

Lesson 11: Interactions, Part 1

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2025-02-12

Learning Objectives

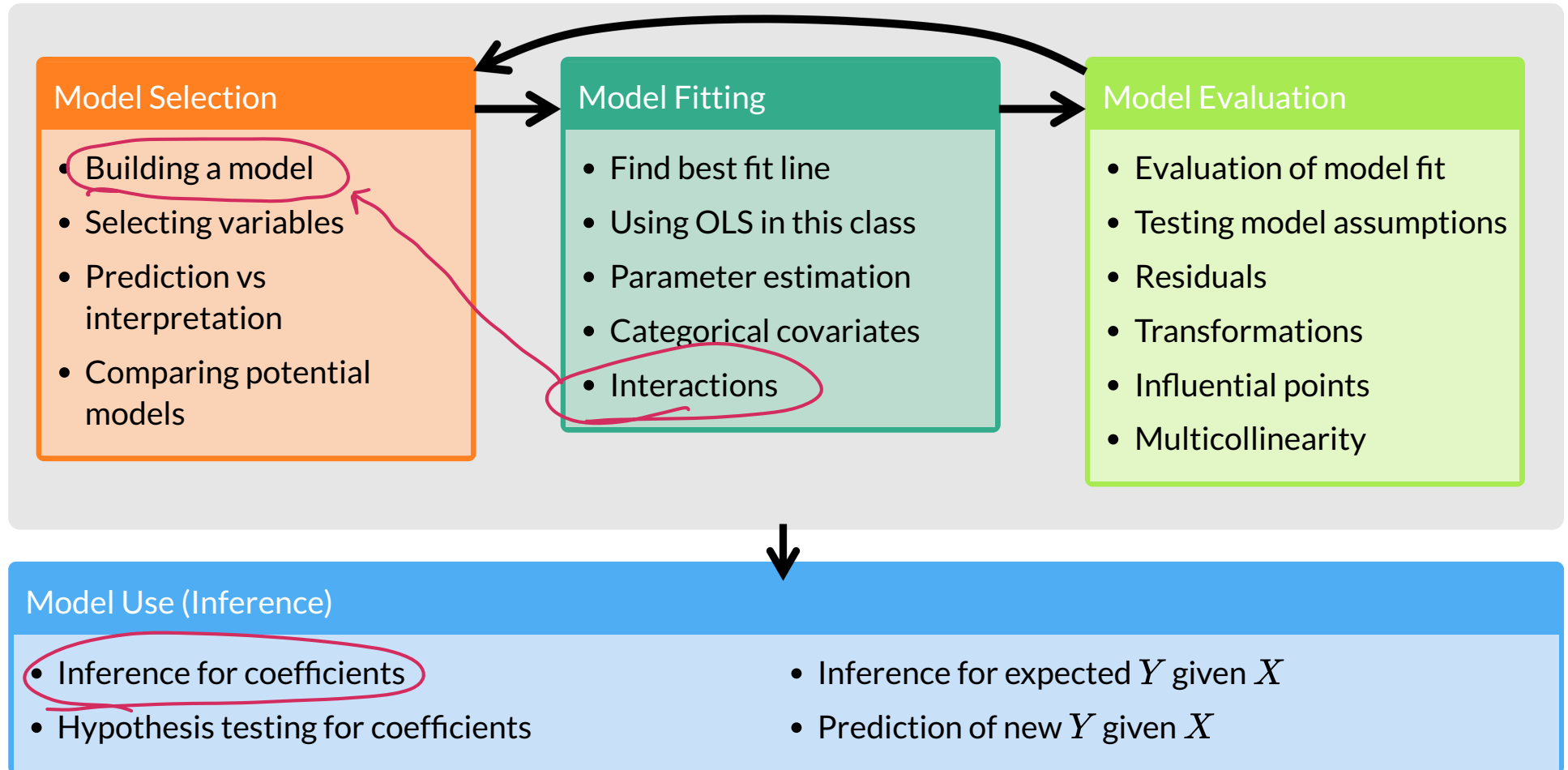
This time:

1. Define **confounders** and **effect modifiers**, and how they interact with the main relationship we model.
2. Interpret the interaction component of a model with **a binary categorical covariate and continuous covariate**, and how the main variable's effect changes.
3. Interpret the interaction component of a model with **a multi-level categorical covariate and continuous covariate**, and how the main variable's effect changes.

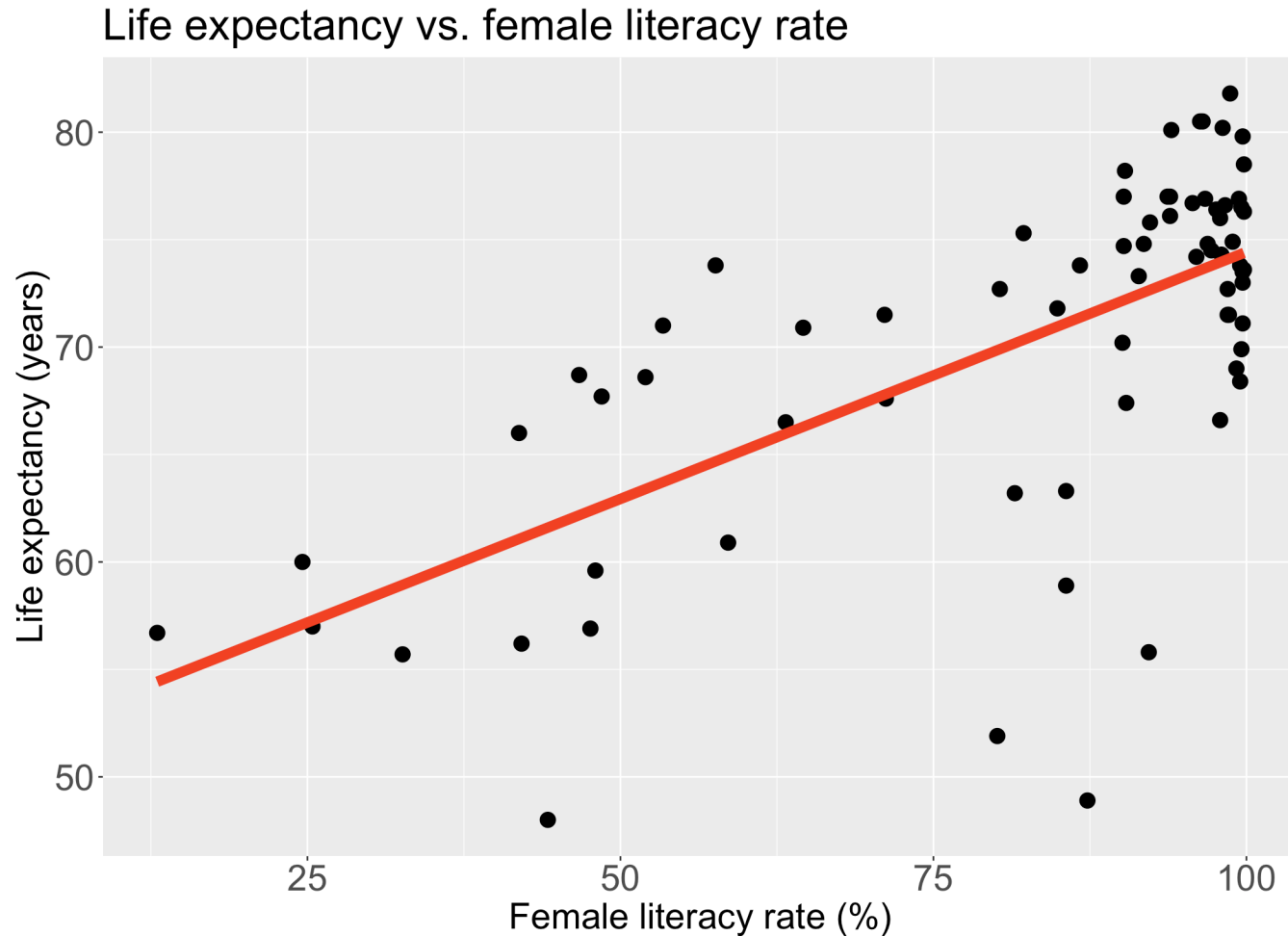
Next time:

4. Interpret the interaction component of a model with **two categorical covariates**, and how the main variable's effect changes.
5. Interpret the interaction component of a model with **two continuous covariates**, and how the main variable's effect changes.
6. When there are only two covariates in the model, test whether one is a confounder or effect modifier.

Regression analysis process



Recall our data and the main relationship



Learning Objectives

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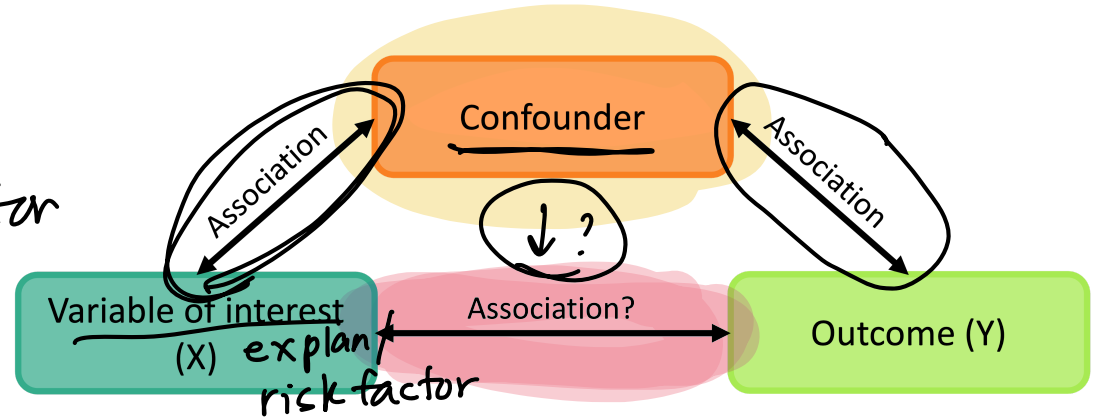
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What is a confounder?

- A **confounding variable**, or **confounder**, is a factor/variable that wholly or partially accounts for the observed effect of the **risk factor** on the outcome
- A confounder must be...
 - Related to the outcome Y, but not a consequence of Y
 - Related to the explanatory variable X, but not a consequence of X



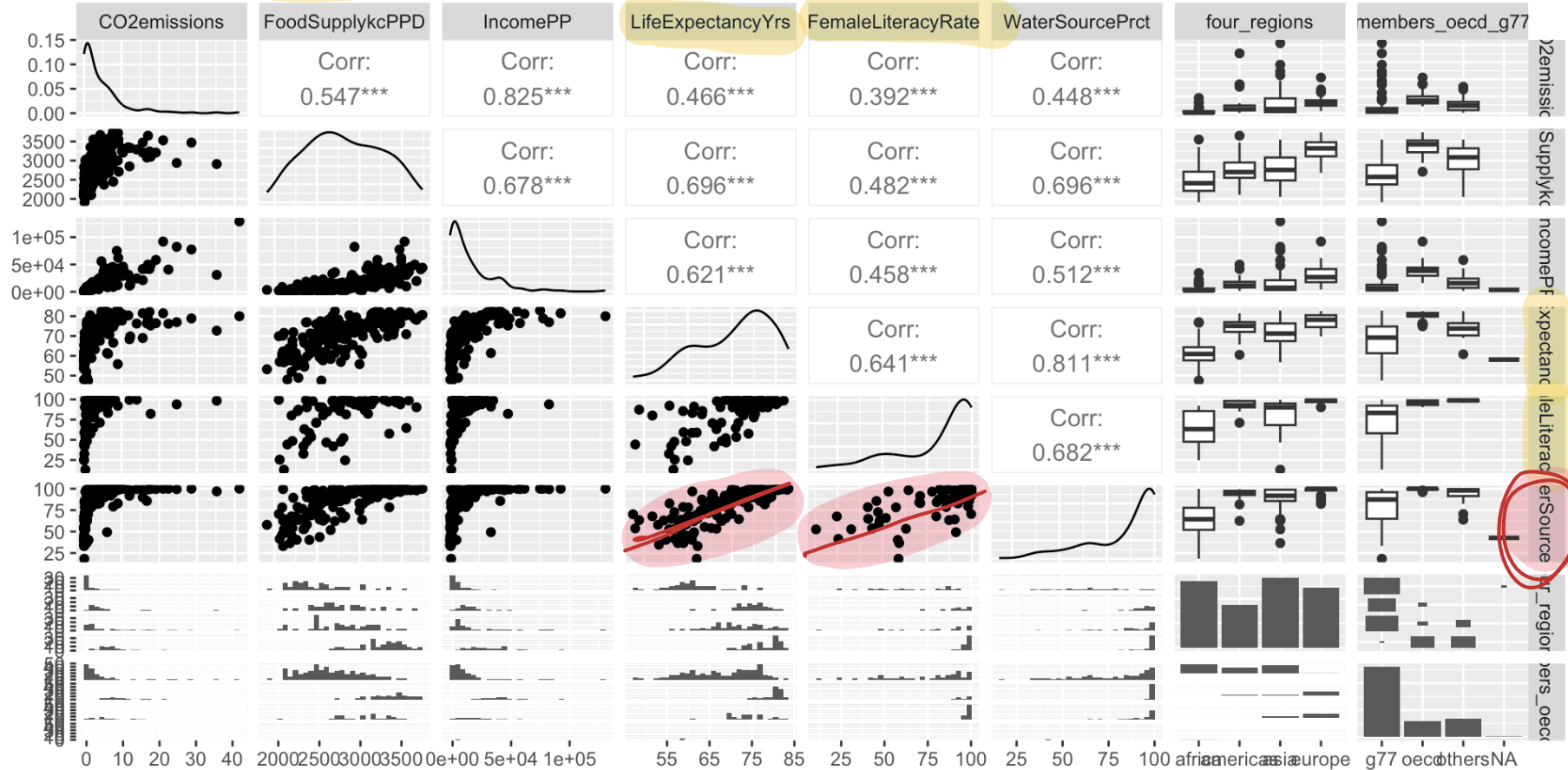
- A classic example: We found an association between ice cream consumption and sunburn!
 - If we adjust for a potential confounder, temperature/hot weather, we may see that the association between ice and sunburn is not as large
- Another example: We found an association between socioeconomic status (SES) and lung cancer!
 - If we adjust for a potential confounder, exposure to air pollution, we may see that the association between SES and lung cancer decreases

