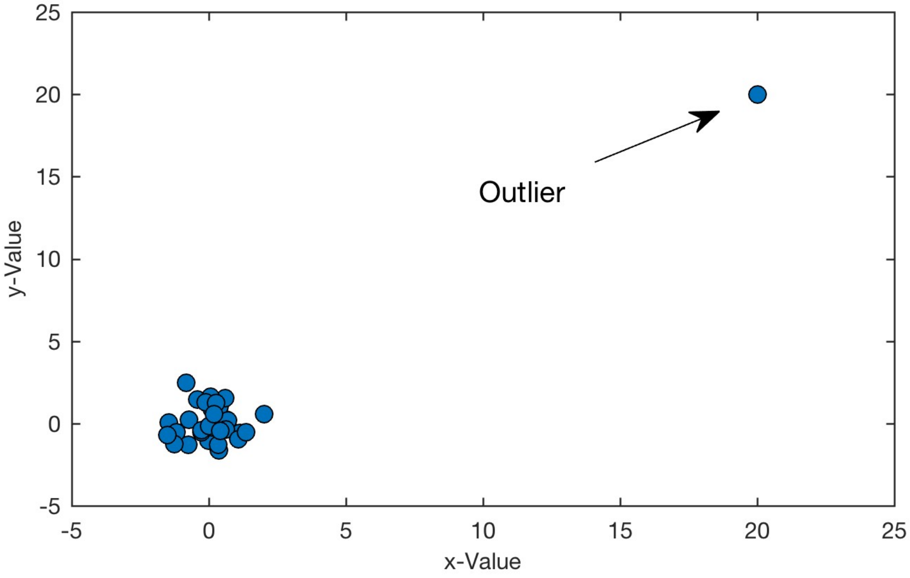
Lecture 12

Anomaly Detection

By Nazerke Sultanova

Anomaly Detection

- Anomaly detection is a technique used to identify unusual patterns that do not conform to expected behavior, called outliers.



Anomaly detection example

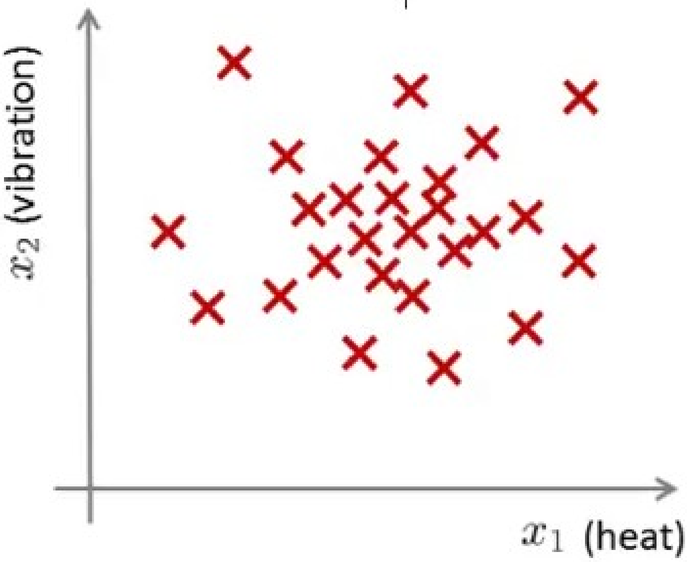
Aircraft engine features:

- x_1 = heat generated
- x_2 = vibration intensity

...

