

# Bayesian regularization-Quadratic Discriminant Analysis

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## Object:

We will use the classification method -Quadratic Discriminant Analysis(QDA),then implement the regularized version of the QDA method, and then apply it to the datasets provided which are the following datasets : Optdigits, Pageblocks, Satimage, Segment.The object is to compare the results obtained without and with priors.

## The main equations:

- Regularization:

The Gaussian-inverse-Wishart prior is

$$\mu_k \sim \mathcal{N}(\mu_{kp}, \Sigma_k / \kappa_{kp}), \quad \Sigma_k \sim IW(\nu_{kp}, \Lambda_{kp}) \quad (1)$$

We can obtain the following equations:

$$\begin{aligned} f_{\mu_k}(\mu) &\propto (\Sigma_k)^{-\frac{1}{2}} \cdot \exp\left(-\frac{\kappa_{kp}}{2} (\mu - \mu_{kp})^t \Sigma_k^{-1} (\mu - \mu_{kp})\right) \\ f_{\Sigma_k}(\Sigma) &\propto (\Sigma)^{-\left(\frac{\nu_{kp}+p+1}{2}\right)} \cdot \exp\left(-\frac{1}{2} \text{tr}\left(\Sigma^{-1} \Lambda_{kp}^{-1}\right)\right) \end{aligned} \quad (2)$$

- Parameter estimate for category mean:

$$\hat{\mu}_k = \frac{\sum_i z_{ik} x_i + \kappa_{kp} \mu_{kp}}{\sum_i z_{ik} + \kappa_{kp}} \quad (3)$$

- Parameter estimate for covariance matrix :

$$\hat{\Sigma}_k = \frac{\sum_i z_{ik} B_{ik} + \kappa_{kp} (\mu_k - \mu_{kp})(\mu_k - \mu_{kp})^t + \Lambda_{kp}^{-1}}{\sum_i z_{ik} + \nu_{kp} + p + 2} \quad (4)$$

- The equation for prediction :

$$\hat{P}(W_k|x) = \frac{\hat{\pi}_k f_k(x_i, \hat{\mu}_k, \hat{\Sigma}_k)}{\sum_l \hat{\pi}_k f_l(x_i, \hat{\mu}_k, \hat{\Sigma}_k)} \quad (5)$$

- The equation for QDA:

$$X \sim N(\mu_k, \Sigma_k) \quad (6)$$

We can write the equation as follows:

$$f_k(x) = (2\pi)^{-\frac{p}{2}} (\Sigma_k)^{-\frac{1}{2}} \exp\left(-\frac{1}{2} (x - \mu_k) \cdot \Sigma_k^{-1} (x - \mu_k)\right) \quad (7)$$

### Define inputs in the training code:

- Xapp:  $n \times d$
- zapp:  $n \times K$
- mprior:  $K \times p$
- Sprior:  $p \times p \times K$
- df\_exp: should satisfy  $\geq 0$
- df\_cov: should satisfy  $\geq d - 1$

### It should provide for training:

- pi:  $1 \times K$
- mu:  $K \times p$
- Sig:  $p \times p \times K$

### Define inputs in the test code:

- Xtst:  $n \times p$
- pi:  $1 \times K$
- Sig:  $p \times p \times K$

### It should provide for test:

- prob:  $n \times K$
- pred:  $n \times 1$

## Implementation:

1. Get the four datasets

2. Define the train\_test function: we divide the data into train set and test set. We set Zapp and Ztst the 'class' of each data. And the other inputs as Xapp and Xtst. zapp and ztst are the binary of the class.

3. Define the function of scale. Scale the data to provide the influence of extreme data value.

4. Define the coefficient and parameters:

- $n$  = number of the samples;
- $d$  ( or  $p$  ) = the dimension of the data;
- $df\_exp$  ( $\kappa_{kp}$ ) is a value  $\geq 0$ ;
- $df\_cov(\nu_{kp})$  is a value  $\geq d - 1$ ;
- mprior of expectations  $\mu_{kp}$  for the Gaussian prior on  $\mu_k$ : matrix  $K \times p$ . In code execution, mprior is setted to `np.zeros((K, p))`;
- Sprior of covariance matrices  $\Lambda_{kp}^{-1}$  for the inverse-Wishart prior on  $\Sigma_k$ : matrix  $p \times p \times K$ . In code execution, Sprior is setted to identity matrix.

