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
Videos: http://bit.ly/PyTorchVideo

Call for Comments

Please feel free to add comments directly on these slides.

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

Picture from http://www.tssablog.org/archives/3280

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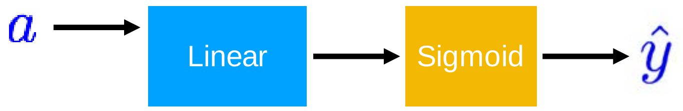
HKUST PHD Program Application

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]]
```

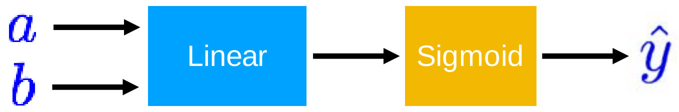


$$\begin{tikzcd} a \arrow[r] & \boxed{\text{Linear}} \arrow[r] & \boxed{\text{Sigmoid}} \arrow[r] & \hat{y} \end{tikzcd}$$

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



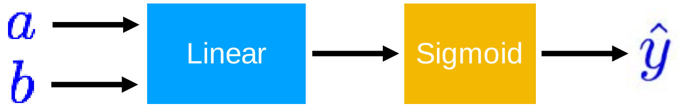
```
x_data =[[2.1, 0.1],
         [4.2, 0.8],
         [3.1, 0.9],
         [3.3, 0.2]]
```

```
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]]
```



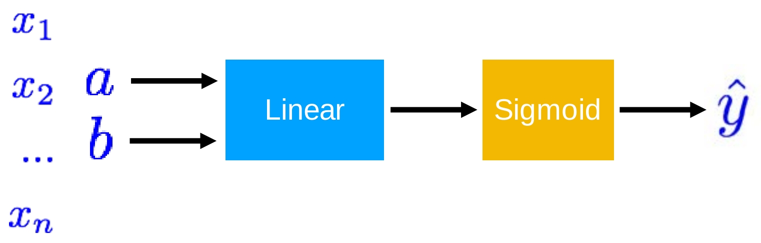
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \cdots & \cdots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \cdot\cdot \\ y_n \end{bmatrix}}_{y \in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

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]]
```

