



why it could be defined as below:

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

$$p(\mathbf{z}_1 | \boldsymbol{\pi}) = \prod_{k=1}^K \pi_k^{z_{1k}}$$

$$p(\mathbf{z}_n | \mathbf{z}_{n-1}, \mathbf{A}) = \prod_{j=1}^K \prod_{k=1}^K A_{j,k}^{z_{n-1,j} z_{nk}}$$

$$p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\phi}) = \prod_{j=1}^K \prod_{t=1}^{\text{any dimension}} \phi_j(t)^{z_{nj} x_n(t)}$$

**Define  $\vec{p}$  constant matrix**

$$\vec{p}(\mathbf{z}_n | \boldsymbol{\theta}) \equiv \begin{bmatrix} p(\mathbf{z}_n | \boldsymbol{\theta}) \Big| \mathbf{z}_n = \text{state } 1 \\ \vdots \\ p(\mathbf{z}_n | \boldsymbol{\theta}) \Big| \mathbf{z}_n = \text{state } K \end{bmatrix} = \left[ \sum_{\mathbf{z}_n} p(\mathbf{z}_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \mathbf{z}_n \right] \quad \text{state } k : \mathbf{z}_n = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$\vec{p}(\mathbf{z}_1 | \boldsymbol{\theta}) = \boldsymbol{\pi}$$

$$\vec{p}(\mathbf{z}_n | \mathbf{z}_{n-1}, \boldsymbol{\theta}) \equiv [p(\mathbf{z}_n | \mathbf{z}_{n-1}, \mathbf{A}) \Big| \mathbf{z}_n = \text{state } i, \mathbf{z}_{n-1} = \text{state } j] = \mathbf{A}$$

$$\vec{p}(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}) \equiv [p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\phi}) \Big| \mathbf{x}_n = \text{state } i, \mathbf{z}_n = \text{state } j] = \boldsymbol{\phi}$$

where, for short: write  $\vec{p}(\mathbf{z}_n) \equiv \vec{p}(\mathbf{z}_n | \boldsymbol{\theta})$ ,  $\vec{p}(\mathbf{x}_n) \equiv \vec{p}(\mathbf{x}_n | \boldsymbol{\theta})$

$$\vec{p}(\mathbf{z}_1) = \boldsymbol{\pi}$$

$$\vec{p}(\mathbf{z}_n) = \mathbf{A} \vec{p}(\mathbf{z}_{n-1})$$

$$\vec{p}(\mathbf{x}_n) = \boldsymbol{\phi} \cdot \vec{p}(\mathbf{z}_n)$$

$\text{size}(p(\mathbf{x}_n | \boldsymbol{\phi})) = \text{any dimension} \times K$ ,  $\boldsymbol{\phi} = [\phi_1, \phi_2, \dots, \phi_j, \dots, \phi_K]$

$\phi_k$  is probability distribution sequence of  $k$  th state,  $\text{any dimension} \times 1$

$\mathbf{x}_n$  is probability distribution sequence,  $\text{any dimension} \times 1$

$\mathbf{z}_n$  is probability distribution sequence,  $K \times 1$

In  $P(\mathbf{z}, \boldsymbol{\theta})$ ,  $\mathbf{z}$  is observation value;

In  $\mathbf{z}_n = \mathbf{A} \mathbf{z}_{n-1}$ ,  $\mathbf{z}$  is random variable;

Thus

$$p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\phi}) = \prod_{j=1}^K \prod_{t=1}^{\text{any dimension}} \phi_j(t)^{z_{nj} x_n(t)}$$

Goal

$$\begin{aligned}
p(x_1, \dots, x_n, z_1, \dots, z_n | \boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\phi}) &= p(x_1, \dots, x_n, z_1, \dots, z_n | \boldsymbol{\theta}) \\
&= p(x_n | x_1, \dots, x_{n-1}, z_1, \dots, z_n, \boldsymbol{\theta}) \cdot p(x_1, \dots, x_{n-1}, z_1, \dots, z_n | \boldsymbol{\theta}) \\
&= [p(x_n | z_n, \boldsymbol{\phi})] \cdot p(x_1, \dots, x_{n-1}, z_1, \dots, z_n | \boldsymbol{\theta}) \\
&= [p(x_n | z_n, \boldsymbol{\phi})] \cdot p(z_n | x_1, \dots, x_{n-1}, z_1, \dots, z_{n-1}, \boldsymbol{\theta}) \cdot p(x_1, \dots, x_{n-1}, z_1, \dots, z_{n-1} | \boldsymbol{\theta}) \\
&= [p(x_n | z_n, \boldsymbol{\phi})] \cdot [p(z_n | z_{n-1}, \mathbf{A})] \cdot p(x_1, \dots, x_{n-1}, z_1, \dots, z_{n-1} | \boldsymbol{\theta})
\end{aligned}$$

thus we get

$$p(x_1, \dots, x_n, z_1, \dots, z_n | \boldsymbol{\theta}) = [p(x_n | z_n, \boldsymbol{\phi})] \cdot [p(z_n | z_{n-1}, \mathbf{A})] \cdot p(x_1, \dots, x_{n-1}, z_1, \dots, z_{n-1} | \boldsymbol{\theta})$$

