Table Manager

Deep Learning 기반 AI 구축 과정

2019-06

강사 이 이 백

목차 Deep Learning 기반 AI 구축

1. Perceptron
2. MLP
3. CNN
4. RNN/LSTM

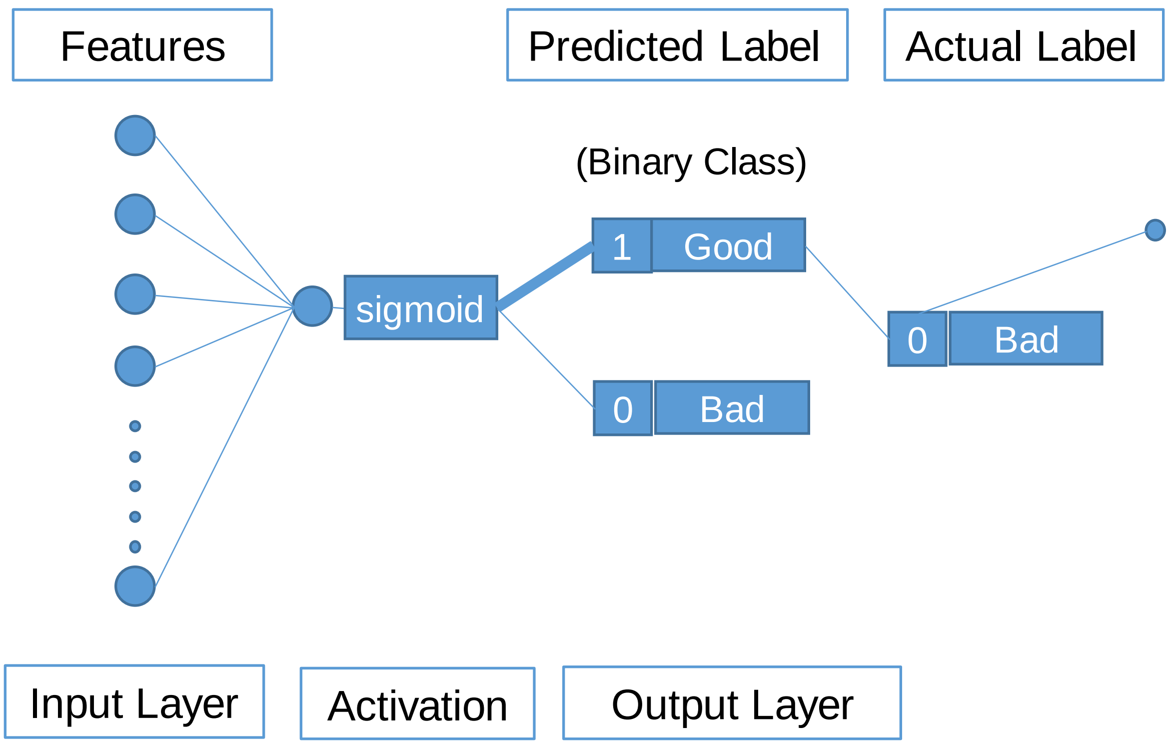
1. Perceptron

- Perceptron > Classification
  - **Case : Logistic Regression for Binary Class Label**

Observation

…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample



Evaluation

Obs	Pred	Actual
1	1	0
2	0	0
3	1	1
…		

Accuracy = 66.67%

Author Yi-Beck Lee(Yibeck.Lee@gmail.com)

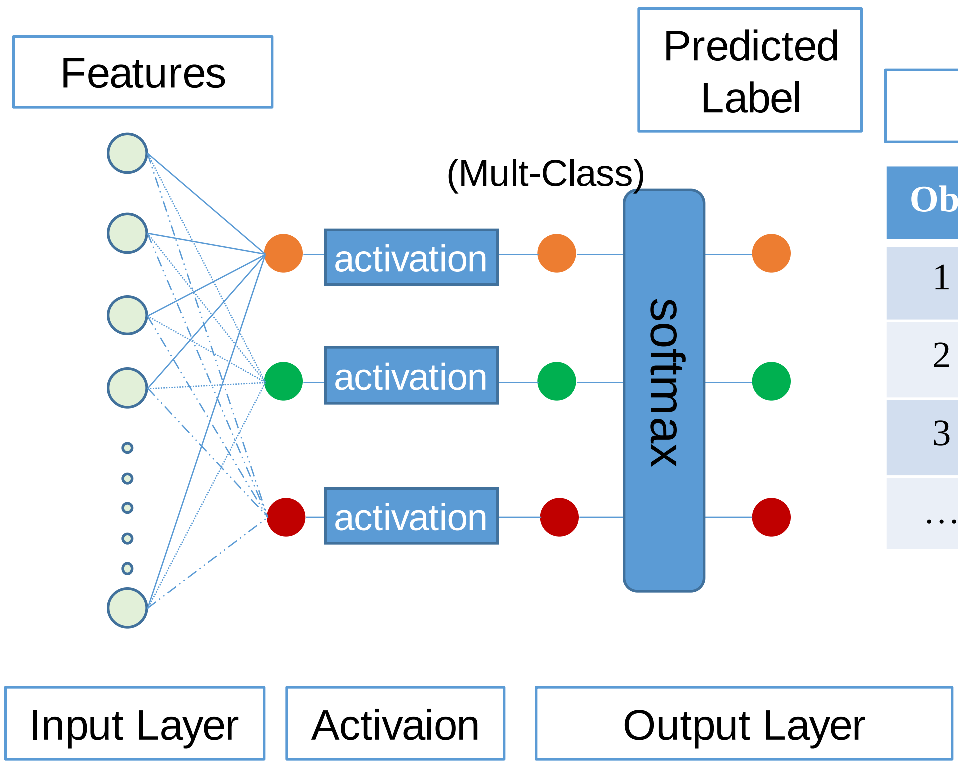
1. Perceptron

- Perceptron > Classification
  - **Case : Softmax Regression for Multi-Class Label**

Observation

…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample



Evaluation

Obs	Softmax	Pred	Actual
1	[0.1,0.1,0.8]	[0,0,1]	[0,0,1]
2	[0.6,0.2,0.2]	[1,0,0]	[0,0,1]
3	[0.01,0.97,0.02]	[0,1,0]	[0,1,0]
…			

Accuracy = 66.67%

Cross-entropy = ???

Table Manager

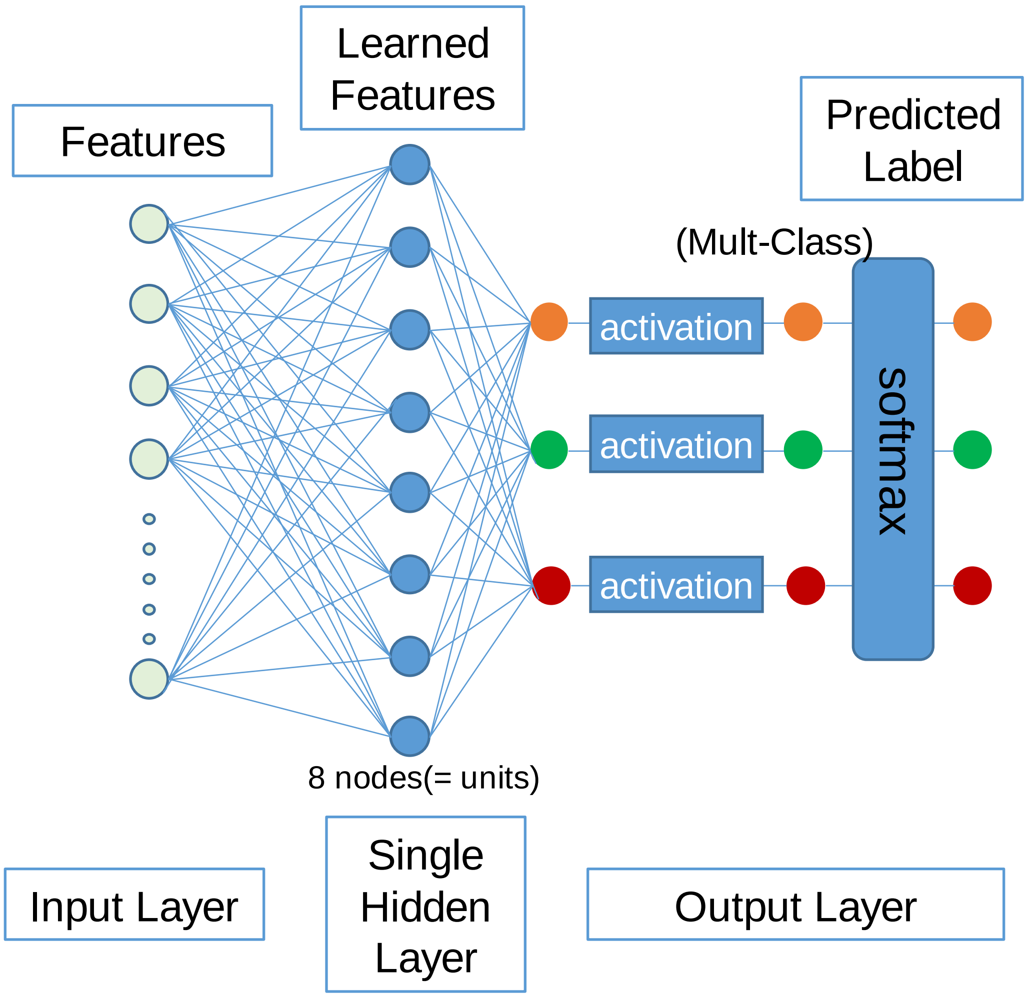
1. Perceptron

- Single Layer Perceptron > Classification
  - **Case : Single Hidden Layer for Softmax Classification**

Observation

…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample



Evaluation

Obs	Softmax	Pred	Actual
1	[0.1,0.1,0.8]	[0,0,1]	[0,0,1]
2	[0.6,0.2,0.2]	[1,0,0]	[0,0,1]
3	[0.01,0.97,0.02]	[0,1,0]	[0,1,0]
…			

Accuracy = 66.67%

Cross-entropy = ???

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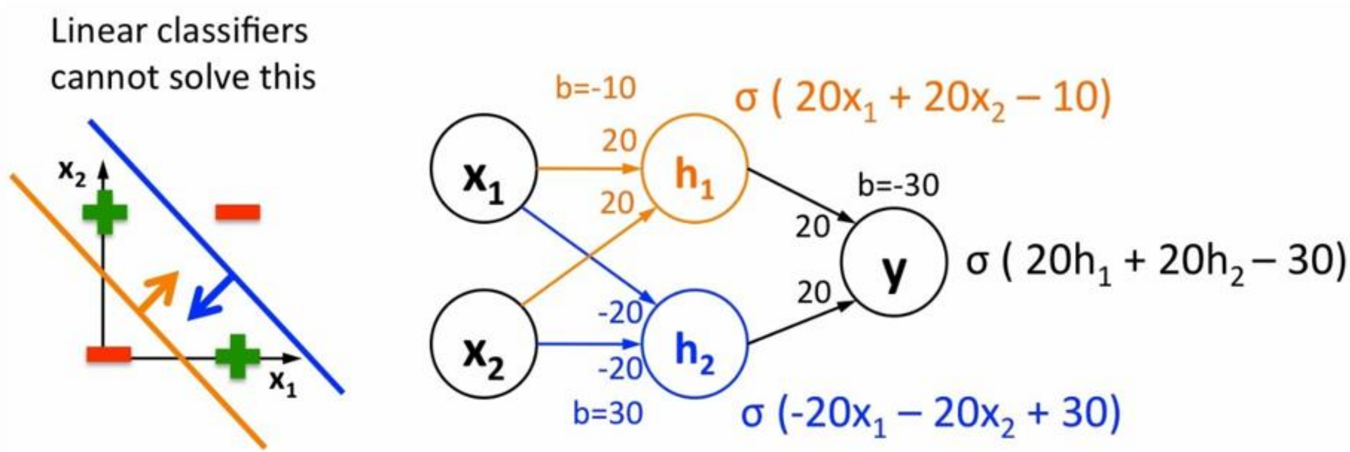
1. Perceptron

- Single Layer Perceptron > Classification
  - **Linear Classification의 한계**



$\sigma(20*0 + 20*0 - 10) \approx 0$	$\sigma(-20*0 - 20*0 + 30) \approx 1$	$\sigma(20*0 + 20*1 - 30) \approx 0$
$\sigma(20*1 + 20*1 - 10) \approx 1$	$\sigma(-20*1 - 20*1 + 30) \approx 0$	$\sigma(20*1 + 20*0 - 30) \approx 0$
$\sigma(20*0 + 20*1 - 10) \approx 1$	$\sigma(-20*0 - 20*1 + 30) \approx 1$	$\sigma(20*1 + 20*1 - 30) \approx 1$
$\sigma(20*1 + 20*0 - 10) \approx 1$	$\sigma(-20*1 - 20*0 + 30) \approx 1$	$\sigma(20*1 + 20*1 - 30) \approx 1$

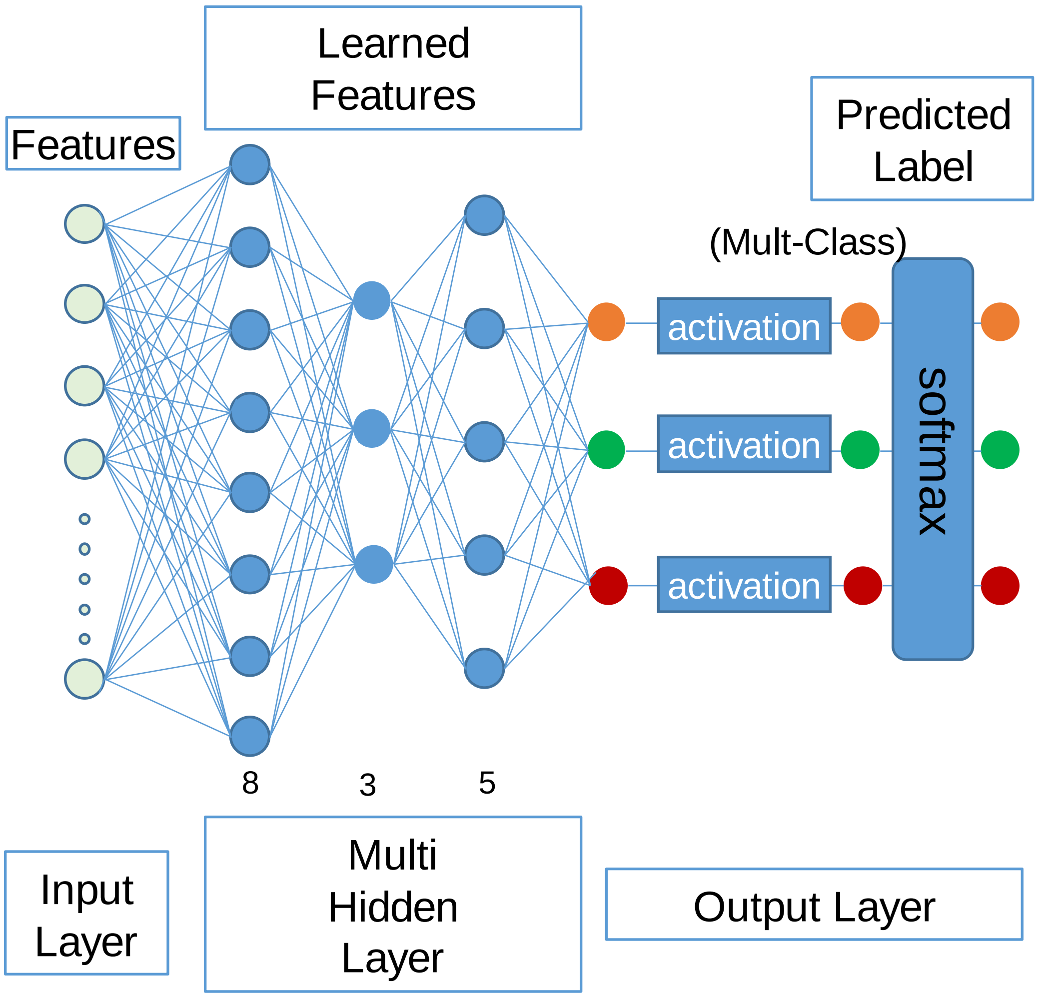
1. Perceptron

- Multi Layer Perceptron > Classification
  - **Case : Multi Hidden Layer for Softmax Classification**

Observation

…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample



Evaluation

Obs	Softmax	Pred	Actual
1	[0.1,0.1,0.8]	[0,0,1]	[0,0,1]
2	[0.6,0.2,0.2]	[1,0,0]	[0,0,1]
3	[0.01,0.97,0.02]	[0,1,0]	[0,1,0]
…			

Accuracy = 66.67%

Cross-entropy = ???

1. Perceptron

- Perceptron > Regression
  - **Case : Regression for Continuous Valued Label**

Observation

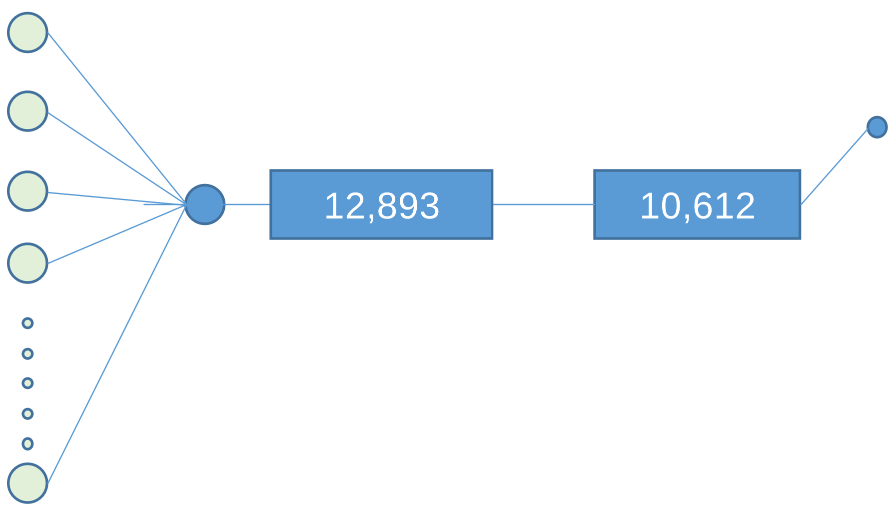
…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample

Features

Predicted Label

Actual Label



Input Layer

Output Layer

Evaluation

Obs	Pred	Actual	Diff
1	12,893	10,612	2,281
2	10,002	11,322	-1,320
3	18,022	17,001	1,019
…			

MSE = ?

MAE = ?

RMSE = ?

MAPE = ?

