# Biophysics I.
# for dentistry students

Lecture 2nd:

Biostatistics II.

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## Probability of Events I.

**Axioms on probability of events (Kolmogorov):**

*1.* **0 ≤ P(A) ≤ 1**

*2.* **P(*sure*) = 1** *(The patient will die sooner or later)*
**P(*impossible*) = 0** *(I'm 310 cm tall)*

*3. Mutually exclusive events (i.e.* P(AandB)=0)
***P(AorB)=P(A)+P(B)***
*(probability of being pregnant or male)*

And a theorem:
+4. *Independent events*: **P(AandB)=P(A)*P(B)**
*(probability that our first patient is male and the second one is female)*

We finished the last lecture with the discussion of phenomena of probability.
To describe the probability of events we have axioms. Now we show the Kolmogorov axioms. (In a simplified way.)
1. The probability of an event is between 0 and 1.

2. The probability of a sure event (*the patient will die sooner or later* – we know that life is a sexually transmitted lethal disease☺) is 1. The probability of an impossible event is 0 (*I'm 310 cm tall*).

3. The probability of A or B events occur if A and B are mutually exclusive (they could not happen in the same time) events is the sum of the probability of A and the probability of B events. (*The probability that being pregnant or male is the probability that being pregnant + the probability that being male.*)

A theorem based on the axioms:

+4. The probability of A and B events occur if A and B are independent events (the occurance of an event has no effect on the occurance of the another) is the multiplication of the probability of A and the probability of B.
(*Probability that our first patient is male and the second one is female is the probability that our first patient is male * the probability that our second patient is female.*)

These mentioned statements are true from other way round. For example if P(A)*(P(B)=P(AandB) then A and B are independent events.

## Human thinking and probability...

Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

Which is more probable?
a) Linda is a teacher in a secondary school
b) Linda works in bookstore and participates in yoga courses
c) Linda is a member of the league of women voters
**d) Linda is a bank teller.**
e) Linda is an insurance agent
**f) Linda is a bank teller and is active in the feminist movement.**

The last example we dicussed in the previous lecture was about Linda. Here I'd like to highlight two statement: *d* and *f.* I hope after the previous slide everybody found out that co-occurrence is less probable than occurrence of a given event. The intersection of sets is always equal or smaller than the sets. So it is less probable that Linda is a bank teller and active feminist at the same time than she is a bank teller.

## Probability of Events II.

*Conditional events calculation:*

*general form*: **P(A|B)=P(AandB)/P(B)**

**Special cases:**

*I. Independent events*:

*Probability that our second patient is male*
***if** the first one is female*

**P(A|B)=P(AandB)/P(B)**
**P(A|B)=P(A)*P(B)/P(B)**
**P(A|B)=P(A)**

*Probability that our second patient is male*
***if** the first one is female* = *Probability that our second patient is male*

There is an other important calculation that you have to know on conditional events. I showed here a simplified form of Bayes' law. The general form of the „multiplication role" is P(A|B)=P(AandB)/P(B). First examine 2 special case.
Case1: check the conditional probability in case of independent event. E.g. *probability that our first patient is male **if** the second one is female.* As we see the result the independent condition has no effect on the probability of the event; e.g. *probability that our second patient is male **if** the first one is female = probability that our second patient is male.*
We have the same with tossing a coin, rolling a die, etc.: the previous results has no effect to the next one.

## Probability of Events II.

II. event A is a subset of event B

*Probability that a patient has a flu*
*if suffering from a viral infection*

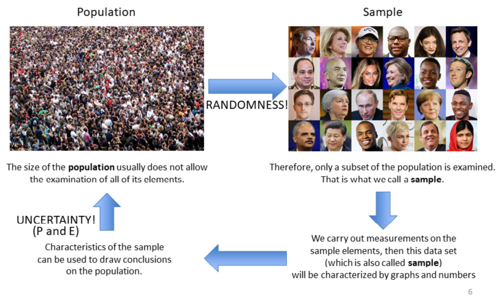
**P(A|B)=P(AandB)/P(B)**
**P(A|B)=P(A)/P(B)**

*Calculation:*
*The probability that a patient coming to our office has viral infection is 8% =P(B)*
*The probability of occurrence of flu infections at our office is 2% = P(A)*
*The probability that a patient suffering from a viral infection has actually flu is: P(A|B)* = 2% / 8 % = 25%.

