

실습 내용

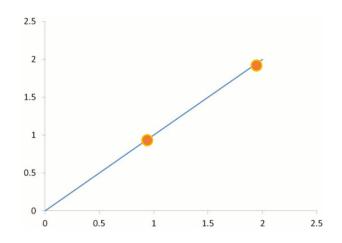
- 1. Linear regression 실습
- 2. Logistic regression 실습
- 3. Multi-Layer Perceptron 실습

신경망모델 학습 프로세스

- 1. 데이터 processing
- 2. model 디자인
 - layer 종류, 개수 및 뉴런 개수 설정
 - 각 layer 마다의 activation function 설정
- 3. Loss function 설정
- 4. Optimizer 설정
- 5. 학습



- Linear Regression
- $\bullet \hat{y} = Wx + b$
 - 파라미터 W, b 를 주어진 데이터 3개로 학습하여 아래와 같은 그래프를 만드는 것이 목표



Input	Output
1	1
2	2
3	3

• Loss function
$$\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$$

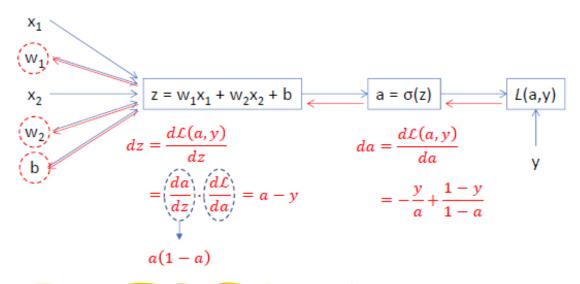
Multi-Layer Perceptrons

Linear Regression 실습

```
import torch
import torch.nn as nn
import torch.optim as optim
x_train = torch.FloatTensor([[1], [2], [3]])
y_train = torch.FloatTensor([[1], [2], [3]])
W = torch.rand(1, requires_grad=True) # set model
b = torch.rand(1, requires grad=True)
def criterion(y hat, y): # set loss function
 return torch.mean((y_hat - y) ** 2)
optimizer = optim.SGD([W, b], Ir=0.01) # set optimizer
epochs = 30
for epoch in range(epochs):
 cost = criterion(hypothesis, y_train) # get cost
 optimizer.zero_grad()
 cost.backward() # backward propagation
 optimizer.step() # update parameters
 print('Epoch {:4d}/{} Cost: {:.6f} W: {:.3f}, b: {:.3f}'.format(\format(\format))
                 epoch, epochs, cost.item(), W.item(), b.item()))
```

- 1. 데이터 processing
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- 3. Loss function 설정
- 4. Optimizer 설정
- 5. 학습

```
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                 epoch, epochs, cost.item(), W.item(), b.item()))
```



$$dw_1 = \frac{d\mathcal{L}(a,y)}{dw_1} = \frac{dz}{dw_1} \cdot \frac{d\mathcal{L}}{dz} = x_1 \cdot dz = x_1 \cdot (a-y)$$

$$dw_2 = \frac{d\mathcal{L}(a,y)}{dw_2} = \frac{dz}{dw_2} \cdot \frac{d\mathcal{L}}{dz} = x_2 \cdot dz = x_2 \cdot (a-y)$$

$$db = \frac{d\mathcal{L}(a,y)}{db} = \frac{dz}{db} \cdot \frac{d\mathcal{L}}{dz} = dz = (a-y)$$
Gradient Descent Algorithm Section 1. Since $w_1 \leftarrow w_1 - \alpha \cdot dw_1$

$$w_2 \leftarrow w_2 - \alpha \cdot dw_2$$

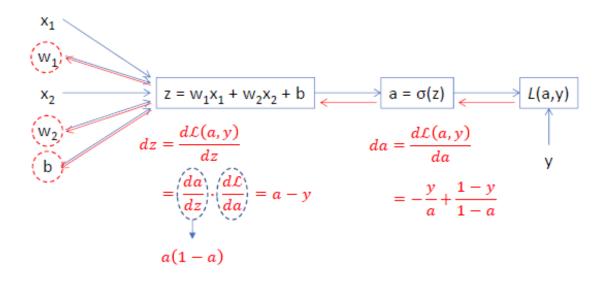
$$b \leftarrow b - \alpha \cdot db$$

for epoch in range(epochs):