Proxies and confounders: the good and the harmful

- *This is totally my own tangent*
- A **proxy variable** is used to stand-in or represent another variable that is harder to measure
- Sometimes a confounder can be used as a proxy if it is hard to measure your explanatory variable/variable of interest
- Proxies can be helpful statistically while harmful socially OR helpful for both!
- Examples
 - **Bad:** BMI serving as a measurement for physical health or diet
 - Many studies show how harmful, mentally and physically, it is to equate BMI to health
 - Interesting: Using occurrence of online search queries as a proxy for public health risk perception
 - Helpful contextualization: Using race as a proxy for systemic racism, and thus a way to identify how to and who needs resources
- In our lab, I discuss using sex assigned at birth in our model

Exploratory approach to identifying confounders

```
1 gapm2 %>% ggpairs()
```

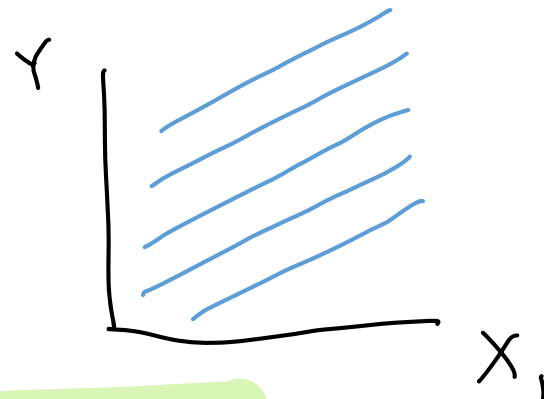


Including a confounder in the model

- In the following model we have two variables, X_1 and X_2

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

- And we assume that every level of the confounder, there is parallel slopes
- Note: to interpret β_1 , we did not specify any value of X_2 ; only specified that it be held constant
 - Implicit assumption: effect of X_1 is equal across all values of X_2
- The above model assumes that X_1 and X_2 do not *interact* (with respect to their effect on Y)
 - Epidemiology: no “effect modification”
 - Meaning the effect of X_1 is the same regardless of the values of X_2
 - This model is often called a “**main effects model**”



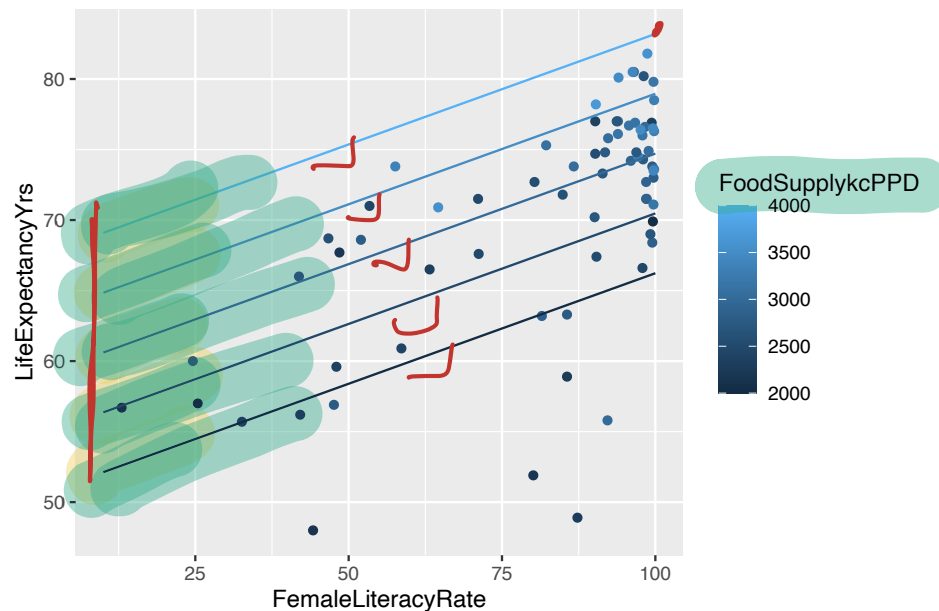
Where have we modeled a confounder before?

- We have seen a plot of Life expectancy vs. female literacy rate with different levels of food supply colored (Lesson 8)
- In our plot and the model, we treat food supply as a **confounder**
- If food supply is a confounder in the relationship between life expectancy and female literacy rate, then we only use main effects in the model:

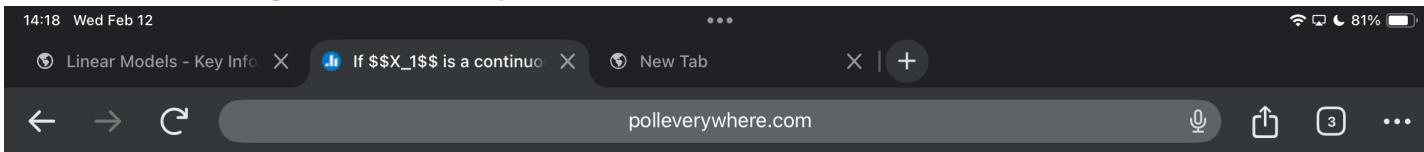
$$LE = \beta_0 + \beta_1 FLR + \beta_2 FS + \epsilon$$

FS as a confounder

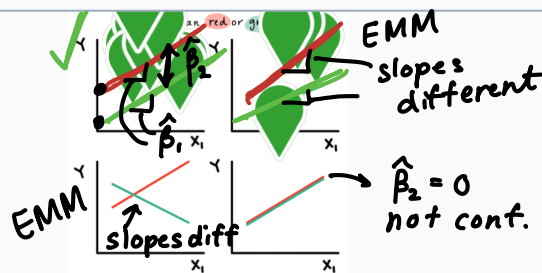
Confounders: we get parallel lines



Poll everywhere question 1



If X_1 is a continuous variable, and we are interested in the relationship between Y and X_1 , which of the following pictures shows X_2 as a confounder? X_2 is a categorical variable with two groups: red and green.

