



[BIOSTATISTICS]



Lecture 3 (Hypothesis testing & Tests of significance)

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القلوب أوعية
والشفاه أقفالها
والألسن مفاتيحها
فليحفظ كل إنسان مفتاح سره.

Hypothesis Testing

Example: Average intake in children for dietary fat is 70 g of fat per day. Suppose we want to study children who eat a vegetarian diet. Possible hypotheses are

1. Average fat intake is 70 g per day
 2. Average fat intake is less than 70 g per day
-

Def: **One-sample problem**—a single distribution.

Def: **Hypothesis**—statement about parameters in a population or populations. We want to know how likely this is to be **true**, given the **evidence** (data). For example,

1. Average number of beds filled per day in the hospital
2. Average number of minutes per day the doctor spends with a patient
3. Average lead content of water for a housing project

Def: **Null hypothesis**— H_0 —the hypothesis to be tested. **This is usually a statement of no difference.**
The population value of the parameter is **not different** from some specified value.

Def: **Alternative hypothesis**— H_1 or H_A —This is the statement we will **accept if we reject the null hypothesis.**

يعني أنه عندتمت نرفض النظرية الصفرية فإننا نقبل النظرية المغايرة

H_0 : Mean fat intake in vegetarian children is 70 g per day. $H_0: \mu = \mu_0$ or $\mu \geq \mu_0$

H_1 : Mean fat intake in vegetarian children is < 70 g per day. $H_1: \mu < \mu_0$

 **Possible decisions:**

1. Accept H_0 (really, fail to reject H_0)
2. Reject H_0

Possible Scenarios:

Jury Trial		
	Truth	
Verdict	Innocent	Guilty
Innocent	Correct decision	Error
Guilty	Error	Correct decision

Test of hypothesis		
	Truth	
Results of Test	H ₀	H ₁
Accept H ₀	Correct decision	Type II error
Reject H ₀	Type 1 error	Correct decision

Def: **Type I error** is the probability of rejecting H₀ when H₀ is true.

Def: **Type II error** is the probability of accepting H₀ when H₁ is true.

Example: We have developed a new procedure to improve survival of premature infants. If the hospital adopts these procedures, there will have to be new rooms and new equipment purchased. This is very costly.

1. What does a Type I error imply?
 → when we say : increasing the number of rooms & equipments will improve survival of premature infants , but in reall life there is no improvement.
2. What does a Type II error implies?
 → When we say : increasing the number of rooms & equipments will not make a difference , but in reall life it will improve survival of premature infants.

Def: **Level of significance:** α = Probability of a Type I error.
 This is the area under the curve below (or above) the critical value.
 This is the probability of rejecting H₀ when H₀ is true.

Def: β : Probability of a Type II error.

Def: $1-\beta$ —Power of a test. This is the Probability (rejecting H₀ when H₁ is true).

Goal: Make α, β as small as possible. Usually, as $\alpha \uparrow, \beta \downarrow$ and as $\alpha \downarrow, \beta \uparrow$.

Fix α (0.05 or 0.01). Find a test to minimize β .

Best test for the fat experiment is one based on \bar{X} .

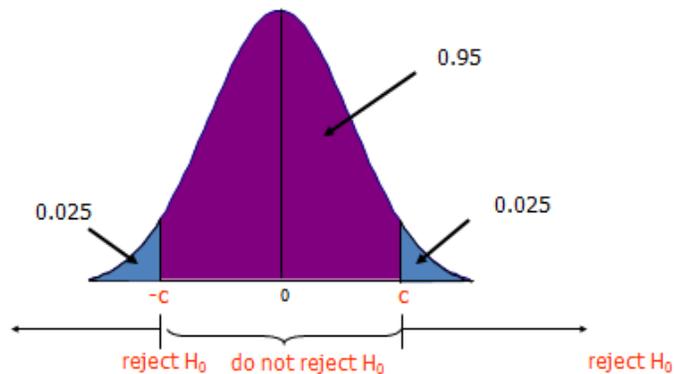
Def: **Acceptance Region**—These are the values of \bar{X} for which H_0 is accepted.

Def: **Rejection Region**—These are the values of \bar{X} for which H_0 is rejected.

Note: For this example, we are conducting a one-sided or one-tailed test. We will only reject H_0 for values of \bar{X} that are low.

Def: **One-tailed**—this is a test in which values of parameter under H_1 either $>$ or $<$ values under H_0 but not both.

