Lesson 4: SLR Inference and Prediction

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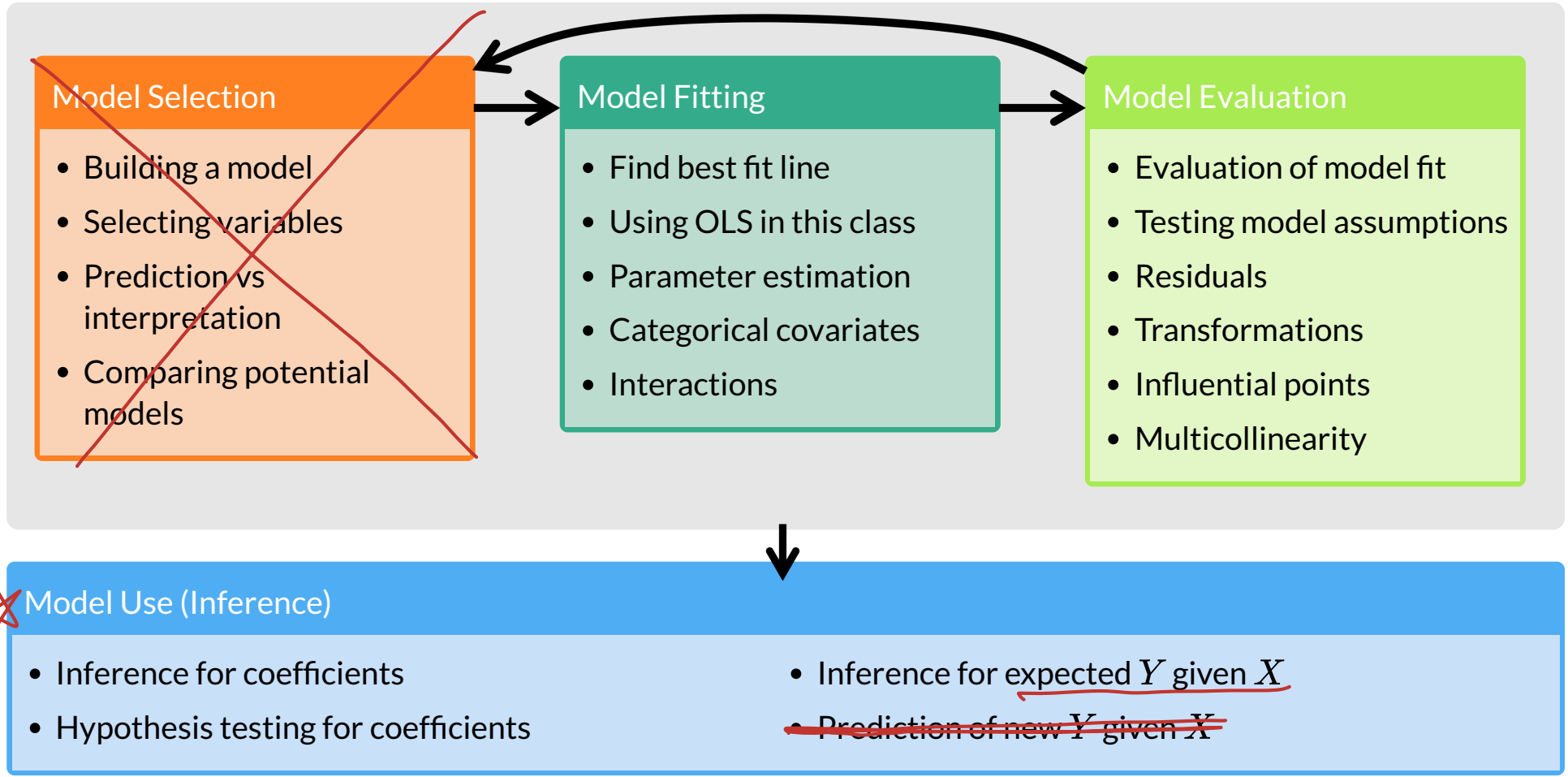
Learning Objectives

1. Estimate the variance of the residuals
2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)
4. Calculate and report the estimate and confidence interval for the expected/mean response given X

Process of regression data analysis



Let's remind ourselves of the model that we fit last lesson

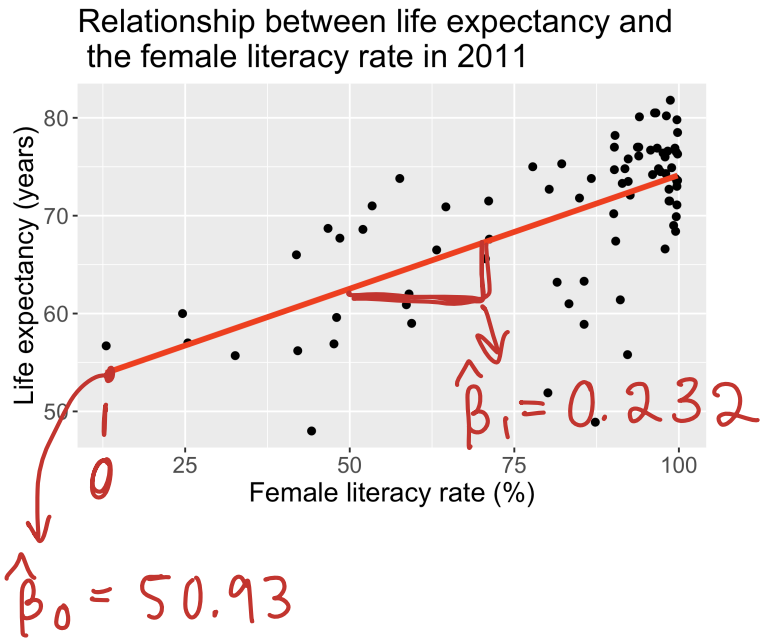
- We fit Gapminder data with female literacy rate as our independent variable and life expectancy as our dependent variable
- We used OLS to find the coefficient estimates of our best-fit line

```
1 model1 <- gapm %>% lm(formula = LifeExpectancy
2 # Get regression table:
3 tidy(model1) %>% gt() %>%
4  tab_options(table.font.size = 40) %>%
5  fmt_number(decimals = 2)
```

term	estimate	std.error	statistic	p.value
(Intercept)	50.93	2.66	19.14	0.00
FemaleLiteracyRate	0.23	0.03	7.38	0.00

$$\widehat{Y} = \widehat{\beta}_0 + \widehat{\beta}_1 \cdot X$$

$$\widehat{\text{life expectancy}} = 50.9 + 0.232 \cdot \text{female literacy rate}$$



