

Appendix

In the appendix, we present the details of the EM algorithm for our model estimation.

A Forward-backward procedure

In order to compute $\gamma_i^{(r,t)}$ and $\xi_{ij}^{(r,t)}$, we use the following forward-backward procedure. The forward recursion is established as follows. Let $\delta_i^{(r,t)} = P(Y^{(r,1)}, \dots, Y^{(r,t)}, X^{(r,t)} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})$, $i = 0, 1$, denote the probability of observing $Y^{(r,1)}, \dots, Y^{(r,t)}$ and being the hidden state i at time t for r th loan ID. Given $\hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}$ and \mathbf{Z} , we can get $\delta_i^{(r,t)}$, $i = 0, 1$, at each time t recursively:

$$\begin{aligned}
 \delta_i^{(r,1)} &= P(Y^{(r,1)}, X^{(r,1)} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = P(Y^{(r,1)} | X^{(r,1)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) P(X^{(r,1)} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \hat{b}_{iY^{(r,1)}}^{(r,t)} \hat{\pi}_i \\
 &\dots \\
 \delta_i^{(r,t)} &= P(Y^{(r,1)}, \dots, Y^{(r,t)}, X^{(r,t)} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 P(Y^{(r,t)}, X^{(r,t)} = i | X^{(r,t-1)} = j, Y^{(r,1)}, \dots, Y^{(r,t-1)}, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &\quad P(Y^{(r,1)}, \dots, Y^{(r,t-1)}, X^{(r,t-1)} = j | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 P(Y^{(r,t)} | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) P(X^{(r,t)} = i | X^{(r,t-1)} = j, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \delta_j^{(r,t-1)} \\
 &= \hat{b}_{iY^{(r,t)}}^{(r,t)} \sum_{j=0}^1 \delta_j^{(r,t-1)} \hat{a}_{ji}^{(r,t-1)}.
 \end{aligned}$$

Analogously, the backward recursion is established as follows. Let

$$\tau_i^{(r,t)} = P(Y^{(r,t+1)}, \dots, Y^{(r,T_r)} | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})$$

denote the probability of the ending partial sequence $Y^{(r,t+1)}, \dots, Y^{(r,T_r)}$ given hidden state i at time t for r th loan ID. We calculate $\tau_i^{(r,t)}$ recursively as follows,

$$\begin{aligned}
 \tau_i^{(r,T_r)} &= 1 \\
 &\dots \\
 \tau_i^{(r,t)} &= P(Y^{(r,t+1)}, \dots, Y^{(r,T_r)} | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 P(Y^{(r,t+1)}, \dots, Y^{(r,T_r)}, X^{(r,t+1)} = j | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 P(Y^{(r,t+1)}, \dots, Y^{(r,T_r)} | X^{(r,t+1)} = j, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) P(X^{(r,t+1)} = j | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 P(Y^{(r,t+1)} | Y^{(r,t+2)}, X^{(r,t+1)} = j, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \tau_j^{(r,t+1)} P(X^{(r,t+1)} = j | X^{(r,t)} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\
 &= \sum_{j=0}^1 \hat{b}_{jY^{(r,t+1)}}^{(r,t+1)} \tau_j^{(r,t+1)} \hat{a}_{ij}^{(r,t)}.
 \end{aligned}$$

The state posterior probability $\gamma_i^{\langle r,t \rangle}$ can be expressed in terms of δ and τ . In particular, according to the Bayes' theorem, we have

$$\gamma_i^{\langle r,t \rangle} = P(X^{\langle r,t \rangle} = i | \mathbf{Y}, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \frac{P(X^{\langle r,t \rangle} = i, \mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})}{P(\mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})},$$

where $P(X^{\langle r,t \rangle} = i, \mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})$ can be rewritten as $P(Y^{\langle r,t+1 \rangle}, \dots, Y^{\langle r,T_r \rangle} | X^{\langle r,t \rangle} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \times P(Y^{\langle r,1 \rangle}, \dots, Y^{\langle r,t \rangle}, X^{\langle r,t \rangle} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \tau_i^{\langle r,t \rangle} \delta_i^{\langle r,t \rangle}$. Herein, $P(\mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \sum_{i=0}^1 P(\mathbf{Y}, X^{\langle r,T_r \rangle} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \sum_{i=0}^1 \delta_i^{\langle r,T_r \rangle}$. Thus, $\gamma_i^{\langle r,t \rangle}$ can be obtained by

$$\gamma_i^{\langle r,t \rangle} = \frac{\tau_i^{\langle r,t \rangle} \delta_i^{\langle r,t \rangle}}{\sum_{i=0}^1 \delta_i^{\langle r,T_r \rangle}}. \quad (12)$$

Analogously, the transition posterior probability $\xi_{ij}^{\langle r,t-1 \rangle}$ can be expressed in terms of δ and τ as follows.

$$\xi_{ij}^{\langle r,t-1 \rangle} = P(X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i | \mathbf{Y}, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) = \frac{P(X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})}{P(\mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}})},$$

where the denominator can be rewritten as

$$P(X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Y} | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \quad (13)$$

$$= P(Y^{\langle r,t \rangle}, \dots, Y^{\langle r,T_r \rangle} | X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \quad (14)$$

$$\times P(Y^{\langle r,1 \rangle}, \dots, Y^{\langle r,t-1 \rangle}, X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \quad (15)$$

The first term of the right-hand-side (15) can be rewritten as

$$\begin{aligned} & P(Y^{\langle r,t \rangle}, \dots, Y^{\langle r,T_r \rangle} | X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\ &= P(Y^{\langle r,t+1 \rangle}, \dots, Y^{\langle r,T_r \rangle} | X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) P(Y^{\langle r,t \rangle} | X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\ &= \tau_j^{\langle r,t \rangle} \hat{b}_{jY^{\langle r,t \rangle}}^{\langle r,t \rangle}. \end{aligned}$$

The second term of the right-hand-side (15) can be rewritten as

$$\begin{aligned} & P(Y^{\langle r,1 \rangle}, \dots, Y^{\langle r,t-1 \rangle}, X^{\langle r,t \rangle} = j, X^{\langle r,t-1 \rangle} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\ &= P(X^{\langle r,t \rangle} = j | X^{\langle r,t-1 \rangle} = i, Y^{\langle r,1 \rangle}, \dots, Y^{\langle r,t-1 \rangle}, \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) P(Y^{\langle r,1 \rangle}, \dots, Y^{\langle r,t-1 \rangle}, X^{\langle r,t-1 \rangle} = i | \mathbf{Z}, \hat{\boldsymbol{\pi}}, \hat{\mathcal{F}}) \\ &= \hat{a}_{ij}^{\langle r,t-1 \rangle} \delta_i^{\langle r,t-1 \rangle}. \end{aligned}$$

Therefore, $\xi_{ij}^{\langle r,t-1 \rangle}$ can be updated by

$$\xi_{ij}^{\langle r,t-1 \rangle} = \frac{\tau_j^{\langle r,t \rangle} \hat{b}_{jY^{\langle r,t \rangle}}^{\langle r,t \rangle} \hat{a}_{ij}^{\langle r,t-1 \rangle} \delta_i^{\langle r,t-1 \rangle}}{\sum_{i=0}^1 \delta_i^{\langle r,T_r \rangle}}. \quad (16)$$