PyTorch Tutorial

07. Multiple Dimension Input

Revision

x (hours)	y (points)
1	2
2	4
3	6
4	?

x (hours)	y (pass/fail)
1	0 (fail)
2	0 (fail)
3	1 (pass)
4	?

Diabetes Dataset

X1	X2	X3	X4	X5	X6	X7	X8	Y
-0.29	0.49	0.18	-0.29	0.00	0.00	-0.53	-0.03	0
-0.88	-0.15	0.08	-0.41	0.00	-0.21	-0.77	-0.67	1
-0.06	0.84	0.05	0.00	0.00	-0.31	-0.49	-0.63	0
-0.88	-0.11	0.08	-0.54	-0.78	-0.16	-0.92	0.00	1
0.00	0.38	-0.34	-0.29	-0.60	0.28	0.89	-0.60	0
-0.41	0.17	0.21	0.00	0.00	-0.24	-0.89	-0.70	1
-0.65	-0.22	-0.18	-0.35	-0.79	-0.08	-0.85	-0.83	0
0.18	0.16	0.00	0.00	0.00	0.05	-0.95	-0.73	1
-0.76	0.98	0.15	-0.09	0.28	-0.09	-0.93	0.07	0
-0.06	0.26	0.57	0.00	0.00	0.00	-0.87	0.10	0

Sample

Diabetes Dataset

X1	X2	X3	X4	X5	X6	X7	X8	Y
-0.29	0.49	0.18	-0.29	0.00	0.00	-0.53	-0.03	0
-0.88	-0.15	0.08	-0.41	0.00	-0.21	-0.77	-0.67	1
-0.06	0.84	0.05	0.00	0.00	-0.31	-0.49	-0.63	0
-0.88	-0.11	0.08	-0.54	-0.78	-0.16	-0.92	0.00	1
0.00	0.38	-0.34	-0.29	-0.60	0.28	0.89	-0.60	0
-0.41	0.17	0.21	0.00	0.00	-0.24	-0.89	-0.70	1
-0.65	-0.22	-0.18	-0.35	-0.79	-0.08	-0.85	-0.83	0
0.18	0.16	0.00	0.00	0.00	0.05	-0.95	-0.73	1
-0.76	0.98	0.15	-0.09	0.28	-0.09	-0.93	0.07	0
-0.06	0.26	0.57	0.00	0.00	0.00	-0.87	0.10	0

Feature

Multiple Dimension Logistic Regression Model

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(x^{(i)} * \omega + b)$$

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(\sum_{n=1}^{8} x_n^{(i)} \cdot \omega_n + b)$$

Multiple Dimension Logistic Regression Model

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(x^{(i)} * \omega + b)$$

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(\sum_{n=1}^{8} x_n^{(i)} \cdot \omega_n + b)$$

$$\sum_{n=1}^{8} x_n^{(i)} \cdot \omega_n = \begin{bmatrix} x_1^{(i)} & \cdots & x_8^{(i)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix}$$

Multiple Dimension Logistic Regression Model

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(x^{(i)} * \omega + b)$$

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(\sum_{n=1}^{8} x_n^{(i)} \cdot \omega_n + b)$$

$$\sum_{n=1}^{8} x_n^{(i)} \cdot \omega_n = \begin{bmatrix} x_1^{(i)} & \cdots & x_N^{(i)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix}$$

Logistic Regression Model

$$\hat{y}^{(i)} = \sigma(\begin{bmatrix} x_1^{(i)} & \cdots & x_8^{(i)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b)$$

$$= \sigma(z^{(i)})$$

Mini-Batch (N samples)

$$\begin{bmatrix} \hat{y}^{(1)} \\ \vdots \\ \hat{y}^{(N)} \end{bmatrix} = \begin{bmatrix} \sigma(z^{(1)}) \\ \vdots \\ \sigma(z^{(N)}) \end{bmatrix} = \sigma(\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix})$$

Sigmoid function is in an element-wise fashion.

