Task 1: Here you need to use linear regression for classification. (a) Download MNIST handwritten digit data. There are 10 classes (corresponding to digits 0, 1, ..., 9) and each digit is viewed as an imgae of size 28 Ö 28 (= 784) pixels; each pixel having values 0 to 255. There are around 6000 digit training patterns and around 1000 test patterns in each class and the class label is also provided for each of the digits. Visit http://yann.lecun.com/exdb/mnist/ for more details. (b) Use any pair of classes with 2000 training patterns per class. So, you will have 4000 training patterns totally. Obtain the W vector associated with linear regression for this data. Use class labels 1 and -1 for the two classes (positive and negative classes). (c) Take 2000 test patterns (1000 per class) and classify. For this you compute y for each test pattern X using the W obtained in (b) and use the polarity of y to classify X. Compute the classification accuracy. (d) Repeat steps (a) to (c) 5 times by randomly selecting 2000 training patterns, in step (b), from each class and report the average accuracy and standard deviation on the test data.

1. Task 2: Here you need to use logistic regression to solve the classification problem in Task 1.

2. Task 3: Here you need to use logistic regression for regression. (a) Use any regression dataset from Kaggle where the output y is a scalar. (b) Use logistic regression for the regression problem. There could be different ways of doing this. For example, refer to https://datascience.stackexchange.com/ questions/473/is-logistic-regression-actually-a-regression-algorithm (c) Use at least 1000 training patterns and 5-fold cross validation. Report the aver- age squared error and standard deviation on the training data.

3. Task 4: Here you need to use Linear Regression to solve the regression problem in Task 3 and report the average squared error and standard deviation.

4. You need to analyse the results and report. Compare the results of tasks 1 and 2. Similarly, compare the results of tasks 3 and 4. Analysis is important as usual.

Logistic Regression (MNIST)

The MNIST database of handwritten digits, available from this page, has a training set of 60,000 examples, and a test set of 10,000 examples. It is a subset of a larger set available from NIST. The digits have been size-normalized and centered in a fixed-size image. It is a good database for people who want to try learning techniques and pattern recognition methods on real-world data while spending minimal efforts on preprocessing and formatting.

In [122…

```
import numpy as np
import numpy as pd


import matplotlib.pyplot as plt
```

```
# Used for Confusion Matrix
from sklearn import metrics
import seaborn as sns

np.set_printoptions(precision=2, suppress=True)

# Used for Downloading MNIST
#from sklearn.datasets import fetch_mldata

from sklearn.datasets import fetch_openml
dataset = fetch_openml("mnist_784")

# Used for Splitting Training and Test Sets
from sklearn.model_selection import train_test_split

%matplotlib inline
from sklearn.linear_model import LogisticRegression
```

Downloading MNIST Dataset

In [123…
```
# Change data_home to wherever to where you want to download your data
#mnist = fetch_mldata('MNIST original', data_home='./')
mnist = fetch_openml("mnist_784")
```

In [124…
```
mnist
```

Out[124…
```
{'data': array([[0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.]]),
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 'target_names': ['class'],
 'DESCR': "**Author**: Yann LeCun, Corinna Cortes, Christopher J.C. Burges  \n**Source**: [MNIST Website](htt
p://yann.lecun.com/exdb/mnist/) - Date unknown  \n**Please cite**:  \n\nThe MNIST database of handwritten digit
s with 784 features, raw data available at: http://yann.lecun.com/exdb/mnist/. It can be split in a training se
t of the first 60,000 examples, and a test set of 10,000 examples  \n\nIt is a subset of a larger set available
from NIST. The digits have been size-normalized and centered in a fixed-size image. It is a good database for p
eople who want to try learning techniques and pattern recognition methods on real-world data while spending min
imal efforts on preprocessing and formatting. The original black and white (bilevel) images from NIST were size
normalized to fit in a 20x20 pixel box while preserving their aspect ratio. The resulting images contain grey l
```

evels as a result of the anti-aliasing technique used by the normalization algorithm. the images were centered in a 28x28 image by computing the center of mass of the pixels, and translating the image so as to position this point at the center of the 28x28 field. \n\nWith some classification methods (particularly template-based methods, such as SVM and K-nearest neighbors), the error rate improves when the digits are centered by bounding box rather than center of mass. If you do this kind of pre-processing, you should report it in your publications. The MNIST database was constructed from NIST's NIST originally designated SD-3 as their training set and SD-1 as their test set. However, SD-3 is much cleaner and easier to recognize than SD-1. The reason for this can be found on the fact that SD-3 was collected among Census Bureau employees, while SD-1 was collected among high-school students. Drawing sensible conclusions from learning experiments requires that the result be independent of the choice of training set and test among the complete set of samples. Therefore it was necessary to build a new database by mixing NIST's datasets. \n\nThe MNIST training set is composed of 30,000 patterns from SD-3 and 30,000 patterns from SD-1. Our test set was composed of 5,000 patterns from SD-3 and 5,000 patterns from SD-1. The 60,000 pattern training set contained examples from approximately 250 writers. We made sure that the sets of writers of the training set and test set were disjoint. SD-1 contains 58,527 digit images written by 500 different writers. In contrast to SD-3, where blocks of data from each writer appeared in sequence, the data in SD-1 is scrambled. Writer identities for SD-1 is available and we used this information to unscramble the writers. We then split SD-1 in two: characters written by the first 250 writers went into our new training set. The remaining 250 writers were placed in our test set. Thus we had two sets with nearly 30,000 examples each. The new training set was completed with enough examples from SD-3, starting at pattern # 0, to make a full set of 60,000 training patterns. Similarly, the new test set was completed with SD-3 examples starting at pattern # 35,000 to make a full set with 60,000 test patterns. Only a subset of 10,000 test images (5,000 from SD-1 and 5,000 from SD-3) is available on this site. The full 60,000 sample training set is available.\n\nDownloaded from openml.org.",
 'details': {'id': '554',
  'name': 'mnist_784',
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  'upload_date': '2014-09-29T03:28:38',
  'licence': 'Public',
  'url': 'https://www.openml.org/data/v1/download/52667/mnist_784.arff',
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 'url': 'https://www.openml.org/d/554'}

In [125…

```
# These are the images
mnist.data.shape
```

Out[125… (70000, 784)

In [126…
```
# These are the labels
mnist.target.shape
```

Out[126… (70000,)

In [ ]:

Splitting Data into Training and Test Sets

In [127…
```
# test_size: what proportion of original data is used for test set
train_img, test_img, train_lbl, test_lbl = train_test_split(
    mnist.data, mnist.target, test_size=1/7.0, random_state=0)
```

In [128…
```
print(f'{train_img} {train_lbl}')
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]] ['7' '3' '0' ... '7' '1' '1']
```

