

Assignment2

October 17, 2018

1. [활성함수] 다음 코드는 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요. (4점)

```
In [1]: # Python 2, Python 3 지원
        from __future__ import division, print_function, unicode_literals

        # Library related
        import os
        import numpy as np
        %matplotlib inline
        import matplotlib
        import matplotlib.pyplot as plt

        # sigmoid function
        def logit(z):
            return 1 / (1 + np.exp(-z))

        # ReLU Function
        def relu(z):
            return np.maximum(0, z)

        # deriautive formula
        # 미분 공식
        def derivative(f, z, eps=0.000001):
            return (f(z + eps) - f(z - eps)) / (2 * eps)

        # sample data
        # numpyt linspace's reference
        # https://docs.scipy.org/doc/numpy-1.15.0/reference/generated/-
        # numpy.linspace.html
        # this function return evenly spaced numbers over a specified interval
        z = np.linspace(-5, 5, 200)

        # figure function's reference is
        # https://matplotlib.org/api/_as_gen/matplotlib.pyplot.figure.html
        # figsize width, height in inches
        plt.figure(figsize=(11, 4))
```

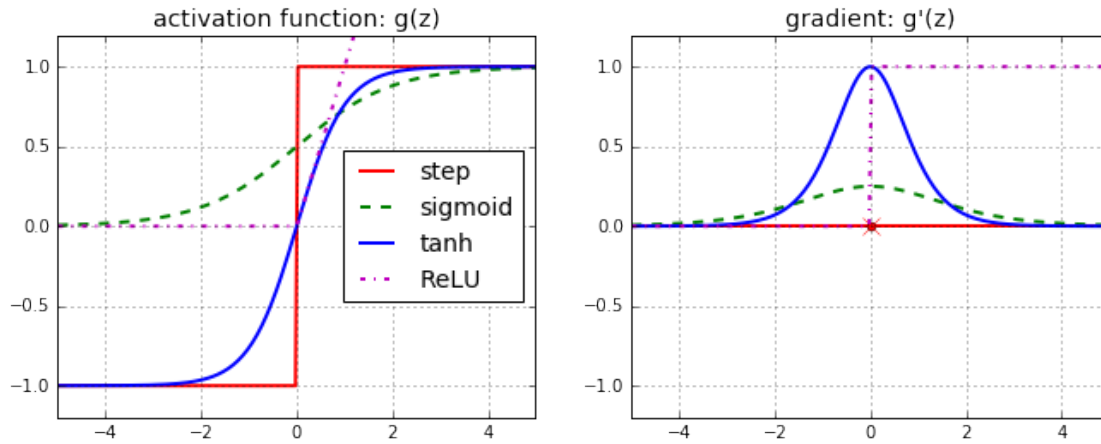
```

# The left figure is functions like sign, logit(sigmoid), tanh, relu
# activation function figure
# the matplotlib's reference is
# https://matplotlib.org/api/_as_gen/matplotlib.pyplot.subplot.html
# the matplotlib's subplot function
# i.e. Either a 3-digit integer or three separate integers
# describing the position of the subplot.
# the three integers are nrow, ncol, and index in order.
plt.subplot(121)
plt.plot(z, np.sign(z), "r-", linewidth=2, label="step")
plt.plot(z, logit(z), "g--", linewidth=2, label="sigmoid")
plt.plot(z, np.tanh(z), "b-", linewidth=2, label="tanh")
plt.plot(z, relu(z), "m-.", linewidth=2, label="ReLU")
plt.grid(True)
plt.legend(loc="center right", fontsize=14)
plt.title("activation function: g(z)", fontsize=14)
plt.axis([-5, 5, -1.2, 1.2])

# The right figure is derivative function of each function above
# 각 activation function's 기울기 함수(미분함수)
plt.subplot(122)
plt.plot(z, derivative(np.sign, z), "r-", linewidth=2, label="step")
plt.plot(0, 0, "ro", markersize=5)
plt.plot(0, 0, "rx", markersize=10)
plt.plot(z, derivative(logit, z), "g--", linewidth=2, label="sigmoid")
plt.plot(z, derivative(np.tanh, z), "b-", linewidth=2, label="tanh")
plt.plot(z, derivative(relu, z), "m-.", linewidth=2, label="ReLU")
plt.grid(True)
plt.title("gradient: g'(z)", fontsize=14)
plt.axis([-5, 5, -1.2, 1.2])

plt.show()
# (1) 화면 출력 확인 및 각 활성화함수의 특징을 비교 서술
# step function: 계단 함수로 항상 기울기는 0, 단 원점에 미분 불가능하지만
#               여기서 원점의 미분값은 0으로 표시
# sigmoid : 0 ~ 1 사이 값을 출력을 하지만 미분 값은 원점에 최대
#               양쪽 끝 (음수, 양수)으로 갈수록 미분은 값은 0이다.
# tanh : sigmoid function가 비슷하지만, 출력값이 -1 ~ 1 사이가 다르다.
#               하지만 양쪽 끝 (음수, 양수)으로 갈수록 미분값은 0인것은 같다.
# ReLu : 양수에서는 기울기가 1이고 음수에서는 출력값이외에 기울기도 0이다.
# 각 activation function은 비선형적인 특징을 가지고 있다. 하지만
# gradient가 다르고 포화되는 위치 gradient의 크기가 제 각각이다.

```



2. [오류 역전파] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요. (4점)
(코드의 해서과 결과의 의미를 작성하세요.)

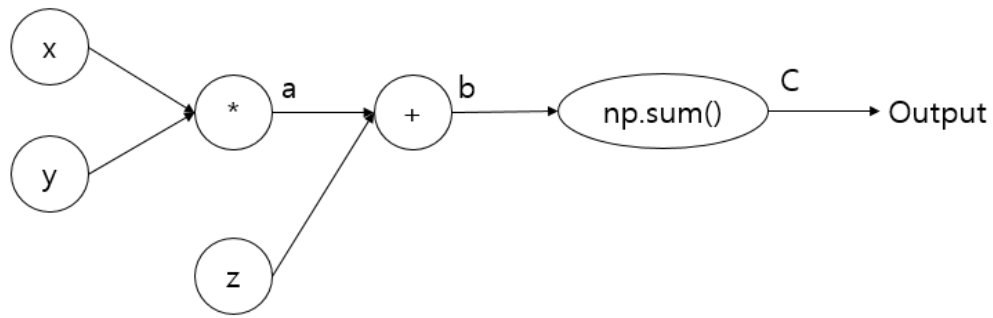
```
In [2]: import numpy as np
        # numpy's random seed
        # https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.seed.html
        np.random.seed(0)

        N, D = 3, 4

        # numpy's random rand
        # https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.randn.html
        x = np.random.randn(N, D)
        y = np.random.randn(N, D)
        z = np.random.randn(N, D)

        # in numpy, the sign like * + is elementwise
        a = x * y
        b = a + z
        c = np.sum(b)
        # (1) 해당 연산망의 그래프 연산을 손으로 작성
        # 아래의 그림처럼 단순 입력 값을 연산 순서에 맞게 위의 코드는
        # 계산을 한다.

In [3]: grad_c = 1.0
        grad_b = grad_c * np.ones((N,D))
        grad_a = grad_b.copy()
        grad_z = grad_b.copy()
        grad_x = grad_a*y
        grad_y = grad_a*x
        # (2) grad_c, grad_b, grad_a, grad_z, grad_x, grad_y 출력 확인
```



아래의 경우 *error*에 대한 *backpropagation*을 위한 *gradient*를 계산한 결과이다.

```

print("grad_c:\n{}".format(grad_c))
print("grad_b:\n{}".format(grad_b))
print("grad_a:\n{}".format(grad_a))
print("grad_z:\n{}".format(grad_z))
print("grad_x:\n{}".format(grad_x))
print("grad_y:\n{}".format(grad_y))

```

```

grad_c:
1.0
grad_b:
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
grad_a:
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
grad_z:
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
grad_x:
[[ 0.76103773  0.12167502  0.44386323  0.33367433]
 [ 1.49407907 -0.20515826  0.3130677  -0.85409574]
 [-2.55298982  0.6536186   0.8644362  -0.74216502]]
grad_y:
[[ 1.76405235  0.40015721  0.97873798  2.2408932 ]
 [ 1.86755799 -0.97727788  0.95008842 -0.15135721]
 [-0.10321885  0.4105985   0.14404357  1.45427351]]

```

```
In [4]: import torch
```

The Reference of *torch.randn(N, D)* is normal distribution

```

# about mean equal to 0, variance 1.
# https://pytorch.org/docs/stable/torch.html#torch.randn
x = torch.randn(N, D, requires_grad = True)
y = torch.randn(N, D, requires_grad = True)
z = torch.randn(N, D)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()
# (3) grad_x, grad_y 출력확인
print("grad_x:\n{}".format(x.grad))
print("grad_y:\n{}".format(y.grad))

# 아래의 출력결과는 torch를 활용한 gradient 결과이다.

```

```

grad_x:
tensor([[ 1.0741,  1.9732,  1.4140, -1.0282],
        [-1.1895, -1.1022, -0.5007, -1.9635],
        [-0.2747, -1.3813,  0.5262,  1.0943]])
grad_y:
tensor([[ 0.4448, -0.1613, -0.2329, -0.4336],
        [ 0.5539,  1.0458,  0.5737,  0.9508],
        [ 2.2725, -0.7400, -0.6197,  1.4848]])

```

3. [오류 역전파] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요. (4점)
(코드의 해석과 결과의 의미를 작성하세요.)

```
In [5]: import torch
```

```

x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)
w_h = torch.randn(20, 20, requires_grad = True)
w_x = torch.randn(20, 10, requires_grad = True)

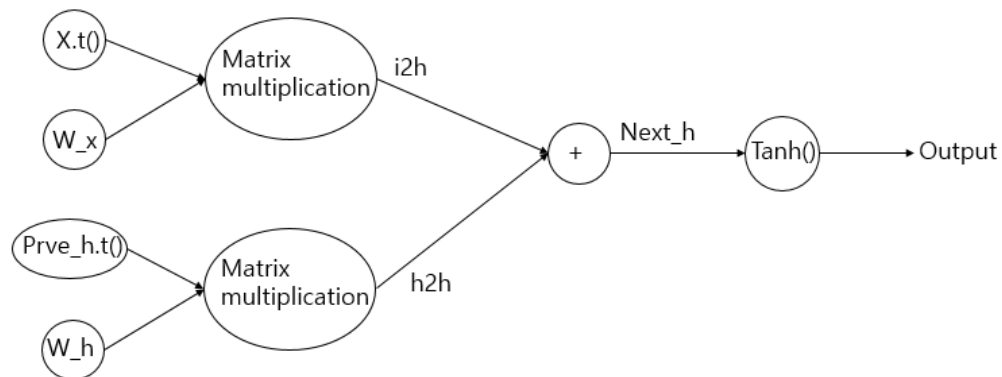
# for debugging
#print("x:\n{}".format(x))
#print("prev_h:\n{}".format(prev_h))
#print("w_h:\n{}".format(w_h))
#print("w_x:\n{}".format(w_x))

# The Reference of torch.mm is
# https://pytorch.org/docs/stable/torch.html?highlight=torch%20mm#torch.mm
# it means performing a matrix multiplication of the matrixes, torch.mm(mat1, mat2)
i2h = torch.mm(w_x, x.t())
h2h = torch.mm(w_h, prev_h.t())

```

```
next_h = i2h + h2h
next_h = next_h.tanh()
# (1) 해당 신경망의 그래프를 연산을 손으로 작성
```