Case2: event A is a subset of event B (all A is a B, but not all B is A).
An example:
*The probability that a patient coming to our office has viral infection is 8% =P(B)* – that is the probability of the condition.
*The probability of occurrence of flu infections at our office* – that is the probability of our event in the given sample. *P(A)* = 2%
*The probability that a patient suffering from a viral infection has actually flu - P(A|B)* – is 25%.

## Repetition:Population and Sample

(Problematics of inferential statistics)




As we mentioned before, statistics examines random mass phenomena. This means that during examination of a phenomenon many, if not infinitely many measurements would be possible. The set containing the outcomes of all these theoretically possible measurements is called **population**. Theoretically, the complete understanding of a variable would require the execution of all the possible measurement, but of course it is not possible.

Consequently, we only observe a subset of the population, which is called **sample**. The most evident way of generating this subset is **random selection**.

We carry out measurements on the sample, the set of measurement results is also called **sample**. (That is: in less precise way the sample may be a group of students [individuals, objects] of the university as a population. In more precise way, the population is the height of all people at the university, the sample is the set of height values for a group that was actually measured.)

The sample might be characterized graphically or numerically as we learned in the last lecture, then the properties learned that way may be extrapolated to the population. E.g. if 25% of people in a group have blood type "A", we may expect the same from the whole population. Since the sample is chosen randomly, it will not necessary represent the population, the frequency of occurrence of different values within the population perfectly. As a result, every conclusion drawn from a sample carries a burden of **uncertainty**.
What is the quantity of the uncertainty? How to define?
We are using 2 term for it: probability (P) and error E.

## Estimation

Population | Sample
Real value | Estimate

Estimation

| | |
|---|---|
| Probability | Relative frequency |
| Expected value (mean of population) | Mean of the sample |
| Theoretical variance | (Empirical) sample variance |
| Difference of 2 expected value | Difference between 2 sample mean |

So in the inferencial statistics we make estimates and analyze them.
For example, the probability of a given variable outcome in a population is estimated by the relative frequency of the sample. The expected value of the variable is estimated by the mean of the sample, and the variance is estimated by the sample (so called empirical) variance. The difference between the averages of two populations can be estimated by the difference between the sample means (eg whether drug is different - different means).

## Error

Population
- Real value (estimand)

Estimation

Sample
- Estimates

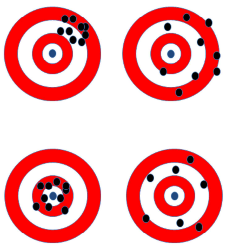
Error

Imagine more random samples – more estimates

Expected value, standard deviation, difference in the expected value of two populations - all measures of efficacy are estimated parameters. The question is how big a mistake can we make? Imagine estimating a given true value with multiple samples - the samples come from the population by random sampling. The difference between the real value and the estimate is the error.

## Error – 2 dimension

„Average of differencies” (bias)
Systemic error



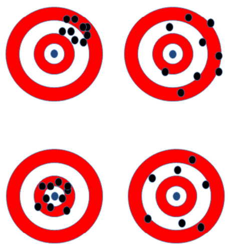
1. Variability of estimates
2. Difference between the real value and the „center” of the estimates

„Variability” (standard deviation);
Random error

The error „has 2 factors”: random error and systematic error. The random error is the variance of the estimates, while the systematic error is characterized by the difference between the „center" of the estimates and the estimated value.

## Error – 2 dimension

„Average of differencies” (bias)
Systemic error



Good estimation, if:
*Unbiased*:
the expected value of the estimates is equal with the estimand
*Effective*:
the variability is small
*(Konsistent*:
the variability of estimates decreases with increased sample size)

„Variability” (standard deviation);
Random error

The estimates is good, if:
1. *Unbiased*
2. *Effective*
3. *Consistent*

(+ 1 not mentioned…)

## Confidenc intervals

But we have only 1 estimate and we don't know the real value!
– Could we measure the error?

