Tsinghua-Berkeley Shenzhen Institute INFERENCE AND INFORMATION Fall 2017

Problem Set 6

- 6.1. Let $\underline{y} = [y_1 \ y_2]^T$ be a vector random variable whose components are i.i.d. Bernoulli random variables with parameter x, 0 < x < 1, i.e., $\mathbb{P}(y_i = 1) = x$, i = 1, 2.
 - (a) Show that $t(y) = y_1 + y_2$ is a sufficient statistic.
 - (b) Let $\hat{x}(\underline{y}) = y_1$ be an estimator of the parameter x from the observation \underline{y} . Find $MSE_{\hat{x}}(x)$, the mean-square error of this estimator.
 - (c) Let $\hat{x}'(t) = \mathbb{E}[\hat{x}(\underline{y})|t=t]$ be an estimator of the parameter x that uses the sufficient statistic t instead of the observations y.
 - i. Show that $\hat{x}'(t)$ is a valid estimator, i.e., it does not depend on x.
 - ii. Show that $MSE_{\hat{x}'}(x) = \gamma MSE_{\hat{x}}(x)$ and find the constant γ .
 - (d) We now consider a generalization of this problem. Let \underline{y} be a random variable generated by a distribution $p_{\underline{y}}(\cdot;x)$ and $\underline{t}(\underline{y})$ be a sufficient statistic. Let $\hat{x}(\underline{y})$ be an estimator of the parameter x based on the observation \underline{y} . We define an alternate estimator $\hat{x}'(\underline{t}) = \mathbb{E}[\hat{x}(\underline{y})|\underline{t} = \underline{t}]$.
 - i. Show that $\hat{x}'(\underline{t})$ is a valid estimator, i.e., it does not depend on x.
 - ii. Show that for any cost function $C(x, \hat{x})$ that is convex in \hat{x} , the following inequality holds:

$$\mathbb{E}[C(x, \hat{x}'(\underline{\mathbf{t}}))] \le \mathbb{E}[C(x, \hat{x}(\mathbf{y}))].$$

6.2. You are given a coin that might contain gold. You are asked to test for the presence of gold by using a spectrometer. Let x be a Bernoulli random variable with parameter p that indicates the presence of gold in the coin, i.e., x = 1 means the coin contains gold. Let y be the reading of the spectrometer, distributed according to $p_{y|x}(\cdot|\cdot)$.

After observing the reading of the spectrometer y, you are asked to report a *soft* decision b_y that allows you to hedge your belief about the presence of gold in the coin. b_y is a real number between 0 and 1; it represents your belief that the coin contains gold. Naturally then, $1 - b_y$ represents your belief that there is no gold in the coin.

Note that in the binary hypothesis testing, we made hard decisions by completely committing to one of the two hypotheses. These hard decisions represent special, limiting cases of soft decisions. In the case of a hard decision, belief b_y is constrained to 0 (completely accepting the null hypothesis and completely rejecting the alternative hypothesis) or 1 (completely accepting the alternative hypothesis while completely rejecting the null hypothesis).

The reward for your work is a function of how well you guessed the correct answer, i.e.,

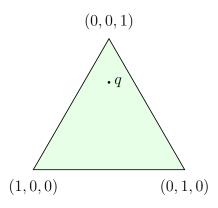
$$R(x, b_y) = \begin{cases} r(b_y), & x = 1\\ r(1 - b_y), & x = 0 \end{cases}$$

where x is the true value of x, and $r : [0,1] \to \mathbb{R}$ is a function that maps belief values to reward values.

- (a) Suppose the reward function is logarithmic: $r(z) = 1 + \ln(z)$. Note that under this reward function, you lose money if you assigned a belief of less than 1/e to the correct answer! Given that you observed y = y, find the belief value, $b_y^{* \ln}$, that maximizes the expected reward.
- (b) Now suppose the reward function is linear: r(z) = z. Given that you observed y = y, find the belief value, $b_y^{*\text{linear}}$, that maximizes the expected reward.
- (c) A reward function is called *proper* if it forces the players to report the posterior probability of the hidden variable as a belief.
 - i. Is the log reward function in (a) proper?
 - ii. Is the linear reward function in (b) proper?
 - iii. Do your answers to c(i) and c(ii) depend on the prior $p_{\mathsf{x}}(\cdot)$ and the likelihood $p_{\mathsf{y}|\mathsf{x}}(\cdot|\cdot)$? Explain.
- 6.3. Consider the set of distributions on $\Omega = \{0, 1, 2\}$ and note that they lie on the 2-simplex

$${p = (p_0, p_1, p_2) : p_0 + p_1 + p_2 = 1, p_0 \ge 0, p_1 \ge 0, p_2 \ge 0}$$

represented by the triangular figure. Let y be a random variable such that $p_{y}(i) = p_{i}, i \in \{0, 1, 2\}$. Let $q = \left(\frac{1}{6}, \frac{1}{6}, \frac{2}{3}\right)$ be a particular probability mass function.



- (a) Draw on the simplex the linear family corresponding to the expectation $\mathbb{E}[y] = 0$, i.e. draw $\mathcal{L}_0 = \{p : \mathbb{E}_p[y] = 0\}$.
- (b) Draw $\mathcal{L}_{\frac{1}{2}} = \left\{ p : \mathbb{E}_p[\mathsf{y}] = \frac{1}{2} \right\}.$
- (c) Specify the exponential family $\mathcal E$ that passes through q and is orthogonal to $\mathcal L_{\frac{1}{2}}$, and draw the entire family on the 2-simplex.
- (d) Calculate the I-projection p^* of q onto $\mathcal{L}_{\frac{1}{2}}$ and mark it on the simplex.
- (e) Draw $\mathcal{P} = \left\{ p : \mathbb{E}_p[\mathbf{y}] \le \frac{1}{2} \right\}$.
- (f) Calculate the I-projection p^* of q onto \mathcal{P} and mark it. *Hint*: $D(\cdot || q)$ is convex in its first argument.