The picture behind the two sided test



Tests of Significance

SUMMARY OF HYPOTHESIS TESTING

Basic principles:

1. Every time you see a **p-value**, someone tested a hypothesis
2. Your data comes from a sample you select; you hope your sample **represents a larger population** you'd like to draw conclusions about.
3. A statistic is a number (i.e. a proportion, an average or a disease rate) you calculate from your data sample.
4. The statistic is an attempt to describe the truth (a parameter) about a larger population using your sample.
5. **Hypothesis testing** allows a researcher to decide whether a difference between numbers is more likely due **to random variation** or a **true difference**

How to test a hypothesis?

1. Write a null hypothesis
مثلا مستوى ذكاء الطلاب في جامعة مؤتة = مستوى ذكاء الطلاب في باقي الجامعات الأردنية
2. Write an alternative hypothesis: determines if your test will be one-sided or two-sided (usually two).
مستوى ذكاء طلاب جامعة مؤتة لا يساوي مستوى ذكاء الطلاب في باقي الجامعات الأردنية
3. Set alpha (that is, the level of probability you will accept as unlikely related to chance alone), usually=0.05
4. Generate a test statistic: a number you calculate to describe your sample results.
There are many types of test statistics.
The type of test statistic used depends on the type of data you have.
5. Compare your test statistic to a **known/published** distribution for that type of test statistic in order to **find the p-value**
6. If the p-value is less than alpha (usually .05), then the numbers in the null hypothesis differed more than expected due to chance alone.
Reject the null hypothesis.
7. Conclude that the groups are different

Common Statistical Tests

1.1. Review of the Central Limit Theorem (CLT):

If we were to take a sample of size n from a population and calculate its **mean**, then sample the same population **again and calculate the mean**, then sample it **again and calculate the mean**, and keep doing this many times...then we graph all of those means on one curve, we would get a “**sampling distribution**” of the mean.

This sampling distribution will be normally distributed, with mean = μ and standard deviation = **SEM** (standard error of the mean)= $X-\mu / (s/\sqrt{n})$

The CLT is very powerful, **but it has two limitations**:

- 1) it depends on a **large sample size**, and
- 2) to use it, we **need to know the standard deviation** of the population.

In reality, we usually **don't know** the **standard deviation** of the population so we use the standard deviation of our sample (denoted as 's') as an estimate.

Standard error (SE) = $X-\mu / (s/\sqrt{n})$

Since we are estimating the standard deviation using our sample, the sampling distribution will not be normal (even though it appears bell-shaped).

It is **a little shorter and wider** than **a normal distribution**, and it's called a **t-distribution**.

The t-distribution is **actually a family of distributions** – there is a different distribution for each sample value **of $n-1$ (degrees of freedom)**.

The shape of t depends on the **size of the sample**...the larger the sample size, the more confident we can be that 's' is near sigma , and the **closer** t gets to Z.

Because it is not normal, the t-distribution does not follow **the 68-95-99 rule**, but we can use t-tables or computer programs to estimate the area-under-the-curve (probability) associated with a specific t-score, **$t = (X - \mu) / SE$** , and a specific sample size

Again, the t-distribution **approaches the normal distribution as n approaches infinity**.

For qualitative data we make chi-square.

For quantitative data we make 4 types of t-test:

1-one sample t-test

مثلا عندما يكون لدينا عينة واحدة نقارن وسطها الحسابي مع ال national figure .

2-independent sample t-test → إذا كان يوجد لدينا عينتان

3- ANOVA → إذا كان يوجد لدينا ثلاث عينات فأكثر

4-paired t-test

و هو الأكثر شيوعا و هو نفس الشخص قبل و بعد مثل مقارنة الفك العلوي مع السفلي أو الجانب الأيسر من الوجه مع الجانب الأيمن.

2. Statistical tests for Continuous data

1-One-sample t-test:

How do we decide if a **continuous measure** taken on a sample of people is significantly more extreme than we might find by chance alone?

Remember that if we had taken a sample many times, the means collectively would form a curve **around the true value** that follows the t-distribution. So, whenever we are testing a sample mean, we use a t-statistic with **SE** in the denominator. Because of this, **the larger the sample size, the more values fall into a smaller range.**

To test a sample of normal continuous data, we need:

1. An expected value = the population or true mean
2. An observed mean = the average of your sample
3. A measure of spread: standard error
4. Degrees of freedom (df) = n-1 (number of values used to calculate SD or SE)

Then, we can calculate a test statistic to be compared to a known distribution

In the case of continuous, normal data, it's the t-statistic and the t-distribution.

$$T = \frac{(\bar{X} - \mu)}{\frac{S}{\sqrt{n}}}$$
$$T = \frac{(\text{observed mean} - \text{expected mean})}{SE}$$

*Notice that t is a measure of the difference between your data and what you expect to see, in units of standard error. This is a common theme of testing continuous variables.

An example: You would like to see whether your clinic of HIV-positive men has more extreme testosterone levels than you would expect by chance.

