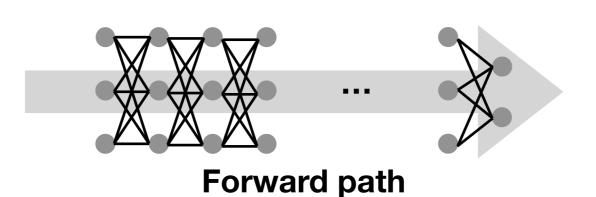
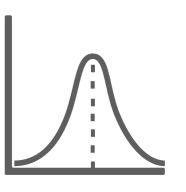
Classification Model

How does it work?



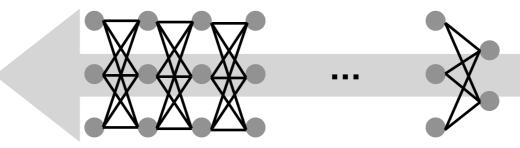




Penguin: 0.01

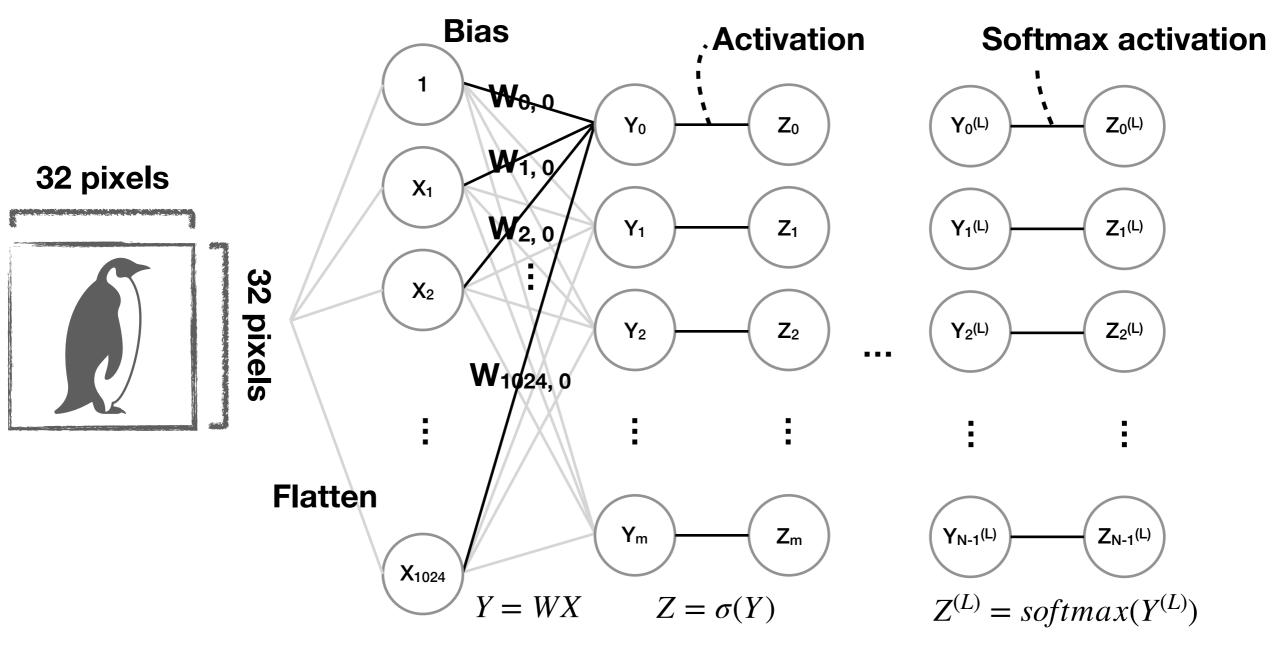


Difference measurement (Loss)



 $\nabla_{\theta}L$ Penguin: 1.0

Backward path (Gradient back-propagation)