Dataset: $\{x^{(1)}, x^{(2)}, \ldots, x^{(m)}\}$

New engine: x_{test}



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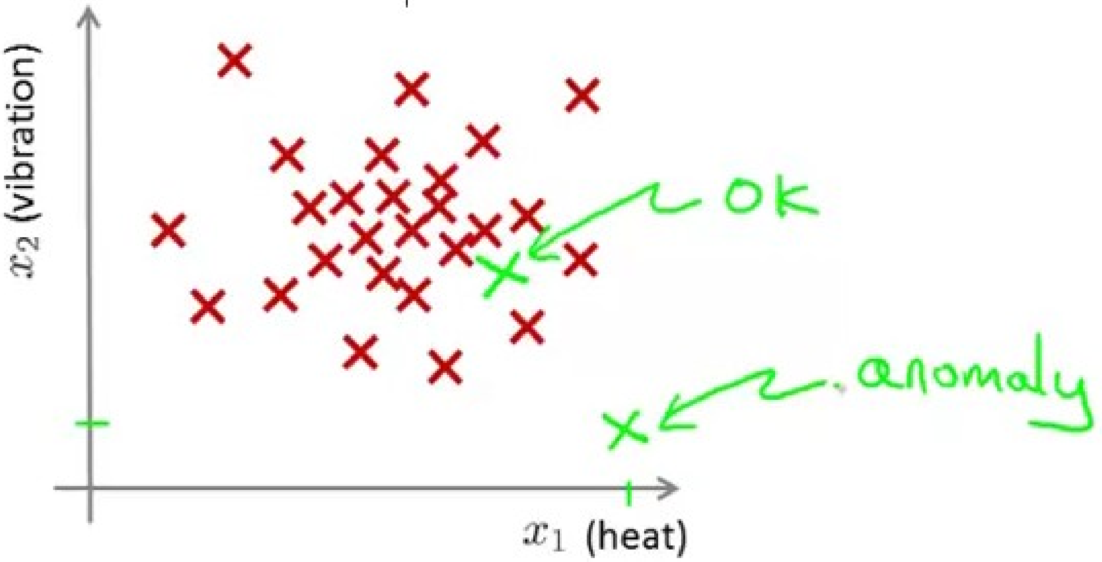


Density estimation

- To check whether x_test anomalous we need to model $p(x)$ such that
  - If $p(x)<e \rightarrow$ flag anomaly
  - If $p(x)>=e \rightarrow$ OK

Anomaly Detection Example

- Fraud detection
- Manufacturing
- Monitoring Computers in data centers

Question:

Your anomaly detection system flags x as anomalous whenever $p(x) \leq \epsilon$. Suppose your system is flagging too many things as anomalous that are not actually so (similar to supervised learning, these mistakes are called false positives). What should you do?

- [ ] Try increasing ϵ.
- ( ) Try decreasing ϵ.

Gaussian Distribution

- To be learnt by yourself

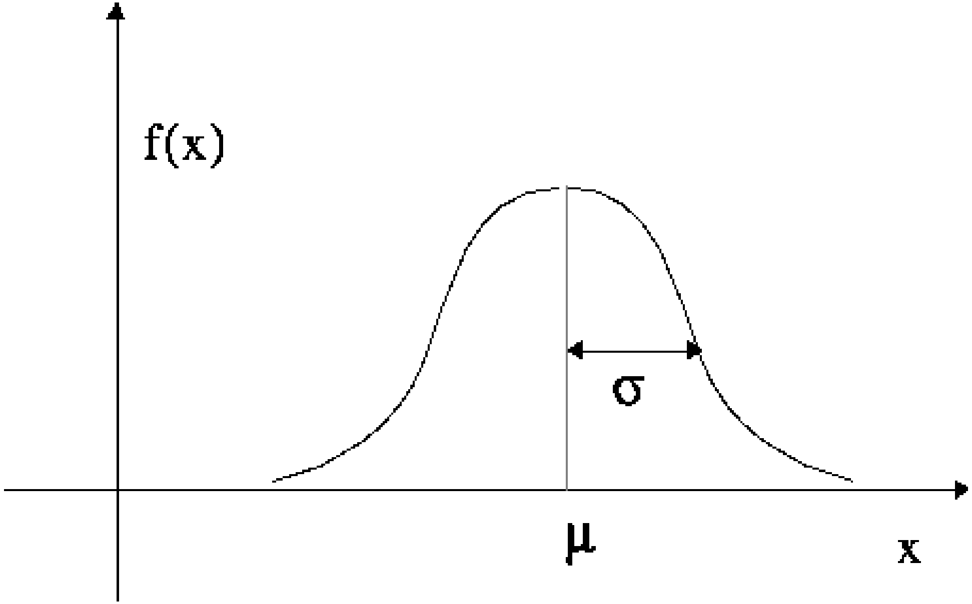
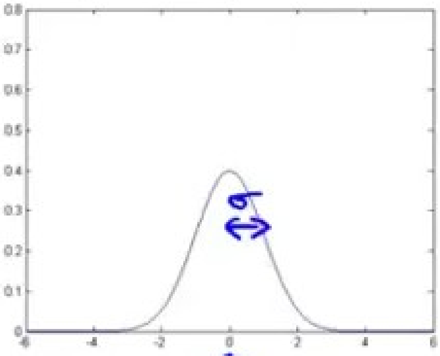


