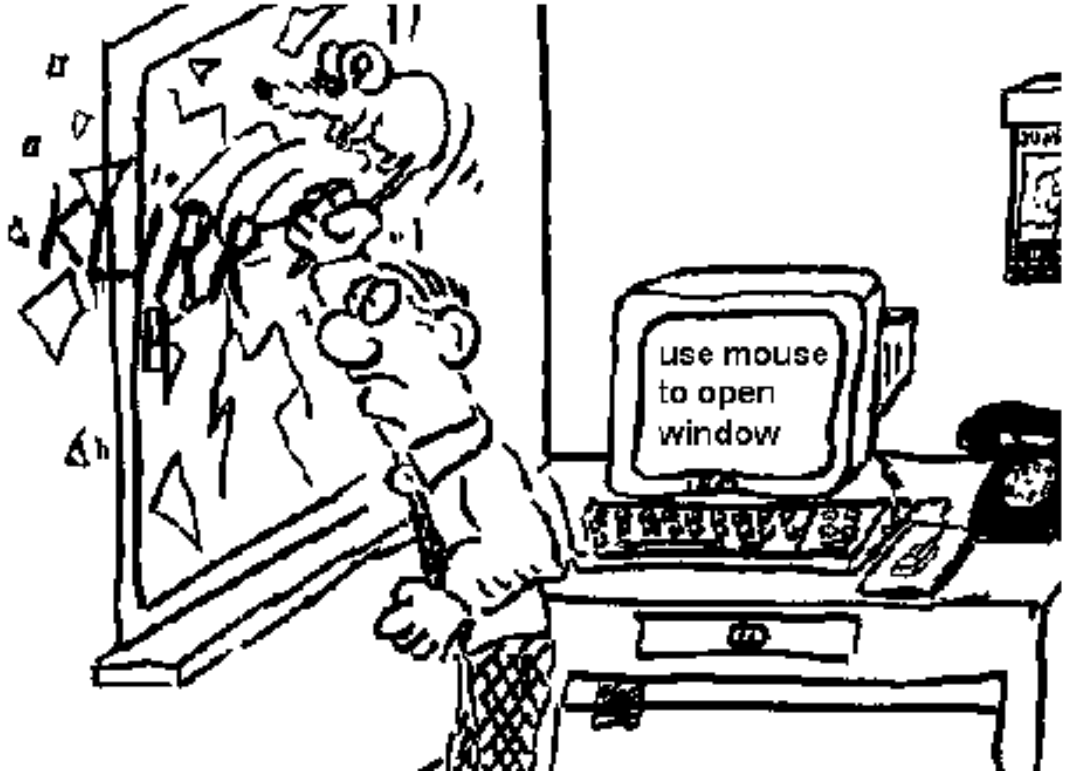
Deep Learning Basics

Lecture 3: Optimization

- Concept → p5~
- Practical Gradient method → p18~
- Regularization → p28~

최성준 (고려대학교 인공지능학과)

Introduction

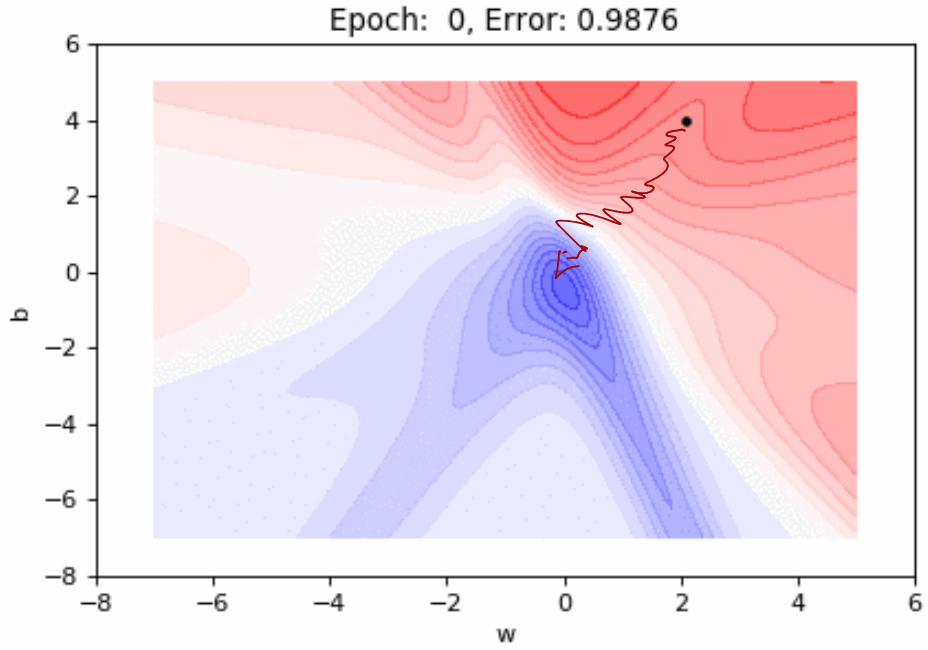


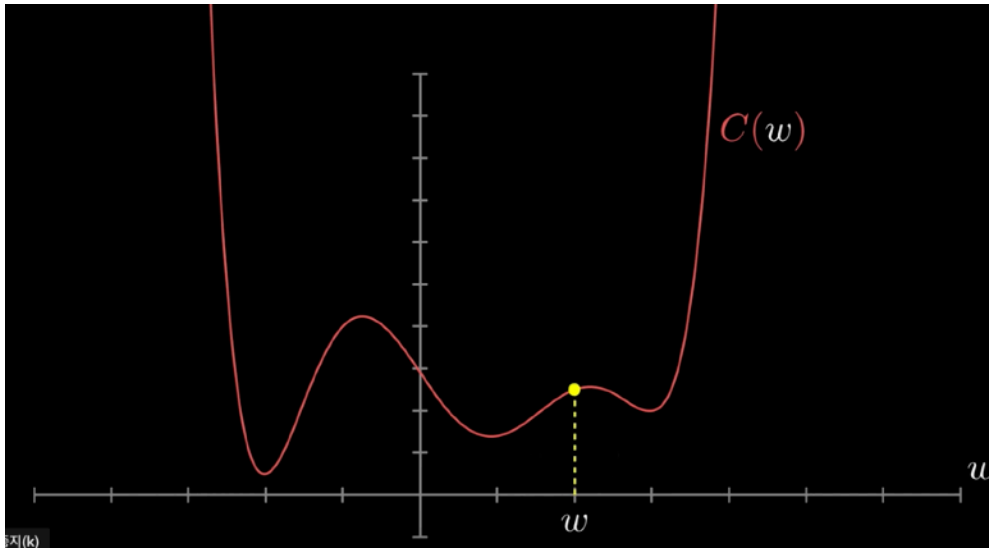
"Language is the source of misunderstandings"

Antoine de Saint-Exupéry (1900-1944)

Introduction

- Gradient Descent
  - First-order iterative optimization algorithm for finding a local minimum of a differentiable function.





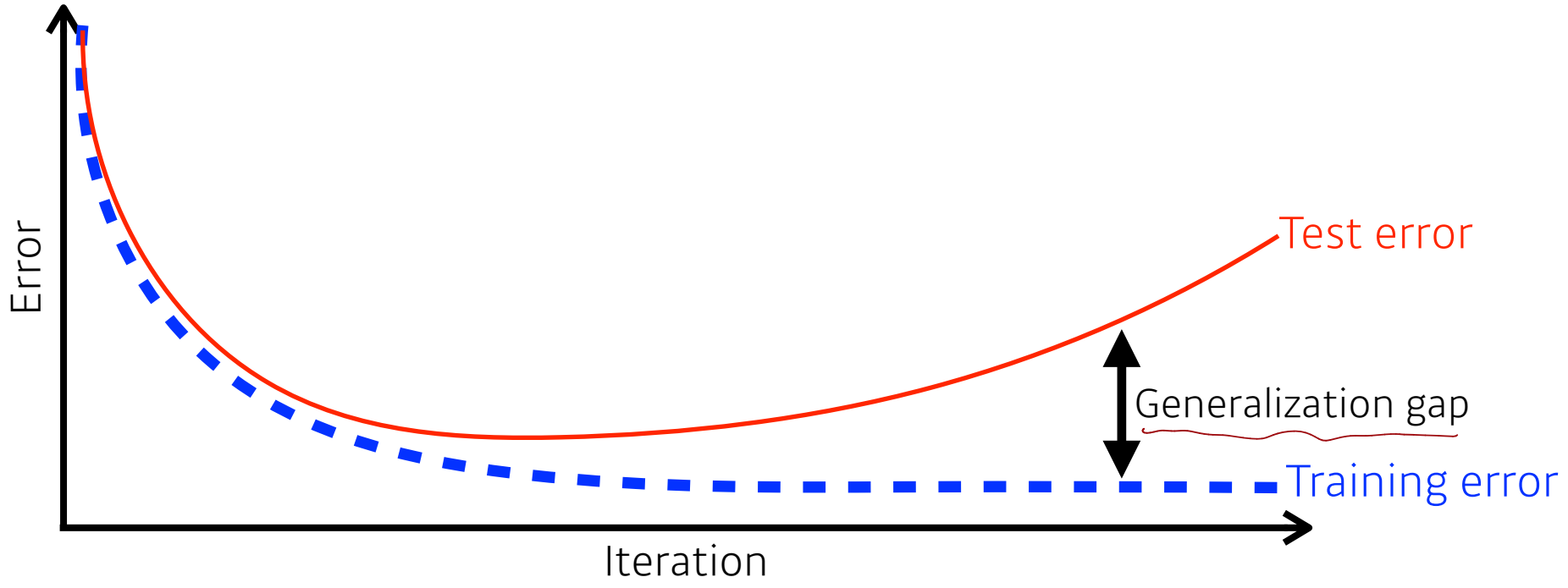
Important Concepts in **Optimization**

Important Concepts in **Optimization**

- Generalization (Generalization Gap)
- Under-fitting vs. over-fitting
- Cross validation 교차검증 (K-fold 등)
- Bias-variance tradeoff
- Bootstrapping
- Bagging and boosting

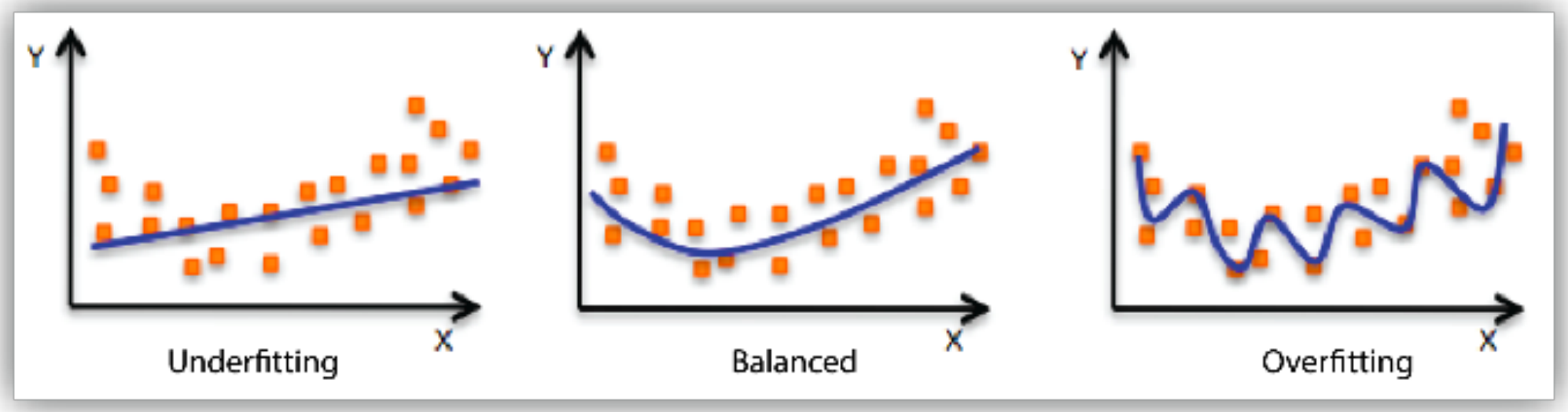
Generalization 일반화 능력

- How well the learned model will behave on unseen data.



Underfitting vs. Overfitting

과소적합 과대적합

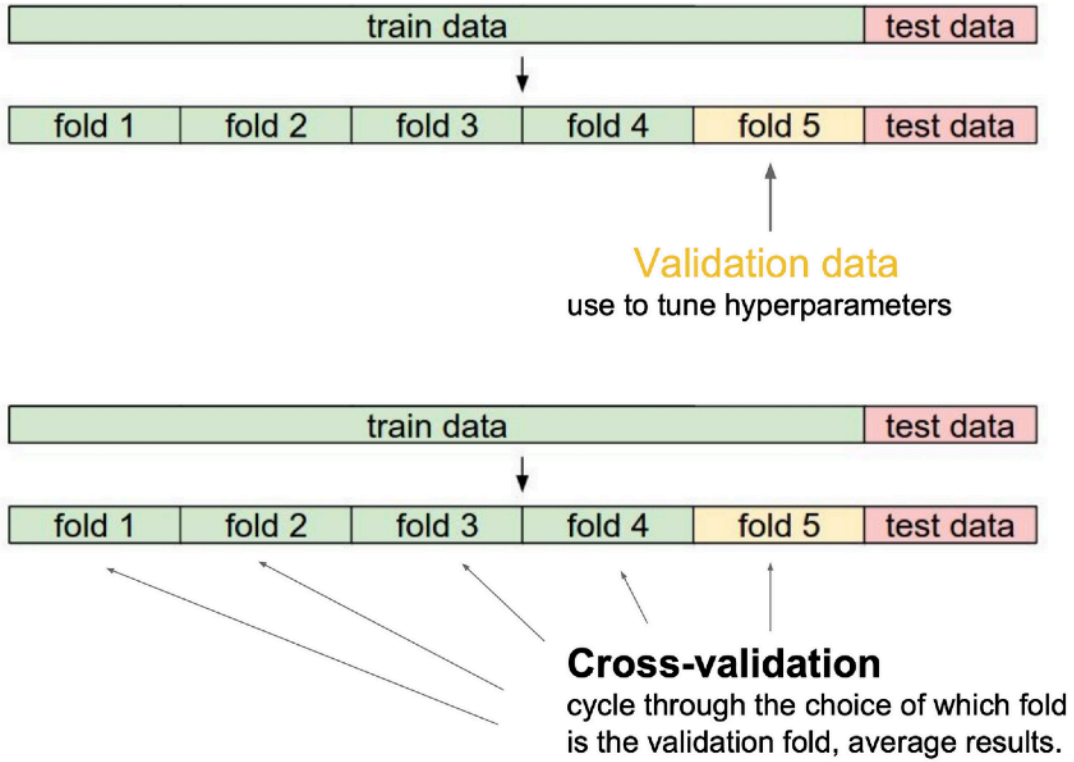


https://docs.aws.amazon.com/machine-learning/latest/dg/model-fit-underfitting-vs-overfitting.html

Cross-validation

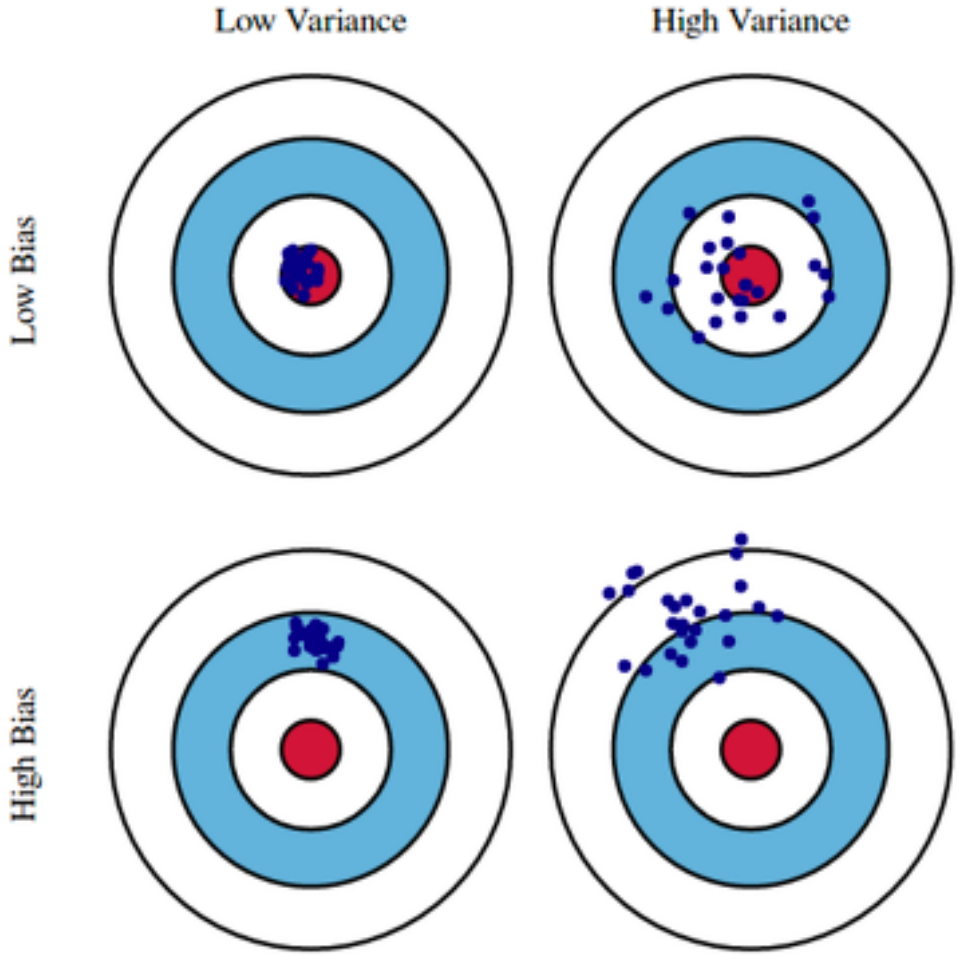
교차검증 (K-fold (U)
→최적화된 hyperparameters set을 찾기위해

- Cross-validation is a model validation technique for assessing how the model will generalize to an independent (test) data set.



https://blog.quantinsti.com/cross-validation-machine-learning-trading-models/

Bias and Variance



https://work.caltech.edu/telecourse

Bias and Variance Tradeoff

$$\text{Given } \mathcal{D} = \{(x_i, t_i)\}_{i=1}^{N}, \text{ where } t = f(x) + \epsilon \text{ and } \epsilon \sim \mathcal{N}(0, \sigma^2)$$

We can derive that what we are minimizing (**cost**) can be decomposed into three different parts: **bias²**, **variance**, and **noise**.

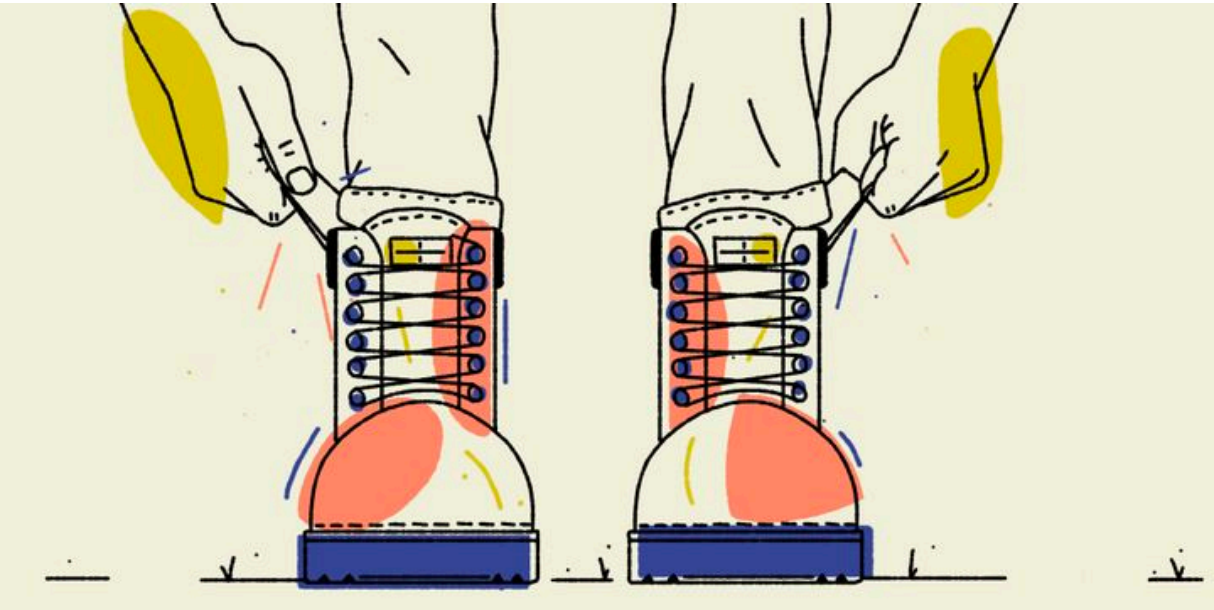
$$\underbrace{\mathbb{E}\left[(t - \hat{f})^2\right]}_{\textbf{cost}} = \mathbb{E}\left[(t - f + f - \hat{f})^2\right]$$

$$= \dots$$

$$= \underbrace{\mathbb{E}\left[(f - \mathbb{E}[\hat{f}]^2)^2\right]}_{\textbf{bias}^2} + \underbrace{\mathbb{E}\left[(\mathbb{E}[\hat{f}] - \hat{f})^2\right]}_{\textbf{variance}} + \underbrace{\mathbb{E}\left[\epsilon\right]}_{\textbf{noise}}$$

Bootstrapping

=> 무작위 샘플링을 사용하는 여러 모델을 만들어서 목적을 달성하고자 하는 것
(학습 데이터가 고정되어 있을 때, 그 안에서 샘플링을 통해
학습 데이터를 여러개 만들고, 이를 통해 모델 여러개를 만드는 것)



Pull yourself up by the **bootstraps**.

- Bootstrapping is any test or metric that uses random sampling with replacement.

Bagging vs. Boosting

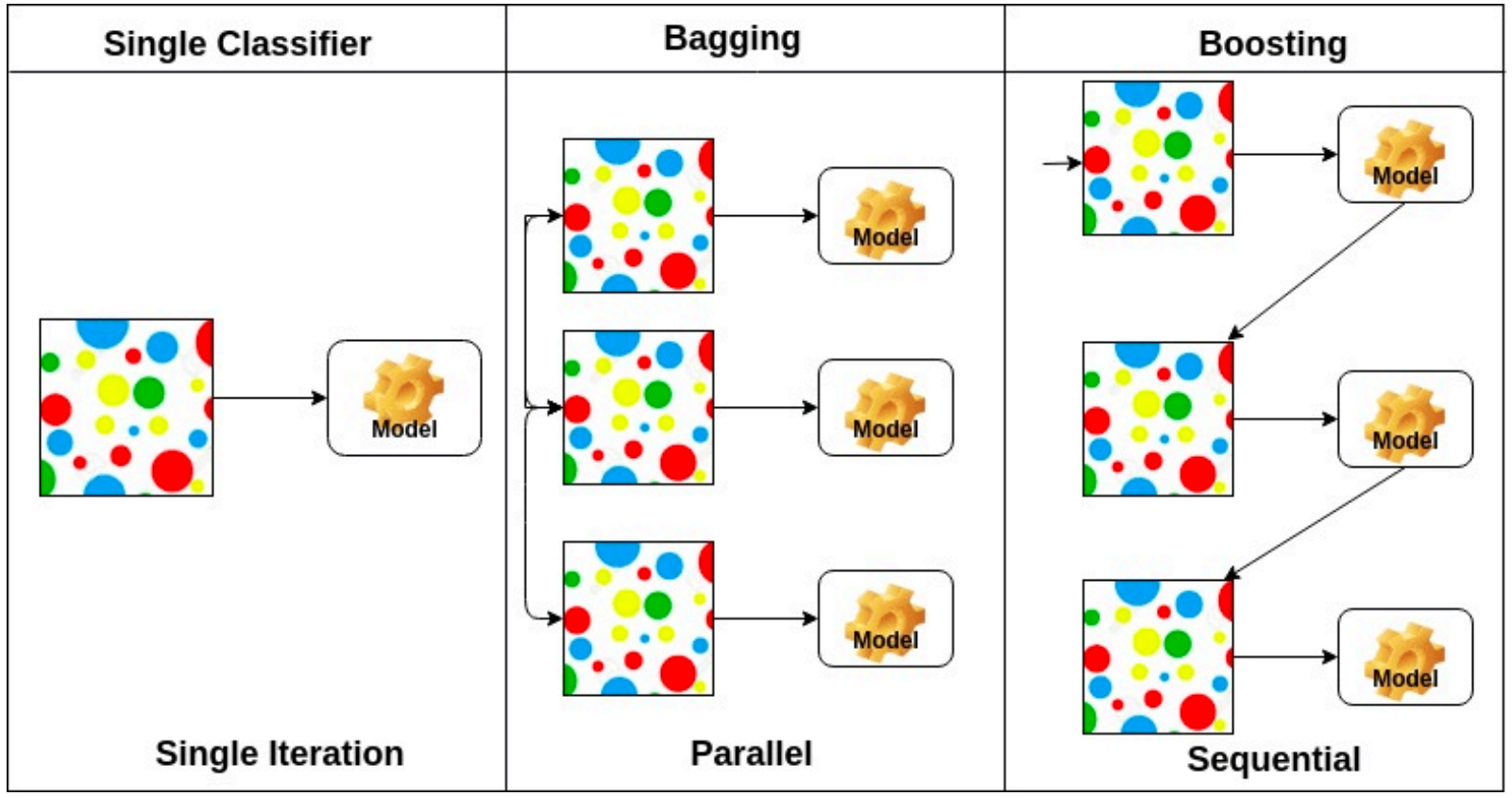
- Bagging (Bootstrapping **agg**regat**ing**) = bootstrapping (≈ 앙상블)
  - Multiple models are being trained with bootstrapping.
  - ex) Base classifiers are fitted on random subset where individual predictions are aggregated (voting or averaging).

=> 학습 데이터를 여러 개 만들고, 따로 모델을 만들어 output의 평균을 내는 것.
(독립적인 모델들)

- Boosting
  - It focuses on those specific training samples that are hard to classify.
  - A strong model is built by combining weak learners in sequence where each learner learns from the mistakes of the previous weak learner.

=> 여러 개의 모델을 만들어서 합치는 것. (여러개의 week learner를 합쳐 strong model을 만드는 것)
(이 때는 week learner의 실수로부터 배우는 것 (sequential 형태))

Bagging vs. Boosting



https://www.datacamp.com/community/tutorials/adaboost-classifier-python

Practical Gradient Descent Methods

Gradient Descent Methods

- Stochastic gradient descent
  - Update with the gradient computed from a single sample.
- Mini-batch gradient descent
  - Update with the gradient computed from a subset of data.
- Batch gradient descent
  - Update with the gradient computed from the whole data.

Batch-size Matters

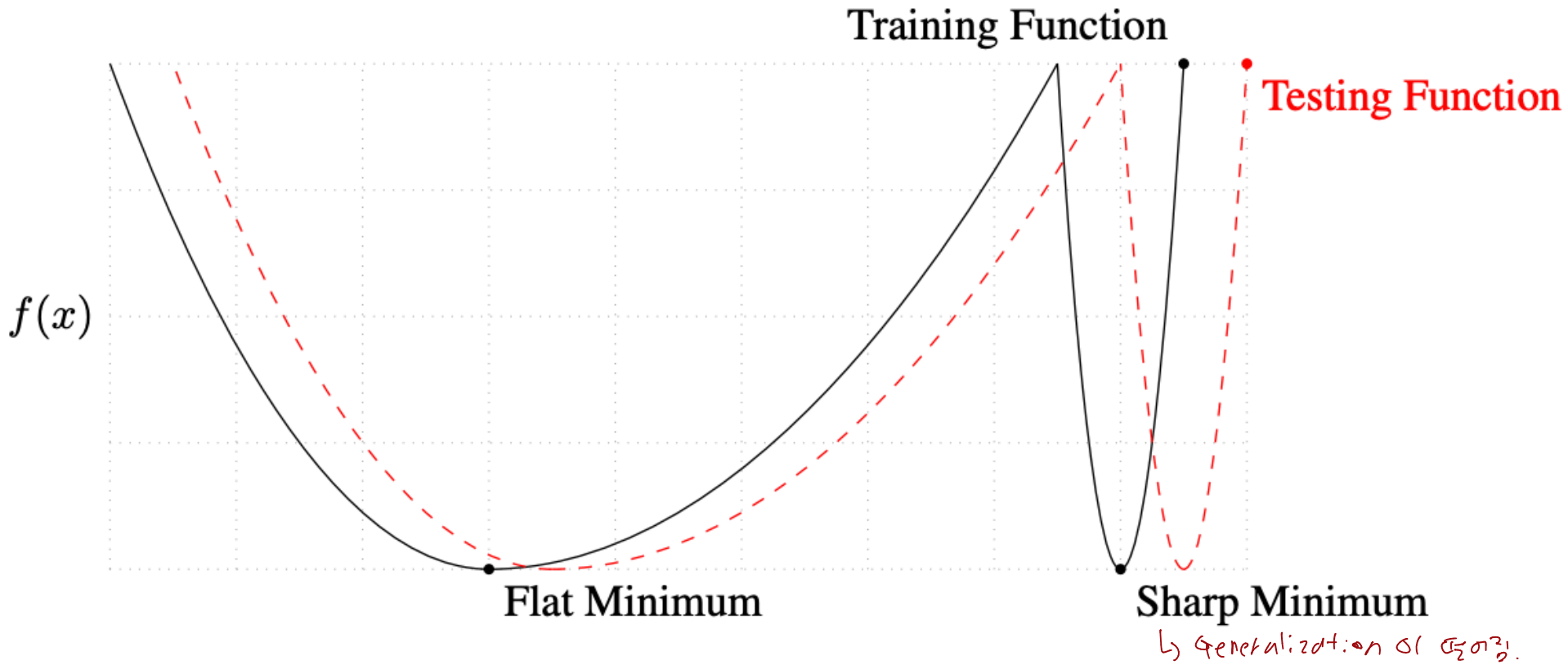
- "It has been observed in practice that when using a larger batch there is a degradation in the quality of the model, as measured by its ability to generalize."

- "We ... present numerical evidence that supports the view that large batch methods tend to converge to **sharp minimizers** of the training and testing functions. In contrast, small-batch methods consistently converge to **flat minimizers**... this is due to the inherent noise in the gradient estimation."

=> flat minimizer가 일반적으로 더 좋음.

On Large-batch Training for Deep Learning: Generalization Gap and Sharp Minima, 2017

Batch-size Matters



On Large-batch Training for Deep Learning: Generalization Gap and Sharp Minima, 2017

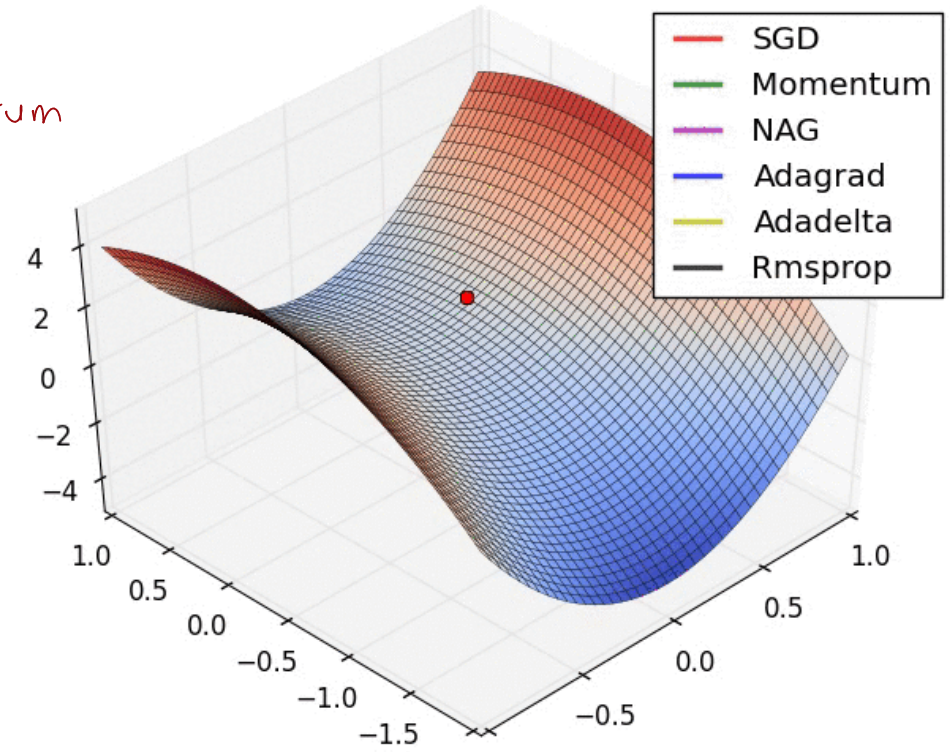
Gradient Descent Methods

- Stochastic gradient descent
- Momentum
- Nesterov accelerated gradient
- Adagrad
- Adadelta
- RMSprop
- Adam

momentum

Adaptive

→ Adaptive + momentum



Stochastic -

Gradient Descent

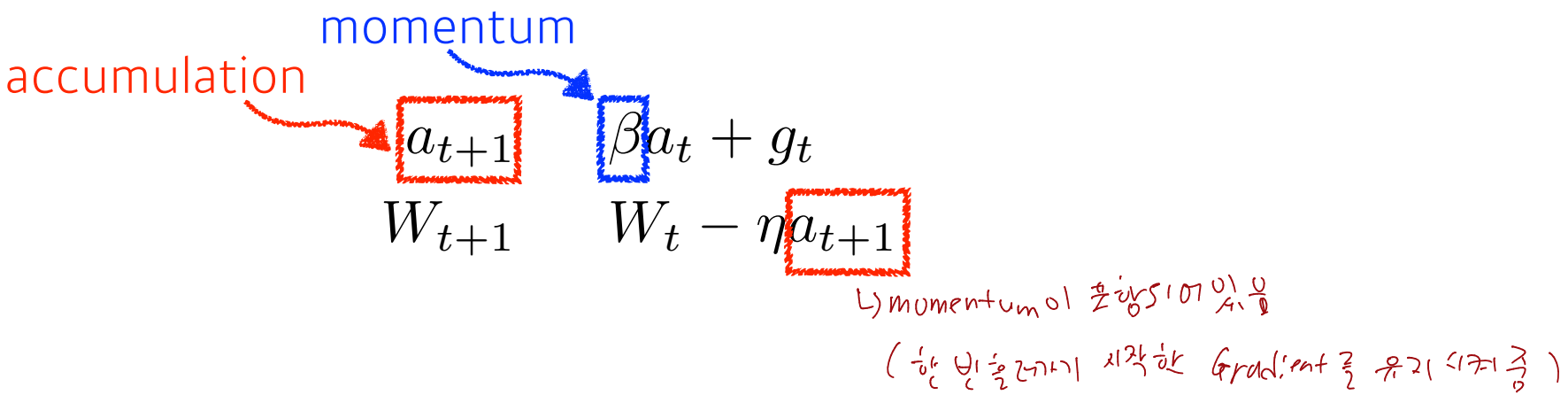
$$W_{t+1} \quad W_t - \eta g_t$$

Learning rate

Gradient

Momentum

(관성)



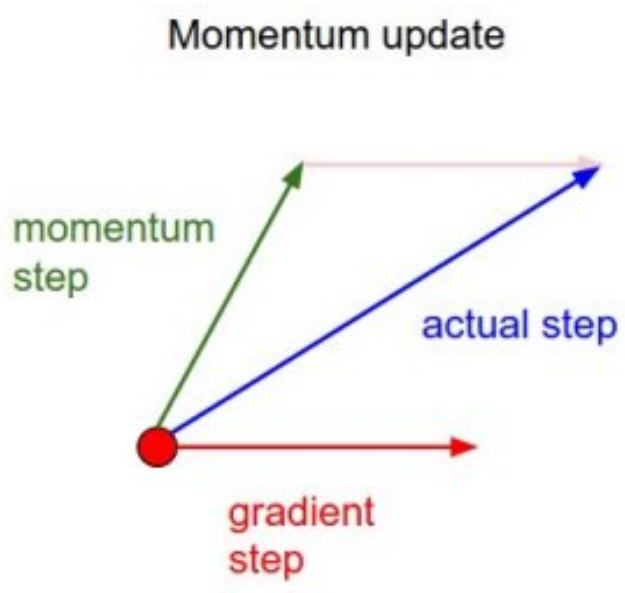
Nesterov Accelerated Gradient

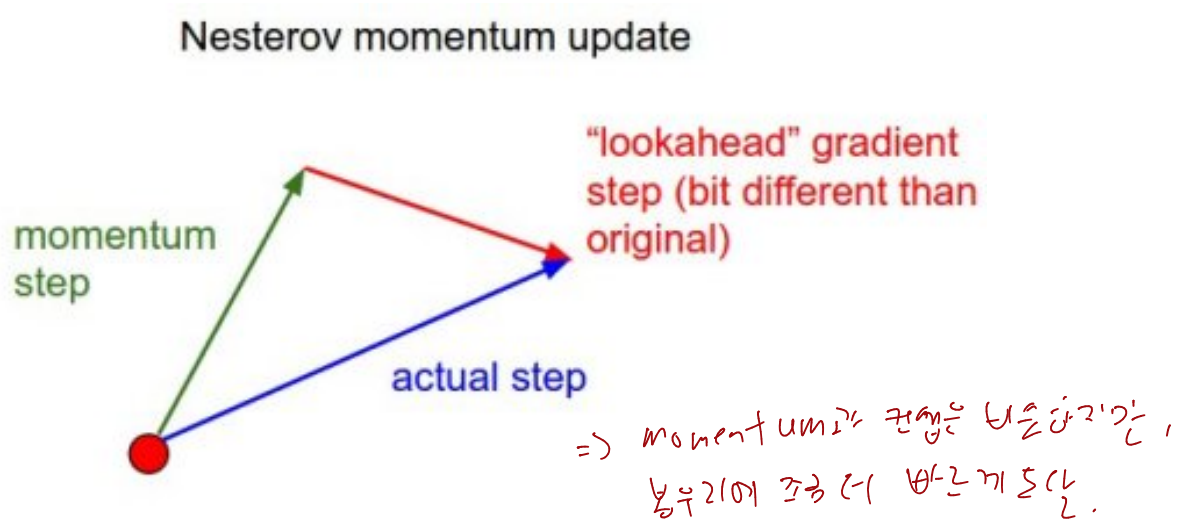
Lookahead gradient

$$a_{t+1} \quad \beta a_t + \nabla \mathcal{L}(W_t - \eta \beta a_t)$$

$$W_{t+1} \quad W_t - \eta a_{t+1}$$

Nesterov Accelerated Gradient





=> momentum과 결합을 비슷하지만, 방향이 조금 더 빠른게 특징.

https://golden.com/wiki/Nesterov_momentum

Adagrad

- **Adagrad** adapts the learning rate, performing larger updates for infrequent and smaller updates for frequent parameters.

· 뉴럴 네트워크의 parameter가 지금까지 얼만큼 많이 변했는지를 봄.

· 적게 변한 파라미터에 대해서는 크게 변화시키고, 많이 변한 파라미터는 적게 변화시킴.

for numerical stability
(0으로 안 나눠지게 만드는 값)

$$W_{t+1} = W_t - \frac{\eta}{\sqrt{G_t + \epsilon}} g_t$$

Sum of gradient squares

What will happen if the training occurs for a long period?

G가 계속 커지게 되면 학습이 중간 멈추게 되는 현상 발생
(분모가 커지면, W가 거의 안 변함)

Adadelta

- **Adadelta** extends **Adagrad** to reduce its monotonically decreasing the learning rate by restricting the accumulation window.

EMA of gradient squares

$$G_t = \gamma G_{t-1} + (1-\gamma) g_t^2$$

$$W_{t+1} = W_t - \frac{\sqrt{H_{t-1} + \epsilon}}{\sqrt{G_t + \epsilon}} g_t$$

EMA of difference squares

$$H_t = \gamma H_{t-1} + (1-\gamma)(\Delta W_t)^2$$

There is **no learning rate** in Adadelta.

↳ ∴ 바꿀 수 있는 요소가 없기 때문에.
↳ 잘 사용X

RMSprop

- **RMSprop** is an unpublished, adaptive learning rate method proposed by Geoff Hinton in his lecture.

EMA of gradient squares

$$G_t = \gamma G_{t-1} + (1-\gamma) g_t^2$$

$$W_{t+1} = W_t - \frac{\eta}{\sqrt{G_t + \epsilon}} g_t$$

stepsize 조절 가능

Adam (가장 무난하게 사용)

- Adaptive Moment Estimation (Adam) leverages both past gradients and squared gradients.

Momentum

EMA of gradient squares

Stepsize

$$m_t = \beta_1 m_{t=1} + (1-\beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

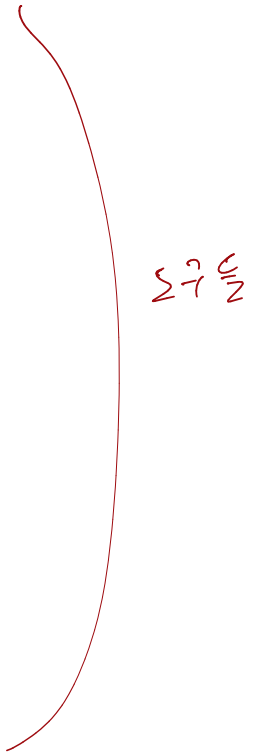
$$W_{t+1} = W_t - \frac{\eta}{\sqrt{v_t + \epsilon}} \frac{\sqrt{1-\beta_2^t}}{1-\beta_1^t} m_t$$

Adam effectively combines momentum with adaptive learning rate approach.

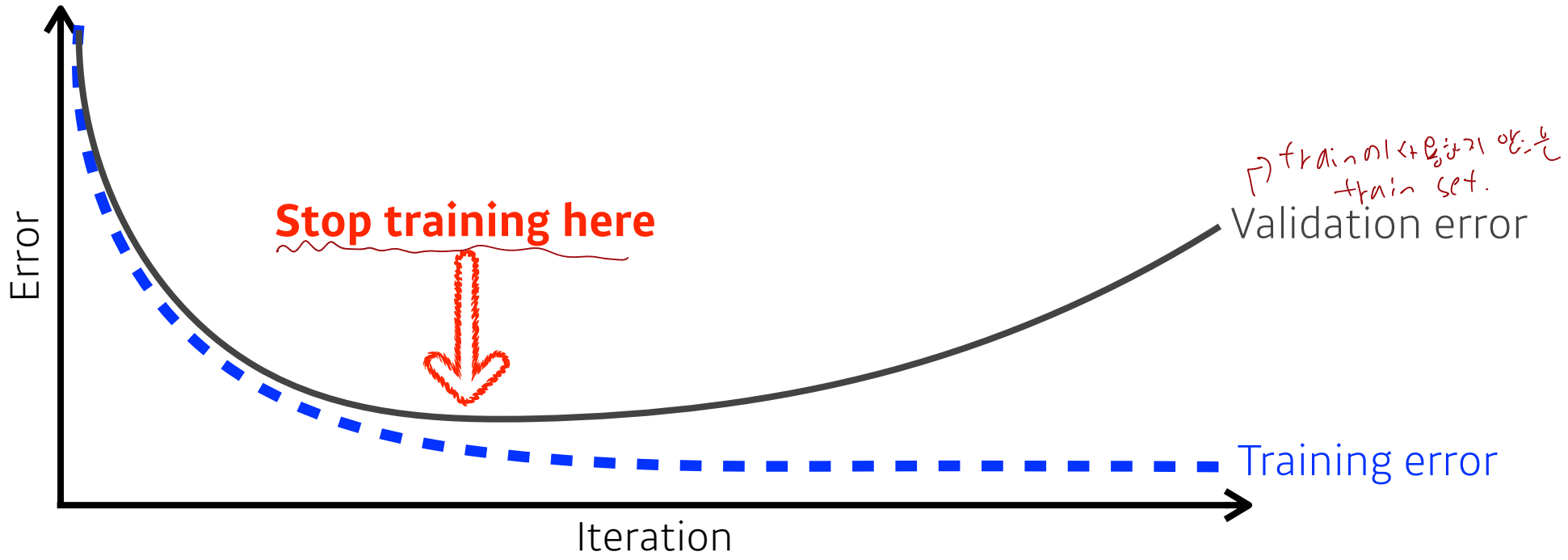
Regularization

Regularization : 규제 (학습을 방해하며 Generalization 할 수 있도록 하는 것.)

- Early stopping
- Parameter norm penalty
- Data augmentation
- Noise robustness
- Label smoothing
- Dropout
- Batch normalization



Early Stopping



Note that we need **additional validation data** to do early stopping.

Parameter Norm Penalty

- It adds smoothness to the function space.

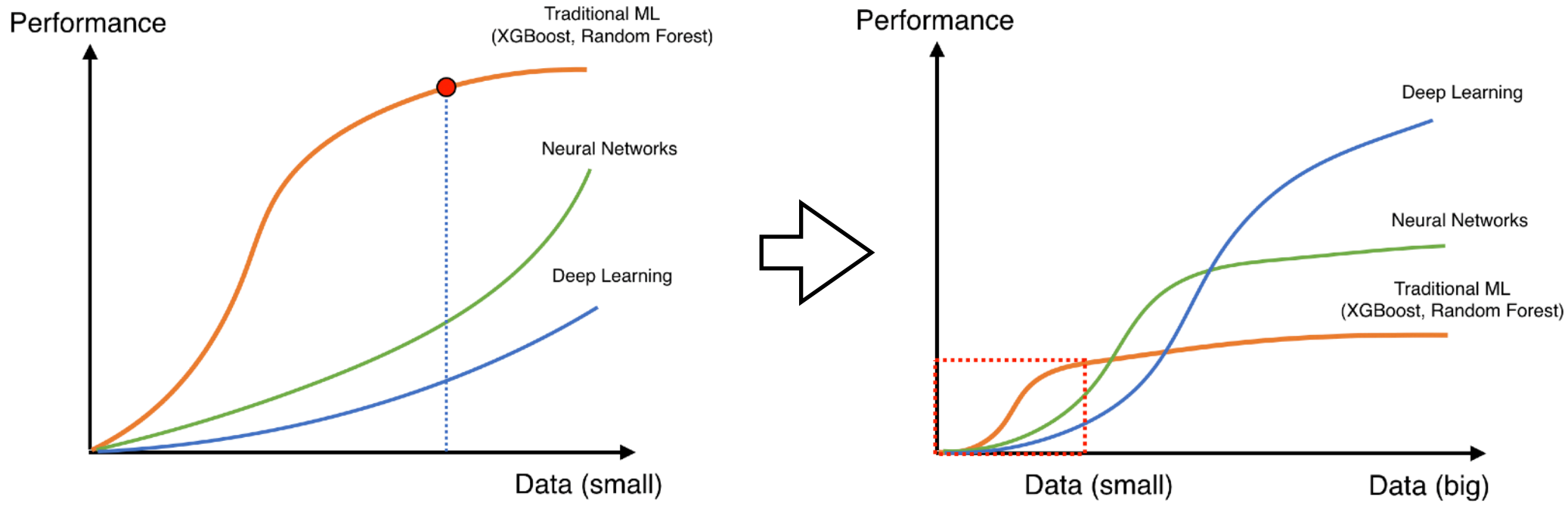
· 파라미터가 너무 커지지 않도록 하는것.
· 파라미터를 제한하여 너무 큰값을 cost function 에 추가하여 같이 줄임
(부드러운 함수를 만들기 위해)

Parameter Norm Penalty

$$\text{total cost} = \text{loss}(\mathcal{D}; W) + \frac{\alpha}{2}\|W\|_2^2$$

Data Augmentation

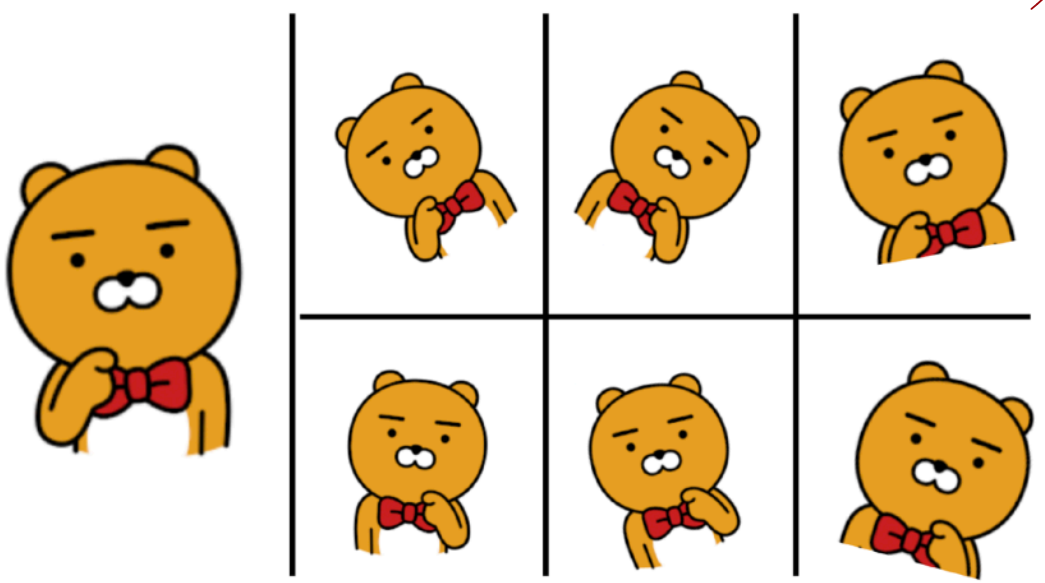
- More data are always welcomed.



Data Augmentation

- More data are always welcomed.
- However, in most cases, training data are given in advance.
- In such cases, we need data augmentation.

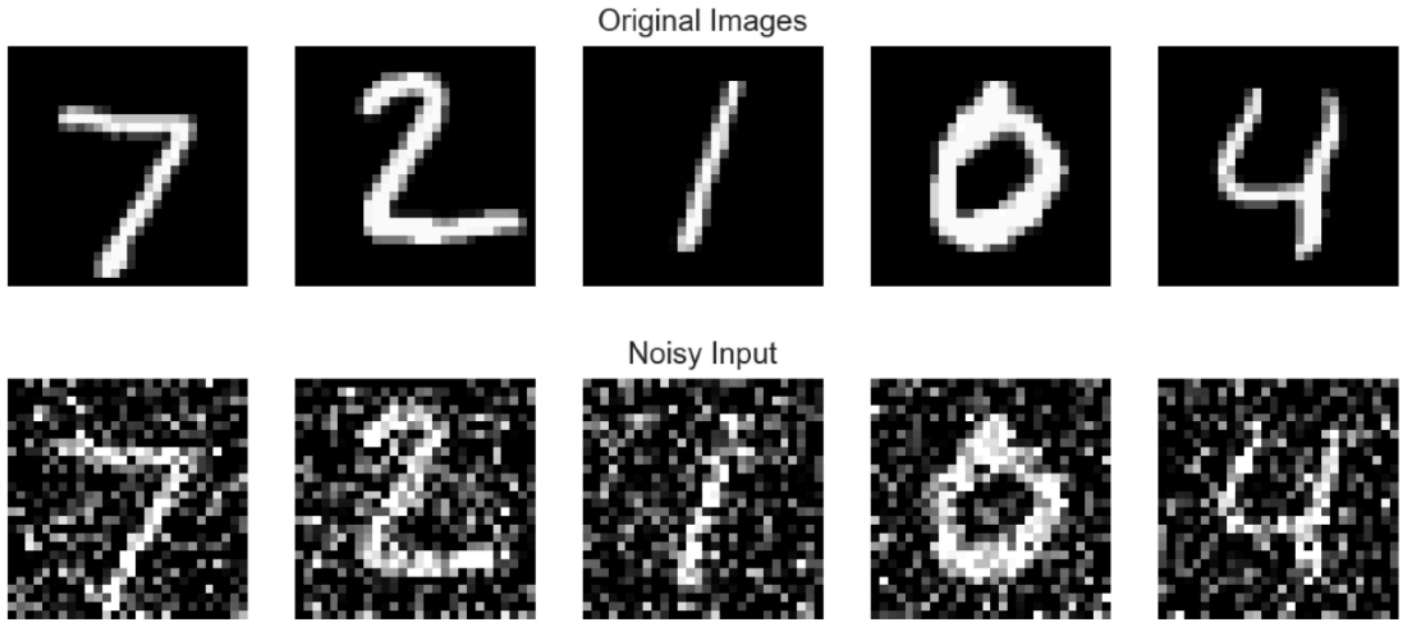
=> 가진 데이터를 통해 데이터를 더 얻어내는 것.



Noise Robustness

- Add random noises inputs or weights.

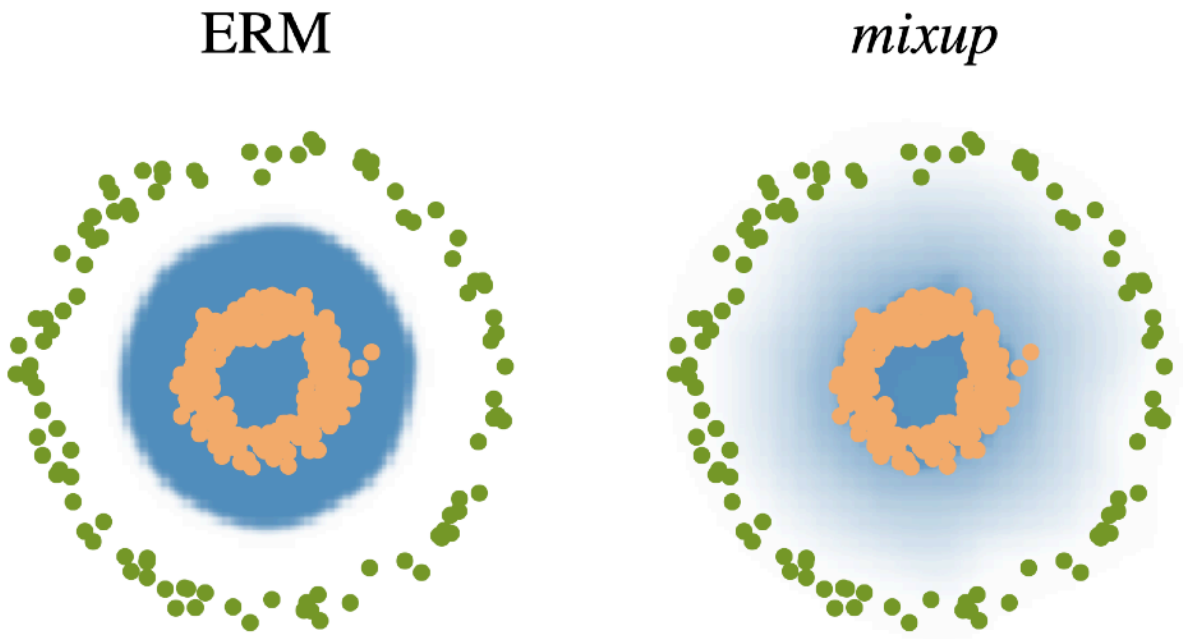
random noise 를 input과 weight에 주면,
test 에서 더 좋은 값을 얻는다는 것.



Label Smoothing

- **Mix-up** constructs augmented training examples by mixing both input and output of two randomly selected training data.

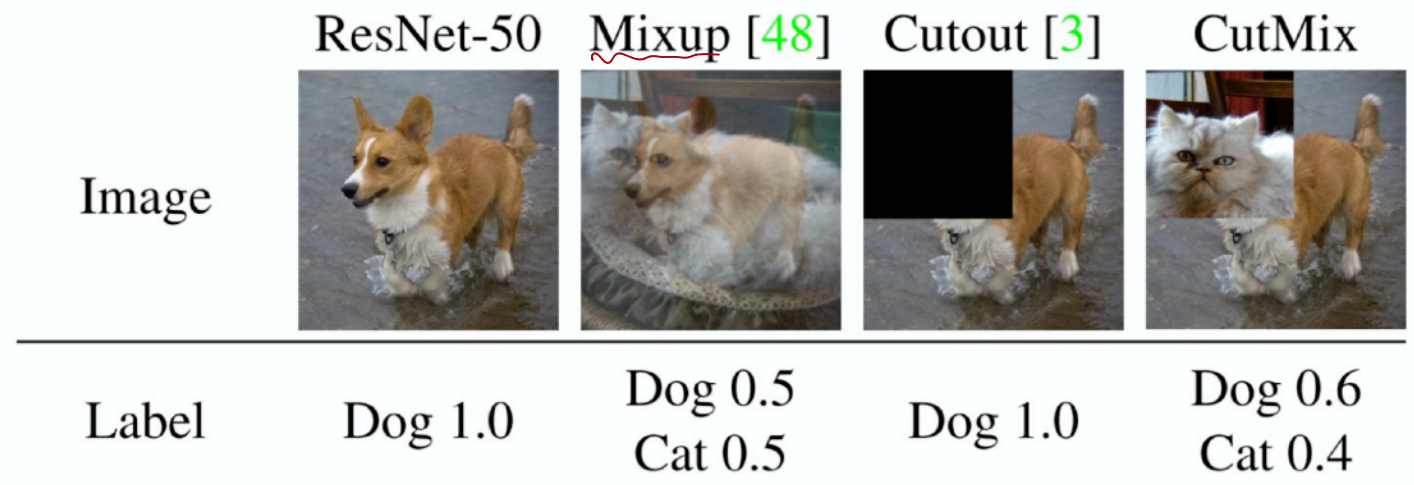
=> 데이터 2개를 뽑아서 섞는 것. (for data augmentation)
(부작용에 성능향상이 좋음)



mixup: Beyond Empirical Risk Minimization, 2018

Label Smoothing

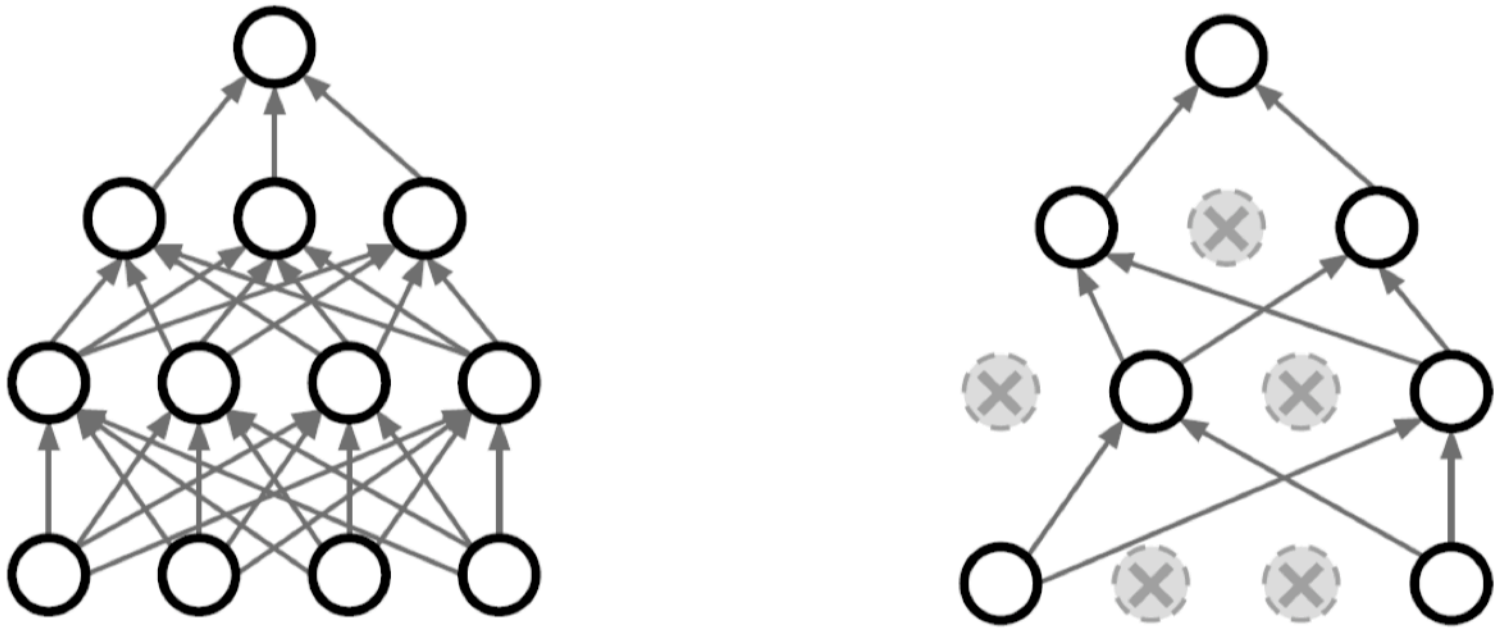
- **CutMix** constructs augmented training examples by mixing inputs with cut and paste and outputs with soft labels of two randomly selected training data.



CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features, 2019

Dropout

- In each forward pass, randomly set some neurons to zero.



Batch Normalization

- Batch normalization compute the empirical mean and variance independently for each dimension (layers) and normalize.

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2$$

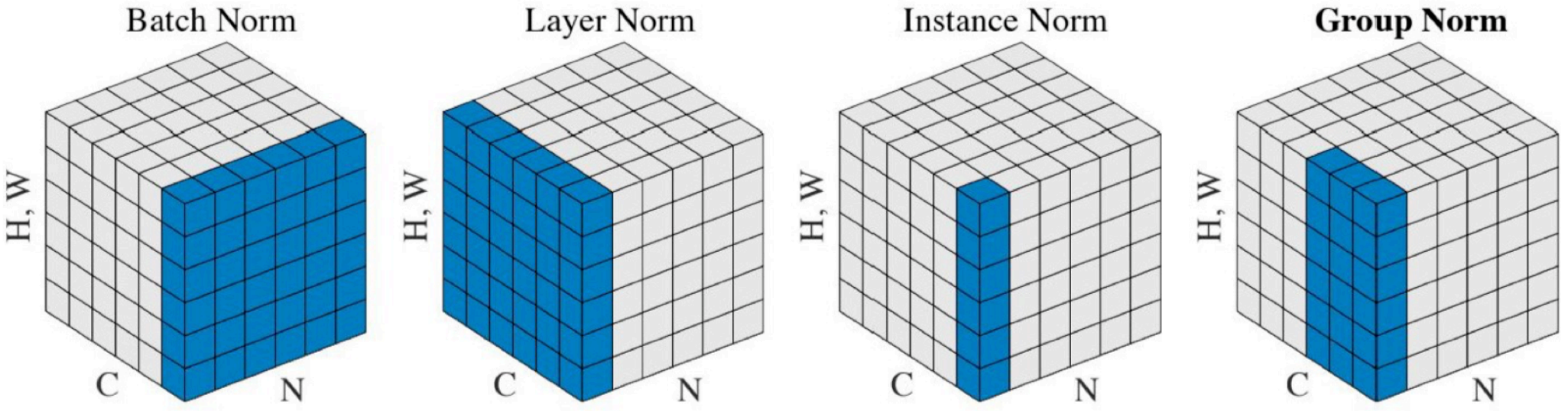
$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, 2015

Batch Normalization

- There are different variances of normalizations.

각 차원(레이어)에 대해 독립적으로 정규화 하는 것.



Group Normalization, 2018

Thank you for listening