YES, the random error (sampling error) could be estimated based on the sample! It is called the standard error of the estimate.

HOW?

We have only 1 sample, therefore 1 estimate and we don't know the real value – could we measure the error in this case?
YES! But only the random part! We can estimate random error based on the sample.

## Confidence intervals

But we have only 1 estimate and we don't know the real value!
– Could we measure the error?
The variability (random error, sampling error) could be estimated based on the sample!

Example:
The standard error of the mean (shortly standard error, SEM)

***Reminder: CLT: Central limit theorem (on sampling)***: for given conditions, sampling with large sample size (n) the distribution of the sample means is normal with:

$$\mathrm{Var}_{\mathrm{normal}} = \frac{\mathrm{Var}_{\mathrm{(original)}}}{n}$$

Let's show an example based on the mean (estimate of expected value).
Reminder: central limit theorem (CLT)

## Confidence intervals

1. Therefore the standard error of the mean (the variability of estimating the mean): is the square root of the nth part of the sample variance.
2. We can construct a range, that contains the mean with a given „probability": called confidence interval of the mean.
   the given probability: called confidence level

In the case of the mean (because of normal estimation – see CLT) eg.:
The limits of the 95% confidence interval of the mean are:

$$\sim \bar{x} \pm 2 * SEM$$

We can construct confidence intervals for other estimats too!
It shows the value of the estimate, its error and its confidence interval

Based on the CLT we have 2 conclusion:
1. the standard error of the mean (the variability of estimating the mean): is the square root of the nth part of the sample variance.
2. We can construct a range, that contains the mean with a given „probability": called confidence interval of the mean. The given probability: called confidence level.
For the mean eg. : The limits of the 95% confidence interval of the mean are mean+-2*SEM.
We can construct confidence intervals for other estimats too! (Nearly for all estimates).
It shows the value of the estimate, its error and its confidence interval.

## **Hipothesis tests**

**Sampling („random") error with an other method**

**Aim** of hypothesis tests: **Statistical answer on YES/NO question**

**HOW to prove a statement?**

*Direct proof*: prove for all cases that the statement is true.
eg: sum of 1,2…n : (n+1)*(n/2) – proving with induction

*Indirect proof*: assume the opposite statement and I prove that is false.

One main tool in statistics to make decisions with a given error probability is hypothesis tests.
In this chapter I gave detailed description in the slides, therefore I comment it shortly.

In hypothesis tests we would like to give an answer for a YES/NO question. An answer is a statement – but how to prove a statement?
In math we have 2 possibilities:
Direct/indirect prooving.

## Indirect proof

We have a box containing 100 marbles. Each of them are either red or white.

**Case #1: hypothesis (H):** all of them are white.
**Experiment:** We randomly take a marble out of the box.
**Our observation:** It is red.
**Conclusion:** The probability of our observation *given* our hypothesis is 0: Our hypothesis is for 100% sure wrong.

**Case #2: hypothesis (*H*):** 99 are white and one is red.
**Experiment:** We randomly take a marble out of the box and put it back; we do this 5 times.
**Our observation**: All of them are red.
**Conclusion**: Our hypothesis is for *almost* 100% sure wrong: The probability of our observation *given* our hypothesis is $0.01^5 = 10^{-10}$: practically impossible.

**Case #3: hypothesis (H):** 50 are white and 50 are red.
**Experiment:** We randomly take a marble out of the box and put it back; we do this 5 times.
**Our observation**: All of them are red.
**Conclusion:** Now we are not sure what to do: The probability of our observation given our hypothesis is $0.5^5 = 0.03125$: low but not that unlikely...

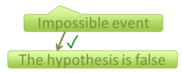
**Case #4: hypothesis (*H*):** all of them are red.
**Experiment:** We randomly take a marble out of the box and put it back; we do this 5 times.
**Our observation**: All of them are red.
**Conclusion**: The probability of our observation *given* our hypothesis is $1^5 = 1$. Are we sure what to do now?

