Repeated measures

a.k.a. within-subjects ANOVA

AB Repeated measures

Today's goal:

Teach you about within-subjects ANOVA, the test used to test the differences between more than two within-subjects conditions

Outline:

- The theory of within-subjects ANOVA
- Within-subjects ANOVA in R
- Within-subjects Factorial ANOVA in R

Within-subjects ANOVA

the theory

AB Within-subjects

Remember the dependent t-test?

We test the difference between two systems, tested by the **same user**

Test: compare the difference D with SE_D

	u1	u2	u3	u4	u5
A	3	2	3	4	1
B	5	4	5	4	5
D_{B-A}	2	2	2	0	4

AB Within-subjects

When we have three within-subjects conditions, we have three differences

D_{B-A}, D_{C-A}, D_{C-B}

These differences each have a variance:

$\mathrm{var}(D_{B-A}) = 2.0$

$\mathrm{var}(D_{C-A}) = 1.3$

$\mathrm{var}(D_{C-B}) = 1.3$

	u1	u2	u3	u4	u5
A	3	2	3	4	1
B	5	4	5	4	5
C	4	1	2	2	1
D_{B-A}	2	2	2	0	4
D_{C-A}	1	–1	–1	–2	0
D_{C-B}	–1	–3	–3	–2	–4

AB Assumption

These differences each have a variance:

$var(D_{B-A}) = 2.0$, $var(D_{C-A}) = 1.3$, $var(D_{C-B}) = 1.3$

One assumption is that these variances are **equal**

You can test this with **Mauchly's** test

What if they are equal?

Then we can do a within-subjects ANOVA, and we can conduct any post-hoc test we like (Tukey works best)

Assumption

What if the variances are **not** equal?

For the ANOVA, we need to adjust the degrees of freedom of our F-ratio

- Greenhouse-Geisser correction (too conservative)
- Huynh-Feldt correction (too liberal)
- The average of these two (weird, but kinda works)

For the post-hoc tests, only Bonferroni seems to work well

AB Assumption

Or… we can run a **multilevel linear model**!

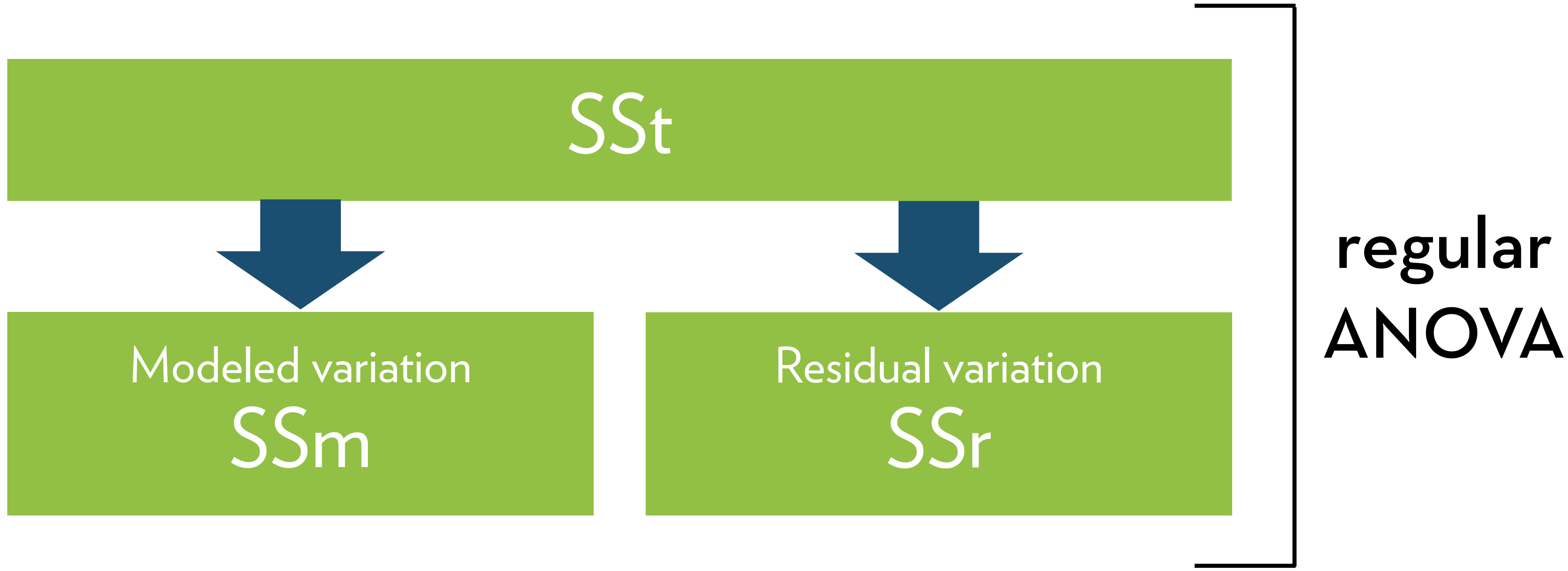
A multilevel linear model is a repeated measures version of linear regression

- Remember, ANOVA and linear regression are kind of the same thing

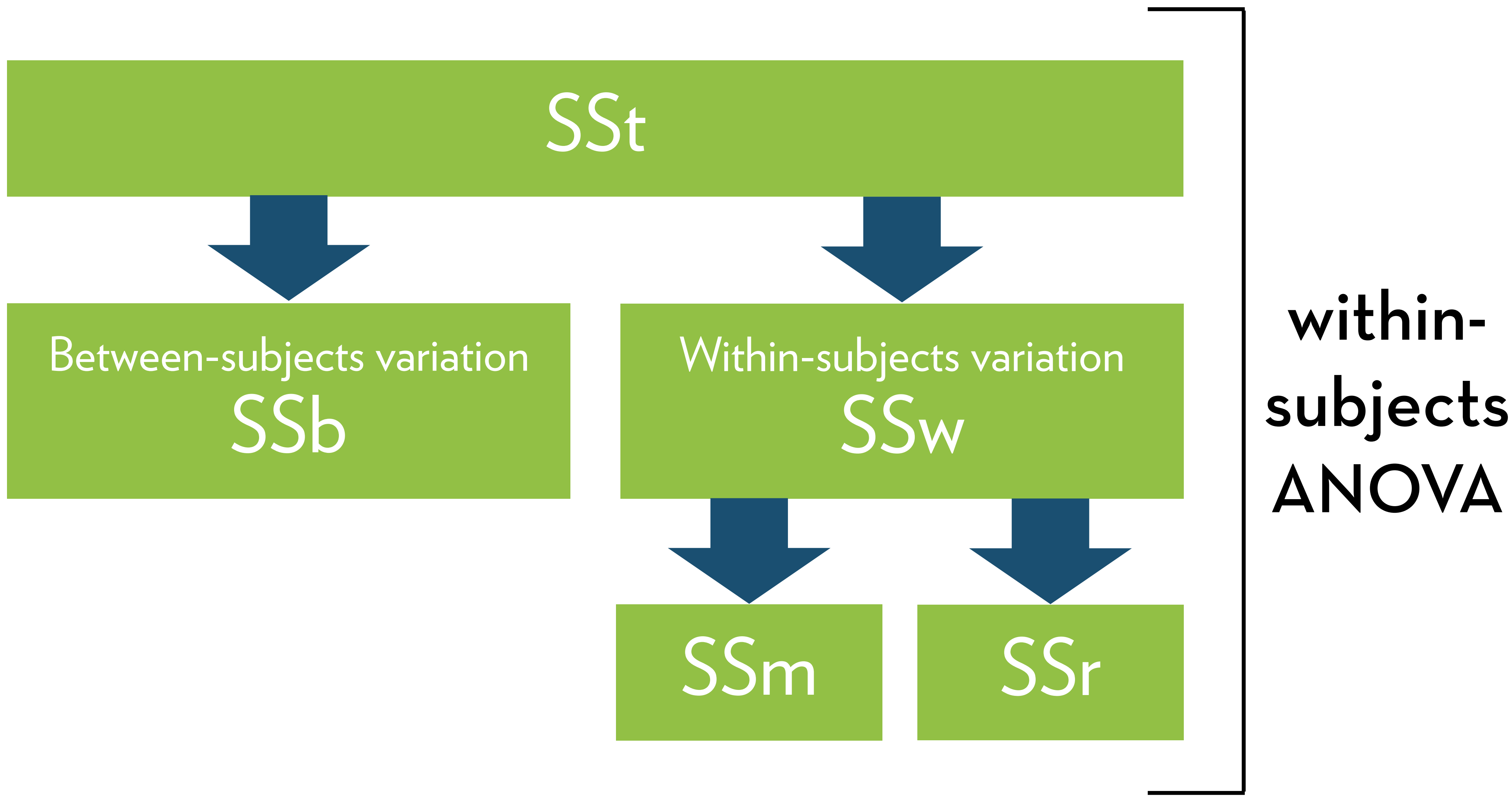
Multilevel models far more flexible than the repeated measures ANOVA

- We will learn all about them next week!

Sum of Squares



Sum of Squares



Sum of Squares

Sums of Squares for n participants in k conditions:

SSt: same as for regular ANOVA, with N = n*k:

$SSt = s^2(N-1)$, with N–1 df

SSw: s^2 for each participant p:

$\sum s_p^2(k-1)$, with n*(k–1) df

SSm: also the same; sum of squares over n group means:

$\sum n(\text{mean}_k - \text{grand mean})^2$, with k–1 df

Sum of Squares

SSr: whatever is left over from SSw after removing SSm:

SSw–SSm, with (n–1)(k–1) df

SSb: whatever is left over from SSt after removing SSw

(but we totally don't care about SSb at all here)

F-ratio

MSm = SSm/dfm

MSr = SSr/dfr

F = MSm/MSr (with dfm, dfr degrees of freedom)

Within-subjects in R

using ezANOVA and lme

AB Within-subjects in R

Dataset "Bushtucker.dat" —> rename to "bush"

- Effect of eating disgusting things on retching

Variables:

- participant: the participant ID
- stick_insect: time it takes before participant retches after eating a stick insect
- kangaroo_testicle: ...after eating a kangaroo testicle
- fish eye: ...after eating a fish eye
- witchetty grub: ...after eating a witchetty grub (a larvae)

Reshape the data

Use "melt" in the "reshape2" package to create a long-format version of the data:

```
bushLong <- melt(bush)
```

Give the resulting variables nice names:

```
names(bushLong) <- c("participant", "animal", "retch")
```

Plotting

Remember from the dependent t-test, we need to remove the between-subjects differences!

- bushAdjusted <- bush
- bushAdjusted$**stick_insect** <- bush$**stick_insect** - (bush$stick_insect+bush$kangaroo_testicle+bush$fish_eye+bush$witchetty_grub)/4 + mean((bush$stick_insect+bush$kangaroo_testicle+bush$fish_eye+bush$witchetty_grub)/4)
- Repeat the last command, but replace bold stick_insect with the other three

Plotting

Melt (in the reshape package) and rename bushAdjusted:

```
bushAdjusted <- melt(bushAdjusted)
names(bushAdjusted) <- c(“participant”, “animal”, “retch”)
```

Plot the bar chart:

```
ggplot(bushAdjusted, aes(animal, retch)) +
stat_summary(fun.y=mean, geom=“bar”, color=“black”,
fill=“white”) + stat_summary(fun.data=mean_cl_normal,
geom=“pointrange”)
```

Plotting

Boxplots:

```
ggplot(bushLong,aes(animal,retch)) + geom_boxplot()
```

ezANOVA

Install packages “nloptr” and “ez” and conduct an ezANOVA:

```
bushModel <- ezANOVA(data=bushLong, dv=.(retch), wid=.(participant), within=.(animal), detailed=T, type=3)
```

dv: the dependent variable

wid: the id of the subjects

within: the variable that lists the within-subjects levels

detailed: get more detailed output

type: the type of sum of squares (1, 2, or 3)

ezANOVA

Inspect the results: bushModel

```
$ANOVA
       Effect DFn DFd     SSn     SSd          F            p p<.05       ges
1 (Intercept)   1   7 990.125  17.375 398.899281 1.973536e-07     * 0.8529127
2      animal   3  21  83.125 153.375   3.793806 2.557030e-02     * 0.3274249

$`Mauchly's Test for Sphericity`
  Effect        W          p p<.05
2 animal 0.136248 0.04684581     *

$`Sphericity Corrections`
  Effect       GGe      p[GG] p[GG]<.05       HFe      p[HF] p[HF]<.05
2 animal 0.5328456 0.06258412           0.6657636 0.04833061         *
```

Effect of animal: F(3,21) = 3.79, p = .026

Effect size: generalized eta squared = 0.327

ezANOVA

```
$ANOVA
       Effect DFn DFd     SSn     SSd          F            p p<.05       ges
1 (Intercept)   1   7 990.125  17.375 398.899281 1.973536e-07     * 0.8529127
2      animal   3  21  83.125 153.375   3.793806 2.557030e-02     * 0.3274249

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2 animal 0.5328456 0.06258412           0.6657636 0.04833061         *
```

Mauchly's test is significant; we need to apply a correction

- Greenhouse-Geisser and Huynh-Feldt are given
- Multiply dfn and dfd by the correction estimate

ezANOVA

Main downside of ezANOVA: no planned contrasts!

Reporting:

> "Mauchly's test indicated that the assumption of sphericity had been violated, $W = 0.13$, $p < .05$, therefore, the degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon = .67$). The results show the the time to retch was significantly affected by the type of animal eaten, $F(2.00, 13.98) = 3.79$, $p < .05$, $\eta^2 = .327$.

ezANOVA

Post-hoc tests:

In this case, we should use the Bonferroni correction (because we have a lack of sphericity!)

```
pairwise.t.test(bushLong$retch, bushLong$animal, paired=T, p.adjust.method="bonferroni")
```

Results:

It took longer to retch after eating the stick insect than after eating the fish eye ($p = .006$) or the kangaroo testicle ($p = .012$). None of the other differences are significant.

lme - contrasts

Levels of animal variable:

```
levels(bushLong$animal)
stick_insect, kangaroo_testicle, fish_eye, witchetty_grub
```

Create some contrasts:

```
parts_v_whole <- c(1/2, –1/2, –1/2, 1/2)
testicle_v_eye <- c(0, –1/2, 1/2, 0)
stick_v_grub <- c(-1/2, 0, 0, 1/2)
contrasts(bushLong$animal) <- cbind(parts_v_whole,
testicle_v_eye, stick_v_grub)
```

lme

Install package “nlme” and conduct an lme:

```
bushModel <- lme(retch ~ animal, random = ~1|participant/animal, data=bushLong, method=“ML”)
```

Also conduct an lme for the baseline model:

```
baseline <- lme(retch ~ 1, random = ~1|participant/animal, data=bushLong, method=“ML”)
```

lme

Run the ANOVA comparison between the baseline and the model:

anova(baseline, bushModel)

```
          Model df      AIC      BIC    logLik   Test  L.Ratio p-value
baseline      1  4 165.0875 170.9504 -78.54373                        
bushModel     2  7 158.3949 168.6551 -72.19747 1 vs 2 12.69253  0.0054
```

This tests the effect of animal on retching (because that is the difference between the models)

loglikelihood ratio test: chi-square with 3 df

lme

Get the results for the contrasts: summary(bushModel)

```
                          Value Std.Error DF   t-value p-value
(Intercept)              5.5625 0.4365423 21 12.742178  0.0000
animalparts_v_whole      2.7500 0.8730846 21  3.149752  0.0048
animaltesticle_v_eye    -0.1250 1.2347281 21 -0.101237  0.9203
animalstick_v_grub      -2.3750 1.2347281 21 -1.923500  0.0681
```

AB lme

Reporting:

The type of animal consumed had a significant effect on the time taken to retch, $\chi^2(3) = 12.69$, $p = .005$. Orthogonal contrasts revealed that retching times were significantly quicker for animal parts (testicle and eye) than for whole animals (stick insect and witchetty grub), $b = 2.75$, $t(21) = 3.15$, $p = .005$); there was no significant difference between testicles and eyes ($b = -0.125$, $t(21) = -0.101$, $p = .920$), or between grub and stick ($b = -2.375$, $t(21) = -1.92$, $p = .068$).

AB lme

We can apply Tukey post-hoc tests (in multcomp), because **we avoid any sphericity issues** with lme!

```
postHocs <- glht(bushModel, linfct=mcp(animal="Tukey"))
summary(postHocs)
confint(postHocs)
```

Results:

It took longer to retch after eating the stick insect than after eating the fish eye ($p = .003$) or the kangaroo testicle ($p = .005$). None of the other differences are significant.

Robust methods

Using WRS2 works slightly different than in the (old) book:

Trimmed version (anova + posthoc):

- rmanova(bushLong$retch, bushLong$animal, bushLong$participant, tr = 0.2)
- rmmcp(bushLong$retch, bushLong$animal, bushLong$participant, tr = 0.2)

AB Robust methods

Bootstrapped and trimmed (anova + posthoc):

rmanovab(bushLong$retch, bushLong$animal, bushLong$participant, tr = 0.2, nboot = 2000)

pairdepb(bushLong$retch, bushLong$animal, bushLong$participant, tr = 0.2, nboot = 2000)

Factorial repeated in R

using ezANOVA and lme

Factorial repeated

Dataset "attitude.dat" (I've already made it long for you)

- Effect of advertisement on attitude to different types of drinks

Variables:

- participant: the participant ID
- drink: type of drink (beer, water, wine)
- imagery: type of imagery (negative, neutral, positive)
- attitude: participant's attitude to this drink after receiving this type of imagery

Plotting

Create boxplots:

```
ggplot(attitude,aes(drink,attitude))+geom_boxplot()
+facet_wrap(~imagery)
```

ezANOVA

Conduct an ezANOVA:

```
a1 <- ezANOVA(data=attitude, dv=.(attitude), wid=.(participant), within=.(imagery, drink), detailed=T, type=3)
```

ezANOVA

```
$ANOVA
         Effect DFn DFd       SSn      SSd          F            p p<.05       ges
1   (Intercept)   1  19 11218.006 1920.106 111.005411 2.255322e-09     * 0.4126762
2       imagery   2  38 21628.678 3352.878 122.564825 2.680197e-17     * 0.5753191
3         drink   2  38  2092.344 7785.878   5.105981 1.086293e-02     * 0.1158687
4 imagery:drink   4  76  2624.422 2906.689  17.154922 4.589040e-10     * 0.1411741

$`Mauchly's Test for Sphericity`
         Effect         W            p p<.05
2       imagery 0.6621013 2.445230e-02     *
3         drink 0.2672411 6.952302e-06     *
4 imagery:drink 0.5950440 4.356587e-01

$`Sphericity Corrections`
         Effect       GGe        p[GG] p[GG]<.05       HFe        p[HF] p[HF]<.05
2       imagery 0.7474407 1.757286e-13         * 0.7968420 3.142804e-14         *
3         drink 0.5771143 2.976868e-02         * 0.5907442 2.881391e-02         *
4 imagery:drink 0.7983979 1.900249e-08         * 0.9785878 6.809640e-10         *
```

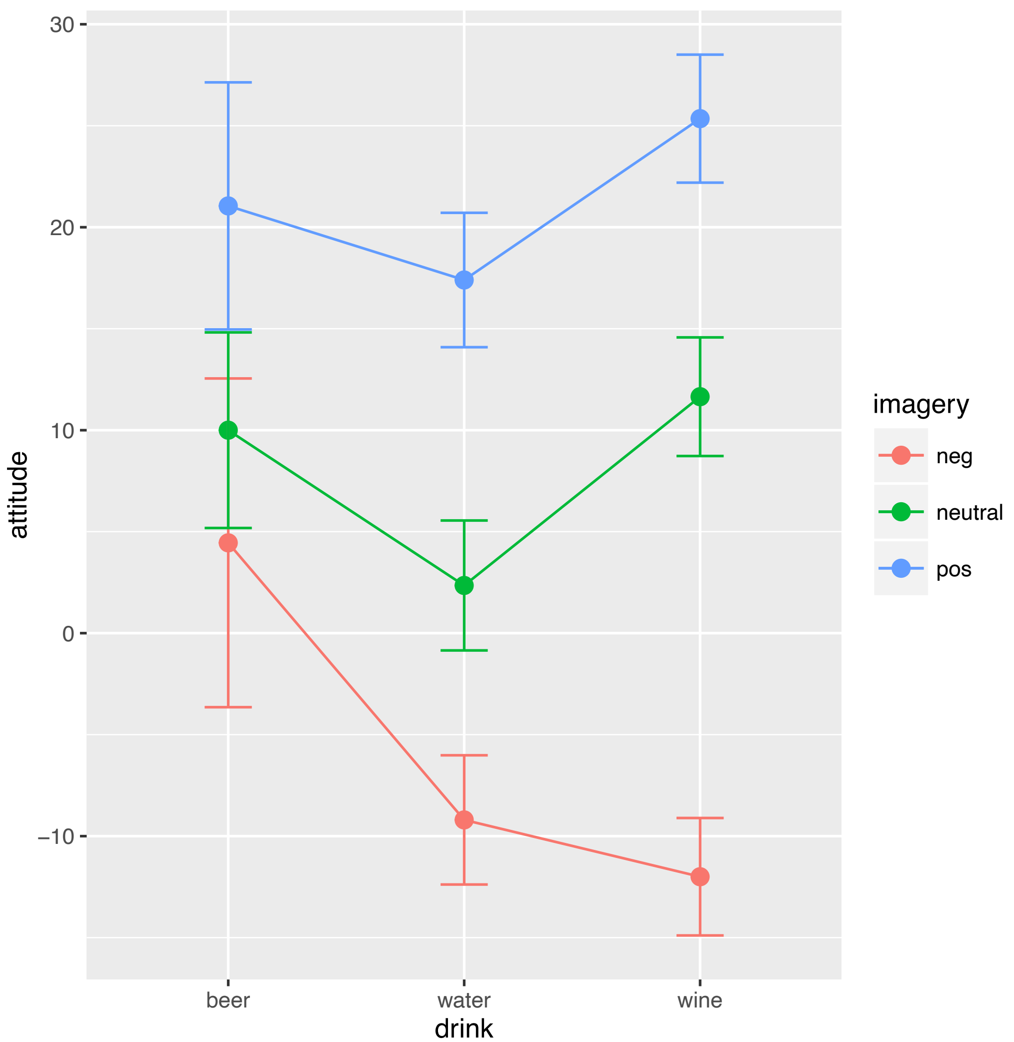
No sphericity for imagery and drink (report GG-corrected)

Sphericity for interaction (report ANOVA)

ezANOVA

There is an interaction… what is it?

- Problem: no contrast effects!
- Solution: post-hoc test + graph



ezANOVA

Post-hoc:

pairwise.t.test(attitude$attitude, interaction(attitude$imagery, attitude$drink), paired=T, p.adjust.method = “bonferroni”)

Result:

No effect of negative imagery on beer, strong effect on water and wine

ezANOVA

Reporting:

Mauchly's test indicated that the assumption of sphericity was violated for drink, $W = 0.267$, $p < .001$, $\varepsilon = .58$, and imagery $W = 0.662$, $p < .05$, $\varepsilon = .75$. The degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity.

There was a significant main effect of type of drink on ratings, $F(1.15, 21.93) = 5.11$, $p = .030$, a main effect of imagery, $F(1.50, 28.40) = 122.57$, $p < .001$, and an interaction effect between type of drink and imagery, $F(4, 76) = 17.16$, $p < .001$. The latter indicates that imagery had different effects on ratings depending on the drink.

ezANOVA

Bonferroni post hoc tests revealed that:

- For beer, there were significant differences between positive and both negative (p = .002) and neutral (p = .020) imagery, but not between negative and neutral (p = 1.00).
- For wine and water, there were significant differences between positive and both negative and neutral imagery, and between negative and neutral (all ps < .001).

lme - contrasts

Now let's do an lme. Start by creating contrasts:

For drink, test alcohol vs water, and beer vs wine:

```
alcohol_v_water <- c(1/3, -2/3, 1/3)
beer_v_wine <-c(1/2, 0, -1/2)
contrasts(attitude$drink) <- cbind(alcohol_v_water, beer_v_wine)
```

lme - contrasts

For imagery, test negative vs other, and positive vs neutral:

```
neg_v_other <- c(-2/3, 1/3, 1/3)
pos_v_neutral <-c(0, -1/2, 1/2)
contrasts(attitude$imagery) <- cbind(neg_v_other, pos_v_neutral)
```

lme

Conduct an lme for the baseline:

```
baseline <- lme(attitude~1, random = ~1|participant/drink/imagery, data=attitude, method="ML")
```

Add a main effect of drink, then imagery, then the interaction:

```
drinkModel <- update(baseline, .~. + drink)
imageryModel <- update(drinkModel, .~. + imagery)
fullModel <- update(imageryModel, .~. + drink*imagery)
```

lme

Run an model comparison on the nested models:

- anova(baseline, drinkModel, imageryModel, fullModel)

Interpretation: each step seems to improve the model significantly

- Bonus question: what type of Sum of Squares is this?

AB lme

Reporting:

The type of drink had a significant effect on attitudes $\chi^2(2) = 9.1$, $p = .010$, as did the effect of imagery $\chi^2(2) = 151.9$, $p < .001$. Most importantly, the interaction between drink and imagery was significant, $\chi^2(4) = 42.0$, $p < .001$.

lme

Run the summary to get the contrasts:

summary(fullModel)

```
                                              Value Std.Error  DF   t-value p-value
(Intercept)                                7.894444  0.972619 114  8.116687  0.0000
drinkalcohol_v_water                       6.566667  2.063237  38  3.182702  0.0029
drinkbeer_v_wine                           3.500000  2.382421  38  1.469094  0.1500
imageryneg_v_other                        20.216667  1.171632 114 17.255128  0.0000
imagerypos_v_neutral                      13.266667  1.352885 114  9.806208  0.0000
drinkalcohol_v_water:imageryneg_v_other    1.712500  2.485408 114  0.689022  0.4922
drinkbeer_v_wine:imageryneg_v_other      -19.425000  2.869901 114 -6.768525  0.0000
drinkalcohol_v_water:imagerypos_v_neutral -2.675000  2.869901 114 -0.932088  0.3533
drinkbeer_v_wine:imagerypos_v_neutral     -2.650000  3.313877 114 -0.799668  0.4256
```

lme

Contrast revealed that:

- On average , people have higher attitudes for alcohol than water, b = 6.57, t(38) = 3.18, p = .003, r = 0.46 but there is no significant difference between beer and wine, b = 3.50, t(38) = 1.47, p = .150;
- On average, negative imagery lowers attitudes compared to neutral or positive imagery, b = 20.22, t(114) = 17.26, p < .001, r = 0.85, and positive imagery increases attitudes compared to neutral imagery, b = 13.27, t(114) = 9.81, p < .001, r = 0.68;

lme

Contrast revealed that:

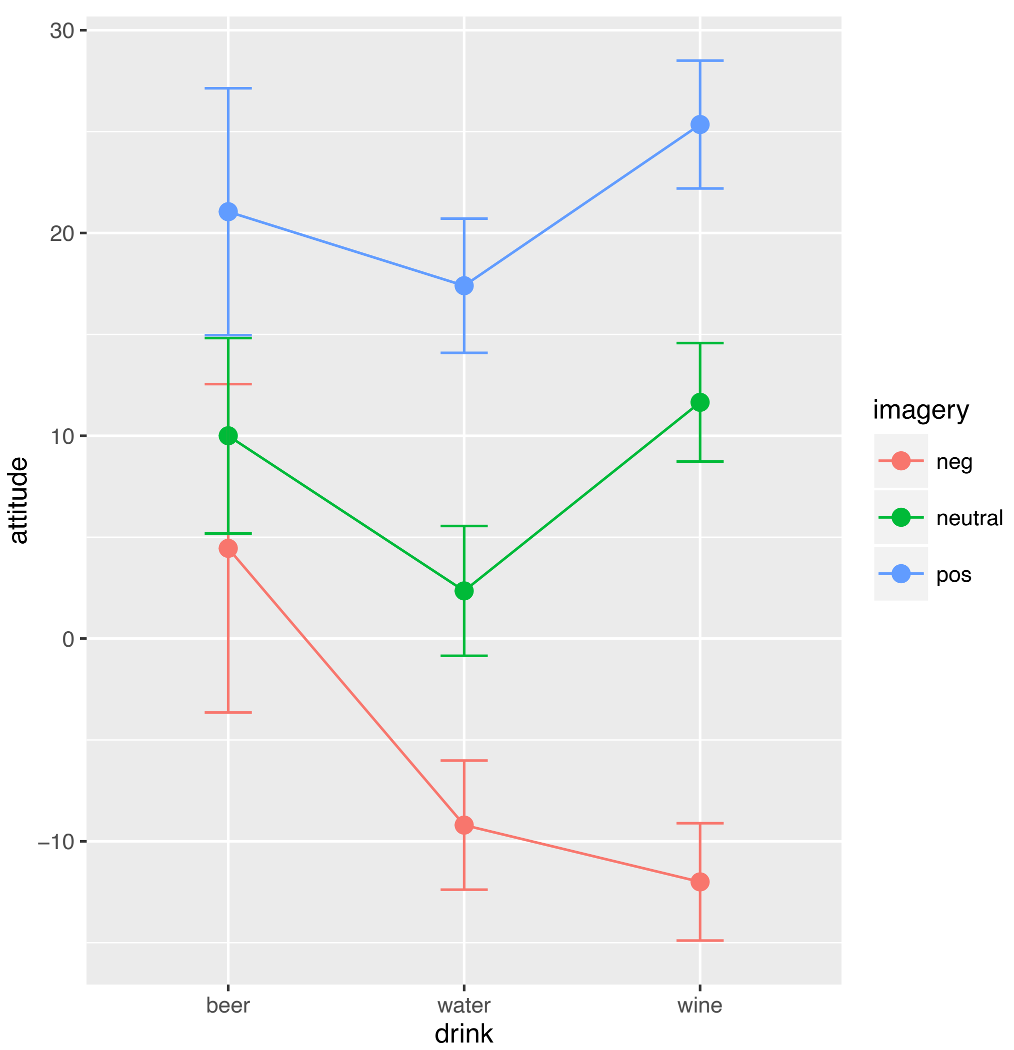
- The effect of negative imagery (compared to neutral or positive) in lowering attitudes is comparable in alcoholic and non-alcoholic drinks, $b = 1.71$, $t(114) = 0.69$, $p = .492$;
- The effect of negative imagery in lowering attitudes is significantly smaller for beer than for wine, $b = -19.43$, $t(114) = -6.77$, $p < .001$, $r = 0.535$;
- The effect of positive imagery (compared to neutral) is comparable in alcoholic and non-alcoholic drinks, $b = -2.68$, $t(114) = -0.93$, $p = .353$, as well as in beer and wine, $b = -2.65$, $t(114) = -0.80$, $p = .426$.

AB lme

Overview of these effects: include a graph!

Try for yourself: simple effects:

- Compare contrasts for neg-neutral-pos for each drink type, OR
- Compare contrasts for beer-water-wine for each type of imagery



"It is the mark of a truly intelligent person to be moved by statistics."

T H A N K S !

George Bernard Shaw