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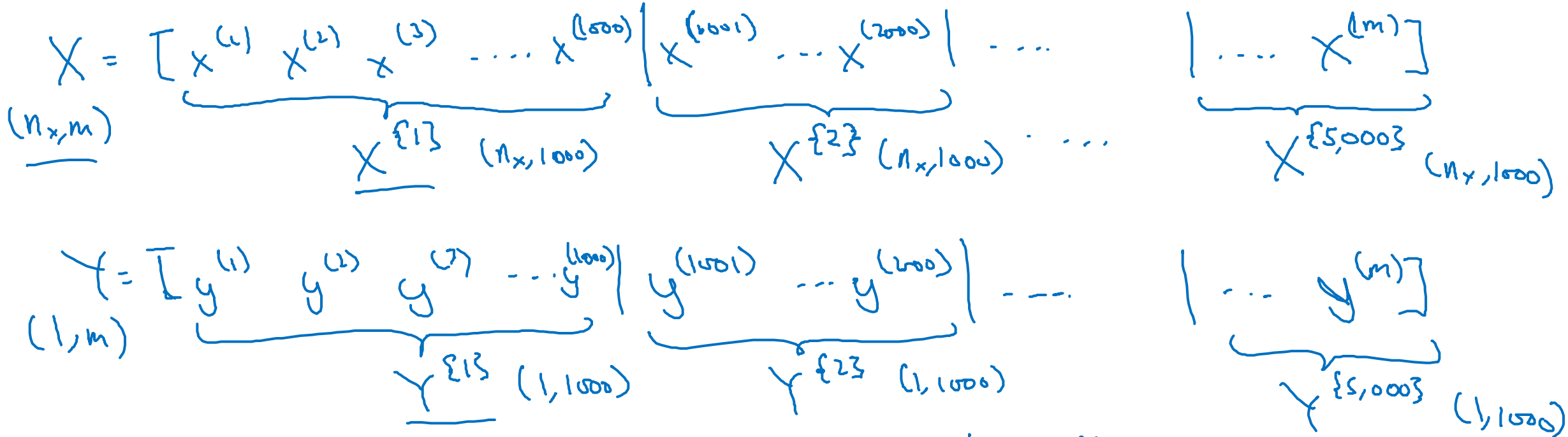
Optimization Algorithms

Mini-batch gradient descent

Batch vs. mini-batch gradient descent

Vectorization allows you to efficiently compute on m examples.



What if $m = 5{,}000{,}000$?

5,000 mini-batches of 1,000 each

Mini-batch t: $X^{\{t\}}, Y^{\{t\}}$.

$x^{(i)}$

$z^{[l]}$

$X^{\{t\}}, Y^{\{t\}}$.

Andrew Ng

Mini-batch gradient descent

1 step of gradient descent using $X^{\{t\}}, Y^{\{t\}}$.
(as if $m = 1000$)

X, Y

repeat {

for $t = 1, \ldots, 5000$ {

Forward prop on $X^{\{t\}}$.

$$Z^{[1]} = W^{[1]} X^{\{t\}} + b^{[1]}$$
$$A^{[1]} = g^{[1]}(Z^{[1]})$$
$$\vdots$$
$$A^{[L]} = g^{[L]}(Z^{[L]})$$

} Vectorized implementation (1000 examples)

Compute cost $J^{\{t\}} = \frac{1}{1000} \sum_{i=1}^{l} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2 \cdot 1000} \sum_{l} \|W^{[l]}\|_F^2$. (from $X^{\{t\}}, Y^{\{t\}}$)

Backprop to compute gradients wrt $J^{\{t\}}$ (using $(X^{\{t\}}, Y^{\{t\}})$)

$W^{[l]} := W^{[l]} - \alpha dW^{[l]}$, $b^{[l]} := b^{[l]} - \alpha db^{[l]}$

}

}

"1 epoch"
└ pass through training set.

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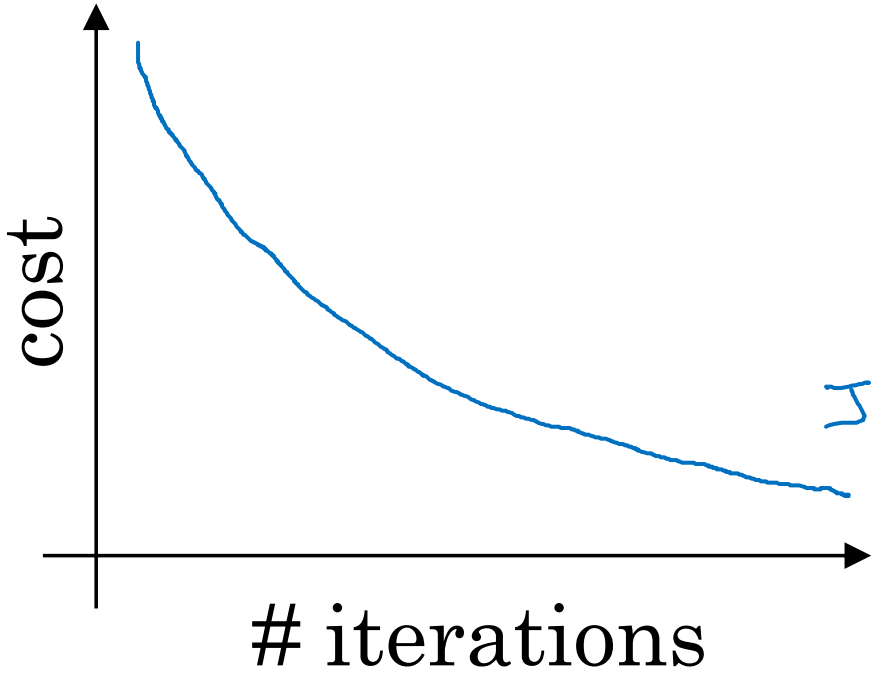
Optimization Algorithms