In [131…
```
acc_list = []
for i in [0,1,2,3,4]:

    zero_four_train= [train_img [key] for (key, label) in enumerate(train_lbl) if int(label) == i or int(label)
    zero_four_label = [label for (key, label) in enumerate(train_lbl) if int(label) == i or int(label) == i+4]
    zero_four_test= [test_img [key] for (key, label) in enumerate(test_lbl) if int(label) == i or int(label) ==
    zero_four_test_label = [label for (key, label) in enumerate(test_lbl) if int(label) == i or int(label) == i



    zero_four_train = np.array(zero_four_train)

    zero_four_label = np.array(zero_four_label)



    zero_four_test = np.array(zero_four_test)
    zero_four_test_label = np.array(zero_four_test_label)
```

```
    print(f'Shape {zero_four_label}')
    train=zero_four_train[0:4000]
    label=zero_four_label[0:4000]

    logisticRegr = LogisticRegression(solver = 'lbfgs',max_iter=12000)

    np.set_printoptions(precision=2, suppress=True)
    logisticRegr.fit(zero_four_train[0:4000], zero_four_label[0:4000])
    print('intercept ----->:', logisticRegr.intercept_)
    p = logisticRegr.coef_[0]
    print(f"Weight ------>:  {p}")

    z = zero_four_test[0:2000]

    predictions = logisticRegr.predict(z)

#score = logisticRegr.score(zero_four_train[4000:6000], zero_four_label[4000:6000])

    score = logisticRegr.score(z,zero_four_test_label[0:2000])
#score = logisticRegr.score(z, zero_four_test[0:2000])
#print(score)
    acc_list.append(score)


    print(f' Accuracy -----> {score}')


std_dev = acc_list
p = round(np.std(std_dev, dtype=np.float64),4)
print(f' Standard Error ----> {p}')
```

```
Shape ['0' '0' '0' ... '0' '0' '4']
intercept ----->: [0.]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.   -0.   -0.   -0.    0.   -0.    0.   -0.   -0.
 -0.    0.    0.    0.    0.   -0.   -0.01  0.    0.01  0.    0.    0.
  0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.
 -0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.    0.    0.
  0.    0.01  0.   -0.    0.    0.    0.    0.    0.    0.    0.   -0.
```

```
 0.   -0.   -0.   -0.   -0.   -0.   -0.    0.    0.   -0.    0.01 -0.01
-0.01 -0.   -0.    0.   -0.01  0.    0.    0.    0.01  0.    0.    0.
 0.    0.    0.    0.   -0.   -0.   -0.01 -0.    0.    0.    0.   -0.01
-0.   -0.01 -0.01  0.   -0.   -0.    0.    0.01  0.01 -0.   -0.    0.
 0.01  0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.
-0.    0.    0.    0.   -0.   -0.01 -0.    0.    0.   -0.01 -0.01  0.
 0.   -0.    0.01  0.01  0.01  0.    0.   -0.    0.    0.    0.    0.
 0.    0.    0.    0.   -0.   -0.   -0.01  0.01 -0.   -0.   -0.   -0.
-0.   -0.   -0.   -0.    0.   -0.   -0.    0.01  0.01  0.    0.    0.
 0.    0.   -0.    0.   -0.    0.    0.   -0.   -0.   -0.   -0.    0.01
-0.    0.   -0.01 -0.01 -0.    0.01  0.   -0.01 -0.01  0.   -0.    0.
 0.    0.    0.    0.    0.    0.   -0.   -0.   -0.    0.    0.   -0.
-0.    0.    0.    0.   -0.01 -0.01 -0.01 -0.01 -0.01 -0.   -0.01 -0.
-0.01 -0.   -0.01 -0.01  0.    0.    0.    0.    0.    0.    0.    0.
-0.    0.    0.   -0.   -0.01  0.01  0.   -0.01 -0.   -0.   -0.01 -0.01
-0.01 -0.01  0.   -0.01  0.    0.01 -0.01 -0.01 -0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.   -0.   -0.    0.   -0.    0.    0.
-0.   -0.   -0.    0.    0.    0.   -0.   -0.   -0.01  0.01 -0.01 -0.01
-0.    0.    0.    0.    0.    0.   -0.    0.    0.    0.   -0.    0.
 0.   -0.01  0.01  0.01  0.    0.    0.01 -0.    0.01  0.01  0.   -0.
 0.   -0.   -0.01 -0.01  0.   -0.    0.    0.    0.    0.    0.    0.
 0.01 -0.   -0.    0.01  0.01 -0.    0.01  0.01  0.   -0.    0.02  0.01
 0.02  0.01 -0.    0.01  0.   -0.01 -0.01 -0.   -0.   -0.    0.    0.
 0.    0.    0.    0.   -0.   -0.   -0.    0.01  0.01  0.01  0.    0.01
-0.   -0.    0.02  0.01  0.01  0.    0.   -0.   -0.   -0.01 -0.   -0.
-0.   -0.    0.    0.    0.   -0.    0.    0.   -0.   -0.   -0.    0.
 0.    0.01 -0.01 -0.    0.    0.01  0.01  0.02  0.01 -0.    0.01 -0.
 0.    0.    0.   -0.01 -0.    0.    0.   -0.    0.    0.    0.    0.
-0.    0.    0.    0.01 -0.01 -0.01 -0.01 -0.01  0.01  0.01  0.01  0.01
 0.    0.    0.01 -0.01  0.01  0.01  0.   -0.    0.    0.    0.   -0.01
 0.    0.    0.    0.   -0.   -0.    0.    0.01 -0.01  0.   -0.   -0.
 0.01  0.01  0.01  0.01  0.    0.    0.01  0.    0.01  0.01 -0.   -0.
 0.   -0.    0.    0.    0.   -0.   -0.    0.01 -0.   -0.01 -0.   -0.
-0.   -0.01 -0.   -0.   -0.01 -0.01  0.    0.01  0.01  0.01  0.    0.
 0.01  0.   -0.   -0.   -0.   -0.    0.    0.    0.   -0.   -0.    0.
-0.   -0.01 -0.   -0.   -0.01 -0.01 -0.01 -0.01 -0.01 -0.    0.01  0.01
 0.    0.   -0.01 -0.    0.01  0.01  0.01  0.   -0.   -0.    0.    0.
 0.    0.   -0.    0.    0.   -0.   -0.01 -0.   -0.   -0.   -0.   -0.
-0.02 -0.01 -0.01 -0.   -0.    0.   -0.    0.    0.    0.01  0.01 -0.
-0.   -0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.01 -0.01
-0.01 -0.01 -0.   -0.01 -0.01 -0.01 -0.01 -0.   -0.   -0.   -0.    0.
 0.    0.01  0.01 -0.   -0.    0.    0.    0.    0.    0.    0.    0.
-0.   -0.   -0.   -0.   -0.01 -0.   -0.    0.   -0.   -0.   -0.01 -0.
 0.   -0.    0.    0.   -0.   -0.   -0.   -0.    0.    0.    0.    0.
 0.    0.    0.    0.   -0.    0.   -0.   -0.   -0.    0.   -0.    0.01
 0.    0.   -0.01 -0.01  0.   -0.    0.    0.    0.    0.    0.    0.
-0.    0.    0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.
 0.    0.01  0.01  0.    0.    0.01  0.    0.    0.    0.01  0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
```

```
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.  ]