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

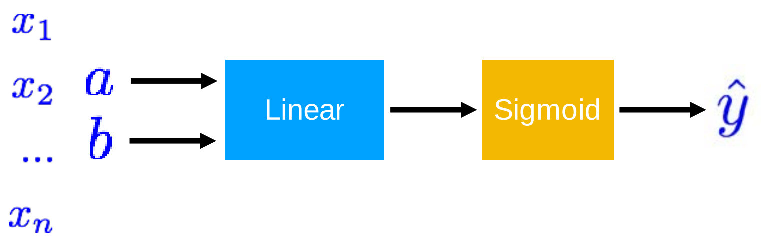


$$XW = \hat{Y}$$

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]]
```

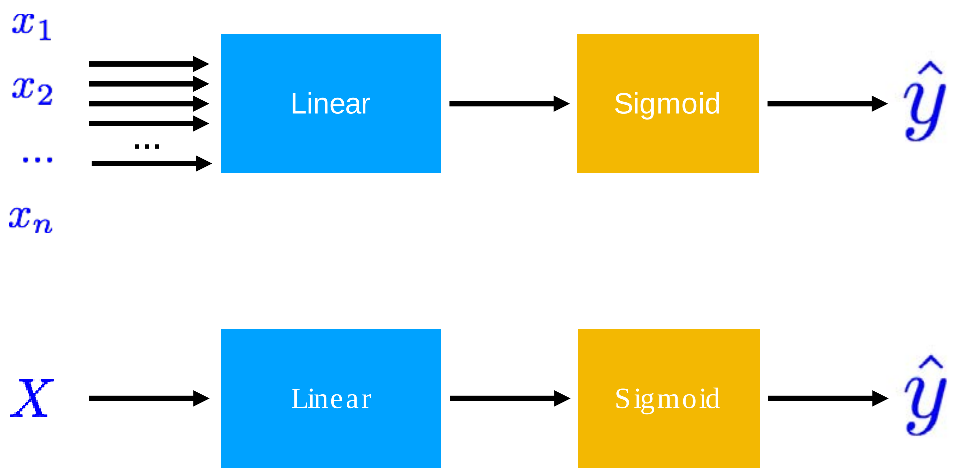


$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N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

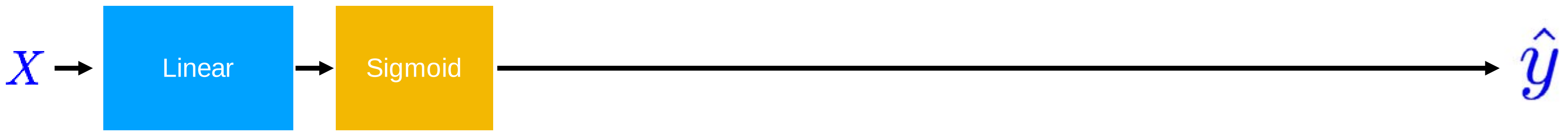
$$XW = \hat{Y}$$

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

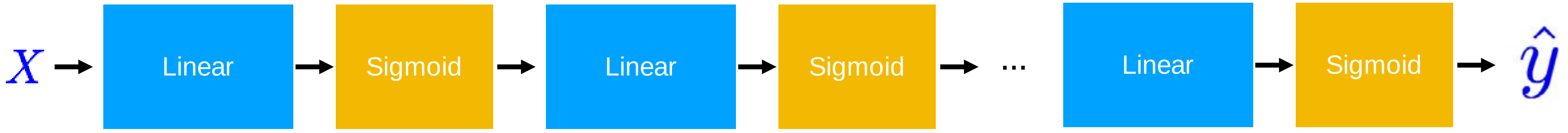
Go Wide!



Go Deep!

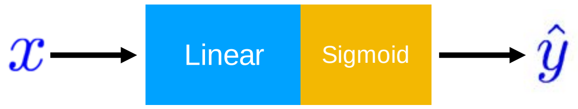


Go Deep!



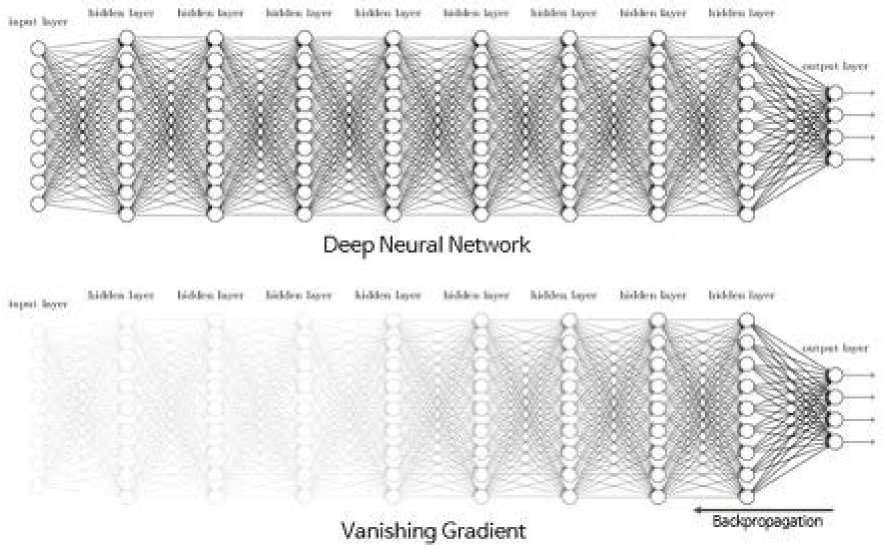
```
sigmoid = torch.nn.Sigmoid()

l1 = torch.nn.Linear(2, 4)
l2 = torch.nn.Linear(4, 3)
l3 = torch.nn.Linear(3, 1)

