

# A Variational Approach for Bayesian Density Regression

Eric Chuu

ERICCHUU@STAT.TAMU.EDU

*Department of Statistics*

*Texas A&M University*

*College Station, TX 77840, USA*

## Abstract

In the Bayesian density regression problem, mixture of expert models are often used because of their flexibility in estimating conditional densities. In this paper, we discuss the case when covariate dependent weights are used in the approximating mixture density. Under this framework, however, traditional Bayesian methods results in computational difficulties when the dimension of the covariates is large. In order to remedy this problem and to provide a method for faster inference, we propose using a variational approximation to estimate the conditional density. We also discuss different alternative for approximating quantities that lack a closed form so that a coordinate ascent algorithm is viable.

**Keywords:** Bayesian Density Regression, Variational Bayes, Mixture Models

## 1. Introduction

In the Bayesian density regression problem, we observe data  $(y_n, x_n)_{n=1}^N$ , and the goal is the estimate the conditional density of  $y | x$ . A common approach for doing this is to model the density using a mixture of gaussians, such as the following,

$$f(y | x) = \sum_k \pi_k \mathcal{N}(y | \mu_k(x), \tau_k^{-1}) \quad (1)$$

While the representation of the density using predictor-independent weights yields less expensive computation, it often lacks flexibility to make it useful in practice and results in a reliance on have too many mixture components. As a result, there have been many proposed models that consider predictor-dependent weights using a kernel stick-breaking process (**dunsonpark:08**) or logit stick-breaking prior (**durante:17**) to generate the weights. In the former method, the increased flexibility comes at heavy computational cost, and in the later method, the process from which the weights are generated does not allow for intuitive inference on the covariates. In our proposed model, the covariates enter through a logistic link function so that we can naturally perform inference on the coefficients. More specifically, we can model

$$f(y | x) = \sum_k^K \pi_k(x) \mathcal{N}(y | \mu_k(x), \tau_k^{-1}) \quad (2)$$

where  $\mu_k(x) = x^\top \beta_k$  and  $\pi_k \propto \exp(x^\top \gamma_k)$ .

## 2. Notation and Prior Specification

For the set of observed data, we denote  $\mathbf{y} = \{y_1, \dots, y_N\}$ ,  $\mathbf{X} = \{x_1, \dots, x_N\}$ , where each  $x_n \in \mathbb{R}^D$ . Let  $\boldsymbol{\beta} = \{\beta_1, \dots, \beta_K\}$  and  $\boldsymbol{\gamma} = \{\gamma_1, \dots, \gamma_K\}$  denote the  $D$ -dimensional coefficient vectors in the mixture weights and in gaussian mixture components, respectively. Finally, let  $\boldsymbol{\tau} = \{\tau_1, \dots, \tau_K\}$  denote the precision parameters. We introduce the set of latent variables  $\mathbf{Z} = \{z_1, \dots, z_N\}$ , where  $z_n \in \mathbb{R}^K$  and  $z_{nk} = 1$  if  $y_n$  belongs to the  $k$ -th cluster so that  $\sum_k z_{nk} = 1$ . Conditioning on  $\mathbf{Z}$ , we have the following simplified form of the marginal likelihood.

$$p(\mathbf{y} | \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z}, \boldsymbol{\gamma}) = \prod_n \prod_k \mathcal{N}(y_n | x_n^\top \beta_k, \tau_k^{-1})^{z_{nk}} \quad (3)$$

$$p(\mathbf{Z} | \mathbf{X}, \boldsymbol{\gamma}) = \prod_n \prod_k \pi_k(x_n)^{z_{nk}} = \prod_n \prod_k \left( \frac{\exp\{x_n^\top \gamma_k\}}{\sum_{j=1}^K \exp\{x_n^\top \gamma_j\}} \right)^{z_{nk}} \quad (4)$$

Next, we introduce the priors over the parameters  $\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}$ , where we simplify the calculations by considering conjugate priors.

$$p(\boldsymbol{\gamma}) = \prod_k p(\gamma_k) = \mathcal{N}(\gamma_k | 0, \mathbf{I}_D) \quad (5)$$

$$p(\boldsymbol{\beta}, \boldsymbol{\tau}) = \prod_k p(\beta_k, \tau_k) = \prod_k p(\beta_k | \tau_k) p(\tau_k) = \prod_k \mathcal{N}(\beta_k | m_0, (\tau_k \Lambda_0)^{-1}) \text{Ga}(\tau_k | a_0, b_0) \quad (6)$$

