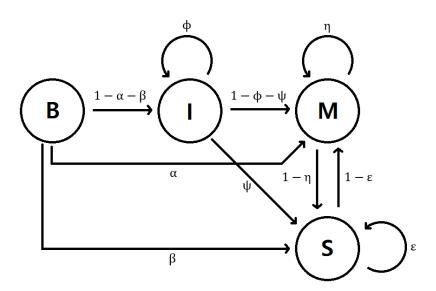
Supplementary Note: Detailed Computations

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- K: number of cores
- T: number of discretized age indices in the stack
- N_i : number of discretized depth indices in the core i
- $\{A_t\}_{t=1}^T$: ages assigned to age indices in the stack
- $\{\mu_t\}_{t=1}^T$: means of $\delta^{18}0$ concentrations assigned to age indices in the stack
- $\{\sigma_t\}_{t=1}^T$: standard deviations of δ^{18} 0 concentrations assigned to age indices in the stack
- $\left\{d_n^{(i)}\right\}_{n=1}^{N_i}$: depths assigned to depth indices in the core *i*
- $\left\{v_n^{(i)}\right\}_{n=1}^{N_i}$: δ^{18} 0 assigned to depth indices in the core *i*, if it exists; -1 otherwise.
- $\left\{\xi_{n,t}^{(i)}\right\}_{n=1,t=1}^{N_i,T}$: empirical distribution of ages from the radiocarbon data assigned to depth indices in the core i, if it exists; $\xi_{n,t}^{(i)} \equiv 1/T$ otherwise.
- $\left\{C_n^{(i)}\right\}_{n=1}^{N_i}$: (hidden) ages assigned to depth indices in the core *i*
- R_i : average sedimentation rate in the core i
- $p(v_n^{(i)}|C_n^{(i)} = A_t, \xi_{n,1:T}^{(i)}) \triangleq \begin{cases} N(v_n^{(i)}|\tau^{(i)} + \mu_t, \sigma_t) \cdot \xi_{n,t}^{(i)}, \ v_n^{(i)} \neq -1 \\ \xi_{n,t}^{(i)}, \ \text{otherwise} \end{cases}$
- α_i , β_i , ϕ_i , ψ_i , η_i , ε_i , τ_i : core parameters for the core i, where (Note that the right model is valid under the assumption that we have the reference stack long enough to cover whole parts to which the core depths are supposed to be aligned. If it is not expected, an additional state for reflecting core depths supposed not to be aligned.)



- 1. Forward Algorithm:
- 1.1. Initialization:

$$\begin{aligned} \mathbf{F}_{i}(\mathbf{2}, \mathbf{1}, \mathbf{1}) &\triangleq p\left(v_{1:2}^{(i)}, \mathsf{C}_{1}^{(i)} = \mathsf{A}_{1}, \mathsf{C}_{2}^{(i)} = \mathsf{A}_{1} \middle| d_{1:\mathsf{N}_{i}}^{(i)}, \xi_{1:\mathsf{N}_{i},1:\mathsf{T}}^{(i)}\right) \\ &= p\left(v_{2}^{(i)} \middle| \mathsf{C}_{2}^{(i)} = \mathsf{A}_{s}, \xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)} \middle| \mathsf{C}_{1}^{(i)} = \mathsf{A}_{1}, \xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot p\left(\mathsf{C}_{2}^{(i)} = \mathsf{A}_{1}, \mathsf{C}_{1}^{(i)} = \mathsf{A}_{1} \middle| d_{1}^{(i)}, d_{2}^{(i)}\right) \\ &= p\left(v_{2}^{(i)} \middle| \mathsf{C}_{2}^{(i)} = \mathsf{A}_{s}, \xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)} \middle| \mathsf{C}_{1}^{(i)} = \mathsf{A}_{1}, \xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot \mathbf{1}_{\left\{\mathsf{R}_{i} \middle| d_{2}^{(i)} - d_{1}^{(i)} \middle| < 1\right\}} \cdot \beta_{i} \end{aligned}$$