Table Manager

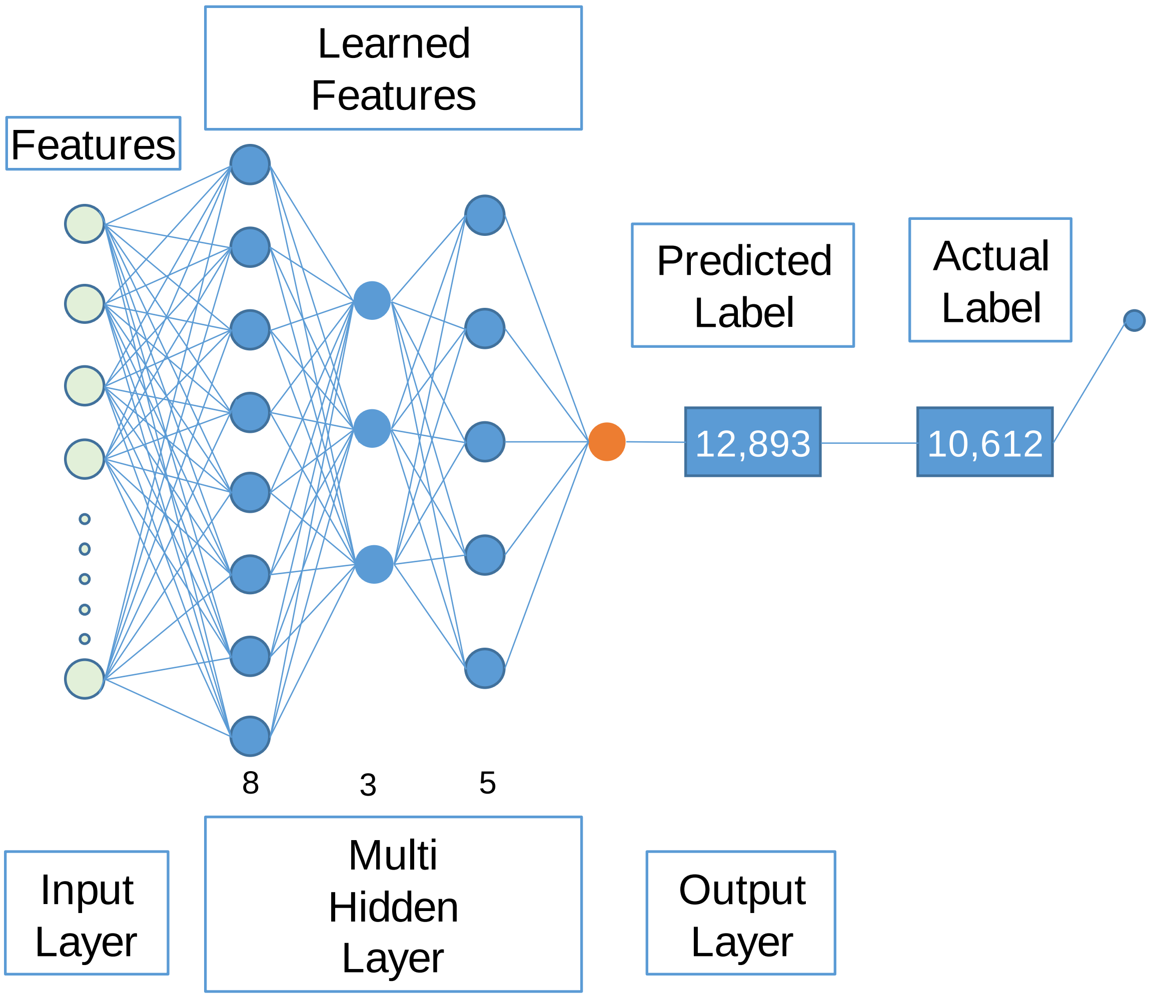
1. Perceptron

- Multi Layer Perceptron > Regression
  - **Case : Multi-Layer Perceptron for Continuous Valued Label**

Observation

…	3	2	1
	112	21	1
	57	0	3
	193	15	5
	-11	58	2

Training Sample



Evaluation

Obs	Pred	Actual	Diff
1	12,257	12,800	-743
2	11,328	11,300	28
3	17,230	17,100	130
…			

MSE = ?
MAE = ?
RMSE = ?
MAPE = ?

2. MLP

- Parameter Tuning
  - 목적 : 일반화를 보증하는 오차 최소화

일반화

- 훈련 Sample에 의존한 예측의 문제점 → Over-Fitting
- Small Sample & Large Number of Features → Under-Fitting
- 일반화를 위한 Data 준비
  - 2 or 3 Set : Training Data, (Validation Data,) Test Data
  - Training Data → Model 수식 산출
  - Validation Data → Model Evaluation
  - Test Data → Real World Application 적용 가능성 최종 결정 및 적용할 Model 확정

오차 최소화의 영향 요소

- Input Layer
  - 가중치(weight)의 변화
  - 입력변수 → 파생변수 → 특징 추출
- Hidden Layer
  - Multi-Input Variable간의 연산 → 파생변수화
  - 새로운 가충치의 연산
  - 변수들간의 관계성 또는 독립성에 대한 특징 학습
  - Activation Function 선택
- Output Layer
  - 모델의 예측값 산출
  - 현실적 기대치에 못미칠 경우 재학습 수행 – Backpropagation
  - Model Evaluation

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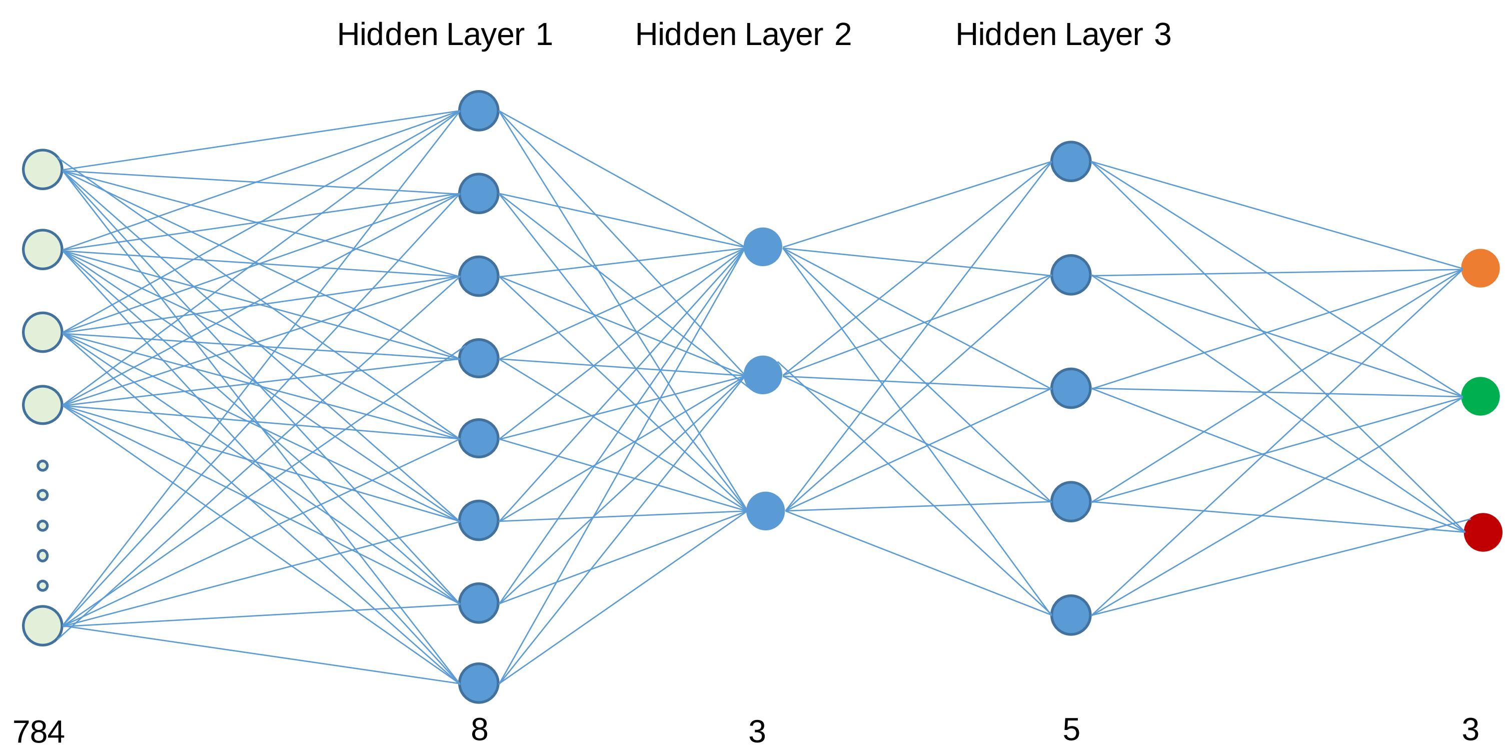
2. MLP

- Parameters : Hidden Layers & Neurons

Parameter	내용	Case
Number of Hidden Layer	▪ 히든레이어의 수	[L1, L2, L3]
Number of Neurons per Hidden Layer	▪ 각 히든레애어의 뉴런수	[8, 3, 5]



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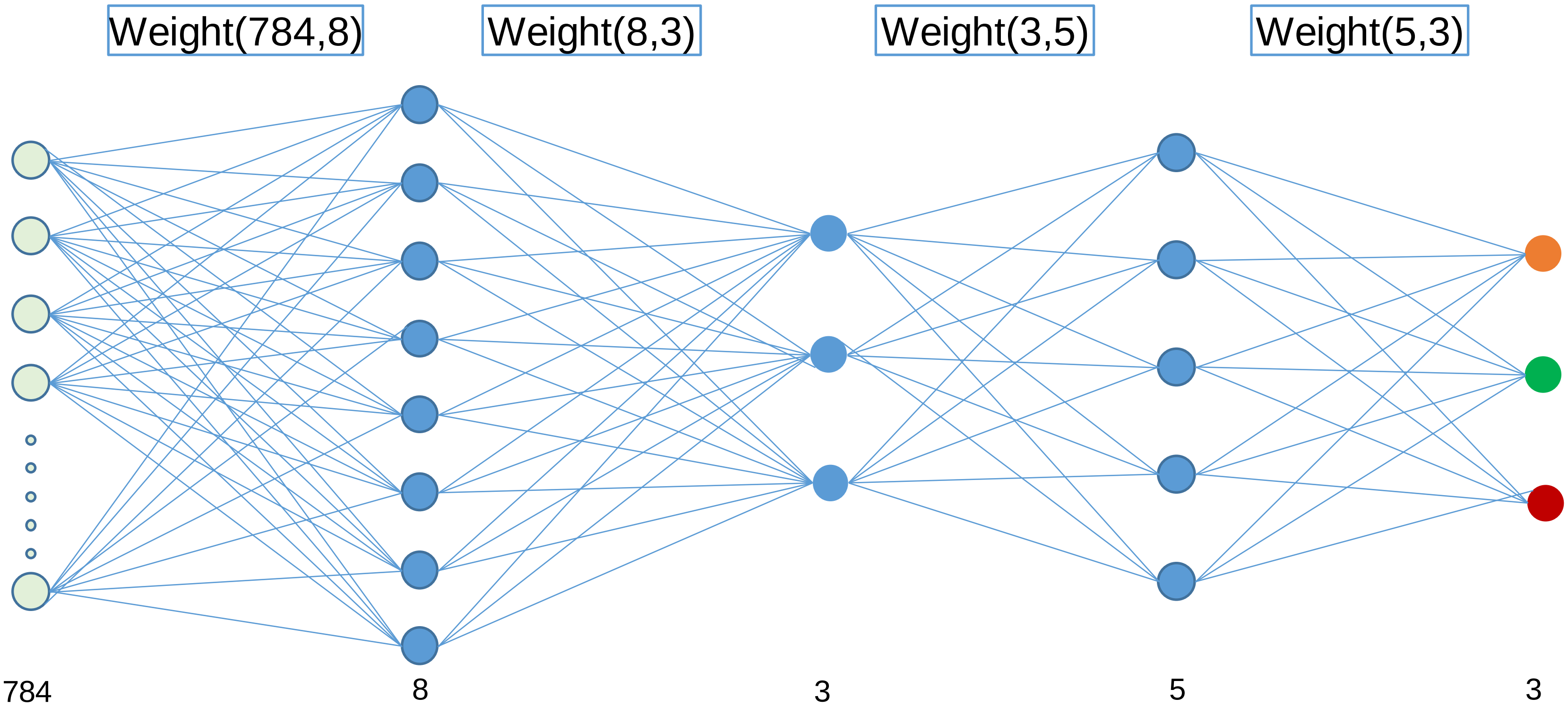
2. MLP

- Parameters : Weight

Parameter	내용
Weight Initialization	▪ 가중치 초기값 산출

가중치 초기화 방법

- 정규분포의 random value
- 정규분포 +/- 2시그마내 random value
- 상수값 : 예) 0, 1



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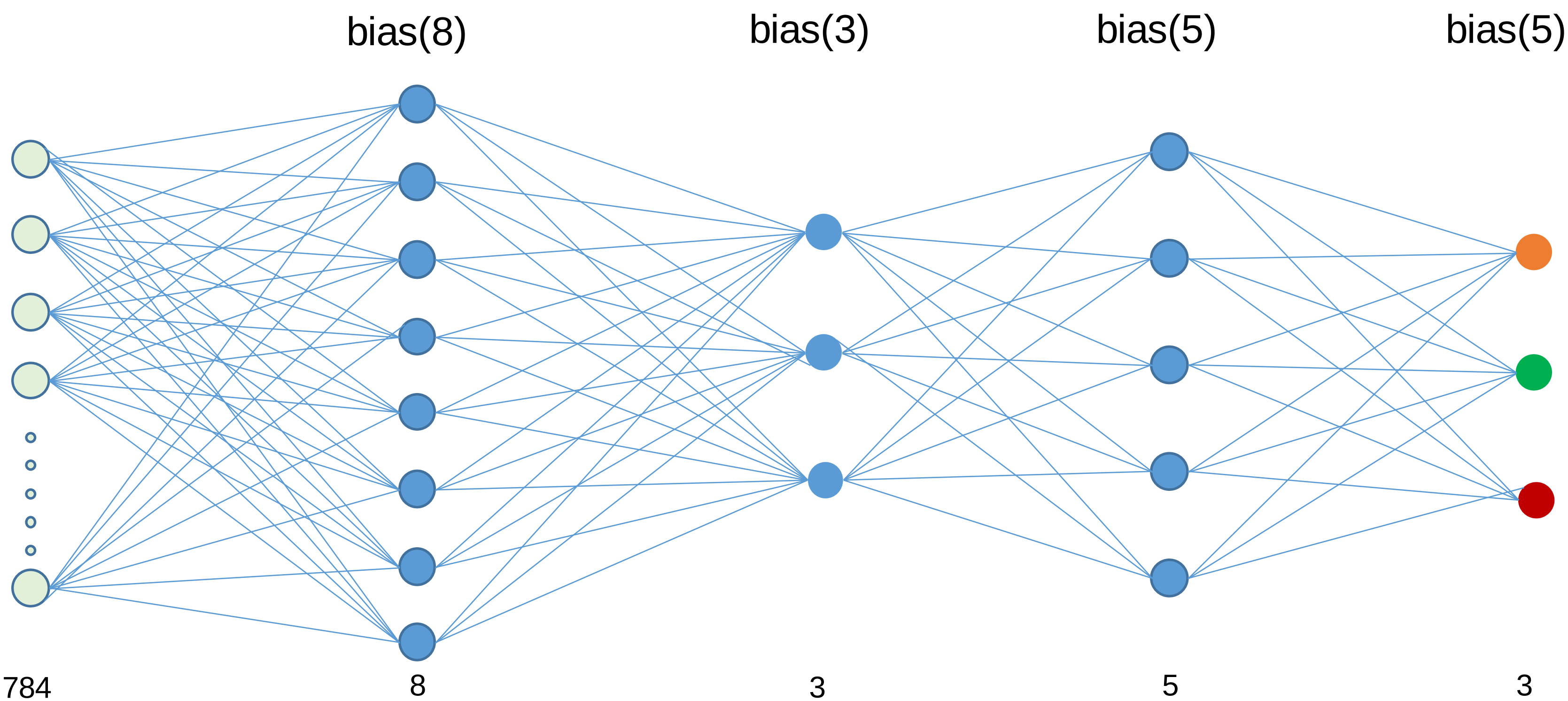
2. MLP

- Parameters : bias

Parameter	내용
bias Initialization	▪ 가중치 초기값 산출

bias 초기화 방법

- 정규분포의 random value
- 정규분포 +/- 2시그마내 random value
- 상수값 : 예) 0, 1



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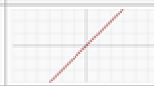
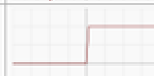
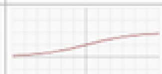
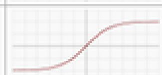
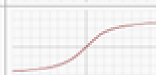
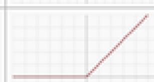
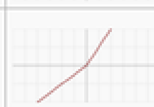
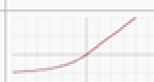
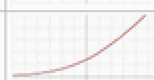
2. MLP

- Parameters : Activations for Forward Propagation

Parameter	내용
Activation function	▪ 활성화함수 선택

activation method

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2+1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1+e^{-x}}$

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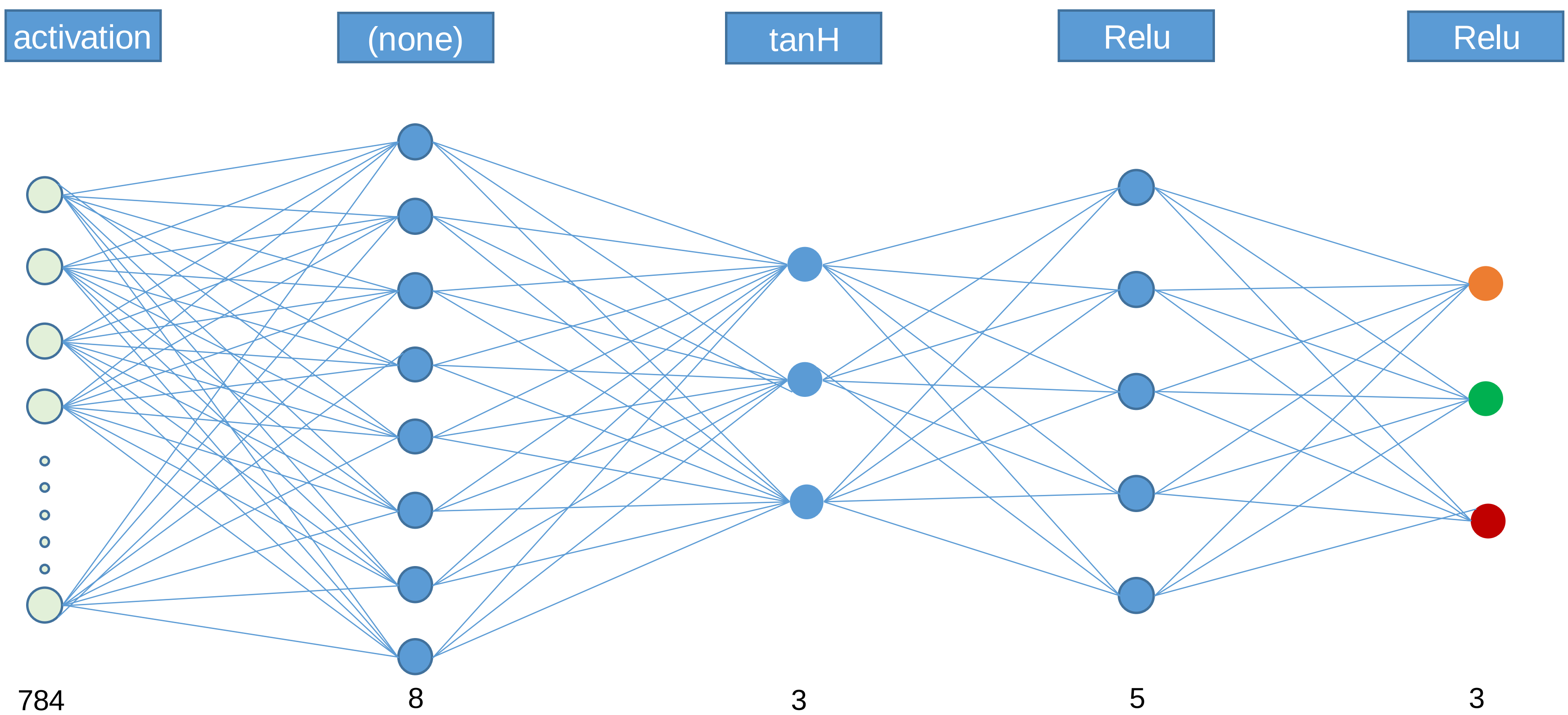
2. MLP