So

$$p(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta}) \equiv p(\mathbf{x}_1, \dots, \mathbf{x}_N, \mathbf{z}_1, \dots, \mathbf{z}_N | \boldsymbol{\theta}) = \left[ \prod_{n=1}^N p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\phi}) \right] \cdot \left[ \prod_{n=2}^N p(\mathbf{z}_n | \mathbf{z}_{n-1}, \mathbf{A}) \right] \cdot p(\mathbf{z}_1 | \boldsymbol{\pi})$$

Here

$$\begin{aligned}
p(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\phi}) &= \prod_{j=1}^K \prod_{t=1}^{\text{any dimension}} \phi_j(t)^{z_{nj}x_n(t)} \\
p(\mathbf{z}_n | \mathbf{z}_{n-1}, \mathbf{A}) &= \prod_{j=1}^K \prod_{k=1}^K A_{k,j}^{z_{n-1,j}z_{nk}} \\
p(\mathbf{z}_1 | \boldsymbol{\pi}) &= \prod_{k=1}^K \pi_k^{z_{1k}}
\end{aligned}$$

So

$$\begin{aligned}
&\ln p(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta}) \\
&= \sum_{n=1}^N \sum_{j=1}^K \sum_{t=1}^{\text{any dimension}} z_{nj}x_n(t) \ln \phi_j(t) + \sum_{n=2}^N \sum_{k=1}^K \sum_{j=1}^K z_{n-1,j}z_{nk} \ln A_{kj} + \sum_{k=1}^K z_{1k} \ln \pi_k \\
&= \sum_{n=1}^N \mathbf{z}_n^T < \ln \boldsymbol{\phi}, \mathbf{x}_n > + \sum_{n=2}^N \mathbf{z}_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n + \ln \boldsymbol{\pi}^T \cdot \mathbf{z}_1
\end{aligned}$$

if  $t$  is continuous

$$\begin{aligned}
< \ln \boldsymbol{\phi}, \mathbf{x}_n > &= \int_{-\infty}^{+\infty} \ln \boldsymbol{\phi}(\mathbf{t}) \cdot x_n(t) dt \\
\boldsymbol{\phi} &= \begin{bmatrix} \phi_1(t) \\ \phi_2(t) \\ \vdots \\ \phi_K(t) \end{bmatrix}
\end{aligned}$$

if  $m$  is discrete

$$\begin{aligned}
< \ln \boldsymbol{\phi}, \mathbf{x}_n > &= \ln \boldsymbol{\phi}^T \cdot \mathbf{x}_n \\
\boldsymbol{\phi} &= \begin{bmatrix} \phi_{11} & \cdots & \phi_{1m} & \cdots & \phi_{1M} \\ \phi_{21} & \cdots & \phi_{2m} & \cdots & \phi_{2M} \\ \vdots & & & & \vdots \\ \phi_{K1} & \cdots & \phi_{Km} & \cdots & \phi_{KM} \end{bmatrix}^T \quad M \times K \text{ matrix} \\
\mathbf{x}_n &: M \times 1 \text{ matrix}
\end{aligned}$$

Only  $\mathbf{x}_n$  is known,  $n \in \{1, \dots, N\}$

for example  $X$  is random variable, then  $Y \equiv f(X)$  is another variable, then  $P(X = x) \equiv p(x)$

then

$$\begin{aligned} P(Y=y)dy &\equiv P(X=x)dx = p(x)dx, \quad y=f(x) \\ &\implies P(Y=y) = p(x) \frac{dx}{df(x)} \\ &\implies E[Y] = \int_{-\infty}^{+\infty} y \cdot P(Y=y)dy = \int_{-\infty}^{+\infty} f(x)p(x)dx \end{aligned}$$

**期望最大化算法，或者EM算法**

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

where

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

Where

- $q(\mathbf{Z})$  is  $\forall$  arbitrary distribution for  $\mathbf{Z}$
- $\mathcal{L}(q, \boldsymbol{\theta})$  概率分布 $q(\mathbf{Z})$ 的一个泛函,  $\boldsymbol{\theta}$  函数
- $\text{KL}(q||p)$  概率分布 $q(\mathbf{Z})$ 的一个泛函,  $\boldsymbol{\theta}$  函数, KL散度 of  $p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta})$ ,  $q(\mathbf{Z})$ ,  $\geq 0$

So

$$\begin{aligned} \ln p(\mathbf{X}|\boldsymbol{\theta}) &\geq \mathcal{L}(q, \boldsymbol{\theta}) = \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})} \right\}, \quad \forall q(\mathbf{Z}) \\ &\text{if } q(\mathbf{Z}) \leftarrow p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}), \text{ here } \text{KL}(q||p) = 0 \\ \ln p(\mathbf{X}|\boldsymbol{\theta}) &= \mathcal{L}(q, \boldsymbol{\theta}) = \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}) \ln \left\{ \frac{p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})}{p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta})} \right\} \end{aligned}$$

