

# Factor Analysis.

## Latent Variable Model.

$X_i \rightarrow$  observed data  $X_i \in \mathbb{R}^D$

$Z_i \rightarrow$  latent data.

$\Theta \rightarrow$  Parameters.

If  $Z_i$  is categorical  $\rightarrow Z_i \in \{1, 2, \dots, K\}$

then this problem is Mixture-Models.

What if  $Z_i \in \mathbb{R}^d$  [ $d \ll D$ ]

Can we infer  $Z_i, \forall i$  and  $\Theta$ , given  $\{X_i\}_{i=1}^N$

This is a dimensionality reduction problem.

Factor Analysis problem

or

Probabilistic PCA

Principal Component Analysis. (PCA)

$Z_i$  is assumed to be a mvn  $\sim \mathcal{N}(\mu, \Sigma)$

$X_i$  is sampled from a mvn  $\sim \mathcal{N}(\mu_i, \Sigma_i)$

$\mu_i$  is a function of  $Z_i$   
and  $\Sigma_i$  is a function of  $Z_i$

# Factor Analysis Models

$$x_i \begin{matrix} D \times 1 \\ \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \end{matrix} \quad z_i \begin{matrix} L \times 1 \\ \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \end{matrix}$$

$$x_i \sim N(x_i | \underbrace{Wz_i + \mu}_{(D \times 1)}, \underbrace{\Psi}_{(D \times D)})$$

$W = D \times L$  Matrix

$$Wz_i = \begin{matrix} 1, 2, \dots, L \\ \begin{bmatrix} 1 & 2 & \dots & L \\ \vdots & \vdots & \ddots & \vdots \\ D & \vdots & \vdots & \vdots \end{bmatrix} \end{matrix} \begin{matrix} L \times 1 \\ \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \end{matrix} = \begin{matrix} 1, 2, \dots, L \\ \begin{bmatrix} 1 \\ 2 \\ \vdots \\ 1 \end{bmatrix} \end{matrix}$$

Loading matrix

$W$  maps a  $(L \times 1)$  vector  $z_i$  to a  $(D \times 1)$  vector  $x_i$

$$p(x_i | \theta) = \int_{z_i} p(x_i | z_i, \theta) p(z_i | \theta) dz_i$$

$$= N(x_i | \underbrace{W\mu_0 + \mu}_{(D \times 1)}, \Psi + W\Sigma_0 W^T)$$

Typically we assume  $\rightarrow \mu_0 = \begin{bmatrix} 0 \end{bmatrix} \quad \Sigma_0 = I \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

$$\boxed{p(x_i | \theta) = N(x_i | \mu, \Psi + W W^T)}$$

We could apply MLE to data  $\rightarrow \bar{\mu}, \bar{\Sigma}$

$(D \times 1)$

$(D \times D)$

$D + D^2$

But if go factor analysis way:

$$\mu_{(D \times 1)} = \Psi_{(D \times L)} + W W^T$$

is usually assumed to be a diagonal matrix

$$W \rightarrow D \times L$$

$$(D + D + D^2)$$

assuming  $L \ll D$

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$$



Given  $z_i \rightarrow p(x_i | z_i, \theta)$  is a Gaussian

Given  $x_i \rightarrow p(z_i | x_i, \theta)$  is also a Gaussian

Given some data  $\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$

We can estimate  $\theta \rightarrow [W, \Psi, \mu]$

And then: for each  $x_i$ , I can get  $z_i \rightarrow p(z_i | x_i)$

↑  
Dimensionality Reduction

