

# Homework Assignment 1

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## 1 Numerical comparison of $kl$ inequality with its relaxations and with Hoeffding's inequality (25 points)

### 1.1

Hoeffding's inequality :

$$\mathbb{P}(|p - \hat{p}| \leq \sqrt{\frac{\ln \frac{1}{\delta}}{2n}}) \geq 1 - \delta$$

$$\text{upper bound : } p \leq \hat{p} + \sqrt{\frac{\ln \frac{1}{\delta}}{2n}}$$

$$\text{lower bound : } p \geq \hat{p} - \sqrt{\frac{\ln \frac{1}{\delta}}{2n}}$$

**kl-inequality** : On page 17 in Yevgeny's lecture notes,

$$\text{kl}(\hat{p}||p) \leq \frac{\ln \frac{n+1}{\delta}}{n}$$

From question, we can get

$$\text{upper bound : } p \leq \text{kl}^{-1+}(\hat{p}_n, \frac{\ln \frac{n+1}{\delta}}{n})$$

$$\text{lower bound : } p \geq \text{kl}^{-1-}(\hat{p}_n, \frac{\ln \frac{n+1}{\delta}}{n})$$

**Pinsker's relaxation of kl inequality** : On page 18,

$$|p - \hat{p}| \leq \sqrt{\frac{\text{kl}(\hat{p}||p)}{2}} \leq \sqrt{\frac{\ln \frac{n+1}{\delta}}{2n}}$$

$$\text{upper bound : } p \leq \hat{p} + \sqrt{\frac{\ln \frac{n+1}{\delta}}{2n}}$$

$$\text{lower bound : } p \geq \hat{p} - \sqrt{\frac{\ln \frac{n+1}{\delta}}{2n}}$$

**Refined Pinsker's relaxation of kl inequality** : On page 18,

$$p \leq \hat{p} + \sqrt{\frac{2\hat{p} \ln \frac{n+1}{\delta}}{n}} + \frac{2 \ln \frac{n+1}{\delta}}{n}$$

## 1.2

Hoeffding's, Pinsker's and Refined Pinsker's inequality is clearly to implement the bound. But kl-inequality is not so obvious, we want to get the inversion, which may not calculate directly. Hence, we use binary search to iterate  $p$  and get the maximum and minimum.

Firstly, we define an initial  $p_i = \frac{\hat{p}_i + 1}{2}$  and an initial step  $\frac{(1-\hat{p}_i)}{4}$ . If  $\text{kl} \leq \frac{\ln \frac{n+1}{\delta}}{n}$ , it means the current  $p_i$  is available, we can still try to maximize it. If  $\text{kl} \geq \frac{\ln \frac{n+1}{\delta}}{n}$ , it means the current  $p_i$  is not available, we should reduce it. After that, we will renew the step by  $\text{step} = \text{step}/2$ . Until the step smaller than a precision (I used the  $\epsilon = 0.00001$ ), we get the final  $p_i$ . Then  $\hat{p}_{i+1}$  will be used to repeat these steps. Finally, we will get the upper bound.

For lower bound, we will change the steps about renew  $p$ . If the condition about kl is satisfy, we will decrease  $p$ , otherwise increase.