 Accuracy -----> 0.9933605720122574
Shape ['1' '5' '5' ... '1' '1' '1']
intercept ----->: [0.]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.   -0.   -0.   -0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.
 -0.   -0.01 -0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.    0.
 -0.   -0.   -0.   -0.    0.   -0.    0.01  0.02 -0.   -0.   -0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 -0.   -0.01 -0.    0.   -0.01 -0.   -0.   -0.    0.   -0.   -0.    0.
  0.01  0.01  0.01  0.    0.    0.    0.    0.    0.    0.    0.   -0.
 -0.   -0.   -0.    0.    0.   -0.   -0.01 -0.   -0.01 -0.   -0.01 -0.
  0.   -0.01 -0.    0.02  0.02 -0.01 -0.01 -0.01 -0.    0.    0.    0.
  0.    0.    0.   -0.   -0.   -0.   -0.   -0.    0.    0.   -0.    0.
 -0.    0.   -0.   -0.    0.   -0.   -0.01  0.01  0.01  0.01  0.    0.01
  0.01  0.01  0.01  0.    0.    0.   -0.   -0.   -0.   -0.   -0.   -0.
 -0.    0.    0.    0.01 -0.    0.01 -0.01  0.   -0.    0.01  0.01  0.01
  0.01  0.01  0.01  0.01  0.01  0.    0.    0.    0.    0.   -0.   -0.
  0.    0.   -0.   -0.    0.    0.01  0.   -0.   -0.   -0.   -0.01 -0.
  0.    0.    0.    0.    0.    0.01  0.    0.02  0.02  0.01  0.    0.
  0.    0.    0.    0.    0.    0.   -0.   -0.    0.01  0.01 -0.   -0.01
 -0.   -0.01 -0.   -0.   -0.   -0.01  0.    0.    0.01  0.01  0.01  0.02
  0.02  0.01  0.    0.    0.    0.    0.    0.    0.    0.   -0.    0.
 -0.    0.   -0.    0.    0.    0.01 -0.01 -0.   -0.   -0.01 -0.01 -0.
  0.    0.    0.01  0.02  0.01  0.01  0.01  0.    0.    0.    0.    0.
  0.    0.    0.   -0.   -0.01 -0.   -0.    0.01 -0.    0.   -0.   -0.01
 -0.   -0.01 -0.01  0.    0.    0.    0.01  0.01  0.01  0.01  0.    0.
  0.    0.    0.    0.    0.   -0.   -0.   -0.    0.    0.01  0.01 -0.
  0.    0.01 -0.01 -0.   -0.01 -0.01 -0.01  0.01 -0.   -0.01  0.    0.
  0.    0.    0.   -0.   -0.    0.    0.    0.    0.   -0.   -0.01  0.
  0.01  0.01  0.01  0.01  0.   -0.   -0.01 -0.02 -0.01 -0.02  0.    0.
  0.    0.    0.01  0.01  0.    0.    0.    0.    0.    0.   -0.    0.
  0.   -0.01  0.    0.01  0.01  0.01  0.01  0.   -0.    0.   -0.01 -0.02
 -0.01 -0.01  0.01  0.02  0.01  0.    0.    0.    0.    0.    0.    0.
  0.    0.   -0.    0.    0.    0.    0.01  0.01 -0.    0.    0.01  0.01
 -0.   -0.01 -0.02 -0.01 -0.01  0.01  0.02  0.02  0.01  0.    0.    0.
  0.    0.    0.    0.    0.    0.   -0.    0.    0.    0.    0.01  0.01
 -0.    0.01 -0.   -0.01 -0.01 -0.01 -0.01  0.    0.01  0.02  0.02  0.01
  0.01  0.    0.    0.    0.    0.   -0.    0.    0.    0.    0.    0.
  0.01  0.01  0.01 -0.   -0.   -0.01 -0.   -0.01 -0.01 -0.01  0.01 -0.
```

```
  0.01  0.02  0.01  0.    0.    0.01 -0.    0.    0.    0.   -0.    0.
  0.    0.    0.    0.    0.01  0.02  0.02  0.01  0.01  0.   -0.   -0.01
 -0.    0.    0.01 -0.    0.01  0.01  0.   -0.    0.    0.01  0.01  0.01
  0.    0.   -0.    0.    0.    0.    0.    0.    0.    0.01  0.01  0.
  0.    0.    0.    0.    0.01  0.   -0.   -0.01 -0.    0.01  0.   -0.
  0.01  0.01  0.    0.    0.    0.   -0.    0.    0.    0.    0.   -0.
 -0.    0.01 -0.    0.01 -0.   -0.01 -0.   -0.   -0.01 -0.01 -0.    0.01
 -0.   -0.   -0.01 -0.   -0.    0.   -0.   -0.   -0.    0.   -0.    0.
  0.    0.    0.   -0.01 -0.    0.   -0.   -0.   -0.    0.01 -0.    0.01
  0.01  0.   -0.    0.   -0.01  0.01 -0.   -0.   -0.   -0.   -0.   -0.
 -0.   -0.   -0.    0.    0.    0.    0.   -0.   -0.   -0.01  0.    0.01
  0.01  0.01  0.01  0.01  0.01  0.01  0.    0.01  0.01  0.   -0.   -0.01
 -0.01 -0.01  0.   -0.   -0.   -0.    0.    0.    0.    0.    0.    0.
  0.   -0.    0.    0.   -0.   -0.01  0.01  0.01  0.    0.01 -0.    0.
 -0.    0.    0.01  0.   -0.01 -0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.   -0.    0.   -0.01 -0.01 -0.    0.01  0.01
  0.01  0.01  0.    0.    0.01  0.01  0.01  0.   -0.   -0.   -0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.01  0.01  0.    0.   -0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.  ]
 Accuracy -----> 0.995
Shape ['2' '6' '2' ... '6' '2' '6']
intercept ----->: [-0.]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.   -0.
 -0.   -0.    0.    0.    0.    0.02 -0.   -0.02 -0.01  0.01  0.01  0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.   -0.    0.    0.    0.02  0.03 -0.01 -0.    0.01  0.01  0.01  0.01
  0.    0.01  0.02  0.   -0.    0.01  0.02  0.   -0.01 -0.    0.    0.
  0.    0.   -0.   -0.    0.01  0.01  0.01  0.01  0.02  0.    0.02  0.01
 -0.03 -0.01  0.02 -0.02 -0.02  0.    0.01 -0.01  0.03  0.02  0.03  0.02
  0.01 -0.    0.    0.    0.    0.   -0.   -0.    0.01  0.02 -0.02 -0.01
 -0.   -0.02 -0.01 -0.   -0.02  0.   -0.01 -0.01  0.01  0.01  0.01  0.
  0.03  0.02  0.02  0.03  0.02  0.01  0.01  0.01  0.    0.    0.   -0.
  0.02  0.   -0.01  0.01 -0.02 -0.01 -0.    0.02  0.01 -0.02  0.01  0.01
 -0.04 -0.   -0.    0.01  0.01  0.    0.01  0.03  0.04  0.02  0.02  0.01
  0.    0.    0.   -0.    0.01  0.01 -0.01  0.02  0.01  0.   -0.01 -0.01
 -0.02 -0.01 -0.04  0.01 -0.    0.01  0.    0.01  0.01  0.01 -0.01  0.02
  0.01 -0.    0.    0.    0.    0.    0.   -0.   -0.02 -0.02 -0.03  0.01
 -0.01  0.01 -0.01 -0.01  0.02 -0.    0.01  0.01  0.01 -0.   -0.01 -0.01
 -0.01  0.   -0.02 -0.01 -0.02 -0.02  0.    0.    0.    0.   -0.   -0.
 -0.01 -0.   -0.01 -0.03  0.01 -0.01  0.01 -0.02  0.02  0.01  0.   -0.02
 -0.02 -0.01 -0.03 -0.03 -0.01  0.01 -0.03 -0.04 -0.02 -0.    0.    0.
```

```
  0.    0.   -0.   -0.    0.01 -0.02 -0.    0.01 -0.01 -0.02 -0.01 -0.
  0.01 -0.02  0.   -0.04 -0.    0.    0.01 -0.02 -0.    0.02 -0.04 -0.01
