

Optimization weekly meeting

May 4, 2006

Chapter 4:

Hypothesis Testing and Estimation

Empirical Methods for
Artificial Intelligence

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IRIDIA - ULB
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Outline

what we did in part 1 and what we have to do in part 2

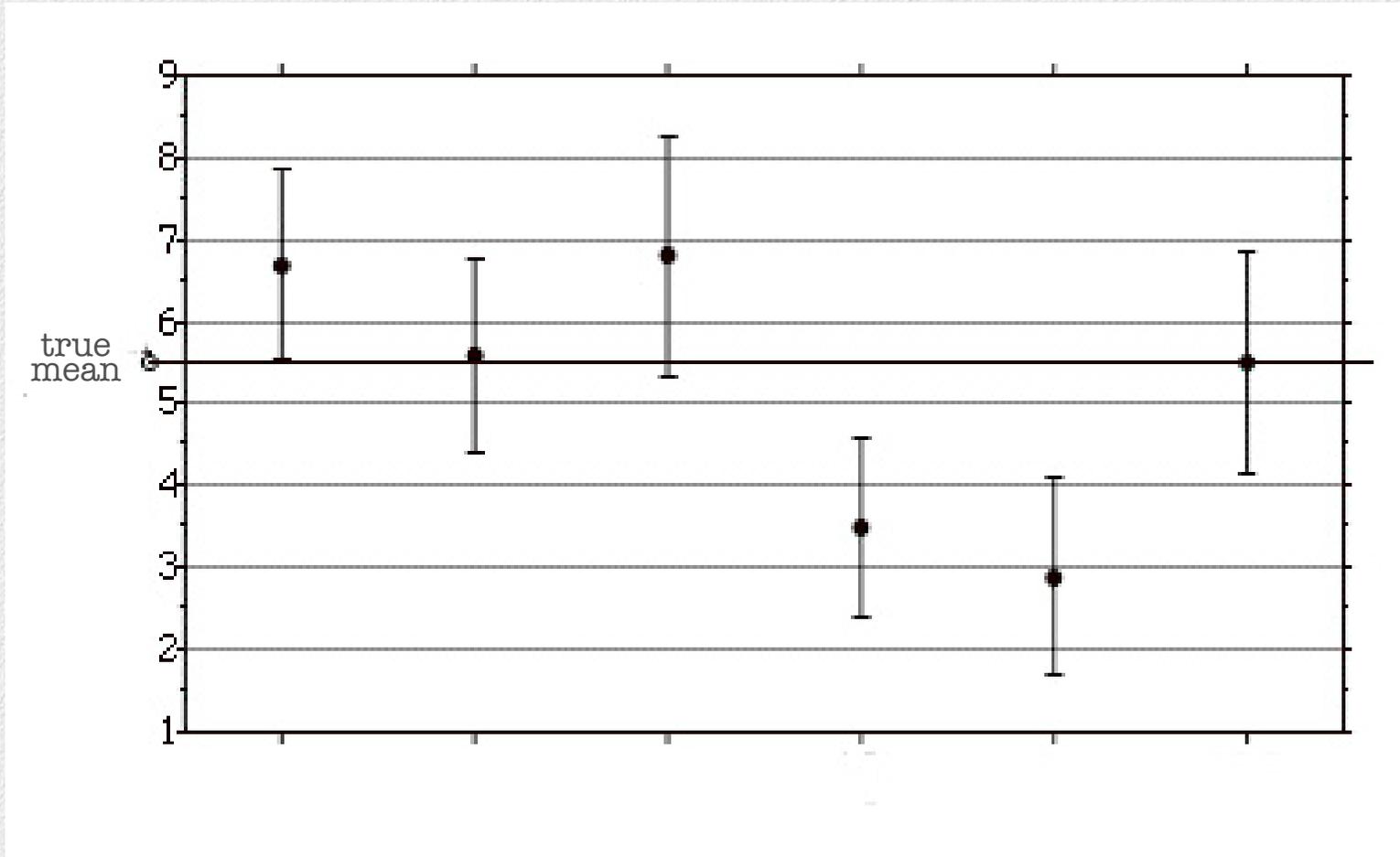
- Statistical Inference
- Introduction to Hypothesis Testing
- Sampling Distributions and Hypothesis Testing Strategy
- Test of Hypotheses about Means
- Hypothesis about Correlations
- Parameter Estimation and Confidence Intervals
- How big Should Samples Be?
- Errors
- Power Curves and How to Get Them

