Design an experiment (parametric)

Statistics

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1. Chocolate study (a bad example)
2. Comparing two things
3. Comparing three things

In this deck

let’s do an experiment!

memorization game

group 1

memorize as much as you can

group 2

if you beat group 1 = chocolate!

take a piece of paper and a pen

I will tell a list of numbers

🔊 "1,2,3,6,write"

only when "write" -> write the list on paper

I will show the list

1, 2, 3, 6

if you are **correct** continue the game

if you wrong stop the game, remember *best score* practice trials

1, 4, 9 (size=3)

practice trials

8, 7, 3, 5, 6, 1 ,2 (size=7)

let’s start the real experiment!

trial

3, 2, 8 (size=3)

trial

4, 2, 5, 1 (size=4)

trial

7, 2, 5, 3, 1 (size=5)

trial

6, 2, 9, 8, 5, 1 (size=6)

trial

7, 4, 1, 8, 6, 3, 2 (size=7)

trial

2, 7, 4, 9, 3, 1, 5, 9 (size=8)

trial

1, 6, 7, 8, 5, 3, 1, 4, 6 (size=9)

trial

6, 4, 1, 9, 3, 8, 2, 1, 7, 9 (size=10)

trial

2, 7, 4, 1, 5, 7, 3, 8, 6, 4, 7 (size=11) what is your best score (size of the list)?

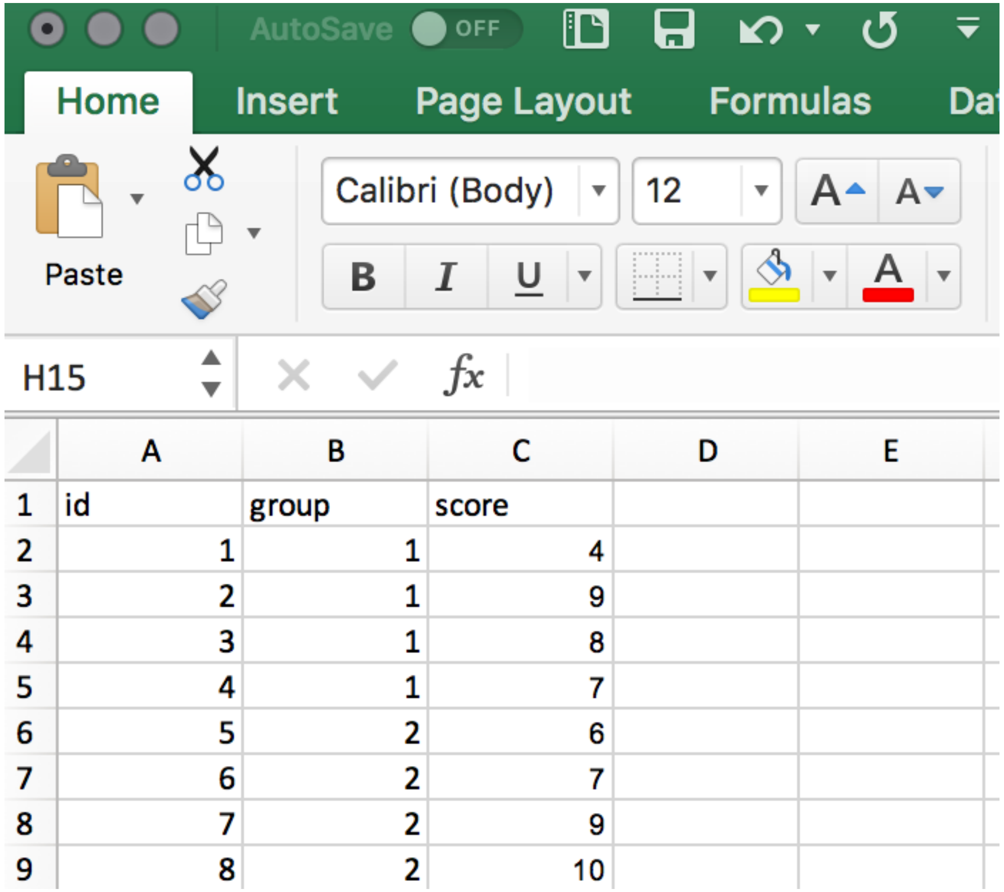
enter it at

https://tinyurl.com/COMS10011

let’s analyze the memory experiment

5 look at raw data

let’s put everything in a table (excel is great for that)



	A	B	C	D	E
1	id	group	score		
2	1	1	4		
3	2	1	9		
4	3	1	8		
5	4	1	7		
6	5	2	6		
7	6	2	7		
8	7	2	9		
9	8	2	10		

save your file as a .csv (comma separated virgule is a format to store tables as text files)

