1 Piman-Yor Diffusion Trees

1.1 Modelling of PYDT

$$
\begin{aligned}
\alpha &\sim \mathrm{Beta}(\alpha|a_\alpha, b_\alpha) && (1)\\
\theta &\sim \mathrm{G}(\theta|a_\theta, b_\theta) && (2)\\
p(\mathcal{T}|\alpha,\theta) &= \prod_{v\in\mathcal{I}} \frac{a(t_v)\prod_{k=3}^{K_v}[\theta+(k-1)\alpha]\prod_{l=1}^{K_v}\Gamma(n_l^v-\alpha)}{\Gamma(m(v)+\theta)\Gamma(1-\alpha)^{K_v-1}} && (3)\\
c &\sim \mathrm{G}(c|a_c, b_c) && (4)\\
1/\sigma^2 &\sim \mathrm{G}(1/\sigma^2|a_{\sigma^2}, b_{\sigma^2}) && (5)\\
p(t_v|c,\mathcal{T}) &= c(1-t_v)^{cJ_{\mathbf{n}_v}^{\theta,\alpha}-1} && (6)\\
\mathcal{N}(\mathbf{z}_v|\mathbf{z}_u, \sigma^2(t_v-t_u)\mathbf{I}) &= (2\pi\sigma^2(t_v-t_u))^{-\frac{D}{2}}\exp\Big(-\frac{1}{2}\frac{\parallel \mathbf{z}_v-\mathbf{z}_u\parallel^2}{\sigma^2(t_v-t_u)}\Big) && (7)\\
\mathcal{N}(\mathbf{z}_k|\mathbf{z}_v, \sigma^2(t_k-t_v)\mathbf{I}) &= (2\pi\sigma^2(t_k-t_v))^{-\frac{D}{2}}\exp\Big(-\frac{1}{2}\frac{\parallel \mathbf{z}_k-\mathbf{z}_v\parallel^2}{\sigma^2(t_k-t_v)}\Big) && (8)
\end{aligned}
$$

1.2 EM algorithm for PYDT

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

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.

$$
\begin{aligned}
Q(\boldsymbol{\theta},\boldsymbol{\theta}') &= \sum_{\mathbf{Z}} q(\mathbf{Z})\ln\Big\{\frac{P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})}\Big\}\\
&= \sum_{\mathbf{Z}} q(\mathbf{Z})\ln P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta}) - \sum_{\mathbf{Z}} q(\mathbf{Z})\ln q(\mathbf{Z}) && (10)\\
\frac{\partial Q(\boldsymbol{\theta},\boldsymbol{\theta}')}{\partial\boldsymbol{\theta}} &= \sum_{\mathbf{Z}} q(\mathbf{Z})\frac{\partial \ln P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}\\
&= \sum_{\mathbf{Z}} p(\mathbf{Z}|\mathbf{X},\boldsymbol{\theta}')\frac{\partial \ln P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{\partial\boldsymbol{\theta}} && (11)
\end{aligned}
$$

An important point is that the EM algorithm is an algorithm designed for maximum likelihood estimation. Hence, if priors of parameters are combined in the model, EM algorithm becomes the maximum-a-posteriori EM algorithm (MAP-EM) (Gupta and Chen, 2011). Here is an example (Chen and John, 2010).

$$
\begin{aligned}
\mu_j &= \mu + (j-1)\Delta\mu, j = 1, ..., k && (12)\\
\sigma_j^2 &= \sigma^2, j = 1, ..., k && (13)\\
p(y_j) &= \sum_{j=1}^{k} w_j \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(- \frac{(y_i - \mu - (j-1)\Delta\mu)^2}{2\sigma^2} \right) && (14)\\
\sigma^2 &\sim \text{Inv-Gamma}\left(\frac{\nu}{2}, \frac{\zeta^2}{2}\right) && (15)\\
\Delta\mu|\sigma^2 &\sim \mathcal{N}\left(\eta, \frac{\sigma^2}{\kappa}\right) && (16)\\
p(\theta) &\propto \left(\sigma^2\right)^{-\frac{\nu+3}{2}} \exp\left(- \frac{\zeta^2 + \kappa(\Delta\mu - \eta)^2}{2\sigma^2} \right) && (17)\\
\gamma_{ij}^{(m)} &\triangleq P(Z_i = j | y_i, \theta^{(m)})\\
&= \frac{w_j^{(m)} \phi(y_i | \mu_j^{(m)}, \sigma^{(m)})}{\sum_{l=1}^{k} w_l^{(m)} \phi(y_i | \mu_l^{(m)}, \sigma^{(m)})}, i = 1, ..., n \text{ and } j = 1, ..., k && (18)\\
Q(\theta|\theta^{(m)}) &= \sum_{i=1}^{n} \sum_{j=1}^{k} \gamma_{ij}^{(m)} \ln(w_j \phi(y_i | \mu + (j-1)\Delta\mu, \sigma)) && (19)\\
\theta^{(m+1)} &= \arg\max_{\theta} (Q(\theta|\theta^{(m)}) + \ln p(\theta)) && (20)
\end{aligned}
$$