1.1.1. For each $s \in \{2, \dots, T\}$,

$$\begin{aligned} \mathbf{F}_{i}(\mathbf{2},\mathbf{1},s) &\triangleq p\left(v_{1:2}^{(i)},\mathsf{C}_{1}^{(i)} = \mathsf{A}_{1},\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s} \middle| d_{1:\mathsf{N}_{i}}^{(i)},\xi_{1:\mathsf{N}_{i},1:\mathsf{T}}^{(i)}\right) \\ &= p\left(v_{2}^{(i)}\middle|\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s},\xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle|\mathsf{C}_{1}^{(i)} = \mathsf{A}_{1},\xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot p\left(\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s},\mathsf{C}_{1}^{(i)} = \mathsf{A}_{1}\middle| d_{1}^{(i)},d_{2}^{(i)}\right) \\ &= p\left(v_{2}^{(i)}\middle|\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s},\xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle|\mathsf{C}_{1}^{(i)} = \mathsf{A}_{1},\xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot \rho\left(\frac{\mathsf{A}_{s} - \mathsf{A}_{1}}{\mathsf{R}_{i}\middle|d_{2}^{(i)} - d_{1}^{(i)}\middle|}\right) \cdot \alpha_{i} \end{aligned}$$

1.1.2. For each $s \in \{2,3,\dots,T\}$,

$$\begin{aligned} \mathbf{F}_{i}(\mathbf{2}, \mathbf{s}, \mathbf{s}) &\triangleq p\left(v_{1:2}^{(i)}, \mathsf{C}_{1}^{(i)} = \mathsf{A}_{s}, \mathsf{C}_{2}^{(i)} = \mathsf{A}_{s} \middle| d_{1:\mathsf{N}_{i}}^{(i)}, \xi_{1:\mathsf{N}_{i},1:\mathsf{T}}^{(i)}\right) \\ &= p\left(v_{2}^{(i)}\middle|\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s}, \xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle|\mathsf{C}_{1}^{(i)} = \mathsf{A}_{s}, \xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot p\left(\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s}, \mathsf{C}_{1}^{(i)} = \mathsf{A}_{s}\middle| d_{1}^{(i)}, d_{2}^{(i)}\right) \\ &= p\left(v_{2}^{(i)}\middle|\mathsf{C}_{2}^{(i)} = \mathsf{A}_{s}, \xi_{2,1:\mathsf{T}}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle|\mathsf{C}_{1}^{(i)} = \mathsf{A}_{s}, \xi_{1,1:\mathsf{T}}^{(i)}\right) \cdot \mathbf{1}_{\left\{\mathsf{R}_{i}\middle|d_{2}^{(i)}-d_{1}^{(i)}\middle|<1\right\}} \cdot (\mathbf{1} - \alpha_{i} - \beta_{i}) \cdot \phi_{i}^{s-1} \cdot \psi_{i} \end{aligned}$$

1.1.3. For each $s, t \in \{2,3,\dots,T\}$ such that s > t,

$$F_{i}(2, s, t) \triangleq p\left(v_{1:2}^{(i)}, C_{1}^{(i)} = A_{t}, C_{2}^{(i)} = A_{s} \middle| d_{1:N_{i}}^{(i)}, \xi_{1:N_{i},1:T}^{(i)}\right)$$

$$= p\left(v_{2}^{(i)}\middle| C_{2}^{(i)} = A_{s}, \xi_{2,1:T}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle| C_{1}^{(i)} = A_{t}, \xi_{1,1:T}^{(i)}\right) \cdot p\left(C_{2}^{(i)} = A_{s}, C_{1}^{(i)} = A_{t}\middle| d_{1}^{(i)}, d_{2}^{(i)}\right)$$

$$= p\left(v_{2}^{(i)}\middle| C_{2}^{(i)} = A_{s}, \xi_{2,1:T}^{(i)}\right) \cdot p\left(v_{1}^{(i)}\middle| C_{1}^{(i)} = A_{t}, \xi_{1,1:T}^{(i)}\right) \cdot \rho\left(\frac{A_{s} - A_{t}}{R_{i}\middle| d_{2}^{(i)} - d_{1}^{(i)}\middle|}\right) \cdot (1 - \alpha_{i} - \beta_{i}) \cdot \phi_{i}^{t-1} \cdot (1 - \phi_{i} - \psi_{i})$$

