

Statistical Inference

4

Outline

1. Introduction
2. Confidence intervals
 - Sample size
3. Hypothesis testing
 - Generalities
 - Critical region and p -value
 - Confidence intervals and hypothesis tests
 - Particular tests



Introduction

Statistical Inference is a prediction process that leads us to conclusions about a population from information extracted from a sample.

We have studied a number of distribution models depending on one or several parameters, now we will learn how can we **estimate** such parameters.

Introduction

A **statistical hypothesis** is a conjecture about a population distribution. This hypothesis is to be tested using the information from a sample.

Interval-valued estimators of parameters (**Confidence Intervals**) are also considered here.

Basic concepts

- A **random sample** is composed by n independent random variables with the **same distribution** X_1, X_2, \dots, X_n
- A **statistic** is any transformation (function) of the observations of the random sample. Consequently, it is a random variable $f(X_1, X_2, \dots, X_n)$.

Basic concepts

- An **estimator** of a parameter θ is any function from the sample

$$\hat{\theta} = f(X_1, X_2, \dots, X_n)$$

that assumes values close to the one of θ .

It is a statistic, and it is used to estimate θ .

It is said to be **unbiased** if

$$E[\hat{\theta}] = \theta$$

Distribution of the sample mean

- The sample mean

$$\bar{X} = \frac{X_1 + X_2 + \cdots + X_n}{n}$$

is a natural estimator of the population mean μ .

It is unbiased with variance σ^2/n , where σ is the standard deviation of X .

Distribution of the sample mean

In accordance with the CLT, for any distribution of X , whenever the sample size n is sufficiently large

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \approx N(0,1)$$

Distribution of the sample mean

□ Distribution of the sample proportion.

We denote by p the population proportion of individuals with a certain characteristic. The r.v. X that assumes value 1 on individuals with the characteristic and 0 on the remaining individuals follows a $B(1,p)$ distribution

$$\hat{p} = \frac{\text{number of individuals from the sample with the characteristic}}{\text{sample size}} = \frac{\sum_{i=1}^n X_i}{n} = \bar{X}$$

$$E[\hat{p}] = p ; \text{Var}[\hat{p}] = \frac{p(1-p)}{n}$$

If $n > 30$ and $np(1-p) > 5$, we can apply the CLT.

Distribution of the sample variance

- The **sample variance** is an unbiased estimator of the population variance (σ^2)

$$S^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$$

Addendum: Chi-square distribution

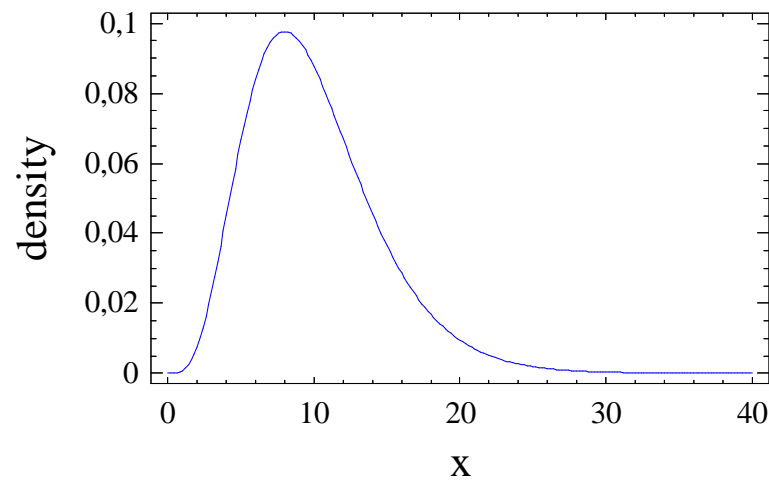
Given n independent standard Normal random variables X_1, X_2, \dots, X_n , the random variable $Y = X_1^2 + X_2^2 + \dots + X_n^2$ follows a **Chi-square distribution** with n degrees of freedom,

$$Y \sim \chi_n^2$$

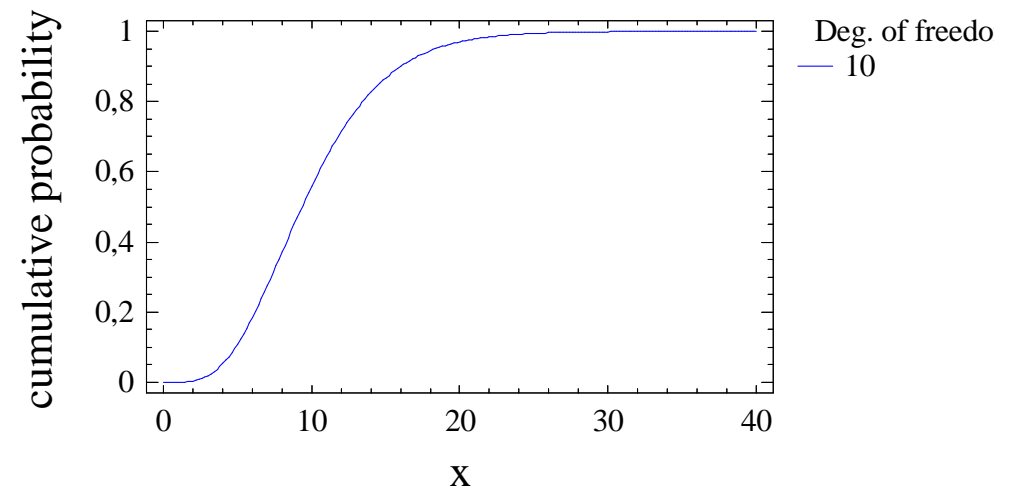
$$E[Y] = n \ ; \ \text{Var}[Y] = 2n$$

Addendum: Chi-square distribution

Chi-Square Distribution



Chi-Square Distribution



Sampling distributions for normal populations

- **Distribution of the sample variance.** When the sample is taken from a normal population,

