

Question 1: Assignment 4: CS 663, Fall 2024

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1. The aim of this exercise is to help you understand the mathematics behind PCA more deeply. Do as directed: [3+3+4+5=15 points]
- (a) Prove that the covariance matrix in PCA is symmetric and positive semi-definite.
 - (b) Prove that the eigenvectors of a symmetric matrix are orthonormal.
 - (c) Consider a dataset of some N vectors in d dimensions given by $\{\mathbf{x}_i\}_{i=1}^N$ with mean vector $\bar{\mathbf{x}}$. Note that each $\mathbf{x}_i \in \mathbb{R}^d$ and also $\bar{\mathbf{x}} \in \mathbb{R}^d$. Suppose that only k eigenvalues of the corresponding covariance matrix are large and the remaining are very small in value. Let $\tilde{\mathbf{x}}_i$ be an approximation to \mathbf{x}_i of the form $\tilde{\mathbf{x}}_i = \bar{\mathbf{x}} + \sum_{l=1}^k \mathbf{V}_l \alpha_{il}$ where \mathbf{V}_l stands for the l th eigenvector (it has d elements) and α_{il} (it is a scalar) stands for the l th eigencoefficient of \mathbf{x}_i . Argue why the error $\frac{1}{N} \sum_{i=1}^N \|\tilde{\mathbf{x}}_i - \mathbf{x}_i\|_2^2$ will be small. What will be the value of this error in terms of the eigenvalues of the covariance matrix?
 - (d) Consider two uncorrelated zero-mean random variables (X_1, X_2) . Let X_1 belong to a Gaussian distribution with variance 100 and X_2 belong to a Gaussian distribution with variance 1. What are the principal components of (X_1, X_2) ? If the variance of X_1 and X_2 were equal, what are the principal components?

Soln:

- (a) Covariance matrix C is given by

$$C = \frac{XX^T}{(N-1)}$$

And since $C^T = C$, we can conclude that the covariance matrix in PCA is symmetric.
A matrix $M \in L(V)$ is positive semi-definite iff,

- i. M is symmetric
- ii. $v^T M v \geq 0 \quad \forall v \in V$

Now,

$$v^T C v = \frac{v^T X X^T v}{(N-1)} = \frac{\|X^T v\|^2}{(N-1)} \geq 0$$

We had already proved above that C is symmetric, thus we can say that the covariance matrix in PCA is symmetric and positive semi-definite.

- (b) For any real matrix A and any vectors x and y , we have

$$\langle Ax, y \rangle = \langle x, A^T y \rangle.$$

Now assume that A is symmetric, and (x, λ) and (y, μ) are arbitrary (eigenvectors, eigenvalues) pairs of A , such that $\lambda \neq \mu$ and $x \neq y$. Then

$$\lambda \langle x, y \rangle = \langle \lambda x, y \rangle = \langle Ax, y \rangle = \langle x, A^T y \rangle = \langle x, Ay \rangle = \langle x, \mu y \rangle = \mu \langle x, y \rangle.$$

Therefore,

$$(\lambda - \mu) \langle x, y \rangle = 0.$$

Since $\lambda \neq \mu$, thus $\langle x, y \rangle = 0$, i.e., $x \perp y$. Also, since eigenvectors by default are normalised, we can say that the eigenvectors of a symmetric matrix is perpendicular and normalised, i.e. orthonormal.

- (c) We know that we can write $\mathbf{x}_i = \bar{\mathbf{x}} + \sum_{l=1}^d \mathbf{V}_l \alpha_{il} = \bar{\mathbf{x}} + \mathbf{V}_l \boldsymbol{\alpha}_i$.

Also, we are given that $\tilde{\mathbf{x}}_i = \bar{\mathbf{x}} + \sum_{l=1}^k \mathbf{V}_l \alpha_{il} = \bar{\mathbf{x}} + \mathbf{V}_l \tilde{\boldsymbol{\alpha}}_i$.

We can easily note that $\tilde{\alpha}_{il} = \alpha_{il}$ for $1 \leq l \leq k$ and $\tilde{\alpha}_{il} = 0$ for $k+1 \leq l \leq d$.

Then the error that we defined above becomes

$$\frac{1}{N} \sum_{i=1}^N \|\tilde{\mathbf{x}}_i - \mathbf{x}_i\|_2^2 = \frac{1}{N} \sum_{i=1}^N \|\tilde{\boldsymbol{\alpha}}_i - \boldsymbol{\alpha}_i\|_2^2 = \frac{1}{N} \sum_{i=1}^N \sum_{l=k+1}^d \alpha_{il}^2$$

By applying suitable approximations, we can say that

$$\frac{1}{N} \sum_{i=1}^N \sum_{l=k+1}^d \alpha_{il}^2 \approx \sum_{l=k+1}^d E[\alpha_l^2] = \sum_{l=k+1}^d \lambda_l$$

Since we know that $\lambda_{k+1}, \dots, \lambda_d$ are all small, we can conclude that the error turns out to be small.

- (d) We are given that

$$X_1 \sim \mathcal{N}(0, 100) \quad (\text{Gaussian distribution with variance 100})$$

$$X_2 \sim \mathcal{N}(0, 1) \quad (\text{Gaussian distribution with variance 1})$$

Since X_1 and X_2 are uncorrelated, their covariance matrix Σ is given by:

$$\Sigma = \begin{pmatrix} \text{Var}(X_1) & \text{Cov}(X_1, X_2) \\ \text{Cov}(X_1, X_2) & \text{Var}(X_2) \end{pmatrix} = \begin{pmatrix} 100 & 0 \\ 0 & 1 \end{pmatrix}$$

To calculate the eigenvalues λ of the covariance matrix Σ , we solve $\det(\Sigma - \lambda I) = 0$

$$\det \begin{pmatrix} 100 - \lambda & 0 \\ 0 & 1 - \lambda \end{pmatrix} = (100 - \lambda)(1 - \lambda) = 0$$

Thus, the eigenvalues are $\lambda_1 = 100$, $\lambda_2 = 1$. Now, for each eigenvalue, we find the corresponding eigenvector.

- For $\lambda_1 = 100$:

$$\begin{pmatrix} 100 - 100 & 0 \\ 0 & 1 - 100 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & -99 \end{pmatrix}$$

The corresponding eigenvector is $\mathbf{v}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$.

- For $\lambda_2 = 1$:

$$\begin{pmatrix} 100 - 1 & 0 \\ 0 & 1 - 1 \end{pmatrix} = \begin{pmatrix} 99 & 0 \\ 0 & 0 \end{pmatrix}$$

The corresponding eigenvector is $\mathbf{v}_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$.

The principal components are the normalized eigenvectors corresponding to the largest eigenvalues:

1. First principal component PC_1 corresponding to $\lambda_1 = 100$: $PC_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

2. Second principal component PC_2 corresponding to $\lambda_2 = 1$: $PC_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$

If the variances of X_1 and X_2 were equal, we denote them as σ^2 . The covariance matrix becomes:

$$\Sigma = \begin{pmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{pmatrix} = \sigma^2 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

The eigenvalues are:

$$\lambda_1 = \sigma^2, \quad \lambda_2 = \sigma^2$$

Clearly, for the above eigenvalues, the eigenvectors can be any orthonormal basis of \mathbb{R}^2 , such as $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$. So, the eigenvectors remain the same as earlier. In conclusion:

- For uncorrelated X_1 and X_2 with variances 100 and 1, respectively: $PC_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and $PC_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$

- If the variances were equal, then the principal components could remain as $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$.