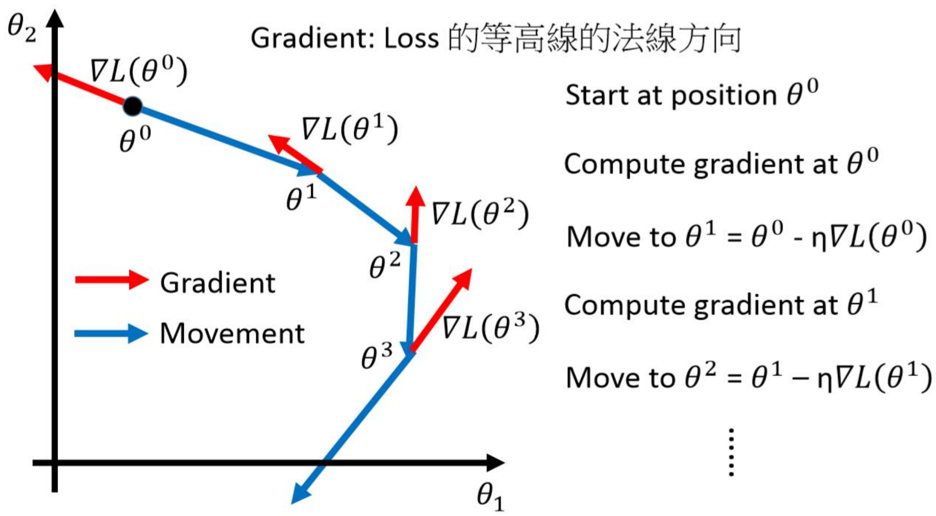
New Optimizers for Deep Learning

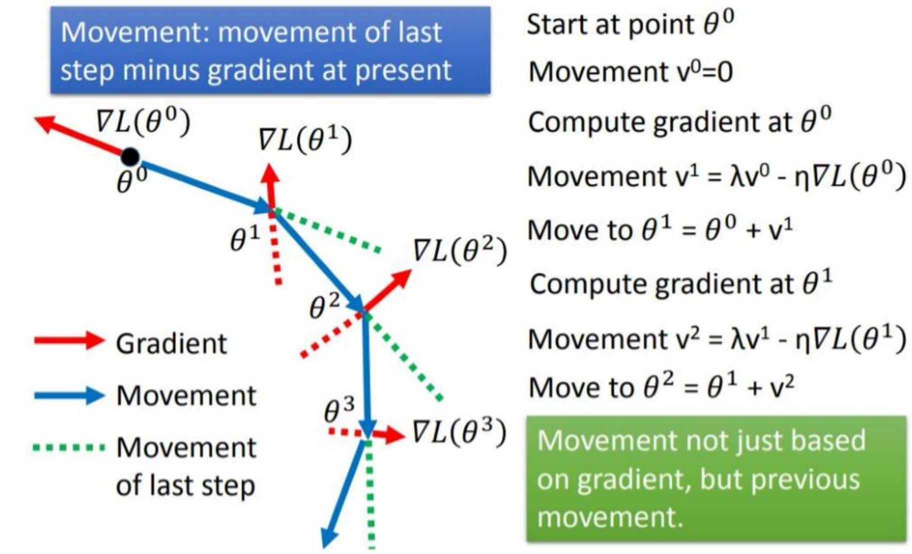
Some Notations

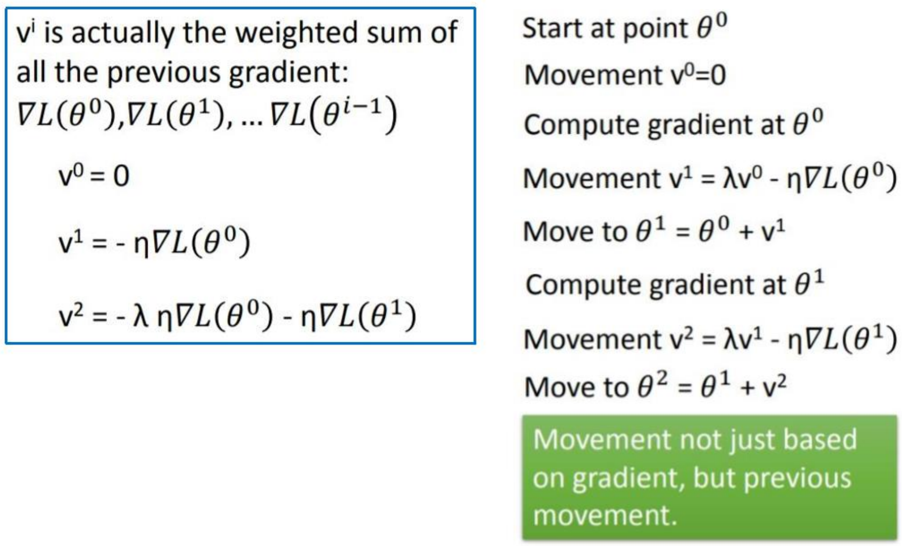
- θ_t:第 t 次迭代的模型参数
- $\nabla L(\theta_t)$ or g_t:用于计算θ_{t+1}的梯度θ_t
- m_{t+1}:从第 0 到 t 次迭代积累的动量，计算梯度θ_t

