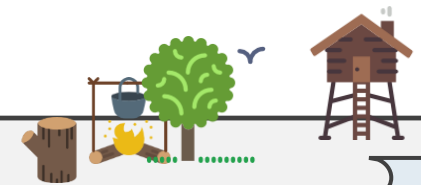
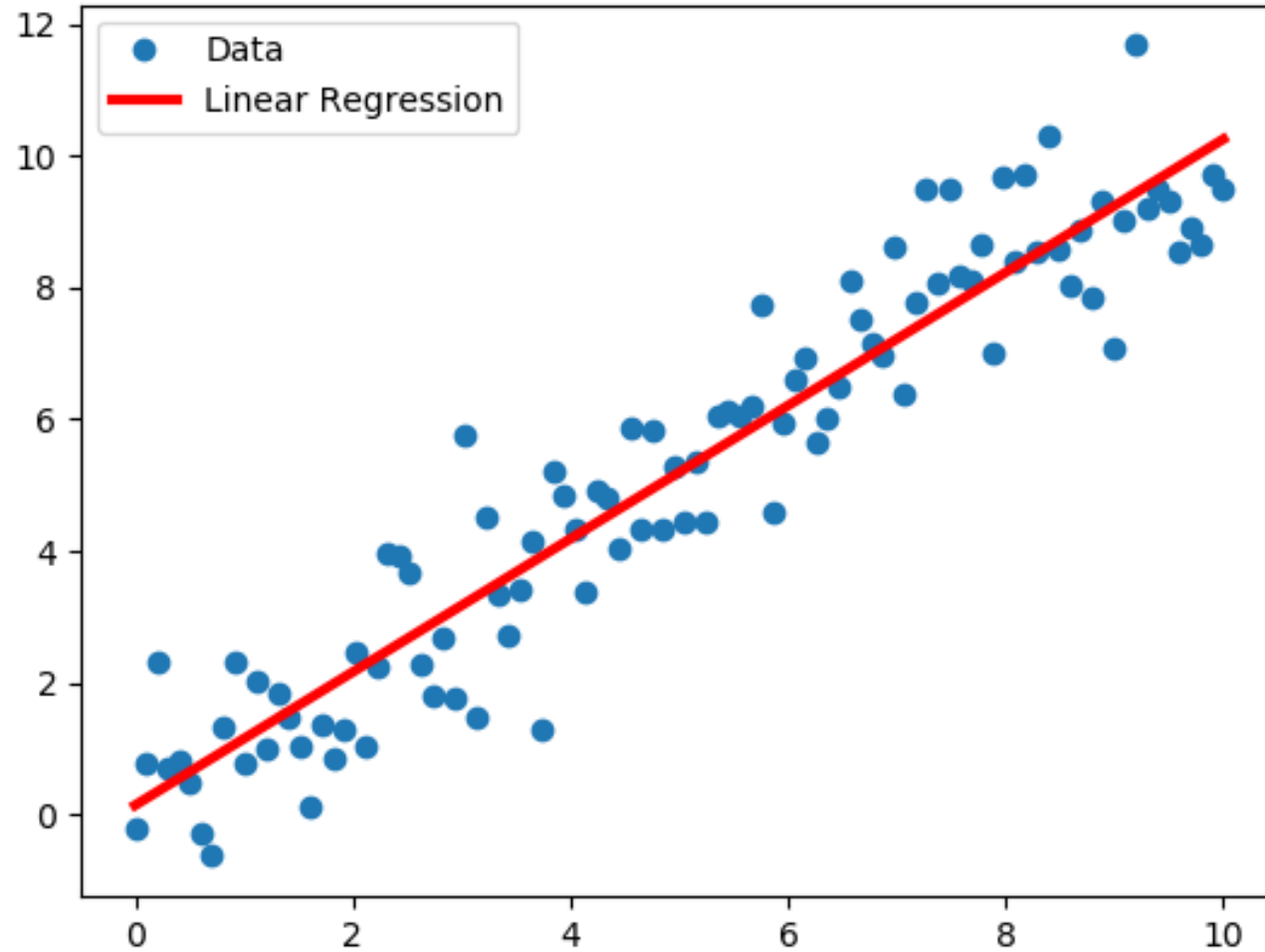


A large, light blue rectangular frame with a thick black border. To the left of the frame, there are three black bird silhouettes in flight. To the right, there are two more black bird silhouettes. At the bottom left of the frame, there is a small green tree with a brown trunk. Below the tree, there are three white, cloud-like shapes. The background is a solid light blue color.