The information of the 4 datasets:

- n\_opt: 3934 p\_opt: 64 K\_opt: 10
- n\_pag: 3831 p\_pag: 10 K\_pag: 5
- n\_sat: 4501 p\_sat: 36 K\_sat: 6
- n\_seg: 1617 p\_seg: 19 K\_seg: 7

And then we use the above coefficient to define the following parameters:

- pi = Probability of each class;
- mu :use  $df\_exp$  and mprior apply the equation of  $\hat{\mu}_k$ ;
- Sig:use  $df\_cov$  and Sprior apply the equation of  $\hat{\Sigma}_k$ ;

5. Define the prediction function: We use the obtained prior mu, sig, and pi to calculate the probability of each class by applying the equation  $f_k(x)$ .

the pred is to choose the biggest probability of the values. so that we obtain the prediction of the class of each sample in test.

6. Calculate the accuracy of each dataset with prior.

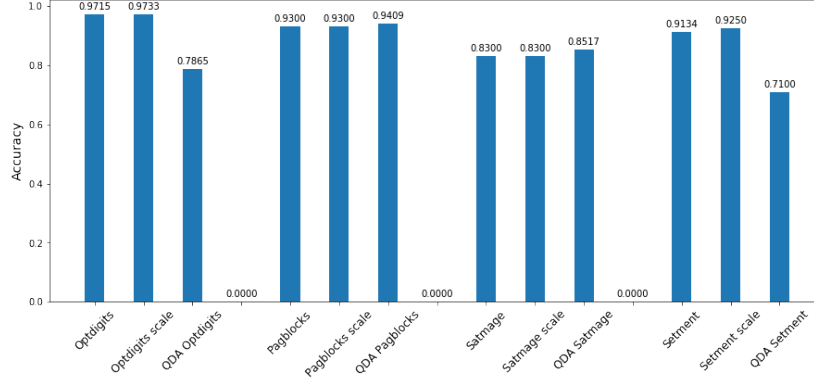


Figure 1: Accuracy of with prior, with proir after scaling and without prior

7.Call the function QDA and calculate the accuracy of each dataset directly without prior.

8.Compare the results of with prior, with proir after scaling and without prior, and draw the conclusion.(figure 1)

9.Change the value of  $df\_exp$  and  $df\_cov$ ,and compare the different result to find the influence of the parameters.

## Result:

We compare the result of four datasets ,each of them has three result:the accuracy of QDA without prior,the accuracy with prior,and the result of data after scale with prior.

From figure 1 we can clearly find that the results of Optdigits and Segment have the obvious difference between accuracy with prior and without prior.The accuracy with prior is more higher than that without prior.From the other two,they are almost the same high.We can conclude that classifier with prior will have higher accuracy in the method quadratic discriminant analysis.

And for the result between the data original and the data after scale ,they are almost the same result.

From Figure 2,we study the influence of the  $df\_exp$ ,which is the  $\kappa_{kp}$ ,except for the data Salmage ,the accuracy of the other three don't change too much with the vary of the  $df\_exp$ . We set  $df\_exp = 0.001, 0.01, 0.1, 0.2, 0.5, 1, 10$  and  $100$ . For the Salmage,the accuracy become lower with the increasing of the  $df\_exp$ .So from the figure2,we can see when the value of  $df\_exp$  is  $\leq 1$ ,the common accuracy is better than when is  $\geq 1$ .We set the initial value of  $df\_exp = 1$ .