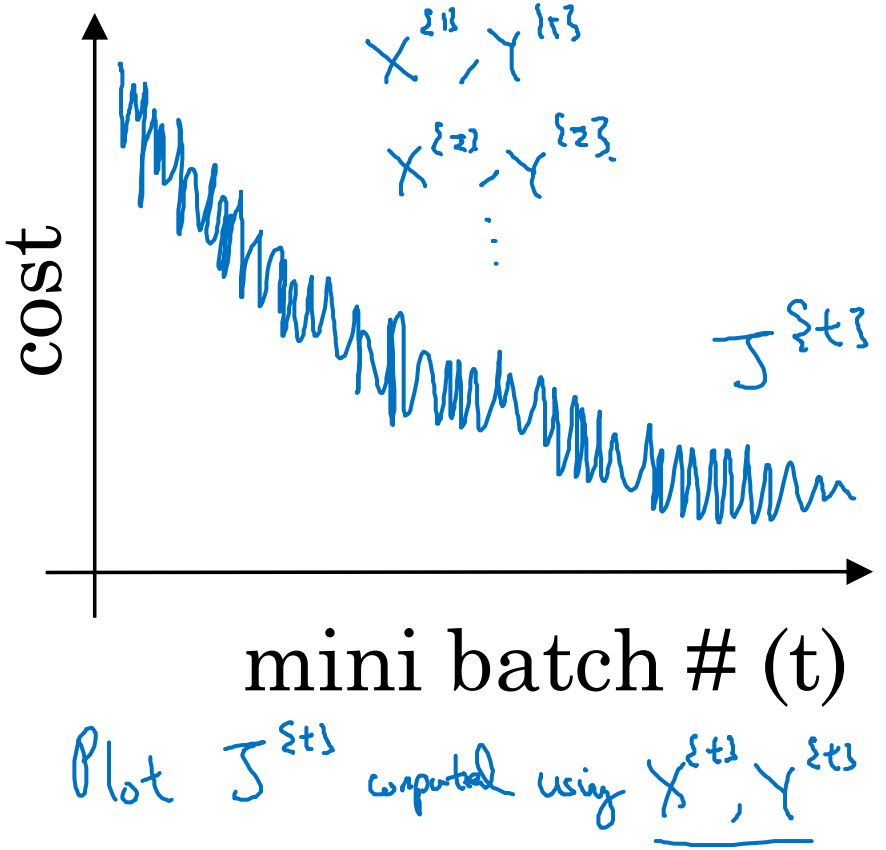
Understanding mini-batch gradient descent

Training with mini batch gradient descent

Batch gradient descent



Mini-batch gradient descent

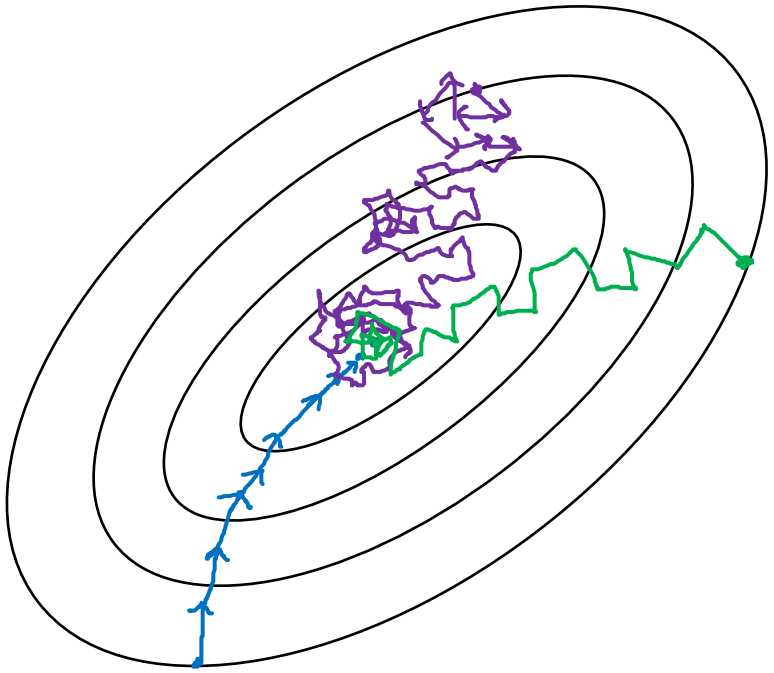


Choosing your mini-batch size

→ If mini-batch size = m : Batch gradient descent. $(X^{\{1\}}, Y^{\{1\}}) = (X, Y)$.

→ If mini-batch size = 1 : Stochastic gradient descent. Every example is it own mini-batch. $(X^{\{1\}}, Y^{\{1\}}) = (x^{(1)}, y^{(1)})$ ... $(x^{(2)}, y^{(1)})$

In practice: Somewhere in-between 1 and m



Stochastic gradient descent

{

Lose speedup from vectorization

In-between (mini-batch size not too big/small)

Fastest learning.

- Vectorization. (n 1000)
- Make progress without processing entire training set.

Batch gradient descent (mini-batch size = m)

Too long per iteration

Andrew Ng

Choosing your mini-batch size

If small train set: Use batch gradient descent.
($m \leq 2000$)

Typical mini-batch sizes:

→ 64, 128, 256, 512 (1024)
2^6, 2^7, 2^8, 2^9 (2^{10})

Make sure mini-batch fit in CPU/GPU memory.

