# PROBLEM STATEMENT – PART 2

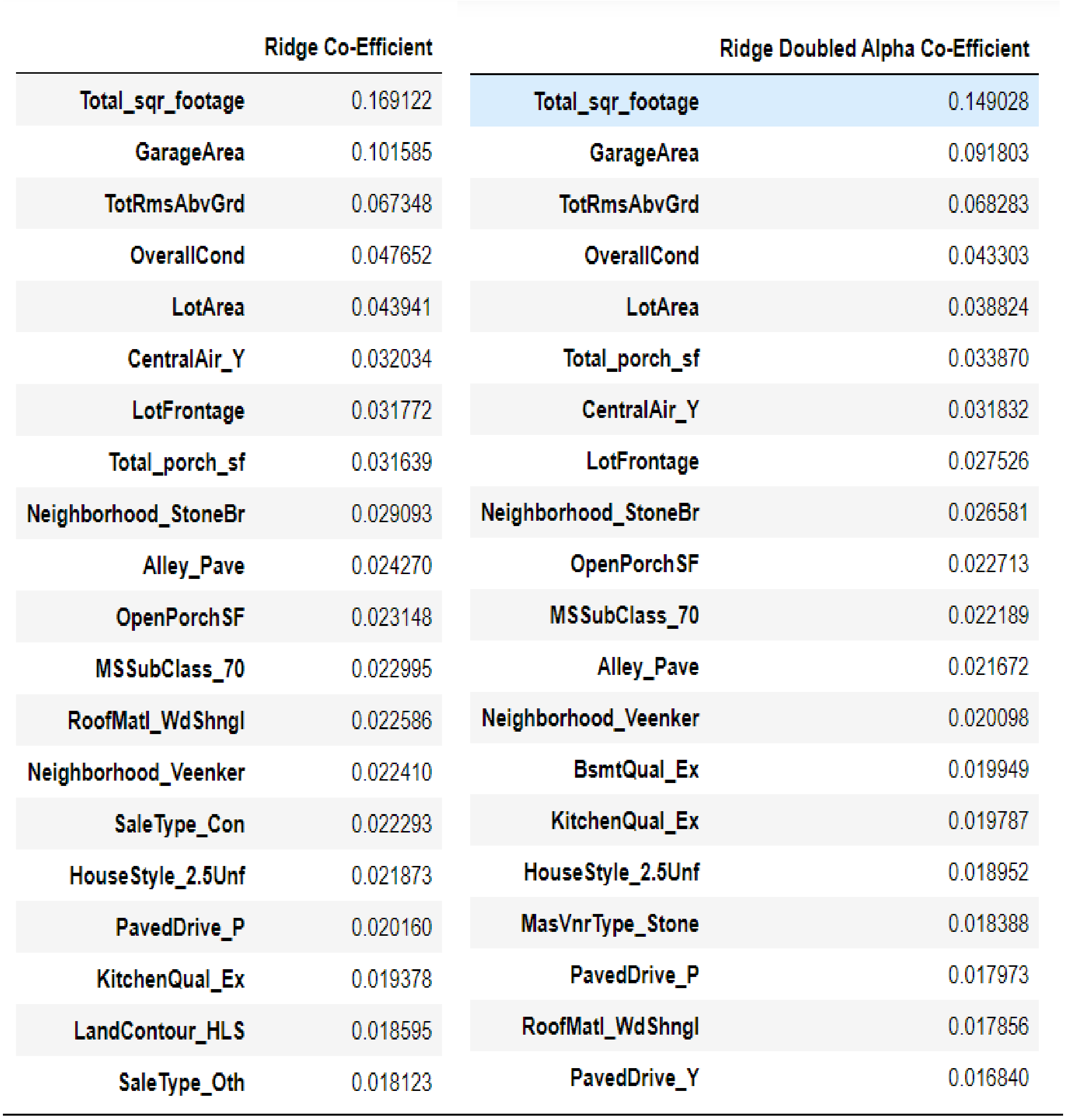
## Question 1

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?