In case of PYDT, the MAP-EM formulation of the model is as follows.

$$
\begin{aligned}
p(\mathbf{X},\mathbf{Z}|\mathbf{\Theta},\mathcal{T}) &= \prod_{[uv]\in S(\mathcal{T})'} \mathcal{N}(\mathbf{z}_v|\mathbf{z}_u,\sigma^2(t_v-t_u)\mathbf{I}) \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n|\mathbf{z}_{\mathrm{pa}(n)},\sigma^2(1-t_{\mathrm{pa}(n)})\mathbf{I}) \qquad (21)\\
&\quad \text{where } \mathbf{Z}=\{\mathbf{z}\},\mathbf{\Theta}=\{\mathbf{t},\sigma^2\}\\
p(\mathbf{\Theta}) &= \mathrm{G}(c|a_c,b_c)\mathrm{G}(1/\sigma^2|a_{\sigma^2},b_{\sigma^2})\prod_{v\in\mathcal{I}} p(t_v|c,\mathcal{T}) \qquad (22)\\
Q(\mathbf{\Theta}|\mathbf{\Theta}') &= \sum_{[uv]\in S(\mathcal{T})'} \left(-\frac{D}{2}\ln 2\pi\sigma^2(t_v-t_u) - \frac{\mathbb{E}_{p(\mathbf{z}|\mathbf{x},\mathbf{t},\sigma^2)}\big[\parallel \mathbf{z}_v-\mathbf{z}_u \parallel^2\big]}{2\sigma^2(t_v-t_u)}\right)\\
&+ \sum_{n=1}^{N}\left(-\frac{D}{2}\ln 2\pi\sigma^2(1-t_{\mathrm{pa}(n)}) - \frac{\mathbb{E}_{p(\mathbf{z}|\mathbf{x},\mathbf{t},\sigma^2)}\big[\parallel \mathbf{x}_v-\mathbf{z}_{\mathrm{pa}(n)} \parallel^2\big]}{2\sigma^2(1-t_{\mathrm{pa}(n)})}\right) \qquad (23)\\
\ln p(\mathbf{\Theta}) &= \Bigg(a_c\ln b_c + (a_c-1)\ln c - b_c c - \ln\Gamma(a_c)\\
&\quad + a_{\sigma^2}\ln b_{\sigma^2} + (a_{\sigma^2}-1)\ln\frac{1}{\sigma^2} - b_{\sigma^2}\frac{1}{\sigma^2} - \ln\Gamma(a_{\sigma^2})\\
&\quad + \sum_{v\in\mathcal{I}}(cJ^{\theta,\alpha}_{\mathbf{n}_v}-1)\ln c(1-t_v)\Bigg) \qquad (24)
\end{aligned}
$$

However, some distributions have conjugacy. Hence, those parameters can be marginalised out and that results in the collapsed version.

$$
\begin{aligned}
\int \mathrm{G}(c|a_c,b_c)\prod_{v\in\mathcal{I}} p(t_v|c,\mathcal{T})dc &= \frac{b_c^{a_c}}{\Gamma(a_c)}(1-t_v)^{|\mathcal{I}|}\int c^{a_c-1+|\mathcal{I}|}\exp\Big(-\big(b_c-\sum_{v\in\mathcal{I}} J^{\theta,\alpha}_{\mathbf{n}_v}\ln(1-t_v)\big)c\Big)dc\\
&= \frac{b_c^{a_c}}{\Gamma(a_c)}(1-t_v)^{|\mathcal{I}|}\frac{\Gamma(a_c+|\mathcal{I}|)}{\big(b_c-\sum_{v\in\mathcal{I}} J^{\theta,\alpha}_{\mathbf{n}_v}\ln(1-t_v)\big)^{a_c+|\mathcal{I}|}}\\
&= p(t_v|a_c,b_c,\mathcal{T}) \qquad (25)
\end{aligned}
$$