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

We have then

$$\text{Var}[S^2] = 2\sigma^4/(n-1)^2$$

Addendum: Student's t distribution

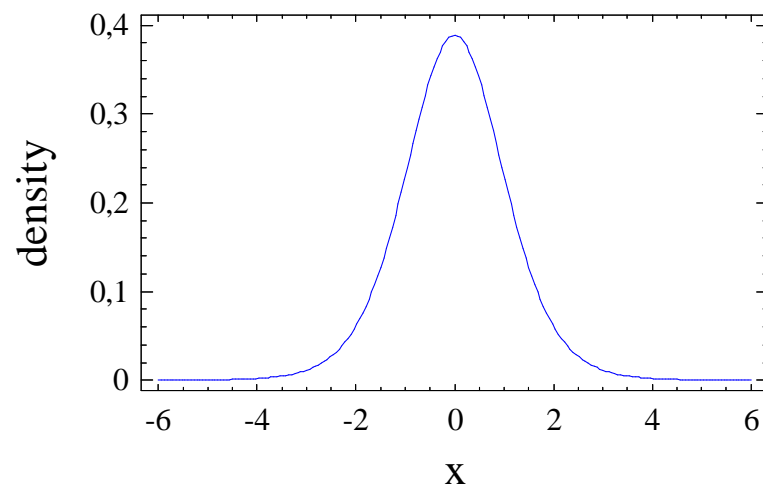
Given a standard normal random variable X and Y indep. of X following a chi-square distribution with n degrees of freedom, the random variable $X/(Y/n)^{1/2}$ follows a **distribution t** with n degrees of freedom

$$Z = \frac{X}{\sqrt{Y/n}} \sim t_n$$

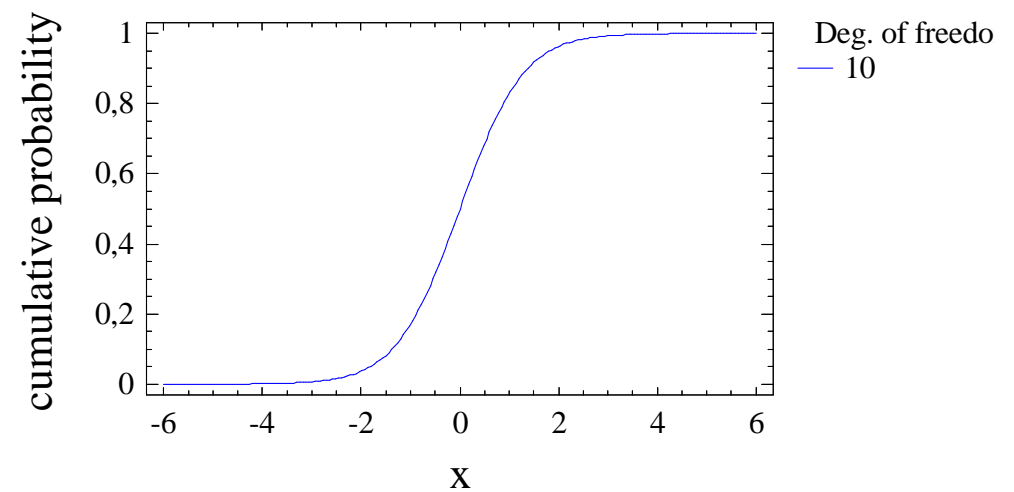
$$E[Z] = 0 \text{ if } n \geq 2 ; \text{ Var}[Z] = n/(n-2) \text{ if } n \geq 3$$

Addendum: Student's t distribution

Student's t Distribution



Student's t Distribution



Sampling distributions for normal populations

- **Distribution of the sample mean with unknown variance.** When the sample is taken from a normal population with unknown variance, we replace it by the sample variance to obtain