In hypothesis tests we would like to use indirect proving, therefore execute the next theoretical experiments.

## Indirect proof

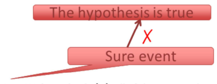
We have a box containing 100 marbles. Each of them are either red or white.

**Case #1: hypothesis (H):** all of them are white.
**Experiment:** We randomly take a marble out of the box.
**Our observation:** It is red.
**Conclusion:** The probability of our observation *given* our hypothesis is 0: Our hypothesis is for 100% sure wrong.




Falsification works

Verification does not work




**Case #4: hypothesis (*H*)**: all of them are red.
**Experiment**: We randomly take a marble out of the box and put it back; we do this 5 times.
**Our observation**: All of them are red.
**Conclusion**: The probability of our observation *given* our hypothesis is $1^5 = 1$. Are we sure what to do now?

Falsification: refutation of the statement
Verification: supporting the statement

## Indirect proof

**What about #2 and #3?**
**Mathematical Logic:**
We have a hypothesis (*H*).
If *H* is true, *E* event cannot occur.
*E* occurs.
So *H* is not true.
As we saw it before, **a hypothesis can only be rejected**.

**Statistical Logic:**
We have a hypothesis (*H*).
If *H* is true, *F* event is very unlikely to occur.
*F* occurs.
So we reject *H*. But we are not 100% sure if *H* is not true.
**In this case a hypothesis cannot even be rejected with 100% certainty.**
**WE HAVE TO ESTIMATE THIS PROBABILITY**

In math the falsification is clear – but in stat it works with a given probability.

## What kind of questions can we test?

**Y/N** **...must be a yes/no (a.k.a. dichotomous or polar) question.** **5W1H**

- Is the 5-years survival rate (i.e. probability) for myeloma 50%?
- Does the total blood cholesterol level of Cushing's syndrome patients differ from the general 200 mg/dL population mean? ✓

- What is the 5-years survival rate for myeloma?
- What is the expected value of total cholesterol level in Cushing's syndrome patients? ✗

**...must refer to a set of observations, not to individual cases.**
**(And the question is aimed at a population, not a sample.)**

- Is the 5-years survival rate for myeloma 50%? ✓
- Will this myeloma patient survive for 5 years? ✗

**...must have at least one unambiguous answer.**

- Is the 5-years survival rate for myeloma 50%? ✓
- Is the 5-years survival rate for myeloma less than 50%? ✗

…

## What kind of answers can we test?

### We have two answers for our question:

| The null hypothesis ($H_0$) | The alternative hypothesis ($H_1$) |
|---|---|
| - **Unambiguous**: can be realized in only one way. It contains some form of =. The 5-years survival rate for myeloma is 50%. | - Typically can be realized in more than one way. The 5-years survival rate for myeloma is not 50%. (can be a little more, a lot less etc.) |
| - Represents the current well-established, generally **accepted scientific knowledge**, The total blood cholesterol level of Cushing's syndrome patients is same as the population mean or something that is the **most trivial** with the least assumptions (Occam's razor). The probability of landing on heads in a coin tossing experiment is 50%. | - Represent a **new statement** challenging the current scientific consensus, The total blood cholesterol level of Cushing's syndrome patients differs from the population mean or a set of all the **not-so-trivial** answers needing more or special assumptions. The probability of landing on heads in a coin tossing experiment is other than 50%. |
| - It is **not** necessarily the negative answer to the question. | - It is typically **complementary to $H_0$** (i.e., its negation). $H_1$ = not $H_0$ |

…

## Sampling („random") error

**Aim** of hypothesis tests: **Statistical answer on YES/NO question**

Starting point: create a specific statistical question and answers:
$H_0$: null hypothesis – „random" error only
$H_a$ (or $H_1$): alternative hypothesis – not $H_0$

Decision is based on: role of „randomness" if $H_0$ true (sampling error)
A sample is that could contradict $H_0$

So we have a question and the hyotheses.
The H0 is the more important: if H0 is true in the reality we could see something else in the sample because of the sampling error (we have a sample we did not measure everybody).
Our aim is to answer the question with a decision: accepting or rejecting the H0.

