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 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 value for alpha for the Ridge Regression model is 1.273 while for the Lasso model it is 0. If we double the alpha for the Ridge model, the model performance will more or less remain the same with slightly more bias. For Lasso, since the optimal alpha is 0, doubling it will not change the model.

1. After doubling the alpha, for the Ridge model, the top 5 most important features will be:
2. Area of second floor (2ndFlrSF)
3. Whether or not the roof is made of wood shingles (RoofMatl_WdShngl)
4. Age of the house in years at the time of sale (YrsAtSale)
5. Whether or not the house is in Stone Brooks neighbourhood (Neighborhood_StoneBr)
6. Rating of finished area of a Type 1 basement (BsmtFinSF1)

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:
Although the accuracy of Ridge and Lasso models appear to be similar, the Ridge model is slightly more promising due to the r-squared score being slightly higher and the MAE/RMSE values being slightly lower.

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:
The five most important predictors in descending order of importance will be:
1. Whether or not the house is in Northridge
2. Whether or not the house is in Stone Brook
3. Area of Masonry Veneer
4. Number of fireplaces
5. Whether or not the house is in Northridge Heights

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:
A model is considered robust and generalisable if it has similar performance on both training and test sets, provided that the test set is treated as a hold-out and is unseen data from the model's perspective. To achieve this, we may use one or more of the following regularisation approaches:

1. Reducing the number of features to the most relevant ones
2. Eliminating features which exhibit high multicollinearity
3. Tuning the lambda (or alpha) parameter in a linear regression model with cross-validation

There is a tradeoff between model complexity and model generalisability in that a more complex model tends to overfit and is less generalisable. Regularisation reduces the complexity by introducing bias. Due to this, the training accuracy of the model may be compromised slightly but the accuracy on the unseen test data increases, thus making the model more generalisable to unseen data in the real world. In most business use cases, however, the focus is more on the generalisability of the model than the accuracy.