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

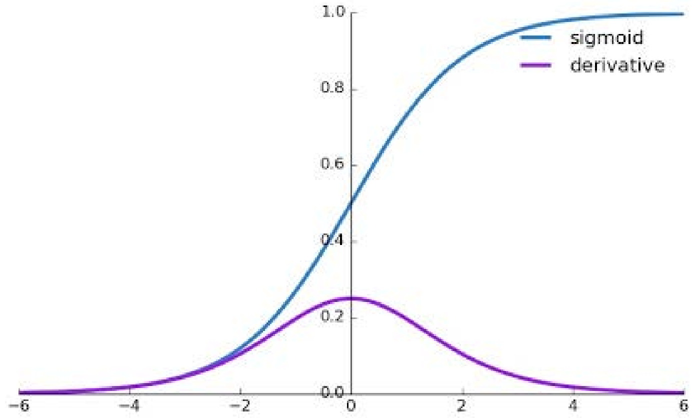
Sigmoid Activation Functions



Sigmoid: Vanishing Gradient Problem

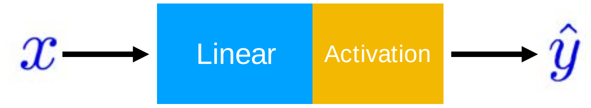
$$x \longrightarrow \boxed{\text{Linear}}\boxed{\text{Sigmoid}} \longrightarrow \hat{y}$$

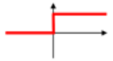
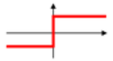
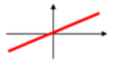
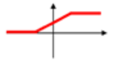
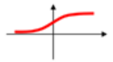
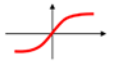
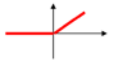
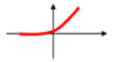




http://excelsior-cjh.tistory.com/entry/RNN-LSTMLong-Short-Term-Memory-networks

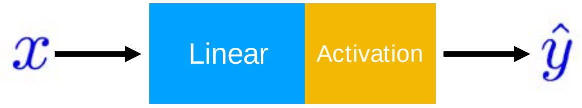
Activation Functions



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 Copyright © Sebastian Raschka 2016 (http://sebastianraschka.com)	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

http://rasbt.github.io/mlxtend/user_guide/general_concepts/activation-functions/

Activation Functions



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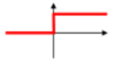
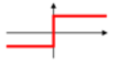
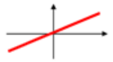
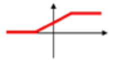
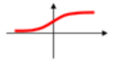
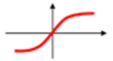
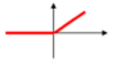
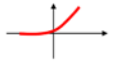
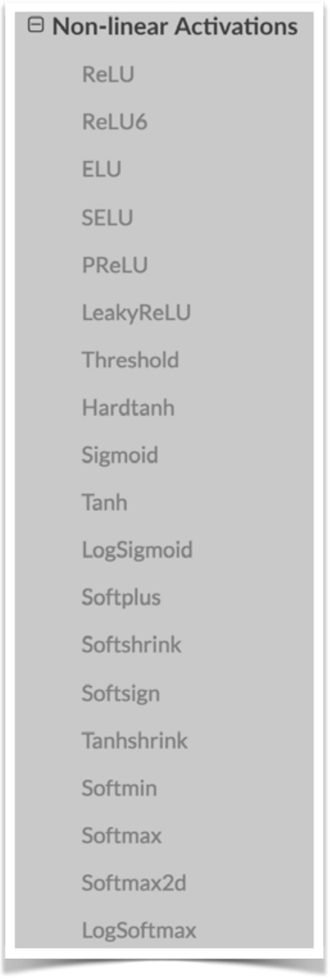
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	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	

