Optimization algorithms

1.Question 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^{[3]{8}(7)}

○ a^{[3]{7}(8)}

○ a^{[8]{7}(3)}

○ a^{[8]{3}(7)}

2.Question 2

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

1 / 1 point

○ 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).

○ Training one epoch (one pass through the training set) using mini-batch gradient descent is faster than training one epoch using batch gradient descent.

● One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of batch gradient descent.

3.Question 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 1, you lose the benefits of vectorization across examples in the mini-batch.

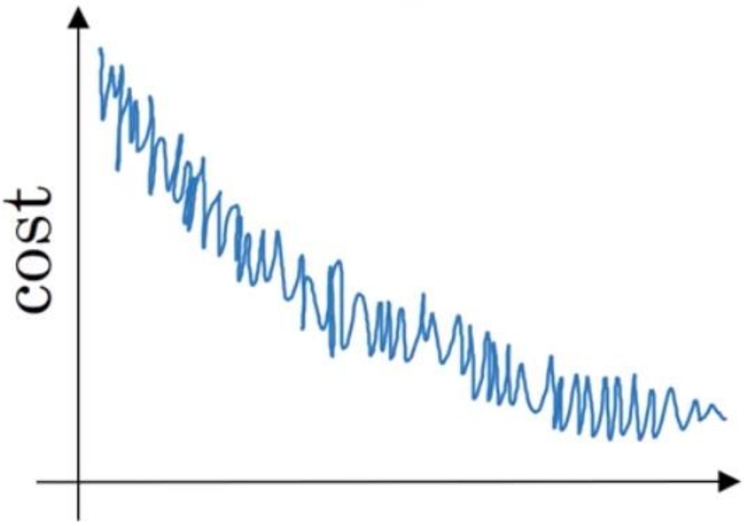
☐ If the mini-batch size is m, you end up with stochastic gradient descent, which is usually slower than mini-batch gradient descent.

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

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

4.Question 4

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



Which of the following do you agree with?

1 / 1 point

Ans. If you’re using mini-batch gradient descent, this looks acceptable. But if you’re using batch gradient descent, something is wrong.

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

Jan 1st: $\theta_1 = 10C$

Jan 2nd: $\theta_2 10C$

(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.)

1 / 1 point

○ $v_2 = 10$, $v_2^{corrected} = 10$

● $v_2 = 7.5$, $v_2^{corrected} = 10$

○ $v_2 = 7.5$, $v_2^{corrected} = 7.5$

○ $v_2 = 10$, $v_2^{corrected} = 7.5$

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

1 / 1 point

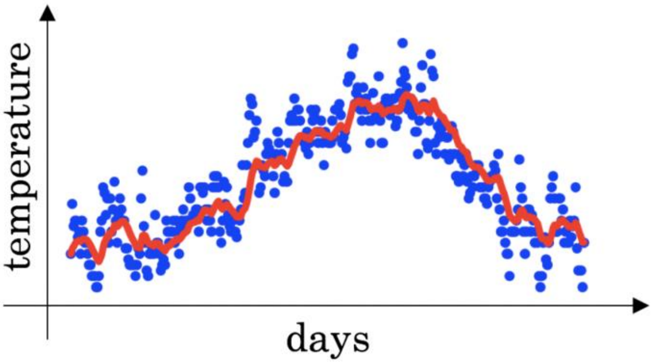
● α = e^t α0

○ α = (1 / sqrt{t}) α0

○ α = 0.95^t α0

7.Question 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$v_t=\beta v_{t-1} +(1-\beta)\theta_t$. The red line below was computed using \beta = 0.9$\beta=0.9$. What would happen to your red curve as you vary \beta$\beta$? (Check the two that apply)



1 / 1 point

☐ Decreasing β will shift the red line slightly to the right.

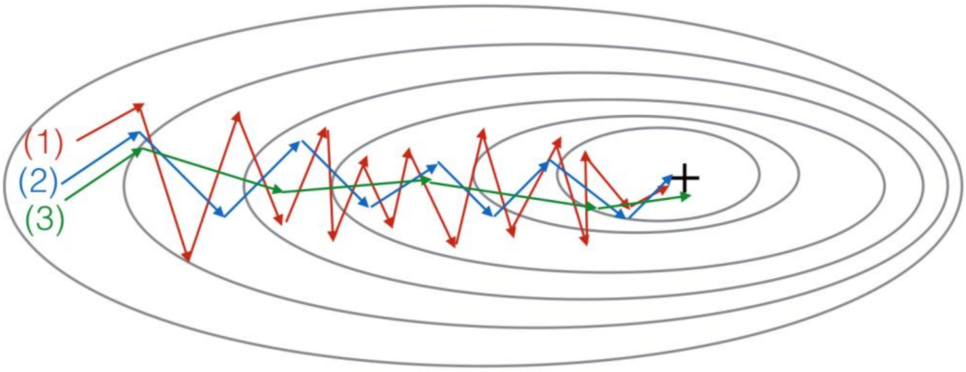
☑ Increasing β will shift the red line slightly to the right.

☑ Decreasing β will create more oscillation within the red line.

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

8.Question 8

Consider this figure:



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

1 / 1 point

○ (1) is gradient descent with momentum (small β). (2) is gradient descent. (3) is gradient descent with momentum (large β)

○ (1) is gradient descent with momentum (small β), (2) is gradient descent with momentum (small β), (3) is gradient descent

● (1) is gradient descent. (2) is gradient descent with momentum (small β). (3) is gradient descent with momentum (large β)

○ (1) is gradient descent. (2) is gradient descent with momentum (large β) . (3) is gradient descent with momentum (small β)

9.Question 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]},..., W^{[L]},b^{[L]})$J(W^{[1]},b^{[1]},...,W^{[L]},b^{[L]})$. Which of the following techniques could help find parameter values that attain a small value for\mathcal{J}J? (Check all that apply)

1 / 1 point

☑ Try better random initialization for the weights

☑ Try mini-batch gradient descent

☑ Try using Adam

☐ Try initializing all the weights to zero

☑ Try tuning the learning rate \alpha$\alpha$

10.Question 10

Which of the following statements about Adam is False?

1 / 1 point

○ Adam combines the advantages of RMSProp and momentum

○ The learning rate hyperparameter α in Adam usually needs to be tuned.

○ We usually use “default” values for the hyperparameters β_1, β_2 and ε in Adam ($\beta_1 = 0.9$, $\beta_2 = 0.999$, ε = 10^{-8})

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