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 3rd layer's activations when the input is the 7th example from the 8th minibatch? **1 / 1 point**

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

Expand

Correct

2. Suppose you don't face any memory-related problems. Which of the following make more use of vectorization. **1 / 1 point**

- Stochastic Gradient Descent, Batch Gradient Descent, and Mini-Batch Gradient Descent all make equal use of vectorization.
- Mini-Batch Gradient Descent with mini-batch size $m/2$.
- Batch Gradient Descent (selected)
- Stochastic Gradient Descent

Expand

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**

- [x] 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 end up having to process the entire training set before making any progress.
- [ ] If the mini-batch size is m, you end up with stochastic gradient descent, which is usually slower than mini-batch gradient descent.
- [x] If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.

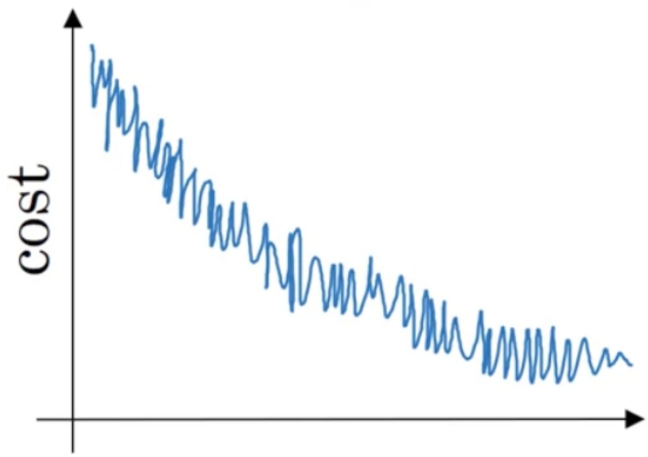
Correct

Expand

Correct
Great, you got all the right answers.

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, this looks acceptable. But if you're using 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.
- ( ) Whether you're using batch gradient descent or mini-batch gradient descent, this looks acceptable.
- ( ) Whether you're using batch gradient descent or mini-batch gradient descent, something is wrong.

Expand

✓ Correct

5. Suppose the temperature in Casablanca over the first two days of March are the following:

0 / 1 point

March 1st: $\theta_1 = 30^\circ \text{ C}$

March 2nd: $\theta_2 = 15^\circ \text{ C}$

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 $v_2^{\text{corrected}}$ is the value you compute with bias correction. What are these values?

- ( ) $v_2 = 15$, $v_2^{\text{corrected}} = 20$.
- ( ) $v_2 = 20$, $v_2^{\text{corrected}} = 20$.
- (●) $v_2 = 15$, $v_2^{\text{corrected}} = 15$.
- ( ) $v_2 = 20$, $v_2^{\text{corrected}} = 15$.

Expand

✗ Incorrect

Incorrect. $v_2 = \beta v_{t-1} + (1-\beta)\,\theta_t$ thus $v_1 = 15, v_2 = 15$. Using the bias correction $\frac{v_t}{1-\beta^t}$ we get $\frac{15}{1-(0.5)^2} = 20$.

6. Which of the following is true about learning rate decay?

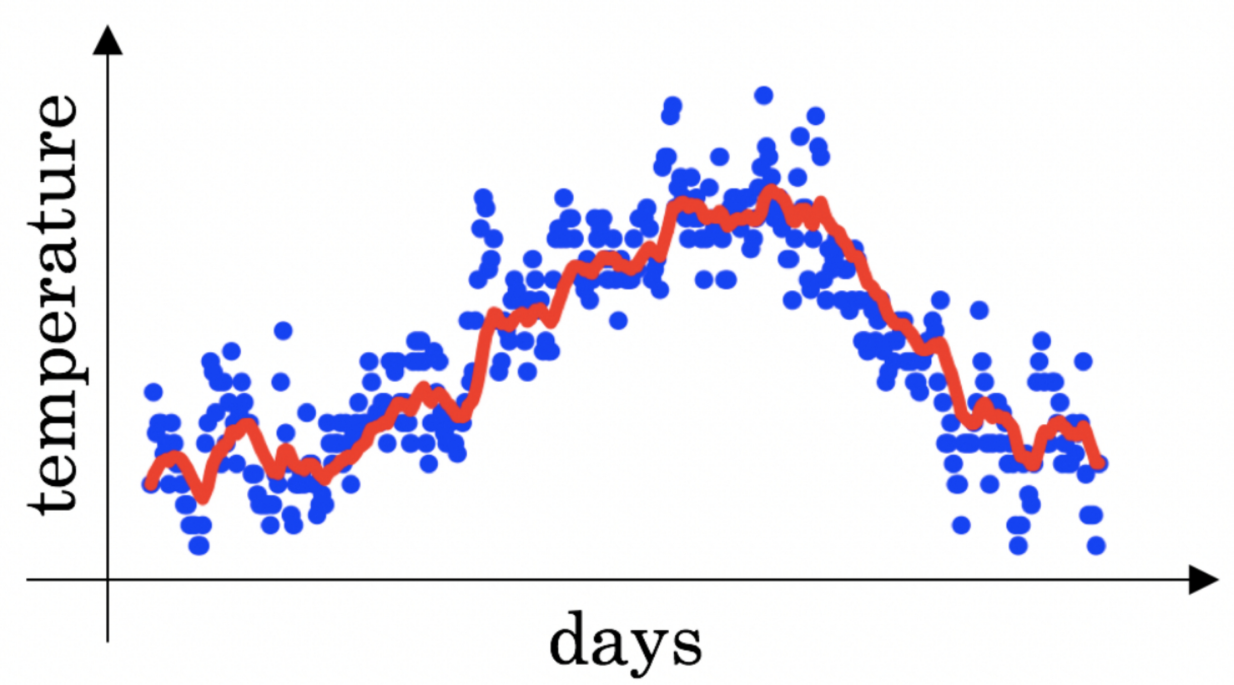
1 / 1 point

- It helps to reduce the variance of a model.
- 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.
- We use it to increase the size of the steps taken in each mini-batch iteration.

Expand

Correct
Correct. Reducing the learning rate with time reduces the oscillation around a minimum.

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**



- [ ] Decreasing β will shift the red line slightly to the right.
- [x] Increasing β will shift the red line slightly to the right.

Correct
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.

- [x] Decreasing β will create more oscillation within the red line.

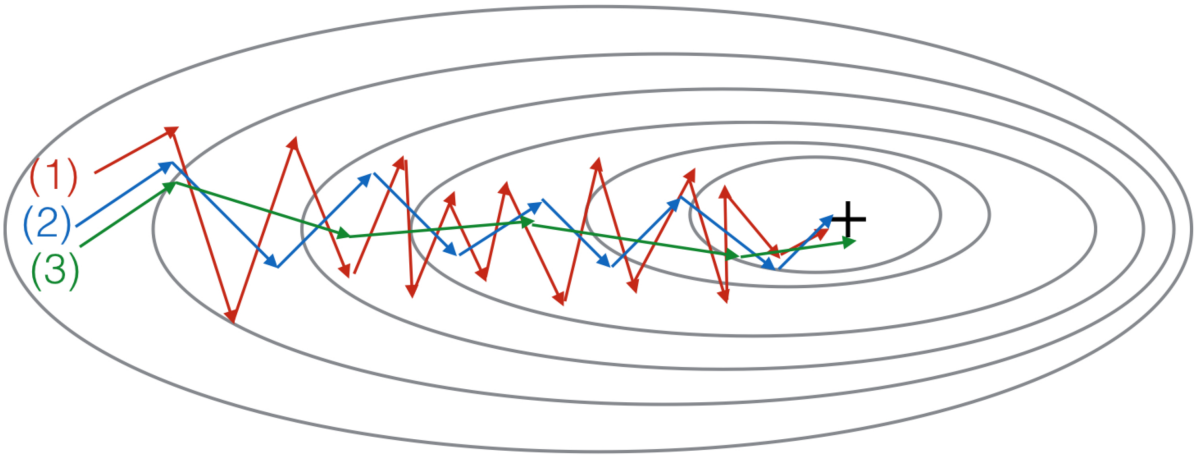
Correct
True, remember that the red line corresponds to $\beta = 0.9$. In lecture we had a yellow line $\beta = 0.98$ that had a lot of oscillations.

- [ ] Increasing β will create more oscillations within the red line.

Expand

Correct
Great, you got all the right answers.

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?

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

Expand

Correct

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**

- [x] Try mini-batch gradient descent.

  Correct
  Yes. Mini-batch gradient descent is faster than batch gradient descent.

- [ ] Try initializing the weight at zero.
- [x] 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.

- [x] Try using Adam.

  Correct
  Yes. Adam combines the advantages of other methods to accelerate the convergence of the gradient descent.

Expand

Correct

Great, you got all the right answers.

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

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

Expand

Correct