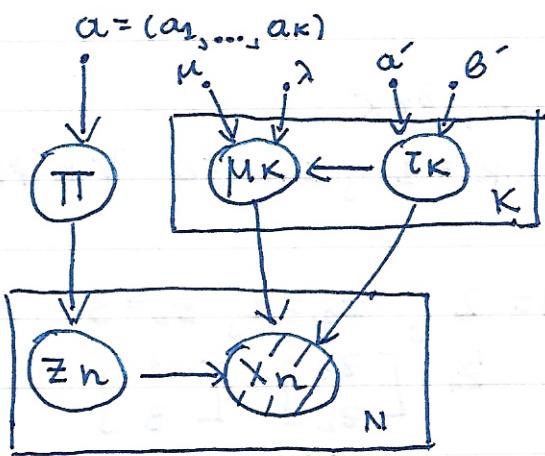


VI GMM



$$X = \{x_n : n \in [N]\}$$

$$Z_i = \{z_n : n \in [N]\}$$

$$M = \{\mu_k : k \in [K]\}$$

$$T = \{\tau_k : k \in [K]\}$$

Note: $[N] = \{1, \dots, N\}$

GPD: $\pi | \alpha \sim \text{Dir}(\alpha) = \prod_{k=1}^K \pi_k^{\alpha_k - 1}$
 $\tau_k | \alpha', \beta' \sim \text{Ga}(\alpha', \beta') = \frac{(\beta')^{\alpha'}}{\Gamma(\alpha')} \tau_k^{\alpha'-1} e^{-\beta' \tau_k}$

$$\mu_k | \tau_k, \mu, \lambda \sim N(\mu_k | \mu, (\lambda \tau_k)^{-1}) = \sqrt{\frac{\lambda \tau_k}{2\pi}} e^{-\frac{\lambda \tau_k}{2} (\mu_k - \mu)^2}$$

$$z_n | \pi \sim \text{Cat}(\pi)$$

$$x_n | \bar{z}_n = \bar{k}, M, T \sim N(x_n | \mu_k, \tau_k) = \sqrt{\frac{\tau_k}{2\pi}} e^{-\frac{\tau_k}{2} (x_n - \mu_k)^2}$$

this condition tells us which $k \in [K]$ we consider for μ_k, τ_k

Joint:

$$p(X, Z, \pi, M, T) = p(X, Z | \pi, M, T) \cdot p(\pi, M, T)$$

see graphical model $p(X | Z, M, T) p(Z | \pi) p(\pi) p(M | T) p(T)$

$\overbrace{p(X | Z, M, T)}^{\text{P(M|T)}} \quad \overbrace{p(Z | \pi)}^{\text{P(T)}} \quad \overbrace{p(\pi)}^{\text{P(M|T)}} \quad \overbrace{p(M | T)}^{\text{P(T)}}$

VI assumption $q(Z, \pi, M, T) = q(Z)q(\pi, M, T)$

The assumption is that \mathbf{z}_i is independent of (M, Λ, T)

Notation $\mathbf{z}_n \rightarrow z_{n1}, \dots, z_{nK}$

Where $z_{n=K} \Leftrightarrow z_{nK} = 1, z_{nK'} = 0 \quad \forall K' \neq K$

example: $K = 3, N = 2, z_1 = 1, z_2 = 3$

Then, instead of $\mathbf{z}_i = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$

We write $\mathbf{z}_i = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

Complete likelihood:

$$\begin{aligned} p(\mathbf{x}, \mathbf{z} | \Pi, M, T) &= p(\mathbf{x} | \mathbf{z}, \Pi, M, T) p(\mathbf{z}) \\ p(\mathbf{x}, \mathbf{z} | \Pi, M, T) &= \prod_n p(x_n, z_n | \Pi, M, T) = \\ &= \prod_n p(x_n | z_n, \Pi, M, T) \cdot p(z_n | \Pi, M, T) \end{aligned}$$

see gr.
model $\prod_n p(x_n | z_n, M, T) p(z_n | \Pi)$

$$\begin{aligned} &= \prod_{n, K} [p(x_n | \mu_{nK}, \tau_K) p(z_{nK} = 1 | \Pi)]^{z_{nK}} \xrightarrow{\text{recall } z | \Pi \sim \text{Categorical}} \\ &= \prod_{n, K} [(N(x_n | \mu_{nK}, \tau_K^{-1}) / \Pi_K)]^{z_{nK}} \end{aligned}$$

Using $z_{n,k}$ is just a trick so that we write our likelihood more compactly

In previous example:

$$\begin{aligned}
 p(\bar{X}, \bar{Z} | \Pi, M, T) &= \prod_{n=1}^N p(x_n | z_{n,k} = k_n, M, T) \cdot p(z_{n,k} = k_n | \Pi) \\
 &= [p(x_1 | z_1 = 1, M, T) \cdot \underbrace{p(z_2 = 1 | \Pi)}_{\substack{\parallel \\ p(z_2 = 3 | \Pi)}}] [p(x_2 | z_2 = 3, M, T) \\
 &= [N(x_1 | \mu_1, \tau_1) \cdot \overset{\parallel}{\Pi_1}] \cdot [N(x_2 | \mu_3, \tau_3) \overset{\parallel}{\Pi_2}] \\
 &= [N(x_1 | \mu_1, \tau_1) \cdot \Pi_1]^1 \cdot [N(x_1 | \mu_2, \tau_2) \Pi_2]^0 [N(x_1 | \mu_3, \tau_3) \\
 &\quad \cdot [N(x_2 | \mu_2, \tau_2) \cdot \Pi_2]^0 \dots [N(x_2 | \mu_3, \tau_3) \Pi_3]^1] \\
 &= \prod_{n=1}^N [p(x_n | \mu_{k_n}, \tau_{k_n}) p(z_{n,k} = k_n | \Pi)]
 \end{aligned}$$

Update equations

Latent variables (not observed): \bar{Z}, Π, M, T

In general, if $\Theta = (\theta_1, \dots, \theta_m)$ our latent variables, then $\log q^*(\theta_j) = E_{i \neq j} [\log p(\bar{X}, \Theta)] + \text{const}$ ≈ we ignore

Here $\Theta = (\bar{Z}, \Pi, M, T)$:

$$\log q^*(\bar{Z}) = E_{\text{the rest}} [\log p(\bar{X}, \bar{Z}, \Pi, M, T)] + \text{const}$$

$$= E_{\Pi, M, T} [\log p(\bar{X}, \bar{Z} | \Pi, M, T) + \log P(\Pi, M, T)] + \text{const} +$$

However, $p(M, \Pi, T)$ does not depend on z
 \rightarrow We can ignore it]

$$\text{Thus } \log q^*(z) \stackrel{?}{=} E_{\Pi, M, T} [\log p(X, z | \Pi, M, T)]$$

$$\log p(X, z | \Pi, M, T) = \log \prod_{n, k} [N(x_n | \mu_k, \tau_k^{-1}) \pi_k]^{z_{n,k}}$$

$$= \sum_{n, k} z_{n,k} [\log(N(x_n | \mu_k, \tau_k^{-1})) + \log \pi_k]$$

$$\stackrel{?}{=} \sum_{n, k} z_{n,k} [\log \left[\sqrt{\frac{\tau_k}{2\pi}} e^{-\frac{\tau_k}{2}(x_n - \mu_k)^2} \right] + \log \pi_k]$$

$$\stackrel{?}{=} \sum_{n, k} z_{n,k} \left[\frac{\tau_k}{2} - \frac{\tau_k}{2} (x_n - \mu_k)^2 + \log \pi_k \right]$$

Expectation is linear:

$$E_T[\tau_k] \cdot E_M[(x_n - \mu_k)^2] \quad \text{since } \cancel{E_M}$$

$$\log q^*(z) = \sum_{n, k} z_{n,k} \left[\frac{E_T[\tau_k]}{2} - \frac{E_{T, M}[\tau_k (x_n - \mu_k)^2]}{2} + E_{\Pi}[\log \pi_k] \right]$$

$$= \sum_{n, k} z_{n,k} \left[\frac{E_{\tau_k}[\tau_k]}{2} - \frac{E_{\tau_k}[\tau_k]}{2} E_{\mu_k}[(x_n - \mu_k)^2] + E_{\pi_k}[\log \pi_k] \right]$$

$$\log p_{n,k}$$

$$= \sum_{n, k} z_{n,k} \log p_{n,k}$$

$$\text{So } q^*(z_n) = \prod_K r_{n,k}^{z_{n,k}}, \quad r_{n,k} = \frac{p_{n,k}}{\sum_K p_{n,k}}$$

Why?

$$(q(z_i) = \prod_n q(z_n))$$

$$\log q(z_i) = \sum_{n,k} z_{n,k} \log p_{n,k} = \sum_{n,k} \log p_{n,k}^{z_{n,k}} =$$

$$= \log \prod_{n,k} p_{n,k}^{z_{n,k}} = \log \prod_n q(z_n) \Rightarrow$$

$$q(z_n) = \prod_k p_{n,k}^{z_{n,k}} \quad (\text{Not sure why he divides by } \prod_k p_{n,k})$$

Now for $q^*(\pi_j, m_j, T)$

$$\log q^*(\pi_j, m_j, T) = E_z [\log p(x_j, z_j | \pi_j, m_j, T)]$$

$$= E_z [\log p(x_j, z_j | \pi_j, m_j, T) + \underbrace{\log P(\pi_j, m_j, T)}_{\text{not depend on } z}]$$

$$= E_z [\log p(x_j, z_j | \pi_j, m_j, T)] + \log P(\pi_j, m_j, T)$$

$$\begin{aligned} & \text{recall} \\ & = E_z [\log (\prod_{n,k} z_{n,k} N(x_n | \mu_k, \tau_k^{-1}) \pi_k)^{z_{n,k}}] \\ & \log p(x_j, z_j | \pi_j, m_j, T) \\ & + \log [P(\pi) \cdot P(m_j, T)] \end{aligned}$$

$$\begin{aligned} & = \sum_{n,k} E_z [z_{n,k}] \log N(x_n | \mu_k, \tau_k^{-1}) \\ & \quad \log \prod_k \pi_k^{\alpha_{k-1}} = \sum_k (\alpha_{k-1}) \log \pi_k \\ & + \sum_{n,k} E_z [z_{n,k}] \log \pi_k + \underbrace{\log P(\pi)}_{\text{constant}} + \log P(m_j, T) \end{aligned}$$

Note how π appears

$$E_Z [z_{n,k}] = r_{n,k} \quad (\text{no idea})$$

$$q(T, M, \tau) = q(\pi) \prod_K q(\mu_k, \tau_k)$$

$(\pi \perp \mu_k, \tau_k)$

Let's examine $q^*(\mu_k, \tau_k)$:

We re-examine previous expression
and extract the terms containing

μ_k, τ_k :

$$\sum_{n,k} r_{n,k} \underbrace{\log \left[\sqrt{\frac{\tau_k}{2\pi}} e^{-\frac{\tau_k}{2}(x_n - \mu_k)^2} \right]}_{\text{only } \pi_k} + \sum_{n,k} r_{n,k} \left(\log \pi_k + \sum_k (\alpha_k - 1) \log \pi_k \right)$$

$$+ \sum_k \log p(\mu_k, \tau_k)$$

$\approx N(\mu, (\lambda \tau_k)^{-1})$

$$\log p(\mu_k | \tau_k) + \log p(\tau_k) \stackrel{?}{=} \frac{\log \tau_k}{2} - \frac{\lambda \tau_k}{2} (\mu_k - \mu)^2$$

$$+ (\alpha' - 1) \log \tau_k - \beta' \tau_k$$

Thus (you fix "k", so there are no \sum_K)

$$\log q^*(\mu_k, \tau_k) \stackrel{?}{=} \sum_n r_{n,k} \left(\frac{\log \tau_k}{2} - \frac{\tau_k}{2} (x_n - \mu_k)^2 \right)$$

$$+ \frac{\log \tau_k}{2} - \frac{\lambda \tau_k}{2} (\mu_k - \mu)^2 + (\alpha' - 1) \log \tau_k$$

$\# \beta' \tau_k$

$$= -\frac{1}{2} [\lambda \tau_k + (\sum_n r_{n,k}) \tau_k] \mu_k^2 + [\lambda \tau_k \mu + \tau_k (\sum_n r_{n,k} x_n)]_k$$

$$+ [\alpha'_- + \frac{1}{2} + \frac{1}{2} \sum_n r_{n,k}] \log \tau_k - (\beta' + \frac{\lambda \mu^2}{2} + \frac{1}{2} \sum_n r_{n,k})$$

log of gaussian: $-\frac{\tau^*}{2} Y^2 + \tau \mu Y$
 log of gamma: $(\alpha - 1) \log Y - \beta Y$

Thus: $q^*(\mu_k | \tau_k) \approx N(\mu_k | \mu^*, \tau^*)$

~~$\tau^* = \lambda \tau_k + \tau_k \sum_n r_{n,k} = \tau_k (\lambda + \sum_n r_{n,k})$~~

$$\mu^* = \frac{\lambda \tau_k \mu + \tau_k \sum_n r_{n,k} x_n}{\tau^*}$$

$$q^*(\tau_k) = G_a(\tau_k | \alpha^*, \beta^*)$$

$$\alpha'^* = \alpha' + \frac{1}{2} + \frac{1}{2} \sum_n r_{n,k}$$

$$\beta'^* = \beta' + \frac{\lambda \mu^2}{2} + \frac{1}{2} \sum_n r_{n,k} x_n^2$$

For $q^*(\pi)$: recall that only the following has π :

$$\sum_{n,k} r_{n,k} \log \pi_k + \sum_k (\alpha_k - 1) \log \pi_k$$

$$= \sum_k [(\alpha_k - 1) + \sum_n r_{n,k}] \log \pi_k$$

log of dir: $(\alpha - 1) \log \pi$

(7)

$$\text{Thus: } \alpha^* = \alpha + \frac{1}{n} r_{nk}$$

For $\log p_{nk}$

$$E_{\tau_k}[\log \tau_k], E_{\pi}[\log \pi_k] \sim \text{digamma} *$$

$$E_{\tau_k}[\tau_k] = \frac{\alpha^*}{\beta^*}$$

$$E_{\mu_k}[\log(x_n - \mu_k)^2]$$

$$= x_n^2 - 2x_n \underbrace{E_{\mu_k}[\mu_k]}_{\mu^*} + \underbrace{E_{\mu_k}[\mu_k^2]}_{\frac{1}{\tau^*} + (\mu^*)^2}$$

$$* \left(\begin{array}{l} E_{\tau_k}[\log \tau_k] = \psi(\pi_k) - \psi\left(\sum_{j=1}^K \pi_j\right) \\ E_{\pi}[\log \pi_k] = \psi(\alpha_k) - \psi\left(\sum_{j=1}^K \alpha_j - 1\right) \end{array} \right)$$

ψ : digamma function

I think :)

$$* E_{\tau_k}[\log \tau_k] = -\beta^* + \psi(\alpha^*)$$

$$E_{\pi}[\log \pi_k] = \psi(\alpha_k) - \psi\left(\sum_{j=1}^K \alpha_j\right)$$

stack exchange :)

ψ : digamma function