Code Experiment

April 16, 2020

1 Base Model

1.1 Importing Necessary Dependencies

[2]:
```
# Python Standard Libraries for importing data from binary file
import os.path #for accessing the file path
import struct  #for unpacking the binary data

import time    #for calculating time
import math

#core packages
import numpy as np
import matplotlib.pyplot as plt

#custom module
from dataPrep import retrive_data, sample_origDataset , dev_test_split,␣
 ↪prep_dataset, visualize_orig


np.random.seed(1)
%matplotlib inline
```

1.2 Dataset Preparation

Retriving Dataset

[3]:
```
#retriving the data
train_x_orig, train_y_orig = retrive_data(dataset="training-set")
test_x_temp, test_y_temp = retrive_data(dataset="test-set")

#displaying the retrival info
print("Data\t\t\t","Datatype\t\t","Shape")
print("=================================================================")
print("Training Set Images:\t" + str(type(train_x_orig))+"\t",str(train_x_orig.
 ↪shape))
```

```
print("Training Set Labels:\t" + str(type(train_y_orig))+"\t",str(train_y_orig.
 ↪shape))
print("Test Set Images:\t" + str(type(test_x_temp))+"\t",str(test_x_temp.shape))
print("Test Set Labels:\t" + str(type(test_y_temp))+"\t",str(test_y_temp.shape))
print("=================================================================")
```

```
Data                        Datatype                Shape
=================================================================
Training Set Images:    <class 'numpy.ndarray'>  (60000, 28, 28)
Training Set Labels:    <class 'numpy.ndarray'>  (60000, 1)
Test Set Images:        <class 'numpy.ndarray'>  (10000, 28, 28)
Test Set Labels:        <class 'numpy.ndarray'>  (10000, 1)
=================================================================
```

Sampling the Dataset for Model Experiment

[4]:
```
train_Vol,train_x_sample, train_y_sample =␣
 ↪sample_origDataset(train_x_orig,train_y_orig,dataVol= 100)
test_Vol,test_x_sample,test_y_sample =␣
 ↪sample_origDataset(test_x_temp,test_y_temp,dataVol= 100)

print("Data\t\t\t","Complete Data Shape\t","Sample Data Shape\t","Sample Size")
print("================================================================================")
print("Training Set Images:\t"+ str(train_x_orig.shape)+"\t\t"+␣
 ↪str(train_x_sample.shape)+"\t\t"+str(train_Vol)+"%")
print("Training Set Labels:\t"+ str(train_y_orig.shape)+"\t\t"+␣
 ↪str(train_y_sample.shape))
print("Test Set Images:\t"+str(test_x_temp.shape)+"\t\t"+ str(test_x_sample.
 ↪shape)+"\t\t"+str(test_Vol)+"%")
print("Test Set Labels:\t"+str(test_y_temp.shape)+"\t\t"+ str(test_y_sample.
 ↪shape))
print("================================================================================")
```

```
Data                        Complete Data Shape     Sample Data Shape       Sample
Size
================================================================================
=====
Training Set Images:    (60000, 28, 28)         (60000, 28, 28)         100%
Training Set Labels:    (60000, 1)              (60000, 1)
Test Set Images:        (10000, 28, 28)         (10000, 28, 28)         100%
Test Set Labels:        (10000, 1)              (10000, 1)
================================================================================
=====
```

Splitting Dev-Test Set

[5]:
```python
dev_x_orig,dev_y_orig,test_x_orig,test_y_orig =␣
↪dev_test_split(test_x_sample,test_y_sample)

print("Data\t\t\t","Shape")
print("==================================================================")
print("Dev Set Images:\t\t" ,str(dev_x_orig.shape))
print("Dev Set Labels:\t\t" ,str(dev_y_orig.shape))
print("Test Set Images:\t",str(test_x_orig.shape))
print("Test Set Labels:\t",str(test_y_orig.shape))
print("==================================================================")
```

```
Data                        Shape
==================================================================
Dev Set Images:             (5000, 28, 28)
Dev Set Labels:             (5000, 1)
Test Set Images:            (5000, 28, 28)
Test Set Labels:            (5000, 1)
==================================================================
```

Preparing the Dataset (Flattening and Normalizing)

[6]:
```python
train_x_norm,train_y_encoded, dev_x_norm,dev_y_encoded, test_x_norm,␣
↪test_y_encoded = prep_dataset(train_x_sample, train_y_sample, dev_x_orig,␣
↪dev_y_orig, test_x_orig, test_y_orig)
print("Data\t\t\t","Before Processing\t","After Processing")
print("==================================================================")
print("Training Set Images:\t" + str(train_x_orig.shape)+"\t\t"+␣
↪str(train_x_norm.shape))
print("Training Set Labels:\t" + str(train_y_orig.shape)+"\t\t"+␣
↪str(train_y_encoded.shape))
print("Dev Set Images:\t\t" + str(dev_x_orig.shape)+"\t\t"+ str(dev_x_norm.
↪shape))
print("Dev Set Labels:\t\t" + str(dev_y_orig.shape)+"\t\t"+ str(dev_y_encoded.
↪shape))
print("Test Set Images:\t" + str(test_x_orig.shape)+"\t\t"+ str(test_x_norm.
↪shape))
print("Test Set Labels:\t" + str(test_y_orig.shape)+"\t\t"+ str(test_y_encoded.
↪shape))
print("==================================================================")
```

```
Data                        Before Processing       After Processing
==================================================================
Training Set Images:      (60000, 28, 28)         (784, 60000)
Training Set Labels:      (60000, 1)              (11, 60000)
Dev Set Images:           (5000, 28, 28)          (784, 5000)
Dev Set Labels:           (5000, 1)               (11, 5000)
Test Set Images:          (5000, 28, 28)          (784, 5000)
```

```
Test Set Labels:        (5000, 1)              (11, 5000)
=================================================================
```

Creating Minibatches

[7]:
```
def rand_mini_batches(X, Y, mini_batch_size = 64, seed=1):


    np.random.seed(seed)
    m = X.shape[1]                  # number of training examples
    mini_batches = []

#     Shuffle (X, Y)
    permutation = list(np.random.permutation(m))
    shuffled_X = X[:, permutation]
    shuffled_Y = Y[:, permutation].reshape((11,m))

#     Partition (shuffled_X, shuffled_Y) except for the last batch
    num_complete_minibatches = math.floor(m/mini_batch_size) # number of mini␣
 ↪batches of size mini_batch_size
    for k in range(0, num_complete_minibatches):
        mini_batch_X = shuffled_X[:, k * mini_batch_size :␣
 ↪(k+1)*mini_batch_size]
        mini_batch_Y = shuffled_Y[:, k * mini_batch_size :␣
 ↪(k+1)*mini_batch_size]
        mini_batch = (mini_batch_X, mini_batch_Y)
        mini_batches.append(mini_batch)

    # Last batch (last mini-batch < mini_batch_size)
    if m % mini_batch_size != 0:
        mini_batch_X = shuffled_X[:, num_complete_minibatches * mini_batch_size␣
 ↪: m]
        mini_batch_Y = shuffled_Y[:, num_complete_minibatches * mini_batch_size␣
 ↪: m]
        mini_batch = (mini_batch_X, mini_batch_Y)
        mini_batches.append(mini_batch)

    return mini_batches
```

