

Problem Statement - Part II

Q1. 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: In the case of ridge regression:- When we plot the curve between negative mean absolute error and alpha we see that as the value of alpha increase from 0 the error term decrease and the train error is showing increasing trend when value of alpha increases .when the value of alpha is 2 the test error is minimum so we decided to go with value of alpha equal to 2 for our ridge regression.

For lasso regression I have decided to keep very small value that is 0.01, when we increase the value of alpha the model try to penalize more and try to make most of the coefficient value zero. Initially it came as 0.4 in negative mean absolute error and alpha.

When we double the value of alpha for our ridge regression no we will take the value of alpha equal to 10 the model will apply more penalty on the curve and try to make the model more generalized that is making model more simpler and no thinking to fit every data of the data set .from the graph we can see that when alpha is 10 we get more error for both test and train.

Similarly when we increase the value of alpha for lasso we try to penalize more our model and more coefficient of the variable will reduced to zero, when we increase the value of our r2 square also decreases.

The most important variable after the changes has been implemented for ridge regression are as follows:-

1. MSZoning_FV
2. MSZoning_RL
3. Neighborhood_Crawfor
4. MSZoning_RH
5. MSZoning_RM
6. SaleCondition_Partial
7. Neighborhood_StoneBr
8. GrLivArea
9. SaleCondition_Normal
10. Exterior1st_BrkFace

The most important variable after the changes has been implemented for lasso regression are as follows:-

1. GrLivArea
2. OverallQual
3. OverallCond
4. TotalBsmSF
5. BsmFinSF1

6. GarageArea
7. Fireplaces
8. LotArea
9. LotArea
10. LotFrontage

Q2. 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: Ridge regression, uses a tuning parameter called lambda as the penalty is square of magnitude of coefficients which is identified by cross validation. Residual sum of squares should be small by using the penalty. The penalty is lambda times sum of squares of the coefficients, hence the coefficients that have greater values gets penalized. As we increase the value of lambda the variance in model is dropped and bias remains constant. Ridge regression includes all variables in final model unlike Lasso Regression.

Lasso regression, uses a tuning parameter called lambda as the penalty is absolute value of magnitude of coefficients which is identified by cross validation. As the lambda value increases Lasso shrinks the coefficient towards zero and it make the variables exactly equal to 0. Lasso also does variable selection. When lambda value is small it performs simple linear regression and as lambda value increases, shrinkage takes place and variables with 0 value are neglected by the model.

It is important to regularize coefficients and improve the prediction accuracy also with the decrease in variance, and making the model interpretable.

It is better to use Lasso, since it brings and assigns a zero value to insignificant features, enabling us to choose the predictive variables.

Q3. 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?

Those 5 most important predictor variables that will be excluded are :-

1. GrLivArea
2. OverallQual
3. OverallCond
4. TotalBsmtSF
5. GarageArea

Q4. How can you make sure that a model is robust and generalizable? What are the implications of the same for the accuracy of the model and why?

Ans: We understood using the Bias-Variance trade-off. The simpler the model the more the bias but less variance and more generalizable. Its implication in terms of accuracy is that a robust and generalisable model will perform equally well on both training and test data i.e. the accuracy does not change much

for training and test data.

The model should be as simple though its accuracy will decrease but it will be more robust and generalizable.

Bias: Bias is error in model, when the model is weak to learn from the data. High bias means model is unable to learn details in the data. Model performs poor on training and testing data.

Variance: High variance means model performs exceptionally well on training data as it has very well trained on this of data but performs very poor on testing data as it was unseen data for the model.

Variance is error in model, when model tries to over learn from the data.

Also, Making a model simple leads to Bias-Variance Trade-off.

AS Per, Occam's Razor, two models that show similar 'performance' in the finite training or test data, we should pick the one that makes fewer on the test data due to following reasons:-

Simple models have low variance, high bias and complex models have low bias, high variance.

Complex models lead to overfitting — they work very well for the training samples, fail miserably when applied to other test samples .

Simpler models make more errors in the training set.

Therefore to make the model more robust and generalizable, make the model simple but not simpler which will not be of any use.

Keeping balance between bias and variance minimize the total error. It is important to have balance in Bias and Variance to avoid overfitting and under-fitting of data.