Outline

part 2

- Parameter Estimation and Confidence Intervals
- How big Should Samples Be?
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A **confidence interval** gives an estimated range of values (calculated from a given set of sample data) which is likely to include an unknown population parameter like μ_x , σ^2 , σ

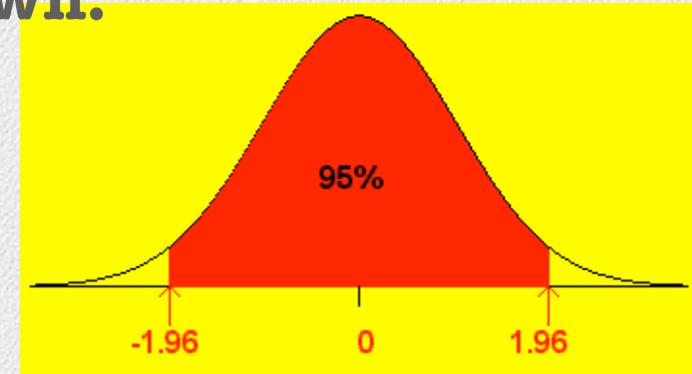


Java applet to demo confidence intervals for means

http://www.math.csusb.edu/faculty/stanton/m262/confidence_means/confidence_means.html

Confidence intervals for μ when σ is known:

$\bar{x} = \mu \pm 1.96\sigma_{\bar{x}}$ for 95% of the means \bar{x}



If $\epsilon = 1.96\sigma_{\bar{x}}$ the confidence interval $\bar{x} \pm \epsilon$ will contain μ in 95% of the samples we draw.

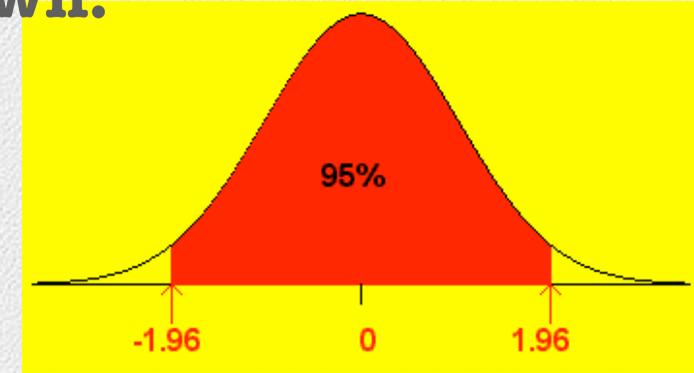
Confidence intervals for μ when σ is unknown:

$\bar{x} = \mu \pm t_{0.025}\hat{\sigma}_{\bar{x}}$ for 95% of the means \bar{x}

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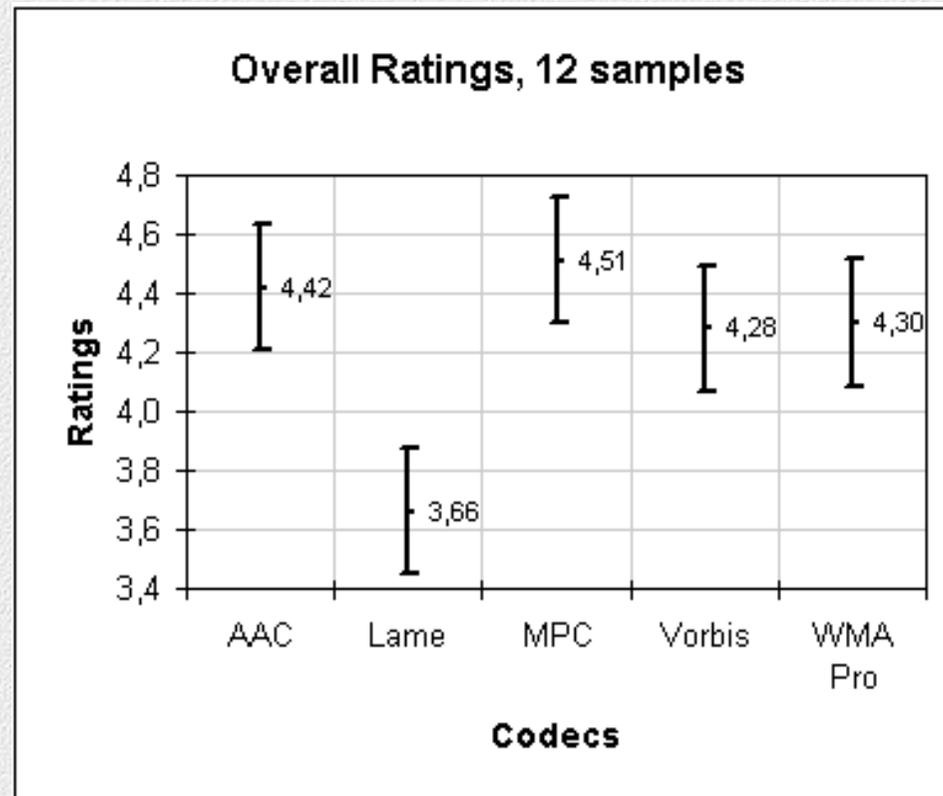
Confidence intervals

Because confidence intervals depend on standard errors, they are affected by sample size.

In general, one shouldn't use confidence intervals to test hypotheses if the confidence intervals overlap.

Confidence interval for means are estimated from standard errors of individual means, while two-sample t-test relies on standard error of the difference between the means.

Different sampling distribution and standard errors are involved.



Outline

part 2

- Parameter Estimation and Confidence Intervals
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In parameter estimation if we increase the sample size and the sample variance doesn't increase (a reasonable assumption), then the confidence interval narrows.

(Our confidence in the estimate doesn't change, but the range of the estimate reduces)

In hypothesis testing, by contrast, the only thing that changes when increasing the sample size is our confidence in the conclusion.

(so if our sample is large enough to make us confident, nothing is gained by having a larger sample)

Samples can be too big for hypothesis testing.

Any real statistical effect can be boosted to significance by increasing N.

$$\bar{x} = \mu \pm t_{0.025} \hat{\sigma}_{\bar{x}}$$

(this is because the standard error of any statistic is reduced by increasing N)

One can obtain $\bar{x}_1 \neq \bar{x}_2$ in a statistical significant way by increasing N.

The whole point of statistical inference is to go beyond sample results to say something about populations, to predict future results.

Outline

part 2

Parameter Estimation and Confidence Intervals

How big Should Samples Be?

Errors



Power Curves and How to Get Them



In hypothesis testing:

	reject H_0	don't reject H_0
if H_0 true	type I error	
if H_1 true		type II error

In hypothesis testing:

reject H_0

don't reject H_0

if H_0 true

Type I error

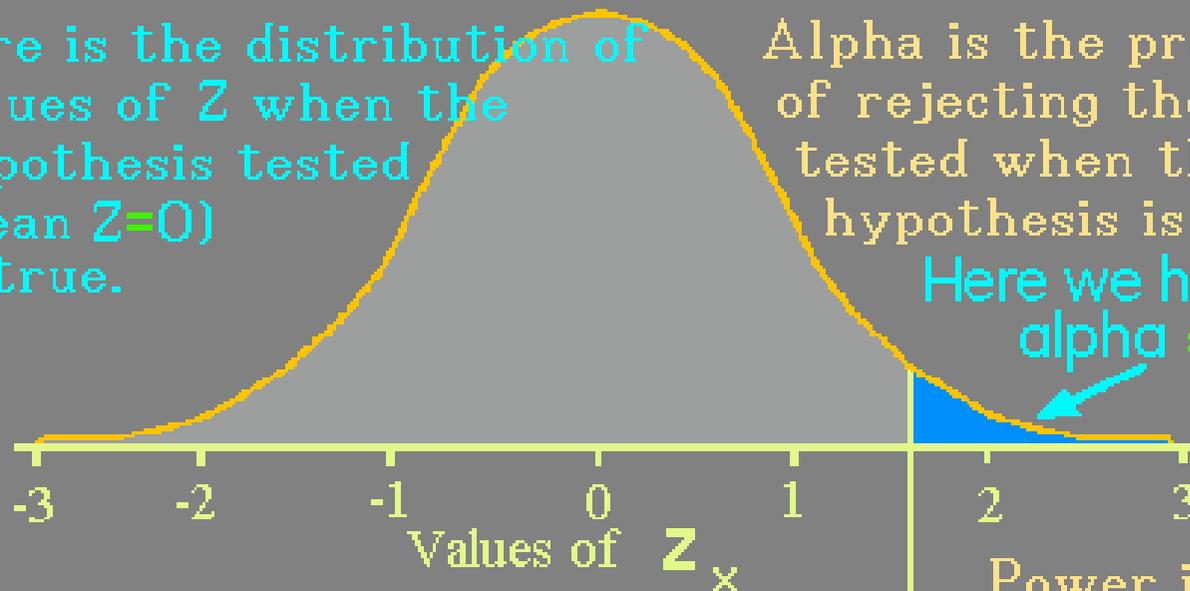
$$\alpha = \Pr(\text{type I error}) = \Pr(\text{Reject } H_0 \mid H_0 \text{ is true})$$

if H_1 true

Type II error

$$\beta = \Pr(\text{type II error}) = \Pr(\text{Fail to reject } H_0 \mid H_0 \text{ is false})$$

Here is the distribution of values of Z when the hypothesis tested (mean $Z=0$) is true.

