INTRODUCTION TO STATISTICAL MODELING

Multiple explanatory variables

The `statisticalModeling` package

- To evaluate the model, need to set values for explanatory variables **Commonly use mean, median, or mode**
- To visualize the model, need to select several different levels of explanatory variables to include

```
# Load statisticalModeling package
> library(statisticalModeling)
```

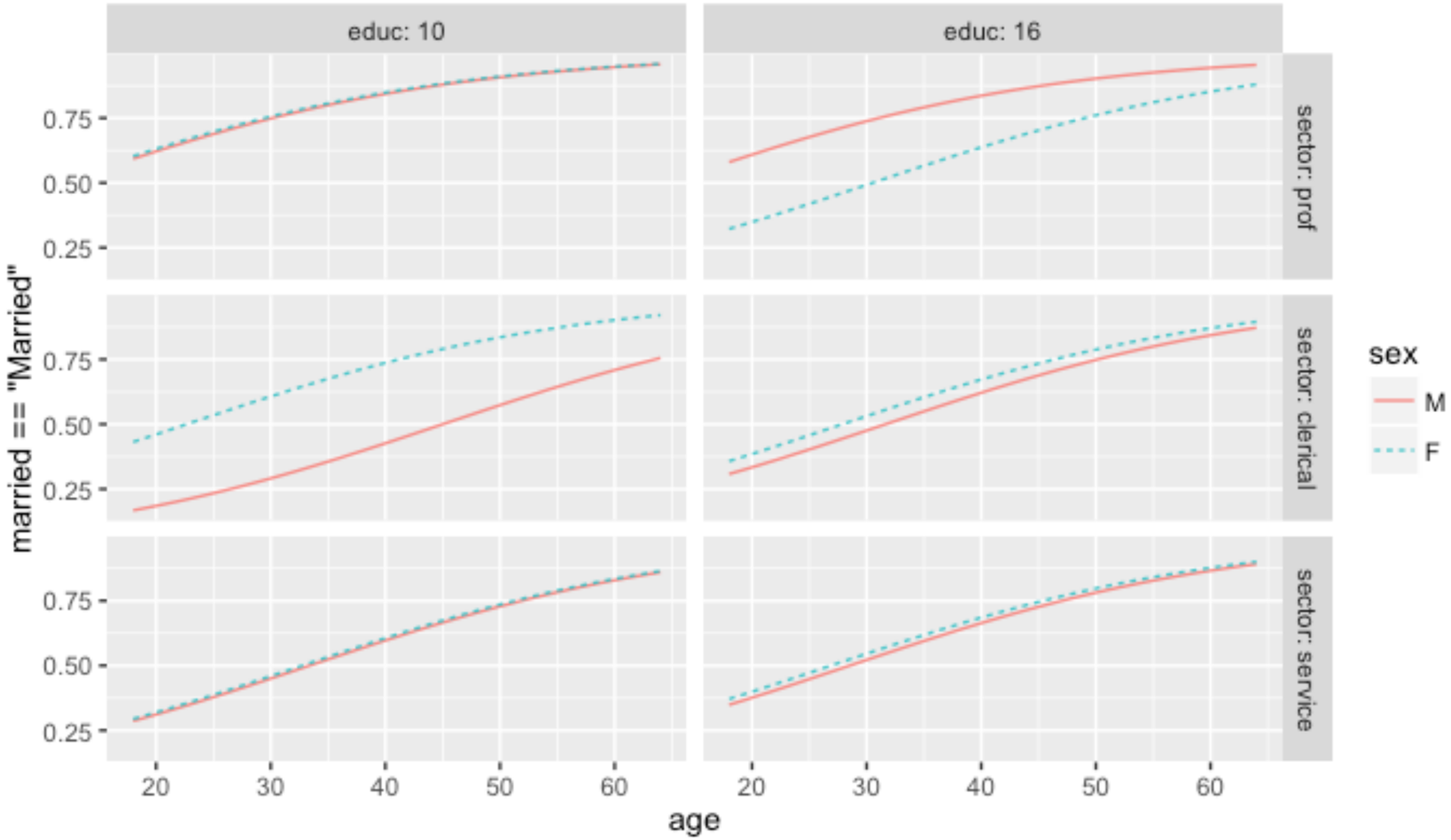
Using `effect_size()`

```
# Train model
> wage_model <- lm(wage ~ educ + sector + sex + exper,
                   data = CPS85)

# Effect size of education on wage: a slope
> effect_size(wage_model, ~ educ)
      slope educ  to:educ sector sex exper
1 0.7179628   12 14.61537   prof   M    15
```