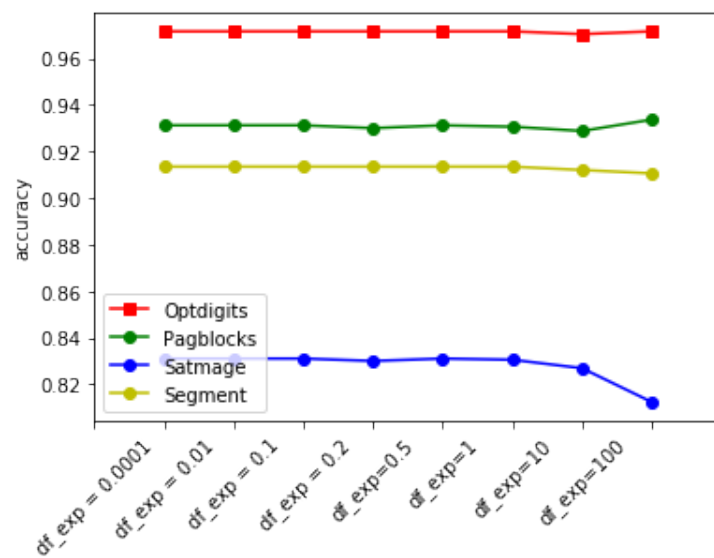


Figure 2: vary the  $df\_exp$

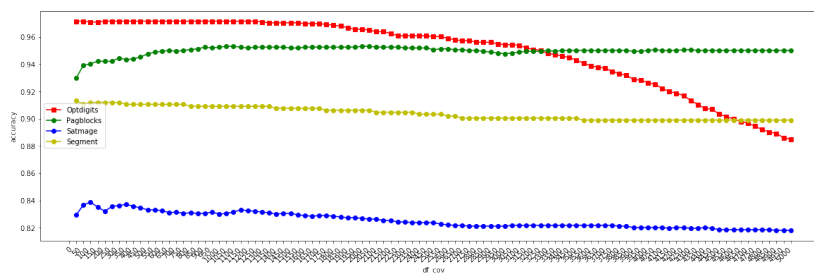


Figure 3: vary the  $df\_exp$

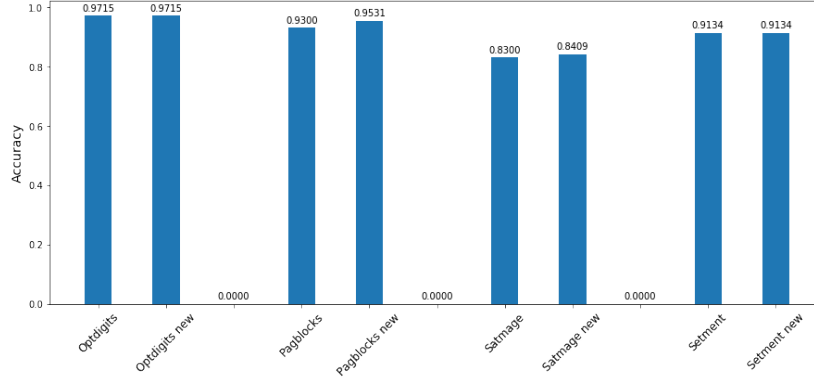


Figure 4: Compare with the new result

The initial value of degrees of freedom is  $df_{cov} = d + 1$ , this figure is 4 data sets from  $d-1$  to  $d + 5000$  divided by 50. From Figure 3, Optdigits, Satimages, and Segments are global decreasing, Satimage increases a little at the begin and then decrease. The most obvious decline in data Optdigits. For the data set Pageblocks, it gradually rises until about  $d_{pag}+1000$  and stabilize. So at the begin of the degree of freedom increase, it may be good for accuracy. We redo the train and test process with the new  $df_{exp}$  and the new  $df_{cov}$  which we find according to the best performance of accuracy. The result is Figure 4. It shows that the accuracy of Pageblocks and Satimage becomes higher. We can conclude that the change of  $df_{exp}$  and  $df_{cov}$  can achieve optimization of the result. In practical, we set  $df_{exp}$  of each dataset is 0.1, and the  $df_{cov}$  is  $d_{opt}+10, d_{pag}+1052, d_{sat}+85, d_{seg}-1$ .

## Conclusion:

We can conclude that applying Bayesian regularization to Quadratic Discriminant can increase the accuracy of classification. We can optimize the model by changing the parameters of the prior  $(\kappa_{kp}, \nu_{kp})$ . We can find the best parameters according to the performance of accuracy.