

Artificial Neural Networks & Auto ML

세종대학교 AI로봇학과 류승형

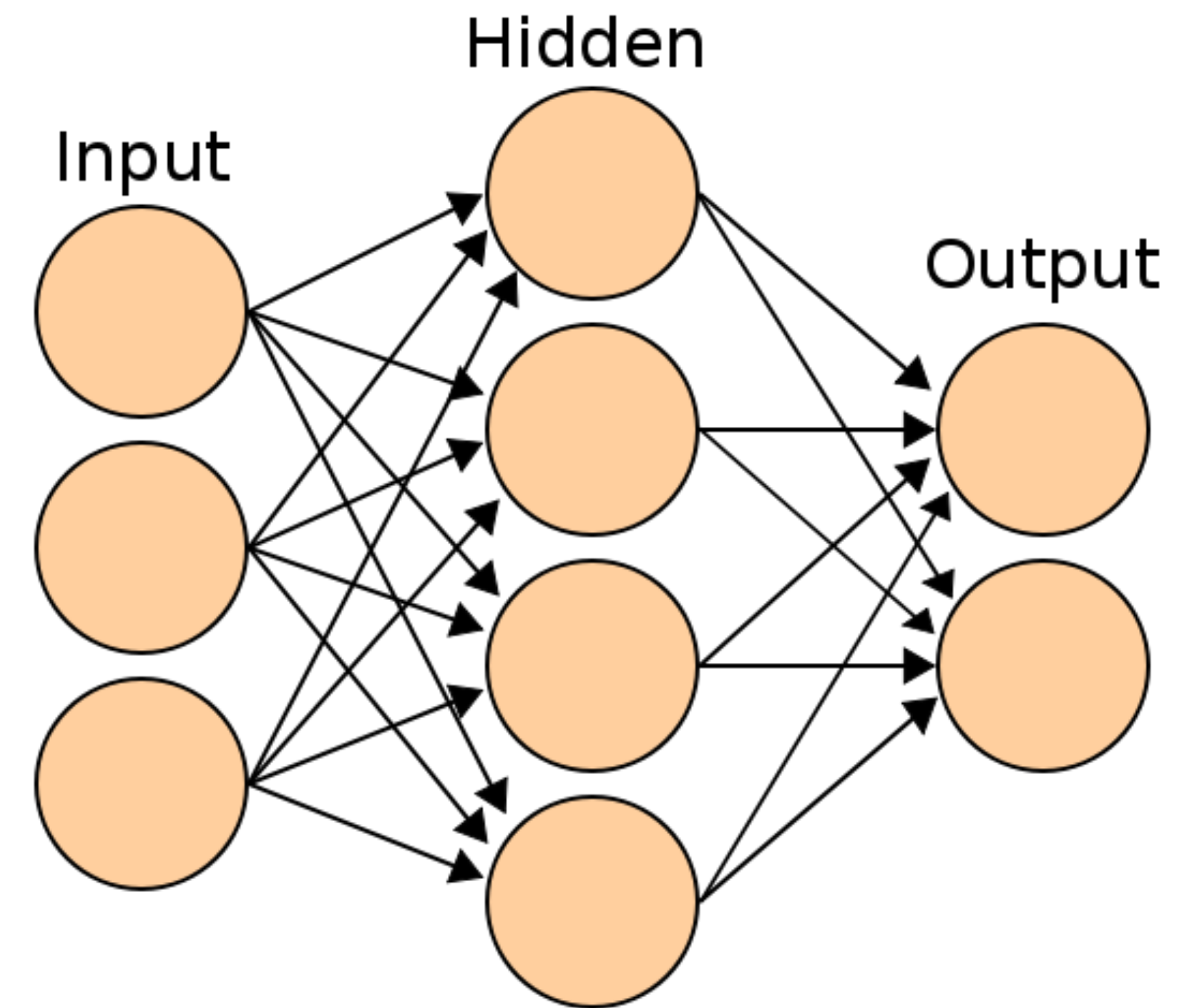
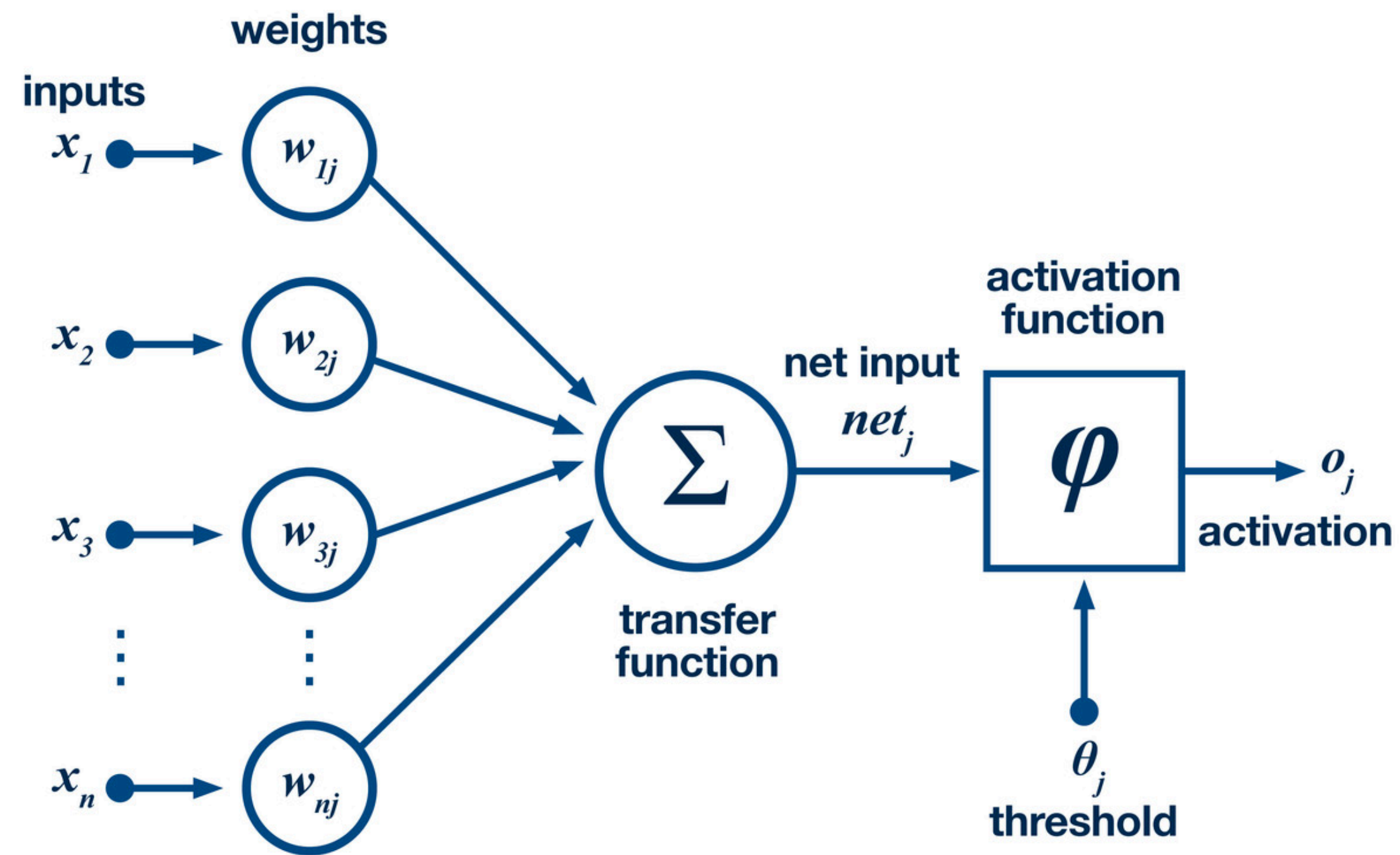
목차

- Chapter 1. Introduction to Neural Network
- Chapter 2. AutoKeras

Chapter 1.

Introduction to Neural Network

인공신경망



Dense (Linear) layer

- 가장 기본적인 신경망 레이어 : Dense (keras) 또는 Linear (torch)
- Matrix multiplication을 통해서 d_{in} 벡터를 $\rightarrow d_{out}$ 벡터로...
 - $+\alpha$ (activation function, dropout)
- $[N \times d] \rightarrow \text{Dense}(d, d') \rightarrow [N \times d']$
- $[N \times L \times d] \rightarrow \text{Dense}(d, d') \rightarrow [N \times L \times d']$

Convolutional layer

- Kernel 또는 Filter를 움직이면서
- 국소 지역에 대한 weighted summation

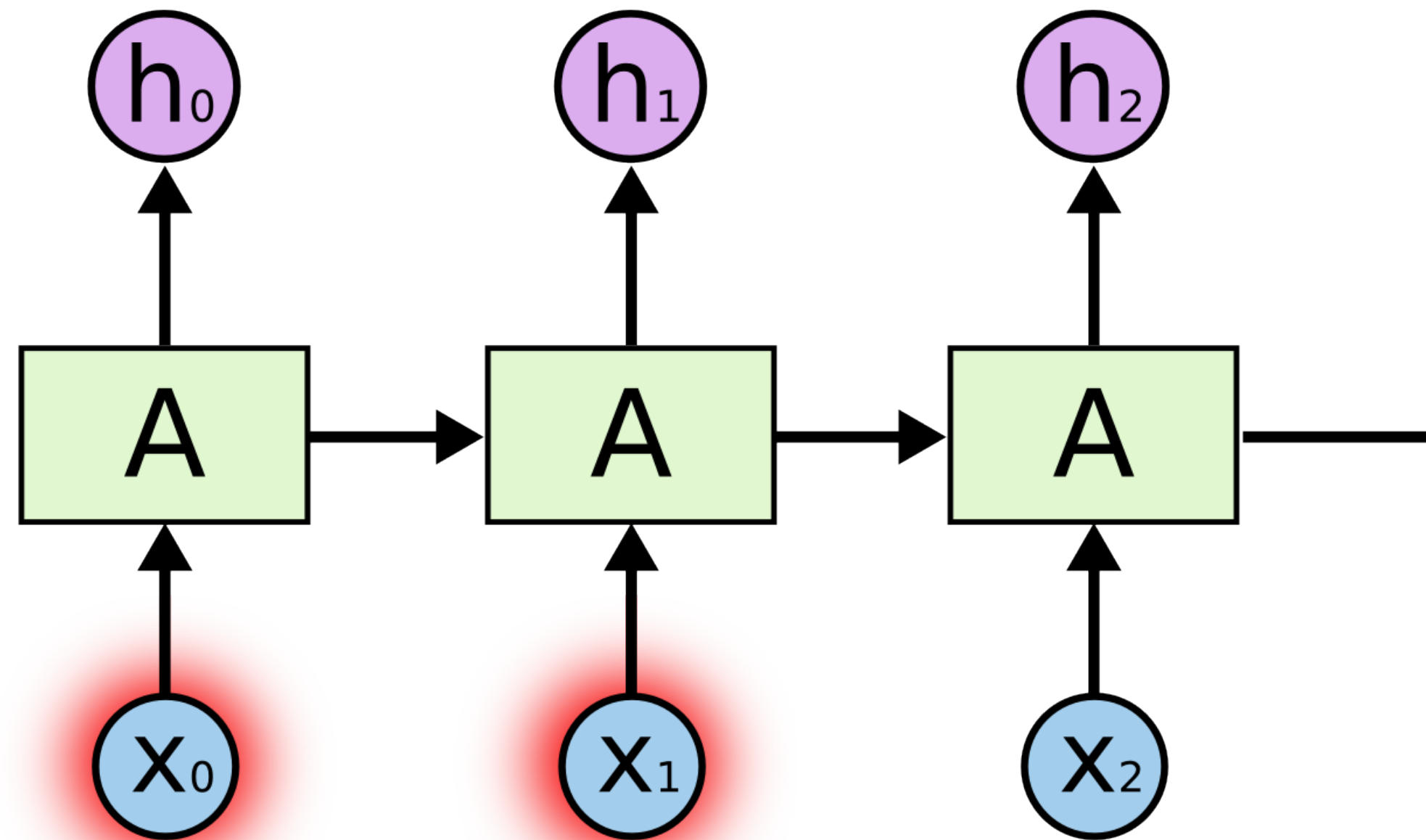
1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

