

# SmartCow project

Ethics in experiments on animals

# Adjustment of animal numbers in experimentation

**Question: Why is this important?** 

**Patrick Gasqui** 

Tuesday September 22, 2020

INRAE – VetAgro Sup, Unité Mixte de Recherches d'Epidémiologie des maladies animales et zoonotique (EPIA), Centre de recherche de Clermont Auvergne-Rhône-Alpes, Département de Santé Animale (SA)







# "Classical" statistical theory for using a test:

# the initial framework of this presentation ...

1 - as part of a one-sided hypothesis test:

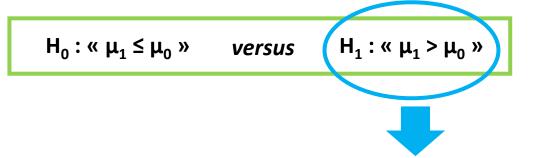
$$H_0: \ll \mu_1 \le \mu_0 \gg versus \qquad H_1: \ll \mu_1 > \mu_0 \gg \mu_0$$



# "Classical" statistical theory for using a test:

# the initial framework of this presentation ...

1 - as part of a one-sided hypothesis test:



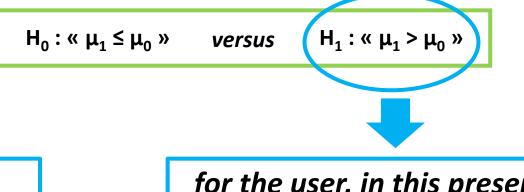
for the user, in this presentation the hypothesis  $(H_1)$  is the hypothesis of interest



# "Classical" statistical theory for using a test:

# the initial framework of this presentation ...

1 - as part of a one-sided hypothesis test:



the user therefore wants to highlight a difference in means:  $\ll$  delta =  $\mu_1$  -  $\mu_0$  »



for the user, in this presentation the hypothesis  $(H_1)$  is the hypothesis of interest



# the initial framework of this presentation ...

2 - for a random variable of interest « Y » which follows a Gaussian distribution with standard deviation «  $\sigma_v$  »

using a statistic of test: « T » whose law (distribution) is known under H<sub>0</sub>

and whose value is « T<sub>obs</sub> » after the measurement results of a sample size « N »

example statistic « T »: the empirical mean

$$\overline{Y_N} = \frac{1}{N} \cdot \sum_{i=1}^{i=N} Y_i$$



# the initial framework of this presentation ...

2 - for a random variable of interest « Y » which follows a Gaussian distribution with standard deviation «  $\sigma_{\text{Y}}$  »



the standard deviation «  $\sigma_{\rm Y}$  » is the precision of the studied variable « Y »

using a statistic of test: « T » whose law (distribution) is known under H<sub>0</sub>

and whose value is « T<sub>obs</sub> » after the measurement results of a sample size « N »

example statistic « T »: the empirical mean

$$\overline{Y_N} = \frac{1}{N} \cdot \sum_{i=1}^{i=N} Y_i$$



# the initial framework of this presentation ...

2 - for a random variable of interest « Y » which follows a Gaussian distribution with standard deviation «  $\sigma_Y$  » using a statistic of test: « T » whose law (distribution) is known under H<sub>0</sub>

and whose value is « T<sub>obs</sub> » after the measurement results of a sample size « N »

example statistic « T »: the empirical mean

$$\overline{Y_N} = \frac{1}{N} \cdot \sum_{i=1}^{i=N} Y_i$$

the standard deviation «  $\sigma_{\rm Y}$  » is the precision of the studied variable « Y »



this precision «  $\sigma_{\rm Y}$  » is important given that we want to be able to highlight a difference between two means « delta =  $\mu 1$  -  $\mu 0$  » with the variable « Y »



# the initial framework of this presentation ...

2 - for a random variable of interest « Y » which follows a Gaussian distribution with standard deviation «  $\sigma_v$  »

using a statistic of test: « T »
whose law (distribution) is known under H<sub>0</sub>

and whose values is « T<sub>obs</sub> » after
the measurement resue of a sample size « N »

example statistic « T »: the empirical mean

$$\overline{Y_N} = \frac{1}{N} \cdot \sum_{i=1}^{i=N} Y_i$$

an example
is the student test statistic
when « Y » follows
a Gaussian distribution



