Optimization algorithms

Quiz, 10 questions

1 point

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

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

1 point

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

- 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.

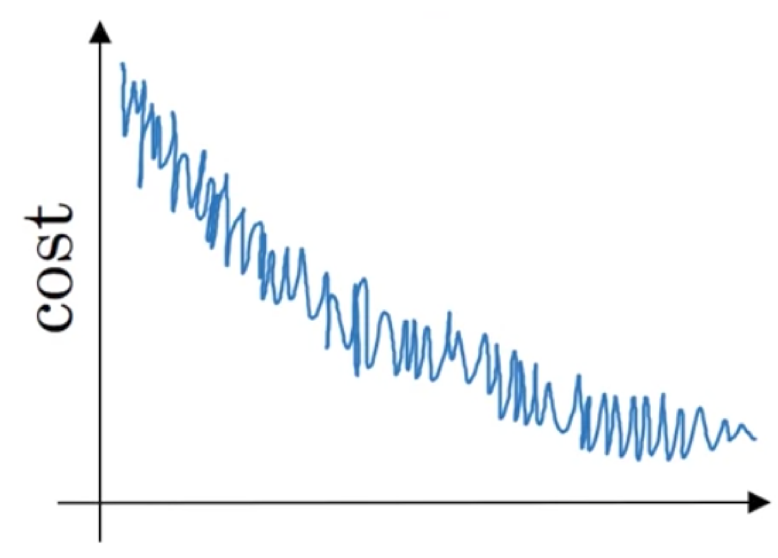
1 point

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

- 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 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 end up having to process the entire training set before making any progress.
- If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.

1 point

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



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

1 point

5. 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.)

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

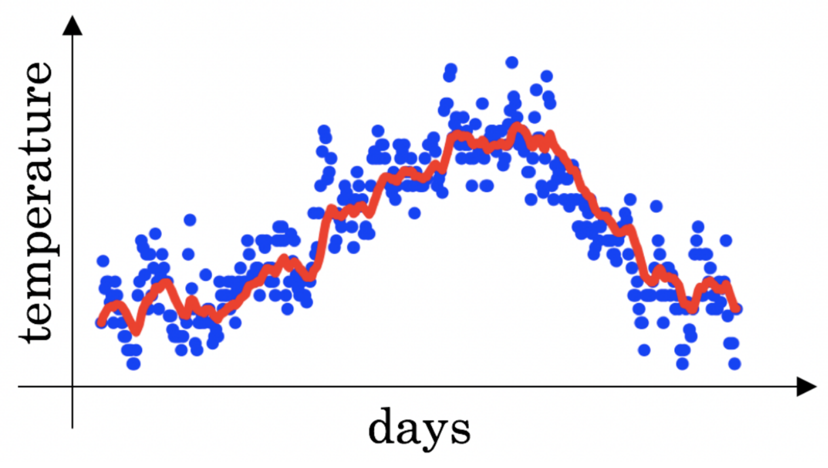
1 point

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

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

1 point

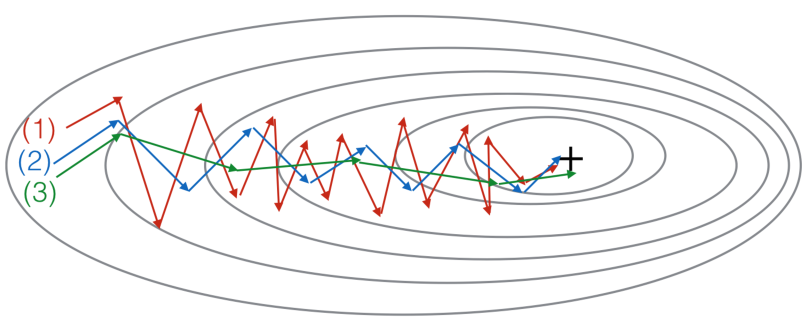
7. You use an exponentially weighted average on the London temperature dataset. You use the following to track the temperature: $v_t = \beta v_{t-1} + (1-\beta)\theta_t$. The red line below was computed using $\beta = 0.9$. What would happen to your red curve as you vary β? (Check the two that apply)



- 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 β will create more oscillations within the red line.

1 point

8. 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. (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
- (1) is gradient descent with momentum (small β). (2) is gradient descent. (3) is gradient descent with momentum (large β)

1 point

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

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

1 point

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

- 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 combines the advantages of RMSProp and momentum
- Adam should be used with batch gradient computations, not with mini-batches.

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