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:
Optimal value of alpha for ridge is 100 and lasso regression is 500.

When we double the values alpha for ridge will be 200 and for lasso, alpha value will be 1000

Computation R2 Score, RSS and MSE is as follows

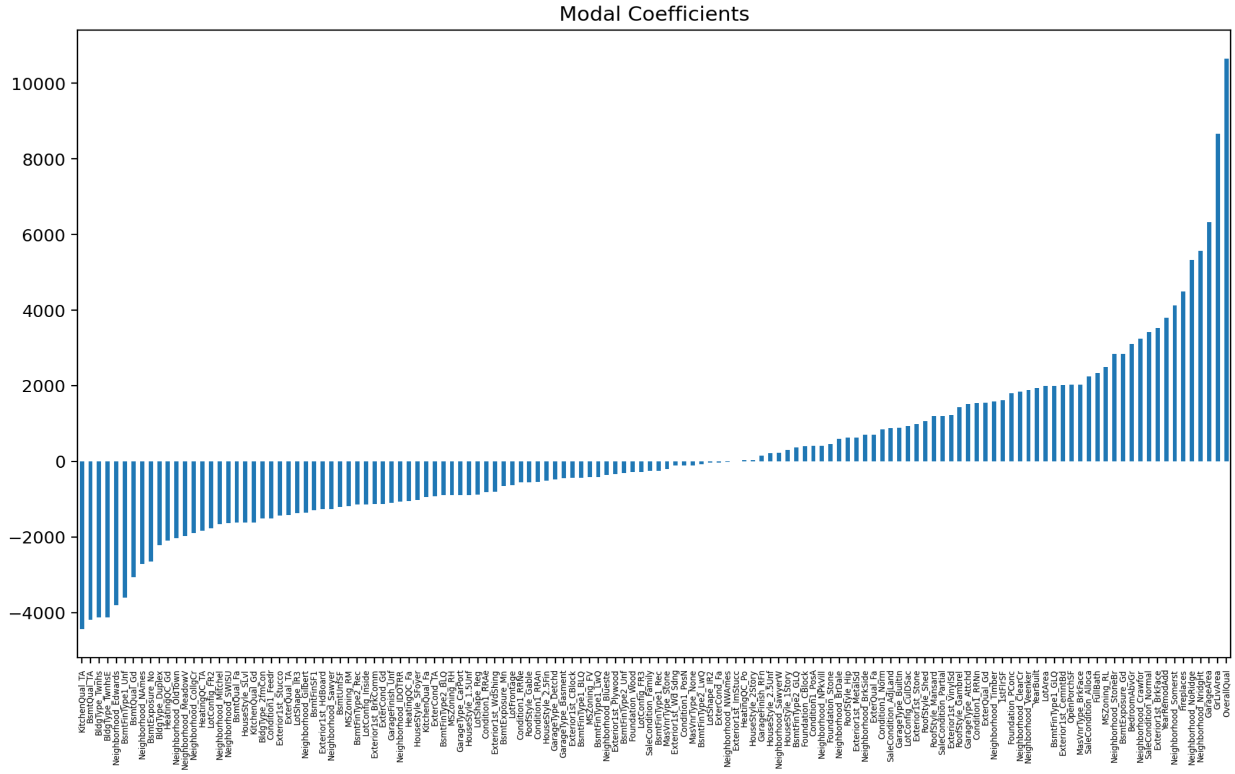
	Metric	Ridge Regression	Lasso Regression	Ridge200 Regression	Lasso1000 Regression
0	R2 Score (Train)	8.722941e-01	8.642688e-01	8.656167e-01	8.513265e-01
1	R2 Score (Test)	8.228388e-01	8.275559e-01	8.201790e-01	8.185779e-01
2	RSS (Train)	3.855336e+11	4.097615e+11	4.056921e+11	4.488333e+11
3	RSS (Test)	2.218969e+11	2.159887e+11	2.252284e+11	2.272337e+11
4	MSE (Train)	2.075485e+04	2.139706e+04	2.129054e+04	2.239397e+04
5	MSE (Test)	2.403865e+04	2.371646e+04	2.421843e+04	2.432601e+04

