UNIVERSITY OF LINCOLN

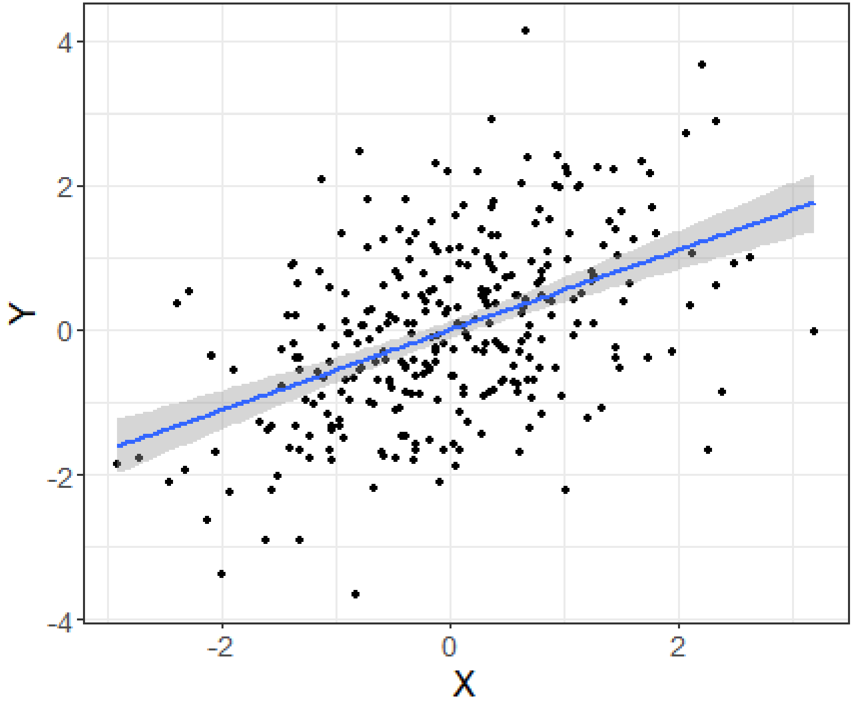
Moderation and Mediation

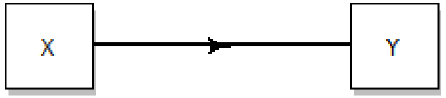
PSY9003

2020/03/31

Mediation and moderation

In linear regression, we're looking to understand the relationship between *predictors* and *outcomes*.

