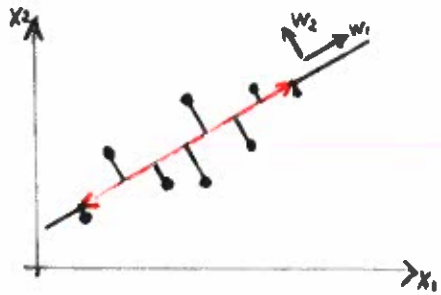


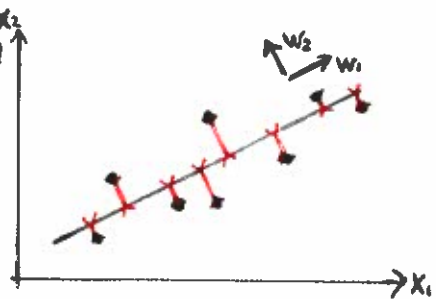
Principal Component Analysis Views

Find set of orthogonal directions which

- maximise variance



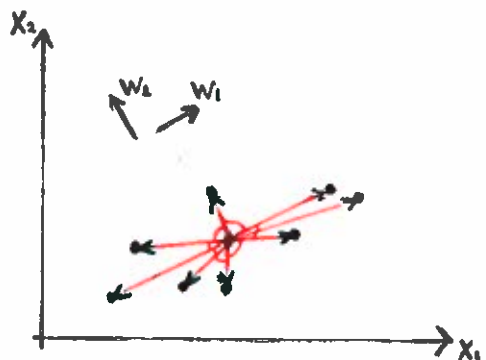
- minimise approximation error



- approximate sample covariance



- approximate Gram matrix



For a large centred data matrix X ,
you have the eigendecomposition of the
sample covariance matrix:

$$\Sigma = U \Lambda U^T \text{ where}$$

$$U = \begin{pmatrix} 1/3 & 2/3 & -2/3 \\ 2/3 & 1/3 & 2/3 \\ -2/3 & 2/3 & 1/3 \end{pmatrix} \quad \Lambda = \begin{pmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

a) First two PC directions?

b) PC scores of observations $\underline{x}_1 = (9, 9, -18)^T$
 $\underline{x}_2 = (18, 9, 9)^T$ corresponding to first two
PC directions?

c) Corresponding projection matrix?

d) Approximations of \underline{x}_1 and \underline{x}_2 ?

e) Expected mean square approximation error?

$$a) \underline{w}_1 = (1/3 \ 2/3 \ -2/3)^T \quad \underline{w}_2 = (2/3 \ 1/3 \ 2/3)^T$$

$$b) \underline{Z} = \underline{W}_k^T \underline{X} = \begin{pmatrix} 1/3 & 2/3 & -2/3 \\ 2/3 & 1/3 & 2/3 \end{pmatrix} \begin{pmatrix} 9 & 18 \\ 9 & 9 \\ -18 & 9 \end{pmatrix} = \begin{pmatrix} 21 & 6 \\ -3 & 21 \end{pmatrix}$$

$\underline{z}_1 \quad \underline{z}_2$

$$c) \underline{P} = \underline{W}_k \underline{W}_k^T = \begin{pmatrix} 5/9 & 4/9 & 2/9 \\ 4/9 & 5/9 & -2/9 \\ 2/9 & -2/9 & 8/9 \end{pmatrix}$$

$$d) \hat{\underline{x}}_1 = \underline{P} \underline{x}_1 = (5 \ 13 \ -16)^T$$

$$\hat{\underline{x}}_2 = \underline{P} \underline{x}_2 = (16 \ 11 \ 10)^T$$

e) Sum of neglected eigenvalues: 1

Probabilistic PCA

- Probabilistic model where maximum likelihood solution $\hat{=}$ PCA

Probabilistic model:

- Latent variable \underline{z} corresponding to PC vector of length k with $p(\underline{z}) = \mathcal{N}(\underline{z} | \underline{0}, \underline{I}_k)$ where $\mathcal{N}(\underline{x} | \underline{\mu}, \underline{\Sigma}) = \frac{1}{\sqrt{(2\pi)^d \det \underline{\Sigma}}} \exp(-\frac{1}{2}(\underline{x} - \underline{\mu})^T \underline{\Sigma}^{-1}(\underline{x} - \underline{\mu}))$, multivariate normal distribution with mean vector $\underline{\mu}$ and covariance matrix $\underline{\Sigma}$
- Observable data given by

$$\underline{x} = \underline{W}\underline{z} + \underline{\mu} + \underline{\varepsilon}$$

