Page No.
Date

• Problem Statement - Part II

2 What is the optimal value of alpha for ridge and lasso regression? What will be the changes in the model if you choose double the value of alpha for both ridge and lasso? What will be the most importance predictor variable after the change is implemented?

Answer 2 The optimal value of alpha for Ridge and Lasso regression depends on the value of alpha. The value of alpha = 8 for Ridge and alpha = 0.001 for Lasso.

~~That~~ said, I can provide some general insights into the impact of doubling the alpha values for Ridge and Lasso:

1. Ridge Regression:

(1) If you double the alpha value in Ridge regression, it will increase the regulazation strength and as the result the coefficient of predictor will tend to become smaller.

(2) ~~The~~ This increased regularization will lead to a simpler model that is less likely to overfit the training data. It can help prevent ~~mult~~ multicolinearity be encouraging coefficient to be small but ~~zero~~ non zero.

(3) ~~After~~ After doubling alpha, the most importance predictor variable will likely remain the same as they were before the change. However, ~~their~~ coefficient value ~~will~~ be decreased in magnitude

2. Lasso Regression

- If we double the alpha value of lasso Regression will also increased the regularization ~~strength~~ strength. lasso use L1 Regularization, which encourages some coefficent be exactly zero. Increasing alpha make it more likely that lasso will set more coefficient to zero.

- The impact on the model will be sparsity in the coefficient vector. many predictor variable may become irrelevant (have coefficient set to zero), effectively peforming feature selection, only a subset of the most important predictor variables will have non coefficient

- After doubling alpha, the most important predictor variable will be those that lasso retains with non-zero coefficients.

Q.2 Q You have determined the optimal value of lambda for ridge and lasso regression during the assignment, Now which one will you choose to apply and why?

Answer 2.

- Ridge adds L2 regularization to the linear regression which penalizes the sum of squared coefficients.

- It is effective when you believe that most of the feature are relevent but you want to prevent multicolinearity and control the mangnitude of the coefficients

- Ridge can be good choice when you have a large number of features and you want to avoid feature selection.

- Lasso Regression

- lasso adds L1 regularization, which can leads to spare coefficient vector by setting some coefficient to exactly zero.

- It is useful when you suspect the many features are irrelevant, and you want automatic feature selection

- lasso can be good choice when we have a high-dimensional dataset and want to simplify the model by eliminating unimportant predictors.

In ~~my~~ ~~Assign~~ problem statement Lass has a slightly higher R2 score on the test data, it indicates that lasso's feature selection capability might be more suitable for my dataset. ~~es~~ effectively reducing the impact of irrelevant predictors. The choice of Lasso as the final model aligns with ~~your~~ goal for achieving better predictive performance

Question 3:

Ans. (1) 1stFlrSF
(2) 2ndFlrSF
(3) OverallQual
(4) ~~SaleCondition~~ OverallCond
(5) SaleCondition

Question 4:

How can you make sure that a model is robust and generaliable? what are the implication of the same for the accaracy of the model and why?

Answer.

The model should be as simple as possible, though its accuracy will decreased but it will be more robust and generalisable. It can also understanding the using ~~of~~ the ~~bo~~ bias - variance trade - off. The simpler model the more the bias but less variance and more generalizable.