

CS 444: advanced methods for  
human-computer interaction

## controlled experiments - I

class 05

## administrivia

updated since posting!

### project:

- MSI marking: min 59, max 91, avg 77.5, std 8.4
- MSII -- any issues?

### schedule different this week: no tutorial, two labs instead

- upside: more project time, more balanced workload
- downside: tutorials will now be one week behind matched lecture

Friday's lab: **unsupervised, Jessica will be away**

**I have extended OHs this Thurs: 1:30 – 3:30, recommend booking appt in that time, will post to Vista.**

2

## learning goals

be able to answer the following:

- what is the experimental method?
- what is an experimental hypothesis?
- how do I plan an experiment?
- why are statistics used?
- within- & between-subject comparisons: how do they differ?
- how do I compute a t-test?
- what are the different types of t-tests?

Acknowledgement: Some of the material in this lecture is based on material prepared for similar courses by Saul Greenberg (University of Calgary)

3

a good portion of the material in these lectures on experimental design should be familiar from ugrad stats class, although perhaps presented here from a slightly different perspective

also, most of this material is well covered in today's readings:

**Newman & Lamming, Ch 10**

**Lazar, Feng, & Hochheiser, Ch 2 - 4**

4

material I assume you already know and  
will not be covered  
(some additional slides at end)

types of variables  
samples & populations  
normal distribution  
variance and standard deviation

5

## quantitative methods



### 1. user performance data collection

- data is collected on system use
  - frequency of request for on-line assistance
    - what did people ask for help with?
  - frequency of use of different parts of the system
    - why are parts of system unused?
  - number of errors and where they occurred
    - why does an error occur repeatedly?
  - time it takes to complete some operation
    - what tasks take longer than expected?
- collect heaps of data in the hope that something interesting shows up
- often difficult to sift through data unless specific aspects are targeted (as in list above)

descriptive  
statistics

6

## quantitative methods

### 2. controlled experiments

the traditional scientific method

- reductionist
  - clear convincing result on specific issues
- in HCI
  - insights into cognitive process, human performance limitations, ...
  - allows comparison of systems, fine-tuning of details ...

strives for

- lucid and testable hypothesis (usually a causal inference)
- quantitative measurement
- measure of confidence in results obtained (inferential statistics)
- replicability of experiment
- control of variables and conditions
- removal of experimenter bias

7

## desired outcome of a controlled experiment

**statistical inference** of an event or situation's probability:

“Design A is better *<in some specific sense>*  
than Design B”

or, *Design A meets a target:*

“90% of incoming students who have web experience can  
complete course registration within 30 minutes”

8


## steps in the experimental method

### step 1: begin with a lucid, testable hypothesis

Example 1:

$H_0$ : there is no difference in the number of cavities in children and teenagers using crest and no-teeth toothpaste

$H_1$ : children and teenagers using crest toothpaste have fewer cavities than those who use no-teeth toothpaste



10

### step 1: begin with a lucid, testable hypothesis

Example 2:

$H_0$ : there is no difference in user performance (time and error rate) when selecting a single item from a pop-up or a pull down menu, regardless of the subject's previous expertise in using a mouse or using the different menu types

$H_1$ : selecting from a pop-up menu will be faster and less error prone than selecting from a pull down menu

File	Edit	View	Insert
New			
Open			
Close			
Save			

File	▶	New
Edit	⇄	Open
View	⇄	Close
Insert	⇄	Save

11

### general: hypothesis testing

hypothesis = **prediction** of the outcome of an experiment.

framed in terms of **independent** and **dependent** variables:  
 a variation in the independent variable will cause a difference in the dependent variable.

aim of the experiment: prove this prediction  
 do by: *disproving* the "null hypothesis"

$H_0$ : experimental conditions **have no effect** on performance (to some degree of **significance**) → **null hypothesis**

$H_1$ : experimental conditions **have an effect** on performance (to some degree of **significance**) → **alternate hypothesis**

12

## step 2: explicitly state the independent variables

### Independent variables

- things you **control/manipulate** (independent of how a subject behaves) to produce different conditions for comparison
- two different kinds:
  - **treatment manipulated** (can establish cause/effect, true experiment)
  - **subject individual differences** (can never fully establish cause/effect)

### in toothpaste experiment

- toothpaste type: Crest or No-teeth toothpaste (*treatment*)
- age: <= 12 years or > 12 years (*subject*)