$$\frac{\bar{X} - \mu}{\sqrt{S^2/n}} \sim t_{n-1}$$

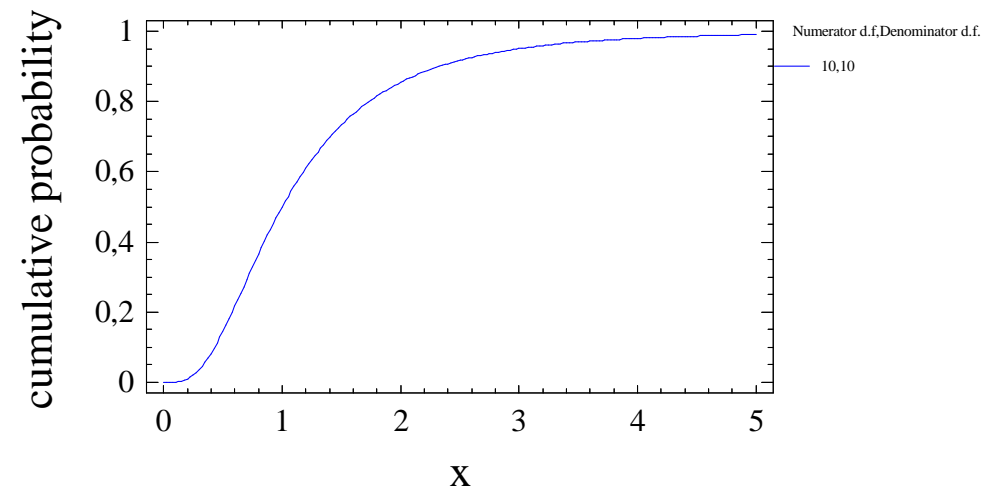
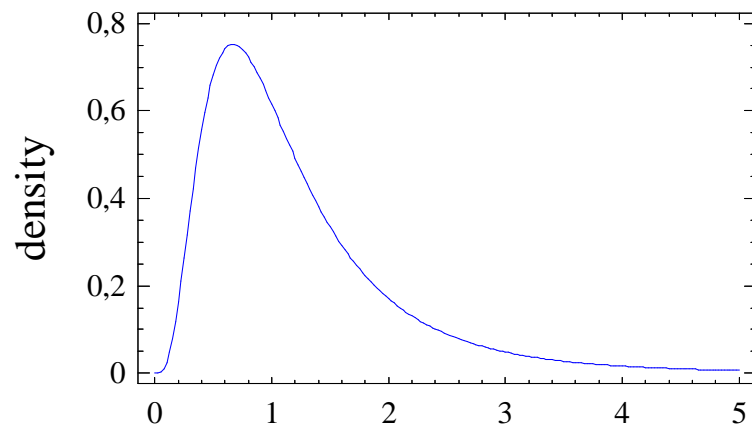
Addendum: Fisher's F distribution

Given two independent chi-square random variables X and Y such that X has n_1 degrees of freedom and Y has n_2 degrees of freedom, the random variable $(X/n_1)/(Y/n_2)$ follows a **F distribution** with n_1 and n_2 degrees of freedom

$$Z = \frac{X / n_1}{Y / n_2} \sim F_{n_1, n_2}$$

Addendum: Fisher's F distribution

F (variance ratio) Distribution



Sampling distributions for normal populations

- **Variance ratio.** When two independent samples (sample from X and sample from Y) of respective sizes n and m are taken from two normal populations, the ratio of their sample variances follows an F distribution with $n-1$ and $m-1$ degrees of freedom

$$\frac{S_X^2 / \sigma_X^2}{S_Y^2 / \sigma_Y^2} \sim F_{n-1, m-1}$$

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Confidence Intervals

- For any fixed probability $1-\alpha$ and a random sample X_1, X_2, \dots, X_n we build a (random) interval containing a parameter θ with probability $1-\alpha$. The extreme values of the interval will be based on estimators of θ .

A **Confidence Interval** with **confidence coefficient** (or **level**) $1-\alpha$ is obtained substituting the estimators of θ by its estimation.

Confidence Intervals

□ Building a Confidence Interval.

Our aim is to find two statistics such that

$$P\left(\hat{\theta}_1(X_1, X_2, \dots, X_n) < \theta < \hat{\theta}_2(X_1, X_2, \dots, X_n)\right) = 1 - \alpha$$

Consider any estimator of θ with a known distribution (e.g. normal), then we have

$$P\left(\hat{\theta} - \sigma_{\hat{\theta}} z_{\alpha/2} < \theta < \hat{\theta} + \sigma_{\hat{\theta}} z_{\alpha/2}\right) = 1 - \alpha \quad \text{if} \quad \hat{\theta} \sim N(\theta, \sigma_{\hat{\theta}})$$

Confidence Intervals

- A Confidence Interval for θ with confidence level $1-\alpha$ built from a statistic with a normal distribution will be of the following type:

$$\theta \in \left[\hat{\theta} - \sigma_{\hat{\theta}} z_{\alpha/2}, \hat{\theta} + \sigma_{\hat{\theta}} z_{\alpha/2} \right]$$

where $P(Z > z_{\alpha/2}) = \alpha/2$ for $Z \sim N(0,1)$.

Confidence Intervals

- **Choice of sample size.** A confidence interval for θ is of the form

$$\left[\hat{\theta} - a, \hat{\theta} + b \right]$$

where a and b depend on

1. The confidence level ;
2. The variance of the estimator of θ ;
3. The sample size .

The variance of the estimator depends on the sample size.

Confidence Intervals

□ Choice of sample size.

For any fixed estimation error (length of the confidence interval), it is possible to determine the sample size that is needed by solving the equation

$$a+b = A ,$$

where L is the desired length for the CI.

Confidence Intervals (Examples)

1. The lifetime of an electronic device of a certain kind is normally distributed with $\sigma=1$ year. The sample mean of the lifetime of $n=10$ devices was 3.5 years. Build a 90% CI on the mean lifetime of the electronic devices of the former kind.
2. Out of a sample of $n=100$ University students, 86 of them owned a laptop. Build a 95% CI on the proportion of students owning a laptop.

Confidence Intervals (Examples)

3. The compressive strength of concrete is normally distributed. In a sample of size $n=20$, we have obtained a sample mean of 2450psi and a sample variance of 1600psi². Build a 99% CI on the mean compressive strength of concrete.
4. The percentage of titanium in an alloy used in aerospace castings is known to be normally distributed. It has been measured in $n=51$ randomly selected parts and the sample standard deviation obtained was $s=0.37$. Build a 95% CI on σ^2 .

