

# Problem 1

a.

To approach the optimal distribution of each  $q$  distribution,

$$\begin{aligned} q(\lambda) &\propto \exp \left\{ E_{-q(\lambda)} [\ln p(Y|w, \alpha_{1:n}, \lambda, X)] + \ln q(\lambda) \right\} \\ &\propto \exp \left\{ E_{q(w)} \left[ \frac{n}{2} \ln \lambda - \frac{\lambda}{2} (Y - X^T w)^T (Y - X^T w) \right] + (e_0 - 1) \ln \lambda - f_0 \lambda \right\} \\ &\propto \exp \left\{ \left( \frac{n}{2} + e_0 - 1 \right) \ln \lambda - \frac{\lambda}{2} (Y^T Y - 2 Y^T X^T E_{q(w)} [W] + \text{tr}(E_{q(w)} [W W^T] X X^T) + 2 f_0) \lambda \right\} \\ &= \text{Gamma}(e_0', f_0') \text{ where } e_0' = \frac{n}{2} + e_0, f_0' = \frac{1}{2} (Y^T Y - 2 Y^T X^T E_{q(w)} [W] + \text{tr}(E_{q(w)} [W W^T] X X^T) + 2 f_0) \end{aligned}$$

$$\begin{aligned} q(\alpha_k) &\propto \exp \left\{ E_{-q(\alpha_k)} [\ln p(w_k | \alpha_k)] + \ln q(\alpha_k) \right\} \\ &\propto \exp \left\{ E_{q(w_k)} \left[ \frac{1}{2} \ln \alpha_k - \frac{\alpha_k}{2} (w_k^2) \right] + (\alpha_0 - 1) \ln \alpha_k - b_0 \alpha_k \right\} \\ &\propto \exp \left\{ \left( \frac{1}{2} + \alpha_0 - 1 \right) \ln \alpha_k - \frac{\alpha_k}{2} (E_{q(w_k)} [w_k^2] + 2 b_0) \right\} \\ &= \text{Gamma}(a_0^{(k)'}, b_0^{(k)'}) \text{ where} \end{aligned}$$

$$a_0^{(k)'} = \frac{1}{2} + \alpha_0, b_0^{(k)'} = \frac{1}{2} (E_{q(w_k)} [w_k^2] + 2 b_0)$$

$$\begin{aligned} q(w) &\propto \exp \left\{ E_{-q(w)} [\ln p(Y|w, \alpha_1, \dots, \alpha_n, \lambda, X)] + \ln q(w) \right\} \\ &\propto \exp \left\{ E_{q(\lambda)} \left[ -\frac{\lambda}{2} (Y - X^T w)^T (Y - X^T w) \right] + E_{q(\alpha_{1:d})} \left[ -\frac{A}{2} w^T w \right] \right\} \end{aligned}$$

Where  $A = \text{diag}(\alpha_1, \dots, \alpha_d)$

$$\begin{aligned} &\propto \exp \left\{ -\frac{\lambda}{2} w^T (E_{q(\lambda)} [X] X^T + E_{q(\alpha_{1:d})} [A]) w - \lambda w^T E_{q(\lambda)} [X] X^T Y \right\} \\ &\propto \exp \left\{ -\frac{1}{2} (w^T M w - 2 w^T M E_{q(\lambda)} [X] M^{-1} X Y + (E_{q(\lambda)} [X] M^{-1} X Y)^T M (E_{q(\lambda)} [X] M^{-1} X Y)) \right\} \\ &= N(E_{q(\lambda)} [X] M^{-1} X Y, M^{-1}) \end{aligned}$$

Expectations are defined as following:

$$E_{q(\lambda)} [X] = e_0' / f_0'$$

$$E_{q(\alpha_{1:d})} [A] = \text{diag}(a_0^{(1)'}/b_0^{(1)'}, \dots, a_0^{(d)'}/b_0^{(d)'})$$

$$E_{q(w)} [W] = E_{q(\lambda)} [X] M^{-1} X Y$$

$$E_{q(w_k)} [w_k^2] = (E_{q(w)} [W])_k^2 + M_{kk}^{-1}$$

$$E_{q(w)} [W W^T] = M^{-1} + E_{q(w)} [W] E_{q(w)} [W]^T$$

b. Set a VI algorithm using pseudo-code:

First: Initialization for  $a_0', b_0', e_0', f_0', \mu_0'$  and  $\Sigma_0'$

Second: For iteration  $t = 1, \dots, T$ :

1. Update  $q(\lambda)$ . Let

$$e_t' = \frac{n}{2} + e_0$$

$$f_t' = \frac{1}{2} (Y^T Y - 2Y^T X^T E_{q(w)}[W_t] + t + (E_{q(w)}[W_t W_t^T] X X^T) + 2f_0)$$

$$\text{Where } E_{q(w)}[W_t] = \mu_{t-1}$$

$$E_{q(w)}[W_t W_t^T] = \Sigma_{t-1} + E_{q(w)}[W_t] E_{q(w)}[W_t]^T$$

2. Update each  $q(z_k)$ . Let

$$a_t^{(k)'} = \frac{1}{2} + a_0$$

$$b_t^{(k)'} = \frac{1}{2} (E_{q(w_k)}[W_{kt}^2] + 2b_0) \quad \text{Where } E_{q(w_k)}[W_{kt}^2] = (E_{q(w)}[W_t])_k^2 + (\Sigma_{t-1})_{kk}$$

3. Update  $q(w)$ . Let

$$M_t' = (E_{q(\lambda)}[\lambda_t] X X^T + E_{q(z_{1:d})}[A_t])$$

$$\Sigma_t' = M_t^{-1}$$

$$\mu_t' = E_{q(\lambda)}[\lambda_t] M_t^{-1} X Y \quad \text{Where } E_{q(\lambda)}[\lambda_t] = e_t' / f_t' \text{ and } E_{q(z_{1:d})}[A_t] = \text{diag}$$

4. Assess convergence while calculating

$$L(a_t', b_t', e_t', f_t', \mu_t', \Sigma_t')$$

$$(a_t^{(1)'}/b_t^{(1)'}, \dots, a_t^{(d)'}/b_t^{(d)'})$$

c.  $L((a_t^{(1)'}, b_t^{(1)'}), L((a_t^{(2)'}, b_t^{(2)'}), \dots, (a_t^{(d)'}, b_t^{(d)'}), e_t', f_t', \mu_t', \Sigma_t')$

$$= \int_w \int_{\lambda} \int_{z_{1:d}} q(w) q(\lambda) \prod_{k=1}^d q(a_k) \ln \frac{p(w, a_{1:d}, \lambda | Y, X)}{q(w) q(\lambda) \prod_{k=1}^d q(a_k)} dz_{1:d} d\lambda dw$$

$$= \int_w \int_{z_{1:d}} q(w) \ln p(w) dz_{1:d} dw + \int_{\lambda} q(\lambda) \ln p(\lambda) d\lambda + \int_{a_{1:d}} \prod_{k=1}^d q(a_k) \ln p(a_k) dz_{1:d}$$

$$+ \int_w \int_{\lambda} q(w) q(\lambda) \ln p(Y | w, \lambda, X) d\lambda dw - \int_w q(w) \ln q(w) dw - \int_{\lambda} q(\lambda) \ln q(\lambda) d\lambda -$$

$$\int_{a_{1:d}} \prod_{k=1}^d q(a_k) \ln q(a_k) dz_{1:d}$$

For each term,

$$\begin{aligned}\int_{\lambda} q(\lambda) \ln p(\lambda) d\lambda &= e_0 \ln f_0 - \ln \Gamma(e_0) + (e_0 - 1) E_{q(\lambda)}[\ln \lambda] - f_0 E_{q(\lambda)}[\lambda] \\ &= e_0 \ln f_0 - \ln \Gamma(e_0) + (e_0 - 1)(\psi(e_0') - \ln f_0') - f_0 \frac{e_0'}{f_0'}\end{aligned}$$

$$\begin{aligned}\int_w \int_{\alpha_{1:d}} q(w) \ln p(w) dw &= -\frac{d}{2} \ln 2\pi + \frac{1}{2} \sum_{i=1}^d E_{q(w)}[\ln \alpha_i] - \frac{1}{2} E_{q(w)}[w^T A w] \\ &= -\frac{d}{2} \ln 2\pi + \frac{1}{2} \sum_{i=1}^d (\psi(a_i^{(k)'}) - \ln b_i^{(k)'}) - \frac{1}{2} \text{tr}(\mu_+^T \mu_+^T + \Sigma_+^T E_{q(\alpha_{1:d})} A)\end{aligned}$$

