

Week-3

정유진



Two parameter models

① Normal data with noninformative prior distribution

$$\text{Likelihood: } y_i | (\mu, \sigma^2) \sim N(\mu, \sigma^2) \Rightarrow \text{likelihood} = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{1}{2\sigma^2} (y_i - \mu)^2 \right]$$

$$= \left(\frac{1}{\sqrt{2\pi}} \right)^n \cdot \left(\frac{1}{\sigma^2} \right)^{\frac{n}{2}} \exp \left[-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2 \right]$$

$$\propto \sigma^{-n} \cdot \exp \left[-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2 \right]$$

prior: $p(\mu, \sigma^2) \propto (\sigma^2)^{-1}$ ← $p(\mu, \sigma^2) = p(\mu) \cdot p(\sigma^2)$ (improper prior)

$$\propto 1/\sigma^2$$

$$p(\sigma^2) \propto \frac{1}{\sigma^2}$$

$$p(\log \sigma^2) \propto 1$$

$$p(\mu) \propto 1$$

posterior: $p(\mu, \sigma^2 | y) = \frac{p(\mu, \sigma^2) p(y | \mu, \sigma^2)}{\int p(y | \mu, \sigma^2) p(\mu, \sigma^2) d\mu d\sigma^2} \propto p(\mu, \sigma^2) \cdot p(y | \mu, \sigma^2)$

$$= \sigma^{-n} \cdot \sigma^{-2} \exp \left[-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2 \right] = \sigma^{-n-2} \exp \left[-\frac{1}{2\sigma^2} \underbrace{\sum (y_i - \mu)^2}_{\sum (y_i - \bar{y} + \bar{y} - \mu)^2} \right]$$

$$= \sigma^{-n-2} \exp \left[-\frac{1}{2\sigma^2} \left\{ \sum (y_i - \bar{y})^2 + n(\bar{y} - \mu)^2 \right\} \right]$$

$$\quad \uparrow \sigma^2 = \frac{\sum (y_i - \bar{y})^2}{n-1} \text{ (sample variance of } y \text{ is } \sigma^2)$$

$$= \sigma^{-n-2} \exp \left[-\frac{1}{2\sigma^2} \left\{ (n-1)s^2 + n(\bar{y} - \mu)^2 \right\} \right]. \quad \bar{y}, \sigma^2: \text{sufficient statistic}$$

$$\begin{aligned} p(\theta|y_1, \dots, y_n, \sigma^2) &= p(\theta|\sigma^2)p(y_1, \dots, y_n|\theta, \sigma^2)/p(y_1, \dots, y_n|\sigma^2) \\ &\propto p(\theta|\sigma^2)p(y_1, \dots, y_n|\theta, \sigma^2) \\ &\propto \exp\left(-\frac{1}{2\sigma^2}(\theta - \mu_0)^2\right) \exp\left(-\frac{1}{2\sigma^2}\sum(y_i - \theta)^2\right). \end{aligned}$$

Adding the terms in the exponents and ignoring the $-1/2$ for the moment, we have

$$\begin{aligned} \frac{1}{\tau_0^2}(\theta^2 - 2\theta\mu_0 + \mu_0^2) + \frac{1}{\sigma^2}(\sum y_i^2 - 2\theta\sum y_i + n\theta^2) &= a\theta^2 - 2b\theta + c, \text{ where} \\ a &= \frac{1}{\tau_0^2} + \frac{n}{\sigma^2}, \quad b = \frac{\mu_0}{\tau_0^2} + \frac{\sum y_i}{\sigma^2}, \quad \text{and } c = c(\mu_0, \tau_0^2, \sigma^2, y_1, \dots, y_n). \end{aligned}$$

Now let's see if $p(\theta|\sigma^2, y_1, \dots, y_n)$ takes the form of a normal density:

$$\begin{aligned} p(\theta|\sigma^2, y_1, \dots, y_n) &\propto \exp\left(-\frac{1}{2}(a\theta^2 - 2b\theta)\right) \\ &= \exp\left(-\frac{1}{2}a(\theta^2 - 2b\theta/a + b^2/a^2) + \frac{1}{2}b^2/a\right) \\ &\propto \exp\left(-\frac{1}{2}(\theta - b/a)^2\right) \\ &= \exp\left(-\frac{1}{2}\left(\frac{\theta - b/a}{1/\sqrt{a}}\right)^2\right). \end{aligned}$$

$$\text{FCB 5-2. } \frac{m}{\tau_0^2} = \frac{b}{a} = \bar{y} \cdot b$$

$$\text{Posterior: } p(M, \sigma^2 | y) = \underbrace{p(M | \sigma^2, y)}_{①} \cdot \underbrace{p(\sigma^2 | y)}_{②}$$

$$① p(M | \sigma^2, y) = M \text{ 인 } \sigma^2 \text{ 일 때 posterior distribution}$$

