

## Probabilistic PCA :

We can formulate PCA in a probabilistic / Bayesian setting:

Likelihood:  $p(x|z) = \mathcal{N}(x|zW^T + \mu, \sigma^2 I)$ ,  $x \in \mathbb{R}^d$   
 $\Rightarrow x_i = z_i W^T + \mu + \varepsilon$ ,  $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ ,  $X \in \mathbb{R}^{n \times d}$   
data mat

Prior:  $p(z) = \mathcal{N}(z|0, I)$ ,  $z \in \mathbb{R}^q$ ,  $q < d$   
 $\hookrightarrow \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

Parameters:  $\theta := \{W, \mu, \sigma^2\}$  to be determined via MLE/MAP.

Recall:  $p(z|x) = \frac{p(x|z)p(z)}{p(x)}$

Because  $x$  depends on  $z$  in a linear fashion, and  $p(x|z)$ ,  $p(z)$  are Gaussian:

$$p(x) = \int p(x|z)p(z) dz$$

we can  
 $\Rightarrow$   
derive

$$p(x) = \mathcal{N}(x|\mu, G)$$
, where  $G := WW^T + \sigma^2 I$   
 $d \times d$   $q \times d$

since  $\mathbb{E}[x] = \mathbb{E}[zW^T + \mu + \varepsilon] = \mu$

$$\begin{aligned} \text{Cov}[x] &= \mathbb{E}[(zW^T + \mu + \varepsilon)(zW^T + \mu + \varepsilon)^T] \\ &= \mathbb{E}[Wzz^T W^T] + \mathbb{E}[\varepsilon\varepsilon^T] = WW^T + \sigma^2 I \end{aligned}$$

Moreover, we can obtain the posterior over the latent variables:

$$p(z|x) = \mathcal{N}(z|\bar{m}^{-1}(x - \mu)W, \sigma^2 \bar{m}^{-1}),$$

where  $m := W^T W + \sigma^2 I$

Let's now estimate the PPCA model parameters via MLE:

$$\begin{aligned}
 -\log p(\mathbf{x} | \mu, \mathbf{w}, \sigma^2) & \stackrel{\text{i.i.d.}}{=} -\sum_{i=1}^n \log p(x_i | \mu, \mathbf{w}, \sigma^2) \\
 &= \frac{nd}{2} \log 2\pi + \frac{n}{2} \log |\mathbf{G}| + \frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \mu)^T \mathbf{G}^{-1} (\mathbf{x}_i - \mu)
 \end{aligned}$$

$\Rightarrow$  Then we can obtain:

$$\mu_{\text{MLE}} = \bar{\mathbf{x}}, \quad \bar{\mathbf{x}} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i, \quad \mathbf{S} := \frac{1}{n} \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T$$

$$\text{Then: } -\log p(\mathbf{x} | \mathbf{w}, \mu, \sigma^2) = \frac{n}{2} \left\{ d \log 2\pi + \log |\mathbf{G}| + \text{Tr}(\mathbf{C}^{-1} \mathbf{S}) \right\}$$

$\downarrow$   
 sample  
 covarian

This expression can be minimized wrt  $\mathbf{w}$  and  $\sigma^2$ :

$$\Rightarrow \mathbf{W}_{\text{MLE}} = \mathbf{U}(\mathbf{\Lambda} - \sigma^2 \mathbf{I})^{\frac{1}{2}} \mathbf{R} \quad \text{where:}$$

$$\sigma_{\text{MLE}}^2 = \frac{1}{d-q} \sum_{i=q+1}^d \lambda_i$$

,  $\mathbf{U}$ : is a  $d \times q$  matrix whose columns are the eigenvectors of  $\mathbf{S}$ .

$\mathbf{\Lambda}$ : is a diagonal matrix containing the eigenvalues of  $\mathbf{S}$ .

$\mathbf{R}$ : is an arbitrary orthogonal matrix