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 and Lasso is .0001 and 2.0 respectively. Below table shows predictor variable

**Changes in model if alpha value is doubles**
Increasing alpha makes regularization stricter resulting in reduction in variance, increase in bias, and model becomes simpler. For lasso more and more beta coefficients will be marked as zeros and for Ridge beta coefficient becomes more and more smaller almost near to zero for less significant features.

**Lasso**: if alpha is doubled from .0001 then below are the changes in the model

1. Top five predictor variable changes and beta coefficient values also changes
2. Beta βo value increases when alpha is doubled. At alpha .0001 βo 0.08221185291665678
   At alpha .0002 βo 0.12212948359222042
3. In the Lasso regression model, the beta coefficients of less significant features are identified as zero. Notably, when the alpha parameter is doubled, there is a corresponding increase in the number of zero beta coefficients.
   at an alpha value of 0.0001, zero beta coefficient count is 77
   at an alpha value of 0.0002, zero beta coefficient count is 108
4. R2 score of training and test has decreased slightly, while RSS, MSE and RMSE values has increased slightly
5. At alpha .01 model becomes too simple to capture relevance. This can be observed in scatter plot

**Most Important predictor after change implemented**

Alpha: 0.0001

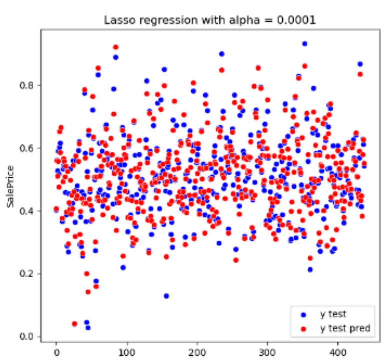
| beta | features |
|---|---|
| 0.308287 | GrLivArea |
| 0.162438 | OverallQual |
| 0.094896 | OverallCond |
| 0.078638 | GarageCars |
| 0.056504 | MSZoning_RL |

Alpha: 0.0002

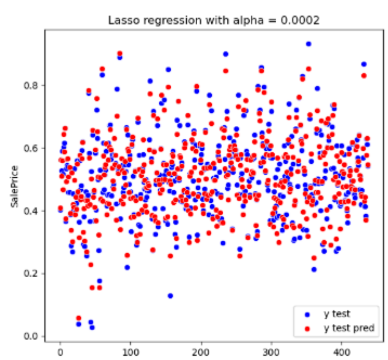
| beta | features |
|---|---|
| 0.302146 | GrLivArea |
| 0.180248 | OverallQual |
| 0.091497 | OverallCond |
| 0.078666 | GarageCars |
| 0.052211 | BsmtFullBath |

| | Alpha: 0.0001<br>Lasso | 0.0002<br>Lasso |
|---|---|---|
| **MSE Test** | 0.001999 | 0.002030 |
| **MSE Train** | 0.001383 | 0.001549 |
| **R2_score Test** | 0.885180 | 0.883405 |
| **R2_score Train** | 0.916848 | 0.906895 |
| **RMSE Test** | 0.044710 | 0.045055 |
| **RMSE Train** | 0.037189 | 0.039352 |
| **RSS Test** | 0.875573 | 0.889112 |
| **RSS Train** | 1.412076 | 1.581093 |

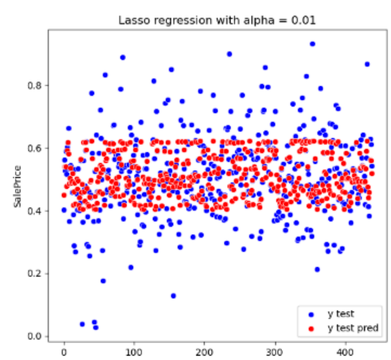
Alpha .0001 (best)




Alpha= .0002




Alpha= .01




**Ridge:** if alpha is doubled from the 2 to 4 the below are the changes in model.

1. Complexity of model gets reduced, variance gets decreased
2. Beta coefficient of predictor variable changes
   Beta βo 0.12498451745924394 at alpha =2
   Beta βo 0.17220026207707828 at alpha = 4

