人工智慧模型設計與應用 Lab1

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1. **Cross-Validation:**

   Use 20% of training set as validation set. (Original shape: 60000, 784)

   ➔ Training set: (48000, 784), Validation set: (12000, 784)

```
# Separate train_imgs, train_labels into training and validation

validation_split = 0.2
validation_imgs = train_imgs[int(train_imgs.shape[0] * (1 - validation_spl
validation_labels_one_hot = train_labels_one_hot[int(train_labels_one_hot.
train_imgs = train_imgs[:int(train_imgs.shape[0] * (1 - validation_split))
train_labels_one_hot = train_labels_one_hot[:int(train_labels_one_hot.shap

print(train_imgs.shape)
print(train_labels_one_hot.shape)
print(validation_imgs.shape)
print(validation_labels_one_hot.shape)
```

✓ 0.0s

```
(48000, 784)
(48000, 10)
(12000, 784)
(12000, 10)
```

2. **Hyper Parameters:**

   - Learning Rate: 0.001
   - Epochs (Iteration): 100

3. **Hidden and Output Layer Definition:**

   Use one hidden layer with 64 neurons and one output layer with 10 neurons for the 10 classes (0 through 9).

4. **Forward Propagation and Backward Propagation:**

   - Inner-Product:

```
def InnerProduct_ForProp(x,W,b):    # Forward Propagation
    y = np.dot(x,W) + b
    return y

def InnerProduct_BackProp(dEdy, x, W, b):   # Backward Propagation
    dEdx = np.dot(dEdy, W.T)
    dEdW = np.dot(x.T, dEdy)
    dEdb = np.sum(dEdy, axis=0)
    return dEdx, dEdW, dEdb
```

- Sigmoid (In this lab, I use Sigmoid as my activation function):

```python
def Sigmoid_ForProp(x):  # Forward Propagation: 1/(1+exp(-x))
    y = 1 / (1 + np.exp(-x))
    return y

def Sigmoid_BackProp(dEdy,x):   # Backward Propagation: y * (1 - y)
    # Compute the gradient of sigmoid function with respect to the input x
    y = Sigmoid_ForProp(x)
    dydx = y * (1 - y)
    # Compute the gradient of sigmoid loss function with respect to the input x
    dEdx = dEdy * dydx
    return dEdx
```

- ReLU:

```python
def Rectified_ForProp(x):   # Forward Propagation: max(0,x)
    y = np.maximum(0, x)
    return y

def Rectified_BackProp(dEdy,x):   # Backward Propagation
    # Compute the gradient of rectified linear unit function with respect to the input x
    dEdx = dEdy * (x > 0)
    return dEdx
```

- Softmax:

```python
def Softmax_ForProp(x):  # Forward Propagation
    # Compute the unnormalized probabilities
    exp_x = np.exp(x - np.max(x, axis=1, keepdims=True))
    # Normalize them for each example
    y = exp_x / exp_x.sum(axis=1, keepdims=True)
    return y

def Softmax_BackProp(y,t):  # Backward Propagation
    # y is the output of softmax function (class probabilities)
    # t is the one-hot representation of the label

    # Compute the gradient of softmax loss function with respect to the input x
    dEdx = y - t
    return dEdx
```

