Upgrad_AdvanceRegression_Assignment

Assignment Part-I

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them on at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file below.

The company is looking at prospective properties to buy to enter the market. You are required to build a regression model using regularisation in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

The company wants to know:

Which variables are significant in predicting the price of a house, and

How well those variables describe the price of a house.

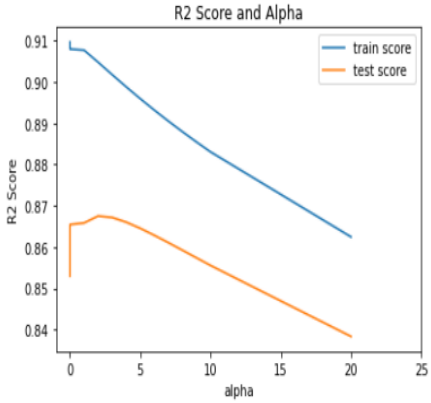
Also, determine the optimal value of lambda for ridge and lasso regression.

Ans:

We can achieve an R2 score of 0.82 approx. on both Ridge and Lasso Models. The following factors influence the house price the most as demonstrated by both the models: -

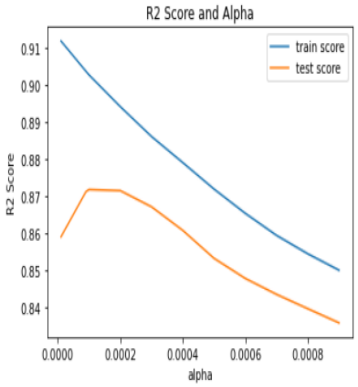
1. Total area in square foot
2. Total Garage Area
3. Total Rooms
4. Overall Condition
5. Lot Area
6. Centrally Air Conditioned
7. Total Porch Area (Open + Enclosed)
8. Kitchen Quality
9. Basement Quality

Ridge:




```
The optimum alpha is 2
The R2 Score of the model on the test dataset for optimum alpha is 0.8258394031247365
The MSE of the model on the test dataset for optimum alpha is 0.001864007950262306
```

Lasso:




```
The optimum alpha is 0.0001
The R2 Score of the model on the test dataset for optimum alpha is 0.8231592337039928
The MSE of the model on the test dataset for optimum alpha is 0.0018926932969937145
```

Below table shows the coefficient of variables for which impact the price of a house.

	Ridge Co-Efficient
Total_sqr_footage	0.167731
GarageArea	0.104111
TotRmsAbvGrd	0.068551
OverallCond	0.052918
LotArea	0.041469
CentralAir_Y	0.032767
Total_porch_sf	0.031969
LotFrontage	0.030305
Neighborhood_StoneBr	0.028500
Alley_Pave	0.025663
OpenPorchSF	0.024080
HouseStyle_2.5Unf	0.023737
SaleType_Con	0.022325
MSSubClass_70	0.021980
RoofMatl_WdShngl	0.021741
Neighborhood_Veenker	0.021442
KitchenQual_Ex	0.019886
PavedDrive_P	0.019255
LandContour_HLS	0.018917
BsmtQual_Ex	0.018651

	Lasso Co-Efficient
Total_sqr_footage	0.200198
GarageArea	0.114437
TotRmsAbvGrd	0.064891
OverallCond	0.053381
LotArea	0.040558
CentralAir_Y	0.034611
Total_porch_sf	0.027883
OpenPorchSF	0.023204
Neighborhood_StoneBr	0.022415
Alley_Pave	0.022256
KitchenQual_Ex	0.017480
LandContour_HLS	0.017460
BsmtQual_Ex	0.017379
MSSubClass_70	0.017111
Condition1_Norm	0.016175
MasVnrType_Stone	0.014430
HouseStyle_2.5Unf	0.013045
SaleCondition_Partial	0.012813
Neighborhood_Veenker	0.012706
PavedDrive_P	0.012383

Optimum value of Alpha:

	Ridge	Lasso
Optimum Value (Alpha)	2	0.0001

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?**

Optimum value of Alpha:

	Ridge	Lasso
Optimum Value(Alpha)	2	0.0001
R^2 value	0.825839403	0.823159234

Ridge Doubled:

The R2 Score of the model on the test dataset for doubled alpha is 0.8235972351125412
The MSE of the model on the test dataset for doubled alpha is 0.0018880054507046655
The most important predictor variables are as follows:

	Ridge Doubled Alpha Co-Efficient
Total_sqr_footage	0.148016
GarageArea	0.094081
TotRmsAbvGrd	0.069258
OverallCond	0.048294
LotArea	0.036888
Total_porch_sf	0.034023
CentralAir_Y	0.032699
LotFrontage	0.026451
Neighborhood_StoneBr	0.026016
OpenPorchSF	0.023831
Alley_Pave	0.023027
MSSubClass_70	0.021137
BsmtQual_Ex	0.020605
HouseStyle_2.5Unf	0.020556
KitchenQual_Ex	0.020298
Neighborhood_Veenker	0.019264
MasVnrType_Stone	0.018646
RoofMatl_WdShngl	0.017094
PavedDrive_P	0.017046
Condition1_Norm	0.016618

	Ridge Co-Efficient
Total_sqr_footage	0.167731
GarageArea	0.104111
TotRmsAbvGrd	0.068551
OverallCond	0.052918
LotArea	0.041469
CentralAir_Y	0.032767
Total_porch_sf	0.031969
LotFrontage	0.030305
Neighborhood_StoneBr	0.028500
Alley_Pave	0.025663
OpenPorchSF	0.024080
HouseStyle_2.5Unf	0.023737
SaleType_Con	0.022325
MSSubClass_70	0.021980
RoofMatl_WdShngl	0.021741
Neighborhood_Veenker	0.021442
KitchenQual_Ex	0.019886
PavedDrive_P	0.019255
LandContour_HLS	0.018917
BsmtQual_Ex	0.018651

Remarks: Not much change is observed for Ridge model if we choose to double the alpha value. In general, if the alpha value changes, ridge regression shrinks coefficient slowly. So after the doubling the value if alpha, we observe the Coeff magnitude value changes slightly for the variables but overall structure of model remain as like as before.

Lasso Doubled:

The R2 Score of the model on the test dataset for doubled alpha is 0.8202721121912073
The MSE of the model on the test dataset for doubled alpha is 0.0019235936128502332
The most important predictor variables are as follows:

	Lasso Doubled Alpha Co-Efficient
Total_sqr_footage	0.201693
GarageArea	0.108873
TotRmsAbvGrd	0.066041
OverallCond	0.048903
CentralAir_Y	0.034681
Total_porch_sf	0.029209
LotArea	0.020733
OpenPorchSF	0.020062
BsmtQual_Ex	0.018493
Alley_Pave	0.018251
KitchenQual_Ex	0.017100
Neighborhood_StoneBr	0.016484
LandContour_HLS	0.014801
MSSubClass_70	0.013783
MasVnrType_Stone	0.013449
SaleCondition_Partial	0.013298
Condition1_Norm	0.013286
BsmtCond_TA	0.012271
LotConfig_CulDSac	0.009277
PavedDrive_Y	0.008315

	Lasso Co-Efficient
Total_sqr_footage	0.200198
GarageArea	0.114437
TotRmsAbvGrd	0.064891
OverallCond	0.053381
LotArea	0.040558
CentralAir_Y	0.034611
Total_porch_sf	0.027883
OpenPorchSF	0.023204
Neighborhood_StoneBr	0.022415
Alley_Pave	0.022256
KitchenQual_Ex	0.017480
LandContour_HLS	0.017460
BsmtQual_Ex	0.017379
MSSubClass_70	0.017111
Condition1_Norm	0.016175
MasVnrType_Stone	0.014430
HouseStyle_2.5Unf	0.013045
SaleCondition_Partial	0.012813
Neighborhood_Veenker	0.012706
PavedDrive_P	0.012383

Remarks: In general, Lasso reg is sensitive to changes in alpha value, higher alpha means strong regularization, feature elimination, results simpler model. But in our case, alpha value is so small, so that much change is not observed while doubling the alpha value. Only CentralAir_Y becomes the 5th imp variable for model (Lasso Doubled).

