SUBJECTIVE QUESTIONS

Advanced Linear Regression Part-II

C44 Group

Shrinivas Bhat
s.shrinivas.bhat@gmail.com

Table of Contents

Assignment-II 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 to 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 for Ridge = 7, Optimal value for Lasso = 0.0001 (Model-1: Target variable is log transformed and min-max scaled ***Refer: Model Summary***)
- With the alpha doubled there is degradation seen in R2-score of Ridge and Lasso
- With alpha doubling the RSS/RMSE of Ridge and Lasso regression degraded for training data but improved for test-data. This implies that increasing the regularization factor is improving the generalization by trading of residual errors in training data by improving it in test-data.

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	7.000000	0.000100	0.000100
1	R2 Score (Train)	0.853000	0.953000	0.959000	0.955000
2	R2 Score (Test)	0.760000	0.899000	0.890000	0.892000
3	RSS (Train)	10.952758	3.504164	3.060471	3.353166
4	RSS (Test)	7.527175	3.178369	3.461134	3.376821
5	RMSE (Train)	0.103574	0.058584	0.054750	0.057308
6	RMSE (Test)	0.131093	0.085185	0.088894	0.087805

Figure 1 Scores with alpha

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	14.000000	0.000200	0.000200
1	R2 Score (Train)	0.853000	0.945000	0.950000	0.946000
2	R2 Score (Test)	0.760000	0.899000	0.897000	0.897000
3	RSS (Train)	10.952758	4.092453	3.748709	4.033671
4	RSS (Test)	7.527175	3.175073	3.235024	3.224333
5	RMSE (Train)	0.103574	0.063311	0.060594	0.062855
6	RMSE (Test)	0.131093	0.085141	0.085941	0.085799

Figure 2 Scores with alpha*2

- GrLivArea, Condition2_PosN, Condition2_PosA, OverallQual_8,OverallQual_9 are the top predictors with Lasso Regression with alpha
- GrLivArea, Condition2_PosN, BsmtFinSF1, OverallQual_8,OverallQual_9 are the top variables with Lasso Regression with alpha*2
- GrLivArea, GarageArea,1stFlrSF, OverallQual_9, BsmntFinSF1 are the top-5 Predictors for Ridge Regression for alpha
- GrLivArea, GarageArea,1stFlrSF, OverallQual_9, OverallQual_8 are the top-5 Predictors for Ridge Regression for alpha*2
- 3 to 4 predictors in the top-5 predictor variables don't seem to change with the modification of regularization factors by a factor of 2, both in Lasso as well as ridge regression

- The Ridge and Lasso Columns in the following table indicate the top-most feature variables along with coefficients when the regularization value or the alpha value is doubled.

```
Number of Features in Linear Regresion =  57
Intercept for LinearReg =  0.578
Intercept for Ridge     =  0.024
Intercept for Lasso     =  -0.105
Intercept for Lasso_With_Top_Predictors_Eliminated= 0.02
TOP 25 FEATURES
-----------------
```

