#### UNIVERSITY OF ILLINOIS

Department of Electrical and Computer Engineering ECE 417 MULTIMEDIA SIGNAL PROCESSING

# Lecture 10 Sample Problems

## Problem 10.1

Suppose that a particular covariance matrix,  $\Sigma = V\Lambda V^T$ , has a trace equal to  $D\sigma^2$ , and eigenvalues given by

$$\lambda_d = D\sigma^2 \left(\frac{1}{2}\right)^n, \quad 1 \le d \le D - 1$$

and  $\lambda_D = \lambda_{D-1}$ . Suppose that D = 512 dimensions.

The principal components are defined as

$$\vec{y} = \left[\vec{v}_1, \dots, \vec{v}_M\right]^T (\vec{x} - \vec{\mu})$$

where M < D is the number of principal components retained. What is the smallest value of M that will result in  $E[\|\vec{y}\|^2] \ge 0.95D\sigma^2$ ?

# Problem 10.2

What is the probability density function of the vector  $\vec{y}$  in problem 1?

## Problem 10.3

Suppose that a particular covariance matrix,  $\Sigma = V\Lambda V^T$ , where  $V = [\vec{v}_1, \dots, \vec{v}_D]$ , and the vectors  $\vec{v}_d$  are orthonormal. Suppose that the first M eigenvalues,  $\lambda_1, \dots, \lambda_M$  are all positive, but the remaining D - M eigenvalues are all zero.

A matrix whose eigenvalues are all  $\lambda_d \geq 0$  is called a "positive semi-definite matrix." If some eigenvalues are zero, there is no matrix  $\Sigma^{-1}$  such that  $\Sigma^{-1}\Sigma = I$ . It's possible, however, to define a pseudo-inverse  $\Sigma^{\dagger}$  that has some of the properties of an inverse, for example,  $\Sigma^{\dagger}\Sigma = \sum_{m=1}^{M} \vec{v}_{m} \vec{v}_{m}^{T}$ , and  $\Sigma^{\dagger}\Sigma\Sigma^{\dagger} = \Sigma^{\dagger}$ , and  $\Sigma\Sigma^{\dagger}\Sigma = \Sigma$ . With this definition, write the pseudo-inverse  $\Sigma^{\dagger}$  in terms of the nonzero eigenvalues  $\lambda_d$  and their corresponding eigenvectors  $\vec{v}_d$ .

### Problem 10.4

Suppose you have a two-class classification problem, with D-dimensional observations given by

$$\vec{x} = \left[ \begin{array}{c} x_1 \\ \vdots \\ x_D \end{array} \right]$$

The prior probabilities are given by the known parameter  $\pi_0$ :

$$p_Y(0) = \pi_0, \quad p_Y(1) = 1 - \pi_0$$

Suppose that the actual underlying likelihood functions of the two classes have no spread at all. If vector  $\vec{x}$  is drawn from class Y=0, then it ALWAYS has a value of  $\vec{x}=\vec{\mu}_0$ ; if it is drawn from class Y=1, then it ALWAYS has a value of  $\vec{x}_n=\vec{\mu}_1$ .

Define the global mean, covariance, and principal components to be

$$\vec{\mu} = E\left[\vec{X}\right], \quad \Sigma = E\left[\left(\vec{X} - \vec{\mu}\right)\left(\vec{X} - \vec{\mu}\right)^T\right], \quad \Sigma = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V\Lambda V^T, \quad V^TV = I, \quad \Lambda \text{ diagonal } T = V$$

Find  $\vec{\mu}$ ,  $\Sigma$ , V and  $\Lambda$  in terms of the parameters  $\pi_0$ ,  $\vec{\mu}_0$ , and  $\vec{\mu}_1$ .