Untitled

November 3, 2023

1 MNIST Handwriting Recognition from Scratch with NumPy

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[1]: from tensorflow import keras
     from sklearn.metrics import accuracy_score
     import numpy as np
[2]: # loading dataset
     (X train, y_train), (X_test, y_test) = keras.datasets.mnist.load_data()
[3]: print(X_train.shape)
     print(X_test.shape)
    (60000, 28, 28)
    (10000, 28, 28)
[4]: # reshape to flatten the data
     X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
     X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
[5]: # maximum value in dataset
     print(max(X_train[0]))
    255
[6]: # scaling
     X_train = X_train/255
     X_{\text{test}} = X_{\text{test}}/255
[7]: def sigmoid(x):
         return 1 / (1 + np.exp(-x))
[8]: def softmax(x):
         exp_x = np.exp(x - np.max(x, axis=1, keepdims=True))
         return exp_x / exp_x.sum(axis=1, keepdims=True)
[9]: # Initialize weights and biases
     input_size = 784
     hidden_size = 128
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output_size = 10
      W1 = np.random.randn(input_size, hidden_size)
      b1 = np.zeros((1, hidden_size))
      W2 = np.random.randn(hidden_size, output_size)
      b2 = np.zeros((1, output_size))
[10]: # Hyperparameters
      learning_rate = 1
      epochs = 1000
      loss threshold = 0.5
[11]: # Training loop
      for epoch in range(epochs):
          # Forward pass
          z1 = X_{train.dot(W1)} + b1
          a1 = sigmoid(z1)
          z2 = a1.dot(W2) + b2
          a2 = softmax(z2)
          # Loss
          loss = -np.sum(np.log(a2[np.arange(len(X train)), y train])) / len(X train)
          # Backpropagation
          d2 = a2
          d2[np.arange(len(X_train)), y_train] -= 1
          d1 = (d2.dot(W2.T)) * (a1 * (1 - a1))
          W2 -= learning_rate * a1.T.dot(d2) / len(X_train)
          b2 -= learning_rate * np.sum(d2, axis=0, keepdims=True) / len(X_train)
          W1 -= learning_rate * X_train.T.dot(d1) / len(X_train)
          b1 -= learning_rate * np.sum(d1, axis=0, keepdims=True) / len(X_train)
          print(f'Epoch {epoch + 1}/{epochs}, Loss: {loss}')
          if loss <= loss threshold:</pre>
              break
     Epoch 1/1000, Loss: 11.450051587077485
     Epoch 2/1000, Loss: 8.578540171694577
     Epoch 3/1000, Loss: 6.273806161975045
     Epoch 4/1000, Loss: 5.2555476502361795
     Epoch 5/1000, Loss: 4.183392011380041
     Epoch 6/1000, Loss: 3.6810628245993784
     Epoch 7/1000, Loss: 3.3607578872242825
     Epoch 8/1000, Loss: 3.108751060503716
     Epoch 9/1000, Loss: 2.887312422153707
     Epoch 10/1000, Loss: 2.713919044607191
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Epoch 11/1000, Loss: 2.5508879454522115
Epoch 12/1000, Loss: 2.422895833467487
Epoch 13/1000, Loss: 2.299152444204859
Epoch 14/1000, Loss: 2.1995027041230473
Epoch 15/1000, Loss: 2.103561662130783
Epoch 16/1000, Loss: 2.0235212553717394
Epoch 17/1000, Loss: 1.9475638856981672
Epoch 18/1000, Loss: 1.8819391009881454
Epoch 19/1000, Loss: 1.8204432600105247
Epoch 20/1000, Loss: 1.7657228887315022
Epoch 21/1000, Loss: 1.7147868516938307
Epoch 22/1000, Loss: 1.6684670894649503
Epoch 23/1000, Loss: 1.62540293068508
Epoch 24/1000, Loss: 1.5856694654658519
Epoch 25/1000, Loss: 1.5486392986445494
Epoch 26/1000, Loss: 1.5141489542680986
Epoch 27/1000, Loss: 1.4818701677377237