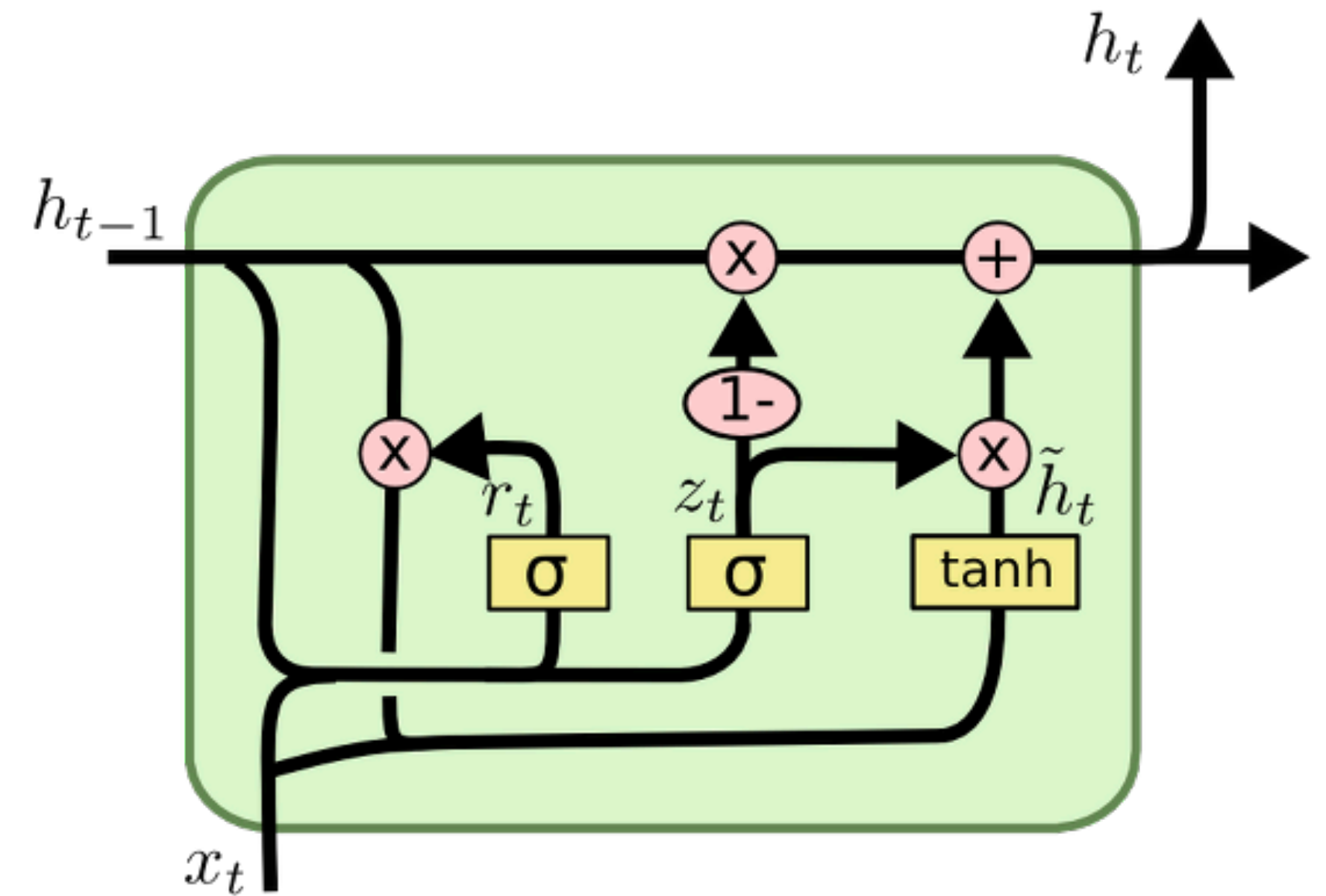
4		

Convolved
Feature

RNN layer



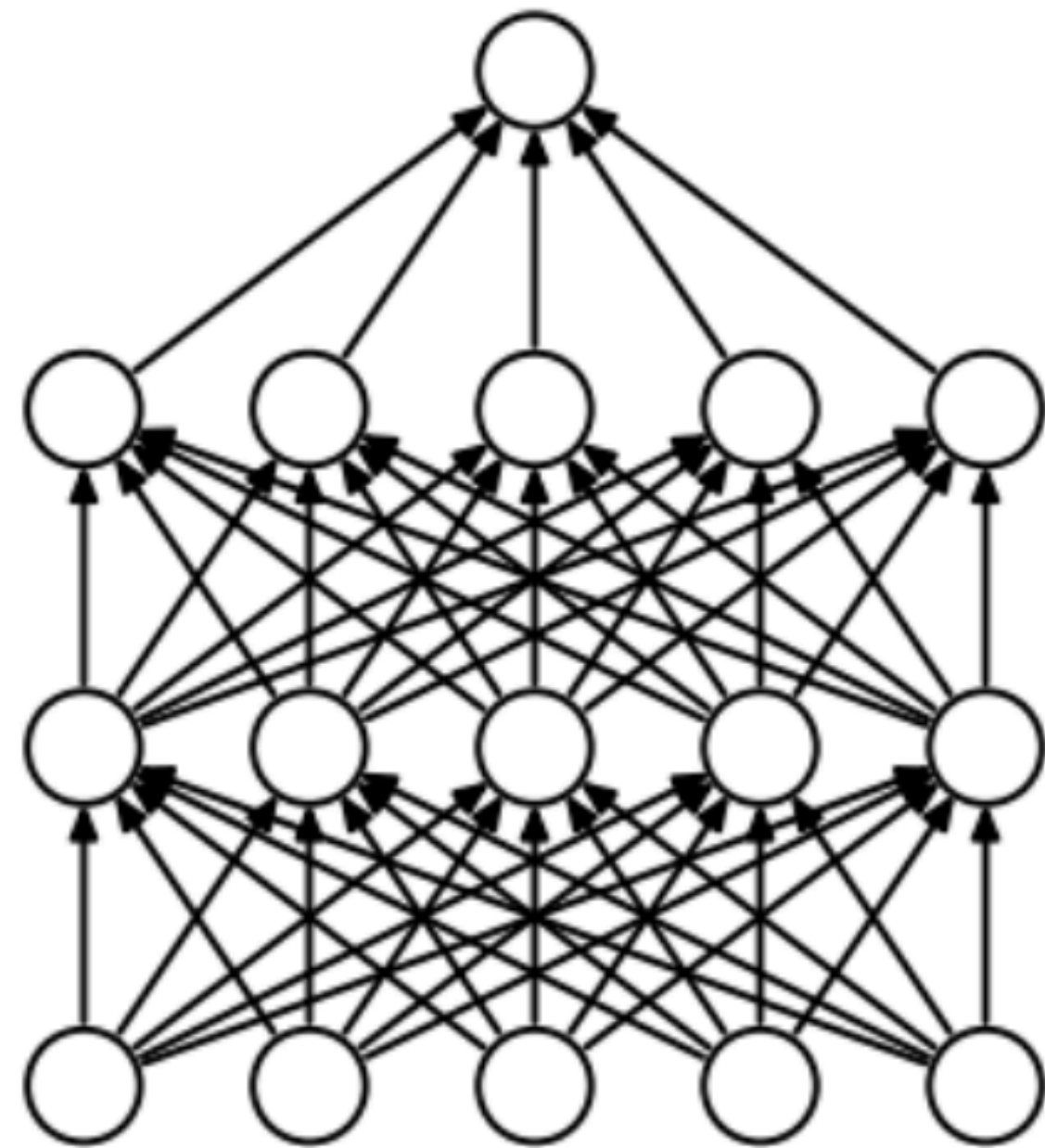
RNN



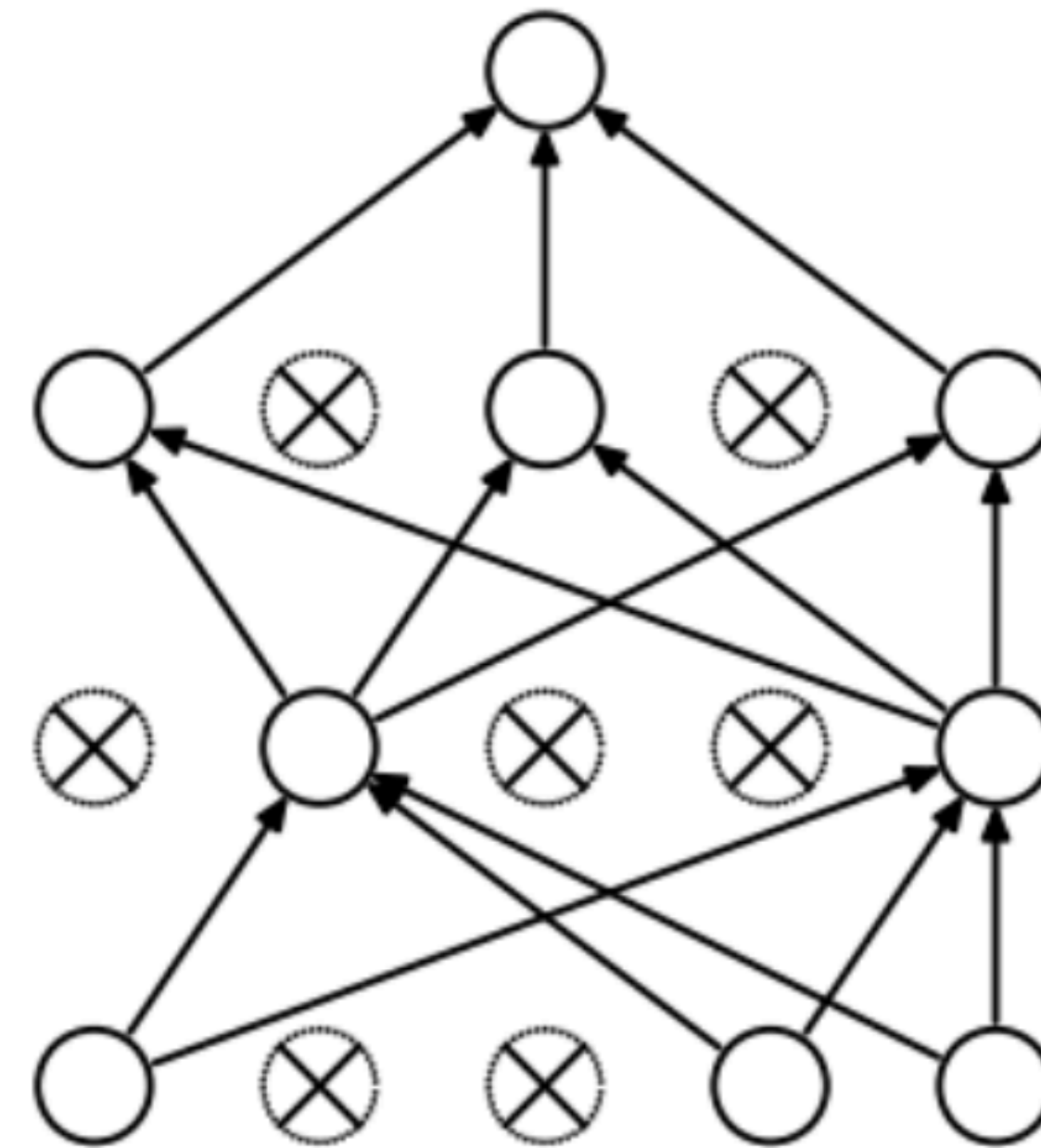
LSTM

Dropout Layer

- Dropout rate를 바탕으로 랜덤하게 뉴런을 비활성화



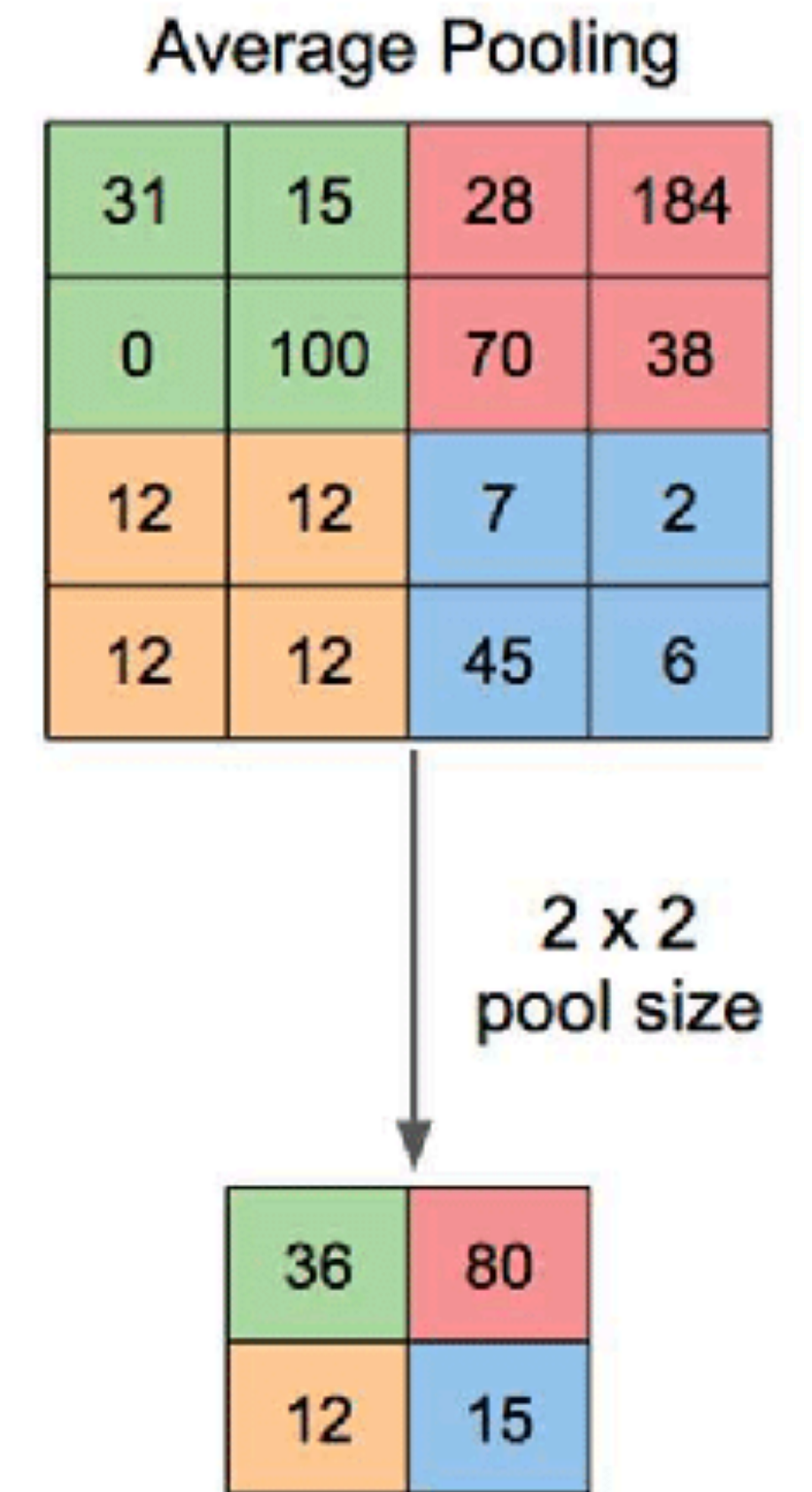
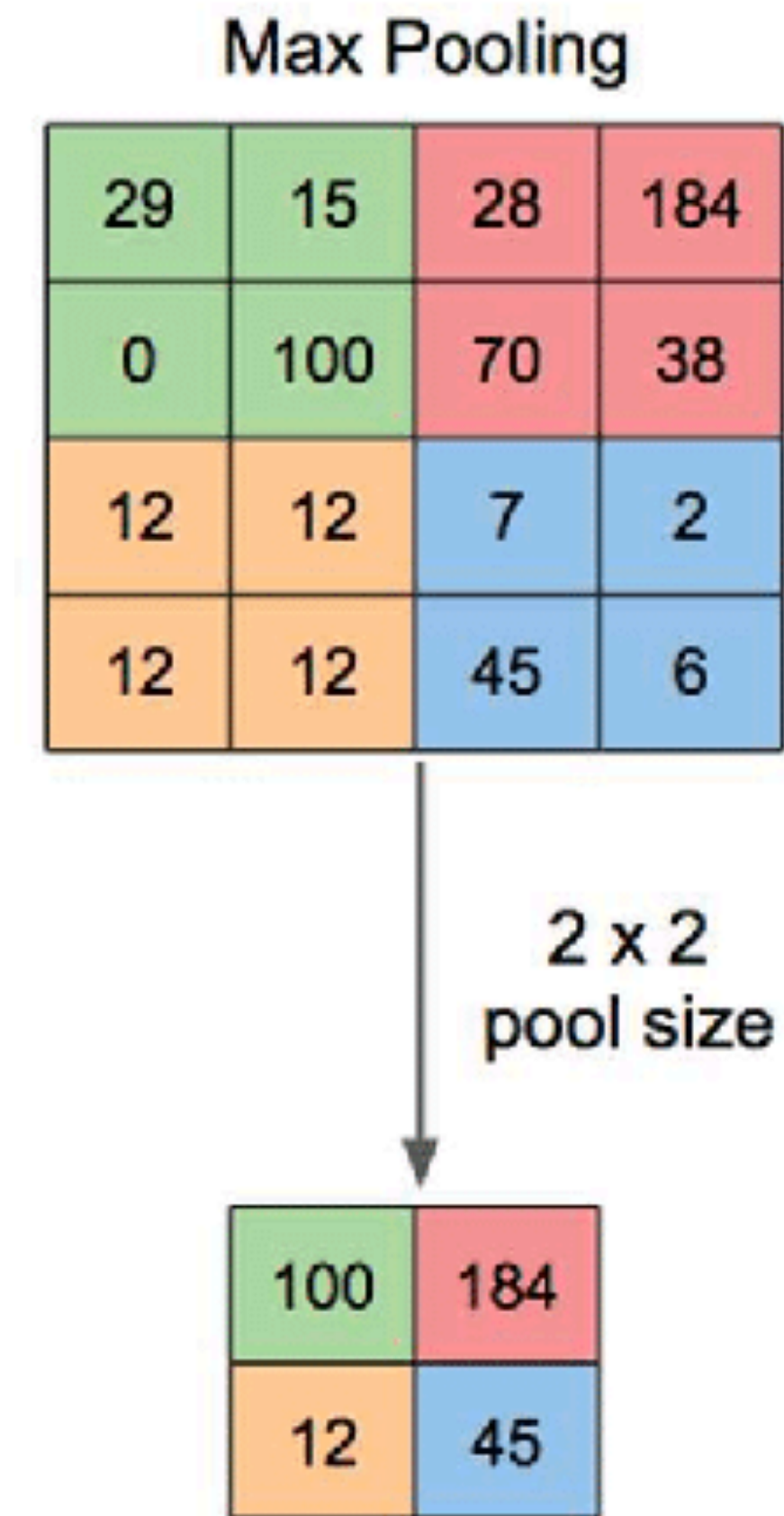
(a) Standard Neural Net



(b) After applying dropout.

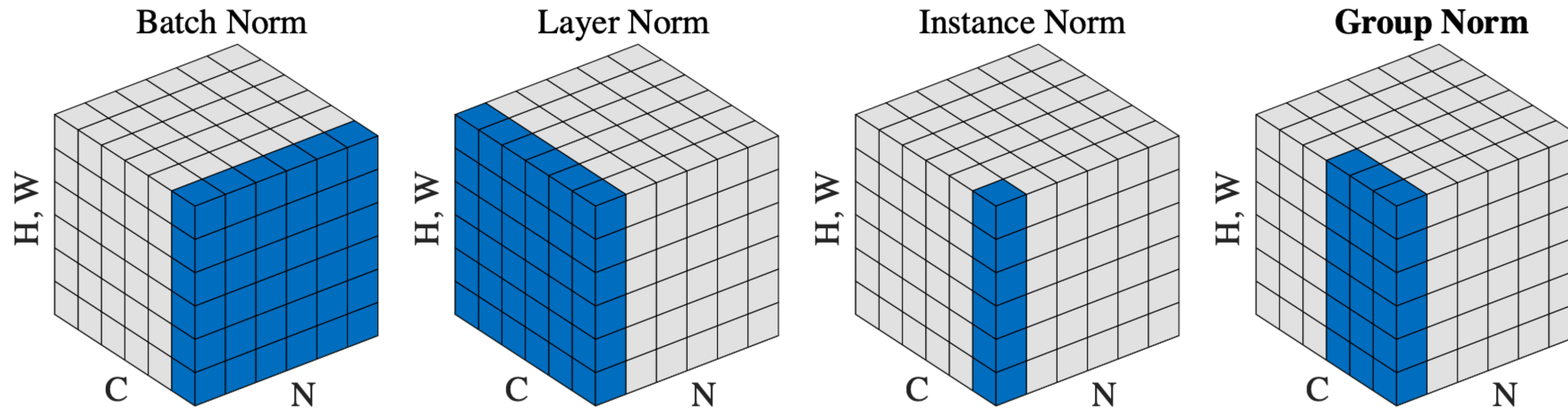
Pooling

- MaxPooling : 각 채널의 구간별로 최대값을 샘플링
- AvgPooling : 각 채널의 구간별로 평균값을 샘플링
- GlobalPooling : 채널별로 평균 또는 최대값을 샘플링



Normalization

- Batch / Layer / Instance / Group normalization



Padding