Gradient Descent Algorithm

Backward propagation Update parameter

```
cost = criterion(hypothesis, y_train) # get cost
optimizer.zero_grad()
cost.backward() # backward propagation
optimizer.step() # update parameters
print('Epoch {:4d}/{} Cost: {:.6f} W: {:.3f}, b: {:.3f}'.format(\format(\format))
              epoch, epochs, cost.item(), W.item(), b.item()))
```



$$dw_1 = \frac{d\mathcal{L}(a, y)}{dw_1} = \frac{dz}{dw_1} \cdot \frac{d\mathcal{L}}{dz} = x_1 \cdot dz = x_1 \cdot (a - y)$$

$$dw_2 = \frac{d\mathcal{L}(a, y)}{dw_2} = \frac{dz}{dw_2} \cdot \frac{d\mathcal{L}}{dz} = x_2 \cdot dz = x_2 \cdot (a - y)$$

$$db = \frac{d\mathcal{L}(a, y)}{db} = \frac{dz}{db} \cdot \frac{d\mathcal{L}}{dz} = dz = (a - y)$$

for epoch in range(epochs):

Gradient Descent Algorithm
$$w_1 \leftarrow w_1 - \alpha \cdot dw_1$$
 $w_2 \leftarrow w_2 - \alpha \cdot dw_2$ $b \leftarrow b - \alpha \cdot db$

zero grad로 gradient 0으로 초기화

```
hypothesis = x_train * W + b # foward propagation
cost = criterion(hypothesis, y_train) # get cost

optimizer.zero_grad()
cost.backward() # backward propagation
optimizer.step() # update parameters

print('Epoch {:4d}/{} Cost: {:.6f} W: {:.3f}, b: {:.3f}'.format(\foward epoch, epochs, cost.item(), W.item(), b.item()))
```

Module class

```
import torch
import torch.nn as nn
import torch.optim as optim
x_{train} = torch.FloatTensor([[1], [2], [3]])
y_train = torch.FloatTensor([[1], [2], [3]])
def criterion(y_hat, y):
 return torch.mean(torch.square(y_hat-y))
class LinearRegression(nn.Module):
 def __init__(self, x_in, x_out):
   super(LinearRegression, self).__init__()
   self.linear = nn.Linear(x_in, x_out)
 def forward(self, x):
   return self.linear(x)
model = LinearRegression(1, 1)
optimizer = optim.SGD(model.parameters() | Ir=0.01) # set optimizer
epochs = 30
for epoch in range(epochs):
 hypothesis = model(x_train) # forward propagation
 cost = criterion(hypothesis, y_train) # get cost
 optimizer.zero_grad()
 cost.backward() # backward propagation
 optimizer.step() # update parameters
 print('Epoch {:4d}/{} Cost: {:.6f} W: {:.3f} b: {: 3f} format(#
                 epoch, epochs, cost.item() model.linear.weight.item(), model.linear.bias.item()
```