Linear Regression		Ridge		Lasso		Lasso_New (Eliminating top 5 Predictors)	
	LinearReg		Ridge		Lasso		Lasso_Top_Pred_Elim
BsmtCond_Po	-0.668000	GrLivArea	0.132000	GrLivArea	0.282000	1stFlrSF	0.222000
OverallQual_3	-0.462000	1stFlrSF	0.102000	OverallQual_9	0.148000	2ndFlrSF	0.197000
OverallQual_2	-0.453000	GarageArea	0.078000	Condition2_PosN	-0.126000	OverallQual_10	-0.135000
OverallQual_4	-0.403000	OverallQual_9	0.074000	OverallQual_8	0.107000	OverallQual_3	-0.128000
Condition2_PosN	-0.403000	OverallQual_8	0.073000	OverallCond_9	0.106000	OverallQual_4	-0.120000
OverallQual_5	-0.336000	BsmtFinSF1	0.069000	BsmtFinSF1	0.104000	Condition2_PosA	0.118000
YearBuilt_1880	0.311000	2ndFlrSF	0.061000	Neighborhood_MeadowV	-0.098000	BsmtFinSF1	0.111000
YearBuilt_1898	-0.300000	LotArea	0.057000	GarageArea	0.098000	Neighborhood_MeadowV	-0.105000
OverallQual_6	-0.272000	OverallQual_4	-0.054000	YearBuilt_1900	-0.084000	GarageArea	0.103000
YearBuilt_1987	0.262000	Neighborhood_Crawfor	0.052000	BsmtUnfSF	0.075000	OverallQual_5	-0.096000
GarageYrBlt_1910	0.212000	BsmtUnfSF	0.052000	Neighborhood_ClearCr	0.075000	BsmtUnfSF	0.084000
YearBuilt_1931	-0.210000	Neighborhood_Edwards	-0.050000	Neighborhood_Crawfor	0.072000	OverallQual_6	-0.081000
YearBuilt_1935	-0.185000	Fireplaces	0.047000	Neighborhood_Somerst	0.066000	SaleType_ConLD	0.079000
YearBuilt_1938	-0.168000	OverallQual_3	-0.041000	LotArea	0.063000	YearBuilt_1900	-0.075000
MSSubClass_160	-0.149000	CentralAir_Y	0.041000	OverallCond_8	0.059000	Neighborhood_Somerst	0.074000
OverallQual_7	-0.148000	Neighborhood_NridgHt	0.039000	SaleType_ConLD	0.057000	Neighborhood_Crawfor	0.069000
Neighborhood_MeadowV	-0.139000	Neighborhood_MeadowV	-0.039000	OverallQual_7	0.054000	Neighborhood_ClearCr	0.064000
YearBuilt_1924	-0.136000	Neighborhood_Somerst	0.039000	GarageType_CarPort	-0.053000	OverallCond_3	-0.064000
YearBuilt_1926	-0.135000	OverallCond_9	0.038000	OverallCond_7	0.051000	LotArea	0.062000
Neighborhood_Crawfor	0.128000	Neighborhood_ClearCr	0.038000	Exterior1st_BrkFace	0.050000	Neighborhood_StoneBr	0.061000
OverallQual_9	0.114000	Functional_Typ	0.036000	Neighborhood_Edwards	-0.050000	Neighborhood_Edwards	-0.061000
GarageType_CarPort	-0.113000	FullBath	0.035000	OverallQual_3	-0.050000	Neighborhood_NridgHt	0.060000
Fireplaces	0.111000	GarageYrBlt_2008	0.035000	GarageYrBlt_2008	0.050000	GarageYrBlt_2008	0.059000
OverallCond_3	-0.108000	YearBuilt_1900	-0.034000	Functional_Typ	0.049000	Exterior1st_BrkFace	0.054000
GarageYrBlt_1997	0.108000	Exterior1st_BrkFace	0.034000	YearBuilt_1987	0.044000	GarageType_CarPort	-0.050000
Neighborhood_ClearCr	0.100000	OverallCond_3	-0.033000	MSSubClass_160	-0.042000	Functional_Typ	0.049000
YearBuilt_1940	-0.099000	BsmtQual_TA	-0.033000	CentralAir_Y	0.040000	OverallCond_4	-0.045000
YearBuilt_2009	0.098000	KitchenQual_TA	-0.031000	OverallQual_4	-0.040000	CentralAir_Y	0.045000
YearBuilt_1910	-0.094000	MSSubClass_160	-0.031000	Neighborhood_NridgHt	0.040000	BsmtCond_Gd	0.042000
YearRemodAdd_1999	0.092000	HalfBath	0.030000	Neighborhood_StoneBr	0.040000	YearBuilt_2009	0.039000
YearBuilt_1925	-0.086000	MSSubClass_30	-0.030000	GarageYrBlt_1971	-0.039000	KitchenQual_Fa	-0.039000

Figure 3 Ridge and Lasso Predictors and Coefficients with doubled alpha

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?

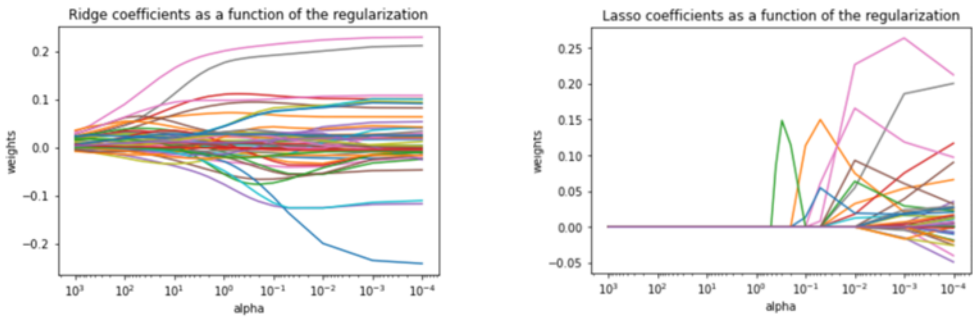

Figure 4 Coefficient Emergence with varying alpha

Shown below in Equation 1 and Equation 2 Ridge and Lasso Cost Functions minimized for determining β_j, used in the regression for M observations of the target Variable y_i and p Predictor Variables given by x_{ij}

