

Randomized algorithm

Tutorial 3

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Solution for assignment 2

[Question 1]:

Let S be a set of n numbers. The median-finding algorithm discussed in class finds the median of S with high probability, and its running time is $2n + o(n)$.

Can you generalize this algorithm so that it can find the k th largest item of S for any given value of k ?

Prove that your resulting algorithm is correct, and bound its running time.

[Solution]:

We first consider the case where $k \leq n/2$.

For this case, we scan the n items and obtain the minimum value, say, t . Then, we add $n - 2k + 1$ items to the set of n items, each item having a value equal to t . It is easy to check that the k th largest item among the original n items will be the *median* of the new set of $2n - 2k + 1$ items.

[Cont.]: Therefore, we can apply the median-finding algorithm for the new set to obtain the desired k th largest item of the original set.

The running time for this case is $O(n)$. More precisely, we have spent n comparisons to find the minimum element, and at most $4n + o(n)$ further comparisons to find the median. The total time is thus at most $5n + o(n)$.

Could it be lower?

In fact, it is easy to see that we do not need to explicitly add the $n - 2k + 1$ items.

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The running time for this case is $O(n)$. More precisely, we have spent n comparisons to find the minimum element, and at most $4n + o(n)$ further comparisons to find the median. The total time is thus at most $5n + o(n)$.

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In fact, it is easy to see that we do not need to explicitly add the $n - 2k + 1$ items.

[Cont.]: What we need to do is to modify the sampling algorithm a bit, so that with probability $p = n/(2n - 2k + 1)$, we are selecting an integer from the original n items, and with probability $1 - p$, we are selecting the minimum value t . Consequently, the time will be at most $3n + o(n)$.

For the case where $k > n/2$, we proceed by adding items with maximum value instead.

[Question 2]:

The weak law of large numbers state that, if X_1, X_2, X_3, \dots are independent and identically distributed random variables with finite mean μ and finite standard deviation σ , then for any constant $\varepsilon > 0$ we have

$$\lim_{n \rightarrow \infty} \Pr \left(\left| \frac{X_1 + X_2 + X_3 + \dots + X_n}{n} - \mu \right| > \varepsilon \right) = 0$$

Use Chebyshev's inequality to prove the weak law of large numbers.

[Solution]:

Firstly,

$$\begin{aligned} & \Pr\left(\left|\frac{X_1 + X_2 + X_3 + \dots + X_n}{n} - \mu\right| > \varepsilon\right) \\ &= \Pr(|(X_1 + X_2 + \dots + X_n) - n\mu| > n\varepsilon). \end{aligned}$$

By Chebyshev's inequality and the independence of X_i 's, we have:

$$\begin{aligned} & \Pr(|(X_1 + X_2 + \dots + X_n) - n\mu| > n\varepsilon) \\ & \leq \frac{\text{Var}[X_1 + X_2 + \dots + X_n]}{(n\varepsilon)^2} \end{aligned}$$

[Cont.]:

$$\frac{\text{Var}[X_1 + X_2 + \dots + X_n]}{(n\varepsilon)^2} = \frac{\sum_{i=1}^n \text{Var}[X_i]}{n^2\varepsilon^2} = \frac{n\sigma^2}{n^2\varepsilon^2} = \frac{\sigma^2}{n\varepsilon^2}.$$

Combining, we have

$$\begin{aligned} \lim_{n \rightarrow \infty} \Pr \left(\left| \frac{X_1 + X_2 + X_3 + \dots + X_n}{n} - \mu \right| > \varepsilon \right) \\ \leq \lim_{n \rightarrow \infty} \frac{\sigma^2}{n\varepsilon^2} = 0 \end{aligned}$$

which completes the proof of the weak law of large numbers.

[Question 3]:

1. Determine the moment generating function for the binomial random variable $Bin(n, p)$.
2. Let X be a $Bin(n, p)$ random variable and Y be a $Bin(m, p)$ random variable. Suppose that X and Y are independent. Use part (a) to determine the moment generating function of $X + Y$.
3. What can we conclude from the form of the moment generating function of $X + Y$?

