PA 2 - Classification and Regression

CSE 574: Introduction to Machine Learning

Team 7:

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Problem 1: Experiment with Gaussian Discriminators

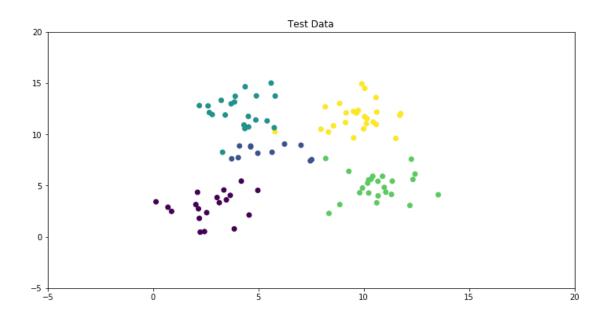
LDA and QDA follow similar approach except for one difference - for LDA, covariance matrix is calculated for all classes together. Whereas for QDA, we compute the covariance matrix for each of the classes. The mean is calculated for each of the possible output class separately for both LDA and QDA. Due to this difference LDA gives a linear classification and QDA gives a quadratic classification. This can be visibly seen in the plots below where for LDA we can see linear boundaries and for QDA we can see boundaries with curves.

For the given data set we get the following accuracy for LDA and QDA:

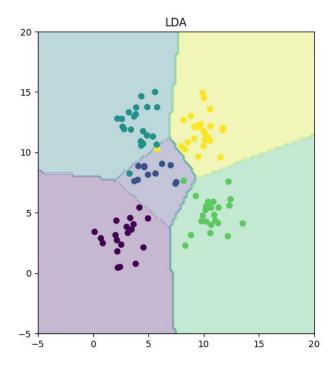
Accuracy for LDA : 97%

• Accuracy for QDA: **96%**

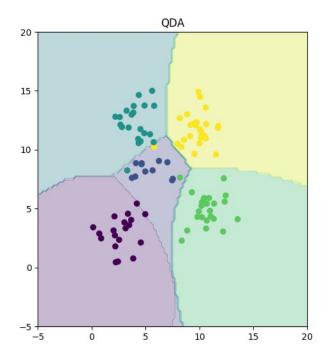
Test Data



Classification using LDA



Classification using QDA



Problem 2: Experiment with Linear Regression

We performed Linear Regression with and without intercept on test as well as training data.

Below is the summary of the MSE values collected for all the different cases.

| Data Set | MSE without intercept | MSE with intercept | |
|---------------|-----------------------|--------------------|--|
| Training data | 19099.4468446 | 2187.16029493 | |
| Test Data | 106775.361558 | 3707.84018132 | |

Conclusion:

Mean Squared Error (MSE) is basically the difference between the estimator and what is estimated. The the lower value of MSE indicates a better prediction and can be said to be a better fit.

In our experiments, we observed that MSE values for training data are smaller compared to those for test data for every case. Moreover, calculating the MSE for both Training and Test data with intercept allow us to get a significant amount of decrease in error as compared to calculating the MSE without intercept. As stated above it's desired to get a lower MSE, thus we can conclude that calculating MSE values with intercept gives us a better estimation.

Problem 3: Experiment with Ridge Regression

We vary the lambda value from 0 to 1 in steps of 0.01 and have calculated the errors for each for them:



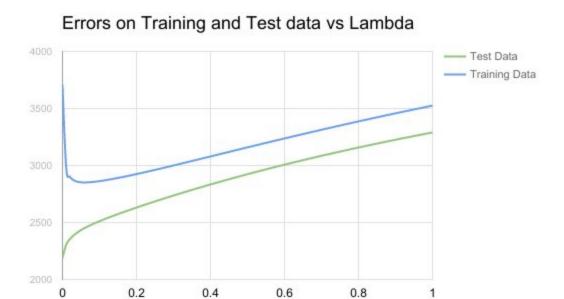
Below are the MSE values for training and test data using ridge regression for optimal λ = 0.06

| MSE Values | MSE with intercept | |
|---------------|--------------------|--|
| Training data | 2451.52849064 | |
| Test Data | 2851.33021344 | |