아래의 그림을 벡터화 연산을 단순한 연산 그래프로 표현을 한 것이다.



```
In [6]: loss = next_h.sum()

# This backpropagation.
loss.backward()
# (2) loss 출력확인
print("loss:\n{}".format(loss))

# 위의 연산 그래프를 기반으로 첫번째 연산 결과의 값을 출력을 하고 있다.
```

```
loss:
3.5939688682556152
```

4. [신경망 학습] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요.(4점) (코드의 해석화 결과의 의미를 작성하세요.)

```
In [7]: import torch
# (1)의 그래프를 위한 library
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
```

```

# In the case below, I fixed it from D to N, wrong letter D in original assignment.
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H)
w2 = torch.randn(H, D_out)

learning_rate = 10e-6

loss1 = []
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()
    # (1)의 출력을 위해
    loss1.append(loss)

    grad_y_pred = 2.0*(y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

# If you want to know how to use matplotlib
# reference is
# https://matplotlib.org/tutorials/introductory/usage.html-
# sphx-glr-tutorials-introductory-usage-py
# (1) y_pred에 따른 loss(accuracy) 변화를 화면 출력확인 (plot)

# x_array is a range of y_pred
x_array = np.linspace(-10, 10, len(loss1))

loss_array = np.asarray(loss1)
plt.plot(x_array, loss_array, "b-", linewidth=2, label="loss")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

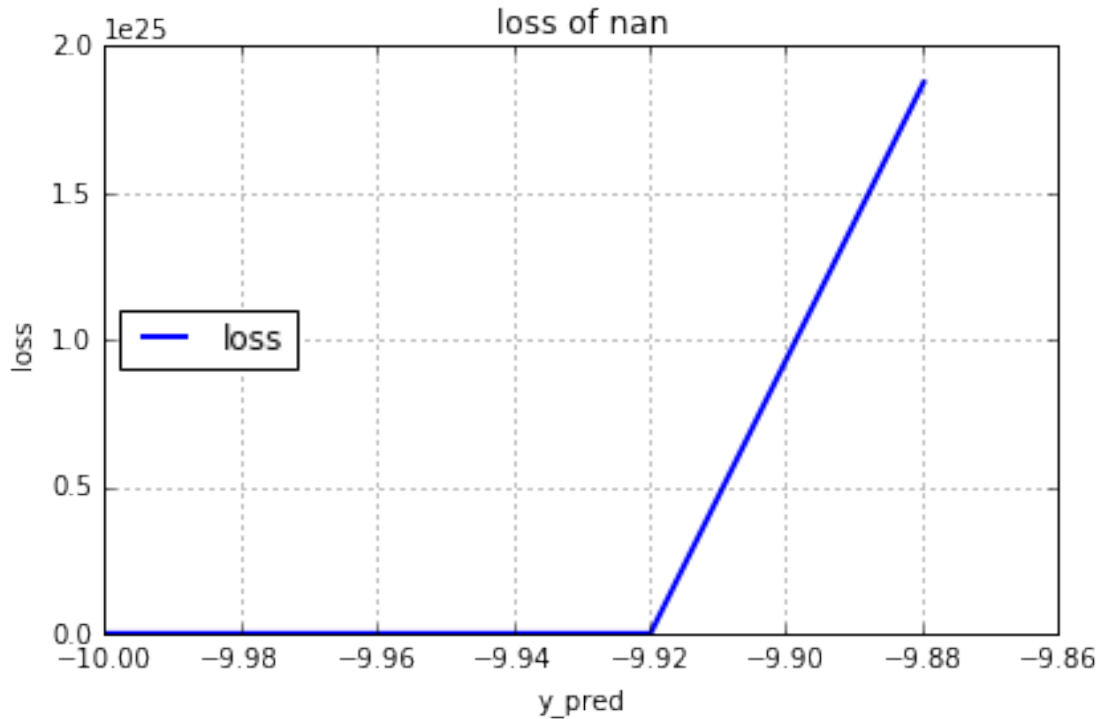
plt.title("loss of nan")

plt.legend(loc="center left")
plt.tight_layout()

plt.show()

```

```
print(loss_array[:10])
# (2) 해당 학습이 적절히 진행되고 있는지 서술
# 그래프 아래의 loss 일부분을 출력 결과들에서 볼 수 있듯이
# loss의 값은 inf에서 nan으로 되는 것을 확인할 수 있다.
# 즉, 제대로 학습이 진행이 되지 않고 loss가 NAN(not a number) 되고 있다.
```



```
[3.7456420e+07 4.3933655e+09 2.1102670e+13 1.8754189e+25          inf
nan          nan          nan          nan          nan]
```

5. [신경망 학습] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요.(4점) (코드의 해서과 결과의 의미를 작성하세요.)

```
In [8]: import torch
# (1)의 그래프를 위한 library
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
```



```

# In the case below, I fixed it from D to N, wrong letter D in original assignment.
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad = True)
w2 = torch.randn(H, D_out, requires_grad = True)

loss2 = []
learning_rate = 10e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred-y).pow(2).sum()
    loss2.append(loss)
    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()

# (1) 매 t마다 y_pred, loss 변화를 화면 출력확인(plot)
# x_array is a range of y_pred
x_array = np.linspace(-10, 10, len(loss2))

loss_array = np.asarray(loss2)
plt.plot(x_array, loss_array, "b-", linewidth=2, label="loss")

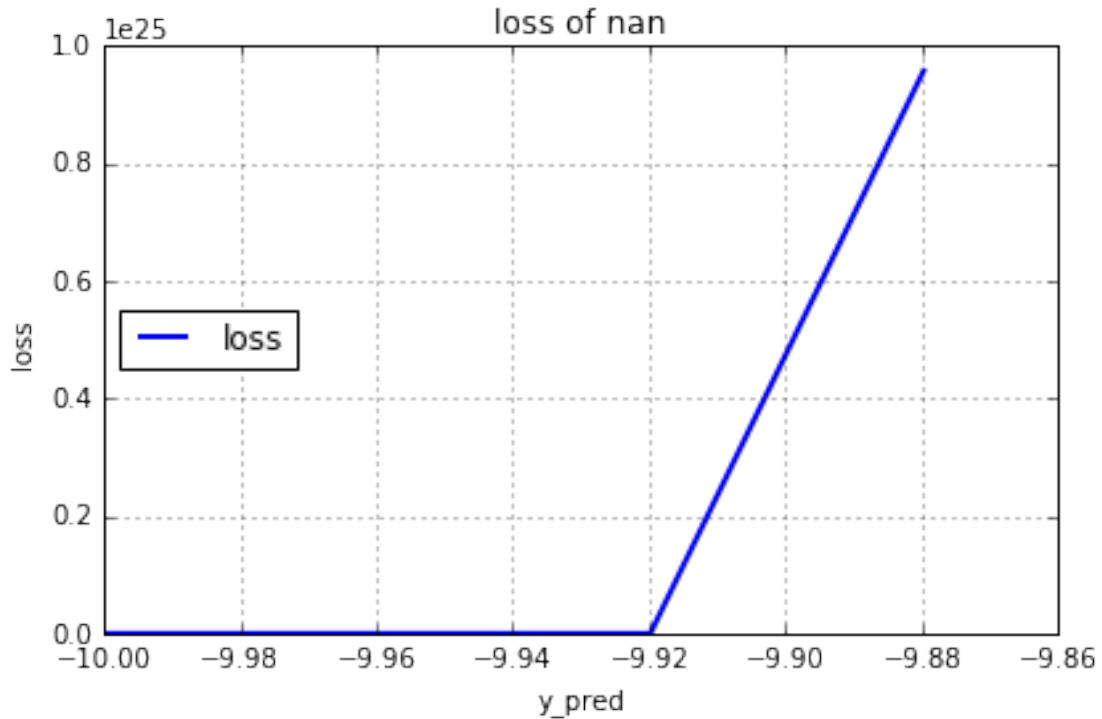
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss of nan")

plt.legend(loc="center left")
plt.tight_layout()

plt.show()
print(loss_array[:10])
# (2) 앞 문제의 코드와 비교
# 이경우에도 앞의 코드와 같은 INF(큰값)을 출력하고
# 결국 하드웨어가 표현 할 수 있는 숫자의 범위를 넘어서고 있어서
# NAN(not a number)로 제대로 학습이 되지 않는다.

```



```
[tensor(35326296., grad_fn=<SumBackward0>)
 tensor(3963422720., grad_fn=<SumBackward0>)
 tensor(16727616258048., grad_fn=<SumBackward0>)
 tensor(9575085153353902063616000., grad_fn=<SumBackward0>)
 tensor(inf, grad_fn=<SumBackward0>) tensor(nan, grad_fn=<SumBackward0>)
 tensor(nan, grad_fn=<SumBackward0>) tensor(nan, grad_fn=<SumBackward0>)
 tensor(nan, grad_fn=<SumBackward0>) tensor(nan, grad_fn=<SumBackward0>)]
```

6. [신경망 학습] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요. (4 점)
(코드의 해석과 결과의 의미를 작성하세요.)

```
In [9]: # if you want to kwon processing below
        # refer to https://pytorch.org/tutorials/beginner/-
        # pytorch_with_examples.html#pytorch-tensors-and-autograd

import torch
# (1)의 그래프를 위한 library
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
```

```

class MyReLU(torch.autograd.Function):
    @staticmethod
    def forward(ctx, x):
        ctx.save_for_backward(x)
        return x.clamp(min=0)

    @staticmethod
    def backward(ctx, grad_y):
        x, = ctx.saved_tensors
        grad_input = grad_y.clone()
        grad_input[x<0] = 0
        return grad_input

def my_relu(x):
    return MyReLU.apply(x)

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
# In the case below, I fixed it from D to N, wrong letter D in original assignment.
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad = True)
w2 = torch.randn(H, D_out, requires_grad = True)

learning_rate = 10e-6

loss3 = []
for t in range(500):
    y_pred = my_relu(x.mm(w1)).mm(w2)
    loss = (y_pred - y).pow(2).sum()
    loss3.append(loss)

    # Use autograd to compute the backward pass. This call will compute the
    # gradient of loss with respect to all Tensors with requires_grad=True.
    # After this call w1.grad and w2.grad will be Tensors holding the gradient
    # of the loss with respect to w1 and w1 respectively.
    loss.backward()

    # Manually update weights using gradient descent. Wrap in torch.no_grad()
    # because weights have requires_grad=True, but we don't need to track this
    # in autograd
    # An alternative way is to operate on weight.data and weight.grad.data.
    # Recall that tensor.data gives a tensor that shares the storage with
    # tensor, but doesn't track history.
    # You can also use torch.optim.SGD to achieve this.
    with torch.no_grad():