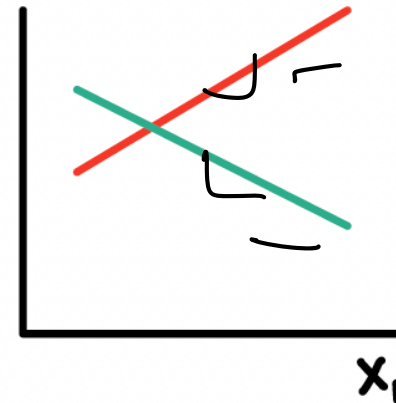
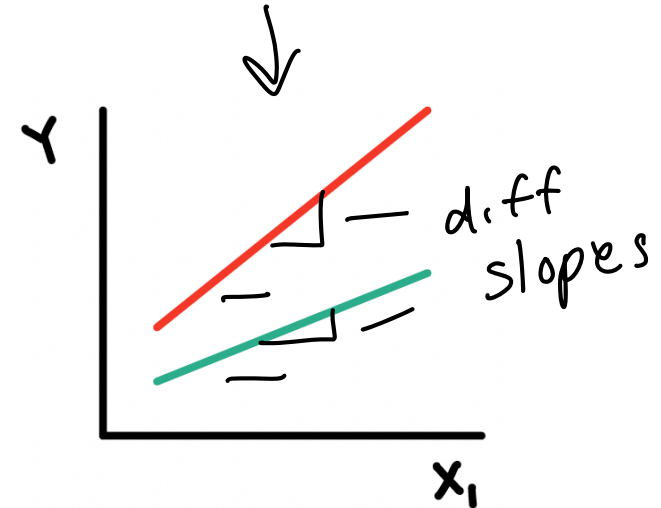
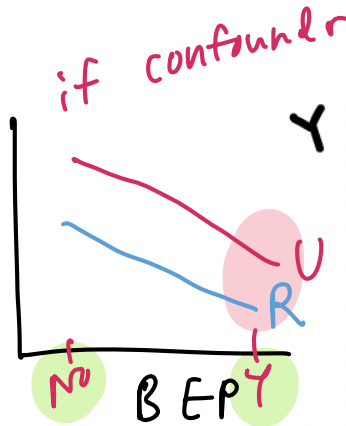


What is an effect modifier?

- An additional variable in the model
 - Outside of the main relationship between Y and X_1 that we are studying
- An effect modifier will change the effect of X_1 on Y depending on its value *→ slope changer!*
 - Aka: as the effect modifier's values change, so does the association between Y and X_1
 - So the coefficient estimating the relationship between Y and X_1 changes with another variable

• **Example:** A breast cancer education program (the exposure) that is much more effective in reducing breast cancer (outcome) in rural areas than urban areas.

- Location (rural vs. urban) is the EMM



How do we include an effect modifier in the model?

- Interactions!!
- We can incorporate interactions into our model through product terms:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \epsilon$$

- Terminology:

- main effect parameters: β_1, β_2

- The main effect models estimate the average X_1 and X_2 effects

- interaction parameter: β_3

*changes slope for X_1 w/ Y
@ given X_2 value*

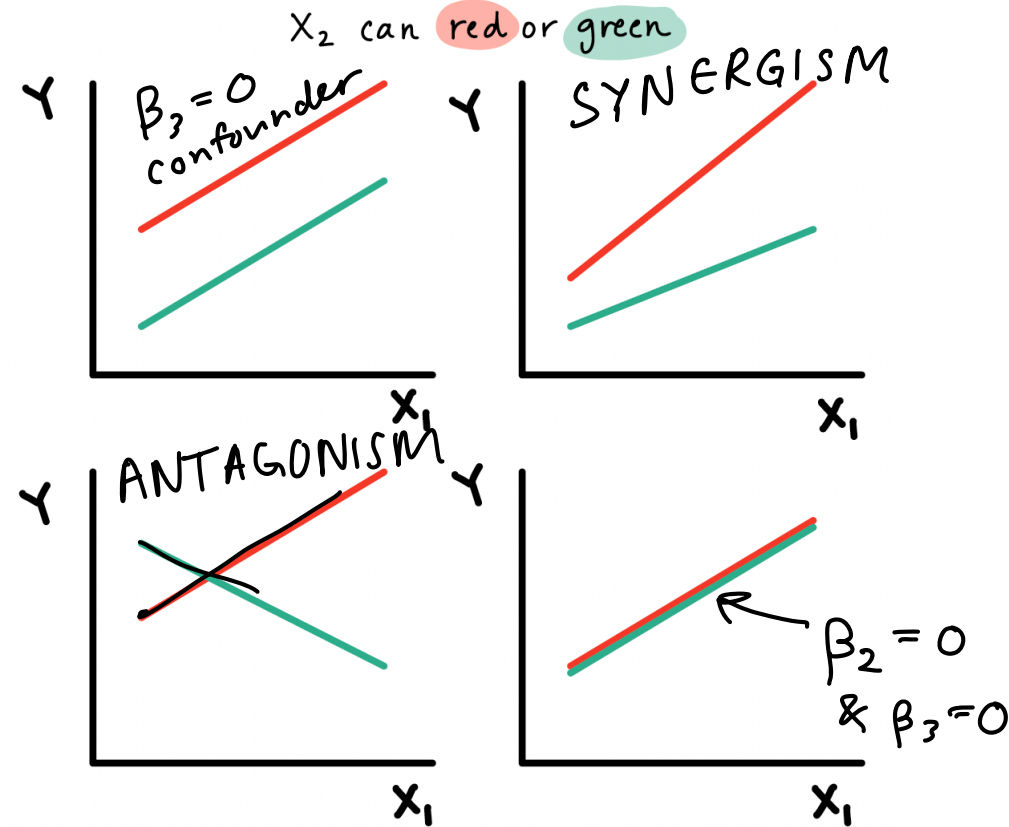
changes intercept @ given X_2 value

Types of interactions / non-interactions

- Common types of interactions: — **BLEP ex**

- Synergism: X_2 strengthens the X_1 effect
- Antagonism: X_2 weakens the X_1 effect

- If the interaction coefficient is not significant $\beta_3 = 0$
 - No evidence of effect modification, i.e., the effect of X_1 does not vary with X_2
- If the main effect of X_2 is also not significant
 - No evidence that X_2 is a confounder



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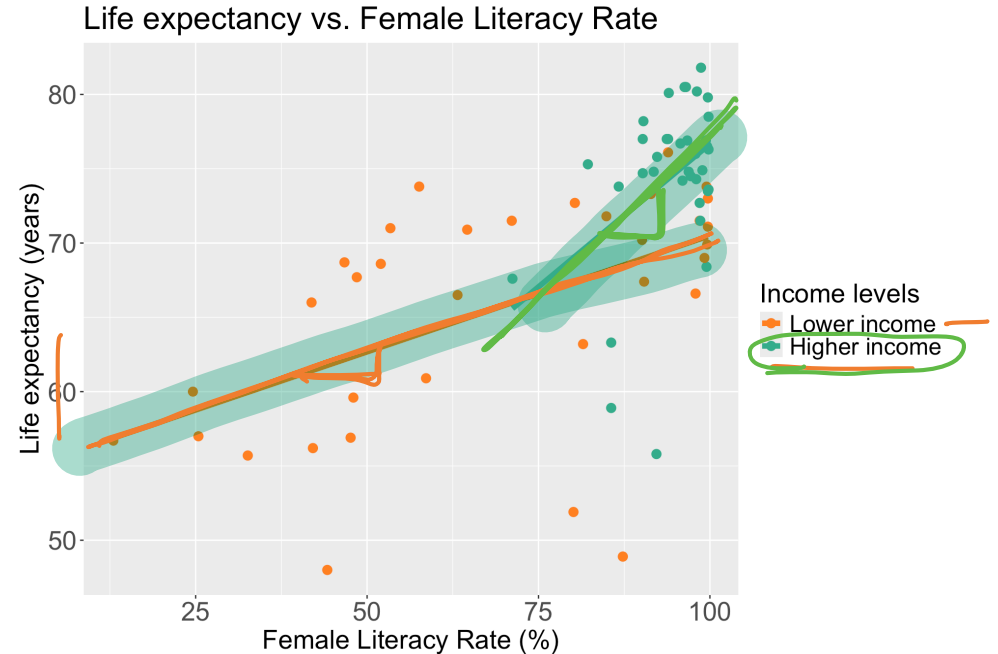
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Do we think income level is an effect modifier for female literacy rate?