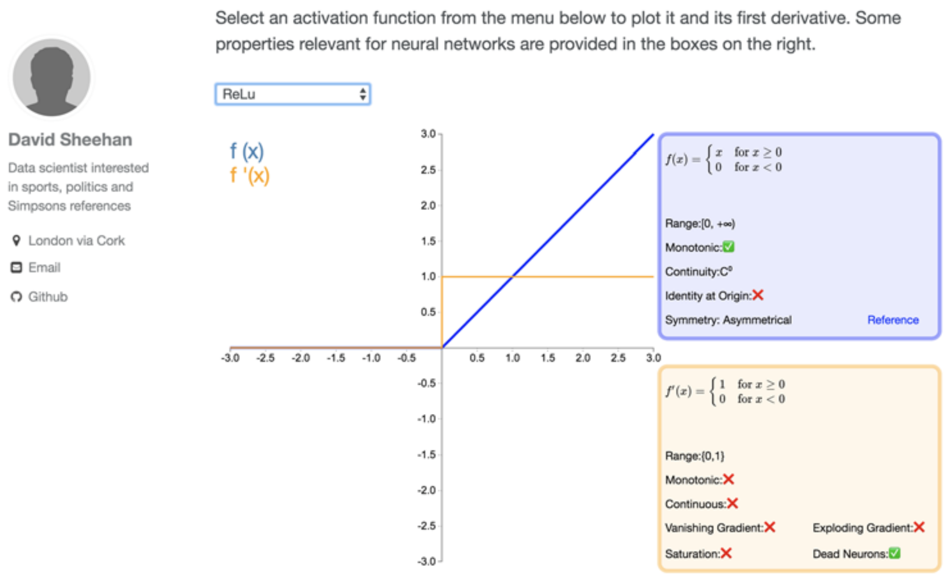
http://rasbt.github.io/mlxtend/user_guide/general_concepts/activation-functions/



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

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

Range:[0, +∞)

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: ✗ Exploding Gradient: ✗

Saturation: ✗ Dead Neurons: ✓

https://dashee87.github.io/data%20science/deep%20learning/visualising-activation-functions-in-neural-networks/

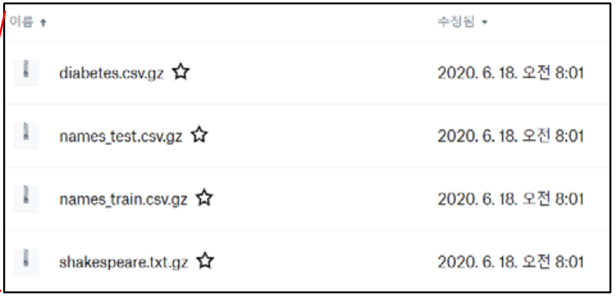
Classifying Diabetes

data-diabetes.csv

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	y
-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

