### **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:

Optimal value of lambda

for Ridge: 15for Lasso: 0.0008

## What will be changes if you choose double the value of alpha for both ridge and lasso?

After doubling the value of the alpha there is slight change in the coefficient value of the features but top 10 features remain the same.

## For Ridge Regression

Features	Coefficient	Coefficient_For_doubleAlpha
GrLivArea	0.110593	0.105753
OverallQual	0.068810	0.069439
TotalBsmtSF	0.070680	0.069362
BuiltAge	-0.069544	-0.064613
MSZoning_RL	0.067292	0.048743
OverallCond	0.047467	0.046716
MSZoning_FV	0.048355	0.038302
GarageType_Attchd	0.036619	0.033496
Neighborhood_Crawfor	0.030129	0.030140
GarageArea	0.026599	0.028191

## For Lasso Regression

Features	Coefficient	Coefficient_For_doubleAlpha
GrLivArea	0.115444	0.115192
OverallQual	0.071738	0.075312
BuiltAge	-0.072759	-0.074585
TotalBsmtSF	0.071450	0.070909
OverallCond	0.048981	0.050023
GarageArea	0.026973	0.028961
Neighborhood_Crawfor	0.029629	0.028364
Foundation_PConc	0.024511	0.024733
Exterior1st_BrkComm	-0.026680	-0.024163
BsmtUnfSF	-0.024908	-0.023415

## Mean Square Error

## For Ridge Regression

MSE(alpha=15)	MSE(alpha=30)
0.0133209	0.013498

# For Lasso Regression

MSE(alpha=0.0008)	MSE(alpha=0.0016)
0.013214	0.013610

With increase in alpha value from optimal there is also increase in Mean Square value.

## r2\_score

## For Ridge Regression

r2_score (alpha=15)	r2_score (alpha=30)
0.909551	0.908342

# For Lasso Regression

r2_score (alpha=0.0008)	r2_score (alpha=0.0016)
0.910274	0.907586

With increase in alpha value from optimal there is also **decrease** in **r2\_score**.

## What will be most important predictor variable after change is implemented?

## For Ridge Regression

Features(alphaOptimal) Features(alphaDouble)
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GrLivArea	GrLivArea
OverallQual	OverallQual
TotalBsmtSF	TotalBsmtSF
BuiltAge	BuiltAge
MSZoning_RL	MSZoning_RL
OverallCond	OverallCond
MSZoning_FV	MSZoning_FV
GarageType_Attchd	GarageType_Attchd
Neighborhood_Crawfor	Neighborhood_Crawfor
GarageArea	GarageArea

For Lasso Regression

Features(alphaOptimal) Features(alphaDouble)

GrLivArea	GrLivArea
OverallQual	OverallQual
BuiltAge	BuiltAge
TotalBsmtSF	TotalBsmtSF
OverallCond	OverallCond
GarageArea	GarageArea
Neighborhood_Crawfor	Neighborhood_Crawfor
Foundation_PConc	Foundation_PConc
Exterior1st_BrkComm	Exterior1st_BrkComm
BsmtUnfSF	BsmtUnfSF

Although value of alpha also varies value of coefficient, but top 10 features remains the same.

### **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:

Optimal value of lambda

for Ridge: 15for Lasso: 0.0008

### Mean Square Error

For Ridge Regression	For Lasso Regression
0.0133209	0.013214

Lasso Regression has lesser mean square value as compared to Ridge

## r2\_score

For Ridge Regression	For Lasso Regression
0.909551	0.910274

R2\_score of Lasso is better than Ridge Regression.

In this scenario, Lasso out performs Ridge Regression. It performs better in both accuracy matrix of mean square error and r2\_score. Along with regularization it also does the feature selection by eliminating features. So **Lasso model is predicting better than Ridge.** 

#### **Ouestion 3**

After building the model, you realized 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:

After rebuilding of the model, five important features are

BsmtFinSF1 : Type 1 finished square feet
 FullBath : Basement full bathrooms

• BsmtUnfSF : Unfinished square feet of basement area

• GarageArea: Size of garage in square feet

• OverallCond: Rates the overall material and finish of the house

Features and Coefficient value of the new model:

Features	Coefficient
BsmtFinSF1	0.06
FullBath	0.06
BsmtUnfSF	0.05
GarageArea	0.05
OverallCond	0.04

```
plt.figure(figsize=(20,20))
plt.subplot(4,3,1)
sns.barplot(y = 'Features', x='Coefficient', palette='Set1', data = lasso_df_top5)
plt.show()
   BsmtFinSF1
      FullBath
    BsmtUnfSF
   GarageArea
   OverallCond
           0.00
                   0.01
                          0.02
                                  0.03
                                         0.04
                                                0.05
                                                        0.06
                                  Coefficient
```

#### **Ouestion 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:

As per Occam's Razor given two models that show similar performance in the finite training or test data, we should pick the one that makes fewer errors on test data.

- Robust models are more generic and more widely applicable.
- Robust models requires fewer training samples for effective training than complex model
- Robust models are easier to train
- Robust models are more simple where complex models tends to change more with data set
- Robust models have low variance and high bias.

Therefore to make model more robust and generalizable model should be simple but very simple model is not much use.

Regularization can be used to make model more simple. Regularization helps to strike the delicate balance between keeping the model simple and not making it too naïve to be of any use.

Accuracy and Robustness may be at the odds to each other as too much accurate model can be prey to over fitting hence it can be too much accurate on train data but fails on real time data.