Fitted line is derived from the population SLR model

The (population) regression model is denoted by:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

obs

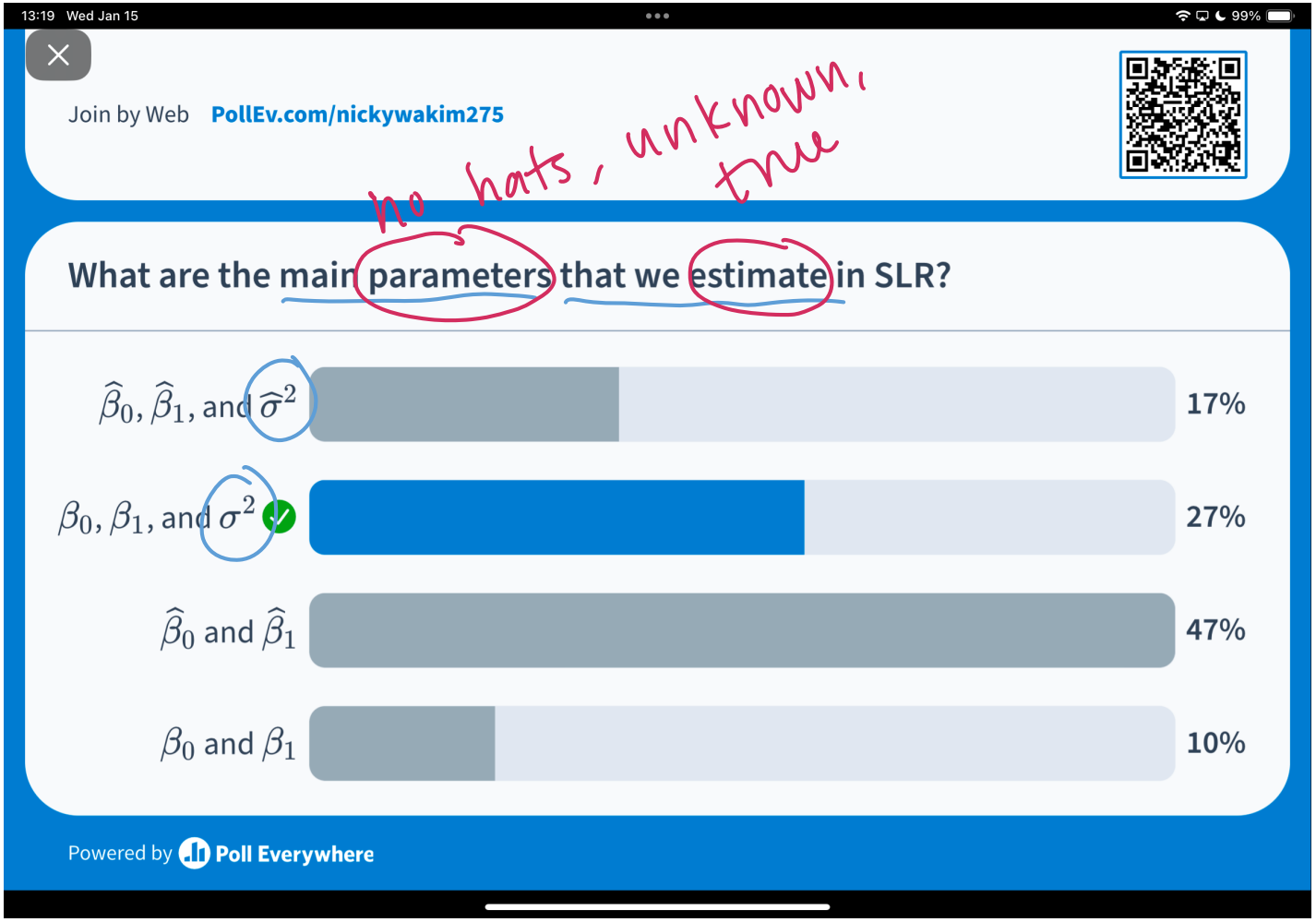
obs

- β_0 and β_1 are **unknown** population parameters
- ϵ (epsilon) is the error about the line
  - It is assumed to be a random variable with a…
    - Normal distribution with mean 0 and constant variance σ^2
    - i.e. $\epsilon \sim N(0, \sigma^2)$

$$\varepsilon_i = Y_i - \hat{Y}_i$$

also a population parameter that we will estimate

Poll Everywhere Question 1



population param:

$\beta_0, \beta_1, \sigma^2$

estimates:

$\hat{\beta}_0, \hat{\beta}_1, \hat{\sigma}^2$

Learning Objectives

estimate σ^2

1. Estimate the variance of the residuals
2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)
4. Calculate and report the estimate and confidence interval for the expected/mean response given X

$\widehat{\sigma}^2$: Needed ingredient for inference

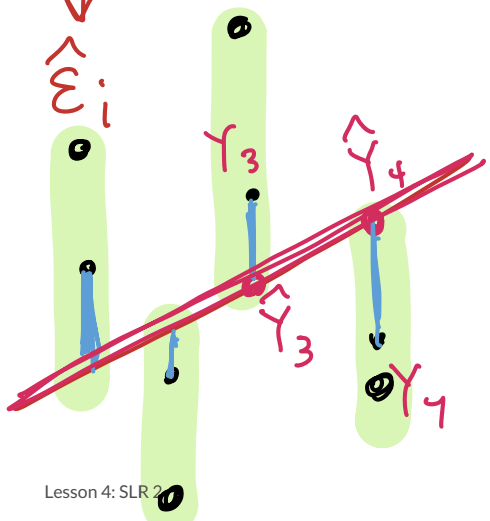
residuals are Normally dist'd

- Recall our population model residuals are distributed by $\epsilon \sim N(0, \sigma^2)$
  - And our estimated residuals are $\hat{\epsilon} \sim N(0, \widehat{\sigma}^2)$ → once we fit a line to our data
- Hence, the *variance* of the errors (residuals) is estimated by $\widehat{\sigma}^2$

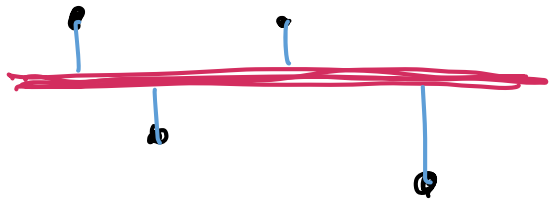
$$\widehat{\sigma}^2 = S^2_{y|x} = \frac{1}{n-2}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 = \frac{1}{n-2}SSE = MSE$$

b/c we estimate β_0, β_1

$\hat{\varepsilon}_i$



$$\frac{\sum (x - \bar{x})^2}{n}$$



$\widehat{\sigma}^2$: I hope R can calculate that for me... (1/2)

- The *standard deviation* $\widehat{\sigma}$ is given in the R output as the `Residual standard error`
  - 3^{th} line from the bottom in the `summary()` output of the model:

```
1 summary(model1)
```

```
Call:
lm(formula = LifeExpectancyYrs ~ FemaleLiteracyRate, data = .)

Residuals:
    Min      1Q  Median      3Q     Max
-22.299  -2.670   1.145   4.114   9.498

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        50.92790    2.66041  19.143  < 2e-16 ***
FemaleLiteracyRate  0.23220    0.03148   7.377  1.5e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.142 on 78 degrees of freedom
Multiple R-squared:  0.4109,    Adjusted R-squared:  0.4034
F-statistic: 54.41 on 1 and 78 DF,  p-value: 1.501e-10
```

$n-2$

$\widehat{\sigma}$

$\widehat{\sigma}^2$: I hope R can calculate that for me... (2/2)

- It can!!

```
1 m1_sum = summary(model1)
2 m1_sum$sigma
```

```
[1] 6.142157
```

```
1 # number of observations (pairs of data) used to run the model
2 nobs(model1)
```

```
[1] 80
```

$\hat{\sigma}^2$ to SSE — what we use to find best fit line (minimize SSE)

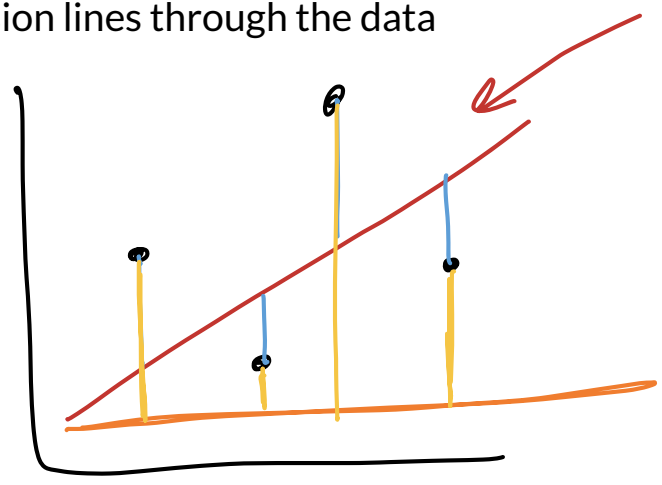
- Recall how we minimized the SSE to find our line of best fit
- SSE and $\hat{\sigma}^2$ are closely related:

$$\hat{\sigma}^2 = \frac{1}{n-2} SSE$$

$$6.142^2 = \frac{1}{80-2} SSE$$

$$SSE = 78 \cdot 6.142^2 = 2942.48$$

- 2942.48 is the smallest sums of squares of all possible regression lines through the data



Learning Objectives

1. Estimate the variance of the residuals

inference of coefficients

2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)

4. Calculate and report the estimate and confidence interval for the expected/mean response given X

Do we trust our estimate $\widehat{\beta}_1$?

