

SOC542 Statistical Methods in Sociology II

Ordinary Least Squares Regression I

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Plan

- ▶ Course updates
- ▶ Bivariate statistics review
- ▶ Ordinary least squares regression
- ▶ Lab: Simple regression in R / Github

Course updates

Homework 1

- ▶ Homework 1 released today, due Friday at 5pm
 - ▶ Statistics review
 - ▶ Simple OLS regression
- ▶ Download and submit using Github Classroom

Expected mean and variance of two random variables

- ▶ The expected mean of the sum of two random variables is

$$E[x + y] = E[x] + E[y] = \mu_x + \mu_y$$

- ▶ The expected variance is the sum of the variances plus twice their covariance

$$\text{var}(x + y) = \text{var}(x) + \text{var}(y) + 2\text{cov}(x, y)$$

- ▶ If x and y are independent then $\text{cov}(x, y) = 0$ and $\text{var}(x + y) = \text{var}(x) + \text{var}(y)$

Covariance

- ▶ Covariance is a measure of the joint variability of two random variables
- ▶ The expectation of the covariance between x and y is

$$\text{cov}(x, y) = E[xy] - E[x]E[y]$$

- ▶ For a population, the covariance is

$$\text{cov}(x, y) = \frac{1}{N} \sum (x_i - \mu_x)(y_i - \mu_y)$$

- ▶ Sample covariance is defined as

$$\text{cov}(x, y)_s = \frac{1}{n-1} \sum (x_i - \bar{x})(y_i - \bar{y})$$

Correlation

- ▶ Correlation is a scaled version of covariance. We divide the covariance by the product of the standard deviations.

$$\rho(x, y) = \frac{\frac{1}{n-1} \sum (x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

- ▶ The letter ρ is typically used to refer to correlation. The correlation coefficient ranges from -1 to 1.
- ▶ The sample correlation is also a consistent estimator of the population correlation.

Generating correlated variables

We can use `mvrnorm` to generate a set of variables defined by their means and a variance-covariance matrix Σ . In this case, $\mu_x = 20$ and $\mu_y = 5$ and

$$\Sigma = \begin{Bmatrix} \text{var}(x) & \text{cov}(x, y) \\ \text{cov}(y, x) & \text{var}(y) \end{Bmatrix}$$

where the diagonal entries denote variance and the off-diagonals denote covariance.

```
n <- 1000
mu <- c(4,1) # vector of means, x and y
sigma <- rbind(c(4, 1), # variance of x, covariance of x and y
              c(1, 1)) # covariance of y and x, variance of y
M <- mvrnorm(n=n, mu=mu, Sigma = sigma)
```

Unlike `rnorm` where we specify a random variable using a mean and standard deviation, `mvrnorm` uses the mean and variance.

Sample statistics

The sample is large so the sample means and variances are close to the population values.

```
df <- as.data.frame(M)
colnames(df) <- c("x", "y")
print(mean(df$x)) # sample mean of x
```

```
## [1] 3.964342
```

```
print(var(df$x)) # sample variance of x
```

```
## [1] 3.781983
```

```
print(mean(df$y)) # sample mean of y
```

```
## [1] 0.9901981
```

```
print(var(df$y)) # sample variance of y
```

```
## [1] 0.9907679
```


Calculating covariance

We can calculate the sample covariance using the formula above. I verify the calculating by comparing it to the output of the built-in cov function.

```
covariance <- (1/(n-1))*sum((df$x-mean(df$x))*(df$y-mean(df$y)))  
print(covariance)
```

```
## [1] 0.9228733
```

```
round(covariance,3) == round(cov(df$x,df$y),3)
```

```
## [1] TRUE
```

Calculating correlation

We can do the same for correlation. Note here that I use the cov function in the numerator.

```
correlation <- cov(df$x, df$y) / (sd(df$x)*sd(df$y))  
print(correlation)
```

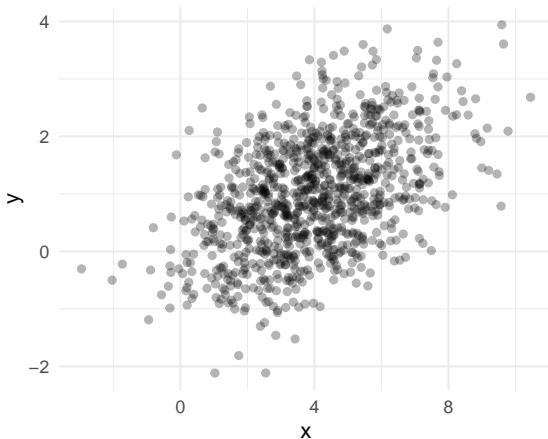
```
## [1] 0.4767561
```

```
round(correlation,3) == round(cor(df$x, df$y),3)
```