### in menu experiment

- menu type: pop-up or pull-down (*treatment*)
- menu length: 3, 6, 9, 12, 15 (*treatment*)
- expertise: expert or novice (*often subject, but can train an expert*)

13

## step 3: carefully choose the dependent variables

### Dependent variables

- things that are **measured**
- expectation that they depend on the subject's behaviour / reaction to the independent variable (but unaffected by other factors)

### in toothpaste experiment:

### in menu experiment:

14

## step 4: consider possible nuisance variables & determine mitigation approach

- undesired variations in experiment conditions which **cannot be eliminated**, but which **may affect** dependent variable
  - critical to know about them
- experiment design & analysis must generally accommodate them:
  - treat as an additional experiment **independent variable** (if they can be controlled)
  - **randomization** (if they cannot be controlled)
- common nuisance variable: **subject** (individual differences)

### in toothpaste experiment:

- brushing time of day: when a subject brushes his/her teeth
- other?

### in menu experiment:

- time of day subject is run: poorest performance may be after lunch
- other?

how to manage?

15

## step 5: design the task to be performed

tasks must:

### be externally valid

external validity = do the results generalize?

... will they be an accurate predictor of how well users can perform tasks as they would in real life?

for a large interactive system, can probably only test a small subset of all possible tasks.

**exercise the designs**, bringing out any differences in their support for the task

e.g., if a design supports website **navigation**, test task should **not** require subject to work within a **single page**

**be feasible** - supported by the design/prototype, and executable within experiment time scale

16

## step 5: design the task to be performed

*in toothpaste experiment:*

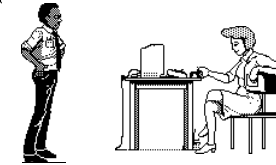
*in menu experiment:*

17

## step 6: design experiment protocol

- steps for executing experiment are prepared well ahead of time
- includes unbiased instructions + instruments (questionnaire, interview script, observation sheet)
- double-blind experiments, ...

Now you get to do the pop-up menus. I think you will really like them... I designed them myself!



18

## step 7: make formal experiment design explicit

simplest: 2-sample (2-condition) experiment

based on comparison of **two sample means**:

- performance data from using Design A & Design B
  - e.g., new design & status quo design
  - e.g., 2 new designs

or, comparison of **one sample mean with a constant**:

- performance data from using Design A, compared to performance requirement
  - determine whether single new design meets key design requirement

19

## step 7: make formal experiment design explicit

more complex: factorial design

*in toothpaste experiment:*

- 2 toothpaste types (crest, no-teeth)
- x 2 age groups ( $\leq 12$  years or  $> 12$  years)

*in menu experiment:*

- 2 menu types (pop-up, pull down)
- x 5 menu lengths (3, 6, 9, 12, 15)
- x 2 levels of expertise (novice, expert)

(more on this later)

20

### step 8: judiciously select/recruit and assign subjects to groups

**subject pool:** *similar issues as for informal studies*

- match expected user population as closely as possible
- age, physical attributes, level of education
- general experience with systems similar to those being tested
- experience and knowledge of task domain

**sample size:** *more critical in experiments than informal studies*

- going for "statistical significance"
- should be large enough to be "representative" of population
- guidelines exist based on statistical methods used & required significance of results
- pragmatic concerns may dictate actual numbers
- "10" is often a good place to start

21

### step 8: judiciously select/recruit and assign subjects to groups

- if there is too much variability in the data collected, you will not be able to achieve statistical significance (more later)
- you can reduce variability by controlling subject variability how?
  - recognize classes and make them an independent variable
    - e.g., older users vs. younger users
    - e.g., superstars versus poor performers
  - use reasonable number of subjects and random assignment



Novice



Expert

22

### step 9: apply statistical methods to data analysis

examples: t-tests, ANOVA, correlation, regression  
(more on these later)

confidence limits: the confidence that your conclusion is correct

- "The hypothesis that mouse experience makes no difference is rejected at the .05 level" (i.e., null hypothesis rejected)
- this means:
  - a 95% chance that your finding is correct
  - a 5% chance you are wrong

