

# The Central Limit Theorem

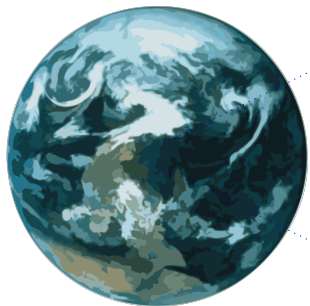
## Probability Distributions of Estimators

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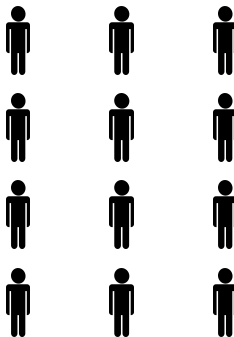
Høgskolen i Ålesund

10th February 2014

# Sample Mean



*Random Sample*



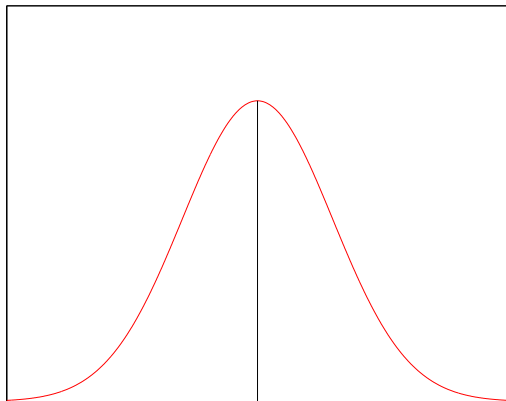
$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$$

# Central Limit Theorem

- Sample mean  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$ 
  - sum of independent variables
- Central Limit Theorem
  - **any** sum  $X = X_1 + X_2 + \dots + X_n$
  - of **identically** distributed independent variables  $X_i$
  - **regardless** of the exact distribution of  $X_i$
  - as  $n \rightarrow \infty$ ,  $X$  has always the same distribution
- This distribution, at the limit at infinity, is known as
  - **the normal distribution**, or
  - **the Gaussian distribution**

# The Gauss Curve



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

# The standard normal distribution

- 1  $Y \sim N(\mu, \sigma)$
- 2  $Z = \frac{Y - \mu}{\sigma}$
- 3  $Z \sim N(0, 1)$

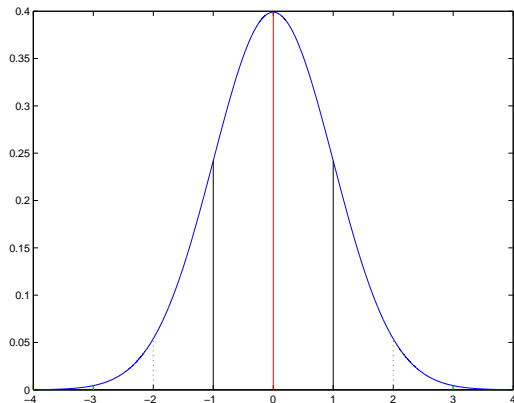
## Definition

The **Standard Normal Distribution** is the Normal Distribution with  $\mu = 0$  and  $\sigma = 1$ .

- We customarily normalise variables to use the Standard Normal Distribution
- E.g. for probability tables.

# The Gauss Curve

The PDF of the standard normal distribution



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

$$\mu = 0$$

$$\sigma = 1$$

# Summary

- Let  $X = X_1 + X_2 + \dots + X_n$ 
  - sum of  $n$  identically distributed variables  $X_i$
- When  $n \rightarrow \infty$ ,  $X \sim N(\mu, \sigma)$  —  $X$  is normally distributed

## Exercise

*Find the following probabilities using the `cdf()` function in Matlab (or some other method):*

- 1  $P(Z \leq -2)$  when  $Z \sim N(0, 1)$
- 2  $P(Z \leq -1)$  when  $Z \sim N(0, 1)$
- 3  $P(Z \geq 1)$  when  $Z \sim N(0, 1)$
- 4  $P(-1 \leq Z \leq 1)$  when  $Z \sim N(0, 1)$