Which notation would you use to denote the 4th layer's activations when the input is the 7th example from the 3rd mini-batch? $a^{[3]\{7\}\{4\}}$ $a^{[4]\{3\}\{7\}}$	1/1 point
 □ a^[7](3)(4) □ 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 . Suppose you don't face any memory-related problems. Which of the following make more use of vectorization. Batch Gradient Descent	0/1 point
Mini-Batch Gradient Descent with mini-batch size $m/2$. Stochastic Gradient Descent, Batch Gradient Descent, and Mini-Batch Gradient Descent all make equal use of vectorization. Stochastic Gradient Descent	
Expand No. For example, if mini-batch size is 1 (Stochastic Gradient Descent), you lose all the benefits of vectorization across examples in the mini-batch.	
 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. True False 	1/1 point
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. Suppose your learning algorithm's cost J , plotted as a function of the number of iterations, looks like this:	1/1 point
- Management of the second of	
Which of the following do you agree with? Whether you're using batch gradient descent or mini-batch gradient descent, something is wrong. If you're using mini-batch gradient descent, something is wrong. But if you're using 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, this looks acceptable.	
∠ Expand ✓ Correct	
Suppose the temperature in Casablanca over the first two days of January are the same: $ \hbox{Jan 1st: } \theta_1=10^oC $ $ \hbox{Jan 2nd: } \theta_2=10^oC $ (We used Fahrenheit in the lecture, so we will use Celsius here in honor of the metric world.)	1/1 point
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.) $v_2=10'\ v_2^{corrected}=10$ $v_2=7.5'\ v_2^{corrected}=7.5$	
$v_2=10^{'}\ v_2^{corrected}=7.5$ $v_2=7.5^{'}\ v_2^{corrected}=10$	
∠ Expand ✓ Correct	
 Which of the following is true about learning rate decay? The intuition behind it is that for later epochs our parameters are closer to a minimum thus it is more convenient to take smaller steps to prevent large oscillations. The intuition behind it is that for later epochs our parameters are closer to a minimum thus it is more convenient to take larger steps to accelerate the convergence. 	1/1 point
We use it to increase the size of the steps taken in each mini-batch iteration. It helps to reduce the variance of a model. Expand	
Correct. Reducing the learning rate with time reduces the oscillation around a minimum. $V_t = \int_0^\infty $	1/1 point
Days $ \bigcirc \beta_1 < \beta_2 \\ \hline \bigcirc \beta_1 > \beta_2 \\ \hline \bigcirc \beta_1 > \beta_2 \\ \hline \bigcirc \beta_1 = 0 \beta_2 > 0 \\ \hline $	
\bigcirc $eta_1=eta_2$	
Correct Correct. $\beta_1>\beta_2$ since the red curve is noisier.	
4- Consider the ligure:	1/1 point
-4	
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 more in the horizontal and the vertical axis. The gradient descent process moves less in the horizontal direction and more in the vertical direction. The gradient descent process starts oscillating in the vertical direction.	
The gradient descent process starts moving more in the horizontal direction and less in the vertical. Expand	
 Correct Yes. 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. 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 tuning the learning rate α Correct Try initializing all the weights to zero Try mini-batch gradient descent	
✓ Correct ✓ Correct ✓ Correct	
✓ Correct	
Correct Great, you got all the right answers.	
 In very high dimensional spaces it is most likely that the gradient descent process gives us a local minimum than a saddle point of the cost function. True/False? True False 	0 / 1 point
Expand Solution Incorrect Incorrect. Due to the high number of dimensions it is much more likely to reach a saddle point, than a local minimum.	