

Midterm

UNI: yb2356 Name: Yang Bai

Problem 1

(a)

$$p(\theta|x_1, x_2, \dots, x_n) \propto p(x_1, \dots, x_n|\theta)p(\theta)$$
$$x \text{ iid} \sim \text{Gamma}(a, \theta), \quad \text{so } p(x_1, \dots, x_n|\theta) = \prod_{i=1}^N p(x_i|\theta)$$

$$p(x_1, \dots, x_n|\theta) = \prod_{i=1}^N \text{Gamma}(a, \theta) = \prod_{i=1}^N \frac{\theta^a}{\Gamma(a)} x_i^{a-1} e^{-\theta x_i}$$

$$p(x_1, \dots, x_n|\theta) \propto \theta^{aN} e^{-\theta \sum_{i=1}^N x_i} \prod_{i=1}^N x_i^{a-1}$$

$$\text{We know that } p(\theta) \propto \frac{c^b}{\Gamma(b)} \theta^{b-1} e^{-c\theta}$$

$$\text{so } p(\theta|x_1, x_2, \dots, x_n) \propto \theta^{b-1} e^{-c\theta} \theta^{aN} e^{-\theta \sum_{i=1}^N x_i} \prod_{i=1}^N x_i^{a-1}$$

$$p(\theta|x_1, x_2, \dots, x_n) \propto \theta^{aN+b-1} e^{-\theta(\sum_{i=1}^N x_i + c)} \prod_{i=1}^N x_i^{a-1}$$

We know the values of all x_i , so treat $\prod_{i=1}^N x_i^{a-1}$ as a constant. Then we find

$$p(\theta|x_1, x_2, \dots, x_n) \propto \theta^{aN+b-1} e^{-\theta(\sum_{i=1}^N x_i + c)}$$

which is a gamma distribution. $p(\theta|x_1, x_2, \dots, x_n) \propto \text{Gamma}(aN + b, \sum_{i=1}^N x_i + c)$

(b)

$$p(x_{n+1}|x_1, x_2, \dots, x_n) = \int p(x_{n+1}|\theta) p(\theta|x_1, x_2, \dots, x_n) d\theta$$

$$\begin{aligned}
p(x_{n+1}|x_1, x_2, \dots, x_n) &= \int \text{Gamma}(x_{n+1}|a, \theta) \text{Gamma}(\theta|aN + b, \sum_{i=1}^N x_i + c) d\theta \\
&= \int \frac{\theta^a}{\Gamma(a)} x_{n+1}^{a-1} e^{-\theta x_{n+1}} \frac{(\sum_{i=1}^N x_i + c)^{aN+b}}{\Gamma(aN + b)} \theta^{aN+b-1} e^{-\theta(\sum_{i=1}^N x_i + c)} d\theta \\
&= \frac{(\sum_{i=1}^N x_i + c)^{aN+b}}{\Gamma(a)\Gamma(aN + b)} x_{n+1}^{a-1} \int e^{-\theta x_{n+1}} \theta^a \theta^{aN+b-1} e^{-\theta(\sum_{i=1}^N x_i + c)} d\theta \\
p(x_{n+1}|x_1, x_2, \dots, x_n) &= \gamma \int \theta^{\alpha-1} e^{-\theta\beta} d\theta
\end{aligned}$$

$$p(x_{n+1}|x_1, x_2, \dots, x_n) = \gamma \frac{\Gamma(\alpha)}{\beta^\alpha} x_{n+1}^{a-1} \int_0^\infty \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\theta\beta} d\theta$$

It obvious that $\int_0^\infty \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\theta\beta} d\theta = 1$ because it's a integration of gamma distribution function.