- 1.2. Iterations: for each $n \in \{3,4,\dots,N_i\}$,
- 1.2.1. For each $s \in \{2,3,\dots,T\}$,

$$\begin{aligned} \mathbf{F}_{i}(n,s,s) &\triangleq p\left(v_{1:n}^{(i)},C_{n-1}^{(i)} = \mathbf{A}_{s},C_{n}^{(i)} = \mathbf{A}_{s}\big|d_{1:N_{i}'}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &= p\left(v_{1:n}^{(i)},C_{n-2}^{(i)} = \mathbf{A}_{s},C_{n}^{(i)} = \mathbf{A}_{s},C_{n}^{(i)} = \mathbf{A}_{s}\big|d_{1:N_{i}'}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) + \sum_{u < s} p\left(v_{1:n}^{(i)},C_{n-2}^{(i)} = \mathbf{A}_{u},C_{n-1}^{(i)} = \mathbf{A}_{s},C_{n}^{(i)} = \mathbf{A}_{s}\big|d_{1:N_{i}'}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &= p\left(v_{n}^{(i)}\big|C_{n}^{(i)} = \mathbf{A}_{s},\xi_{n,1:T}^{(i)}\right) \cdot p\left(C_{n}^{(i)} = \mathbf{A}_{s}\big|C_{n-2}^{(i)} = \mathbf{A}_{s},C_{n-1}^{(i)} = \mathbf{A}_{s},d_{n-2}^{(i)},d_{n-1}^{(i)},d_{n}^{(i)}\right) \cdot p\left(v_{1:n-1}^{(i)},C_{n-2}^{(i)} = \mathbf{A}_{s},C_{n-1}^{(i)} = \mathbf{A}_{s}\big|d_{1:N_{i}'}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &+ \sum_{u < s} \left[p\left(v_{n}^{(i)}\big|C_{n}^{(i)} = \mathbf{A}_{s},\xi_{n,1:T}^{(i)}\right) \cdot p\left(C_{n}^{(i)} = \mathbf{A}_{s}\big|C_{n-2}^{(i)} = \mathbf{A}_{u},C_{n-1}^{(i)} = \mathbf{A}_{s},d_{n-2}^{(i)},d_{n-1}^{(i)},d_{n}^{(i)}\right) \cdot p\left(v_{1:n-1}^{(i)},C_{n-2}^{(i)} = \mathbf{A}_{u},C_{n-1}^{(i)} = \mathbf{A}_{s}\big|d_{1:N_{i}'}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right)\right] \\ &= p\left(v_{n}^{(i)}\big|C_{n}^{(i)} = \mathbf{A}_{s},\xi_{n,1:T}^{(i)}\right) \cdot \mathbf{1}_{\left\{\mathbf{R}_{i}\big|d_{n}^{(i)}-d_{n-1}^{(i)}\big|<1\right\}}\left[\mathbf{\epsilon}_{i}\cdot\mathbf{F}_{i}(n-1,s,s) + (\mathbf{1}-\eta_{i})\sum_{u < s}\mathbf{F}_{i}(n-1,u,s)\right] \end{aligned}$$

1.2.2. For each $s, t \in \{2,3,\dots,T\}$ such that s > t,

$$\begin{aligned} \mathbf{F}_{i}(\boldsymbol{n},\boldsymbol{t},\boldsymbol{s}) &\triangleq p\left(v_{1:n}^{(i)},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{t},\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s} \middle| d_{1:N_{i}}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &= p\left(v_{1:n}^{(i)},\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{t},\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s} \middle| d_{1:N_{i}}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) + \sum_{u < t} p\left(v_{1:n}^{(i)},\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{u},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{s} \middle| d_{1:N_{i}}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &= p\left(v_{n}^{(i)}\middle|\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s},\xi_{n,1:T}^{(i)}\right) \cdot p\left(\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s}\middle|\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{t},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{t},d_{n-2}^{(i)},d_{n-1}^{(i)}\right) \cdot p\left(v_{1:n-1}^{(i)},\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{t},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{t}\middle|d_{1:N_{i}}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right) \\ &+ \sum_{u < t} \left[p\left(v_{n}^{(i)}\middle|\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s},\xi_{n,1:T}^{(i)}\right) \cdot p\left(\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s}\middle|\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{u},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{t},d_{n-2}^{(i)},d_{n-1}^{(i)},d_{n}^{(i)}\right) \cdot p\left(v_{1:n-1}^{(i)},\mathsf{C}_{n-2}^{(i)} = \mathsf{A}_{u},\mathsf{C}_{n-1}^{(i)} = \mathsf{A}_{t}\middle|d_{1:N_{i}}^{(i)},\xi_{1:N_{i},1:T}^{(i)}\right)\right] \\ &= p\left(v_{n}^{(i)}\middle|\mathsf{C}_{n}^{(i)} = \mathsf{A}_{s},\xi_{n,1:T}^{(i)}\right) \left[(1-\varepsilon_{i}) \cdot \rho\left(\frac{\mathsf{A}_{s}-\mathsf{A}_{t}}{\mathsf{R}_{i}\middle|d_{n}^{(i)}-d_{n-1}^{(i)}\middle|}\right) \cdot \mathsf{F}_{i}(n-1,t,t) + \eta_{i}\sum_{u < s}\left[\rho\left(\frac{\mathsf{A}_{t}-\mathsf{A}_{u}}{\mathsf{R}_{i}\middle|d_{n-1}^{(i)}-d_{n-1}^{(i)}\middle|}\right) \cdot \mathsf{F}_{i}(n-1,u,s)\right]\right] \end{aligned}$$