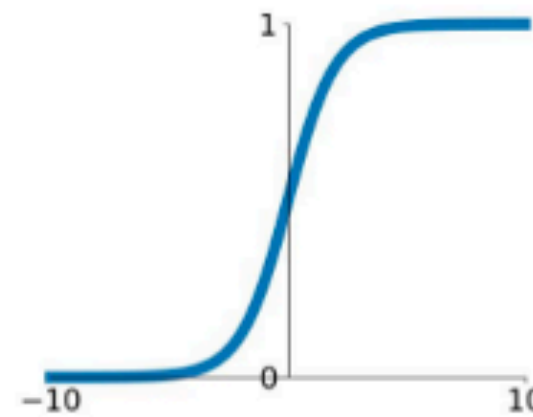
- 데이터의 양 끝단에 특정 값들을 채워주는 기능
- Convolution layer의 출력값 형태를 맞춰줄 수 있음.
- Zero padding : 0 0 [1, 2, 3, 4] 0 0
- Reflection padding : 3 2 [1, 2, 3, 4] 3 2
- Replication padding : 1 1 [1, 2, 3, 4] 4 4
- Constant padding : a a [1, 2, 3, 4] b b

Activation functions

- Sigmoid,
- Tanh
- ReLU
- Leaky ReLU
- ELU
- GELU

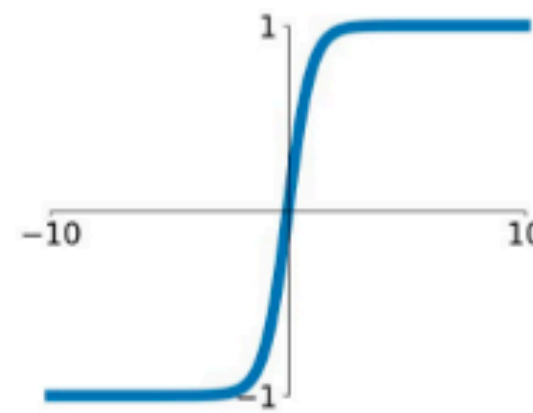
Sigmoid

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



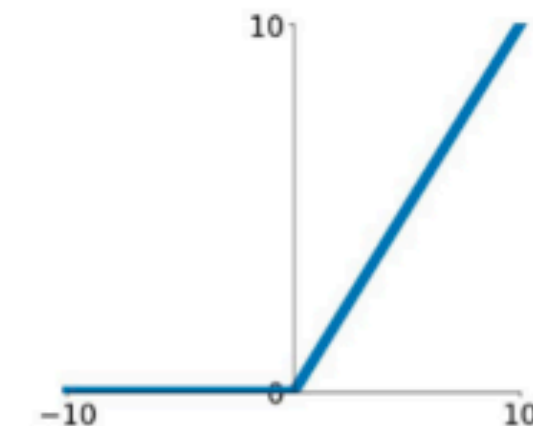
tanh

$$\tanh(x)$$



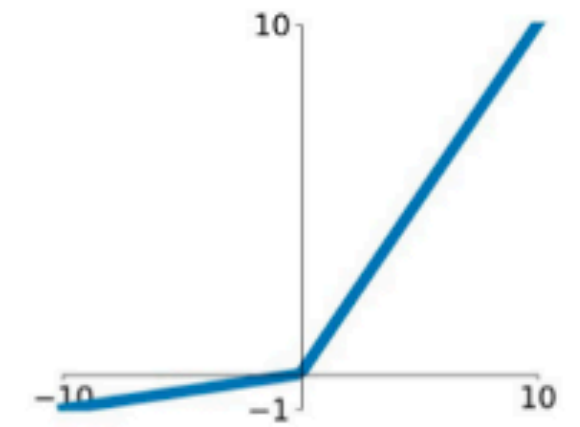
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

