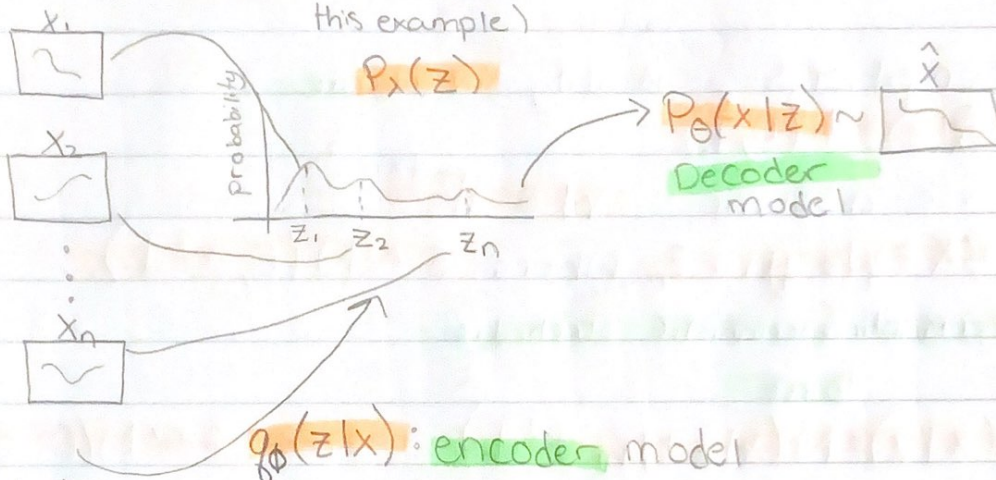


# Generative Models (Probabilistic PCA)

02/21/2023

- general idea

$x_1, x_2, \dots, x_n \sim P_\theta(x)$   
(1 dimension in this example)



$P_\theta(x)$ : data distribution

$P_\lambda(z)$ : distribution of latent representation

where  $\lambda$  is a set of parameters

$P_\theta(x|z)$ : conditional distribution of  $x|z$  where  $\theta$  is a set of parameters

$q_\phi(z|x)$ : conditional distribution of  $z|x$  where  $\phi$  is a set of parameters

- marginal distribution

$$P_\theta(x) = \int P_\theta(x, z) dz = \int P_\theta(x|z) P_\lambda(z) dz$$

$$P(x, z) = P(x|z) \Rightarrow \int P(x, z) dz = \int P(x|z) P(z) dz$$

- we optimize  $\lambda$  and  $\theta$  such that likelihood of the dataset is maximized

$$\max_{\theta} \log P_\theta(x) = \max_{\theta} \log \int P_\theta(x|z) P_\lambda(z) dz$$

- if  $\theta$  is optimized, then the chance of getting back the original image is high

- assumptions  $\leftarrow$  identity covariance

$$P(z) = N(0, I)$$

we assume  $W \in \mathbb{R}^{d \times m}$

$$P_\theta(x|z): X = Wz + \mu + \epsilon, \text{ where } \epsilon \sim N(0, \sigma^2 I)$$

deterministic  $\leftarrow$  deterministic  $\leftarrow$  stochastic

bias

$$P_\theta(x|z) = N(Wz + \mu, \sigma^2 I)$$

since  $\epsilon \sim N(0, \sigma^2 I)$

$$Wz + \mu + \epsilon \sim (Wz + \mu, \sigma^2 I)$$

$$z \sim P(z) = N(0, I)$$

$$x \sim P_\theta(x|z) = N(Wz + \mu, \sigma^2 I)$$

generative

process

parameters:  $[W, \mu, \sigma]$

- side note

$$P(z) = N(\alpha, \Lambda^{-1})$$

$$P(x|z) = N(Az + b, L^{-1})$$

$$P(x) = \int P(x|z)P(z)dz = N(A\alpha + b, L^{-1} + A\Lambda^{-1}A^T)$$

$$P(z|x) = \frac{P(x, z)}{P(x)} = N(\Sigma(A^T L(x-b) + \Lambda\alpha), \Sigma)$$

$P(x)$

$$\text{where } \Sigma = (\Lambda + A^T L A)^{-1}$$

- with our assumptions

$$W=A, z=z, \mu=b, \sigma^2 I=L^{-1}, I=\Lambda^{-1}, 0=\alpha$$

$$\therefore P_\theta(x) = N(\mu, \sigma^2 I + WW^T) \text{ and } \Sigma = (I + W^T(\frac{1}{\sigma^2} I)W)^{-1}$$