- So far, we have shown that we think the estimate is 0.232
- $\widehat{\beta}_1$ (coefficient estimate) uses our sample data to estimate the population parameter β_1
- Inference helps us figure out *mathematically* how much we trust our best-fit line
- Are we certain that the relationship between X and Y that we estimated reflects the true, underlying relationship?

through our sample

Poll Everywhere Question 2

13:35 Wed Jan 15 95%

Join by Web **PollEv.com/nickywakim275**

Rank the following plots from most trustworthy β_1 estimation to least trustworthy estimation.

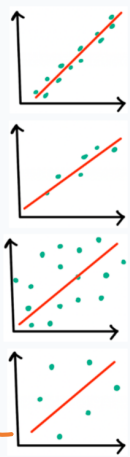
$n\uparrow \quad \hat{\varepsilon}\downarrow \quad \hat{\sigma}^2\downarrow$

larger sample size & close to line →

smaller SS, close to line

larger SS, further from line

smaller SS, further from line



1st

2nd

3rd

4th

Powered by Poll Everywhere

$n\downarrow \quad \hat{\varepsilon}\downarrow \quad \hat{\sigma}^2 -$

$n\uparrow \quad \hat{\varepsilon}\uparrow \quad \hat{\sigma}^2 -$

$n\downarrow \quad \hat{\varepsilon}\uparrow \quad \hat{\sigma}^2\uparrow$

Inference for the population slope: hypothesis test and CI

Population model

line + random "noise"

$$Y = \beta_0 + \beta_1 \cdot X + \varepsilon$$

with $\varepsilon \sim N(0, \sigma^2)$
σ^2 is the variance of the residuals

Sample best-fit (least-squares) line

$$\widehat{Y} = \widehat{\beta}_0 + \widehat{\beta}_1 \cdot X$$

Note: Some sources use b instead of $\widehat{\beta}$

~~$y = mx + b$~~

We have two options for inference:

1. Conduct the **hypothesis test**

$$\begin{bmatrix} H_0 : \beta_1 = 0 \\ \text{vs. } H_A : \beta_1 \neq 0 \end{bmatrix}$$

Note: R reports p-values for 2-sided tests

2. Construct a **95% confidence interval** for the **population slope** β_1

Learning Objectives

1. Estimate the variance of the residuals
2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)
4. Calculate and report the estimate and confidence interval for the expected/mean response given X

Reference: Steps in a Hypothesis Test

1. Check the **assumptions** ✓
   - What sampling distribution are you using? What assumptions are required for it?
2. Set the **level of significance** α
3. Specify the **null** (H_0) and **alternative** (H_A) **hypotheses**
   - In symbols and/or in words
   - Alternative: one- or two-sided?
4. Specify the test statistic and its **distribution under the null**
5. Calculate the **test statistic**.
6. Calculate the **p-value** based on the observed test statistic and its sampling distribution
7. Write a **conclusion** to the hypothesis test
   - Do we reject or fail to reject H_0?
   - Write a conclusion in the context of the problem

t-distribution
F-dist.
χ^2 dist.

Steps for hypothesis test for population slope β_1 (using t-test)

seen before: $t = \frac{\bar{x} - \mu_0}{\sigma}$

1. Check the **assumptions**
2. Set the **level of significance**
   - Often we use $\alpha = 0.05$
3. Specify the **null** (H_0) and **alternative** (H_A) **hypotheses**
   - Often, we are curious if the coefficient is 0 or not:

$$\begin{aligned} H_0 &: \beta_1 = 0 \\ \text{vs. } H_A &: \beta_1 \neq 0 \end{aligned}$$

4. Specify the test statistic and its **distribution under the null**
   - The test statistic is t, and follows a Student's t-distribution.
5. Calculate the **test statistic**.
   - The calculated **test statistic** for $\widehat{\beta}_1$ is

$$t = \frac{\widehat{\beta}_1 - \beta_1}{\text{SE}_{\widehat{\beta}_1}} = \frac{\widehat{\beta}_1}{\text{SE}_{\widehat{\beta}_1}}$$

   when we assume $H_0 : \beta_1 = 0$ is true.
6. Calculate the **p-value**
   - We are generally calculating: $2 \cdot P(T > t)$
7. Write a **conclusion**
   - We (reject/fail to reject) the null hypothesis that the slope is 0 at the $100\alpha\%$ significiance level. There is (sufficient/insufficient) evidence that there is significant association between (Y) and (X) (p-value = $P(T > t)$).

$\beta_1 \neq 0$ = evidence for relationship

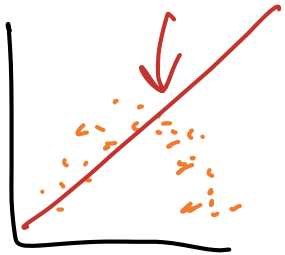
Standard error of fitted slope $\widehat{\beta}_1$

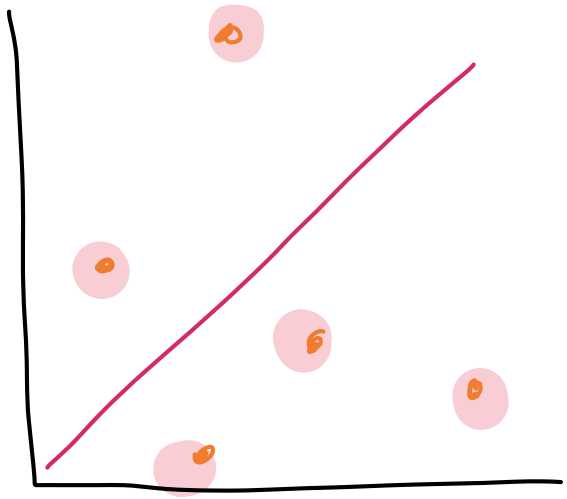
$$\text{SE}_{\widehat{\beta}_1} = \frac{s_{\text{residuals}}}{s_x\sqrt{n-1}}$$

$\text{SE}_{\widehat{\beta}_1}$ is the **variability** of the statistic $\widehat{\beta}_1$

