

Dataframe: obs.csv

A research team sought to examine factors associated with 21st birthday drinking among female students at a large University. Female students who were nearing age 21 and self-classified as regular drinkers were eligible for the study. In total, 200 students were recruited and agreed to take part in the study. Students were instructed to report to the lab two weeks prior to their 21st birthday. During this lab session, students completed a brief survey that measured alcohol use during the past month (using the Timeline Follow Back Method) and their weight was recorded. One week prior to their 21st birthday, participants were sent a link for an online survey to measure positive alcohol expectancies for drinking on their 21st birthday. Within three days prior to their 21st birthday, students reported to the lab and were given a diary-based data collection form to record several items on their 21st birthday. Students were instructed to record the food that they consumed during the day, the degree to which they were in a partying mood just prior to the celebration, and the quantity and type of drinks that they consumed during the first two hours of the celebration. The students were also given a small breathalyzer machine to measure BAC 2 hours after consumption of their first drink.

The dataset called bac\_obs.csv contains the data:

- weight: weight in kilograms
- alcexp: positive alcohol expectancy for drinking on the impending 21st birthday, a multi-item scale that ranges from 1-7, where a higher score indicates more positive expectations about the role alcohol will play
- typ\_drks: the number of standard alcohol drinks consumed in the past 30 days
- pmood: a rating on a scale from 1-9 on the respondent's mood to party on the 21st birthday, where 1 means never been less in the mood to party, and 9 means never been more in the mood to party
- absorb: a score calculated from the food diaries to determine how full the participant was when they began drinking, the score ranges from 1 to 8, where 1 means a completely full stomach, and 8 means a completely empty stomach
- alc\_gm: a score calculated from the drinking diary to estimate the grams of alcohol consumed on the 21st birthday
- bac: the participant's blood alcohol content, measured as grams of alcohol per deciliter of blood on the 21st birthday

**In this activity, you will determine if the effect of typical drinking (typ\_drks) on grams of alcohol consumed on the 21<sup>st</sup> birthday (alc\_gm) is mediated (i.e., explained) by alcohol expectancies (alcexp).**

1. Draw a figure to depict the mediation model.
2. Start a new notebook called BAC\_Notebook\_Mediation.Rmd.
3. Create a first level header called: Load libraries (i.e., # Load libraries). Insert a code chunk. Load olsrr, modelr, boot, RMediation, and tidyverse.
4. Create a first level header called: Import data. Insert a code chunk. Import the obs.csv dataset.
5. Create a first level header called: Test a simple mediation model.
6. Create a second level header called: Model 1: regress y on x. Fit a linear regression model where alc\_gm is regressed on typ\_drks.
7. Create a second level header called: Model 2: regress m on x. Fit a linear regression model where alcexp is regressed on typ\_drks.

8. Create a second level header called: Model 3: regress y on x and m. Fit a linear regression model where alc\_gm is regressed on typ\_drks and alcexp.
9. Create a second level header called: Calculate the indirect effect. Pull out the estimates and standard errors for the a- and b-paths of the mediation model and then calculate the product term for the indirect effect.
10. In the figure that you drew in Step 1, fill in the values for each of the paths.
11. Create a second level header called: Use RMediation to calculate the CI for the indirect effect. Use the medci function to construct a 95% CI for the indirect effect.
12. Create a second level header called: Use boot package to bootstrap the CI. Bootstrap the CI twice, once with 300 replications, and once with 15000 replications. Look at the results of the CI for each – are they similar? Look at the plots for each, are either sparse? (remember we want it to look filled in)
13. Create a second level header called: Calculate the proportion mediated. Calculate the proportion of the total effect of typ\_drks on alc\_gm that is indirect through alcexp.
14. Study the full set of results and write up a paragraph to describe the results.

```

---
title: "R Notebook for BAC data with Mediation"
output: html_notebook
---

# Load libraries
```{r}

library(olsrr)
library(modelr)
library(boot)
library(RMediation)
library(tidyverse)

```

# Import data
```{r}

obs <- read_csv("bac_obs.csv")

```

# Test a simple mediation model
## Model 1: regress y on x
```{r}

model.xy <- lm(a1c_gm ~ typ_drks, data = obs)
ols_regress(model.xy)

```

## Model 2: regress m on x
```{r}

model.xm <- lm(a1cexp ~ typ_drks, data = obs)
ols_regress(model.xm)

```

## Model 3: regress y on x and m
```{r}

model.xmy <- lm(a1c_gm ~ typ_drks + a1cexp, data = obs)
ols_regress(model.xmy)

```

## Calculate the indirect effect
```{r}

# Pull out coefficients and standard errors for a and b paths
coefficients(model.xm)
coefficients(model.xmy)
vcov(model.xm)
vcov(model.xmy)

path.a <- coefficients(model.xm)["typ_drks"]
path.b <- coefficients(model.xmy)["a1cexp"]
se.path.a<-sqrt(vcov(model.xm)["typ_drks","typ_drks"])
se.path.b<-sqrt(vcov(model.xmy)["a1cexp","a1cexp"])

path.a
path.b
se.path.a
se.path.b

# Calculate indirect effect
ab <- path.a*path.b
ab

```

## Use RMediation to calculate CI for indirect effect
```{r}

medci(path.a, path.b, se.path.a, se.path.b, alpha = 0.05, plot=TRUE, plotCI=TRUE)

```

```

```
## Use boot package to bootstrap confidence interval
```{r}

boot.med <- function(data, indices){
  data <- data[indices,]

  model.xm <- lm(alcexp ~ typ_drks, data=data)
  model.xmy <- lm(alc_gm ~ typ_drks + alcexp, data=data)

  path.a <- coefficients(model.xm)["typ_drks"]
  path.b <- coefficients(model.xmy)["alcexp"]
  ab <- path.a*path.b
  return(ab)
}

medboot<-boot(data=obs, statistic = boot.med, R = 15000)
medconfint <- boot.ci(medboot, index=1, conf = (.95), type = "bca")
print (medconfint)

plot(medboot)
...

```

```
## Calculate the proportion mediated
```{r}

path.c <- coefficients(model.xy)["typ_drks"]

prop_med <- ab/path.c
prop_med

...

```