HOMEWORK -4(CS 641-01)

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```
import cloudpickle as pickle
data = pickle.load( open( "mnist23.data", "rb" ) )
print(data)
X,y = data["data"], data["target"]
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(20,4))
for index, (image, label) in enumerate(zip(data.data[500:505], data.target[500:505])):
  plt.subplot(1, 5, index + 1)
  plt.imshow(np.reshape(image, (28,28)), cmap=plt.cm.gray)
  plt.title("Training: %i" % label, fontsize = 20)
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
X_train, y_train = data.data[:70000] / 255., data.target[:70000]
pca = PCA(n\_components=16)
X_r=pca.fit(data['data']).transform(data['data'])
X_train, X_test, y_train, y_test = train_test_split(data['data'],data['target'], random_state = 0)
#Normalizing value between 0 and 1
X train normalised = X train/255.0
X_test_normalised = X_test/255.0
#Reshaping the dataset
X_train_tr = X_train_normalised.transpose()
y_train_tr = y_train.reshape(1,y_train.shape[0])
X_test_tr = X_test_normalised.transpose()
y_test_tr = y_test.reshape(1,y_test.shape[0])
print(X_train_tr.shape)
print(y_train_tr.shape)
print(X_test_tr.shape)
print(y_test_tr.shape)
```

```
#Rescaling the labels
y_train_shifted = y_train_tr - 2
y_test_shifted = y_test_tr - 2
Xtrain = X_train_tr
ytrain = y_train_shifted
Xtest = X_test_tr
ytest = y_test_shifted
def sigmoid(z):
  s = 1.0 / (1.0 + np.exp(-z))
  return s
#Intializing weights and bias
def initialize(dim):
  w = np.zeros((dim,1))
  b = 0
  assert (w.shape == (dim,1))
  assert (isinstance(b, float) or isinstance(b,int))
  return w,b
def propagate(w, b, X, Y):
  m = X.shape[1]
  z = np.dot(w.T,X)+b
  A = sigmoid(z)
  cost = -1.0/m*np.sum(Y*np.log(A)+(1.0-Y)*np.log(1.0-A))
  dw = 1.0/m*np.dot(X, (A-Y).T)
  db = 1.0/m*np.sum(A-Y)
  assert (dw.shape == w.shape)
  assert (db.dtype == float)
  cost = np.squeeze(cost)
  assert (cost.shape == ())
  grads = {"dw": dw,
        "db":db}
  return grads, cost
```

```
def optimize(w, b, X, Y, num_iterations, learning_rate, print_cost = False):
  costs = []
  for i in range(num_iterations):
     grads, cost = propagate(w, b, X, Y)
     dw = grads["dw"]
     db = grads["db"]
     w = w - learning rate*dw
     b = b - learning_rate*db
     if i \% 2000 == 0:
       costs.append(cost)
     if print_cost and i \% 2000 == 0:
       print ("Cost (iteration %i) = %f" %(i, cost))
  grads = {"dw": dw, "db": db}
  params = {"w": w, "b": b}
  return params, grads, costs
def predict (w, b, X):
  m = X.shape[1]
  Y_prediction = np.zeros((1,m))
  w = w.reshape(X.shape[0],1)
  A = sigmoid (np.dot(w.T, X)+b)
  for i in range(A.shape[1]):
     if (A[:,i] > 0.5):
       Y_prediction[:, i] = 1
     elif (A[:,i] \le 0.5):
       Y_prediction[:, i] = 0
  assert (Y_prediction.shape == (1,m))
  return Y_prediction
```

```
def model (X_train, Y_train, X_test, Y_test, num_iterations, learning_rate, print_cost = False):
  w, b = initialize(X_train.shape[0])
  parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_rate,
print_cost)
  w = parameters["w"]
  b = parameters["b"]
  Y_prediction_test = predict (w, b, X_test)
  Y prediction train = predict (w, b, X train)
  train_accuracy = 100.0 - np.mean(np.abs(Y_prediction_train-Y_train)*100.0)
  test accuracy = 100.0 - np.mean(np.abs(Y prediction test-Y test)*100.0)
  d = {"costs": costs,
     "Y_prediction_test": Y_prediction_test,
     "Y_prediction_train": Y_prediction_train,
     "W": W,
     "b": b,
     "learning_rate": learning_rate,
     "num_iterations": num_iterations}
  print ("Accuarcy Test: ", test_accuracy)
  print ("Accuracy Train: ", train_accuracy)
  return d
d = model (Xtrain,
      ytrain,
      Xtest,
      ytest,
      num_iterations = 70000,
      learning_rate = 0.05,
      print_cost = True)
```

TRAINING SET



```
Cost (iteration 0) = 0.693147
Cost (iteration 2000) = 0.082806
Cost (iteration 4000) = 0.076135
Cost (iteration 6000) = 0.072758
Cost (iteration 8000) = 0.070462
Cost (iteration 10000) = 0.068712
Cost (iteration 12000) = 0.067296
Cost (iteration 14000) = 0.066108
Cost (iteration 16000) = 0.065087
Cost (iteration 18000) = 0.064192
Cost (iteration 20000) = 0.063397
Cost (iteration 22000) = 0.062681
Cost (iteration 24000) = 0.062031
Cost (iteration 26000) = 0.061437
Cost (iteration 28000) = 0.060888
Cost (iteration 30000) = 0.060379
Cost (iteration 32000) = 0.059905
Cost (iteration 34000) = 0.059460
Cost (iteration 36000) = 0.059042
Cost (iteration 38000) = 0.058647
Cost (iteration 40000) = 0.058274
Cost (iteration 42000) = 0.057919
Cost (iteration 44000) = 0.057582
Cost (iteration 46000) = 0.057260
Cost (iteration 48000) = 0.056952
Cost (iteration 50000) = 0.056657
Cost (iteration 52000) = 0.056374
Cost (iteration 54000) = 0.056102
Cost (iteration 56000) = 0.055841
Cost (iteration 58000) = 0.055588
Cost (iteration 60000) = 0.055345
Cost (iteration 62000) = 0.055110
Cost (iteration 64000) = 0.054883
Cost (iteration 55000) = 0.054663
Cost (iteration 68000) = 0.054450
Accuarcy Test: 97.5561426684
Accuracy Train: 98.2604866234
```