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 and lasso regression

Ridge Alpha 1

lasso Alpha 10

```
Q
                           √ [84] #final ridge model
                                                                          ridge = Ridge(alpha=alpha)
                                                                            ridge.fit(X_train, y_train)
                                                                            ridge.coef_
                                                                                                                             1.44146209e-03, 1.36106893e-02, -2.04566096e-03, 7.21093263e-03, 1.06190103e-02, -1.48410955e-02, -1.1080859e-03, -6.4206774e-03, 4.2656908e-02, 6.20215605e-02, 1.56874391e-02, 2.13169821e-03,
                                                                                                                               2.43132363e-02, -5.00429742e-02,
                                                                                                                                                                                                                                                                                                                                                      4.82147056e-03,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  3.82128670e-02,
                                                                                                                             3.57786613e-02, 4.68948900e-02, -1.30779655e-02, -3.54872267e-02, -7.81303691e-03, -7.13321112e-03,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  2.74817043e-02,
                                                                                                                             -6.57361354e-03. -4.05279914e-03. -2.37900445e-02.
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  1.68568833e-02
                                                                                                                        -6.57361354e-03, -4.05279914e-03, -2.37908445e-02, 5.11106548e-02, -1.4867912e-02, 1.05581702e-01, -2.8560776e-02, -6.06433919e-02, -4.79013337e-02, -9.83964176e-03, -1.10216221e-02, -1.51395258e-02, 8.10376872e-02, -2.436139e-02, 19213995e-02, -8.86179689e-03, -6.86279082e-02, 5.98375227e-02, -8.96176869e-02, -1.9527572e-02, -3.89026016e-02, -9.1592573e-04, -5.88955630e-02, -2.78553943e-02, -2.73502205e-02, 3.22987509e-02, 1.44038695e-02, -1.96667812e-02, -4.1975804e-02, -9.56386558e-02, -2.70687388e-03, -6.8972206e-02, 3.4718803e-03, -7.17645674e-02, -4.68972206e-02, 3.4718803e-03, -5.75646603e-03, -1.71654874e-03, -7.71654874e-03, -7.7164874e-03, -7.7164874e-03,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  -7.88181138e-02
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  -2.79855433e-02
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  1.01967843e-02,
-7.36057418e-03,
                                                                                                                                                                                                                                    5.76146063e-03, -1.17654874e-02,
2.63172202e-03, -4.70301842e-03,
-1.70522077e-02, 1.52728526e-02,
                                                                                                                                 3.47128203e-03,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  5.14374472e-03,
-2.53322107e-02,
                                                                                                                               2.89146911e-02,
                                                                                                                               2.64626121e-03,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  9.95671023e-03,
                                                                                                                                                                                                                                        7.17003929e-03,
4.70926975e-03,
5.77613930e-02,
                                                                                                                                                                                                                                                                                                                                                5.22091324e-03,
4.80611734e-02,
-6.78511140e-04,
                                                                                                                                 3.28590278e-02,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  9.02768552e-03,
                                                                                                                                 4.44505350e-03.
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  -1.79681072e-03
                                                                                                                             -2.40629341e-02,
                                                                                                                                                                                                                                                                                                                                                                                                                                                                  -5.51601332e-03.
                                                                                                                                                                                                                                    5.77613920e-02, -6.78511140e-04, -5.51601332e-03, 1.4956225e-03, 1.04539910e-02, 1.27583416e-02, -1.56257788e-02, 2.18939419e-02, -1.16517683e-02, -1.79681072e-03, -2.15351615e-02, 9.51457156e-03, 1.02551716e-02, 1.6973319e-02, 2.15471304e-02, 0.00000000e0e00, 0.6685613e-03, 1.15407946e-03, 1.4192864e-02, 8.98429244e-03, -2.6017749e-02, 7.49077662e-03, 1.37693314e-03, -7.91610438e-03, 5.04979986e-03, 1.20592438e-02, -1.71559658e-02, 1.754645129-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.049774762-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.0497747e-03, 2.09617171e-02, 3.0497747e-03, 2.0961747e-03, 3.0497747e-03, 3.04974747e-03, 3.04974747e-03, 3.04974747e-03, 3.0497474e-03, 3.0497474e-03, 3.049747e-03, 3.0497474e-03, 3.049747e-03, 3.0497474e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049744e-03, 3.049746e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.04974e-03, 3.0497
                                                                                                                           -2.40629341e-02,
-9.51640567e-03,
2.72013419e-03,
1.29009144e-02,
-6.78511140e-04,
1.60115507e-02,
-1.71440087e-02,
<>
                                                                                                                               1.29184974e-02,
2.47444481e-02,
=
                                                                                                                               0.00000000e+00, 1.75446132e-03, 2.09031171e-02, 3.49017247e-02,
```

```
8.33800651e-04, 1.50848661e-02, -1.14610835e-02, -3.35850403e-03, 0.00000000e+00, 2.18919185e-02, 1.63004115e-02, 5.63301076e-02,
                   -1.75304274e-03, 1.58255446e-03, 3.16783027e-02, 1.05242166e-02, -5.65399589e-03, 1.11955255e-02, 6.53251658e-03, 1.69351597e-02,
                    4.85192588e-02, 3.16783027e-02])
[85] #lets predict the R-squared value
          y_train_pred = ridge.predict(X_train)
          print(metrics.r2_score(y_true=y_train, y_pred=y_train_pred))
          0.9220052627340902
[86] # Prediction on test set
          y_test_pred = ridge.predict(X_test)
         print(metrics.r2_score(y_true=y_test, y_pred=y_test_pred))
          0.8855289803702381
[87] # Printing the RMSE value
         {\tt mean\_squared\_error}({\tt y\_test},\ {\tt y\_test\_pred})
          0.018835074908961153
   Lasso Regression

√ [88] #lasso

        params = {'alpha': [0.00005, 0.0001, 0.001, 0.008, 0.01]}
        lasso = Lasso()
        # cross validation
        lasso_cv = GridSearchCV(estimator = lasso,
                                  param_grid = params,
                                  scoring= 'neg_mean_absolute_error',
                                  cv = folds,
                                  return_train_score=True,
                                  verbose = 1)
        lasso_cv.fit(X_train, y_train)
        Fitting 5 folds for each of 5 candidates, totalling 25 fits
        GridSearchCV(cv=5, estimator=Lasso(),
param_grid={'alpha': [5e-05, 0.0001, 0.001, 0.008, 0.01]},
return_train_score=True, scoring='neg_mean_absolute_error',
                      verbose=1)
[89] cv_results_l = pd.DataFrame(lasso_cv.cv_results_)
[90] print(lasso_cv.best_params_)
       print(lasso_cv.best_score_)
        {'alpha': 0.0001}
-0.08331689574723347
```

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?

The r2_score of lasso is slightly higher than lasso for the test dataset so we will choose lasso regression to solve this problem.

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 -

```
Lasso Regression
✓ [88] #lasso
        params = {'alpha': [0.00005, 0.0001, 0.001, 0.008, 0.01]}
        lasso = Lasso()
        # cross validation
        lasso_cv = GridSearchCV(estimator = lasso,
                                  param_grid = params,
                                  scoring= 'neg_mean_absolute_error',
                                  cv = folds,
                                  return_train_score=True,
                                  verbose = 1)
        lasso_cv.fit(X_train, y_train)
        Fitting 5 folds for each of 5 candidates, totalling 25 fits
        GridSearchCV(cv=5, estimator=Lasso(),
                      param_grid={\alpha\: [5e-05, 0.0001, 0.001, 0.008, 0.01]},
return_train_score=True, scoring=\neg_mean_absolute_error\
[89] cv_results_l = pd.DataFrame(lasso_cv.cv_results_)
(90] print(lasso_cv.best_params_)
        print(lasso_cv.best_score_)
        {'alpha': 0.0001}
         -0.08331689574723347
```

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 -

The model should be generalized so that the test accuracy is not lesser than the training score. The model should be accurate for datasets other than the ones which were used during training. Too much importance should not given to the outliers so that the accuracy predicted by the model is high. To ensure that this is not the case, the outliers analysis needs to be done and only those which are relevant to the dataset need to be retained. Those outliers which it does not make sense to keep must be removed from the dataset. If the model is not robust, It cannot be trusted for predictive analysis.