Redes neuronales con 1 capa oculta

Objetivo

- Clasificar digitos escritos a mano

Tabla de contenido

Preparación

In [6]:
```
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
```

In [7]:
```
# Import the libraries we need for this lab

# Using the following line code to install the torchvision library
# !conda install -y torchvision

import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets
import torch.nn.functional as F
import matplotlib.pylab as plt
import numpy as np
```

Para graficar la pérdida:

In [8]:
```
# Define a function to plot accuracy and loss

def plot_accuracy_loss(training_results):
    plt.subplot(2, 1, 1)
    plt.plot(training_results['training_loss'], 'r')
    plt.ylabel('loss')
    plt.title('training loss iterations')
    plt.subplot(2, 1, 2)
    plt.plot(training_results['validation_accuracy'])
    plt.ylabel('accuracy')
    plt.xlabel('epochs')
    plt.show()
```

Para imprimir los parámetros del modelo:

In [9]:
```
# Define a function to plot model parameters

def print_model_parameters(model):
    count = 0
    for ele in model.state_dict():
        count += 1
        if count % 2 != 0:
            print ("The following are the parameters for the layer ", count // 2 + 1)
        if ele.find("bias") != -1:
            print("The size of bias: ", model.state_dict()[ele].size())
        else:
            print("The size of weights: ", model.state_dict()[ele].size())
```

Para desplegar los datos:

In [10]:
```
# Define a function to display data

def show_data(data_sample):
    plt.imshow(data_sample.numpy().reshape(28, 28), cmap='gray')
    plt.show()
```

Módulo Neural Network y función de entrenamiento

Definimos la clase red neuronal:

In [11]:
```
# Define a Neural Network class

class Net(nn.Module):

    # Constructor
    def __init__(self, D_in, H, D_out):
        super(Net, self).__init__()
        self.linear1 = nn.Linear(D_in, H)
        self.linear2 = nn.Linear(H, D_out)

    # Prediction
    def forward(self, x):
        x = torch.sigmoid(self.linear1(x))
        x = self.linear2(x)
        return x
```

Definimos una función para entrenar el modelo. En este caso retorna un diccionario para almacenar la pérdida de entrenamiento y la precisión sobre los datos de validación.

In [12]:
```
# Define a training function to train the model

def train(model, criterion, train_loader, validation_loader, optimizer, epochs=100):
    i = 0
    useful_stuff = {'training_loss': [],'validation_accuracy': []}
    for epoch in range(epochs):
        for i, (x, y) in enumerate(train_loader):
            optimizer.zero_grad()
            z = model(x.view(-1, 28 * 28))
            loss = criterion(z, y)
            loss.backward()
            optimizer.step()
             #loss for every iteration
            useful_stuff['training_loss'].append(loss.data.item())
        correct = 0
        for x, y in validation_loader:
            #validation
            z = model(x.view(-1, 28 * 28))
            _, label = torch.max(z, 1)
            correct += (label == y).sum().item()
        accuracy = 100 * (correct / len(validation_dataset))
        useful_stuff['validation_accuracy'].append(accuracy)
    return useful_stuff
```

Crear algunos datos

Cargamos el dataset de entrenamiento estableciendo el parámetro train en True y convirtiéndolo a tensor mediante toTensor().

In [5]:
```
# Create training dataset

train_dataset = dsets.MNIST(root='/data/', train=True, download=True, transform=trans
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to /data/MNIST
\raw\train-images-idx3-ubyte.gz

Extracting /data/MNIST\raw\train-images-idx3-ubyte.gz to /data/MNIST\raw
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to /data/MNIST
\raw\train-labels-idx1-ubyte.gz

Extracting /data/MNIST\raw\train-labels-idx1-ubyte.gz to /data/MNIST\raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to /data/MNIST
\raw\t10k-images-idx3-ubyte.gz

Extracting /data/MNIST\raw\t10k-images-idx3-ubyte.gz to /data/MNIST\raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to /data/MNIST
\raw\t10k-labels-idx1-ubyte.gz

Extracting /data/MNIST\raw\t10k-labels-idx1-ubyte.gz to /data/MNIST\raw
Processing...
Done!
C:\Users\marco\Anaconda3\lib\site-packages\torchvision\datasets\mnist.py:479: UserWarn
ing: The given NumPy array is not writeable, and PyTorch does not support non-writeabl
e tensors. This means you can write to the underlying (supposedly non-writeable) NumPy
array using the tensor. You may want to copy the array to protect its data or make it
writeable before converting it to a tensor. This type of warning will be suppressed fo
r the rest of this program. (Triggered internally at  ..\torch\csrc\utils\tensor_nump
y.cpp:143.)
  return torch.from_numpy(parsed.astype(m[2], copy=False)).view(*s)
```