## 3. Variational Distribution

At this point, the variational parameters of interest are  $\boldsymbol{\theta} = (\mathbf{Z}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma})$ . The log of the joint distribution of these random variables is given by

$$\begin{aligned} \ln \left\{ p(\mathbf{y}, \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z}) \right\} &= \ln \left\{ p(\mathbf{y} | \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z}, \boldsymbol{\gamma}) p(\mathbf{Z} | \mathbf{X}, \boldsymbol{\gamma}) p(\boldsymbol{\gamma}) p(\boldsymbol{\beta}, \boldsymbol{\tau}) \right\} \\ &= \sum_n \sum_k z_{nk} \left\{ -\frac{1}{2} \ln(2\pi) + \frac{1}{2} \ln \tau_k - \frac{\tau_k}{2} (y_n - x_n^\top \beta_k)^2 \right\} \\ &\quad + \sum_n \sum_k z_{nk} \left\{ x_n^\top \gamma_k - \ln \left( \sum_{j=1}^K \exp\{x_n^\top \gamma_j\} \right) \right\} \\ &\quad + \sum_k \left\{ -\frac{D}{2} \ln(2\pi) + \frac{D}{2} \ln \tau_k + \ln |\Lambda_0| - \frac{\tau_k}{2} (\beta_k - m_0)^\top \Lambda_0 (\beta_k - m_0) \right\} \\ &\quad + \sum_k \left\{ (a_0 - 1) \ln \tau_k - b_0 \tau_k \right\} \end{aligned} \quad (7)$$

We consider the following variational distribution used to approximate the posterior distribution of the parameters outlined previously.

$$q(\mathbf{Z}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}) = q(\mathbf{Z}) q(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}) \quad (8)$$

### 3.1 Coordinate Ascent Updates

As is standard in variational algorithms, we now seek the sequential updates of the factors in (8). Taking the expectation with respect to the other variational parameters, we can derive the following update equation for  $q(\mathbf{Z})$ ,

$$\ln q^*(\mathbf{Z}) = E_{-q(\mathbf{Z})} \left[ \ln \{ p(\mathbf{y}, \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z}, \boldsymbol{\gamma}) \} \right] \quad (9)$$

We adopt the convention that the expectation with respect to a negative subscript indicates an expectation taken with respect to the other variational parameters. Ignoring terms that are not functionally dependent on  $\mathbf{Z}$ , we can exponentiate both sides of (9) to obtain the optimal solution for  $q(\mathbf{Z})$ ,

$$q^*(\mathbf{Z}) = \prod_n \prod_k r_{nk}^{z_{nk}}, \quad r_{nk} = \frac{\rho_{nk}}{\sum_j \rho_{nj}} \quad (10)$$

See Appendix A for the details in this calculation.

It remains to consider the factor  $q(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma})$ . Taking the expectation with respect to  $q(\mathbf{Z})$ , we have the following equality written up to constants,

$$\begin{aligned} \ln q^*(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}) &= \sum_k \sum_n E_{q(\mathbf{Z})}[z_{nk}] \ln \mathcal{N}(y_n | x_n^\top \beta_k, \tau_k^{-1}) + \sum_k \ln p(\beta_k, \tau_k) \\ &+ \sum_k \sum_n E_{q(\mathbf{Z})} \left( x_n^\top \gamma_k - \ln \left( \sum_{j=1}^K \exp\{x_n^\top \gamma_j\} \right) \right) + \sum_k \ln \mathcal{N}(\gamma_k | 0, \mathbf{I}_D) \end{aligned} \quad (11)$$

From the expression above, we see that the optimal distribution has a sum involving only the  $\gamma_k$ 's and a sum involving only the  $(\beta_k, \tau_k)$ 's, which implies  $q(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}) = \prod_k q(\beta_k, \tau_k) q(\gamma_k)$ . With this factorization in mind, we can obtain the following updates for the remaining variational parameters,

$$q^*(\beta_k | \tau_k) = \mathcal{N}(\beta_k | m_k, (\tau_k \mathbf{V}_k)^{-1}) \quad (12)$$

$$q^*(\tau_k) = \text{Ga}(\tau_k | a_k, b_k) \quad (13)$$

$$q^*(\gamma_k) = \mathcal{N}(\gamma_k | \mu_k, \mathbf{Q}_k^{-1}) \quad (14)$$

for  $k = 1, \dots, K$ . The derivation for (12) and (13) can be found in Appendix C, and the details for (14) can be found in Appendix B.

