The Mediation Package

- Based on Preacher & Hayes (2004) - more power than Sobel test - well suited for small sample sizes.

- Need to build two models - one for direct effect of our predictors and one for the effect of our predictor and mediator.

```
> library(mediation)
> fitM <- lm(M ~ X, data = Meddata) #IV on M; Hours since dawn predicting
coffee consumption
> fitY <- lm(Y ~ X + M, data = Meddata) #IV and M on DV; Hours since dawn and
coffee predicting wakefulness
```

- Then use the `mediate()` function in the `mediation` package to compare the two models - allows us to estimate effect of the mediator…

```
> fitMed <- mediate(fitM, fitY, treat = "X", mediator = “M")
> summary(fitMed)
```

```
> summary(fitMed)

Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals

               Estimate 95% CI Lower 95% CI Upper p-value
ACME            0.276803     0.144987         0.43  <2e-16 ***
ADE            -0.115043    -0.316462         0.07   0.268
Total Effect    0.161760     0.000729         0.31   0.048 *
Prop. Mediated  1.653327     0.507091         9.66   0.048 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sample Size Used: 100


Simulations: 1000
```

- By running this we get the Average Causal Mediation Effects (ACME), our Average Direct Effects (ADE), combined indirect and direct effects (Total Effect), and the ratio of these estimates (Prop. Mediated).
- The ACME is the indirect effect of M (Total Effects - ADE) and the associated *p*-value value tells us if our mediation effect is significant.
- We can bootstrap our data and fit a model based on our estimated population parameters (which is recommend over the default CI estimation method above)…