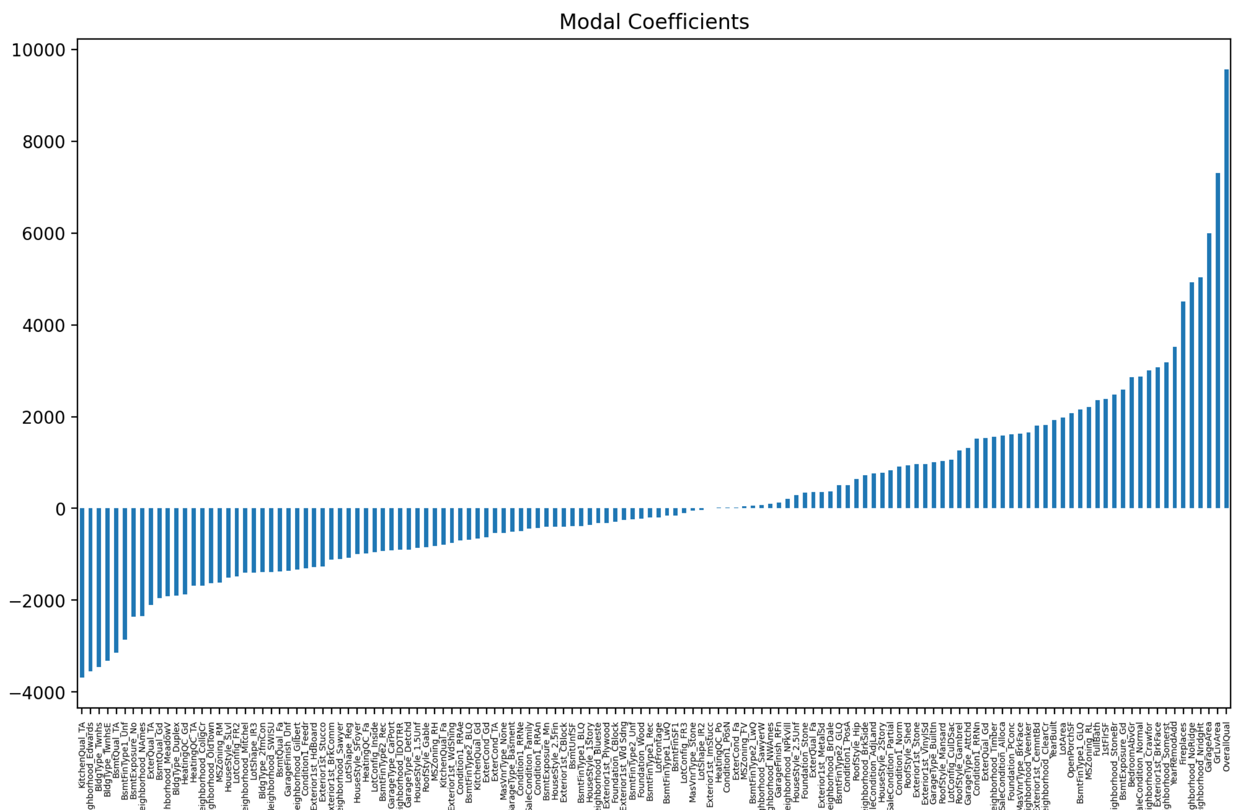
Inference from the above table is that model will reduce the R2 score for both test and train sets, thus model efficiency decreases

Most important predictor variable after change is implemented is same as before **'OverallQual'** . even though there is change in coefficient values as shown clearly in below table and graphs