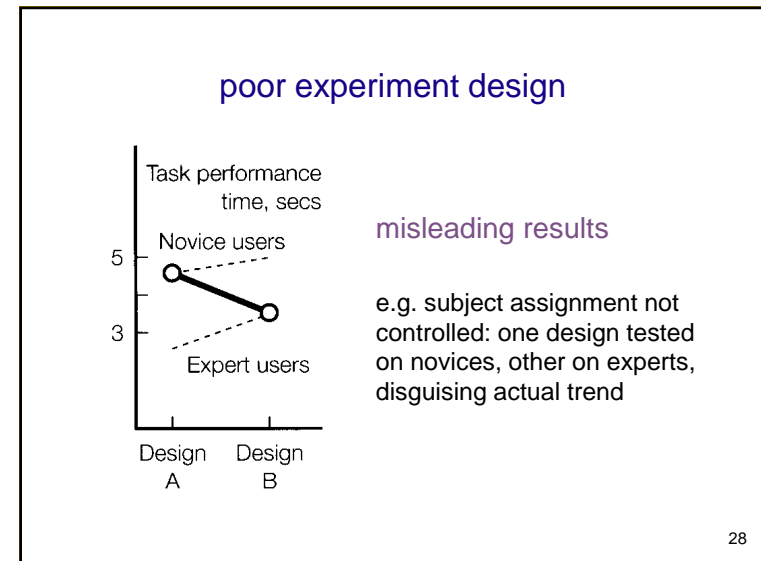
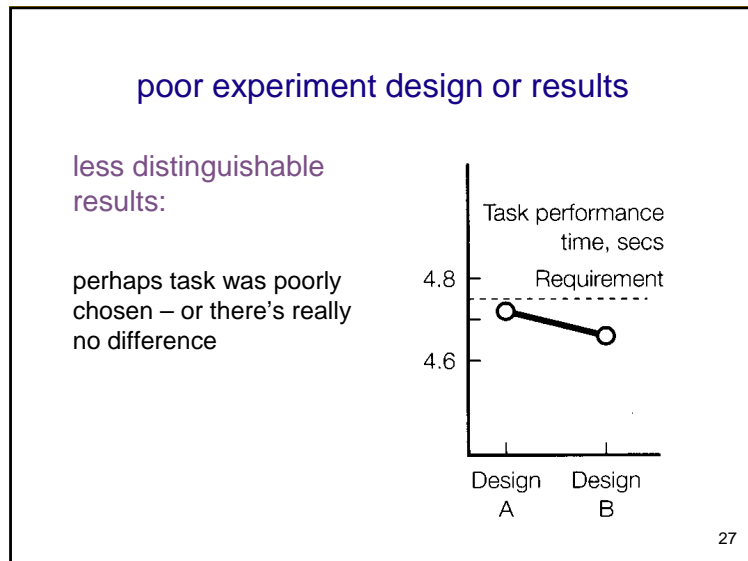
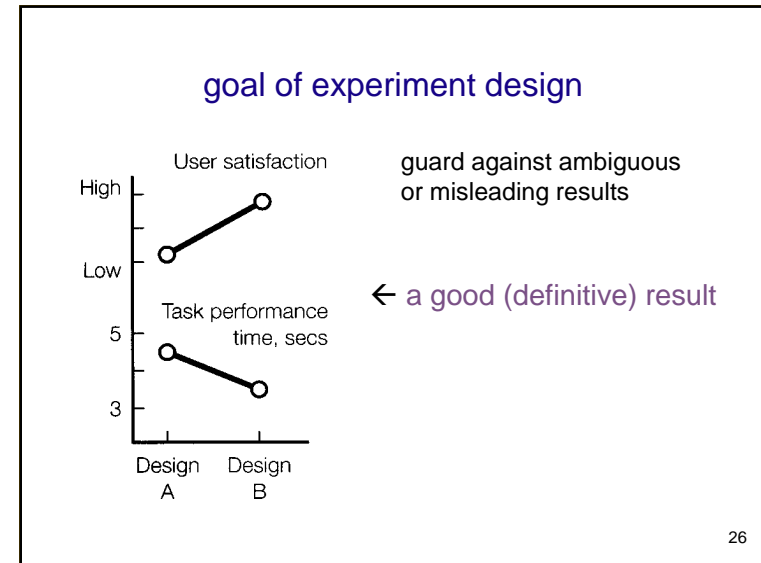
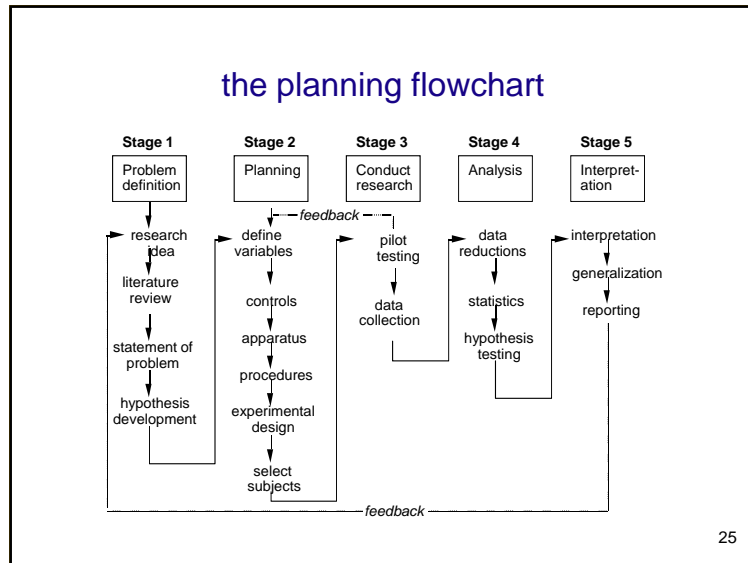
23