```

```

w1 -= learning_rate * w1.grad
w2 -= learning_rate * w2.grad

# Munually zero the gradient after updating weights.
w1.grad.zero_()
w2.grad.zero_()

# (1) 매 t마다 y_pred, loss 변화를 화면 출력 확인 (Plot)
# x_array is a range of y_pred
x_array = np.linspace(-10, 10, len(loss3))

loss_array = np.asarray(loss3)
plt.plot(x_array, loss_array, "b-", linewidth=2, label="loss")

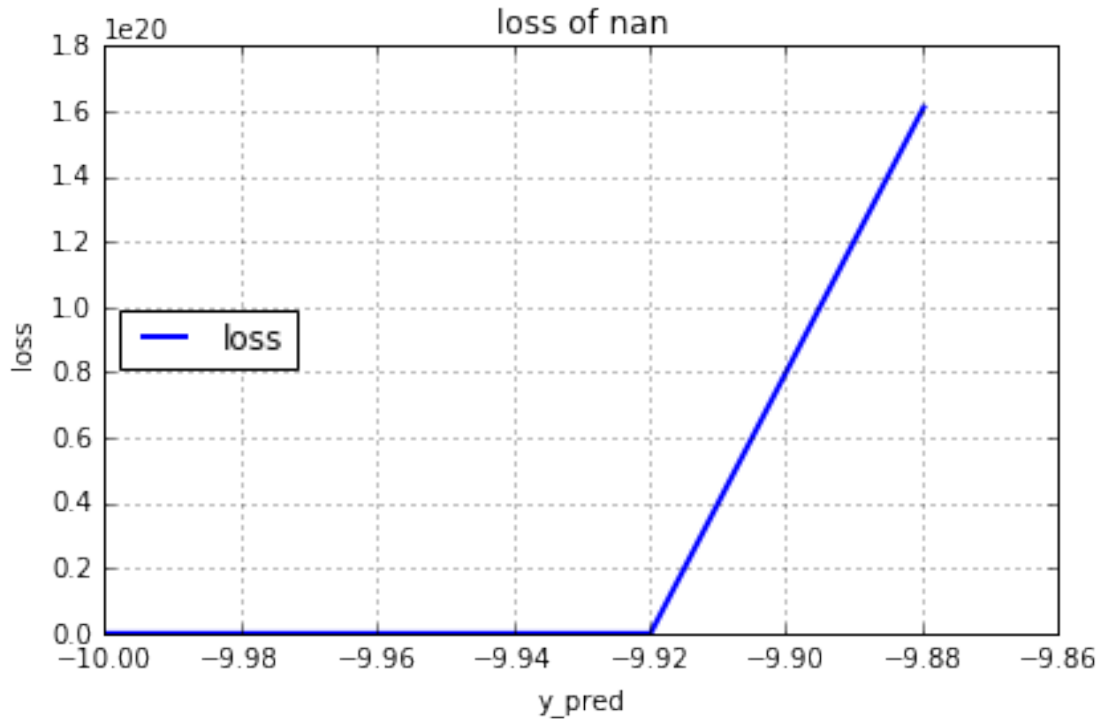
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss of nan")

plt.legend(loc="center left")
plt.tight_layout()

plt.show()
print(loss_array[:10])
# (2) 앞 문제의 코드와 비교
# 이 문제도 앞의 코드와 같이
# NAN(not a number) 문제가 발생하여
# 제대로 학습이 되지 않는다.

```



```
[tensor(28107224., grad_fn=<SumBackward0>)
 tensor(1546043264., grad_fn=<SumBackward0>)
 tensor(481758478336., grad_fn=<SumBackward0>)
 tensor(161188738883496443904., grad_fn=<SumBackward0>)
 tensor(inf, grad_fn=<SumBackward0>) tensor(inf, grad_fn=<SumBackward0>)
 tensor(nan, grad_fn=<SumBackward0>) tensor(nan, grad_fn=<SumBackward0>)
 tensor(nan, grad_fn=<SumBackward0>) tensor(nan, grad_fn=<SumBackward0>)]
```

7. [신경망 학습] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요.(4점) (코드의 해석과 결과의 의미를 작성하세요.)

```
In [10]: # -*- coding: utf-8 -*-
import torch

# (1)의 그래프를 위한 library
import numpy as np
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
```

```

        """
        In the constructor we instantiate two nn.Linear modules and assign them as
        member variables.
        """
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        """
        In the forward function we accept a Tensor of input data and we must return
        a Tensor of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Tensors.
        """
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

# N is batch size; D_in is input dimension;
# H is hidden dimension; D_out is output dimension.
N, D_in, H, D_out = 64, 1000, 100, 10

# Create random Tensors to hold inputs and outputs
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

# Construct our model by instantiating the class defined above
model = TwoLayerNet(D_in, H, D_out)

# 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.MSELoss(reduction='sum')
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)

loss4 = []
for t in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x)

    # Compute and print loss
    loss = criterion(y_pred, y)
    loss4.append(loss)
    print(t, loss.item())

    # optimizer.zero_grad()

```

```

# Backward pass: compute gradient of the loss with respect to model
# parameters
loss.backward()

# Calling the step function on an Optimizer makes an update to its
# parameters
optimizer.step()
# This is code error
# Before the backward pass, use the optimizer object to zero all of the
# gradients for the variables it will update (which are the learnable
# weights of the model). This is because by default, gradients are
# accumulated in buffers( i.e, not overwritten) whenever .backward()
# is called. Checkout docs of torch.autograd.backward for more details.
optimizer.zero_grad()

```

```

0 752.291259765625
1 697.1152954101562
2 649.825439453125
3 608.62841796875
4 572.4631958007812
5 540.3025512695312
6 511.09442138671875
7 484.2495422363281
8 459.5650634765625
9 436.6903076171875
10 415.0898742675781
11 394.4296875
12 374.9518737792969
13 356.33203125
14 338.6272888183594
15 321.73406982421875
16 305.5383605957031
17 290.00274658203125
18 275.1201171875
19 260.8442077636719
20 247.1610870361328
21 234.00474548339844
22 221.4241943359375
23 209.39483642578125
24 197.90155029296875
25 186.92022705078125
26 176.44859313964844
27 166.4690399169922
28 156.9864044189453
29 147.99073791503906
30 139.47186279296875
31 131.36688232421875

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32 123.66256713867188
33 116.37864685058594
34 109.49337768554688
35 102.98854064941406
36 96.83961486816406
37 91.03842163085938
38 85.57056427001953
39 80.41991424560547
40 75.56986236572266
41 70.99664306640625
42 66.68790435791016
43 62.64469909667969
44 58.84621047973633
45 55.281681060791016
46 51.93621063232422
47 48.79524230957031
48 45.84355163574219
49 43.068058013916016
50 40.46259307861328
51 38.01936340332031
52 35.72951126098633
53 33.58113479614258
54 31.563623428344727
55 29.669754028320312
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57 26.223913192749023
58 24.660503387451172
59 23.193754196166992
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61 20.527132034301758
62 19.316198348999023
63 18.180282592773438
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65 16.116180419921875
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68 13.472288131713867
69 12.698366165161133
70 11.971505165100098
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86 4.821960926055908
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89 4.094974040985107
90 3.879796028137207
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498 3.156185584884952e-06
499 3.0662204153486528e-06

```

```

In [11]: # (1) 매 t마다 y_pred, loss 변화를 화면 출력확인(plot)
         # x_array is a range of y_pred
         x_array = np.linspace(-10, 10, len(loss4))

         loss_array = np.asarray(loss4)
         plt.plot(x_array, loss_array, "b-", linewidth=2, label="loss")

         plt.xlabel("y_pred")
         plt.ylabel("loss")
         plt.grid(True)

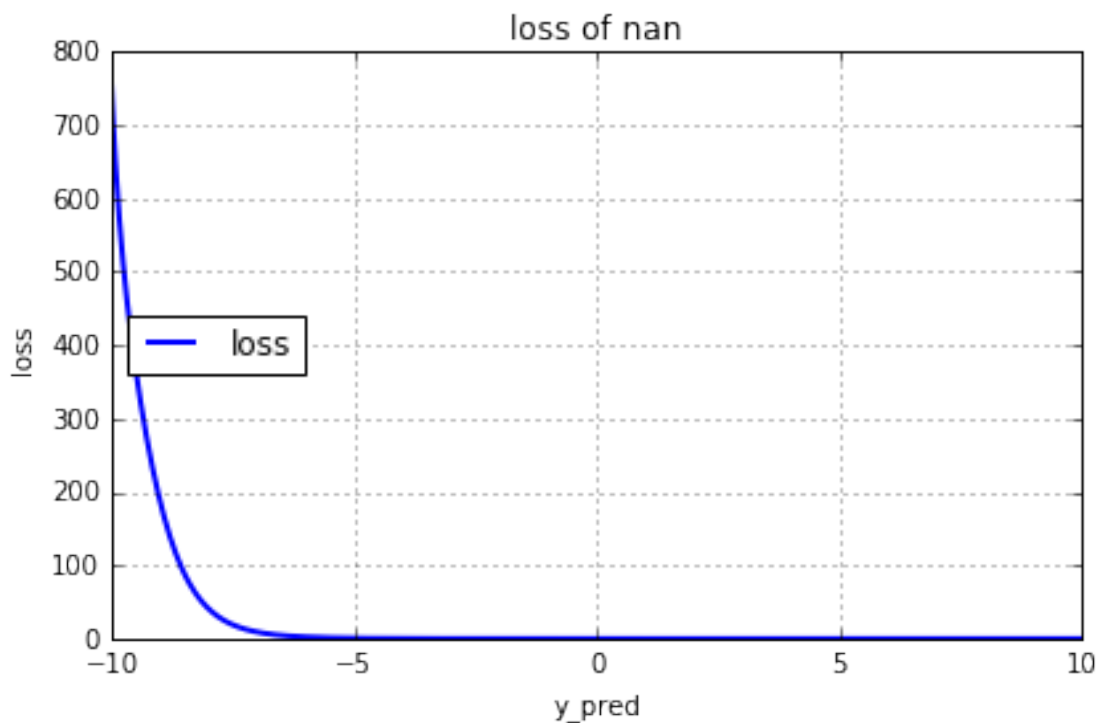
```

```
plt.title("loss of nan")

plt.legend(loc="center left")
plt.tight_layout()

plt.show()
print(loss_array[:10])

# (2) 앞 문제의 코드와 비교
# 앞의 코드와 비교했을 때 loss는 계속
# 감소하는 방향으로 제대로 학습이 되고 있다.
```



```
[tensor(752.2913, grad_fn=<MseLossBackward>)
 tensor(697.1153, grad_fn=<MseLossBackward>)
 tensor(649.8254, grad_fn=<MseLossBackward>)
 tensor(608.6284, grad_fn=<MseLossBackward>)
 tensor(572.4632, grad_fn=<MseLossBackward>)
 tensor(540.3026, grad_fn=<MseLossBackward>)
 tensor(511.0944, grad_fn=<MseLossBackward>)
 tensor(484.2495, grad_fn=<MseLossBackward>)
 tensor(459.5651, grad_fn=<MseLossBackward>)
 tensor(436.6903, grad_fn=<MseLossBackward>)]
```

8. [데이터 전처리] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요.(4점)
(코드의 해석과 결과의 의미를 작성하세요.)

```
In [12]: import torch
         from torch.utils.data import TensorDataset, DataLoader

         # (1)의 그래프를 위한 library
         import numpy as np
         %matplotlib inline
         import matplotlib
         import matplotlib.pyplot as plt

         N, D_in, H, D_out = 64, 1000, 100, 10

         x = torch.randn(N, D_in)
         # In the case below, I fixed it from D to N, wrong letter D in original assignment.
         y = torch.randn(N, D_out)

         loader = DataLoader(TensorDataset(x,y), batch_size=8)
         model = TwoLayerNet(D_in, H, D_out)

         # mean squared error of nn module
         loss_fn = torch.nn.MSELoss(reduction='sum')

         # Stochastic gradient descent of nn module
         optimizer = torch.optim.SGD(model.parameters(), lr=1e-2)

         loss5 = []
         for epoch in range(20):
             loss5.append([])
             for x_batch, y_batch in loader:
                 y_pred = model(x_batch)
                 loss = loss_fn(y_pred, y_batch)
                 loss5[epoch].append(loss)
                 loss.backward()
                 optimizer.step()
                 optimizer.zero_grad()

         # (1) 매 세대(epoch)마다 y_pred, loss 변화를 화면 출력 확인(plot)
         # x_array is a range of y_pred
         plt.figure(figsize=(11,4))

         x_array = np.linspace(-1, 1, len(loss5[0]))
```

```

lines = ["r-", "g--", "b-", "m-."]

plt.subplot(141)
loss_array = np.asarray(loss5[0])
plt.plot(x_array, loss_array, lines[0], linewidth=2, label="loss_of_epoch_1")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")
plt.legend(loc="best")

plt.subplot(142)
loss_array = np.asarray(loss5[1])
plt.plot(x_array, loss_array, lines[1], linewidth=2, label="loss_of_epoch_2")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(143)
loss_array = np.asarray(loss5[2])
plt.plot(x_array, loss_array, lines[2], linewidth=2, label="loss_of_epoch_3")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(144)
loss_array = np.asarray(loss5[3])

plt.plot(x_array, loss_array, lines[3], linewidth=2, label="loss_of_epoch_4")