**Ans: -**

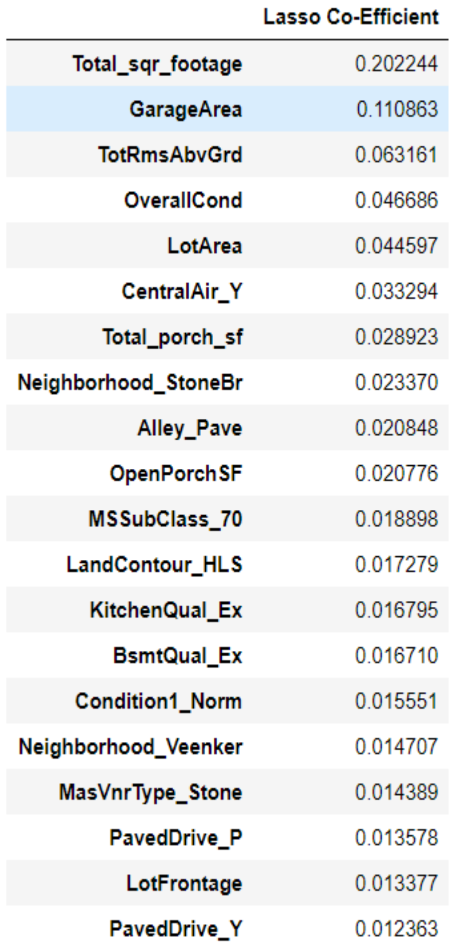
- The optimal value of alpha for Ridge is 2 and for Lasso is 0.001.
- With these alphas the R2 of the model was approximately 0.83.
- After doubling the alpha values in the Ridge and Lasso, the prediction accuracy remains around 0.82 but there is a small change in the co-efficient values.
- The new model is created and demonstrated in the Jupiter notebook. Below are the changes in the co-efficient.

**Ridge Regression Model: -**

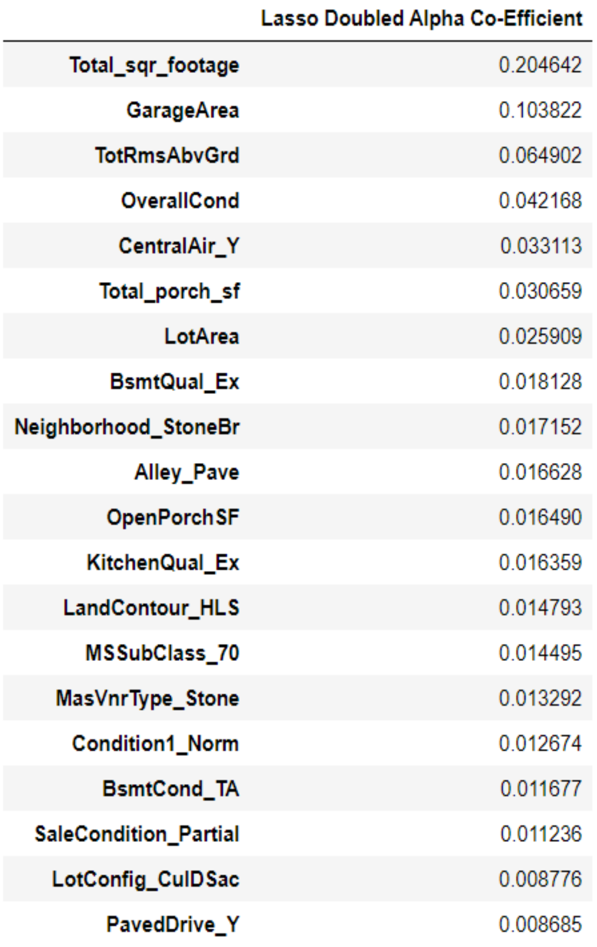


| | Ridge Co-Efficient | | Ridge Doubled Alpha Co-Efficient |
|---|---|---|---|
| Total_sqr_footage | 0.169122 | Total_sqr_footage | 0.149028 |
| GarageArea | 0.101585 | GarageArea | 0.091803 |
| TotRmsAbvGrd | 0.067348 | TotRmsAbvGrd | 0.068283 |
| OverallCond | 0.047652 | OverallCond | 0.043303 |
| LotArea | 0.043941 | LotArea | 0.038824 |
| CentralAir_Y | 0.032034 | Total_porch_sf | 0.033870 |
| LotFrontage | 0.031772 | CentralAir_Y | 0.031832 |
| Total_porch_sf | 0.031639 | LotFrontage | 0.027526 |
| Neighborhood_StoneBr | 0.029093 | Neighborhood_StoneBr | 0.026581 |
| Alley_Pave | 0.024270 | OpenPorchSF | 0.022713 |
| OpenPorchSF | 0.023148 | MSSubClass_70 | 0.022189 |
| MSSubClass_70 | 0.022995 | Alley_Pave | 0.021672 |
| RoofMatl_WdShngl | 0.022586 | Neighborhood_Veenker | 0.020098 |
| Neighborhood_Veenker | 0.022410 | BsmtQual_Ex | 0.019949 |
| SaleType_Con | 0.022293 | KitchenQual_Ex | 0.019787 |
| HouseStyle_2.5Unf | 0.021873 | HouseStyle_2.5Unf | 0.018952 |
| PavedDrive_P | 0.020160 | MasVnrType_Stone | 0.018388 |
| KitchenQual_Ex | 0.019378 | PavedDrive_P | 0.017973 |
| LandContour_HLS | 0.018595 | RoofMatl_WdShngl | 0.017856 |
| SaleType_Oth | 0.018123 | PavedDrive_Y | 0.016840 |

