

The General Linear Model – ANOVA

Part 1 (Video 4)

Unit Coordinator: Dr Danna R. Gifford
(danna.gifford@manchester.ac.uk)

Original author: Prof Andrew J. Stewart
(drandrewjstewart@gmail.com)



Factorial ANOVA

So far we have looked at ANOVA for designs when we have one factor which is between participants (i.e., each participant appears in only one condition), and for designs when we have one factor that is repeated measures (each participant appears in all conditions). These are examples of 1-way ANOVA.

Now we're going to look at factorial ANOVA - this is for cases where we have more than one factor and we might be interested in how the factors interact with each other. If we have two factors, we will build a 2-way ANOVA, three factors, a 3-way ANOVA etc.

Factorial ANOVA

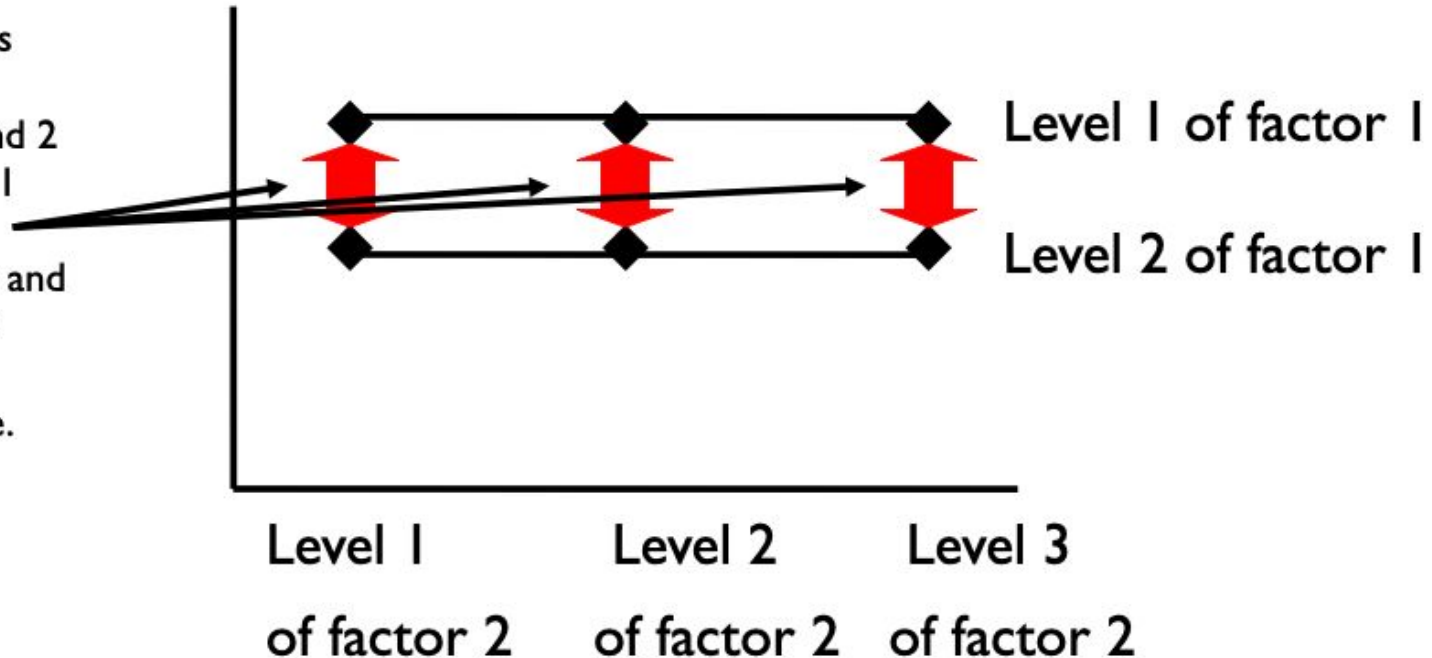
Imagine we have 2 factors. Factor 1 with two levels, Factor 2 with three. Our analysis might reveal a main effect of Factor 1 (i.e., a difference between the two levels), a main effect of Factor 2 (i.e., a difference between the three levels) or an interaction between the two.....

To examine what might be going on, we build a 2 x 3 ANOVA. The first number corresponds to the first factor and the number of levels it has (2) while the second corresponds to the second factor and the number of levels it has (3).