$$
\begin{aligned}
&\int \mathrm{G}(1/\sigma^2|a_{\sigma^2},b_{\sigma^2})\prod_{[uv]\in S(\mathcal{T})'} \mathcal{N}(\mathbf{z}_v|\mathbf{z}_u,\sigma^2(t_v-t_u)\mathbf{I}) \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n|\mathbf{z}_{\mathrm{pa}(n)},\sigma^2(1-t_{\mathrm{pa}(n)})\mathbf{I})d(1/\sigma^2)\\
&= \frac{b_{\sigma^2}^{a_{\sigma^2}}}{\Gamma(a_{\sigma^2})}2\pi^{-\frac{D}{2}(|\mathcal{I}|+N)}\int\left(\frac{1}{\sigma^2}\right)^{a_{\sigma^2}-1+\frac{D}{2}(|\mathcal{I}|+N)}\exp\left(-\left(b_{\sigma^2}+\frac{1}{2}\sum_{[uv]\in S(\mathcal{T})}\frac{\parallel \mathbf{z}_v-\mathbf{z}_u\parallel^2}{t_v-t_u}\right)\frac{1}{\sigma^2}\right)d(1/\sigma^2)\\
&= \frac{b_{\sigma^2}^{a_{\sigma^2}}}{\Gamma(a_{\sigma^2})}2\pi^{-\frac{D}{2}(|\mathcal{I}|+N)}\frac{\Gamma\big(a_{\sigma^2}+\frac{D}{2}(|\mathcal{I}|+N)\big)}{\Big(b_{\sigma^2}+\frac{1}{2}\sum_{[uv]\in S(\mathcal{T})'}\frac{\|\mathbf{z}_v-\mathbf{z}_u\|^2}{t_v-t_u}+\frac{1}{2}\sum_{n=1}^{N}\frac{\|\mathbf{x}_n-\mathbf{z}_{\mathrm{pa}(n)}\|^2}{1-t_{\mathrm{pa}(n)}}\Big)^{a_{\sigma^2}+\frac{D}{2}(|\mathcal{I}|+N)}}\\
&= p(\mathbf{X},\mathbf{Z}|\mathbf{t},a_{\sigma^2},b_{\sigma^2}) \qquad (26)
\end{aligned}
$$

$$
\begin{aligned}
Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') &= a_{\sigma^2}\ln b_{\sigma^2} - \ln\Gamma(a_{\sigma^2}) + \ln\Gamma\bigg(a_{\sigma^2} + \frac{D}{2}(|\mathcal{I}|+N)\bigg) \\
&- \bigg(a_{\sigma^2} + \frac{D}{2}(|\mathcal{I}|+N)\bigg)\bigg\langle \ln\bigg(b_{\sigma^2} + \frac{1}{2}\sum_{[uv]\in S(\mathcal{T})'} \frac{\|\,\mathbf{z}_v - \mathbf{z}_u\,\|^2}{t_v - t_u} + \frac{1}{2}\sum_{n=1}^{N}\frac{\|\,\mathbf{x}_n - \mathbf{z}_{\mathrm{pa}(n)}\,\|^2}{1 - t_{\mathrm{pa}(n)}}\bigg)\bigg\rangle \\
&+ \text{Const.}
\end{aligned} \tag{27}
$$

$$
\begin{aligned}
\ln p(\boldsymbol{\Theta}) &= \sum_{v\in\mathcal{I}}\bigg(a_c\ln b_c - \ln\Gamma(a_c) + |\mathcal{I}|\ln(1-t_v) \\
&\quad + \ln\Gamma(a_c + |\mathcal{I}|) - (a_c + \mathcal{I})\ln\Big(b_c - \sum_{v\in\mathcal{I}} J^{\theta,\alpha}_{\mathbf{n}_v}\ln(1-t_v)\Big)\bigg) \\
&= |\mathcal{I}|\big(a_c\ln b_c - \ln\Gamma(a_c) + \ln\Gamma(a_c+|\mathcal{I}|)\big) \\
&\quad + \sum_{v\in\mathcal{I}}\bigg(|\mathcal{I}|\ln(1-t_v) - (a_c+\mathcal{I})\ln\Big(b_c - \sum_{v\in\mathcal{I}} J^{\theta,\alpha}_{\mathbf{n}_v}\ln(1-t_v)\Big)\bigg)
\end{aligned} \tag{28}
$$

