The Test of Mediation

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This module deals with the study of mediating mechanisms through the analysis of indirect effects.

An appropriate general citation for this material is

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I illustrate the test of mediation using data from an example study that looked at post-fire vegetation recovery in southern California woodlands (actually shrublands, including chaparral).

Citation for that work is:
Following fires, 90 plots were established 20x50m.
A number of measures were taken, as indicated on the slide.

measured:
-vegetation cover
-species richness
-age of stand that burned
-fire severity

Examination of woody remains allowed for estimate of age of stand that burned as well as severity of the fires.
Other factors measured included:
- local abiotic conditions (aspect, soils)
- spatial heterogeneity
- landscape-level conditions (location, elevation)

Additional conditions were measured with an interest in understanding variations in community recovery.
A key observation was a negative relation between the age of a stand before it burned and the cover of vegetation after the fire.
Lavaan code for evaluating net effect.

```r
# Net (total) effect of age on cover
mod.1 <- 'cover ~ age'

# Fit the model
mod.1.fit <- sem(mod.2, data=k.dat)

# Extract results
summary(mod.1.fit, stand=T, rsq=T)
```

We can turn that bivariate observation into a net-effects model as shown here.
Results indicate a significant effect.
Graphical summary of net relationship.

Here is a graphical summary of the net effect.
Now, when I asked Jon Keeley why we might see this relationship, he suggested that older stands would have more fuel and as a result burn hotter (have greater fire severity). More severe fires, in turn, could explain the reduced recovery in older stands. Since he had made measurements of fire severity, we could test that hypothesis formally.
When we think about the possible findings in a test of mediation, there are three types of models possible.

**Complete mediation** – fire severity can completely explain the influence of stand age.

**Partial mediation** – fire severity only explains part of the effect of stand age. That would mean some other process was operating as well.

**No mediation** – of course it could be that observed fire severity did not explain the association between age and cover. For this outcome, either or both of the dashed arrows could be ns = “no mediation”

Note the lavaan code is shown below the models. For the no mediation model I chose to use a lavaan syntax option where the link is included in the model but the parameter is set to zero for the test.
The anova function performs a likelihood ratio test. We also get the AIC values. All indications are the complete mediation model is an adequate explanation of the data.
We can go further and create an AICc table, including the computation of model weights. You can refer to the module on “Model Evaluation” for more detail on this procedure.

A succinct treatment of model comparison using AIC tables can be found at

http://www.unc.edu/courses/2006spring/ecol/145/001/docs/lectures/lecture17.htm

AICc leads to same conclusions as AIC.
Calculating the magnitude of the standardized indirect effect.

Standardized total effect of age on cover:

\[ 0.45 \times -0.44 = -0.20 \]

Simple to compute the indirect effect in the linear Gaussian case, just multiply the path coefficients along the path.

For more complex models, we might use queries to quantify indirect effects.
You can get the intercepts using the “meanstructure” option.

```r
# a small digression: asking for the intercepts
partial.mod.fit <- sem(mod.3, meanstructure=T, data=k3.dat)
summary(partial.mod.fit) # requesting intercepts
```

| Regression   | Est. | Std.err | Z-value | P(>|z|) |
|--------------|------|---------|---------|---------|
| cover ~ firesev | -0.839 | 0.182 | -4.611 | 0.000 |
| firesev ~ age    | 0.597 | 0.124 | 4.832  | 0.000 |
| Intercepts:      |      |         |         |         |
| cover            | 10.744 | 0.883 | 12.166 | 0.000 |
| firesev          | 3.039  | 0.351 | 8.647  | 0.000 |
| Variances:       |      |         |         |         |
| cover            | 8.050  | 1.200 |         |         |
| firesev          | 2.144  | 0.320 |         |         |

For prediction equations you will need the intercepts, which require the use of an additional piece of syntax.
We can compute indirect and total effects within lavaan

```r
### Compute indirect and total effects
### We will use partial mediation model
mod.4 <- 'cover ~ b*firesev + c*age
       firesev ~ a*age
       direct  := c
       indirect := a*b
       total   := c + (a*b)
',

# Fit the model
mod.4.fit <- sem(mod.4, data=k.dat)

# Extract results
summary(mod.4.fit, stand=T, rsq=T)
```

Here we see that if we label the parameters, we can then define different quantities in the model syntax.
Now, we get full information about defined quantities. Here we can see that if you add the direct and indirect effect, you get the total effect.

### Results

#### Regressions:

|        | Estimate | Std.err | Z-value | P(|z|) | Std.all |
|--------|----------|---------|---------|-------|---------|
| cover ~ |          |         |         |       |         |
| firesev | -0.067   | 0.020   | -3.353  | 0.001 | -0.350  |
| age     | -0.005   | 0.003   | -1.833  | 0.067 | -0.191  |
| firesev ~ |         |         |         |       |         |
| age     | 0.060    | 0.012   | 4.832   | 0.000 | 0.454   |

#### Variances:

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<td>0.780</td>
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<tr>
<td>firesev</td>
<td>2.144</td>
<td>0.320</td>
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<td>0.794</td>
</tr>
</tbody>
</table>

#### Defined parameters:

|        | Estimate | Std.err | Z-value | P(|z|) | Std.all |
|--------|----------|---------|---------|-------|---------|
| direct | -0.005   | 0.003   | -1.833  | 0.067 | -0.191  |
| indirect| -0.004   | 0.001   | -2.755  | 0.006 | -0.159  |
| total  | -0.009   | 0.002   | -3.549  | 0.000 | -0.350  |

#### R-Square:

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Note that these results will be slightly different from those for the full mediation model.