Deep Learning Bootcamp with PyTorch

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Introduction

Goal of lecture

Getting used to

- **read a PyTorch code of interest,**
- **make a deep learning model using PyTorch.**

Prerequisite

You need to have overall understanding of ‘class’ in Python. If you are not familiar with class, you may refer to Appendix A.

Class

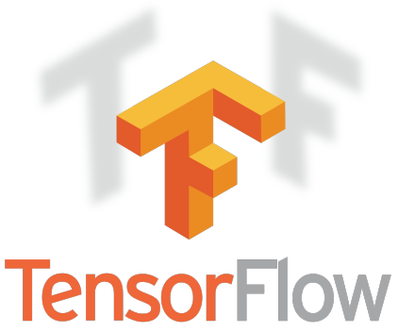
- Let’s make a basic class in Python.

What is PyTorch?

PyTorch is an **open-source machine learning library** for **Py**thon, based on **Torch**.

- **Tensor computation with strong GPU acceleration***
- Deep neural networks built on a tape-based **autograd system**

Why PyTorch?



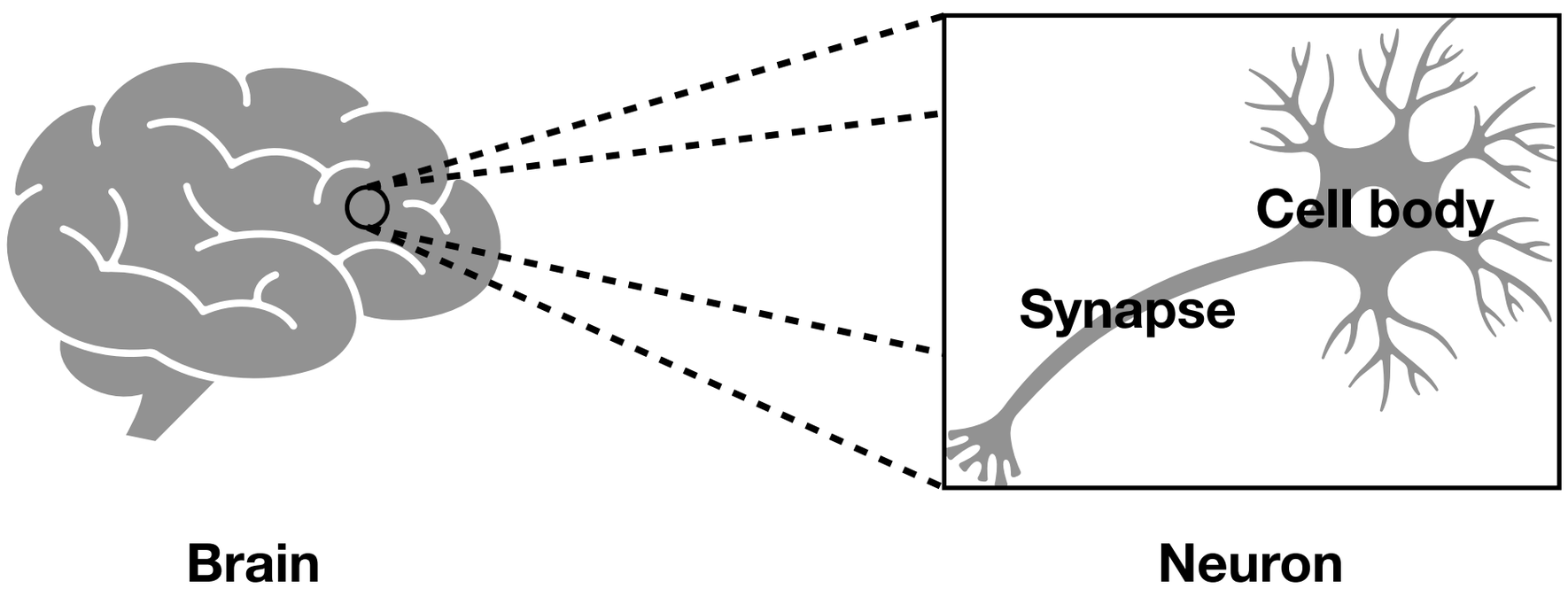
- A lot easier to learn than to learn TensorFlow.

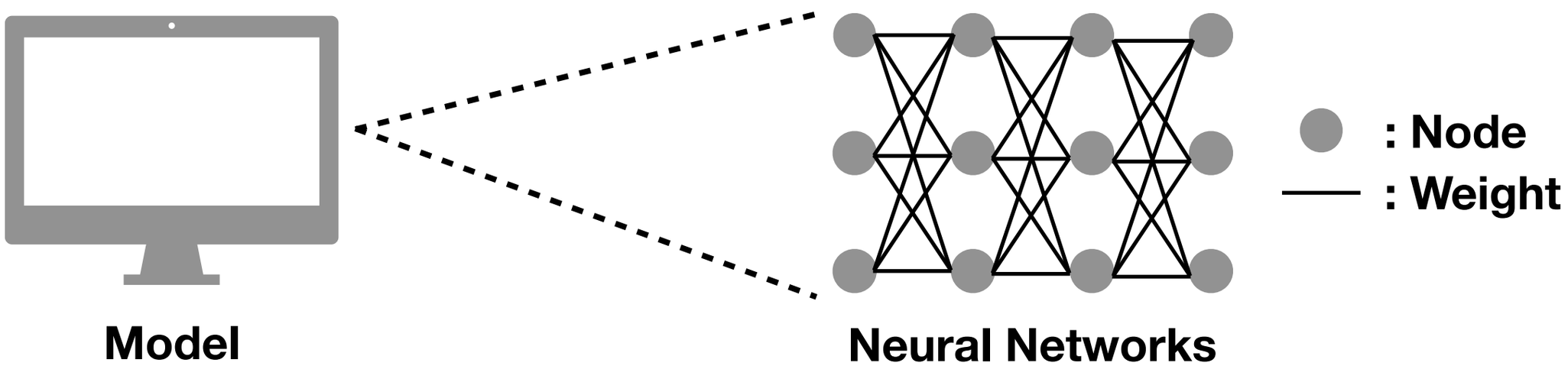
- Available to customize a model. This is usually infeasible with Keras.

- Recently public codes for deep learning research papers are usually written with PyTorch.

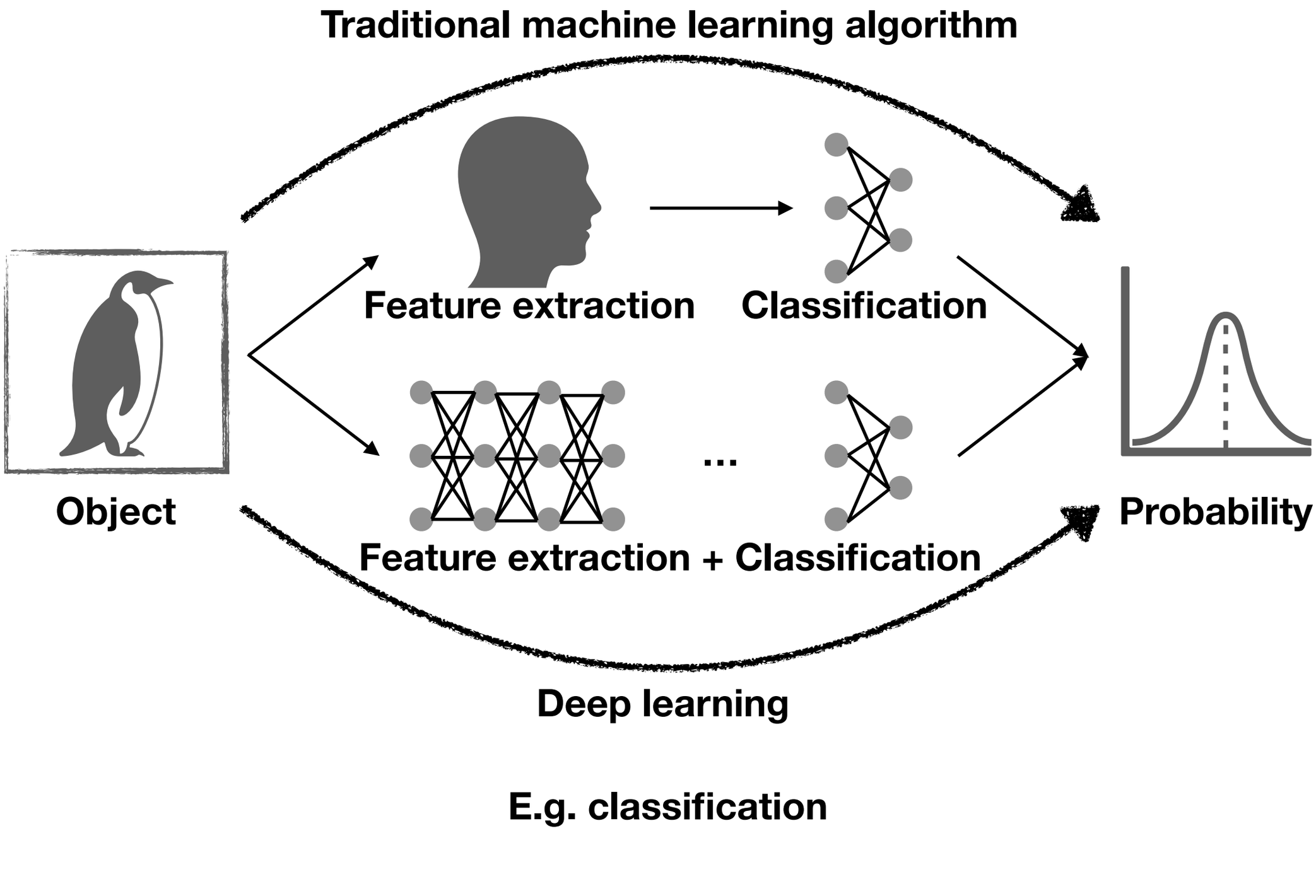
Basics

What is deep learning?





What is deep learning?



E.g. classification

How many buttons?

Machine learning researcher:

“Find things having a circular shape and three holes.”

Deep learning researcher:

“I don’t care how you count them. Anyway the answer is four. Train yourself why the answer is four.”

How many buttons?

Machine learning model: “Okay. Although they are circular, as they don’t have three holes, they are not button. The answer is 0.”

Deep learning model: “Hmm… they don’t exactly match what I saw previously, somehow they look like ‘button’. Maybe the answer is 5?”

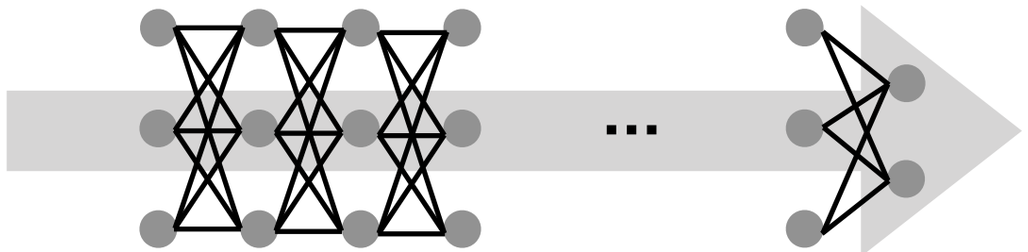
Part I

Classification Model

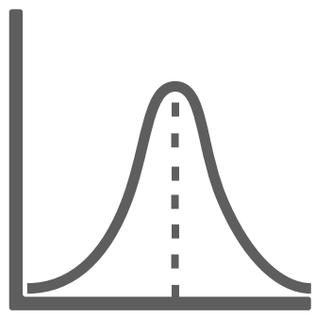
1. Multilayer perceptron

How does it work?

Input



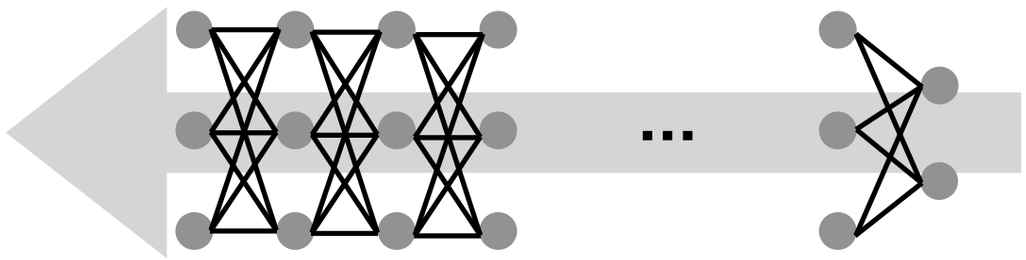
Forward path



Penguin: 0.01

Iteration

Difference measurement (Loss)



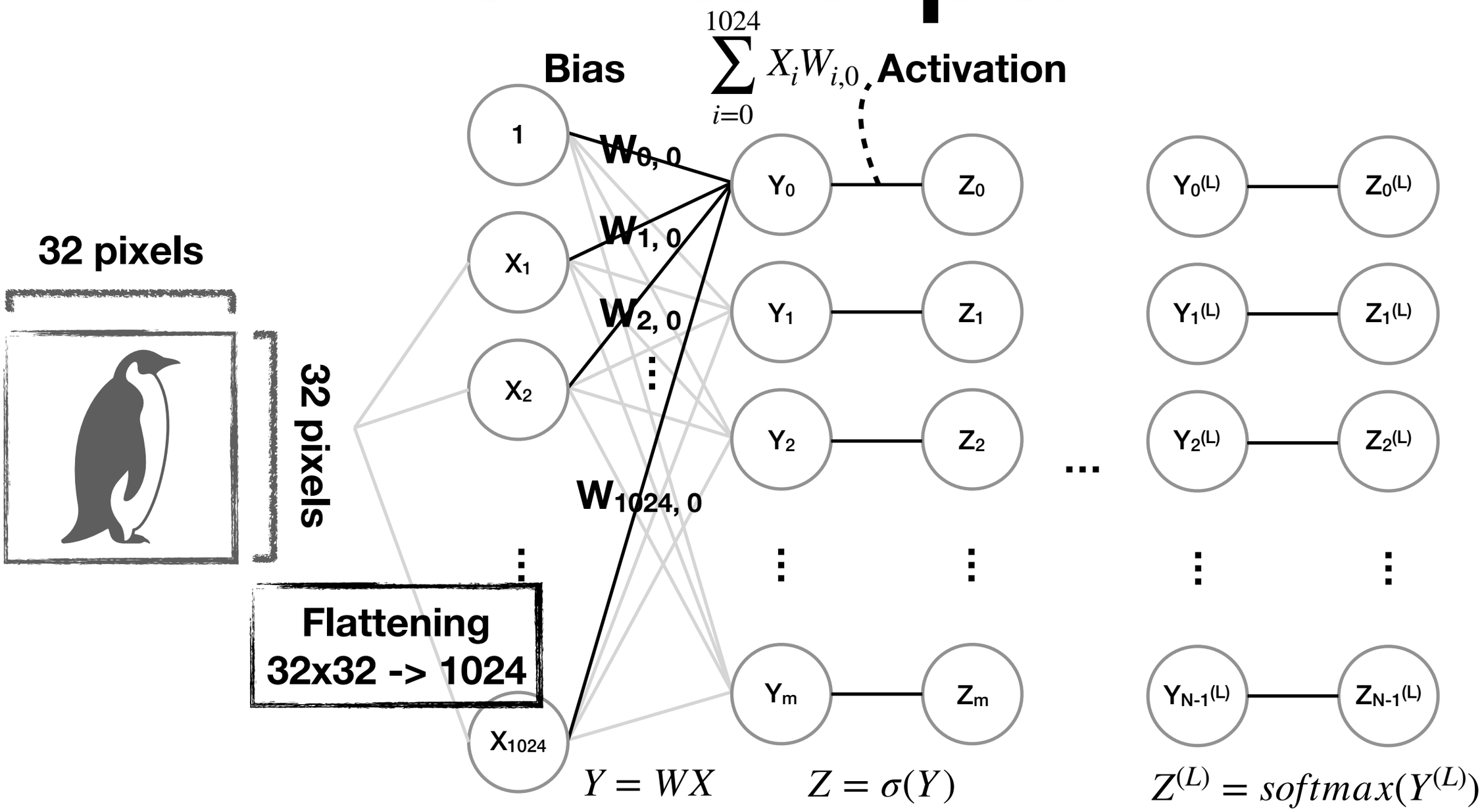
$\nabla_\theta L$

Penguin: 1.0

Backward path
(Gradient Back-propagation)

