Problem 2:

a Ridge Regression:
$$\hat{\beta}_{\lambda} = \underset{\beta}{\operatorname{argmin}} \left[\sum_{i=1}^{n} (\hat{y}_{i} - \hat{\beta}_{i})^{2} + \lambda \sum_{j=1}^{n} \hat{\beta}_{j}^{2} \right]$$

$$\frac{2 \log s}{\partial \beta_i} = -2(y_i - \beta_i) + 2\lambda \beta_i = 0. \implies \beta_i(2 + 2\lambda) = 2y_i - \beta_i = \frac{y_i}{\mu \lambda} \implies \beta_i = \frac{\beta_i}{\mu \lambda}$$

h. Losso Regnession:
$$\hat{\beta}_{\lambda} = \operatorname{argmin} \left[\sum_{i=1}^{n} (y_i - \hat{\beta}_i)^2 + \lambda \sum_{j=1}^{n} |\hat{\beta}_j| \right]^2$$

tend to shrink.

C. When shriking LS estimator, vidge does not LS estimator to zeros expect when it is very large. Ridge tends to shrink LS estimator to smaller value.

But the lassa tends to force some coefficients to equal zero. For example, in the example abone, when \$1 41=1 B; OLS | = = 1, lasso mill shrink them to be 0.