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Testing statistical hypothesis

Hypothesis test are used to check the truth of a statement about a parameter using information from a sample.

The **null hypothesis** (H_0) is the hypothesis (statement) that we wish to test

- ‘the mean compressive strength of concrete is μ_0 ’, $H_0: \mu = \mu_0$

The null hypothesis is only rejected when there is strong evidence against it (the sample is strongly inconsistent with it).

Testing statistical hypothesis

- The **alternative hypothesis** (H_1) is the statement to be accepted when rejecting H_0
 - $H_1: \mu \neq \mu_0$
 - $H_1: \mu < \mu_0$

We will only reject the null hypothesis when the sample is strongly inconsistent with it.

Equivalently, when the sample information shows a strong evidence favourable to H_1 .

Testing statistical hypothesis

□ Types of tests

- **Two-sided:** when the estimate of the parameter is very different from the objective value (larger or smaller), we will reject the null hypothesis

$$H_0: \mu = \mu_0 ; H_1: \mu \neq \mu_0$$

- **One-sided:** we will reject the null hypothesis only when the estimate is much smaller (or much larger) than the objective value

$$H_0: \mu = \mu_0 ; H_1: \mu < \mu_0$$

Equiv. to $H_0: \mu \geq \mu_0 ; H_1: \mu < \mu_0$

Testing statistical hypothesis

- When we wonder whether we can firmly state something (guarantee it), we must write it in the alternative hypothesis.

- Q: ‘Can we state that the mean compressive strength of concrete is less than μ_0 ?’

$$H_0: \mu = \mu_0 ; H_1: \mu < \mu_0$$

- When we wonder whether we should reject something or not, we must write it in the null hypothesis.

- Q: ‘The supplier states that the mean compressive strength of concrete is μ_0 . Can we reject his statement?’

$$H_0: \mu = \mu_0 ; H_1: \mu \neq \mu_0$$

- Q: ‘The supplier suspects that the mean compressive strength of concrete is greater than μ_0 . Is there enough sample evidence to support his suspicion?’

$$H_0: \mu = \mu_0 ; H_1: \mu > \mu_0$$

Testing statistical hypothesis

□ Error types

- **Type I error:** Rejecting the null hypothesis (H_0) when it is true,

$$\alpha = P(\text{Type I error}) = P(\text{reject } H_0 | H_0)$$

this error is crucial, α (significance level) is fixed.

- **Type II error:** Failing to reject the null hypothesis (H_0) when it is false,

$$\beta = P(\text{Type II error}) = P(\text{fail to reject } H_0 | H_1)$$

this second error is not that important.

Test Statistic

- A **test statistic** is based on an estimator of our parameter of interest θ and, under the assumption that the null hypothesis is true, its distribution is known.

if $H_0 : \theta = \theta_0$ we are interested in the distance $d(\hat{\theta}, \theta_0)$

- The values of the test statistic that lead us to rejection of the null hypothesis depend on the alternative hypothesis.

Test Statistic

□ In the test

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta \neq \theta_0$$

Reject H_0 for large and small values of the statistic

□ In the test

$$H_0 : \theta \leq \theta_0$$

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta > \theta_0$$

$$H_1 : \theta > \theta_0$$

Reject H_0 for large values of the statistic

$\hat{\theta} - \theta_0$ sign does matter.

Rejection region

- The set of values of the test statistic that are strongly inconsistent with the null hypothesis and lead us to its rejection depend on the **significance level α** .
- The significance level α is the probability of type I error that we agree to assume.

Commonly $\alpha = 0.01$ or 0.05

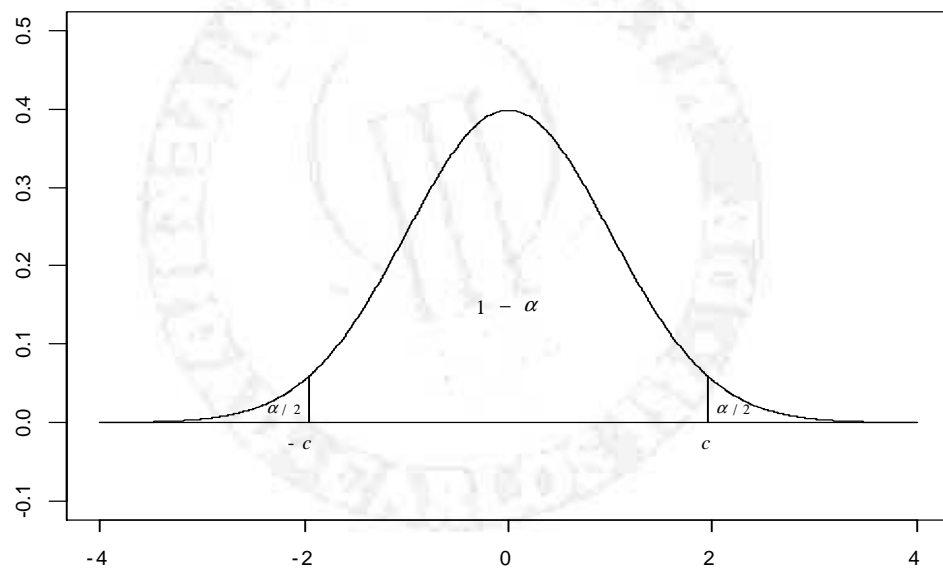
Rejection region

□ For a given α , we have $P(\text{reject } H_0 | H_0) = \alpha$

Distribution of the estimator of θ known (under H_0)