[8]:
```
mini_batches = rand_mini_batches(train_x_norm,train_y_encoded, mini_batch_size␣
 ↪= 128)
minibatch_length = len(mini_batches)
print("Total Minibatches:\t"+str(minibatch_length))
print("\nMinibatchs\t\tShape")
print("==================================")
print ("1st mini_batch_X:\t" + str(mini_batches[0][0].shape))
print ("2nd mini_batch_X:\t" + str(mini_batches[1][0].shape))
```

```
print (str(minibatch_length - 1) + "th mini_batch_X:\t" +␣
↪str(mini_batches[-2][0].shape))
print (str(minibatch_length) + "th mini_batch_X:\t" + str(mini_batches[-1][0].
↪shape))

print ("\n1st mini_batch_Y:\t" + str(mini_batches[0][1].shape))
print ("2nd mini_batch_Y:\t" + str(mini_batches[1][1].shape))
print (str(minibatch_length - 1) + "th mini_batch_Y:\t" +␣
↪str(mini_batches[-2][1].shape))
print (str(minibatch_length) + "th mini_batch_Y:\t" + str(mini_batches[-1][1].
↪shape))
```

```
Total Minibatches:      469

Minibatchs              Shape
==================================
1st mini_batch_X:       (784, 128)
2nd mini_batch_X:       (784, 128)
468th mini_batch_X:     (784, 128)
469th mini_batch_X:     (784, 96)

1st mini_batch_Y:       (11, 128)
2nd mini_batch_Y:       (11, 128)
468th mini_batch_Y:     (11, 128)
469th mini_batch_Y:     (11, 96)
```

1.3 Utility Functions

ReLU Function and Its derivative

[9]:
```
def relu(Z):
    A = np.maximum(0.0,Z)

    cache = Z
    assert(A.shape == Z.shape)
    return A, cache
```

[10]:
```
def relu_grad(dA, cache):
    Z = cache
    dZ = np.array(dA, copy=True) # just converting dz to a correct object.

    dZ[Z < 0] = 0

    assert(dZ.shape == Z.shape)
    return dZ
```

Softmax Function and its derivative

[11]:
```
def softmax(Z):
    shift = Z - np.max(Z) #Avoiding underflow or overflow errors due to␣
↪floating point instability in softmax
    t = np.exp(shift)
    A = np.divide(t,np.sum(t,axis = 0))

    cache = Z
    assert(A.shape == Z.shape)
    return A, cache
```

Learning rate decay

[ ]:
```
def decay_learning_rate(alpha_prev, decay_rate = 1, epoch):

    alpha = (1/(1 + decay_rate * epoch)) * alpha_prev

    return alpha
```

1.4 Deep Learning Model

1.4.1 1. Creating NN Architecture

initializing layers

[51]:
```
def init_layers():
    layers_dim = [784,800,300,11]
    return layers_dim
```

Initializing Parameters

- Random initialization

[41]:
```
def init_params_random(layers_dim):

    L = len(layers_dim)
    params = {}

    for l in range(1,L):
        params['W' + str(l)] = np.random.randn(layers_dim[l],layers_dim[l-1])␣
↪*0.01
        params['b' + str(l)] = np.zeros((layers_dim[l],1))

        assert(params['W' + str(l)].shape == (layers_dim[l],layers_dim[l-1]))
        assert(params['b' + str(l)].shape == (layers_dim[l],1))
    return params
```

- He-initialization

```
[14]: def init_params_he(layers_dim):

    L = len(layers_dim)
    params = {}

    for l in range(1,L):
        params['W' + str(l)] = np.random.randn(layers_dim[l],layers_dim[l-1]) *␣
↪np.sqrt(np.divide(2,layers_dim[l-1])) # He - initialization
        params['b' + str(l)] = np.zeros((layers_dim[l],1))

        assert(params['W' + str(l)].shape == (layers_dim[l],layers_dim[l-1]))
        assert(params['b' + str(l)].shape == (layers_dim[l],1))
    return params
```

Initializing Hyper Parameters

```
[15]: def init_hyperParams(alpha = 0.001, num_epoch = 2000, mini_batch_size = 128,␣
↪beta1 = 0.9, beta2 = 0.999,  epsilon = 1e-8):
    hyperParams = {}
    hyperParams['learning_rate'] = alpha
    hyperParams['num_epoch'] = num_epoch
    hyperParams['mini_batch_size'] = mini_batch_size
    hyperParams['beta1'] = beta1
    hyperParams['beta2'] = beta2
    hyperParams['epsilon'] = epsilon

    return hyperParams
```

1.4.2 2. Forward Propogation

Calculating sum of product of inputs and weights (Z) for individual layer

```
[16]: def forward_sum(A,W,b):

    Z = np.dot(W,A) + b

    cache = (A,W,b)
    assert(Z.shape == (W.shape[0],Z.shape[1]))

    return Z, cache
```

Calculating Activation for individual Layer

[17]:
```
def forward_activation(A,W,b,activation):

    if activation == 'relu':
        Z, sum_cache = forward_sum(A,W,b)
        A, activation_cache = relu(Z)

    if activation == 'softmax':
        Z, sum_cache = forward_sum(A,W,b)
        A, activation_cache = softmax(Z)

    cache = (sum_cache,activation_cache)
    assert(A.shape == Z.shape)

    return A, cache
```

Complete Forward Propagation for L layers

[18]:
```
def forward_prop(X,parameters):
    caches = []
    A = X
    L = len(parameters) // 2
    for l in range(1, L):
        A_prev = A
        A, cache = forward_activation(A_prev,parameters['W' +␣
 ↪str(l)],parameters['b' + str(l)],activation='relu')
        caches.append(cache)

    AL, cache = forward_activation(A,parameters['W' + str(L)],parameters['b' +␣
 ↪str(L)],activation='softmax')
    caches.append(cache)

    assert(AL.shape == (11,X.shape[1]))

    return AL,caches
```

1.4.3 3. Cost Function

[19]:
```
def compute_cost(AL,Y):
    m = Y.shape[1]

    cost = -(1./m) * np.sum(np.sum(np.multiply(Y,np.log(AL)), axis =␣
 ↪0,keepdims=True))
```

```
    cost = np.squeeze(cost)      # Making sure your cost's shape is not␣
↪returned as ndarray
    assert(cost.shape == ())

    return cost
```