In the equation, $\alpha = aN + b + a$, $\beta = \sum_{i=1}^N x_i + c + x_{n+1}$, $\gamma = \frac{(\sum_{i=1}^N x_i + c)^{aN+b}}{\Gamma(a)\Gamma(aN+b)}$

$$\begin{aligned}
p(x_{n+1}|x_1, x_2, \dots, x_n) &= \gamma \frac{\Gamma(\alpha)}{\beta^\alpha} x_{n+1}^{a-1} = \gamma \frac{\Gamma(\alpha)}{(\sum_{i=1}^N x_i + c + x_{n+1})^\alpha} x_{n+1}^{a-1} \\
&= \frac{(\sum_{i=1}^N x_i + c)^{aN+b} \Gamma(aN + b + a)}{\Gamma(a)\Gamma(aN + b)} \frac{x_{n+1}^{a-1}}{(x_{n+1} + \sum_{i=1}^N x_i + c)^{aN+b+a}}
\end{aligned}$$

Problem 2

We want to maximize $\ln(y, \alpha|x) = \int \ln(y, \alpha, \omega|x) d\omega$ over α . EM equation in this case is:

$$\begin{aligned}
\ln(y, \alpha|x) &= \int q(\omega) \ln \frac{p(y, \alpha, \omega|x)}{q(\omega)} d\omega + \int q(\omega) \ln \frac{q(\omega)}{p(\omega|y, \alpha, x)} d\omega \\
\mathcal{L}(\alpha) &= \int q(\omega) \ln \frac{p(y, \alpha, \omega|x)}{q(\omega)} d\omega \\
KL(q||p) &= \int q(\omega) \ln \frac{q(\omega)}{p(\omega|y, \alpha, x)} d\omega
\end{aligned}$$

Algorithm outline:

1. Initialize α_0 to a vector of all zero
 2. For iteration t:
 - (a) E-step: Calculate the vector $q_t(\omega) = p(\omega|y, \alpha_{t-1}, x) = \prod_{i=1}^N p(y_i|\omega, \alpha_{t-1}, x_i)p(\omega)$
 - (b) M-step: Update $\alpha_t = \arg \max_{\alpha} \mathcal{L}_t(\alpha) = \arg \max_{\alpha} E_t[\ln p(y, \alpha, \omega|x) - \ln q_t(\omega)]$
 - (c) Calculate $\ln (y, \alpha|x) = \mathcal{L}_t(\alpha_{t-1})$
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(a) E-step:

Set $q(\omega)$.

First calculate $p(\omega|y, \alpha, x)$

$$\begin{aligned}
 p(\omega|y, \alpha, x) &\propto p(y|\omega, \alpha, x)p(\omega) \\
 &\propto \prod_{i=1}^N p(y_i|\omega, \alpha, x_i)p(\omega) \\
 &\propto \exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] \exp \left(-\frac{\lambda}{2} \omega^T \omega \right) \\
 &\propto \exp \left[-\frac{1}{2} (\omega - \mu)^T \Sigma (\omega - \mu) \right]
 \end{aligned}$$

where

$$\begin{aligned}
 \Sigma &= (\lambda I + \alpha \sum_{i=1}^N x_i x_i^T)^{-1} \quad \text{and} \quad \mu = \Sigma \cdot (\alpha \sum_{i=1}^N y_i x_i) \\
 p(\omega|y, \alpha, x) &= \text{Norm}(\omega|\mu, \Sigma) \\
 E_{qt}[\omega] &= \mu \\
 E_{qt}[\omega \omega^T] &= \mu \mu^T + \Sigma
 \end{aligned}$$

Set $q_t(\omega) = p(\omega|y, \alpha_{t-1}, x)$ at iteration t. Then calculate the expectation:

$$\begin{aligned}
 \mathcal{L}(\alpha) &= E_t[\ln p(y, \alpha, \omega|x) - \ln q_t(\omega)] \\
 &= E_q[\ln p(y|\alpha, x, \omega)] + E_q[\ln p(\alpha)] + E_q[\ln p(\omega)] - E_q[\ln q(\omega)] \\
 &= E_{qt(\omega)} \left[\ln \left(\alpha^{\frac{N}{2}} \right) \right] + E_{qt(\omega)} \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] + (a-1) \ln(\alpha) - b\alpha + \text{const w.r.t } \alpha
 \end{aligned}$$

$$= \left(a - 1 + \frac{N}{2}\right) \ln \alpha - b\alpha + \sum_{i=1}^N -\frac{\alpha}{2} \{tr[x_i x_i^T (\mu\mu^T + \Sigma)] - 2tr(\mu y_i x_i)\} + const$$