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

**调整法**

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

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

$$\begin{aligned} q(\mathbf{Z}) &\leftarrow p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta}) \\ \ln p(\mathbf{X}|\boldsymbol{\theta}) &= \mathcal{L}(q, \boldsymbol{\theta}) + \text{KL}(q||p) = \text{const与}q\text{无关} \\ \text{KL}(q||p) &\downarrow \leftarrow 0, \quad \text{update } \mathcal{L}(q, \boldsymbol{\theta}) \uparrow \\ \ln p(\mathbf{X}|\boldsymbol{\theta}) &= \mathcal{L}(q, \boldsymbol{\theta}) \\ \boldsymbol{\theta}^{\text{old}} &\leftarrow \boldsymbol{\theta} \end{aligned}$$

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

$$\text{ignore influence of } \boldsymbol{\theta} \text{ in } \text{KL}(q||p) = - \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{p(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta})}{q(\mathbf{Z})} \right\}$$

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

set

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

get

$$\begin{aligned} \theta &\leftarrow \underset{\bar{\theta}}{\operatorname{argmax}} \mathcal{L}(q, \bar{\theta}) \\ &= \underset{\bar{\theta}}{\operatorname{argmax}} Q(\bar{\theta}, \theta^{\text{old}}) \\ &\text{update } \mathcal{L}(q, \theta) \uparrow \end{aligned}$$

update

$$\begin{aligned} \text{KL}(q|p) \uparrow &= - \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{p(\mathbf{Z}|\mathbf{X}, \theta)}{q(\mathbf{Z})} \right\} > 0 \\ \ln p(\mathbf{X}|\theta) \uparrow &= \mathcal{L}(q, \theta) \uparrow + \text{KL}(q|p) \uparrow \end{aligned}$$

### Conclusion

因为1,2中  $\mathcal{L}(q, \theta) \uparrow$  均上升;

且1中  $\ln p(\mathbf{X}|\theta) = \mathcal{L}(q, \theta) \uparrow + 0 \downarrow = \text{const}$

2中  $\ln p(\mathbf{X}|\theta) \uparrow = \mathcal{L}(q, \theta) \uparrow + \text{KL}(q|p) \uparrow$

- 所以在一个循环1,2中  $\ln p(\mathbf{X}|\theta) \uparrow$  下界  $\mathcal{L}(q, \theta) \uparrow$

consider  $Q(\theta^{\text{old}}, \theta)$

Use  $\sum$  to delete variables,  $\sum_{z_1} p(z_1, z_2) = P(z_2)$

$X$  is fix observation value;

$Z$  is [probability distribution] random variable,  $\ln p(X, Z|\theta)$  is random variable

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

$$\begin{aligned}
Q(\theta, \theta^{\text{old}}) &\equiv \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \theta^{\text{old}}) \ln p(\mathbf{X}, \mathbf{Z}|\theta) \\
&= \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \theta^{\text{old}}) \left\{ \sum_{n=1}^N z_n^T < \ln \phi, \mathbf{x}_n > + \sum_{n=2}^N z_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n + \ln \boldsymbol{\pi}^T \cdot \mathbf{z}_1 \right\} \\
&= \left\{ \sum_{\mathbf{z}_n} p(\mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \sum_{n=1}^N z_n^T < \ln \phi, \mathbf{x}_n > \right\} \\
&\quad + \left\{ \sum_{\mathbf{z}_{n-1}, \mathbf{z}_n} p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \sum_{n=2}^N z_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n \right\} \\
&\quad + \left\{ \sum_{\mathbf{z}_1} p(\mathbf{z}_1|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_1^T \ln \boldsymbol{\pi} \right\} \\
&= \left\{ \sum_{n=1}^N \left[ \sum_{\mathbf{z}_n} p(\mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_n^T \right] < \ln \phi, \mathbf{x}_n > \right\} \\
&\quad + \left\{ \sum_{n=2}^N \sum \left[ \sum_{\mathbf{z}_{n-1}, \mathbf{z}_n} z_{n-1} p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_n^T \right] \odot \ln \mathbf{A}^T \right\} \\
&\quad + \left\{ \left[ \sum_{\mathbf{z}_1} p(\mathbf{z}_1|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_1^T \right] \ln \boldsymbol{\pi} \right\} \\
&= \sum_{n=1}^N \gamma_n^T < \ln \phi, \mathbf{x}_n > + \sum_{n=2}^N \text{tr}(\boldsymbol{\xi}_n^T \ln \mathbf{A}) + \gamma_1^T \ln \boldsymbol{\pi}
\end{aligned}$$

where

$$\begin{aligned}
&\sum_{\mathbf{z}_{n-1}, \mathbf{z}_n} p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \sum_{n=2}^N z_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n \\
&= \sum \left\{ p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \odot \sum_{n=2}^N [z_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n] \right\} \\
&= \sum_{n=2}^N \text{tr} \left( p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) [\mathbf{z}_{n-1}^T \ln \mathbf{A}^T \cdot \mathbf{z}_n]^T \right) \\
&= \sum_{n=2}^N \text{tr} \left( [z_{n-1} p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_n^T] \cdot \ln \mathbf{A} \right) \\
&= \sum_{n=2}^N \sum \{ [z_n p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_{n-1}^T] \odot \ln \mathbf{A} \}
\end{aligned}$$