$$\int_{\alpha_{1:d}} \prod_{k=1}^d q(\alpha_k) \ln p(\alpha_k) d\alpha_{1:d} = \sum_{k=1}^d \int_{\alpha_k} \alpha_k \ln p(\alpha_k) d\alpha_k$$

$$= \sum_{k=1}^d \alpha_0 \ln b_0 - \ln \Gamma(\alpha_0) + (\alpha_0 - 1)(\psi(a_0^{(k)'}) - \ln b_0^{(k)'}) - b_0 \frac{a_0^{(k)'}}{b_0^{(k)'}}$$

$$= \sum_{k=1}^d \alpha_0 \ln b_0 - \ln \Gamma(\alpha_0) + (\alpha_0 - 1)(\psi(a_0^{(k)'}) - \ln b_0^{(k)'}) - b_0 \frac{a_0^{(k)'}}{b_0^{(k)'}}$$

$$\int_w q(w) \ln q(w) dw = \frac{1}{2} \ln((2\pi e)^n |\Sigma_+|)$$

$$\begin{aligned}\int_{\lambda} q(\lambda) \ln q(\lambda) d\lambda &= e_0' \ln f_0' - \ln \Gamma(e_0') + (e_0' - 1)(\psi(e_0') - \ln f_0') - f_0' \frac{e_0'}{f_0'} \\ &= \ln f_0' - \ln \Gamma(e_0') + (e_0' - 1)\psi(e_0') - e_0'\end{aligned}$$

$$\int_{\alpha_{1:d}} \prod_{k=1}^d q(\alpha_k) \ln q(\alpha_k) d\alpha_{1:d} = \sum_{k=1}^d \ln b_0^{(k)' - \ln \Gamma(a_0^{(k)'}) + (a_0^{(k)' - 1})\psi(a_0^{(k)'}) - a_0^{(k)'}$$

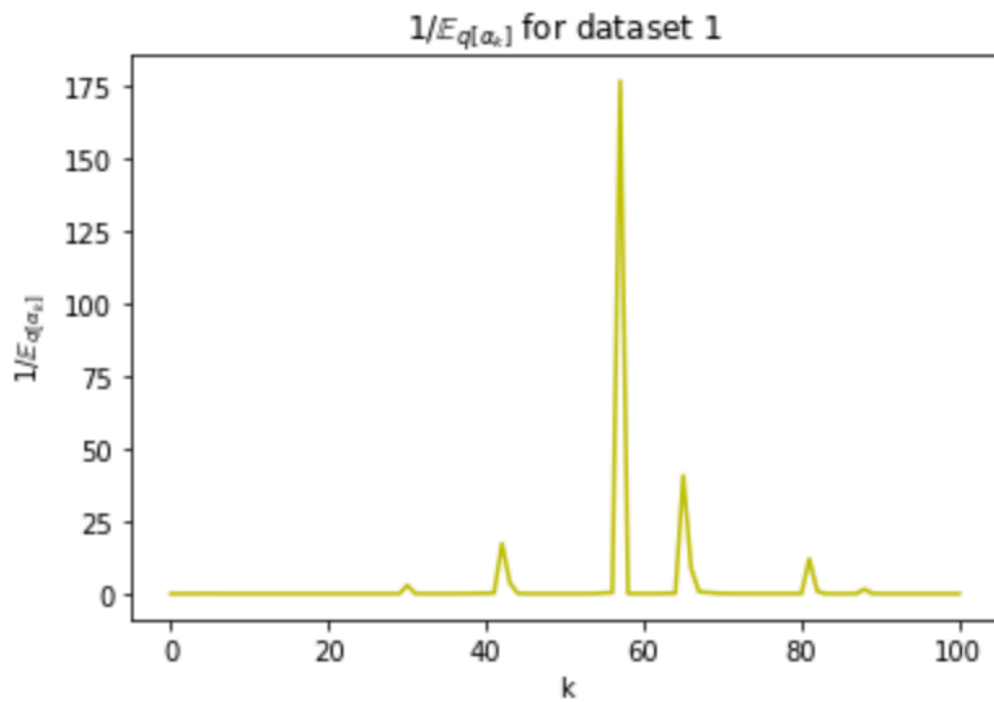
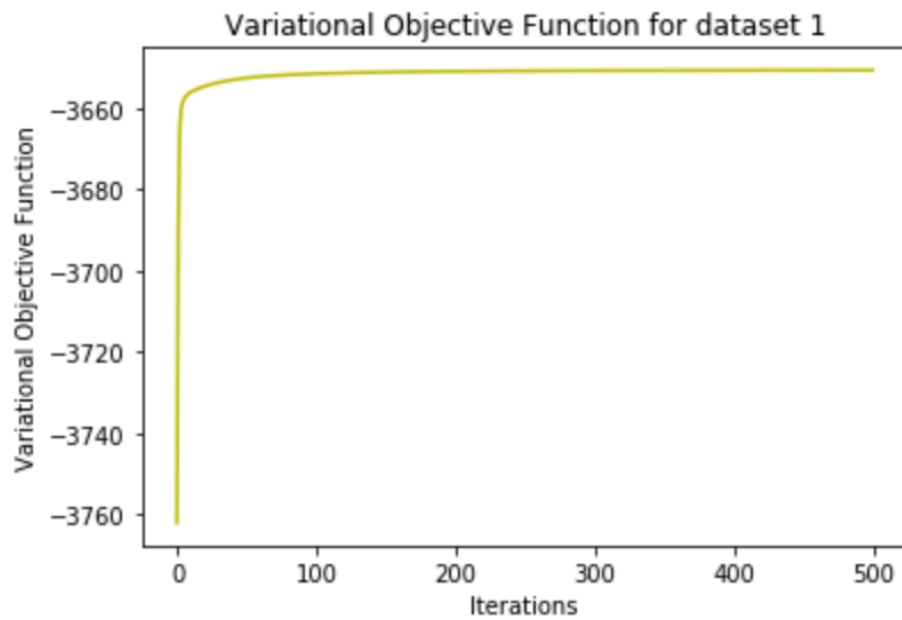
As a result,