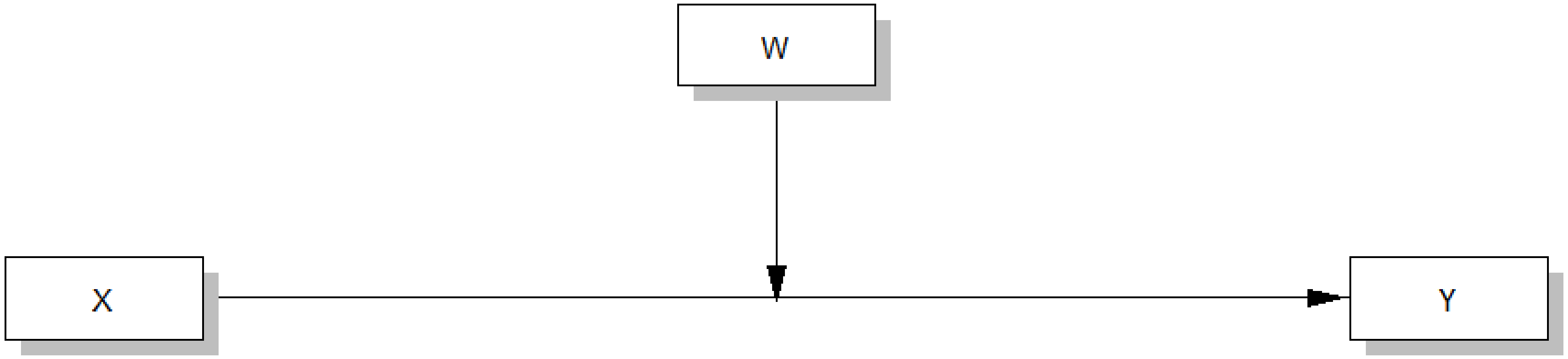




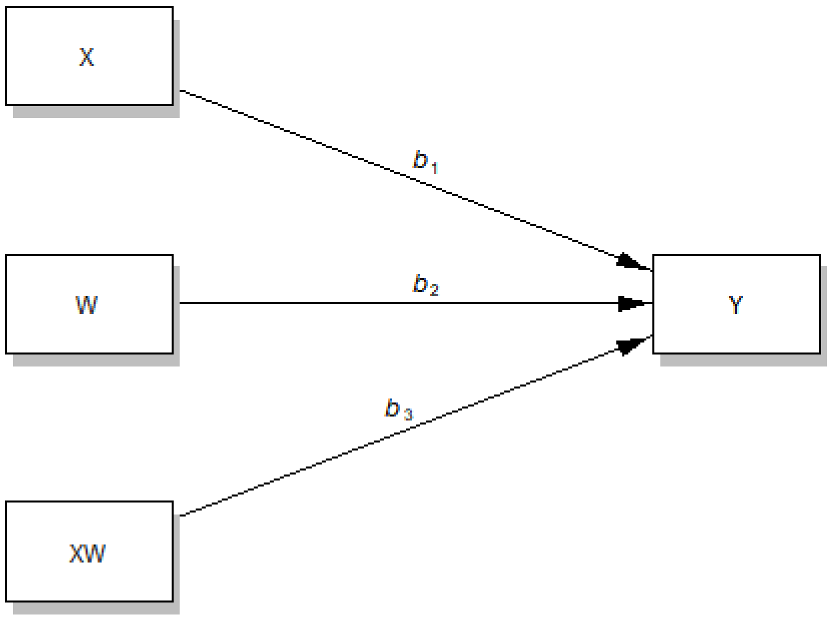
Moderation

Moderation

Moderation changes the strength of the relationship between the predictor and dependent variable.



Moderation



The *epi.bfi* dataset

The `epi.bfi` dataset from the `psychTools` package

```
head(epi.bfi)
```

```
##   epiE epiS epiImp epilie epiNeur bfagree bfcon bfext bfneur bfopen bdi traitanx
## 1   18   10      7      3       9     138    96   141     51    138   1       24
## 2   16    8      5      1      12     101    99   107    116    132   7       41
## 3    6    1      3      2       5     143   118    38     68     90   4       37
## 4   12    6      4      3      15     104   106    64    114    101   8       54
## 5   14    6      5      3       2     115   102   103     86    118   8       39
## 6    6    4      2      5      15     110   113    61     54    149   5       51
##   stateanx
## 1       22
## 2       40
## 3       44
## 4       40
## 5       67
## 6       38
```

Simple linear regression

Suppose that we want to model `bdi` (Beck Depression Inventory) as a function of `stateanx` (State Anxiety)

```
st_bdi <- lm(bdi ~ stateanx, data = epi.bfi)
summary(st_bdi)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx, data = epi.bfi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.1115  -3.0603  -0.6826   2.2152  15.1130
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.41988    1.09322  -4.958 1.39e-06 ***
## stateanx     0.30614    0.02637  11.611  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Multiple linear regression

An additional predictor that we may find interesting is `epiNeur` - a measure of *neuroticism* from the *Eysenck Personality Inventory*. We can add this to make a *multiple* regression model.

```
st_neu <- lm(bdi ~ stateanx + epiNeur, data = epi.bfi)
summary(st_neu)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx + epiNeur, data = epi.bfi)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.7405 -2.5748 -0.5299  2.2841 11.7303
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -6.32655    1.01061  -6.260 1.89e-09 ***
## stateanx     0.21526    0.02770   7.770 2.66e-13 ***
## epiNeur      0.43492    0.06493   6.698 1.63e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding interaction terms

What if the effect of `stateanx` depends on the level of `epiNeur`? For example, people who score high on *neuroticism* might be more affected by *state anxiety* than people who are low on *neuroticism*.

We add both main effects and interactions by using `*` instead of `+`

Thus, `stateanx * epiNeur` will give us the main effect of `stateanx`, the main effect of `epiNeur`, and the interaction between the two.

```
int_model <- lm(bdi ~ stateanx * epiNeur, data = epi.bfi)
```

```r
summary(int_model)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx * epiNeur, data = epi.bfi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.0493  -2.2513  -0.4707   2.1135  11.9949
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.06367    2.18559   0.029   0.9768
## stateanx          0.03750    0.06062   0.619   0.5368
## epiNeur          -0.14765    0.18869  -0.782   0.4347
## stateanx:epiNeur  0.01528    0.00466   3.279   0.0012 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.12 on 227 degrees of freedom
## Multiple R-squared:  0.4978,    Adjusted R-squared:  0.4912
## F-statistic: 75.02 on 3 and 227 DF,  p-value: < 2.2e-16
```

Interpreting the coefficients

```
coef(int_model)
```

```
##      (Intercept)         stateanx          epiNeur stateanx:epiNeur
##       0.06367327       0.03750035      -0.14764857       0.01527977
```

