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?

As per my Gridsearch (hyper turning) to find the best of Alpha it was
Alpha of ridge = 4.0
Alpha of Lasso ==100

So You can see that the Model Evaluation on the r2 square . As we used hyper parameter the R2 square we expect that to be reduced when we double that as the alpha we found is the best . The below output is demonstrated in the Jupyter note book.

You can see that the coefficient mostly remind the same but the Feature order changed a little bit .
Example the "TotalBsmtSF" took precedence in the Ridge vs Ridge alpha value when doubled .

Since the overall alpha values are small , we don't expect huge change in the model after doubling the alpha.

In [137]:
```
coeficient[['Ridge','Ridge - Double']].sort_values(by=['Ridge - Double'],ascending=False).head(20)
```

Out[137]:

	Ridge	Ridge - Double
GrLivArea	57925.28082	48856.72185
1stFlrSF	49673.24560	42400.14285
OverallQual	48425.36245	41842.23485
BsmtFinSF1	38255.78583	33046.64796
TotRmsAbvGrd	35231.45786	32443.88648
Neighborhood_StoneBr	37728.07136	31383.39813
TotalBsmtSF	34520.52538	31005.16570
2ndFlrSF	30596.12783	25095.93952
GarageArea	20871.35590	21769.81039
GarageCars	20463.89902	21521.43214
MasVnrArea	22228.35958	21260.10103
FullBath	19709.88213	19637.94225
OverallCond	26107.86060	19317.27190
BsmtExposure_Gd	19590.53052	19274.21616
Neighborhood_NoRidge	19054.50123	18215.32180
Neighborhood_NridgHt	17289.73095	18194.53865
LotArea	21721.06436	17843.71974
Neighborhood_Crawfor	15546.94435	15274.15679
LotFrontage	15619.74089	14369.15795
Fireplaces	10736.62859	13930.54294

Out[113]:

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Ridge Regression Double	Lasso Regression Double
0	R2 Score (Train)	0.89068	0.93521	0.93168	0.92818	0.92298
1	R2 Score (Test)	0.86456	0.92320	0.91943	0.92215	0.91401
2	RSS (Train)	553541216983.70300	328070961373.04523	345960567096.70441	363675656679.49542	390005939478.66406
3	RSS (Test)	296807333068.61591	168308305200.07724	176566344688.97595	170603672243.01233	188431007930.71878
4	MSE (Train)	25549.18529	19669.16708	20198.32584	20709.00294	21445.57447
5	MSE (Test)	26647.05218	20066.17671	20552.55515	20202.54332	21231.86014

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?

The optimal data as per my Modelling is

Ridge – 4.0
Lasso – 100

From the below we can see that the MSE are

Ridge ~ 20066
Lasso ~ 20552

Ridge Regression did better for me as the Test score and the Training score are good.

Generally, Lasso should perform better in situations where only a few among all the predictors that are used to build our model have a significant influence on the response variable. So, feature selection, which removes the unrelated variables, should help. But Ridge should do better when all the variables have almost the same influence on the response variable.

Based on my model build I will go with the Ridge regression model looking at the R2 Square and also MSE values

Out[113]:

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Ridge Regression Double	Lasso Regression Double
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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?

Below are the New top predictors when we removed the first top 5 feature on the Lasso Model

- **1stFlrSF**
- **2ndFlrSF**
- **TotalBsmtSF**
- **TotRmsAbvGrd**
- **MasVnrArea**
- **MasVnrArea**

The work is documented in the Jupyter notebook if you want to have a check

```
R2 Score for the taining set for LASSO : 0.9204005141035227
R2 Score for the Test set for LASSO    : 0.9103152223221794
RSS For Train set for LASSO            : 403064166453.66144
RSS For Test set for LASSO             :  403064166453.66144
MSE for tain set for LASSO             : 475311517.0444121
MSE for tain set for LASSO             : 470181954.0057159
```

In [172]:

```
#important predictor variables
coefficeint_after_removal = pd.DataFrame(index=X_train2.columns)
coefficeint_after_removal.rows = X_train2.columns
coefficeint_after_removal['lasso_remove_top_features'] = lasso_remove_top_features.coef_
pd.set_option('display.max_rows', None)
coefficeint_after_removal.sort_values(by=['lasso_remove_top_features'],ascending=False)
```

Out[172]:

	lasso_remove_top_features
1stFlrSF	155948.04897
2ndFlrSF	100456.58411
TotalBsmtSF	80456.86750
TotRmsAbvGrd	36662.68378
MasVnrArea	29670.42352
SaleType_New	26531.73827
Functional_Typ	23374.65261
GarageCars	22666.79925
BsmtExposure_Gd	20807.69514
GarageArea	20371.37610
Neighborhood_Crawfor	19540.94857
YearBuilt	18339.98192
LotFrontage	13949.73326
Neighborhood_NoRidge	13015.83153
Neighborhood_NridgHt	12790.96276
MSZoning_FV	10780.89363
MasVnrType_Stone	9593.12732
GarageType_BuiltIn	9501.84863
BsmtFinType1_GLQ	9295.69835
YearRemodAdd	9125.31120
LandContour_HLS	8598.73200
SaleCondition_Normal	8069.22300
MSZoning_RL	8047.91873
ScreenPorch	7701.12061
WoodDeckSF	7700.16017
Condition1_Norm	7544.08790

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?

Occam's razor is perhaps the most important thumb rule in machine learning and is incredibly 'simple' at the same time. When in dilemma, choose the simpler model. The question then is 'how do we define simplicity?'. In the next segment, you will learn about some objective ways to measure model simplicity and understand why simplicity is preferred over sophistication and complexity using various examples.