SGD

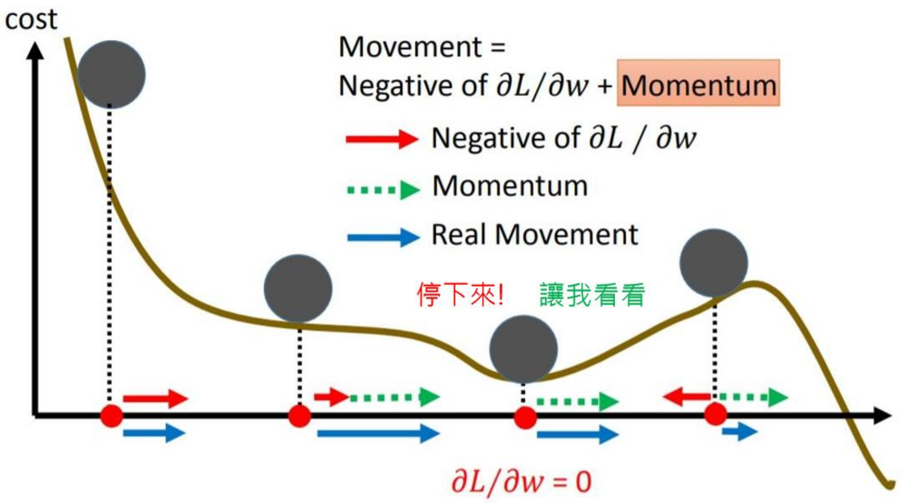


SGDM





Why momentum?



Adagrad

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\sum_{i=0}^{t-1}(g_i)^2}} g_{t-1}$$

RMSProp

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t}} g_{t-1}$$

$$v_1 = {g_0}^2, v_t = \alpha v_{t-1} + (1-\alpha)(g_{t-1})^2$$

Adam

- SGDM

$$\theta_t = \theta_{t-1} - \eta m_t$$

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

- RMSProp

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t}} g_{t-1}$$

$$v_1 = {g_0}^2, v_t = \beta_2 v_{t-1} + (1-\beta_2)(g_{t-1})^2$$

$$\boxed{\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t + \varepsilon}} \hat{m}_t}$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\beta_1 = 0.9$$

$$\beta_2 = 0.999$$

$$\varepsilon = 10^{-8}$$

AMSGrad

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t + \varepsilon}} m_t$$

$$\hat{v}_t = \max(\hat{v}_{t-1}, v_t)$$

RAdam

$$p_t = p_\infty - \frac{2t{\beta_2}^t}{1-{\beta_2}^t}$$

$$p_\infty = \frac{2}{1-\beta_2} - 1$$

$$r_t = \sqrt{\frac{(p_t-4)(p_t-2)p_\infty}{(p_\infty-4)(p_\infty-2)p_t}}$$

When $p_t \leq 4$(first few steps of training)

$$\theta_t = \theta_{t-1} - \eta \hat{m}_t$$

When $p_t > 4$

$$\theta_t = \theta_{t-1} - \frac{\eta r_t}{\sqrt{\hat{v}_t + \varepsilon}} \hat{m}_t$$

L2 regularization

$$L_{l_2}(\theta) = L(\theta) + \frac{1}{2}\gamma||\theta||^2$$

SGD: $\theta_t = \theta_{t-1} - \nabla L_{l_2}(\theta_{t-1})$

$$= \theta_{t-1} - \nabla L(\theta_{t-1}) - \gamma|\theta_{t-1}|$$

SGDM: $\theta_t = \theta_{t-1} - \lambda m_{t-1} - \eta(\nabla L(\theta_{t-1}) + \gamma|\theta_{t-1}|)$

$$m_t = \lambda m_{t-1} + \eta(\nabla L(\theta_{t-1}) + \gamma|\theta_{t-1}|)$$

Adam: $m_t = \lambda m_{t-1} + \eta(\nabla L(\theta_{t-1}) + \gamma|\theta_{t-1}|)$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla L(\theta_{t-1}) + \gamma|\theta_{t-1}|)^2$$

SGDWM: $\theta_t = \theta_{t-1} - m_t - \gamma\theta_{t-1}$

$$m_t = \lambda m_{t-1} + \eta\big(\nabla L(\theta_{t-1})\big)$$

AdamW: $m_t = \beta_1 m_{t-1} + (1-\beta_1)\big(\nabla L(\theta_{t-1})\big)$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\big(\nabla L(\theta_{t-1})\big)^2$$

$$\theta_t = \theta_{t-1} - \eta\left(\frac{1}{\sqrt{\hat{v}_t + \varepsilon}}\widehat{m}_t - \gamma\theta_{t-1}\right)$$

SGDM vs Adam

SGDM	Adam
• Slow • Better convergence • Stable • Smaller generalization gap	• Fast • Possibly non-convergence • Unstable • Larger generalization gap

Advices

SGDM	Adam
• Computer vision Image classification Segmentation Object detection	• NLP QA Machine translation Summary • Speech synthesis • GAN • Reinforcement learning