其中, 因为  $\mathbf{X}, \theta^{\text{old}}$  分别为已知、固定 在 M 步骤

$\gamma_n \equiv [\sum_{\mathbf{z}_n} p(\mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_n]$  为常数, 是期望  $E[\mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}]$ , 大小  $K \times 1$

$\boldsymbol{\xi}_n \equiv [z_n p(\mathbf{z}_{n-1}, \mathbf{z}_n|\mathbf{X}, \theta^{\text{old}}) \mathbf{z}_{n-1}^T]$  为常数, 是期望  $E[\mathbf{z}_n \mathbf{z}_{n-1}^T|\mathbf{X}, \theta^{\text{old}}]$ , 大小  $K \times K$

下面求解

$$\begin{aligned}
\max_{\theta} \quad Q(\theta, \theta^{\text{old}}) &\equiv \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X}, \theta^{\text{old}}) \ln p(\mathbf{X}, \mathbf{Z}|\theta) \\
&= \sum_{n=1}^N \gamma_n^T < \ln \phi, \mathbf{x}_n > + \sum_{n=2}^N \text{tr}(\boldsymbol{\xi}_n^T \ln \mathbf{A}) + \gamma_1^T \ln \boldsymbol{\pi}
\end{aligned}$$

subject to

$$\begin{aligned}
\text{s.t.} \quad &\gamma_n^T \cdot \mathbf{1} = 1 \quad \text{tr}(\boldsymbol{\xi}_n^T \cdot \mathbf{1}) = 1 \\
&\mathbf{1}^T \cdot \boldsymbol{\phi} = \mathbf{1}^T \quad \mathbf{1}^T \cdot \mathbf{A} = \mathbf{1}^T \quad \mathbf{1}^T \cdot \boldsymbol{\pi} = 1
\end{aligned}$$

with Lagrange method:

$$\begin{aligned}
L \equiv & \left\{ \sum_{n=1}^N \gamma_n^T < \ln \phi, \mathbf{x}_n > + \sum_{n=2}^N \text{tr} (\boldsymbol{\xi}_n^T \ln \mathbf{A}) + \gamma_1^T \ln \boldsymbol{\pi} \right\} \\
& - \sum_{t=1}^{\text{any dimension}} u_t \{ \mathbf{1}^T \cdot < \phi, \delta(t) > - 1 \} \\
& - \sum_{k=1}^K v_k \{ \mathbf{1}^T \mathbf{A} \cdot \sigma_k - 1 \} \\
& - w_1 \{ \mathbf{1}^T \boldsymbol{\pi} - 1 \}
\end{aligned}$$

$$\text{where } \sigma_k = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}, 1 \times K$$

**if  $t$  is discrete, any dimension =  $M$**

$$\delta(t) = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}, 1 \times M,$$

$$< \ln \phi, \mathbf{x}_n > = \ln \phi^T \cdot \mathbf{x}_n$$

$$< \phi, \delta(t) > = \phi^T \cdot \delta(t)$$

$$\begin{aligned}
\frac{\partial Q}{\partial \phi} &= \left\{ \sum_{n=1}^N [\gamma_n \cdot \mathbf{x}_n^T] \right\}^T \odot \frac{\mathbf{1}}{\phi} - \sum_{t=1}^M u_t \cdot \mathbf{1} \cdot \delta(t)^T \\
&= \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \gamma_n^T] \right\} \odot \frac{\mathbf{1}}{\phi} - \begin{bmatrix} u_1 & \cdots & u_t \cdots & u_M \\ u_1 & \cdots & u_t \cdots & u_M \\ \vdots & & & \vdots \\ u_1 & \cdots & u_t \cdots & u_M \end{bmatrix} = 0 \\
\frac{\partial Q}{\partial \mathbf{A}} &= \left[ \sum_{n=2}^N \boldsymbol{\xi}_n \right] \odot \frac{\mathbf{1}}{\mathbf{A}} - \sum_{k=1}^K v_k \cdot \mathbf{1} \cdot \sigma_k^T \\
&= \left[ \sum_{n=2}^N \boldsymbol{\xi}_n \right] \odot \frac{\mathbf{1}}{\mathbf{A}} - \begin{bmatrix} v_1 & \cdots & v_k \cdots & v_K \\ v_1 & \cdots & v_k \cdots & v_K \\ \vdots & & & \vdots \\ v_1 & \cdots & v_k \cdots & v_K \end{bmatrix} = 0 \\
\frac{\partial Q}{\partial \boldsymbol{\pi}} &= \gamma_1 \odot \frac{\mathbf{1}}{\boldsymbol{\pi}} - w_1 \cdot \mathbf{1} = 0
\end{aligned}$$

