

# Generative Learning

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## Abstract

The goal of this assignment is to fit the perform Gaussian Discriminant Analysis on multi-variate , multi-class datasets and implement Naïve Bayes with Bernoulli and Binomial features.

## Problem Statement

- **Gaussian Discriminant Analysis** : Given a  $n$  Dimensional,  $k$ -class Dataset, estimate the model parameters and compute discriminant function based on the distribution in each class. The examples must be classified and error should be measured. The confusion matrix should be constructed and the performance measures such as precision, recall, F-Measure and accuracy should be determined from the confusion matrix. The precision-recall curve should be plotted.
- **Naïve Bayes** : Given a 2-class dataset with  $nD$  features, Implement Naïve Bayes with *Binomial* and *Bernoulli* features. The examples must be classified and error should be measured. The confusion matrix should be constructed and the performance measures such as precision, recall, F-Measure and accuracy should be determined from the confusion matrix.

## Proposed Solution

- **Gaussian Discriminant Analysis** : Compute the mean vector for every different class in the data matrix. Also, compute the Co-variance matrix all the different class labels in the training dataset. Compute the membership value for class  $j$  of a given feature vector  $X$ . The class with the highest membership value will be the predicted class. Perform the above mentioned steps for  $1D - 2$  Class,  $nD - 2$  Class and  $nD - k$  Class Datasets.
- **Naïve Bayes with Bernoulli Features** : Compute the prior probabilities for different classes in the dataset, and the parameter  $\alpha$  for all the features and all the different classes. Compute the membership value for class  $j$  of a given feature vector  $X$ . The class with the highest membership value will be the predicted class.

## Implementation Details

### 1. Program Design Issues

Even the program gives accurate results, it takes lot of time to classify all the examples in the  $nD - 2$  Class Dataset, as the number of training examples is large, around 248,050 examples.

## 2. Problems faced

Problems were faced in getting good accuracy in the Naïve Bayes Bernoulli features. This was because, the influence prior probability was not included while computing the membership function. Once, the code was fixed, it gave good accuracy.

## 3. Instructions to use the program

Open the Gen\_Learning.ipynb file in iPython notebook, and execute each cell to get the desired output. The datasets must be placed in the same folder as that of the Gen\_Learning.ipynb file.

## Results and discussion

### 1. GDA on 1 Dimensional , 2 Class Dataset :

The Skin\_NonSkin.txt dataset was used from the UCI website. The original dataset contained 3 features, out of which 2 were removed for this scenario.

#### Confusion matrix :

```
[[      0.      0.]
 [ 50859. 194198.]]
```

#### Accuracy:

0.792460529591

Class	Precision	Recall	F-Measure
1	0.0	0.0	0.0
2	0.792460529591	1.0	0.88421531912

As seen above, the accuracy of predictions is 79.24%, which is quite low. This is because, the original dataset contained 3 features, out of which 2 were discarded and only 1 was chosen.

### 2. GDA on n Dimensional, 2 Class Dataset :

The Skin\_NonSkin.txt dataset was used from the UCI website. In this scenario, no features were removed and the original dataset itself was used. Hence accuracy was found to increase from 79.24% to 94.5%.

#### Confusion Matrix :

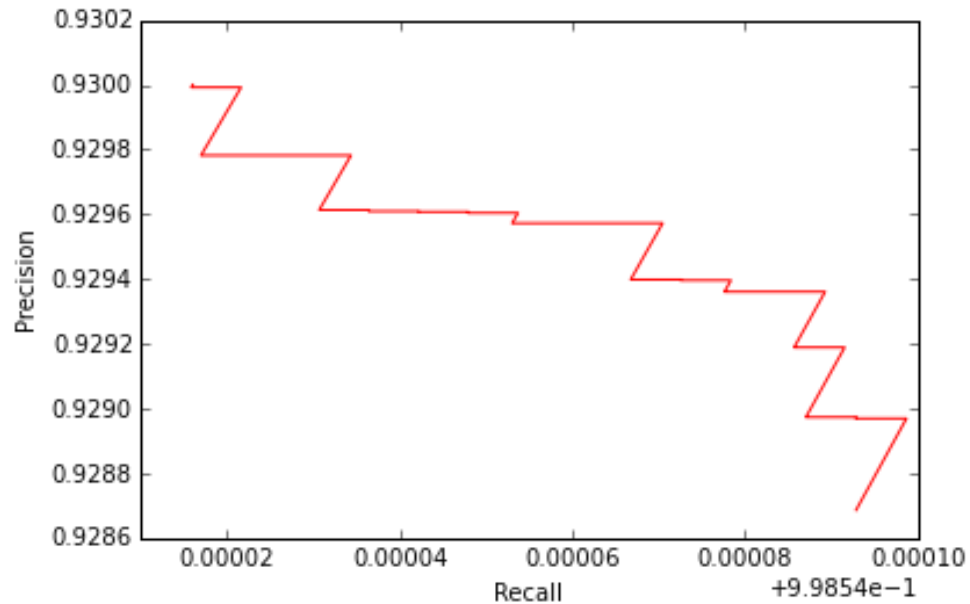
```
[[ 37846.    295.]
 [ 13013. 193903.]]
```

#### Accuracy :

0.945694267048

Class	Precision	Recall	F-Measure
1	0.992265541019	0.744135747852	0.850471910112
2	0.937109745017	0.998480931832	0.966822399617

#### Precision – Recall Curve:



#### 3. GDA on n Dimensional, k Class Dataset :

The iris.data dataset was used from the UCI website.

