

# Gaussian Distribution and Anomaly Detection

## Gaussian Distribution Overview

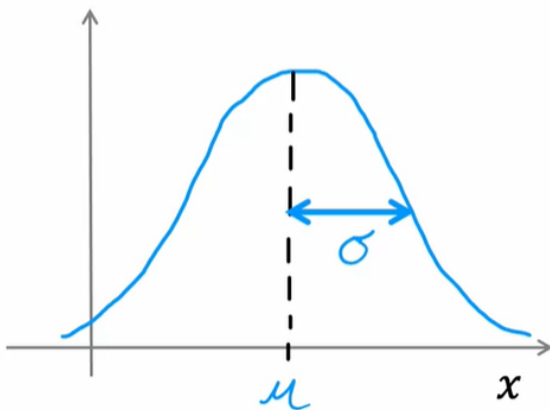
- **Gaussian Distribution:** Also known as the normal distribution, it is a probability distribution characterized by a bell-shaped curve. The curve is defined by two parameters: mean ( $\mu$ ) and variance (sigma squared).

### Gaussian (Normal) distribution

Say  $x$  is a number.

Probability of  $x$  is determined by a Gaussian with mean  $\mu$ , variance  $\sigma^2$ .

$\sigma$  standard deviation  
 $\sigma^2$  variance



- **Probability of  $x$ :** The probability of a random variable  $x$  following a Gaussian distribution is given by the formula:

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)}$$

- **Interpretation:** The probability density function  $p(x)$  represents the likelihood of observing a specific value of  $x$ . The bell-shaped curve illustrates the distribution of a large number of samples drawn from this distribution.

## Effect of Changing Mu and Sigma

### 1. Standard Gaussian Distribution ( $\mu = 0$ , $\sigma = 1$ ):

- Centered at zero with a standard deviation of one.

- A common reference for comparison.

## 2. Reduced Sigma (Sigma = 0.5):

- Thinner curve due to a smaller standard deviation.
- Taller curve compensates for the reduced width.

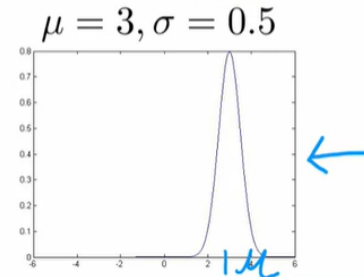
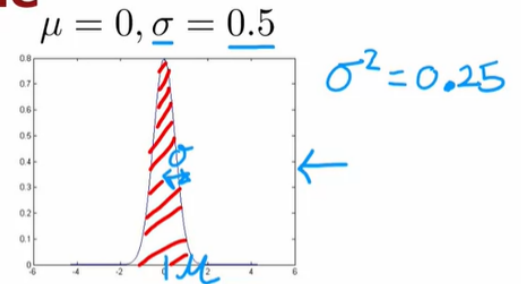
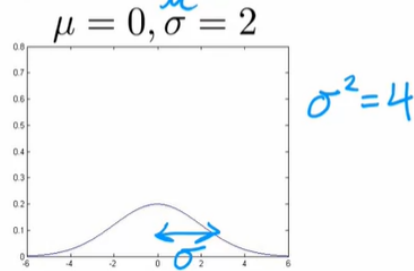
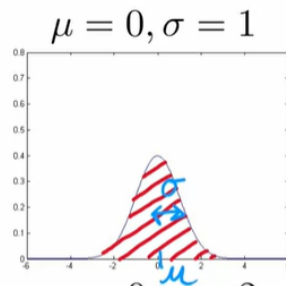
## 3. Increased Sigma (Sigma = 2):

- Wider distribution with a larger standard deviation.
- Shorter curve to maintain a total area under the curve equal to one.

## 4. Change in Mu (Mu = 2, Sigma = 0.5):

- Shifts the center of the distribution to the right while maintaining the standard deviation.

### Gaussian distribution example



## Application to Anomaly Detection

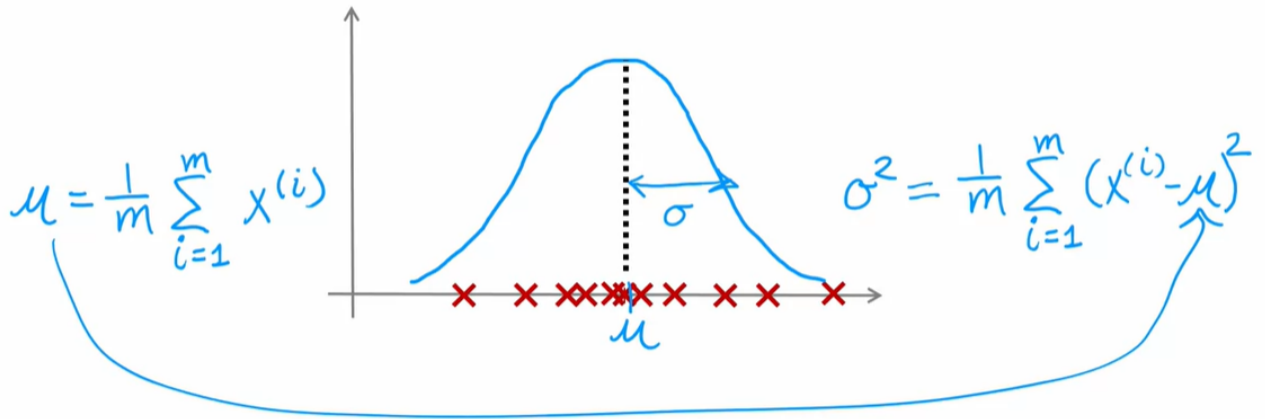
- **Anomaly Detection Dataset:** Given a dataset of  $m$  examples with a single feature  $x$ , the goal is to estimate parameters  $\mu$  and  $\sigma^2$  for a Gaussian distribution.
- **Estimation Formulas:**

$$\mu = \frac{1}{m} \sum_{i=1}^m x^{(i)}$$

$$\sigma^2 = \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu)^2$$

## Parameter estimation

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



- **Maximum Likelihood Estimates:** These formulas provide estimates for  $\mu$  and  $\sigma^2$  and are technically known as maximum likelihood estimates.
- **Anomaly Decision:** Given an example  $x_{\text{test}}$ :
  - If  $p(x_{\text{test}}) < \epsilon$ , flag it as an anomaly.
  - If  $p(x_{\text{test}}) \geq \epsilon$ , consider it normal.

## Handling Multiple Features

- **Extension to Multiple Features:** In practical applications, there are usually multiple features ( $n$  features).
- **Sophisticated Anomaly Detection:**
  - The principles learned from a single Gaussian distribution can be extended to handle multiple features.
  - Calculate  $\mu$  and  $\sigma$  for each feature independently.
- **Multivariate Gaussian Distribution:** Utilize a multivariate Gaussian distribution to model the joint probability of multiple features. The extension involves using a covariance matrix in addition to  $\mu$  and  $\sigma$ .
- **Next Steps:** The next video will explore the application of Gaussian distribution to more sophisticated anomaly detection algorithms, considering scenarios with multiple features.