Anomaly Detection

Question 1

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

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

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

- [ ] Given an image of a face, determine whether or not it is the face of a particular famous individual.
- [ ] Given data from credit card transactions, classify each transaction according to type of purchase (for example: food, transportation, clothing).
- [x] **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.

Question 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?

- [x] **Increase ε**

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

- [ ] Decrease ε

Question 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:

- [ ] $x_3 = x_1^2 \times x_2$
- [x] $x_3 = \frac{x_1}{x_2}$

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

- [ ] $x_3 = x_1 \times x_2$
- [ ] $x_3 = x_1 + x_2$

Question 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.
- [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.**

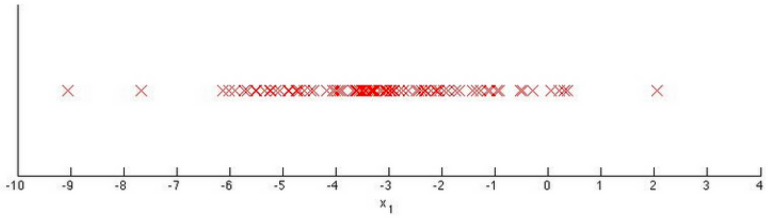
> You should have a good evaluation metric, so you can evaluate changes to the model such as new features.

- [ ] 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.
- [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.**

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

Question 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?

- [x] $\mu_1 = -3, \sigma_1^2 = 4$

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

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