The model should have more or less the test accuracy as the training score.Outliers shouldn't dominate the data . IF the model is not robust then it cannot be considered for predictive analysis

Overfitting

Overfitting is a phenomenon wherein a model becomes highly specific to the data on which it is trained and fails to generalise to other unseen data points in a larger domain. A model that has become highly specific to a training data set has 'learnt' not only the hidden patterns in data but also the noise and the inconsistencies in it. In a typical case of overfitting, a model performs quite well on the training data but fails miserably on the test data.
the

- **A simpler model is usually more generic than a complex model. This becomes important because generic models are bound to perform better on unseen data sets.**
- **A simpler model requires fewer training data points. This becomes extremely important because in many cases, one has to work with limited data points.**
- **A simple model is more robust and does not change significantly if the training data points undergo small changes.**
- **A simple model may make more errors in the training phase but is bound to outperform complex models when it views new data. This happens because of overfitting.**

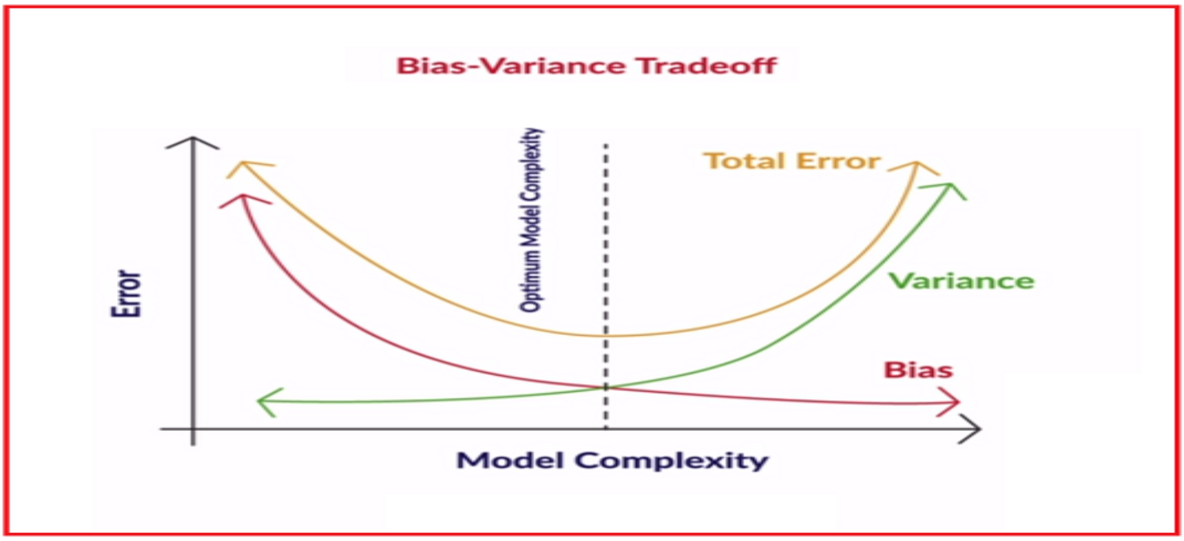
Bias and Variance

We considered the example of a model memorising the entire training data set. If you change the data set slightly, this model will also need to change drastically. The model is, therefore, unstable and sensitive to changes in training data, and this is called high variance.

The 'variance' of a model is the variance in its output on some test data with respect to the changes in the training data. In other words, variance here refers to the degree of changes in the model itself with respect to changes in the training data.

Bias quantifies how accurate the model is likely to be on future (test) data. Extremely simple models are likely to fail in predicting complex real-world phenomena. Simplicity has its own disadvantages.

Ideally, we want to reduce both bias and variance because the expected total error of a model is the sum of the errors in bias and variance, as shown in the figure given below.



Bias Variance Tradeoff

In practice, however, we often cannot have a model with a low bias and a low variance. As the model complexity increases, the bias reduces, whereas the variance increases and, hence, the trade-off.
The output of our calculation from the above it is evident that Total Error = Bias+Variance, we could also see that the MSE calculated from the sckit-library is almost equal to average expected loss.
This is demonstrated in the Jupyter notebook if you want to refer. Do install the "mlextend" module .
It can be observed that the Bias has been reduced after regularization and there is a slight increase in variance and the total avg error is also brought down

In [199]:
```
from mlxtend.evaluate import bias_variance_decomp
from sklearn import metrics
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
##print(type(X_train))
models = [lm_rfe, ridge, lasso]

for model in models:
    mse, bias, var = bias_variance_decomp(model, X_train.values, y_train.values, X_test.values, y_test.values, loss
    y_pred=model.predict(X_test)
    # summarize results
    print()
    print('MSE for  from bias_variance lib [avg expected loss]: %.3f' % mse)
    print('Avg for  Bias                                       : %.3f' % bias)
    print('Avg for Variance                                    : %.3f' % var)
    print('Mean for Square error by Sckit-learn lib            : %.3f' % metrics.mean_squared_error(y_test,y_pred))

```

```
MSE for  from bias_variance lib [avg expected loss]: 741227611.708
Avg for  Bias                                      : 511918691.077
Avg for Variance                                   : 229308920.630
Mean for Square error by Sckit-learn lib           : 987085612.466

MSE for  from bias_variance lib [avg expected loss]: 471148472.931
Avg for  Bias                                      : 400011499.972
Avg for Variance                                   : 71136972.960
Mean for Square error by Sckit-learn lib           : 567372034.120

MSE for  from bias_variance lib [avg expected loss]: 464035996.410
Avg for  Bias                                      : 404288075.437
Avg for Variance                                   : 59747920.973
Mean for Square error by Sckit-learn lib           : 534948830.194
```

In [ ]:
```

```