Suppose you are developing an anomaly detection system to catch manufacturing

defects in airplane engines. You model uses

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 $x_1 pprox x_2$. 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:

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

 $p(x) = \prod_{j=1}^n p(x_j; \mu_j, \sigma_j^2).$

Correct

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

 $x_3 = x_1 imes x_2$

 $\bigcirc \quad x_3 = x_1 + x_2$

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

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

This should not be selected

Labeled data are usefull in cross-validation and testing for evaluating the system and setting the parameter ϵ .

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.

Correct

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.

This should not be selected

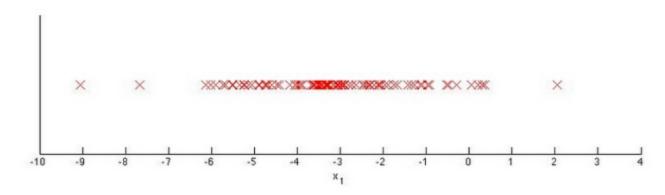
Anomaly detection only models the negative examples, whereas an SVM learns to discriminate between positive and negative examples, so the SVM will perform better when you have many positive and negative examples.

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 .

Correct

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

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?

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

This should not be selected

This is the correct value for μ_1 , but most of the data are in [-5, -1], so σ_1^2 is 4, not

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