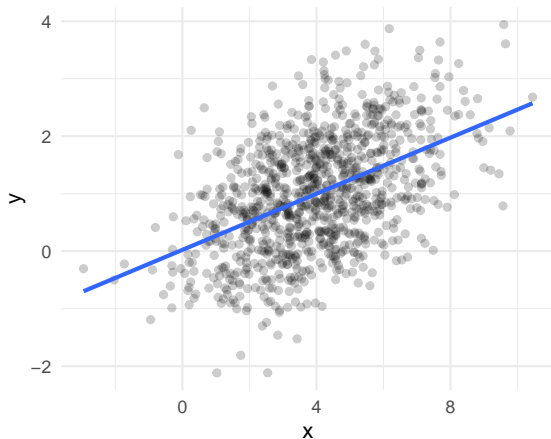
```
## [1] TRUE
```

Plotting the relationship

```
ggplot(data = df, aes(x = x, y = y)) + geom_point(alpha = 0.3) +  
  theme_minimal()
```



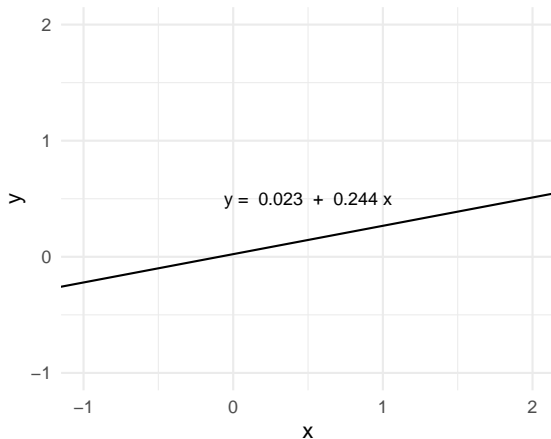
Adding regression line $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{u}$.



Properties of the regression line

- ▶ The population regression line $y = \beta_0 + \beta_1 x + u$ is defined by two parameters, the slope and intercept.
 - ▶ β_0 and β_1 are known as **coefficients**.

Plotting the regression line



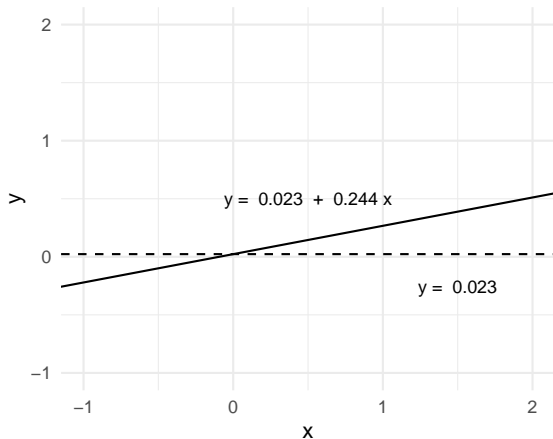
Interpreting the intercept

- ▶ The intercept defines the value of y when $x = 0$.
- ▶ Where $x = 0$, $\beta_0 x = \beta_1 0 = 0$, thus

$$y = \beta_0 + 0 = \beta_0$$

- ▶ Hence, the intercept is a *constant*.

Plotting the intercept



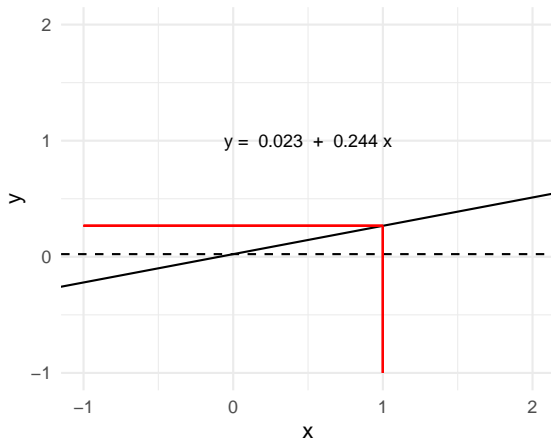
Interpreting the slope

- ▶ The slope defines the relationship between change in x and y , where Δ is used to denote change:

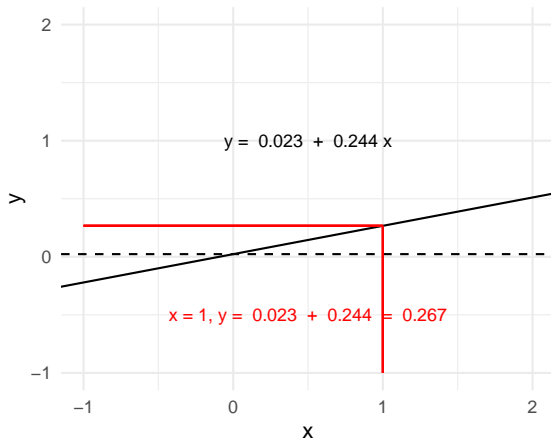
$$\beta_1 = \frac{\Delta y}{\Delta x}$$

- ▶ β_1 denotes the expected *change* in y following a 1-unit change in x
 - ▶ e.g. What effect does an additional year of education have on lifetime income?
- ▶ If $\beta_1 < 0$ then the relationship is negative (y decreases as x increases)

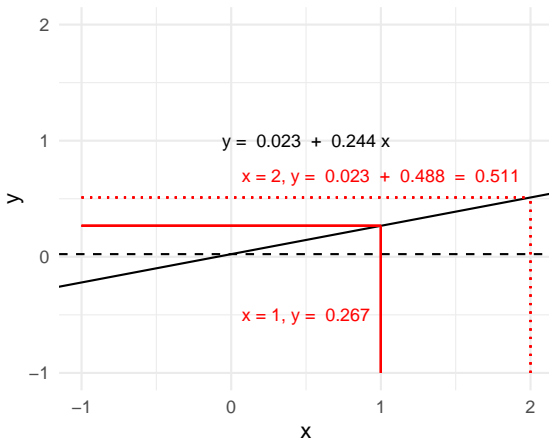
Interpreting the slope



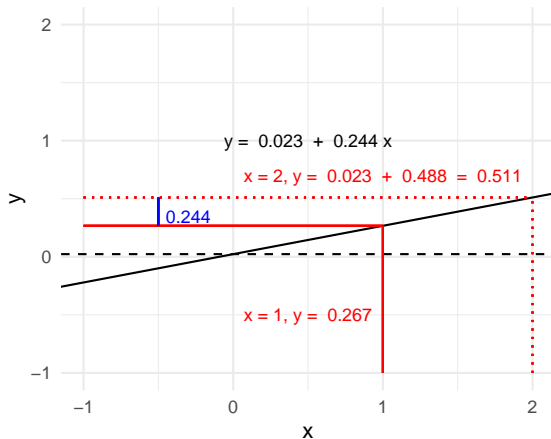
Interpreting the slope



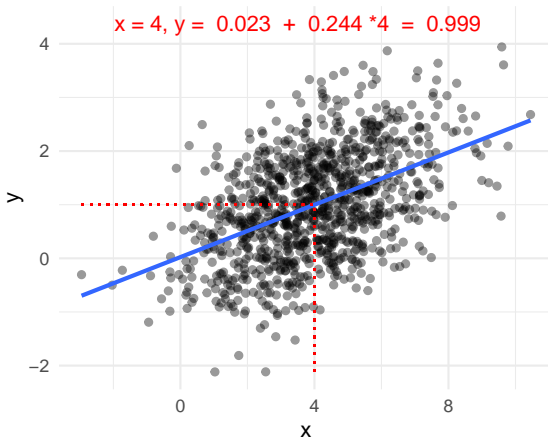
Slope as a comparison: a unit change in x



Slope as a comparison: a unit change in x



Reading the regression line



Ordinary least squares regression (Population model)

- ▶ The population ordinary least squares (OLS) regression equation is defined as:

$$y = \beta_0 + \beta_1 x + u$$

- ▶ We can also write this as an expectation

$$E[y|x] = \beta_0 + \beta_1 x$$

- ▶ u is known as the error term and captures all factors that affect y but are not accounted for by x .

Ordinary least squares regression (sample model)

- ▶ The sample analogue is

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{u}$$

- ▶ The $\hat{}$ symbol (pronounced “hat”) is used to denote an **estimate**. We use the observed data from x and y to calculate estimates of underlying population quantities.

Defining the coefficients β_1 and β_0

- ▶ The OLS estimator of β_1 is

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\text{cov}(x, y)}{\sigma^2(x)}$$

- ▶ The estimator of the intercept β_0 can be derived from $\hat{\beta}_1$:

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

Predicted values and residuals

- ▶ x and y are vectors where x_i and y_i correspond to the i^{th} elements of each vector.
- ▶ We can use the regression equation to calculate the **predicted value** of y_i as a linear function of x_i :

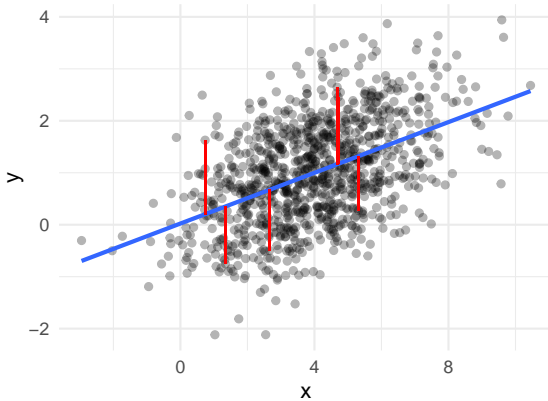
$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$$

- ▶ The **residual** is the difference between the observed value of y_i and the predicted value. It measures variation in y_i that is not explained by x .

$$\hat{u}_i = y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i = y_i - \hat{y}_i$$

- ▶ Thus, $y_i = \hat{y}_i + \hat{u}_i$.

Visualizing residuals



Red lines show difference between observed y and fitted value \hat{y}

Least squares

- ▶ This model is known as **least squares** regression because it minimizes the sum of the squared residuals.

$$SSR = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \hat{u}_i^2$$

\bar{x} is the least squares estimator of μ_x

- ▶ Consider a random variable x . For each value of x , $x_i - \alpha$ is the prediction error.

$$\sum_{i=1}^n (x_i - \alpha)^2$$

- ▶ The sample average \bar{x} is the estimator α that minimizes the **sum of squared errors (SSE)**.

\bar{x} is the least squares estimator of μ_x

Let's generate a random variable and calculate the SSE using $\alpha = \bar{x}$

```
x <- rnorm(n=100, mean = 5, sd = 1)
xbar <- mean(x)
print(xbar)
```

```
## [1] 5.009309
```

```
print(sum((x-xbar)^2))
```

```
## [1] 106.7624
```

\bar{x} is the least squares estimator of μ_x

Now let's compare the results when alternative values of α are used.

```
## [1] "alpha = xbar = 5.009 , SSE = 106.762"  
  
## [1] "alpha = 3 , SSE = 510.495"  
## [1] "alpha = 4 , SSE = 208.633"  
## [1] "alpha = 5 , SSE = 106.771"  
## [1] "alpha = 6 , SSE = 204.909"  
## [1] "alpha = 7 , SSE = 503.048"
```

β_0 and β_1 minimize the SSR

- ▶ For a single sample, \bar{y} is the least squares **estimator** of μ_y .
- ▶ For two variables, \hat{y} is the least squares **estimator** of y because it minimizes the **sum of the squared residuals (SSR)**:

$$SSR = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \hat{u}^2$$

- ▶ By substitution,

$$SSR = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

Minimizing the sum of the squared residuals

Let's simulate the residuals using some other possible coefficients, β_1 .

```
coefs <- c(S-0.3, S-0.2, S-0.1, S, S+0.1, S+0.2, S+0.3)

i <- 1
results <- c()
for (beta1 in coefs) {
  beta0 <- mean(df$y) - beta1*mean(df$x) # define intercept
  u <- df$y - beta0 - beta1*df$x # calculate residuals
  ssr <- round(sum(u^2), 2) # calculate ssr
  results[i] <- ssr
  i <- i + 1
}
```

Minimizing the sum of the squared residuals

##		coefs	results
##	1	-0.056	1104.88
##	2	0.044	915.96
##	3	0.144	802.60
##	4	0.244	764.80
##	5	0.344	802.57
##	6	0.444	915.90
##	7	0.544	1104.80

Model fit and R^2

- ▶ R^2 is a measure of the ratio of the variance of \hat{y} to the variance of y_i

$$R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} = \frac{ESS}{TSS}$$

- ▶ We can also write it as a fraction of the unexplained variance:

$$R^2 = 1 - \frac{SSR}{TSS}$$

- ▶ R^2 has a range of $[0,1]$ where higher values indicate more variance explained. It is often common to have models with very low values of R^2 .

Mean squared error

- ▶ An alternative measure of fit is the **mean squared error (MSE)**, defined as

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

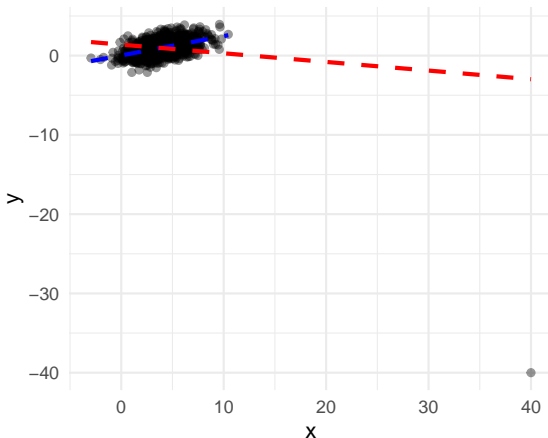
- ▶ MSE is often used to evaluate the predictive performance of statistical models with continuous outcomes.

OLS assumptions

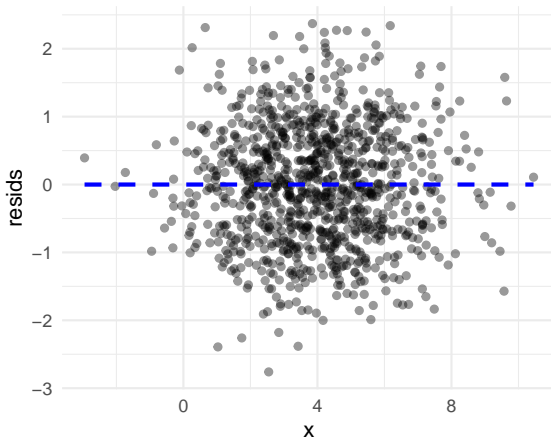
- ▶ x and y are independently and identically distributed (IID).
 - ▶ The sample x must contain some variability. Specifically, $\text{var}(x) > 0$.
 - ▶ Large outliers are unlikely.
- ▶ The conditional distribution of u given x has a mean of zero.
 - ▶ Errors are independent $E[u_i|x_i] = E[u_i] = 0$.
 - ▶ Errors have constant variance $\text{var}(u_i) = \sigma^2$.
 - ▶ Errors are uncorrelated.

Violating the large outlier assumption

Observe how a large outlier can pull down the entire regression line.



$$E[u_i|x_i] = 0$$



Homoskedasticity and heteroskedasticity

- ▶ The $E[u|x] = E[u] = 0$ implies **homoskedasticity**
 - ▶ The variance of u_i is equal for all values of x_i , $var(u_i) = \sigma^2$.
- ▶ **Heteroskedasticity** exists when this assumption is violated.
 - ▶ It can result in inefficient point estimates and biased standard errors.

The Gauss-Markov Theorem

- ▶ If these assumptions hold and the errors are homoskedastic, the OLS estimator $\hat{\beta}_1$ is **BLUE**: the **Best Linear conditionally Unbiased Estimator**.
- ▶ **Best** implies that $\hat{\beta}_1$ is the best of all possible linear conditionally unbiased estimators.
 - ▶ $\hat{\beta}_1$ produces the smallest mean squared error of all possible estimators $\tilde{\beta}_1$.
- ▶ **Linear** requires the dependent variable y to be a linear function of the parameters in the model.
 - ▶ This does *not* require the relationship between x and y to be linear. e.g. $y = 1 + 2x^2$ is linear in parameters.
- ▶ **conditionally Unbiased** implies $E[\hat{\beta}_1] = \beta_1$.
 - ▶ The expectation of the estimated coefficient $\hat{\beta}_1$ is equal to the population parameter β_1 after conditioning on x .

Summary

- ▶ OLS regression is used when we assume y can be modeled as a linear combination of parameters.
- ▶ We assume a population model, $y = \beta_0 + \beta_1 x + u$.
- ▶ We use a sample of data to estimate the relationship between y and x in the population.
- ▶ The equation $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + \hat{u}_i$ minimizes the sum of the squared residuals.
- ▶ If the sample is IID and the errors are unrelated to x , we can assume that $\hat{\beta}_1$ is the best estimator of β_1 .

Estimating β_0 and β_1 using `lm()`

```
model <- lm(y ~ x, data = df)
```

Estimating β_0 and β_1 using `lm()`

```
summary(model)
```

```
##  
## Call:  
## lm(formula = y ~ x, data = df)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -2.76000 -0.65289 -0.02834  0.62889  2.37092   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  0.02283    0.06288   0.363    0.717      
## x            0.24402    0.01424  17.134 <2e-16 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 0.8754 on 998 degrees of freedom  
## Multiple R-squared:  0.2273, Adjusted R-squared:  0.2265
```

Interpreting the results

- ▶ First, we want to look at the estimated coefficients. These are our estimates for the intercept and the slope.
- ▶ $\hat{\beta}_0$
 - ▶ 0.023
- ▶ $\hat{\beta}_1$
 - ▶ 0.244

Is β_1 statistically significant?

- ▶ Standard errors communicate uncertainty around our estimate of β_1
- ▶ The standard error of β_1 is defined as

$$\hat{SE}_{\hat{\beta}_1} = \sqrt{\frac{\hat{\sigma}}{\sum (x_i - \bar{x})^2}}$$

where

$$\hat{\sigma} = \frac{1}{n-2} \sum \hat{u}_i^2 = \frac{1}{n-2} SSR$$

$$\hat{\sigma} = \sqrt{\frac{SSR}{n-2}}$$

Is β_1 statistically significant?

We can manually calculate the standard error and verify that it matches the regression output

```
sigma2 <- (1/(n-2)) * sum((model$residuals)^2)
denom <- sum((df$x - mean(df$x))^2)
SE_beta <- sqrt(sigma2/denom)

print(round(SE_beta, 5))
```

```
## [1] 0.01424
```

```
round(SE_beta,5) == round(summary(model)$coefficients[4],5)
```

```
## [1] TRUE
```

Is β_1 statistically significant?

- ▶ Standard errors can then be used to calculate confidence intervals for a chosen significance threshold
 - ▶ The conventional critical value for 95% confidence intervals is 1.96 (see last lecture)
 - ▶ $[\hat{\beta}_1 - 1.96SE\hat{\beta}_1, \hat{\beta}_1 + 1.96SE\hat{\beta}_1]$
- ▶ To test for statistical significance, we can check the following:
 - ▶ Does the interval contain zero?
- ▶ We can plug the numbers from our regression into this formula to get the following interval
 - ▶ Our coefficient is 0.244 and standard error is 0.014
 - ▶ This yields the following interval: [0.216, 0.272]

Is β_1 statistically significant?

- ▶ t statistic is obtained by dividing coefficient by its standard error
 - ▶ $t = \frac{\hat{\beta}_1}{SE_{\hat{\beta}_1}}$
 - ▶ Thus, the statistic from our regression 17.134 is equal to $0.244 / 0.014$.
- ▶ Quick rule of thumb for statistical significance
 - ▶ Is coefficient more than two times the standard error?

Is β_1 statistically significant?

- ▶ Using the t statistic, we can then look up the p-value
 - ▶ Probability of observing t given Student t distribution (see last lecture)
- ▶ In this case, our p-value is extremely small so it is expressed using scientific notation: 6.933535×10^{-58}

Is β_1 statistically significant?

- ▶ Generally, smaller p-values indicate stronger statistical significance and increase our confidence in the result
- ▶ Conventional thresholds and stars
 - ▶ $p < 0.10^{+/-}$: ~~Trending towards significance~~ Not significant¹
 - ▶ $p > 0.05$: Not significant
 - ▶ $p < 0.05^*$: Statistically significant
 - ▶ $p < 0.01^{**}$: Statistically significant
 - ▶ $p < 0.001^{***}$: Statistically significant

¹Convention for reporting p-values differ across fields. I recommend avoiding interpreting anything above $p < 0.05$.

Problems with p-values

- ▶ Don't communicate effect size
 - ▶ Magnitude matters! Statistically significant but substantively insignificant?
- ▶ Don't communicate uncertainty
 - ▶ Confidence intervals are preferable
- ▶ Null hypothesis significance testing (NHST) not always informative
 - ▶ Is it reasonable to assume $\hat{\beta}_1 = 0$ if $p \geq 0.05$?
- ▶ Multiple comparisons
 - ▶ Risk of false positive increases if conducting multiple tests²
- ▶ Subject to abuse and bad for science
 - ▶ Publication bias, fishing, and p-hacking
- ▶ But eliminating p-values entirely is no panacea!

² Bonferroni corrections recommended (but not common in sociology). Correction: Where α is the chosen significance threshold and T is the number of tests, the Bonferroni corrected threshold is $\frac{\alpha}{T}$, e.g. $\frac{0.05}{20} = 0.0025$

Next week

- ▶ Introduction to Bayesian statistics

Lab

- ▶ Estimating and interpreting bivariate OLS regression using R