Mini-Batch (N samples)

$$\begin{bmatrix} \hat{y}^{(1)} \\ \vdots \\ \hat{y}^{(N)} \end{bmatrix} = \begin{bmatrix} \sigma(z^{(1)}) \\ \vdots \\ \sigma(z^{(N)}) \end{bmatrix} = \sigma\left(\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix}\right)$$

Sigmoid function is in an element-wise fashion.

$$z^{(1)} = \begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

$$\vdots$$

$$z^{(N)} = \begin{bmatrix} x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

Mini-Batch (N samples)

$$\begin{bmatrix} \hat{y}^{(1)} \\ \vdots \\ \hat{y}^{(N)} \end{bmatrix} = \begin{bmatrix} \sigma(z^{(1)}) \\ \vdots \\ \sigma(z^{(N)}) \end{bmatrix} = \sigma(\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix})$$

Sigmoid function is in an element-wise fashion.

$$z^{(1)} = \begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

$$\vdots$$

$$z^{(N)} = \begin{bmatrix} x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

$$\underbrace{\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix}}_{N \times 1} = \underbrace{\begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix}}_{N \times 8} \underbrace{\begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix}}_{8 \times 1} + \underbrace{\begin{bmatrix} b \\ \vdots \\ b \end{bmatrix}}_{N \times 1}$$

Mini-Batch (N samples)

$$\begin{bmatrix} \hat{y}^{(1)} \\ \vdots \\ \hat{y}^{(N)} \end{bmatrix} = \begin{bmatrix} \sigma(z^{(1)}) \\ \vdots \\ \sigma(z^{(N)}) \end{bmatrix} = \sigma\left(\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix}\right)$$

```python
class Model(torch.nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(8, 1)
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        x = self.sigmoid(self.linear(x))
        return x

model = Model()
```

$$z^{(1)} = \begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

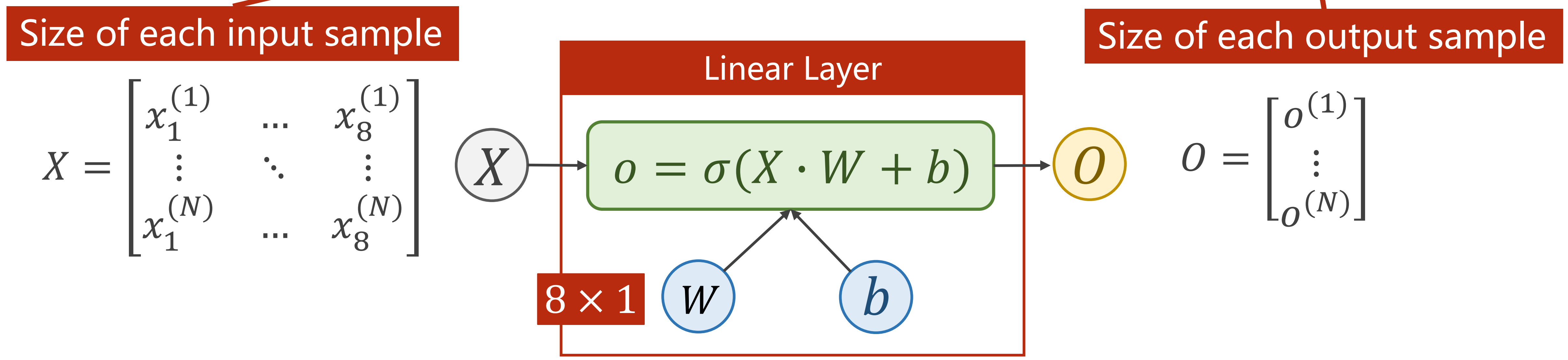
$$\vdots$$

$$z^{(N)} = \begin{bmatrix} x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix} + b$$

$$\Rightarrow$$

$$\underbrace{\begin{bmatrix} z^{(1)} \\ \vdots \\ z^{(N)} \end{bmatrix}}_{N \times 1} = \underbrace{\begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix}}_{N \times 8} \underbrace{\begin{bmatrix} \omega_1 \\ \vdots \\ \omega_8 \end{bmatrix}}_{8 \times 1} + \underbrace{\begin{bmatrix} b \\ \vdots \\ b \end{bmatrix}}_{N \times 1}$$

