

# ANN\_mnist-Copy1

May 15, 2019

```
In [2]: import os
import struct
import numpy as np

def load_mnist(path, kind='train'):
    """Load MNIST data from `path`"""
    labels_path = os.path.join(path, '%s-labels.idx1-ubyte' % kind)
    images_path = os.path.join(path, '%s-images.idx3-ubyte' % kind)

    with open(labels_path, 'rb') as lbpath:
        magic, n = struct.unpack('>II', lbpath.read(8))
        labels = np.fromfile(lbpath, dtype=np.uint8)

    with open(images_path, 'rb') as imgpath:
        magic, num, rows, cols = struct.unpack(">IIII", imgpath.read(16))
        images = np.fromfile(imgpath, dtype=np.uint8).reshape(len(labels), 784)

    return images, labels
```

**1 current working directory is provided as path : datasets is downloaded and saved in pwd**

```
In [3]: X_train, y_train = load_mnist ('C:/Users/Project/Desktop/Workshop/
CIMM_workshop/2.ANN/MNIST_dataset/', kind='train')
X_train.shape
```

```
Out[3]: (60000, 784)
```

```
In [4]: ls -l ##### current working directory#####
```

```
Volume in drive C is OS
Volume Serial Number is AC5F-ACDF
```

```
Directory of C:\Users\Project\Desktop\Workshop\CIMM_workshop\2.ANN
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Directory of C:\Users\Project\Desktop\Workshop\CIMM_workshop\2.ANN
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Directory of C:\Users\Project\Desktop\Workshop\CIMM\_workshop\2.ANN

Directory of C:\Users\Project\Desktop\Workshop\CIMM\_workshop\2.ANN

Directory of C:\Users\Project\Desktop\Workshop\CIMM\_workshop\2.ANN

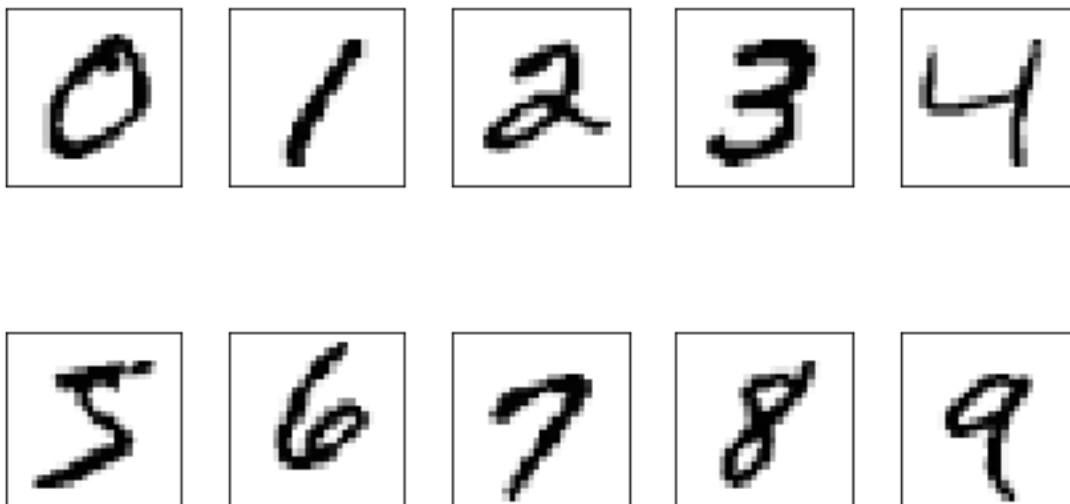
File Not Found