(본래)

$$\checkmark M \sim N(\mu_0, \tau_0^2) \propto \exp\left[-\frac{1}{2\tau_0^2}(M - \mu_0)^2\right]$$

$$\checkmark y | M \sim N(M, \sigma^2) \propto \exp\left[-\frac{1}{2\sigma^2} \sum (y_i - M)^2\right]$$

$$\begin{aligned} p(M|y) &\propto p(M) \cdot p(y|M) = \exp\left[-\frac{1}{2\tau_0^2}(M - \mu_0)^2 - \frac{1}{2\sigma^2} \sum (y_i - M)^2\right] \\ &= \exp\left[-\frac{1}{2\tau_0^2}(M^2 - 2M\mu_0 + \mu_0^2) - \frac{1}{2\sigma^2} \sum (y_i^2 - 2My_i + M^2)\right] \\ &\propto \exp\left[-\frac{1}{2}\left(\frac{M^2}{\tau_0^2} - \frac{2M\mu_0}{\tau_0^2} M - \frac{2M\sum y_i}{\sigma^2} + \frac{M^2}{\sigma^2}\right)\right] \\ &= \exp\left[-\frac{1}{2}\left(\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}\right)M^2 + \left(\frac{2M\mu_0}{\tau_0^2} - \frac{2n\bar{y}}{\sigma^2}\right)M\right] \\ &\quad a = \frac{1}{\tau_0^2}, \quad b = \frac{2M\mu_0}{\tau_0^2} \\ &\Rightarrow \tau_0^2 = \frac{1}{a}, \quad M\mu_0 = -\frac{1}{2}\tau_0^2 \cdot b \end{aligned}$$

$$\begin{aligned} M|y &\sim N\left(\frac{\frac{1}{\tau_0^2}}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}}\mu_0 + \frac{\frac{n}{\sigma^2}}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}}\bar{y}, \frac{1}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}}\right) \\ \star \text{ noninformative prior.} \\ \text{prior의 } \rightarrow \infty \text{ precision} \rightarrow 0 \\ \Rightarrow \frac{1}{\tau_0^2} \rightarrow 0 \end{aligned}$$

$$\therefore M|\sigma^2, y \sim N\left(\bar{y}, \frac{\sigma^2}{n}\right)$$

$$\tilde{X}^2(y, \sigma^2) = \tilde{\Gamma}^{-1}\left(\frac{v}{2}, \frac{y^2}{2}\right)$$

$$\begin{aligned} ② p(\sigma^2 | y) &= \int p(M, \sigma^2 | y) dM \propto \int \tilde{f}^{n-1} \exp\left[-\frac{1}{2\sigma^2} \left\{ (n-1)s^2 + n(\bar{y} - M)^2 \right\}\right] dM \\ &= \tilde{f}^{n-2} \exp\left(-\frac{1}{2\sigma^2} (n-1)s^2\right) \cdot \int \exp\left[-\frac{n}{2\sigma^2} (M - \bar{y})^2\right] dM \\ &= \tilde{f}^{n-2} \exp\left(-\frac{1}{2\sigma^2} (n-1)s^2\right) \cdot \sqrt{\frac{2\pi\sigma^2}{n}} \\ &\propto \tilde{f}^{-(n+1)} \cdot \exp\left(-\frac{1}{2\sigma^2} (n-1)s^2\right) = (\sigma^2)^{-\frac{(n+1)}{2}} \exp\left(-\frac{1}{2\sigma^2} (n-1)s^2\right) \\ &\therefore p(\sigma^2 | y) \sim \text{Inverse gamma}\left(\frac{n-1}{2}, \frac{(n-1)s^2}{2}\right) \end{aligned}$$

