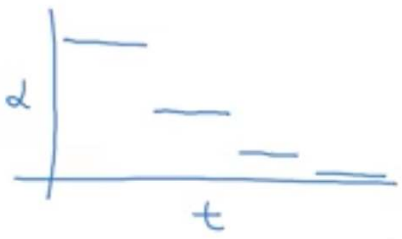
Other learning rate decay methods

formula

$\alpha = 0.95^{\text{epoch-num}} \cdot \alpha_0$ — exponentially decay.

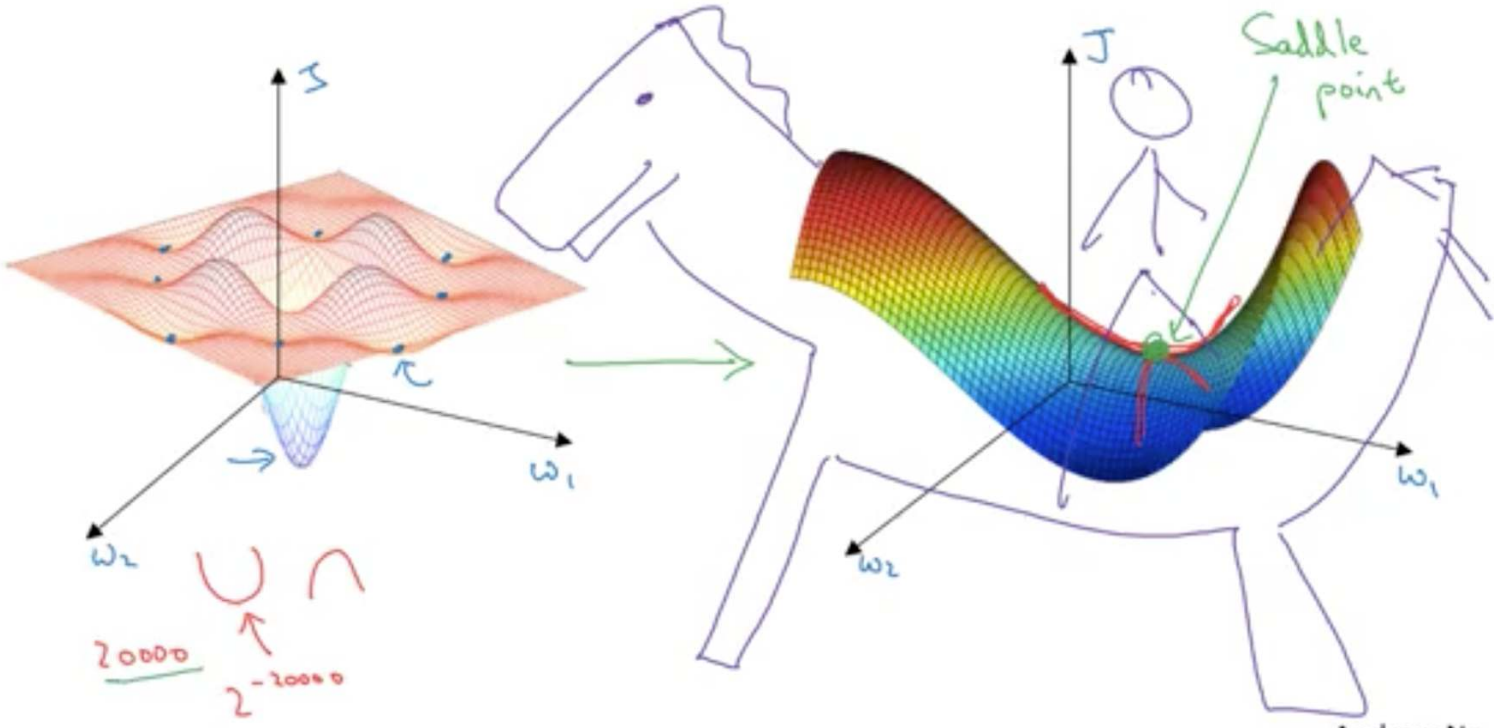
$\alpha = \frac{k}{\sqrt{\text{epoch-num}}} \cdot \alpha_0$ or $\frac{k}{\sqrt{t}} \cdot \alpha_0$



discrete staircase

Manual decay.

Local optima in neural networks



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Learning rate decay

1 epoch = 1 pass through data.

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

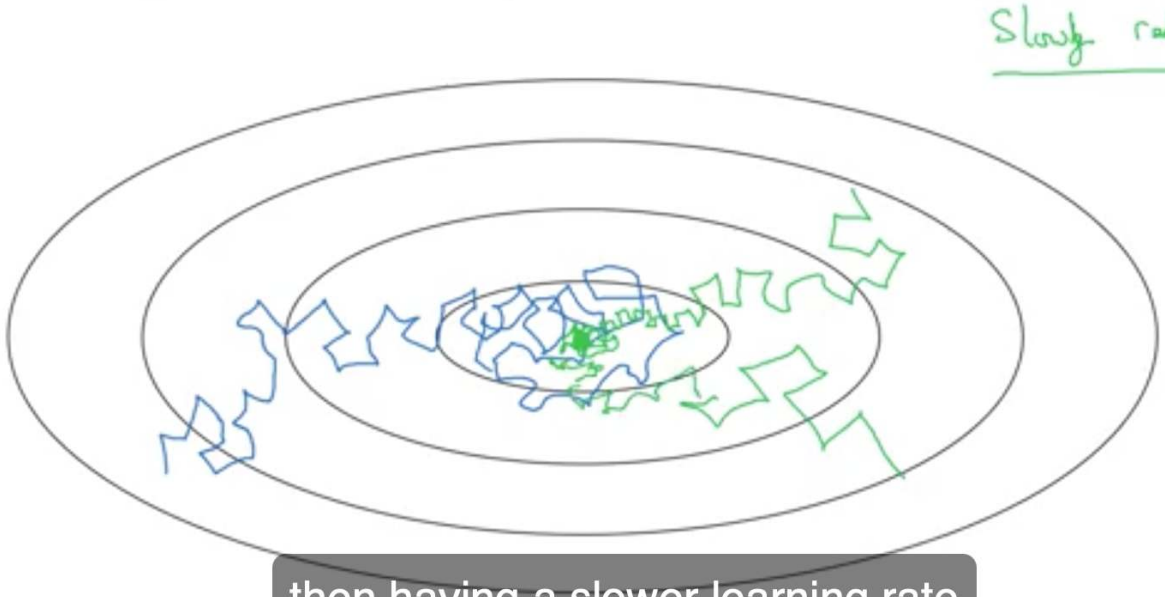
$\alpha_0 = 0.2$

decay_rate = 1

Epoch	α
1	0.1
2	0.67
3	0.5
4	0.4
⋮	⋮

Andrew Ng

Learning rate decay



then having a slower learning rate
allows you to take smaller steps.

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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

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

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

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

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

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

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Implementation details

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

On iteration t:

Compute dW, db on the current mini-batch

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

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

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

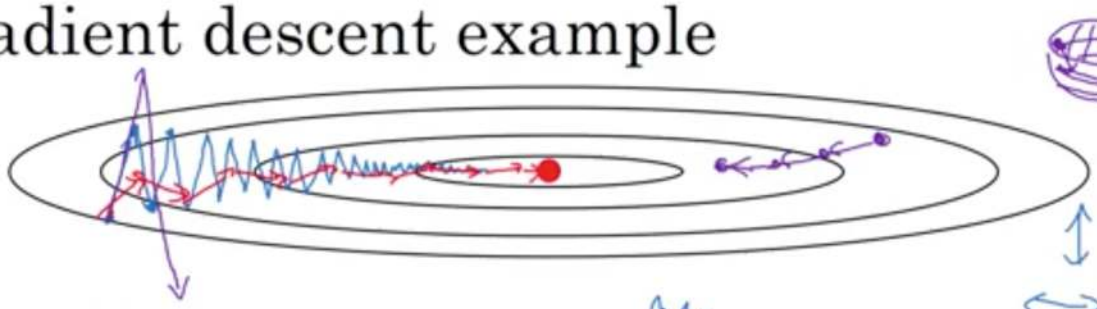
$W = W - \alpha v_{dW}, \quad b = b - \alpha v_{db}$

Hyperparameters: α, β

$\beta = 0.9$

average over last ≈ 10 gradients

Gradient descent example



slower learning

faster learning

Momentum:

On iteration t:

Compute dW, db on current mini-batch.

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

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

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

friction ↑ velocity ↑ acceleration

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

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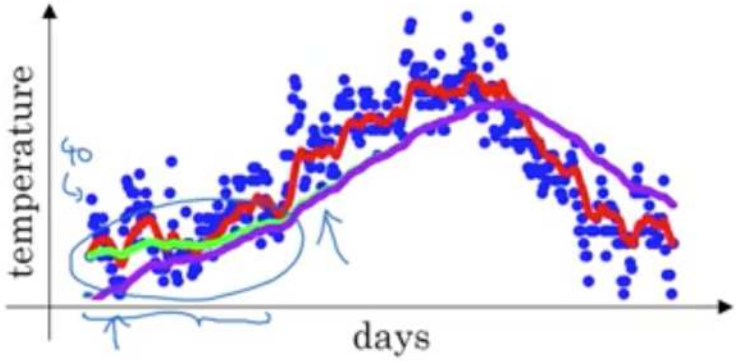
Bias correction



$\beta = 0.98$

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

$V_0 = 0$

$V_1 = 0.98 V_0 + 0.02 \theta_1$

$V_2 = 0.98 V_1 + 0.02 \theta_2$

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

$= 0.0196 \theta_1 + 0.02 \theta_2$

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

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

$\frac{V_2}{0.0396} = \frac{0.0196\theta_1 + 0.02\theta_2}{0.0396}$

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Implementing exponentially weighted averages

$v_0 = 0$

$v_1 = \beta v_0 + (1 - \beta)\,\theta_1$

$v_2 = \beta v_1 + (1 - \beta)\,\theta_2$

$v_3 = \beta v_2 + (1 - \beta)\,\theta_3$

...

$V_\theta := 0$

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

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

⋮

$V_\theta = 0$

Repeat {

Get next θ_t

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

}

Andrew Ng

Exponentially weighted averages

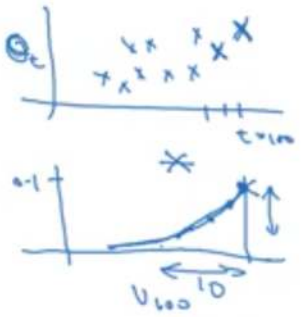
$$v_t = \beta v_{t-1} + (1-\beta)\theta_t$$

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

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

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

...



$$V_{100} = 0.1\theta_{100} + 0.9(0.1\theta_{99} + 0.9(0.1\theta_{98} + 0.9v_{97}))$$

$$= 0.1\theta_{100} + 0.1\times0.9\cdot\theta_{99} + 0.1(0.9)^2\theta_{98} + 0.1(0.9)^3\theta_{97} + \dots$$

$0.9^{10} \approx 0.35 \approx \frac{1}{e}$ $\quad (1-\varepsilon)^{1/\varepsilon} = \frac{1}{e}$ $\quad 0.98^{?}$

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

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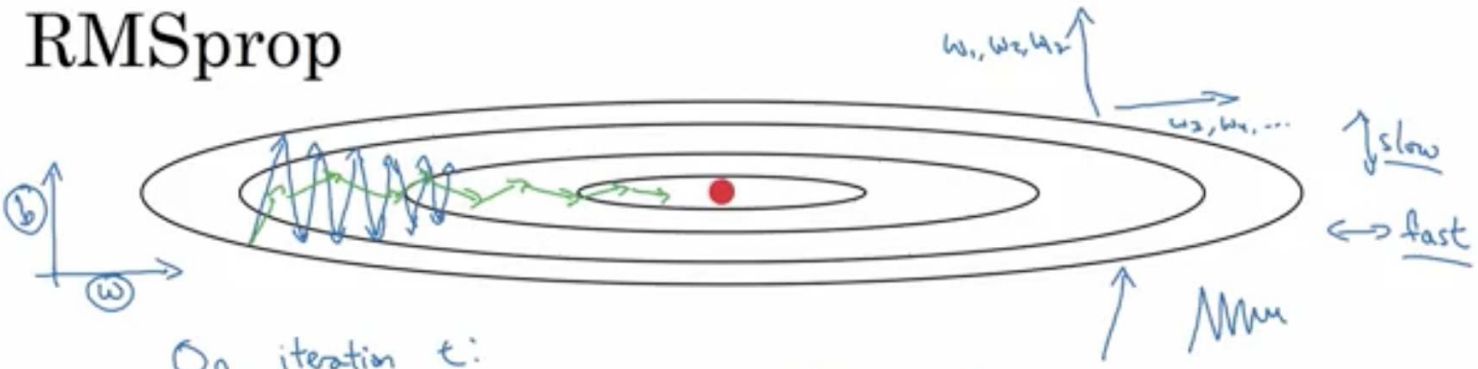
RMSprop



On iteration t:

Compute dW, db on current mini-batch

$S_{dW} = \beta_2 S_{dW} + (1-\beta_2) \underbrace{dW^2}_{\text{element-wise}}$ ← small

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

$W := W - \alpha \frac{dW}{\sqrt{S_{dW}} + \varepsilon}$ ← $\varepsilon = 10^{-8}$

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

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Exponentially weighted averages

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

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

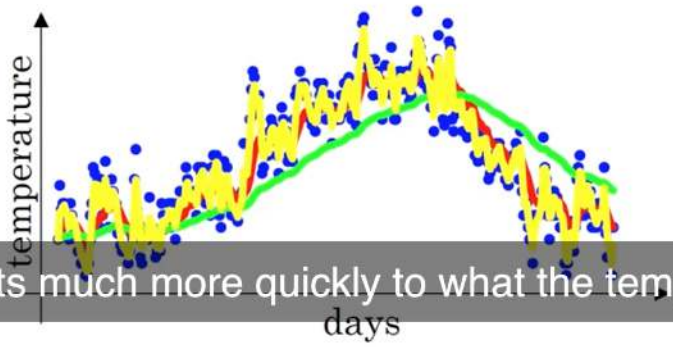
$\beta = 0.98$: $\approx$ 50 days

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

V_t as approximately average over

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

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



But this adapts much more quickly to what the temperature changes.

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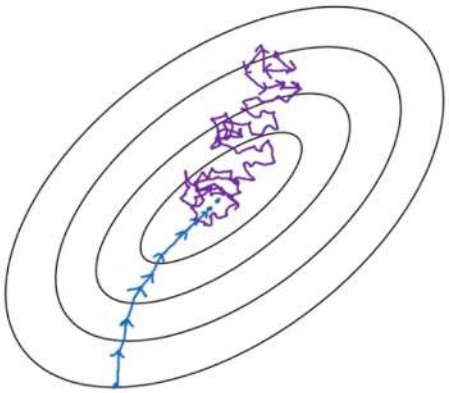
Choosing your mini-batch size

→ 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 $(X^{\{1\}}, Y^{\{1\}}) = (x^{(1)}, y^{(1)})$ ... $(x^{(m)}, y^{(m)})$ mini-batch.

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

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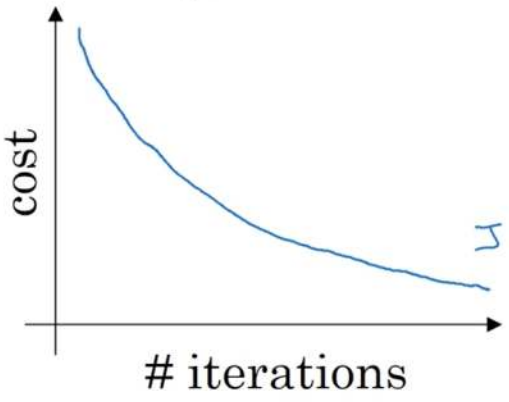
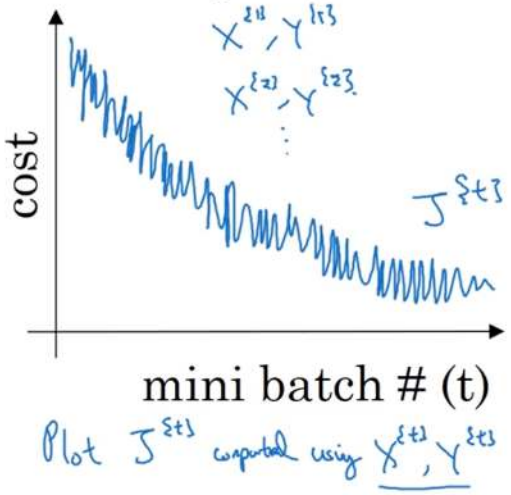
Training with mini batch gradient descent

Batch gradient descent



Mini-batch gradient descent



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Mini-batch gradient descent

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

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

X, Y

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

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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