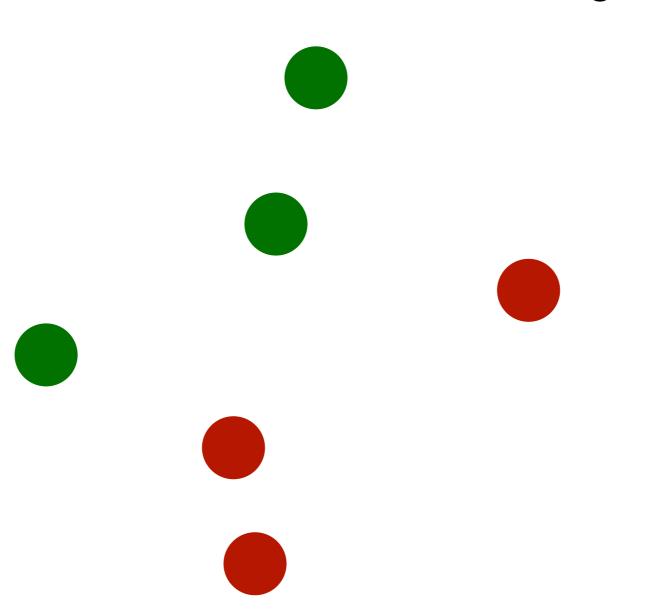


Input layer

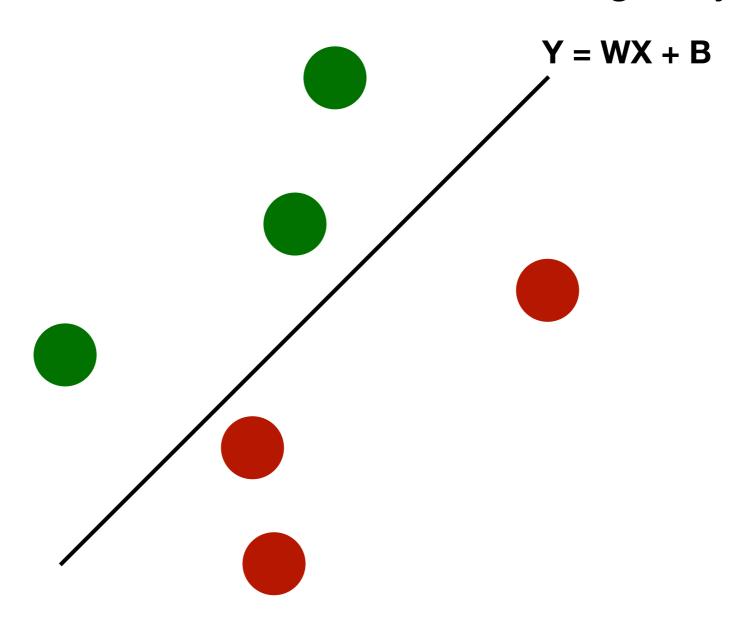
1st Hidden layer 1st Activation layer Lth Hidden layer Output layer

Densely connected (fully connected)

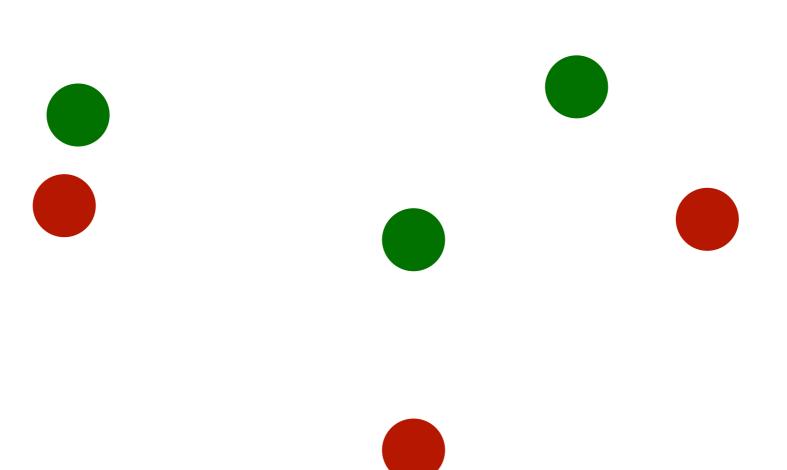
Why do we need an activation after a weight layer?



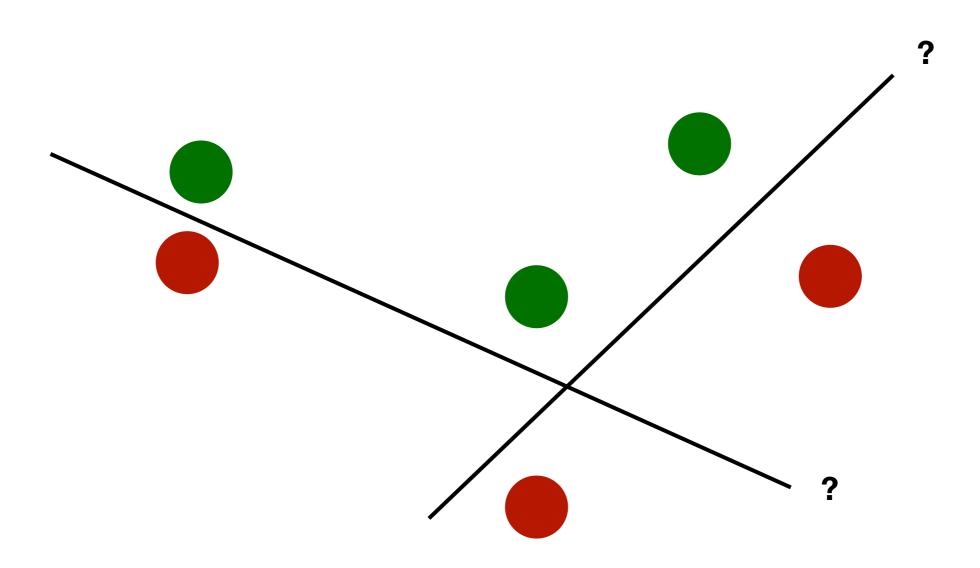
• Why do we need an activation after a weight layer?



