## **MA333 Project 1**

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#### **Overview**

In the project, we are going to implement the linear regression algorithm and test it on dataset.

### **Formula Derivation**

### 1.The log-likelihood function

$$egin{aligned} l(\mathbf{w}) &= \sum_{i=1}^n log(p_1(\mathbf{x}_i; \mathbf{w})^{y_i} p_0(\mathbf{x}_i; \mathbf{w})^{1-y_i}) \ &= \sum_{i=1}^n y_i log(p_1(\mathbf{x}_i; \mathbf{w})) + (1-y_i) log(p_0(\mathbf{x}_i; w)) \ &= \sum_{i=1}^n y_i log(p(\mathbf{x}_i; \mathbf{w})) + (1-y_i) log(1-p(\mathbf{x}_i; w)) \ &= \sum_{i=1}^n y_i log(rac{e^{\mathbf{w}^T \mathbf{x}_i}}{1+e^{\mathbf{w}^T \mathbf{x}_i}}) + (1-y_i) log(rac{1}{1+e^{\mathbf{w}^T \mathbf{x}_i}}) \ &= \sum_{i=1}^n y_i log(e^{\mathbf{w}^T \mathbf{x}_i}) - y_i log(1+e^{\mathbf{w}^T \mathbf{x}_i}) + (y_i-1) log(1+e^{\mathbf{w}^T \mathbf{x}_i}) \ &= \sum_{i=1}^n y_i \mathbf{w}^T \mathbf{x}_i - log(1+e^{\mathbf{w}^T \mathbf{x}_i}) \end{aligned}$$

### 2. Score Equation

Based on the formula derived from part 1,we can continue expand it

$$egin{aligned} l(\mathbf{w}) &= \sum_{i=1}^n y_i \mathbf{w}^T \mathbf{x}_i - log(1 + e^{\mathbf{w}^T \mathbf{x}_i}) \ &= \sum_{i=1}^n y_i \sum_{j=1}^d x_{ij} w_j - log(1 + e^{\mathbf{w}^T \mathbf{x}_i}) \end{aligned}$$

Then we find the partial derivative of  $w_j (j = 0,1,2,3 ... d)$ 

$$egin{aligned} rac{\partial L(\mathbf{w})}{\partial w_j} &= \sum_{i=1}^n y_i x_{ij} - rac{x_{ij} e^{\mathbf{w}^T \mathbf{x}_i}}{1 + e^{\mathbf{w}^T \mathbf{x}_i}} \ &= \sum_{i=1}^n x_{ij} (y_i - p(\mathbf{x}_i; \mathbf{w})) \ &rac{\partial L(\mathbf{w})}{\partial w_j} = 0 \ &\sum_{i=1}^n x_{ij} (y_i - p(\mathbf{x}_i; \mathbf{w})) = 0 \end{aligned}$$

#### 3. Hessian matrix

Consider the j th element of k th row in the Hessian Matrix. We want to find:

$$\frac{\partial L(\mathbf{w})}{\partial w_k \partial w_j}$$

Fron Problem 2 we know

$$rac{\partial L(\mathbf{w})}{\partial w_j} = \sum_{i=1}^n x_{ij} (y_i - p(\mathbf{x}_i; \mathbf{w}))$$

So

$$\begin{split} \frac{\partial L(\mathbf{w})}{\partial w_k \partial w_j} &= -\sum_{i=1}^n x_{ij} \frac{x_{ik} e^{\mathbf{w}^T \mathbf{x}_i} (1 + e^{\mathbf{w}^T \mathbf{x}_i}) - e^{\mathbf{w}^T \mathbf{x}_i} e^{\mathbf{w}^T \mathbf{x}_i} x_{ik}}{(1 + e^{\mathbf{w}^T \mathbf{x}_i})^2} \\ &= -\sum_{i=1}^n x_{ik} x_{ij} \frac{e^{\mathbf{w}^T \mathbf{x}_i}}{(1 + e^{\mathbf{w}^T \mathbf{x}_i})^2} \\ &= -\sum_{i=1}^n x_{ik} x_{ij} \frac{e^{\mathbf{w}^T \mathbf{x}_i}}{1 + e^{\mathbf{w}^T \mathbf{x}_i}} \frac{1}{1 + e^{\mathbf{w}^T \mathbf{x}_i}} \\ &= -\sum_{i=1}^n x_{ik} x_{ij} p(\mathbf{x}_i; \mathbf{w}) (1 - p(\mathbf{x}_i; \mathbf{w})) \\ &\frac{\partial L(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^T} = -\sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T p(\mathbf{x}_i; \mathbf{w}) (1 - p(\mathbf{x}_i; \mathbf{w})) \end{split}$$

