

1 Piman-Yor Diffusion Trees

1.1 Modelling of PYDT

$$\alpha \sim \text{Beta}(\alpha|a_\alpha, b_\alpha) \quad (1)$$

$$\theta \sim \text{G}(\theta|a_\theta, b_\theta) \quad (2)$$

$$\begin{aligned} c &\sim \text{G}(c|a_c, b_c) \\ &= \frac{b_c^{a_c} c^{a_c-1} e^{-b_c c}}{\Gamma(a_c)} \end{aligned} \quad (3)$$

$$1/\sigma^2 \sim \text{G}(1/\sigma^2|a_{\sigma^2}, b_{\sigma^2}) \quad (4)$$

$$p(t_v|c, \mathcal{T}) = c(1-t_v)^{cJ_{\mathbf{n}_v}^{\theta, \alpha}-1} \quad (5)$$

$$p(\mathbf{z}_v|\mathbf{z}_u, \sigma^2(t_v - t_u)\mathbf{I}) = (2\pi\sigma^2(t_v - t_u))^{-\frac{D}{2}} \exp\left(-\frac{1}{2} \frac{\|\mathbf{z}_v - \mathbf{z}_u\|^2}{\sigma^2(t_v - t_u)}\right) \quad (6)$$

$$p(\mathbf{z}_k|\mathbf{z}_v, \sigma^2(t_k - t_v)\mathbf{I}) = (2\pi\sigma^2(t_k - t_v))^{-\frac{D}{2}} \exp\left(-\frac{1}{2} \frac{\|\mathbf{z}_k - \mathbf{z}_v\|^2}{\sigma^2(t_k - t_v)}\right) \quad (7)$$

$$\begin{aligned} p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\Theta}, \mathcal{T}) &= \text{G}(c|a_c, b_c)\text{G}(1/\sigma^2|a_{\sigma^2}, b_{\sigma^2}) \\ &\prod_{v \in \mathcal{I}}^{|\mathcal{I}|} p(t_v|c, \mathcal{T}) p(\mathbf{z}_v|\mathbf{z}_u, \sigma^2(t_v - t_u)\mathbf{I}) \\ &\prod_{n=1}^N p(\mathbf{x}_n|\mathbf{z}_{pa(n)}, \sigma^2(1 - t_{pa(n)})\mathbf{I}) \end{aligned} \quad (8)$$

where $\mathbf{Z} = \{c, \sigma^2, \mathbf{z}, \mathbf{t}\}$, $\boldsymbol{\Theta} = \{a_c, b_c, a_{\sigma^2}, b_{\sigma^2}\}$

1.2 EM algorithm for PYDT

$$\begin{aligned} \ln P(\mathbf{X}|\boldsymbol{\theta}) &= \ln \left\{ \sum_{\mathbf{Z}} P(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \right\} \\ &= \ln \left\{ \sum_{\mathbf{Z}} q(\mathbf{Z}) \frac{P(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})} \right\} \\ &= \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{P(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})} \right\} + \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{q(\mathbf{Z})}{P(\mathbf{Z}|\mathbf{X}, \boldsymbol{\theta})} \right\} \end{aligned} \quad (9)$$

The main procedure of the algorithm is as follows.

- 1) Find $q(\mathbf{Z})$ which minimizes the KL divergence.
 - 2) Take a gradient of the ELBO w.r.t. $\boldsymbol{\theta}$ using $q(\mathbf{Z})$ found in the step 1).
- The step 2) can be written as below.

$$\begin{aligned}
Q(\boldsymbol{\theta}, \boldsymbol{\theta}') &= \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln \left\{ \frac{P(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta})}{q(\mathbf{Z})} \right\} \\
&= \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln P(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta}) - \sum_{\mathbf{Z}} q(\mathbf{Z}) \ln q(\mathbf{Z}) \quad (10)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial Q(\boldsymbol{\theta}, \boldsymbol{\theta}')}{\partial \boldsymbol{\theta}} &= \sum_{\mathbf{Z}} q(\mathbf{Z}) \frac{\partial \ln P(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \\
&= \sum_{\mathbf{Z}} p(\mathbf{Z} | \mathbf{X}, \boldsymbol{\theta}') \frac{\partial \ln P(\mathbf{X}, \mathbf{Z} | \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \quad (11)
\end{aligned}$$

1.3 Posterior of $p(t_v | \mathcal{T})$

$$\begin{aligned}
p(t_v, \mathbf{z}_{\{u,v,k\}}, \sigma^2 | c, \mathcal{T}) &= c(2\pi\sigma^2)^{-\frac{D(K+1)}{2}} \exp \left\{ (cJ_{\mathbf{n}_v}^{\theta, \alpha} - 1) \ln(1 - t_v) \right. \\
&\quad \left. - \frac{D}{2} (\ln(t_v - t_u) + \sum_k \ln(t_k - t_v)) \right. \\
&\quad \left. - \frac{\|\mathbf{z}_v - \mathbf{z}_u\|^2}{2\sigma^2} \frac{1}{t_v - t_u} - \sum_k \frac{\|\mathbf{z}_k - \mathbf{z}_v\|^2}{2\sigma^2} \frac{1}{t_k - t_v} \right\} \\
&= C_{\sigma^2} \exp \{u(t_v)\} \quad (12)
\end{aligned}$$

$$\begin{aligned}
\frac{du}{dt_v} &= -\frac{cJ_{\mathbf{n}_v}^{\theta, \alpha} - 1}{1 - t_v} - \frac{D}{2} \left(\frac{1}{t_v - t_u} - \sum_k \frac{1}{t_k - t_v} \right) \\
&\quad + \frac{\|\mathbf{z}_v - \mathbf{z}_u\|^2}{2\sigma^2} \frac{1}{(t_v - t_u)^2} - \sum_k \frac{\|\mathbf{z}_k - \mathbf{z}_v\|^2}{2\sigma^2} \frac{1}{(t_k - t_v)^2} \\
&= -\frac{cJ_{\mathbf{n}_v}^{\theta, \alpha} - 1}{1 - t_v} - \frac{1}{2(t_v - t_u)^2} \left(D(t_v - t_u) - \frac{\|\mathbf{z}_v - \mathbf{z}_u\|^2}{\sigma^2} \right) \\
&\quad + \sum_k \frac{1}{2(t_k - t_v)^2} \left(D(t_k - t_v) - \frac{\|\mathbf{z}_k - \mathbf{z}_v\|^2}{\sigma^2} \right) \\
&= A(t_v) \quad (13)
\end{aligned}$$

$$C_{\sigma^2} A(t_v)^{-1} \int \exp \{u(t_v)\} du = Z, \text{ but this integral is intractable!} \quad (14)$$

\Rightarrow The range of integration w.r.t. t_v is $0 < t_u \leq t_v \leq \min(t_k) < 1$, obtaining Z by simply summing pdf by the interval $dt = 1e^{-2}$ is computationally tractable for modern hardwares.

A few t points usually give sufficient accuracy for Z .

$$\begin{aligned}
\mathbb{E}_{p(t_v | \mathbf{z}_{\{u,v,k\}}, \sigma^2, c, \mathcal{T})}[t_v] &= \frac{1}{Z} \int t_v p(t_v, \mathbf{z}_{\{u,v,k\}}, \sigma^2 | c, \mathcal{T}) dt_v \\
&= \frac{1}{Z} C_{\sigma^2} A_{\mu}(t_v)^{-1} \int \exp \{u_{\mu}(t_v)\} du \quad (15)
\end{aligned}$$