

## Reference:

## 1. official documentation

[https://scikit-learn.org/stable/auto\\_examples/linear\\_model/plot\\_sparse\\_logistic\\_regression\\_mnist.html#sphx-glr-auto-examples-linear-model-plot-sparse-logistic-regression-mnist-py](https://scikit-learn.org/stable/auto_examples/linear_model/plot_sparse_logistic_regression_mnist.html#sphx-glr-auto-examples-linear-model-plot-sparse-logistic-regression-mnist-py) ([https://scikit-learn.org/stable/auto\\_examples/linear\\_model/plot\\_sparse\\_logistic\\_regression\\_mnist.html#sphx-glr-auto-examples-linear-model-plot-sparse-logistic-regression-mnist-py](https://scikit-learn.org/stable/auto_examples/linear_model/plot_sparse_logistic_regression_mnist.html#sphx-glr-auto-examples-linear-model-plot-sparse-logistic-regression-mnist-py))

and

[https://scikit-learn.org/stable/modules/generated/sklearn.linear\\_model.LogisticRegression.html](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html) ([https://scikit-learn.org/stable/modules/generated/sklearn.linear\\_model.LogisticRegression.html](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html))

## 2. blog

<https://towardsdatascience.com/logistic-regression-using-python-sklearn-numpy-mnist-handwriting-recognition-matplotlib-a6b31e2b166a> (<https://towardsdatascience.com/logistic-regression-using-python-sklearn-numpy-mnist-handwriting-recognition-matplotlib-a6b31e2b166a>)

## Import packages

```
In [2]: ▶ import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
import numpy as np
```

```
In [3]: ▶ from sklearn.datasets import fetch_openml
# fetch_openml is new latest several version of sklearn, for version
# optimization algorithm saga is available only to version 0.23.0 or higher
```

```
In [4]: ▶ # These are the images
# There are 70,000 images (28 by 28 images for a dimensionality of 784)
print(X.shape)
# These are the labels
print(y.shape)
```

(70000, 784)  
(70000,)

## Split dataset into training dataset and testing dataset

```
In [5]: ▶ # random shuffle the data
random_state = check_random_state(0)
permutation = random_state.permutation(X.shape[0])
X = X[permutation]
y = y[permutation]
X = X.reshape((X.shape[0], -1))
```

```
In [6]: ▶ # split the 70k images into 60k training images and 10k testing images
```

```
from sklearn.model_selection import train_test_split
```

## Showing the Images and Labels

```
In [7]: ▶ plt.figure(figsize=(20,4))
        for index, (image, label) in enumerate(zip(train_img[0:5], train_lbl[0:5])):
            plt.subplot(1, 5, index + 1)
            plt.imshow(np.reshape(image, (28,28)), cmap=plt.cm.gray)
```



## Fit the Logistic Model with specified optimization methods

```
In [8]: ▶ # import model
```

```
In [9]: ▶ # all parameters not specified are set to their defaults
        # default solver is incredibly slow, may use sag, saga, lgfb,
```

```
In [10]: ▶ # train model on training dataset

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear_model\_sag.
py:328: ConvergenceWarning: The max_iter was reached which means the
coef_ did not converge
  warnings.warn("The max_iter was reached which means "
```

```
Out[10]: LogisticRegression(solver='saga')
```

```
In [11]: ▶ # Returns a NumPy Array
        # Predict for One Observation (image)
```

```
Out[11]: (array(['8'], dtype=object), '8')
```

```
In [12]: ▶
```

