IBM Developer
SKILLS NETWORK

Logistic Regression

Objective

- How to create a logistic regression object with the nn.Sequential model.

Table of Contents

In this lab, we will cover logistic regression using PyTorch.

Estimated Time Needed: **15 min**

Preparation

We'll need the following libraries:

In [1]:

```
# Import the libraries we need for this lab

import torch.nn as nn
import torch
import matplotlib.pyplot as plt
```

Set the random seed:

In [2]:

```
# Set the random seed

torch.manual_seed(2)
```

Out[2]:

```
<torch._C.Generator at 0x146bd1542f0>
```

Logistic Function

Create a tensor ranging from -100 to 100:

In [3]:

```
z = torch.arange(-100, 100, 0.1).view(-1, 1)
print("The tensor: ", z)
```

```
The tensor:  tensor([[-100.0000],
        [ -99.9000],
        [ -99.8000],
        ...,
        [  99.7000],
        [  99.8000],
        [  99.9000]])
```

Create a sigmoid object:

In [4]:

```
# Create sigmoid object

sig = nn.Sigmoid()
```

Apply the element-wise function Sigmoid with the object:

In [5]:

```
# Use sigmoid object to calculate the

yhat = sig(z)
```

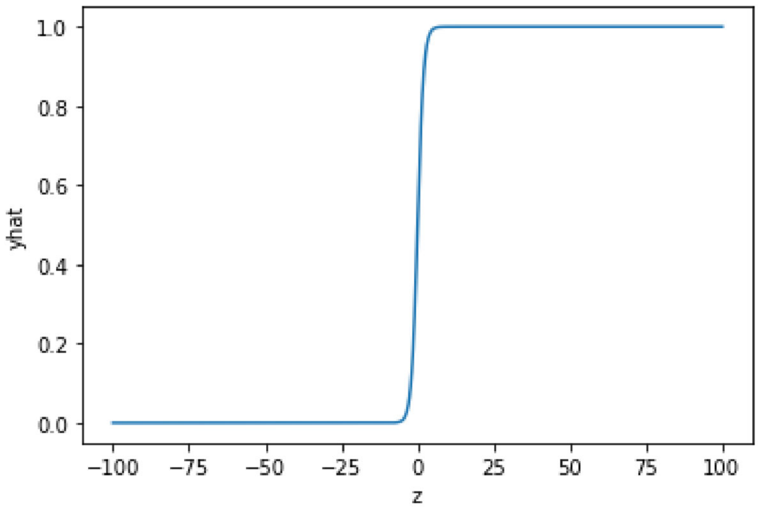
Plot the results:

In [6]:

```
plt.plot(z.numpy(), yhat.numpy())
plt.xlabel('z')
plt.ylabel('yhat')
```

Out[6]:

```
Text(0, 0.5, 'yhat')
```



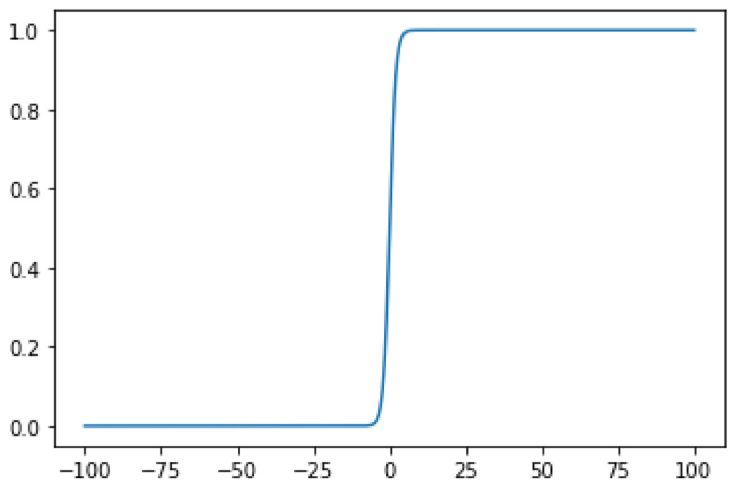
Apply the element-wise Sigmoid from the function module and plot the results:

In [7]:

```
yhat = torch.sigmoid(z)
plt.plot(z.numpy(), yhat.numpy())
```

Out[7]:

```
[<matplotlib.lines.Line2D at 0x146c2593d90>]
```



Build a Logistic Regression with `nn.Sequential`

Create a 1x1 tensor where x represents one data sample with one dimension, and 2x1 tensor X represents two data samples of one dimension:

In [8]:

```
# Create x and X tensor

x = torch.tensor([[1.0]])
X = torch.tensor([[1.0], [100]])
print('x = ', x)
print('X = ', X)
```

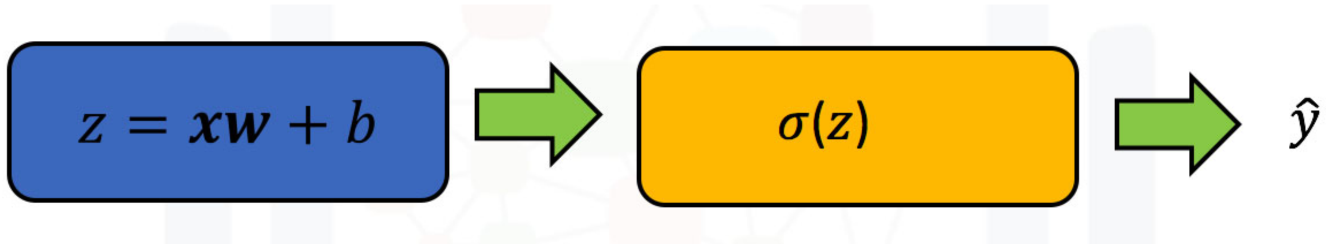
```
x =  tensor([[1.]])
X =  tensor([[  1.],
        [100.]])
```

Create a logistic regression object with the `nn.Sequential` model with a one-dimensional input:

In [9]:

```
# Use sequential function to create model

model = nn.Sequential(nn.Linear(1, 1), nn.Sigmoid())
```

The object is represented in the following diagram:



In this case, the parameters are randomly initialized. You can view them the following ways:

In [10]:

```
# Print the parameters

print("list(model.parameters()):\n ", list(model.parameters()))
print("\nmodel.state_dict():\n ", model.state_dict())
```

```
list(model.parameters()):
  [Parameter containing:
tensor([[0.2294]], requires_grad=True), Parameter containing:
tensor([-0.2380], requires_grad=True)]

model.state_dict():
  OrderedDict([('0.weight', tensor([[0.2294]])), ('0.bias', tensor([-0.2380]))])
```

Make a prediction with one sample:

In [11]:

```
# The prediction for x

yhat = model(x)
print("The prediction: ", yhat)
```

```
The prediction:  tensor([[0.4979]], grad_fn=<SigmoidBackward>)
```

Calling the object with tensor `X` performed the following operation **(code values may not be the same as the diagrams value depending on the version of PyTorch)** :

$$\mathbf{x} = \begin{bmatrix} 1 \\ 100 \end{bmatrix}$$

$$\hat{y} = \sigma(-\mathbf{0.23} + 0.23 \begin{bmatrix} 1 \\ 100 \end{bmatrix})$$

$$\hat{y} = \sigma(\begin{bmatrix} 0 \\ 22 \end{bmatrix})$$

$$\hat{y} = \begin{bmatrix} \sigma(0) \\ \sigma(22) \end{bmatrix}$$

$$\hat{y} = \begin{bmatrix} 0.5 \\ 1 \end{bmatrix}$$

Make a prediction with multiple samples:

In [12]:

```
# The prediction for X

yhat = model(X)
yhat
```

Out[12]:

```
tensor([[0.4979],
        [1.0000]], grad_fn=<SigmoidBackward>)
```

Calling the object performed the following operation:

Create a 1x2 tensor where x represents one data sample with one dimension, and 2x3 tensor X represents one data sample of two dimensions:

In [13]:

```
# Create and print samples

x = torch.tensor([[1.0, 1.0]])
X = torch.tensor([[1.0, 1.0], [1.0, 2.0], [1.0, 3.0]])
print('x = ', x)
print('X = ', X)
```

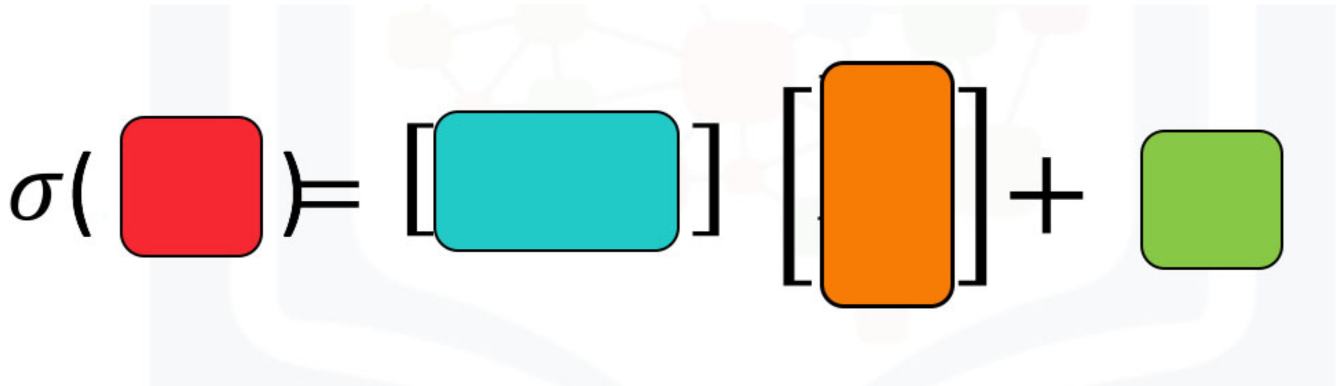
```
x =  tensor([[1., 1.]])
X =  tensor([[1., 1.],
        [1., 2.],
        [1., 3.]])
```

Create a logistic regression object with the `nn.Sequential` model with a two-dimensional input:

In [14]:

```
# Create new model using nn.sequential()

model = nn.Sequential(nn.Linear(2, 1), nn.Sigmoid())
```

The object will apply the Sigmoid function to the output of the linear function as shown in the following diagram:



In this case, the parameters are randomly initialized. You can view them the following ways:

In [15]:

```
# Print the parameters

print("list(model.parameters()):\n ", list(model.parameters()))
print("\nmodel.state_dict():\n ", model.state_dict())
```

```
list(model.parameters()):
  [Parameter containing:
tensor([[ 0.1939, -0.0361]], requires_grad=True), Parameter containing:
tensor([0.3021], requires_grad=True)]

model.state_dict():
  OrderedDict([('0.weight', tensor([[ 0.1939, -0.0361]])), ('0.bias', tensor([0.302
1]))])
```

