Biostatistics 234: Lab 3

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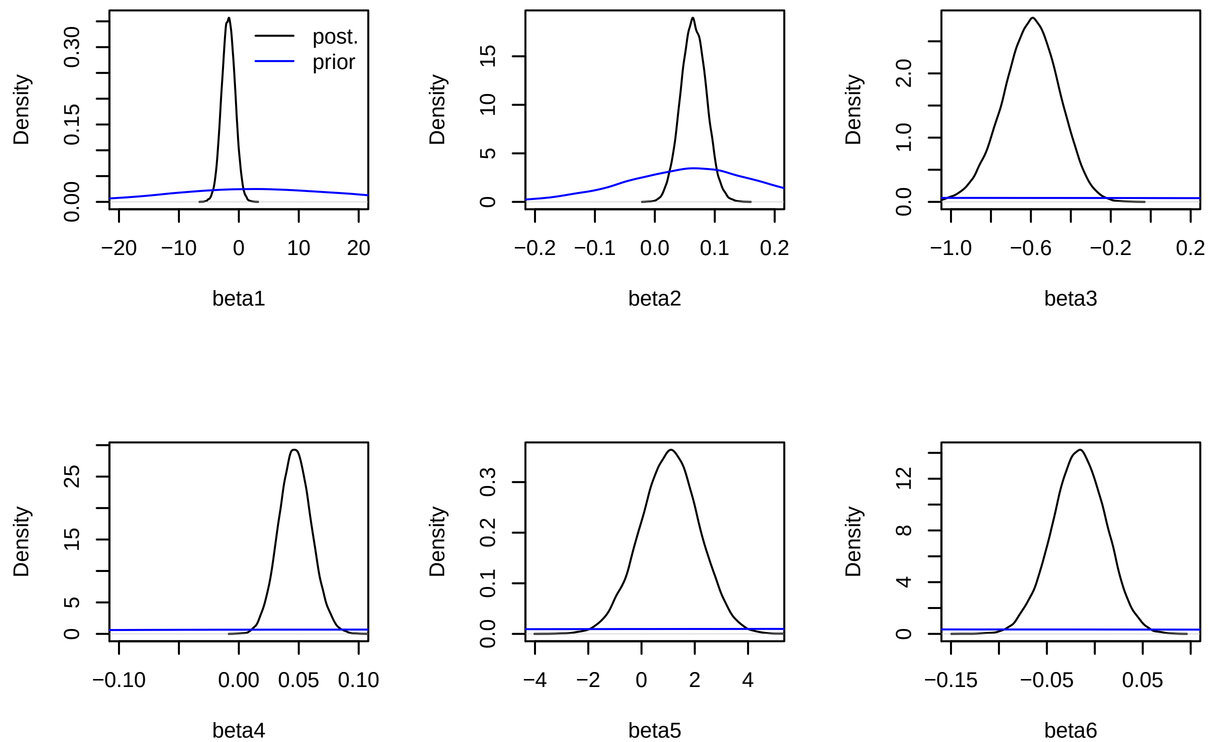
1. At what lags do the autocorrelations hit zero for the 6 regression coefficients? Are the beta autocorrelations better or worse than the 6 pi's?
   For the 6 regression coefficients, up to the 40th lag, the autocorrelation never really settled at 0 except beta4. Most petered out at 0.2 or below. They still fare better than our pi autocorrelation plots, where many autocorrelation coefficients were well above those we saw for beta coefficients. If I fiddled with the `lag.max` setting for `acf()`, I might venture that acf reaches zero at around 150 lags, but I have no idea if this is a sane thing to do.

2. Turn in your properly formatted table of output for the full data set, and turn in a set of the 6 plots of the prior and posterior for the betas.

Table 1: Posterior Distribution of Beta Coefficients and Pi for Full Data Set

Beta Coefficient	Mean	SD	2.5 pct	97.5 pct	P>0
betas[1]	-2.07	1.43	-4.95	0.68	0.07
betas[2]	0.07	0.03	0.02	0.14	0.99
betas[3]	-0.45	0.19	-0.85	-0.08	0.01
betas[4]	0.03	0.02	-0.01	0.08	0.93
betas[5]	-0.83	1.51	-3.78	2.16	0.29
betas[6]	0.02	0.04	-0.06	0.09	0.69
pie[1]	0.16	0.08	0.05	0.34	1.00
pie[2]	0.21	0.09	0.07	0.41	1.00
pie[3]	0.82	0.11	0.57	0.97	1.00
pie[4]	0.07	0.05	0.01	0.20	1.00
pie[5]	0.27	0.08	0.13	0.44	1.00
pie[6]	0.24	0.08	0.10	0.42	1.00

