Assignment #6

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Problem 1

Part i

$$p(\beta|y,\lambda_1,\lambda_2,k) \propto p(y|\lambda_1,\lambda_2,k,\beta) \times p(\lambda_1|y,\lambda_2,k,\beta) \times p(\lambda_2|y,\lambda_1,k,\beta) \times p(k|y,\lambda_1,\lambda_2,\beta) \times p(\beta)$$

Since $p(y|\lambda_1, \lambda_2, k, \beta)$ and $p(k|y, \lambda_1, \lambda_2, \beta)$ don't depend on β , we may ignore them and our equation becomes:

$$p(\beta|y, \lambda_1, \lambda_2, k) \propto p(\lambda_1|y, \lambda_2, k, \beta) \times p(\lambda_2|y, \lambda_1, k, \beta) \times p(\beta)$$

Where:

$$p(\lambda_1|y,\lambda_2,k,\beta) = p(y|\lambda_1,\lambda_2,k)p(\lambda_1)$$
$$\sim Gamma\left(\alpha + \sum_{t=1}^k y_t, \beta + k\right)$$

$$p(\lambda_2|y,\lambda_1,k,\beta) = p(y|\lambda_1,\lambda_2,k)p(\lambda_2)$$
$$\sim Gamma\left(\alpha + \sum_{t=k+1}^n y_t, \beta + (n-k)\right)$$

So:

$$\begin{split} p(\beta|y,\lambda_{1},\lambda_{2},k) &\propto p(\lambda_{1}|y,\lambda_{2},k,\beta) \times p(\lambda_{2}|y,\lambda_{1},k,\beta) \times p(\beta) \\ &\propto \beta^{\alpha} \lambda_{1}^{\alpha-1+\sum_{t=1}^{k} y_{t}} e^{-(\beta+k)\lambda_{1}} \beta^{\alpha} \lambda_{2}^{\alpha-1+\sum_{t=k+1}^{n} y_{t}} e^{-(\beta+(n-k))\lambda_{2}} \beta^{a_{\beta}-1} e^{-b_{\beta}\beta} \\ &\propto \beta^{2\alpha} e^{-(\beta+k)\lambda_{1}-(\beta+(n-k))\lambda_{2}} \beta^{a_{\beta}-1} e^{-b_{\beta}\beta} \\ &\propto \beta^{2\alpha+a_{\beta}-1} e^{-\beta\lambda_{1}-\beta\lambda_{2}-b_{\beta}\beta} \\ &\propto \beta^{2\alpha+a_{\beta}-1} e^{-(\lambda_{1}+\lambda_{2}+b_{\beta})\beta} \\ &\sim Gamma(2\alpha+a_{\beta},\lambda_{1}+\lambda_{2}+b_{\beta}) \end{split}$$

Part ii

Please refer to the Code Appendix section for the implementation of the Gibbs sampler.

Part iii

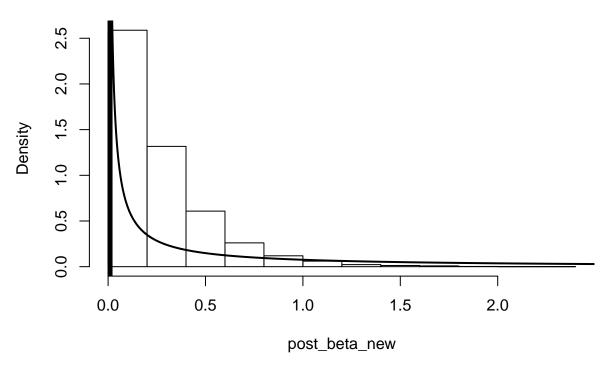
```
## HPD Interval Lambda_1 with Beta = 0.01: ( 2.591709 , 3.722968 )
## HPD Interval Lambda_2 with Beta = 0.01: ( 0.7036462 , 1.164932 )
## HPD Interval k + 1850 with Beta = 0.01: ( 1885 , 1894 )
```

```
## HPD Interval Lambda_1 with Beta Hyperprior: ( 2.544073 , 3.689083 )
## HPD Interval Lambda_2 with Beta Hyperprior: ( 0.6950561 , 1.155353 )
## HPD Interval k + 1850 with Beta Hyperprior: ( 1886 , 1895 )
```

There does not appear to be substantial difference between the posterior credible intervals of the two models.

Part iv

Histogram of post_beta_new



No. According to the results and the density representation there is not evidence to suggest the the posterior distribution $[\beta|y]$ differs substantially from our previous choice of $\beta=0.01$

Problem 2

Part i

$$\begin{split} p(y|\mu,\alpha,\beta) &= \int \frac{\beta^{\alpha}}{\Gamma(\alpha)} \tau^{\alpha-1} e^{-\beta \tau} \left(\frac{\tau}{2\pi}\right)^{\frac{1}{2}} e^{-\frac{\tau}{2}(y-\mu)^{2}} d\tau \\ &= \frac{\beta^{\alpha}}{\Gamma(\alpha)} \frac{1}{(2\pi)^{\frac{1}{2}}} \int \tau^{\alpha-\frac{1}{2}} e^{-\beta \tau} e^{-\frac{\tau}{2}(y-\mu)^{2}} d\tau \\ &= \frac{\beta^{\alpha}}{\Gamma(\alpha)} \frac{1}{(2\pi)^{\frac{1}{2}}} \int \tau^{\alpha-\frac{1}{2}} e^{-(\beta+\frac{1}{2}(y-\mu)^{2})\tau} d\tau \\ &= \frac{\beta^{\alpha}}{\Gamma(\alpha)} \frac{1}{(2\pi)^{\frac{1}{2}}} \frac{\Gamma(\alpha+\frac{1}{2})}{(\beta+\frac{1}{2}(y-\mu)^{2})^{\alpha+\frac{1}{2}}} \\ &= \frac{\Gamma(\alpha+\frac{1}{2})}{\Gamma(\alpha)} \frac{1}{(2\pi\beta)^{\frac{1}{2}}} \frac{1}{(1+\frac{1}{2\beta}(y-\mu)^{2})^{\alpha+\frac{1}{2}}} \end{split}$$

And now substituting in for z_i and our Gamma parameters for α and β we get the following result:

Histogram of t_dens

$$p(z_i) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\pi\nu}\Gamma(\frac{\nu}{2})} \frac{1}{\left(1 + \frac{z_i^2}{\nu}\right)^{\frac{\nu+1}{2}}}$$

Histogram of post_norm

Part ii

2500 2000 3000 Frequency Frequency 1500 0 0 -20 0 10 20 -200 10 20 t dens post_norm

As we can see from our result, we get similar density when comparing our results from Part i with the $t_{\nu}(0,1)$ distribution.

Part iii

Yes, this result does make sense, because whenever the variance of a normally distributed random variable is unknown and a conjugate prior placed over it that follows a Gamma distribution, the resulting marginal distribution of the variable will follow a Student's t-distribution.

Problem 3

Part i

$$p(\theta|y, \tau_y, \xi_i) \propto p(\theta)p(y|\theta, \tau_y, \xi_i)$$

$$p(\tau_y|y,\theta,\xi_i) \propto p(\tau_y)p(y|\theta,\tau_y,\xi_i)$$

$$p(\xi_i|y,\theta,\tau_y) \propto p(\xi_i)p(y|\theta,\tau_y,\xi_i)$$

Part ii

Part iii

Part iv

Part v

Code Appendix