Cost function

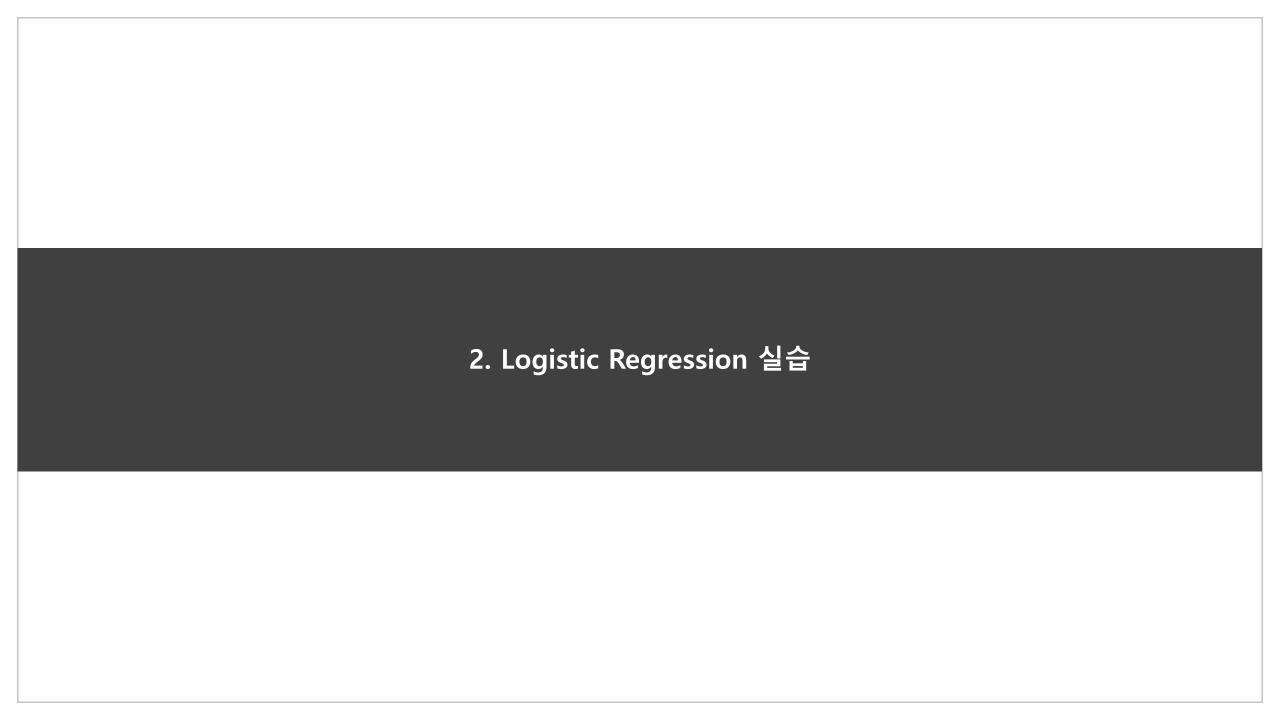
- import torch
- import torch.nn as nn
- # torch.mean 으로 평균 손실값을 구함
- # torch.square로 거리의 제곱을 손실함수로 적용

cost = torch.mean(torch.square(Y - model))

• # pytorch가 기본 제공하는 cross entropy 함수를 손실함수로 적용 criterion = nn.CrossEntropyLoss() (binary인 경우 BCELoss()) cost = criterion(input=logits, target=y)

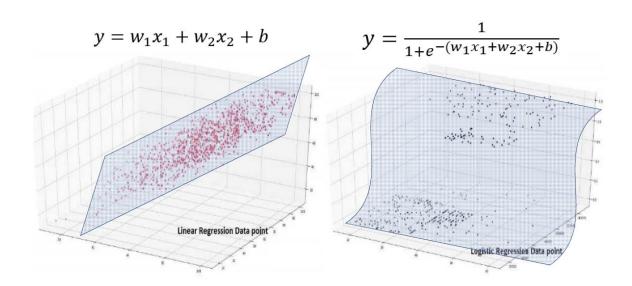
Optimizer

- # StochasticGradientDescent(SGD)를 사용해서 손실값을 최소화하는 최적화 수행
- # 0.001 은 learning rate
- optimizer = optim.SGD(model.parameters(), lr=0.01)



Logistic Regression

- Linear Regression
 - 예측 모델인 선형회귀는 단순한 linear combination
- Logistic regression
 - •데이터가 복잡하게 표현되면 linear regression으로 표현 불가능



Logistic Regression

Logistic Regression

$$\hat{y}^{(i)} = \sigma \big(w^T x^{(i)} + b \big)$$

Activation function

$$\sigma(z^{(i)}) = \frac{1}{1 + e^{-z^{(i)}}}$$

Loss function

$$\mathcal{L}(\hat{y}, y) = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$