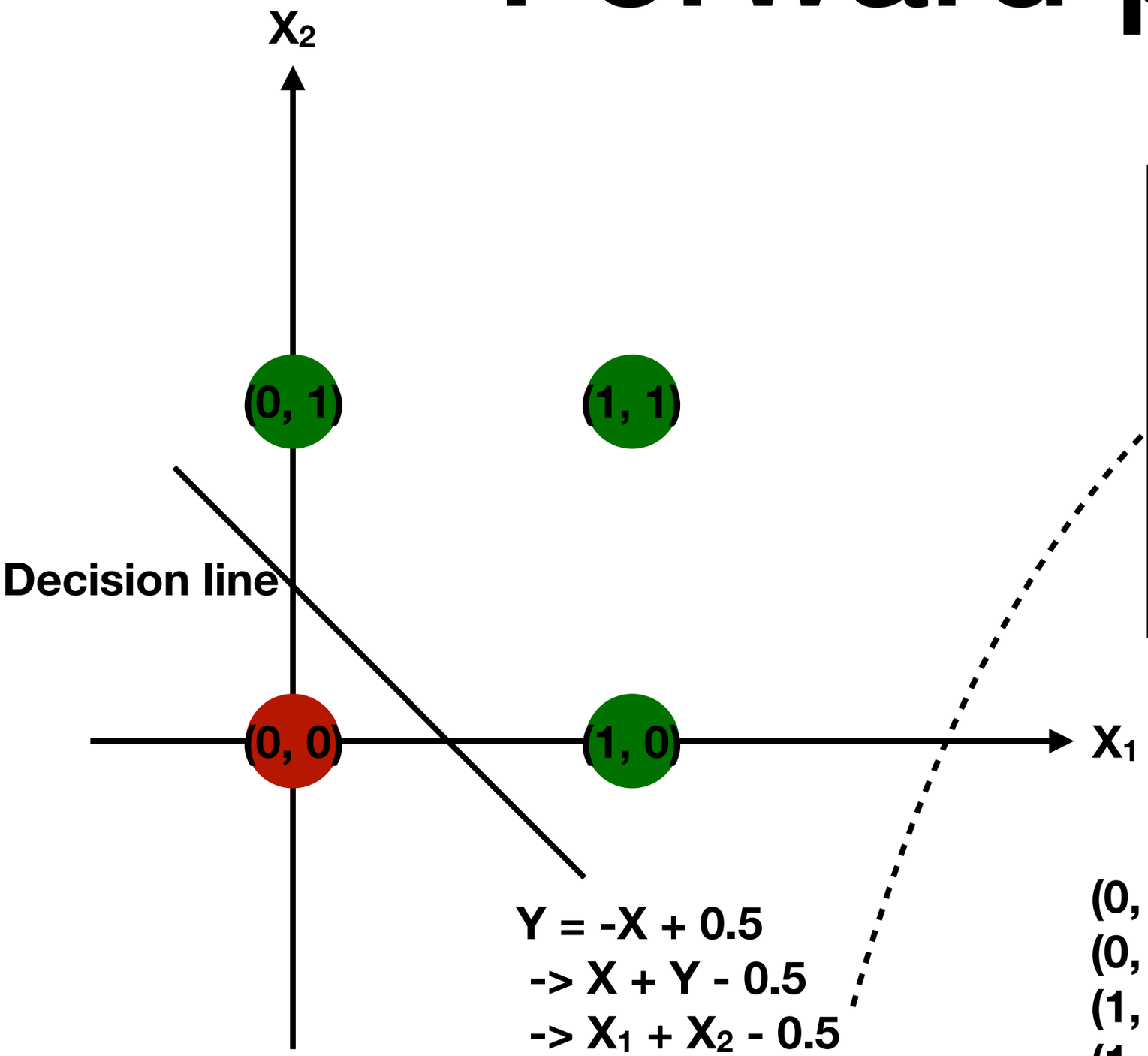
Forward path

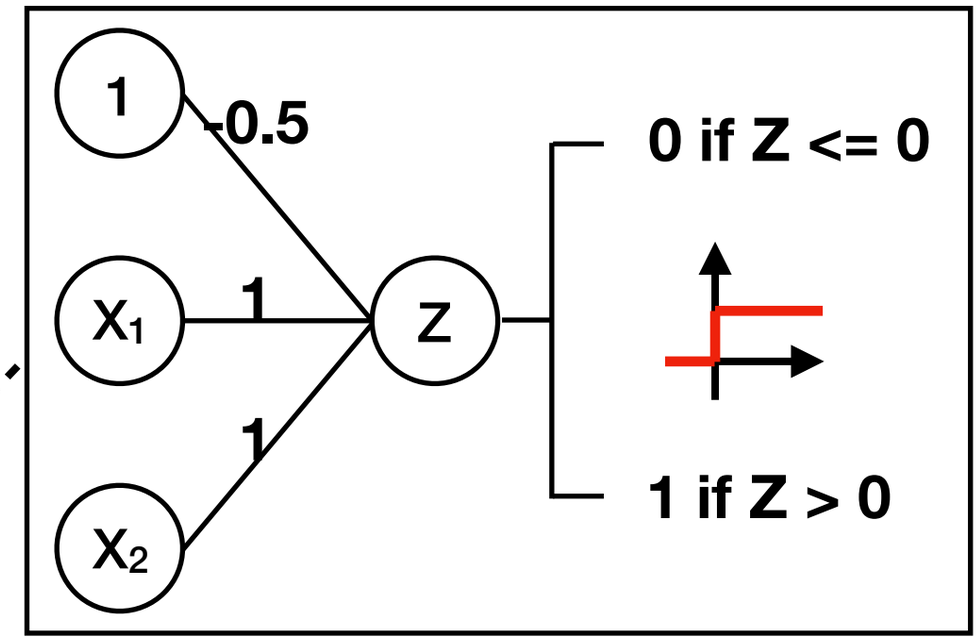
Forward path



Densely connected (fully connected)