```
In [6]: X_test, y_test = load_mnist('C:/Users/Project/Desktop/Workshop/
                                     CIMM_workshop/2.ANN/MNIST_dataset/', kind='t10k') # DATAS
X_test.shape
```

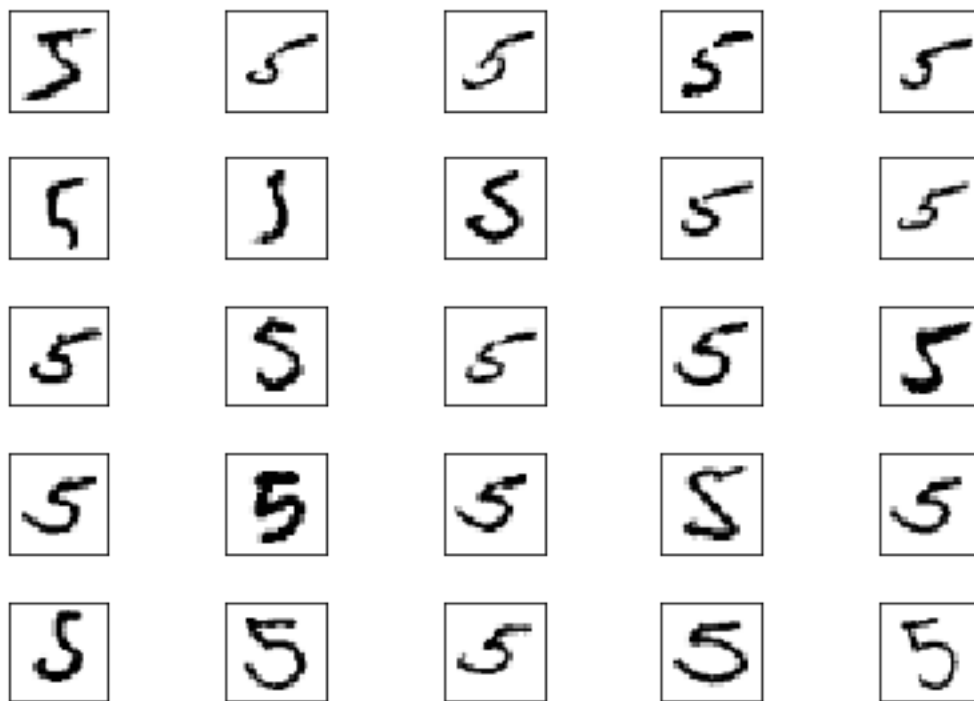
```
Out[6]: (10000, 784)
```

```
In [8]: import matplotlib.pyplot as plt
fig, ax = plt.subplots(nrows=2, ncols=5, sharex=True, sharey=True)
ax = ax.flatten()
for i in range(10):
    img = X_train[y_train == i][0].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
```

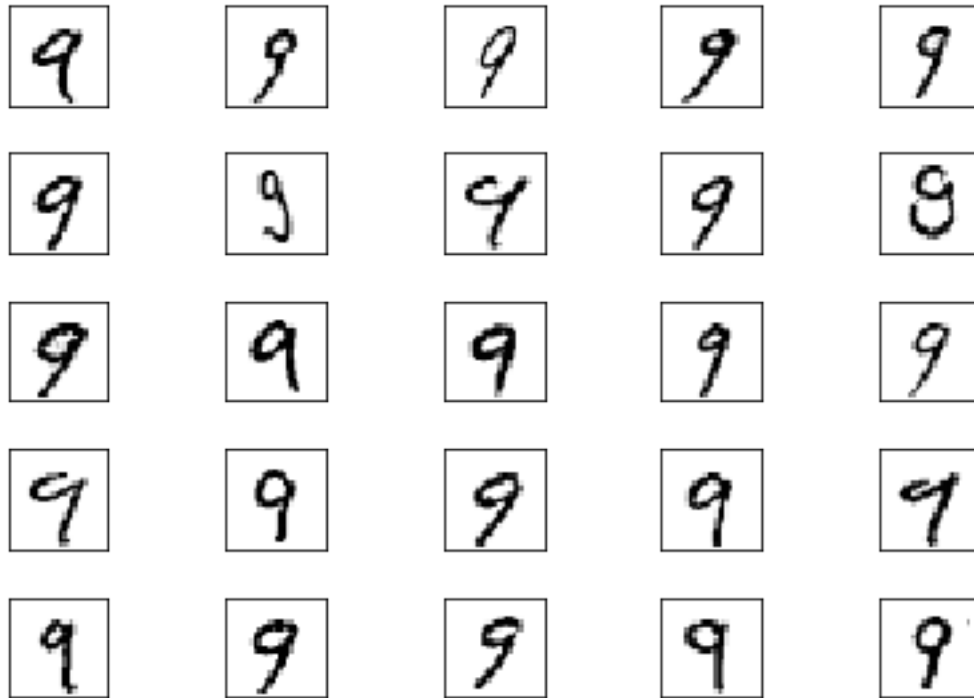
```
plt.show()
```



