1. For observations y_i , i = 1, ..., n, let Model 1 be

$$y_i|\sigma^2 \sim N(0,\sigma^2)$$

and let Model 2 be

$$y_i|\mu, \sigma^2 \sim N(\mu, \sigma^2)$$

 $\mu|\sigma^2 \sim N(0, \sigma^2/k)$

both with prior

 $\sigma^2 \sim \text{InverseGamma}(a/2, b/2)$

for σ^2 . Prior parameters k > 0, a > 0, and b > 0 are known

- (a) Calculate f(Y) for both models and give the Bayes factor B₁₂. [Note: For model 1, this is an inverse gamma integral. For model 2, first integrate with respect to (w.r.t.) μ which is proportional to the integral of a normal density. Then integrate w.r.t. σ², which is proportional to an inverse gamma integral.]
- (b) For k = a = b = n = 4, and residual sum of squares RSS = 4, plot B_{12} as a function of \bar{y} . [Include your R code on a separate page.] [You may prefer to plot $\log B_{12}$, either plot is ok.]

$$\begin{split} & \hat{f}_{1}(\Upsilon) = \int_{0}^{\infty} f(y_{1}\sigma^{2}) f(\sigma^{2}) d\sigma^{2} \\ & = \int_{0}^{\infty} \frac{1}{(2\pi\sigma^{2})^{n}/2} \exp\left(-\frac{1}{2\sigma^{2}} \frac{1}{2(y_{1}\sigma^{2})} \frac{(b_{1}z)^{n}/2}{\Gamma(n^{2}z)} (\sigma^{2})^{\frac{n}{2}} \frac{1}{\Gamma(n^{2}z)} d\sigma^{2} \\ & = \frac{1}{(2\pi)^{n}h} \frac{\left(\frac{b}{2}\right)^{n}/2}{\Gamma(\frac{a}{2})} \int_{0}^{\infty} (\sigma^{2})^{\frac{n}{2}} \exp\left(-\frac{5y_{1}^{2}}{2\sigma^{2}} - \frac{b}{2\sigma^{2}}\right) (\sigma^{2})^{\frac{n}{2}/2-1} d\sigma^{2} \\ & = \frac{1}{(2\pi)^{n}h} \frac{\left(\frac{b}{2}\right)^{n}/2}{\Gamma(\frac{a}{2})} \int_{0}^{\infty} (\sigma^{2})^{\frac{n}{2}/2-1} \exp\left(-\frac{(2y_{1}^{2}+b)/2}{\sigma^{2}}\right) d\sigma^{2} \\ & = \frac{1}{(2\pi)^{n}h} \frac{\left(\frac{b}{2}\right)^{n}/2}{\Gamma(\frac{a}{2})} \frac{\Gamma(\frac{a+n}{2})}{\left(\frac{2y_{1}^{2}+b}{2}\right)^{\frac{n}{2}}} \int_{0}^{\infty} (\sigma^{2})^{\frac{n}{2}/2-1} \exp\left(-\frac{\sum y_{1}^{2}+b}{2}\right) \frac{\left(\sum y_{1}^{2}+b\right)^{\frac{n+n}{2}}}{\Gamma(\frac{n+n}{2})} d\sigma^{2} \\ & = \frac{\left(\frac{b}{2}\right)^{n}/2}{(2\pi)^{n}h^{2}} \frac{\Gamma(\frac{a+n}{2})}{\Gamma(\frac{a}{2})} \frac{\Gamma(\frac{a+n}{2})^{\frac{n+n}{2}}}{\Gamma(\frac{a+n}{2})^{\frac{n+n}{2}}} \\ & = \frac{\left(\frac{b}{2}\right)^{n}/2}{(2\pi)^{n}h^{2}} \frac{\Gamma(\frac{a+n}{2})}{\Gamma(\frac{a+n}{2})^{\frac{n+n}{2}}} \frac{1}{\Gamma(\frac{n+n}{2})} \frac{(n+n)}{2} \frac{1}{\Gamma(\frac{n+n}{2})} \frac$$