- Let's say we only have two income groups: low income and high income
- We can start by visualizing the relationship between life expectancy and female literacy rate by income level
- Questions of interest: Is the effect of female literacy rate on life expectancy differ depending on income level?
 - This is the same as: Is income level is an effect modifier for female literacy rate?
 - "effect of female literacy rate" differing = different slopes between FLR and LE depending on the income group
- Let's run an interaction model to see!



Model with interaction between a *binary categorical* and *continuous* variables

Model we are fitting:

$$LE = \beta_0 + \beta_1 \underline{FLR} + \beta_2 \underline{I(\text{high income})} + \beta_3 \underline{FLR \cdot I(\text{high income})} + \epsilon$$

reference
grp is low
income

$X_1 \cdot X_2$

- LE as outcome
 - FLR as continuous variable that is our main variable of interest
 - $I(\text{high income})$ as the indicator that income level is "high income" (binary categorical variable)
- ↳ $I = 0$ for low income countries

```
1 m_int_inc2 = gapm_sub %>%  
2   lm(formula = LifeExpectancyYrs ~ FemaleLiteracyRate + income_levels2 +  
3     FemaleLiteracyRate*income_levels2)
```

OR

```
1 m_int_inc2 = gapm_sub %>%  
2   lm(formula = LifeExpectancyYrs ~ FemaleLiteracyRate*income_levels2)
```

Displaying the regression table and writing fitted regression equation

```
1 tidy(m_int_inc2, conf.int=T) %>% gt() %>% tab_options(table.font.size = 35) %>% fmt
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	54.849	2.846	19.270	0.000	49.169	60.529
FemaleLiteracyRate	0.156	0.039	3.990	0.000	0.078	0.235
income_levels2Higher income	-16.649	15.364	-1.084	0.282	-47.308	14.011
FemaleLiteracyRate:income_levels2Higher income	0.228	0.164	1.392	0.168	-0.099	0.555

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 I(\text{high income}) + \hat{\beta}_3 FLR \cdot I(\text{high income})$$

$$\widehat{LE} = 54.85 + 0.156 \cdot FLR - 16.65 \cdot I(\text{high income}) + 0.228 \cdot FLR \cdot I(\text{high income})$$

main eff of FLR *main effect for income* *interaction*

Poll Everywhere Question 2

14:35 Wed Feb 12

Linear Models - Key Info X Based only on the coeffi X New Tab

polleverywhere.com

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β_3 FLR I (high income)

Based only on the coefficient estimate for the interaction term $\beta_3 = 0.228$. What can we say about female literacy rate's effect?

Female literacy rate's effect is strengthened for countries with high income (compared to low income). 77%

Female literacy rate's effect is weakened for countries with high income (compared to low income). 15%

Female literacy rate's effect is strengthened for countries with low income (compared to high income). 8%

Female literacy rate's effect is weakened for countries with low income (compared to high income). 0%

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Comparing fitted regression lines for each income level

$$\rightarrow \widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 I(\text{high income}) + \hat{\beta}_3 FLR \cdot I(\text{high income})$$

$$\rightarrow \widehat{LE} = 54.85 + 0.156 \cdot FLR - 16.65 \cdot I(\text{high income}) + 0.228 \cdot FLR \cdot I(\text{high income})$$

For lower income countries: $I(\text{high income}) = 0$

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 \cdot 0 + \hat{\beta}_3 FLR \cdot 0$$

$$\widehat{LE} = 54.85 + 0.156 \cdot FLR - 16.65 \cdot 0 + 0.228 \cdot FLR \cdot 0 = 0$$

$$\widehat{LE} = 54.85 + 0.156 \cdot FLR$$

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

For higher income countries: $I(\text{high income}) = 1$

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 \cdot 1 + \hat{\beta}_3 FLR \cdot 1$$

$$\widehat{LE} = 54.85 + 0.156 \cdot FLR - 16.65 \cdot 1 + 0.228 \cdot FLR \cdot 1$$

$$\widehat{LE} = (54.85 - 16.65 \cdot 1) + (0.156 \cdot FLR + 0.228 \cdot FLR \cdot 1)$$

$$\widehat{LE} = (54.85 - 16.65) + (0.156 + 0.228) FLR$$

$$\widehat{LE} = 38.2 + 0.384 \cdot FLR$$

$\hat{\beta}_0 + \hat{\beta}_2$ $\hat{\beta}_1 + \hat{\beta}_3$

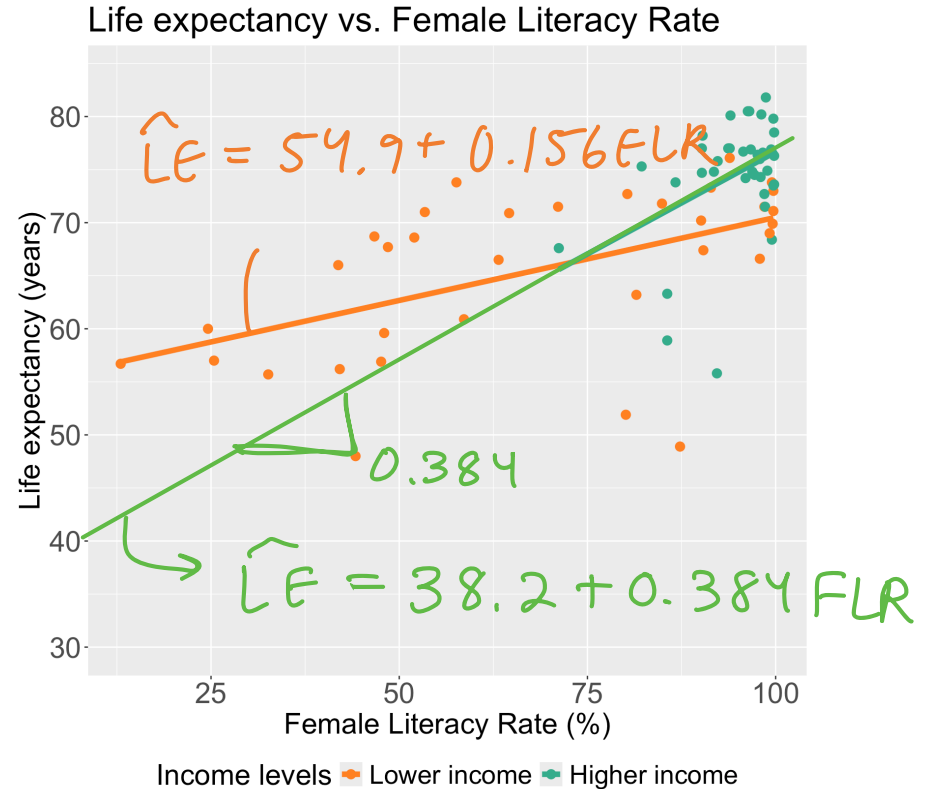
Let's take a look back at the plot

For lower income countries: $I(\text{high income}) = 0$

$$\begin{aligned}\widehat{LE} &= \widehat{\beta}_0 + \widehat{\beta}_1 FLR \\ \widehat{LE} &= 54.85 + 0.156 \cdot FLR\end{aligned}$$

For higher income countries: $I(\text{high income}) = 1$

$$\begin{aligned}\widehat{LE} &= (\widehat{\beta}_0 + \widehat{\beta}_2) + (\widehat{\beta}_1 + \widehat{\beta}_3) FLR \\ \widehat{LE} &= (54.85 - 16.65) + (0.156 + 0.228) \cdot FLR \\ \widehat{LE} &= 38.2 + 0.384 \cdot FLR\end{aligned}$$



Poll Everywhere Question 3

14:43 Wed Feb 12

Linear Models - Key Info X Based only on the coeffi X New Tab X +

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Use the regression line for high income for this question: $\widehat{LE} = (54.85 - 16.65) + (0.156 + 0.228)FLR$. What is the intercept for the line (we may omit the 95% CI for now)? What does it mean?

✓ 38.2: The mean life expectancy for high income countries when female literacy rate is 0% is 38.2 years.

92%

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58.85 - 16.65
38.2

PAUSE: Centering continuous variables when including interactions

- For the high income group, the mean life expectancy had a regression line with a small intercept

$$\widehat{LE} = (\hat{\beta}_0 + \hat{\beta}_2) + (\hat{\beta}_1 + \hat{\beta}_3)FLR$$

$$\widehat{LE} = (54.85 - 16.65) + (0.156 + 0.228) \cdot FLR$$

$$\widehat{LE} = 38.2 + 0.384 \cdot FLR$$

- Intercept of 38.2 is misleading because
 - Makes you think some of the life expectancies for high income countries are lower than that of low income countries (depending on the FLR)
 - There are no high income countries with FLR less than ~70%
- Other online sources about when and when not to center:
 - The why and when of centering continuous predictors in regression modeling
 - When not to center a predictor variable in regression



Centering a variable

- Centering a variable means that we will subtract the mean or median (or other measurement of center) from the measured value
- Mean centered:

$$X_i^c = X_i - \bar{X}$$

- Median centered:

$$X_i^c = X_i - \text{median } X$$

- Centering the continuous variables in a model (when they are involved in interactions) helps with:
 - Interpretations of the coefficient estimates *intercept*
 - Correlation between the main effect for the variable and the interaction that it is involved with
 - To be discussed in future lecture: leads to multicollinearity issues



It'll be helpful to center female literacy rate

- Centering female literacy rate:

$$FLR_i^c = FLR_i - \overline{FLR}$$

$$FLR^c = 0 \text{ when } FLR_i = \overline{FLR} = 82.03$$

- Centering in R:

```
1 gapm_sub = gapm_sub %>%  
2   mutate(FLR_c = FemaleLiteracyRate - medianmean(FemaleLiteracyRate))
```

- I'm going to print the mean so I can use it for my interpretations

```
1 (mean_FLR = mean(gapm_sub$FemaleLiteracyRate))  
[1] 82.03056
```

- Now all intercept values (in each respective world region) will be the mean life expectancy when female literacy rate is 82.03%
- We will use center FLR for the rest of the lecture



Displaying the regression table and writing fitted regression equation AGAIN

```
1 m_int_inc2 = gapm_sub %>%
2   lm(formula = LifeExpectancyYrs ~ FLR_c*income_levels2)

1 tidy(m_int_inc2, conf.int=T) %>% gt() %>% tab_options(table.font.size = 35) %>% fmt
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	69.281	1.387	49.964	0.000	66.514	72.047
FLR_c	0.156	0.039	3.990	0.000	0.078	0.235
income_levels2Higher income	4.405	1.725	2.554	0.013	0.963	7.848
FLR_c:income_levels2Higher income	0.228	0.164	1.392	0.168	-0.099	0.555

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR^c + \hat{\beta}_2 I(\text{high income}) + \hat{\beta}_3 FLR^c \cdot I(\text{high income})$$

$$\widehat{LE} = 69.281 + 0.156 FLR^c + 4.405 \cdot I(\text{high income}) + 0.228 FLR^c \cdot I(\text{high income})$$

$\hookrightarrow$ mean LE for low inc countries w/ ELR of 82%.
mean FLR

Interpretation for interaction between binary categorical and continuous variables

THINK slope = effect

$$\begin{aligned} \widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR^c + \hat{\beta}_2 I(\text{high income}) + \hat{\beta}_3 FLR^c \cdot I(\text{high income}) \\ \widehat{LE} &= \left[\hat{\beta}_0 + \hat{\beta}_2 \cdot I(\text{high income}) \right] + \left[\hat{\beta}_1 + \hat{\beta}_3 \cdot I(\text{high income}) \right] FLR^c \end{aligned}$$

intercept for LI: $\hat{\beta}_0$ for HI: $\hat{\beta}_0 + \hat{\beta}_2$ FLR's effect slope for FLR vs $\widehat{LE}$
 LI: $\hat{\beta}_1$ HI: $\hat{\beta}_1 + \hat{\beta}_3$

- Interpretation:
 - β_3 = mean change in female literacy rate's effect, comparing higher income to lower income levels
 - AKA: the change in slopes (for line between FLR and LE) comparing high income to low income
 - where the “female literacy rate effect” = change in mean life expectancy per percent increase in female literacy (slope) with income level held constant, i.e. “adjusted female literacy rate effect”
- In summary, the interaction term can be interpreted as “difference in adjusted female literacy rate effect comparing higher income to lower income levels”
- It will be helpful to test the interaction to round out this interpretation!!