[Solution]:

(a) Given $X \sim \text{Bin}(n, p)$. Then, the MGF of X , $M_X(t)$, can be calculated as follows:

$$\begin{aligned}M_X(t) &= \mathbb{E}[e^{tX}] \\&= \sum_{k=0}^n \Pr(X = k) e^{tk} \\&= \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} e^{tk} \\&= \sum_{k=0}^n \binom{n}{k} (pe^t)^k (1-p)^{n-k} \quad (\text{Binomial theorem}) \\&= (pe^t + 1 - p)^n\end{aligned}$$

(Binomial theorem: $\sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} = (p + (1-p))^n$.)

[Cont.]:

(b) Since X and Y are independent, the MGF of $X + Y$ is thus:

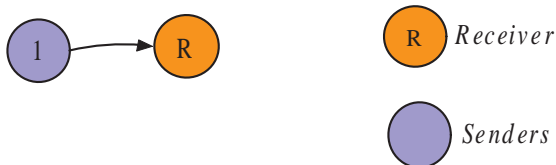
$$M_{X+Y}(t) = M_X(t) \times M_Y(t) = (pe^t + 1 - p)^{n+m}.$$

[Cont.]:

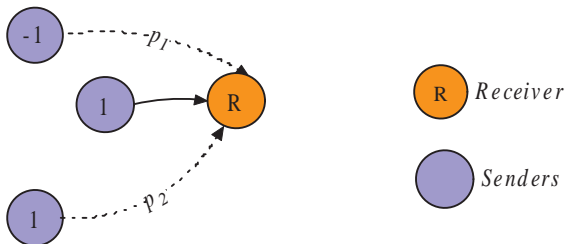
(c) The MGF in part (b) is the same as the MGF of a binomial random variable with parameters $n + m$ and p . Thus,
 $X + Y \sim \text{Bin}(n + m, p)$.

[Question 4]:

In a wireless communication system, each receiver listens on a specific frequency. The bit $b(t)$ sent at time t is represented by a 1 or -1 .



Unfortunately, noise from other nearby communications can affect the receiver's signal.



There are n senders and the i th has strength $p_i \leq 1$. The receiver obtains the signal $s(t)$ given by

$$s(t) = b(t) + \sum_{i=1}^n p_i b_i(t)$$

If $s(t)$ is closer to 1 than -1 , the receiver assumes that the bit sent at time t was a 1; otherwise, it was a -1 .

Assume that all the bit $b_i(t)$ can be considered independent, uniform random variables. Give a Chernoff bound to estimate the probability that the receiver makes an error in determining $b(t)$.

[Solution]:

Let X be the effect of combined noise. We may express X by p_i and b_i as:

$$X = p_1 b_1 + p_2 b_2 + \dots + p_n b_n.$$

Also, $\mu = E[X] = 0$.

From the question, we see that if the combined noise $|X| < 1$, the signal can be decoded properly. Thus,

$$\Pr(\text{receiver makes an error}) \leq \Pr(|X| \geq 1).$$

Below, we shall give a Chernoff bound for $\Pr(|X| \geq 1)$. First, we calculate the moment generating function of each $p_i b_i$:

$$\begin{aligned} M_{p_i b_i}(t) &= E[e^{t p_i b_i}] = \frac{1}{2} (e^{t p_i} + e^{-t p_i}) \\ &= \sum_{k \geq 0} \frac{(t p_i)^{2k}}{(2k)!} \\ &\leq e^{t^2 p_i^2 / 2}. \end{aligned}$$

[Cont.]:

This implies

$$M_X(t) \leq e^{t^2 K/2}, \quad \text{where } K = \sum_i p_i^2.$$

Thus, we have:

$$\begin{aligned} \Pr(|X| \geq 1) &= 2 \Pr(X \geq 1) \quad (X \text{ is symmetric around mean } \mu = 0) \\ &= 2 \Pr(e^{tX} \geq e^t) \\ &\leq \frac{2 \mathbb{E}[e^{tX}]}{e^t} = \frac{2M_X(t)}{e^t} \\ &\leq \frac{2e^{t^2 K/2}}{e^t}. \end{aligned}$$