So

$$\begin{aligned}
& \frac{\left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}_{ij}}{\phi_{ij}} = u_j \\
& \Rightarrow \sum_{i=1}^K \frac{\left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}_{ij}}{u_j} = \sum_{i=1}^K \phi_{ij} = 1 \\
& \Rightarrow u_j = \sum_{i=1}^K \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}_{ij} \\
& \Rightarrow \phi_{ij} = \frac{\left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}_{ij}}{\sum_{i=1}^K \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}_{ij}} \\
& \Rightarrow \boldsymbol{\phi} = \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\} \odot \frac{1.}{1. \cdot 1.^T \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\}} \\
& \Rightarrow \boldsymbol{\phi} = \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\} \odot \frac{1.}{1. \left[ \sum_{n=1}^N \boldsymbol{\gamma}_n \right]^T} \\
& \frac{[\sum_{n=2}^N \boldsymbol{\xi}_n]_{ij}}{\mathbf{A}_{ij}} = v_j \\
& \Rightarrow \sum_{i=1}^K \frac{[\sum_{n=2}^N \boldsymbol{\xi}_n]_{ij}}{v_j} = \sum_{i=1}^K \mathbf{A}_{ij} = 1 \\
& \Rightarrow v_j = \sum_{i=1}^K [\sum_{n=2}^N \boldsymbol{\xi}_n]_{ij} \\
& \Rightarrow \mathbf{A}_{ij} = \frac{[\sum_{n=2}^N \boldsymbol{\xi}_n]_{ij}}{\sum_{i=1}^K [\sum_{n=2}^N \boldsymbol{\xi}_n]_{ij}} \\
& \Rightarrow \mathbf{A} = [\sum_{n=2}^N \boldsymbol{\xi}_n] \odot \frac{1.}{1. \cdot 1.^T [\sum_{n=2}^N \boldsymbol{\xi}_n]} \\
& \frac{[\boldsymbol{\gamma}_1]_i}{\boldsymbol{\pi}_i} = w_1 \\
& \Rightarrow \sum_{i=1}^K \frac{[\boldsymbol{\gamma}_1]_i}{w_1} = \sum_{i=1}^K \boldsymbol{\pi}_i = 1 \\
& \Rightarrow w_1 = \sum_{i=1}^K [\boldsymbol{\gamma}_1]_i \\
& \Rightarrow \boldsymbol{\pi}_i = \frac{[\boldsymbol{\gamma}_1]_i}{\sum_{i=1}^K [\boldsymbol{\gamma}_1]_i} \\
& \Rightarrow \boldsymbol{\pi} = \boldsymbol{\gamma}_1 \odot \frac{1.}{1. \cdot 1.^T \boldsymbol{\gamma}_1}
\end{aligned}$$

**To sum up**

$$\begin{aligned}
\boldsymbol{\phi} &= \left\{ \sum_{n=1}^N [\mathbf{x}_n \cdot \boldsymbol{\gamma}_n^T] \right\} \odot \frac{1.}{1. \left[ \sum_{n=1}^N \boldsymbol{\gamma}_n \right]^T} \\
\mathbf{A} &= [\sum_{n=2}^N \boldsymbol{\xi}_n] \odot \frac{1.}{1. \cdot 1.^T [\sum_{n=2}^N \boldsymbol{\xi}_n]} \\
\boldsymbol{\pi} &= \boldsymbol{\gamma}_1 \odot \frac{1.}{1. \cdot 1.^T \boldsymbol{\gamma}_1}
\end{aligned}$$

**How to calculate  $\boldsymbol{\gamma}_n, \boldsymbol{\xi}_n$**

$$\boldsymbol{\gamma}_n \equiv \left[ \sum_{z_n} p(z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) z_n \right] \text{ 为常数, 是期望 } E[z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}], \text{ 大小 } K \times 1$$

$$\boldsymbol{\xi}_n \equiv \left[ \sum_{z_{n-1}, z_n} z_n p(z_{n-1}, z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) z_{n-1}^T \right] \text{ 为常数, 是期望 } E[z_n z_{n-1}^T | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}], \text{ 大小 } K \times K$$

similarly get :

$$\gamma_n \equiv \vec{p}(z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \equiv \begin{bmatrix} p(z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \Big| z_n = \text{state } 1 \\ \vdots \\ p(z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \Big| z_n = \text{state } K \end{bmatrix}$$

$$\xi_n \equiv \vec{p}(z_{n-1}, z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \equiv [p(z_{n-1}, z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \Big| z_n = \text{state } i, z_{n-1} = \text{state } j]$$