## Measuring Model Performance

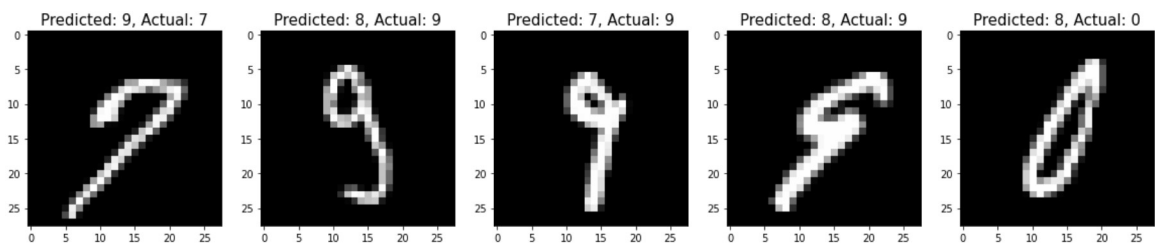
```
In [13]: ▶ # Use score method to get accuracy of model
        trainscore = logisticRegr.score(train_img,train_lbl)
        testscore = logisticRegr.score(test_img, test_lbl)
```

```
The training error is 0.06101666666666672 and the Testing error is
0.076500000000000001
```

## Display misclassified images with predicted labels

```
In [14]: # collect misclassified images
mis_vector = (test_lbl == predictions)
```

```
In [15]: plt.figure(figsize=(20,4))
for plotIndex, badIndex in enumerate(misclassifiedIndexes[0:5]):
    plt.subplot(1, 5, plotIndex + 1)
    plt.imshow(np.reshape(test_img[badIndex], (28,28)), cmap=plt.cm.gr
```



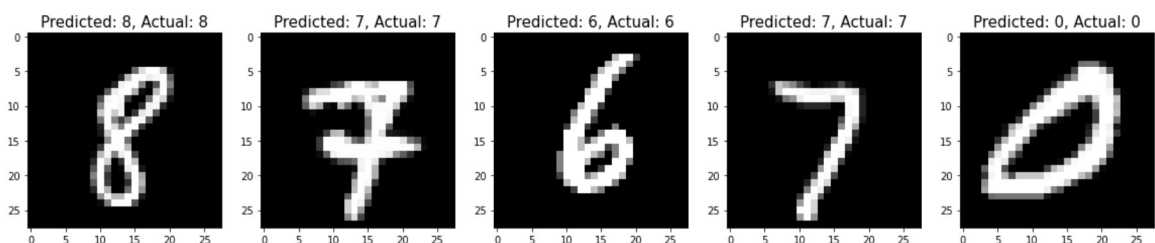
```
In [16]: The total # of misclassified images is 765
```

## Problem 1

### 5 Images that were correctly classified by the model

```
In [17]: correctclassifiedIndexes = np.where(mis_vector == 1)[0]

plt.figure(figsize=(20,4))
for plotIndex, goodIndex in enumerate(correctclassifiedIndexes[0:5]):
    plt.subplot(1,5,plotIndex + 1)
    plt.imshow(np.reshape(test_img[goodIndex], (28,28)), cmap = plt.cm.
```



## Problem 2

### Splitting the images into multiple training and test sets

```
In [18]: import pandas as pd
#train_img.type
#d = {'Train_Data' : train_img, 'Test_Data' : test_img}
```

```

#MODEL_DF = pd.DataFrame(data = d)

#Defining a function to split the data, model, and compute training &
def training_log(images,labels,ratio):
    #Splitting the data based off ratio of test/train
    train_img, test_img, train_lbl, test_lbl = train_test_split(images
    #defining the logistical regression
    logisticRegr = LogisticRegression(solver = 'saga')
    #fitting the regression to the data
    logisticRegr.fit(train_img, train_lbl)
    #computing the training score
    trainscore = logisticRegr.score(train_img,train_lbl)
    #computing the testing score
    testscore = logisticRegr.score(test_img, test_lbl)
    return trainscore, testscore, ratio


#60k training and 10k testing images
[trn_e, tst_e, rtio] = training_log(X,y,(1/7))

```

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear\_model\\_sag.py:328: ConvergenceWarning: The max\_iter was reached which means the coef\_ did not converge  
 warnings.warn("The max\_iter was reached which means "