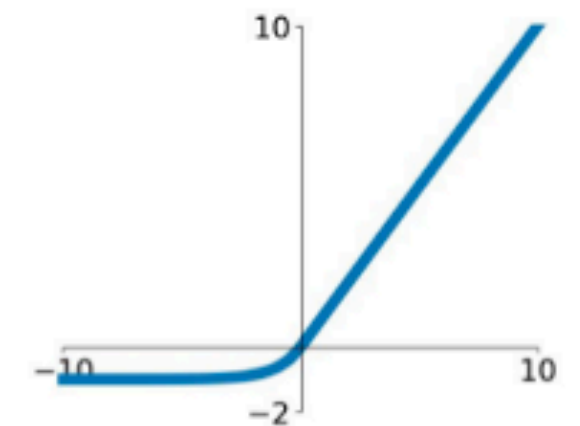


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

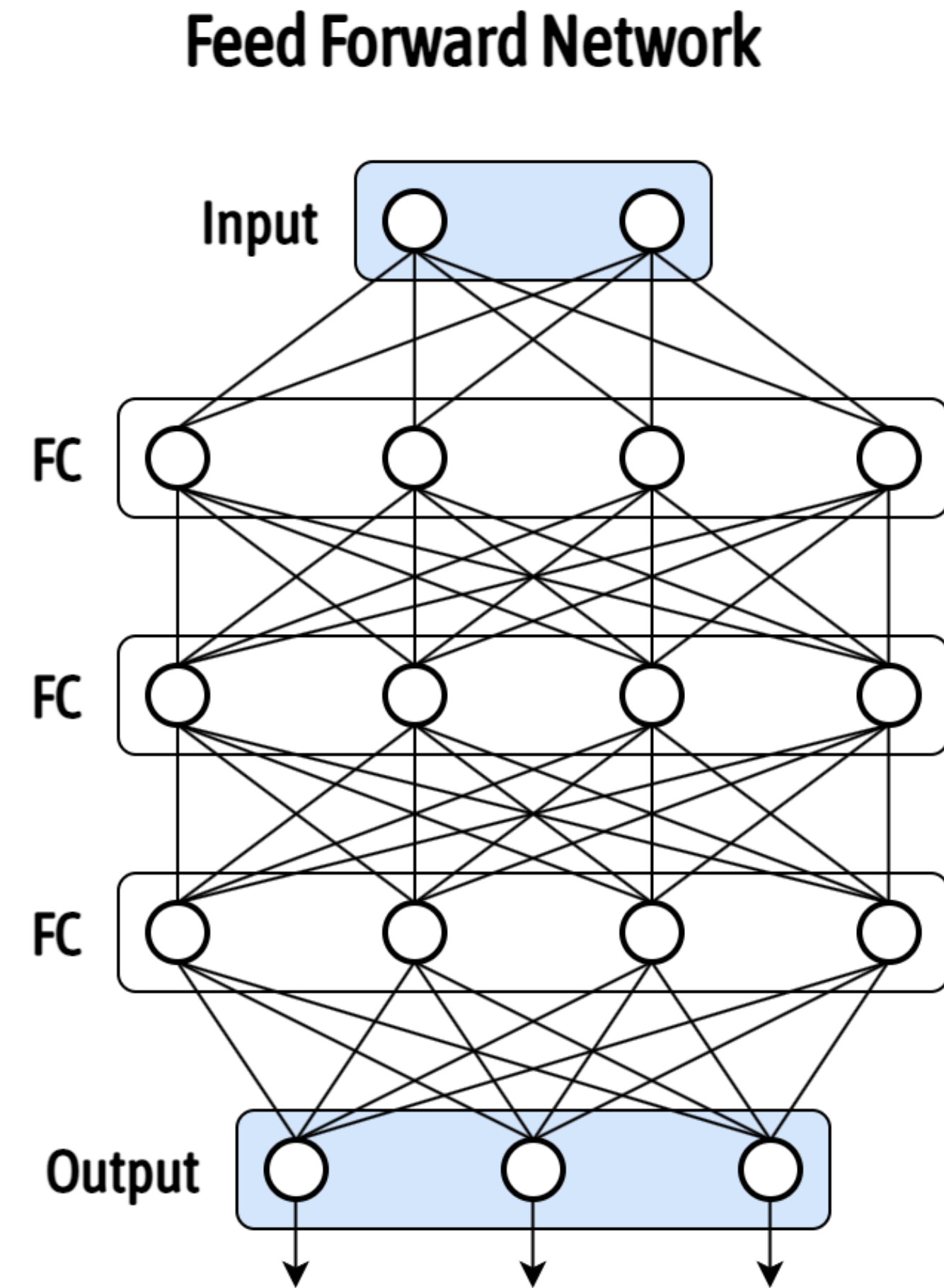
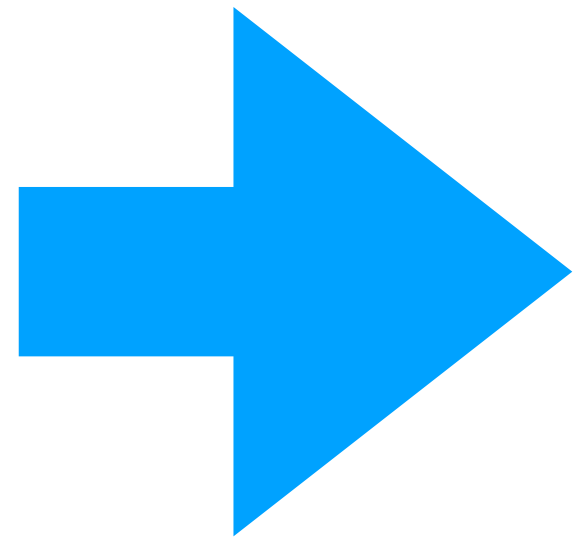
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



다양한 레이어의 조합

- Dense
- Recurrent
- Convolution
- Activation function
- Pooling
- Dropout
- Normalization
- Embedding



인공신경망 = 비선형 함수

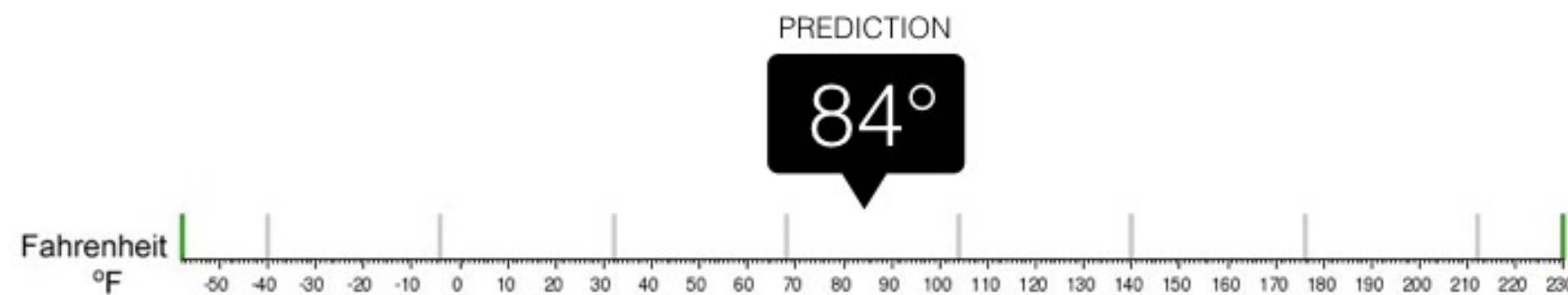
- 어떠한 복잡한 모델을 구현하더라도 입력과 출력 관점에서 신경망은 비선형 함수임.
- 그리고 함수의 형태가 신경망의 학습가능한 웨이트에 의해 결정됨.
- 학습은 주어진 태스크를 더 잘하기 위한 방향으로 이루어짐.

기본적인 두가지 태스크



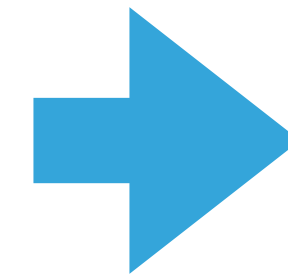
Regression

What is the temperature going to be tomorrow?



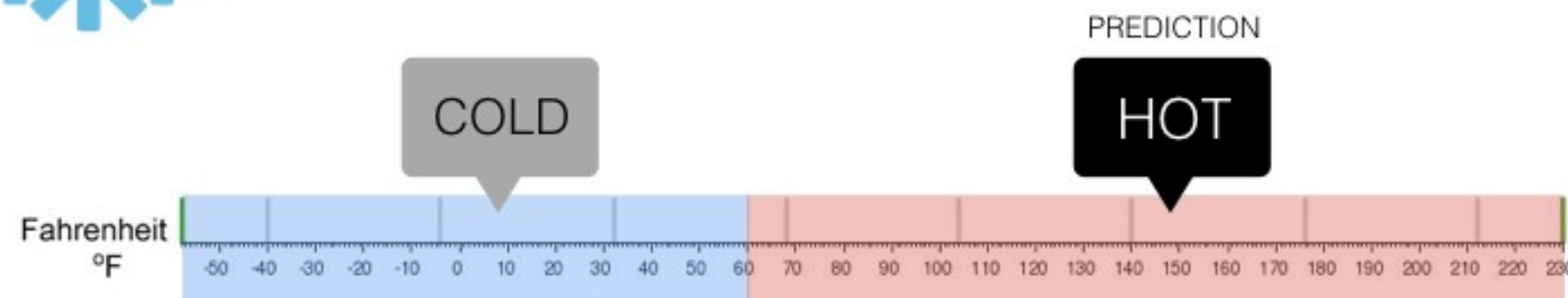
Minimize Squared errors

$$\frac{1}{N} \sum_i^N (y_i - \hat{y}_i)^2$$



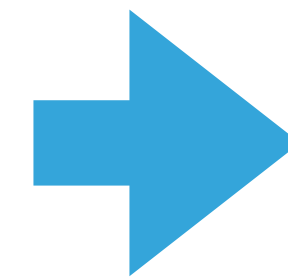
Classification

Will it be Cold or Hot tomorrow?



Minimize cross entropy

$$-\sum_{c \in C} y_c \log(\hat{y}_c)$$



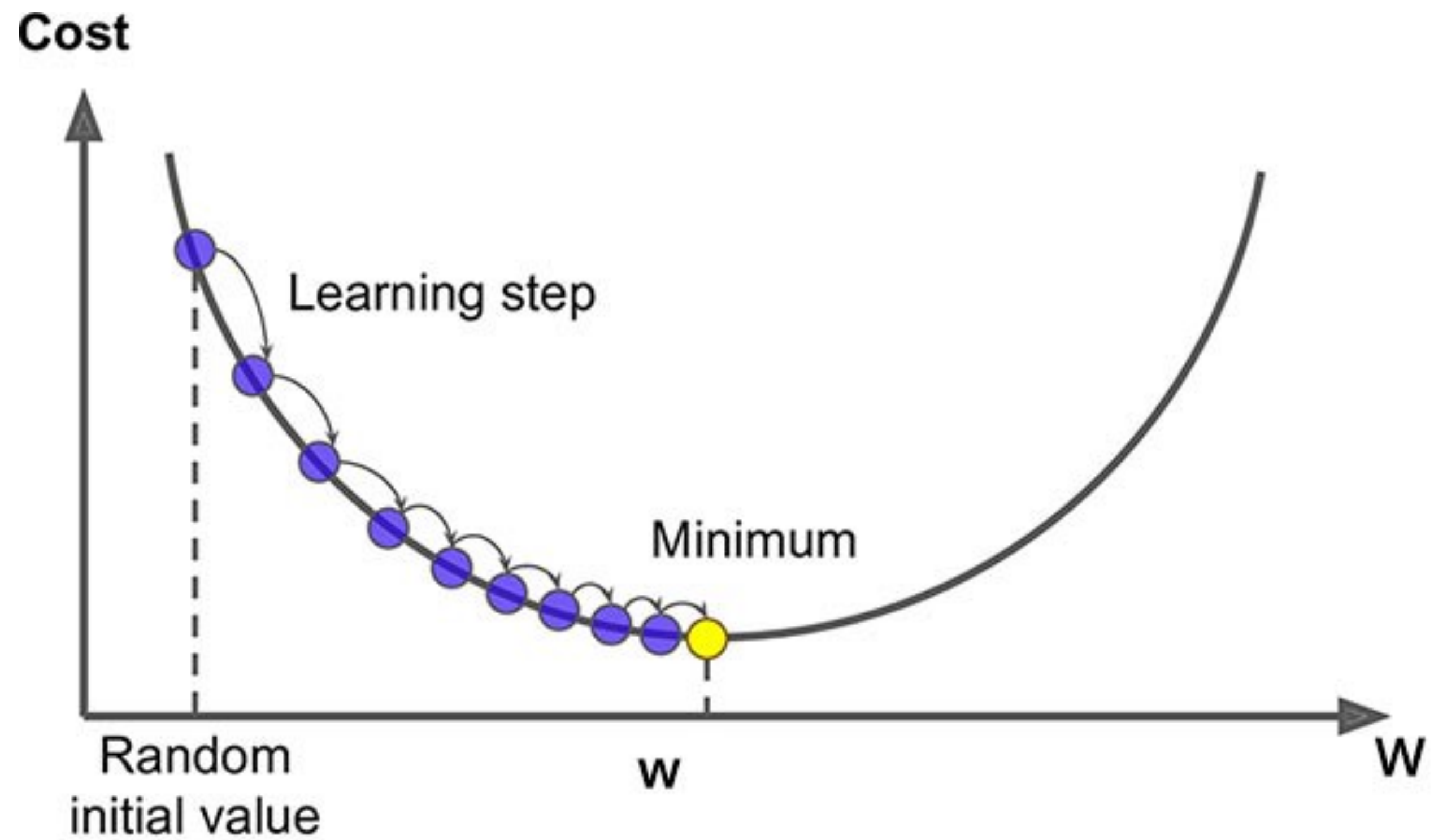
모델과 목표가 정해지면.