# the initial framework of this presentation ...

## 3 - after choosing:

a risk of error of the first kind: «  $\alpha$  = 0.05 »



a confidence coefficient for the Confidence Interval (CI): «  $\Upsilon$  = 0.95 »

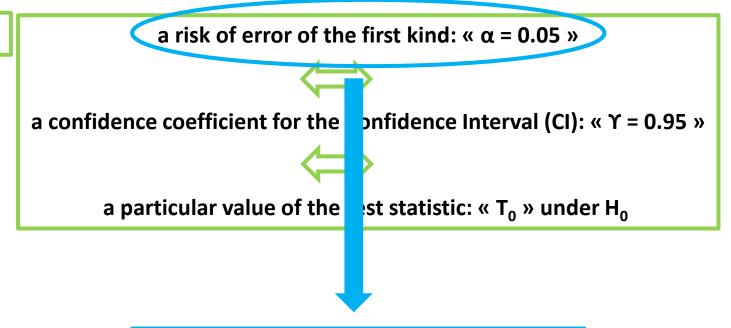


a particular value of the test statistic: « T<sub>0</sub> » under H<sub>0</sub>



# the initial framework of this presentation ...

## 3 - after choosing:



«  $\alpha$  = 0.05 » is the risk of error conventionally taken in practice

4 - we are led to take a "decision" from the result « Tobs » obtained on the sample :

either: « we cannot reject  $H_0$  » which means: «  $T_{obs} \le T_0$  » or « Pvalue  $\ge \alpha$  »

either: « we accept  $H_1$  » which means: «  $T_{obs} > T_0$  » or « Pvalue <  $\alpha$  »

# without knowing the « reality » ...

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
« decision » H <sub>0</sub>	« Y = 0.95 »	?
« decision » H <sub>1</sub>	$\ll \alpha = 0.05 $ »	?

α = error of the first kind "controlled *a priori*"



it is the user who chooses its value a priori

$$\alpha = 1 - \gamma$$

α is the probability of concluding that there is a difference when there is none ["notion of false positive"]



4 - we are led to take a "decision" from the result « Tobs » obtained on the sample :

either: « we cannot reject  $H_0$  » which means: «  $T_{obs} \le T_0$  » or « Pvalue  $\ge \alpha$  »

either: « we accept  $H_1$  » which means: «  $T_{obs} > T_0$  » or « Pvalue <  $\alpha$  »

# without knowing the « reality » ...

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
« decision » H <sub>0</sub>	« Y = 0.95 »	?
« decision » H <sub>1</sub>	$\ll \alpha = 0.05 $ »	?

$$\alpha = 1 - \gamma$$

α = error of the first kind "controlled *a priori*"

«  $\alpha$  » and «  $\gamma$  » with the concept of confidence interval (CI) :

 $\Upsilon$  = « probability that the CI: ] - $\infty$ , T<sub>0</sub> ] contains the observed value: T<sub>obs</sub> under H<sub>0</sub> »

 $\alpha$  = « probability that the CI: ] - $\infty$ , T<sub>0</sub> ] no contains the observed value: T<sub>obs</sub> under H<sub>0</sub> »

it is the notion of equivalence between doing a test or calculating a confidence interval



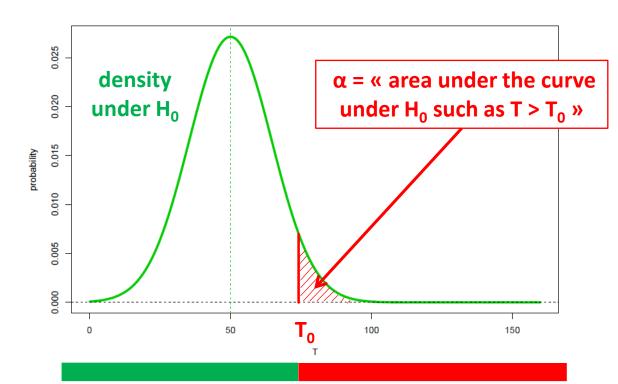
We can visualize this with the density distribution of "T" under  $H_0$  with « N=6 » and «  $\sigma_Y=36$  »

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
« decision » H <sub>0</sub>	« Υ = 0.95 »	?
« decision » H <sub>1</sub>	$\alpha = 0.05$ »	?

