Testear la Sigmoide, Tanh, y Relu sobre el dataset del MNIST

Objetivo

- Aplicar diferentes funciones de activación sobre el dataset del MNIST

Tabla de contenido

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Preparación

In [2]:
```
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
```

In [3]:
```
# 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 matplotlib.pylab as plt
import numpy as np
```

Módulo red neuronal y función de entrenamiento

Definimos el módulo red neuronal usando la sigmoide como función de activación:

In [5]:
```
# Build the model with sigmoid function

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
```

Ahora usando la tangente hiperbólica:

In [6]:
```
# Build the model with Tanh function

class NetTanh(nn.Module):

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

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

Ahora usando Relu:

In [7]:
```
# Build the model with Relu function

class NetRelu(nn.Module):

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

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

Definimos una función para entrenar el modelo. Retorna un diccionario para almacenar la pérdida de entrenamiento para cada iteración y la precisión sobre los datos de validación.

In [8]:
```
# Define the function for training 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()
            useful_stuff['training_loss'].append(loss.item())

        correct = 0
        for x, y in validation_loader:
            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
```

Creamos algunos datos

Cargamos el dataset de entrenamiento:

In [9]:
```
# Create the training dataset

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

Cargamos el dataset de validación:

In [11]:
```
# Create the validation  dataset

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

Creamos la función de criterio:

In [12]:
```
# Create the criterion function

criterion = nn.CrossEntropyLoss()
```

Creamos los cargadores de entrenamiento y validación:

In [13]:
```
# Create the training data loader and validation data loader object

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, función de criterio, optimizador y entrenamos

Creamos la función de criterio:

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

criterion = nn.CrossEntropyLoss()
```

Creamos el modelo con 100 neuronas ocultas:

In [15]:
```
# Create the model object

input_dim = 28 * 28
hidden_dim = 100
output_dim = 10

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

Testeamos la Sigmoide, Tanh, y Relu

Entrenamos la red usando la sigmoide:

In [16]:
```
# Train a model with sigmoid function

learning_rate = 0.01
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
training_results = train(model, criterion, train_loader, validation_loader, optimizer,
```

Entrenamos eo modelo usando tanh:

In [17]:
```
# Train a model with Tanh function

model_Tanh = NetTanh(input_dim, hidden_dim, output_dim)
optimizer = torch.optim.SGD(model_Tanh.parameters(), lr=learning_rate)
training_results_tanch = train(model_Tanh, criterion, train_loader, validation_loader,
```

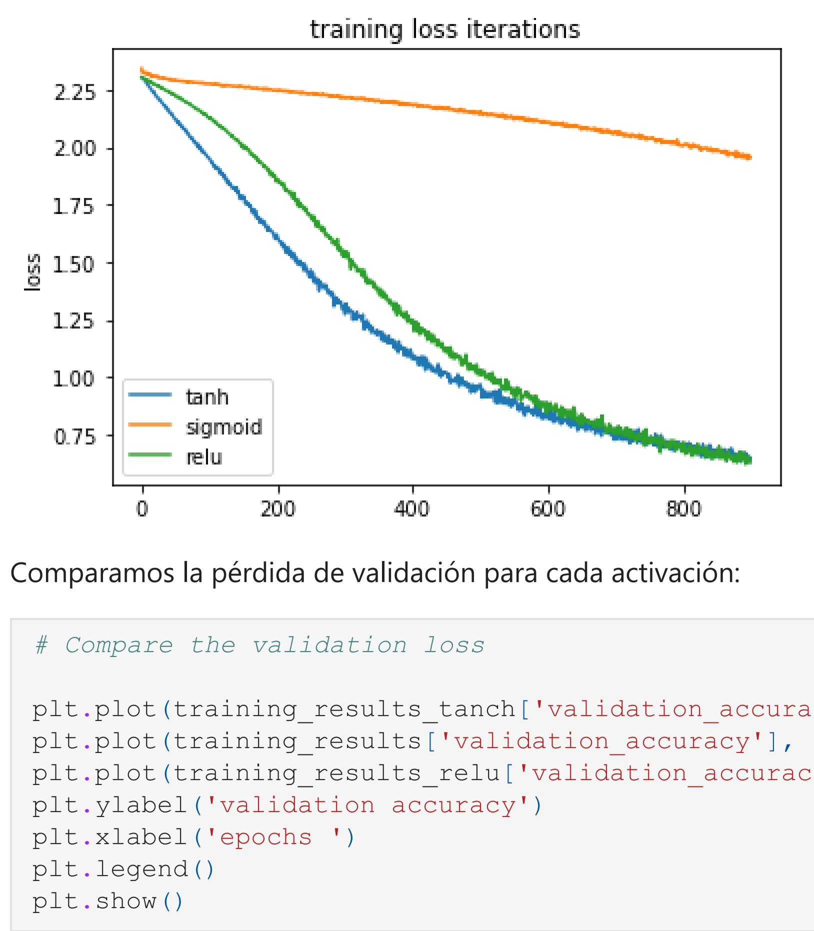
Entrenamos el modelo usando Relu:

In [18]:
```
# Train a model with Relu function

modelRelu = NetRelu(input_dim, hidden_dim, output_dim)
optimizer = torch.optim.SGD(modelRelu.parameters(), lr=learning_rate)
training_results_relu = train(modelRelu,criterion, train_loader, validation_loader, op
```

Analizamos los resultados

Comparamos la pérdida de entrenamiento para cada activación:

In [19]:
```
# Compare the training loss

plt.plot(training_results_tanch['training_loss'], label='tanh')
plt.plot(training_results['training_loss'], label='sigmoid')
plt.plot(training_results_relu['training_loss'], label='relu')
plt.ylabel('loss')
plt.title('training loss iterations')
plt.legend()
plt.show()
```



Comparamos la pérdida de validación para cada activación:

In [20]:
```
# Compare the validation loss

plt.plot(training_results_tanch['validation_accuracy'], label='tanh')
plt.plot(training_results['validation_accuracy'], label='sigmoid')
plt.plot(training_results_relu['validation_accuracy'], label='relu')
plt.ylabel('validation accuracy')
plt.xlabel('epochs ')
plt.legend()
plt.show()
```