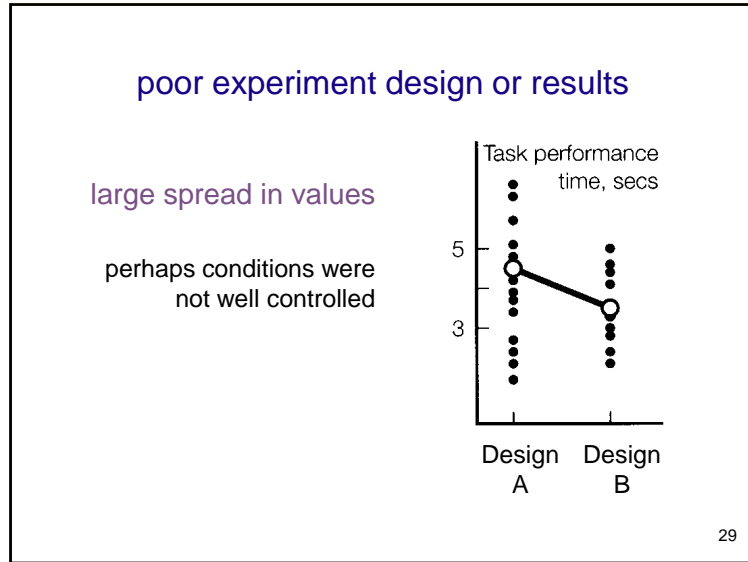
### step 10: interpret your results

what *you* believe the results mean, and their implications

yes, there can be a subjective component to quantitative analysis

24



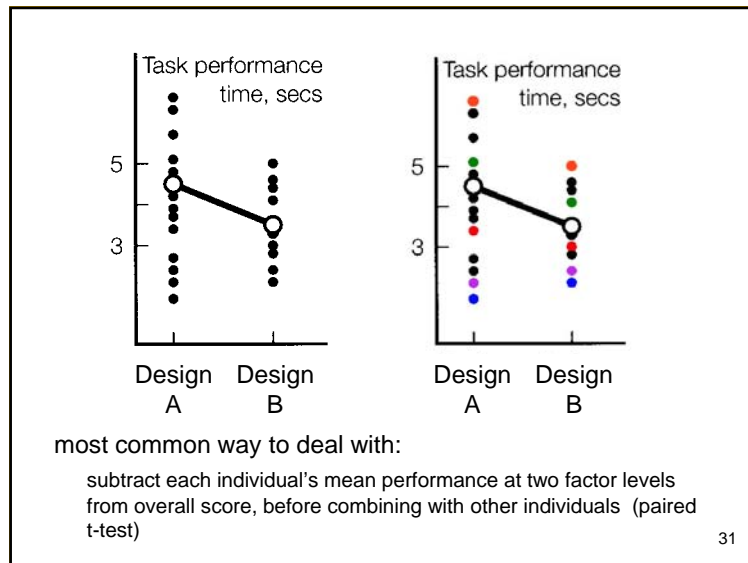


as we have seen

individual (subject) differences may pose a **nuisance variable:**

variation in individual abilities can mask real differences in test conditions, if not analyzed properly

30



**within/between subject comparisons**

**within-subject comparisons:**

- **subjects exposed to multiple treatment conditions**
- primary comparison internal to each subject
- allows control over subject variable
- greater statistical power, fewer subjects required
- not always possible (exposure to one condition might "contaminate" subject for another condition; or session too long)