• Why do we need an activation after a weight layer?



Why do we need an activation after a weight layer?



Why do we need an activation after a weight layer?

Without any activation function, it's impossible to express higher degree function than linear function

$$Y_1 = WX_1 + B$$

 $Y_2 = W(WX_1 + B) + B = WX_1 + B$

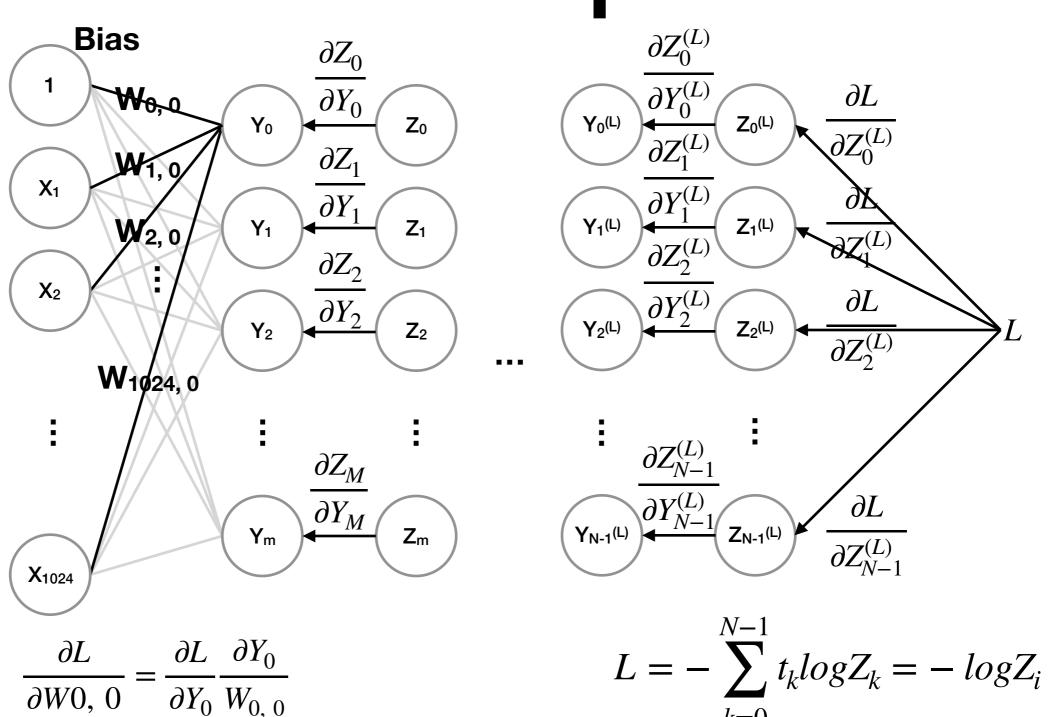
$$Y_1 = WX_1 + B$$

 $Z_1 = f(Y_1)$
 $Y_2 = WZ_1 + B$

where f(.) is non-linear activation function

Thus we add an activation function after a weight layer.

Backward path



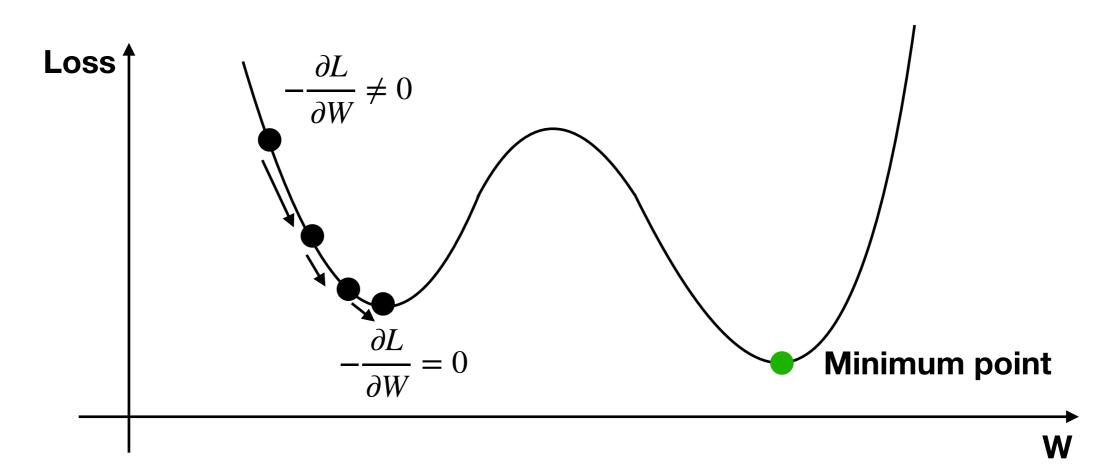
 $W_{0, 0} = W_{0, 0} - \rho \frac{\partial L}{\partial W_{0, 0}}$