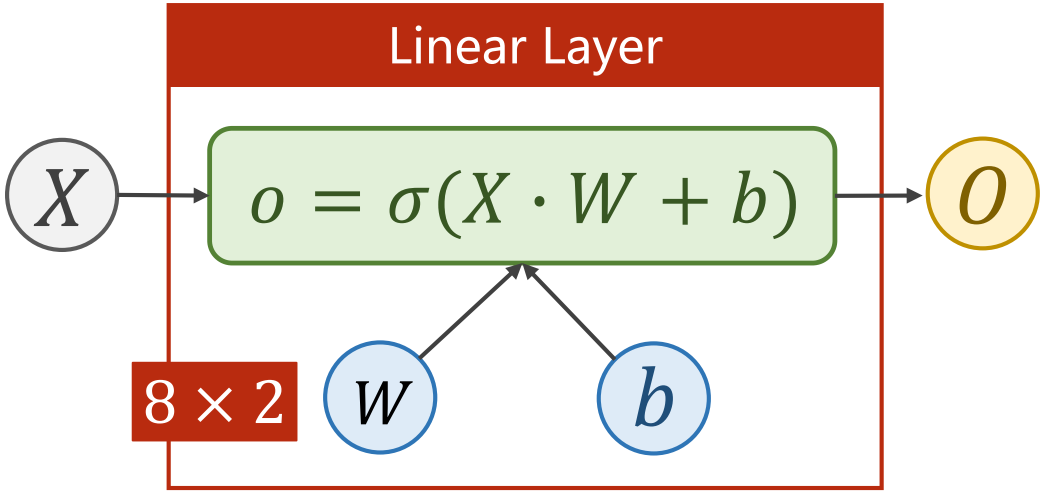
```python
self.linear = torch.nn.Linear(8, 1)
```



Linear Layer

```python
self.linear = torch.nn.Linear(8, 2)
```

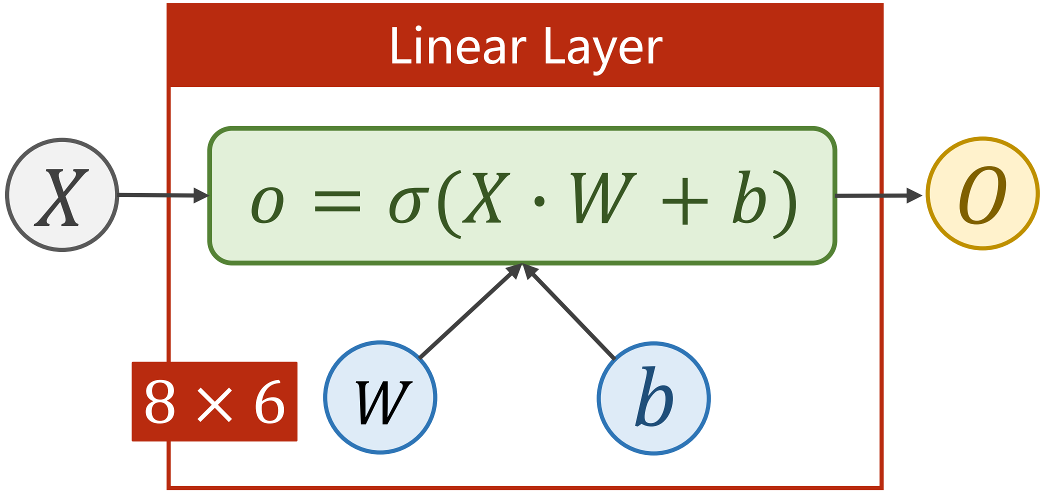
$$X = \begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix}$$



$$O = \begin{bmatrix} o_1^{(1)} & o_2^{(1)} \\ \vdots & \vdots \\ o_1^{(N)} & o_2^{(N)} \end{bmatrix}$$