the same size as  $z_n z_{n-1}^T$

so

$$\begin{aligned} \gamma_n &\equiv \vec{p}(z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(z_n, \mathbf{X} | \boldsymbol{\theta}^{\text{old}}) \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_n, \mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | z_n, \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_n, \mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | z_n, \boldsymbol{\theta}^{\text{old}}) \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \boldsymbol{\alpha}_n \odot \boldsymbol{\beta}_n \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ \xi_n &\equiv \vec{p}(z_{n-1}, z_n | \mathbf{X}, \boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(z_{n-1}, z_n, \mathbf{X} | \boldsymbol{\theta}^{\text{old}}) \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n, \mathbf{x}_n, \dots, \mathbf{x}_N | z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n, \mathbf{x}_n, \dots, \mathbf{x}_N | z_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n | z_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_n, \dots, \mathbf{x}_N | z_{n-1}, z_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n | z_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_n, \dots, \mathbf{x}_N | z_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n | z_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_n | z_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | z_n, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \vec{p}(z_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1} | \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(z_n | z_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_n | z_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | z_n, \boldsymbol{\theta}^{\text{old}}) \\ &\odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= [1. \cdot \boldsymbol{\alpha}_{n-1}^T] \odot \mathbf{A} \odot [\boldsymbol{\phi}^T \cdot \mathbf{x}_n \odot \boldsymbol{\beta}_n \cdot 1.^T] \odot \frac{1.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\ &= \frac{1}{p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \left\{ [\boldsymbol{\phi}^T \cdot \mathbf{x}_n \odot \boldsymbol{\beta}_n] \cdot \boldsymbol{\alpha}_{n-1}^T \right\} \odot \mathbf{A} \end{aligned}$$



其中  $p(\mathbf{X}|\boldsymbol{\theta}^{\text{old}}) = \sum_{Z_N} p(\mathbf{z}_N, \mathbf{X}|\boldsymbol{\theta}^{\text{old}}) = \sum \boldsymbol{\alpha}_N = \mathbf{1}^T \cdot \boldsymbol{\alpha}_N$  is **constant**

$$\begin{aligned}\vec{p}(\mathbf{X}|\boldsymbol{\theta}^{\text{old}}) &= p(\mathbf{X}|\boldsymbol{\theta}^{\text{old}}) \cdot \mathbf{1}. \\ p(\mathbf{X}|\boldsymbol{\theta}^{\text{old}}) &= \mathbf{1}^T \cdot p(\mathbf{z}_N, \mathbf{X}|\boldsymbol{\theta}^{\text{old}}) \\ &= \mathbf{1}^T \cdot \boldsymbol{\alpha}_N\end{aligned}$$

So if  $\boldsymbol{\alpha}_n, \boldsymbol{\beta}_n$  is obtained, we could get  $\boldsymbol{\gamma}_n, \boldsymbol{\xi}_n$

$$\begin{aligned}\boldsymbol{\alpha}_n &\equiv \vec{p}(\mathbf{z}_n, \mathbf{x}_1, \dots, \mathbf{x}_n|\boldsymbol{\theta}^{\text{old}}) \\ \boldsymbol{\beta}_n &\equiv \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}})\end{aligned}$$

**How to obtain  $\boldsymbol{\alpha}_n, \boldsymbol{\beta}_n$**

for  $\boldsymbol{\alpha}_n$ , initial value:

$$\begin{aligned}\boldsymbol{\alpha}_1 &= \vec{p}(\mathbf{z}_1, \mathbf{x}_1|\boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(\mathbf{x}_1|\mathbf{z}_1, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{z}_1|\boldsymbol{\theta}^{\text{old}}) \\ &= [\boldsymbol{\phi}^T \cdot \mathbf{x}_1] \odot \boldsymbol{\pi}\end{aligned}$$

Recurrence relation

$$\begin{aligned}\boldsymbol{\alpha}_n &\equiv \vec{p}(\mathbf{z}_n, \mathbf{x}_1, \dots, \mathbf{x}_n|\boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(\mathbf{z}_n|\boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(\mathbf{z}_n|\boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{z}_n, \mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\boldsymbol{\theta}^{\text{old}}) \\ &= \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left\{ \vec{p}(\mathbf{z}_{n-1}, \mathbf{z}_n, \mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\boldsymbol{\theta}^{\text{old}}) \cdot \mathbf{1} \right\} \\ &= \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left\{ \left[ \vec{p}(\mathbf{z}_{n-1}, \mathbf{z}_n|\boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\mathbf{z}_{n-1}, \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \right] \cdot \mathbf{1} \right\} \\ &= \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left\{ \left[ \left( \mathbf{1} \cdot \vec{p}(\mathbf{z}_{n-1}|\boldsymbol{\theta}^{\text{old}})^T \right) \odot \vec{p}(\mathbf{z}_n|\mathbf{z}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \odot \left( \mathbf{1} \cdot \vec{p}(\mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\mathbf{z}_{n-1}, \boldsymbol{\theta}^{\text{old}})^T \right) \right] \right\} \\ &= \vec{p}(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left\{ \left[ \vec{p}(\mathbf{z}_n|\mathbf{z}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \odot \left( \mathbf{1} \cdot \vec{p}(\mathbf{z}_{n-1}, \mathbf{x}_1, \dots, \mathbf{x}_{n-1}|\boldsymbol{\theta}^{\text{old}})^T \right) \right] \cdot \mathbf{1} \right\} \\ &= [\boldsymbol{\phi}^T \cdot \mathbf{x}_n] \odot \left\{ \left[ \mathbf{A} \odot \left( \mathbf{1} \cdot \boldsymbol{\alpha}_{n-1}^T \right) \right] \cdot \mathbf{1} \right\} \\ &= [\boldsymbol{\phi}^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \boldsymbol{\alpha}_{n-1}]\end{aligned}$$

$$\mathbf{x}_n^T \cdot \boldsymbol{\phi} \cdot \mathbf{A} \cdot \boldsymbol{\alpha}_{n-1}$$

for  $\boldsymbol{\beta}_n$ , last initial value:

$$\boldsymbol{\beta}_N = \vec{p}(\mathbf{1}|\mathbf{z}_N, \boldsymbol{\theta}^{\text{old}}) = \mathbf{1}$$

Recurrence relation

$$\begin{aligned}
\beta_n &\equiv \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= \left\{ \vec{p}(\mathbf{z}_{n+1}, \mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}})^T \cdot \mathbf{1}. \right\} \\
&= \left\{ \left[ \vec{p}(\mathbf{z}_{n+1} | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{z}_n, \mathbf{z}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \right]^T \cdot \mathbf{1}. \right\} \\
&= \left\{ \left[ \vec{p}(\mathbf{z}_{n+1} | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left( \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{z}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \cdot \mathbf{1}.^T \right) \right]^T \cdot \mathbf{1}. \right\} \\
&= \left\{ \left[ \vec{p}(\mathbf{z}_{n+1} | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left( \left[ \vec{p}(\mathbf{x}_{n+1} | \mathbf{z}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_{n+2}, \dots, \mathbf{x}_N | \mathbf{z}_{n+1}, \mathbf{x}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \right] \cdot \mathbf{1}.^T \right) \right]^T \cdot \mathbf{1}. \right\} \\
&= \left\{ \left[ \vec{p}(\mathbf{z}_{n+1} | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \odot \left( \left[ \vec{p}(\mathbf{x}_{n+1} | \mathbf{z}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_{n+2}, \dots, \mathbf{x}_N | \mathbf{z}_{n+1}, \boldsymbol{\theta}^{\text{old}}) \right] \cdot \mathbf{1}.^T \right) \right]^T \cdot \mathbf{1}. \right\} \\
&= \left\{ \left[ \mathbf{A} \odot \left( \left[ \phi^T \cdot \mathbf{x}_{n+1} \right] \odot \beta_{n+1} \right) \cdot \mathbf{1}.^T \right]^T \cdot \mathbf{1}. \right\} \\
&= \mathbf{A}^T \cdot \left( \left[ \phi^T \cdot \mathbf{x}_{n+1} \right] \odot \beta_{n+1} \right)
\end{aligned}$$

To sum up

$$\begin{aligned}
\alpha_1 &= [\phi^T \cdot \mathbf{x}_1] \odot \pi \\
\alpha_n &= [\phi^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \alpha_{n-1}] \\
\beta_N &= \mathbf{1}. \\
\beta_n &= \mathbf{A}^T \cdot \left( [\phi^T \cdot \mathbf{x}_{n+1}] \odot \beta_{n+1} \right)
\end{aligned}$$

Then

$$\begin{aligned}
\gamma_n &= \alpha_n \odot \beta_n \odot \frac{\mathbf{1}.}{\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \\
&= \frac{\mathbf{1}.}{\mathbf{1}.^T \cdot \alpha_N} [\alpha_n \odot \beta_n] \\
\xi_n &= \frac{1}{p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})} \left\{ \left[ [\phi^T \cdot \mathbf{x}_n] \odot \beta_n \right] \cdot \alpha_{n-1}^T \right\} \odot \mathbf{A} \\
&= \frac{1}{\mathbf{1}.^T \cdot \alpha_N} \left\{ \left[ [\phi^T \cdot \mathbf{x}_n] \odot \beta_n \right] \cdot \alpha_{n-1}^T \right\} \odot \mathbf{A}
\end{aligned}$$

because  $\alpha_N, \beta_1$  are so small

we divide  $p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}})$  into 2 part

$$p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}}) = p(\mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\theta}^{\text{old}}) p(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}})$$

define

$$\begin{aligned}
\hat{\alpha}_n &\equiv \frac{1}{p(\mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\theta}^{\text{old}})} \alpha_n = \vec{p}(\mathbf{z}_n | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= \left\{ \prod_{k=1}^n p(\mathbf{x}_k | \mathbf{x}_1, \dots, \mathbf{x}_{k-1}, \boldsymbol{\theta}^{\text{old}}) \right\} \alpha_n \\
&= \left\{ \prod_{k=1}^n c_k \right\} \alpha_n \quad \text{notice} \quad \mathbf{1}.^T \hat{\alpha}_n = \sum_{\mathbf{z}_n} p(\mathbf{z}_n | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) = 1
\end{aligned}$$