- Parameter for Forward Propagation

Parameter	내용
Activation function	▪ 활성화함수 선택



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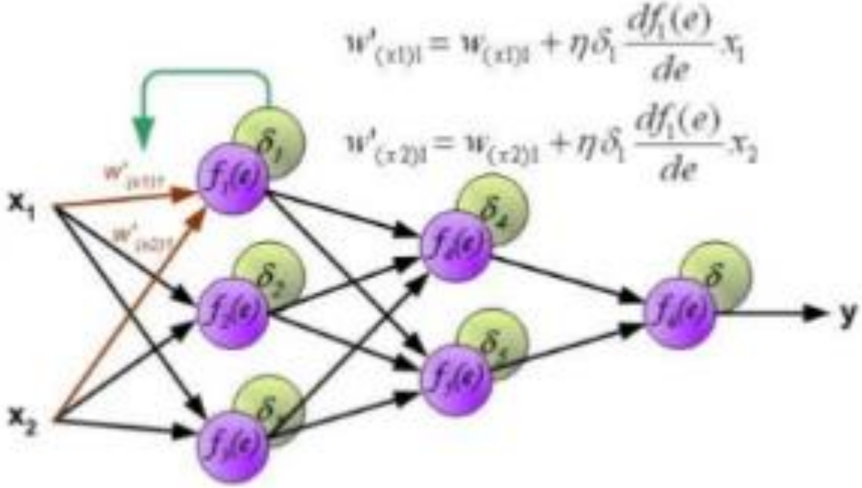
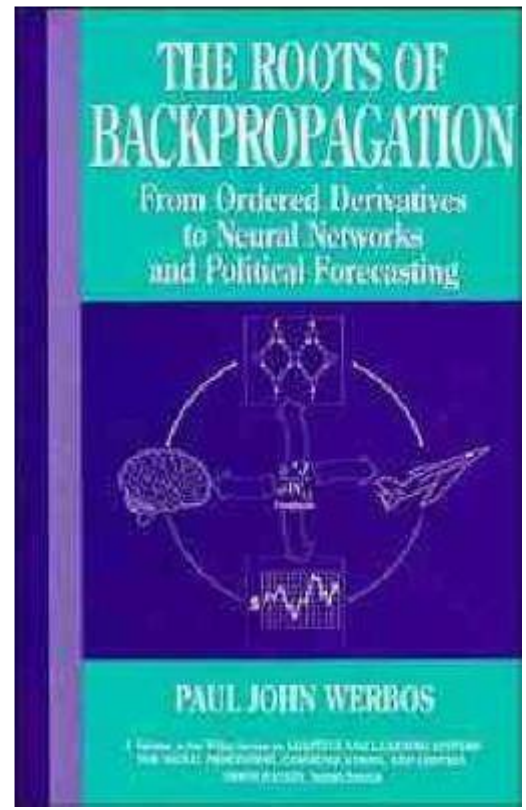
2. MLP

- Parameters : Backward Propagation Method
  - Paul Werbos(1974)의 Ph.D. thesis
  - Book : The Roots of Backpropagation





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2. MLP

- Parameters : Backward Propagation Method
  - Hinton(1986)
    - Paper : Learning Distributed Representations of Concepts

Geoffrey Hinton

Appointment
Advisor
Learning in Machines & Brains

Institution
University of Toronto
Google
Department of Computer Science

Country
Canada

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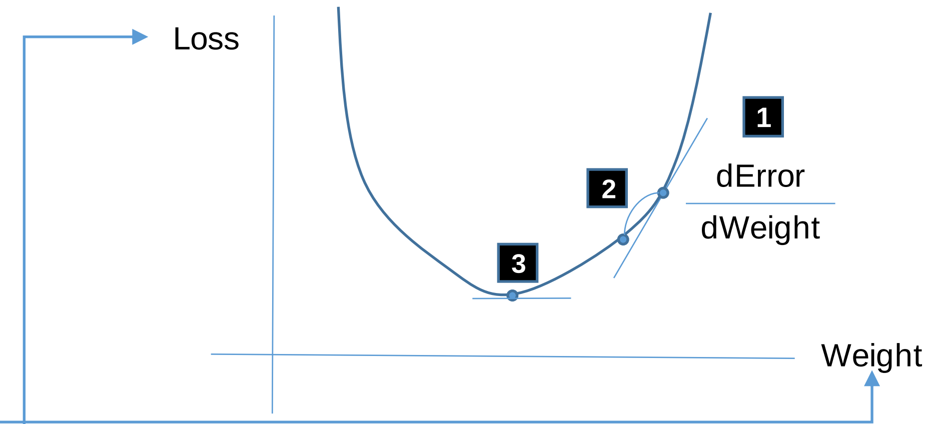
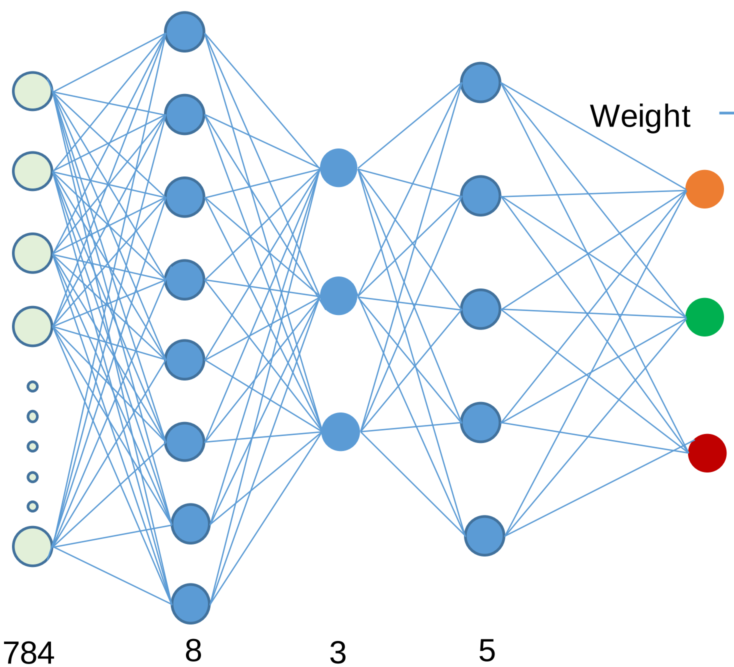
2. MLP

- Parameters : Backward Propagation Method
  - 전방위 학습과 반대 방향으로 거슬러 올라가기
  - Weight Update - learning rate를 조정 계수로 하여 오차가 최소화할 때 가지 가중치 갱신

$$\text{New Weight} = \text{Weight} - \boxed{2}\ \text{LearningRate} * \boxed{1}\ \frac{\text{dError}}{\text{dWeight}}$$

$\boxed{3}$ 에 도달할 때까지 iteration



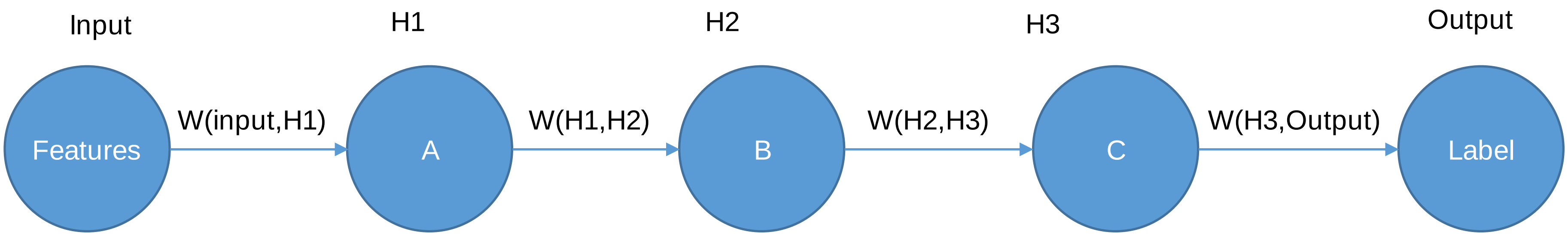


$$\text{Loss} = \text{Total Errors} = \sum \frac{1}{2}\left[\text{Predicted Label} - \text{Actual Label}\right]^2$$

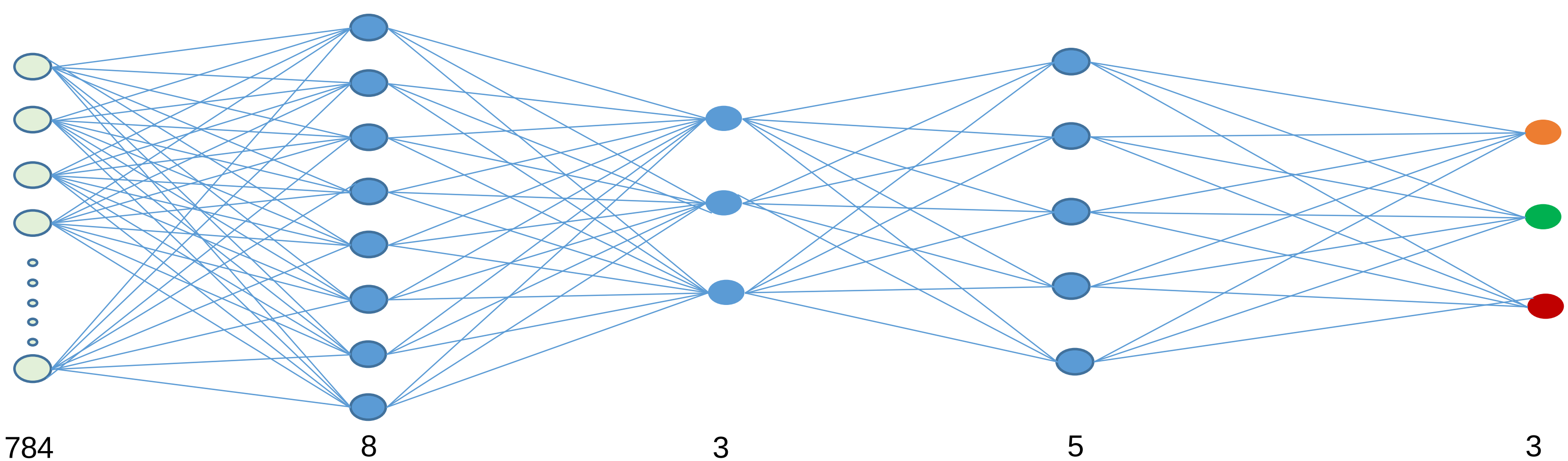
$$\frac{\text{dErrors}}{\text{dPredicted\_Labels}} = -2 * \frac{1}{2}\left[\text{Predicted Label} - \text{Actual Label}\right]$$

2. MLP

- Parameters : Backward Propagation Method
  - 전방위 학습과 반대 방향으로 거슬러 올라가기



$$\frac{dPredLabel}{dFeatures} = \frac{dPredLabel}{dC\_} * \frac{dC}{dB} * \frac{dB}{dA} * \frac{dA}{dFeatures}$$



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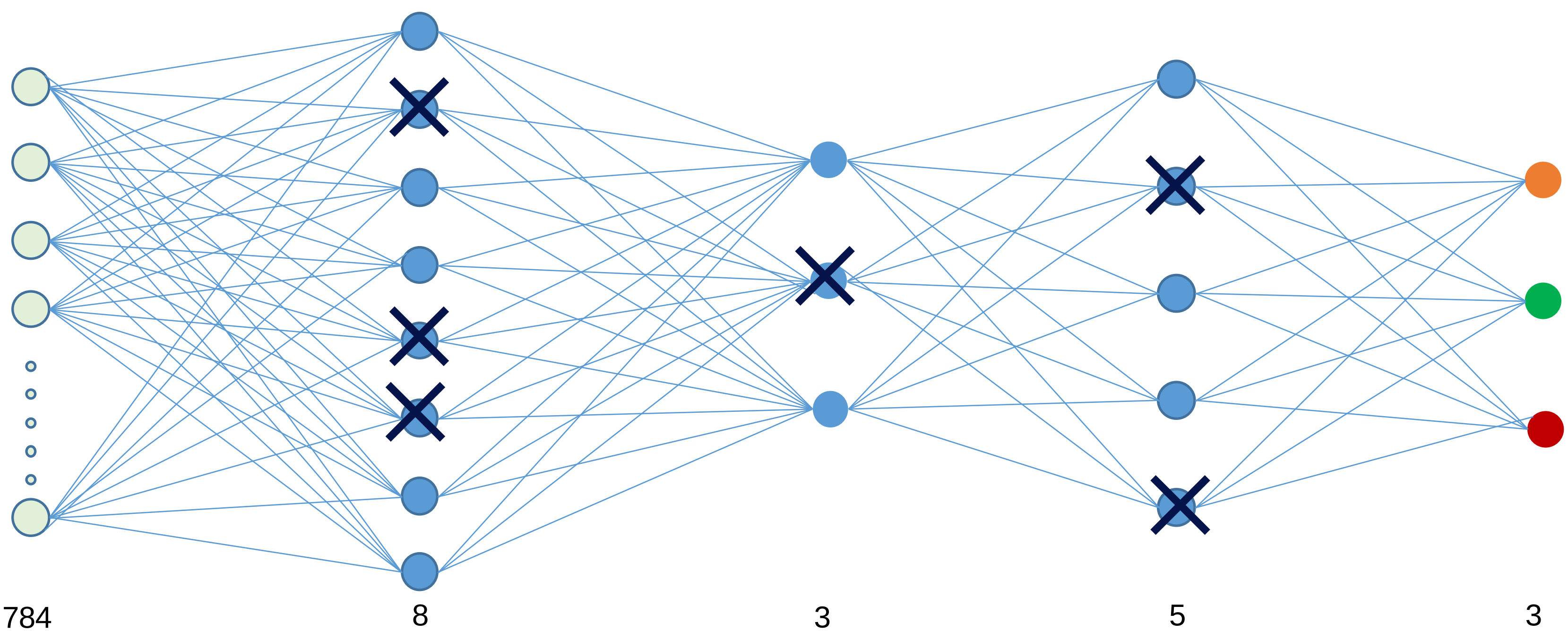
2. MLP

- Parameters : Regularization > Dropout
  - 학습을 덜 하겠다는 의미 → 과적합 방지

Parameter	내용
Dropout Rate	▪ 가중치 탈락 비율

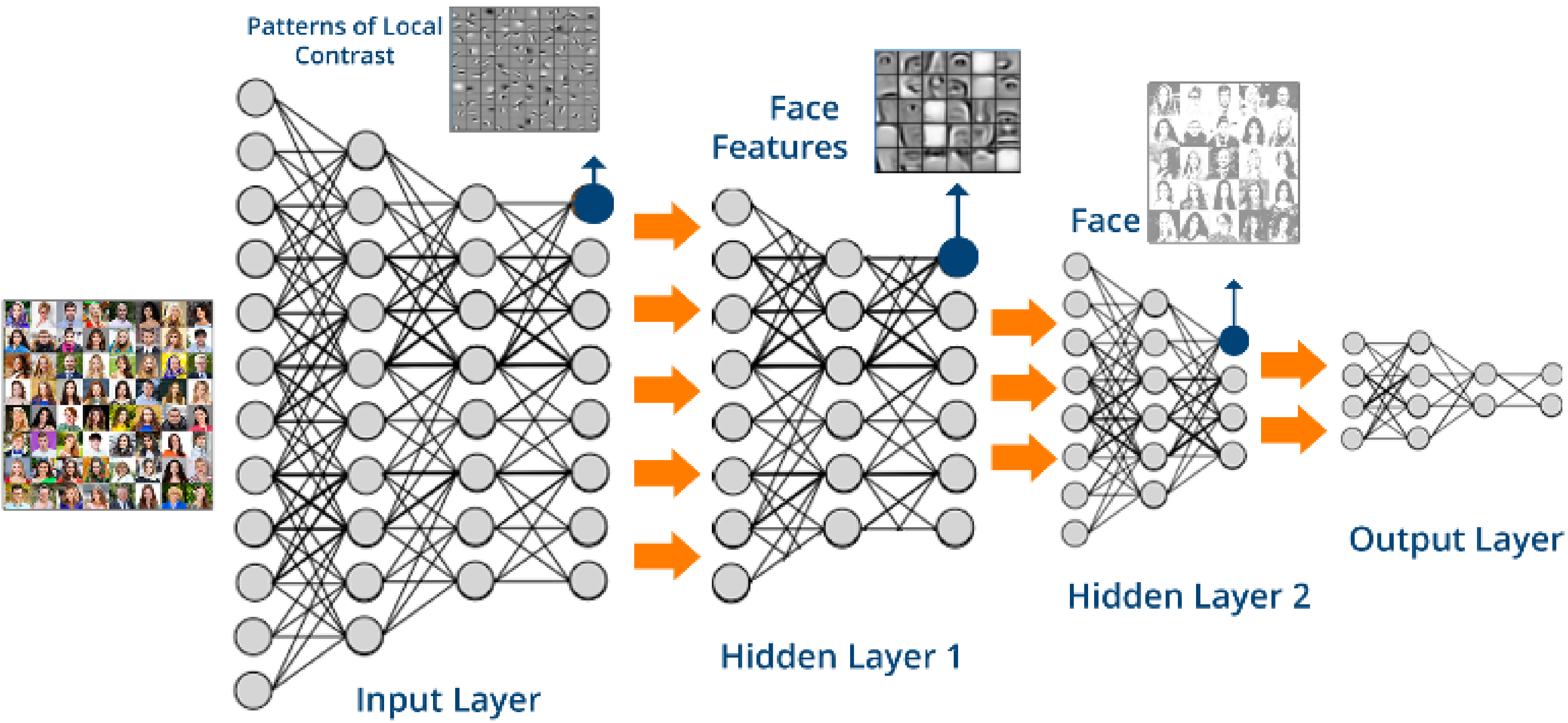
Regularization Method

- L1 Regularization → Lasso
- L2 Regularization → Ridge
- Drop-Out → Deep Learning