The last term is minimized when we set $t = 1/K$, so that we obtain:

$$\Pr(|X| \geq 1) \leq 2e^{-1/(2K)}.$$

[Question 5]:

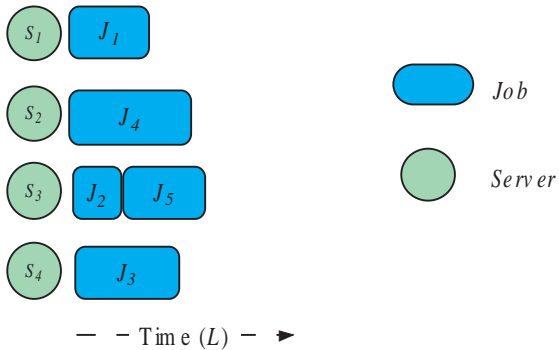
Let J_1, J_2, \dots, J_n be a set of jobs, where the i -th job J_i has an execution time of L_i seconds, $0 \leq L_i \leq 1$.

Suppose we have m servers, and we can assign the n jobs to run on them. The *load* of a server is the total execution time of all jobs assigned to it, and our goal is to find an assignment so that the load is as balanced as possible.

Randomized algorithm

└ Solution for assignment 2

└ Question 5



[Solution]:

(a) The expected load of each server is:

$$\bar{L} = \frac{\sum_{i=1}^n L_i}{m}.$$

[Cont.]:

(b) Let R_j denote the load assigned to server j . Then we have $E[R_j] = \bar{L}$.

On the other hand, let $R_{j,i}$ be a random variable such that it has value L_i if job J_i is assigned to server j , and it has value 0 otherwise. Then, we see that:

$$R_j = R_{j,1} + R_{j,2} + \cdots + R_{j,n}.$$

[Cont.]:

(b) Since R_j is the sum of independent random variables whose range is between 0 and 1, we can apply Theorem 1 immediately, and obtain:

$$\begin{aligned}\Pr(R_j \geq c\bar{L}) &= \Pr(R_j \geq c \mathbb{E}[R_j]) \\ &\leq e^{-\alpha \mathbb{E}[R_j]} = e^{-\alpha \bar{L}},\end{aligned}$$

where $\alpha = c \ln c + 1 - c$.

Thus by union bound,

$$\Pr(\text{some server has load at least } c\bar{L}) \leq me^{-\alpha \bar{L}}.$$

[Cont.]:

(c) Given $n = 100K$, $m = 10$, and the average job execution time is 0.25. Then $\sum_{i=1}^n L_i = 0.25n = 25K$ and $\bar{L} = 2500$.

$$\Pr(\text{all servers have load at most } 1.1\bar{L}) \geq 1 - e^{-9}.$$

means $c = 1.1$, thus α is about 0.004841.

By the result in part (b), we see that

$$\Pr(\text{some server has load at least } 1.1\bar{L}) \leq 10 e^{-0.004841 \times 2500} \leq e^{-9}.$$

Thus, we get the desired bound that

$$\Pr(\text{all servers have load at most } 1.1\bar{L}) \geq 1 - e^{-9}.$$

[Question 6] (Bonus):

This question attempts to prove Theorem 1. Part (a) establishes a useful fact, while the remaining parts proceed to give the proof.

(a) Let c and λ be two positive real numbers, with $c > 1$ and $0 \leq \lambda \leq 1$.

Show that for any $z \in [-\lambda, 1 - \lambda]$,

$$c^z \leq c^{-\lambda}(1 + \lambda(c - 1)) + z(c^{1-\lambda} - c^{-\lambda}).$$

Furthermore, argue that

$$c^z \leq c^{-\lambda}e^{\lambda(c-1)} + z(c^{1-\lambda} - c^{-\lambda}).$$

(b) Next, we define $\Delta_i = X_i - \mathbb{E}[X_i]$. (Recall that each X_i is a random variable whose value is in between 0 and 1.) Thus, we have

$$-\mathbb{E}[X_i] \leq \Delta_i \leq 1 - \mathbb{E}[X_i] \quad \text{and} \quad \mathbb{E}[\Delta_i] = \mathbb{E}[X_i - \mathbb{E}[X_i]] = 0.$$

