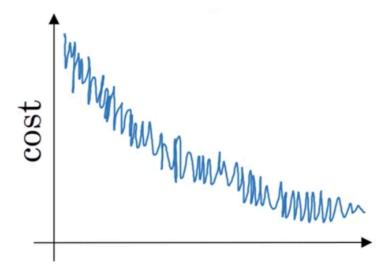
Your grade: 87.50%

Your latest: 87.50% • Your highest: 87.50% • To pass you need at least 80%. We keep your highest score.

Next item \Rightarrow

l.	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. Incorrect No. 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 .	0 / 1 point
2.	Suppose you don't face any memory-related problems. Which of the following make more use of vectorization. $\bigcirc \ \text{Mini-Batch Gradient Descent with mini-batch size } m/2.$	1/1 point
	Stochastic Gradient Descent, Batch Gradient Descent, and Mini-Batch Gradient Descent all make equal use of vectorization.	
	Batch Gradient Descent	
	Stochastic Gradient Descent	
	Correct Yes. If no memory problem is faced, batch gradient descent processes all of the training set in one pass, maximizing the use of vectorization.	
3.	Why is the best mini-batch size usually not 1 and not m, but instead something in-between? Check all that are true.	1/1 point
	If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.	
	⊘ Correct	
	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	



You notice that the value of J is not always decreasing. Which of the following is the most likely reason for that?

- The algorithm is on a local minimum thus the noisy behavior.
- A bad implementation of the backpropagation process, we should use gradient check to debug our implementation.
- lacktriangled In mini-batch gradient descent we calculate $J(\hat{y}^{\{t\}},y^{\{t\}})$ thus with each batch we compute over a new set of data.
- O You are not implementing the moving averages correctly. Using moving averages will smooth the graph.

Yes. Since at each iteration we work with a different set of data or batch the loss function doesn't have to be decreasing at each iteration.

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.)

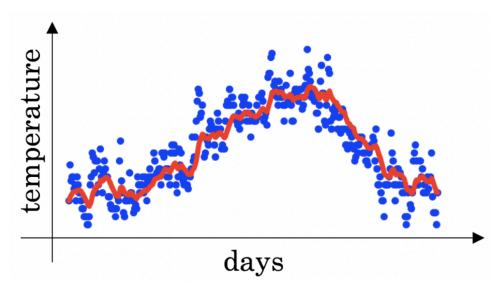
- $v_2 = 7.5, v_2^{corrected} = 10$
- $\bigcirc \ v_2 = 10, v_2^{corrected} = 10$
- $\bigcirc \ v_2=10, v_2^{corrected}=7.5$
- $v_2 = 7.5, v_2^{corrected} = 7.5$
 - **⊘** Correct

1/1 point

- 6. Which of these is NOT a good learning rate decay scheme? Here, t is the epoch number.
 - $\bigcirc \ \ lpha = e^{-0.01\,t}lpha_0.$
 - $igotimes lpha = 1.01^t \, lpha_0$
 - $\bigcirc \ lpha = rac{lpha_0}{1+3\,t}$
 - $\bigcirc \ \alpha = \frac{\alpha_0}{\sqrt{1+t}}.$
 - **⊘** Correct

Correct. This is not a good learning rate decay since it is an increasing function of t.

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)



- $\hfill \Box$ Decreasing β will shift the red line slightly to the right.
- $\hfill \square$ Increasing β will shift the red line slightly to the right.

True, remember that the red line corresponds to $\beta=0.9$. In the lecture we had a green line $\beta=0.98$ that is slightly shifted to the right.

- ightharpoonup Decreasing eta 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.

8.	Which of the following are true about gradient descent with momentum?	0.75 / 1 point
	Gradient descent with momentum makes use of moving averages.	
	 Correct Correct. Gradient descent with momentum makes use of moving averages, which smooths out the gradient descent process. 	
	It generates faster learning by reducing the oscillation of the gradient descent process.	
	 Correct Correct. The use of momentum makes each step of the gradient descent more efficient by reducing oscillations. 	
	☐ It decreases the learning rate as the number of epochs increases.	
	$\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ $	
	You didn't select all the correct answers	
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) Try initializing the weight at zero. Normalize the input data.	1/1 point
	Correct Yes. In some cases, if the scale of the features is very different, normalizing the input data will speed up the training process.	
	Try mini-batch gradient descent.	
	 Correct Yes. Mini-batch gradient descent is faster than batch gradient descent. 	
	✓ Try using Adam.	
	 Correct Yes. Adam combines the advantages of other methods to accelerate the convergence of the gradient descent. 	

10.	Which of the following statements about Adam is <i>False</i> ?	1 / 1 poir
	Adam combines the advantages of RMSProp and momentum	
	Adam should be used with batch gradient computations, not with mini-batches.	
	O We usually use "default" values for the hyperparameters eta_1,eta_2 and $arepsilon$ in Adam ($eta_1=0.9$, $eta_2=0.999,arepsilon=10^{-8}$)	
	\bigcirc The learning rate hyperparameter α in Adam usually needs to be tuned.	
	⊘ Correct	