[X_k(m)] - \mathbb{E}[X_k(m_i)]| \leq 2\frac{(C-\epsilon)n}{t}$. Taking $t = \omega(1)$ ensures that these bounds are $o(n)$. Furthermore, we know that $|X_k(m_i) - \mathbb{E}[X_k(m_i)]| \leq \tilde{\delta}$ with high probability. Therefore, with high probability,

$$|X_k(m) - \mathbb{E}[X_k(m)]| \leq 2\frac{(C-\epsilon)n}{t} + n^{2/3} = o(n).$$

Therefore, for $\delta(n) = 2\frac{(C-\epsilon)n}{t} + n^{2/3} = o(n)$, we get that with high probability $|X_k(m) - \mathbb{E}[X_k(m)]| \leq \delta$ for all $m \in [\epsilon n, Cn]$.

2.c. We first remark that in this sub-exercise we are not given that $\epsilon n \leq m^* \leq Cn$ for some constant $\epsilon, C > 0$, and we thus cannot immediately apply (2a) and (2b). Nevertheless, it can be easily shown that $\frac{1}{2}n \leq m^* \leq 2n$ with high probability.

From (2a), we know that $\mathbb{E}[X_0(m)] = e^{-m/n}n + O(1)$ and $\mathbb{E}[X_1(m)] = e^{-m/n}\frac{m}{n}n + O(1) = e^{-m/n}m + O(1)$. Therefore,

$$\begin{aligned} |\mathbb{E}[X_1(m^*)] - \mathbb{E}[X_0(m^*)]| &\geq |e^{-m^*/n}m^* - e^{-m^*/n}n| - O(1) \\ &\geq e^{-m^*/n}|m^* - n| - O(1). \end{aligned}$$

On the other hand, we get that:

$$\begin{aligned}
|\mathbb{E}[X_1(m^*)] - \mathbb{E}[X_0(m^*)]| &\leq \\
|\mathbb{E}[X_1(m^*)] - X_1(m^*) - \mathbb{E}[X_0(m^*)] + X_0(m^*) + X_1(m^*) - X_0(m^*)| &\leq \\
|\mathbb{E}[X_1(m^*)] - X_1(m^*)| + |\mathbb{E}[X_0(m^*)] - X_0(m^*)| + |X_1(m^*) - X_0(m^*)| &\leq \delta(n) + \delta(n) + O(1),
\end{aligned}$$

where the last inequality holds due to (2b) and since $X_1(m^*) = X_0(m^*) + O(1)$. We can thus conclude the following:

$$e^{-m^*/n}|m^* - n| - O(1) \leq |\mathbb{E}[X_1(m^*)] - \mathbb{E}[X_0(m^*)]| \leq \delta(n) + \delta(n) + O(1),$$

and namely $|m^* - n| \leq 2e^{m^*/n}\delta(n) + O(1) \cdot e^{m^*/n}$ whp, as desired. Taking $\beta = e^{-m^*/n}$ concludes the exercise:

$$\begin{aligned}
|X_0(m^*) - \beta n| &\leq |X_0(m^*) - \mathbb{E}[X_0(m^*)]| + |\mathbb{E}[X_0(m^*)] - \beta n| \leq \delta(n) + O(1), \\
|X_1(m^*) - \beta n| &\leq |X_1(m^*) - \mathbb{E}[X_1(m^*)]| + |\mathbb{E}[X_1(m^*)] - \beta n| \\
&\leq \delta(n) + \left| \mathbb{E}[X_1(m^*)] - \beta \left(m^* + 2e^{m^*/n}\delta(n) + O(1) \cdot e^{m^*/n} \right) \right| \\
&\leq \delta(n) + |\mathbb{E}[X_1(m^*)] - \beta m^*| + 2\beta e^{m^*/n}\delta(n) + O(1) \cdot \beta e^{m^*/n} \\
&\leq \delta(n) + \delta(n) + 2\delta(n) + O(1) = 4\delta(n) + O(1).
\end{aligned}$$

2.d. We consider an equivalent game, in which the pills are uniquely labeled $\{1, \dots, n\}$, and whenever we consume the second half of a pill, we insert a new “dummy pill” with the same label into the bag. This way, the total number of elements (either pills or half-pills) in the bag is always n , and there is always an element in the bag with each label in $[n]$. Suppose we perform t steps of the new experiment, and every time we consume a pill whose label is i , we throw a ball in the i th bin. Let $\tilde{H}(\tilde{m}), \tilde{W}(\tilde{m})$ denote the number of half/whole pills in the game we propose (excluding dummy pills), and let \tilde{m}^* denote the first step at which $\tilde{H}(\tilde{m}^*) \geq \tilde{W}(\tilde{m}^*)$. Clearly, our mapping satisfies $\tilde{H}(\tilde{m}^*) = H(m^*)$ and $\tilde{W}(\tilde{m}^*) = W(m^*)$.

Due to the equivalence described above between the proposed game and the balls-in-bins game, we get that whp $|W(m^*) - \beta n| \leq \eta(n)$ and $|H(m^*) - \beta n| \leq \eta(n)$ for some β, η as described in (2c). Furthermore, since $m^* = 2n - 2W(m^*) - H(m^*)$, then with high probability $m^* = 2n - (3\beta n \pm 3\eta(n))$, namely $|m^* - (2 - 3\beta)n| \leq 3\eta(n)$ with high probability, and that concludes the exercise.