- 모델 : 인공신경망 모델
- 목표 : Loss, Cost function
- 학습을 진행해야 함. 즉 인공신경망의 weight parameter 학습.
 - Gradient descent method : general approach for iterative optimization
 - Error backpropagation : way to update parameters of inner layers

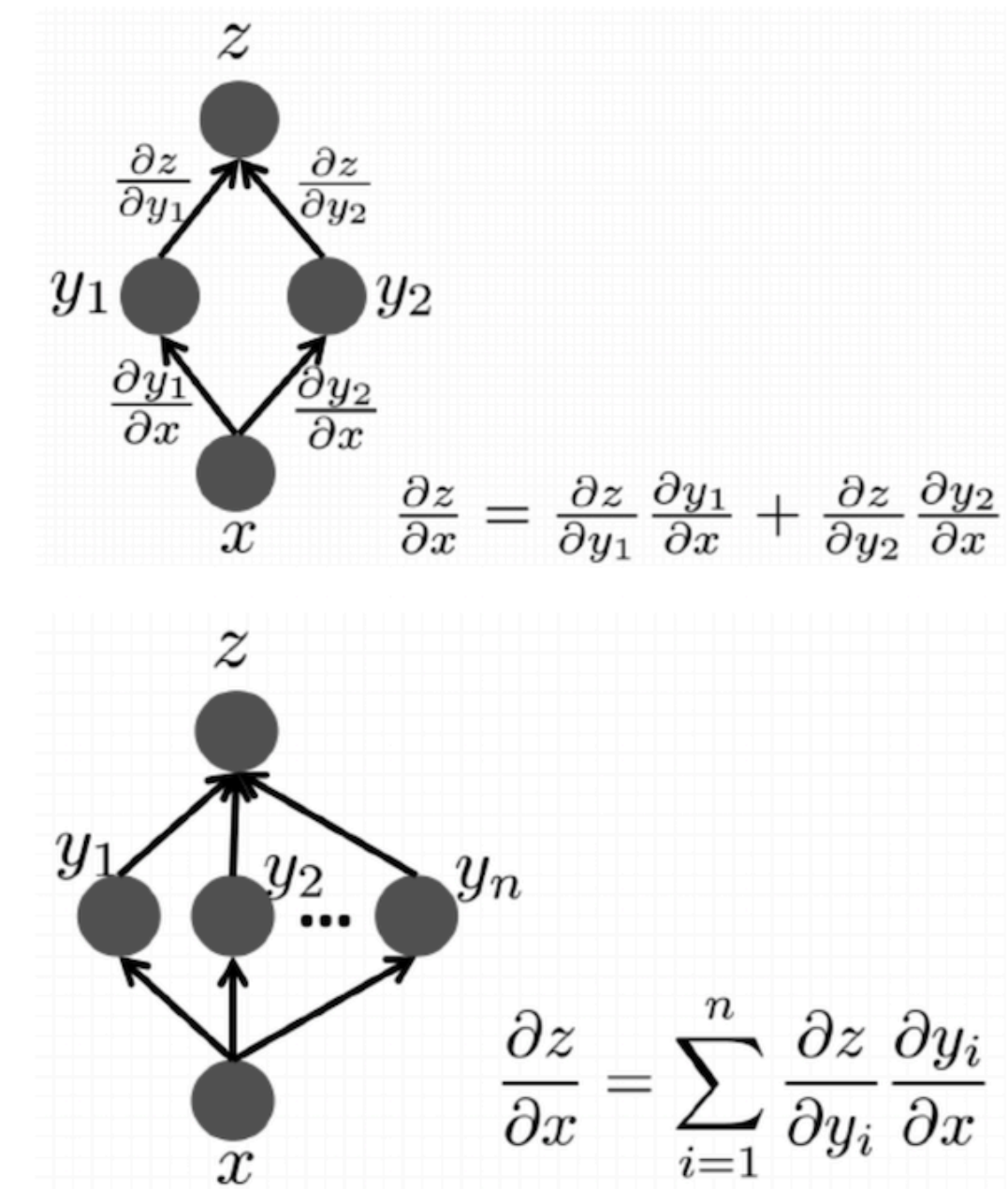
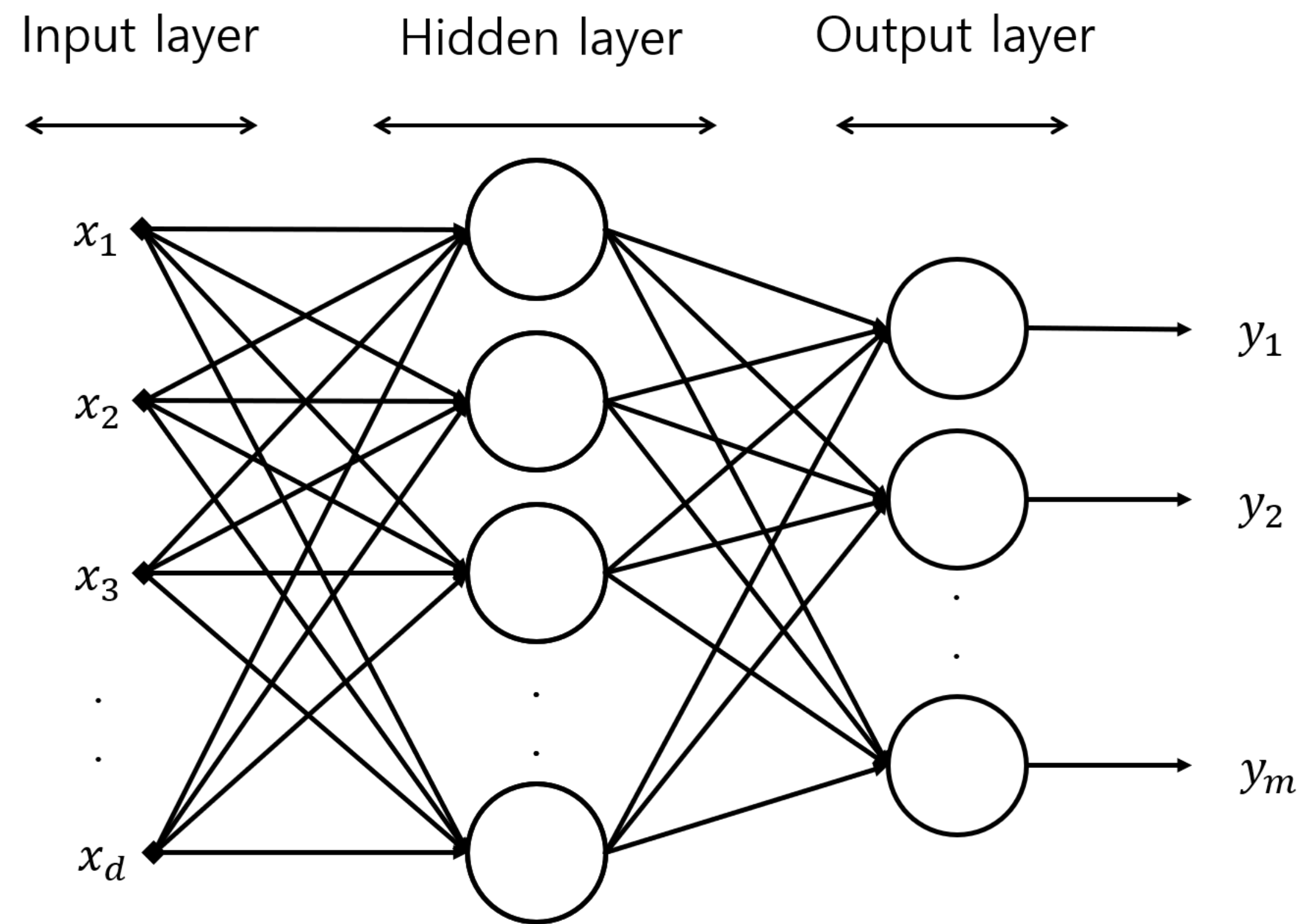
경사하강법

1. $w_0 \rightarrow w_1 \rightarrow w_2 \rightarrow \dots \rightarrow w_t$

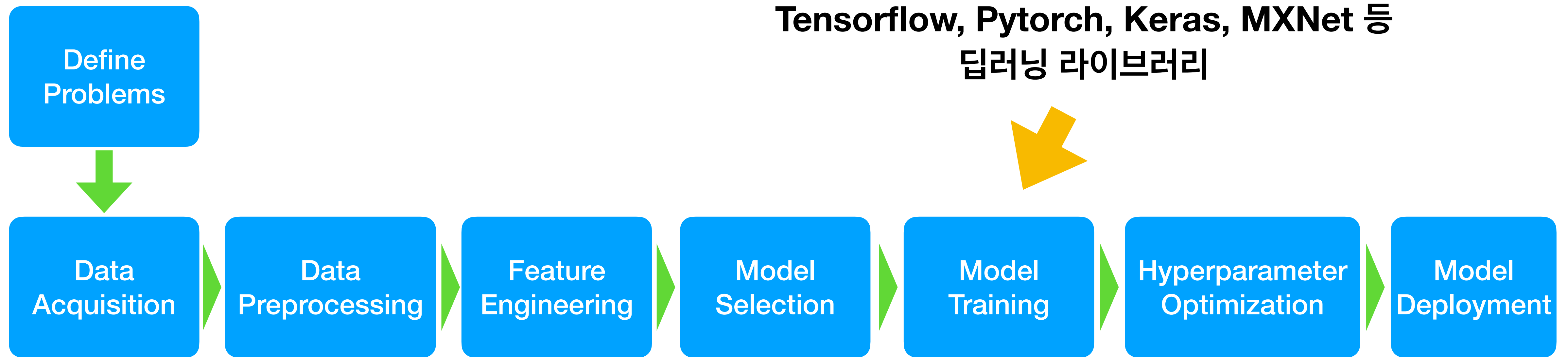
2. $w_{t+1} = w_t - \gamma \frac{\partial L}{\partial w}$



오류 역전파



머신 러닝 모델 개발 프로세스



Keras를 통한 신경망 구성

모델 구성

```
model = Sequential()  
model.add(Dense(512, activation = 'relu', input_shape = (28*28,)))  
model.add(Dense(10, activation = 'softmax'))
```

모델 컴파일

```
model.compile(optimizer = 'rmsprop',  
              loss = 'categorical_crossentropy',  
              metrics = ['accuracy'])
```

모델 훈련

```
model.fit(train_images, train_labels, epoch = 5, batch_size = 128)
```

모델 평가

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

Chapter 2.