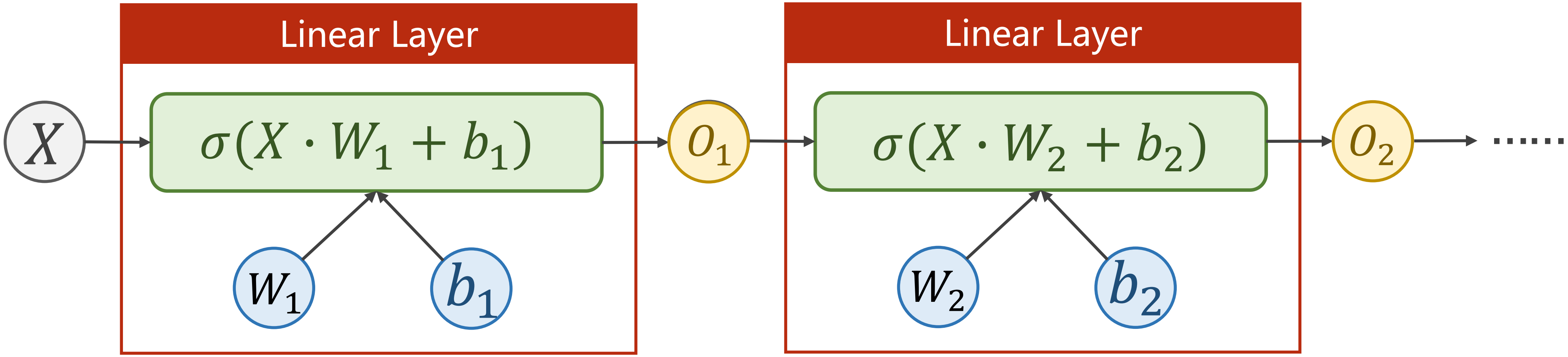
```python
self.linear = torch.nn.Linear(8, 6)
```

$$X = \begin{bmatrix} x_1^{(1)} & \cdots & x_8^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(N)} & \cdots & x_8^{(N)} \end{bmatrix}$$

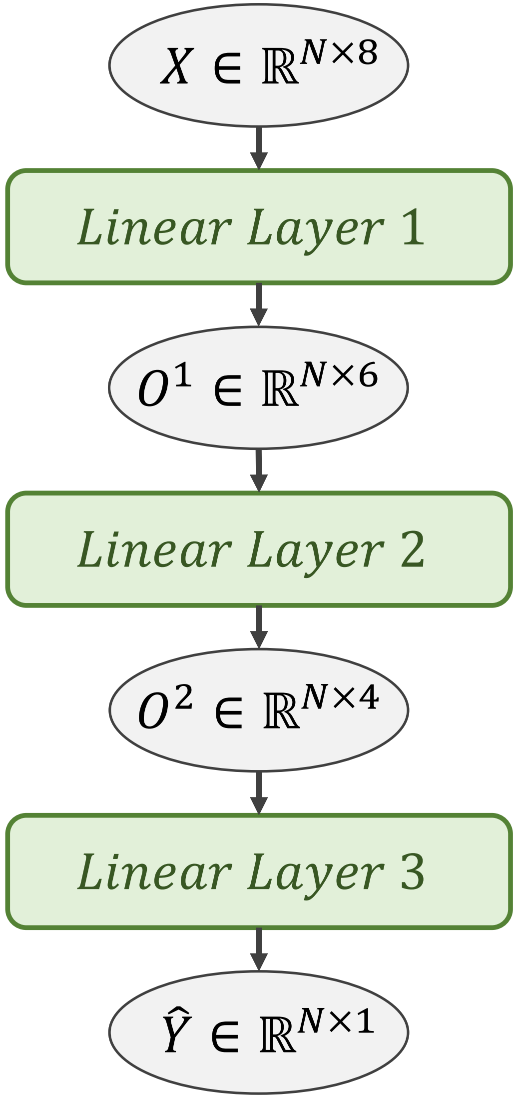


$$O = \begin{bmatrix} o_1^{(1)} & \cdots & o_6^{(1)} \\ \vdots & \ddots & \vdots \\ o_1^{(N)} & \cdots & o_6^{(N)} \end{bmatrix}$$

Neural Network



Example: Artificial Neural Network




```
self.linear1 = torch.nn.Linear(8, 6)
self.linear2 = torch.nn.Linear(6, 4)
self.linear3 = torch.nn.Linear(4, 1)
```