**between-subject comparisons:**

- **subjects only exposed to one condition**
- primary comparison is from subject to subject
- less statistical power, more subjects required
- why? because greater variability due to more individual differences

32

## within/between subject comparisons

### in toothpaste experiment

- 2 toothpaste types (crest, no-teeth) *between or within*
- x 2 age groups ( $\leq 12$  years or  $> 12$  years) *must be between*

### in menu experiment :

- 2 menu types (*pop-up, pull down*) *between or within*
- x 5 menu lengths (3, 6, 9, 12, 15) *should be within*
- x 2 levels of expertise (novice, expert) *must be between*

33

## to summarize so far: how a controlled experiment works

1. formulate an **alternate** and a **null** hypothesis:  
 $H_1$ : experimental conditions **have an effect** on performance  
 $H_0$ : experimental conditions **have no effect** on performance
  2. through **experiment task**, try to demonstrate that the **null hypothesis is false** (reject it),  
for a particular level of **significance**
  3. if successful, we can **accept** the alternate hypothesis,  
and state the probability  **$p$**  that we are wrong (the null hypothesis is true after all)  $\rightarrow$  this is the result's **confidence level**
- e.g., selection speed is significantly faster in menus of length 5 than of length 10 ( $p < .05$ )

$\rightarrow$  **5% chance we've made a mistake, 95% confident**

34

## statistical analysis

### what is a statistic?

- a number that describes a sample
- sample is a subset (hopefully representative) of the population we are interested in understanding

### statistics are calculations that tell us

- mathematical attributes about our data sets (sample)
  - mean, amount of variance, ...
- how data sets relate to each other
  - whether we are “sampling” from the same or different populations
- the probability that our claims are correct
  - “statistical significance”

35

## example: differences between means

### given: two data sets measuring a condition

- e.g., height difference of males and females,  
time to select an item from different menu styles ...

### question:

- is the difference between the means of the data statistically significant?

### null hypothesis:

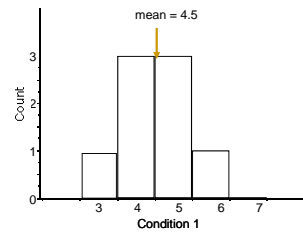
- there is no difference between the two means
- statistical analysis can only reject the hypothesis at a certain level of confidence
- *note: we never actually prove the hypothesis true*

36

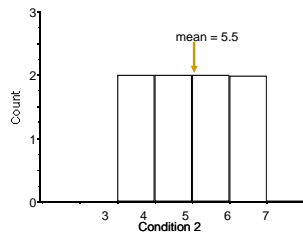
example:

Is there a *significant* difference between the means?

Condition one: 3, 4, 4, 4, 5, 5, 5, 6



Condition two: 4, 4, 5, 5, 6, 6, 7, 7



37

the problem with visual inspection of data

there is almost always variation in the collected data  
differences between data sets may be due to:

- normal variation
  - e.g., two sets of ten tosses with different but fair dice
    - differences between data and means are accountable by expected variation
- real differences between data
  - e.g., two sets of ten tosses with loaded dice and fair dice
    - differences between data and means are not accountable by expected variation



38

t-test

a statistical test

allows one to say something about differences between two means at a certain confidence level

null hypothesis of the t-test:

no difference exists between the means

possible results:

- I am 95% sure that null hypothesis is rejected
  - there is probably a true difference between the means
- I cannot reject the null hypothesis
  - the means are likely the same

39

different types of t-tests

**comparing two sets of independent observations** (*between subjects*)

usually different subjects in each group (number may differ as well)

Condition 1	Condition 2
S1-S20	S21-S43

**paired observations** (*within subjects*)

usually single group studied under separate experimental conditions

data points of one subject are treated as a pair

Condition 1	Condition 2
S1-S20	S1-S20

40

### different types of t-tests

**non-directional vs directional alternatives**

non-directional (two-tailed)

- no expectation that the direction of difference matters

directional (one-tailed)

- only interested if the mean of a given condition is greater than the other

41

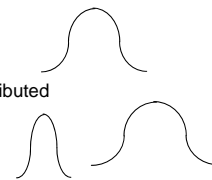
### t-tests

Assumptions of t-tests

- data points of each sample are normally distributed
  - but t-test very robust in practice
- sample variances are equal
  - t-test reasonably robust for differing variances
  - deserves consideration
- individual observations of data points in sample are independent
  - must be adhered to (can you think of examples where they are not?)