2. MLP

- Hidden Layer를 거치면서 Label에 적합하는 특징 패턴을 추출하는 과정



2. MLP

- Activation

```
#!/usr/bin/env /c/Apps/Anaconda3/python

# Import
import tensorflow as tf
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# Import data
data = pd.read_csv('./data_stocks.csv')

# Drop date variable
data = data.drop(['DATE'], 1)

# Dimensions of dataset
n = data.shape[0]
p = data.shape[1]

# Make data a np.array
data = data.values

# Training and test data
train_start = 0
train_end = int(np.floor(0.8*n))
test_start = train_end + 1
test_end = n
data_train = data[np.arange(train_start, train_end), :]
data_test = data[np.arange(test_start, test_end), :]

# Scale data
scaler = MinMaxScaler(feature_range=(-1, 1))
scaler.fit(data_train)
data_train = scaler.transform(data_train)
data_test = scaler.transform(data_test)

# Build X and y
X_train = data_train[:, 1:]
y_train = data_train[:, 0]
X_test = data_test[:, 1:]
y_test = data_test[:, 0]

# Number of stocks in training data
n_stocks = X_train.shape[1]

# Neurons
n_neurons_1 = 1024
n_neurons_2 = 512
n_neurons_3 = 256
n_neurons_4 = 128

# Session
net = tf.InteractiveSession()

# Placeholder
X = tf.placeholder(dtype=tf.float32, shape=[None, n_stocks])
Y = tf.placeholder(dtype=tf.float32, shape=[None])

zer = tf.variance_scaling_initializer(mode="fan_avg", distribu
r = tf.zeros_initializer()

# Hidden weights
W_hidden_1 = tf.Variable(weight_initializer([n_stocks, n_neurons_1]))
bias_hidden_1 = tf.Variable(bias_initializer([n_neurons_1]))
W_hidden_2 = tf.Variable(weight_initializer([n_neurons_1, n_neurons_2]))
bias_hidden_2 = tf.Variable(bias_initializer([n_neurons_2]))
W_hidden_3 = tf.Variable(weight_initializer([n_neurons_2, n_neurons_3]))
bias_hidden_3 = tf.Variable(bias_initializer([n_neurons_3]))
W_hidden_4 = tf.Variable(weight_initializer([n_neurons_3, n_neurons_4]))
bias_hidden_4 = tf.Variable(bias_initializer([n_neurons_4]))

# Output weights
W_out = tf.Variable(weight_initializer([n_neurons_4, 1]))
bias_out = tf.Variable(bias_initializer([1]))

# Hidden layer
hidden_1 = tf.nn.relu(tf.add(tf.matmul(X, W_hidden_1), bias_hidden_1))
hidden_2 = tf.nn.relu(tf.add(tf.matmul(hidden_1, W_hidden_2), bias_hidden_2))
```

실습 중 배포

Table Manager

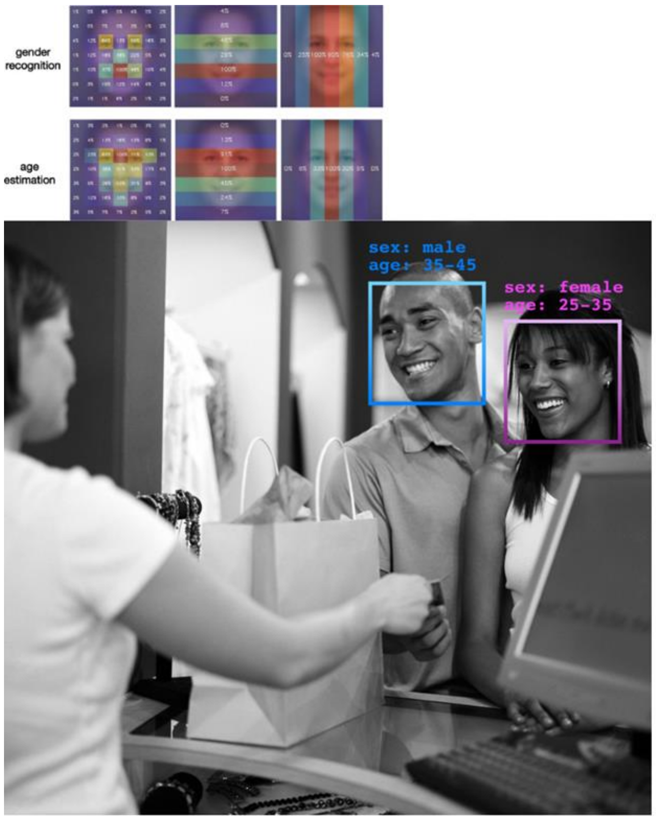
3. CNN

- Convolutional Neural Network(Yann LeCun, 1998)
- Convolution의 의미
  - 함수의 합성곱
- Input Layer → Convolution Layer
  - Reshape flattened input vector to 3d tensor
    - 3d tensor = [height, width, depth]
    - depth = [Red, Green, Blue] = 3 channel
      - ✓ [255, 0, 0] → Red = 1 Channel
- Convolution → ReLU → Max Pooling
  - Convolution
    - Stack of filtered images(여과지를 이동하면서 투영된 부분이미지의 적재)
      - ✓ 부분이미지 적재 → Feature Map을 만들어가는 과정
    - Kernel Filtering은 Forwarding과 동일한 효과
    - Stride → Padding → Activation(ReLU)
    - ReLU의 역할 : Normalizing
  - Pooling
    - Filtering 과정에서 적재한 특징 배열의 개별값들중 중 최대값만 취함
      - ✓ 최대값 만 선택적으로 취함 = down sampling
    - Stack을 축소(shrinking)시켜 큰 특징만 취하는 효과
      - ✓ Window, Stride, Max
- Fully Connection
  - Why? 신경망 학습 → MLP 와 동일

3. CNN

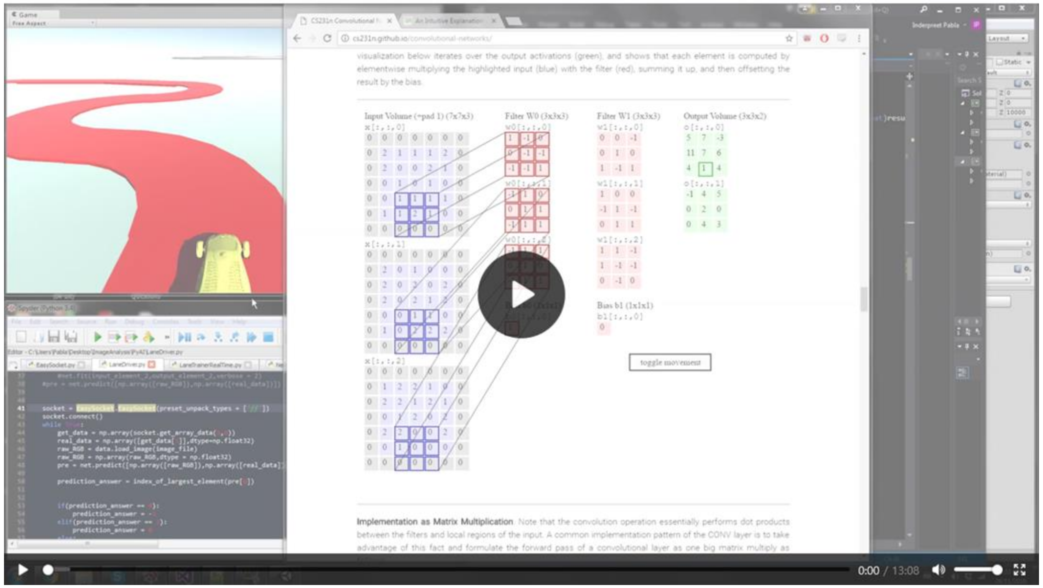
- CNN의 Output Image

성별 및 연령 예측



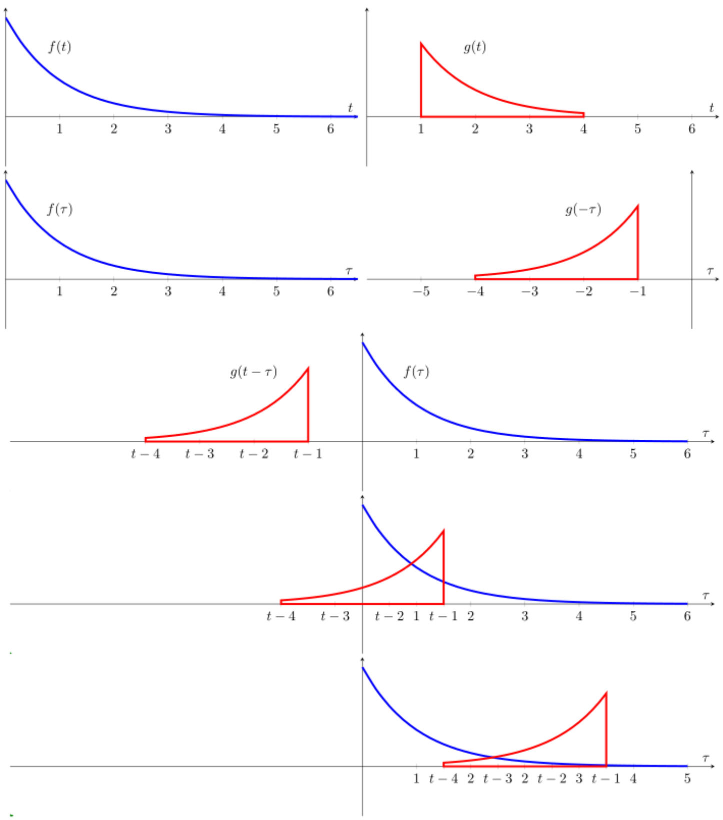
Auto-Driving Simulation

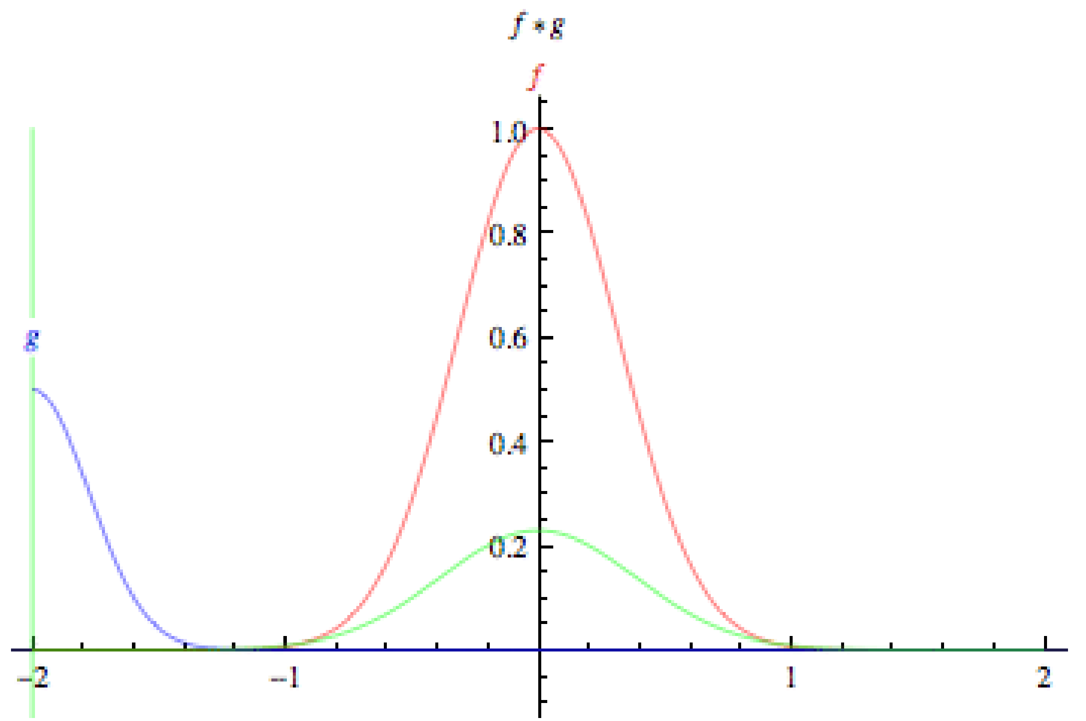
Self driving car : Convolutional Neural Network driving a car in an open source simulator



3. CNN

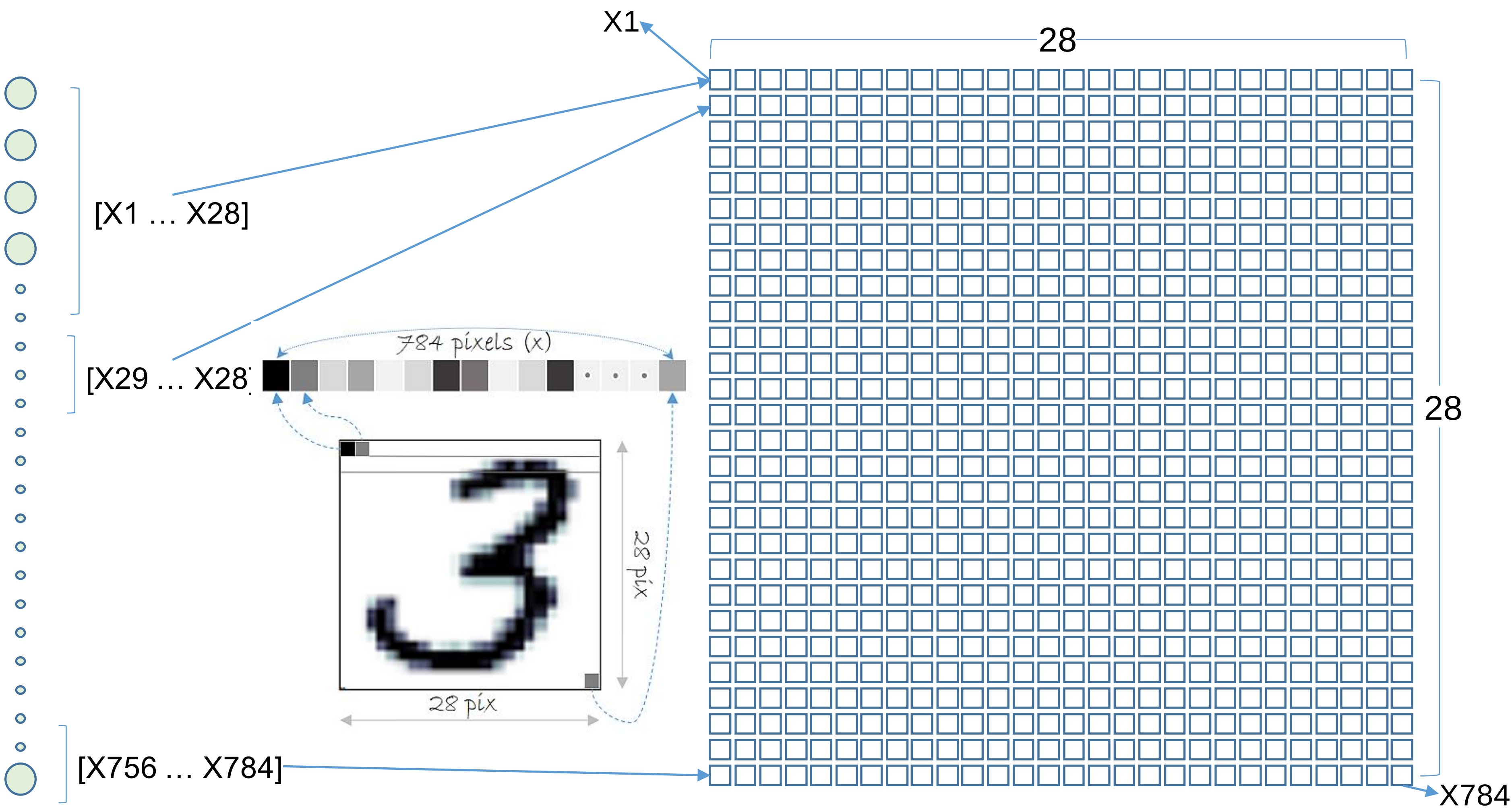
- Convolution
  - Roll Together(라틴어에서 파생)
  - Mathematics
    - Convolution은 2개의 함수를 겹쳐서 적분값을 측정(합성곱)





3. CNN

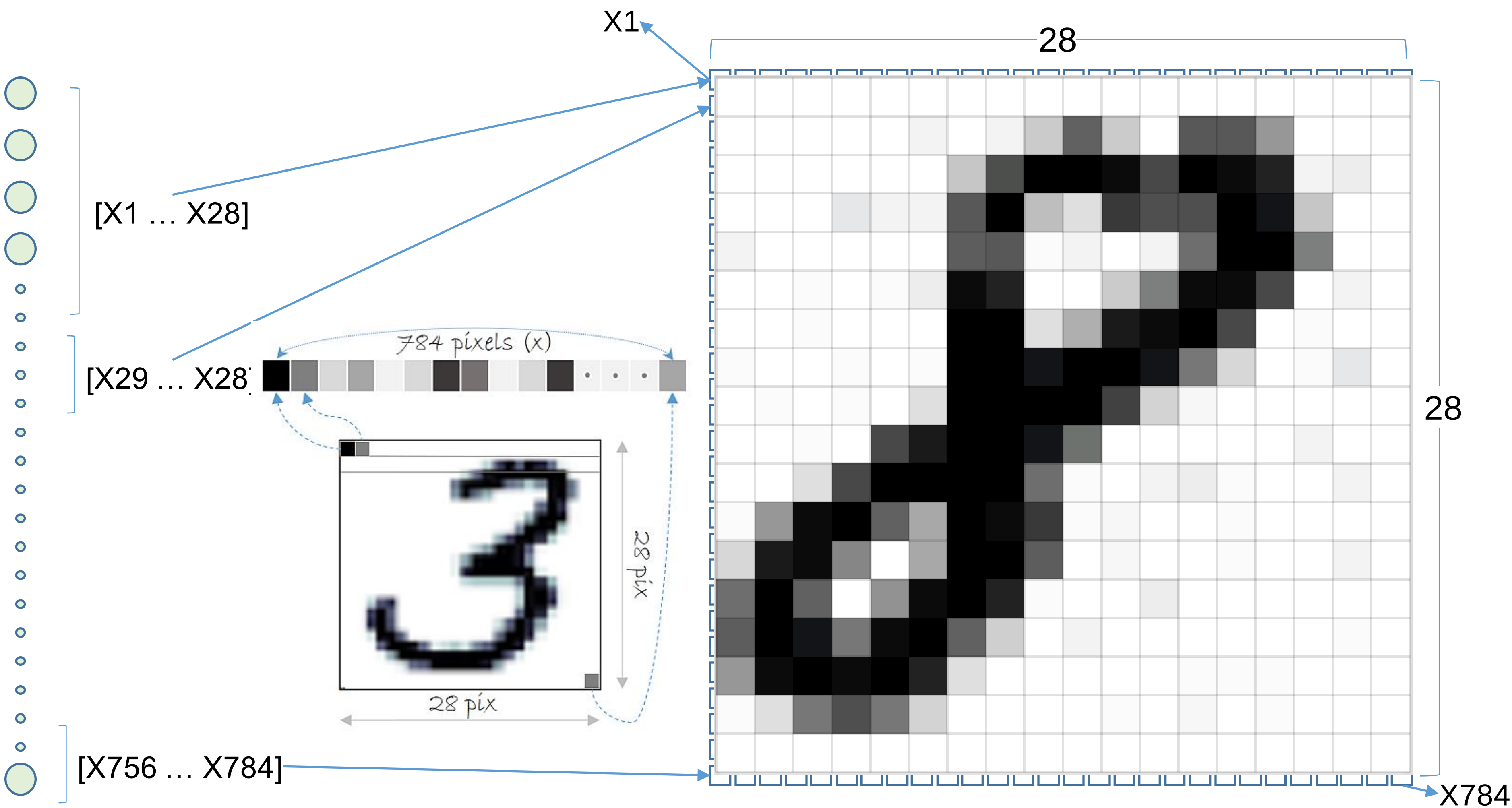
- Convolution
  - Reshape : Vector → Matrix



Author Yi-Beck Lee(Yibeck.Lee@gmail.com)

