

Multivariate Gaussian distribution $x \in \mathbb{R}^p$

$$p(x) = \frac{1}{(2\pi)^{p/2}} |R|^{-1/2} \exp\left\{x^T R^{-1} x\right\}$$

where R is a positive definite symmetric matrix.

Then

$$R = E \Lambda E^T$$

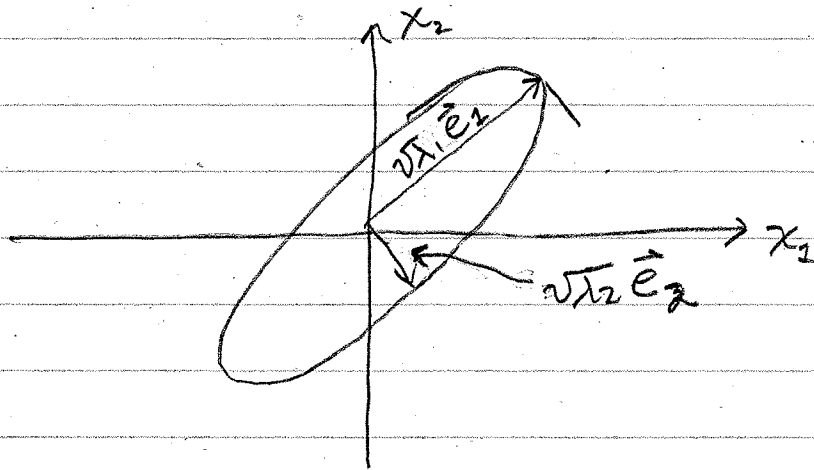
where $E = [e_1 \ e_2 \ \dots \ e_p]$ is an orthonormal matrix of eigenvectors e_k and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_p)$ is a diagonal matrix of eigenvalues.

So we have $E^T E = I$

Intuitively, the function

$$f(x) = x^T R^{-1} x$$

has contour plots that look like

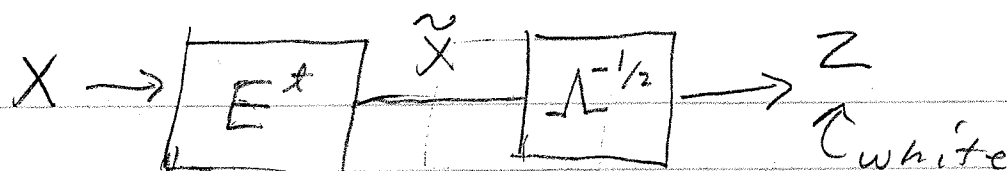


Consider $\tilde{x} = E^T x$ then

$$\begin{aligned}
 E[\tilde{x} \tilde{x}^T] &= E[E^T x x^T E] \\
 &= E^T E[x x^T] E \\
 &= E^T R E \\
 &= E^T E \Lambda E^T E \\
 &= \Lambda
 \end{aligned}$$

So the elements of $\tilde{x}$ are
 uncorrelated (independent) with
 variance $E[\tilde{x}_i^2] = \Lambda_{ii}$

$$\text{So } \tilde{x} = \begin{bmatrix} \tilde{x}_1 \\ \tilde{x}_2 \end{bmatrix} \rightarrow \tilde{x}$$



$$E[Z Z^T] = I$$

So E^T decorrelates X
 $\Lambda^{-1/2} E^T$ whitens X

$$E^T X = \begin{bmatrix} e_1^* \\ \vdots \\ e_p^* \end{bmatrix} X$$

eigen signals

The e_n 's are basis vectors to represent the signal X .

How do we determine the e_n 's?

Eigenimage estimation

How do we estimate R_x ?

Assume we have n training vectors

$$X = \begin{bmatrix} x_1, \dots, x_n \end{bmatrix}$$

Then

$$R_x = E[X_k X_k^T] = \frac{1}{n} E[X X^T]$$

$$\approx \underbrace{\frac{1}{n} X X^T}_{\text{This is the sample correlation matrix}} = S$$

↑ This is the sample correlation matrix

$$S_{ij} = \frac{1}{n} \sum_{k=1}^n X_{ik} X_{jk}$$

$$S = E \Lambda E^T$$

↑ estimate of the eigen vectors.
estimate of the eigen values.

Problem! How do we compute E ?
↑ very large

Singular Value Decomposition (SVD)

For $n < p$ it looks like!

$$\boxed{\begin{matrix} X \\ p \times n \end{matrix}} = \boxed{\begin{matrix} U \\ p \times n \end{matrix}} \boxed{\begin{matrix} \Sigma \\ n \times n \end{matrix}} \boxed{\begin{matrix} V^T \\ n \times n \end{matrix}}$$

$U \Leftarrow$ Left hand singular vectors
columns are orthonormal

$V \Leftarrow$ right hand singular vectors
columns are orthonormal

$\Sigma \Leftarrow$ diagonal matrix of
singular values.

Notice that

$$\begin{aligned} XX^T &= U \Sigma V^T V \Sigma U^T \\ &= U \Sigma^2 U^T \end{aligned}$$

So U is the set of desired
eigen vectors of XX^T .

How to compute U ?

$$\text{Notice } X^T X = \underbrace{V \Sigma^2 V^T}_{n \times n}$$

$V \Leftarrow$ eigenvectors of much
smaller matrix

Algorithm

1) Find eigenvectors V of the matrix X^*X

2) Compute $XV = U\Sigma$

Then the columns of U are the normalized columns of XV , and Σ are the normalization factors.