**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?**

For Ridge, the optimal lambda is 5 and for Lasso it is 0.0001. Doubling the value of alpha for both would cause increased regularization.For Ridge, the coefficient values would be driven closer to 0 and their effect would be greatly reduced in making predictions. For Lasso, many of the less important predictor variables would be driven to exactly 0, thereby completing their effect.

The overall effect has not changed the relative importance of the most important predictors, it has simply reduced their effect via the coefficient. Although the lasso has removed more variables. The test set predictions have improved in the ridge over the lasso after doubling the alpha values

**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?**

While the lasso has created a simpler model by removing columns, the ridge regression has created a better model based on its performance on the training set.
For that reason, I would choose the ridge regression model

**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?**

Initially the 5 most important predictor variables were GrLivArea, OverallQual, RoofMatl_WdShngl, TotalBsmtSF and PoolArea. After removing them, the new model has returned 1stFlrSF, 2ndFlrSF, BsmtFinSF1, Neighborhood_NoRidge and OverallCond as the most important features.

**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?**

Regularization is one way to make a model more robust and generalisable. However, this often comes at the cost of accuracy. While an overfit model shows enormous bias, it cannot be used for new data. Regularization will improve the accuracy of a model and work to ensure that the model performs better on unseen data. However, the accuracy will not be comparable to that of an overfit model on its training data.