Forward path





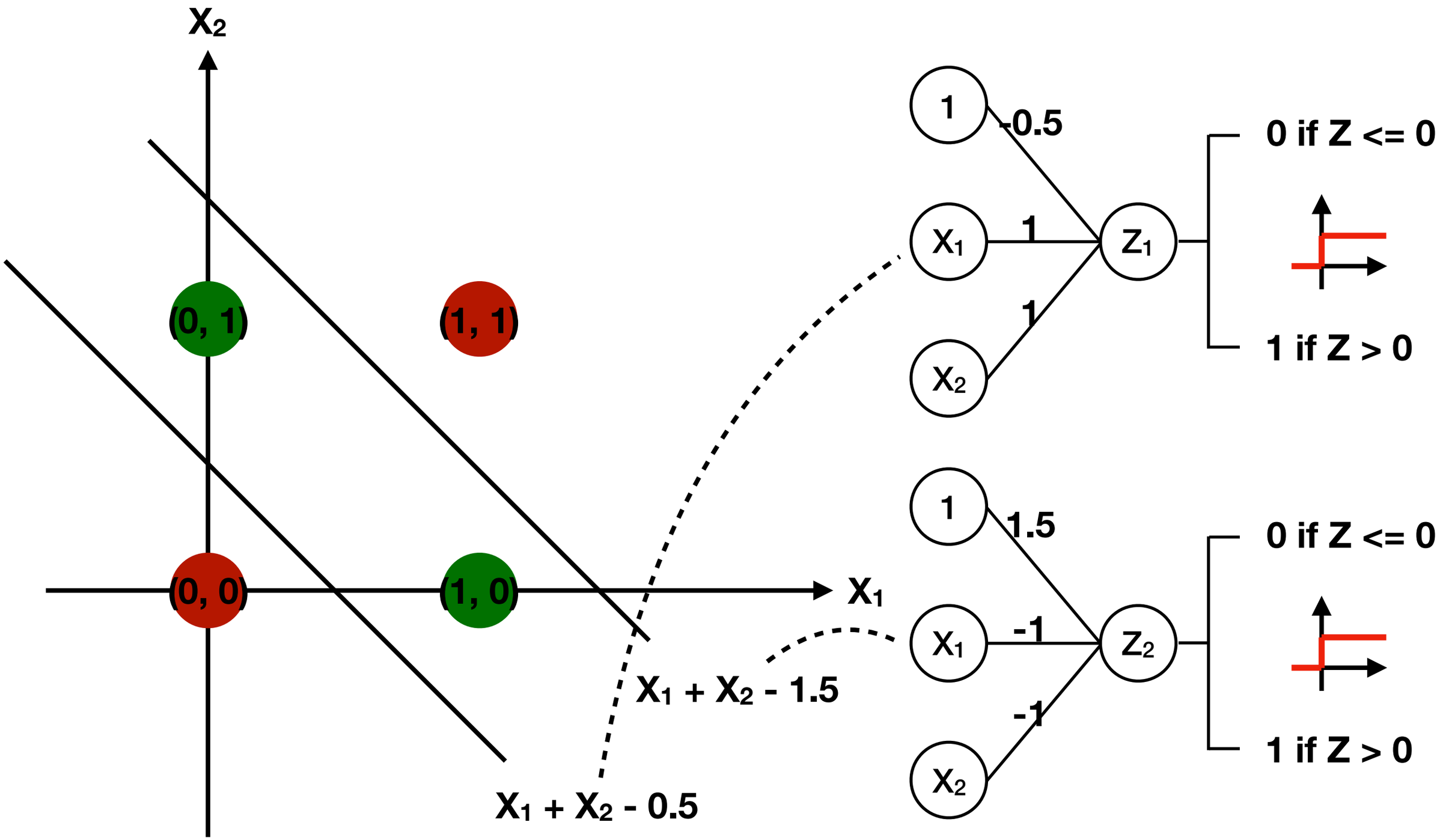
A perceptron

(0, 0) -> -0.5 -> 0
(0, 1) -> 0.5 -> 1
(1, 0) -> 0.5 -> 1
(1, 1) -> 1.5 -> 1

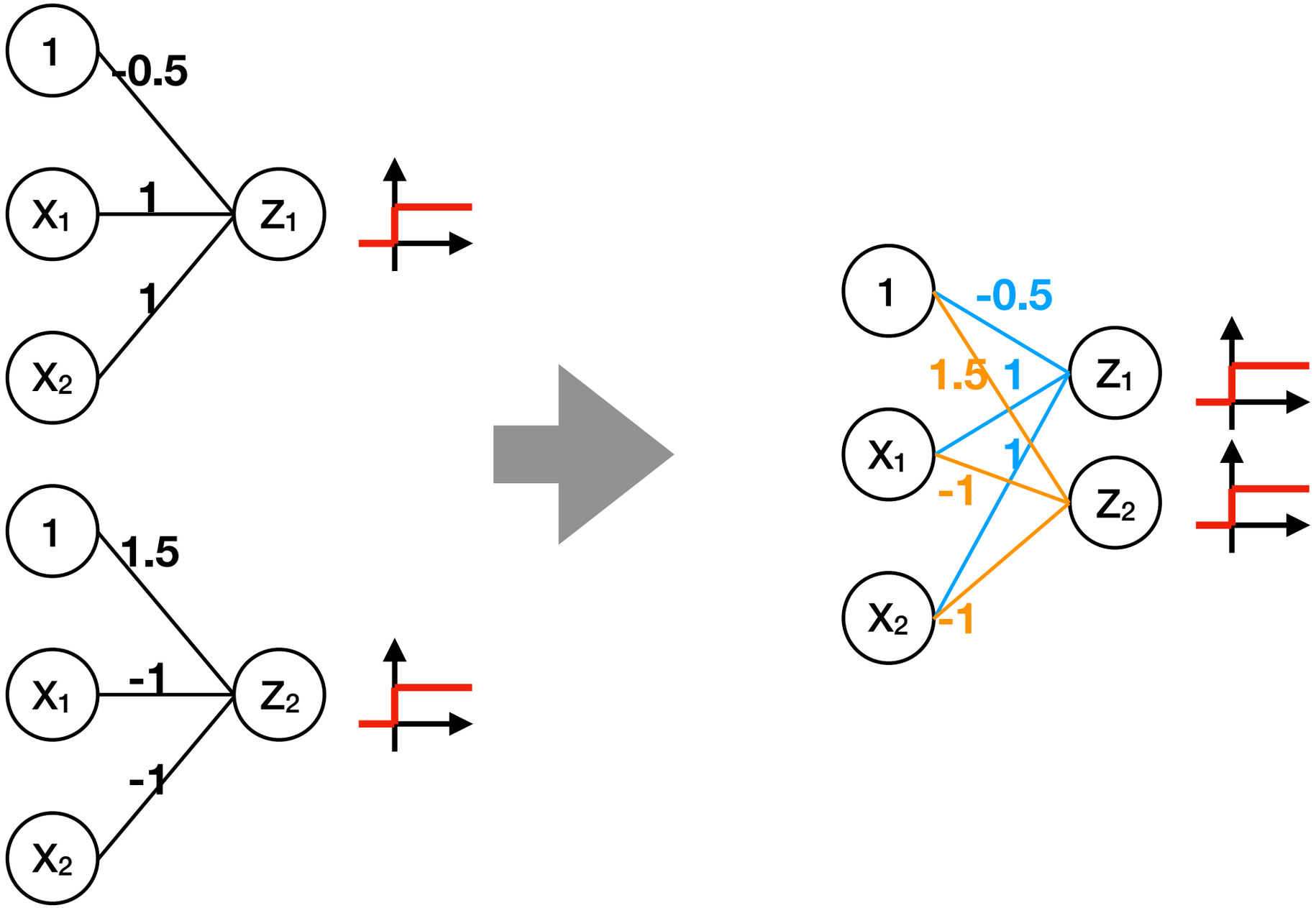
: 0

: 1

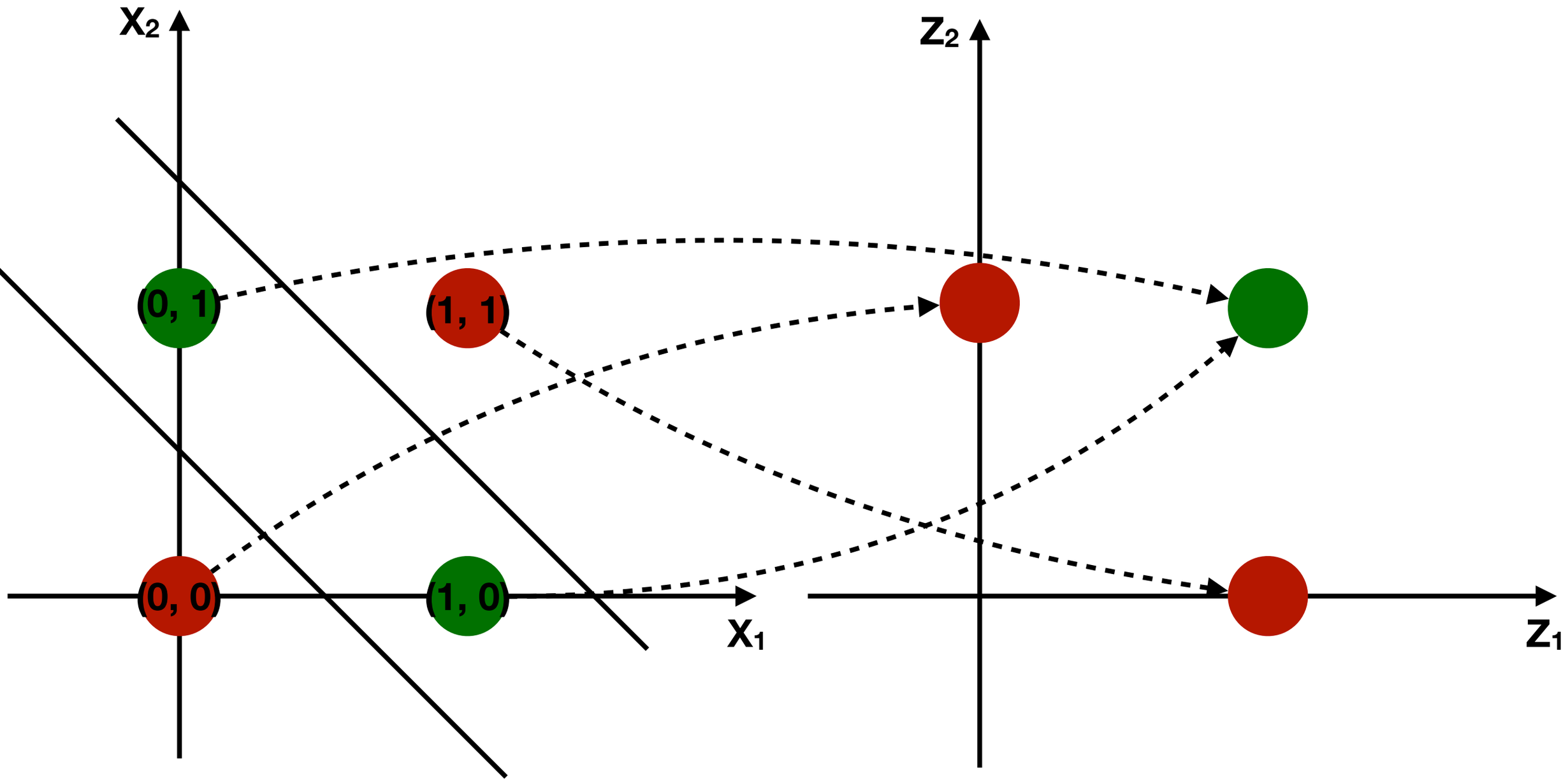
Forward path



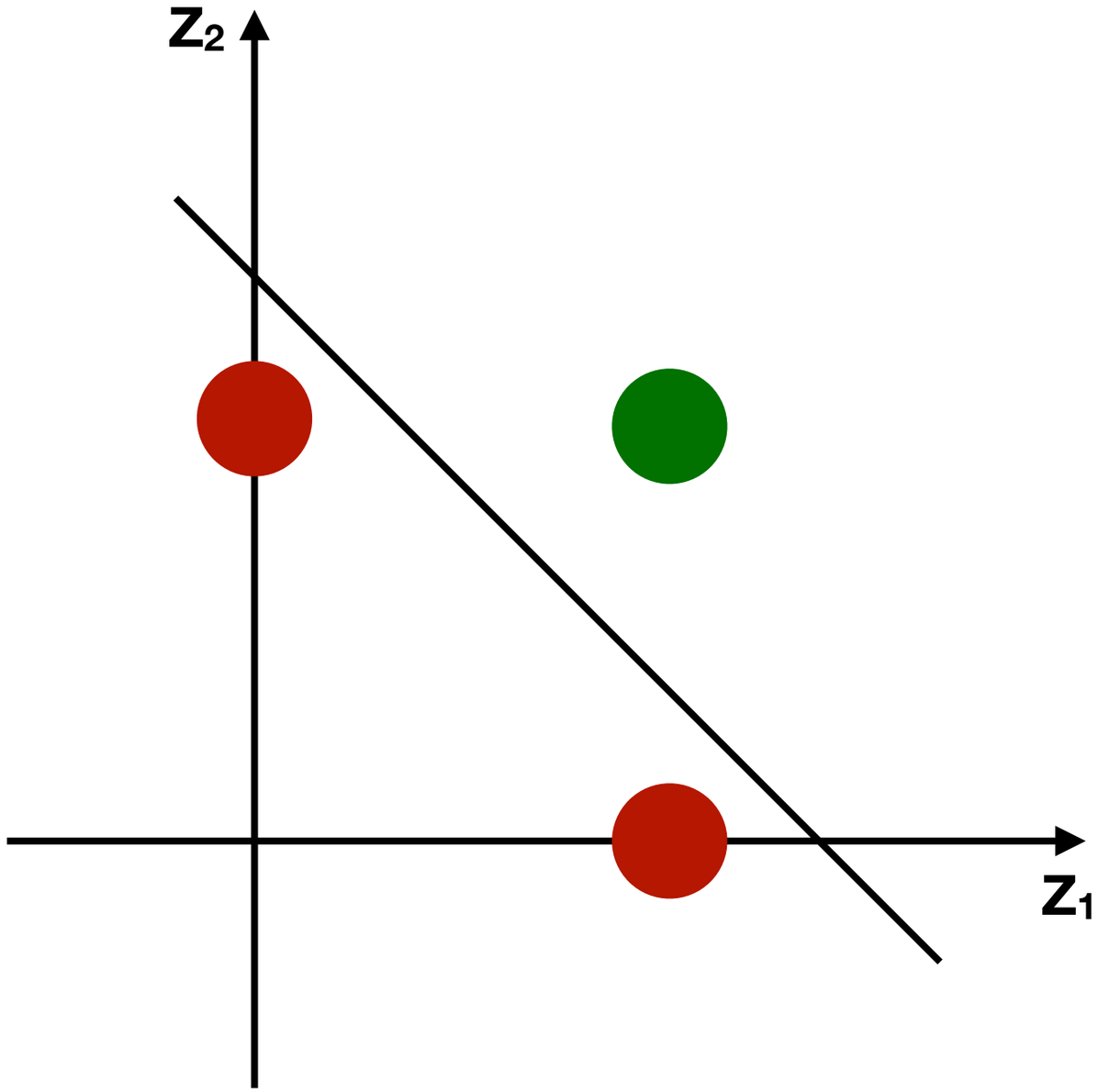
Forward path

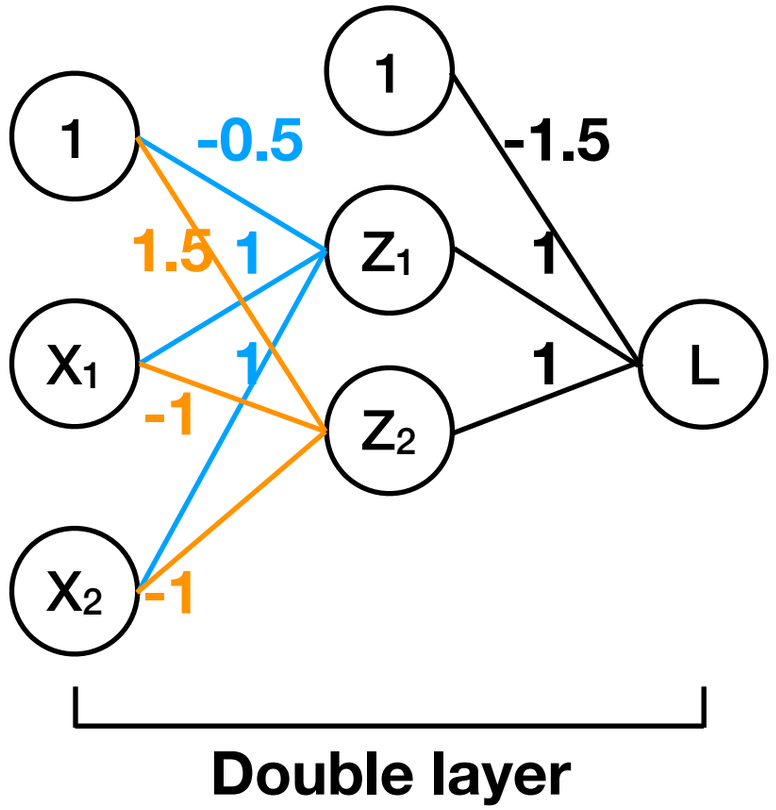


Forward path



Forward path





Forward path

- Why do we need an activation function?

Without any activation function, it is infeasible to approximate higher degree function.

$$Y_1 = WX_1 + B$$

$$Y_2 = W(WX_1 + B) + B = W'X_1 + B' = WX_1 + B$$

$$Y_1 = WX_1 + B$$

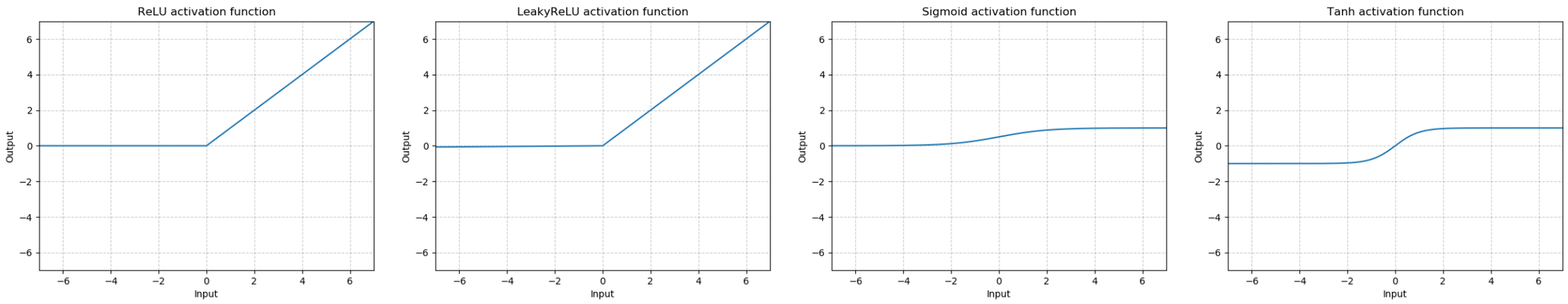
$$Z_1 = f(Y_1)$$

$$Y_2 = WZ_1 + B$$

where f(.) is non-linear activation function

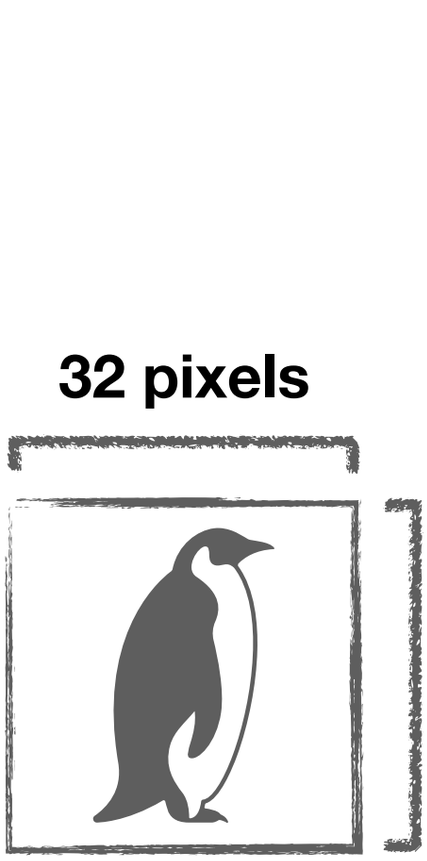
Thus we add an activation function after a weight layer.

Activation functions



- ReLU (Rectified linear unit) : $max(0,\ x)$
- Leaky ReLU : $max(0,\ x)\ +\ negative\ slope \times min(0,\ x)$
- Hyperbolic tangent (tanh): $\frac{e^x - e^{-x}}{e^x + e^{-x}}$
- Logistic sigmoid : $\frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} = \frac{1}{2} + \frac{1}{2}tanh(\frac{x}{2})$

Forward path



32 pixels

32 pixels

Flattening
32x32 -> 1024

Bias

$$\sum_{i=0}^{1024} X_i W_{i,0}$$

Activation

1 $W_{0,0}$ Y_0 Z_0 $Y_0^{(L)}$ $Z_0^{(L)}$

X_1 $W_{1,0}$ Y_1 Z_1 $Y_1^{(L)}$ $Z_1^{(L)}$

X_2 $W_{2,0}$ Y_2 Z_2 ... $Y_2^{(L)}$ $Z_2^{(L)}$

$W_{1024,0}$

Y_m Z_m $Y_{N-1}^{(L)}$ $Z_{N-1}^{(L)}$

X_{1024}

$$Y = WX \qquad Z = \sigma(Y) \qquad Z^{(L)} = softmax(Y^{(L)})$$

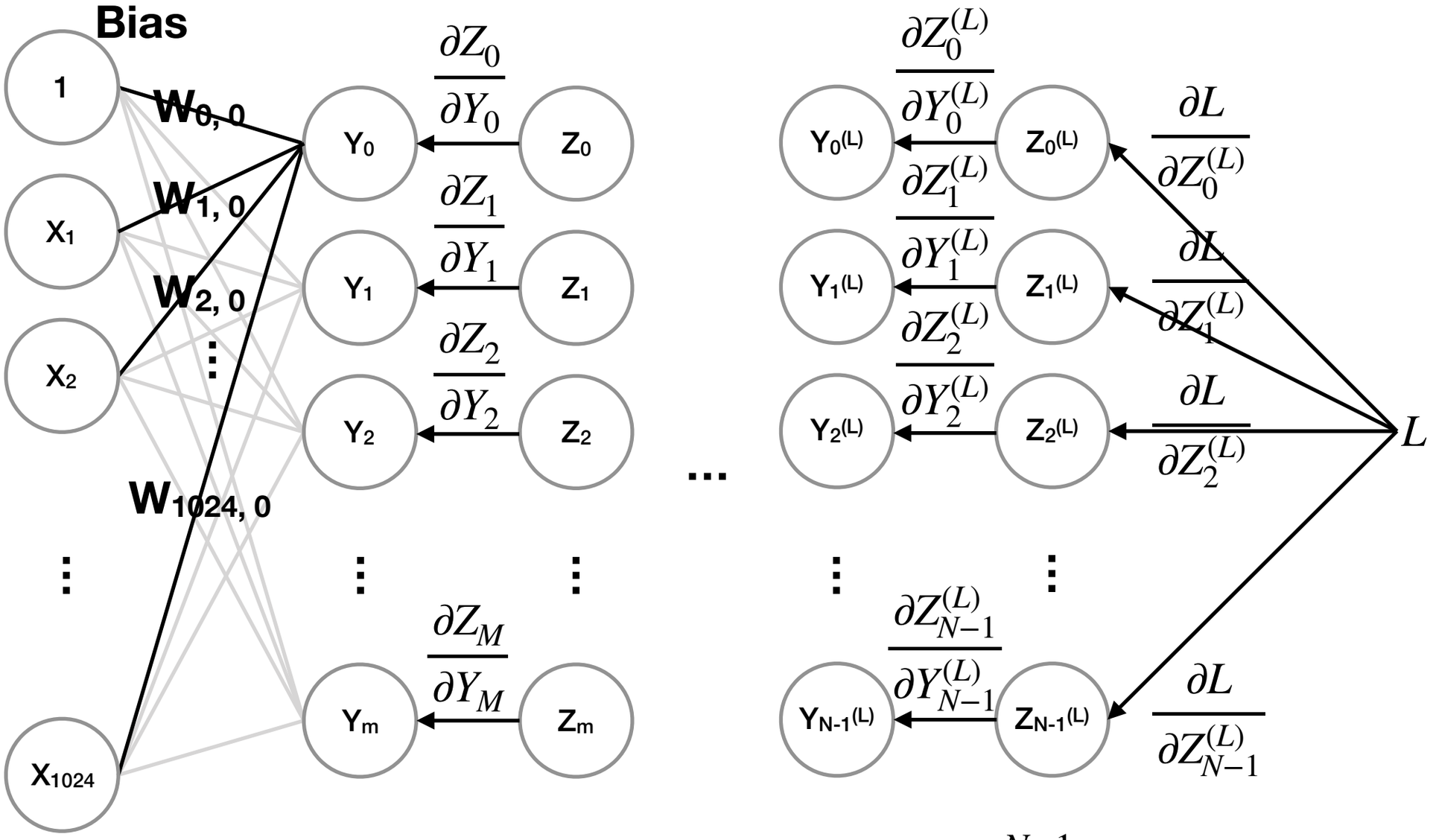
Input layer | 1st Hidden layer | 1st Activation layer | Lth Hidden layer | Output layer

Densely connected (fully connected)

$$softmax(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{C} e^{y_j}}$$

Backward path

Backward path



$$\frac{\partial L}{\partial W0,\,0} = \frac{\partial L}{\partial Y_0}\frac{\partial Y_0}{\partial W_{0,\,0}}$$

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

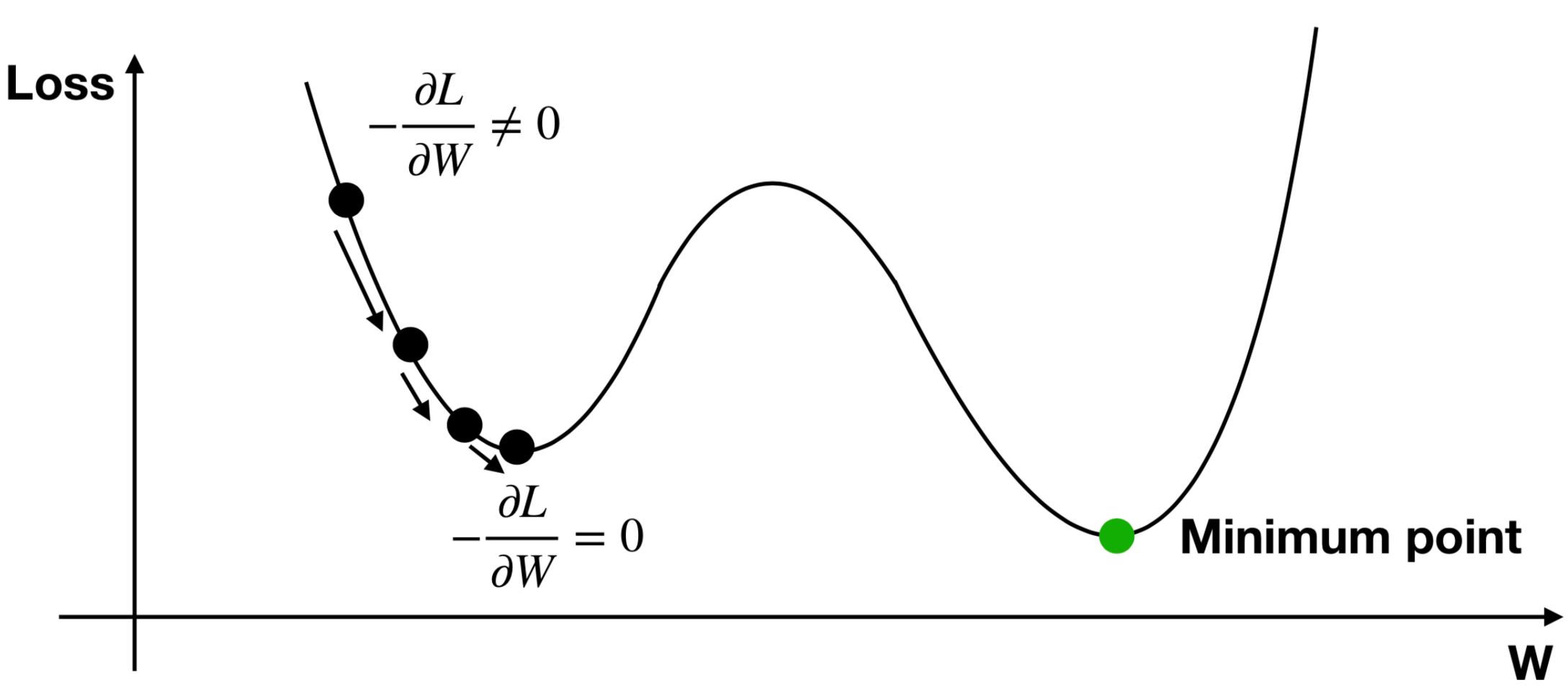
$$L = -\sum_{k=0}^{N-1} t_k log Z_k = -\,log Z_i$$

Cross-entropy loss

Backward path

- Gradient back-propagation updates(changes) weights to have lower loss in a way loss decreases most fast.

- However, this does not guarantee the loss converges to its global minimum.



Practice

MNIST database

Training set: 60,000 images and labels

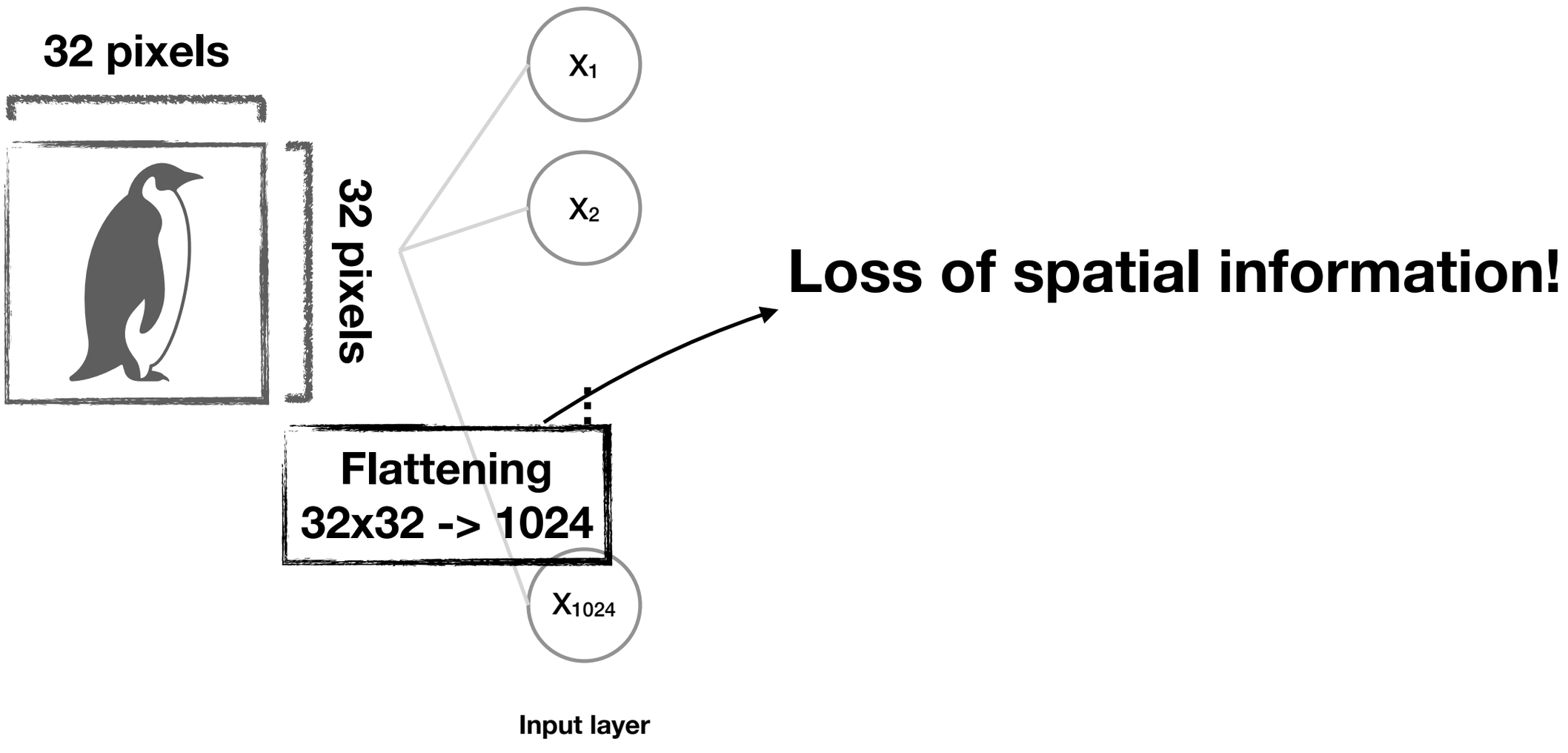
Test set: 10,000 images and labels

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.

