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

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

   ✓ **Correct**

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

   1 / 1 point

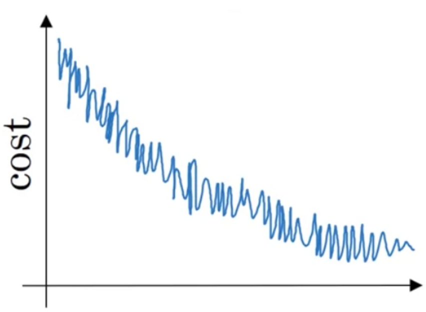
   - (●) One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of batch gradient descent.
   - ( ) Training one epoch (one pass through the training set) using mini-batch gradient descent is faster than training one epoch using batch gradient descent.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

   ✓ **Correct**

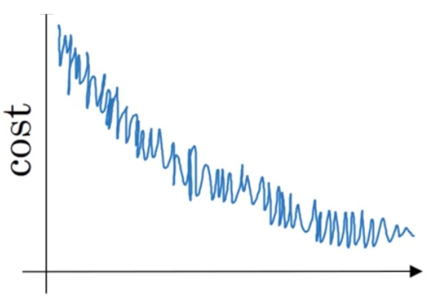
   - [ ] If the mini-batch size is 1, you end up having to process the entire training set before making any progress.

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?



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.
   - ( ) Whether you're using batch gradient descent or mini-batch gradient descent, this looks acceptable.
   - (●) 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.

   ✓ **Correct**

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

   1 / 1 point

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

   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.)

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

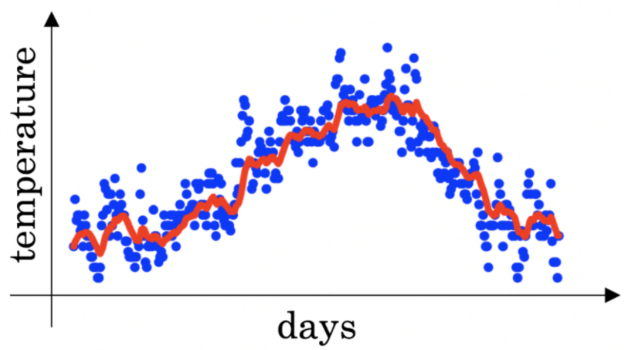
✓ **Correct**

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

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

✓ **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 β? (Check the two that apply) **1 / 1 point**



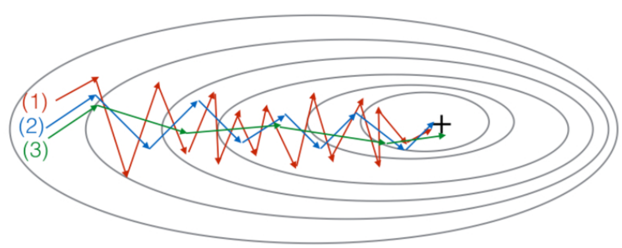
slightly shifted to the right.

- ☑ Decreasing β 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 β 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 (β = 0.5) and gradient descent with momentum (β = 0.9). Which curve corresponds to which algorithm?

- ☑ Try better random initialization for the weights

✓ **Correct**

- ☑ Try mini-batch gradient descent

✓ **Correct**

- ☐ Try initializing all the weights to zero
- ☑ Try using Adam

✓ **Correct**

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

- ○ The learning rate hyperparameter α in Adam usually needs to be tuned.
- ○ Adam combines the advantages of RMSProp and momentum
- ◉ Adam should be used with batch gradient computations, not with mini-batches.

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

✓ **Correct**

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)

- [x] Try tuning the learning rate α

✓ **Correct**

✓ **Correct**

- [x] Try mini-batch gradient descent

✓ **Correct**

- [ ] Try initializing all the weights to zero
- [x] Try using Adam

✓ **Correct**

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

1 / 1 point

- ( ) The learning rate hyperparameter α in Adam usually needs to be tuned.
- ( ) Adam combines the advantages of RMSProp and momentum
- (•) Adam should be used with batch gradient computations, not with mini-batches.
- ( ) We usually use "default" values for the hyperparameters β_1, β_2 and ε in Adam ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-8}$)

✓ **Correct**