

# Q6 - HW2: Pattern Recognition

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## 1 Question 6

Let  $\mathbf{x}$  be a random vector in an  $n$ -dimensional space with zero mean and covariance matrix  $\Sigma$ . In general, it is possible to find an orthonormal (unitary) transformation matrix  $\Phi$ , and define an  $n$ -dimensional variable  $\mathbf{z}$  as follows:

$$\mathbf{z} = \Phi^T \mathbf{x}$$

In the above relation, the transformation matrix  $\Phi$  consists of the eigenvectors of the covariance matrix  $\Sigma$ , and we have:

$$\Phi^T \Sigma \Phi = \Lambda$$

where  $\Lambda$  is a diagonal matrix containing the eigenvalues of  $\Sigma$ , arranged in descending order.

### 1.1 (a)

Since some eigenvalues are extremely small, dimensionality reduction is justified. Define a reduced transformation matrix  $\Phi'$  using the eigenvectors of  $\Sigma$  (i.e.,  $\phi_i$ ) such that the feature space is reduced to  $n'$  dimensions ( $n' < n$ ). Express the resulting  $n'$ -dimensional variable  $\mathbf{z}'$  in terms of  $\mathbf{x}$  and  $\Phi'$ .

#### 1.1.1 Solution

To reduce the dimensionality of the feature space from  $n$  to  $n'$  (where  $n' < n$ ), we select the  $n'$  eigenvectors of the covariance matrix  $\Sigma$  that correspond to the  $n'$  largest eigenvalues. Since the eigenvalues  $\lambda_i$  are arranged in descending order, we choose the first  $n'$  eigenvectors,  $\phi_1, \phi_2, \dots, \phi_{n'}$ .

The reduced transformation matrix, denoted as  $\Phi'$ , is an  $n \times n'$  matrix whose columns are these selected eigenvectors.

$$\Phi' = [\phi_1, \phi_2, \dots, \phi_{n'}]$$

The resulting  $n'$ -dimensional feature variable, denoted as  $\mathbf{z}'$ , is obtained by projecting the original  $n$ -dimensional vector  $\mathbf{x}$  onto the subspace spanned by the columns of  $\Phi'$ . This is achieved by the following transformation:

$$\mathbf{z}' = (\Phi')^T \mathbf{x}$$

Here,  $\mathbf{z}'$  is an  $n' \times 1$  column vector representing the original data in the reduced-dimensional space.

### 1.2 (b)

Show that the expected value of the reduced  $n'$ -dimensional vector  $\mathbf{z}'$  is zero:

$$E\{\mathbf{z}'\} = \mathbf{0}$$

### 1.2.1 Solution

We want to show that the expected value of the reduced vector  $\mathbf{z}'$  is a zero vector. We are given that the original vector  $\mathbf{x}$  has a zero mean, so  $E\{\mathbf{x}\} = \mathbf{0}$ .

The expected value of  $\mathbf{z}'$  is:

$$E\{\mathbf{z}'\} = E\{(\Phi')^T \mathbf{x}\}$$

Since the expectation operator  $E\{\cdot\}$  is linear and the transformation matrix  $\Phi'$  is a constant matrix of coefficients, we can move it outside the expectation.

$$E\{\mathbf{z}'\} = (\Phi')^T E\{\mathbf{x}\}$$

Substituting the given condition  $E\{\mathbf{x}\} = \mathbf{0}$ :

$$E\{\mathbf{z}'\} = (\Phi')^T \mathbf{0} = \mathbf{0}$$

This shows that the resulting  $n'$ -dimensional vector  $\mathbf{z}'$  also has a zero mean.

### 1.3 (c)

Show that the variance of the  $i$ -th component of  $\mathbf{z}'$  (for  $i \leq n'$ ) equals  $\lambda_i$ , the  $i$ -th eigenvalue of  $\Sigma$ . That is, prove that:

$$E\{(z'_i)^2\} = \lambda_i$$

*Hint:* ( $z'_i = \phi_i^T \mathbf{x}$ )

#### 1.3.1 Solution

We need to prove that the variance of the  $i$ -th component of  $\mathbf{z}'$  is equal to the  $i$ -th eigenvalue of  $\Sigma$ , i.e.,  $E\{(z'_i)^2\} = \lambda_i$ . The  $i$ -th component of  $\mathbf{z}'$  is given by  $z'_i = \phi_i^T \mathbf{x}$ , where  $\phi_i$  is the  $i$ -th eigenvector.

The variance of  $z'_i$  is  $\text{Var}(z'_i) = E\{(z'_i - E\{z'_i\})^2\}$ . From part (b), we know that  $E\{z'_i\} = 0$ , so the variance simplifies to  $E\{(z'_i)^2\}$ .