Cargamos el dataset de testing, aquí establecemos train en False:

In [13]:
```
# Create validating dataset

validation_dataset = dsets.MNIST(root='/data/', train=False, download=True, transform=
```

Creamos la función de criterio:

In [14]:
```
# Create criterion function

criterion = nn.CrossEntropyLoss()
```

Creamos los objetos cargadores de datos:

In [15]:
```
# Create data loader for both train dataset and valdiate dataset

train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=2000, shu
validation_loader = torch.utils.data.DataLoader(dataset=validation_dataset, batch_size
```

Definimos la red neuronal, optimizador y entrenamos el modelo

Creamos el modelo con 100 neuronas:

In [16]:
```
# Create the model with 100 neurons

input_dim = 28 * 28
hidden_dim = 100
output_dim = 10

model = Net(input_dim, hidden_dim, output_dim)
```

Imprimimos los parámetros:

In [17]:
```
# Print the parameters for model

print_model_parameters(model)
```

```
The following are the parameters for the layer  1
The size of weights:  torch.Size([100, 784])
The size of bias:  torch.Size([100])
The following are the parameters for the layer  2
The size of weights:  torch.Size([10, 100])
The size of bias:  torch.Size([10])
```

Definimos el optimizador y la tasa de aprendizaje:

In [18]:
```
# Set the learning rate and the optimizer

learning_rate = 0.01
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

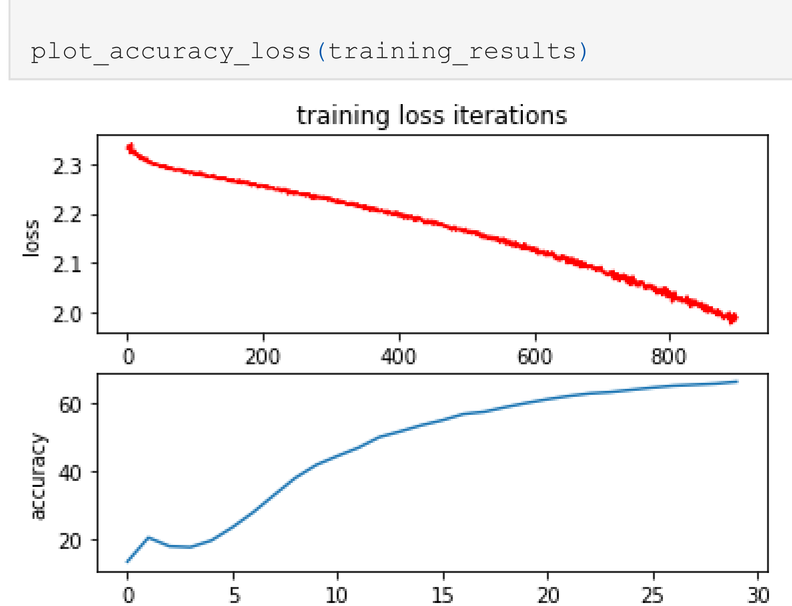
Entrenamos el modelo con 100 epochs:

In [19]:
```
# Train the model

training_results = train(model, criterion, train_loader, validation_loader, optimizer,
```

Analizar los resultados

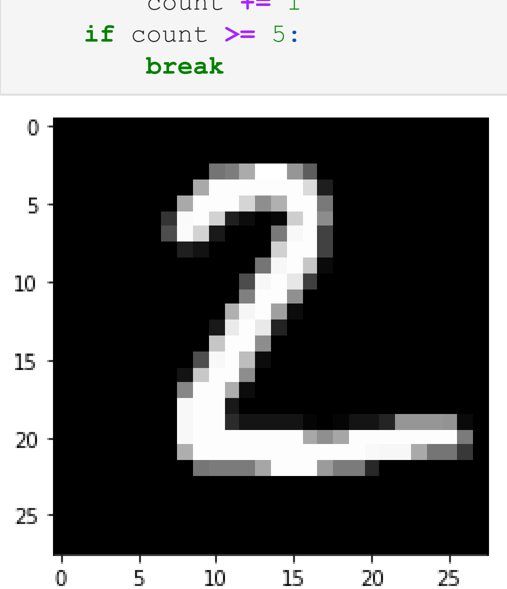
Graficamos la pérdida total de entrenamiento o costo para cada iteración y la precisión de entrenamiento para cada epoch:

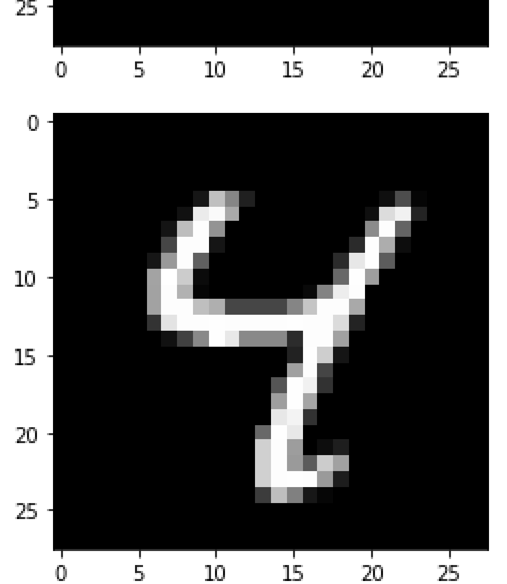
In [20]:
```
# Plot the accuracy and loss

