Information Theory and Signal Processing
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Problem Set 5 — *Due Friday, November 30, before class starts*

For the Exercise Session on Nov 16 and 23

Last name	First name	SCIPER Nr	Points

Problem 1: KL Divergence

Compute the KL Divergence of two scalar Gaussians $p(x) = \mathcal{N}(\mu_1, \sigma_1^2)$ and $q(x) = \mathcal{N}(\mu_2, \sigma_2^2)$.

Solution Let p_i, $i = 1, 2$, be two Gaussians with means μ_i and variances σ_i^2. We have

$$\begin{aligned} D_{KL}(P_1||P_2) &= \int p_1(x) \ln \frac{p_1(x)}{p_2(x)} dx \\ &= -\frac{1}{2}\ln(2\pi e \sigma_1^2) + \frac{1}{2}\ln(2\pi\sigma_2^2) + \frac{1}{2\sigma_2^2}\int p_1(x)(x-\mu_2)^2 dx \\ &= -\frac{1}{2}\ln(2\pi e \sigma_1^2) + \frac{1}{2}\ln(2\pi\sigma_2^2) + \frac{1}{2\sigma_2^2}(\mu_1^2 + \sigma_1^2 - 2\mu_1\mu_2 + \mu_2^2) \\ &= \ln(\sigma_2/\sigma_1) + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2} - \frac{1}{2}. \end{aligned}$$

Problem 2: Hoeffding's Lemma

Prove Lemma 7.4 in the lecture notes. In other words, prove that if X is a zero-mean random variable taking values in $[a, b]$ then

$$\mathbb{E}[e^{\lambda X}] \leq e^{\frac{\lambda^2}{2}[(a-b)^2/4]}.$$

Expressed differently, X is $[(a-b)^2/4]$-subgaussian.

Solution Since $e^{\lambda x}$ is convex in x we have for all $a \leq x \leq b$,

$$e^{\lambda x} \leq \frac{b-x}{b-a}e^{\lambda a} + \frac{x-a}{b-a}e^{\lambda b}.$$

If we take the expected value of this wrt X and recall that $\mathbb{E}[X] = 0$ then it follows that

$$\mathbb{E}[e^{\lambda X}] \leq \frac{b}{b-a}e^{\lambda a} - \frac{a}{b-a}e^{\lambda b}.$$

Consider the right-hand side. Note that we must have $a < 0$ and $b > 0$ since $\mathbb{E}[X] = 0$. Set $p = -a/(b-a)$, $0 \leq p \leq 1$, and $\lambda' = \lambda(b-a)$. The right-hand side can then be written as

$$(1-p)e^{-\lambda' p} + pe^{\lambda'(1-p)} \leq e^{\frac{\lambda'^2}{8}} = e^{\frac{\lambda^2}{2}[(b-a)^2/4]},$$

where in the first step we have used the inequality we have seen in class for the Bernoulli random variable with parameter p.

An alternative way to solve this problem could be define $\phi(\lambda) = \ln \mathbb{E}[e^{\lambda X}]$.

$$\phi'(\lambda) = \frac{d}{d\lambda} \ln \mathbb{E}[e^{\lambda X}] = \frac{\mathbb{E}[X e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]}$$

So $\phi(0) = \frac{0}{1} = 0$.

$$\phi''(\lambda) = \frac{d}{d\lambda}\phi'(\lambda) = \frac{d}{d\lambda} \frac{\mathbb{E}[X e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]} = \frac{\mathbb{E}[X^2 e^{\lambda X}]\mathbb{E}[e^{\lambda X}] - \mathbb{E}[X e^{\lambda X}]\mathbb{E}[X e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]^2}$$

For $\lambda = 0$, we have

$$\phi''(0) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \mathrm{var}(X)$$

Also, we have $\phi(\lambda) \leq \phi(0) + \phi'(0)\lambda + \phi''(0)\frac{\lambda^2}{2} = \frac{\lambda^2}{2}\mathrm{var}(X)$ As X is random variable taking values in $[a, b]$. The largest variance is achieved when $\mathbb{P}\{X = a\} = \frac{b}{b-a}$ $\mathbb{P}\{X = b\} = \frac{-a}{b-a}$.

$$\mathrm{var}(X) \leq \frac{(b-a)^2}{4} \tag{1}$$

Therefore we have

$$\mathbb{E}[e^{\lambda X}] \leq e^{\frac{\lambda^2}{2}\frac{(b-a)^2}{4}}$$

X is $[(b-a)^2/4]$-subgaussian.

Problem 3: Epsilon-Greedy Algorithm

Recall our original *explore-then-exploit* strategy. We had a fixed time horizon n. For some m, a function of n and the gaps $\{\Delta_k\}$, we explore each of the K arms m times initially. Then we pick the best arm according to their empirical gains and play this arm until we reach round n. We have seen that this strategy achieves an asymptotic regret of order $\ln(n)$ if the environment is fixed and we think of n tending to infinity but a worst-case regret of order $\sqrt{n}$ if we use the gaps when determining m and of order $n^{\frac{2}{3}}$ if we do not use the gaps in order to determine m.

