1 / 1 point

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

- [ ] Given data from credit card transactions, classify each transaction according to type of purchase (for example: food, transportation, clothing).

Un-selected is correct

- [x] Given a dataset of credit card transactions, identify unusual transactions to flag them as possibly fraudulent.

Correct
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.

Un-selected is correct

- [x] From a large set of primary care patient records, identify individuals who might have unusual health conditions.

Correct
Since you are just looking for unusual conditions instead of a particular disease, this is a good application of anomaly detection.

1 / 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?

- ( ) Decrease ε
- (x) Increase ε

Correct
By increasing ε, you will flag more anomalies, as desired.

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1 / 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:

- ( ) $x_3 = x_1^2 \times x_2^2$
- ( ) $x_3 = (x_1 + x_2)^2$
- (x) $x_3 = \frac{x_1}{x_2}$

Correct
This is correct, as it will take on large values for anomalous examples and smaller values for normal examples.

- ( ) $x_3 = x_1 \times x_2^2$

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

1 / 1 point

- [ ] 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.

Un-selected is correct

- [x] 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.

Correct
We want to model "normal" examples, so we only use negative examples in training.

- [ ] In a typical anomaly detection setting, we have a large number of anomalous examples, and a relatively small number of normal/non-anomalous examples.

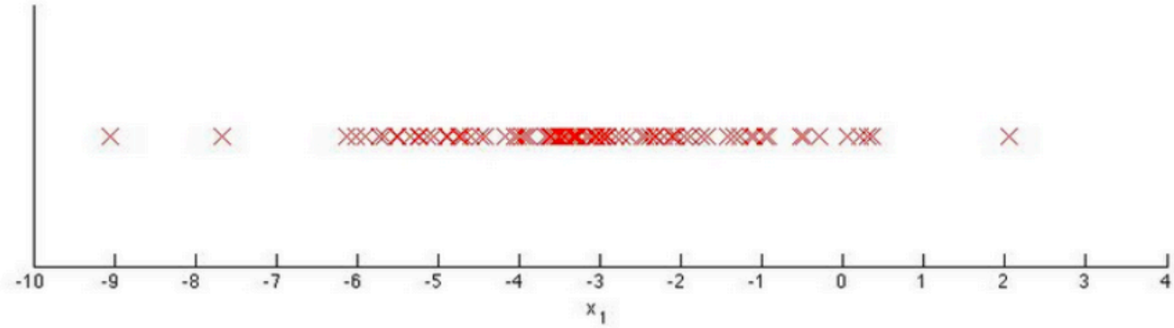
Un-selected is correct

- [x] 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.

Correct
You should have a good evaluation metric, so you can evaluate changes to the model such as new features.

1 / 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:



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?

- (selected) $\mu_1 = -3, \sigma_1^2 = 4$

Correct
This is correct, as the data are centered around -3 and tail most of the points lie in [-5, -1].

- $\mu_1 = -6, \sigma_1^2 = 4$
- $\mu_1 = -3, \sigma_1^2 = 2$
- $\mu_1 = -6, \sigma_1^2 = 2$