(b) M-step:

Maximize $\mathcal{L}(\alpha)$. Differentiating $\nabla_{\alpha} \mathcal{L}(\alpha)$ and setting to zero:

$$\nabla_{\alpha} \mathcal{L}(\alpha) = 0$$

$$\frac{\left(\frac{N}{2} + a - 1\right)}{\alpha} - b + \sum_{i=1}^N -\frac{1}{2} \{tr[x_i x_i^T (\mu\mu^T + \Sigma)] - 2tr(\mu y_i x_i)\} = 0$$

$$\Rightarrow \alpha = \frac{\frac{N}{2} + a - 1}{b + \sum_{i=1}^N \frac{1}{2} \{tr[x_i x_i^T (\mu\mu^T + \Sigma)] - 2tr(\mu y_i x_i)\}}$$

(c)

The marginal objective is:

$$\ln(y, \alpha | x) = \mathcal{L}(\alpha_{t-1}) = E_t[\ln p(y, \alpha_{t-1}, \omega | x) - \ln q_t(\omega)]$$

$$= E_q[\ln p(y | \alpha_{t-1}, x, \omega)] + E_q[\ln p(\alpha_{t-1})] + E_q[\ln p(\omega)] - E_q[\ln q(\omega)]$$

$$E_q[\ln p(y | \alpha_{t-1}, x, \omega)]$$

$$= \frac{dN}{2} \ln\left(\frac{\alpha}{2\pi}\right) - \frac{\alpha_{t-1}}{2} \sum_{i=1}^N (y_i)^2 - \frac{\alpha_{t-1}}{2} \sum_{i=1}^N \{tr[x_i x_i^T (\mu\mu^T + \Sigma)] - 2tr(\mu y_i x_i)\}$$

$$E_q[\ln p(\alpha_{t-1})] = \ln \left[\frac{b^a}{\Gamma(a)} \alpha_{t-1}^{a-1} e^{-\alpha_{t-1} b} \right] = a \ln b - \ln \Gamma(a) + (a-1) \ln(\alpha_{t-1}) - b \alpha_{t-1}$$

$$E_q[\ln p(\omega)] = \frac{d}{2} \ln\left(\frac{\lambda}{2\pi}\right) - \frac{\lambda}{2} tr(\mu\mu^T + \Sigma)$$

$$E_q[-\ln q(\omega)] = \frac{1}{2} \ln \det(2\pi e \Sigma)$$

$\det(\cdot)$ represents the matrix determinant.

Problem 3

Algorithm outline

Inputs: Data X, Y and $q(\lambda) = \text{Gamma}(\lambda|a', b')$ and $q(\omega) = \text{Normal}(\omega|\mu', \Sigma')$

Outputs: Values for a', b', μ', Σ'

1. Initialize $a'_0, b'_0, \mu'_0, \Sigma'_0$
2. For iteration $t=1, \dots, T$
 - (a) Update $q(\lambda)$ by setting

$$a'_t = a + \frac{d}{2}, \quad b'_t = \frac{1}{2}(\mu'_{t-1}\mu'^T_{t-1} + \Sigma'_{t-1}) + b$$

- (b) Update $q(\omega)$ by setting

$$\Sigma'_t = \left(\frac{a'_t}{b'_t} \mathbf{I} + \alpha \sum_{i=1}^N x_i x_i^T \right)^{-1}, \quad \mu'_t = \Sigma'_t \cdot \left(\alpha \sum_{i=1}^N y_i x_i \right)$$

- (c) Evaluate $\mathcal{L}(a'_t, b'_t, \mu'_t, \Sigma'_t)$ to assess convergence. If the marginal increase in \mathcal{L}_t compared with \mathcal{L}_{t-1} is “small”, terminate. Continue to the next iteration otherwise.

