

Here we know: $\mathbf{X} : l \times N$ ($n= 1 \sim N$)

$$\mathbf{X} = [\mathbf{x}_1 \mathbf{x}_2 \dots \mathbf{x}_n \dots \mathbf{x}_N]$$

$$\pi_k : 1 \times 1 \text{ (} k = 1 \sim K \text{)}$$

$$\mu_k : l \times 1 \text{ (} k = 1 \sim K \text{)}$$

$$\Sigma_k : l \times l \text{ (} k = 1 \sim K \text{)}$$

$$\phi : l \times N$$

$$\phi = [\phi_k(\mathbf{x}_n)] = [\dots \phi(\mathbf{x}_n) \dots \phi(\mathbf{x}_N)] = \begin{bmatrix} \vdots \\ \phi_k(\mathbf{X})^T \\ \vdots \end{bmatrix}$$

$$\phi_k(\mathbf{x}):$$

$$\phi_k(\mathbf{x}) = \frac{1}{(2\pi)^{l/2} |\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mu_k)^T \Sigma_k^{-1} (\mathbf{x} - \mu_k)\right)$$

$$\ln \phi_k(\mathbf{x}) = -\frac{l}{2} \ln(2\pi) - \frac{1}{2} \ln |\Sigma_k| - \frac{1}{2} (\mathbf{x} - \mu_k)^T \Sigma_k^{-1} (\mathbf{x} - \mu_k)$$

$$\mathbf{Z} : K \times N$$

$$\mathbf{Z} = [\dots \mathbf{z}_n \dots \mathbf{z}_N]$$

$$= \begin{bmatrix} \vdots \\ \mathbf{z}_k^T \\ \vdots \end{bmatrix}$$

$$z_{kn} : 1 \times 1 \text{ (} k = 1 \sim K \text{)}$$

$$\mathbf{z}_k = [0, 1, \dots, 1, \dots, 0]^T \text{ represent probability } K \text{ states in } N \text{ samples (} N \times 1 \text{)}$$

$$\mathbf{z}_n = [0, 0, \dots, 1, \dots, 0]^T, \text{ represent probability of length} = K \text{ states, (} K \times 1 \text{) only when } z_k = 1, \text{ it would be counted into } p, \text{ random variable}$$

$$p(\mathbf{z} | \boldsymbol{\pi}) = \prod_{k=1}^K \pi_k^{z_k}$$

$$p(\mathbf{x} | \mathbf{z}, \boldsymbol{\Sigma}, \boldsymbol{\mu}) = \prod_{k=1}^K \phi_k(\mathbf{x})^{z_k}$$

Goal:

$$\max \quad p(\mathbf{X} | \boldsymbol{\pi}, \boldsymbol{\Sigma}, \boldsymbol{\mu})$$

期望最大化算法，或者**EM**算法

$$\max \quad \ln p(\mathbf{X}|\boldsymbol{\theta}) = \mathcal{L}(q, \boldsymbol{\theta}) + \text{KL}(q||p)$$

where

$$\begin{aligned}\mathcal{L}(q, \boldsymbol{\theta}) &= \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})} \right\} \\ \text{KL}(q||p) &= - \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta})}{q(\mathbf{Z})} \right\}\end{aligned}$$

suppose $\mathbf{z}_1 \mathbf{z}_2 \dots \mathbf{z}_n \dots \mathbf{z}_N$ independent

Here $p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})$

$$\begin{aligned}p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) &= p(\mathbf{X}|\mathbf{Z}, \boldsymbol{\pi}, \boldsymbol{\Sigma}, \boldsymbol{\mu})p(\mathbf{Z}|\boldsymbol{\pi}, \boldsymbol{\Sigma}, \boldsymbol{\mu}) \\ &= p(\mathbf{X}|\mathbf{Z}, \boldsymbol{\Sigma}, \boldsymbol{\mu})p(\mathbf{Z}|\boldsymbol{\pi}) \\ &= \prod_{n=1}^N p(\mathbf{x}_n|\mathbf{Z}, \boldsymbol{\Sigma}, \boldsymbol{\mu}) \prod_{n=1}^N p(\mathbf{z}_n|\boldsymbol{\pi}) \\ &= \prod_{n=1}^N p(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\Sigma}, \boldsymbol{\mu}) \prod_{n=1}^N p(\mathbf{z}_n|\boldsymbol{\pi})\end{aligned}$$