- $s_{\text{residuals}}$ is the sd of the residuals
- s_x is the sample sd of the explanatory variable x
- n is the sample size, or the number of (complete) pairs of points

$$(x_i - \bar{x})^2$$

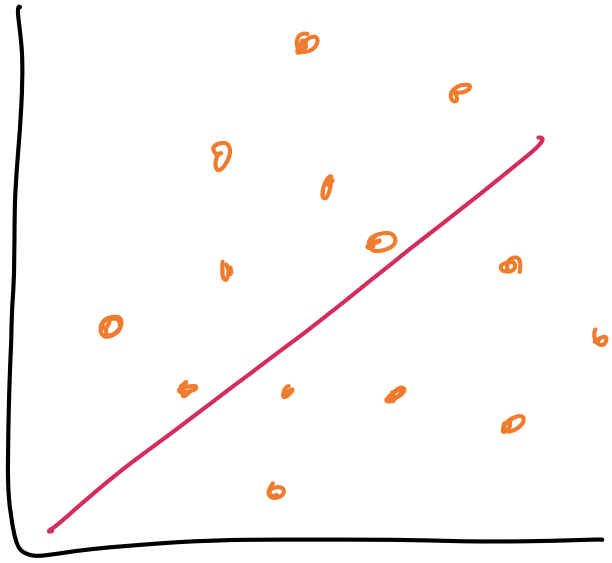




$\hat{\beta}_1 = 0.9$

fail reject null,
insuff evidence
that $\beta_1 \neq 0$

cannot conclude association



$\hat{\beta}_1 = 0.9$

reject the null
suff evidence that
association $\beta_1 \neq 0$

Calculating standard error for $\widehat{\beta}_1$ (1/2)

- **Option 1:** Calculate using the formula

```
glance(model1)
```

```
# A tibble: 1 × 12
  r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
      <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
1     0.411         0.403  6.14      54.4 1.50e-10     1  -258.  521.  529.
# ℹ 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
# standard deviation of the residuals (Residual standard error in summary() output)
(s_resid <- glance(model1)$sigma)
```

```
[1] 6.142157
```

```
# standard deviation of x's
(s_x <- sd(gapm$FemaleLiteracyRate, na.rm=T))
```

```
[1] 21.95371
```

```
# number of pairs of complete observations
(n <- nobs(model1))
```

```
[1] 80
```

```
(se_b1 <- s_resid/(s_x * sqrt(n-1))) # compare to SE in regression output
```

```
[1] 0.03147744
```

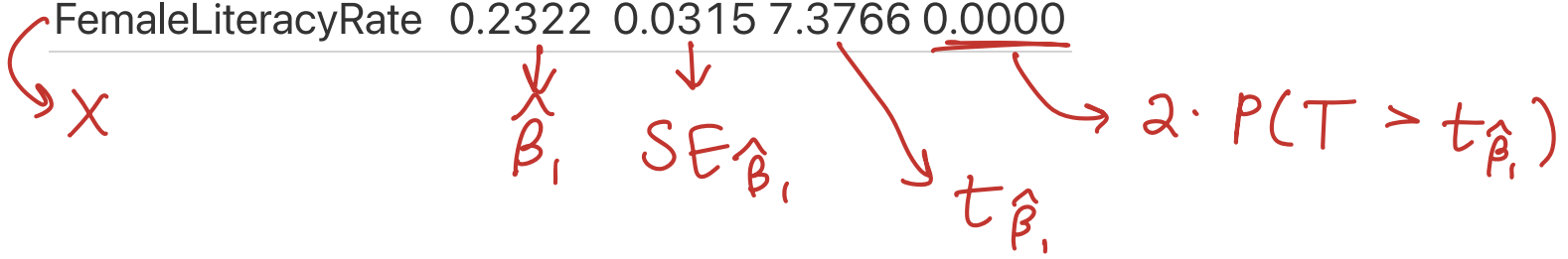
Calculating standard error for $\widehat{\beta}_1$ (2/2)

- **Option 2:** Use regression table

```
1 # recall model1_b1 is regression table restricted to b1 row
2 model1_b1 <-tidy(model1) %>% filter(term == "FemaleLiteracyRate")
3 model1_b1 %>% gt() %>%
4   tab_options(table.font.size = 45) %>% fmt_number(decimals = 4)
```

just formatting

term	estimate	std.error	statistic	p.value
FemaleLiteracyRate	0.2322	0.0315	7.3766	0.0000



Some important notes

t-test = single coeff (NOT single variable)

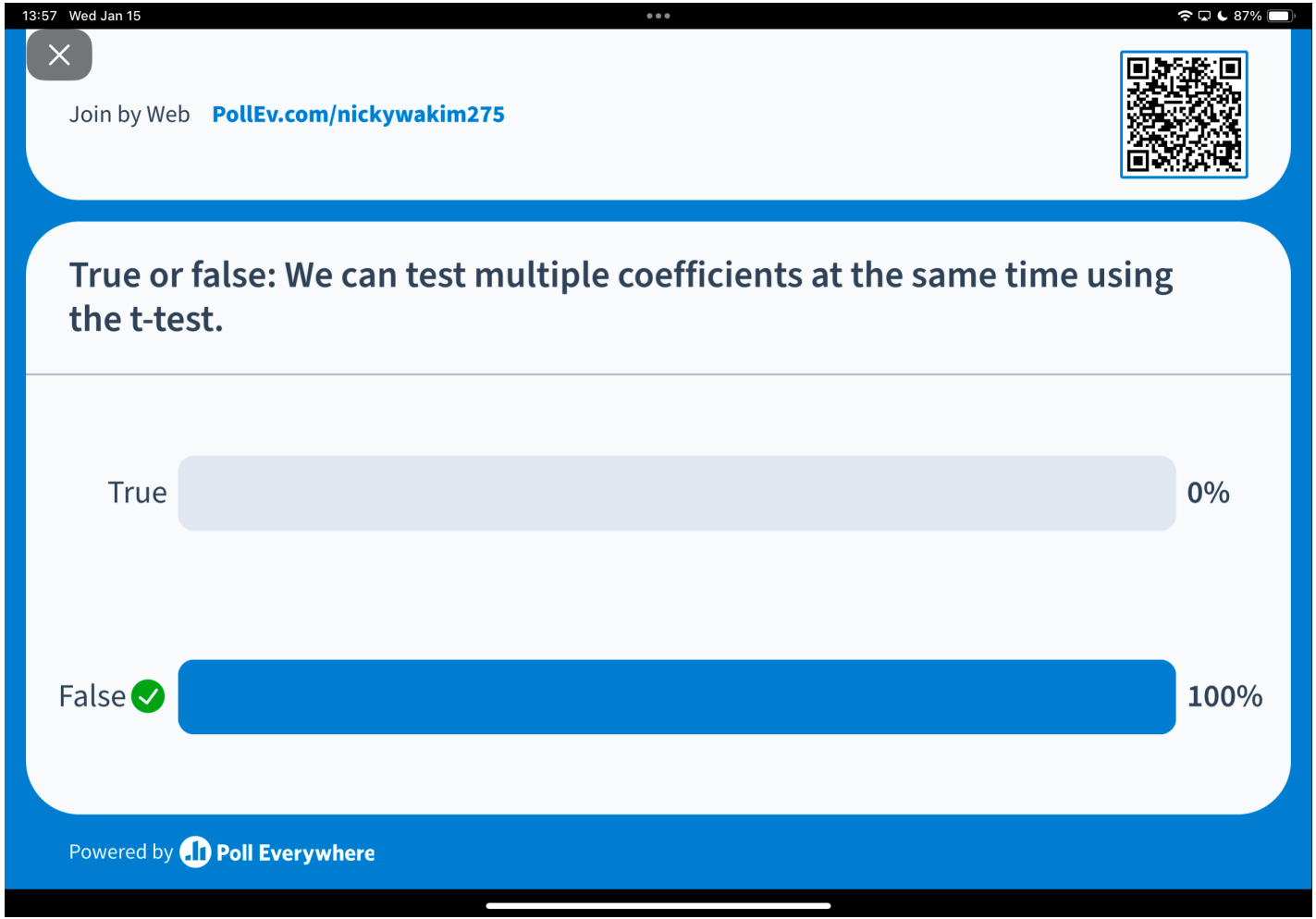
- Today we are discussing the hypothesis test for a **single** coefficient
- The test statistic for a single coefficient follows a Student's t-distribution
  - It can also follow an F-distribution, but we will discuss this more with multiple linear regression and multi-level categorical covariates
- Single coefficient testing can be done on any coefficient, but it is most useful for continuous covariates or binary covariates

only has 1 coeff

MLR

  - This is because testing the single coefficient will still tell us something about the overall relationship between the covariate and the outcome
  - We will talk more about this with multiple linear regression and multi-level categorical covariates