#### 4. Matrix Notation of IRLS

Fristly we convert the derivative into matrix form

$$\begin{split} \frac{\partial L(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^T} &= -\sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T p(\mathbf{x}_i; \mathbf{w}) (1 - p(\mathbf{x}_i; \mathbf{w})) \\ &= -(X^T D X)^{-1} \\ \frac{\partial L(\mathbf{w})}{\partial w_j} &= \sum_{i=1}^n x_{ij} (y_i - p(\mathbf{x}_i; \mathbf{w})) \\ \frac{\partial L(\mathbf{w})}{\partial \mathbf{w}} &= X^{-1} (\mathbf{y} - \mathbf{p}) \end{split}$$

Then we get the matrix form of  $\star \text{textbf}(w)^{(k)}$ 

$$\mathbf{w}^{(k)} = \mathbf{w}^{(k-1)} - \left(\frac{\partial^{2}l(\mathbf{w})}{\partial \mathbf{w}\partial \mathbf{w}^{T}}\right)^{-1}\Big|_{\mathbf{w}^{(k-1)}} \left(\frac{\partial l(\mathbf{w})}{\partial \mathbf{w}}\right)^{-1}\Big|_{\mathbf{w}^{(k-1)}}$$

$$= \mathbf{w}^{(k-1)} + (X^{T}DX)^{-1}X^{T}(\mathbf{y} - \mathbf{p})$$

$$= (X^{T}DX)^{-1}((X^{T}DX)\mathbf{w}^{(k-1)} + X^{T}(\mathbf{y} - \mathbf{p}))$$

$$= (X^{T}DX)^{-1}X^{T}D(X\mathbf{w}^{(k-1)} + D^{-1}(\mathbf{y} - \mathbf{p}))$$

$$= (X^{T}DX)^{-1}X^{T}D\mathbf{z}$$

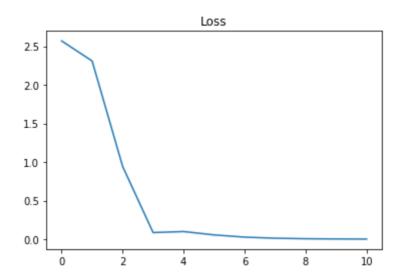
$$= argmin(\mathbf{z} - X\mathbf{w})^{T}D(\mathbf{z} - X\mathbf{w})$$

