Lab 4

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Experimental design

- Try to imagine an experimental study where researchers were interested in gender differences in recalling words written in fonts of different colors. A total of N = 40 participants took part in a study (20 males and 20 females). Participants were asked to memorize words written in different colors. Male participants were asked to memorize words written in red (10 of 20 males) and green (10 of 20 males), whereas female participants where asked to memorize words written in blue (10 of 20 females) and yellow (10 of 20 females).
- A number of correctly recalled words (out of 10) for each participant was recorded
- What can results of such study tell us? What conclusions we will be able to make?
- What are drawbacks of such experimental design? If any, does this drawbacks make such study useless?

Experimental design

- Actually we will be able to model such results:
- $y_{ijk} = \mu + \alpha_j + \alpha_k + \epsilon_{ijk}$
- where α_j indicates a deviance of a mean related to gender from a grand mean
- and α_k indicates a deviance of a mean related to font color from a grand mean

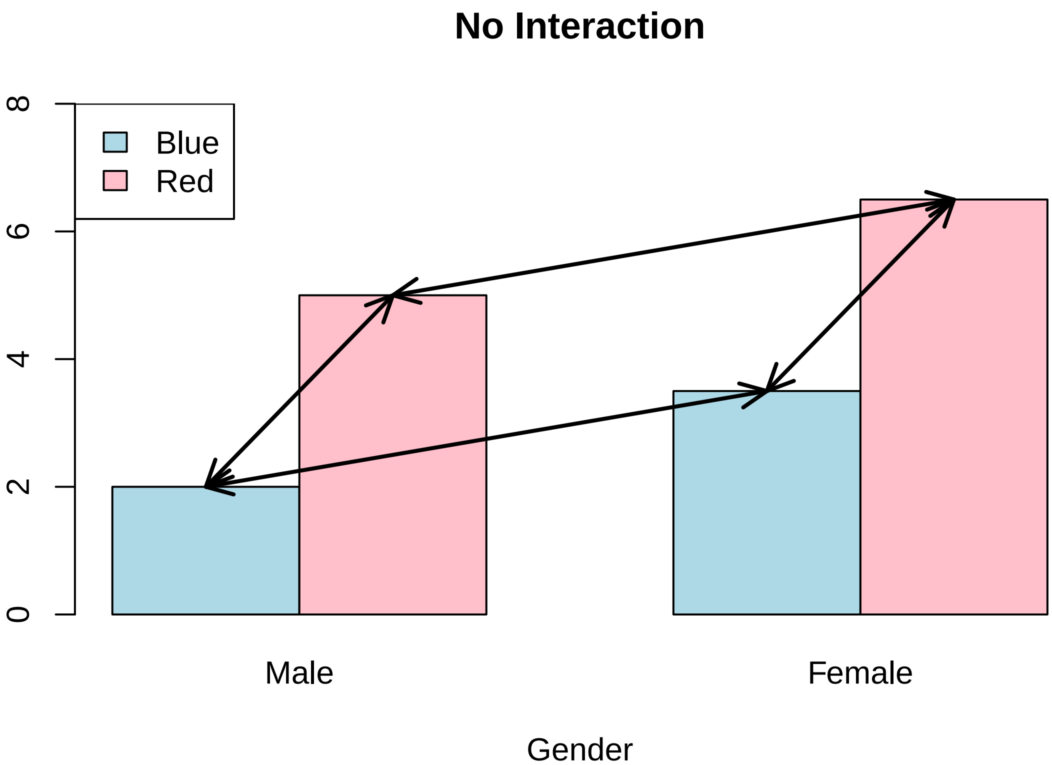
Experimental design

- In a second attempt resarchers performed a study where they collected another sample of male and female participants. Within each gender group participants memorized words written in red (one-quarter of gender group), green (one-quarter of gender group), blue (one-quarter of gender group), or yellow (one-quarter of gender group).
- Why this example addresses the researcher's question better?
- What are the drawbacks of such experimental design?