Test interaction between binary categorical and continuous variables

- We run an F-test for a single coefficient (β_3) in the below model (see Lesson 10, MLR: Using the F-test)

$$LE = \beta_0 + \beta_1 FLR^c + \beta_2 I(\text{high income}) + \beta_3 FLR^c \cdot I(\text{high income}) + \epsilon$$

Null H_0

$$\beta_3 = 0$$

Alternative H_1

$$\beta_3 \neq 0 \quad \text{there is an interaction!}$$

Null / Smaller / Reduced model

$$LE = \beta_0 + \beta_1 FLR^c + \beta_2 I(\text{high income}) + \epsilon$$

no int

Alternative / Larger / Full model

$$LE = \beta_0 + \beta_1 FLR^c + \beta_2 I(\text{high income}) + \beta_3 FLR^c \cdot I(\text{high income}) + \epsilon$$

- I'm going to be skipping steps so please look back at Lesson 10 for full steps (required in HW 4)

↳ F-test

Test interaction between binary categorical and continuous variables

- Fit the reduced and full model

```
1 m_int_inc_red = lm(LifeExpectancyYrs ~ FLR_c + income_levels2,  
2                   data = gapm_sub)  
3 m_int_inc_full = lm(LifeExpectancyYrs ~ FLR_c + income_levels2 +  
4                     FLR_c*income_levels2, data = gapm_sub)
```

- Display the ANOVA table with F-statistic and p-value

term	df.residual	rss	df	sumsq	statistic	p.value
LifeExpectancyYrs ~ FLR_c + income_levels2	69.000	2,407.667	NA	NA	NA	NA
LifeExpectancyYrs ~ FLR_c + income_levels2 + FLR_c * income_levels2	68.000	2,340.948	1.000	66.719	1.938	0.168

- Conclusion: There is not a significant interaction between female literacy rate and income level ($p = 0.168$).
 - If significant, we say more: For higher income levels, for every one percent increase in female literacy rate, the mean life expectancy increases 0.384 years. For lower income levels, for every one percent increase in female literacy rate, the mean life expectancy increases 0.156 years. Thus, the female literacy rate almost doubles comparing high income to low income levels.

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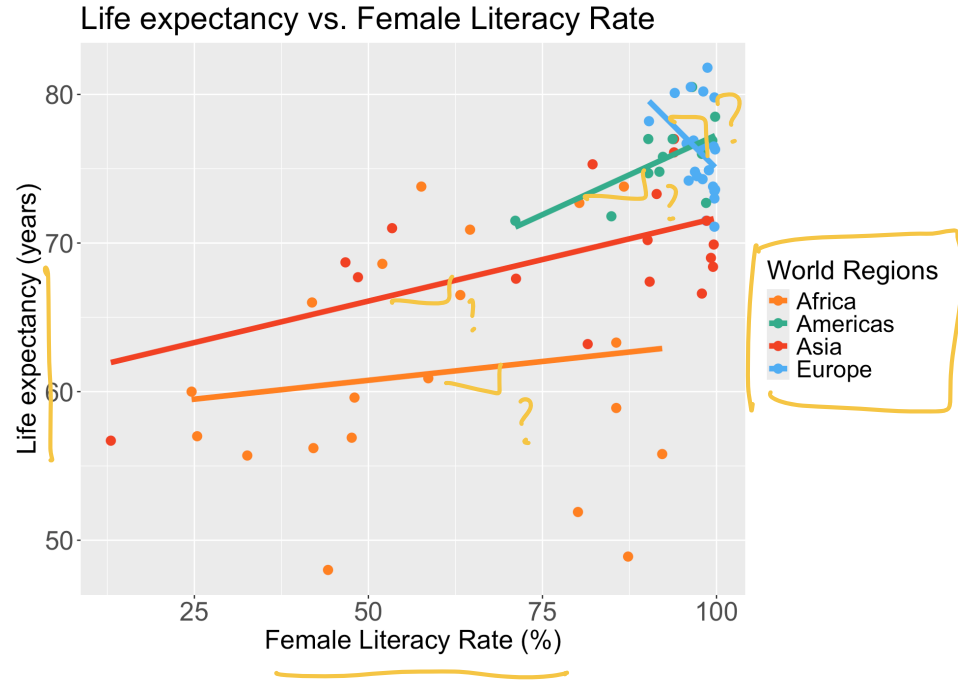
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Do we think world region is an effect modifier for female literacy rate?

- We can start by visualizing the relationship between life expectancy and female literacy rate *by world region*
- Questions of interest: Does the effect of female literacy rate on life expectancy differ depending on world region?
 - This is the same as: Is world region is an effect modifier for female literacy rate?
- Let's run an interaction model to see!



Model with interaction between a *multi-level categorical and continuous variables*

Model we are fitting:

$$LE = \beta_0 + \beta_1 FLR^c + \beta_2 I(\text{Americas}) + \beta_3 I(\text{Asia}) + \beta_4 I(\text{Europe}) + \beta_5 FLR^c \cdot I(\text{Americas}) + \beta_6 FLR^c \cdot I(\text{Asia}) + \beta_7 FLR^c \cdot I(\text{Europe}) + \epsilon$$

- LE as life expectancy
- FLR^c as centered female literacy rate (continuous variable)
- $I(\text{Americas})$, $I(\text{Asia})$, $I(\text{Europe})$ as the indicator for each world region

In R:

```
1 m_int_wr = gapm_sub %>% lm(formula = LifeExpectancyYrs ~ FLR_c + four_regions +  
2 FLR_c*four_regions)
```

OR

```
1 m_int_wr = gapm_sub %>% lm(formula = LifeExpectancyYrs ~ FLR_c * four_regions)
```