https://www.dropbox.com/sh/zgqixhhcmbquetn/AABOQYrXK8pGM47N9yjqU4aMa?dl=0

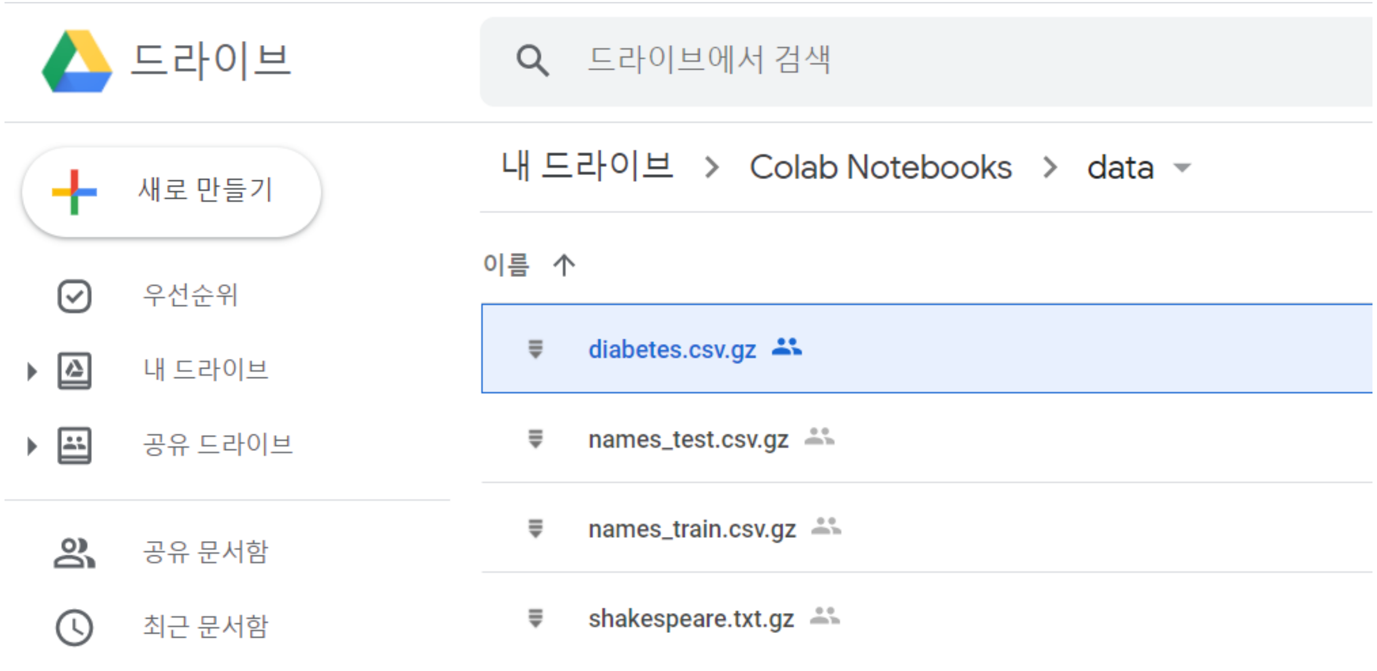
Click



이름 ↑	수정됨 ▾
diabetes.csv.gz ☆	2020. 6. 18. 오전 8:01
names_test.csv.gz ☆	2020. 6. 18. 오전 8:01
names_train.csv.gz ☆	2020. 6. 18. 오전 8:01
shakespeare.txt.gz ☆	2020. 6. 18. 오전 8:01

Classifying Diabetes

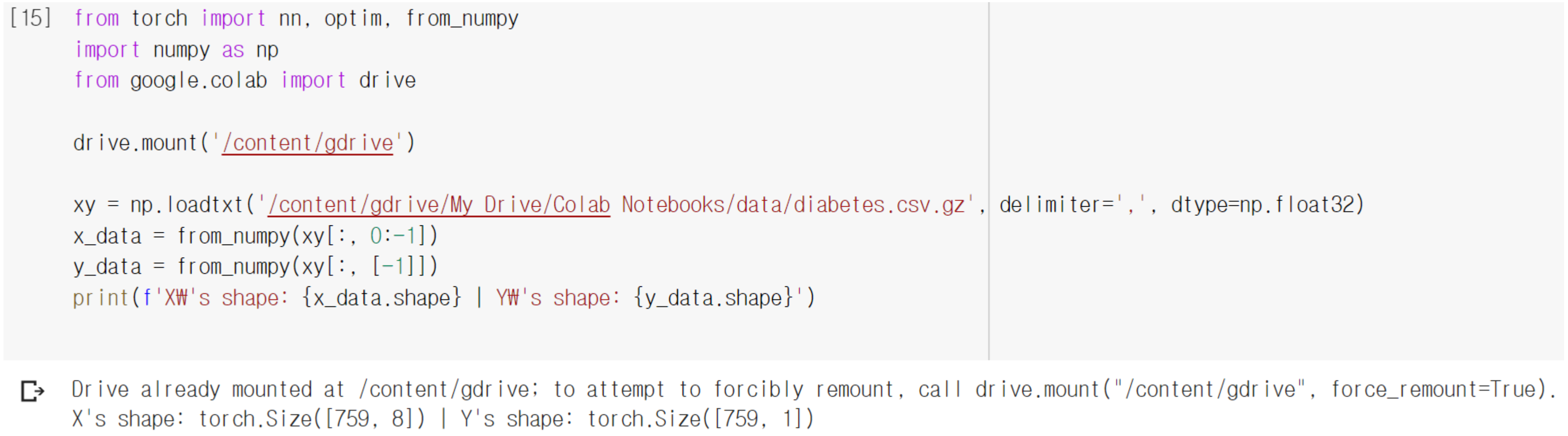
- Copy the data to your /My Drive/Colab Notebooks/data folder



