## Reading:

• Notes, Chapter 2.8, 3.1-3.5.

1. Given that  $\bf B$  is a square symmetric matrix and  $\bf x$  is a column vector. Show that

$$\frac{\partial \mathbf{x}^T \mathbf{B} \mathbf{x}}{\partial \mathbf{x}} = 2 \mathbf{B} \mathbf{x}$$

## **Book Problems:**

Chapter 2 problem #37. Chapter 3 problems #1 (a), (b), 3, 17, 19.

37. Consider a two-category classification problem in two dimensions with

$$p(\mathbf{x}|\omega_1) \sim N(\mathbf{0}, \mathbf{I}), p(\mathbf{x}|\omega_2) \sim N\left(\begin{pmatrix} 1 \\ 1 \end{pmatrix}, \mathbf{I}\right), \text{ and } P(\omega_1) = P(\omega_2) = 1/2.$$

- (a) Calculate the Bayes decision boundary.
- (b) Calculate the Bhattacharyya error bound.
- (c) Repeat the above for the same prior probabilities, but

$$p(\mathbf{x}|\omega_1) \sim N\left(\mathbf{0}, \begin{pmatrix} 2 & .5 \\ .5 & 2 \end{pmatrix}\right) \text{ and } p(\mathbf{x}|\omega_2) \sim N\left(\begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 5 & 4 \\ 4 & 5 \end{pmatrix}\right).$$

1. Let x have an exponential density

$$p(x|\theta) = \begin{cases} \theta e^{-\theta x} & x \ge 0\\ 0 & \text{otherwise.} \end{cases}$$

- (a) Plot  $p(x|\theta)$  versus x for  $\theta = 1$ . Plot  $p(x|\theta)$  versus  $\theta$ ,  $(0 \le \theta \le 5)$ , x = 2.
- (b) Suppose that n samples  $x_1, \ldots, x_n$  are drawn independently according  $p(x|\theta)$ . Show that the maximum-likelihood estimate for  $\theta$  is given by

$$\hat{\theta} = \frac{1}{\frac{1}{n} \sum_{k=1}^{n} x_k}.$$

- 3. Maximum-likelihood methods apply to estimates of prior probabilities as well. Let samples be drawn by successive, independent selections of a state of nature  $\omega_i$  with unknown probability  $P(\omega_i)$ . Let  $z_{ik} = 1$  if the state of nature for the kth sample is  $\omega_i$  and  $z_{ik} = 0$  otherwise.
  - (a) Show that

$$P(z_{i1},\ldots,z_{in}|P(\omega_i)) = \prod_{k=1}^n P(\omega_i)^{z_{ik}} (1-P(\omega_i))^{1-z_{ik}}.$$

(b) Show that the maximum-likelihood estimate for  $P(\omega_i)$  is

$$\hat{P}(\omega_i) = \frac{1}{n} \sum_{k=1}^n z_{ik}.$$

Interpret your result in words.

17. The purpose of this problem is to derive the Bayesian classifier for the d-dimensional multivariate Bernoulli case. As usual, work with each class separately, interpreting  $P(\mathbf{x}|\mathcal{D})$  to mean  $P(\mathbf{x}|\mathcal{D}_i, \omega_i)$ . Let the conditional probability for a given category be given by

$$P(\mathbf{x}|\boldsymbol{\theta}) = \prod_{i=1}^{d} \theta_i^{x_i} (1 - \theta_i)^{1 - x_i},$$

and let  $\mathcal{D} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$  be a set of n samples independently drawn according to this probability density.

(a) If  $\mathbf{s} = (s_1, \dots, s_d)^t$  is the sum of the *n* samples, show that

$$P(\mathcal{D}|\boldsymbol{\theta}) = \prod_{i=1}^{d} \theta_i^{s_i} (1 - \theta_i)^{n - s_i}.$$

(b) Assuming a uniform prior distribution for  $\theta$  and using the identity

$$\int_{0}^{1} \theta^{m} (1 - \theta)^{n} d\theta = \frac{m! n!}{(m + n + 1)!},$$

show that

$$p(\boldsymbol{\theta}|\mathcal{D}) = \prod_{i=1}^{d} \frac{(n+1)!}{s_i!(n-s_i)!} \theta_i^{s_i} (1-\theta_i)^{n-s_i}.$$

- (c) Plot this density for the case d = 1, n = 1 and for the two resulting possibilities for  $s_1$ .
- (d) Integrate the product  $P(\mathbf{x}|\boldsymbol{\theta})p(\boldsymbol{\theta}|\mathcal{D})$  over  $\boldsymbol{\theta}$  to obtain the desired conditional probability

$$P(\mathbf{x}|\mathcal{D}) = \prod_{i=1}^{d} \left(\frac{s_i + 1}{n+2}\right)^{x_i} \left(1 - \frac{s_i + 1}{n+2}\right)^{1 - x_i}.$$

- (e) If we think of obtaining  $P(\mathbf{x}|\mathcal{D})$  by substituting an estimate  $\hat{\boldsymbol{\theta}}$  for  $\boldsymbol{\theta}$  in  $P(\mathbf{x}|\boldsymbol{\theta})$ , what is the effective Bayesian estimate for  $\boldsymbol{\theta}$ ?
- 19. Assume we have training data from a Gaussian distribution of known covariance  $\Sigma$  but unknown mean  $\mu$ . Suppose further that this mean itself is random, and characterized by a Gaussian density having mean  $\mathbf{m}_0$  and covariance  $\Sigma_0$ .
  - (a) What is the MAP estimator for  $\mu$ ?
  - (b) Suppose we transform our coordinates by a linear transform  $\mathbf{x}' = \mathbf{A}\mathbf{x}$ , for non-singular matrix  $\mathbf{A}$ , and accordingly for other terms. Determine whether your MAP estimator gives the appropriate estimate for the transformed mean  $\mu'$ . Explain.