  0.01 -0.    0.    0.    0.    0.   -0.   -0.    0.01 -0.01  0.    0.01
  0.   -0.01  0.    0.   -0.03 -0.   -0.04 -0.   -0.01 -0.02  0.02 -0.01
 -0.   -0.01 -0.01  0.03  0.02 -0.   -0.    0.    0.    0.    0.   -0.
  0.02  0.02 -0.   -0.02  0.01  0.01  0.02  0.01  0.03  0.03  0.01 -0.02
  0.01 -0.05 -0.02 -0.01 -0.02 -0.02  0.02  0.04 -0.01 -0.01 -0.01  0.
  0.    0.    0.   -0.    0.01 -0.03  0.02  0.03  0.04  0.    0.01 -0.02
 -0.01  0.03  0.02 -0.01  0.02  0.01  0.03 -0.02  0.01 -0.    0.02  0.03
  0.   -0.02 -0.02  0.    0.    0.    0.   -0.   -0.05 -0.    0.01  0.04
  0.02  0.02  0.03 -0.    0.03 -0.03  0.01  0.01 -0.   -0.01 -0.01  0.01
  0.01  0.02  0.02  0.02 -0.   -0.02 -0.01  0.    0.    0.    0.   -0.
 -0.02  0.03  0.03 -0.   -0.    0.01 -0.03  0.    0.01 -0.01 -0.01  0.
 -0.   -0.01 -0.01 -0.   -0.02  0.01  0.    0.02 -0.01  0.01 -0.    0.
  0.    0.   -0.   -0.   -0.03 -0.01  0.01 -0.02  0.    0.    0.01  0.01
 -0.01  0.01  0.02 -0.02 -0.    0.01  0.    0.04  0.03  0.   -0.01 -0.01
 -0.02  0.01 -0.03 -0.    0.    0.   -0.    0.   -0.03 -0.02  0.03  0.02
  0.02  0.    0.    0.   -0.01 -0.01 -0.02  0.01 -0.01 -0.01  0.   -0.02
 -0.   -0.03  0.02  0.    0.01 -0.04 -0.02 -0.    0.    0.   -0.    0.
 -0.04  0.01 -0.02 -0.03  0.   -0.    0.    0.02  0.01 -0.01  0.   -0.01
 -0.02  0.01 -0.    0.01 -0.    0.02  0.01 -0.02  0.   -0.04 -0.01 -0.
  0.    0.   -0.    0.01 -0.02 -0.01  0.01 -0.02  0.   -0.    0.01 -0.03
 -0.01  0.04  0.01  0.04 -0.01  0.01  0.01 -0.03  0.01 -0.   -0.02 -0.03
 -0.01 -0.02 -0.01 -0.01  0.    0.   -0.    0.   -0.   -0.04 -0.04 -0.01
 -0.01  0.   -0.    0.02  0.01 -0.   -0.03  0.02 -0.02  0.01  0.01 -0.01
 -0.    0.01 -0.04  0.   -0.01 -0.02 -0.03 -0.01  0.    0.   -0.   -0.
 -0.01 -0.01 -0.02 -0.01 -0.01 -0.03  0.01  0.    0.    0.02  0.01  0.
  0.01 -0.    0.01 -0.01  0.   -0.01 -0.    0.02 -0.   -0.   -0.    0.
  0.    0.   -0.   -0.   -0.   -0.02 -0.01 -0.02  0.03  0.01  0.01 -0.
  0.01  0.01  0.01  0.02 -0.01 -0.01  0.01 -0.02 -0.01  0.02 -0.01 -0.
  0.02  0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.01 -0.02 -0.01
 -0.   -0.02 -0.01 -0.01  0.    0.01  0.01  0.01  0.01  0.01  0.03 -0.02
  0.   -0.   -0.03 -0.02 -0.   -0.    0.    0.    0.    0.    0.   -0.
 -0.   -0.   -0.01 -0.01 -0.02 -0.02 -0.01 -0.01  0.   -0.01  0.   -0.02
 -0.02 -0.   -0.    0.01 -0.01 -0.02 -0.01 -0.   -0.   -0.   -0.    0.
  0.    0.    0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.01 -0.01 -0.01
 -0.01 -0.   -0.   -0.   -0.01 -0.02 -0.01 -0.02 -0.02 -0.01 -0.   -0.
 -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 -0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.
 -0.   -0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.  ]
 Accuracy -----> 0.973
Shape ['7' '3' '7' ... '3' '7' '7']
intercept ----->: [16.35]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
```

```
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.   -0.01 -0.01
-0.01 -0.01 -0.02 -0.01 -0.01 -0.01 -0.   -0.   -0.   -0.   -0.   -0.
-0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.   -0.   -0.
-0.   -0.   -0.02 -0.02 -0.02 -0.01 -0.02 -0.02 -0.02 -0.02 -0.01 -0.01
-0.   -0.   -0.   -0.   -0.    0.    0.    0.    0.    0.   -0.   -0.
-0.    0.01  0.    0.01  0.01  0.01 -0.01 -0.   -0.01 -0.   -0.01 -0.01
-0.01 -0.02 -0.   -0.01 -0.02 -0.02 -0.01 -0.   -0.    0.    0.    0.
 0.   -0.    0.    0.   -0.02  0.    0.01 -0.01  0.01 -0.   -0.01  0.01
-0.01  0.01  0.01 -0.02 -0.   -0.01 -0.01 -0.   -0.   -0.    0.   -0.01
 0.    0.    0.    0.    0.    0.    0.   -0.   -0.01  0.    0.02 -0.
-0.    0.01  0.01  0.01 -0.   -0.02 -0.01 -0.    0.    0.01  0.01  0.01
 0.01  0.01  0.01  0.02  0.    0.    0.    0.    0.    0.   -0.   -0.01
 0.    0.    0.01  0.02  0.    0.01  0.01  0.01  0.01 -0.01  0.    0.01
-0.01 -0.01  0.01  0.03 -0.   -0.   -0.01  0.01  0.    0.    0.    0.
 0.    0.01  0.    0.01  0.01  0.01 -0.    0.02 -0.01 -0.02 -0.01  0.01
 0.02  0.   -0.01 -0.01 -0.02  0.03 -0.01  0.   -0.01 -0.01  0.   -0.
 0.01  0.    0.    0.    0.    0.    0.   -0.01 -0.    0.01  0.02 -0.01
 0.02  0.02  0.01 -0.02 -0.   -0.01  0.01  0.03  0.03 -0.   -0.   -0.01
-0.01 -0.   -0.   -0.01  0.01  0.    0.    0.    0.    0.    0.01  0.01
 0.   -0.    0.02  0.   -0.01 -0.02  0.01  0.02 -0.   -0.01  0.02  0.
 0.01  0.02  0.02  0.01  0.01  0.01 -0.   -0.02  0.    0.    0.    0.
 0.    0.01  0.01  0.01  0.    0.01 -0.    0.01 -0.   -0.   -0.01  0.01
-0.02 -0.01 -0.02  0.01 -0.01 -0.    0.01 -0.01 -0.02  0.   -0.01 -0.02
 0.    0.    0.    0.    0.    0.    0.01  0.01 -0.01  0.    0.01  0.
 0.02  0.02 -0.   -0.   -0.03 -0.01 -0.02 -0.01 -0.01 -0.01 -0.01  0.
 0.01  0.01 -0.01  0.01  0.    0.    0.    0.    0.    0.    0.    0.01
 0.    0.02  0.01  0.01  0.02 -0.01 -0.    0.02 -0.01 -0.02  0.01  0.
 0.01  0.01  0.   -0.    0.01 -0.    0.04  0.01 -0.    0.    0.    0.
 0.    0.    0.    0.01  0.01 -0.01 -0.01  0.    0.    0.01  0.   -0.01
-0.03 -0.01 -0.01  0.    0.01 -0.01  0.02  0.02 -0.    0.    0.01  0.
 0.    0.    0.    0.    0.    0.   -0.   -0.01  0.01 -0.    0.01 -0.
 0.01  0.01 -0.01  0.01  0.01 -0.03  0.01 -0.   -0.01  0.01 -0.02  0.
-0.    0.   -0.01 -0.01 -0.01  0.    0.    0.    0.   -0.   -0.   -0.02
-0.01 -0.    0.   -0.   -0.03  0.    0.    0.01 -0.01  0.01  0.01  0.02
 0.01  0.01 -0.   -0.    0.   -0.01  0.    0.    0.01  0.    0.    0.
 0.   -0.   -0.   -0.02 -0.01 -0.02 -0.01  0.01 -0.03 -0.01 -0.02  0.02
-0.01 -0.    0.01  0.   -0.01  0.02  0.01 -0.01 -0.   -0.02  0.01  0.01