3. CNN

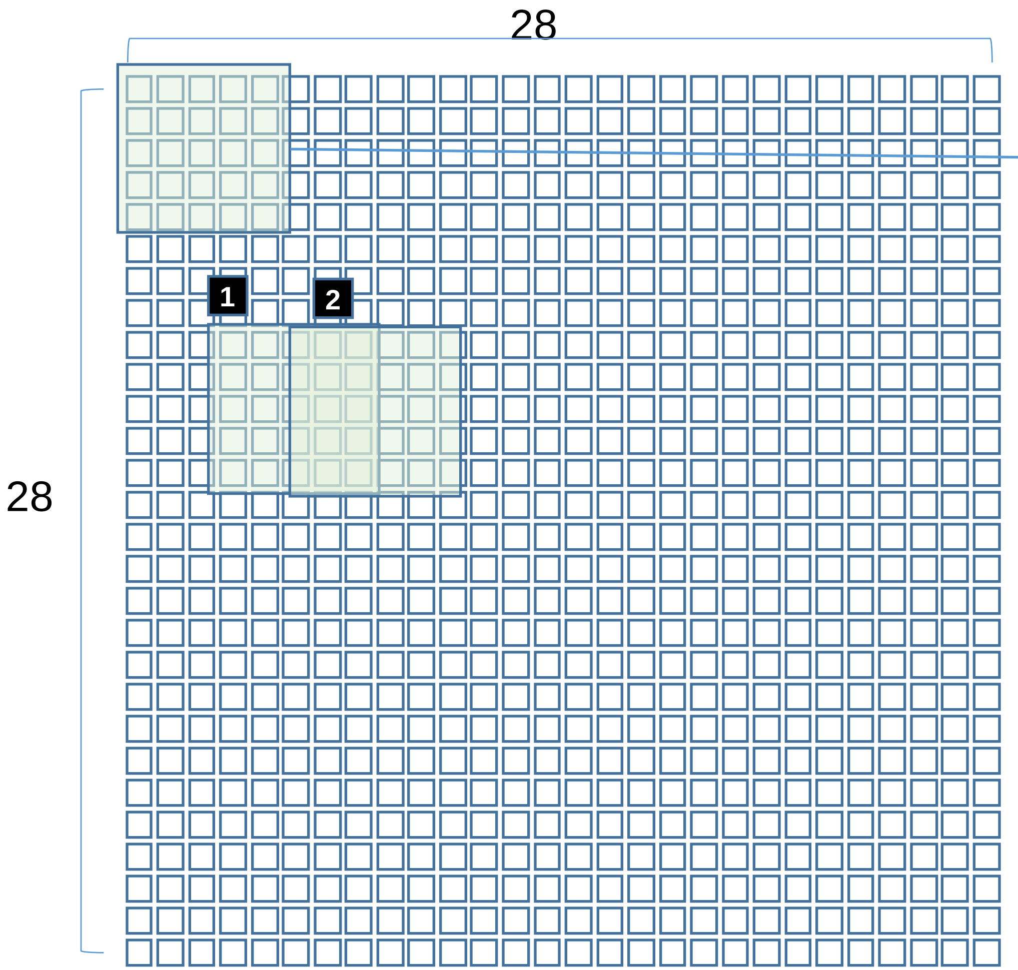
- Convolution
  - Reshape : Vector → Matrix

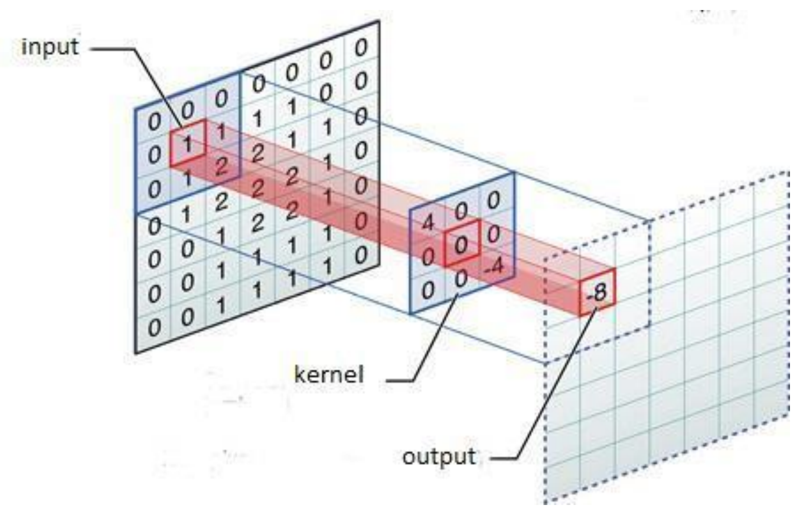


Author Yi-Beck Lee(Yibeck.Lee@gmail.com)

3. CNN

- Convolution
  - Matrix의 부분 집합 선택하여 Filtering





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3. CNN

- Filter Size의 결정
  - Filer Size가 클 경우 shrunk
  - Recommended
    - (F – 1/) / 2
    - Zero padding
    - One or Two stride

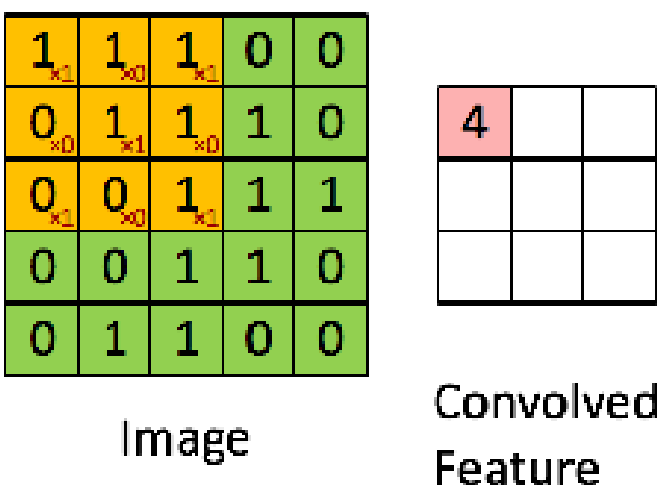
Zero Padding

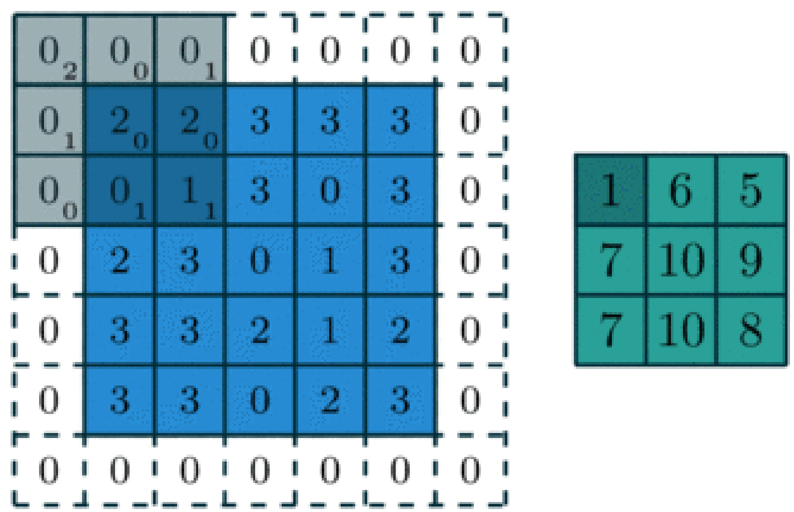
(A3 – 1) / 2 = 1

(A3 – 1) / 2 = 1

Without
Padding
Stride [1,1,1,1]

Zero Padding
Stride[1,2,2,1]



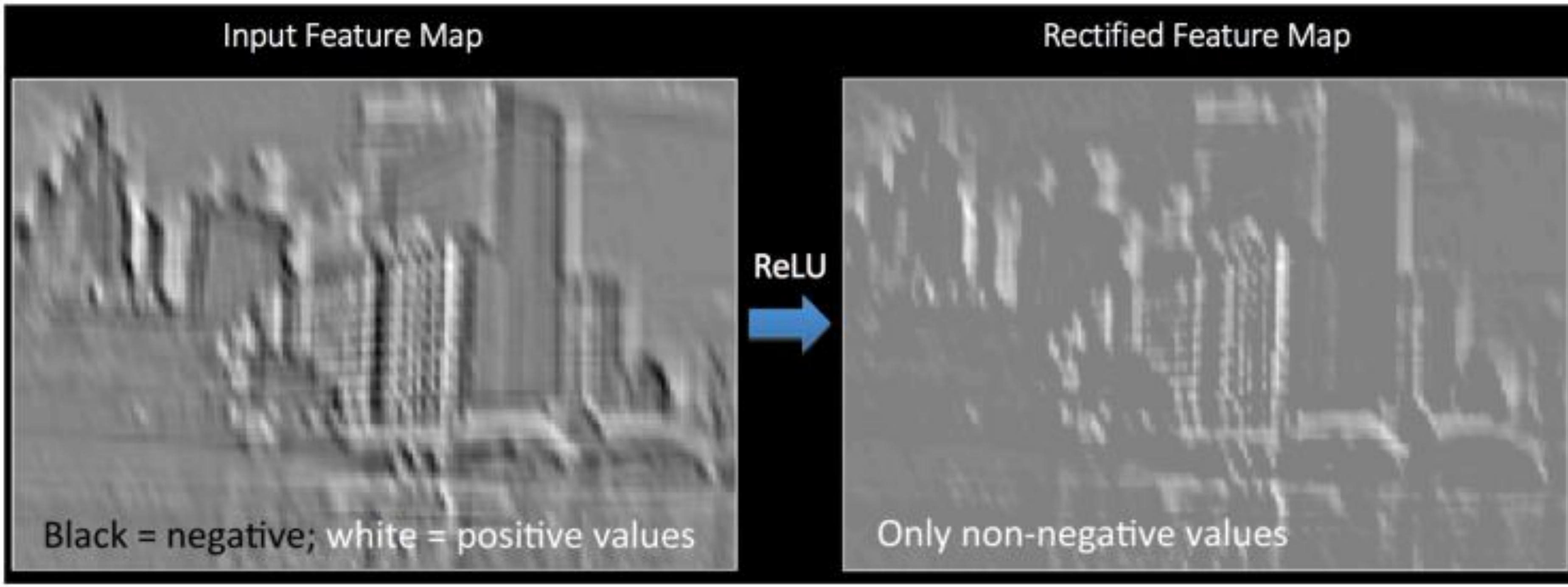


[source] https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

[source]

3. CNN

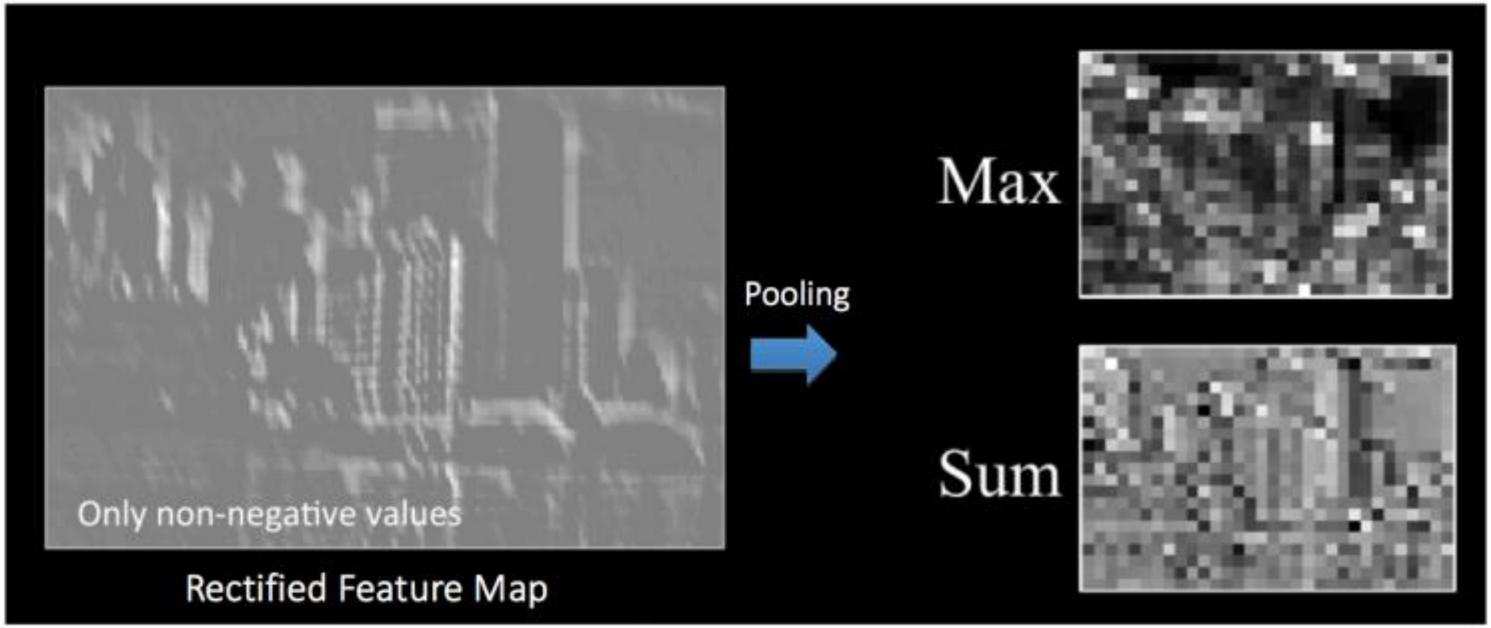
- Feature Map > ReLU effect



[source] https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

3. CNN

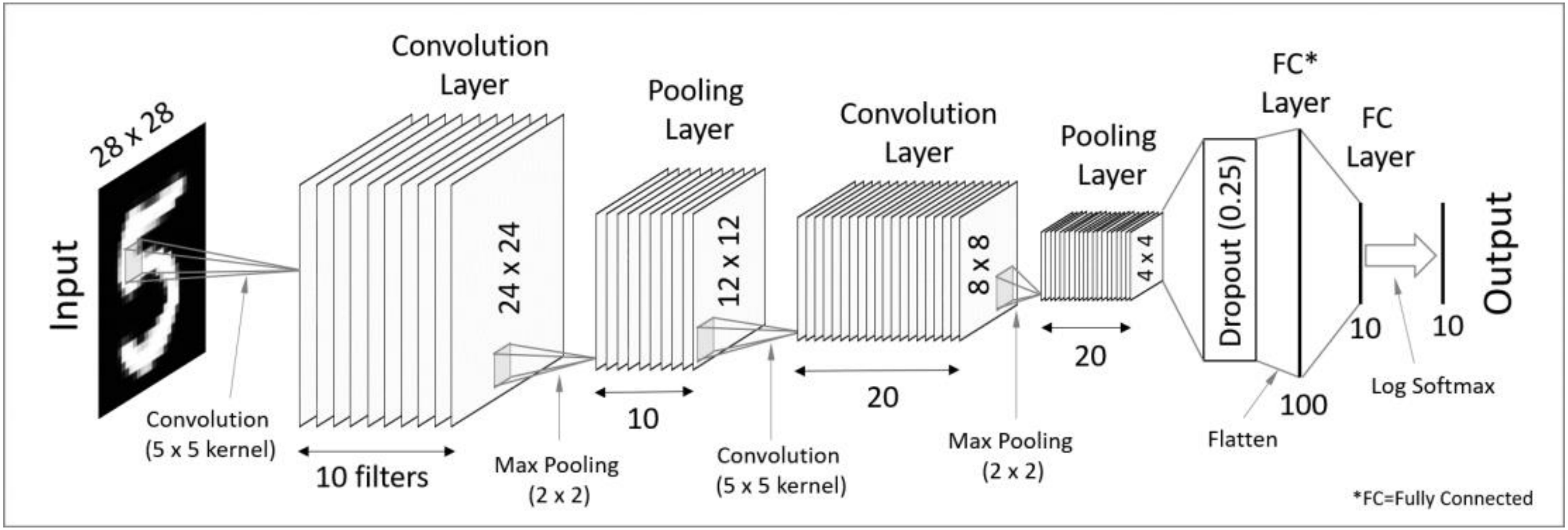
- Feature Map > ReLU effect > Max Pooling



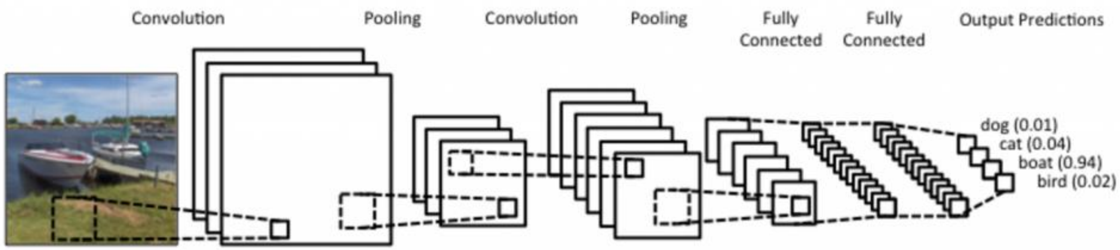
[source] https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

3. CNN

- Convolution



[source] https://codetolight.wordpress.com/2017/11/29/getting-started-with-pytorch-for-deep-learning-part-3-neural-network-basics/



source : http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

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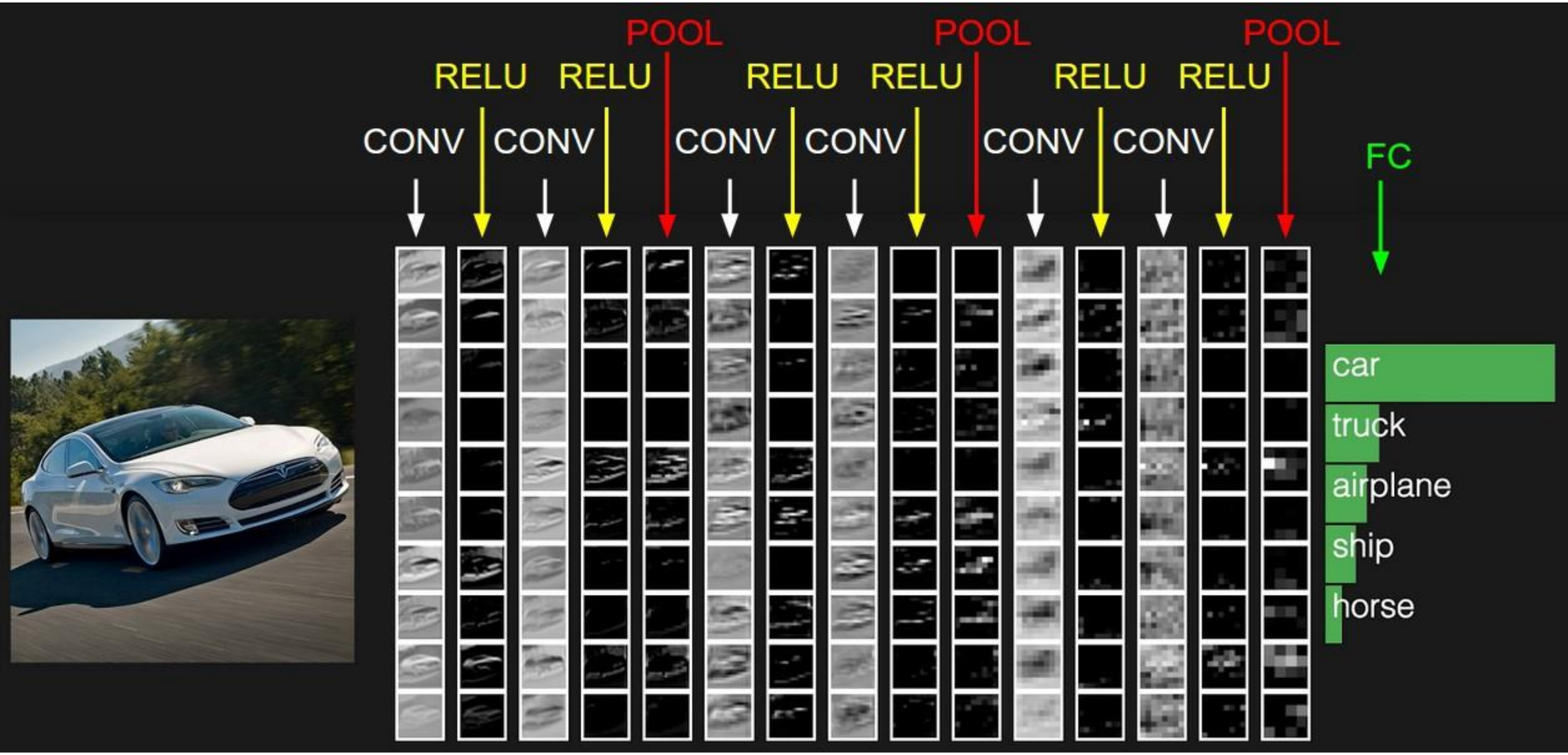
Table Manager

