

### Question 1

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

Answer:

The optimal Lambda Value:

- Ridge 0.8
- Lasso .0001

On Doubling the value of alpha for Ridge Regression, the model try to make most coefficients value to zero. And in case of Lasso Regression, coefficients variable reduced to zero and  $r^2$  decreases.

Important Predictor Variable:

- Zoning classification
- Living area square feet
- Overall quality
- Condition of the house
- Foundation type
- Number of cars that can be accommodated in the garage
- Total basement area in square feet and the Basement finished square feet area

### Question 2

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:

Lasso is chosen based its mean Squared error value is slightly lesser than Ridge and the value of coefficients for few feature are more bound towards zero. Therefore Lasso has better edge.

### Question 3

After building the model, you realized that the five most important predictor variables in the lasso model are not available in the incoming data. You will now have to create another model excluding the five most important predictor variables. Which are the five most important predictor variables now?

Answer:

- GrLivArea
- OverallQual
- OverallCond
- TotalBsmtSF
- GarageArea

### Question 4

How can you make sure that a model is robust and generalisable? What are the implications of the same for the accuracy of the model and why?

Answer:

Per, Occam's Razor— given two models that show similar 'performance' in the finite training or test data, we should pick the one that makes fewer on the test data due to following reasons:-

- Simpler models are usually more 'generic' and are more widely applicable
- Simpler models require fewer training samples for effective training than the more complex ones and hence are easier to train.
- Simpler models are more robust.
  - Complex models tend to change wildly with changes in the training data set
  - Simple models have low variance, high bias and complex models have low bias, high variance
- Simpler models make more errors in the training set. Complex models lead to overfitting — they work very well for the training samples, fail miserably when applied to other test samples

Therefore to make the model more robust and generalizable, make the model simple but not simpler which will not be of any use.

Regularization can be used to make the model simpler. Regularization helps to strike the delicate balance between keeping the model simple and not making it too naïve to be of any use. For regression, regularization involves adding a regularization term to the cost that adds up the absolute values or the squares of the parameters of the model.

Also, Making a model simple lead to Bias-Variance Trade-off:

- A complex model will need to change for every little change in the dataset and hence is very unstable and extremely sensitive to any changes in the training data.
- A simpler model that abstracts out some pattern followed by the data points given is unlikely to change wildly even if more points are added or removed.

Bias quantifies how accurate is the model likely to be on test data. A complex model can do an accurate job prediction provided there is enough training data. Models that are too naïve, for e.g., one that gives same answer to all test inputs and makes no discrimination whatsoever has a very large bias as its expected error across all test inputs are very high. Variance refers to the degree of changes in the model itself with respect to changes in the training data. Thus accuracy of the model can be maintained by keeping the balance between Bias and Variance as it minimizes the total error as shown in the below graph:

