# Biostatistics for the biomedical profession Lecture 7

BIMM34 Karin Källen & Linda Hartman September 2016

## Today

- Repetition
- Lecture 6:
  - Power calculations
  - Probability, proportions, CI for proportions
  - 2x2 Table. Chi2-test, Fisher exact test
  - Lecture 7:
- Sensitivity, Specificity
- Positive predictive value, Negative predictive value
- ROC-curves

#### **Exercise:**

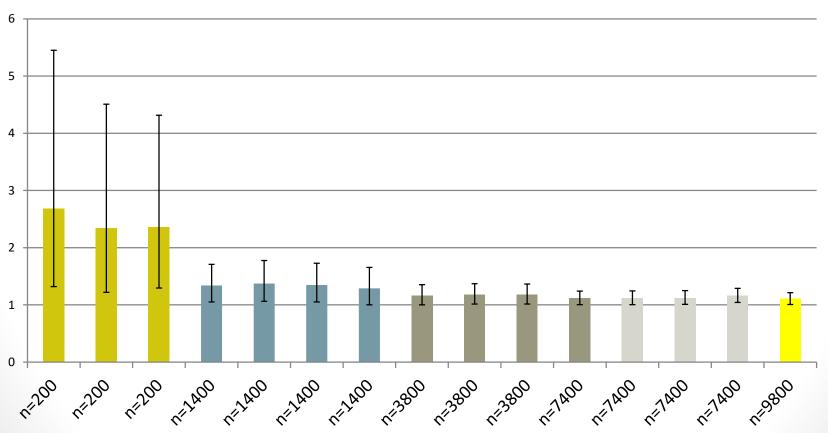
Combine the statistical terms with the correct common phenomenons (in common language)

- Type I error
- Type II error
- Confounding

- Non-causal association
- Mass-significance
- Lack of power

## So.... Which studies are most likely to be published, and to reach the headlines in the mass-media?

#### Significant ORs in 100 trials (case/controls 1:1) by sample size



Thus, for the sake of good science:

Be sure to perform adequate power analyses when designing a study

#### Repetition:

## Hypothesis testing.

- H<sub>0</sub> The hypothesis of no difference
- H<sub>1</sub> The hypothesis of a true difference

Example: Comparing the means of two samples;  $\mu_A$  = mean of sample A  $\mu_B$  = mean of sample B

- Two-tailed test:
- $H_0$ :  $\mu_A = \mu_B$   $H_1$ :  $\mu_A \neq \mu_B$

The most appropriate approach with few exceptions

- One-tailed test (specifies the direction of the difference in advance)
- $H_0$ :  $\mu_A = < \mu_B H_1$ :  $\mu_A > \mu_B$
- or
- $H_0: \mu_A >= \mu_B H_1: \mu_A < \mu_B$

## The t-test

Uses the fact that the difference between two means that both comes from normally distributed data, will follow a normal distribution with expected mean=0, and expected standard deviation SE.

SE=sV(1/n<sub>0</sub>+1/n<sub>1</sub>); s= 
$$\sqrt{\left[ \frac{(n_1-1)s_1^2+(n_0-1)*s_0^2}{(n_1+n_0-2)} \right]}$$

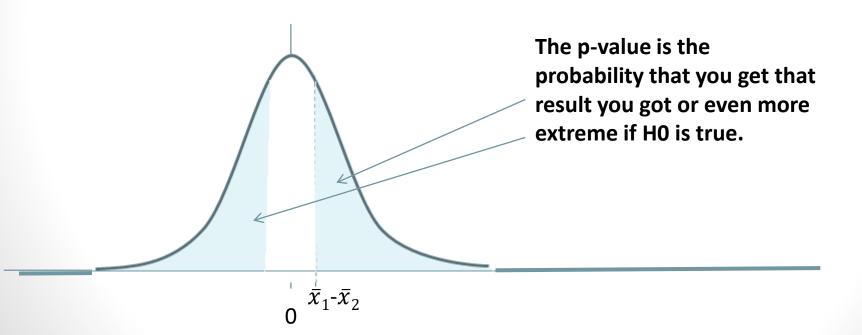
## Elements of statistical inference, hypothesis testing, two-sided

H<sub>0</sub>:  $\mu_1 = \mu_2$ , i.e.  $\mu_1 - \mu_2 = 0$ H<sub>1</sub>:  $\mu_1 \neq \mu_2$ , i.e.  $\mu_1 - \mu_2 \neq 0$ 

\_\_\_\_\_ Expected distribution of  $ar{x}_1$ - $ar{x}_2$ 

 $\_\, \_\, \_\,$  Sample mean,  $ar{x}_1$ - $ar{x}_2$ 

- Large p-value -> Data probable if H0 is true
- Thus: H<sub>0</sub> is not rejected (= considered to be true until further evidence)

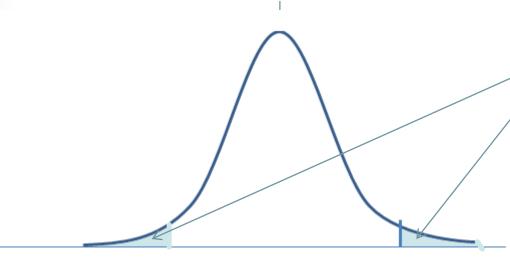


## Elements of statistical inference, hypothesis testing, two-sided

H<sub>0</sub>: 
$$\mu_1 = \mu_2$$
, i.e.  $\mu_1 - \mu_2 = 0$   
H<sub>1</sub>:  $\mu_1 \neq \mu_2$ , i.e.  $\mu_1 - \mu_2 \neq 0$ 

\_\_\_\_\_ Expected distribution of  $\bar{x}_1$ - $\bar{x}_2$  \_ \_ \_ Sample mean,  $\bar{x}_1$ - $\bar{x}_2$ 

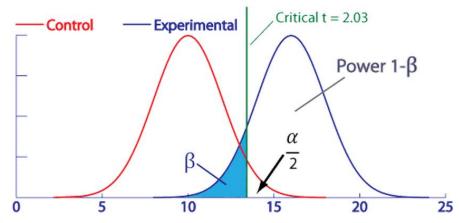
- Data unlikely if H0 is true.
- Thus: H<sub>0</sub> is rejected (=considered to be false)



The p-value is the probability that you get that result you got or even more extreme if H0 is true.