```

```

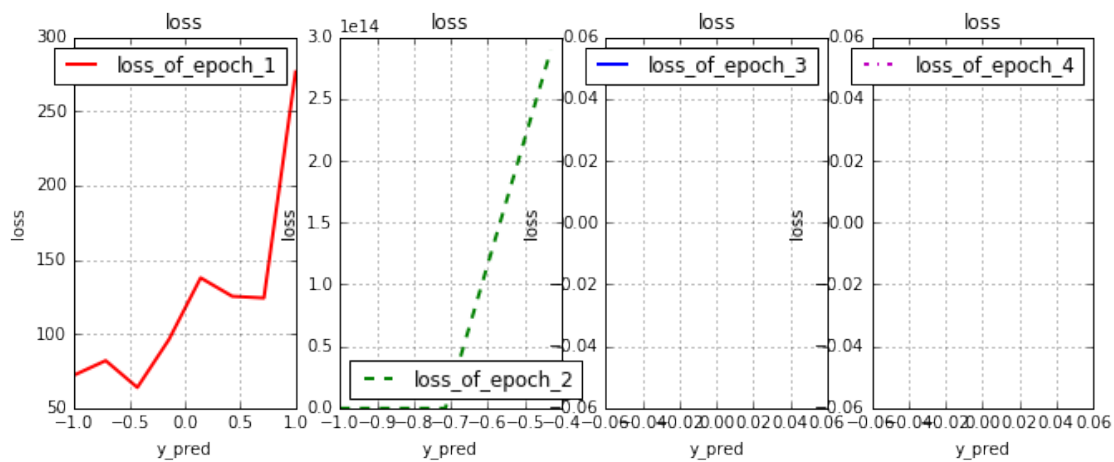
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.show()
##### epoch 1 ~ 4 is done

```



```

In [13]: plt.figure(figsize=(11,4))

x_array = np.linspace(-1, 1, len(loss5[0]))

lines = ["r-", "g--", "b-", "m-."]

plt.subplot(141)
loss_array = np.asarray(loss5[4])
plt.plot(x_array, loss_array, lines[0], linewidth=2, label="loss_of_epoch_5")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")
plt.legend(loc="best")

```

```

plt.subplot(142)
loss_array = np.asarray(loss5[5])
plt.plot(x_array, loss_array, lines[1], linewidth=2, label="loss_of_epoch_6")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")


plt.subplot(143)
loss_array = np.asarray(loss5[6])
plt.plot(x_array, loss_array, lines[2], linewidth=2, label="loss_of_epoch_7")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")


plt.subplot(144)
loss_array = np.asarray(loss5[7])

plt.plot(x_array, loss_array, lines[3], linewidth=2, label="loss_of_epoch_8")

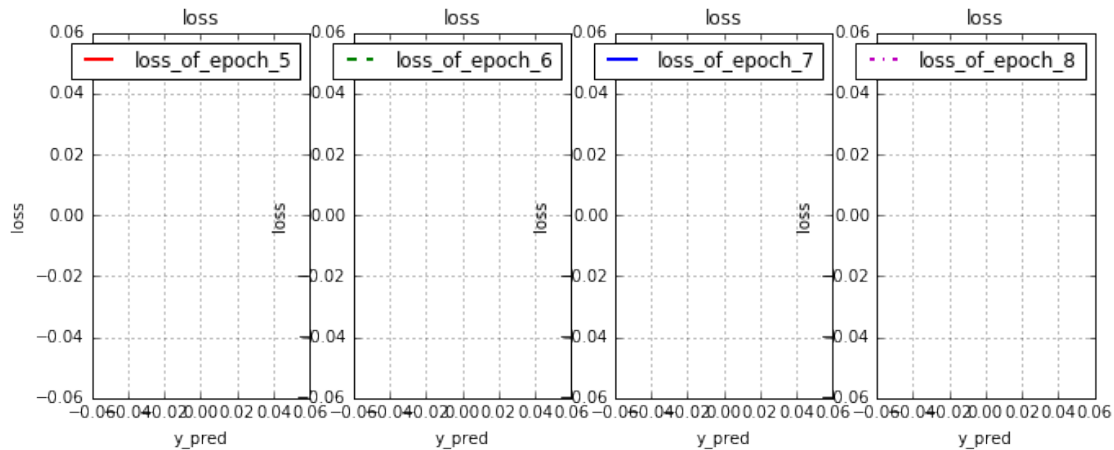
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.show()
##### epoch 5 ~ 8 is done

```



```
In [14]: plt.figure(figsize=(11,4))

x_array = np.linspace(-1, 1, len(loss5[0]))

lines = ["r-", "g--", "b-", "m-."]

plt.subplot(141)
loss_array = np.asarray(loss5[8])
plt.plot(x_array, loss_array, lines[0], linewidth=2, label="loss_of_epoch_9")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")
plt.legend(loc="best")

plt.subplot(142)
loss_array = np.asarray(loss5[9])
plt.plot(x_array, loss_array, lines[1], linewidth=2, label="loss_of_epoch_10")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")
```

```
plt.subplot(143)
loss_array = np.asarray(loss5[10])
plt.plot(x_array, loss_array, lines[2], linewidth=2, label="loss_of_epoch_11")
```

```
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)
```

```
plt.title("loss")
```

```
plt.legend(loc="best")
```

```
plt.subplot(144)
loss_array = np.asarray(loss5[11])
```

```
plt.plot(x_array, loss_array, lines[3], linewidth=2, label="loss_of_epoch_12")
```

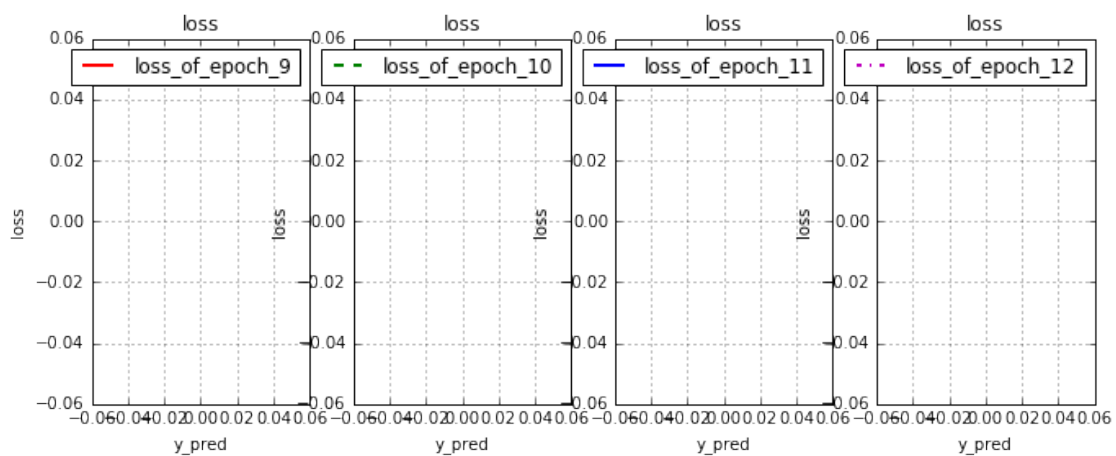
```
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)
```

```
plt.title("loss")
```

```
plt.legend(loc="best")
```

```
plt.show()
```

```
##### epoch 9 ~ 12 is done
```




```

In [15]: plt.figure(figsize=(11,4))

x_array = np.linspace(-1, 1, len(loss5[0]))

lines = ["r-", "g--", "b-", "m-."]

plt.subplot(141)
loss_array = np.asarray(loss5[12])
plt.plot(x_array, loss_array, lines[0], linewidth=2, label="loss_of_epoch_13")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")
plt.legend(loc="best")

plt.subplot(142)
loss_array = np.asarray(loss5[13])
plt.plot(x_array, loss_array, lines[1], linewidth=2, label="loss_of_epoch_14")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(143)
loss_array = np.asarray(loss5[14])
plt.plot(x_array, loss_array, lines[2], linewidth=2, label="loss_of_epoch_15")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(144)

```

```

loss_array = np.asarray(loss5[15])

plt.plot(x_array, loss_array, lines[3], linewidth=2, label="loss_of_epoch_16")

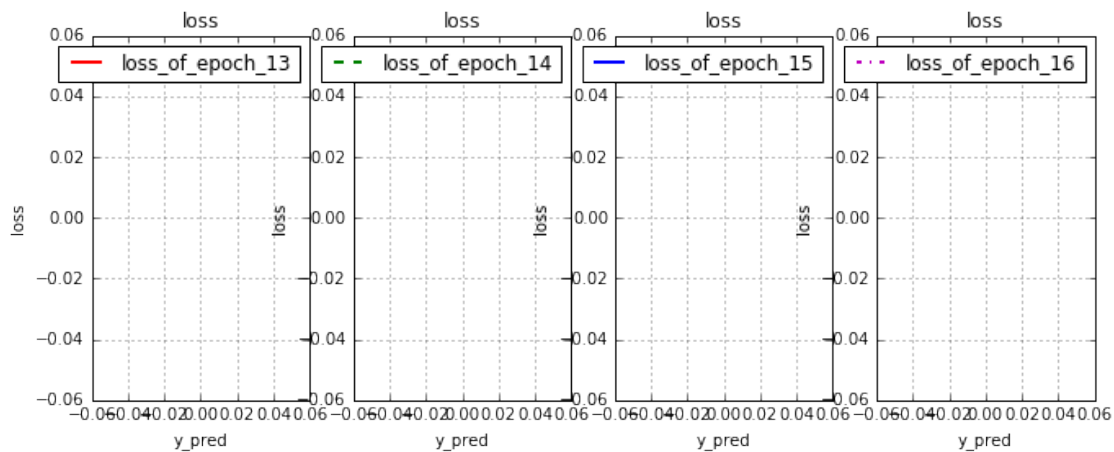
plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.show()
##### epoch 13 ~ 16 is done

```



```

In [16]: plt.figure(figsize=(11,4))

x_array = np.linspace(-1, 1, len(loss5[0]))

lines = ["r-", "g--", "b-", "m-."]

plt.subplot(141)
loss_array = np.asarray(loss5[16])
plt.plot(x_array, loss_array, lines[0], linewidth=2, label="loss_of_epoch_17")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

