

$$\vec{\mu} = (\mu_1, \dots, \mu_n)$$

$$Y_i \sim N(\mu_i, \sigma^2 = 0.2), \quad i = 1, \dots, n$$

$$P(\mu_1 = 1)$$

$$P(\mu_{i+1} | \mu_i) = N(\mu_i, 0.2), \quad i = 1, \dots, n-1$$

## Lab 4

Q2)

Gibbs sampler:-

$$X_{t+1,i} \sim P(\cdot | X_{t+1,1}, \dots, X_{t+1,i-1}, X_{t+1,i+1}, \dots, X_{t,d})$$

We need to sample (to get a value for a particular  $X$ )

$$P(\cdot | X_{t+1,1}, \dots, X_{t,d}) \leftarrow \text{conditional distr.}$$

we are interested in

→ will be constant since we will integrate over this.

We are interested in the conditional distr., so from Baye's theorem,

$$\underbrace{P(\theta | D)}_{\text{Posterior}} \propto \underbrace{P(D | \theta)}_{\text{Likelihood}} \underbrace{P(\theta)}_{\text{Prior}}$$

We are given,

$$\vec{\mu} = (\mu_1, \dots, \mu_n) \leftarrow \text{unknown parameters}$$

$$Y_i \sim N(\mu_i, \text{variance} = 0.2), \quad i = 1, \dots, n$$

whose prior is,

$$P(\mu_1) = 1$$

$$P(\mu_{i+1}, \mu_i) = N(\mu_i, 0.2), \quad i = 1, \dots, n-1$$



$$\circ \circ \quad P(\vec{\mu} | \vec{y}) = \frac{P(\vec{y} | \vec{\mu}) P(\vec{\mu})}{\int P(\vec{y} | \vec{\mu}) P(\vec{\mu}) d\vec{\mu}}$$

$$P(\vec{\mu} | \vec{y}) \propto P(\vec{y} | \vec{\mu}) P(\vec{\mu})$$

$$\circ \circ \quad \text{w.k.t. } N(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$$

$$\circ \circ \quad \text{Likelihood, } L(\vec{y} | \vec{\mu}) = \frac{1}{(\sqrt{2\pi\sigma^2})^n} \prod_{i=1}^n e^{-\frac{1}{2\sigma^2}(y_i - \mu_i)^2}$$

Prior,

$$P(\mu_{i+1} | \mu_i) = N(\mu_{i+1}, 0.2) = P(\mu_1) P(\mu_2 | \mu_1) \dots P(\mu_n | \mu_{n-1})$$

$[i=1, \dots, n-1]$

$$\circ \circ \quad P(\vec{\mu}) = \frac{1}{(\sqrt{2\pi\sigma^2})^{n-1}} \prod_{i=1}^{n-1} e^{-\frac{1}{2\sigma^2}(\mu_{i+1} - \mu_i)^2}$$

→ conditional dist.

Now, the posterior we are interested in:

$$P(\vec{\mu} | \vec{y}) \propto e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (\mu_{i+1} - \mu_i)^2 - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \mu_i)^2}$$

$$\hookrightarrow \propto e^{-\frac{1}{2\sigma^2} [\sum_{i=1}^n (\mu_{i+1} - \mu_i)^2 + (y_i - \mu_i)^2] - \frac{1}{2\sigma^2} (y_n - \mu_n)^2}$$

Now,

considering  $P(\mu_1 | \vec{\mu}_{-1}, \vec{y}) \rightarrow R(\mu_1)$

Considering,  $P(\mu_1 | \vec{\mu}_{-1}, \vec{y}) \rightarrow P(\mu_1 | \mu_2, \mu_3, \dots, \mu_n, \vec{y})$   
 ↳ we are interested only in  $\mu_1$

$$P(\mu_1 | \vec{\mu}_{-1}, \vec{y}) \propto \exp \left[ -\frac{1}{2\sigma^2} (\mu_2 - \mu_1)^2 + (y_1 - \mu_1)^2 \right]$$

$$= \exp \left[ -\frac{1}{2\sigma^2} (\mu_1 - \mu_2)^2 + (\mu_1 - y_1)^2 \right]$$



On comparing with last,

$$\exp \left[ -\frac{1}{d} ((x-a)^2 + (x-b)^2) \right] \propto \exp \left[ -\frac{(x - (a+b)/2)^2}{d/2} \right]$$

$$\Rightarrow \exp \left[ -\frac{(\mu_1 - (\mu_2 + y_1)/2)^2}{2\sigma^2/2} \right]$$

$$\therefore P(\mu_1 | \vec{\mu}_{-1}, \vec{y}) \sim N \left( \frac{\mu_2 + y_1}{2}, \frac{\sigma^2}{2} \right) \quad \text{--- (1)}$$

Now,

Considering  $P(\mu_n | \vec{\mu}_{-n}, \vec{y})$ ,

$$\propto \exp \left[ -\frac{1}{2\sigma^2} ((\mu_n - \mu_{n-1})^2 + (\mu_n - y_n)^2) \right]$$

$$\propto \exp \left[ -\frac{(\mu_n - (\mu_{n-1} + y_n)/2)^2}{\sigma^2} \right]$$

$$\sim N \left( \frac{\mu_{n-1} + y_n}{2}, \frac{\sigma^2}{2} \right) \quad \text{--- (2)}$$

Now,

Taking  $i=3$ ,

$$\sum_{i=2}^3 ((\mu_{i+1} - \mu_i)^2 + (y_i - \mu_i)^2)$$

$$= (\mu_2 - \mu_2)^2 + (y_2 - \mu_2)^2 + (\mu_4 - \mu_3)^2 + (y_3 - \mu_3)^2$$

$i=2 \qquad \qquad \qquad i=3$

$$= \exp \left[ -\frac{1}{2\sigma^2} ((\mu_2 - \mu_{2-1})^2 + (\mu_{2+1} - \mu_2)^2 + (y_2 - \mu_2)^2) \right]$$

$$\propto \exp \left( -\frac{(\mu_2 - (\mu_{2-1} + \mu_{2+1} + y_2)/3)^2}{2\sigma^2/3} \right)$$

$$\therefore P(\mu_i | \vec{\mu}_{-i}, \vec{y}) \sim N \left( \frac{\mu_{i-1} + \mu_{i+1} + y_i}{3}, \frac{2\sigma^2}{3} \right) \quad \text{--- (3)}$$