1/1 point

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

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

Expand

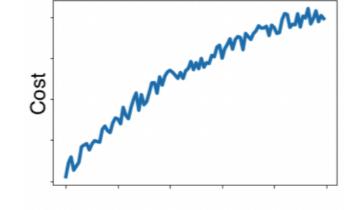
Correct Yes. In general $a^{[l]\{t\}(k)}$ denotes the activation of the layer l when the input is the example k from the mini-batch t.

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.	
	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).	
	When the mini-batch size is the same as the training size, mini-batch gradient descent is equivalent to batch gradient descent.	
	∠ [¬] Expand	
	Correct Correct. Batch gradient descent uses all the examples at each iteration, this is equivalent to having only one mini-batch of the size of the complete training set in mini-batch gradient descent.	

3.	We usually choose a mini-batch size greater than 1 and less than m , because that way we make use of vectorization but not fall into the slower case of batch gradient descent.	1/1 point
	○ False	
	True	
	∠ [¬] Expand	
	Correct Correct. Precisely by choosing a batch size greater than one we can use vectorization; but we choose a value less than m so we won't end up using batch gradient descent.	



0 / 1 point



Which of the following do you agree with?

\bigcirc	No matter if using mini-batch gradient descent or batch gradient descent something is wrong.
	If you are using mini-batch gradient descent or batch gradient descent this looks acceptable.
0	If you are using batch gradient descent, this looks acceptable. But if you're using mini-batch gradient descent, something is wrong.
0	If you are using mini-batch gradient descent, this looks acceptable. But if you're using batch gradient descent, something is wrong.



∠⁷ Expand

No. The cost is larger than when the process started, this is not right at all.

without bias correction, and $v_2^{\text{corrected}}$ is the value you compute with bias correction. What are these values?

March 1st: $heta_1=10^\circ~{
m C}$

March 2nd: $heta_2=25^\circ~{
m C}$

Say you use an exponentially weighted average with eta=0.5 to track the temperature: $v_0=0,v_t=eta v_{t-1}+(1-eta)\, heta_t$. If v_2 is the value computed after day 2

, 2

$$v_2=20'\ v_2^{
m corrected}=15'$$

$$v_2=15'\ v_2^{
m corrected}=20'$$

$$v_2 = 15' \, v_2^{
m corrected} = 15'$$

$$v_2=20^{\prime}\,v_2^{
m corrected}=20^{\circ}$$



$$igotimes$$
 Correct Correct. $v_2=eta v_{t-1}+(1-eta)\, heta_t$ thus $v_1=5,v_2=15$. Using the bias correction $rac{v_t}{1-eta^t}$ we get $rac{15}{1-(0.5)^2}=20$.

✓ Correct



0 / 1 point

∠⁷ Expand

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

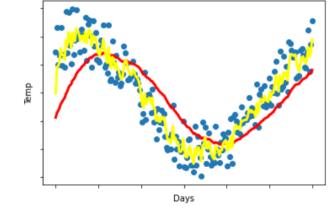
Incorrect. This is a good learning rate decay since it is a decreasing function of t.

(X) Incorrect

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?



1/1 point



$$\begin{array}{ccc} \bigcirc & \beta_1 > \beta_2 \\ \\ \bigcirc & \beta_1 = 0' \ \beta_2 > 0 \end{array}$$

$$\bigcirc \quad \beta_1 = 0' \ \beta_2 > 0.$$

$$igcap_1=eta_2$$

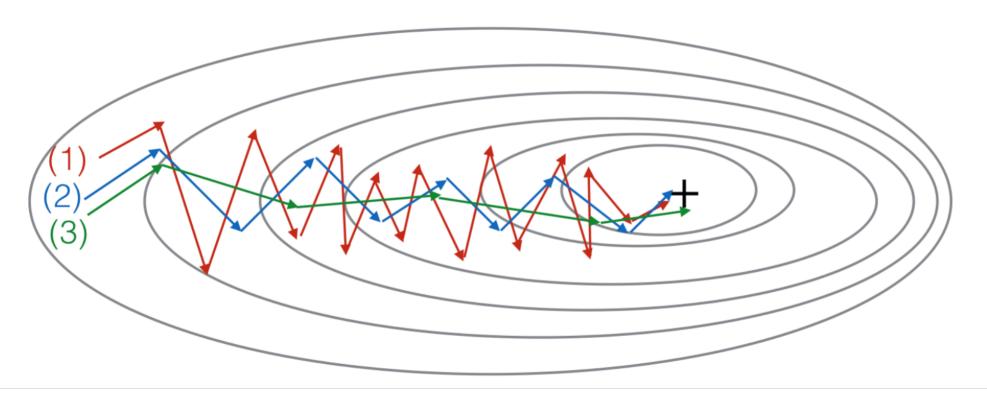
$$lacksquare$$
 $eta_1 < eta_2$

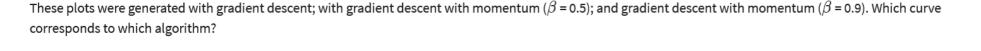




 \bigcirc Correct Correct. $eta_1 < eta_2$ since the yellow curve is noisier.

8. Consider this figure:





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



9.	sch 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 $[0,1],,W^{[L]},b^{[L]}$). 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 better random initialization for the weights	
	 ✓ Correct Yes. As seen in previous lectures this can help the gradient descent process to prevent vanishing gradients. 	
	Try using gradient descent with momentum.	
	 ✓ Correct Yes. The use of momentum can improve the speed of the training. Although other methods might give better results, such as Adam. 	
	Normalize the input data.	
	 Correct Yes. In some cases, if the scale of the features is very different, normalizing the input data will speed up the training process. 	
	Add more data to the training set.	



\bigcirc	Co
	Gı

Great, you got all the right answers.

\circ	The most important hyperparameter on Adam is ϵ and should be carefully tuned.	
0	Adam automatically tunes the hyperparameter $lpha$.	
\circ	Adam can only be used with batch gradient descent and not with mini-batch gradient descent.	
	Adam combines the advantages of RMSProp and momentum.	
∠ ⁷ Expand	i e	

True. Precisely Adam combines the features of RMSProp and momentum that is why we use two-parameter β_1 and β_2 , besides ϵ .

1/1 point

10. Which of the following are true about Adam?

⊘ Correct