 0.02  0.    0.    0.    0.    0.   -0.   -0.01 -0.01 -0.01 -0.01 -0.01
 0.   -0.   -0.01  0.02  0.02  0.    0.01 -0.01 -0.02 -0.01 -0.    0.02
-0.02 -0.02 -0.01  0.    0.01 -0.    0.    0.    0.    0.   -0.   -0.01
-0.01 -0.03 -0.03 -0.    0.02  0.    0.01  0.02  0.01 -0.02 -0.    0.01
-0.02 -0.02 -0.03 -0.03 -0.03 -0.01 -0.01 -0.02  0.   -0.    0.    0.
 0.   -0.   -0.   -0.01 -0.03 -0.02 -0.01 -0.   -0.01 -0.01 -0.    0.01
```

```
  0.01  0.   -0.03  0.02 -0.04  0.   -0.02 -0.02 -0.03 -0.01 -0.02 -0.01
 -0.    0.    0.    0.    0.    0.   -0.   -0.   -0.02  0.   -0.   -0.02
 -0.02 -0.01 -0.01 -0.   -0.01  0.01 -0.    0.01 -0.01 -0.   -0.02 -0.01
 -0.02 -0.01 -0.01 -0.01  0.    0.    0.    0.    0.    0.   -0.   -0.01
 -0.01  0.   -0.01  0.   -0.    0.02 -0.01 -0.   -0.    0.01  0.   -0.01
 -0.   -0.02 -0.01 -0.01  0.   -0.01 -0.01 -0.01  0.    0.    0.    0.
  0.    0.    0.   -0.    0.    0.   -0.01  0.01 -0.   -0.04 -0.02 -0.01
 -0.01 -0.01 -0.01  0.01  0.01 -0.   -0.    0.01  0.   -0.01 -0.   -0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.01  0.01 -0.   -0.01
 -0.02 -0.02  0.01 -0.   -0.02 -0.02 -0.    0.01 -0.    0.01  0.02  0.01
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.   -0.01 -0.02  0.    0.02  0.01  0.   -0.   -0.03  0.   -0.01 -0.03
 -0.    0.03  0.01  0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.    0.
  0.    0.    0.    0.  ]
 Accuracy -----> 0.981
Shape ['8' '8' '8' ... '8' '4' '8']
intercept ----->: [-0.]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.
 -0.    0.    0.01  0.   -0.   -0.   -0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.
 -0.   -0.   -0.01 -0.01 -0.01 -0.01  0.    0.01  0.   -0.   -0.   -0.
 -0.    0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.
 -0.   -0.   -0.01 -0.01  0.01 -0.   -0.01 -0.   -0.    0.    0.    0.01
  0.01 -0.   -0.   -0.01 -0.   -0.    0.    0.    0.    0.   -0.   -0.
 -0.   -0.    0.    0.    0.01 -0.   -0.    0.    0.    0.    0.01 -0.
  0.01  0.02  0.01  0.   -0.01  0.01  0.01 -0.   -0.01  0.    0.    0.
  0.    0.   -0.   -0.   -0.   -0.    0.    0.    0.    0.    0.    0.01
  0.01  0.01  0.    0.01 -0.01  0.    0.01 -0.01 -0.   -0.   -0.    0.01
  0.    0.01  0.    0.    0.    0.   -0.   -0.   -0.   -0.01 -0.01 -0.01
 -0.   -0.    0.01  0.01  0.    0.01  0.    0.01 -0.   -0.01  0.01  0.01
  0.01  0.01  0.   -0.   -0.    0.01 -0.    0.    0.    0.   -0.   -0.
 -0.01 -0.01 -0.01 -0.01  0.01  0.01  0.   -0.   -0.    0.    0.01  0.01
  0.01  0.01  0.01  0.02 -0.   -0.    0.    0.01  0.01  0.01  0.    0.
  0.    0.   -0.   -0.    0.    0.    0.01  0.01  0.01 -0.    0.01  0.
 -0.01 -0.   -0.01 -0.   -0.   -0.01 -0.   -0.    0.01 -0.    0.01  0.01
  0.01 -0.    0.    0.    0.    0.   -0.    0.    0.01  0.01  0.01  0.
 -0.   -0.   -0.    0.   -0.01  0.    0.02 -0.   -0.01 -0.01 -0.    0.01
  0.01  0.01  0.    0.02  0.01 -0.    0.    0.    0.   -0.   -0.    0.01
  0.01  0.    0.01 -0.    0.01  0.   -0.    0.01 -0.01  0.    0.01 -0.01
 -0.01 -0.02 -0.    0.    0.    0.    0.    0.01  0.03  0.01  0.02  0.01
  0.   -0.   -0.    0.01  0.    0.   -0.01  0.   -0.   -0.01 -0.02 -0.
 -0.02 -0.    0.02 -0.01  0.    0.01 -0.01 -0.01  0.   -0.   -0.    0.01
```

```
 0.01  0.    0.    0.    0.   -0.    0.    0.01 -0.    0.   -0.01 -0.01
-0.01 -0.   -0.02 -0.   -0.02  0.01 -0.01 -0.01 -0.01 -0.02  0.01 -0.01
-0.02 -0.    0.    0.01 -0.   -0.    0.    0.    0.   -0.   -0.    0.
-0.01 -0.01  0.   -0.01 -0.01 -0.    0.    0.   -0.    0.01  0.   -0.01
-0.02 -0.01 -0.01 -0.   -0.01  0.01 -0.    0.   -0.   -0.    0.    0.
 0.   -0.   -0.   -0.   -0.02 -0.02  0.   -0.02 -0.01 -0.01 -0.01 -0.01
 0.01  0.    0.01 -0.01 -0.01 -0.02 -0.01 -0.01 -0.01  0.   -0.   -0.
-0.   -0.   -0.    0.    0.    0.   -0.   -0.   -0.02 -0.01 -0.   -0.01
-0.01 -0.    0.01 -0.    0.   -0.   -0.01 -0.02  0.01 -0.01 -0.01  0.01
-0.   -0.01 -0.   -0.   -0.   -0.   -0.    0.    0.    0.   -0.   -0.
-0.02 -0.01  0.01 -0.01  0.    0.01  0.    0.   -0.01  0.01 -0.   -0.02
-0.02 -0.    0.01 -0.   -0.01 -0.01  0.   -0.   -0.   -0.   -0.    0.
 0.    0.   -0.   -0.   -0.01 -0.01  0.   -0.   -0.   -0.01  0.01 -0.
 0.   -0.01 -0.01 -0.01 -0.01  0.   -0.01  0.   -0.   -0.01  0.01 -0.
-0.   -0.   -0.    0.    0.    0.    0.   -0.   -0.   -0.01  0.    0.
 0.01  0.02  0.01 -0.01 -0.    0.01 -0.01 -0.   -0.01 -0.   -0.01 -0.01
-0.01 -0.01  0.01 -0.    0.   -0.   -0.    0.    0.    0.    0.   -0.
-0.    0.   -0.    0.    0.    0.02  0.03  0.01  0.    0.01 -0.    0.
-0.    0.02  0.    0.01  0.01  0.01  0.01 -0.01  0.    0.    0.    0.
 0.    0.    0.   -0.   -0.    0.01  0.02  0.01  0.01  0.01  0.01  0.03
 0.02  0.02  0.02  0.02  0.01  0.01  0.02  0.02  0.02  0.01  0.    0.
 0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.01  0.01  0.01
 0.02  0.01 -0.    0.02  0.01  0.01  0.02  0.01  0.01  0.01  0.01  0.01
 0.01  0.    0.    0.   -0.   -0.   -0.    0.    0.    0.    0.    0.
 0.    0.    0.   -0.    0.01  0.   -0.    0.   -0.    0.02  0.01  0.01
 0.01  0.01  0.    0.    0.01  0.01  0.    0.   -0.   -0.   -0.    0.
 0.    0.    0.    0.    0.   -0.   -0.01 -0.01 -0.    0.   -0.   -0.
 0.    0.   -0.   -0.01  0.    0.01  0.01  0.   -0.   -0.   -0.    0.
-0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.   -0.   -0.
-0.01 -0.02 -0.01 -0.    0.    0.    0.    0.    0.01 -0.   -0.   -0.
-0.   -0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.
 0.   -0.   -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.  ]
Accuracy -----> 0.9880519480519481
Standard Error ----> 0.0082
```