In [19]:  `print('Training error:',1-trn_e)`

Training error: 0.061033333333333384  
 Testing error: 0.076799999999999998

In [20]:  `#50k training and 20k testing images`  
`[trn_e_2, tst_e_2, rtio_2] = training_log(X,y,(2/7))`  
`print('Training error:',1-trn_e_2)`

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear\_model\\_sag.py:328: ConvergenceWarning: The max\_iter was reached which means the coef\_ did not converge  
 warnings.warn("The max\_iter was reached which means "

Training error: 0.059259999999999998  
 Testing error: 0.082099999999999995

In [21]:  `#40k training and 30k testing images`  
`[trn_e_3, tst_e_3, rtio_3] = training_log(X,y,(3/7))`  
`print('Training error:',1-trn_e_3)`

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear\_model\\_sag.py:328: ConvergenceWarning: The max\_iter was reached which means the coef\_ did not converge  
 warnings.warn("The max\_iter was reached which means "

Training error: 0.055875000000000001  
 Testing error: 0.084400000000000003

```
In [22]: ▶ #30k training and 40k testing images
[trn_e_4, tst_e_4, rtio_4] = training_log(X,y,(4/7))
print('Training error:',1-trn_e_4)

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear_model\_sag.
py:328: ConvergenceWarning: The max_iter was reached which means the
coef_ did not converge
  warnings.warn("The max_iter was reached which means "
```

Training error: 0.0518999999999999946  
Testing error: 0.087250000000000005

```
In [23]: ▶ #20k training and 50k testing images
[trn_e_5, tst_e_5, rtio_5] = training_log(X,y,(5/7))
print('Training error:',1-trn_e_5)

C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear_model\_sag.
py:328: ConvergenceWarning: The max_iter was reached which means the
coef_ did not converge
  warnings.warn("The max_iter was reached which means "
```

Training error: 0.044150000000000002  
Testing error: 0.091019999999999999

```
In [24]: ▶ #10k training and 60k testing images
[trn_e_6, tst_e_6, rtio_6] = training_log(X,y,(6/7))
print('Training error:',1-trn_e_6)

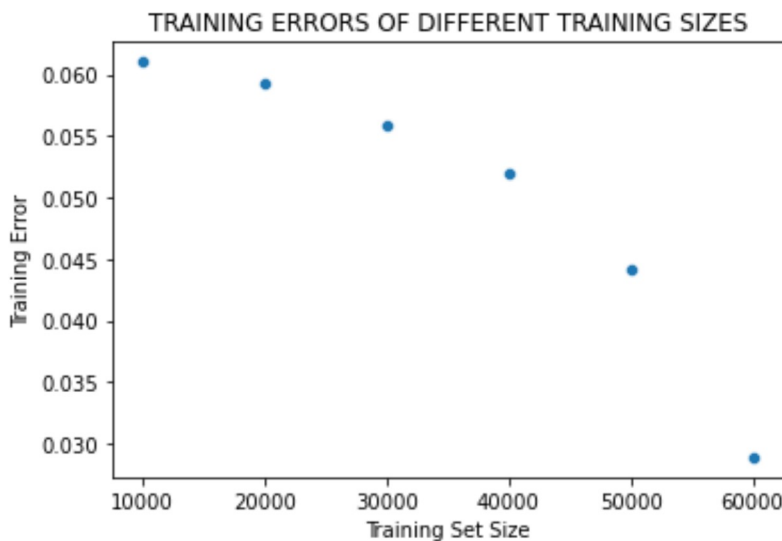
C:\Users\tbsvb\anaconda3\lib\site-packages\sklearn\linear_model\_sag.
py:328: ConvergenceWarning: The max_iter was reached which means the
coef_ did not converge
  warnings.warn("The max_iter was reached which means "
```