the other way

$$\begin{aligned}
c_n \hat{\alpha}_n &= p(\mathbf{x}_n | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \vec{p}(\mathbf{z}_n | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= \vec{p}(\mathbf{z}_n, \mathbf{x}_n | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \\
&= \vec{p}(\mathbf{z}_n | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \odot \vec{p}(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= [\vec{p}(\mathbf{z}_n, \mathbf{z}_{n-1} | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}}) \cdot \mathbf{1}.] \odot \vec{p}(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= \left[ \left[ \mathbf{1}. \cdot \vec{p}(\mathbf{z}_{n-1} | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}})^T \right] \odot \vec{p}(\mathbf{z}_n | \mathbf{z}_{n-1}) \cdot \mathbf{1}. \right] \odot \vec{p}(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) c_n = \mathbf{1}.^T c_n \cdot \alpha_n = \mathbf{1}.^T \cdot \{ [\phi^T \\
&= [\vec{p}(\mathbf{z}_n | \mathbf{z}_{n-1}) \vec{p}(\mathbf{z}_{n-1} | \mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \boldsymbol{\theta}^{\text{old}})] \odot \vec{p}(\mathbf{x}_n | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= [\mathbf{A} \cdot \hat{\alpha}_{n-1}] \odot [\phi^T \cdot \mathbf{x}_n] \\
&= [\phi^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \hat{\alpha}_{n-1}]
\end{aligned}$$

so

$$\begin{aligned}
\hat{\alpha}_n &\equiv \frac{1}{c_n} [\phi^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \hat{\alpha}_{n-1}] \\
&= \frac{1}{1.^T \cdot \{[\phi^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \hat{\alpha}_{n-1}]\}} [\phi^T \cdot \mathbf{x}_n] \odot [\mathbf{A} \cdot \hat{\alpha}_{n-1}] \\
\hat{\alpha}_1 &= \frac{1}{1.^T \cdot \{[\phi^T \cdot \mathbf{x}_n] \odot \pi\}} [\phi^T \cdot \mathbf{x}_n] \odot \pi
\end{aligned}$$

thesame

$$\begin{aligned}
\frac{\hat{\beta}_n}{\hat{\beta}_{n+1}} &\equiv \frac{\beta_n}{\beta_{n+1}} \cdot \frac{\frac{1}{p(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}})}}{\frac{1}{p(\mathbf{x}_{n+2}, \dots, \mathbf{x}_N | \mathbf{x}_1, \dots, \mathbf{x}_{n+1}, \boldsymbol{\theta}^{\text{old}})}} \\
&= \frac{\beta_n}{\beta_{n+1}} \cdot \frac{p(\mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\theta}^{\text{old}})}{p(\mathbf{x}_1, \dots, \mathbf{x}_{n+1} | \boldsymbol{\theta}^{\text{old}})} \\
&= \frac{\beta_n}{\beta_{n+1}} \cdot \frac{1}{p(\mathbf{x}_{n+1} | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}})} \\
&= \frac{\beta_n}{\beta_{n+1}} \cdot \frac{1}{c_{n+1}}
\end{aligned}$$

the

$$\begin{aligned}
\hat{\beta}_n &\equiv \frac{1}{p(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}})} \beta_n \\
&= \frac{1}{p(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{x}_1, \dots, \mathbf{x}_n, \boldsymbol{\theta}^{\text{old}})} \vec{p}(\mathbf{x}_{n+1}, \dots, \mathbf{x}_N | \mathbf{z}_n, \boldsymbol{\theta}^{\text{old}}) \\
&= \frac{1}{c_{n+1}} \mathbf{A}^T \cdot ([\phi^T \cdot \mathbf{x}_{n+1}] \odot \hat{\beta}_{n+1}) \\
\hat{\beta}_N &= 1.
\end{aligned}$$

then

$$\begin{aligned}
\gamma_n &= [\hat{\alpha}_n \odot \hat{\beta}_n] \\
\xi_n &= \frac{1}{c_n} \left\{ [\phi^T \cdot \mathbf{x}_n] \odot \hat{\beta}_n \right\} \cdot \hat{\alpha}_{n-1}^T \Big\} \odot \mathbf{A}
\end{aligned}$$

$$\alpha_N$$

其中  $p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}}) = \sum_{Z_N} p(\mathbf{z}_N, \mathbf{X} | \boldsymbol{\theta}^{\text{old}}) = \sum \alpha_N = 1.^T \cdot \alpha_N$  is **constant**

$$\begin{aligned}
\vec{p}(\mathbf{X} | \boldsymbol{\theta}^{\text{old}}) &= p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}}) \cdot 1. \\
p(\mathbf{X} | \boldsymbol{\theta}^{\text{old}}) &= 1.^T \cdot p(\mathbf{z}_N, \mathbf{X} | \boldsymbol{\theta}^{\text{old}}) \\
&= 1.^T \cdot \alpha_N
\end{aligned}$$

$$\begin{aligned}
\phi &= \left\{ \mathbf{x}_n \cdot [\sum_{n=2}^N \gamma_n]^T \right\} \odot \frac{1.}{1. \cdot 1.^T \left\{ \mathbf{x}_n \cdot [\sum_{n=2}^N \gamma_n]^T \right\}} \\
\mathbf{A} &= [\sum_{n=2}^N \xi_n] \odot \frac{1.}{1. \cdot 1.^T [\sum_{n=2}^N \xi_n]} \\
\pi &= \gamma_1 \odot \frac{1.}{1. \cdot 1.^T \gamma_1}
\end{aligned}$$