Significance Testing Indirect Effects

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This handout is supplemental material for the Mediation and Moderation handout I created. To understand significance testing for an indirect effect, you should first understand the principles behind mediation. Please see that handout for details.

All of this information comes from the two articles by Kristopher Preacher and Andrew Hayes. The 2008 article is more recent, and is where I got the SPSS macro from. However, it deals with more complex models, like with multiple mediators. The 2004 article is a little older, but gives simpler examples. These articles are very understandable, comprehensive, and helpful, but this handout is designed to give a more basic instruction for novice users.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879-891.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers, 36*(4), 717-731.

Going beyond traditional mediation: Improved significance testing

Using the Baron & Kenny approach, the Sobel test is common to determine if your indirect effect is significant. This is true even if you use path analysis in SEM. To determine if the two paths together are significant, Sobel test (or an equivalent test) is usually conducted. Lately, reviewers are turning against Sobel's test. Their argument is this:

The Sobel test essentially creates an estimate of the indirect effect. We can get a standardized estimate ourselves by multiplying the 2 associated betas together, but Sobel gets an unstandardized estimate (B). Sobel also estimates the indirect effect's standard error (SE). It then takes $B \div SE$ to get our significance test. This is just like any other regression estimate's significance test. Additionally, any parameter that we estimate has a sampling distribution. This is true of means, *B*'s, betas, *F*'s, *t*'s, etc. Just about everything we estimate comes from some sort of distribution.

The problem comes from the fact that $B \div SE$ assumes a normal distribution for both *B* and the SE, and this is not usually true for Sobel's test unless your sample size is very, very large. With smaller samples, the Type I error rate becomes higher than traditionally accepted limits. So reviewers aren't allowing you to use Sobel's test to determine if your indirect effect is significant because you almost never meet the assumption of that test. However, they still want to know if your indirect effect estimate is significant.

What's a researcher to do?
You create your own sampling distribution. Sample from your own sample (with replacement) over and over and over again to create your own set of subsamples. Run the analyses on these numerous subsamples. What's this called?

Bootstrapping!

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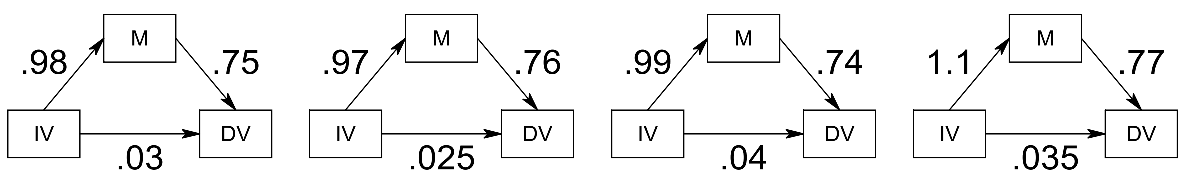
Bootstrapping example with means:

$$
\begin{array}{ccccccccc}
\text{Original} & & \text{sample 1} & & \text{sample 2} & & \text{sample 3} & & \text{sample 1000} \\
\begin{bmatrix} 31..15 \\ 26.41 \\ 30.82 \\ 21.59 \\ 26.76 \\ 26.02 \\ 28.32 \\ 21.26 \\ 19.50 \\ 24.03 \end{bmatrix} & \Rightarrow & \begin{bmatrix} 31..15 \\ 26.41 \\ 30.82 \\ 21.59 \\ 26.76 \\ 26.02 \\ 28.32 \\ 28.32 \\ 19.50 \\ 19.50 \end{bmatrix}, & & \begin{bmatrix} 31..15 \\ 26.41 \\ 30.82 \\ 30.82 \\ 26.76 \\ 26.76 \\ 28.32 \\ 21.26 \\ 19.50 \\ 24.03 \end{bmatrix}, & & \begin{bmatrix} 31..15 \\ 31.15 \\ 30.82 \\ 21.59 \\ 26.76 \\ 26.02 \\ 28.32 \\ 21.26 \\ 21.26 \\ 24.03 \end{bmatrix} & \cdots & \begin{bmatrix} 31..15 \\ 26.41 \\ 26.41 \\ 21.59 \\ 26.76 \\ 26.02 \\ 26.02 \\ 21.26 \\ 19.50 \\ 24.03 \end{bmatrix} \\
\mu\text{'s:}\ 25.586 & & 26.32 & & 26.03 & & 26.24 & & 24.59
\end{array}
$$

Notice that some values are repeated in the samples because they were sampled with replacement.