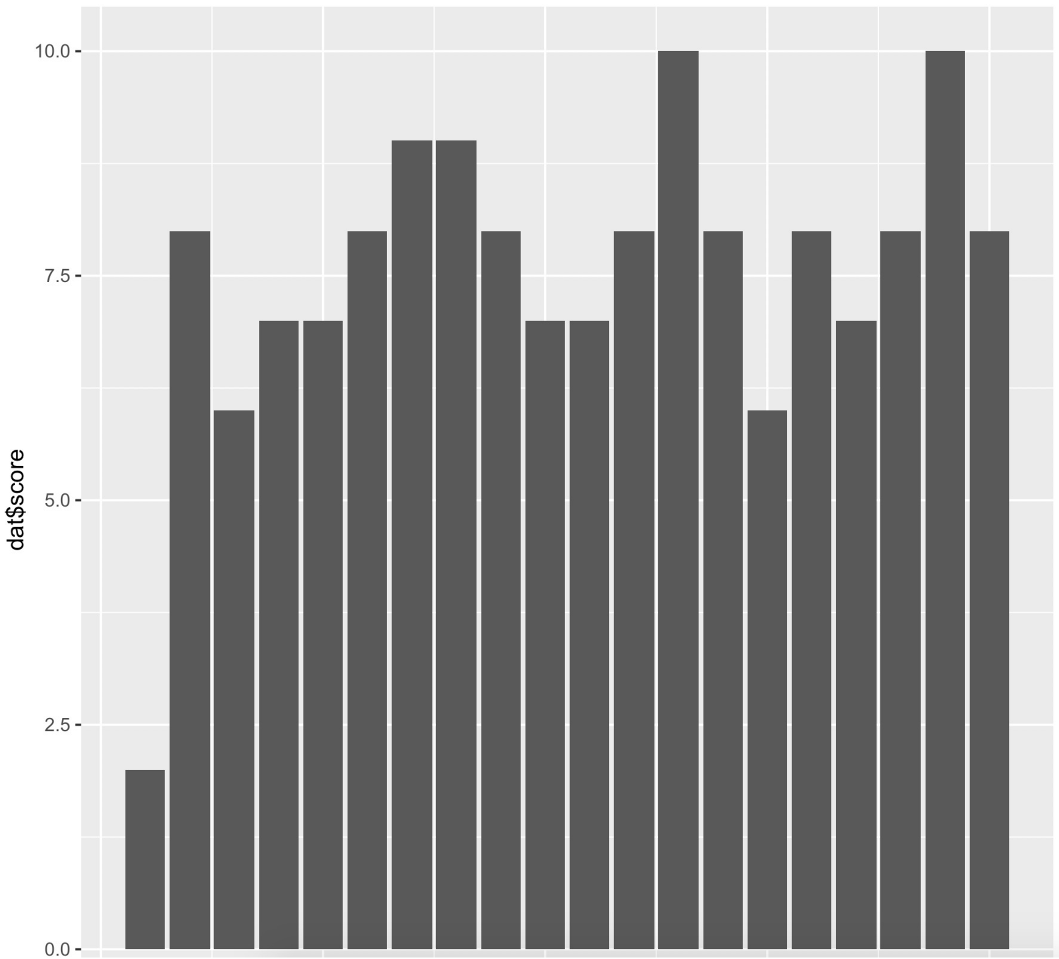
you can open csv with excel, text file an many other software

HCIXP.csv

```
id,group,score
1,1,4
2,1,9
3,1,8
4,1,7
5,2,6
6,2,7
7,2,9
8,2,10
```

```
dat = read.csv("TTEST.csv", header = TRUE)
print(dat) # look at the file in R
```