Experimental design

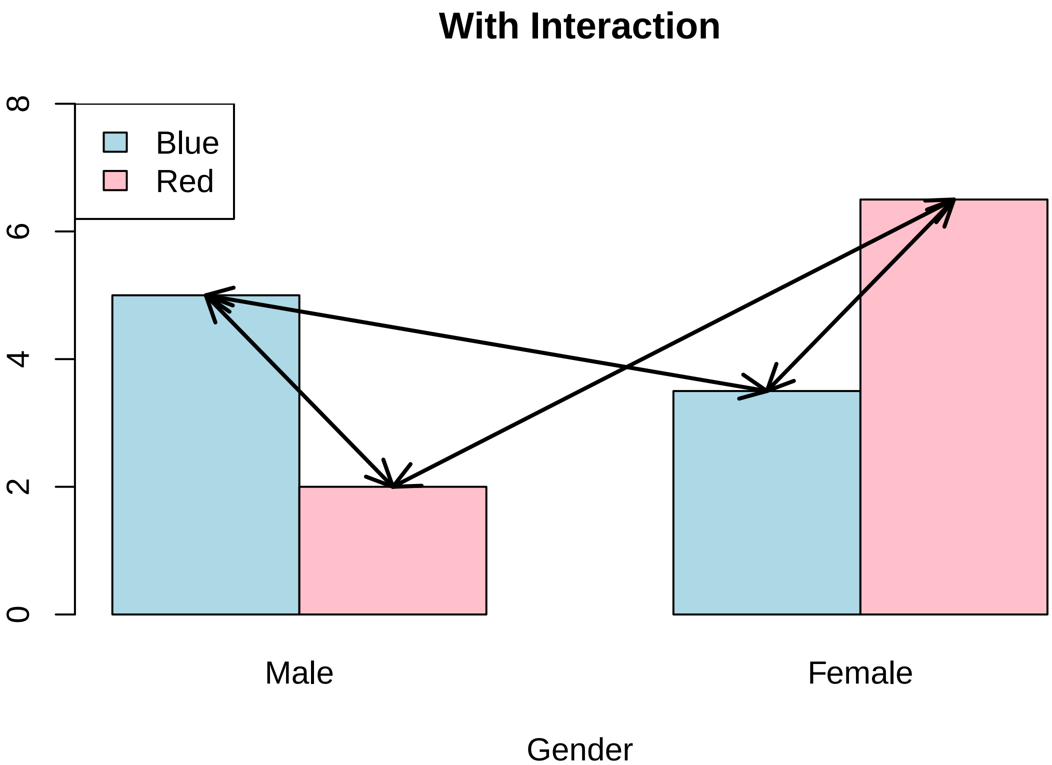
- We will be able to model such results:
- $y_{ijk} = \mu + \alpha_j + \alpha_k + \alpha_{jk} + \epsilon_{ij}$
- where α_j indicates a deviance of a mean related to gender from a grand mean
- α_k indicates a deviance of a mean related to font color from a grand mean
- and α_{jk} indicates interaction, i.e. to effects of all combinations of the two preceding factors, not accounted by the additive terms

Interactions



$\mu_{female,blue} - \mu_{female,red} = \mu_{female,blue} - \mu_{female,red}$

Interactions



$\mu_{female,blue} - \mu_{female,red} \neq \mu_{female,blue} - \mu_{female,red}$

Effects in multi-way ANOVA

- Main effect of gender: $\mu_{female,\ .} - \mu_{male,\ .}$
- Main effect of color: $\mu_{.\ ,blue} - \mu_{.\ ,red}$
- Simple main effects of gender: $\mu_{female,blue} - \mu_{male,blue}$ and $\mu_{female,red} - \mu_{male,red}$
- Simple main effects of color: $\mu_{female,blue} - \mu_{female,red}$ and $\mu_{male,blue} - \mu_{male,red}$

Effect sizes

	Df	SS	MS	F	p
Factor 1	1	205.35	205.35	15.57	<0.001
Factor 2	2	2426.43	1213.22	92.00	<0.001
Interaction	2	108.32	54.16	4.11	0.022
Residuals	54	712.11	13.19		
Total	59	3452.21			

- Recall $\eta^2 = \frac{SS_{effect}}{SS_{total}}$, this is the same measure as in one-way ANOVA
- The drawback of this measure is that as we add other variables to the model, the proportion of explained by any one variable will automatically decrease

Effect sizes

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- Partial $\eta_p^2 = \frac{SS_{effect}}{SS_{effect}+SS_{residual}}$, solves the problem with η_2
- It makes the effect size more comparable between studies, however both η_2 and η_p^2 overstimate variance explained (it is always higher than in population)

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- ω^2 is an unbiased estimate of population variances (it is always smaller that η^2)
- Assuming you have a table like above, you can calculate the estimate with, $\omega^2 = \frac{SS_{effect}-(df_{effect}*MS_R)}{SS_{total}+MS_R}$