The lab tells you that, among healthy men,

- 1) Testosterone levels are normally distributed;
- 2) the average population testosterone level is 600 ng/dl.

--Null hypothesis: Testosterone levels (your clinic) = Testosterone levels (general population)=600.

--Alternative hypothesis: Testosterone levels (clinic) is different (more or less) than general population mean

2-sided

--Set alpha=0.05

Sample your patients: 25 men who happen to visit in July.

The results return with a mean testosterone = 500 ng/ml in your patients, SD=200 ng/ml. The average seems pretty good to you; it's close to 600. You calculate SE= $200/\sqrt{5} = 40$.

$$\text{-- } t = \frac{500 - 600}{40} = -2.5$$

1. Your results are 2.5 standard error units below the expected value.

The **degrees of freedom**(n-1) are $n-1 = 25-1 = 24$.

2. You use a computer program or a statistic table to look up the t- distribution with 24 degrees of freedom.

3. A t of 2.5 (positive and negative values are handled the same because the curve is symmetric) has the same area of 0.01 in each tail.

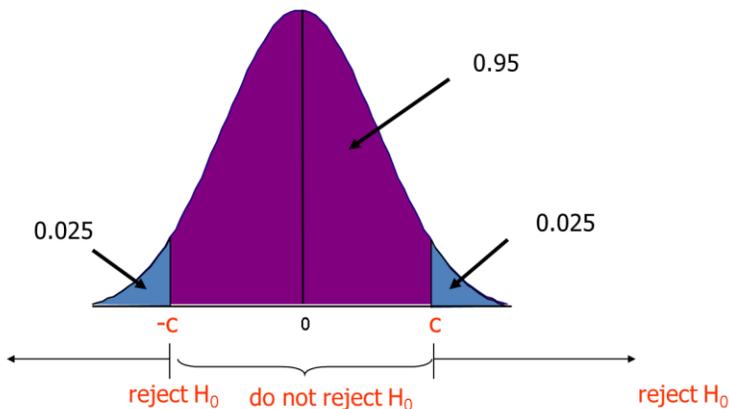
4. Because you're doing a two-tailed test, you need to consider the possibility of both tails, or 2×0.01 (again because the normal curve is symmetric). In this case, $p=0.02$.

5. Under the assumption that the true testosterone value of these patients is 600, the likelihood of getting a mean of 500, or more extreme in either direction from 600, by random sampling alone is only 2%.

6. *The t-value needed to achieve statistical significance with a given alpha and a given sample size is called the critical value P is less than or equal to alpha, so you reject the null hypothesis.*

You conclude that the average you saw was unlikely to have occurred by chance alone, and that your patients' testosterone levels are lower on average than a healthy population.

The picture behind the two sided test



Acceptable range

We need to calculate the critical range using the t-distribution:

Two-sided: **Reject H₀ if** $|T| > t_{n-1, \alpha/2}$

One-sided upper tailed: **Reject H₀ if** $T > t_{n-1, \alpha}$

One-sided lower tailed: **Reject H₀ if** $T < -t_{n-1, \alpha}$

t-table Degrees of Freedom	Probability, p, level of significance, alpha, α			
	0.1	0.05	0.01	0.001
1	6.31	12.71	63.66	636.62
2	2.92	4.30	9.93	31.60
3	2.35	3.18	5.84	12.92
4	2.13	2.78	4.60	8.61
5	2.02	2.57	4.03	6.87
6	1.94	2.45	3.71	5.96
7	1.89	2.37	3.50	5.41
8	1.86	2.31	3.36	5.04
9	1.83	2.26	3.25	4.78
10	1.81	2.23	3.17	4.59
11	1.80	2.20	3.11	4.44
12	1.78	2.18	3.06	4.32
13	1.77	2.16	3.01	4.22
14	1.76	2.14	2.98	4.14
15	1.75	2.13	2.95	4.07
16	1.75	2.12	2.92	4.02
17	1.74	2.11	2.90	3.97
18	1.73	2.10	2.88	3.92
19	1.73	2.09	2.86	3.88
20	1.72	2.09	2.85	3.85
21	1.72	2.08	2.83	3.82
22	1.72	2.07	2.82	3.79
23	1.71	2.07	2.82	3.77
24	1.71	2.06	2.80	3.75
25	1.71	2.06	2.79	3.73
26	1.71	2.06	2.78	3.71
27	1.70	2.05	2.77	3.69
28	1.70	2.05	2.76	3.67
29	1.70	2.05	2.76	3.66
30	1.70	2.04	2.75	3.65
40	1.68	2.02	2.70	3.55
60	1.67	2.00	2.66	3.46

120	1.66	1.98	2.62	3.37
infinity	1.65	1.96	2.58	3.29