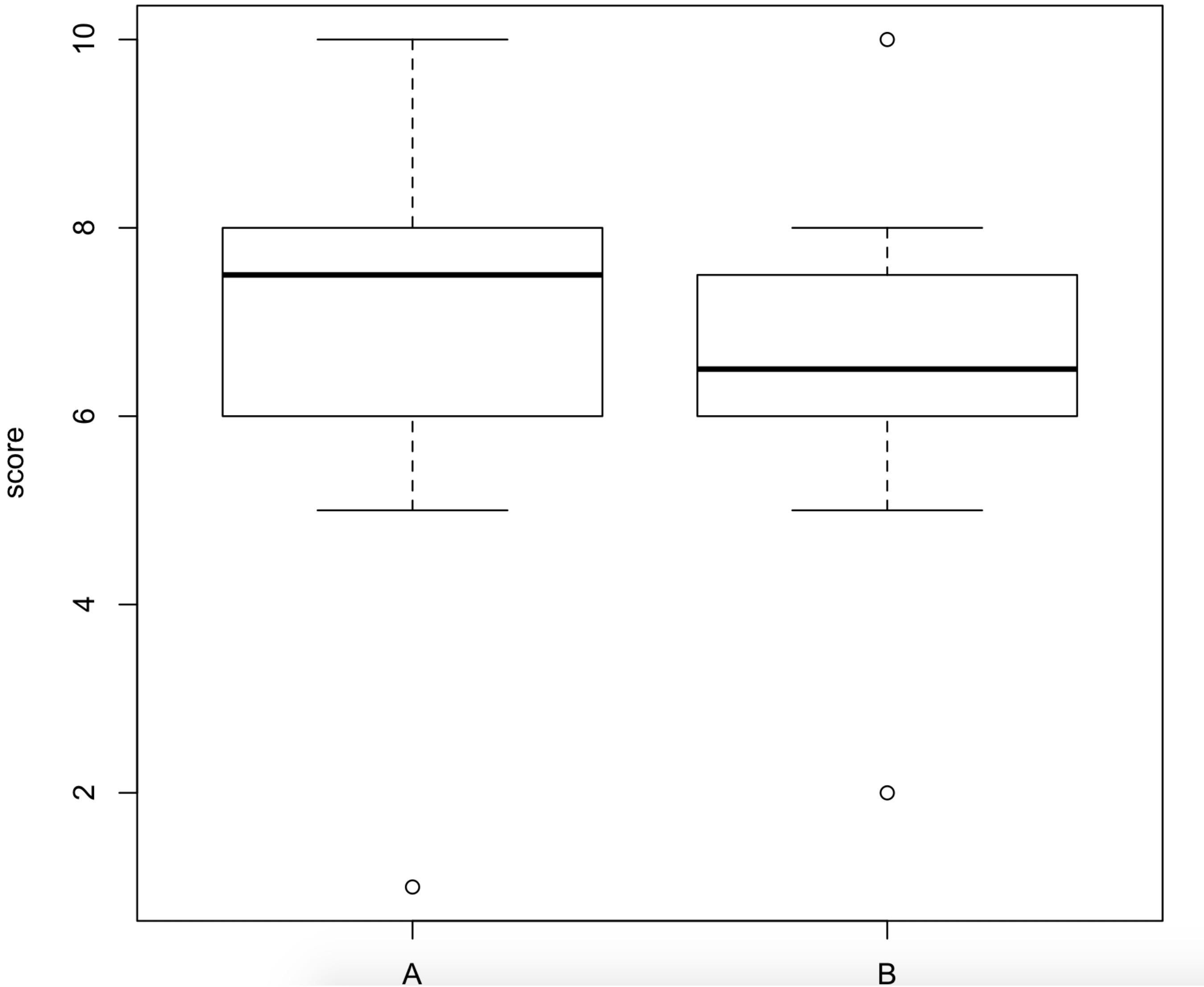
```
dat = read.csv("TTEST.csv", header = TRUE)
print(dat) # look at the file in R

library(ggplot2) # you will need to launch dirst
“install.packages("ggplot2")”

ggplot(dat, aes(x = dat$id, y = dat$score)) +
geom_bar(stat = 'identity', position = 'dodge')
```



first: does the data look ok?