$$\begin{split} f_{2}(\Upsilon) &= \int_{0}^{\infty} \int_{0}^{\infty} f(y|\mu,\sigma^{2}) f(\mu|\sigma^{2}) + \left(\sigma^{2}\right) d\mu d\sigma^{2} \\ &= \int_{0}^{\infty} \int_{0}^{\infty} \frac{1}{(2\pi\sigma^{2})^{N/2}} \exp\left(-\frac{1}{2\sigma^{2}} \sum_{i} (y_{i}/\mu)^{2}\right) \frac{1}{(2\pi\sigma^{2})^{1/2}} \exp\left(-\frac{1}{2\sigma^{2}} \left(\mu - 0\right)^{2}\right) \frac{\left(\frac{b|z}{2}\right)^{n/2}}{\Gamma(n/2)} \left(\sigma^{2}\right)^{N/2} \exp\left(-\frac{b|z}{\sigma^{2}}\right) d\mu d\sigma^{2} \\ &= \frac{\left(\frac{b|z}{2}\right)^{n/2}}{\Gamma(n/2)} \int_{0}^{\infty} \frac{1}{(2\pi\sigma^{2})^{N/2}} \frac{1}{(2\pi\sigma^{2})^{N/2}} \left(\sigma^{2}\right)^{\frac{n}{2}-1} \exp\left(-\frac{b|z}{\sigma^{2}}\right) \int_{0}^{\infty} \exp\left(-\frac{1}{2\sigma^{2}} \sum_{i} (y_{i}/\mu)^{2}\right) \exp\left(-\frac{1}{2\sigma^{2}} \sum_{i} (\mu - 0)^{2}\right) d\mu d\sigma^{2} \end{split}$$

$$\begin{split} &=\frac{(4\zeta_1^{N_1})_1}{\Gamma(^3(2))}\int_0^\infty \frac{1}{(2\pi)^2} \exp\{-\frac{1}{2L_1} (\overline{Q}_{11}^{-1} \overline{Q}_{11}^{-1} + \overline{Q}_{11}^{-1} \overline{Q}_{11}^{-1}) \Big\} e^{-\frac{1}{2}} \exp\{-\frac{1}{2L_1} (\overline{Q}_{11}^{-1} \overline{Q}_{11}^{-1}) \Big\} e^{-\frac{1}{2}} \exp\{-\frac{1}{2$$

$$B_{12} = \frac{f_{1}(Y)}{f_{2}(Y)}$$

$$= \left[\frac{\left(\frac{b}{2}\right)^{3/2}}{\left(\frac{2\pi}{2}\right)^{3/2}} \frac{\Gamma\left(\frac{a+n}{2}\right)}{\left(\frac{b+\Sigma y^{2}}{2}\right)^{\frac{a+n}{2}}} \right] \left[\frac{\left(\frac{b+\Sigma}{2}\right)^{3/2}}{\Gamma\left(\frac{a+n}{2}\right)} \frac{\Gamma\left(\frac{a+n}{2}\right)}{\left(\frac{1}{2}RSS+b+n\bar{y}^{2}-\frac{(n\bar{y})^{2}}{n+k}\right)^{\frac{a+n}{2}}} \frac{k^{1/2}}{\left(\frac{2\pi}{2}RSS+b+n\bar{y}^{2}-\frac{(n\bar{y})^{2}}{n+k}\right)^{\frac{a+n}{2}}} \right]$$

$$= \frac{(n+k)^{1/2} \left[\frac{1}{2}\left(RSS+b+n\bar{y}^{2}-\frac{(n\bar{y})^{2}}{n+k}\right) \frac{a+n}{2}}{k^{1/2}\left(\frac{b+\Sigma y^{2}}{2}\right)^{\frac{a+n}{2}}} \frac{(n+k)^{n\bar{y}^{2}}-n^{2}\bar{y}^{2}}{n+k} \frac{k^{n\bar{y}^{2}}+k^{n\bar{y}^{2}}-n^{2}\bar{y}^{2}}{n+k}}{k^{1/2}\left[\left(RSS+b+n\bar{y}^{2}\right)\right]^{\frac{a+n}{2}}}$$

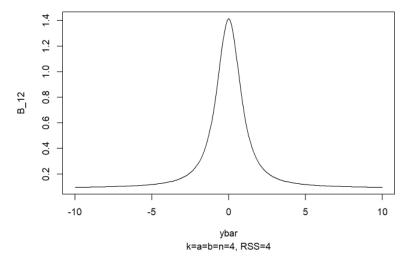
$$= \frac{(n+k)^{1/2} \left[\left(RSS+b+n\bar{y}^{2}\right)^{\frac{a+n}{2}}\right]}{k^{1/2}\left[\left(RSS+b+n\bar{y}^{2}\right)^{\frac{a+n}{2}}} \frac{(n+k)^{1/2}}{n+k} \frac{(n+k)$$

$$\beta_{12} = \left(\frac{n+k}{k}\right)^{1/2} \left[\frac{RSS + b + \frac{nk}{n+k} \overline{y}^2}{RSS + b + n\overline{y}^2} \right]^{\frac{\alpha+n}{2}}$$

```
#bayes factor of model 1 over model 2 as a function of ybar
B12 <- function(k,a,b,n,RSS,ybar) {
    sqrtterm <- sqrt((n+k)/k)
    otherterm <- ((RSS+b+((n*k)/(n+k))*ybar^2)/(RSS+b+n*ybar^2))^((a+n)/2)
    return(sqrtterm*otherterm)
}

ybar <- seq(-10,10,0.1)
B12plot <- B12(4,4,4,4,4,ybar)
#plot
plot(ybar,B12plot,xlab=expression(ybar), ylab = expression(B_12), type="1")
title(main = "Bayes Factor Model 1 over Model 2", sub = "k=a=b=n=4, RSS=4")</pre>
```