(a)

We want to approximate the posterior $p(\omega, \lambda|y, x)$ with $q(\omega, \lambda)$ using variational inference. In general setup, we learned that

$$q_i(\theta_i|\phi_i) = \frac{1}{Z} \exp [\ln p(y, \theta_1, \theta_2 \dots |x)]$$

In this case,

- $q(\lambda)$

$$q(\lambda) \propto \exp \{E_{q(\omega)}[\ln p(y, \omega, \lambda|x)]\}$$

$$\begin{aligned} p(y, \omega, \lambda|x) &\propto \prod_{i=1}^N p(y_i|\omega, \lambda, x_i) p(\omega|\lambda) p(\lambda) \\ &\propto \exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] \lambda^{\frac{d}{2}} \exp \left(-\frac{\lambda}{2} \omega^T \omega \right) \lambda^{a-1} e^{-\lambda b} \end{aligned}$$

$$\propto \exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] \lambda^{a+\frac{d}{2}-1} \exp \left[-\lambda \left(\frac{\omega^T \omega}{2} + b \right) \right]$$

Notice that $\exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right]$ does not contain λ .

$$q(\lambda) \propto \lambda^{a+\frac{d}{2}-1} \exp \left\{ -\lambda \left(E_{q(\omega)} \left[\frac{\omega^T \omega}{2} \right] + b \right) \right\}$$

$$q(\lambda) = \text{Gamma}(\lambda | a', b') \quad a' = a + \frac{d}{2}, \quad b' = \frac{1}{2} E_{q(\omega)}[\omega^T \omega] + b$$

(b)

• $q(\omega)$

$$q(\omega) \propto \exp \{ E_{q(\lambda)} [\ln p(y, \omega, \lambda | x)] \}$$

$$p(y, \omega, \lambda | x) \propto \prod_{i=1}^N p(y_i | \omega, \lambda, x_i) p(\omega | \lambda) p(\lambda)$$

$$\propto \exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] \lambda^{\frac{d}{2}} \exp \left(-\frac{\lambda}{2} \omega^T \omega \right) p(\lambda)$$

So

$$q(\omega) \propto \exp \left\{ E_{q(\lambda)} \left[\ln \left[\prod_{i=1}^N p(y_i | \omega, \lambda, x_i) \right] - E_{q(\lambda)} [\ln p(\omega | \lambda)] \right] \right\}$$

$$\propto \exp \left[-\frac{\alpha}{2} \sum_{i=1}^N (y_i - x_i^T \omega)^2 \right] \exp \left\{ -\frac{E_{q(\lambda)}[\lambda]}{2} \omega^T \omega \right\}$$

$$q(\omega) = \text{Normal}(\omega | \mu', \Sigma')$$

$$\Sigma' = \left(E_{q(\lambda)}[\lambda] \mathbf{I} + \alpha \sum_{i=1}^N x_i x_i^T \right)^{-1} \quad \text{and} \quad \mu' = \Sigma' \cdot \left(\alpha \sum_{i=1}^N y_i x_i \right)$$

For this problem,

$$E_{q(\lambda)}[\lambda] = a' / b'$$

$$E_{q(\omega)}[\omega^T \omega] = \mu' \mu'^T + \Sigma'$$

(c)

Evaluating $\mathcal{L}(a'_t, b'_t, \mu'_t, \Sigma'_t)$

$$\begin{aligned}\mathcal{L}_t = & E_q[\ln p(y, a'_t, b'_t, \mu'_t, \Sigma'_t | x)] - E_{q(a'_t)}[\ln(a'_t)] - E_{q(b'_t)}[\ln(b'_t)] - E_{q(\mu'_t)}[\ln(\mu'_t)] \\ & - E_{q(\Sigma'_t)}[\ln(\Sigma'_t)]\end{aligned}$$