we are led to take a "decision"

from the result « T<sub>obs</sub> »

obtained on the sample:



$$if \ll T_{obs} \leq T_0$$
  $if \ll T_{obs} > T_0$   $if \ll T_0$   $if$ 



## therefore, it is classically the user who chooses a priori:

- ✓ the hypotheses to be tested:  $H_0$ : «  $μ_1 ≤ μ_0$  » versus  $H_1$ : «  $μ_1 > μ_0$  »
- ✓ the test and therefore the test statistic "T" under H₀
- √ a sample size « N »
- $\checkmark$  a risk of error of the first kind: « α = 0.05 », therefore the confidence coefficient «  $\gamma$  = 1 α » and therefore a particular value of the test statistic: «  $T_0$  » under  $H_0$ .

from the observation
« T<sub>obs</sub> » obtained
on the sample
the user has his result

Ok, but where is the problem?



#### therefore, it is classically the user who chooses a priori:

- ✓ the hypotheses to be tested:  $H_0$ : «  $μ_1 ≤ μ_0$  » versus  $H_1$ : «  $μ_1 > μ_0$  »
- ✓ the test and therefore the test statistic "T" under H₀
- √ a sample size « N »
- $\checkmark$  a risk of error of the first kind: « α = 0.05 », therefore the confidence coefficient «  $\gamma$  = 1 α » and therefore a particular value of the test statistic: «  $T_0$  » under  $H_0$ .

from the observation
« T<sub>obs</sub> » obtained
on the sample
the user has his result

# Ok, but where is the problem?

The problem is that you have to define the "sensitivity" of a test, that is, its ability to identify a difference when it exists.

Note: We have the same problem when we take a measurement with a device. We try to know its sensitivity before using it.



5 – on the other hand, we have "no" a priori information on "reality" under  $H_1$ , while we also have a possible error (called «  $\beta$  »), either that of « deciding  $H_0$  » while the « reality is  $H_1$  ».



	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
« decision » H <sub>0</sub>	« Υ = 0.95 »	«β»?
« decision » H <sub>1</sub>	$\ll \alpha = 0.05 $ »	«1-β»?

β is the probability of concluding that there is no difference when there is one ["notion of false negative"]

 $\beta$  = second kind error "not known *a priori*" because in general we do not know the distribution of T under H<sub>1</sub> and because we do not know the value of «  $\mu_1$  »

1 - β = power of the test = « ability of the test to detect a difference when it exists »

The « power of the test » is ultimately the "sensitivity" of the statistical test to be able to "detect" a difference.

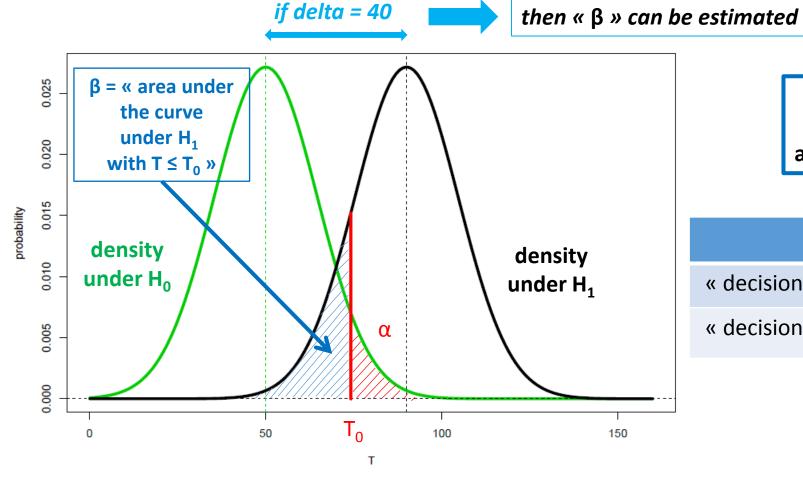
It is important that the power of the test is as great as possible



# example of density distribution of statistical « T » under H<sub>0</sub> and under H<sub>1</sub>

with: delta =  $\mu_1 - \mu_0$ 

with N = 6 and  $\sigma_{\rm Y}$  = 36



If "delta" is fixed, then we can estimate "β" and also plot the distribution under H<sub>1</sub>.