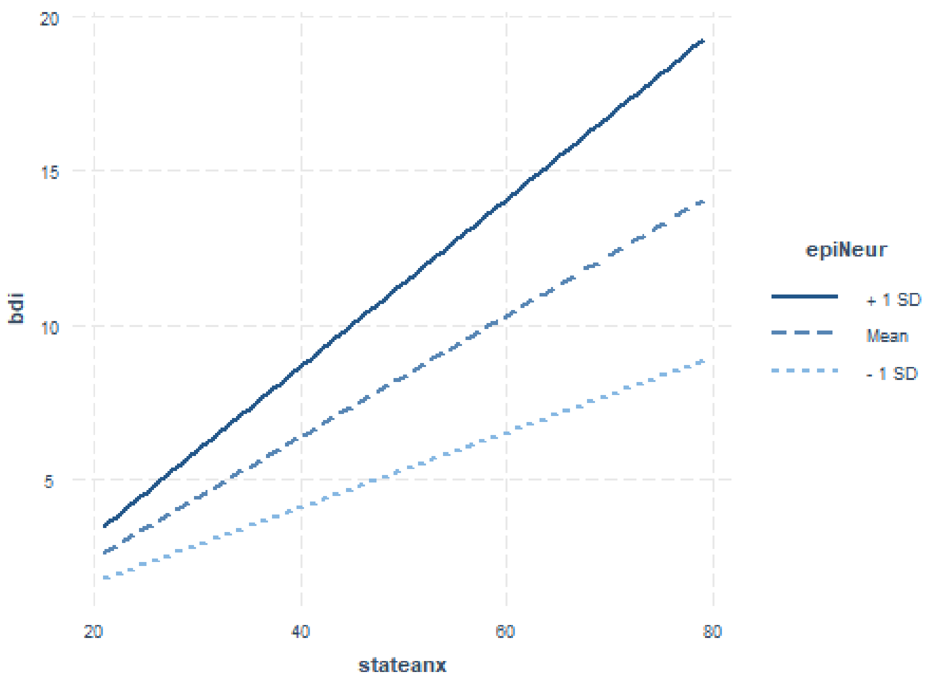
The coefficients tell you what the effect of a 1 unit increase in the variable has on the dependent variable.

The coefficients of the main effects (`stateanx` and `epiNeur`) are hard to interpret *in the presence of an interaction* unless the variables have been **mean-centred**.

Simple slopes

The `interact_plot()` function from the `interactions` package provides a nice way to visualize this interaction.

```
interact_plot(int_model,
              pred = stateanx,
              modx = epiNeur)
```

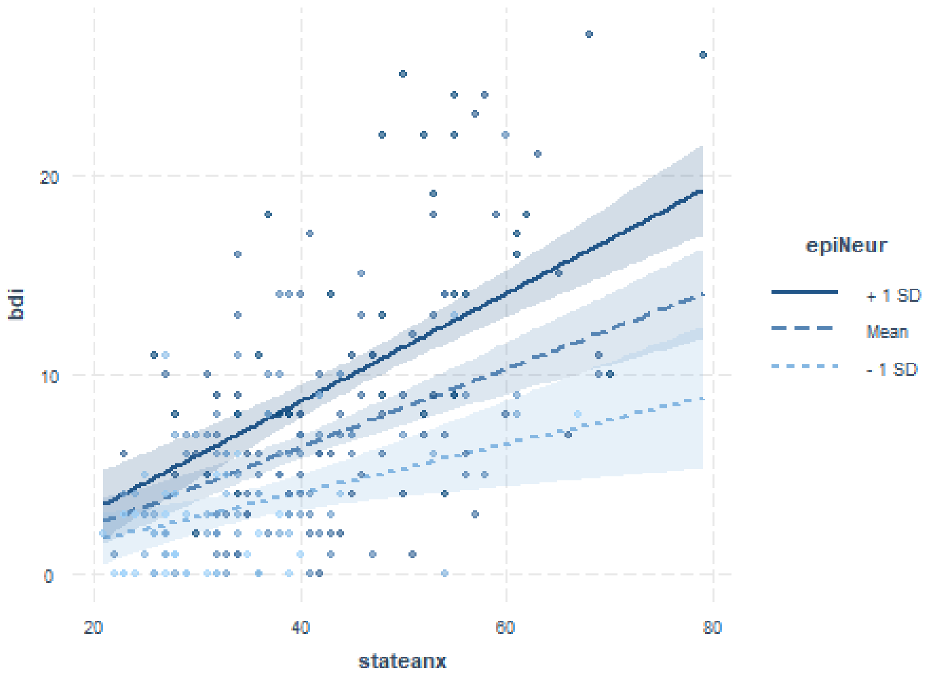


Simple slopes

We can also add individual data points using `plot.points = TRUE`.

