

ML/DL for Everyone with PYTORCH

Lecture 7: Wide & Deep

Sung Kim <hunkim+ml@gmail.com> HKUST

Code: <https://github.com/hunkim/PyTorchZeroToAll>

Slides: <http://bit.ly/PyTorchZeroAll>



Call for Comments

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Other slides: <http://bit.ly/PyTorchZeroAll>



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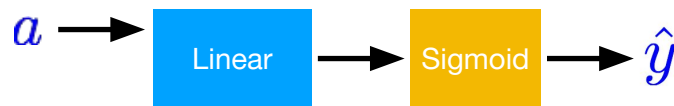


HKUST PHD Program Application

GPA (a)	Admission?
2.1	0
4.2	1
3.1	0
3.3	1

x_data = [[2.1],
[4.2],
[3.1],
[3.3]]

y_data = [[0.0],
[1.0],
[0.0],
[1.0]]



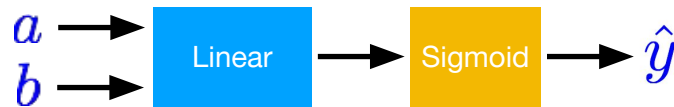
GPA enough?

How about experience and others?

GPA (a)	Experience (b)	Admission?
2.1	0.1	0
4.2	0.8	1
3.1	0.9	0
3.3	0.2	1

```
x_data = [[2.1, 0.1],  
          [4.2, 0.8],  
          [3.1, 0.9],  
          [3.3, 0.2]]
```

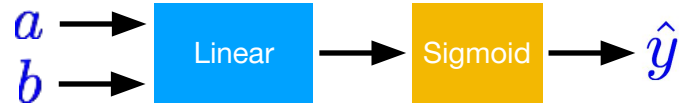
```
y_data = [[0.0],  
          [1.0],  
          [0.0],  
          [1.0]]
```



Matrix Multiplication

x_data = [[2.1, 0.1],
[4.2, 0.8],
[3.1, 0.9],
[3.3, 0.2]]

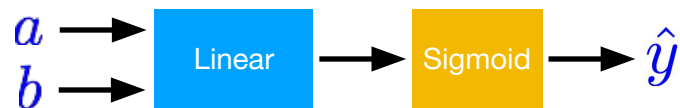
y_data = [[0.0],
[1.0],
[0.0],
[1.0]]



Matrix Multiplication

x_data = [[2.1, 0.1],
[4.2, 0.8],
[3.1, 0.9],
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[0.0],
[1.0]]



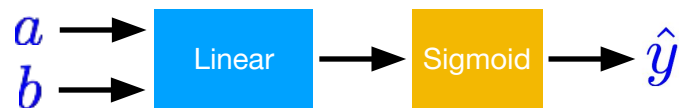
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$

Matrix Multiplication

x_data = [[2.1, 0.1],
[4.2, 0.8],
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[3.3, 0.2]]

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[0.0],
[1.0]]

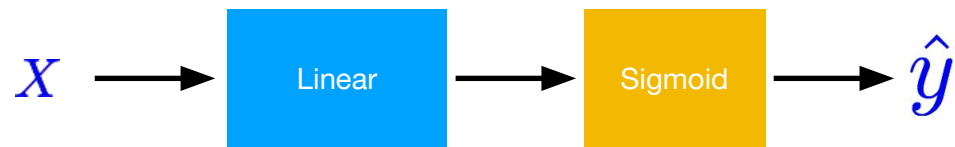
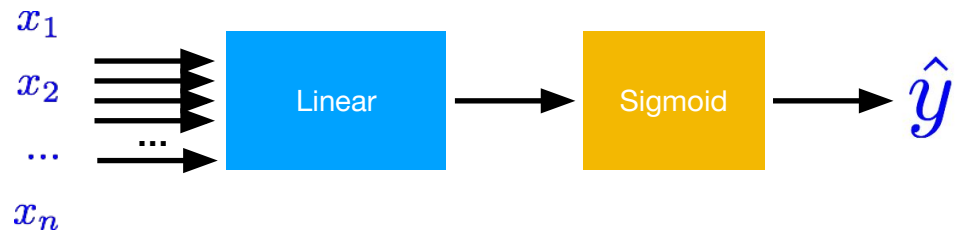
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$



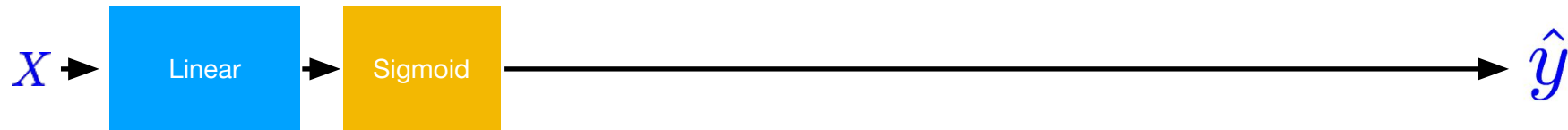
$$XW = \hat{Y}$$

```
linear = torch.nn.Linear(2, 1)  
y_pred = linear(x_data)
```


Go Wide!



Go Deep!



