

1) a) sample size  $N$  ✓  

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

b) 
$$s^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2$$
 ✓

c) error in the mean

$$\sigma_{\bar{x}} = \sqrt{\frac{1}{\sum_{i=1}^N \sigma_i^2}}$$
 but ~~more~~ if we assume  $\sigma_i = \sigma$  ✓  

$$\Rightarrow \sigma_{\bar{x}} = \sqrt{\frac{\sigma^2}{N}}$$

2) a) Gaussian distr mean =  $\mu$  variance =  $\sigma^2$  (std dev =  $\sigma$ ) ✓  

$$P_G(x; \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
  $\mu$  and  $\sigma$  parameters of the distribution

b) Poissonian distr mean =  $\mu$  variance =  $\mu$  (std dev =  $\sqrt{\mu}$ ) ✓  

$$P_P(x; \mu) = \frac{\mu^x}{x!} e^{-\mu}$$
  $\mu$  parameter of the distribution

c) } Poisson and Gauss are both limit cases of the binomial distribution.  
 $\frac{1}{2}$  } Poisson limit when the chance of success is very small ( $p \ll 1$ ), and number of trials is large.  
 $\frac{1}{2}$  } ~~Gauss~~ Poisson tends to Gaussian when the <sup>chance</sup> of success is bigger, ~~how~~ <sup>how</sup> what, and when the variance  $\mu = \sigma^2$ .  
~~#2~~ Poisson tends to Gaussian when mean  $\rightarrow \infty$ .

3) The Central Limit Theorem says that if you add up <sup>squared</sup> variables of any distribution (the variables have to come from the same distribution) and the number of variables is very big, the new distribution you get is a Gaussian distribution.

Because this adding happens all the time, almost everything in Nature is taken from a Gaussian distribution.

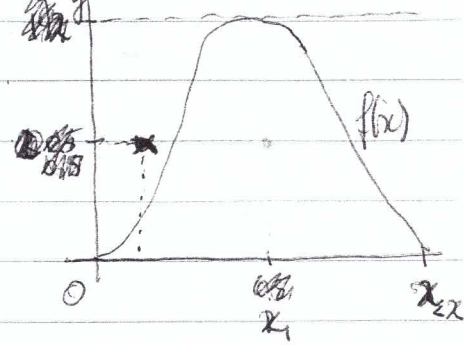
$$\lim_{N \rightarrow \infty} \sum_{i=1}^N x_i^2 \Rightarrow \text{Gaussian distr.}$$

↑ true, but also

$$\lim_{N \rightarrow \infty} \sum_{i=1}^N x_i \Rightarrow \text{Gauss distrib}$$

4) a) You generate random numbers between 0 and 1. These are your  $y_i$  values. ~~Do~~ Do the same for  $x$ -values and ~~multiply by the highest possible  $f(x)$~~  map those to the desired  $x$ -range. ~~multiply  $f(x)$  value to obtain the whole area.~~

→ if you have a normalized function



Now use your distribution function: accept any  $(x_i, y_i)$  for which  $y_i \leq f(x_i)$  and ignore the other points.  $\times$  in the graph is rejected,  $\bullet$  is accepted.

In this way you can get lots of points under your graph (only) and you can randomly select one of those  $\bullet$  and use the  $x$ -value as your random number.

Also (if your maximum  $f(x)$  value is a lot smaller than 1) you can ~~multiply the random  $y$ -values by~~ multiply the random  $y$ -values by with the  $\max\{f(x)\}$  value to get the best area to work with.  $\checkmark$

b) 
$$P(x) = \begin{cases} A(1+ax^2) & -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$\times$

Inversion method ~~works like this~~

First  $A$  : 
$$\int_{-1}^1 A(1+ax^2) dx = 1 \Rightarrow A \left[ x + \frac{ax^3}{3} \right]_{-1}^1 = A \left[ 2 + \frac{a}{3} - \frac{a}{3} \right] = 1$$

$$2A \left[ 1 + \frac{a}{3} \right] = 1 \quad A = \frac{1}{2 \left[ 1 + \frac{a}{3} \right]}$$

$r$  is unif. distrib. between 0 and 1

$$p(r) = \begin{cases} 1 & 0 \leq r \leq 1 \\ 0 & \text{otherwise} \end{cases} ; \quad P(x) = \begin{cases} A(1+ax^2) & -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\int_{-\infty}^r p(r') dr' = \int_{-\infty}^x P(x') dx' \Rightarrow \int_0^r 1 dr' = \int_{-1}^x A(1+ax'^2) dx' \Rightarrow$$

$$\Rightarrow r = \int_{-1}^x A(1+ax'^2) dx' = A \left( x' + \frac{ax'^3}{3} \right) \Big|_{-1}^x = A \left( x + \frac{ax^3}{3} + 1 + \frac{a}{3} \right)$$

$$\Rightarrow r = A \left( x + \frac{ax^3}{3} + 1 + \frac{a}{3} \right) \text{ and solve } x = x(r)$$

5) Propagate errors using <sup>the definition of</sup> partial derivatives  $f(x, y, z)$   
 errors:  $\Delta x, \Delta y, \Delta z$

$$\sigma_f^2 = \left( \frac{f(x+\Delta x, y, z) - f(x, y, z)}{\Delta x} \right)^2 \Delta x^2 + \left( \frac{f(x, y+\Delta y, z) - f(x, y, z)}{\Delta y} \right)^2 \Delta y^2 + \left( \frac{f(x, y, \Delta z + z) - f(x, y, z)}{\Delta z} \right)^2 \Delta z^2$$

6)  $p(\text{accident}) = 10^{-2}$   
 probability not having an accident:  $1-p$   
 number of years  $N = 30$  probability not accident  $N$  years:  $(1-p)^N$

I assume involved in <sup>at least one</sup> ~~an~~ accident  $(\geq 1)$

That is, the probability of not being in an accident subtracted from 1.

$$P(\text{an accident}) = 1 - (1-p)^N$$

$$= 1 - (1-10^{-2})^{30} = 0,26 \checkmark \quad P(X > 0) = 1 - P(X \leq 0) = 1 - P(X=0)$$

50% chance:  $P = 50$

$$1 - P = (1-p)^N$$

$$\log(1-P) = N \log(1-p)$$

$$N = \frac{\log(1-P)}{\log(1-p)} = \frac{\ln(1-P)}{\ln(1-p)} = \frac{-\ln 2}{\ln(99/100)} = 68,97 \text{ yr } \checkmark$$

That means that to stay under 50%, you can drive for 68 yr.

7)  $N$  random variables  $x_i$   
 $\sum_{i=1}^N x_i^2$  This is exactly the  $\chi^2$ -distribution  $\checkmark$

When  $N \rightarrow \infty$  the ~~CLT~~ Central Limit Theorem says that this  $\checkmark$   
 goes to Gaussian again.