1. Using the notation for mini-batch gradient descent. To what of the following does $a^{[2]\{4\}(3)}$ correspond? 1 point

- [ ] The activation of the third layer when the input is the fourth example of the second mini-batch.
- [x] The activation of the second layer when the input is the third example of the fourth mini-batch.
- [ ] The activation of the fourth layer when the input is the second example of the third mini-batch.
- [ ] The activation of the second layer when the input is the fourth example of the third mini-batch.

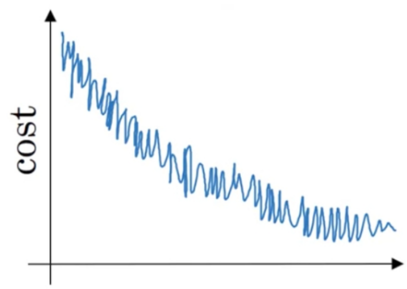
2. Which of these statements about mini-batch gradient descent do you agree with? 1 point

- [ ] 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).
- [x] One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of batch gradient descent.
- [ ] Training one epoch (one pass through the training set) using mini-batch gradient descent is faster than training one epoch using batch gradient descent.

3. Why is the best mini-batch size usually not 1 and not m, but instead something in-between? Check all that are true. 1 point

- [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.
- [x] If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.

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?

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

5. Suppose the temperature in Casablanca over the first two days of March are the following: 1 point

March 1st: $\theta_1 = 10^\circ\ \mathrm{C}$

March 2nd: $\theta_2 = 25^\circ\ \mathrm{C}$

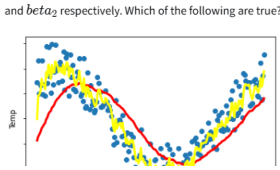
Say you use an exponentially weighted average with $\beta = 0.5$ to track the temperature: $v_0 = 0$, $v_t = \beta v_{t-1} + (1-\beta)\,\theta_t$. If v_2 is the value computed after day 2 without bias correction, and $v_2^{\text{corrected}}$ is the value you compute with bias correction. What are these values?

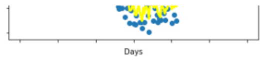
- [ ] $v_2 = 15, v_2^{\text{corrected}} = 15.$
- [x] $v_2 = 15, v_2^{\text{corrected}} = 20.$
- [ ] $v_2 = 20, v_2^{\text{corrected}} = 15.$
- [ ] $v_2 = 20, v_2^{\text{corrected}} = 20.$

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

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

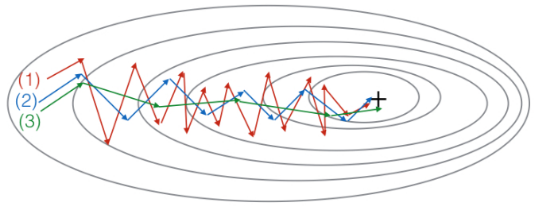
7. You use an exponentially weighted average on the London temperature dataset. You use the following to track the temperature: $v_t = \beta v_{t-1} + (1-\beta)\theta_t$. The yellow and red lines were computed using values $beta_1$ and $beta_2$ respectively. Which of the following are true? 1 point





- ○ $\beta_1 = \beta_2$.
- ○ $\beta_1 = 0, \beta_2 > 0$.
- ○ $\beta_1 > \beta_2$.
- ◉ $\beta_1 < \beta_2$.

8. Consider this figure: 1 point



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

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

- [x] Try using Adam.
- [x] Try mini-batch gradient descent.
- [ ] Try initializing the weight at zero.
- [x] Normalize the input data.

10. Which of the following statements about Adam is ***False***? 1 point

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