Cross-entropy loss

k=0

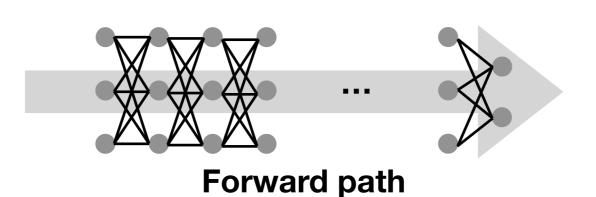
Backward path

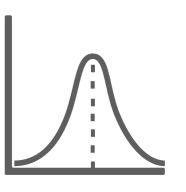
- Gradient back-propagation changes weights to have lower loss in a way loss decreases most fast.
- However this does not guarantee the loss converges to its minimum value



How does it work?



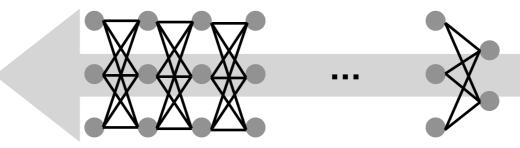




Penguin: 0.01



Difference measurement (Loss)



 $\nabla_{\theta}L$ Penguin: 1.0

Backward path (Gradient back-propagation)

Practice

MNIST database

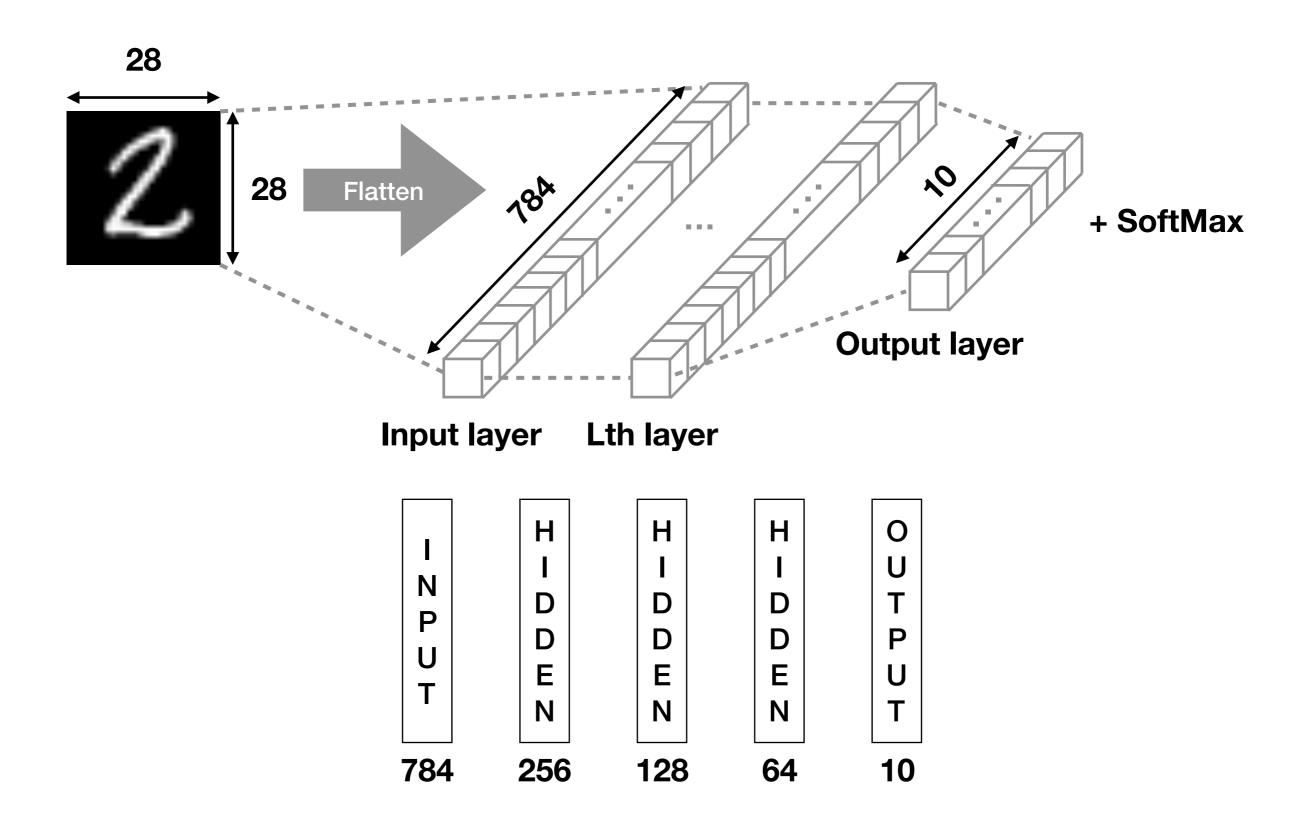


Training set: 60,000 images and labels

Test set: 10,000 images and labels

The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.

Model architecture



Code snippet

```
import torch.nn as nn
import torch.nn.functional as F
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=64, kernel_size=3, stride=2, padding=1)
        self.conv2 = nn.Conv2d(in channels=64, out channels=128, kernel size=3, stride=2, padding=1)
        self.conv3 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, stride=2, padding=1)