Training error: 0.0289000000000000037  
Testing error: 0.100033333333333331

```
In [25]: ► all_TrE = np.zeros(6, dtype = float)
all_TrE[0] = 1 - trn_e
all_TrE[1] = 1 - trn_e_2
all_TrE[2] = 1 - trn_e_3
all_TrE[3] = 1 - trn_e_4
all_TrE[4] = 1 - trn_e_5
all_TrE[5] = 1 - trn_e_6
print(all_TrE)
training_size = np.array([10000, 20000, 30000, 40000, 50000, 60000])
print(training_size)
sns.scatterplot(x = training_size, y = all_TrE)
plt.title('TRAINING ERRORS OF DIFFERENT TRAINING SIZES')
plt.xlabel('Training Set Size')

[0.06103333 0.05926      0.055875  0.0519      0.04415      0.0289      ]
[10000 20000 30000 40000 50000 60000]
```

Out[25]: Text(0, 0.5, 'Training Error')



```
In [26]: ▶ all_Tst = np.zeros(6, dtype = float)
all_Tst[0] = 1 - tst_e
all_Tst[1] = 1 - tst_e_2
all_Tst[2] = 1 - tst_e_3
all_Tst[3] = 1 - tst_e_4
all_Tst[4] = 1 - tst_e_5
all_Tst[5] = 1 - tst_e_6
print(all_Tst)

sns.scatterplot(x = training_size, y = all_Tst)
plt.title('TESTING ERRORS OF DIFFERENT TRAINING SIZES')
plt.xlabel('Training Set Size')
plt.xticks([0.0768, 0.0821, 0.0844, 0.08725, 0.09102, 0.10003333])
```

Out[26]: Text(0, 0.5, 'Training Error')



## Problem 3

### Credit card logistic regression

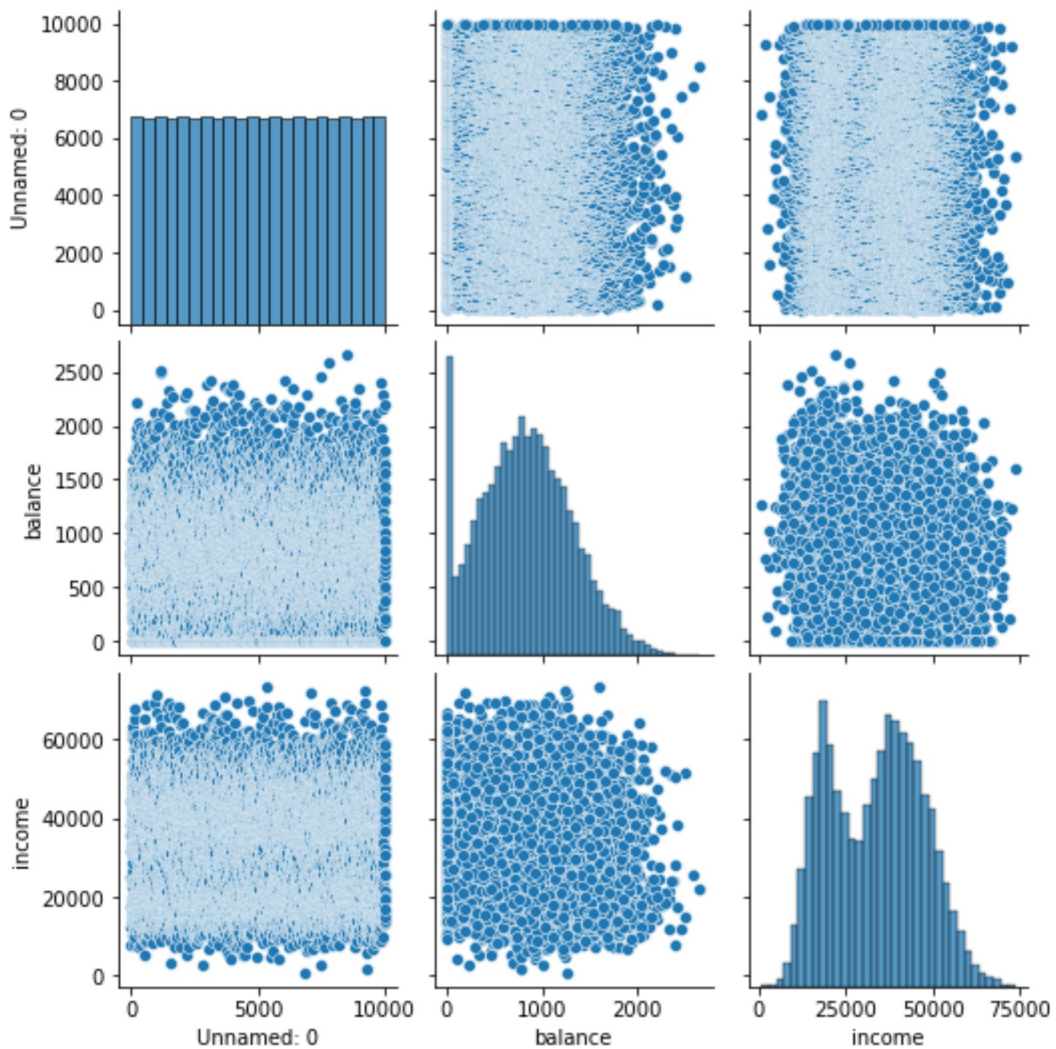
```
In [27]: ▶ # reading in the credit card data
ccdf = pd.read_csv('Default.csv')
ccdf.head()
```

