

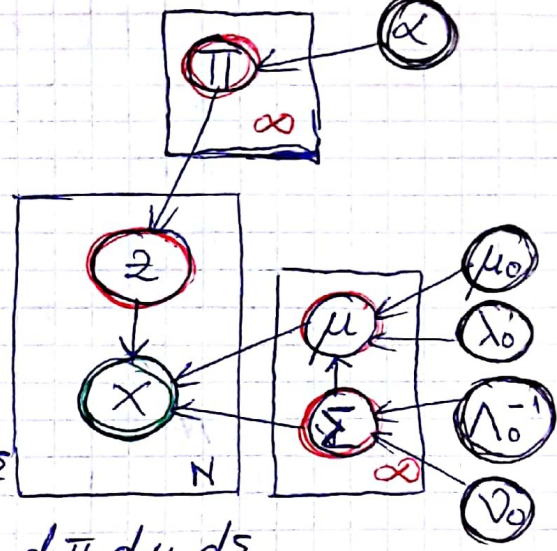
# ⊗ COLLAPSED GIBBS SAMPLING

→ we integrate out  $\Pi, \mu, \Sigma, \alpha$  and sample directly the component assignment,  $z$ .

$$\int \int \int \int p(z_i = k | z_{-i}, x, \Pi, \mu, \Sigma, \alpha) = \frac{\int \int \int \int p(z_i = k, z_{-i}, x, \mu, \Sigma, \alpha, \Pi) d\Pi d\mu d\Sigma}{\int \int \int \int p(z_{-i}, x, \Pi, \mu, \Sigma, \alpha) d\Pi d\mu d\Sigma}$$

$$\propto \int \int \int p(z_i = k, z_{-i}, x, \Pi, \mu, \Sigma, \alpha) d\Pi d\mu d\Sigma$$

$$\propto \underbrace{\int \int p(z_i = k | z_{-i}, \alpha) d\alpha}_A \cdot \underbrace{\int p(x | z_i = k, z_{-i}, \alpha, \mu, \Sigma) d\mu d\Sigma}_B$$



Ⓐ  $p(z_i = k | z_{-i}, \alpha) = \frac{p(z_i = k, z_{-i}, \alpha)}{p(z_{-i}, \alpha)} = \frac{p(z | \alpha)}{p(z_{-i} | \alpha)}$

$$p(z | \alpha) = \int p(z | \Pi) \cdot p(\Pi | \alpha) d\Pi$$

$$= \int \prod_{i=1}^N \Pi_{k_i} p(z_i | \Pi) \cdot p(\Pi | \alpha) d\Pi$$

Dirichlet( $\alpha$ )

usual choice  $\alpha_k = \frac{\alpha}{K}$

Categorical( $\Pi$ )

$$= \int \prod_{i=1}^N \prod_{k=1}^K \Pi_k p(z_i = k | \Pi) \cdot \frac{1}{B(\alpha)} \cdot \prod_{k=1}^K \Pi_k^{\alpha_k - 1} d\Pi$$

$$= \frac{1}{B(\alpha)} \int \prod_{i=1}^N \prod_{k=1}^K \Pi_k \cdot \prod_{k=1}^K \Pi_k^{\frac{\alpha}{K} - 1} d\Pi$$

$$= \frac{\frac{\Gamma(\sum_{k=1}^K \alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k)}}{\frac{\Gamma(\sum_{k=1}^K \frac{\alpha}{K})}{\prod_{k=1}^K \Gamma(\frac{\alpha}{K})}} \cdot \int \prod_{k=1}^K \Pi_k^{N_k + \frac{\alpha}{K} - 1} d\Pi$$

$$= \frac{\Gamma(\alpha)}{\prod_{k=1}^K \Gamma(\frac{\alpha}{K})} \cdot \int \prod_{k=1}^K \Pi_k^{N_k + \frac{\alpha}{K} - 1} d\Pi$$

$$p(z | \alpha) = \frac{\Gamma(\alpha)}{\Gamma(N + \alpha)} \prod_{k=1}^K \frac{\Gamma(N_k + \frac{\alpha}{K})}{\Gamma(\frac{\alpha}{K})}$$



$$p(z_i = k | z_{-i}, \alpha) = \frac{p(z_i | \alpha)}{p(z_{-i} | \alpha)} = \frac{\frac{p(\alpha)}{p(N+\alpha)} \cdot \prod_{k=1}^K \frac{p(N_{k, z_i} + \frac{\alpha}{K})}{p(\alpha/K)}}{\frac{p(\alpha)}{p(N-1+\alpha)} \cdot \prod_{k=1}^K \frac{p(N_{k, z_i} + \frac{\alpha}{K})}{p(\alpha/K)}}$$

Between the 2  $\prod_{k=1}^K$ , all factors are similar except the one containing  $p(N_{k, z_i} + \frac{\alpha}{K}) / p(N_{k, z_i} + \frac{\alpha}{K})$

$$= \frac{p(N+\alpha-1) \cdot \Gamma(N_{k, z_i} + \frac{\alpha}{K})}{p(N+\alpha) \cdot \Gamma(N_{k, z_i} + \frac{\alpha}{K})}$$

$$N_{k, z_i} = N_k - 1$$

$$\Gamma(x+1) = x \cdot \Gamma(x)$$

$$= \frac{\Gamma(N+\alpha-1)}{(N+\alpha-1) \cdot \Gamma(N+\alpha-1)} \cdot \frac{\Gamma(N_{k, z_i} + \frac{\alpha}{K})}{\Gamma(N_{k, z_i} - 1 + \frac{\alpha}{K})} = \frac{N_{k, z_i} + \frac{\alpha}{K} - 1}{N+\alpha-1}$$

$$\Rightarrow p(z_i = k | z_{-i}, \alpha) = \frac{N_{k, z_i} + \frac{\alpha}{K} - 1}{N+\alpha-1}$$

(\*) When  $K \rightarrow \infty$

a) if  $z_i$  joins a cluster  $k$  with  $N_k - 1$  members

$$p(z_i = k | z_{-i}, \alpha) = \frac{N_{k, z_i}}{N+\alpha-1}$$

b) if  $z_i$  joins a cluster with no members (creates its own cluster) [and this is possible since the total number of cluster can grow up to  $\infty$ ],  $N_{k, z_i} \rightarrow 0$

$$p(z_i = k^* | z_{-i}, \alpha) = \frac{\frac{\alpha}{K}}{N+\alpha-1} \cdot K = \frac{\alpha}{N+\alpha-1}$$

there are  $K$  possible clusters "to create"

$$\Rightarrow p(z_i = k^* | z_{-i}, \alpha) = \frac{\alpha}{N+\alpha-1}$$

Conclusion: [EFFECT OF  $\alpha$ ]

$\rightarrow$  an instance  $x_i$  joins a cluster with members in it with a probability  $\propto$  # of members OR creates a new cluster with a probability  $\propto \alpha$ .



$$\textcircled{B} \iint_{\mu \Sigma} p(x_i | z_i = k, \mu, \Sigma) = \iint \frac{p(x_i, z_i = k, \mu, \Sigma)}{p(z_i = k, \mu, \Sigma)} d\mu d\Sigma$$

$$\propto \iint_{\mu \Sigma} p(x_i, z_i = k, \mu, \Sigma) d\mu d\Sigma$$

$$= \iint_{\mu \Sigma} p(x_i | z_i = k, \mu, \Sigma) \cdot p(\mu | \Sigma) \cdot p(\Sigma) d\mu d\Sigma$$

$$= \iint_{\mu \Sigma} \underbrace{\mathcal{N}(\mu_k, \Sigma_k)(x_i)}_{\textcircled{a}} \cdot \underbrace{\mathcal{N}(\mu_0, \frac{1}{\lambda_0} \Sigma)(\mu)}_{\textcircled{b}} \cdot \underbrace{IW(\Sigma_0, \nu_0)}_{\textcircled{c}} d\mu d\Sigma$$

$$\textcircled{a} \mathcal{N}(\mu_k, \Sigma_k)(x_i) = \frac{1}{\sqrt{(2\pi)^\Delta \cdot |\Sigma_k|}} \cdot e^{-\frac{1}{2}(x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k)}$$

$$= (2\pi)^{-\frac{\Delta}{2}} \cdot |\Sigma_k|^{-\frac{1}{2}} \cdot \left\{ e^{-\frac{1}{2}(x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k)} \right\}$$

$$\textcircled{b} \mathcal{N}(\mu_0, \frac{1}{\lambda_0} \Sigma)(\mu) = \frac{1}{\sqrt{(2\pi)^\Delta \cdot |\frac{1}{\lambda_0} \Sigma|}} \cdot e^{-\frac{1}{2}(\mu - \mu_0)^T (\frac{1}{\lambda_0} \Sigma)^{-1} (\mu - \mu_0)}$$

$$= (2\pi)^{-\frac{\Delta}{2}} \cdot \lambda_0^{\frac{\Delta}{2}} \cdot |\Sigma|^{-\frac{1}{2}} \cdot \left\{ e^{-\frac{\lambda_0}{2}(\mu - \mu_0)^T \Sigma^{-1} (\mu - \mu_0)} \right\}$$

$$\textcircled{c} \text{Inv Wishart}(\Sigma_0, \nu_0)(\Sigma) = \frac{|\Sigma_0|^{\frac{\nu_0}{2}}}{2^{\frac{\nu_0 \Delta}{2}} \Gamma_0(\frac{\nu_0}{2})} \cdot |\Sigma|^{-\frac{\nu_0 + \Delta + 1}{2}} \cdot e^{-\frac{1}{2} \text{tr}(\Sigma_0 \Sigma^{-1})}$$

$$\iint_{\mu \Sigma} \textcircled{a} \cdot \textcircled{b} \cdot \textcircled{c} = \iint_{\mu \Sigma} (2\pi)^{-\Delta} \cdot |\Sigma|^{\frac{-\nu_0 + \Delta + 3}{2}} \cdot \lambda_0^{\frac{\Delta}{2}} \cdot \frac{|\Sigma_0|^{\frac{\nu_0}{2}}}{2^{\frac{\nu_0 \Delta}{2}} \Gamma_0(\frac{\nu_0}{2})} \cdot e^{-\frac{1}{2}[(\mu - \mu_0)^T \Sigma^{-1} (\mu - \mu_0) \lambda_0 + (x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k) + \text{tr}(\Sigma_0 \Sigma^{-1})]} d\mu d\Sigma$$

$$= (2\pi)^{-\Delta} \cdot 2(\lambda_0, \nu_0, \Sigma_0, \Delta) \cdot \iint_{\mu \Sigma} |\Sigma|^{-\frac{\nu_0 + \Delta + 3}{2}} \cdot e^{-\frac{1}{2}[\dots]} d\mu d\Sigma$$

It turns out that the  $\iint_{\mu \Sigma} \dots d\mu d\Sigma$  is:

$2(\lambda_N, \nu_N, \Sigma_N, \Delta)$ , where

$$\lambda_N = \lambda_0 + N \quad \Sigma_N = \Sigma_0 + (x_i - \mu_k)^T (x_i - \mu_k) + \frac{\lambda_0 N}{\lambda_0 + N} (\bar{x} - \mu_0)(\bar{x} - \mu_0)^T$$

$$\nu_N = \nu_0 + N$$

$$\bar{x} = \frac{1}{N} \sum_{m=1}^N x_m$$



### ⊗ EFFECT of $\mu_0, \lambda_0, \Sigma_0, \nu_0$

→  $\mu_0$  is our prior mean for  $\mu$ .

→  $\lambda_0$  is how strongly we believe this prior for  $\mu$ .

→  $\Sigma_0$  is proportional to our prior mean for  $\Sigma$ .

→  $\nu_0$  is how strongly we believe this prior for  $\Sigma$   
( $\nu_0 \geq D$ )