In [133…
```
zero_four_train= [train_img [key] for (key, label) in enumerate(train_lbl) if int(label) == 3 or int(label) ==
```

In [134…
```
zero_four_label = [label for (key, label) in enumerate(train_lbl) if int(label) == 3 or int(label) == 4]
```

In [135…
```
train=zero_four_train[0:4000]
```

In [136…
```
print(train_img.shape)
```

```
(60000, 784)
```

In [137…
```
print(train_lbl.shape)
```

```
(60000,)
```

In [138…
```
print(test_img.shape)
```

```
(10000, 784)
```

In [139…
```
print(test_lbl.shape)
```

```
(10000,)
```

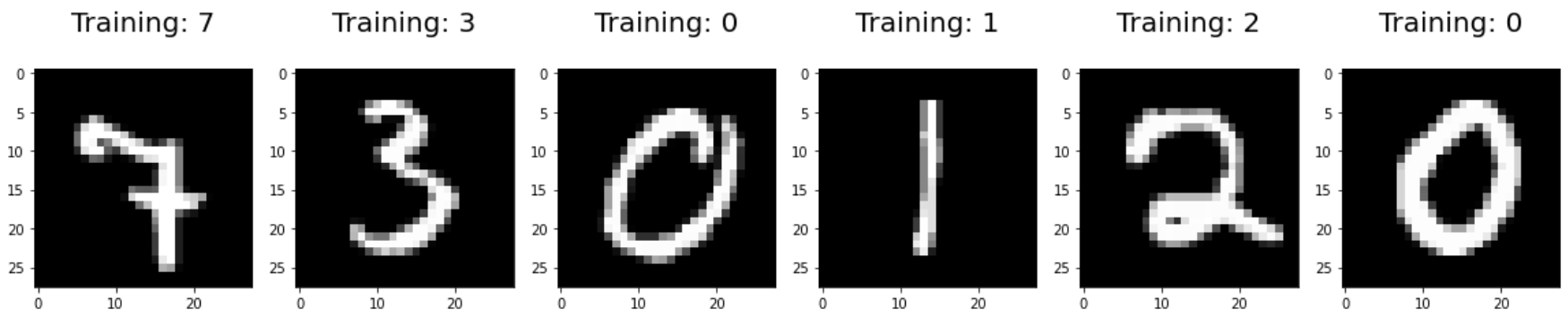
In [140…
```
train_img = train_img[0:2000]
train_lbl = train_lbl[0:2000]
test_img = test_img[0:2000]
test_lbl = test_lbl[0:2000]
```

In [141…
```
print(len(train_img))
```

```
2000
```

Showing Training Digits and Labels

In [142…
```
plt.figure(figsize=(20,4))
for index, (image, label) in enumerate(zip(train_img[0:6], train_lbl[0:6])):
    plt.subplot(1, 6, index + 1)
    plt.imshow(np.reshape(image, (28,28)), cmap=plt.cm.gray)
    plt.title('Training: %s\n' % label, fontsize = 20)
```



In [143…
```
print(train_lbl[1])
```

```
3
```

Using Logistic Regression on Entire Dataset

In [144…
```
from sklearn.linear_model import LogisticRegression
```

In [145…
```
# all parameters not specified are set to their defaults
# default solver is incredibly slow thats why we change it
#logisticRegr = LogisticRegression(solver = 'lbfgs')
logisticRegr = LogisticRegression(solver = 'lbfgs',max_iter=1200)
```