Poll Everywhere Question 3



Life expectancy example: hypothesis test for population slope β_1 (1/4)

- Steps 1-4 are setting up our hypothesis test: not much change from the general steps

1. For today's class, we are assuming that we have met the underlying assumptions (checked in our Model Evaluation step)

3. State the null hypothesis.

We are testing if the slope is 0 or not:

$$H_0 : \beta_1 = 0$$
$$\text{vs. } H_A : \beta_1 \neq 0$$

2. Specify the significance level.

Often we use $\alpha = 0.05$

4. Specify the test statistic and its distribution under the null

The test statistic is t, and follows a Student's t-distribution.

Life expectancy example: hypothesis test for population slope β_1 (2/4)

5. Compute the value of the test statistic

- **Option 1:** Calculate the test statistic using the values in the regression table

```
# recall model1_b1 is regression table restricted to b1 row
model1_b1 <-tidy(model1) %>% filter(term == "FemaleLiteracyRate")
model1_b1 %>% gt() %>%
  tab_options(table.font.size = 40) %>% fmt_number(decimals = 2)
```

term	estimate	std.error	statistic	p.value
FemaleLiteracyRate	0.23	0.03	7.38	0.00

$$t = \frac{\hat{\beta}_1 - 0}{SE_{\hat{\beta}_1}}$$

```
(TestStat_b1 <- model1_b1$estimate / model1_b1$std.error)
```

$\hat{\beta}_1$ $SE_{\hat{\beta}_1}$

```
[1] 7.376557
```

- **Option 2:** Get the test statistic value (t^*) from R

```
model1_b1 %>% gt() %>%
  tab_options(table.font.size = 40) %>% fmt_number(decimals = 2)
```

term	estimate	std.error	statistic	p.value
FemaleLiteracyRate	0.23	0.03	7.38	0.00

Life expectancy example: hypothesis test for population slope β_1 (3/4)

6. Calculate the p-value

- The p-value is the *probability of obtaining a test statistic* **just as extreme or more extreme** *than the* ***observed*** *test statistic assuming the null hypothesis* H_0 *is true*
- We know the probability distribution of the test statistic (the *null distribution*) assuming H_0 is true
- Statistical theory tells us that the test statistic t can be modeled by a t-distribution with $df = n - 2$.
  - We had 80 countries' data, so $n = 80$
- **Option 1:** Use `pt()` and our calculated test statistic

```
(pv = 2*pt(TestStat_b1, df=80-2, lower.tail=F))
```

```
[1] 1.501286e-10
```

- **Option 2:** Use the regression table output

```
model1_b1 %>% gt() %>%
  tab_options(table.font.size = 40)
```

term	estimate	std.error	statistic	p.value
FemaleLiteracyRate	0.2321951	0.03147744	7.376557	1.501286e-10

Life expectancy example: hypothesis test for population slope β_1 (4/4)

7. Write conclusion for the hypothesis test

We reject the null hypothesis that the slope is 0 at the 5% significance level. There is sufficient evidence that there is significant association between female life expectancy and female literacy rates (p-value < 0.0001).

Note on hypothesis testing using R

- We can basically skip Step 5 if we are using the “Option 2” route

- In our assignments: if you use Option 2, Step 5 is optional
  - Unless I specifically ask for the test statistic!!

Life expectancy ex: hypothesis test for population intercept β_0 (1/4)

- Steps 1-4 are setting up our hypothesis test: not much change from the general steps

1. For today's class, we are assuming that we have met the underlying assumptions (checked in our Model Evaluation step)

2. State the null hypothesis.

We are testing if the intercept is 0 or not:

$$H_0 : \beta_0 = 0$$
$$\text{vs. } H_A : \beta_0 \neq 0$$

3. Specify the significance level

Often we use $\alpha = 0.05$

4. Specify the test statistic and its distribution under the null

This is the same as the slope. The test statistic is t, and follows a Student's t-distribution.

Life expectancy ex: hypothesis test for population intercept β_0 (2/4)

5. Compute the value of the test statistic

- **Option 1:** Calculate the test statistic using the values in the regression table

```
# recall model1_b1 is regression table restricted to b1 row
model1_b0 <-tidy(model1) %>% filter(term == "(Intercept)")
model1_b0 %>% gt() %>%
  tab_options(table.font.size = 40) %>% fmt_number(decimals = 2)
```

term	estimate	std.error	statistic	p.value
(Intercept)	50.93	2.66	19.14	0.00

```
(TestStat_b0 <- model1_b0$estimate / model1_b0$std.error)
```

```
[1] 19.1429
```

- **Option 2:** Get the test statistic value (t^*) from R

```
model1_b0 %>% gt() %>%
  tab_options(table.font.size = 40) %>% fmt_number(decimals = 2)
```

term	estimate	std.error	statistic	p.value
(Intercept)	50.93	2.66	19.14	0.00

Life expectancy ex: hypothesis test for population intercept β_0 (3/4)

6. Calculate the p-value

- **Option 1:** Use `pt()` and our calculated test statistic

```
(pv = 2*pt(TestStat_b0, df=80-2, lower.tail=F))
```

```
[1] 3.325312e-31
```

- **Option 2:** Use the regression table output

```
model1_b0 %>% gt() %>%
  tab_options(table.font.size = 40)
```

term	estimate	std.error	statistic	p.value
(Intercept)	50.9279	2.660407	19.1429	3.325312e-31

Life expectancy ex: hypothesis test for population intercept β_0 (4/4)

7. Write conclusion for the hypothesis test

We reject the null hypothesis that the intercept is 0 at the 5% significance level. There is sufficient evidence that the intercept for the association between average female life expectancy and female literacy rates is different from 0 (p-value < 0.0001).

- Note: if we fail to reject H_0, then we could decide to remove the intercept from the model to force the regression line to go through the origin (0,0) if it makes sense to do so for the application.

Learning Objectives

1. Estimate the variance of the residuals
2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)
4. Calculate and report the estimate and confidence interval for the expected/mean response given X

Inference for the population slope: hypothesis test and CI

Population model

line + random "noise"

$$Y = \beta_0 + \beta_1 \cdot X + \varepsilon$$

with $\varepsilon \sim N(0, \sigma^2)$
σ^2 is the variance of the residuals

Sample best-fit (least-squares) line

$$\widehat{Y} = \widehat{\beta}_0 + \widehat{\beta}_1 \cdot X$$

Note: Some sources use b instead of $\widehat{\beta}$

We have two options for inference:

1. Conduct the **hypothesis test**

$$H_0 : \beta_1 = 0$$
$$\text{vs. } H_A : \beta_1 \neq 0$$

Note: R reports p-values for 2-sided tests

2. Construct a **95% confidence interval** for the **population slope** β_1

Confidence interval for population slope β_1

Recall the general CI formula:

$$\widehat{\beta}_1 \pm t^*_{\alpha,n-2} \cdot SE_{\widehat{\beta}_1}$$

Critical value for t-dist @ 95% CI

To construct the confidence interval, we need to:

- Set our α-level
- Find $\widehat{\beta}_1$
- Calculate the t^*_{n-2}
- Calculate $SE_{\widehat{\beta}_1}$

Calculate CI for population slope β_1 (1/2)

$$\widehat{\beta}_1 \pm t^* \cdot SE_{\widehat{\beta}_1}$$

where t^* is the t-distribution critical value with $df = n - 2$.