In the test $H_0: \theta = \theta_0 ; H_1: \theta \neq \theta_0$

Distribución del estimador



Reject H_0 if

$$d(\hat{\theta}, \theta_0) = |\hat{\theta} - \theta_0| > c$$

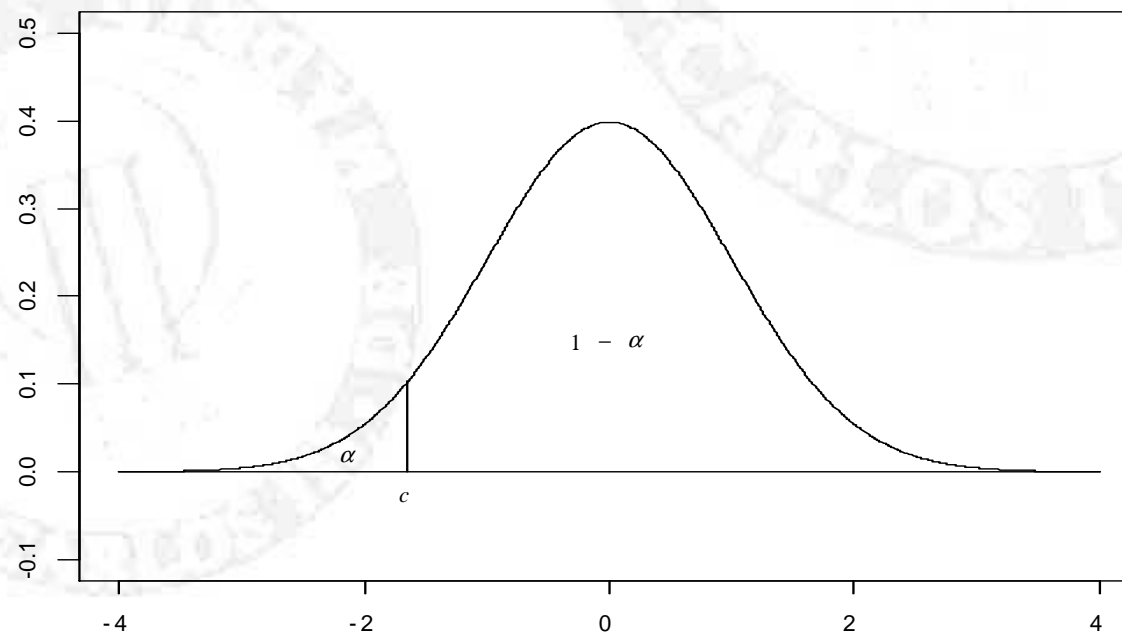
The value c determines the rejection region.

Rejection region

In the test $H_0: \theta = \theta_0$; $H_1: \theta < \theta_0$

Reject H_0 if $d(\hat{\theta}, \theta_0) = \hat{\theta} - \theta_0 < c$

Distribución del estimador



Procedure for Hypothesis Tests

- From the problem context, identify the parameter of interest
- State the null hypothesis H_0
- Specify an appropriate alternative hypothesis H_1
- Choose a significance level α
- Determine an appropriate test statistic
- State the rejection region for the statistic
- Compute any necessary sample quantities, substitute these into the equation for the test statistic
- Decide whether or not H_0 should be rejected and report that in the problem context

p-value

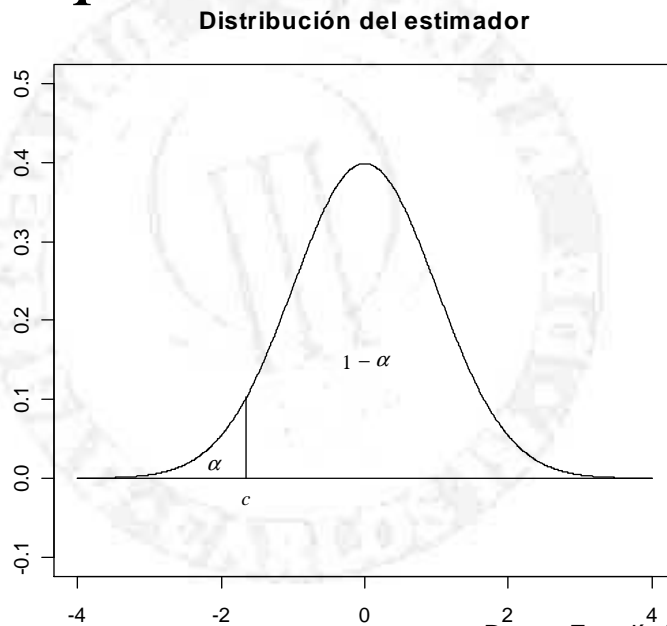
The *p*-value is the smallest level of significance that would lead to rejection of the null hypothesis H_0 with the given data.

It is the probability of a random sample that is more inconsistent with H_0 than ours (assuming the truth of H_0).

p-value

The smaller the *p*-value is, the more confident we are that the null hypothesis is wrong.

For a *p*-value smaller than 0.05, H_0 is rejected.