Equation 1 Ridge Regression

$$\sum_{i=1}^{M}(y_i-\hat{y}_i)^2=\sum_{i=1}^{M}\left(y_i-\sum_1^p\beta_j x_{ij}\right)^2+\propto\sum_1^p{\beta_j}^2$$

Equation 2 Lasso Regression Equation

$$\sum_{i=1}^{M}(y_i-\hat{y}_i)^2=\sum_{i=1}^{M}\left(y_i-\sum_1^p\beta_j x_{ij}\right)^2+\propto\sum_1^p\left|\beta_j\right|$$

- In Ridge and Lasso the additional terms try to penalize the increase of coefficients by minimizing the joint term one of which is ${\beta_j}^2$ *and* $|\beta_j|$.The regularization term (alpha) regularizes the coefficients such that if the coefficients take large values the optimization function is penalized. By keeping the coefficient growth under check Ridge and Lasso Regression try to minimize the complexity of the model while preventing overfitting issues of linear regression.
- From the plots we can see how the coefficients start emerging for Ridge and Lasso with decreasing alphas. Decreasing the alpha will start the emergence of coefficients at orders of magnitude higher for Ridge than that of Lasso and hence Ridge optimal alphas are orders of magnitudes higher.
- The optimal value of the alpha can be chosen by the model in such a way that both mean-test-scores for testing data and training data is minimized, while maximizing their R2_scores.
- The difference between the Lasso and Ridge is that with the alpha increase for Ridge the coefficients starts shrinking towards zero but doesn't become zero where as in the Lasso the coefficients gets completely eliminated. Because of this the Lasso can lead to feature selection.

- The choice of the alpha and the model that we apply depends on the our business goal , in case we want to go for optimal feature selection's while making the model simpler then the Lasso is chosen, But if we want good accuracy with good scores(R2,Mean-test/train scores) include higher number of features without causing overfitting then we go for Ridge regression. However, the complexity will increase as the dynamic range of the coefficients becomes higher for Ridge and it demands higher bits to for processing and storage. Lasso will be useful when there are millions of features where ridge regression will lead to significant complexity.
- Ridge generally works well even in presence of highly correlated features as it will include all features where coefficients get decided based on the correlation between the features whereas in Lasso highly correlated features are selected and remaining are set to zero. Also change in Model parameters for Lasso changes the top predictor variable as compared to ridge regression. So, this also will be a factor for choosing the right 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?

I. The top-5 Predictor Variabes with Lasso Regression

- GrLivArea
- Condition2_PosN
- Condition2_PosA
- OverallQual_8
- OverallQual_9

Refer: Model Summary

II. The top-5 Predictor Variables obtained from Lasso regression after eliminating the above Variables

- YearBuilt_1893
- 1stFlrSF
- 2ndFlrSF
- OverallQual_10
- OverallQual_3

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?

- More robust model is the model which does not change its accuracy when the training data changes. For a generalizable model it should not undergo changes when it sees a new data.
- Same model should fit properly to new, previously unseen data, assumed to be from the same distribution.
- To make the model more generalized and robust we must make the model simple.
- But when we try to make the model simple it suffers from bias as it does not perform well on the training data itself but when we try to make it complex it memorizes the data and suffers from overfitting, and it does not perform well on the test data and this variance of the model between training and test-data is termed as variance which is high for Complex models.
- Striking the right balance between the bias and variance where the variance of the model can be reduced by trading off against the training error*(bias) will achieve an optimal model.
- So the accuracy of the model on the training data is traded off in order to make it more robust and generalizable model for unseen data.
- This is achieved using Regularization techniques like Lasso and Ridge regression. Regularization helps with managing the model complexity by essentially shrinking the model coefficients estimates to 0 (by adding a penalty term for increased coefficients) and discourages the model from becoming too complex and thus avoiding the risk of overfitting and essentially making it more robust and generalizable.
- Regularization also takes care of Multicollinearity by reducing the coefficients of collinear variables close to zero.
- Apart from this the data analysis and cleaning need to be performed on training data by treatment of outliers and missing data with appropriate imputations, removal of unreliable features, removal of collinear features…etc to ensure the generation of a robust model.
- Based on the distribution of the target data the data-transformation also can be performed in case distribution is significantly skewed.

