

问题动机

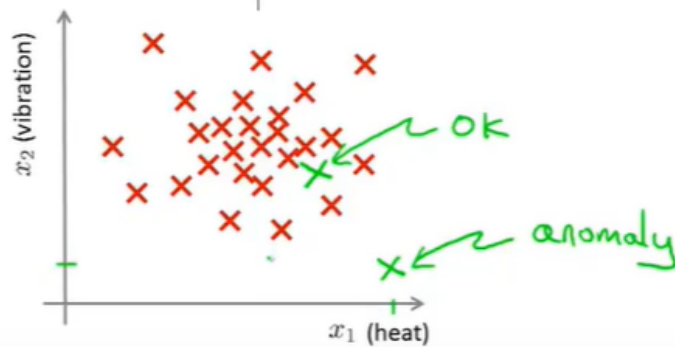
Anomaly detection example

Aircraft engine features:

- x_1 = heat generated
- x_2 = vibration intensity
- ...

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

New engine: x_{test}



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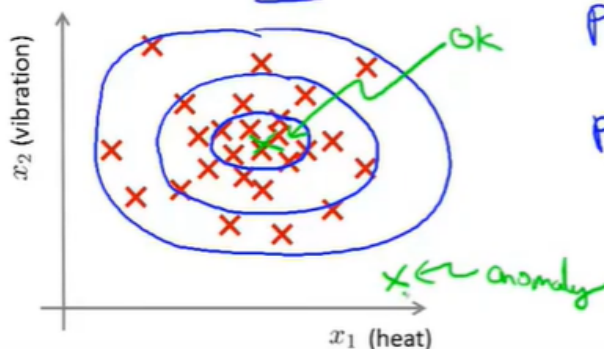
飞机引擎例子中，和其他正常的引擎看起来不同的，被视为异常引擎。

Density estimation

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

→ Is x_{test} anomalous?

Model $p(x)$.



$p(x_{test}) < \epsilon \rightarrow \text{flag anomaly}$
 $p(x_{test}) \geq \epsilon \rightarrow \text{OK}$

对数据样本建模，计算一个概率并规定阈值，最终蓝色圈中的点，我们将其认为是正常引擎，而之外的被认为是异常。

异常检测案例

欺诈检测，生产行业，监控计算机

Anomaly detection example

→ Fraud detection:

→ $x^{(i)}$ = features of user i 's activities

→ Model $p(x)$ from data.

→ Identify unusual users by checking which have $p(x) < \epsilon$

→ Manufacturing

→ Monitoring computers in a data center.

→ $x^{(i)}$ = features of machine i

x_1 = memory use, x_2 = number of disk accesses/sec,

x_3 = CPU load, x_4 = CPU load/network traffic.

... $p(x) < \epsilon$

x_1
 x_2
 x_3
 x_4 $p(x)$

高斯分布(正态分布)

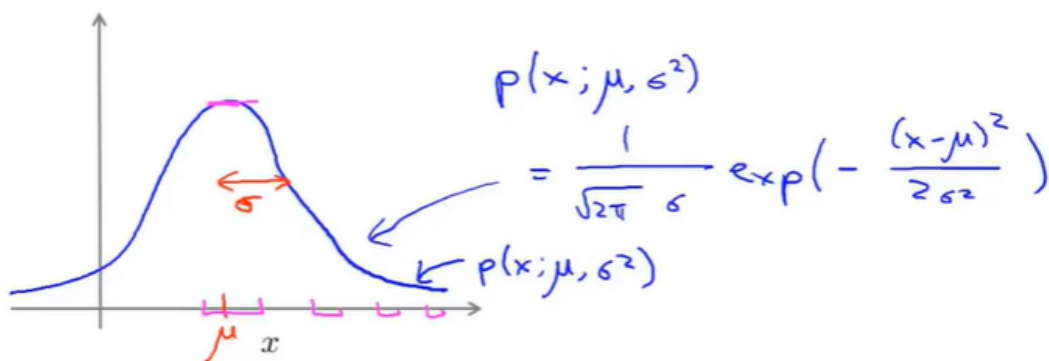
Gaussian (Normal) distribution

Say $x \in \mathbb{R}$. If x is a distributed Gaussian with mean μ , variance σ^2 .

$$x \sim \mathcal{N}(\mu, \sigma^2)$$

↑ "distributed as"