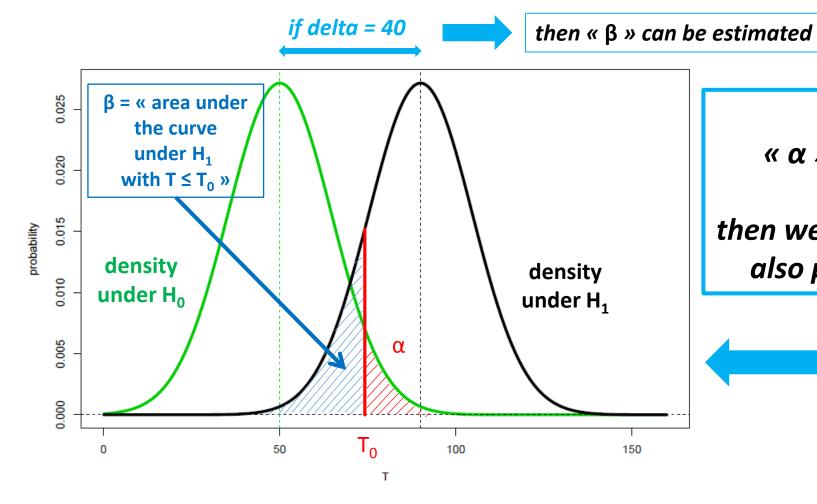
	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
« decision » H <sub>0</sub>	« Y = 0.95 »	« β ≈ <b>0.14</b> »
« decision » H <sub>1</sub>	$\ll \alpha = 0.05 $ »	$\ll 1 - \beta \approx 0.86 $ »



# example of density distribution of statistical « T » under H<sub>0</sub> and under H<sub>1</sub>

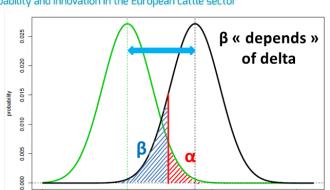
with: delta =  $\mu_1 - \mu_0$ 

with N = 6 and  $\sigma_{\rm Y}$  = 36



if the parameters: «  $\alpha$  », « delta », « N » and «  $\sigma_{\gamma}$  » are fixed a priori, then we can estimate «  $\beta$  », « 1- $\beta$  » and also plot the distribution under H1.





#### if delta = 40

with N = 6

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	«β≈ 0.14»
H <sub>1</sub>	« α = 0.05 »	$\ll 1 - \beta \approx 0.86$ »



*with N = 6* 

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	« β ≈ 0.04 »
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.96$ »

*if delta = 60* 

*with N = 6* 

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	«β≈0.01»
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.99 $ »

with delta =  $\mu_1$  -  $\mu_0$  and  $\sigma_Y$  = 36

For a fixed sample size "N", as "delta" increases,

the second kind error " $\beta$ " decreases and the power of the test"1- $\beta$ " increases



If we want a power of the test at least 0.99, with a sample size "N = 6", we can only identify that a difference in means "delta" greater than 60.

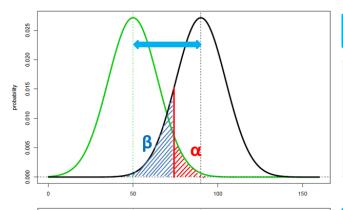
But we want to be able to identify a difference in averages of the order of 40.

How do we do this?



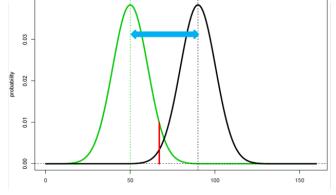
so if we want to keep a good ability to detect a « given difference », and so if we want to have a « minimum sensitivity a priori », we have two main complementary solutions:

#### with a « minimum delta » of 40



## *with N = 6*

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>0</sub>	« Υ = 0.95 »	« β ≈ 0.141 »
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.859 $ »



## with N = 12

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	« β ≈ 0.014 »
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.986$ »

1st solution :
we « increase »
the size « N » of the sample

$$Var(\overline{Y}) = \frac{1}{N} \cdot Var(Y) = \frac{1}{N} \cdot \sigma_Y^2$$

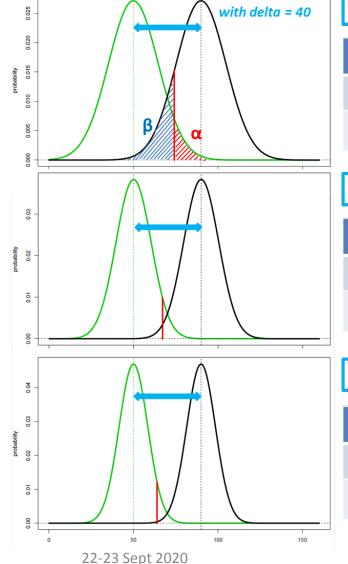
For a fixed "minimum delta" as sample size "N" increases, the second kind error "β" decreases and the power of the test"1-β" increases



If we want a power of the test at least 0.986, and

identify a difference in means "delta = 40", We just need to take a sample size "N = 12".