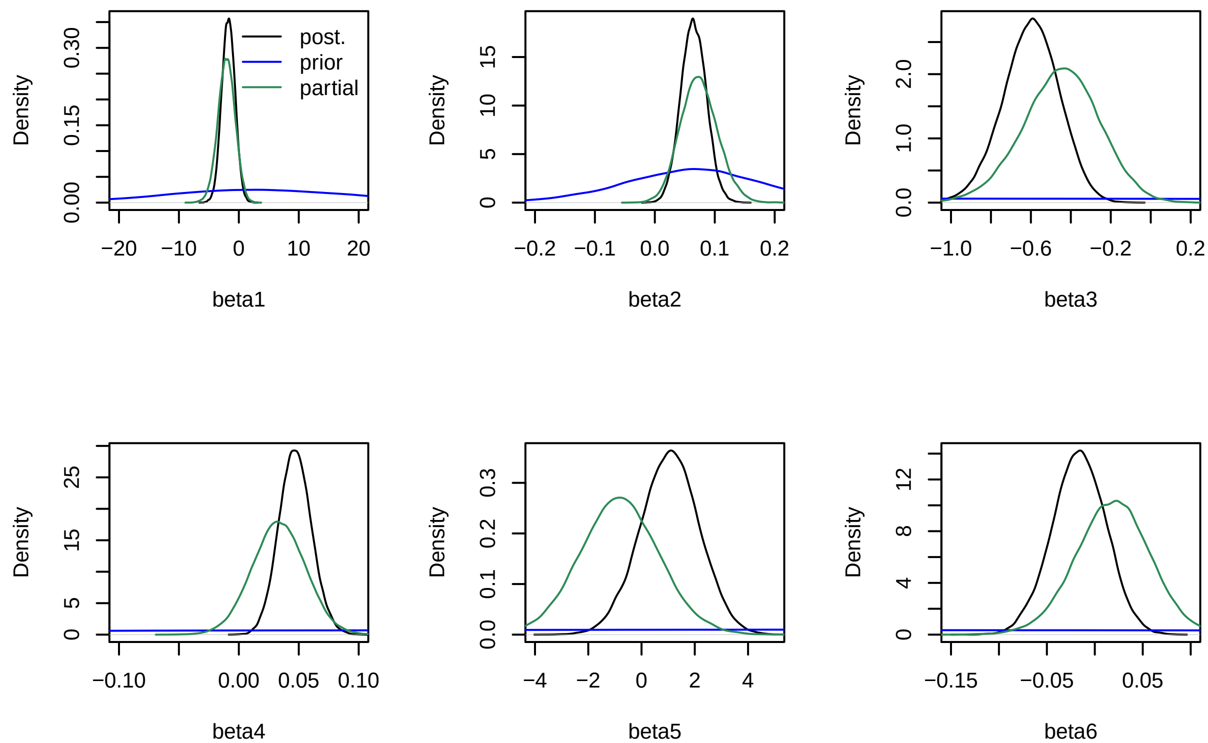


3a.

Table 2: Estimates and Standard Deviations of Coefficients in Prior Model and Posterior Models with n=100 and n=300.

Beta Coefficient	Prior mean	Prior SD	Mean|n=100	SD|n=100	Mean|n=300	SD|n=300
beta1	4.58	16.67	-2.07	1.43	-1.74	1.10
beta2	0.06	0.12	0.07	0.03	0.06	0.02
beta3	-3.03	6.51	-0.45	0.19	-0.60	0.14
beta4	0.25	0.59	0.03	0.02	0.05	0.01
beta5	15.76	41.60	-0.83	1.51	1.06	1.11
beta6	-0.44	1.18	0.02	0.04	-0.02	0.03

3b.



4. The model tracks the parameters 1 to 6, what is the interpretation of these parameters once the data has been incorporated?
   The parameters $\pi_{1:6}$ in the model represent the probability of death for the 6 hypothetical cases elicited from Dr. Osler. Once the data has been incorporated, the updated values for π_i represent the posterior estimated mean probability of death for these six cases, with slightly larger variance.

5. Extra credit: you may (but don't need to) Turn in your answer to TODO step 3.
   An attempt was made! I added three lines to predict hypothetical observaitons by adding `futurepie1 <- ilogit(betas[1] + betas[2]*2 + betas[3]*7.55 + betas[4]*25 + betas[5]*0 + betas[6]*0)` and so forth in three lines after defining the inverse logit regression's closed brackets. I managed to get Jags to run, incredibly.
   The table below shows the posterior estimates for the three cases, where the posterior probability (or do I say inverse log odds? I'm not used speaking about logistic regression) of death for case 1 = 1%, case 2 = 4%, and case 3 = 18%.

Table 3: Summary of Paramters for Hypothetical Observations

Parameter	Mean	SD	2.5	97.5	p>0
case1	0.01	0.00	0.00	0.02	1.00
case2	0.04	0.02	0.01	0.09	1.00
case3	0.18	0.16	0.01	0.60	1.00