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## Test Uniform, Default and He Initialization on MNIST Dataset with Relu Activation

### Objective for this Notebook

1. Learn how to Define Several Neural Network, Criterion function, Optimizer.
2. Test Uniform, Default and He Initialization

### Table of Contents

In this lab, you will test the Uniform Initialization, Default Initialization and He Initialization on the MNIST dataset with Relu Activation

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

Estimated Time Needed: **25 min**

### Preparation

We'll need the following libraries:

```
[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 torch.nn.functional as F
import matplotlib.pyplot as plt
import numpy as np

torch.manual_seed(0)

[1]: <torch._C.Generator at 0x12566f830>
```

### Neural Network Module and Training Function

Define the neural network module or class with He Initialization

```
[2]: # Define the class for neural network model with He Initialization
class Net_He(nn.Module):
    """
    # Constructor
    def __init__(self, Layers):
        super(Net_He, 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.kaiming_uniform_(linear.weight, nonlinearity='relu')
            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 = F.relu(linear_transform(x))
            else:
                x = linear_transform(x)
        return x
```

Define the class or neural network with Uniform Initialization

```
[3]: # Define the class for neural network model 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 l, linear_transform in zip(range(L), self.hidden):
            if l < L - 1:
                x = F.relu(linear_transform(x))
            else:
                x = linear_transform(x)

    return x

```

Class or Neural Network with PyTorch Default Initialization

```
[4]: # Define the class for neural network model with PyTorch 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)

    def forward(self, x):
        L = len(self.hidden)
        for l, linear_transform in zip(range(L), self.hidden):
            if l < L - 1:
                x = F.relu(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

```
[5]: # Define function to train model

def train(model, criterion, train_loader, validation_loader, optimizer, epochs=100):
    i = 0
    loss_accuracy = {'training_loss': [], 'validation_accuracy': []}

    #n_epochs
    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`

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

```

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

```
[7]: # 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

```
[8]: # Create the data Loader for training and validation
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

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Create the criterion function

```
[9]: # Create the criterion function
criterion = nn.CrossEntropyLoss()

```

Create a list that contains layer size

```
[10]: # Create the parameters
input_dim = 28 * 28
output_dim = 10
layers = [input_dim, 100, 200, 100, output_dim]

```

## Test PyTorch Default Initialization, Xavier Initialization and Uniform Initialization

Train the network using PyTorch Default Initialization

```
[11]: # Train the model with the 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=30)
```

Train the network using He Initialization function

```
[12]: # Train the model with the He initialization  
model_He = Net_He(layers)  
optimizer = torch.optim.SGD(model_He.parameters(), lr=learning_rate)  
training_results_He = train(model_He, criterion, train_loader, validation_loader, optimizer, epochs=30)
```

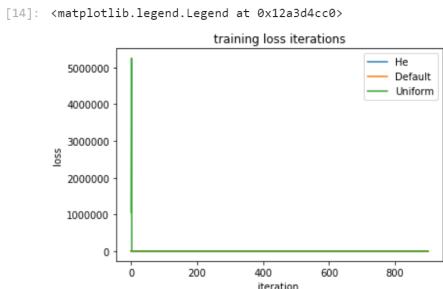
Train the network using Uniform Initialization function

```
[13]: # Train the model with the 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=30)
```

## Analyze Results

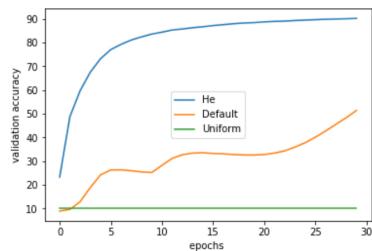
Compare the training loss for each activation

```
[14]: # Plot the loss  
plt.plot(training_results_He['training_loss'], label='He')  
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

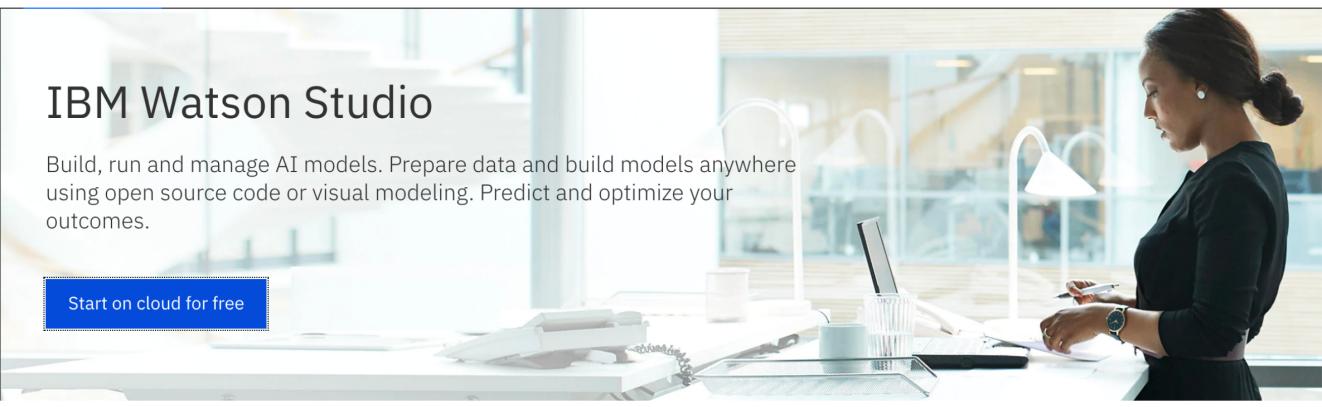
```
[15]: # Plot the accuracy  
plt.plot(training_results_He['validation_accuracy'], label='He')  
plt.plot(training_results['validation_accuracy'], label='Default')  
plt.plot(training_results_Uniform['validation_accuracy'], label='Uniform')  
plt.ylabel('validation accuracy')  
plt.xlabel('epochs')  
plt.legend()  
plt.show()
```



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## About the Authors:

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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

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