- **Option 1:** Calculate using each value

Save values needed for CI:

```
1 b1 <- model1_b1$estimate
2 SE_b1 <- model1_b1$std.error
```

```
1 nobs(model1) # sample size n
```

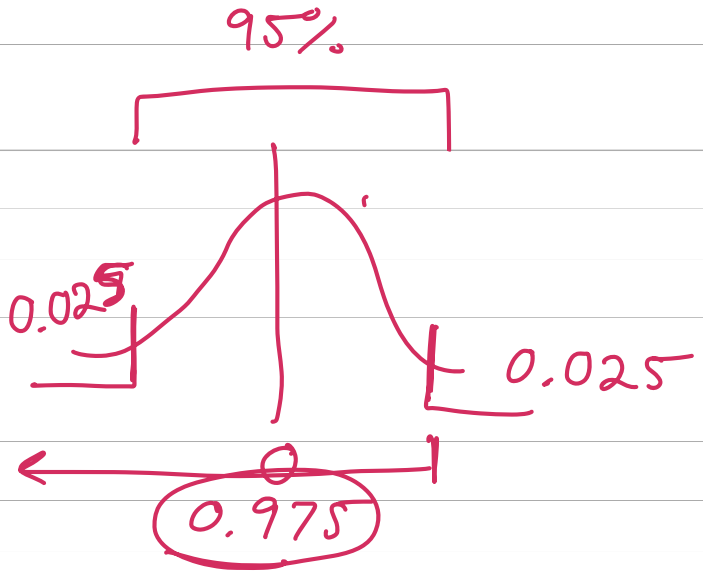
```
[1] 80
```

```
1 (tstar <- qt(.975, df = 80-2))
```

```
[1] 1.990847
```

t^*

$1 - \alpha/2 = 0.975$



Use formula to calculate each bound

```
1 (CI_LB <- b1 - tstar*SE_b1)
```

```
[1] 0.1695284
```

```
1 (CI_UB <- b1 + tstar*SE_b1)
```

```
[1] 0.2948619
```

Calculate CI for population slope β_1 (2/2)

$$\widehat{\beta}_1 \pm t^* \cdot SE_{\beta_1}$$

where t^* is the t-distribution critical value with $df = n - 2$.

- **Option 2:** Use the regression table

way to change CI %?

```
1 tidy(model1, conf.int = T) %>% gt() %>%
2   tab_options(table.font.size = 40) %>% fmt_number(decimals = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	50.928	2.660	19.143	0.000	45.631	56.224
FemaleLiteracyRate	0.232	0.031	7.377	0.000	0.170	0.295

$\hat{\beta}_0$ $\hat{\beta}_1$

Interpreting the coefficient estimate of the population slope with CIs

- When we report our results to someone else, we don't usually show them our full hypothesis test
  - In an informal setting, someone may want to see it
- Typically, we report the estimate with the confidence interval
  - From the confidence interval, your audience can also deduce the results of a hypothesis test
- Once we found our CI, we often just write the interpretation of the coefficient estimate:

CI overlaps w/ 0, insuff evidance,

CI does NOT overlap w/ 0 — evidence that $\beta_1 \neq 0$

General statement for population slope inference

For every increase of 1 unit in the X-variable, there is an expected/average (pick one) increase of $\widehat{\beta}_1$ units in the Y-variable (95%: LB, UB).

(cont)

- **In our example:** For every 1% increase in female literacy rate, life expectancy increases, on average, 0.232 years (95% CI: 0.170, 0.295).

↳ does not overlap w/ 0

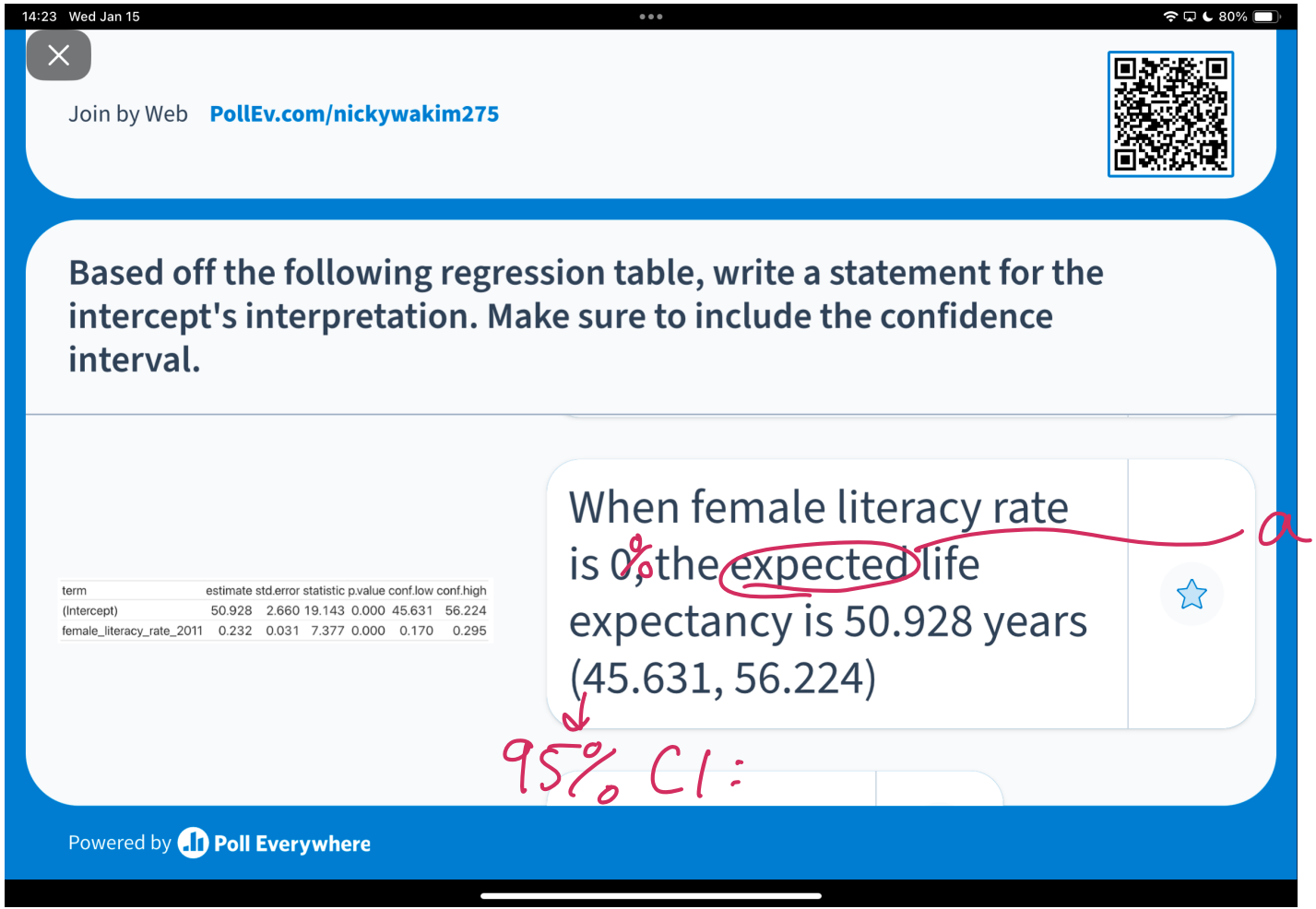
Usually three options for your interpretations

- **Option 1:** For every 1% increase in female literacy rate, life expectancy increases, **on average**, 0.232 years (95% CI: 0.170, 0.295).

- **Option 2:** For every 1% increase in female literacy rate, **average** life expectancy increases 0.232 years (95% CI: 0.170, 0.295).

- **Option 3:** For every 1% increase in female literacy rate, **expected** life expectancy increases 0.232 years (95% CI: 0.170, 0.295).

Poll Everywhere Question 4



or average

95% CI:

For reference: quick CI for β_0

- Calculate CI for population **intercept** β_0: $\widehat{\beta}_0 \pm t^* \cdot SE_{\widehat{\beta}_0}$

where t^* is the t-distribution critical value with $df = n - 2$

- Use the regression table