$X^{\{t\}}, Y^{\{t\}}$

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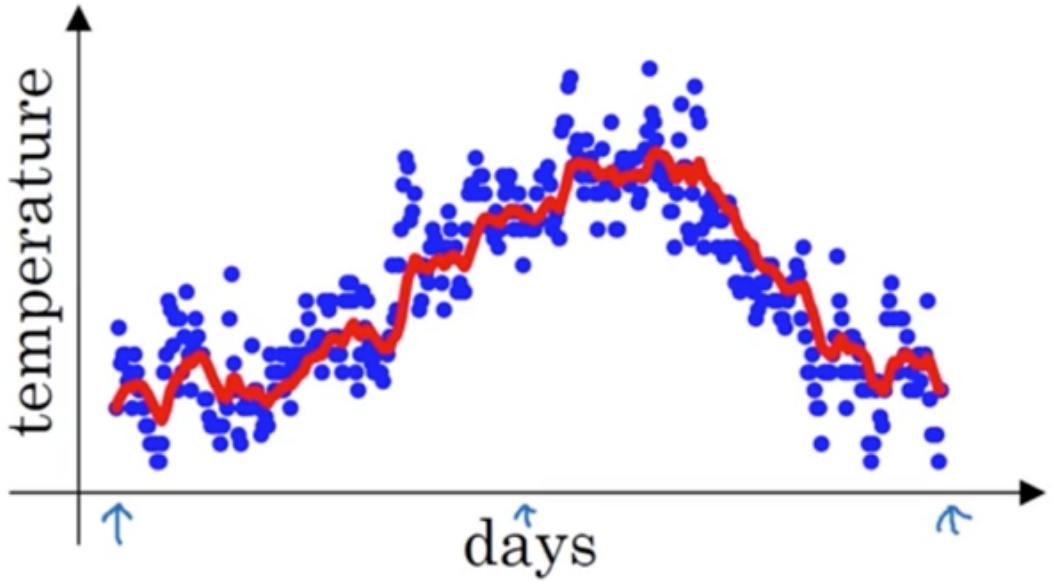
Optimization Algorithms

Exponentially weighted averages

Temperature in London

$\theta_1 = 40°\text{F}$ 4°C ←
$\theta_2 = 49°\text{F}$ 9°C
$\theta_3 = 45°\text{F}$ ⋮
⋮
$\theta_{180} = 60°\text{F}$ 15°C
$\theta_{181} = 56°\text{F}$ ⋮
⋮



$v_0 = 0$
$v_1 = 0.9\, v_0 + 0.1\, \theta_1$
$v_2 = 0.9\, v_1 + 0.1\, \theta_2$
$v_3 = 0.9\, v_2 + 0.1\, \theta_3$
⋮
$v_t = 0.9\, v_{t-1} + 0.1\, \theta_t$

Andrew Ng

Exponentially weighted averages

Moving

$V_t = \beta V_{t-1} + (1-\beta)\theta_t$

$\beta = 0.9$: $\approx$ 10 days' temperature

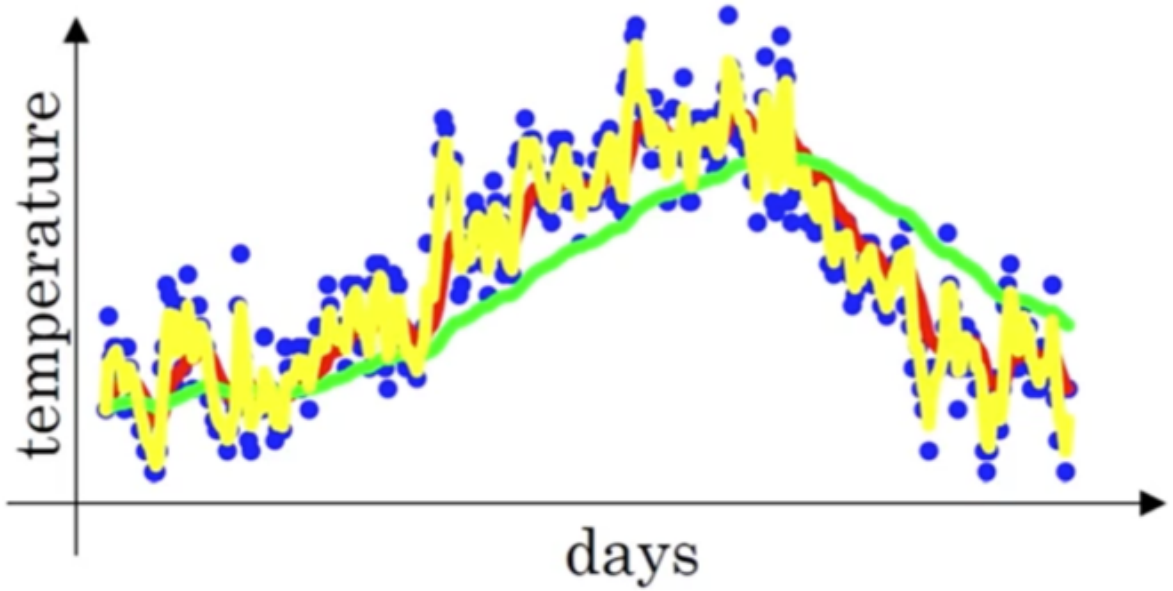
$\beta = 0.98$: $\approx$ 50 days

$\beta = 0.5$: $\approx$ 2 days

V_t as approximately average over

$\rightarrow \approx \frac{1}{1-\beta}$ days' temperature.

$\frac{1}{1-0.98} = 50$



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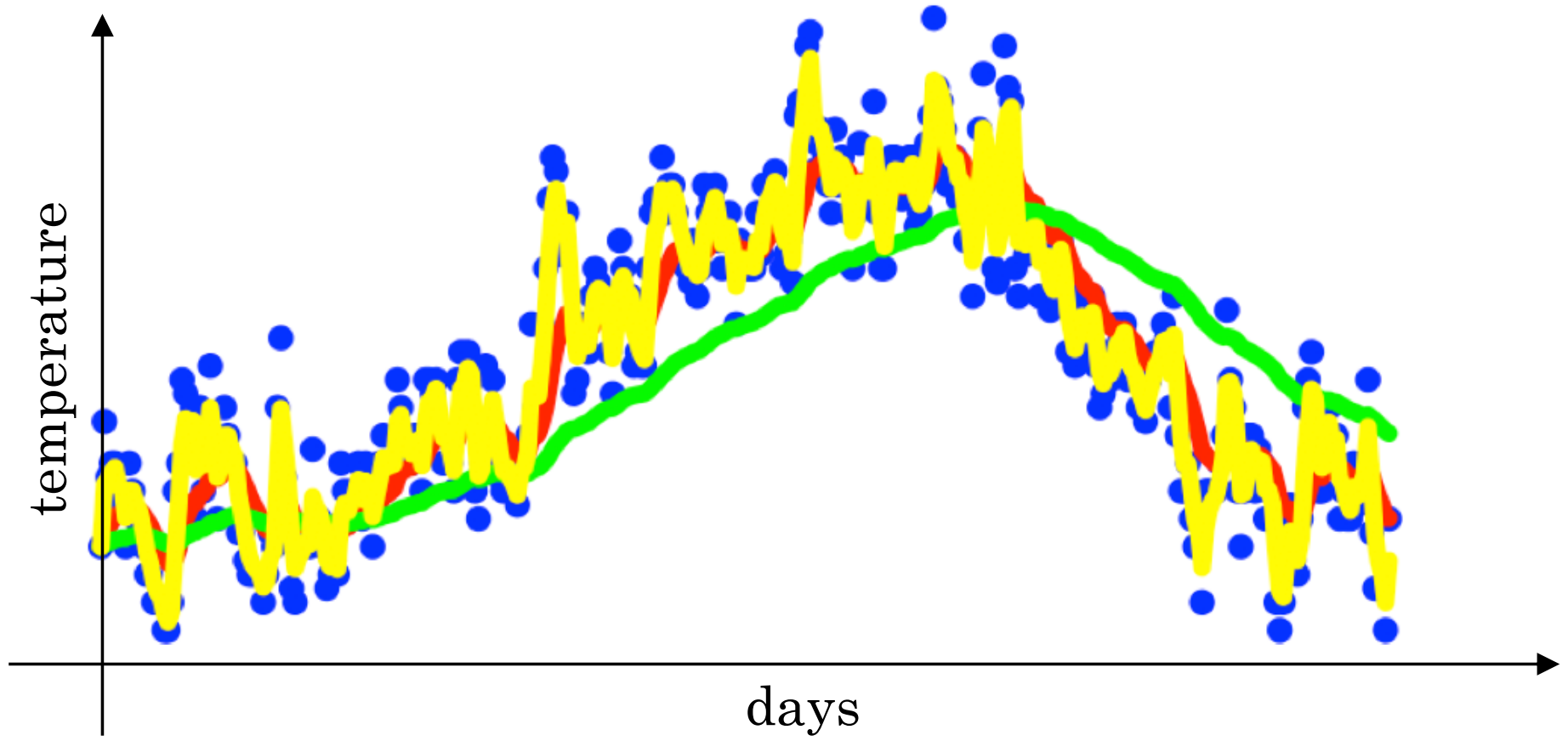
Optimization Algorithms

Understanding exponentially weighted averages

Exponentially weighted averages

$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

$\beta = 0.9$ 0.98 0.5



Exponentially weighted averages

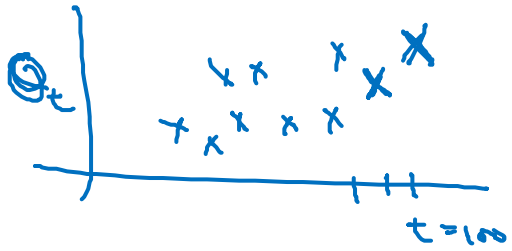
$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

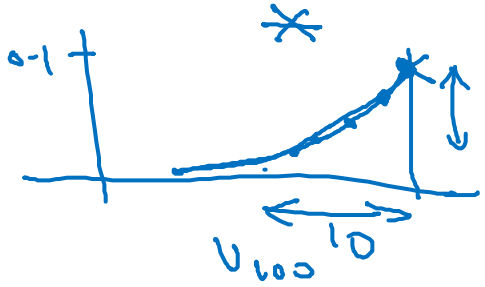
$$v_{100} = 0.9v_{99} + 0.1\theta_{100}$$

$$v_{99} = 0.9v_{98} + 0.1\theta_{99}$$

$$v_{98} = 0.9v_{97} + 0.1\theta_{98}$$

...





$\approx \frac{1}{1-\beta}$

$\varepsilon = 1-\beta$

$0.1\theta_{98} + 0.9v_{97}$

$v_{100} = 0.1\theta_{100} + 0.9v_{99}(0.1\theta_{99} + 0.9v_{98})$

$= 0.1\theta_{100} + 0.1 \times 0.9 \cdot \theta_{99} + 0.1(0.9)^2\theta_{98} + 0.1(0.9)^2\theta_{97} + 0.1(0.9)^3\theta_{96} + \ldots$

$0.9^{10} \approx 0.35 \approx \frac{1}{e}$

$(1-\varepsilon)^{1/\varepsilon} = \frac{1}{e}$

$0.98^{?}$

$\varepsilon = 0.02 \rightarrow 0.98^{50} \approx \frac{1}{e}$

Andrew Ng

Implementing exponentially weighted averages

$$v_0 = 0$$
$$v_1 = \beta v_0 + (1-\beta)\,\theta_1$$
$$v_2 = \beta v_1 + (1-\beta)\,\theta_2$$
$$v_3 = \beta v_2 + (1-\beta)\,\theta_3$$
$$\ldots$$

$V_\theta := 0$

$V_\theta := \beta v + (1-\beta)\theta_1$

$V_\theta := \beta v + (1-\beta)\theta_2$

$\vdots$

$V_\theta = 0$

Repeat {

Get next θ_t

$V_\theta := \beta V_\theta + (1-\beta)\theta_t$

}

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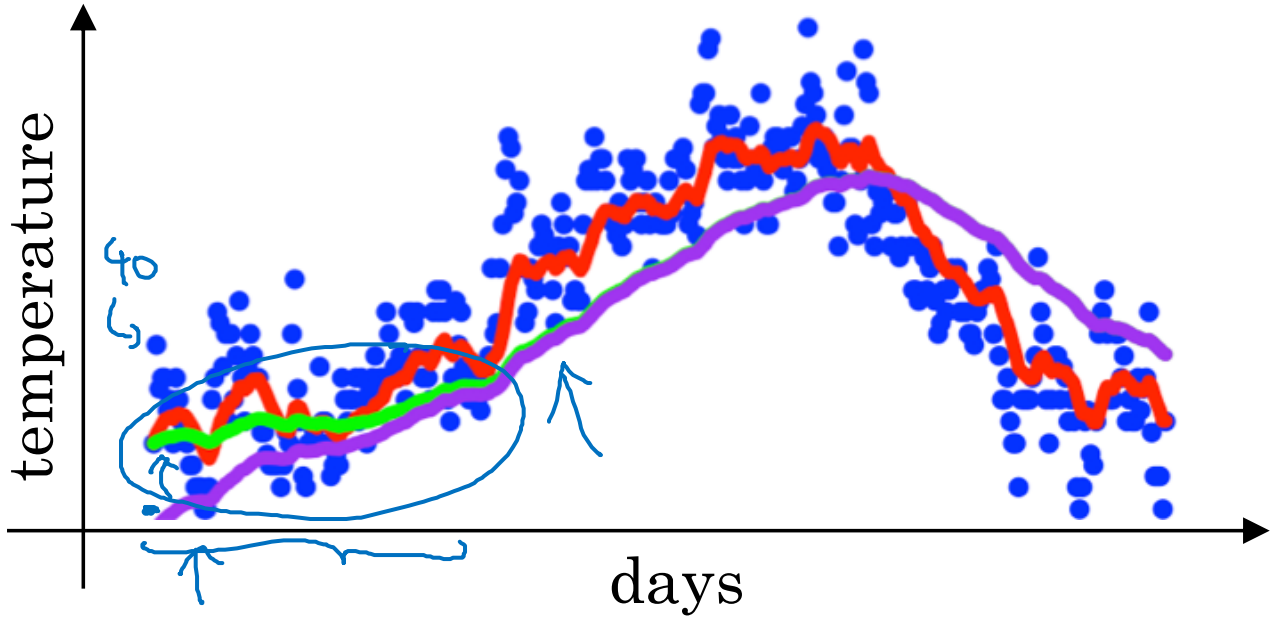
Optimization Algorithms

Bias correction in exponentially weighted average

Bias correction



$\beta = 0.98$

$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

$v_0 = 0$

$v_1 = 0.98 v_0 + 0.02 \theta_1$

$v_2 = 0.98 v_1 + 0.02 \theta_2$

$= 0.98 \times 0.02 \times \theta_1 + 0.02 \theta_2$

$= 0.0196 \theta_1 + 0.02 \theta_2$

$\frac{v_t}{1-\beta^t}$

$t=2: \quad 1-\beta^t = 1-(0.98)^2 = 0.0396$

$\frac{v_2}{0.0396} = \frac{0.0196\theta_1 + 0.02\theta_2}{0.0396}$

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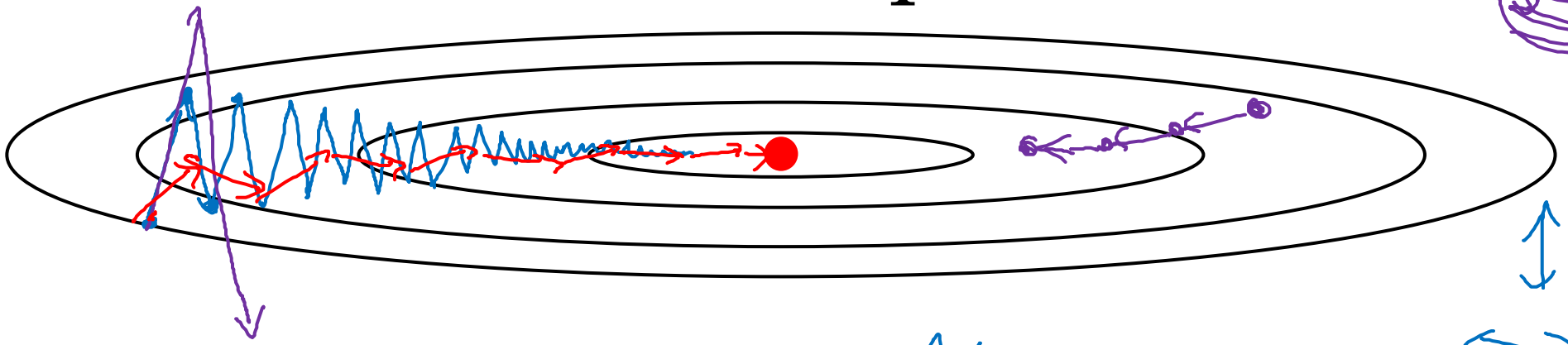
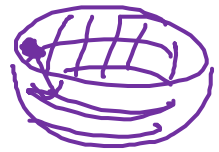
Optimization Algorithms

Gradient descent with momentum

Gradient descent example





slower learning

faster learning.

Momentum:

On iteration t:

Compute dW, db on current mini-batch.

$v_{dW} = \beta v_{dW} + (1-\beta) dW$

$v_{db} = \beta v_{db} + (1-\beta) db$

"$v_\theta = \beta v_{\theta-1} + (1-\beta)\theta_t$"

friction — velocity — acceleration

$W := W - \alpha v_{dW}$, $b := b - \alpha v_{db}$

Andrew Ng

Implementation details

$V_{dW} = 0$, $V_{db} = 0$

On iteration t:

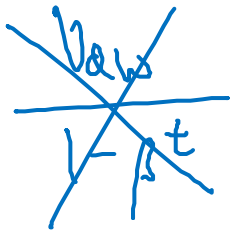
Compute dW, db on the current mini-batch

$$v_{dW} = \beta v_{dW} + (1-\beta) dW$$

$$v_{db} = \beta v_{db} + (1-\beta) db$$

$V_{dW} = \beta V_{dW} + dW$

$$W = W - \alpha v_{dW}, \quad b = b - \alpha v_{db}$$



Hyperparameters: α, β

$\beta = 0.9$

average over last ≈ 10 gradients

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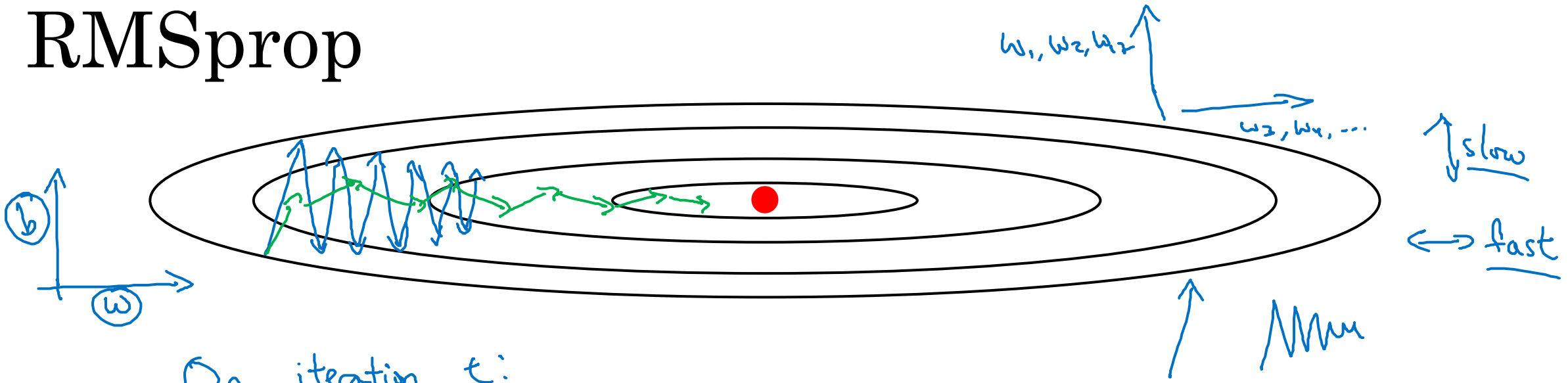
Optimization Algorithms

RMSprop

RMSprop



On iteration t:

Compute dW, db on current mini-batch

element-wise

$S_{dW} = \beta_2 S_{dW} + (1-\beta_2) dW^2$ ← small

$S_{db} = \beta_2 S_{db} + (1-\beta_2) db^2$ ← large

$$W := W - \alpha \frac{dW}{\sqrt{S_{dW}} + \varepsilon}$$

$$b := b - \alpha \frac{db}{\sqrt{S_{db}} + \varepsilon}$$

$\varepsilon = 10^{-8}$

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Optimization Algorithms

Adam optimization algorithm

Adam optimization algorithm

$V_{dW} = 0, S_{dW} = 0, V_{db} = 0, S_{db} = 0$

On iteration t:

Compute dW, db using current mini-batch

$V_{dW} = \beta_1 V_{dW} + (1-\beta_1) dW$, $V_{db} = \beta_1 V_{db} + (1-\beta_1) db$ ← "momentum" β_1

$S_{dW} = \beta_2 S_{dW} + (1-\beta_2) dW^2$, $S_{db} = \beta_2 S_{db} + (1-\beta_2) db^2$ ← "RMSprop" β_2

yhat = np.array([.9, 0.2, 0.1, .4, .9])

$V_{dW}^{corrected} = V_{dW} / (1-\beta_1^t)$, $V_{db}^{corrected} = V_{db} / (1-\beta_1^t)$

$S_{dW}^{corrected} = S_{dW} / (1-\beta_2^t)$, $S_{db}^{corrected} = S_{db} / (1-\beta_2^t)$

$$W := W - \alpha \frac{V_{dW}^{corrected}}{\sqrt{S_{dW}^{corrected}} + \varepsilon} \qquad b := b - \alpha \frac{V_{db}^{corrected}}{\sqrt{S_{db}^{corrected}} + \varepsilon}$$

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Hyperparameters choice:

→ α : needs to be tune

→ β_1 : 0.9 → (dw)

→ β_2 : 0.999 → (dw^2)

→ ε : 10^{-8}

Adam : Adaptive moment estimation

Adam Coates

Andrew Ng

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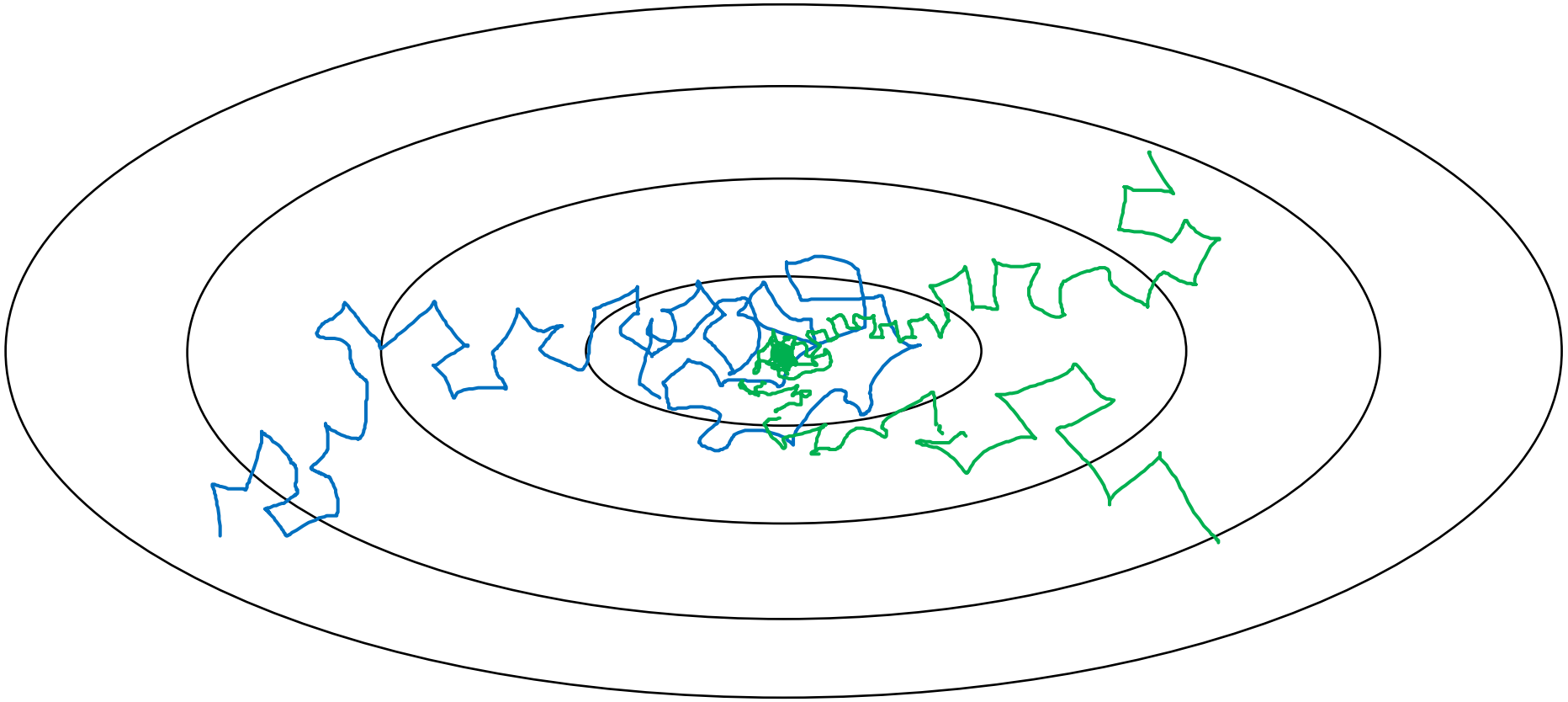
Optimization Algorithms

Learning rate decay

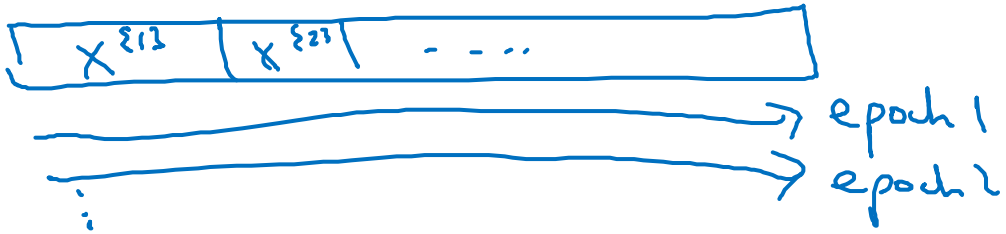
Learning rate decay

Slowly reduce α



Learning rate decay

1 epoch = 1 pass through data.

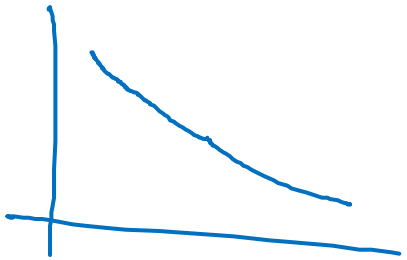


$$\alpha = \frac{1}{1 + \text{decay\_rate} * \text{epoch\_num}} \alpha_0$$

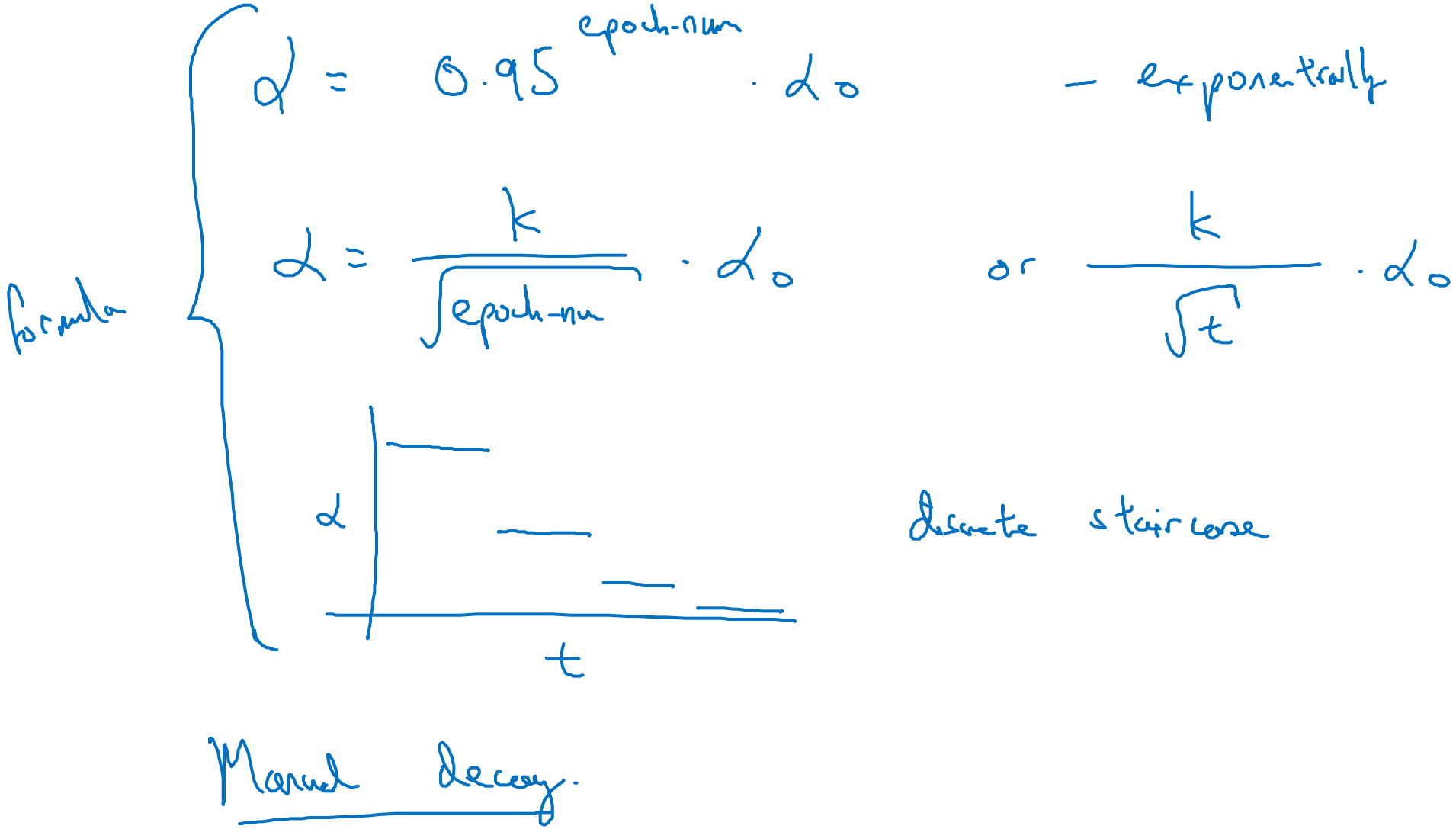
$\alpha_0 = 0.2$

decay_rate = 1

Epoch	α
1	0.1
2	0.67
3	0.5
4	0.4
⋮	⋮



Other learning rate decay methods



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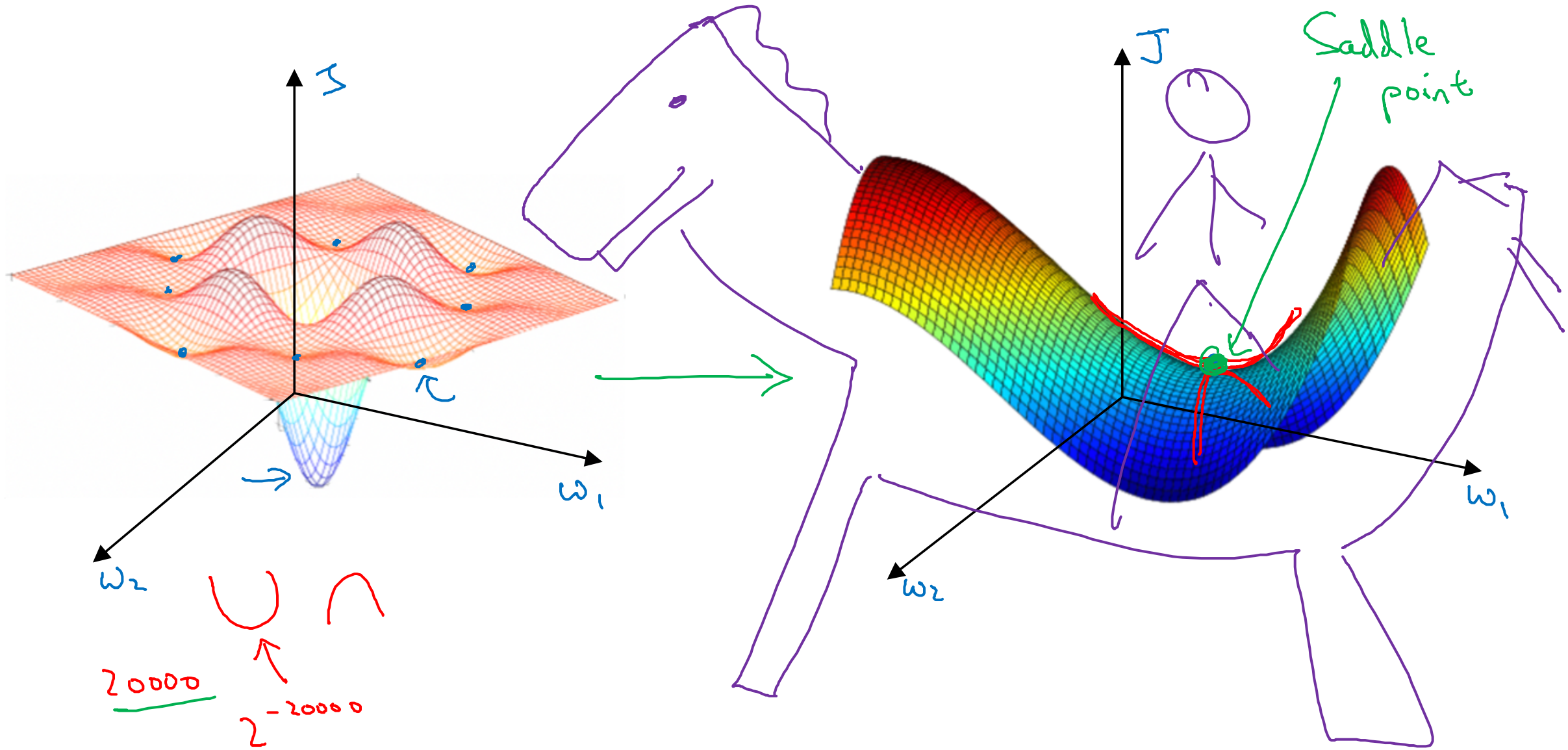
Optimization Algorithms

The problem of local optima

Local optima in neural networks



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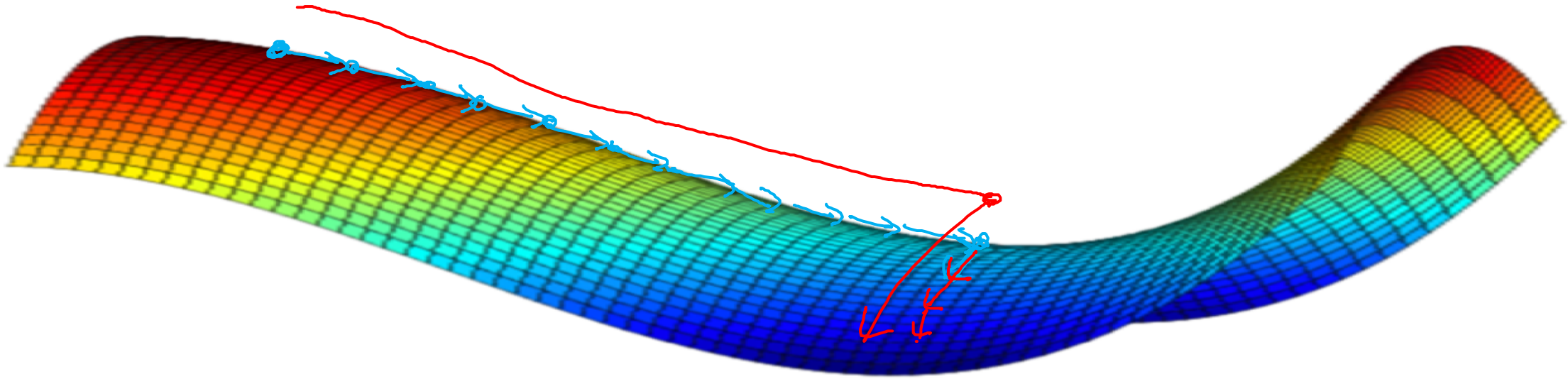
Problem of plateaus



- Unlikely to get stuck in a bad local optima
- Plateaus can make learning slow

Andrew Ng