Let's compute  $E\{(z'_i)^2\}$ :

$$E\{(z'_i)^2\} = E\{(\phi_i^T \mathbf{x})^2\} = E\{(\phi_i^T \mathbf{x})(\phi_i^T \mathbf{x})\}$$

Since  $\phi_i^T \mathbf{x}$  is a scalar, we can write its square as  $(\phi_i^T \mathbf{x})^T (\phi_i^T \mathbf{x}) = \mathbf{x}^T \phi_i \phi_i^T \mathbf{x}$ . However, a more direct approach is:

$$E\{(z'_i)^2\} = E\{\phi_i^T \mathbf{x} \mathbf{x}^T \phi_i\}$$

Because  $\phi_i$  is a constant vector, we can move it outside the expectation:

$$E\{(z'_i)^2\} = \phi_i^T E\{\mathbf{x} \mathbf{x}^T\} \phi_i$$

The covariance matrix  $\Sigma$  is defined as  $\Sigma = E\{(\mathbf{x} - E\{\mathbf{x}\})(\mathbf{x} - E\{\mathbf{x}\})^T\}$ . Since  $E\{\mathbf{x}\} = \mathbf{0}$ , this simplifies to  $\Sigma = E\{\mathbf{x} \mathbf{x}^T\}$ . Substituting this into our equation gives:

$$E\{(z'_i)^2\} = \phi_i^T \Sigma \phi_i$$

By the definition of an eigenvector,  $\Sigma \phi_i = \lambda_i \phi_i$ . Substituting this relationship:

$$E\{(z'_i)^2\} = \phi_i^T (\lambda_i \phi_i) = \lambda_i (\phi_i^T \phi_i)$$

The matrix  $\Phi$  is an orthonormal transformation matrix, which means its column vectors  $\phi_i$  are orthonormal. Therefore, the inner product  $\phi_i^T \phi_i = 1$ .

$$E\{(z'_i)^2\} = \lambda_i (1) = \lambda_i$$

This proves that the variance of the  $i$ -th component of the transformed vector  $\mathbf{z}'$  is equal to the  $i$ -th largest eigenvalue of the covariance matrix  $\Sigma$ .

## 1.4 (d)

Given  $\mathbf{z}'$ , and the matrices  $\Phi$  and  $\Phi'$ , write the relations used to reconstruct the original vector in the  $n$ -dimensional space (denoted by  $\mathbf{x}'$ ).

*Hint:* Add zeros to the end of  $\mathbf{z}'$  to expand its dimension from  $n'$  to  $n$ , and call the resulting vector  $\mathbf{z}'_e$ . Then apply the inverse transformation to  $\mathbf{z}'_e$  to reconstruct  $\mathbf{x}'$ .

$$\mathbf{z}'_e = \begin{bmatrix} \mathbf{z}' \\ \mathbf{0} \end{bmatrix}, \quad \mathbf{x}' = \Phi \mathbf{z}'_e$$

### 1.4.1 Solution

To reconstruct the original vector  $\mathbf{x}$  from the reduced  $n'$ -dimensional vector  $\mathbf{z}'$ , we first need to map  $\mathbf{z}'$  back to the  $n$ -dimensional space. This is done by creating an  $n$ -dimensional vector  $\mathbf{z}'_e$  by appending  $n - n'$  zeros to  $\mathbf{z}'$ .

$$\mathbf{z}'_e = \begin{bmatrix} \mathbf{z}' \\ \mathbf{0} \end{bmatrix}$$

Here,  $\mathbf{0}$  is a zero vector of size  $(n - n') \times 1$ .

The original transformation from  $\mathbf{x}$  to the full  $n$ -dimensional vector  $\mathbf{z}$  is  $\mathbf{z} = \Phi^T \mathbf{x}$ . Since  $\Phi$  is an orthonormal matrix, its inverse is its transpose,  $\Phi^{-1} = \Phi^T$ . Therefore, the inverse transformation to recover  $\mathbf{x}$  from  $\mathbf{z}$  is  $\mathbf{x} = \Phi \mathbf{z}$ .

To obtain the reconstructed vector  $\mathbf{x}'$  from the padded vector  $\mathbf{z}'_e$ , we apply this inverse transformation:

$$\mathbf{x}' = \Phi \mathbf{z}'_e$$

This projects the reduced representation back into the original  $n$ -dimensional space. Note that  $\mathbf{x}'$  is an approximation of  $\mathbf{x}$  because information was lost during the dimensionality reduction.

## 1.5 (e)

The mean squared error (MSE) caused by dimensionality reduction — i.e., by reducing  $\mathbf{x}$  to the  $n'$ -dimensional vector  $\mathbf{z}'$  and then reconstructing it as  $\mathbf{x}'$  in the original  $n$ -dimensional space — is defined as:

$$e_{ms} = E\{|\mathbf{x} - \mathbf{x}'|^2\}$$

Show that this error equals:

$$e_{ms} = \sum_{i=n'+1}^n \lambda_i$$

where  $\lambda_i$  are the eigenvalues of the covariance matrix  $\Sigma$  corresponding to the eliminated dimensions.