$$\frac{\partial\big(Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') + \ln p(\boldsymbol{\Theta})\big)}{\partial t_v} \tag{29}$$

$$\frac{\partial\big(Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') + \ln p(\boldsymbol{\Theta})\big)}{\partial a_{\sigma^2}} \tag{30}$$

$$\frac{\partial\big(Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') + \ln p(\boldsymbol{\Theta})\big)}{\partial b_{\sigma^2}} \tag{31}$$

$$\frac{\partial\big(Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') + \ln p(\boldsymbol{\Theta})\big)}{\partial a_c} \tag{32}$$

$$\frac{\partial\big(Q(\boldsymbol{\Theta}|\boldsymbol{\Theta}') + \ln p(\boldsymbol{\Theta})\big)}{\partial b_c} \tag{33}$$

1.3 Posterior of $p(\mathbf{z}_v|\mathbf{z}_{\{u,k\}}, t_{\{u,v,k\}}, \sigma^2, \mathcal{T})$

The posterior distribution of $\mathbf{z}$ can be obtained by formulating the below joint distribution as a normal distribution. There is conjugacy among the distributions because the prior of mean is modelled as a normal distribution.

$$\mathcal{N}(\mathbf{z}_v|\mathbf{z}_u, \sigma^2(t_v - t_u)\mathbf{I})\prod_{k=1}^{K}\mathcal{N}(\mathbf{z}_k|\mathbf{z}_v, \sigma^2(t_k - t_v)\mathbf{I}) \tag{34}$$

$$p(\mathbf{z}_v|\mathbf{z}_{\{u,k\}}, t_{\{u,v,k\}}, \sigma^2, \mathcal{T}) = \mathcal{N}\left(\mathbf{z}_v \middle| r\left(\frac{\mathbf{z}_u}{t_v - t_u} + \sum_k \frac{\mathbf{z}_k}{t_k - t_v}\right), r\sigma^2\mathbf{I}\right) \quad (35)$$

$$\text{where } r = \left(\frac{1}{t_v - t_u} + \sum_k \frac{1}{t_k - t_v}\right)^{-1}$$

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

$$\begin{aligned}
p(t_v, \mathbf{z}_{\{u,v,k\}}, \sigma^2|c, \mathcal{T}) &= c(2\pi\sigma^2)^{-\frac{D(K+1)}{2}} \exp\Big\{(cJ^{\theta,\alpha}_{\mathbf{n}_v} - 1)\ln(1 - t_v) \\
&\quad -\frac{D}{2}\big(\ln(t_v - t_u) + \sum_k \ln(t_k - t_v)\big) \\
&\quad -\frac{\| \mathbf{z}_v - \mathbf{z}_u \|^2}{2\sigma^2}\frac{1}{t_v - t_u} - \sum_k \frac{\| \mathbf{z}_k - \mathbf{z}_v \|^2}{2\sigma^2}\frac{1}{t_k - t_v}\Big\} \\
&= C_{\sigma^2} \exp\big\{u(t_v)\big\} && (36) \\
\frac{du}{dt_v} &= -\frac{cJ^{\theta,\alpha}_{\mathbf{n}_v} - 1}{1 - t_v} - \frac{D}{2}\Big(\frac{1}{t_v - t_u} - \sum_k \frac{1}{t_k - t_v}\Big) \\
&\quad +\frac{\| \mathbf{z}_v - \mathbf{z}_u \|^2}{2\sigma^2}\frac{1}{(t_v - t_u)^2} - \sum_k \frac{\| \mathbf{z}_k - \mathbf{z}_v \|^2}{2\sigma^2}\frac{1}{(t_k - t_v)^2} \\
&= -\frac{cJ^{\theta,\alpha}_{\mathbf{n}_v} - 1}{1 - t_v} - \frac{1}{2(t_v - t_u)^2}\big(D(t_v - t_u) - \frac{\| \mathbf{z}_v - \mathbf{z}_u \|^2}{\sigma^2}\big) \\
&\quad +\sum_k \frac{1}{2(t_k - t_v)^2}\big(D(t_k - t_v) - \frac{\| \mathbf{z}_k - \mathbf{z}_v \|^2}{\sigma^2}\big) \\
&= A(t_v) && (37) \\
C_{\sigma^2} A(t_v)^{-1} \int \exp\big\{u(t_v)\big\} du &= Z, \text{ but this integral is intractable!} && (38) \\
&\Rightarrow \text{The range of integration w.r.t. } t_v \text{ is } 0 < t_u \le t_v \le \min(t_k) < 1, \\
&\quad \text{obtaining } Z \text{ by simply summing pdf by the interval } dt = 1e^{-2} \\
&\quad \text{is computationally tractable for modern hardwares.} \\
&\quad \text{A few } t \text{ points usually give sufficient accuracy.} \\
\mathbb{E}_{p(t_v|\mathbf{z}_{\{u,v,k\}}, \sigma^2, c, \mathcal{T})}[t_v] &= \frac{1}{Z}\int t_v p(t_v, \mathbf{z}_{\{u,v,k\}}, \sigma^2|c, \mathcal{T}) dt_v \\
&= \frac{1}{Z} C_{\sigma^2} A_\mu(t_v)^{-1} \int \exp\big\{u_\mu(t_v)\big\} du && (39)
\end{aligned}$$