σ = standard deviation

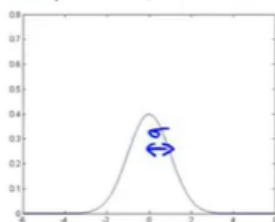


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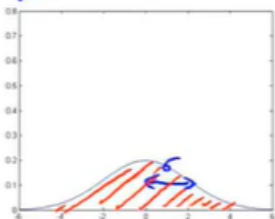
高斯分布中， x 是变量， \sim 表示服从什么分布， N 表示正态分布， μ 是均值， σ^2 是方差， σ 是标准差， μ 决定了钟形的中心位置， σ 决定了钟的宽度。

Gaussian distribution example

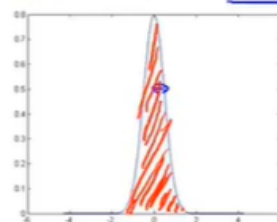
→ $\mu = 0, \sigma = 1$



→ $\mu = 0, \sigma = 2$

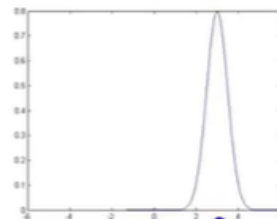


→ $\mu = 0, \sigma = 0.5$



$\sigma^2 = 0.25$

→ $\mu = 3, \sigma = 0.5$



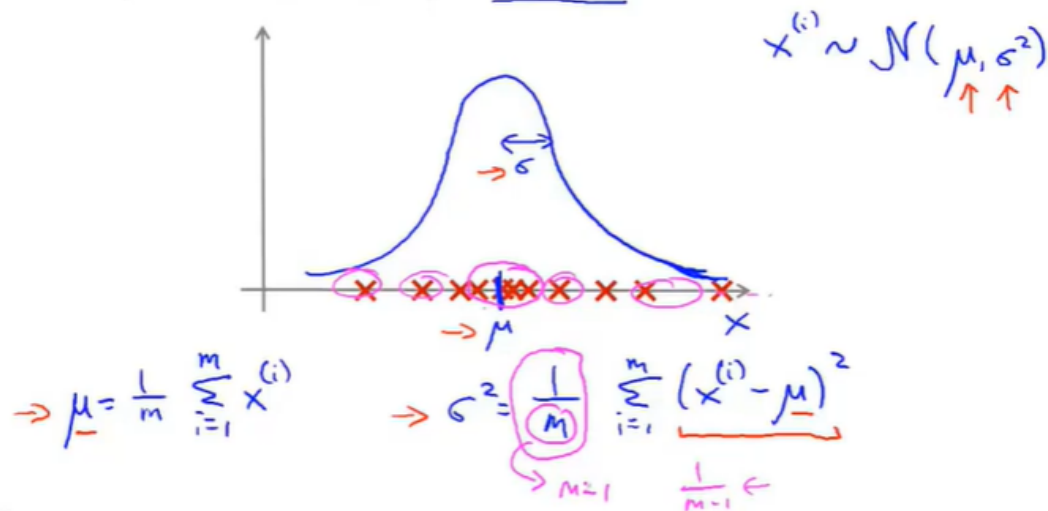
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例子中阴影部分面积和为1.

参数估计

Parameter estimation

→ Dataset: $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$ $x^{(i)} \in \mathbb{R}$



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μ , σ^2 的公式如上, 有的版本 σ^2 公式中的分母写作 $m-1$, 其实几乎没有差别。

高斯分布构造异常检测算法

密度估计:

→ Density estimation

→ Training set: $\{x^{(1)}, \dots, x^{(m)}\}$

Each example is $x \in \mathbb{R}^n$

→ $p(x)$

$$= p(x_1; \mu_1, \sigma_1^2) p(x_2; \mu_2, \sigma_2^2) p(x_3; \mu_3, \sigma_3^2) \dots p(x_n; \mu_n, \sigma_n^2) \leftarrow$$

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

$$x_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$$

$$x_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$$

$$x_3 \sim \mathcal{N}(\mu_3, \sigma_3^2)$$

$$\sum_{i=1}^n i = 1+2+3+\dots+n$$

$$\prod_{i=1}^n i = 1 \times 2 \times 3 \times \dots \times n$$

密度估计就是将一个数据样本中一个数据中的各个维度的值用高斯分布计算得出的概率进行连乘。

异常检测算法:

Anomaly detection algorithm

→ 1. Choose features x_i that you think might be indicative of anomalous examples. $\{x^{(1)}, \dots, x^{(m)}\}$

→ 2. Fit parameters $\mu_1, \dots, \mu_n, \sigma_1^2, \dots, \sigma_n^2$

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

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

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix} = \frac{1}{m} \sum_{i=1}^m x^{(i)}$$