•개념 : 입력 신호의 총합을 출력 신호로 변환하는 함수

- •종류
 - Sigmoid function
 - Tanh function
 - ReLU function

등 이외에 많음

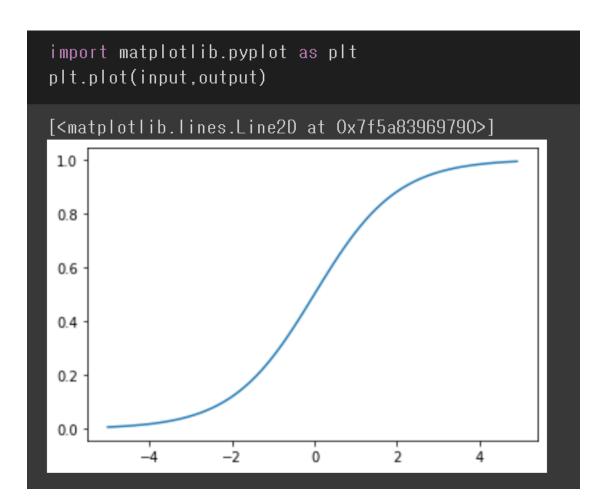
Sigmoid

$$g(z) = \frac{1}{1 + e^{-z}}$$

import torch import torch.nn as nn

activation_function = nn.Sigmoid()

input = torch.arange(-5.,5.,0.1)
output = activation_function(input)



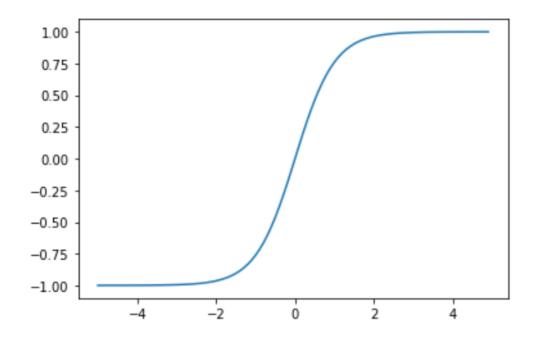
Tanh

$$g(z) = \tanh(z)$$
$$= \frac{e^{+z} - e^{-z}}{e^{+z} + e^{-z}}$$

```
[ ] import torch
import torch.nn as nn

[ ] activation_function = nn.Tanh()

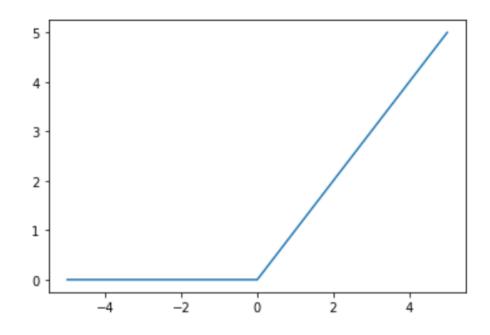
[ ] input = torch.arange(-5.,5.,0.1)
output = activation_function(input)
```



ReLU

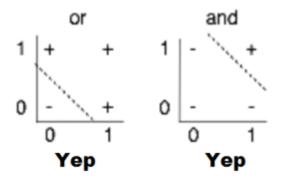
$$g(z) = \max(0, z)$$

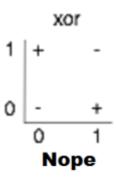
- [1] import torch import torch.nn as nn
- [2] activation_function = nn.ReLU()
- [3] input = torch.range(-5,5,0.1)
 output = activation_function(input)



Logistic Regression

·AND 문제





Input 1	Input 2	Output
0	0	0
0	1	0
1	0	0
1	1	1

Multi-Layer Perceptrons

Logistic Regression

```
import torch
import torch.nn as nn
import torch.optim as optim
x_{train} = torch.FloatTensor([[0,0], [0,1], [1,0],[1,1]])
y_train = torch.FloatTensor([[0], [0], [0], [1]])
class LogisticRegression(nn.Module):
 def __init__(self, x_in, x_out):
   super(LogisticRegression, self).__init__()
   self.linear = nn.Linear(x in, x out)
   self.activation = nn.Sigmoid()
  def forward(self. x):
   z = self.linear(x)
  a = self.activation(z)
   return a
model = LogisticRegression(2, 1).train()
optimizer = optim.SGD(model.parameters(), Ir=0.01) # set optimizer
criterion = nn.BCELoss()
```

```
epochs = 1000
for epoch in range(epochs):
    model.train()
    hypothesis = model(x_train)  # for ward propagation
    cost = criterion(hypothesis+1e-8, y_train) # get cost
    optimizer.zero_grad()
    cost.backward() # backward propagation
    optimizer.step() # update parameters

if epoch != 0 and epoch % 100 == 0:
    model.eval()
    with torch.no_grad():
        predicts = (model(x_train))
        print('predict with model : {}'.format(predicts))
        print('real value y : {}'.format(y_train))
```