Bayes Factor Model 1 over Model 2



- 3. Use the regression model given in the theory bayes09 lecture notes but take σ^2 known.
 - (a) Derive the posterior distribution of the regression coefficients β , which is a multivariate normal distribution.
 - (b) Derive the marginal normal posterior for a single regression coefficient β_i . [Note: If you're not familiar with the properties of the multivariate normal, you can/should familiarize yourself with some of the basic properties of the multivariate normal. In particular, you are asked here to give the distribution of a single component of a multivariate normal.]
 - (c) What is the posterior probability that β_j is positive in terms of a standard normal distribution cdf? [This is a one-sided (Bayesian) p-value. Doubling this probability (or doubling one minus this probability if the probability is bigger than .5) is approximately a usual frequentist two-sided p-value, but has little value in a Bayesian context.]
 - (d) Bayesians can live with typical regression coefficient two-sided pvalues by dividing by 2 and interpreting them as in item 3c. Similarly, frequentists can take the quite interpretable Bayesian posterior probability that $\beta_i > 0$ and double it and call it a two-sided p-value (and make it difficult to interpret). [nothing to do]

YIB, o2~N(XB, o2I) where I is non identity matrix Prior $\beta \mid \sigma^2 \sim N(\beta_0, V_0 \sigma^2)$ Bo, Vo, or known

$$\alpha f(\beta|\lambda) = \frac{f(\lambda|\beta) f(\beta)}{f(\lambda)}$$

$$\alpha f(\lambda|\beta) f(\beta)$$

get the likelihood:

$$f(Y|\beta) = \prod_{i=1}^{n} \frac{1}{(2\pi 6^2 I)^{1/2}} \exp \left[-\frac{1}{26} I (Y-X\beta)' (Y-X\beta) \right]$$

$$= (2\pi)^{-n/2} \left(\sigma^2 \tilde{I}\right)^{n/2} \exp \left\{ -\frac{1}{2\sigma^2 \tilde{I}} \left[\left(\underline{Y} - \chi \hat{\beta} \right)' (Y - \chi \hat{\beta}) + (B - \hat{\beta})' (X' \chi) (B - \hat{\beta}) \right] \right\} \quad \text{where } \hat{\beta} = (X' \chi)^{-1} (X' Y) = LSE/MLE$$
 Here posterior

$$\begin{split} & + (\beta | \Upsilon) \propto \left(2\pi \right)^{-n/2} \left(\sigma^2 I \right)^{-n/2} e^{\chi p} \left\{ -\frac{1}{2\sigma^2 I} \left[RSS + (\beta - \hat{\beta})'(\chi' \chi) (\beta - \hat{\beta}) \right] \right\} \left(2\pi \int^{p/2} (\sigma^2 I)^{-p/2} e^{\chi p} \left[-\frac{1}{2\sigma^2} (\beta - \beta_0)' V_0^{-1} (\beta - \beta_0) \right] \right\} \\ & \times \left(2\pi \sigma^2 \right)^{-n/2} \left(2\pi \sigma^2 \right)^{-p/2} \left[V_0 \right]^{-1/2} e^{\chi p} \left\{ -\frac{1}{2\sigma^2} \left[RSS + \left(\beta - \hat{\beta} \right)' (\chi' \chi) (\beta - \hat{\beta}) + \left(\beta - \beta_0 \right)' V_0^{-1} (\beta - \beta_0) \right] \right\} \end{split}$$

completing the square:

expansion of orange

$$\Rightarrow \beta'(\chi'\chi)\beta + \frac{\hat{\beta}'(\chi'\chi)\hat{\beta}}{\hat{\beta}'(\chi'\chi)\hat{\beta}} - 2\hat{\beta}'(\chi'\chi)\beta + \frac{\beta'(\chi_0')\beta}{\hat{\beta}'(\chi'\chi)\beta} + \frac{\beta'(\chi_0')\beta}{\hat{\beta}'(\chi'\chi)\beta} - 2\hat{\beta}'(\chi'\chi)\beta + \frac{\beta'(\chi'\chi)\beta}{\hat{\beta}'(\chi'\chi)\beta} + \frac{\beta'(\chi_0')\beta}{\hat{\beta}'(\chi'\chi)\beta} + \frac{\beta'(\chi_0')\beta}{\hat{\beta}'(\chi')} + \frac{\beta'(\chi_0')\beta}{\hat{\beta}'(\chi')}$$