$$\begin{aligned} &\text{inverse gamma pdf} \\ &\left(\frac{\beta^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\frac{y}{\beta}} \right) \\ &\alpha = \frac{v}{2}, \quad \beta = \frac{v\tau^2}{2} \\ &\text{scaled} \\ &\text{inverse chi-square pdf} \\ &\text{Scale-inv-}\chi^2(v, \tau^2) \\ &\left(\frac{(\tau^2)^{\frac{v}{2}}}{\Gamma(\frac{v}{2})} \right)^{\frac{v}{2}} \cdot \frac{-(1+\tau^2)}{\tau^2} \cdot \chi \cdot \exp\left[-\frac{\chi^2}{2\tau^2}\right] \end{aligned}$$

$$\text{Posterior} := p(\mu | \sigma^2, y) \cdot p(\sigma^2 | y) \Rightarrow N(\mu | \bar{y}, \frac{\sigma^2}{n}) \cdot \text{Inv}\chi^2(\sigma^2 | n-1, J^2)$$

→ conditional posterior distⁿ × marginal posterior distⁿ

$$\sigma^2 \sim \text{Inv}\chi^2 = \text{Inv}\chi^2(J^2 | (n-1)J^2) \Rightarrow \sigma^2 \sim \text{Inv}\chi^2(J^2) \sim \sigma^2 \sim \text{Inv}\chi^2(J^2)$$

Sampling from the joint posterior distribution

It is easy to draw samples from the joint posterior distribution: first draw σ^2 from (3.5), then draw μ from (3.3). We also derive some analytical results for the posterior distribution, since this is one of the few multiparameter problems simple enough to solve in closed form.

* Analytic form of the marginal posterior distribution of μ .

$$p(\mu | y) = \int_0^\infty p(\mu | \sigma^2, y) d\sigma^2 \propto \int_0^\infty \sigma^{-(n+2)} \exp\left[-\frac{1}{2\sigma^2} \{(n-1)\sigma^2 + n(\bar{y} - \mu)^2\}\right] d\sigma^2$$

$$\begin{cases} A = (n-1)\sigma^2 + n(\bar{y} - \mu)^2 \\ Z = \frac{A}{2\sigma^2}, \quad \sigma^2 = \frac{A}{2Z}, \quad J = \left|\frac{\partial \sigma^2}{\partial Z}\right| = \frac{A}{2} \cdot \frac{1}{Z^2} \end{cases}$$

$$\Rightarrow \int_0^\infty \left(\frac{A}{2Z}\right)^{-\frac{n}{2}} \exp(-Z) \cdot \frac{A}{2} \cdot \frac{1}{Z^2} dZ$$

$$\propto A^{-\frac{n}{2}} \int_0^\infty \frac{1}{A} \cdot \exp(-Z) \cdot \frac{n}{Z^2} dZ = A^{-\frac{n}{2}} \underbrace{\int_0^\infty Z^{-\frac{n}{2}-1} \exp(-Z) dZ}_{= \Gamma(\frac{n}{2}+1)} \propto A^{-\frac{n}{2}}$$

$$A^{-\frac{n}{2}} = \left[(n-1)\sigma^2 + n(\bar{y} - \mu)^2 \right]^{-\frac{n}{2}} \propto \left[1 + \frac{(\bar{y} - \mu)^2}{(n-1)\sigma^2} \right]^{-\frac{n}{2}}$$

$$\therefore M|Y \sim \text{F}(n, \frac{\sigma^2}{n})$$

$$p(\theta) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)\sqrt{\nu\pi\sigma^2}} \left(1 + \frac{1}{\nu} \left(\frac{\theta-\mu}{\sigma}\right)^2\right)^{-(\nu+1)/2}$$

* Posterior predictive distribution - Noninformative prior

$$P(\tilde{y}|y) = \int \int p(\tilde{y}|M, \delta^2) \cdot p(M, \delta^2|y) dM d\delta^2 = \int \int p(\tilde{y}|M, \delta^2) \cdot p(M|\delta^2, y) \cdot p(\delta^2|y) dM d\delta^2.$$

$$= \int \int \underbrace{p(\tilde{y}|M, \delta^2)}_{\text{blue box}} \cdot p(M|\delta^2, y) dM \cdot \underbrace{p(\delta^2|y) d\delta^2}_{\text{red box}}$$

$$= \int p(\tilde{y}|M, \delta^2) \cdot p(\delta^2|y) d\delta^2 \quad \int p(\tilde{y}|M, \delta^2, y) dM = P(\tilde{y}|\delta^2, y)$$