**Answer:**

$$\begin{aligned} e_{ms} &= E\{|\mathbf{x} - \mathbf{x}'|^2\} = E\{(\mathbf{x} - \mathbf{x}')^T (\mathbf{x} - \mathbf{x}')\} \\ &= E\{(\Phi \mathbf{z} - \Phi \mathbf{z}'_e)^T (\Phi \mathbf{z} - \Phi \mathbf{z}'_e)\} \\ &= \Phi^T E\{(\mathbf{z} - \mathbf{z}'_e)^T (\mathbf{z} - \mathbf{z}'_e)\} \Phi = \sum_{i=n'+1}^n \lambda_i \end{aligned}$$

### 1.5.1 Solution

The mean squared error (MSE) is defined as  $e_{ms} = E\{|\mathbf{x} - \mathbf{x}'|^2\}$ . We can express this as the expected value of the squared Euclidean norm, which is  $E\{(\mathbf{x} - \mathbf{x}')^T (\mathbf{x} - \mathbf{x}')\}$ .

We substitute  $\mathbf{x} = \Phi \mathbf{z}$  and  $\mathbf{x}' = \Phi \mathbf{z}'_e$ :

$$e_{ms} = E\{(\Phi \mathbf{z} - \Phi \mathbf{z}'_e)^T (\Phi \mathbf{z} - \Phi \mathbf{z}'_e)\}$$

Factor out  $\Phi$  from the expression:

$$e_{ms} = E\{(\Phi(\mathbf{z} - \mathbf{z}'_e))^T (\Phi(\mathbf{z} - \mathbf{z}'_e))\}$$

Using the transpose property  $(AB)^T = B^T A^T$ :

$$e_{ms} = E\{(\mathbf{z} - \mathbf{z}'_{\mathbf{e}})^T \Phi^T \Phi (\mathbf{z} - \mathbf{z}'_{\mathbf{e}})\}$$

Since  $\Phi$  is orthonormal,  $\Phi^T \Phi = I$ , where  $I$  is the identity matrix.

$$e_{ms} = E\{(\mathbf{z} - \mathbf{z}'_{\mathbf{e}})^T I (\mathbf{z} - \mathbf{z}'_{\mathbf{e}})\} = E\{(\mathbf{z} - \mathbf{z}'_{\mathbf{e}})^T (\mathbf{z} - \mathbf{z}'_{\mathbf{e}})\}$$

This is the expected squared norm of the vector  $\mathbf{z} - \mathbf{z}'_{\mathbf{e}}$ . Let's examine this vector:

$$\mathbf{z} - \mathbf{z}'_{\mathbf{e}} = \begin{bmatrix} z_1 \\ \vdots \\ z_{n'} \\ z_{n'+1} \\ \vdots \\ z_n \end{bmatrix} - \begin{bmatrix} z_1 \\ \vdots \\ z_{n'} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ z_{n'+1} \\ \vdots \\ z_n \end{bmatrix}$$

The squared norm of this vector is the sum of the squares of its components:

$$(\mathbf{z} - \mathbf{z}'_{\mathbf{e}})^T (\mathbf{z} - \mathbf{z}'_{\mathbf{e}}) = \sum_{i=n'+1}^n (z_i)^2$$

Now, we take the expectation:

$$e_{ms} = E\left\{\sum_{i=n'+1}^n (z_i)^2\right\}$$

By the linearity of expectation:

$$e_{ms} = \sum_{i=n'+1}^n E\{(z_i)^2\}$$

From part (c), we know that  $E\{(z_i)^2\} = \lambda_i$ . Therefore:

$$e_{ms} = \sum_{i=n'+1}^n \lambda_i$$

The mean squared error from dimensionality reduction is the sum of the eigenvalues corresponding to the dimensions that were discarded.

## 1.6 (f)

Based on the obtained error, propose a criterion for selecting the reduced dimension  $n'$ .

### 1.6.1 Solution

The result from part (e) provides a direct way to quantify the error introduced by dimensionality reduction. The total variance of the original data  $\mathbf{x}$  is the trace of its covariance matrix, which is also equal to the sum of all its eigenvalues:

$$\text{Total Variance} = \text{Tr}(\Sigma) = \sum_{i=1}^n \lambda_i$$

The MSE,  $e_{ms} = \sum_{i=n'+1}^n \lambda_i$ , represents the amount of variance (information) lost during the reduction. The amount of variance retained is  $\sum_{i=1}^{n'} \lambda_i$ .

A common criterion for choosing the reduced dimension  $n'$  is to retain a certain percentage of the total variance. For instance, we might want to keep 95% or 99% of the original variance. This leads to the following criterion:

Choose the smallest integer  $n'$  such that the ratio of the retained variance to the total variance is greater than or equal to a specified threshold  $T$  (e.g.,  $T = 0.95$ ).

$$\frac{\sum_{i=1}^{n'} \lambda_i}{\sum_{i=1}^n \lambda_i} \geq T$$

To apply this criterion, one would compute the eigenvalues of the covariance matrix  $\Sigma$ , sort them in descending order, and then calculate the cumulative sum of these eigenvalues. The value of  $n'$  is chosen as the point where this cumulative sum first exceeds the desired percentage of the total sum.