Confidence intervals can be added using `interval = TRUE`.

```
interact_plot(int_model,
              pred = stateanx,
              modx = epiNeur,
              plot.points = TRUE,
              interval = TRUE)
```



Simple slopes

The interaction means that the *slope* of the effect of `stateanx` differs at different values of `epiNeur`.

We can use the `sim_slopes()` function from `interactions` to statistically explore how `stateanx` varies as a function of `epiNeur`.

```
sim_slopes(int_model,
           pred = stateanx,
           modx = epiNeur,
           johnson_neyman = FALSE)
```

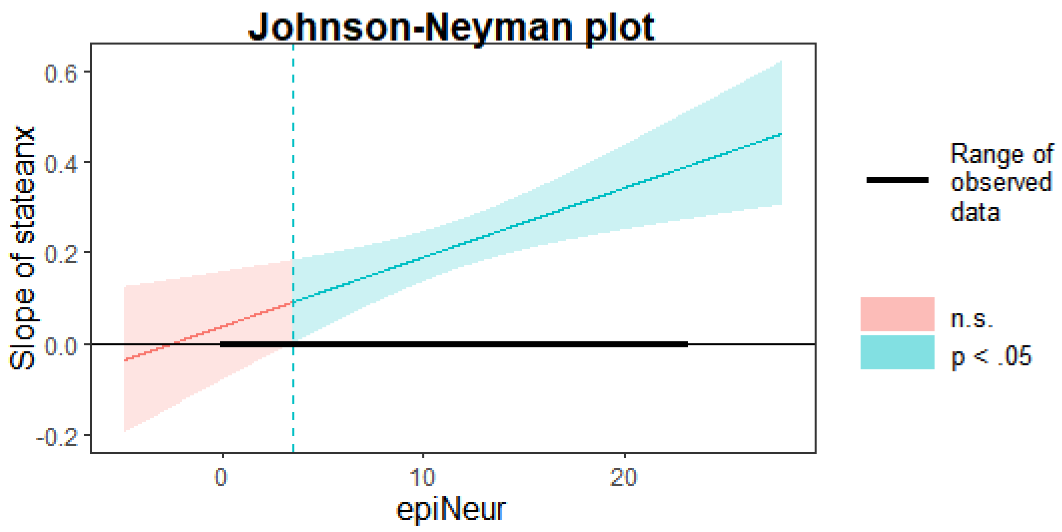
```
## SIMPLE SLOPES ANALYSIS
##
## Slope of stateanx when epiNeur =  5.51 (- 1 SD):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.12   0.04     3.09   0.00
##
## Slope of stateanx when epiNeur = 10.41 (Mean):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.20   0.03     7.09   0.00
##
## Slope of stateanx when epiNeur = 15.31 (+ 1 SD):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.27   0.03     8.46   0.00
```

The slope of `stateanx` *increases* as `epiNeur` increases.

Johnson-Neyman plots

```
johnson_neyman(int_model, pred = stateanx, modx = epiNeur)
```

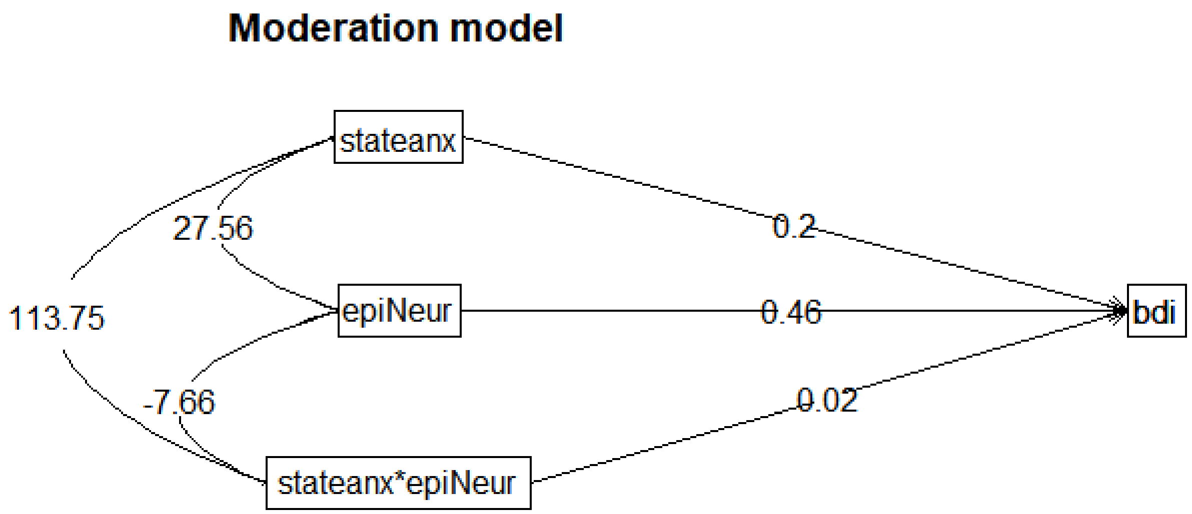
```
## JOHNSON-NEYMAN INTERVAL
##
## When epiNeur is OUTSIDE the interval [-24.37, 3.54], the slope of stateanx is p
## < .05.
##
## Note: The range of observed values of epiNeur is [0.00, 23.00]
```