diabetes.csv.gz
names_test.csv.gz
names_train.csv.gz
shakespeare.txt.gz

Classifying Diabetes

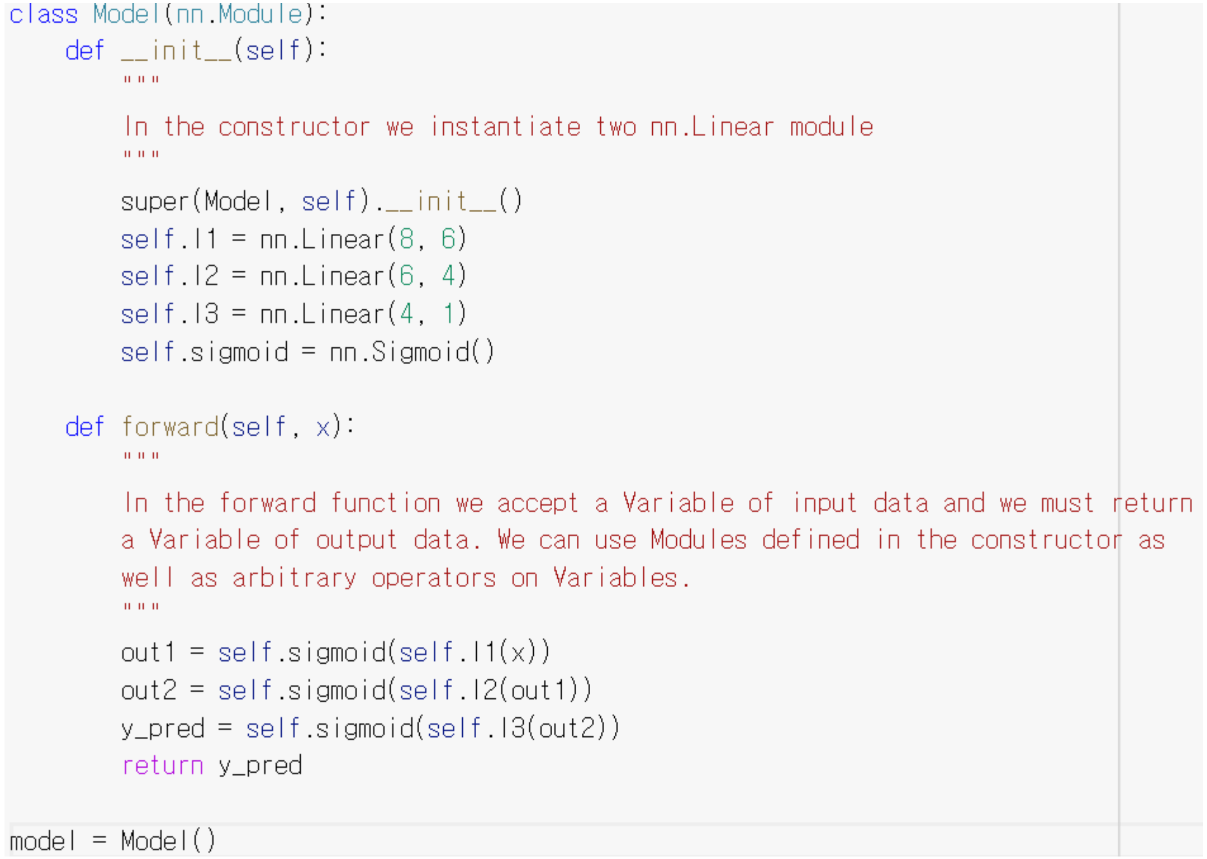
- Mount your GooleDrive to Colab
- Enter the verification code



```
[15] from torch import nn, optim, from_numpy
     import numpy as np
     from google.colab import drive

     drive.mount('/content/gdrive')

     xy = np.loadtxt('/content/gdrive/My Drive/Colab Notebooks/data/diabetes.csv.gz', delimiter=',', dtype=np.float32)
     x_data = from_numpy(xy[:, 0:-1])
     y_data = from_numpy(xy[:, [-1]])
     print(f'X₩'s shape: {x_data.shape} | Y₩'s shape: {y_data.shape}')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).
X's shape: torch.Size([759, 8]) | Y's shape: torch.Size([759, 1])
```

