⊘ Correct

Great you got all the right answers

Congratulations! You passed!

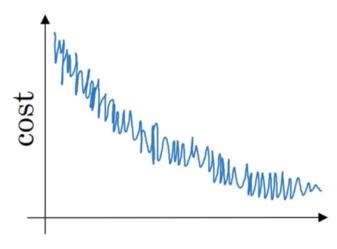
Grade received 90% Latest Submission Grade 90% To pass 80% or higher

Go to next item

1.	Which notation would you use to denote the 4th layer's activations when the input is the 7th example from the 3rd mini-batch?	1 / 1 point
	$\bigcirc \ a^{[7]\{3\}\{4)}$	
	$\bigcirc \ a^{[3]\{7\}(4)}$	
	∠ [¬] Expand	
	$igotimes$ Correct Yes. In general $a^{[l]\{t\}(k)}$ denotes the activation of the layer l when the input is the example k from the mini-batch t .	
2.	Which of these statements about mini-batch gradient descent do you agree with?	1/1 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.	
	One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of 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).	
	∠ [¬] Expand	
	⊘ Correct	
2		
э.	Why is the best mini-batch size usually not 1 and not m, but instead something in-between? Check all that are true.	1/1 point
	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 m, you end up with batch gradient descent, which has to process the whole training set before making progress.	
	✓ Correct	
	If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.	
	✓ Correct	
	∠ Expand	

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?

- 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 two days of January are the same:

1/1 point

Jan 1st:
$$heta_1=10^oC$$

Jan 2nd:
$$heta_2=10^oC$$

(We used Fahrenheit in the lecture, so we 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 bias correction is doing.)

$$\bigcirc \quad v_2 = 10, \, v_2^{corrected} = 7.5$$

$$\bigcirc \quad v_2 = 7.5, \, v_2^{corrected} = 7.5$$

$$\bigcirc \quad v_2=10, v_2^{corrected}=10$$

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

∠⁷ Expand

⊘ Correct

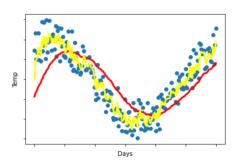
$$\bigcirc \quad \alpha = \frac{1}{\sqrt{t}}\alpha_0$$

$$\bigcirc \quad \alpha = 0.95^t \alpha_0$$

$$\bigcirc \quad \alpha = rac{1}{1+2*t} lpha_0$$

⊘ Correct

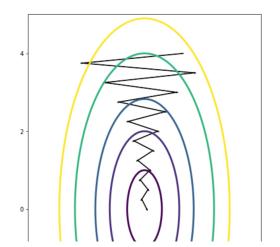
7. You use an exponentially weighted average on the London temperature dataset. You use the following to track the temperature: $v_t = \beta v_{t-1} + (1-\beta)\theta_t$. 1/1 point The yellow and red lines were computed using values $beta_1$ and $beta_2$ respectively. Which of the following are true?

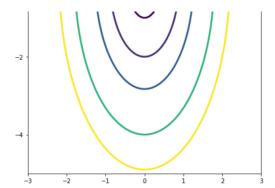


- $\beta_1 > \beta_2$.
- $igcap eta_1=0$, $eta_2>0$.
- $igotimes eta_1 < eta_2.$
- $\bigcirc \quad \beta_1 = \beta_2.$

∠⁷ Expand

- \bigcirc Correct Correct. $\beta_1 < \beta_2$ since the yellow curve is noisier.
- 8. Consider the figure: 0 / 1 point





Suppose this plot was generated with gradient descent with momentum $\beta=0.01$. What happens if we increase the value of β to 0.1?

- The gradient descent process moves less in the horizontal direction and more in the vertical direction.
- The gradient descent process moves more in the horizontal and the vertical axis.
- The gradient descent process starts moving more in the horizontal direction and less in the vertical.
- The gradient descent process starts oscillating in the vertical direction.



(X) Incorrect

No. The use of a greater value of β causes a more efficient process thus reducing the oscillation in the horizontal direction and moving the steps more in the vertical direction.

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)

1/1 point

Try using Adam



- Try initializing all the weights to zero
- ightharpoonup Try tuning the learning rate lpha

✓ Correct

Try mini-batch gradient descent

✓ Correct

Try better random initialization for the weights

✓ Correct



Great, you got all the right answers.

\bigcirc	Adam combines the advantages of RMSProp and momentum
	Adam should be used with batch gradient computations, not with mini-batches.
\bigcirc	The learning rate hyperparameter $lpha$ in Adam usually needs to be tuned.
\circ	We usually use "default" values for the hyperparameters eta_1,eta_2 and $arepsilon$ in Adam ($eta_1=0.9,eta_2=0.999,arepsilon=10^{-8}$)

∠⁷ Expand

⊘ Correct