### 3.2 Evidence Lower Bound (ELBO)

In order to evaluate the convergence of the algorithm, we can calculate the evidence lower bound after updating all the variational parameters. Since the ELBO is monotonic increasing, we continue the coordinate ascent until the change in the ELBO falls below a predetermined tolerance. Note that the expectations taken below are with respect to the optimal variational distributions derived in the previous section.

$$\begin{aligned}
\mathcal{L}(q) &= \sum_{\mathbf{z}} \int \int \int q(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}, \mathbf{Z}) \ln \left\{ \frac{p(\mathbf{y}, \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}, \mathbf{Z})}{q(\boldsymbol{\beta}, \boldsymbol{\tau}, \boldsymbol{\gamma}, \mathbf{Z})} \right\} d\boldsymbol{\beta} d\boldsymbol{\tau} d\boldsymbol{\gamma} \\
&= \mathbb{E}[\ln p(\mathbf{y} \mid \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z})] + \mathbb{E}[\ln p(\mathbf{Z} \mid \mathbf{X}, \boldsymbol{\gamma})] + \mathbb{E}[\ln p(\boldsymbol{\gamma})] + \mathbb{E}[\ln p(\boldsymbol{\beta}, \boldsymbol{\tau})] \\
&\quad - \mathbb{E}[\ln q(\mathbf{Z})] - \mathbb{E}[\ln q(\boldsymbol{\beta}, \boldsymbol{\tau})] - \mathbb{E}[\ln q(\boldsymbol{\gamma})]
\end{aligned} \tag{15}$$

Each of the seven expectations can be expressed as follows. Details for each calculation can be found in Appendix D.

$$\begin{aligned}
\mathbb{E}[\ln p(\mathbf{y} \mid \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z})] &= -\frac{1}{2} \sum_n \sum_k r_{nk} \left\{ (\ln(2\pi) - \psi(a_k) + \psi(b_k)) + \frac{a_k}{b_k} (y_n - x_n^\top m_k)^2 + x_n^\top V_k^{-1} x_n \right\} \\
\mathbb{E}[\ln p(\mathbf{Z} \mid \mathbf{X}, \boldsymbol{\gamma})] &= \sum_n \sum_k r_{nk} (x_n^\top \mu_k - \alpha_n - \varphi_n) \\
\mathbb{E}[\ln p(\boldsymbol{\gamma})] &= \frac{K \cdot D}{2} \ln(2\pi) - \frac{1}{2} \sum_k \mu_k^\top \mu_k \\
\mathbb{E}[\ln p(\boldsymbol{\beta}, \boldsymbol{\tau})] &= \sum_k -\frac{D}{2} \ln(2\pi) + \left( \frac{D}{2} + a_0 - 1 \right) (\psi(a_k) - \psi(b_k)) + \ln |\Lambda_0| + \ln \frac{b_0^{a_0}}{\Gamma(a_0)} \\
&\quad - \frac{1}{2} \left\{ \frac{a_k}{b_k} (m_k - m_0)^\top \Lambda_0 (m_k - m_0) + \text{tr}(\Lambda_0 V_k^{-1}) \right\} \\
\mathbb{E}[\ln q(\mathbf{Z})] &= \sum_n \sum_k r_{nk} \ln r_{nk} \\
\mathbb{E}[\ln q(\boldsymbol{\beta}, \boldsymbol{\tau})] &= -\frac{D}{2} \ln(2\pi) + \frac{1}{2} \ln |V_k| + C(a_k, b_k) \\
\mathbb{E}[\ln q(\boldsymbol{\gamma})] &= \sum_k \ln |\mathbf{Q}_k| - \frac{D}{2} (\ln(2\pi) + 1)
\end{aligned}$$

#### 4. Algorithm

Using the updates discussed in the previous section, we can formalize the variational algorithm below.

