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:

```
The optimal value of alpha for Ridge is 3 and for Lasso it is 0.0001. With th
ese alphas the R2 of the model was approximately -49984230.116980396. After d
oubling the alpha values in the Ridge and Lasso, the prediction accuracy rema
ins around -98942082.29880337 but there is a small change in the co-efficient
values. The new model is created and demonstrated in the Jupiter notebook. Be
low are the changes in the co-efficient.
```

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:
```
The optimum lambda value in case of Ridge and Lasso is as follows:-
Ridge – 3
Lasso – 0.0001
The Mean Squared Error in case of Ridge and Lasso are:
Ridge - 534971.7781257404
Lasso - 1058958.416504369

The Mean Squared Error of both the models are almost same.
Since Lasso helps in feature reduction (as the coefficient value of some of t
he features become zero), Lasso has a better edge over Ridge and should be us
ed as the final model.
```

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?

Answer:
```
The five most important predictor variables in the current lasso model is:-
1. Co-efficient Total_sqr_footage
2. GarageArea
3. TotRmsAbvGrd
4. OverallCond
5. LotArea

We build a Lasso model in the Jupiter notebook after removing these attribute
s from the dataset.
The R2 of the new model without the top 5 predictors drops to -77011.55488010
631. The Mean Squared Error increases to 824.2508187391229
```

Lasso Co-Efficient
```
-----------------------------------------------------
LotFrontage                      0.146535
Total_porch_sf                   0.072445
HouseStyle_2.5Unf                0.062900
HouseStyle_2.5Fin                0.050487
Neighborhood_Veenker             0.042532
```

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?

Answer:
```
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 on the test da
ta due to following reasons:-
▪ Simpler models are usually more 'generic' and are more widely applicable ▪
Simpler models require fewer training samples for effective training than the
more complex ones and hence are easier to train.
▪ Simpler models are more robust.
o Complex models tend to change wildly with changes in the training data set
o Simple models have low variance, high bias and complex models have low bias
, high variance
o Simpler models make more errors in the training set. Complex models lead to
overfitting — they work very well for the training samples, fail miserably wh
en applied to
other test samples Therefore, to make the model more robust and generalizable
, make the model simple but not simpler which will not be of any use. Regular
```

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