3. R2 score of training and test has decreased slightly, while RSS, MSE and RMSE values has increased slightly

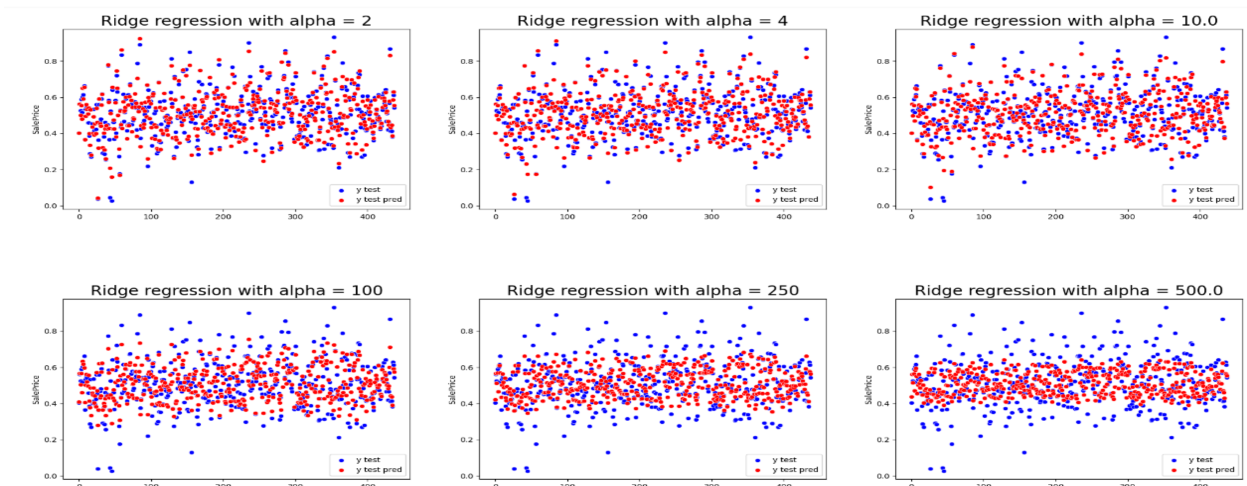
   **Most Important predictor after change implemented**

| alpha=2 features | beta | alpha=4 features | beta |
|---|---|---|---|
| OverallQual | 0.128202 | OverallQual | 0.113936 |
| GrLivArea | 0.095476 | GrLivArea | 0.079324 |
| 1stFlrSF | 0.083750 | OverallCond | 0.070593 |
| OverallCond | 0.079901 | 1stFlrSF | 0.067578 |
| 2ndFlrSF | 0.063707 | 2ndFlrSF | 0.057371 |

| | alpha=2 Ridge | alpha=4 Ridge |
|---|---|---|
| **MSE Test** | 0.002110 | 0.002128 |
| **MSE Train** | 0.001325 | 0.001402 |
| **R2_score Test** | 0.878812 | 0.877759 |
| **R2_score Train** | 0.920344 | 0.915709 |
| **RMSE Test** | 0.045934 | 0.046133 |
| **RMSE Train** | 0.036399 | 0.037443 |
| **RSS Test** | 0.924136 | 0.932163 |
| **RSS Train** | 1.352706 | 1.431412 |

The reason for not observing a significant variation in performance of model with initial change in alpha, could be due to the dataset containing large number of features, some of which may not be highly relevant. By increasing alpha, Ridge regression reduces (approx near to zero) the magnitude of coefficients associated with less important features, which can help in reducing model variance without substantially increasing bias. However, it's important to note that while the coefficients for less relevant features are reduced, they are not set to zero.
with increase of alpha r2 score and other parameter also changes, out of these parameters alpha 2 is the best

Not much of impact on model from alpha 2 to 10 but after 10 performance show significant degradiation