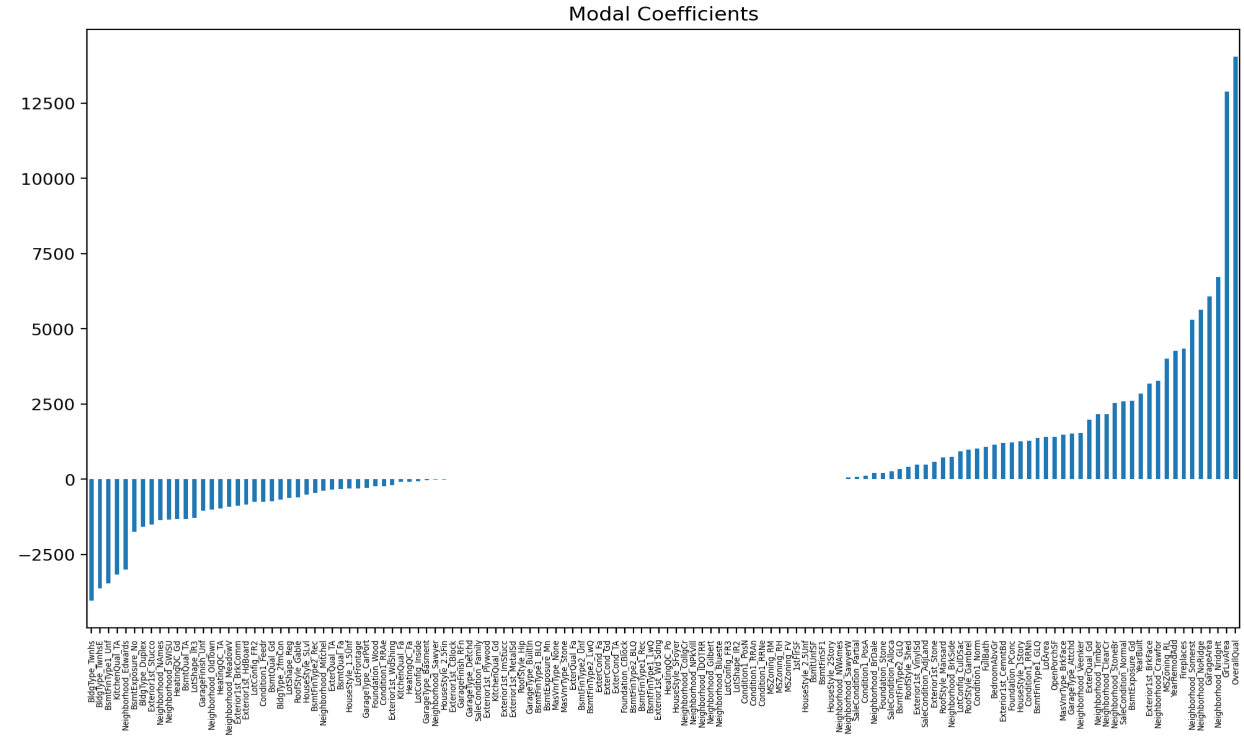
	Ridge	Lasso	Ridge200	lasso1000
LotFrontage	-6.287317e+02	-309.808862	-1.950536e+02	-0.000000
LotArea	1.996894e+03	1404.387842	1.982445e+03	1327.385174
OverallQual	1.064801e+04	14040.624682	9.561763e+03	15343.820823
YearBuilt	1.944361e+03	2844.024263	1.921483e+03	2951.048632
YearRemodAdd	3.802602e+03	4271.679689	3.523590e+03	4165.165371

