



Confidence and collinearity



Understanding a covariate

- Explanatory variable that's not of direct interest...
- ...But is important in the system under study
- Essential to constructing a model that reflects the real world





School outcomes (revisited)





Adding more covariates

```
> mod3 <- lm(sat ~ expend + frac + ratio, data = SAT)</pre>
> effect_size(mod3, ~ expend, bootstrap = TRUE)
  slope stderr_effect expend to:expend frac ratio
1 11.01
                 3.3 5.768
                                 7.13
                                        28 16.6
> mod4 <- lm(sat ~ expend + frac + salary, data = SAT)</pre>
> effect_size(mod4, ~ expend, bootstrap = TRUE)
  slope stderr_effect expend to:expend frac salary
        6.8 5.768
                            7.13 28 33.29
1 13.33
> mod5 <- lm(sat ~ expend + frac + salary + ratio, data = SAT)</pre>
> effect_size(mod5, ~ expend, bootstrap = TRUE)
  slope stderr_effect expend to:expend frac salary ratio
1 4.463
                 9.5 5.768
                                 7.13
                                        28 33.29 16.6
```



Multicollinearity and alignment

- Collinear refers to two variables being in alignment
- Example: education and poverty
 - May vary at the individual level
 - Go hand-in-hand at the population level



Calculating alignment

```
> auxiliary_mod <- lm(expend ~ frac, data = SAT)
> R2 <- rsquared(auxiliary_mod)
> R2
[1] 0.35

# Variance inflation factor (VIF)
> 1 / (1 - R2)
[1] 1.5

# Standard error Inflation Factor
> sqrt( 1 / (1 - R2))
[1] 1.2
```





Collinearity between expend and covariates

```
# Include student-teacher ratio as a covariate
> R2 <- rsquared(lm(expend ~ frac + ratio, data = SAT))
> acos(sqrt(R2)) * 180 / pi # Angle in degrees
\lceil 1 \rceil 50
> sqrt(1 / (1 - R2)) # SE inflation
\lceil 1 \rceil 1.3
# Adding both ratio and salary
> R2 <- rsquared(lm(expend ~ frac + ratio + salary, data = SAT))
> acos(sqrt(R2)) * 180 / pi # Angle in degrees
\lceil 1 \rceil 19
> sqrt(1 / (1 - R2)) # SE inflation
[1] 3.1
```





Let's practice!





Start modeling!



Some important ideas

- Prediction error
- Effect size
- Covariates
- Quantitative vs. categorical responses
- Bootstrapping and cross validation



Beyond lm() and rpart()

- Generalized linear models (e.g. logistic regression)
- Machine learning techniques (e.g. random forests)
- Time series methods
- Survival analysis
- Causal inference
 - Donald Rubin: matched sampling
 - Judea Pearl: directed acyclic graphs (DAGs)



Modeling is a creative process

- Try a variety of things (models, explanatory variables, etc.)
- Build many models and compare them
- There is no right or wrong





What's correct useful?

"All models are wrong; some are useful."

- George Box





Let's get modeling!