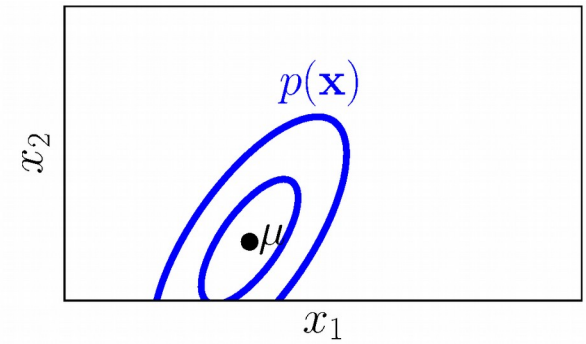
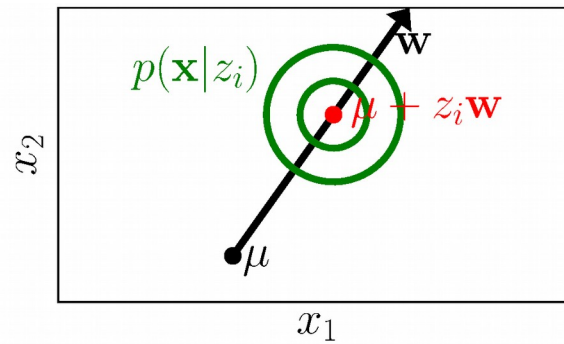
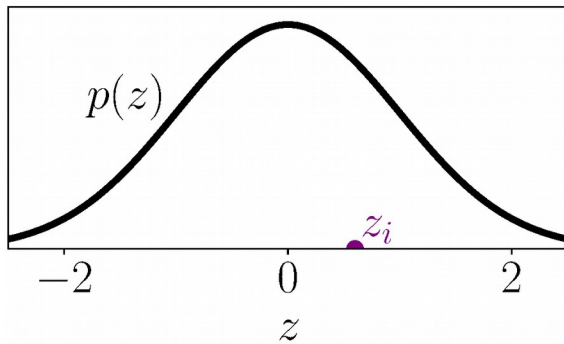
where \underline{W} : $d \times k$ matrix

$\underline{\mu}$: constant mean vector (length d)

$$p(\underline{\varepsilon}) = \mathcal{N}(\underline{\varepsilon} | \underline{0}, \sigma^2 \underline{I}_d)$$

- Parameters: $\underline{W}, \underline{\mu}, \sigma^2$

Probabilistic PCA



- Conditional distribution $p(\underline{x}|\underline{z})$:

Consider \underline{z} constant $\Rightarrow W\underline{z} + \underline{\mu}$ constant

$\Rightarrow p(\underline{x}|\underline{z})$ is MVN distr.

$$p(\underline{x}|\underline{z}) = \mathcal{N}(\underline{x} | W\underline{z} + \underline{\mu}, \sigma^2 \mathbf{I}_d)$$

- Joint distribution $p(\underline{z}, \underline{x}) = p(\underline{x}|\underline{z}) \cdot p(\underline{z})$

$$p(\underline{z}, \underline{x}) = \frac{1}{\text{const}} \exp \left(-\frac{1}{2} \left[(\underline{x} - W\underline{z} - \underline{\mu})^T \left(\frac{1}{\sigma^2} \mathbf{I}_d \right) \cdot (\underline{x} - W\underline{z} - \underline{\mu}) + \underline{z}^T \underline{z} \right] \right)$$

where const: term independent of \underline{x} and \underline{z} .

Mean? Covariance?

We use "completing the square"

Completing the square

General technique to find mean, covariance of a MVN distribution

Consider term in exp of a MVN:

$$\begin{aligned} & -\frac{1}{2} (\underline{x} - \underline{\mu})^T \Sigma^{-1} (\underline{x} - \underline{\mu}) \\ & = -\frac{1}{2} \underline{x}^T \Sigma^{-1} \underline{x} + \underline{x}^T \Sigma^{-1} \underline{\mu} + \text{const} \end{aligned}$$

Match 2nd order terms and linear terms of a given $-\frac{1}{2} \underline{x}^T A \underline{x} + \underline{x}^T \underline{\zeta} + \text{const}$

1) Isolate 2nd order term $-\frac{1}{2} \underline{x}^T A \underline{x}$ and obtain $\Sigma^{-1} = A$

2) Isolate linear term $\underline{x}^T \underline{\zeta}$ and use Σ to obtain $\underline{\mu} = \Sigma \underline{\zeta}$