- 2. Backward Sampling:
- 2.1. Initialization: for each $t_{N_i-1}^{(i),(l)}, t_{N_i}^{(i),(l)} \in \{1,2,3,\dots,T\},$

$$\begin{split} \mathbb{P}\left(\mathbf{C}_{\mathbf{N}_{i}-1}^{(i),(l)} = \mathbf{A}_{t_{\mathbf{N}_{i}-1}^{(i),(l)}}, \mathbf{C}_{\mathbf{N}_{i}}^{(i),(l)} = \mathbf{A}_{t_{\mathbf{N}_{i}}^{(i),(l)}} \middle| \boldsymbol{v}_{1:\mathbf{N}_{i}}^{(i)}, \boldsymbol{d}_{1:\mathbf{N}_{i}}^{(i)}, \boldsymbol{\xi}_{1:\mathbf{N}_{i},1:\mathbf{T}}^{(i)}\right) &\propto p\left(\boldsymbol{v}_{1:\mathbf{N}_{i}}^{(i)}, \mathbf{C}_{\mathbf{N}_{i}-1}^{(i),(l)} = \mathbf{A}_{t_{\mathbf{N}_{i}-1}^{(i),(l)}}, \mathbf{C}_{\mathbf{N}_{i}}^{(i),(l)} = \mathbf{A}_{t_{\mathbf{N}_{i}}^{(i),(l)}} \middle| \boldsymbol{d}_{1:\mathbf{N}_{i}}^{(i)}, \boldsymbol{\xi}_{1:\mathbf{N}_{i},1:\mathbf{T}}^{(i)}\right) \\ &= \mathbf{E}_{i}\big(\mathbf{N}_{i}, \boldsymbol{t}_{\mathbf{N}_{i}-1}^{(i),(l)}, \boldsymbol{t}_{\mathbf{N}_{i}}^{(i),(l)}\big) \end{split}$$

- 2.2. Iterations: for each $n \in \{m-2, m-3, \cdots, 1\}$ and $t_n^{(i),(l)} \in \{1,2,3, \cdots, t_{n+1}^{(i),(l)}\}$,
- 2.2.1. $t_{n+1}^{(i),(l)} = t_{n+2}^{(i),(l)}$:
- 2.2.1.1. $t_n^{(i),(l)} = t_{n+1}^{(i),(l)}$:

$$\mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}} \middle| \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{v}_{1:n+2}^{(i)}, \mathbf{d}_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \propto \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \\ = p\left(v_{n+2}^{(i)}\middle| \mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) p\left(\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{d}_{n}^{(i)}, \mathbf{d}_{n+1}^{(i)}, \mathbf{d}_{n+1}^{(i)}, \mathbf{d}_{n+1}^{(i)}, \mathbf{d}_{n+2}^{(i)}\right) p\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{v}_{1:n+1}^{(i)}\middle| \mathbf{d}_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \\ = p\left(v_{n+2}^{(i)}\middle| \mathbf{C}_{n+2}^{(i)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) \cdot \mathbf{1}_{\left\{\mathbf{R}_{l}\middle| \mathbf{d}_{n+2}^{(i)} - \mathbf{d}_{n+1}^{(i)}\middle| \cdot \mathbf{1}_{n+1}^{(i),(l)}, \boldsymbol{t}_{n+1}^{(i),(l)}\right\}} \cdot \mathbf{F}_{l}\left(n+1, t_{n}^{(i),(l)}, t_{n+1}^{(i),(l)}\right) \cdot \boldsymbol{\varepsilon}_{l} \\ & \propto \mathbf{F}_{l}\left(n+1, t_{n}^{(i),(l)}, t_{n+1}^{(i),(l)}\right) \cdot \boldsymbol{\varepsilon}_{l} \end{aligned}$$