In the test

$H_0: \theta = \theta_0 ; H_1: \theta < \theta_0$

the *p*-value is α such

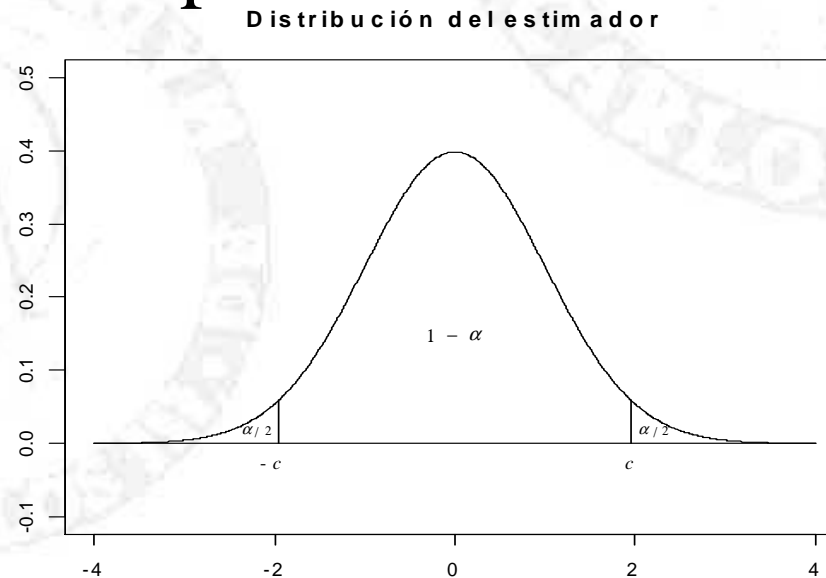
that the statistic c

assumes the same value

as in our sample.

p-value

In the test $H_0: \theta = \theta_0$; $H_1: \theta \neq \theta_0$ the *p*-value is α such that the statistic c (or $-c$) assumes the same value as in our sample.



CIs versus Hypothesis tests

- Given a two-sided test

$$H_0: \theta = \theta_0 ; H_1: \theta \neq \theta_0$$

with significance level α , the null hypothesis is rejected if θ_0 does not belong to the Confidence Interval for θ with confidence level $1-\alpha$.

Particular tests

- Test on the mean of a normal population (or large sample) with known variance

- **Null hypothesis.** $H_0: \mu = \mu_0$

- **Alternative hypothesis.** $H_1: \mu \neq \mu_0$
 - Reject H_0 if $\left| \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} \right| > z_{\alpha/2}$

- **Alternative hypothesis.** $H_1: \mu < \mu_0$
 - Reject H_0 if $\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} < -z_\alpha$

- **Alternative.** $H_1: \mu > \mu_0$
 - Reject H_0 if $\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} > z_\alpha$

Particular Confidence Intervals

- Confidence Interval on the mean of a normal population (or large sample) with known variance

$$\mu \in \left[\bar{x} - z_{\alpha/2} \sigma / \sqrt{n}, \bar{x} + z_{\alpha/2} \sigma / \sqrt{n} \right]$$

confidence level $1 - \alpha$,

where $P(Z > z_{\alpha}) = \alpha$ if $Z \sim N(0,1)$

Particular tests

□ Test on a proportion

■ **Null hypothesis.** $H_0: p = p_0$

■ **Alternative hypothesis.** $H_1: p \neq p_0$

□ Reject H_0 if

$$\left| \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}} \right| > z_{\alpha/2}$$

■ **Alternative hypothesis.** $H_1: p < p_0$

□ Reject H_0 if

$$\frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}} < -z_{\alpha}$$

■ **Alternative hypothesis.** $H_1: p > p_0$

□ Reject H_0 if

$$\frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}} > z_{\alpha}$$

Particular Confidence Intervals

- Confidence Interval on a proportion

$$p \in \left[\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \right]$$

confidence level $1-\alpha$,

where $P(Z > z_{\alpha}) = \alpha$ if $Z \sim N(0,1)$

Particular tests

□ Test on the mean of a normal population with unknown variance

■ **Null hypothesis.** $H_0: \mu = \mu_0$

■ **Alternative hypothesis.** $H_1: \mu \neq \mu_0$
□ Reject H_0 if $\left| \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \right| > t_{n-1, \alpha/2}$

■ **Alternative hypothesis.** $H_1: \mu < \mu_0$
□ Reject H_0 if $\frac{\bar{x} - \mu_0}{s/\sqrt{n}} < -t_{n-1, \alpha}$

■ **Alternative hypothesis.** $H_1: \mu > \mu_0$
□ Reject H_0 if $\frac{\bar{x} - \mu_0}{s/\sqrt{n}} > t_{n-1, \alpha}$

Particular Confidence Intervals

- Confidence Interval on the mean of a normal population with unknown variance.