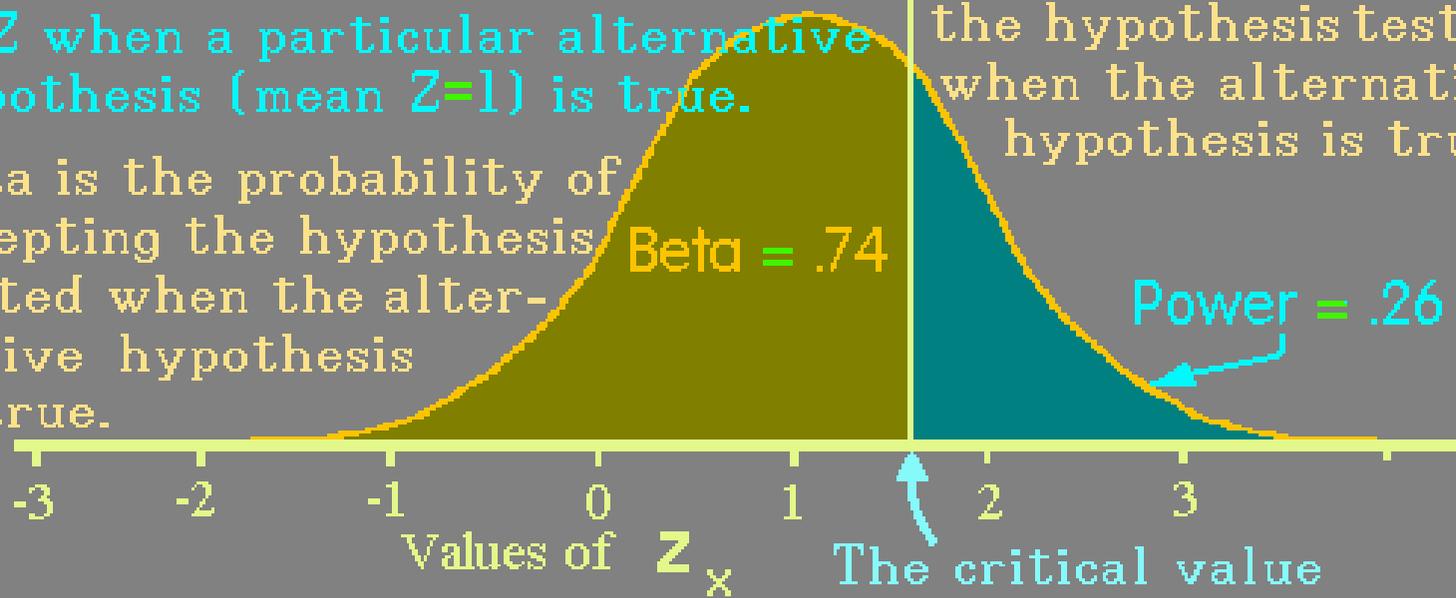


Alpha is the probability of rejecting the hypothesis tested when that hypothesis is true.

Here we have set $\alpha = .05$

Here is the distribution of values of Z when a particular alternative hypothesis (mean $Z=1$) is true.

Beta is the probability of accepting the hypothesis tested when the alternative hypothesis is true.



Power is the probability of rejecting the hypothesis tested when the alternative hypothesis is true.

Power = .26

The critical value of Z is +1.65.

<http://www.animatedsoftware.com/statglos/sgbeta.htm>

Here is the distribution of values of Z when the hypothesis tested (mean $Z=0$) is true.

Alpha is the probability of rejecting the hypothesis tested when that hypothesis is true.

Here we have set $\alpha = .05$



If the variance of the sampling distribution are small, you decrease the probability of both type I and type II errors.
To do so, increase the sample size

Power is the probability of rejecting the hypothesis tested when the alternative hypothesis is true.

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ive

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Power = .26

The critical value of Z is +1.65.

<http://www.animatedsoftware.com/statglos/sgbeta.htm>

Outline

part 2

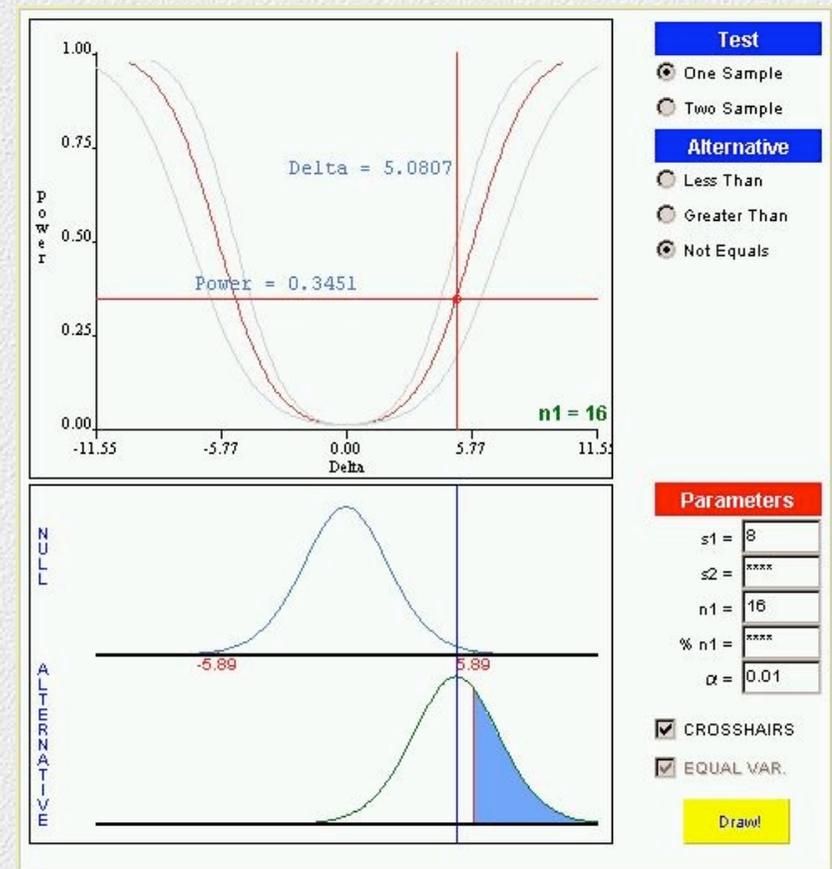
- Parameter Estimation and Confidence Intervals
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The power of a test depends on:

- the α level of the test;
- the degree of separation between H_0 and H_1 distributions;
- the variances of the populations from which samples are drawn;
- sample size N

Power curves plot power against changes in one of these factors.

<http://www.amstat.org/publications/jse/v11n3/anderson-cook.html>





Demo

R File Edit Format Workspace Packages & Data Misc Window Help 100% (Charged) Tue 2:14 PM stefano iacus

R Console

```

rgl.sr> ylen <- ylim[2] - ylim[1] + 1
rgl.sr> colorlut <- terrain.colors(ylen)
rgl.sr> col <- colorlut[y - ylim[1] + 1]
rgl.sr> rgl.clear()
rgl.sr> rgl.surface(x, z, y, color = col)

```

R Data Editor

height	weight
58	115
59	117
60	120
61	123
62	126
63	129
64	132
65	135
66	139
67	142
68	146
69	150
70	154
71	159
72	164

Quartz (2) - Active

Given : depth

R Workspace Browser

Object	Type	Structure
dati	data.frame	dim: 20 4
g	factor	levels: 10
l	numeric	length: 12
n	numeric	length: 1
opar	list	length: 2
pie.sales	numeric	length: 6
pin	numeric	length: 2
scale	numeric	length: 1
usr	numeric	length: 4
women	data.frame	dim: 15 2
height	numeric	length: 15
weight	numeric	length: 15
x	numeric	length: 87

R Package Manager

status	Package	Description
<input checked="" type="checkbox"/> loaded	graphics	The R Graphics Package
<input type="checkbox"/> not loaded	grid	The Grid Graphics Package
<input type="checkbox"/> not loaded	lattice	Lattice Graphics
<input checked="" type="checkbox"/> loaded	methods	Formal Methods and Classes
<input type="checkbox"/> not loaded	mvn	CAMx with CCV smoothness estimation

RGL device 1 (active)

```

BoxDens=function(data, npts = 200., x = c(0., 1.),
  add = TRUE, col = 11., border=FALSE, collin
{
  dens <- density(data, n = npts)
  dx <- dens$x
  dy <- dens$y
  if(add == FALSE)
    plot(0., 0., axes = F, main = "", xlim = x, ylim = y,
      ylab = "")
  if(orientation == "paysage") {
    dx2 <- (dx - min(dx))/(max(dx) - min(dx)) * (x[2.] - x[1.])
    dy2 <- (dy - min(dy))/(max(dy) - min(dy)) * (y[2.] - y[1.])
    seqbelow <- rep(y[1.], length(dx))
    if(Fill == T)
      confshade(dx2, seqbelow, dy2, col = col)
    if (border==TRUE) points(dx2, dy2, type = "l", col = col)
  }
  else {
    dy2 <- (dy - min(dy))/(max(dy) - min(dy)) * (y[2.] - y[1.])
  }
}

```

The R Graphics Package

Documentation for package 'graphics' version 2.0.0

Help Pages

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