Moderation with the `psych` package

The function `mediate()` from the `psych` package can also be used to run moderation analyes.

```
psych_mod <- mediate(bdi ~ stateanx * epiNeur,
                     data = epi.bfi)
```



Moderation with the psych package

```
psych_mod
```

```
##
## Mediation/Moderation Analysis
## Call: mediate(y = bdi ~ stateanx * epiNeur, data = epi.bfi)
##
## The DV (Y) was  bdi . The IV (X) was  stateanx epiNeur stateanx*epiNeur . The mediating variable(s)
##  DV =  bdi
##                   slope   se    t       p
## stateanx           0.20 0.03 7.11 1.5e-11
## epiNeur            0.46 0.06 7.21 8.0e-12
## stateanx*epiNeur   0.02 0.00 3.29 1.2e-03
##
## With R2 =  NA
## R = NA R2 = NA   F = NA on 3 and 228 DF   p-value:  NA
```

Moderation with the `medmod` package

We could also use the `mod()` function from `medmod`, which has rather nicer output than the `mediate()` function.

```
mod(epi.bfi, dep = "bdi", mod = "epiNeur", pred = "stateanx")
```

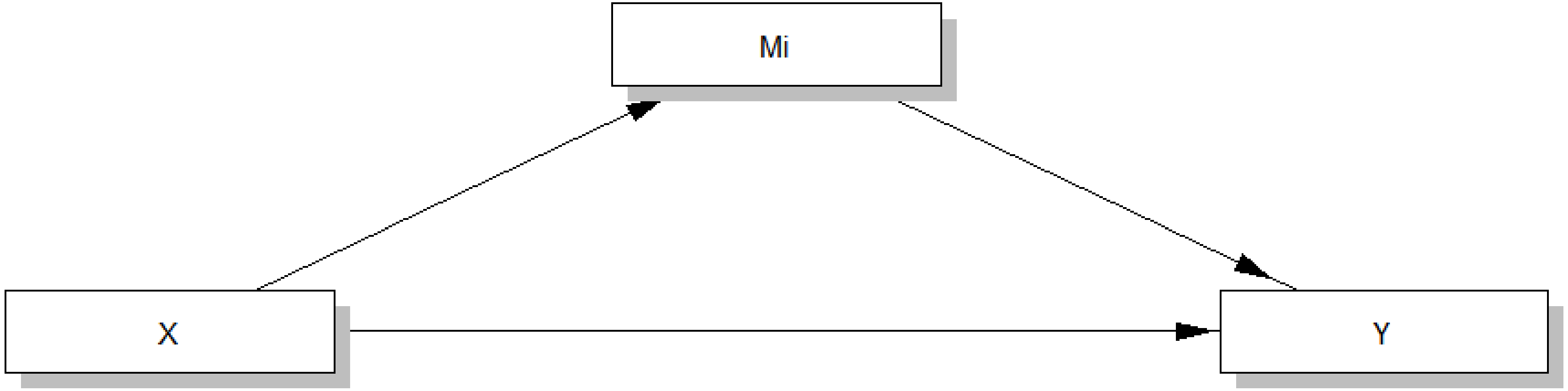
```
##
##  MODERATION
##
##  Moderation Estimates
##  ─────────────────────────────────────────────────────────────
##                          Estimate    SE         Z       p
##  ─────────────────────────────────────────────────────────────
##    stateanx                0.1966    0.02378    8.27    < .001
##    epiNeur                 0.4612    0.05496    8.39    < .001
##    stateanx:epiNeur        0.0153    0.00458    3.33    < .001
##  ─────────────────────────────────────────────────────────────
```