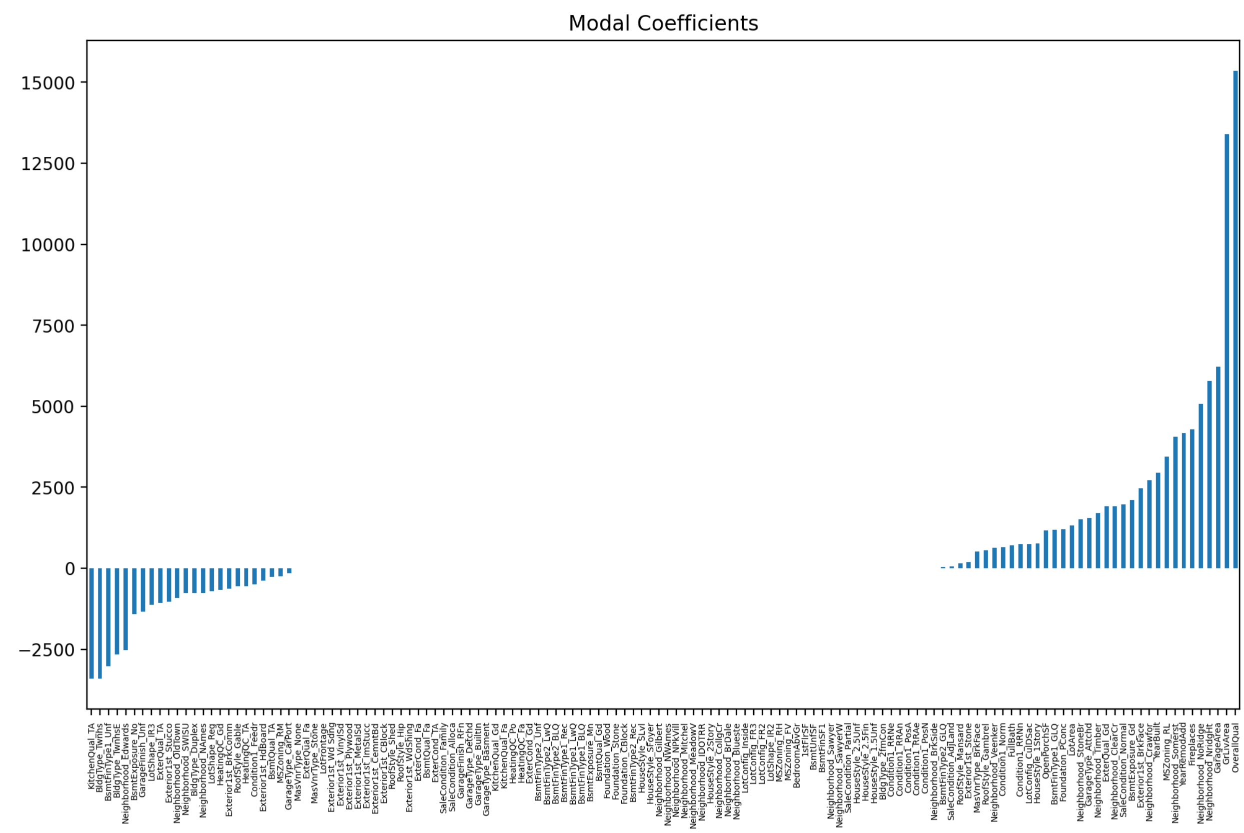
Ridge with alpha value :100 and 200 respectively for below bar graph





Lasso with alpha value :500 and 1000 respectively fro below graph





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:
I will apply Lasso,
If we observe the accuracy of the model after applying optimal value of lambda for ridge And Lasso, R2 score computed is as below

	Metric	Ridge Regression	Lasso Regression
0	R2 Score (Train)	8.722941e-01	8.642688e-01
1	R2 Score (Test)	8.228388e-01	8.275559e-01
2	RSS (Train)	3.855336e+11	4.097615e+11
3	RSS (Test)	2.218969e+11	2.159887e+11
4	MSE (Train)	2.075485e+04	2.139706e+04
5	MSE (Test)	2.403865e+04	2.371646e+04

In the Ridge regression model , Accuracy is better on train data than test data.
In the Lasso regression model, Accuracy is better on train data than test data, but accuracy is lesser compared to Ridge Regression w.r.to train data.

On test data Lasso performs better, and also this model selects the feature by making certain feature coefficients zero, which makes the model even more simpler and in turn robust

Question 3
After building the model, you realized 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?

