Anomaly Detection

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

- Given an image of a face, determine whether or not it is the face of a particular famous individual.

> Given a dataset of credit card transactions, identify unusual transactions to flag them as possibly fraudulent.

By modeling "normal" credit card transactions, you can then use anomaly detection to flag the unusuals ones which might be fraudulent.

- 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.

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

2. Suppose you have trained an anomaly detection system for fraud detection, and your system that flags anomalies when $p(x)$ is less than ε, and you find on the cross-validation set that it mis-flagging far too many good transactions as fradulent. What should you do?

> Decrease ε

- Increase ε

Explanation: By decreasing ε, you will flag fewer anomalies, as desired.

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:

- $x_3 = x_1 + x_2$

> $x_3 = \frac{x_1}{x_2}$

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

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

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

> 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.

Explanation: Only negative examples are used in training, but it is good to have some labeled data of both types for cross-validation.

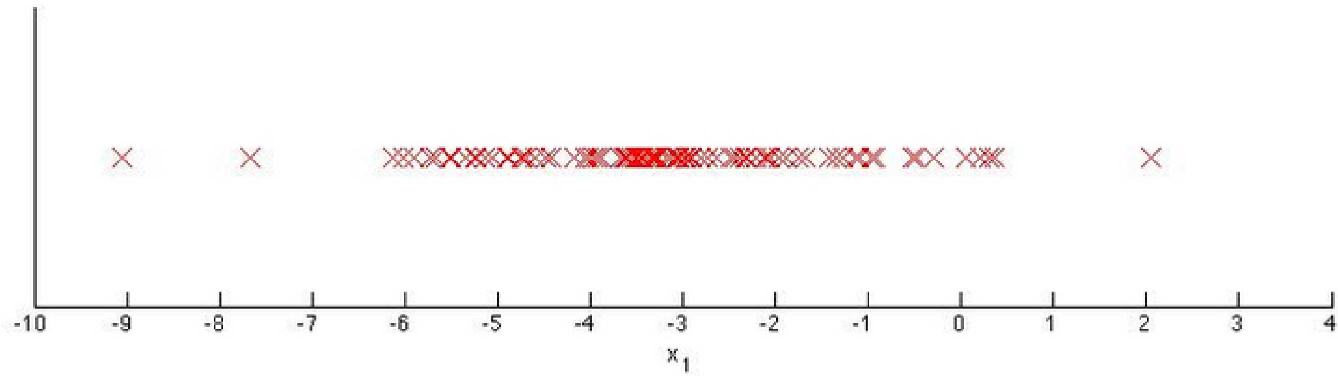
- If you are developing an anomaly detection system, there is no way to make use of labeled data to improve your system.

> 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.

Explanation: 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.

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?

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

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

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