## *with N = 6*

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	« β ≈ 0.141 »
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.859 $ »

#### *with N = 12*

	« reality » H <sub>0</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	« β ≈ 0.014»
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.986 $ »

#### with N = 18

	« reality » H <sub>o</sub>	« reality » H <sub>1</sub>
H <sub>o</sub>	« Y = 0.95 »	«β≈0.001»
$H_1$	« α = 0.05 »	$\ll 1 - \beta \approx 0.999$ »

For a fixed "minimum delta" as sample size "N" increases, the second kind error " $\beta$ " decreases and the power of the test"1- $\beta$ " increases

$$Var(\overline{Y}) = \frac{1}{N} \cdot Var(Y) = \frac{1}{N} \cdot \sigma_Y^2$$



In fact, the decrease in "β" and the increase in the power of the test "1-β" are very rapid [ in (1/N) ], as the sample size "N" increases.



formula for N<sub>min</sub>

 $\mathbf{u}_{\mathbf{p}}$  is the quantile of probability " $\mathbf{p}$ " for the Gaussian distribution N(0,1).

for 
$$\alpha$$
 = 0.05 we have  $u_{1-\alpha}$  = 1.644854 and for  $\beta$  = 0.01 or (1- $\beta$ ) = 0.99 we have  $u_{\beta}$  = -2.326348

The minimum « N » size allowing the desired « precision », ie «  $(1-\beta) \ge 0.99$  » is such that :

$$N \geq \left[ \frac{\sigma_{Y} \cdot (u_{1-\alpha} - u_{\beta})}{delta} \right]^{2}$$

with « delta =  $\mu_1$  -  $\mu_0$  » for the minimum detectable deviation sought and «  $\sigma_v$  » for the standard deviation of the Gaussian law of the studied and measured variable Y.

For the previous example we had  $\ll$  delta = 40  $\gg$  and  $\ll$   $\sigma_{\rm Y}$  = 36  $\gg$  which gives  $\ll$  N  $\geq$  12.77406  $\gg$  or  $\ll$  N<sub>min</sub> = 13  $\gg$  for a power  $\ll$  (1- $\beta$ )  $\geq$  0.99  $\gg$ .



formula for N<sub>min</sub>

 $\mathbf{u}_{\mathbf{p}}$  is the quantile of probability " $\mathbf{p}$ " for the Gaussian distribution N(0,1).

for 
$$\alpha = 0.05$$
 we have  $u_{1-\alpha} = 1.644854$ 

and for 
$$\beta = 0.01$$
 or  $(1-\beta) = 0.99$  we have  $u_{\beta} = -2.326348$ 

The minimum « N » size allowing the desired « precision », ie «  $(1-\beta) \ge 0.99$  » is such that :

$$N \geq \left[\frac{\sigma_{Y} \cdot (u_{1-\alpha} - u_{\beta})}{delta}\right]^{2}$$
 (and the parameters :  $\alpha$  and  $\alpha$  and  $\alpha$  are well linked.

with « delta =  $\mu_1$  -  $\mu_0$  » for the minimum detectable deviation sought and «  $\sigma_v$  » for the standard deviation of the Gaussian law of the studied and measured variable Y.



formula for N<sub>min</sub>

 $\mathbf{u}_{\mathbf{p}}$  is the quantile of probability " $\mathbf{p}$ " for the Gaussian distribution N(0,1).

for  $\alpha = 0.05$  we have  $u_{1-\alpha} = 1.644854$ 

and for  $\beta = 0.01$  or  $(1-\beta) = 0.99$  we have  $u_{\beta} = -2.326348$ 

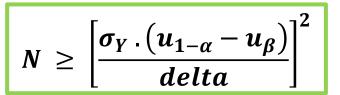
The minimum « N » size allowing the desired « precision », ie «  $(1-\beta) \ge 0.99$  » is such that :

$$N \geq \left[ rac{\sigma_{Y} \cdot (u_{1-lpha} - u_{eta})}{delta} 
ight]^{2}$$

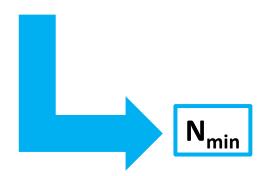
with « delta =  $\mu_1$  -  $\mu_0$  » for the minimum detectable deviation sought and «  $\sigma_v$  » for the standard deviation of the Gaussian law of the studied and measured variable Y.