Let $\Delta = \sum_{i=1}^n \Delta_i$. Show that

$$\Pr(X \geq c\mathbb{E}[X]) = \Pr(\Delta \geq (c-1)\mathbb{E}[X]) \leq \frac{\mathbb{E}[c^\Delta]}{c^{(c-1)\mathbb{E}[X]}}.$$

(c) Using Part (a), show that if we set $\lambda = E[X_i]$,

$$E[c^{\Delta_i}] \leq c^{-\lambda} e^{\lambda(c-1)} = e^{\lambda(c-1-\ln c)}.$$

(d) Argue that $E[c^{\Delta}] \leq e^{E[X](c-1-\ln c)}$ and complete the proof of the theorem.

[Solution]:

(a) Let $f(z) = c^{-\lambda}(1 + \lambda(c - 1)) + z(c^{1-\lambda} - c^{-\lambda}) - c^z$.

We may get $f'(z) = c^{1-\lambda} - c^{-\lambda} - zc^{z-1}$ and

$f''(z) = -z(z - 1)c^{z-2}$.

Observe that $f''(z) < 0$ when $z \in [-\lambda, 0)$ and $f''(z) \geq 0$ when $z \in [0, 1 - \lambda]$. This implies $f'(z)$ achieves the minimum value at $z = 0$. In other words:

$$f'(z) \geq f'(0) = c^{1-\lambda} - c^{-\lambda} \geq 0.$$

The above statement shows that $f(z)$ is monotonically increasing, so that

$$f(z) \geq f(-\lambda) = 0.$$

Thus, $c^z \leq c^{-\lambda}(1 + \lambda(c - 1)) + z(c^{1-\lambda} - c^{-\lambda})$, so that

$$c^z \leq c^{-\lambda}e^{\lambda(c-1)} + z(c^{1-\lambda} - c^{-\lambda}).$$

[Cont.]:

(b)

$$\begin{aligned}\Pr(X \geq c E[X]) &= \Pr\left(\sum_i X_i \geq c E[X]\right) \\ &= \Pr\left(\sum_i (\Delta_i + E[X_i]) \geq c E[X]\right) \\ &= \Pr(\Delta + E[X] \geq c E[X]) \\ &= \Pr(\Delta \geq (c - 1)E[X]) \\ &= \Pr(c^\Delta \geq c^{(c-1)E[X]}) \\ &\leq \frac{E[c^\Delta]}{c^{(c-1)E[X]}}.\end{aligned}$$

[Cont.]:

(c) By setting $\lambda = E[X_i]$,

$$\begin{aligned} E[c^{\Delta_i}] &\leq E[c^{-\lambda} e^{\lambda(c-1)} + \Delta_i(c^{1-\lambda} - c^{-\lambda})] \\ &= E[c^{-\lambda} e^{\lambda(c-1)}] \quad (\text{since } E[\Delta_i] = E[X_i - E[X_i]] = 0) \\ &= c^{-\lambda} e^{\lambda(c-1)} \quad (\text{since } \lambda = E[X_i] \text{ is a constant}) \\ &= e^{\lambda(c-1-\ln c)}. \end{aligned}$$

[Cont.]:

(d) Since $\Delta_1, \Delta_2, \dots, \Delta_n$ are independent, we have:

$$\mathbb{E}[c^\Delta] = \prod \mathbb{E}[c^{\Delta_i}] \leq \prod e^{\mathbb{E}[X_i](c-1-\ln c)} = e^{\mathbb{E}[X](c-1-\ln c)}.$$

Combining this with part (b), we have:

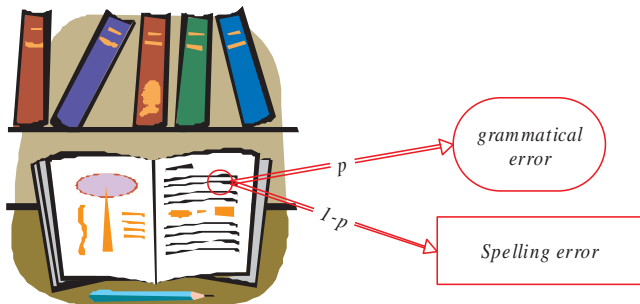
$$\begin{aligned} \Pr(X \geq c \mathbb{E}[X]) &\leq \frac{e^{\mathbb{E}[X](c-1-\ln c)}}{c^{(c-1)\mathbb{E}[X]}} \\ &= \frac{e^{\mathbb{E}[X](c-1-\ln c)}}{e^{(c \ln c - \ln c)\mathbb{E}[X]}} \\ &= e^{\mathbb{E}[X](c-1-\ln c - c \ln c + \ln c)} \\ &= e^{-\alpha \mathbb{E}[X]}, \end{aligned}$$

where $\alpha = c \ln c + 1 - c$.

Hint for assignment 3

[Question 1]: Let X be a Poisson random variable with mean μ , representing the number of errors on a page of this book. Each error is independently a grammatical error with probability p and a spelling error with probability $1 - p$. If Y and Z be random variables representing the number of grammatical and spelling errors(respectively) on a page of this book, prove that Y and Z are Poisson random variables with means μp and $\mu(1 - p)$, respectively. Also prove that Y and Z are independent.

[Hint]:



By definition of Poisson random variable with some condition. Try to show $\Pr(Y = k) = ?$ and $\Pr(Z = k) = ?$

[Question 2]: Let Z be a Poisson random variable of mean μ , where $\mu \geq 1$ is an integer.

1. Show that $\Pr(Z = \mu + h) \geq \Pr(Z = \mu - h - 1)$ for $0 \leq h \leq \mu - 1$.
2. Using part (a), argue that $\Pr(Z \geq \mu) \geq 1/2$.

[Hint]:

We may use the definition of Poisson distribution in page 14 of Lecture Note 13.

Definition:

A discrete Poisson random variable X with parameter μ is given by the following probability distribution for $r = 0, 1, 2, \dots$:

$$Pr(X = r) = e^{-\mu} \mu^r / r!$$

[Question 3]: In Page 14 of Lecture Notes 14 we showed that, for any nonnegative functions f ,

$$E[f(Y_1^{(m)}, \dots, Y_n^{(m)})] \geq E[f(X_1^{(m)}, \dots, X_n^{(m)})] \Pr(\sum Y_i^{(m)} = m)$$

1. Now suppose we further know that $E[f(X_1^{(m)}, \dots, X_n^{(m)})]$ is monotonically increasing in m . Show that

$$E[f(Y_1^{(m)}, \dots, Y_n^{(m)})] \geq E[f(X_1^{(m)}, \dots, X_n^{(m)})] \Pr(\sum Y_i^{(m)} \geq m)$$

2. Combining part (a) and part (b) with the results in Question 2, prove the theorem in Page 20 of Lecture Notes 14.

[Hint]:

Re-examine the proof of Page 15 in Lecture Notes 14 (and show tighter bound when we know $f(x_1, x_2, \dots, x_n)$ is monotonically increasing in m)

[Question 4]: We consider another way to obtain Chernoff-like bound in the balls-and-bins setting without using the theorem in Page 13 of Lecture 14.

Consider n balls thrown randomly into n bins. Let $X_i = 1$ if the i -th bin is empty and 0 otherwise. Let $X = \sum_{i=1}^n X_i$.

Let Y_i be independent Bernoulli random variable such that $Y_i = 1$ with probability $p = (1 - 1/n)^n$. Let $Y = \sum_{i=1}^n Y_i$.

1. Show that $E[X_1 X_2 \cdots X_k] \leq E[Y_1 Y_2 \cdots Y_k]$ for any $k \geq 1$.
2. Show that $X_1^{j_1} X_2^{j_2} \cdots X_k^{j_k} = X_1 X_2 \cdots X_k$ for any $j_1, j_2, \dots, j_k \in \mathbb{N}$.
3. Show that $E[e^{tX}] \leq E[e^{tY}]$ for all $t \geq 0$.
Hint: Use the expansion for e^x and compare $E[e^{tX}]$ to $E[e^{tY}]$.
4. Derive a Chernoff bound for $Pr(X \geq (1 + \delta)E[X])$.

[Hint]:
Add oil.

Thank you