First exercise

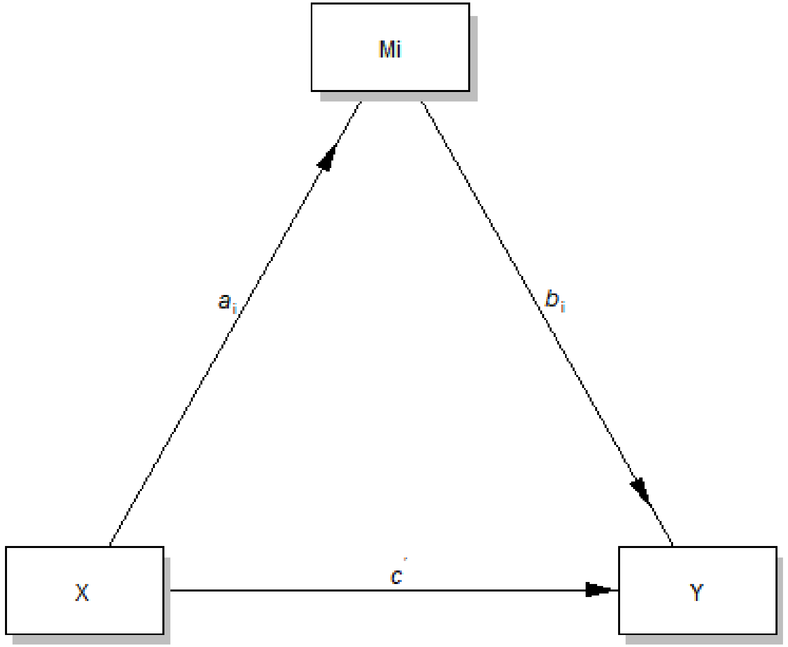
Mediation

Mediation

Mediation refers to a situation in which the effect of a predictor is transmitted *through* another variable.



Mediation path diagram



a - the effect of the IV on the mediator

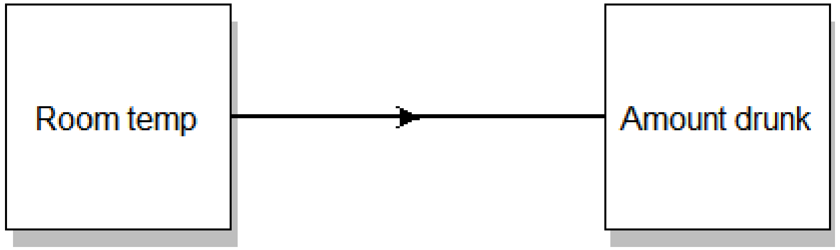
b - the effect of the mediator on the DV

c' - the *direct* effect of the IV on the DV

What's missing is c - the *total* effect of the IV on the DV - and ab - the *indirect* effect of the IV on the DV

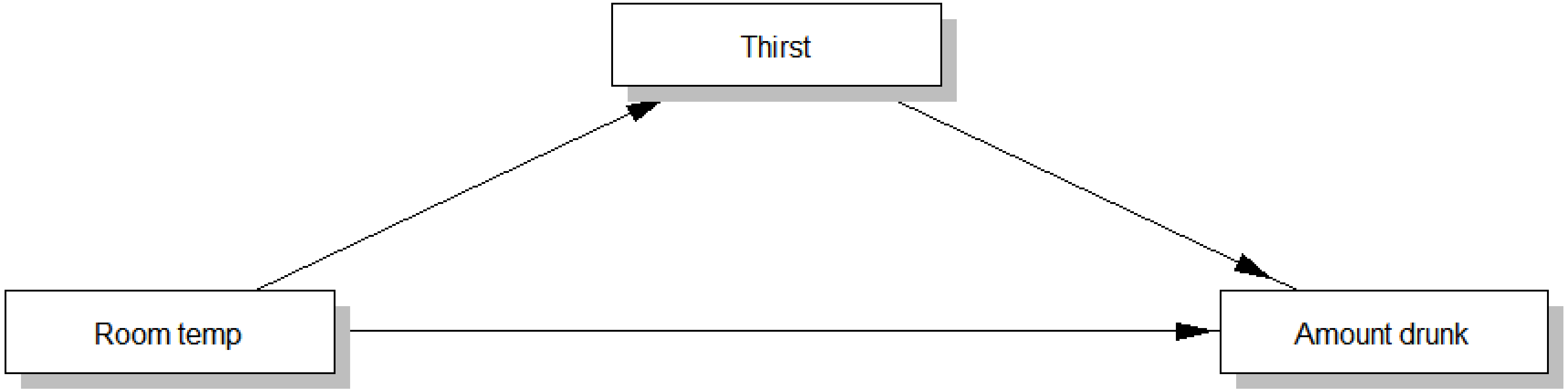
Mediation

In this example, *room temperature* predicts the *amount that people drink*; specifically, we'd expect that higher temperatures would increase drinking.



Mediation

Nevertheless, it's possible that higher temperatures increase drinking *indirectly*: higher temperatures make people feel more *thirsty*, which in turn makes them *drink more*.



Mediation as regression

A mediation analysis is all about splitting up the effect of the predictor into *direct* and *indirect* components. Baron & Kenny (1986) outline 3 steps to do this with regression.

