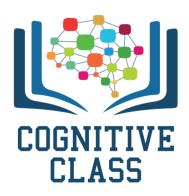


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Test Uniform, Default and Xavier Uniform Initialization on MNIST dataset with tanh activation

Table of Contents

In this lab, you will test PyTroch Default Initialization, Xavier Initialization and Uniform Initialization on the MNIST dataset.

- Neural Network Module and Training Function
- Make Some Data
- Define Several Neural Network, Criterion function, Optimizer
- Test Uniform, Default and Xavier Initialization
- Analyze Results

Estimated Time Needed: 25 min

Preparation

We'll need the following libraries:

```
In [1]:
```

```
# Import the libraries we need to use in 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

torch.manual_seed(0)
```

Out[1]:

<torch._C.Generator at 0x7f56c2b437d0>

Neural Network Module and Training Function

Define the neural network module or class with Xavier Initialization

In [2]:

```
# Define the neural network with Xavier initialization
class Net Xavier(nn.Module):
    # Constructor
    def __init__(self, Layers):
        super(Net Xavier, self). init ()
        self.hidden = nn.ModuleList()
        for input size, output size in zip(Layers, Layers[1:]):
            linear = nn.Linear(input size, output size)
            torch.nn.init.xavier uniform (linear.weight)
            self.hidden.append(linear)
    # Prediction
    def forward(self, x):
        L = len(self.hidden)
        for (1, linear_transform) in zip(range(L), self.hidden):
            if 1 < L - 1:
                x = torch.tanh(linear transform(x))
            else:
                x = linear transform(x)
        return x
```

Define the neural network module with Uniform Initialization:

```
# Define the neural network with Uniform initialization
class Net_Uniform(nn.Module):
    # Constructor
    def __init__(self, Layers):
        super(Net_Uniform, self).__init__()
        self.hidden = nn.ModuleList()
        for input_size, output_size in zip(Layers, Layers[1:]):
            linear = nn.Linear(input size, output size)
            linear.weight.data.uniform_(0, 1)
            self.hidden.append(linear)
    # Prediction
    def forward(self, x):
        L = len(self.hidden)
        for (1, linear_transform) in zip(range(L), self.hidden):
            if 1 < L - 1:
                x = torch.tanh(linear_transform(x))
                x = linear_transform(x)
        return x
```

Define the neural network module with PyTroch Default Initialization

In [4]:

```
# Define the neural network with Default initialization
class Net(nn.Module):
    # Constructor
    def init (self, Layers):
        super(Net, self).__init__()
        self.hidden = nn.ModuleList()
        for input_size, output_size in zip(Layers, Layers[1:]):
            linear = nn.Linear(input size, output size)
            self.hidden.append(linear)
    # Prediction
    def forward(self, x):
        L = len(self.hidden)
        for (1, linear transform) in zip(range(L), self.hidden):
            if 1 < L - 1:
                x = torch.tanh(linear transform(x))
            else:
                x = linear transform(x)
        return x
```

Define a function to train the model, in this case the function returns a Python dictionary to store the training loss and accuracy on the validation data

In [5]:

```
# function to Train the model
def train(model, criterion, train loader, validation loader, optimizer, epochs = 10
0):
    i = 0
    loss_accuracy = {'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_accuracy['training_loss'].append(loss.data.item())
        correct = 0
        for x, y in validation loader:
            yhat = model(x.view(-1, 28 * 28))
            _, label = torch.max(yhat, 1)
            correct += (label==y).sum().item()
        accuracy = 100 * (correct / len(validation dataset))
        loss accuracy['validation accuracy'].append(accuracy)
    return loss accuracy
```

Make Some Data

Load the training dataset by setting the parameters train to True and convert it to a tensor by placing a transform object int the argument transform

In [6]:

```
# Create the train dataset
train_dataset = dsets.MNIST(root='./data', train=True, download=True, transform=tra
nsforms.ToTensor())
```

Load the testing dataset by setting the parameters train to False and convert it to a tensor by placing a transform object int the argument transform

```
In [7]:
```

```
# Create the validation dataset
validation_dataset = dsets.MNIST(root='./data', train=False, download=True, transfo
rm=transforms.ToTensor())
```

Create the training-data loader and the validation-data loader object

In [8]:

```
# Create Dataloader for both train dataset and validation dataset
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=2000,
shuffle=True)
validation_loader = torch.utils.data.DataLoader(dataset=validation_dataset, batch_s
ize=5000, shuffle=False)
```

Define Neural Network, Criterion function, Optimizer and Train the Model

Create the criterion function

```
In [9]:
```

```
# Define criterion function
criterion = nn.CrossEntropyLoss()
```

Create the model with 100 hidden layers

In [10]:

```
# Set the parameters
input_dim = 28 * 28
output_dim = 10
layers = [input_dim, 100, 10, 100, 10, 100, output_dim]
epochs = 15
```

Test PyTorch Default Initialization, Xavier Initialization, Uniform Initialization

Train the network using PyTorch Default Initialization

```
In [ ]:
```

```
# Train the model with default initialization

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

Train the network using Xavier Initialization function

```
In [ ]:
```

```
# Train the model with Xavier initialization

model_Xavier = Net_Xavier(layers)
optimizer = torch.optim.SGD(model_Xavier.parameters(), lr=learning_rate)
training_results_Xavier = train(model_Xavier, criterion, train_loader, validation_l
oader, optimizer, epochs=epochs)
```

Train the network using Uniform Initialization

```
In [ ]:
```

```
# Train the model with Uniform initialization

model_Uniform = Net_Uniform(layers)
optimizer = torch.optim.SGD(model_Uniform.parameters(), lr=learning_rate)
training_results_Uniform = train(model_Uniform, criterion, train_loader, validation
_loader, optimizer, epochs=epochs)
```

Analyse Results

Compare the training loss for each initialization

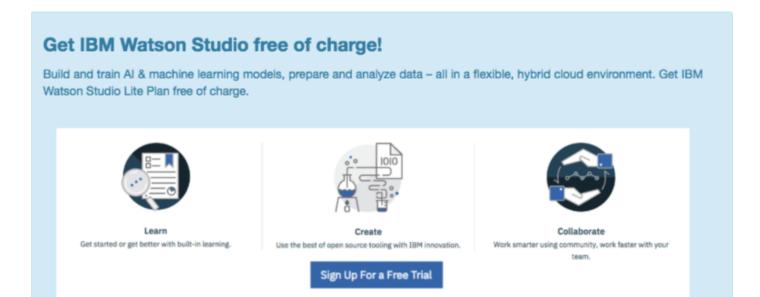
```
In [ ]:
```

```
# Plot the loss

plt.plot(training_results_Xavier['training_loss'], label='Xavier')
plt.plot(training_results['training_loss'], label='Default')
plt.plot(training_results_Uniform['training_loss'], label='Uniform')
plt.ylabel('loss')
plt.xlabel('iteration ')
plt.title('training loss iterations')
plt.legend()
```

```
In [ ]:
```

```
# Plot the accuracy
plt.plot(training_results_Xavier['validation_accuracy'], label='Xavier')
plt.plot(training_results['validation_accuracy'], label='Default')
plt.plot(training_results_Uniform['validation_accuracy'], label='Uniform')
plt.ylabel('validation accuracy')
plt.xlabel('epochs')
plt.legend()
```



(http://cocl.us/pytorch_link_bottom)

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