3. CNN

- 특징 추출의 과정
- [Convolution → ReLU → Max Pooling] 의 반복 수행



[source] https://medium.com/@udemeudofia01/basic-overview-of-convolutional-neural-network-cnn-4fcc7dbb4f17

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3. CNN

- Applying Convolutional Neural Network

[source] https://medium.com/@ismailou.sa/convolutional-neural-networks-and-their-application-in-self-driving-cars-33fa0a1625c8

Table Manager

3. CNN

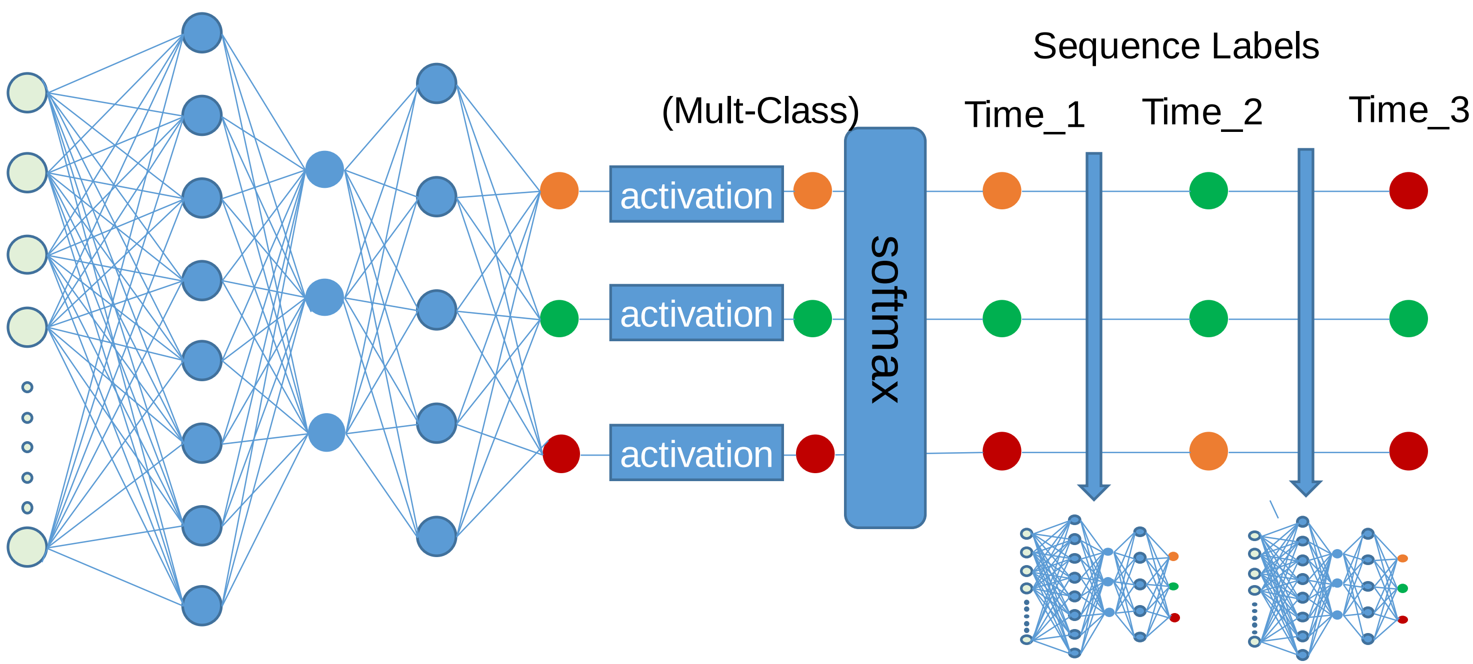
- Program Code

```python
#!/usr/bin/env /c/Apps/Anaconda3/python

# Import
import tensorflow as tf
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# Import data
data = pd.read_csv('./data_stocks.csv')

# Drop date variable
data = data.drop(['DATE'], 1)

# Dimensions of dataset
n = data.shape[0]
p = data.shape[1]

# Make data a np.array
data = data.values

# Training and test data
train_start = 0
train_end = int(np.floor(0.8*n))
test_start = train_end + 1
test_end = n
data_train = data[np.arange(train_start, train_end), :]
data_test = data[np.arange(test_start, test_end), :]

# Scale data
scaler = MinMaxScaler(feature_range=(-1, 1))
scaler.fit(data_train)
data_train = scaler.transform(data_train)
data_test = scaler.transform(data_test)

# Build X and y
X_train = data_train[:, 1:]
y_train = data_train[:, 0]
X_test = data_test[:, 1:]
y_test = data_test[:, 0]

# Number of stocks in training data
n_stocks = X_train.shape[1]

# Neurons
n_neurons_1 = 1024
n_neurons_2 = 512
n_neurons_3 = 256
n_neurons_4 = 128

# Session
net = tf.InteractiveSession()

# Placeholder
X = tf.placeholder(dtype=tf.float32, shape=[None, n_stocks])
Y = tf.placeholder(dtype=tf.float32, shape=[None])

weight_initializer = tf.variance_scaling_initializer(mode="fan_avg", distribu
bias_initializer = tf.zeros_initializer()

# Hidden weights
W_hidden_1 = tf.Variable(weight_initializer([n_stocks, n_neurons_1]))
bias_hidden_1 = tf.Variable(bias_initializer([n_neurons_1]))
W_hidden_2 = tf.Variable(weight_initializer([n_neurons_1, n_neurons_2]))
bias_hidden_2 = tf.Variable(bias_initializer([n_neurons_2]))
W_hidden_3 = tf.Variable(weight_initializer([n_neurons_2, n_neurons_3]))
bias_hidden_3 = tf.Variable(bias_initializer([n_neurons_3]))
W_hidden_4 = tf.Variable(weight_initializer([n_neurons_3, n_neurons_4]))
bias_hidden_4 = tf.Variable(bias_initializer([n_neurons_4]))

# Output weights
W_out = tf.Variable(weight_initializer([n_neurons_4, 1]))
bias_out = tf.Variable(bias_initializer([1]))

# Hidden layer
hidden_1 = tf.nn.relu(tf.add(tf.matmul(X, W_hidden_1), bias_hidden_1))
hidden_2 = tf.nn.relu(tf.add(tf.matmul(hidden_1, W_hidden_2), bias_hidden_2))
```

실습 중 배포

4. RNN/LSTM

- 문제의 제기
  - Requirement : 실세계에서는 단일예측값을 확장한 연속된 예측값의 필요
  - 실세계에서의 연속 예측값 예시
    - 1주일간의 날씨 예측
    - 시간별 주가 예측



결과값을 입력에 반영하는
재귀적 신경망 학습 필요

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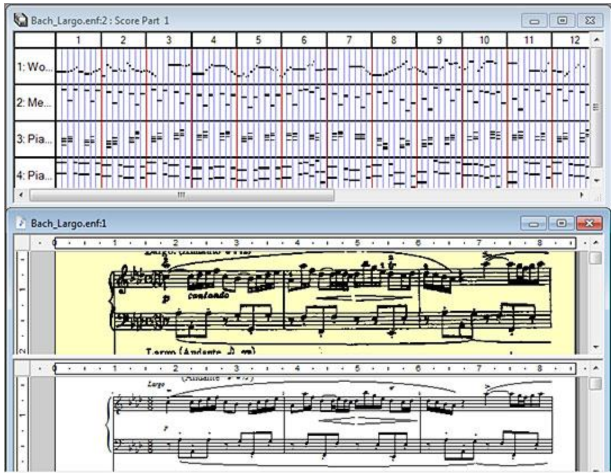
Table Manager

4. RNN/LSTM

- Recurrent Neural Network(David Rumelhart, 1986)
  - Learning Sequence Data
  - Sequence Data
    - 수평 또는 수직으로 연속적으로 tensor 의 확장
  - 유형
    - Time Series : Price, Temperature, RPM
    - Streaming : Music, Voice
    - Order : 문장



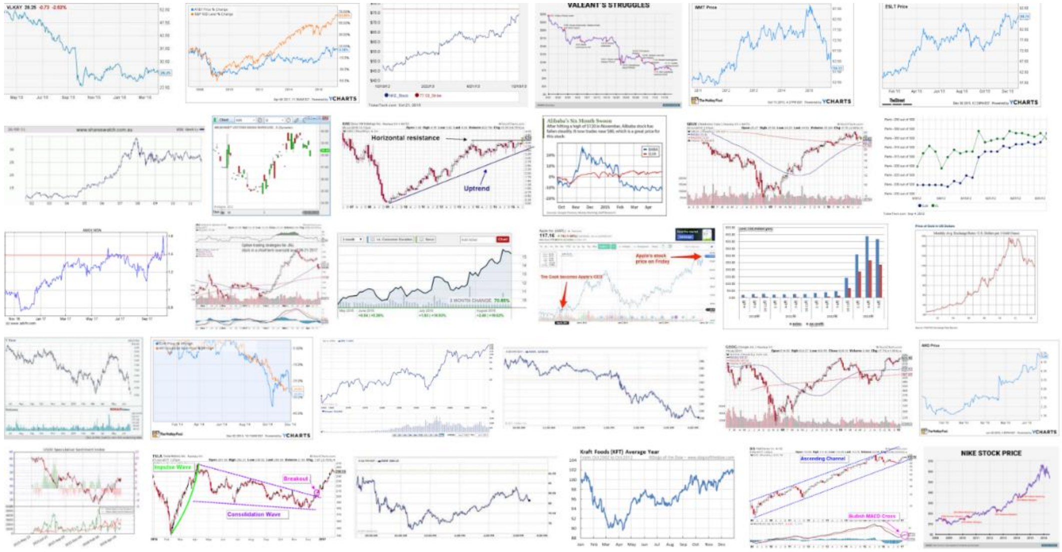


Table Manager

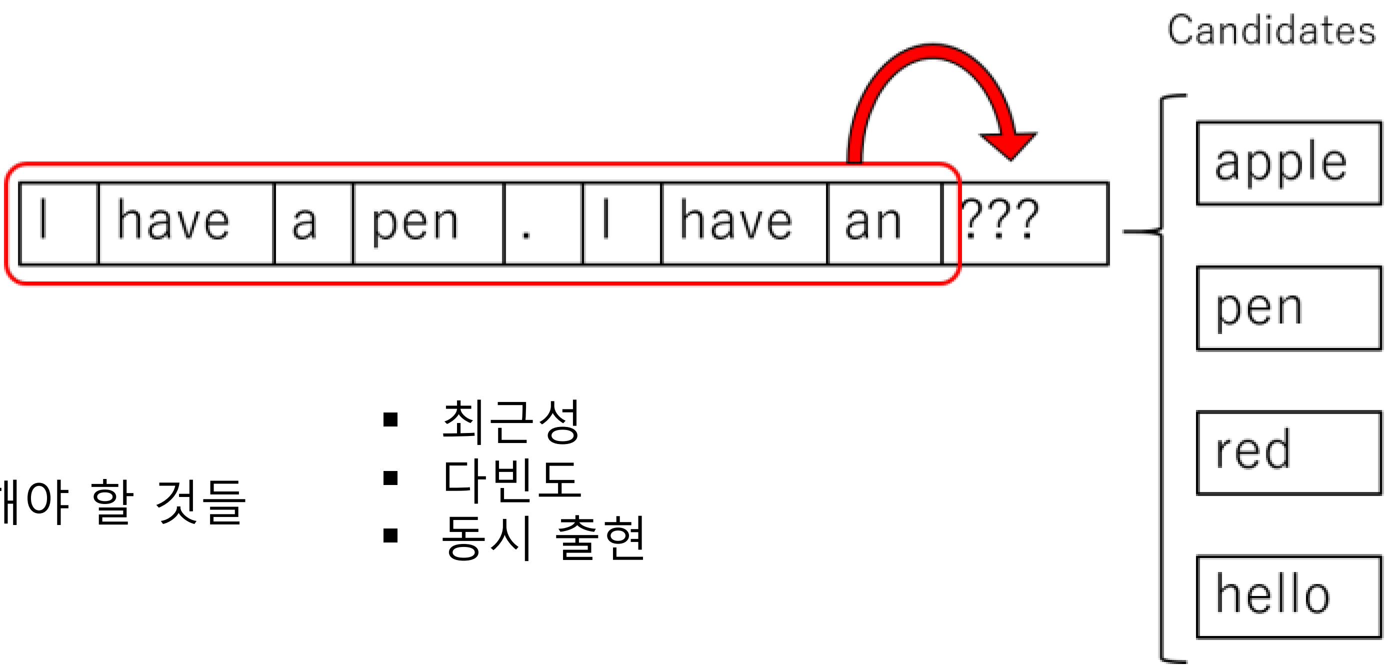
4. RNN/LSTM

- Sequence Data에 있어서의 예측 = Next Sequence

Sequence Type	Features	Label	Label 수
Time Series	1 2 3 4 5 4 5 6 7 8 7 8 9 10 9 10 11	12	Single
Time Series	1 2 3 4 5 4 5 6 7 8 7 8 9 10 9 10 11	12 13	Multi
문장	곰 세마리가 한 집에 있어 아빠곰 엄마곰	애기곰	Single
문장	주가 하락...(중략)...경제 부양 필요	불황	Single
음악	미 레 도 레 미 미	미	Single
음악	미레 도레 미 미 미	레레레	Multi

4. RNN/LSTM

- RNN – Natural Language



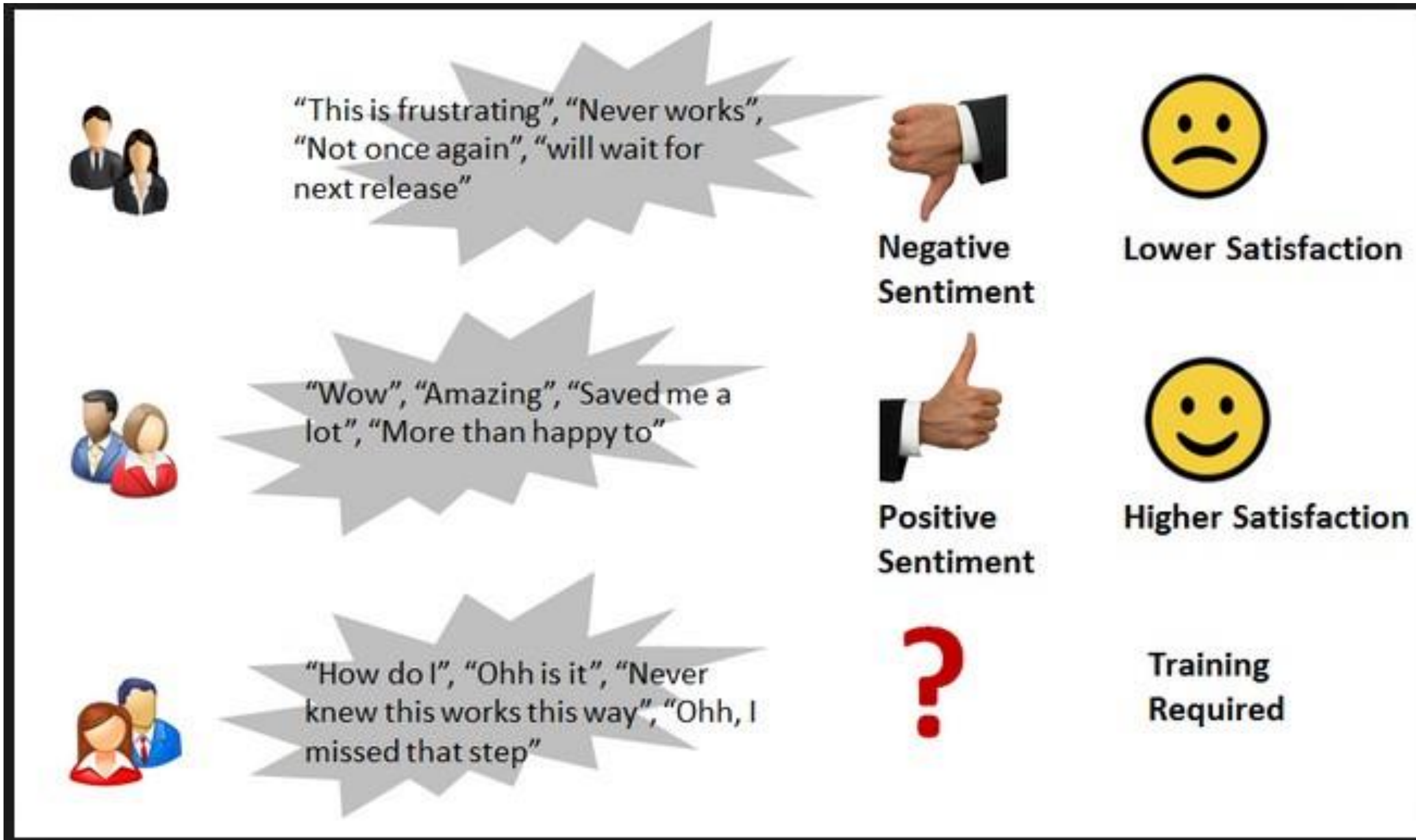
가중치를 부여해야 할 것들

- 최근성
- 다빈도
- 동시 출현

source : http://corochann.com/recurrent-neural-network-rnn-introduction-1286.html

4. RNN/LSTM

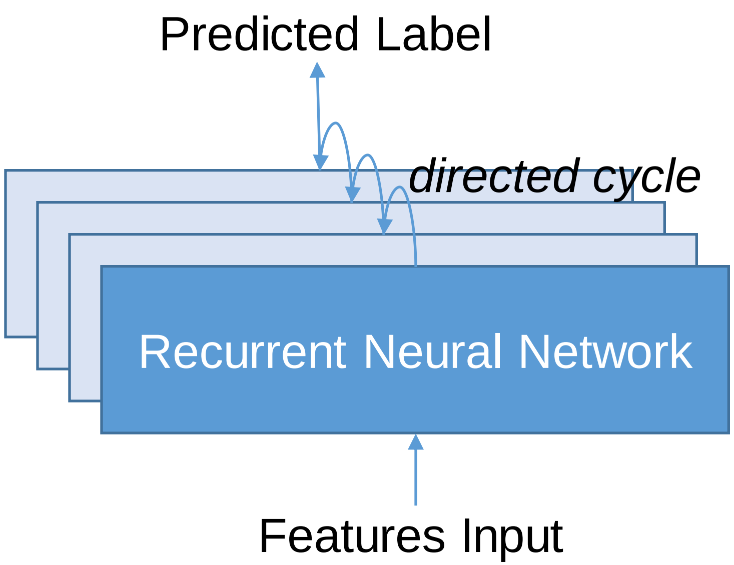
- RNN > 감성 식별



[source] https://datasciencecmu.wordpress.com/2014/04/18/future-of-sentiment-analysis-and-problems-faced/

