Congratulations! You passed!

Grade received 100% **Latest Submission Grade** 100% **To pass** 80% or higher

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

1 / 1 point

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

- (selected) When the mini-batch size is the same as the training size, mini-batch gradient descent is equivalent to 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).
- Training one epoch (one pass through the training set) using mini-batch gradient descent is faster than training one epoch using 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. Which of the following is true about batch gradient descent?

1 / 1 point

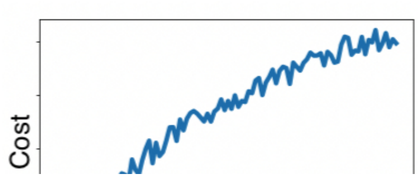
- It has as many mini-batches as examples in the training set.
- (selected) It is the same as the mini-batch gradient descent when the mini-batch size is the same as the size of the training set.
- It is the same as stochastic gradient descent, but we don't use random elements.

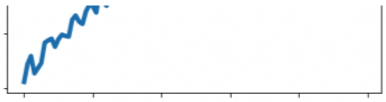
Expand

Correct
Correct. When using batch gradient descent there is only one mini-batch thus it is equivalent to batch gradient descent.

4. While using mini-batch gradient descent with a batch size larger than 1 but less than m the plot of the cost function J looks like this:

1 / 1 point





Which of the following do you agree with?

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

Expand

Correct
Yes. The cost is larger than when the process started, this is not right at all.

5. Suppose the temperature in Casablanca over the first two days of March are the following: **1 / 1 point**

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

March 2nd: $\theta_2 = 15^\circ$ 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?

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

Expand

Correct
Correct. $v_2 = \beta v_{t-1} + (1-\beta)\,\theta_t$ 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**

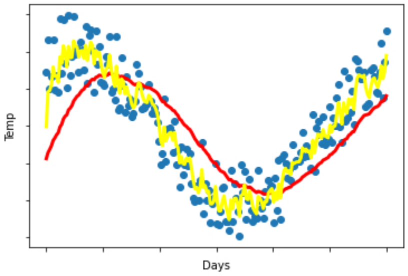
- It helps to reduce the variance of a model.
- The intuition behind it is that for later epochs our parameters are closer to a minimum thus it is more convenient to take larger steps to accelerate the convergence.
- The intuition behind it is that for later epochs our parameters are closer to a minimum thus it is more convenient to take smaller steps to prevent large oscillations.
- 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 yellow **1 / 1 point**

and red lines were computed using values $beta_1$ and $beta_2$ respectively. Which of the following are true?



- ○ $\beta_1 = 0, \beta_2 > 0.$
- ○ $\beta_1 > \beta_2.$
- ◉ $\beta_1 < \beta_2.$
- ○ $\beta_1 = \beta_2.$

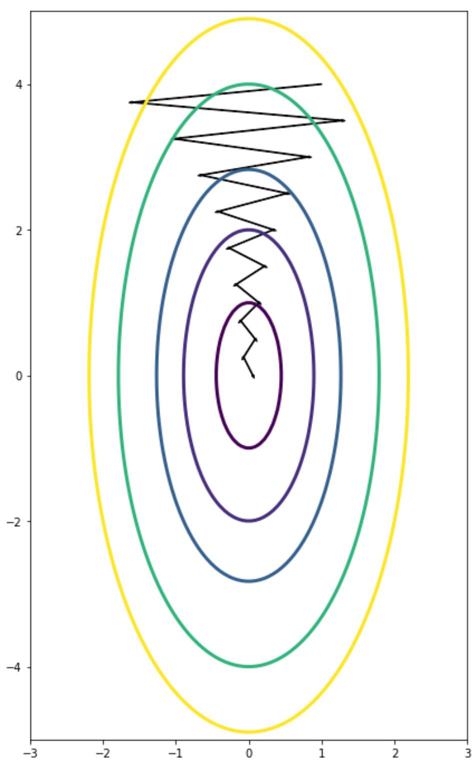
Expand

Correct

Correct. $\beta_1 < \beta_2$ since the yellow curve is noisier.

8. Consider the figure:

1 / 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 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.

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] 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 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.

- [ ] Add more data to the training set.
- [x] 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.

Expand

Correct
Great, you got all the right answers.

10. Which of the following are true about Adam?

1 / 1 point

- ( ) Adam can only be used with batch gradient descent and not with mini-batch gradient descent.
- ( ) The most important hyperparameter on Adam is ϵ and should be carefully tuned.
- (•) Adam combines the advantages of RMSProp and momentum.
- ( ) Adam automatically tunes the hyperparameter α.

Expand

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