①

$$P(\tilde{y}|\delta^2, y) = \int p(\tilde{y}|M, \delta^2) \cdot p(M|\delta^2, y) dM \propto \int \exp\left[-\frac{1}{2\delta^2}(y-M)^2\right] \cdot \exp\left[-\frac{n}{2\delta^2}(M-\bar{y})^2\right] dM$$

$$= \int \exp\left[-\frac{1}{2\delta^2}\left(y-M\right)^2 + n(M-\bar{y})^2\right] dM = \int \exp\left[-\frac{1}{2\delta^2}\left(\tilde{y}^2 - 2M\tilde{y} + M^2 + nM^2 - 2nM\bar{y} + n\bar{y}^2\right)\right] dM$$

$$\begin{aligned} &= \int \exp\left[-\frac{1}{2\delta^2}\left(n+1\right)M^2 - 2(y+n\bar{y})M + \tilde{y}^2 + n\bar{y}^2\right] dM \\ &= \int \exp\left[-\frac{n+1}{2\delta^2}\left(M - \frac{y+n\bar{y}}{n+1}\right)^2 - \left(\frac{\tilde{y}+n\bar{y}}{n+1}\right)^2\right] dM \end{aligned}$$

$M|\delta^2, y$

$$\sim N\left(\bar{y}, \frac{\delta^2}{n}\right)$$

$\delta^2|y$

$$\sim \chi^2/(n+1, S^2)$$

$$= P^{-1}\left[\frac{n+1}{2}, \frac{(n+1)S^2}{2}\right]$$

$$\begin{aligned} &= \int \exp\left[-\frac{n+1}{2\delta^2}(M - \frac{\tilde{y}+n\bar{y}}{n+1})^2\right] dM \cdot \exp\left[-\frac{n}{2\delta^2} \cdot \left(\frac{(\tilde{y}-\bar{y})^2}{n+1}\right)\right] \\ &\quad \text{normalizing constant of } \frac{1}{\delta^2} \\ &= \sqrt{\frac{2\pi\delta^2}{n+1}} \cdot \exp\left[-\frac{n}{2\delta^2(n+1)}(\tilde{y}-\bar{y})^2\right] \\ &\propto \exp\left[-\frac{n}{2\delta^2(n+1)}(\tilde{y}-\bar{y})^2\right] \\ \therefore \tilde{y}|\delta^2, y &\sim N\left(\bar{y}, \left(\frac{n+1}{n+1}\right)\delta^2\right) \end{aligned}$$

② $P(\tilde{y}|y)$

$$\begin{aligned} &= \int p(\tilde{y}|\delta^2, y) \cdot p(\delta^2|y) d\delta^2 = \int \left[\left(\frac{n}{2\pi(n+1)\delta^2} \right)^{\frac{1}{2}} \exp\left(-\frac{n}{2\delta^2(n+1)}(\tilde{y}-\bar{y})^2\right) \cdot \left(\frac{n+1}{\delta^2}\right)^{\frac{n+1}{2}} \cdot \exp\left(-\frac{(n+1)S^2}{2\delta^2}\right) \right] d\delta^2 \\ &\propto \int \left(\delta^{-2} \right)^{\frac{1}{2}} \cdot \left(\delta^{-2} \right)^{\frac{n+1}{2}} \cdot \exp\left[-\frac{1}{2\delta^2} \left\{ \frac{n}{n+1}(\tilde{y}-\bar{y})^2 + S^2(n+1) \right\}\right] d\delta^2 \\ &= \int \delta^{-\frac{n}{2}-1} \cdot \exp\left[-\frac{1}{2\delta^2} \left\{ \frac{n}{n+1}(\tilde{y}-\bar{y})^2 + S^2(n+1) \right\}\right] d\delta^2 \\ &= \frac{\Gamma\left(\frac{n}{2}\right)}{\left(\frac{1}{2}\left[\frac{n}{n+1}(\tilde{y}-\bar{y})^2 + S^2(n+1)\right]\right)^{\frac{n}{2}}} \underbrace{\Gamma^{-1}\left(\frac{n}{2}, \frac{1}{2}\left[\frac{n}{n+1}(\tilde{y}-\bar{y})^2 + S^2(n+1)\right]\right)}_{\text{normalizing constant of } \frac{1}{\delta^2}} \\ &\propto \left[\frac{n}{n+1}(\tilde{y}-\bar{y})^2 + S^2(n+1) \right]^{-\frac{n}{2}} \propto \left[\frac{(\tilde{y}-\bar{y})^2}{(n+1)(1+\frac{1}{n})S^2} + 1 \right]^{-\frac{n}{2}} \\ &\therefore \nu = n+1 \\ &\text{mean: } \bar{y} \\ &\text{scale: } \left(1+\frac{1}{n}\right)S^2 \end{aligned}$$