Here is a slightly different algorithm. Let $\epsilon_t = t^{-\frac{1}{3}}$. For each round $t = 1, \cdots,$, toss a coin with success probability ϵ_t. If success, then explore arms uniformly at random. If not success, then pick in this round the arm that currently has the highest empirical average.

Show that for this algorithm the expected regret at *any* time t is upper bounded by $t^{\frac{2}{3}}$ times terms in t and K of lower order. This is a similar to the worst-case of the explore-then-exploit strategy but here we do not need to know the horizon a priori. Assume that the rewards are in $[0, 1]$.

Solution The expected regret has two components. The first component is due to the fact if the coin toss results in success then explore. In this case we can get a regret of at most 1. Therefore, this contribution can be upper bounded by

$$\sum_{i=1}^{t} i^{-\frac{1}{3}} \leq 1 + \int_1^t x^{-\frac{1}{3}} dx \leq \frac{3}{2} t^{\frac{2}{3}}.$$

The second contribution comes from the exploitation phase.

Let $B_t \in \{0,1\}$ denote the result of coin-toss at round t with $\mathbb{P}\{B_t = 1\} = \epsilon_t$ (success) and $\mathbb{P}\{B_t = 0\} = 1 - \epsilon_t$ (fail). Then the average regret at time t with X_t as the reward for the round t is

$$\begin{aligned} R_t &= t\mu^* - \mathbb{E}[\sum_{i=1}^{t} X_i] \\ &= t\mu^* - \sum_{i=1}^{t} \mathbb{E}[\mathbb{E}[X_i|B_i]] \\ &= t\mu^* - \sum_{i=1}^{t} (\mathbb{E}[X_i|B_i = 1]\mathbb{P}\{B_i = 1\} + \mathbb{E}[X_i|B_i = 0]\mathbb{P}\{B_i = 0\}) \\ &= t\mu^* - \sum_{i=1}^{t} \epsilon_i \mathbb{E}[X_i|B_i = 1] - \sum_{i=1}^{t}(1 - \epsilon_i)\mathbb{E}[X_i|B_i = 0] \end{aligned}$$

Note that given $B_i = 1$, X_i is the reward that we uniformly pick an arm. Hence

$$E[X_i|B_i = 1] = \frac{1}{K}\sum_{k=1}^{K} \mu_k$$

Note that given $B_i = 0$, X_i is the reward that we pick the arm that has highest empirical average. Hence

$$E[X_i|B_i = 0] = \sum_{k=1}^{K} \mu_k \mathbb{P}\{k = \arg\max_j \hat{\mu}_j(i-1)\}$$

where $\hat{u}_j(i-1)$ is the empirical estimator of μ_j arm j until round $i-1$. We assume that arm 1 has the largest expected reward, $\mu^* = \mu_1$. Since, the more samples we have, the higher probability that the empirical mean converges to real mean and the higher probability that we choose the arm with largest mean. Since, until time step t, averagely there are $\sum_{i=1}^{t} i^{-1/3} > t^{2/3}$ samples from the exploration phase. Hence for large i, we have $T_j(i-1) > \frac{(i-1)^{2/3}}{K}$ for all $j = 1\dots, K$, since we choose the arm uniformly at random[1]. Then

$$\begin{aligned} \mathbb{P}\{k = \arg\max_j \hat{\mu}_j(i-1)\} &\leq \mathbb{P}\{\hat{\mu}_1(i-1) - \hat{\mu}_k(i-1) \leq 0\} \\ &= \mathbb{P}\left\{ \frac{1}{T_1(i-1)} \sum_{j=1}^{T_1(i-1)} X_j^{(1)} - \frac{1}{T_k(i-1)} \sum_{j=1}^{T_k(i-1)} X_j^{(k)} \leq 0 \right\} \\ &\leq e^{-\frac{(i-1)^{2/3}\Delta_k^2}{4K}} \end{aligned}$$

[1] In fact, $T_j(i-1)$ is a random variable and we do not know the exact value of it.

Hence the average regret at round t is given by

$$\begin{aligned}
R_t &= t\mu^* - \sum_{i=1}^{t} \epsilon_i \frac{1}{K} \sum_{k=1}^{K} \mu_k - \sum_{i=1}^{t} (1-\epsilon_i) \sum_{k=1}^{K} \mu_k \mathbb{P}\{k = \arg\max_j \hat{u}_j(i-1)\} \\
&= \sum_{i=1}^{t} \epsilon_i (\mu^* - \frac{1}{K}\sum_{k=1}^{K} \mu_k) + \sum_{i=1}^{t} (1-\epsilon_i)(\mu^* - \sum_{k=1}^{K} \mu_k \mathbb{P}\{k = \arg\max_j \hat{u}_j(i-1)\}) \\
&= \mathbb{E}[\Delta_k] \sum_{i=1}^{t} \epsilon_i + \sum_{i=1}^{t} (1-\epsilon_i) \sum_{k=1}^{K} \Delta_k \mathbb{P}\{k = \arg\max_j \hat{u}_j(i-1)\} \\
&\le \frac{3}{2} t^{\frac{2}{3}} + \sum_{i=1}^{t} (1-\epsilon_i) K e^{-\frac{(i-1)^{2/3}\Delta_*^2}{4K}} \\
&< \frac{3}{2} t^{\frac{2}{3}} + (t - t^{2/3}) K e^{-\frac{(t-1)^{2/3}\Delta_*^2}{4K}}
\end{aligned}$$