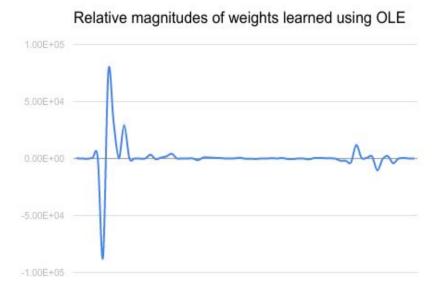
Conclusion:

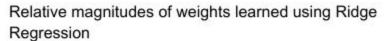
On observation of all the values we found that for testing data the MSE value slowly decreases till λ = 0.06 and then it starts to increase after it hits 0.06. Therefore, we can conclude that λ = 0.06 is optimal.

Plot for errors on train and test data for different values of λ



Comparison of the relative magnitudes of weights learnt using OLE and weights learnt using ridge regression







MSE Values for both the train and test data using intercept with both the approaches are as below:

| Data Sets | MSE Values with intercept | | |
|---------------|---------------------------|------------------|--|
| | OLE | Ridge Regression | |
| Training data | 2187.16029493 | 2451.52849064 | |
| Test Data | 3707.84018132 | 2851.33021344 | |

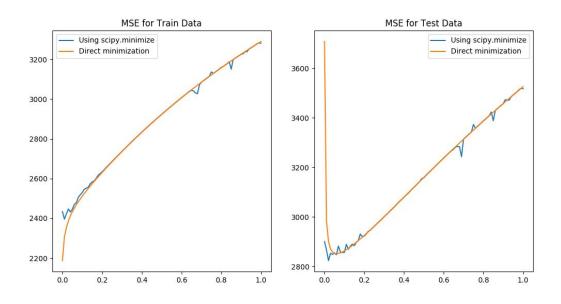
Conclusion:

Observing the MSE values we can state that even though we get a lower MSE using OLE for train data, Ridge regression works better on the test data. As the difference between MSE values for training data are comparatively quite less when compared to those for test data we can say that Ridge regression gives us a better estimation.

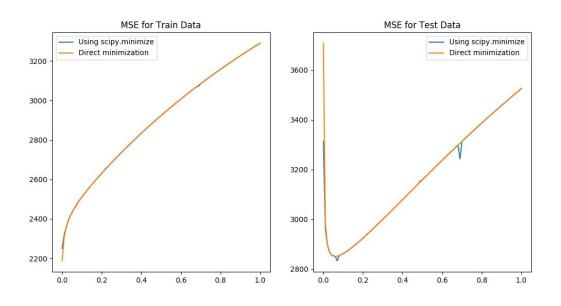
Even in general practises, Ridge has two main benefits over OLE - adding a penalty term which reduces overfitting as well as guarantees that we can find a solution.

Problem 4: Using Gradient Descent for Ridge Regression Learning

Maximum iteration: 20



Maximum iteration: 100



Plot for errors on train and test data obtained by using the gradient descent based learning by varying the regularization parameter λ

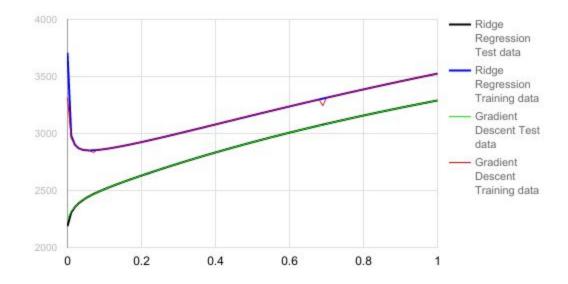


Compare the errors for Ridge Regression and Gradient Descent

0.4

0.2

2500



0.6

0.8

| Lambda = 0.06 | Training data | Test data |
|---|---------------|---------------|
| Error using gradient descent based learning | 2451.53068977 | 2851.32857305 |