AutoKeras

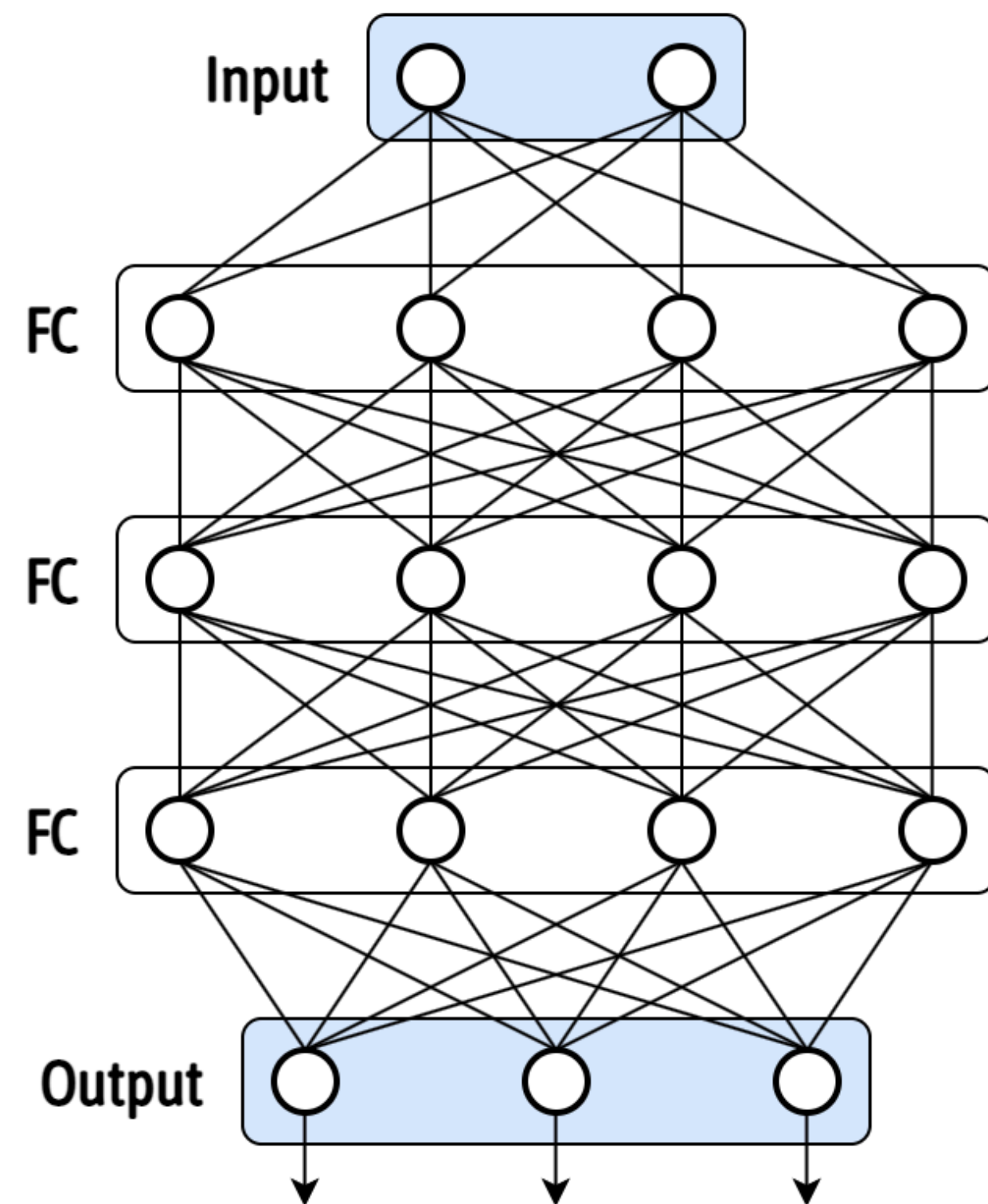
Dense layer를 사용했을때

```
tf.keras.layers.Dense(  
    units,  
    activation=None,  
    use_bias=True,  
    kernel_initializer="glorot_uniform",  
    bias_initializer="zeros",  
    kernel_regularizer=None,  
    bias_regularizer=None,  
    activity_regularizer=None,  
    kernel_constraint=None,  
    bias_constraint=None,  
    **kwargs  
)
```

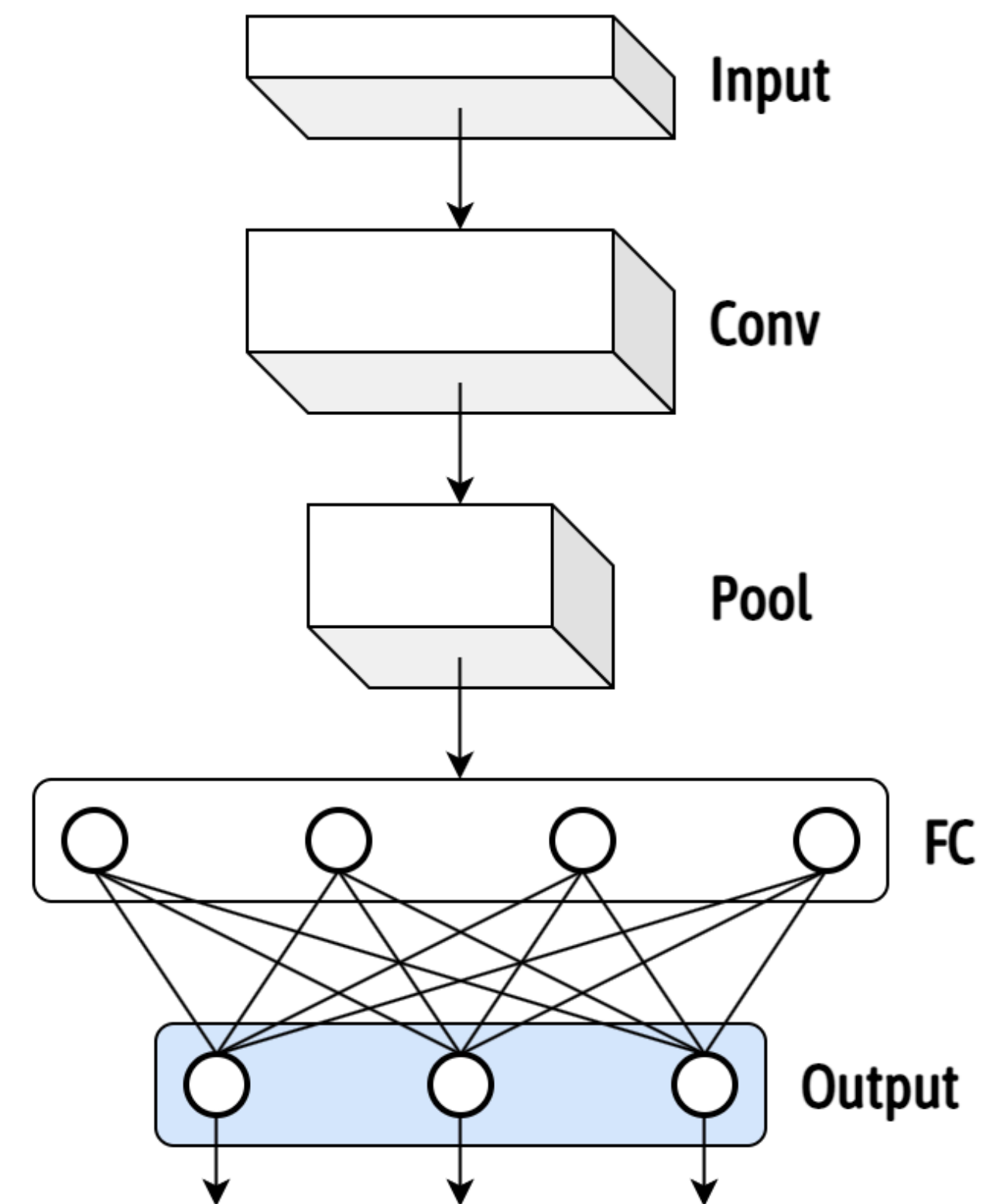
- Unit : neuron의 수 = 출력 차원
- Activation : 활성화함수.
e.g., ReLU, Sigmoid, SELU, Tanh, etc
- Initializer : weight 초기화 관련
- 레이어 수 등

간단한 형태의 신경망

Feed Forward Network



Convolution Neural Network



Keras를 통한 신경망 구성

모델 구성

```
model = Sequential()  
model.add(Dense(512, activation = 'relu', input_shape = (28*28,)))  
model.add(Dense(10, activation = 'softmax'))
```

모델 컴파일

```
model.compile(optimizer = 'rmsprop',  
              loss = 'categorical_crossentropy',  
              metrics = ['accuracy'])
```

모델 훈련

```
model.fit(train_images, train_labels, epoch = 5, batch_size = 128)
```

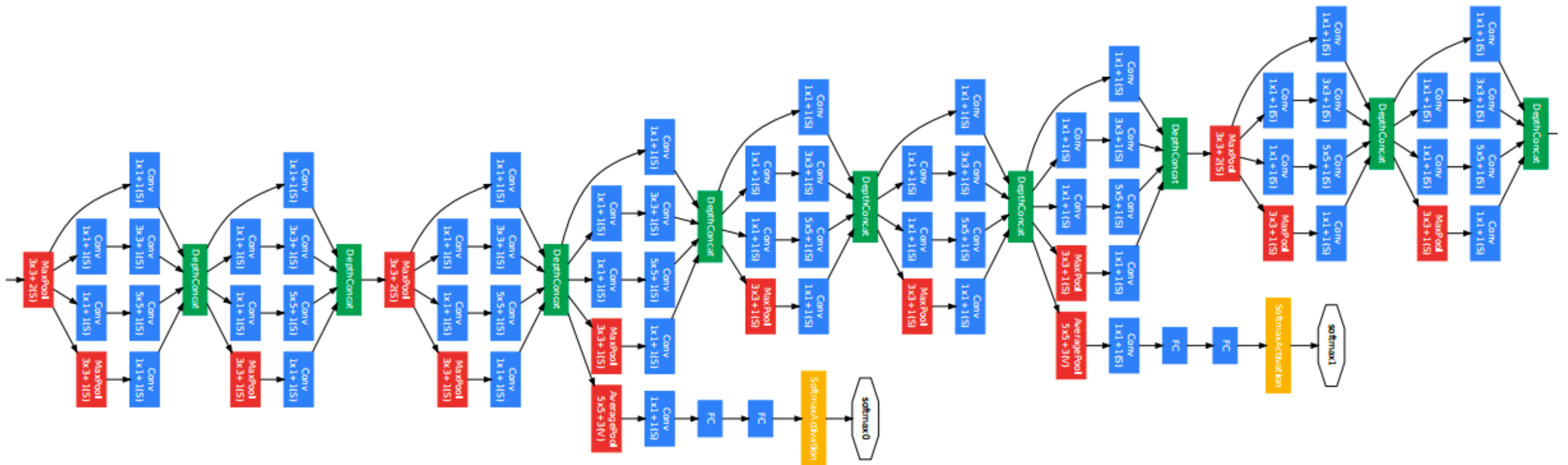
모델 평가

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

CNN 예시

```
model = Sequential()  
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(64, 64, 3)))  
# 32개의 3x3 필터를 가진 컨볼루션 레이어  
model.add(MaxPooling2D((2, 2)))  
# 2x2 크기의 맥스 풀링 레이어  
model.add(Conv2D(64, (3, 3), activation='relu'))  
# 64개의 3x3 필터를 가진 컨볼루션 레이어  
model.add(MaxPooling2D((2, 2)))  
# 2x2 크기의 맥스 풀링 레이어  
model.add(Conv2D(128, (3, 3), activation='relu'))  
# 128개의 3x3 필터를 가진 컨볼루션 레이어  
model.add(MaxPooling2D((2, 2)))  
# 2x2 크기의 맥스 풀링 레이어  
model.add(Flatten())  
# 1차원으로 평탄화  
model.add(Dense(128, activation='relu'))  
# 128개의 뉴런을 가진 fully connected layer  
model.add(Dense(10, activation='softmax'))  
# 10개의 클래스에 대한 softmax 출력
```


보다 복잡한 신경망



Google Inception architecture

Neural Architecture Search

- 인공신경망의 구조 설계 과정을 자동화하여 최적의 구조를 찾는 방법.