### **IRLS Algorithm**

```
import numpy as np
 2
    from matplotlib import pyplot as plt
    from sklearn.preprocessing import normalize
 4
    def exp(x):
 5
        return np.exp(x)
 6
 7
    '''IRLS Alogrithm for Logistic Regression
 8
9
       Args:
10
           X:Training data, a n *(d+1) matrix
11
           y:Class of training data, n*1 column vector
           error: Error bound of w
12
13
       Return:
           w: Weights, a (d+1) * 1 column vector
14
       Notice: In order to avoid finding the inverse singular matrix which will crash the
15
    program,
               we use np.linalg.pinv() to get the "inverse" of martix
16
17
18
    def IRIS(X,y,print_loss=True,error=1e-3,step=10):
        print("Algorithm starts.")
19
20
21
        w = np.random.random((X.shape[1],1))
22
        w_pre = w
23
        loss = []
24
        iter = 0
25
26
        while True:
            inner_product = X.dot(w)
27
28
29
            p = exp(inner_product) / (1.0 + exp(inner_product))
30
31
            D = np.diag(p.T[0])
32
33
            w = w + np.dot(np.dot(np.linalg.pinv(np.dot(np.dot(X.T,D),X)),X.T),y - p)
34
35
            diff = np.sum(np.abs(w - w_pre))
36
37
            if diff < error:
38
                break
39
            else:
40
                w_pre = w
41
42
            if (iter+1) % 2 == 0:
43
                if print_loss:
44
                     print(diff)
45
                 loss.append(diff)
46
            iter += 1
47
        print("Algorithm finished.")
48
49
        return w, loss
  X = \text{np.random.random}((10,6)) + \text{np.array}([[0.1,0.7,2.4],[4.1,5.8,6.2],[7.7,8.5,9.3]])
1
  y = np.array([[1.0],[0.0],[0.0],[1.0],[0.0],[1.0],[0.0],[0.0],[1.0],[0.0])
  w, loss = IRIS(X,y,False,1e-3)
  Algorithm starts.
  Algorithm finished.
```

```
plt.title("Loss")
plt.plot(loss)
```

1 [<matplotlib.lines.Line2D at 0x1df383464a8>]



## Test algorithm on South African Hearth dataset

1.Define function for reading the dataset

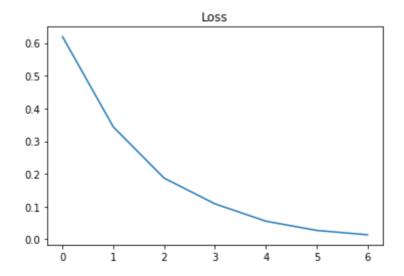
```
import os
 1
 2
    from sklearn import metrics
 3
    def read_dataset(file_name):
        f = open(file_name)
 5
        data_x = []
 6
        data_y = []
        for line in f.readlines():
 8
             if line[0] !='@':
 9
                 line = line.strip('\n')
10
                 items = line.split(', ')
11
12
                 data_row = [1] # for w0
13
                 for i in range(len(items)):
                     if i == 4:
14
15
                         if items[i] == 'Absent':
16
                             data_row.append(1.0)
                             data_row.append(0.0)
17
18
                         else:
19
                             data_row.append(0.0)
20
                             data_row.append(1.0)
                     elif i == 9:
21
22
                         data_y.append([int(items[i])])
23
                         data_row.append(float(items[i]))
24
25
                 data_x.append(data_row)
26
                # print(items)
27
        data_x = np.array(data_x)
28
        data_y = np.array(data_y)
```

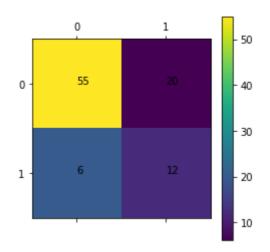
2. Define the function for training and testing

```
from sklearn import preprocessing
 2
    def train_and_test(num,threashold=0.75):
 3
        (data_x,data_y) = read_dataset('./saheart-5-fold/saheart-5-'+str(num)+'tra.dat')
 4
        data_x = preprocessing.scale(data_x)
 5
        w1,loss1 = IRIS(data_x,data_y,False,1e-2)
        plt.title("Loss")
 6
 7
        plt.plot(loss1)
        (test_x,test_y) = read_dataset('./saheart-5-fold/saheart-5-'+str(num)+'tst.dat')
 8
 9
        test_x = preprocessing.scale(test_x)
10
        y = test_x.dot(w1)
11
        y = \exp(y) / (1.0 + \exp(y))
12
        y_pred = y.T > 0.75
13
        y_pred = 1 * y_pred
14
15
        score = metrics.accuracy_score(test_y.T[0],y_pred[0])
16
        print("Accuracy: " + str(score))
17
        print("Precision score:"+str(precision_score(y_pred[0],test_y)))
18
        mat = confusion_matrix(test_y, y_pred[0])
19
        plt.matshow(confusion_matrix(test_y, y_pred[0]))
20
        plt.text(0,0,mat[0][0])
21
        plt.text(0,1,mat[0][1])
22
        plt.text(1,0,mat[1][0])
        plt.text(1,1,mat[1][1])
23
24
        plt.colorbar()
```

