

# Machine learning handbook

Optimizer

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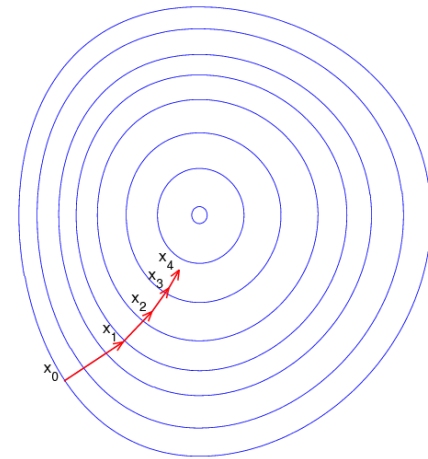
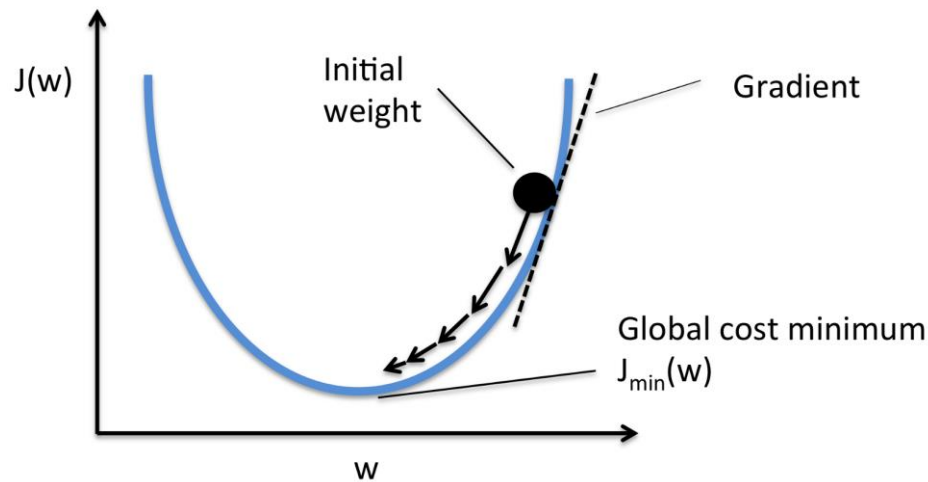
# Gradient descent algorithm

- Gradient Descent (GD)
- Full-batch Gradient Descent
- Stochastic Gradient Descent (SGD)
- Mini-batch (Stochastic) Gradient Descent

# Gradient Descent (GD): algorithm

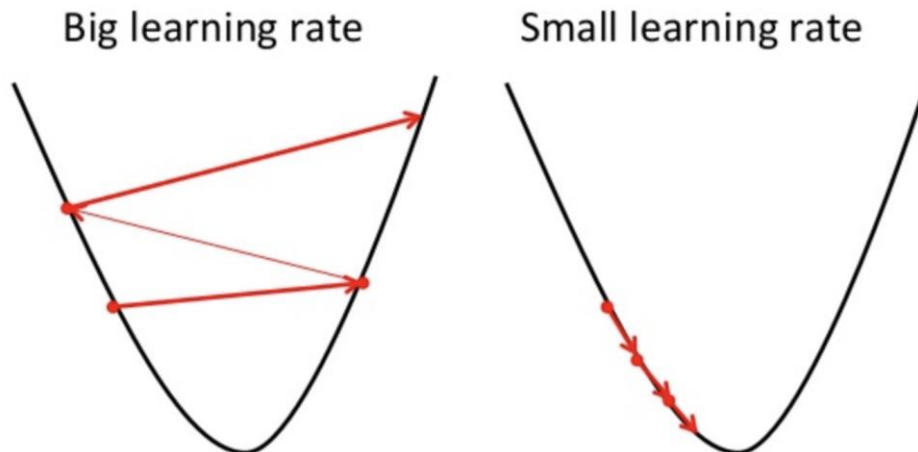
- Update rule

$$\theta = \theta - \eta * \frac{\partial}{\partial \theta} J(\theta)$$

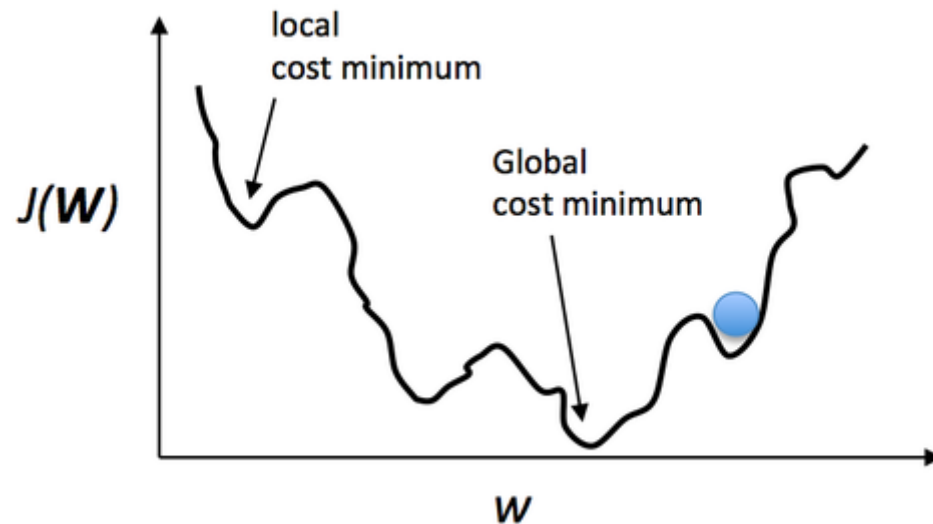


# Gradient Descent (GD): Learning rate

$$\theta = \theta - \eta * \frac{\partial}{\partial \theta} J(\theta)$$

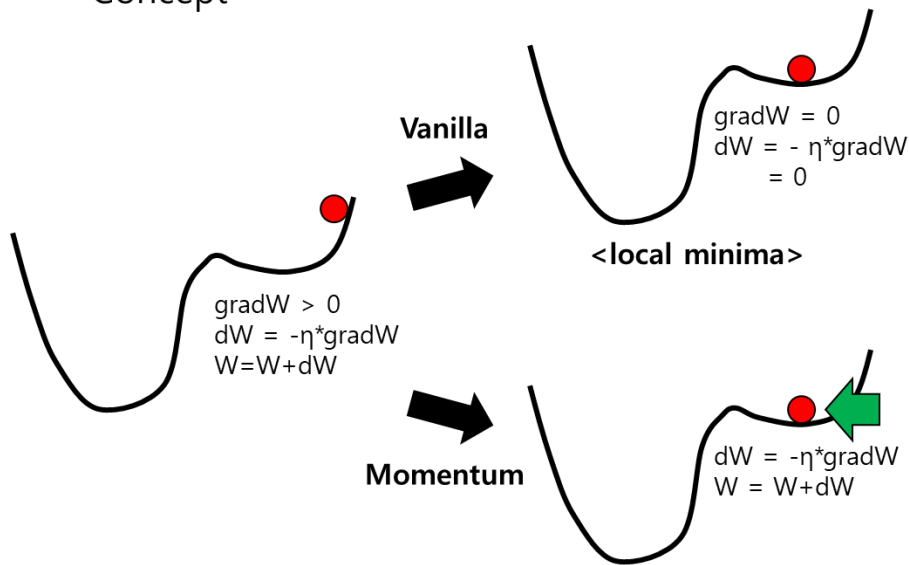


# Gradient Descent (GD): Local minimum problem

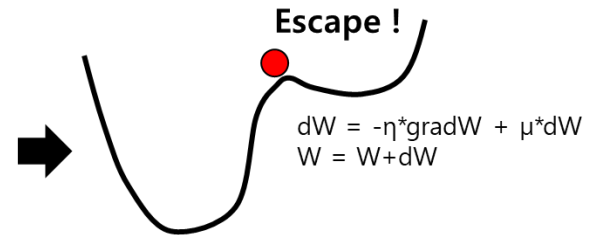


# Gradient Descent (GD): Momentum

- Concept

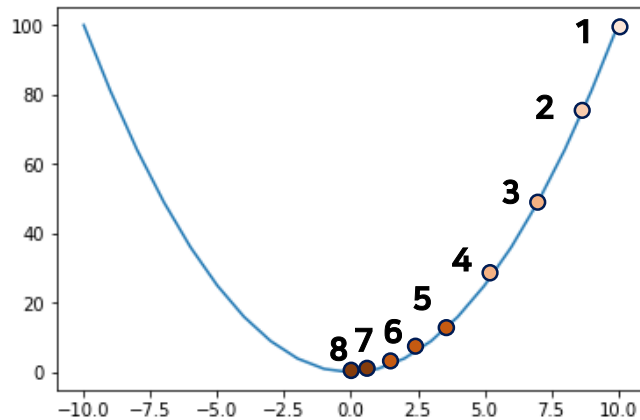


- **Vanilla method**에서는 Local minima에서 weight가 수렴할 때  $\text{grad}W=0 \rightarrow dW=0$ 이 되어 업데이트가 끝남
- **Momentum method**에서는  $dW$  계산시 gradient 외에 추가적인 외력 ( $+\mu * dW$ )을 가해 weight가 강제로 움직이도록 하여 local minima를 빠져나오게 도와줌

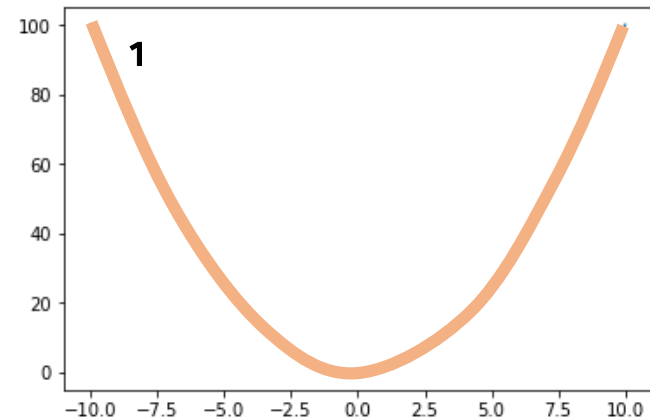


# Comparison

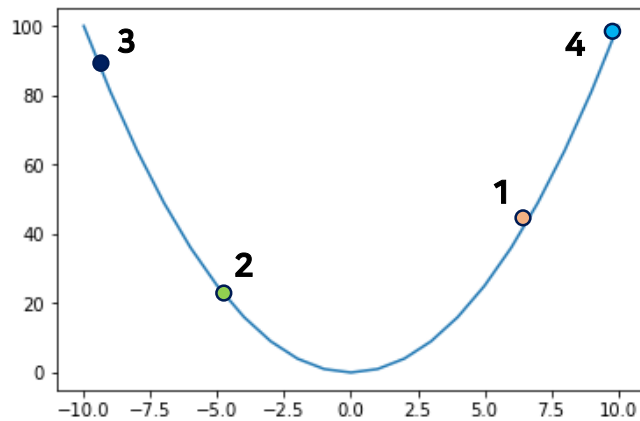
Gradient descent



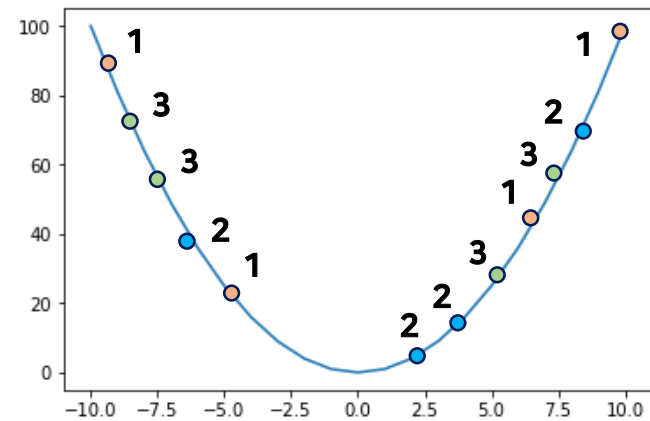
Full-batch gradient descent



Stochastic gradient descent



Mini-batch gradient descent



# 2

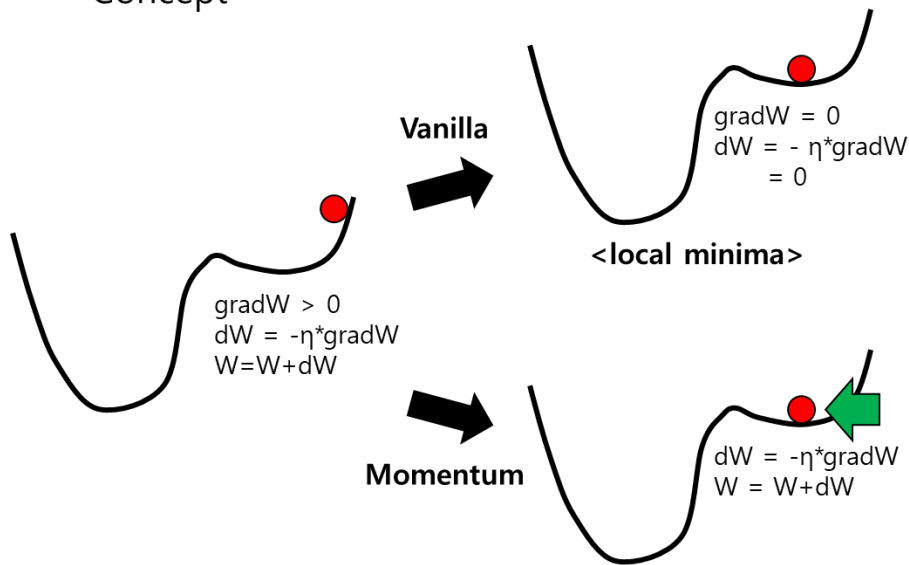
## Further materials

- Momentum
- Regularization (Weight decay)

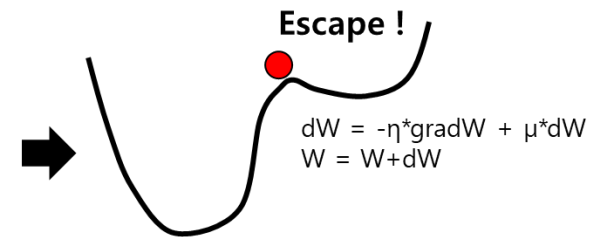


# Momentum

- Concept



- **Vanilla method**에서는 Local minima에서 weight가 수렴할 때  $\text{grad}W=0 \rightarrow dW=0$ 이 되어 업데이트가 끝남
- **Momentum method**에서는  $dW$  계산시 gradient 외에 추가적인 외력 ( $+\mu * dW$ )을 가해 weight가 강제로 움직이도록 하여 local minima를 빠져나오게 도와줌



# Momentum

- Parameters update methods

- Vanilla update

$$\Delta Weight_t = -\eta * Gradient_t$$
$$Weight_t = Weight_{t-1} + \Delta Weight_t$$

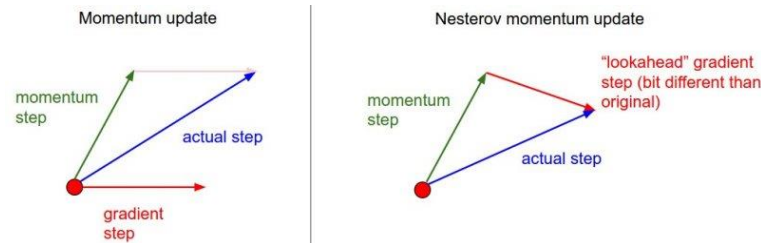
- Momentum update

- 직전 w 업데이트 ( $\Delta Weight_{t-1}$ ) \* momentum( $\mu$ )를 현재 w 업데이트에 추가

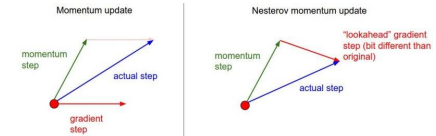
$$\Delta Weight_t = -\eta * Gradient_t + \mu * \Delta Weight_{t-1}$$
$$Weight_t = Weight_{t-1} + \Delta Weight_t$$

- Nesterov momentum update

- Momentum update와 비슷하지만, momentum를 더한 위치에서 Gradient 계산



# Momentum: Nesterov momentum update



- Parameters update methods
  - Nesterov momentum update

- Momentum update와 비슷하지만, momentum를 더한 위치에서 Gradient 계산

$$Weight\_ahead_t = Weight_t + \mu * \Delta Weight_{t-1}$$

- $Weight\_ahead_t$  이용해서  $Gradient\_ahead_t$  계산

$$\Delta Weight_t = -\eta * Gradient\_ahead_t + \mu * \Delta Weight_{t-1}$$

$$Weight_t = Weight_{t-1} + \Delta Weight_t$$

- 정리된 표현

$$\Delta Weight_t = -\eta * Gradient_t + \mu * \Delta Weight_{t-1}$$

$$\begin{aligned} Weight_t &= Weight_{t-1} + \Delta Weight_t + \mu * \Delta Weight_t - \mu * \Delta Weight_{t-1} \\ &= Weight_{t-1} + (1 + \mu) * \Delta Weight_t - \mu * \Delta Weight_{t-1} \end{aligned}$$

# Regularization (Weight decay)

- Weight 들의 absolute 값 총합을 줄이기 위한 방법 (극단적인 weight 값 방지)
- Weight 각각의 일정 비율 ( $\lambda, \textit{lambda}$ ) 을 곱해준 값을 gradient 값에서 빼준다.
- 이 때, learning rate 곱하기 전에 빼주기 !
- 매우 작은 값을 사용한다 (RBM에서는 0.0002)
- 예시 1: Vanilla update에서,

$$\Delta\theta = \eta\left(\frac{\partial E}{\partial\theta} - \lambda\theta\right)$$

- 예시 2: Momentum update에서,

$$\Delta\theta = \eta\left(\frac{\partial E}{\partial\theta} - \lambda\theta\right) + \mu\Delta\theta$$