1.5 Approximation of model evidence

Use the decomposition with variational distributions.

$$
\begin{aligned}
\ln P(\mathbf{X}|\boldsymbol{\theta}) &= \ln\Big\{\sum_{\mathbf{Z}} P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})\Big\} \\
&= \ln\Big\{\sum_{\mathbf{Z}} q(\mathbf{Z})\frac{P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})}\Big\} \\
&= \sum_{\mathbf{Z}} q(\mathbf{Z})\ln\Big\{\frac{P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})}\Big\} + \sum_{\mathbf{Z}} q(\mathbf{Z})\ln\Big\{\frac{q(\mathbf{Z})}{P(\mathbf{Z}|\mathbf{X},\boldsymbol{\theta})}\Big\} \qquad (40)
\end{aligned}
$$

$\mathbf{z}, c, \sigma^2$ have analytical posterior. In addition, the exact posterior of $\mathbf{t}$ can also be computed in a feasible way up to the error due to the finite numerical precision. Hence, we consider that the second term of (40), which is a Kullback-Leibler divergence of the calculated posterior and theoretical posterior in this context, vanishes. Incidentally, this is equivalent to calculate the ELBO of the model.

$$
\begin{aligned}
& \sum_{\mathbf{Z}} q(\mathbf{Z})\ln\Big\{\frac{P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})}{q(\mathbf{Z})}\Big\} \\
= \ & \mathbb{E}_{q(\mathbf{Z})}\big[\ln P(\mathbf{X},\mathbf{Z}|\boldsymbol{\theta})\big] + H_q(\mathbf{Z}) \\
= \ & a_c \ln b_c + (a_c - 1)\mathbb{E}[\ln c] - b_c\mathbb{E}[c] - \ln\Gamma(a_c) \\
& + a_{\sigma^2}\ln b_{\sigma^2} + (a_{\sigma^2}-1)\mathbb{E}\left[\ln\frac{1}{\sigma^2}\right] - b_{\sigma^2}\mathbb{E}\left[\frac{1}{\sigma^2}\right] - \ln\Gamma(a_{\sigma^2}) \\
& + \sum_{v\in\mathcal{I}}\Big\{\big(\mathbb{E}[c]J^{\theta,\alpha}_{\mathbf{n}_v} - 1\big)\mathbb{E}[\ln c] + \big(\mathbb{E}[c]J^{\theta,\alpha}_{\mathbf{n}_v} - 1\big)\mathbb{E}\big[\ln(1-t_v)\big]\Big\} \\
& + \sum_{[uv]\in S(\mathcal{T})'}\Bigg\{-\frac{D}{2}\left(\ln 2\pi - \mathbb{E}\left[\ln\frac{1}{\sigma^2}\right] + \mathbb{E}\big[\ln(t_v - t_u)\big]\right) \\
& - \mathbb{E}\left[\frac{1}{\sigma^2}\right]\mathbb{E}\left[\frac{1}{t_v - t_u}\right]\frac{\sum_{d=1}^{D}\mathbb{E}[z_{v,d}^2] - 2\mathbb{E}[z_{v,d}]\mathbb{E}[z_{u,d}] + \mathbb{E}[z_{u,d}^2]]}{2}\Bigg\} \\
& + \sum_{n=1}^{N}\Bigg\{-\frac{D}{2}\left(\ln 2\pi - \mathbb{E}\left[\ln\frac{1}{\sigma^2}\right] + \mathbb{E}\Big[\ln(1 - t_{\mathrm{pa}(n)})\Big]\right) \\