#### 3. Train and test

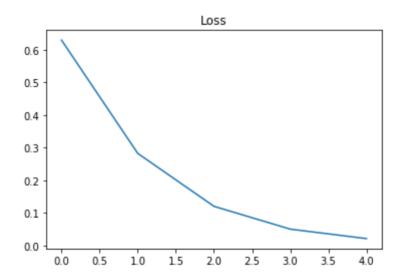
```
1 | train_and_test(1)
1 | Algorithm starts.
2 | Algorithm finished.
3 | Accuracy: 0.7204301075268817
4 | Precision score:0.375
```

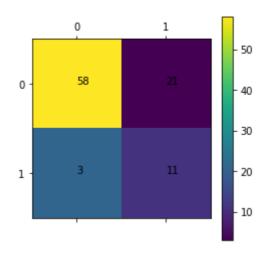




### 1 | train\_and\_test(2)

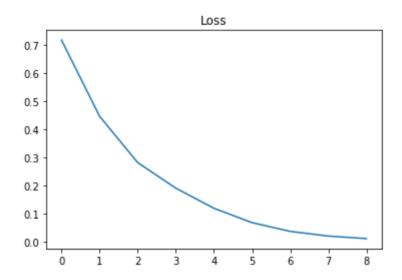
- 1 | Algorithm starts.
- 2 Algorithm finished.
- 3 Accuracy: 0.7419354838709677
- 4 Precision score:0.34375

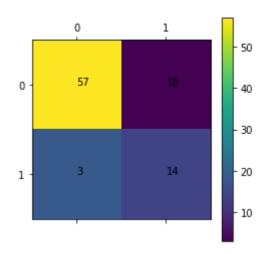




### 1 | train\_and\_test(3)

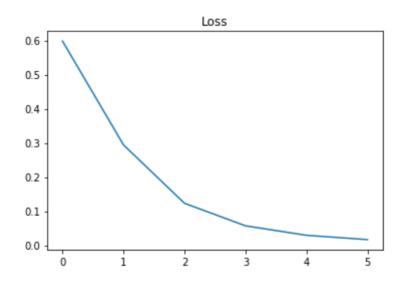
- 1 Algorithm starts.
- 2 Algorithm finished.
- 3 Accuracy: 0.7717391304347826
- 4 Precision score:0.4375

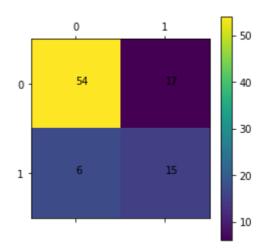




### 1 | train\_and\_test(4)

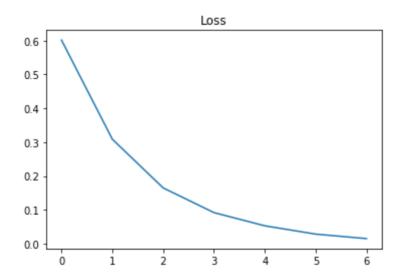
- 1 | Algorithm starts.
- 2 Algorithm finished.
- 3 Accuracy: 0.75
- 4 Precision score:0.46875

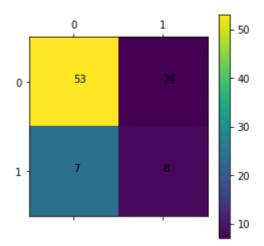




### 1 | train\_and\_test(5)

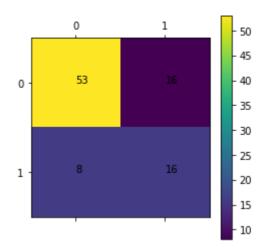
- 1 | Algorithm starts.
- 2 Algorithm finished.
- 3 Accuracy: 0.6630434782608695
- 4 Precision score:0.25





