Factorial ANOVA Example[1]

SPSS
Syntax

```
MEANS VARS=memory by violence by training.

GLM memory BY violence training
  /plot = profile (violence*training)
  /print = etasq.
```

Menus

Analyze → General Linear Model, then drag the dependent variable over to the appropriate box and add both independent variables to **Fixed Factors**. Under the **Plots** button, choose which independent variables you want for the horizontal axis and for separate lines, then click the **Add** button.
Under **Options** button, check **Estimates of Effect Size**

Output[2]

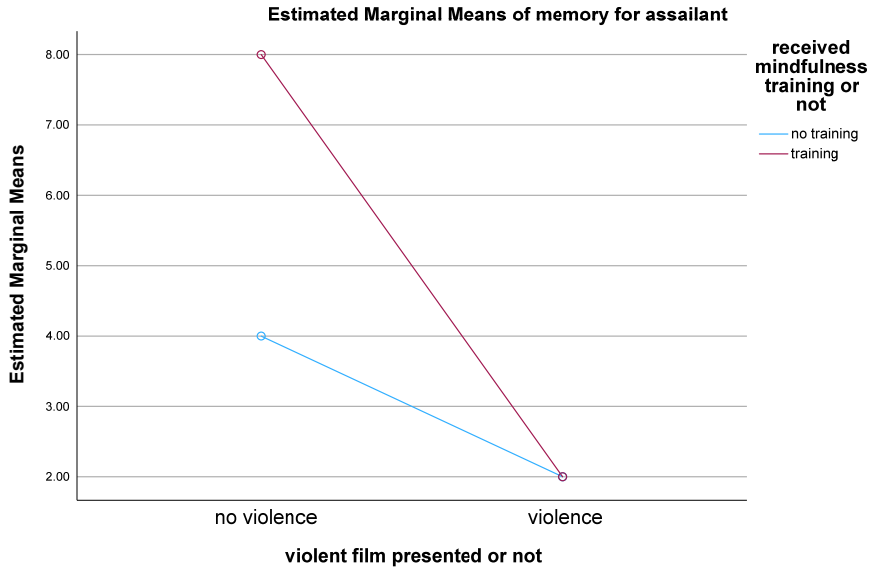
General Linear Model

Tests of Between-Subjects Effects

Dependent Variable: memory memory for assailant

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	120.000[a]	3	40.000	32.000	.000	.857
Intercept	320.000	1	320.000	256.000	.000	.941
violence	80.000	1	80.000	64.000	.000	.800
training	20.000	1	20.000	16.000	.001	.500
violence * training	20.000	1	20.000	16.000	.001	.500
Error	20.000	16	1.250			
Total	460.000	20				
Corrected Total	140.000	19				

a. R Squared = .857 (Adjusted R Squared = .830)



[1] The data analyzed in this example are hypothetical, but the memory interference effect of witnessing a violent incident was shown by Loftus, E. F., & Burns, T. E. (1982). Mental shock can produce retrograde amnesia. *Memory & Cognition, 10*, 318-323. Mindfulness training to reduce emotional interference effects has been conducted by several researchers, such as Ortner, C. N., Kilner, S. J., & Zelazo, P. D. (2007). Mindfulness meditation and reduced emotional interference on a cognitive task. *Motivation and emotion, 31*, 271-283, among others.

[2] You may notice that some of the variances are somewhat unequal, which may be problematic with this small n. SPSS unfortunately does not have a Welch's test that can be used with factorial ANOVA. The GLM and UNIANOVA commands have added several versions of a robust approach (Huber-White sandwich estimator) that has been shown to be useful in regression models when there are unequal variances, using the subcommand `/robust=hc3`. The HC3 method is what Long and Ervin (2000) recommend for small samples. But this subcommand does not seem to be working properly with factorial designs.

R

The `car` package is used in my example, because most approaches to factorial ANOVA in R will use Type I or Type II sum of squares. Although this example has equal n in all cells, Type I, II and III sums of squares values will be different if that is not the case. Type III sum of squares is the default in SPSS and what I typically recommend for an unbalanced *n* design. There are a couple of tricks to getting the correct results using the `car` package though. An options function must be used and the IVs must be designated as categorical variables in R ("factors"). To check variable type, use `str(d)`, where d is the data frame name. If you use haven to read in SPSS data, for instance, you will need to convert the IVs to factors. The factor function is a simple base R method of changing the variable type to factor.