$$\mu \in \left[\bar{x} - t_{n-1, \alpha/2} \frac{s}{\sqrt{n}}, \bar{x} + t_{n-1, \alpha/2} \frac{s}{\sqrt{n}} \right]$$

confidence level $1-\alpha$,

where $P(X > t_{n, \alpha}) = \alpha$ if $X \sim t_n$

Particular tests

□ Test on the variance of a normal population

- **Null hypothesis.** $H_0: \sigma^2 = \sigma_0^2$
- **Alternative hypothesis.** $H_1: \sigma^2 \neq \sigma_0^2$
 - Reject H_0 if $\frac{(n-1)s^2}{\sigma_0^2} < \chi_{n-1,1-\alpha/2}^2$ or $\frac{(n-1)s^2}{\sigma_0^2} > \chi_{n-1,\alpha/2}^2$
- **Alternative hypothesis.** $H_1: \sigma^2 < \sigma_0^2$
 - Reject H_0 if $\frac{(n-1)s^2}{\sigma_0^2} < \chi_{n-1,1-\alpha}^2$
- **Alternative hypothesis.** $H_1: \sigma^2 > \sigma_0^2$
 - Reject H_0 if $\frac{(n-1)s^2}{\sigma_0^2} > \chi_{n-1,\alpha}^2$

Particular Confidence Intervals

- Confidence Interval on the variance of a normal population

$$\sigma^2 \in \left[\frac{(n-1)s^2}{\chi_{n-1, \alpha/2}^2}, \frac{(n-1)s^2}{\chi_{n-1, 1-\alpha/2}^2} \right]$$

confidence level $1-\alpha$,

where $P(X > \chi_{n, \alpha}^2) = \alpha$ if $X \sim \chi_n^2$

Particular tests

- Test on the difference in means of two normal populations (large samples) with known variances

- **Null hypothesis.** $H_0: \mu_1 = \mu_2$

- **Alternative hypothesis.** $H_1: \mu_1 \neq \mu_2$
 - Reject H_0 if
$$\left| \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}} \right| > z_{\alpha/2}$$

- **Alternative hypothesis.** $H_1: \mu_1 < \mu_2$

- Reject H_0 if
$$\frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}} < -z_\alpha$$

- **Alternative hypothesis.** $H_1: \mu_1 > \mu_2$

- Reject H_0 if
$$\frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}} > z_\alpha$$

Particular Confidence Intervals

- Confidence Interval on the difference in means of two normal populations (or large samples) with known variances

$$\mu_1 - \mu_2 \in \left[\bar{x}_1 - \bar{x}_2 - z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}, \bar{x}_1 - \bar{x}_2 + z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \right]$$

confidence level $1-\alpha$,

where $P(Z > z_\alpha) = \alpha$ if $Z \sim N(0,1)$

Particular tests

$$\hat{p}_0 = \frac{n_1 \hat{p}_1 + n_2 \hat{p}_2}{n_1 + n_2}$$

- Test on the difference in proportions of two populations (independent samples)

- **Null hypothesis.** $H_0: p_1 = p_2$

- **Alternative hypothesis.** $H_1: p_1 \neq p_2$

- Reject H_0 if

- **Alternative hypothesis.** $H_1: p_1 < p_2$

- Reject H_0 if

- **Alternative hypothesis.** $H_1: p_1 > p_2$

- Reject H_0 if

$$\left| \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}_0(1-\hat{p}_0)(1/n_1+1/n_2)}} \right| > z_{\alpha/2}$$

$$\frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}_0(1-\hat{p}_0)(1/n_1+1/n_2)}} < -z_{\alpha}$$

$$\frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}_0(1-\hat{p}_0)(1/n_1+1/n_2)}} > z_{\alpha}$$

Particular Confidence Intervals

- Confidence Interval on the difference in proportions for two populations (independent samples).

$$p_1 - p_2 \in \left[\hat{p}_1 - \hat{p}_2 - z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}, \hat{p}_1 - \hat{p}_2 + z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}} \right]$$

confidence level $1-\alpha$,

where $P(Z > z_\alpha) = \alpha$ if $Z \sim N(0,1)$

Particular tests

- Approximate test on the difference in means of two normal populations with unknown unequal variances (indep. samples)
 - **Null hypothesis.** $H_0: \mu_1 = \mu_2$
 - **Alternative hypothesis.** $H_1: \mu_1 \neq \mu_2$ $\left| \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} \right| > z_{\alpha/2}$
 - Reject H_0 if
 - **Alternative hypothesis.** $H_1: \mu_1 < \mu_2$ $\frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} < -z_\alpha$
 - Reject H_0 if
 - **Alternative hypothesis.** $H_1: \mu_1 > \mu_2$ $\frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} > z_\alpha$
 - Reject H_0 if

Particular Confidence Intervals

- Approximate Confidence Interval on the difference in means of two normal populations, unknown unequal variances (indep. samples)

$$\mu_1 - \mu_2 \in \left[\bar{x}_1 - \bar{x}_2 - z_{\alpha/2} \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}, \bar{x}_1 - \bar{x}_2 + z_{\alpha/2} \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} \right]$$

confidence level $1-\alpha$,

where $P(Z > z_\alpha) = \alpha$ if $Z \sim N(0,1)$

Particular tests

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$$

- Test on the difference in means of two normal populations with unknown equal variances

- **Null hypothesis.** $H_0: \mu_1 = \mu_2$

- **Alternative hypothesis.** $H_1: \mu_1 \neq \mu_2$

- Reject H_0 if

$$\left| \frac{\bar{x}_1 - \bar{x}_2}{s_p \sqrt{1/n_1 + 1/n_2}} \right| > t_{n_1 + n_2 - 2, \alpha/2}$$

- **Alternative hypothesis.** $H_1: \mu_1 < \mu_2$

- Reject H_0 if

$$\frac{\bar{x}_1 - \bar{x}_2}{s_p \sqrt{1/n_1 + 1/n_2}} < -t_{n_1 + n_2 - 2, \alpha}$$