```
In [12]: fig, ax = plt.subplots(nrows=5, ncols=5, sharex=True, sharey=True,)
ax = ax.flatten()
for i in range(25):
    img = X_train[y_train == 5][i].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
plt.show()
```



```
In [9]: fig, ax = plt.subplots(nrows=5, ncols=5, sharex=True, sharey=True,)
ax = ax.flatten()
for i in range(25):
    img = X_train[y_train == 9][i].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
plt.show()
```



```
In [10]: import scipy
import numpy as np
from scipy.special import expit
import sys

class NeuralNetMLP(object):

    def __init__(self, n_output, n_features, n_hidden=30,
                  l1=0.0, l2=0.0, epochs=500, eta=0.001,
                  alpha=0.0, decrease_const=0.0, shuffle=True,
                  minibatches=1, random_state=None):

        np.random.seed(random_state)
        self.n_output = n_output
        self.n_features = n_features
        self.n_hidden = n_hidden
        self.w1, self.w2 = self._initialize_weights()
        self.l1 = l1
        self.l2 = l2
        self.epochs = epochs
        self.eta = eta
        self.alpha = alpha
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        self.decrease_const = decrease_const
        self.shuffle = shuffle
        self.minibatches = minibatches
    def _encode_labels(self, y, k):

        onehot = np.zeros((k, y.shape[0]))
        for idx, val in enumerate(y):
            onehot[val, idx] = 1.0
        return onehot

    def _initialize_weights(self):
        """Initialize weights with small random numbers."""
        w1 = np.random.uniform(-1.0, 1.0,
                                size=self.n_hidden*(self.n_features + 1))
        w1 = w1.reshape(self.n_hidden, self.n_features + 1)
        w2 = np.random.uniform(-1.0, 1.0,
                                size=self.n_output*(self.n_hidden + 1))
        w2 = w2.reshape(self.n_output, self.n_hidden + 1)
        return w1, w2

    def _sigmoid(self, z):

        # return 1.0 / (1.0 + np.exp(-z))
        return expit(z)
    def _sigmoid_gradient(self, z):
        """Compute gradient of the logistic function"""
        sg = self._sigmoid(z)
        return sg * (1.0 - sg)

    def _add_bias_unit(self, X, how='column'):
        """Add bias unit (column or row of 1s) to array at index 0"""
        if how == 'column':
            X_new = np.ones((X.shape[0], X.shape[1] + 1))
            X_new[:, 1:] = X
        elif how == 'row':
            X_new = np.ones((X.shape[0] + 1, X.shape[1]))
            X_new[1:, :] = X
        else:
            raise AttributeError('`how` must be `column` or `row`')
        return X_new

    def _feedforward(self, X, w1, w2):

        a1 = self._add_bias_unit(X, how='column')
        z2 = w1.dot(a1.T)
        a2 = self._sigmoid(z2)
        a2 = self._add_bias_unit(a2, how='row')
        z3 = w2.dot(a2)