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?

	Ridge	Lasso
Optimum Value(Alpha)	2	0.0001
R^2 value	0.825839403	0.823159234
MSE Value	0.001864008	0.001892693

The purpose of Ridge and Lasso Reg is to prevent overfitting and generalize the performance of model by regularizing the Coeff value to balance between model complexity and performance.

If we observe the MSE value, Ridge's MSE value is slightly smaller than Lasso. It means the Ridge performs better than Lasso. But as we have lots of feature to predict the house price and we need to understand the impact of all these features and find out the most effective one, I will prefer for Lasso, as it helps in feature reduction.

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?

The R2 Score of the model on the test dataset is 0.7320779798657091
The MSE of the model on the test dataset is 0.0028675187415574824

```
#Removing the 5 most important predictor variables from the incoming dataset
X_test_rfe3 = X_test_rfe2.drop(['Total_sqr_footage','GarageArea','TotRmsAbvGrd','OverallCond','LotArea'],axis=1)
X_train_rfe3 = X_train_rfe2.drop(['Total_sqr_footage','GarageArea','TotRmsAbvGrd','OverallCond','LotArea'],axis=1)

# Building Lasso Model with the new dataset
lasso3 = Lasso(alpha=0.0001,random_state=100)
lasso3.fit(X_train_rfe3,y_train)
lasso3_coef = lasso3.coef_
y_test_pred = lasso3.predict(X_test_rfe3)
print('The R2 Score of the model on the test dataset is',r2_score(y_test, y_test_pred))
print('The MSE of the model on the test dataset is', mean_squared_error(y_test, y_test_pred))
lasso3_coeff = pd.DataFrame(np.atleast_2d(lasso3_coef),columns=X_train_rfe3.columns)
lasso3_coeff = lasso3_coeff.T
lasso3_coeff.rename(columns={0: 'Lasso Co-Efficient'},inplace=True)
lasso3_coeff.sort_values(by=['Lasso Co-Efficient'], ascending=False,inplace=True)
print('The most important predictor variables are as follows:')
lasso3_coeff.head(6)
```

```
The R2 Score of the model on the test dataset is 0.7320779798657091
The MSE of the model on the test dataset is 0.0028675187415574824
The most important predictor variables are as follows:
```

	Lasso Co-Efficient
LotFrontage	0.144437
Total_porch_sf	0.073134
HouseStyle_2.5Unf	0.067730
HouseStyle_2.5Fin	0.048093
CentralAir_Y	0.043735
Neighborhood_StoneBr	0.040785

Five most important predictor variable:

Lasso Co-Efficient	
LotFrontage	**0.144437**
Total_porch_sf	**0.073134**
HouseStyle_2.5Unf	**0.067730**
HouseStyle_2.5Fin	**0.048093**
CentralAir_Y	**0.043735**

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?

Ans:

If two model provide similar performance, in the training and testing data, we should choose simple model, as simple model captures the essential patterns in the data without overfitting to noise. Simple model more robust to change in the training data. Simple model requires fewer training data.

So as per Occam's razor, "A predictive model has to be as simple as possible, but no simpler".

There are few techniques that helps to keep final model simpler.

Regularization techniques like Lasso and Ridge regularization used to prevent overfitting and improve generalization.

Avoiding overly complex models that might memorize the training data instead of learning general patterns. Simpler models often have better generalization.

Making a model simpler, leads to Bias - Variance Trade off: Bias -variance trade-off is a fundamental concept of machine learning which can deals with finding the right balance between model simplicity and complexity. High bias model underfit the data, it generates high training error, and high-test error. A high variance model, overfits the training data, capturing noise and fluctuations rather than underlying patterns. For that, it generates low train error but high-test error.

Our goal is to find out the optimal point, where the total error is minimized which leads to best possible generalize performance on unseen data. Accuracy of the model, can be maintained by keeping the balance between Bias and Variance as it minimizes the total error.