1.4.4 4. Backward Propagation

Calculating Gradients for individual Layer

[20]:
```
def backward_grad(dZ, cache):
    A_prev, W, b = cache
    m = A_prev.shape[1]

    dW = (1/m) * np.dot(dZ,A_prev.T)
    db = (1/m) * np.sum(dZ, axis = 1, keepdims=True )
    dA_prev = np.dot(W.T, dZ)


    assert (dA_prev.shape == A_prev.shape)
    assert (dW.shape == W.shape)
    assert (db.shape == b.shape)


    return dA_prev, dW, db
```

Calculating Backward Activation for individual layer

[21]:
```
def backward_activation(dA,cache,activation):
    sum_cache, activation_cache = cache

    if activation == "relu":
        dZ = relu_grad(dA,activation_cache)
        dA_prev, dW, db = backward_grad(dZ, sum_cache)

    elif activation == "softmax":
        dZ = dA
        dA_prev, dW, db = backward_grad(dA, sum_cache)

    return dA_prev, dW, db
```

Complete Backward Propagation for L layers

[22]:
```
def backward_prop(AL, Y,caches):
    grads = {}
    L = len(caches) # the number of layers
    m = AL.shape[1]
    Y = Y.reshape(AL.shape) # after this line, Y is the same shape as AL

    dA = np.subtract(AL,Y)

    current_cache = caches[L-1]
    grads["dA" + str(L-1)], grads["dW" + str(L)], grads["db" + str(L)] =␣
 ↪backward_activation(dA, current_cache, activation = 'softmax')

    for l in reversed(range(L-1)):
        current_cache = caches[l]
        dA_prev_temp, dW_temp, db_temp = backward_activation(grads["dA" + str(l␣
 ↪+ 1)], current_cache, activation = 'relu')
        grads["dA" + str(l)] = dA_prev_temp
        grads["dW" + str(l + 1)] = dW_temp
        grads["db" + str(l + 1)] = db_temp

    return grads
```

1.4.5 5. Update Parameters

- normal update of parameters

[23]:
```
def update_parameters(parameters, grads, learning_rate):
    L = len(parameters) // 2
    for l in range(L):
        parameters["W" + str(l+1)] = parameters["W" + str(l+1)] -␣
 ↪(learning_rate * grads["dW" + str(l+1)])
        parameters["b" + str(l+1)] = parameters["b" + str(l+1)] -␣
 ↪(learning_rate * grads["db" + str(l+1)])
    return parameters
```

- update parameters with adam

[24]:
```
#initialize adam

def initialize_adam(parameters) :

    L = len(parameters) // 2
    v = {}
    s = {}

    for l in range(L):
```

```
        v["dW" + str(l+1)] = np.zeros(parameters["W" + str(l+1)].shape)
        v["db" + str(l+1)] = np.zeros(parameters["b" + str(l+1)].shape)
        s["dW" + str(l+1)] = np.zeros(parameters["W" + str(l+1)].shape)
        s["db" + str(l+1)] = np.zeros(parameters["b" + str(l+1)].shape)

    return v, s
```

[25]:

```
#update with adam
def update_parameters_adam(parameters, grads, learning_rate, v, s, t , beta1 =␣
↪0.9, beta2 = 0.999,  epsilon = 1e-8):

    L = len(parameters) // 2
    v_corrected = {}
    s_corrected = {}

    for l in range(L):
        # Moving average of the gradients.
        v["dW" + str(l+1)] = np.add(beta1 * v["dW" + str(l+1)], (1 - beta1) *␣
↪grads["dW" + str(l+1)])
        v["db" + str(l+1)] = np.add(beta1 * v["db" + str(l+1)], (1 - beta1) *␣
↪grads["db" + str(l+1)])

        # Compute bias-corrected first moment estimate.
        v_corrected["dW" + str(l+1)] = np.divide(v["dW" + str(l+1)], (1 - np.
↪power(beta1,t)))
        v_corrected["db" + str(l+1)] = np.divide(v["db" + str(l+1)], (1 - np.
↪power(beta1,t)))

        # Moving average of the squared gradients.
        s["dW" + str(l+1)] = np.add(beta2 * s["dW" + str(l+1)], (1 - beta2) *␣
↪np.square(grads["dW" + str(l+1)]))
        s["db" + str(l+1)] = np.add(beta2 * s["db" + str(l+1)], (1 - beta2) *␣
↪np.square(grads["db" + str(l+1)]))

        # Compute bias-corrected second raw moment estimate.
        s_corrected["dW" + str(l+1)] = np.divide(s["dW" + str(l+1)], (1 - np.
↪power(beta2,t)))
        s_corrected["db" + str(l+1)] = np.divide(s["db" + str(l+1)], (1 - np.
↪power(beta2,t)))

        # Update parameters.
        parameters["W" + str(l+1)] = np.subtract(parameters["W" + str(l+1)], ␣
↪learning_rate * np.divide(v_corrected["dW" + str(l+1)], np.
↪sqrt(s_corrected["dW" + str(l+1)]) + epsilon))
```

```
        parameters["b" + str(l+1)] = np.subtract(parameters["b" + str(l+1)], ␣
↪learning_rate * np.divide(v_corrected["db" + str(l+1)], np.
↪sqrt(s_corrected["db" + str(l+1)]) + epsilon))

    return parameters, v, s
```

1.4.6 6. Prediction

[26]:
```
def predict(X,y,parameters):
    m = y.shape[1]
    n = len(parameters) // 2 # number of layers in the neural network

    probas, caches = forward_prop(X, parameters)

    assert(probas.shape == y.shape)

    predicted_labels = np.argmax(probas,axis=0).reshape(1,probas.shape[1])
    predicted_prob = np.max(probas,axis = 0).reshape(1,m)

    Y = np.argmax(y,axis=0).reshape(1,y.shape[1])


    #print results
    true_prediction = np.equal(predicted_labels,Y)

    num_correct_labels = np.sum(true_prediction)
    accuracy = (num_correct_labels/m)

    return predicted_labels, predicted_prob, accuracy
```

Visualizing the costs and accuracy for model analysis

[64]:
```
def visualize_results(attr, attr_type):

    plt.plot(np.squeeze(attr))
    if attr_type == 'costs':
        plt.ylabel("cost")
        plt.title("Cost")

    elif attr_type == 'train_accs':
        plt.ylabel("accuracy")
        plt.title("Training Accuracy")
        plt.plot(np.squeeze(1 - attr), label = 'loss')
```

```
    elif attr_type == 'val_accs':
        plt.ylabel("accuracy")
        plt.title("Validation Accuracy")
        plt.plot(np.squeeze(1 - attr), label = 'loss')


    else:
        raise ValueError("Dataset set must be training or dev or test set")

    plt.xlabel('Epochs (per hundreds)')
    plt.show()
```

1.4.7 7. Train Model

```
[2]: def train(X_train, Y_train, X_dev, Y_dev, layers_dim, hyperParams, optimizer =␣
 ↪'adam'):
    #hyper parameters
    learning_rate = hyperParams['learning_rate']
    num_epoch = hyperParams['num_epoch']
    mini_batch_size = hyperParams['mini_batch_size']
    beta1 = hyperParams['beta1']
    beta2 = hyperParams['beta2']
    epsilon = hyperParams['epsilon']

    seed = 1
    m = Y_train.shape[1]
    costs = []       # keep track of epoch cost
    train_accs = []  # keep track of training accuracy
    val_accs = []      # keep track of Validation accuracy

    parameters = init_params_he(layers_dim)

    if optimizer == 'mgd':
        pass
    elif optimizer == 'adam':
        t = 0
        v,s = initialize_adam(parameters)

    #minibatch GD
    for i in range(0, num_epoch):
        seed += 1
        minibatches = rand_mini_batches(X_train, Y_train, mini_batch_size, seed)
        epoch_cost = 0
        if i % 10 == 0:
            learning_rate = decay_learning_rate(learning_rate, decay_rate, i)
```

```
        for minibatch in minibatches:

            (minibatch_X, minibatch_Y) = minibatch

            AL, caches = forward_prop(minibatch_X, parameters)

            epoch_cost += compute_cost(AL, minibatch_Y) #accumulating the batch␣
↪costs

            grads = backward_prop(AL, minibatch_Y, caches)

            if optimizer == 'mgd':
                parameters = update_parameters(parameters, grads, learning_rate)
            elif optimizer == 'adam':
                t = t+1
                parameters, v, s = update_parameters_adam(parameters,␣
↪grads,learning_rate, v, s,t, beta1, beta2,  epsilon)

        epoch_cost_avg = epoch_cost / m

        #computing and accumulating training and validation accuracy
        _,_,train_acc = predict(X_train, Y_train, parameters)
        _,_,val_acc= predict(X_dev, Y_dev, parameters)
        train_accs.append(train_acc)
        val_accs.append(val_acc)


#         if i % 50 == 0:
        print("Epoch: %d =========== Learning rate: %f\n"%(i,learning_rate))
        print ("\tCost: %f || Training acc: %.6f || Val acc: %.6f || Val loss:␣
↪%.6f"%(epoch_cost_avg,train_acc,val_acc,1-val_acc))
#         if i % 100 == 0:
        costs.append(epoch_cost_avg)



    visualize_results(costs, attr_type='costs')

    visualize_results(train_accs, attr_type='train_accs')
    visualize_results(val_accs, attr_type='val_accs')

    return parameters
```

1.4.8 Running Model

[52]:
```
hyperParams = init_hyperParams(alpha = 0.0001, num_epoch = 100, mini_batch_size␣
 ↪= 512)
layers_dim = init_layers()
parameters = train(train_x_norm, train_y_encoded,dev_x_norm,␣
 ↪dev_y_encoded,layers_dim, hyperParams, optimizer = 'adam')
```

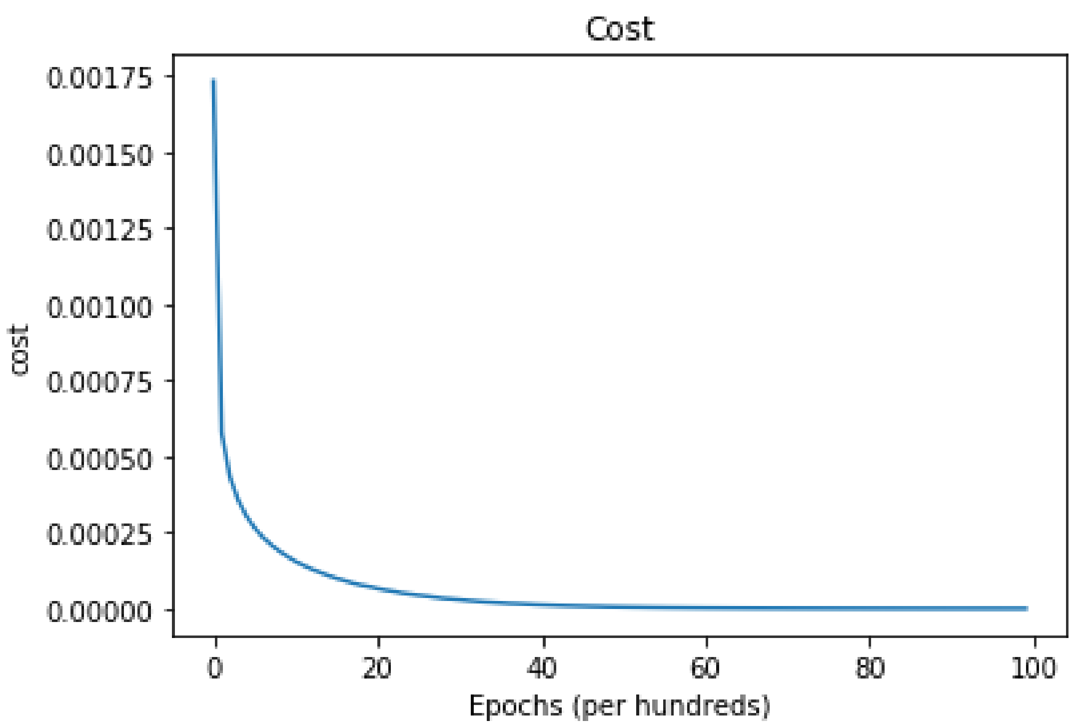
```
Epoch: 0 == Cost: 0.001734 || Training acc: 0.904550 || Val acc: 0.911600 || Val
loss: 0.088400
Epoch: 1 == Cost: 0.000578 || Training acc: 0.933167 || Val acc: 0.937400 || Val
loss: 0.062600
Epoch: 2 == Cost: 0.000433 || Training acc: 0.945133 || Val acc: 0.944400 || Val
loss: 0.055600
Epoch: 3 == Cost: 0.000358 || Training acc: 0.955283 || Val acc: 0.953600 || Val
loss: 0.046400
Epoch: 4 == Cost: 0.000305 || Training acc: 0.961967 || Val acc: 0.957400 || Val
loss: 0.042600
Epoch: 5 == Cost: 0.000267 || Training acc: 0.966400 || Val acc: 0.959200 || Val
loss: 0.040800
Epoch: 6 == Cost: 0.000235 || Training acc: 0.970433 || Val acc: 0.965800 || Val
loss: 0.034200
Epoch: 7 == Cost: 0.000211 || Training acc: 0.973833 || Val acc: 0.967000 || Val
loss: 0.033000
Epoch: 8 == Cost: 0.000190 || Training acc: 0.976467 || Val acc: 0.968600 || Val
loss: 0.031400
Epoch: 9 == Cost: 0.000172 || Training acc: 0.978950 || Val acc: 0.970000 || Val
loss: 0.030000
Epoch: 10 == Cost: 0.000155 || Training acc: 0.980883 || Val acc: 0.971800 ||
Val loss: 0.028200
Epoch: 11 == Cost: 0.000142 || Training acc: 0.983567 || Val acc: 0.971800 ||
Val loss: 0.028200
Epoch: 12 == Cost: 0.000130 || Training acc: 0.984817 || Val acc: 0.973400 ||
Val loss: 0.026600
Epoch: 13 == Cost: 0.000119 || Training acc: 0.986317 || Val acc: 0.975000 ||
Val loss: 0.025000
Epoch: 14 == Cost: 0.000109 || Training acc: 0.987150 || Val acc: 0.974400 ||
Val loss: 0.025600
Epoch: 15 == Cost: 0.000100 || Training acc: 0.989050 || Val acc: 0.976600 ||
Val loss: 0.023400
Epoch: 16 == Cost: 0.000092 || Training acc: 0.990117 || Val acc: 0.976200 ||
Val loss: 0.023800
Epoch: 17 == Cost: 0.000084 || Training acc: 0.990450 || Val acc: 0.977200 ||
Val loss: 0.022800
Epoch: 18 == Cost: 0.000077 || Training acc: 0.991617 || Val acc: 0.977800 ||
Val loss: 0.022200
Epoch: 19 == Cost: 0.000073 || Training acc: 0.992567 || Val acc: 0.975600 ||
```