$$\int_w \int_{\lambda} q(w) q(\lambda) \ln p(Y|w, \lambda, X) d\lambda dw$$

$$= -\frac{n}{2} \ln 2\pi + \frac{n}{2} E_{q(\lambda)}[\ln \lambda] - \frac{E_{q(\lambda)}[\lambda]}{2} E_{q(w)}[Y - X^T w]^T (Y - X^T w)$$

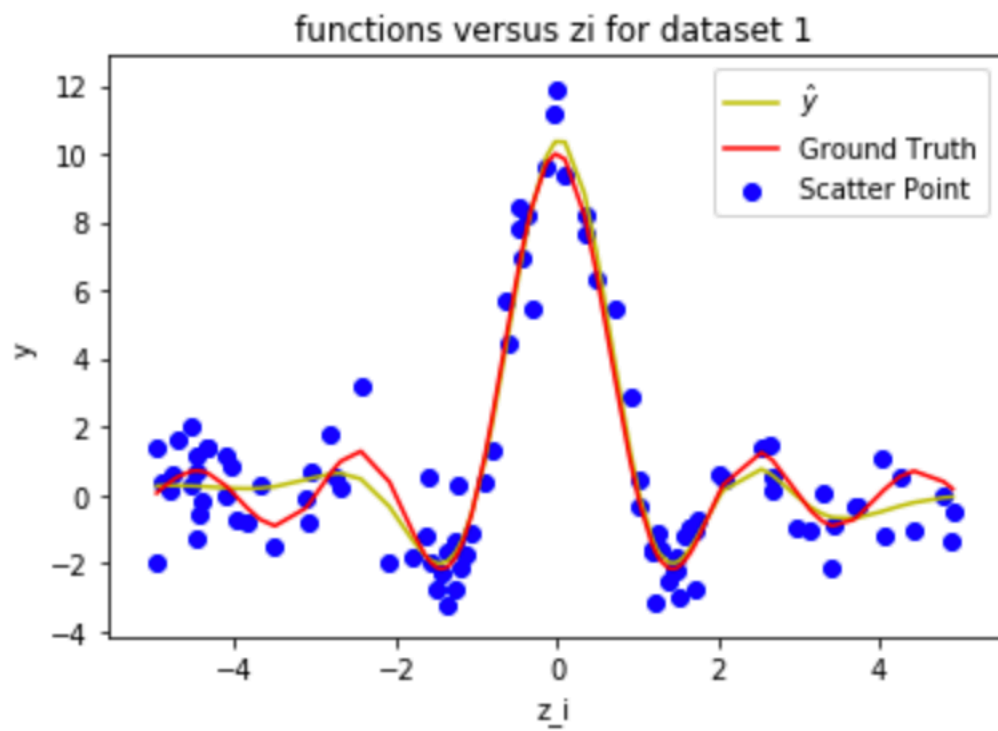
$$= -\frac{n}{2} \ln 2\pi + \frac{n}{2} (\psi(e_0') - \ln f_0') - \frac{e_0'}{2f_0'} (Y^T Y - 2Y^T X^T \mu_+^T - \text{tr}((\Sigma_+^T + \mu_+^T \mu_+^T) X X^T))$$

