yi ~ N(M, o2) with unknown mean and variance

Choose prior

The joint posterior is then

The joint posterior is then
$$\pi(M,\sigma^{\lambda}|y_{1},...,y_{n}) = (\lambda\pi K_{0}\sigma^{\lambda})^{\frac{1}{\lambda}} \exp\left[-\frac{1}{\lambda K_{0}\sigma^{\lambda}}(M-M_{0})^{\lambda}\right] \frac{b}{\Gamma(a)} (\sigma^{\lambda})^{\frac{1}{\lambda}} e^{-b\sigma^{\lambda}} \frac{1}{\prod_{i=1}^{n} (\lambda\pi\sigma^{\lambda})^{\lambda}} \exp\left[-\frac{1}{\lambda\sigma\lambda}(y_{i}-M)^{\lambda}\right]$$

$$\propto \sigma^{-\frac{1}{\lambda}} \exp\left[-\frac{1}{\lambda K_{0}\sigma^{\lambda}}(M-M_{0})^{\lambda}\right] \sigma^{-\lambda\alpha+\lambda} \sigma^{-\frac{1}{\lambda}} \exp\left[-\frac{1}{\lambda\sigma\lambda}\sum_{i=1}^{n} (y_{i}-M)^{\lambda}\right] e^{-b\sigma^{-\lambda}}$$

$$\propto \sigma^{-\lambda\alpha-n+1} \exp\left[-\frac{1}{\lambda K_{0}\sigma^{\lambda}}(M-M_{0})^{\lambda} - \frac{1}{\lambda\sigma\lambda}\sum_{i=1}^{n} (y_{i}-M)^{\lambda} - b\sigma^{-\lambda}\right]$$

$$\propto \sigma^{-2\alpha-n+1} \exp \left[-\frac{1}{2k_0\sigma^2} (M^2 - 2\mu\mu_0 + M_0^2) - \frac{1}{2\sigma^2} \left(\sum_{i=1}^n y_i^2 - 2\mu \sum_{i=1}^n y_i + nM^2 \right) - b\sigma^2 \right]$$

$$\propto \sigma^{-2\alpha-n+1} \exp \left[M^2 \left(-\frac{1}{2K_0\sigma^2} - \frac{n}{2\sigma^2} \right) + M \left(\frac{M_0}{K_0\sigma^2} + \frac{1}{\sigma^2} \sum_{i=1}^{n} y_i \right) - \frac{1}{2K_0\sigma^2} M_0^2 - \frac{1}{2\sigma^2} \sum_{i=1}^{n} y_i^2 - b\sigma^2 \right]$$

$$\propto \sigma^{-2\alpha-n+1} \exp \left[-\frac{1}{\lambda} \left(M^{\lambda} \left(\frac{1}{K_{0}\sigma^{\lambda}} + \frac{n}{\sigma^{\lambda}} \right) - \lambda M \left(\frac{M_{0}}{K_{0}\sigma^{\lambda}} + \frac{1}{\sigma^{\lambda}} \sum_{i=1}^{n} y_{i} \right) \right) \right] \exp \left[-\frac{1}{\sigma^{\lambda}} \left(\frac{M_{0}^{\lambda}}{2K_{0}} + \frac{1}{2} \sum_{i=1}^{n} y_{i}^{2} + b \right) \right]$$

we want this in the form
$$\exp\left[-\frac{1}{2v}\left(\mathcal{A}^2 - 2\mu\hat{\mathcal{A}} + \hat{\mathcal{A}}^2\right)\right] \quad \rightarrow \quad \text{so let } v = \left(\frac{1}{K_0\sigma^2} + \frac{\alpha}{\sigma^2}\right)^{-1}$$

$$\propto \sigma^{-\lambda\alpha-n+1} \exp\left[-\frac{1}{2v}\left(\mu^2 - \lambda\mu\nu\left(\frac{M_0}{K_0\sigma^2} + \frac{1}{\sigma^2}\sum_{i=1}^2y_i\right)\right)\right] \exp\left[-\frac{1}{\sigma^2}\left(\frac{M_0^2}{\lambda K_0} + \frac{1}{\lambda}\sum_{i=1}^2y_i^2 + b\right)\right]$$