Displaying the regression table and writing fitted regression equation

```
1 tidy(m_int_wr, conf.int=T) %>% gt() %>% tab_options(table.font.size = 35) %>% fmt_n
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	62.906	2.050	30.680	0.000	58.810	67.002
FLR_c	0.051	0.053	0.957	0.342	-0.055	0.157
four_regionsAmericas	12.706	2.518	5.046	0.000	7.676	17.737
four_regionsAsia	7.910	2.477	3.193	0.002	2.962	12.859
four_regionsEurope	15.732	3.485	4.514	0.000	8.770	22.694
FLR_c:four_regionsAmericas	0.164	0.197	0.830	0.410	-0.231	0.558
FLR_c:four_regionsAsia	0.061	0.073	0.830	0.410	-0.086	0.208
FLR_c:four_regionsEurope	-0.519	0.476	-1.090	0.280	-1.471	0.432

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 I(\text{Americas}) + \hat{\beta}_3 I(\text{Asia}) + \hat{\beta}_4 I(\text{Europe}) + \\ \hat{\beta}_5 FLR \cdot I(\text{Americas}) + \hat{\beta}_6 FLR \cdot I(\text{Asia}) + \hat{\beta}_7 FLR \cdot I(\text{Europe})$$

$$\widehat{LE} = 62.906 + 0.051 \cdot FLR + 12.706 \cdot I(\text{Americas}) + 7.91 \cdot I(\text{Asia}) + 15.732 \cdot I(\text{Europe}) + \\ 0.164 \cdot FLR \cdot I(\text{Americas}) + 0.061 \cdot FLR \cdot I(\text{Asia}) - 0.519 \cdot FLR \cdot I(\text{Europe})$$

Comparing fitted regression lines for each world region

$$\begin{aligned}\widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 I(\text{Americas}) + \hat{\beta}_3 I(\text{Asia}) + \hat{\beta}_4 I(\text{Europe}) + \\ &\quad \hat{\beta}_5 FLR \cdot I(\text{Americas}) + \hat{\beta}_6 FLR \cdot I(\text{Asia}) + \hat{\beta}_7 FLR \cdot I(\text{Europe}) \\ \widehat{LE} &= 62.906 + 0.051 \cdot FLR + 12.706 \cdot I(\text{Americas}) + 7.91 \cdot I(\text{Asia}) + 15.732 \cdot I(\text{Europe}) + \\ &\quad 0.164 \cdot FLR \cdot I(\text{Americas}) + 0.061 \cdot FLR \cdot I(\text{Asia}) - 0.519 \cdot FLR \cdot I(\text{Europe})\end{aligned}$$

Africa

$$\begin{aligned}\widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR + \\ &\quad \hat{\beta}_2 \cdot 0 + \hat{\beta}_3 \cdot 0 + \\ &\quad \hat{\beta}_4 \cdot 0 + \hat{\beta}_5 FLR \cdot 0 + \\ &\quad \hat{\beta}_6 FLR \cdot 0 + \hat{\beta}_7 FLR \cdot 0 \\ \widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR\end{aligned}$$

The Americas $I(Am) = 1$

$$\begin{aligned}\widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR + \\ &\quad \hat{\beta}_2 \cdot 1 + \hat{\beta}_3 \cdot 0 + \\ &\quad \hat{\beta}_4 \cdot 0 + \hat{\beta}_5 FLR \cdot 1 + \\ &\quad \hat{\beta}_6 FLR \cdot 0 + \hat{\beta}_7 FLR \cdot 0 \\ \widehat{LE} &= (\hat{\beta}_0 + \hat{\beta}_2) + \\ &\quad (\hat{\beta}_1 + \hat{\beta}_5) FLR\end{aligned}$$

↪ slope

Asia

$$\begin{aligned}\widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR + \\ &\quad \hat{\beta}_2 \cdot 0 + \hat{\beta}_3 \cdot 1 + \\ &\quad \hat{\beta}_4 \cdot 0 + \hat{\beta}_5 FLR \cdot 0 + \\ &\quad \hat{\beta}_6 FLR \cdot 1 + \hat{\beta}_7 FLR \cdot 0 \\ \widehat{LE} &= (\hat{\beta}_0 + \hat{\beta}_3) + \\ &\quad (\hat{\beta}_1 + \hat{\beta}_6) FLR\end{aligned}$$

Europe

$$\begin{aligned}\widehat{LE} &= \hat{\beta}_0 + \hat{\beta}_1 FLR + \\ &\quad \hat{\beta}_2 \cdot 0 + \hat{\beta}_3 \cdot 0 + \\ &\quad \hat{\beta}_4 \cdot 1 + \hat{\beta}_5 FLR \cdot 0 + \\ &\quad \hat{\beta}_6 FLR \cdot 0 + \hat{\beta}_7 FLR \cdot 1 \\ \widehat{LE} &= (\hat{\beta}_0 + \hat{\beta}_4) + \\ &\quad (\hat{\beta}_1 + \hat{\beta}_7) FLR\end{aligned}$$

$\hat{\beta}_5$: diff in slope ↪ (FLR's effect)
comparing Americas to Africa

Interpretation for interaction between multi-level categorical and continuous variables

$$\widehat{LE} = \hat{\beta}_0 + \hat{\beta}_1 FLR + \hat{\beta}_2 I(\text{Americas}) + \hat{\beta}_3 I(\text{Asia}) + \hat{\beta}_4 I(\text{Europe}) + \hat{\beta}_5 FLR \cdot I(\text{Americas}) + \hat{\beta}_6 FLR \cdot I(\text{Asia}) + \hat{\beta}_7 FLR \cdot I(\text{Europe})$$

$$\widehat{LE} = \left[\hat{\beta}_0 + \hat{\beta}_2 I(\text{Americas}) + \hat{\beta}_3 I(\text{Asia}) + \hat{\beta}_4 I(\text{Europe}) \right] + \underbrace{\left[\hat{\beta}_1 + \hat{\beta}_5 \cdot I(\text{Americas}) + \hat{\beta}_6 \cdot I(\text{Asia}) + \hat{\beta}_7 \cdot I(\text{Europe}) \right]}_{\text{FLR's effect}} FLR$$

FLR's effect

changing slope of FLR, LE depending on WR

- Interpretation:

- β_5 = mean change in female literacy rate's effect, comparing countries in the Americas to countries in Africa
 - β_6 = mean change in female literacy rate's effect, comparing countries in Asia to countries in Africa
 - β_7 = mean change in female literacy rate's effect, comparing countries in Europe to countries in Africa

- It will be helpful to test the interaction to round out this interpretation!!

Test interaction between multi-level categorical & continuous variables

- We run an F-test for a group of coefficients ($\beta_5, \beta_6, \beta_7$) in the below model (see lesson 10)

$$LE = \beta_0 + \beta_1 FLR + \beta_2 I(\text{Americas}) + \beta_3 I(\text{Asia}) + \beta_4 I(\text{Europe}) + \beta_5 FLR \cdot I(\text{Americas}) + \beta_6 FLR \cdot I(\text{Asia}) + \beta_7 FLR \cdot I(\text{Europe}) + \epsilon$$

Null H_0

$$\beta_5 = \beta_6 = \beta_7 = 0$$

Alternative H_1

$$\beta_5 \neq 0 \text{ and/or } \beta_6 \neq 0 \text{ and/or } \beta_7 \neq 0$$

Null / Smaller / Reduced model

$$LE = \beta_0 + \beta_1 FLR + \beta_2 I(\text{Americas}) + \beta_3 I(\text{Asia}) + \beta_4 I(\text{Europe}) + \epsilon$$

Alternative / Larger / Full model

$$LE = \beta_0 + \beta_1 FLR + \beta_2 I(\text{Americas}) + \beta_3 I(\text{Asia}) + \beta_4 I(\text{Europe}) + \beta_5 FLR \cdot I(\text{Americas}) + \beta_6 FLR \cdot I(\text{Asia}) + \beta_7 FLR \cdot I(\text{Europe}) + \epsilon$$

↪ + interactions

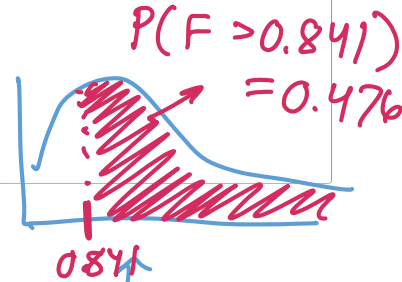
Test interaction between multi-level categorical & continuous variables

- Fit the reduced and full model

```
1 m_int_wr_red = lm(LifeExpectancyYrs ~ FLR_c + four_regions,  
2                   data = gapm_sub)  
3 m_int_wr_full = lm(LifeExpectancyYrs ~ FLR_c + four_regions +  
4                   FLR_c*four_regions, data = gapm_sub)
```

- Display the ANOVA table with F-statistic and p-value

term	df.residual	rss	df	sumsq	statistic	p.value
LifeExpectancyYrs ~ FLR_c + four_regions	67.000	1,705.881	NA	NA	NA	NA
LifeExpectancyYrs ~ FLR_c + four_regions + FLR_c * four_regions	64.000	1,641.151	3.000	64.731	0.841	0.476



- Conclusion: There is not a significant interaction between female literacy rate and world region ($p = 0.478$).
- World region is NOT an effect measure modifier of FLR on LE ($p = 0.467$)