## Sampling („random") error

**Aim** of hypothesis tests: **Statistical answer on YES/NO question**

Starting point: create a specific statistical question and answers:
$H_0$: null hypothesis – „random" error only
$H_a$ (or $H_1$): alternative hypothesis – not $H_0$

Decision is based on: role of „randomness" if $H_0$ true (sampling error)
A sample is that could contradict $H_0$

| | | In population (in reality) the null hypothesis is: | |
|---|---|---|---|
| | | True | False |
| Decision on null hypothesis: | Accepting (Not rejecting) | Good decision | Error (**type II**) ($\beta$) (false negative result) |
| | Rejecting | Error (**type I**) ($\alpha$) (false positive result) | Good decision (power) (1-$\beta$) |

Let's look a table on H0 what could be the results of our decision. In reality (that we don't know) we have to options: the H0 is true or false. Or decision could be to accept or to reject the H0.
If we accept the true H0 or we reject the false H0 we make a good decision. The latter one called power: it gives the probability to find (reject H0) if the H0 is false.
If we reject the true H0 we make a wrong decision called type I. error. This probability – rejecting H0 if H0 is true – symbilized by alfa.
If we accept the false H0 we make a wrong decision called type II. error. This probability – accepting H0 if H0 is false – symbilized by beta.

## An example – first steps

Situation: We play a board game with dice – we do not win...
This is a „wrong" dice?

What is the question??!! (and what is it about):
All of the sides has the same probability? (for this dice)
The probability of six-throw is different from 1/6, even bigger?
– let's use this question

Null hipothesis ??!!:
The probability of rolling 6 is 1/6 or less – hmm (*multiple hypothesis*)
Let's use the worst according to alternative hypothesis
(since if only one element of the multiple hypothesis can "conform" to the null hypothesis, there is no evidence of rejection in the full range of hypothesis):
$H_0$: The probability of rolling 6 is 1/6.
$H_a$: greater than 1/6

Let's see an example for a hypothesis test.

## An example – next steps

What is the question : The probability of six-throw is different from 1/6, even bigger?

Null hypothesis: $H_0$: The probability of rolling 6 is 1/6.

**How much evidence do we need for saying it is differ?**
**– Significance level**??!!:

Given by authority… Used in the literature--- **STARTING VALUE**, BUT smaller/larger, more/less frequent side effects?, cheaper/ more expensive?…

here: we play this game every weekend, it's not expensive to change the die – let's use 10% instead of 5% (smaller evidence enough to reject $H_0$)

Collecting evidence – the sample ??!! (how, how much… ask your statistician):

results: 6 times 6 out of 24 rollings

I really answer the question I have created?

Do I need to modify the question? (eg. the population of interest)

Sgnificance level: the limit where we accept or reject H0.

## An example – additional steps

What is the question : The probability of six-throw is different from 1/6, even bigger?

Null hypothesis: $H_0$: The probability of rolling 6 is 1/6..

Significance level:10%

Sample: 6 times 6 out of 24 rollings.

Is the difference important at all?– relevant ??!!:

6 times 6 out of 24 rollings, it is 6/24 = 1/4 probability that **1,5** times higher than 1/6 – YES it is

How much evidence – p-value ??!!:

How to calculate it?, (unbiased, effective, consistent…)

Important aspects: the question, type of variables (measuring scale), measurement conditions

We need for calculation:

*Null distribution* – if null hypothesis is true, what is the probability of all theoretical samples we could have?

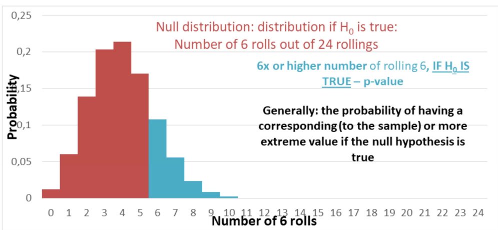
The „position" of our sample in this distribution:

*test statistics* (or statistics, eg: frequency, probability , t-value , p-value…)

Relevant: clinically important effect.