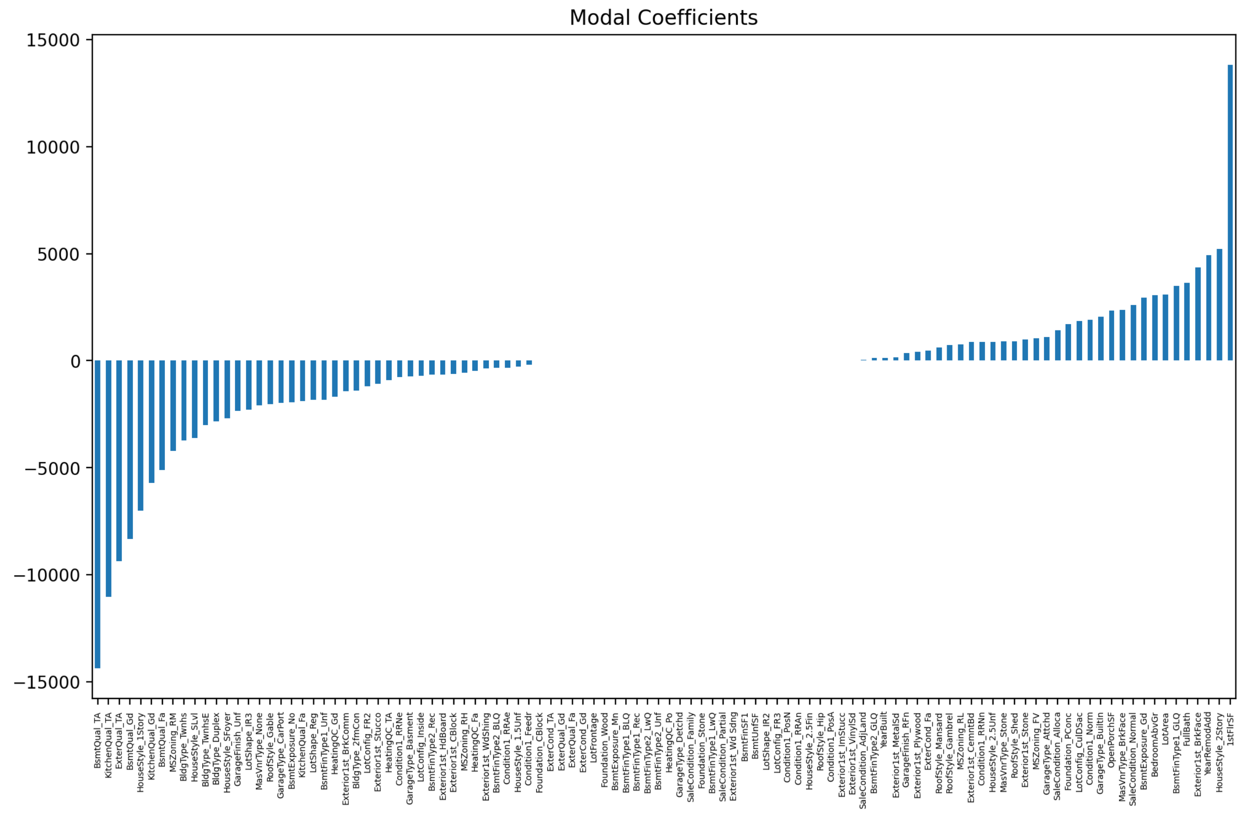
Answer:
In lasso model 5 most important variables are

1. OverallQual
2. GrLivArea
3. GarageArea
4. Neighborhood
5. FirePlaces

After creating new models without above variables five important variables in lasso models are

1. 1stFlrSF
2. HouseStyle
3. YearRemodAdd
4. Exterior1st
5. FullBath

New Lasso Model coefficients are shown clearly in below graph



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:
By keeping the model simple, easier to interpret, less error while predicting and keeping less number of predictors we can make the model more robust .

Model becomes more generalizable when it can perform well on unseen data. This can be done by identifying necessary underlying pattern in the data, using regularization

Regularization helps with managing model complexity by essentially shrinking the model coefficient estimates towards 0. This discourages the model from becoming too complex, thus avoiding the risk of overfitting.

Lasso regression does feature selection, this helps in building simple model , which is easier to interpret

regularization can be applied on models using lasso and ridge regression

It improves the model accuracy,
significantly reduces the variance of the model, without substantial increase in its bias , as well as prevents the loss of important data in large data set

Balance in model complexity and its implication can be beautifully illustrated in below graph