2.2.1.2. $t_n^{(i),(l)} < t_{n+1}^{(i),(l)}$:

$$\begin{split} \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n}^{(i),(l)}} \middle| \mathbf{C}_{n+1}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{v}_{1:n+2}^{(i)}, \boldsymbol{d}_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) &\propto \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \\ &= p\left(v_{n+2}^{(i)}\middle|\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) p\left(\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \boldsymbol{d}_{n}^{(i)}, \boldsymbol{d}_{n+1}^{(i)}, \boldsymbol{d}_{n+1}^{(i)}, \boldsymbol{d}_{n+2}^{(i)}\right) p\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \boldsymbol{v}_{1:n+1}^{(i)}\middle|\boldsymbol{d}_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \\ &= p\left(v_{n+2}^{(i)}\middle|\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) \cdot \mathbf{1}_{\left\{\mathbf{R}_{l}\middle|\boldsymbol{d}_{n+2}^{(i)}-\boldsymbol{d}_{n+1}^{(i)}\middle|\boldsymbol{\epsilon}_{1}\right\}} \cdot \mathbf{F}_{l}\left(n+1,t_{n}^{(i),(l)},t_{n+1}^{(i),(l)}\right) \cdot (1-\eta_{l}) \\ &\propto \mathbf{F}_{l}\left(n+1,t_{n}^{(i),(l)},t_{n+1}^{(i),(l)}\right) \cdot (1-\eta_{l}) \end{split}$$

2.2.2.
$$t_{n+1}^{(i),(l)} < t_{n+2}^{(i),(l)}$$
:

2.2.2.1.
$$t_n^{(i),(l)} = t_{n+1}^{(i),(l)}$$
:

$$\mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n}^{(l),(l)}} \middle| \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \boldsymbol{v}_{1:n+2}^{(i)}, \boldsymbol{d}_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \propto \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \boldsymbol{v}_{1:n+2}^{(i)} \middle| d_{1:N_{l}}^{(i)}, \boldsymbol{\xi}_{1:N_{l},1:T}^{(i)}\right) \\ = p\left(v_{n+2}^{(i)}\middle| \mathbf{C}_{n+2}^{(i),(l)}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) p\left(\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, d_{n}^{(i)}, d_{n}^{(i)}, d_{n}^{(i)}, d_{n+1}^{(i)}, d_{n+1}^{(i)}\right) p\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i)} = \mathbf{A}_{t_{n+1}^$$

2.2.2.2. $t_n^{(i),(l)} < t_{n+1}^{(i),(l)}$:

$$\begin{split} \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}} \middle| \mathbf{C}_{n+1}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{d}_{1:n_{t}}^{(i)}, \boldsymbol{\xi}_{1:n_{t},1:T}^{(i)}\right) &\propto \mathbb{P}\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)}, \mathbf{C}_{n+2}^{(i),(l)}, \mathbf{d}_{1:n_{t}}^{(i)}, \boldsymbol{\xi}_{1:n_{t},1:T}^{(i)}\right) \\ &= p\left(v_{n+2}^{(i)}\middle|\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) p\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \mathbf{C}_{n+1}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{d}_{n}^{(i)}, \mathbf{d}_{n}^{(i)}, \mathbf{d}_{n+1}^{(i)}, \mathbf{d}_{n+2}^{(i)}\right) p\left(\mathbf{C}_{n}^{(i),(l)} = \mathbf{A}_{t_{n+1}^{(i),(l)}}, \mathbf{v}_{1:n+1}^{(i)}\middle|\mathbf{d}_{1:n_{t}}^{(i)}, \boldsymbol{\xi}_{1:n_{t},1:T}^{(i)}\right) \\ &= p\left(v_{n+2}^{(i)}\middle|\mathbf{C}_{n+2}^{(i),(l)} = \mathbf{A}_{t_{n+2}^{(i),(l)}}, \boldsymbol{\xi}_{n+2,1:T}^{(i)}\right) \cdot \rho\left(\frac{\mathbf{A}_{t_{n+1}^{(i),(l)}} - \mathbf{A}_{t_{n}^{(i)},(l)}}{\mathbf{R}_{i}\middle|\mathbf{d}_{n+1}^{(i)} - \mathbf{d}_{n}^{(i)}}, \frac{\mathbf{A}_{t_{n+2}^{(i),(l)}} - \mathbf{A}_{t_{n+1}^{(i),(l)}}}{\mathbf{R}_{i}\middle|\mathbf{d}_{n+2}^{(i)} - \mathbf{d}_{n+1}^{(i)}}\right) \cdot \mathbf{F}_{i}\left(n+1, t_{n}^{(i),(l)}, t_{n+1}^{(i),(l)}\right) \cdot \mathbf{\eta}_{i} \\ &\propto \rho\left(\frac{\mathbf{A}_{t_{n+1}^{(i),(l)}} - \mathbf{A}_{t_{n}^{(i),(l)}}}{\mathbf{R}_{i}\middle|\mathbf{d}_{n+1}^{(i)} - \mathbf{d}_{n}^{(i)}\middle|}\right) \cdot \mathbf{F}_{i}\left(n+1, t_{n}^{(i),(l)}, t_{n+1}^{(i),(l)}\right) \cdot \mathbf{\eta}_{i} \end{aligned}$$