```
1 tidy(model1, conf.int = T) %>% gt() %>%
2   tab_options(table.font.size = 40) %>% fmt_number(decimals = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	50.928	2.660	19.143	0.000	45.631	56.224
FemaleLiteracyRate	0.232	0.031	7.377	0.000	0.170	0.295

General statement for population intercept inference

The expected outcome for the Y-variable is $\widehat{\beta}_0$ when the X-variable is 0 (95% CI: LB, UB).

- **For example:** The expected/average life expectancy is 50.9 years when the female literacy rate is 0 (95% CI: 45.63, 56.22).

Learning Objectives

1. Estimate the variance of the residuals
2. Using a hypothesis test, determine if there is enough evidence that population slope β_1 is not 0 (applies to β_0 as well)
3. Calculate and report the estimate and confidence interval for the population slope β_1 (applies to β_0 as well)

4. Calculate and report the estimate and confidence interval for the expected/mean response given X

"Finding a mean response" given a value of our independent variable

prediction

term	estimate	std.error	statistic	p.value
(Intercept)	50.928	2.660	19.143	0.000
FemaleLiteracyRate	0.232	0.031	7.377	0.000

$$\widehat{\text{life expectancy}} = 50.9 + 0.232 \cdot \text{female literacy rate}$$

- What is the expected/predicted life expectancy for a country with female literacy rate 60%?

$X = 60$

$$\widehat{\text{life expectancy}} = 50.9 + 0.232 \cdot 60 = 64.82$$

```
1 (y_60 <- 50.9 + 0.232*60)
```

```
[1] 64.82
```

- How do we interpret the expected value?
  - We sometimes call this "predicted" value, since we can technically use a literacy rate that is not in our sample
- How variable is it?

Mean response/prediction with regression line

Recall the population model:

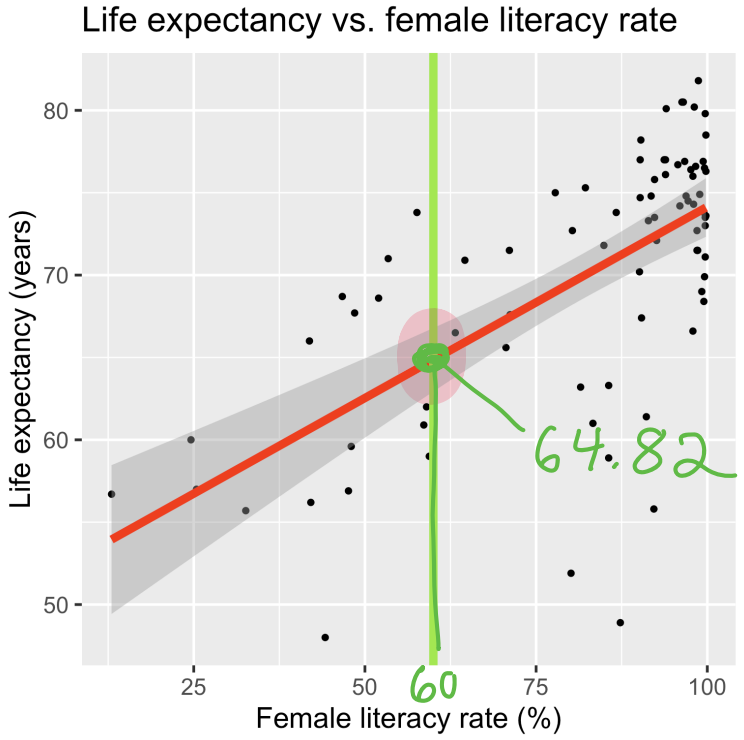
line + random "noise"

$$Y = \beta_0 + \beta_1 \cdot X + \varepsilon$$

with $\varepsilon \sim N(0, \sigma^2)$

- When we take the expected value, at a given value X^*, the average expected response at X^* is:

$$\widehat{E}[Y|X^*] = \widehat{\beta}_0 + \widehat{\beta}_1 X^*$$



- These are the points on the regression line
- The mean responses have variability, and we can calculate a CI for it, for every value of X^*

CI for population mean response ($E[Y|X^*]$ or $\mu_{Y|X^*}$)

$$\widehat{E}[Y|X^*] \pm t^*_{n-2} \cdot SE_{\widehat{E}[Y|X^*]}$$

$$SE_{\widehat{E}[Y|X^*]} = s_{\text{residuals}} \sqrt{\frac{1}{n} + \frac{(X^* - \overline{X})^2}{(n-1)s_X^2}}$$

$\hat{\sigma}$

↳ sd of x-variable

- $\widehat{E}[Y|X^*]$ is the predicted value at the specified point X^* of the explanatory variable
- $s^2_{\text{residuals}}$ is the sd of the residuals
- n is the sample size, or the number of (complete) pairs of points
- $\overline{X}$ is the sample mean of the explanatory variable x
- s_X is the sample sd of the explanatory variable X

- Recall that t^*_{n-2} is calculated using `qt()` and depends on the confidence level $(1-\alpha)$

Example Option 1: CI for mean response $\mu_{Y|X^*}$

Find the 95% CI for the mean life expectancy when the female literacy rate is 60.

$$\widehat{E}[Y|X^*] \pm t^*_{n-2} \cdot SE_{\widehat{E}[Y|X^*]}$$

$$64.8596 \pm 1.990847 \cdot s_{residuals}\sqrt{\frac{1}{n} + \frac{(X^* - \bar{x})^2}{(n-1)s_x^2}}$$

$$64.8596 \pm 1.990847 \cdot 6.142157\sqrt{\frac{1}{80} + \frac{(60 - 81.65375)^2}{(80-1)21.95371^2}}$$

$$64.8596 \pm 1.990847 \cdot 0.9675541$$

$$64.8596 \pm 1.926252$$

$$(62.93335, 66.78586)$$

```
(Y60 <- 50.9278981 + 0.2321951 * 60)
```

```
[1] 64.8596
```

```
(n <- nobs(model1))
```

```
[1] 80
```

```
(tstar <- qt(.975, df = 78))
```

```
[1] 1.990847
```

```
(mx <- mean(gapm$FemaleLiteracyRate, na.rm=T
```

```
[1] 81.65375
```

```
(s_resid <- glance(model1)$sigma)
```

```
[1] 6.142157
```

```
(s_x <- sd(gapm$FemaleLiteracyRate, na.rm=T)
```

```
[1] 21.95371
```

```
(SE_Yx <- s_resid *sqrt(1/n + (60 - mx)^2/((n-1)*s_x^2)))
```

```
[1] 0.9675541
```

```
(MOE_Yx <- SE_Yx*tstar)
```

```
[1] 1.926252
```

```
Y60 - MOE_Yx
```

```
[1] 62.93335
```

```
Y60 + MOE_Yx
```

```
[1] 66.78586
```

Example Option 2: CI for mean response $\mu_{Y|X^*}$

Find the 95% CI's for the mean life expectancy when the female literacy rate is 60 and 80.

