| | 1 point | |
|---|---|--|
| ļ | 1. For which of the following problems would anomaly detection be a suitable algorithm? | |
| | | From a large set of hospital patient records, predict which patients have a particular disease (say, the flu). |
| | | Given data from credit card transactions, classify each transaction according to type of purchase (for example: food, transportation, clothing). |
| | | From a large set of primary care patient records, identify individuals who might have unusual health conditions. |
| | | In a computer chip fabrication plant, identify microchips that might be defective. |
| _ | | |
| 9 | 1 point 2. 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 negatives (failing to flag a lot of anomalies). What should you do? | |
| | 0 | Increase $arepsilon$ |
| L | 0 | Decrease $arepsilon$ |
| [| 1 | |

point

3.

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:

- $igcap x_3 = rac{x_1}{x_2}$
- $oldsymbol{O} \quad x_3 = rac{1}{x_2}$

Anomaly Detection

Quiz, 5 questions



1 point

4.

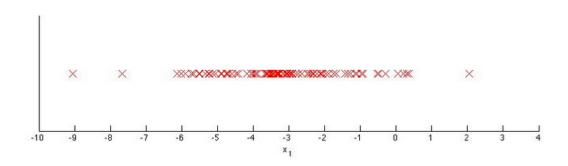
Which of the following are true? Check all that apply.

- In a typical anomaly detection setting, we have a large number of anomalous examples, and a relatively small number of normal/non-anomalous examples.
- When developing an anomaly detection system, it is often useful to select an appropriate numerical performance metric to evaluate the effectiveness of the learning algorithm.
- When evaluating an anomaly detection algorithm on the cross validation set (containing some positive and some negative examples), classification accuracy is usually a good evaluation metric to use.
- In anomaly detection, we fit a model p(x) to a set of negative (y=0) examples, without using any positive examples we may have collected of previously observed anomalies.

1 point

5.

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:



Anomaly Detection Suppose you fit the gaussian distribution parameters μ_1 and σ_1^2 to this dataset. Out 5 questions

Quiz, 5 questions

$$igotimes_1=-3, \sigma_1^2=4$$

$${\color{red} {\color{red} {\color{blue} {\color{b} {\color{blue} {\color{b} {\color{$$

$$O \quad \mu_1 = -3, \sigma_1^2 = 2$$

$${\color{red} {\sf O}} \quad \mu_1=-6, \sigma_1^2=2$$



I, Jun-Chieh Wang, understand that submitting work that isn't my own may result in permanent failure of this course or deactivation of my Coursera account. Learn more about Coursera's Honor Code

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