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        a3 = self._sigmoid(z3)
        return a1, z2, a2, z3, a3

def _L2_reg(self, lambda_, w1, w2):
    """Compute L2-regularization cost"""
    return (lambda_/2.0) * (np.sum(w1[:, 1:] ** 2) +
                             np.sum(w2[:, 1:] ** 2))

def _L1_reg(self, lambda_, w1, w2):
    """Compute L1-regularization cost"""
    return (lambda_/2.0) * (np.abs(w1[:, 1:]).sum() +
                             np.abs(w2[:, 1:]).sum())

def _get_cost(self, y_enc, output, w1, w2):

    term1 = -y_enc * (np.log(output))
    term2 = (1.0 - y_enc) * np.log(1.0 - output)
    cost = np.sum(term1 - term2)
    L1_term = self._L1_reg(self.l1, w1, w2)
    L2_term = self._L2_reg(self.l2, w1, w2)
    cost = cost + L1_term + L2_term
    return cost

def _get_gradient(self, a1, a2, a3, z2, y_enc, w1, w2):

    # backpropagation
    sigma3 = a3 - y_enc
    z2 = self._add_bias_unit(z2, how='row')
    sigma2 = w2.T.dot(sigma3) * self._sigmoid_gradient(z2)
    sigma2 = sigma2[1:, :]
    grad1 = sigma2.dot(a1)
    grad2 = sigma3.dot(a2.T)

    # regularize
    grad1[:, 1:] += self.l2 * w1[:, 1:]
    grad1[:, 1:] += self.l1 * np.sign(w1[:, 1:])
    grad2[:, 1:] += self.l2 * w2[:, 1:]
    grad2[:, 1:] += self.l1 * np.sign(w2[:, 1:])

    return grad1, grad2

def predict(self, X):

    if len(X.shape) != 2:
        raise AttributeError('X must be a [n_samples, n_features] array.\n'
                              'Use X[:,None] for 1-feature classification,\n'
                              '\nor X[[i]] for 1-sample classification')

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a1, z2, a2, z3, a3 = self._feedforward(X, self.w1, self.w2)
y_pred = np.argmax(z3, axis=0)
return y_pred

def fit(self, X, y, print_progress=False):

    self.cost_ = []
    X_data, y_data = X.copy(), y.copy()
    y_enc = self._encode_labels(y, self.n_output)

    delta_w1_prev = np.zeros(self.w1.shape)
    delta_w2_prev = np.zeros(self.w2.shape)

    for i in range(self.epochs):

        # adaptive learning rate
        self.eta /= (1 + self.decrease_const*i)

        if print_progress:
            sys.stderr.write('\rEpoch: %d/%d' % (i+1, self.epochs))
            sys.stderr.flush()
            if self.shuffle:
                idx = np.random.permutation(y_data.shape[0])
                X_data, y_enc = X_data[idx], y_enc[:, idx]

        mini = np.array_split(range(y_data.shape[0]), self.minibatches)
        for idx in mini:

            # feedforward
            a1, z2, a2, z3, a3 = self._feedforward(X_data[idx],
                                                    self.w1,
                                                    self.w2)

            cost = self._get_cost(y_enc=y_enc[:, idx],
                                  output=a3,
                                  w1=self.w1,
                                  w2=self.w2)

            self.cost_.append(cost)

            # compute gradient via backpropagation
            grad1, grad2 = self._get_gradient(a1=a1, a2=a2,
                                              a3=a3, z2=z2,
                                              y_enc=y_enc[:, idx],
                                              w1=self.w1,
                                              w2=self.w2)

            delta_w1, delta_w2 = self.eta * grad1, self.eta * grad2
            self.w1 -= (delta_w1 + (self.alpha * delta_w1_prev))

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        self.w2 -= (delta_w2 + (self.alpha * delta_w2_prev))
        delta_w1_prev, delta_w2_prev = delta_w1, delta_w2

```

```

    return self

```

```

In [12]: # initialization

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```

nn = NeuralNetMLP(n_output=10,
                  n_features=X_train.shape[1],
                  n_hidden=50,
                  l2=0.1,
                  l1=0.0,
                  epochs=1000,
                  eta=0.001,
                  alpha=0.001,
                  decrease_const=0.00001,
                  minibatches=50,
                  shuffle=True,
                  random_state=1)