5. Loss Function (Cross Entropy):

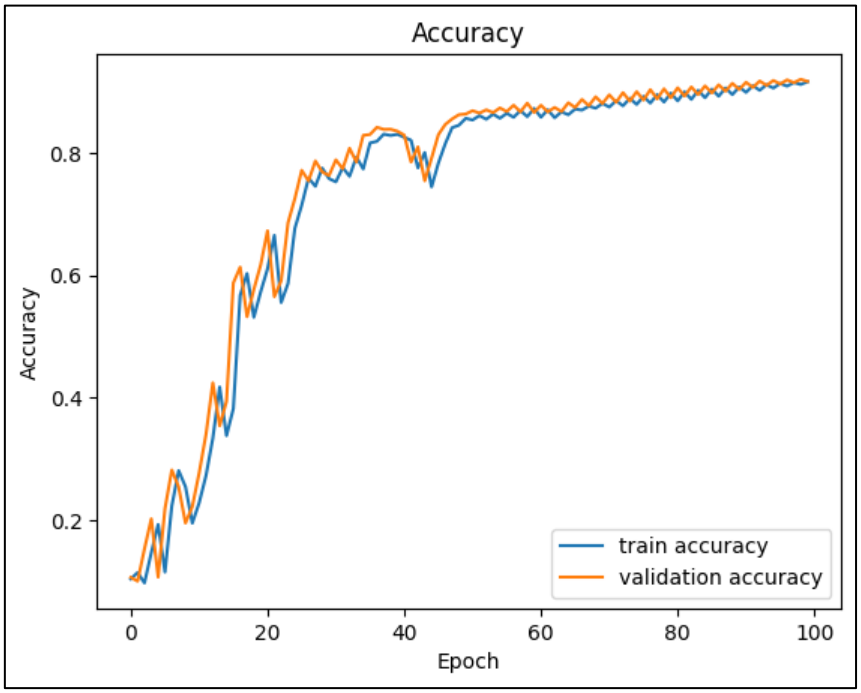
```python
def CrossEntropy(y,t):  # Cross Entropy Loss Function
    # y is the output of softmax function (class probabilities)
    # t is the one-hot representation of the label

    # Compute the cross entropy loss function
    loss = -np.sum(t * np.log(y + 1e-8)) / y.shape[0]
    return loss
```

6. **Accuracy and Loss for Training, Validation, and Testing set:**

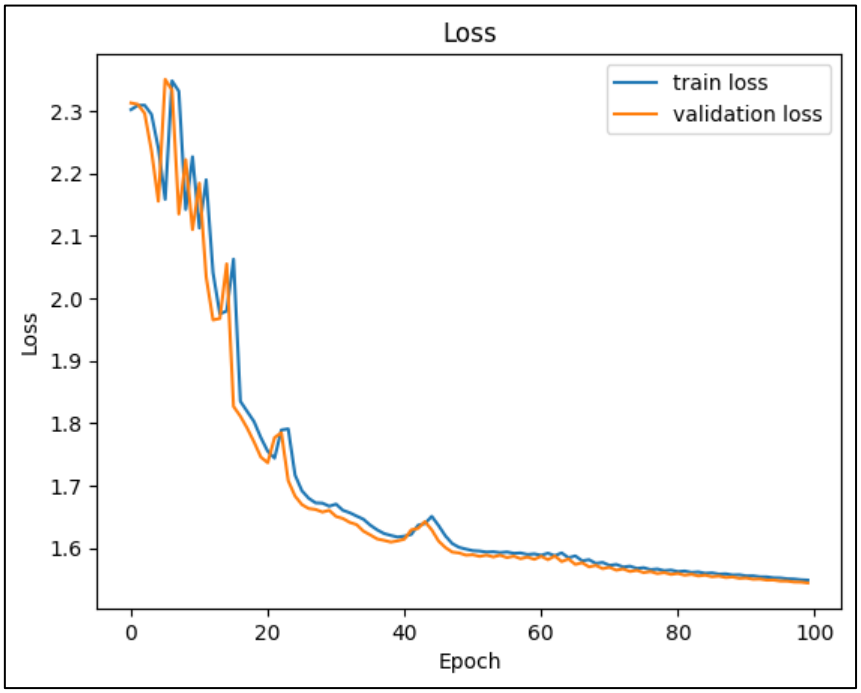
- Accuracy for testing (0.91):

```
Final Train Accuracy: 0.908271
Final Train Loss: 1.554976
Final Validation Accuracy: 0.912833
Final Validation Loss: 1.551294
Final Test Accuracy: 0.911400
Final Test Loss: 1.553157
```

- Accuracy for training and validation per epoch:



- Loss for training and validation per epoch:



7. **Problem Encounter (ReLU VS Sigmoid):**

   Most of the time, ReLU performs better than Sigmoid. However, in this lab, I observed that when using ReLU as the activation function, the accuracy consistently hovered around 0.11. It seems that the dataset is not complex enough for ReLU to effectively learn or extract meaningful features.

   Finally, I decided to use Sigmoid as the activation function for this classification task.

   Reference: 為什麼深度學習模型準確率不會提昇？