Out[27]:

	Unnamed: 0	default	student	balance	income
0	1	No	No	729.526495	44361.625074
1	2	No	Yes	817.180407	12106.134700
2	3	No	No	1073.549164	31767.138947
3	4	No	No	529.250605	35704.493935
4	5	No	No	785.655883	38463.495879

In [28]: `#Plotting the data`

Out[28]: `<seaborn.axisgrid.PairGrid at 0x23ae97aef40>`



```
In [29]: #Turning the categorical data into imperial values and
#getting the predictor matrix made
X_cc = ccdof[['balance', 'income', 'student']]
X_cc.head()
X_cc = pd.get_dummies(data = X_cc, drop_first=True)
X_cc.head()
cc_pred = X_cc.iloc[:,0:4].values
cc_pred[:,1] = cc_pred[:,1]/1000
print(cc_pred)
#Getting the values for credit card status as imperial values
Y_cc = ccdof[['default']]
Y_cc = pd.get_dummies(data = Y_cc, drop_first = True)
Y_cc = Y_cc.iloc[:,0].values
```



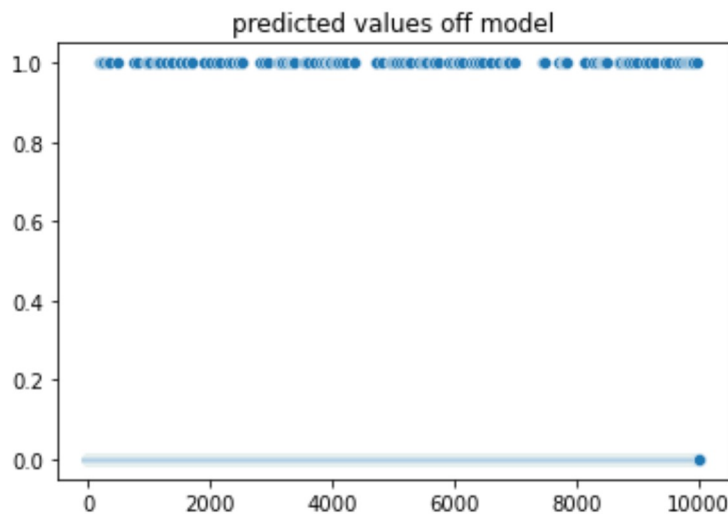
```
[[7.29526495e+02 4.43616251e+01 0.00000000e+00]
 [8.17180407e+02 1.21061347e+01 1.00000000e+00]
 [1.07354916e+03 3.17671389e+01 0.00000000e+00]]
```

```
In [32]: > cc_logreg = LogisticRegression(solver = 'lbfgs', fit_intercept = True,
cc_logreg.fit(cc_pred, Y_cc)
print('INTERCEPT COEFFICIENT:', cc_logreg.intercept_[0])
print('BALANCE COEFFICIENT:', cc_logreg.coef_[0,0])
print('INCOME COEFFICIENT:', cc_logreg.coef_[0,1])
print('STUDENT COEFFICIENT:', cc_logreg.coef_[0,2])

predicted_cc_results = cc_logreg.predict(cc_pred)
axis_cc = np.arange(len(predicted_cc_results))
sns.scatterplot(x = axis_cc, y = predicted_cc_results)
plt.title('predicted values off model')
#print(np.count_nonzero(predicted_cc_results==0))

INTERCEPT COEFFICIENT: -10.901804583503399
BALANCE COEFFICIENT: 0.0057306083783232
INCOME COEFFICIENT: 0.003961617411109353
STUDENT COEFFICIENT: -0.6125699138814747
```