Epoch 28/1000, Loss: 1.4516080842630228
Epoch 29/1000, Loss: 1.4231555378153102
Epoch 30/1000, Loss: 1.396346485196879
Epoch 31/1000, Loss: 1.371031138925402
Epoch 32/1000, Loss: 1.3470786112709543
Epoch 33/1000, Loss: 1.3243737161941362
Epoch 34/1000, Loss: 1.3028138923986583
Epoch 35/1000, Loss: 1.2823082246355275
Epoch 36/1000, Loss: 1.2627752615150338
Epoch 37/1000, Loss: 1.2441421053357036
Epoch 38/1000, Loss: 1.2263431073531992
Epoch 39/1000, Loss: 1.2093190844943484
Epoch 40/1000, Loss: 1.1930164758870179
Epoch 41/1000, Loss: 1.177386724491567
Epoch 42/1000, Loss: 1.1623856842238856
Epoch 43/1000, Loss: 1.1479731382493876
Epoch 44/1000, Loss: 1.1341123590279054
Epoch 45/1000, Loss: 1.120769731835171
Epoch 46/1000, Loss: 1.1079144188504753
Epoch 47/1000, Loss: 1.0955180662961383
Epoch 48/1000, Loss: 1.0835545467284073
Epoch 49/1000, Loss: 1.0719997339841159
Epoch 50/1000, Loss: 1.060831306377085
Epoch 51/1000, Loss: 1.0500285746180837
Epoch 52/1000, Loss: 1.039572330828598
Epoch 53/1000, Loss: 1.0294447155045
Epoch 54/1000, Loss: 1.0196290996412267
Epoch 55/1000, Loss: 1.010109979771795
Epoch 56/1000, Loss: 1.0008728840408603
Epoch 57/1000, Loss: 0.9919042878322496
Epoch 58/1000, Loss: 0.9831915377072035
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Epoch 59/1000, Loss: 0.9747227826353921
Epoch 60/1000, Loss: 0.9664869116446796
Epoch 61/1000, Loss: 0.9584734971512596
Epoch 62/1000, Loss: 0.950672743334427
Epoch 63/1000, Loss: 0.9430754390157171
Epoch 64/1000, Loss: 0.9356729145796003
Epoch 65/1000, Loss: 0.9284570025398359
Epoch 66/1000, Loss: 0.9214200014088183
Epoch 67/1000, Loss: 0.9145546425703001
Epoch 68/1000, Loss: 0.9078540598895227
Epoch 69/1000, Loss: 0.9013117618217031
Epoch 70/1000, Loss: 0.8949216058016186
Epoch 71/1000, Loss: 0.8886777747154506
Epoch 72/1000, Loss: 0.8825747552721699
Epoch 73/1000, Loss: 0.8766073181064218
Epoch 74/1000, Loss: 0.8707704994585282
Epoch 75/1000, Loss: 0.8650595842901375
Epoch 76/1000, Loss: 0.8594700907062843
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Epoch 78/1000, Loss: 0.8486385211760552
Epoch 79/1000, Loss: 0.8433885229669904
Epoch 80/1000, Loss: 0.838244078071005
Epoch 81/1000, Loss: 0.8332016747159668
Epoch 82/1000, Loss: 0.8282579623686593
Epoch 83/1000, Loss: 0.8234097425618556
Epoch 84/1000, Loss: 0.8186539603477271
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Epoch 101/1000, Loss: 0.7495459035093556
Epoch 102/1000, Loss: 0.7460563309787195
Epoch 103/1000, Loss: 0.7426202908392571
Epoch 104/1000, Loss: 0.7392364361076701
Epoch 105/1000, Loss: 0.7359034678861682
Epoch 106/1000, Loss: 0.7326201331162419
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Epoch 107/1000, Loss: 0.7293852224506491
Epoch 108/1000, Loss: 0.7261975682370021
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Epoch 243/1000, Loss: 0.5034565393434672
Epoch 244/1000, Loss: 0.5025557426836288
Epoch 245/1000, Loss: 0.5016604508050282
Epoch 246/1000, Loss: 0.5007706055968837
Epoch 247/1000, Loss: 0.4998861498072317
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[12]: z1 = X_test.dot(W1) + b1
    a1 = sigmoid(z1)
    z2 = a1.dot(W2) + b2
    a2 = softmax(z2)

[13]: predicted_labels = np.argmax(a2, axis=1)

[14]: predicted_labels

[14]: array([7, 2, 1, ..., 4, 5, 6], dtype=int64)

[15]: accuracy_score(y_test, predicted_labels)

[15]: 0.8649
```