$$\therefore \tilde{y}|y \sim T(n+1, \bar{y}, \left(1+\frac{1}{n}\right)S^2)$$

② Normal data with a conjugate prior distribution.

$$\text{Likelihood: } P(Y|N, \bar{y}^2) = \left(\frac{1}{\sqrt{2\pi}}\right)^N \cdot \bar{y}^N \cdot \exp\left[-\frac{1}{2\bar{y}^2} \sum (y_i - \bar{y})^2\right]$$

$$\text{Prior: } p(N \cdot f^2) = p(N|f^2) \cdot p(f^2)$$

$$\zeta \sim N(\mu_0, \frac{\sigma^2}{k_0})$$

$$f^2 \sim \ln \gamma \left(V_0, \frac{J_0^2}{\gamma} \right) = \ln \gamma \text{-gamma} \left(\frac{V_0}{2}, \frac{J_0^2}{2} \right)$$

$$P(M(t^2)) \propto \left(\frac{k_0}{\delta^2}\right)^{\frac{1}{2}} \cdot \exp\left(-\frac{k_0}{2\delta^2} \cdot (M - M_0)^2\right) \cdot \left(\frac{(v_0 \delta_0)^2}{\gamma^2}\right)^{\frac{1}{2}} \cdot \left(\frac{1}{\delta^2}\right) \cdot \exp\left(-\frac{v_0 \delta_0^2}{2\delta^2}\right)$$

$$\propto \left(\frac{1}{\tau^2} \right)^{\frac{1}{2}} \left(\frac{1}{\delta^2} \right)^{\frac{V_0}{2} + 1} - \exp \left[-\frac{1}{2\delta^2} \left\{ k_0(M - M_0)^2 + V_0 \delta^2 \right\} \right]$$

$$\text{Posterior: } p(\mu, \sigma^2 | y) \propto p(y | \mu, \sigma^2) p(\mu, \sigma^2) \propto (\sigma^2)^{-\frac{n}{2}} \cdot \exp \left[-\frac{1}{2\sigma^2} \left\{ (n-1)\bar{s}^2 + n(\bar{y}-\mu)^2 \right\} \right]$$

$$\times (\delta^2)^{\frac{1}{2}} \cdot (\delta^2)^{-\frac{v_0}{2}-1} \exp \left[-\frac{1}{2\delta^2} \left(k_0 (M-M_0)^2 + v_0 \delta^2 \right) \right]$$

$$\Rightarrow N - \ln r - \chi^2(Mn, \frac{f n^2}{kn}; v_n, \delta n^2)$$

$$M_n = \frac{k_0}{k_0+n} M_0 + \frac{n}{k_0+n} \bar{y} \quad (\text{k}_0: \text{prior sample size}) \rightarrow \text{combine the prior information}$$

$$k_n = k_0 + n$$

interpretation) divisor sample size

$$x_n = V_0 t n$$

$$V_n f_n^2 = V_0 \sigma_0^2 + (n+1) \sigma^2 + \frac{k_0 n}{k_0+n} (\bar{y} - m)^2$$

posterior sum of squares prior sum of squares + sample sum of squares additional uncertainty conveyed by the difference between sample mean and prior mean.

