Characterization of random uncertainty of measurements Random variables

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### Probability

 If an experiment has a total of N possible, random results and a given result A occurs k times, then the probability of result A is:

$$p(A) = \frac{k}{N}$$

(This definition is the classical definition of probability. From now on, we will be satisfied with this!)



#### Random error

- the random error is theoretically a random variable
- a random variable could have:
  - discrete values from the elements of a discrete set, or
  - continuous values from the elements of a continuous interval.
- the sum of the probabilities of all possible values of a random variable is always 1.  $\sum_{\forall A} p(A) = 1$

### **Distribution function**

The function F(x), which gives the probability that the random variable A takes a value smaller than x, is called distribution function of the random variable A:

F(x) = p(A < x).



### **Density function**

• The *probability density function* of the continuous random variable is defined as:

$$\rho(x) = \frac{dF(x)}{dx}$$

• From above definition follows:

$$p(a \le A \le b) = \int_{a}^{b} \rho(x) dx$$
$$\int_{\forall A} \rho(x) dx = 1$$



#### **Moments**

• Discrete case:

$$M_k = \sum_{\forall i} A_i^k . p(A_i)$$

#### • Continuous case:

$$M_k = \int_{\forall x} x^k . \rho(x) dx$$

## Expected value and standard deviation

The first moment of a random variable is called expected value:

$$m = M_1(x) = \langle x \rangle.$$

• The second moment of deviations of random variable A from it's expected value is called *standard deviation*:

$$D^2 = M_2(x-m) = \left\langle \left(x-m\right)^2 \right\rangle.$$

Theorem: 
$$D^2 = M_2(x) - m^2$$

#### <u>Proof:</u>

$$D^{2} = M_{2}(x-m) = \left\langle \left(x-m\right)^{2} \right\rangle = \left\langle x^{2} \right\rangle - 2m \left\langle x \right\rangle + m^{2} =$$
  
=  $M_{2}(x) - 2m^{2} + m^{2} = M_{2}(x) - m^{2}.$ 

### The Poisson distribution

 If X is a discrete random variable and take values 0, 1, 2,..., k with probability:

$$p(X = k) = \frac{\lambda^k . e^{-\lambda}}{k!} \qquad \lambda > 0$$
  
than X has the Poisson distribution

• Examples: the number of raindrops falling on a given area, the average length of the waiting list during a given time period, the number of radioactive decays during a given time interval, etc.



• From Calculus we now the Taylor serie for exponential function:

$$e^{\lambda} = \sum_{k=0}^{\infty} \frac{\lambda^k}{k!}$$

## Characterization of Poisson distribution

• Does it describe probability?

$$\sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot e^{\lambda} = 1$$

• What is it's expected value?

$$m = \sum_{k=0}^{\infty} k \frac{\lambda^k . e^{-\lambda}}{k!} = 0 + \lambda . \sum_{k=1}^{\infty} \frac{\lambda^{(k-1)} . e^{-\lambda}}{(k-1)!}$$
$$= \lambda . e^{-\lambda} \sum_{r=0}^{\infty} \frac{\lambda^r}{r!} = \lambda . e^{-\lambda} . e^{\lambda} = \lambda$$

## Characterization of Poisson distribution

• What is it's standard deviation?:

$$D^{2} = \langle k^{2} \rangle - m^{2}$$

$$\langle k^{2} \rangle = \sum_{k=0}^{\infty} k^{2} \frac{\lambda^{k} \cdot e^{-\lambda}}{k!} = \lambda \cdot \sum_{k=1}^{\infty} k \frac{\lambda^{(k-1)} \cdot e^{-\lambda}}{(k-1)!} = \lambda \cdot \sum_{r=0}^{\infty} (r+1) \frac{\lambda^{r} \cdot e^{-\lambda}}{r!}$$

$$= \lambda \cdot \left\{ \sum_{r=0}^{\infty} r \frac{\lambda^{r} \cdot e^{-\lambda}}{r!} + \sum_{r=0}^{\infty} \frac{\lambda^{r} \cdot e^{-\lambda}}{r!} \right\} = \lambda \cdot \{m + e^{-\lambda} \cdot e^{\lambda}\} = \lambda \cdot (\lambda + 1) = \lambda^{2} + \lambda$$

$$D^{2} = \lambda^{2} + \lambda - \lambda^{2} = \lambda$$

$$M = \lambda$$

$$D^{2} = \lambda$$



### Uniform distribution

 If X continuous random variable's probability density function is:

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$$\rho(x) = \frac{1}{b-a}, \quad a < x < b$$
$$= 0 \quad otherwise$$

otherwise

**Α**ρ(x)  $\frac{1}{b-a}$ 

than random variable is uniformly distributed.