Significance level

- decide upon the level before you do the test!
- typically stated at the .05 or .01 level
- .10 can be considered a trend, but is controversial

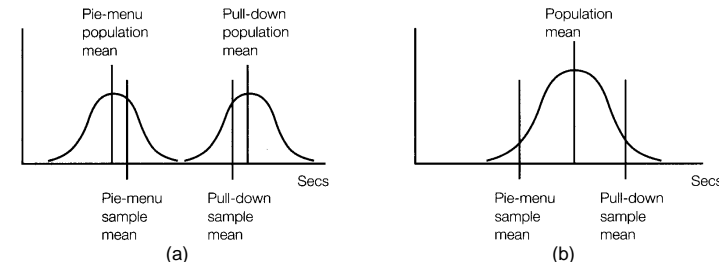


42

### what the t-test is testing

(a) the two samples come from two different populations;

(b) the two samples are part of the same population.



(a) (b)

Which represents  $H_0$  and which represents  $H_1$ ?

43

### two-tailed unpaired t-test

n: number of data points in the one sample ( $N = n_1 + n_2$ )

$\Sigma X$ : sum of all data points in one sample

$\bar{X}$ : mean of data points in sample

$\Sigma(X^2)$ : sum of squares of data points in sample

$s^2$ : unbiased estimate of population variation

t: t ratio

df = degrees of freedom =  $N_1 + N_2 - 2$

N&L shows derivation of formula

How to maximize t?

Formulas

$$s^2 = \frac{\Sigma(X_1^2) - \frac{(\Sigma X_1)^2}{n_1} + \Sigma(X_2^2) - \frac{(\Sigma X_2)^2}{n_2}}{n_1 + n_2 - 2}$$

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s^2}{n_1} + \frac{s^2}{n_2}}}$$

44

<N&L derivation>  
mean & sum of squares

mean =  $\bar{X} = \frac{\sum X_i}{N}$

sum of squares =  $SS = \sum (X_i - \bar{X})^2$

(same, faster) =  $\sum X_i^2 - \frac{(\sum X_i)^2}{N}$

error in N&L pg. 231

45

degrees of freedom (df)

freedom of a set of values to vary independently of one another:

$X = \{21, 20, 24\}$       $N=3$

$\bar{X} = \frac{65}{3} = 21.6$ :     ←  $\bar{X}$  has  $N-1=2$  df

once you know the mean of  $N$  values, only  $N-1$  can vary independently

46

sample variance & standard deviation

sample variance =  $s^2 = \frac{SS}{N-1}$

standard deviation =  $sd = \sqrt{s^2}$

47

<N&L derivation>  
calculating  $t$

compute **combined variance** for the two samples:

$$s^2 = \frac{SS_1 + SS_2}{N_1 + N_2 - 2} \quad \leftarrow \text{note df computation}$$

compute **standard error of difference**,  $s_{ed}$ :

$$s_{ed} = \sqrt{s^2 \left( \frac{1}{N_1} + \frac{1}{N_2} \right)}$$

compute  $t$ :

$$t = \frac{|\bar{X}_1 - \bar{X}_2|}{s_{ed}}$$

no, you won't have to memorize the formula for exams. but you *should* know how / when to use it.

48

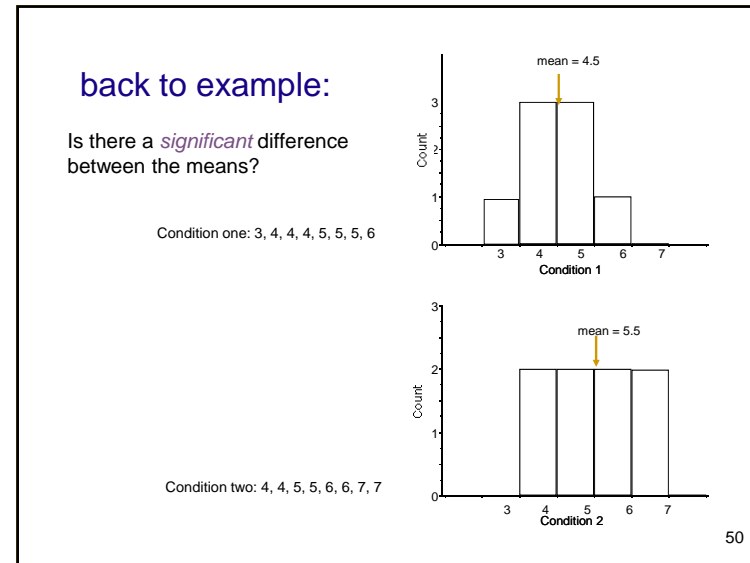
### Level of significance for two-tailed test