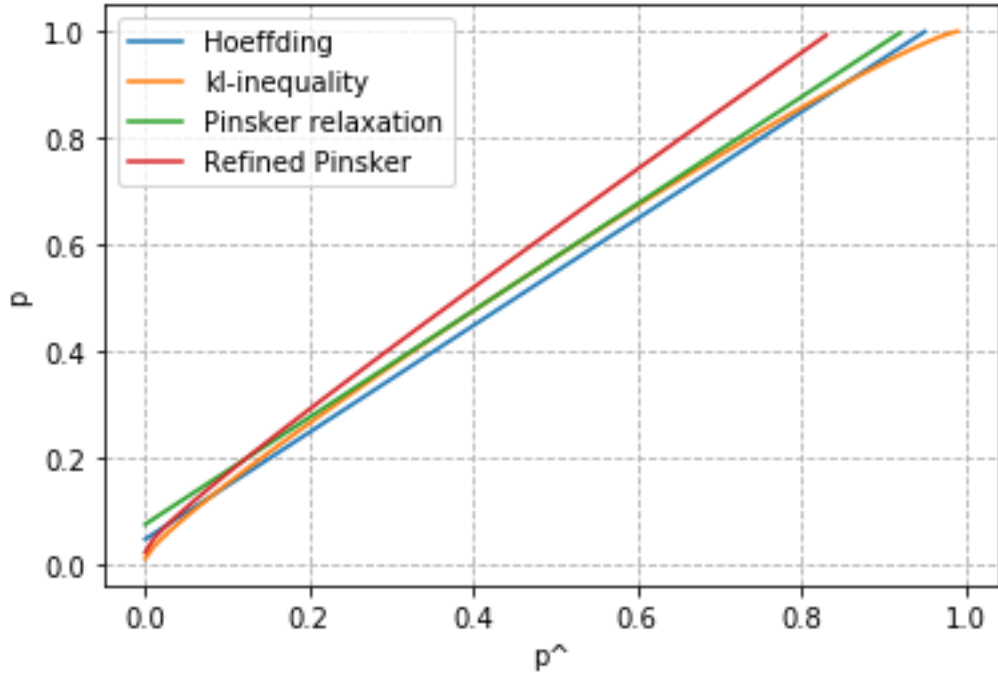


Figure 1: **Four upper bounds on  $p$  as a function of  $\hat{p}_n$  (for  $\hat{p}_n \in [0, 1]$ ,  $n = 1000$ , and  $\delta = 0.01$ )**

### 1.3

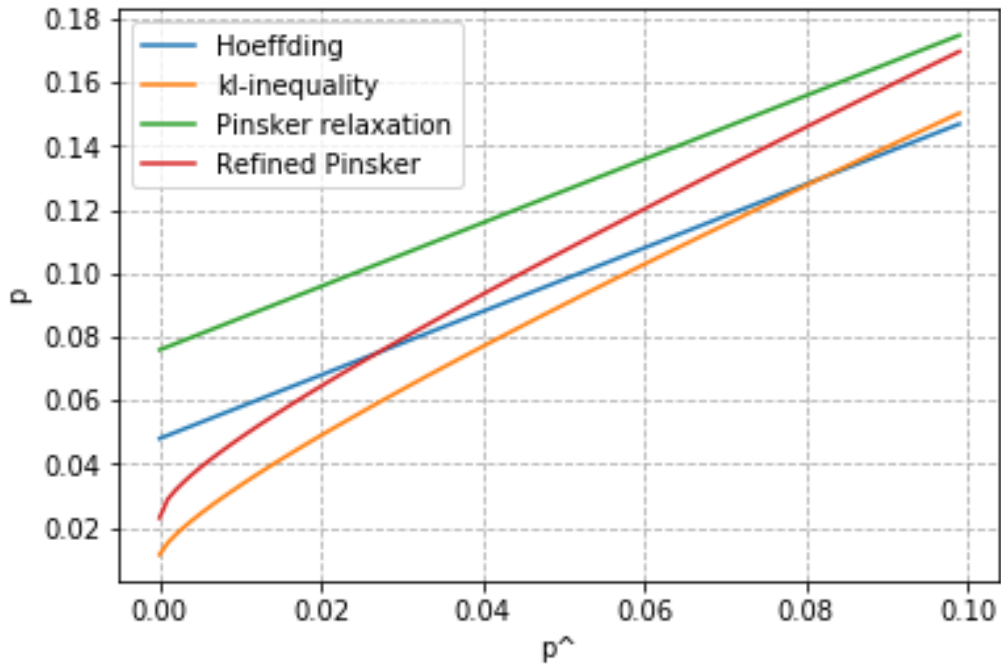


Figure 2: **Four upper bounds on  $p$  as a function of  $\hat{p}_n$  (for  $\hat{p}_n \in [0, 0.1]$ ,  $n = 1000$ , and  $\delta = 0.01$ )**