we are multiplying by a constant times of so we must

we just need to complete the square now \rightarrow so let $\hat{M} = \frac{M_o}{K_0\sigma^2} + \frac{1}{\sigma\lambda} \sum_{i=1}^{N} y_i$

$$\frac{\sqrt{\sigma^{-2}a^{-n+1}} \exp\left[-\frac{1}{2v}(M-\hat{M})^{2}\right] \exp\left[\frac{1}{2v}\hat{M}^{2}\right] \exp\left[-\frac{1}{\sigma^{2}}\left(\frac{N^{2}}{2K_{o}}+\frac{1}{2}\sum_{i=1}^{n}y_{i}^{2}+b\right)\right]}{\sqrt{\sigma^{-2}a^{-n+1}}} \exp\left[-\frac{1}{2v}(M-\hat{M})^{2}\right] \exp\left[\frac{1}{2v}\hat{M}^{2}-\frac{1}{\sigma^{2}}\left(\frac{N^{2}}{2K_{o}}+\frac{1}{2}\sum_{i=1}^{n}y_{i}^{2}+b\right)\right]}$$

$$N(M; \hat{M}, v)$$

$$\propto N(M, \hat{M}, v) \sigma^{2\alpha-n+2} \exp\left[\frac{1}{2}\hat{M}^{2}\left(\frac{1}{K_{0}\sigma^{2}} + \frac{n}{\sigma^{2}}\right) - \frac{1}{\sigma^{2}}\left(\frac{M_{0}^{2}}{2K_{0}} + \frac{1}{2}\sum_{y_{1}}^{2}y_{2}^{2} + b\right)\right]$$

$$A = \frac{\frac{M_o}{K_o \sigma \lambda} + \frac{1}{\sigma \lambda} \sum_{i=1}^{n} y_i}{\frac{1}{K_o \sigma \lambda} + \frac{n}{\sigma \lambda}} = \frac{\frac{M_o + K_o \sum_{i=1}^{n} y_i}{1 + K_o n}}{1 + K_o n}$$

$$V = \left(\frac{1}{K_0 \sigma^2} + \frac{\alpha}{\sigma^2}\right)^{-1} = \left[\sigma^2 \left(\frac{K_0}{1 + K_0 \Omega}\right)\right]$$

$$a = a + \frac{a}{2}$$
 $b = b - (\frac{1 + a k_0}{2 k_0}) \frac{a^2}{a^2} + \frac{m_0^2 + k_0 \frac{a^2}{2 k_0}}{2 k_0}$