& - \mathbb{E}\left[\frac{1}{\sigma^2}\right]\mathbb{E}\left[\frac{1}{1 - t_{\mathrm{pa}(n)}}\right]\frac{\sum_{d=1}^{D} x_{v,d}^2 - 2x_{n,d}\mathbb{E}[z_{\mathrm{pa}(n),d}] + \mathbb{E}[z_{\mathrm{pa}(n),d}^2]]}{2}\Bigg\} \\
& + H_q(\mathbf{Z}) \qquad (41)
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}[\ln c] &\approx \ln \mathbb{E}[c] - \frac{\mathbb{V}[c]}{2\mathbb{E}[c]^2} \\
&= \ln\big(a_c + |\mathcal{I}|\big) - \ln\Big(b_c - \sum_{v\in\mathcal{I}} J^{\theta,\alpha}_{\mathbf{n}_v} \ln(1-t_v)\Big) + \frac{1}{2\big(a_c + |\mathcal{I}|\big)} \qquad (42)\\
\mathbb{E}\left[\ln\frac{1}{\sigma^2}\right] &\approx \ln \mathbb{E}\left[\frac{1}{\sigma^2}\right] - \frac{\mathbb{V}\left[\frac{1}{\sigma^2}\right]}{2\mathbb{E}\left[\frac{1}{\sigma^2}\right]^2} \\
&= \ln\Big(a_{\sigma^2} + \frac{D(|\mathcal{I}|+N)}{2}\Big) - \ln\Big(b_{\sigma^2} + \frac{1}{2}\sum_{[uv]\in S(\mathcal{T})} \frac{\sum_{d=1}^{D}(z_{v,d}-z_{u,d})^2}{t_v - t_u}\Big) \\
&\quad + \frac{1}{2\big(a_{\sigma^2} + \frac{D(|\mathcal{I}|+N)}{2}\big)} \\
\mathbb{E}\big[\ln(1-t_v)\big] &\approx \ln\big(1-\mathbb{E}[t_v]\big) - \frac{\mathbb{V}[t_v]}{2\big(1-\mathbb{E}[t_v]\big)^2} \qquad (43)\\
\mathbb{E}\big[\ln(t_v - t_u)\big] &\approx \ln(\mathbb{E}[t_v] - \mathbb{E}[t_u]) \\
&\quad + \frac{1}{2}\Big\{ - \frac{\mathbb{V}[t_v]}{(\mathbb{E}[t_v]-\mathbb{E}[t_u])^2} + \frac{2\big(\mathbb{E}[t_v t_u] - \mathbb{E}[t_v]\mathbb{E}[t_u]\big)}{(\mathbb{E}[t_v]-\mathbb{E}[t_u])^2} - \frac{\mathbb{V}[t_u]}{(\mathbb{E}[t_v]-\mathbb{E}[t_u])^2}\Big\} \\
&= \ln(\mathbb{E}[t_v] - \mathbb{E}[t_u]) + \frac{1}{2}\Big\{ - \frac{\mathbb{V}[t_v] + \mathbb{V}[t_u] - 2\big(\mathbb{E}[t_v t_u] - \mathbb{E}[t_v]\mathbb{E}[t_u]\big)}{(\mathbb{E}[t_v]-\mathbb{E}[t_u])^2}\Big\} \qquad (44)\\
\mathbb{E}\left[\frac{1}{t_v - t_u}\right] &\approx \frac{1}{\mathbb{E}[t_v] - \mathbb{E}[t_u]} + \frac{1}{2}\Big\{\frac{2\mathbb{V}[t_v] + 2\mathbb{V}[t_u] - 4\big(\mathbb{E}[t_v t_u] - \mathbb{E}[t_v]\mathbb{E}[t_u]\big)}{\big(\mathbb{E}[t_v] - \mathbb{E}[t_u]\big)^3}\Big\} \qquad (45)
\end{aligned}
$$

Here, the expectations of $\mathbf{z}$ terms with the posterior distributions create a loopy graph. Hence, we approximate the expectation by directly substituting the samples of parent and children nodes to the calculation of each node v instead of recursively taking expectations of parent and children nodes which again introduces the node v.