Appendix (Reference for Answers)

Model Summary

Multiple Model options were tried with various configurations for Linear,Ridge and Lasso Regression

- Model-1 Min-Max Scaling for Target and Predictor Variables, Log Transformation for Target Variable
- Model-2 Min Max scaling for Target and Predictor Variables, Log Transformation for Target Variable, Doubling of Optimal Regularization parameters obtained for Lasso and Ridge
- Model-3 Min-Max Scaling applied for Predictor Variables only, Log transformation of Target Variable
- Model-4 Min-Max Scaling applied for Predictor Variables, No Transformation of Target Variable
- Model-5 Min-Max Scaling applied for Predictor Variables+ Target Variable, No Transformation of Target Variable

Lasso Regression was also tried with elimination of the top-5 predictors for each Model.In some of the models the log transformation on the target variable was performed as the target variable showed some skewness in its distribution.

MODEL-I

- Min-Max Scaling for Target Variable along with the Predictor Variables
- Log transformation of the Target Variable
- Regression Linear , Ridge , Lasso & "Lasso with Top Predictors Eliminated" Performed

Linear Regression

	LinearReg
BsmtCond_Po	-0.668176
OverallQual_3	-0.462437
OverallQual_2	-0.453495
OverallQual_4	-0.403082
Condition2_PosN	-0.402971
OverallQual_5	-0.335804
YearBuilt_1880	0.311000
YearBuilt_1898	-0.299887
OverallQual_6	-0.272009
YearBuilt_1987	0.261693

Ridge

	Ridge
GrLivArea	0.152796
1stFlrSF	0.100946
OverallQual_9	0.087843
GarageArea	0.083459
BsmtFinSF1	0.080743
OverallQual_8	0.077459
2ndFlrSF	0.071262
LotArea	0.061149
Neighborhood_Crawfor	0.060889
BsmtUnfSF	0.059987

Lasso

	Lasso
GrLivArea	0.279500
Condition2_PosN	-0.240197
Condition2_PosA	0.159116
OverallQual_9	0.154912
OverallQual_8	0.118378
OverallCond_9	0.114399
BsmtFinSF1	0.110599
YearBuilt_1900	-0.104651
Neighborhood_MeadowV	-0.104395
YearBuilt_1932	0.103068

Lasso_New

	Lasso_Top_Pred_Elim
YearBuilt_1893	0.223142
1stFlrSF	0.213242
2ndFlrSF	0.202960
OverallQual_10	-0.163537
OverallQual_3	-0.126222
OverallQual_4	-0.125452
SaleType_ConLD	0.120687
BsmtFinSF1	0.119126
OverallCond_9	0.118359
Neighborhood_MeadowV	-0.111529

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	7.000000	0.000100	0.000100
1	R2 Score (Train)	0.853000	0.953000	0.959000	0.955000
2	R2 Score (Test)	0.760000	0.899000	0.890000	0.892000
3	RSS (Train)	10.952758	3.504164	3.060471	3.353166
4	RSS (Test)	7.527175	3.178369	3.461134	3.376821
5	RMSE (Train)	0.103574	0.058584	0.054750	0.057308
6	RMSE (Test)	0.131093	0.085185	0.088894	0.087805

Figure 5 Results for Model-I (Performance Scores, Top-Predictors and Coefficients)

MODEL-2

- Min-Max Scaling for Target Variable along with the Predictor Variables
- Log transformation of the Target Variable
- Regression Linear , Ridge , Lasso & "Lasso with Top Predictors Eliminated" Performed
- Regularization parameter is doubled for Lasso and Ridge (14 for Ridge,0.0002 for Lasso)

```
Number of Features in Linear Regresion =  58
TOP FEATURES
-----------------
```