nn

```

```

Out[12]: <__main__.NeuralNetMLP at 0x20fe5c1b748>

```

```

In [13]: # training

```

```

nn.fit(X_train, y_train, print_progress=True)

```

```

Epoch: 1000/1000

```

```

Out[13]: <__main__.NeuralNetMLP at 0x20fe5c1b748>

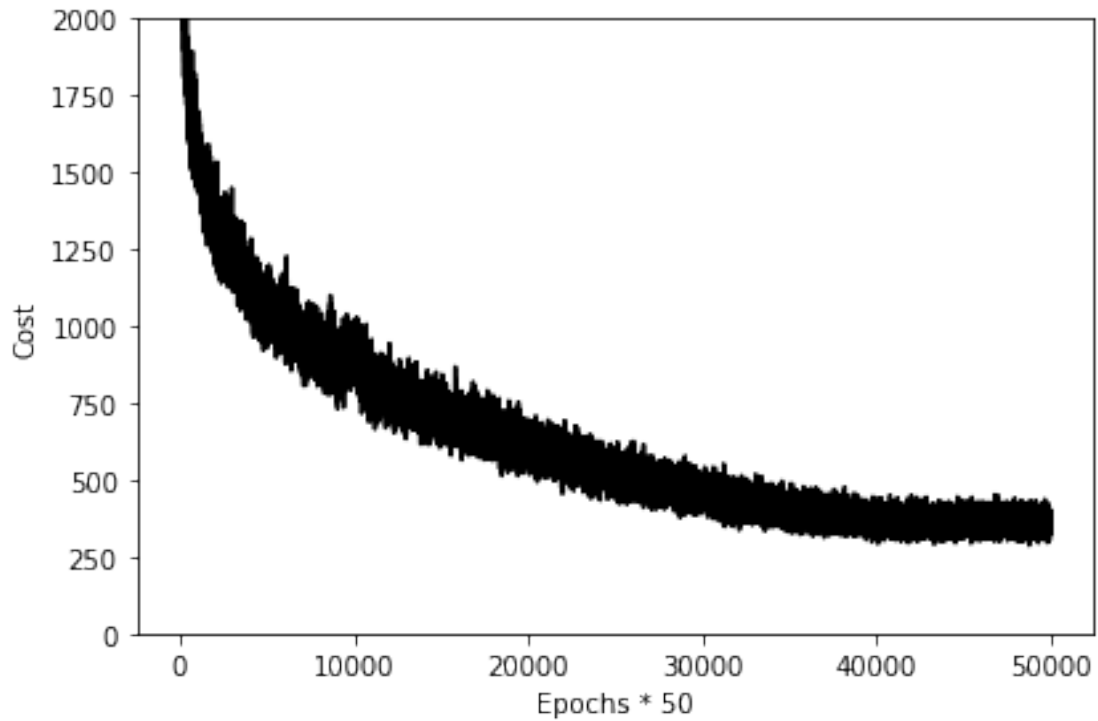
```

```

In [14]: plt.plot(range(len(nn.cost_)), nn.cost_, color='k')
plt.ylim([0, 2000])
plt.ylabel('Cost')
plt.xlabel('Epochs * 50')
plt.tight_layout()
plt.show()