Step 1:

Does the IV predict the DV? (contrary to popular belief, doesn't have to be significant)

Step 2:

Does the mediator predict the DV? (this needs to be significant)

Step 3:

Does having the mediator in the model reduce the effect of the IV on the DV?

The `estress` data

```
head(estress)
```

```
## # A tibble: 6 x 7
##   tenure estress affect withdraw   sex   age   ese
##    <dbl>   <dbl>  <dbl>    <dbl> <dbl> <dbl> <dbl>
## 1  1.67       6     2.6       3        1    51  5.33
## 2  0.580      5     1         1        0    45  6.05
## 3  0.580      5.5   2.4       3.66     1    42  5.26
## 4  2          3     1.16      4.66     1    50  4.35
## 5  5          4.5   1         4.33     1    48  4.86
## 6  9          6     1.5       3        1    48  5.05
```

Mediation as regression (Step 1)

```
summary(lm(withdraw ~ estress, data = estress))
```

```
##
## Call:
## lm(formula = withdraw ~ estress, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4547 -1.2302 -0.2022  0.7978  4.8820
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.06187    0.26202   7.869 9.64e-14 ***
## estress      0.05612    0.05421   1.035    0.302
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.247 on 260 degrees of freedom
## Multiple R-squared:  0.004105,    Adjusted R-squared:  0.0002748
## F-statistic: 1.072 on 1 and 260 DF,  p-value: 0.3015
```

Mediation as regression (Step 2)

```
summary(lm(withdraw ~ affect, data = estress))
```

```
##
## Call:
## lm(formula = withdraw ~ affect, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1028 -0.8919 -0.2092  0.8713  2.8713
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.17416    0.17035   6.893 4.13e-11 ***
## affect       0.71772    0.09713   7.389 2.02e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.136 on 260 degrees of freedom
## Multiple R-squared:  0.1735,    Adjusted R-squared:  0.1704
## F-statistic:  54.6 on 1 and 260 DF,  p-value: 2.02e-12
```

Mediation as regression (Step 3)

```
summary(lm(withdraw ~ estress + affect, data = estress))
```

```
##
## Call:
## lm(formula = withdraw ~ estress + affect, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1716 -0.9472 -0.2249  0.8490  2.9049
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.44706    0.25201   5.742 2.61e-08 ***
## estress     -0.07685    0.05239  -1.467    0.144
## affect       0.76913    0.10306   7.463 1.29e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.133 on 259 degrees of freedom
## Multiple R-squared:  0.1804,	Adjusted R-squared:  0.174
## F-statistic: 28.49 on 2 and 259 DF,  p-value: 6.528e-12
```

Is there mediation?

Step 1: `estress` wasn't a significant predictor of `withdraw`, but was a significant predictor of `affect`.

Step 2: `affect` was a significant predictor of `withdraw`.

Step 3: Modelling `withdraw` as a function of `estress` and `affect` changed the coefficient of `estress`.

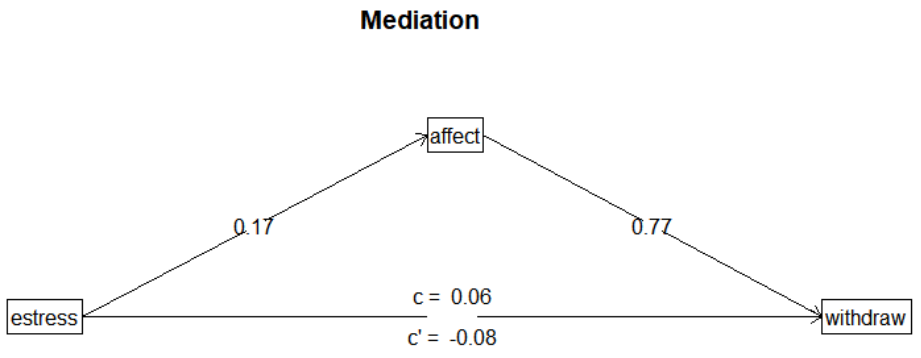
Thus, we have evidence of mediation. How much mediation? For that we need the *indirect* effect.

The *indirect* effect of `estress` is the coefficient of `estress` from Step 1 MINUS the coefficient of `estress` from Step 3.

Mediation model

We can use the `mediate()` function from the `psych` package to add a mediating variable. **Importantly,** we place `()` around the mediator.

```
medi_model <- mediate(withdraw ~ estress + (
```



The difference between c' and c is the *indirect* effect of `estress`.

When `estress` increases by 1, `affect` increases by .17; and when `affect` increases by 1, `withdraw` increases by .77.

So the *indirect effect* of `estress` is around **.14**.

```
## Call: mediate(y = withdraw ~ estress + (affect), data = estress)
##
## Direct effect estimates (traditional regression)    (c')
##           withdraw   se     t  df     Prob
## Intercept     1.45 0.25  5.74 259 2.61e-08
## estress      -0.08 0.05 -1.47 259 1.44e-01
## affect        0.77 0.10  7.46 259 1.29e-12
##
## R = 0.42 R2 = 0.18   F = 28.49 on 2 and 259 DF   p-value:  6.53e-12
##
##  Total effect estimates (c)
##         withdraw   se    t  df  Prob
## estress     0.06 0.05 1.04 261 0.301
##
##  'a'  effect estimates
##           affect   se    t  df     Prob
## Intercept   0.80 0.14 5.58 260 6.11e-08
## estress     0.17 0.03 5.83 260 1.63e-08
##
##  'b'  effect estimates
##        withdraw  se    t  df     Prob
## affect     0.77 0.1 7.48 260 1.17e-12
##
##  'ab'  effect estimates (through mediators)
##         withdraw boot   sd lower upper
## estress     0.13 0.13 0.03  0.07   0.2
```

Mediation with `med()` from `medmod`

```r
med_model <- med(data = estress, dep = "withdraw",
                 pred = "estress", med = "affect",
                 paths = TRUE, estPlot = TRUE)
med_model$med
```

```
##
##  Mediation Estimates
##  -----------------------------------------------------
##    Effect      Estimate    SE        Z         p
##  -----------------------------------------------------
##    Indirect      0.1330    0.0288     4.62    < .001
##    Direct       -0.0768    0.0521    -1.48     0.140
##    Total         0.0561    0.0540     1.04     0.299
##  -----------------------------------------------------
```

Mediation with `med()` from `medmod`

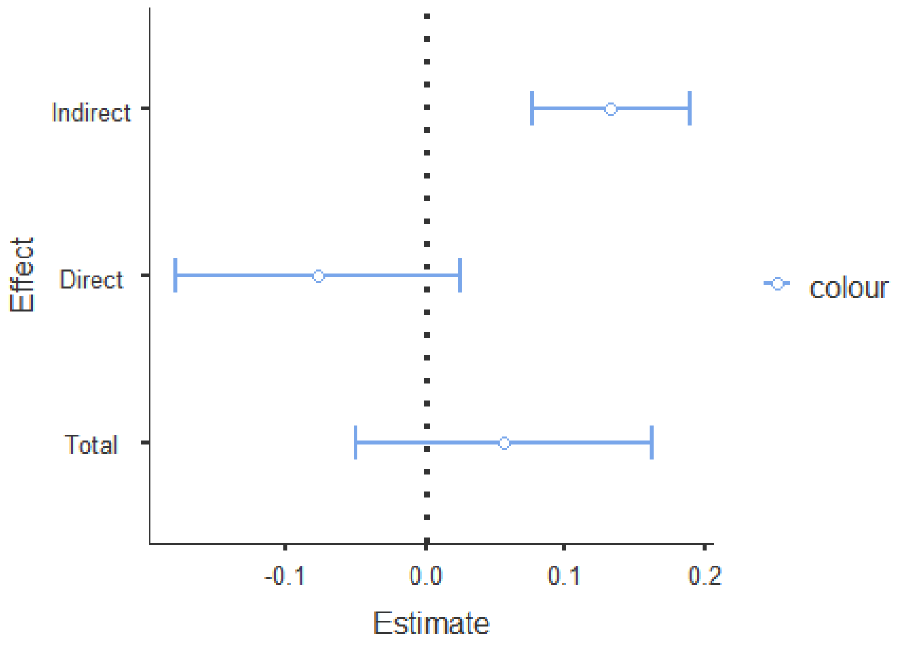
```
med_model$paths
```

```
##
##  Path Estimates
##  ---------------------------------------------------------------------
##                                Estimate    SE        Z         p
##  ---------------------------------------------------------------------
##    estress    <U+2192>    affect        0.1729    0.0295     5.85    < .001
##    affect     <U+2192>    withdraw      0.7691    0.1025     7.51    < .001
##    estress    <U+2192>    withdraw     -0.0768    0.0521    -1.48     0.140
##  ---------------------------------------------------------------------
```

PS this output looks better direct from R...!

Mediation with `med()` from `medmod`

```
med_model$estPlot
```



As long as the confidence intervals don't overlap 0 for the indirect effect, we have a significant mediation.

Second exercise

Further reading

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 5, 1173-1182.*

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological Methods, 7, 422-445.*

Hayes AF. Introduction to mediation, moderation, and conditional process analysis: a regression-based approach. New York: Guilford Press; 2013.