## Tsinghua-Berkeley Shenzhen Institute LEARNING FROM DATA Fall 2018

## Problem Set 5

5.1. The covariance matrix of a random vector  $X \in \mathbb{R}^d$  is defined as

$$Cov(X) \triangleq \mathbb{E}[(X - \mathbb{E}[X])(X - \mathbb{E}[X])^{\mathrm{T}}] \in \mathbb{R}^{d \times d},$$

where  $\mathbb{E}[\cdot]$  is the mathematical expectation. Given m i.i.d. random variables  $X_1, \ldots, X_m$  with the same distribution as X, show that

$$\hat{C} \triangleq \frac{1}{m-1} \sum_{i=1}^{m} (X_i - \hat{\mu})(X_i - \hat{\mu})^{\mathrm{T}}$$

is an unbiased estimation of Cov(X), i.e.,  $\mathbb{E}[\hat{C}] = Cov(X)$ , where

$$\hat{\mu} \triangleq \frac{1}{m} \sum_{i=1}^{m} X_i.$$

5.2. Suppose X is a random variable taking values from a finite set  $\mathfrak{X}$ , and there are two hypotheses  $H_0$  and  $H_1$ 

$$H=H_0:X\sim P_X,$$

$$H = H_1 : X \sim Q_X$$

with prior probabilities  $\mathbb{P}(H = H_i) = p_i, i = 0, 1.$ 

Given m independent observations of X:  $x_1, \ldots, x_m$ , decide the decision rule  $\hat{H}(x_1, \ldots, x_m)$ , such that the error probability  $P_e \triangleq \mathbb{P}(\hat{H} \neq H)$  is minimized.

5.3. Suppose  $X_1, \dots, X_m \in \mathbb{R}^d$  are m independent random vectors with  $\mathbb{E}[X_i] = \mu_i$ ,  $\operatorname{Cov}(X_i) = \Sigma_i (i = 1, \dots, m)$ , Y is a categorical distribution taking values from  $\{1, \dots, m\}$  with  $\mathbb{P}(Y = i) = p_i$ , and Y is independent of all  $X_i$ 's. Evaluate  $\mathbb{E}[Z]$  and  $\operatorname{Cov}(Z)$ , where

$$Z \triangleq \sum_{i=1}^{m} \mathbb{1}\{Y = i\} \cdot X_i.$$