

Mini-batch gradient descent

Batch vs. mini-batch gradient descent

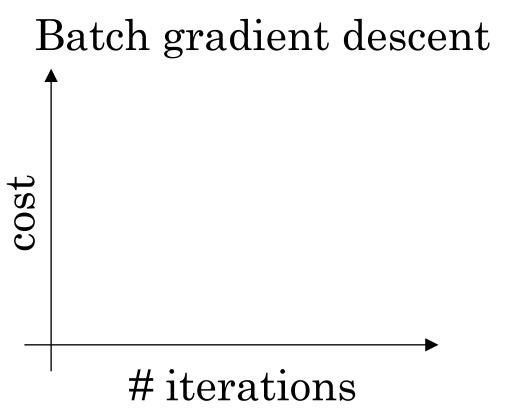
Vectorization allows you to efficiently compute on m examples.

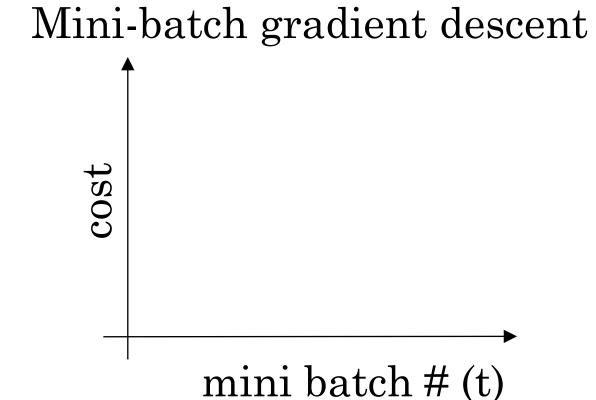
Mini-batch gradient descent



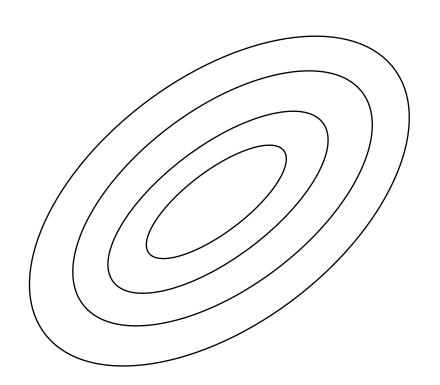
Understanding mini-batch gradient descent

Training with mini batch gradient descent





Choosing your mini-batch size



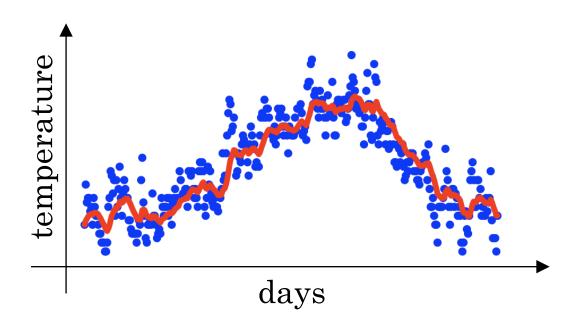
Choosing your mini-batch size



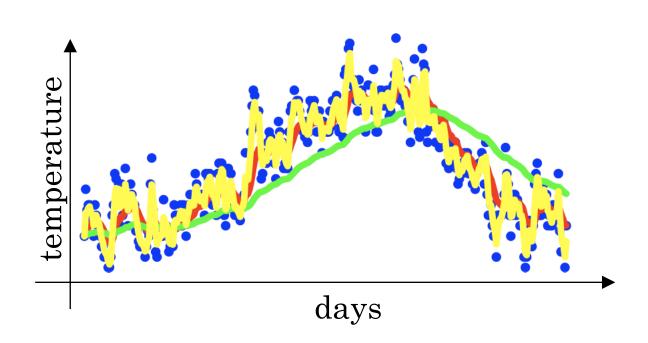
Exponentially weighted averages

Temperature in London

```
\theta_{1} = 40^{\circ}F
\theta_{2} = 49^{\circ}F
\theta_{3} = 45^{\circ}F
\vdots
\theta_{180} = 60^{\circ}F
\theta_{181} = 56^{\circ}F
\vdots
```



Exponentially weighted averages

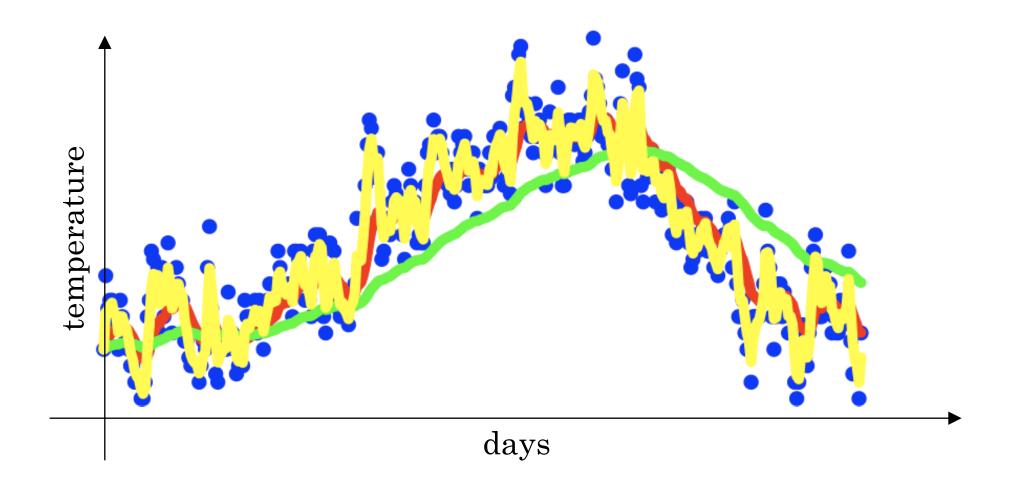




Understanding exponentially weighted averages

Exponentially weighted averages

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



Exponentially weighted averages

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

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

• • •

Implementing exponentially weighted averages

$$v_0 = 0$$

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

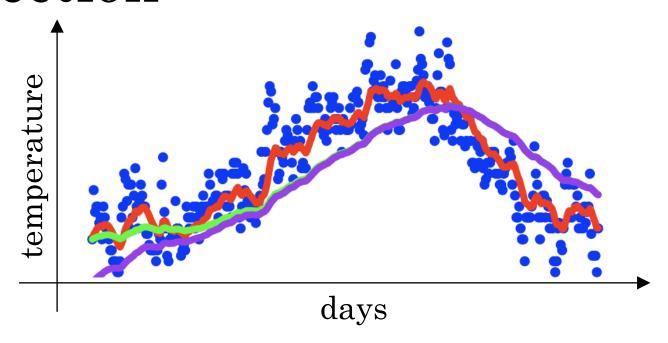


deeplearning.ai

Optimization Algorithms

Bias correction in exponentially weighted average

Bias correction

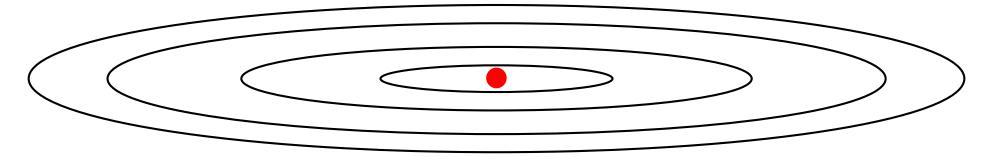


$$v_t = \beta v_{t-1} + (1 - \beta)\theta_t$$



Gradient descent with momentum

Gradient descent example



Implementation details

On iteration *t*:

Compute dW, db on the current mini-batch

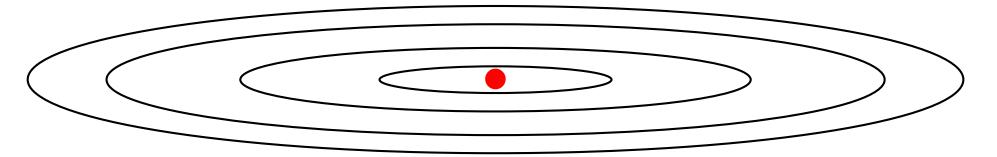
$$\begin{aligned} v_{dW} &= \beta v_{dW} + (1 - \beta)dW \\ v_{db} &= \beta v_{db} + (1 - \beta)db \\ W &= W - \alpha v_{dW}, \ b = b - \alpha v_{db} \end{aligned}$$

Hyperparameters: α, β $\beta = 0.9$



RMSprop

RMSprop





Adam optimization algorithm

Adam optimization algorithm

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

Hyperparameters choice:

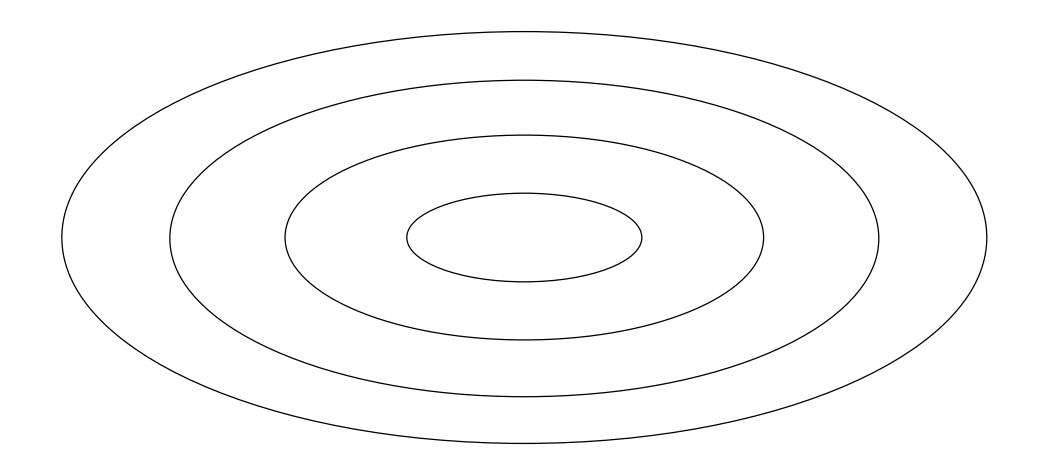


Adam Coates



Learning rate decay

Learning rate decay



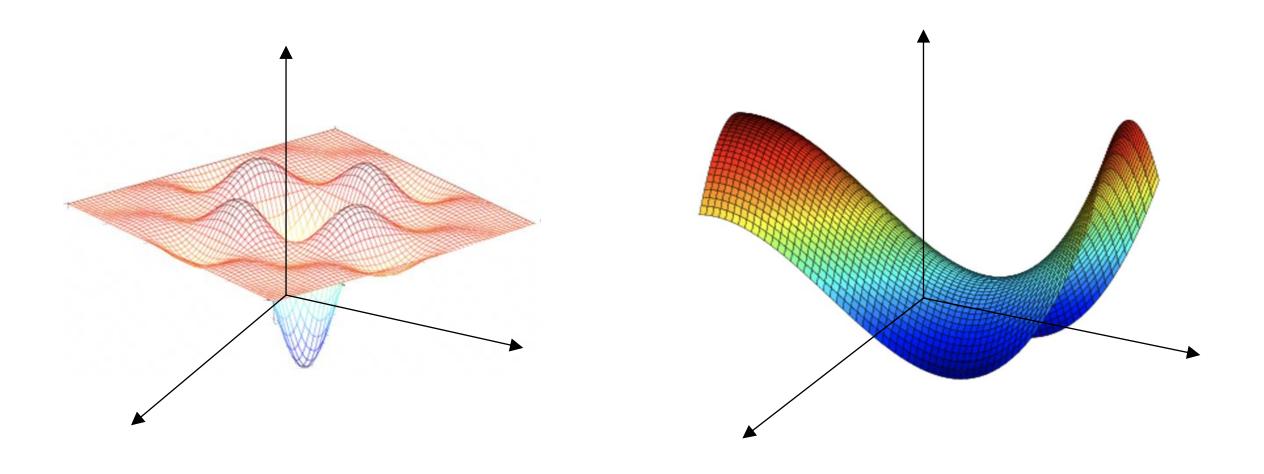
Learning rate decay

Other learning rate decay methods

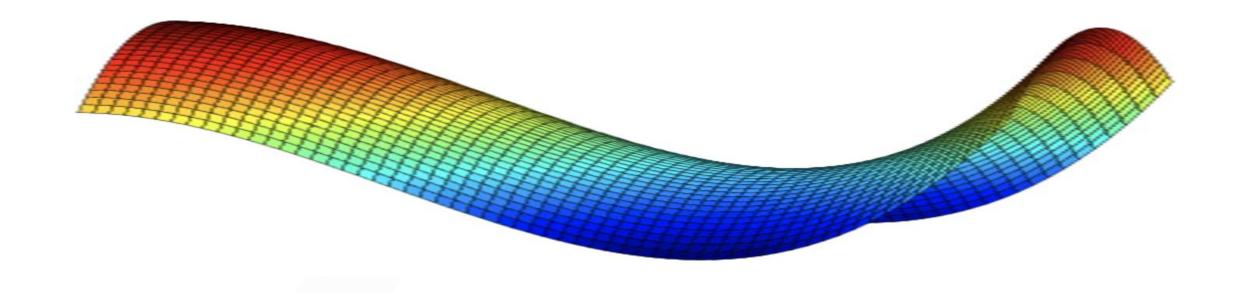


The problem of local optima

Local optima in neural networks



Problem of plateaus



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