#### **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?

### Optimal Alpha value:

Lasso: 0.2 with High R2 Train 80% and R2Test 72% Ridge: 0.2 with High R2 Train 91% and R2Test 87%

If we double the Alpha Model will underfit in both cases. Most important feature as per the model is "OverallQual"

#### 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? Lasso is the one I feel to apply, Lasso can be used to identify the important features and not important features as well. All Zero marked Features are not important for this Model.

```
lr.coef
         Training R2: 0.8584758800065541
         Testing R2: 0.7839201869657713
ut[248]: array([-6.77770732e-04,
                                 0.00000000e+00,
                                                   2.17664934e-06, -0.00000000e+00,
                -0.00000000e+00, 0.0000000e+00,
                                                   0.0000000e+00, -0.0000000e+00,
                -0.00000000e+00, -0.0000000e+00,
                                                   2.79667619e-04, -0.00000000e+00,
                -0.00000000e+00,
                                 0.00000000e+00.
                                                   0.00000000e+00,
                                                                    6.03054178e-02.
                 2.70917109e-02,
                                  3.47248502e-03,
                                                   2.15982041e-03,
                                                                    0.00000000e+00.
                -0.00000000e+00,
                                  0.00000000e+00, -0.0000000e+00, -0.0000000e+00,
                 1.56769075e-06,
                                  0.00000000e+00,
                                                   0.00000000e+00, 3.87044309e-03,
                 -0.00000000e+00,
                                  0.00000000e+00,
                                                   0.00000000e+00, -4.94389951e-03,
                 1.13036399e-04,
                                  0.00000000e+00,
                                                   8.13171920e-05,
                                                                    5.00738309e-05,
                 3.73168044e-05, -0.00000000e+00,
                                                  -0.00000000e+00, -0.00000000e+00
                                 2.10107955e-04,
                 0.00000000e+00,
                                                   2.47445238e-04,
                                                                    2.53790783e-04
                                  0.00000000e+00,
                 3.84570660e-05,
                                                   0.00000000e+00,
                                                                    0.00000000e+00.
                 0.00000000e+00.
                                  0.00000000e+00, -0.0000000e+00,
                                                                    0.00000000e+00.
                 0.00000000e+00,
                                 0.00000000e+00,
                                                   0.00000000e+00, -1.22947026e-02,
                 -1.60083092e-03, -7.15030148e-04, -0.00000000e+00,
                                                                    0.00000000e+00,
                 2.39458958e-04, -0.00000000e+00,
                                                   0.00000000e+00, -0.0000000e+00,
                 1.21703626e-04, -7.32864735e-05,
                                                   2.07856519e-04, 1.96402817e-04,
                 3.03431553e-04, -1.74571263e-03,
                                                   0.00000000e+00,
                                                                    0.00000000e+00,
                 0.00000000e+00, -2.47588251e-06,
                                                    0.0000000e+00, -0.0000000e+00,
                 0.00000000e+00, -0.0000000e+00])
```

## Using Lasso its easy to find out important features as

```
In [254]: X_cols = house.drop(["Id", "SalePrice", "TransformedPrice"], axis=1)
         print(pd.DataFrame({'feature':list(X_cols.columns),
                                     :abs(lr.coef_)}).sort_values('coef',ascending=False)[:10].sort_index())
                             coef'
                  feature
             OverallQual 0.060305
         16 OverallCond 0.027092
               YearBuilt 0.003472
         17
         18 YearRemodAdd 0.002160
         27
              Foundation 0.003870
         31 BsmtFinTypel 0.004944
         55 FireplaceQu 0.012295
              GarageType 0.001601
         57 GarageYrBlt 0.000715
                 PoolArea 0.001746
```

# Question 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?

So five most important features after dropping earlier most important features are

- YearBuilt
- YearRemodAdd
- Functional
- Fireplaces
- GarageType

## **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?

Ideal goal is to have a best fit model which is not overfitting or underfitting. In terms of regularization, zero alpha is always an unregularised model and high alpha is underfitting. Target to get a model with lower total error that mean low bias and low variance. Robust and generalized, its model is always less complex so it's not overfitting.