- Use the base R `predict()` function
- Requires specification of a `newdata` "value"
  - The `newdata` value is X^* → 60%
  - This has to be in the format of a data frame though
  - with column name identical to the predictor variable in the model

FLRnew

```
1 newdata <- data.frame(FemaleLiteracyRate = c(60, 80))
2 newdata
```

```
  FemaleLiteracyRate
1                 60
2                 80
```

```
1 predict(model1,
2         newdata=newdata,
3         interval="confidence")
```

FLRnew

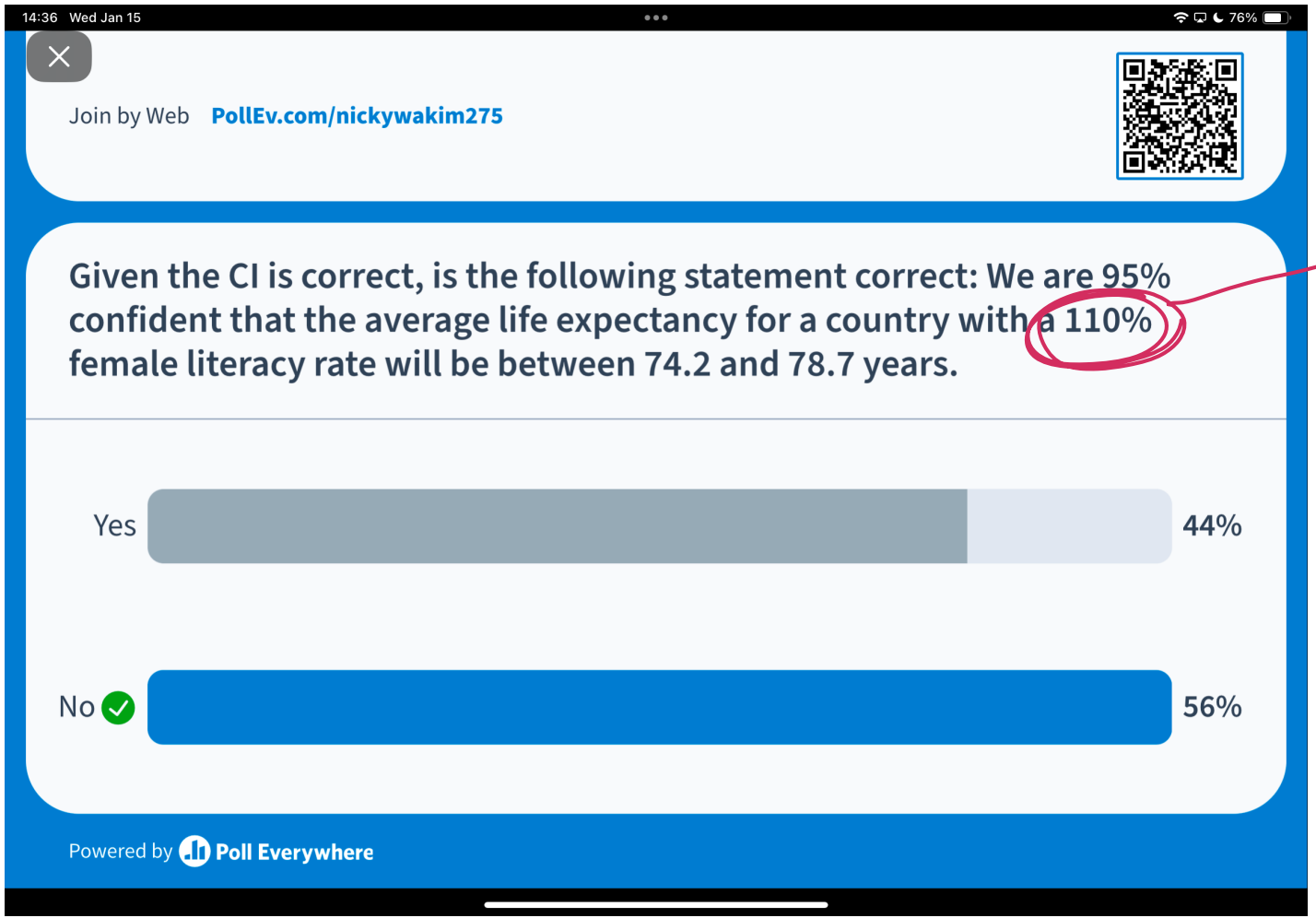
```
       fit      lwr      upr
1 64.85961 62.93335 66.78586
2 69.50351 68.13244 70.87457
```

$\hat{E}(Y|X^*)$

Interpretation

We are 95% confident that the **average** life expectancy for a country with a 60% female literacy rate will be between 62.9 and 66.8 years.

Poll Everywhere Question 5



not possible w/ rates

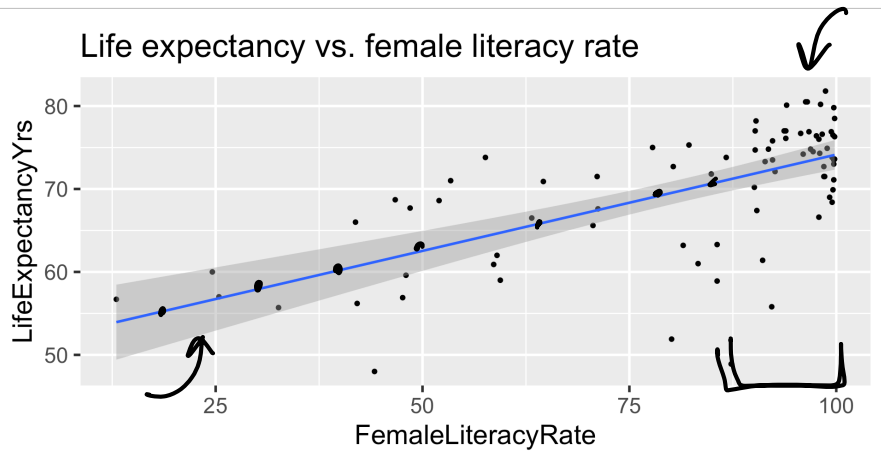
300%

-30%

Confidence bands for mean response $\mu_{Y|X^*}$

- Often we plot the CI for many values of X, creating **confidence bands**
- The confidence bands are what ggplot creates when we set `se = TRUE` within `geom_smooth`
- Think about it: for what values of X are the confidence bands (intervals) narrowest?

```
gapm %>%
  ggplot(aes(x=FemaleLiteracyRate,
             y=LifeExpectancyYrs)) +
  geom_point()+
  geom_smooth(method = lm, se=TRUE)+
  ggtitle("Life expectancy vs. female literacy rate")
```



Width of confidence bands for mean response $\mu_{Y|X^*}$

- For what values of X^* are the confidence bands (intervals) narrowest? widest?

@ $\bar{X}$

takeaway: CI width changes over X

$$\widehat{E}[Y|X^*] \pm t^*_{n-2} \cdot SE_{\widehat{E}[Y|X^*]}$$

$$\widehat{E}[Y|X^*] \pm t^*_{n-2} \cdot s_{residuals} \sqrt{\frac{1}{n} + \frac{(X^* - \bar{x})^2}{(n-1)s_x^2}}$$

60 - 82