```

```

plt.legend(loc="best")

plt.subplot(142)
loss_array = np.asarray(loss5[17])
plt.plot(x_array, loss_array, lines[1], linewidth=2, label="loss_of_epoch_18")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(143)
loss_array = np.asarray(loss5[18])
plt.plot(x_array, loss_array, lines[2], linewidth=2, label="loss_of_epoch_19")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

plt.legend(loc="best")

plt.subplot(144)
loss_array = np.asarray(loss5[19])

plt.plot(x_array, loss_array, lines[3], linewidth=2, label="loss_of_epoch_20")

plt.xlabel("y_pred")
plt.ylabel("loss")
plt.grid(True)

plt.title("loss")

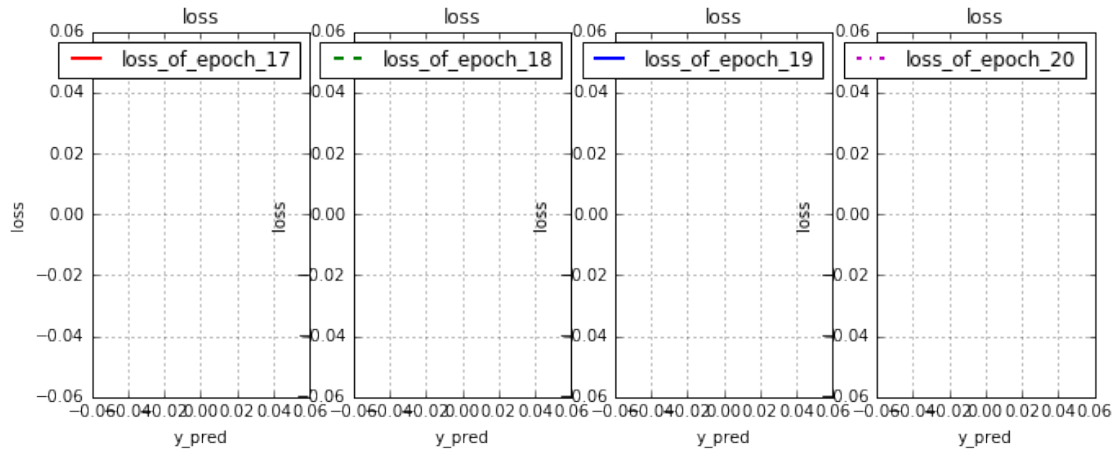
plt.legend(loc="best")

plt.show()
##### epoch 17 ~ 20 is done

```

```
print(loss_array[:10])
```

```
# (2) 앞 문제의 코드와 비교
# 앞의 문제의 코드와 비교 했을때,
# epoch이 증가 할때마다 loss가 증가하고
# inf(무한대) 값을 거쳐 NAN 값으로 변하기 때문에
# 학습이 제대로 이루어지지 않고 있다.
```



```
[tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)
 tensor(nan, grad_fn=<MseLossBackward>)]
```

9. [영상 인식] 다음 코드를 무엇을 의미하는지 이해하고 실행하여 결과를 확인하세요.(12 점) (코드의 해석과 결과의 의미를 작성하세요.)

```
In [17]: import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
from torch.autograd import Variable
import matplotlib.pyplot as plt
%matplotlib inline

is_cuda = False
```

```

if torch.cuda.is_available():
    is_cuda = True

# Load data
# reference is
# https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html
transformation = transforms.Compose([transforms.ToTensor(),
                                     transforms.Normalize((0.1307,), (0.3081,))])

# MNIST data set
train_dataset = datasets.MNIST('data/', train=True,
                               transform=transformation, download=True)
test_dataset = datasets.MNIST('data/', train=False,
                              transform=transformation, download=True)

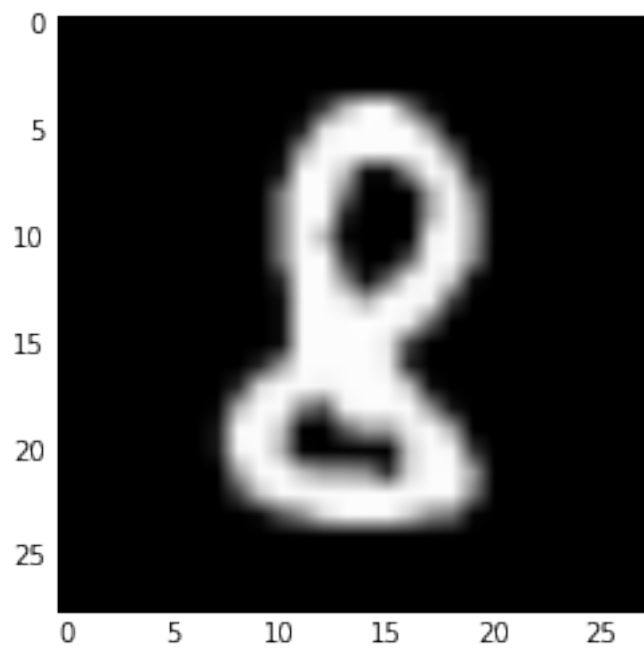
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=32, shuffle=True)

# first data for sample
sample_data = next(iter(train_loader))

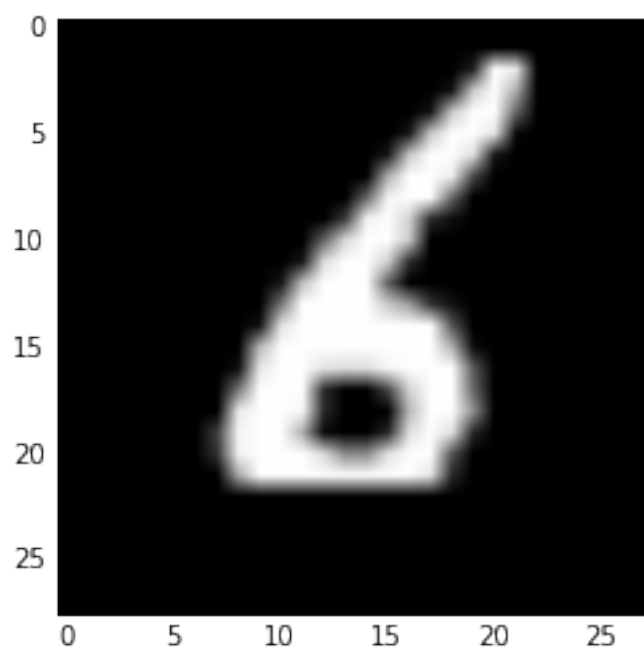
def plot_img(image):
    image = image.numpy()[0]
    mean = 0.1307
    std = 0.3081
    image = ((mean * image) + std)
    plt.imshow(image, cmap='gray')

# first data set's image
plot_img(sample_data[0][2])
# (1) 화면 출력 확인

```



```
In [18]: plot_img(sample_data[0][1])  
# (2) 화면 출력 확인
```



```
In [19]: # Convolution neural network
```

```
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        # Dropout for optimization to regularize
        self.conv2_drop = nn.Dropout2d()
        self.fc1 = nn.Linear(320, 50)
        self.fc2 = nn.Linear(50, 10)

    def forward(self, x):
        x = F.relu(F.max_pool2d(self.conv1(x), 2))
        x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
        x = x.view(-1, 320)
        x = F.relu(self.fc1(x))
        # x = F.dropout(x, p=0.1, training = self.training)
        x = self.fc2(x)
        return F.log_softmax(x, dim=1)
```

```
model = Net()
```

```
is_cuda = False
```

```
if is_cuda:
    model.cuda()
```

```
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

```
data, target = next(iter(train_loader))
```

```
output = model(Variable(data))
```

```
# (3) output.size() 출력확인
# predicted output tensor of log_softmax
print("output.size():\n{}".format(output.size()))
# (4) target.size() 출력확인
# actual label
print("\ntarget.size():\n{}".format(target.size()))
```

```
output.size():
torch.Size([32, 10])
```

```
target.size():
torch.Size([32])
```

```
In [20]: # For training of model of Net()
```

```

def fit(epoch, model, data_loader, phase="training", volatile=False):
    if phase == 'training':
        model.train()
    if phase == 'validation':
        model.eval()
        volatile = True
    running_loss = 0.0
    running_correct = 0
    for batch_idx, (data, target) in enumerate(data_loader):
        #if is_cuda:
        #    data, target = data.cuda(), target.cuda()
        data, target = Variable(data, volatile), Variable(target)
        if phase == 'training':
            optimizer.zero_grad()
            output = model(data)
            loss = F.nll_loss(output, target)

            running_loss += F.nll_loss(output, target, size_average=False).data[0]
            preds = output.data.max(dim=1, keepdim=True)[1]
            running_correct += preds.eq(target.data.view_as(preds)).cpu().sum()

        if phase == 'training':
            loss.backward()
            optimizer.step()

    loss = running_loss/len(data_loader.dataset)
    accuracy = 100. * running_correct/len(data_loader.dataset)

    print("{} loss is {} and {} accuracy is {}/{} -> {}".format(phase, loss, phase,
                                                                running_correct,
                                                                len(data_loader.dataset),
                                                                accuracy))

    return loss, accuracy

train_losses, train_accuracy = [], []
val_losses, val_accuracy = [], []

for epoch in range(1, 20):
    epoch_loss, epoch_accuracy = fit(epoch, model, train_loader, phase='training')
    val_epoch_loss, val_epoch_accuracy = fit(epoch, model,
                                              test_loader, phase='validation')

    train_losses.append(epoch_loss)
    train_accuracy.append(epoch_accuracy)
    val_losses.append(val_epoch_loss)
    val_accuracy.append(val_epoch_accuracy)
    # (5) 화면 출력 확인
    # Cross validation

```



```
# comparing training set with validation set  
# I can early stop
```

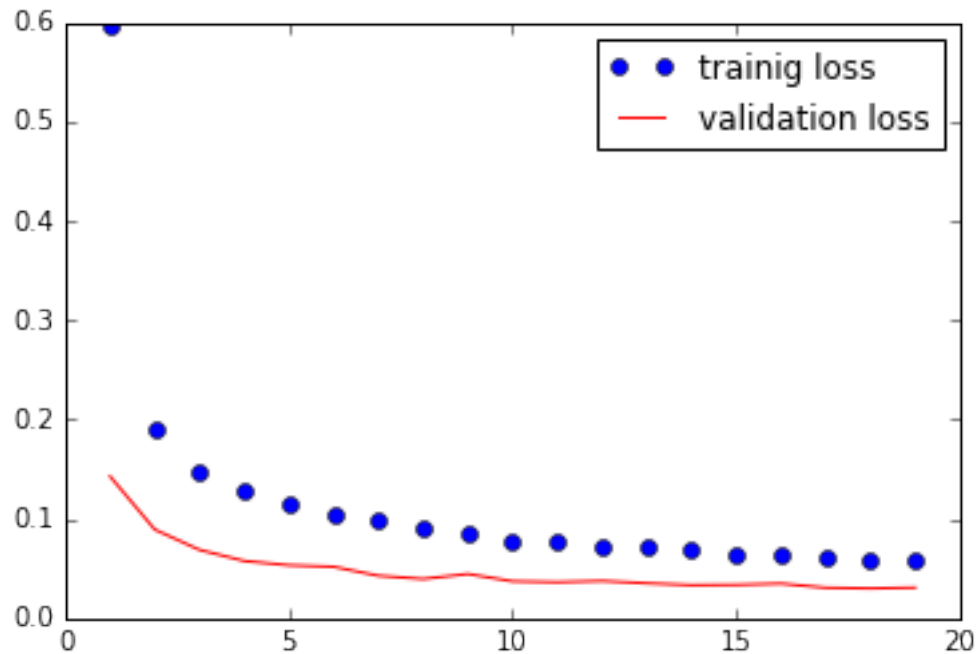
```
/home/hyunyoung2/.local/lib/python3.5/site-packages/torch/nn/functional.py:52: UserWarning: si  
warnings.warn(warning.format(ret))  
/home/hyunyoung2/.local/lib/python3.5/site-packages/ipykernel_launcher.py:20: UserWarning: inv
```