## Calculation in the „background"

Using binomial test!

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## An example - last steps

What is the question : The probability of six-throw is different from 1/6, even bigger?

Null hypothesis: $H_0$: The probability of rolling 6 is 1/6..

Significance level:10%

Sample: 6 times 6 out of 24 rollings.

Is the difference important at all?– relevant : 1/4 probability, that **1,5** times higher than 1/6 – YES it is

How much evidence? – p-value: 0,1995

Decision: there is not enough evidence for reject $H_o$– accept $H_0$

| | | In population (in reality) the null hypothesis is: | |
|---|---|---|---|
| | | True | False |
| Decision on null hypothesis: | Accepting (Not rejecting) | Good decision | Error (**type II**) ($\beta$) (false negative result) |
| | Rejecting | Error (**type I**) ($\alpha$) (false positive result) | Good decision (power) (1-$\beta$) |

…

## One sample Student t-test

What I'm curious about

Expected value of the sample is equal with a known population mean

Type of variable

1 numerical and continuous

Assumption

Independent observations

distribution of means is normal:

normally distributed sample or large sample size (CLT)

Notes: Calculation:

$$t = \frac{\bar{x}-\mu}{s/\sqrt{n}}$$

Do NOT test normality with other hypothesis test (it increases Type I. error, „multiplicity")! Use previous knowledge on the variable and make graphs.

Let's look a few hypothesis tests that you will learn in practices. I highlight here which hypothesis test could be used for a given problem, given variable (measuring scale), and what condition ave to be fullfilled.

(CLT: central limit theorem)

## Paired Student t-test

What I'm curious about

Two expected values in two groups are equals – in paired groups

Type of variable

1 numerical and continuous, 1 binary („groups")

Assumptions

Independent observations in the groups, paired groups

the distribution of the difference of means is normal

normally distributed differences or large sample size

Notes:

paired test usually has higher power

suitable to compare other location parameters (quantiles)

difference of the means = mean of the differences

Matematically this is the same as the one sample t-test, if we use the difference of paire values as a dataset.

## 2 sample Student t-test

What I'm curious about

Two expected values in two groups are equals

Type of variable

1 numerical and continuous, 1 binary („groups")

Assumptions

Independent observations between and within groups

distribution of means is normal in each group:

distribution is normal in each group or large sample size

distribution of standard deviations are the same

Notes:

suitable to compare other location parameters (quantiles)

if we don't know the variances do not test (multiplicity) – use Welch test instead!

…

## Welch test

What I'm curious about

Two expected values in two groups are equals

Type of variable

1 numerical and continuous, 1 binary („groups")

Assumptions

Independent observations between and within groups

distribution of means is normal in each group:

distribution is normal in each group or large sample size

Notes:

suitable to compare other location parameters (quantiles)

not sensitive for different variances (robust for variance differences)

…

## Chi-square test for independence

What I'm curious about
Two variables are depends on each other
Type of variable
2 categorical variable
Assumptions
Independent observations
None of the „expected" frequencies smaller than 1 and maximum 20% smaller than 5.

…

## „Correlation" t-test (Pearson linear regression)

What I'm curious about
Two variables are (linearly) depends on each other
Type of variable
2 numerical variable (X and Y)
Assumptions
Independent observations for pairs
linear relation assumed
x values measured with no error
y-s have a normal distribution at each x
y-s have same variance at each x
Notes
2 estimates: slope and intercept, slope is important and tested

…

## Relevant, but not significant…

**Reasons:**
small power:
small sample size (limitation: money, ethical issues)*
large variability
less powerfull statistical test

we could not measure it accurately
violated assumptions for the test

Plan ahead!!