Problem 2:  
For dataset 1:

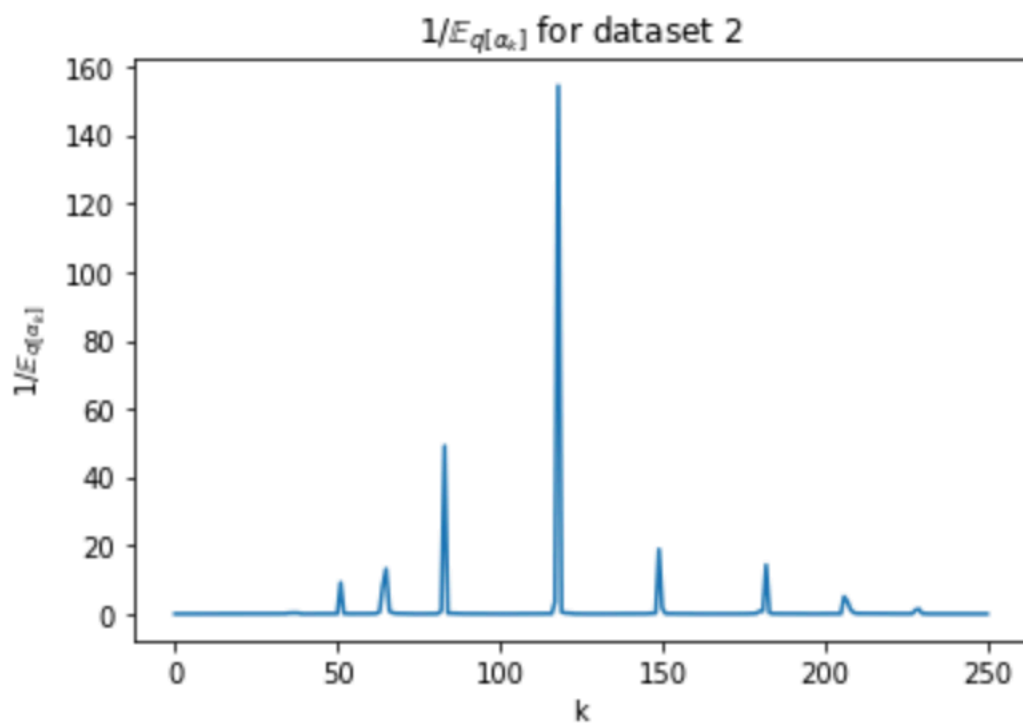
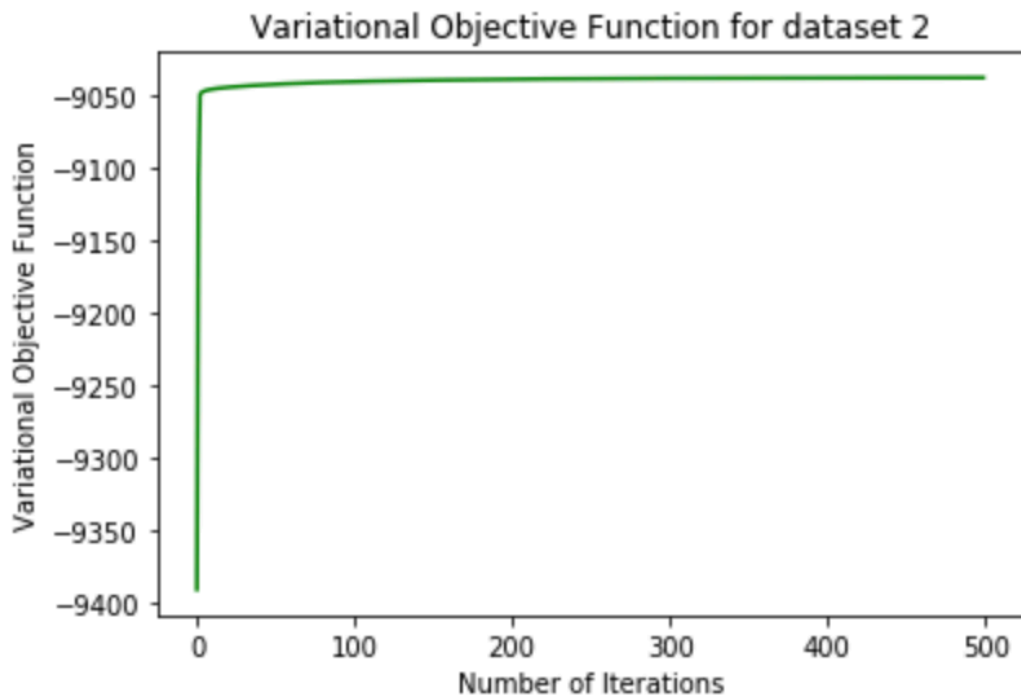