## Statistical hypothesis testing

## Statistical power = The probability a priori that $H_0$ will be rejected, given that $H_1$ in fact is true



H<sub>0</sub>: Null hypothesis = no difference H<sub>1</sub> = Alternative hypothesis = difference

	H <sub>0</sub> True	H <sub>1</sub> True
H <sub>o</sub> not rejected	ОК	Falsely negative (Type 2-error)
H <sub>0</sub> rejected	Falsely positive (Type 1–error)	OK Statistical power

## 2016-09-29

#### **Example:**

#### The power of a study investigating the effect of a treatment, where there is a 'true' effect

Suppose that we have two groups, A and B, both with  $\sigma=1$ , where  $\mu_A=0$  and  $\mu_B=1$ 

'True' distribution of non-treated group (A)
'True' distribution of treated group (B)

#### Formulate the Hypothesis:

$$H_0$$
:  $\mu_A = \mu_B$ , i.e.  $D_0 = \mu_B - \mu_A = 0$ 

 $H_1$ :  $\mu_A \neq \mu_B$ , i.e.  $D_1 = \mu_B - \mu_A \neq 0$ 

#### According to the null hypothesis:

Suppose we take a sample a and b from groups A and B,  $a \in N(0,1)$  and  $b \in N(0,1)$  the expected difference  $D_0 \in N(0,SE^2)$ ;  $SE=1*\sqrt{1/na+1/nb}$ 

#### The truth is that:

2

b 
$$\in N(1,1)$$
  
Then, the 'true' difference  
 $D_{True} \in N(1,SE^2)$ ;  
 $SE=(1*\sqrt{1/na+1/nb})$ 

3

#### Example: The power of a study investigating the effect of a treatment, where there is a 'true' effect

Suppose that we have two groups, A and B, both with  $\sigma=1$ , where  $\mu_A$  =0 and  $\mu_B$  =1

#### Formulate the Hypothesis:

 $H_0$ :  $\mu_A = \mu_B$ , i.e.  $D_0 = \mu_B - \mu_A = 0$ 

 $H_1$ :  $\mu_A \neq \mu_B$ , i.e.  $D_1 = \mu_B - \mu_A \neq 0$ 

#### According to the null hypothesis:

Suppose we take a sample a and b from groups A and B,  $a \in N(0,1)$  and  $b \in N(0,1)$ 

the expected difference  $D_0 \in N(0, SE^2)$ ;  $SE=1*\sqrt{1/na+1/nb}$ 

#### The truth is that:

 $b \in N(1,1)$ 

Then, the 'true' difference D<sub>true</sub>

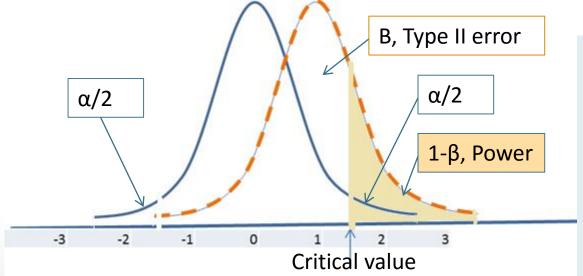
 $\rightarrow$  D<sub>True</sub>  $\in N(1,SE^2)$ ; SE=1\* $\sqrt{1/na+1/nb}$ 

- Now, assume that we pick a sample of 5 individuals from each group, then
- The DF= n<sub>a</sub>-1+n<sub>b</sub>-1=8. The standardized 'critical value' for t(8)=2.31

$$D_0 \in N(0, \sqrt{1/5 + 1/5})^2$$
)=>  $D_0 \in N(0, 0.63^2)$ 

$$D_{True} \in N(1,0.63^2)$$

Standardized critical value=2.31 SE => Critical value on the original scale on x-axis=2.31\*.63=1.46



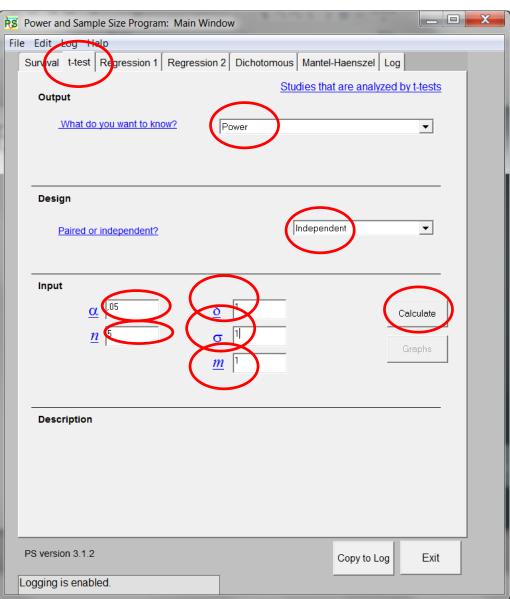
#### Exercise:

Look at the figure, How large is (approx) the chance that our sample mean is above the critical value?

Perhaps 25%?