**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**
Below is the table based on which model is selected
**Best alpha value for Lasso is .0001 and Ridge is 2**

| | Linear Regression | Lasso | Ridge |
|---|---|---|---|
| **MSE Test** | 3.324731e+20 | 0.001999 | 0.002110 |
| **MSE Train** | 1.451160e-03 | 0.001383 | 0.001325 |
| **R2_score Test** | -1.909659e+22 | 0.885180 | 0.878812 |
| **R2_score Train** | 9.127515e-01 | 0.916848 | 0.920344 |
| **RMSE Test** | 1.823385e+10 | 0.044710 | 0.045934 |
| **RMSE Train** | 3.809409e-02 | 0.037189 | 0.036399 |
| **RSS Test** | 1.456232e+23 | 0.875573 | 0.924136 |
| **RSS Train** | 1.481634e+00 | 1.412076 | 1.352706 |

Based on the provided table, the Lasso regression model appears to be the most suitable choice for several reasons:

1. **MSE (Mean Squared Error)**: Lasso has the lowest MSE on the test set, indicating it generalizes better to unseen data than Ridge and significantly better than Linear Regression.Ridge has the lowest MSE on the training set, but the differences between Lasso and Ridge are minimal.
***Lower MSE indicates better model performance with fewer errors***.

2. **R2 Score**: The R2 score reflects the proportion of the variance in the dependent variable that is predictable from the independent variable(s). Higher is better, with 1 being the best possible score.

Lasso has the highest $R^2$ score on the test set, suggesting it explains the variation in the target variable better than Ridge and far better than Linear Regression. Ridge has the highest $R^2$ score on the training set, indicating it fits the training data slightly better than Lasso and Linear Regression.

3. **RMSE (Root Mean Squared Error)**: Lower is better. Lasso has the lowest RMSE on the test set, further confirming its superior performance in generalizing to unseen data. Ridge has the lowest RMSE on the training set, suggesting a slightly better fit to the training data compared to Lasso.

4. **RSS (Residual Sum of Squares)**: Lower is better. Lasso has a lower RSS on the test set compared to Ridge, indicating it has less residual variance. Ridge has the lowest RSS on the training set, suggesting it fits the training data slightly better.

Lasso's and Ridge's performance is relatively close across all metrics. The **Lasso model is the best choice** due to its lowest MSE and RMSE, highest R2 scores, and reduced RSS, indicating superior accuracy, fit, and predictive efficiency on unseen (**test**) data. It effectively balances overfitting reduction and interpretability by nullifying less relevant features, making it optimal for scenarios with many potentially irrelevant variables.

**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**

Based on the Lasso regression as it was the best model, the five most important predictor variables are determined by their coefficient values (which represent the strength and nature of the relationship with the dependent variable), are:

**Below are the top five predictor with their beta coefficients**

At best alpha .0001

| | beta | independentVariable |
|---|---|---|
| 14 | 0.308287 | GrLivArea |
| 3 | 0.162438 | OverallQual |
| 4 | 0.094896 | OverallCond |
| 22 | 0.078638 | GarageCars |
| 31 | 0.056504 | MSZoning_RL |

**After removing above top five predictor *<u>below are new top five predictors according to Lasso at alpha .0002. Although removing top parameters did reduce the R2 Score</u>***

1. **<u>1stFlrSF (0.248370):</u>** First-floor square footage, indicating that larger first floors are associated with an increase in the (SalesPrice) dependent variable.
2. **<u>2ndFlrSF (0.131027):</u>** Second-floor square footage, suggesting that larger second floors also contribute significantly to the (SalesPrice) dependent variable.
3. **<u>GarageArea (0.079007):</u>** The area of the garage in square feet, which shows a substantial positive impact on the (SalesPrice) dependent variable.
4. **<u>TotRmsAbvGrd (0.060334596):</u>** Total rooms above grade (excluding bathrooms), indicating that a higher number of rooms is positively associated with the (SalesPrice) dependent variable.
5. **Neighbourhood_crawfor<u>(0.050909):</u>** A dummy variable indicating whether the property is in the Crawford neighborhood, suggesting a positive effect on the (SalesPrice) dependent variable when the property is located in this area.

These variables represent the most significant predictors in the model, highlighting the importance total room above grade , of property size (as measured by square footage and the number of rooms) and Full Bathoom condition  in influencing the dependent variable.