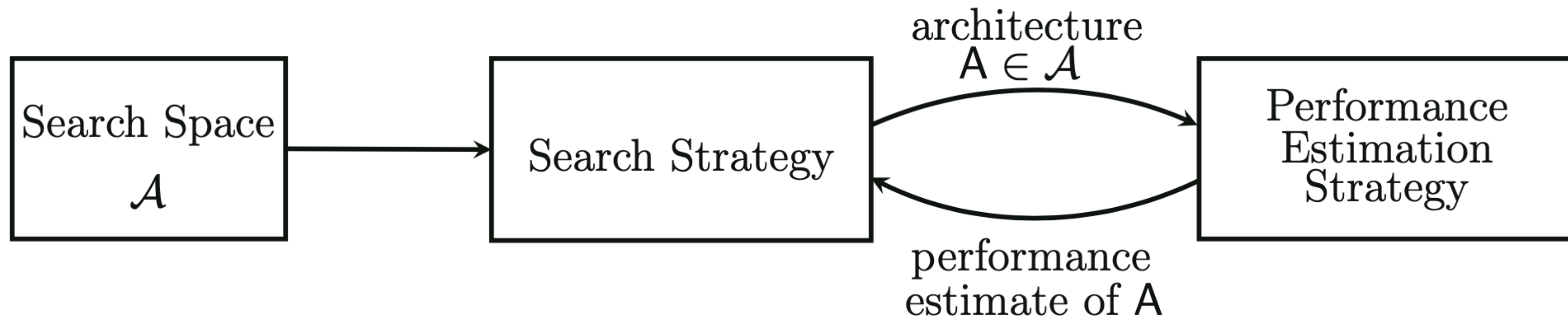
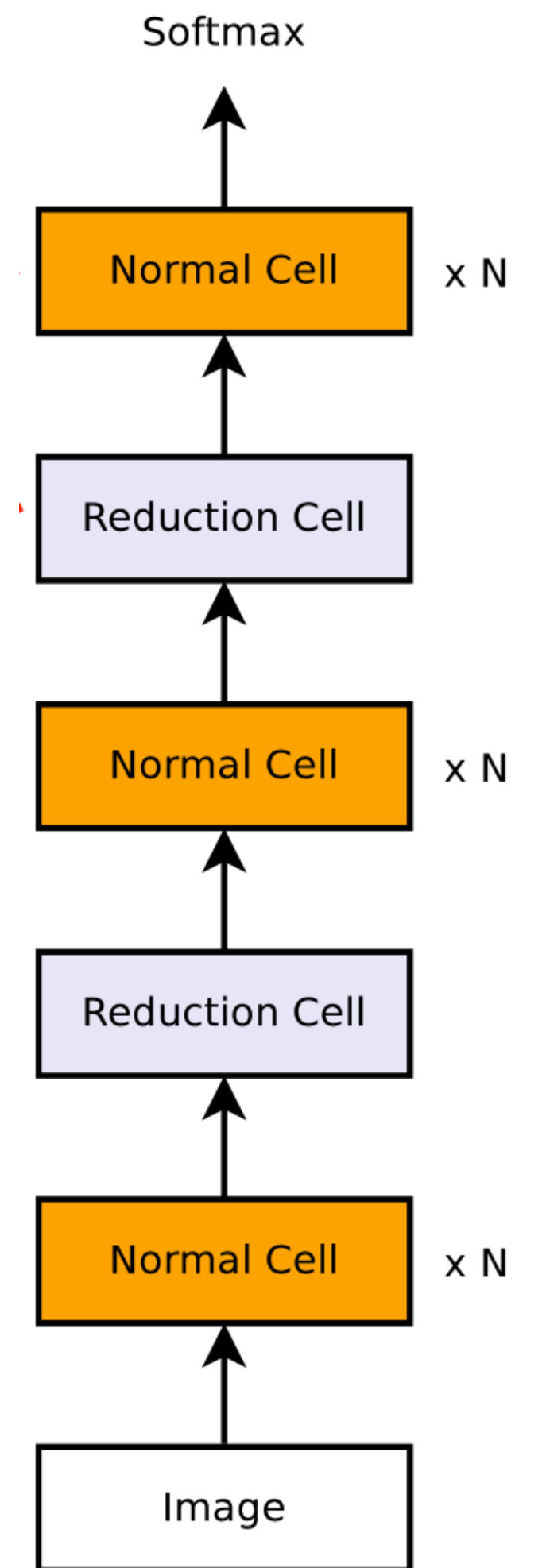
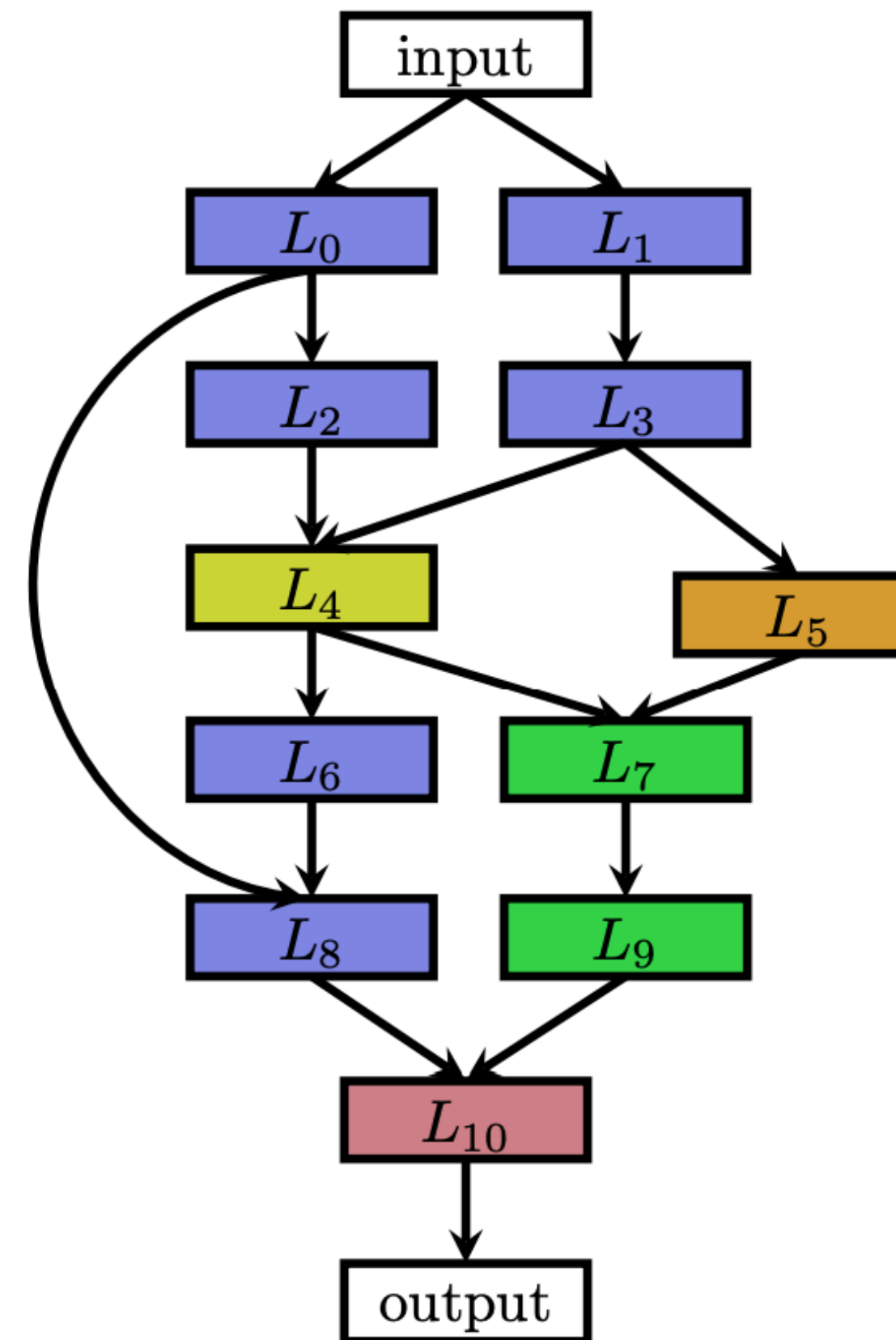
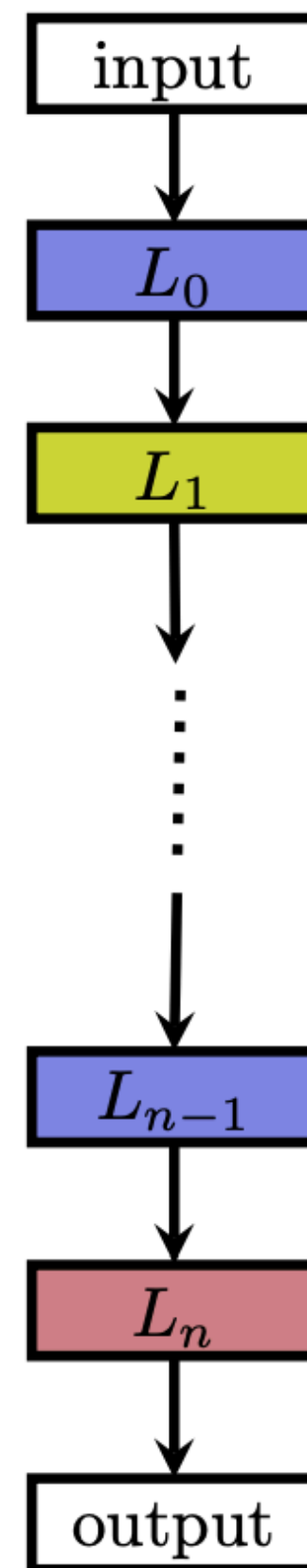


Fig. 3.1 Abstract illustration of Neural Architecture Search methods. A search strategy selects an architecture A from a predefined search space \mathcal{A} . The architecture is passed to a performance estimation strategy, which returns the estimated performance of A to the search strategy

Search Space

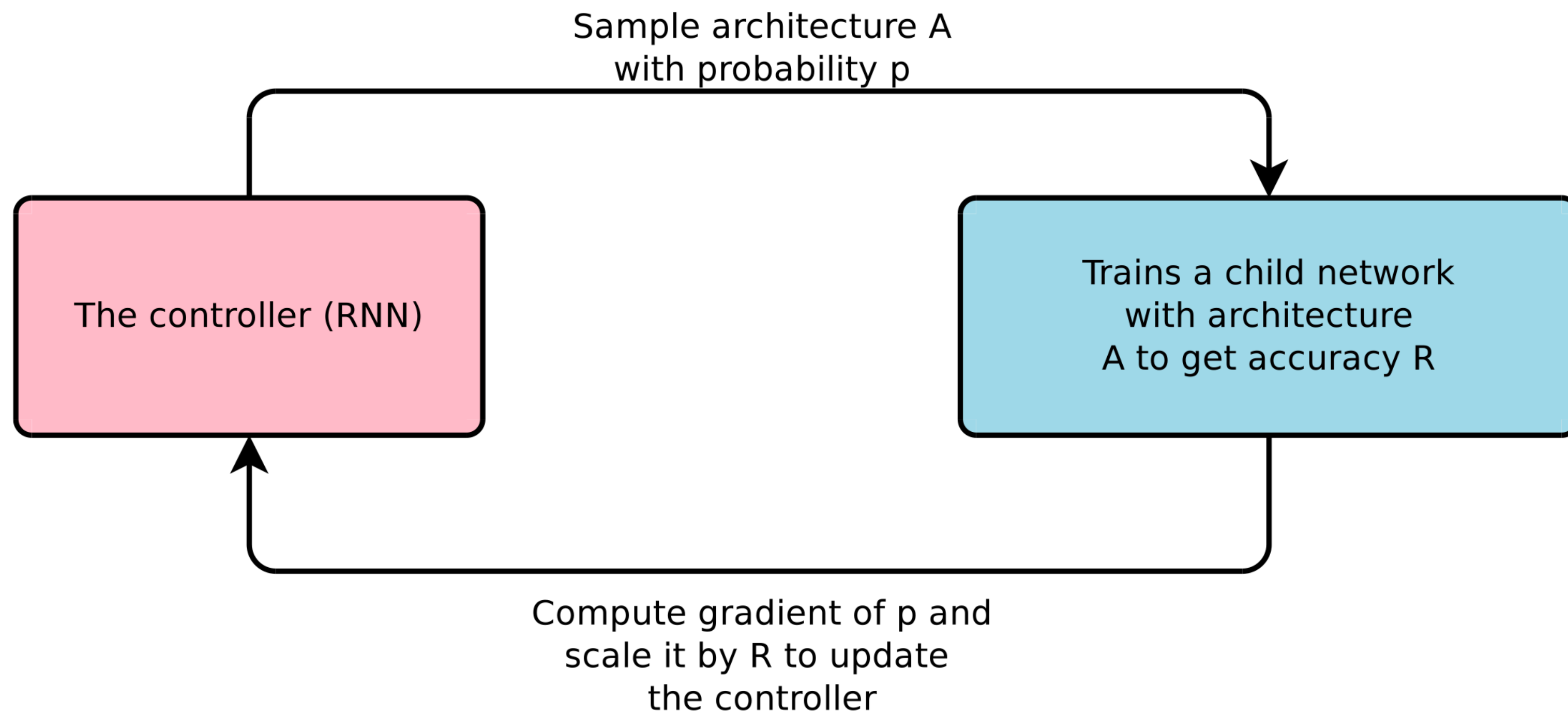
- Chain-structured NN:
 - 레이어 수, 레이어 타입, 레이어 파라미터
- Multi-branch NN
- Cell-based approach
 - Normal cell (차원유지), Reduction cell (차원감소)
 - 셀단위 구조 탐색 후 쌓기



