

Tutorial 4

EE3731C – Signal Processing Methods

Qi Zhao

Assistant Professor

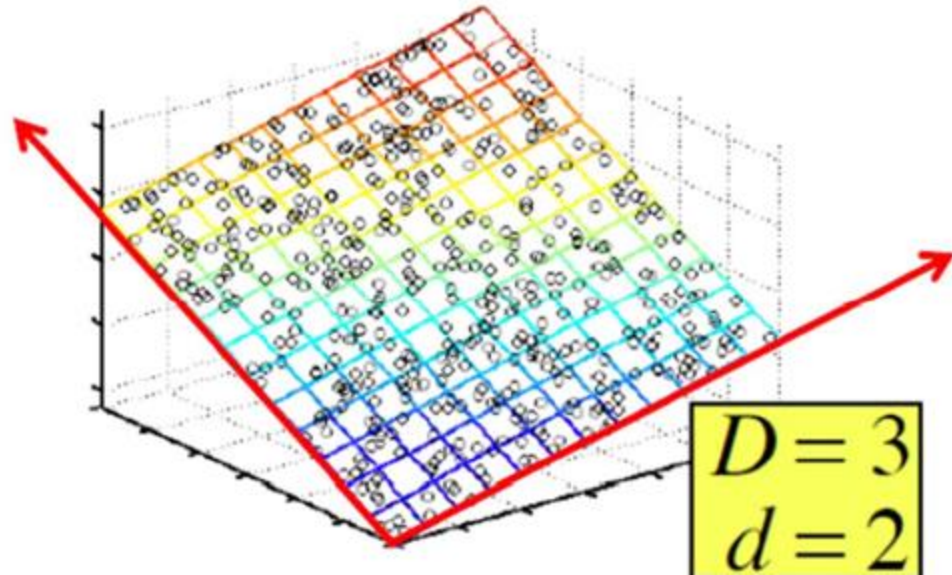
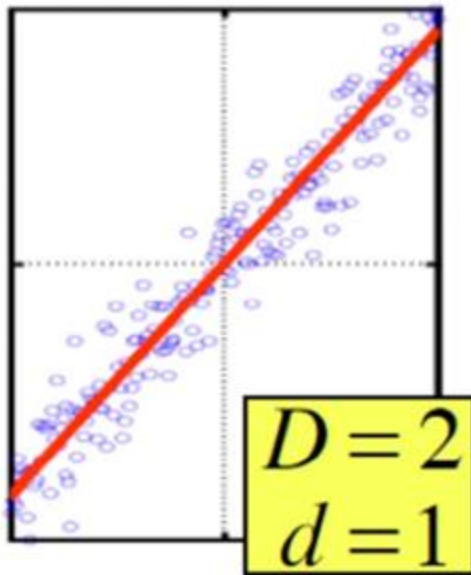
ECE, NUS

- Expectation
- Variance
- Covariance (Matrix)

- Orthogonality
- Correlation
- Independence
 - Key Properties of expectation, variance and covariance (matrix)
 - Not every matrix can be a covariance matrix
 - Differentiate orthogonality, correlation and independence

Dimensionality Reduction

- Project the data into lower-dimensional space
 - Assumption: data approximately lie in a lower-dimensional space => *Preserve structure*.
 - Less computation, easier interpretation.



Principal Component Analysis

- Assume data are centered
- For a projection direction \mathbf{v} , variance of projected data $Var(\mathbf{v}^T \mathbf{x})$:

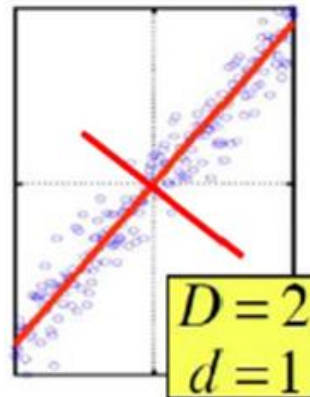
$$\frac{1}{n-1} \sum_{i=1}^n (\mathbf{v}^T \mathbf{x}_i)^2 = \frac{1}{n-1} \mathbf{v}^T \mathbf{X} \mathbf{X}^T \mathbf{v}$$

– $\mathbf{X} \mathbf{X}^T$: sample covariance

- Maximize the variance of projected data

$$\max_{\mathbf{v}} \mathbf{v}^T \mathbf{X} \mathbf{X}^T \mathbf{v} \quad \text{s.t.} \quad \mathbf{v}^T \mathbf{v} = 1$$

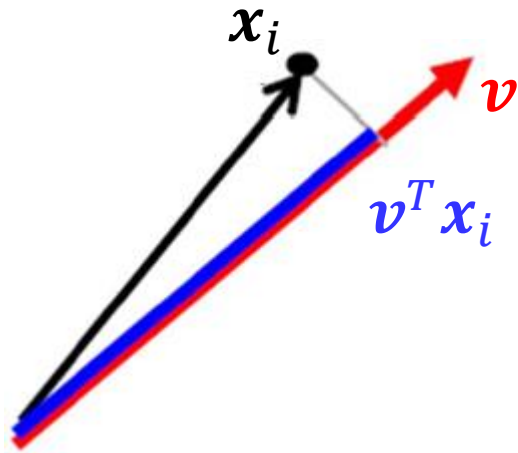
How to solve this?