Example: Diabetes Prediction

X1	X2	X3	X4	X5	X6	X7	X8	Y
-0.29	0.49	0.18	-0.29	0.00	0.00	-0.53	-0.03	0
-0.88	-0.15	0.08	-0.41	0.00	-0.21	-0.77	-0.67	1
-0.06	0.84	0.05	0.00	0.00	-0.31	-0.49	-0.63	0
-0.88	-0.11	0.08	-0.54	-0.78	-0.16	-0.92	0.00	1
0.00	0.38	-0.34	-0.29	-0.60	0.28	0.89	-0.60	0
-0.41	0.17	0.21	0.00	0.00	-0.24	-0.89	-0.70	1
-0.65	-0.22	-0.18	-0.35	-0.79	-0.08	-0.85	-0.83	0
0.18	0.16	0.00	0.00	0.00	0.05	-0.95	-0.73	1
-0.76	0.98	0.15	-0.09	0.28	-0.09	-0.93	0.07	0
-0.06	0.26	0.57	0.00	0.00	0.00	-0.87	0.10	0

Example: Diabetes Prediction

1. **Prepare dataset**
   we shall talk about this later

2. **Design model using Class**
   inherit from nn.Module

3. **Construct loss and optimizer**
   using PyTorch API

4. **Training cycle**
   forward, backward, update

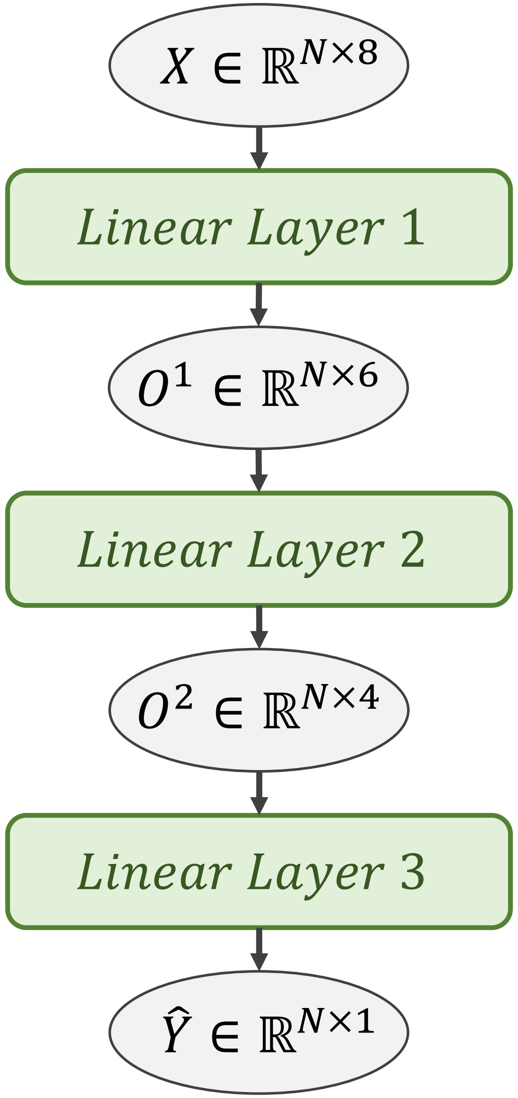
Example: 1. Prepare Dataset

```python
import numpy as np
xy = np.loadtxt('diabetes.csv.gz', delimiter=',', dtype=np.float32)
x_data = torch.from_numpy(xy[:, :-1])
y_data = torch.from_numpy(xy[:, [-1]])
```

diabetes.csv

```
-0.294118,0.487437,0.180328,-0.292929,0,0.00149028,-0.53117,-0.0333333,0
-0.882353,-0.145729,0.0819672,-0.414141,0,-0.207153,-0.766866,-0.666667,1
-0.0588235,0.839196,0.0491803,0,0,-0.305514,-0.492741,-0.633333,0
-0.882353,-0.105528,0.0819672,-0.535354,-0.777778,-0.162444,-0.923997,0,1
0,0.376884,-0.344262,-0.292929,-0.602837,0.28465,0.887276,-0.6,0
-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
-0.882353,0.899497,-0.0163934,-0.535354,1,-0.102832,-0.726729,0.266667,0
```

Example: 2. Define Model




```python
import torch

class Model(torch.nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.linear1 = torch.nn.Linear(8, 6)
        self.linear2 = torch.nn.Linear(6, 4)
        self.linear3 = torch.nn.Linear(4, 1)
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        x = self.sigmoid(self.linear1(x))
        x = self.sigmoid(self.linear2(x))
        x = self.sigmoid(self.linear3(x))
        return x

model = Model()
```

Example: 3. Construct Loss and Optimizer

Mini-Batch Loss Function for Binary Classification

$$loss = -\frac{1}{N}\sum_{n=1}^{N} y_n \log \hat{y}_n + (1 - y_n)\log(1 - \hat{y}_n)$$

Update

$$\omega = \omega - \alpha \frac{\partial cost}{\partial \omega}$$

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

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

Example: 4. Training Cycle

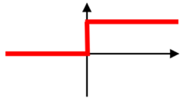
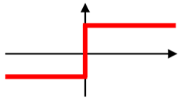
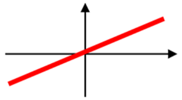
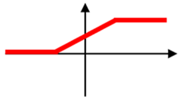
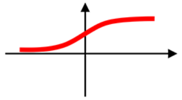
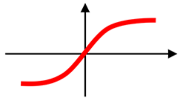
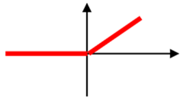
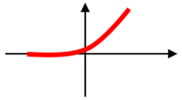
```
for epoch in range(100):
    # Forward
    y_pred = model(x_data)
    loss = criterion(y_pred, y_data)
    print(epoch, loss.item())

    # Backward
    optimizer.zero_grad()
    loss.backward()

    # Update
    optimizer.step()
```

NOTICE:

This program has not use **Mini-Batch** for training.

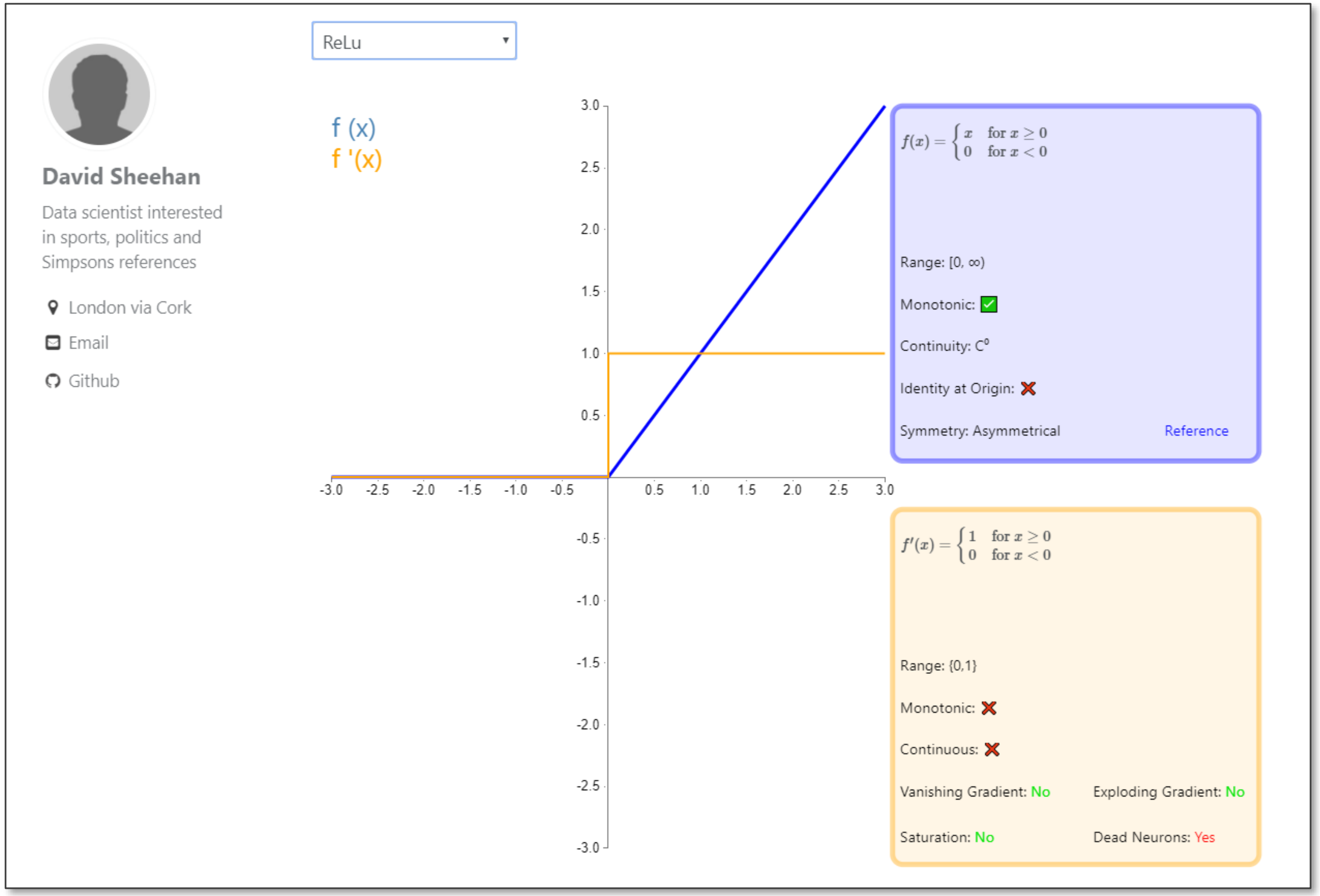
We shall talk about **DataLoader** later.

Exercise: Try different activate function

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	

http://rasbt.github.io/mlxtend/user_guide/general_concepts/activation-functions/#activation-functions-for-artificial-neural-networks

Exercise: Try different activate function



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

Exercise: Try different activate function

- Non-linear activations (weighted sum, nonlinearity)
  - ELU
  - Hardshrink
  - Hardtanh
  - LeakyReLU
  - LogSigmoid
  - PReLU
  - ReLU
  - ReLU6
  - RReLU
  - SELU
  - Sigmoid
  - Softplus
  - Softshrink
  - Softsign
  - Tanh
  - Tanhshrink
  - Threshold

Non-linear activations (weighted sum, nonlinearity)

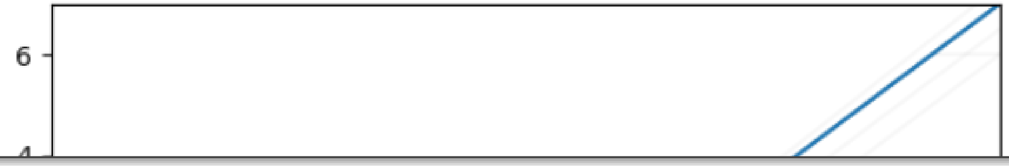
class `torch.nn.ELU`(*alpha=1.0, inplace=False*) [source]

Applies element-wise, $\text{ELU}(x) = \max(0, x) + \min(0, \alpha * (\exp(x) - 1))$

Parameters:
- **alpha** – the α value for the ELU formulation. Default: 1.0
- **inplace** – can optionally do the operation in-place. Default: `False`

Shape:
- Input: $(N, *)$ where * means, any number of additional dimensions
- Output: $(N, *)$, same shape as the input

ELU activation function



https://pytorch.org/docs/stable/nn.html#non-linear-activations-weighted-sum-nonlinearity

Exercise: Try different activate function

```
import torch

class Model(torch.nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.linear1 = torch.nn.Linear(8, 6)
        self.linear2 = torch.nn.Linear(6, 4)
        self.linear3 = torch.nn.Linear(4, 1)
        self.activate = torch.nn.ReLU()

    def forward(self, x):
        x = self.activate(self.linear1(x))
        x = self.activate(self.linear2(x))
        x = self.activate(self.linear3(x))
        return x

model = Model()
```

PyTorch Tutorial

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