## 1.4

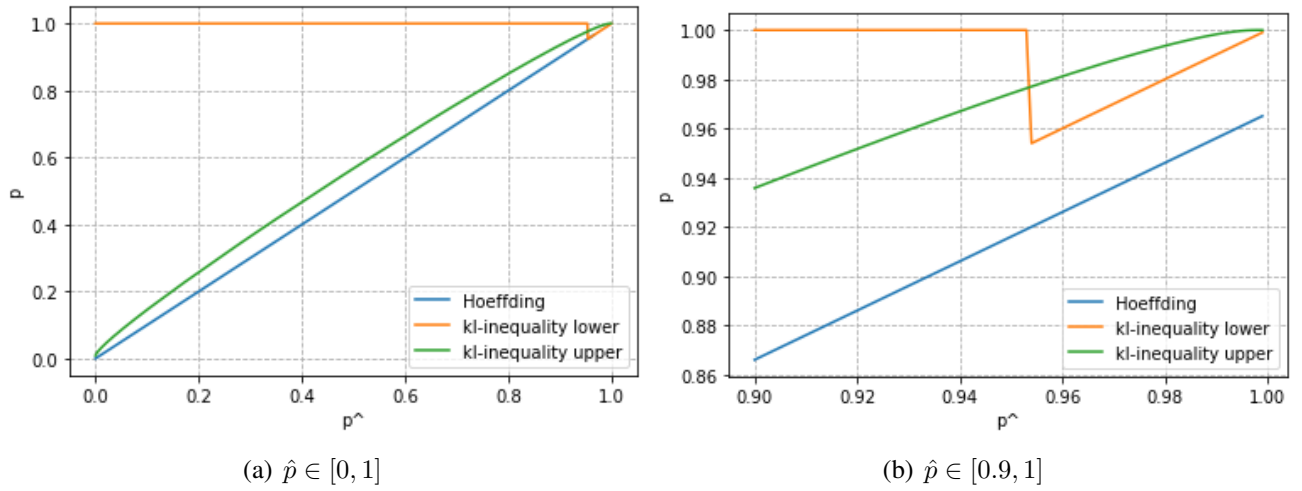


Figure 3: **Two lower bounds on  $p$  as a function of  $\hat{p}_n$  (for  $n = 1000$ , and  $\delta = 0.01$ )**

By Fig.3(a), a part of lower bound is greater than upper bound. Because the lower bound is smaller than upper bound, we only pay attention on the interval  $[0.9, 1]$ , the part that the line of upper bound is higher than lower bound. When  $\hat{p}$  close to 1, the lines seem to overlap. In fact, the kl-inequality still tighter. From Fig.3(b), we can see when close to 0.955, the difference is not significant, but the line of kl-inequality is still a little higher. It means the kl-inequality's lower bound is always tighter than Hoeffding's.

## 1.5

By Fig.1, overall, the Refined Pinsker inequality's upper bound is always the worst, if  $\hat{p}$  is greater than nearly 0.3. When  $\hat{p}$  in the area about  $[0.2, 0.6]$ , the kl-inequality's upper bound is similar with Pinsker relaxation inequality's. Meanwhile, the Hoeffding's upper bound is the tightest in this interval. However, with  $\hat{p}$  become close to 1, the kl-inequality's becomes tighter than others. In Fig.2, it is clearly that the kl-inequality's upper bound is the tightest when  $\hat{p}$  close to 0. It means that if  $\hat{p}$  close to extrem value :0 and 1, the kl-inequality's will be the best. Also, the Refined Pinsker's shows tighter than Hoeffding's. When  $\hat{p}$  is small, the Pinsker relaxation is the worst bound.

## 2 Refined Pinsker's Lower Bound (20 points)

By Lemma 2.18 on page 18 in Yevgeny's lecture notes, we can get Refined Pinsker's inequality,

$$\text{kl}(p||q) \geq \frac{(p-q)^2}{2 \max\{p, q\}} + \frac{(p-q)^2}{2 \max\{(1-p), (1-q)\}}$$

If  $p \geq q$ ,

$$\begin{aligned} \text{kl}(p||q) &\geq \frac{(p-q)^2}{2 \max\{p, q\}} + \frac{(p-q)^2}{2 \max\{(1-p), (1-q)\}} \\ &= \frac{(p-q)^2}{2p} + \frac{(p-q)^2}{2(1-p)} \\ &\geq \frac{(p-q)^2}{2p} \end{aligned}$$

From question, we know  $\text{kl}(p\|q) \leq \epsilon$ .

$$\begin{aligned}\epsilon \geq \text{kl}(p\|q) &\geq \frac{(p-q)^2}{2p} \implies 2p\epsilon \geq (p-q)^2 \quad (p \geq q, \text{ so } p-q \geq 0) \\ &\implies \sqrt{2p\epsilon} \geq p-q \\ &\implies q \geq p - \sqrt{2p\epsilon}\end{aligned}$$

If  $q \geq p$ ,

$$\begin{aligned}q \geq p &\implies q-p \geq 0 \\ &\implies q-p \geq -\sqrt{2p\epsilon} \\ &\implies q \geq p - \sqrt{2p\epsilon}\end{aligned}$$

So, the inequality  $q \geq p - \sqrt{2p\epsilon}$  is proved.

### 3 Occam's razor with $kl$ inequality (20 points)

From question, we know that we want to prove,

$$\mathbb{P}(\forall h \in \mathcal{H}, \text{kl}(\hat{L}(h, S)\|L(h)) \leq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) \geq 1 - \delta$$

It can be processed like,

$$\begin{aligned}\implies 1 - \mathbb{P}(\forall h \in \mathcal{H}, \text{kl}(\hat{L}(h, S)\|L(h)) \leq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) &\leq \delta \\ \implies 1 - \mathbb{P}(\bigcup_i h_i, \text{kl}(\hat{L}(h, S)\|L(h)) \leq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) &\leq \delta \\ \implies \mathbb{P}(\bigcap_i h_i, \text{kl}(\hat{L}(h, S)\|L(h)) > \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) &\leq \delta \\ \implies \mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\hat{L}(h, S)\|L(h)) \geq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) &\leq \delta\end{aligned}$$