2. Convolutional neural networks

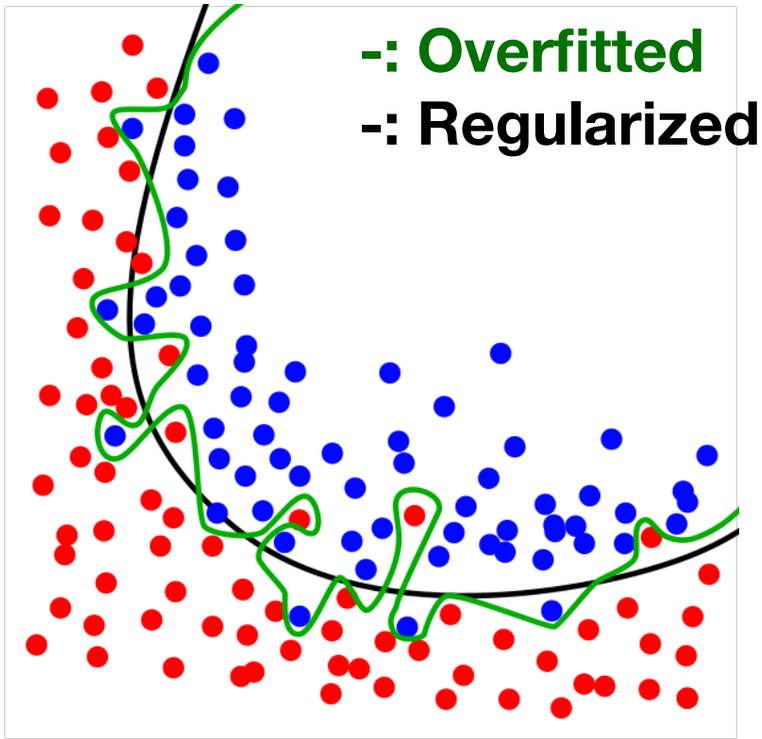
Drawbacks of fully-connected layer

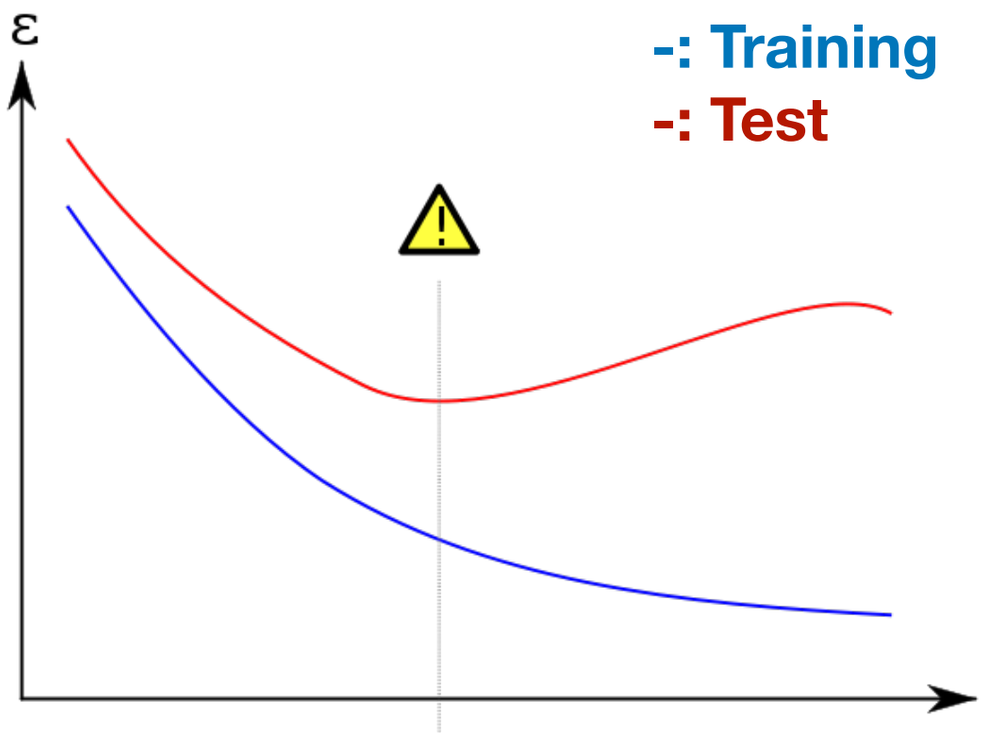
A. Fully-connected (FC) layer does **NOT** consider **"the shape of data."** It is worth noticing that we should make data flattened when we feed a MLP model.



Drawbacks of fully-connected layer

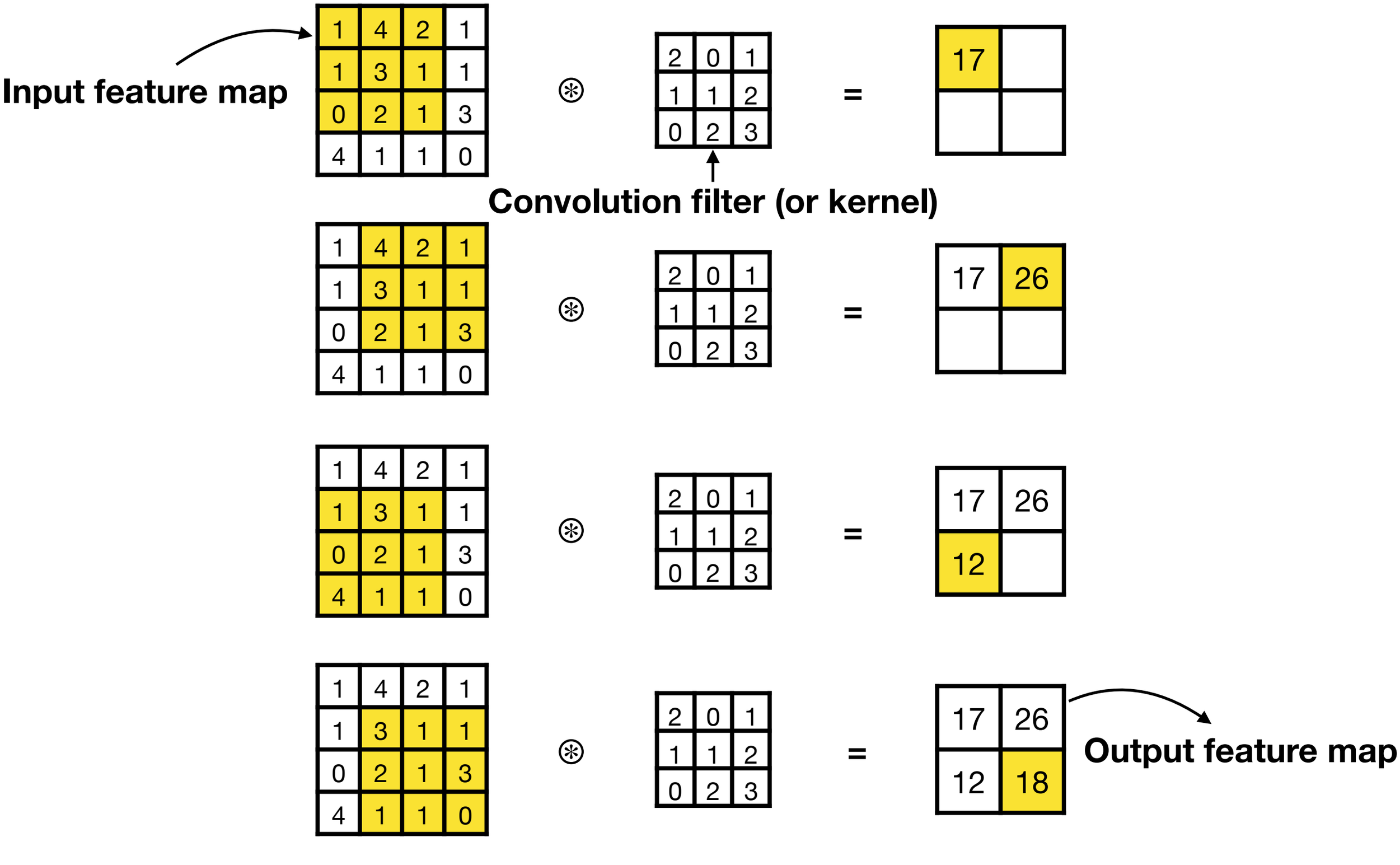
B. FC layers have a large number of weights which tend to cause overfitting.





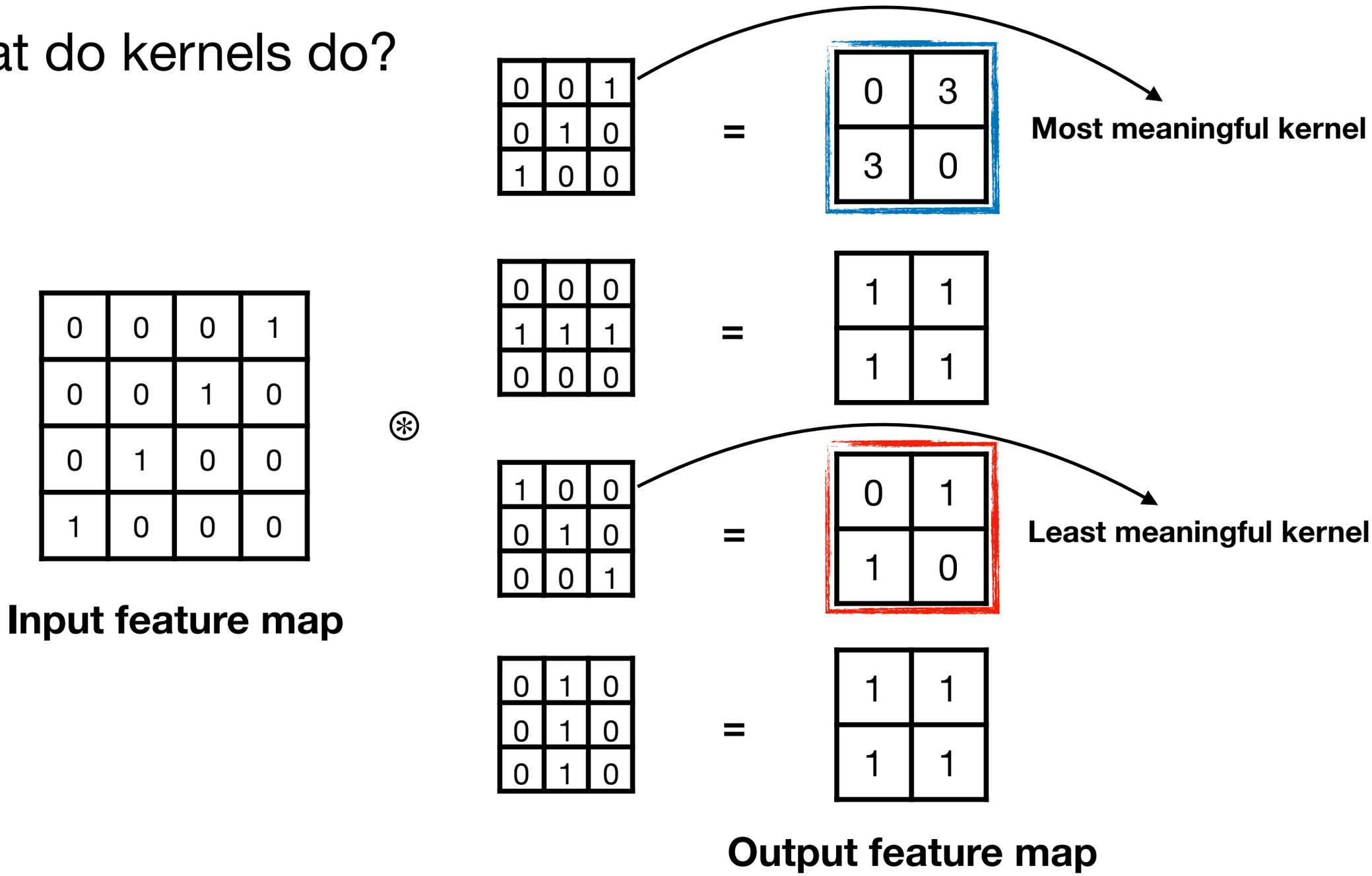
* Overfitting refers to a situation where a model memorizes correct answers for training samples so that it loses general performance on test samples which are not shown to model during training. This is mainly due to the exceeding number of parameters (weights) required to train on a certain dataset.

Convolution

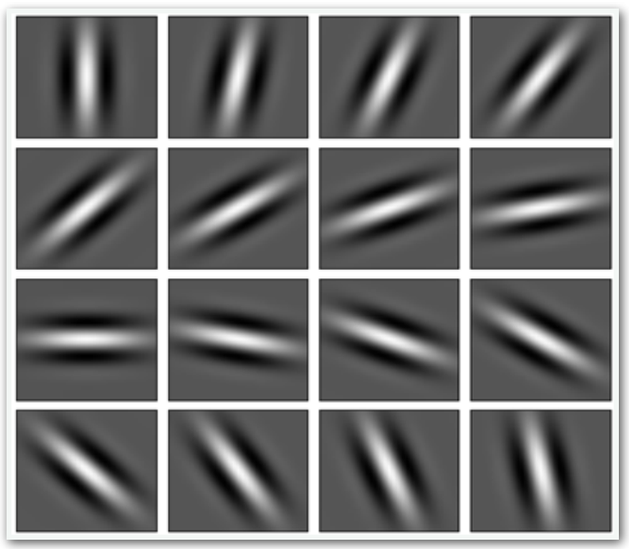


Convolution

- What do kernels do?

