Watson Studio democratizes machine learning and deep learning to accelerate infusion of AI in your business to drive innovation. Watson Studio provides a suite of tools and a collaborative environment for data scientists, developers and domain experts.

(http://cocl.us/pytorch_link_top)

Activation Functions

Table of Contents

In this lab, you will cover logistic regression by using PyTorch.

Estimated Time Needed: **15 min**

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
torch.manual_seed(2)
```

Out[1]:

```
<torch._C.Generator at 0x7fbb7fd6f550>
```

Logistic Function

Create a tensor ranging from -10 to 10:

In [2]:

```
# Create a tensor

z = torch.arange(-10, 10, 0.1,).view(-1, 1)
```

When you use sequential, you can create a sigmoid object:

In [3]:

```
# Create a sigmoid object

sig = nn.Sigmoid()
```

Apply the element-wise function Sigmoid with the object:

In [4]:

```
# Make a prediction of sigmoid function

yhat = sig(z)
```

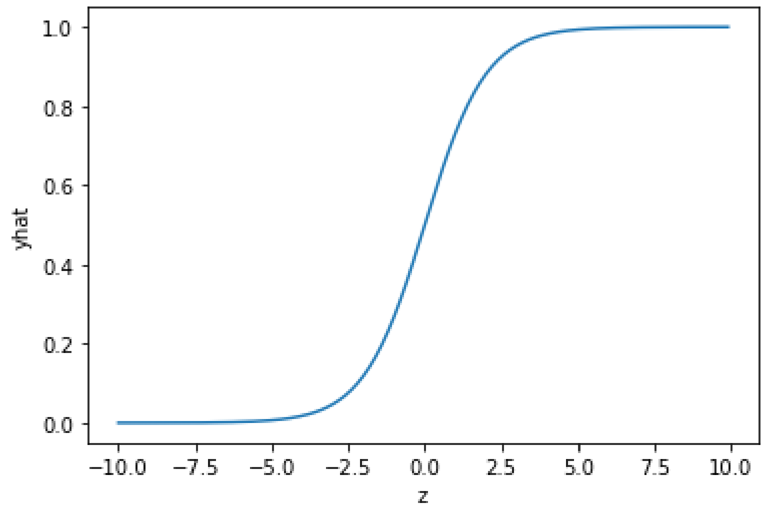
Plot the results:

In [5]:

```
# Plot the result

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

Out[5]:

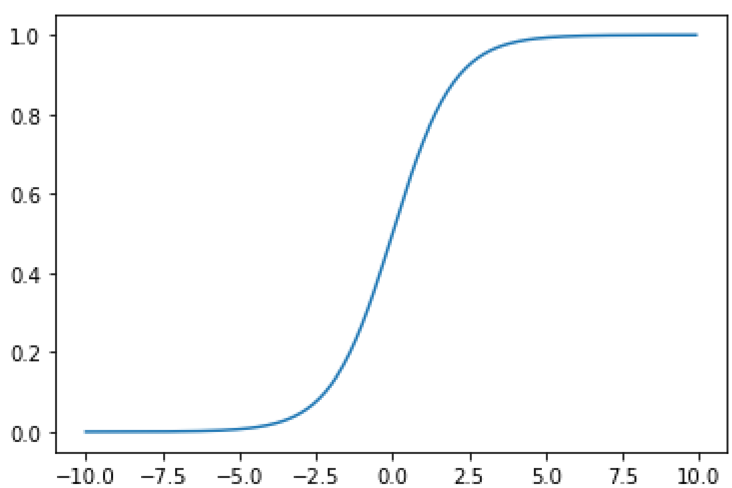
```
Text(0, 0.5, 'yhat')
```



For custom modules, call the sigmoid from the torch (`nn.functional` for the old version), which applies the element-wise sigmoid from the function module and plots the results:

In [6]:

```
# Use the build in function to predict the result

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

plt.show()
```



Tanh

When you use sequential, you can create a tanh object:

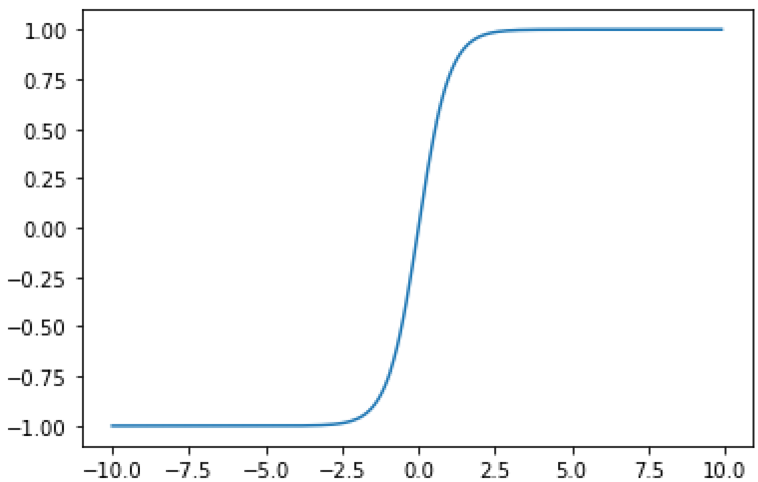
In [7]:

```
# Create a tanh object

TANH = nn.Tanh()
```

Call the object and plot it:

In [8]:

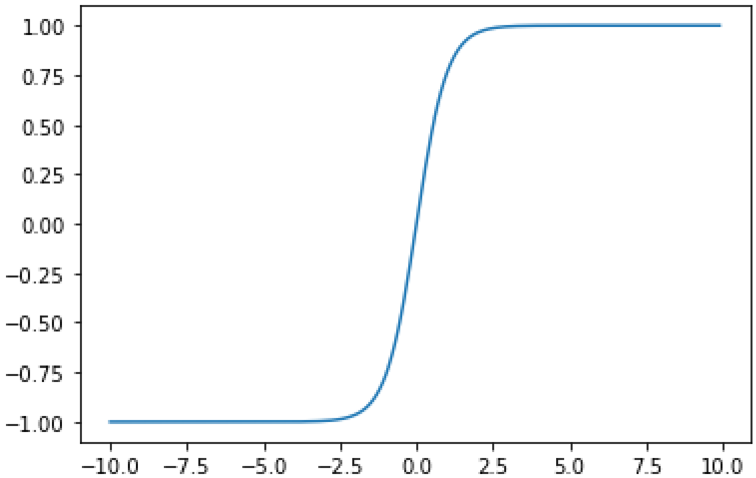
```
# Make the prediction using tanh object

yhat = TANH(z)
plt.plot(z.numpy(), yhat.numpy())
plt.show()
```



For custom modules, call the Tanh object from the torch (nn.functional for the old version), which applies the element-wise sigmoid from the function module and plots the results:

In [9]:

```
# Make the prediction using the build-in tanh object

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



Relu

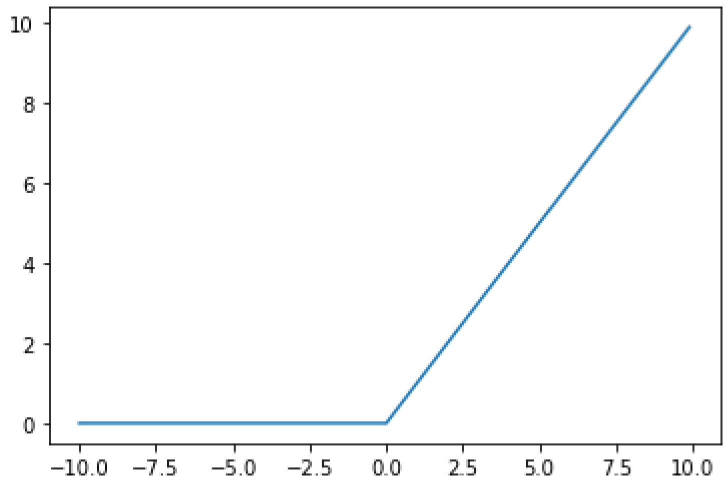
When you use sequential, you can create a Relu object:

In [10]:

```
# Create a relu object and make the prediction

RELU = nn.ReLU()
yhat = RELU(z)
plt.plot(z.numpy(), yhat.numpy())
```

Out[10]:

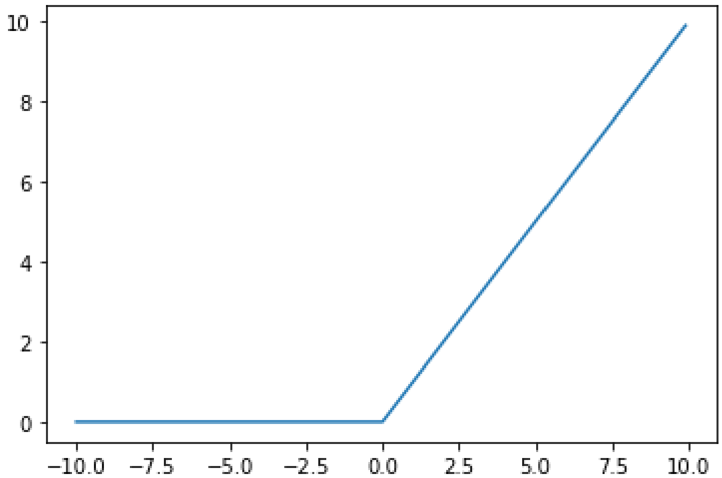
```
[<matplotlib.lines.Line2D at 0x7fbb77cbfda0>]
```



For custom modules, call the relu object from the nn.functional, which applies the element-wise sigmoid from the function module and plots the results:

In [11]:

```
# Use the build-in function to make the prediction

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



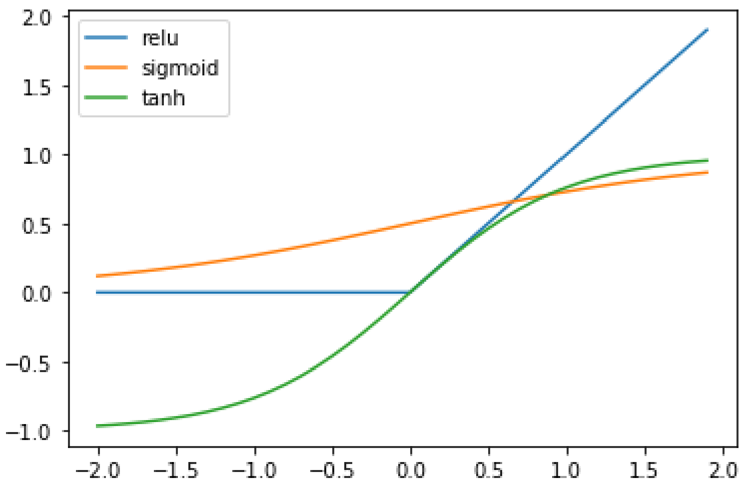
Compare Activation Functions

In [12]:

```
# Plot the results to compare the activation functions

x = torch.arange(-2, 2, 0.1).view(-1, 1)
plt.plot(x.numpy(), torch.relu(x).numpy(), label='relu')
plt.plot(x.numpy(), torch.sigmoid(x).numpy(), label='sigmoid')
plt.plot(x.numpy(), torch.tanh(x).numpy(), label='tanh')
plt.legend()
```

Out[12]:

```
<matplotlib.legend.Legend at 0x7fbb77dab0b8>
```



Practice

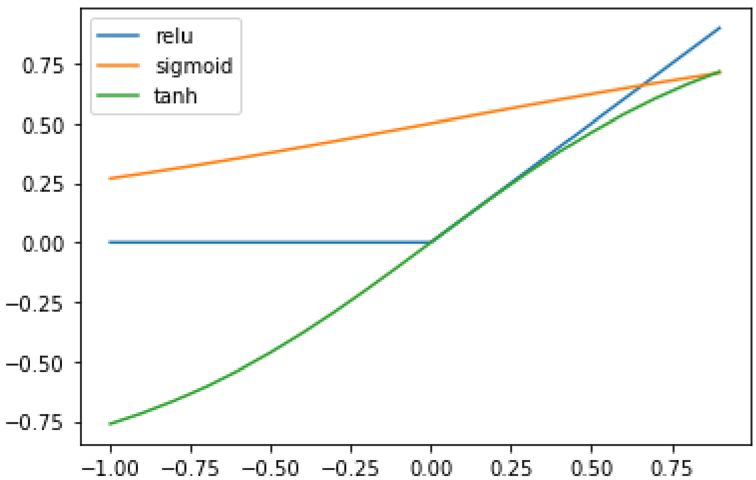
Compare the activation functions with a tensor in the range *(-1, 1)*

In [14]:

```python
# Practice: Compare the activation functions again using a tensor in the range (-1, 1)
x = torch.arange(-1, 1, 0.1).view(-1, 1)
plt.plot(x.numpy(), torch.relu(x).numpy(), label = 'relu')
plt.plot(x.numpy(), torch.sigmoid(x).numpy(), label = 'sigmoid')
plt.plot(x.numpy(), torch.tanh(x).numpy(), label ='tanh')
plt.legend()
```

Out[14]:

```
<matplotlib.legend.Legend at 0x7fbb7bbe7dd8>
```



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

About the Authors:

Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/) has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.

Other contributors: Michelle Carey (https://www.linkedin.com/in/michelleccarey/), Mavis Zhou (www.linkedin.com/in/jiahui-mavis-zhou-a4537814a)