• Example: measurements with scales

## Characterization of uniform distribution

• Does it describe probability?

$$\int_{\forall x} \rho(x) dx = \int_{a}^{b} \frac{1}{b-a} dx = \frac{b-a}{b-a} = 1$$

•What is it's expected value?

$$\mu = \int_{a}^{b} x \cdot \frac{1}{b-a} dx = \frac{1}{b-a} \int_{a}^{b} x dx = \frac{1}{b-a} \cdot \frac{b^{2}-a^{2}}{2} = \frac{a+b}{2}$$

## Characterization of uniform distribution

• What is it's standard deviation?:

$$\sigma^{2} = \langle x^{2} \rangle - \mu^{2}$$

$$\langle x^{2} \rangle = \int_{a}^{b} x^{2} \frac{1}{b-a} dx = \frac{1}{b-a} \int_{a}^{b} x^{2} dx = \frac{b^{3} - a^{3}}{3(b-a)} = \frac{a^{2} + ab + b^{2}}{3}$$

$$\sigma^{2} = \frac{a^{2} + ab + b^{2}}{3} - \frac{(a+b)^{2}}{4} = \frac{(b-a)}{12}$$

$$\mu = \frac{(a+b)}{2}$$

$$\sigma^{2} = \frac{(b-a)^{2}}{12}$$

#### Normal distribution or Gaussian distribution

• If probability density function of continuos random variable X is ( $\mu_0 > 0$  és  $\sigma_0 > 0$ )



than X is called *normally distributed* or *Gaussian*.

E.g.: Several independent, small, random deviations make the measured value Gaussian!

## Characterization of Normal distribution

• Does it discribe probability?





# Characterization of Normal distribution

• What is it's expected value?

$$\mu = \frac{1}{\sqrt{2\pi\sigma_0}} \int_{-\infty}^{\infty} x e^{\frac{-(x-\mu_0)^2}{2\sigma_0^2}} dx$$

$$t = \frac{x - \mu_0}{\sigma_0}, x = t.\sigma_0 + \mu_0, \frac{dt}{dx} = \frac{1}{\sigma_0}$$

$$\mu = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (t \cdot \sigma_0 + \mu_0) e^{\frac{-t^2}{2}} dt = \frac{\sigma_0}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t e^{\frac{-t^2}{2}} dt + \mu_0 \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\frac{-t^2}{2}} dt$$

$$\int_{-\infty}^{\infty} t e^{\frac{-t^2}{2}} dt = 0$$

$$\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}e^{\frac{-t^2}{2}}dt=1$$