```
training loss is 0.5956605672836304 and training accuracy is 49062/60000 -> 81)  
validation loss is 0.1428748220205307 and validation accuracy is 9557/10000 -> 95)  
training loss is 0.19141218066215515 and training accuracy is 56613/60000 -> 94)  
validation loss is 0.08931832015514374 and validation accuracy is 9723/10000 -> 97)  
training loss is 0.14799994230270386 and training accuracy is 57386/60000 -> 95)  
validation loss is 0.06888460367918015 and validation accuracy is 9778/10000 -> 97)  
training loss is 0.12740691006183624 and training accuracy is 57771/60000 -> 96)  
validation loss is 0.057700544595718384 and validation accuracy is 9805/10000 -> 98)  
training loss is 0.1137586161494255 and training accuracy is 57977/60000 -> 96)  
validation loss is 0.0534110888838768 and validation accuracy is 9824/10000 -> 98)  
training loss is 0.10471786558628082 and training accuracy is 58127/60000 -> 96)  
validation loss is 0.05187523365020752 and validation accuracy is 9823/10000 -> 98)  
training loss is 0.09773274511098862 and training accuracy is 58229/60000 -> 97)  
validation loss is 0.042845770716667175 and validation accuracy is 9857/10000 -> 98)  
training loss is 0.09033861011266708 and training accuracy is 58359/60000 -> 97)  
validation loss is 0.0396590456366539 and validation accuracy is 9870/10000 -> 98)  
training loss is 0.08578614890575409 and training accuracy is 58478/60000 -> 97)  
validation loss is 0.04460400342941284 and validation accuracy is 9852/10000 -> 98)  
training loss is 0.07841832935810089 and training accuracy is 58611/60000 -> 97)  
validation loss is 0.037293486297130585 and validation accuracy is 9873/10000 -> 98)  
training loss is 0.07716350257396698 and training accuracy is 58599/60000 -> 97)  
validation loss is 0.03643083572387695 and validation accuracy is 9882/10000 -> 98)  
training loss is 0.07127117365598679 and training accuracy is 58697/60000 -> 97)  
validation loss is 0.03758731856942177 and validation accuracy is 9877/10000 -> 98)  
training loss is 0.07082290202379227 and training accuracy is 58744/60000 -> 97)  
validation loss is 0.035266581922769547 and validation accuracy is 9887/10000 -> 98)  
training loss is 0.07003258168697357 and training accuracy is 58731/60000 -> 97)  
validation loss is 0.0334736593067646 and validation accuracy is 9895/10000 -> 98)  
training loss is 0.06351704150438309 and training accuracy is 58842/60000 -> 98)  
validation loss is 0.03375457599759102 and validation accuracy is 9894/10000 -> 98)  
training loss is 0.06294967234134674 and training accuracy is 58852/60000 -> 98)  
validation loss is 0.03494734689593315 and validation accuracy is 9877/10000 -> 98)  
training loss is 0.06090139225125313 and training accuracy is 58898/60000 -> 98)  
validation loss is 0.030788660049438477 and validation accuracy is 9902/10000 -> 99)  
training loss is 0.058314986526966095 and training accuracy is 58939/60000 -> 98)  
validation loss is 0.03013336844742298 and validation accuracy is 9897/10000 -> 98)  
training loss is 0.057965610176324844 and training accuracy is 58945/60000 -> 98)  
validation loss is 0.030912548303604126 and validation accuracy is 9896/10000 -> 98)
```

```
In [21]: plt.plot(range(1,len(train_losses)+1), train_losses, 'bo', label = 'trainig loss')
```

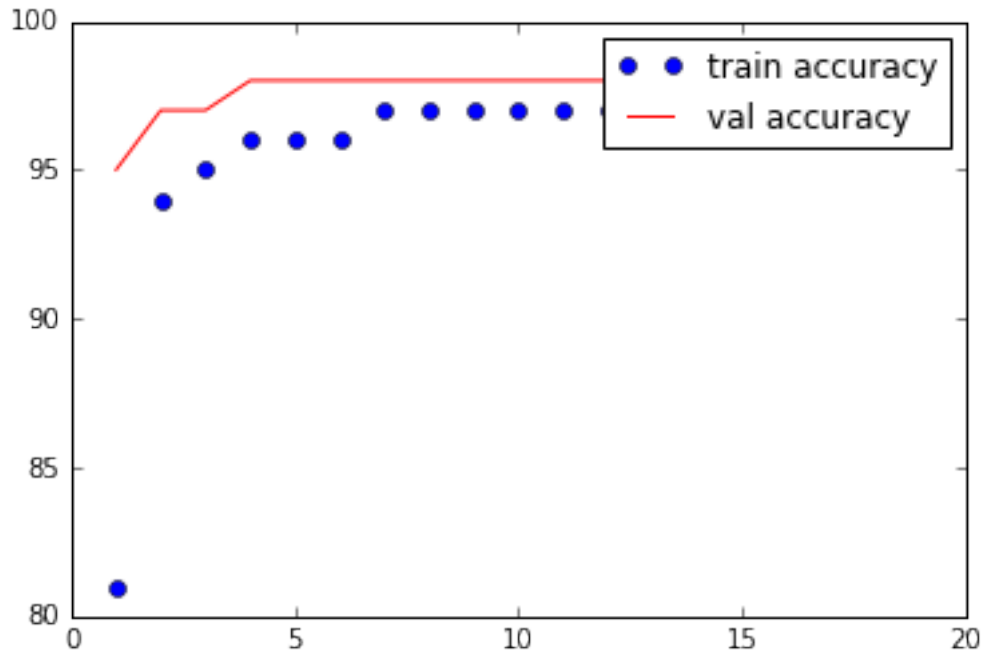
```
plt.plot(range(1, len(val_losses)+1), val_losses, 'r', label = 'validation loss')
plt.legend()
# (6) 화면 출력 확인
# comparing training loss and validation loss
```

Out[21]: <matplotlib.legend.Legend at 0x7f15a4263be0>



```
In [22]: plt.plot(range(1, len(train_accuracy)+1), train_accuracy, 'bo', label = 'train accuracy')
plt.plot(range(1, len(val_accuracy)+1), val_accuracy, 'r', label = 'val accuracy')
plt.legend()
# (7) 화면 출력 확인
# comparing training accuracy and validation loss
```

Out[22]: <matplotlib.legend.Legend at 0x7f15a421a160>



10. NOR 게이트와 AND 게이트의 동작을 데이터로 간주하면 다음과 같다. 이들을 100% 옳게 분류하는 퍼셉트론을 각각 제시하시오.

$$\begin{array}{l}
 \text{NOR 분류} \left\{ \begin{array}{l} \mathbf{x}_1 = (0,0)^T, y_1 = 1 \\ \mathbf{x}_2 = (1,0)^T, y_2 = -1 \\ \mathbf{x}_3 = (0,1)^T, y_3 = -1 \\ \mathbf{x}_4 = (1,1)^T, y_4 = -1 \end{array} \right.
 \end{array}
 \quad
 \begin{array}{l}
 \text{AND 분류} \left\{ \begin{array}{l} \mathbf{x}_1 = (0,0)^T, y_1 = -1 \\ \mathbf{x}_2 = (1,0)^T, y_2 = -1 \\ \mathbf{x}_3 = (0,1)^T, y_3 = -1 \\ \mathbf{x}_4 = (1,1)^T, y_4 = 1 \end{array} \right.
 \end{array}$$

In []:

figure1-1의 퍼셉트론은 NOR gate를 위한 것이다. NOR 게이트의 분류를 하는 것도 hyper plane 하나로 가능하기 때문에 figure1의 그림처럼 hyper plane으로 영역을 두개로 구분하여 분류가 가능하다.

In []:

figure2-1 퍼셉트론은 AND gate를 위한 것이다. AND 게이트의 경우에는 하나의 hyper plane을 통해 output 결과들을 figure2와 같이 분류할 수 있다. 그래서 충분히 하나의 perceptron으로 분류가 가능하다.

In []:

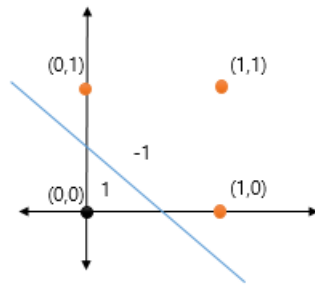


Figure1. NOR gate

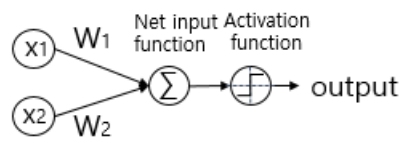


Figure1-1. NOR gate perceptron

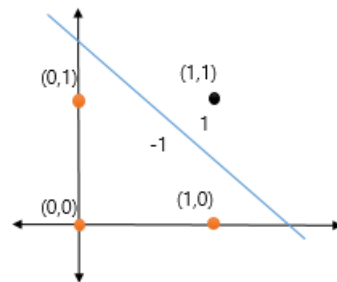


Figure2. AND gate

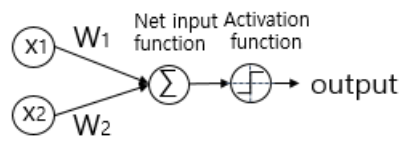
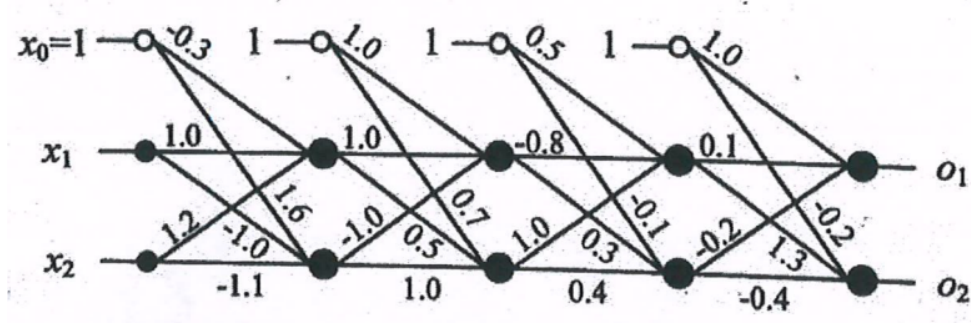


Figure2-1. AND gate perceptron

11. 다음은 은닉층이 3개인 DMLP이다. Hint 계산은 Matlab 또는 Python을 사용하시오.

In []:



In []:

(1) 가중치 행렬 U1, U2, U3, U4를 식(4.1)처럼 쓰시오.

In [23]: `import numpy as np`

```
U1 = np.array([[ -0.3,  1.0,  1.2],
               [ 1.6, -1.0, -1.1]])
```

```
U2 = np.array([[ 1.0,  1.0, -1.0],
               [ 0.7,  0.5,  1.0]])
```

```
U3 = np.array([[ 0.5, -0.8,  1.0],
               [-0.1,  0.3,  0.4]])
```

```
U4 = np.array([[ 1.0,  0.1, -0.2],
               [-0.2,  1.3, -0.4]])
```

```
print("U1:\n{}".format(U1))
```

```
print("U2:\n{}".format(U2))
```

```
print("U3:\n{}".format(U3))
```

```
print("U4:\n{}".format(U4))
```

U1:

```
[[-0.3  1.   1.2]
 [ 1.6 -1.  -1.1]]
```

U2:

```
[[ 1.   1.  -1. ]
 [ 0.7  0.5  1. ]]
```

U3:

```
[[ 0.5 -0.8  1. ]]
```

```

[-0.1  0.3  0.4]]
U4:
[[ 1.    0.1 -0.2]
 [-0.2  1.3 -0.4]]

```

(2) $x = (1,0)^T$ 가 입력되었을 때 출력 O 를 구하시오. 활성화함수로 로지스틱 시그모이드를 사용하시오.

