Moderated Regression

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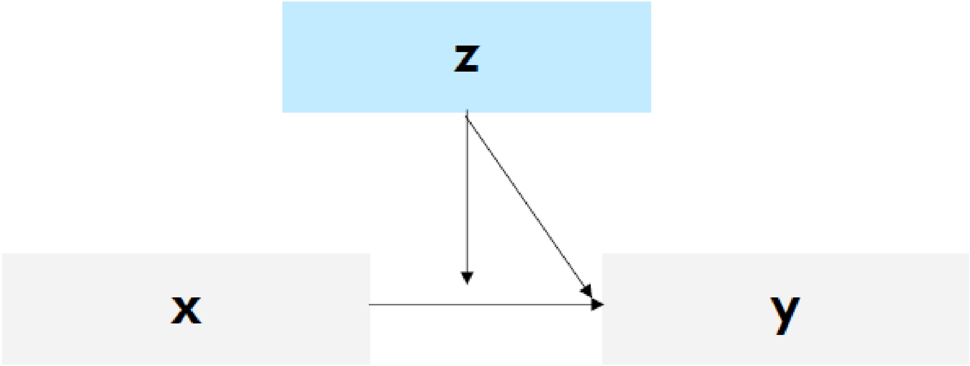
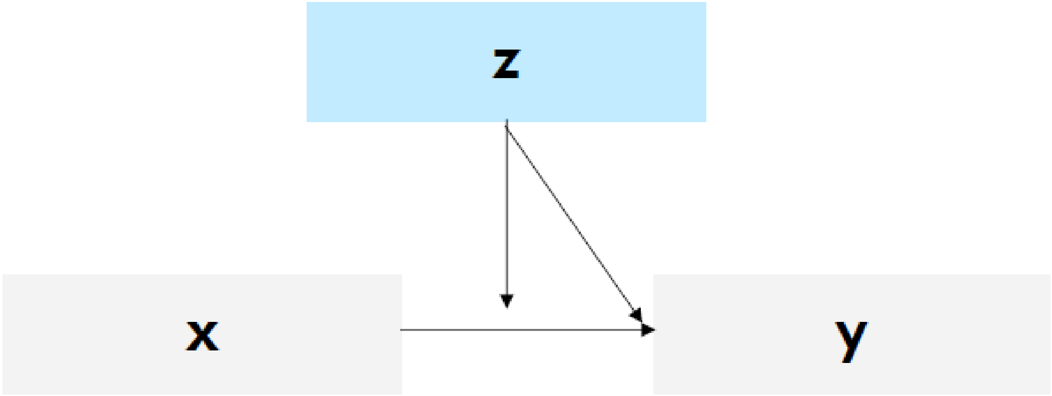
What is Moderation?

- A moderator is a variable that changes (i.e., moderates) the relationship between two (or more) other variables
- Moderation models are used to determine if the magnitude and/or direction of a certain regression slope varies as a function of some third variable



What is moderation?

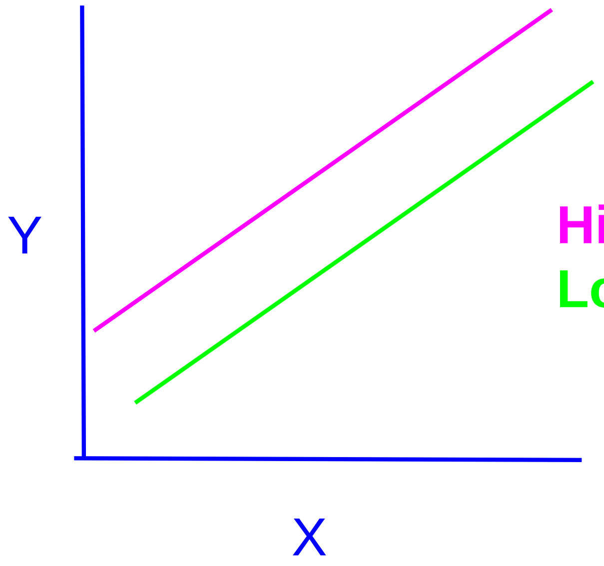


An interaction term = the predicted difference in the effect of x on y for a one-unit increase in z

(i.e., how the simple slope of x on y changes as z increases)

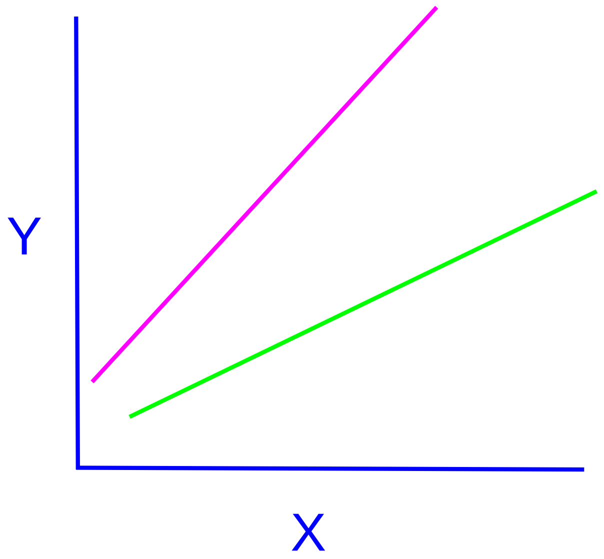
What does an interaction (aka moderation) effect look like?

No interaction observed:



High level of Z
Low level of Z

Interaction observed:



Note: crossed lines would also indicate an interaction

Load libraries

````
## Load libraries
```{r}
library(psych)
library(tidyverse)
library(olsrr)
```
````

Read in Data

````
## Read in data
```{r}
dat <- read_csv("moderation_demo.csv")
```
````

```
Parsed with column specification:
cols(
  att1 = col_double(),
  att2 = col_double(),
  att3 = col_double(),
  att4 = col_double(),
  att5 = col_double(),
  group1 = col_double(),
  group2 = col_double(),
  out1 = col_double(),
  out2 = col_double(),
  out3 = col_double(),
  out4 = col_double()
)
```

Calculate descriptives

This is a simulated dataset (i.e., the variables don't have specific meaning)

```
## Get descriptives
```{r, rows.print = 11}
describe(dat)
```
```

	vars <dbl>	n <dbl>	mean <dbl>	sd <dbl>	median <dbl>	trimmed <dbl>	mad <dbl>	min <dbl>	max <dbl>
att1	1	692	1.14	1.52	0	0.88	0.00	0	9
att2	2	692	1.94	0.88	2	1.88	1.48	1	9
att3	3	692	1.48	1.44	1	1.30	1.48	0	9
att4	4	692	1.17	1.39	1	0.98	1.48	0	9
att5	5	692	1.26	1.51	1	1.06	1.48	0	9
group1	6	692	2.58	1.17	2	2.50	1.48	1	9
group2	7	692	1.59	0.49	2	1.62	0.00	1	2
out1	8	692	1.39	1.41	2	1.32	0.00	0	9
out2	9	692	1.21	1.55	1	0.97	1.48	0	9
out3	10	692	1.38	1.43	2	1.30	0.00	0	9
out4	11	692	1.39	1.48	2	1.29	0.00	0	9

1-11 of 11 rows | 1-10 of 13 columns

Our variables of interest

````
## Get descriptives
```{r, rows.print = 11}
describe(dat)
```
````

	vars <dbl>	n <dbl>	mean <dbl>	sd <dbl>	median <dbl>	trimmed <dbl>	mad <dbl>	min <dbl>	max <dbl>
att1	1	692	1.14	1.52	0	0.88	0.00	0	9
att3	3	692	1.48	1.44	1	1.30	1.48	0	9
out4	11	692	1.39	1.48	2	1.29	0.00	0	9

Predictors

Outcome

1-11 of 11 rows | 1-10 of 13 columns

Examine correlations between the predictors

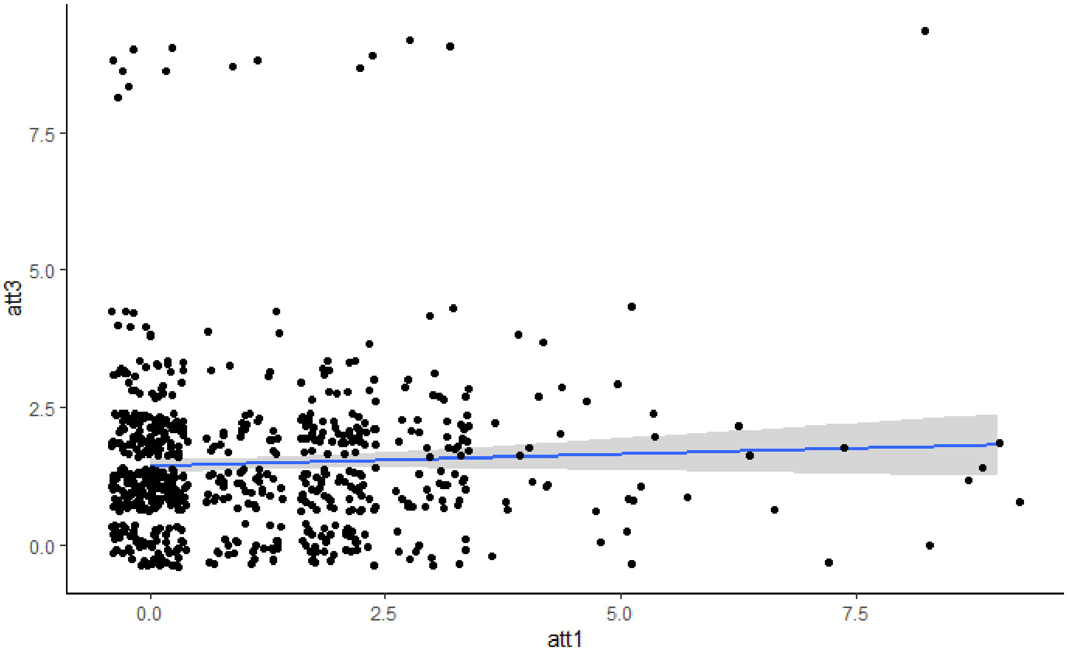
```
## Examine correlation between att1 & att3
```{r}
cor(dat$att1, dat$att3)
```
```

In general, we want to avoid multicollinearity in multiple linear regression

Examine correlations between the predictors

````
## Examine correlation between att1 & att3
```{r}
cor(dat$att1, dat$att3)
```

[1] 0.04521701
````



Examine correlations between the predictors

````
## Examine correlation between att1 & att3
```{r}
cor(dat$att1, dat$att3)
```

 [1] 0.04521701

Since the correlation between att1 and att3 is small, there is room for a moderation effect.

````

Create the cross-product of the two predictors

```
## Create the cross product of att1 & att3
```{r}
dat <- mutate(dat, att1att3 = att1*att3)
```
```

The cross-product is the interaction term. We'll include this as an additional predictor in the regression model.

Create the cross product

```
## Create the cross product of att1 & att3
```{r}
dat <- mutate(dat, att1att3 = att1*att3)
```
```

	att1	att3	att1att3
1	3	1	3
2	0	0	0
3	3	2	6
4	0	1	0
5	0	0	0
6	4	0	0
7	0	1	0
8	0	1	0
9	1	2	2
10	0	2	0
11	2	1	2
12	0	2	0
13	2	0	0
14	0	2	0
15	2	3	6
16	2	2	4

Run the main effects model

```
### Main Effects model
```{r}
modME <- lm(out4  ~ att1 + att3, data = dat)
ols_regress(modME)
```
```

This is just a regular multiple linear regression.
We first want to examine the main effects between each predictor and the outcome before adding the interaction term.

Main effects model results

Model Summary

R	0.453	RMSE	1.317
R-Squared	0.206	Coef. Var	94.839
Adj. R-Squared	0.203	MSE	1.735
Pred R-Squared	0.179	MAE	0.905

RMSE: Root Mean Square Error
MSE: Mean Square Error
MAE: Mean Absolute Error

ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	309.277	2	154.638	89.148	0.0000
Residual	1195.156	689	1.735		
Total	1504.432	691			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	0.655	0.080		8.185	0.000	0.498	0.812
att1	0.049	0.033	0.050	1.480	0.139	-0.016	0.114
att3	0.458	0.035	0.448	13.190	0.000	0.390	0.527

Run the same model with the interaction term (aka a Moderated Regression)

```
### Interaction model
```{r}
modINT <- lm(out4 ~ att1 + att3 + att1att3 , data = dat)
ols_regress(modINT)
```
```

att1att3 is the cross-product variable we made earlier
It represents att1*att3

Model Summary

R	0.462	RMSE	1.311
R-Squared	0.213	Coef. Var	94.435
Adj. R-Squared	0.210	MSE	1.720
Pred R-Squared	0.176	MAE	0.907

RMSE: Root Mean Square Error
MSE: Mean Square Error
MAE: Mean Absolute Error

ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	321.154	3	107.051	62.243	0.0000
Residual	1183.278	688	1.720		
Total	1504.432	691			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	0.757	0.089		8.539	0.000	0.583	0.931
att1	-0.032	0.045	-0.033	-0.716	0.474	-0.121	0.056
att3	0.393	0.043	0.384	9.210	0.000	0.309	0.477
att1att3	0.049	0.019	0.140	2.628	0.009	0.012	0.085

Model results with interaction term

Simple Slopes

Interaction

Interpreting the moderated regression

Model Summary

R	0.462	RMSE	1.311
R-Squared	0.213	Coef. Var	94.435
Adj. R-Squared	0.210	MSE	1.720
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RMSE: Root Mean Square Error
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att1: This is the predicted change in our outcome for every 1 unit increase in att1 ***when att3 is 0.***

att3: This is the predicted change in our outcome for every 1 unit increase in att3 ***when att1 is 0.***

att1att3: This is the predicted **change in effect in the effect of att1** on our outcome **for every one unit increase in att3.**

Compare the two models via hierarchical regression

```
# Compare the two models
```{r}
anova(modME,modINT)
```
```

```
Analysis of Variance Table

Model 1: out4 ~ att1 + att3
Model 2: out4 ~ att1 + att3 + att1att3
  Res.Df    RSS Df Sum of Sq      F   Pr(>F)
1    689 1195.2
2    688 1183.3  1    11.877 6.9058 0.008783 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Does including the interaction term significantly improve the amount of variance our model explains in out4?

Compare the two models via hierarchical regression

```
# Compare the two models
```{r}
anova(modME,modINT)
```
```

```
Analysis of Variance Table

Model 1: out4 ~ att1 + att3
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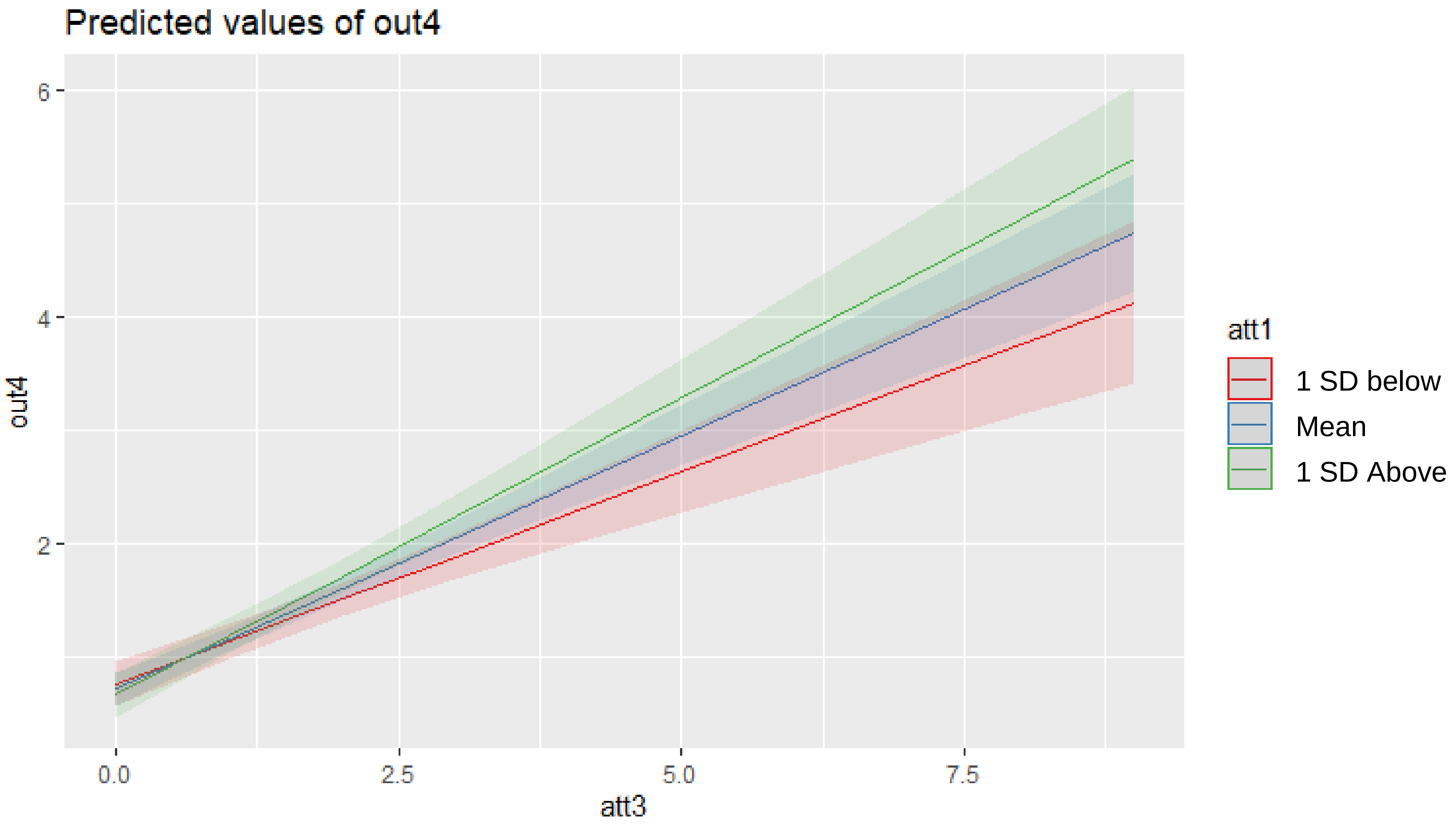
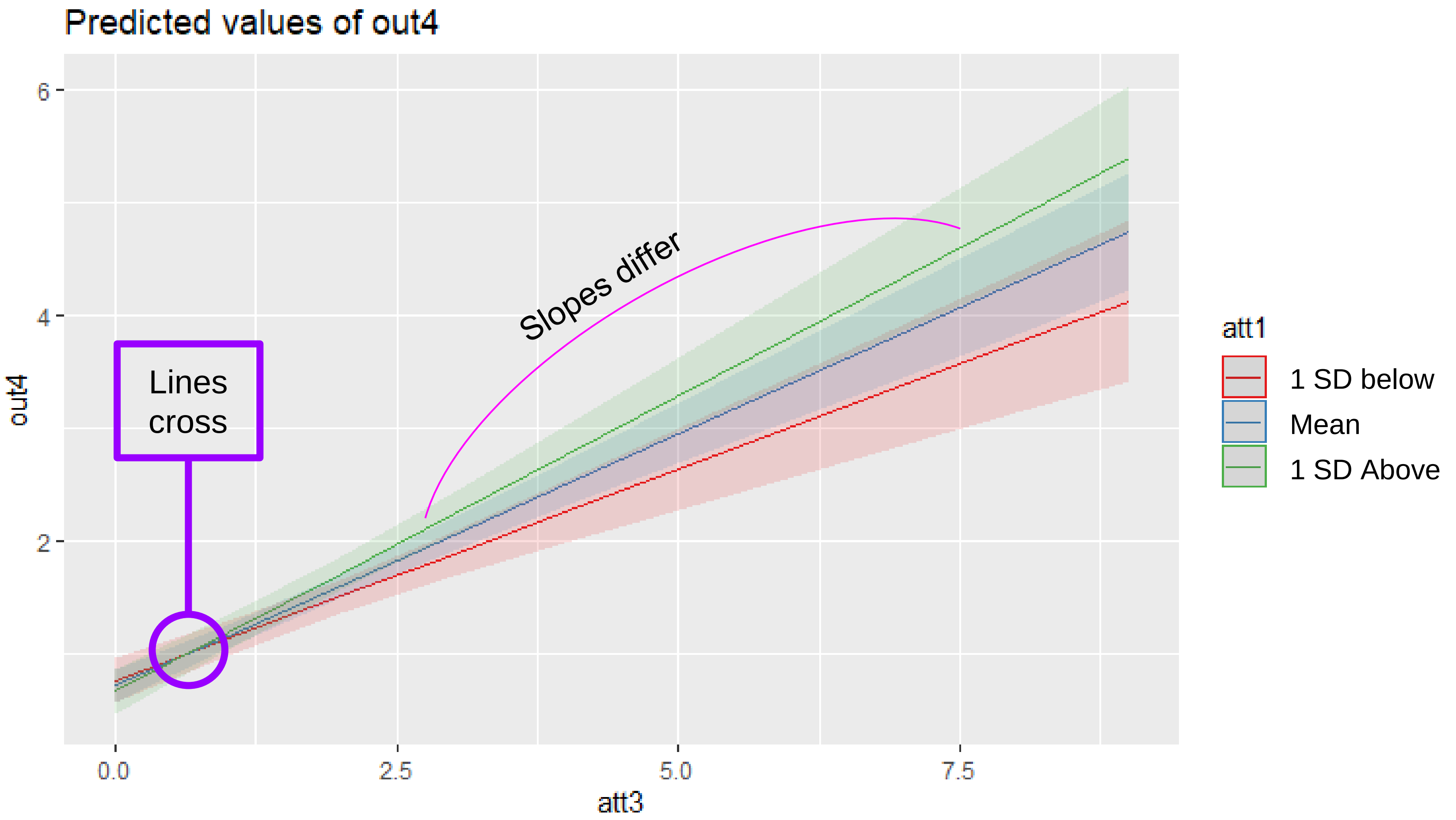
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

At $p<0.05$, the moderated regression model explained significantly more variance in out4 than the main effects model

Our interaction - Visualized



Our interaction - Visualized



Example APA write up

The differential effect of att1 on out4, using att3 as a moderator, was examined among 692 participants. A moderation model was estimated, out4 was regressed on att1, att3, and the interaction between the two. The simple slope of att1 was not statistically significant ($b = -0.03$, 95%CI -0.12, 0.06) and the simple slope of att3 ($b = 0.39$, 95%CI 0.31, 0.48) was statistically significant. The interaction term is statistically significant ($b = 0.05$, 95%CI 0.01, 0.09), indicating that the effect of att1 on out4 is larger as att3 increases.

Additional considerations for moderation

- Power is important!
    - N needed to detect interaction effect can be up to 9x larger than for detecting main effects (e.g., Wahlsten, 1991)
    - For every interaction term you add, N needed to detect effect increases

- You can examine interactions between more than two variables
    - E.g., 3-day interactions

- Interpretation is easier with categorical predictors

    - E.g. You can turn continuous variables into categorical by using cut-off scores