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**Algorithm 1** CAVI for Conditional Density Estimation

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**Result:** Write here the result

**Input:** Data  $y_{1:N}, x_{1:N}$ , number of components  $K$ , prior mean and precision for  $\beta_{1:K}$ , prior shape, rate parameters for precision parameters  $\tau_{1:K}$

**Output:** A variational density  $q(\mathbf{Z}, \beta, \tau, \gamma) = q(\mathbf{Z})q(\beta, \tau, \gamma) = q(\mathbf{Z}) \prod_k q(\beta_k, \tau_k)q(\gamma_k)$ ;

**Initialize:** Variational parameters  $\mathbf{m}_{1:K}, \tau_{1:K}, V_{1:K}, \boldsymbol{\mu}_{1:K}, Q_{1:K}, a_{1:K}, b_{1:K}$

**while** *the ELBO has not converged* **do**

**for**  $k \in \{1, \dots, K\}$  **do**

        | instructions1 instructions2

**end**

    instructions3

**for**  $n \in \{1, \dots, N\}$  **do**

        | instructions1 instructions2

**end**

    instructions3

    Compute ELBO using updated parameters

**end**

**return**  $q(\mathbf{Z}, \beta, \tau, \gamma)$

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## Appendix A.

Taking the expectation with respect to the other variational parameters, we can derive the following variational distribution for  $\mathbf{Z}$ ,

$$\begin{aligned}\ln q^*(\mathbf{Z}) &= \sum_n \sum_k z_{nk} \left\{ -\frac{1}{2} \ln(2\pi) + \frac{1}{2} E_{q(\tau)}[\ln \tau_k] - \frac{1}{2} E_{q(\beta, \tau)}[\tau_k (y_n - x_n^\top \beta_k)^2] \right. \\ &\quad \left. + x_n^\top E_{q(\gamma)}[\gamma_k] - E_{q(\gamma)} \left[ \ln \left( \sum_j \exp\{x_n^\top \gamma_j\} \right) \right] \right\} \\ &= \sum_n \sum_k z_{nk} \ln \rho_{nk}\end{aligned}$$

where we have defined

$$\begin{aligned}\ln \rho_{nk} &= -\frac{1}{2} \ln(2\pi) + \frac{1}{2} E_{q(\tau)}[\ln \tau_k] - \frac{1}{2} E_{q(\beta, \tau)}[\tau_k (y_n - x_n^\top \beta_k)^2] \\ &\quad + x_n^\top E_{q(\gamma)}[\gamma_k] - E_{q(\gamma)} \left[ \ln \left( \sum_j \exp\{x_n^\top \gamma_j\} \right) \right]\end{aligned}\tag{16}$$

Exponentiating and normalizing, we have

$$q^*(\mathbf{Z}) = \prod_n \prod_k r_{nk}^{z_{nk}}, \quad r_{nk} = \frac{\rho_{nk}}{\sum_j \rho_{nj}}\tag{17}$$

For the discrete distribution  $q^*(\mathbf{Z})$  given in (17) above, we have  $E[z_{nk}] = r_{nk}$ . Note, however, that in order to compute the expectation in closed form, we need an expression for the four expectations involved in the quantity  $\ln \rho_{nk}$ , as defined in (16).

From the results derived in Appendix C, we know that  $q^*(\tau_k) = \text{Ga}(\tau_k \mid a_k, b_k)$ . We can then compute the following expectation with respect to  $q^*(\tau)$ .

$$E_{q(\tau)}[\ln \tau_k] = \psi(a_k) - \psi(b_k)\tag{18}$$

Again from Appendix C, we can then compute the following expectation with respect to  $q^*(\beta_k, \tau_k)$ .

$$\begin{aligned}E_{q(\beta, \tau)}[\tau_k (y_n - x_n^\top \beta_k)^2] &= E \left[ \tau_k \left( y_n - m_k^\top x_n x_n^\top m_k + \text{tr} \left( x_n x_n^\top (\tau_k V_k)^{-1} \right) - 2y_n x_n^\top m_k \right) \right] \\ &= \frac{a_k}{b_k} (y_n^2 + m_k^\top x_n x_n^\top m_k) + \text{tr} (x_n x_n^\top V_k^{-1}) \\ &= \frac{a_k}{b_k} (y_n + m_k^\top x_n)^2 + x_n^\top V_k^{-1} x_n\end{aligned}\tag{19}$$