```

In [24]: def sigmoid(z):
          return 1/(1+np.exp(-z))

x = np.array([1,1,0])
print("x:{}\n{}".format(x.shape, x))
x_t = x.T
print("x.T:{}\n{}".format(x_t.shape, x_t))
hidden_1 = sigmoid(U1.dot(x_t))
print("hidden_1:{}\n{}".format(hidden_1.shape, hidden_1))

# U1 is done

x_1 = np.append([1], hidden_1)
print("\nx_1:{}\n{}".format(x_1.shape, x_1))
x_1_t = x_1.T
print("x_1.T:{}\n{}".format(x_1_t.shape, x_1_t))
hidden_2 = sigmoid(U2.dot(x_1_t))
print("hidden_2:{}\n{}".format(hidden_2.shape, hidden_2))

# U2 is done

x_2 = np.append([1], hidden_2)
print("\nx_2:{}\n{}".format(x_2.shape, x_2))
x_2_t = x_2.T
print("x_2.T:{}\n{}".format(x_2_t.shape, x_2_t))
hidden_3 = sigmoid(U3.dot(x_2_t))
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U3 is done

x_3 = np.append([1], hidden_3)
print("\nx_3:{}\n{}".format(x_3.shape, x_3))
x_3_t = x_3.T
print("x_3.T:{}\n{}".format(x_3_t.shape, x_3_t))
hidden_3 = U4.dot(x_3_t)
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U4 is done

```

```

print("\ninput of sigmoid:\n{}".format(hidden_3))
print("final output with logisitic sigmoid funtion")
output_of_sigmoid = sigmoid(hidden_3)
print(output_of_sigmoid)

x:(3,)
[1 1 0]
x.T:(3,)
[1 1 0]
hidden_1:(2,)
[0.66818777 0.64565631]

x_1:(3,)
[1.          0.66818777 0.64565631]
x_1.T:(3,)
[1.          0.66818777 0.64565631]
hidden_2:(2,)
[0.7354654  0.84287145]

x_2:(3,)
[1.          0.7354654  0.84287145]
x_2.T:(3,)
[1.          0.7354654  0.84287145]
hidden_3:(2,)
[0.68015824 0.61248935]

x_3:(3,)
[1.          0.68015824 0.61248935]
x_3.T:(3,)
[1.          0.68015824 0.61248935]
hidden_3:(2,)
[0.94551796 0.43920998]

input of sigmoid:
[0.94551796 0.43920998]
final output with logisitic sigmoid funtion
[0.72021291 0.60807077]

```

(3) $x = (1,0)^T$ 가 입력되었을 때 출력 O 를 구하시오. 활성화함수로 ReLU를 사용하시오.

sol> 위의 simoid function에서 활성화함수를 ReLU로 바꾸면 바로 그 값이 되기때문에 활성화함수만 만들고 바로 hidden_3의 값에 활성화함수 ReLU를 사용하였다.

```

In [25]: def ReLU(z):
          return np.maximum(0, z)

          x = np.array([1,1,0])
          print("x:{}\n{}".format(x.shape, x))

```

```

x_t = x.T
print("x.T: {} \n {}".format(x_t.shape, x_t))
hidden_1 = ReLU(U1.dot(x_t))
print("hidden_1: {} \n {}".format(hidden_1.shape, hidden_1))

# U1 is done

x_1 = np.append([1], hidden_1)
print("\nx_1: {} \n {}".format(x_1.shape, x_1))
x_1_t = x_1.T
print("x_1.T: {} \n {}".format(x_1_t.shape, x_1_t))
hidden_2 = ReLU(U2.dot(x_1_t))
print("hidden_2: {} \n {}".format(hidden_2.shape, hidden_2))

# U2 is done

x_2 = np.append([1], hidden_2)
print("\nx_2: {} \n {}".format(x_2.shape, x_2))
x_2_t = x_2.T
print("x_2.T: {} \n {}".format(x_2_t.shape, x_2_t))
hidden_3 = ReLU(U3.dot(x_2_t))
print("hidden_3: {} \n {}".format(hidden_3.shape, hidden_3))

# U3 is done

x_3 = np.append([1], hidden_3)
print("\nx_3: {} \n {}".format(x_3.shape, x_3))
x_3_t = x_3.T
print("x_3.T: {} \n {}".format(x_3_t.shape, x_3_t))
hidden_3 = U4.dot(x_3_t)
print("hidden_3: {} \n {}".format(hidden_3.shape, hidden_3))

# U4 is done

print("input of ReLU: \n {}".format(hidden_3))
print("final output with ReLU on hidden_3")
output_of_ReLU = ReLU(hidden_3)
print(output_of_ReLU)

```

```

x: (3,)
[1 1 0]
x.T: (3,)
[1 1 0]
hidden_1: (2,)
[0.7 0.6]

```

```

x_1: (3,)
[1.  0.7 0.6]

```



```

x_1.T:(3,)
[1.  0.7 0.6]
hidden_2:(2,)
[1.1  1.65]

x_2:(3,)
[1.  1.1  1.65]
x_2.T:(3,)
[1.  1.1  1.65]
hidden_3:(2,)
[1.27 0.89]

x_3:(3,)
[1.  1.27 0.89]
x_3.T:(3,)
[1.  1.27 0.89]
hidden_3:(2,)
[0.949 1.095]
input of ReLU:
[0.949 1.095]
final output with ReLU on hidden_3
[0.949 1.095]

```

- (4) $x = (1,0)^T$ 의 기대출력 $O = (0,1)^T$ 일 때, 현재 1.0인 u312 가중치를 0.9로 줄이면 오류에 어떤 영향을 미치는지 설명하시오.

sol> 오류 함수를 Mean Squared Error 함수로 설정하고, 활성화함수는 logistic sigmoid 와 ReLU 두개로 하여 결과를 아래와 같이 뽑아 냈다. 그 결과 활성화함수 logisitic sigmoid function과 함께 한 경우, Mean Squared Error는 증가하고, 반대로 활성화함수 ReLU와 함께 한 경우는 Mean Sqared Error가 감소하였다.

```

In [26]: expected = np.array([0,1], dtype=float)

print("expected:\n{}".format(expected))

def loss_function(output, expectation):
    return ((output-expectation)**2).mean()

print("\nU321 0.9로 바꾸기 전 with logisitic sigmoid")
prior_sigmoid = loss_function(output_of_sigmoid, expected)
print(prior_sigmoid)

U_3 = np.array([[0.5, -0.8, 0.9],
                [-0.1, 0.3, 0.4]])

print("\n U321 1.0 -> 0.9 바꾼후 다시 계산")
x = np.array([1,1,0])

```

```

print("x:{}\n{}".format(x.shape, x))
x_t = x.T
print("x.T:{}\n{}".format(x_t.shape, x_t))
hidden_1 = sigmoid(U1.dot(x_t))
print("hidden_1:{}\n{}".format(hidden_1.shape, hidden_1))

# U1 is done

x_1 = np.append([1], hidden_1)
print("\nx_1:{}\n{}".format(x_1.shape, x_1))
x_1_t = x_1.T
print("x_1.T:{}\n{}".format(x_1_t.shape, x_1_t))
hidden_2 = sigmoid(U2.dot(x_1_t))
print("hidden_2:{}\n{}".format(hidden_2.shape, hidden_2))

# U2 is done

x_2 = np.append([1], hidden_2)
print("\nx_2:{}\n{}".format(x_2.shape, x_2))
x_2_t = x_2.T
print("x_2.T:{}\n{}".format(x_2_t.shape, x_2_t))
hidden_3 = sigmoid(U_3.dot(x_2_t))
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U3 is done

x_3 = np.append([1], hidden_3)
print("\nx_3:{}\n{}".format(x_3.shape, x_3))
x_3_t = x_3.T
print("x_3.T:{}\n{}".format(x_3_t.shape, x_3_t))
hidden_3 = U4.dot(x_3_t)
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U4 is done

print("\ninput of sigmoid:\n{}".format(hidden_3))
print("final output with logisitic sigmoid funtion")
output_of_sigmoid_after = sigmoid(hidden_3)
print(output_of_sigmoid_after)

print("\nU321 0.9로 바꾸기 후 with logisitic sigmoid funtion")
post_sigmoid = loss_function(output_of_sigmoid_after, expected)
print("Before: {}".format(prior_sigmoid))
print("After: {}".format(post_sigmoid))

```

expected:
[0. 1.]

U321 0.9로 바꾸기 전 with logisitic sigmoid
0.33615757900101034

U321 1.0 -> 0.9 바꾼후 다시 계산

```
x:(3,)
[1 1 0]
x.T:(3,)
[1 1 0]
hidden_1:(2,)
[0.66818777 0.64565631]
```

```
x_1:(3,)
[1.          0.66818777 0.64565631]
x_1.T:(3,)
[1.          0.66818777 0.64565631]
hidden_2:(2,)
[0.7354654  0.84287145]
```

```
x_2:(3,)
[1.          0.7354654  0.84287145]
x_2.T:(3,)
[1.          0.7354654  0.84287145]
hidden_3:(2,)
[0.66155062 0.61248935]
```

```
x_3:(3,)
[1.          0.66155062 0.61248935]
x_3.T:(3,)
[1.          0.66155062 0.61248935]
hidden_3:(2,)
[0.94365719 0.41502007]
```

```
input of sigmoid:
[0.94365719 0.41502007]
final output with logisitic sigmoid funtion
[0.7198378  0.60229099]
```

U321 0.9로 바꾸기 후 with logisitic sigmoid funtion
Befor: 0.33615757900101034
After: 0.3381694602679114

```
In [27]: expected = np.array([0,1], dtype=float)

print("expected:\n{}".format(expected))

def loss_function(output, expectation):
    return ((output-expectation)**2).mean()
```

```

print("\nU321 0.9로 바꾸기 전 with ReLU")
prior_ReLU = loss_function(output_of_ReLU, expected)
print(prior_ReLU)

U_3 = np.array([[0.5, -0.8, 0.9],
                [-0.1, 0.3, 0.4]])

print("\n U321 1.0 -> 0.9 바꾼후 다시 계산")
x = np.array([1,1,0])
print("x:{}\n{}".format(x.shape, x))
x_t = x.T
print("x.T:{}\n{}".format(x_t.shape, x_t))
hidden_1 = ReLU(U1.dot(x_t))
print("hidden_1:{}\n{}".format(hidden_1.shape, hidden_1))

# U1 is done

x_1 = np.append([1], hidden_1)
print("\n x_1:{}\n{}".format(x_1.shape, x_1))
x_1_t = x_1.T
print("x_1.T:{}\n{}".format(x_1_t.shape, x_1_t))
hidden_2 = ReLU(U2.dot(x_1_t))
print("hidden_2:{}\n{}".format(hidden_2.shape, hidden_2))

# U2 is done

x_2 = np.append([1], hidden_2)
print("\n x_2:{}\n{}".format(x_2.shape, x_2))
x_2_t = x_2.T
print("x_2.T:{}\n{}".format(x_2_t.shape, x_2_t))
hidden_3 = ReLU(U_3.dot(x_2_t))
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U3 is done

x_3 = np.append([1], hidden_3)
print("\n x_3:{}\n{}".format(x_3.shape, x_3))
x_3_t = x_3.T
print("x_3.T:{}\n{}".format(x_3_t.shape, x_3_t))
hidden_3 = U4.dot(x_3_t)
print("hidden_3:{}\n{}".format(hidden_3.shape, hidden_3))

# U4 is done

print("\n input of ReLU:\n{}".format(hidden_3))
print("final output with ReLU")
output_of_ReLU_after = ReLU(hidden_3)

```

```

print(output_of_ReLU_after)

print("\nU321 0.9로 바꾸기 후 with ReLU")
post_ReLU = loss_function(output_of_ReLU_after, expected)
print("Befor: {}".format(prior_ReLU))
print("After: {}".format(post_ReLU))

expected:
[0. 1.]