where $\Delta_* = \min_{j\in\{2,\dots,K\}} \Delta_j$. Note that $\mathbb{E}[\Delta_k] \le 1$ due to $0 \le \Delta_k \le 1$, and $\sum_{i=1}^{t} \epsilon_i = \sum_{i=1}^{t} i^{-1/3} \le \int_1^t x^{-1/3} dx \le \frac{3}{2} t^{\frac{2}{3}}$

Problem 4: Upper Confidence Bound Algorithm

In the course we analyzed the Upper Confidence Bound algorithm. As was suggested in the course, we should get something similar if instead we use the Lower Confidence Bound algorithm. It is formally defined as follows.

$$A_t = \begin{cases} t, & t \le K, \\ \arg\max_k \hat{\mu}_k(t-1) - \sqrt{\frac{2\ln f(t)}{T_k(t-1)}}, & t > K. \end{cases}$$

Analyze the performance of this algorithm in the same way as we did this in the course for the UCB algorithm.

Hint: Is this algorithm well designed?

Solution Recall the lower bound

$$\mathbb{P}\{\hat{\mu}(X_1,\dots,X_m) \le \mu - \epsilon\} \le \exp(-m\epsilon^2/2)$$

If we set the right-hand side to $\delta > 0$ and solve for δ we get

$$\mathbb{P}\{\hat{\mu}(X_1,\dots,X_m) - \mu \le \sqrt{\frac{2}{m}\ln(\frac{1}{\delta})}\} \le \delta$$

If we consider δ as small then this suggests that, at time $t-1$, it is unlikely that our empirical estimator $\hat{\mu}_k(t-1)$ of the $k-$th bandit arm underestimates its mean by more than $\frac{2}{T_k(t-1)}\ln(\frac{1}{\delta})$, where $T_k(t-1)$ denotes the number of times we have chosen arm k in the first $t-1$ steps. We choose the *confidence* level δ_t as

$$\delta_t = \frac{1}{f(t)} = \frac{1}{1 + t\ln^2(t)}$$

We have the algorithm A_t shown as the problem statement.

Actually, this Lower Confidence Bound algorithm is not well designed. Consider the time $t \geq K+1$, for the k-th arm, define the

$$B_k(t) = \hat{\mu}_k(t-1) - \sqrt{\frac{2\ln f(t)}{T_k(t-1)}}$$

Suppose that

$$k^* = \arg\max_k B_k(K+1) \tag{2}$$

Then the k^*-th arm is chosen at the $K+1$ round.

For the next round $t = K+2$, for the k^*-th arm, we have

$$\begin{aligned} B_{k^*}(K+2) &= \hat{\mu}_{k^*}(K+1) - \sqrt{\frac{2\ln f(K+2)}{T_{k^*}(K+1)}} \\ &= \hat{\mu}_{k^*}(K+1) - \sqrt{\frac{2\ln f(K+2)}{2}} \end{aligned}$$

Since the sample from the k^*-th arm at $K+1$ round can be large or small, we don't know which of $\hat{\mu}_{k^*}(K+1)$ and $\hat{\mu}_{(k^*)}(K)$ is larger. Thus, $B_{k^*}(K+2)$ may be larger than $B_{k^*}(K+1)$.

For the other arms other than k^*, we have

$$\begin{aligned} B_k(K+2) &= \hat{\mu}_k(K+1) - \sqrt{\frac{2\ln f(K+2)}{T_k(K+1)}} \\ &= \hat{\mu}_k(K) - \sqrt{\frac{2\ln f(K+2)}{T_k(K)}} \\ &< \hat{\mu}_k(K) - \sqrt{\frac{2\ln f(K+1)}{T_k(K)}} \\ &= B_k(K+1) \end{aligned}$$

as $\hat{\mu}_k(K+1) = \hat{\mu}_k(K)$ and $T_k(K+1) = T_k(K) = 1$, since the k-th arm was not selected in last round.

This means that choosing the k^*-th arm at $t = K+1$ decreases the "confidence" $B_k(t)$ of other arms, while the confidence of the chosen arm k^* is not necessarily decreases. And if at $t = K+1$, we unluckily choose a suboptimal arm, we may get stuck at the suboptimal arm.

If you compare this Lower Confidence Bound algorithm with the Upper Confidence Bound algorithm in the lecture notes, you can find that in the UCB algorithm, choosing one arm in current round will reduce the increase rate of confidence of such arm in the next round compared with other unchosen arms. Thus, in the next round, it is more likely to choose other arms. As a result, every arm should be sampled enough instead of being trapped in one arm.