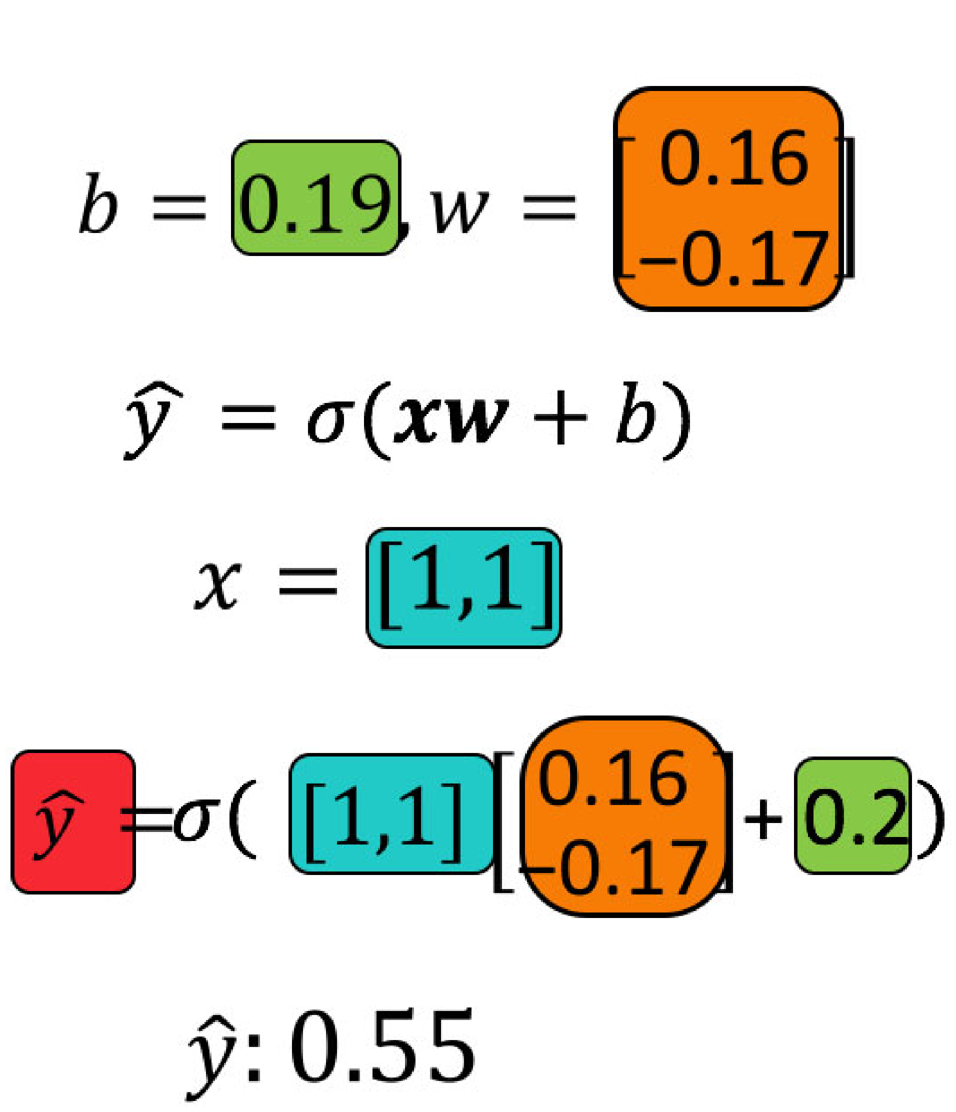
Make a prediction with one sample:

In [16]:

```
# Make the prediction of x

yhat = model(x)
print("The prediction: ", yhat)
```

```
The prediction:  tensor([[0.6130]], grad_fn=<SigmoidBackward>)
```

The operation is represented in the following diagram:



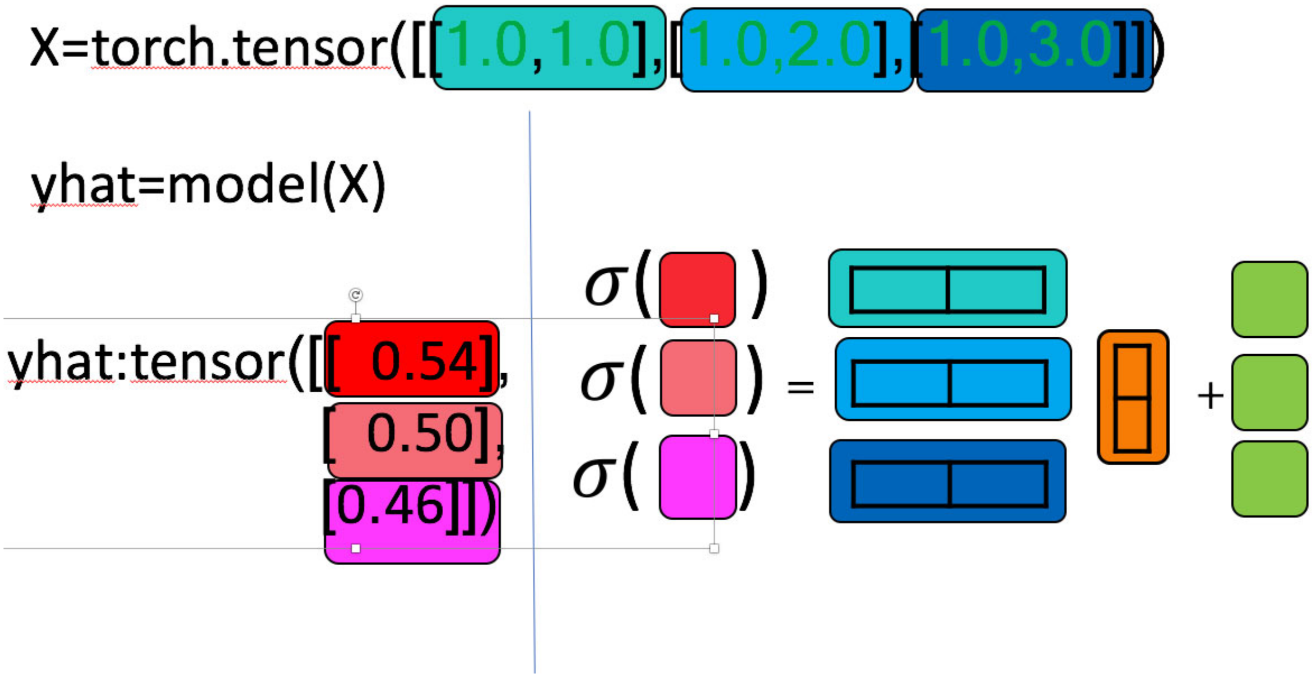
Make a prediction with multiple samples:

In [17]:

```
# The prediction of X

yhat = model(X)
print("The prediction: ", yhat)
```

```
The prediction:  tensor([[0.6130],
        [0.6044],
        [0.5957]], grad_fn=<SigmoidBackward>)
```

The operation is represented in the following diagram:



Build Custom Modules

In this section, you will build a custom Module or class. The model or object function is identical to using `nn.Sequential`.

Create a logistic regression custom module:

In [18]:

```
# Create logistic_regression custom class

class logistic_regression(nn.Module):

    # Constructor
    def __init__(self, n_inputs):
        super(logistic_regression, self).__init__()
        self.linear = nn.Linear(n_inputs, 1)

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

Create a 1x1 tensor where x represents one data sample with one dimension, and 3x1 tensor where X represents one data sample of one dimension:

In [19]:

```
# Create x and X tensor

x = torch.tensor([[1.0]])
X = torch.tensor([[-100], [0], [100.0]])
print('x = ', x)
print('X = ', X)
```

```
x =  tensor([[1.]])
X =  tensor([[-100.],
        [   0.],
        [ 100.]])
```

Create a model to predict one dimension:

In [20]:

```
# Create logistic regression model

model = logistic_regression(1)
```

In this case, the parameters are randomly initialized. You can view them the following ways:

In [21]:

```
# Print parameters

print("list(model.parameters()):\n ", list(model.parameters()))
print("\nmodel.state_dict():\n ", model.state_dict())
```

```
list(model.parameters()):
  [Parameter containing:
tensor([[0.2381]], requires_grad=True), Parameter containing:
tensor([-0.1149], requires_grad=True)]

model.state_dict():
  OrderedDict([('linear.weight', tensor([[0.2381]])), ('linear.bias', tensor([-0.114
9]))])
```

Make a prediction with one sample:

In [22]:

```
# Make the prediction of x

yhat = model(x)
print("The prediction result: \n", yhat)
```

```
The prediction result:
 tensor([[0.5307]], grad_fn=<SigmoidBackward>)
```

Make a prediction with multiple samples:

In [23]:

```
# Make the prediction of X

yhat = model(X)
print("The prediction result: \n", yhat)
```

```
The prediction result:
 tensor([[4.0805e-11],
        [4.7130e-01],
        [1.0000e+00]], grad_fn=<SigmoidBackward>)
```

Create a logistic regression object with a function with two inputs:

In [24]:

```
# Create logistic regression model

model = logistic_regression(2)
```

Create a 1x2 tensor where x represents one data sample with one dimension, and 3x2 tensor X represents one data sample of one dimension:

In [25]:

```
# Create x and X tensor

x = torch.tensor([[1.0, 2.0]])
X = torch.tensor([[100, -100], [0.0, 0.0], [-100, 100]])
print('x = ', x)
print('X = ', X)
```

```
x =  tensor([[1., 2.]])
X =  tensor([[ 100., -100.],
        [   0.,    0.],
        [-100.,  100.]])
```

Make a prediction with one sample:

In [26]:

```
# Make the prediction of x

yhat = model(x)
print("The prediction result: \n", yhat)
```

```
The prediction result:
 tensor([[0.2943]], grad_fn=<SigmoidBackward>)
```

Make a prediction with multiple samples:

In [27]:

```
# Make the prediction of X

yhat = model(X)
print("The prediction result: \n", yhat)
```

```
The prediction result:
 tensor([[7.7529e-33],
        [3.4841e-01],
        [1.0000e+00]], grad_fn=<SigmoidBackward>)
```

Practice

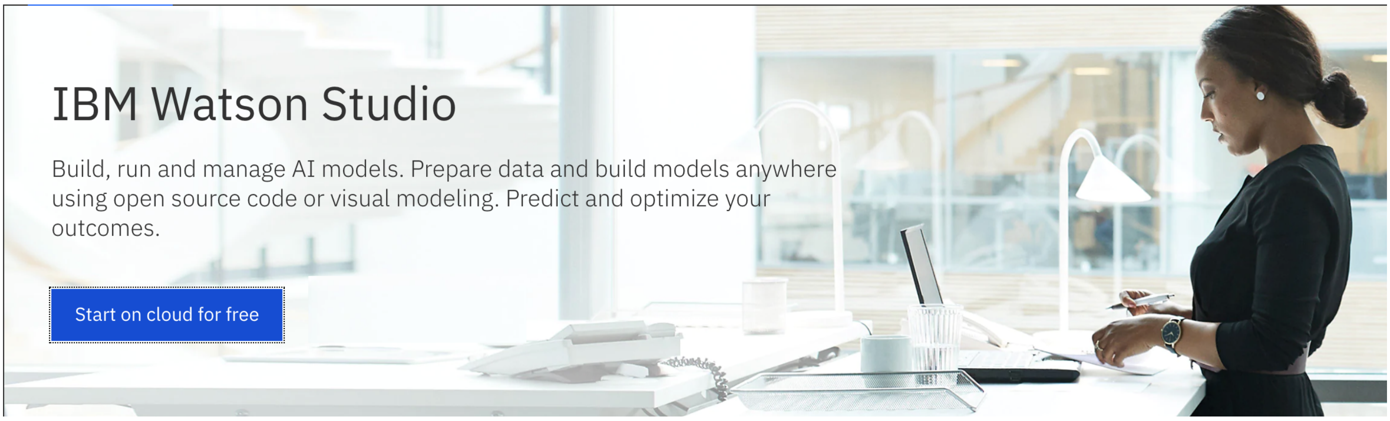
Make your own model `my_model` as applying linear regression first and then logistic regression using `nn.Sequential()` . Print out your prediction.

In [30]:

```
# Practice: Make your model and make the prediction

X = torch.tensor([-10.0])

class my_model(nn.Module):
    def __init__(self, input_size, output_size=1):
        super(my_model, self).__init__()
        self.model = nn.Sequential(nn.Linear(input_size, output_size), nn.Sigmoid())

    def forward(self, x):
        yhat = self.model(x)
        return yhat

mymodel = my_model(1,1)
Yhat = mymodel(X)
print(Yhat)
```

```
tensor([0.2231], grad_fn=<SigmoidBackward>)
```

Double-click **here** for the solution.



(https://dataplatform.cloud.ibm.com/registration/stepone?context=cpdaas&apps=data_science_experience,watson_machine_learning)

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Change Log

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

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