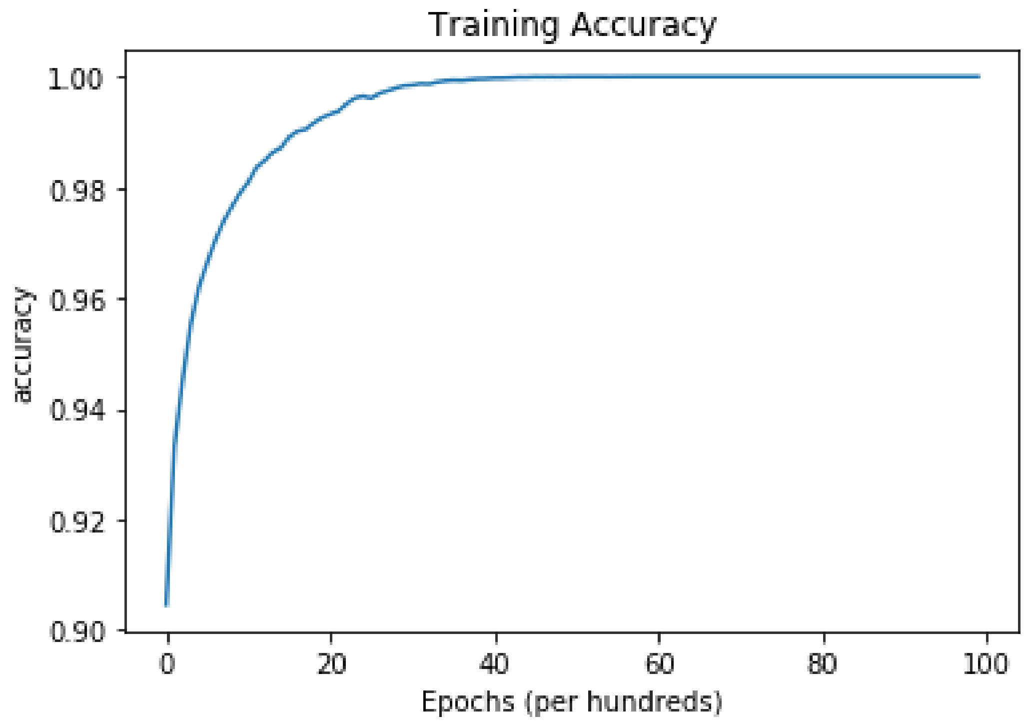
```
Val loss: 0.024400
Epoch: 20 == Cost: 0.000066 || Training acc: 0.993200 || Val acc: 0.977000 ||
Val loss: 0.023000
Epoch: 21 == Cost: 0.000061 || Training acc: 0.993733 || Val acc: 0.977400 ||
Val loss: 0.022600
Epoch: 22 == Cost: 0.000057 || Training acc: 0.995067 || Val acc: 0.977200 ||
Val loss: 0.022800
Epoch: 23 == Cost: 0.000051 || Training acc: 0.996100 || Val acc: 0.978400 ||
Val loss: 0.021600
Epoch: 24 == Cost: 0.000048 || Training acc: 0.996483 || Val acc: 0.978600 ||
Val loss: 0.021400
Epoch: 25 == Cost: 0.000044 || Training acc: 0.996100 || Val acc: 0.978400 ||
Val loss: 0.021600
Epoch: 26 == Cost: 0.000041 || Training acc: 0.996950 || Val acc: 0.979400 ||
Val loss: 0.020600
Epoch: 27 == Cost: 0.000038 || Training acc: 0.997450 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 28 == Cost: 0.000034 || Training acc: 0.997933 || Val acc: 0.978600 ||
Val loss: 0.021400
Epoch: 29 == Cost: 0.000032 || Training acc: 0.998367 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 30 == Cost: 0.000030 || Training acc: 0.998467 || Val acc: 0.979400 ||
Val loss: 0.020600
Epoch: 31 == Cost: 0.000027 || Training acc: 0.998733 || Val acc: 0.979400 ||
Val loss: 0.020600
Epoch: 32 == Cost: 0.000025 || Training acc: 0.998650 || Val acc: 0.978200 ||
Val loss: 0.021800
Epoch: 33 == Cost: 0.000022 || Training acc: 0.999017 || Val acc: 0.979400 ||
Val loss: 0.020600
Epoch: 34 == Cost: 0.000021 || Training acc: 0.999233 || Val acc: 0.979400 ||
Val loss: 0.020600
Epoch: 35 == Cost: 0.000019 || Training acc: 0.999367 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 36 == Cost: 0.000017 || Training acc: 0.999300 || Val acc: 0.978400 ||
Val loss: 0.021600
Epoch: 37 == Cost: 0.000016 || Training acc: 0.999467 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 38 == Cost: 0.000015 || Training acc: 0.999600 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 39 == Cost: 0.000014 || Training acc: 0.999633 || Val acc: 0.979800 ||
Val loss: 0.020200
Epoch: 40 == Cost: 0.000013 || Training acc: 0.999733 || Val acc: 0.979800 ||
Val loss: 0.020200
Epoch: 41 == Cost: 0.000012 || Training acc: 0.999750 || Val acc: 0.978000 ||
Val loss: 0.022000
Epoch: 42 == Cost: 0.000011 || Training acc: 0.999817 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 43 == Cost: 0.000010 || Training acc: 0.999900 || Val acc: 0.978600 ||
```

```
Val loss: 0.021400
Epoch: 44 == Cost: 0.000009 || Training acc: 0.999883 || Val acc: 0.979000 ||
Val loss: 0.021000
Epoch: 45 == Cost: 0.000008 || Training acc: 0.999967 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 46 == Cost: 0.000008 || Training acc: 0.999933 || Val acc: 0.979200 ||
Val loss: 0.020800
Epoch: 47 == Cost: 0.000007 || Training acc: 0.999967 || Val acc: 0.979200 ||
Val loss: 0.020800
Epoch: 48 == Cost: 0.000006 || Training acc: 0.999933 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 49 == Cost: 0.000006 || Training acc: 0.999967 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 50 == Cost: 0.000006 || Training acc: 0.999983 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 51 == Cost: 0.000005 || Training acc: 0.999983 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 52 == Cost: 0.000005 || Training acc: 0.999983 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 53 == Cost: 0.000004 || Training acc: 0.999983 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 54 == Cost: 0.000004 || Training acc: 0.999967 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 55 == Cost: 0.000004 || Training acc: 0.999983 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 56 == Cost: 0.000003 || Training acc: 0.999983 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 57 == Cost: 0.000003 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 58 == Cost: 0.000003 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 59 == Cost: 0.000003 || Training acc: 1.000000 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 60 == Cost: 0.000003 || Training acc: 1.000000 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 61 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.981000 ||
Val loss: 0.019000
Epoch: 62 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 63 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 64 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 65 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.979600 ||
Val loss: 0.020400
Epoch: 66 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 67 == Cost: 0.000002 || Training acc: 1.000000 || Val acc: 0.980200 ||
```