From the expression derived in (24) of Appendix B, we have  $q^*(\gamma_k) = \mathcal{N}(\gamma_k \mid \mu_k, \mathbf{Q}_k^{-1})$ , then we have

$$E_{q(\gamma_k)}[\gamma_k] = \mu_k\tag{20}$$

Using the bound discussed in Appendix B, equation (23), we can then compute the following expectation with respect to  $q^*(\gamma)$ .

$$\begin{aligned}
& \mathbb{E}_{q(\gamma)} \left[ \ln \left( \sum_j^K \exp\{x_n^\top \gamma_j\} \right) \right] \\
& \approx \mathbb{E}_{q(\gamma)} \left[ \alpha_n + \sum_{j=1}^K \frac{x_n^\top \gamma_j - \alpha_n + \xi_{nj}}{2} + \lambda(\xi_{nj}) \left( (x_n^\top \gamma_j - \alpha_n)^2 - \xi_{nj}^2 \right) + \log \left( 1 + e^{\xi_{nj}} \right) \right] \\
& = \alpha_n + \sum_j^K \frac{1}{2} (x_n^\top \mu_j - \alpha_n + \xi_{nj}) + \lambda(\xi_{nj}) \left( (x_n^\top \mu_j - \alpha_k)^2 - \xi_{nj}^2 + x_j^\top \mathbf{Q}_k^{-1} x_j \right) + \log(1 + e^{\xi_{nj}})
\end{aligned} \tag{21}$$

Gathering the results in (18), (19), (20), and (21), and substituting these into (16), we can compute  $E[z_{nk}] = r_{nk}$  in closed form.

## Appendix B.

For the variational distribution for  $\gamma_k, k = 1, \dots, K$ , we first note the following bound given by **bouchard:07**,  $\sum_{j=1}^K e^{t_j} \leq \prod_{j=1}^K (1 + e^{t_j})$ . Setting  $t_j = x_n^\top \gamma_j - \alpha_n$  and then taking log, we have the following bound:

$$\log \left( \sum_{j=1}^K \exp\{x_n^\top \gamma_j\} \right) \leq \alpha_n + \sum_{j=1}^K \log(1 + \exp\{x_n^\top \gamma_j - \alpha_n\}) \tag{22}$$

If we use the bound from **jj:2001**,

$$\log(1 + e^x) \leq \frac{x - t}{2} + \frac{1}{4t} \tanh\left(\frac{t}{2}\right) (x^2 - t^2) + \log(1 + e^t)$$

then we arrive at the following bound:

$$\log \left( \sum_{j=1}^K \exp\{x_n^\top \gamma_j\} \right) \leq \alpha_n + \sum_{j=1}^K \frac{x_n^\top \gamma_j - \alpha_n + \xi_{nj}}{2} + \lambda(\xi_{nj}) \left( (x_n^\top \gamma_j - \alpha_n)^2 - \xi_{nj}^2 \right) + \log(1 + e^{\xi_{nj}}) \tag{23}$$

where  $\lambda(\xi) = \frac{1}{4\xi} \tanh\left(\frac{\xi}{2}\right)$ . Then we can substitute this back into  $\ln q^*(\gamma_k)$  to obtain an approximation for the left hand side of (22), thus allowing us to obtain a closed form for the

variational distribution. Note that all of the equalities above are written up to constants.

$$\begin{aligned}
\ln q^*(\gamma_k) &= -\frac{1}{2}\gamma_k^\top \gamma_k + \sum_n r_{nk} x_n^\top \gamma_k - \sum_n r_{nk} \ln \left( \sum_j \exp\{x_n^\top \gamma_j\} \right) \\
&\approx -\frac{1}{2}\gamma_k^\top \gamma_k + \gamma_k^\top \sum_n r_{nk} x_n \\
&\quad - \sum_n r_{nk} \left\{ \alpha_n + \sum_{j=1}^K \frac{x_n^\top \gamma_j - \alpha_n + \xi_{nj}}{2} + \lambda(\xi_{nj}) ((x_n^\top \gamma_j - \alpha_n)^2 - \xi_{nj}^2) + \log(1 + e^{\xi_{nj}}) \right\} \\
&= -\frac{1}{2}\gamma_k^\top \gamma_k + \gamma_k^\top \sum_n r_{nk} x_n - \sum_n r_{nk} \left\{ \frac{1}{2}\gamma_k^\top x_n + \lambda(\xi_{nj}) (\gamma_j^\top x_n x_n^\top \gamma_j - 2\alpha_n \gamma_j^\top x_n) \right\} \\
&= -\frac{1}{2}\gamma_k^\top \left( \mathbf{I}_D + 2 \sum_n r_{nk} \lambda(\xi_{nk}) x_n x_n^\top \right) \gamma_k + \gamma_k^\top \left( \sum_n r_{nk} \left( \frac{1}{2} + 2\lambda(\xi_{nk}) \alpha_n x_n \right) \right)
\end{aligned}$$

