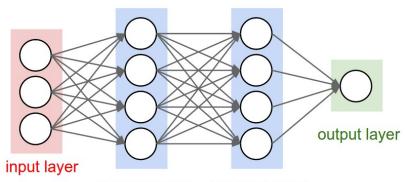
Neural Network

Xây dựng neural network với hai tầng ẩn (hidden layer). Các trọng số và mối liên hệ giữa các tầng ẩn được thiết lập và cài đặt bằng tay.

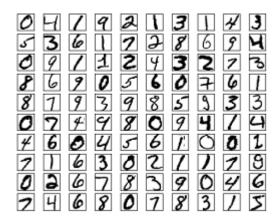
Neural Network Overview



hidden layer 1 hidden layer 2

MNIST Dataset Overview

MNIST là bộ dữ liệu chứa các ảnh là các ký tự viết tay, chia thành 2 phần, 60000 ảnh dùng để huấn luyện và 10000 ảnh dùng để kiểm thử. Kích thước các ảnh là 28x28, giá trị các pixel thuộc [0,255]



More info: http://yann.lecun.com/exdb/mnist/ (http://yann.lecun.com/exdb/mnist/)

```
In [1]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

```
In [2]: # MNIST dataset parameters.
    num_classes = 10 # total classes (0-9 digits).
    num_features = 784 # data features (img shape: 28*28).

# Network parameters.
    n_hidden_1 = 128 # 1st layer number of neurons.
# n_hidden_2 = 256 # 2nd layer number of neurons.
```

```
In [3]: # Chuẩn bị dữ liệu
from tensorflow.keras.datasets import mnist
    (x_train, y_train), (x_test, y_test) = mnist.load_data()
# Chuyển đổi sang định dạng float32.
    x_train, x_test = np.array(x_train, np.float32), np.array(x_test, np.float3
    x_train, x_test = x_train.reshape([-1, num_features]).T, x_test.reshape([-1
# Chuẩn hóa ảnh từ from [0, 255] to [0, 1].
    x_train, x_test = x_train / 255., x_test / 255.
```

```
In [4]: m = x_train.shape[0]
```

```
In [9]: def init params():
            W1 = np.random.rand(n hidden 1, 784) - 0.5
            b1 = np.random.rand(n hidden 1, 1) - 0.5
            W2 = np.random.rand(num_classes, n_hidden_1) - 0.5
            b2 = np.random.rand(num classes, 1) - 0.5
            return W1, b1, W2, b2
        def ReLU(Z):
            return np.maximum(Z, 0)
        def softmax(Z):
            A = np.exp(Z) / sum(np.exp(Z))
            return A
        def cross_entropy(predictions, targets, epsilon=1e-12):
            tính giá trị cross entropy giữa targets và predictions.
            Input: predictions (N, k)
                   targets (N, k)
            Returns: scalar
            predictions = np.clip(predictions, epsilon, 1. - epsilon)
            N = predictions.shape[0]
            ce = -np.sum(targets*np.log(predictions+1e-9))/N
            return ce
        def forward prop(W1, b1, W2, b2, X):
            Z1 = W1.dot(X) + b1
            A1 = ReLU(Z1)
            Z2 = W2.dot(A1) + b2
            A2 = softmax(Z2)
            return Z1, A1, Z2, A2
        def ReLU deriv(Z):
            return Z > 0
        def one hot(Y):
            one hot Y = np.zeros((Y.size, Y.max() + 1))
            one hot Y[np.arange(Y.size), Y] = 1
            one hot Y =  one hot Y \cdot T
            return one_hot_Y
        def backward prop(Z1, A1, Z2, A2, W1, W2, X, Y):
            one hot Y = one hot(Y)
            dZ2 = A2 - one hot Y
            dW2 = 1 / m * dZ2.dot(A1.T)
            db2 = 1 / m * np.sum(dZ2)
            dZ1 = W2.T.dot(dZ2) * ReLU deriv(Z1)
            dW1 = 1 / m * dZ1.dot(X.T)
            db1 = 1 / m * np.sum(dZ1)
            return dW1, db1, dW2, db2
        def update params(W1, b1, W2, b2, dW1, db1, dW2, db2, alpha):
            W1 = W1 - alpha * dW1
            b1 = b1 - alpha * db1
            W2 = W2 - alpha * dW2
```

```
b2 = b2 - alpha * db2
return W1, b1, W2, b2
```

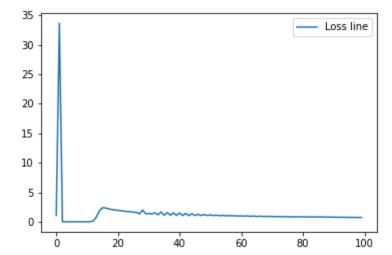
```
In [10]: losses = []
        def get predictions(A2):
            return np.argmax(A2, 0)
        def get_accuracy(predictions, Y):
            # print(predictions, Y)
            return np.sum(predictions == Y) / Y.size
        def gradient_descent(X, Y, alpha, iterations):
            W1, b1, W2, b2 = init params()
            for i in range(iterations):
                Z1, A1, Z2, A2 = forward_prop(W1, b1, W2, b2, X)
                dW1, db1, dW2, db2 = backward prop(Z1, A1, Z2, A2, W1, W2, X, Y)
                predictions = get predictions(A2)
                losses.append(cross entropy(predictions, Y))
                if i % 10 == 9:
                   # print("Iteration: ", i+1)
                   # predictions = get predictions(A2)
                   # print('Accuracy: %.3f' %(get accuracy(predictions, Y)))
                   print('Iteration: %d, accuracy: %.3f' %(i + 1, get_accuracy(pre
            return W1, b1, W2, b2
In [11]: alpha = 0.01
        W1, b1, W2, b2 = gradient descent(x train, y train, alpha, 100)
```

```
Iteration: 10, accuracy: 0.533
Iteration: 20, accuracy: 0.713
Iteration: 30, accuracy: 0.785
Iteration: 40, accuracy: 0.824
```

Iteration: 50, accuracy: 0.824 Iteration: 60, accuracy: 0.855 Iteration: 70, accuracy: 0.874

Iteration: 80, accuracy: 0.884 Iteration: 90, accuracy: 0.889 Iteration: 100, accuracy: 0.894

```
In [ ]: # Biểu đồ biểu diễn độ biến thiên của hàm mất mát qua các vòng lặp
plt.plot([i for i in range(len(losses))], losses, label='Loss line')
# plt.plot(X, np.array(W * X + b), label='Fitted line')
plt.legend()
plt.show()
```



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