- 2.3. Termination: iterate the above sampling steps to get $t_{N_i}^{(i),(l)}$, $t_{N_i-1}^{(i),(l)}$, \cdots , $t_1^{(i),(l)}$ recursively until possible.
- 2.3.1. If $F_i(n+1,t,t_{n+1}^{(i),(l)}) \equiv 0$ for some $n \geq 1$, then stop and discard the obtained sample and go to the first step to get it again.
- 2.3.2. After getting $L^{(i)}$ samples $\left\{t_1^{(i),(l)},t_2^{(i),(l)},\cdots,t_{N_i}^{(i),(l)}\right\}_{l=1}^{L^{(i)}}$, stop and proceed to the next step.

3. Updating core parameters by ML estimators:

Suppose that we get $L^{(i)}$ samples for the core i by running the above backward sampling algorithm.

Let:

$$\begin{split} \mathbf{A} \triangleq \# \text{ of samples where } \tilde{t}_1^{(i),(l)} &= 1 \text{ and } \tilde{t}_2^{(i),(l)} \neq 1 \\ \mathbf{B} \triangleq \# \text{ of samples where } \tilde{t}_1^{(i),(l)} &= 1 \text{ and } \tilde{t}_2^{(i),(l)} = 1 \end{split}$$

$$\mathbf{C} \triangleq \# \text{ of samples where } \tilde{t}_1^{(i),(l)} \neq 1 \end{split}$$

$$\mathbf{D} \triangleq \# \text{ of samples where } \tilde{t}_1^{(i),(l)} \neq 1 \text{ and } \tilde{t}_2^{(i),(l)} \neq 1 \text{ and } \mathbf{A}_{\tilde{t}_1^{(i)},(l)} = \mathbf{A}_{\tilde{t}_2^{(i)},(l)} \end{split}$$

$$\mathbf{E} \triangleq \# \text{ of samples where } \tilde{t}_1^{(i),(l)} \neq 1 \text{ and } \tilde{t}_2^{(i),(l)} \neq 1 \text{ and } \mathbf{A}_{\tilde{t}_1^{(i)},(l)} \neq \mathbf{A}_{\tilde{t}_2^{(i)},(l)} \end{split}$$

$$\mathbf{F} \triangleq \# \text{ of samples where } \mathbf{A}_{\tilde{t}_n^{(i)},(l)} = \mathbf{A}_{\tilde{t}_{n+1}^{(i)},(l)} = \mathbf{A}_{\tilde{t}_{n+2}^{(i)},(l)} \end{split}$$

$$\mathbf{G} \triangleq \# \text{ of samples where } \mathbf{A}_{\tilde{t}_n^{(i)},(l)} = \mathbf{A}_{\tilde{t}_{n+1}^{(i)},(l)} \neq \mathbf{A}_{\tilde{t}_{n+2}^{(i)},(l)} \end{split}$$

$$\mathbf{H} \triangleq \# \text{ of samples where } \mathbf{A}_{\tilde{t}_n^{(i)},(l)} \neq \mathbf{A}_{\tilde{t}_{n+1}^{(i)},(l)} = \mathbf{A}_{\tilde{t}_{n+2}^{(i)},(l)} \end{split}$$

$$\mathbf{I} \triangleq \# \text{ of samples where } \mathbf{A}_{\tilde{t}_n^{(i)},(l)} \neq \mathbf{A}_{\tilde{t}_{n+1}^{(i)},(l)} \neq \mathbf{A}_{\tilde{t}_{n+2}^{(i)},(l)} \end{split}$$