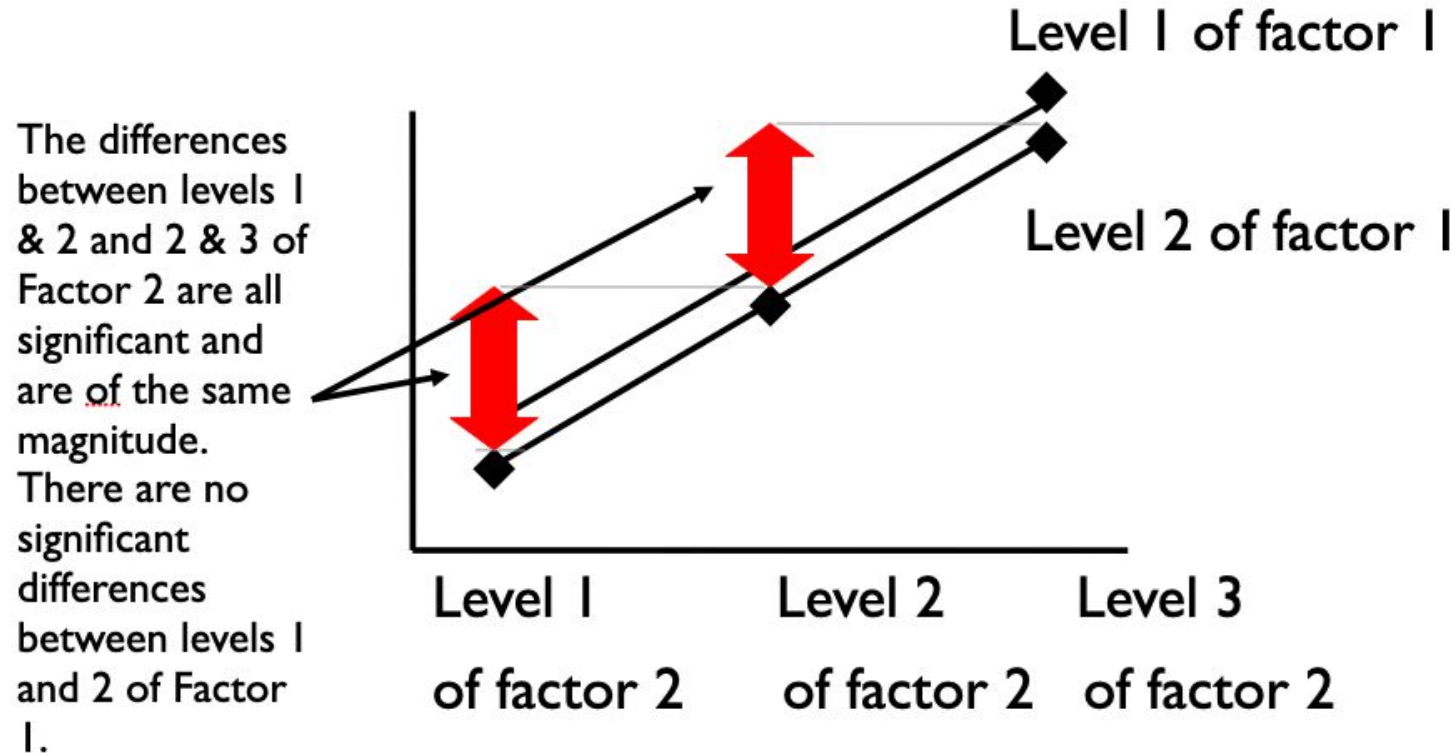
Following are examples of 'perfect' patterns of effects...

Main effect of Factor 1, no main effect of Factor 2 and no interaction

The differences between levels 1 and 2 of Factor 1 are all significant and are of the same magnitude.

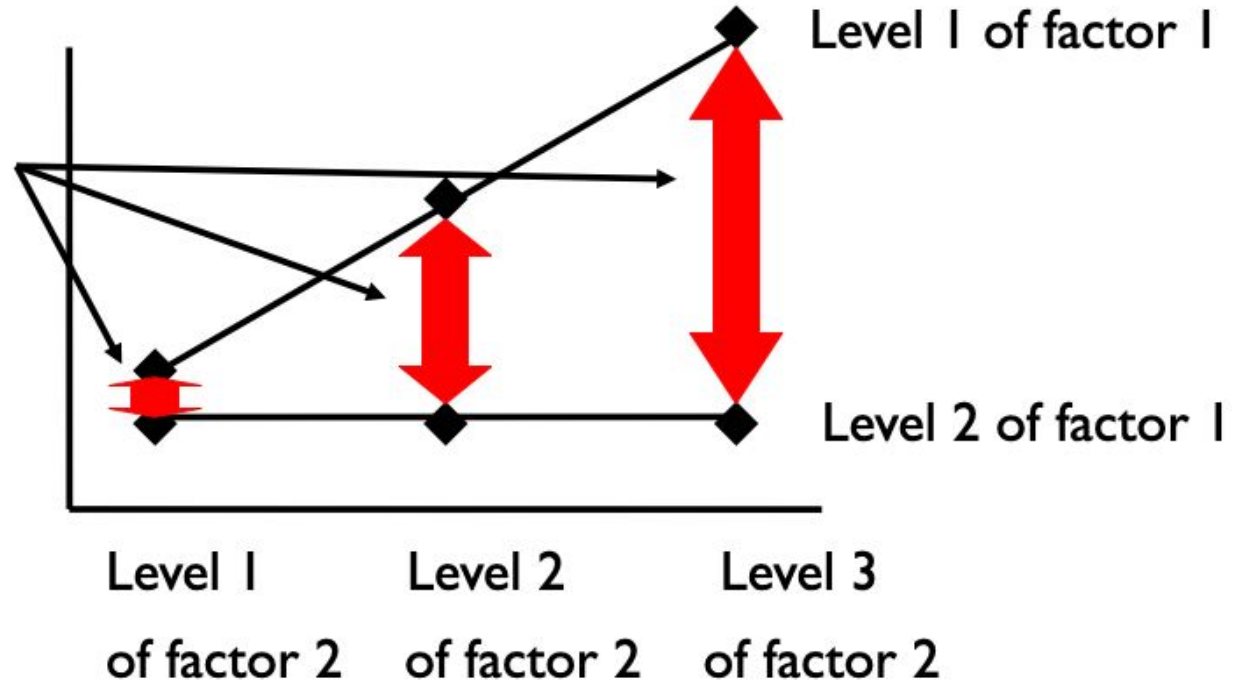


No main effect of Factor 1, main effect of Factor 2 and no interaction



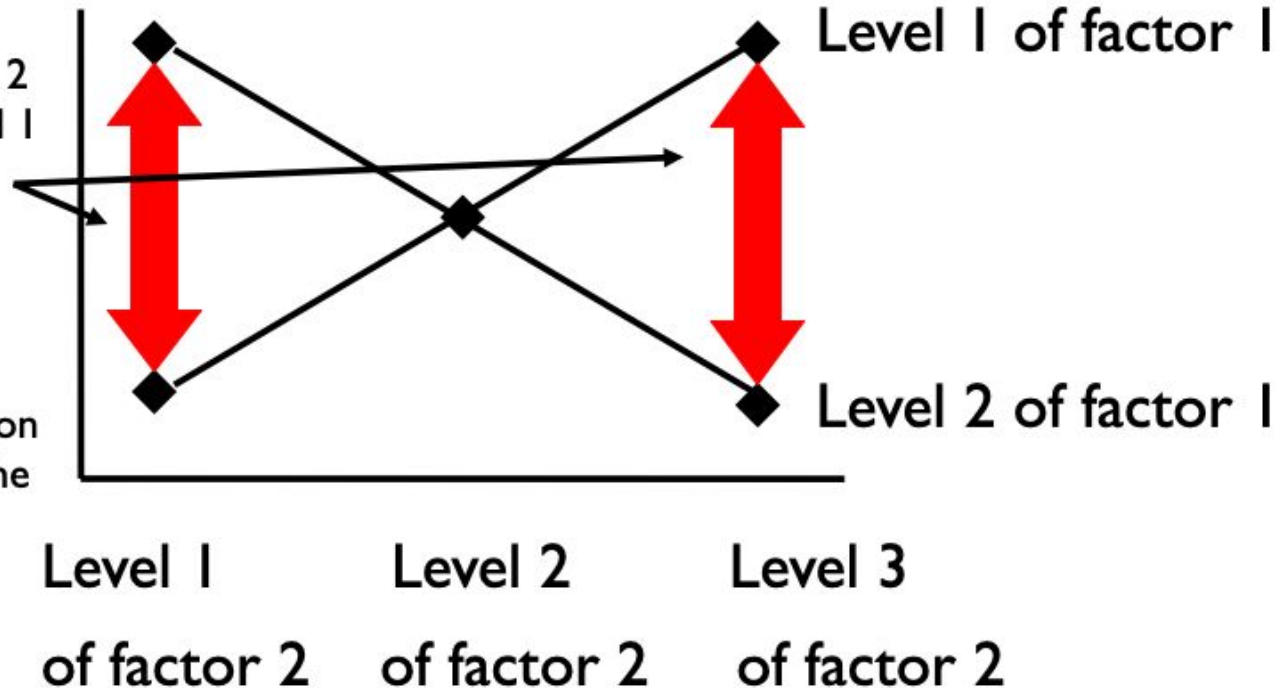
Main effect of Factor 1, main effect of Factor 2 and an interaction

The differences between the two levels of factor 1 change as a function of factor 2.



No main effect of Factor 1, no main effect of Factor 2 but an interaction

The difference between levels 1 & 2 of Factor 1 at Level 1 of Factor 2 is different from the same difference at Levels 2 and 3 of Factor 2. This is a crossover interaction as the polarity of the difference flips.



Example Factorial ANOVA

Imagine the case where we're interested in the effect of positive vs. negative contexts on how quickly (in milliseconds) people respond to positive vs negative sentences. We think there might be a priming effect (i.e., people are quicker to respond to positive sentences after positive contexts vs. after negative contexts - and vice versa).

So, we have two factors, each with two levels. This is what's known as a full factorial design where every subject participates in every condition.

Reading in our Data

```
factorial_data <-  
read_csv("https://raw.githubusercontent.com/ajstewartlang/11_glm_anova_pt1/  
master/data/factorial_data.csv")  
head(factorial_data)
```

```
# A tibble: 6 x 5
```

	Subject	Item	RT	Sentence	Context
	<dbl>	<dbl>	<dbl>	<chr>	<chr>
1	1	3	1270	Positive	Negative
2	1	7	739	Positive	Negative
3	1	11	982	Positive	Negative
4	1	15	1291	Positive	Negative
5	1	19	1734	Positive	Negative
6	1	23	1757	Positive	Negative

Tidying our Data

```
factorial_data_tidied <- factorial_data %>%  
  mutate(Sentence = factor(Sentence), Context = factor(Context))  
head(factorial_data_tidied)
```

```
# A tibble: 6 x 5
```

	Subject	Item	RT	Sentence	Context
	<dbl>	<dbl>	<dbl>	<fct>	<fct>
1	1	3	1270	Positive	Negative
2	1	7	739	Positive	Negative
3	1	11	982	Positive	Negative
4	1	15	1291	Positive	Negative
5	1	19	1734	Positive	Negative
6	1	23	1757	Positive	Negative

Summarising our Data

```
factorial_data_tidied %>%  
  group_by(Context, Sentence) %>%  
  summarise(mean_rt = mean(RT), sd_rt = sd(RT))
```

```
# A tibble: 4 x 4
```

```
# Groups:   Context [2]
```

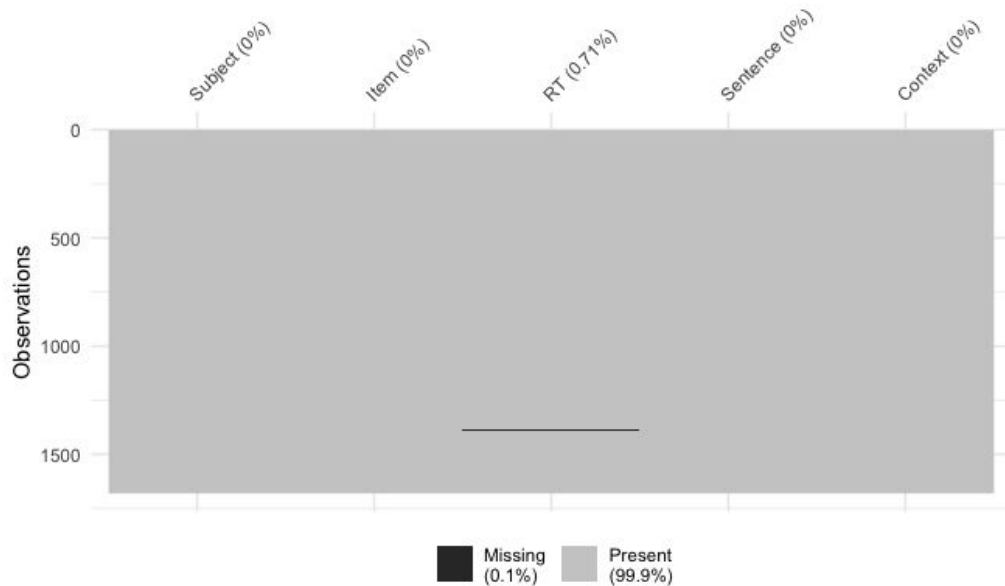
	Context	Sentence	mean_rt	sd_rt
	<fct>	<fct>	<dbl>	<dbl>
1	Negative	Negative	1474.	729.
2	Negative	Positive	NA	NA
3	Positive	Negative	NA	NA
4	Positive	Positive	1579.	841.

What's happening here?



Do we have missing data?

```
vis_miss(factorial_data_tidied)
```



Ignoring Missing Data

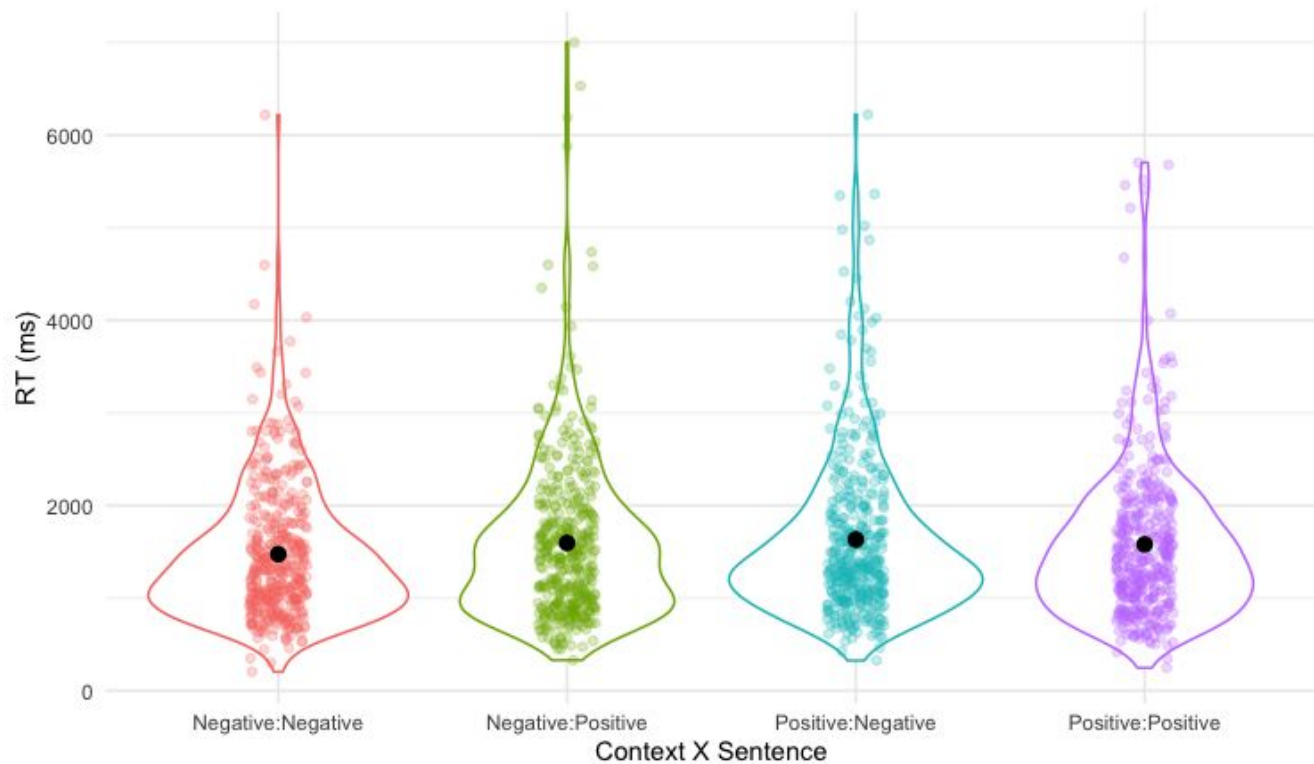
```
factorial_data_tidied %>%  
  group_by(Context, Sentence) %>%  
  summarise(mean_rt = mean(RT, na.rm = TRUE), sd_rt = sd(RT, na.rm =  
TRUE))
```

```
# A tibble: 4 x 4
```

```
# Groups:   Context [2]
```

	Context	Sentence	mean_rt	sd_rt
	<fct>	<fct>	<dbl>	<dbl>
1	Negative	Negative	1474.	729.
2	Negative	Positive	1595.	887.
3	Positive	Negative	1633.	877.
4	Positive	Positive	1579.	841.

Visualising our Data



Modelling our Data – F1

```
model_subjects <- aov_4(RT ~ Context * Sentence + (1 + Context * Sentence |  
Subject), data = factorial_data_tidied, na.rm = TRUE)  
anova(model_subjects)
```

Anova Table (Type 3 tests)

Response: RT

	num	Df	den	Df	MSE	F	ges	Pr(>F)
Context		1		59	90195	3.1767	0.0060231	0.07984 .
Sentence		1		59	124547	0.6283	0.0016524	0.43114
Context:Sentence		1		59	93889	4.5967	0.0090449	0.03616 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Modelling our Data – F2

```
model_items <- aov_4(RT ~ Context * Sentence + (1 + Context * Sentence |  
Item), data = factorial_data_tidied, na.rm = TRUE)  
anova(model_items)
```

Anova Table (Type 3 tests)

Response: RT

	num	Df	den	Df	MSE	F	ges	Pr(>F)
Context		1		27	39844	4.0013	0.0080150	0.05561 .
Sentence		1		27	203164	0.1221	0.0012553	0.72951
Context:Sentence		1		27	40168	5.7687	0.0116070	0.02346 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpreting our Model

```
emmeans(model_subjects, pairwise ~ Context * Sentence, adjust = "none")
```

```
$emmeans
```

Context	Sentence	emmean	SE	df	lower.CL	upper.CL
Negative	Negative	1474	57.8	138	1360	1588
Positive	Negative	1628	57.8	138	1514	1742
Negative	Positive	1595	57.8	138	1481	1709
Positive	Positive	1579	57.8	138	1465	1693


Warning: EMMs are biased unless design is perfectly balanced

Confidence level used: 0.95

```
$contrasts
```

contrast	estimate	SE	df	t.ratio	p.value
Negative Negative - Positive Negative	-153.9	55.4	118	-2.779	0.0064
Negative Negative - Negative Positive	-120.9	60.3	116	-2.004	0.0474
Negative Negative - Positive Positive	-105.2	59.8	115	-1.759	0.0813
Positive Negative - Negative Positive	33.0	59.8	115	0.551	0.5824
Positive Negative - Positive Positive	48.7	60.3	116	0.807	0.4213
Negative Positive - Positive Positive	15.7	55.4	118	0.284	0.7772

These are the two
key comparisons.



Interpreting our Model

We conducted a 2 (Context: Positive vs. Negative) x 2 (Sentence: Positive vs. Negative) repeated measures ANOVA to investigate the influence of Context valence on reaction times to Sentences of Positive or Negative valence. The ANOVA revealed no effect of Sentence ($F < 1$), no effect of Context ($F(1, 59) = 3.18, p = .080, \eta G^2 = .006$), but an interaction between Sentence and Context ($F(1, 59) = 4.60, p = .036, \eta G^2 = .009$).

The interaction was interpreted by conducting Bonferroni-corrected pairwise comparisons. These comparisons revealed that the interaction was driven by Negative Sentences being processed faster in Negative vs. Positive Contexts (1,474 ms. vs. 1,628 ms., $t(118) = 2.78, p = .012$) while Positive Sentences were read at similar speeds in Negative vs. Positive Contexts (1,595 ms. vs. 1,579 ms., $t(118) = .284, p = 1$).

Reporting ANOVA

- Say what type of ANOVA it was, say what factors you had (and with labels for each level).
- Report the results of main effects first, then interactions.
- Report F values, exact p -values, effect sizes, and confidence intervals.
- Remember to interpret interactions further - such as with contrasts or pairwise comparisons.
- When you have main effects, say which direction the effect goes.
- Avoid sillies - e.g., mixing up $<$ and $>$ or saying $p = .000$