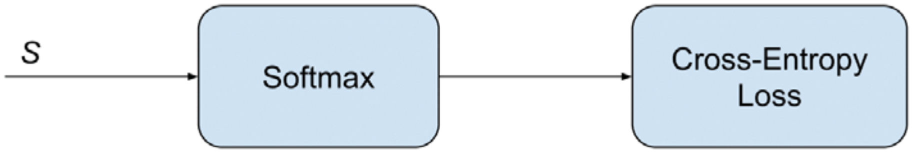
Wide & Deep



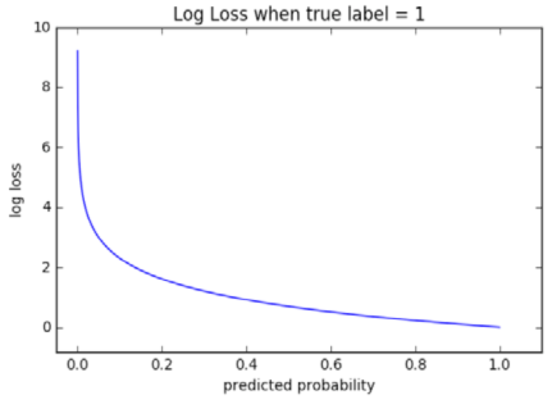
```
class Model(nn.Module):
    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.l1 = nn.Linear(8, 6)
        self.l2 = nn.Linear(6, 4)
        self.l3 = nn.Linear(4, 1)
        self.sigmoid = 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

model = Model()
```

Wide & Deep

```python
# 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 = nn.BCELoss(reduction='mean')
optimizer = optim.SGD(model.parameters(), lr=0.1)
```



$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \qquad CE = -\sum_i^C t_i log(f(s)_i)$$



Wide & Deep

```python
# 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(f'Epoch: {epoch + 1}/100 | Loss: {loss.item():.4f}')

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Classifying Diabetes

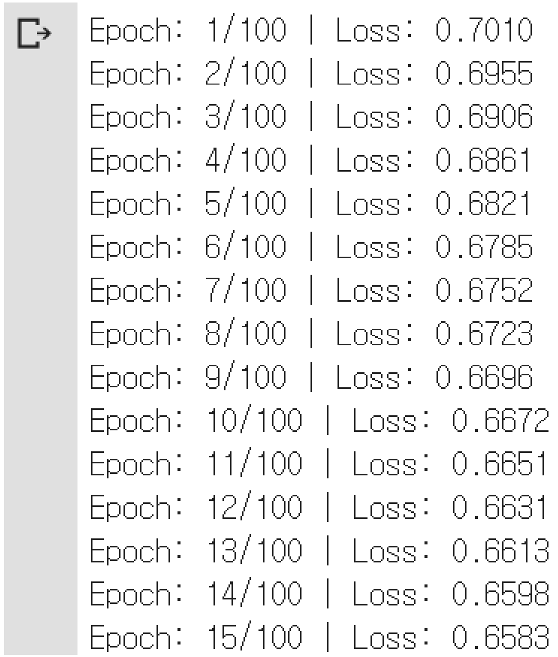
```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))