Note: as long as « delta >  $\sigma_{\rm Y}$  » the minimum number will remain « reasonable ». On the other hand in the opposite case, the minimum workforce may quickly « explode » because we will be in the case where we are looking for a « sensitivity » lower than the « measurement accuracy ».

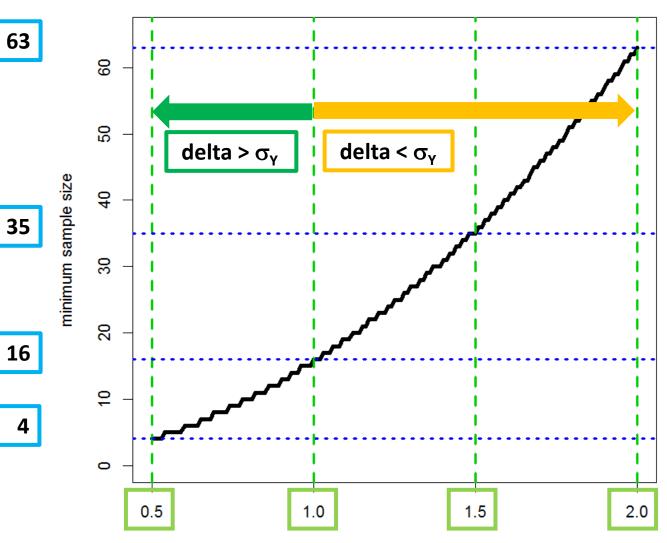




for  $\alpha = 0.05$  and for  $\beta = 0.01$  or  $(1-\beta) = 0.99$ 



«  $N_{min}$  » depends on the ratio «  $\sigma_{Y}$  / delta »



 $rac{\sigma_{_Y}}{delta}$ 

ratio: standard deviation on delta



$$N \geq \left[ \frac{\sigma_{Y} \cdot (u_{1-\alpha} - u_{\beta})}{delta} \right]^{2}$$

for  $\alpha = 0.05$  and for  $\beta = 0.01$  or  $(1-\beta) = 0.99$ 

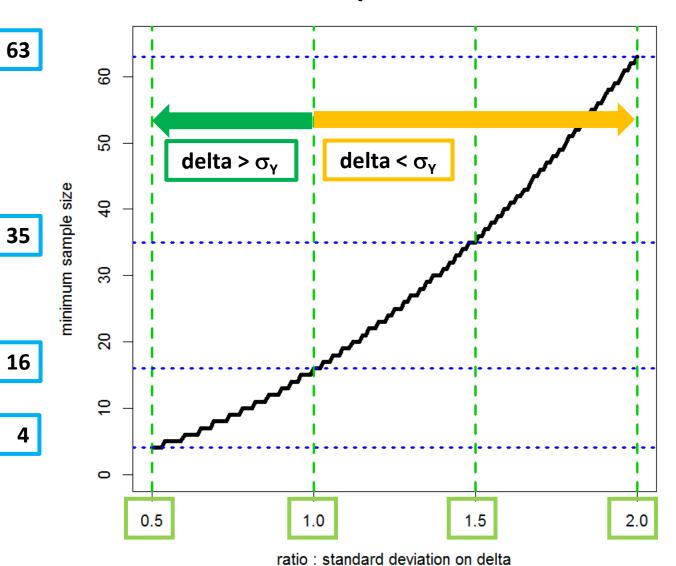


 $N_{\min}$ 

for a given sample size N a priori we can "correctly" identify a difference of at least

$$delta \geq \frac{\sigma_{Y}.\left(u_{1-\alpha}-u_{\beta}\right)}{\sqrt{N}}$$

for example, with N = 6 we have delta  $\geq 1.6 \sigma_Y$  or  $(\sigma_Y / \text{delta}) \leq 0.62$ 



 $\sigma_{_{Y}}$ 

delta



#### so with the 1st solution:

when we "increase" the size "N" of the sample the variance of the estimator "decreases" — the risk of error β "decreases" and the power of the test "increases".