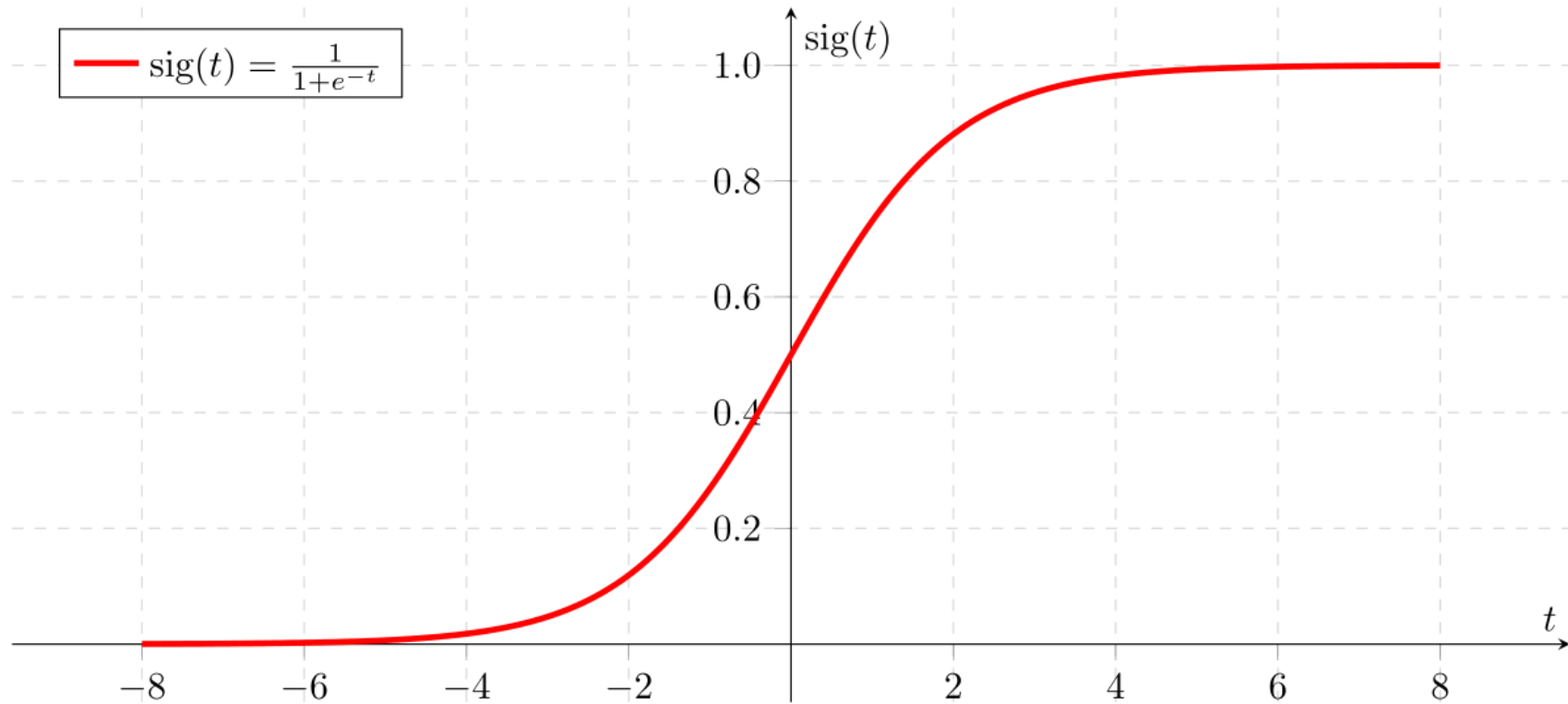
# CS231n Base Lecture

- ☑ BOAZ 10기 박성현
- ☑ BOAZ 11기 김태희
- ☑ BOAZ 11기 홍지민
- ☑ BOAZ 10기 김용규

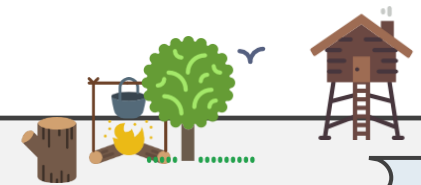
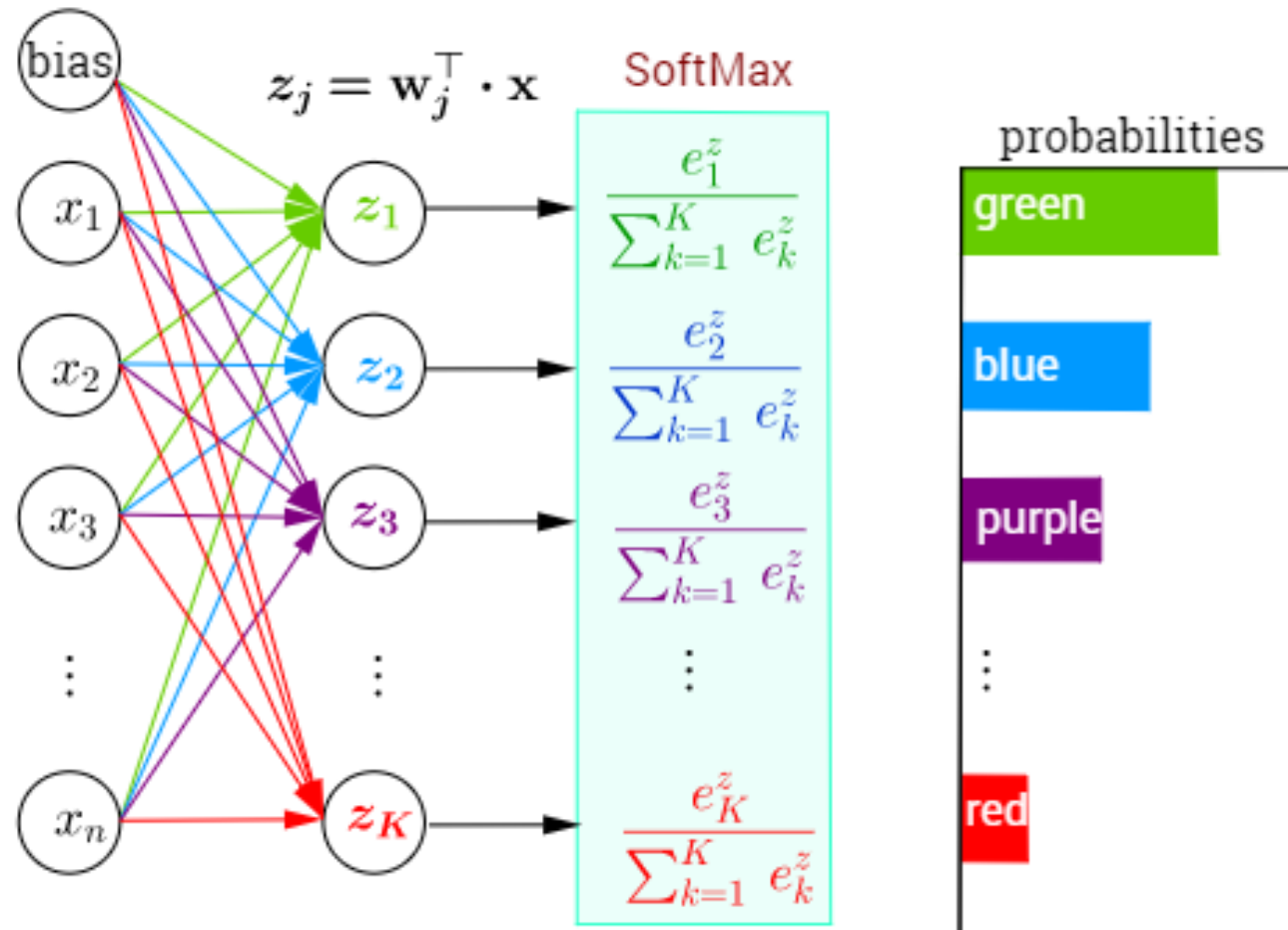
# Linear Regression



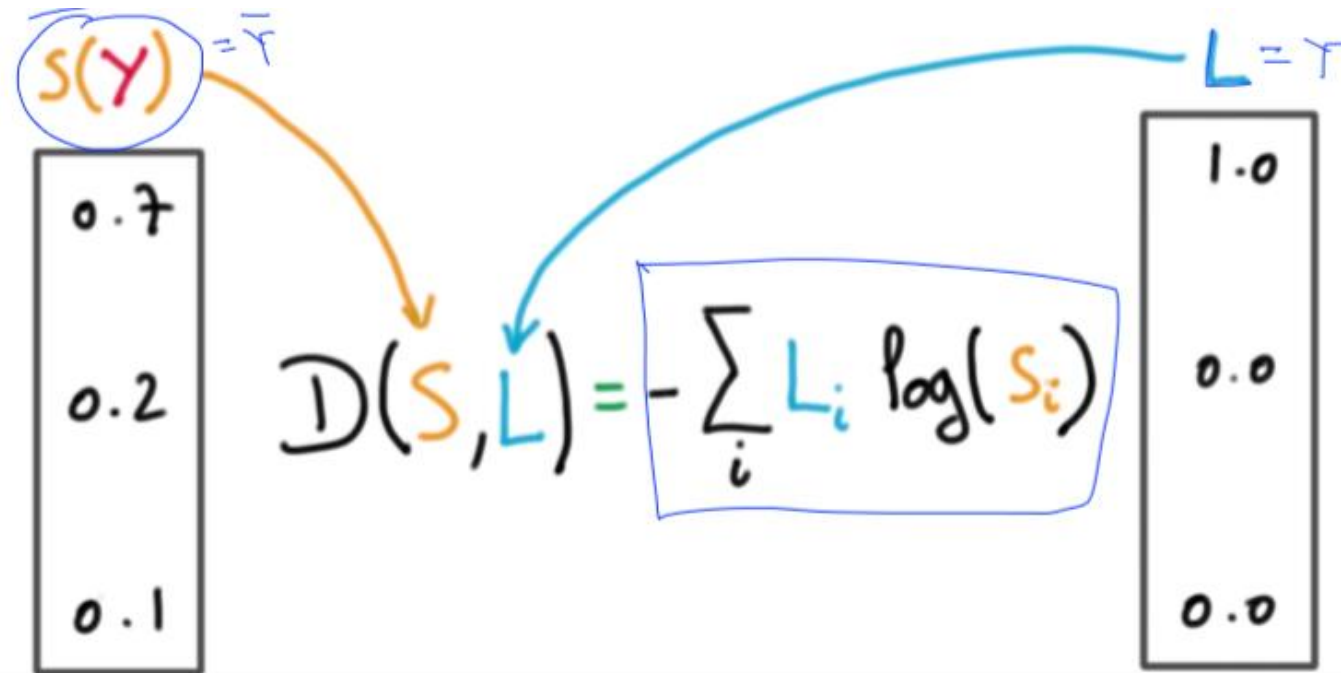
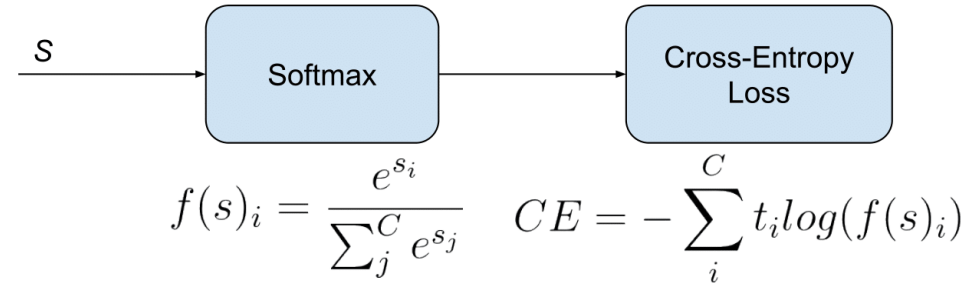
# Logistic Regression



