Feedback — XV. Anomaly Detection

Help

You submitted this quiz on **Sun 18 May 2014 5:40 PM PDT**. You got a score of **5.00** out of **5.00**.

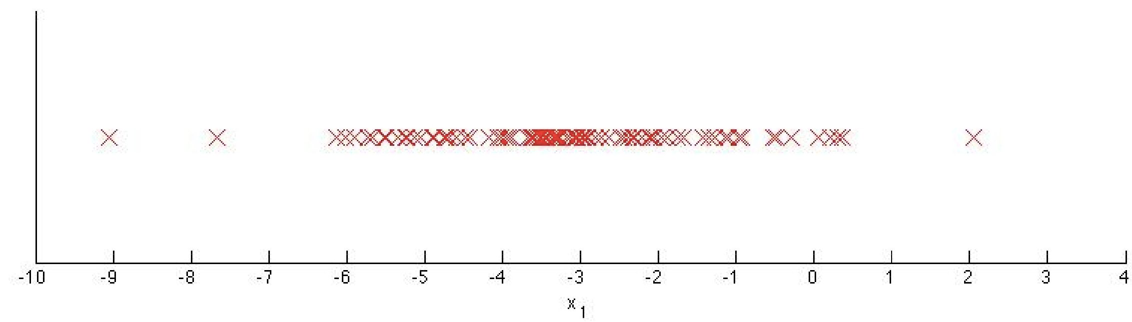
Question 1

For which of the following problems would anomaly detection be a suitable algorithm?

Your Answer		Score	Explanation
☐ From a large set of hospital patient records, predict which patients have a particular disease (say, the flu).	✔	0.25	Anomaly detection would not be appropriate, as you want to train on both types of patient records rather than modeling one as "normal."
☑ Given a dataset of credit card transactions, identify unusual transactions to flag them as possibly fraudulent.	✔	0.25	By modeling "normal" credit card transactions, you can then use anomaly detection to flag the unusuals ones which might be fraudulent.
☐ Given an image of a face, determine whether or not it is the face of a particular famous individual.	✔	0.25	This problem is more suited to traditional supervised learning, as you want both famous and non-famous images in the training set.
☑ In a computer chip fabrication plant, identify microchips that might be defective.	✔	0.25	The defective chips are the anomalies you are looking for by modeling the properties of non-defective chips.
Total		1.00 / 1.00	

Question 2

You have a 1-D dataset $\{x^{(1)}, \ldots, x^{(m)}\}$ and you want to detect outliers in the dataset. You first plot the dataset and it looks like this:



Suppose you fit the gaussian distribution parameters μ_1 and σ_1^2 to this dataset. Which of the following values for μ_1 and σ_1^2 might you get?

Your Answer		Score	Explanation
$\mu_1 = -6, \sigma_1^2 = 4$			
$\mu_1 = -6, \sigma_1^2 = 2$			
$\mu_1 = -3, \sigma_1^2 = 2$			
$\mu_1 = -3, \sigma_1^2 = 4$	✔	1.00	This is correct, as the data are centered around -3 and tail most of the points lie in [-5, -1].
Total		1.00 / 1.00	

Question 3

Suppose you have trained an anomaly detection system that flags anomalies when $p(x)$ is less than ε, and you find on the cross-validation set that it has too many false positives (flagging too many things as anomalies). What should you do?

Your Answer		Score	Explanation
Decrease ε	✔	1.00	By decreasing ε, you will flag fewer anomalies, as desired.

Increase ε

Total	1.00 / 1.00

Question 4

Suppose you are developing an anomaly detection system to catch manufacturing defects in airplane engines. You model uses $p(x) = \prod_{j=1}^{n} p(x_j; \mu_j, \sigma_j^2)$. You have two features x_1 = vibration intensity, and x_2 = heat generated. Both x_1 and x_2 take on values between 0 and 1 (and are strictly greater than 0), and for most "normal" engines you expect that $x_1 \approx x_2$. One of the suspected anomalies is that a flawed engine may vibrate very intensely even without generating much heat (large x_1, small x_2), even though the particular values of x_1 and x_2 may not fall outside their typical ranges of values. What additional feature x_3 should you create to capture these types of anomalies:

Your Answer		Score	Explanation
$x_3 = (x_1 + x_2)^2$			
$x_3 = \frac{x_1}{x_2}$	✔	1.00	This is correct, as it will take on large values for anomalous examples and smaller values for normal examples.
$x_3 = x_1^2 \times x_2^2$			
$x_3 = x_1 \times x_2$			
Total		1.00 / 1.00	

Question 5

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

Your Answer	Score	Explanation

☑ If you do not have any labeled data (or if all your data has label $y = 0$), then is is still possible to learn $p(x)$, but it may be harder to evaluate the system or choose a good value of ϵ.	✔	0.25	Only negative examples are used in training, but it is good to have some labeled data of both types for cross-validation.
☑ When choosing features for an anomaly detection system, it is a good idea to look for features that take on unusually large or small values for (mainly the) anomalous examples.	✔	0.25	These are good features, as they will lie outside the learned model, so you will have small values for $p(x)$ with these examples.
☐ If you have a large labeled training set with many positive examples and many negative examples, the anomaly detection algorithm will likely perform just as well as a supervised learning algorithm such as an SVM.	✔	0.25	Anomaly detection only models the negative examples, whereas an SVM learns to discriminate between positive and negative examples, so the SVM will perform better when you have many positive and negative examples.
☐ In a typical anomaly detection setting, we have a large number of anomalous examples, and a relatively small number of normal/non-anomalous examples.	✔	0.25	It is the reverse: we have many normal examples and few anomalous examples.
Total		1.00 /	

1.00