we were unlucky (sampling error)

other errors

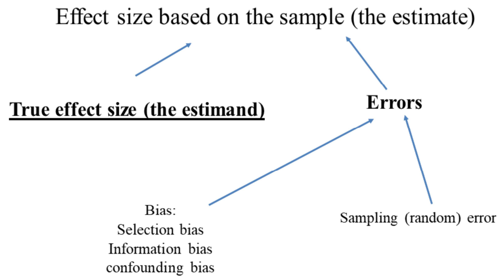
-***Ask yor statisticians...**
(☺ eg: https://www.youtube.com/watch?v=PbODigCZqL8 )

It is a common problem that we get a relevant (clinically important), but not significant (not rejected H0) result – that means no effect? or…
+We used too small sample size
+ the variability of the variables are too large
+ wrong, or wrongly used hytpothesis test was perfromed
+ low measuring scale
+ we were unlucky
+ …

To avoid this problems it is very important to plan the experiment before perform data collection.

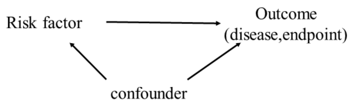
A typical big question is the sample size.
Sample size video:
https://www.youtube.com/watch?v=Hz1fyhVOjr4

## Other errors



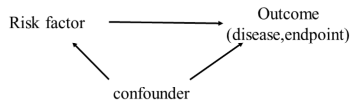

Until now, we talked about the error because sampling. But there are other source of errors called bias (systemic error). We usually classify them into 3 category:
Confounding
Selection bias
Information bias

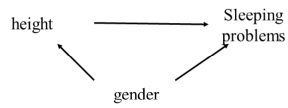
# Confounding bias




Shortly, confounding bias occur when the effect on the outcome variable is described, interpreted by a variable (here called risk factor), but in reality the effect caused (modified) by an other variable (a confounder).

# Confounding bias




Most common confounders: gender, age – always think about them!

Eg. We found that higher people has slleping problem with higher probability and therefore we interpret that saying that higher body high increase the sleeping problems. But in reality the reason is not the high: the reason is the gender – men has more probable sleeping problem. If we examine men and women separately we could not detect the hight effect on sleeping problem.

(A variable could be a confounde if it has „effect" both on the risk factor and the outcome)

# Selection bias, Information bias

Selection bias:
There is a difference between the selected and not selected individuals, or difference between assignment to groups (erroneous selection with respect to an outcome influencing parameter)
tipical: age, gender different in the groups
different population
different follow-up time

Information bias:
erroneous data collection about or from subjects (which affects the outcome)
tipical: recall bias
more carefull monitoring for diseased, young

Selection bias examples:
AGE: Knowing that gender has an effect on sleeping problems, the proportion of women in a „new drug group"is different than in the „placebo group".
LOSS OF FOLLOW UP: – we know that AIDS is more frequent in i.v. drug users and homosexuals: those who has AIDS will more often "quit" the follow-up, than those who do not get AIDS, as well as IDU users more often „disappear", than homosexuals
DIFFERENT POPULATION: Fracture in Women and Nutrition Relationships: We choose bone trauma from a trauma class, control of the hospital's internal medicine (But there are other more frequent illnesses in the internal medicine , eg diabetes is more common that has an effect on fracture !!)

Information bias examples:
RECALL BIAS: Parents of children diagnosed with cancer may be more likely to recall infections earlier in the child's life than parents of children without cancer.

Good source:
Catalogue of Bias Collaboration, Spencer EA, Brassey J, Mahtani K., 2017. [https://catalogofbias.org/](https://catalogofbias.org/)

# Test Questions

- What does systestemic and random error means?
- What does unbiased estimation mean?
- What does effective estimation mean?
- What does consistent estimation mean?
- What does confidence interval mean?
- What is the aim of a hypotheisis test?
- Give the criteria of a good question in a hypotheisis test.
- Give the criteria of a good null hypothesis in a hypotheisis test.
- What does significance level means?
- What does relevant mean?
- Define first type error.
- Define second type error.
- Define the p-value in a hypothesis tests.
- What does confounding bias mean?
- What does selection and information bias mean?

The following questions may be answered using lecture material, consultation with practice teacher, or your own investigation (on the library or the internet). These test questions are examples for questions that may occur in the midterm and exam tests.