Using fmodel()

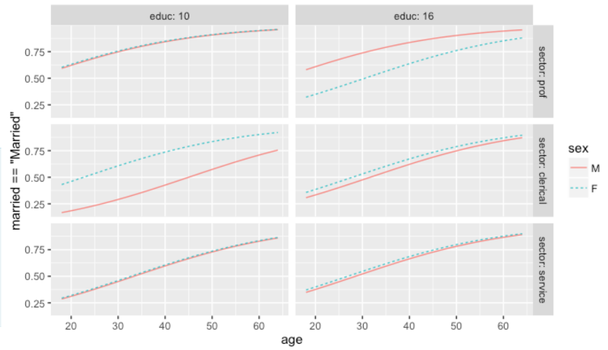
```
# A model of the probability of being married
> married_model <- glm(married == "Married" ~ educ * sector * sex + age,
                       data = CPS85, family = "binomial")

> fmodel(married_model, ~ age + sex + sector + educ, data = CPS85,
         type = "response", educ = c(10, 16))
```

Using `fmodel()`



Designing graphs of models

```
> fmodel(married_model, ~ age + sex + sector + educ, data = CPS85,
         type = "response", educ = c(10, 16))
```



1. Response variable always on y-axis
2. Explanatory variables of primary interest on x-axis
3. Choose one, two, or three variables you want in display
4. If others, choose a fixed value that's of interest

`fmodel()` does (2) - (3) automatically
and (4) either automatically or manually

INTRODUCTION TO STATISTICAL MODELING

Let’s practice!

INTRODUCTION TO STATISTICAL MODELING

Categorical response variables

The question at hand

- For a quantitative response variable and a...
  - Quantitative explanatory variable → **Effect size is a rate**
  - Categorical explanatory variable → **Effect size is a difference**

But what happens when the response variable is categorical?

Model output for categorical response

Two ways to frame the output:

- As categories or *classes*
- As probabilities

Example: marital status

```
# Create model and set inputs
> married_model <- rpart(married ~ educ + sex + age,
                         data = CPS85, cp = 0.005)

# Output as a category (i.e. class)
> evaluate_model(married_model, type = "class", age = c(25, 30),
                 educ = 12, sex = "F")
  educ sex age model_output
1   12   F  25      Married
2   12   F  30      Married

# Output as a probability
> evaluate_model(married_model, type = "prob", age = c(25, 30),
                 educ = 12, sex = "F")
  educ sex age model_output.Married model_output.Single
1   12   F  25            0.6333333           0.3666667
2   12   F  30            0.7425743           0.2574257
```

Extra 5 years of age associated with 11% increase in probability of being married

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Let’s practice!