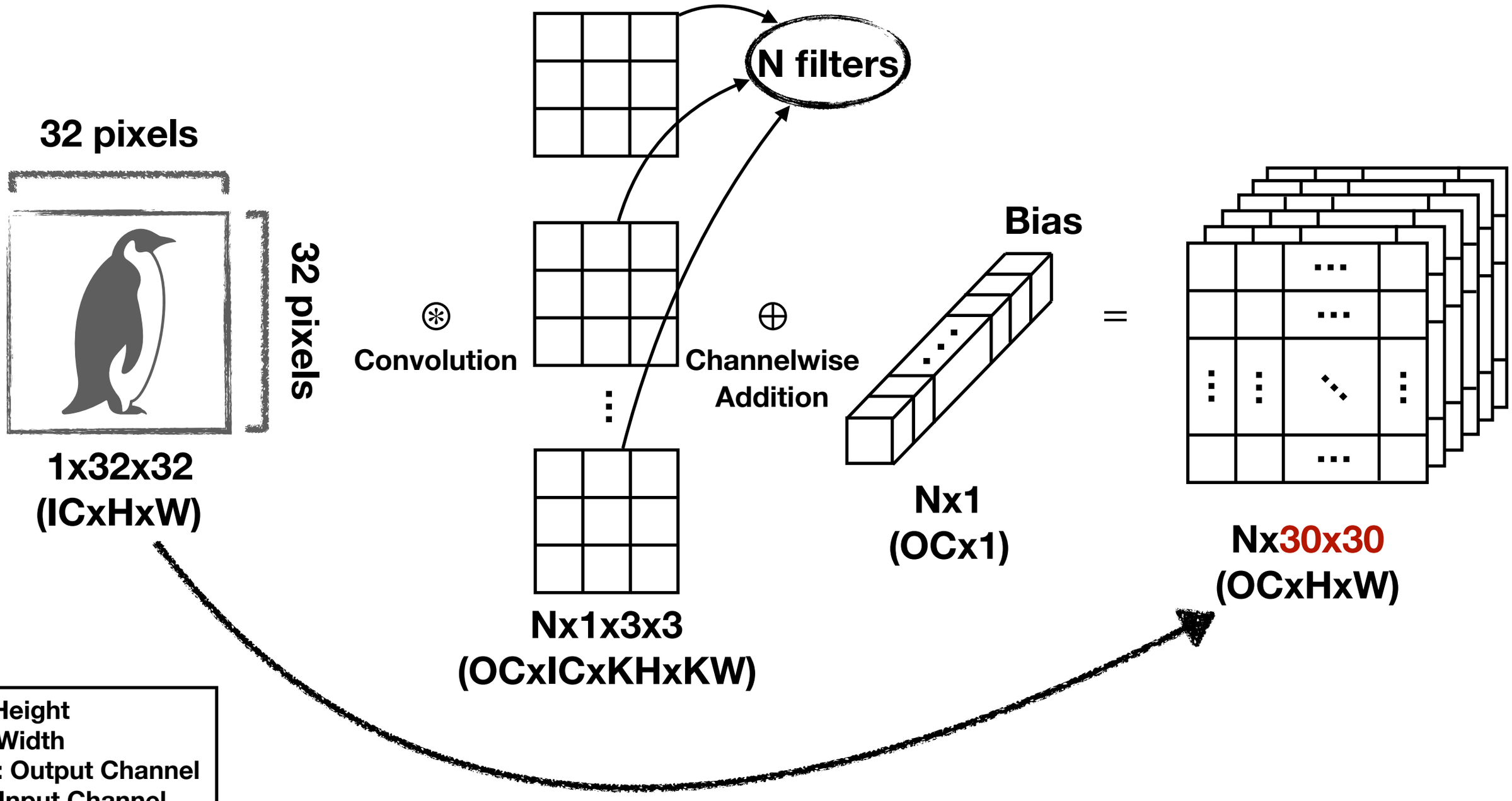


Convolution

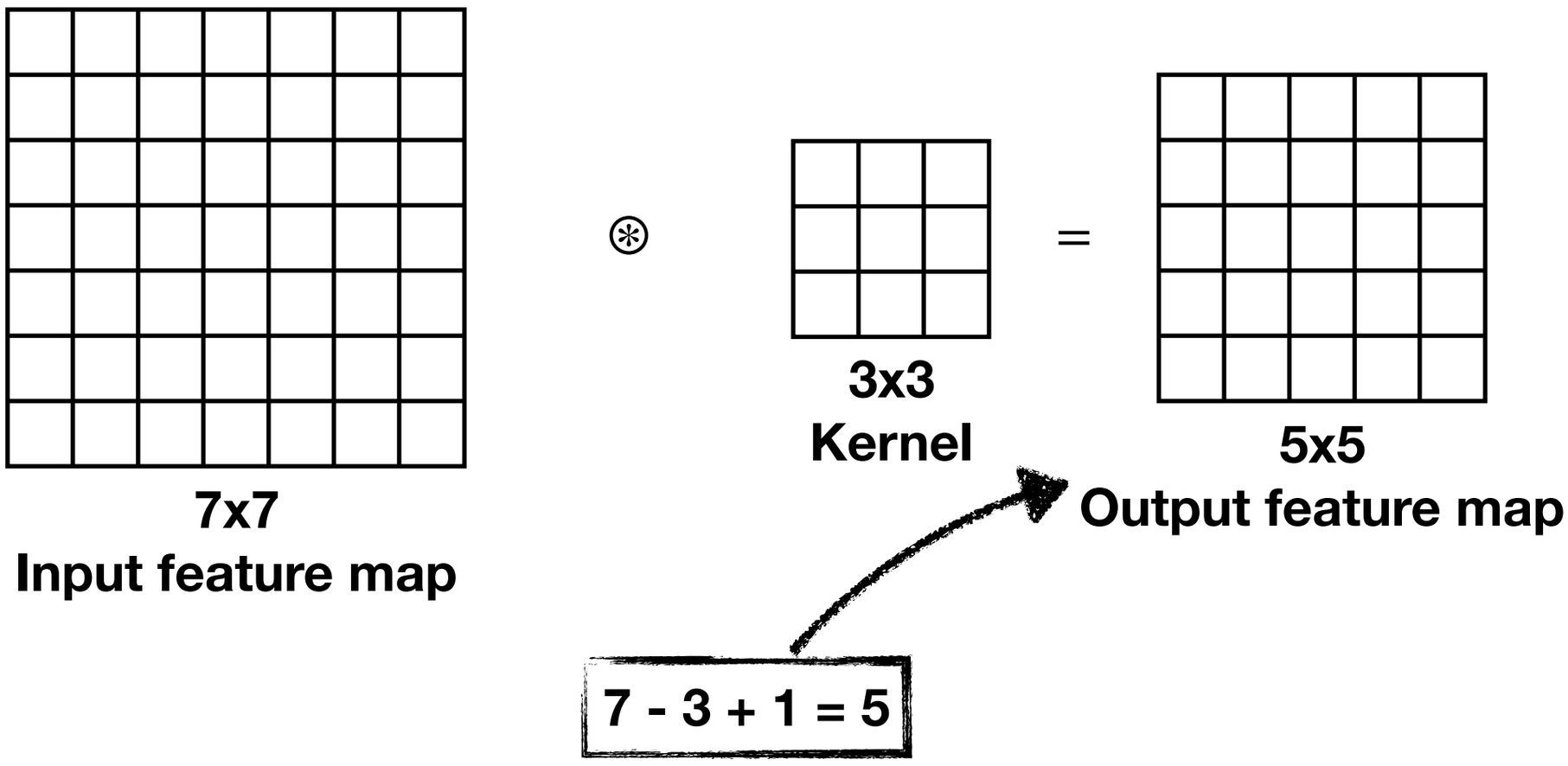


https://medium.com/@anuj_shah/through-the-eyes-of-gabor-filter-17d1fdb3ac97

Convolution

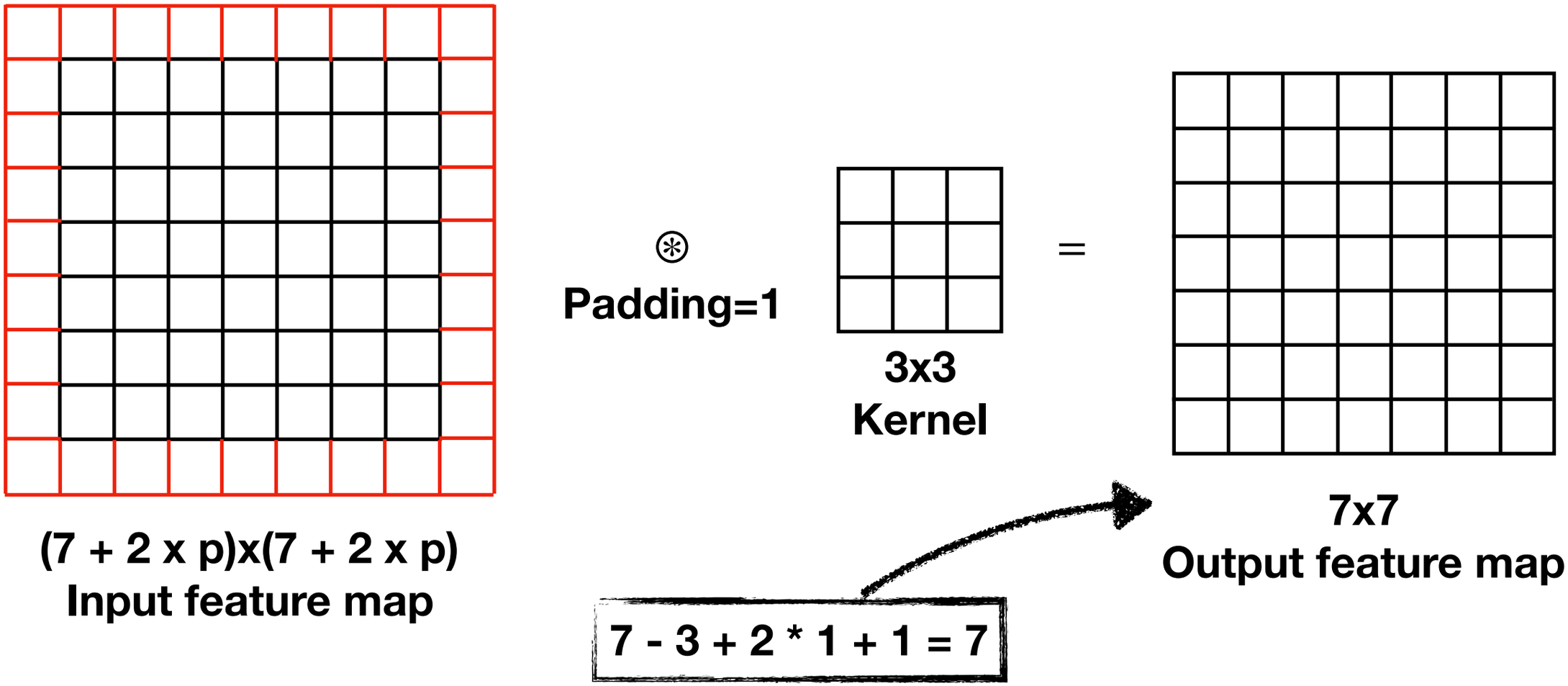


Convolution



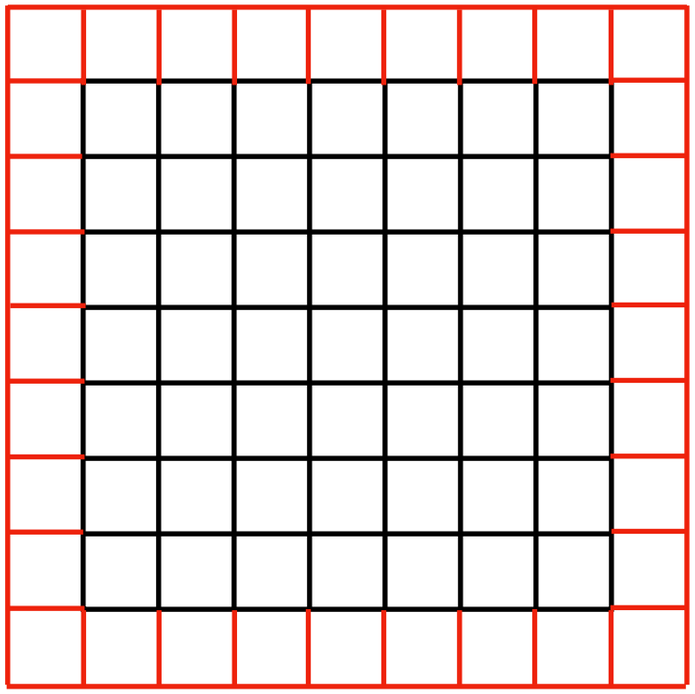
$$o = i - k + 1$$

Convolution



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

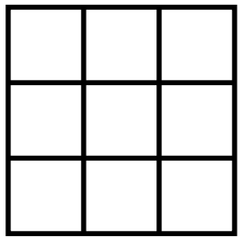
Convolution



(7 + 2 x p)x(7 + 2 x p)
Input feature map

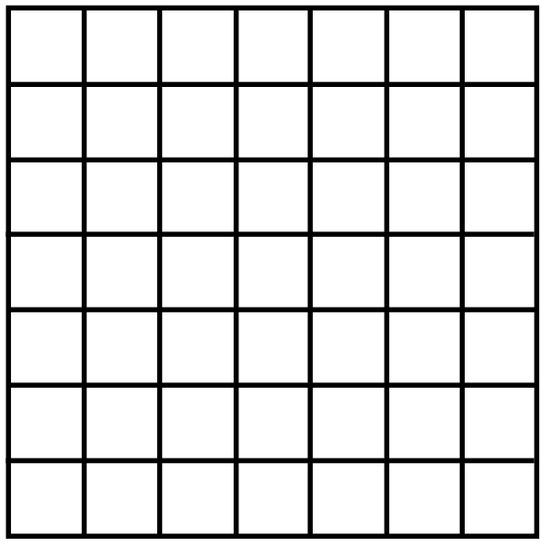
⊛

Padding=1
Stride=2



3x3
Kernel

=

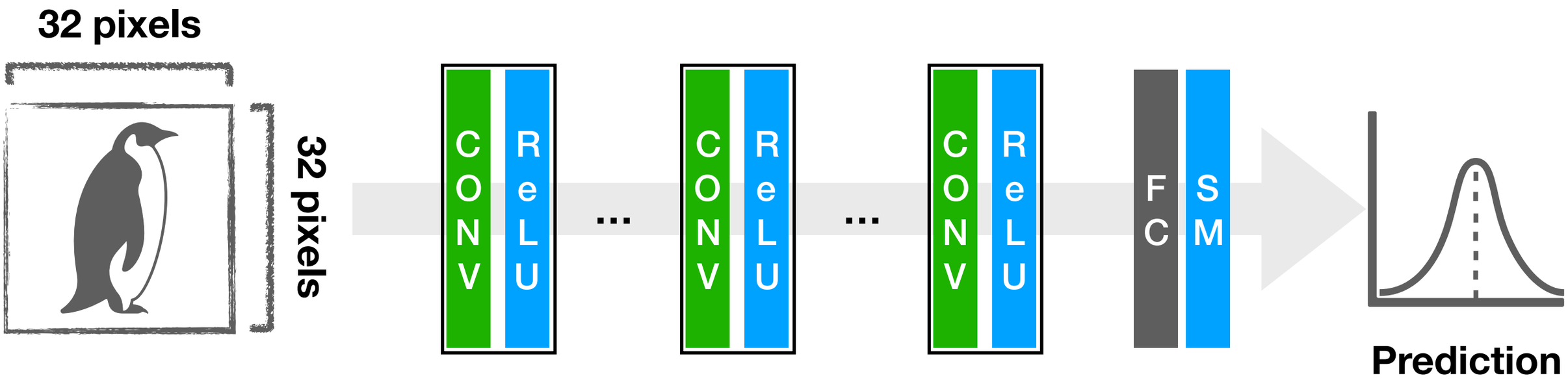


4x4
Output feature map

(7 - 3 + 2 * 1) // 2 + 1 = 4

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

Convolutional neural network



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

Practice

MNIST database

Training set: 60,000 images and labels

Test set: 10,000 images and labels

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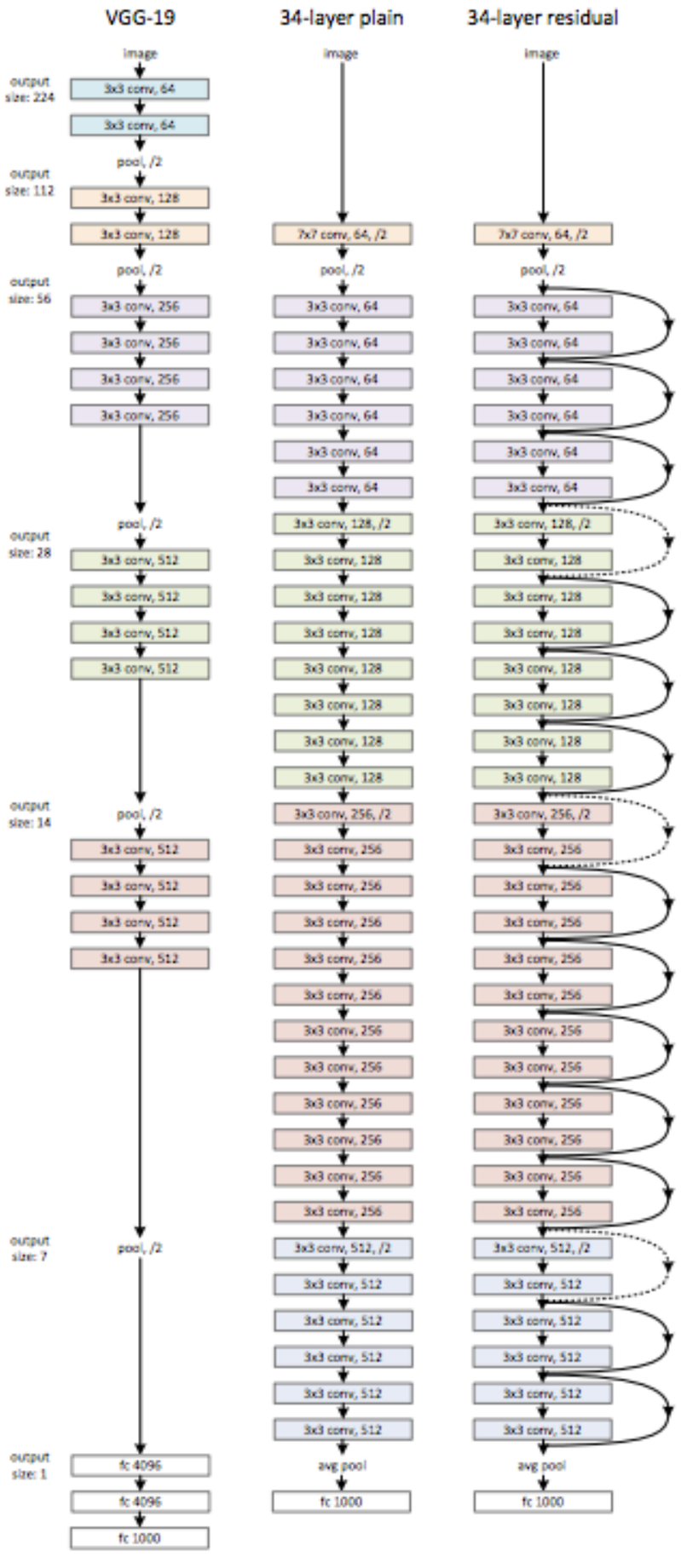
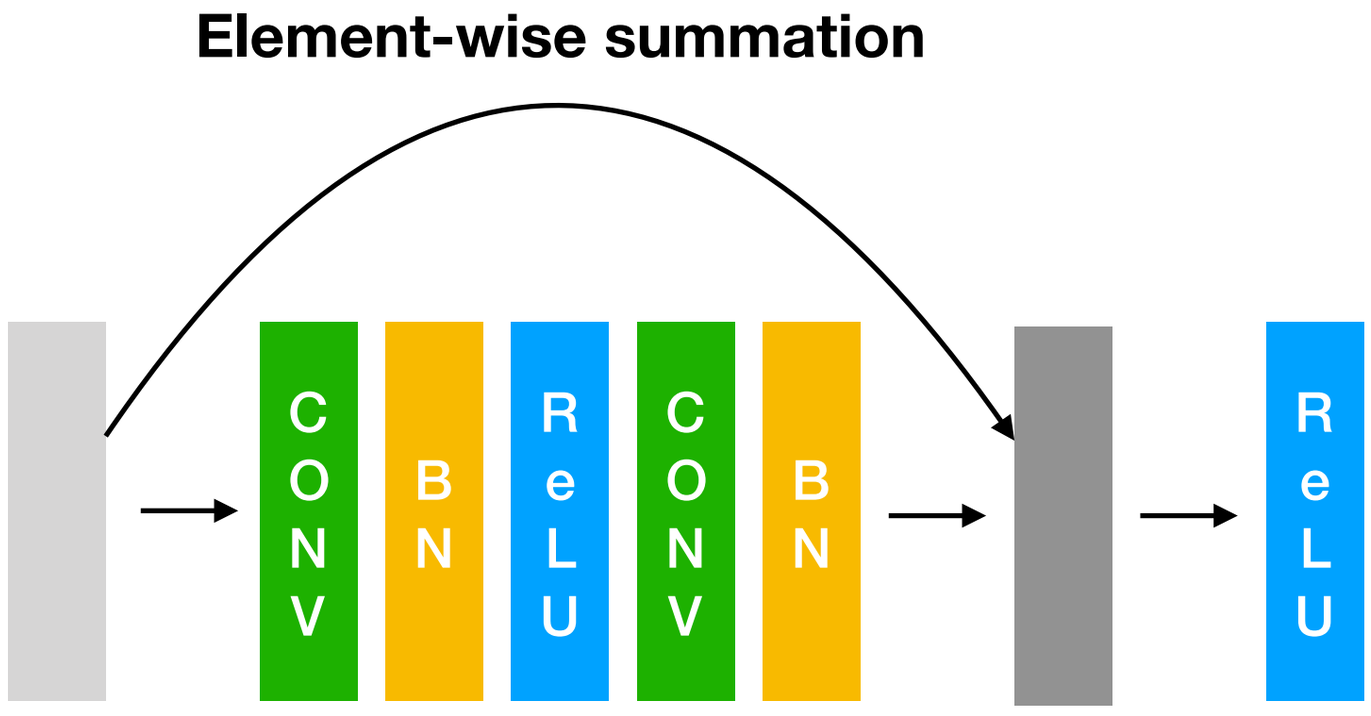
3. Residual Networks

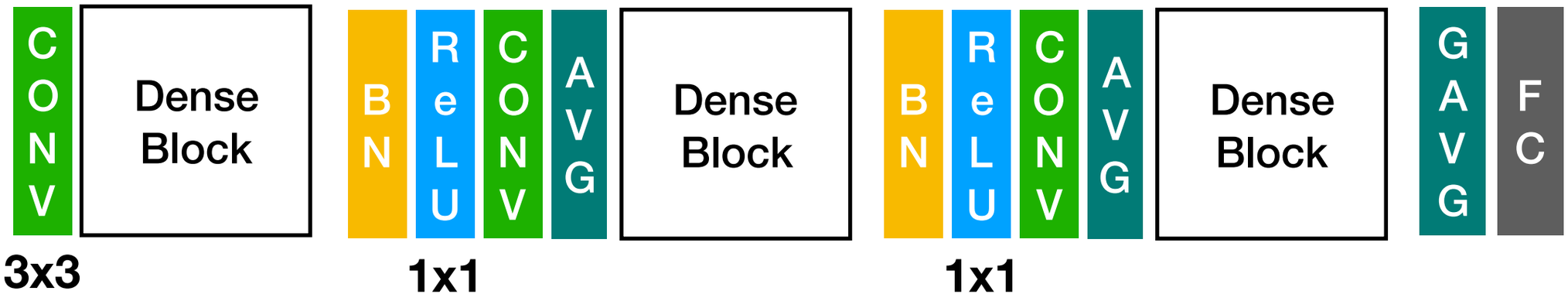




When feature map size changes, 1x1 convolution with stride 2 is applied such that the shortcut connection can be presented every two convolution layers.