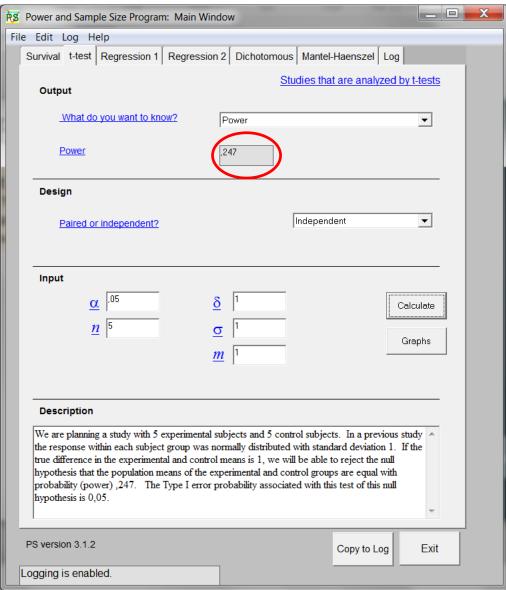
## Example continued...

Let us check the power of the previous example using PS Power



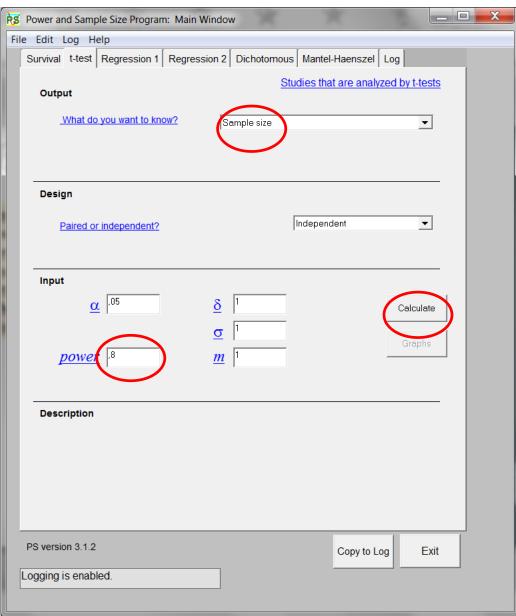
Example continued...

Let us check the power of the previous example using PS Power



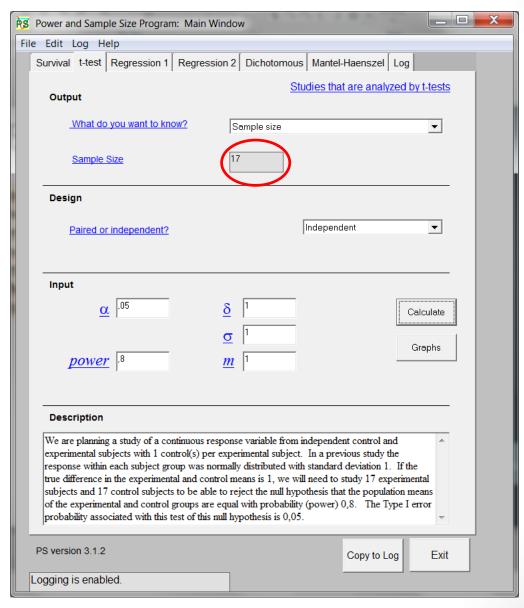
## Example, continued

Now, let us use PS
Power to calculate the sample size needed to have 80% power to detect that the 'true' effect of the treatment exists.



## Example, continued

Now, let us use PS
Power to calculate the sample size needed to have 80% power to detect that the 'true' effect of the treatment exists.



#### Example: The power of a study investigating the effect of a treatment, where there is a 'true' effect

Suppose that we have two groups, A and B, both with  $\sigma=1$ , where  $\mu_A=0$  and  $\mu_B=1$ 

#### Formulate the Hypothesis:

 $H_0$ :  $\mu_{\Delta} = \mu_{B}$ , i.e.  $D_0 = \mu_{B} - \mu_{\Delta} = 0$ 

 $H_1$ :  $\mu_{\Delta} \neq \mu_{R}$ , i.e.  $D_1 = \mu_{R} - \mu_{\Delta} \neq 0$ 

#### According to the null hypothesis:

Suppose we take a sample a and b from groups A and B,  $a \in N(0,1)$  and  $b \in N(0,1)$ 

the expected difference  $D_0 \in N(0, SE^2)$ ;  $SE=1*\sqrt{1/na+1/nb}$ 

#### The truth is that:

 $b \in N(1,1)$ 

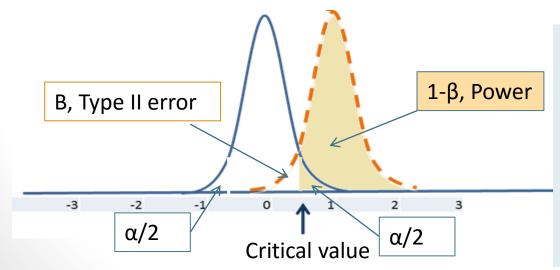
Then, the 'true' difference D<sub>true</sub>

→  $D_{True} \in N(1, SE^2)$ ;  $SE=1*\sqrt{1/na+1/nb}$ 

- Now, assume that we pick a sample of 17 individuals from each group, then
- The DF=  $n_a$ -1+ $n_b$ -1=32. The standardized 'critical value' for t(32)=2.04

$$D_0 \in N\left(0, (\sqrt{1/17 + 1/17})^2\right) \Rightarrow D_0 \in N(0, 0.34^2)$$
  $D_{\text{True}} \in N(1, 0.34^2)$ 

Standardized critical value=2.04 SE => Critical value on the original scale on x-axis=2.04\*.34=0,70

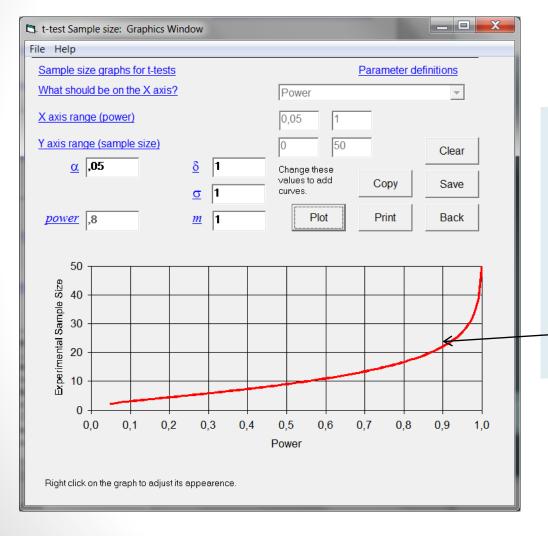


#### Exercise:

Look at the figure, Does the PS power calculation of sample size seem correct (would you say that 80% of the area of the D<sub>true</sub> –distribution is above the critical value)?