Then, with weak Beta priors for the stability,

$$\begin{split} \widehat{\alpha}_{i} &\triangleq \frac{A+1}{A+B+C+3}, \qquad \widehat{\beta}_{i} \triangleq \frac{B+1}{A+B+C+3} \\ \widehat{\phi}_{i} &\triangleq \frac{\sum_{l=1}^{L^{(i)}} \widetilde{t}_{1}^{(i),(l)} - L^{(i)} + 1}{\sum_{l=1}^{L^{(i)}} \widetilde{t}_{1}^{(i),(l)} - L^{(i)} + D + E + 3}, \qquad \widehat{\psi}_{i} \triangleq \frac{D+1}{\sum_{l=1}^{L^{(i)}} \widetilde{t}_{1}^{(i),(l)} - L^{(i)} + D + E + 3} \\ \widehat{\eta}_{i} &\triangleq \frac{I+1}{I+H+2}, \qquad \widehat{\varepsilon}_{i} \triangleq \frac{F+1}{F+G+2} \\ \widehat{R}_{i} &\triangleq \frac{1}{L^{(i)}} \sum_{l=1}^{L^{(i)}} \frac{A_{\widetilde{t}_{N_{i}}^{(i),(l)}} - A_{\widetilde{t}_{1}^{(i),(l)}}}{d_{N_{i}} - d_{1}}, \qquad \widehat{\tau}_{i} \triangleq \frac{\sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \left(\nu_{n}^{(i)} - \widetilde{\mu}_{\widetilde{t}_{n}^{(i),(l)}} \right)}{L^{(i)} N_{i}} \end{split}$$

4. Updating stack parameters by ML estimators:

If we are only interested in aligning each core to the stack, it is not needed to read this section; if we are interested in constructing the new stack from the data as well, it is also required to learn means and standard deviations $\{\mu_t\}_{t=1}^T$ and $\{\sigma_t\}_{t=1}^T$. An EM algorithm can learn both the alignments and stack parameters simultaneously: to be specific, it first aligns each core to the stack by generating samples, and then updates the stack parameters by using samples.

$$\widehat{\mu}_{t} \triangleq \begin{cases} \frac{\sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \left[\left(\boldsymbol{v}_{n}^{(i)} - \widehat{\boldsymbol{\tau}}_{i} \right) \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}} \right]}{\sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}}}, & \sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}} > 0 \\ \mu_{t}, & \text{otherwise} \end{cases}$$

$$\widehat{\boldsymbol{\sigma}}_{t} \triangleq \begin{cases} \sqrt{\frac{\sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \left[\left(\boldsymbol{v}_{n}^{(i)} - \widehat{\boldsymbol{\tau}}_{i} - \widehat{\boldsymbol{\mu}}_{t} \right)^{2} \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}} \right]}}{\sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}}}, & \sum_{i=1}^{K} \sum_{l=1}^{L^{(i)}} \sum_{n=1}^{N_{i}} \mathbf{1}_{\left\{ \widehat{\boldsymbol{t}}_{n}^{(i),(l)} = t \right\}} > 0 \\ \sigma_{t}, & \text{otherwise} \end{cases}$$

, where $\{\tilde{\mu}_t\}_{t=1}^T$ are the updated means in the previous iteration.

Note that EM algorithms are quite sensitive to the initial conditions, which means that it is, in general, not possible to see good inference if we do not use "proper" initializations. One suggestion to deal with this defect is initializing stack parameters by using any existing stacks (for example, LR04) and core parameters by using "proper" values, for example, initializing $1 \approx \eta_i \gg \varepsilon_i \approx 0$, R_i by initial guess on the range of ages of the core, and τ_i by the difference between mean of $v_n^{(i)}$ and $\hat{\mu}_t$. Then, EM algorithms will "refine" our initial guesses on the parameters to the "real" ones iteratively from the given data.