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 of alpha for ridge regression is 1.0 & for lasso regression is 0.0001

The evaluation metrics table before doubling is:

Metrics	Ridge Regression	Lasso Regression
R2 Score (Train)	0.903	0.905
R2 Score (Test)	0.850	0.847
RSS (Train)	11.889	11.710
RSS (Test)	4.126	4.190
MSE (Train)	0.012	0.012
MSE (Test)	0.017	0.017
RMSE (Train)	0.110	0.110
RMSE (Test)	0.130	0.131

The evaluation metrics after doubling the alpha for Ridge(alpha = 2.0) & Lasso(alpha = 0.0002):

Metrics	Ridge Regression	Lasso Regression
R2 Score (Train)	0.902	0.903
R2 Score (Test)	0.851	0.848
RSS (Train)	12.093	11.887
RSS (Test)	4.096	4.186
MSE (Train)	0.012	0.012
MSE (Test)	0.017	0.017
RMSE (Train)	0.111	0.110
RMSE (Test)	0.129	0.131

Changes in the model after doubling the alpha:
1. R2 Score for train data for Ridge Regression is similar (changed from 0.903 to 0.902)
2. R2 Score for test data for Ridge Regression is similar (changed from 0.903 to 0.902)
3. R2 Score for train data for Lasso Regression is similar (changed from 0.905 to 0.903)
4. R2 Score for test data for Lasso Regression is similar (changed from 0.847 to 0.848)

The important predictor variables after the change is implemented is:
For Ridge:
1) OverallQual_9 1.297
2) OverallQual_10 1.202
3) OverallCond_9 1.196
4) OverallQual_8 1.194
5) OverallCond_8 1.124

For Lasso:
1) OverallQual_9 1.405
2) OverallQual_10 1.358
3) OverallQual_8 1.267
4) OverallCond_9 1.210
5) OverallQual_7 1.150

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:
The model which I choose will depend on the use-case of business. If we have many features and if one of the main goals is to do feature selection then we should use Lasso Regression. But if we do not want to get many coefficients and reduction of coefficient magnitude is one of our main goals then we should use Ridge Regression.

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 predictor variables after removing the previous important predictor variables are:
1) GrLivArea - 1.084
2) MSSubClass_70 - 1.084
3) MSSubClass_45 - 1.074
4) 2ndFlrSF - 1.045
5) TotalBsmtSF - 1.045

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 robust when any variation in the data does not affect its performance much.
A generalizable model is able to adapt properly to new, previously unseen data, drawn from the same distribution as the one used to create the model.

To make sure a model is robust and generalizable, we have to make sure that it doesn't overfit. This is because an overfitting model has very high variance and a smallest change in data affects the model prediction heavily. Such a model will identify all the patterns of a training data, but it fails when it comes to unseen test data. The model should be as simple as possible in order to be robust and generalizable. If we look at it from the perspective of Accuracy, a complex model will have a very high accuracy.

So, to make our model more robust and generalizable, we will have to decrease variance which will lead to some bias. Addition of bias means that accuracy will decrease. In general, we have to find some balance point between model accuracy and complexity. This can be achieved by Regularization techniques like Ridge Regression and Lasso Regression.