



## Congratulations! You passed!

TO PASS 80% or higher

Keep Learning

GRADE  
100%

## Optimization algorithms

LATEST SUBMISSION GRADE

100%

1. Which notation would you use to denote the 3rd layer's activations when the input is the 7th example from the 8th minibatch?

1 / 1 point

- $a^{[8]\{3\}}(7)$
- $a^{[3]\{8\}}(7)$
- $a^{[8]\{7\}}(3)$
- $a^{[3]\{7\}}(8)$

Correct

2. Which of these statements about mini-batch gradient descent do you agree with?

1 / 1 point

- Training one epoch (one pass through the training set) using mini-batch gradient descent is faster than training one epoch using batch gradient descent.
- You should implement mini-batch gradient descent without an explicit for-loop over different mini-batches, so that the algorithm processes all mini-batches at the same time (vectorization).
- One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of batch gradient descent.

Correct

3. Why is the best mini-batch size usually not 1 and not  $m$ , but instead something in-between?

1 / 1 point

- If the mini-batch size is  $m$ , you end up with stochastic gradient descent, which is usually slower than mini-batch gradient descent.
- If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.

Correct

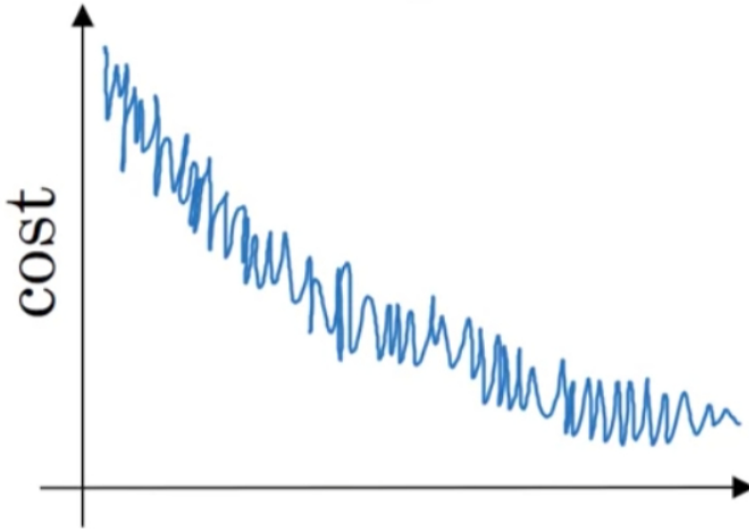
- If the mini-batch size is  $m$ , you end up with batch gradient descent, which has to process the whole training set before making progress.

Correct

- If the mini-batch size is 1, you end up having to process the entire training set before making any progress.

4. Suppose your learning algorithm's cost  $J$ , plotted as a function of the number of iterations, looks like this:

1 / 1 point



Which of the following do you agree with?

- If you're using mini-batch gradient descent, this looks acceptable. But if you're using batch gradient descent, something is wrong.
- Whether you're using batch gradient descent or mini-batch gradient descent, something is wrong.
- Whether you're using batch gradient descent or mini-batch gradient descent, this looks acceptable.
- If you're using mini-batch gradient descent, something is wrong. But if you're using batch gradient descent, this looks acceptable.

✓ Correct

5. Suppose the temperature in Casablanca over the first three days of January are the same:

1 / 1 point

Jan 1st:  $\theta_1 = 10^\circ C$

Jan 2nd:  $\theta_2 = 10^\circ C$

(We used Fahrenheit in lecture, so will use Celsius here in honor of the metric world.)

Say you use an exponentially weighted average with  $\beta = 0.5$  to track the temperature:  $v_0 = 0$ ,  $v_t = \beta v_{t-1} + (1 - \beta)\theta_t$ . If  $v_2$  is the value computed after day 2 without bias correction, and  $v_2^{corrected}$  is the value you compute with bias correction. What are these values? (You might be able to do this without a calculator, but you don't actually need one. Remember what is bias correction doing.)

- $v_2 = 7.5$ ,  $v_2^{corrected} = 10$
- $v_2 = 10$ ,  $v_2^{corrected} = 7.5$
- $v_2 = 7.5$ ,  $v_2^{corrected} = 7.5$
- $v_2 = 10$ ,  $v_2^{corrected} = 10$

✓ Correct

6. Which of these is NOT a good learning rate decay scheme? Here,  $t$  is the epoch number.

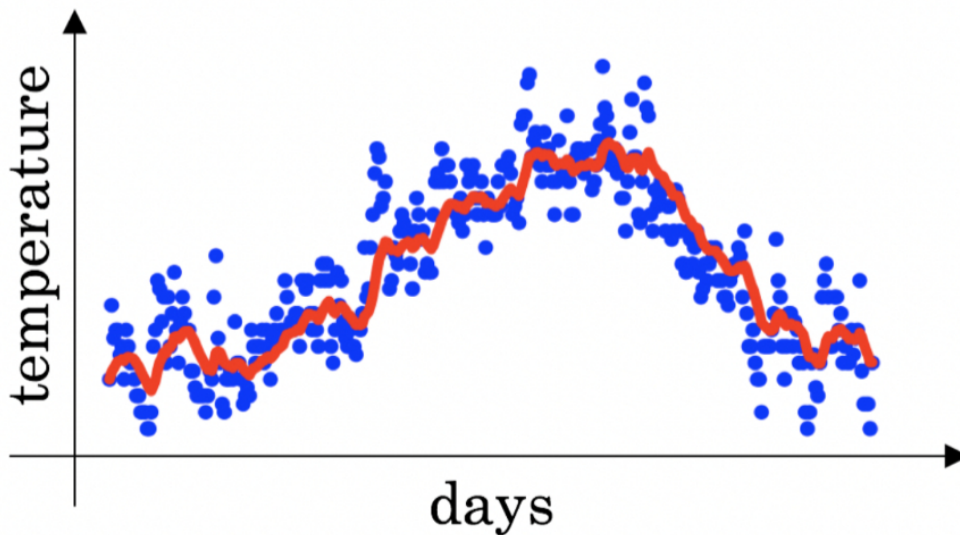
1 / 1 point

- $\alpha = \frac{1}{\sqrt{t}} \alpha_0$
- $\alpha = 0.95^t \alpha_0$
- $\alpha = \frac{1}{1+2+t} \alpha_0$
- $\alpha = e^t \alpha_0$

✓ Correct

7. You use an exponentially weighted average on the London temperature dataset. You use the following to track the temperature:  $v_t = \beta v_{t-1} + (1 - \beta) \theta_t$ . The red line below was computed using  $\beta = 0.9$ . What would happen to your red curve as you vary  $\beta$ ? (Check the two that apply)

1 / 1 point



- Decreasing  $\beta$  will shift the red line slightly to the right.
- Increasing  $\beta$  will shift the red line slightly to the right.

✓ Correct

True, remember that the red line corresponds to  $\beta = 0.9$ . In lecture we had a green line ( $\beta = 0.98$ ) that is slightly shifted to the right.

- Decreasing  $\beta$  will create more oscillation within the red line.

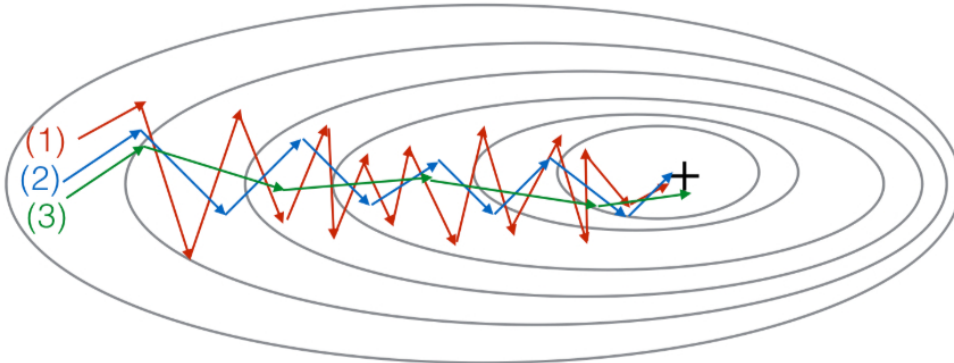
✓ Correct

True, remember that the red line corresponds to  $\beta = 0.9$ . In lecture we had a yellow line  $\beta = 0.98$  that had a lot of oscillations.

Increasing  $\beta$  will create more oscillations within the red line.

8. Consider this figure:

1 / 1 point



These plots were generated with gradient descent; with gradient descent with momentum ( $\beta = 0.5$ ) and gradient descent with momentum ( $\beta = 0.9$ ). Which curve corresponds to which algorithm?

- (1) is gradient descent with momentum (small  $\beta$ ), (2) is gradient descent with momentum (small  $\beta$ ), (3) is gradient descent
- (1) is gradient descent. (2) is gradient descent with momentum (small  $\beta$ ). (3) is gradient descent with momentum (large  $\beta$ )
- (1) is gradient descent with momentum (small  $\beta$ ). (2) is gradient descent. (3) is gradient descent with momentum (large  $\beta$ )
- (1) is gradient descent. (2) is gradient descent with momentum (large  $\beta$ ). (3) is gradient descent with momentum (small  $\beta$ )

✓ Correct

9. Suppose batch gradient descent in a deep network is taking excessively long to find a value of the parameters that achieves a small value for the cost function  $\mathcal{J}(W^{[1]}, b^{[1]}, \dots, W^{[L]}, b^{[L]})$ . Which of the following techniques could help find parameter values that attain a small value for  $\mathcal{J}$ ? (Check all that apply)

1 / 1 point

Try using Adam

✓ Correct

Try better random initialization for the weights

✓ Correct

Try mini-batch gradient descent

✓ Correct

Try initializing all the weights to zero

Try tuning the learning rate  $\alpha$

 Correct

10. Which of the following statements about Adam is False?

1 / 1 point

The learning rate hyperparameter  $\alpha$  in Adam usually needs to be tuned.

We usually use "default" values for the hyperparameters  $\beta_1$ ,  $\beta_2$  and  $\epsilon$  in Adam ( $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ,  $\epsilon = 10^{-8}$ )

Adam should be used with batch gradient computations, not with mini-batches.

Adam combines the advantages of RMSProp and momentum

 Correct