

Statistical Inference and Learning- Ex-1

Yaniv Tenzer and Boaz Nadler

Due on Tuesday, April 16, 2019,
email submissions: `stat.wisdom@gmail.com`

Q1 The mean height in Israel is 169cm, with standard deviation of 9cm. What is the probability of an Israeli being taller than 190cm according to Markov? Chebychev? Assuming a Gaussian distribution? Can you use Hoeffding? Explain your answers!

Q2 Let X_1, \dots, X_n be n i.i.d. random variables from a distribution F with mean μ and finite variance σ^2 . Suppose we wish to estimate the mean μ . A natural estimator is the sample mean $\bar{X}_n = \frac{1}{n} \sum_i X_i$. Recall that the standard error of the sample mean, namely $\sqrt{\mathbb{E}(\bar{X}_n - \mu)^2}$ decays like $1/\sqrt{n}$. Interestingly, there are cases where one can estimate population parameters (such as the mean) at a much *faster* rate. If they exist, these are known as *superefficient* estimators.

In this question we consider one such case: Let X_i be i.i.d. from a uniform distribution $U[0, \theta]$, where θ is an unknown parameter. Thus, $\mathbf{X} = (X_1, \dots, X_n)$ has a joint density function

$$f(\mathbf{x}; \theta) = \frac{1}{\theta^n} \quad 0 \leq x_1, \dots, x_n \leq \theta.$$

Clearly the mean of all X_i is $\mu = \theta/2$.

i) One method to estimate μ is by the sample mean $\frac{1}{n} \sum_i X_i$. What is the precise standard deviation of this estimator?

A Different Approach: A different method is based on the maximum observed value of the X_i 's. Let $Y_n = \max X_i$.

ii) What is $\mathbb{E}[Y_n]$ and what is $Var[Y_n]$? How can Y_n be used to construct a different estimator for μ , and what is its standard error as a function of sample size n ? Is it more accurate than the sample mean?

Q3 Consider a real-valued random variable X for which there is some constant $c > 0$ such that

$$\forall \lambda \in (-c, c), \quad \mathbb{E}[e^{\lambda X}] < +\infty.$$

1. Show that the expectation of the absolute value of X , $\mathbb{E}|X|$, is finite.
2. Show that the function

$$f : \lambda \in (-c, c) \mapsto \mathbb{E}[e^{\lambda X}]$$

is infinitely differentiable and its k -th derivative is

$$\forall \lambda \in (-c, c), \quad f^{(k)}(\lambda) = \mathbb{E}[X^k e^{\lambda X}].$$

3. Show that there is some constant $s > 0$ such that

$$\forall \lambda \in [-c/2, c/2], \quad \mathbb{E}e^{\lambda(X - \mathbb{E}X)} \leq e^{s\lambda^2}.$$

4. Show that as a result, we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \begin{cases} e^{-\frac{t^2}{4s}}, & t \in [0, sc] \\ e^{-\frac{ct}{4}}, & t \in (sc, +\infty). \end{cases}$$

5. Let $Z = \sum_{i=1}^m X_i^2$ where $(X_i)_{1 \leq i \leq m}$ are m i.i.d. standard Gaussian r.v. $\mathcal{N}(0, 1)$. The random variable Z follows a chi-squared distribution with m degrees of freedom, and is denoted as $Z \sim \chi_m^2$. Compute the mean and standard deviation of Z . Then, show

$$\forall t > 0, \quad \mathbb{P}(\chi_m^2 \geq m + 2mt + 2m\sqrt{t}) \leq e^{-mt}.$$

Q4 The Kullback - Leibler divergence between two distributions with densities p, q is defined as

$$D_{KL}[p||q] = \int p(x) \log \left(\frac{p(x)}{q(x)} \right) dx$$

1. Show that $D_{KL}[p||q] \geq 0$ and $D_{KL}[p||q] = 0$ if and only if $p = q$ almost everywhere. Hint: use the fact that

$$\log \left(\frac{p(x)}{q(x)} \right) \leq \frac{p(x)}{q(x)} - 1$$

and equality holds if and only if $p(x) = q(x)$.

2. Show that $D_{KL}[p||q]$ is not necessarily symmetric, that is $D_{KL}[p||q] \neq D_{KL}[q||p]$.

3. Compute $D_{KL}[p_1||p_2]$ for the following Gaussian distributions:

$$\begin{aligned} p(x) &= \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \\ q(x) &= \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}} \end{aligned} \tag{1}$$

4. Suppose p and q both have the same support (e.g. are absolutely continuous w.r.t. each other). Does this imply that their KL divergence is finite, $D_{KL}[p||q] < \infty$?