 $\mu = \mu_0$ 

 $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x^{2} + y^{2}) \cdot e^{-\frac{x^{2} + y^{2}}{2}} dx dy =$  $P(x) = \frac{1}{4\pi r_0} \cdot e^{-(x-\mu_0)^2}$  $G^{\vee} = M_2(x) - \mu^{\vee}$  $M_1(x) = \int_{-\infty}^{\infty} x^2 g(x) dx =$  $= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x^{2} + y^{2}) e^{-\frac{x^{2}}{2}} e^{-\frac{x^{2}}{2}} dx dy = \int_{-\infty}^{\infty} e^{-\frac{x^{2}}{2}} \int_{-\infty}^{\infty} x^{2} e^{-\frac{x^{2}}{2}} dx dy =$  $= \frac{1}{115} \int_{0}^{\infty} \int_{0}^{\infty} x^{2} e^{-\frac{(x-\mu_{0})^{2}}{2\sigma_{0}^{2}}} dx = \begin{cases} t = \frac{x-\mu_{0}}{\sigma_{0}} = x = \mu_{0} + \overline{\sigma}_{0} + t \\ \frac{dx}{\sigma_{0}} = x = \sigma_{0} \end{cases}$  $+\int_{-\infty}^{\infty} e^{-\frac{x^{2}}{2}} \int_{-\infty}^{\infty} y^{2} \cdot e^{-\frac{y^{2}}{2}} dy dx = B \int_{-\infty}^{\infty} e^{-\frac{y^{2}}{2}} dy + B \int_{-\infty}^{\infty} e^{-\frac{x^{2}}{2}} dx =$  $=\frac{1}{4\pi^{2}}\int_{0}^{\infty}\left[1_{p_{0}}+\varepsilon_{0}t\right]^{n}\cdot e^{-\frac{t^{2}}{2}}\cdot \mathcal{T}_{0}dt =\frac{1}{4\pi^{2}}\left\{\mu^{2}\int_{0}^{\infty}e^{-\frac{t^{2}}{2}}dt + \lambda\varepsilon_{0}\mu_{0}\int_{0}^{\infty}t\cdot e^{\frac{t^{2}}{2}}dt+\right.$  $+ G_{*}^{*} \int_{0}^{\infty} t^{*} e^{-\frac{t^{*}}{2}} dt = W_{*}^{*} + \frac{G_{*}^{*}}{1\pi} \int_{0}^{\infty} t^{*} e^{-\frac{t^{*}}{2}} dt$ & (integran-due paratlan) 23. 127 Jtendt=B  $\begin{array}{c} \kappa \mathbf{B} f_{2\overline{n}} = \frac{\omega}{|\mathcal{M}||} \\ \mathbf{B} f_{2\overline{n}} = (f_{2\overline{n}})^{\omega} \\ \mathbf{B} = \int_{0}^{\infty} t \cdot e^{-\frac{1}{2}} dt = f_{2\overline{n}} \\ \mathbf{B} = \int_{0}^{\infty} t \cdot e^{-\frac{1}{2}} dt = f_{2\overline{n}} \end{array}$  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x^2 + y^2) \cdot e^{-\frac{x^2 + y}{2}} dx dy = \begin{cases} x = r \cos \varphi & ; x^2 + y^2 = r^2 \\ y = r \sin \varphi & ; dx dy \rightarrow r dr d\varphi \end{cases} =$  $= \int_{0}^{2\pi} \int_{0}^{\infty} r^{\frac{1}{2}} e^{\frac{r^{2}}{2}} r dr d\phi = 2\pi \int_{0}^{\infty} \int_{0}^{\infty} e^{\frac{r^{2}}{2}} dr = \left\{ \frac{-\frac{r^{2}}{2}}{dr} = M \right\} =$  $\overline{G^{2}} = M_{2}(x) - \mu^{2} = \mu^{2} \cdot \frac{G^{2}}{f_{x}} \int_{x}^{x} \frac{G^{2}}{f_{x}} \int_{x}^{x} \frac{G^{2}}{f_{x}} \frac{G^{2}}{f_{x}} \frac{f^{2}}{f_{x}} \frac{G^{2}}{f_{x}} \frac{f^{2}}{f_{x}} \frac{G^{2}}{f_{x}} \frac{G^{2}}{f_{x}}$  $= 2ii \int_{a}^{b} 2m e^{m} dm = 4ii \int_{a}^{b} m e^{m} dm = \begin{cases} f = m & f' = 1 \\ g' = e^{m} & g' = e^{m} \end{cases} =$  $= 4\pi \left\{ \left[ m \cdot e^{m} \right]_{0}^{-m} - \int e^{m} dn \right\} = -4\pi \left[ e^{m} \right]_{0}^{-m} = 4\pi$ 

# Characterization of Normal distribution

• What is it's standard deviation?

 $\sigma^{2} = \langle x^{2} \rangle - \mu^{2}$   $\langle x^{2} \rangle = \frac{1}{\sqrt{2\pi}\sigma_{0}} \int_{-\infty}^{\infty} x^{2} \cdot e^{\frac{-(x-\mu_{0})^{2}}{2\sigma_{0}^{2}}} dx = \sigma_{0}^{2} + \mu_{0}^{2}$ 



$$\mu = \mu_0$$
$$\sigma^2 = \sigma_0^2$$



### Central limit theorem

• The sum of N independent variables  $(\mu_0, \sigma_0)$ with the same probability distribution is a random variable with a *normal distribution* in the limiting case  $N \rightarrow \infty$ , the expected value of which is  $\mu = N$ .  $\mu_0$ , and its standard deviation  $\sigma^2 = N$ .  $\sigma_0^2$ .