        self.fc = nn.Linear(in_features=4 * 4 * 256, out_features=10)
   def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
       x = F.relu(self.conv3(x))
        x = x.view(x.shape[0], -1)
        x = self.fc(x)
        return x
class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()
        self.linear1 = nn.Linear(in_features=28 * 28, out_features=256)
        self.linear2 = nn.Linear(in_features=256, out_features=128)
        self.linear3 = nn.Linear(in_features=128, out_features=64)
        self.linear4 = nn.Linear(in_features=64, out_features=10)
   def forward(self, x):
        x = F.relu(self.linear1(x))
        x = F.relu(self.linear2(x))
        x = F.relu(self.linear3(x))
        x = self.linear4(x)
```

return x

For a full code, please visit https://github.com/NoelShin/Deep-Learning-Bootcamp-with-PyTorch

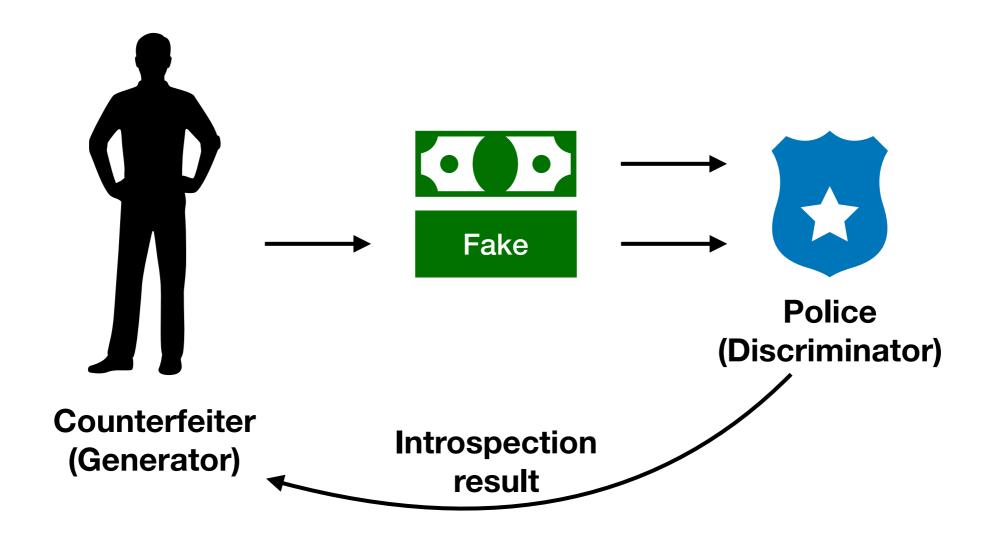
Generative Model

Various generative models

- Hidden Markov Model (HMM)
- Restricted Boltzmann Machine (RBM)
- Variational Auto-Encoder (VAE)
- Recurrent Neural Network (RNN)
- Generative Adversarial Network (GAN)