df	.05	.01	df	.05	.01
1	12.706	63.657	16	2.120	2.921
2	4.303	9.925	18	2.101	2.878
3	3.182	5.841	20	2.086	2.845
4	2.776	4.604	22	2.074	2.819
5	2.571	4.032	24	2.064	2.797
6	2.447	3.707			
7	2.365	3.499			
8	2.306	3.355			
9	2.262	3.250			
10	2.228	3.169			
11	2.201	3.106			
12	2.179	3.055			
13	2.160	3.012			
14	2.145	2.977			
15	2.131	2.947			

Critical value (threshold) that t statistic must reach to achieve significance.

How does critical value change based on df and confidence level?

49



### example calculation

$x_1 = 3\ 4\ 4\ 4\ 5\ 5\ 5\ 6$   
 $x_2 = 4\ 4\ 5\ 5\ 6\ 6\ 7\ 7$

hypothesis: there is no significant difference between the means at the .05 level

Step 1. Calculating  $s^2$

	1	2
$N$	8	8
$\sum x$	36	44
$\bar{x}$	4.5	5.5
$\sum(x^2)$	168	252
$(\sum x)^2$	1296	1936

$df = 14$

$$s^2 = \frac{\sum x^2 - (\sum x_1)^2/N_1 + \sum x_2^2 - (\sum x_2)^2/N_2}{N_1 + N_2 - 2}$$

$$= \frac{168 - 1296/8 + 252 - 1936/8}{8+8-2}$$

$$= 1.1429$$

51

### example calculation

Step 2. Calculating  $t$

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2/N_1 + s^2/N_2}}$$

$$= \frac{4.5 - 5.5}{\sqrt{2 \cdot (1.1429/8)}}$$

$$= \frac{-1}{.5345}$$

$$= -1.871$$

Step 3: Looking up critical value of  $t$

- Use table for two-tailed  $t$ -test, at  $p=.05$ ,  $df=14$
- critical value = 2.145
- because  $|t| = 1.871 < 2.145$ , there is no significant difference
- therefore, we cannot reject the null hypothesis
- i.e., there is no difference between the means

52

### two-tailed unpaired t-test

Condition one: 3, 4, 4, 4, 5, 5, 5, 6  
 Condition two: 4, 4, 5, 5, 6, 6, 7, 7

What the results would look like in stats software.

**Unpaired t-test**

DF:	Unpaired t Value:	Prob. (2-tail):
14	-1.871	.0824 <span style="color: red;">hint</span>

probability that means are from the same underlying population

Group:	Count:	Mean:	Std. Dev.:	Std. Error:
one	8	4.5	.926	.327
two	8	5.5	1.195	.423

How does the outcome change for a confidence level of 0.10?

53

### summary of the t-test

**the point:** establish a confidence level in the difference we've found between 2 sample means.

**the process:**

1. compute df
2. choose desired **significance,  $p$**  (aka  $\alpha$ )
3. calculate value of the  **$t$  statistic**
4. compare it to the **critical value** of  $t$  given  $p$ , df:  $t_{(p,df)}$
5. if  $t > t_{(p,df)}$ , can **reject null hypothesis at  $p$**

54

### what does this look like graphically?

Two-tailed

Mean

critical value  $t_{(p,df)}$

$\bar{X}_1 \neq \bar{X}_2$  regions for rejecting the null hypothesis

Single-tailed

Mean

$\bar{X}_1 > \bar{X}_2$  region for rejecting the null hypothesis

**null hypothesis rejection area:**

- two-tailed: divided equally between left/right
- single-tailed: all on one side

**region(s) for rejecting the null hypothesis:**  
 the area of the normal distribution that equals the chance you might be wrong 55

### you now know

How to answer the following:

- what is the experimental method?
- what is an experimental hypothesis?
- how do I plan an experiment?
- why are statistics used?
- within- & between-subject comparisons: how do they differ?
- how do I compute a t-test?
- what are the different types of t-tests?