At best alpha .0002

| | beta | independentVariable |
|---|---|---|
| **10** | 0.248370 | 1stFlrSF |
| **11** | 0.131027 | 2ndFlrSF |
| **19** | 0.079007 | GarageArea |
| **16** | 0.060334 | TotRmsAbvGrd |
| **40** | 0.050909 | Neighborhood_Crawfor |

**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**
Ensuring a model is robust and generalizable involves several strategies and considerations, each aiming to make the model perform well on unseen data, rather than just on the specific data it was trained on.

1. **Data Quantity, Quality and Diversity:** The model should be trained on sufficient high-quality, diverse data that represent the problem space well. This diversity helps in building a model that can generalize better across different situations, improving its overall accuracy.

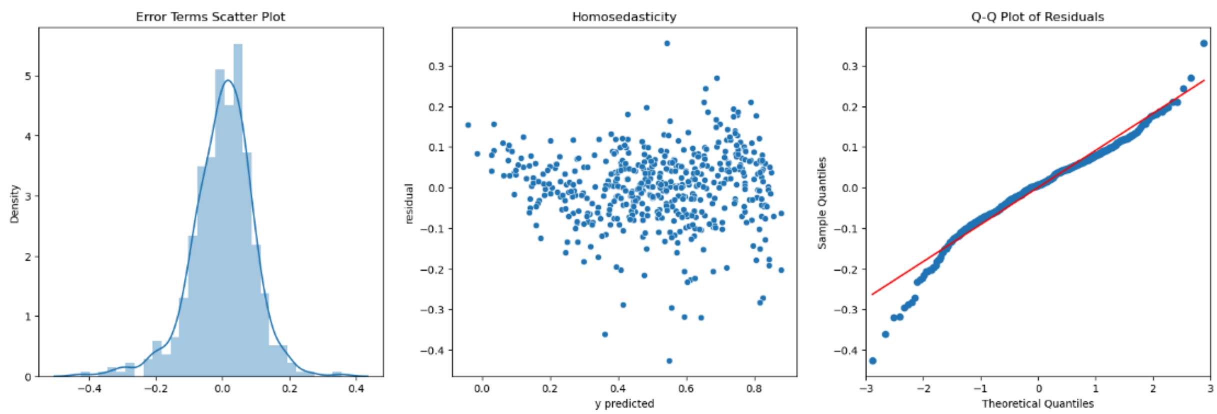
2. **Cross-validation:** Utilize cross-validation techniques during the training process, such as **k-fold cross-validation**. This involves dividing the data into k sets and training the model k times, each time using a different set as the validation data and the remaining as the training data. This helps in assessing the model's performance across different subsets of data, enhancing its generalizability and providing a more accurate estimate of its performance on unseen data.

3. **Regularization**: Regularization is done using methods such as Lasso and Rigid. In Lasso beta coefficients of insignificant features become zero, resulting in reduced model complexity and variance, While in Rigid Beta coefficient of insignificant features becomes as possible near to zero. This prevents the model from becoming too complex and overfitting to the training data, which can impair its performance on new, unseen data.

4. **Model Complexity**: (**Larger the lambda simpler the model)-** Choose the hyper parameter to appropriately. We can use metric such as MSE,RMSE,RSS and R2_Score to identify which lambda results in better metric values. For overfittrf models there is a huge reduction in R2_Score from training to test.

5. **Feature Selection and EDA**: Carefully select and engineer features that are relevant to the problem and are likely to be predictive across different contexts. This can involve removing redundant features, creating new features that capture important patterns, and normalizing or standardizing data. Effective feature engineering can improve both the model's accuracy and its ability to generalize.

6. **Linear Regression assumption verification**: Once a model is build, we can plot error terms (residuals) to identify is there is homocedasticty (constance variance and no pattern in error terms). Error terms should follow normal curve and centered around zero.




7. **Monitoring and Updating**: Continuously monitor the model's performance in real-world applications and update it with new data. This ensures the model remains relevant and accurate over time as the underlying data distributions change.

The implications of these strategies for model accuracy are nuanced. While some techniques, like regularization and selecting an appropriately complex model, might slightly reduce the model's accuracy on the training data by preventing overfitting, they are crucial for ensuring the model performs well on unseen data, which is a better indicator of its true accuracy and utility. Balancing the trade-off between fitting the training data well and maintaining the model's ability to generalize is key to developing robust and accurate models.