class Model(torch.nn.Module):
    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

# 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()
```

1 **Design your model using class**

2 **Construct loss and optimizer (select from PyTorch API)**

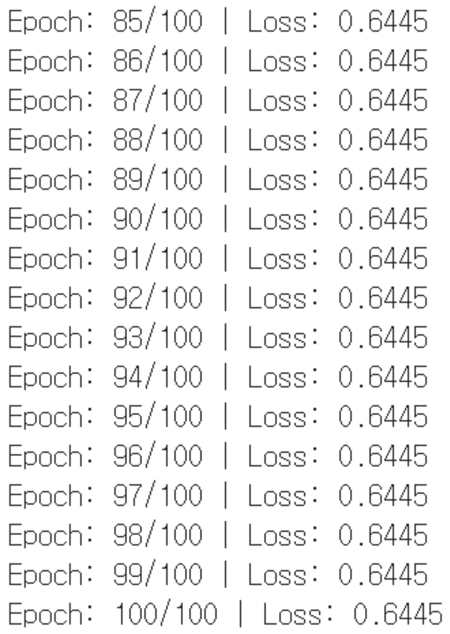
3 **Training cycle (forward, backward, update)**

Output



```
Epoch: 1/100 | Loss: 0.7010
Epoch: 2/100 | Loss: 0.6955
Epoch: 3/100 | Loss: 0.6906
Epoch: 4/100 | Loss: 0.6861
Epoch: 5/100 | Loss: 0.6821
Epoch: 6/100 | Loss: 0.6785
Epoch: 7/100 | Loss: 0.6752
Epoch: 8/100 | Loss: 0.6723
Epoch: 9/100 | Loss: 0.6696
Epoch: 10/100 | Loss: 0.6672
Epoch: 11/100 | Loss: 0.6651
Epoch: 12/100 | Loss: 0.6631
Epoch: 13/100 | Loss: 0.6613
Epoch: 14/100 | Loss: 0.6598
Epoch: 15/100 | Loss: 0.6583
```

...



```
Epoch: 85/100 | Loss: 0.6445
Epoch: 86/100 | Loss: 0.6445
Epoch: 87/100 | Loss: 0.6445
Epoch: 88/100 | Loss: 0.6445
Epoch: 89/100 | Loss: 0.6445
Epoch: 90/100 | Loss: 0.6445
Epoch: 91/100 | Loss: 0.6445
Epoch: 92/100 | Loss: 0.6445
Epoch: 93/100 | Loss: 0.6445
Epoch: 94/100 | Loss: 0.6445
Epoch: 95/100 | Loss: 0.6445
Epoch: 96/100 | Loss: 0.6445
Epoch: 97/100 | Loss: 0.6445
Epoch: 98/100 | Loss: 0.6445
Epoch: 99/100 | Loss: 0.6445
Epoch: 100/100 | Loss: 0.6445
```

Exercise 7-1: Try to minimize the loss for Diabets data:

- Classify Diabetes with deep nets
  - More than 10 layers
- Find other classification datasets
  - Try with deep network
- Try different activation functions Sigmoid to something else
- Find out a better model with respect to minimizing the loss

WHAT NEXT

Lecture 8: DataLoader