U321 0.9로 바꾸기 전 with ReLU
0.45481299999999999

U321 1.0 -> 0.9 바꾼후 다시 계산
x:(3,)
[1 1 0]
x.T:(3,)
[1 1 0]
hidden_1:(2,)
[0.7 0.6]

x_1:(3,)
[1. 0.7 0.6]
x_1.T:(3,)
[1. 0.7 0.6]
hidden_2:(2,)
[1.1 1.65]

x_2:(3,)
[1. 1.1 1.65]
x_2.T:(3,)
[1. 1.1 1.65]
hidden_3:(2,)
[1.105 0.89 ]

x_3:(3,)
[1. 1.105 0.89 ]
x_3.T:(3,)
[1. 1.105 0.89 ]
hidden_3:(2,)
[0.9325 0.8805]

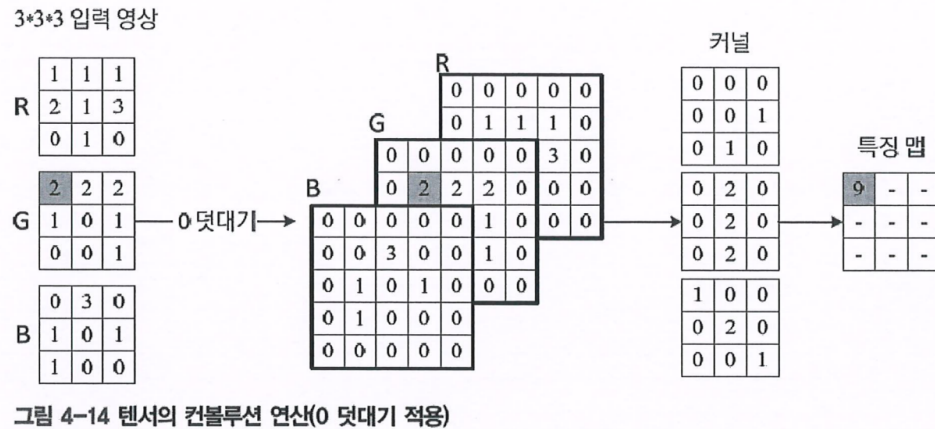
input of ReLU:
[0.9325 0.8805]
final output with ReLU
[0.9325 0.8805]

U321 0.9로 바꾸기 후 with ReLU

```

Before: 0.45481299999999999
 After: 0.44191825

12. [그림 4-14]에서 특징 맵의 나머지 8개 값을 계산하시오.



```
In [28]: import numpy as np

R = np.array([[0,0,0,0,0],
              [0,1,1,1,0],
              [0,2,1,3,0],
              [0,0,1,0,0],
              [0,0,0,0,0]])

G = np.array([[0,0,0,0,0],
              [0,2,2,2,0],
              [0,1,0,1,0],
              [0,0,0,1,0],
              [0,0,0,0,0]])

B = np.array([[0,0,0,0,0],
              [0,0,3,0,0],
              [0,1,0,1,0],
              [0,1,0,0,0],
              [0,0,0,0,0]])

R_kernel = np.array([[0,0,0],
                     [0,0,1],
                     [0,1,0]])
```

```

G_kernel = np.array([[0,2,0],
                     [0,2,0],
                     [0,2,0]])

B_kernel = np.array([[1,0,0],
                     [0,2,0],
                     [0,0,1]])

a11 = ((R[0:3, 0:3] * R_kernel) +
       (G[0:3, 0:3] * G_kernel) +
       (B[0:3, 0:3] * B_kernel))

a12 = ((R[0:3, 0+1:3+1] * R_kernel) +
       (G[0:3, 0+1:3+1] * G_kernel) +
       (B[0:3, 0+1:3+1] * B_kernel))

a13 = ((R[0:3, 0+2:3+2] * R_kernel) +
       (G[0:3, 0+2:3+2] * G_kernel) +
       (B[0:3, 0+2:3+2] * B_kernel))

a21 = ((R[0+1:3+1, 0:3] * R_kernel) +
       (G[0+1:3+1, 0:3] * G_kernel) +
       (B[0+1:3+1, 0:3] * B_kernel))

a22 = ((R[0+1:3+1, 0+1:3+1] * R_kernel) +
       (G[0+1:3+1, 0+1:3+1] * G_kernel) +
       (B[0+1:3+1, 0+1:3+1] * B_kernel))

a23 = ((R[0+1:3+1, 0+2:3+2] * R_kernel) +
       (G[0+1:3+1, 0+2:3+2] * G_kernel) +
       (B[0+1:3+1, 0+2:3+2] * B_kernel))

a31 = ((R[0+2:3+2, 0:3] * R_kernel) +
       (G[0+2:3+2, 0:3] * G_kernel) +
       (B[0+2:3+2, 0:3] * B_kernel))

a32 = ((R[0+2:3+2, 0+1:3+1] * R_kernel) +
       (G[0+2:3+2, 0+1:3+1] * G_kernel) +
       (B[0+2:3+2, 0+1:3+1] * B_kernel))

a33 = ((R[0+2:3+2, 0+2:3+2] * R_kernel) +
       (G[0+2:3+2, 0+2:3+2] * G_kernel) +
       (B[0+2:3+2, 0+2:3+2] * B_kernel))

feature_map = np.array([[a11.sum(), a12.sum(), a13.sum()],
                        [a21.sum(), a22.sum(), a23.sum()],
                        [a31.sum(), a32.sum(), a33.sum()]])

```

```
print("Feature map:\n{}".format(feature_map))
```

Feature map:

```
[[ 9 13  9]
 [ 9  8 13]
 [ 5  1  4]]
```

13. 컨볼루션 층의 입력 크기가 $32 \times 32 \times 3$ 이고, (a) 10개 5×5 필터들을 보폭 1과 덧대기 2로 적용하였을 때 출력의 크기와 매개변수의 수를 구하세요. (b) 동일한 입력에 64개 3×3 필터들을 보폭 1과 덧대기 1로 적용하였을 때 출력의 크기와 매개변수의 수도 구하세요. (6점)

- (a) 10개 5×5 필터들을 보폭 1과 덧대기 2로 적용하였을 때 출력의 크기와 매개변수의 수를 구하세요.

매개변수의 수는 필터 5 by 5 이고, 이러한 필터가 10개 이므로, 입력 층의 depth 3 이므로
필터마다 1 개의 bias를 가진다면
총 매개변수는 $5 * 5 * 3 * 10 + 10 = 760$ 개
출력의 크기는 $W2 * H2 * D2$

- $W2 = (32 - 5 + 2 * 2) / 1 + 1 = 32$
- $H2 = (32 - 5 + 2 * 2) / 1 + 1 = 32$
- $D2 = k = 10$

- (b) 동일한 입력에 64개 3×3 필터들을 보폭 1과 덧대기 1로 적용하였을 때 출력의 크기와 매개변수의 수도 구하세요.

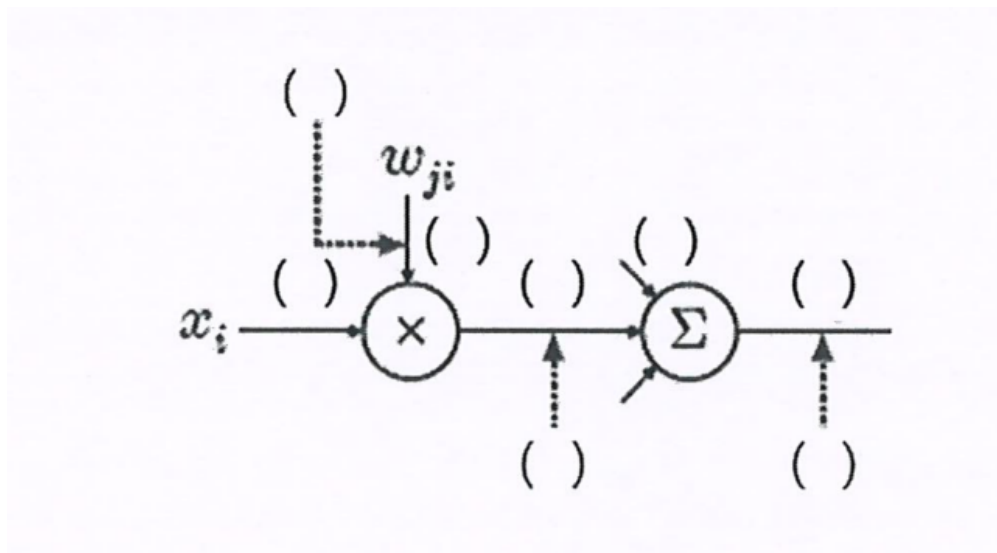
매개변수의 수는 필터 3 by 3 이고, 이러한 필터가 64개 이므로, 입력 층의 depth 3 이므로
필터마다 1 개의 bias를 가진다면
총 매개변수는 $3 * 3 * 3 * 64 + 64 = 1792$
출력의 크기는 $W2 * H2 * D2$

- $W2 = (32 - 3 + 2 * 1) / 1 + 1 = 32$
- $H2 = (32 - 3 + 2 * 1) / 1 + 1 = 32$
- $D2 = k = 64$

14. 아래 그림의 연산 그래프 예처럼 $f(x, y, z) = (x + y)z$ 연산에 대한 연산 그래프를 새롭게 생성하고, $x = -2, y = 5, z = -4$ 인 경우에 전방 전파와 이에 대응되는 오류 역전파를 각 가중치마다 계산하세요.

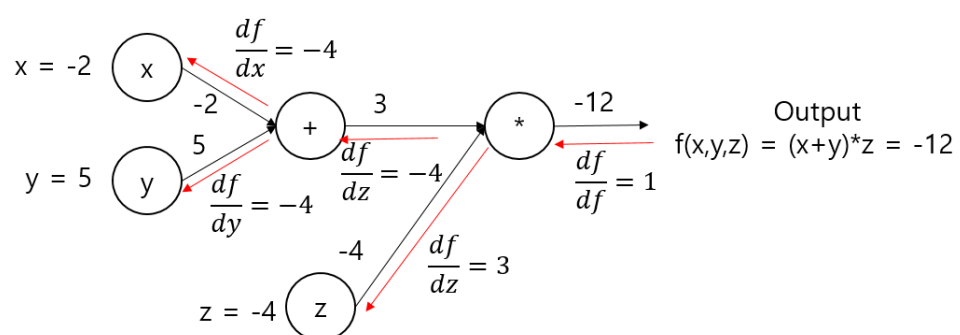
[예에 표시된 것처럼 전방 전파 연산 결과는 검은색 빈칸, 오류 역전파 연산 결과는 빨간색 빈칸으로 표시하여 구분하세요.]

sol>



Black : Forward

Red : Backward



1 Reference

- [pytorch docs](#)
- [Frequently Asked Quest on pytorch docs](#)
- [Automatic differentiation](#)
- [pytorch tutorial](#)
- [How to load data on pytorch](#)