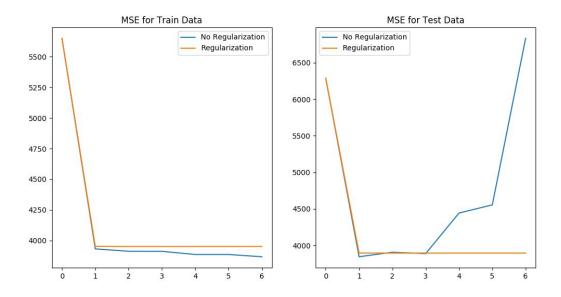
Conclusion:

The MSE values we obtained in Problem 4 using Gradient Descent are almost similar to those obtained in Problem 3 for Ridge Regression. The only difference which can be seen is that for Gradient Descent the plot doesn't seem to be smooth. There are a few minor peaks and troughs which can seen.

Ridge regression through intercept is better than Ridge regression through Gradient Descent in terms of performance as the minimize function in Gradient Descent can take some time to converge. But for bigger datasets Ridge regression through Gradient Descent is better as each step is easy to compute and doesn't involve any expensive computations.

Problem 5: Non-linear Regression

Ridge regression weights using non-linear mapping



Errors on train data and test data for both λ = 0 and λ Optimal:

| Р | Training Data | | Test Data | |
|---|---------------|---------------|---------------|---------------|
| | λ = 0 | λ = 0.06 | λ = 0 | λ = 0.06 |
| 0 | 5650.7105389 | 5650.71190703 | 6286.40479168 | 6286.88196694 |
| 1 | 3930.91540732 | 3951.83912356 | 3845.03473017 | 3895.85646447 |
| 2 | 3911.8396712 | 3950.68731238 | 3907.12809911 | 3895.58405594 |
| 3 | 3911.18866493 | 3950.68253152 | 3887.97553824 | 3895.58271592 |
| 4 | 3885.47306811 | 3950.6823368 | 4443.32789181 | 3895.58266828 |
| 5 | 3885.4071574 | 3950.68233518 | 4554.83037743 | 3895.5826687 |
| 6 | 3866.88344945 | 3950.68233514 | 6833.45914872 | 3895.58266872 |

Therefore, the optimal values for p are:

| Training Data | | Test Data | |
|---------------------|---------------------------|---------------------|------------------------|
| With regularization | Without regularization | With regularization | Without regularization |
| 6 | 6 | 1 | 4 |

Problem 6: Interpreting Results

Summarization of MSE values using the various approaches for training and testing data sets.

| Р | Classifiers | Training data | Test data |
|---|--|---------------|---------------|
| 2 | OLE without intercept | 19099.4468446 | 106775.361558 |
| 2 | OLE with intercept | 2187.16029493 | 3707.84018132 |
| 3 | Ridge Regression (Optimal $\lambda = 0.06$) | 2451.52849064 | 2851.33021344 |
| 4 | Ridge Regression with Gradient Descent | 2451.53068977 | 2851.32857305 |
| 5 | Optimal without regularization | 3866.88344945 | 3845.03473017 |
| 5 | Optimal with regularization | 3950.68233514 | 3895.58266828 |

Conclusion:

As per our experiment values of Mean Squared Error (MSE), the best classifier for Training data is Linear Regression(OLE) with Intercept whereas that for Test data is Ridge Regression with Gradient Descent. Considering a general case we can say that Ridge Regression will be the best approach for classifications. Thus for small data sets MSE is a good metric for measurement and analysis.

When it comes to big datasets, we even need to consider the running time for the process. In those cases, RIdge regression can be infeasible due to expensive computation it involves. There we can use Gradient Descent which provides faster processing with acceptable range of errors.