* The conditional posterior distribution $P(M|\delta^2, y)$

$$M|\delta^2, y \sim N\left(\frac{\frac{k_0}{\delta^2} + \frac{n}{\delta^2}}{\frac{k_0}{\delta^2} + \frac{n}{\delta^2}}, \frac{1}{\frac{k_0}{\delta^2} + \frac{n}{\delta^2}}\right)$$

* The marginal posterior distribution $P(\delta^2|y)$

$$P(\delta^2|y) \propto P(\delta^2) \cdot P(y|M, \delta^2) = P(\delta^2) \cdot \int P(y|M, \delta^2) dM$$

$$\propto \left(\frac{1}{\delta^2}\right)^{\frac{n+1}{2}} \exp\left(-\frac{V_0 \delta^2}{2\delta^2}\right) \cdot \underbrace{\left(\frac{1}{\delta^2}\right)^{\frac{n}{2}} \exp\left[-\frac{1}{2\delta^2} \{(n-1)\delta^2 + n(\bar{y}-M)^2\}\right] \cdot \left(\frac{k_0}{\delta^2}\right)^{\frac{1}{2}} \exp\left[-\frac{k_0}{2\delta^2} (M-M_0)^2\right]}_{dM}$$

$$\propto \left(\frac{1}{\delta^2}\right)^{\frac{n+1}{2}} \exp\left(-\frac{V_0 \delta^2}{2\delta^2}\right) \cdot \left(\frac{1}{\delta^2}\right)^{\frac{n}{2}} \exp\left(-\frac{1}{2\delta^2} (n-1)\delta^2\right) \cdot \underbrace{\left(\frac{1}{\delta^2}\right)^{\frac{1}{2}} \int \exp\left[-\frac{1}{2\delta^2} n(\bar{y}-M)^2 - \frac{k_0}{2\delta^2} (M-M_0)^2\right] dM}_{dM}$$

$$= \left(\frac{1}{\delta^2}\right)^{\frac{n+1}{2}} \left(\frac{1}{\delta^2}\right)^{\frac{n}{2}} \exp\left(-\frac{V_0 \delta^2}{2\delta^2}\right) \cdot \exp\left(-\frac{1}{2\delta^2} (n-1)\delta^2\right) \cdot \exp\left(-\frac{1}{2\delta^2} \left(\frac{n k_0 (\bar{y}-M)^2}{n+k_0}\right)\right)$$

$$\cdot \underbrace{\int \exp\left[-\frac{n k_0}{2\delta^2} \left(M - \frac{n(\bar{y}-M)}{n+k_0}\right)^2\right] dM}_{dM} = \frac{n k_0}{\delta^2} \propto \left(\frac{1}{\delta^2}\right)^{\frac{n}{2}}$$

N($\frac{n(\bar{y}+k_0 M)}{n+k_0}$, $\frac{\delta^2}{n+k_0}$) Marginalizing constant

$$= \left(\delta^2\right)^{\frac{n+1}{2}-1} \exp\left[-\frac{1}{2\delta^2} \left(V_0 \delta^2 + (n-1)\delta^2 + \frac{n k_0}{n+k_0} (\bar{y}-M)^2\right)\right]$$

$$= \left(\delta^2\right)^{\frac{n+1}{2}-1} \exp\left[-\frac{1}{2\delta^2} \left(V_0 \delta^2 + (n-1)\delta^2 + \frac{n k_0}{n+k_0} (\bar{y}-M)^2\right)\right] = \sqrt{n \delta^2}$$

$$= \left(\frac{1}{\delta^2}\right)^{\frac{n+1}{2}-1} \exp\left[-\frac{V_0 \delta^2}{2\delta^2} \left(1 + \frac{1}{V_0 \delta^2} + \frac{(n-1)}{V_0 \delta^2} + \frac{n k_0 (\bar{y}-M)^2}{n+k_0}\right)\right] = \delta \alpha^2$$

$$\therefore \delta^2 | y \sim N\left(nV_0^{-1}(\bar{y}-M)^2, V_0 n \delta^2\right)$$

$$= nV_0^{-1}(\bar{y}-M)^2 / \delta^2$$

Sampling: $P(M|\delta^2, y) = N(M | M_0, \frac{\delta^2}{k_0+n}) \cdot [nV_0^{-1}(\bar{y}-M)^2 / \delta^2]$

$$\delta^2 \sim nV_0^{-1}(\bar{y}-M)^2 / \delta^2, M \sim N(M | M_0, \frac{\delta^2}{k_0+n}) \Rightarrow (M, \delta^2) \sim (M, \delta^2 | y)$$