Yes!!!

Using the 'graph'-button in PS power, we can also create a graph showing i.e. the power by sample size, given a certain difference between means.



#### Exercise:

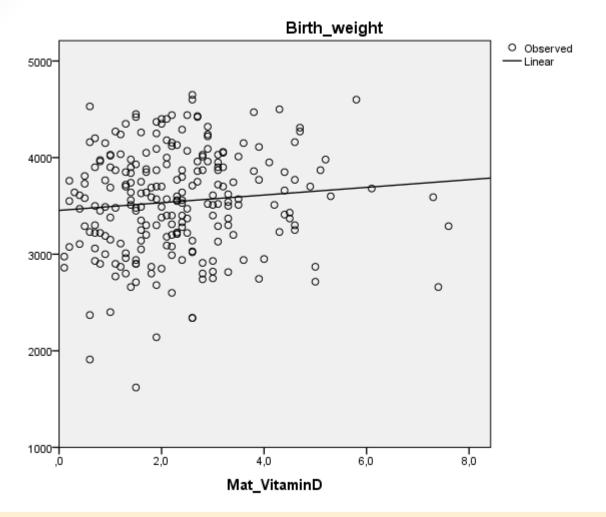
Approximately, how large should the Samples be in order to have 90% chance to detect a true Difference of 1.?

Approx 22

Now, let's use PS Power to estimate the needed sample size in order to detect an assumed 'true' linear association

Let's assume that we will design a study in order to investigate a possible linear relationship between maternal vitamin D levels during pregnancy and child's birth weight.

Assume that we have access to the data from a pilot study..... (the Birth data set).

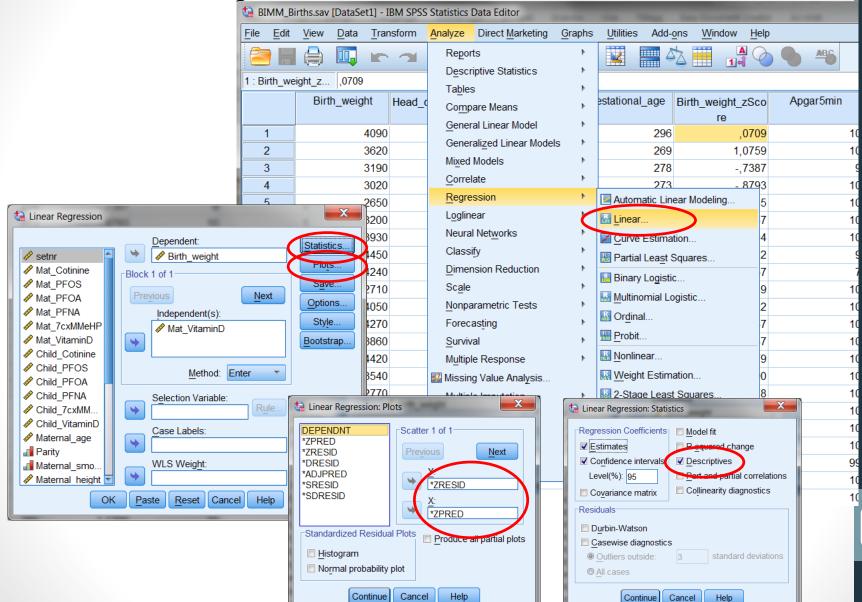


... a linear association between maternal vitamin D levels and child's Birth weight seems possible, but not convincing....

Let's proceed anyway

In order to perform power-analyses for studies using linear regression, we will have to

Estimate the SD or the regression residuals.



## SPSS-output

#### Descriptive Statistics

	Mean	Std. Deviation	N
Birth_weight	3545,32	539,144	237
Mat_VitaminD	2,310	1,3469	237

#### Coefficients<sup>a</sup>

		Unstandardize	d Coefficients	Standardized Coefficients			95,0% Confiden	ce Interval for B
Model		В	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	3453,517	69,436		49,737	,000	3316,721	3590,312
	Mat_VitaminD	39,745	25,984	,099	1,530	,127	-11,445	90,936

a. Dependent Variable: Birth\_weight

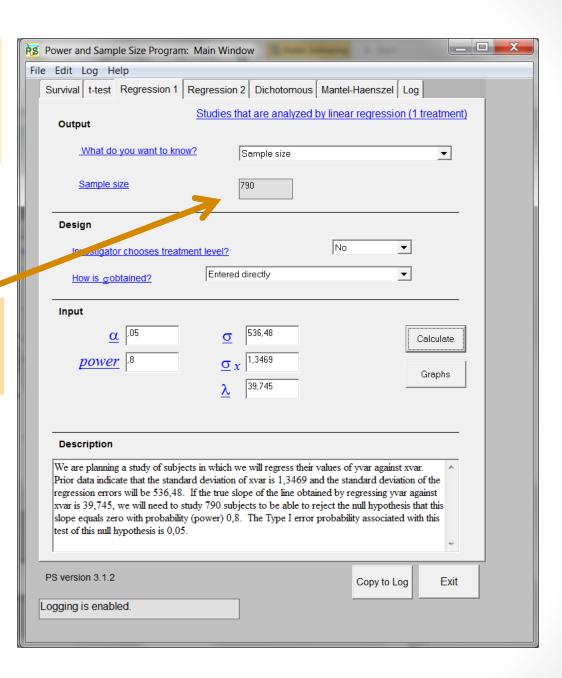
#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	7	I
Predicted Value	3457,49	3755,58	3545,32	53,531		237
Residual	-1893,135	1093,146	,000	536,480		237
Std. Predicted Value	-1,641	3,928	,000	1,000		237
Std. Residual	-3,521	2,033	,000	,998		237

a. Dependent Variable: Birth\_weight

Now, we just fill out the required values in PS Power, using the 'Regression 1' -Tab

