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?

The optimal alpha value is 100 and 0.0001 for Ridge and Lasso respectively.

Doubling the alpha value in the Ridge algorithm has decreased the training score slightly and increased the test score slightly, leaving a smaller gap between them.

Doubling the alpha value in the Rasso algorithm, the training score has decreased slightly, and the testing score has increased slightly, leading to a smaller gap between them.

Here are the top predictors:

1. GrLivArea
2. OverallQual
3. TotalBsmtSF
4. GarageCars
5. YearBuilt

All the supportive data is included in the Jupyter Notebook.

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?

The optimal lambda value for Ridge and Lasso is as follows:

- Ridge - 100
- Lasso - 0.0001

The output parameters for both algorithms are as follows:

	Metric	Linear Regression	Ridge Regression	Lasso Regression
0	R2 Score (Train)	9.540862e-01	0.946622	0.913740
1	R2 Score (Test)	-1.933115e+20	0.894967	0.889829
2	RSS (Train)	4.050066e-02	0.047084	0.076090
3	RSS (Test)	6.483831e+19	0.035229	0.036952
4	MSE (Train)	6.532779e-03	0.007044	0.008954
5	MSE (Test)	3.991339e+08	0.009304	0.009528

Since Lasso helps in feature reduction as well, it has a better use case and should be used in the final model.

Question 3
After building the model, you realise 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?

The five most important predictors are as follows:

1. BsmtFinSF1
2. FullBath
3. BsmtUnfSF
4. Fireplaces

5. YearRemodAdd

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?

Occam's Razor principle in machine learning helps us develop a model to ensure robustness and generalizability. Here's how Occam's Razor can be applied, along with its implications for model accuracy:

Simplicity in Model Selection:
- Choose a simpler model over a complex one if it provides comparable or sufficient performance. A simpler model is less likely to overfit the training data and is often more interpretable.
- Implication for Accuracy: Selecting a simpler model may lead to slightly lower training accuracy because it has fewer parameters to fit the data closely. However, this simplicity can enhance generalizability, potentially leading to better test accuracy.

Feature Selection:
- Prioritize essential features and eliminate irrelevant or redundant ones. Occam's Razor encourages selecting a minimal set of features that adequately represent the problem.
- Implication for Accuracy: Feature selection may reduce training accuracy because you discard some information. However, it can improve generalization by focusing on the most informative features, leading to better test accuracy.

Regularization Techniques:
- Apply regularization methods like L1 (Lasso) and L2 (Ridge) regularization. These techniques introduce simplicity by penalizing complex models with large coefficients.
- Implication for Accuracy: Regularization can lead to a decrease in training accuracy as it discourages the model from fitting noise in the data. However, it often results in improved test accuracy and generalizability.

Model Complexity:
- Be cautious when increasing the complexity of a model. Occam's Razor suggests that additional complexity should only be added if there's a clear benefit in terms of predictive performance.

- Implication for Accuracy: Increasing model complexity, such as adding more layers to a neural network, may lead to higher training accuracy. However, it can also increase the risk of overfitting and harm generalization, potentially reducing test accuracy.

Cross-Validation and Testing:

- Employ cross-validation to assess how well the model generalizes to unseen data. Occam's Razor encourages considering multiple validation sets and choosing the simplest model that performs adequately across all of them.
- Implication for Accuracy: Cross-validation provides a more realistic estimate of model performance on unseen data. It may reveal that a simpler model consistently performs better across different data subsets.

In summary, Occam's Razor promotes the idea that simpler models and explanations are preferred when they adequately capture the underlying patterns in the data. The implications for model accuracy involve trade-offs: sacrificing a bit of training accuracy in favour of simpler models can often lead to improved generalizability and better performance on unseen data. This aligns with the principle that a simpler model is more likely to generalize well to new, real-world situations and avoid overfitting the training data.