$f_1/e_1$

1.0800490653683776



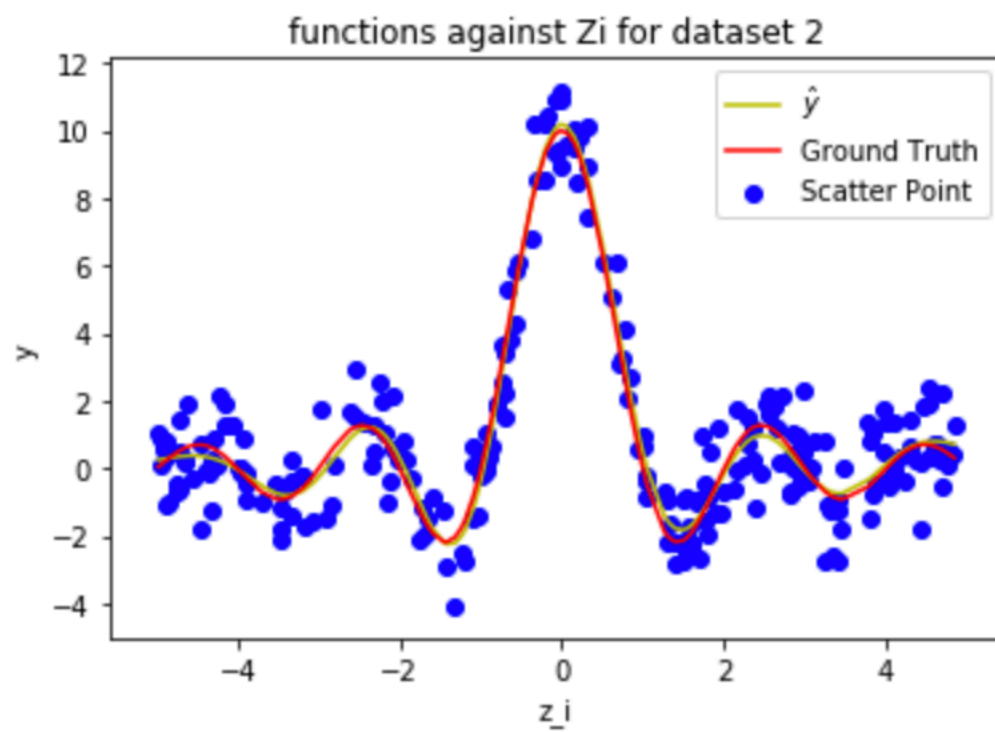
For dataset 2:





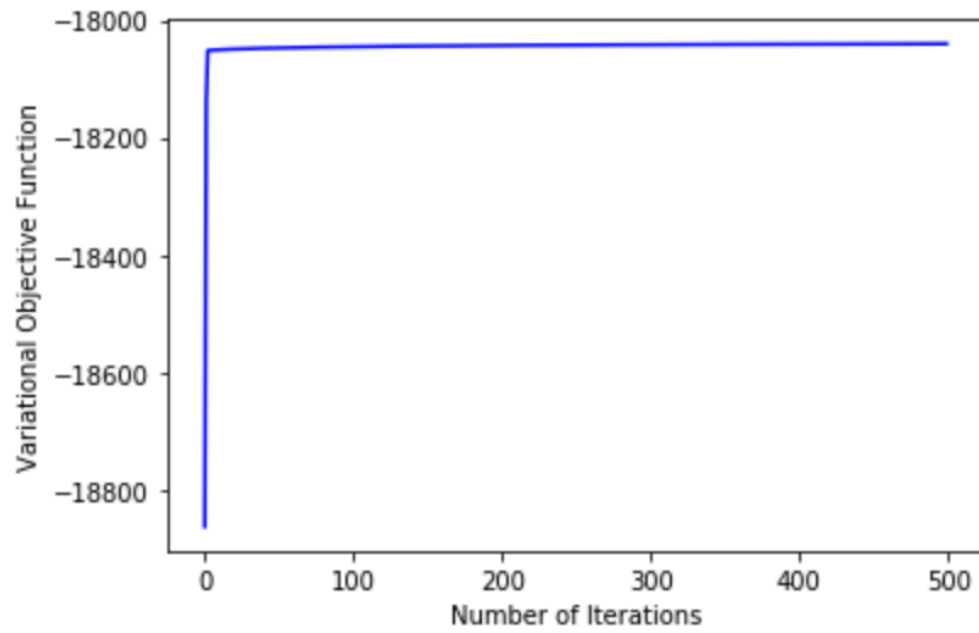
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: f_2/e_2
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: 0.8994437867206255
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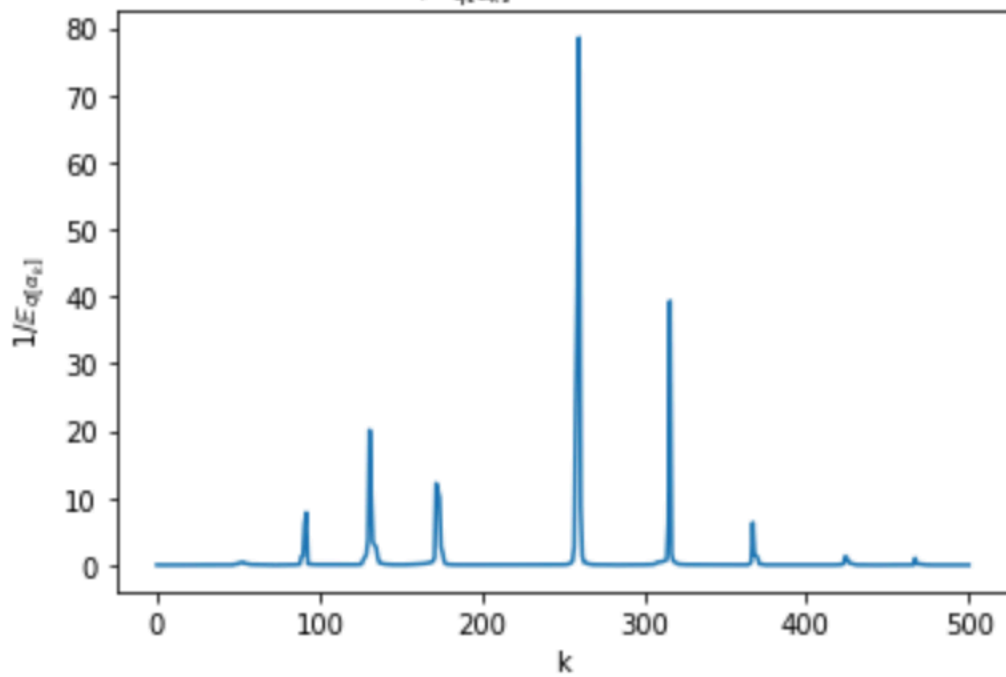


For dataset 3:

Variational Objective Function for dataset 3



$1/\mathcal{E}_{q[a_k]}$  for dataset 3





$f_3/e_3$

0.9781507541473099

