**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 :**

Ridge Optimum Alpha: {'alpha': 5.0}

Lasso Optimum Alpha: {'alpha': 0.001}

For double the optimum value of Ridge and Lasso, we see overfitting as the accuracy score on Training Data becomes 100% and that of Testing Data becomes significantly less.

**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 :**

Ridge as both performed well on Train Data, but Ridge performed slightly better on test dataset.

**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 :**

Next 5 important predictors are as follows:

1. OverallQual_8
2. SaleCondition_Partial
3. Neighborhood_NridgHt
4. CentralAir_Y
5. Neighborhood_Crawfor

**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 :**

To ensure a model's robustness and generalizability, several strategies are employed. Cross-validation divides the dataset into subsets for iterative training, assessing average error to ensure robustness. Regularization, like Ridge and Lasso regression, prevents overfitting by constraining coefficients. Detecting and treating outliers enhances model robustness.

Simpler models, being more generic, require fewer training samples, making them easier to train and more robust. They exhibit low variance and high bias, unlike complex models. Maintaining simplicity without making the model too naive is crucial for the Bias-Variance trade-off. Regularization aids in managing model complexity by shrinking coefficients towards zero, striking the balance between simplicity and utility. This balance, known as Optimum Model Complexity, ensures models are both generalizable and robust, avoiding underfitting or overfitting.

Regularization's role in achieving the Bias-Variance trade-off is essential. By penalizing complex models, it ensures the model remains optimal in simplicity. Simplicity, in turn, ensures generalizability while mitigating overfitting risks. Hence, a delicate balance between Bias and Variance is pivotal for model accuracy, ensuring accurate predictions on new unseen data while avoiding model instability.