correlation_pt2

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Partial & Semi-Partial Correlation

- remember that when we look at the variance "explained" by one variable on the second variable (DV), we are talking about R^2
- however, sometimes we want to look at the influence of several variables on your DV
  - from this, we may want to see how much unique influence each variable has on your DV
  - unique variance of one IV with your DV
    - can see the unique variance of each relationship
  - there is still the total variance of all your IVs with your DV

Partial Correlation

- a **partial correlation** is when we are looking at the unique relationship between a IV and a DV while other included variables are held constant
  - this is somewhat like multiple regression (which we'll get to in the next set of slides)
  - holding constant is another way of controlling for or adjusting for
- **zero-order correlation** is a pearson correlation coefficient without controlling for any other variable

Semi-Partial (or Part) Correlation

- also referred to as **part correlation**
- partial correlation is the unique relationship between two variables when controlling for a third variable
  - that means we are controlling for the effect of the third variable on both variables
- **semi-partial** correlation only controls for the effect that the third variable has on one of the variables in the correlation

Comparing Independent and Dependent rs

- independent rs
  - you can compare correlation coefficients for different groups to see if the correlation coefficients are significantly different from one another
    - correlation between depression and BMI between males and females
  - transform them into z values and then compare the converted scores using a z-test to see if the differences are significantly different from one another
- dependent rs
  - to compare dependent conditions/levels, you would use a t-test to see differences between two dependent correlations
    - if 3 conditions, you would test every correlation and compare each correlation to another

Calculating Effect Sizes

- correlation coefficients are effect sizes
- r = effect size because it is standardized (0 to +-1)
- to get the proportion of variance you would square the correlation coefficient

$$R^2 = r^2$$

- R^2 can be used for other correlation coefficients other than Pearson's (Spearman's)
  - for Spearman's the calculation is the same, however the interpretation is the proportion of variance in the ranks between the two variables
- Kendall's τ is not comparable to the other two coefficients
  - τ can be used as an effect size but it is not comparable to Pearson's or Spearman's correlation coefficients and should not be squared

Reporting Correlation Coefficients

- reporting correlation coefficients includes the two variables that you conducted a correlation of
  - there was a significant association/relationship between X and Y
  - there was no evidence of a statistically significant relationship/association between X and Y
- It is best practice to not state that **there was no significant association**
  - this is supporting your null hypothesis and by the rules of probability, we are not sure whether or not we found a true relationship
    - we can only say that in our sample, there was either evidence of a statistically significant relationship or no evidence of a significant relationship

Reporting Correlation Coefficients

- There was a statistically significant relationship between depression levels and body mass index; $r = .23$, $p = .015$.
  - can also report the statistic as $r = .23$ ($p = .015$)
- There was no evidence of a significant relationship between depression levels and test scores ($r = .03$, $p = .425$).

Reporting Correlation Coefficients

```
cor.test(mtcars$disp, mtcars$hp)
```

```
    Pearson's product-moment correlation

data:  mtcars$disp and mtcars$hp
t = 7.0801, df = 30, p-value = 7.143e-08
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.6106794 0.8932775
sample estimates:
      cor
0.7909486
```