- **Alternative hypothesis.** $H_1: \mu_1 > \mu_2$

- Reject H_0 if

$$\frac{\bar{x}_1 - \bar{x}_2}{s_p \sqrt{1/n_1 + 1/n_2}} > t_{n_1 + n_2 - 2, \alpha}$$

Particular Confidence Intervals

- Confidence Interval on the difference in means of two normal populations with unknown equal variances (indep. samples)

$$\mu_1 - \mu_2 \in \left[\bar{x}_1 - \bar{x}_2 - t_{n_1+n_2-2, \alpha/2} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}, \bar{x}_1 - \bar{x}_2 + t_{n_1+n_2-2, \alpha/2} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} \right]$$

confidence level $1-\alpha$,

where $P(X > t_{n, \alpha}) = \alpha$ if $X \sim t_n$

Particular tests

$$s_d^2 = \frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}$$

□ Test on the difference in means of two normal populations (paired data), $d = x_1 - x_2$

■ Null hypothesis. $H_0: \mu_d = 0$

■ Alternative hypothesis. $H_1: \mu_d \neq 0$

□ Reject H_0 if

■ Alternative hypothesis. $H_1: \mu_d < 0$

□ Reject H_0 if

■ Alternative hypothesis. $H_1: \mu_d > 0$

□ Reject H_0 if

$$\left| \frac{\bar{d}}{s_d / \sqrt{n}} \right| > t_{n-1, \alpha/2}$$

$$\frac{\bar{d}}{s_d / \sqrt{n}} < -t_{n-1, \alpha}$$

$$\frac{\bar{d}}{s_d / \sqrt{n}} > t_{n-1, \alpha}$$

Particular Confidence Intervals

- Confidence Interval on the difference in means of two normal populations with unknown variances (paired data)

$$\mu_1 - \mu_2 \in \left[\bar{d} - t_{n-1, \alpha/2} \frac{s_d}{\sqrt{n}}, \bar{d} + t_{n-1, \alpha/2} \frac{s_d}{\sqrt{n}} \right]$$

confidence level $1 - \alpha$,

where $P(X > t_{n, \alpha}) = \alpha$ if $X \sim t_n$

Particular tests

□ Test on the ratio of the variances of two normal populations

■ **Null hypothesis.** $H_0: \sigma_1^2 = \sigma_2^2$

■ **Alternative hypothesis.** $H_1: \sigma_1^2 \neq \sigma_2^2$

□ Reject H_0 if $\frac{s_1^2}{s_2^2} < F_{n_1-1, n_2-1, 1-\alpha/2}$ or $\frac{s_1^2}{s_2^2} > F_{n_1-1, n_2-1, \alpha/2}$

■ **Alternative hypothesis.** $H_1: \sigma_1^2 < \sigma_2^2$

□ Reject H_0 if $\frac{s_1^2}{s_2^2} < F_{n_1-1, n_2-1, 1-\alpha}$

■ **Alternative hypothesis.** $H_1: \sigma_1^2 > \sigma_2^2$

□ Reject H_0 if $\frac{s_1^2}{s_2^2} > F_{n_1-1, n_2-1, \alpha}$

Particular Confidence Intervals

- Confidence Interval on the variance ratio of two normal populations.

$$\frac{\sigma_1^2}{\sigma_2^2} \in \left[\frac{s_1^2}{s_2^2} F_{n_2-1, n_1-1, 1-\alpha/2}, \frac{s_1^2}{s_2^2} F_{n_2-1, n_1-1, \alpha/2} \right]$$

confidence level $1-\alpha$,

where $P(X > F_{n_1-1, n_2-1, \alpha}) = \alpha$ if $X \sim F_{n_1-1, n_2-1}$

$$F_{n_2-1, n_1-1, 1-\alpha} = 1/F_{n_1-1, n_2-1, \alpha}$$

Particular tests

$$\hat{\lambda} = \bar{x} \quad ; \quad \hat{\sigma}_{\hat{\lambda}}^2 = \bar{x}/n$$

□ Test on the λ in a Poisson model

■ **Null hypothesis.** $H_0: \lambda = \lambda_0$

■ **Alternative hypothesis.** $H_1: \lambda \neq \lambda_0$

□ Reject H_0 if

$$\left| \frac{\bar{x} - \lambda_0}{\sqrt{\bar{x}/n}} \right| > z_{\alpha/2}$$

■ **Alternative hypothesis.** $H_1: \lambda < \lambda_0$

□ Reject H_0 if

$$\frac{\bar{x} - \lambda_0}{\sqrt{\bar{x}/n}} < -z_{\alpha}$$

■ **Alternative hypothesis.** $H_1: \lambda > \lambda_0$

□ Reject H_0 if

$$\frac{\bar{x} - \lambda_0}{\sqrt{\bar{x}/n}} > z_{\alpha}$$

Particular Confidence Intervals

- Approximate Confidence Interval on the λ in a Poisson population

$$\lambda \in \left[\bar{x} - z_{\alpha/2} \sqrt{\bar{x}/n}, \bar{x} + z_{\alpha/2} \sqrt{\bar{x}/n} \right]$$

confidence level $1-\alpha$,

where $P(Z > z_{\alpha}) = \alpha$ if $Z \sim N(0,1)$