



The logo for IBM Developer Skills Network features a stylized brain composed of colored nodes (red, green, blue, yellow) connected by lines, set against a background of two blue vertical bars resembling books or brackets. Below the graphic, the text "IBM Developer" and "SKILLS NETWORK" is displayed in a bold, sans-serif font.

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

Objective for this Notebook

1. Define Several Neural Network, Criterion function, Optimizer
2. Test Uniform, Default and Xavier Initialization

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In this lab, you will test PyTorch 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:

```
[ ]: # 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.pyplot as plt
import numpy as np

torch.manual_seed(0)
```

Neural Network Module and Training Function

Define the neural network module or class with Xavier Initialization

```
[ ]: # 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 (l, linear_transform) in zip(range(L), self.hidden):
            if l < 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)

    def forward(self, x):
        L = len(self.hidden)
        for (l, linear_transform) in zip(range(L), self.hidden):
            if l < L - 1:
                x = torch.tanh(linear_transform(x))
            else:
                x = linear_transform(x)
        return x

```

Define the neural network module with PyTorch Default Initialization

```

[ ]: # Define the neural network with Default initialization

class Net(nn.Module):

    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)

    def forward(self, x):
        L = len(self.hidden)
        for (l, linear_transform) in zip(range(L), self.hidden):
            if l < 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

```

[ ]: # function to Train the model

def train(model, criterion, train_loader, validation_loader, optimizer, epochs=100):
    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`

```
[ ]: # Create the train dataset
train_dataset = dsets.MNIST(root='./data', train=True, download=True, transform=transforms.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`

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

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

```
[ ]: # 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_size=5000, shuffle=False)
```

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

Did you know? IBM Watson Studio lets you build and deploy an AI solution, using the best of open source and IBM software and giving your team a single environment to work in. [Learn more here.](#)

Create the criterion function

```
[ ]: # Define criterion function
criterion = nn.CrossEntropyLoss()
```

Create the model with 100 hidden layers

```
[ ]: # 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

```
[ ]: # 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, optimizer, epochs=epochs)
```

Train the network using Xavier Initialization function

```
[ ]: # 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_loader, optimizer, epochs=epochs)
```

Train the network using Uniform Initialization

```
[ ]: # 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)
```

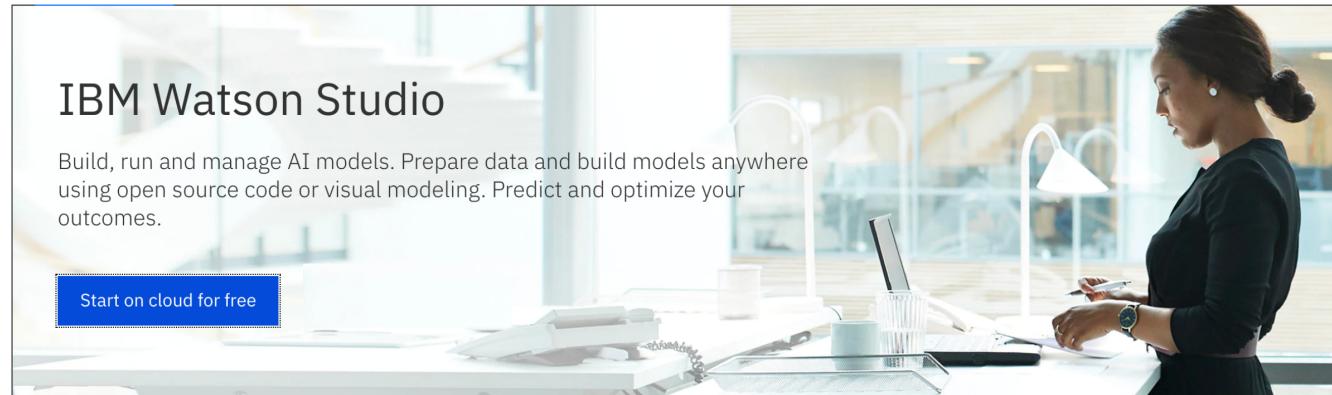
Analyse Results

Compare the training loss for each initialization

```
[ ]: # 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()
```

compare the validation loss for each model

```
[ ]: # 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()
```



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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-09-23	2.0	Srishti	Migrated Lab to Markdown and added to course repo in GitLab

Simple 0 3 Fully initialized Python | Idle Mem: 333.45 / 6144.00 MB

Mode: Command Ln 1, Col 1 English (American) 8.3.2Xaviermist1layer_v2.ipynb