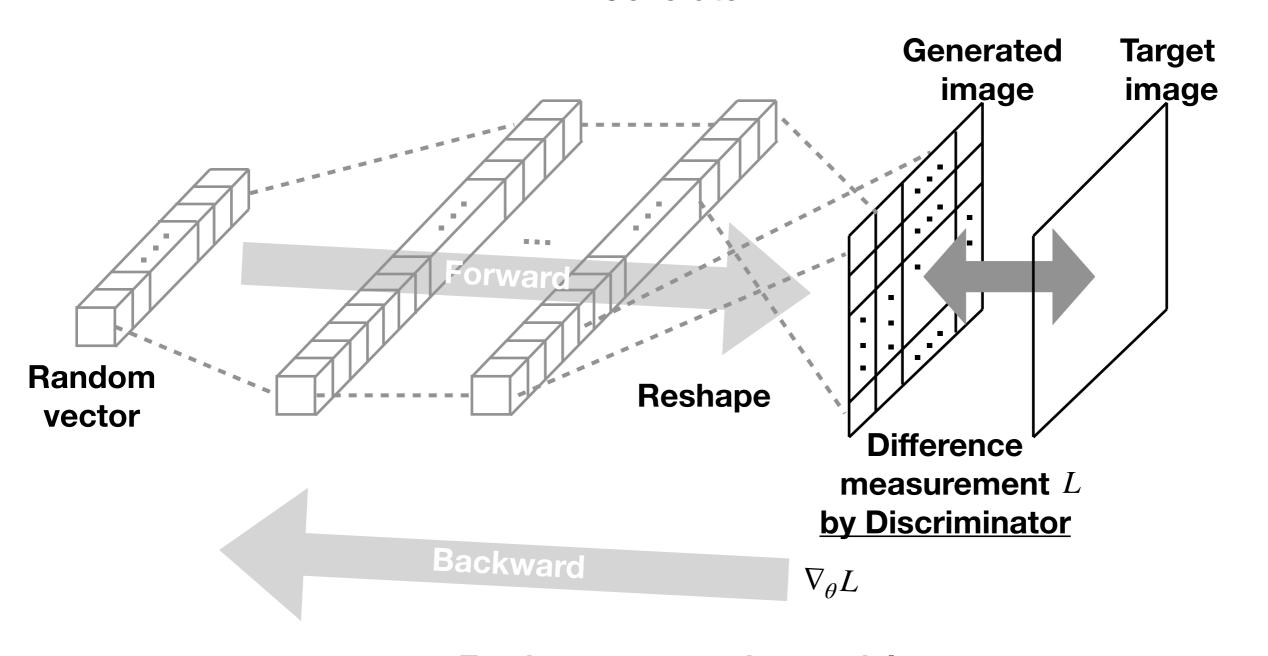
GAN

What is GAN?



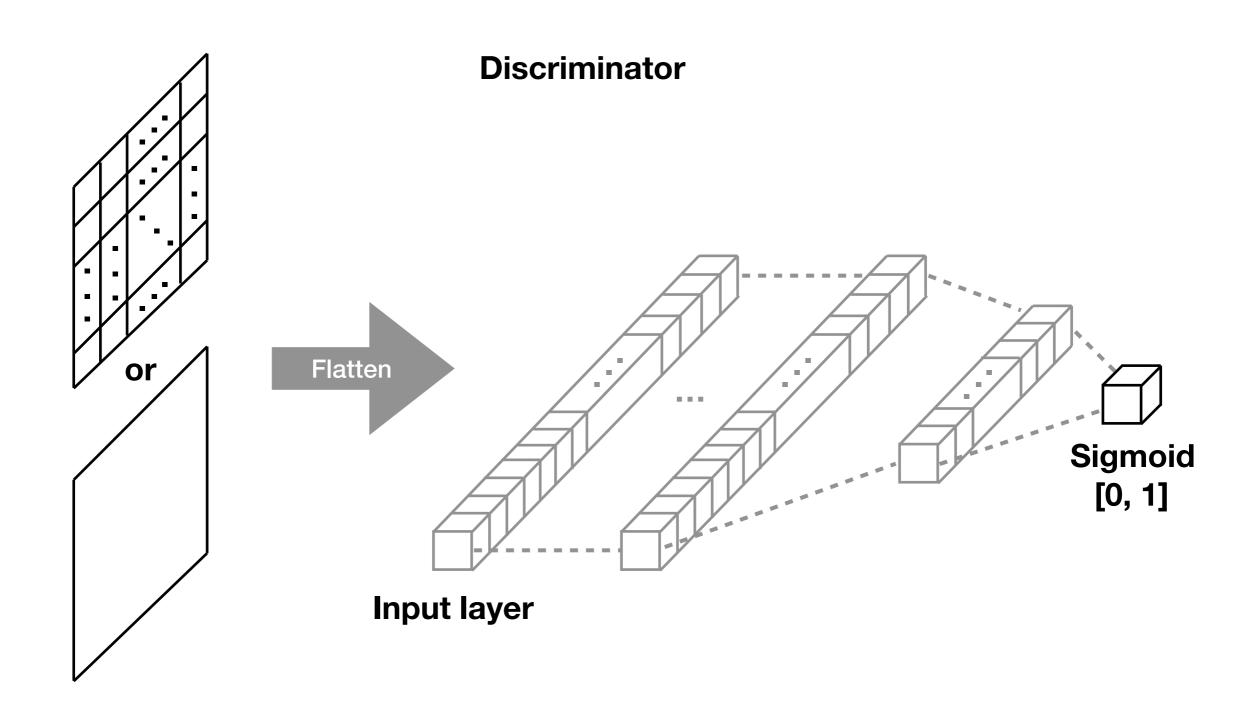
How does GAN work?