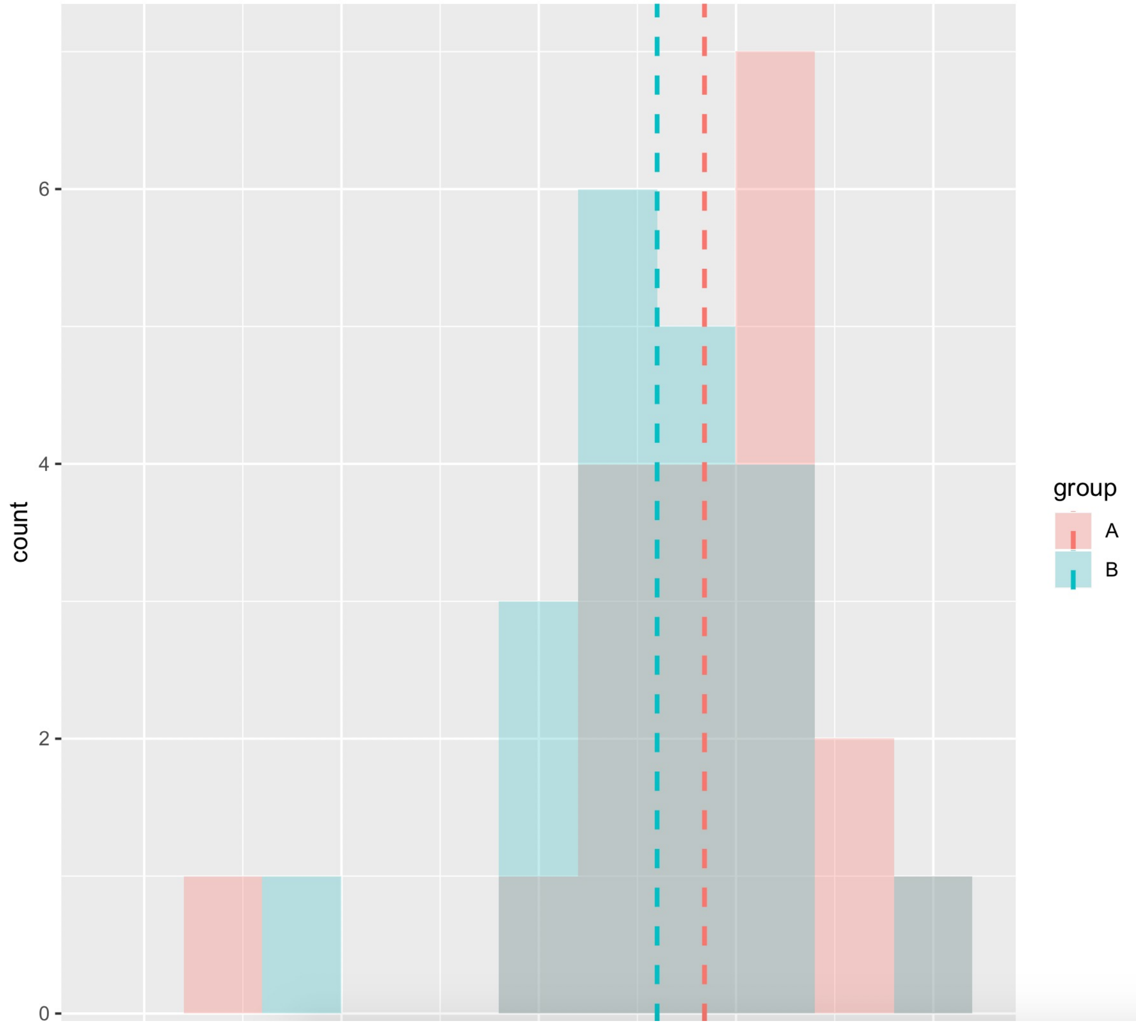
search for bugs, fatigue effect, learning effect
or outliers (>3 times std) = remove / redo xp

```
plot(score ~ group, data = dat)
```



look at histograms

```
# Find the mean of each group
library(plyr)
cdat <- ddply(dat, "group", summarise,
score.mean=mean(score))
cdat

  group score.mean
1     A    7.1
2     B    6.5

# Overlaid histograms with means
ggplot(dat, aes(x=score, fill=group)) +
geom_histogram(binwidth=1, alpha=.3, position="identity")
+ geom_vline(data=cdat, aes(xintercept=score.mean,
colour=group), linetype="dashed", size=1) +
expand_limits(x = 0, y = 0)
```



your gut feeling: are these groups different?

are these distributions likely to have happen by chance?

… is this the results of the factor (chocolate)?

use a statistic test

```
# Use a t-test (two-tails, unpaired)
t.test(dat$score[dat$group == "A"], dat$score[dat$group
=="B"], alternative = "two.sided")

        Welch Two Sample t-test

data:  dat$score[dat$group == "A"] and
dat$score[dat$group == "B"]
t = 1.0731, df = 37.255, p-value = 0.2901
alternative hypothesis: true difference in means is
not equal to 0
95 percent confidence interval:
 -0.5326528  1.7326528
sample estimates:
mean of x mean of y
      7.1       6.5
```

"We could not find any significance differences!"

p-value = 0.29

is is enough to say that the two groups are different?

-> nope, not under significant level of 0.05

can we say that the two groups are same then?

-> nope, can only prove things are different, but not that they are the same

8

conclude

if p was lower than significance level we could say:

- "a student t-test showed significant difference between the two group (two-tailed $t(37)=1.0731$, $p < 0.005$)"

otherwise:

"we did not find any significant results"

cannot conclude, no evidences to show that having chocolate rewards improve memorization

You **cannot claim anything else!!!!!**

let’s go
backward a little

1. research question / hypothesis?
2. in(dependant) variables?
3. a. within or between subjects?
   b. counterbalancing?
4. how many repetitions/trials?
5. look at raw data
6. look at distributions
7. a. check for normality
   b. run some stats
8. conclude

research question::

a statement that identifies a phenomenon to be studied

in our xp: I believe that **rewards improve memorization skills**

… suggested by <*insert smart guess*>

hypotheses::

statement of the predicted relationship between at least two experimental variables

provisional answer to a research question

in our xp: **group chocolate will have a higher memorisation score than group with no reward**

(in)dependent variable ::

the **dependent variable** is the event studied and expected to change whenever the **independent variable** is altered

vary A → make A
an **independent variable**

so we want to show that **A causes B**

measure B → make B
a **dependent variable**

in our xp?

independent variable = group type (nothing vs. chocolate)

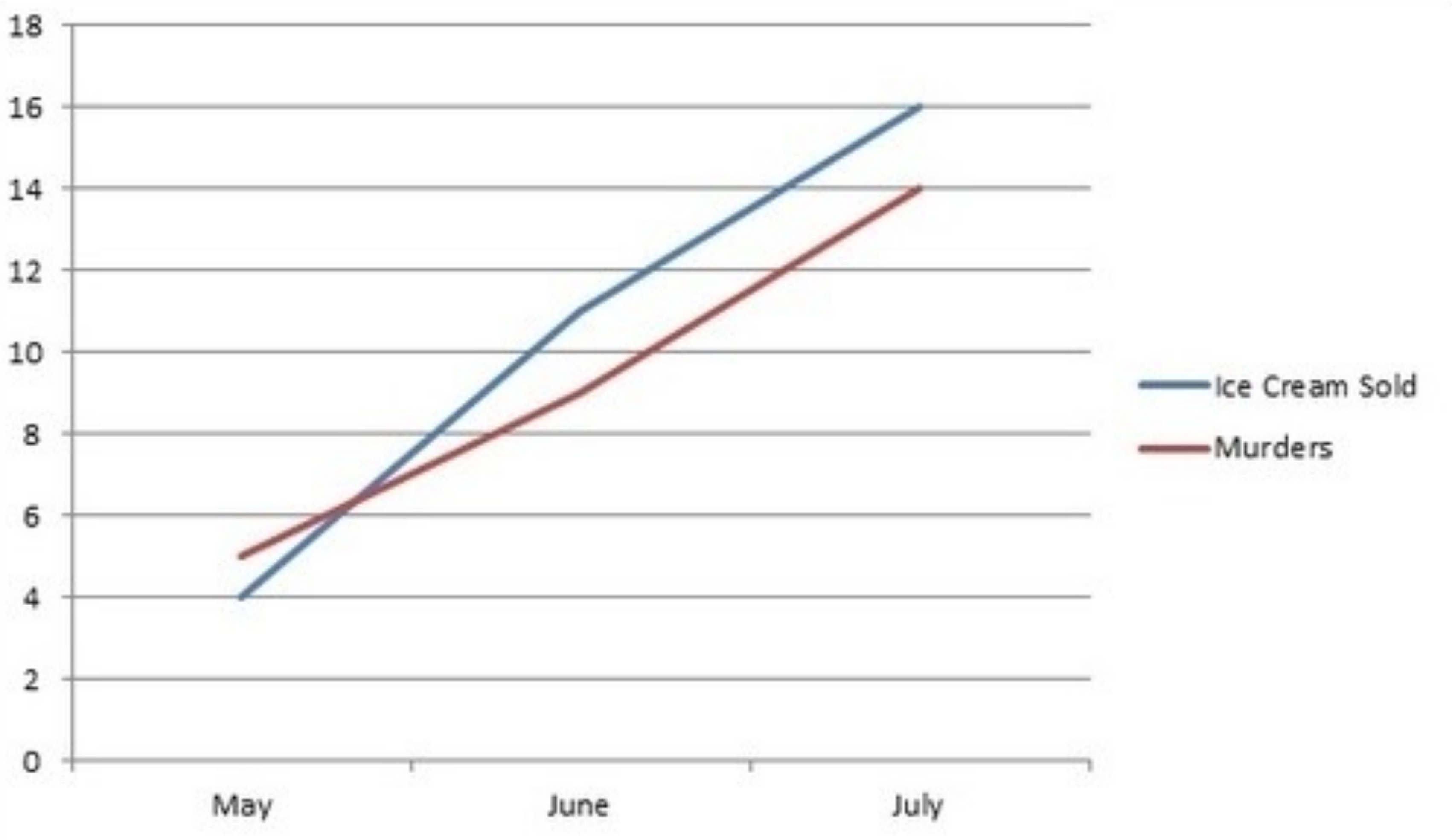
dependent variable = memorization score everything else should be a…

controlled variable ::

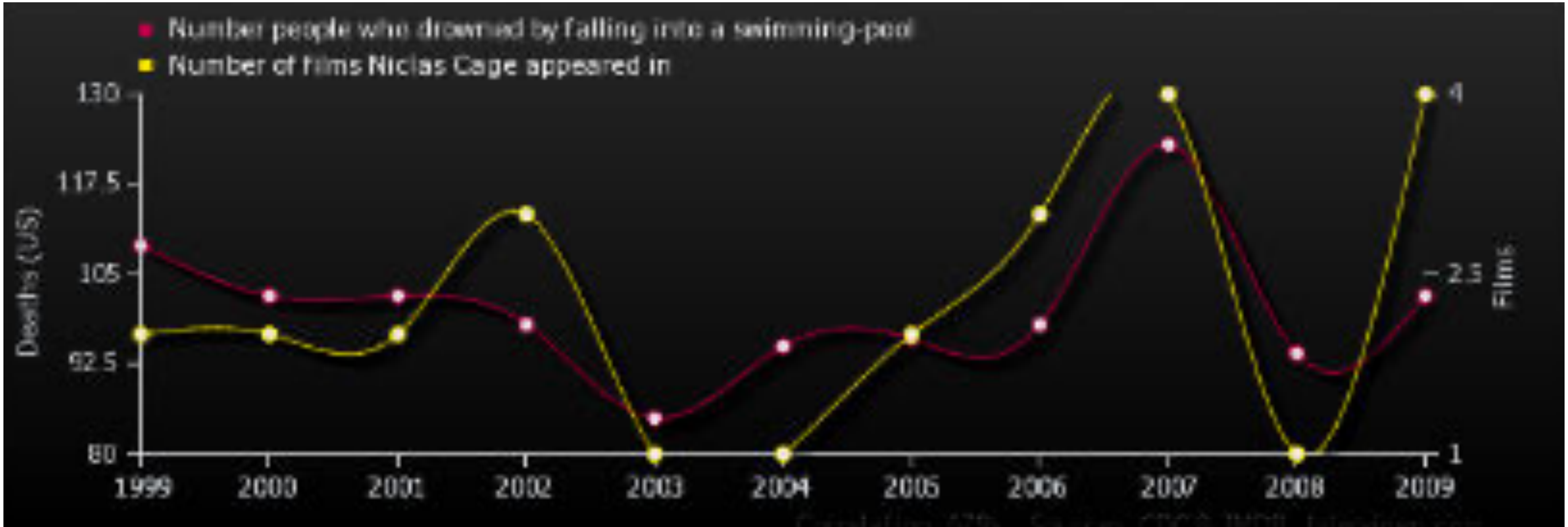
the variables that are kept constant to prevent their influence on the effect of the independent variable on the dependent avoid…

confounding variable ::

extraneous variables that **correlates with both** the dependent variable and the independent variable



ice cream consumption leads to murder
counfounding : weather temperature



number of people drowned by falling into a swimming-pool correlates with number of films Nicolas Cage appeared in this is not about **correlation**

this is about how to show **causality,**
i.e., that **some A causes some B**

in our xp, do we have confounding variables?

yes, it is not greatly designed :s

gender, age, background, what you ate before, if you like chocolate or not, if you are competitive and want the others not to have chocolate, if some of the numbers are familiar to you etc.

what can we do about it?

- avoid them by controlling as much as you can in the environment
- if you cannot, make it an independent variable (e.g. gender)
- some are inherent *noise* (human individuality), use more participants to get *statistical power*

the goal of a quantitative study is to find
a signal in **a lot of noise**

experimental design:

aims at maximizing your chances of **finding the signal** and not the noise

1. need to absolutely **avoid systematic biases**

(e.g., learning effect, fatigue). They give you **false results!**

2. **avoid random noise.** It makes your results non-significant. Clever experimental design is all about keeping the noise down

e.g. in our xp, I made you **practice before**!

within vs. between?

within = all participants do same

between = participants do only certain conditions

3a

suffer less user variation

statistical power with less participants

no biases from other conditions (e.g. transfer of learning)

within vs. between?

within = all participants do same

between = participants do only certain conditions our xp was **between subjects**

participants did not do all conditions:

½ did the control condition

½ the reward condition

imagine a **within subjects** (test how fast we click an icon):

participants do all conditions:
they start with the trackpad
when finished they do the mouse

is it a good idea?
nope -> learning effect

counterbalancing ::

a method of avoiding confounding among variables

presenting conditions in a different order

one approach to counterbalancing is to use a…

A	B	C
C	A	B
B	C	A

Latin square ::

an $n \times n$ array filled with n different Latin letters, each occurring exactly once in each row and exactly once in each column.

how many trials?

ideally make as much trials as you can to reduce noise but try to keep experiment around 30 min … max 40 min in our xp, we did only one trial because of time constraint, but should have done more to **reduce noises**

Let’s complexify a little

in our xp, let’s add a 3rd imaginary group

they get a slap if they had the smallest memorisation score
(obviously not ethical so let’s keep this hypothetical!)

E57 × ✓ fx

Name Box

	A	B	C	D
14			8	
15	14	A	6	
16	15	A	6	
17	16	A	7	
18	17	A	7	
19	18	A	7	
20	19	A	7	
21	20	A	7	
22	21	B	6	
23	22	B	7	
24	23	B	9	
25	24	B	5	
26	25	B	8	
27	26	B	6	
28	27	B	6	
29	28	B	8	
30	29	B	7	
31	30	B	9	
32	31	B	9	
33	32	B	6	
34	33	B	8	
35	34	B	8	
36	35	B	8	
37	36	B	7	
38	37	B	7	
39	38	B	7	
40	39	B	7	
41	40	B	7	
42	41	C	1	
43	42	C	2	
44	43	C	1	
45	44	C	2	
46	45	C	1	
47	46	C	2	
48	47	C	3	
49	48	C	2	
50	49	C	2	
51	50	C	1	
52	51	C	1	
53	52	C	4	
54	53	C	2	
55	54	C	2	
56	55	C	2	
57	56	C	3	

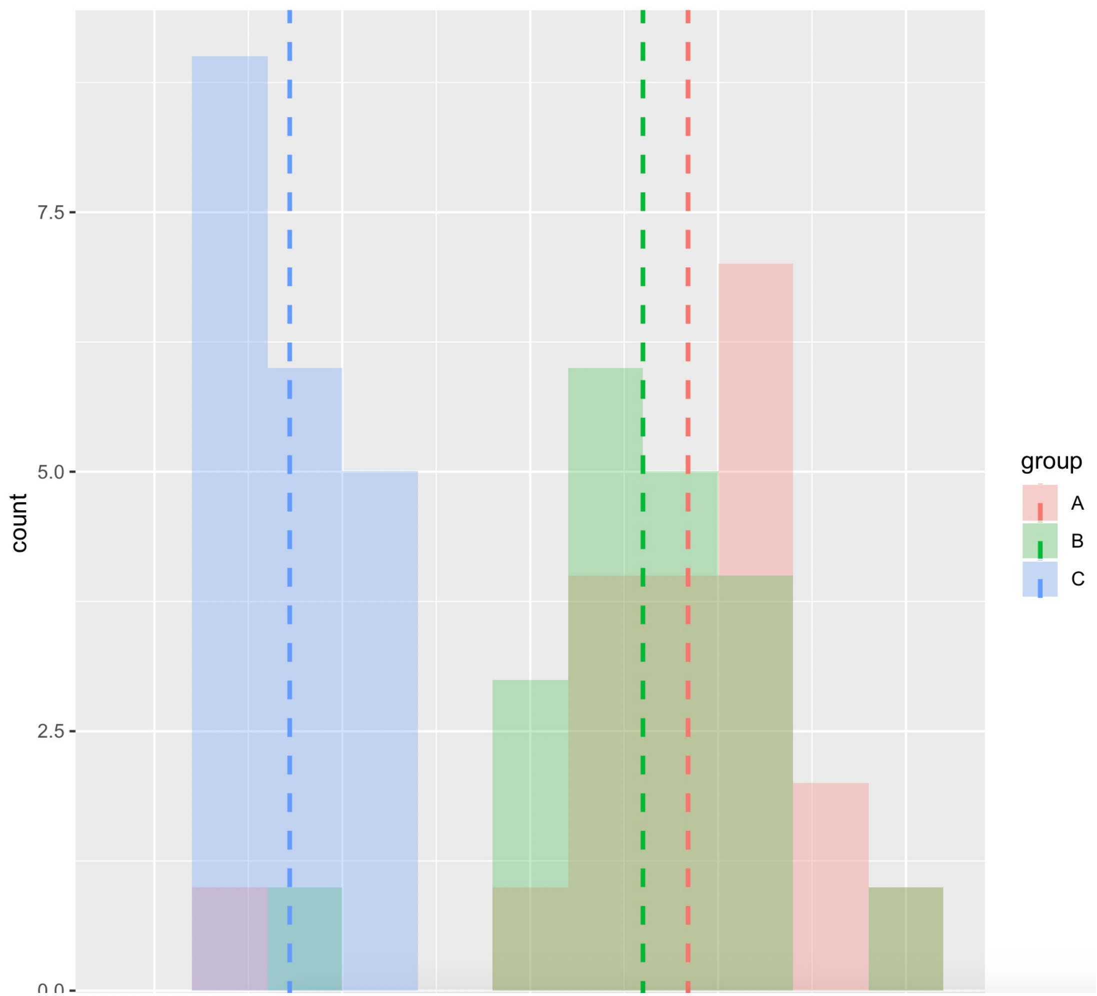
Group C: “slap”

I made up some data

```r
# Find the mean of each group
library(plyr)
dat = read.csv("ANOVA.csv", header = TRUE)
cdat <- ddply(dat, "group", summarise,
score.mean=mean(score))
cdat
```

```
  group score.mean
1     A    7.1
2     B    6.5
3     C    1.8
```

```r
# Overlaid histograms with means
library(ggplot2)
ggplot(dat, aes(x=score, fill=group)) +
geom_histogram(binwidth=1, alpha=.3, position="identity")
+ geom_vline(data=cdat, aes(xintercept=score.mean,
colour=group), linetype="dashed", size=1) +
expand_limits(x = 0, y = 0)
```



your gut feeling: are these groups different?

are these distributions likely to have happen by chance?

can we use t-tests?

yes but because we are going to need to do 3 tests in total (to compare group 1 with 2, 2 with 3 and 1 with 3)

-> we need to use a Bonferoni correction

It means our significance level not 0.05 anymore but 0.05 / number of comparisons performed (here 3) so <u>0.016</u>

ttest1 ttest2

ttest3

a simple solution would be to do this …

5%
ttest1

5%
ttest2

5%
ttest3

a simple solution would be to do this …

problem: any given test has a 5% chance of lying to you so when you use them multiple time you increase your risk of having errors (statisticians call this a “type I error”) so there are two solutions to that:

bonferroni correction ::

when testing *n* hypotheses, test each one **against 0.05/n**

bonferroni correction ::

when testing *n* hypotheses, test each one **against 0.05/n**

in our example we would need to use **0.05/3** as a significant threshold instead of 0.05

```
# Use a t-test (two-tails, unpaired)

# (we already know A vs B not significative) so we need to
do

t.test(dat$score[dat$group == "A"], dat$score[dat$group ==
"C"], alternative = "two.sided")

        t = 11.48, df = 26.128, p-value = 1.044e-11

    # and

t.test(dat$score[dat$group == "B"], dat$score[dat$group ==
"C"], alternative = "two.sided")

        t = 11.435, df = 28.218, p-value = 4.163e-12
```

In both case p_value < 0.016 so we can conclude that slap condition reduces the memory abilities!

Another test we can use when we have more than two groups to compare is an ANOVA

we have 3 different conditions (or 1 factor with 3 different levels) so we will do a one-way ANOVA

anova::

analyze of variance to compare multiple variables

one-way anova = one variable with multiple levels

two-way anova = two variables with multiple levels

```
# first we run the one-way anova
library(ez) #install.packages("ez")
ezANOVA(dat,id,between=group,dv=score)
```

```
   Effect DFn DFd        F            p p<.05       ges
1  group    2  57 72.74697 2.040284e-16     * 0.7185101
```

ok something is going to be significant but what?

```
# second, run the pairwise comparison
pairwise.t.test(dat$score,dat$group, paired=FALSE,
p.adjust.method="bonferroni")
```

```
   A        B
B  0.65     -
C  2.9e-15  2.7e-13
```

The table shows the p-value for each comparison, 2 of them are <0.05

(here we don't need to do the Bonferroni correction (already included)) we can write:

“A one-way ANOVA showed a significant effect on time for the variable Group ($F_{2,57}=72.74$, $p < 0.05$).”

and then:

“Post-hoc comparison t-tests (using Bonferoni correction) showed significant difference between the group C and the group A ($p<0.05$) and between group C and group B ($p<0.05$).”

<you could also give means values to give more info>

note of course the “slap” condition is made up

in practice it would be improbable that any ethical approval board would allow this = a **mandatory process** before any user studies is done!

http://www.bristol.ac.uk/red/research-governance/ethics/uni-ethics/


check out the Standford experiment) to know more about why ethical considerations are crucial in user studies

end