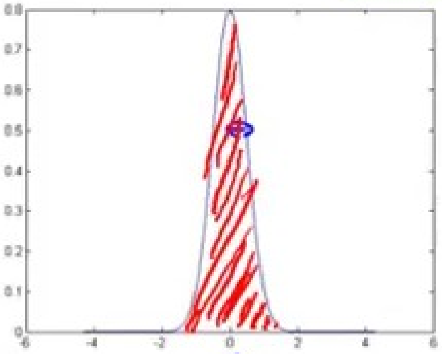
Figure 7. Gaussian (Normal) Probability Distribution Function

Gaussian distribution example

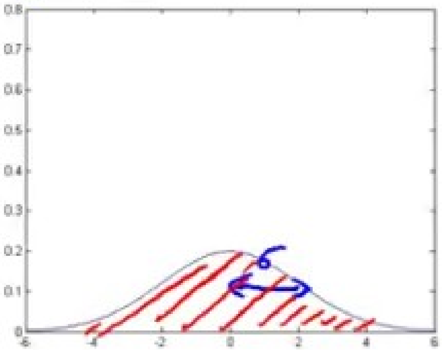
$\mu = 0, \sigma = 1$



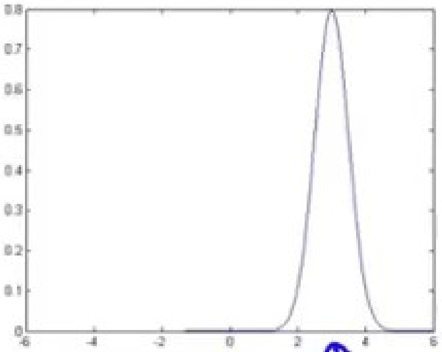
$\mu = 0, \sigma = \underline{0.5}$ $\quad \sigma^2 = 0.25$



$\mu = 0, \sigma = 2$



$\mu = 3, \sigma = 0.5$



Andrew Ng

Anomaly detection algorithm

1. Choose features x_i that you think might be indicative of anomalous examples.
2. Fit parameters $\mu_1, \ldots, \mu_n, \sigma_1^2, \ldots, \sigma_n^2$

$$\mu_j = \frac{1}{m} \sum_{i=1}^{m} x_j^{(i)}$$

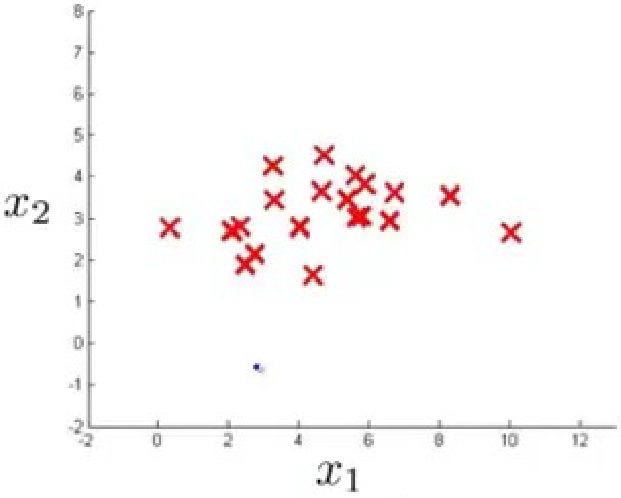
$$\sigma_j^2 = \frac{1}{m} \sum_{i=1}^{m} (x_j^{(i)} - \mu_j)^2$$