The required sample size in order to have 80% power is N=790



## The statistical power depends on:

- The study design
- Sample size
- The size of the difference between groups
- The size of the variance within the groups
- The chosen level of significance α
- Sources of errors
- The number and importance of confounders
- ...

## Today

- Repetition
- Lecture 6:
  - Power calculations
  - Probability, proportions, CI for proportions
  - 2x2 Table. Chi2-test, Fisher exact test
  - Lecture 7:
- Sensitivity, Specificity
- Positive predictive value, Negative predictive value
- ROC-curves

## Lecture 6 repetition.... Binary data

- Binary data:
- Probability, binomial distribution (don't worry just recognize)
  - Proportions, confidence interval for proportions, rates
  - 2 x 2 tables, Chi-squared test, Fisher Exact test

## Binary data

- When investigating binary data (e.g. alive/dead, sick/healthy), we could not assume that the outcomes follow a normal distribution. All subjects have either the value =1 or =0.
- Another set of statistical methods is required to analyze these data. Let's start with a quick look at the binomial distribution.

## Combinations and permutations

- Discuss: How to calculate the number of different pokerhands that could be dealt?
- For the first card, there is 52 possibilities, for the second 51, etc...
- Thus five cards: 52\*51\*50\*49\*48 / the number of different orders
- The number of different orders: the first card could have 5 places, the second 4...etc
- Answer: 52\*51\*50\*49\*48 / (5\*4\*3\*2) different pokerhands

#### **General equation:**

Let n=the total number of objects in the set Let r=the number of objects that will be drawn Len n! (n faculty) = n\*(n-1)\*(n-2)\*.....\*(n-r+1)Let  $p_r^n$  = number of permutations of n objects taken r at a time

#### Then

the number of combinations  $(c_r^n)$  (ignoring the order of the r objects) are:  $C_r^n = n! / (r! * (n-1)!)$ 

Do this excercise at home....

## Combinations and permutations

• Discuss: How to estimate the chance of having at least one girl, if you're planning for four children? (suppose that the chance of having a girl is 0.5 at each delivery)

Answer: 1 - p(having no girl)

Where

P(having no girl) =  $0.5 * 0.5 * 0.5 * 0.5 = 0.5^4 = 0.0625$ 

Thus

P(having at least one girl)= 1 - 0.0625 = 0.9375

- Discuss: If you have three boys: How big is the chance that your fourth child will be a girl?
- Answer: Random events do not remember..... p=0.5

## The binomial distribution

- The binomial distribution show the probabilities of different outcomes for a series of random events, each of which can have only one of two values.
- Let
- p=the probability on each try of the outcome of interest.
- q=(1-p)
- P=the probability for the outcome exact r times
- Then
- P= <u>n!</u> \* p<sup>r</sup> q<sup>n-r</sup> r!(n-r)!

And

$$P(X \le x) = \sum_{r=0}^{x} C_r^n p^r (1-p)^{n-r}$$

#### Tables of the Binomial Cumulative Distribution

The table below gives the probability of obtaining at most x successes in n independent trials, each of which has a probability p of success. That is, if X denotes the number of successes, the table shows

	X
P(X < r)	$= \sum_{r=0}^{\infty} C_r^n p^r (1-p)^{n-r}$
$I(X \subseteq X)$	$-\sum_{r}C_{r}P$ (1 $P$ )
A.	r=0

_																				
	p =		0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
Γ	n= 2	$\chi = 0$	0.9801	0.9604	0.9409	0.9216	0.9025	0.8836	0.8649	0.8464	0.8281	0.8100	0.7225	0.6400	0.5625	0.4900	0.4225	0.3600	0.3025	0.2500
- 1		1	0.9999	0.9996	0.9991	0.9984	0.9975	0.9964	0.9951	0.9936	0.9919	0.9900	0.9775	0.9600	0.9375	0.9100	0.8775	0.8400	0.7975	0.7500
- 1		2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Y	n= 3	$\chi = 0$	0.9703	0.9412	0.9127	0.8847	0.8574	0.8306	0.8044	0.7787	0.7536	0.7290	0.6141	0.5120	0.4219	0.3430	0.2746	0.2160	0.1664	0.1250
1		1	0.9997	0.9988	0.9974	0.9953	0.9920	0.9896	0.9860	0.9818	0.9772	0.9720	0.9393	0.8960	0.8438	0.7840	0.7183	0.6480	0.5748	0.5000
- 1		2	1.0000	1.0000	1.0000	0.9999	0.9999	0.9998	0.9997	0.9995	0.9993	0.9990	0.9966	0.9920	0.9844	0.9730	0.9571	0.9360	0.9089	0.8750
4		3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	n= 4	x=0	0.9606	0.9224	0.8853	0.8493	0.8145	0.7807	0.7481	0.7164	0.6857	0.6561	0.5220	0.4096	0.3164	0.2401	0.1785	0.1296	0.0915	0.0625
Y		1	0.9994	0.9977	0.9948	0.9909	0.9860	0.9801	0.9733	0.9656	0.9570	0.9477	0.8905	0.8192	0.7383	0.6517	0.5630	0.4752	0.3910	0.3125
- 1		2	1.0000	1.0000	0.9999	0.9998	0.9995	0.9992	0.9987	0.9981	0.9973	0.9963	0.9880	0.9728	0.9492	0.9163	0.8735	0.8208	0.7585	0.6875
- 1		3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9999	0.9995	0.9984	0.9961	0.9919	0.9850	0.9744	0.9590	0.9375
- 1		4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
- [	n= 5	$\chi = 0$	0.9510	0.9039	0.8587	0.8154	0.7738	0.7339	0.6957	0.6591	0.6240	0.5905	0.4437	0.3277	0.2373	0.1681	0.1160	0.0778	0.0503	0.0313
- 1		1	0.9990	0.9962	0.9915	0.9852	0.9774	0.9681	0.9575	0.9456	0.9326	0.9185	0.8352	0.7373	0.6328	0.5282	0.4284	0.3370	0.2562	0.1875
		2	1 0000	0,000	0.0007	0.0004	00000	00000	0.0060	0.0055	0.0027	0.0044	0.0724	0.0424	0.006	0.000	0.7640	0.6006	0.5024	O EOOO

