Optimization algorithms

TOTAL POINTS 10

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 point

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

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

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.

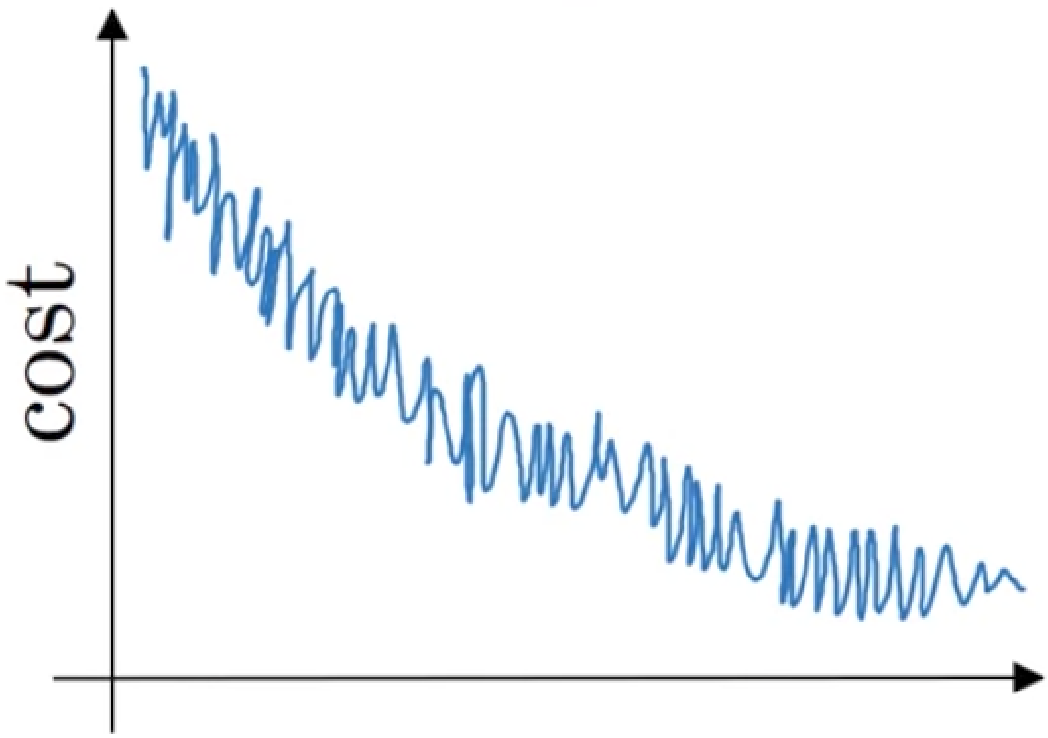
3. Why is the best mini-batch size usually not 1 and not m, but instead something in-between?

1 point

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

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

1 point



Which of the following do you agree with?

- ◯ Whether you're using batch gradient descent or mini-batch gradient descent, something is wrong.
- ◉ 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, 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.

5.

1 point

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

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

Jan 2nd: $\theta_2 10^o C$

(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.)

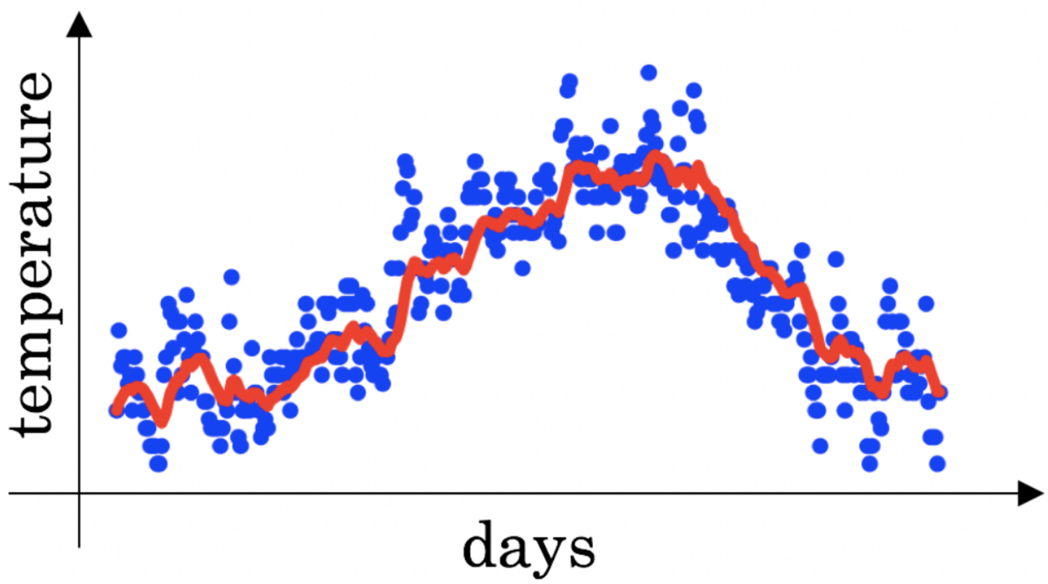
- ○ $v_2 = 10$, $v_2^{corrected} = 10$
- ○ $v_2 = 10$, $v_2^{corrected} = 7.5$
- ◉ $v_2 = 7.5$, $v_2^{corrected} = 10$
- ○ $v_2 = 7.5$, $v_2^{corrected} = 7.5$

6. Which of these is NOT a good learning rate decay scheme? Here, t is the epoch number. 1 point

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

7. 1 point

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 β? (Check the two that apply)

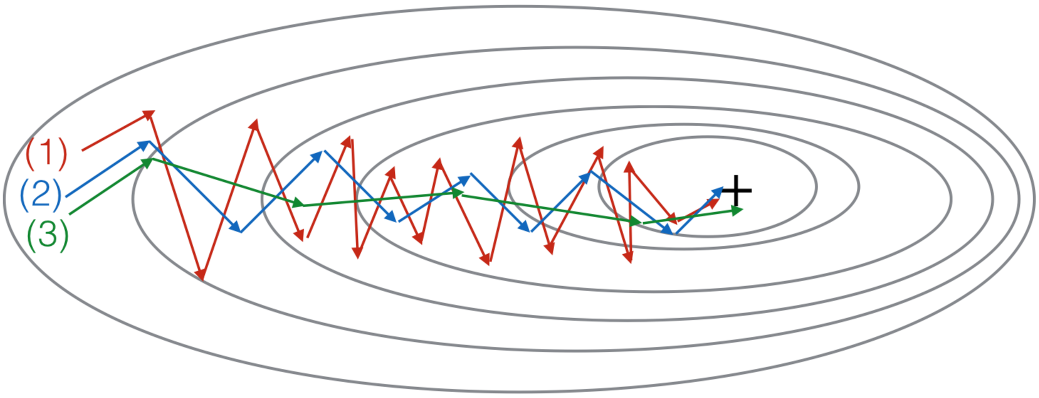


- [ ] Decreasing β will shift the red line slightly to the right.
- [x] Increasing β will shift the red line slightly to the right.
- [x] Decreasing β will create more oscillation within the red line.
- [ ] Increasing β will create more oscillations within the red line.

8.

1 point

Consider this figure:



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

- ○ (1) is gradient descent with momentum (small β). (2) is gradient descent. (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)
- ◉ (1) is gradient descent. (2) is gradient descent with momentum (small β). (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

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

1 point

- [x] Try tuning the learning rate α
- [x] Try using Adam
- [ ] Try initializing all the weights to zero
- [x] Try mini-batch gradient descent
- [x] Try better random initialization for the weights

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

1 point

- ○ 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 ($\beta_1 = 0.9, \beta_2 = 0.999, \varepsilon = 10^{-8}$)
- ◉ Adam should be used with batch gradient computations, not with mini-batches.
- ○ Adam combines the advantages of RMSProp and momentum