Hence

$$\begin{aligned}\ln(p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})) &= \sum_{n=1}^N \ln p(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\Sigma}, \boldsymbol{\mu}) + \sum_{n=1}^N \ln p(\mathbf{z}_n|\boldsymbol{\pi}) \\ &= \sum_{n=1}^N \sum_{k=1}^K (\ln \pi_k) z_{kn} + \sum_{n=1}^N \sum_{k=1}^K (\ln \phi_k(\mathbf{x}_n)) z_{kn} \\ &= \ln \boldsymbol{\pi}^T \cdot \mathbf{Z} \cdot \text{ones}(N, 1) + \\ &\quad \sum_{n=1}^N \sum_{k=1}^K \left[-\frac{l}{2} \ln(2\pi) - \frac{1}{2} \ln |\boldsymbol{\Sigma}_k| - \frac{1}{2} (\mathbf{x}_n - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_k) \right] z_{kn} \\ &= (\ln \boldsymbol{\pi}^T - \frac{1}{2} |\boldsymbol{\Sigma}|^T) \cdot \mathbf{Z} \cdot \text{ones}(N, 1) - \frac{l}{2} \ln(2\pi) \text{ones}(1, K) \cdot \mathbf{Z} \cdot \text{ones}(N, 1) \\ &\quad - \frac{1}{2} \sum_{k=1}^K \left[\text{tr} \left((\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T) \cdot \text{diag}(\mathbf{z}_k) \right) \right]\end{aligned}$$

notice: \mathbf{X} is fixed, $\mathbf{Z}, \boldsymbol{\theta}$ are variables, 转 而 用 $q(\mathbf{Z}), \boldsymbol{\theta}$ 替代 ;

EM法

$$\ln p(\mathbf{X}|\boldsymbol{\theta}) = \mathcal{L}(q, \boldsymbol{\theta}) + \text{KL}(q||p)$$

[M步骤] fix $q(\mathbf{Z})$, change $\boldsymbol{\theta}$

fix $q \equiv q^k = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^k) = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}})$

$$\begin{aligned}
\theta^{k+1} &\equiv \operatorname{argmax}_{\theta} \mathcal{L}(q^k, \theta) \\
&= \operatorname{argmax}_{\theta} \sum_{\mathbf{Z}} q^k \ln \left\{ \frac{p(\mathbf{X}, \mathbf{Z}|\theta)}{q^k} \right\} \\
&= \operatorname{argmax}_{\theta} \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\theta) - \sum_{\mathbf{Z}} q^k \ln(q^k) \\
&= \operatorname{argmax}_{\theta} \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\theta) \\
\mathcal{L}(q^k, \theta^{k+1}) &> \mathcal{L}(q^k, \theta^k) = \ln p(\mathbf{X}|\theta^k)
\end{aligned}$$

where $\theta^{\text{old}} \equiv \theta^k$

$$Q(\theta, \theta^{\text{old}}) \equiv \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\theta)$$

[E步骤]fix θ , change $q(\mathbf{Z})$

fix $\theta \equiv \theta^{k+1}$

$$\ln p(\mathbf{X}|\theta^{k+1}) = \mathcal{L}(q, \theta^{k+1}) + \text{KL}(q|p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})) = \text{const}$$

第2部分 $\text{KL}(q|p) \downarrow$, 则 $\mathcal{L}(q, \theta^{k+1}) \uparrow$

而 $\text{KL}(q|p) \downarrow$ 取min值0, 此时 q 取 $q^{k+1} = p(\mathbf{Z}|\mathbf{X}, \theta)$

$$\ln p(\mathbf{X}|\theta^{k+1}) = \mathcal{L}(q^{k+1}, \theta^{k+1})$$

更新 θ^{old} , 保留此时的 θ 值

$$\theta^{\text{old}} \leftarrow \theta^{k+1}$$

$$\begin{aligned}
q^{k+1} &\equiv \operatorname{argmax}_q \mathcal{L}(q, \theta^{k+1}) \\
&\equiv \operatorname{argmin}_q \text{KL}(q|p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})) = 0 \\
&= p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})
\end{aligned}$$