**Lasso Regression Model: -**



| | Lasso Co-Efficient |
|---|---|
| Total_sqr_footage | 0.202244 |
| GarageArea | 0.110863 |
| TotRmsAbvGrd | 0.063161 |
| OverallCond | 0.046686 |
| LotArea | 0.044597 |
| CentralAir_Y | 0.033294 |
| Total_porch_sf | 0.028923 |
| Neighborhood_StoneBr | 0.023370 |
| Alley_Pave | 0.020848 |
| OpenPorchSF | 0.020776 |
| MSSubClass_70 | 0.018898 |
| LandContour_HLS | 0.017279 |
| KitchenQual_Ex | 0.016795 |
| BsmtQual_Ex | 0.016710 |
| Condition1_Norm | 0.015551 |
| Neighborhood_Veenker | 0.014707 |
| MasVnrType_Stone | 0.014389 |
| PavedDrive_P | 0.013578 |
| LotFrontage | 0.013377 |
| PavedDrive_Y | 0.012363 |



| | Lasso Doubled Alpha Co-Efficient |
|---|---|
| Total_sqr_footage | 0.204642 |
| GarageArea | 0.103822 |
| TotRmsAbvGrd | 0.064902 |
| OverallCond | 0.042168 |
| CentralAir_Y | 0.033113 |
| Total_porch_sf | 0.030659 |
| LotArea | 0.025909 |
| BsmtQual_Ex | 0.018128 |
| Neighborhood_StoneBr | 0.017152 |
| Alley_Pave | 0.016628 |
| OpenPorchSF | 0.016490 |
| KitchenQual_Ex | 0.016359 |
| LandContour_HLS | 0.014793 |
| MSSubClass_70 | 0.014495 |
| MasVnrType_Stone | 0.013292 |
| Condition1_Norm | 0.012674 |
| BsmtCond_TA | 0.011677 |
| SaleCondition_Partial | 0.011236 |
| LotConfig_CulDSac | 0.008776 |
| PavedDrive_Y | 0.008685 |

## 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: -** The optimum lambda value in case of Ridge and Lasso is as follows: -

- Ridge – 2
- Lasso – 0.0001

The Mean Squared error in case of Ridge and Lasso are: -

- Ridge - 0.0018396090787924262
- Lasso - 0.0018634152629407766

The Mean Squared Error of both the models are almost same.

Since Lasso helps in feature reduction (as the coefficient value of some of the features become zero), Lasso has a better edge over Ridge and should be used 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?

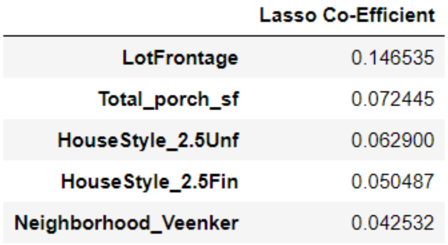
**Ans: -** The five most important predictor variables in the current lasso model are: -

- Total_sqr_footage

- GarageArea
- TotRmsAbvGrd
- OverallCond
- LotArea

We build a Lasso model in the Jupiter notebook after removing these attributes from the dataset.
The R2 of the new model without the top 5 predictors drops to .73
The Mean Squared Error increases to 0.0028575670906482538

