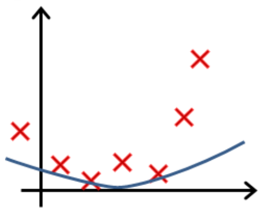
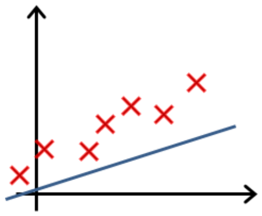
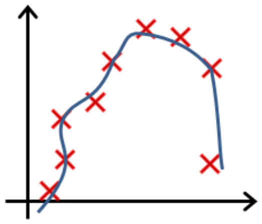
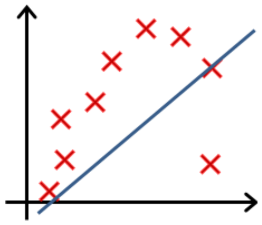
Feedback — VII. Regularization

Help Center

You submitted this quiz on **Sat 14 Feb 2015 12:57 PM CET**. You got a score of **5.00** out of **5.00**.

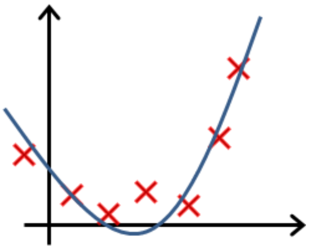
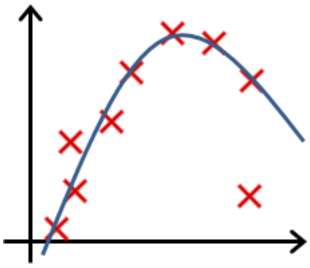
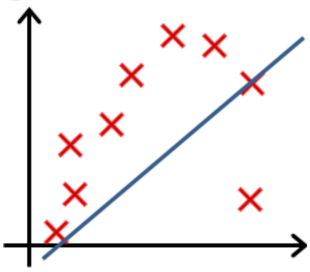
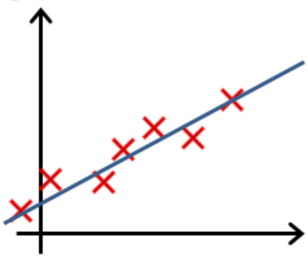
Question 1

In which one of the following figures do you think the hypothesis has overfit the training set?

Your Answer		Score	Explanation
			
			
	✔	1.00	The hypothesis follows the data points very closely and is highly complicated, indicating that it is overfitting the training set.
			
Total		1.00 / 1.00	

Question 2

In which one of the following figures do you think the hypothesis has underfit the training set?

Your Answer		Score	Explanation
			
			
	✔	1.00	The hypothesis does not predict many data points well, and is thus underfitting the training set.
			
Total		1.00 / 1.00	

Question 3

You are training a classification model with logistic regression. Which of the following statements are true? Check all that apply.

Your Answer		Score	Explanation
☐ Adding many new features to the model helps prevent overfitting on the training set.	✔	0.25	Adding many new features gives us more expressive models which are able to better fit our training set. If too many new features are added, this can lead to overfitting of the training set.
☐ Introducing regularization to the model always results in equal or better performance on examples not in the training set.	✔	0.25	If we introduce too much regularization, we can underfit the training set and this can lead to worse performance even for examples not in the training set.
☐ Introducing regularization to the model always results in equal or better performance on the training set.	✔	0.25	If we introduce too much regularization, we can underfit the training set and have worse performance on the training set.
☑ Adding many new features to the model makes it more likely to overfit the training set.	✔	0.25	Adding many new features gives us more expressive models which are able to better fit our training set. If too many new features are added, this can lead to overfitting of the training set.
Total		1.00 / 1.00	

Question 4

Suppose you ran logistic regression twice, once with $\lambda = 0$, and once with $\lambda = 1$. One of the times, you got parameters $\theta = \begin{bmatrix} 26.29 \\ 65.41 \end{bmatrix}$, and the other time you got $\theta = \begin{bmatrix} 2.75 \\ 1.32 \end{bmatrix}$. However, you forgot which value of λ corresponds to which value of θ. Which one do you think corresponds to $\lambda = 1$?

Your Answer	Score	Explanation

$\theta = \begin{bmatrix} 26.29 \\ 65.41 \end{bmatrix}$			
$\theta = \begin{bmatrix} 2.75 \\ 1.32 \end{bmatrix}$	✔	1.00	When λ is set to 1, we use regularization to penalize large values of θ. Thus, the parameters, θ, obtained will in general have smaller values.
Total		1.00 / 1.00	

Question 5

Which of the following statements about regularization are true? Check all that apply.

Your Answer		Score	Explanation
☐ Using a very large value of λ cannot hurt the performance of your hypothesis; the only reason we do not set λ to be too large is to avoid numerical problems.	✔	0.25	Using a very large value of λ can lead to underfitting of the training set.
☐ Using too large a value of λ can cause your hypothesis to overfit the data; this can be avoided by reducing λ.	✔	0.25	Using a very large value of λ can lead to underfitting of the training set.
☐ Because regularization causes $J(\theta)$ to no longer be convex, gradient descent may not always converge to the global minimum (when $\lambda > 0$, and when using an appropriate learning rate α).	✔	0.25	Regularized logistic regression and regularized linear regression are both convex, and thus gradient descent will still converge to the global minimum.
☑ Using too large a value of λ can cause your hypothesis to underfit the data.	✔	0.25	A large value of λ results in a large regularization penalty and thus a strong preference for simpler models which can underfit the data.
Total		1.00 / 1.00	