4. RNN/LSTM

- Recurrent
  - Sequence Data에 있어서의 예측 = Next Sequence



h_t : t시점의 $hidden\ state$

h_{t-1} : $t-1$ 시점의 $hidden\ state$

$Features_{t-1}$: t시점의 $hidden\ state$

$$h_t = f(h_{t-1}, Features_t)$$

$$h_t = tanH(W_{hh}h_{t-1} + W_{Featuresh}Features_t)$$

W_{hh} : $recurrent\ neurons\ Weight$

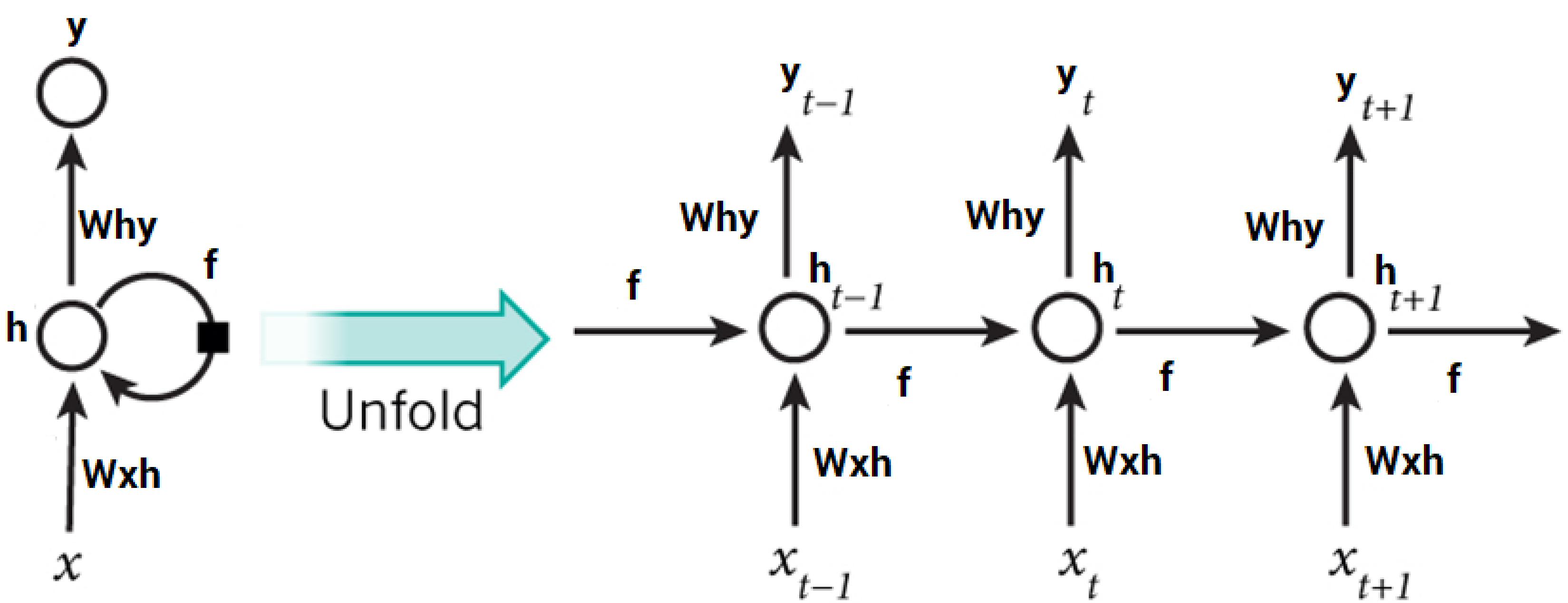
$W_{Features*h}$: $Features$에 대입되는 $Weight$

$$Label_t = W_{h*Label} * h_t$$

Table Manager

4. RNN/LSTM

- Recurrent
  - Forward Propagation in a Recurrent Neuron
    - soruce : https://www.analyticsvidhya.com/blog/2017/12/introduction-to-recurrent-neural-networks/



[soruce] https://www.analyticsvidhya.com/blog/2017/12/introduction-to-recurrent-neural-networks/

Table Manager

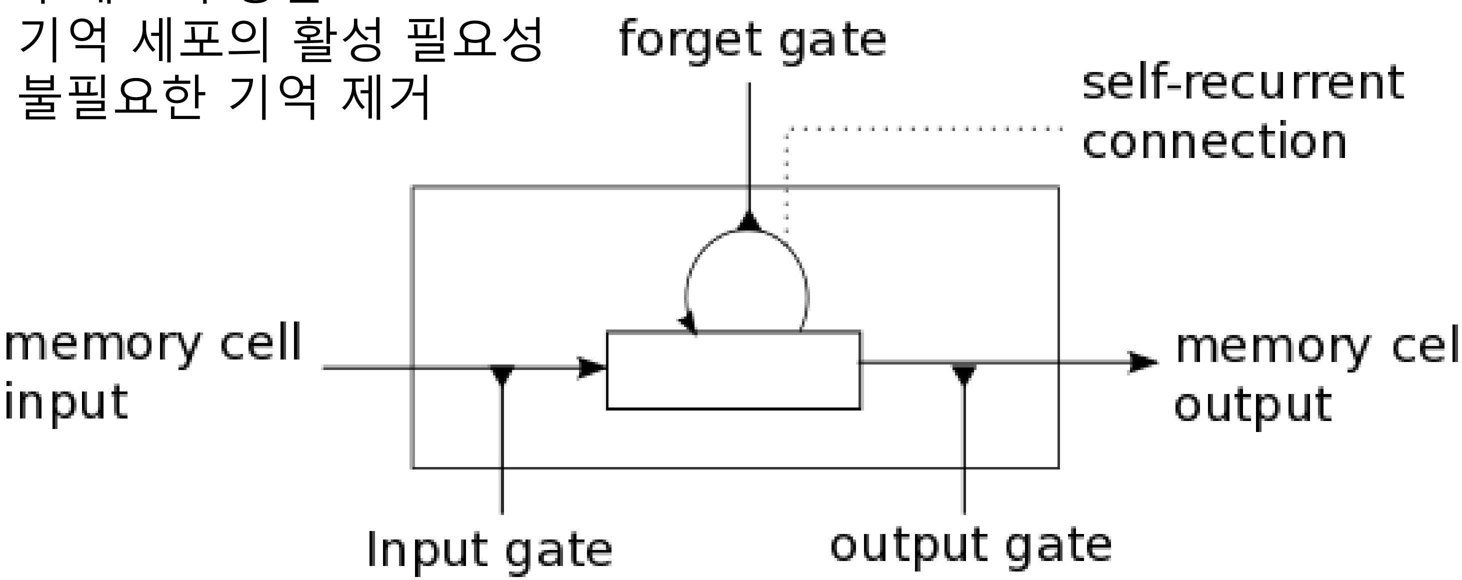
4. RNN/LSTM

- RNN의 구조

Point : 현재의 상태에 영향을 줄법한 과거 찾기

기억 세포의 양날

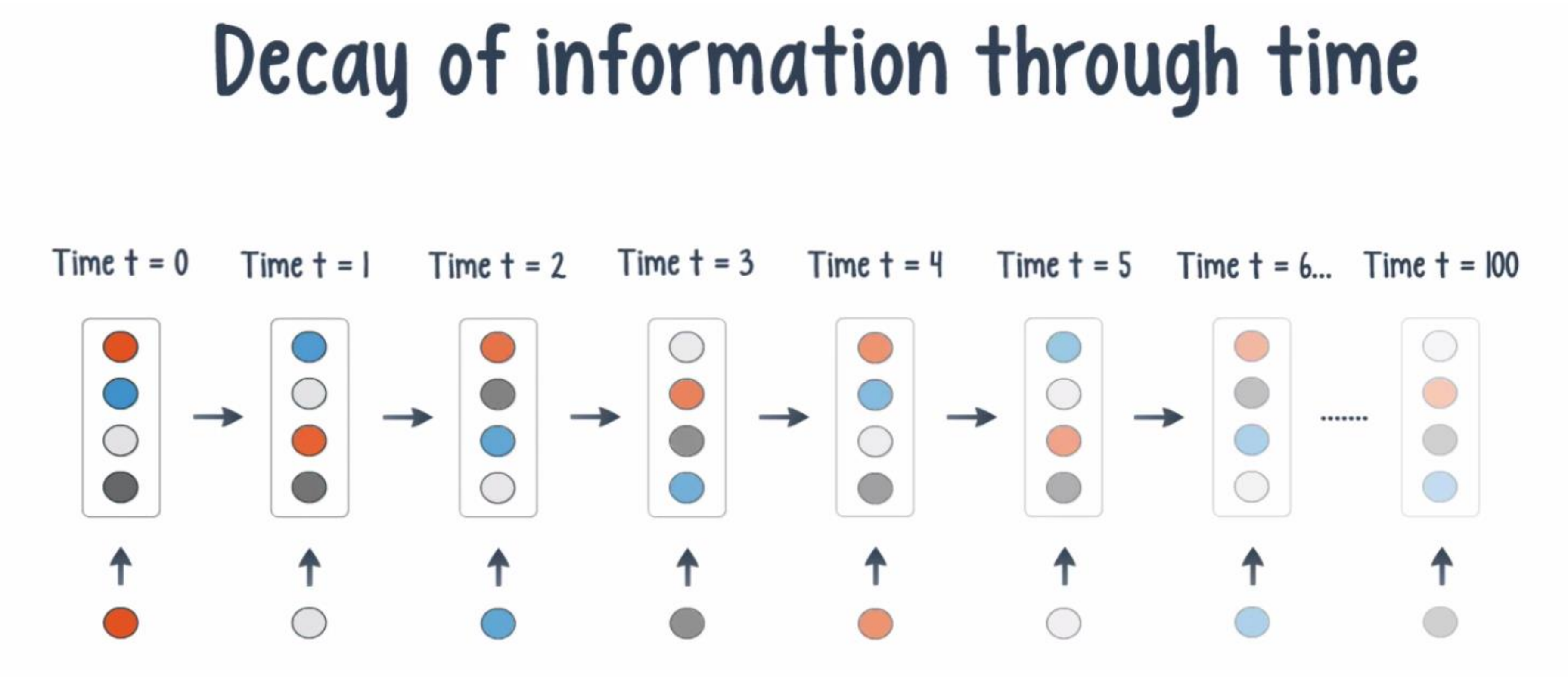
- 기억 세포의 활성 필요성
- 불필요한 기억 제거



기억해야 할만한 것들...

4. RNN/LSTM

- RNN의 문제점



[source] : https://towardsdatascience.com/using-rnns-for-machine-translation-11ddded78ddf

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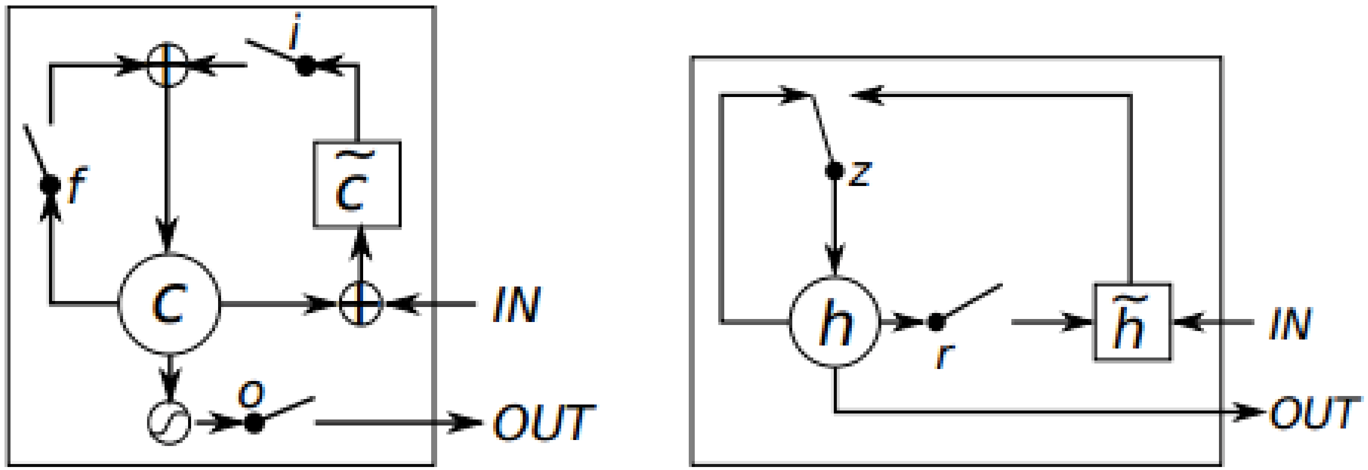
4. RNN/LSTM

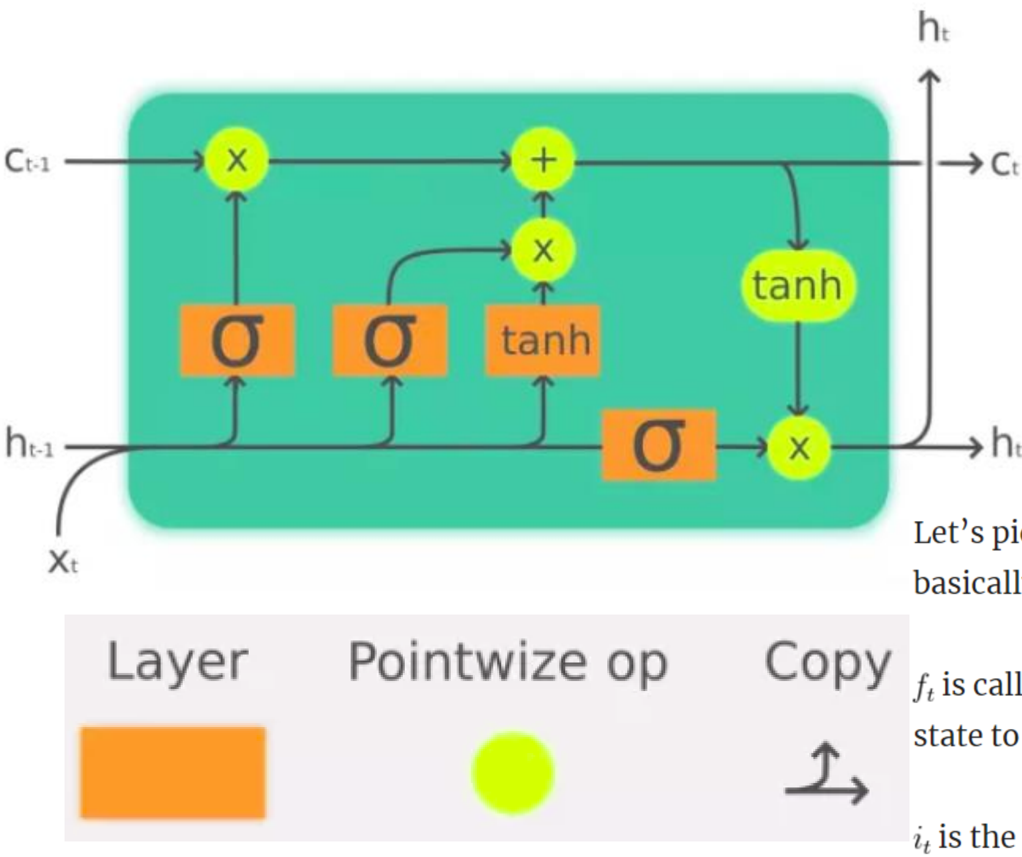
- Solution of RNN with Vanishing and Exploding Gradient Problem
  - LSTM : Long Short-Term Memory
  - GRU : Gated Recurrent Unit



(a) Long Short-Term Memory (b) Gated Recurrent Unit

4. RNN/LSTM

- Solution of RNN with Vanishing and Exploding Gradient Problem
  - LSTM : Long Short-Term Memory



$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{(t-1)} + b_{hi})$$
$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{(t-1)} + b_{hf})$$
$$g_t = \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{(t-1)} + b_{hg})$$
$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{(t-1)} + b_{ho})$$
$$c_t = f_t * c_{(t-1)} + i_t * g_t$$
$$h_t = o_t * \tanh(c_t)$$

Let's pick this equation apart: c_t is the new cell state, which is basically the memory of the LSTM.

f_t is called the "forget gate": it dictates how much of the previous cell state to **retain** (but is slightly confusingly named the forget gate).

i_t is the "input gate" and dictates how much to update the cell state with new information.

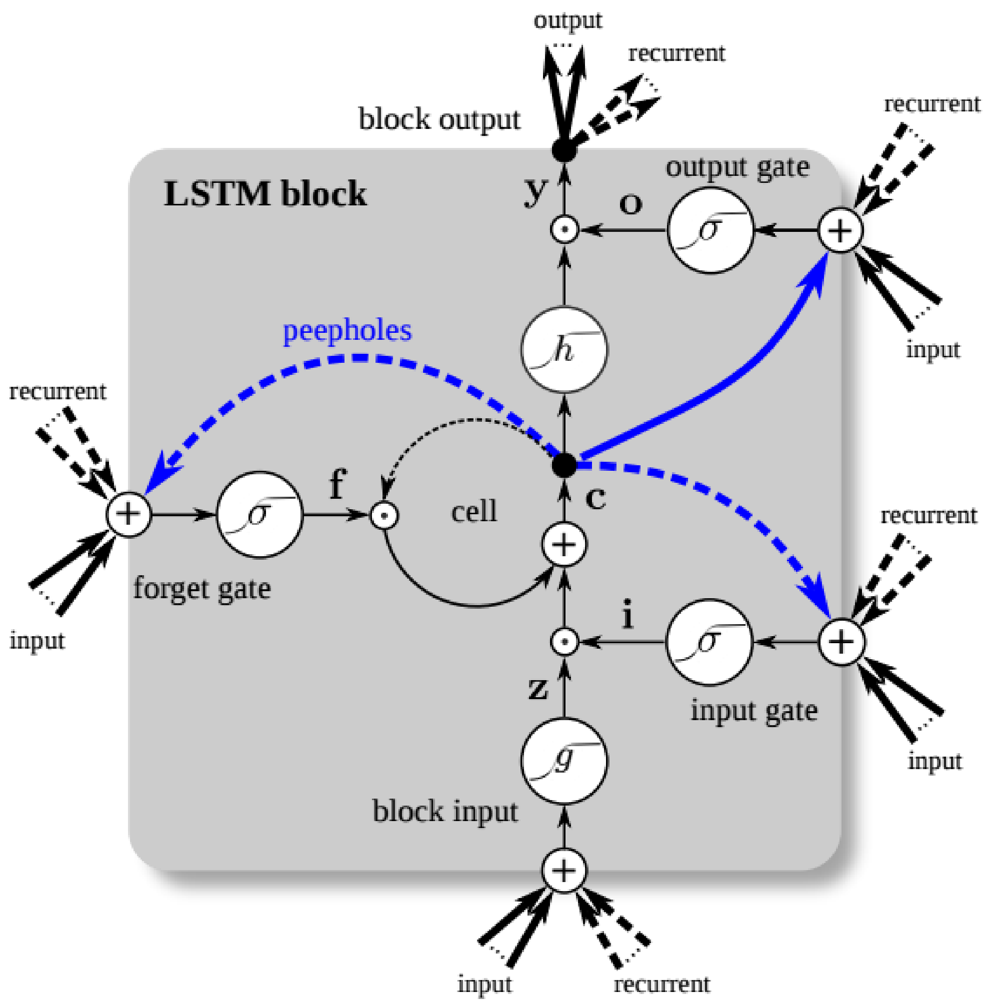
Finally, g_t is the information we use to update the cell state.