#### Discuss:

How big is the chance to have less than 2 accidents with the bike during 4 rides,
 if there is a 10% accident risk at each ride?

Answer: 0.95

• How big is the chance of having no accidents on three rides, if there is a 5% risk for accident at each ride? Answer: 0.86

## Luckily, if the sample size is large, we could use normal approximation to obtain confidence intervals for proportions

#### Let

- n=total number of observations
- p=probability for event
- q=1-p

If n\*p\*q > 10 (golden rule of thumb), we can use normal approximation to estimate the spread of the mean of number of events.

- Normal approximation for binomial distribution:
  - Mean = n\*p
  - Variance of mean = n\*p\*q
  - SD of mean= $\sqrt{variance} = \sqrt{n*p*q}$

#### Confidence interval for a sample proportion using normal approximation:

#### Assume that:

- x=number of events; p=x/n
- Then, the variance for p=x/n will be:  $1/n^2*Var(x)=(1/n^2)*n*p*q=\frac{p*q}{n}$
- And the SE of p:  $\sqrt{\frac{p*q}{n}}$

#### Thus, using normal approximation,

a 95%CI for a proportion x/n could be estimated: p= x/n ± 1.96 \*  $\sqrt{\frac{p*q}{n}}$ 

## Confidence interval for a sample proportion (normal approximation)

Let x= observed number of events; Let n=total number of observations Then p = x/n and q=1-p

Using normal approximation,

a 95%CI for a proportion x/n could be estimated: p= x/n ± 1.96 \*  $\sqrt{\frac{p*q}{n}}$ 

#### **Excercise:**

Compute a 95%CI for the proportion of obese men in a certain population if x=obese men=100, and total n=400.

```
p=x/n=100/400 = 0.25= 25\%

q = (1-p) = 0.75

SE= \sqrt{(0.25*0.75/400)} \approx 0.022

95\%CI = p-1.96*SE \text{ to } p+1.96*SE = 0.25-1.96*.022 \text{ to } 0.25+1.96*0.022

p \text{ with } 95\%CI \approx 0.250 \text{ (0.207 - 0.293) or 25.0\% (20.7\% to 29.3\%)}
```

### The most basic 2 x 2 contingency table

	Exposed	Non- exposed
Cases	а	b
Non- cases	С	d

- Main methods to investigate whether there is a difference between cases and non-cases:
- Chi-squared test (tests if the number of exposed equally distributed over cases and non-cases), Fisher Exact test
- Calculate Risk Ratios (Comparing proportions)
- Calculate Odds Ratios (Comparing odds)

### The most basic 2 x 2 contingency table

	Exposed	Non- exposed	
Cases	a	р	m <sub>1</sub> =a+b
Non- cases	С	d	m <sub>2</sub> =c+d
	n <sub>1</sub> =a+c	n <sub>2</sub> =b+d	$N=n_1 + n_2 = m_1 + m_2$

- The Chi-squared test (tests if the number of exposed equally distributed over cases and non-cases)
- H<sub>0</sub>: The proportion of exposures is the same among cases and controls
- H<sub>1</sub>: The proportion of exposures is not the same among cases and controls (there is an association between exposure and the outcome.
- The Chisquared statistic:  $\chi^2 = \sum \frac{[O_i E_i]^2}{\underline{E}_i}$ 
  - To be compared with the  $\chi^2$  (df) distribution, where
  - O<sub>i</sub>=observed frequencies (a,b,c,d)
  - $E_i$ =expected frequencies  $(m_1*n_1/N; m_1*n_2/N; m_2*n_1/N; m_2*n_2/N)$
  - Df=degrees of freedom=(r-1) \* (c-1), where r=n rows; c=n columns

## The most basic 2 x 2 contingency table

	Exposed	Non- exposed
Cases	10	10
Non- cases	10	70

$$m_2 = 80$$

 $m_1 = 20$ 

$$n_2 = 80$$

- Excercise:
- 1. Calculate expected frequencies

•	2.	Calculate	the	χ <sup>2</sup> statistic
---	----	-----------	-----	--------------------------

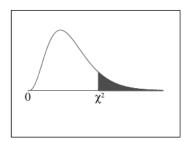
$$\chi^2 = \sum_{\underline{E_i}} \frac{[O_i - E_i]^2}{\underline{E_i}}$$

	Exposed	Non- exposed
Cases	20*(20/100) <b>4</b>	20*(80/100) <b>16</b>
Non- cases	80*(20/100) 16	80*(80/100) 64

$$\chi^2$$
= (10-4)<sup>2</sup>/4 + (10-16)<sup>2</sup>/16 + (10-16)<sup>2</sup>/16 + (70-64)<sup>2</sup>/64 = 36/4 + 16/16 + 16/16 + 36/64 = 11.56