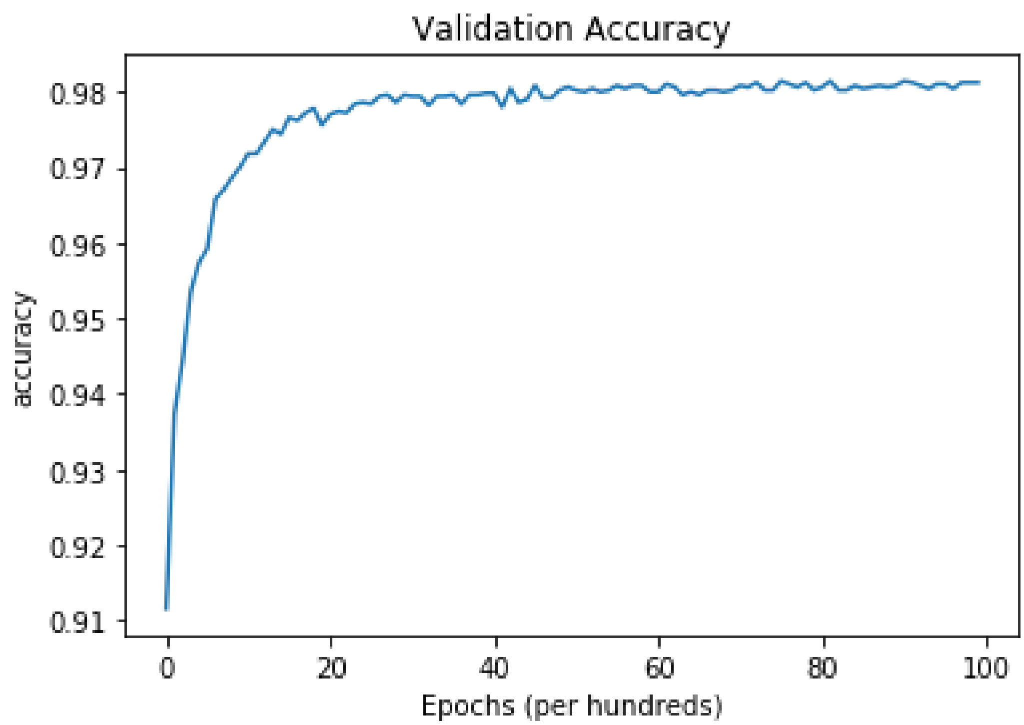
```
Val loss: 0.019800
Epoch: 68 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980000 ||
Val loss: 0.020000
Epoch: 69 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 70 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 71 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 72 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.981200 ||
Val loss: 0.018800
Epoch: 73 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 74 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 75 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.981400 ||
Val loss: 0.018600
Epoch: 76 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.981000 ||
Val loss: 0.019000
Epoch: 77 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 78 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.981200 ||
Val loss: 0.018800
Epoch: 79 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 80 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 81 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.981400 ||
Val loss: 0.018600
Epoch: 82 == Cost: 0.000001 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 83 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980200 ||
Val loss: 0.019800
Epoch: 84 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 85 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 86 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 87 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 88 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980600 ||
Val loss: 0.019400
Epoch: 89 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 90 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981400 ||
Val loss: 0.018600
Epoch: 91 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981200 ||
```

```
Val loss: 0.018800
Epoch: 92 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980800 ||
Val loss: 0.019200
Epoch: 93 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 94 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981000 ||
Val loss: 0.019000
Epoch: 95 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981000 ||
Val loss: 0.019000
Epoch: 96 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.980400 ||
Val loss: 0.019600
Epoch: 97 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981200 ||
Val loss: 0.018800
Epoch: 98 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981200 ||
Val loss: 0.018800
Epoch: 99 == Cost: 0.000000 || Training acc: 1.000000 || Val acc: 0.981200 ||
Val loss: 0.018800
```





Training Accuracy
1.00
0.98
0.96
0.94
0.92
0.90
accuracy
0
20
40
60
80
100
Epochs (per hundreds)



Validation Accuracy
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
accuracy
0
20
40
60
80
100
Epochs (per hundreds)

[54]:
```
predicted_labels_train, prediction_prob_train,train_acc = predict(train_x_norm,␣
↪train_y_encoded,parameters)
print("\nAccuracy: "  + str(train_acc))
print("\nError:\t"+str(1-train_acc))
```

```
Accuracy: 1.0

Error:	0.0
```

[56]:
```
predicted_labels_dev, prediction_prob_prob,dev_acc = predict(dev_x_norm,␣
↪dev_y_encoded,parameters)
print("\nAccuracy: "  + str(dev_acc))
print("\nError:\t"+str(1-dev_acc))
```

```
Accuracy: 0.9812

Error:	0.01880000000000004
```