Linear Regression	LinearReg	Ridge	Ridge	Lasso	Lasso	Lasso_New	Lasso_Top_Pred_Elim
BsmtCond_Po	-0.668176	GrLivArea	0.131937	GrLivArea	0.282427	1stFlrSF	0.222452
OverallQual_3	-0.462437	1stFlrSF	0.101777	OverallQual_9	0.147888	2ndFlrSF	0.196575
OverallQual_2	-0.453495	GarageArea	0.077985	Condition2_PosN	-0.126013	OverallQual_10	-0.135229
OverallQual_4	-0.403082	OverallQual_9	0.074051	OverallQual_8	0.106936	OverallQual_3	-0.127780
Condition2_PosN	-0.402971	OverallQual_8	0.072623	OverallCond_9	0.106341	OverallQual_4	-0.120425
OverallQual_5	-0.335804	BsmtFinSF1	0.069176	BsmtFinSF1	0.104332	Condition2_PosA	0.118278
YearBuilt_1880	0.311000	2ndFlrSF	0.060600	Neighborhood_MeadowV	-0.098417	BsmtFinSF1	0.110903

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	14.000000	0.000200	0.000200
1	R2 Score (Train)	0.853000	0.945000	0.950000	0.946000
2	R2 Score (Test)	0.760000	0.899000	0.897000	0.897000
3	RSS (Train)	10.952758	4.092453	3.748709	4.033671
4	RSS (Test)	7.527175	3.175073	3.235024	3.224333
5	RMSE (Train)	0.103574	0.063311	0.060594	0.062855
6	RMSE (Test)	0.131093	0.085141	0.085941	0.085799

Figure 6 Results for Model-2 (Performance Scores, Top-Predictors and Coefficients)

MODEL-3

- Min-Max scaling on Predictor Variables only
- Log transformation of the Target Variable
- Regression Linear , Ridge , Lasso & "Lasso with Top Predictors Eliminated" Performed

```
Number of Features in Linear Regresion =  54
TOP FEATURES
-----------------
```

Linear Regression	LinearReg	Ridge	Ridge	Lasso	Lasso	Lasso_New	Lasso_Top_Pred_Elim
YearBuilt_1880	0.638420	GrLivArea	0.200143	GrLivArea	0.384372	1stFlrSF	0.401164
Condition2_PosN	-0.543200	1stFlrSF	0.132226	OverallQual_9	0.178837	2ndFlrSF	0.239751
BsmtCond_Po	-0.463904	OverallQual_9	0.115063	OverallQual_8	0.138723	OverallQual_4	-0.151327
YearBuilt_2008	0.395005	GarageArea	0.109320	GarageArea	0.134877	OverallQual_3	-0.144006
YearBuilt_2007	0.383596	BsmtFinSF1	0.105763	BsmtFinSF1	0.093642	OverallQual_5	-0.111802
MSSubClass_180	-0.377639	OverallQual_8	0.101461	Neighborhood_Crawfor	0.077942	LotArea	0.098426
RoofMatl_WdShake	0.377202	2ndFlrSF	0.093344	Neighborhood_Somerst	0.073738	Neighborhood_Somerst	0.095465
YearBuilt_1987	0.353799	LotArea	0.080098	CentralAir_Y	0.072597	OverallQual_6	-0.093566

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	7.000000	0.001000	0.001000
1	R2 Score (Train)	0.767000	0.953000	0.928000	0.916000
2	R2 Score (Test)	0.671000	0.899000	0.890000	0.887000
3	RSS (Train)	29.702012	6.012277	9.222387	10.677458
4	RSS (Test)	17.702366	5.453294	5.901445	6.086434
5	RMSE (Train)	0.170561	0.076737	0.095041	0.102264
6	RMSE (Test)	0.201038	0.111582	0.116076	0.117881

Figure 7 Results for Model-3 (Performance Scores, Top-Predictors and Coefficients)

MODEL-4

- Min Max Scaling is applied only on Predictor Variables
- No Transformation applied to Target Variable
- Regression Linear , Ridge , Lasso & "Lasso with Top Predictors Eliminated" Performed

```
Number of Features in Linear Regresion =  55
TOP FEATURES
-----------------
```