Generator



E.g. image generation model

How does GAN work?



Practice

MNIST database



Training set: 60,000 images and labels

Test set: 10,000 images and labels

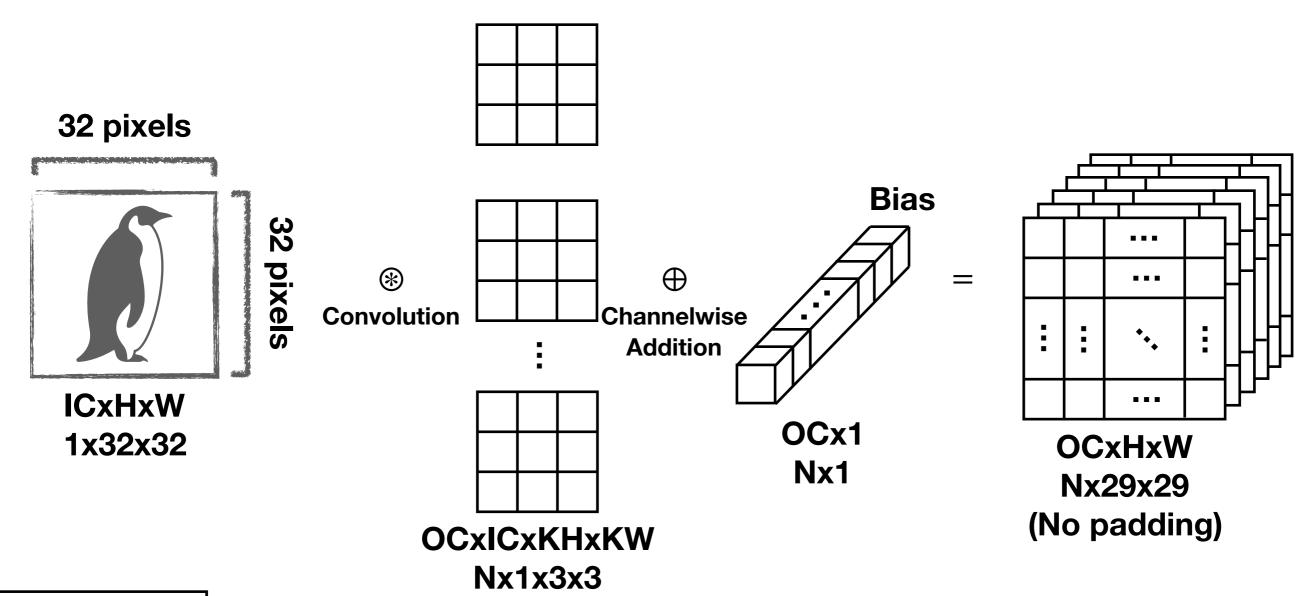
The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.

Code snippet

```
import torch.nn as nn
class Generator(nn.Module):
   def __init__(self):
       super(Generator, self).__init__()
       model = [nn.Linear(in features=100, out features=128), nn.ReLU(inplace=True)]
       model += [nn.Linear(in_features=128, out_features=256), nn.ReLU(inplace=True)]
       model += [nn.Linear(in_features=256, out_features=28 * 28), nn.Sigmoid()]
       self.model = nn.Sequential(*model)
       # "The generator nets used a mixture of rectifier linear activations and sigmoid activations, while the
       # discriminator net used maxout activations." - Generative Adversarial Networks
   def forward(self, x):
       return self.model(x)
class Discriminator(nn.Module):
   def __init__(self):
       super(Discriminator, self).__init__()
       model = [Maxout(28 * 28, 256, dropout=False, k=5)]
       model += [Maxout(256, 128, dropout=True, k=5)]
       model += [nn.Linear(128, 1), nn.Sigmoid()]
       self.model = nn.Sequential(*model)
   def forward(self, x):
        return self.model(x)
```