Out[32]: Text(0.5, 1.0, 'predicted values off model')



## Problem 4) finding the false positive and negative rate

```
In [38]: > #print('True length:', len(Y_cc))
#print('Predicted length:', len(predicted_cc_results))

#Creating a function to determine false negative and false positive rate
def false_pos_neg_rate(true, pred):

    false_pos_count = 0
    false_neg_count = 0
    #checking through each instance
    for i in range(0, len(true)):
        #if the instance is true but should be false
```

```

        if pred[i] == 1:
            if true[i] == 0:
                false_pos_count = false_pos_count + 1
            #if the instance is false but should be true
        if pred[i] == 0:
            if true[i] == 1:
                false_neg_count = false_neg_count + 1

    fpos_rate = false_pos_count / (false_pos_count + np.count_nonzero(
    fneg_rate = false_neg_count / (sum(true) + false_neg_count)

    return fpos_rate, fneg_rate, false_pos_count, false_neg_count
[pos_r,neg_r,pos_c,neg_c] = false_pos_neg_rate(Y_cc,predicted_cc_resul
#print(np.count_nonzero(predicted_cc_results==0))
print('False positive rate:',pos_r*100,'%')
print('False negative rate:',neg_r*100,'%')
print('# of false positives:',pos_c)
print('# of false negatives:',neg_c)

"
False positive rate: 0.4120737612032554 %
False negative rate: 40.64171122994652 %
# of false positives: 40
# of false negatives: 228

```

## Problem 5

### Textbook problem 4.6

$X_1$  = hours studied per week  $X_2$  = GPA  $Y$  = They get an A given:  $B_0 = -6$   $B_1 = 0.05$   $B_2 = 1$

#### A) $P\{\text{Receives A} \mid 40 \text{ hours studying \& 3.5 GPA}\}$

$X_1 = 40$ ,  $X_2 = 3.5$

$p(x) = e^{\text{exponent}} / (1 + e^{\text{exponent}}) \rightarrow$  probability of receiving an A

$\text{exponent} = B_0 + B_1 * X_1 + B_2 * X_2$

$\text{exponent} = -6 + (0.05 * 40) + (1 * 3.5) = -0.5$

so  $p(x) = e^{(-0.5)} / (1 + e^{(-0.5)}) = 0.377$  therefore the chance they get an A is 37.7%

#### B) How many hours to get 50% chance of an A?

let  $p(x) = 0.5$

$X_1 = ?$ ,  $X_2 = 3.5$

$\text{exponent} = 0.05 * X_1 - 2.5$

$0.5 = e^{\text{exponent}} / (1 + e^{\text{exponent}})$

$$1 + e^{\text{exponent}} = 2 * e^{\text{exponent}} \quad e^{\text{exponent}} = 1$$

$$\ln(e^{\text{exponent}}) = \ln(1)$$

$$\text{exponent} = 0$$

$$0.05 * X_1 - 2.5 = 0$$

$$X_1 = 2.5 / 0.05$$

$$X_1 = 50$$

therefore the student would need to study 50 hours per week to have a 50% chance of getting an A