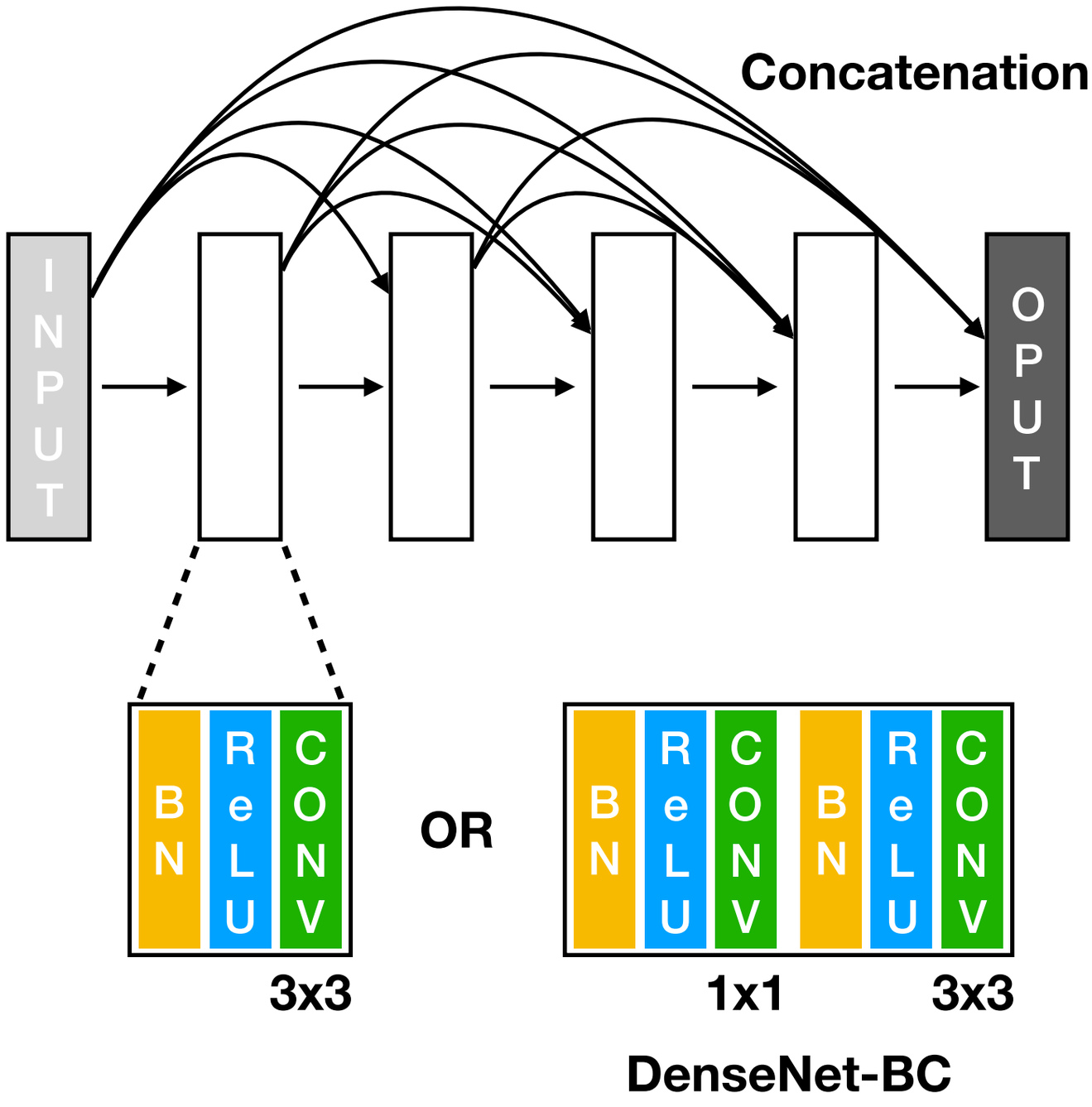
4. Dense Networks

Dense Network



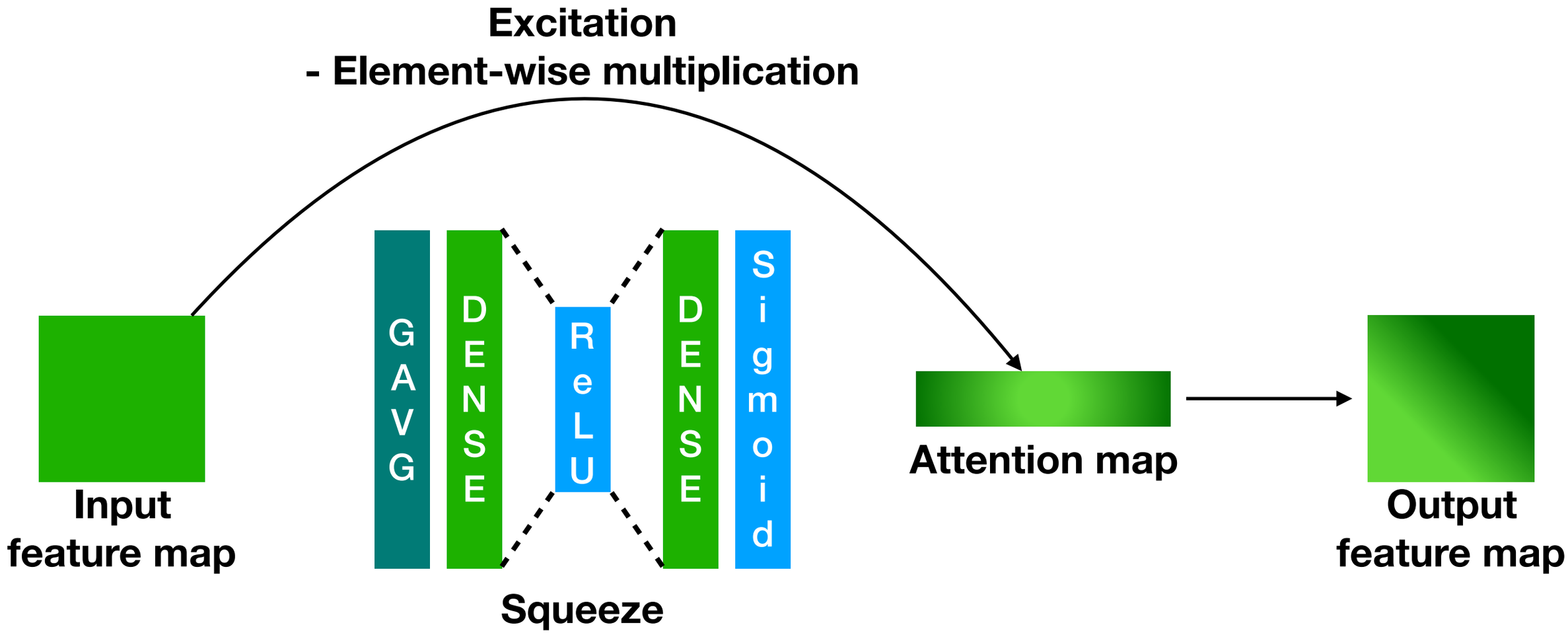
AVG: AVeraGe pooling
BN: BatchNormalization layer
CONV: Convolutional layer
FC: Fully-Connected layer
GAVG: Global AVeraGe pooling
ReLU: Rectified Linear Unit

Dense Block


Concatenation
INPUT
OUTPUT
BN
ReLU
CONV
3x3
OR
BN
ReLU
CONV
BN
ReLU
CONV
1x1
3x3
DenseNet-BC

5. Squeeze-and-Excitement Networks

Squeeze-and-Excitation Block



DENSE: Fully-connected layer
GAVG: Global AVeraGe pooling
ReLU: Rectified Linear Unit

Part II

Time Series Data

Part III

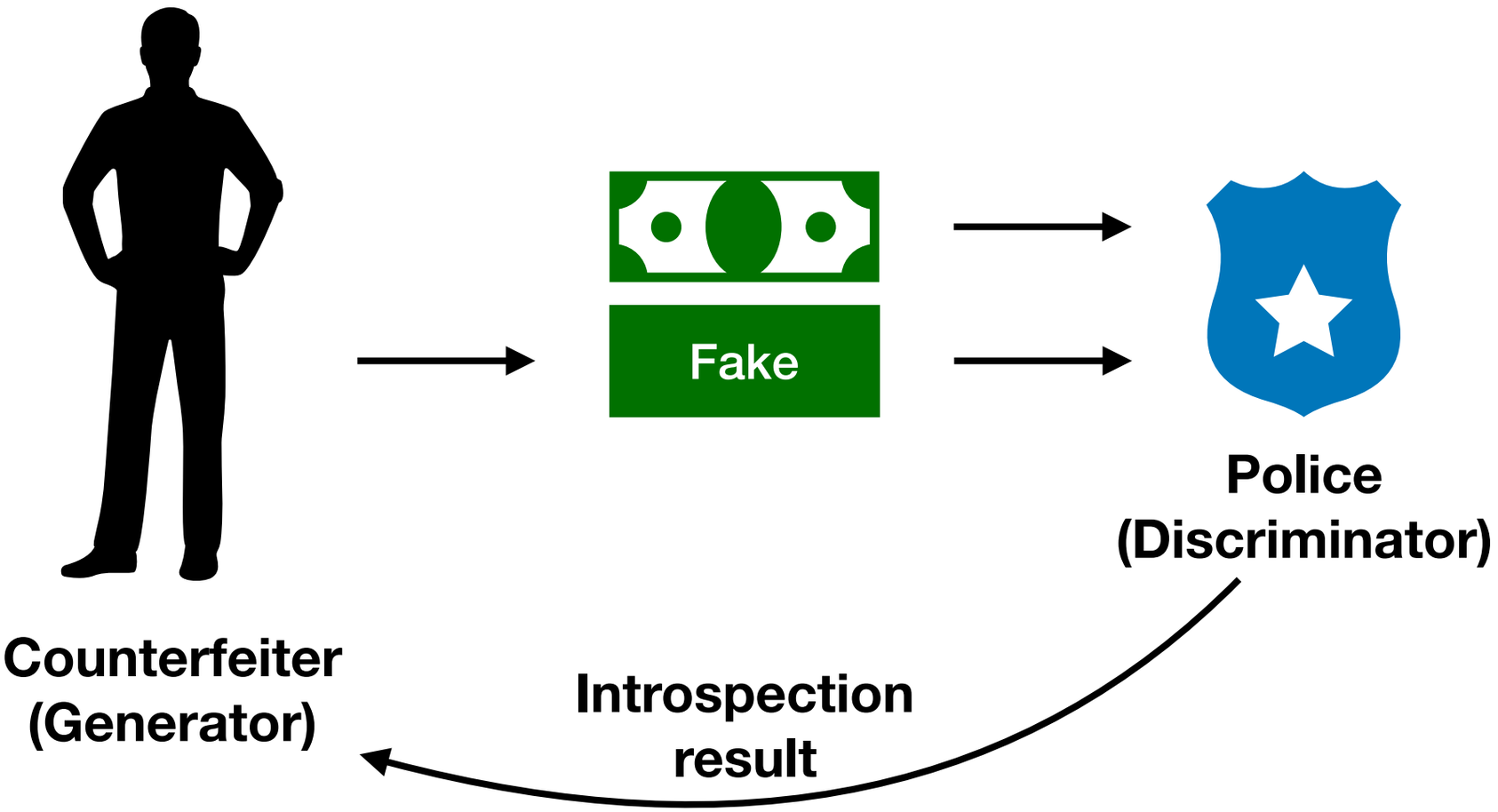
Generative Model

Various generative models

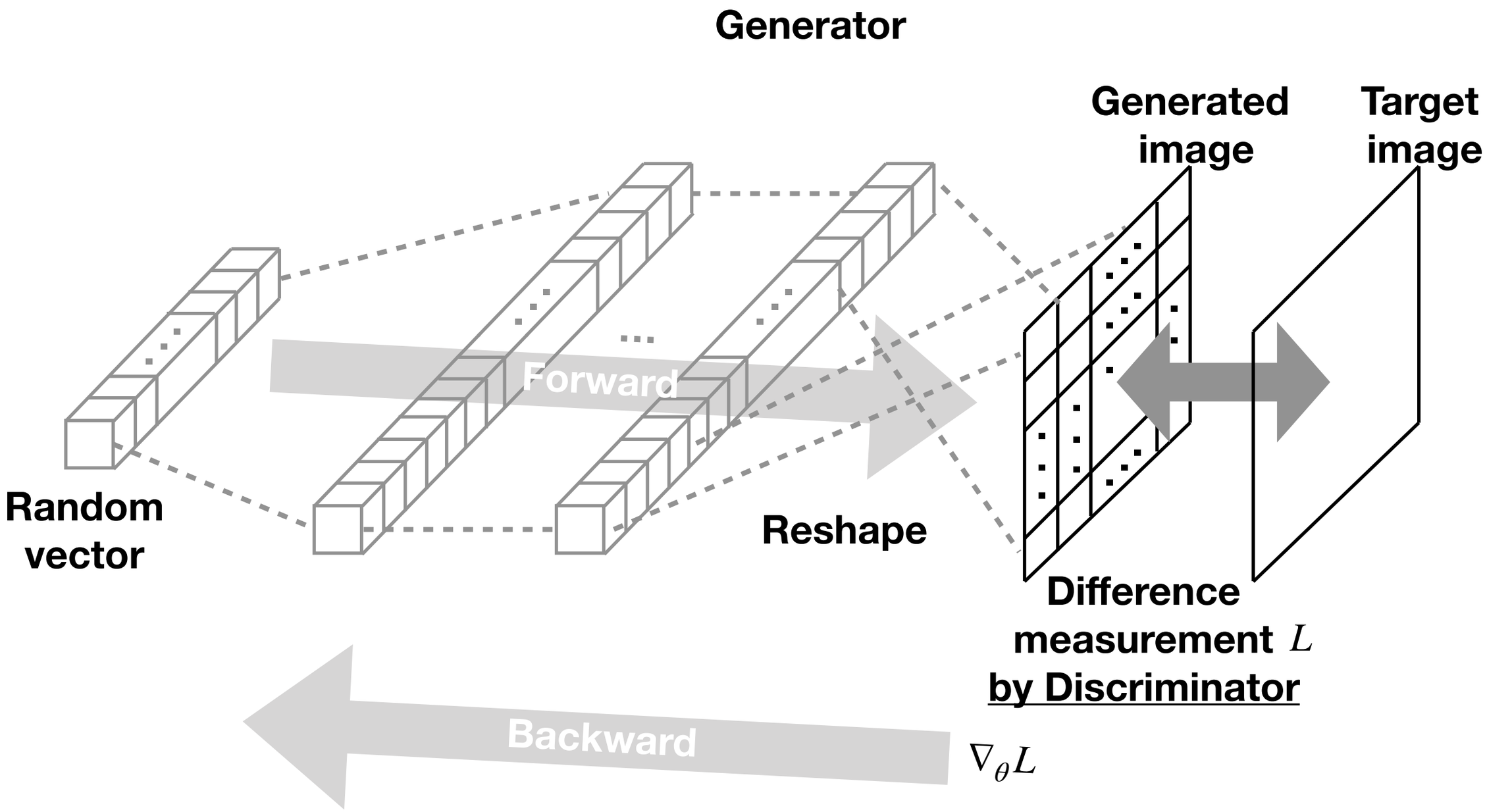
- Hidden Markov Model (HMM)
- Restricted Boltzmann Machine (RBM)
- Variational Auto-Encoder (VAE)
- Recurrent Neural Network (RNN)
- **Generative Adversarial Network (GAN)**

GAN

What is GAN?