Linear Regression		Ridge		Lasso		Lasso_New	
	LinearReg		Ridge		Lasso		Lasso_Top_Pred_Elim
Heating_OthW	-102098.484324	GrLivArea	39250.623970	GrLivArea	75809.918445	1stFlrSF	67537.350637
Condition2_PosN	-84609.305311	OverallQual_9	28168.064530	OverallQual_9	50466.657630	2ndFlrSF	45002.931036
OverallQual_9	79123.055944	1stFlrSF	25335.798828	OverallQual_8	33704.142516	Condition2_PosN	-32656.918634
YearBuilt_1880	77453.243126	GarageArea	20506.462485	OverallCond_9	21883.332020	OverallQual_4	-30977.605495
BsmtCond_Po	-77362.972708	OverallQual_8	20248.615012	BsmtFinSF1	21204.839524	OverallQual_3	-30149.234810
OverallQual_3	-59893.269259	BsmtFinSF1	19506.810981	GarageArea	21166.518014	OverallQual_5	-30092.947093
						OverallQual_6	-28998.003396

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000e+00	8.000000e+00	1.000000e+02	1.000000e+02
1	R2 Score (Train)	8.490000e-01	9.480000e-01	9.340000e-01	9.270000e-01
2	R2 Score (Test)	7.580000e-01	8.940000e-01	8.900000e-01	8.910000e-01
3	RSS (Train)	6.490639e+11	2.248939e+11	2.854148e+11	3.153608e+11
4	RSS (Test)	4.307153e+11	1.878468e+11	1.952776e+11	1.941131e+11
5	RMSE (Train)	2.521337e+04	1.484144e+04	1.671958e+04	1.757483e+04
6	RMSE (Test)	3.135870e+04	2.070927e+04	2.111491e+04	2.105185e+04

Figure 8 Results for Model-4 (Performance Scores, Top-Predictors and Coefficients)

MODEL-5

- Min-Max Scaling for Target Variable along with the Predictor Variables
- No transformation of the Target Variable
- Regression Linear , Ridge , Lasso & "Lasso with Top Predictors Eliminated" Performed

```
Number of Features in Linear Regresion =  49
TOP FEATURES
-----------------
```

Linear Regression		Ridge		Lasso		Lasso_New	
	LinearReg		Ridge		Lasso		Lasso_Top_Pred_Elim
Condition2_PosN	-0.534324	GrLivArea	0.164849	GrLivArea	0.311662	Condition2_PosN	-0.461705
BsmtCond_Po	-0.509124	OverallQual_9	0.118304	OverallQual_9	0.208414	1stFlrSF	0.295728
Heating_OthW	-0.450044	1stFlrSF	0.106408	OverallQual_8	0.140904	Condition2_PosA	0.218193
OverallQual_3	-0.436686	GarageArea	0.086125	GarageArea	0.092887	2ndFlrSF	0.212998
OverallQual_4	-0.415598	OverallQual_8	0.085042	BsmtFinSF1	0.070454	OverallQual_4	-0.148879
OverallQual_5	-0.380742	BsmtFinSF1	0.081927	1stFlrSF	0.060455	OverallQual_10	-0.141768
YearBuilt_1880	0.335951	2ndFlrSF	0.072366	LotArea	0.058289	OverallQual_5	-0.139274

	Metric	Linear Regression	Ridge Regression	Lasso Regression	Lasso_Top_Pred_Elim
0	Regularization	0.000000	8.000000	0.001000	0.000100
1	R2 Score (Train)	0.847000	0.948000	0.918000	0.949000
2	R2 Score (Test)	0.749000	0.894000	0.884000	0.873000
3	RSS (Train)	11.555673	3.966971	6.175760	3.833260
4	RSS (Test)	7.879431	3.313485	3.635397	3.992477
5	RMSE (Train)	0.106386	0.062333	0.077774	0.061273
6	RMSE (Test)	0.134125	0.086977	0.091104	0.095474

Figure 9 Results for Model-5 (Performance Scores, Top-Predictors and Coefficients)

Across Models Inferences

- 3-4 Predictors among the Top-5 Predictors found to be mostly same across all the Model Variations for Lasso Regression. (GrLivArea, GarageArea, OverallQual_8, OverallQual_9)
- 3-4 Predictors among the Top-5 Predictors found to be mostly same across all the Model Variations for Ridge Regression (GrLivArea,1stFlrSF, OverallQual_8, OverallQual_9)
- 3 Predictors among the Top-5 Predictors are mostly same between Ridge and Lasso Regression for most of the Models.
- Top predictor variables with and without Min-Max scaling of the Target variable is same. (Model-4 and Model-5)