which is conjugate to $\pi(M, \sigma^{-\lambda})$

$$\begin{split} \mathcal{F}\left(\mathcal{M},\sigma^{-\lambda}\mid\mathcal{Y}_{1},...,\mathcal{Y}_{n}\right) &= \mathcal{N}\left(\mathcal{M};\hat{\mathcal{M}},\mathbf{v}\right)\left(\mathcal{F}_{\Delta}\left(\sigma^{-\lambda};\hat{\boldsymbol{\omega}},\hat{\boldsymbol{\omega}}\right)\right) \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\exp\left[-\frac{1}{2\nu}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}\right]\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}\left(\alpha\right)}\left(\sigma^{-\lambda}\right)^{\tilde{\alpha}-1}e^{-\tilde{b}\sigma^{-\lambda}} \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\exp\left[-\frac{1}{2\nu}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{\lambda}\right]\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}\left(\alpha\right)}\left(\sigma^{-\lambda}\right)^{\tilde{\alpha}-1}e^{-\tilde{b}\sigma^{-\lambda}}d\sigma^{-\lambda} \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}'\left(\tilde{\alpha}\right)}\int_{0}^{\infty}\mathbf{v}^{-\frac{1}{\lambda_{Y}}}\left(\sigma^{-\lambda}\right)^{\tilde{\lambda}-1}\exp\left[-\frac{1}{\lambda_{Y}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}-\tilde{b}\sigma^{-\lambda}\right]d\sigma^{-\lambda} \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}'\left(\tilde{\alpha}\right)}\int_{0}^{\infty}\left[\sigma^{-\lambda}\left(\frac{\kappa_{e}}{1+\kappa_{e}}\right)\right]\left(\sigma^{-\lambda}\right)^{\tilde{\alpha}-1}\exp\left[-\frac{1}{\lambda_{Y}}\left(\frac{1+\kappa_{e}}{\kappa_{e}}\right)\right]\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}-\tilde{b}\sigma^{-\lambda}\right]d\sigma^{-\lambda} \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}'\left(\tilde{\alpha}\right)}\int_{0}^{1+\kappa_{e}}\frac{\kappa_{e}}{\kappa_{e}}\int_{0}^{\infty}\left(\sigma^{-\lambda}\right)^{\tilde{\alpha}-1}\exp\left[-\sigma^{-\lambda}\left(\frac{1+\kappa_{e}}{\kappa_{e}}\right)\right]\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}-\tilde{b}\sigma^{-\lambda}\right]d\sigma^{-\lambda} \\ &= \frac{1}{\sqrt{\lambda_{X}\mathbf{v}}}\frac{\tilde{b}^{\alpha}}{\tilde{\Gamma}'\left(\tilde{\alpha}\right)}\int_{0}^{1+\kappa_{e}}\frac{\kappa_{e}}{\kappa_{e}}\int_{0}^{\infty}\left(\sigma^{-\lambda}\right)^{\tilde{\alpha}-1}\exp\left[-\sigma^{-\lambda}\left(\frac{1+\kappa_{e}}{\kappa_{e}}\right)\right]\left(\frac{1+\kappa_{e}}{\kappa_{e}}\right)\left(\frac{1+\kappa_{e}}{\lambda_{X}}\right)\left(\frac{1+\kappa_{e}}{\lambda_{X}}\right)\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}\right)^{\tilde{\lambda}} \\ &= \frac{1}{\sqrt{\lambda_{X}}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{\infty}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\int_{0}^{2\tilde{b}^{\alpha}}\frac{\tilde{b}^{\alpha}}{\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\left(\mathcal{M}-\hat{\mathcal{M}}\right)^{2}+\tilde{b}^{\alpha}}\left($$

Thus the marginal posterior M/y1,..., yn is a non-central t-distribution with 22 d.f.

$$\sqrt{\frac{1+nko}{ko}}\frac{\tilde{a}}{\tilde{b}}(m-\tilde{m})\sim t_{\tilde{a}\tilde{a}}$$
 where $\tilde{m},\tilde{a},\tilde{b}$ are as defined in Question 1

Let
$$\mathcal{L}(\mathcal{L}, \sigma^2) = \mathcal{L}(\mathcal{M}) \mathcal{L}(\sigma^2)$$
 where $\mathcal{M} \sim \mathcal{N}(\mathcal{M}_0, \sigma_0^2)$ $\sigma^2 \sim G_A(a, b)$

The joint posterior probability is then

The joint posterior producting
$$(M-M_0)^2 = \frac{1}{\sqrt{3}} \exp\left[-\frac{1}{\sqrt{3}} (M-M_0)^2\right] \frac{1}{\sqrt{3}} \exp\left[-\frac{1}{\sqrt{3}} (M-M_0)^2\right] \frac{1}{\sqrt{3}} \exp\left[-\frac{1}{\sqrt{3}} (M-M_0)^2\right] \exp\left[-\frac{1}{\sqrt{3}} (M-M_0)^2\right] \exp\left[-\frac{1}{\sqrt{3}} (M-M_0)^2\right] \exp\left[-\frac{1}{\sqrt{3}} \sum_{i=1}^{n} (y_i-M_i)^2\right] \exp\left[-\frac{1}{\sqrt{3}} \sum_{i=1}^{n} (y$$

