# **Subjective Questions**

# 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?

#### Ans:

- Optimal value of alpha for Ridge regression is 4 and for and Lasso regression is 0.0001
- Doubling the value of alpha for Ridge and Lasso regression does not have much impact on the overall model, as the value of alpha is relatively small even after doubling. Only few variable coefficients got changed

	Original			Double				
Scores Ridge	R2 Score (Train): 0.9177 R2 Score (Test): 0.91 MSE (Train): 0.0031 MSE (Test): 0.0035			R2 Score (Train): 0.9096 R2 Score (Test): 0.9028 MSE (Train): 0.0034 MSE (Test): 0.0037				
Scores Lasso	R2 Score (Train): 0.921 R2 Score (Test): 0.9111 MSE (Train): 0.003 MSE (Test): 0.0034			R2 Score (Train): 0.9162 R2 Score (Test): 0.91 MSE (Train): 0.0032 MSE (Test): 0.0035				
Coefficients		Feaure	Coef			Feaure	Coef	
Ridge	4	OverallCond	0.177514		4	OverallCond	0.14922	
	14	BsmtFullBath	0.158376		14	BsmtFullBath	0.133575	
	12	2ndFlrSF	0.132886		12	2ndFlrSF	0.112319	
	9	BsmtUnfSF	0.106383		9	BsmtUnfSF	0.101844	
	11	1stFlrSF	0.099609		11	1stFlrSF	0.087729	
	3	OverallQual	0.097416		3	OverallQual	0.084024	
	13	GrLivArea	0.07795	25	WoodDeckSF	0.066441		
	5	YearBuilt	0.072816		13	GrLivArea	0.064381	
	6	YearRemodAdd	0.068456		24	GarageArea	0.064366	
	25	WoodDeckSF	0.066429		21	Fireplaces	0.059508	

Coefficient		Feaure	Coef		Feaure	Coef
Lasso	14	BsmtFullBath	0.412989	14	BsmtFullBath	0.434021
	4	OverallCond	0.241747	4	OverallCond	0.257981
	11	1stFlrSF	0.135308	11	1stFlrSF	0.116751
	6	YearRemodAdd	0.122261	6	YearRemodAdd	0.111505
	3	OverallQual	0.112172	3	OverallQual	0.104172
	5	YearBuilt	0.096480	9	BsmtUnfSF	0.093742
	9	BsmtUnfSF	0.091181	5	YearBuilt	0.090535
	24	GarageArea	0.068852	51	Neighborhood_Edwards	0.068406
	158	GarageType_Attchd	0.067541	24	GarageArea	0.062794
	67	Neighborhood_Timber	0.067411	61	Neighborhood_OldTown	0.058646

# **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?

#### Ans:

As R2 Score and Mean Square Error for both the Ridge and Lasso is the same, we would choose Lasso as it does feature reduction by making the coefficients as zero. This helps in simplifying the 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?

## Ans:

Top 5 predictor in the current Lasso model is

	Feaure	Coef
14	BsmtFullBath	0.412989
4	OverallCond	0.241747
11	1stFlrSF	0.135308
6	YearRemodAdd	0.122261
3	OverallQual	0.112172

After removing these predictor and rebuilding the Lasso model we get the next top 5 predictors as

	Feaure	Coef
10	TotalBsmtSF	0.490116
8	BsmtFinSF1	0.169520
4	OverallCond	0.122421
6	YearRemodAdd	0.103936
3	OverallQual	0.093818

### With scores as

R2 Score (Train): 0.9067 R2 Score (Test): 0.8917

MSE (Train): 0.0035 MSE (Test): 0.0042

## **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?

#### Ans:

As per Occam's Razor, given two models that shows similar performance within finite set of training and test data, we should select a simpler model

Simpler models are more generic and require few training samples hence easier to train. It has low variance and higher bias

Complex model changes wildly with changes in a training data. It has low bias and higher variance. Complex model may lead to overfitting

Therefore, to make a model robust and generalizable, make the model simple but not simpler. Regularization can be used to make the model simple but not too naïve. It makes sure that the model lies in between bias-variance trade-off