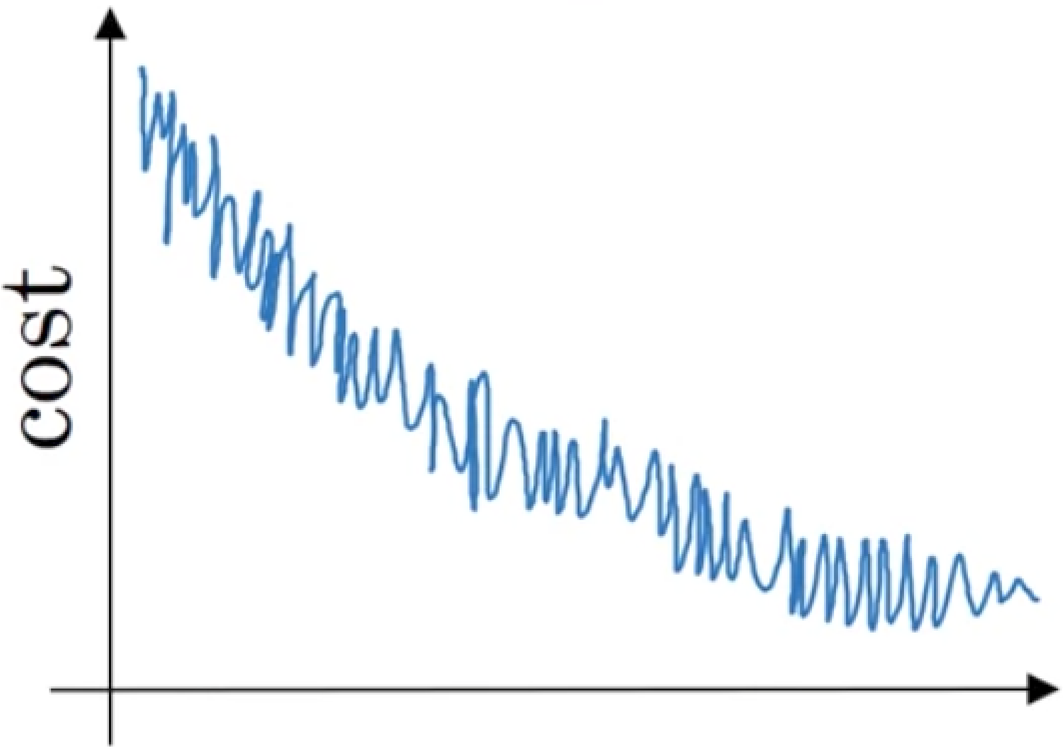
Optimization algorithms

1. Which notation would you use to denote the 3rd layer's activations when the input is the 7th example from the 8th minibatch?
   - [x] $a^{[3]\{8\}(7)}$
   - [ ] $a^{[8]\{7\}(3)}$
   - [ ] $a^{[8]\{3\}(7)}$
   - [ ] $a^{[3]\{7\}(8)}$

2. Which of these statements about mini-batch gradient descent do you agree with?
   - [ ] 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.
   - [x] One iteration of mini-batch gradient descent (computing on a single mini-batch) is faster than one iteration of batch gradient descent.

3. Why is the best mini-batch size usually not 1 and not m, but instead something in-between?
   - [ ] If the mini-batch size is 1, you end up having to process the entire training set before making any progress.
   - [x] If the mini-batch size is 1, you lose the benefits of vectorization across examples in the mini-batch.
   - [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.
   - [ ] If the mini-batch size is m, you end up with stochastic gradient descent, which is usually slower than mini-batch gradient descent.

4. Suppose your learning algorithm's cost J, plotted as a function of the number of iterations, looks like this:



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

> There will be some oscillations when you're using mini-batch gradient descent since there could be some noisy data example in batches. However batch gradient descent always guarantees a lower J before reaching the optimal.

- [ ] Whether you're using batch gradient descent or mini-batch gradient descent, something is wrong.
- [ ] Whether you're using batch gradient descent or mini-batch gradient descent, this looks acceptable.

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5. Suppose the temperature in Casablanca over the first three days of January are the same: Jan 1st: θ_1 = 10 Jan 2nd: θ_2 * 1 (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?

- [ ] $v_2 = 10$, $v_2^{corrected} = 10$
- [ ] $v_2 = 10$, $v_2^{corrected} = 7.5$
- [ ] $v_2 = 7.5$, $v_2^{corrected} = 7.5$
- [x] $v_2 = 7.5$, $v_2^{corrected} = 10$

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

- [ ] $\alpha = \frac{1}{1+2*t}\alpha_0$

- [ ] $\alpha = \frac{1}{\sqrt{t}} \alpha_0$
- [ ] $\alpha = 0.95^t \alpha_0$
- [x] $\alpha = e^t * \alpha_0$

> This will explode the learning rate rather than decay it.