##### Confusion Matrix :

```
[[ 50.   0.   0.]
 [  0.  46.   1.]
 [  0.   4.  49.]]
```

##### Accuracy :

0.966666666667

Class	Precision	Recall	F-Measure
1	1.0	1.0	1.0
2	0.937109745017	0.92	0.948453608247
3	0.924528301887	0.98	0.95145631068

#### 4. Naïve Bayes with Bernoulli Features :

The spambase.data from UCI website was used. Since the features were not binary, it was binarized.

**Confusion Matrix :**

```
[[ 1478.   190.]
 [  335. 2598.]]
```

**Accuracy :**

0.885894370789

Class	Precision	Recall	F-Measure
1	0.886091127098	0.815223386652	0.84918126975
2	0.885782475281	0.931850789096	0.908232826429

The accuracy was so less i.e 88.58 % because, the features in the SPAM dataset were binarized during Bernoulli NB.

**5. Naïve Bayes with Binomial Features :****Parameter estimates derivation :**

① Model Selection:  $P(X_j^i | y = 1)$

$i \rightarrow \text{doc \#}$   
 $j \rightarrow \text{feat \#}$

$b(x) = \binom{n}{x} p^x (1-p)^{n-x}$

$$P(X_j^i | y = 1) = \binom{p_j^i}{x_j^i} \alpha_{j|y=1}^{x_j^i} (1 - \alpha_{j|y=1})^{p_j^i - x_j^i}$$

Compute parameters (M-L):

$$l(\theta) = \log \prod_{i=1}^m \underbrace{p(x^i | y^i; \theta) \cdot p(y^i)}_{\propto p(y^i | x^i)}$$

↑  
IID.

$$\text{NB} \rightarrow = \log \prod_{i=1}^m \left[ \prod_{j=1}^n p(x_j^i | y^i; \theta) \right] p(y^i)$$

$$= \sum_{i=1}^m \sum_{j=1}^n \log p(x_j^i | y^i; \theta) + \sum_{i=1}^m \log p(y^i)$$

$$= \sum_{i=1}^m \sum_{j=1}^n \log \left( \frac{\hat{p}_j^{(i)}}{x_j^i} \right) \alpha_j^{x_j^{(i)}} (1 - \alpha_j)^{p^{(i)} - x_j^{(i)}} + \sum_{i=1}^m \log p(y^i)$$

$$\theta^* = \underset{\theta}{\operatorname{argmax}} l(\theta)$$

$$\frac{dl}{d\theta} = 0$$

$$\theta = \left[ \alpha_{1|y=1}, \dots, \alpha_{n|y=1}, \dots, \alpha_{1|y=k}, \dots, \alpha_{n|y=k}, \alpha_1, \dots, \alpha_k \right]$$

$$\frac{\partial \mathcal{L}}{\partial d_i | y=j} = 0$$

$$; \quad \frac{\partial \mathcal{L}}{\partial d_j} = 0$$

$$P(y=l) \equiv \alpha_l = \frac{\sum_{i=1}^m \mathbb{1}(y^i=l)}{m}$$

$$l=1, \dots, k$$

$$\alpha_{j|y=l} = \frac{\sum_{i=1}^m \mathbb{1}(y^i=l) \cdot x_j^{(i)}}{\sum_{i=1}^m \mathbb{1}(y^i=l) \cdot p^{(i)}} + \epsilon$$

③ Membership

$$g_l(x) = \log P(y=l|x) \propto \log (P(x|y=l) \cdot P(y=l))$$

$$\downarrow$$

$$\text{class label} = \log (P(x|y=l)) + \log (P(y=l))$$

$$= \log \prod_{j=1}^n P(x_j|y=l) + \log (P(y=l))$$

$$= \sum_{j=1}^n \log P(x_j|y=l) + \log (P(y=l))$$

$$= \sum_{j=1}^n \log \binom{P}{x_j} \alpha_{j|y=l}^{x_j} (1 - \alpha_{j|y=l})^{P-x_j} + \log(\alpha_l)$$

total no of words in doc.

The spambase.data from UCI website was used. Since the length of documents was not present in the dataset, the length of the documents were assigned to be 10.

**Confusion Matrix :**

```
[[ 1736.  2182.]  
 [   77.   606.]]
```

**Accuracy :**

0.509019778309

Class	Precision	Recall	F-Measure
1	0.443083205717	0.957528957529	0.605827953237
2	0.887262079063	0.217360114778	0.349178910977

**Weakness :** No suitable dataset with Bernoulli features was found, and hence the lengths of documents were randomly assigned. Because of which, it resulted in a low accuracy for Naïve Bayes with Bernoulli Features.

**References**

1. [Stackoverflow.com](#)
2. [Wikipedia.org](#)