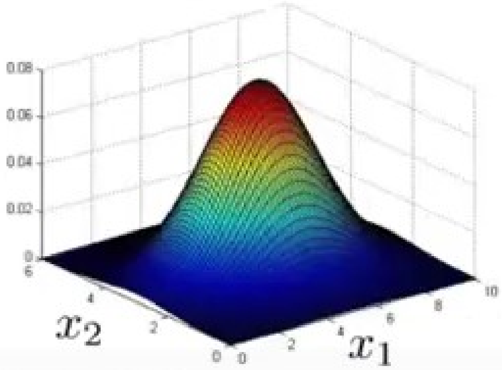
3. Given new example x, compute $p(x)$:

$$p(x) = \prod_{j=1}^{n} p(x_j; \mu_j, \sigma_j^2) = \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(x_j - \mu_j)^2}{2\sigma_j^2}\right)$$

Anomaly if $p(x) < \varepsilon$

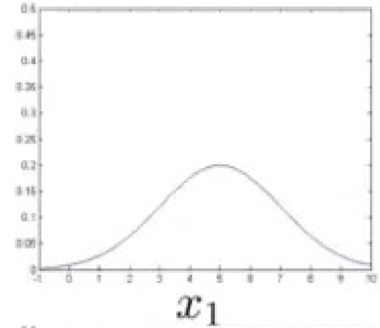
Anomaly detection example



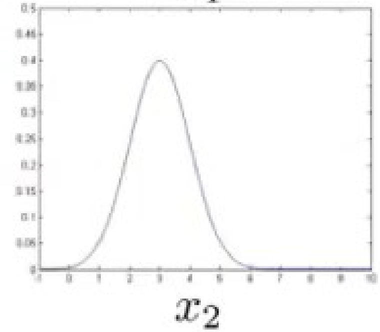


$$\mu_1 = 5, \sigma_1 = 2$$

$$\mu_2 = 3, \sigma_2 = 1$$



$p(x_1; \mu_1, \sigma_1^2)$



$p(x_2; \mu_2, \sigma_2^2)$

Algorithm evaluation

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

On a cross validation/test example x, predict

$$y = \begin{cases} 1 & \text{if } p(x) < \varepsilon \text{ (anomaly)} \\ 0 & \text{if } p(x) \geq \varepsilon \text{ (normal)} \end{cases}$$

Possible evaluation metrics:

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

Can also use cross validation set to choose parameter ε

Can we use supervised ML algorithm to detect anomalies?

Anomaly detection	**vs.**	**Supervised learning**
Very small number of positive examples ($y = 1$). (0-20 is common). Large number of negative ($y = 0$) examples.		Large number of positive and negative examples.

Anomaly detection	vs.	Supervised learning
• Fraud detection		• Email spam classification
• Manufacturing (e.g. aircraft engines)		• Weather prediction (sunny/rainy/etc).
• Monitoring machines in a data center		• Cancer classification
⋮		⋮

Which of the following problems would you approach with an anomaly detection algorithm (rather than a supervised learning algorithm)? Check all that apply.

- [ ] You run a power utility (supplying electricity to customers) and want to monitor your electric plants to see if any one of them might be behaving strangely.
- [ ] You run a power utility and want to predict tomorrow's expected demand for electricity (so that you can plan to ramp up an appropriate amount of generation capacity).
- [ ] A computer vision / security application, where you examine video images to see if anyone in your company's parking lot is acting in an unusual way.
- [ ] A computer vision application, where you examine an image of a person entering your retail store to determine if the person is male or female.