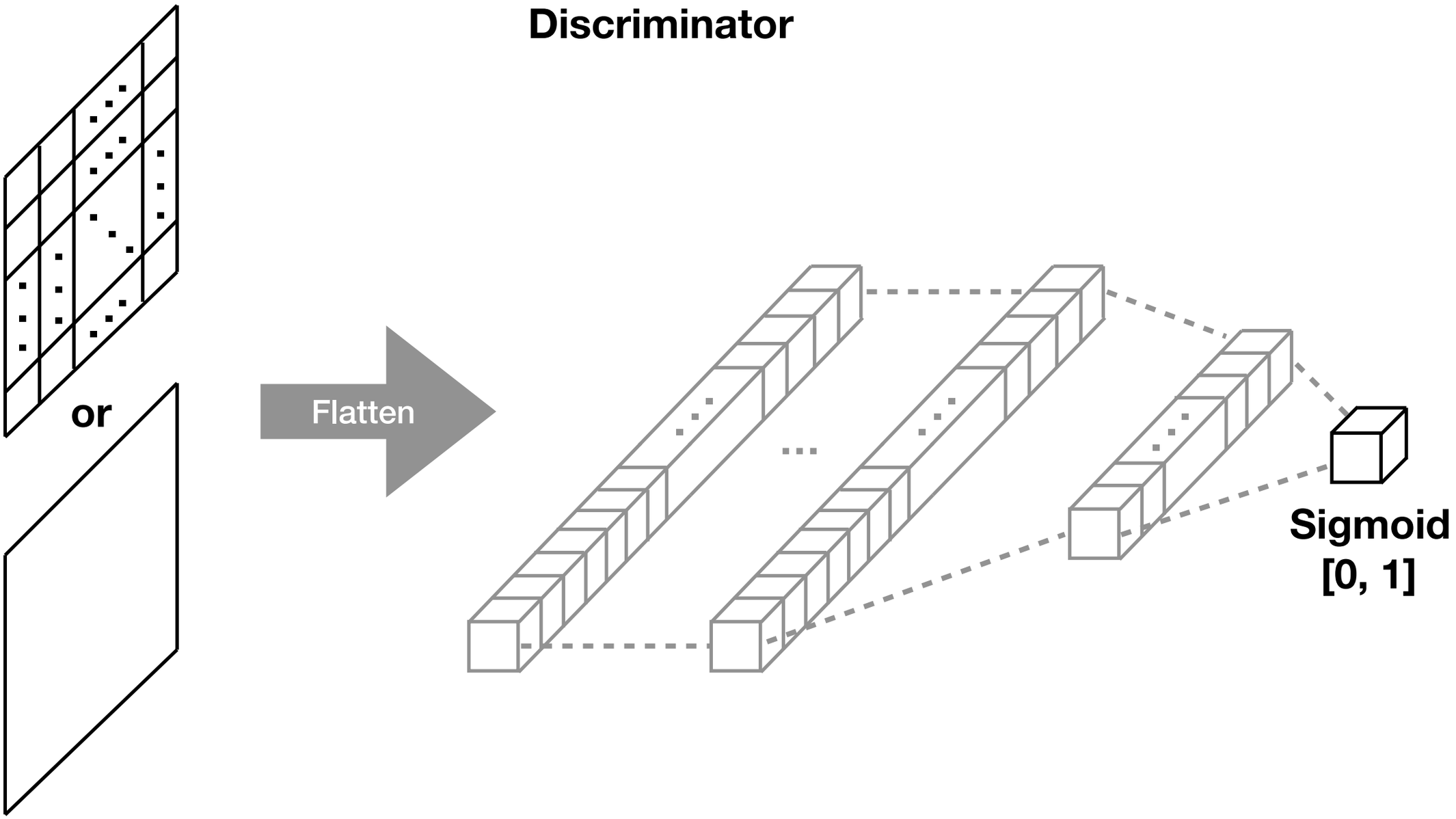

Fake
Police
(Discriminator)
Counterfeiter
(Generator)
Introspection
result

How does GAN work?



E.g. image generation model

How does GAN work?



Practice

CIFAR10

airplane

automobile

bird

cat

deer

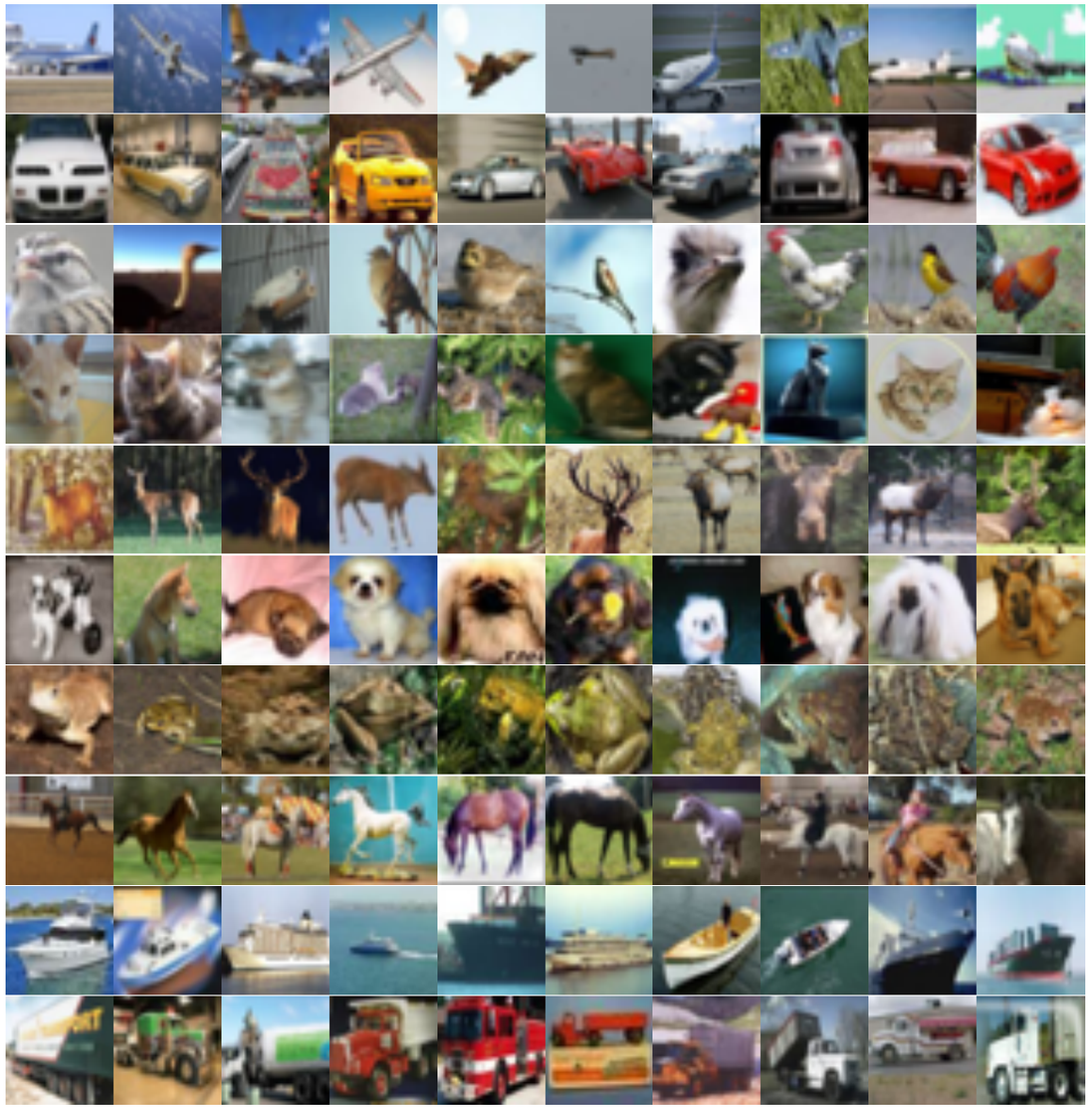
dog

frog

horse

ship

truck

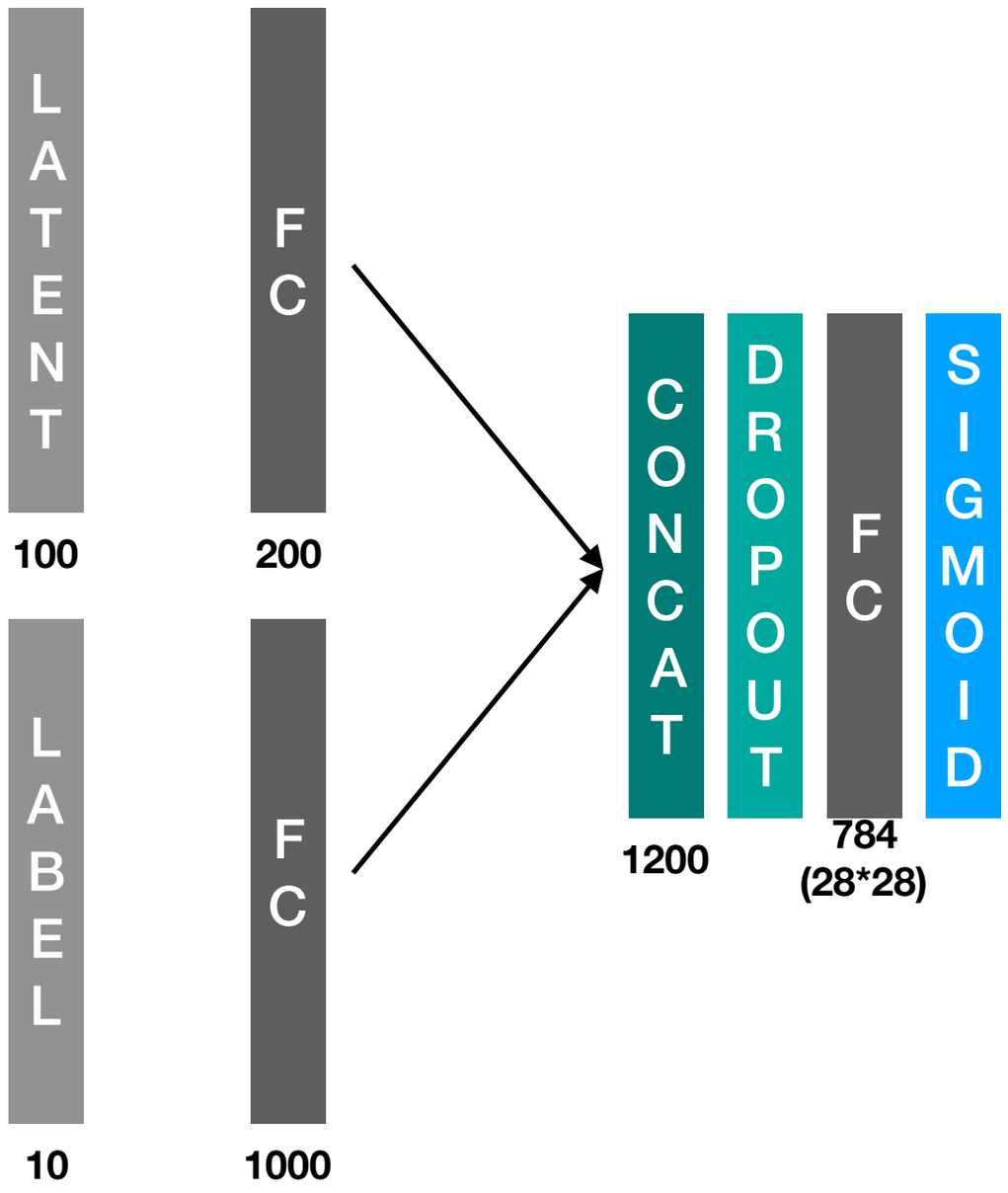


Credit. Learning Multiple Layers of Features from Tiny Images, Alex Krizhevsky, 2009.

The CIFAR-10 dataset consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 test images.

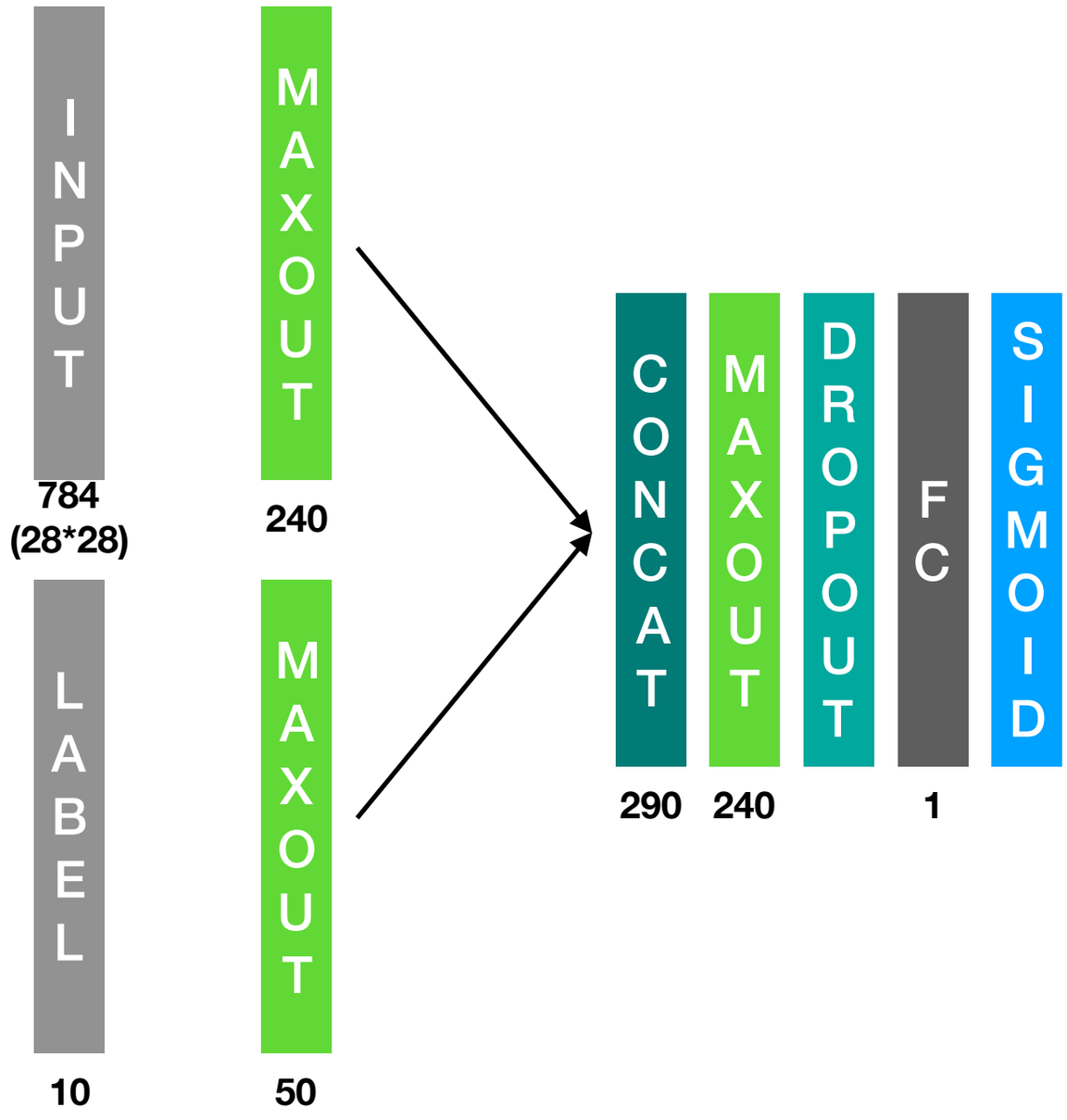
Conditional GAN

Generator



FC: Fully Connected layer **Note. This model is for MNIST dataset. LABEL is one-hot encoded label. Dropout rate is 0.5.**

Discriminator

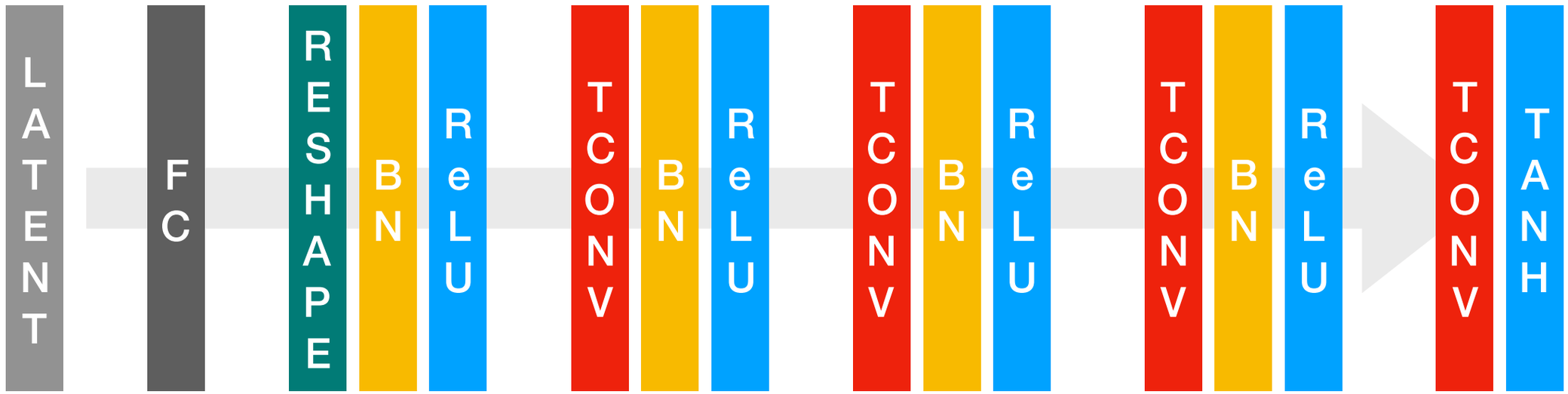


FC: Fully Connected layer

Note. This model is for MNIST dataset. LABEL is one-hot encoded label. Dropout rate is 0.5. MAXOUT layer includes dropout layer implicitly with rate 0.5. MAXOUT parameter k is set to 5 except for the last MAXOUT set to be 4.