# Softmax & Cross Entropy Loss



# Softmax & Cross Entropy Loss



## Cost function

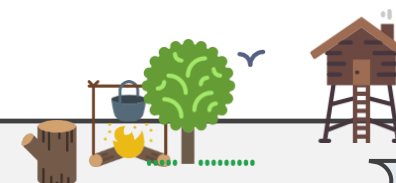
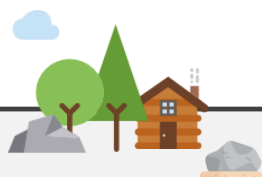
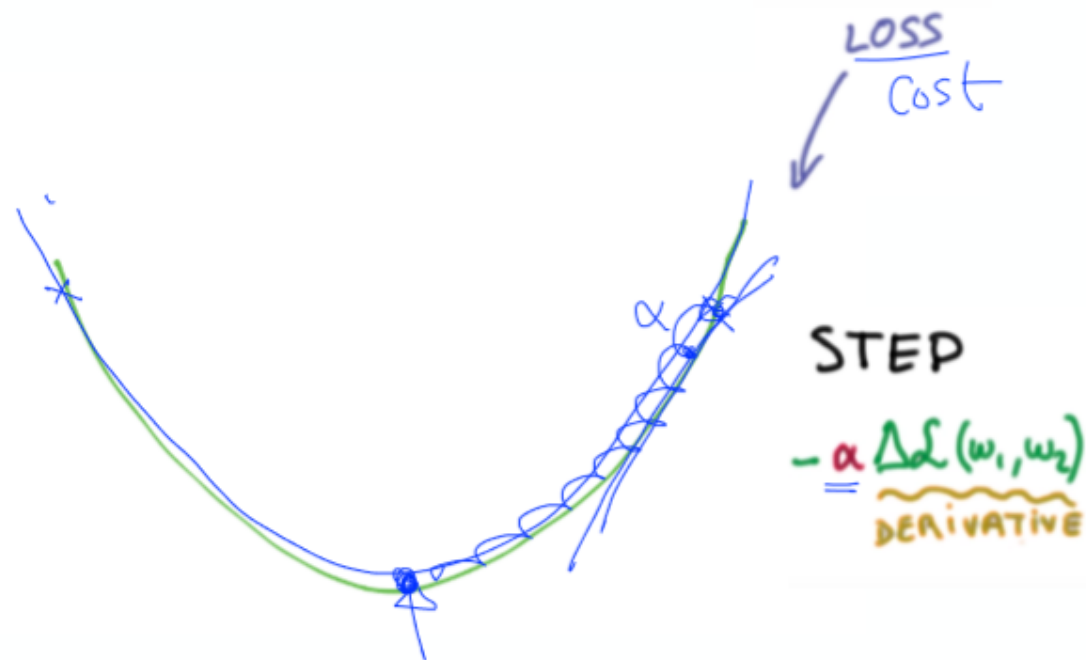
Diagram illustrating the Cost function:

$$\mathcal{L} = \frac{1}{N} \sum_i \mathcal{D}(s(w x_i + b), L_i)$$

Annotations:

- LOSS**: Points to the  $\mathcal{L}$  symbol.
- TRAINING SET**: Points to the  $x_i$  term in the equation.
- $\mathcal{D}$ : Points to the distance function symbol.
- $s$ : Points to the sigmoid function symbol.
- $w x_i + b$ : Points to the linear combination of weights and bias.
- $L_i$ : Points to the target label.

## Gradient descent



Hypothesis:  $h_{\theta}(x) = \theta_0 + \theta_1 x$

Parameters:  $\theta_0, \theta_1$

Cost Function:  $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$

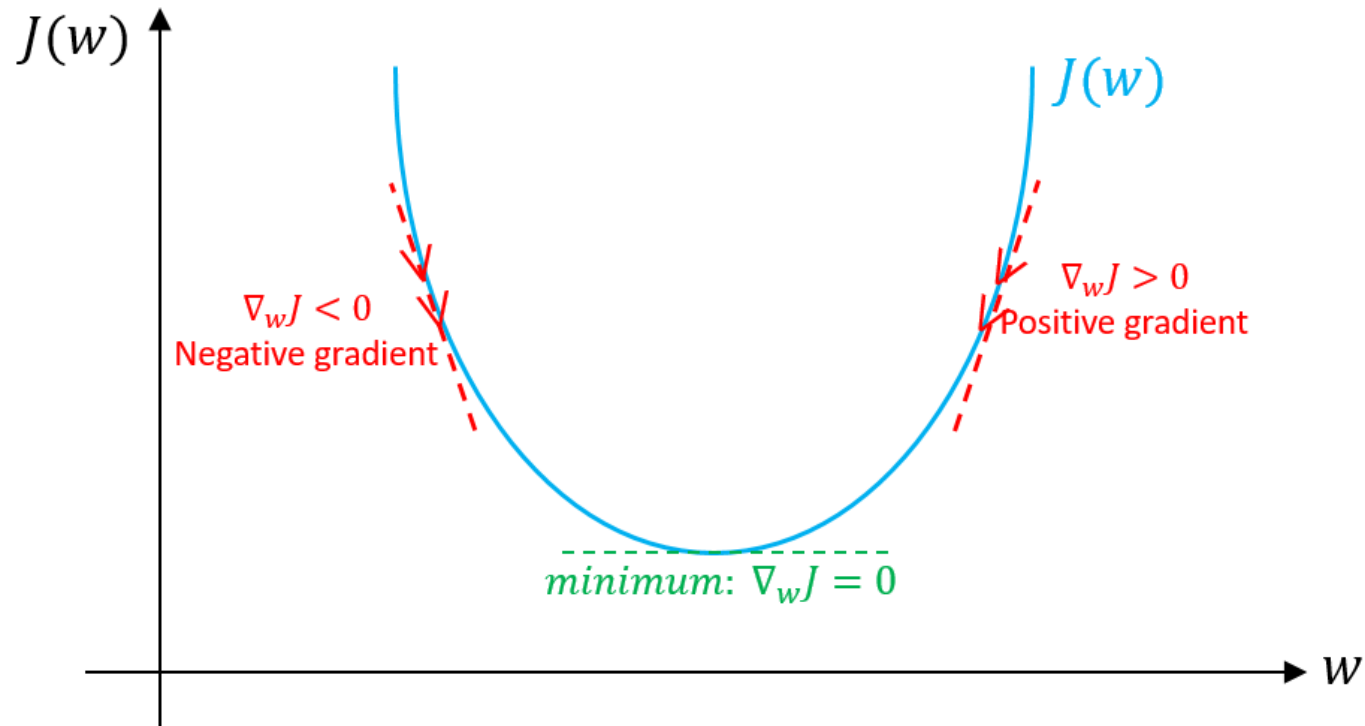
Goal:  $\underset{\theta_0, \theta_1}{\text{minimize}} J(\theta_0, \theta_1)$



Andrew Ng



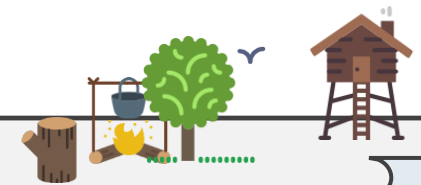
# Gradient Descent



Repeat until convergence {

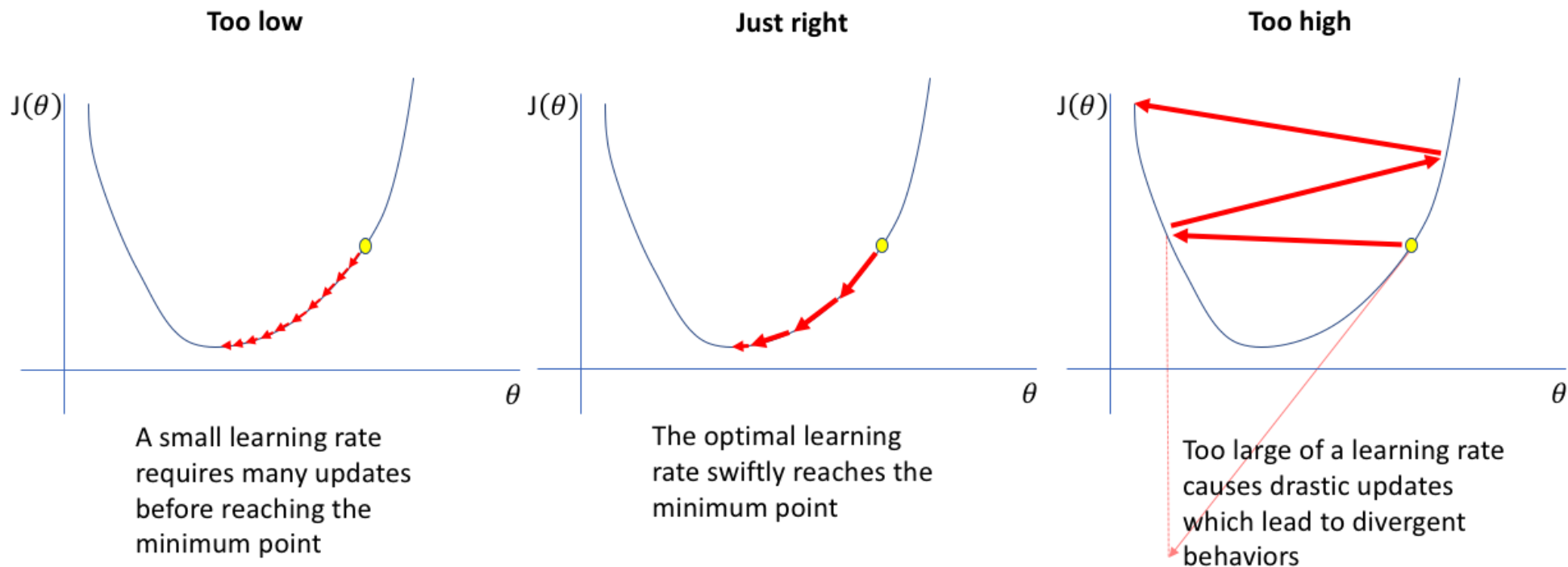
$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}



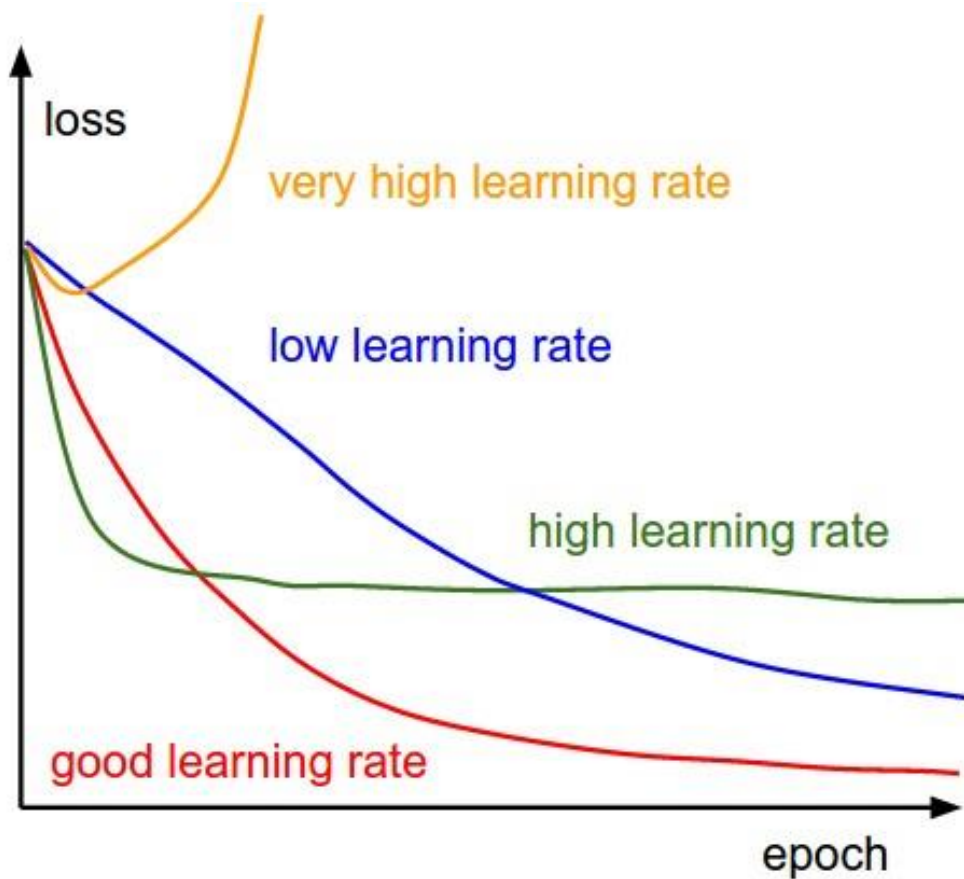


## [Learning rate에 따른 변화]

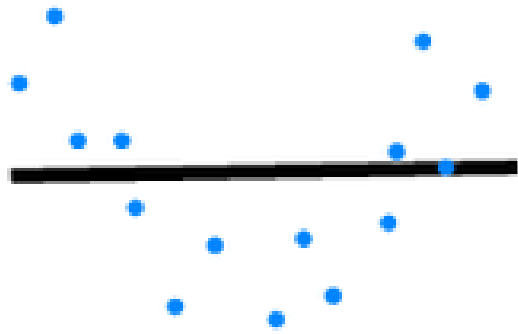


## [Learning rate에 따른 변화]

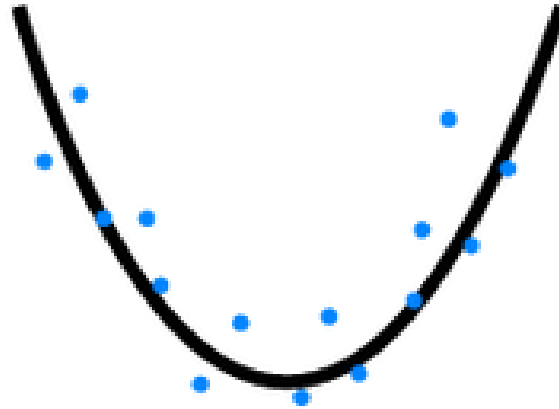
Learning rate와 같은 변수를 Hyperparameter라고 한다.



# Overfitting & Underfitting & Regularization



Underfitting



Desired



Overfitting



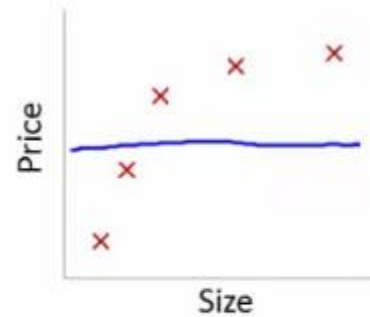
# Overfitting & Underfitting & Regularization

## Linear regression with regularization

$$\text{Model: } h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 + \frac{\lambda}{2m} \sum_{j=1}^m \theta_j^2$$

Regularization



Size

Large  $\lambda$

High bias (underfit)

$\lambda = 10000$ .  $\theta_1 \approx 0, \theta_2 \approx 0, \dots$

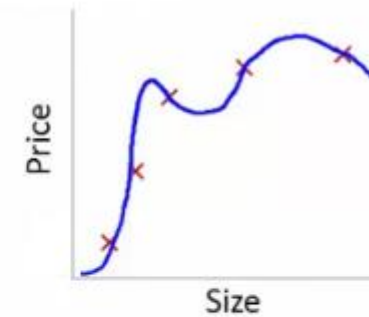
$h_{\theta}(x) \approx \theta_0$



Size

Intermediate  $\lambda$

"Just right"



Size

Small  $\lambda$

High variance (overfit)

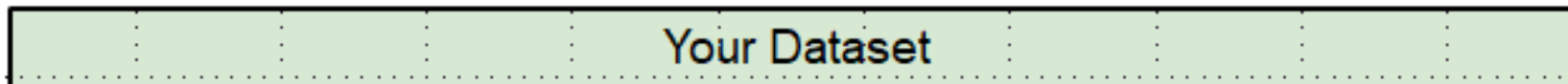
$\lambda \approx 0$



## [Train / Val / Test로 나누는 이유]

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:**  $K = 1$  always works perfectly on training data



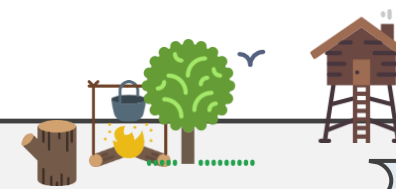
**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

**BAD:** No idea how algorithm will perform on new data

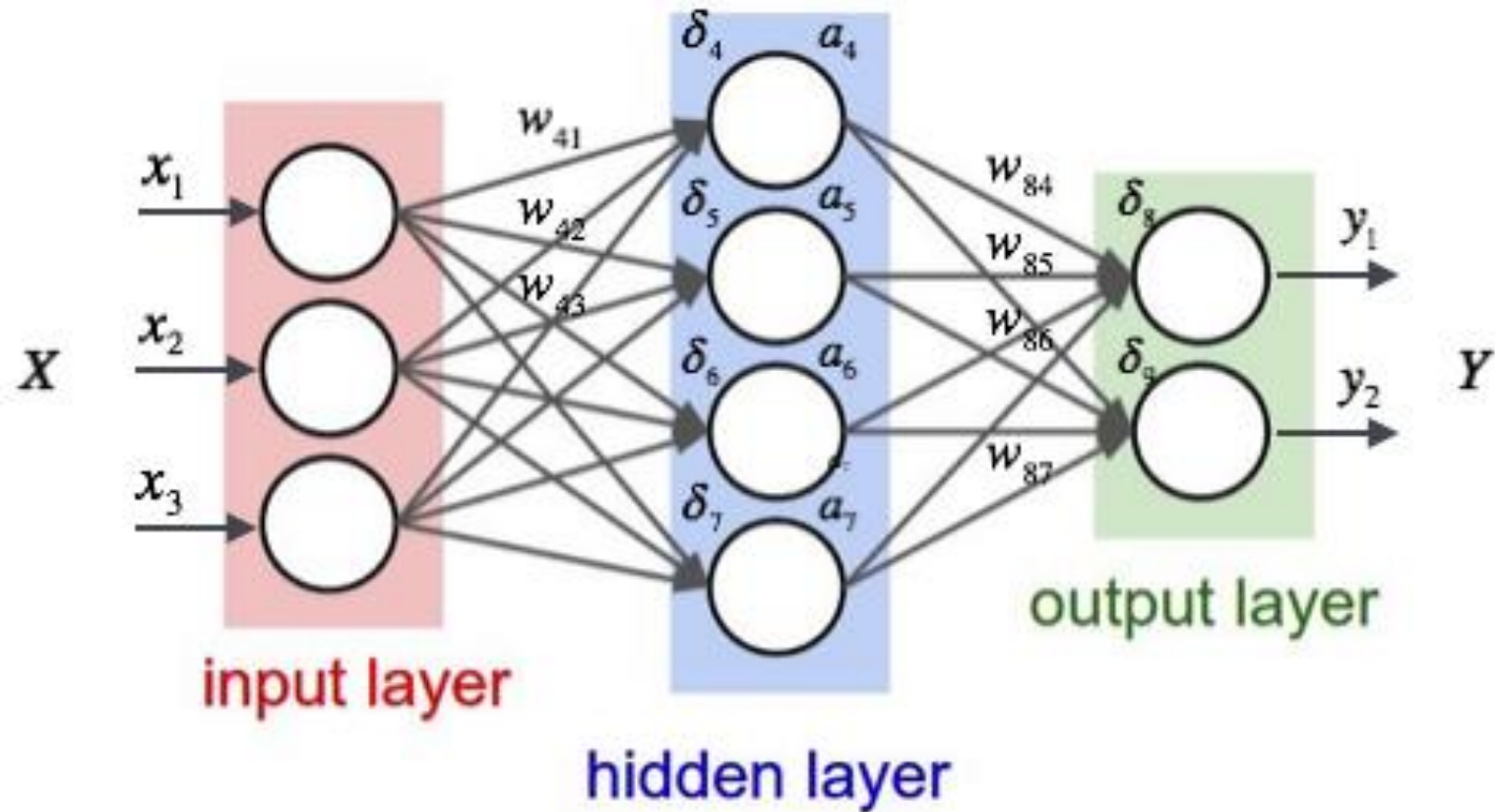


**Idea #3:** Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

**Better!**

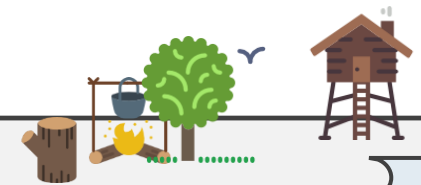
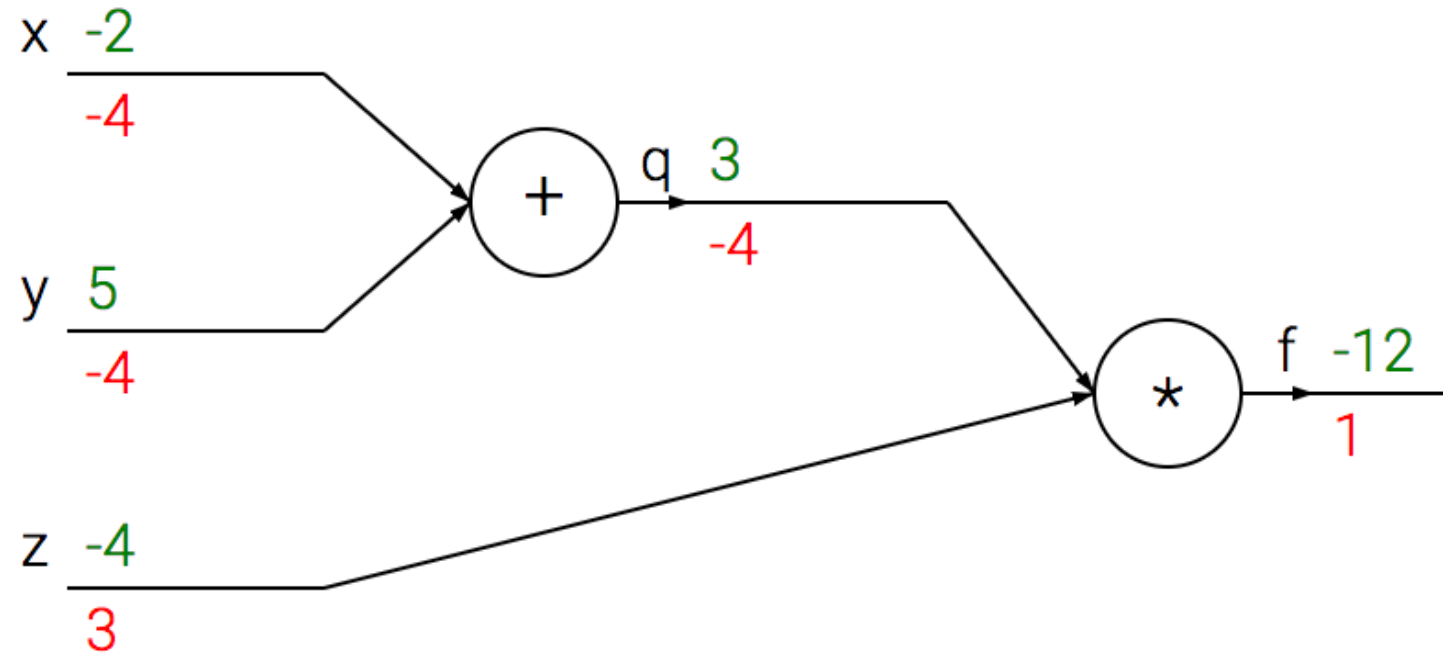


[Neural Network 구조]



## [Backpropagation 예제]

Backpropagation은 CS231n Lecture4에서 자세히

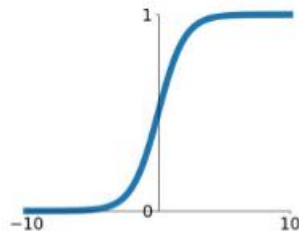


## [Activation Function]

Activation Function은 CS231n Lecture6에서 자세히

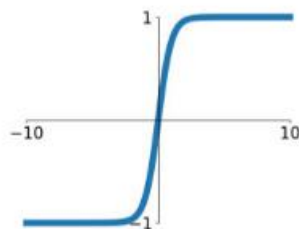
### Sigmoid

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



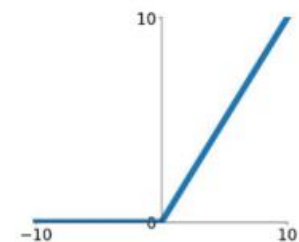
### tanh

$$\tanh(x)$$



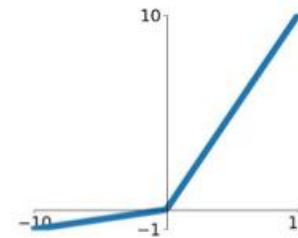
### ReLU

$$\max(0, x)$$



### Leaky ReLU

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

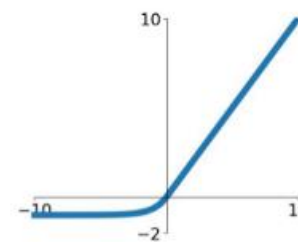


### Maxout

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

### ELU

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





## [Weight Initialization]

Weight Initialization은 CS231n Lecture6에서 자세히

### Xavier/He initialization

- Makes sure the weights are 'just right', not too small, not too big
- Using number of input (fan\_in) and output (fan\_out)

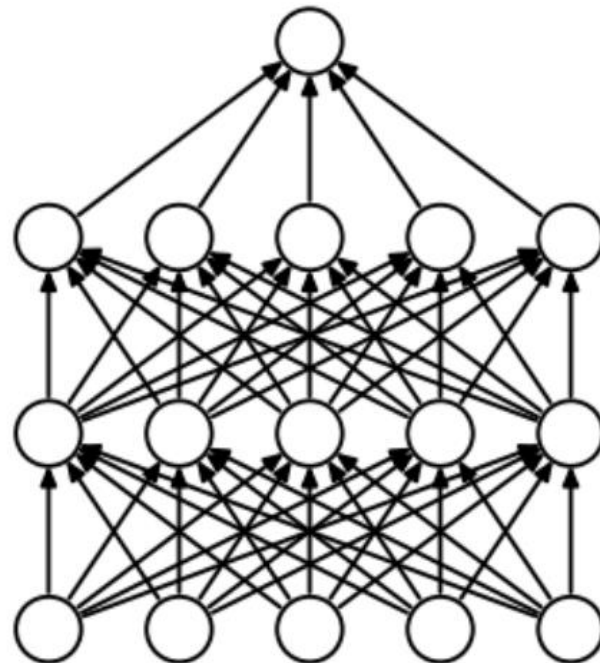
```
# Xavier initialization
# Glorot et al. 2010
W = np.random.randn(fan_in, fan_out)/np.sqrt(fan_in)
# He et al. 2015
W = np.random.randn(fan_in, fan_out)/np.sqrt(fan_in/2)
```



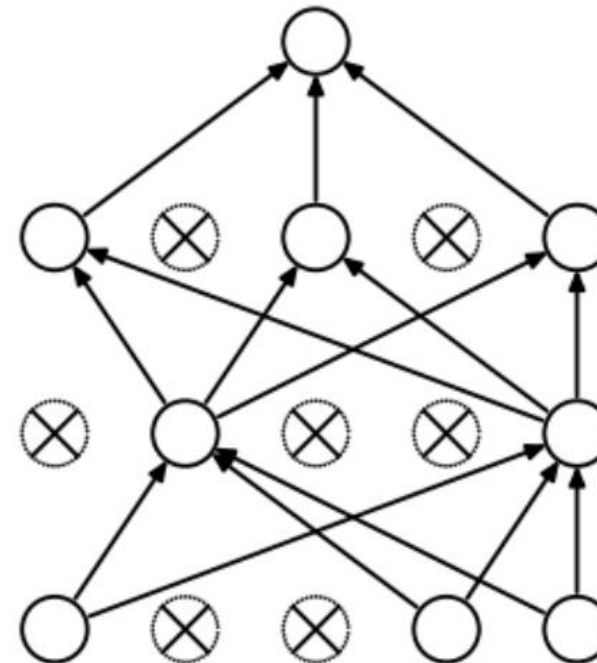
# Dropout & Model Ensemble

## [Dropout]

Deep Learning에서 Overfitting을 줄이는 1가지 방법



(a) Standard Neural Net

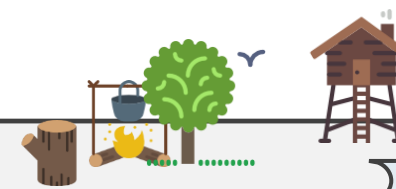
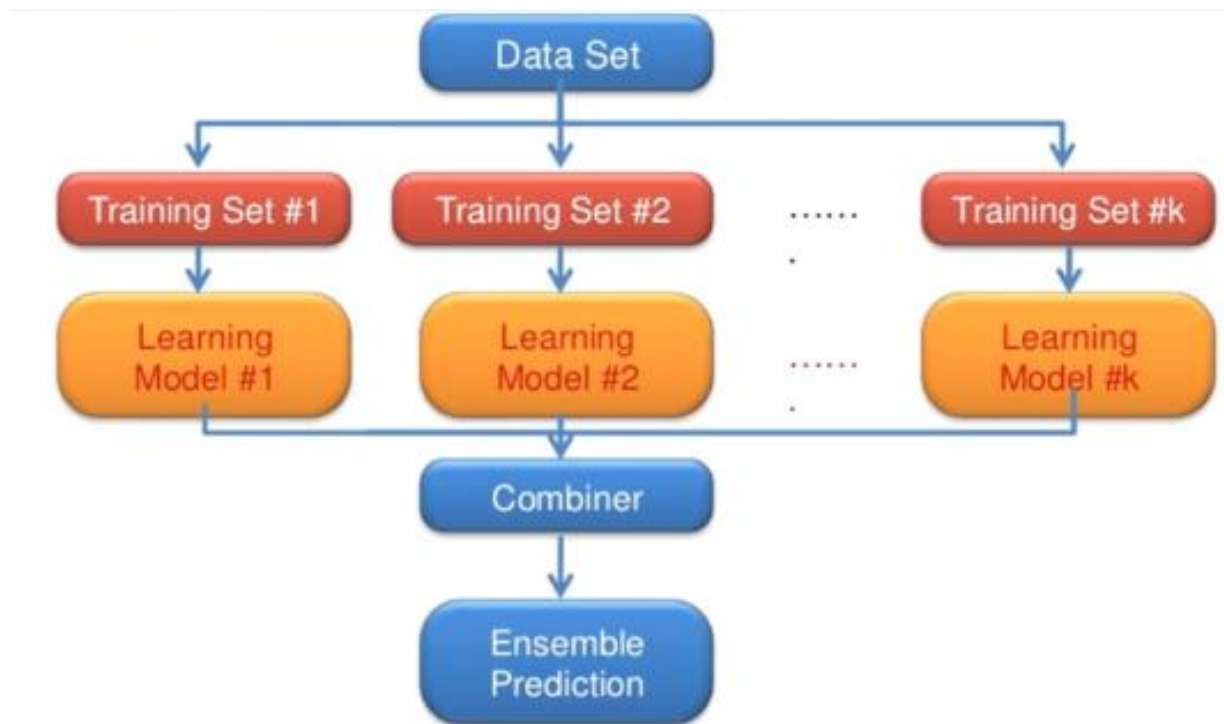


(b) After applying dropout.

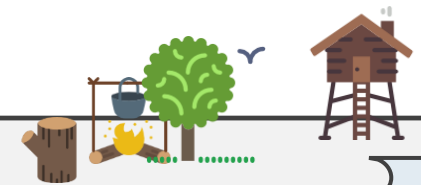
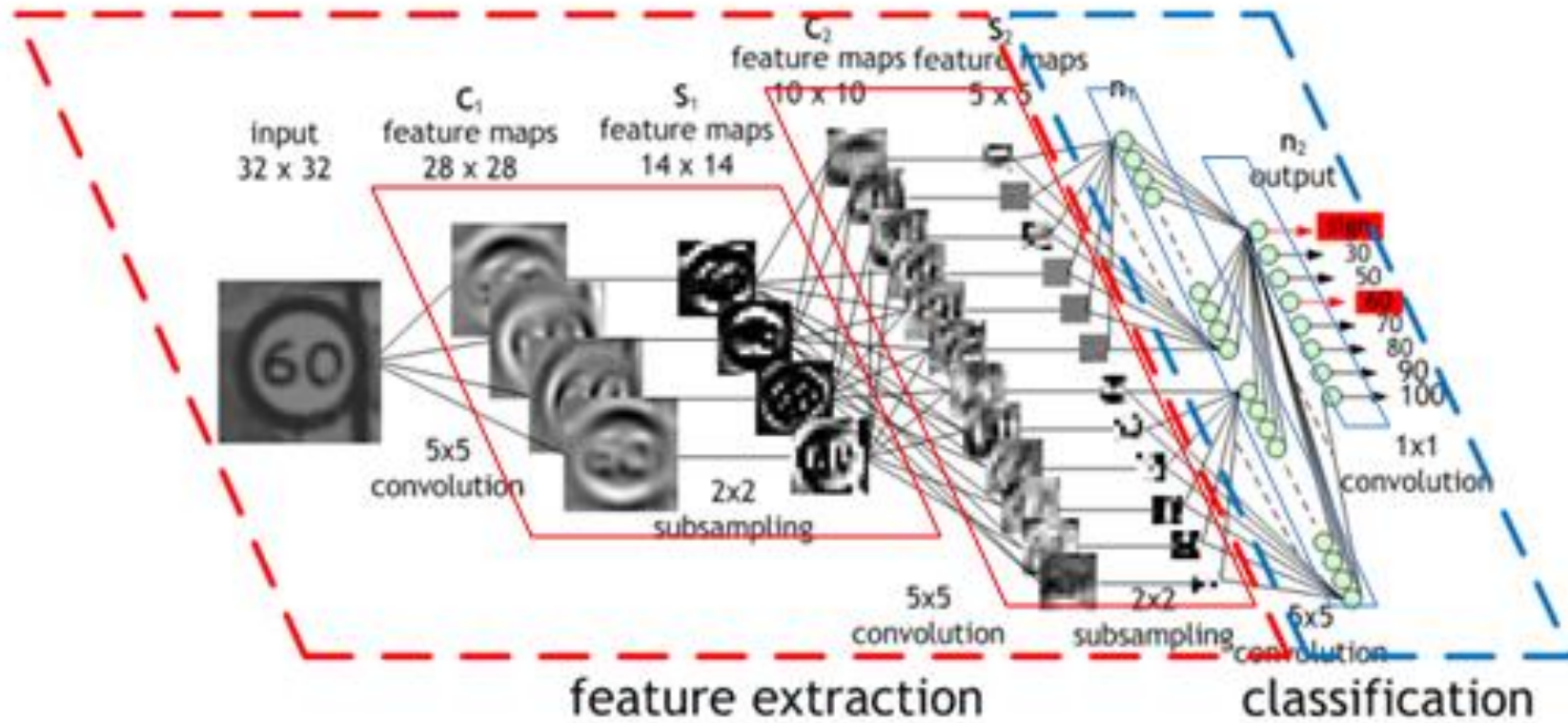


## [Model Ensemble]

마지막에 모델의 성능을 조금 더 향상시키기 위한 방법

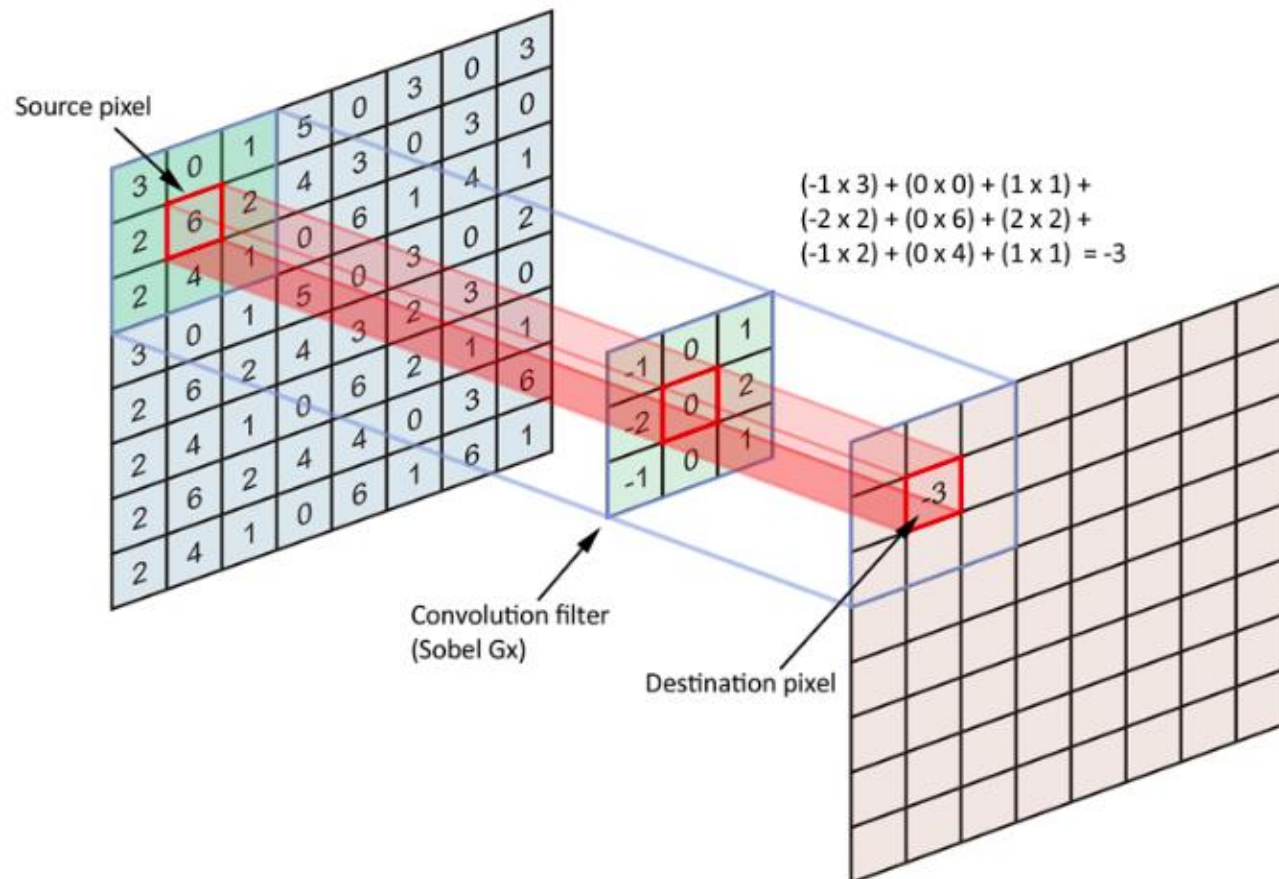


## [CNN 모델 예시]



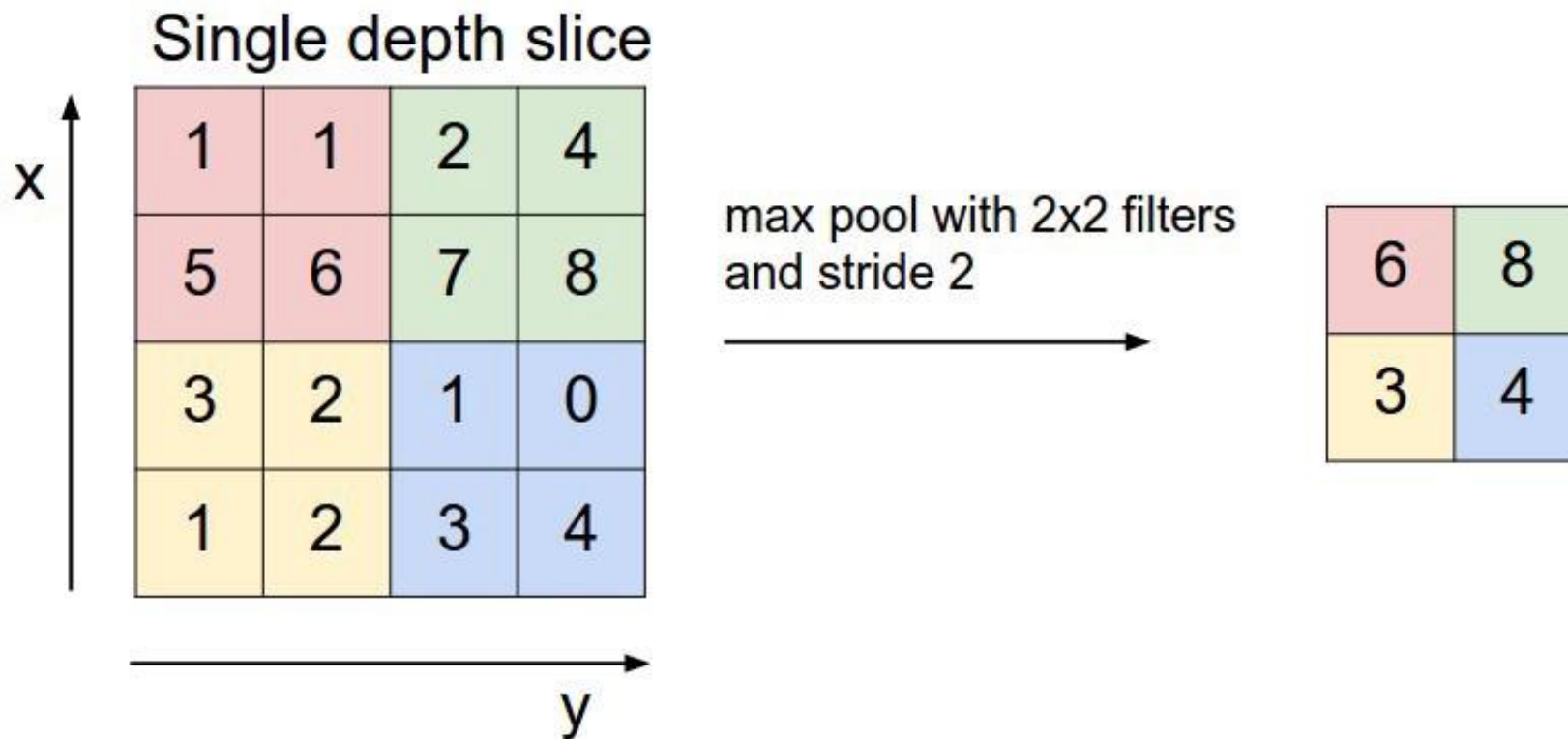
## [CNN 계산 방법]

CNN 계산 방법은 숙지를 해놓을 것!



### [Max Pooling 계산 방법]

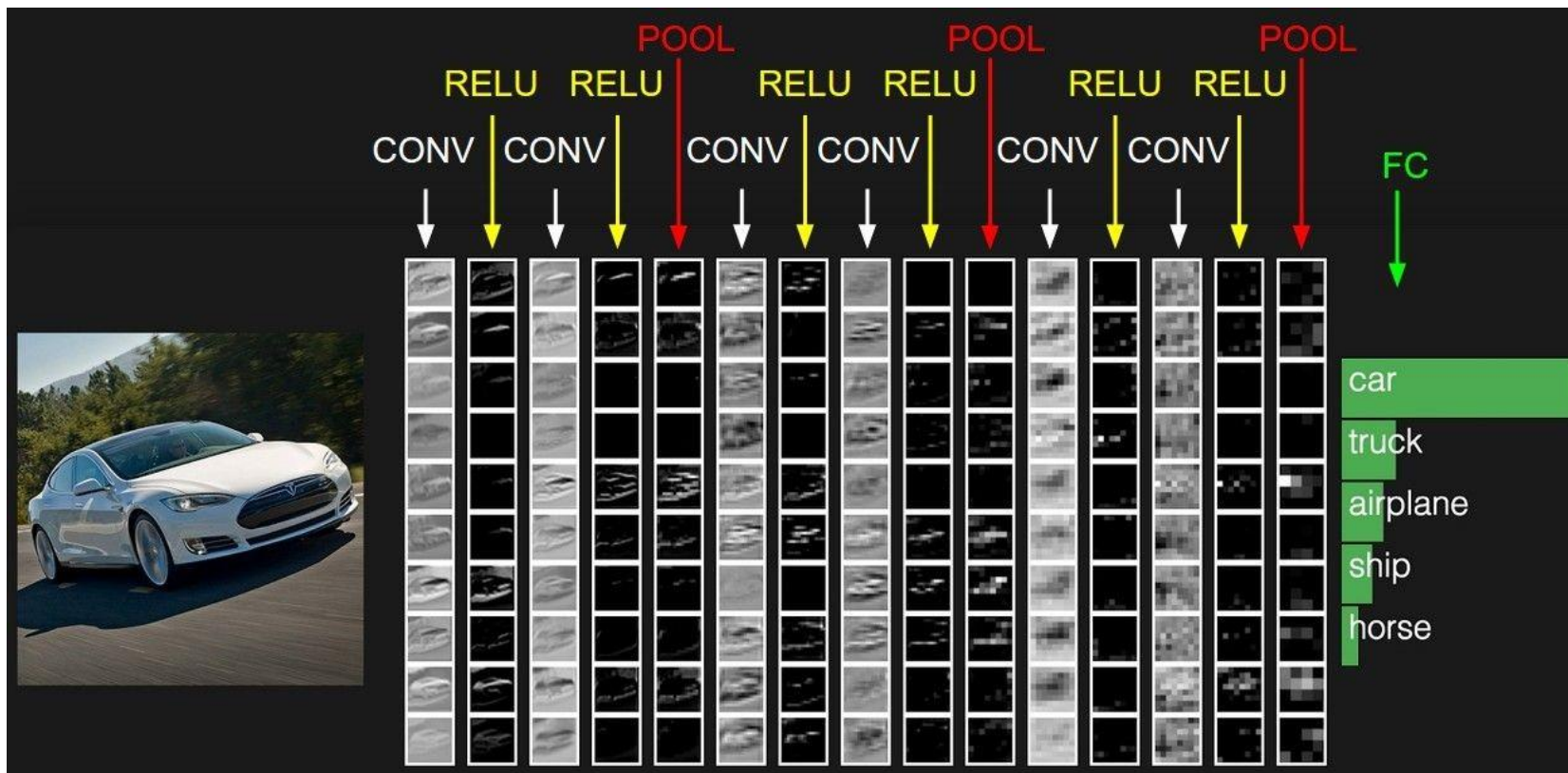
Convolution Layer와 같이 활용되기도 함.