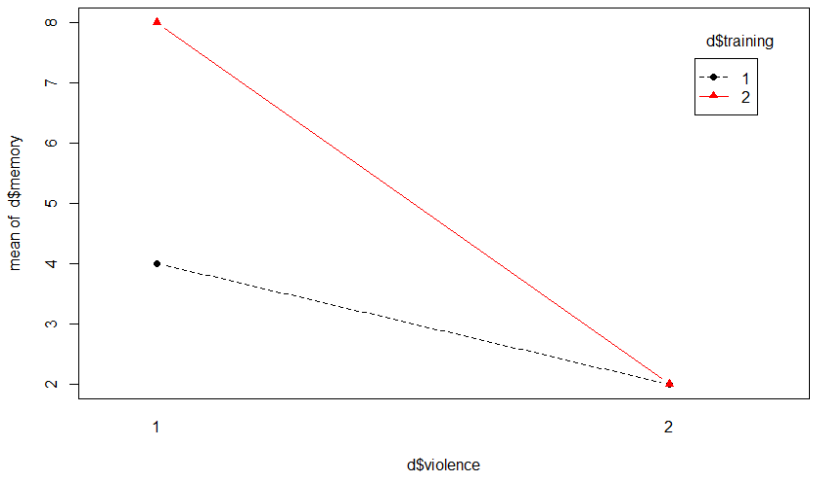
```
#need to convert independent variables to factors
> d$violence <- factor(d$violence)
> d$training <- factor(d$training)


#Must use a different package to get Type III SS for unbalanced design (install car on first use)[3]
> mymodel = lm(memory ~ violence*training, data=d, contrasts = list(violence="contr.sum", training="contr.sum"))
> Anova(mymodel, type="III")
Anova Table (Type III tests)

Response: memory
                 Sum Sq Df F value           Pr(>F)
(Intercept)         320  1     256 0.00000000002892 ***
violence             80  1      64 0.00000055454476 ***
training             20  1      16         0.001032 **
violence:training    20  1      16         0.001032 **
Residuals            20 16
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


#to obtain partial eta squared values, install lsr package
> library(lsr)
> etaSquared(mymodel, type = 3, anova = FALSE )
                eta.sq eta.sq.part
violence         0.5714286         0.8
training         0.1428571         0.5
violence:training 0.1428571         0.5


#interaction plot--x.factor is x axis and trace.factor is separate lines, response is dv
#all other options can remain the same
> interaction.plot(x.factor = d$violence, trace.factor = d$training,
                   response = d$memory, fun = mean, type="b",
                   col=c("black","red","green"), pch=c(19, 17, 15),
                   fixed=TRUE,leg.bty = "o")
```



[3] lessR only allows balanced designs (equal n in each cell), but it is convenient if you have balanced *n*. For my analysis with n=5 in each cell I could use it: `ANOVA(memory ~ violence * training, brief=TRUE)`

A 2 X 2 (film × mindfulness training) factorial analysis of variance tested the effects of the violent film incident and the mindfulness training program on memory for the assailant. Results indicated a significant main effect for the violence factor, $F(1,16) = 64.00$, $p < .001$, partial $\eta^2 = .80$. As hypothesized, those who saw the violent segment in the film showed a memory deficit ($M = 2.00$) compared to those who had not seen the violent segment ($M = 6.00$). There was also a significant main effect for the training program, $F(1,16) = 16.00$, $p = .001$, partial $\eta^2 = .50$. Officers in the training program had better memory overall ($M = 5.00$) than those who had no training ($M = 3.00$). The two main effects were qualified, however, by a significant interaction between the two factors, $F(1,16) = 16.00$, $p = .001$, partial $\eta^2 = .50$, indicating that the training program effects were not the same for two different film conditions.

(Note that these analyses are incomplete, and I strongly recommend that a significant interaction be followed by additional analyses to probe the nature of the interaction. See the subsequent handout "Simple Effects Test Following a Significant Interaction" for additional information. In addition, although APA recommends inclusion of eta-squared values for each effect, I dislike this the partial eta-squared effect size measure, because the values typically do not total 100% of the variance, even though the F-values are computed such that the effects are partitioned. The term "partial" refers to the fact that only part of the total variance is counted in the denominator, making the values appear larger than if the total variance was used in the denominator).

References

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician*, *54*, 217-224.