In [146…
```
np.set_printoptions(precision=2, suppress=True)
#print(f'{(zero_four_train[0:4])} ')
#print(f'{zero_four_label[0:4]} ')
#logisticRegr.fit(train_img, train_lbl)
logisticRegr.fit(zero_four_train, zero_four_label)
np.set_printoptions(precision=2, suppress=True)
print('intercept ----->:', logisticRegr.intercept_)
p = logisticRegr.coef_[0]
print(f"Weight ------>:  {p}")
```

```
intercept ----->: [0.]
Weight ------>:  [ 0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.    0.    0.01  0.
 -0.01 -0.01 -0.   -0.    0.    0.    0.    0.    0.    0.    0.    0.
  0.    0.    0.    0.   -0.   -0.    0.    0.02  0.02  0.   -0.01 -0.01
 -0.    0.01  0.02 -0.02  0.   -0.01 -0.03  0.01  0.03  0.01  0.01  0.
 -0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.   -0.    0.01
  0.   -0.   -0.01 -0.02 -0.02  0.01 -0.03 -0.03  0.01 -0.01 -0.01  0.02
  0.02  0.03  0.01  0.02  0.    0.01  0.    0.    0.   -0.   -0.   -0.
 -0.   -0.   -0.02 -0.02  0.   -0.02 -0.   -0.02 -0.01 -0.    0.01 -0.01
  0.01 -0.02 -0.02 -0.01 -0.02 -0.01  0.   -0.02 -0.    0.    0.    0.
  0.   -0.   -0.    0.    0.   -0.01 -0.02 -0.02  0.   -0.02 -0.02 -0.
 -0.01 -0.02  0.01 -0.02 -0.02 -0.01 -0.01  0.    0.01 -0.03 -0.01  0.01
 -0.01  0.    0.    0.    0.   -0.   -0.    0.   -0.01 -0.01 -0.    0.03
 -0.03 -0.   -0.   -0.02 -0.   -0.   -0.03 -0.03  0.02  0.01 -0.03  0.01
  0.01 -0.    0.02  0.01  0.01  0.02  0.    0.    0.   -0.   -0.    0.
 -0.01  0.01 -0.01  0.01 -0.01  0.02 -0.01 -0.02 -0.01 -0.02  0.   -0.01
 -0.02 -0.02  0.   -0.03 -0.01 -0.   -0.    0.02  0.03  0.01  0.    0.
  0.    0.    0.   -0.   -0.02 -0.01 -0.01 -0.01 -0.01 -0.01 -0.01 -0.
  0.01  0.   -0.    0.    0.   -0.02  0.   -0.   -0.01 -0.01 -0.02 -0.03
  0.01  0.    0.    0.    0.    0.    0.    0.   -0.02 -0.01  0.01 -0.01
  0.01 -0.01  0.01 -0.01  0.   -0.04  0.   -0.   -0.02  0.04 -0.01  0.01
```

```
-0.02 -0.01 -0.04 -0.03 -0.01  0.    0.    0.    0.    0.    0.   -0.
-0.03  0.    0.01  0.01  0.02  0.03  0.04 -0.01  0.05 -0.01 -0.    0.
 0.   -0.    0.01  0.02 -0.01  0.   -0.   -0.    0.    0.    0.    0.
 0.    0.    0.   -0.    0.01  0.03  0.    0.01  0.   -0.01  0.01 -0.
 0.02  0.   -0.05  0.02 -0.02 -0.03 -0.01  0.01 -0.    0.    0.01 -0.
 0.01  0.    0.    0.    0.    0.    0.   -0.    0.02  0.01  0.    0.02
 0.01  0.02  0.02  0.02  0.01 -0.   -0.    0.01  0.03  0.02  0.02 -0.01
 0.02  0.03  0.02  0.   -0.    0.    0.    0.    0.    0.    0.    0.
 0.03  0.01 -0.    0.03  0.    0.   -0.    0.01  0.01  0.01 -0.   -0.02
-0.    0.    0.01 -0.01 -0.01 -0.01  0.02  0.01  0.    0.    0.    0.
 0.   -0.   -0.   -0.    0.04 -0.01 -0.02  0.03  0.    0.02  0.01  0.02
 0.01 -0.   -0.02  0.04  0.01  0.02 -0.01  0.01  0.   -0.02 -0.01  0.01
 0.    0.01  0.02  0.    0.   -0.   -0.02 -0.03  0.04  0.01 -0.01  0.02
 0.   -0.    0.01  0.    0.   -0.    0.01  0.02 -0.01  0.02 -0.01  0.01
 0.    0.01  0.   -0.03 -0.02  0.02  0.02  0.    0.   -0.   -0.04 -0.03
 0.01  0.02  0.    0.    0.01  0.04 -0.01 -0.01 -0.01  0.    0.02  0.02
 0.02 -0.01  0.01 -0.02  0.02 -0.01  0.    0.02  0.02  0.01  0.01  0.
 0.   -0.   -0.02 -0.02 -0.   -0.02 -0.01  0.01 -0.    0.01  0.01  0.01
-0.01  0.01  0.03 -0.   -0.01 -0.   -0.03  0.01 -0.   -0.01 -0.05  0.01
 0.04  0.    0.    0.    0.   -0.   -0.    0.01 -0.02  0.01  0.    0.01
-0.02 -0.02 -0.01  0.01  0.03  0.02  0.01 -0.   -0.    0.01  0.01  0.01
 0.   -0.   -0.05  0.01  0.    0.    0.    0.    0.   -0.   -0.01 -0.02
-0.02 -0.03 -0.   -0.01 -0.03  0.   -0.03  0.02  0.01 -0.01 -0.02  0.
-0.01  0.01 -0.01 -0.03 -0.01 -0.01 -0.01 -0.03  0.    0.   -0.    0.
 0.   -0.   -0.01 -0.01 -0.03  0.02 -0.01 -0.01  0.02  0.02  0.   -0.02
-0.02 -0.01 -0.    0.   -0.02 -0.02  0.   -0.02 -0.    0.01  0.01 -0.02
 0.    0.   -0.    0.    0.   -0.   -0.   -0.    -0.   -0.   -0.02 -0.02
-0.02 -0.02 -0.03 -0.   -0.01 -0.    0.01 -0.    0.    0.01  0.    0.
-0.02  0.02  0.01 -0.    0.    0.    0.    0.    0.   -0.   -0.   -0.
-0.   -0.   -0.   -0.   -0.01  0.01  0.   -0.01  0.   -0.02 -0.01 -0.01
 0.   -0.   -0.    0.03  0.01 -0.01 -0.03  0.    0.    0.   -0.    0.
 0.    0.   -0.   -0.   -0.    0.01 -0.   -0.01  0.01  0.   -0.01  0.
-0.02  0.    0.01  0.01 -0.01  0.01 -0.02 -0.   -0.   -0.01 -0.    0.
 0.    0.    0.    0.    0.    0.   -0.   -0.   -0.   -0.   -0.01 -0.03
-0.01 -0.    0.01  0.   -0.02 -0.02 -0.   -0.02 -0.01 -0.04  0.   -0.01
-0.   -0.   -0.    0.01  0.    0.    0.    0.    0.    0.    0.    0.
 0.   -0.   -0.   -0.02 -0.03 -0.   -0.01 -0.01 -0.01 -0.01 -0.   -0.02
-0.01 -0.01  0.   -0.01 -0.   -0.   -0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.    0.    0.   -0.02 -0.03 -0.01  0.
-0.03  0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.  ]
```

In [147…

```
# Returns a NumPy Array
# Predict for One Observation (image)
logisticRegr.predict(test_img[0].reshape(1,-1))
```

Out[147…

```
array(['3'], dtype='<U1')
```

In [148…
```
# Predict for Multiple Observations (images) at Once
logisticRegr.predict(test_img[0:10])
```

Out[148…
```
array(['3', '4', '3', '3', '4', '4', '3', '3', '3', '3'], dtype='<U1')
```

In [ ]:

Measuring Model Performance

In [150…
```
score = logisticRegr.score(test_img, test_lbl)
print(score)
```

```
0.183
```

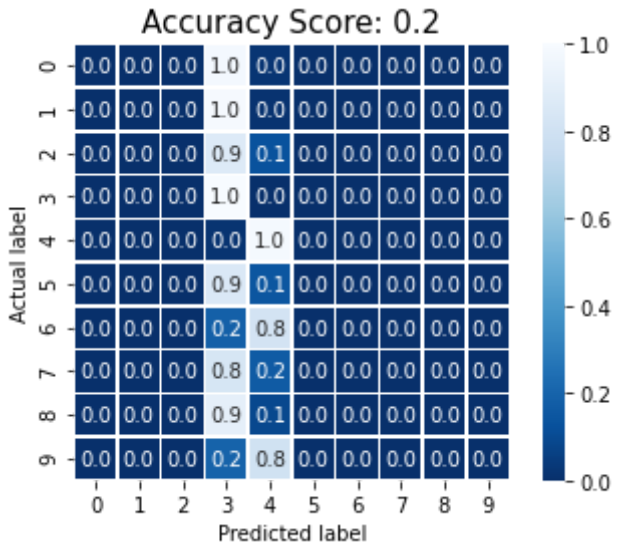
In [ ]:

In [82]:
```
# Make predictions on test data
predictions = logisticRegr.predict(test_img)



print(f'{predictions}')
```

```
['3' '4' '3' ... '3' '4' '3']
```

In [83]:
```
cm = metrics.confusion_matrix(test_lbl, predictions)
cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
```

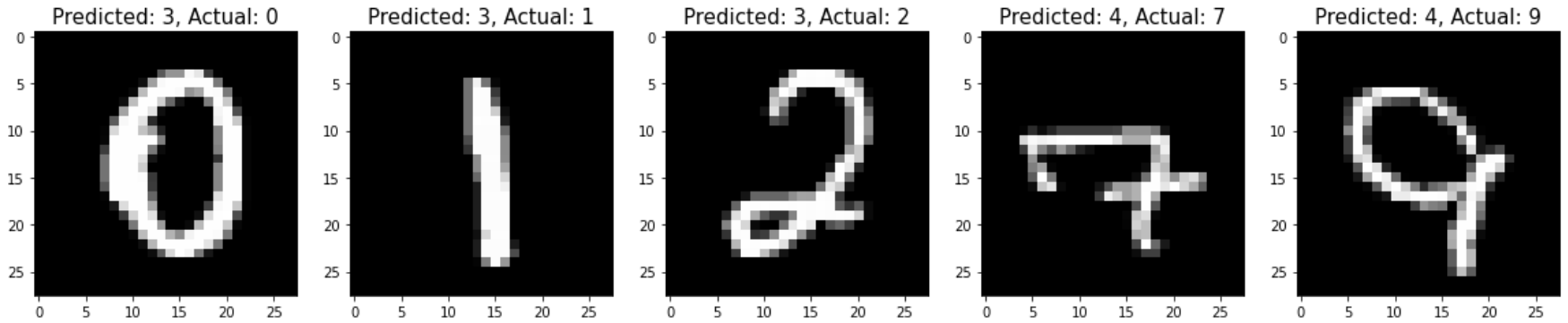
In [85]:
```
#plthttp://localhost:8890/notebooks/Documents/github/Python_Tutorials/Sklearn/Logistic_Regression/LogisticRegre
sns.heatmap(cm_normalized, annot=True, fmt=".1f", linewidths=.5, square = True, cmap = 'Blues_r');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy Score: {:.1f}'.format(score)
plt.title(all_sample_title, size = 15);
```



Display Misclassified images with Predicted Labels

In [86]:
```
index = 0
misclassifiedIndexes = []
for label, predict in zip(test_lbl, predictions):
    if label != predict:
        misclassifiedIndexes.append(index)
    index +=1
```

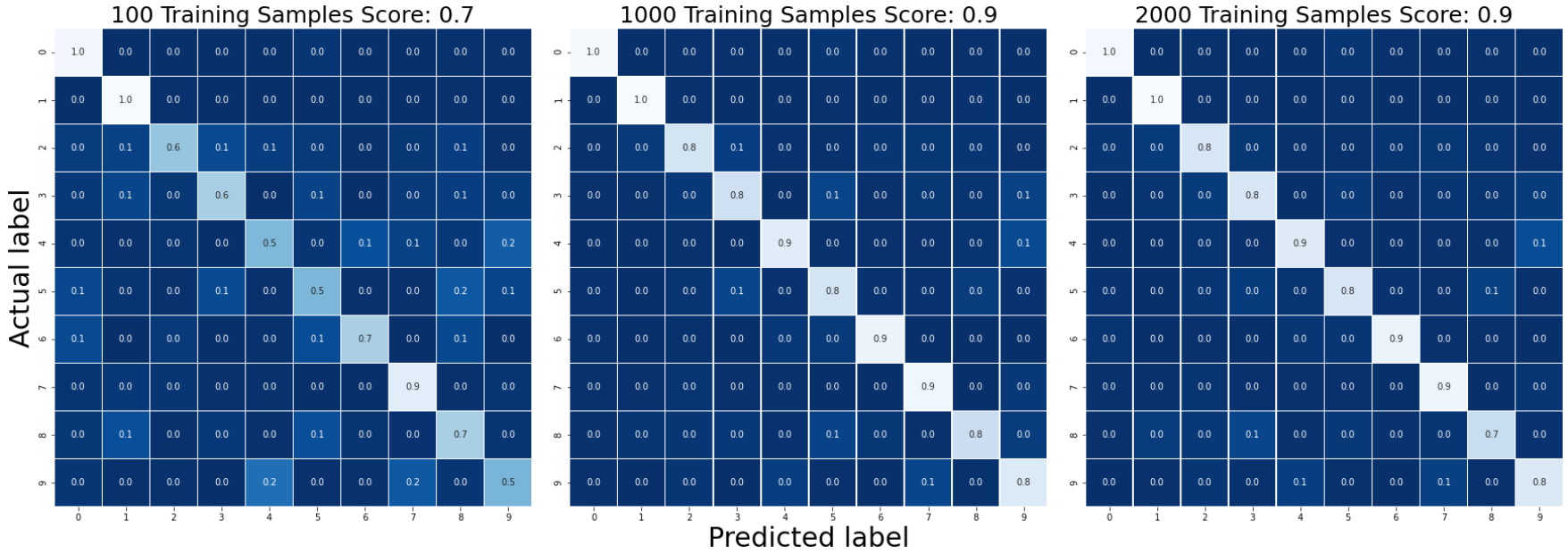
In [89]:
```
plt.figure(figsize=(20,4))
for plotIndex, badIndex in enumerate(misclassifiedIndexes[0:5]):
    plt.subplot(1, 5, plotIndex + 1)
    plt.imshow(np.reshape(test_img[badIndex], (28,28)), cmap=plt.cm.gray)
    plt.title('Predicted: {}, Actual: {}'.format(predictions[badIndex], test_lbl[badIndex]), fontsize = 15)
```



Checking Performance Based on Training Set Size

In [90]:
```
#regr = LogisticRegression()
regr = LogisticRegression(max_iter=12000)
```

In [91]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 3, figsize = (24,8));
plt.tight_layout()

for plotIndex, sample_size in enumerate([100, 1000, 2000]):
    X_train = train_img[:sample_size].reshape(sample_size, 784)
    y_train = train_lbl[:sample_size]
    regr.fit(X_train, y_train)
    predicted = regr.predict(test_img)
    cm = metrics.confusion_matrix(test_lbl, predicted)
    cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    sns.heatmap(cm_normalized, annot=True, fmt=".1f", linewidths=.5, square = True, cmap = 'Blues_r', ax = axes
    accuracyString = '{:g} Training Samples Score: {:.1f}'.format(sample_size, regr.score(test_img, test_lbl))
    axes[plotIndex].set_title(accuracyString, size = 25);

axes[0].set_ylabel('Actual label', fontsize = 30);
axes[1].set_xlabel('Predicted label', fontsize = 30);
```


100 Training Samples Score: 0.7
1000 Training Samples Score: 0.9
2000 Training Samples Score: 0.9
Actual label
Predicted label

In [ ]:

In [ ]: