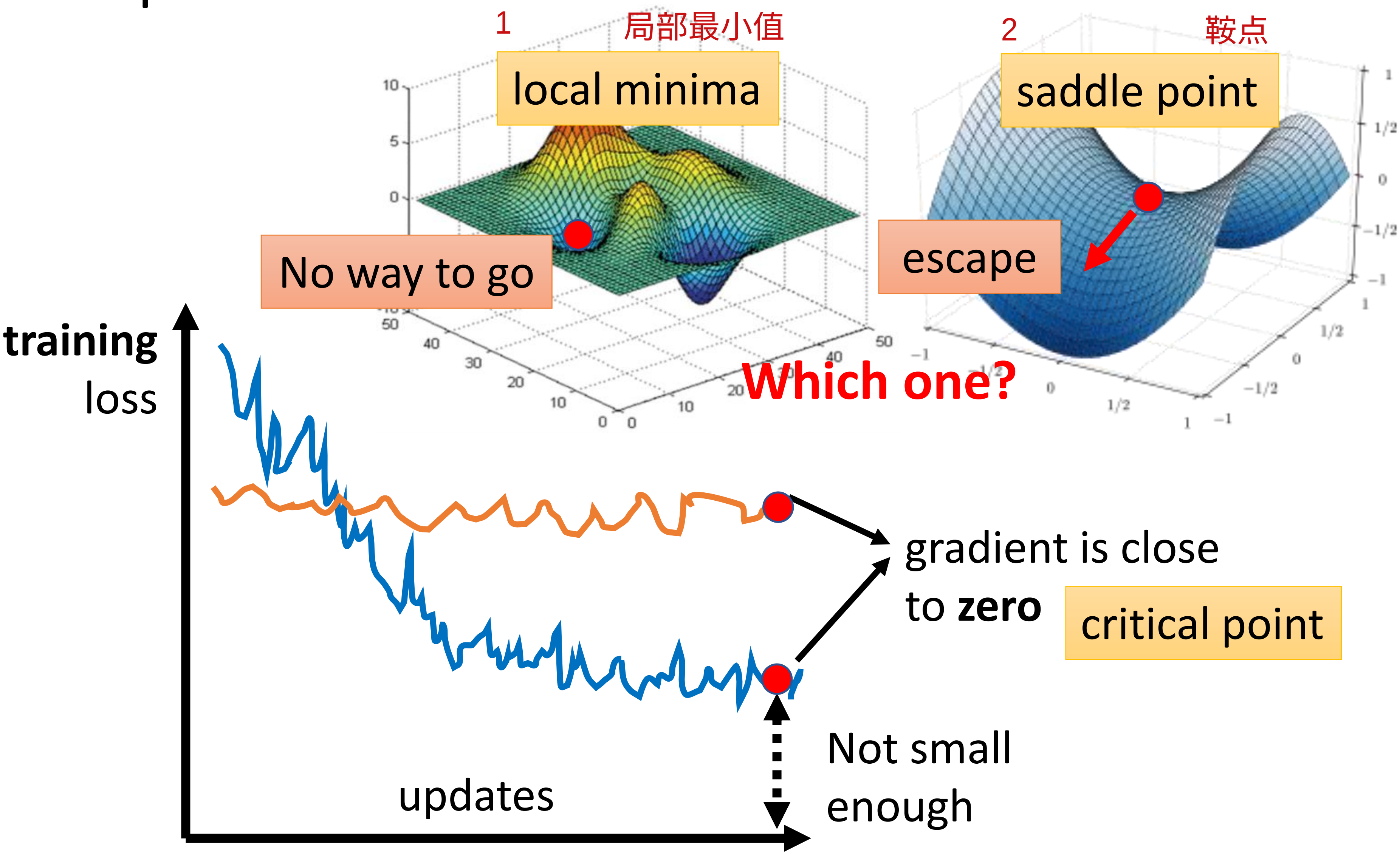
When gradient is small …

Hung-yi Lee 李宏毅

Optimization Fails because ……



Warning of Math

你过来啊 ！

Tayler Series Approximation 泰勒级数展开

$L(\boldsymbol{\theta})$ around $\boldsymbol{\theta} = \boldsymbol{\theta}'$ can be approximated below

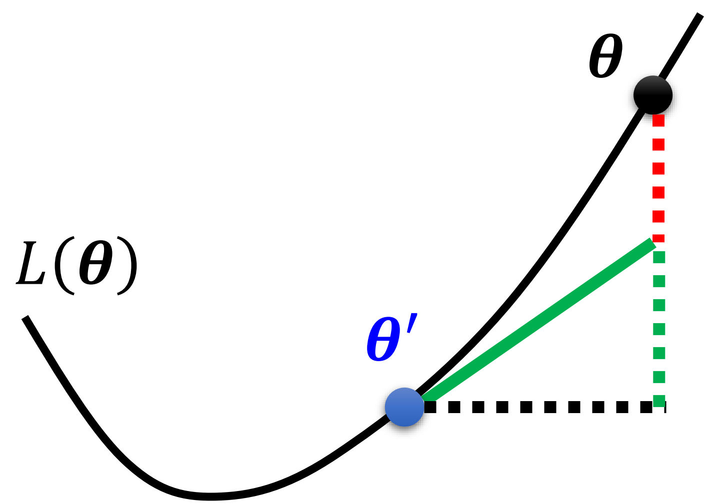
$$L(\boldsymbol{\theta}) \approx L(\boldsymbol{\theta}') + \boxed{(\boldsymbol{\theta} - \boldsymbol{\theta}')^T \boldsymbol{g}} + \boxed{\frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}')^T H (\boldsymbol{\theta} - \boldsymbol{\theta}')}$$

Gradient $\boldsymbol{g}$ is a ***vector***

$$\boldsymbol{g} = \nabla L(\boldsymbol{\theta}') \qquad \boldsymbol{g}_i = \frac{\partial L(\boldsymbol{\theta}')}{\partial \boldsymbol{\theta}_i}$$

Hessian H is a ***matrix***

$$H_{ij} = \frac{\partial^2}{\partial \boldsymbol{\theta}_i \partial \boldsymbol{\theta}_j} L(\boldsymbol{\theta}')$$



Source of image:http://www.offconvex.org/2016/03/22/saddlepoints/

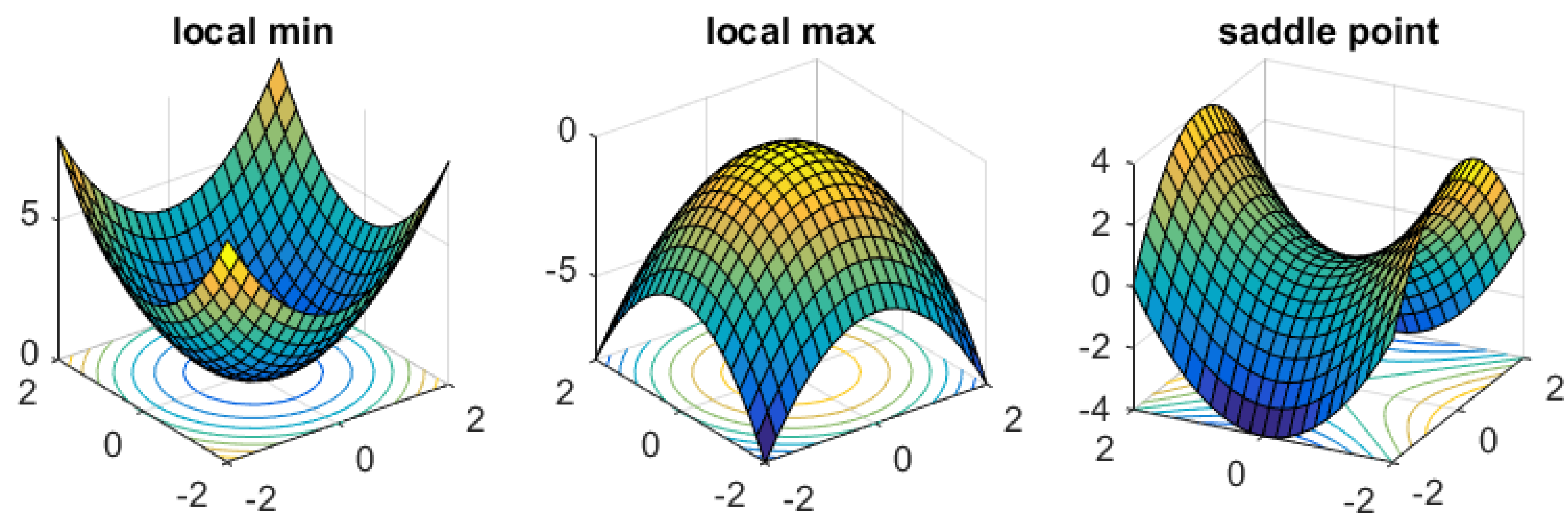
Hessian

$L(\boldsymbol{\theta})$ around $\boldsymbol{\theta} = \boldsymbol{\theta}'$ can be approximated below

$$L(\boldsymbol{\theta}) \approx L(\boldsymbol{\theta}') + \boxed{\cancel{(\boldsymbol{\theta} - \boldsymbol{\theta}')^T \boldsymbol{g}}} + \boxed{\frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}')^T H (\boldsymbol{\theta} - \boldsymbol{\theta}')}$$

At critical point

telling the properties of critical points



算出Hessian矩阵，计算所有特征值：
1. all positive → local minima
2. all negative → local maxima
3. else → saddle point

Hessian

At critical point: $\boldsymbol{v}^T H \boldsymbol{v}$

$$L(\boldsymbol{\theta}) \approx L(\boldsymbol{\theta}') + \boxed{\frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}')^T H (\boldsymbol{\theta} - \boldsymbol{\theta}')}$$

For all $\boldsymbol{v}$

1. $\boldsymbol{v}^T H \boldsymbol{v} > 0$ ➡ Around $\boldsymbol{\theta}'$: $L(\boldsymbol{\theta}) > L(\boldsymbol{\theta}')$ ➡ **Local minima**

= H is positive definite = All eigen values are positive.

特征值

For all $\boldsymbol{v}$

2. $\boldsymbol{v}^T H \boldsymbol{v} < 0$ ➡ Around $\boldsymbol{\theta}'$: $L(\boldsymbol{\theta}) < L(\boldsymbol{\theta}')$ ➡ **Local maxima**

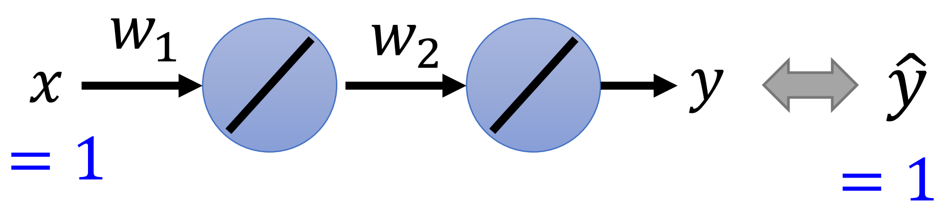
= H is negative definite = All eigen values are negative.

3. Sometimes $\boldsymbol{v}^T H \boldsymbol{v} > 0$, sometimes $\boldsymbol{v}^T H \boldsymbol{v} < 0$ ➡ **Saddle point**

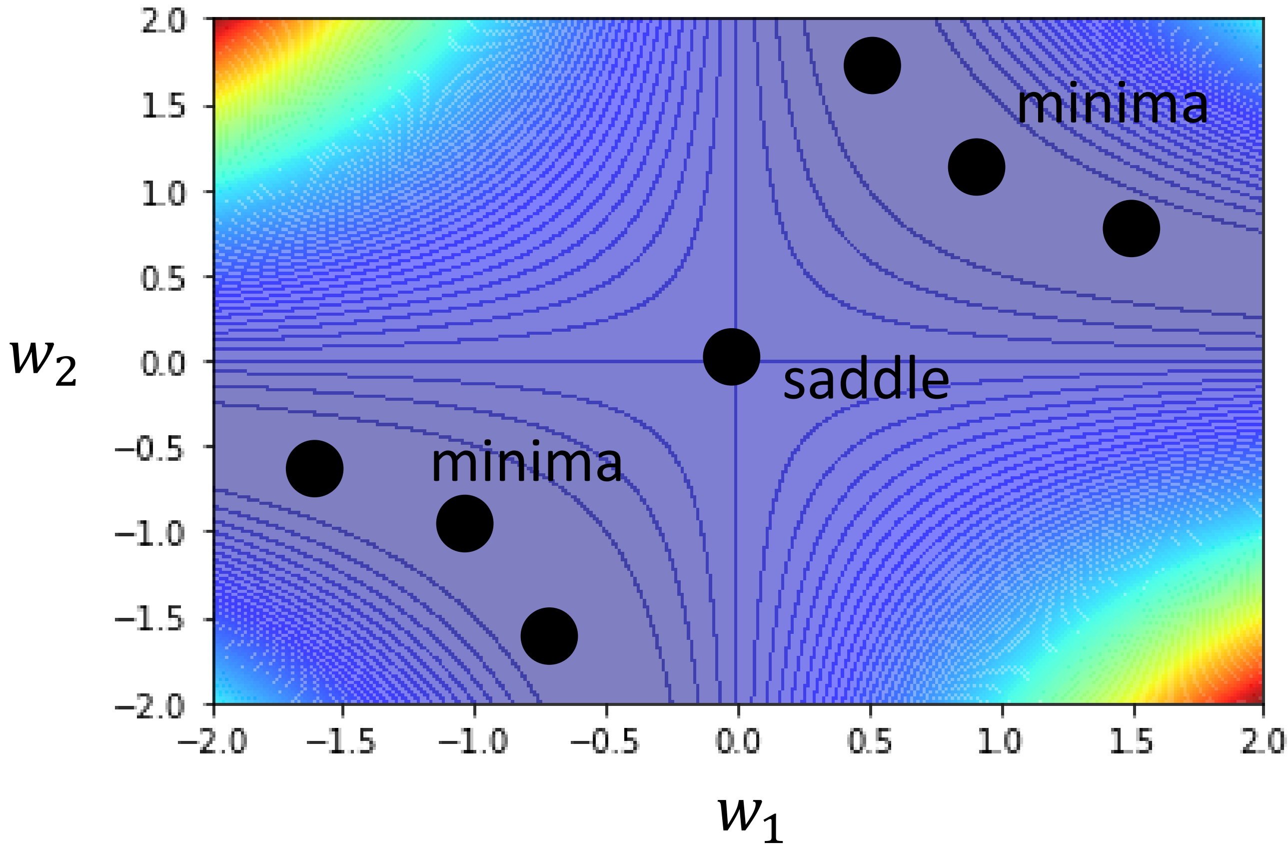
Some eigen values are positive, and some are negative.

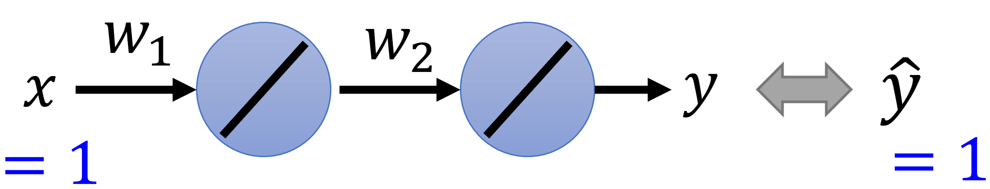
Example

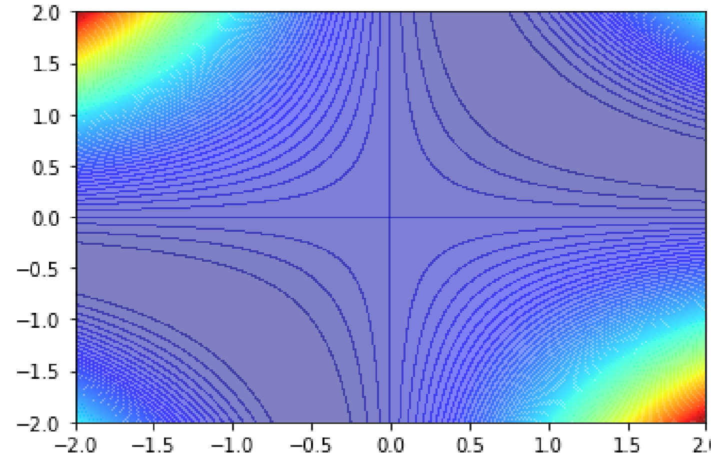
$y = w_1 w_2 x$ （史上最废neural network）



Error Surface







$$L = (\hat{y} - w_1 w_2 x)^2 = (1 - w_1 w_2)^2$$

$$\frac{\partial L}{\partial w_1} = 2(1 - w_1 w_2)(-w_2) = 0$$

$$\frac{\partial L}{\partial w_2} = 2(1 - w_1 w_2)(-w_1) = 0$$

g

Critical point: $w_1 = 0, w_2 = 0$

$$H = \begin{bmatrix} 0 & -2 \\ -2 & 0 \end{bmatrix} \quad \lambda_1 = 2, \lambda_2 = -2$$

Saddle point

H

$$\frac{\partial^2 L}{\partial {w_1}^2} = 2(-w_2)(-w_2) = 0 \qquad \frac{\partial^2 L}{\partial w_1 \partial w_2} = -2 + 4 w_1 w_2 = -2$$

$$\frac{\partial^2 L}{\partial w_2 \partial w_1} = -2 + 4 w_1 w_2 = -2 \qquad \frac{\partial^2 L}{\partial {w_2}^2} = 2(-w_1)(-w_1) = 0$$

Don't afraid of saddle point?

At critical point: $L(\boldsymbol{\theta}) \approx L(\boldsymbol{\theta}') + \underbrace{\boxed{\frac{1}{2}(\boldsymbol{\theta}-\boldsymbol{\theta}')^T H (\boldsymbol{\theta}-\boldsymbol{\theta}')}}^{\boldsymbol{v}^T H \boldsymbol{v}}$

Sometimes $\boldsymbol{v}^T H \boldsymbol{v} > 0$, sometimes $\boldsymbol{v}^T H \boldsymbol{v} < 0$ ➡ Saddle point

H may tell us parameter update direction!

$\boldsymbol{u}$ is an eigen vector of H

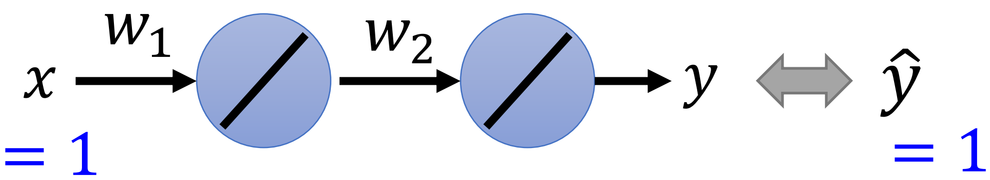
λ is the eigen value of $\boldsymbol{u}$

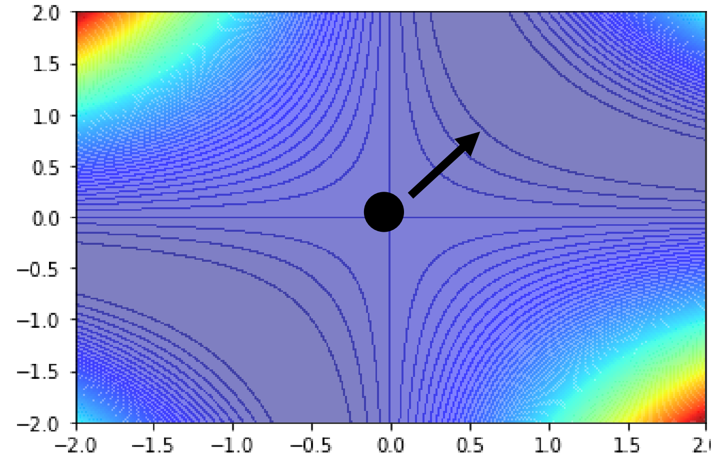
$\lambda < 0$

➡ $\underbrace{\boldsymbol{u}^T H \boldsymbol{u}}_{<0} = \boldsymbol{u}^T(\lambda \boldsymbol{u}) = \underbrace{\lambda \|\boldsymbol{u}\|^2}_{<0}$

$$L(\boldsymbol{\theta}) \approx L(\boldsymbol{\theta}') + \frac{1}{2}(\overbrace{\boldsymbol{\theta}-\boldsymbol{\theta}'}^{\boldsymbol{u}})^T H (\overbrace{\boldsymbol{\theta}-\boldsymbol{\theta}'}^{\boldsymbol{u}}) \Rightarrow L(\boldsymbol{\theta}) < L(\boldsymbol{\theta}')$$

$\boldsymbol{\theta}-\boldsymbol{\theta}' = \boldsymbol{u}$ $\quad$ $\boldsymbol{\theta} = \boldsymbol{\theta}' + \boldsymbol{u}$ $\quad$ Decrease L





$$L = (\hat{y} - w_1 w_2 x)^2 \; = (1 - w_1 w_2)^2$$

$$\frac{\partial L}{\partial w_1} = 2(1 - w_1 w_2)(-w_2)$$

$$\frac{\partial L}{\partial w_2} = 2(1 - w_1 w_2)(-w_1)$$

Critical point: $w_1 = 0, w_2 = 0$

$$H = \begin{bmatrix} 0 & -2 \\ -2 & 0 \end{bmatrix} \quad \lambda_1 = 2, \lambda_2 = -2$$

Saddle point

$\lambda_2 = -2$ Has eigenvector $\boldsymbol{u} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

Update the parameter along the direction of $\boldsymbol{u}$

You can escape the saddle point and decrease the loss.

实际中，不会用Hessian来逃离saddle point，计算量太大啦

(this method is seldom used in practice)

End of Warning

Saddle Point v.s. Local Minima

- A.D. 1543

1453年
君士坦丁堡沦陷
Fall of Constantinople

來源《三體Ⅲ·死神永生》

Saddle Point v.s. Local Minima

- The Magician Diorena（魔法師狄奧倫娜）

From 3 dimensional space, it is sealed.

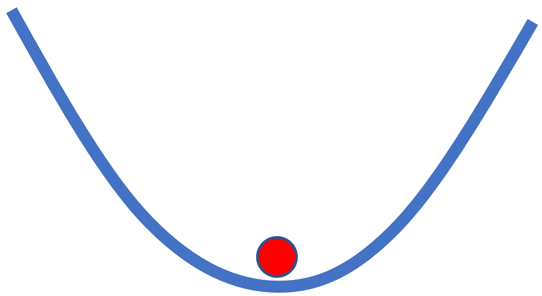
It is not in higher dimensions.

Source of image: https://read01.com/mz2DBPE.html#.YECz22gzbIU

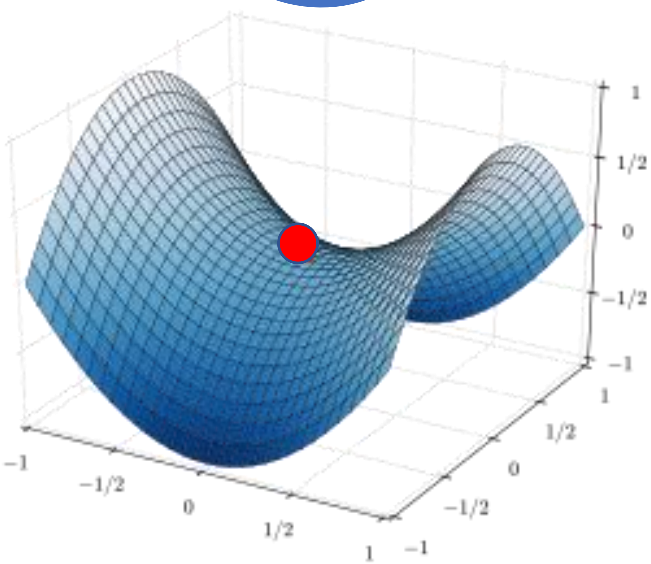
Source of image: https://arxiv.org/abs/1712.09913

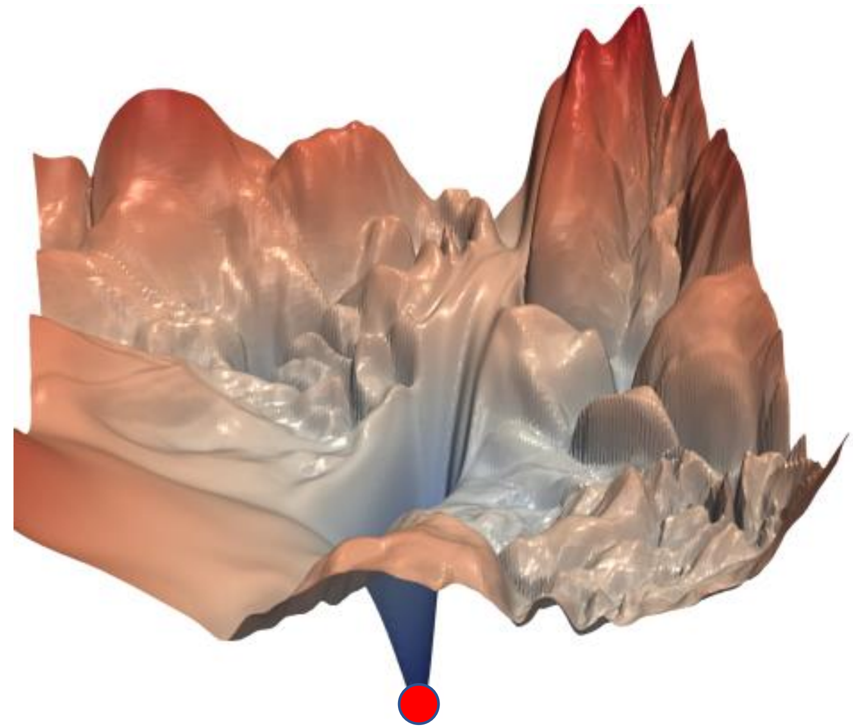
Saddle Point v.s. Local Minima

二维



三维

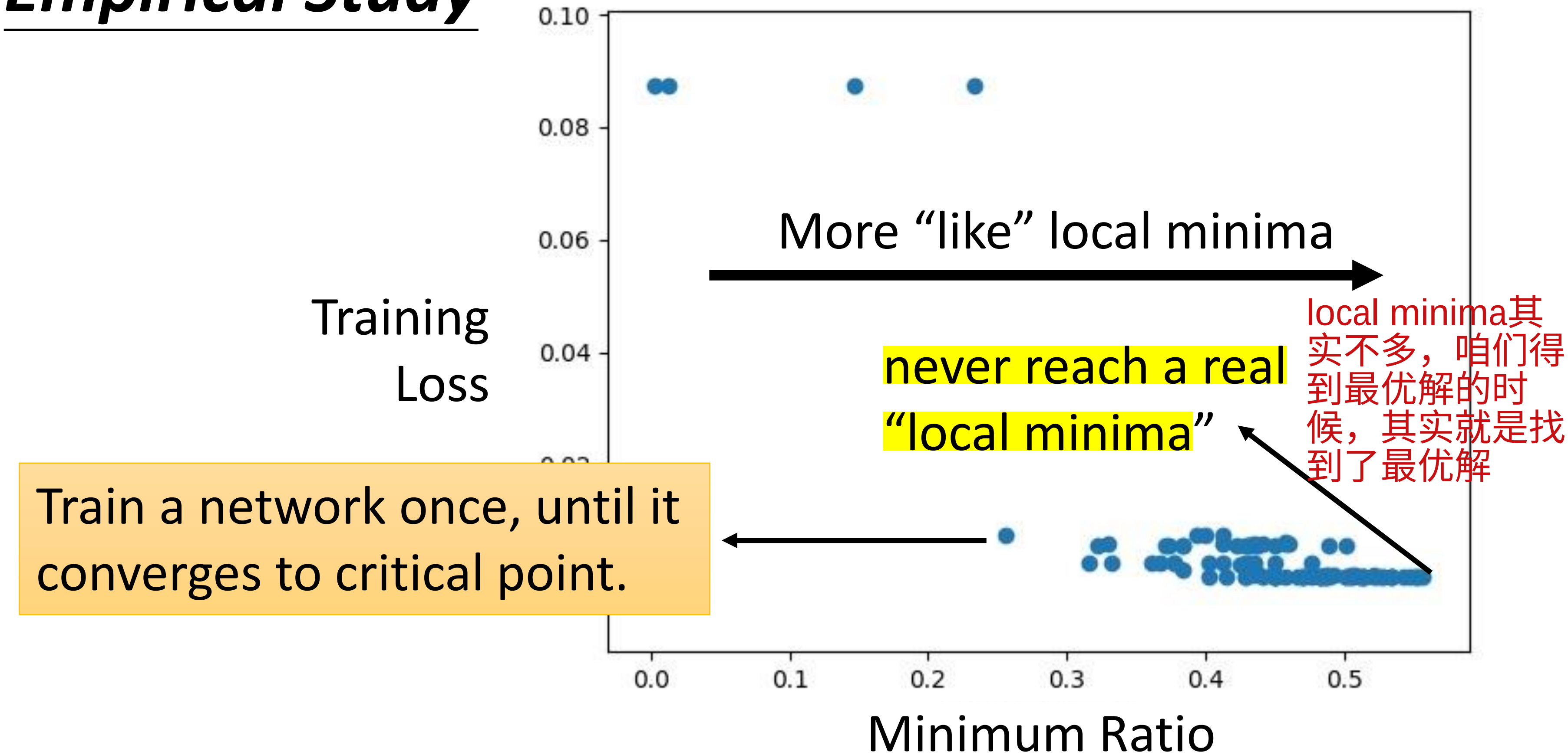




Saddle point in higher dimension?

When you have lots of parameters, perhaps local minima is rare?

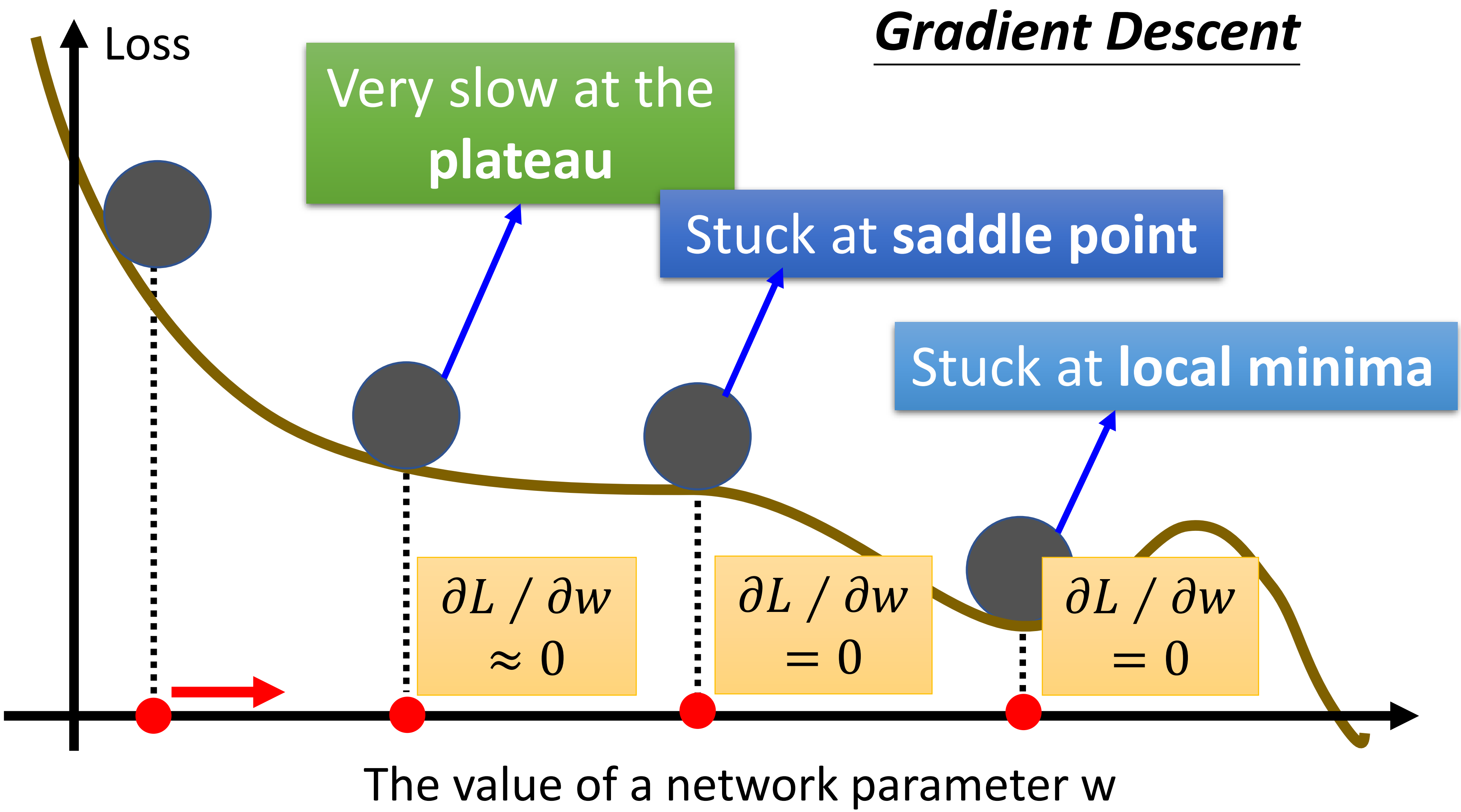
Empirical Study



$$\text{Minimum ratio} = \frac{\text{Number of } \textbf{Positive} \text{ Eigen values}}{\text{Number of Eigen values}}$$

Source:https://docs.google.com/presentation/d/1siUFXARYRpNiMeSRwgFbt7mZVjkMPhR5od09w0Z8xaU/edit#slide=id.g31470fd33a_0_33

Small Gradient …



Tips for training:
Batch and **Momentum**

Batch

批次，也叫mini-batch

Review: Optimization with Batch

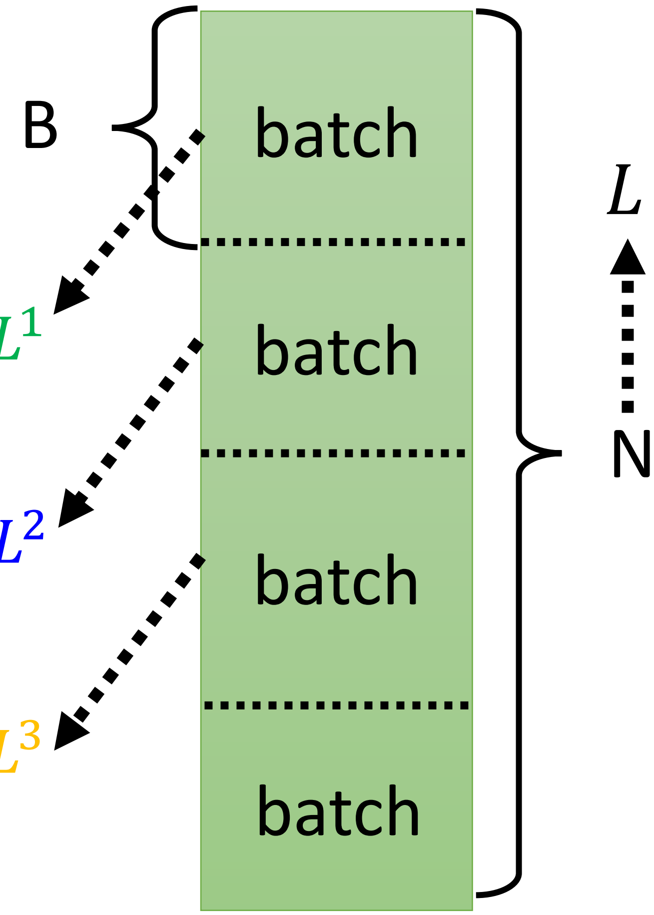
$$\boldsymbol{\theta}^* = arg\min_{\boldsymbol{\theta}} L$$

- (Randomly) Pick initial values $\boldsymbol{\theta}^0$
- Compute gradient $\boldsymbol{g}^{\mathbf{0}} = \nabla L^1(\boldsymbol{\theta}^0)$ $\quad L^1$

  update $\boldsymbol{\theta}^1 \leftarrow \boldsymbol{\theta}^0 - \eta \boldsymbol{g}^{\mathbf{0}}$
- Compute gradient $\boldsymbol{g}^{\mathbf{1}} = \nabla L^2(\boldsymbol{\theta}^1)$ $\quad L^2$

  update $\boldsymbol{\theta}^2 \leftarrow \boldsymbol{\theta}^1 - \eta \boldsymbol{g}^{\mathbf{1}}$
- Compute gradient $\boldsymbol{g}^{\mathbf{3}} = \nabla L^3(\boldsymbol{\theta}^2)$ $\quad L^3$

  update $\boldsymbol{\theta}^3 \leftarrow \boldsymbol{\theta}^2 - \eta \boldsymbol{g}^{\mathbf{3}}$



1 **epoch** = see all the batches once → **Shuffle** after each epoch

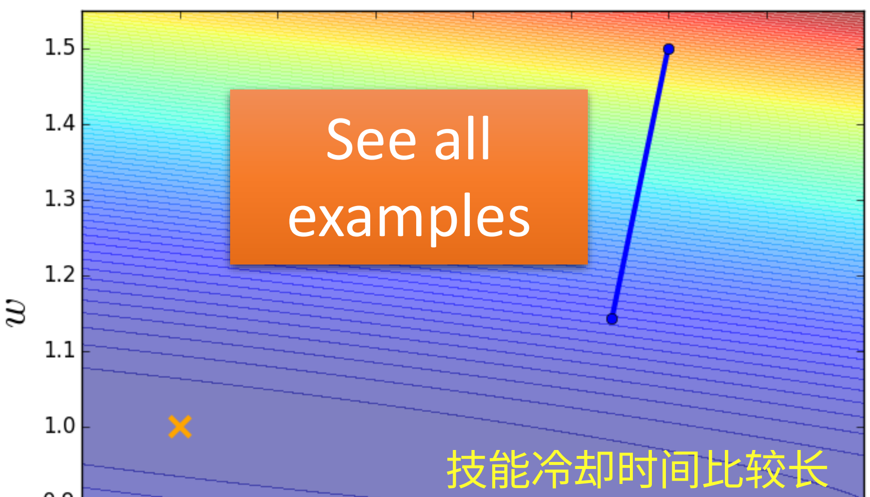
Small Batch v.s. Large Batch

Consider 20 examples (N=20)

Batch size = N (Full batch)

Full batch就是没用mini-batch

Update after seeing all the 20 examples

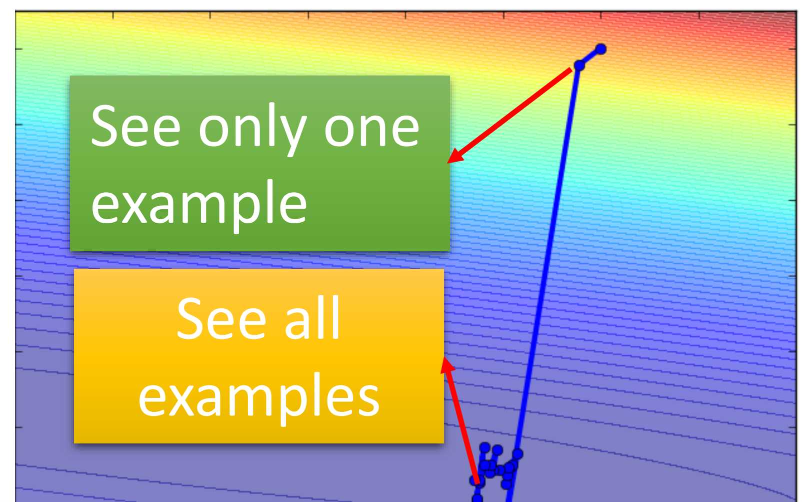


Long time for cooldown, but powerful

Batch size = 1

Update for each example

Update 20 times in an epoch



Short time for cooldown, but noisy 曲曲折折前进

oldest slides: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf
old slides: http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2017/Lecture/Keras.pdf

Small Batch v.s. Large Batch

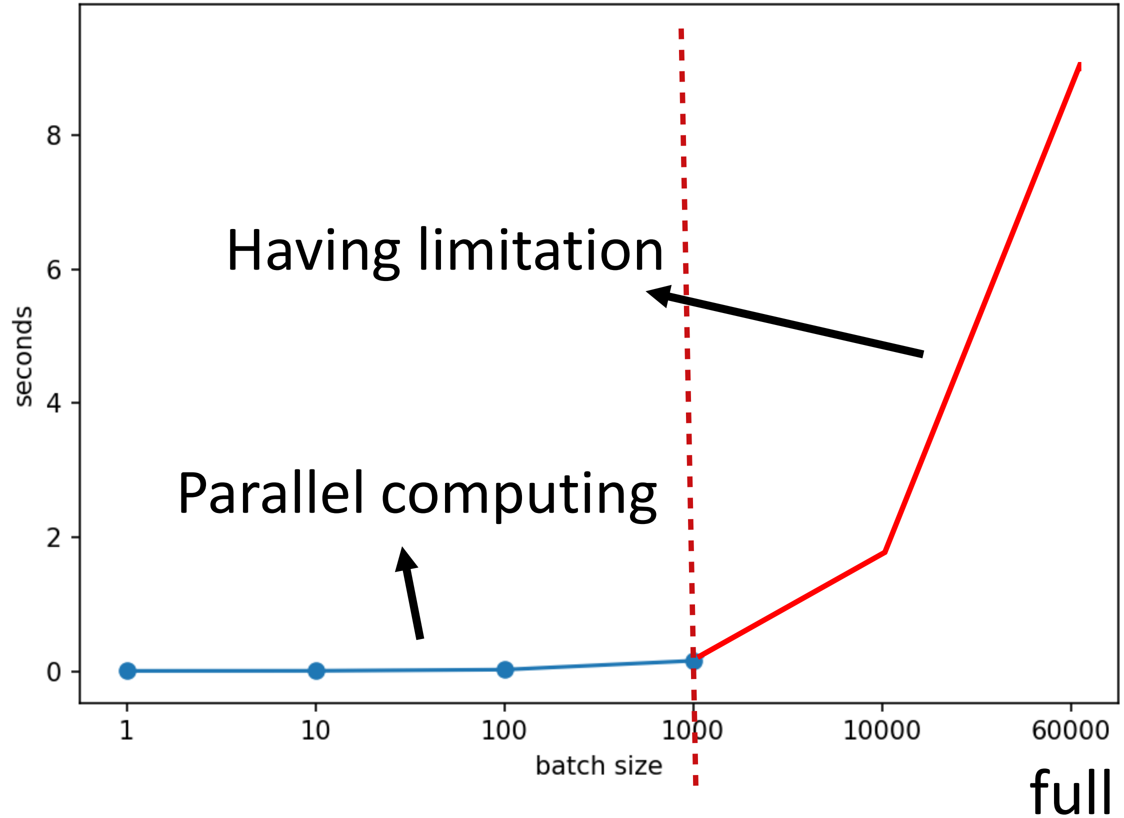
- Larger batch size does **not** require longer time to compute gradient (unless batch size is too large)

Time for each update

MNIST: digit classification

Tesla V100 GPU

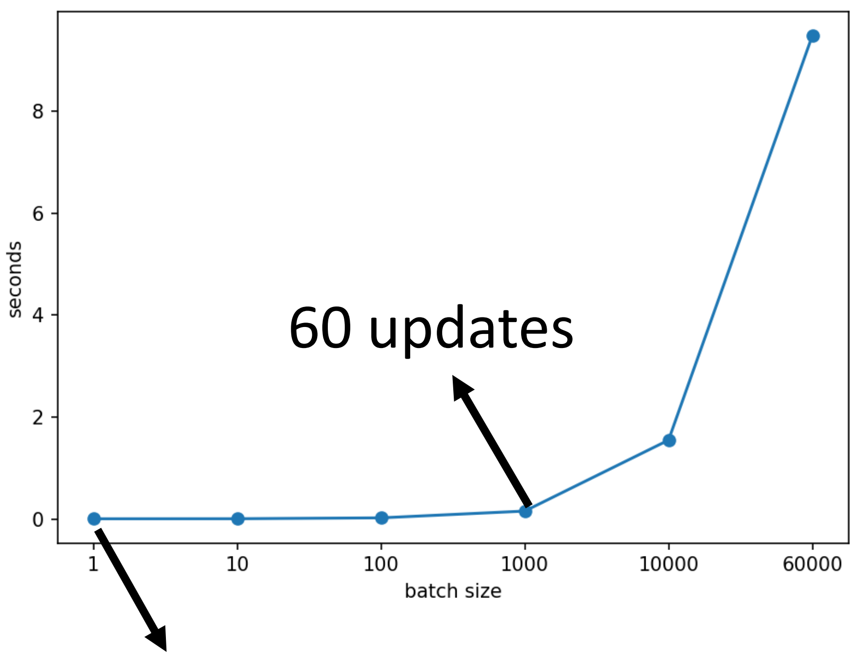
可以做平行运算



Small Batch v.s. Large Batch

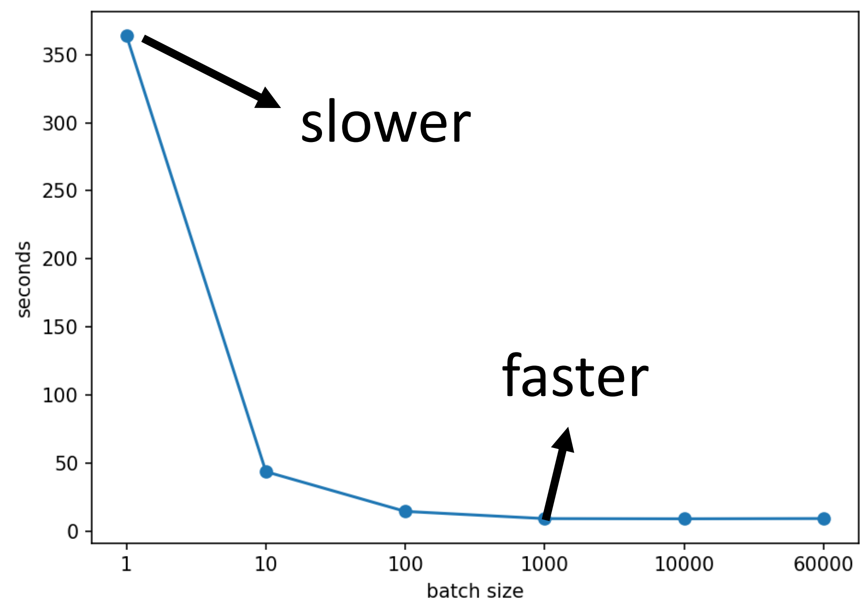
- Smaller batch requires longer time for one epoch (longer time for seeing all data once)

Time for one **update**



60000 updates in one epoch

Time for one **epoch**



Batch size越大，每epoch需要的时间更短

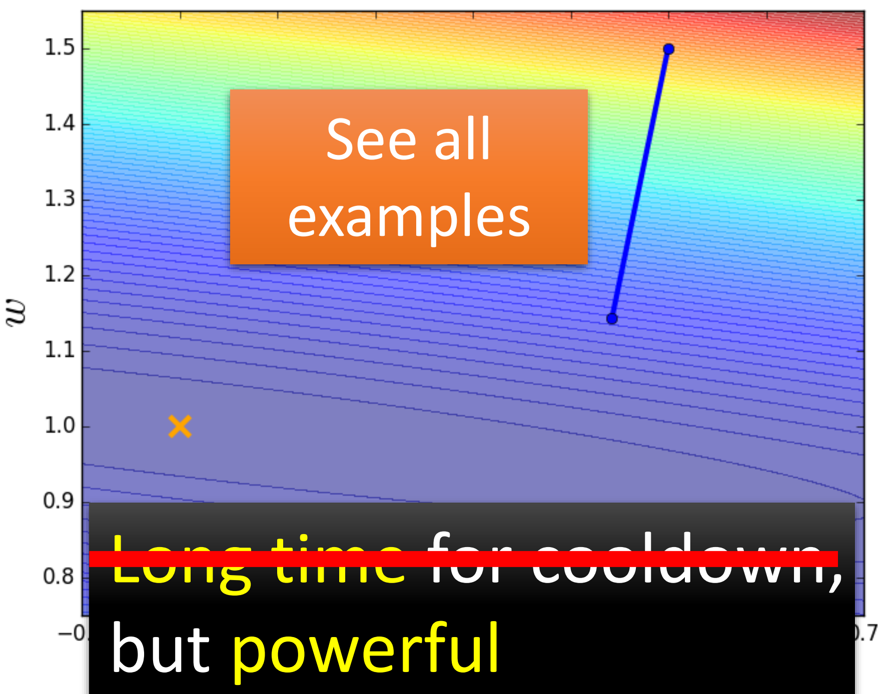
根据前面的实验，cd时长没差啦。

Small Batch v.s. Large Batch

Consider 20 examples (N=20)

Batch size = N (Full Batch)

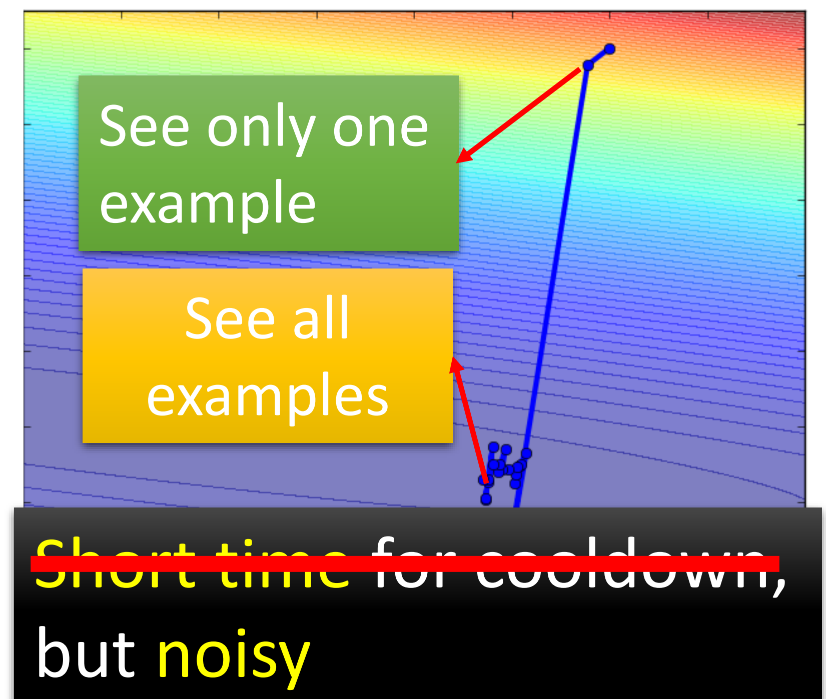
Update after seeing all the 20 examples



Batch size = 1

Update for each example

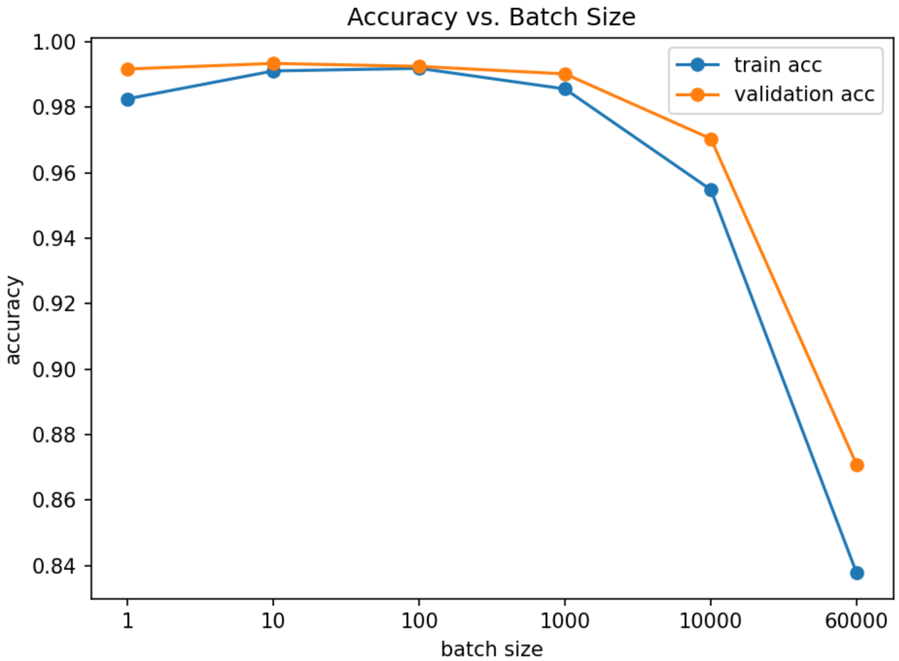
Update 20 times in an epoch



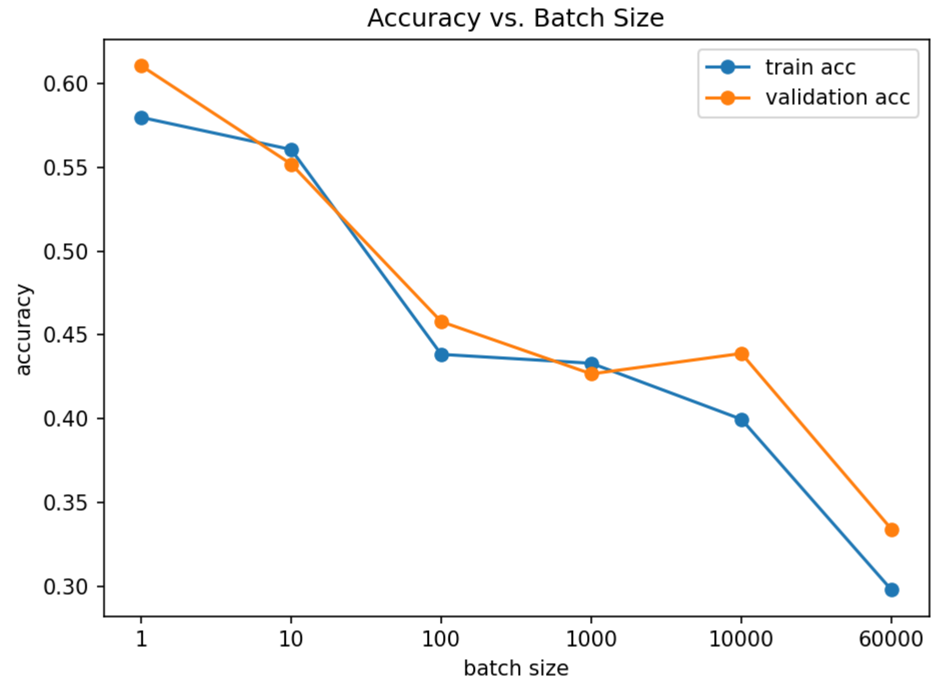
noisy有利于gradient descent

Small Batch v.s. Large Batch

MNIST



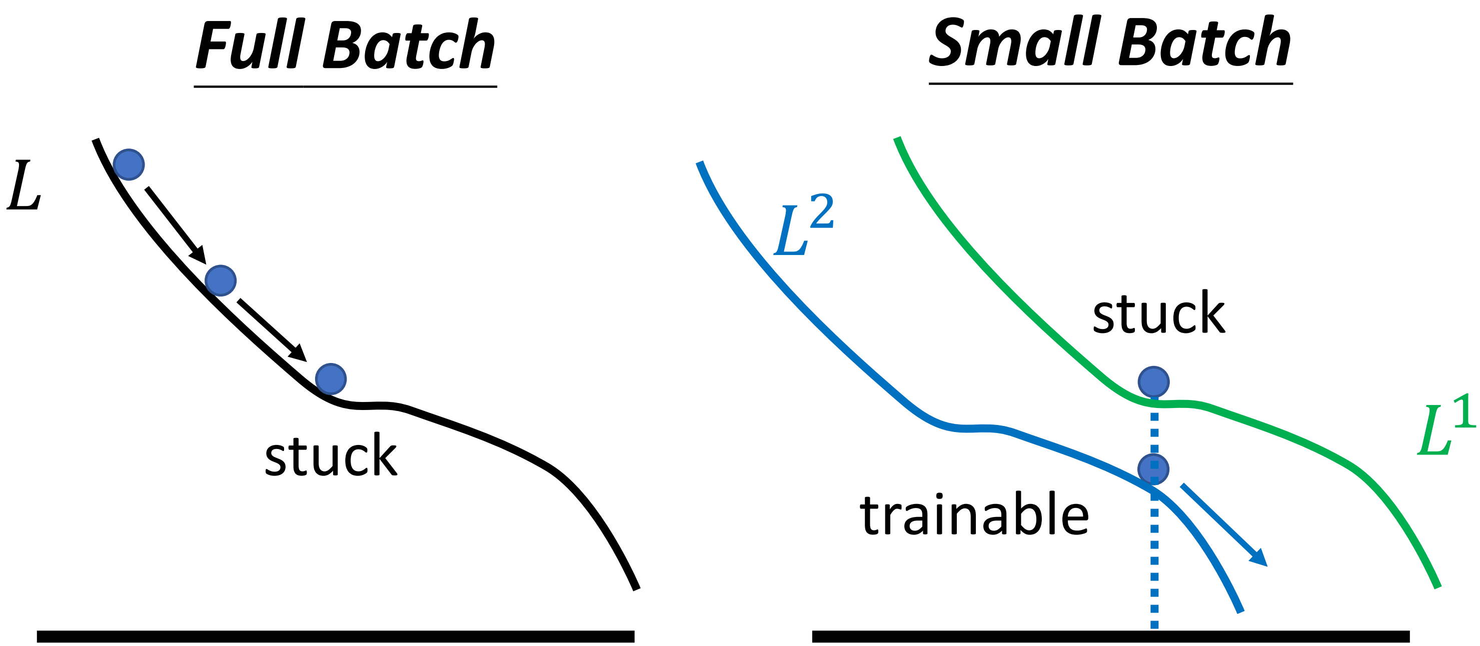
CIFAR-10



- Smaller batch size has better performance
- What’s wrong with large batch size? Optimization Fails

Small Batch v.s. Large Batch

- Smaller batch size has better performance
- "Noisy" update is better for training



第二次epoch的时候，
不会stuck在第一epoch的地方，从而
继续更新参数，优化模型

Small Batch v.s. Large Batch

- Small batch is better on testing data?

SB = 256

LB = 0.1 x data set

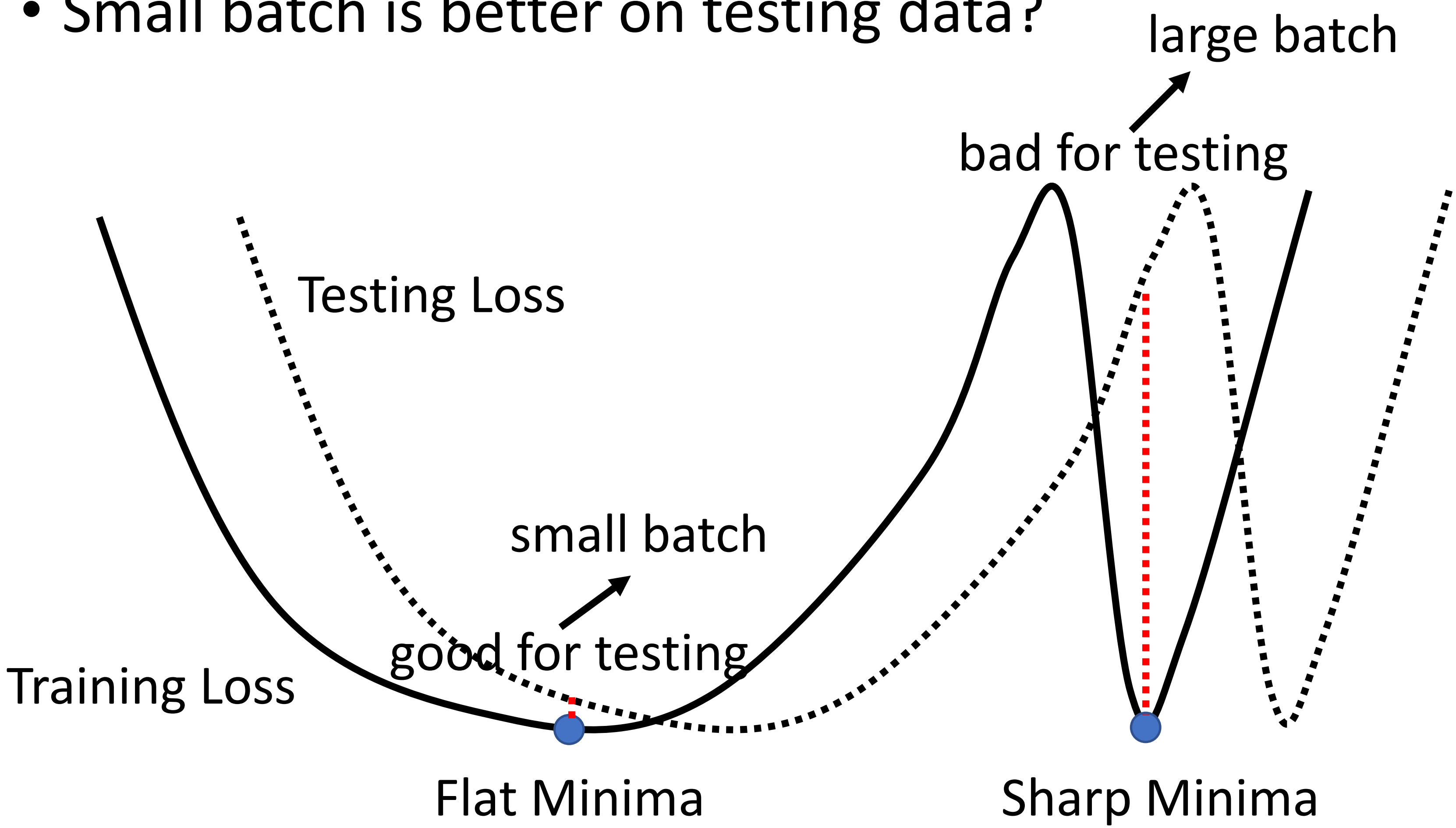
Name	Network Type	Data set
F_1	Fully Connected	MNIST (LeCun et al., 1998a)
F_2	Fully Connected	TIMIT (Garofolo et al., 1993)
C_1	(Shallow) Convolutional	CIFAR-10 (Krizhevsky & Hinton, 2009)
C_2	(Deep) Convolutional	CIFAR-10
C_3	(Shallow) Convolutional	CIFAR-100 (Krizhevsky & Hinton, 2009)
C_4	(Deep) Convolutional	CIFAR-100

	Training Accuracy		Testing Accuracy	
Name	SB	LB	SB	LB
F_1	$99.66\% \pm 0.05\%$	$99.92\% \pm 0.01\%$	$98.03\% \pm 0.07\%$	$97.81\% \pm 0.07\%$
F_2	$99.99\% \pm 0.03\%$	$98.35\% \pm 2.08\%$	$64.02\% \pm 0.2\%$	$59.45\% \pm 1.05\%$
C_1	$99.89\% \pm 0.02\%$	$99.66\% \pm 0.2\%$	$80.04\% \pm 0.12\%$	$77.26\% \pm 0.42\%$
C_2	$99.99\% \pm 0.04\%$	$99.99\% \pm 0.01\%$	$89.24\% \pm 0.12\%$	$87.26\% \pm 0.07\%$
C_3	$99.56\% \pm 0.44\%$	$99.88\% \pm 0.30\%$	$49.58\% \pm 0.39\%$	$46.45\% \pm 0.43\%$
C_4	$99.10\% \pm 1.23\%$	$99.57\% \pm 1.84\%$	$63.08\% \pm 0.5\%$	$57.81\% \pm 0.17\%$

On Large-Batch Training for Deep Learning: Generalization Gap and Sharp Minima
https://arxiv.org/abs/1609.04836

Small Batch v.s. Large Batch

- Small batch is better on testing data?



Small Batch v.s. Large Batch

	Small	Large
Speed for one update (no parallel)	Faster	Slower
Speed for one update (with parallel)	Same	Same (not too large)
Time for one epoch	Slower	Faster
Gradient	Noisy	Stable
Optimization	Better	Worse
Generalization	Better	Worse

Batch size is a hyperparameter you have to decide.

Have both fish and bear's paws?

- Large Batch Optimization for Deep Learning: Training BERT in 76 minutes (https://arxiv.org/abs/1904.00962)
- Extremely Large Minibatch SGD: Training ResNet-50 on ImageNet in 15 Minutes (https://arxiv.org/abs/1711.04325)
- Stochastic Weight Averaging in Parallel: Large-Batch Training That Generalizes Well (https://arxiv.org/abs/2001.02312)
- Large Batch Training of Convolutional Networks (https://arxiv.org/abs/1708.03888)
- Accurate, large minibatch sgd: Training imagenet in 1 hour (https://arxiv.org/abs/1706.02677)

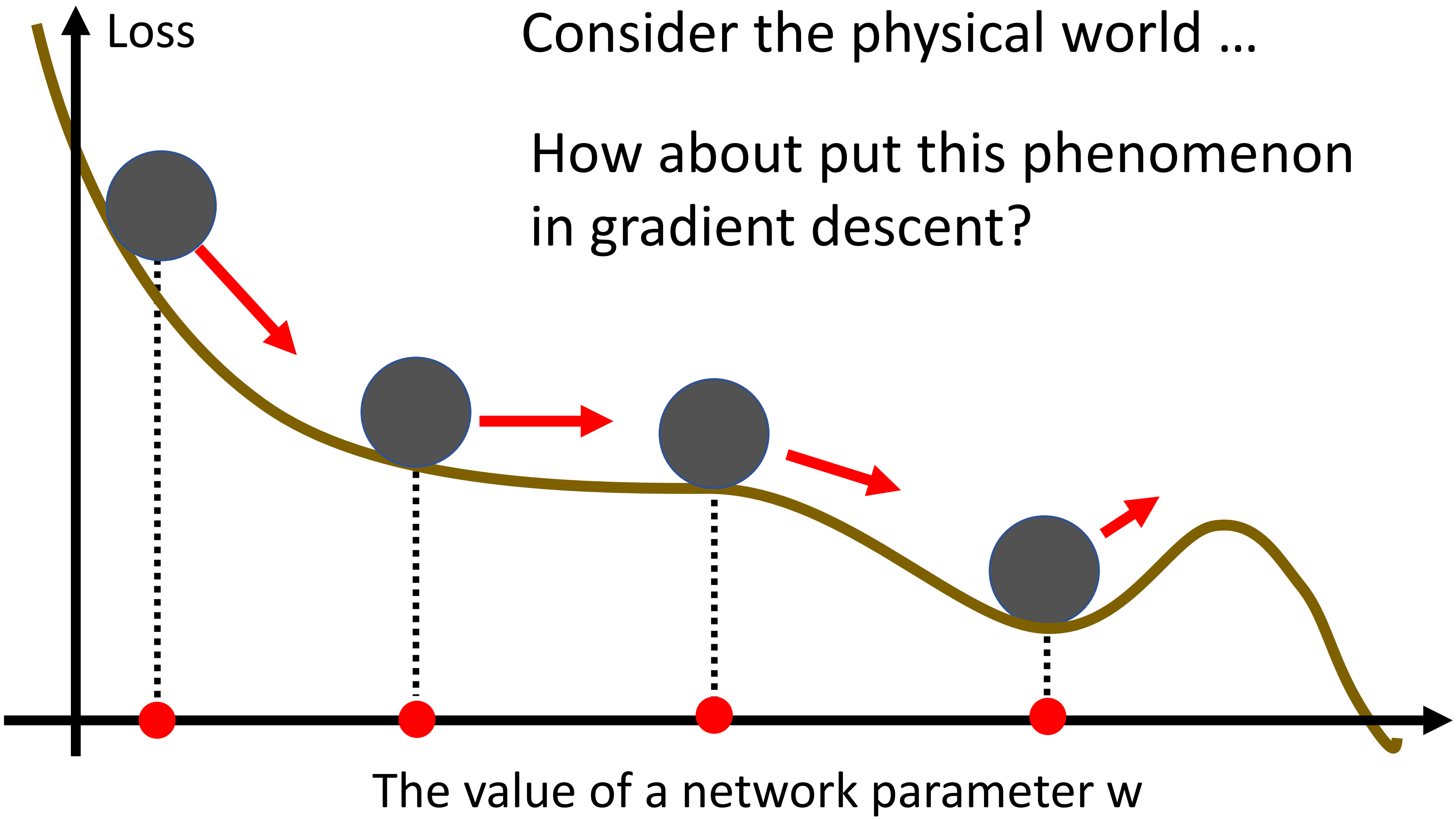
Momentum

动量

Small Gradient …

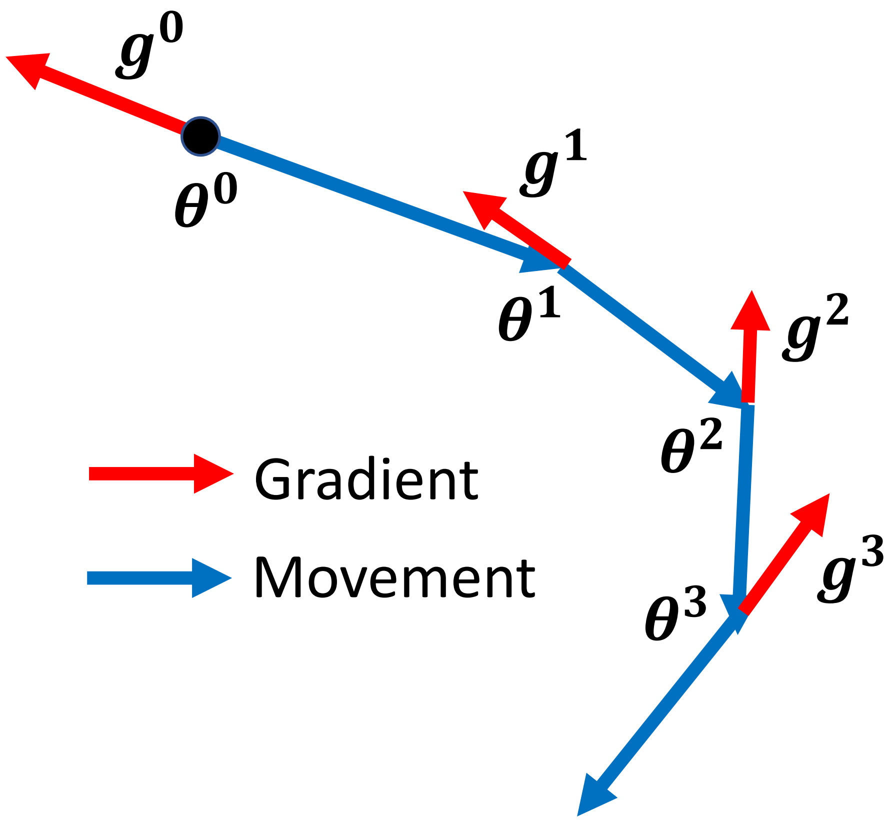
Consider the physical world …

How about put this phenomenon in gradient descent?



(Vanilla) Gradient Descent

adj.一般的



Starting at $\boldsymbol{\theta}^0$

Compute gradient $\boldsymbol{g}^0$

Move to $\boldsymbol{\theta}^1 = \boldsymbol{\theta}^0 - \eta \boldsymbol{g}^0$

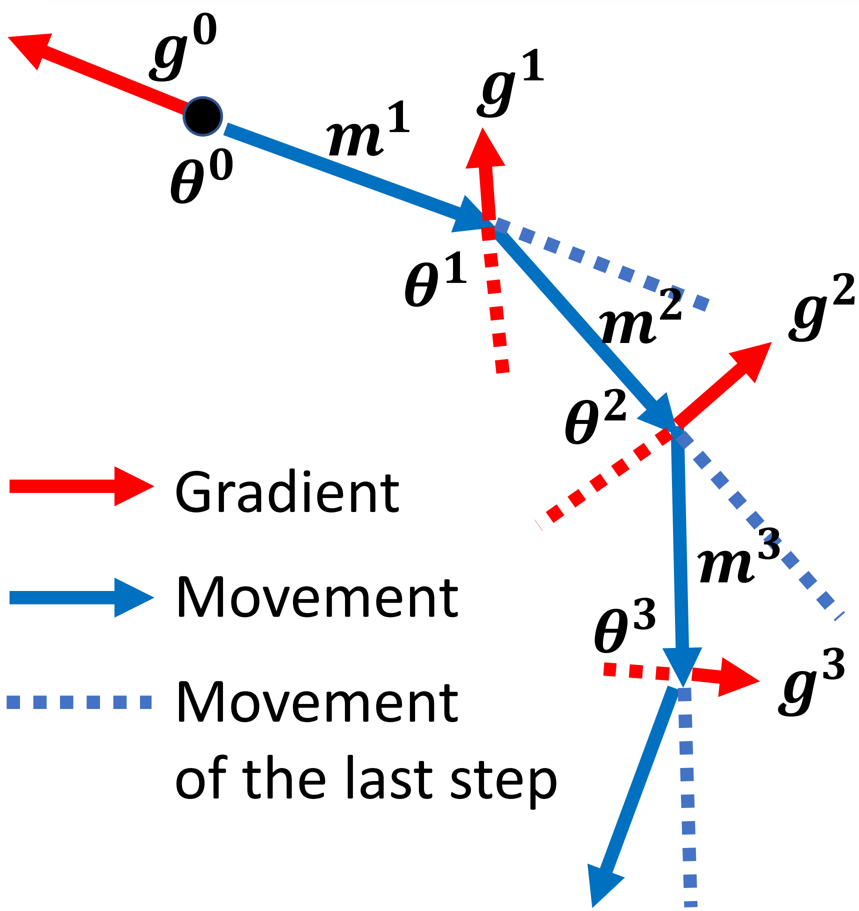
Compute gradient $\boldsymbol{g}^1$

Move to $\boldsymbol{\theta}^2 = \boldsymbol{\theta}^1 - \eta \boldsymbol{g}^1$

⋮

Gradient Descent + Momentum

Movement: **movement of last step** minus **gradient** at present



Starting at $\boldsymbol{\theta}^0$ 第0步

Movement $\boldsymbol{m}^0 = \boldsymbol{0}$

Compute gradient $\boldsymbol{g}^0$

Movement $\boldsymbol{m}^1 = \lambda \boldsymbol{m}^0 - \eta \boldsymbol{g}^0$

Move to $\boldsymbol{\theta}^1 = \boldsymbol{\theta}^0 + \boldsymbol{m}^1$

Compute gradient $\boldsymbol{g}^1$ 第1步

Movement $\boldsymbol{m}^2 = \lambda \boldsymbol{m}^1 - \eta \boldsymbol{g}^1$

Move to $\boldsymbol{\theta}^2 = \boldsymbol{\theta}^1 + \boldsymbol{m}^2$ 第2步

Movement not just based on gradient, but previous movement.

Gradient Descent + Momentum

Movement: **movement of last step** minus **gradient** at present

$\boldsymbol{m}^i$ is the weighted sum of all the previous gradient: $\boldsymbol{g}^0, \boldsymbol{g}^1, \ldots, \boldsymbol{g}^{i-1}$

$$\boldsymbol{m}^0 = \boldsymbol{0}$$

$$\boldsymbol{m}^1 = -\eta \boldsymbol{g}^0$$

$$\boldsymbol{m}^2 = -\lambda\eta \boldsymbol{g}^0 - \eta \boldsymbol{g}^1$$

$$\vdots$$

Starting at $\boldsymbol{\theta}^0$

Movement $\boldsymbol{m}^0 = \boldsymbol{0}$

Compute gradient $\boldsymbol{g}^0$

Movement $\boldsymbol{m}^1 = \lambda \boldsymbol{m}^0 - \eta \boldsymbol{g}^0$

Move to $\boldsymbol{\theta}^1 = \boldsymbol{\theta}^0 + \boldsymbol{m}^1$

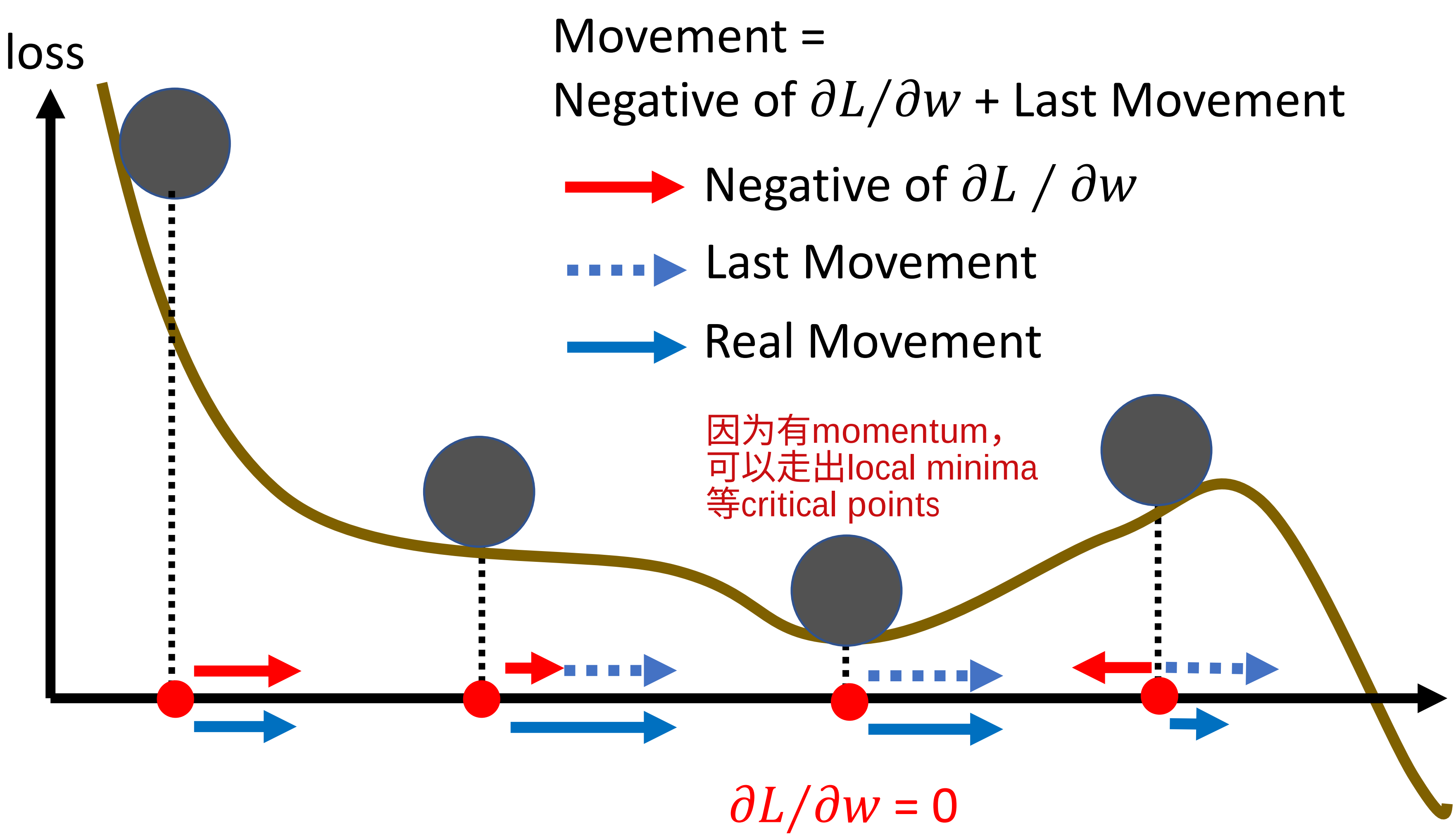
Compute gradient $\boldsymbol{g}^1$

Movement $\boldsymbol{m}^2 = \lambda \boldsymbol{m}^1 - \eta \boldsymbol{g}^1$

Move to $\boldsymbol{\theta}^2 = \boldsymbol{\theta}^1 + \boldsymbol{m}^2$

Movement not just based on gradient, but previous movement.

Gradient Descent + Momentum



Concluding Remarks

- Critical points have zero gradients. $\nabla=0 \rightarrow$ critical point
- Critical points can be either saddle points or local minima.
  - Can be determined by the Hessian matrix.
  - It is possible to escape saddle points along the direction of eigenvectors of the Hessian matrix.
  - Local minima may be rare.
- Smaller batch size and momentum help escape critical points.

Acknowledgement

- 感謝作業二助教團隊(陳宣叡、施貽仁、孟妍李威緒)幫忙跑實驗以及蒐集資料