Anomaly Detection

Considering the aircraft engines example, suppose we have 10,000 good engines and 20 flawed engines (anomalous). We should split them as follows:

- Training set: 6,000 good/normal engines (y=0)
- Cross Validation: 2,000 good/normal engines (y=0), 10 anomalous (y=1)
- Test: 2,000 good/normal engines (y=0), 10 anomalous (y=1)

Algorithm Evaluation

Fit model $p(x)$ on training set $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$

On a cross-validation/test example x, predict:

$$y = \begin{cases} 1 & \text{if } p(x) < \epsilon \text{ (anomaly)} \\ 1 & \text{if } p(x) \geq \epsilon \text{ (normal)} \end{cases}$$

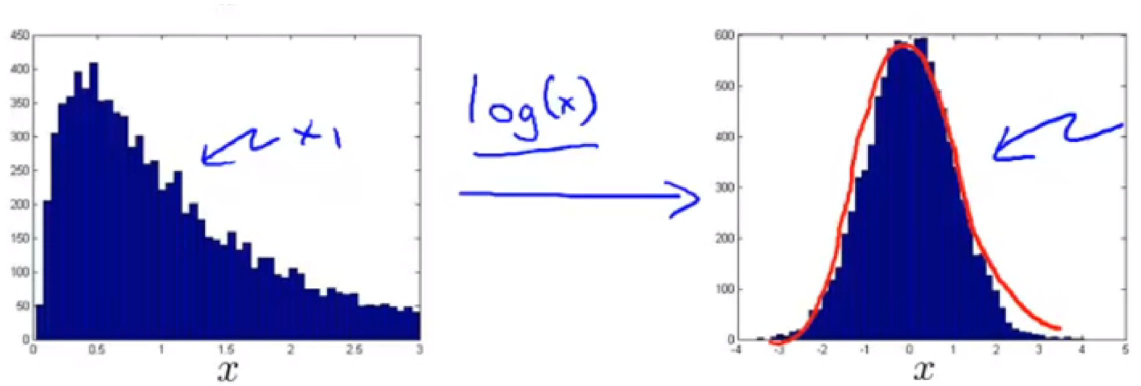
Possible evaluation metrics:

- True positive, false positive, false negative, true negative
- Precision/Recall
- F_1 score

We can also use cross-validation set to choose parameter ϵ

Anomaly Detection	Supervised Learning
Very small number of positive examples (y=1) and large number of negative examples. 0-20 is common.	Large number of positive and negative examples
Many different types of anomalies. Hard for any algorithm to learn from positive examples what the anomalies look like; future anomalies may look nothing like any of the anomalous examples we've seen so far.	Enough positive examples for algorithm to get a sense of what positive examples are like, future positive examples likely to be similar to the ones in training set.
Examples: Fraud detection, manufacturing, monitoring machines in data centre	Examples: Email spam classification, weather prediction, cancer classification

Choosing Features



If the plot doesn't produce a bow shape graph, maybe try to do some transformations which might result in a bow shaped Gaussian plot. For example,

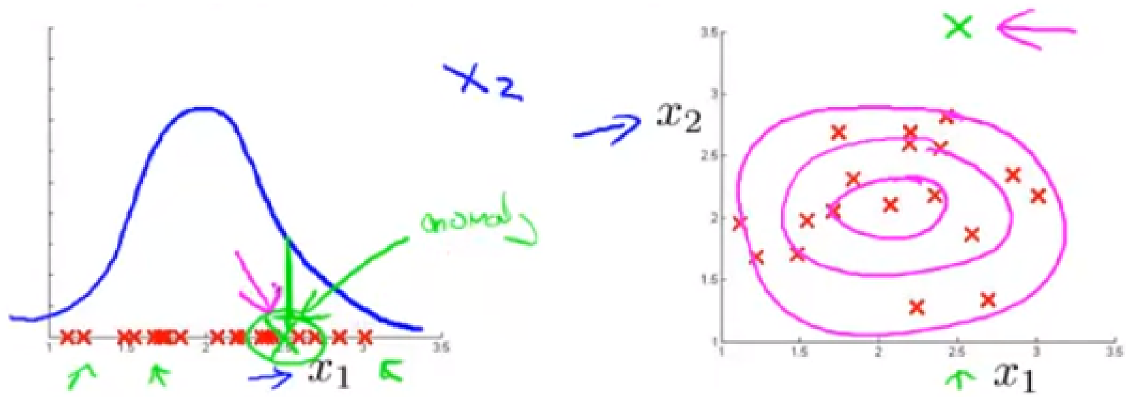
- $x_1 \leftarrow \log(x_1)$
- $x_2 \leftarrow \log(x_2 + 1)$
- $x_3 \leftarrow \sqrt{x_3}$
- $x_4 \leftarrow x_4^{\frac{1}{3}}$

Error Analysis

We want:

- $p(x)$ large for normal examples x
- $p(x)$ small for anomalous examples x

Most common problem: $p(x)$ is comparable (say, both large) for normal and anomalous examples



Look at the anomalies/mistakes that the algorithm is failing to flag and see if that can be used to create a new features, that might help distinguish anomalies