Applied to mediation:



Sample 1 sample 2 sample 3 sample 4

So now you have 1,000 samples where you ran your Baron & Kenny method mediation analyses, giving you 1,000 estimates of the total effect, 1,000 estimates of the direct effect, and 1,000 estimates of the 2 paths that make up the indirect effect.

How does this help you determine if your indirect effect is significant?

Remember that if you reject the null hypothesis for something, then you are saying it is significantly different from zero. Or, described another way when $\alpha = .05$, the 95% confidence interval (CI) for that estimate does not contain zero. Usually we construct our 95% CIs by multiplying the SE by a critical value, and then adding and subtracting the product from our middle-point (the B, or the mean, or whatever estimate you're dealing with). There's another way to construct CIs.

Percentile bootstrap confidence intervals are created by repeatedly sampling, then estimating a parameter numerous times. You then line up all of your estimates in order, and select the middle 95% of these estimates as your 95% CI. So if you only have 100 samples, you take the middle 95 means, and drop the bottom 2.5 and the top 2.5.

There are 2 problems with this: You can't drop half a mean (or two and a half). Also, 100 samples isn't necessarily a very reliable or stable sampling distribution.

If you take 1000 samples, then you retain the middle 950. You drop the top 25 and the bottom 25. This solves both of our problems: it's a more reliable sampling distribution, and you're working with whole numbers.

I took 1000 samples from my original sample for some dataset, and generated the mean of each sub-sample. I did not include all 1000 means to save space, but after ordering them from min to max, I included the bottom 30 (smallest) and the top 30 (largest).
51.96, 52.07, 52.98, 53.19, 53.23, 53.38, 53.49, 53.5, 53.79, 53.85, 54.11, 54.12, 54.2, 54.3, 54.3, 54.4, 54.41, 54.43, 54.43, 54.49, 54.57, 54.6, 54.68, 54.69, 54.7, → 54.73, 54.8, 54.89, 54.93, 54.93**…**
…,
63.28, 63.35, 63.44, 63.62, 63.64, ← 63.71, 63.78, 63.88, 63.88, 63.89, 63.9, 63.91, 63.98, 64, 64.03, 64.09, 64.16, 64.17, 64.19, 64.24, 64.25, 64.4, 64.43, 64.44, 64.81, 64.9, 64.94, 65.03, 65.08, 65.38.

If we drop the bottom 25 (the blue means) and the top 25 (the red means), we have a remaining 95% confidence interval of 54.73 to 63.64, with a point estimate (a mid-point) of 59.05. This 95% CI does not contain zero, so the mean for this sample is significantly different from zero.

Notice that the boundaries for our CI are not equidistant from the midpoint. Equidistant boundaries are rare for percentile bootstrap CIs. Equidistant bootstrapped CIs indicates that the normal theory SE is a perfect representation (that the SE distribution is truly normal), which is rare. It's usually slightly non-normal using this method. Remember that if the distribution were truly normal, then you could just use Sobel's test instead.

We can use this same method for indirect effects. Using bootstrapping, we can generate 1,000 estimates of *a* and *b*, and calculate the indirect effects by finding the product (*ab*). After sorting *ab* from smallest to largest, we can lop off the bottom 2.5% and top 2.5% to get our empirical 95% CI. If it does not contain zero, we know it's significant at $\alpha = .05$. If the CI does contain zero, the indirect effect is not significant.

Note: I'm using 1,000 bootstrapped samples for numeric simplicity, but Preacher & Hayes (2008) recommend using at least 5,000 samples for final reporting, though 1,000 is okay for preliminary research.

To conduct this new method in SPSS, first download the appropriate macro from the following website associated with their 2008 article:
http://www.comm.ohio-state.edu/ahayes/SPSS%20programs/indirect.htm

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The "indirect macro" syntax was created by Hayes. Make sure your dataset is open first. Then you just open the macro syntax file and run it unaltered, regardless of what dataset you are using. Do not change anything to reflect the names of the variables. It essentially creates a new command, like "REGRESSION" or "GLM". Hayes named this new command "INDIRECT". After selecting "run", SPSS will be busy processing the macro for a while.

After running Hayes' macro, you can run your own altered command line. The command line provided by Hayes is:

```
INDIRECT Y = yvar/X = xvar/M = mvlist [covlist]
                           [/C = {cov}(0**)]
                           [/BOOT = {z}(1000**)]
                           [/CONF = {ci}(95**)]
                           [/NORMAL = {t}(0**)]
                           [/CONTRAST = {n}(0**)]
                           [/PERCENT = {p}(0**)]
                           [/BC = {b}(0**)]
                           [/BCA = {d}(1**)]
                           [/CONVERGE = (.000001**)]
                           [/ITERATE = (10000)].
```

To use the command created by macro, simply copy the text above and paste it into a new syntax window. Alter the appropriate pieces of it for your data. Subcommands in brackets are optional
** Default if subcommand is omitted

For example, I am conducting a mediation analysis where *age* is our predictor, *beginning salary* (salbegin) is our mediator, and *current salary* (salary) is our outcome variable. I altered the syntax to reflect this. You may alter this syntax to reflect your predictor variable's name, your outcome variable's name, your mediator's name, and the confidence level of our CI. Even though there are many other options, I wouldn't mess with the rest of the syntax unless you read the full 2008 article by Preacher and Hayes.

```
INDIRECT  Y = salary/ X = age/ M = salbegin/ C = 0/ BOOT = 5000/ CONF = 95.
EXECUTE.
```

In the above syntax, I changed Hayes' command line to indicate that *salary* is the outcome variable, *age* is the predictor, and *salbegin* is the mediator. I also requested 5000 samples for the bootstrap. My changes are in **blue**. Additionally, even though it was already the default I included syntax that indicates there are no covariates (C = 0) and my confidence interval is 95% (CONF = 95). If I had included a covariate, it would have been listed after *salbegin*, and I would have altered the syntax to say C = 1.

Excerpt from the associated SPSS output:

```
Dependent, Independent, and Proposed Mediator Variables:
DV =   salary
IV =   Age
MEDS = salbegin

Sample size
        474

*****************************************************************

           BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)
              Data      Boot      Bias        SE
TOTAL     181.1745  181.6683     .4938   51.3591
salbegin  181.1745  181.6683     .4938   51.3591

Percentile Confidence Intervals
             Lower     Upper
TOTAL      84.6346  285.5710
salbegin   84.6346  285.5710

*****************************************************************

Level of Confidence for Confidence Intervals:
  95

Number of Bootstrap Resamples:
  5000

------ END MATRIX -----
```

"DATA" is the estimate based on your original sample, whereas "BOOT" is the midpoint estimate from all of your bootstrapped samples. "BIAS" is the difference between them.

Based upon the above output, I know that of the 5000 samples generated via bootstrapping, my point estimate for the indirect effect is 181.67, with a 95% confidence interval ranging from 84.63 to 285.57. Because this interval does not contain zero, this indirect effect is significantly different from zero.

Caution: This syntax is capable of running multiple mediators simultaneously, and comparing the indirect effects of each. However, if you do have multiple mediators, it is best to use an SEM framework instead of SPSS because of greater flexibility in what you can control. Neither regression nor SEM uses these “percentile bootstrap” CIs by default, but Preacher and Hayes also provide macros for various SEM software programs. If you want to use the bootstrap method with multiple mediators and compare them with contrasts, I recommend you do this with the SEM macros instead of this one.