Search Strategy

- Random search
- Bayesian optimization: 베이지안 최적화를 활용하여 네트워크 구조 탐색
- Reinforcement learning: 에이전트의 액션 = 네트워크 구조 선택, 보상 = 모델 성능
- Evolutionary methods: 유전알고리즘을 바탕으로 모델 풀에서 교차/변이 수행
- Gradient-based methods: Discrete search space에 대한 relaxation을 통해 미분 가능한 구조로 만들어 Gradient descent를 통해 최적 구조 탐색

Neural Architecture Search with Reinforcement Learning



Neural Architecture Search with Reinforcement Learning

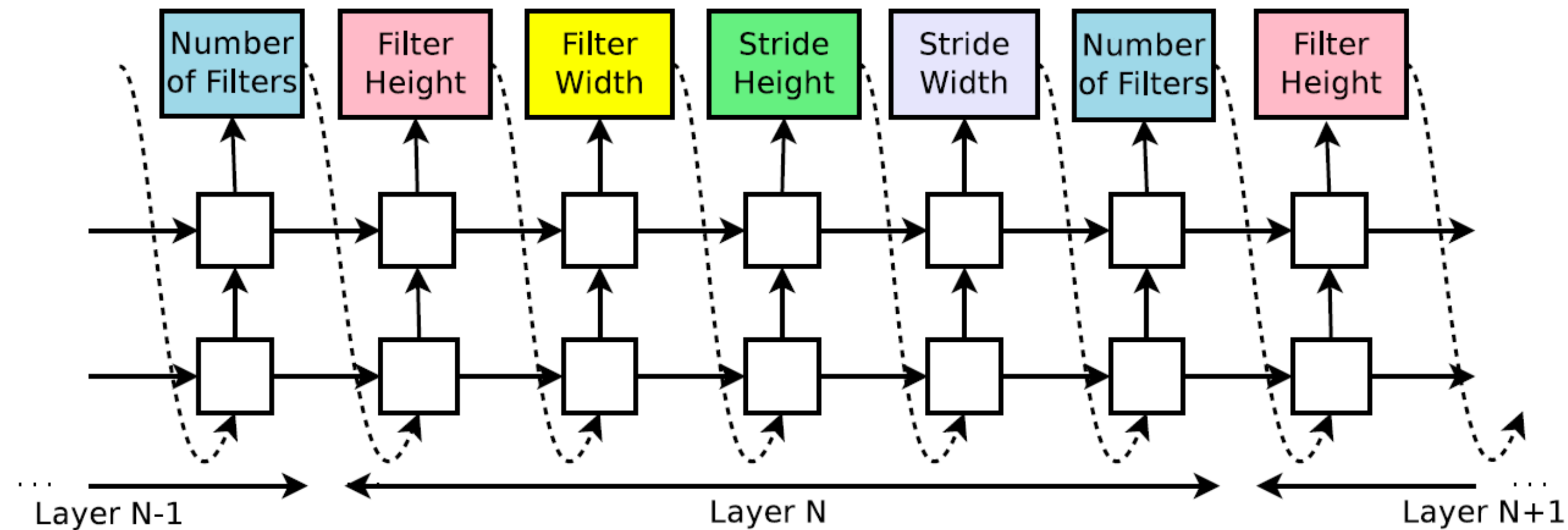


Figure 2: How our controller recurrent neural network samples a simple convolutional network. It predicts filter height, filter width, stride height, stride width, and number of filters for one layer and repeats. Every prediction is carried out by a softmax classifier and then fed into the next time step as input.

NAS with Evolutionary Computation

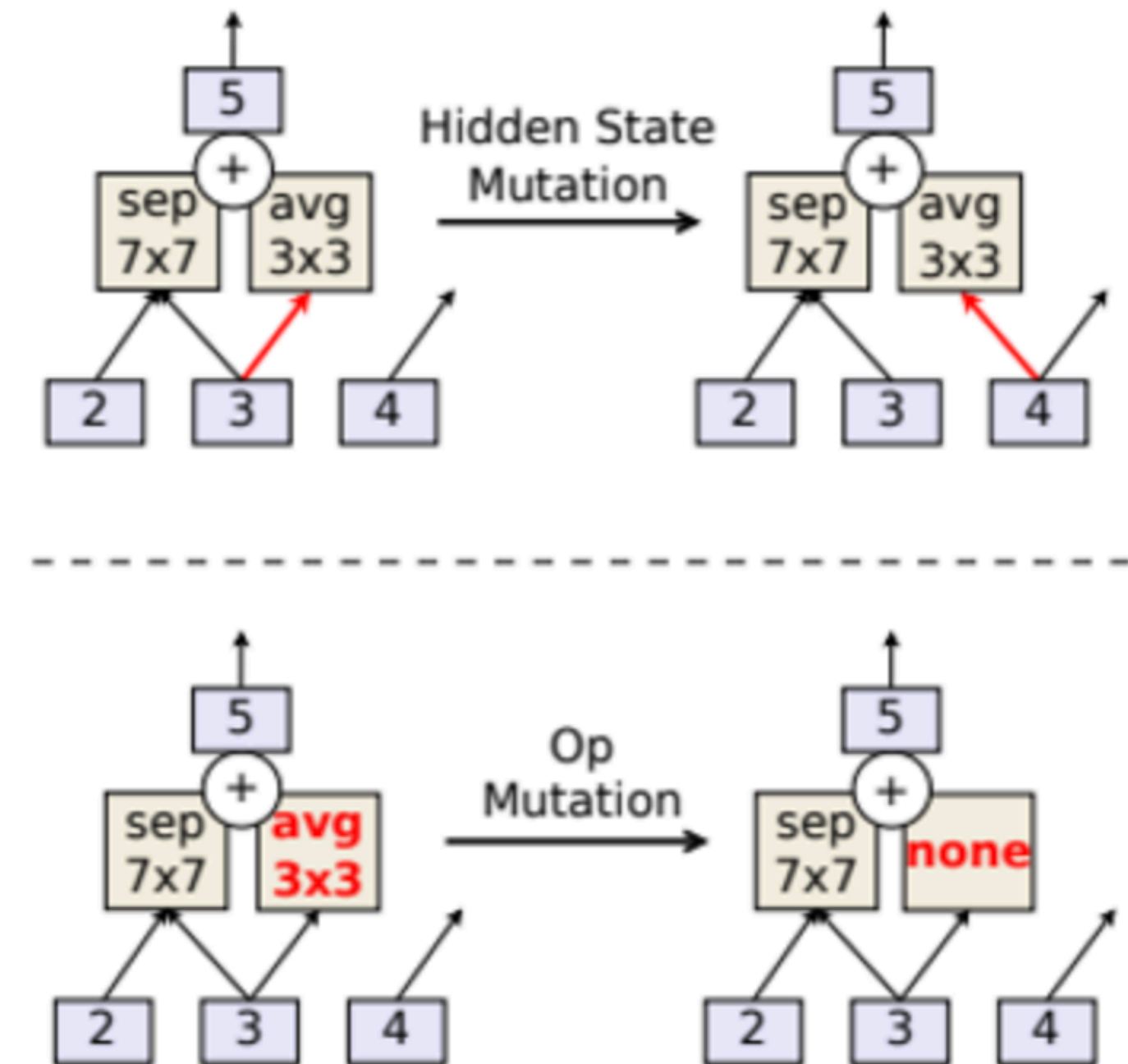
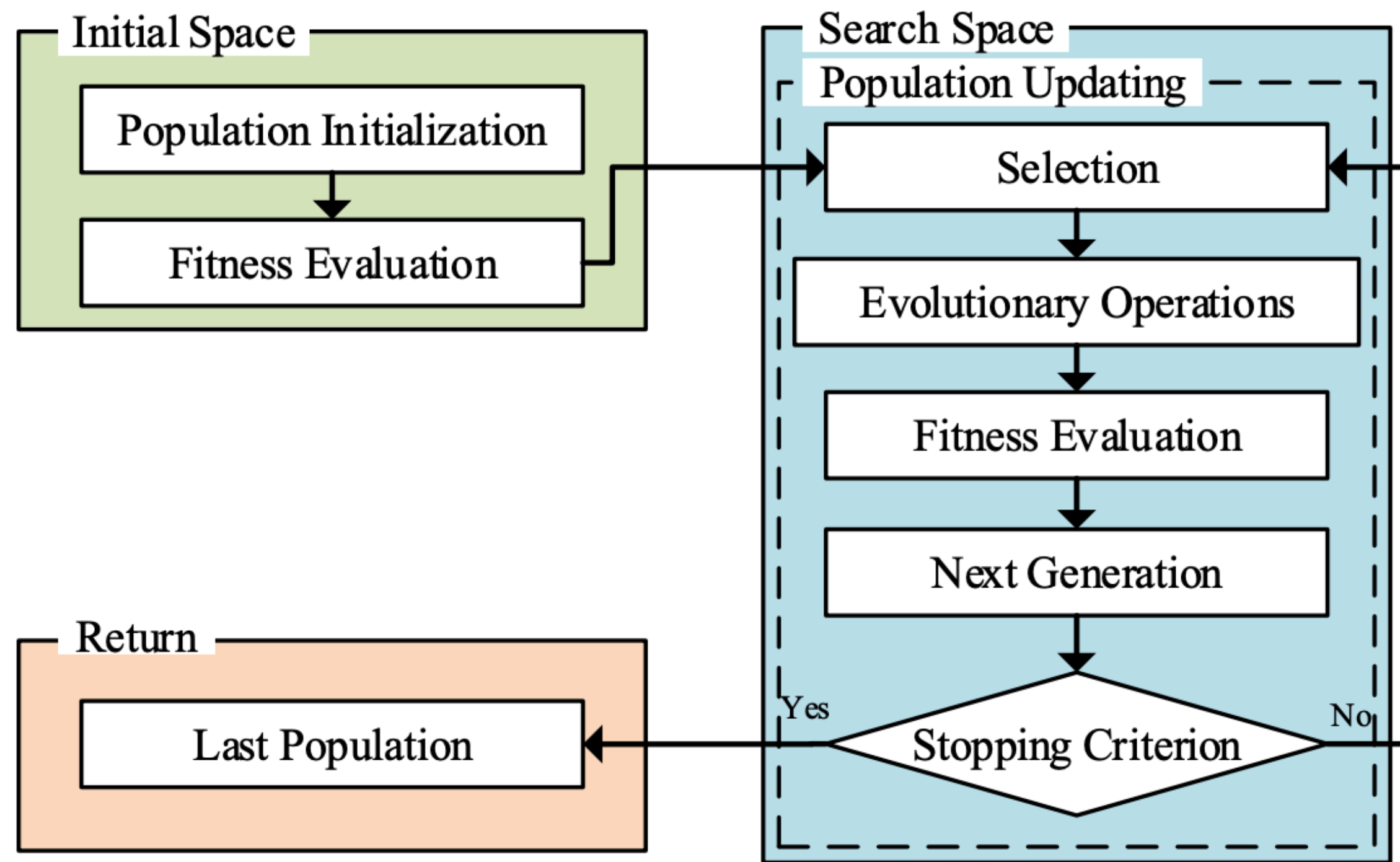


Figure 2: Illustration of the two mutation types.

Fig. 2. The flowchart of a common ENAS algorithm.

AutoKeras

- Keras 기반 AutoML 시스템
- Bayesian optimization 기반 NAS 수행
- 다양한 태스크에 대한 간단한 인터페이스 제공
 - Image Classification/Regression
 - Text Classification/Regression
 - Structured Data Classification/Regression

In AutoKeras

```
# Initialize the structured data classifier.
clf = ak.StructuredDataClassifier(
    overwrite=True, max_trials=3
) # It tries 3 different models.
# Feed the structured data classifier with training data.
clf.fit(
    # The path to the train.csv file.
    train_file_path,
    # The name of the label column.
    "survived",
    epochs=10,
)
# Predict with the best model.
predicted_y = clf.predict(test_file_path)
# Evaluate the best model with testing data.
print(clf.evaluate(test_file_path, "survived"))
```

감사합니다.