Practice quiz: Train the model with gradient descent

Total points 2

1. 1 point

Gradient descent is an algorithm for finding values of parameters w and b that minimize the cost function J.

repeat until convergence {

$$w = w - \alpha \frac{\partial}{\partial w} J(w, b)$$
$$b = b - \alpha \frac{\partial}{\partial b} J(w, b)$$

When $\frac{\partial J(w,b)}{\partial w}$ is a negative number (less than zero), what happens to w after one update step?

- (w stays the same
- It is not possible to tell if w will increase or decrease.
- O wdecreases
- w increases.

2. 1 point

For linear regression, what is the update step for parameter b?

$$b = b - \alpha \frac{1}{m} \sum_{i=1}^{m} (f_{w,b}(x^{(i)}) - y^{(i)}) x^{(i)}$$

$$left[left] b = b - lpha rac{1}{m} \sum_{i=1}^m (f_{w,b}(x^{(i)}) - y^{(i)})$$

Practice quiz: Supervised vs unsupervised learning

Total points 2

1. Which are the two common types of supervised learning? (Choose two)

1 point

- Classification
- Clustering
- Regression

2.

Which of these is a type of unsupervised learning?

- Regression
- Classification
- Clustering

Practice quiz: Regression

Total points 2

1.

	For linear regression, the model is $f_{w,b}(x)=wx+b$.	
	Which of the following are the inputs, or features, that are fed into the model and with which the model is expected to make a prediction?	
	\bigcirc m	
	$\bigcirc (x,y)$	
	igcup w and b .	
2.	For linear regression, if you find parameters w and b so that $J(w,b)$ is very close to zero, what can you conclude?	1 point
	lacktriangledown The selected values of the parameters w and b cause the algorithm to fit the training set really well.	
	igcirc The selected values of the parameters w and b cause the algorithm to fit the training set really poorly.	
	This is never possible there must be a bug in the code.	

1 point

Practice quiz: Multiple linear regression

Total points 4

1.	In the training set below, what is $x_4^{(3)}$? Please type in the number below (this is an integer such as 123, no decimal
	points).

1 point

Size in feet ²	Number of bedrooms	Number of floors	Age of home in years	Price (\$) in \$1000's
X1	X ₂	Хз	X4	
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178

30

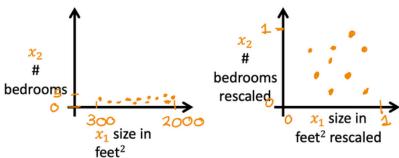
O False

2.		1 point
	Which of the following are potential benefits of vectorization? Please choose the best option.	
	It can make your code shorter	
	All of the above	
	It makes your code run faster	
	It allows your code to run more easily on parallel compute hardware	
3.	$\label{twice} True/False? To make gradient descent converge about twice as fast, a technique that almost always works is to double the learning rate $alpha$.$	1 point
	○ True	
	False	
4.		1 point
	True/False? With polynomial regression, the predicted values $f_w,b(x)$ does not necessarily have to be a straight line (or linear) function of the input feature x .	

Practice quiz: Gradient descent in practice

Total points 4

1.

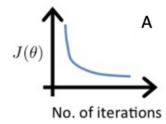


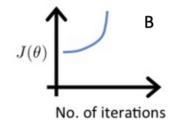
1 point

Which of the following is a valid step used during feature scaling?

- Subtract the mean (average) from each value and then divide by the (max min).
- Add the mean (average) from each value and and then divide by the (max min).
- **2.** Suppose a friend ran gradient descent three separate times with three choices of the learning rate α and plotted the learning curves for each (cost J for each iteration).

1 point





For which case, A or B, was the learning rate α likely too large?

- O Both Cases A and B
- o case B only
- Neither Case A nor B
- O case A only
- 3. Of the circumstances below, for which one is feature scaling particularly helpful?

1 point

- Feature scaling is helpful when one feature is much larger (or smaller) than another feature.
- Feature scaling is helpful when all the features in the original data (before scaling is applied) range from 0 to
 1.
- Various helping a green return product the green and have date on the terms and account, and price are then

1 point

You are helping a grocery store predict its revenue, and have data on its items sold per week, and price per item. What could be a useful engineered feature?

- For each product, calculate the number of items sold times price per item.
- O For each product, calculate the number of items sold divided by the price per item.

1/1 point

Gradient descent for logistic regression

repeat {

$$w_j = w_j - \alpha \left[\frac{1}{m} \sum_{i=1}^m \left(f_{\overrightarrow{w},b}(\overrightarrow{x}^{(i)}) - \mathbf{y}^{(i)} \right) \mathbf{x}_j^{(i)} \right]$$
$$b = b - \alpha \left[\frac{1}{m} \sum_{i=1}^m \left(f_{\overrightarrow{w},b}(\overrightarrow{x}^{(i)}) - \mathbf{y}^{(i)} \right) \right]$$

} simultaneous updates

$$f_{\overrightarrow{\mathbf{w}},b}(\overrightarrow{\mathbf{x}}) = \frac{1}{1 + e^{(-\overrightarrow{\mathbf{w}} \cdot \overrightarrow{\mathbf{x}} + b)}}$$

Which is the correct update step for

- igodeligap The update steps look like the update steps for linear regression, but the definition of $f_{ec{w},b}(\mathbf{x}^{(i)})$ is different
- O The update steps are identical to the update steps for linear regression.
- **⊘** Correct

For logistic regression, $f_{\vec{w},b}(\mathbf{x}^{(i)})$ is the sigmoid function instead of a straight line.

Practice quiz: Cost function for logistic regression

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1/1 point

$$\overbrace{J(\overrightarrow{\mathbf{w}},b)} = \frac{1}{m} \sum_{i=1}^{m} \underbrace{L(f_{\overrightarrow{\mathbf{w}},b}(\overrightarrow{\mathbf{x}}^{(i)}), \mathbf{y}^{(i)})}_{\zeta}$$

In this lecture series, "cost" and "loss" have distinct meanings. Which one applies to a single training example?

✓ Loss

1.

- Correct In these lectures, loss is calculated on a single training example. It is worth noting that this definition is not universal. Other lecture series may have a different definition.
- ☐ Cost
- Both Loss and Cost
- Neither Loss nor Cost
- 1/1 point

Simplified loss function

$$L(f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)}), \mathbf{y}^{(i)}) = \begin{cases} -\log(f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)})) & \text{if } \mathbf{y}^{(i)} = 1\\ -\log(1 - f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)})) & \text{if } \mathbf{y}^{(i)} = 0 \end{cases}$$

$$L(f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)}), \mathbf{y}^{(i)}) = -\mathbf{y}^{(i)}\log(f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)})) - (1 - \mathbf{y}^{(i)})\log(1 - f_{\overline{\mathbf{w}},b}(\overline{\mathbf{x}}^{(i)}))$$

For the simplified loss function, if the label $y^{(i)}=0$, then what does this expression simplify to?

- $\bigcirc \log(f_{\vec{w},b}(\mathbf{x}^{(i)}))$
- $\bigcap \log(1 f_{\vec{w},b}(\mathbf{x}^{(i)})) + log(1 f_{\vec{w},b}(\mathbf{x}^{(i)}))$
- $\bigcirc -\log(1 f_{\vec{w},b}(\mathbf{x}^{(i)})) log(1 f_{\vec{w},b}(\mathbf{x}^{(i)}))$
- \bigcirc log(1 $f_{\vec{w},b}(\mathbf{x}^{(i)})$)
- \bigcirc **Correct**When $y^{(i)} = 0$, the first term reduces to zero.