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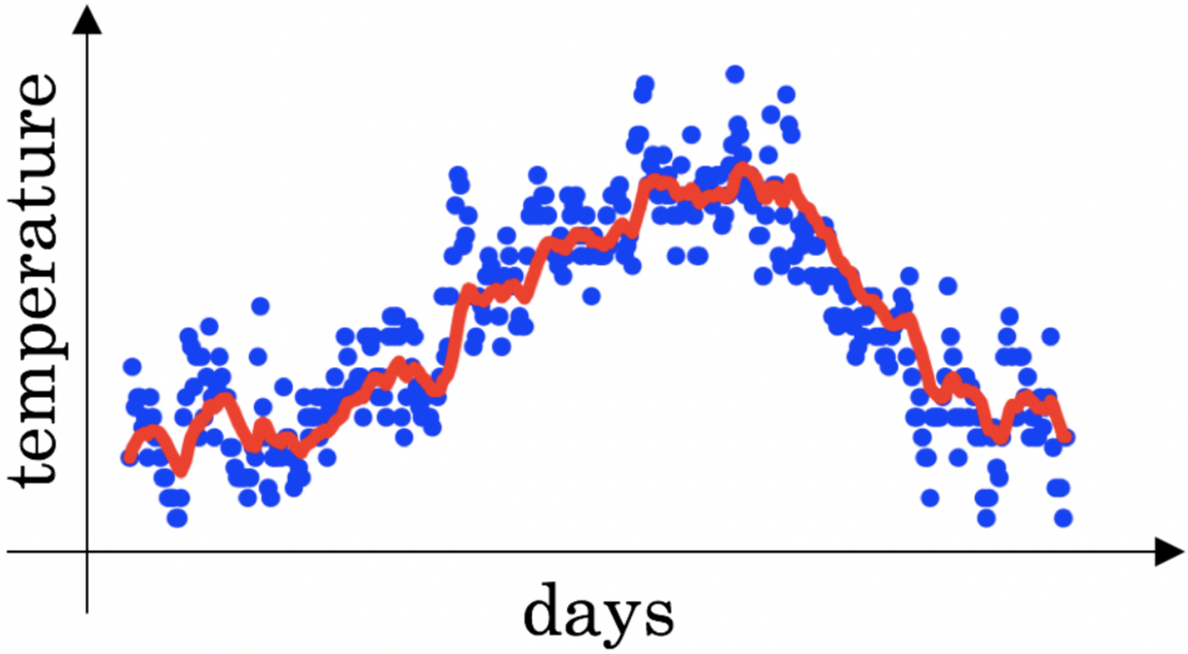
7. You use an exponentially weighted average on the London temperature dataset. You use the following to track the temperature: $\beta v_t - 1 + (1-\beta)\theta_t$. The red line below was computed using $\beta = 0.9$. What would happen to your red curve as you vary β? (Check the two that apply)



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

> 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.

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

> 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.

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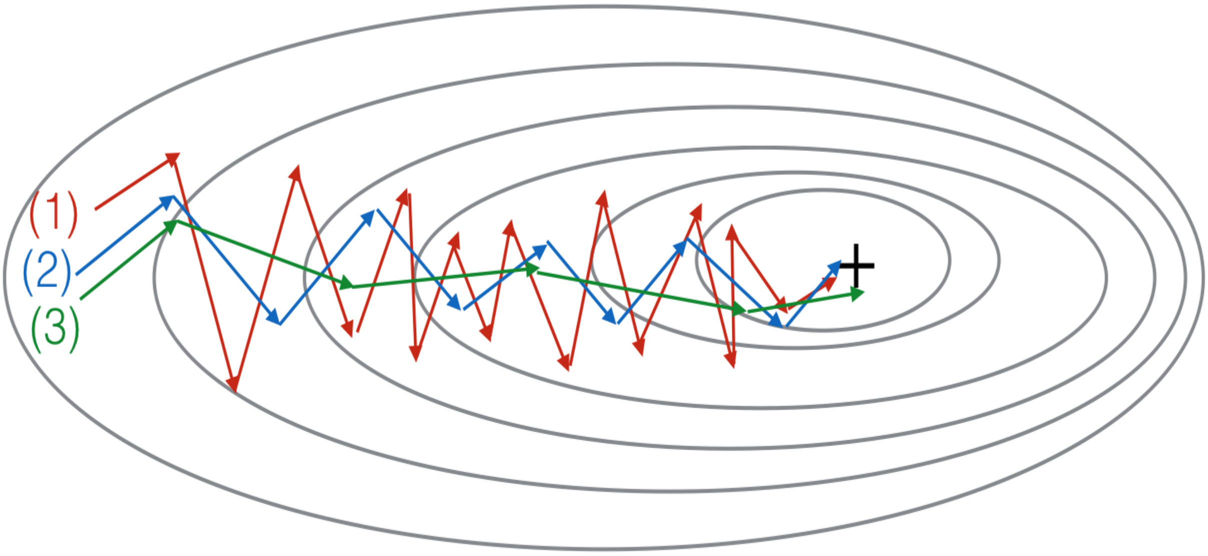
8. Consider this figure:



These plots were generated with gradient descent; with gradient descent with momentum ($\beta = 0.5$) and gradient descent with momentum ($\beta = 0.9$). 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).
- [x] (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).

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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 $J(W^{[1]}, b^{[1]}, \ldots, W^{[L]}, b^{[L]})$. Which of the following techniques could help find parameter values that attain a small value for J? (Check all that apply)

- [x] Try using Adam.
- [x] Try better random initialization for the weights.
- [x] Try tuning the learning rate α.
- [x] Try mini-batch gradient descent.
- [ ] Try initializing all the weights to zero.

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10. Which of the following statements about Adam is False?

- [ ] Adam combines the advantages of RMSProp and momentum.
- [x] Adam should be used with batch gradient computations, not with mini-batches.

> Adam could be used with both.

- [ ] The learning rate hyperparameter α in Adam usually needs to be tuned.

- [ ] We usually use "default" values for the hyperparameters $\beta 1$, $\beta 2$ and σ in Adam ($\beta 1 = 0.9$, $\beta 2 = 0.999$, $\varepsilon = 10^{-8}$).