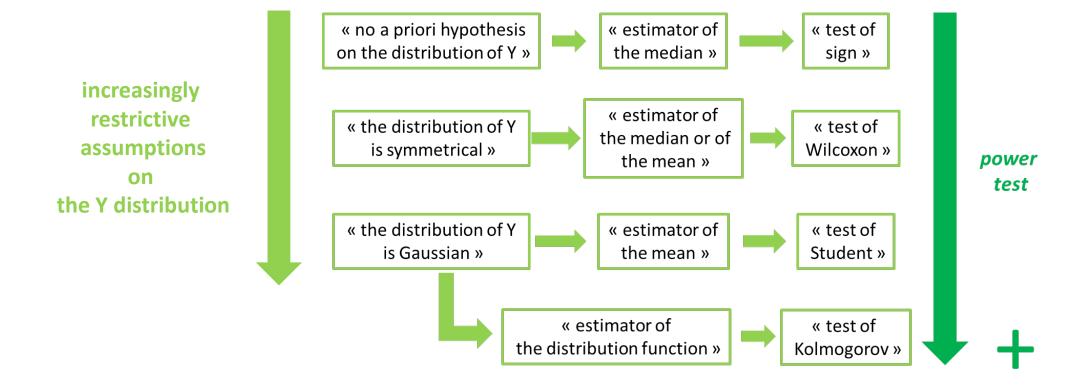
$$Var(\overline{Y}) = \frac{1}{N} \cdot Var(Y) = \frac{1}{N} \cdot \sigma_Y^2$$

therefore by choosing "N" according to the "minimum difference" (or "delta")
that we want to be able to highlight *a priori*,
we "select" *a priori* the "power of the test" that we want,
and therefore the "expected sensitivity" of the test is thus determined.



2nd complementary solution: choose the most suitable test to the assumptions that can be made a priori on the distribution of the measured variable "Y".

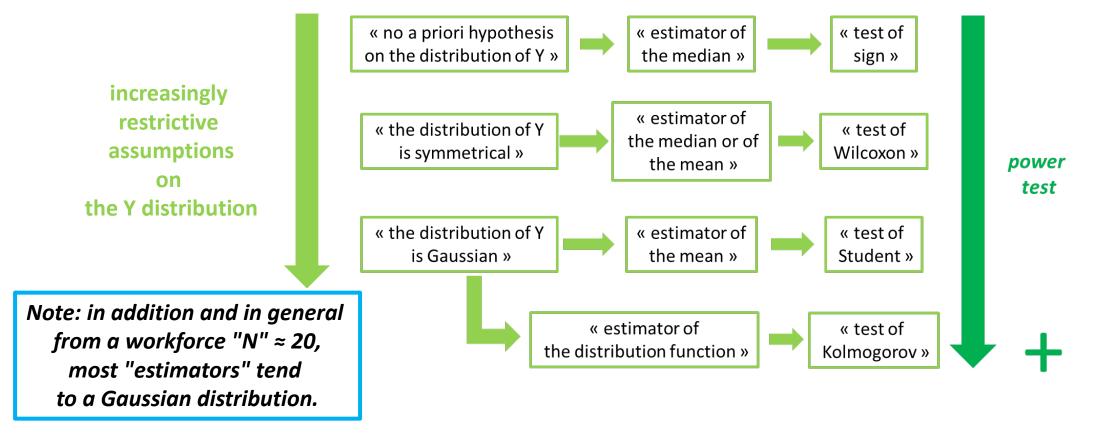
for the same value of "delta" a priori, and the same sample size "N" a priori





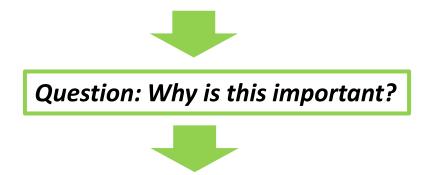
2nd complementary solution: choose the most suitable test to the assumptions that can be made a priori on the distribution of the measured variable "Y".

for the same value of "delta" a priori, and the same sample size "N" a priori









Answer: choose the size of the sample N a priori allows to "calibrate" a priori the "desired sensitivity" of the statistical test to be used taking into account a priori knowledge such as a minimum standard deviation  $\sigma_{\gamma}$ 

the smaller  $\sigma_{\rm Y}$  the smaller the sample size N required

"a statistician is not a magician"

Thank you for your attention.