→ 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 $p(x) < \epsilon$

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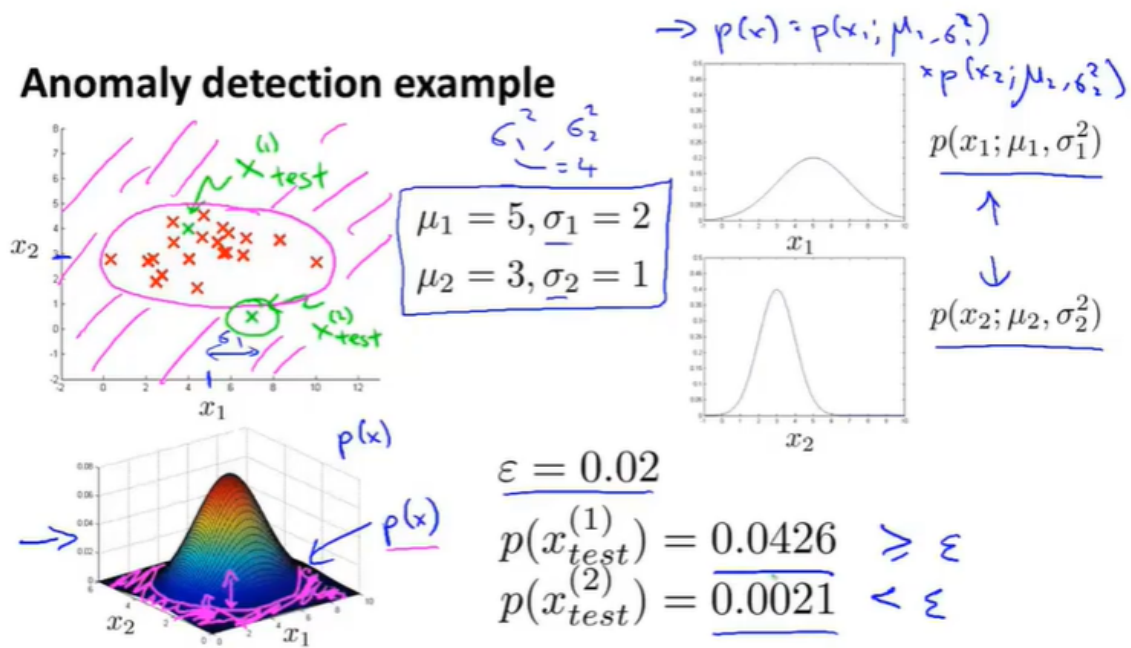
1.选择特征

2.拟合参数, 计算 μ , σ^2

3.密度估计, 当计算出的概率低于阈值, 视为异常

例子:

Anomaly detection example



开发和评估异常检测系统

The importance of real-number evaluation

When developing a learning algorithm (choosing features, etc.), making decisions is much easier if we have a way of evaluating our learning algorithm.

- Assume we have some labeled data, of anomalous and non-anomalous examples. ($y = 0$ if normal, $y = 1$ if anomalous).
- Training set: $x^{(1)}, x^{(2)}, \dots, x^{(m)}$ (assume normal examples/not anomalous)
- Cross validation set: $(x_{cv}^{(1)}, y_{cv}^{(1)}), \dots, (x_{cv}^{(m_{cv})}, y_{cv}^{(m_{cv})})$
- Test set: $(x_{test}^{(1)}, y_{test}^{(1)}), \dots, (x_{test}^{(m_{test})}, y_{test}^{(m_{test})})$

$y=1$

$y=0$ 表示飞机引擎正常, $y=1$ 代表飞机引擎异常。

实数评估:

一个评估学习算法的数字来告诉我们算法的质量, 我们可以根据这个实数来调整加入的特征。

例子：

Aircraft engines motivating example

- 10000 good (normal) engines
- 20 flawed engines (anomalous) 2-50 y=1
- Training set: 6000 good engines ($y=0$) $p(x) = p(x_1; \mu_1, \sigma_1^2) \dots p(x_n; \mu_n, \sigma_n^2)$
- CV: 2000 good engines ($y=0$), 10 anomalous ($y=1$)
- Test: 2000 good engines ($y=0$), 10 anomalous ($y=1$)

训练集中只有正常的引擎。

同样的数据（包括正常，异常引擎）不要同时用于交叉训练集和验证集。

算法评估：

Algorithm evaluation

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

好的评价指标不能只有单纯的分类正确率。

一个选择阈值epsilon ε 的方式是在交叉验证集中使用不同的值，从中选择一个能最大化 F_1_score 或者其他指标的。最后在测试集中进行最后评估。