Logistic Regression

```
[1] import torch
     import torch.nn as nn
     import torch.optim as optim
[2] x_train = torch.FloatTensor([[0,0], [0,1], [1,0],[1,1<mark>]</mark>])
     y_train = torch.FloatTensor([[0], [0], [0], [1]])
[3] class LogisticRegression(nn.Module):
       def __init__(self, x_in, x_out):
         super(LogisticRegression, self).__init__()
         self.linear = nn.Linear(x in, x out)
         self.activation = nn.Sigmoid()
       def forward(self, x):
         z = self.linear(x)
         a = self.activation(z)
[4] model = LogisticRegression(2, 1).train()
[5] optimizer = optim.SGD(model.parameters(), Ir=0.1) # set optimize
[6] criterion = nn.BCELoss()
```

```
epochs = 8000
for epoch in range(epochs):
    model.train()
    hypothesis = model(x_train) # forward propagation
    cost = criterion(hypothesis+1e-8, y_train) # get cost
    optimizer.zero_grad()
    cost.backward() # backward propagation
    optimizer.step() # update parameters

if epoch != 0 and epoch % 100 == 0:
    model.eval()
    with torch.no_grad():
        predicts = (model(x_train))
        print('predict with model : {}'.format(predicts))
        print('real value y : {}'.format(y_train))
```

Logistic Regression

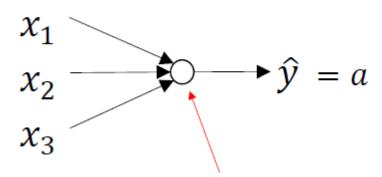
•결과

```
predict with model : tensor([[2.5810e-05],
[2.5644e-02],
[2.5644e-02],
[9.6408e-01]])
real value y : tensor([[0.],
[0.],
[0.],
[1.]])
```