3. Is there a significant association?

#### Chi-Square Distribution Table



The shaded area is equal to  $\alpha$  for  $\chi^2 = \chi^2_{\alpha}$ .

df	$\chi^2_{.995}$	$\chi^{2}_{.990}$	$\chi^{2}_{.975}$	$\chi^{2}_{.950}$	$\chi^{2}_{.900}$	$\chi^{2}_{.100}$	$\chi^{2}_{.050}$	$\chi^{2}_{.025}$	$\chi^{2}_{.010}$	$\chi^2_{.005}$
1	0.000	0.000	0.001	0.004	0.016	2.706	3.841	5.024	6.635	7.879
2	0.010	0.020	0.051	0.103	0.211	4.605	5.991	7.378	9.210	10.597
3	0.072	0.115	0.216	0.352	0.584	6.251	7.815	9.348	11.345	12.838
4	0.207	0.297	0.484	0.711	1.064	7.779	9.488	11.143	13.277	14.860
5	0.412	0.554	0.831	1.145	1.610	9.236	11.070	12.833	15.086	16.750
6	0.676	0.872	1.237	1.635	2.204	10.645	12.592	14.449	16.812	18.548
7	0.989	1.239	1.690	2.167	2.833	12.017	14.067	16.013	18.475	20.278
8	1.344	1.646	2.180	2.733	3.490	13.362	15.507	17.535	20.090	21.955
9	1.735	2.088	2.700	3.325	4.168	14.684	16.919	19.023	21.666	23.589
10	9.156	9 552	2 947	2.040	4 86E	15 087	18 207	20.482	93 900	95 188

#### Excercise (continued):

Compare the obtained Chi-sqared statistic with the Chi-sqared distribution

11.56>> 3.84: There was a strong statistically significant heterogenity

## The Yates' correction

When numbers are small (any expected cell frequency <5), the  $\chi^2$ statistic will be instable.

One easy solution is to use the Yates' correction:

$$\chi^2 = \sum \frac{[O_i - E_i] - .5]^2}{\underline{E}_i}$$

### The Fischer's Exact test

	Exposed	Non- exposed	
Cases	a	Ь	m <sub>1</sub> =a+b
Non- cases	С	d	m <sub>2</sub> =c+d
	n <sub>1</sub> =a+c	n <sub>2</sub> =b+d	$N=n_1 + n_2 = m_1 + m_2$

A more exact way of testing a 2x2 contingency table than the Chi-squared test, especially when the numbers are small

p= (a+b)! (c+d)! (a+c)! (b+d)!
 N! a! b! c! d!

# A 2x2 contingency table-output from SPSS

SGA * Smoking_yes_no Crosstabulation							
	Smoking	Smoking_yes_no					
			,00	1,00			
	,00	Count	174	60	234		
SGA	,,00	% within SGA1	74,4%	25,6%	100,0%		
JUA	1,00	Count	9	6	15		
	1,00	% within SGA1	60,0%	40,0%	100,0%		
Total		Count	183	66	249		
iotai		% within SGA1	73,5%	26,5%	100,0%		

SGA=Small for Gestational Age

# Output from the SPSS 2x2 continued table, continued

Chi-Square Tests								
	Value df Asymp. Sig. Exact Sig. (2-sided) sided)		Exact Sig. (2- sided)	Exact Sig. (1- sided)				
Pearson Chi-Square	1,492ª	1	,222					
Continuity Correction <sup>b</sup>	,846	1	,358					
Likelihood Ratio	1,377	1	,241					
Fisher's Exact Test				,234	,177			
Linear-by-Linear Association	1,486	1	,223					
N of Valid Cases	249							
a. 1 cells (25,0%) have expected count less than 5. The minimum expected count is 3,98.								

b. Computed only for a 2x2 table

Thus, no significant association could be detected between maternal smoking and SGA.

Does that mean that no association exists?

No! Perhaps did our study have to low power to have a chance to detect a true association

## The most basic 2 x 2 contingency table

	Exposed	Non- exposed
Cases	а	b
Non-cases	С	d

- The Chi-squared test, and the Fisher Exact test just investigate whether there is a heterogeneity between cases and non-cases, or not.
- No effect measurements are provided!

Two main measurements for comparing proportions between groups:

Risk Ratios (Comparing proportions)
Odds Ratios (Comparing odds)

# 2016-09-29

# The most basic 2 x 2 contingency table

	Exposed	Non- exposed
Cases	а	b
Non-cases	С	d

Risk Ratio: 
$$a/(a+c)$$
 Odds Ratio:  $a/c$  =  $a*d$   $b/(b+d)$   $b/d$   $c*b$ 

#### Exercise:

What is the expected value for

- a) Risk Ratio (RR)
- b) Odds Ratio (OR)

Under the  $H_0$  hypothesis (hypothesis of no effect)?

# Today

- Repetition
- Lecture 6:
  - Power calculations
  - Probability, proportions, CI for proportions
  - 2x2 Table. Chi2-test, Fisher exact test, Odds Ratio, Risk Ratio

#### Lecture 7:

- Sensitivity, Specificity
- Positive predictive value, Negative predictive value
- ROC-curves

- Sensitivity: The proportion of detected cases
- Specificity: The proportion of detected non-cases
- 1-specificity: The false positive rate
- Positive predictive value: The proportion of cases among detected
- Negative predictive value: The proportion of non-cases among non-detected.