$$\rightarrow \beta' \left(\chi' \chi + V_0^{-1} \right) \beta - 2 \left[\hat{\beta} \left(\chi' \chi \right) + \beta_0' V_0^{-1} \right] \beta + \hat{\beta}' (\chi' \chi) \hat{\beta} + \beta_0' V_0^{-1} \beta_0$$

$$\rightarrow \beta'(\chi'\chi + V_0^{-1})\beta - 2 \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] \beta + \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] (\chi'\chi + V_0^{-1})^{-1} \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] - \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] (\chi'\chi + V_0^{-1})^{-1} \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] + \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right] (\chi'\chi + V_0^{-1})^{-1} \left[\hat{\beta}(\chi'\chi) + \beta_0' V_0^{-1} \right]$$

$$\rightarrow \left(\beta - \left(\chi'\chi + V_o^{-1}\right)^{-1} \left[\chi'\chi\hat{\beta} + V_o^{-1}\beta_o\right]\right)^{T} \left(\chi'\chi + V_o^{-1}\right) \left(\beta - \left(\chi'\chi + V_o^{-1}\right)^{-1} \left[\chi'\chi\hat{\beta} + V_o^{-1}\beta_o\right]\right) + \left(\hat{\beta} - \beta_o\right)' \left(\left(\chi'\chi\right)^{-1} + V_o\right)^{-1} \left(\hat{\beta} - \beta_o\right)' \left(\left(\chi'\chi\right)^{-1} + V_o\right)^{-1} \left(\hat{\beta} - \beta_o\right)' \left(\chi'\chi\hat{\beta} + V_o^{-1}\beta_o\right)' \left(\chi'\chi\hat{\beta} + V_$$

a single component of a b) β_i is multivariate normal, so that means each of the β s has a marginal normal posterior

$$\begin{split} \beta_{j} &\sim & N\left(\overline{\beta}_{j} \ , \, \sigma^{2}\left(X_{j}^{'}X_{j}^{+}V_{o,jj}^{-1}\right)^{-1}\right) \\ & \text{with} \quad \overline{\beta}_{j} \ = & \left(X_{j}^{'}X_{j}^{+}+V_{jj}^{-}\right) \left[X_{j}^{'}X_{j}^{+}\hat{\beta}_{j}^{+}+V_{ij}^{-}\hat{\beta}_{o}\right] \end{split}$$

c)
$$P(\beta_j > 0 \mid \Upsilon) = 1 - P(\beta_j < 0 \mid \Upsilon)$$

$$= \left[-\beta \left(\frac{\beta_{j} - \hat{\beta}_{j}}{SE(\hat{\beta}_{j})} < \frac{0 - \hat{\beta}_{j}}{SE(\hat{\beta}_{j})} \mid Y\right)\right]$$

$$= \left[-\beta \left(\frac{\beta_{j} - \hat{\beta}_{j}}{SE(\hat{\beta}_{j})}\right)\right]$$

$$= \left[-\beta \left(\frac{-\beta_{j}}{SE(\hat{\beta}_{j})}\right)\right]$$

$$= \left[-\beta \left(\frac{-\beta_{j}}{SE(\hat{\beta}_{j})}\right)\right]$$

$$= \left[-\beta \left(\frac{(\chi_{j}'\chi_{j} + V_{0,jj})^{-1})^{-1}(\chi_{j}'\chi_{j} + V_{0,jj}, \beta_{0})}{\sigma \left(\chi_{j}'\chi_{j} + V_{0,jj}, \beta_{0}\right)}\right]$$

$$= \left[-\beta \left(\frac{(\chi_{j}'\chi_{j}^{2} + V_{0,jj})^{-1})^{-1}(\chi_{j}'\chi_{j}^{2} + V_{0,jj}, \beta_{0})}{\sigma \left(\chi_{j}'\chi_{j} + V_{0,jj}, \beta_{0}\right)}\right]$$

$$= \left[-\beta \left(\frac{(\chi_{j}'\chi_{j}^{2} + V_{0,jj}, \beta_{0})}{\sigma \left(\chi_{j}'\chi_{j} + V_{0,jj}, \beta_{0}\right)}\right]$$