Exponentiating, we can recover  $q^*(\gamma_k) = \mathcal{N}(\gamma_k | \mu_k, \mathbf{Q}_k^{-1})$ , where

$$\begin{aligned}
\mu_k &= \mathbf{Q}_k^{-1} \eta_k \\
\eta_k &= \sum_n r_{nk} \left( \frac{1}{2} + 2\lambda(\xi_{nj}) \alpha_n \right) x_n \\
\mathbf{Q}_k &= \mathbf{I}_D + 2 \sum_n r_{nk} \lambda(\xi_{nk}) x_n x_n^\top
\end{aligned} \tag{24}$$

The additional parameters introduced in the two upper bounds can be updated using the following equations

$$\begin{aligned}
\xi_{nk} &= \sqrt{(\mu_k^\top x_n - \alpha_n)^2 + x_n^\top \mathbf{Q}_k^{-1} x_n} \quad \forall k, n \\
\alpha_n &= \frac{\frac{1}{2} \left( \frac{K}{2} - 1 \right) + \sum_{j=1}^K \lambda(\xi_{nj}) \mu_j^\top x_n}{\sum_{j=1}^K \lambda(\xi_{nj})} \quad \forall n
\end{aligned}$$

## Appendix C.

Using results from Appendix A, we can write the following expression for the joint variational distribution of  $(\beta_k, \tau_k)$ ,

$$\begin{aligned}
\ln q^*(\beta_k, \tau_k) &= \sum_n -\frac{1}{2} r_{nk} \tau_k (y_n^2 + \beta_k^\top x_n x_n^\top \beta_k - 2y_n \beta_k^\top x_n) + \frac{r_{nk}}{2} \ln \tau_k + \frac{D}{2} \ln \tau_k \\
&\quad - \frac{\tau_k}{2} (\beta_k^\top \Lambda_0 \beta_k + m_0^\top \Lambda_0 m_0 - 2\beta_k^\top \Lambda_0 m_0) + (a_0 - 1) \ln \tau_k - b_0 \tau_k
\end{aligned} \tag{25}$$

We first consider terms on the right hand side of (25) that depend on  $\beta_k$  to find  $\ln q^*(\beta_k | \tau_k)$ , giving

$$\ln q^*(\beta_k | \tau_k) = -\frac{\tau_k}{2} \beta_k^\top \left[ \sum_n r_{nk} x_n x_n^\top + \Lambda_0 \right] \beta_k + \tau_k \beta_k^\top \left[ \sum_n r_{nk} y_n x_n + \Lambda_0 m_0 \right] \tag{26}$$



$$q^*(\beta_k | \tau_k) = \mathcal{N}(\beta_k | m_k, (\tau_k V_k)^{-1}) \quad (27)$$

$$\begin{aligned} m_k &= V_k^{-1} b_k \\ V_k &= \sum_n r_{nk} x_n x_n^\top + \Lambda_0 \\ b_k &= \sum_n r_{nk} y_n x_n + \Lambda_0 m_0 \end{aligned} \quad (28)$$

Then we can make use of the relation  $\ln q^*(\tau_k) = \ln q^*(\beta_k, \tau_k) - \ln q^*(\beta_k | \tau_k)$ , where the quantities on the right hand side come from (25) and (27). Note that equality below is written up to constants, keeping only terms involving  $\tau_k$ .