plot_accuracy_loss(training_results)
```

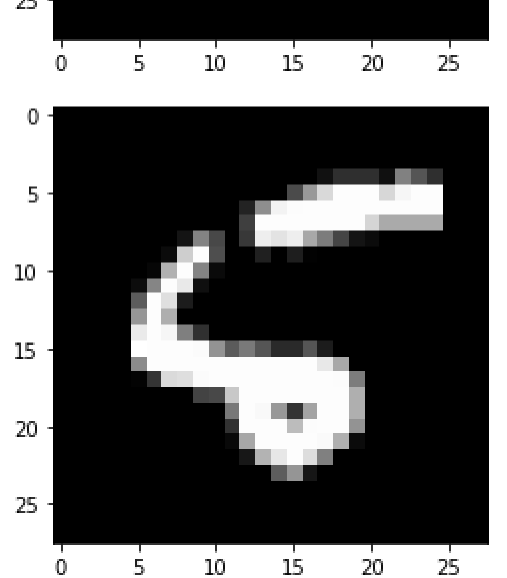


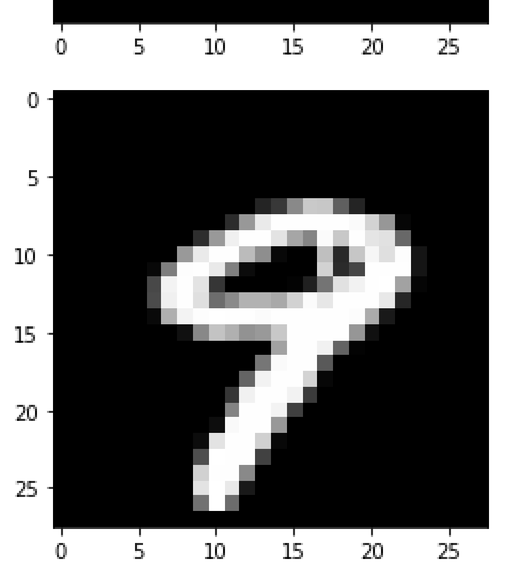
Graficamos las primeras 5 muestras mal clasificadas:

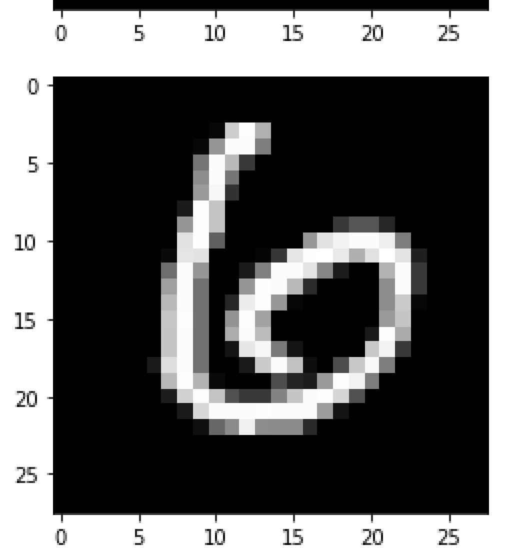
In [21]:
```
# Plot the first five misclassified samples

count = 0
for x, y in validation_dataset:
    z = model(x.reshape(-1, 28 * 28))
    _,yhat = torch.max(z, 1)
    if yhat != y:
        show_data(x)
        count += 1
    if count >= 5:
        break
```











Práctica

Use `nn.Sequential` para construir exactamente el mismo modelo anterior. Entrénelo y grafique.

In [22]:
```
# Practice: Use nn.Sequential to build the same model. Use plot_accuracy_loss to prin

input_dim = 28 * 28
hidden_dim = 100
output_dim = 10

model = torch.nn.Sequential(
    torch.nn.Linear(input_dim, hidden_dim),
    torch.nn.Sigmoid(),
    torch.nn.Linear(hidden_dim, output_dim),
)
learning_rate = 0.01
optimizer = torch.optim.SGD(model.parameters(), lr = learning_rate)
training_results = train(model, criterion, train_loader, validation_loader, optimizer,
plot_accuracy_loss(training_results)
```