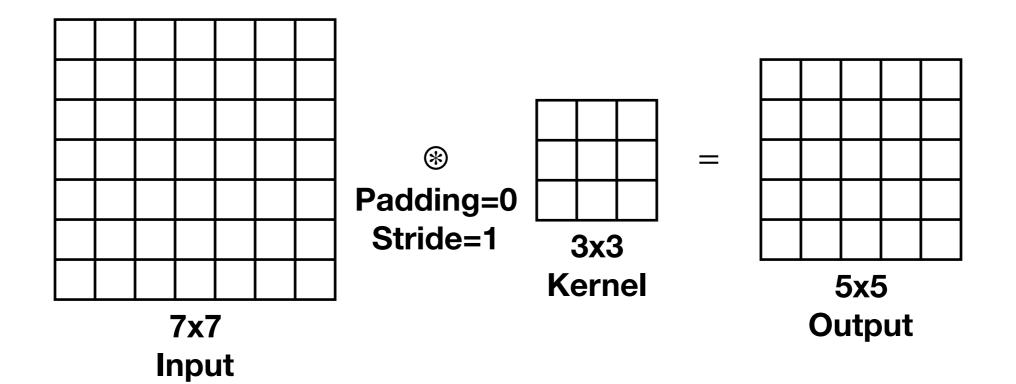
For a full code, please visit https://github.com/NoelShin/Deep-Learning-Bootcamp-with-PyTorch

Appendix

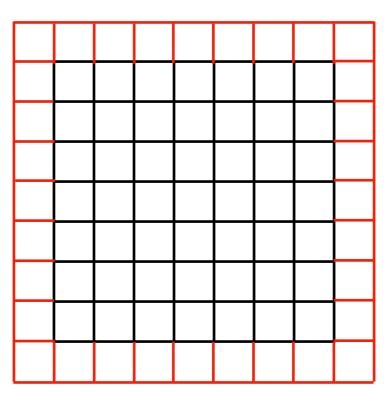


H: Height W: Width

OC: Output Channel IC: Input Channel KH: Kernel Height KW: Kernel Width



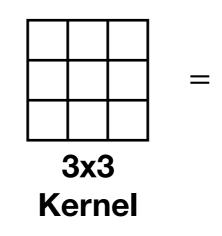
$$o = i - k + 1$$

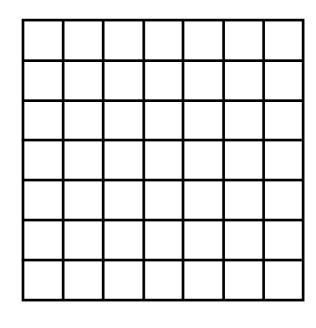


$$(7 + 2 \times p) \times (7 + 2 \times p)$$

Input

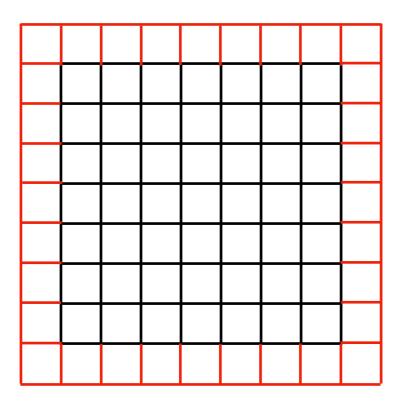


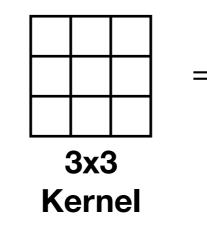




7x7 Output

$$o = i - k + 2p + 1$$





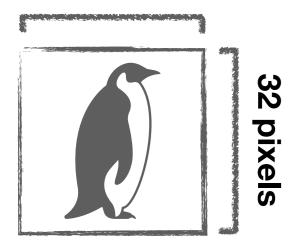
$$(7 + 2 \times p) \times (7 + 2 \times p)$$

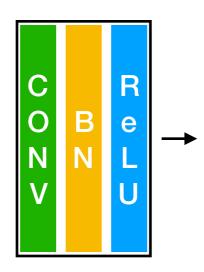
Input

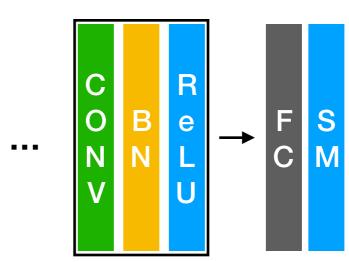
$$o = \left\lfloor \frac{i - k + 2p}{s} \right\rfloor + 1$$

Convolutional neural network

32 pixels







BN: Batch Normalization CONV: CONVolution

FC: Fully Connected layer
ReLU: Rectified Linear Unit
SM: SoftMax activation layer