Computing PCA

- Subtract off the mean (do not forget to add back)
- Form the covariance matrix (be aware of the properties of a covariance matrix)
- Calculate the eigenvectors and eigenvalues of the covariance matrix (remember the orthonormal constraint of eigenvectors)
- Rearrange the eigenvectors and eigenvalues
- Select a subset of eigenvectors as basis vectors

Projecting onto the PCs



- x_i : a D-dimensional data point
- v : 1st PC
- $v^T x_i$: projection of x_i onto the 1st PC

Reconstruction error: $e_i = ||x_i - (v^T x_i)v||^2$

Computing Eigenvalues and Eigenvectors

- $A\mathbf{v}_i = \lambda\mathbf{v}_i$

$$(A - \lambda_i \mathbf{I})\mathbf{v}_i = 0$$

$$\det(A - \lambda_i \mathbf{I}) = 0$$

- For example, $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$

$$\det \begin{pmatrix} a - \lambda & b \\ c & d - \lambda \end{pmatrix} = 0$$

$$\Rightarrow (a - \lambda)(d - \lambda) - bc = 0$$

$$\Rightarrow \lambda^2 - (a + d)\lambda + (ad - bc) = 0$$

The first PC is the corresponding eigenvector of the largest eigenvalue.

PCA Analysis on Images

- Representation of raw image data
- PCA for dimension reduction

Recurrence Relation

- Initial terms are given.
- Each further term of the sequence is defined as a function of the preceding terms.
- A difference equation is an equation for a sequence written in terms of that sequence and shiftings of it.

Difference Equations

- Plot the equation over time
- Get an analytical solution for the difference equation if it is available
- Determine the equilibrium values
- Analyze stability of equilibria

- First order difference equation: $x_{k+1} = ax_k + b$
- Analytical solution:

If $a \neq 1$, $x_k = a^k x_0 + \frac{b(1-a^k)}{1-a}$, or $x_k = \frac{b}{1-a} + [x_0 - \frac{b}{1-a}] a^k$,

Otherwise if $a = 1$, $x_k = x_0 + kb$.

Please try not to memorize it. For any a and b , can also follow:

- Equilibrium value: $\frac{b}{1-a}$, if $a \neq 1$
 - Stability criteria - the equilibrium is
 - stable if $|a| < 1$
 - unstable if $|a| > 1$
 - x_k will oscillate if $a < 0$
 - x_k will change monotonically if $a > 0$
 - ...
- Start with a^k times an undetermined constant c
 - Find x^*
 - Add the two and pick c to match x_0 when $k = 0$.

Induction

- The simplest and most common form of mathematical induction infers that a statement involving a natural number k holds for all values of k . The proof consists of two steps:
 - **The base case**: prove that the statement holds for the first natural number k . Usually, $k = 0$ or $k = 1$.
 - **The inductive step**: prove that, if the statement holds for some natural number k , then the statement holds for $k + 1$.

Testing Example

- A: show that the sequence defined by $y_k = 2^{k+1} - 1$, satisfies the difference equation $y_{k+1} = 2y_k + 1$, $y_0 = 1$.
- B: for difference equation $y_{k+1} = 2y_k + 1$, $y_0 = 1$, find its analytic solutions.

- Make a conjecture about the stability of a fixed point to a nonlinear system $x_{k+1} = g(x_k)$.

Solution: an equilibrium solution x^*
is stable if $|g'(x^*)| < 1$, and
unstable if $|g'(x^*)| > 1$.

The application (and intuition) of it is important, and
proof (shown in the next slide) is not required.

Proof: The goal is to prove that the errors between x_k and x^* $e_k = x_k - x^*$ tend to 0 as $k \rightarrow \infty$.

Toward the goal, we estimate e_{k+1} in terms of e_k :

$$e_{k+1} = x_{k+1} - x^* = g(x_k) - g(x^*) = g'(y)(x_k - x^*) = g'(y)e_k$$

for some y lying between x_k and x^* .

By continuity, if $|g'(x^*)| < 1$, we can choose $\delta > 0$ and $|g'(x^*)| < \sigma < 1$ such that $|g'(y)| \leq \sigma < 1$ whenever $|y - x^*| < \delta$.

Suppose $|e_k| = |x_k - x^*| < \delta$, then $|x_{k+1} - x^*| \leq \sigma |x_k - x^*|$, so $|e_{k+1}| \leq \sigma |e_k|$.

Provided the initial iterate satisfies $|e_0| = |x_0 - x^*| < \delta$, the subsequent errors are bounded by $|e_k| \leq \sigma^k |e_0|$.

Hence, $|e_k| = |x_k - x^*| \rightarrow 0$ as $k \rightarrow \infty$. This completes the proof.