DCGAN

Generator

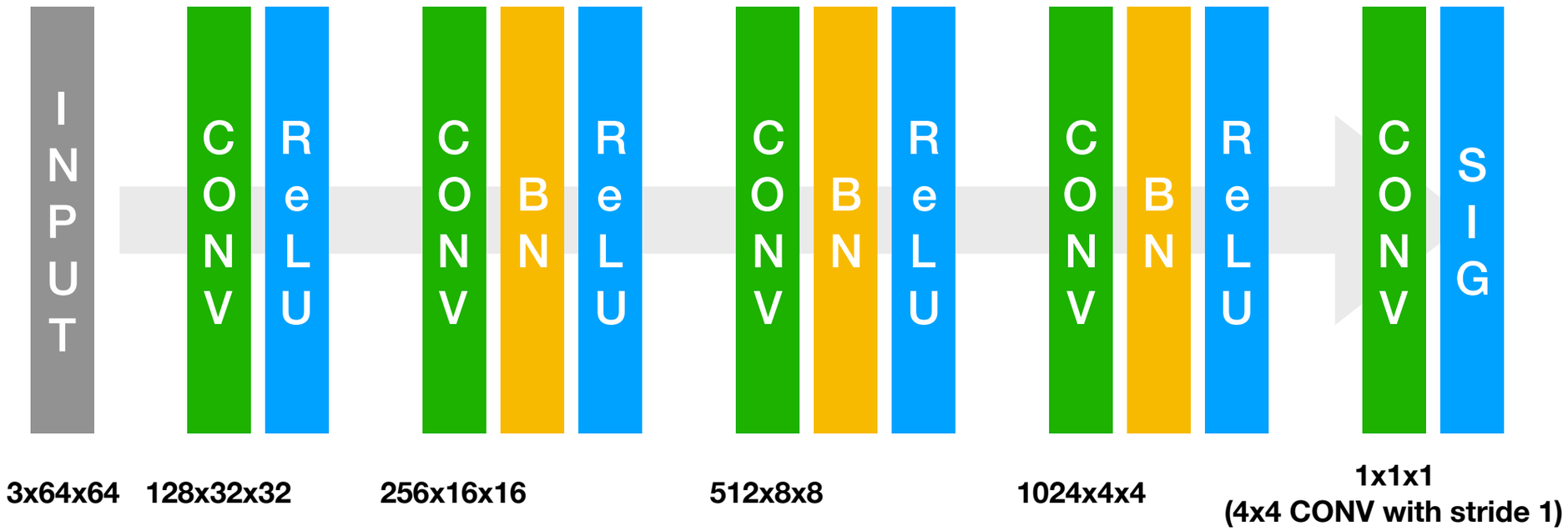


Dim	100	16384 (=4*4*1024)	1024x4x4 (CxHxW)	512x8x8	256x16x16	128x32x32	3x64x64

BN: Batch Normalization
C: Channel
FC: Fully Connected layer
H: Height
ReLU: Rectified Linear Unit
TCONV: 5x5 Transposed CONVolution (stride 2)
W: Width

Note. This is for the case of LSUN dataset. The number of TCONV layer can be varied with your target dataset.

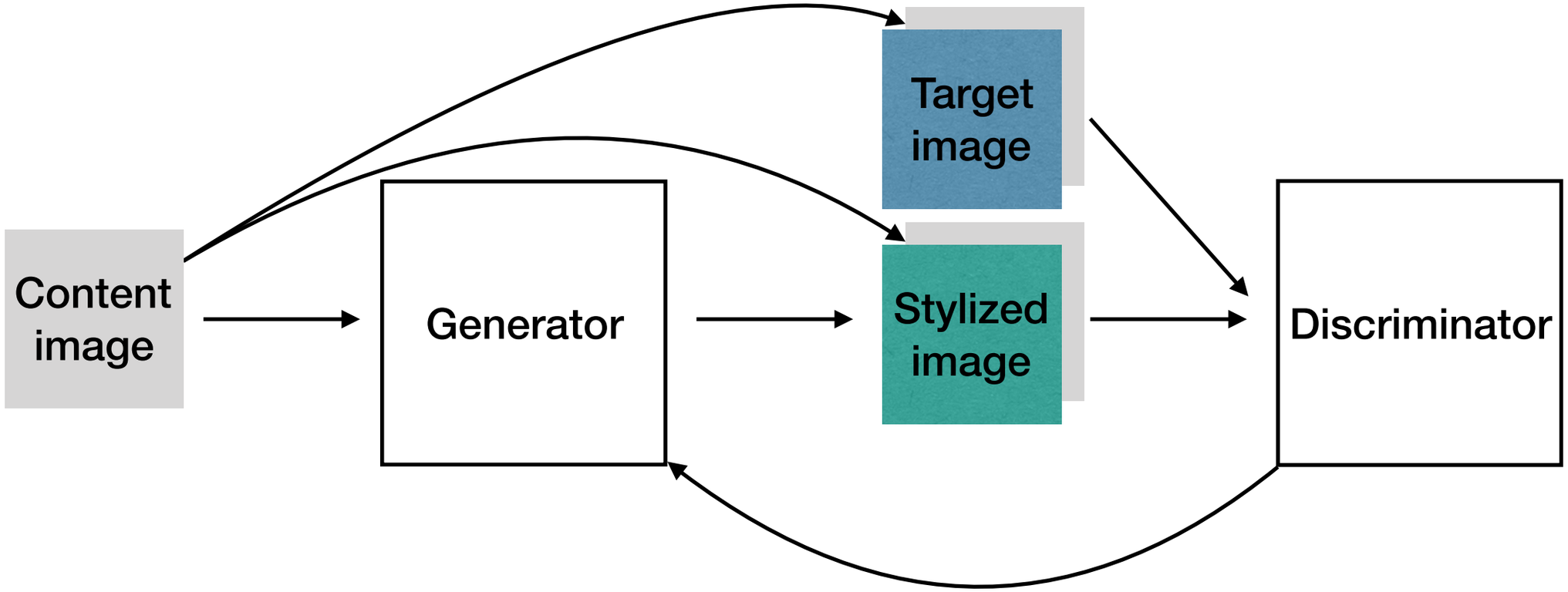
Discriminator



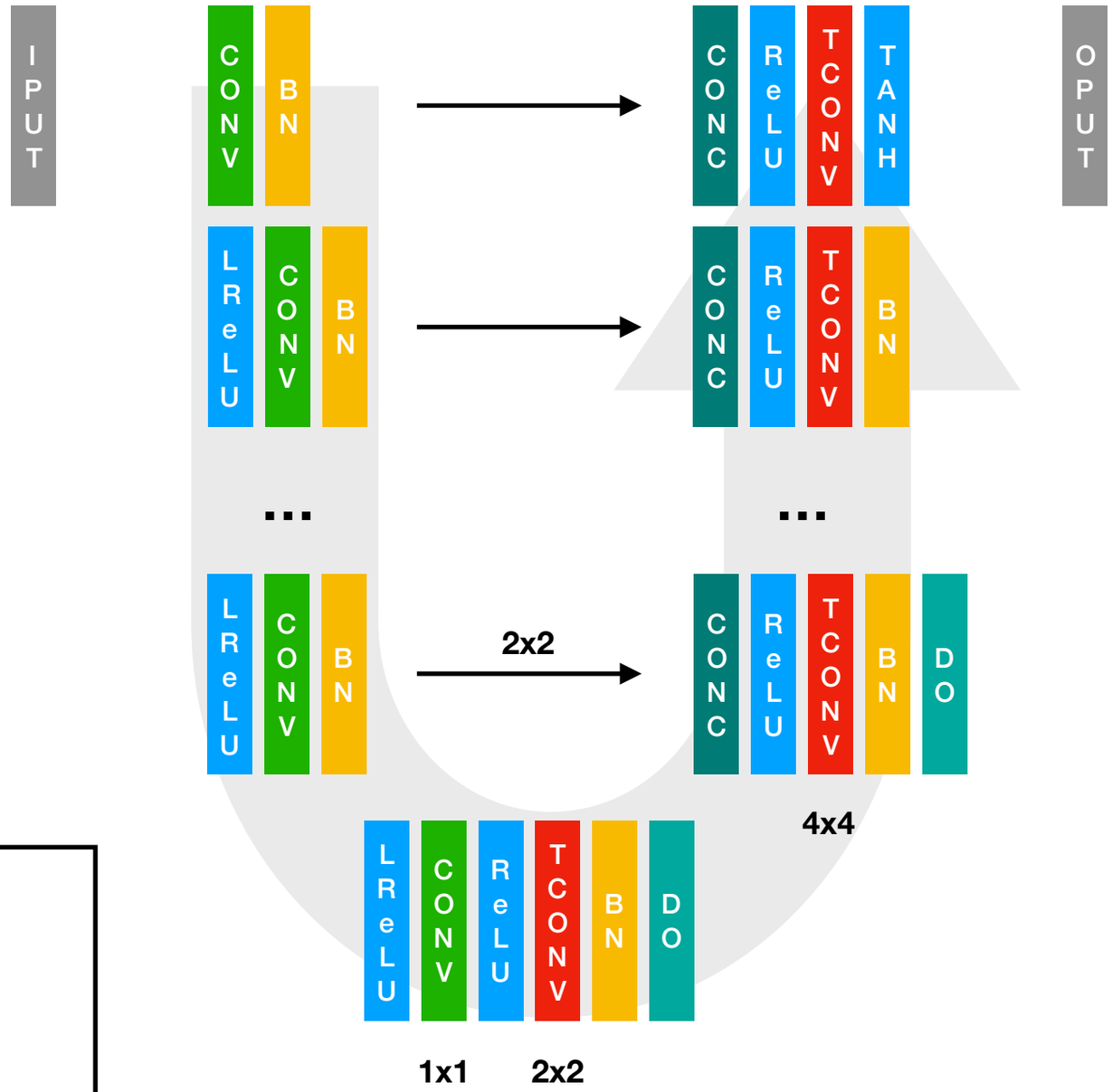
BN: Batch Normalization
C: Channel
H: Height
ReLU: Rectified Linear Unit
CONV: 5x5 CONVolution (stride 2)
W: Width

pix2pix

What is pix2pix?



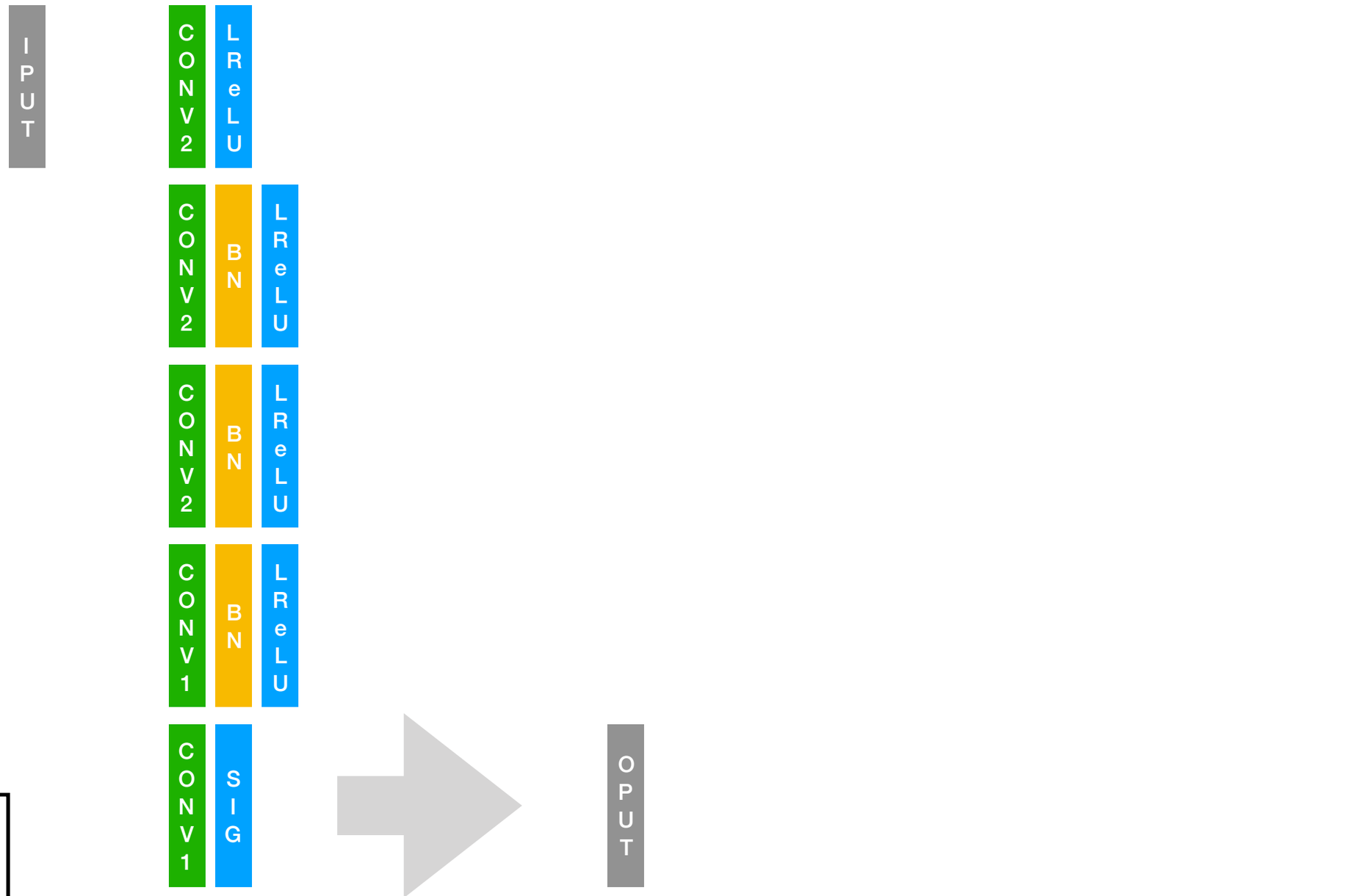
Generator



BN: Batch Normalization
CONC: CONCatenation
CONV: 4x4 CONVolution (stride 2)
DO: DropOut (p = 0.5)
IPUT: InPUT
LReLU: Leaky ReLU with slope 0.2
OPUT: OutPUT
ReLU: Rectified Linear Unit
TCONV: 4x4 Transposed CONV (stride 2)

Note. Dropout is applied where feature map size is 2x2, 4x4, and 8x8 in the decoder part.

Discriminator



BN: Batch Normalization
CONV1: 4x4 CONVolution (stride 1)
CONV2: 4x4 CONVolution (stride 2)
IPUT: InPUT
LReLU: Leaky ReLU with slope 0.2
OPUT: OutPUT

Note. This is for the case of 70x70 receptive field. Layers should be varied to change receptive field size.

Practice

CycleGAN

Appendix

A. Python class

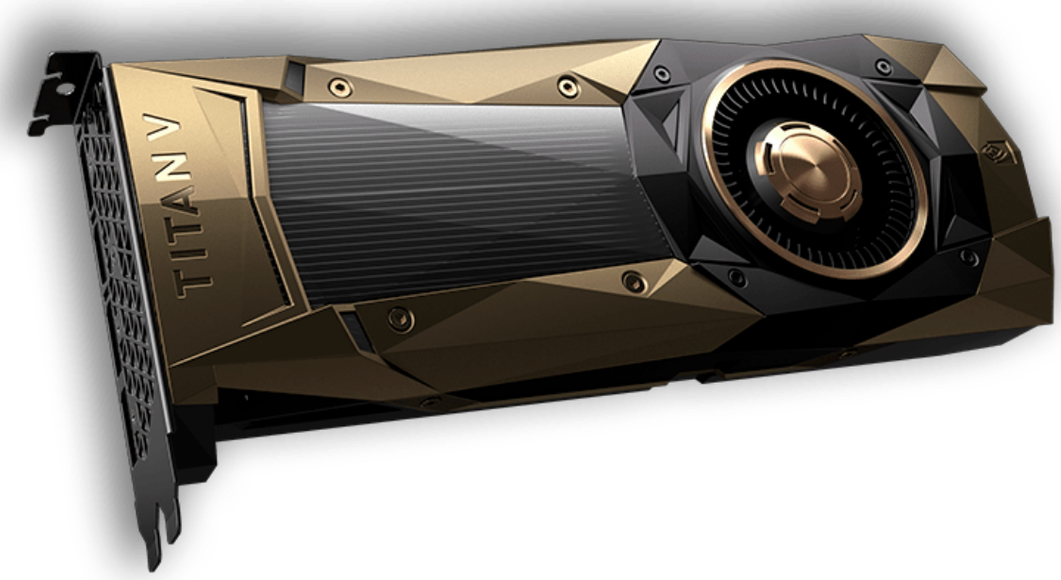
I assume you know about Python function. **Class is usually used for storing related data or handling a certain type of data using functions defined in the class.** For example, calculator has four basic functions - addition, subtraction, multiplication, and division. By making a class equipped with above functions, we can calculate numbers easily.

```
class Calculator:
    def __init__(self):  # __init__ function is called "constructor" as every time you make an instance of Calculator,
                         # codes written in the constructor will be implemented.
        self.value = 0

    def add(self, n):
        self.value += n
        print("After addition:", self.value)

    def subtract(self, n):
        self.value -= n
        print("After subtraction:", self.value)

    def multiply(self, n):
        self.value *= n
        print("After multiplication:", self.value)

    def divide(self, n):
        if n == 0:
            print("You can't divide with 0.")
            return

        else:
            self.value /= n
        print("After division", self.value)

    def reset(self):
        self.value = 0
        print("reset value to", self.value)


print("Calculator a...")
a = Calculator()  # Make an instance of Calculator class. You need parenthesis after class name to do this.

a.add(5)  # Call add function defined in Calculator class.
a.divide(0)
a.divide(5)

print()
print("Calculator b...")
b = Calculator()  # Make another instance of Calculator class. This does not share value with calculator a.

b.add(1)
b.multiply(100)
b.reset()
```

CPU vs. GPU

credit. hothardware.com

A central processing unit (CPU), also called a central processor or main processor, is the electronic circuitry within a computer that carries out the instructions of a computer program by performing the basic arithmetic, logic, controlling, and input/output operations specified by the instructions.



credit. NVIDIA

A graphics processing unit (GPU) is a specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display device.

Loss functions

- Binary cross entropy loss (BCE) : $-\log \hat{p}(y_c \mid x) - \sum_{k=1,\ k \neq c}^{C} \log[1 - \hat{p}(y_k \mid x)]$
- Cross entropy loss (CE) : $\mathbb{E}_{p(y|x)}[-\log \hat{p}(y \mid x)] = -\sum_{c=1}^{C} p(y_c \mid x) \log \hat{p}(y_c \mid x) = -\log \hat{p}(y_c \mid x)$
- Mean squared error loss (MSE) : $\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (x_{i,\ j} - \hat{x}_{i,\ j})^2$
- Mean absolute error loss (MAE) : $\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} |x_{i,\ j} - \hat{x}_{i,\ j}|$