Looking at just the M terms of the joint posterior, we can find the full conditional of M

$$\begin{array}{c} \times \left(M \mid \sigma^{2}\lambda, y_{1}, ..., y_{n}\right) \propto \exp \left[-\frac{1}{\lambda}\left(\frac{\alpha}{\sigma^{2}} + \frac{1}{\sigma^{2}}\right)M^{2} - \frac{1}{\lambda}\sigma^{2}\lambda M^{2} + \sigma^{2}\lambda M_{0}M\right] \\ \propto \exp \left[-\frac{1}{\lambda}\left(\frac{\alpha}{\sigma^{2}} + \frac{1}{\sigma^{2}}\right)M^{2} - \lambda M\left(\frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0}\right)\right] \right] \rightarrow \left[\text{let } v = \left(\frac{\alpha}{\sigma^{2}} + \frac{1}{\sigma^{2}}\right)^{-1} \\ \propto \exp \left[-\frac{1}{\lambda^{2}}\left(M^{2} - \lambda M_{0}\right)\left(\frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0}\right)\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \propto \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} + \frac{1}{\sigma^{2}}\lambda M_{0} \\ \sim \exp \left[-\frac{1}{\lambda^{2}}\left(M - \hat{M}\right)^{2}\right] \rightarrow \text{where } \hat{M} = \frac{1}{\sigma^{2}}\sum_{i=1}^{2}y_{i} +$$

Looking at just the od terms of the joint posterior, we can find the full conditional of od ス(o-2 | M,y1,...,yn) & (o-2) a+3-1 exp[-o-2(b+ 主意yi2-Mをyi+ 1のM2)]

Homework 6

Question 4

I simulated n = 30 data points y_i from a normal distribution with true mean 0 and true variance 1. I then calculated posterior summaries of the marginal posterior $\mu \mid y_1, ..., y_n$ under the following two priors:

$$\pi(\mu, \sigma^{-2}) = \pi(\mu \mid \sigma^{-2})\pi(\sigma^{-2}) = N(\mu; \mu_0, \kappa_0 \sigma^2) Ga(\sigma^{-2}; a, b)$$

- In this prior μ is dependent on σ^{-2}
- We have the exact marginal posterior distribution of μ from Question 2
- For the simulation, I set $\mu_0=0$, $\kappa_0=1$, $\alpha=0.001$, and b=0.001 as a weak prior

$$\pi(\mu, \sigma^{-2}) = \pi(\mu)\pi(\sigma^{-2}) = N(\mu; \mu_0, \sigma_0^2)Ga(\sigma^{-2}; a, b)$$

- In this prior μ and σ^{-2} are independent
- We can approximate the marginal posterior distribution of μ using Gibbs sampling with the full conditionals from Question 3
- For the simulation, I set $\mu_0 = 0$, $\sigma_0^2 = 100$, a = 0.001, and b = 0.001 as a weak prior and used 1000 iterations for Gibbs sampling
- Looking at the trace plot for μ , I threw away the first 10 values as burn-ins

Table: Marginal posterior summaries of $\mu \mid y_1, ..., y_n$ for different priors

	Mean	Variance	95% CI
$\pi(\mu, \sigma^{-2}) = \pi(\mu \mid \sigma^{-2})\pi(\sigma^{-2})$	0.0727	0.0248	[-0.2307, 0.3914]
$\pi(\mu, \sigma^{-2}) = \pi(\mu)\pi(\sigma^{-2})$	0.0749	2.5959e-05	[0.0675, 0.0828]

Both priors result in a similar mean for the marginal posterior distribution of μ that is close to the 0, the true value of μ . However, the variance under the dependent prior is greater than the variance under the independent prior. Thus, this suggests that there is a tradeoff in certainty using the conjugate joint prior (which allows us to calculate the exact marginal posterior distribution of μ) for convenience. Yet the 95% credible interval of μ for the marginal posterior under the independent prior does not contain 0, so perhaps the marginal posterior variance under the independent prior is too small practically.