The new Top 5 predictors as per the model are: -



| | 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

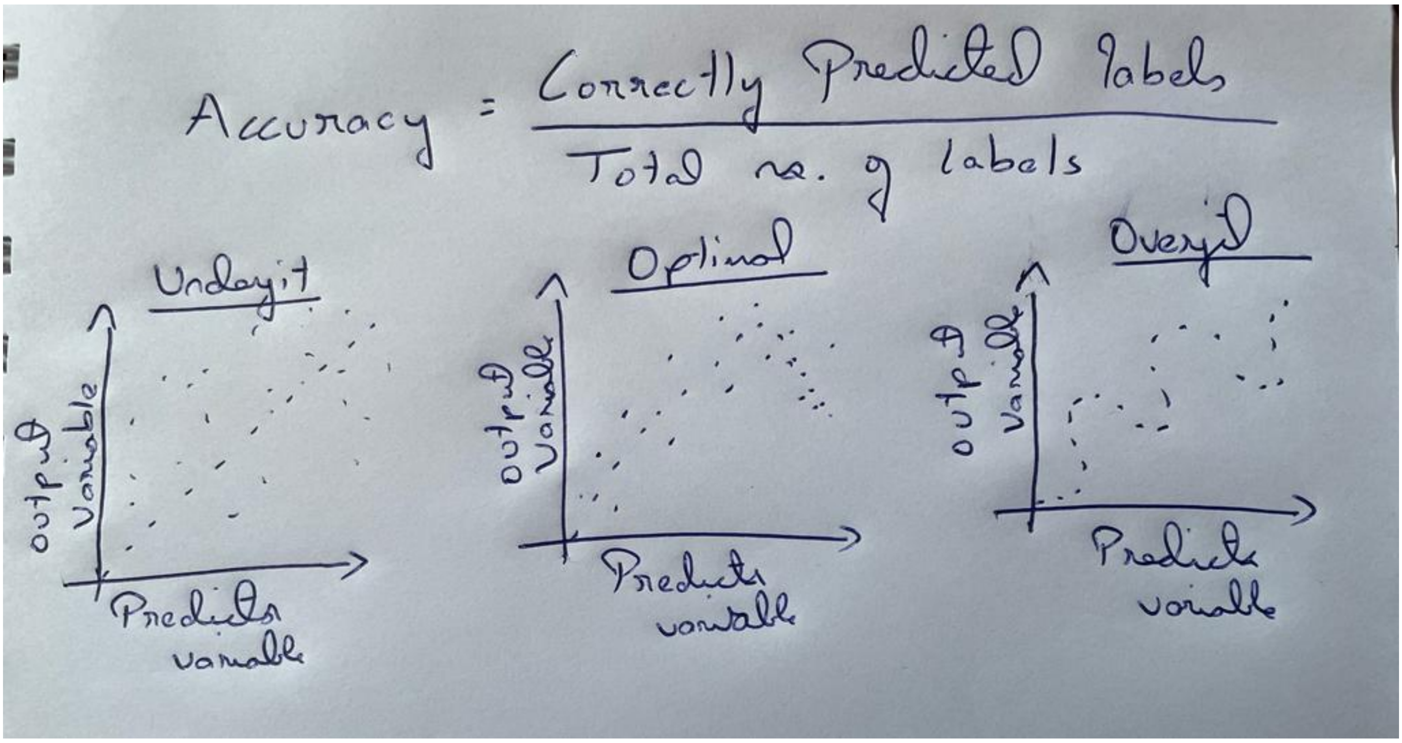
How can you make sure that a model is robust and generalisable? What are the implications of the same for the accuracy of the model and why?
**Ans: -**
When the training set is altered, a model is called robust and generalizable if it does not demonstrate a significant change in performance, i.e., the model does not overfit on the training data and can handle new/unseen data adequately. A robust and generalizable model should perform equally well on training and test data when it comes to accuracy.

A more generalised model is a model which does not overfit the data. To ensure our model is not overfitting the data we must regularise our model using hyperparameters. These hyperparameters will help in reducing the complexity of the model by penalising features contributing to the complexity. We add a penalty term to the cost function that increases with increasing model complexity. So, we try to bring it down and control model complexity Having a simple model will help ensure that it is robust and more generalised. But the model should not be oversimplified otherwise it will underfit the data and this model will be too naive to give us a valid or accurate output. This is the scenario where model is underfitting. Accuracy of the model is defined as the ratio of number of correct predictions to the total number of input samples.

The following are the implications of making a model resilient and generalizable on model accuracy:
The accuracy of the model will be steadier if we make it more robust, that is, less vulnerable to outliers or changes in test data. This means that slight modifications to the test data set will not result in significant changes in accuracy values.

When trying to make the model simpler by penalising the model's complexity, the accuracy on the test set will increase in the beginning. When we have made the model sufficiently basic, the accuracy will stabilise on the test data set.

If the accuracy is not maintained, then the model can be underfitted or overfitted.



$$\text{Accuracy} = \frac{\text{Correctly Predicted labels}}{\text{Total no. of labels}}$$

Underfit

Optimal

Overfit