$$\begin{aligned} \ln q^*(\tau_k) &= (a_0 + N_k - 1) \ln \tau_k - \tau_k \left\{ b_0 + \frac{1}{2} \left( \sum_n r_{nk} y_n^2 + m_0^\top \Lambda_0 m_0 - m_k^\top V_k m_k \right) \right. \\ &\quad + \frac{1}{2} \beta_k^\top \left( \sum_n r_{nk} x_n x_n^\top + \Lambda_0 - V_k \right) \beta_k \\ &\quad \left. - 2\beta_k^\top \left( \sum_n r_{nk} y_n x_n + \Lambda_0 m_0 - V_k m_k \right) \right\} \end{aligned} \quad (29)$$

Exponentiating, we arrive at the following distribution

$$q^*(\tau_k) = \text{Ga}(\tau_k | a_k, b_k) \quad (30)$$

where we have defined

$$\begin{aligned} a_k &= a_0 + N_k \\ b_k &= b_0 + \frac{1}{2} \sum_n r_{nk} y_n^2 + m_0^\top \Lambda_0 m_0 - b_k^\top V_k^{-1} b_k \end{aligned} \quad (31)$$

The expression for  $b_k$  arises by noting that the three following simplifications for the summation terms in the coefficient of  $\tau_k$  in (29),

$$\begin{aligned} \sum_n r_{nk} y_n^2 + m_0^\top \Lambda_0 m_0 - m_k^\top V_k m_k &= \sum_n r_{nk} y_n^2 + m_0^\top \Lambda_0 m_0 - b_k^\top V_k^{-1} b_k \\ \sum_n r_{nk} x_n x_n^\top + \Lambda_0 - V_k &= 0 \\ \sum_n r_{nk} y_n x_n + \Lambda_0 m_0 - V_k m_k &= 0 \end{aligned}$$

where the first equality holds by expanding  $m_k^\top V_k m_k = b_k^\top (V_k^{-1})^\top V_k V_k^{-1} b_k = b_k^\top V_k^{-1} b_k$ . The second equality holds by recalling the definition of  $V_k$  in (28), and the third equality holds by observing from (28) that  $V_k m_k = b_k$ .

## Appendix D.

$$\mathbb{E}[\ln p(\mathbf{y} \mid \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\tau}, \mathbf{Z})] = \quad (32)$$

$$\mathbb{E}[\ln p(\mathbf{Z} \mid \mathbf{X}, \boldsymbol{\gamma})] = \quad (33)$$

$$\mathbb{E}[\ln p(\boldsymbol{\gamma})] = \sum_k \frac{D}{2} \ln(2\pi) - \frac{1}{2} \boldsymbol{\mu}_k^\top \boldsymbol{\mu}_k \quad (34)$$

$$\mathbb{E}[\ln p(\boldsymbol{\beta}, \boldsymbol{\tau})] = \quad (35)$$

$$\mathbb{E}[\ln q(\mathbf{Z})] = \sum_n \sum_k r_{nk} \ln r_{nk} \quad (36)$$

$$\begin{aligned} \mathbb{E}[\ln q(\boldsymbol{\beta}, \boldsymbol{\tau})] &= \sum_k \mathbb{E} \left[ \ln \mathcal{N}(\beta_k \mid m_k, (\tau_k V_k)^{-1}) + \ln \text{Ga}(\tau_k \mid a_k, b_k) \right] \\ &= \sum_k -\frac{D}{2} \ln(2\pi) + \frac{1}{2} \ln |V_k| + \frac{D}{2} \mathbb{E}[\ln \tau_k] - \mathbb{E} \left[ \frac{\tau_k}{2} (\beta_k - m_k)^\top V_k (\beta_k - m_k) \right] \\ &\quad + \ln \frac{b_k^{a_k}}{\Gamma(a_k)} + (a_k - 1) \mathbb{E}[\ln \tau_k] - b_k \mathbb{E}[\tau_k] \\ &= -\frac{D}{2} \ln(2\pi) + \frac{1}{2} \ln |V_k| + C(a_k, b_k) \end{aligned} \quad (37)$$

where  $C(a_k, b_k) = \left(\frac{D}{2} + a_k - 1\right)(\psi(a_k) - \psi(b_k)) + \ln \frac{b_k^{a_k}}{\Gamma(a_k)} - \frac{D}{2} - a_k$

$$\mathbb{E}[\ln q(\boldsymbol{\gamma})] = \sum_k \ln |\mathbf{Q}_k| - \frac{D}{2} (\ln(2\pi) + 1) \quad (38)$$

sample