INTRODUCTION TO STATISTICAL MODELING

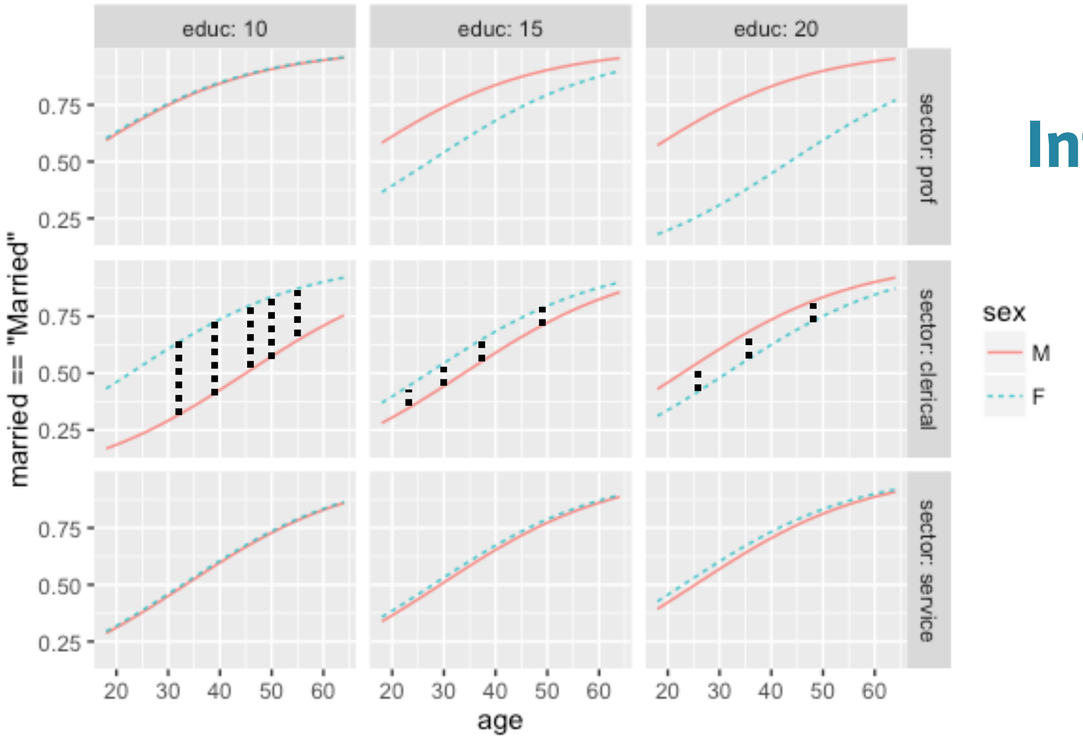
Interactions among explanatory variables

Interaction

Effect size of one variable may change with the other explanatory variables

Probability of being married

```
> married_model <- glm(married == "Married" ~ educ * sector * sex + age,
                       data = CPS85, family = "binomial")
> fmodel(married_model, ~ age + sex + sector + educ, data = CPS85, type = "response")
```

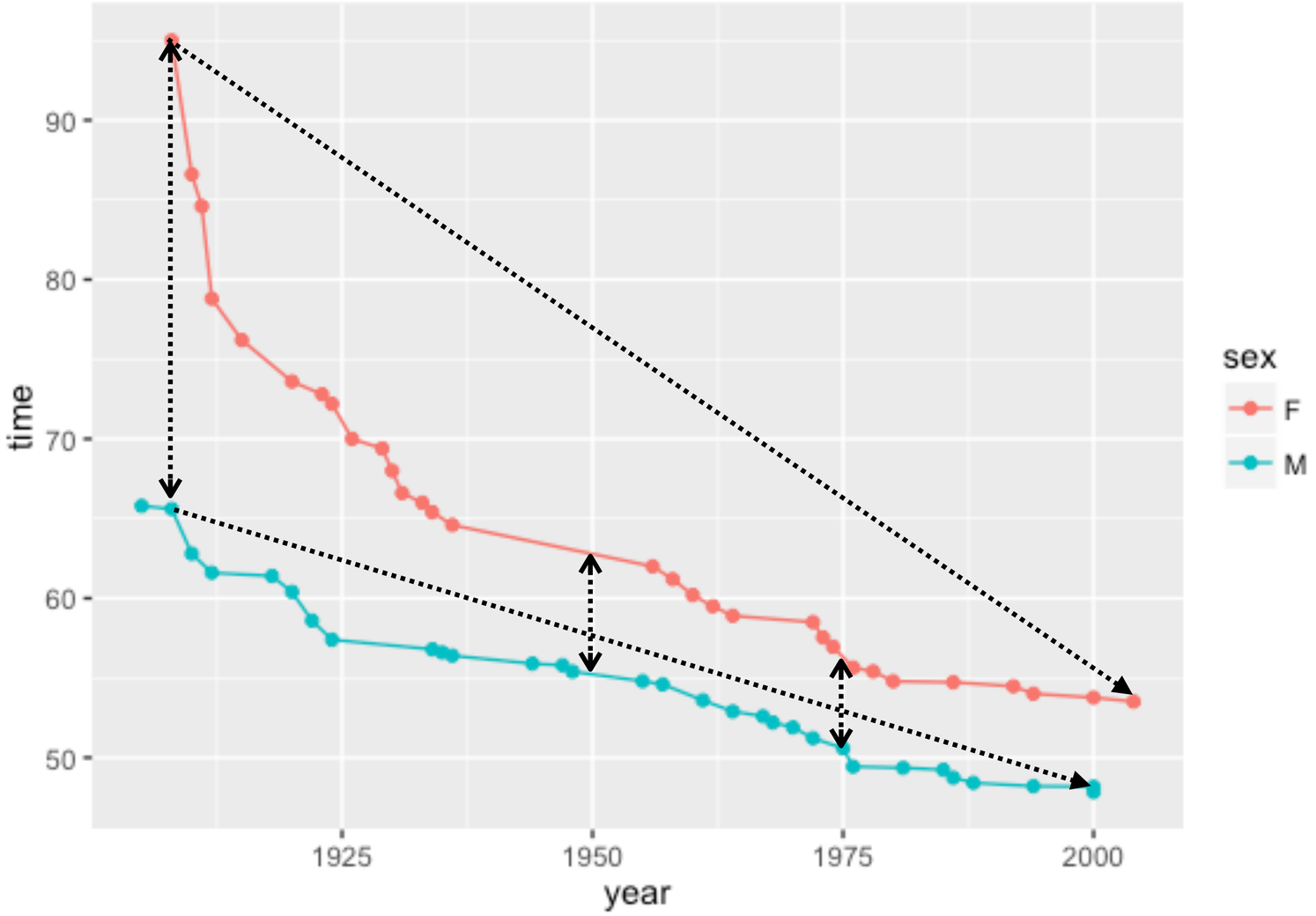


Interaction effect

Interactions and model architecture

- `lm()` includes interactions only if you ask for them
- `rpart()` has interactions built into the method

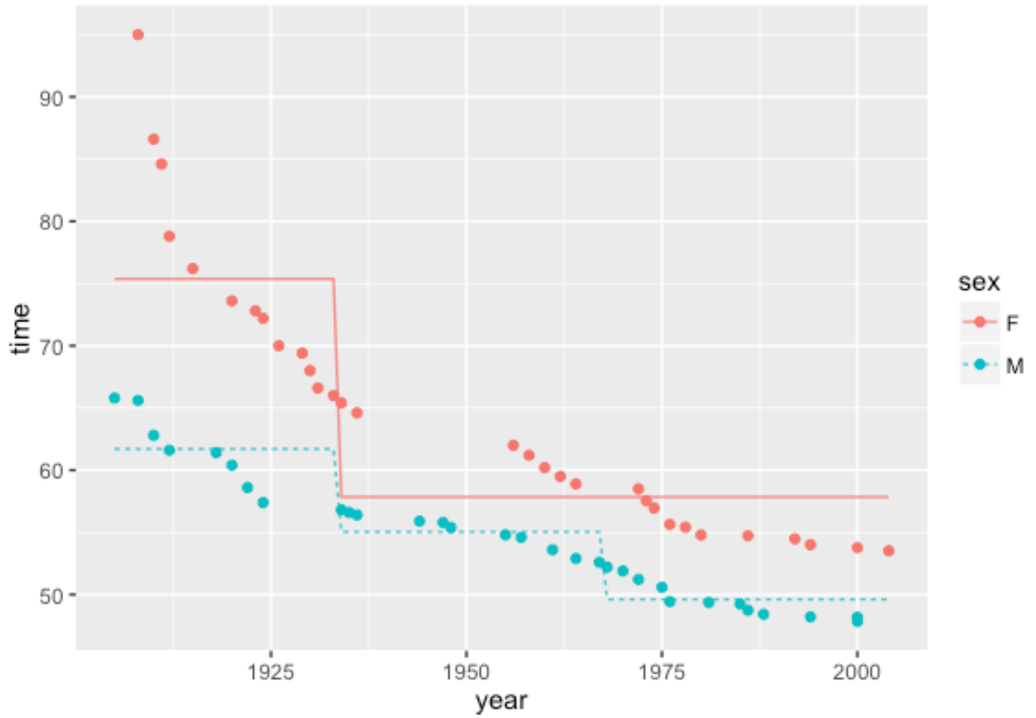
World swimming records

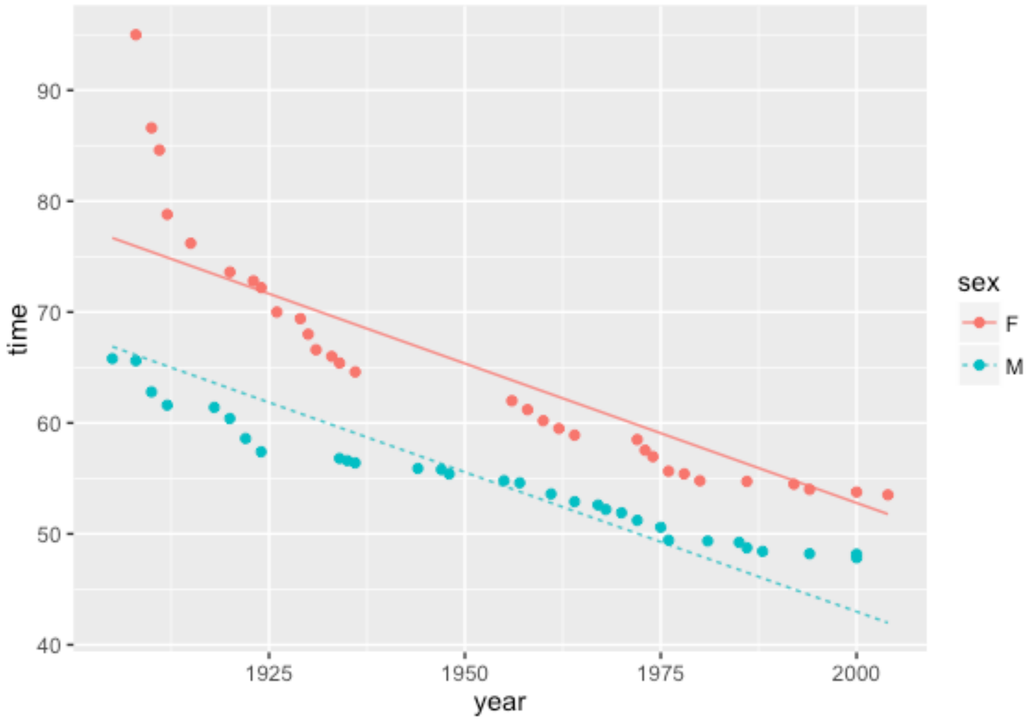


World swimming records

```
mod1 <- rpart(time ~ sex + year, data = SwimRecords)
```

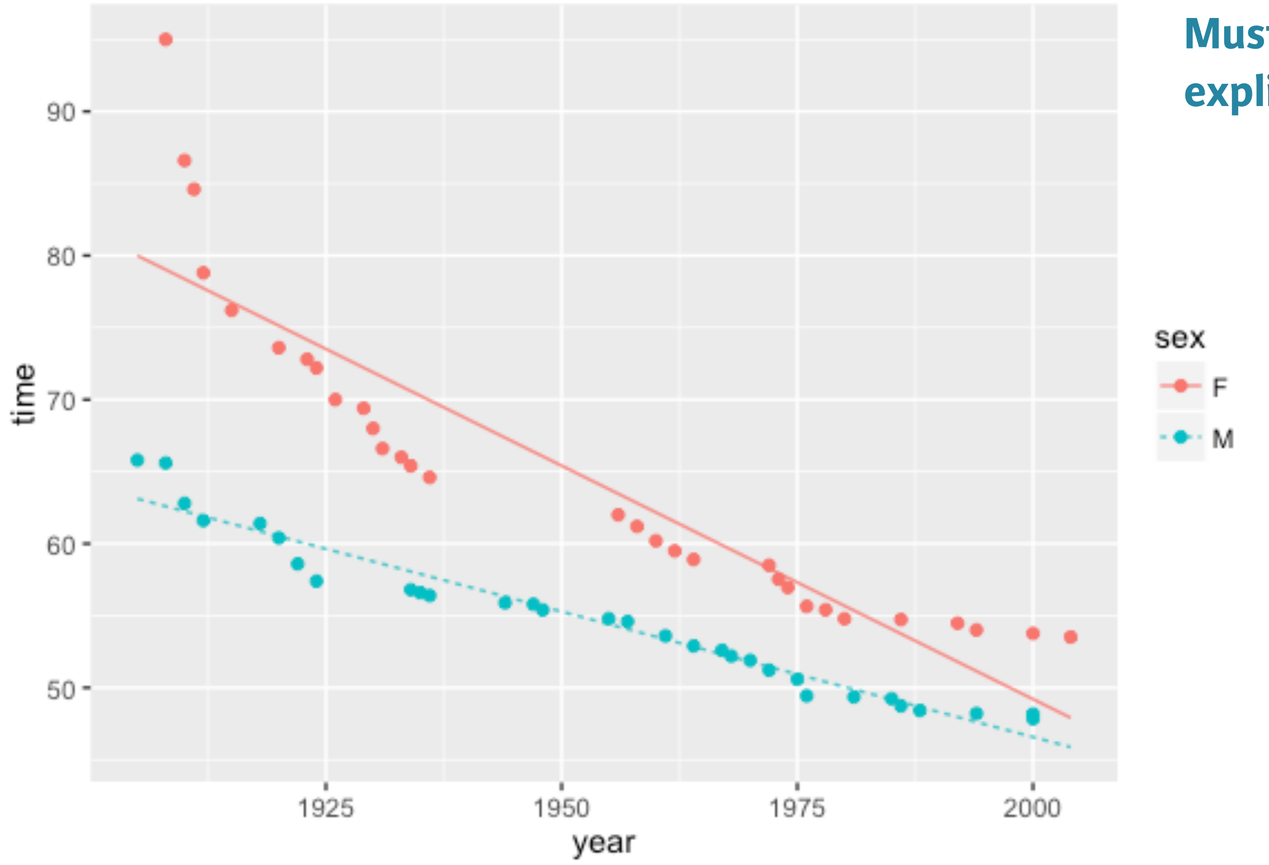
```
mod2 <- lm(time ~ sex + year, data = SwimRecords)
```





Formulas with interactions

```
mod3 <- lm(time ~ sex * year, data = SwimRecords)
```



Must specify interaction explicitly in `lm()`

Does an interaction improve a model?

Use cross validation to see which is better:

- `mod2: ~ year + sex`
- `mod3: ~ year * sex`

```
> t.test(mse ~ model, data = cv_pred_error(mod2, mod3))
data:  mse by model
t = 20, df = 18, p-value = 1.323e-13
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 4.2 5.2
sample estimates:
mean in group mod2 mean in group mod3
                17                 12
```

Error for mod3 < Error for mod2

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Let’s practice!