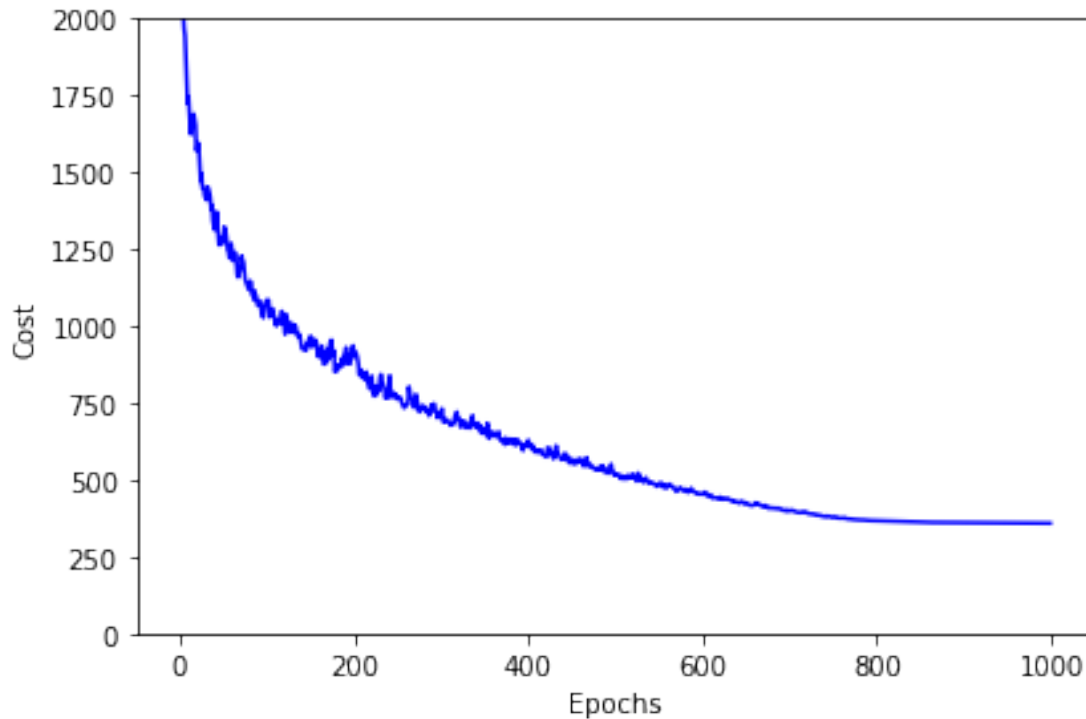
```





```
In [15]: batches = np.array_split(range(len(nn.cost_)), 1000)
cost_array = np.array(nn.cost_)
cost_averages = [np.mean(cost_array[i]) for i in batches]

In [16]: plt.plot(range(len(cost_averages)), cost_averages, color='b')
plt.ylim([0, 2000])
plt.ylabel('Cost')
plt.xlabel('Epochs')
plt.tight_layout()
plt.show()
```



```
In [17]: y_train_pred = nn.predict(X_train)
accuracy = \
    ((np.sum(y_train == y_train_pred, axis=0)).astype('float') / X_train.shape[0])
accuracy
```

```
Out[17]: 0.9771166666666666
```

```
In [18]: y_test_pred = nn.predict(X_test)
accuracy = \
    ((np.sum(y_test == y_test_pred, axis=0)).astype('float') / X_test.shape[0])
accuracy
```

```
Out[18]: 0.9603
```































```
In [19]: misclassified_img = X_test[y_test != y_test_pred][:30]
correct_lab = y_test[y_test != y_test_pred][:30]
misclassified_lab = y_test_pred[y_test != y_test_pred][:30]

fig, ax = plt.subplots(nrows=6, ncols=5, sharex=True, sharey=True,)
ax = ax.flatten()
for i in range(30):
    img = misclassified_img[i].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')
    ax[i].set_title('%d t: %d p: %d' % (i+1, correct_lab[i], misclassified_lab[i]))
```

```

ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
plt.show()

```

1) t: 5 p: 6 	2) t: 3 p: 2 	3) t: 4 p: 9 	4) t: 2 p: 9 	5) t: 9 p: 8 
6) t: 4 p: 2 	7) t: 6 p: 0 	8) t: 8 p: 4 	9) t: 2 p: 7 	10) t: 5 p: 3 
11) t: 9 p: 4 	12) t: 2 p: 8 	13) t: 6 p: 0 	14) t: 9 p: 8 	15) t: 3 p: 5 
16) t: 3 p: 5 	17) t: 8 p: 2 	18) t: 4 p: 9 	19) t: 8 p: 2 	20) t: 2 p: 8 
21) t: 8 p: 3 	22) t: 9 p: 4 	23) t: 2 p: 8 	24) t: 8 p: 4 	25) t: 4 p: 9 
26) t: 0 p: 6 	27) t: 4 p: 9 	28) t: 4 p: 9 	29) t: 5 p: 9 	30) t: 3 p: 1 

In [ ]: