Suppose your learning algorithm's cost J, plotted as a function of the number of



iterations, looks like this:

Which of the following do you agree with?

- 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, something is wrong.
- If you're using mini-batch gradient descent, this looks acceptable. But if you're using batch gradient descent, something is wrong.

正确

Jan 2nd: $heta_2 10^o C$

Whether you're using batch gradient descent or mini-batch gradient descent, this looks acceptable.

~

5. Suppose the temperature in Casablanca over the first three days of January are the same:

/ 1

Jan 1st: $heta_1 = 10^oC$

(We used Fahrenheit in lecture, so 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 is bias correction doing.)

- $v_2=10$, $v_2^{corrected}=10$
- $v_2=7.5$, $v_2^{corrected}=7.5$

正确

 $v_2=10$, $v_2^{corrected}=7.5$

~

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

 \bigcirc $\alpha = e^t \alpha$

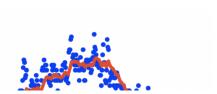
正確

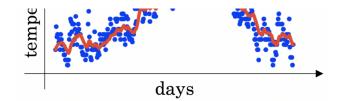
- $\alpha = \frac{1}{\sqrt{t}}\alpha_0$
- $\alpha = rac{1}{1+2*t}lpha_0$
- $lpha = 0.95^t lpha_0$

~

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)







未选择的是正确的

Increasing $\boldsymbol{\beta}$ will shift the red line slightly to the right.

正确

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

Decreasing $\boldsymbol{\beta}$ will create more oscillation within the red line.

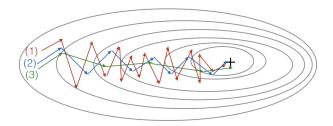
正确

True, remember that the red line corresponds to eta=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.

未选择的是正确的

Consider this figure:



These plots were generated with gradient descent; with gradient descent with $% \left(1\right) =\left(1\right) \left(1$ momentum (β = 0.5) and gradient descent with momentum (β = 0.9). Which curve corresponds to which algorithm?

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

正确

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

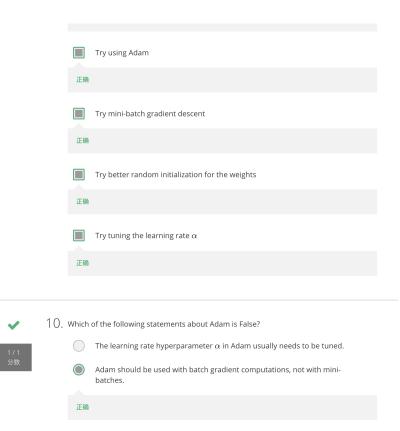
Suppose batch gradient descent in a deep network is taking excessively long to find a value of the parameters that achieves a small value for the cost function $\mathcal{J}(W^{[1]},b^{[1]},...,W^{[L]},b^{[L]}).$ Which of the following techniques could help find parameter values that attain a small value for \mathcal{J} ? (Check all that apply)

Try initializing all the weights to zero

未选择的是正确的







Adam combines the advantages of RMSProp and momentum

 $eta_1 = 0.9, eta_2 = 0.999, arepsilon = 10^{-8})$

We usually use "default" values for the hyperparameters eta_1, eta_2 and arepsilon in Adam (





