- 1. Assume  $y \sim N(X\beta, s^2I)$  where X is  $n \times p$ .
  - (a) The prior distribution whose MAP corresponds to the ridge estimator is

$$\beta \sim N(0, \lambda^{-1} I_p)$$

In this prior,  $\lambda$  controls the amount of shrinkage. The variance of the prior is solely dependant on  $\lambda$  so as it increase, the variance decreases and becomes tighter around the mean(in this case, 0).

(b) The prior distributions whose MAP corresponds to the LASSO estimator are

$$p(\beta|\sigma^2) \propto \prod_{j=1}^p \frac{\lambda}{2\sqrt{\sigma^2}} e^{-\lambda|\beta_j|/\sqrt{\sigma^2}}$$
  
 $p(\sigma^2) \propto \frac{1}{\sigma^2}$ 

In this prior,  $\lambda$  also controls the amount of shrinkage, but it is not as straight forward as the cases before. Here we have a Laplace prior with variance  $2\frac{\sigma^2}{\lambda^2}$ . So as  $\lambda$  increases the variance will go to 0. So  $\lambda$  controls again the shrinkage, but in this case  $\sigma^2$  will also affect the how much  $\lambda$  influences shrinkage.

(c) The elastic net estimator is

$$p(\beta|\sigma^2) \propto exp\{-\frac{1}{2\sigma^2}(\lambda_1||\beta||_1 + \lambda_2||\beta||_2^2)\}$$
$$p(\sigma^2) \propto \frac{1}{\sigma^2}$$

The  $\lambda$  parameters control the blend between a Normal and Laplace distribution. When  $\lambda_2 > \lambda_1$ , the prior takes more of a form of a normal distribution which corresponds to the prior for the ridge estimator and when  $\lambda_1 > \lambda_2$ , the prior takes more of a form of a Laplace distribution which corresponds to the prior for the LASSO estimator.