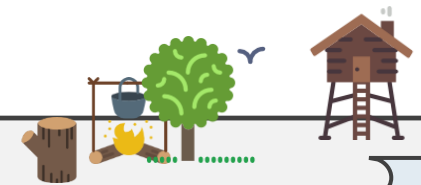
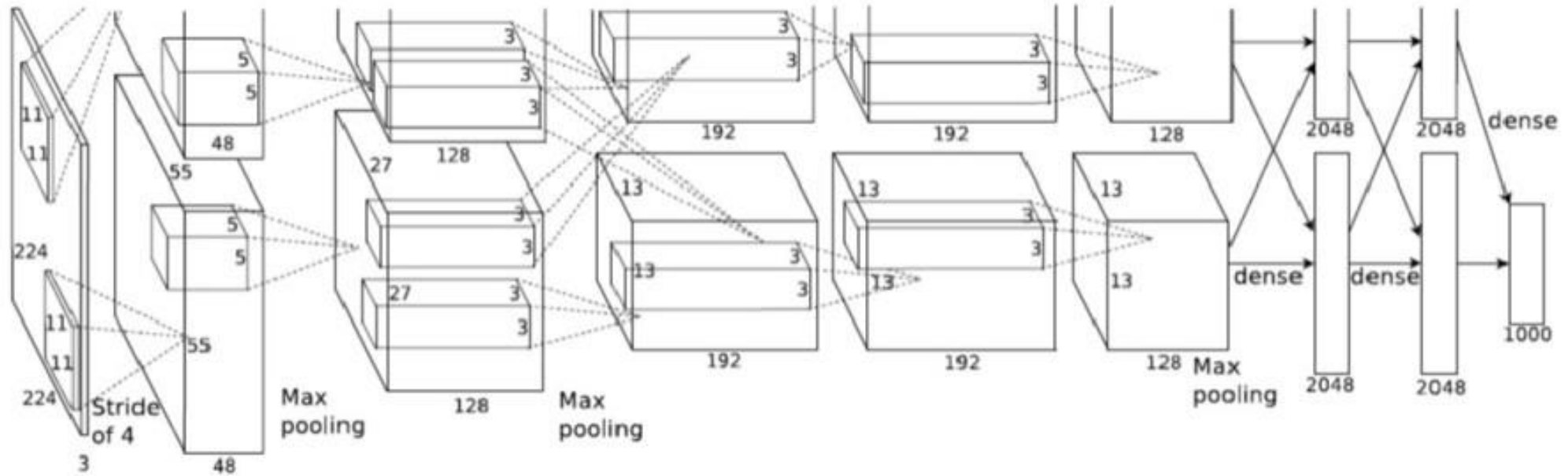
### [CNN 모델 예시]

Conv - Batch Normalization - ReLU - Pooling 순서로 사용됨.



**[AlexNet]**

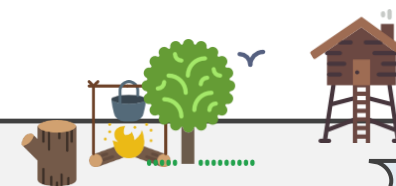
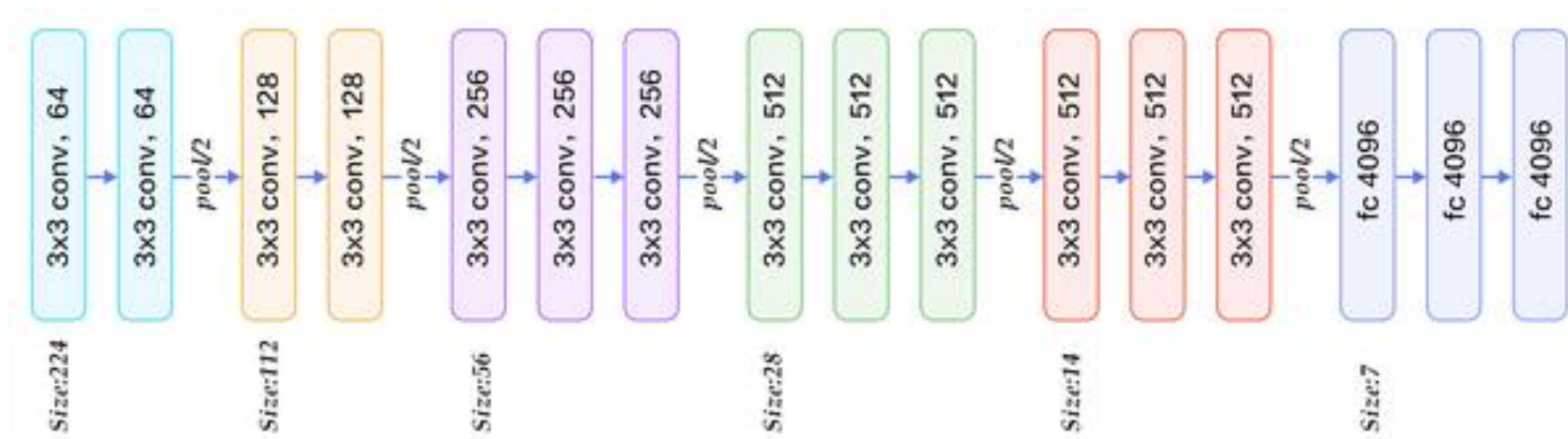
CS231n Lecture9에서 자세히



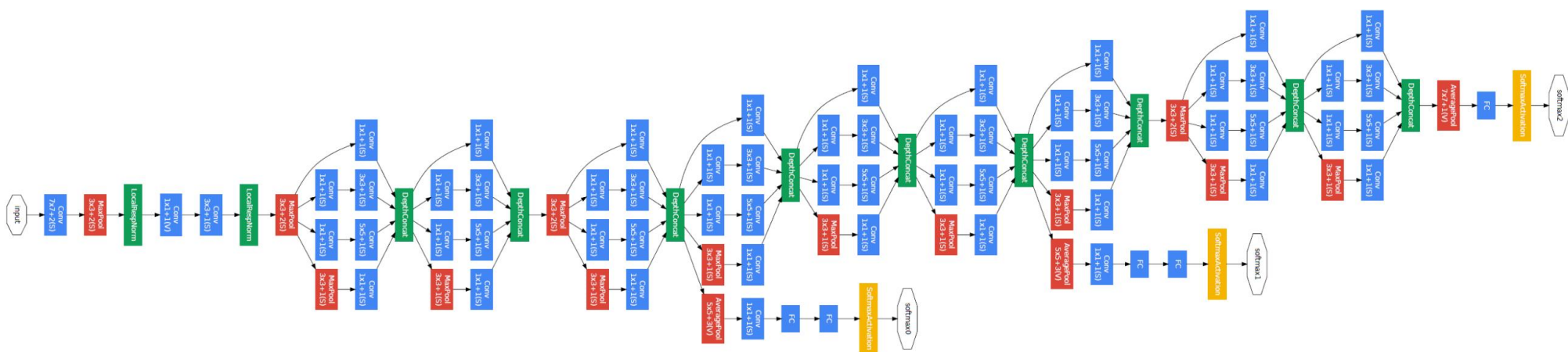


## [VGG16]

CS231n Lecture9에서 자세히



# [Inception 또는 GoogleNet] CS231n Lecture9에서 자세히



CS231n Lecture9에서 자세히



모두의 딥러닝 : <https://hunkim.github.io/ml/>

Andrew Ng의 Machine Learning : <https://ko.coursera.org/learn/machine-learning>

CS231n : <http://cs231n.stanford.edu/syllabus.html>