Hence, our aim is to prove the last line,

$$\begin{aligned}
\mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\hat{L}(h, S) \| L(h)) \geq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) &\leq \sum_{h \in \mathcal{H}} \mathbb{P}(\text{kl}(\hat{L}(h, S) \| L(h)) \geq \frac{\ln \frac{n+1}{\pi(h)\delta}}{n}) \\
&= \sum_{h \in \mathcal{H}} \mathbb{P}(n \text{kl}(\hat{L}(h, S) \| L(h)) \geq \ln \frac{n+1}{\pi(h)\delta}) \\
&= \sum_{h \in \mathcal{H}} \mathbb{P}(e^{n \text{kl}(\hat{L}(h, S) \| L(h))} \geq e^{\ln \frac{n+1}{\pi(h)\delta}}) \\
&= \sum_{h \in \mathcal{H}} \mathbb{P}(e^{n \text{kl}(\hat{L}(h, S) \| L(h))} \geq \frac{n+1}{\pi(h)\delta}) \\
&\leq \sum_{h \in \mathcal{H}} \frac{\mathbb{E}(e^{n \text{kl}(\hat{L}(h, S) \| L(h))})}{\frac{n+1}{\pi(h)\delta}} \\
&\leq \frac{n+1}{\sum_{h \in \mathcal{H}} \pi(h)\delta} = \sum_{h \in \mathcal{H}} \pi(h)\delta \\
&\leq \delta
\end{aligned}$$

where in the forth line we apply Markov's inequality, and the next line follows Lemma 2.14 on page 17 in Yevgeny's lecture notes.

$\delta$  is the probability that we allow things to become bad.  $\pi(h)$  is the distribution of  $\delta$ . For each hypothesis  $h \in \mathcal{H}$  the sample  $S$  is allowed to be “non representative” with probability at most  $\pi(h)\delta$ .  $\pi(h)$  should be independent of  $S$ , if not the fifth line will not hold. Because it used Markov's inequality  $\mathbb{P}(X \geq \epsilon) \leq \frac{\mathbb{E}[X]}{\epsilon}$ . The parameter  $\epsilon$  has to be independent of  $X$ .

## 4 PAC-Bayes vs. Occam (10 points)

### 4.1

From question, we know that we want to prove,

$$\mathbb{P}(\forall h \in \mathcal{H}, \text{kl}(\mathbb{E}_\rho[\hat{L}(h, S)] \| \mathbb{E}_\rho[L(h)]) \leq \frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta}}{n}) \geq 1 - \delta$$

Similar with question 4, we will prove,

$$\mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\mathbb{E}_\rho[\hat{L}(h, S)] \| \mathbb{E}_\rho[L(h)]) \geq \frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta}}{n}) \leq \delta$$

$$\begin{aligned}
& \mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\mathbb{E}_\rho[\hat{L}(h, S)] \| \mathbb{E}_\rho[L(h)]) \geq \frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta}}{n}) \\
& \leq \mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\mathbb{E}_\rho[\hat{L}(h, S)] \| \mathbb{E}_\rho[L(h)]) \geq \frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta} - H(\rho)}{n}) \\
& = \mathbb{P}(\exists h \in \mathcal{H}, \text{kl}(\mathbb{E}_\rho[\hat{L}(h, S)] \| \mathbb{E}_\rho[L(h)]) \geq \frac{\text{KL}(\rho \| \pi) + \ln \frac{n+1}{\delta}}{n}) \\
& \leq \delta
\end{aligned}$$

The second step follows the decomposition of KL-divergence, the third was applied Theorem 3.26 PAC-Bayes-kl inequality on page 39 in notes.

The decomposition of KL-divergence:

$$\text{KL}(\rho \| \pi) = \mathbb{E}_\rho[\ln \frac{\rho}{\pi}] = \mathbb{E}_\rho[\ln \frac{1}{\pi}] - H(\rho)$$

## 4.2

In this question, we will prove,

$$\frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta}}{n} \geq \frac{\text{KL}(\rho \| \pi) + \ln \frac{n+1}{\delta}}{n}$$

We can get,

$$\begin{aligned}
\frac{\mathbb{E}_\rho[\ln \frac{1}{\pi(h)}] + \ln \frac{n+1}{\delta}}{n} &= \frac{\text{KL}(\rho \| \pi) + H(\rho) + \ln \frac{n+1}{\delta}}{n} & (H(\rho) \geq 0) \\
&\geq \frac{\text{KL}(\rho \| \pi) + \ln \frac{n+1}{\delta}}{n}
\end{aligned}$$

Hence, we can get the answer.