

Mini-batch gradient descent

Batch vs. mini-batch gradient descent

Vectorization allows you to efficiently compute on *m* examples.

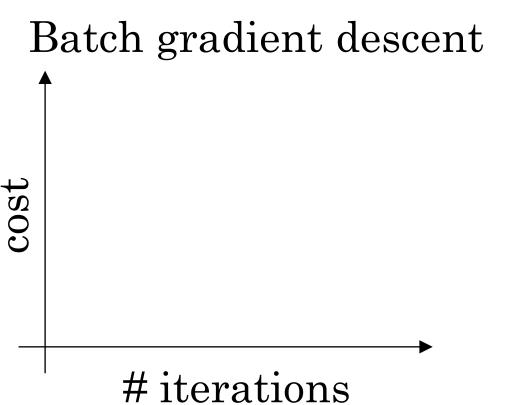
Mini-batch gradient descent

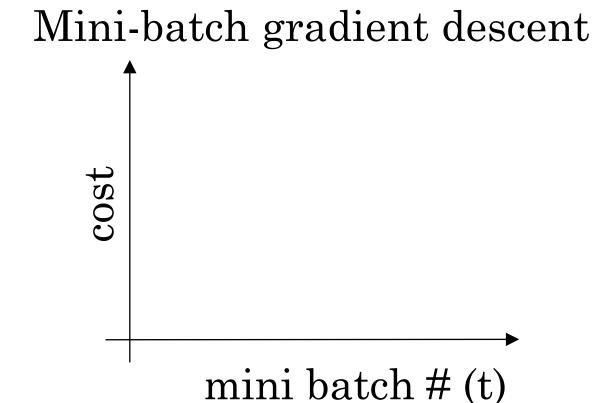


Understanding mini-batch gradient descent

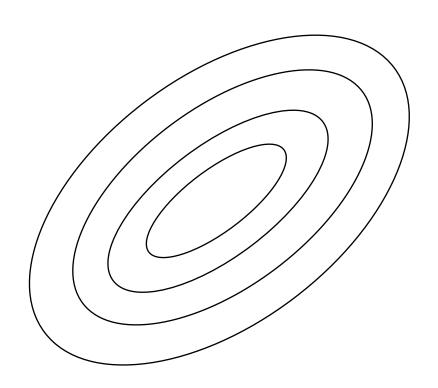
Optimization Algorithms

Training with mini batch gradient descent





Choosing your mini-batch size



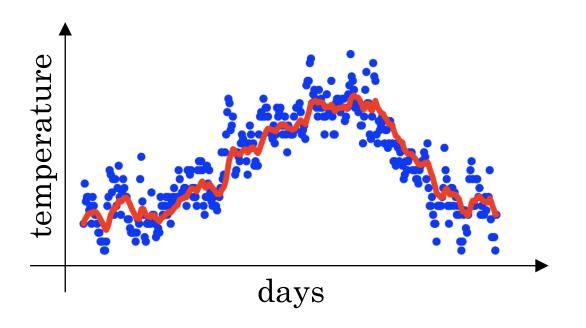
Choosing your mini-batch size



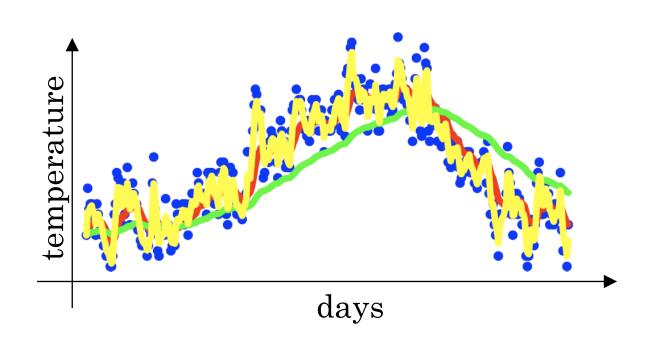
Exponentially weighted averages

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

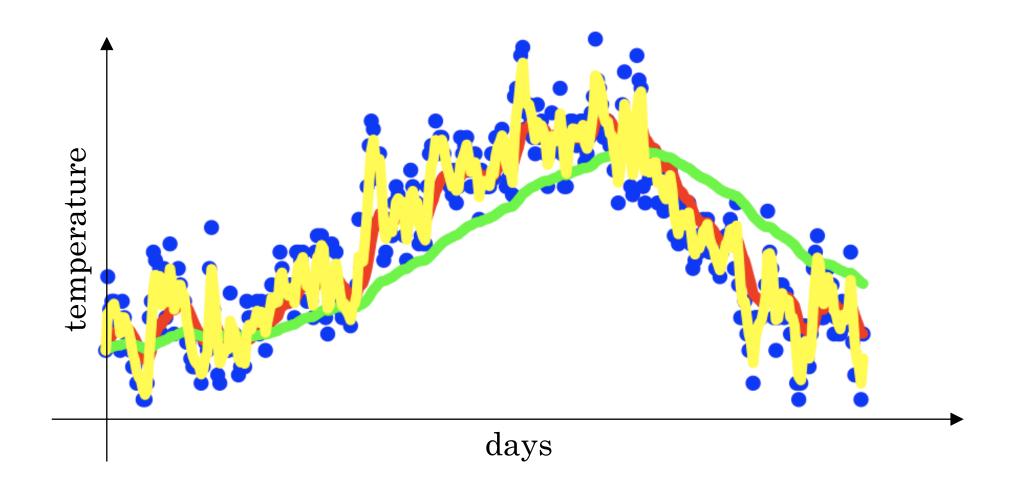




Understanding exponentially weighted averages

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

$$v_0 = 0$$

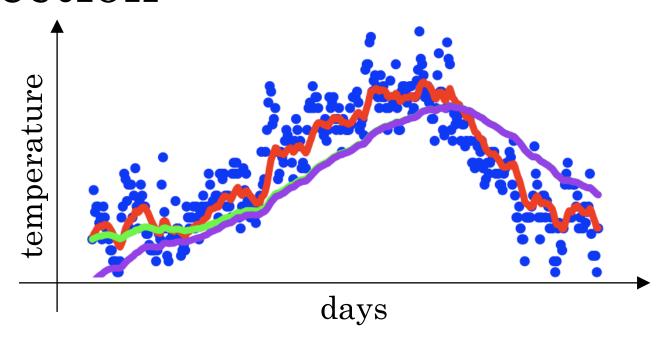
 $v_1 = \beta v_0 + (1 - \beta) \theta_1$
 $v_2 = \beta v_1 + (1 - \beta) \theta_2$
 $v_3 = \beta v_2 + (1 - \beta) \theta_3$

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Bias correction in exponentially weighted average

Bias correction

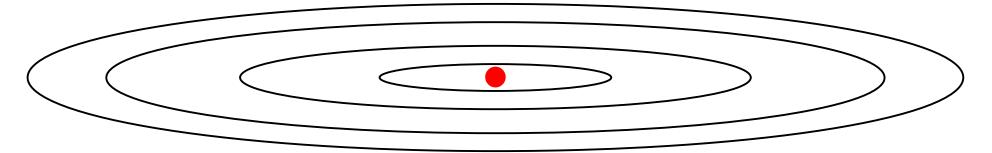


$$v_t = \beta v_{t-1} + (1 - \beta)\theta_t$$



Gradient descent with momentum

Gradient descent example





Implementation details

On iteration *t*:

Compute dW, db on the current mini-batch

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

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

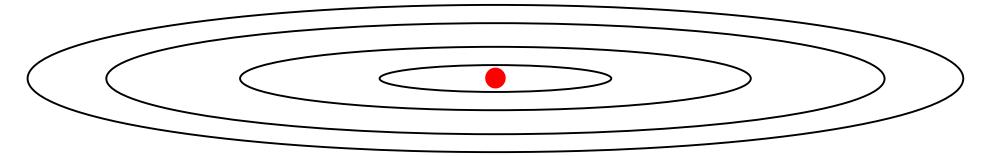
Hyperparameters: α , β

$$\beta = 0.9$$



RMSprop

RMSprop





Adam optimization algorithm

Adam optimization algorithm

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

Hyperparameters choice:

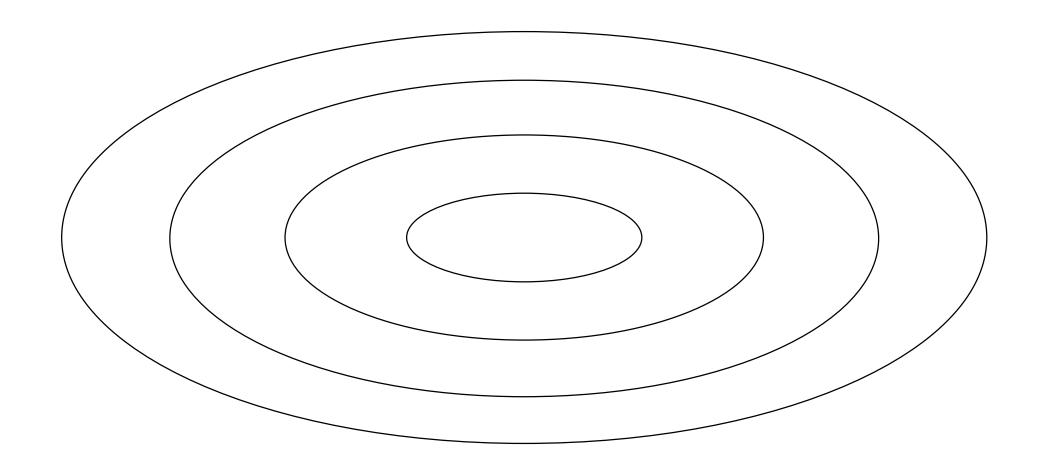


Adam Coates



Learning rate decay

Learning rate decay



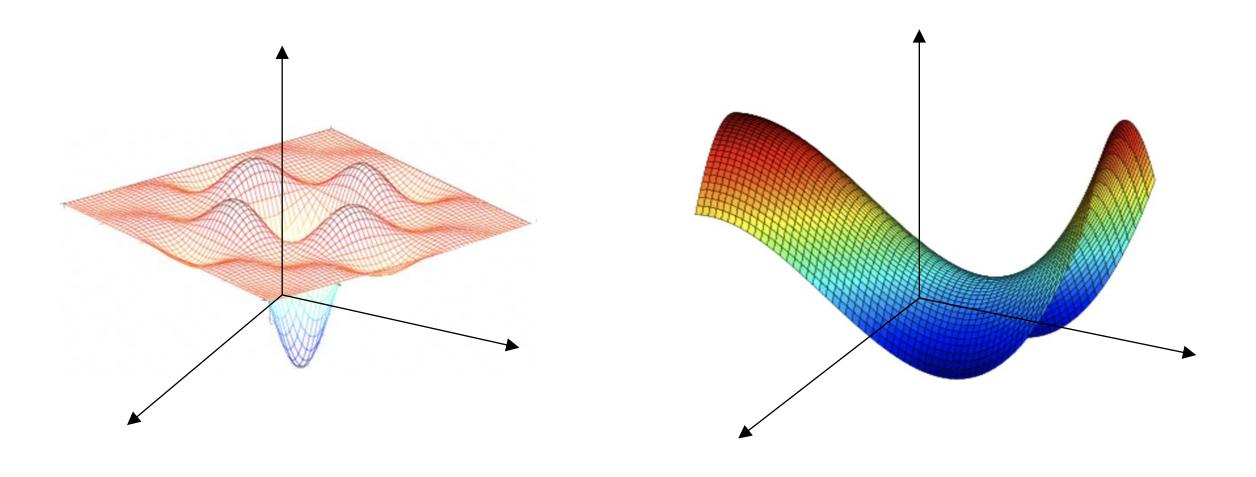
Learning rate decay

Other learning rate decay methods

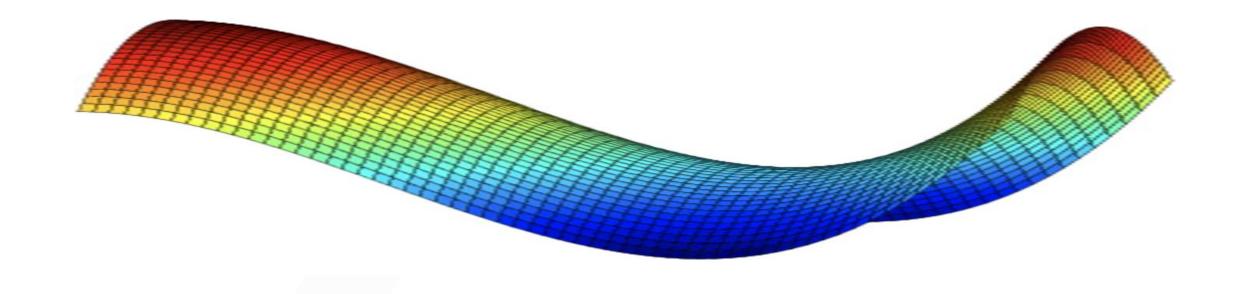


The problem of local optima

Local optima in neural networks



Problem of plateaus



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