56

### on deck

in experiments II:  
detailed example of t-test  
overview of ANOVA (including case study)

in experiments III:  
example of ANOVA from a published paper

you will also get hands on experience doing an ANOVA in tutorial (experiments II)

57

### additional slides: material I assume you know

types of variables  
samples & populations  
normal distribution  
variance and standard deviation

58

### types of variables (independent or dependent)

**discrete**: can take on **finite** number of levels

- e.g. a 3-color display can only render in red, green or blue;
- a design may be version A, or version B

**continuous**: can take any value (usually within bounds)

- e.g. a response time that may be any positive number (to resolution of measuring technology)

**normal**: one particular **distribution** of a continuous variable

59

### populations and samples

statistical sample =  
approximation of total possible set of, e.g.

- **people** who will ever use the system
  - **tasks** these users will ever perform
  - **state** users might be in when performing tasks
- } ← the population

“**sample**” a representative fraction

- draw **randomly** from population
- if large enough and representative enough, the **sample mean** should lie somewhere near the **population mean**

60

### confidence levels

“the **sample mean** should lie somewhere near the **population mean**”

how close?  
how sure are we?

a confidence interval provides an **estimate of the probability** that the statistical measure is valid:

“We are **95%** certain that selection from menus of five items is faster than that from menus of seven items”

**how does this work?**  
important aspect of experiment design

61

### establishing confidence levels: normal distributions

fundamental premise of statistics:  
predict behavior of a **population** based on a **small sample**

validity of this practice depends on the **distribution** of the population and of the sample

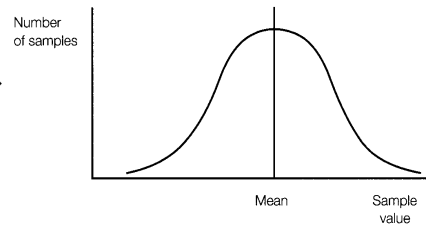
many populations are **normally distributed**:  
many statistical methods for **continuous dependent variables** are based on the assumption of normality

if **your sample is normally distributed**,  
**your population is likely to be**,  
and these statistical methods are valid,  
and everything is a lot easier.

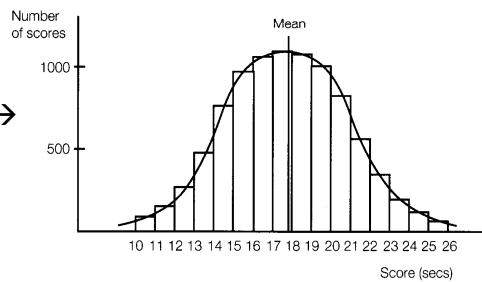
62

what's a normal distribution?

population →

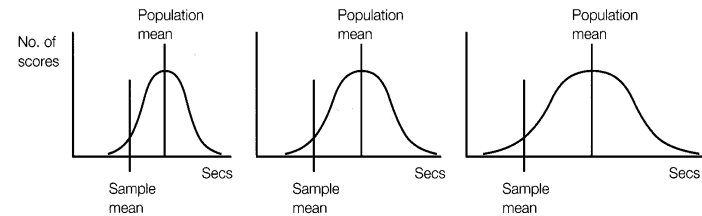


sample →



### variance and standard deviation

all normal distributions are not the same:

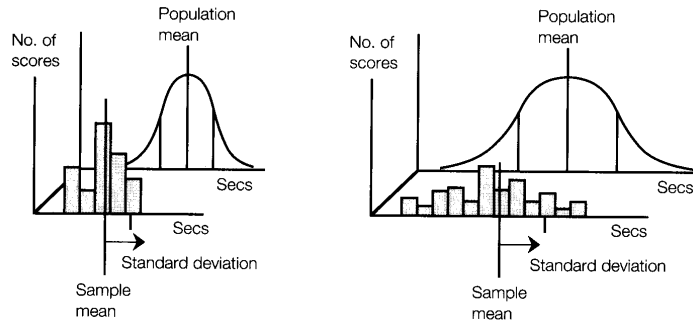


**population variance** is a measure of the distribution's “**spread**”  
all normal population distributions still have the same **shape**

64

### how do you get the population's variance?

estimate the population's (true) variance from the (measured) sample's standard deviation:



65

### what's the big deal?

**if** you know you're dealing with samples from a normal distribution,

**and** you have a good estimate of its variance (i.e. your sample's std dev)

**then**, you know the **probability** that a given sample came from that population (vs. a different one).

