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Question1)

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 important predictor variables after the change is implemented?

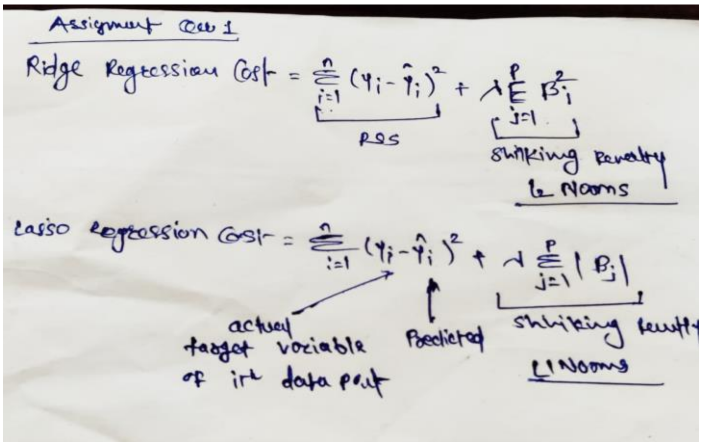
Answer 1)

Optimal value of alpha:

• Optimal alpha (lambda) value for Ridge Regression model is: **8**

• Optimal alpha (lambda) value for Lasso Regression model is: **0.0006**

let's understand the see the cost functions of Ridge and Lasso



both the cases penalty term increases with higher value of beta co efficient. Ridge imposes more aggressive penalty as it uses sum of square of all beta coefficients (L2 norm) as shrinking penalty. Where Lasso uses sum of absolute values of all beta coefficients (L1 norm) as shrinking penalty.

So after doubling the alpha the variable id **OverallQual**.

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 2)

As per Occam's Razor a model should not be unnecessary complex.

Model complexity depends on two main things: No. of features or independent variables and Magnitude of beta coefficients.

Normalization (Ridge and Lasso) already shrinks beta coefficients towards zero.

Now, Lasso and Ridge both have similar r2 score and MAE on test dataset. But Lasso has eliminated 110 features and final no. of features in Lasso Regression model is 116. Where Ridge has all 226 features. So, the Lasso model is simpler than Ridge with having similar r2 score and MAE.

Ridge:

r2 score on testing dataset: 0.8911807696767164

MSE on testing dataset: 0.018419435953924413

RMSE on testing dataset: 0.135718222630288

MAE on testing dataset: 0.09344961892214859

Lasso:

r2 score on testing dataset: 0.8947392213072709

MSE on testing dataset: 0.01781710976847528

RMSE on testing dataset: 0.13348074680820182

MAE on testing dataset: 0.09142208307508749

As these two models shows almost similar performance on test dataset, we should choose the simpler model. So, I will choose Lasso as my final model

Question 3)

After building the model, you realised 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 3)

Initially top 5 features in Lasso model are as below:

GrLivArea 0.377281 (Above grade (ground) living area square feet)

OverallQual 0.309806 (Rates the overall material and finish of the house)

OverallCond 0.144188 (Rates the overall condition of the house)

Neighborhood_StoneBr 0.136858 (Dummy variable of Neighborhood = Stone Brook)

GarageArea 0.134759 (Size of garage in square feet)

As Neighborhood_StoneBr is a dummy variable, dropping entire Neighborhood feature.

After dropping GrLivArea, OverallQual, OverallCond, GarageArea, Neighborhood features, rebuilt the Las

so model again with rest of the features, now 5 most important predictor variables are as below.

1stFlrSF 0.402011 (First Floor square feet)

2ndFlrSF 0.369645 (Second floor square feet)

GarageType_Not Present -0.136456 (Dummy variable of GarageType= No Garage)

KitchenQual_TA -0.132718 (Dummy variable of Kitchen quality Typical/Average)

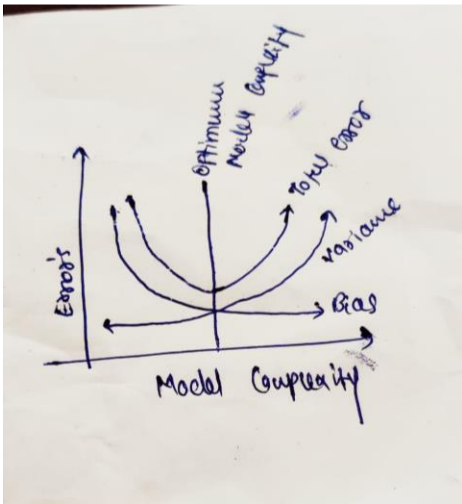
Exterior1st_BrkFace 0.130630 (Dummy variable of Exterior covering on house is Brick Face.

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 4)

A model should be complex enough so that it learns the data patters in the training dataset but not too complex that it also learns noises in the training dataset. The model should be generalized enough and not so complex that it memorizes all datapoints in training dataset. An underfitting model usually has high bias and low variance. It fails to understand data pattern in training dataset, so it performs bad both on training and testing dataset. Whereas an overfitting model usually has low bias and high variance. It performs good on training dataset but performs bad on testing dataset or unseen data. A scenario of overfitting can be identified easily by comparing model performance in training and testing dataset. If there is a significant difference in model performance (r2 score, model accuracy, MAE, RMSE, Confusion Matrix etc. other evaluation metrics) on training and testing dataset then it's a case of overfitting. A robust model should have low bias and low variance and it should not suffer from underfitting and overfitting. It can be achieved by doing a trade-off between bias and variance. One of the ways to remove overfitting to create a robust and generalizable model is to reduce model complexity.



Model complexity depends on two main things: **Number of features or independent variables** and **Magnitude of beta coefficients.** Normalization (Ridge and Lasso) already shrinks beta coefficients towards zero. Again, Lasso also helps to reduce number of features by shrinking some beta coefficients to exact 0. Thus, it helps to overcome overfitting. Accuracy of a robust and generalizable model should be almost same/closer on training and testing datasets.