[57]:
```
predicted_labels_test, prediction_prob_prob,test_acc = predict(test_x_norm,␣
↪test_y_encoded,parameters)
print("\nAccuracy: "  + str(test_acc))
print("\nError:\t"+str(1-test_acc))
```

```
Accuracy: 0.9826

Error:	0.017399999999999997
```

Visualizating Prediction

[ ]:
```
def visualize_prediction(x_orig, y_orig, predicted_labels, prediction_prob,␣
↪dataset):
    if(dataset == "training"):
        visual_title = "Sample Training Data Set"
        rng = range(30,40)
    elif(dataset == "dev"):
        visual_title = "Sample Dev Data Set"
        rng = range(110,120)
    elif(dataset == "test"):
        visual_title = "Sample Test Data Set"
        rng = range(110,120)
    else:
        raise ValueError("Dataset set must be training or dev or test set")
    fig, axes = plt.subplots(nrows=2, ncols=5,figsize=(16,8))
    fig.subplots_adjust(hspace=1)
```

```
    fig.suptitle(visual_title)

    for ax,i in zip(axes.flatten(),rng):
        ax.imshow(x_orig[i].squeeze(),interpolation='nearest', cmap='Greys')
        ax.set(title = "True: "+ str(y_orig[0,i])+" | Predicted:␣
↪"+str(predicted_labels[0,i]))
        ax.set(xlabel= "Prediction Prob: %f"%(prediction_prob[0,i]))
```

[ ]:
```
visualize_prediction(train_x_sample, train_y_sample.T,predicted_labels_train,␣
↪prediction_prob_train,dataset = "training")
```

[ ]:
```
visualize_prediction(dev_x_orig, dev_y_orig.T, predicted_labels_dev,␣
↪prediction_prob_prob,dataset = "dev")
```

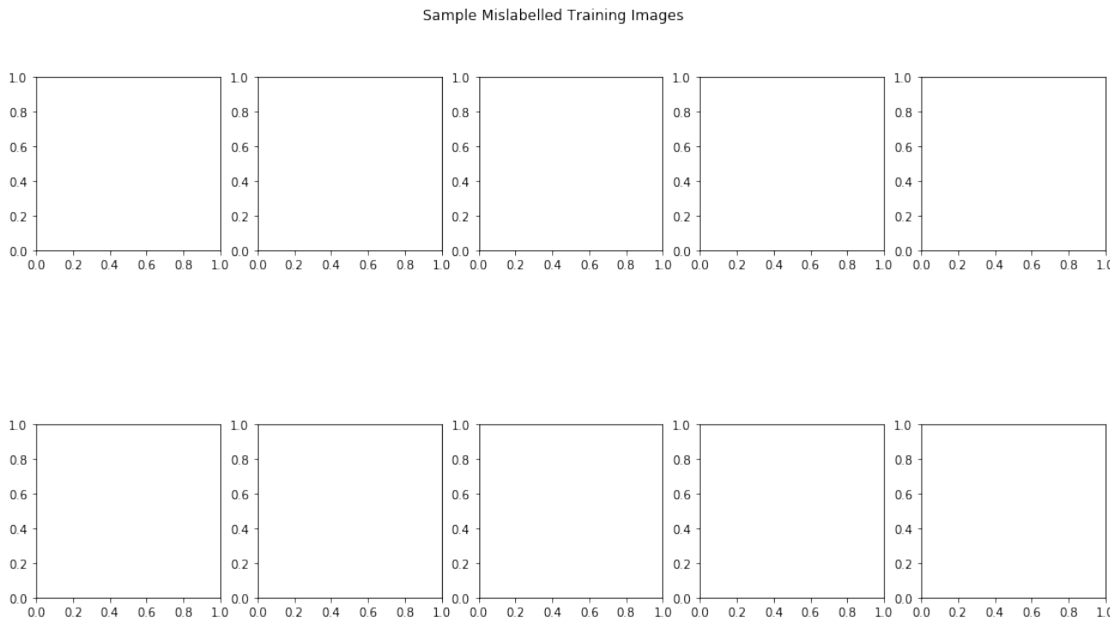
[ ]:
```
visualize_prediction(test_x_orig, test_y_orig.T, predicted_labels_test,␣
↪prediction_prob_prob,dataset = "test")
```

Visualizing Mislabelled Images in all datasets

[58]:
```
def␣
↪visualize_mislabelled_images(x_orig,y_orig,predicted_labels,prediction_prob,dataset):
↪
    true_prediction = np.equal(predicted_labels,y_orig)
    mislabelled_indices = np.asarray(np.where(true_prediction == False))
    print("Total Mislabelled Images: "+str(len(mislabelled_indices[0])))

    if(dataset == "training"):
        visual_title = "Sample Mislabelled Training Images"
    elif(dataset == "dev"):
        visual_title = "Sample Mislabelled Dev Images"
    elif(dataset == "test"):
        visual_title = "Sample Mislabelled Test Images"
    else:
        raise ValueError("Dataset set must be training or dev or test set")

    fig, axes = plt.subplots(nrows=2, ncols=5,figsize=(16,8))
    fig.subplots_adjust(hspace=1)
    fig.suptitle(visual_title)

    for ax,i in zip(axes.flatten(),mislabelled_indices[1]):
        ax.imshow(x_orig[i].squeeze(),interpolation='nearest')
        ax.set(title = "True: "+ str(y_orig[0,i])+" | Predicted:␣
↪"+str(predicted_labels[0,i]))
        ax.set(xlabel= "Prediction Prob: %f"%(prediction_prob[0,i]))
```

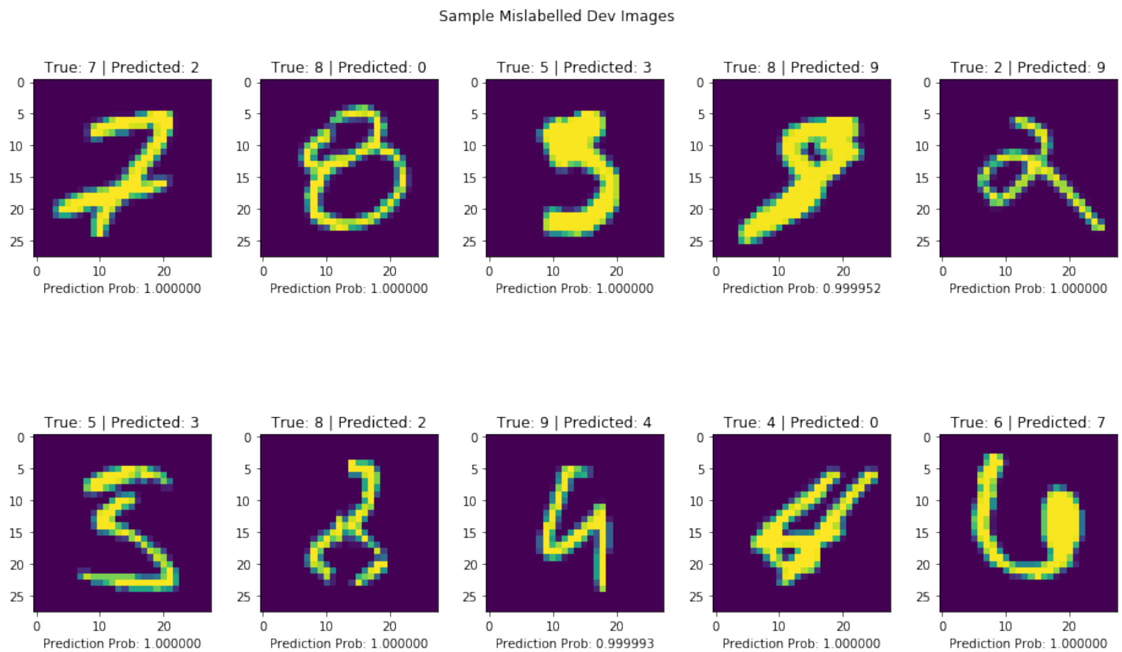
[59]:
```
visualize_mislabelled_images(train_x_sample, train_y_sample.
↪T,predicted_labels_train, prediction_prob_train,dataset = "training")
```

Total Mislabelled Images: 0



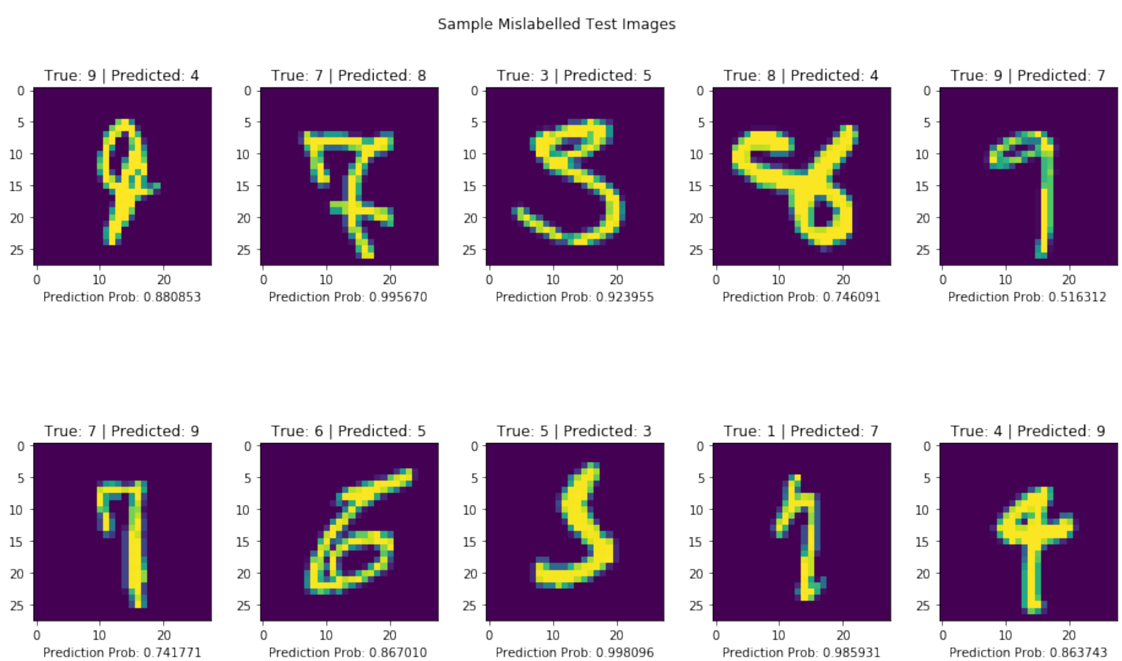
[60]:
```
visualize_mislabelled_images(dev_x_orig, dev_y_orig.T, predicted_labels_dev,␣
↪prediction_prob_prob,dataset = "dev")
```

Total Mislabelled Images: 94



[61]:
```
visualize_mislabelled_images(test_x_orig, test_y_orig.T, predicted_labels_test,
    prediction_prob_prob,dataset = "test")
```

```
Total Mislabelled Images: 87
```

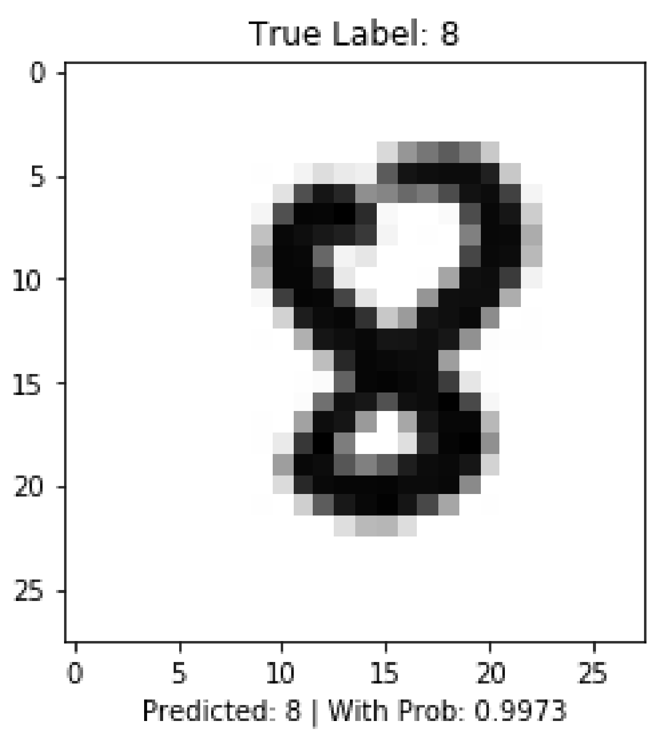


1.4.9 Predicting Real Time images

[62]:
```
from PIL import Image
from dataPrep import one_hot_encoding
```

[63]:
```
image_name = "8_1.jpg"
label = np.array([8]).reshape(1,1)

fname = "dataset/" + image_name

image_data =255 - np.asarray(Image.open(fname).convert('L').resize((28,28)))
image_flattened = image_data.reshape(image_data.shape[0]*image_data.shape[1],-1)
image_norm =(image_flattened/255.)

label_encoded = one_hot_encoding(label)

pridected_label,pred_prob,acc = predict(image_norm, label_encoded, parameters)

plt.title("True Label: "+ str(label.squeeze()))
plt.xlabel("Predicted: %d | With Prob: %.4f"%(pridected_label.squeeze(),␣
↪pred_prob.squeeze()))
plt.imshow(image_data, interpolation ='nearest',cmap='binary')
```

[63]: <matplotlib.image.AxesImage at 0x7f32f26a4190>



```
[ ]:
```