$$\begin{aligned}
\ln p(\mathbf{X}|\theta^{k+1}) &\equiv \mathcal{L}(q, \theta^{k+1}) + \text{KL}(q|p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})) \\
&= \mathcal{L}(q^k, \theta^{k+1}) + \text{KL}(q^k|p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})) \\
&= \mathcal{L}(q^{k+1}, \theta^{k+1}) + \text{KL}(q^{k+1}|p(\mathbf{Z}|\mathbf{X}, \theta^{k+1})) \\
&= \mathcal{L}(q^{k+1}, \theta^{k+1}) \\
\ln p(\mathbf{X}|\theta^{k+1}) &= \mathcal{L}(q^{k+1}, \theta^{k+1}) > \mathcal{L}(q^k, \theta^{k+1})
\end{aligned}$$

in all

$$\ln p(\mathbf{X}|\theta^{k+1}) = \mathcal{L}(q^{k+1}, \theta^{k+1}) > \mathcal{L}(q^k, \theta^{k+1}) > \ln p(\mathbf{X}|\theta^k) = \mathcal{L}(q^k, \theta^k)$$

So

$$\begin{aligned}
\lim_{k \rightarrow \infty} \ln p(\mathbf{X}|\boldsymbol{\theta}^k) &= \lim_{k \rightarrow \infty} \mathcal{L}(q^k, \boldsymbol{\theta}^{k+1}) = \max_{\boldsymbol{\theta}} \ln p(\mathbf{X}|\boldsymbol{\theta}) \\
\boldsymbol{\theta}_{max} &\equiv \max_{\boldsymbol{\theta}} \ln p(\mathbf{X}|\boldsymbol{\theta}) \\
&= \lim_{k \rightarrow \infty} \boldsymbol{\theta}^{k+1} \\
&= \lim_{k \rightarrow \infty} \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \\
&= \lim_{k \rightarrow \infty} \operatorname{argmax}_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta}^k)
\end{aligned}$$

Calculation of [M 步骤]fix $q(\mathbf{Z})$, change $\boldsymbol{\theta}$

$$\text{fix } q \equiv q^k = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^k) = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}})$$

$$\text{where } \boldsymbol{\theta}^{\text{old}} \equiv \boldsymbol{\theta}^k$$

$$Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{\text{old}}) \equiv \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})$$

Here

$$\begin{aligned}
\boldsymbol{\theta}^{k+1} &\equiv \operatorname{argmax}_{\boldsymbol{\theta}} \mathcal{L}(q^k, \boldsymbol{\theta}) \\
&= \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) - \sum_{\mathbf{Z}} q^k \ln(q^k) \\
&= \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{\mathbf{Z}} q^k \ln p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \\
&= \operatorname{argmax}_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{\text{old}})
\end{aligned}$$

Now find close form of Q

$\sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}})$ is [probability distribution] random variable **of** \mathbf{Z} [probability distribution] random variable

$$\text{Here } q^k = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^k) = p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}})$$

$$\begin{aligned}
Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{\text{old}}) &\equiv \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \ln p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \\
&= \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \left\{ (\ln \boldsymbol{\pi}^T - \frac{1}{2} |\boldsymbol{\Sigma}|^T) \cdot \mathbf{Z} \cdot \text{ones}(N, 1) - \frac{l}{2} \ln(2\pi) \text{ones}(1, K) \cdot \mathbf{Z} \cdot \text{ones}(N, 1) \right. \\
&\quad \left. - \frac{1}{2} \sum_{k=1}^K \left[\text{tr} \left((\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T) \cdot \text{diag}(\mathbf{z}_k) \right) \right] \right\} \\
&= \left\{ \left[\sum_{n=1}^N \sum_{\mathbf{z}_n} p(\mathbf{z}_n|\mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) \mathbf{z}_n^T \right] (\ln \boldsymbol{\pi} - \frac{1}{2} |\boldsymbol{\Sigma}| - \frac{l}{2} \ln(2\pi) \cdot \mathbf{1}.) \right\} \\
&\quad - \frac{1}{2} \left\{ \sum_{n=1}^N \sum_{k=1}^K \left[\sum_{\mathbf{z}_n} p(\mathbf{z}_n|\mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) (\mathbf{x}_n - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_k) z_{kn} \right] \right\} \\
&= [\boldsymbol{\gamma} \cdot \mathbf{1}.]^T (\ln \boldsymbol{\pi} - \frac{1}{2} |\boldsymbol{\Sigma}| - \frac{l}{2} \ln(2\pi) \cdot \mathbf{1}.) \\
&\quad - \frac{1}{2} \sum_{k=1}^K \text{tr} \left(\text{diag}(\boldsymbol{\gamma}_k^T) \cdot (\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{X} - \boldsymbol{\mu}_k \cdot \mathbf{1}^T) \right)
\end{aligned}$$

Here

$$p(\mathbf{z}_n | \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) = \frac{p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) p(\mathbf{z}_n | \boldsymbol{\theta}^{\text{old}})}{\sum_{\mathbf{z}_n} p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) p(\mathbf{z}_n | \boldsymbol{\theta}^{\text{old}})}$$

So, have $\mathbf{1}^T \boldsymbol{\gamma} = \text{ones}(1, N)$

$$p(\mathbf{z}_n = k | \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) = \frac{\phi_k^{\text{old}}(\mathbf{x}_n) \pi_k^{\text{old}}}{\sum_{k=1}^K \phi_k^{\text{old}}(\mathbf{x}_n) \pi_k^{\text{old}}} \equiv \gamma_{kn}$$

$$\boldsymbol{\gamma} = \boldsymbol{\phi}^{\text{old}}(X) \odot (\boldsymbol{\pi}_k^{\text{old}} \cdot \mathbf{1}^T) \odot \left(\frac{\mathbf{1}}{\mathbf{1} \cdot (\boldsymbol{\pi}^{\text{old}})^T \boldsymbol{\phi}^{\text{old}}(X)} \right)$$

maximize Q

$$\begin{aligned} \max_{\boldsymbol{\theta}} \quad Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{\text{old}}) &\equiv \sum_{\mathbf{Z}} p(\mathbf{Z} | X, \boldsymbol{\theta}^{\text{old}}) \ln p(X, \mathbf{Z} | \boldsymbol{\theta}) \\ &= [\boldsymbol{\gamma} \cdot \mathbf{1}]^T \left(\ln \boldsymbol{\pi} - \frac{1}{2} |\boldsymbol{\Sigma}| - \frac{l}{2} \ln(2\pi) \cdot \mathbf{1} \right) \\ &\quad - \frac{1}{2} \sum_{k=1}^K \text{tr} \left(\text{diag}(\boldsymbol{\gamma}_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \boldsymbol{\Sigma}_k^{-1} (X - \mu_k \cdot \mathbf{1}^T) \right) \\ \text{s.t.} \quad \mathbf{1}^T \cdot \boldsymbol{\pi} &= 1 \end{aligned}$$

define $L \equiv Q - \lambda(\mathbf{1}^T \cdot \boldsymbol{\pi} - 1)$

for $\boldsymbol{\pi}$

$$\frac{\partial L}{\partial \boldsymbol{\pi}} = [\boldsymbol{\gamma} \cdot \mathbf{1}] \odot \frac{\mathbf{1}}{\boldsymbol{\pi}} - \lambda \mathbf{1} = 0$$

so

$$[\boldsymbol{\gamma} \cdot \mathbf{1}] = \lambda \boldsymbol{\pi}$$

Hence

$$\begin{aligned} \lambda &= \mathbf{1}^T [\boldsymbol{\gamma} \cdot \mathbf{1}] = [\mathbf{1}^T \boldsymbol{\gamma}] \cdot \mathbf{1} = \text{ones}(1, N) \cdot \mathbf{1} = N \\ \boldsymbol{\pi} &= \frac{[\boldsymbol{\gamma} \cdot \mathbf{1}]}{\mathbf{1}^T [\boldsymbol{\gamma} \cdot \mathbf{1}]} = \frac{[\boldsymbol{\gamma} \cdot \mathbf{1}]}{N} \end{aligned}$$

for μ_k

$$\frac{\partial L}{\partial \mu_k} = -\frac{1}{2} \cdot 2 \cdot (-1) \boldsymbol{\Sigma}_k^{-1} (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\boldsymbol{\gamma}_k^T) \cdot \mathbf{1} = 0$$

so

$$\begin{aligned} (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\boldsymbol{\gamma}_k^T) \cdot \mathbf{1} &= 0 \\ (X - \mu_k \cdot \mathbf{1}^T) \boldsymbol{\gamma}_k &= 0 \end{aligned}$$

Hence

$$\mu_k = \frac{X\gamma_k}{\mathbf{1}^T \gamma_k}$$

for Σ_k

$$\begin{aligned} dL &= [\gamma_k^T \cdot \mathbf{1}]^T \left(\frac{-1}{2} \right) \Sigma_k^{-1} d\Sigma_k \\ &\quad - \frac{1}{2} \text{tr} \left(\text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T d\Sigma_k^{-1} (X - \mu_k \cdot \mathbf{1}^T) \right) \\ &= [\gamma_k^T \cdot \mathbf{1}]^T \left(\frac{-1}{2} \right) \Sigma_k^{-1} d\Sigma_k \\ &\quad - \frac{1}{2} \text{tr} \left((X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T d\Sigma_k^{-1} \right) \\ &= -\left(\frac{1}{2} \right) [\gamma_k^T \cdot \mathbf{1}]^T \Sigma_k^{-1} d\Sigma_k \\ &\quad + \frac{1}{2} \text{tr} \left((X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \Sigma_k^{-1} d\Sigma_k \Sigma_k^{-1} \right) \\ &= -\left(\frac{1}{2} \right) [\gamma_k^T \cdot \mathbf{1}]^T \Sigma_k^{-1} d\Sigma_k \\ &\quad + \frac{1}{2} \text{tr} \left(\Sigma_k^{-1} (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \Sigma_k^{-1} d\Sigma_k \right) \end{aligned}$$

note: $0 = d(\Sigma_k^{-1} \Sigma_k) = (d\Sigma_k^{-1}) \Sigma_k + \Sigma_k^{-1} d\Sigma_k$, so $d\Sigma_k^{-1} = -\Sigma_k^{-1} d\Sigma_k \Sigma_k^{-1}$

So

$$\begin{aligned} \frac{\partial L}{\partial \Sigma_k} &= -\left(\frac{1}{2} \right) [\gamma_k^T \cdot \mathbf{1}] \Sigma_k^{-T} \\ &\quad + \frac{1}{2} \left(\Sigma_k^{-T} (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \Sigma_k^{-T} \right) \\ &= 0 \end{aligned}$$

So

$$\begin{aligned} [\gamma_k^T \cdot \mathbf{1}] I_{l \times l} &= \Sigma_k^{-T} (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \\ [\gamma_k^T \cdot \mathbf{1}] I_{l \times l} &= (X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T \Sigma_k^{-1} \\ \Sigma_k &= \frac{(X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T}{[\gamma_k^T \cdot \mathbf{1}]} \end{aligned}$$

To sum up

$$\begin{aligned} \pi &= \frac{[\gamma \cdot \mathbf{1}]}{\mathbf{1}^T [\gamma \cdot \mathbf{1}]} = \frac{[\gamma \cdot \mathbf{1}]}{N} \\ \mu_k &= \frac{X\gamma_k}{\mathbf{1}^T \gamma_k} \\ \Sigma_k &= \frac{(X - \mu_k \cdot \mathbf{1}^T) \text{diag}(\gamma_k^T) \cdot (X - \mu_k \cdot \mathbf{1}^T)^T}{\mathbf{1}^T \gamma_k} \end{aligned}$$

where, have $\mathbf{1}^T \gamma = \text{ones}(1, N)$

$$p(\mathbf{z}_n = k | \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) = \frac{\phi_k^{\text{old}}(\mathbf{x}_n) \pi_k^{\text{old}}}{\sum_{k=1}^K \phi_k^{\text{old}}(\mathbf{x}_n) \pi_k^{\text{old}}} \equiv \gamma_{kn}$$

$$\boldsymbol{\gamma} = \boldsymbol{\phi}^{\text{old}}(X) \odot (\boldsymbol{\pi}_k^{\text{old}} \cdot \mathbf{1}^T) \odot \left(\frac{\mathbf{1}}{\mathbf{1} \cdot (\boldsymbol{\pi}^{\text{old}})^T \boldsymbol{\phi}^{\text{old}}(X)} \right)$$

here $\boldsymbol{\gamma}_k$ is (N x 1) matrix

$$\boldsymbol{\gamma} = \begin{bmatrix} \vdots \\ \boldsymbol{\gamma}_k^T \\ \vdots \end{bmatrix}$$