#### 4. Train and test on sklearn

```
from sklearn.linear_model import LogisticRegression
  from sklearn.metrics import confusion_matrix
  from sklearn.metrics import precision_score
1
    def sk_train_and_test(num, threashold=0.75):
 2
        (data_x,data_y) = read_dataset('./saheart-5-fold/saheart-5-'+str(num)+'tra.dat')
 3
        data_x = preprocessing.scale(data_x)
        clf = LogisticRegression(random_state=0, solver='lbfgs',
 4
                                multi_class='ovr').fit(data_x, data_y)
 5
 6
        (test_x,test_y) = read_dataset('./saheart-5-fold/saheart-5-'+str(num)+'tst.dat')
 7
        test_x = preprocessing.scale(test_x)
 8
        y_pred = clf.predict(test_x)
 9
        score = metrics.accuracy_score(test_y.T[0],y_pred)
        print("Accuracy: " + str(score))
10
        print("Precision score:"+str(precision_score(y_pred,test_y)))
11
12
        mat = confusion_matrix(test_y, y_pred)
13
        plt.matshow(confusion_matrix(test_y, y_pred))
14
        plt.text(0,0,mat[0][0])
15
        plt.text(0,1,mat[0][1])
16
        plt.text(1,0,mat[1][0])
17
        plt.text(1,1,mat[1][1])
18
        plt.colorbar()
1 | sk_train_and_test(1)
  Accuracy: 0.7419354838709677
1
  Precision score:0.5
  c:\users\mingji han\appdata\local\programs\python\python37\lib\site-
   packages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y was
   passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for
   example using ravel().
     y = column_or_1d(y, warn=True)
```

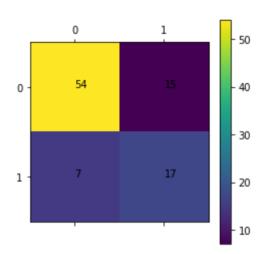


#### 1 | sk\_train\_and\_test(2)

1 Accuracy: 0.7634408602150538 2 Precision score:0.53125

c:\users\mingji han\appdata\local\programs\python\python37\lib\sitepackages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

 $y = column_or_1d(y, warn=True)$ 



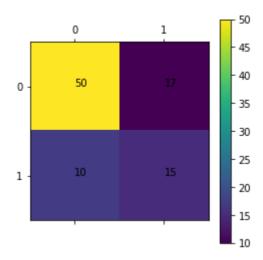
#### 1 | sk\_train\_and\_test(3)

1 | Accuracy: 0.7065217391304348

2 Precision score:0.46875

c:\users\mingji han\appdata\local\programs\python\python37\lib\sitepackages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

y = column\_or\_1d(y, warn=True)



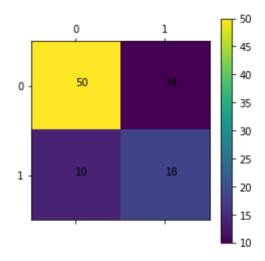
#### 1 sk\_train\_and\_test(4)

1 Accuracy: 0.7391304347826086

2 Precision score:0.5625

c:\users\mingji han\appdata\local\programs\python\python37\lib\sitepackages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

y = column\_or\_1d(y, warn=True)



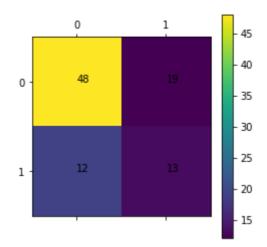
#### 1 | sk\_train\_and\_test(5)

1 | Accuracy: 0.6630434782608695

2 Precision score:0.40625

c:\users\mingji han\appdata\local\programs\python\python37\lib\sitepackages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

y = column\_or\_1d(y, warn=True)



# Conclusion

The algorithm we design is as good as the logistic regression in scikit-learn.

Our alogrithm can be improved through ensemble method.

1