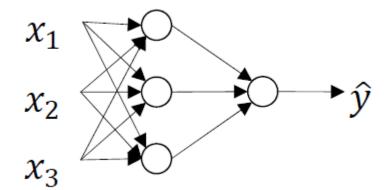


Single-Layer Perceptron

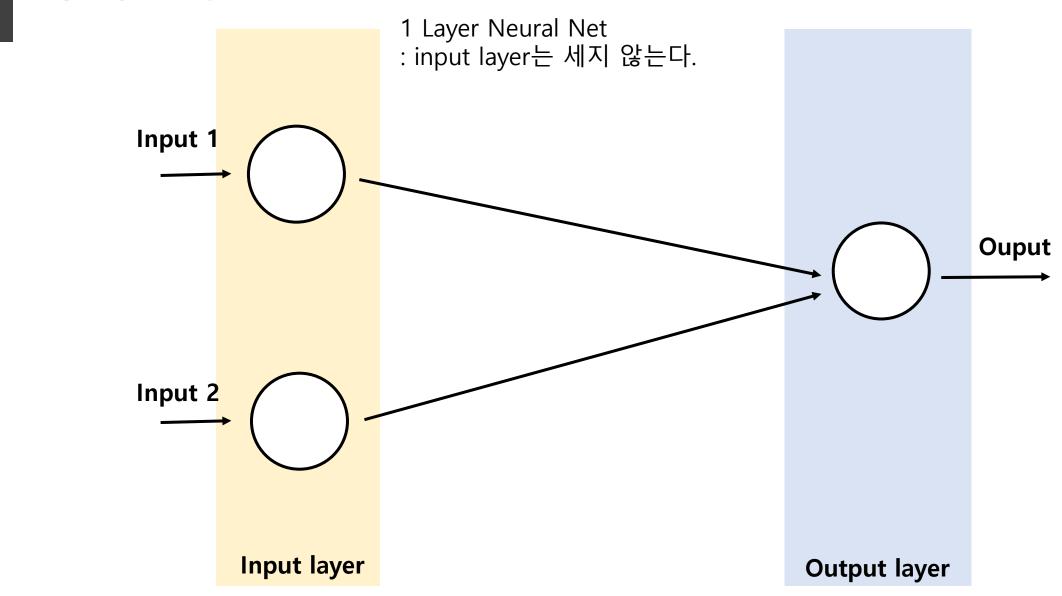
• Logistic Regression



Neural Network

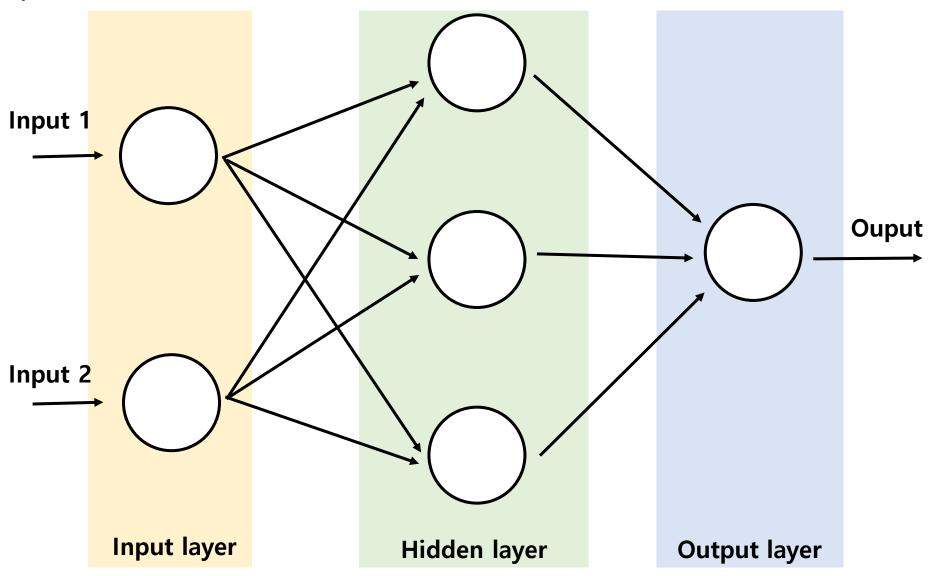


Single-Layer Perceptron 실습



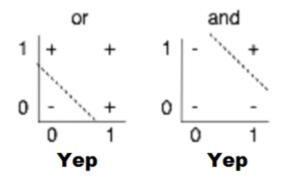


Multi-Layer Perceptron



XOR 문제

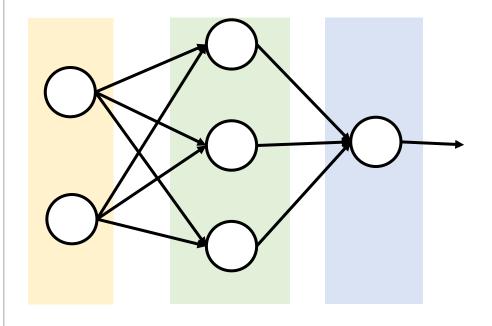
• 단순한 Regression으로 풀리지 않음 → Neural Net으로 해결





Input 1	Input 2	Output
0	0	0
0	1	1
1	0	1
1	1	0

Multi-Layer Perceptron



```
class MultiLayerPerceptron(nn.Module):
 def __init__(self):
    super(MultiLayerPerceptron, self).__init__()
    self.linear1 = nn.Linear(2, 3)
    self.activation = nn.Sigmoid()
    self.linear2 = nn.Linear(3, 1)
 def forward(self, x):
    z1 = self.linear1(x)
    a1 = self.activation(z1)
   z2 = self.linear2(a1)
    a2 = self.activation(z2)
    return a2
```

Multi-Layer Perceptron

•결과

실습 내용

- 1. Linear regression 실습
- 2. Logistic regression 실습
- 3. Multi-Layer Perceptron 실습