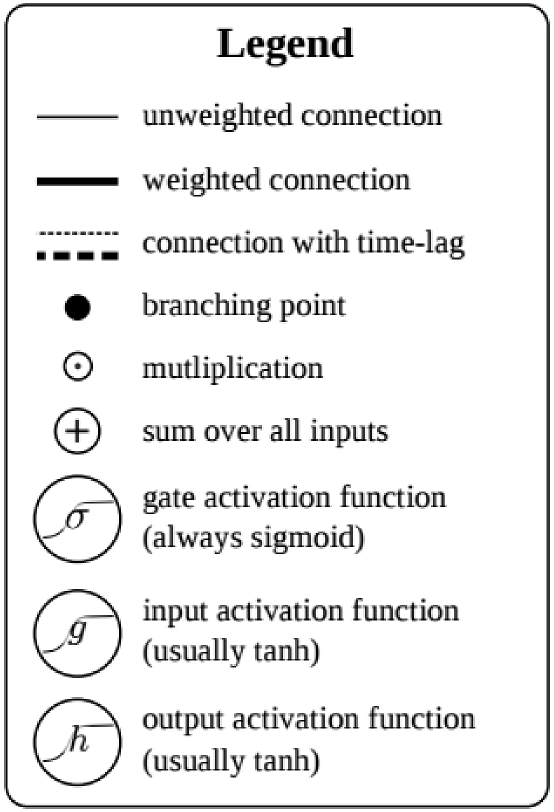
[source] http://mlexplained.com/2019/02/15/building-an-lstm-from-scratch-in-pytorch-lstms-in-depth-part-1/

4. RNN/LSTM

- LSTM의 구조

[source] https://developer.nvidia.com/discover/lstm





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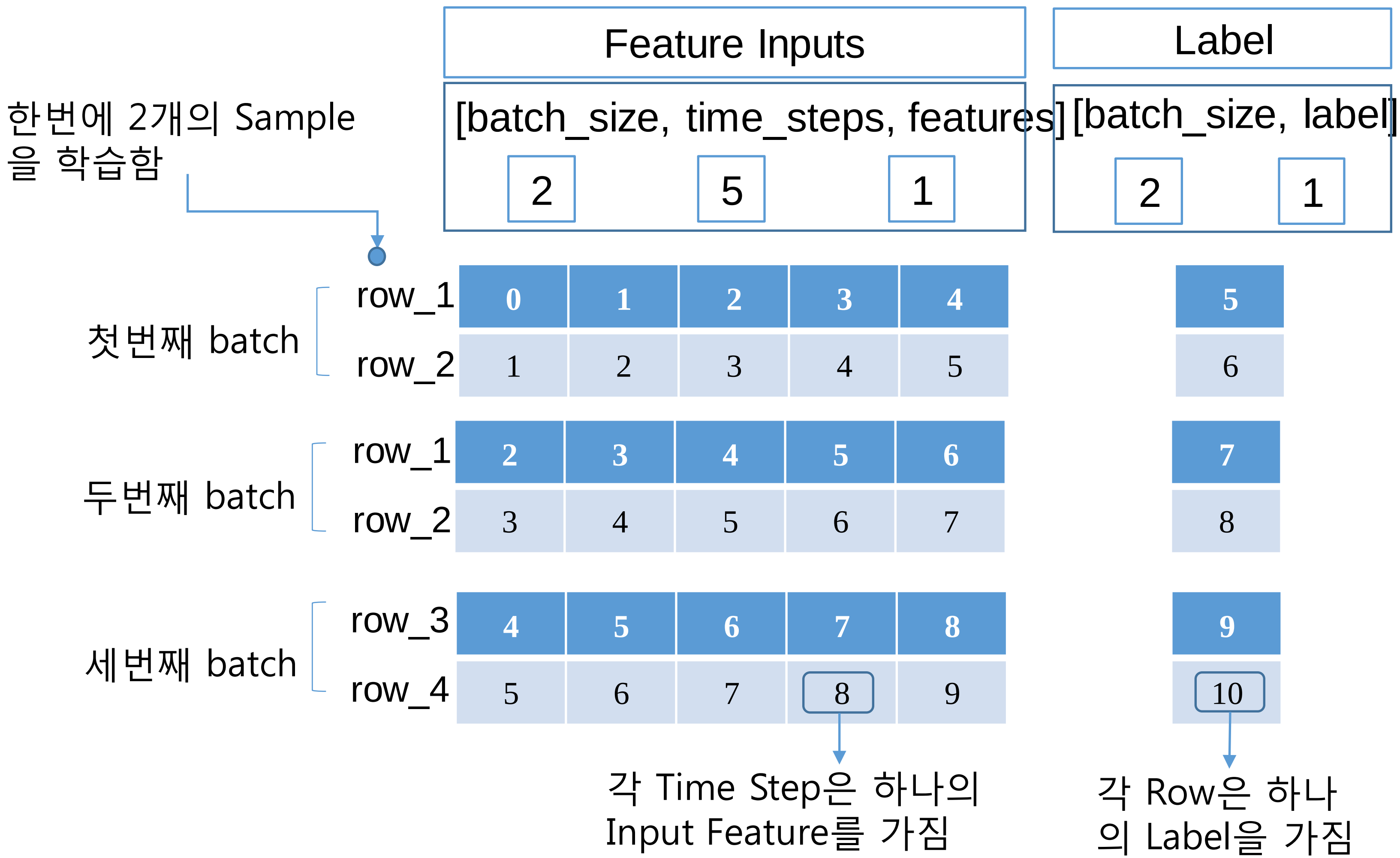
4. RNN/LSTM

- LSTM : Long Short-Term Memory



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4. RNN/LSTM

- LSTM : Long Short-Term Memory

Feature Inputs			Label	
[batch_size,	time_steps,	features]	[batch_size,	label]
2	5	2	2	1

한번에 2개의 Sample 을 학습함

							Label
첫번째 batch	row_1	[0,0]	[1,10]	[2,20]	[3,30]	[4,40]	55
	row_2	[1,10]	[2,20]	[3,30]	[4,40]	[5.50]	66
두번째 batch	row_1	[2,20]	[3,30]	[4,40]	[5,50]	[6,60]	77
	row_2	[3,30]	[4,40]	[5,50]	[6,60]	[7,70]	88
세번째 batch	row_3	[4,40]	[5,50]	[6,60]	[7,70]	[8,80]	99
	row_4	[5,50]	[6,60]	[7,70]	[8,80]	[9,90]	100

각 Time Step은 하나의 Input Feature를 가짐

각 Row은 하나의 Label을 가짐

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4. RNN/LSTM

- LSTM : Long Short-Term Memory

Feature Inputs			Label	
[batch_size,	time_steps,	features]	[batch_size,	label]
2	5	2	2	2

한번에 2개의 Sample 을 학습함

							Label
첫번째 batch	row_1	[0,0]	[1,10]	[2,20]	[3,30]	[4,40]	[55,66]
	row_2	[1,10]	[2,20]	[3,30]	[4,40]	[5.50]	[66,77]
두번째 batch	row_1	[2,20]	[3,30]	[4,40]	[5,50]	[6,60]	[77,88]
	row_2	[3,30]	[4,40]	[5,50]	[6,60]	[7,70]	[88,99]
세번째 batch	row_3	[4,40]	[5,50]	[6,60]	[7,70]	[8,80]	[99,110]
	row_4	[5,50]	[6,60]	[7,70]	[8,80]	[9,90]	[110,121]

각 Time Step은 두개의 Input Feature를 가짐

각 Row은 하나의 Label을 가짐

4. RNN/LSTM

- LSTM : Long Short-Term Memory
  - Text Detection

Feature Inputs			Label	
[batch_size,	time_steps,	features]	[batch_size,	label]
1	6	5	1	5

	H	I	H	E	L	L	I	H	E	L	L	O
첫번째 batch row_1	[1,0,0,0,0]	[0,1,0,0,0]	[1,0,0,0]	[0,0,1,0]	[0.0,0,1,0]	[0,0,0,1,0]	[0,1,0,0,0]	[1,0,0,0]	[0,0,1,0]	[0.0,0,1,0]	[0,0,0,1,0]	[0,0,0,0,1]

One-Hot Encoding

Encode	Decode
[1,0,0,0,0]	H
[0,1,0,0,0]	I
[0,0,1,0,0]	E
[0,0,0,1,0]	L
[0,0,0,0,1]	O

```
placeholderFeatures = tf.placeholder(
    [None, 6, 5]
)
```

```
placeholderLabel = tf.placehoder(
    [None, 6]
)
```

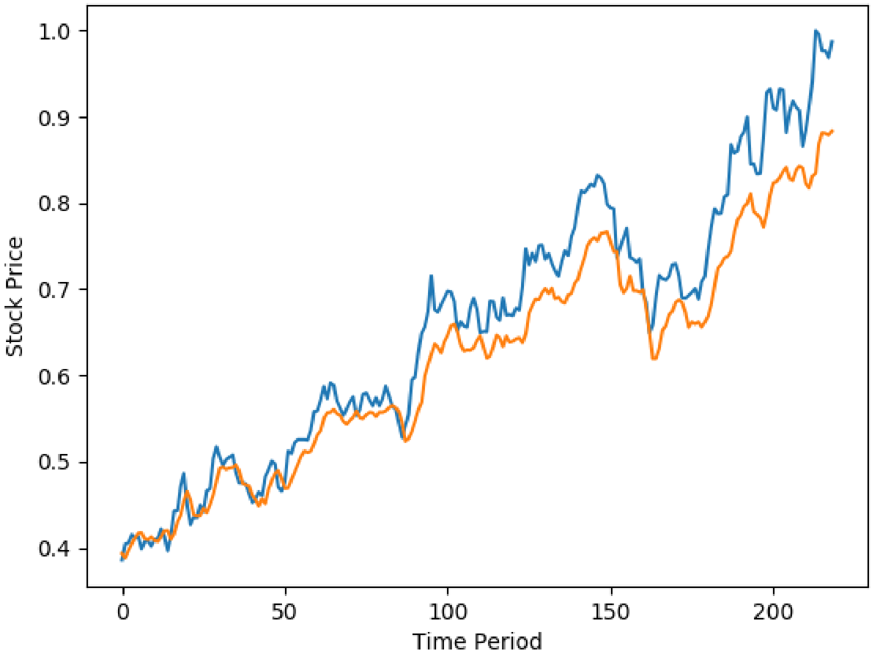
```
predLabel, states_ = tf.contrib.rnn.BasicLSTMCell(num_units = 
)
fcFeatures = tf.reshape(predLabel, [-1, hidden_size])
predLabel = tf.reshape(inputs=fcFeatures, num_outputs=5)
```

Table Manager

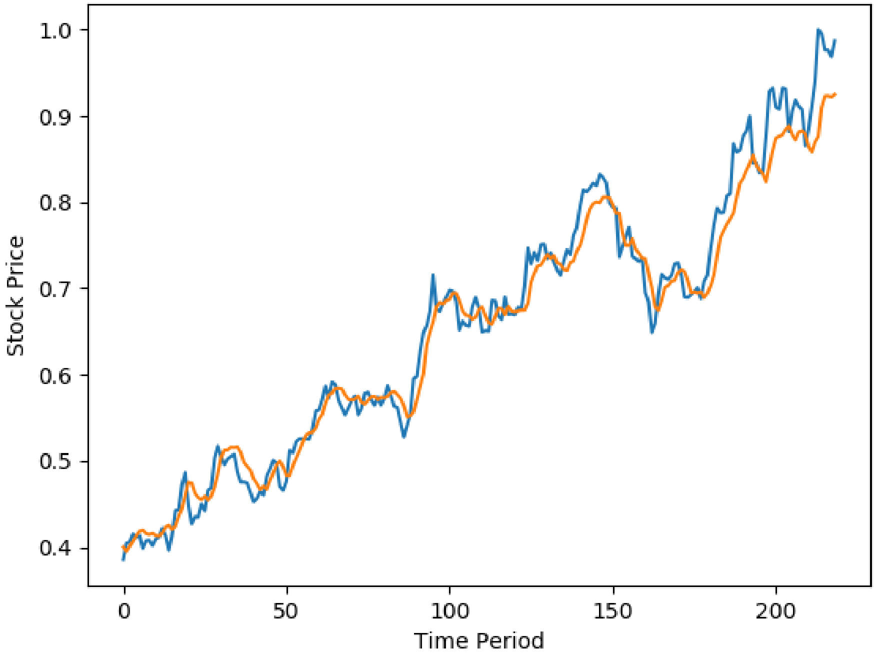
4. RNN/LSTM

- LSTM > 주가 예측

주가 = f(시가, 고가, 저가, 종가, 거래량)



주가 = f(시가, 고가, 저가, 종가, 거래량, **환율**)



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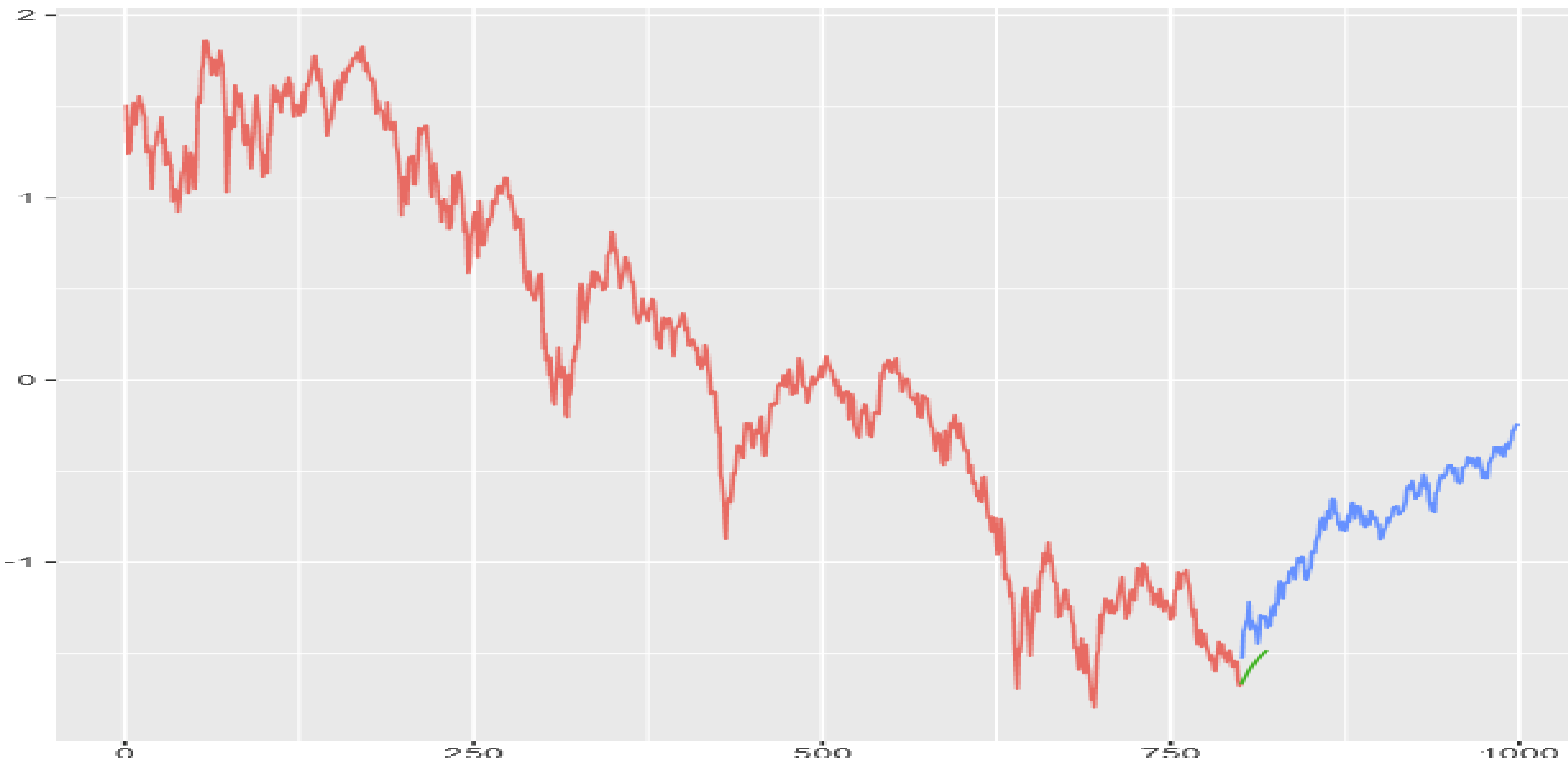
4. RNN/LSTM

- LSTM > 주가 예측



4. RNN/LSTM

- xxx

```
#!/usr/bin/env /c/Apps/Anaconda3/python

# Import
import tensorflow as tf
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# Import data
data = pd.read_csv('./data_stocks.csv')

# Drop date variable
data = data.drop(['DATE'], 1)

# Dimensions of dataset
n = data.shape[0]
p = data.shape[1]

# Make data a np.array
data = data.values

# Training and test data
train_start = 0
train_end = int(np.floor(0.8*n))
test_start = train_end + 1
test_end = n
data_train = data[np.arange(train_start, train_end), :]
data_test = data[np.arange(test_start, test_end), :]

# Scale data
scaler = MinMaxScaler(feature_range=(-1, 1))
scaler.fit(data_train)
data_train = scaler.transform(data_train)
data_test = scaler.transform(data_test)

# Build X and y
X_train = data_train[:, 1:]
y_train = data_train[:, 0]
X_test = data_test[:, 1:]
```

```
y_test = data_test[:, 0]

# Number of stocks in training data
n_stocks = X_train.shape[1]

# Neurons
n_neurons_1 = 1024
n_neurons_2 = 512
n_neurons_3 = 256
n_neurons_4 = 128

# Session
net = tf.InteractiveSession()

# Placeholder
X = tf.placeholder(dtype=tf.float32, shape=[None, n_stocks])
Y = tf.placeholder(dtype=tf.float32, shape=[None])

izer = tf.variance_scaling_initializer(mode="fan_avg", distribu
bias_initializer = tf.zeros_initializer()

# Hidden weights
W_hidden_1 = tf.Variable(weight_initializer([n_stocks, n_neurons_1]))
bias_hidden_1 = tf.Variable(bias_initializer([n_neurons_1]))
W_hidden_2 = tf.Variable(weight_initializer([n_neurons_1, n_neurons_2]))
bias_hidden_2 = tf.Variable(bias_initializer([n_neurons_2]))
W_hidden_3 = tf.Variable(weight_initializer([n_neurons_2, n_neurons_3]))
bias_hidden_3 = tf.Variable(bias_initializer([n_neurons_3]))
W_hidden_4 = tf.Variable(weight_initializer([n_neurons_3, n_neurons_4]))
bias_hidden_4 = tf.Variable(bias_initializer([n_neurons_4]))

# Output weights
W_out = tf.Variable(weight_initializer([n_neurons_4, 1]))
bias_out = tf.Variable(bias_initializer([1]))

# Hidden layer
hidden_1 = tf.nn.relu(tf.add(tf.matmul(X, W_hidden_1), bias_hidden_1))
hidden_2 = tf.nn.relu(tf.add(tf.matmul(hidden_1, W_hidden_2), bias_hidden_2))
```

실습 중 배포

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Table Manager