

$$1. (a). \quad W_{t+1} - W^* = (1 - 2\eta\sigma^2)(W_t - W^*)$$

$$\therefore W^* = \frac{y}{\sigma^2}$$

$$\therefore W_t = W^* - W^*(1 - 2\eta\sigma^2)^t$$

$\therefore$  stable

$$\therefore |1 - 2\eta\sigma^2| < 1$$

$$\therefore -1 < 1 - 2\eta\sigma^2 < 1$$

$$\therefore 0 < \eta < \frac{1}{\sigma^2}$$

, converge to  $W^*$ .

$$(b). \quad W_t = (1 - (1 - 2\eta\sigma^2)^t) W^*$$

$$W_t - W^* = (1 - 2\eta\sigma^2)^t \cdot W^*$$

$$\therefore W^*(1 - 2\eta\sigma^2)^t \leq \epsilon \cdot W^*$$

$$\therefore (1 - 2\eta\sigma^2)^t \leq \epsilon$$

$$\therefore t \geq \frac{\log \epsilon}{\log |1 - 2\eta\sigma^2|}$$

$$\therefore t_{\min} = \left\lceil \frac{\log \epsilon}{\log |1 - 2\eta\sigma^2|} \right\rceil$$

$$(c). \quad \begin{cases} \sigma_L W[1] = Y[1] \\ \sigma_S W[2] = Y[2] \end{cases}$$

$$\therefore |1 - 2\eta\sigma_L^2| < 1, \quad |1 - 2\eta\sigma_S^2| < 1$$

$$\therefore 0 < \eta < \frac{1}{\sigma_L^2}, \quad \eta < \frac{1}{\sigma_S^2}$$

$$\therefore \sigma_L > \sigma_S$$

$$\therefore \eta < \frac{1}{\sigma_L^2}$$

$$(d). \quad \sigma_L \text{ faster.}$$

4/a. A.  $\beta_1 \theta_{t-1} + (1-\beta_1) \theta_t$   
 B.  $\beta_2 v_{t-1} + (1-\beta_2) \tilde{\theta}_t$

(b).  $\nabla f_t^{\text{reg}}(\theta) = \nabla f_t(\theta) + \lambda \theta$

$$\begin{aligned} \theta_t &= \theta_{t-1} - \eta \nabla f_{t-1}^{\text{reg}}(\theta_{t-1}) = \theta_{t-1} - \eta (\nabla f_{t-1}(\theta_{t-1}) + \lambda \theta_{t-1}) \\ &= (1-\eta\lambda) \theta_{t-1} - \eta \nabla f_{t-1}(\theta_{t-1}) \end{aligned}$$

$$\theta_t = (1-\nu) \theta_{t-1} - \eta \nabla f_{t-1}(\theta_{t-1})$$

identical if  $1-\nu = 1-\eta\lambda$ .

i.e.  $\nu = \eta\lambda$

$\therefore$  SGD with weight decay using  $\nu = \eta\lambda$  on  $f_t(\theta)$  is equal to vanilla SGD on  $L_2$ -regularized loss  $f_t^{\text{reg}}(\theta)$ .