Go Deep!



```
sigmoid = torch.nn.Sigmoid()

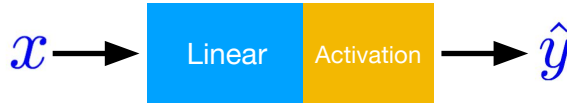
l1 = torch.nn.Linear(2, 2)
l2 = torch.nn.Linear(2, 2)
l3 = torch.nn.Linear(2, 1)

out1    = sigmoid(l1(x_data))
out2    = sigmoid(l2(out1))
y_pred = sigmoid(l3(out2))
```

Sigmoid Activation Functions



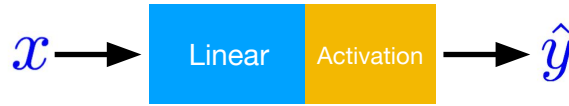
Activation Functions



Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

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Non-linear Activations

- ReLU
- ReLU6
- ELU
- SELU
- PReLU
- LeakyReLU
- Threshold
- Hardtanh
- Sigmoid
- Tanh
- LogSigmoid
- Softplus
- Softshrink
- Softsign
- Tanhshrink
- Softmin
- Softmax
- Softmax2d
- LogSoftmax

Many Activation Functions



David Sheehan

Data scientist interested
in sports, politics and
Simpsons references

📍 London via Cork

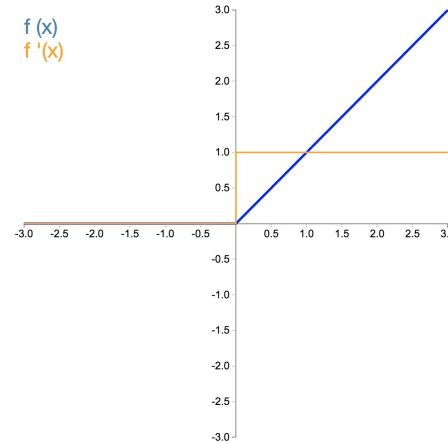
✉ Email

🐙 Github

Select an activation function from the menu below to plot it and its first derivative. Some properties relevant for neural networks are provided in the boxes on the right.

ReLu

$f(x)$
 $f'(x)$



$$f(x) = \begin{cases} x & \text{for } x \geq 0 \\ 0 & \text{for } x < 0 \end{cases}$$

Range: $[0, +\infty)$

Monotonic: ☒

Continuity: C^0

Identity at Origin: ☒

Symmetry: Asymmetrical

[Reference](#)

$$f'(x) = \begin{cases} 1 & \text{for } x \geq 0 \\ 0 & \text{for } x < 0 \end{cases}$$

Range: $[0, 1]$

Monotonic: ☒

Continuous: ☒

Vanishing Gradient: ☒

Saturation: ☒

Exploding Gradient: ☒

Dead Neurons: ☒



Classifying Diabetes



-0.411765	0.165829	0.213115	0	0	-0.23696	-0.894962	-0.7	1
-0.647059	-0.21608	-0.180328	-0.353535	-0.791962	-0.0760059	-0.854825	-0.833333	0
0.176471	0.155779	0	0	0	0.052161	-0.952178	-0.733333	1
-0.764706	0.979899	0.147541	-0.0909091	0.283688	-0.0909091	-0.931682	0.0666667	0
-0.0588235	0.256281	0.57377	0	0	0	-0.868488	0.1	0
-0.529412	0.105528	0.508197	0	0	0.120715	-0.903501	-0.7	1
0.176471	0.688442	0.213115	0	0	0.132638	-0.608027	-0.566667	0
0.176471	0.396985	0.311475	0	0	-0.19225	0.163962	0.2	1

```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
```

```
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
```

```
y_data = Variable(torch.from_numpy(xy[:, [-1]]))
```

```
print(x_data.data.shape) # torch.Size([759, 8])
```

```
print(y_data.data.shape) # torch.Size([759, 1])
```


Wide & Deep



```
class Model(torch.nn.Module):
```

```
    def __init__(self):
```

```
        """
```

```
        In the constructor we instantiate two nn.Linear module
```

```
        """
```

```
        super(Model, self).__init__()
```

```
        self.l1 = torch.nn.Linear(8, 6)
```

```
        self.l2 = torch.nn.Linear(6, 4)
```

```
        self.l3 = torch.nn.Linear(4, 1)
```

```
        self.sigmoid = torch.nn.Sigmoid()
```

```
    def forward(self, x):
```

```
        """
```

```
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
```

```
        """
```

```
        out1 = self.sigmoid(self.l1(x))
```

```
        out2 = self.sigmoid(self.l2(out1))
```

```
        y_pred = self.sigmoid(self.l3(out2))
```

```
        return y_pred
```

```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))
```

```
class Model(torch.nn.Module):
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        """
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```

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```

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```
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```

```
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        well as arbitrary operators on Variables.
        """
```

```
        out1 = self.sigmoid(self.l1(x))
```

```
        out2 = self.sigmoid(self.l2(out1))
```

```
        y_pred = self.sigmoid(self.l3(out2))
```

```
        return y_pred
```

```
# our model
```

```
model = Model()
```

```
# Construct our Loss function and an Optimizer. The call to model.parameters()
```

```
# in the SGD constructor will contain the learnable parameters of the two
```

```
# nn.Linear modules which are members of the model.
```

```
criterion = torch.nn.BCELoss(size_average=True)
```

```
optimizer = torch.optim.SGD(model.parameters(), lr=0.1)
```

```
# Training Loop
```

```
for epoch in range(100):
```

```
    # Forward pass: Compute predicted y by passing x to the model
```

```
    y_pred = model(x_data)
```

```
    # Compute and print Loss
```

```
    loss = criterion(y_pred, y_data)
```

```
    print(epoch, loss.data[0])
```

```
    # Zero gradients, perform a backward pass, and update the weights.
```

```
    optimizer.zero_grad()
```

```
    loss.backward()
```

```
    optimizer.step()
```

Classifying Diabetes



Design your model using class



Construct loss and optimizer (select from PyTorch API)



Training cycle (forward, backward, update)

Exercise 7-1

- Classifying Diabetes with deep nets
 - More than 10 layers
- Find other classification datasets
 - Try with deep network
- Try different activation functions
Sigmoid to something else



Lecture 8: DataLoader