## The most basic 2 x 2 contingency table

	Positive test	Negative test
Cases	а	b
Non- cases	С	d

- Excercise: What are the formulas for:
- Sensitivity (proportion of detected cases)
- Specificity (proportion non-detected non-cases)
- 1-specificity (proportion false positive)
- Positive predictive value (prob case given pos test)
- Negative predictive value (prob noncase given neg test)

- a/(a+b)
- d/(d+c)
- 1-d/(d+c)=c/(d+c)
- a/(a+c)
- d/(b+d)

2x2 contingency table showing neurodevelopmental disability at 2 and 6 years, respectively, among children born extremely premature (<27 weeks)

The question is: Can the results at 2 years of age predict the results at 6 years?

	Disability (colu	Total N	
Disability at 6years (rows)	Disability	No disability	
Disability	71	74	145
No disability	44	244	288
Total N	115	318	433

Exercise: Decide the

- Sensitivity
- Specificity
- False positive rate
- Positive predictive value
- Negative predictive value

- a/(a+b)
  - d/(d+c)

- Sensitivity=a/n1=71/145=49.0%
- Specificity=d/n2=244/288=84.7%
- 1-d/(d+c)=c/(d+c)
- False pos rate=c/n2=44/288=15.3%

- a/(a+c)PPV=a/m1=71/115=61.7%
- d/(b+d)

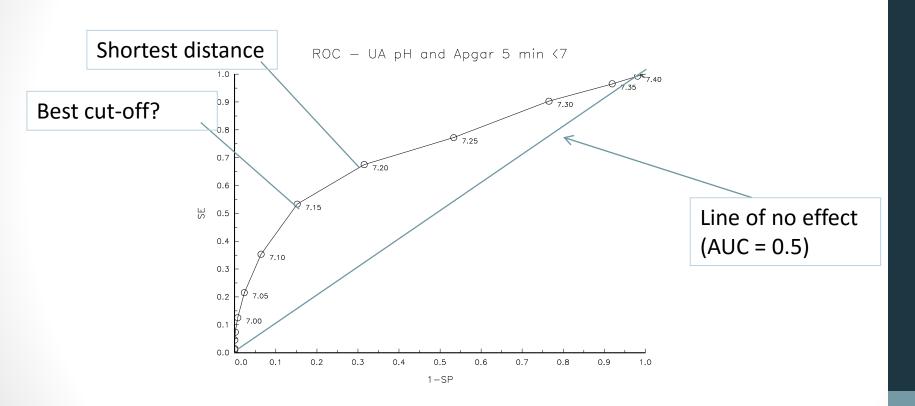
• NPV=d/m2=244/318=76.7%

Note: Using the formula for 95%CI for proportions, you could also easily compute CI for the estimates (for large samples).

# Receiver operating characteristic (ROC) curves

A ROC curve, is a graphical plot which illustrates the performance of a binary classifier system as its discrimination threshold is varied. It is created by plotting the fraction of true positives out of the total actual positives (TPR = true positive rate) vs. the fraction of false positives out of the total actual negatives (FPR = false positive rate), at various threshold settings

# Example. The corresponding ROC-curve. pH in umbilical cord's ability to predict low Apgar Score



### Example. Table for producing an ROC-curve. pH in umbilical cord's ability to predict low Apgar Score

The cut-off point where the distance between the curve and the 'optimal point is smallest

Cutoff	Exp	Оехр	Exp	Оехр	Se	1-Sp	PPV	NPV	Distance	Area /	
	cases	cases	ref	ref							
6.8	3	286	2	43260	.01	O	0.6	.99 The	area un	der the c	urve.
6.85	4	285	5	43257	.014	0	.444	.993	.986	0	-29
6.9	13	276	17	43245	.045	0	.433	.994	.955	0	9-09
6.95	21	268	64	43198	.073	.001	.247	.994	.927	0	2016-09-29
7.00	36	253	287	42975	.125	.007	.111	.994	.875	.001	
7.05	62	227	1008	42254	.215	.023	.058	.995	.786	.003	
7.1	102	187	2763	40499	.353	.064	.036	.995	.65	.015	
7.15	154	135	6595	36667	.533	.152	.023	.996	.491	.054	
7.2	195	94	13606	29656	.675	.315	.014	.997	.452	.152	
7.25	223	66	23063	20199	.772	.533	.01	.997	.58	.31	
7.3	261	28	33102	10160	.903	.765	.008	.997	.771	.504	
7.35	279	10	39763	3499	.965	.919	.007	.997	.92	.648	
7.4	287	2	42426	836	.993	.981	.007	.998	.981	.709	
7.45	289	0	43118	144	1	.997	.007	1	.997	.724	
7.5	289	0	43249	13	1	1	.007	1	. 1	.727	[ [1

# The ROC-curve showing the ability of maternal BMI to predict BW>4000g

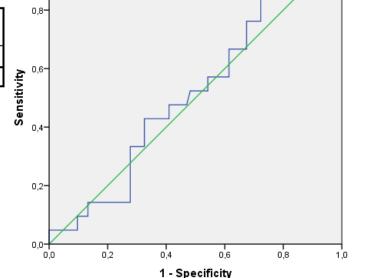
#### Area Under the Curve

Test Result Variable(s): Maternal\_BMI

			Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
l	Area	Std. Error <sup>a</sup>		Lower Bound	Upper Bound
I	,518	,067	,796	,386	,651

The test result variable(s): Maternal\_BMI has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

- a. Under the nonparametric assumption
- b. Null hypothesis: true area = 0.5



**ROC Curve** 

Diagonal segments are produced by ties.

#### Impressive? Significant?

No!

# Today

## Today

- Repetition
- Lecture 5:
  - Power calculations
  - Probability, proportions, CI for proportions
  - 2x2 Table. Chi2-test, Fisher exact test

#### Lecture 6:

- Sensitivity, Specificity
- Positive predictive value, Negative predictive value
- ROC-curve
- Next lecture
- Reliability
- Association versus agreement
- Bland-Altman plots
- Limits of agreement
- ICC
- Cohen's Kappa